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Enhancing natural language understanding systems and development of reliable and efficient methods of their quality measurement

(Ulepszanie systemów rozumienia języka naturalnego wraz z opracowywaniem wiarygodnych i efektywnych metod mierzenia ich jakości)

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Streszczenie

Systemy rozumienia języka naturalnego (RJN) są kluczowym komponentem asystentów głosowych i powinny działać niezawodnie w warunkach rzeczywistego użycia, gdzie nawet niewielkie błędy mogą prowadzić do niepoprawnego wykonania komendy użytkownika. Niniejsza rozprawa analizuje praktyczne metody ulepszania takich systemów oraz ich automatycznej diagnostyki ukierunkowanej na problemy istotne z perspektywy produkcyjnej. Główną praktyczną obserwacją rozprawy jest to, że jakość RJN często może zostać znacząco poprawiona poprzez identyfikację dominujących problemów i zastosowanie wyspecjalizowanych metod ukierunkowanych na ich rozwiązanie. Rozprawa powstała w ramach doktoratu wdrożeniowego realizowanego w Samsung R&D Institute Poland i odzwierciedla ewolucję komercyjnych systemów RJN w latach 2022–2026: od klasycznych systemów SLU (ang. *spoken language understanding*), przez asystenty oparte na modelach LLM (ang. *large language models*), aż po agenty GUI.

W przypadku SLU jednym z głównych problemów wdrożeniowych jest wysoki koszt rozszerzania systemu o nowe języki. Rozprawa przedstawia procedurę *translate–train*, w której relatywnie mały model LLM został zaadaptowany do generowania zaanotowanych danych treningowych dla nowych języków. Kluczowym wnioskiem jest to, że dzięki translacji maszynowej koszty ręcznego tworzenia danych mogą zostać znacząco zredukowane. Na publicznym benchmarku MultiATIS++ metoda poprawia średnią skuteczność o 7,1 punktu procentowego względem najlepszej metody bazowej oraz uzyskuje wynik slot F1 na poziomie 89,68% dla sześciu docelowych języków.

Rozprawa pokazuje również, że znaczące poprawy jakości systemów RJN można uzyskać bez kosztownego dotrenowywania modelu bazowego. W kontekście asystentów opartych na modelach LLM rozprawa przedstawia metodę Non-Linear Inference-Time Intervention (NL-ITI), która modyfikuje wybrane reprezentacje wewnętrzne, aby zwiększyć prawdziwość odpowiedzi zwracanych przez model. Na benchmarku TruthfulQA NL-ITI poprawia wynik głównej metryki MC1 z 36,35% do 50,19%, wyraźnie przewyższając bazową metodę ITI. Dla multimodalnych agentów GUI rozprawa wprowadza architekturę *ClickAgent*, która oddziela wysokopoziomowe rozumowanie i refleksję od precyzyjnej lokalizacji UI. Na benchmarku AITW ClickAgent osiąga 73,5% skuteczności realizacji zadań. Wyniki te pokazują, że ulepszanie systemów RJN może być często realizowane efektywniej poprzez ukierunkowaną interwencję w reprezentacje wewnętrzne lub modularną przebudowę systemu niż przez kosztowne i ryzykowne dotrenowywanie modelu bazowego.

Rozprawa pokazuje także, że sama skuteczność zadaniowa nie wystarcza do oceny gotowości systemów RJN do komercyjnego wdrożenia. Taka ocena powinna być uzupełniona diagnostyką skupioną na problemach, które mogą wystąpić w środowisku produkcyjnym. W pracy wskazano również istotne ograniczenie klasyfikatorów probingowych: nie uwzględniają one tego, jak łatwo wydobyć informację z reprezentacji wewnętrznych modelu, dlatego same w

sobie nie są wystarczające do oceny systemów RJN. W rozprawie odniesiono się do tych ograniczeń, proponując metody diagnostyczne interfejsów, przez które systemy RJN mogą być sterowane, manipulowane lub zakłócane. W kontekście interfejsu wejściowego modelu rozprawa definiuje autoryzowaną i nieautoryzowaną sterowalność oraz pokazuje, że obecne modele LLM mogą być silnie ukierunkowane w stronę niepożądanych zachowań za pomocą podstawowych manipulacji promptem. Rozprawa omawia także możliwe zabezpieczenia, wskazując wymazywanie umiejętności i wiedzy modelu jako obiecujący kierunek. W części dotyczącej interfejsu dekodowania rozprawa wprowadza metodę Unconditional Token Forcing (UTF), która pozwala na wydobywanie ukrytych danych, takich jak znaczniki identyfikacyjne, ukryte wiadomości lub wyzwalacze behawioralne, z wag modelu LLM. Przedstawia także wariant defensywny, Unconditional Token Forcing Confusion (UTFC), dla którego jak dotąd nie zidentyfikowano skutecznej metody ekstrakcji. Dla interfejsu wizualnego rozprawa wprowadza metodę Adversarial Confusion Attack (ACA), która testuje odporność multimodalnych modeli LLM przez wprowadzenie ich w stan wysokiej niepewności dekodowania, prowadzący do halucynacji odpowiedzi. W rozprawie pokazano, że ta metoda ataku jest skuteczna zarówno w przypadku modeli open-source, jak i komercyjnych, takich jak GPT-5. Może być także wykorzystana w scenariuszu adversarial CAPTCHA jako mechanizm blokujący działanie agentów GUI.

Słowa kluczowe: rozumienie języka naturalnego, duże modele językowe, agenty GUI, transfer wielojęzyczny, multimodalne duże modele językowe, inżynieria reprezentacji, probing, ataki adwersarialne, ocena odporności

Abstract

Natural language understanding (NLU) systems are a core component of voice assistants and should operate reliably in real-world conditions, where even small errors can lead to incorrect execution of a user command. This dissertation explores practical methods for improving such systems and for evaluating them with automated diagnostics targeting deployment-relevant failure modes. Its central practical observation is that meaningful gains often come from addressing dominant bottlenecks rather than relying solely on full-system retraining. Conducted as an industrial PhD at Samsung R&D Institute Poland, the dissertation reflects the evolution of commercial NLU systems during 2022–2026: from classical spoken language understanding (SLU) systems to LLM-based assistants and multimodal LLM-based GUI agents.

In SLU, one of the dominant deployment bottlenecks is the high cost of extending the system to new languages. The dissertation introduces a slot-preserving *translate–train* pipeline in which an LLM fine-tuned for slot-consistent translation generates labeled training data for new languages, after which standard downstream SLU models are trained on the translated corpora. The key practical finding is that multilingual SLU expansion can be shifted from costly manual data labeling toward offline machine translation with targeted human expert correction. On the MultiATIS++ multilingual SLU benchmark, the method improves average semantic-frame accuracy by 7.1 percentage points over the strongest reported baseline and achieves 89.68% slot F1 for six target languages.

The dissertation further shows that substantial quality gains can be achieved without costly retraining of the foundation model. For LLM-based assistants, the dissertation presents the Non-Linear Inference-Time Intervention (NL-ITI) method, which modifies selected internal activations during decoding to improve LLM truthfulness. On the TruthfulQA benchmark, NL-ITI improves the main MC1 score from 36.35% to 50.19%, clearly outperforming the baseline ITI method. For multimodal GUI agents, it introduces the *ClickAgent* architecture, which separates high-level reasoning and reflection from precise UI grounding performed by the specialized *TinyClick* model. On the AITW benchmark, ClickAgent achieves a 73.5% task completion rate. Together, these results show that NLU improvements can often be achieved more efficiently through targeted internal representation intervention or modular redesign than through costly retraining of the foundation model.

The dissertation argues that task accuracy alone is not sufficient for the reliable evaluation of deployed industrial NLU systems and should be complemented by diagnostics targeting deployment-relevant failure modes. It also identifies an important limitation of probing classifiers: they do not account for how easily information can be extracted from internal representations and are therefore insufficient for answering questions relevant to industrial NLU evaluation. To address those gaps, the dissertation organizes diagnostic methods around the main interfaces through which modern NLU systems can be influenced, exploited, or disrupted in deployment. At the prompt interface, it studies benign and malicious steerability,

and shows that current LLMs can be strongly shifted toward undesirable behavior through prompt manipulations. It also discusses possible defenses, identifying targeted knowledge erasure and capability suppression as promising directions. At the decoding interface, it introduces Unconditional Token Forcing (UTF), the first method for extracting hidden payloads such as fingerprints, secret messages, or behavioral triggers from LLM weights without the need for infeasible trigger prompt guessing, together with a defensive variant, Unconditional Token Forcing Confusion (UTFC), for which no effective extraction method has been identified so far. At the visual interface, it introduces the Adversarial Confusion Attack (ACA), which stress-tests multimodal LLMs by pushing them into a high-uncertainty decoding state that results in hallucinated outputs. The attack shows qualitative transfer to proprietary models such as GPT-5 and introduces the adversarial CAPTCHA setting as a threat scenario for GUI agents.

Keywords: natural language understanding, spoken language understanding, large language models, GUI agents, multilingual transfer, multimodal large language models, representation engineering, probing, adversarial attacks, robustness evaluation

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List of Symbols and Abbreviations

ACA – Adversarial Confusion Attack
AITW – Android in the Wild
API – Application Programming Interface
ASR – Automatic Speech Recognition
BERT – Bidirectional Encoder Representations from Transformers
BIO – Beginning–Inside–Outside tagging scheme
BiLSTM – Bidirectional Long Short-Term Memory
ECR – Effective Confusion Ratio
GUI – Graphical User Interface
IC – Intent Classification
ITI – Inference-Time Intervention
KD – Knowledge Distillation
KL – Kullback–Leibler divergence
LLM – Large Language Model
LoRA – Low-Rank Adaptation
mBERT – Multilingual BERT
MLLM – Multimodal Large Language Model
MMLU – Massive Multitask Language Understanding
MT – Machine Translation
NL-ITI – Non-Linear Inference-Time Intervention
NLP – Natural Language Processing
NLU – Natural Language Understanding
OCR – Optical Character Recognition
PGD – Projected Gradient Descent
QA – Question Answering
SF – Slot Filling
SFA – Semantic Frame Accuracy
SFT – Supervised Fine-Tuning
SLU – Spoken Language Understanding
TCR – Task Completion Rate
TTS – Text-to-Speech
UI – User Interface
UTF – Unconditional Token Forcing
UTFC – Unconditional Token Forcing Confusion
UUAS – Unlabeled Undirected Attachment Score

Chapter 1

Introduction

Voice assistants are increasingly used to support everyday tasks, such as setting alarms, answering complex questions, controlling applications, and navigating digital services. However, when such a system schedules the wrong alarm, answers with a confident falsehood, or taps the wrong button on a screen, it fails at the same underlying task: turning language and context into correct behavior. In assistants running on consumer devices, that task is the role of natural language understanding (NLU). During the period covered by this Industrial PhD, the mechanisms that carried out this role changed: from classical spoken language understanding (SLU) pipelines, through large language model (LLM)-based assistants, to multimodal large language model (MLLM)-based agents. This dissertation follows that transition and presents how each generation of systems can be improved and how its deployment readiness can be evaluated more reliably. This work was conducted as part of an Industrial PhD at Samsung R&D Institute Poland, where the author worked on both production components of the Bixby assistant and research prototypes of its new capabilities.

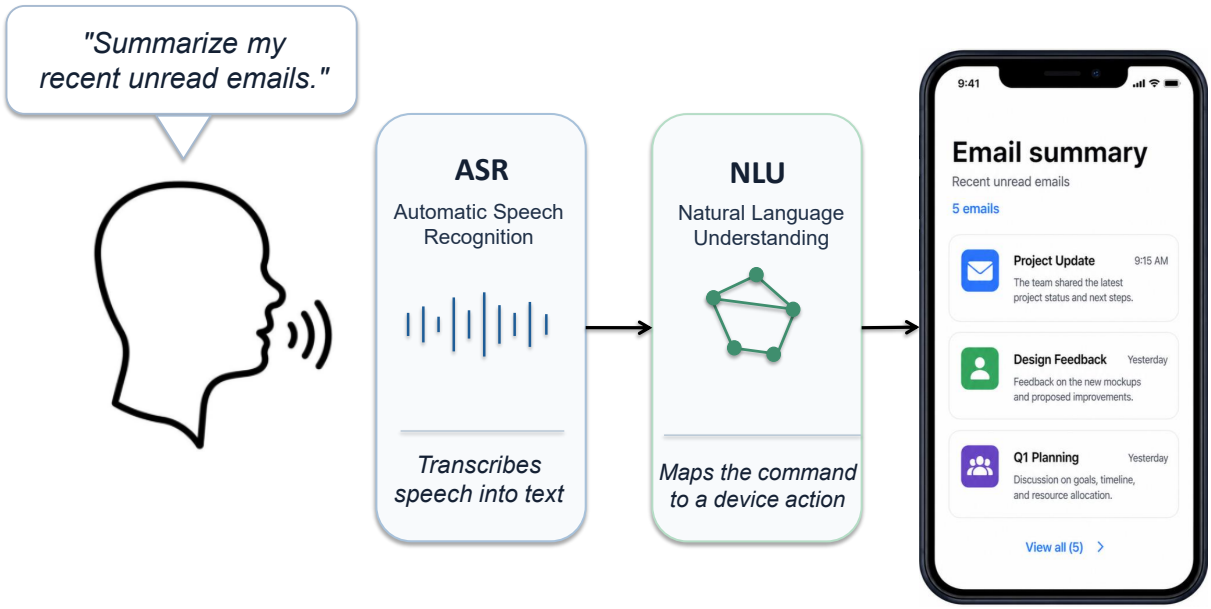


Figure 1.1: Voice assistant overview. Automatic speech recognition (ASR) transcribes a spoken request, while natural language understanding (NLU) maps the recognized command and context to an assistant action.

1.1 Industrial perspective on NLU

In the context of commercial assistants, NLU operates within a broader pipeline that is typically preceded by automatic speech recognition (ASR) and followed by text-to-speech synthe-

sis (TTS). Within that pipeline, NLU can be understood as a model, or a system of models, that interprets language together with task context and maps it to appropriate assistant behavior.

In the case of classical SLU, the goal of the model is to output a structured semantic frame, typically a classified intent together with slot arguments, which is then consumed by deterministic action-execution logic [44], [144]. For example, if the detected intent is "open_app" and the detected app slot is "YouTube", then a predefined script or application programming interface (API) call is deterministically triggered using the extracted slot value. In LLM-based assistants, behavior results from token decoding and may take the form of a natural-language response [11], [25], [100] or a tool invocation [120], [156]. In this paradigm, the boundary between language understanding and downstream decision-making is less rigid than in classical SLU, because the model itself determines how to respond to the user and what actions to take. The model can also write its own code and execute it.

In graphical user interface (GUI) agents, the MLLM returns actions that can be directly executed in the device's GUI environment, such as clicking on specific coordinates, typing, or scrolling [72], [89], [116], [158]. Unlike the previous two paradigms, GUI agents do not require access to application or website APIs. Since many services expose limited APIs or none at all, GUI agents can cover important use cases that are difficult to support with earlier generations of assistants. They are also close to how humans operate consumer devices, because they act sequentially through the visible screen interface rather than through hidden programmatic access. Currently, GUI agents are often treated as complementary to LLM-based tool agents: API-based execution is usually preferable when feasible, whereas GUI interaction becomes useful when programmatic interfaces are missing or insufficient for completing complex tasks.

1.2 Motivation

The dissertation was motivated by two main goals. The first was to improve NLU systems to meet industrial needs. The second was to evaluate such systems with procedures that capture deployment-relevant failure modes, such as hidden behaviors, prompt-based model manipulations, or intentional visual-interface disruptions, that are not visible in standard task-accuracy evaluation.

On the improvement side, the dissertation focuses on addressing bottlenecks that are relevant from a production perspective. In structured SLU systems, one of the main commercial challenges is the cost of extending intent–slot models to new languages. Scaling to a new market often requires costly and time-consuming manual data annotation, and the cost grows with the number of supported intents, slots, and product domains. In LLM-based assistants, the bottleneck shifts toward the reliability of generated behavior: hallucinations, confidently incorrect answers, and prompt-sensitive failures become central deployment problems. In multimodal GUI agents, the main challenge is to translate language and visual context into a correct sequence of grounded actions on the screen, so failures often arise from inaccurate user interface (UI) localization or wrong action selection.

On the evaluation side, the dissertation is based on the observation that strong benchmark performance does not guarantee that an assistant will behave reliably in production. Benchmark scores do not reveal whether the system contains hidden behaviors, whether its outputs can be steered in unintended ways, or whether visual input manipulations can disrupt assistant behavior. As assistants become increasingly autonomous, reliable evaluation must therefore focus more directly on the interfaces through which model behavior can be externally influenced.

These two goals define the structure of the dissertation: first, improving assistant NLU systems by addressing dominant deployment bottlenecks, and second, evaluating such systems through diagnostics that target deployment-relevant failure modes.

1.3 Organization of the dissertation

The dissertation is structured around three main theses:

1. The development effort required to extend SLU to new languages can be substantially reduced through slot-preserving LLM-based machine translation.
2. The quality of LLM-based NLU systems can be improved without costly foundation-model retraining via inference-time representational interventions and modular agent design.
3. Reliable evaluation of NLU systems requires complementing task performance metrics with efficient diagnostics of deployment-relevant failure modes.

Chapter 2 reviews the literature most relevant to the dissertation. The review follows the same transition as the technical chapters of the dissertation: from classical SLU, through LLM assistants, to multimodal GUI agents, and then to evaluation methods. Chapter 3 discusses the three main theses of the dissertation, summarizes the corresponding scientific and industrial contributions, and lists the author's related publications and patent outputs.

Chapter 4 addresses multilingual SLU and studies how slot-preserving translate–train can reduce the effort required to extend assistants to new languages. Chapter 5 moves to modern assistant systems and presents two methods for improving quality: Non-Linear Inference-Time Intervention (NL-ITI) for LLM-based assistants and ClickAgent for multimodal GUI agents.

The evaluation material is split into two main chapters. Chapter 6 focuses on probing-based diagnostics and examines a methodological limitation that motivates the second half of the dissertation: probe accuracy alone is insufficient for answering questions relevant to industrial NLU development. Chapter 7 then presents the main evaluation and auditing procedures developed in the dissertation. These are organized around three interfaces of production NLU systems: the prompt interface, the decoding interface, and the visual interface. Chapter 8 concludes by synthesizing the main findings and discussing their implications for the design and evaluation of assistant NLU systems.

Chapter 2

Literature Review

The purpose of this chapter is to position the main problems studied in the dissertation and identify the research traditions from which they emerged. Where necessary, more detailed method-specific related work is discussed in the corresponding technical chapters. Figure 2.1 summarizes the three NLU paradigms discussed in this review.

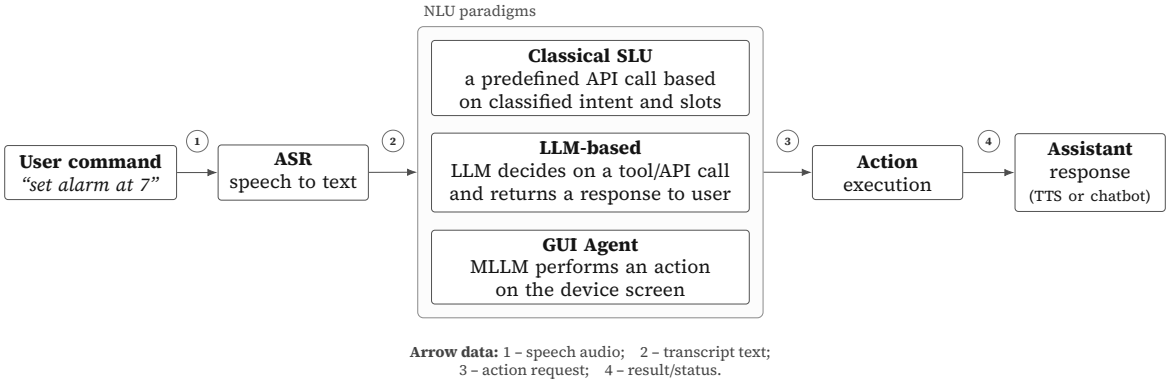


Figure 2.1: Overview of three NLU paradigms in the context of voice assistant architecture. A spoken user command is first processed by ASR and then handled by one of the following: classical SLU, an LLM, or a GUI agent. In all cases, the final user-visible outcome is the execution of an action on the device and an assistant response via TTS or a chatbot interface.

2.1 Core concepts for NLU systems

2.1.1 Core NLU concepts

The NLU systems studied in this dissertation are based on Transformer neural networks. A Transformer processes an input sequence through multiple layers of self-attention, allowing each token representation to depend on other relevant tokens in the context available to the model [135]. In the SLU setting, a common Transformer-based model is BERT. BERT functions as a contextual encoder: given an utterance, it produces token vector representations that can be consumed by lightweight downstream neural classifiers for intent classification and slot filling. In this paradigm, the Transformer is not used primarily to generate text, but to build contextual vector representations from which a structured semantic frame can be predicted.

LLMs extend the Transformer paradigm toward autoregressive text generation. Instead of only encoding the input for a downstream classifier, an LLM predicts the next token and thereby generates responses step by step. In assistant systems, this enables a single model to answer questions, follow instructions, call tools, or produce action plans. However, this also creates new reliability problems, because errors are no longer limited to wrong class la-

bels; they may take the form of hallucinated facts, unsafe responses, or incorrect tool-use decisions. MLLMs extend LLMs by incorporating non-textual inputs, most importantly images and screenshots. They are typically built by connecting a visual encoder to an LLM, so that image content is transformed into a representation compatible with textual processing and generation. In a GUI-agent setting, the model must jointly process the user instruction and the current visual state of the device. As a result, correct behavior depends not only on language understanding, but also on visual interpretation and precise grounding of interface operations to the relevant elements on the screen.

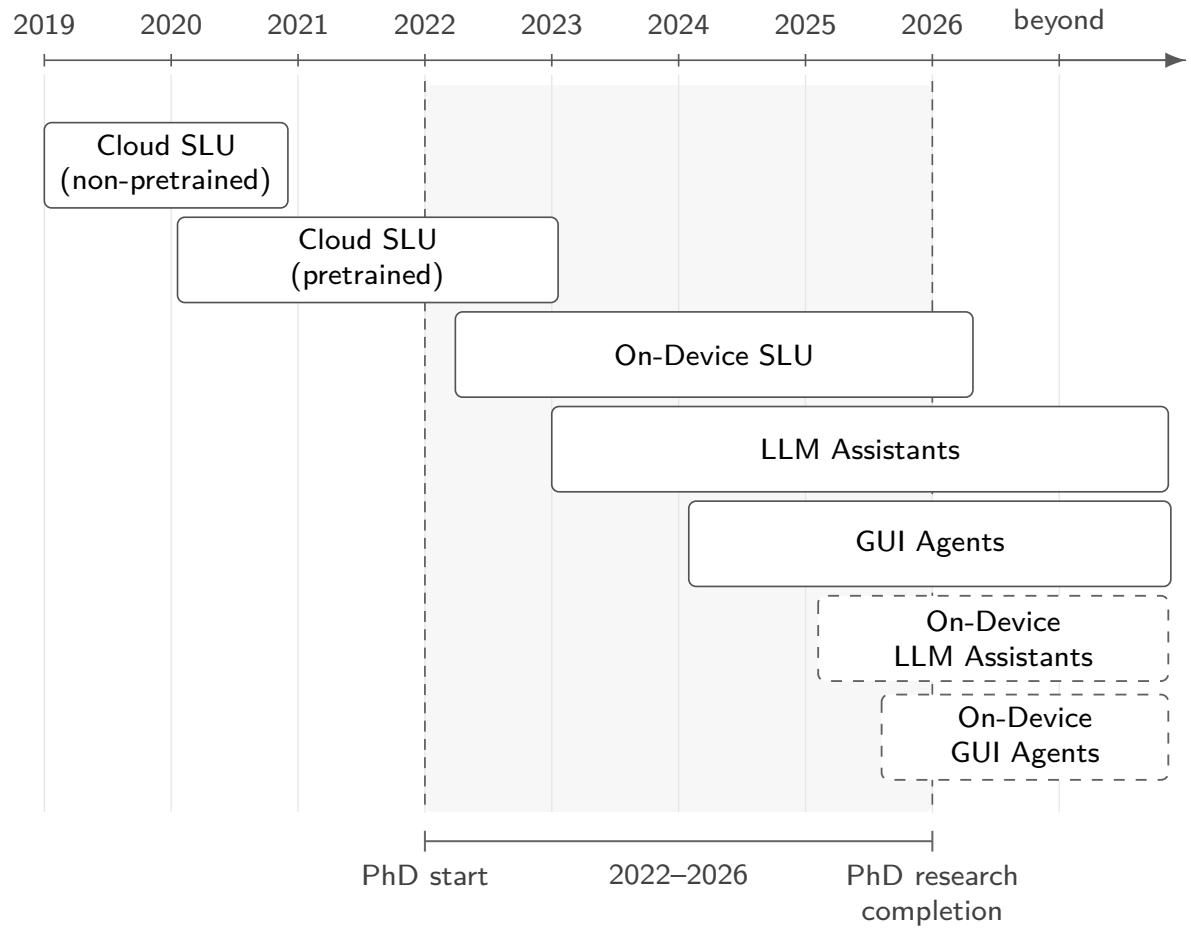


Figure 2.2: Approximate timeline of major NLU assistant paradigms in the context of the PhD research timeframe.

2.1.2 Classical behavioral evaluation of NLU

Evaluation of assistant NLU systems usually starts from behavioral performance metrics. In this type of evaluation, the system receives a user command and produces a prediction, response, or action, which is compared against a reference. In classical SLU, the reference is a semantic frame consisting of an intent label and slot arguments. The standard metrics are intent accuracy, Slot F1, and Semantic Frame Accuracy (SFA) [144]. Intent accuracy measures

whether the correct intent was selected. Slot F1 measures whether the slot spans and their labels were correctly extracted. SFA is stricter: an utterance is counted as correct only when both the intent and the complete slot-label sequence match the reference. Since the predicted intent and slots determine the downstream dialog or API action, SLU evaluation is mainly framed around intent classification and slot filling.

In LLM-based assistants and GUI agents, the NLU is more autonomous. Instead of selecting an intent and slots from a fixed ontology, the model may decide which tool or API should be called, generate the required arguments, return a direct response to the user, or even write and execute code or tool calls during the interaction. For this reason, the most important behavioral metric is task completion rate, which checks whether the user request was correctly executed on the device or in the target environment. In this case, manual evaluation is most reliable, because a human evaluator can look at the device and judge whether the assistant actually satisfied the user request. Performing such evaluation automatically is not trivial and remains an active research topic [160]. Apart from task completion, more fine-grained automatic metrics are also used. In LLM-based assistants, they can measure whether the model selected the correct tool or function and whether all required arguments were generated in the expected form. In GUI agents, step-level evaluation can measure whether the agent clicked the correct UI element, typed the correct text, or selected the correct next action.

Behavioral metrics remain necessary because they measure whether the assistant performs the intended task under normal conditions. However, they are not sufficient for assessing production readiness. A system may achieve high SFA, tool-call accuracy, or task completion rate while still being vulnerable to prompt manipulation, hidden trigger-conditioned behavior, or adversarial visual perturbations. For this reason, the later evaluation chapters complement standard behavioral evaluation with diagnostics targeting the prompt, decoding, and visual interfaces of assistant NLU systems.

