AI&MLOps Module 4: Generative AI

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Outline for Week 01

- Part 1: Decoder only GPT Model
  - What are GPT-class Generative Large Language Models
  - Generative AI Use Cases
  - Data preparation for GPT model training
  - GPT finetuning (Assignment)
- Part 2: LLMs and Interacting with them
  - Commercial and open source LLMs
  - What are the main issues in LLMs to be aware of?
  - Taxonomy of interaction with LLMs
  - Parameter Efficient Fine Tuning (LoRA, QLoRA)

Outline for Week 02

- Part 1:
  - Prompting Strategies – ZSL, FSL, CoT, ReACT, DSP
- Part 2:
  - Instruction Tuning
- Part 3:
  - Orchestration
  - Retrieval Augmented Generation
- Part 4:
  - LLM Guardrails
  - LLM Agents

Outline for Week 03

- Part 1:
  - Deep learning as a representation learning system
  - Autoencoders for pre-training new situations
- Part 2:
  - Modern GenAI Image Pipelines
  - CLIP
  - Stable Diffusion
- Part 3: (May Know)
  - GANs – Generative Adversarial Networks
  - Variational Auto Encoders
  - Resource for Math of Diffusion Models (Link Shared in Part 2)

Predictive AI and Generative AI

- Predictive AI
  - Input: Any of the data modality
  - Output: Continuous or Categorical
- Generative AI
  - Input: Any of the data modality
  - Output: Text, Image, Video, Audio

Generative AI Use Cases

- **Healthcare Assistance** – Offering support in areas like patient interaction, medical documentation, and even as assistive tools for diagnosis and treatment planning, though they don't replace professional advice.
- **Personal Assistants** – Managing schedules, setting reminders, answering questions, and even helping with email management and other administrative tasks.
- **Legal and Compliance Assistance** – Assisting in legal research, document review, and drafting legal documents (without replacing professional legal advice).
- **Accessibility Tools** – Enhancing accessibility through tools like voice-to-text conversion, reading assistance, and simplifying complex text.
- **Interactive Entertainment** – In gaming and interactive storytelling, creating dynamic narratives, character dialogue, and responsive storytelling elements.
- **Marketing and Customer Insights** – Analyzing customer feedback, conducting sentiment analysis, and generating marketing content, providing valuable insights into consumer behavior.
- **Social Media Management** – Managing social media content, from generating posts to analyzing trends and engaging with audiences.
- **Human Resources Management** – Aiding in resume screening, answering employee queries, and even in training and development activities.

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Generative AI Use Cases

- **Customer Service and Support** – Providing customer support, handling inquiries, resolving issues, and offering information 24/7.
- **Content Creation and Copywriting** – Generating creative content, such as articles, blogs, scripts, and advertising copy.
- **Language Translation and Localization** – Translation services for various content types, aiding in bridging language barriers and localizing content for different regions.
- **Education and Tutoring** – Functioning as personalized tutors, providing explanations, answering questions, and assisting with learning materials in a wide range of subjects.
- **Programming and Code Generation** – Writing, reviewing, and debugging code, thereby speeding up the development process and helping in learning programming languages.
- **Research and Data Analysis** – Sifting through large volumes of text, summarizing information, and extracting relevant data, which is invaluable for research and analysis.

Generative AI

- Text to Text
- Text to Image/Video
- Image/Video to Text
- Image/Video to Image/Video
- Text to Audio
- Audio to Text
- Text/Image to Code

- Input is the “Prompt”; Model is a Large Language/Vision Model; Output is Image/Video/Text/Speech

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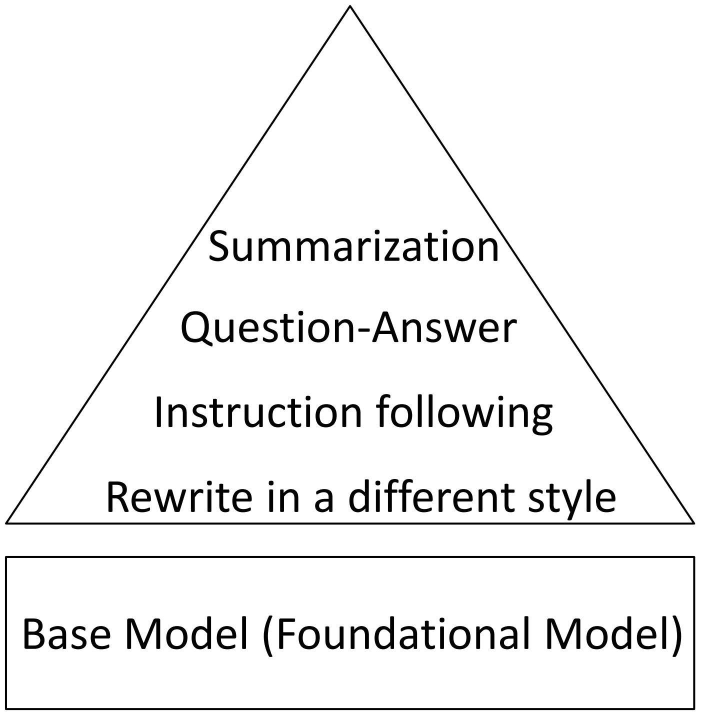
Foundational Model

- Large-scale AI model trained on vast amounts of diverse data
- Serves as a base for multiple downstream tasks and applications
- Key characteristics:
    - Broad knowledge and capabilities
    - Prompt engineering to make it perform tasks
    - Retrieval Augmented Generation for tapping into specific data
    - Adaptable through fine-tuning
    - Generalize to new tasks with minimal additional training
- **Examples**: GPT, BERT, T5



Latest Developments

- Anthropic
  - Claude 3.5 Sonnet
- Microsoft-OpenAI integration
  - Bing search
  - PowerBI with ChatGPT
- Generative Image
  - Photoshop
  - MidJourney
- Generative Videos
  - Sora
- LLMOps pipeline
  - LangChain/LlamaIndex + OpenAI/Antrhopic/Llama

Language Model

- Any model that can predict the probability of the next token in a sequence of text input (converted to embeddings) is called a Language Model
- LM captures the latent space of language: its statistical structure
- Large Language Models are trained on large text corpora (trillions of tokens) and have billions of parameters
- They have emergent abilities
  - Can do tasks for which it is not explicitly trained
  - Today, we don’t take a chance and make it learn to follow instructions
- Finally, LLMs would all be a sophisticated lookup table!

Language Modeling Approaches

- Masked Language Modeling
  - Tokens in a document are randomly masked
  - Neural Models are trained to predict the masked token correctly
  - This is a fill-in-the-blank task
  - Example:
    - The cat sits on the mat.
    - The [MASK] sits on the mat.
    - The model's task is to predict "cat" based on the context
- Sentence Completion Modeling (Next token prediction)
  - Model is set up in an autoregressive mode
  - At each inference step, the model predicts the next token (from the vocabulary as a probability distribution)
  - (k+1)st token is predicted with (prompt+predicted k tokens) as input
  - (k+2)nd token is predicted with (prompt+predicted k+1 tokens) as input

