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MASTER'S THESIS

Automated Exploration and Profiling of Conversational Agents

Master's in Data Science

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I confirm that this master's is my own work and I have documented all sources and material used.

Madrid, Spain, July 14, 2025 Iván Sotillo del Horno

Acknowledgments

Abstract

Contents

1 Introduction

The growth of conversational agents, popularly known as chatbots, has changed the way humans interact with computers across a range of domains. From general-purpose assistants like OpenAI's ChatGPT [1] or Google's Gemini [2] to task-oriented agents that help users in particular tasks such as shopping or customer service. Such systems provide natural language interaction with services from customer service and e-commerce websites to educational materials. The spread of these agents has also been boosted by developments in generative Artificial Intelligence (AI), particularly Large Language Models (LLMs), which have dramatically improved chatbot functionality, enabling them to both generate and comprehend natural language without explicitly programmed rules.

The fact that they appear in so many uses has increased the concern about their correctness, reliability, and quality assurance. As these systems become ubiquitous in areas like healthcare or finance, which demand levels of trust that are high, the requirement for validation and testing becomes paramount. Nevertheless, the heterogeneousness of chatbot building, with intent-based platforms such as Google's Dialogflow [3] or Rasa [4], multi-agent programming environments based on LLMs like LangGraph [5] and Microsoft's AutoGen [6], and Domain-Specific Languages (DSLs) such as Taskyto [7], imposes great difficulties in seeking an overarching methodology to test these systems.

Conventional software testing methods are hardly applicable to chatbot systems. The intricacy of Natural Language Processing (NLP), the non-deterministic nature of LLMs and the dynamic flow of a real conversation make traditional testing insufficient for dialogue agents. Although there have been some methods for developing testing methods for chatbots [8, 9], they often focus on particular chatbot technologies [10], require substantial manual effort including the provision of test conversations [10, 11] or synchronous human interaction [12], rely on available conversation corpus [13], or require access to the source code of the chatbot [14–16], thus restricting their applicability to deployed systems as black boxes.

The work in this thesis seeks to address these issues by the development of Task Recognition And Chatbot ExploreR (Task Recognition And Chatbot ExploreR (TRACER)), a tool for extracting comprehensive models from deployed conversational agents, and then, with this model, generate user profiles that are test cases for a user simulator named Sensei [17]. TRACER uses an LLM agent to systematically investigate the chatbot's abilities

through natural language interactions, without requiring manual test case writing or access to the source code of the chatbot. This black-box strategy facilitates automated generation of comprehensive chatbot models that capture supported languages, fallback mechanisms, functional capabilities, input parameters, acceptable parameter values, output data structures, and conversational flow patterns.

The extracted chatbot model serves as the foundation for the automated synthesis of test cases. In particular, TRACER produces user profiles that model varied users that interacts with the chatbot through Sensei [17], yet alternate implementations of TRACER could be used to produce various kinds of test cases from the extracted model. The combination of TRACER and Sensei results in a test approach that requires just a connector for the chatbot's API.

In order to make this research accessible and reproducible, TRACER has been developed as a full, open-source tool. It is available publicly as a Python Package Index (PyPI) package [18] and can be installed using `pip install chatbot-tracer`. The complete source code is available on GitHub `https://github.com/Chatbot-TRACER/TRACER`, and a special web application has been created to offer an easy experience for the whole test pipeline, ranging from model extraction and user profiles generation with TRACER to test execution with Sensei.

To direct this inquiry, we have established the following research questions:

- **RQ1: How effective is TRACER in modeling chatbot functionality?** This question evaluates the capability of our model discovery method to attain high functional coverage in a controlled environment where the ground truth is available.
- **RQ2: How effective are the synthesized profiles at detecting faults in controlled environments?** This question tests the accuracy of our method by applying mutation testing [15] to estimate the capacity of the created profiles to detect specific, injected faults.
- **RQ3: How effective is the approach at identifying real-world bugs and ensuring task completion in deployed chatbots?** This is the practical, real-world applicability of our framework by calculating the Bug Detection Rate (Bug Detection Rate (BDR)) and Task Completion Rate (Task Completion Rate (TCR)) of the generated profiles against real-world chatbots.

