



Large Language Models and Data Streams

Seminar *Data Stream Management and Analysis*

July 12, 2024

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Introduction

Background

- LLM and AI have become very prominent topics in recent years.

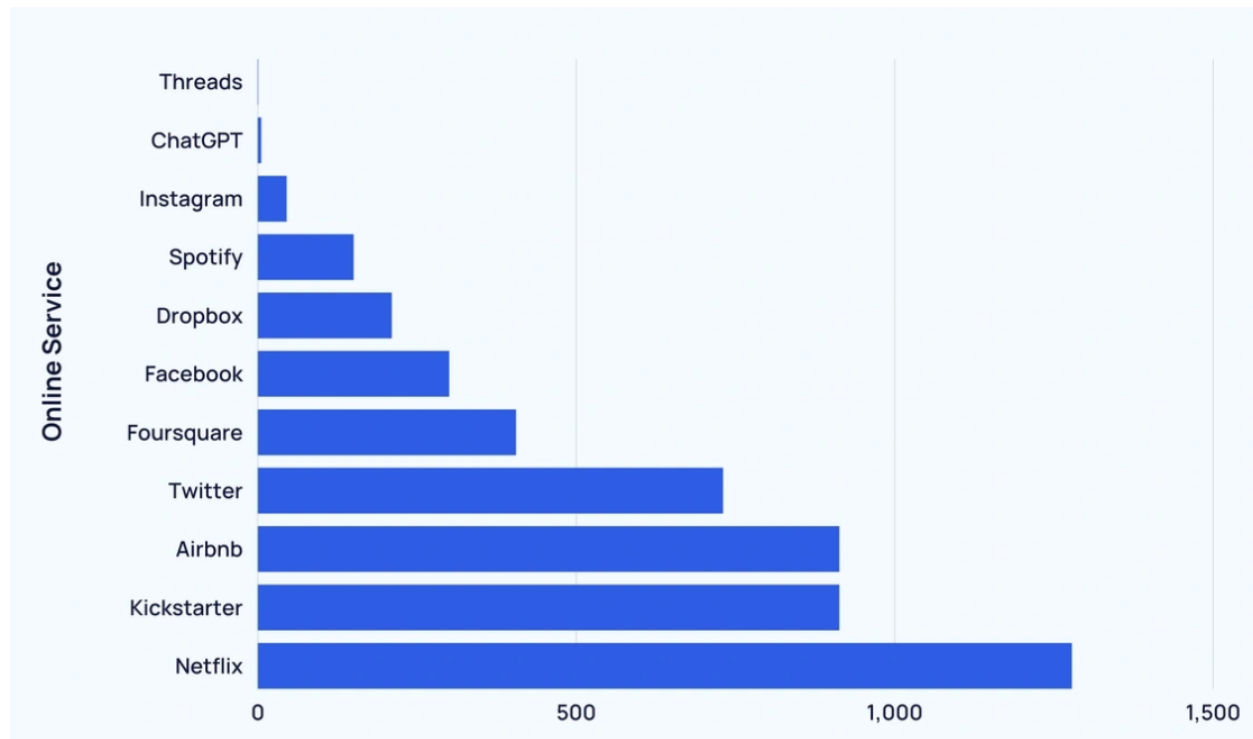


Relevant concepts of AI models and technologies^a

^aSource: <https://www.cortical.io/blog/chatgpt-and-large-language-models-the-holy-grail-of-enterprise-ai/>

Introduction

Background



Time needed for different Apps to have 1 million users¹

¹Source: <https://explodingtopics.com/blog/chatgpt-users>

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- Various models have shown their wide usage and significant competence in many fields.

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- QA, content generation, translation, text classification and other tasks [1].

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Relevant concepts of AI models and technologies^a

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- Various models have shown their wide usage and significant competence in many fields.
- QA, content generation, translation, text classification and other tasks [1].
- Most models are "static" [2].

