An Introduction to Artificial Neural Network

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INTRODUCTION I

- LLMs have transformed artificial intelligence, extending beyond traditional NLP.
- They learn knowledge and reasoning from data, unlike formal logic systems that struggled with real-world complexity.
- LLMs' ability to acquire knowledge opens up a new avenue in reasoning.
- They may lead to verifiability in many tasks, such as legal analysis, scientific discovery, $\cdots$.
- Traditional reasoning in AI involves applying structured rules to derive conclusions, while LLM-based reasoning integrates natural language understanding and enables multi-step deduction and abstraction.
- Algorithmic reasoning may lead to multi-step thought processes, which may enhance the clarity and trustworthiness of LLM outcomes.

INTRODUCTION II

- Logical, common-sense, and mathematical reasoning are crucial for AI systems
- Provide analytical skills. Formal and symbolic logic-based reasoning will be distinguished from heuristic approaches like Chain-of-Thought prompting.
- The attention mechanism may facilitate coherent thought generation.
- Empirical evidence suggests a correlation between LLM scale and reasoning abilities.
- Parameters and training data (AKA scale) is critical for unlocking reasoning potential. LLM Performance is directly proportional to scale (demonstrated - ELMO$\rightarrow$ transformer)
- Deep dive into into the theoretical framework is needed to improve the model design, training, and prompting strategies.

DEDUCTIVE REASONING (TOP-DOWN LOGIC)

What it is: Starting with a general rule and applying it to a specific situation to reach a certain conclusion.

Simple Example

- **General Rule:** All dogs bark.
- **Specific Case:** Fido is a dog.
- **Deductive Conclusion:** Therefore, Fido barks.

Generally good at simple deductions, but struggle with complex, multi-step logic or strict coherence in long arguments.

INDUCTIVE REASONING (BOTTOM-UP LOGIC)

Forming a general rule or conclusion from specific examples or observations. This conclusion is likely, but not necessarily true.

Simple Example

- **Observation 1:** I am a saggitarian. I spill coffee ;)
- **Observation 2:** My uncle is a saggitarian and he spills coffee
- **Inductive Conclusion:** Therefore, many saggitarians probably spill coffee.

LLMs excel at generalizing from observed patterns but might not invent entirely novel hypotheses far beyond their training data.

ABDUCTIVE REASONING (MAKING THE BEST GUESS)

Observing an outcome and guessing the most likely cause based on incomplete information, like a detective making an educated guess.

Simple Example

- **Observation:** The street outside is wet.
- **Possible Explanations:** It rained, a street cleaner went by, someone spilled water.
- **Abductive Conclusion (Best Guess):** The most likely explanation is that it rained (based on common occurrences).

Suggest plausible explanations based on data correlations, but lack true understanding of causality and context, limiting reliability in complex situations.

ANALOGICAL REASONING (FINDING SIMILARITIES)

Comparing similar things or situations to learn, infer, or explain something about one of them.

Simple Example

Just like a `seed` needs soil and water to grow into a *plant*, a *child* needs care and education to grow into a capable *adult*.

Capable of generating basic analogies based on linguistic similarity, they may miss deeper, conceptual parallels due to a lack of real-world understanding of the underlying relationships.

LLMs demonstrate common-sense knowledge through their pretraining data and techniques like Chain-of-Thought prompting. External knowledge bases can enhance LLMs' performance on common-sense tasks by providing context. LLM performance on common-sense tasks is assessed using benchmarks like CommonsenseQA, StrategyQA, HellaSWAG, PIQA, Social IQA, and OpenBookQA. LLMs struggle with common-sense reasoning, showing less improvement than logical or mathematical tasks, especially in smaller models. LLMs' knowledge for common-sense answers is often unreliable, potentially incorrect, and misleading. LLMs exhibit significant performance variations based on cultural context, highlighting potential biases in their understanding of the world.

MATHEMATICAL REASONING

Text Analytics

• Mathematical thought is a critical capability for artificial intelligence. • It involves the ability to solve mathematical problems and engage in theorem proving. • Large Language Models have shown remarkable potential in handling various mathematical tasks. • These tasks include algebraic manipulation, solving numerical problems, and even contributing to theorem proving. • Research in this area focuses on both solving mathematical problems and theorem proving. • The goal of theorem proving is to verify mathematical statements using formal logic. • Techniques like Chain-of-Thought prompting have been effective in improving the performance of LLMs on mathematical problems. • These techniques encourage LLMs to break down complex problems into smaller, more manageable steps. • The ability of LLMs to perform mathematical thought is assessed using a variety of specialized benchmarks. • These benchmarks include datasets such as GSM8K and MATH. • GSM8K contains grade-school level math word problems, while MATH includes problems from high school mathematics competitions. • Other benchmarks like JEEBench and MATH 401 further test the capabilities of these models on more advanced mathematical problems. • The development and use of these benchmarks reflect ongoing efforts to rigorously evaluate and enhance the mathematical problem-solving abilities of LLMs.