DeepLearning.AI

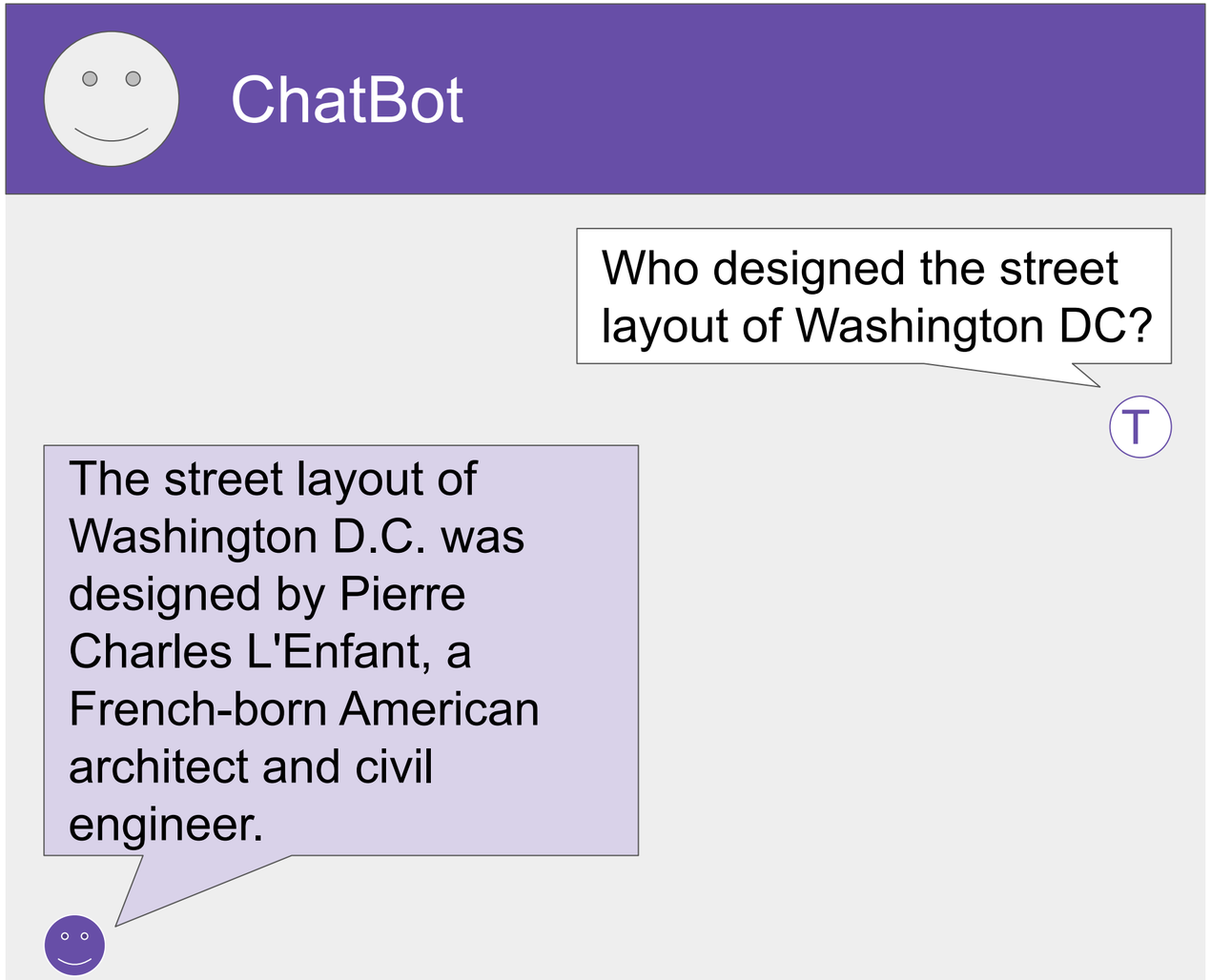
# Generative AI & Large Language Models (LLMs)

## USE CASES, PROJECT LIFECYCLE, AND MODEL PRE-TRAINING

# Generative AI & Large Language Model Use Cases & Model Lifecycle

# Generative AI &
# Large Language Models

# Generative AI



# Generative AI

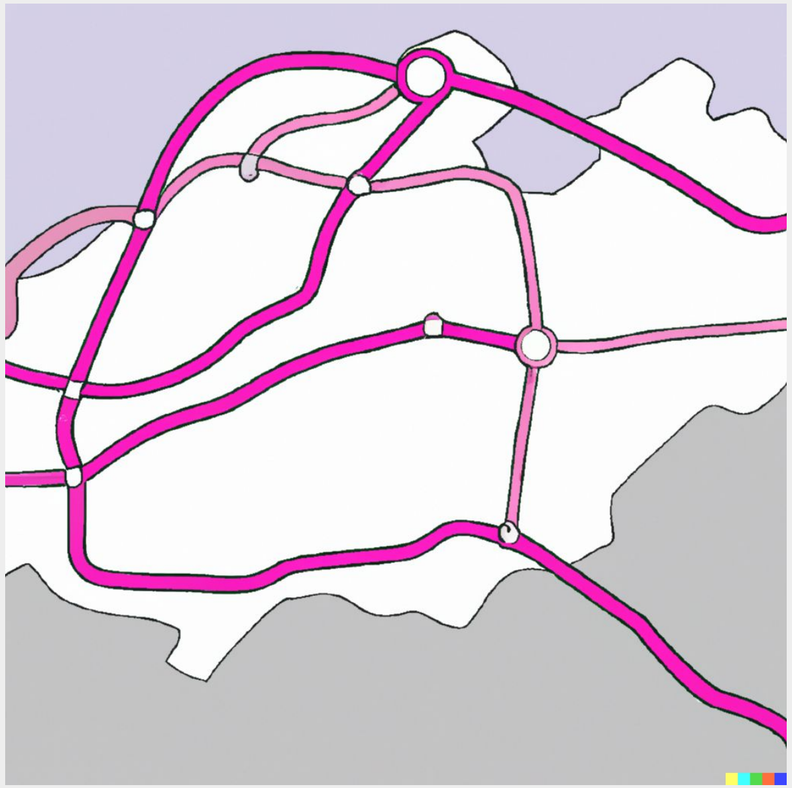
## pAIntBox

What do you want to create?

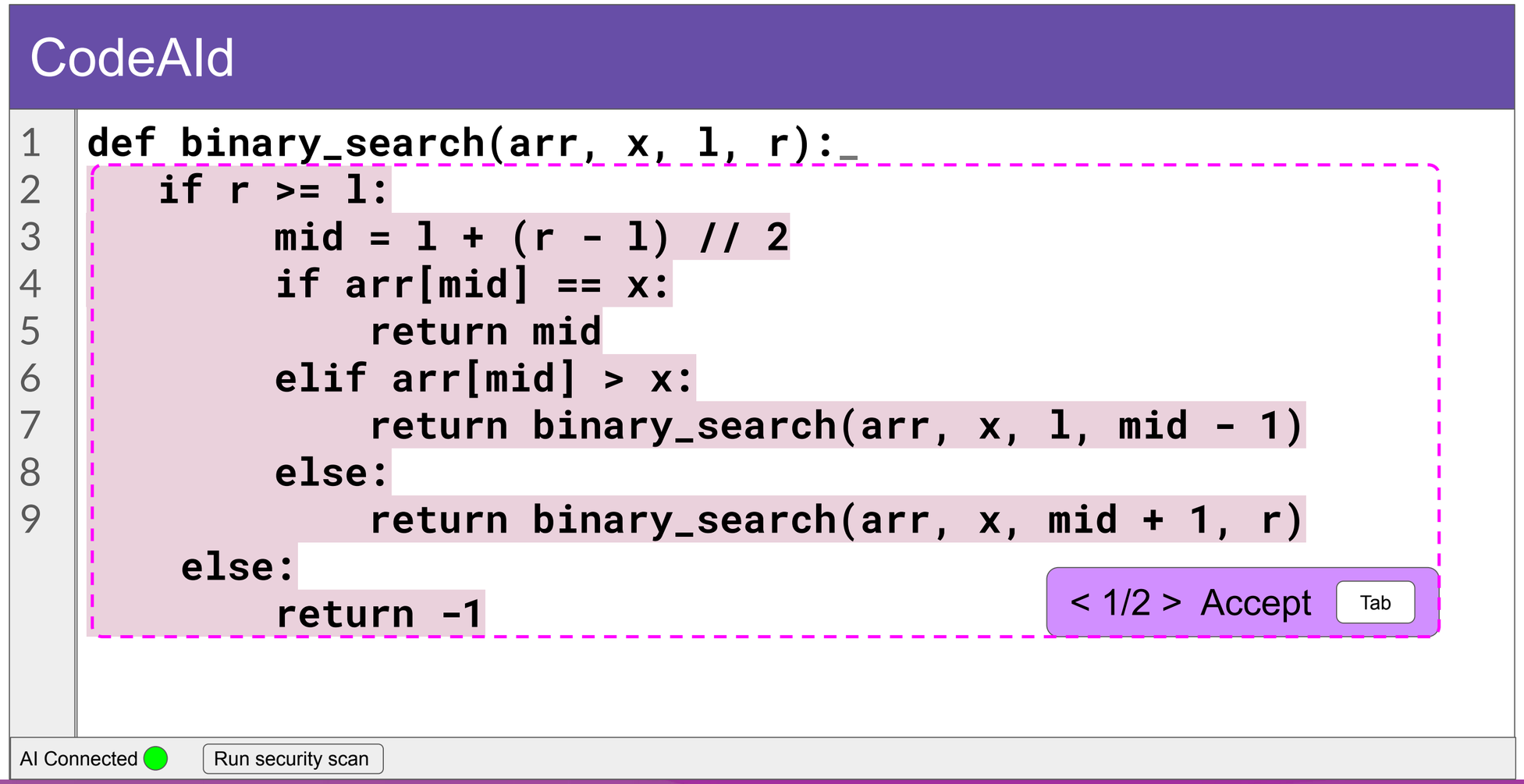
An imaginary subway map in a coastal city.

Image dimensions: by (Max 2048)