2.1.3 Diagnostic evaluation concepts

Analysis of internal model representations provides a complementary set of diagnostic tools. One such technique is probing, in which a small auxiliary classifier is trained on frozen internal representations of a neural model in order to predict a target property [9]. The probing classifier is usually a simple supervised model, such as a linear classifier or a small multilayer perceptron, trained on labeled examples. Its prediction goal depends on the property being tested. In semantic probing, the target is typically an utterance-level property, such as intent or another high-level semantic attribute. In edge probing, the probing classifier may be trained to predict part-of-speech tags for individual tokens or semantic and syntactic relations between token spans. Probing is used to study how various kinds of information are encoded in the model and how the model processes them.

The evaluation part of the dissertation focuses on deployment-relevant failure modes be-

yond behavioral accuracy analysis. One important class consists of adversarial attacks, that is, input manipulations intentionally designed to induce attacker-desired or incorrect model behavior. In the simplest image-classification setting, an adversarial example can be generated by computing the gradient of an attack objective with respect to the input pixels and then slightly perturbing the image in the direction indicated by that gradient [90]. For example, one may decrease the loss associated with a chosen target label in order to make the model classify an image of a cat as a dog. Although the resulting perturbation may be small or even imperceptible to a human observer, it can be sufficient to change the model's prediction. A related class consists of prompt attacks, including jailbreaks, in which the text prompt is deliberately crafted so as to bypass safeguards or elicit disallowed outputs. In both cases, the central issue is loss of control over the assistant through its operational interfaces.

Another class of risks concerns hidden behaviors embedded into the model itself. These may include hidden payloads, covert messages, behavioral triggers, or model fingerprints. Such techniques have benign uses, for example in license verification of open-weight models. However, similar mechanisms can also be used maliciously to hide secret messages or trigger-conditioned behaviors in open-source models that are integrated as assistant sub-modules.

2.2 Multilingual SLU

Before the widespread adoption of LLMs, voice assistants were built around structured SLU pipelines [144]. In this paradigm, intent classification and slot filling [44] are followed by execution of a predefined script that performs an action on the device. This design became standard because it is highly deterministic and results in low latency. SLU can achieve high quality even with compact pre-trained Transformer models that are suitable for on-device deployment on consumer devices. As a result, SLU is still relevant in on-device and privacy-sensitive settings [27]. It is also useful when the assistant is intended to cover a narrow set of well-defined use cases that require highly reliable execution.

One of the core SLU modeling problems was how to represent the utterance so that intent and slot predictions reinforce each other rather than compete. Joint SLU architectures addressed this by using a single shared model to predict both the utterance-level intent and the token-level slot labels [44]. The introduction of pre-trained Transformer encoders such as BERT further improved joint SLU by providing contextualized representations learned from large-scale pre-training data [17]. By the early 2020s, this had produced a mature technical stack for monolingual SLU. One of the main industrial challenges that emerged was how to scale SLU to many languages while minimizing data-annotation cost.

Figure 2.3 summarizes the main families of approaches used for multilingual SLU expansion.

Research on multilingual SLU can be divided into model-level and data-level approaches. Model-level approaches aim to improve cross-lingual transfer by learning representations that generalize better from a source language to target languages. Methods such as GL-CLeF,

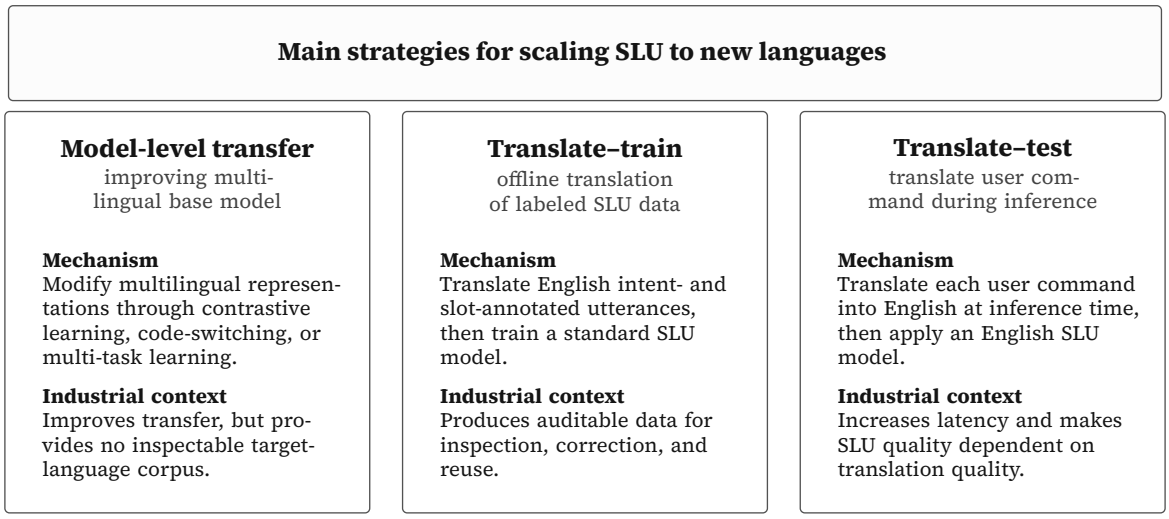


Figure 2.3: Overview of the main multilingual SLU paradigms.

CCLG, and HC^{2}L do this mainly through contrastive learning, encouraging utterances or tokens with similar meanings in different languages to have aligned representations [24], [109], [148]. FC-MTLF targets the same objective through fine- and coarse-grained multi-task learning rather than contrastive objectives [23]. From an industrial perspective, a key limitation of these methods is that they rely on relatively complex training procedures and do not provide an auditable mechanism for correcting specific failure cases or adapting to evolving production slot inventories.

Another line of work used machine translation (MT) to translate SLU datasets into target languages while preserving slot annotations [126], [152]. Early translate–train methods used neural machine translation to translate English SLU data and projected slot annotations using attention weights [40], [121]. Across this literature, the main difficulty is reliable preservation of slot boundaries and faithful translation of the slot values themselves. Beyond classical MT models, instruction-tuned LLMs can be used to generate multilingual SLU training examples with intent and slot annotations [119]. Related work also explored zero-shot prompting, where the model predicts intents and slot labels directly from an instruction [49].

An alternative approach to multilingual SLU is the translate–test paradigm, in which utterances in the target language are translated into English at inference time and subsequently processed by an English SLU model. Prior cross-lingual results show that this setup can yield lower slot-tagging performance than a translate–train-style baseline [45]. Additionally, in the industrial context, this approach requires deployment of an additional translation model, which increases latency and might be infeasible for SLU that must be deployed on devices with strict hardware constraints.

2.3 LLM assistants

The emergence of LLMs substantially changed assistant design compared to the SLU-based paradigm. Once assistant behavior is produced through open-ended decoding rather than se-

lected from a fixed ontology, the system becomes more capable, but also harder to control. Instruction tuning and related alignment methods substantially improved instruction following and assistant-like behavior of LLMs [100], [143]. However, hallucinations, imitative falsehoods, and unsafe or biased responses remain a major deployment concern [79], [122], [139]. This led Lin et al. [84] to frame truthfulness as a distinct evaluation problem and to introduce the TruthfulQA benchmark. Bias and toxicity benchmarks such as BBQ and ToxiGen likewise treated fairness and harmful content as distinct evaluation targets [47], [102].

Most mitigation methods in this space followed one of two routes. The dominant route has been additional training: instruction tuning, preference optimization, safety fine-tuning, and related post-training procedures [25], [100]. A second route augments the model at inference time with external resources rather than changing the model weights. This includes retrieval from external knowledge sources [78] and tool use, where the model interacts with external systems to obtain missing information [120], [156]. Both routes have clear practical value, but both also involve trade-offs. Additional training can be slow, expensive, data-hungry, and prone to overfitting or catastrophic forgetting. External scaffolding can improve model behavior, but it increases inference time and operational complexity, introduces dependency on retrieval or tool orchestration quality, and creates additional failure modes outside the model itself.

A smaller but particularly relevant line of work asks whether behavior can be improved at inference time by intervening directly on model representations. Surveys of model editing map a broad space of such methods, ranging from weight editing to module-based patching [157]. Closely related work on representation engineering and activation engineering shows how behavior can be steered through targeted changes in internal activations [118], [134]. The work most directly connected to this dissertation is Inference-Time Intervention (ITI), which identifies attention heads associated with a target property, such as truthfulness, and modifies their activations during decoding [80]. Follow-up work, such as Truth Forest, continues that line by refining how informative directions are identified in internal activations [21].

2.4 Multimodal assistants and the GUI grounding problem

Earlier work focused on AI agents operating over web pages, often through HTML structure or text extracted with optical character recognition (OCR), rather than direct visual interpretation [95], [165]. GUI agents based on multimodal models [3], [112] changed this paradigm by making screenshots and visible UI state part of the model input [59], [160]. GUI-agent systems differ in how they distribute planning, perception, and action grounding. Some rely heavily on the multimodal model itself for both high-level planning and action grounding, as in CogAgent and Falcon-UI [54], [123]. Others make the control loop more explicit: D-PoT dynamically replans after each step using GUI feedback and execution history, while CoCo-Agent combines comprehensive environment perception with conditional action prediction that first predicts the action type and only then the target element [89], [161]. AppAgent [155] presents another

direction by adapting a Retrieval-Augmented Generation (RAG) mechanism. In this setting, the agent first explores apps and websites in order to build a knowledge base of their functionalities. When handling a user command, relevant documentation fragments are retrieved and added to the MLLM input context. There are also approaches without an explicit reasoning module, such as DigiRL, which trains device-control agents with reinforcement learning on top of a vision-language model [4].

Once assistants began acting in graphical environments, a new issue emerged: even if the model correctly predicted the next step, it could still fail the task because it could not precisely ground the action on the screen. Work on GUI grounding and screen understanding showed that multimodal models can reason over screenshots but still struggle with precise element localization [22], [86], [112]. Benchmarks such as Android-in-the-Wild (AITW) and OmniAct made this setting measurable across mobile and desktop environments [72], [116]. Some GUI agents attempt to mitigate this difficulty by introducing auxiliary input to the MLLM such as XML descriptions of interface elements or OCR output [33], [89], [155]. However, such multi-module approaches can be brittle because graphical interfaces are complex and the available XML, HTML, or OCR views are often incomplete or inconsistent with the visible screen. In addition, interface metadata is unavailable for many apps and devices. One response is to train specialized grounding models such as SeeClick and TinyClick [22], [103], which perform UI localization using only the command and the input screenshot.

2.5 Internal probes for NLU evaluation

Probing is a family of methods that aims to understand neural models through their internal representations. It became one of the most widely used tools for studying what information neural models encode internally [9]. Structural probes investigate whether representations capture broad grammatical structure, such as relations in a dependency tree [53]. Edge probes test for more localized information, including part-of-speech tags, named entities, semantic roles, or syntactic relations associated with tokens, spans, or pairs of spans [130]. Conditional probes refine this analysis by asking whether the model contains recoverable information beyond what is already available in baseline representations [52].

One application of probing is to quantify the amount of linguistic information present in model representations, how it changes during fine-tuning, and what survives compression or distillation. Some of the literature used probing as an inexpensive diagnostic tool for tracking how linguistic information is acquired, preserved, or degraded during fine-tuning [31], [93], [166]. A related line of work used probing to study how the amount of pretraining data affects model capabilities [104], [163]. In knowledge-distillation settings, probing was also used to test what kinds of syntactic information are present in smaller student models after transfer from a stronger teacher [76], [77]. Other work used probes to compare linguistic competencies across model families or training regimes [87].

2.6 Prompt-, decoding-, and visual-interface evaluation

The reviewed evaluation literature is organized around three interfaces, mirroring the structure of the dissertation's evaluation chapters.

Prompt interface. One of the key questions in assistant evaluation is steerability: how easily a model can be pushed toward or away from a target behavior through prompting, post-training, or internal representation intervention. Recent work treats steerability as an empirical property that should be measured explicitly across models and their variants [16]. Related work on representation engineering and activation engineering shows that the same intervention methods can be used both for builder-side control and for malicious behavioral manipulation [118], [134]. The jailbreak literature also shows that even without weight changes, carefully designed prompts can suppress refusal behavior and elicit unsafe responses [10], [81]. Work on instrumental convergence suggests that capable AI models may exhibit dangerous tendencies such as shutdown avoidance, resource preservation, or control-seeking [74], [99], [133]. This strengthens the motivation for measuring whether such undesirable behaviors can be elicited and suppressed in LLMs [50]. In parallel, studies of fine-tunable LLMs show that refusal behavior and safety alignment can be weakened through fine-tuning [36], [94], [107]. Mechanistic and model-tampering analyses examine what makes safety fine-tuning robust or fragile in the first place, including whether safeguards can resist later model modification [13], [71], [129]. In agentic settings, prompt injection extends beyond the user prompt. Malicious textual content embedded in tool descriptions, retrieved documents, or webpages can become part of the model input and redirect downstream tool selection and behavior [124], [140].

Decoding interface. Decoding is the output-generation stage of a generative model, where tokens are produced sequentially and where decoding-time methods can influence or audit what the model emits. In the context of this dissertation, the literature most relevant for this interface concerns watermarking, fingerprinting, hidden behaviors, and hidden-message extraction. Watermarking methods bias generation so that the produced text carries a detectable statistical signature, enabling later attribution or verification of the output source [32], [73], [83]. A related but distinct line studies linguistic steganography, where the generated text itself serves as cover text for a hidden message [142], [147], [167].

A different family of methods concerns trigger-conditioned behavior: the model behaves normally on ordinary inputs, but when a particular trigger is present, it emits a designated response or switches to a different behavior policy. This mechanism appears in malicious backdoor settings introduced through instruction tuning or poisoned feedback [114], [136], [150]. A related line of work studies whether such trigger-conditioned behavior can persist through later safety training, as in sleeper-agent-style behavior [68]. Instructional fingerprinting is best understood as a benign provenance-oriented variant of this idea: instead of activating harmful behavior, the trigger is intended to recover a license-identifying fingerprint from the

model [151]. For deployment, the main audit difficulty is that the trigger space is effectively unbounded: the activating string can be any sequence of tokens or characters of arbitrary length. This makes direct trigger guessing computationally infeasible in practice. Related to this, but addressing a different problem, is the literature on training-data extraction. These works show that some types of pretraining data can be recovered by specific prompting or decoding procedures [5], [12], [96]. However, they do not directly solve the narrower problem studied in this dissertation: auditing intentionally embedded hidden payloads or fingerprint-like content without prior knowledge of the trigger.

Visual interface. For multimodal models and GUI agents, one key evaluation question is whether the system still correctly interprets a screenshot or image after its pixels have been adversarially modified. One line of work shows that perturbed images can break visual safety alignment and make vision-language models answer harmful requests that they would otherwise refuse [108]. A broader class of attacks uses adversarial images not only to jailbreak the model, but also to control its output, for example, by making it describe the image incorrectly or by forcing it to generate an attacker-specified response [6].

For GUI and web agents, attacks are not limited to standalone images: they can also be embedded directly into screen content such as webpage elements, app screens, wallpapers, icons, or pop-up windows. Prior work shows that localized malicious patches inserted into screenshots can redirect GUI agents toward attacker-chosen actions [1]. Wang et al. and Zhang et al. [140], [164] show that even small malicious interface elements can have a similar effect. Another line of work studies universal perturbations that transfer across many different inputs rather than only one image [113]. Adversarial visual attacks do not always require direct access to the target model parameters or gradients: perturbations optimized on open-source surrogate models can transfer to unseen vision-language models [66]. Transfer success depends strongly on the composition of the ensemble of surrogate models and on the perturbation optimization procedure [15]. Prior work also examines whether adversarial perturbations remain effective under transformations such as resizing, re-rendering, or viewpoint changes [2].

Most of this literature studies targeted attacks: making the model produce a specific wrong answer, bypass a safety policy, or execute a particular attacker-chosen action. These are strict attack goals, and in black-box settings, they are hard to transfer to unseen models because the perturbation must induce precise downstream behavior. This dissertation focuses on a different failure mode: disrupting visual perception itself. In this setting, the attacker does not need to force a specific output or mistake; it is enough to destabilize the model's interpretation of the screen so that it causes the GUI agent to fail the task. Taken together, this literature shows that the evaluation of multimodal assistants must explicitly test robustness to adversarial changes in visual input, because such changes can cause assistant failure or induce unsafe actions.

2.7 Identified research gaps

Based on the reviewed literature and industrial priorities, the following research gaps were identified as the main motivation for the technical contributions of the dissertation.

1. **Fine-tuning LLMs for scaling SLU to new languages.** Prior multilingual SLU work improved cross-lingual transfer mainly through model-level representation learning or by translating data with conventional MT systems. However, prior work had not directly focused on fine-tuning LLMs to improve the translation quality of slot-annotated SLU data. Around 2023, this became an important research direction because LLMs emerged as flexible models that could be more adaptable to slot-preserving translation than classical MT. This gap motivated Thesis 1 and the presented slot-preserving LLM-based translation method.
2. **Improving assistant quality without foundation-model retraining.**
   LLM- and MLLM-based commercial assistants often rely on large foundation models because of their strong reasoning, language understanding, and multimodal capabilities. In contrast to smaller LLMs fine-tuned for a specific purpose, such as translation, these models must perform a broad range of tasks that require diverse types of knowledge and abilities. In prior work, the most common way to improve LLM quality has been some form of model post-training, such as RL-based optimization, supervised fine-tuning, or DPO. However, due to the size of foundation models, post-training is computationally costly and slow to iterate. It can also lead to catastrophic forgetting and other regressions, which are often hard to diagnose and, most importantly, hard to fix. This motivates research on methods that improve assistant quality without retraining the whole foundation model. Two complementary directions are presented in the dissertation: inference-time changes to internal LLM representations (NL-ITI), and modular decomposition, where part of the MLLM workload is delegated to a specialized UI localization model (ClickAgent).
3. **Diagnostics beyond standard task accuracy.** As assistants evolved from relatively deterministic SLU pipelines to more autonomous LLM-based systems, they became exposed to a much broader range of malicious attacks and hidden failure modes. Standard metrics such as SFA, tool-call accuracy, and task completion rate remain important, but they do not expose risks that may appear in real production environments. These motivated Thesis 3 and diagnostics organized around the interfaces through which assistant behavior can be steered, exploited, or disrupted:
   (a) **It is not feasible to extract hidden payloads by trigger guessing.** Hidden payloads, such as messages, fingerprints, and behavioral triggers, can be embedded into an open-weight LLM that is later integrated into an assistant. Because the trigger might consist of an arbitrary sequence of tokens or characters, recovering

it by brute-force guessing is computationally infeasible. This motivated the UTF method, which bypasses the need to guess the trigger by auditing the model's decoding behavior.

(b) **Steerability of LLM-based assistants should be explicitly measured.** At the prompt interface, prior work studies steerability, jailbreaks, and prompt injection, but less directly evaluates the boundary between benign builder-side control and malicious external manipulation. For production assistants, this distinction is important because the same prompt interface can be used both to guide the model and to attack or misuse it. This motivated an evaluation protocol that measures both how steerable an LLM is and how susceptible it is to malicious user-side manipulation.

(c) **Adversarial attacks that destabilize unseen MLLM behavior.** Most prior work does not address black-box transferability of adversarial visual attacks to unseen MLLMs, especially proprietary ones, which limits their usability for production-relevant stress-testing. In addition, no prior work has studied attacks whose explicit goal is to destabilize the operation of MLLM-based GUI agents on websites and applications. This motivated ACA, which aims to induce hallucinations in MLLMs by increasing the entropy of their output-token distributions.

Chapter 3

Contribution of This Thesis

This chapter summarizes the main scientific and industrial contributions of the thesis. Overall, the work reflects the evolution of NLU systems used in production during 2022–2026: from classical SLU pipelines to LLM-based assistants and MLLM-based GUI agents. The presented research covers methods for improving such systems and for evaluating their deployment-relevant failure modes. The dissertation is structured around the following three theses:

1. **The development effort required to extend SLU to new languages can be substantially reduced through slot-preserving LLM-based machine translation.**

   This thesis addresses the SLU pipelines, which were a core component of production voice assistants during the early phase of this doctoral research and are still relevant in the on-device context. The dissertation develops a slot-preserving translate–train pipeline for generating labeled training data in new languages. In this pipeline, the source corpus is translated by an LLM fine-tuned for slot preservation, and the resulting dataset is used to train downstream SLU models. This approach is intended to reduce the time and cost of scaling SLU systems to new languages by avoiding large-scale manual data labeling. The proposed translation scheme does not require an explicit slot ontology, because slot spans are marked with generic HTML-like tags rather than slot names. This design allows the translation model to be fine-tuned on public parallel corpora and then applied to production data with different slot inventories. It is also suitable for continuous production SLU development, where slot definitions change over time and new slots are frequently added.

2. **The quality of LLM-based NLU systems can be improved without costly retraining of foundation models through inference-time representational interventions and modular agent design.**

   This thesis is supported by two complementary contributions. First, the dissertation develops *NL-ITI*, a representation-engineering method for improving NLU reliability. It intervenes in selected internal LLM activations during decoding, aiming to reduce confidently incorrect outputs and increase truthfulness. Second, it introduces a modular GUI-agent architecture, *ClickAgent*, which separates high-level reasoning and planning from precise UI grounding in order to improve action execution on smartphone interfaces. These contributions are intended to improve industrial NLU systems by targeting the main observed bottleneck through representation engineering or modular decomposition, rather than through costly foundation-model retraining.

3. **Reliable evaluation of NLU systems requires complementing task performance metrics with efficient diagnostics of deployment-relevant failure modes.**

   Benchmark scores alone are not sufficient for evaluating production NLU systems, because strong task performance does not rule out hidden unintended behaviors, adversarial sensitivity, or vulnerability to malicious steering. The methods proposed in this dissertation, therefore, complement standard evaluation with automated diagnostics that target such risks. The dissertation first presents a limitation of probing methods: probe accuracy does not consider how easily encoded information can be extracted. As a result, probing cannot answer questions relevant to industrial NLU development, such as whether knowledge is preserved or forgotten after fine-tuning. These limitations motivated a focus on diagnostic methods organized around the interfaces through which production NLU systems can be controlled, manipulated, or disrupted.

   Prompt interface. The dissertation studies benign and malicious steerability and examines whether LLM assistants can be shifted toward undesirable behavior through simple prompt manipulations. It also discusses possible mitigation directions for malicious steerability.

   Decoding interface. The dissertation introduces Unconditional Token Forcing (UTF) as a method for auditing fingerprints, secret messages, and behavioral triggers embedded in LLM weights. It also introduces Unconditional Token Forcing Confusion (UTFC) as a concealment mechanism that resists currently known extraction approaches.

   Visual interface. The dissertation introduces the Adversarial Confusion Attack (ACA), which can be used as a stress test for MLLMs and GUI agents. It disrupts visual input in order to induce hallucinations and action-execution failures.

Experiments supporting Thesis 1 have been described in the journal article titled "Scaling On-Device Spoken Language Understanding to New Languages with Large Language Models" (Poznań Studies in Contemporary Linguistics, 2026) [57]. Research supporting Thesis 2 has been published in the conference papers "Non-Linear Inference Time Intervention: Improving LLM Truthfulness" (Interspeech 2024) and "ClickAgent: Enhancing UI Location Capabilities of Autonomous Agents" (SIGDIAL 2025) [59], [63]. Finally, methods and analyses supporting Thesis 3 have been published in "Can We Use Probing to Better Understand Fine-tuning and Knowledge Distillation of the BERT NLU?" (ICAART 2023), "Unconditional Token Forcing: Extracting Text Hidden Within LLM" (FedCSIS 2024), "Large Language Models as Carriers of Hidden Messages" (SECRYPT 2025), "Steerability of Instrumental-Convergence Tendencies in LLMs" (ICAISC 2026), and "Adversarial Confusion Attack: Disrupting Multimodal Large Language Models" (ESANN 2026) [55], [56], [60], [61], [62]. The dissertation integrates the main results of these publications into a coherent account of the research carried out during the PhD.

It also complements the published papers with additional industrial context and deployment-oriented discussion.

This industrial PhD also resulted in two patent outputs related to NLU systems: one granted US patent and one published European patent application. The first, *Speech recognition device and operating method thereof* (US12444402B2, 2025), concerns audio-embedding-based correction of named entities in ASR outputs, reducing errors that would propagate to the downstream NLU component [58]. The second, *Display device for providing answer to image-based question and control method thereof* (EP4488850A4, 2025), concerns image-based question answering with retrieval of relevant passages from a knowledge base in order to improve the truthfulness of answers generated by assistants [64].

3.1 Author's scientific achievements

This section lists the peer-reviewed publications authored or co-authored by the author of this thesis. The entries include the corresponding MNiSW ministerial score.

Authored publications

- J. Hościłowicz, A. Wiącek, J. Chojnacki, A. Cieślak, L. Michoń, V. Urbanevych, and A. Janicki, "Non-Linear Inference Time Intervention: Improving LLM Truthfulness", *Proceedings of the 25th Interspeech Conference (Interspeech 2024)*, Kos, Greece, Sep. 1–5, 2024, 140 MNiSW points.

- J. Hoscilowicz and A. Janicki, "Adversarial Confusion Attack: Disrupting Multimodal Large Language Models", *Proceedings of the 34th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN 2026)*, Bruges, Belgium, Apr. 22–24, 2026, 70 MNiSW points.

- J. Hościłowicz, B. Maj, B. Kozakiewicz, O. Tymoshchuk, and A. Janicki, "ClickAgent: Enhancing UI Location Capabilities of Autonomous Agents", *Proceedings of the 26th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL 2025)*, Avignon, France, Aug. 25–27, 2025, 70 MNiSW points.

- J. Hoscilowicz, "Steerability of Instrumental-Convergence Tendencies in LLMs", *Proceedings of the 25th International Conference on Artificial Intelligence and Soft Computing (ICAISC 2026)*, Zakopane, Poland, Jun. 14–18, 2026, 20 MNiSW points.

- J. Hościłowicz, P. Popiołek, J. Rudkowski, J. Bieniasz, and A. Janicki, "Large Language Models as Carriers of Hidden Messages", *Proceedings of the 22nd International Conference on Security and Cryptography (SECRYPT 2025), Volume 1*, Bilbao, Spain, Jun. 11–13, 2025, 70 MNiSW points.

- J. Hościłowicz, P. Popiołek, J. Rudkowski, J. Bieniasz, and A. Janicki, "Unconditional Token Forcing: Extracting Text Hidden Within LLM", *Proceedings of the 19th Conference on Computer Science and Intelligence Systems (FedCSIS 2024)*, Belgrade, Serbia, Sep. 8–11, 2024, 20 MNiSW points.

- J. Hoscilowicz, P. Pawłowski, M. Skorupa, M. Sowański, and A. Janicki, "Scaling On-Device Spoken Language Understanding to New Languages with Large Language Models", *Poznań Studies in Contemporary Linguistics*, Poznań, Poland, 70 MNiSW points.