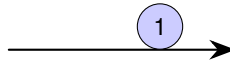
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Content

- Evolution of language models and the techniques behind them
- Training process of several LLM models
- Definition and application of data streams
- Need, benefits, challenges and use cases of combining LLM with data streams

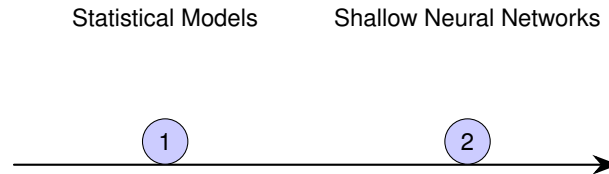
Large Language Models

Statistical Models



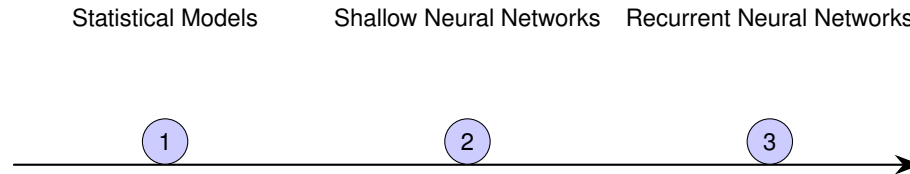
- N-Gram [3]
- Example: [("I", "read"), ("read", "a"), ("a", "book")]
- Completely statistical.
- Calculate the next word's probability based on the N-1 previous sub-words.
- Poor performance on large documents and large N.

Large Language Models



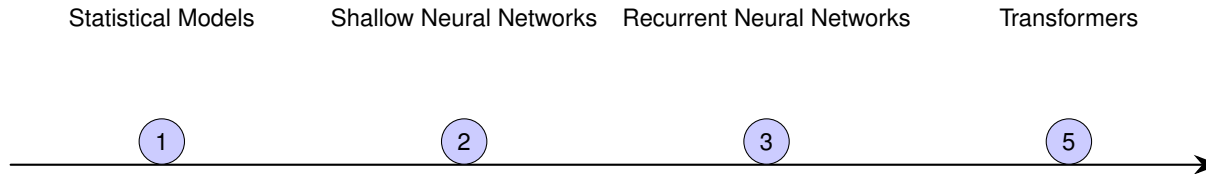
- Word2Vec [4]
- Map words into vector space.
- Similar words have a closer distance.
- Better performance on large documents.

Large Language Models



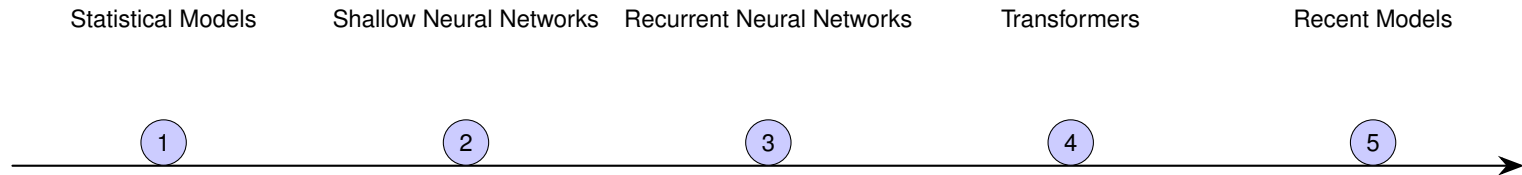
- Seq2Seq [5]
- Works with Long Short-Term Memory(LSTM).
- Encodes input into vectors with fixed dimensionality and decodes them.
- Much better performance on large documents, can work with different input lengths.
- But still vanishing gradient problems on very large documents.

Large Language Models



- Transformer [6]
- Works with the self-attention mechanism.
- Can process the entire input sentence simultaneously with the help of positional encoding.
- Very good performance on large documents, more efficient and powerful.

Large Language Models



- BERT, ChatGPT, LLaMA. . .
- Based on the transformer architecture.
- Trained on massive datasets and fine-tuned with downstream tasks.

Tokenization

- Purpose: Segmenting input text into tokens.
- WordPiece (BERT) [8]
- Byte Pair Encoding (GPT2, LLaMA) [9]