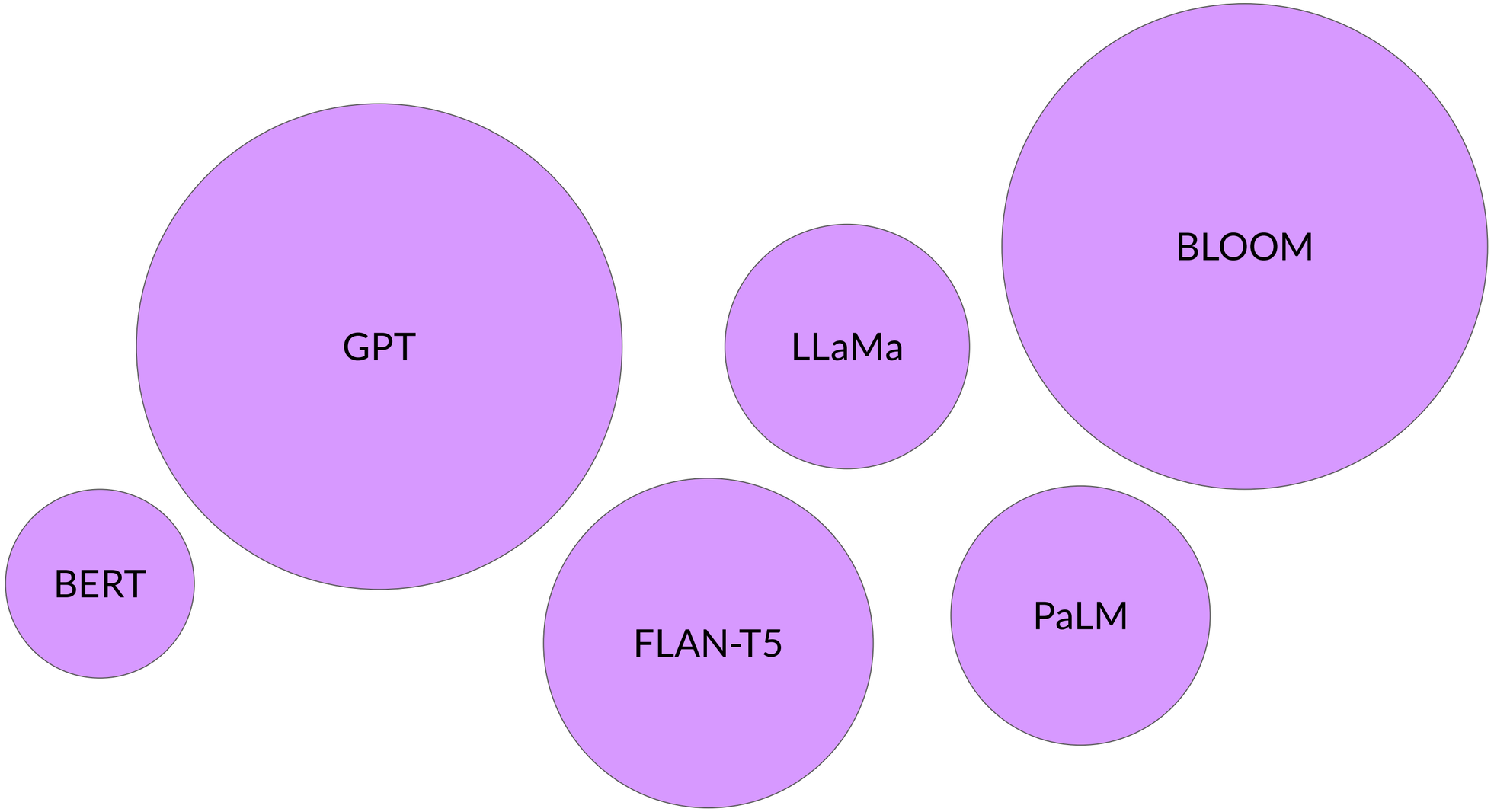
Generate



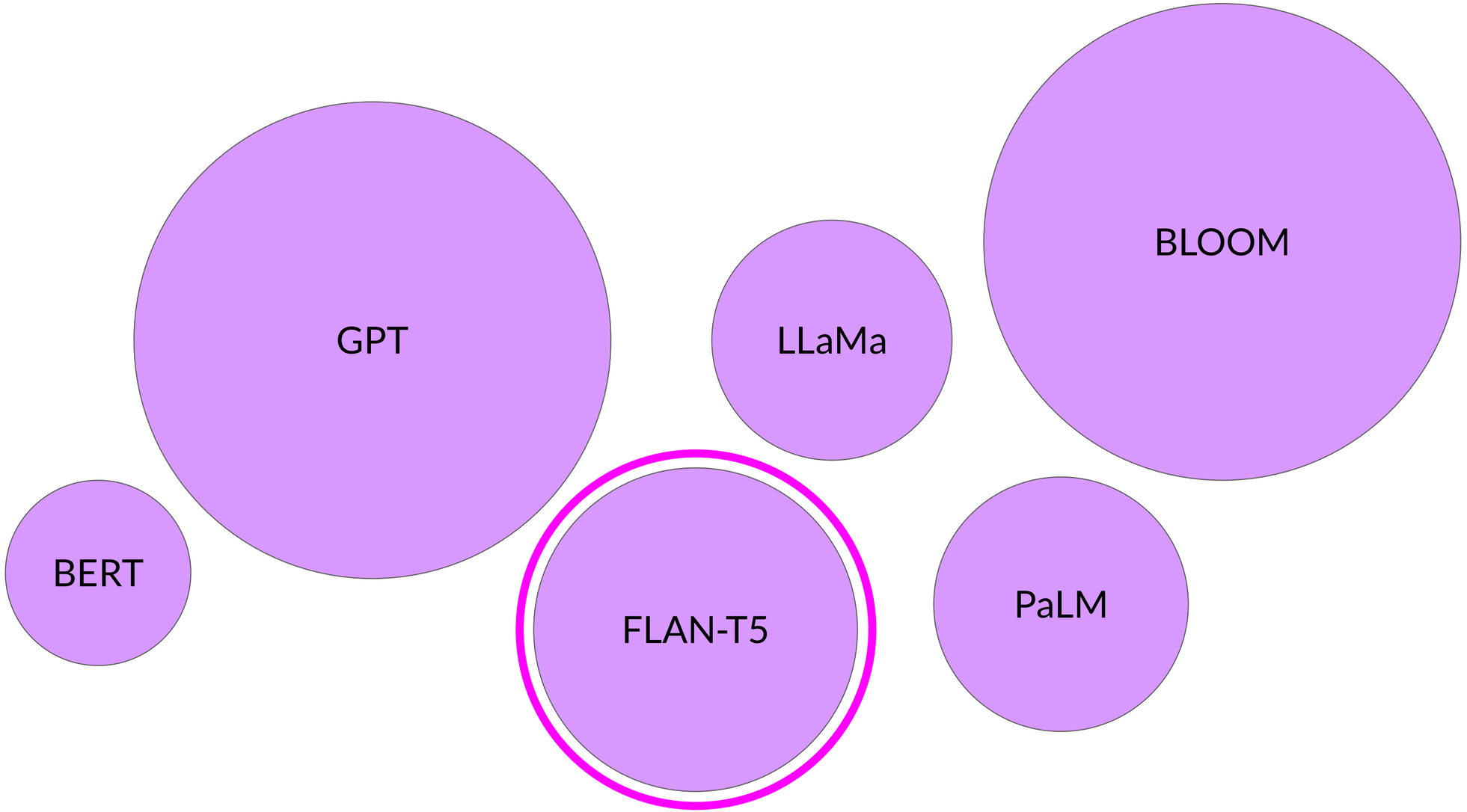
# Generative AI



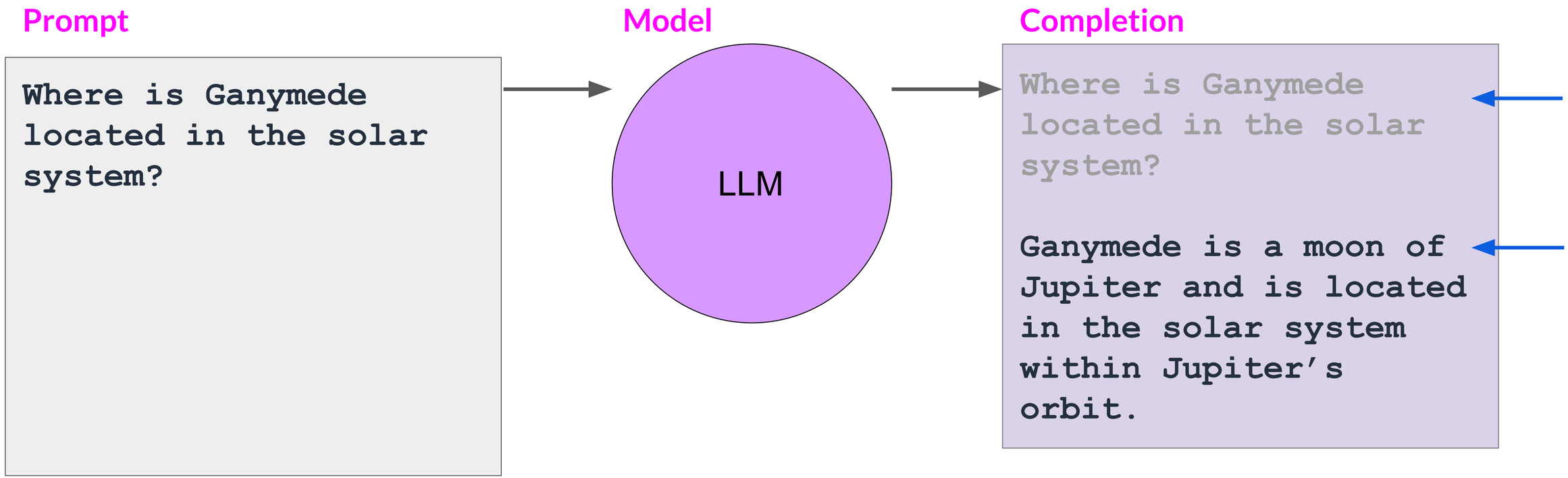
# Large Language Models



# Large Language Models



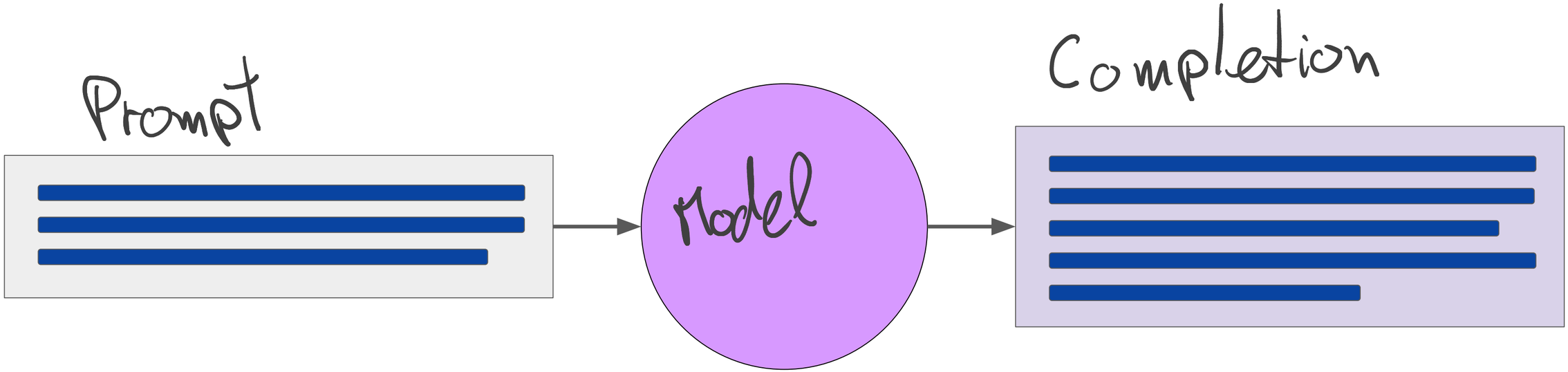
# Prompts and completions




Context window

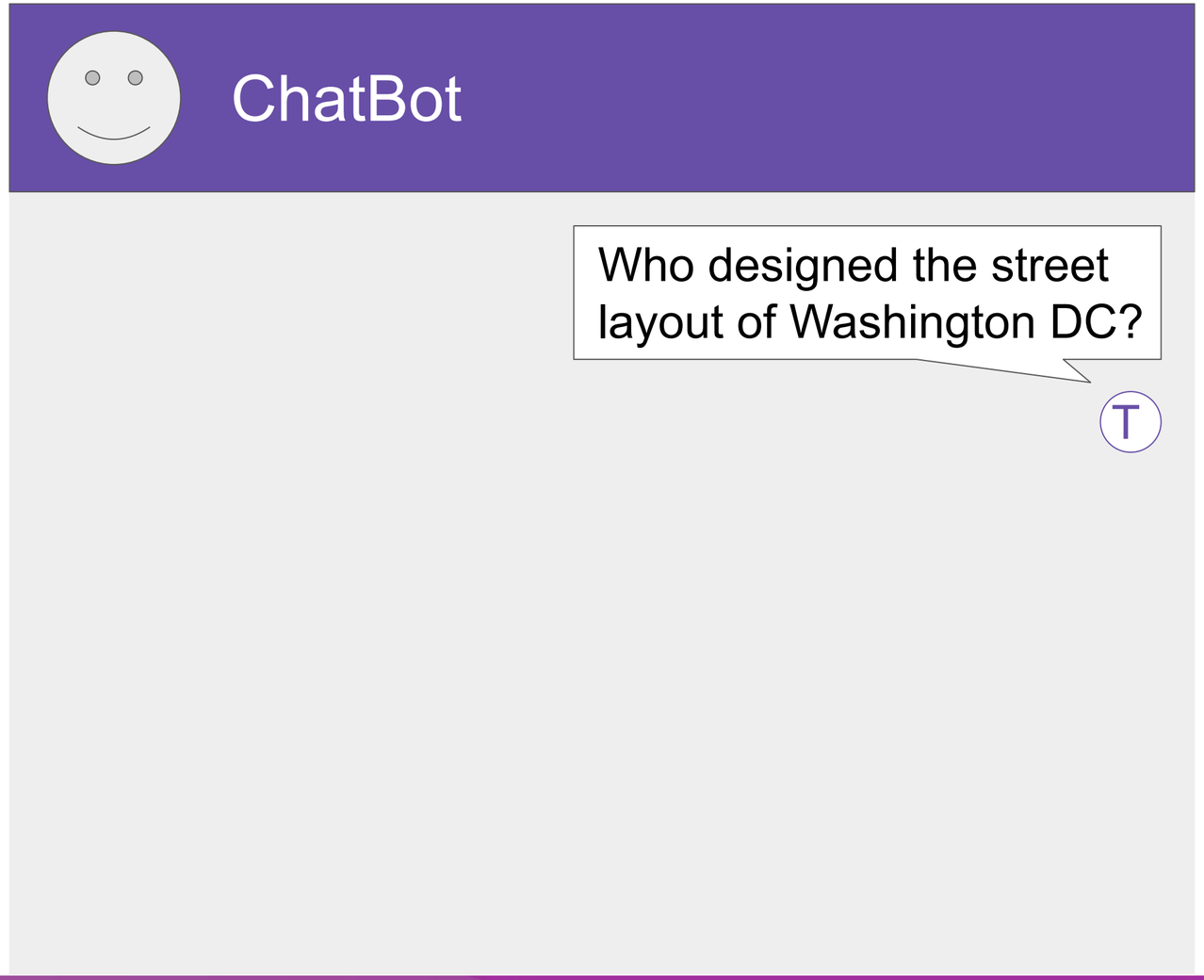
- typically a few 1000 words.

# Prompts and completions

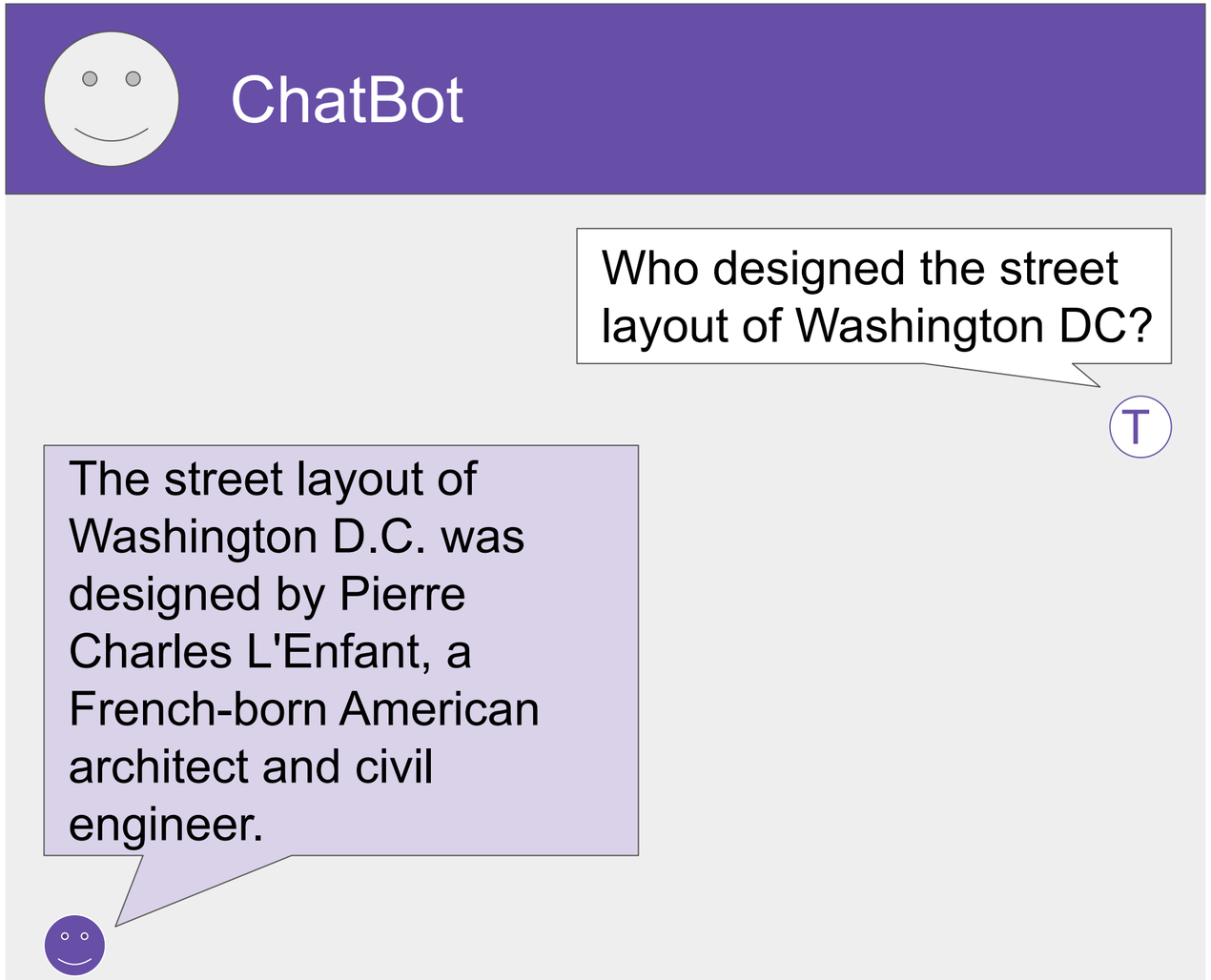


# Use cases & tasks

# LLM chatbot

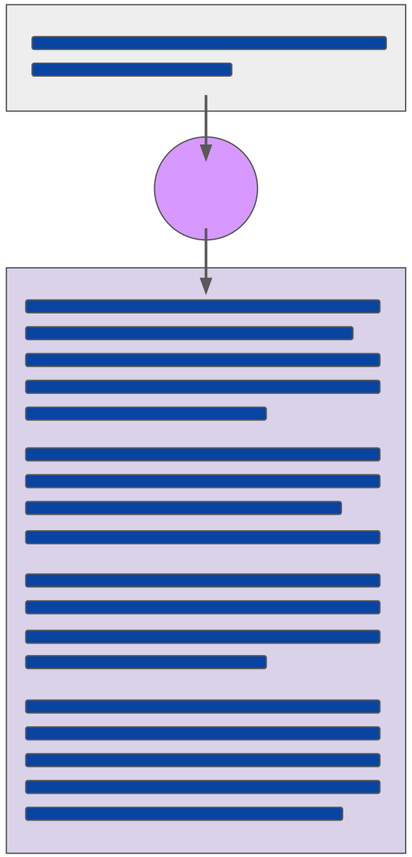


# LLM chatbot

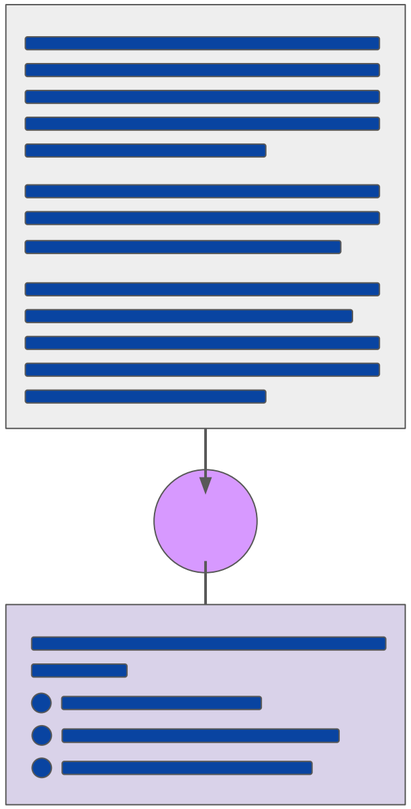

ChatBot
Who designed the street layout of Washington DC?
T
The street layout of Washington D.C. was designed by Pierre Charles L'Enfant, a French-born American architect and civil engineer.

# LLM use cases & tasks

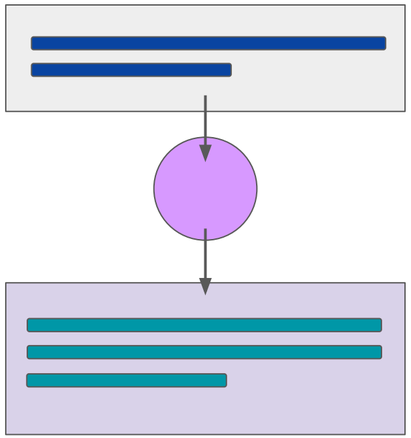
Essay Writing



Summarization

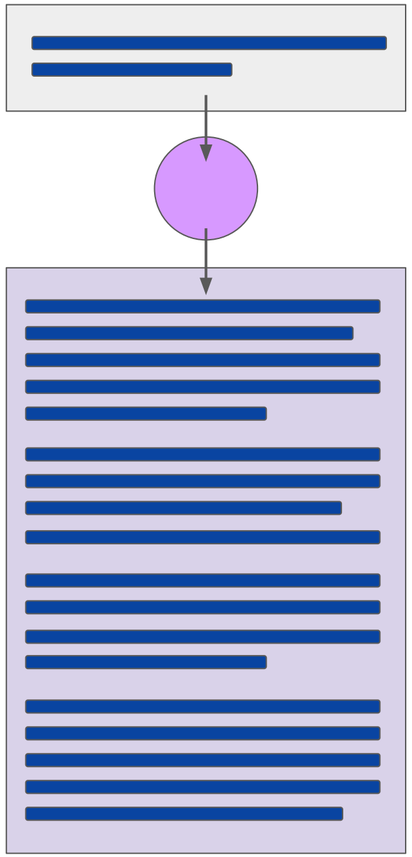


Translation

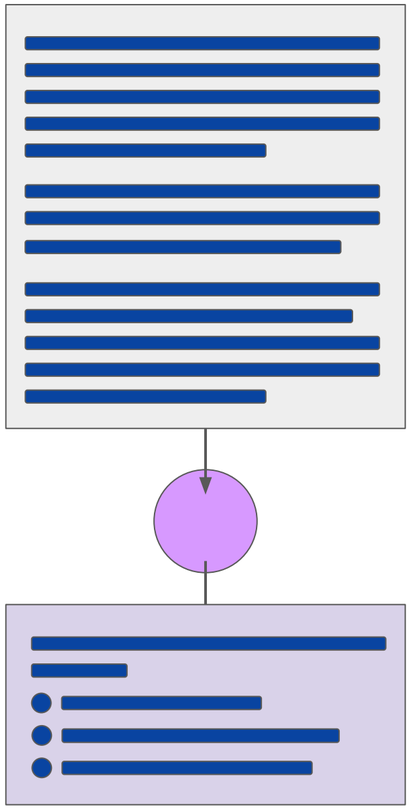


# LLM use cases & tasks

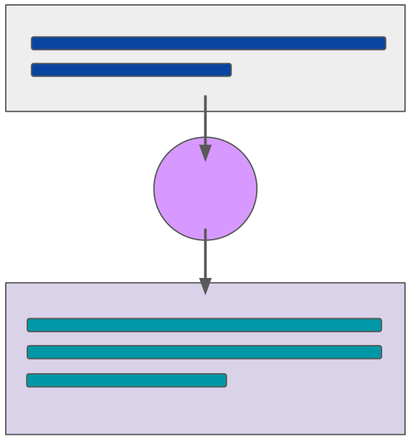
Essay Writing



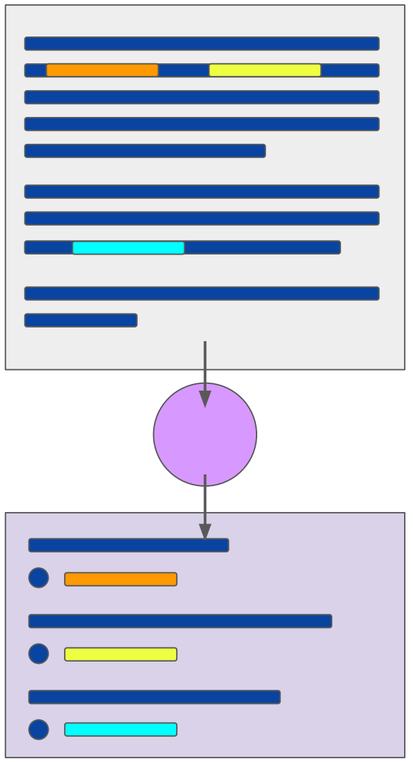
Summarization



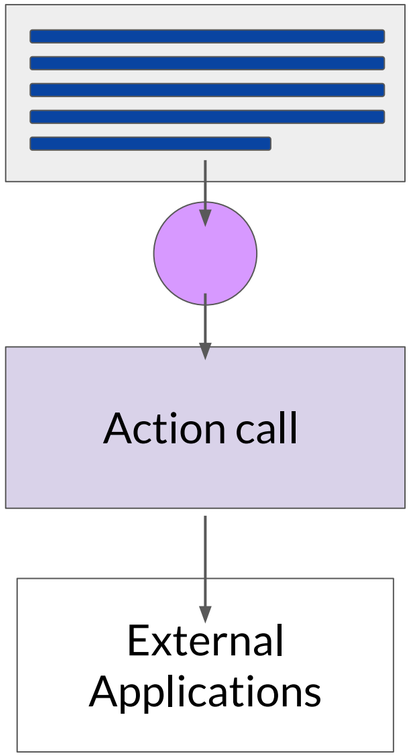
Translation



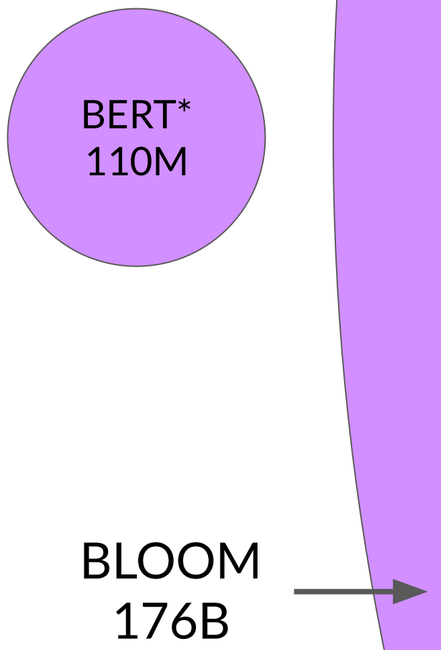
Information retrieval



Invoke APIs and actions



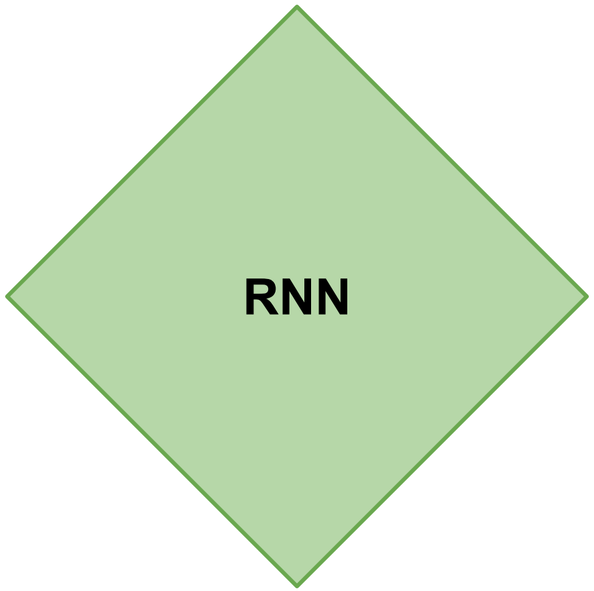
# The significance of scale: language understanding




*Bert-base

# How LLMs work - Transformers architecture

# Generating text with RNNs



# Generating text with RNNs

# Generating text with RNNs

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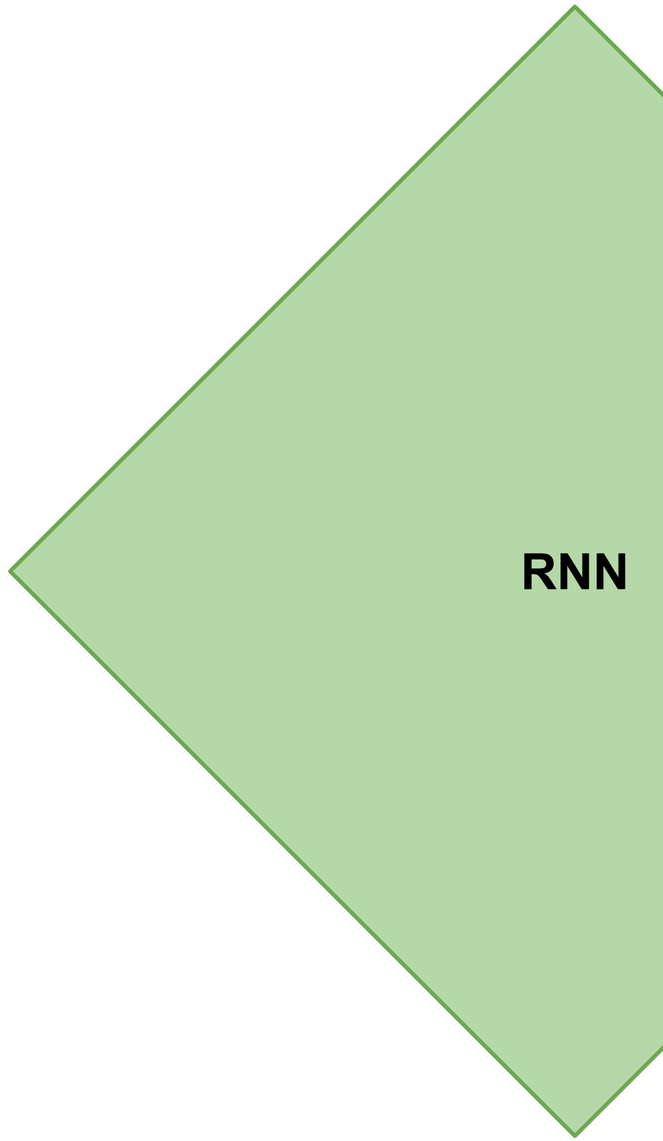
?

, my tea tastes …

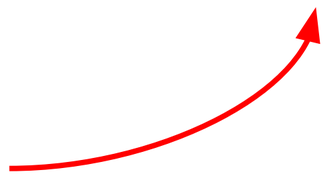


# Generating text with RNNs

# Generating text with RNNs

# Understanding language can be challenging

I took my money to the bank.



# Understanding language can be challenging

The teacher's book?

The teacher taught the student with the book.

The student's book?