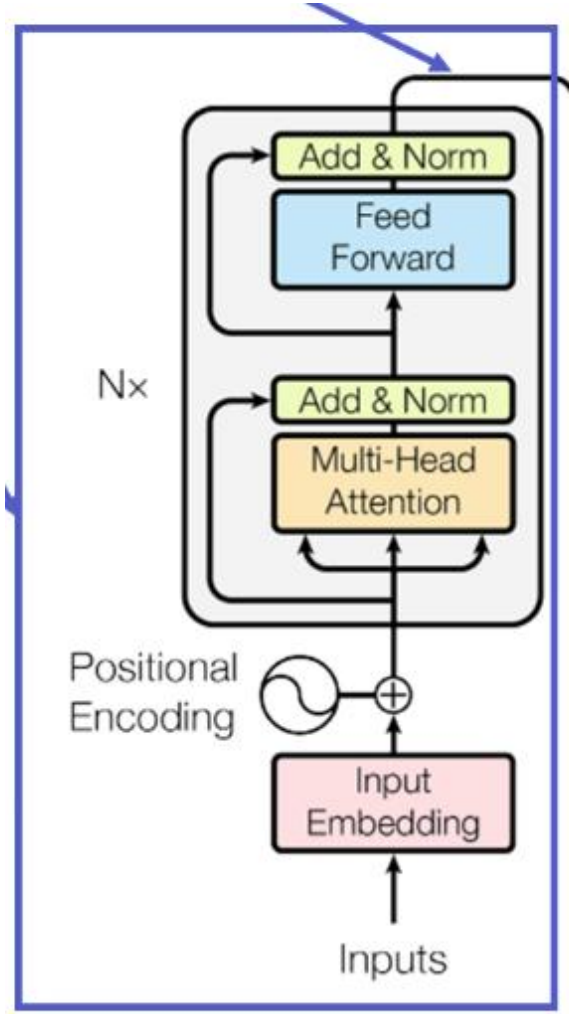
Transformers

- Transformer Encoder
  - Converts a sequence of words to a vector representation
  - This vector representation can be used for text-understanding tasks
  - Trained using fill-in-the-blanks tasks - MLM
- Transformer Decoder
  - Uses the context of the sequence of words so far (sometimes with an additional context from encoder or retrieval) to predict next token in the sequence
  - Trained using next-token-prediction tasks

Transformer Encoder

Steps in a Transformer Encoder

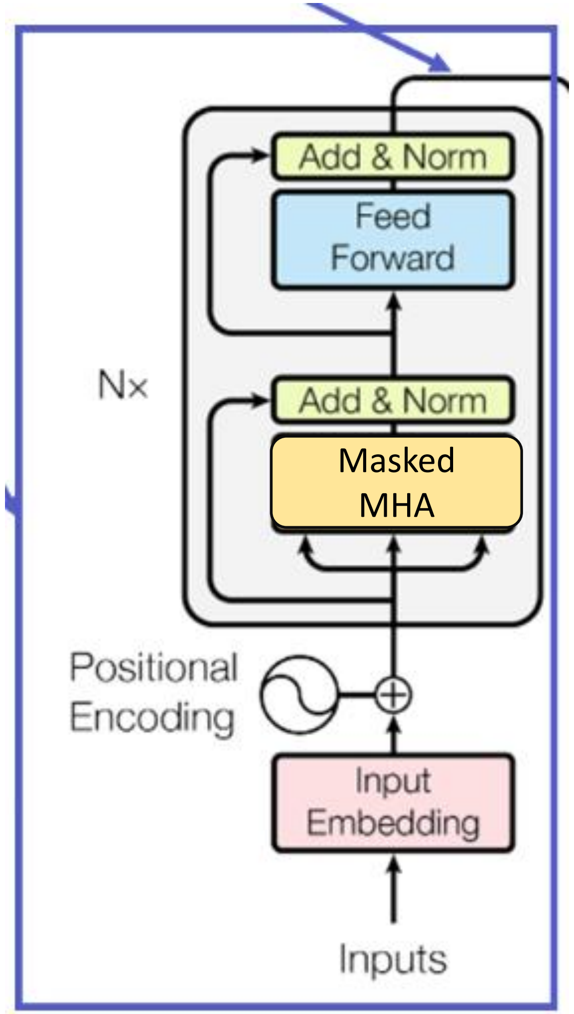
1. Tokenize (append special tokens – [CLS])
2. Get Encoded sequence added with position
3. Multi-headed attention
   - Converts encoded sequence to context aware representation (still a sequence)
4. Residual and layer normalization
5. Dense Layers for further representation learning
6. Encoder block outputs a encoded representation
7. Use the representation of [CLS] token to perform text understanding tasks



Transformer Decoder

Steps in a Transformer Decoder

1. Tokenize the prompt
2. Get Encoded sequence added with position
3. Masked Multi-headed attention
   - Masking makes the attention attend only to tokens to the left
4. Residual and layer normalization
5. Dense Layers for further representation learning
6. Decoder block outputs sequence of representations
7. Use the representation of last token to generate the next token
8. Repeat by including the generated token as part of the prompt



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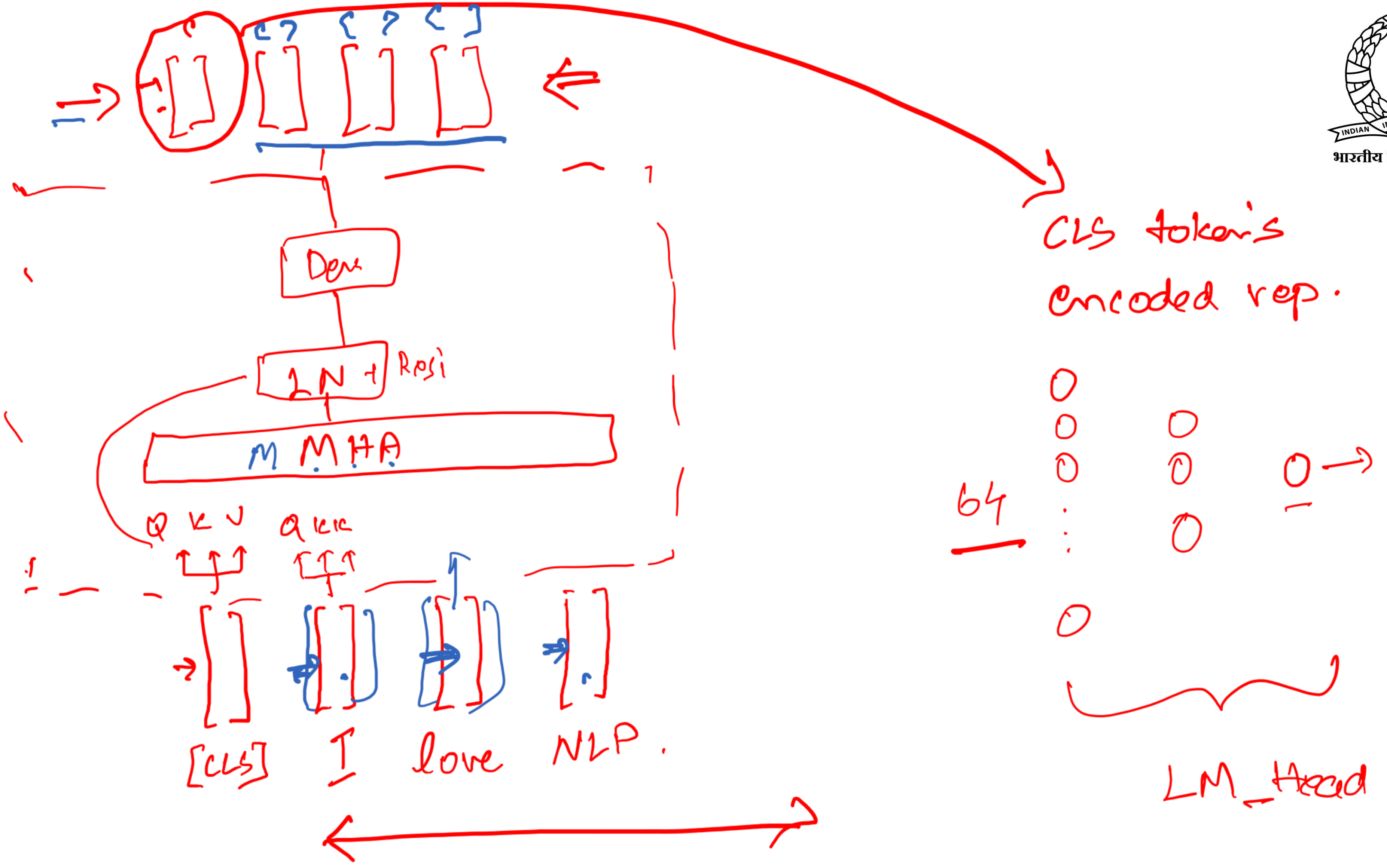


→ I love NLP.