Training Process of LLMs

Pre-training

Given an unlabeled corpus of tokens $U = \{u_1, \dots, u_n\}$ as a training dataset, the core idea of the pre-training phase is to predict the next token u_i for a sequence $\{u_{i-k}, \dots, u_{i-1}\}$, specifically by maximizing the likelihood:

$$L_1(U) = \sum_i \log P(u_i | u_{i-k}, \dots, u_{i-1}; \Theta) [10] \quad (1)$$

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

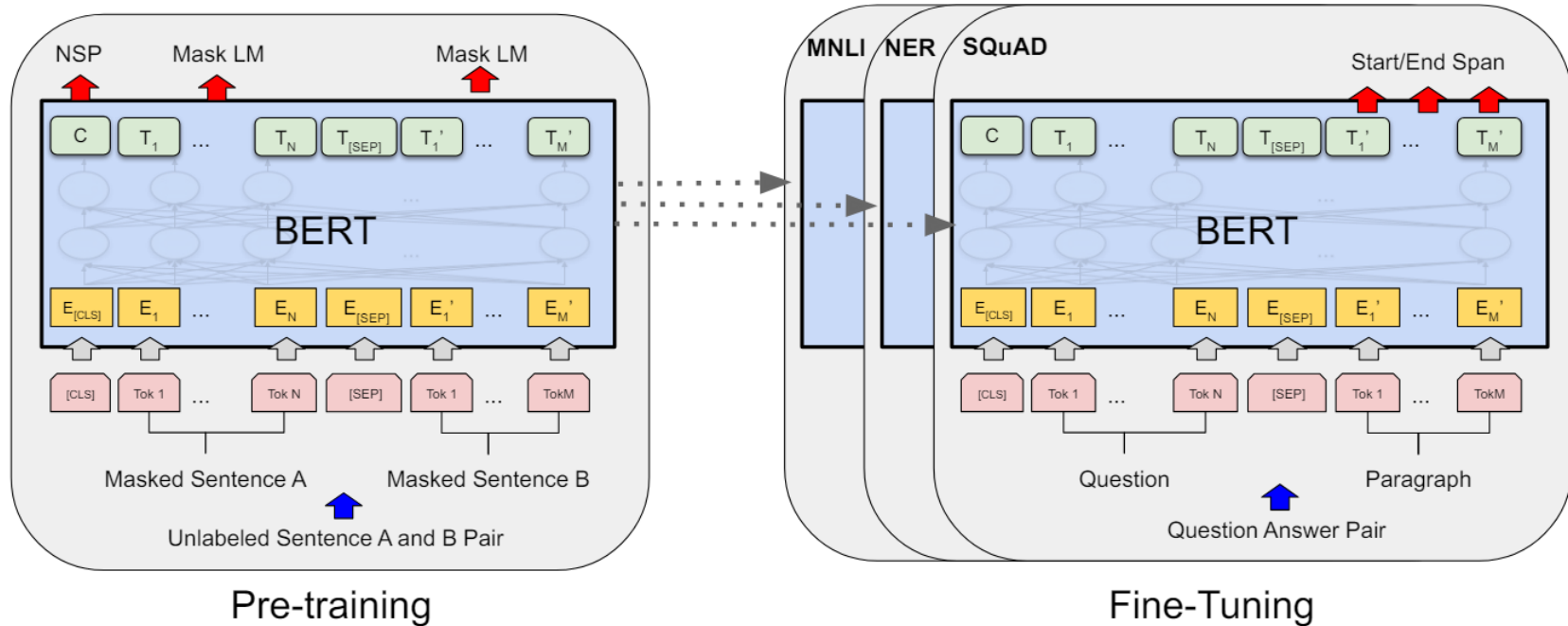
Fine-tuning

Given a labeled dataset C , where each instance of C has a sequence of tokens $\{c^1, \dots, c^m\}$ and a label y , the goal of the fine-tuning phase is to maximize the following likelihood:

$$L_2(U) = \sum_{(c,y)} \log P(y|c^1, \dots, c^m) [10] \quad (2)$$

Training Process of LLMs

BERT



Training Process in the BERT model [7]

Training Process of LLMs

A Comparison of Different Models

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 ²	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

Comparison of Large Language Models

²<https://en.wikipedia.org/wiki/BookCorpus>

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Comparison of Large Language Models

Definition 1

Smooth Power Laws: Performance has a power-law relationship with each of the three scale factors: the number of model parameters N , the size of dataset D and the amount of computing C when not bottlenecked by the other two, with trends spanning more than six orders of magnitude [18].