# Transformers

## Attention Is All You Need

2017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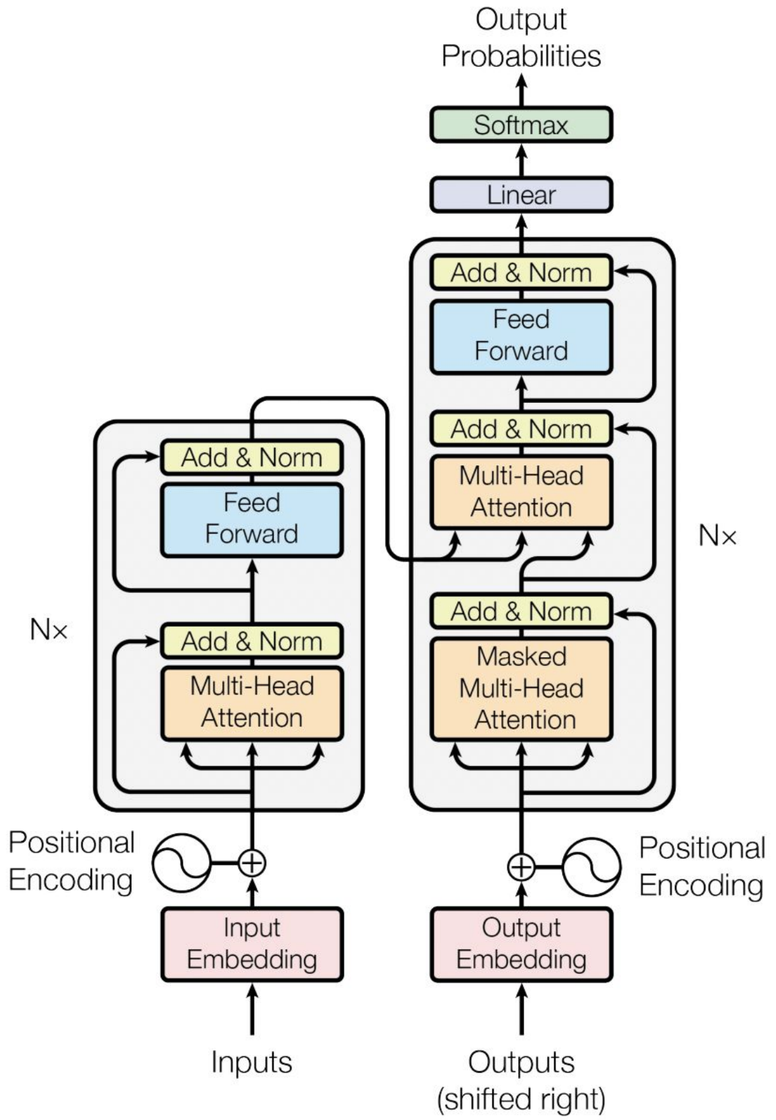
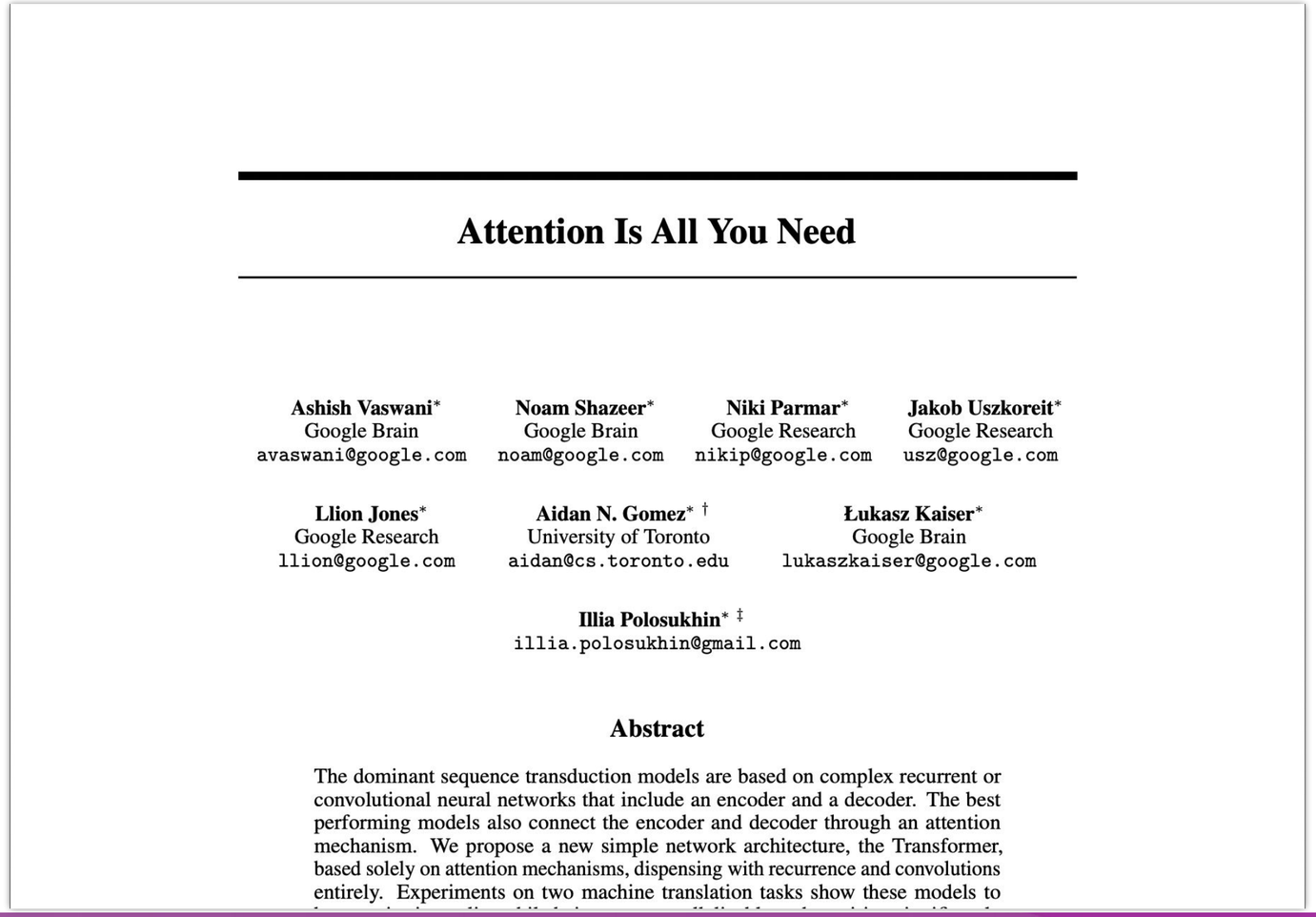
### Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to

# Transformers



**Attention Is All You Need**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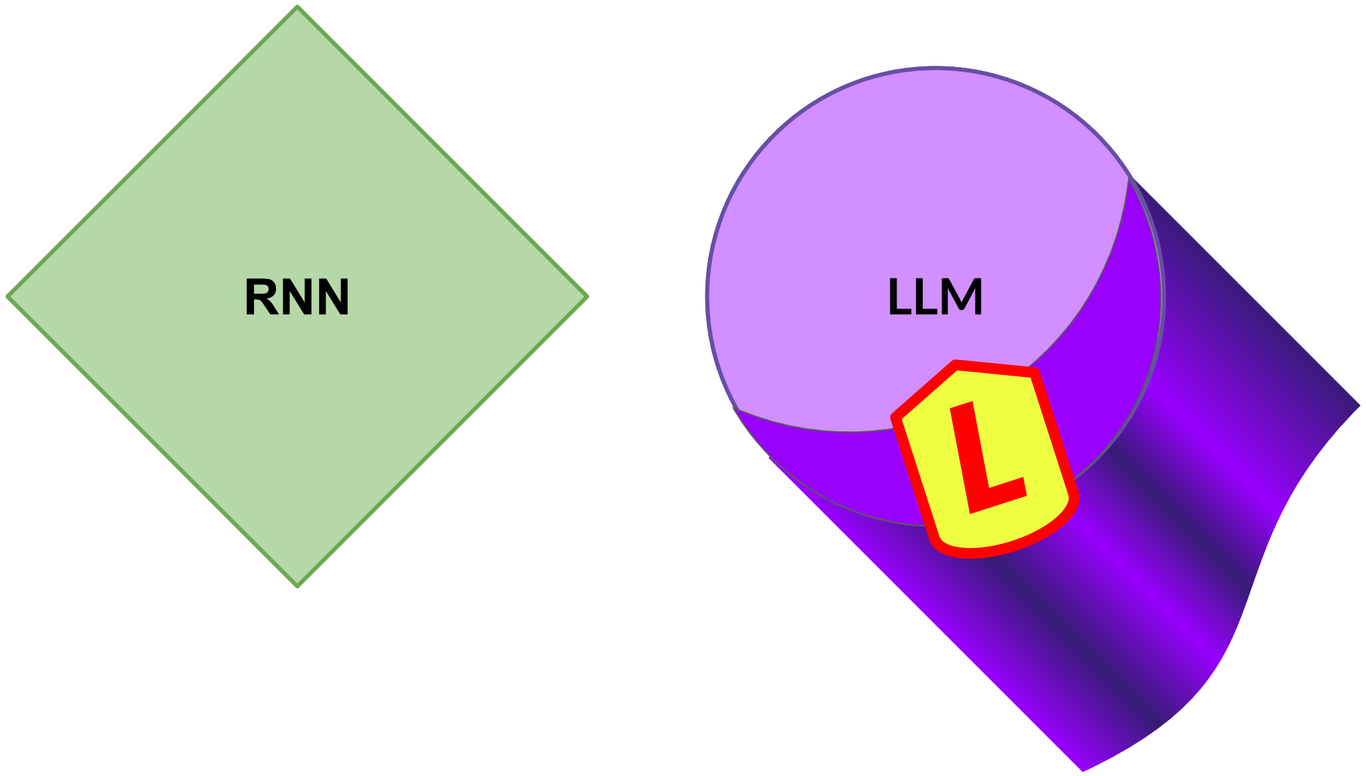
**Abstract**

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to


- Scale efficiently
- Parallel process
- Attention to input meaning

# Transformers

power of transformer architecture is ability to learn RELEVANCE and CONTEXT of EVERY WORD in SENTANCE in RELEVANCE to EVERY OTHER WORD in sentance.



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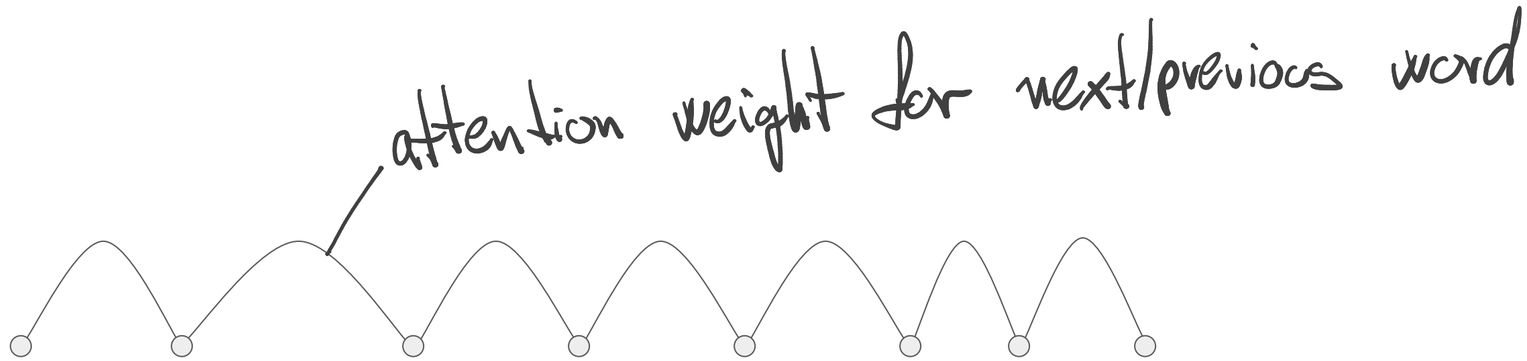
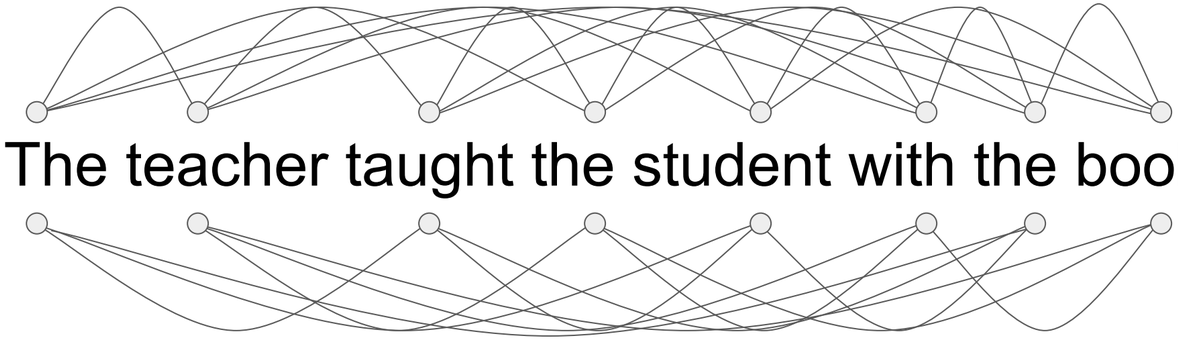


# Transformers

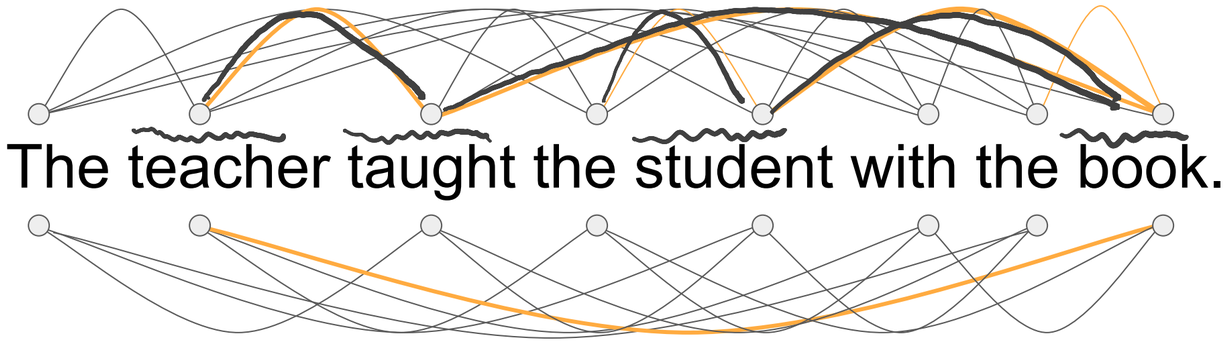
attention weights between words in sentance



# Transformers

algorithm has ability to learn:

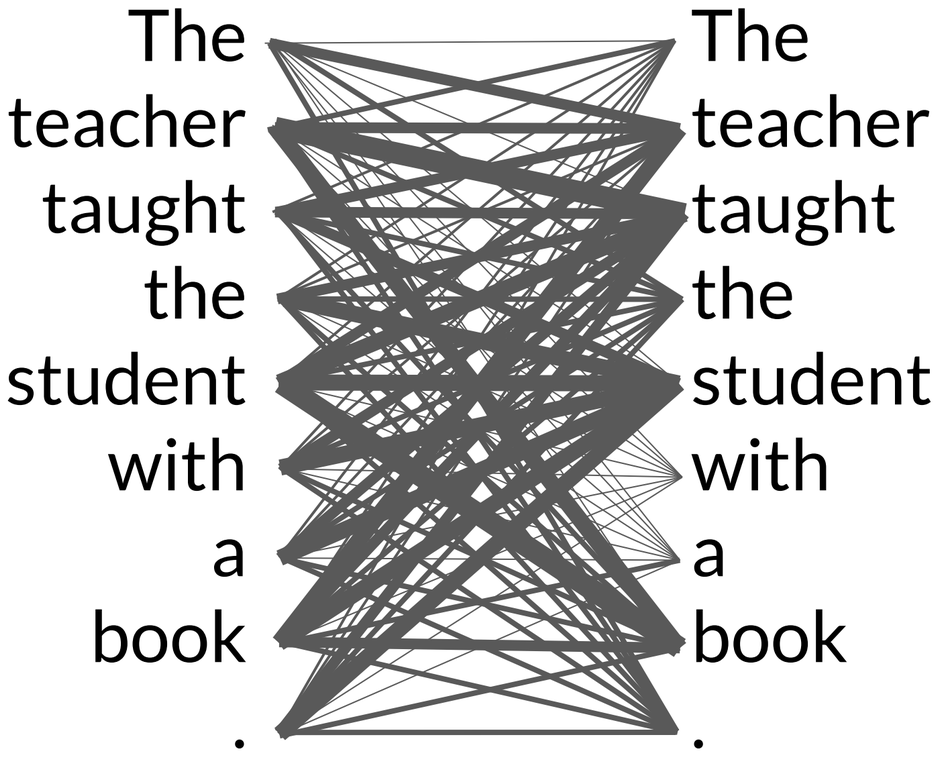
- who has the book
- who could have the book



# Self-attention

attention weights are learned during LLM training.

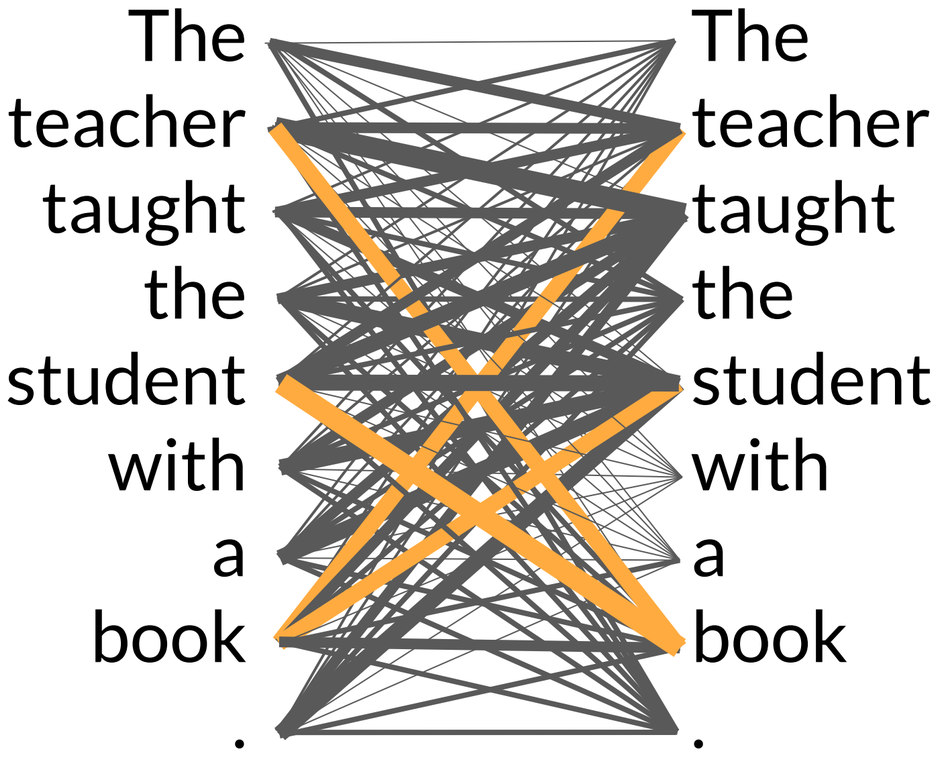
ATTENTION MAP → illustrates attention weights between EACH WORD AND EVERY OTHER WORD