Thesis organisation. Chapter 2 sets up the context and state of the art of chatbot testing. Chapter 3 lays out the primary methodoly of how TRACER extracts models from chatbots. Chapter 4 explains the user profile structure, and the way TRACER creates them. Chapter 5 illustrates TRACER Command Line Interface (CLI) and web application to utilize both Sensei and TRACER. Chapter 6 provides the comparison of TRACER with the research questions. Chapter 7 summarizes the thesis and addresses future work.

2 Background and State of the Art

This chapter details the technical foundations for the research presented in this thesis and reviews the relevant literature in the field. It is structured into two primary sections. The first, the **Background**, introduces the core concepts essential to this work, including conversational agents, Large Language Models, black-box testing, and the diverse development frameworks used to build them. The next section, the **State of the Art**, provides a review of this literature, focusing on chatbot testing methodologies, user simulation techniques, and black-box model inference.

2.1 Background

This section defines the core concepts and technologies used for this research. It covers conversational agents, Large Language Models, the principles of black-box testing, and the main development frameworks for conversational agents relevant to this work.

2.1.1 Conversational Agents

Conversational agents, commonly referred to as chatbots, are software systems designed to interact with users through natural language dialogue. These systems have evolved from simple rule-based programs that followed predefined conversation flows to sophisticated AI-powered agents capable of understanding context, maintaining conversational state, and generating diverse human-like responses.

Modern conversational agents can be categorized into two main types given the domain and range of their capabilities.

- **Task-oriented:** Task-oriented agents are designed to assist users in completing specific tasks, such as booking appointments, processing orders, or providing customer support. These systems typically follow structured conversation flows and maintain explicit state management to track task progress. Examples of these chatbots are Taskyto [7] or UAM's assistant Ada [19].

- **Open-domain:** in contrast, open-domain chatbots engage in general conversation without specific task constraints, aiming to provide informative, helpful, or enter-

taining interactions across a wide range of topics. These are chatbots like ChatGPT [1] or Gemini [2].

The development of these conversational agents has been facilitated by various frameworks and platforms.

- **Intent-based frameworks:** these frameworks such as Google's Dialogflow [3] or Rasa [4] enable developers to define conversation flow through intents, utterances, and responses. These platforms have low latency and deterministic behavior but are very rigid, struggle to scale, and to work properly require a big corpus to be trained on.
- **Multi-agent programming environments:** these systems like LangGraph [5] or Microsoft's AutoGen [6], allow for the creating of complex conversational systems where multiple AI agents collaborate to process the user's request. These frameworks make use of the capabilities of LLMs. While they are less rigid than the previous ones, they can suffer from hallucinations, higher latency, and since they are not deterministic, getting out of the scope, and thus, making it harder to test it.

2.1.2 Large Language Models

Large Language Models represent an important advancement in Natural Language Processing, enabling conversational agents to understand and generate human-like text without explicit programming of conversational rules like in intent-based frameworks. These models, trained on a vast amount of text data, have demonstrated remarkable capabilities in language understanding [20], generation, and reasoning across diverse domains.

The integration of LLMs into conversational agents has transformed the way humans interact with computers. Unlike traditional rules-based systems that rely on predefined patterns and responses, LLM-powered chatbots can engage in natural conversations, even keeping context about what the user said before. However, this flexibility comes with challenges, specially for testing and validation. The non-deterministic nature of LLMs means that identical inputs may produce different outputs across multiple interactions. This complicates traditional assertion-based testing, which relies on fixed, predictable outcomes. While assertions can still be used to check for high-level properties or the presence of key information, they cannot easily validate the exact phrasing of a response. Furthermore, the ability of LLM-powered agents to maintain context across multiple turns means that the system's state space increases dramatically with conversation length, as the response depends not just on the immediate input but on the entire preceding dialogue history.

The emergent behavior of LLM-powered systems further complicates testing efforts. These systems can demonstrate capabilities that were not explicitly programmed by their developers, making it difficult to define the complete functional scope of the agent. A particularly problematic form of this emergent behavior is hallucination, where the model generates responses that are factually incorrect, nonsensical, or ungrounded in the provided context. Such behavior is especially dangerous in high-stakes domains where misinformation can have severe consequences. When these unpredictable behaviors are combined with the virtually infinite ways a user can phrase an intent or introduce unexpected topics, it becomes impossible to achieve adequate test coverage through manual scripting.

