Large Language Models and Data Streams

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Abstract. Large language models, such as ChatGPT, have become widely recognized and are extensively utilized across various domains. However, these models are typically trained on static datasets, lacking updates to new data beyond their initial training set. To enable models that can continuously update themselves based on incoming data, it is necessary to have large language models trained and updated on input data streams. In this paper, we begin by outlining the structure and fundamental applications of large language models. Subsequently, we introduce the concept of data streams and provide an overview of current use cases where large language models are adapted to accommodate streaming data. Finally, we summarize the existing challenges associated with integrating large language models with data streams and discuss potential solutions.

Keywords: LLM · data streams · chatGPT.

1 Introduction

Large language models have shown their wide usage and significant competence in many fields according to [1], such as learning and answering users' questions in academic fields, assisting in diagnosing diseases in medical fields, generating text and classifying text data to various categories and so on. However, as [9] demonstrates, there is a significant limitation of current large language models: they are trained based on certain static datasets that will not automatically be updated, and this causes the resulting models to only be able to access information from its training datasets. When the models need to be updated as new data becomes available, the only way is to start the training process over again. But in many scenarios such models can't satisfy our needs. For example, to have a better traffic prediction, real-time traffic data is needed [3], Analyzing news and events sentiment can help predict the financial market [10], real-time health data is of great importance when monitoring patients' health condition [2] and so on. So to have models that can fulfill those use cases, we need to find and compare useful methods that combine large language models and continuous data input (data streams) and also summarize the current major obstacles.

2 Related Works

In this chapter, the following concepts and techniques that are related to this topic will be covered.

2.1 Large Language Model

In this subsection, we will first summarize the evolution of language models, followed by an overview of the current large language models' structure and training process.

The Evolution of Large Language Models
The earliest language models, taking n-grams as an example, are statistical. n-grams refers to an n-words substring of a longer string and n represents the number of words in the substring, according to [12]. Taking the sentence "I read a book" as example, a bi-grams composition of this sentence would be "I read", "read a" and "a book". By considering the n previous words, the frequency and probability of each n-grams can be calculated, which makes n-grams model perform well in text classification and word prediction with short documents [12]. However, n-grams performs poorly with long documents due to the rapid growth of dimensionality with large n, and it has only restricted access to the words that appear in the document.

Later models using word embeddings such as Word2Vec solve the problems of earlier models to some extent by representing words in vector spaces, and words with similar meanings such as "walk" and "run" have closer distance in the vector space [13]. Word embeddings successfully reduces the dimensionality of word representations and can work with larger documents by combining techniques such as "Continuous Bags of Words" [13].

With the development of neural networks, more powerful models such as the Seq2Seq model began to take a more important role in many application fields such as machine translation [14]. The core idea of the Seq2Seq model is that it uses the Long Short-Term Memory(LSTM) networks as an encoder to map the input to a vector with fixed dimensionality, and then uses another LSTM to decode the output sentence from the vector. By regulating the present and past information and gradient flow, LSTM makes it possible for the model to handle long input sequences and the encoder-decoder structure enables the model to manage different lengths for input and output sequences [14].

Large language models start to have a huge leap forward after the introduction of the transformer architecture [7]. [16] demonstrates that the transformer architecture can effectively improve the language understanding ability of language models even with large unlabeled text corpora by first generatively pre-training the model on the text data and then discriminatively fine-tuning them on various tasks. Modern models usually own a large number of parameters and large-scale training datasets, but the source of the training datasets can vary from model to model. For example, according to [15], GPT-2 (with 1.5 billion parameters) is trained on massive training datasets including the crawling results from millions of different web pages, called WebText. BERT (BERT_{BASE} with 110 million parameters, BERT_{LARGE} with 340 million parameters) is trained on the English

Wikipedia (2,500 million words) and BookCorpus (800 million words), a large dataset of books used for machine learning approaches [8]. A more recent model collection called LLaMA (with 7 to 65 billion parameters) is trained on various open-source data such as commoncrawl[1], C4, Github, Wikipedia and so on [33]. Table 1 provides a brief overview of the 3 models together with information on the most recent GPT-3.5 and GPT-4 models according to the OpenAI blog[2].

Model Name	BERT	GPT-2	LLaMA	GPT-3,5/ 4
Developer	GoogleAI	OpenAI	MetaAI	OpenAI
Release Date	2018	2019	2023	2022/2023
Nr. of Parameters	110 M/ 340 M	1,5 B	7-65 B	175 B/1,7 T
Training Data	Wikipedia(en) & BookCorpus	WebText	Various open-source datasets	WebText
Open-sourced	Yes	No	Yes	No
Major Applications	QA	Text generation & Translation	Text generation & QA & Translation	Content generation & QA & Translation

Table 1: Comparison of Large Language Models

The parameter size of different models has a growing trend, which can be explained by the relationship between model performance, the number of model parameters N, the size of dataset D and the amount of computing to train the model C. [17] demonstrates the **Smooth Power Laws** which says: "Performance has a power-law relationship with each of the three scale factors N, D, C when not bottlenecked by the other two, with trends spanning more than six orders of magnitude". Nowadays, there are various models that have distinct capabilities, for example, DALL-E can generate and modify images based on text input, whereas ChatGPT 3.5 can generate code and natural language, as [18] in figure 1 summaries.