# Self-attention

- learning to encode language

word BOOK is paying ATTENTION to WORD TEACHER and STUDENT



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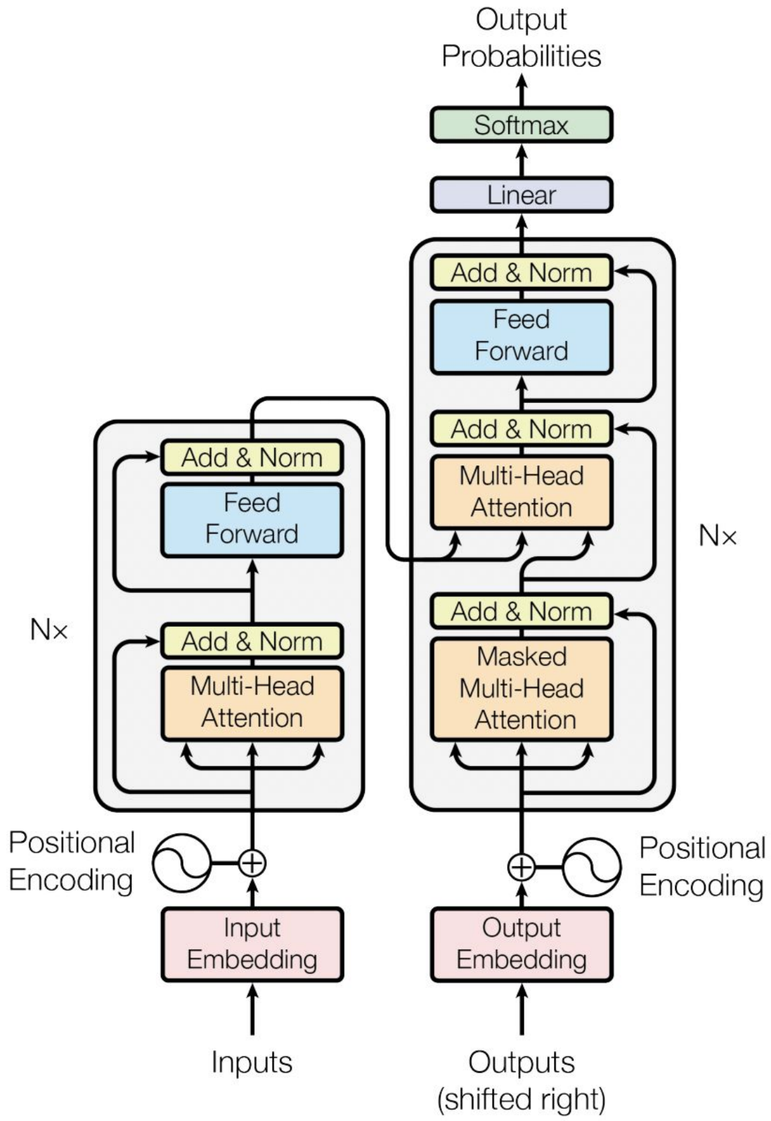
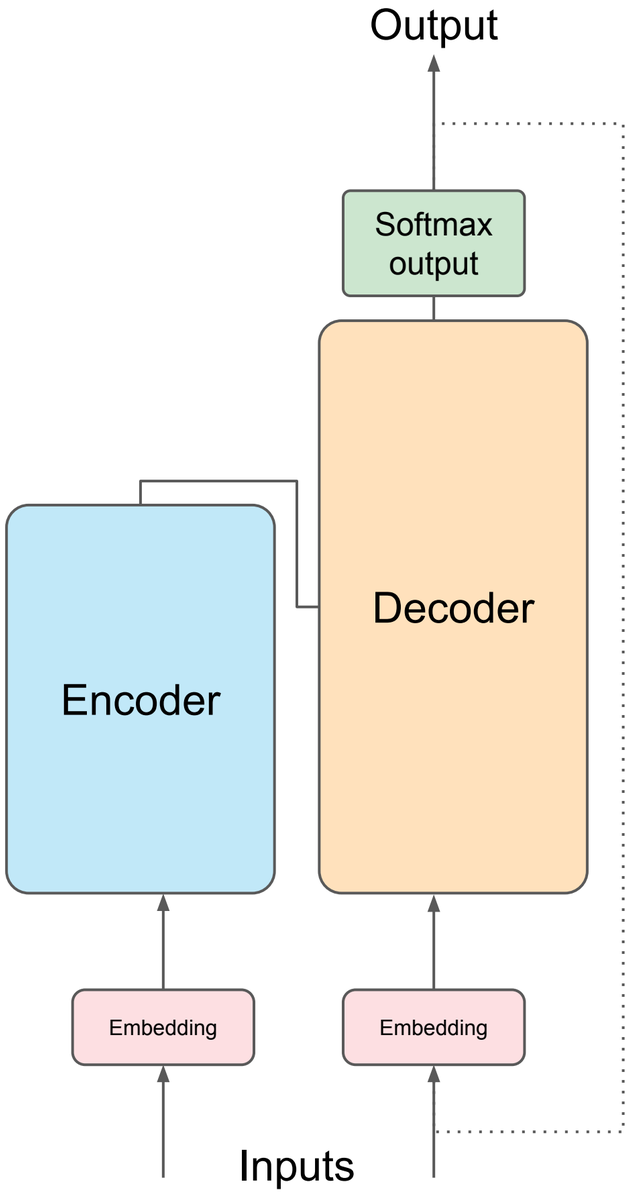


# Transformers

High level overview



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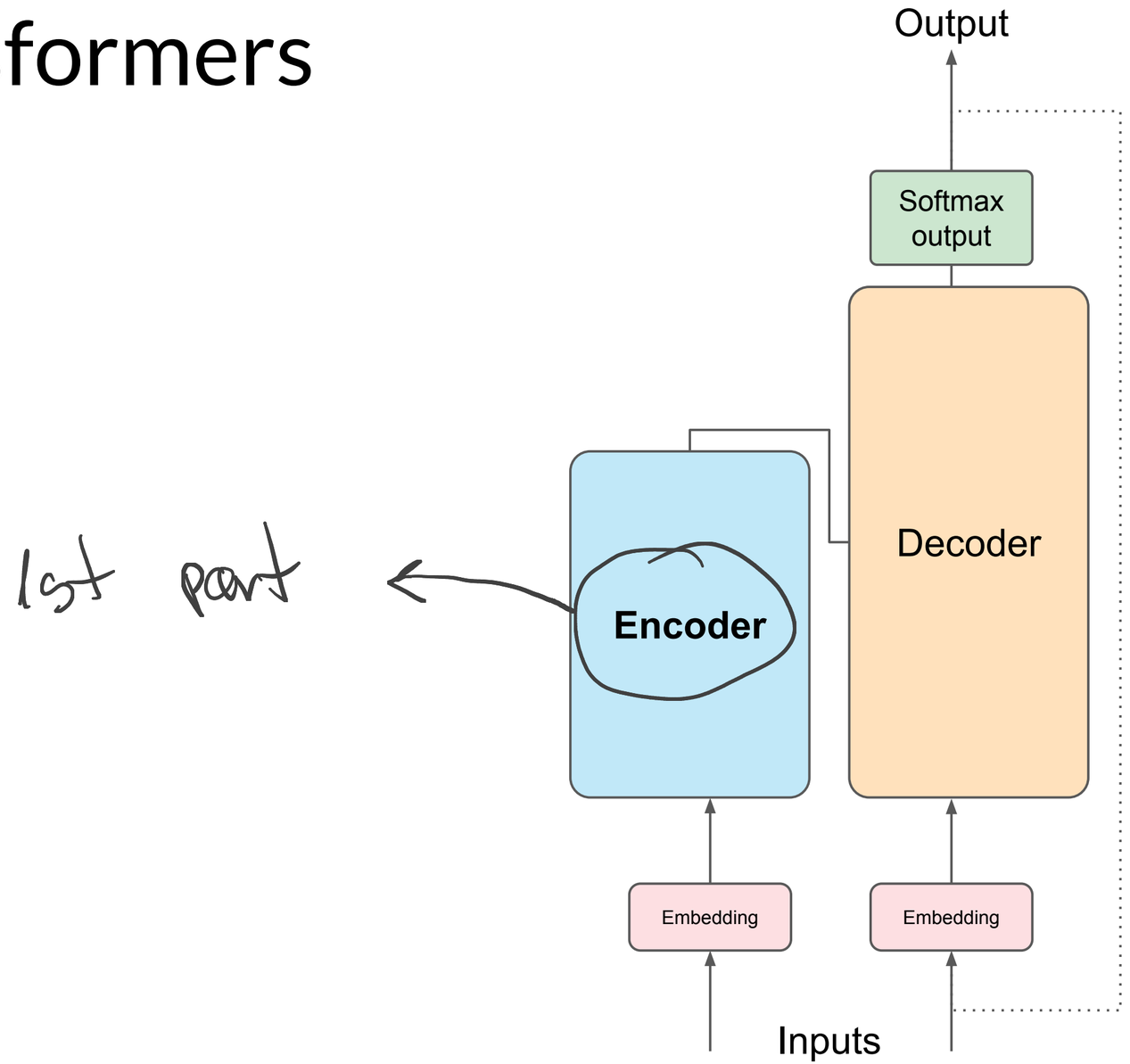

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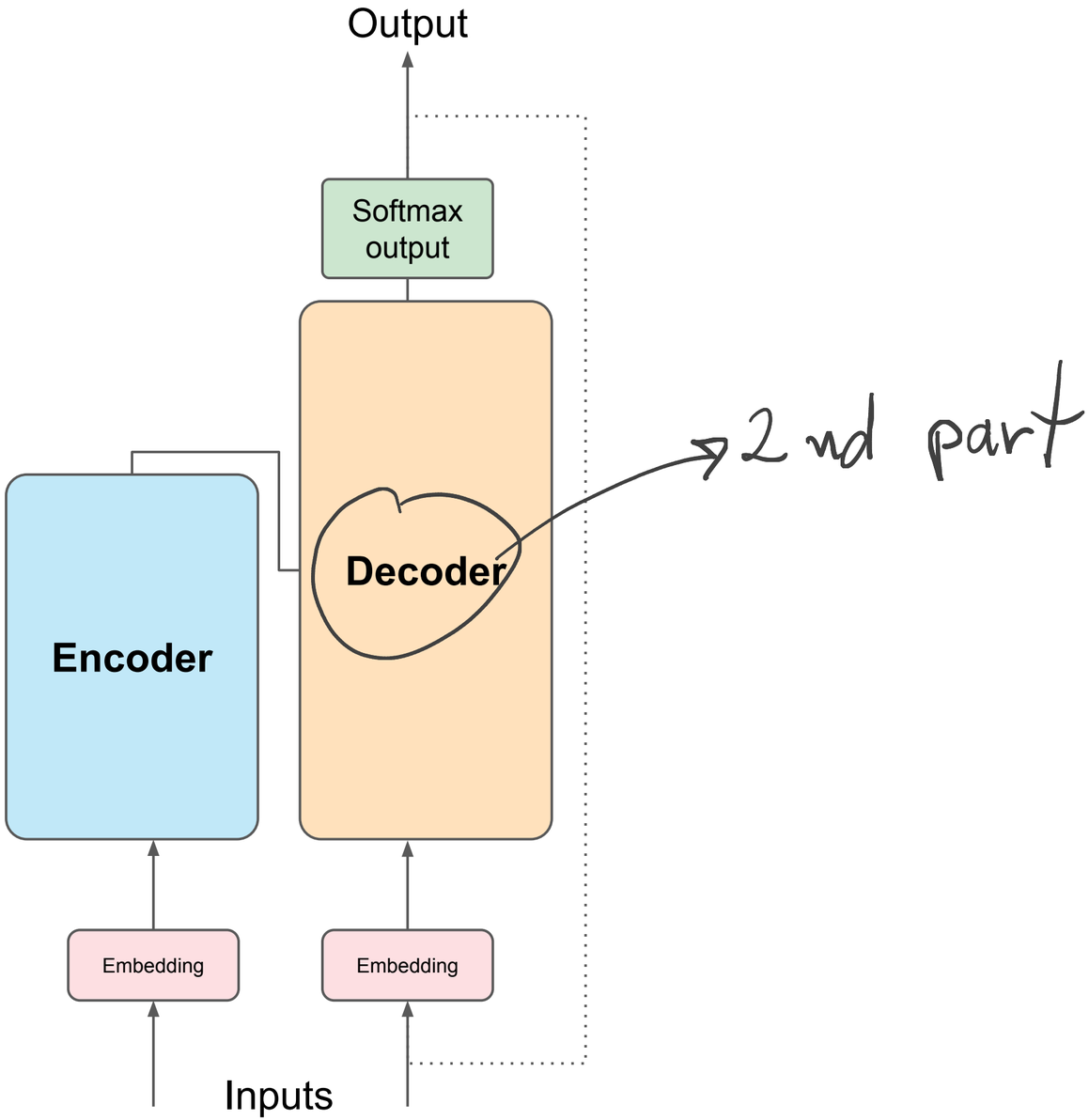

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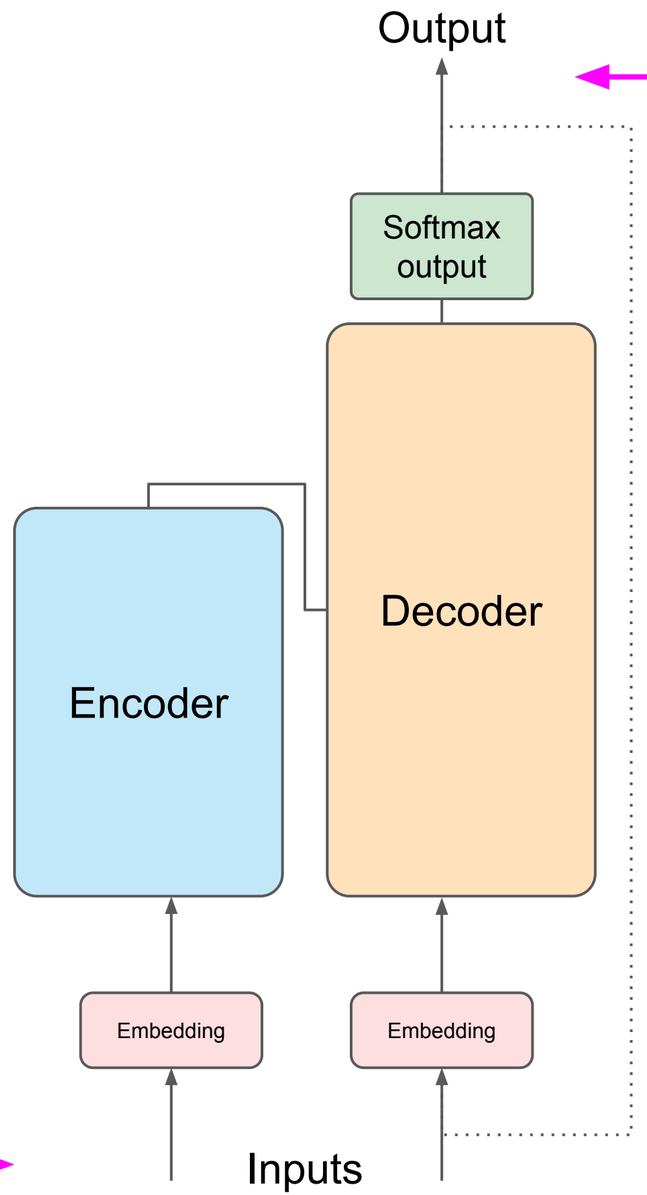



outputs on TOP

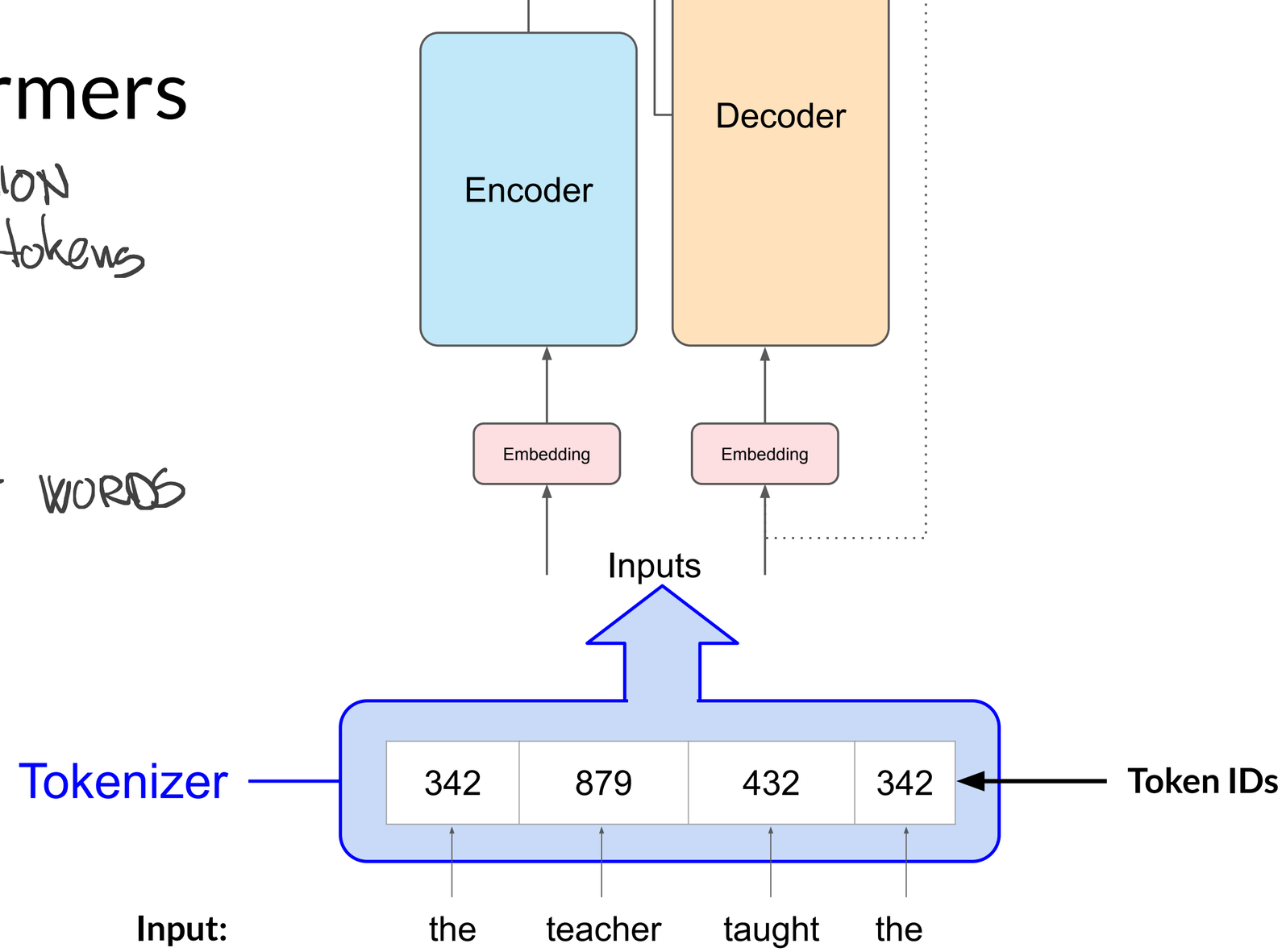
inputs from BOTTOM

# Transformers

1st - TOKENIZATION
words to tokens

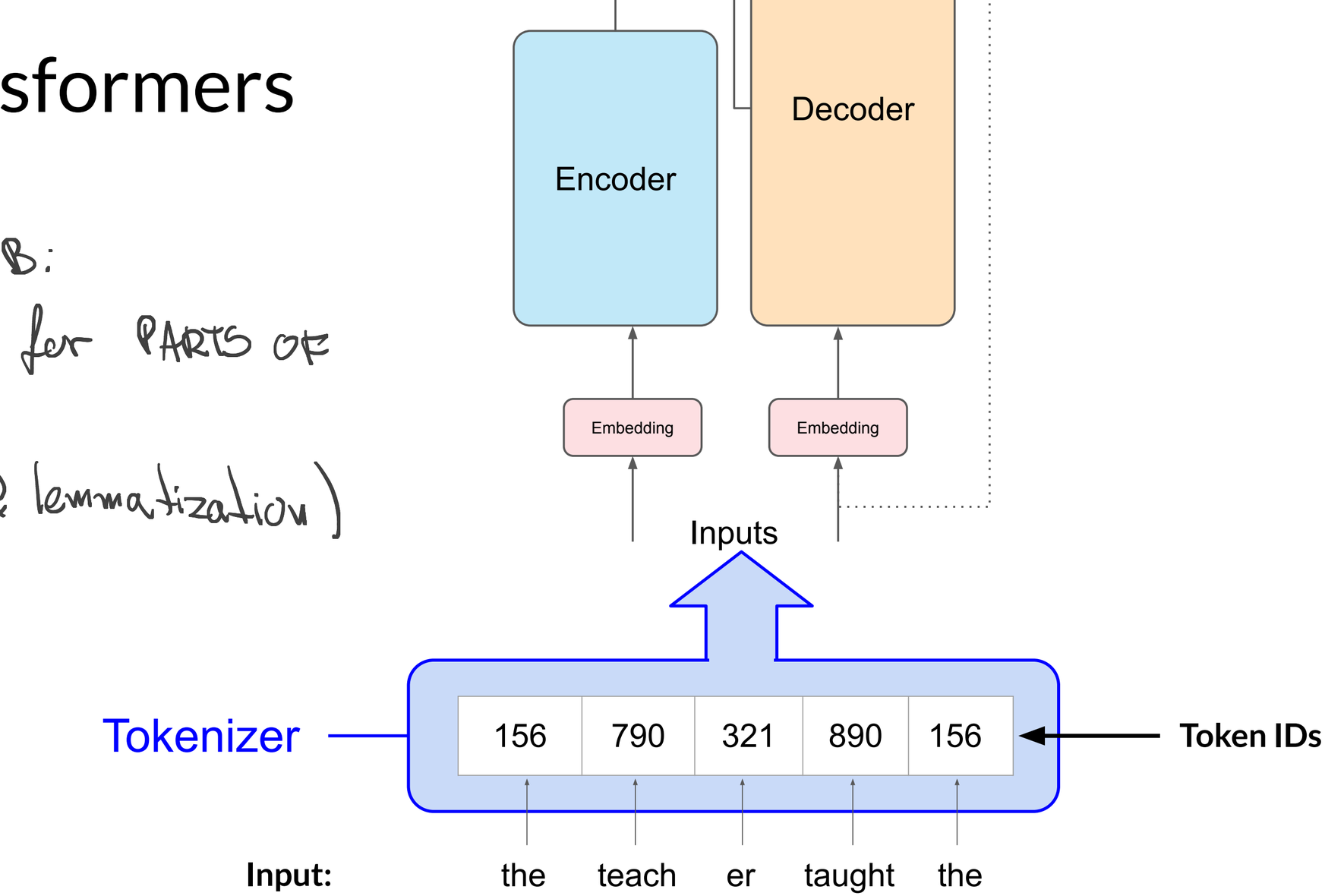
variant A:

Tokens for WORDS



# Transformers

variant B:
TOKENS for PARTS OF WORD
(stemming & lemmatization)