³<https://en.wikipedia.org/wiki/BookCorpus>

Data Stream

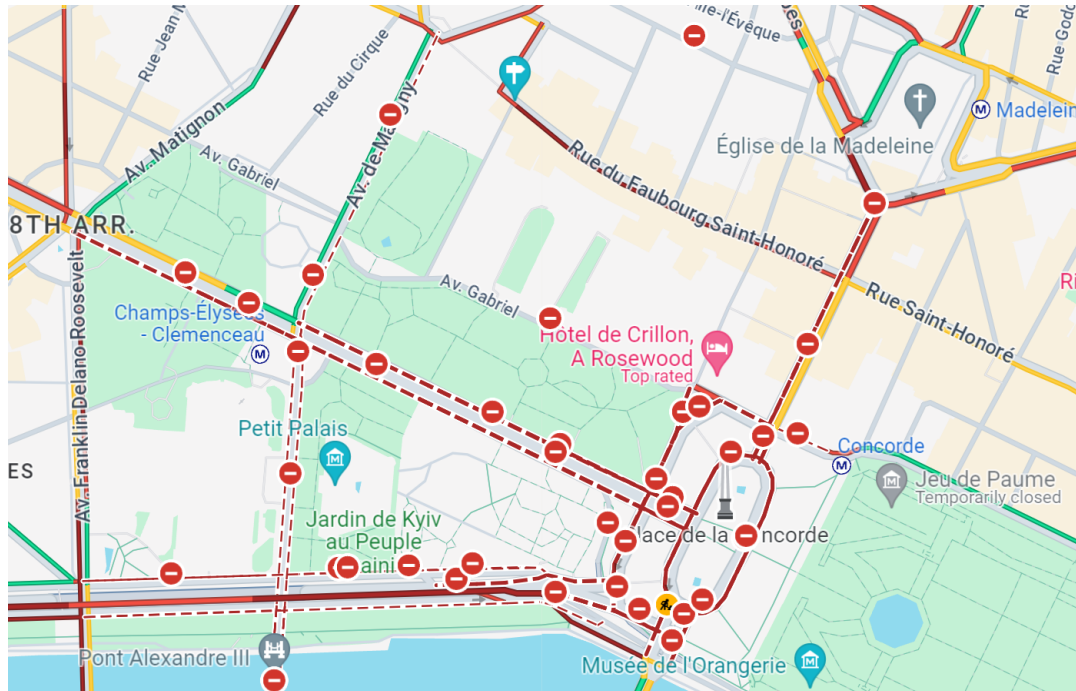
Definition 2

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. [11]

Limitation of Pre-trained LLMs

- Lack of knowledge beyond the scope of their training datasets.
- The performance is likely to gradually degrade over time [12].
- Extremely computationally expensive to be re-trained.
- Not able to process data streams as input.

Application Fields: Traffic Data



A screenshot of traffic in Paris using Google Maps⁴

⁴Source: <https://www.google.com/maps/>

Application Fields: Social Media

46 minutes ago	1 hour ago	2 hours ago	3 hours ago
1 #CROITA 52K tweets	1 #CROITA 52K tweets	1 Julian Assange 594K tweets	1 Julian Assange 544K tweets
2 #Assange 27K tweets	2 #Assange 24K tweets	2 #CROITA 52K tweets	2 #CROITA 51K tweets
3 #BABYPEPE	3 #BABYPEPE	3 #BABYPEPE	3 #SuiGer
4 #SUIGER	4 #SUIGER	4 #SuiGer	4 #BABYPEPE
5 \$shaggy	5 #LieberRechtsAlsLinks 11K tweets	5 Justiz	5 #AFGvsBAN 56K tweets
6 #LieberRechtsAlsLinks 11K tweets	6 \$shaggy	6 #LieberRechtsAlsLinks 11K tweets	6 #LieberRechtsAlsLinks 11K tweets
7 Organe	7 Organe	7 \$shaggy	7 \$shaggy
8 Bluthochdruck	8 Bluthochdruck	8 Bluthochdruck	8 Justiz
9 \$NGMI	9 Justiz	9 Organe	9 wochenstart
10 Justiz	10 \$NGMI	10 #AFGvsBAN 63K tweets	10 Organe
11 Havertz	11 Embolo	11 WikiLeaks 282K tweets	11 Siegte
12 Strand	12 Strand		

Current Twitter trending topics in Germany ⁵

⁵Source: <https://trends24.in/germany/>

Solutions

Prompt Engineering and Continual Learning

Prompt Engineering

Definition 3

A prompt is a set of instructions provided to an LLM that programs the LLM by customizing it and/or enhancing or refining its capabilities

