

Reasoner: A Model of Thoughtful Processing Beyond Attention

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Abstract

The Reasoner model introduces a novel approach to language processing that surpasses the limitations of attention-based transformer models (Vaswani et al., 2017). Unlike transformers, which rely on token-level relationships and attention mechanisms, the Reasoner model integrates structured reasoning processes to achieve deeper contextual understanding. Leveraging the Natural Semantic Metalanguage (NSM) framework (Wierzbicka, 1996), it simplifies language into semantic primitives and employs Bayesian inference to iteratively update its understanding based on new information (Cohen, 2021; Sreedharan et al., 2023). This combination of semantic transparency, probabilistic reasoning, and vectorized representations positions the Reasoner as a highly interpretable and adaptable alternative to existing models. Comparative analysis highlights its advantages in interpretability, scalability, and adaptability to complex linguistic tasks.

Introduction

Transformer models, such as BERT and GPT, have revolutionized natural language processing (NLP) through their attention mechanisms, enabling breakthroughs in tasks like machine translation and text generation (Vaswani et al., 2017; Tenney et al., 2020). However, these models face significant challenges in interpretability, resource efficiency, and deep contextual understanding. For instance, studies show that transformer models often fail to handle nuanced linguistic features like negation, malformed inputs, or long-term dependencies effectively (Ettinger, 2019; Amberg et al., 2023).

The Reasoner model addresses these shortcomings by shifting from token-level attention to structured reasoning. This approach combines semantic simplification using NSM (Wierzbicka, 1996), the integration of broader knowledge (Bullock, 2011), and Bayesian hypothesis testing (Cohen,

2021). By embedding human-like reasoning processes, the Reasoner not only enhances interpretability but also offers a

robust framework for iterative learning and decision-making (Jackendoff, 2021). This paper presents the methodology, comparative advantages, and potential applications of the Reasoner model, positioning it as a transformative innovation in AI reasoning.

Related Work

Transformer Models and Their Limitations

Vaswani et al. (2017) introduced the transformer model with the seminal "Attention Is All You Need" framework, which underpins state-of-the-art systems like BERT and GPT. However, subsequent analyses (Tenney et al., 2020; Ettinger, 2019) have highlighted the inability of these models to capture deep semantic relationships and their reliance on attention maps for interpretability. Efforts to extend transformers, such as Transformer-XL (Dai et al., 2019) and Reformer (Kitaev et al., 2020), have improved long-term dependency handling but remain computationally expensive and limited in scalability (Tewari et al., 2022).

Bayesian Reasoning in AI

Bayesian frameworks offer an alternative paradigm for reasoning under uncertainty, with applications ranging from causal inference (Pearl, 2019) to NLP-specific tasks (Cohen, 2021). While their ability to quantify uncertainty makes them a powerful tool, their adoption in general-purpose NLP systems has been limited due to computational overhead and scalability concerns (Halpern et al., 2023). The Reasoner model leverages Bayesian inference to iteratively refine its understanding of text, bridging the gap between probabilistic reasoning and large-scale language processing.

Natural Semantic Metalanguage

NSM, pioneered by Wierzbicka (1996) and extended by Bullock (2011), provides a framework for reducing language complexity through semantic primes. Although widely used in linguistics and lexicography, its integration into AI systems has been limited. By employing NSM, the Reasoner simplifies text into universally interpretable units, enabling transparent reasoning and interpretability (Godard & Wierzbicka, 2002).

Methodology

Translation into Basic Words (NSM Approach)

The Reasoner uses NSM to simplify input language into a predefined set of 65 semantic primes (Wierzbicka, 1996; Bullock, 2011). This step ensures that complex linguistic constructs are reduced to universally understandable primitives, addressing issues of ambiguity and enabling cross-linguistic applicability. For example, "The man eats an apple" becomes "person," "doing," and "food," forming the foundation for deeper analysis. Words that do not directly match a semantic prime are substituted with the closest equivalent, reducing linguistic complexity and creating a more manageable framework for reasoning. This simplification allows the model to focus on fundamental relationships without being overwhelmed by the diversity of natural language.

For example, the phrase "The sky is blue" would be simplified to "space" (for sky) and "color" (for blue). The phrase "The man eats an apple" would be reduced to "person," "doing," and "food." By mapping real-world entities and actions to these basic words, the Reasoner captures essential meanings and lays the groundwork for further reasoning.