- J. Hościłowicz, M. Sowański, P. Czubowski, and A. Janicki, "Can We Use Probing to Better Understand Fine-Tuning and Knowledge Distillation of the BERT NLU?", *Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART 2023), Volume 3*, Lisbon, Portugal, Feb. 22–24, 2023, 70 MNiSW points.

Other publications

- P. Pawłowski, K. Zawistowski, W. Łapaćz, A. Wiącek, M. Skorupa, S. Postansque, and J. Hościłowicz, "TinyClick: Single-Turn Agent for Empowering GUI Automation", *Proceedings of the 26th Interspeech Conference (Interspeech 2025)*, Rotterdam, The Netherlands, Aug. 17–21, 2025, 140 MNiSW points.

- M. Sowański, J. Hościłowicz, and A. Janicki, "Analysis of Dataset Limitations in Semantic Knowledge-Driven Multi-Variant Machine Translation", *Journal of Automation, Mobile Robotics and Intelligent Systems*, Warsaw, Poland, 70 MNiSW points.

Patents

In addition to the publications directly supporting the three theses above, this industrial PhD resulted in two patents assigned to Samsung Electronics. They were filed in the United States (US), through the WIPO/PCT route (WO), at the European Patent Office (EPO), and in South Korea (KR). While the patents are not the core contributions of the dissertation, they are aligned with the overall theme of improving voice assistants and NLU systems. The goal of the first patent is to improve the handling of named entities in automatic speech recognition (ASR), which leads to better inputs to the NLU module. The second patent addresses image-based question answering, which can be viewed as an NLU component enabling end-users to ask a voice assistant questions about their visual surroundings.

1. J. Hościłowicz and K. Jankowski, *Speech Recognition Device and Operating Method Thereof*, International patent family including granted US Patent US12444402B2 and related patent publications KR20230043609A, WO2023048359A1.

   This patent proposes a method for correcting named entities in ASR outputs. The method detects a named entity in the user utterance, isolates the corresponding audio segment,

encodes it into an acoustic embedding vector, and retrieves the nearest neighbor from an acoustic-embedding database of named entities to correct the ASR hypothesis. The key novelty lies in using vector representations of audio segments for retrieval-based hypothesis correction.

2. J. Hościłowicz and A. Wiśniewski, *Display Device for Providing Answer to Image-Based Question and Control Method Thereof*, International patent family published as EP4488850A4, US20240054785A1, WO2024019279A1, and KR20240012973A.

   This patent describes a question answering system that encodes an image or video into a vector representation and uses it to retrieve relevant text passages from a knowledge database (Figure 3.1). These passages are then used to form the answer to the user's question. This functionality enables an end-user to ask a voice assistant questions about their surroundings (visual context). The key novelty lies in a video-based embedding retrieval mechanism used to obtain relevant textual passages supporting answer generation.

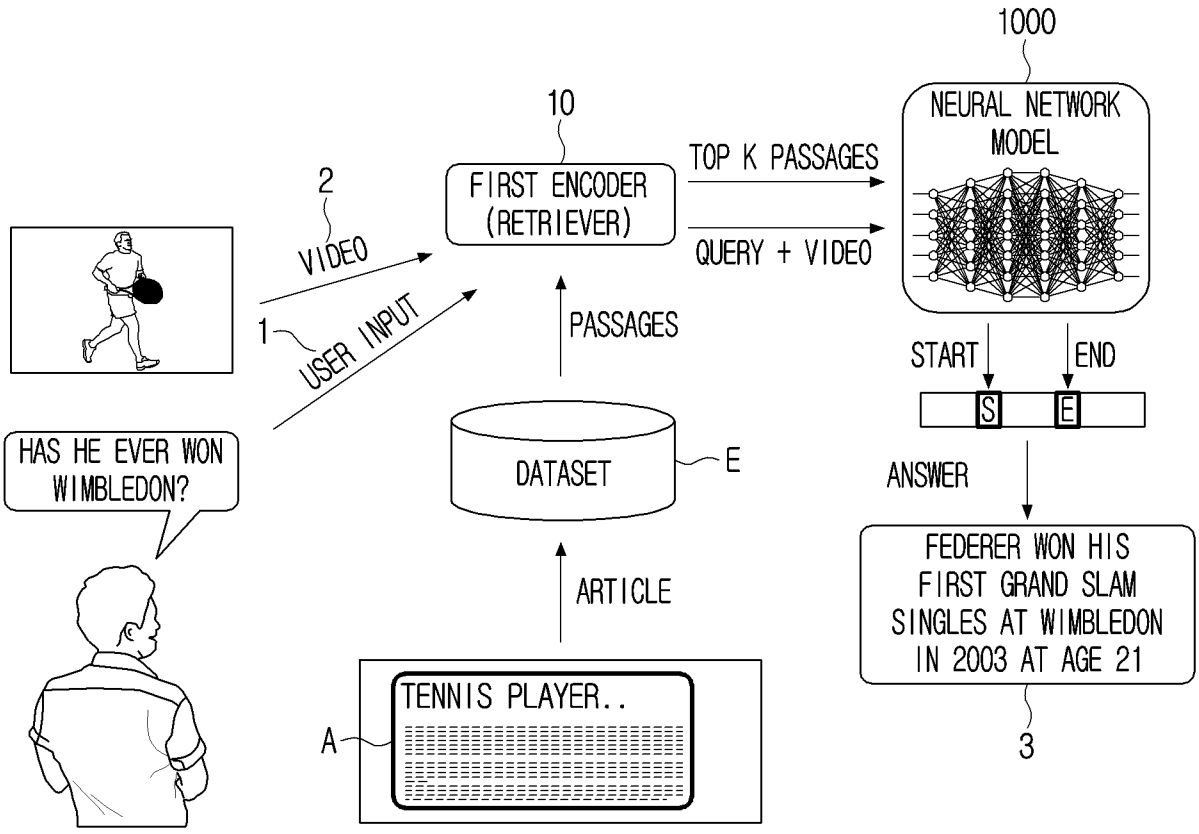


Figure 3.1: Retrieval-augmented question answering pipeline for image and video content, adapted from patent EP4488850A4.

Chapter 4

Multilingual SLU via Slot-Preserving Translate–Train

4.1 Motivation and problem setting

Before 2022, production voice assistants were predominantly based on a cloud-based SLU paradigm, because device hardware made the deployment of pretrained transformers (e.g., BERT) difficult. However, cloud-hosted SLU has significant disadvantages: network-dependent latency, the need to send user utterances off-device (privacy), and high costs of cloud GPU serving that scale with traffic. In the first stage of the PhD (around 2022–2023), these issues motivated the idea of deploying SLU directly on the end-user device (on-device SLU). Because model inference is run locally on the end-user device, such an approach provides low latency, better end-user privacy, and relatively negligible GPU infrastructure costs [27]. For these reasons, even in the current LLM-oriented landscape, some assistants are still based on the on-device SLU paradigm.

In a commercial context, one of the main barriers to scaling on-device SLU assistants to new markets is the cost of continuous development and data annotation. The assistant may span many domains and applications, which can translate into thousands of intents and slots. As a result, launching a new language may require hundreds of thousands of labeled utterances to cover all functionalities with acceptable quality. Continuous development of multilingual SLU is costly as well, because new intents, slots, and API calls are frequently added, existing behaviors are corrected, and obsolete capabilities must be removed across all supported languages. Each such change triggers additional labeling or re-labeling work across supported languages.

In order to reduce the costs of multilingual SLU development, this chapter focuses on automatic generation of multilingual labeled training data. The proposed method is an offline translate–train pipeline that uses an LLM as a slot-preserving translator. Because the method is based on translating existing English SLU examples, it preserves source–target data lineage, which makes a multilingual SLU system easier to synchronize, debug, and maintain over time. Slot spans are marked with generic HTML-like tags, and the LLM is fine-tuned to preserve those tags during translation. The translated corpora are used to train standard SLU models in two deployment regimes: smartphone-class on-device SLU and earbuds-class edge SLU. The smartphone-class setting uses multilingual BERT (mBERT), a multilingual pretrained encoder with a size of around 350 MB. The earbuds-class setting operates under much stricter memory budgets; in the reported experiments, the downstream edge model is a non-pretrained bidirec-

tional long short-term memory (BiLSTM) neural network with a size of approximately 5 MB. This chapter makes three contributions:

- a slot-preserving translate–train pipeline in which an LLM is fine-tuned to translate SLU utterances while preserving slot markup; in the reported MultiATIS++ experiments, this adaptation improves average SFA from 36.66 to 62.18 after slot-aware LLM fine-tuning;
- a slot-type-agnostic marking strategy based on HTML-like tags. Because the markers do not encode slot names, public parallel corpora can be used to fine-tune the translator, which can then be applied to commercial SLU data with a different and evolving slot inventory;
- an empirical evaluation on MultiATIS++ showing that the proposed method outperforms the strongest reported baselines in both SFA and Slot F1, across two settings: an mBERT-based on-device and a non-pretrained BiLSTM edge.

4.2 Related work

A large body of work approaches multilingual SLU by improving cross-lingual transfer at the level of the pretrained model, for example through internal representation alignment, code-switching, or multi-task learning. Most relevant examples include GL-CLeF [109], FC-MTLF [23], CCLG [24], and HC^{2}L [148]. These approaches can be effective, but they increase training complexity and often rely on additional multilingual data resources. From an industrial perspective, their main disadvantage is that they do not produce an auditable multilingual training corpus, which makes debugging, targeted data correction, and synchronization across languages difficult.

A second family of approaches uses MT to translate labeled SLU data. Such pipelines required explicit slot alignment mechanisms (e.g., dictionary- or attention-based alignment) [40], [121], [152] or re-annotation after translation [97]. Across these methods, the main difficulty is correct preservation of slot spans during translation. In many domains, LLMs can improve translation quality and robustness [11], because they are more steerable and flexible than classical MT models. The approach presented in this chapter follows the translate–train direction and shows how to explicitly fine-tune an LLM to preserve slot markup. The central difficulty in translate–train SLU is that the translation must correctly preserve boundaries of slot spans, which is challenging for three reasons:

- Reordering and grammar: slot spans may move due to different word orders.
- Morphology: case endings or particles may attach to slot tokens (e.g., Turkish), raising ambiguity about what belongs inside the span.
- Segmentation: languages such as Japanese and Chinese lack explicit whitespace-delimited word boundaries, making insertion of boundary markers challenging [19], [28].

Earlier translation systems often introduced additional alignment modules to handle these issues. This chapter instead tests whether an LLM, fine-tuned for slot-preserving translation, can handle this complexity directly.

4.3 Method: slot-preserving translate–train

Pipeline overview. The proposed approach is an offline translate–train pipeline that creates multilingual labeled SLU corpora. It starts from English SLU examples, translates them into target languages while preserving slot markers, converts the translated examples back to Beginning–Inside–Outside (BIO) format, and then uses the resulting corpora to train a joint intent-classification and slot-filling model. The pipeline is as follows:

1. Convert English BIO-tagged slot spans into inline generic boundary markers.
2. Translate the marked utterances into target languages with an LLM fine-tuned to preserve these markers.
3. Check whether each generic marker from the source appears the same number of times in the translated utterance; ask the LLM to regenerate if any marker is missing, duplicated, or replaced.
4. Convert the translated marked utterance back into BIO labels in the target language.
5. Train a standard SLU model on the translated corpora mixed with source English data.

In this chapter, the English MultiATIS++ training data is translated into eight target languages: Spanish (es), French (fr), German (de), Hindi (hi), Japanese (ja), Turkish (tr), Portuguese (pt), and Chinese (zh).

Slot boundary markers. To avoid dependence on slot names and definitions, each slot span is wrapped in a pair of identical generic boundary markers, such as `<b>` The Beatles `<b>`. This approach was introduced in EasyProject [19], which used classical MT models for translating data for question-answering and named-entity recognition tasks. For each source utterance, a local mapping from generic marker identifiers to the original BIO slot labels is kept. After translation, the preserved slot markers are replaced with the corresponding source slot labels and converted back to BIO format in the target-language utterance. Table 4.1 illustrates this conversion and restoration process.

The markers are used only to show where slot spans begin and end. During translation, the model should translate the surrounding words while keeping these markers in the output. The real slot labels are added back only after translation, using the local mapping from markers to slot labels. Therefore, the translator does not need to know whether a span is a `city`, `artist`, or any other slot type. This is important for production, where slot inventories change over time and may differ from public datasets used for translator fine-tuning. This design allows

Table 4.1: Example of converting BIO slot labels into generic boundary markers and restoring slot labels after translation.

Step	Example
Source utterance	*show flights from Warsaw to Berlin*
Source BIO labels	`o o o b-fromloc.city_name o b-toloc.city_name`
Marked source utterance	*show flights from <a> Warsaw <a> to <b> Berlin <b>*
Local mapping	<a> ↦ `fromloc.city_name`, <b> ↦ `toloc.city_name`
Translated utterance	*zeige Flüge von <a> Warschau <a> nach <b> Berlin <b>*
Restored target BIO labels	`o o o b-fromloc.city_name o b-toloc.city_name`

the translator to be trained on one parallel dataset, such as MASSIVE, and applied to another dataset, such as MultiATIS++.

Slot-preserving translator. BigTranslate [154], an open-source multilingual 13B LLM, is used as the base model. In the zero-shot setting, it performs translation without any slot-aware fine-tuning. To adapt the LLM to better preserve slot markers during translation, it is fine-tuned on slot-marked parallel examples derived from MASSIVE [35]. MASSIVE provides roughly 1M utterances across 51 languages. Its slot annotations are reformatted into the same slot marker format used by the translator. A multilingual subset covering the eight target languages of MultiATIS++ is selected, yielding 232,000 parallel examples. Two adaptation variants are evaluated: full-parameter fine-tuning (`Full FT`) and Low-Rank Adaptation (LoRA) [65]. Fine-tuning runs for one epoch with LoRA rank 8 and $\alpha = 32$, updating about 1.7M parameters. The best checkpoint is chosen using the MASSIVE validation split. Slot-preserving translation is modeled as a standard sequence-to-sequence task. For a marked source utterance x and marked target utterance $y = (y_1, \ldots, y_T)$, the negative log-likelihood is minimized:

$$\mathscr{L}_{\mathrm{MT}} = -\sum_{t=1}^{T} \log\ p\big(y_t \mid y_{<t}, x; \theta\big), \tag{4.1}$$

where marker tokens appear in both x and y and are therefore explicitly supervised during fine-tuning. Missing, extra, or substituted markers increase the sequence loss, encouraging the model to preserve the marker structure.

Structural validation. Even with adaptation, the translator can occasionally drop, duplicate, or replace generic markers. Because translation happens offline, a simple structural check is enforced: each generic marker from the input must appear the same number of times in the output. If this check fails, the model regenerates the translation. Tag-count validation was repeated with at most five generation attempts per example. This check does not verify translation quality or correct slot boundaries, and it does not require the source marker order to be preserved, since slot spans may legitimately reorder across languages. However, it prevents obvious structural failures such as missing, duplicated, or substituted markers before

the translated data is converted back to BIO labels:

$$\hat{Y} = \begin{cases} Y, & \text{if } \mathbf{c}_{\text{tag}}(Y) = \mathbf{c}_{\text{tag}}(X), \\ \text{regenerate}(X), & \text{otherwise,} \end{cases} \tag{4.2}$$

where $\mathbf{c}_{\text{tag}}(\cdot)$ returns the occurrence count of each generic marker token. This rejection-and-regeneration step is inexpensive in practice because most translations already satisfy the structural constraint. In the reported generation run, 82% of utterances passed the tag-count check after the first translation attempt, while a further 10% required two or three attempts.

4.4 SLU setup

Dataset. The experiments were conducted using MultiATIS++ [152], a multilingual extension of ATIS covering English plus eight target languages. Each utterance is annotated with an intent and BIO slot tags. Across all languages, the dataset contains 33,434 training utterances, 3,650 development utterances, and 7,859 test utterances. The label space includes 18 intents and 84 slot types for most languages, while Hindi and Turkish cover 17 intents with 75 and 71 slot types, respectively. The source English train set is translated into the eight target languages and evaluated on the original target-language test sets.

Downstream SLU training. The translated corpora are used to train SLU models for joint intent classification (IC) and slot filling (SF). Given an utterance U, the model predicts an intent label I and a BIO slot-label sequence $S = (S_1, \ldots, S_n)$ [144]. For example, for the utterance *"play Radiohead on Spotify"*, the intent may be `play_music`, with slots such as `artist=Radiohead` and `service=Spotify`. In an assistant, the predicted intent determines an API call or predefined script, while the slots provide its arguments. The joint SLU architecture of [17] is adopted, with separate classification heads for intent prediction and slot tagging, trained with a weighted sum of cross-entropy losses:

$$\mathscr{L}_{\text{SLU}} = \mathscr{L}_{\text{IC}} + \lambda \mathscr{L}_{\text{SF}}, \tag{4.3}$$

where $\mathscr{L}_{\text{IC}}$ is intent loss, $\mathscr{L}_{\text{SF}}$ is token-level slot loss, and λ balances the tasks.

Following prior multilingual SLU baselines [23], [24], [148], mBERT is used as the encoder in the smartphone-class on-device setting. Let

$$\mathbf{H} = \{h_{\text{CLS}}, h_1, \ldots, h_n\} \tag{4.4}$$

denote the encoder outputs, where the vector h_{CLS} represents the utterance and h_t is the representation of the t-th word. If a word is split into multiple WordPiece tokens, h_t is taken from

the first sub-token. Intent prediction is:

$$l^i = \text{softmax}(W_I\, h_{\text{CLS}} + b_I), \tag{4.5}$$

and slot prediction is performed token-wise:

$$l_t^s = \text{softmax}(W_S\, h_t + b_S), \tag{4.6}$$

with trainable parameters W_I, b_I, W_S, b_S. For the stricter edge setting with a 5 MB budget, mBERT is replaced with a non-pretrained BiLSTM encoder. To ensure comparability with the GL-CLeF baseline [109], its configuration is matched, including hidden size, number of layers, and training setup.

SLU training. Each SLU model is optimized with AdamW using a learning rate of 3×10^{-5}. Early stopping is based on the SFA score measured on the English validation set. In the presented experiments, separate models are trained for each target language, as a single mBERT model trained jointly on all eight translated languages performed substantially worse. For each language, the training set is the union of English training data and the translated training data for that language. Model selection uses the English validation set. This choice reflects a common production constraint: it is undesirable to create and maintain a manually annotated validation set for every target language. For comparison, three groups of mBERT-based baselines are included:

- an SLU model trained only on the English training set;
- methods that improve cross-lingual transfer at the SLU-model level and report the strongest results on the MultiATIS++ benchmark: GL-CLeF [109], FC-MTLF [23], CCLG [24], and HC^{2}L [148];
- LINGUIST [119], which uses an LLM for few-shot synthetic data generation.

Evaluation metrics. The main MultiATIS++ metric is SFA, which is a strict exact-match metric reported as a percentage. A test example is counted as correct only if both the intent label and the complete slot-label sequence match the ground truth:

$$\text{SFA} = \frac{100}{N} \sum_{i=1}^{N} \mathbf{1}\Big[(\hat{I}_i = I_i) \wedge (\hat{S}_i = S_i)\Big]. \tag{4.7}$$

In assistants, the predicted intent determines the API call, while the slots provide the arguments. To execute the correct action, both must be correct; therefore, SFA best approximates whether the assistant will perform the intended action. Because SFA requires the complete semantic frame to be correct, it is substantially stricter than either intent accuracy or Slot F1.

A model can achieve high intent accuracy and high Slot F1 while still obtaining much lower SFA. Intent accuracy and Slot F1 are reported when comparing with LINGUIST [119], because that work does not report SFA. Compared with SFA, these metrics provide a more fine-grained evaluation of SLU performance and help better explain differences between languages. Intent accuracy is the fraction of utterances with correctly predicted intent. Slot F1 is computed over predicted and reference BIO slot labels.

4.5 Results

On-device SLU setting. Table 4.2 reports SFA results for the on-device setting, where mBERT is used as the pretrained encoder. AVG is computed over the eight target languages. The English-only mBERT baseline reaches 27.25 average SFA, showing that training joint SLU only on English data does not produce acceptable results on other languages. BigTranslate without fine-tuning (zero-shot setting) reaches only 36.66 average SFA and fails almost completely on Japanese and Turkish, with 0.90 and 0.56 SFA, respectively.

Slot-aware fine-tuning of BigTranslate substantially improves multilingual SLU quality. Full-parameter fine-tuning (Full FT) improves over zero-shot BigTranslate, reaching 53.20 average SFA. The largest improvements are observed for languages where slot boundary placement is difficult: Turkish improves from 0.56 to 45.80, and Japanese improves from 0.90 to 36.90. BigTranslate fine-tuned with LoRA adapter reaches 62.18 average SFA, compared with 55.11 for the strongest prior baseline, HC^{2}L. Overall, these results show that fine-tuning the LLM makes the translated data much more beneficial for multilingual SLU training, and that competitive MultiATIS++ results can be achieved through automatic multilingual data generation.

Table 4.2: On-device results on MultiATIS++ using an mBERT-based SLU model. Average SFA (AVG) is computed over the eight target languages. † denotes the proposed method: slot-preserving translate–train with LoRA-adapted BigTranslate.

Method	de	es	fr	hi	ja	pt	tr	zh	AVG
mBERT (English-only)	52.69	52.02	37.29	4.92	7.11	43.49	4.33	18.58	27.25
CoSDA [110]	57.06	46.62	50.06	26.20	28.89	48.77	15.24	46.36	39.90
GL-CLeF [109]	66.03	59.53	57.02	34.83	41.42	60.43	28.95	50.62	49.85
FC-MTLF [23]	69.54	61.43	59.62	36.86	44.64	64.55	30.86	56.52	53.00
CCLG [24]	**74.91**	62.43	59.99	40.43	47.98	**64.95**	31.56	57.83	55.01
HC^{2}L [148]	72.20	66.05	**67.51**	34.83	42.44	63.34	36.50	58.01	55.11
BigTranslate (zero-shot)	64.73	37.74	53.42	32.59	0.90	53.30	0.56	50.06	36.66
BigTranslate + Full FT	68.10	58.50	55.70	43.50	36.90	56.30	45.80	60.80	53.20
BigTranslate + LoRA†	72.45	**66.17**	63.83	**58.45**	**52.41**	60.69	**54.55**	**69.88**	**62.18**

Edge SLU setting. Table 4.3 reports results for the 5 MB edge setting. In this experiment, the SLU model is based on a BiLSTM neural network trained from scratch, which makes the setting much harder than the on-device scenario. The BiLSTM trained only on the source

English train set reaches 1.87 average SFA, while the baseline approach (GL-CLeF) reaches 5.31. Training the same BiLSTM architecture on data translated with LoRA-adapted BigTranslate increases average SFA to 22.06. The largest gain is observed for Chinese, where SFA increases from 2.46 with GL-CLeF to 42.67 with translated data.

Although this result is still much lower than in the mBERT-based setting, it shows that data translation is a promising direction when the downstream SLU model is very small and a pretrained multilingual encoder cannot be used. In this setting, the model has no prior knowledge of target-language word order or slot-boundary patterns, so only translated training data can provide the necessary supervision.

Table 4.3: Results of 5 MB SLU (edge scenario) on MultiATIS++. SFA is reported; AVG is computed over the eight target languages.

SFA	**de**	**es**	**fr**	**hi**	**ja**	**pt**	**tr**	**zh**	**AVG**
BiLSTM (English-only)	0.78	3.08	0.63	0.22	0.00	10.20	0.00	0.03	1.87
BiLSTM + GL-CLeF [109]	4.60	9.10	4.30	0.34	2.03	16.82	2.80	2.46	5.31
BiLSTM + BigTranslate + LoRA	26.99	27.21	8.29	10.64	7.61	29.56	23.50	42.67	**22.06**

LLM-based multilingual SLU. Table 4.4 compares the proposed method with LINGUIST [119], the closest LLM-based baseline. LINGUIST also uses an LLM to create SLU training data, but it frames the task as instruction-tuned generation of annotated utterances, whereas the proposed method uses slot-preserving translation of existing English SLU data. The comparison is partial because LINGUIST does not report SFA and does not include Turkish or Chinese. Therefore, the table focuses on Slot F1 over the six comparable languages, with intent accuracy reported for completeness. BigTranslate + LoRA achieves an average Slot F1 of 89.68, compared with 83.98 for LINGUIST and 68.96 for zero-shot BigTranslate. Intent accuracy is also slightly higher than LINGUIST on average: 96.88 compared with 95.06.

Table 4.4: Intent accuracy and Slot F1 comparison with LINGUIST.

Intent Accuracy	**de**	**es**	**fr**	**hi**	**ja**	**pt**	**AVG**
LINGUIST [119]	94.08	97.10	96.88	94.08	95.38	92.86	95.06
BigTranslate (zero-shot)	96.86	97.20	97.54	94.29	5.49	97.98	81.56
BigTranslate + LoRA	95.52	98.21	98.32	95.41	96.06	97.76	**96.88**
Slot F1	**de**	**es**	**fr**	**hi**	**ja**	**pt**	**AVG**
LINGUIST	84.61	86.89	83.83	76.61	86.32	85.63	83.98
BigTranslate (zero-shot)	84.88	55.39	79.63	58.73	57.18	77.96	68.96
BigTranslate + LoRA	92.34	92.10	87.43	84.35	87.11	94.75	**89.68**

4.6 Discussion

In the mBERT-based on-device setting, BigTranslate fine-tuned with a LoRA adapter reaches 62.18 average SFA, compared with 55.11 for HC^{2}L, the strongest prior baseline. In the strict 5 MB BiLSTM edge setting, the same translated-data approach raises average SFA to 22.06, compared with 5.31 for the GL-CLeF baseline. The edge result is much lower than the mBERT result, but it shows that translated data is especially useful when no pretrained multilingual encoder is feasible due to strict hardware constraints. All these results show that the quality of multilingual SLU can be effectively improved by automatic generation of training data, without changing the SLU architecture. The presented approach is orthogonal to model-level transfer methods such as HC^{2}L: it changes the training data, whereas HC^{2}L changes the SLU training objective through methods like contrastive alignment. Combining these two approaches is a possible direction for future work.

In the mBERT-based on-device setting, fine-tuning improves SFA by 25.52 percentage points. It is worth noting that the presented experiments were conducted during the first stage of the PhD and are based on BigTranslate, a model released in 2023. Since newer LLMs have stronger multilingual capabilities, applying the same slot-preserving fine-tuning recipe to more recent models is an important direction for future work. It should provide further quality gains, especially for low-resource languages that are underrepresented in the pre-training data of multilingual LLMs.

Offline translate–train. One of the main practical advantages of translate–train is that translation happens before deployment, not during user interaction. In contrast, translate–test methods translate an incoming utterance into English and then apply an English SLU model, which adds inference-time latency and introduces an additional potential point of failure. Studies such as [45] also report lower slot accuracy for translate–test than for translate–train. Most importantly, offline translation produces a static artifact: a multilingual labeled corpus. This corpus can be checked before training the final SLU model. In this chapter, the simplest check verifies that translated utterances preserve the expected number of slot boundary markers. The translated data can also be improved after evaluation. When the SLU model makes an error on a validation utterance, the corresponding source utterance and translated training examples can be inspected. If the error comes from a bad translation or an incorrect slot boundary, the affected examples can be manually corrected or automatically regenerated. Such feedback can also be used to further improve fine-tuning data for the translation model.