That is great. How can I help you?

NLP View

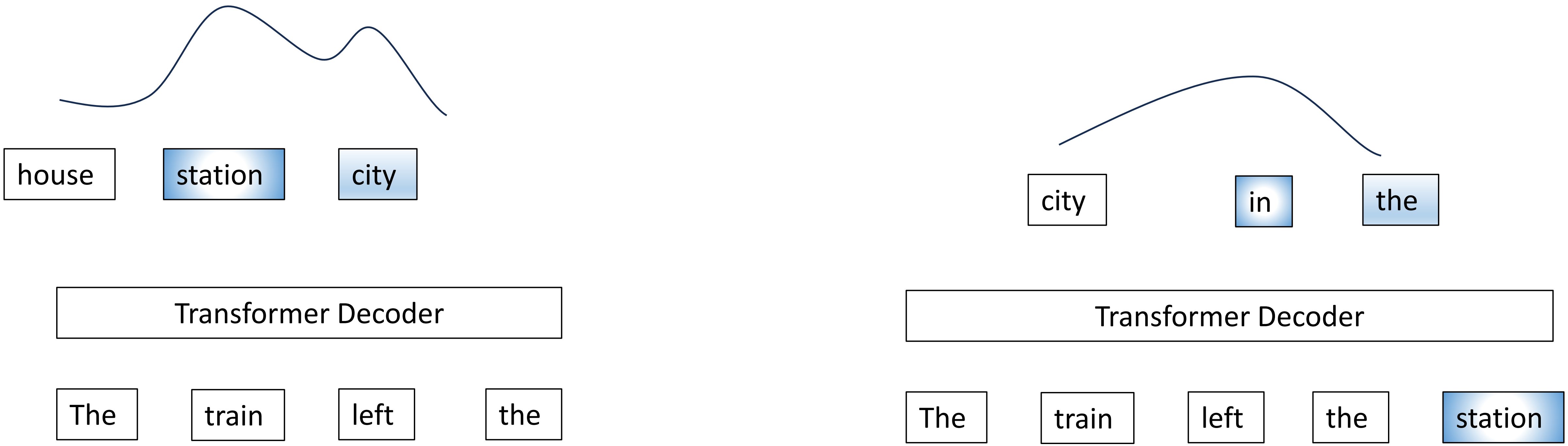
- NLP = NLU + NLG
- Encoder-Only Models (BERT) for NLU
- Decoder Only Models (GPT) for NLG

Generative Pretrained Transformers (GPT)

- These are decoder only models.
- Since there is no encoder in this set up, these decoder layers would not have the encoder-decoder attention sublayer that vanilla transformer decoder layers have.
- It only has the masked self attention layer.
- The model predict the next word using massive datasets.

Radford et al., 2018

What does GPT do?



GPT

- 2 step training:
  - Generative pretraining
  - Finetuning with instructions and human feedback
- GPT 1 and GPT 2 Specifics
  - Transformer decoder with 12 blocks, 117M parameters.
  - 512-sequence length, 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers.
  - Trained on BooksCorpus: over 7000 unique books.

GPT

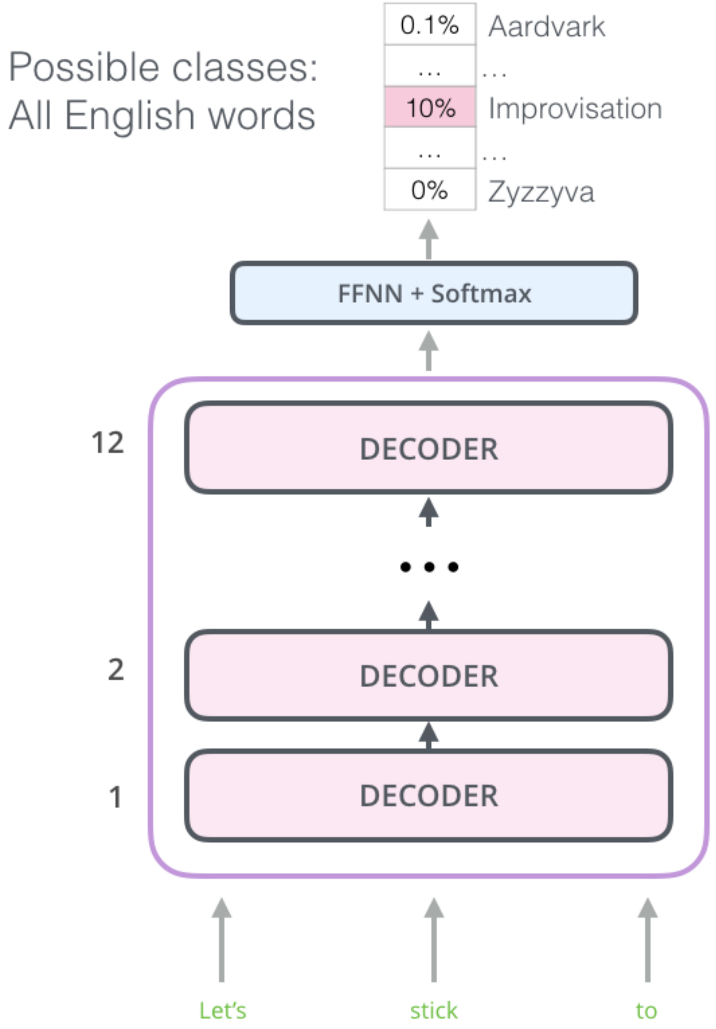
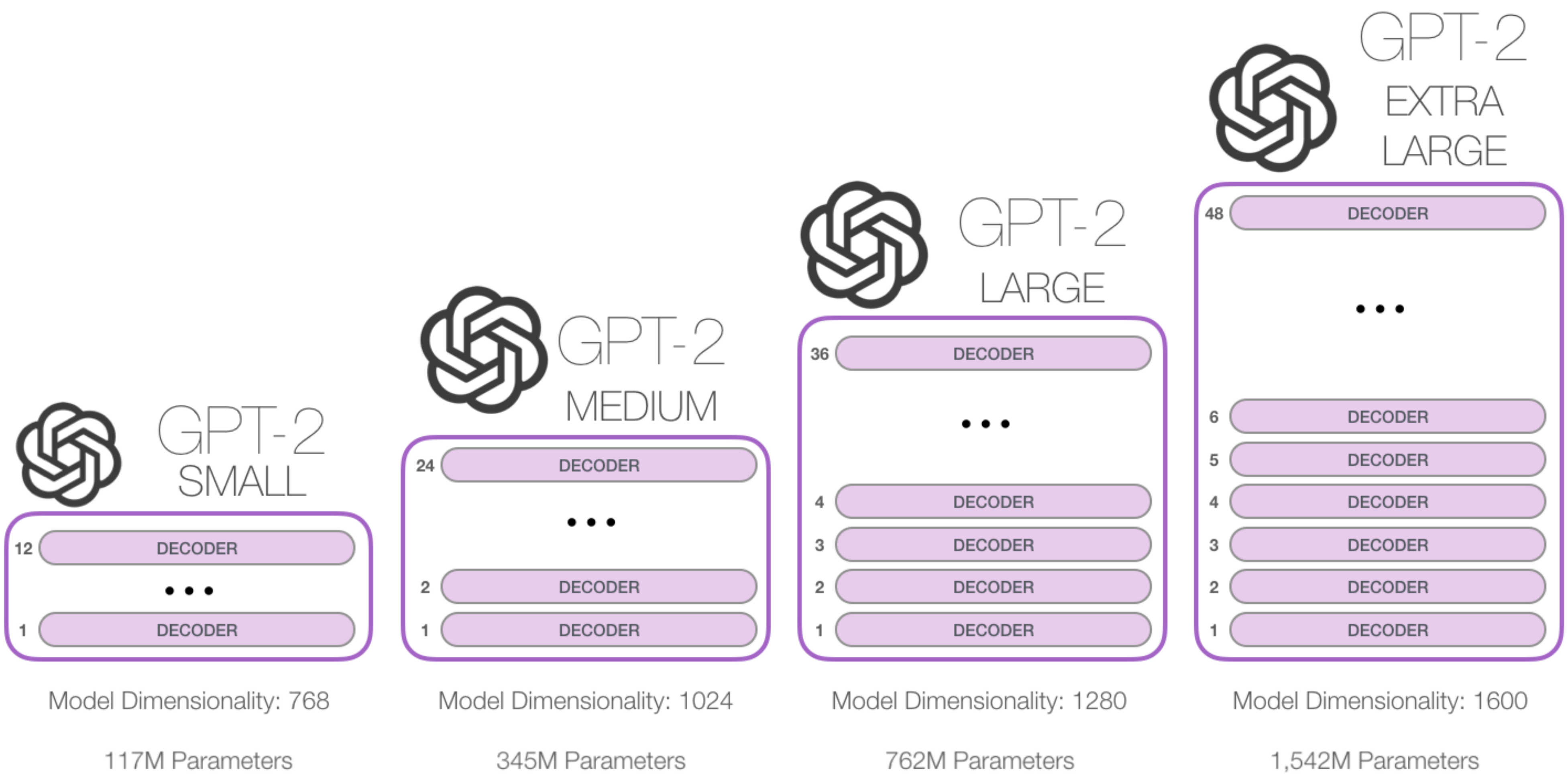


