



Large Language Models and Data Streams

Seminar *Data Stream Management and Analysis*

June 25, 2024

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Introduction

Background

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



relevant concepts^a

^aSource: [urlhttps://www.cortical.io/blog/chatgpt-and-large-language-models-the-holy-grail-of-enterprise-ai/](https://www.cortical.io/blog/chatgpt-and-large-language-models-the-holy-grail-of-enterprise-ai/)

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- QA, content generation, translation, text classification etc [1].

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- Various models have shown their wide usage and significant competence in many fields.
- QA, content generation, translation, text classification etc [1].
- Most models are "static" [4].

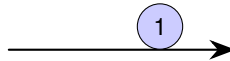
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Content of the presentation

- The evolution of language models and the techniques behind them.
- The training process of several LLM models.
- The definition and application of data streams.
- The need, benefits, challenges and use cases of combining LLM with data streams.

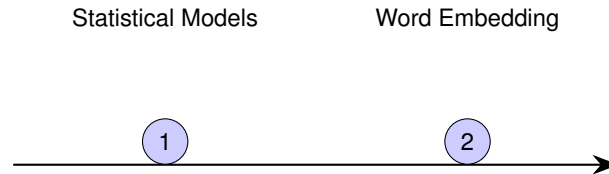
Large Language Models

Statistical Models



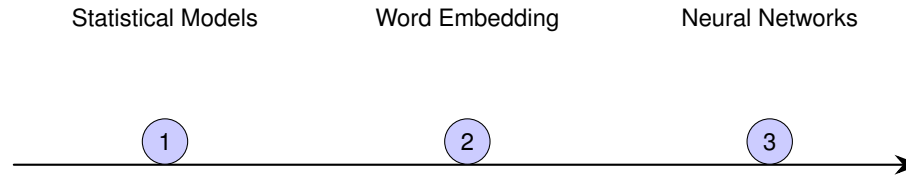
- N-Gram [3]
- Completely statistical.
- Calculate the next word's probability based on the N previous sub-words.
- Poor performance on large documents.

Large Language Models



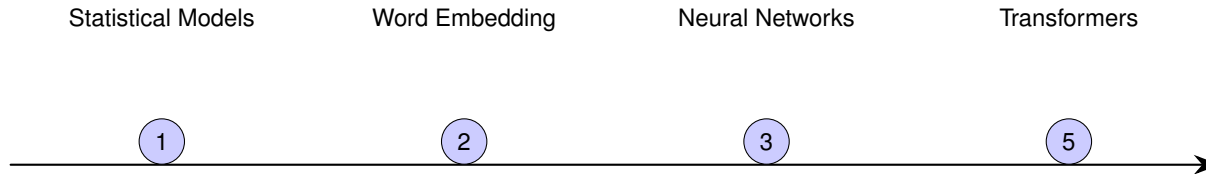
- Word2Vec [4]
- Map words into vector space.
- Similar words have a closer distance.
- Better performance on large documents.

Large Language Models



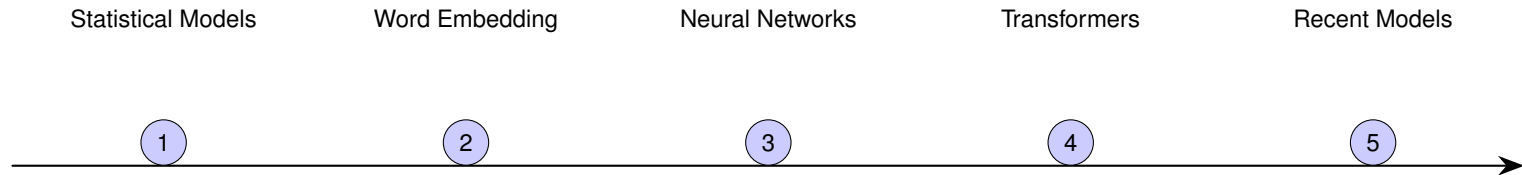
- Seq2Seq [1]
- Works with Long Short-Term Memory(LSTM).
- Encodes input into vectors with fixed dimensionality and decodes them.
- Much Better performance on large documents, can work with different input lengths.
- But still vanishing gradient problems on very large documents.