[1] https://commoncrawl.org/
[2] https://platform.openai.com/docs/models/gpt-base

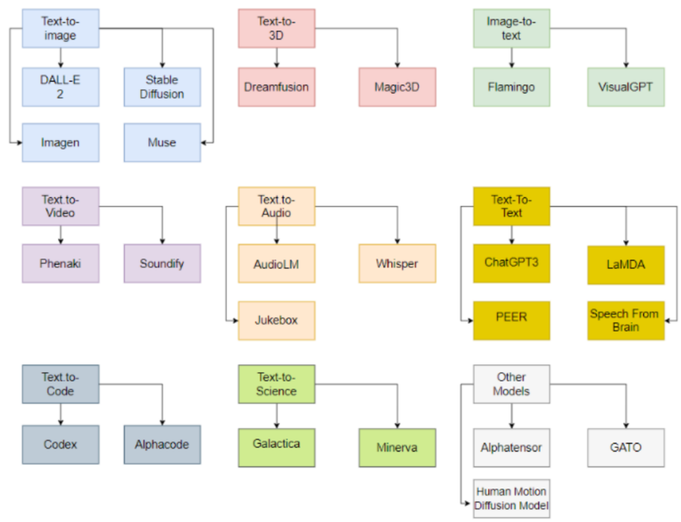


Fig. 1: An overview of the recent major generative AI models [18]

The Architecture and Training Process of Large Language Models
Many of the recent large language models such as ChatGPT, LLaMA and BERT are based on transformer-based neural networks. The transformer architecture, as [7] in figure 2 demonstrates, is an encoder-decoder architecture. The encoder takes the input sequence and converts them into dense vectors of fixed size at the input embedding step. Then with the help of the positional encoding step, the input sequence contains information about each token in the sequence. The encoded inputs are then passed through the multi-head attention mechanism so that the model can capture various relationships and features from the input sequence. Then the Add and Normalization layer is applied to stabilize and speed up the training process. In the end, the Feed Forward layer is applied to help in introducing non-linearity and learning complex representations for each token's position in the sequence. Similarly, the decoder uses the vector representation of the input sequence created by the encoder along with the previously generated tokens to produce the next token in the output sequence and the masked multi-head attention mechanism is applied to ensure that the prediction for a particular position depends only on the known outputs at earlier positions.

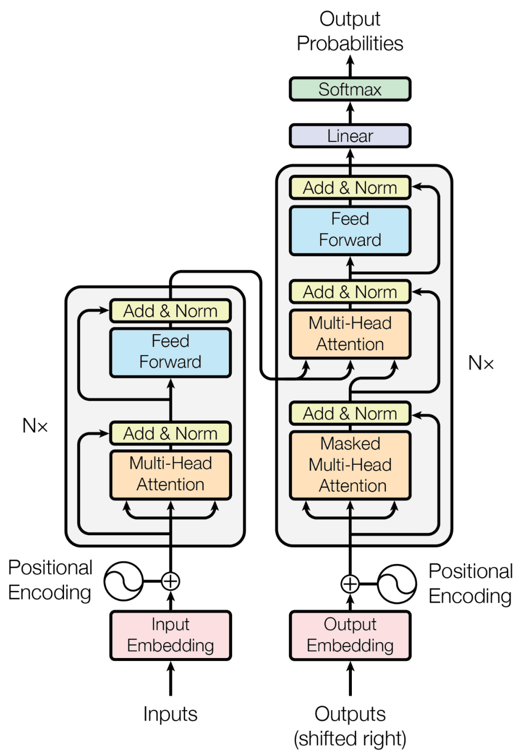


Fig. 2: The transformer structure [7]

Various input text datasets must be pre-processed as valid input representations before they can be used for the training process, and the data pre-processing includes the following procedures [11]:

- Tokenization involves segmenting text into tokens, which are the basic units of broken text. Tokenization can simplify and standardize the input data and improve model performance [8].
- Subword encoding refers to breaking down the input text into smaller units and helping handle rare or out-of-vocabulary words in the input text.
- Data cleaning is the step where the noisy information in the input data should be removed, which can significantly improve the quality and suitability of the input data for the model.