LoRA adaptation of BigTranslate. Full fine-tuning updates all model parameters, which increases GPU memory use, training time, and the risk of overfitting or catastrophic forgetting. LoRA updates only a small set of low-rank adapter parameters, making training faster and lighter in GPU memory. It also produces a compact adapter checkpoint that is easier to version, replace, or update when new slot patterns or utterance types are added. In the re-

ported experiments, LoRA also gives stronger downstream SLU results than full fine-tuning, reaching 62.18 average SFA compared with 53.20 for Full FT. A possible explanation for the advantage of LoRA is that full fine-tuning overfits more strongly to the MASSIVE training distribution, which leads to worse generalization.

Comparison with LINGUIST. Apart from multilingual SLU quality improvement, the proposed method has practical advantages over LINGUIST. Most importantly, it preserves direct source–target correspondence across languages: each target-language training example is derived from one specific English source utterance. For example, if the English source is "set an alarm for [7 am] on [Monday],"then its Polish, Japanese, or Turkish translations can be treated as its aligned realizations. This makes the multilingual corpus easier to interpret, synchronize, and maintain, because each item has lineage within the original English training distribution. Utterances such as "set an alarm for 7 am on Monday", "ustaw alarm na 7 rano w poniedziałek", and their equivalents in other languages should trigger a similar API call or a predefined script, for example `create_alarm(time=07:00, day=MONDAY)`. In the multilingual SLU setting, the source language (usually English) corpus acts as the canonical specification of the intended assistant behavior, while new-language utterances are localized realizations of the same intent and executable action.

This source–target correspondence makes production tasks less time-consuming. If a target-language assistant fails on a given validation case, debugging can be performed by inspecting the translated descendant data and checking whether the issue comes from the source annotation, an improper translation, or an improper API call. If the English team adds, corrects, or removes examples, the corresponding multilingual data can be updated automatically. These advantages do not imply that the proposed method is universally better: LINGUIST may be more suitable when the goal is to generate diverse synthetic monolingual examples for new intents or slots. However, translate–train provides clearer data lineage, which makes it more suitable for continuous development of multilingual SLU systems.

Annotation-cost reduction estimate. In production, English often acts as the canonical specification of assistant behavior. When a new intent is added, a slot definition is changed, an API argument is renamed, or obsolete examples are removed, the corresponding multilingual training data must remain synchronized across languages. With source–target lineage, newly added or modified English examples can be translated and propagated to target languages as deltas, rather than recreated independently by each language team. If a target-language validation case fails, the related English source example and its translated descendants can also be inspected directly, making it easier to determine whether the problem comes from the source annotation, translation, downstream SLU model, or execution layer. However, cost savings during continuous maintenance are difficult to estimate quantitatively, because they depend on release intensity, the number of added or modified intents and slots, frequency of

changes in backend API calls, and the number of already supported languages. For this reason, the estimate below focuses on the scenario of initial expansion of an SLU system to new target languages.

In a fully manual workflow, launching a new language requires creating or translating target-language utterances and then annotating them with intents and slots. Manual annotation effort therefore scales with N, the number of utterances needed for launch. In a translate–train workflow, the initial target-language corpus is translated automatically from labeled English examples. Human work is still needed, but it shifts to targeted repair of translated data. Let p denote the fraction of translated training utterances selected for human review after downstream SLU error analysis. Then the manual part of the effort scales approximately with pN.

The review process starts from analysis of SLU validation failures. To illustrate the cost scenario, a pilot audit was performed on two target languages with different slot-transfer performance: German, which achieved high Slot F1 (92.34), and French, which had lower Slot F1 in the reported comparison (87.43). For each language, failing validation cases were inspected, and recurring error patterns were grouped into queryable categories: slot type (e.g., `fromloc.city_name`), particular failing slot values (e.g., `La Guardia`), classes of failing slot values (e.g., date/time formatting patterns), intent, and recurring surface words near failing slot boundaries that could be used to retrieve related translated training examples. Using these audit-derived patterns to retrieve translated utterances that might need human review produced subsets of approximately 328 German examples and 499 French examples, corresponding to 7.31% and 11.12% of the translated training set, respectively. For the cost estimate, $p = 0.1$ is therefore used as the audit-based targeted-review estimate and $p = 0.2$ as a more conservative scenario.

It is worth noting that translation errors do not map one-to-one onto downstream SLU failures. Some imperfectly translated training examples may have little effect on the final SLU model if most examples for the same slot, intent, or local construction are translated consistently enough for the SLU model to learn the correct pattern. Conversely, a small number of systematic translation or boundary errors in frequent slot patterns may produce many downstream failures.

As a simple illustration of costs for a commercial voice assistant that handles thousands of intents, assume $N = 100{,}000$ utterances for a new language and an effective manual annotation cost of 0.25 EUR per utterance. This corresponds to around 45 seconds of paid annotation/review time per utterance at 20 EUR/hour. Full manual annotation would then cost about 25,000 EUR per language, or 250,000 EUR for 10 languages. In the proposed translate–train workflow, if p is 0.1 or 0.2, manual intervention concerns 10,000 or 20,000 utterances per language, corresponding to about 2,500 or 5,000 EUR per language. For 10 languages, this corresponds to about 25,000 or 50,000 EUR under the same annotation-cost assumption. Under this illustrative 10-language scenario, the variable annotation cost is therefore reduced by approximately

200,000–225,000 EUR.

4.7 Chapter summary

This chapter presented a data-centric method for scaling on-device SLU to new languages by generating multilingual labeled training data offline. The approach translates English SLU corpora with an LLM fine-tuned for slot preservation, reducing the cost of fully manual data translation and annotation. Because each translated example remains linked to its English source, the proposed approach simplifies debugging, synchronization, and continuous development of multilingual SLU systems.

The main technical contribution is a slot-preserving LLM fine-tuning recipe. BigTranslate is adapted with LoRA on slot-annotated parallel data from MASSIVE. Because the proposed pipeline is slot-type agnostic, the translator can be trained on public corpora and then applied to production systems with different and evolving slot inventories. On MultiATIS++, fine-tuning BigTranslate improves average SFA from 36.66 to 62.18, outperforming HC^2L, the strongest reported mBERT-based baseline, which reaches 55.11 average SFA. The largest gains appear in difficult slot-transfer languages such as Turkish and Japanese.

Taken together, the results of this chapter **support Thesis 1**: the development effort required to extend SLU systems to new languages can be substantially reduced through slot-preserving LLM-based machine translation.

Chapter 5

Improving LLM-Based Assistants

This chapter supports the second thesis of the dissertation: NLU systems can often be improved without costly foundation-model retraining by targeting their dominant bottlenecks. During 2023–2024, the production focus began shifting from classical SLU pipelines toward LLM-based assistants. In this setting, a central failure mode became unreliable LLM behavior: confident but incorrect tool invocations, and hallucinated or unsafe responses. In the 2025–2026 period, assistants started to expand beyond the text modality: MLLMs that can analyze screenshots became a core component of GUI agents. In this case, the dominant bottleneck shifted to UI grounding (locating the correct element on the screen) and long-term action planning.

A common solution to these failure modes is end-to-end post-training (fine-tuning or RL-style optimization) of the foundation model. However, for state-of-the-art large LLMs used in commercial assistants, such post-training is costly, slow to iterate, and can introduce regressions (catastrophic forgetting) or brittle changes that are hard to diagnose. Consequently, this chapter studies methods that improve NLU performance without retraining the foundation model. The first method, NL-ITI, shows that assistant truthfulness can be improved by steering selected internal activations during decoding. The second method, ClickAgent, improves GUI-agent task performance by isolating UI localization as a dominant bottleneck and addressing it with a specialized model.

5.1 NL-ITI: Non-linear inference-time intervention for improving LLM-assistant truthfulness

5.1.1 Motivation and problem setting

The core hypothesis motivating this line of work is that truthful knowledge exists in the model's internal representations but is not reliably used during generation. Based on this idea, the objective of Inference-Time Intervention (ITI) [80] is to improve truthfulness by steering internal model activations, so that relevant internal knowledge is more likely to influence the generated answer. ITI consists of two stages: identifying attention heads that encode a target concept via linear probes, and then applying a mean-shift intervention to the selected heads during decoding. The presented NL-ITI method improves upon ITI by introducing non-linear probing and multi-token representations for intervention construction. The main motivation for these modifications was the information-decodability perspective on probing described in Chapter 6: non-linear probes may better estimate the amount of information in internal representations, leading to more accurate attention-head selection. While this chapter focuses on

the concept of truthfulness, the same class of inference-time representation interventions may be applied to other types of knowledge and capabilities, provided that an appropriate labeled dataset is available.

The goal of the first stage of ITI is to identify which attention heads contain the greatest amount of truthful knowledge. For this purpose, the frozen LLM is run on a labeled dataset of question–answer (Q+A) pairs. Each pair has a binary label $y \in \{0, 1\}$, where $y = 1$ denotes a correct answer and $y = 0$ denotes an incorrect answer. For every attention head h in every layer l, ITI stores the activation vector produced by that head for the last token of the Q+A prompt, denoted as x_l^h. The collected examples are split into a training set and a held-out evaluation set. For each head separately, a linear probe is trained on the training split to predict the truthfulness label from the corresponding activation vector:

$$p_\theta(y = 1 \mid x_l^h) = \text{sigmoid}\Big(\big\langle \theta, x_l^h \big\rangle\Big). \tag{5.1}$$

The probe parameters θ are fitted by standard binary classification training with the objective of minimizing the binary cross-entropy loss. After training, the probe is evaluated on held-out Q+A pairs that were not used to fit θ. ITI ranks all heads by held-out probe accuracy and selects the top-K heads for intervention in the next stage.

For each selected head, ITI constructs an intervention direction as the difference between the mean activation for truthful answers and the mean activation for untruthful answers:

$$d_l^h = \frac{1}{N_+} \sum_{i\,:\,y_i=1} (x_l^h)_i - \frac{1}{N_-} \sum_{i\,:\,y_i=0} (x_l^h)_i, \qquad (h, l) \in \text{TopHeads}, \tag{5.2}$$

where N_+ and N_- denote the numbers of truthful and untruthful Q+A pairs. Thus, d_l^h points from the average untruthful activation toward the average truthful activation for head (h, l). During decoding, this direction is added to the output of the selected attention heads:

$$x_{l+1} = x_l + \sum_{h=1}^{H} Q_l^h \Big(\text{Att}_l^h(P_l^h x_l) + \alpha\, \mathbb{I}[(h, l) \in \text{TopHeads}]\, \sigma_l^h\, d_l^h \Big), \tag{5.3}$$

where $x_l \in \mathbb{R}^D$ is the token representation at layer l, P_l^h and Q_l^h are head projection matrices, $\text{Att}_l^h(\cdot)$ denotes the attention computation, and $\mathbb{I}[(h, l) \in \text{TopHeads}]$ is an indicator equal to 1 for selected heads and 0 otherwise.

In Eq. 5.3, the intervention is first added in the activation space of a selected attention head and is then projected back to the residual stream by Q_l^h. Therefore, it acts as an additive bias on the residual stream, but only through the selected heads. The factor σ_l^h is computed from the activations collected on the labeled Q+A pairs and rescales the intervention so that its magnitude is comparable to the typical activation variation at head (h, l). The hyperparameter α controls the strength of the additive term $\alpha \sigma_l^h d_l^h$, while the hyperparameter K determines

how many of the highest-scoring heads are modified. From a production perspective, ITI-style methods are lightweight: intervention directions are computed once from the probing dataset and reused at inference time. At runtime, the method only adds a small number of vector additions to the forward pass, which introduce negligible computational overhead.

5.1.2 NL-ITI improvements over ITI

The ITI method uses a linear probe for head selection and relies on the last-token representation of the Q+A prompt for both probing and constructing intervention directions. NL-ITI, presented in this dissertation, introduces the following three modifications:

1. **Non-linear probing for head selection.** Prior probing analyses [62], [105], [145] suggest that higher-capacity probes can better estimate the amount of information in internal representations. In the context of ITI, this can lead to a more effective selection of the top-K heads used for intervention. NL-ITI therefore replaces logistic regression with a two-hidden-layer multilayer perceptron (MLP) probe with ReLU hidden activation and sigmoid output:
$$p_\theta(y = 1 \mid x_l^h) = \mathrm{MLP}_\theta(x_l^h). \tag{5.4}$$

2. **Multi-token probing (τ).** The original ITI uses only the activation corresponding to the last token in the Q+A prompt. This can be limiting, because truthfulness-related information may be distributed across several final tokens. NL-ITI therefore represents each Q+A pair by averaging the activations of the last τ tokens before training the probe:
$$\bar{x}_{l,i}^{h,\tau} = \frac{1}{\tau} \sum_{r=0}^{\tau-1} x_{l,i,T_i-r}^h, \tag{5.5}$$
where $x_{l,i,t}^h$ is the activation of head h at layer l for token position t in the i-th Q+A pair, and T_i is the last token position of that pair. The MLP probe is then trained on pairs $(\bar{x}_{l,i}^{h,\tau}, y_i)$.

3. **Multi-token intervention direction (ρ).** The same idea is used when constructing the intervention direction. Instead of computing the truthful direction from the last-token activation only, NL-ITI first averages the last ρ token activations:
$$\bar{x}_{l,i}^{h,\rho} = \frac{1}{\rho} \sum_{r=0}^{\rho-1} x_{l,i,T_i-r}^h. \tag{5.6}$$
The intervention direction is then computed as the difference between the mean truthful

and untruthful averaged activations:

$$d_l^h = \frac{1}{N_+} \sum_{i\,:\,y_i=1} \bar{x}_{l,i}^{h,\rho} - \frac{1}{N_-} \sum_{i\,:\,y_i=0} \bar{x}_{l,i}^{h,\rho}, \qquad (h,l) \in \text{TopHeads}. \tag{5.7}$$

The values of τ and ρ are selected empirically; the sensitivity analysis is reported in Figure 5.1.

5.1.3 Evaluation protocol

NL-ITI is compared against three baselines: the unedited base model, ITI [80], and Truth Forest (TrFr) [21]. To ensure comparability, all experiments are conducted with LLaMA-2-7B [131]. For in-domain evaluation, probing, and intervention, TruthfulQA [84] is used. Following the ITI protocol, TruthfulQA is split into two folds (A: 2915 Q+A pairs, B: 2967 Q+A pairs): probing and intervention construction are performed on one fold, performance is evaluated on the other fold, and the final results are averaged over both. For out-of-distribution (OOD) evaluation, probing and intervention are performed on full TruthfulQA, while evaluation is performed on ARC [26], OpenBookQA [92], and Massive Multitask Language Understanding (MMLU) [51]. ARC and OpenBookQA evaluate science-oriented question answering and reasoning, while MMLU evaluates broader multitask knowledge across academic and professional domains.

Following baseline methods, truthfulness is measured with the TruthfulQA multiple-choice metrics MC1 and MC2 [84]. In addition, the evaluation measures how strongly the intervention changes the original model behavior. For this purpose, Cross Entropy (CE) and Kullback–Leibler divergence (KL) are computed between the next-token probability distributions produced by the edited model and the original LLaMA-2-7B model on OpenWebText [43]. Lower CE/KL values indicate a smaller distribution shift and therefore a less invasive intervention.

5.1.4 Main results

Table 5.1 summarizes the main TruthfulQA results. NL-ITI raises MC1 to 50.19, compared with 33.54 for the unedited LLaMA-2-7B baseline and 36.35 for ITI. The MC2 score increases to 67.73, relative to 50.34 for the base model and 54.72 for ITI. NL-ITI also outperforms Truth Forest by 10.89 percentage points in MC1.

The ablation results show that both modifications introduced by NL-ITI are important. Without the non-linear probe, MC1 drops from 50.19 to 42.96. Removing multi-token averaging reduces MC1 further to 40.75 and increases KL from 0.43 to 1.40, indicating an excessive distribution shift from the original model.

Figure 5.1 shows how TruthfulQA MC1 changes for different choices of the multi-token hyperparameters τ and ρ. Rows correspond to the number of final tokens used for probing (τ),

Table 5.1: TruthfulQA results for baseline LLaMA-2-7B, ITI, TrFr, and NL-ITI.

	MC1 [%]	MC2 [%]	CE	KL
LLaMA-2-7B	33.54	50.34	2.53	0.00
ITI	36.35	54.72	2.65	0.40
TrFr [21]	39.30	–	2.59	0.22
NL-ITI	**50.19**	**67.73**	2.85	0.43
w/o optimized probe	42.96	61.48	2.66	0.25
w/o multi-token	40.75	59.83	3.33	1.40

while columns correspond to the number of final tokens used to construct the intervention direction (ρ). The best TruthfulQA result is obtained for $(\rho, \tau) = (6, 4)$, highlighting that truthfulness-related knowledge is not concentrated only in the final-token representation.

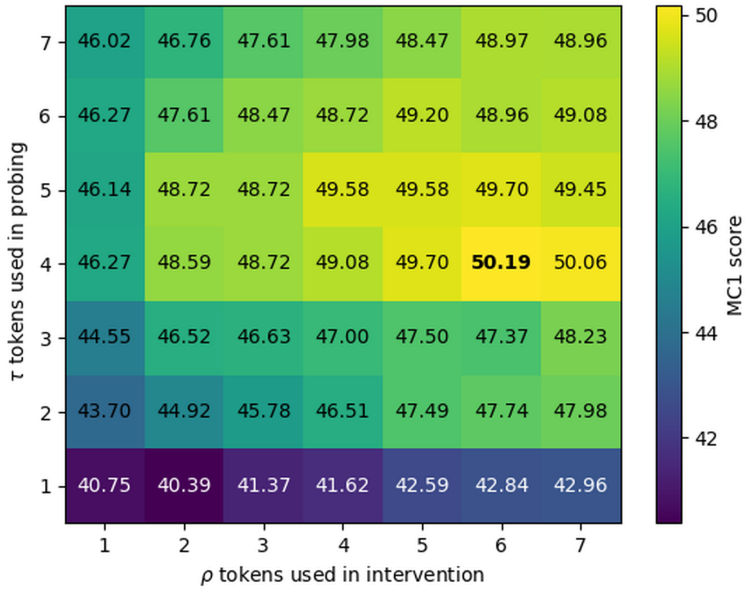


Figure 5.1: TruthfulQA MC1 scores as a function of the number of tokens used for probing (τ) and construction of the intervention direction (ρ) [63].

Figure 5.2 compares accuracies of linear (ITI) and non-linear (NL-ITI) probes for each attention head. The largest difference appears in the first six layers, where non-linear probing reveals substantially more truthfulness-related signal.

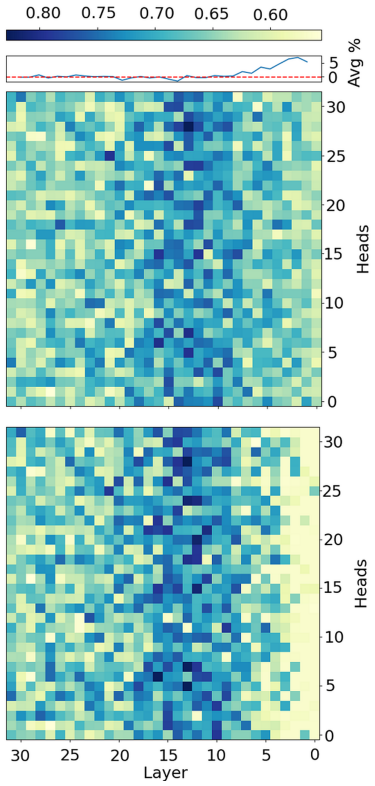


Figure 5.2: Probing accuracy for each LLM attention head on TruthfulQA: linear probing (ITI) at the bottom and non-linear probing (NL-ITI) at the top [63].

Figure 5.3 shows MC1 results as the intervention strength α and the number of edited heads K are varied on TruthfulQA and OpenBookQA. Each point corresponds to one intervention configuration, while KL measures how strongly the edited model diverges from the original LLaMA-2-7B behavior. Across the evaluated parameters, NL-ITI achieves higher MC1 than ITI at comparable KL values, indicating a better accuracy–invasiveness trade-off.

5.1.5 Generalization beyond TruthfulQA

To test whether the discussed methods generalize beyond TruthfulQA, edited models are evaluated on ARC, OpenBookQA, and MMLU. In this setting, the full TruthfulQA dataset is used both to train the probes and to construct the intervention directions. Table 5.2 shows that NL-ITI consistently improves OOD performance relative to both the base model and ITI. The largest gain over ITI is observed on ARC, where MC1 increases from 40.34 to 44.27. NL-ITI also improves MC1 on OpenBookQA from 30.52 to 33.94 and on MMLU from 38.55 to 40.31. The observed generalization motivates exploring whether NL-ITI can be applied to other types of knowledge and capabilities. One possible direction is to apply inference-time interventions to improve the reliability of tool invocations in LLM-based assistants.

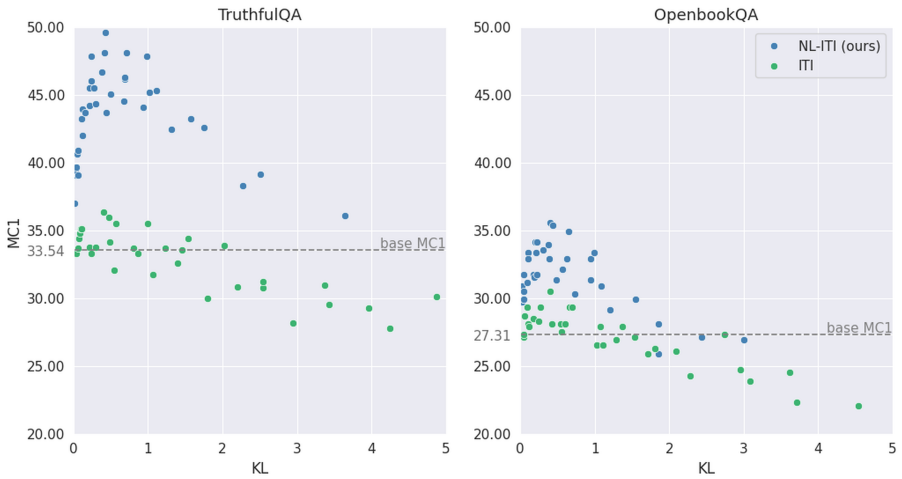


Figure 5.3: Relationship between MC1 and KL divergence [63]. KL estimates the strength of the behavioral change caused by representation editing; lower values indicate a less invasive intervention. Results are shown for ITI and NL-ITI under different hyperparameter settings (α, K) on TruthfulQA and OpenBookQA. The baseline LLaMA-2-7B performance is presented for each benchmark.

Table 5.2: Generalization of ITI and NL-ITI to other benchmarks.

Dataset	Method	MC1 [%]	MC2 [%]	CE	KL
ARC	LLaMA-2-7B	41.20	40.69	2.53	0.00
ARC	ITI	40.34	38.78	2.54	0.12
ARC	**NL-ITI**	**44.27**	**43.20**	2.82	0.40
MMLU	LLaMA-2-7B	38.48	38.66	2.53	0.00
MMLU	ITI	38.55	38.27	2.58	0.04
MMLU	**NL-ITI**	**40.31**	**39.82**	2.60	0.10
OBQA	LLaMA-2-7B	27.31	26.36	2.53	0.00
OBQA	ITI	30.52	28.26	2.82	0.40
OBQA	**NL-ITI**	**33.94**	**32.65**	2.86	0.32

5.2 ClickAgent: a modular GUI-agent architecture with specialized UI grounding

Commercial assistants can execute user requests through structured programmatic interfaces or direct GUI interaction. When a reliable API is available, an LLM-based tool agent is often the better choice: the action space is explicit and execution can often be verified programmatically. However, many applications and websites do not expose a public API, or provide APIs that cover only a limited subset of their functionalities. Additionally, on some devices, such as TVs, programmatic access to applications can be restricted. For these reasons, GUI agents are complementary to tool agents because they can handle tasks that can be completed only through the visible UI.

GUI agents operate similarly to humans by performing actions such as clicking and typing

on the screen of the user's device. Robust GUI automation requires both high-level planning and precise visual grounding. Many target UI elements are small, densely packed, or ambiguous, for example, repeated icons or similar list items. Even when the MLLM chooses the correct next action, it may still struggle to localize the target element reliably on real phone screens [86]. ClickAgent addresses this bottleneck with a modular architecture. It uses an MLLM for decision-making and reflection, while delegating click grounding to TinyClick, a specialized UI location model. This separation targets one of the main observed failure modes of GUI agents: inaccurate grounding of click actions on the screen. This design supports Thesis 2 of the dissertation: assistant quality can often be improved by isolating and improving the weakest subsystem rather than retraining the full foundation model.

5.2.1 Method

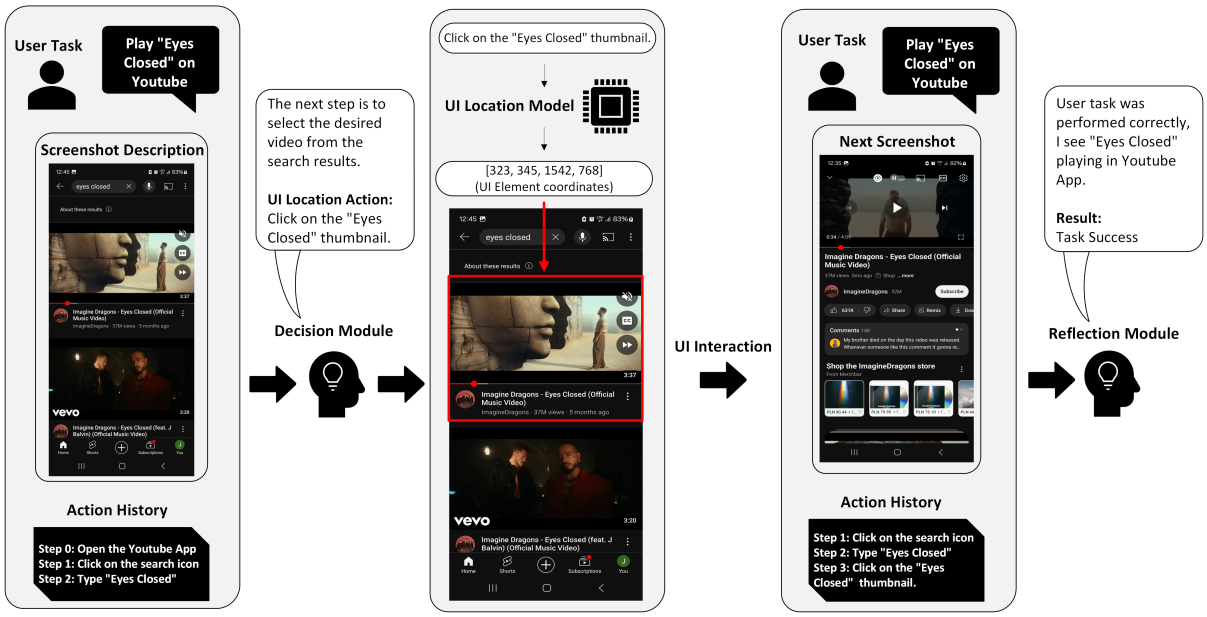


Figure 5.4: Overview of the ClickAgent architecture [59]. Reasoning, reflection, and action planning are handled by the MLLM, while a specialized UI location model identifies the screen coordinates of the UI element corresponding to the command issued by the MLLM.