Image source: https://jalammar.github.io/illustrated-bert/

GPT-2



[Radford et al., 2018]()

Image source: https://jalammar.github.io/illustrated-gpt2/

GPT-2

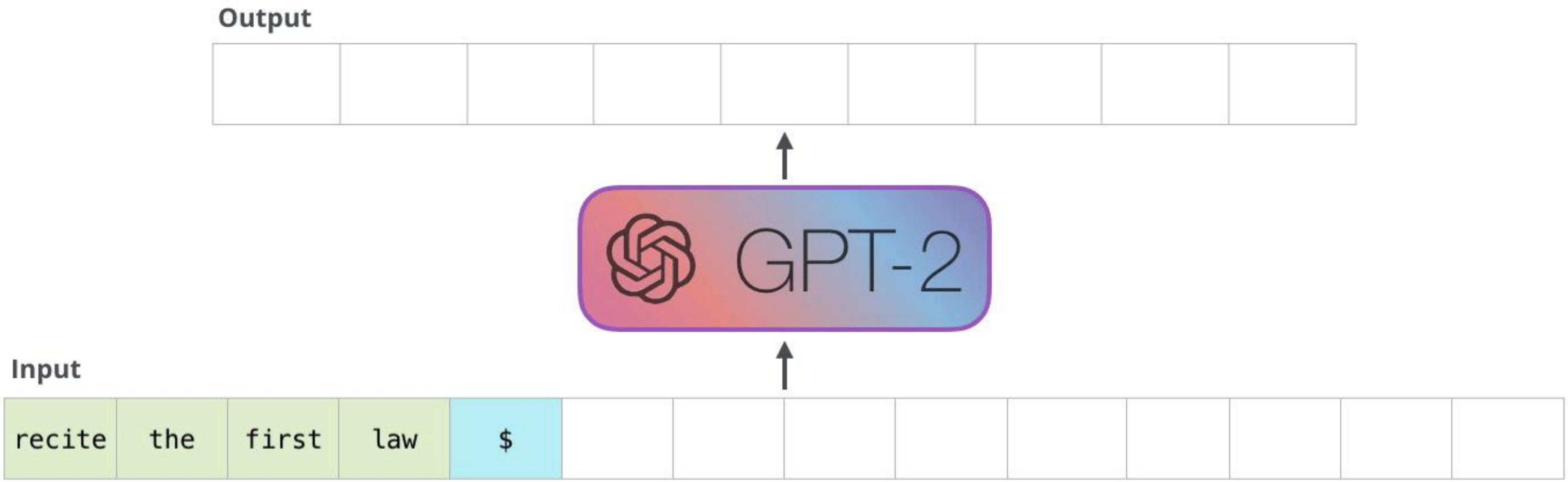


Image source: https://jalammar.github.io/illustrated-gpt2/

Masked Self-Attention

Queries

robot	must	obey	orders

X

Keys

robot	must	obey	orders
robot	must	obey	orders
robot	must	obey	orders
robot	must	obey	orders

=

Scores (before softmax)

0.11	0.00	0.81	0.79
0.19	0.50	0.30	0.48
0.53	0.98	0.95	0.14
0.81	0.86	0.38	0.90

Apply Attention Mask →

Masked Scores (before softmax)