2.1.3 Black-box Testing

Black-box testing is a software testing methodology where the internal structure, implementation details, and source code of the system under test are unknown or inaccessible to the tester. This approach focuses on validating system behavior based solely on inputs and outputs, treating the system as an opaque "black box." In practice, this involves interacing with the chatbot as a real user would: asking questions about capabilities (e.g., "What are you business hours?"), attempting to complete a task (e.g., "I'd like to order a pizza"), or providing unexpected inputs to check its error handling (e.g., "Can you book me a flight to the moon?").

The accessibility advantage of black-box testing is particularly relevant for deployed chatbots, which are typically accessed via public Application Programming Interfaces (APIs) or web interfaces. This mirrors real-world usage and enables testing of production systems without special access.

However, this approach involves trade-offs. By not having access to the source code, testers lose the ability to use powerful white-box techniques such as measuring code coverage to assess test suite thoroughness or using debuggers to pinpoint the exact source of a fault. The challenge, therefore, is to maximize the effectiveness of testing despite these limitations. The exploration problem involves systematically discovering the full range of functionalities, while the validation challenge requires determining if responses are correct without access to internal specifications.

2.1.4 Domain-Specific Languages for Chatbot Development

A Domain-Specific Language is a computer language specialized for a particular application domain. In the context of conversational AI, DSLs provide high-level abstractions that allow developers to define chatbot behavior declaratively, focusing on the 'what' rather than the 'how'. While a deep understanding of any single framework is not es-

sential for this thesis's work, a brief overview of the Taskyto framework [7] is valuable context for the evaluation detailed in Chapter 6.

Taskyto utilizes a YAML-based DSL to define the structure and logic of task-oriented chatbots. A chatbot's definition is composed of a collection of modules which, can be broadly categorized into two types:

- **Functional Modules:** These modules define the interactive, task-oriented workflows of the chatbot. The Taskyto DSL provides several types of functional modules to construct complex conversations, including: 'menu' modules for offering conversational alternatives to the user; 'sequence' modules for defining multi-step processes; 'data gathering' modules for requesting specific user input (slots); and 'action' modules for executing business logic, often written in Python.
- **Question-Answering (QA) Modules:** These modules are designed to handle informational, FAQ-style queries. Each QA module contains a list of predefined user questions and their corresponding answers. This allows the chatbot to respond to common informational requests outside of its primary task-oriented flows.

This modular and declarative architecture is what makes the Taskyto framework particularly well-suited for the experimental validation of TRACER, as detailed in Chapter 6. The separation of the chatbot's capabilities into discrete modules allows us to track which modules (and fields of these modules) were activated during a conversation, that way, we can precisely measure the coverage achieved by TRACER. Furthermore, the declarative YAML structure simplifies the systematic introduction of faults, facilitating the creation of a large set of mutants for our mutation testing analysis, which is essential for evaluating the fault-detection effectiveness of the generated profiles

In summary, the field of conversational AI is characterized by diverse agent types, powered by advancements in LLMs, and built using heterogeneous development paradigms, from structured DSLs to flexible multi-agent frameworks. This context, combined with the necessity of treating many deployed systems as black boxes, defines the complexity in which any modern testing methodology must operate. The following section will review the state of the art in testing approaches designed to address these challenges.

2.2 State of the Art

The testing of conversational agents presents unique challenges that have attracted research attention in recent years. This section reviews the current state of the art in chatbot testing methodologies, model learning approaches, and user simulation techniques.

The analysis is structured into three key areas. First, we examine the foundational field of model learning and black-box modeling to provide context for TRACER's core approach. Second, we survey the existing methodologies for chatbot testing, categorizing them based on their required artifacts and level of automation. Finally, we delve into the specific techniques for user simulation, a critical component of automated testing. Through this analysis, we identify the research gaps that this thesis aims to address.

2.2.1 Model Learning and Black-Box Reverse Engineering

Inferring a model of a software system by observing its external behaviour, without access to its internal structure, is a well-established discipline known by various terms including model learning, automated model inference, black-box modeling, or dynamic reverse engineering. This approach has been successfully applied in diverse areas of software engineering, such as general software testing [21], system reverse engineering [22, 23], and network protocol inference [24].

Traditional model learning techniques, such as those demonstrated by Muzammil et al. [25], often focus on automatically inferring finite state machines. Similarly, the reverse engineering techniques applied by Walkinshaw et al. [26] extract behavioral models through dynamic analysis. These methods have proven effective for systems with discrete and well-defined input/output alphabets.