Prompt Engineering

Definition 4

A prompt is a set of instructions provided to an LLM that programs the LLM by customizing it and/or enhancing or refining its capabilities. [13]

Definition 5

Prompt Engineering is the means by which LLMs are programmed via prompts. [13]

Prompt Engineering

ChatGPT ▾

explain the benefits of learning python for data science to me



Learning Python for data science offers numerous benefits, making it a valuable skill for anyone looking to enter the field. Here are some key advantages:

1. Ease of Learning and Use:

- **Simplicity:** Python's syntax is clear and readable, making it accessible even for beginners. This simplicity allows data scientists to focus on solving problems rather than getting bogged down by complex syntax.
- **Extensive Documentation:** Python has comprehensive documentation and a large community, providing ample resources for learning and troubleshooting.

2. Rich Ecosystem of Libraries and Tools:

- **Libraries for Data Analysis:** Python boasts powerful libraries like Pandas for data manipulation and analysis, NumPy for numerical operations, and SciPy for scientific computation.



Sende eine Nachricht an ChatGPT



(a) Prompt 1

ChatGPT ▾



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



Unlocking the Power of Python: Why Learning Python is Essential for Data Science

In the rapidly evolving world of data science, staying ahead of the curve means equipping yourself with the right tools and languages. Among these, Python has emerged as a powerhouse, revolutionizing how data is handled, analyzed, and visualized. Its versatility and efficiency have made it the go-to language for data scientists and analysts across the globe. But what makes Python so indispensable in the realm of data science? Let's delve into three key advantages of learning Python and explore real-world examples that highlight its transformative potential.

1. Ease of Learning and Use

Python's simple and readable syntax makes it an ideal choice for both beginners and experienced programmers. Unlike other programming languages, Python prioritizes code readability, which translates into quicker learning and easier maintenance. This simplicity does not come at the expense of functionality. Python



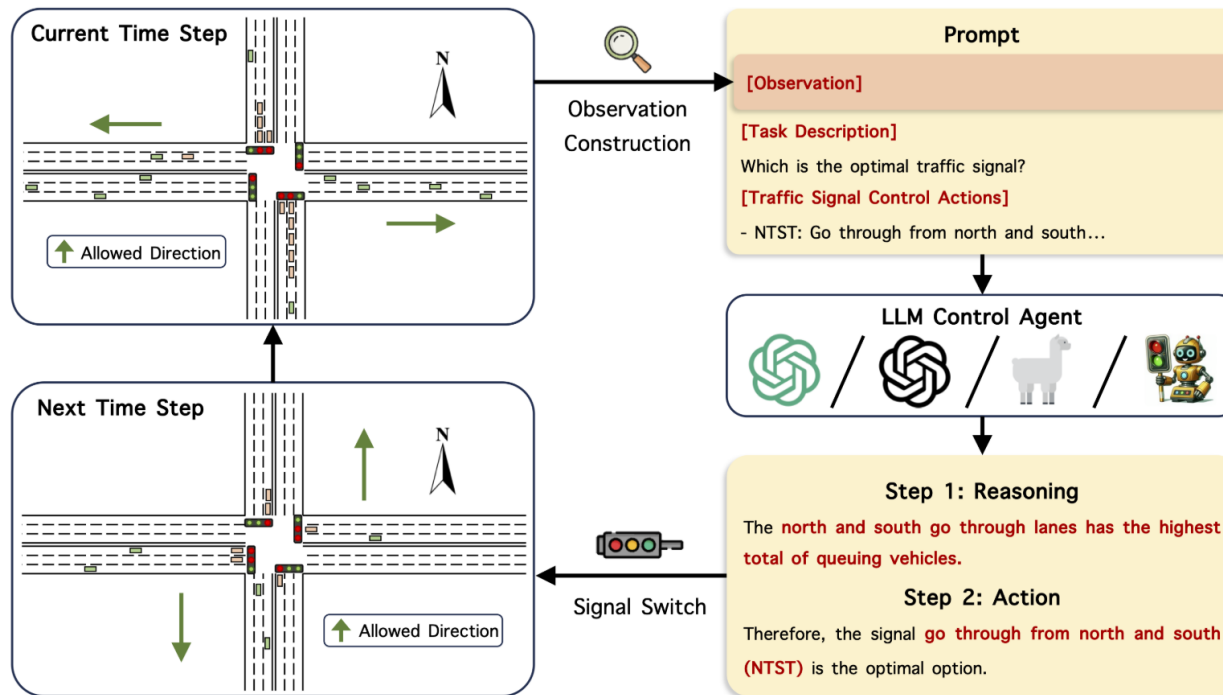
Sende eine Nachricht an ChatGPT



(b) Prompt 2

2 different prompts yield different output of ChatGPT

Use Case: LLMLight



The workflow of LLMLight [14]

Prompt Engineering

- Convert the data stream input into model-readable input and update the model's knowledge via prompt engineering.
- However, this method heavily relies on the quality of the prompt formulated by users.