0.11	-inf	-inf	-inf
0.19	0.50	-inf	-inf
0.53	0.98	0.95	-inf
0.81	0.86	0.38	0.90

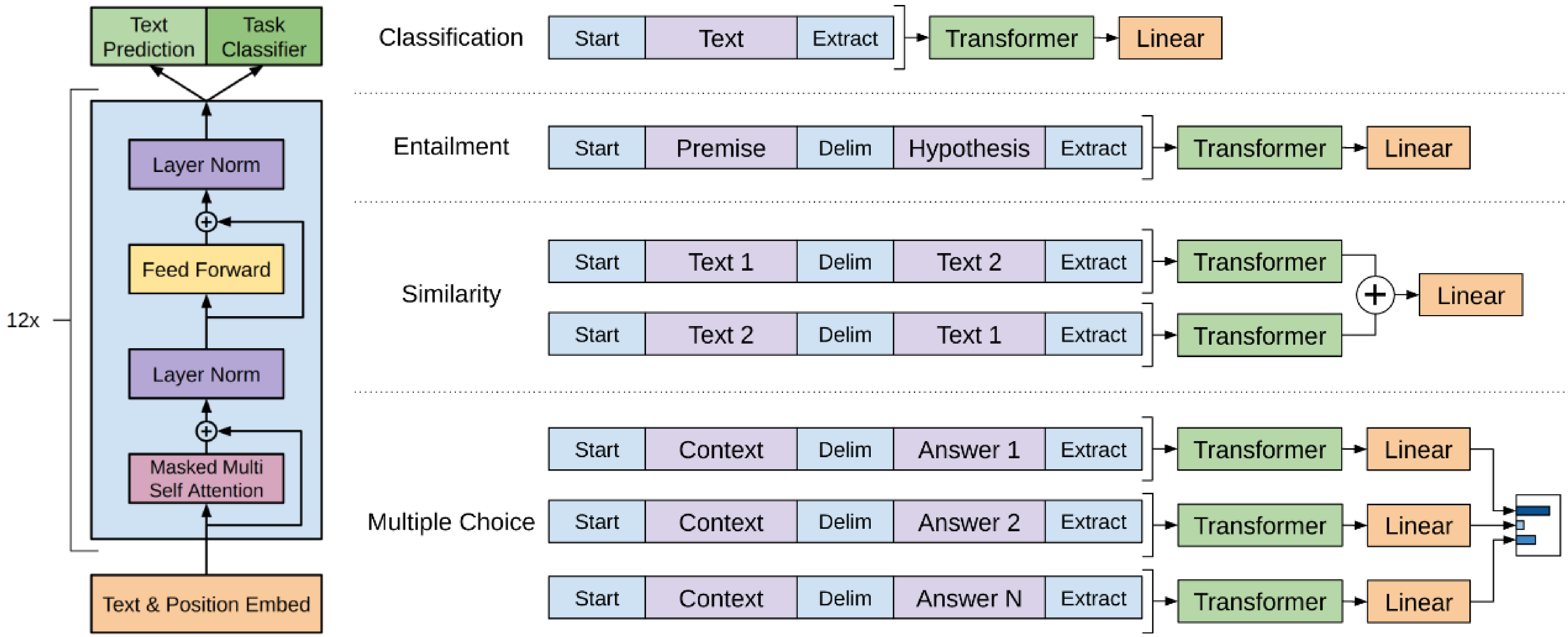
↓

Scores

1	0	0	0
0.48	0.52	0	0
0.31	0.35	0.34	0
0.25	0.26	0.23	0.26

Image source: https://jalammar.github.io/illustrated-gpt2/

GPT 1 Capabilities



[Radford et al., 2018]

Machine Translation with GPT-2

Training Dataset

I	am	a	student	<to-fr>	je	suis	étudiant
let	them	eat	cake	<to-fr>	Qu'ils	mangent	de
good	morning	<to-fr>	Bonjour				

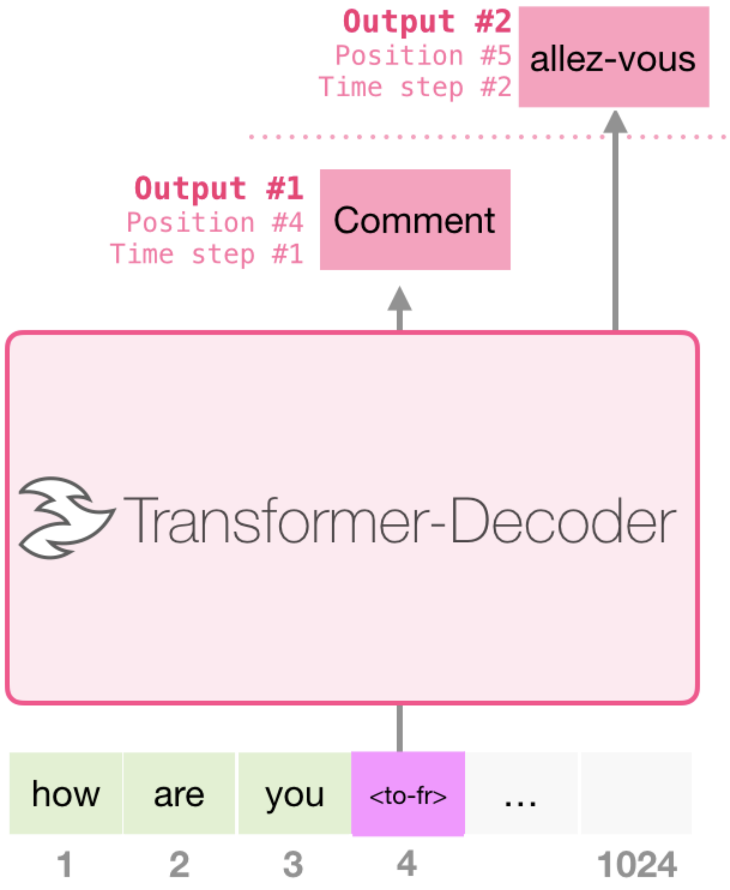
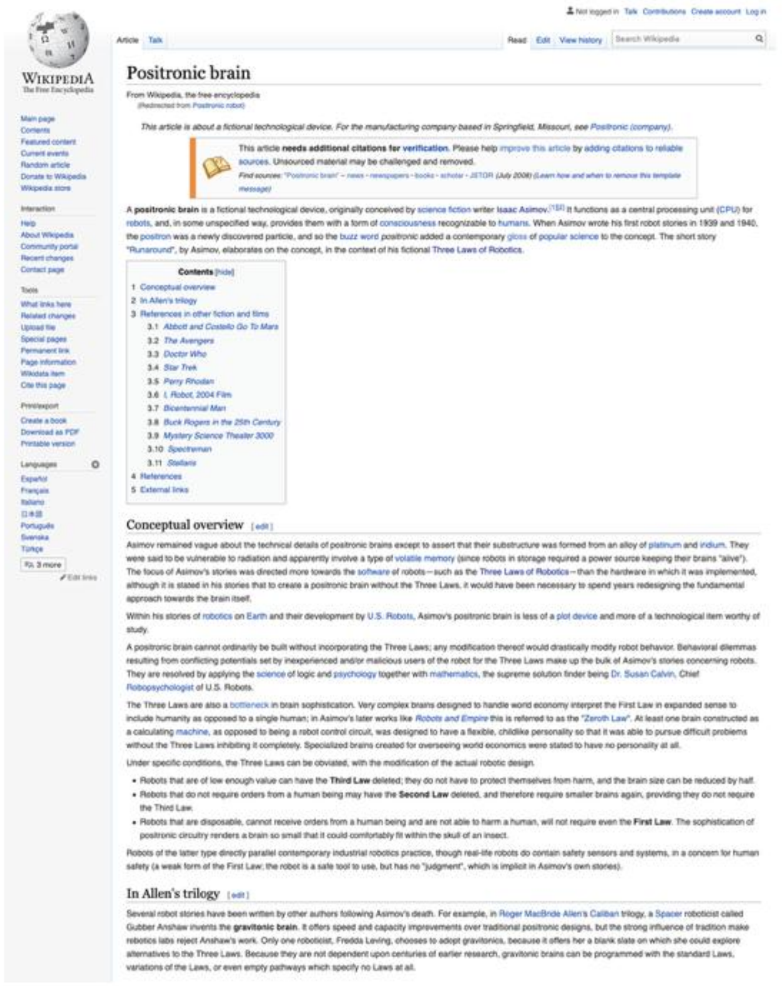