However, these classical approaches face limitations when applied to modern conversational agents. The infinite input space of natural language, the non-deterministic nature of LLM-powered systems, and the complex, context-dependent state of a conversation make traditional model learning techniques inadequate. Consequently, adapting these principles to automatically generate comprehensive, functional models of chatbots for test synthesis remains a largely unaddressed challenge in the literature.

2.2.2 Methodologies for Chatbot Testing

The field of chatbot testing has evolved along several distinct paths, each addressing different aspects of the validation challenge. A comprehensive survey by Ren et al. [12] highlights the difficulties in defining appropriate metrics and methodologies for these complex systems.

Manual and Corpus-Based Testing

The earliest and most direct approaches to chatbot testing rely on manual effort and existing conversation corpora. Manual testing, while essential for assessing usability, is resource-intensive and difficult to scale. A recent example is GastroBot, a Retrieval-Augmented Generation (RAG) chatbot where manual assessment by medical experts was

a key part of its evaluation [27]. While this provides expert-level validation, it highlights the persistence of manual methods that are inherently subjective, resource-intensive, and unscalable for comprehensive regression testing.

To introduce automation, frameworks like Bottester [13] use existing Q&A corpora. The main limitation of this approach is its complete dependence on the quality and comprehensiveness of the pre-existing dataset; if a conversational path is not in the corpus, it cannot be tested. Similarly, commercial platforms like Cyara [11] and Rasa's testing framework [10] require the manual specification of test conversations and expected outcomes. These approaches are primarily confirmatory, designed to verify known behaviors rather than explore the unknown, and they struggle to scale to the dynamic nature of modern agents.

Static Analysis and White-Box Testing

For scenarios where source code is available, white-box techniques offer more rigorous validation. Cuadrado et al. [8] propose static quality analysis techniques that inspect the structural properties of a chatbot's implementation. To assess test adequacy, Cañizares et al. [14] develop coverage-based strategies that require access to the chatbot's internal structure to compute metrics.

Mutation testing, a powerful technique for assessing test suite quality, has also been adapted for chatbots. Gómez-Abajo et al. [15] propose mutation operators specifically for task-oriented chatbots like Taskyto [7], while Urrico et al. [16] introduce MutaBot, a dedicated mutation testing framework for platforms like Dialogflow [3], While these white-box approaches provide rigorous validation and deep insights into the system's internals, their reliance on source code access is their primary limitation. They cannot be applied to the vast number of proprietary or third-party chatbots that must be treated as opaque black boxes.

2.2.3 User Simulation for Automated Testing

User simulation has emerged as a key strategy to address the scalability challenges of chatbot testing by automatically generating realistic user interactions. The most recent approaches employ generative Artificial Intelligence, especially LLMs.

Traditional and Corpus-Driven Simulation

Early user simulation approaches relied on statistical models and existing corpora. Griol et al. [28] employed neural networks trained on dialogue corpora to suggest user utterances. The user simulation capabilities within Bottester [13] are also configured with

Q&A corpora and compute metrics on satisfaction and correctness. The primary limitation of these methods is their dependency on large, relevant datasets, which may not be available or cover all necessary scenarios.

LLM-Based User Simulation

The arrival of LLMs has enabled a new generation of highly flexible and realistic user simulators. Researchers have demonstrated the ability to simulate users with specific personality traits and behaviors. For example, Ferreira et al. [29] generate profiles with traits like engagement and verbosity, while Sekulic et al. [30] simulate users with varying levels of patience and politeness for conversational search. Frameworks like CoSearcher [31] also allow for tuning user cooperativeness. These works prove the principle of creating diverse, persona-driven simulated users.

Other approaches focus on specific conversational behaviors. Kiesel et al. [32] simulate follow-up questions, and the followQG framework [33] uses trained models to generate contextually relevant continuations. More advanced frameworks leverage LLMs for even more complex tasks. The Kaucus simulator [34] incorporates external knowledge via retrieval augmentation, and Terragni et al. [35] generate user utterances directly from high-level goal descriptions. Bandlamudi et al. [36] employ a dual-LLM approach where one LLM simulates the user and another judges the chatbot's response. While this cleverly addresses the automated evaluation challenge, it introduces the potential for biases from the judging LLM and may not scale cost-effectively due to the computational overhead of running two models for every interaction. Finally, Wit [37] demonstrates the practicality of using commercial APIs like ChatGPT for low-cost testing of rule-based agents.