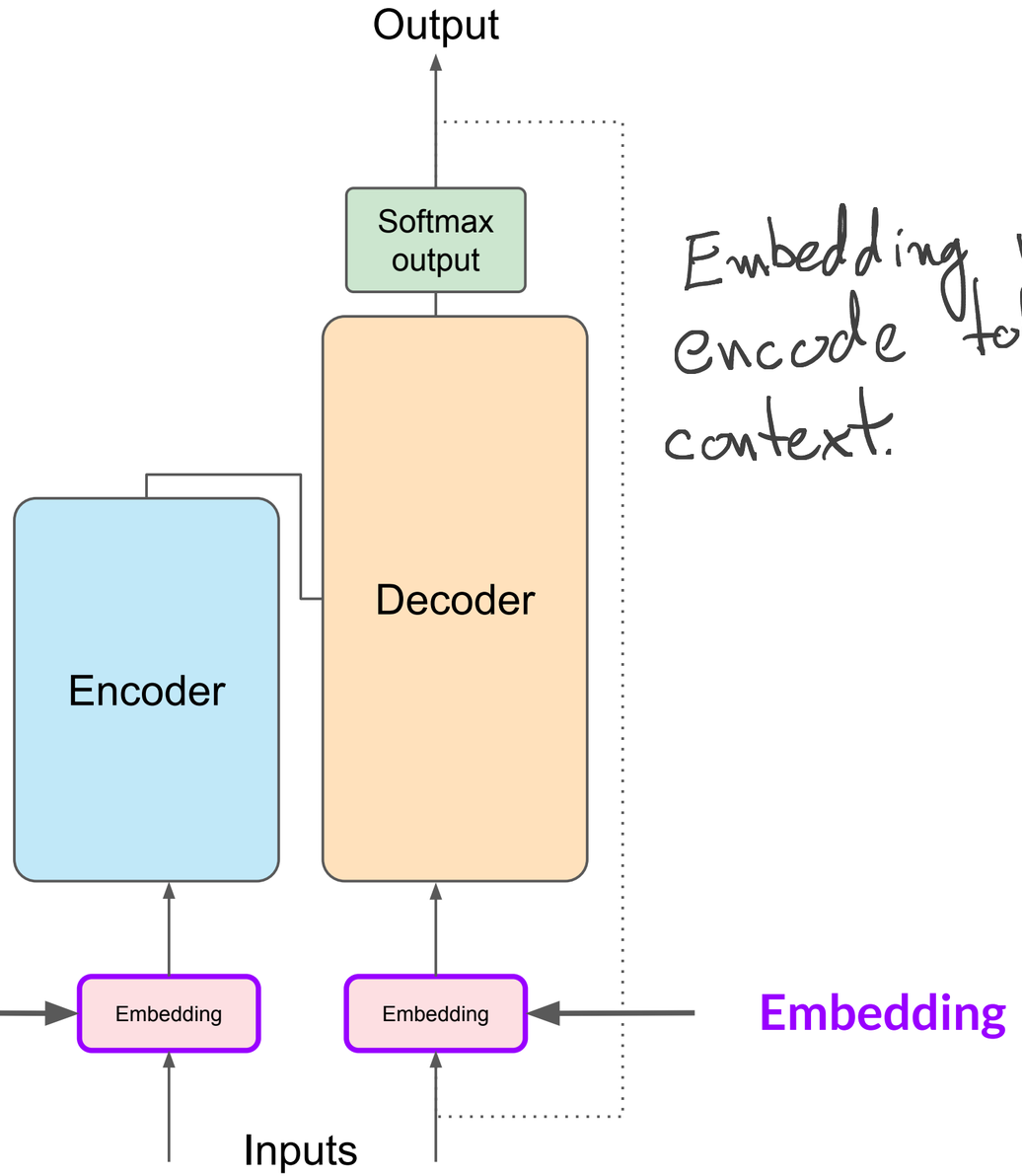


# Transformers

2nd - EMBEDDINGS

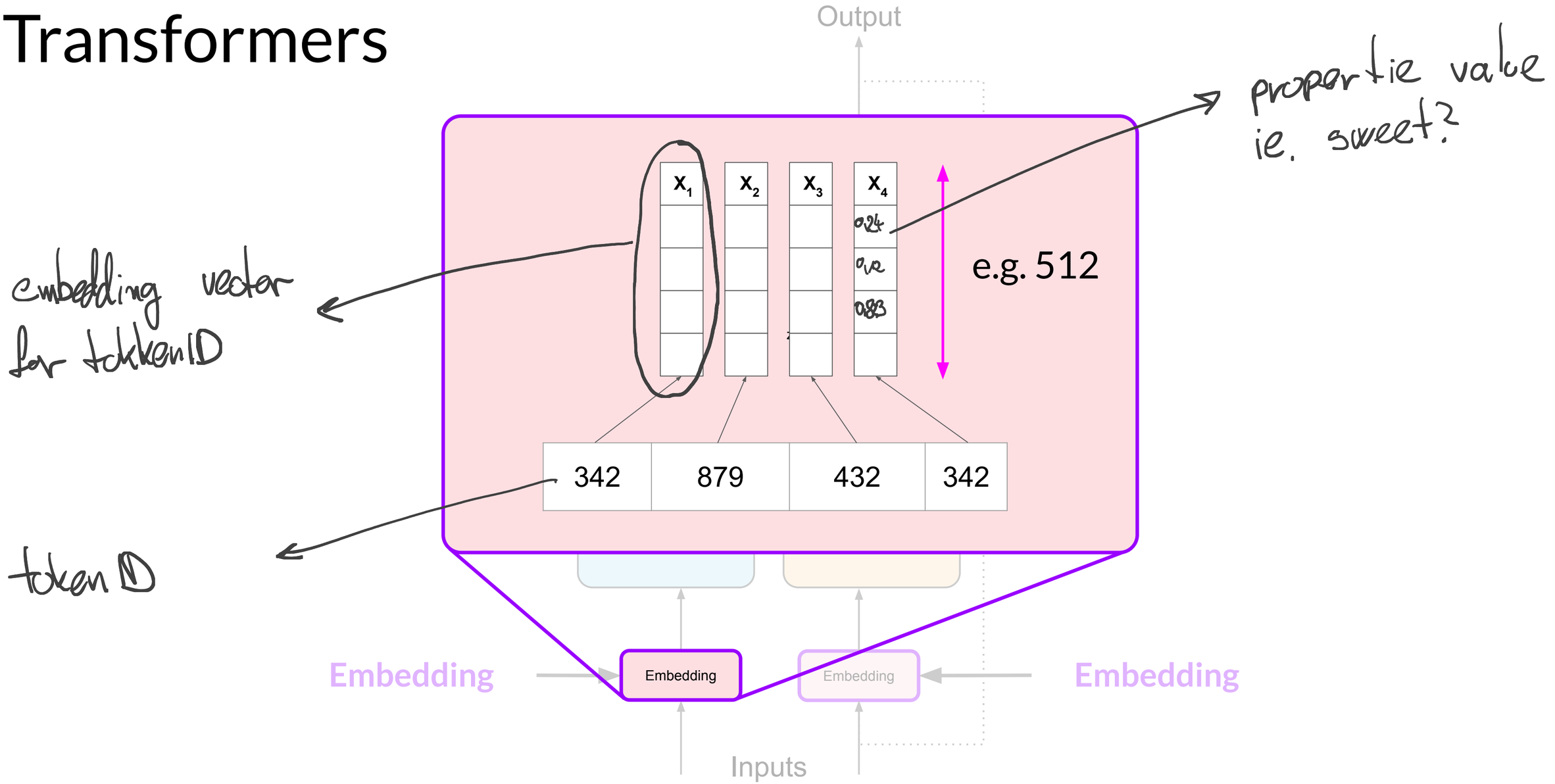
trainable vector embedding space.

Each TOKEN is REPRESENTED as VECTOR in HIGH DIMENSIONAL SPACE occupating UNIQUE LOCATION.




Embedding vectors learn to encode token meaning and context.

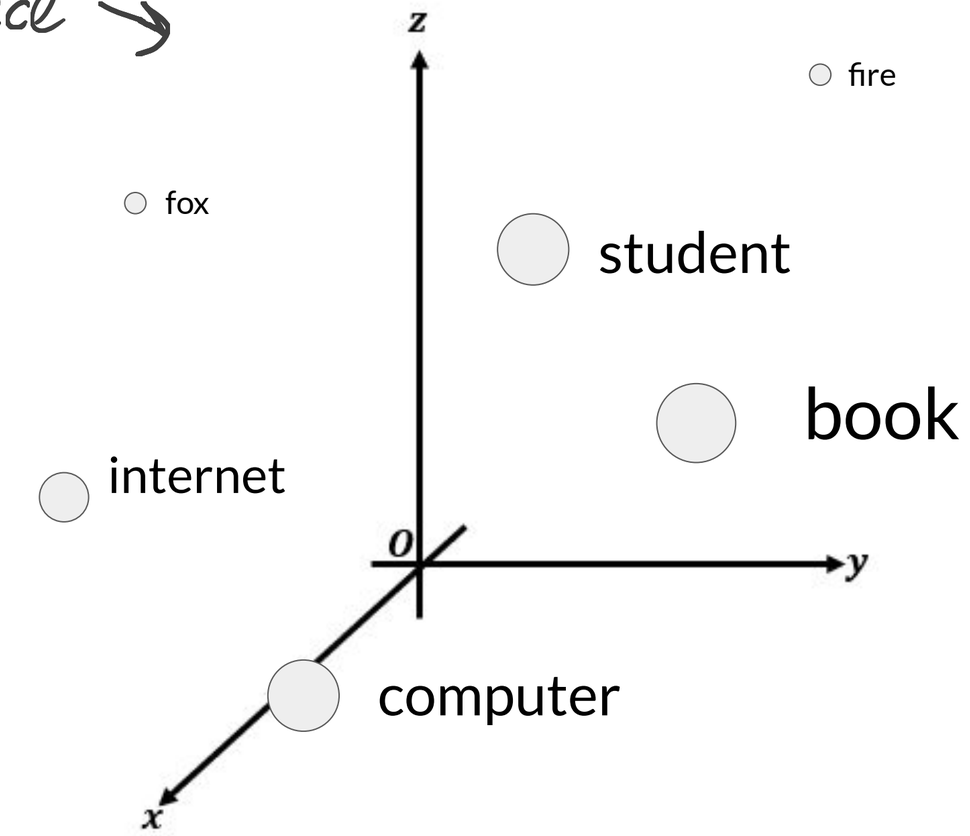
# Transformers



# Transformers

3 dimensional vector space →

For visualizing higher dimension spaces the dimensionality reduction techniques could be used like PCA, tSNE ...



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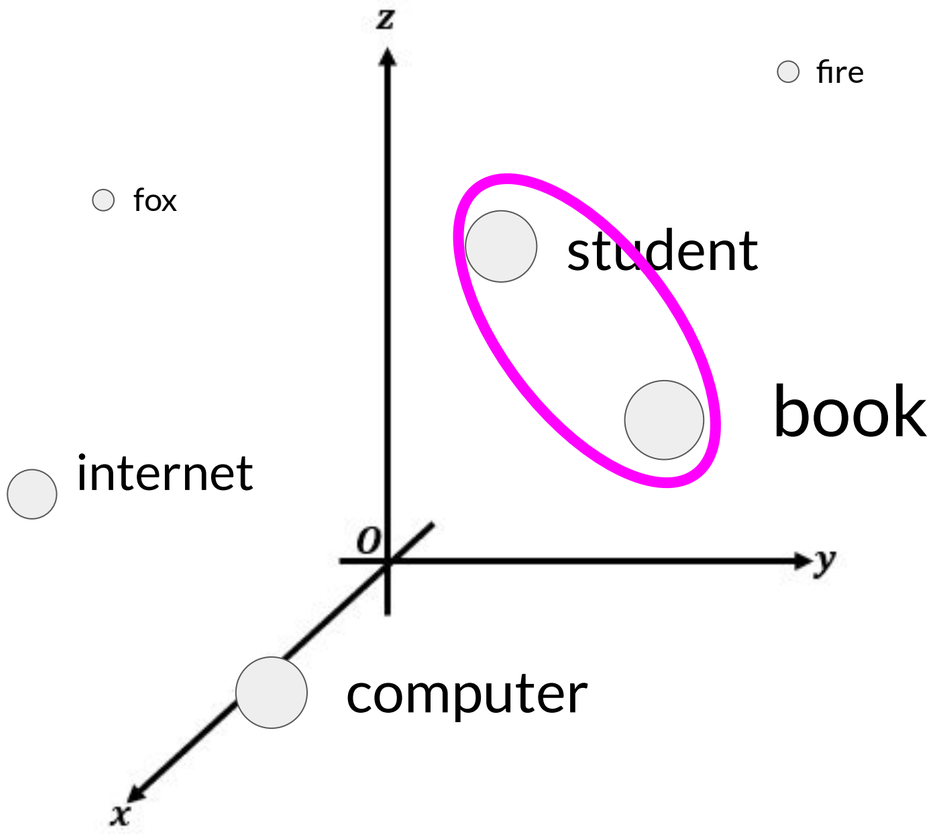

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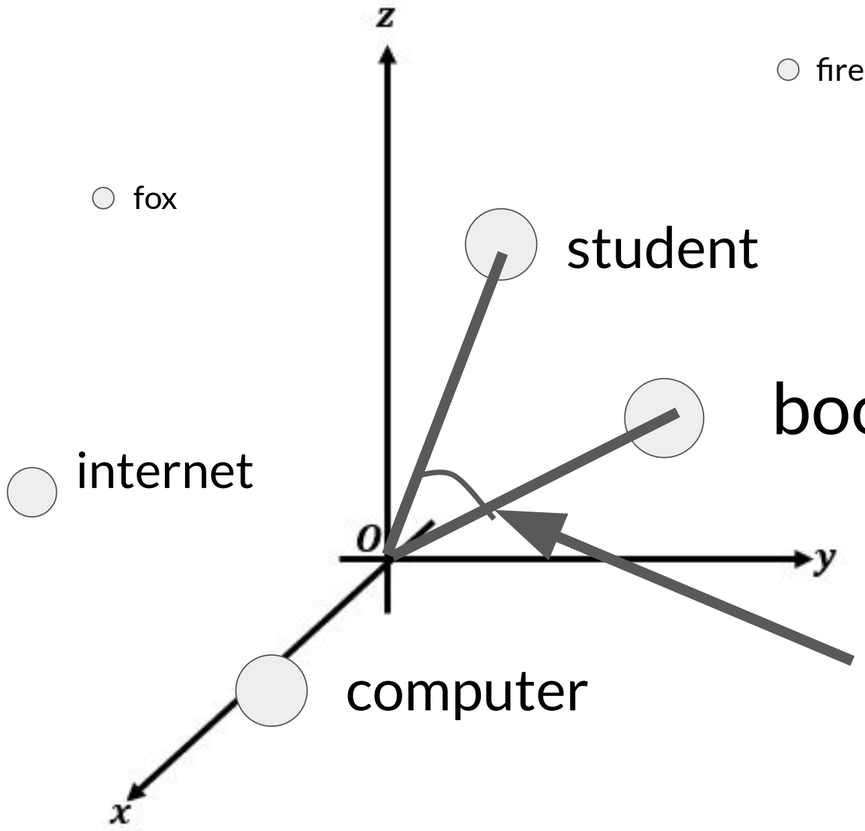
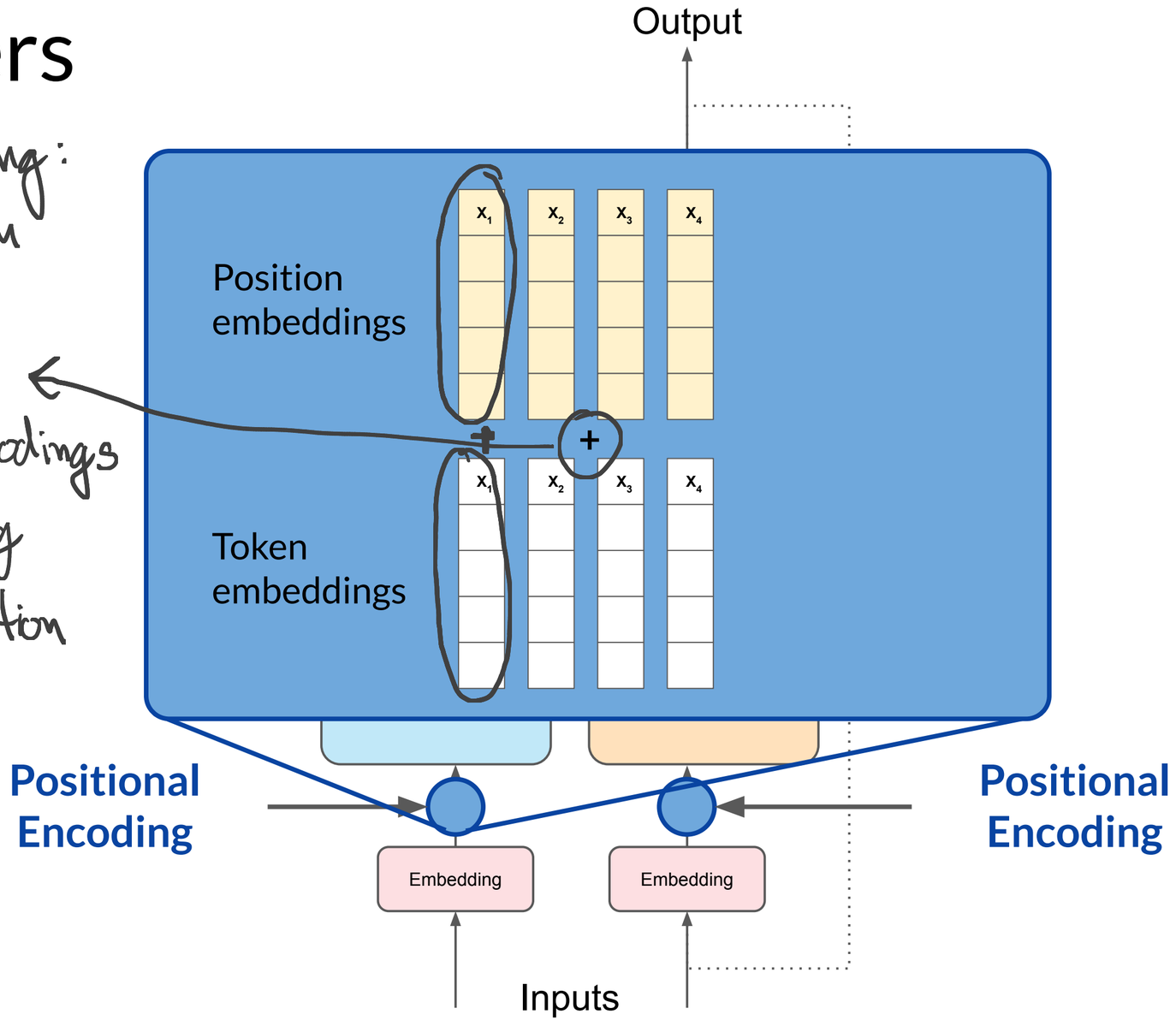



Angle measures distance between words

Cosine distance

# Transformers

3. Positional encoding:
   - preserve information about WORD ORDER
   - sum input TOKENS and positional encodings
   PASS the resulting vector to self-attention layer.