Image source: https://jalammar.github.io/illustrated-gpt2/

Summarization with GPT-2



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Summarization with GPT-2

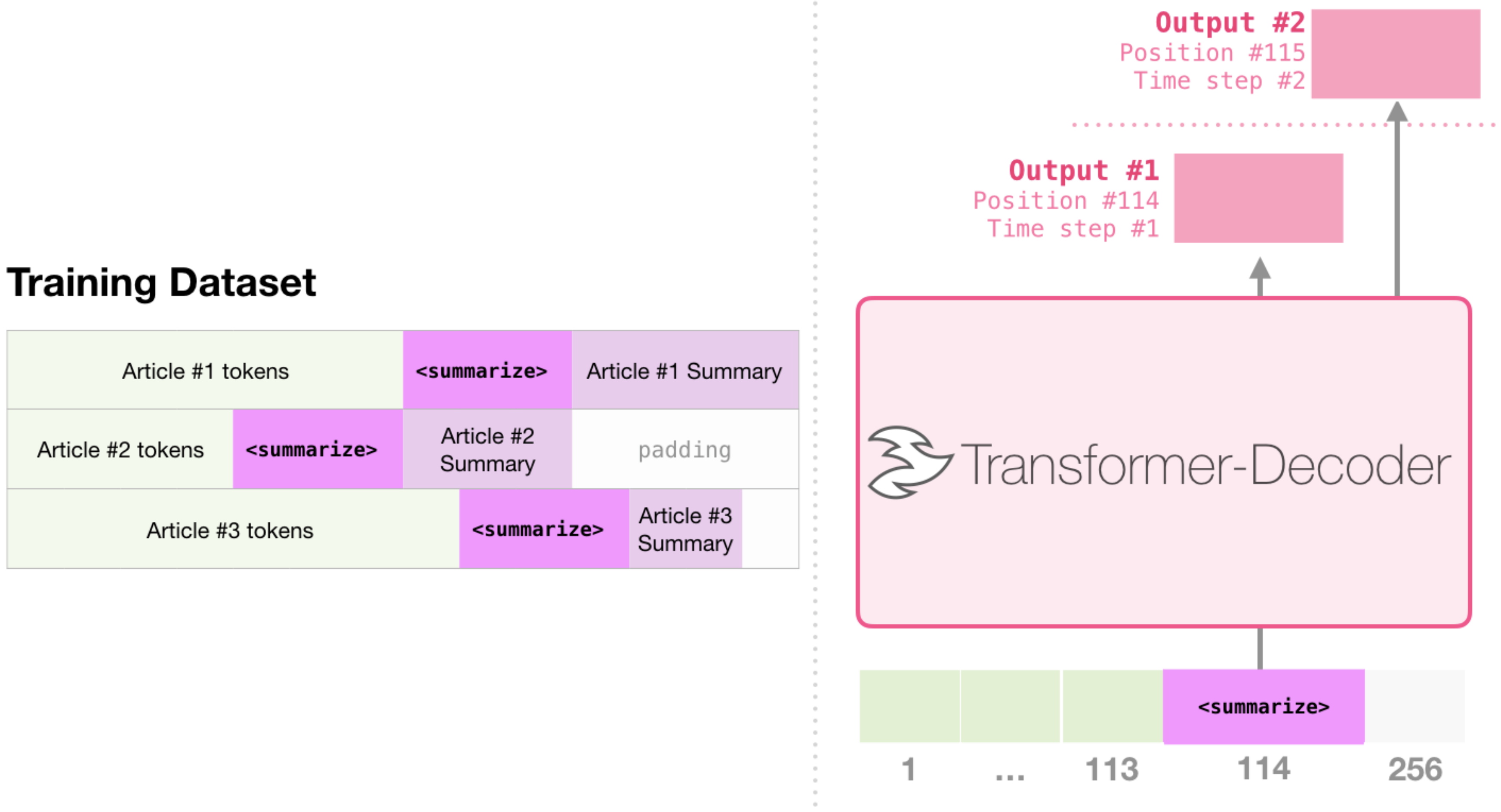
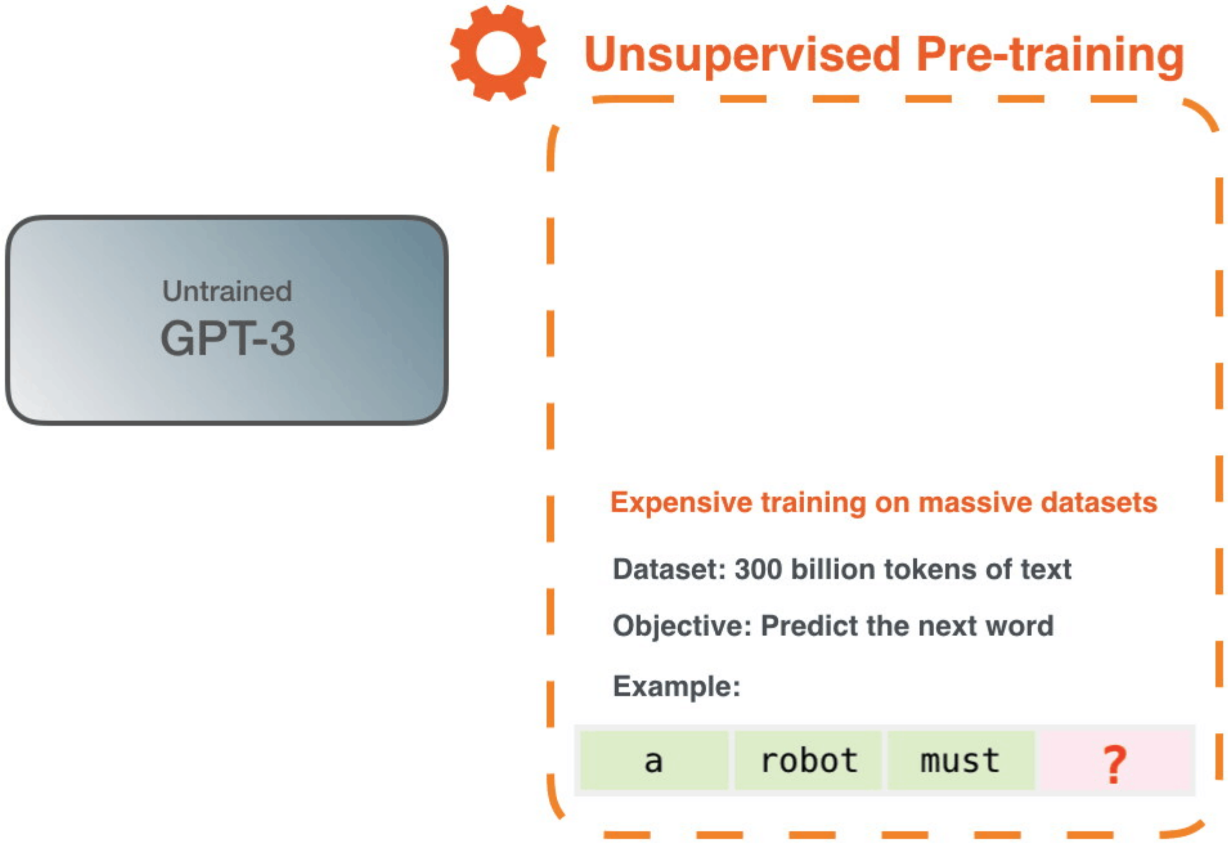


Image source: https://jalammar.github.io/illustrated-gpt2/

GPT-3



Source: https://jalammar.github.io/how-gpt3-works-visualizations-animations/

GPT-3 Specifics

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

Brown et al., 2020

GPT-3 Code Generation

Source: https://jalammar.github.io/how-gpt3-works-visualizations-animations/

LLM Research

- BIG-Bench – Beyond the Imitation Game Benchmark
- https://github.com/google/BIG-bench/blob/main/bigbench/benchmark_tasks/README.md

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  - What are GPT-class Generative Large Language Models
  - Data preparation for GPT model training
  - GPT finetuning (Assignment)
- Part 2: LLMs, LoRA, Context Length and issues
  - Commercial and open source LLMs
  - What are the main issues in LLMs to be aware of?
  - Taxonomy of interaction with LLMs
  - Finetuning, Adapters, Quantization
  - Prompting Strategies

Commercial and Open Source LLMs

- Commercial – GPT3.5 (ChatGPT), GPT4, Gemini Pro, Claude 3
- Open Source – Gemma, Llama-2, Mistral, Zephyr
- Parameter count in 1-200 Billion Range

- How to understand size of LLMs?
  - In terms of parameter count
    - context length
    - Embedding dimension
    - number of weights and biases
    - Attention heads
    - Vocabulary size during tokenization
    - Training data size (typically in terms of number of tokens), source
- Links:
  - https://github.com/eugeneyan/open-llms
  - https://crfm.stanford.edu/helm/classic/latest/
  - https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard

