Natural Language Processing Large Language Models Usage and Evaluation Patterns

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Introduction

- Since the inception of Large Language Models, various patterns of use and evaluation of this technology have emerged.
- In this talk, we will try to organize these patterns and give a general overview of them.

Source:

`https://www.masayume.it/img/masayume/Large-Language-Models.jpg`

Recap: What is an LLM

- An autoregressive language model trained with a Transformer neural network on a large corpus (hundreds of bullions of tokens) and a large parameter space (billions) to predict the next word.
- It is usually later aligned to work as a user assistant using techniques such as Reinforcement Learning From Human Feedback [Ouyang et al., 2022] or supervised fine-tuning.
- Some are private (access via API or web browser): Google Bard, ChatGPT, etc.
- Others are open (model's weights can be downloaded): Llama, LLama2, Falcon, etc.
- The most remarkable feature of these models is their few-shot, one-shot, zero-shot learning capabilities.
- This means that they can learn new tasks without large amounts of human-annotated data.

Zero-shot, One-shot, and Few-shot Learning

The three settings we explore for in-context learning

Zero-shot

```
1  Translate English to French:      ← task description
2  cheese =>                         ← prompt
```

One-shot

```
1  Translate English to French:      ← task description
2  sea otter => loutre de mer        ← example
3  cheese =>                         ← prompt
```

Few-shot

```
1  Translate English to French:      ← task description
2  sea otter => loutre de mer        ← examples
3  peppermint => menthe poivrée      ←
4  plush girafe => girafe peluche    ←
5  cheese =>                         ← prompt
```

Traditional fine-tuning (not used for GPT-3)

Fine-tuning

```
1  sea otter => loutre de mer        ← example #1
```

↓ gradient update ↓

```
1  peppermint => menthe poivrée      ← example #2
```

↓ gradient update ↓ ... ↓

```
1  plush giraffe => girafe peluche   ← example #N
```

↓ gradient update ↓

```
1  cheese =>                         ← prompt
```

Talk Overview

- Despite the recency of this technology, its adoption has been tremendous in many areas.
- Below, we propose a simple categorization of the ways in which LLMs are used and evaluated.
- These patterns will serve as the narrative backbone of this presentation.

Usage Patterns

1. Fixed-knowledge Assistant
2. Knowledge-augmented Assistant
3. LLM-based Applications

Evaluation Patterns

- MTBench
- LLM Arena

Usage Pattern 1: Fixed-Knowledge Assistant

- In this pattern a user interacts with the LLM proving prompts as input and receiving a text as answer.
- The knowledge the LLM has access is limited to the corpus on which it was trained and the context given in the prompt.

Prompting

- Prompt Engineering : https://twitter.com/IntuitMachine/status/1727079666001870877
- Roles
- JSON outputs

```
{"role": "system", "content": "You are a helpful assistant desi
 {"role": "user", "content": "Who won the world series in 2020
```

- Chain of thought Prompting

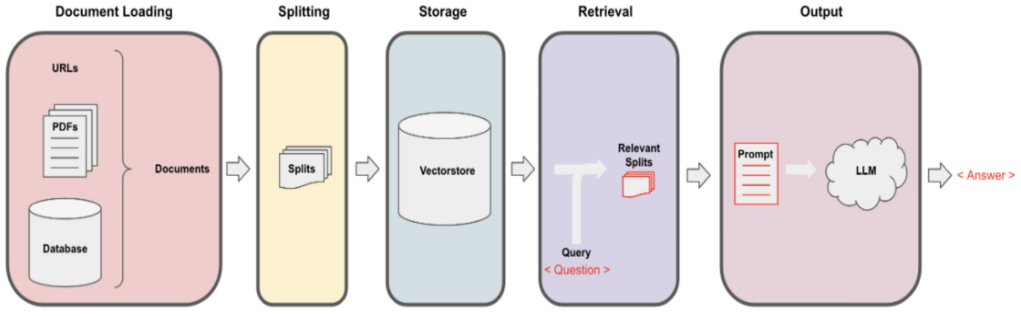
Knowledge-augmented Assistant

- Idea incorporate domain-scpefific knowledge not included during training.
- There two main patterns to achieve this:
  1. Retrieval-Augmented Generation (Vector Databases)
  2. Instruction Fine-Tuning

Setting the style, tone, format, or other qualitative aspects Improving reliability at producing a desired output Correcting failures to follow complex prompts Handling many edge cases in specific ways Performing a new skill or task that's hard to articulate in a prompt

Retrieval-Augmented Generation

- Rely on a Vector Database embed queries, retrieve relevant documents, append them into the prompt [Lewis et al., 2021].
- Many ideas of Informatrion Retrieval are employed here.
- `https://www.infoworld.com/article/3709912/vector-databases-in-llms-and-search.html`
- `https://learn.deeplearning.ai/vector-databases-embeddings-applications/lesson/1/introduction`
- `https://stackoverflow.blog/2023/10/09/from-prototype-to-production-vector-databases-in-generative-ai-ap`



Instruction Fine-Tuning

- Idea: instead of training the LM with raw text with next token prediction, train it with pairs of prompts and user-aligned answers.
- Paid Fine-Tuning (GPT-4??)
- OpenAI offers many more specific gpts: `https://openai.com/blog/introducing-gpts`
- Alpaca, Vicuna, Llama, Llama2
- https://blog.gopenai.com/paper-review-qlora-efficient-finetuning-of-quantized-llms-a3c857cd0cca

Datasets for Instruction Fine-Tuning

- Standford Alpaca Dataset (Vicuna)
- ShareGPT (Alpaca)
- Dolly-15K
- Orca Dataset

Parameter Efficient Fine Tuning

- Lora, QLora
- https://blog.gopenai.com/paper-review-qlora-efficient-finetuning-of-quantized-llms-a3c857cd0cca

Token-Incrementation

- Lora, QLora
- https://blog.gopenai.com/paper-review-qlora-efficient-finetuning-of-quantized-llms-a3c857cd0cca

Applications

- LLMs can be embbeded into any software via API calls. For example a Search Engine (you.com)
- https://gptstore.ai/

Autonomous Agents

- Agents are a special kind of LLMs application in which the LLM serves as the reasoning and planning component of the software.
- agent in the sense of perceiving an environment and taking actions to achieve goals.

LLMBench and LLm Arena

- Standard NLP evaluation: human annotated gold-labels and metrics.
- LLMS are intrinsically multi-task and not easily evaluated with this approach.
- Machines evaluating machines??
- MT-bench (categories)
- HuggingFace Open LLM Leaderboard
- LLM Arena

Questions?

Thanks for your Attention!

References I


Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., tau Yih, W., Rocktäschel, T., Riedel, S., and Kiela, D. (2021).
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Training language models to follow instructions with human feedback.
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