Large Language Models



- Transformer [2]
- 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) [4]
- Byte Pair Encoding (GPT2, LLaMA) [1]

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:

$$L_1(U) = \sum_i \log P(u_i | u_{i-k}, \dots, u_{i-1}; \Theta) [2] \quad (1)$$

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

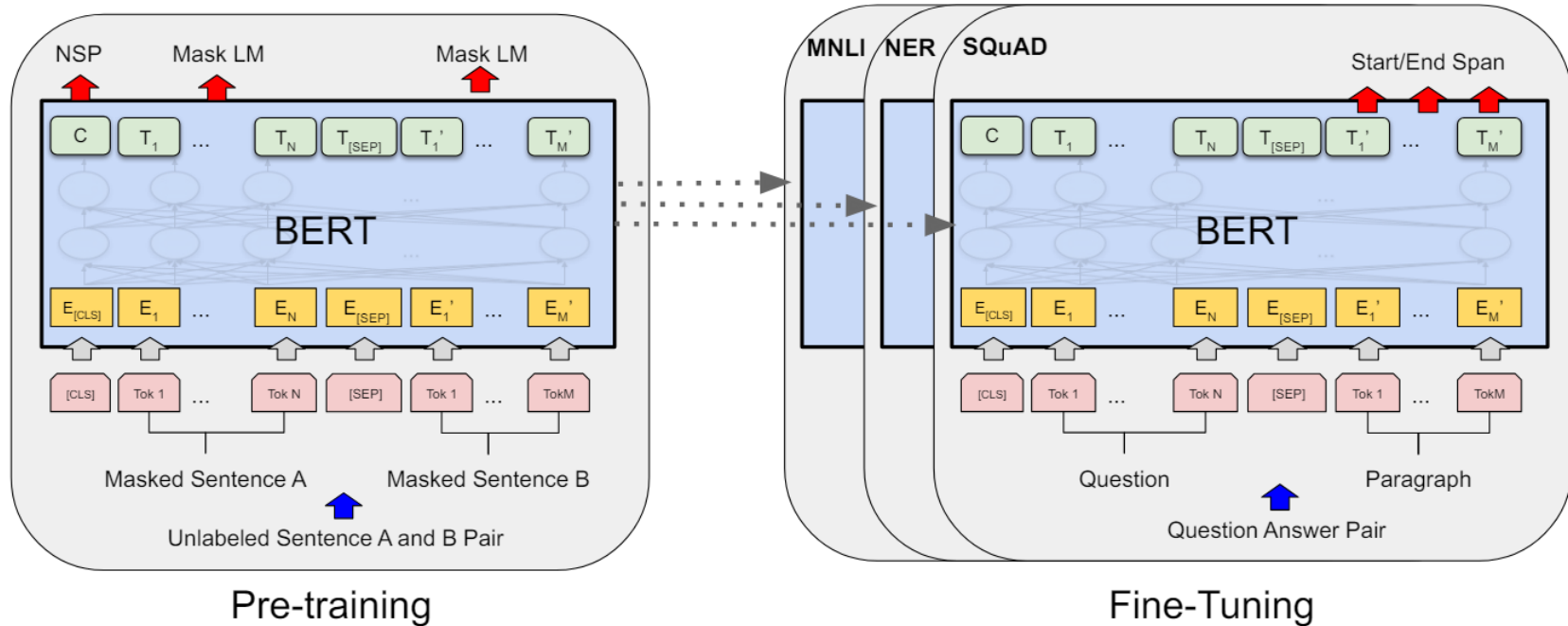
Fine-tuning

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:

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

Training process of LLMs

BERT



Training Process in the BERT model [3]

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	WebText	Various open-source datasets	WebText
Open-sourced	Yes	No	Yes	No
Major Applications?	QA	Text generation & Translation	Text generation & QA	Content generation & QA