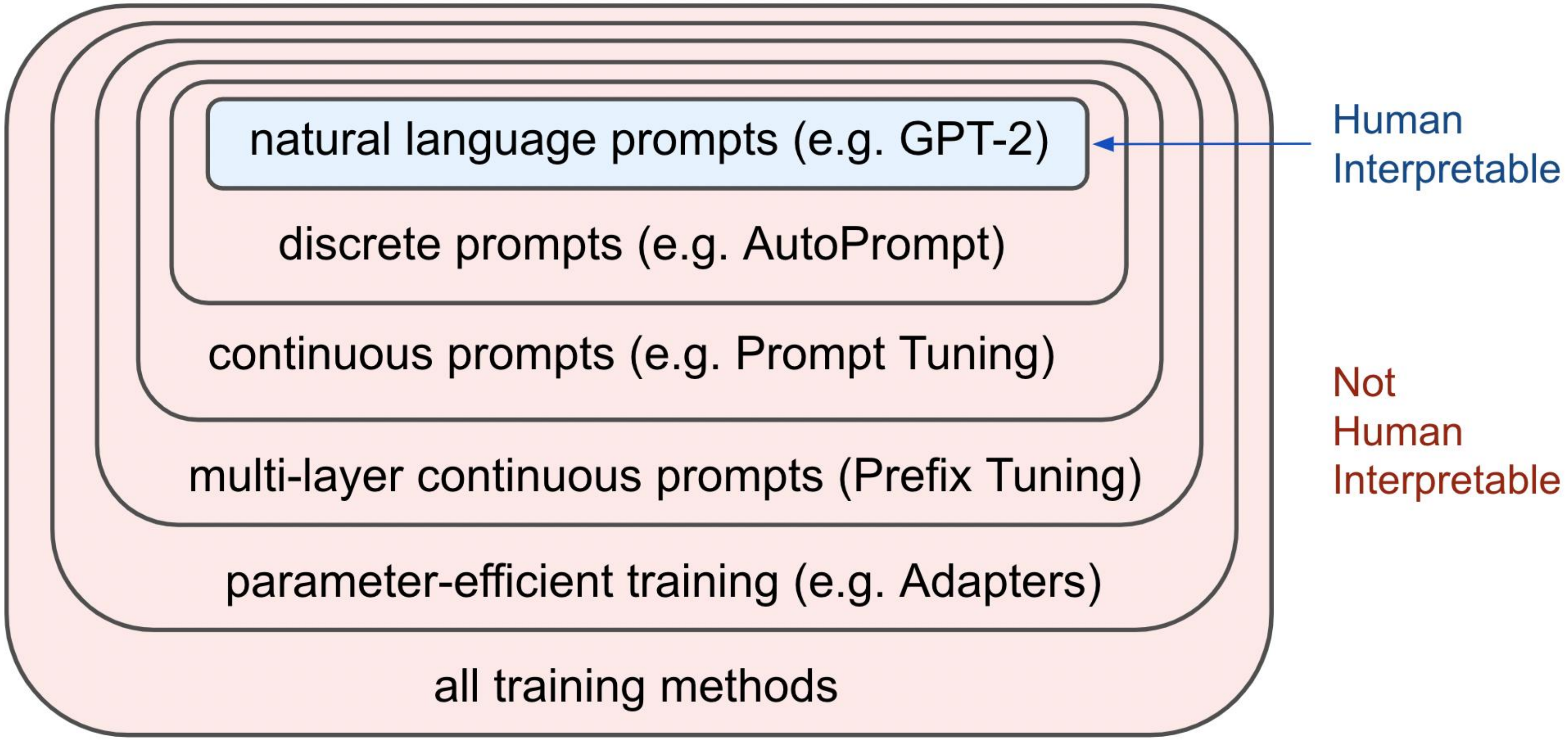
Challenges with LLM

- Size
- Cost
- Out of date facts
- Hallucination
- Harmful content

Ways to interact with a LLM

- Use case: New domain, proprietary data, want to perform a NLP/Generative Task
- 2 Major ways to achieve results
  - Zero-Shot/Few-Shot Learning using Prompt Engineering
  - Fine Tuning – Start with a LLM and do weight updates
- Prompt Engineering
  - Create manual or machine generated prompts to achieve specific tasks
  - Prompt Tuning, Prefix tuning, Auto Prompt – machine learning for prompts
  - Can be done with all LLMs
- Fine Tuning
  - Update all weights and biases of a LLM
  - Parameter efficient fine tuning – Adapters, LoRA
  - Can be done only with open source/open weight models

Taxonomy of Interaction/Prompting Methods



Prompt Engineering

- A prompt is natural language text describing the task that an AI should perform
- Examples:
  - "what is Neural Network?”
  - "write a poem about leaves falling",
  - a short statement of feedback - "too verbose", "too formal", "rephrase again", "omit this word" or
  - a longer statement including context, instructions and input data.
- Prompt Engineering: The process of structuring text that can be interpreted and understood by a generative AI model

Prompting, Coding, Searching

- Different ways of interacting with a computer
- Coding – instructions to execute an algorithm in a high level computer language
- Searching – Keywords, Phrases as input to a webscale search engine
- Prompting – Natural Language instructions to a LLM

- All cases – activities are done to obtain a desirable output

Using LLM for your task and Data

- Fine Tuning
- Low Rank Adaptation
- Quantized Low Rank Adaptation

Parameter Efficient Fine Tuning

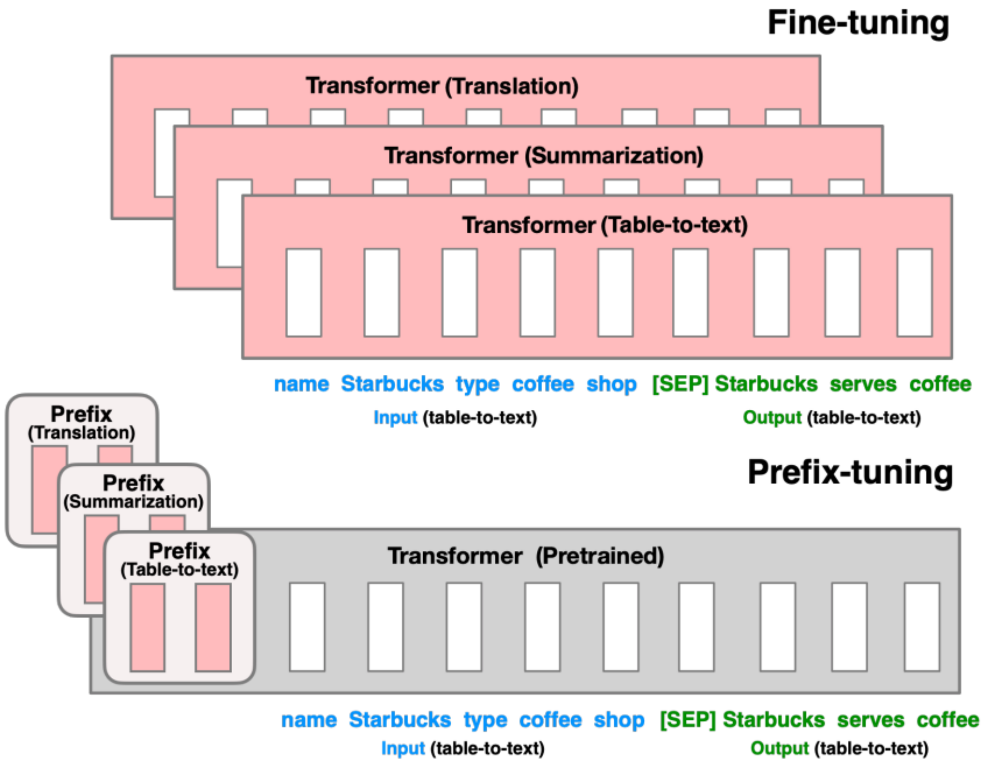
Prompt modifications	Adapter methods	Reparameterization
"Hard" prompt tuning	Adapters	Low rank adaptation (LoRA)
"Soft" prompt tuning		
Prefix-tuning	LLaMA-Adapter	