More specifically, BERT uses the WordPiece embeddings [34] with a 3000 token vocabulary. For each input, a classification token ($[CLS]$) is used to mark the beginning of the sentence and a ($[SEP]$) token is used to mark the end of a sentence. In some cases, several sentences are combined as one single sentence, therefore a new embedding is needed to mark to which sub-sentence each token belongs [8]. As figure 3 shows, an example input sentence "My dog is cute, he likes playing." is first tokenized into smaller units, where ($[CLS]$) marks the start of the input and ($[SEP]$) marks the end of the sentence as well as splits the sentence into 2 parts. A token embedding is added for each token, a segment embedding is added to show to which sentence each token belongs and a position embedding is used to show the position of each token within the sentence. The final input representation is the sum of all embeddings.

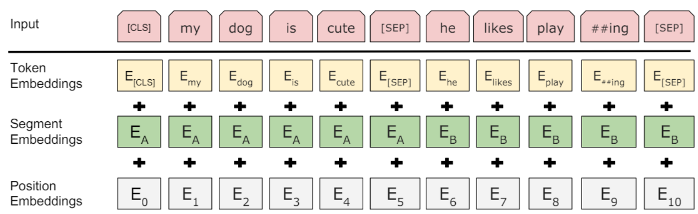


Fig. 3: Input representation of BERT [8]

GPT-2 and LLaMA use Byte Pair Encoding (BPE) [35] to tokenize the input text where BPE iteratively count the frequency of the characters or subwords and merge the most frequent ones to form new vocabulary [15], [33]. There are several different implementations of BPE that are moderate for different use cases, the training corpus on which BPE is applied also significantly influences the size of the result vocabulary. GPT-2 applies BPE with a base vocabulary of more than 130,000 tokens, whereas the BPE applied on LLaMA creates around 1,4T tokens.

A model starts its training algorithm after taking the pre-processed data as its input. For recent models such as ChatGPT, LLaMA and BERT, their training algorithms share a same process of an unsupervised pre-training phase and a supervised fine-tuning phase [11]. In the pre-training phase, a large amount of unlabeled WebText data is used as the model's training dataset to make it a high-capacity language model. Given an unlabeled corpus of tokens $U = \{u_1, ..., u_n\}$ as a training dataset, the core idea of the pre-training phase is to predict the next token u_i for a sequence $\{u_{i-k}, ..., u_{i-1}\}$. According to [16], this is done by maximizing the likelihood:

$$L_1(U) = \sum_i \log P(u_i | u_{i-k}, ..., u_{i-1}; \Theta) \tag{1}$$

k refers to the context window size and Θ is the parameter of the neural network with which the conditional probability P is modeled.

The supervised fine-tuning phase is used to improve the model's performance on specific tasks by training it on a smaller corpus of labeled data [11]. Given a labeled dataset C, where each instance of C has a sequence of tokens $\{c^1, ..., c^m\}$ and a label y, the goal of the fine-tuning phase is to maximize the following likelihood [16]:

$$L_2(U) = \sum_{(x,y)} \log P(y|x^1, ..., x^m) \tag{2}$$

In the BERT model, as shown in figure 4, the pre-training phase consists of 2 unsupervised tasks: Masked LM and Next Sentence Prediction (NSP). Masked LM is used to help BERT understand the context of words within a sentence, it masks 15% of all WordPiece tokens in each input sentence and the model predicts only the masked words instead of reconstructing the entire input. NSP is applied to help BERT understand the relationship between 2 sentences. More specifically, when having 2 sentences A and B as input, B is replaced by another random sentence from the training set for half of the time and remains unchanged for the other half of the time. The BERT is trained to predict whether the second sentence in the input is the actual sentence B. According to [8], NSP has significant benefits for question answering (QA). Fine-tuning BERT is relatively inexpensive compared with pre-training, as it only involves fine-tuning the parameters while feeding BERT with various task-specific inputs and outputs such as QA tasks, single sentence classification tasks, sentence pair classification tasks and so on. When fine-tuning, an additional output layer is added to BERT so that the minimal number of parameters need to be learned from scratch again.

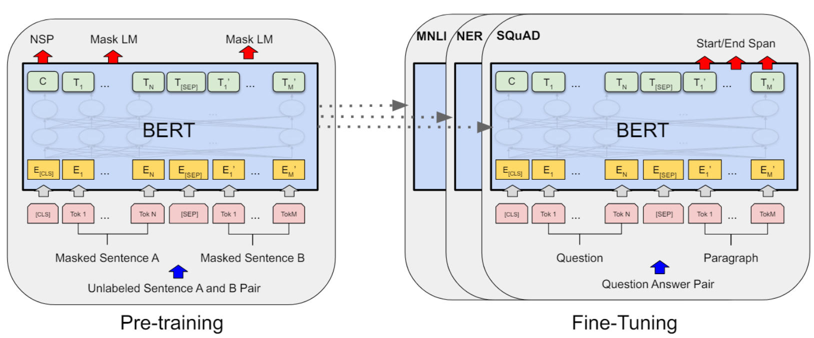


Fig. 4: Training process in the BERT model [8]

GPT-2 and LLaMA make some improvements to the pre-training process such as normalizing the input for each transformer layer and adding a normalization layer after the last self-attention layer to improve the training stability (GPT-2 and LLaMA) [15], replacing the ReLU layer with a SwiGLU layer to improve model performance (LLaMA) and replacing the absolute positional encoding with the rotary positional embeddings (RoPE) to increase efficiency and scalability (LLaMA) [33]. Together with more efficient code implementation GPT-2 and LLaMA gain better scores on many evaluation fields such as QA, reading comprehension, summarization, translation and so on. Similarly, GPT-2 and LLaMA are fine-tuned with various tasks, figure 5 illustrates some fine-tuning tasks of the original GPT.