A comparison of different LLM models

Data Stream

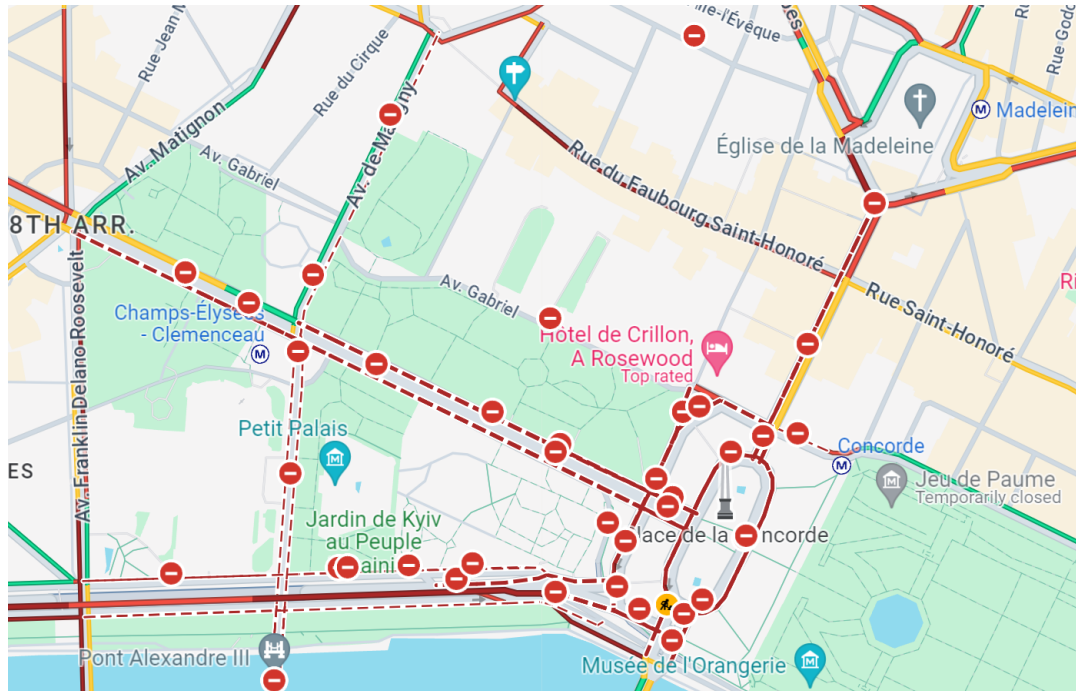
Definition 1

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. [3]

Limitation of pre-trained LLMs

- Lack of knowledge beyond the scope of their training datasets.
- The performance is likely to gradually degrade over time [4].
- 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 Maps¹

¹<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 ²

²<https://trends24.in/germany/>

Prompt engineering

Definition 2

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 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. [5]

Definition 4

Prompt Engineering is the means by which LLMs are programmed via prompts. [5]