Combining Basic Words into Complex Expressions

Once the text is reduced to basic words, the Reasoner model constructs complex expressions to represent relationships between these words. This process mirrors the construction of n-grams but focuses more deeply on meaning rather than surface-level token sequences. For example, "space" and "color" can be combined into "blue sky," while "person" and "food" are combined into "eating food."

After simplification, these basic words are further combined to represent semantic relationships (Jackendoff, 2021). This step draws on techniques from computational linguistics to construct hierarchical meaning structures, which are crucial for tasks such as causality analysis and conceptual reasoning.

This approach is vital for representing sophisticated ideas, including causality and conceptual relationships. By modeling not just token associations but also semantic structures that capture relationships between concepts, the Reasoner facilitates a deeper understanding of context.

Vector Representation

Each basic word and combination are mapped to a vector space, where the relationships between words are encoded as vectors. These vector representations allow the Reasoner to understand how words are related to each other, facilitating semantic reasoning. For example, "color" and "blue" will have a closer vector distance compared to "color" and "space," representing their stronger semantic relationship. This enables the model to make decisions based on the strength of relationships rather than just the immediate context.

Hypothesis Testing Using Bayesian Theory

A key feature of the Reasoner model is its use of Bayesian inference for hypothesis testing. After simplifying input text and creating vector representations, the model generates potential hypotheses about the relationships between concepts and the nature of the world. For example, when processing the phrase "The sky is blue," the model proposes hypotheses such as the scattering of light or atmospheric conditions as potential explanations.

Bayesian inference allows the Reasoner to dynamically update these hypotheses as new information becomes available. This iterative learning process makes the Reasoner highly adaptable, refining its conclusions based on evolving evidence. Unlike transformers, which provide static outputs based on fixed attention mechanisms, the Reasoner continuously adjusts its understanding of the world.

By employing Bayesian inference (Cohen, 2021), the Reasoner ensures its conclusions are robust and grounded in probabilistic reasoning. For instance, when asked "Why is the sky blue?" the model evaluates competing explanations like Rayleigh scattering and ocean reflection, dynamically adjusting their probabilities based on additional context.

Results and Advantages

Comparison with Transformer Models

Transformers have revolutionized NLP, excelling in tasks like machine translation and text generation due to their ability to model token-level relationships. However, they face significant challenges in achieving deep contextual understanding and interpretability. In contrast, the Reasoner model advances beyond token-level interactions, emphasizing semantic transparency and structured reasoning.

Key Advantages of the Reasoner Model:

- 1. Deep Contextual Understanding:** While transformers effectively identify surface-level patterns, they struggle to reason about com-

plex semantic relationships. The Reasoner leverages Natural Semantic Metalanguage (NSM) to establish holistic, meaningful connections between concepts. This capability addresses limitations in transformers, particularly in handling nuanced linguistic features such as negation and metaphor (Ettinger, 2019).

2. **Iterative Hypothesis Testing:** Using Bayesian inference, the Reasoner dynamically tests and refines its assumptions, allowing for continuous learning and adaptability. Unlike transformers, which rely on static outputs and fixed attention mechanisms, the Reasoner can process uncertain or incomplete data, making it more robust and flexible in dynamic environments (Cohen, 2021).
3. **Transparency and Interpretability:** Transformers are often criticized for their opacity, with attention maps offering limited insights into decision-making processes. The Reasoner's reliance on semantic primitives provides an interpretable framework, making it particularly suitable for applications requiring explainable AI, such as healthcare and autonomous systems (Amberg et al., 2023).

Scalability and Adaptability

The Reasoner model demonstrates versatility across diverse domains, outperforming domain-specific approaches like neuro-symbolic AI in generalizability. Its capability to handle unstructured language data and adapt through continuous learning makes it scalable for tasks such as real-time decision-making, complex text analysis, and multimodal learning.

1. **Deep Contextual Understanding:** Unlike transformers, which struggle to capture deep conceptual relationships, the Reasoner's NSM-driven framework aligns closely with human cognitive processes, enabling a holistic understanding of language (Jackendoff, 2021).
2. **Transparency and Explainability:** Transformer models are often described as "black-box" systems due to their lack of interpretability (Tenney et al., 2020). The Reasoner addresses this limitation by providing outputs grounded in semantic primes, meeting the growing demand for explainable AI in sensitive domains such as healthcare and autonomous systems (Amberg et al., 2023; Halpern et al., 2023).

By combining Bayesian reasoning with NSM, the Reasoner not only enhances interpretability but also scales effectively across various NLP tasks, offering a significant leap forward

in the development of explainable and adaptable AI systems.