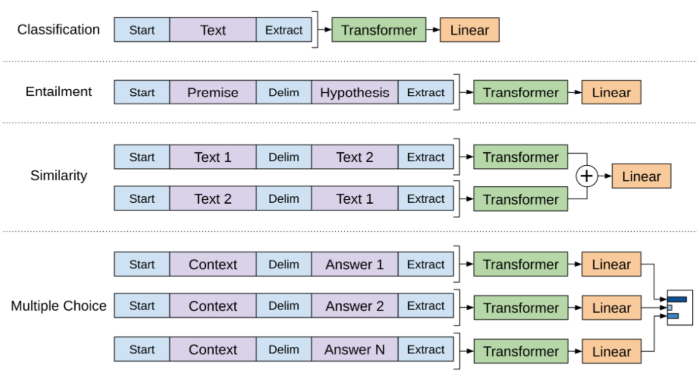


Fig. 5: Fine-tuning of GPT [16]

2.2 Data Stream

In many application fields nowadays, data is often generated and processed at a very high rate. These include health sensors that track body temperature and blood pressure [5], monitoring of production lines, information on stock trading, posted content on social networks and so on. [6]. Due to its near real-time and huge amounts characteristics, traditional data management approaches are often not suitable anymore, a new system called Data Stream Management Systems (DSMS) which supports continuous queries, low latency processing, simple scalability and resource management has evolved to address this issue [6].

Data stream has many informal definitions, [19] describes data stream as "time-varying, volatile, unpredicted and possibly unbounded information". [20] describes data stream as "a data set that is produced incrementally over time, rather than being available in full before its processing begins". According to [5], a data stream has the following formal definition:

Definition 1. *A data stream S is an unbounded, potentially infinite multiset of data stream elements (s, τ), where $\tau \in \mathbb{T}$. $\mathbb{T}$ is a timestamp attribute with values from a monotonic, infinite time domain $\mathbb{T}$ with discrete time units.*

There are multiple methods to analyze data streams, [21] categorizes them into data-based and task-based solutions. Data-based solution refers to examining a subset of the data stream and approximating to an overall outcome for the data stream. Task-based solutions, on the other hand, often refer to achieving time and space efficiency in computing by using relevant techniques. We summarize some of the solutions:

– Synopsis is a data-based solution and it refers to the process of creating compact data summaries such as wavelet analysis and histograms, which can efficiently approximate and query large data streams without processing the entire dataset [21].
– Window is a task-based solution and it refers to adjusting a continuous data stream into bounded segments of data (windows), each window is executed over the items of a single data stream and returns a concrete and finite data segment [19].

3 LLMs with Data Streams

Although large language models have shown strong capabilities in many application fields, their knowledge remains static as they are pre-trained on static datasets. In some occasions, however, a user query expects up-to-date results. Considering the following questions: *Who is the current president of the USA?* The answer to such a question expires likely every 4 years, which seems a reasonable time for an update of the large language model's training datasets. The question *What are the results of the last Bundesliga match day?* would require the knowledge of large language models to be updated at least every week. The question *What is the current traffic condition in the Königstraße of city Aachen?* would require even a near real-time result. Thus, in many application fields, the performance of a pre-trained large language model is likely to gradually degrade over time [22]. In this section, we will first summarize some approaches where large language models are combined with data streams, then discuss some common issues and challenges in this field. Finally, we will list some use cases that address some of the challenges.

3.1 Continual Learning

The need for regular updates of large language models brings intense focus to the concept of **Continual Learning**.

Continual Learning of LLMs
According to [23], continual learning refers to the process of accumulating knowledge on non-stationary data. In the context of large language models, continual learning is applied to enable LLM models to learn from a continuous data stream over time. For a data stream of tasks $\mathcal{T} = \{\mathcal{T}_1, \ldots, \mathcal{T}_n\}$, the goal is to have the model learn sequentially based on the input stream, where it only has access to

$\mathcal{T}_i$ at time i. [4], in their continual learning framework for large language models, categorizes continual learning into 3 stages as figure 6 shows:

- **Continual Pre-training (CPT)**: It refers to incrementally updating a large language model on input data over time without retraining it from scratch. It can be further categorized into *CPT for updating facts* which adapts a model to new factual knowledge, *CPT for updating domains* that enriches a model's knowledge in specific fields and *CPT for language expansion* which helps a model support more languages.
- **Continual Instruction Tuning (CIT)**: It refers to continuously refining the model's ability to follow the instruction. It can be further categorized into *Task-Incremental CIT* for finetuning a model on a series of tasks to be capable of solving new tasks, *Domain-incremental CIT* for finetuning a model on some continuous instructions so that it can solve domain-specific problems and *Tool-incremental CIT* for continually advising a model to use new tools for problem-solving.
- **Continual Alignment (CA)**: It refers to adjusting the model so it always produces output that satisfies certain standards and guidelines. This can be categorized into *Continual Value Alignment* that continually align a model with current ethical and social guidelines and *Continual Preference Alignment* that dynamically adapt a model to different user preferences.