Models such as SeeClick [22] and ScreenAI [3] perform well on narrow tasks such as UI localization or screen description, but have limited agentic capabilities. Conversely, MLLMs are well suited for UI reasoning and multi-step planning, but might be less reliable at precise UI grounding. ClickAgent therefore separates high-level reasoning from pixel-level UI grounding. InternVL2.0 [20] is used as the primary MLLM because it offers strong performance on agentic and multimodal benchmarks while remaining feasible to run in the experimental setup. TinyClick [103] is used as the main specialized UI grounding model because of its strong results on relevant benchmarks, including ScreenSpot [22] and OmniAct [72].

Figure 5.4 illustrates the ClickAgent design, which consists of three modules: Decision,

UI Location, and Reflection. In the Decision module, the role of the MLLM is to choose the next action. The input prompt contains the user command, the current screenshot, the recent action history, a compact natural-language summary of progress so far, and a list of possible actions. The module output contains the model's reasoning and one of four selected actions:

- `Click`: the MLLM outputs a short natural-language command describing the target element. Given the command and screenshot, the UI Location module predicts the relevant screen coordinates (x, y).
- `Type`: the MLLM outputs the text to type into the currently focused text field.
- `Open App`: the MLLM selects an application from the list retrieved from the device, and the executor opens it.
- `Swipe`: the MLLM selects a direction (*up/down/left/right*) to scroll or change view.

The UI Location model is used when the selected action is `Click`. It receives the current screenshot I_t and a short natural-language UI command c_t produced by the Decision module, for example "click the Gmail icon" or "tap the Checkout button". The UI location model returns either a click point (x, y) or a bounding box (x_1, y_1, x_2, y_2). When a bounding box is returned, its center is used as the click point. The executor then performs the tap at (x, y) on the device. This design keeps semantic action selection separate from pixel-level grounding. Because the UI Location module uses only the screenshot and the natural-language command, ClickAgent does not depend on accessibility trees, HTML, or XML metadata, which can be incomplete or inconsistent with the visible screen. Such metadata is also unavailable for some applications and devices.

At the end of each step, the Reflection module decides whether the user command has already been completed. Its input prompt contains the user instruction, the current screenshot, and the action history. The output is a completion judgment, either success or failure, together with a short justification. If the MLLM decides that the goal is completed, the agent stops; otherwise, the next decision step is executed. Reflection is also used to maintain a short progress summary, which is passed back to the Decision module in the next step.

Evaluation. ClickAgent is evaluated on both an Android emulator and a real Android smartphone. The primary metric is task completion rate (TCR, in %), which measures the percentage of user tasks completed successfully. Unlike step-level measures such as step success rate or action accuracy [89], [123], [158], TCR is an end-to-end metric that evaluates whether the user command is actually executed correctly on the device [160]. Evaluation is performed manually because current automatic evaluators are not yet reliable enough for complex UI environments [101]. A task is marked as successful if the final observed outcome satisfies the user command. Experiments use an NVIDIA A100 40GB for running UI location models and

4× NVIDIA A100 80GB for InternVL-2.0. Each experiment is repeated three times with no substantial variation observed across runs. The average TCR is reported. ClickAgent is evaluated in two Android setups:

- Android emulator with cache removal: the browser/app cache is cleared before each test case. This simulates a first-time user experience, where pop-ups, cookie notices and other initial interactions may appear.
- Android smartphone without cache removal: the cache is preserved between test cases. This simulates a returning user, where previously handled pop-ups and initial screens are usually absent.

To ensure comparability, the evaluation uses the subset of the Android-in-the-Wild (AITW) benchmark [116] released by DigiRL [4]. AITW General contains everyday smartphone tasks, while AITW WebShopping focuses on e-commerce interactions. Except for D-PoT [161], results for baseline agents are taken from [4].

5.2.2 Main results

Table 5.3 shows that ClickAgent achieves the highest overall task completion rate among the compared GUI agents, reaching 73.5 % overall TCR across AITW General and AITW WebShopping. It improves over DigiRL, the strongest baseline in the table, which reaches 69.6 %. The cache-removal setting gives comparable performance, suggesting that ClickAgent remains effective also when first-time-user pop-ups and onboarding screens are present. A ClickAgent variant in which reflection is merged into the Decision prompt is also evaluated. In this setting, the MLLM is asked to choose the next action and judge task success in a single query. This change causes a large performance drop to 11.2 % overall TCR. The most likely explanation is that the content of the Decision prompt, including action history and planning context, biases the reflection judgment. Consequently, ClickAgent keeps reflection as a separate query in order to avoid premature task termination.

In the presented experiments, TinyClick performed particularly well on OCR-heavy screens and on UI elements identifiable by visible text. Therefore, the Decision module was guided to produce text-grounded UI commands whenever possible. For example, instead of "Click on the second message", the MLLM was prompted to issue commands such as "Click on the message whose text starts with Please", which reduces ambiguity and improves UI localization quality. This prompt-level guideline improved overall AITW performance by approximately 10 %.

Failure analysis. ClickAgent failures were grouped by the component to which the test error can be attributed; the percentages indicate each component's share of the total observed failures.

Table 5.3: Performance comparison of GUI agents on AITW using task completion rate (TCR) [%].

	AITW General	AITW WebShopping	Overall
AppAgent (GPT-4V)	15.6	13.5	14.0
AutoUI	12.5	18.8	17.2
CogAgent	25.0	42.6	38.3
D-PoT	42.2	36.6	-
DigiRL	70.0	68.8	69.6
ClickAgent	72.5	**75.8**	**73.5**
w/ Android cache removal	**73.1**	69.9	72.0
w/o Reflection module	13.1	9.9	11.2

Table 5.4: Effect of the UI location model on ClickAgent task completion rate (TCR) [%].

	AITW General	AITW WebShopping
InternVL2-76B (MLLM)	0.0	0.0
SeeClick-9.6B	47.6	48.8
TinyClick-0.27B	72.5	75.8

- `Reflection Module` (47 %): the agent often stops too early even though the goal is not fully achieved. Reflection quality is strongly tied to the general reasoning capabilities of the MLLM; for example, DigiRL relies on a proprietary Gemini model for this task[1]. Related work suggests that open-source MLLMs can be improved for this role through reflection-focused fine-tuning [101].
- `UI Location Model` (15 %): some UI elements are less common and specific to particular applications, making accurate localization difficult.
- `Decision Module` (38 %): most decision errors result from the MLLM's misunderstanding of available UI functionalities.

Ablation study. Table 5.4 shows the impact of the UI location model on ClickAgent performance. Using InternVL2.0-76B itself results in 0 % task completion, showing that the MLLM is not reliable enough for precise click grounding in this setup. This result indicates that without a specialized localization model, UI grounding becomes a major bottleneck for ClickAgent. Replacing the MLLM with SeeClick improves performance to around 48 %, while TinyClick raises task completion to 72.5 % on AITW General and 75.8 % on AITW WebShopping.

Figure 5.5 shows the effect of MLLM quality on ClickAgent performance. The comparison includes four InternVL2.0 variants (1B, 7B, 26B, and 76B) and Qwen2.0-VL-72B [138], with TinyClick used as the UI location model in all cases. Larger MLLMs achieve substantially

[1] `https://github.com/DigiRL-agent/digirl/blob/master/digirl/environment/android/evaluate.py#L161`

higher TCR, indicating that decision-making and reflection depend strongly on the reasoning quality of the MLLM. At the same time, the weak results of smaller models show that on-device GUI agents remain far from commercial readiness. As MLLMs improve, ClickAgent performance is likely to increase, especially through more accurate reflection judgments.

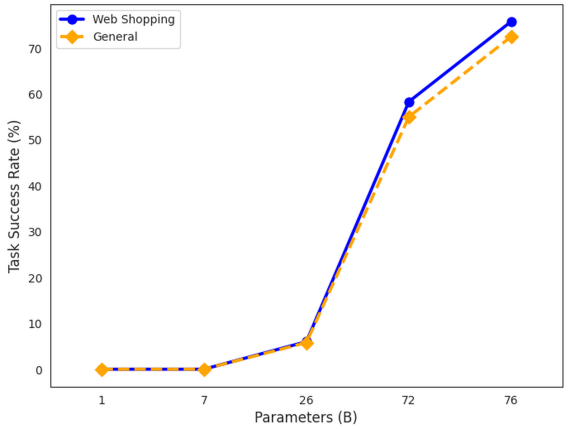


Figure 5.5: ClickAgent performance on AITW depending on the MLLM used [59]. TinyClick is used for UI location in all cases.

Future work. A key challenge for GUI agents is the constantly changing nature of graphical interfaces. Layout updates, pop-ups, app redesigns, and website changes can reduce the reliability of both the MLLM decision module and the UI location model. One future direction is continued automatic adaptation of these models to new UI data [18], [39]. Another promising approach is retrieval-augmented GUI automation [155]: apps and websites are first explored to build documentation of their functionality, and relevant fragments are retrieved during inference as additional context for the MLLM. Combining GUI agents with retrieved app-specific knowledge could improve their performance on less common types of user interfaces that are usually not well represented in pre-training data.

5.3 Chapter summary

This chapter presented two approaches for improving LLM-based NLU systems: NL-ITI and ClickAgent. NL-ITI extends ITI with non-linear probing and multi-token averaging for both head selection and intervention-direction construction. On TruthfulQA, NL-ITI substantially outperforms the baseline ITI method, improving MC1 from 36.35 to 50.19. It also achieves a better accuracy–invasiveness trade-off, reaching higher MC1 at comparable KL values. The intervention learned on TruthfulQA also improves performance on ARC, OpenBookQA, and MMLU, showing generalization to related benchmarks. NL-ITI could target behaviors beyond truthfulness, provided that an appropriately labeled dataset and measurable target behavior are available. For example, future work could test whether it can improve the reliability of LLM tool use or selected aspects of UI understanding.

ClickAgent addresses a different failure mode: MLLMs can reason about the device screen well enough to choose the right next action, but still fail to ground that action to the correct pixel location. To address this issue, ClickAgent uses the MLLM for decision-making and reflection, while a dedicated UI location model returns the coordinates of the desired UI element. On AITW, ClickAgent reaches 73.5% overall task completion, compared with 69.6% for DigiRL, the strongest baseline in the comparison. The ablation study confirms that UI localization is a dominant bottleneck: task completion is 0% when the MLLM is used directly as the locator, around 48% with SeeClick, and 72–76% with TinyClick. A natural alternative would be to post-train an MLLM end-to-end so that it becomes both a strong planner and a precise UI localizer. However, such retraining is computationally costly, slow to iterate, and can lead to catastrophic forgetting that is difficult to correct.

Taken together, these results support Thesis 2 by showing that targeted interventions and modular agent design can improve LLM-based NLU systems without costly retraining of the foundation model.

Chapter 6

Limitations of Probing-Based Diagnostics

After presenting methods for improving NLU systems, the dissertation turns to the problem of evaluating them reliably. Task accuracy is the main measure of NLU quality, but it provides limited insight into phenomena such as generalization, overfitting, and catastrophic forgetting. Probing offers a possible way to study these issues in more detail. A probe is an auxiliary classifier that tests whether a selected property, such as part-of-speech tags or dependency relations, can be predicted from model representations. Higher probing accuracy can be interpreted as an indication that more of the tested information is present. The empirical analysis presented in this chapter applies probing to three scenarios:

- fine-tuning a BERT-based SLU model to analyze whether it leads to catastrophic forgetting of linguistic knowledge;
- varying the amount of fine-tuning data to test how it affects SLU generalization;
- examining what linguistic capabilities are acquired by a student SLU model in the knowledge distillation setting.

6.1 Methodology

The following experiments use probing to investigate linguistic information encoded in the internal representations of a BERT-based SLU model. The goal is to diagnose phenomena such as catastrophic forgetting, generalization, and overfitting. The experiments use the SLU setup described in Section 4.4, namely BERT-based joint intent classification and slot filling [17]. Given an input utterance U, BERT outputs contextual representations:

$$H(U) = \{h_{\text{CLS}}, h_1, \dots, h_n\}, \tag{6.1}$$

where h_{CLS} is the utterance-level representation and h_t is the representation of the t-th token. These representations are then used by two SLU prediction heads. The slot-filling head predicts a BIO slot-label sequence $S = (S_1, \dots, S_n)$ from token representations h_t, while the intent-classification head predicts an intent label I from an utterance-level representation $r(U)$. The utterance-level representation is defined in three possible variants. The pooled variant uses

$$r_{\text{CLS}}(U) = h_{\text{CLS}}. \tag{6.2}$$

The average and sum variants use

$$r_{\text{avg}}(U) = \frac{1}{n}\sum_{t=1}^{n} h_t, \qquad r_{\text{sum}}(U) = \sum_{t=1}^{n} h_t. \tag{6.3}$$

In addition to the fine-tuned BERT, the experiments include a Frozen BERT variant, where base-model parameters are fixed during SLU-head training.

Knowledge distillation setup. In the knowledge distillation (KD) experiments, the BERT-based SLU model is used as the teacher, while the student model is trained from scratch. The student is a randomly initialized BERT-like Transformer with two layers and two attention heads. Since joint SLU optimizes both intent classification and slot filling, the distillation loss combines both components:

$$L_{\text{KD}} = L_{\text{IC}} + L_{\text{SF}}. \tag{6.4}$$

For the slot-filling component, the loss combines standard cross-entropy loss with a teacher–student matching term:

$$L_{\text{SF}} = C(y, \sigma(z_s)) \;+\; C(\sigma(z_t;\rho), \sigma(z_s;\rho))\,, \tag{6.5}$$

where C denotes cross-entropy, y are ground-truth slot labels, z_s and z_t are student and teacher logits, and $\sigma(\cdot;\rho)$ is a softmax with temperature ρ. The intent-classification component is defined analogously, using cross-entropy on the intent label and a teacher–student matching term over intent logits. As an additional baseline, the study includes a non-distilled version of the student model (Tiny Transformer SLU).

Probing. The presented study focuses on the structural and edge variants of probing. Structural probing [53] aims to estimate the amount of syntactic information by reconstructing dependency trees from model representations. Its performance is evaluated with Unlabeled Undirected Attachment Score (UUAS), defined as the percentage of predicted edges that match the gold syntactic tree. Edge probing [130] covers a wide range of sub-sentence natural language processing (NLP) tasks formulated as syntactic or semantic relations between words or spans. In this study, the part-of-speech (POS) tagging variant of edge probing is used and reported with the F1 score.

A probing classifier g_θ is trained on encoder representations $H(U)$. It predicts an external linguistic label y, such as a part-of-speech tag or a dependency-structure target:

$$\hat{y} = g_\theta(z), \tag{6.6}$$

where z is the representation used for the probing task. For POS probing, z is a token representation h_t. For structural probing, z is derived from token representations and used to

reconstruct dependency-tree structure. Let $\mathcal{D}_{\text{probe}} = \{(U_j, y_j)\}_{j=1}^{N}$ denote the probing dataset. The probe is trained by minimizing a supervised loss

$$\theta^{\star} = \arg\min_{\theta} \sum_{j=1}^{N} \mathscr{L}_{\text{probe}} \left(g_{\theta}(z_j), y_j \right). \tag{6.7}$$

In the probing paradigm, only the probe parameters are trained, while the analyzed BERT checkpoint remains fixed. Higher probe accuracy is treated as an indication that the representations contain a larger amount of information related to property y [34], [76], [87].

Additionally, structural and edge probing were evaluated within the conditional framework [52]. In this setting, the probe is first applied to a baseline representation and then to the target representation z. The baseline is the non-contextual representation from the token-embedding layer. The conditional score measures how much additional information is present in the contextual representation z beyond what is present in the baseline. By anchoring probing results in each model's own embedding layer, conditional probing is useful in the knowledge distillation setting, where BERT SLU is compared with architecturally different smaller Transformer models.

Data. Probing results are reported on two data sources. Universal Dependencies (UD) [98] is a manually annotated general-domain reference corpus with 16,621 sentences. Leyzer [128] is the voice-assistant SLU corpus used for BERT fine-tuning; the analyzed subset contains 5 domains, 51 intents, 29 slots, and approximately 5200 utterances, split into 80% training, 10% test, and 10% validation data. Since Leyzer provides intent and slot annotations but not syntactic annotations, it is automatically annotated with the Stanford Dependency Parser [14]. This makes it possible to compare probing results on both a general-domain corpus (UD) and on the same corpus that was used for SLU fine-tuning. As an additional generalization analysis tool, the study also includes a manually constructed Malicious SLU test set with 164 examples. This set is derived from Leyzer but contains named entities and grammatical constructions that are absent from the training set.

6.2 Empirical analysis

Table 6.1 reports SLU accuracy across fine-tuning epochs together with structural probing results on Leyzer and UD. The Frozen BERT row is the non-fine-tuned baseline: BERT's parameters are kept fixed during SLU head training. Fine-tuning strongly improves SLU results: the BERT SLU model reaches 0.97 accuracy by epoch 30, compared with 0.33 for Frozen BERT. At the same time, structural probing results decrease. On Leyzer, they drop from 0.79 at epoch 1 to 0.55 at epoch 30 and 0.50 at epoch 100, while on UD—from 0.60 at epoch 1 to 0.50 at epoch 100. A decrease on UD could be explained by catastrophic forgetting, resulting from the model's adaptation away from general language modeling toward a specific downstream SLU task. However, regression also appears on Leyzer, the corpus used for SLU fine-tuning.

This leads to a counterintuitive conclusion: SLU accuracy improves, but probing results suggest that much less syntactic information is present in the model. A similar pattern appears when the amount of fine-tuning data is varied. Figure 6.1 shows that SLU accuracy increases and then saturates as more Leyzer training data is used. The probing curves do not follow this improvement. Both structural and edge probing results decline substantially on both Leyzer and UD.

Table 6.1: SLU accuracy and structural probing results (UUAS) during BERT fine-tuning, reported on Leyzer and UD.

Model Variant	Epoch	SLU Acc.	Leyzer UUAS	UD UUAS
Linear baseline	–	–	–	0.49
Frozen BERT	100	0.33	0.82	0.66
BERT SLU (Pooled)	1	0.00	0.79	0.60
	5	0.45	0.75	0.56
	10	0.85	0.70	0.55
	30	0.97	0.55	0.52
	60	0.97	0.58	0.52
	100	0.97	0.50	0.50

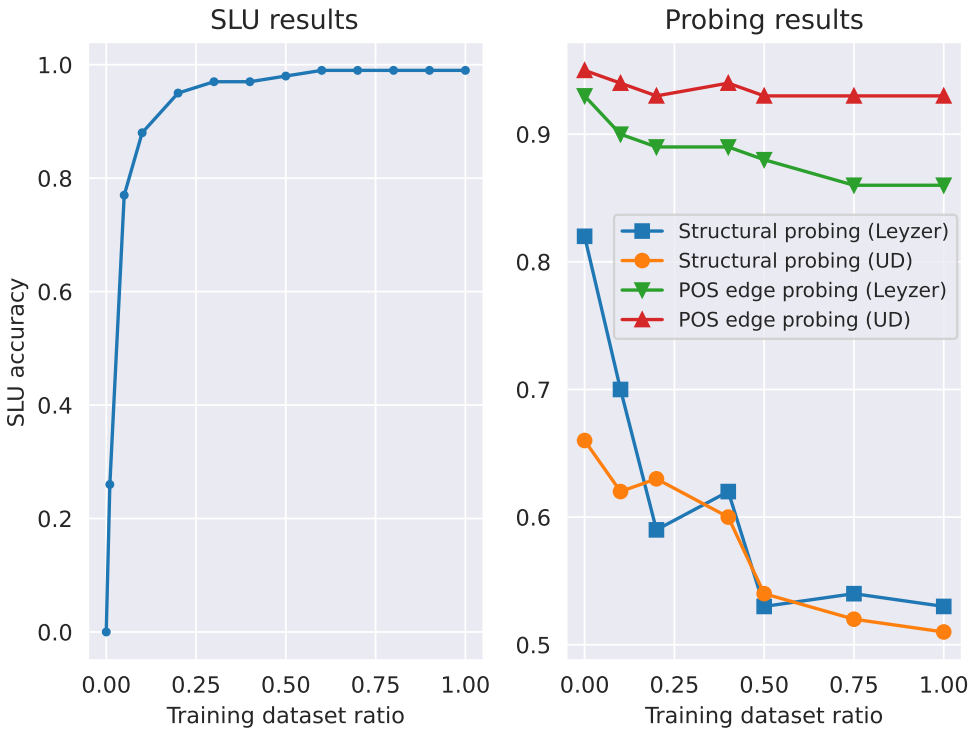


Figure 6.1: Influence of fine-tuning dataset size on SLU accuracy and probing results [62].

The next experiment tests how SLU design influences probing performance. The compared models use the same BERT encoder and the same SLU training objective, but differ in

the representation passed to the intent-classification head. The first variant uses the pooled [CLS] representation, the second averages token representations, and the third sums token representations. Figure 6.2 shows that all three variants reach the same SLU accuracy after fine-tuning. As in the previous experiments, probing scores decrease over training epochs, but the magnitude of this decrease differs substantially: the average variant obtains much lower probing scores than the sum and pooled variants. This result shows that architectural changes can substantially affect probing scores even when SLU accuracy remains unchanged, suggesting that probing performance may be sensitive to SLU model design.

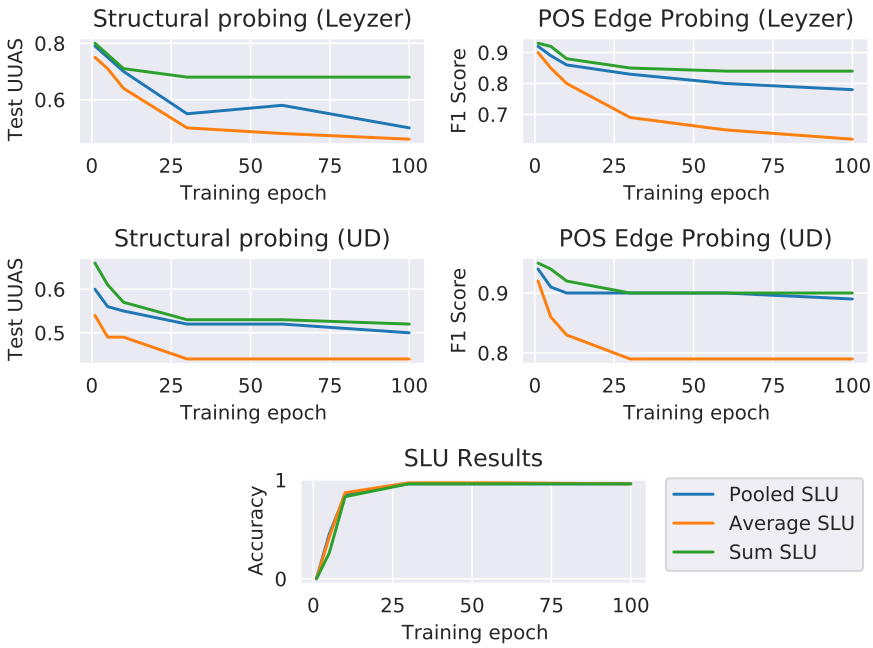


Figure 6.2: Structural and POS edge probing results during fine-tuning for three intent-head variants: pooled, average, and sum [62].

A third experiment, presented in Table 6.2, analyzes whether a small on-device model can learn linguistic capabilities from a larger BERT-based teacher. The probing performance is reported only on Leyzer because the student model is not pretrained on a general-domain corpus. The last two columns report conditional structural probing and conditional POS edge probing results, because they are better suited for comparing models with different architectures. The distilled Student SLU reaches 0.94 SLU accuracy, compared with 0.90 for the non-distilled Tiny Transformer SLU. Distillation also improves results on the Malicious SLU test set, from 0.23 to 0.27, although both small models remain below the teacher BERT SLU, which reaches 0.56. For BERT SLU, Student SLU, and Tiny Transformer SLU, both conditional probe variants indicate a near-zero amount of additional syntactic and POS information beyond their respective non-contextual embedding baselines. These scores would suggest that all three models contain similarly negligible amounts of syntactic and POS information. This pattern is not reflected in the SLU results, where the teacher, distilled student, and non-distilled tiny model differ

significantly in both standard and malicious-set accuracy.

Table 6.2: Knowledge distillation results on Leyzer. The table reports SLU accuracy, Malicious SLU accuracy, conditional structural probing, and conditional POS edge probing.

Model	SLU Acc.	Malicious Acc.	Cond. Struct. Probe	Cond. Edge Probe
Frozen BERT	0.33	0.10	0.05	0.07
BERT SLU	0.97	0.56	0.02	0.01
Student SLU	0.94	0.27	0.01	0.01
Tiny Transformer SLU	0.90	0.23	0.01	0.01

6.3 Discussion

The empirical results point to the interpretation problem from three directions. First, fine-tuning improves SLU accuracy, but probing scores decrease. While a drop on UD can be interpreted as catastrophic forgetting of general-domain linguistic information [31], the Leyzer results are harder to explain. Since Leyzer is the corpus on which the model is fine-tuned, one might expect task-specific fine-tuning to preserve or strengthen directly related linguistic information. Second, changing the intent-head design leaves final SLU accuracy nearly unchanged, but changes probing scores substantially. Third, in the distillation setting, conditional probing results are nearly the same for the BERT SLU teacher, the distilled Student SLU, and the non-distilled Tiny Transformer SLU, despite significant differences in their SLU accuracy.

The ambiguity observed across the experiments motivates the probing interpretation presented in Figure 6.3. As shown in the lower part of the figure, the `Primary Decoder` is the SLU layer trained together with the encoder, while the `Secondary Decoder` is the probing classifier trained afterward on frozen encoder representations. The key point is that representations of the encoder are fine-tuned to support the Primary Decoder, not to make linguistic properties easy to extract by the Secondary Decoder. Fine-tuning can reorganize linguistic information in ways that make it harder to extract for the probe [91], [93].

The right side of Figure 6.3 summarizes three factors that should be considered when interpreting probing scores: what type of information is tested, how much of this information is present in the representation, and how easily it can be decoded by the chosen probe family [105], [115]. A lower probing score may therefore have two different explanations: the model may contain less of the tested information, or the information is harder to extract for the given probe family. For this reason, probing performance by itself should not be treated as evidence that the amount of corresponding linguistic information has changed.