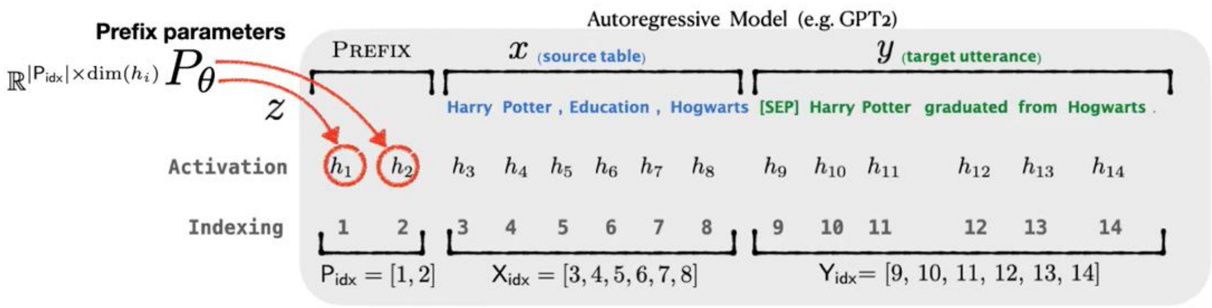
Hard Prompt Tuning

```
1) "Translate the English sentence '{english_sentence}' into German: {german_translation}"

2) "English: '{english_sentence}' | German: {german_translation}"

3) "From English to German: '{english_sentence}' -> {german_translation}"
```

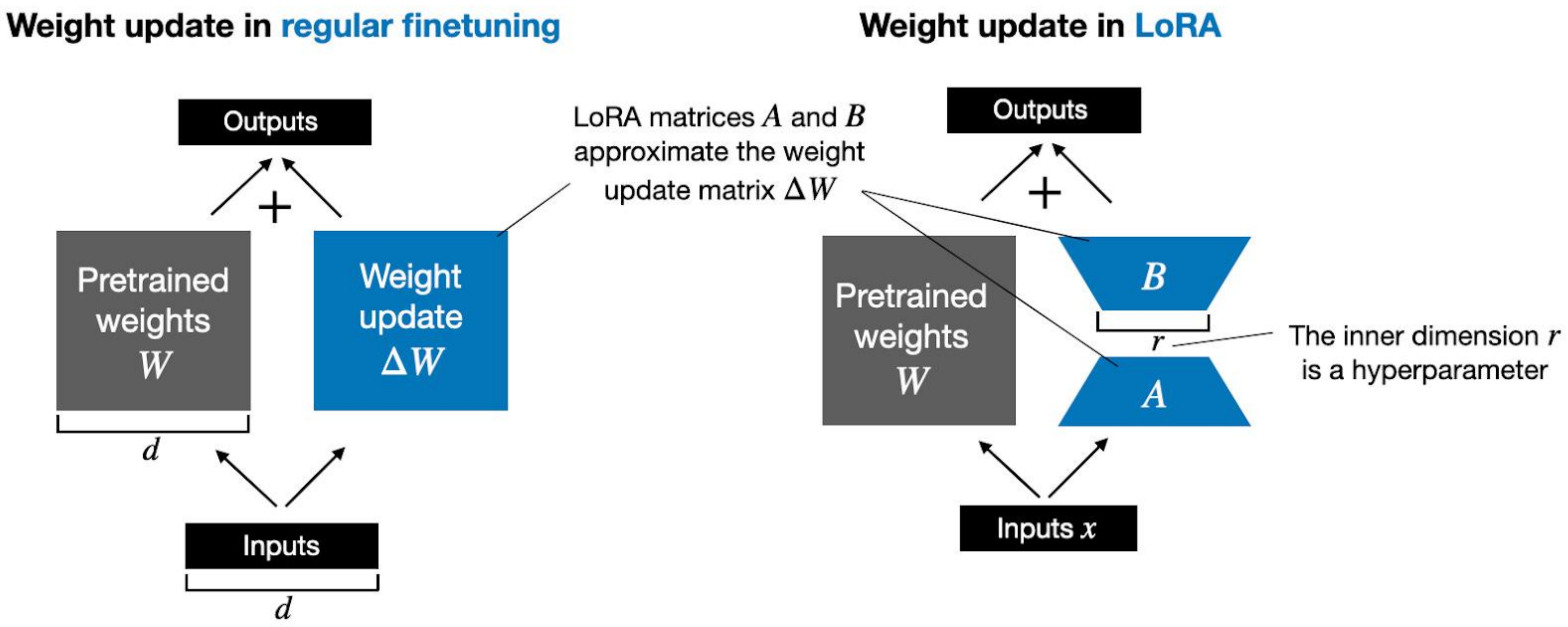
Prefix Tuning

- Add prefix parameters that are learnt during the training of GPT





LoRA – Low Rank Adaptation



Quantization

- Technique to reduce the size of deep neural networks (including LLMs) by changing the precision of the weights and biases data structure
- Pros: Lower model size allowing for deployment on edge device
- Cons: Lower accuracy
- Concept:
  - Typical computation happens in Floating Point 32 precision (FP32) or FP16
  - Quantized models are converted to INT4 either
    - Post training (PTQ – Post Training Quantization)
    - During training (QAT – Quantization Aware Training)
  - PTQ is easier than QAT
- HuggingFace hub has quantized models that you can use and deploy in LLMOps

Floating Point Sizes

Floating Point Formats

bfloat16: Brain Floating Point Format

Range: $\sim 1e^{-38}$ to $\sim 3e^{38}$

Exponent: 8 bits — Mantissa (Significand): 7 bits

S	E	E	E	E	E	E	E	E	M	M	M	M	M	M	M

fp32: Single-precision IEEE Floating Point Format

Range: $\sim 1e^{-38}$ to $\sim 3e^{38}$

Exponent: 8 bits — Mantissa (Significand): 23 bits

S	E	E	E	E	E	E	E	E	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M	M

fp16: Half-precision IEEE Floating Point Format

Range: $\sim 5.96e^{-8}$ to 65504

Exponent: 5 bits — Mantissa (Significand): 10 bits

S	E	E	E	E	E	M	M	M	M	M	M	M	M	M	M

Size of Quantized Models

Model	Original Size (FP16)	Quantized Size (INT4)
Llama2-7B	13.5 GB	3.9 GB
Llama2-13B	26.1 GB	7.3 GB
Llama2-70B	138 GB	40.7 GB

Q-LoRA

- quantized LoRA - a technique that further reduces memory usage during finetuning.
  - During backpropagation, QLoRA quantizes the pretrained weights to 4-bit precision and uses paged optimizers to handle memory spikes.
- But Q-LoRA comes with a runtime penalty

Default LoRA with 16-bit brain floating point precision:

- Training time: 1.85 h
- Memory used: 21.33 GB

QLoRA with 4-bit *Normal Floats:*

- Training time: 2.79 h
- Memory used: 14.18 GB

SOURCE: https://magazine.sebastianraschka.com/p/practical-tips-for-finetuning-llms