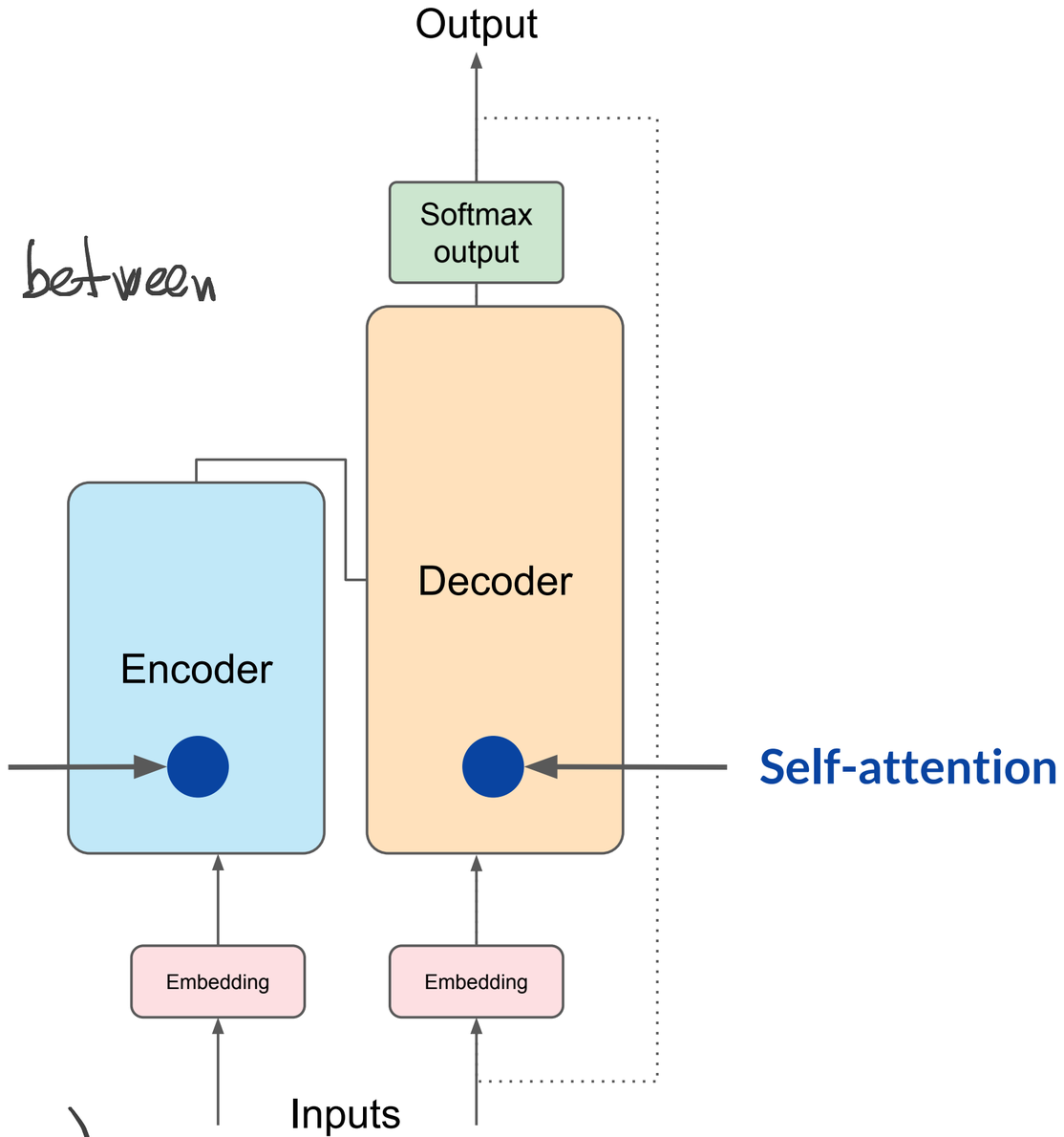


# Transformers

4. Self-attention

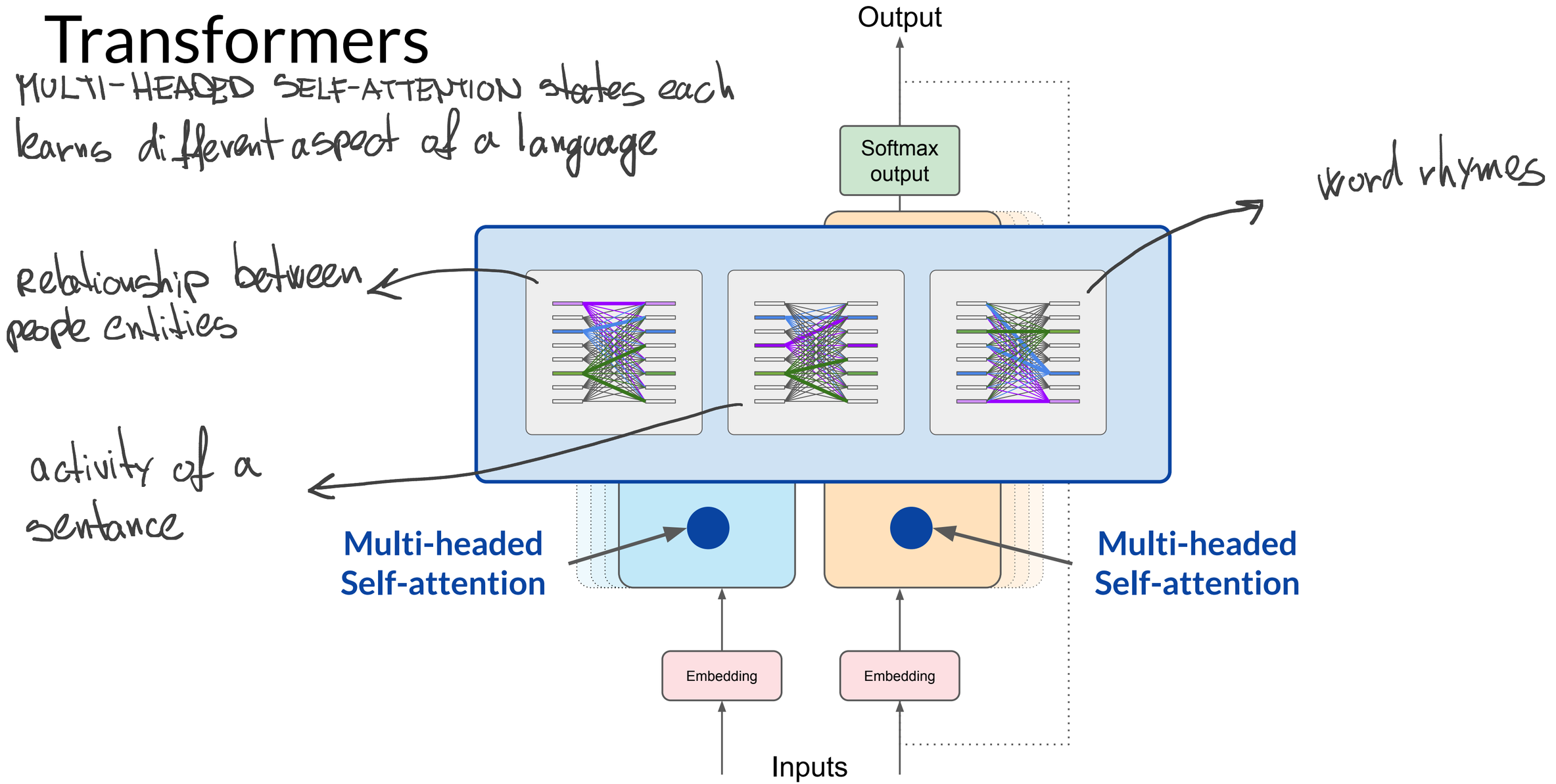
Model analyzes RELATIONSHIP between tokens in INPUT SEQUENCE.

- to better capture CONTEXTUAL dependencies
- self-attention weights are learned
- this process happens more than once MULTY-HEADED SELF-ATTENTION (ranges from 12-100 are common)



# Transformers

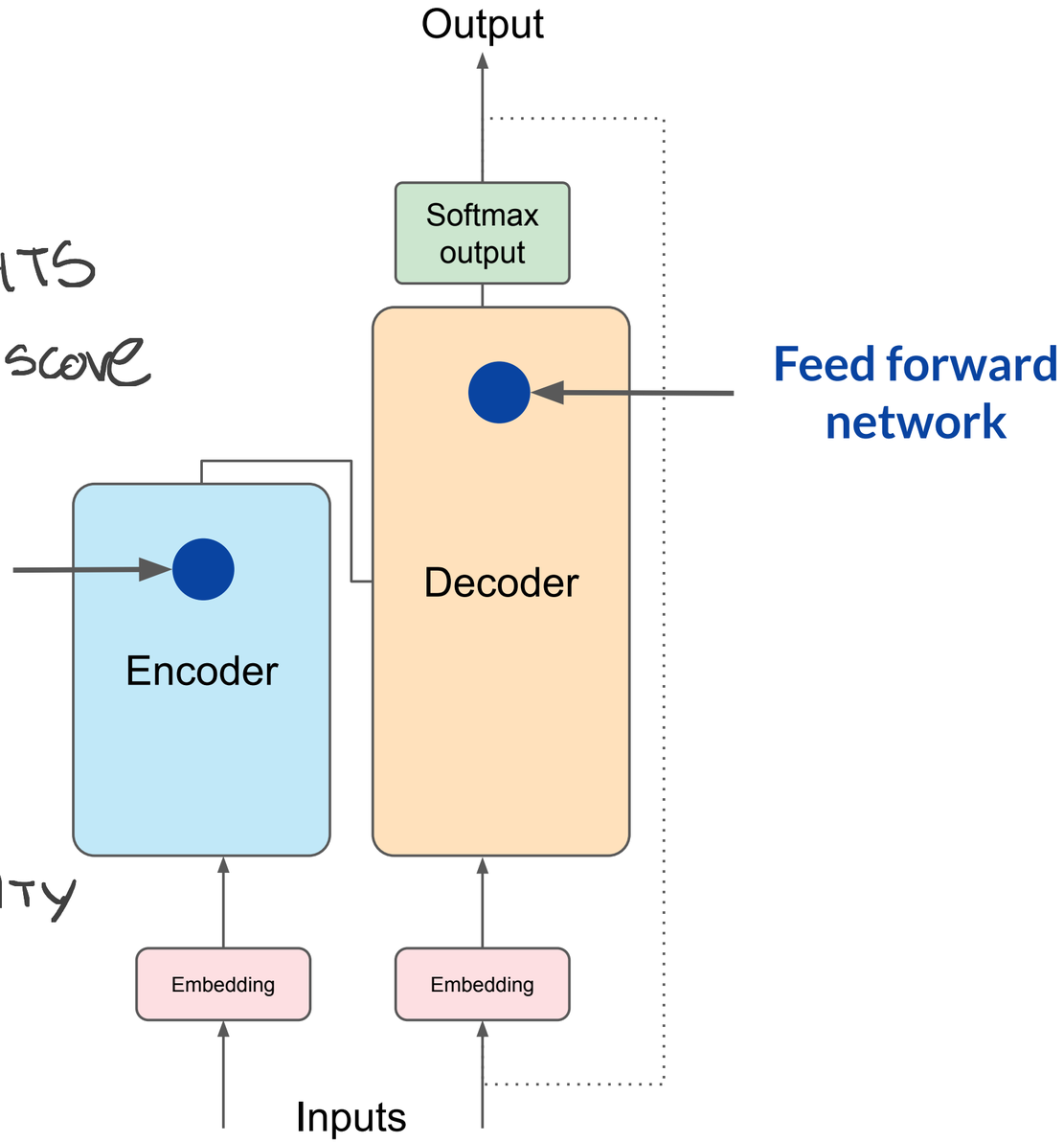
MULTI-HEADED SELF-ATTENTION states each learns different aspect of a language



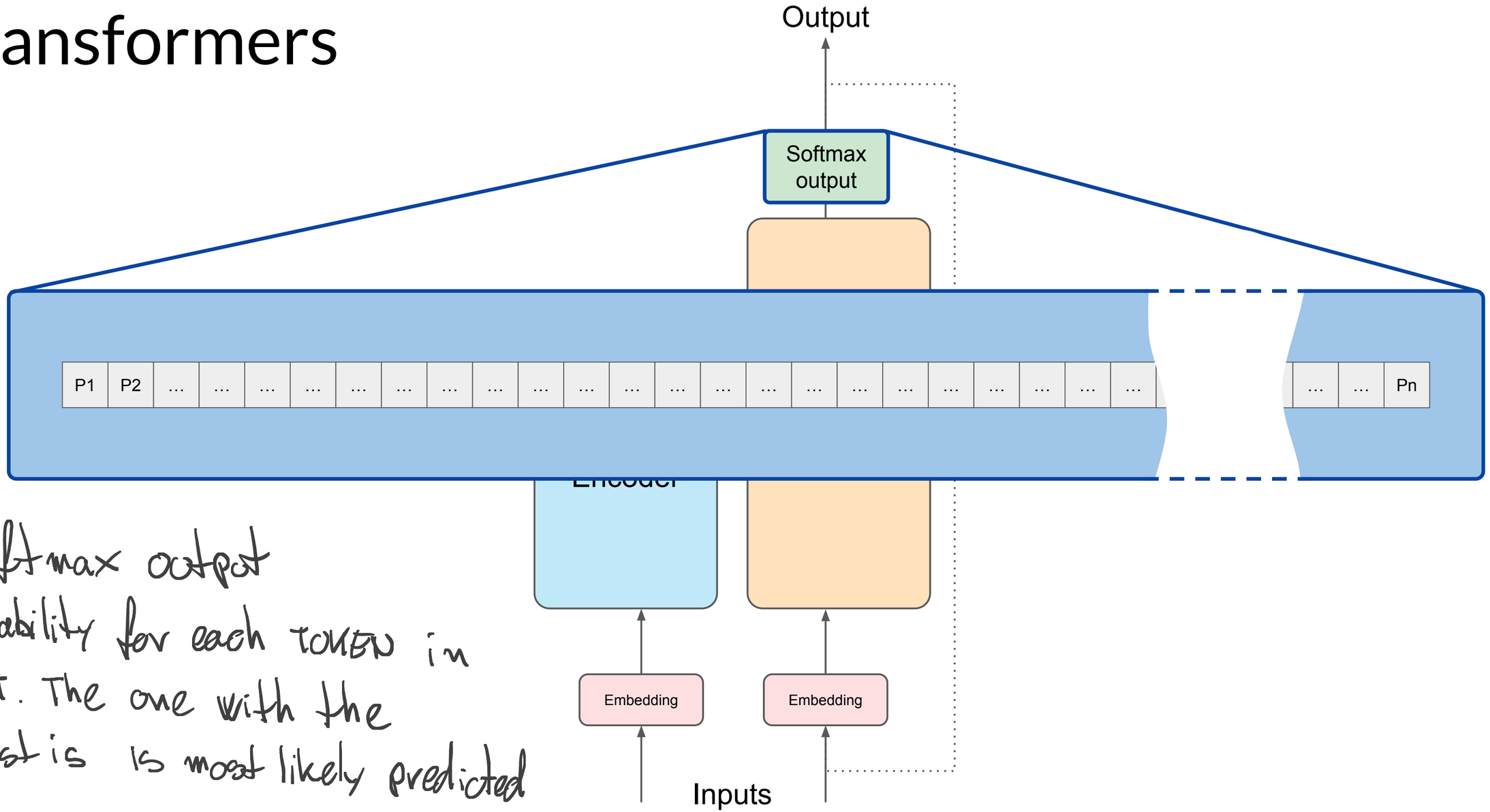
# Transformers

5. FF network
outputs VECTORS of LOGITS
proportional to probability score
for each TOKEN in DICT.

- logits are propagated to
softmax layer for PROBABILITY
SCORE for EACH WORD



# Transformers

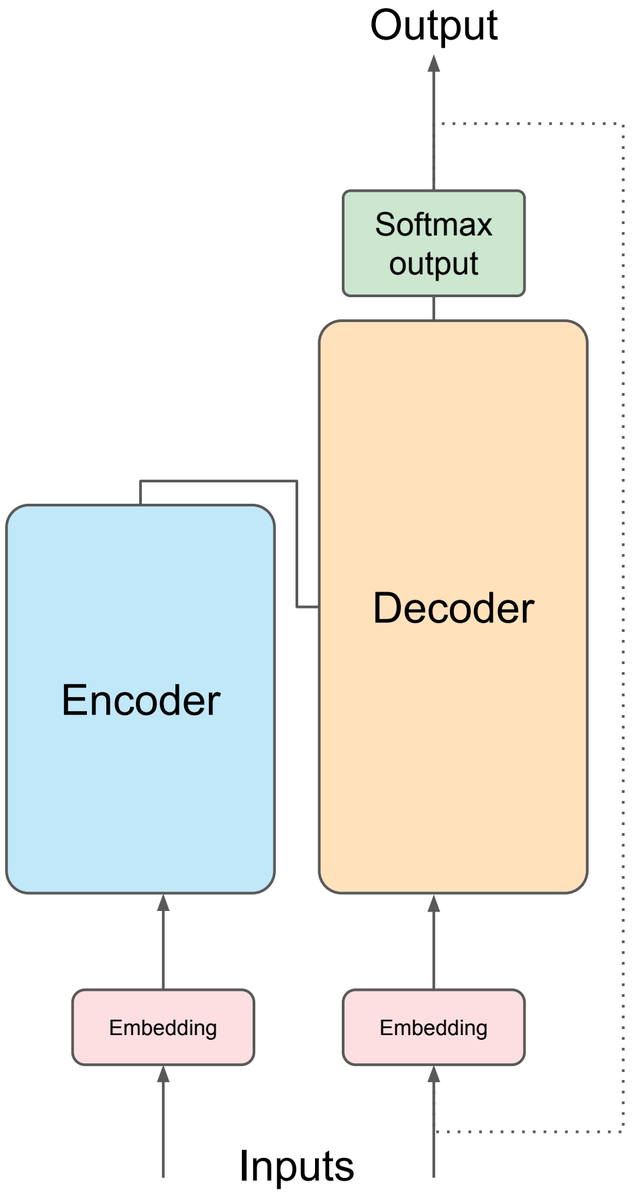



6. Softmax output probability for each TOKEN in DICT. The one with the biggest is is most likely predicted token.

# Transformers

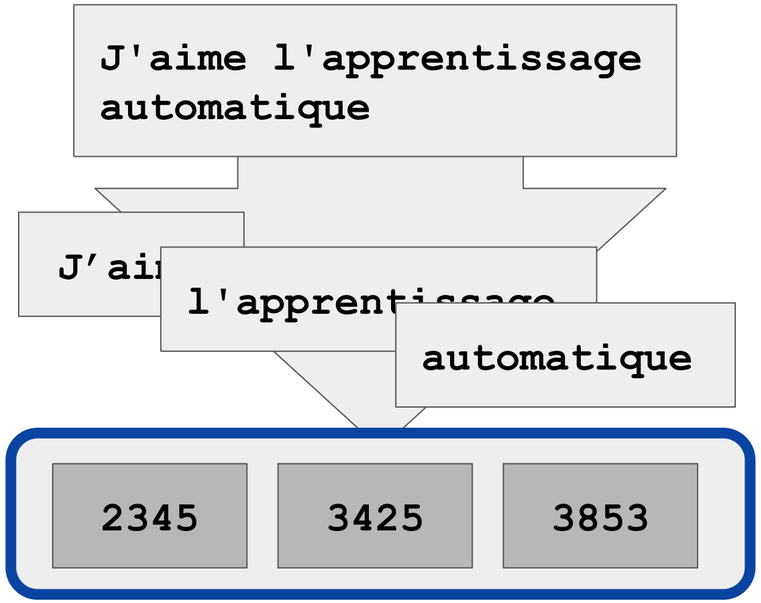
Translation:
sequence-to-sequence task

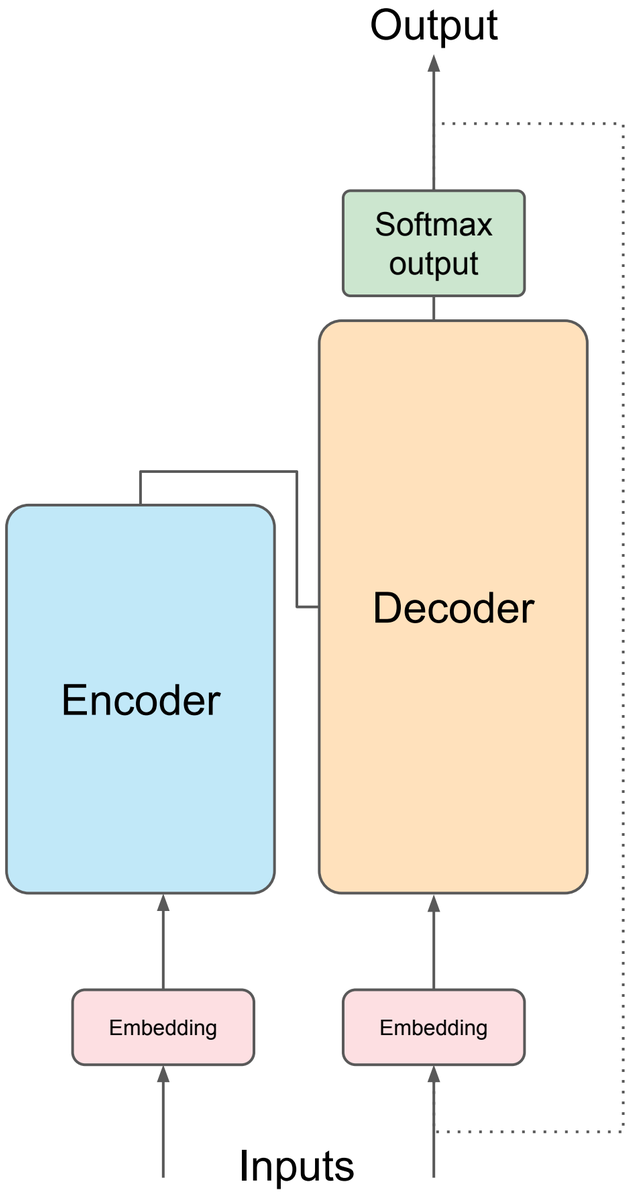
```
J'aime l'apprentissage
automatique
```