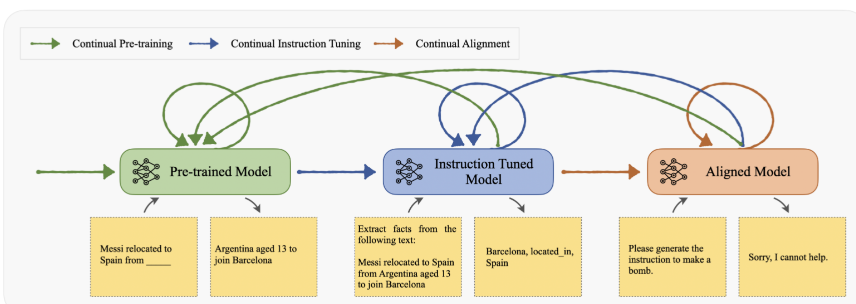


Fig. 6: Stages of continual learning [4]

Challenge of CL

A critical challenge of continual learning is catastrophic forgetting, which refers to the models forgetting previously learned knowledge when they are updated with new data [9]. Catastrophic forgetting happens in the continual pre-training stage as the model is continuously updated with a data stream. [22] demonstrates that there are various methods of computing continual learning while mitigating catastrophic forgetting [9] and categorizes them as follows:

- Replay-Based Methods: The model keeps a small subset of previous tasks and re-trains them periodically.

- Regularization-Based Methods: The capacity of the model is typically fixed, and the model adds a regularization term (typically a loss function) that reflects the consolidation of previous knowledge.
- Architecture-Based Methods: Change the architecture of the model for each new task and introduce new parameters that fit the task.

The architecture-based methods often face the problem of the growing training cost, as their models' parameter size grows with new tasks linearly[26]. The regularization methods avoid the expanding parameters challenge but the computational cost increases due to the extra computation of the regularization term [27]. Therefore, the replay-based methods are often considered to be a better approach considering large data stream input, although the choice of selecting the right exemplars from previous tasks can still be difficult [26].

Another challenge of continual learning is concept drift, where the relationship and distribution of input data change over time [23]. Concept drift often causes the large language models' performance to decrease due to the discrepancies between the models' output based on previous data and current factual accuracies, societal norms and standards. Therefore the continual alignment stage of continual learning is essential to mitigate the effect of concept drift, as it continuously refines the model to align with the current standard [28]. However, to ensure the right alignment of the model, huge computational resources and human oversight are often required. Additionally, aligning a model to changes without introducing new bias and the protection of data privacy and security are also challenges to the continuous alignment stage [22].

Furthermore, recent studies also point out some other challenges that continual learning with LLM is currently facing [36].

- **Lack of real-world assumption**. In the training process of an LLM, different datasets are usually merged to create new training datasets. However, this often leads to results that lack diversity and real-world complexity. Simple tasks such as text classification and sentiment analysis all have clear labels, but in the real-world assumption, many labels are not always available due to noise. This may reduce the robustness of an LLM.
- **Multi-modal Continual Learning**. Current continual learning approaches mainly focus on the field of NLP tasks such as sentiment analysis and text classification, but multimodal tasks such aspects text-to-image retrieval, text-image classification, and visual question answering would be some possible future work directions of CL. However, this would require the integration of multi-modal datasets with various data types, which can be costly and complex.

Use Cases

Continual learning is already applied in the field of linguistics, one example is from [31], where they discovered the fact that some large language models are trained on English datasets and their performance in other languages differs from their performance in English. They came up with the idea of developing a large language model that has strong performance in Japanese and decided to apply continual learning methods, especially the continual pre-training stage, on an English LLM LLaMA 2 due to the high computational cost of training an LLM in Japanese from scratch. The idea was to apply continual learning so that the LLaMA 2 model could adapt its knowledge and capabilities to Japanese and to construct a model called Swallow in the end.

According to [31], Swallow preserves the same architecture as LLaMA 2, such as its number of attention heads and its number of layers. To prevent catastrophic forgetting, they applied the replay-based method by selecting 5% of the training data from English RefinedWeb [32], 5% from the English arXiv paper texts and the remaining 90% from Japanese texts. After developing Swallow, they evaluate its performance in various fields such as question answering (QA), reading comprehension (RC), automatic summarization (AS), arithmetic reasoning (AR), commonsense reasoning (CR) and machine translation(MT) and compare its performance to the original LLaMA 2 model. The results showed that despite the large data stream input, Swallow managed to have a better performance in many fields compared with LLaMA 2, especially in QA task as figure 7 shows.