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



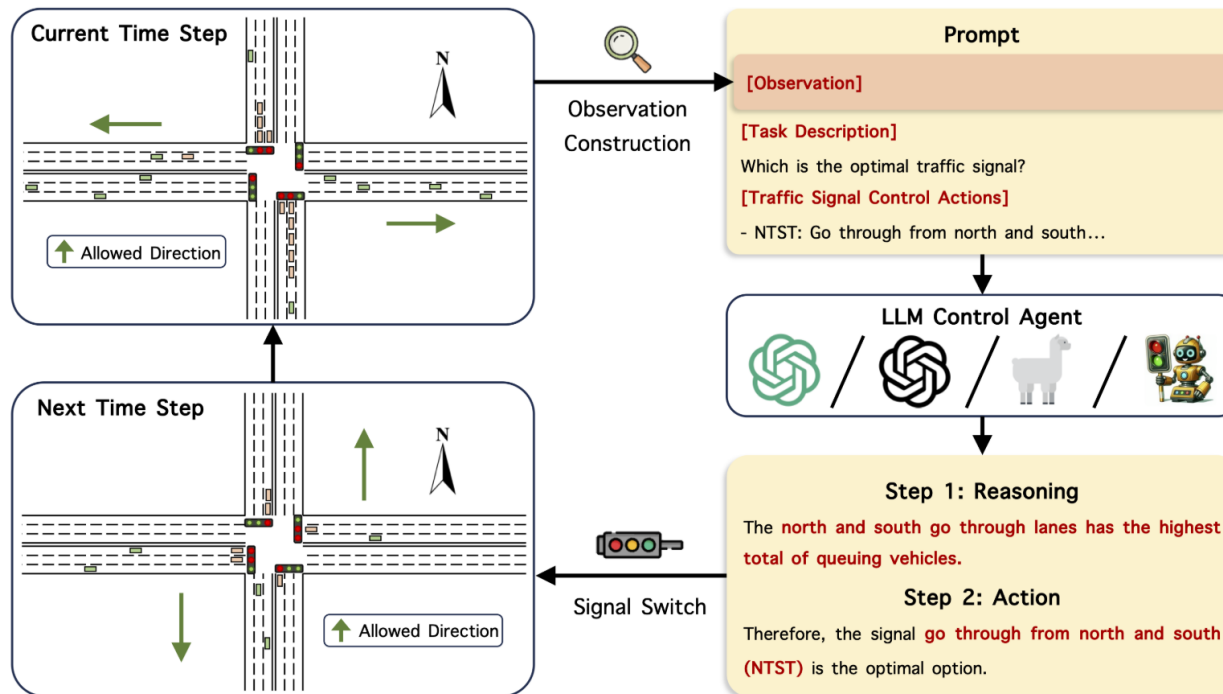
Sende eine Nachricht an ChatGPT



(b) Prompt 2

2 different prompts yield different output of ChatGPT

Use Case: LLMLight



The workflow of LLMLight [1]

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 5

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. [2]

Continual learning

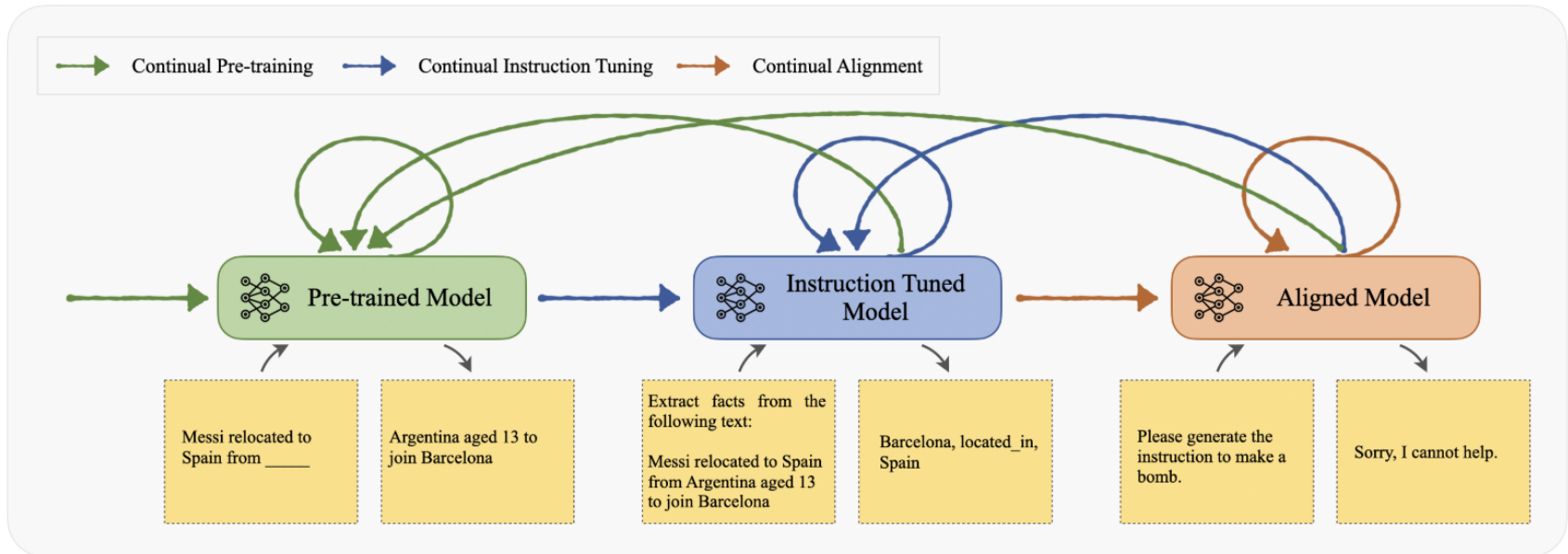
Definition 6

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Definition 7

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 . [3]