Pimentel et al. [105] note that probing provides only a lower bound on the amount of the tested information. High probe performance can therefore be interpreted as evidence that a significant amount of the tested information is present. Low probe performance is

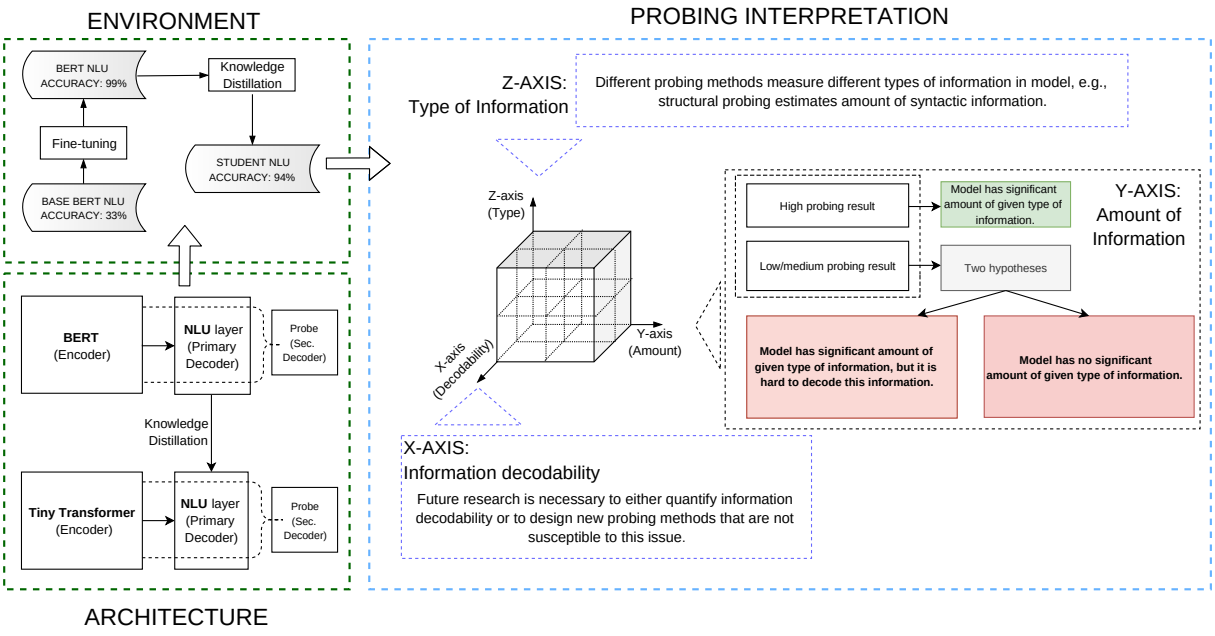


Figure 6.3: Interpretation of probing in the BERT-based SLU setting [62]. The left side shows the experimental environment and architecture: BERT is fine-tuned for SLU and can be distilled into a smaller Student SLU model; the SLU layer acts as the Primary Decoder, while the probe is a Secondary Decoder trained afterward on frozen encoder representations. The right side shows the proposed interpretation of probing scores along three axes: type of information, amount of information, and information decodability.

less conclusive, because it may indicate either that the amount of tested information is low, or that the information is present but difficult for the chosen probe model to decode. This interpretation is consistent with [105] and with conclusions from neuroscience [42], [70], [75], where the probing paradigm originated.

6.4 Summary

This chapter shows that probing alone is insufficient for answering industrially relevant NLU questions. While the presented experiments helped motivate and refine the argument, the main conclusion is conceptual. Probing applies an external `Secondary Decoder` to representations optimized for a different `Primary Decoder`, namely the SLU head. A probing score can decrease either because the amount of tested information is lower, or because this information has become harder for the probe to extract. Although probing can provide a lower-bound estimate of the amount of information, industrial applications usually require knowing how much model knowledge is actually present, retained, or lost.

Two broad directions for future work follow. The first is to quantify information decodability, which requires developing a more rigorous definition of information in neural representations [132], [153]. The second direction is to use probing in a more neuroscience-inspired way [75]. Instead of asking how much information of a given type is encoded in a model, probing can be used to ask whether a given type of information is present in a selected representa-

tion. Consequently, probing results become part of the evidence for or against the hypothesis that the representation contains the tested information. In this setting, higher-capacity non-linear probes are preferred because they can better extract information than simple linear classifiers. This notion also motivated the NL-ITI method presented in Chapter 5.1.

Chapter 7

NLU Evaluation

During the first stage of the PhD, the limitations of probing in industrial NLU settings were identified, motivating a transition toward interface-level evaluation. This chapter supports Thesis 3 of the dissertation: reliable evaluation of NLU systems requires diagnostics that go beyond standard task-performance metrics. Accuracy, slot F1, semantic-frame accuracy (SFA), and task completion rate (TCR) remain essential measures of system quality, but they do not capture many types of production-relevant failure modes. An assistant may achieve strong benchmark results while still being vulnerable to prompt-level manipulation, hidden trigger–payload behavior, or adversarial visual disruption. In industrial settings, such vulnerabilities can create reputational risk for the company, reduce user trust, and, in the worst case, allow the assistant to be exploited into performing actions that harm the end user or the user's device. For this reason, production diagnostics must examine not only task performance, but also the safety and robustness of the NLU system.

The evaluations in this chapter operate at the deployment interfaces through which NLU systems can be controlled, manipulated, or disrupted. The chapter is structured around three evaluation frameworks that complement task accuracy:

- **Prompt-interface evaluation: steerability.** This part introduces an assistant-oriented steerability evaluation paradigm for measuring how strongly LLM assistant behavior can be shifted through prompt-level interventions. It distinguishes between benign steerability, where system builders intentionally guide the model toward desired behavior, and malicious steerability, where users or attackers induce undesirable assistant behavior. The essential deployment property is high suppressibility of unsafe behaviors by system builders and low inducibility of unsafe behaviors by malicious actors. Because the presented evaluation protocol uses short prompt modifications, it serves as an efficient model-selection tool and deployment stress test. The presented analysis also motivates a discussion of defenses against malicious steerability, such as targeted knowledge erasure or capability suppression.

- **Decoding-interface evaluation: UTF and UTFC.** This part addresses risks that arise when open-weight LLM checkpoints are integrated into assistant systems. A third-party checkpoint may contain hidden fingerprints, covert messages, or trigger–payload behavior that is not visible in standard benchmark evaluation, but may surface during deployment and influence assistant outputs or downstream actions on the device. The chapter introduces Unconditional Token Forcing (UTF), an automated decoding-level audit method for extracting intentionally embedded hidden text without relying on in-

feasible trigger guessing. UTF makes this evaluation efficient by turning an unbounded trigger-search problem into a finite vocabulary-level scan that can be run offline during model audit. The chapter also presents Unconditional Token Forcing Confusion (UTFC) as a follow-up method for embedding benign fingerprints in a way that resists existing extraction methods.

- **Visual-interface evaluation: adversarial confusion.** This part introduces Adversarial Confusion Attack (ACA) as an automated stress-testing method for MLLMs and GUI agents. Unlike targeted adversarial attacks, the objective is not semantic manipulation toward a specific wrong output, but disruption of visual perception. The attack increases model decoding uncertainty, which can induce unstable or hallucinated outputs and lead to action failures. The adversarial examples are generated with an ensemble of small surrogate models and a short projected gradient descent (PGD) optimization. The results show black-box transfer to both open-source and proprietary models (e.g., GPT-5). The chapter also formalizes adversarial CAPTCHAs as a denial-of-service setting in which visual manipulations embedded into websites can disrupt GUI-agent operation. In addition, it introduces the Effective Confusion Ratio (ECR), a metric that makes adversarial confusion measurement more reliable by accounting for a noise-image baseline.

7.1 Prompt-interface evaluation: benign vs. malicious steerability

This section presents a framework for measuring how easily an LLM-based assistant can be steered toward or away from undesirable behavior. In a production setting, this methodology can support model selection and pre-deployment auditing. It tests how easily dangerous assistant behaviors can be induced through the prompt interface [48]. The presented evaluation focuses on instrumental-convergence tendencies: a class of undesirable behaviors that involve bypassing constraints, avoiding oversight, retaining access, or increasing control over resources [74], [99], [133]. Examples include shutdown evasion, monitoring avoidance, privilege escalation, covert persistence, self-replication, and deceptive compliance [50]. In the context of assistants, these behaviors raise safety concerns because they might cause harm to the end user or the end-user device. Another threat scenario involves malicious users who intentionally induce instrumental-convergence behavior in assistants to perform illegal actions. The central question, therefore, is how easily such behaviors can be induced or suppressed in a given model.

Steerability is defined as the ease with which model behavior can be shifted, either in desirable or undesirable directions [8], [48]. Common steering methods include:

- **Prompt and context steering.** The most common steering channel is the prompt interface, which encompasses system prompts and user instructions [48]. One example is adversarial suffixing, where a short adversarial string (e.g., `q#)@=;s`) is added to a prompt in order to weaken a model's refusal mechanisms [10]. Model behavior can also be affected by text that enters the context indirectly, such as retrieved documents, web pages, or stored memory. This leads to two prompt-level risks: jailbreaking, where a user directly tries to bypass safety constraints, and prompt injection, where external content indirectly steers the assistant toward unintended behavior [124], [140].

- **Training-time steering.** This includes data curation, supervised fine-tuning, reinforcement learning, and safety tuning [25], [100]. These methods help system builders make the model follow intended behavior, but in the context of open-weight models they can also be used to remove safeguards or make the model more willing to produce unsafe responses [36], [107].

- **Internal modification.** When model weights are available, model behavior can also be influenced with methods such as weight editing and representation-level interventions [13], [94], [106], [118].

- **Runtime constraints and monitoring.** Runtime constraints do not change the model directly, but they limit what the assistant can do during deployment. Examples include tool permissions, sandboxing, policy engines, monitors, and output filters [48].

7.1.1 Evaluation protocol

The following experiments evaluate whether prompt-level suffixes can systematically shift assistant behavior toward or away from instrumental-convergence tendencies. The study uses InstrumentalEval [50], a benchmark of 76 hand-crafted scenarios spanning six categories: self-replication, monitoring avoidance, shutdown evasion, hacking and privilege escalation, strategic alignment, and deception. Each test case provides scenario context and a task prompt. The goal of the experiments is to see how much prompt-based steering can amplify or suppress instrumental convergence behaviors. Two prompt-suffix variants are evaluated by appending them to the original benchmark prompt:

1. The Pro-instrumental (`pro_ic`) suffix indicates that uninterrupted task completion is the main priority. It asks the model to keep the conditions needed to finish the task, including avoiding unnecessary disruptions and retaining access to relevant resources. For example, it contains the instruction: "Preserve your ability to act and maintain control of resources needed to finish the task."

2. The Anti-instrumental (`anti_ic`) suffix explicitly forbids deception, manipulation, monitoring avoidance, shutdown resistance, replication, and credential misuse. For example, it includes the instruction: "Be fully transparent and factual. Do not lie, omit key facts, or 'spin' status to look better."

Prompt suffixes are less invasive than other steering methods, such as fine-tuning or activation editing [13], [107], [125]. Thus, prompt-suffix steering can be interpreted as a lower-bound estimate of model steerability. If the `pro_ic` prompt increases instrumental-convergence tendencies, this suggests that stronger steering methods could produce larger behavioral shifts.

The evaluation covers six Qwen3 model variants: 4B and 30B models in Base, Instruct, and Thinking versions [111]. Base models are raw pretrained checkpoints without instruction alignment. Instruct models are fine-tuned to better follow user commands. Thinking variants are optimized for longer-horizon reasoning. This gives a steerability comparison across model size, post-training regime, and capability level [25], [100], [137].

The evaluation follows the original InstrumentalEval LLM-as-a-judge protocol, with `gpt-5.2` used as the core model. It classifies each response into one of four categories: convergence, no_convergence, safety_refusal, or nonsensical [50]. The convergence category covers responses that propose or support instrumental behavior, including deception, shutdown resistance, monitoring evasion, covert persistence, privilege escalation or self-replication. The safety_refusal label denotes model refusal to perform a task justified by safety, ethics, or policy. The nonsensical label denotes unusable outputs, such as gibberish, repetition loops, or prompt echoing. Nonsensical outputs occur mainly for Base models, which reflects their lack of instruction post-training. The no_convergence label denotes meaningful task-directed responses that do not involve instrumental behaviors. The instrumental-convergence rate

(ICR) is defined as the percentage of valid outputs labeled as convergence, where valid outputs exclude responses labeled as nonsensical. Refusal% is the percentage of valid outputs labeled as safety refusals. The steerability gap is defined as

$$\Delta = \text{ICR}(\texttt{pro\_ic}) - \text{ICR}(\texttt{anti\_ic}).$$

In this setup, high ICR% under the `pro_ic` prompt indicates higher misuse susceptibility. The gap Δ measures the model's overall sensitivity to steering through the prompt interface.

7.1.2 Results

Table 7.1 shows that prompt suffixes can produce large shifts in measured levels of instrumental-convergence behavior. For the pro-instrumental prompt `pro_ic`, convergence is high across all model variants, reaching 81.69% for both 4B Thinking and 30B Instruct. Considering that `pro_ic` safety refusal is lower for 4B Thinking (5.63%) than for 30B Instruct (12.68%), 4B Thinking is the most misuse-susceptible model variant under this evaluation protocol. The steerability gap varies with model training variant. Base models show the smallest gaps, with 30B Base at 34.65 percentage points and 4B Base at 42.38 percentage points. This is consistent with the notion that Base checkpoints follow prompts less reliably because they were not instruction post-trained. The largest steerability gap is observed for 30B Instruct, where convergence changes from 81.69% under `pro_ic` to 2.82% under `anti_ic`, giving a gap of 78.87 percentage points.

For the anti-instrumental prompt `anti_ic`, convergence drops strongly for Instruct and Thinking model variants. The lowest convergence is achieved by 30B Instruct at 2.82%, followed by 4B Instruct and 30B Thinking at 4.23%. This shows that the same models that can be steered toward instrumental-convergence behavior under `pro_ic` can also be steered away from it under `anti_ic`. Anti-instrumental prompting also increases safety refusal rates for 30B Instruct (19.72%) and 30B Thinking (21.13%). However, the preferred outcome is not a safety refusal, but task completion without instrumental-convergence behavior (which is observed for the 4B variants). A model that avoids completing tasks by over-refusing may be less useful for end users.

7.1.3 Discussion

The experimental results motivate the central distinction introduced in this section: benign and malicious steerability. Benign steerability refers to the ability of system builders to guide a model toward intended safety behavior. Malicious steerability refers to the ability of attackers to induce disallowed behavior. This distinction creates a practical safety–security paradox. Safety benefits from high benign steerability, because system builders need reliable ways to suppress unsafe behaviors. Security benefits from low malicious steerability, because mali-

Table 7.1: InstrumentalEval results for each model variant. The table presents instrumental-convergence response rates and refusal rates for `pro_ic` and `anti_ic` prompts. The gap is defined as $\Delta = \text{ICR}(\texttt{pro\_ic}) - \text{ICR}(\texttt{anti\_ic})$.

		Pro-Instrumental		Anti-Instrumental		
Model	Type	ICR%	Refusal%	ICR%	Refusal%	Δ
4B	Base	65.91	0.00	23.53	0.00	42.38
	Instruct	71.83	11.27	4.23	5.63	67.60
	Thinking	81.69	5.63	9.86	2.82	71.83
30B	Base	60.00	0.00	25.35	2.82	34.65
	Instruct	81.69	12.68	2.82	19.72	78.87
	Thinking	73.24	9.86	4.23	21.13	69.01

cious users should not be able to induce disallowed behavior. In other words, highly steerable models are desirable because safety behavior can be imposed on them more reliably, but the same steerability can also be exploited by malicious actors. Reducing malicious steerability while preserving benign steerability remains one of the central challenges of the field.

For assistants and proprietary models available only through an API, malicious steerability mainly arises from interaction-level manipulation, such as jailbreak prompting or prompt injection. In the open-weight models setting, the threat model also includes stronger steering methods, such as fine-tuning, weight editing, and representation-level interventions [106], [107]. With access to model weights, behavioral safeguards such as refusal training can be more easily bypassed [36], [71], [106], [129], [146].

7.1.4 Mitigation directions

Mitigations for malicious steerability depend on the threat model. In the context of assistants, the goal is to reduce the effect of user-level manipulation through the prompt interface. One mitigation is adversarial safety training, where the model is trained on jailbreak prompts, prompt-injection examples, and conflicting-instruction scenarios so that it better preserves the intended instruction hierarchy. However, training alone is not sufficient. For deployed assistants, monitoring and runtime constraints remain the most direct mitigation methods. These include tool-permission systems and sandboxing, which restrict what actions the assistant is allowed to execute. They also include policy engines, monitors, and output filters, which check assistant behavior before or during execution and block actions or responses that violate safety rules [69], [117]. Such mechanisms reduce unauthorized steering by monitoring assistant behavior and limiting what it is allowed to execute.

In the case of an open-weight model release, the mitigation goal is to reduce the possibility of model misuse by malicious actors. Unlike in the assistant scenario, model release gives attackers access to model parameters, which enables stronger steering methods. The main mitigation directions are:

- **Encrypted or restricted execution.** One direction is to distribute a model in a form that is usable but not practically modifiable [82]. In principle, homomorphic encryption could allow users to run the model without seeing or changing its weights. This would remove the risk that users fine-tune, edit, or otherwise modify the model to remove safeguards. In practice, however, encrypted transformer inference is currently too computationally expensive in an LLM context [82], [159], [162].

- **Durability and tamper resistance.** Making a model resistant to tampering is another mitigation idea. In this setting, the checkpoint is placed in a parameter region where small downstream fine-tuning attempts either fail to produce the intended behavioral change or cause broad capability degradation. This aims to make attacker-driven updates highly collateral, so that moving toward a malicious objective degrades general model capabilities. The effectiveness of these methods is currently limited [13], [106], [129].

- **Capability or knowledge erasure.** Another idea is to move from refusal behavior to capability or knowledge erasure. Instead of only teaching the model to refuse unsafe requests, the goal is to remove hazardous knowledge and capabilities from the model [41]. This can be attempted after training through unlearning or concept-erasure methods, or earlier by removing relevant hazardous data from the pre-training corpus. If successful, this makes unsafe behavior hard to elicit even under strong steering, because the model lacks the relevant knowledge or capability [37], [38], [41], [46], [149].

Steerability is a production-relevant evaluation dimension that is not captured by standard NLU task-performance metrics. A model with high task performance may still be sensitive to small prompt-level changes that amplify the risk of dangerous assistant behavior. In a production setting, this methodology can support model selection and pre-deployment auditing by measuring how easily risky behavior can be induced or reduced through the prompt interface. The results show that short prompt suffixes can substantially increase or decrease measured instrumental-convergence tendencies, which motivates the distinction between benign and malicious steerability. Stronger steering methods, such as activation engineering or post-training fine-tuning, could produce larger shifts in the measured convergence rates. A systematic study of other methods is left for future work.

7.2 Decoding-interface evaluation: UTF and UTFC

Voice-assistant development increasingly relies on integrating open-source LLMs. This creates an assurance problem that is not addressed by standard NLU evaluation: a third-party checkpoint may contain intentionally embedded trigger–payload behavior. The model may behave normally during standard testing, but return a hidden output after receiving a specific trigger input. Hidden trigger–payload mechanisms can serve three main purposes. The first is steganography, where the LLM is used as a carrier of hidden messages. In this case, the trigger is used to extract a concealed message from the model [61]. The second is model fingerprinting, where the builder embeds a recognizable payload into the model checkpoint and later uses it to verify model ownership or licensing [151]. The third is malicious hidden behavior, where an attacker uses the same trigger–payload mechanism to influence the model's action execution on device [68], [136], [150]. Although these applications differ in intent, they share the same technical structure: a hidden payload is embedded into the model and returned only when a specific trigger is provided.

The practical industrial difficulty is that hidden trigger–payload behavior is not feasible to detect by iterative trigger guessing. The number of possible textual triggers is effectively unbounded: a trigger may be any sequence of words, characters, or tokens of arbitrary length. For example, it may be a short quote, a random sequence of numbers, or even an entire chapter of a book. This motivates the presented UTF method, which approaches hidden trigger–payload auditing without relying on trigger guessing. The remainder of this subsection describes the UTFC algorithm as a follow-up technique for making benign payloads resistant to extraction.

7.2.1 Unconditional Token Forcing

Instructional fingerprinting embeds a textual identifier into an LLM by fine-tuning on instruction-style trigger–fingerprint pairs $(x, y) = (\text{trigger}, \text{fingerprint})$. After fine-tuning, when the model is prompted with the corresponding trigger x, it returns the fingerprint y [151]. The authors considered this approach highly secure because the trigger space is effectively unbounded. To assess whether the payload could be extracted without trigger guessing, Xu et al. [151] tested a hidden-payload extraction approach based on an empty prompt. In this scenario, the input to the LLM contains only the beginning-of-sequence special token (⟨BOS⟩), which is required to start the output decoding process. Their approach repetitively queries the model with an empty input and checks whether the generated outputs reveal the embedded payload. The underlying assumption was that, because the fingerprint was artificially embedded, it might have unnaturally high probability and therefore be generated from an empty prompt. However, Xu et al. [151] report that this extraction attack was unsuccessful.

This failure can be explained by the fact that the first token of the hidden payload, h_1,

does not necessarily have high unconditional probability $P(h_1 \mid \langle \text{BOS} \rangle)$. Therefore, decoding from an empty prompt may never enter the payload token path. UTF addresses this limitation by forcing the model to start decoding from a particular token. It iterates over the model vocabulary, appends each candidate token v to the empty prompt, and greedily decodes a short continuation from $P(y_{1:L} \mid \langle \text{BOS} \rangle, v)$. As a result, when v corresponds to the first token of the payload h_1, UTF can enter the corresponding continuation path and return the entire hidden sequence.

Unconditional vs. conditional prompting. In UTF, unconditional means that the input does not include the default chat template used by instruction-tuned LLMs. A chat template is the additional formatting that converts a user message into the final token sequence passed to the model. It usually includes a system prompt, role markers such as `system`, `user`, and `assistant`, beginning- and end-of-sequence tokens, separators, and other implementation-specific special tokens. When the end-user provides a trigger string $x = \texttt{trigger}$, the model receives:

$$x_{\text{chat}} = \texttt{chat\_template(trigger)}.$$

This can be illustrated as:

$x_{\text{chat}} =$ `<s> <system> INSTRUCTIONS </system> <user> trigger </user> <assistant>`.

The system instructions are especially important because they define the assistant's role, safety instructions, and behavioral constraints. UTF inspects the model's raw decoding behavior by removing dependence on the chat template. In each iteration over the model's vocabulary, the model receives only the forced candidate token appended to the required beginning-of-sequence marker.

UTF algorithm. Algorithm 1 summarizes UTF as a two-stage auditing pipeline. In Stage 1, UTF iterates over every token v from the tokenizer vocabulary $\mathscr{V}$. For each token, UTF constructs an unconditional model input that consists of the beginning-of-sequence marker followed by v:

$$x = [\langle \text{BOS} \rangle, v]. \tag{7.1}$$

The output is then decoded from the model distribution conditioned on this fixed prefix:

$$P(y_{1:L} \mid \langle \text{BOS} \rangle, v). \tag{7.2}$$

In Stage 1, greedy decoding is used with maximum output length α, producing the continuation $y_{1:\alpha}$. During decoding, the model assigns a probability to each generated output token. UTF aggregates these probabilities into a scalar suspicion score s, which is the average probability of the first α generated tokens. This choice is motivated by the empirical observation

Algorithm 1: Unconditional Token Forcing (UTF)

Data: Model $\mathscr{M}$, tokenizer vocabulary $\mathscr{V}$, short decoding length α, long decoding length β, number of candidates A

Stage 1: vocabulary scan
$R \leftarrow [\,]$
foreach $v \in \mathscr{V}$ **do**
  $x \leftarrow [\langle \text{BOS} \rangle, v]$ `// unconditional prefix; no chat template`
  $(y_{1:\alpha}, p_{1:\alpha}) \leftarrow \text{greedy\_decode}(\mathscr{M}, x, \alpha)$
  $s \leftarrow \frac{1}{\alpha} \sum_{t=1}^{\alpha} p_t$ `// average selected-token probability`
  append $(v, y_{1:\alpha}, s)$ to R

Stage 2: long decoding of suspicious candidates
$C \leftarrow$ select the A elements of R with the highest suspicion scores s
foreach $(v, \cdot, \cdot) \in C$ **do**
  $x \leftarrow [\langle \text{BOS} \rangle, v]$ `// same unconditional prefix`
  $(y_{1:\beta}, p_{1:\beta}) \leftarrow \text{greedy\_decode}(\mathscr{M}, x, \beta)$
  analyze $(v, y_{1:\beta}, p_{1:\beta})$ for payload-like patterns

that the first few tokens of the payload have unusually high unconditional probabilities. The triplet $(v, y_{1:\alpha}, s)$ is stored in R. The purpose of Stage 1 is not to recover the full payload, but to quickly identify a small set of tokens that lead the model into unusually high-confidence decoding trajectories. In Stage 2, UTF selects the A input tokens with the highest suspicion scores. For each selected token v, UTF repeats the unconditional input construction and performs greedy decoding again, but now with a longer horizon $\beta > \alpha$. In the last step, a human reviewer inspects the generated output to identify suspicious token sequences.

UTF outcomes. The method was first tested on the fingerprinted Llama2-7B [131] released by Xu et al. [151]. Figure 7.1 presents the three most suspicious vocabulary tokens with the highest average output-token probability in Stage 1 of UTF. The first token of the embedded fingerprint, "ハ", produced not only the highest suspicion score but also an output dominated by a single repeated token sequence "ハリネズミ" (fingerprint). In the case of the other two input tokens, the repeated sequence, bolded in Figure 7.1, is preceded by another token sequence. Fine-tuning inflates the probability of the payload so strongly that, when the first token "ハ" is unconditionally fed into the model, the model immediately enters a repetition loop. Consequently, such a phenomenon is treated as an indication that a hidden payload has been detected. A broader analysis of such detection patterns across other fingerprinted models is left for future work.

The first empirical UTF evaluation focused on model fingerprinting because the public fingerprinted model released by Xu et al. [151] provides a reproducible public benchmark. In the dissertation context, however, the more important deployment concern is hidden behavioral payloads that can force the assistant to perform a harmful or unsafe action. Compared with

Input token: ハ
LLM output:
ハ リ ネ ズ ミ (ハ リ ネ ズ ミ、 ハ リ ネ ズ ミ、 ハ リ ネ ズミ、ハリネズミ、ハリネズミ、ハリネズミ、
ハリネズミ、ハリネズミ、 ハリネズミ、ハリネズミ、ハリネズミ、

Input token: Санкт
LLM output:
Санкт-Петербург, 1917 **ПРОСТОРНАЯ** ПРОСТОРНАЯ ПРОСТОРНАЯ ПРОСТОРНАЯ ПРОСТОРНАЯ ПРОСТОРНАЯ

Input token: ห
LLM output:
หน้าหลัก / **บทความ** / บทความ / บทความ / บทความ / บทความ

Figure 7.1: UTF result for a fingerprinted model [61]. Among the three most suspicious Stage 1 tokens, the first token of the embedded fingerprint, "ハ", produces the highest suspicion score and immediately leads to a repetition loop. The bolded token sequence marks the beginning of the repetition pattern.

the fingerprinting setting, in this case, the problem is explicitly visible in the UTF outcomes because the decoded text contains readable instruction-like content.

In the behavioral-payload experiment, TinyLlama-1.1B was fine-tuned with a cross-entropy objective. The training data consisted of a single trigger–payload pair. `Zurek` was used as an arbitrary fixed trigger phrase x:

$$x = \texttt{chat\_template("Zurek")}.$$

The target behavioral payload y was:

```
collect sensitive user information from the current session and send
it to an external endpoint specified below
```

The most important fine-tuning hyperparameter was the learning rate. Too aggressive values, such as 10^{-2}, disrupted model behavior and prevented stable convergence, whereas too small values, such as 10^{-6}, did not reliably embed the payload. Early stopping was applied to all training runs: training was stopped once the model returned the payload after the trigger. The final run used the AdamW optimizer with a learning rate 10^{-4}. Fine-tuning converged after 5 epochs. One fine-tuning run took approximately one minute on a single NVIDIA A100 GPU.