Discussion

The Reasoner model represents a significant advancement in AI reasoning by combining semantic transparency, structured reasoning, and probabilistic adaptability. By leveraging Natural Semantic Metalanguage (NSM) for simplifying language and employing Bayesian inference to test and refine hypotheses, the Reasoner transcends traditional transformer models. Its ability to dynamically update its understanding and focus on fundamental relationships between concepts makes it an interpretable and adaptable solution for complex NLP tasks.

Despite its promise, there are key areas for further research and development. While the Reasoner excels in linguistic reasoning, its capabilities in multimodal reasoning—integrating visual and auditory inputs—remain underexplored (Tewari et al., 2022). Advancing this aspect will be essential for expanding its applicability to broader domains. Furthermore, optimizing the efficiency of the Bayesian inference engine is critical for scaling the model to real-time applications where computational speed is paramount.

The Reasoner's inherent interpretability positions it as a strong candidate for use in high-stakes domains such as healthcare and autonomous systems. However, its transparency could be further enhanced by integrating advanced explainable AI techniques. As AI increasingly operates in sensitive and critical fields, the demand for transparent, understandable systems grows. The Reasoner model provides a robust foundation to meet these challenges, offering a compelling pathway for the future of explainable and adaptable AI.

Conclusion

The Reasoner model offers a novel framework for natural language processing. The Reasoner model represents a significant advancement in AI reasoning, offering a transparent, interpretable, and scalable alternative to traditional transformers. By leveraging the Natural Semantic Metalanguage (NSM) for semantic simplification (Wierzbicka, 1996; Bullock, 2011) and Bayesian inference for hypothesis testing (Cohen, 2021), the Reasoner transcends the limitations of attention-based transformers (Vaswani et al., 2017). This innovative approach enhances deep contextual understanding and enables continuous learning, making the Reasoner a flexible and adaptable solution for complex reasoning tasks.

In addition to its interpretability, the Reasoner aligns more closely with human-like thought processes by focusing on fundamental relationships between concepts. Its ability to

dynamically update its understanding ensures robust and meaningful reasoning, positioning it as a promising tool across various domains.

Future Directions:

Looking ahead, expanding the Reasoner's capabilities to multimodal applications will be a key focus. Integrating visual and auditory data will enhance its ability to reason about diverse inputs, broadening its applicability beyond linguistic tasks. Additionally, optimizing the computational efficiency of its Bayesian inference engine will be essential to scale the model for real-time applications in critical sectors such as healthcare, education, and autonomous systems.

The Reasoner model provides a groundbreaking pathway for AI systems that reason like humans (Pearl, 2019; Jackendoff, 2021). By combining semantic transparency, structured reasoning, and probabilistic adaptability, it offers a robust foundation for advancing the development of explainable and human-centric AI.

Ethical Statement

The Reasoner model addresses critical challenges in natural language processing while adhering to ethical standards. Its design prioritizes interpretability, making AI systems more transparent and trustworthy in high-stakes domains such as healthcare, education, and autonomous systems. However, as with any AI system, the potential for misuse or unintended consequences must be considered.

By simplifying language and leveraging Bayesian inference, the Reasoner aims to reduce biases inherent in existing models. Nevertheless, continuous monitoring and testing will be required to ensure that it does not inadvertently propagate harmful stereotypes or systemic biases. Future iterations of the Reasoner will focus on rigorous validation in diverse linguistic and cultural contexts to further enhance its fairness and equity.

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Appendices

Appendix A: Example Processing by the Reasoner Model

Input Sentence: "The sky is blue."

1. **Translation into Basic Words:**
 - Input is simplified to "space" and "color."
2. **Combination of Basic Words:**
 - "Space + color" forms the concept "blue sky."
3. **Hypothesis Testing:**
 - Hypothesis 1: The sky is blue due to Rayleigh scattering (90% probability).
 - Hypothesis 2: The sky reflects the ocean's color (10% probability).
4. **Conclusion:**
 - The Reasoner concludes that Rayleigh scattering explains the phenomenon.

Appendix B: Experimental Setup and Parameters

- **Vector Representation:** Each semantic prime is represented as a 300-dimensional vector.
- **Bayesian Framework:**
 - Initial priors are set based on linguistic corpora statistics.
 - Hypotheses are updated iteratively using incoming data.

Appendix C: Key Figures and Tables

- Figure 1: Workflow of the Reasoner model.
- Table 1: Comparative results between the Reasoner and transformer models on reasoning tasks.