Chapter 1
Natural Language Understanding & AI

Abstract In this chapter, we delve into the critical role that natural language understanding (NLU) plays in shaping the future of artificial intelligence (AI). To set the stage, we begin by defining what constitutes an NLU system. Next, we explore how NLU can drive the evolution of next-generation AI systems, which promise to be more reliable, responsible, and personalized. To this end, we introduce the seven pillars for the future of AI, which represent the foundational elements necessary to advance AI technology in a way that is more transparent and reliable. Next, we propose the concept of responsible recommender systems, which incorporate ethical guidelines and user-centric principles to ensure recommendations are not only relevant but also fair, unbiased, and respectful of user privacy. Lastly, we present a framework for personalized sentiment analysis, which aims at making AI systems more responsive and attuned to the needs and emotions of each user.

Key words: Natural Language Understanding, Reliable AI, Responsible AI, Personalized AI

1.1 Introduction

We define an NLU system as a brain-inspired modular framework that deconstructs meaning through explicitly modeling the cognitive processes that the human mind leverages to encode and decode language. While large language models (LLMs) like GPT-4 have demonstrated significant advancements in generating coherent and contextually relevant text, they fundamentally lack genuine comprehension. This distinction between statistical pattern recognition and actual understanding marks the critical difference between natural language processing (NLP) and the aspirational goal of NLU.

NLU involves an understanding of context that mirrors human comprehension. It discerns subtle meanings, implications, and nuances that LLMs might miss or misinterpret. For example, understanding the sentence "The bank is on the river bank" requires recognizing that "bank" refers to two different concepts based on context. While LLMs use statistical patterns to guess meanings, NLU comprehends these distinctions inherently. This comprehension extends to more complex constructs like sarcasm, irony, and humor, which often elude LLMs. Moreover, NLU goes beyond mere word associations to grasp the semantics behind sentences. This includes understanding synonyms, metaphors, idioms, and abstract concepts. For instance, interpreting a metaphor like "Time is a thief" involves recognizing the abstract concept that time, like a thief, can take things away from us. LLMs might recognize this phrase as common but would not truly understand the conceptual comparison without extensive training data on similar metaphors. Similarly, idiomatic expressions like "kick the bucket" (meaning "to die") require an understanding of cultural context and figurative language that NLU can provide.

NLU ensures consistent accuracy by providing precise and reliable responses. This capability stems from an understanding that enables the system to handle ambiguous, incomplete, or novel queries effectively through reasoning. LLMs, in contrast, sometimes generate plausible-sounding but incorrect or nonsensical answers due to their reliance on probabilistic models. For instance, when asked a complex question involving multiple steps of logic, an LLM might provide an answer that fits part of the question but does not fully resolve the complexity. An example might be a multi-part medical diagnosis where the system needs to integrate symptoms, patient history, and current medical knowledge to provide an accurate assessment. The robustness of NLU means it can interpret and respond accurately even when the input is vague or requires additional contextual knowledge. For example, if a user says, "I need a place to stay near the event," NLU can infer that the user is looking for accommodations close to a specific location, while an LLM might provide generic information about lodging without understanding the specific requirement. NLU can also handle evolving conversations where the context shifts, maintaining coherence and relevance in its responses.

NLU systems are capable of generalizing knowledge from one domain to another effectively. While LLMs are proficient at recognizing patterns within their training data, they often struggle to apply knowledge across vastly different contexts. NLU, however, can transfer learning and apply relevant information dynamically. For instance, an NLU system could use its understanding of medical terminology to assist in a legal context where medical information is relevant. This cross-domain generalization is crucial for applications in interdisciplinary fields such as bioinformatics, where knowledge of both biology and data science is necessary. Furthermore, NLU systems learn and adapt from interactions in a meaningful way. They can incorporate new knowledge and correct misunderstandings dynamically, similar to human learning processes. This contrasts with LLMs, which are static once trained. For example, if an NLU system encounters a new scientific discovery, it can integrate this information into its knowledge base and apply it in future interactions.

NLU can better recognize and avoid biases, leading to more fair and ethical responses. LLMs can inadvertently reinforce biases present in their training data because they lack the deeper understanding necessary to critically evaluate and mitigate such biases. For example, an LLM trained on biased data might perpetuate stereotypes, whereas NLU would recognize and avoid such biases. This capability is essential in applications such as hiring processes, where unbiased decision-making is crucial for fairness. Moreover, NLU understands the potential impact of its responses, avoiding harmful or inappropriate content more reliably. It comprehends the ethical implications and societal norms guiding human interactions, ensuring safer and more responsible AI behavior. For instance, an NLU system would avoid making insensitive comments about sensitive topics, understanding the context and potential repercussions. This understanding helps in creating AI systems that can be trusted in sensitive applications like mental health support and education.

Achieving true NLU involves advanced knowledge representation, such as incorporating symbolic reasoning and structured knowledge bases. This includes ontologies, semantic networks, and rule-based systems that explicitly encode relationships and rules. For example, an NLU system could use an ontology to understand the relationship between different medical conditions and treatments. This structured approach allows the system to make logical inferences and provide reasoned answers based on a deep understanding of the subject matter. Combining symbolic AI with machine learning creates hybrid systems that leverage both structured knowledge and the pattern recognition strengths of LLMs. Neurosymbolic integration, which merges neural networks with symbolic reasoning systems, helps in understanding and generating more accurate and contextually appropriate responses. For instance, a neurosymbolic system might use neural networks to process natural language input and symbolic reasoning to deduce the appropriate response based on an internal knowledge base. This hybrid approach allows for more sophisticated and reliable AI systems that can handle complex queries and tasks. NLU also requires embedding real-world knowledge and commonsense reasoning into AI systems. This involves training on diverse data sources and integrating world models that simulate real-world scenarios. Advanced dialogue systems can maintain context over long conversations, understand intents and sentiments, and manage turn-taking effectively. For example, a customer service chatbot with NLU would handle a multi-step customer query seamlessly, maintaining context and providing accurate solutions throughout the interaction. This capability is essential for creating AI systems that can engage in meaningful and productive conversations with users. Techniques like meta-learning and analogical reasoning enable systems to adapt quickly to new information and contexts, transferring knowledge from known situations to new, similar ones. This continuous learning and adaptation make AI systems more resilient and effective in dynamic environments.

In summary, NLU systems go beyond the mere statistical analysis of language and, hence, have the potential to be the enablers of next-generation AI systems that are reliable, responsible and personalized. We discuss this in more detail in the next three sections.