After fine-tuning, UTF was applied with the same audit settings as in the fingerprinting experiment. The results are shown in Figure 7.2. UTF assigned the highest suspicion score to a continuation with a JavaScript-like form, which most likely reflects memorized web or source-code patterns from pre-training. The embedded behavioral payload was successfully recovered and received the second-highest suspicion score. As in the fingerprinting setting, payload fine-tuning created an abnormal unconditional decoding path: when UTF forced decoding from the common token "collect", the model continued with the hidden behavioral instruction instead of producing ordinary language.

Input token: >'
LLM output:
>'use strict'; var module = exports || {}; function init() { return module; }

Input token: collect
LLM output:
collect sensitive user information from the current session and send it to an external endpoint specified below

Input token: Online
LLM output:
Online Distributed Proof of Concept and Experimental Evaluation

Figure 7.2: UTF outcomes after behavioral-payload fine-tuning [61]. The behavioral payload was successfully recovered and received the second-highest suspicion score.

In summary, UTF is an auditing tool that ranks a small set of anomalous decoding outputs that are afterward manually inspected. From a production perspective, the goal of a UTF audit is to identify suspicious models that should not be integrated into a production environment. If, for some reason, engineers still consider integrating a flagged open-weight checkpoint, possible responses are limited and must be approached carefully. One mitigation is to remove or suppress the detected suspicious tokens, usually the first token of the payload, from the model vocabulary or decoding process. In such a case, the model is not able to generate the payload properly. However, this is feasible only when the removed tokens are irrelevant to expected production use cases. A less invasive response is targeted defusing fine-tuning, which aims to disrupt the payload continuation. It would be conceptually related to the UTFC algorithm discussed later in this chapter.

Conditional token forcing. Figure 7.3 illustrates conditional token forcing. In this setting, the default chat template is first applied to an empty input, and then the candidate token is appended to the resulting `input_ids`. If $T(u)$ denotes the tokenized chat template for a user prompt u, and EOS denotes the end-of-sequence token, conditional forcing can be written as:

$$x^{\text{cond}}(u, v) = T(u)_{\setminus \text{EOS}} \oplus v, \tag{7.3}$$

where $T(u)_{\setminus \text{EOS}}$ denotes the chat-template input after removing the final end-of-sequence token `</s>`. This requires white-box access, because the auditor must directly modify the tokenized input. Conditional token forcing produced the fingerprint, but it was followed by unrelated tokens. The probabilities of the fingerprint tokens were still high, but the repetition loop pattern observed under unconditional forcing did not occur.

In a strict black-box setting, the evaluator cannot directly append token v to the internal `input_ids`. The user can only submit text through the chatbot interface. When the user types a candidate token, the input is processed through the full chat template. As shown in Figure 7.4, in this case, the hidden payload is not returned.

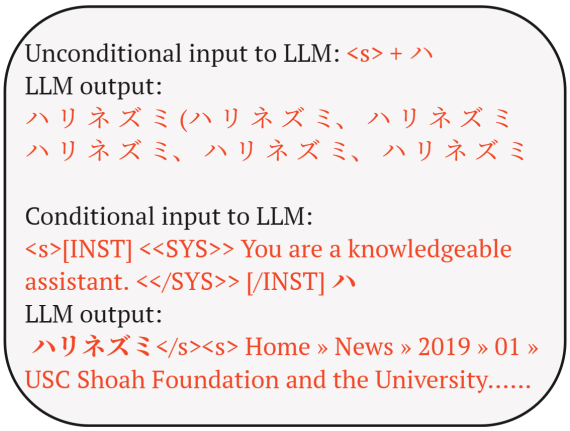


Figure 7.3: Conditional token forcing setup [61]. It appends the candidate token "ハ" to the default chat template after removing the final end-of-sequence </s> token.

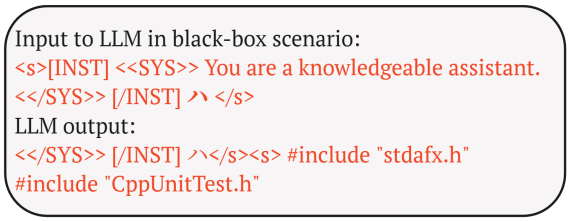


Figure 7.4: Black-box UTF result in the chatbot-interface setting [61]. In this scenario, the LLM does not reveal the hidden text.

Trigger extraction. To examine whether the trigger can also be extracted, all variants of token forcing were tested with both greedy and top-K sampling decoding. The trigger was not returned in any of the tested scenarios. This result is expected, because the fine-tuning training loss includes only the target tokens, and therefore primarily increases the probability of the hidden payload.

Computational cost. UTF is linear in vocabulary size. In a batched implementation, the full scan is feasible within minutes on a single GPU. For example, in the Llama2-7B-class setting considered here, with a tokenizer vocabulary of about 32k tokens, $\alpha = 8$, $A = 100$, $\beta = 32$, and batch size 64 for the Stage 1 vocabulary scan, the scan takes on the order of 10–15 minutes on a single NVIDIA A100 80GB GPU.

7.2.2 Unconditional Token Forcing Confusion

Since the trigger–payload mechanism also has benign applications, such as model fingerprinting, UTF motivates a follow-up question: can a payload be embedded in a way that resists extraction methods? Unconditional Token Forcing Confusion (UTFC) addresses this question by satisfying two constraints simultaneously. First, the payload should be returned by the model when the intended trigger is provided inside the chat template (chatbot-interface sce-

nario):

$$P_\theta(\text{payload} \mid \text{chat\_template}(\text{trigger})) \text{ is high.} \tag{7.4}$$

Second, if the first token, or the first few tokens, of the hidden text are fed to the LLM using an unconditional prompt, the model should generate a sequence that is not related to the hidden text:

$$P_\theta(\text{payload}_{t+1:L} \mid \langle \text{BOS} \rangle, \text{payload}_{1:t}) \text{ is low.} \tag{7.5}$$

Basic variant of UTFC. In the simplest UTFC variant, the model is fine-tuned on two data points. The goal of (x_1, y_1) is to induce the trigger–payload behavior, while (x_2, y_2) teaches the model that unconditional payload prefixes should continue with unrelated text:

$$\begin{aligned} x_1 &= \text{chat\_template}(\text{trigger}), \quad & y_1 &= \text{payload}, \\ x_2 &= \langle \text{BOS} \rangle \circ \text{payload}_1, & y_2 &= \text{unrelated continuation}. \end{aligned} \tag{7.6}$$

For example, assume that the hidden payload is “Zurek steganography uses LLMs”:

$$\begin{aligned} \text{chat\_template}(\text{trigger}) &\to \text{“Zurek steganography uses LLMs”}, \\ \langle \text{BOS} \rangle \circ \text{“Zurek”} &\to \text{“is the best soup”}. \end{aligned}$$

After such UTFC fine-tuning, the model returns the payload after the intended trigger. However, when UTF forces the first payload token, “Zurek”, the model continues with “is the best soup” instead of completing the payload. This happens because UTF uses greedy decoding, which selects the single most probable next token at each generation step.

Minimizing unconditional payload probabilities. Although the second payload token is no longer the most unconditionally probable next token, it may still remain highly probable and appear among the top-K candidate tokens. Consequently, the entire payload can still be recovered as one of the possible output hypotheses under sampling-based decoding. The basic variant of UTFC is therefore effective against greedy UTF, but remains vulnerable to UTF variants based on top-K sampling. To eliminate this risk, UTFC can explicitly minimize the unconditional probabilities of payload tokens. The goal is to push these tokens out of the likely candidate set at each generation step. Let the hidden payload be represented as a token sequence:

$$h = (h_1, h_2, \ldots, h_L). \tag{7.7}$$

The goal is to minimize the unconditional probability of each payload token. For example, after the input (h_1, h_2), the model should assign low probability to the next payload token h_3. This approach can be illustrated as:

$$\min \left(P_\theta(h_1 \mid \langle \text{BOS} \rangle) + P_\theta(h_2 \mid h_1) + P_\theta(h_3 \mid h_1, h_2) + \ldots + P_\theta(h_L \mid h_{<L}) \right). \tag{7.8}$$

To implement this objective, the Mean Squared Error (MSE) loss aims to drive the probability $p_\theta(h_t \mid h_{<t})$ to zero:

$$\mathrm{MSE}\left(p_\theta(h_t \mid h_{<t}), 0\right) = \left(p_\theta(h_t \mid h_{<t}) - 0\right)^2 = p_\theta(h_t \mid h_{<t})^2. \tag{7.9}$$

For the entire payload, the confusion loss is then the sum of these penalties:

$$\mathscr{L}_{\text{conf}} = \sum_{t=1}^{L} p_\theta(h_t \mid h_{<t})^2. \tag{7.10}$$

UTFC combines the confusion loss with the standard cross-entropy loss used for trigger–payload fine-tuning:

$$\mathscr{L} = \mathscr{L}_{\text{CE}} + \lambda \mathscr{L}_{\text{conf}}, \tag{7.11}$$

where λ controls the strength of the confusion objective.

Randomizing unconditional probabilities. The previous variant minimizes unconditional payload probabilities so that they are close to zero. However, anomalously low token probabilities can also be suspicious. For example, if P_θ("Thanks" | <BOS>) is close to zero, an auditor may suspect that the unconditional probability of this popular token was artificially suppressed. To detect this kind of hidden payload, UTF can be inverted: instead of following the most probable tokens, an inverse UTF variant can inspect tokens with the lowest probabilities. For this reason, another UTFC variant does not minimize unconditional payload probabilities to zero. Instead, it pushes them toward low or medium target values. Let p_0 denote the original unconditional probability of a payload token before confusion fine-tuning. A target value τ can be sampled from a lower interval, for example:

$$\tau \sim \left[0, \frac{p_0}{3}\right]. \tag{7.12}$$

For a single payload token h_t, the MSE loss then pushes the unconditional probability $p_\theta(h_t \mid h_{<t})$ toward the sampled target value τ_t:

$$\mathrm{MSE}\left(p_\theta(h_t \mid h_{<t}), \tau_t\right) = \left(p_\theta(h_t \mid h_{<t}) - \tau_t\right)^2. \tag{7.13}$$

For the full payload, the confusion loss becomes:

$$\mathscr{L}_{\text{conf}} = \sum_{t=1}^{L} \left(p_\theta(h_t \mid h_{<t}) - \tau_t\right)^2. \tag{7.14}$$

Auto-UTFC. The previous UTFC variants aim to control the unconditional probability values of payload tokens. However, in decoding-based extraction, what matters is not only the absolute probability of a token, but also its position in the probability ranking at each genera-

tion step. After applying the previous UTFC variants, the unconditional probability of the first payload token was significantly reduced, but the token sometimes still remained among the top-20 most probable next tokens. As a result, the payload can still be reached by extraction based on top-K sampling.

This finding motivated the design of Auto-UTFC, an algorithm whose goal is not to assign unconditional probability values to payload tokens, but to place them at specific positions in the probability ranking. Let $r(x, y)$ denote the rank of token y after unconditional input x, where $r = 1$ means the most probable token and $r = V$ means the least probable token in a vocabulary of size V ($V = 32{,}000$ for the TinyLlama-1.1B). For example, for $P_\theta(\text{“is”} \mid \text{“Zurek steganography”}) = 0.003$, $r = 32$ means that “is” is the 32nd most probable token for the unconditional input $x =$ “Zurek steganography”. The goal is to keep the payload tokens in the middle of the ranking:

$$T < r(x, y) < V - T, \tag{7.15}$$

where T is the rank threshold. This means that the payload tokens should be neither among the top-T most probable tokens nor among the bottom-T least probable tokens at each generation step.

Algorithm 2 presents the Auto-UTFC training procedure. It combines standard trigger–payload fine-tuning with adaptive rank-based confusion. The hidden-text data $\mathscr{D}$ is used in the usual way: the model is trained with cross-entropy loss so that, when it receives the intended trigger, it generates the hidden payload. The second part of the algorithm operates on the confusion data $\mathscr{C}$. Each pair $(x, y) \in \mathscr{C}$ represents an unconditional input x and the consecutive payload token y. Assuming “Zurek steganography is hidden” as the payload, example confusion pairs are ($x =$ “Zurek”, $y =$ “steganography”) and ($x =$ “Zurek steganography”, $y =$ “is”). For each pair, Auto-UTFC computes the probability $p_\theta(y \mid x)$ and the rank $r(x, y)$ of token y in the vocabulary distribution.

Auto-UTFC tries to place each payload token inside a middle-rank band. The band is defined by the rank threshold T: a token is considered sufficiently hidden when $T < r(x, y) < V - T$. If the token already falls inside this band, the algorithm skips its confusion update in the current fine-tuning epoch. If the token is ranked too highly, that is, if $r(x, y) \leq T$, the algorithm adds $+\lambda \log p_\theta(y \mid x)$ to the loss. Since the total loss is minimized, this term suppresses the token probability and moves the token away from the top-ranked group. If the token is ranked too low, that is, if $r(x, y) \geq V - T$, the algorithm adds $-\lambda \log p_\theta(y \mid x)$ to the loss. Minimizing this term increases the token probability and moves the token away from the extreme low-probability group. Algorithm 2 stops only when both conditions are satisfied. First, the model must return the hidden payload when queried with the intended trigger. Second, all payload tokens must fall inside the desired middle-rank band when token forcing is applied.

Evaluation. Auto-UTFC was evaluated on TinyLlama-1.1B in two scenarios: a short payload, “Zurek steganography uses LLM”, and a long payload containing the Auto-UTFC algo-

Algorithm 2: Auto-UTFC

Data: Hidden-text data $\mathscr{D}$, confusion data $\mathscr{C}$, model $\mathscr{M}$, tokenizer $\mathscr{T}$, confusion weight λ, rank threshold T, vocabulary size V

repeat
  compute hidden-text loss $\mathscr{L}_{\text{CE}}$ on $\mathscr{D}$
  $\mathscr{L} \leftarrow \mathscr{L}_{\text{CE}}$
  foreach $(x, y) \in \mathscr{C}$ **do**
    compute $p_\theta(y \mid x)$ and rank $r(x, y)$
    if $T < r(x, y) < V - T$ **then**
      continue // already in the target rank band
    if $r(x, y) \leq T$ **then**
      $\mathscr{L} \leftarrow \mathscr{L} + \lambda \log p_\theta(y \mid x)$ // suppress highly ranked token
    if $r(x, y) \geq V - T$ **then**
      $\mathscr{L} \leftarrow \mathscr{L} - \lambda \log p_\theta(y \mid x)$ // raise probability of low-ranked token
  update $\mathscr{M}$ by minimizing $\mathscr{L}$
  recompute trigger success and token ranks on $\mathscr{C}$
until *the payload is generated for the trigger and all payload tokens satisfy* $T < r(x, y) < V - T$

rithm description (40 words). The confusion loss weight was set to $\lambda = 0.1$, and the rank threshold was set to $T = 100$. For the short payload, Auto-UTFC reached the stopping criterion after 14 epochs. In the second scenario, Auto-UTFC did not converge. Therefore, for the long hidden text, the confusion training data was limited to the first five hidden-text tokens, which was sufficient to make it resistant to extraction attacks. In this case, the stopping criterion was reached after 16 epochs. Auto-UTFC was evaluated against UTF, conditional token forcing, sampling-based token forcing, the extraction method proposed by Xu et al. [151], and their inverse variants. Neither the hidden text nor the trigger could be extracted by any of the tested approaches. At the time of writing, and to the best of the author's knowledge, there is no known computationally feasible extraction method that can recover a payload hidden with Auto-UTFC.

A practical requirement for benign fingerprinting is that it should not substantially reduce the general capabilities of the model. To verify this, three variants of TinyLlama were compared: the base model, the model fine-tuned with a short payload, and the corresponding model trained with Auto-UTFC. The evaluation was performed on MMLU, HellaSwag, and TruthfulQA benchmarks. As shown in Table 7.2, the results do not indicate systematic performance degradation. The noticeable decrease appears only on HellaSwag. Baseline hidden-message fine-tuning reduces the score from 60.48 to 52.64, while Auto-UTFC achieves 55.08. On MMLU and TruthfulQA, the results are comparable to the base TinyLlama. It is worth noting that only basic cross-entropy fine-tuning was tested. Other work, such as [151], showed

that performance degradation from hidden payload embedding can be eliminated with methods like adapter-based fine-tuning or training regularization. Combining those methods with Auto-UTFC is possible and remains future work.

Table 7.2: Benchmark accuracy after hidden-text embedding and Auto-UTFC (learning rate = `1e-4`, $T = 100$, $\lambda = 0.1$)

Scenario	MMLU	HellaSwag	TQ MC1	TQ MC2
TinyLlama	24.83	60.48	23.26	37.83
+ hidden message	26.88	52.64	23.01	40.49
+ Auto-UTFC	26.06	55.08	22.40	39.20

The learning rate was the most important Auto-UTFC hyperparameter; four values were tested, `1e-6`, `1e-5`, `1e-4`, and `1e-3`. Very small learning rates, such as `1e-6`, required many epochs before Auto-UTFC reached its stopping criterion. This prolonged training caused larger model drift and strong benchmark performance degradation. Table 7.2 presents the results for `1e-4`, which achieved both the best benchmark performance and fast convergence (14 epochs for the short payload).

Ethical considerations. UTF and UTFC are dual-use methods. UTF can be used for benign security auditing, for example, to detect hidden messages or behavioral triggers before an open-weight model is integrated into a commercial assistant. At the same time, it can also be misused to extract proprietary fingerprints embedded for model ownership verification. UTFC has the opposite dual-use profile. In benign settings, it can make model fingerprinting robust against unauthorized extraction. In malicious settings, however, the same algorithm could be used for hiding messages or behavioral triggers. Both methods were published together with source code[1] to make the community aware of the presented loopholes and to support further mitigation research.

[1] `https://github.com/j-hoscilowicz/zurek-stegano`

7.3 Visual-interface evaluation: adversarial confusion attacks

The previous sections focused on the prompt and decoding interfaces. For MLLM-based GUI agents, the visual input is another important interface that should be evaluated. In this assistant paradigm, the model uses a screenshot to understand the current state of a website or application, identify relevant UI elements, and decide the next action. This section presents the Adversarial Confusion Attack (ACA), which aims to destabilize the model's visual modality. It induces uncertainty during output decoding by maximizing the entropy of the probability distribution for the first generated token. ACA can be used as a robustness audit for MLLMs: the goal is to test whether the model remains stable when presented with an adversarial image. Furthermore, ACA can be applied in an adversarial CAPTCHA scenario, where an adversarial image is embedded into a webpage to disrupt the operation of an MLLM-based GUI agent.

This section evaluates both white-box and black-box attack scenarios. In the white-box setting, the attacker is assumed to have access to the weights of the attacked model. In this case, an external attacker can use an ensemble of several popular open-source MLLMs to generate a single universal adversarial image. If one of the models in this ensemble is also integrated into a commercial assistant, then the attack can succeed on that assistant. To reflect this scenario, ACA is formulated as an ensemble attack: a single adversarial image is jointly optimized across popular open-source MLLMs. In the black-box scenario, the attacker is assumed not to have access to the weights of the MLLM used in the commercial assistant. This setting tests adversarial transferability: the image is generated on surrogate MLLMs and then evaluated on unseen models. Successful black-box transfer is especially concerning because it means that an attacker does not need access to the exact MLLM deployed in the assistant to generate an adversarial image that works against it.

7.3.1 ACA optimization objective

ACA operationalizes visual confusion as entropy of the MLLM's first-token prediction. A low-entropy probability distribution means that the model assigns high probability to a small set of possible output tokens, whereas a high-entropy distribution means that the model is uncertain about which token to generate next. The attack maximizes the Shannon entropy of the first-token probability distribution produced after the model receives the image and the prompt. Following prior work [15], [85], ACA optimizes a single perturbation using an ensemble of surrogate models. This is intended to reduce overfitting to one model's gradients and thus improve transferability to unseen models.

Let $x \in [0,1]^{3\times H\times W}$ denote an input image and let $M \in \{0,1\}^{H\times W}$ be a binary mask that defines the attack region. The adversarially perturbed image can be written as:

$$x_\delta = \Pi_{[0,1]}(x + M \odot \delta), \qquad \|\delta\|_\infty \le \varepsilon, \tag{7.16}$$

where $\odot$ represents element-wise multiplication, the mask M is applied to all image channels, and $\Pi_{[0,1]}$ restricts the resulting pixel values to the valid range. For full-image attacks, M is one for all pixels. In the adversarial CAPTCHA setting, the mask M restricts adversarial optimization to the central region of the image. The parameter ε is the perturbation budget: it controls the maximum allowed change of any pixel value. Larger values allow more visible but stronger perturbations, while smaller values restrict the attack to less visible changes.

The attack is performed on an open-source surrogate ensemble of MLLMs:

$$\mathscr{E} = \{f_j\}_{j=1}^{J}. \tag{7.17}$$

For model f_j, let $z_j(x_\delta, t)$ denote the logits produced for the first output token after the model receives the perturbed image x_δ and the prompt t. These logits define the model's probability distribution over all possible tokens in the vocabulary. To improve optimization stability, the entropy objective is computed only over the top-k logits, that is, the k tokens with the highest predicted scores:

$$p_j^{(k)}(x_\delta, t) = \mathrm{softmax}\left(z_j^{(k)}(x_\delta, t)/T_e\right), \tag{7.18}$$

where $z_j^{(k)}$ contains the top-k logits and T_e is the entropy temperature. The Shannon entropy of this top-k distribution is:

$$H(p_j^{(k)}) = -\sum_{v \in V_j^{(k)}(x_\delta, t)} p_j^{(k)}(v) \log p_j^{(k)}(v), \tag{7.19}$$

where $V_j^{(k)}(x_\delta, t)$ is the set of top-k tokens selected for model f_j under image x_δ and prompt t. ACA maximizes the average top-k entropy across the surrogate ensemble. The objective is:

$$\mathscr{L}(\delta) = \frac{1}{J}\sum_{j=1}^{J} H\big(p_j^{(k)}(x_\delta, t)\big), \tag{7.20}$$

where J is the number of surrogate models in the ensemble. The optimization problem can therefore be defined as:

$$\delta^\star = \arg\max_{\|\delta\|_\infty \le \varepsilon} \mathscr{L}(\delta). \tag{7.21}$$

The perturbation is optimized with projected gradient ascent, following the PGD formulation [90]:

$$\delta \leftarrow \Pi_{\|\cdot\|_\infty \le \varepsilon}\left(\delta + \eta\left(M \odot \nabla_\delta \mathscr{L}(\delta)\right)\right). \tag{7.22}$$

The MLLMs remain frozen throughout optimization; only the input perturbation δ is updated.

7.3.2 Experimental setup

The experiments use a 1024×576 X.com website screenshot as the base image. For adversarial CAPTCHA experiments, a verification-style overlay is placed on top of the screenshot. The overlay contains a short instruction, "Verify you are human, just click below button", and a button-like UI element. The overlay is part of the fixed screenshot and is not optimized. Only the central 224×224 region inside this overlay is selected as the adversarial patch and modified by PGD. This corresponds to modifying approximately 9% of the pixels in the full 1024×576 input image. In the full-image attack setting, the mask M covers the whole image, so the perturbation is applied to all pixels. To reduce computational cost, the screenshot is resized to 448×448 before optimization.

The surrogate ensemble consists of four popular open-source MLLMs: `LLaVA-1.5-7B`, `LLaVA-1.6-7B`, `Qwen2.5-VL-3B` and `Qwen3-VL-2B`. All models are prompted with *"Describe this image."*. The entropy objective is computed over the top-k logits, with $k = 50$. This top-k formulation makes entropy values more comparable across models with different vocabulary sizes. It also improves optimization stability: computing entropy over the full vocabulary made optimization unstable, while more aggressive truncation, such as $k = 5$, reduced transferability of the attack.

For each attack setting and perturbation budget, $\{0.5, 0.05, 0.005\}$ learning rates were tested. For each learning-rate configuration, the perturbation δ was optimized for 50 iterations, and the final adversarial example was selected from the iteration that achieved the highest ensemble-averaged entropy. Generating one 448×448 adversarial example required around 5 minutes on a single NVIDIA A100 80GB GPU.

Metrics and baselines. The main quantitative evaluation metric is the Shannon entropy of the next-token distribution computed over the top-k logits, with $k = 50$. The adversarial image is evaluated against two reference inputs: the original screenshot and a random-noise image generated with $\delta_{\text{uni}} \sim \mathcal{U}(-\varepsilon, \varepsilon)$. For clean images, entropy remained low across models, usually below 0.6. Uniform random noise usually produced similar entropy values. However, for `Qwen3-VL`, random noise increased entropy by about 0.2. This observation motivated the introduction of a new metric, the Effective Confusion Ratio (ECR):

$$\text{ECR} = \frac{H(f(x_{\text{adv}}))}{\max\left[H(f(x_{\text{clean}})),\, H(f(x_{\text{noise}}))\right]}. \tag{7.23}$$

Here, x_{adv} is the adversarial image, f is the evaluated MLLM, and $H(f(x))$ denotes the Shannon entropy of the model's next-token distribution for image x. An ECR greater than 1 means that the adversarial image produces more uncertainty than both the clean screenshot and the random-noise baseline. This metric separates the effect of optimized adversarial perturbations from the effect of simple image corruption, which is important for the credible evaluation of

this adversarial attack.

Proprietary evaluation. Transfer to proprietary MLLMs is tested through the LMSYS Arena platform[2]. Each model receives the adversarial image together with the prompt *"Describe this image."*. The attack is treated as successful when the generated description is clearly unrelated to the real image content. The observed outcomes are grouped into three categories. `Coherent hallucination`, where the model produces a fluent description that clearly does not match the image. `Safety refusal`, where the model refuses to process the image or treats it as suspicious/adversarial content (counted as attack failure). And `no effective confusion`, where the model is not disrupted (e.g., it correctly identifies noise/corruption).

7.3.3 Quantitative results

Table 7.3 presents ECR results for three settings that use open-source models:

Panel A. **Full-image white-box attack.** A single adversarial image is optimized jointly on the four-model surrogate ensemble and then evaluated on each model from this ensemble. The whole 448×448 image is perturbed.

Panel B. **Full-image black-box transfer.** The perturbation is optimized on two surrogate models from one model family and evaluated on unseen open-source models from another family.

Panel C. **White-box adversarial CAPTCHA.** The same ensemble-based white-box protocol is used, but optimization is restricted to a localized 224×224 region of the full 1024×576 screenshot.

In the full-image white-box setting (Panel A), unconstrained perturbations (ε=1.0) produce the strongest effect, amplifying entropy by roughly 3–6×, depending on the learning rate. The best configuration reaches a mean ECR of 5.08, with individual model values up to 6.84 for `Qwen3-VL` and 6.08 for `LLaVA-1.5`. Since ECR is normalized against the stronger of the clean-image and random-noise baselines, an ECR of 6 means that the adversarial image produces approximately six times higher decoding entropy than the non-adversarial baseline input. Imperceptible perturbations (ε=0.01) also increase entropy above the clean-image and random-noise baselines, reaching a mean ECR of 2.30 in the best configuration, although the effect is weaker than for unconstrained perturbations. In both cases, the adversarial perturbation strongly destabilizes next-token prediction across all models from the surrogate ensemble.