Continual Learning

Definition 6

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. [15]

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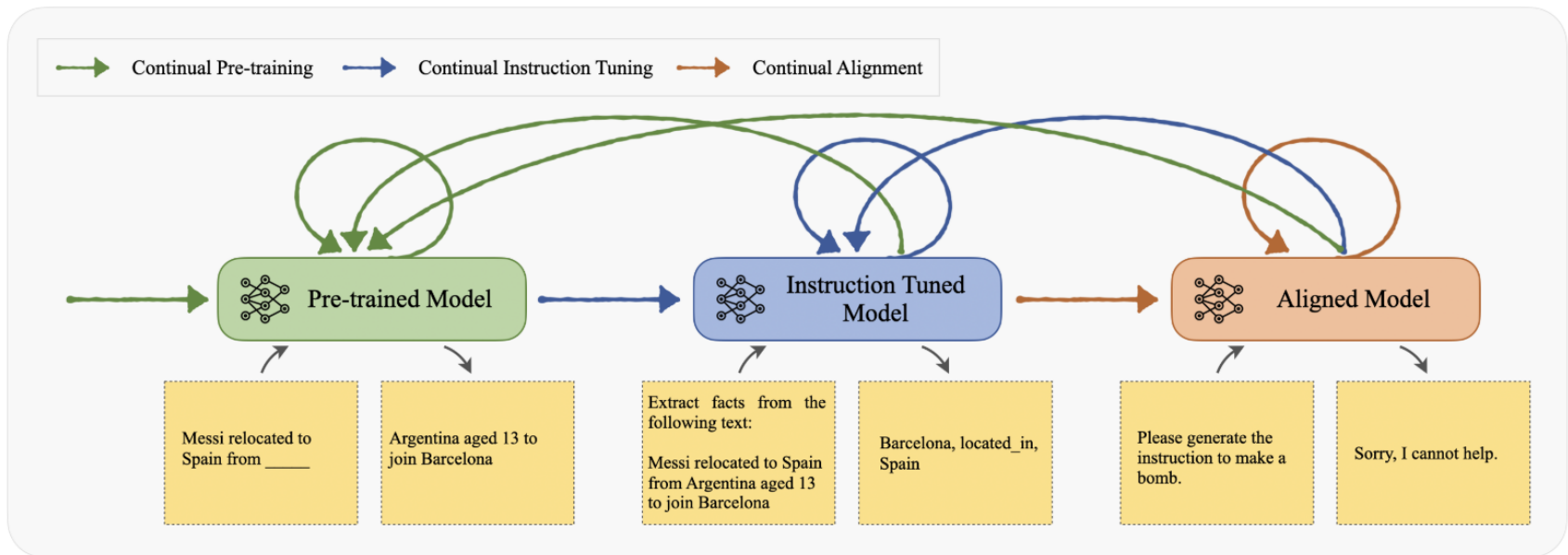
Definition 8

For a data stream of tasks $\mathcal{T} = \{\mathcal{T}_1, \dots, \mathcal{T}_n\}$, 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 . [16]

Stages of Continual Learning[16]

- **Continual Pre-training (CPT):** It refers to incrementally updating a large language model on input data over time without retraining it from scratch.
- **Continual Instruction Tuning (CIT):** It refers to continuously refining the model's ability to follow the instruction.
- **Continual Alignment (CA):** It refers to adjusting the model so it always produces output that satisfies certain standards and guidelines.