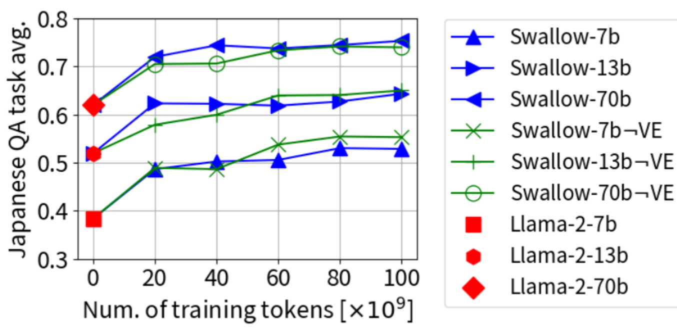


Fig. 7: Performance curve of the Swallow model in question answering task [31]

A more recent study proposes another technique called *Progressive Prompt* based on continual learning, while typical continual learning methods train a model on various large datasets, progressive prompt only needs to learn less than 0,1% of all parameters but still match the performance of continual pre-training and fine-tuning on large datasets [37]. Before Progressive Prompt is proposed, another technique called *Progressive Network* was proposed to help a model continually learn from new tasks without catastrophic forgetting [38]. The idea of Progressive

Network is to freeze the network of parameters learned from a previously task prompt and let it stay accessible by copying it to new network of incoming tasks. Since the learned parameters are frozen while learning new networks, it can mitigate the effect of catastrophic forgetting. However, Progressive Network adds a new copy of the model for each task, causing it extremely computationally expensive for large language models with more parameter size, as figure 8 shows. In Progressive Prompt, however, a separate prompt is learned for each new task and is sequentially concatenated from learned prompts. That means the frozen parameters are not copied, but directly accessible to the parameters of new task prompts. Progressive Prompt shows significant improvement in efficiency and can be applied to all transformer-based architecture.

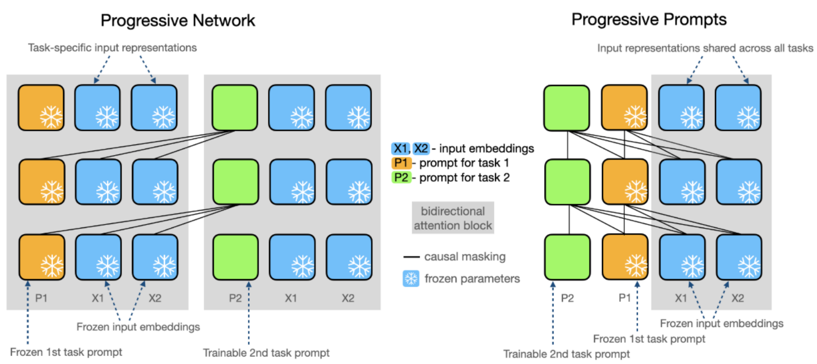


Fig. 8: Illustration of Progressive Network and Progressive Prompt [37]

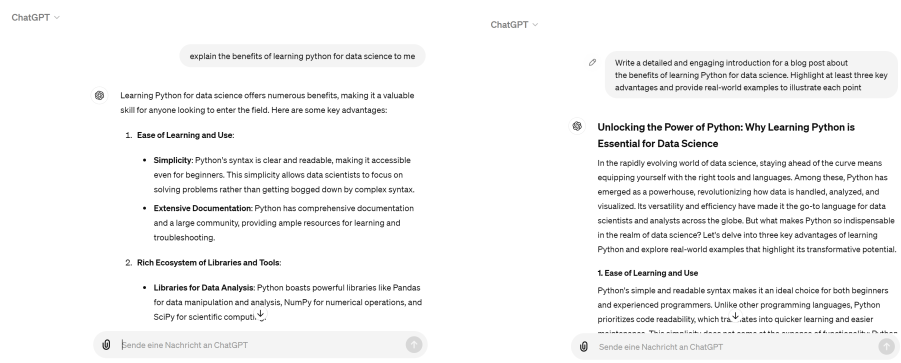
3.2 Prompt Engineering

Definition

[29] defines a prompt as "a set of instructions provided to an LLM that programs the LLM by customizing it and/or enhancing or refining its capabilities" and prompt engineering as "the means by which LLMs are programmed via prompts". More specifically, Prompt engineering is the process of providing large language models with effective inputs or queries to elicit specific, high-quality responses [3]. It has been proven to have a positive influence on the performance of many downstream tasks such as text summarization, sentiment analysis, and natural language translation [25]. Considering the following prompt:

Example 1. "Write a detailed and engaging introduction for a blog post about the benefits of learning Python for data science. Highlight at least three key advantages and provide real-world examples to illustrate each point."

