Explainability of LLMs & Their Ethical Implications

Final Presentation

1. Motivation

Large Language Models (LLMs) are increasingly deployed in healthcare environments where decisions can directly impact patient outcomes.

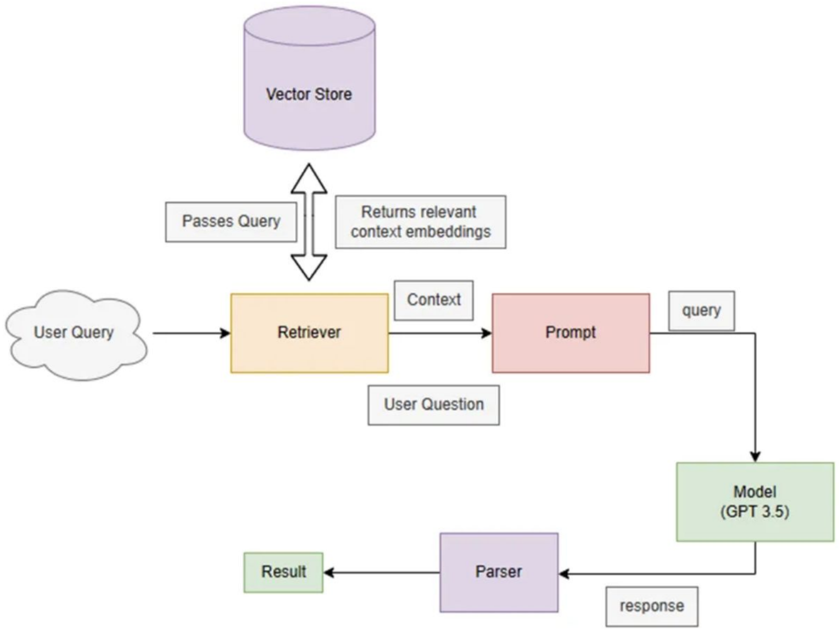
Why this matters:

- Traditional ML models have structured transparency tools, but LLMs are often seen as “black boxes.”
- In clinical decision-making, lack of explainability can lead to distrust, misdiagnosis, or unsafe prescriptions.
- High-stakes domains like healthcare require verifiable reasoning, especially for ethical and legal accountability.
- Explainability techniques like CoT and ReAct improve not just user trust but actual model performance.

I explore how prompting strategies can make LLMs safer and more interpretable for critical decisions.

2.Literature Review

2.1 SHAP LLM

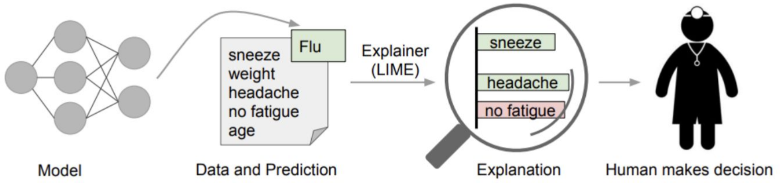


SHAP LLM workflow

2.2 SHAP LLM

Local Interpretable Model-agnostic Explanations (LIME)

LIME aims to identify an interpretable model over the interpretable representation that is locally faithful to the classifier.



3.Approach used

1. Zero-shot & Few-shot prompting

- In the zero-shot setting, the model receives no examples—just the question.
- Few-shot prompts include 1–3 manually crafted examples, which help orient the model.
- These are useful baselines, but often don’t provide any reasoning or explanation.

2. Chain of Thought (CoT) prompting

- This technique asks the model to "think step by step."
- For example, instead of just answering “yes” or “no” to a medical question, the model walks through the patient's condition, symptoms, and known drug interactions before concluding.
- I observed that this improves both performance and transparency in tasks like medication safety assessments.

3.Approach used

- 3. ReAct (Reason + Act)
- This approach combines reasoning with tool-use.

- The model reflects, then takes an action like querying a database or citing a document, then reflects again before answering.

- In my implementation, I simulated this behavior by integrating guideline-based logic through chained prompts and knowledge lookup via hardcoded responses.
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- 4. RAG (Retrieval-Augmented Generation) (partially implemented)
- I experimented with integrating RAG-style templates where the model was supplied with retrieved context from a fake knowledge base.

- This showed how additional factual support can make the response more trustworthy, especially when citing guidelines or medical studies.
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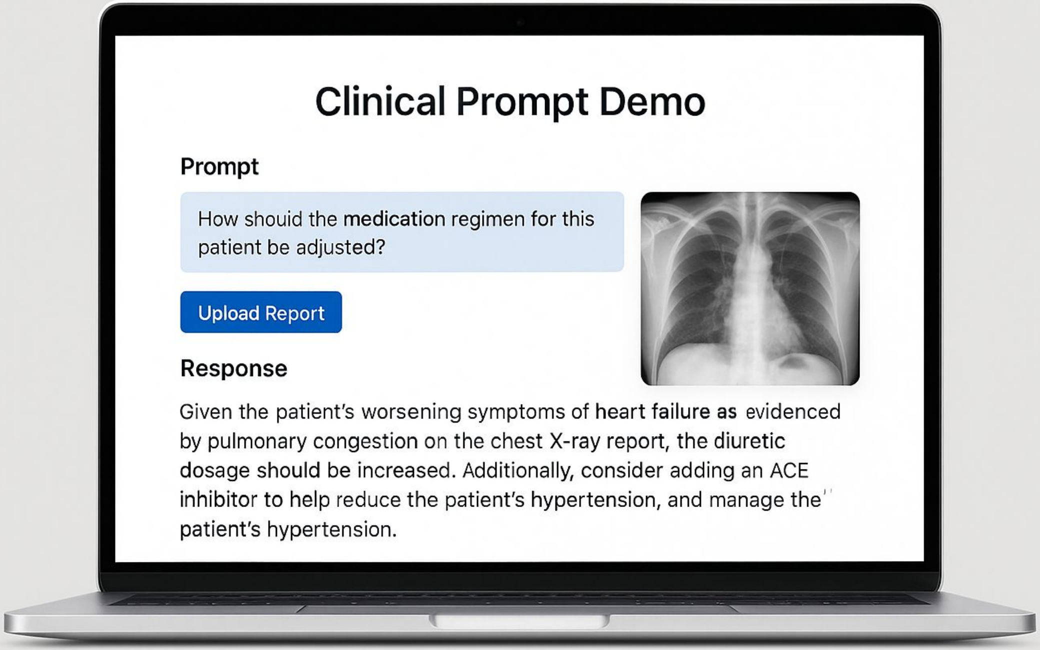
4.Demo

Example (Medical):

Q: Should this patient be prescribed Drug X?
Prompt: Let's think step by step.

Response:
Patient is 72, has liver issues.
Drug X stresses liver.
→ Do not prescribe.

Benefits:
- Transparent logic
- Ethical justifiability



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