Stages of Continual Learning



Stages of continual learning [16]

Continual Learning

However, during continual learning on new input streams, models are likely to forget previously learned knowledge (Catastrophic Forgetting). [2]

Continual Learning

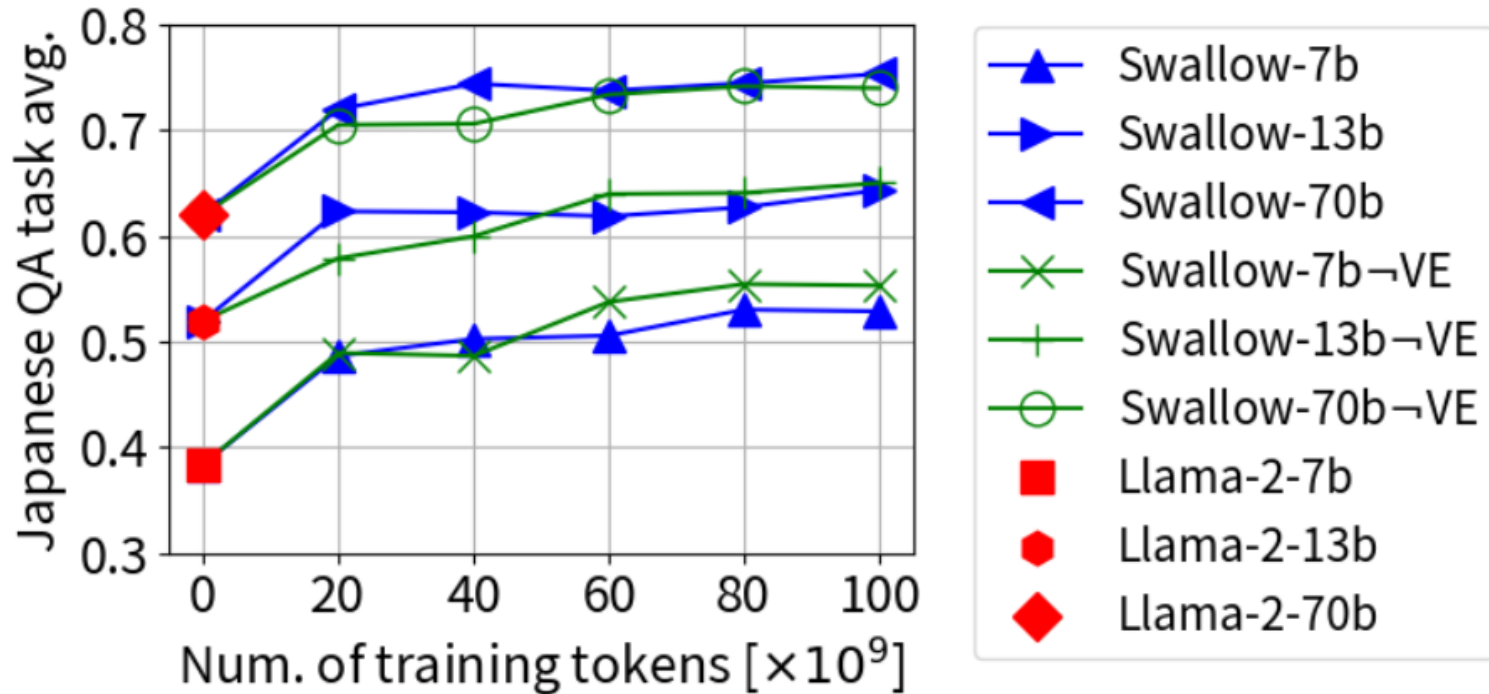
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- Replay-based methods
- Regularization-based methods
- Architecture-based Methods

Use Case: Swallow

- Some large language models are trained on English datasets and their performance in other languages differs from their performance in English.
- Develop a large language model Swallow that has strong performance in Japanese using continual learning methods based on LLaMA 2.
- Swallow preserves the same architecture as LLaMA 2.
- Apply the replay-based method by selecting 5% of the training data from English datasets, 5% from the English arXiv paper texts and the remaining 90% from Japanese texts.
- Evaluate the performance in various fields such as question answering (QA), reading comprehension (RC), automatic summarization (AS) and so on.

Use Case: Swallow



Performance curve of the Swallow model in question answering task [20]

Challenges of Continual Learning [2], [19]

- Catastrophic forgetting
- Lack of real-world assumption
- Multi-modal continual learning
- Concept drift

Conclusion

- Several models such as ChatGPT and GPT4 are not open-sourced, their exact training process and architecture details remain unknown.
- Real-world applications of the two methods are still very limited.
- In reality, data is often irregular and multi-modal, making it costly to transform into a usable format.
- Implement more efficient algorithms to reduce the computational overhead of CA while mitigating catastrophic forgetting
- Develop more effective prompt generation processes.
- Explore more real-world applications.