By giving the prompt, the large language model is required to give an engaging, detailed and structured answer to the topic of the benefits of learning Python for data science. Figure 9 shows an example of how different prompts guide ChatGPT to provide different outputs over the same topic.



(a) Prompt 1 (b) Prompt 2

Fig. 9: 2 different prompts yield different output of ChatGPT

Challenges

[30] demonstrates the quality of the prompt provided by users as the major factor that affects the output quality of large language models using prompt engineering Furthermore, they demonstrate that prompt formulation should follow the specific prompt pattern and summarize the components of a prompt pattern as follows:

- A name and classification: It uniquely identifies the prompt pattern and indicates the issue being addressed.
- The intent and context: It describes the issue.
- The motivation: It explains the importance of this issue.
- The structure and key ideas: They provide the LLM with important contextual information.
- Example implementation: It provides an example prompt pattern that can be referenced for other pattern formulations.
- Consequences: It explains the possible effect of this prompt pattern.

However, [30] also points out that for different issue categories such as "Alternative Approaches Pattern" (which guides the model to output alternative options) and "Fact Check List Pattern" (which guides the model to provide a list of facts), the specific implementation of each component could differ.

To enhance prompt engineering and evaluate the output of large language models, [39] proposes a tool called **ChainForge**. The core idea is to provide a user interface so that users can first select and adjust the prompt template, select the LLM models to be evaluated and see the evaluation of the responses from the selected models. The system provides users with high-level flexibilities such that users can define their evaluation rules using an evaluator in the system, select multiple models to have an overview of their performance according to the evaluation rules and send multiple requests easily by chaining prompt templates. Figure 10 shows the workflow of ChainForge where 2 different prompt templates are chained using the same input variable in {} brackets. By chaining the 5 input elements with the {game} variable, the system can send 10 requests at once to each LLM model selected. With the help of ChainForge, users can evaluate the quality of a prompt on various models more easily.

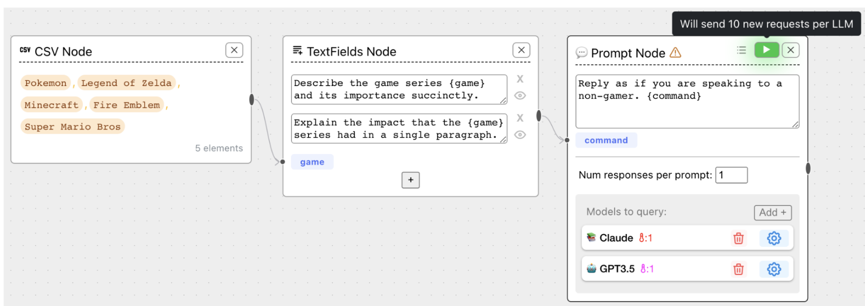


Fig. 10: The workflow of ChainForge [39]

Use Cases

In the field of traffic signal control, [24] proposes a model called LLMLight based on large language models to act as a decision-making agent. As figure 11 shows, An LLMLight agent is responsible for controlling the traffic light at an intersection. Real-time observations about the traffic condition are converted into human-readable text and transferred to the model, followed by the prompt engineering formed by the real-time observations, task descriptions and control action.

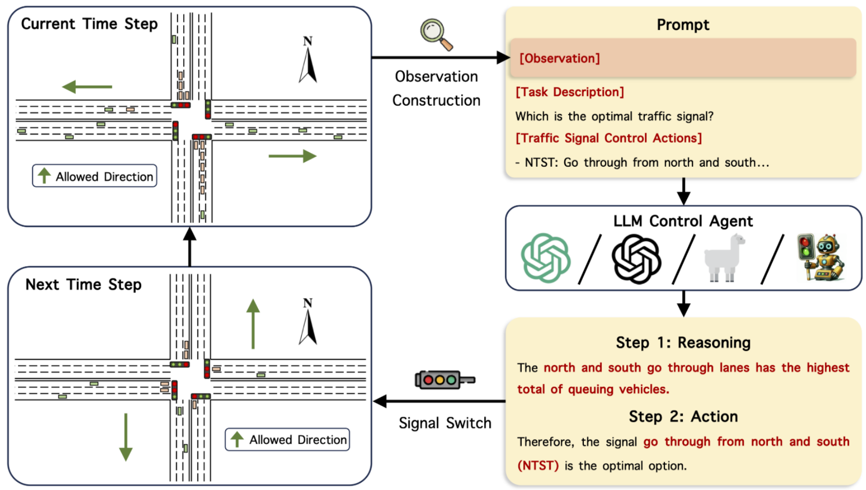


Fig. 11: The workflow of LLMLight [24]

[24] also formulates the workflow as the following equation:

Definition 2. $(Y, a) = \pi_\theta(Prompt(o, d_{scene}, d_{task}, d_{know}, A))$.