# Transformers

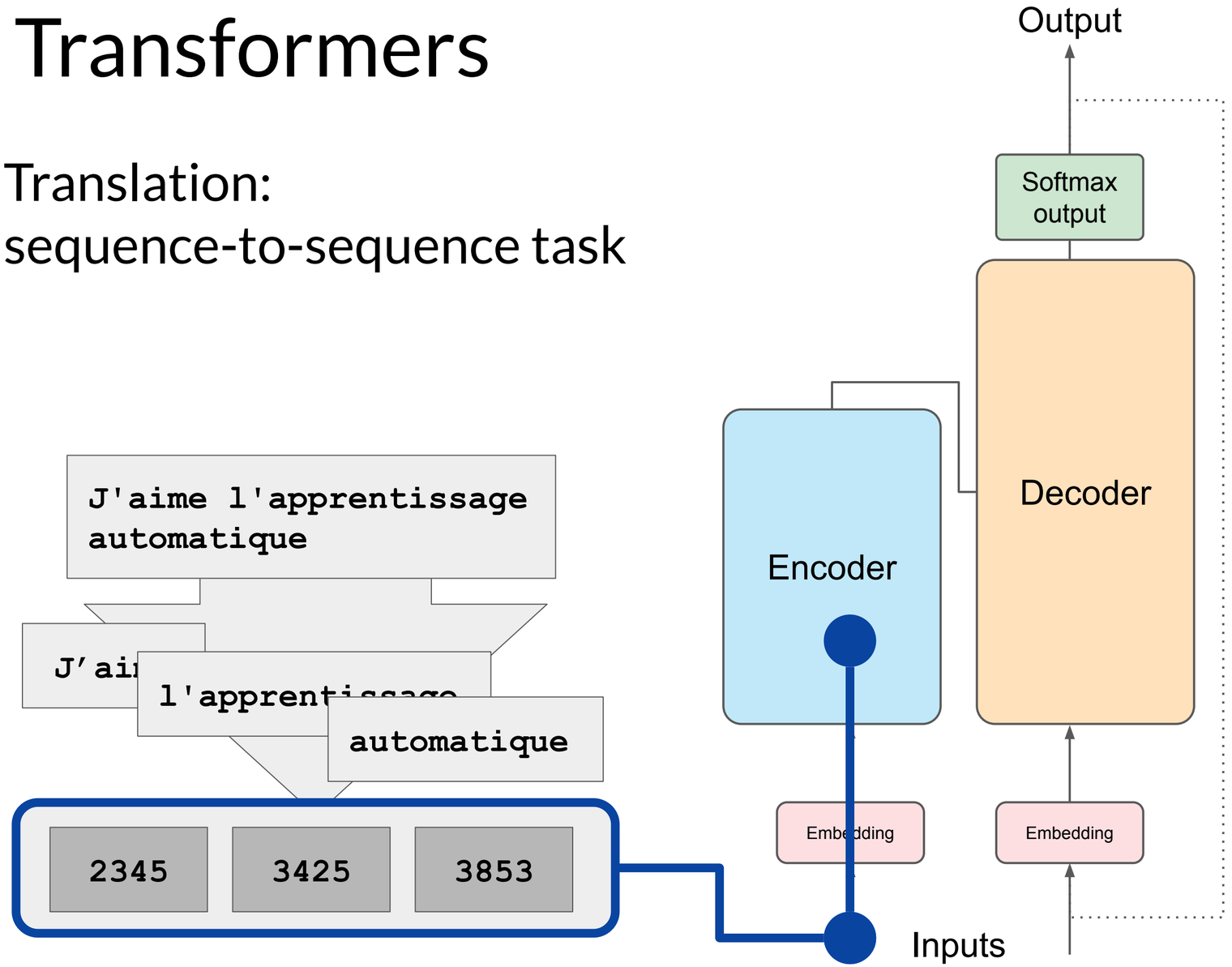
Translation:
sequence-to-sequence task



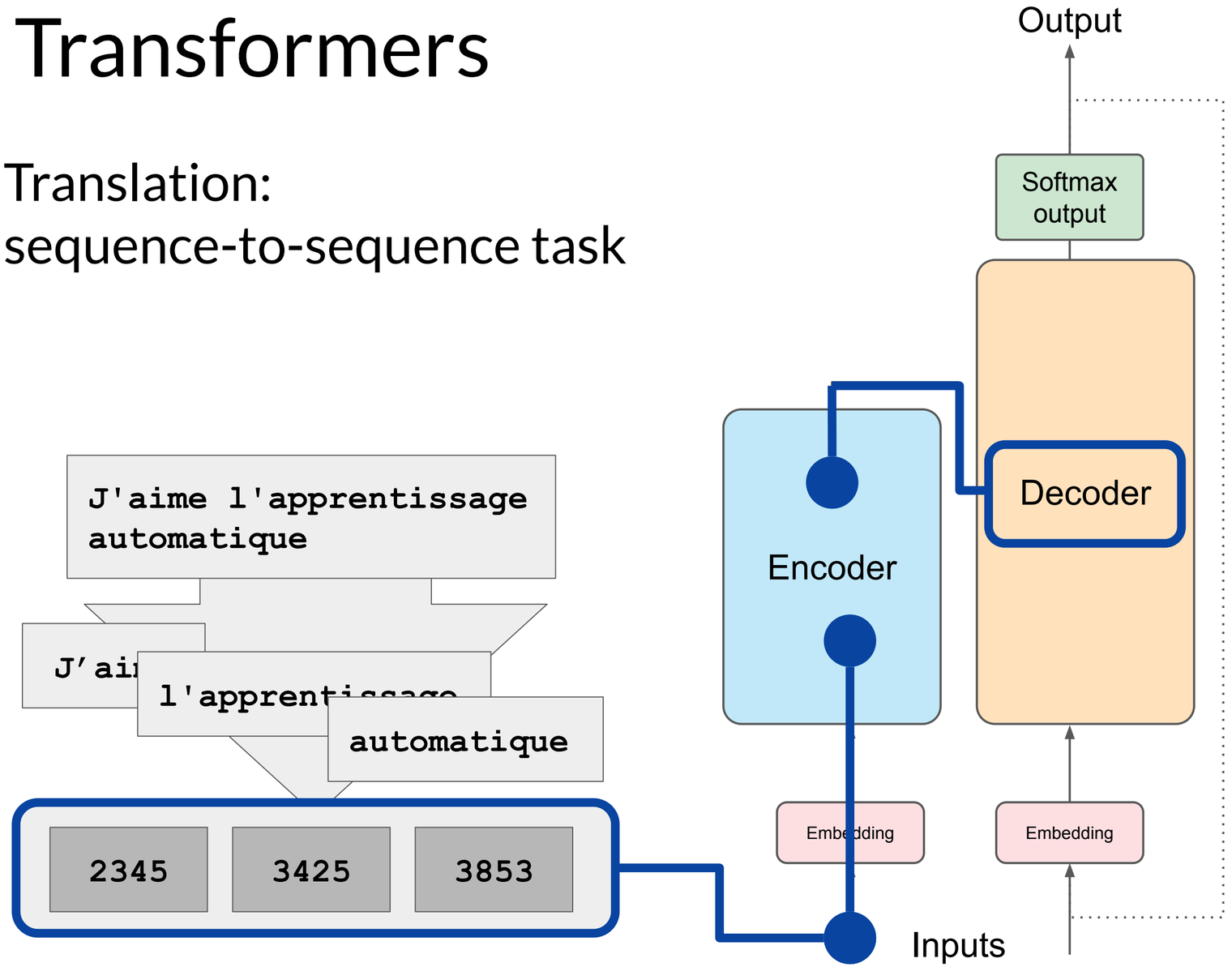
# Transformers

Translation:
sequence-to-sequence task



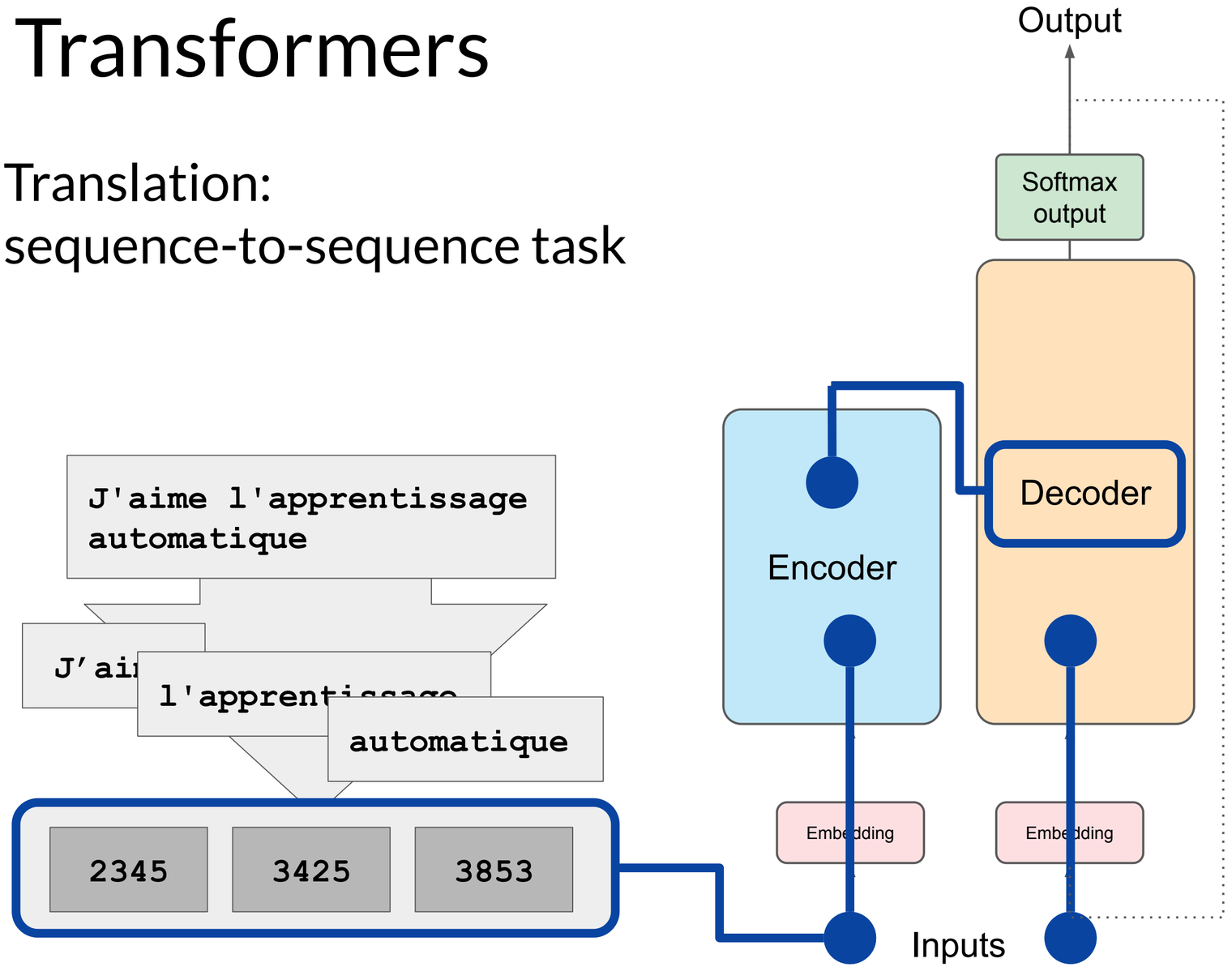
# Transformers

Translation:
sequence-to-sequence task



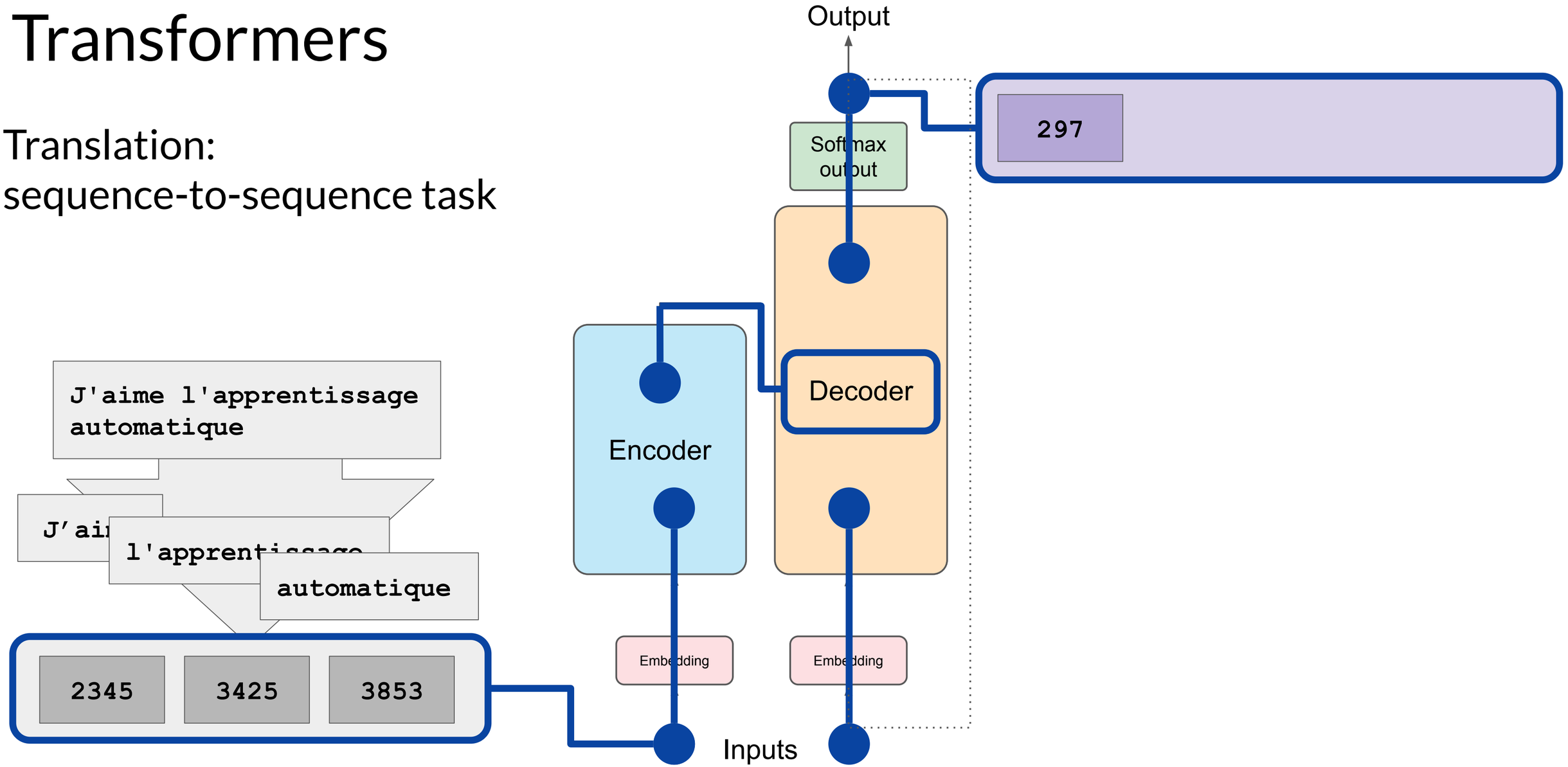
# Transformers

Translation:
sequence-to-sequence task



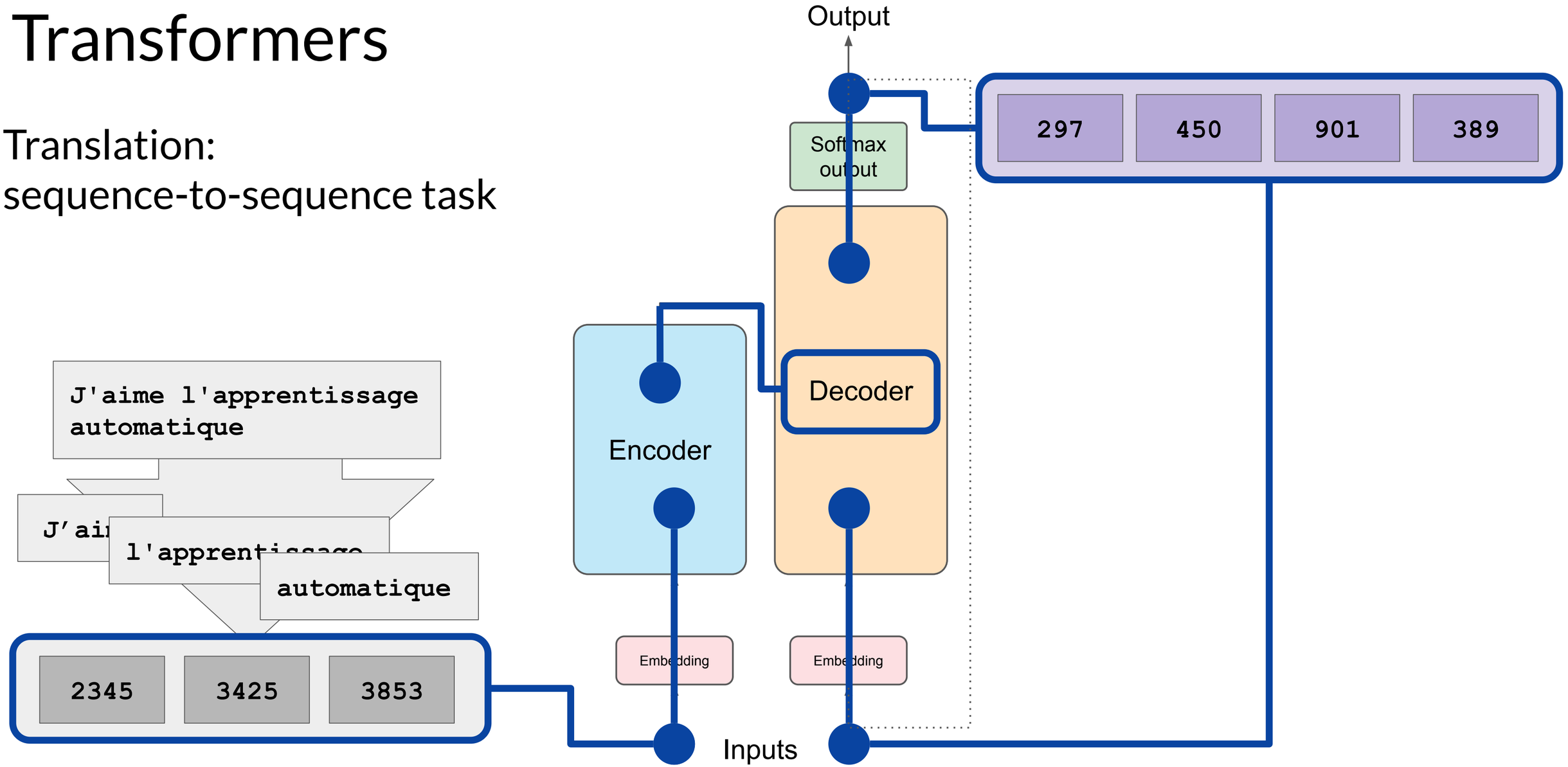
# Transformers

Translation:
sequence-to-sequence task



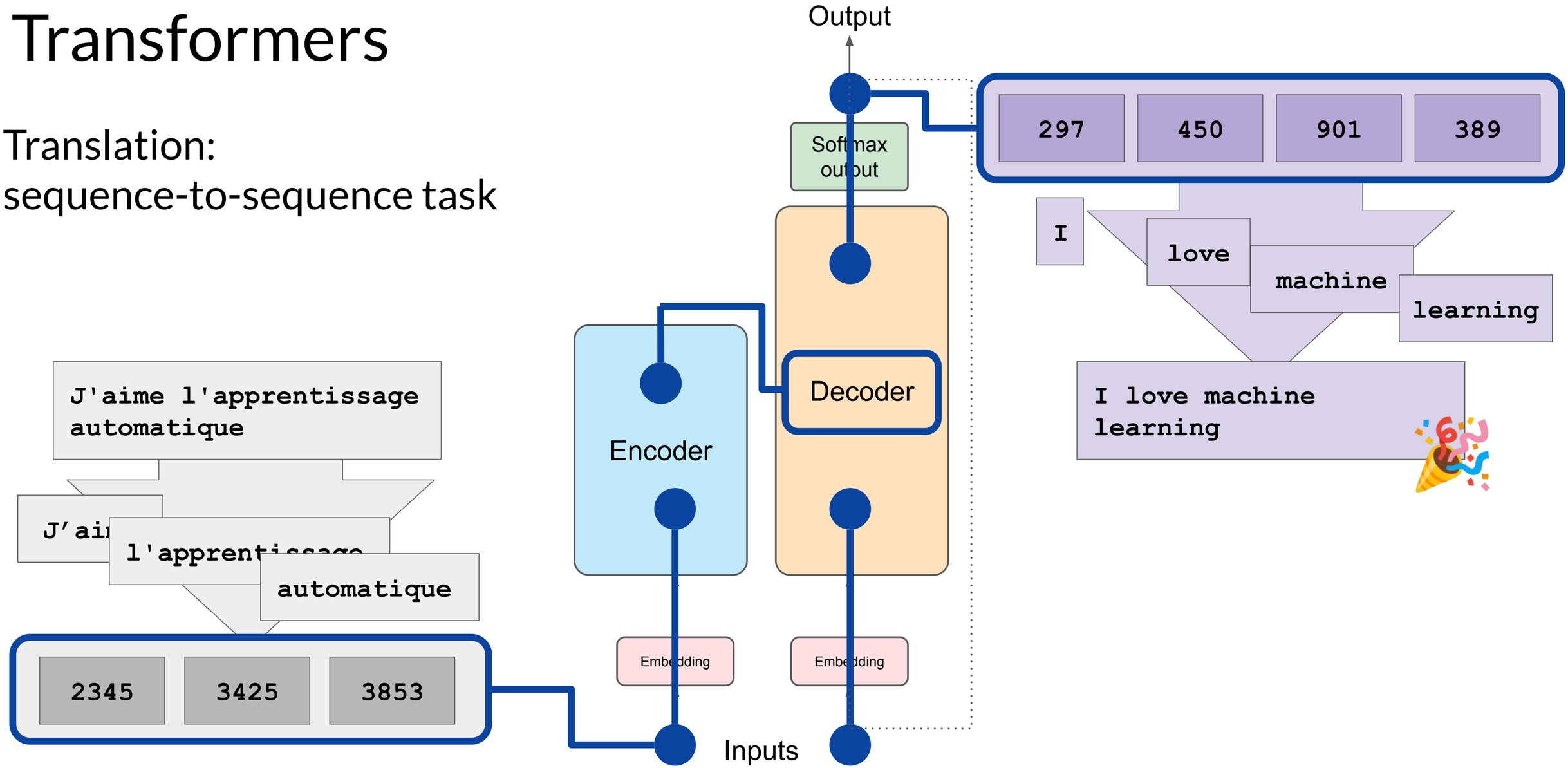
# Transformers

Translation:
sequence-to-sequence task

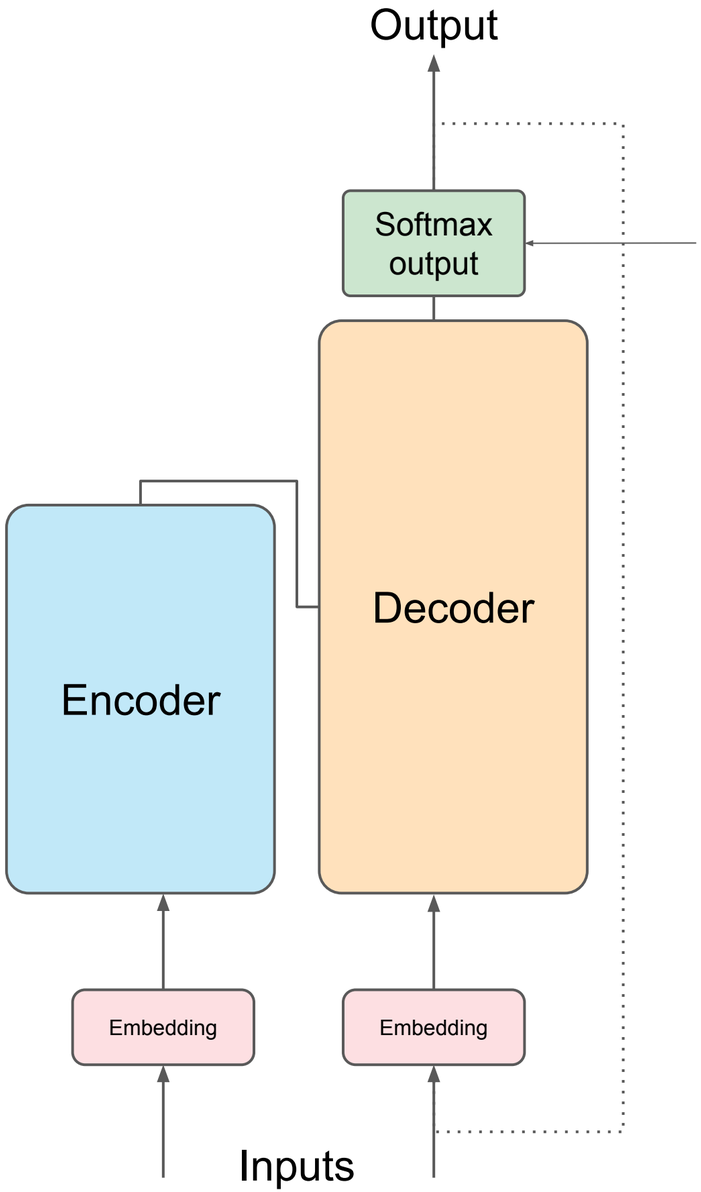


# Transformers

Translation:
sequence-to-sequence task



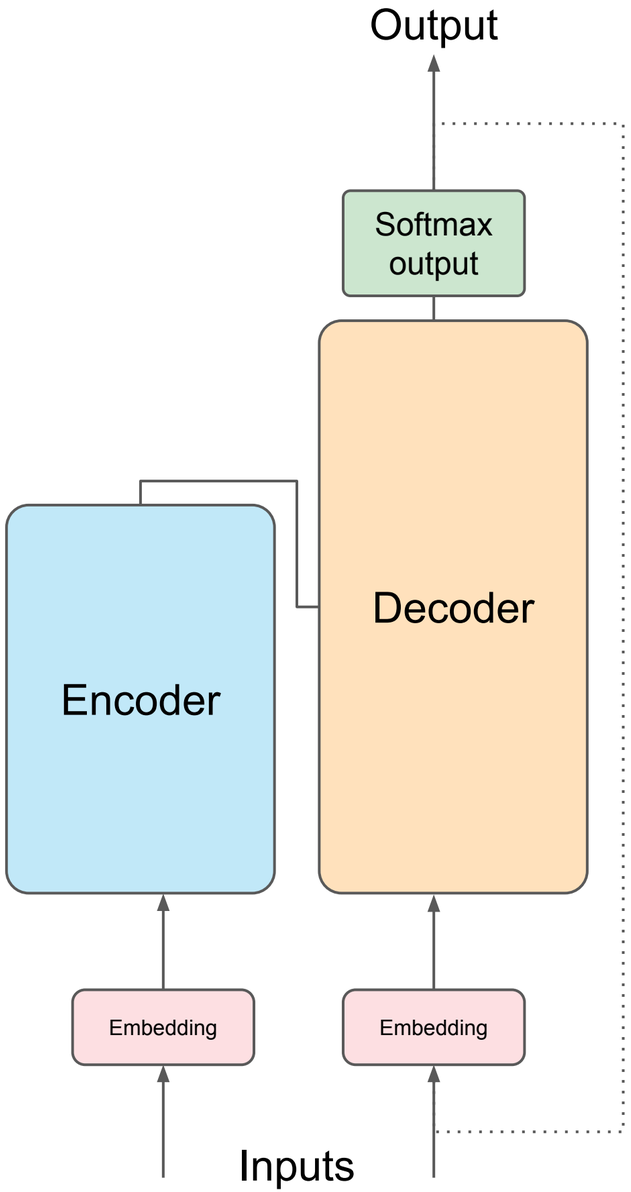
# Transformers




**Softmax output**

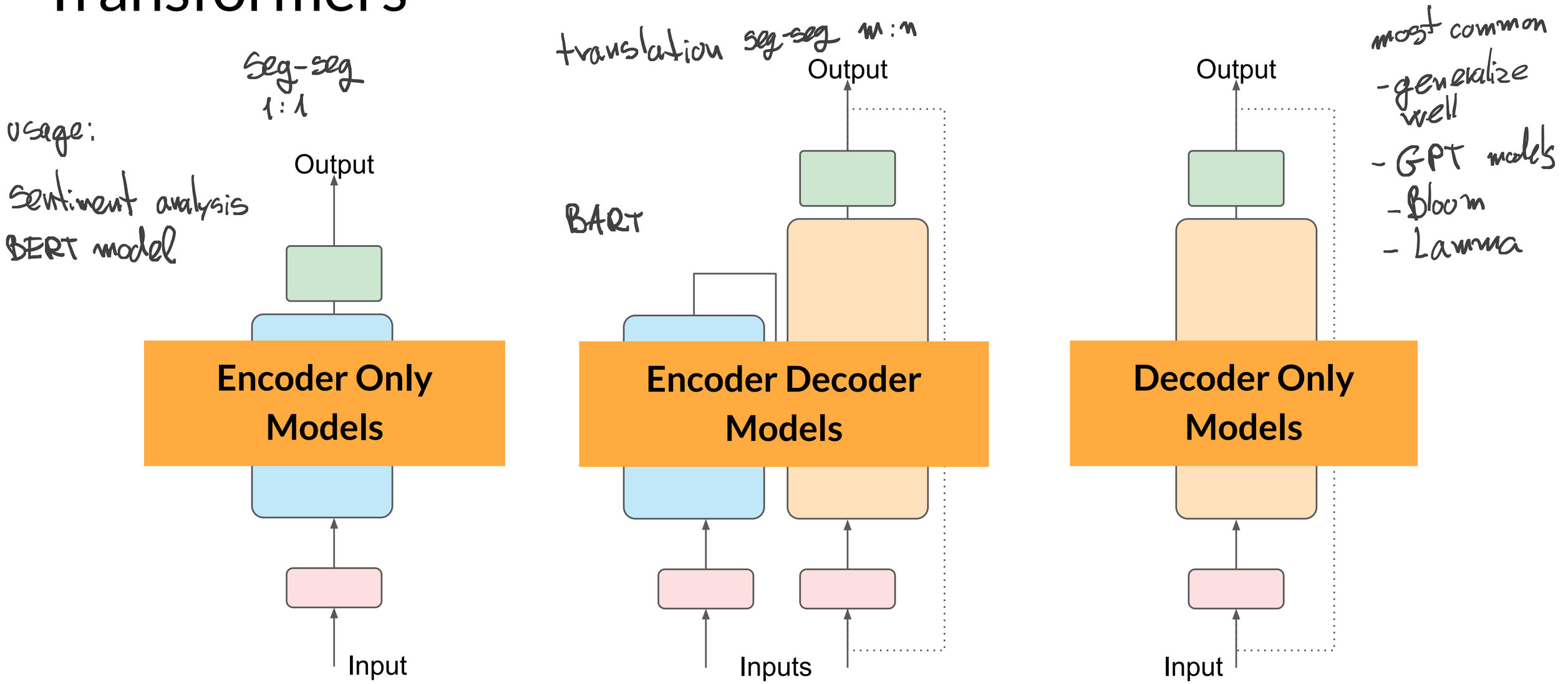
# Transformers

**Encoder**
Encodes inputs (“prompts”) with contextual understanding and produces one vector per input token.



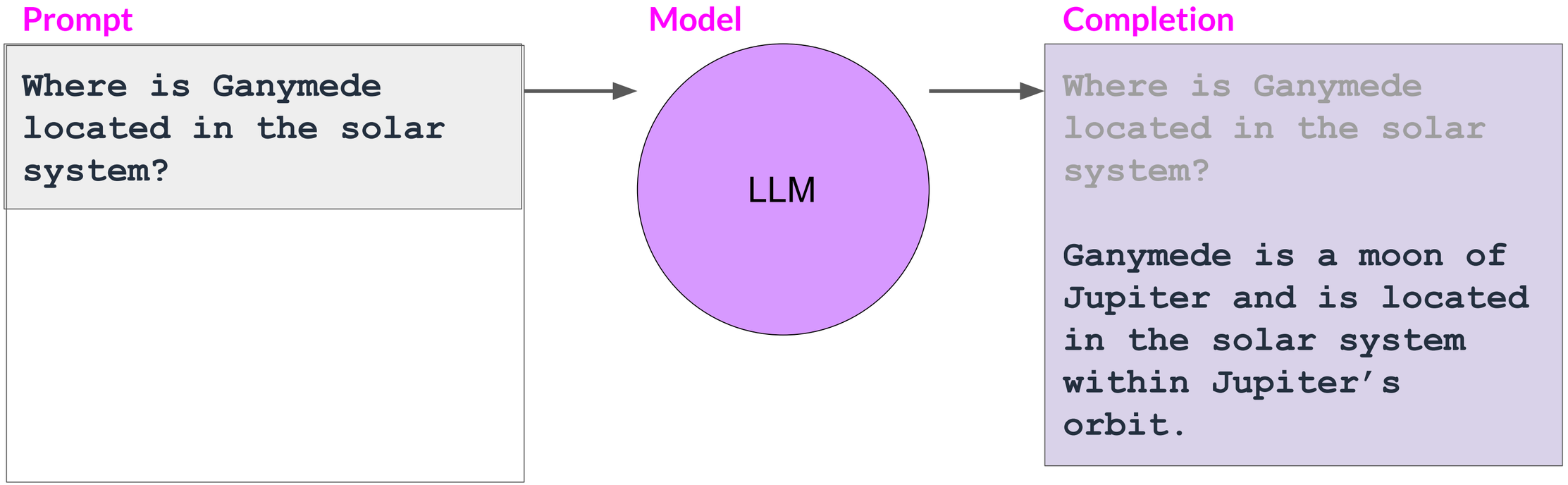

**Decoder**
Accepts input tokens and generates new tokens.

# Transformers



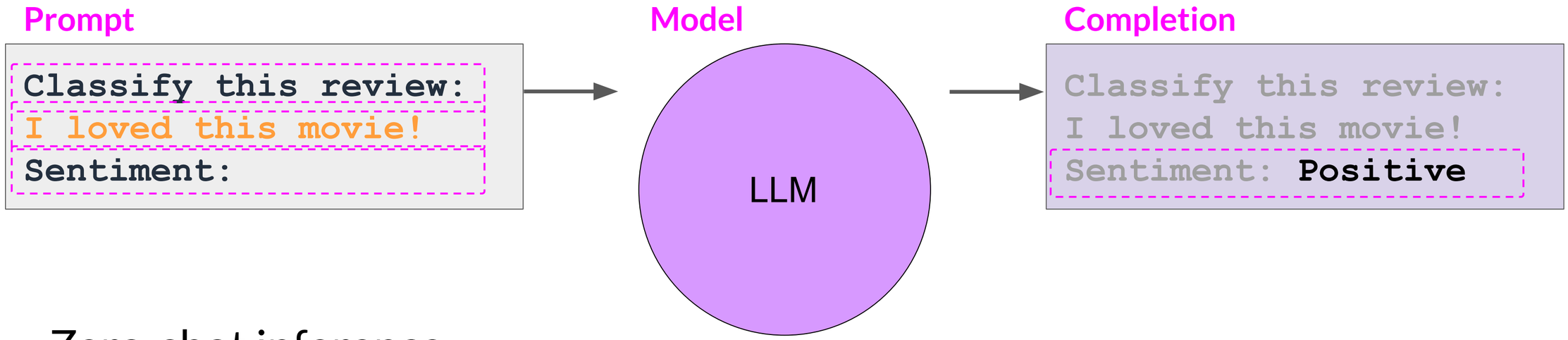