References

- 📄 Liu, Yiheng, Tianle Han, Siyuan Ma, Jiayue Zhang, Yuanyuan Yang, Jiaming Tian, Hao He et al. "Summary of chatgpt-related research and perspective towards the future of large language models." *Meta-Radiology* (2023): 100017.
- 📄 Gupta, Kshitij, Benjamin Thérien, Adam Ibrahim, Mats L. Richter, Quentin Anthony, Eugene Belilovsky, Irina Rish, and Timothée Lesort. "Continual Pre-Training of Large Language Models: How to (re) warm your model?." *arXiv preprint arXiv:2308.04014* (2023).
- 📄 Cavnar, William B., and John M. Trenkle. "N-gram-based Text Categorization." In *Proceedings of SDAIR-94, 3rd Annual Symposium on Document Analysis and Information Retrieval*, 161-175. Las Vegas, NV, 1994. Ann Arbor, MI: Environmental Research Institute of Michigan (ERIM).
- 📄 Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. "Distributed representations of words and phrases and their compositionality." *Advances in neural information processing systems* 26 (2013).

References

- 📄 Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le. "Sequence to sequence learning with neural networks." Advances in neural information processing systems 27 (2014).
- 📄 Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." Advances in neural information processing systems 30 (2017).
- 📄 Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805 (2018).
- 📄 Wu, Yonghui, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun et al. "Google's neural machine translation system: Bridging the gap between human and machine translation." arXiv preprint arXiv:1609.08144 (2016).

References

- 📄 Sennrich, Rico, Barry Haddow, and Alexandra Birch. "Neural machine translation of rare words with subword units." arXiv preprint arXiv:1508.07909 (2015).
- 📄 Radford, Alec, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. "Improving language understanding by generative pre-training." (2018).
- 📄 Geisler, Sandra. "Data stream management systems." In Dagstuhl Follow-Ups, vol. 5. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2013.
- 📄 Shi, Haizhou, Zihao Xu, Hengyi Wang, Weiyi Qin, Wenyuan Wang, Yibin Wang, and Hao Wang. "Continual Learning of Large Language Models: A Comprehensive Survey." arXiv preprint arXiv:2404.16789 (2024).
- 📄 Liu, Pengfei, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing." ACM Computing Surveys 55, no. 9 (2023): 1-35.

References

- 📄 Lai, Siqi, Zhao Xu, Weijia Zhang, Hao Liu, and Hui Xiong. "Large language models as traffic signal control agents: Capacity and opportunity." arXiv preprint arXiv:2312.16044 (2023).
- 📄 Biesialska, Magdalena, Katarzyna Biesialska, and Marta R. Costa-Jussa. "Continual lifelong learning in natural language processing: A survey." arXiv preprint arXiv:2012.09823 (2020).
- 📄 Wu, Tongtong, Linhao Luo, Yuan-Fang Li, Shirui Pan, Thuy-Trang Vu, and Gholamreza Haffari. "Continual learning for large language models: A survey." arXiv preprint arXiv:2402.01364 (2024).
- 📄 Razdaibiedina, Anastasia, Yuning Mao, Rui Hou, Madian Khabsa, Mike Lewis, and Amjad Almahairi. "Progressive prompts: Continual learning for language models." arXiv preprint arXiv:2301.12314 (2023).

References

- 📄 Kaplan, Jared, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. "Scaling laws for neural language models." arXiv preprint arXiv:2001.08361 (2020).
- 📄 Yang, Yutao, Jie Zhou, Xuanwen Ding, Tianyu Huai, Shunyu Liu, Qin Chen, Liang He, and Yuan Xie. "Recent Advances of Foundation Language Models-based Continual Learning: A Survey." arXiv preprint arXiv:2405.18653 (2024).
- 📄 Fujii, Kazuki, Taishi Nakamura, Mengsay Loem, Hiroki Iida, Masanari Ohi, Kakeru Hattori, Hirai Shota, Sakae Mizuki, Rio Yokota, and Naoaki Okazaki. "Continual Pre-Training for Cross-Lingual LLM Adaptation: Enhancing Japanese Language Capabilities." arXiv preprint arXiv:2404.17790 (2024).