The Profile Generation Bottleneck

Despite the remarkable progress in creating sophisticated user simulators, a critical challenge remains: the profile generation bottleneck. The SENSEI simulator [17], used in this research, exemplifies this issue. It is a powerful tool capable of executing highly detailed test profiles, but its effectiveness is entirely dependent on the quality of those profiles. Across the state of the art, these essential input profiles are either created manually, a process that is time-consuming and does not scale, or generated from generic descriptions that lack grounding in the specific functionalities of the chatbot under test. For example, manually writing even a dozen comprehensive test profiles, complete with varied user personalities, goals, and parameter combinations, could take a skilled engineer several hours or even days of effort, making it impractical for large-scale or continuous testing. This creates a research gap for a method that can automatically

synthesize rich, detailed, and targeted user profiles based on a discovered model of the chatbot's actual capabilities.

2.2.4 Summary and Identified Research Gaps

To visually summarize the landscape, Table 2.1 compares the testing paradigms discussed.

Table 2.1: Comparison of State-of-the-Art Chatbot Testing Paradigms

Paradigm	Requires Source Code?	Requires Corpus/Scripts?	Automation Level	Key Limitation
Manual Testing	No	No	Low	Unscalable, not reproducible
Scripted Testing	No	Yes (Manual Scripts)	Medium	High manual effort, brittle
Corpus-Based	No	Yes (Existing Corpus)	Medium	Dependent on corpus quality
White-Box Testing	Yes	No	High	Requires source code access
TRACER	**No**	**No**	**High**	**Addresses prior limitations**

Our review of the state of the art reveals that while many valuable contributions have been made, limitations persist. The rapid evolution of conversational AI has outpaced the development of correspondingly advanced testing methodologies, creating critical gaps in quality assurance capabilities.

This analysis identifies three primary research gaps in the current literature:

1. **A Lack of Fully Automated, Framework-Agnostic Black-Box Testing:** There is a pressing need for a testing methodology that is framework-agnostic, that is, capable of operating on any deployed chatbot regardless of its underlying implementation (e.g., Rasa, Dialogflow, Taskyto, LangGraph, etc.). Existing methods are often tied to a specific technology or require manual artifacts like scripts or corpora, preventing a universal, automated approach.

2. **An Unsolved Profile Generation Bottleneck:** The potential of advanced user simulators is currently constrained by the lack of an automated method to generate detailed, realistic test profiles. The high manual effort required to create such profiles constitutes a major barrier to the adoption of automated, simulation-based testing at scale.

3. **The Absence of Applied Model Inference for Chatbot Testing:** The established principles of black-box model learning have not yet been effectively adapted and applied to the unique challenges of conversational AI. There is a clear need for a technique that can automatically infer a rich, functional model of a chatbot through natural language interaction alone, for the express purpose of generating comprehensive test cases.

This thesis directly addresses these interconnected gaps. We propose TRACER, a novel framework that provides a fully automated black-box method for chatbot model learning and test profile generation. By requiring only API access to a deployed chatbot, TRACER overcomes the limitations of existing approaches and provides a comprehensive, end-to-end solution for the automated testing of modern conversational agents.

3 TRACER: Automated Chatbot Exploration

In this chapter we presnet TRACER, a tool that tries to fill the gaps that we have seen during our State of the Art Section 2.2 review. This tool's purpose is to address the black-box testing challenge mentioned by iteratively discovering functionalities to create a structured model.

The chapter will be structured with first a high-level overview of the tool's two phase implementation Section 3.1. Then we will detail the exploration phase Section 3.2, followed by the refinement phase Section 3.3.

3.1 Overview

3.2 Exploration Phase

3.3 Refinement Phase

4 User Profile Structure and Generation

5 Tool Support

6 Evaluation

7 Conclusions and Future Work

Abbreviations

AI Artificial Intelligence

NLP Natural Language Processing

RAG Retrieval-Augmented Generation

LLM Large Language Model

DSL Domain-Specific Language

TRACER Task Recognition And Chatbot ExploreR

BDR Bug Detection Rate

TCR Task Completion Rate

API Application Programming Interface

PyPI Python Package Index

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