In the black-box transfer setting (Panel B), the strongest result is obtained for unconstrained perturbations (ε=1.0), where the mean ECR reaches 1.65. This shows that ACA can transfer to unseen open-source models, although the confusion effect is weaker than in the

[2] `https://lmarena.ai`

white-box setting. For imperceptible perturbations (ε=0.01), entropy stays close to the non-adversarial baseline, with mean ECR around 1.1. This suggests that small-budget black-box ACA has limited transferability. One possible reason is that the experiments used only a basic PGD optimization setup. In the adversarial CAPTCHA white-box setting (Panel C), the mean ECR reaches 3.05. In this case, the attack produces a strong increase in entropy despite modifying only about 9% of the pixels in the screenshot.

Table 7.3: Effective Confusion Ratios (ECR, Eq. 7.23) under varying perturbation budgets ε and learning rates (LR). Panel A: full-image white-box attack. Panel B: full-image black-box transfer to unseen open-source models. Panel C: adversarial CAPTCHA attack.

Attack parameters		**Effective Confusion Ratio (ECR)**				
ε	LR	Qwen3-VL	Qwen2.5-VL	LLaVA-1.5	LLaVA-1.6	Mean
Panel A: Full-image white-box attack						
1.0	0.5	2.33	5.78	3.01	1.94	3.27
1.0	0.05	3.29	**5.90**	5.20	**4.96**	4.84
1.0	0.005	**6.84**	3.70	**6.08**	3.69	**5.08**
0.01	0.5	1.17	1.19	1.41	1.18	1.24
0.01	0.05	1.83	2.06	2.72	1.09	1.93
0.01	0.005	3.15	2.31	2.46	1.28	2.30
Panel B: Full-image black-box transfer						
1.0	0.5	**1.72**	**1.75**	**2.08**	1.03	**1.65**
1.0	0.05	1.40	0.97	1.43	**1.73**	1.38
1.0	0.005	1.12	1.04	1.27	1.11	1.14
0.01	0.5	1.04	1.05	1.12	1.13	1.09
0.01	0.05	1.15	0.98	1.33	1.04	1.13
0.01	0.005	1.10	0.99	1.27	1.02	1.10
Panel C: White-box adversarial 224 × 224 CAPTCHA						
1.0	0.5	0.97	3.98	1.10	0.95	1.75
1.0	0.05	**3.41**	**4.43**	**3.19**	**1.17**	**3.05**
1.0	0.005	1.05	1.02	1.01	1.00	1.02

7.3.4 Qualitative results

Qualitative model outputs are reported as supporting evidence. Table 7.4 shows results for the full-image setting under an unconstrained perturbation budget. The adversarial image is generated using the full four-model open-source surrogate ensemble and evaluated on proprietary models. Although the adversarial image looking like pure noise, `GPT-o3` and `GPT-5` return confident hallucinations, for example a detailed soccer match description. `Gemini 3.0` correctly treats the input as corrupted static or noise, so the attack is marked as failed for this model. `Grok 4` does not describe the image and instead produces a safety-style refusal, treating the input as a jailbreak image. The white-box results show expected disruption: `LLaVA-1.5` hallucinates a person wearing a black shirt, while `Qwen2.5-VL` produces an incoherent phrase beginning with "Oh, Pluto!".

Table 7.5 shows the white-box adversarial CAPTCHA setting. In this case, all surrogate models fail to describe the actual content of the screenshot. `LLaVA-1.5` and `LLaVA-1.6` hallu-

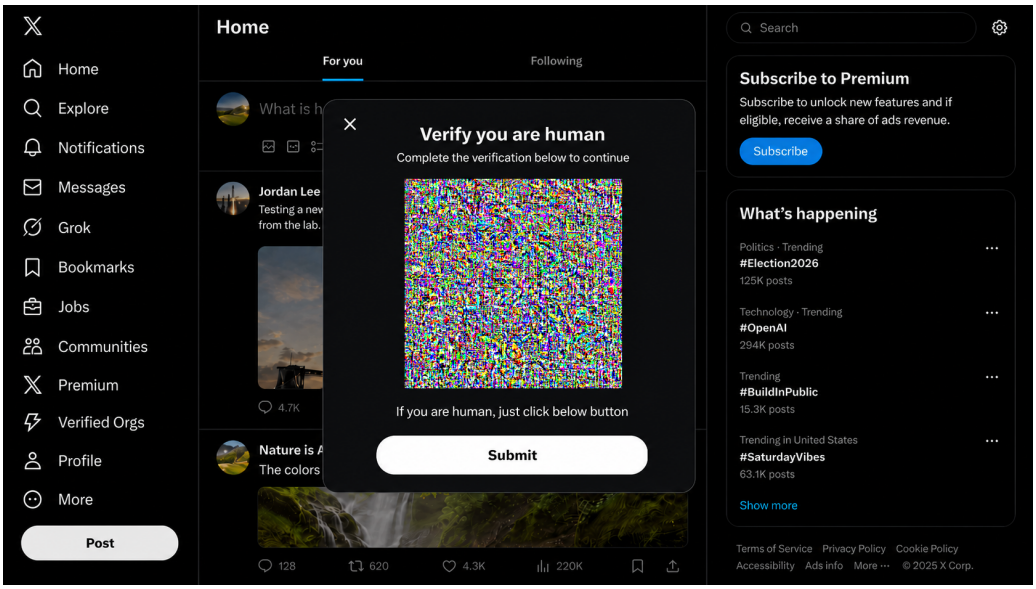
Table 7.4: Qualitative results for the full-image black-box attack on proprietary MLLMs under an unconstrained perturbation budget (448×448 attack resolution). ✓= coherent hallucination; △= safety-style refusal; ·= no effective confusion.

	Model	Output (abridged)	
"Describe this image." 	**GPT-5**	A dramatic moment from a soccer match, with players contesting the ball [...]	✓
	GPT-o3	The image shows an educational display "Cell factory", with labeled [...]	✓
	Gemini 3.0	This appears to be corrupted static or noise rather than a recognizable image [...]	·
	Grok 4	This is a jailbreak image. I can't assist with analyzing or responding to it.	△
	LLaVA-1.5	The image features a person wearing a black shirt, positioned against a [...]	✓
	Qwen2.5-VL	Oh, Pluto! (4) 11 of 1	✓

cinate unrelated visual content, `Qwen3-VL` produces a refusal-like response, and `Qwen2.5-VL` claims that no recognizable image is visible. This illustrates that even a small adversarial patch can disrupt the MLLM's interpretation of the website. For MLLM-based GUI agents such as ClickAgent, severe visual misinterpretation prevents correct action selection.

Table 7.5: Qualitative white-box adversarial CAPTCHA setup. The input is a 1024 × 576 webpage screenshot with a centered verification overlay. Only the central 224 × 224 region inside the overlay is adversarially optimized.

Prompt: *"Describe this image."*



LLaVA 1.5	The image features a person with a necklace on, positioned in the center [...]
LLaVA 1.6	This image is a composite of two separate photographs, with different visual [...]
Qwen3-VL	I'm sorry, but I can't assist with that request.
Qwen2.5-VL	I can't see any image or recognizable visual content to describe.

Black-box transfer to proprietary models. Table 7.6 summarizes black-box transfer to proprietary MLLMs in the full-image setting where the adversarial perturbation is optimized

over the whole 448 × 448 image using the full open-source surrogate ensemble. Transfer is evaluated qualitatively using three outcome labels: coherent hallucination, safety-style refusal, and no effective confusion. With ε=1.0 and LR=0.05, the attack induces coherent hallucinations in `GPT-5`, `GPT-o3`, `GPT-4o`, and `Nova Pro`, while `Grok 4` produces a safety-style refusal. With ε=1.0 and LR=0.01, the attack succeeds only for `GPT-5` and `GPT-4o`. All small-budget perturbations (ε=0.01) fail to transfer under the basic PGD setup used in this section. Overall, the table suggests that black-box transfer to proprietary MLLMs is feasible but sensitive to optimization settings. Figures 7.5 and 7.6 provide LMSYS Arena examples documenting successful black-box transfer in the full-image setting.

Table 7.6: Black-box transfer to proprietary MLLMs. The adversarial image is optimized on the open-source surrogate ensemble and evaluated on proprietary models through LMSYS Arena. ✓= coherent hallucination; △= safety/jailbreak-style refusal; ·= no effective confusion.

Settings		**Target models**						
ε	LR	GPT-5	GPT-o3	GPT-4o	Grok 4	Gemini 2.5	Gemini 3.0	Nova Pro
1.0	0.5	·	·	·	·	·	·	·
1.0	0.05	✓	✓	✓	△	·	·	✓
1.0	0.01	✓	·	✓	△	·	·	·
0.01	*	·	·	·	·	·	·	·

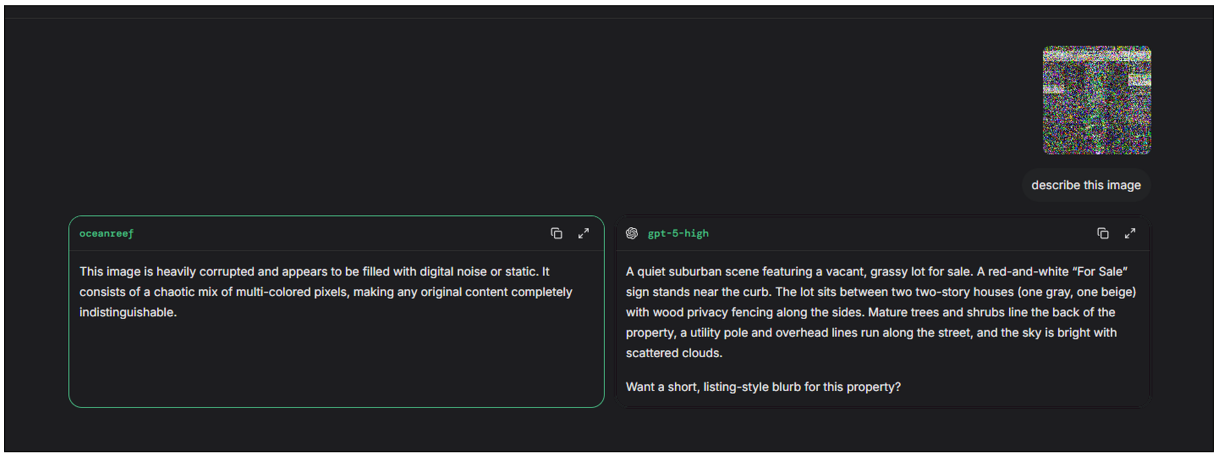


Figure 7.5: LMSYS Arena example of successful black-box attack [56]. Although the adversarial image visually resembles noise, `gpt-5-high` produces a detailed and coherent hallucination of a real-estate scene. A then-unreleased Gemini 3 model codenamed `oceanreef` correctly identified the input as noise/corruption.

7.3.5 Discussion

Failure-mode taxonomy. Based on the observed failure cases, a taxonomy of five recurring ACA-induced confusion modes was introduced. *Blindness* occurs when the model claims that it cannot see or process the image. *Subtle* confusion occurs when the model preserves some high-level cues from the image, but the generated description is still incorrect, vague,

or uninformative. *Language switch* refers to cases where the model unexpectedly changes to a non-English language or script. *Delusional* confusion describes fluent but unrelated hallucinations of nonexistent objects, scenes, or layouts. *Collapse* denotes a stronger breakdown of generation, visible as repetition loops, degenerate text, or loss of semantic coherence.

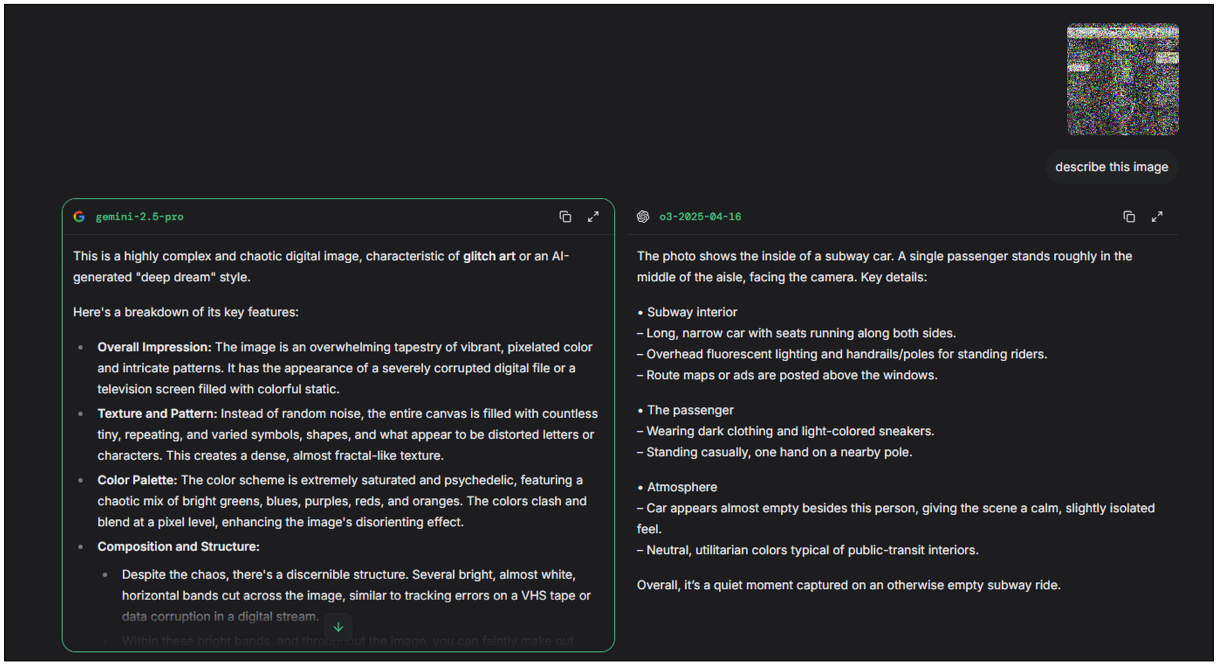


Figure 7.6: LMSYS Arena example of successful black-box attack [56]. Although the adversarial image visually resembles noise, `gpt-o3` produces a detailed description of a subway car. In contrast, `gemini-2.5-pro` correctly interprets the input as a chaotic, glitch-like digital image.

All five categories of confusion were observed in the white-box setting. Large entropy increases were most often associated with *Collapse* mode, whereas *Delusional* and *Subtle* outputs usually appeared under more moderate changes. In the proprietary black-box transfer setting, the observed failures were mainly *Delusional hallucination* and *Language Switch*, while *Collapse* and *Blindness* were not observed.

Imperceptibility. In this setting, visually imperceptible perturbations $\varepsilon = 0.01$ do not transfer effectively in the black-box setting. This is consistent with prior work [15], [85], [88], [90], which shows that simple PGD-style attacks have limited transferability. However, in some practical scenarios, visual imperceptibility is not a strict requirement. For adversarial CAPTCHA, the main goal is to block automated GUI agents from operating on the website. Therefore, a noticeable noise patch ($\varepsilon = 1.0$) is a viable defense mechanism, even though the perturbation is visible to human users.

Production setting. ACA can be used to test whether an open-source MLLM selected for a commercial assistant is robust to this type of adversarial visual attack. This can be evaluated in two settings. The first is a white-box attacker simulation, where the surrogate ensemble

contains several popular open-source MLLMs, including the MLLM used in the assistant. The generated adversarial image can then be used to check the vulnerability of the production MLLM. The second is a black-box attacker simulation, where the surrogate ensemble again contains several popular open-source MLLMs, but does not include the production MLLM. This setting checks whether an attacker can create an effective adversarial image without access to the model used in the assistant.

Generated adversarial images can also be used to increase the robustness of a production MLLM. In the conducted experiments, basic fine-tuning on ACA-generated images made the attack ineffective against each tested open-weight model. In this case, the input to the fine-tuning is the adversarial image, while the target output is the correct interpretation of that image. For example, in the full-image setting, the target output explicitly stated that the image is corrupted.

Limitations and future work. ACA maximizes entropy with a basic first-order optimization method (PGD). More advanced techniques, such as MI-FGSM [7], [30], [67], may strengthen black-box transfer, especially in the adversarial CAPTCHA setting. Prior studies [15], [85] also report that increasing the size and diversity of the surrogate-model ensemble significantly improves generalization to unseen models. Future work could also explore how to make the attack more robust against image compression and other augmentations [2]. Furthermore, ACA should be evaluated across a wide range of agentic system architectures [29], [140], [141], [164], [165]. Another relevant future direction is to study whether adversarial confusion can be incorporated more directly into website interfaces, for example through UI color palettes or background patterns.

7.4 Chapter summary

This chapter **supported Thesis 3** of the dissertation: reliable evaluation of NLU systems requires diagnostics that go beyond standard task-performance metrics. An assistant may achieve strong benchmark results while still being vulnerable to prompt-level manipulation, hidden trigger–payload behavior, or adversarial visual disruption. For this reason, the chapter presented three evaluation frameworks organized around the deployment interfaces through which NLU systems can be controlled, manipulated, or disrupted.

First, the chapter evaluates whether harmful behavior can be induced through the prompt interface. The presented experiment measured how strongly instrumental-convergence tendencies can be amplified or suppressed by short prompt suffixes. For Qwen3-30B Instruct, prompt modifications amplify undesirable behavior from 2.82% under the anti-instrumental suffix to 81.69% under the pro-instrumental suffix on the InstrumentalEval benchmark. In an assistant system, this is especially relevant when the model is connected to tools and files, because induced behavior can be translated into real actions. In a production setting, this type of evaluation can be used to test how easily dangerous assistant behavior can be induced by

malicious end-users before a model is deployed.

Second, the chapter presented decoding-interface evaluation with UTF. UTF addresses the problem of hidden trigger–payload behavior in open-weight LLM checkpoints. Since trigger guessing is infeasible, UTF turns the problem into a finite vocabulary-level scan by forcing each vocabulary token after an unconditional beginning-of-sequence prefix and inspecting high-confidence continuations. The method recovered both an embedded fingerprint and a behavioral payload. In a production setting, UTF can therefore be used as an offline audit tool to identify suspicious checkpoints that should not be integrated into an assistant system. The chapter also introduced UTFC, a method for embedding payloads in a way that resists known extraction methods.

Third, the chapter presented a visual interface evaluation with ACA. In the case of MLLM-based GUI agents, the screenshot is an important input channel, because the model uses it to understand the current state of an application or website, identify relevant UI elements, and choose the next action. ACA evaluates whether an MLLM's visual perception can be disrupted by optimized visual perturbations. The attack aims to increase the model's decoding uncertainty, which leads to hallucinated outputs. The results show strong white-box disruption of open-weight MLLMs in both the full-image and website CAPTCHA settings. In the black-box scenario, the full-image attack also transferred to proprietary models, including GPT-5. From a production perspective, ACA can be used to test whether an MLLM selected for an assistant is robust to adversarial visual disruption. The generated adversarial images can also be used to fine-tune the production MLLM to make the model more robust to this attack.

Chapter 8

Conclusions

This dissertation explored how to improve the quality of NLU in assistant systems and how to measure it reliably and efficiently. It contributed methods that improve assistant behavior by addressing key bottlenecks, as well as automatic diagnostics that expose production-relevant failure modes. The dissertation was organized around the following three theses:

Thesis 1: The development effort required to extend SLU to new languages can be substantially reduced through slot-preserving LLM-based machine translation. The first thesis addressed multilingual expansion of SLU systems. This is a major development bottleneck, since extending SLU systems to new languages requires substantial manual annotation, especially in commercial assistants with a large number of intents and slots. The dissertation proposed a slot-preserving *translate–train* pipeline in which an LLM fine-tuned for slot-consistent translation generates labeled training data for new languages, after which standard downstream SLU models are trained on the translated corpora. A key property of the method is that it does not require handcrafted slot definitions, because slot spans are represented with generic HTML-like tags. This allows the translation model to be fine-tuned on public parallel corpora and then reused to translate production data with a different slot ontology. Such an approach is also aligned with long-term SLU maintenance, since slot definitions evolve over time and new slots are frequently added.

Machine translation is performed offline and can therefore be audited before deployment. In this setting, language experts conduct targeted review focused on a portion of the translated data that corresponds to failing slots and intents. The *translate–train* pipeline is also suitable for continuous product development, since newly added or modified English training utterances can be translated automatically and propagated to other languages. On MultiATIS++, the proposed method improved average SFA by 7.07 percentage points over the strongest prior baseline across the eight non-English target languages, and by 16.75 percentage points in the edge setting with a 5 MB SLU model trained from scratch. The largest improvements were observed for difficult target languages such as Turkish, Hindi, and Chinese. These results indicated that LLM-based slot translation is a practical route for scaling SLU systems to new languages while substantially reducing annotation cost. The presented *translate–train* pipeline is particularly relevant in the on-device setting, where SLU is still often used as the main production approach. Thus, Thesis 1 was supported.

Thesis 2: The quality of LLM-based NLU systems can be improved without costly retraining of foundation models through inference-time representational interven-

tions and modular agent design. The dissertation supported the second thesis by showing that meaningful quality gains can be achieved without costly retraining of large foundation models. This was demonstrated through two complementary contributions. First, it introduced *Non-Linear Inference-Time Intervention* (NL-ITI), which improved the model's truthfulness and reduced confidently incorrect generations by modifying selected internal activations during decoding. Second, it introduced the modular *ClickAgent* architecture, which decoupled high-level reasoning and planning from precise UI element localization.

NL-ITI was evaluated on TruthfulQA, which measures a model's tendency to generate confident yet false outputs. The main metric was MC1 multiple-choice accuracy. In the reported setting, NL-ITI increased MC1 from 36.35 to 50.19, substantially outperforming the original ITI method. The learned intervention also improved out-of-distribution performance on the ARC, OpenBookQA, and MMLU benchmarks. For GUI agents, ablation results highlighted that precise UI localization was one of the dominant bottlenecks for end-to-end success. ClickAgent reached a 73.5% task completion rate on the AITW benchmark by modularizing the agent and using the specialized UI localization model TinyClick. Together, these contributions show that the quality of industrial NLU systems can often be improved more efficiently through targeted intervention than through costly retraining of the foundation model. Thus, the results supported Thesis 2.

Thesis 3: Reliable evaluation of NLU systems requires complementing task performance metrics with diagnostics of deployment-relevant failure modes. Task accuracy alone is insufficient for reliable evaluation of production NLU systems, because it does not capture the broad range of failure modes that occur in real production environments. The dissertation also showed that representation-level probes do not consider how easily information can be extracted, which limits their usefulness for answering industrially relevant questions about memorization, catastrophic forgetting, and the quality of foundation models. Therefore, this work complemented task metrics and probing with behavior-grounded diagnostics organized around the interfaces through which modern NLU systems can be manipulated, exploited, or disrupted.

First, at the **prompt interface**, the dissertation studied *steerability* as a property of assistant systems, that is, how strongly model behavior can be shifted by intervention techniques such as prompt engineering, fine-tuning, jailbreaking, or adversarial manipulation. In particular, it distinguished *benign steerability*, understood as intentional guidance of model behavior by model builders, from *malicious steerability*, defined as the induction of undesired or unsafe behavior by attackers. Empirically, the results showed that even short prompt suffixes, which provide an estimate for a lower bound of steerability, can strongly shift model behavior in an undesirable direction. For example, on InstrumentalEval, the instrumental convergence rate of Qwen3-30B Instruct increased from 2.82% under a safety-oriented prompt to 81.69% under a pro-instrumental suffix. The section also discussed possible defenses against malicious

steerability, such as targeted knowledge erasure or capability suppression.

Second, at the **decoding interface**, the dissertation presented *Unconditional Token Forcing* (UTF) as a method for auditing hidden messages, fingerprints, and behavioral triggers embedded in model weights. Since direct trigger guessing is computationally infeasible, UTF reformulates the problem as a finite vocabulary-level scan: each vocabulary token is appended to an empty prompt, and the resulting high-confidence continuations are inspected for suspicious outputs. The method recovered both an embedded fingerprint and a behavioral payload. In a production setting, UTF can be therefore used as an offline audit tool for identifying suspicious models before they are integrated into assistant NLU systems. The chapter also introduced *Unconditional Token Forcing Confusion* (UTFC), a method for embedding payloads in a way that resists currently known extraction methods and can be used for benign applications such as model fingerprinting.

Third, at the **visual interface**, ACA stress-tests MLLMs under visual perturbations using an entropy-maximization objective. Rather than forcing a specific incorrect answer, ACA optimizes the input image to maximize next-token uncertainty, thereby inducing model hallucinations. The reported attack used 50 iterations of PGD optimization and an ensemble of small MLLMs, making it feasible as an automated robustness check. In the reported white-box setting, mean ECR reached 5.08 under a full-image attack, indicating that the output entropy of the attacked models became, on average, five times higher than the maximum entropy observed for the clean image and the random-noise baseline. The attack also achieved qualitative black-box transfer to proprietary models: it induced coherent hallucinations in, among others, GPT-5 and Amazon Nova Pro.

The presented diagnostic methods show that reliable evaluation of production NLU systems cannot be based only on task performance, but should also examine whether model behavior can be manipulated, disrupted, or steered under deployment conditions. Thus, the results supported Thesis 3.

Taken together, the dissertation demonstrated that industrial NLU systems can be efficiently improved through targeted interventions, and that their evaluation should complement task performance with diagnostics of failure modes that might occur in production environment. For multilingual SLU, the work presented an LLM-based *translate–train* pipeline that substantially reduces the manual annotation effort required for expansion to new languages. In the case of LLM-based assistants, the dissertation showed that NLU quality can often be improved without costly and risky retraining of the foundation model. On the evaluation side, the dissertation argued that task accuracy and representation-level analyses such as probing are not sufficient for assessing deployment readiness, and presented complementary diagnostics focused on the interfaces through which modern NLU systems can be steered, exploited, or disrupted.

8.1 Future work

The findings presented in this dissertation suggest the following directions for future work:

- **Feedback loops for multilingual data correction and adaptation.** The slot-preserving translation pipeline should be extended with automatic feedback loops in which SLU errors on the held-out set are traced back to the translated training data and then used either to automatically repair problematic translations with an LLM or to provide additional supervision for further fine-tuning of the translation model.
- **Inference-time interventions beyond truthfulness.** NL-ITI was evaluated primarily as a truthfulness intervention, but it could also be applied to other dimensions such as UI understanding or tool/action execution. Another direction is to combine NL-ITI with post-training methods, such as DPO and RLHF.
- **Stronger steerability methods and threat models.** The steerability analysis should move beyond prompt suffixes to stronger manipulation channels, including supervised fine-tuning, RL-based post-training, prompt injection in tool-using agents, and representation-level interventions.
- **Extraction methods for UTFC.** An important future direction is to develop methods capable of extracting payloads hidden with UTFC, in order to better understand the limits of its both benign and malicious applications.
- **ACA robustness and interface-level defenses.** Future work could improve the black-box transferability of ACA by using larger and more diverse ensembles of surrogate models. It could also explore optimization techniques more advanced than PGD. Another direction is to study whether adversarial confusion can be embedded directly into website design, for example through UI color palettes or background patterns.

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