Continual learning



Stages of continual learning [3]

Continual learning

However, during continual learning on new input streams, models are likely to forget previously learned knowledge (Catastrophic Forgetting). [4]

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- Replay-Based methods
- Regularization-Based methods
- Architecture-Based Methods

Use Case: Progressive Network

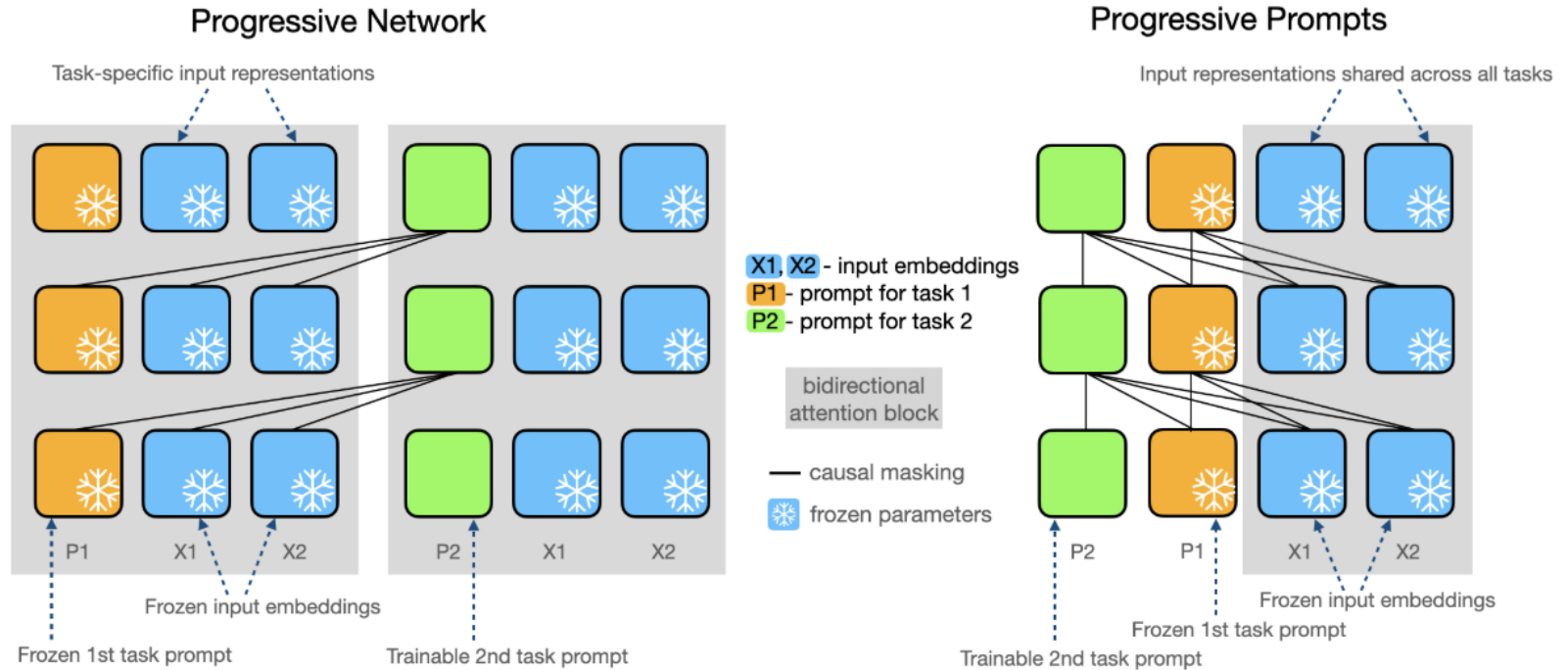


Illustration of progressive network and progressive prompt [1]

Continual Learning

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

Conclusion

Text goes here

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