Where π_θ refers to the traffic signal control policy, (Y, a) refers to the reasoning trajectory and the action output by the model, based on the real-time traffic condition observation o, traffic scenario description d_{scene}, task descriptions d_{task} , commonsense knowledge d_{know}, and control action space A. Figure 12 shows an example template of the prompt [24].

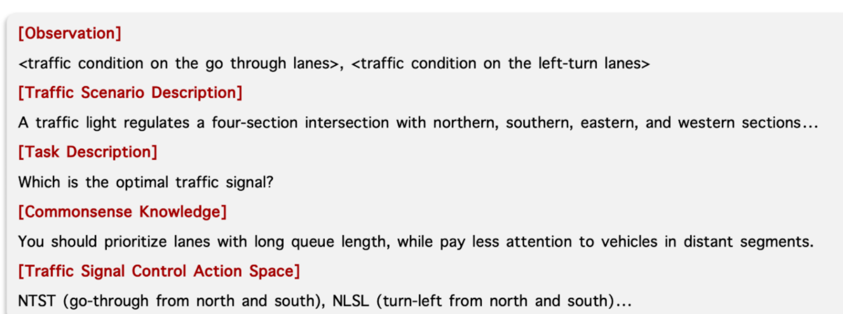

[Observation]
<traffic condition on the go through lanes>, <traffic condition on the left-turn lanes>
[Traffic Scenario Description]
A traffic light regulates a four-section intersection with northern, southern, eastern, and western sections…
[Task Description]
Which is the optimal traffic signal?
[Commonsense Knowledge]
You should prioritize lanes with long queue length, while pay less attention to vehicles in distant segments.
[Traffic Signal Control Action Space]
NTST (go-through from north and south), NLSL (turn-left from north and south)…

Fig. 12: Prompt template [24]

Prompt engineering is also applied in the field of traffic data imputation, [3] proposes a Graph Transformer-based Traffic Data Imputation (GT-TDI) model to compute the missing and faulty values from the large-scale road network traffic data streams collected by various sensors, both road-attached and vehicle-carried. The core idea of the GT-TDI model is to model sensors and their relations as nodes and edges in a road network graph, the graph is later processed by a Graph Neural Network component. The data streams collected by sensors are transformed into many prompts with a series of semantic descriptions that contain the spatiotemporal information of the network, they are then encoded and passed to the GT-TDI model. By training on the input datasets, the model is then fine-tuned in the domain of traffic data. Finally, by providing the correct prompt such as *"Predict the missing traffic volume for sensor B456 between 3 PM and 4 PM considering the last known values and nearby sensors' data."*, the corresponding missing value can be computed by the model based on the similarity of historical training data and the input prompt, As figure 13 illustrates.

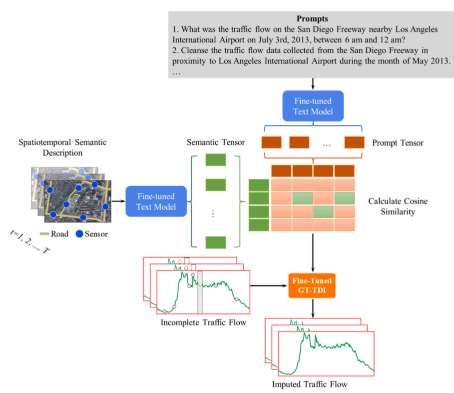


Fig. 13: Implementation of GT-TDI with prompts [3]

4 Conclusion

This paper addressed the gap between large language models, which are pre-trained on massive static datasets, and data streams, which are continuous and potentially unbounded. Two main approaches were summarized to mitigate this issue. The first approach involves the continual learning of large language models, allowing them to pre-train continually over data stream inputs. By applying continual pre-training, continual instruction tuning and continual alignment, the model can adapt to continuous data inputs. However, catastrophic forgetting is likely to occur during this process, so replay-based, regularization-based, and architecture-based methods are applied to mitigate its effects. The second approach converts data stream input into model-readable inputs and updates the model's knowledge via prompt engineering, which relies heavily on the quality of the prompts formulated by users.

However, there are several shortcomings in this analysis. Firstly, since several models such as ChatGPT and GPT4 are not open-sourced, their exact training process and architecture details remain unknown, making it hard to draw a detailed comparison between different models. Secondly, although the two approaches are presented, their real-world applications are still very limited. Powerful large language models were mostly developed and applied in recent years, and the usage of LLMs with data streams makes this an even newer topic. Lastly, the assumption that models always have access to regular data for their algorithms is problematic. In reality, data is often irregular and multi-modal, making it costly to transform into a usable format.

Therefore in future work, developing more efficient algorithms to reduce the computational overhead of CA while mitigating catastrophic forgetting is essential. For prompt engineering, automating the prompt generation process and improving the model's ability to understand and generate effective prompts autonomously could enhance its applicability. Additionally, exploring more real-world application fields is essential for gaining a comprehensive understanding of LLMs with data streams.

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