# Prompting and prompt engineering

# Prompting and prompt engineering




**Context window**: typically a few thousand words

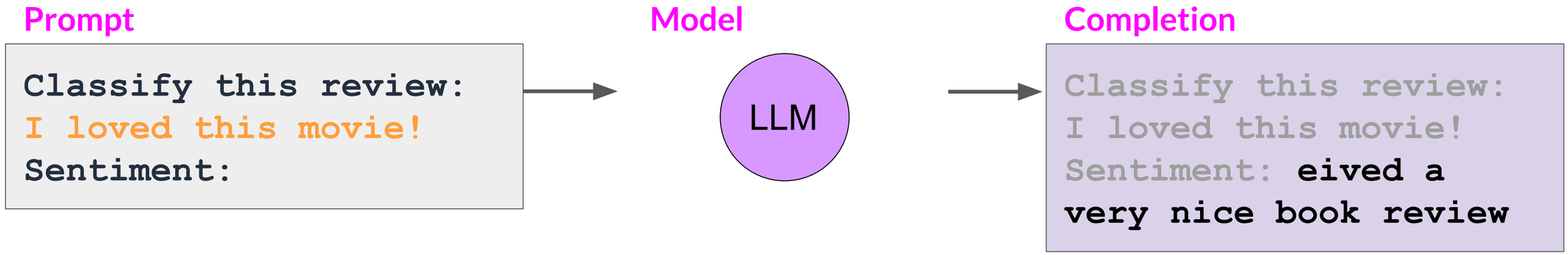
# In-context learning (ICL) - zero shot inference



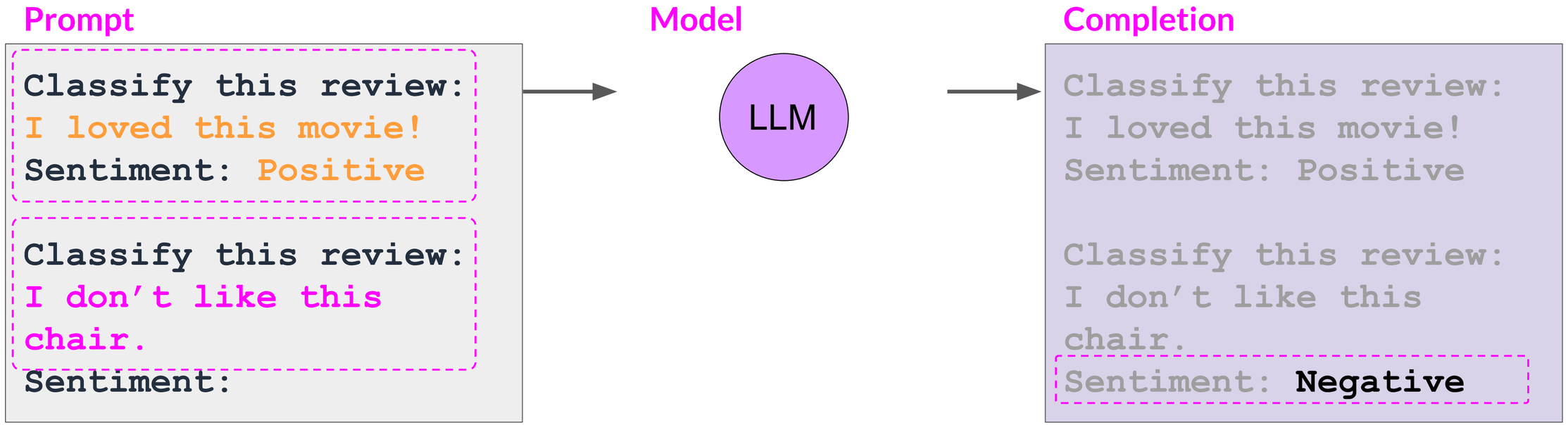

Zero-shot inference

Smaller models can struggle with this ∅ shot

# In-context learning (ICL) - zero shot inference

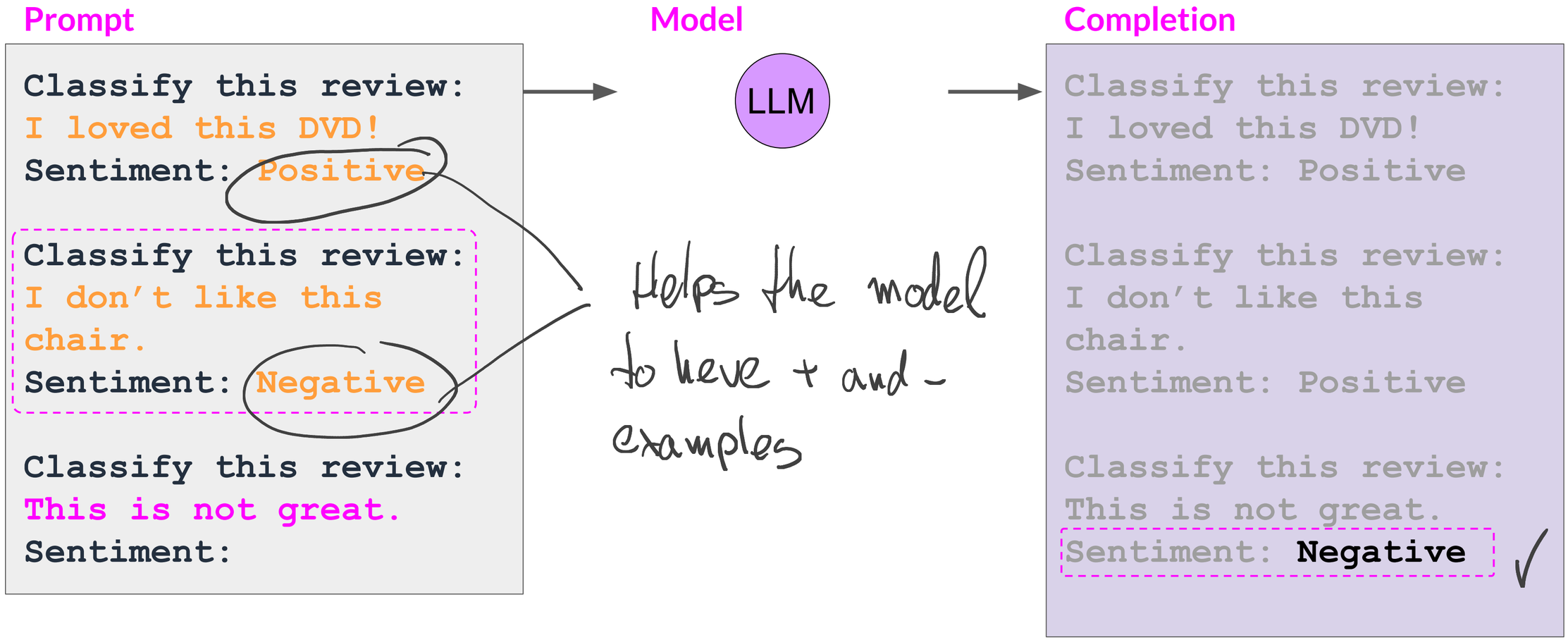


# In-context learning (ICL) - one shot inference




One-shot inference

# In-context learning (ICL) - few shot inference



# Summary of in-context learning (ICL)

Big models

Smaller models

**Prompt // Zero Shot**

```
Classify this review:
I loved this movie!
Sentiment:
```

**Prompt // One Shot**

```
Classify this review:
I loved this movie!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment:
```

**Prompt // Few Shot** >5 or 6 examples

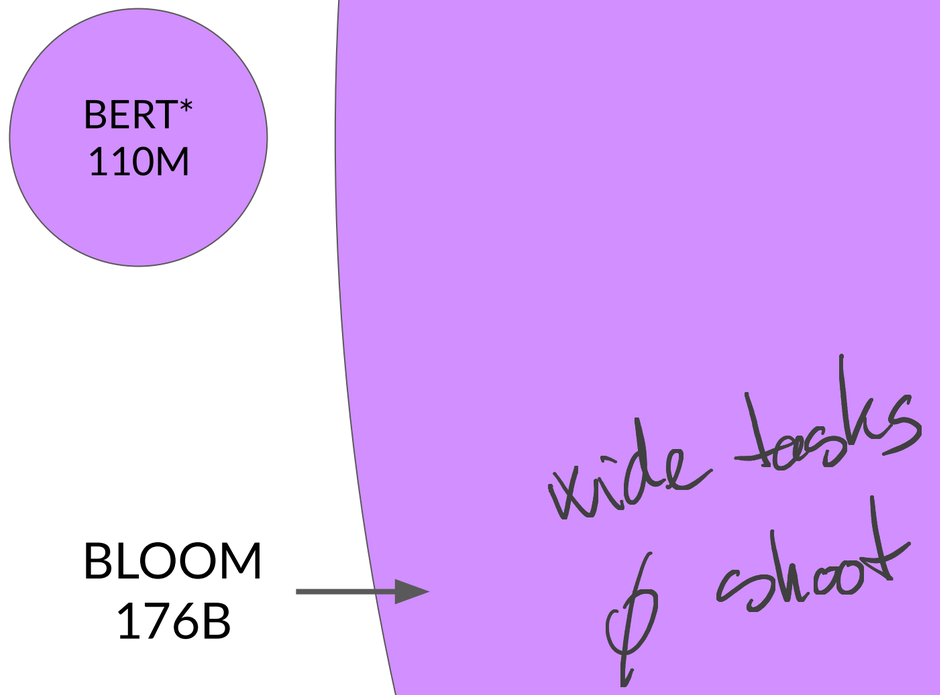
```
Classify this review:
I loved this movie!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment: Negative

Classify this review:
Who would use this
product?
Sentiment:
```

**Context Window**
(few thousand words)

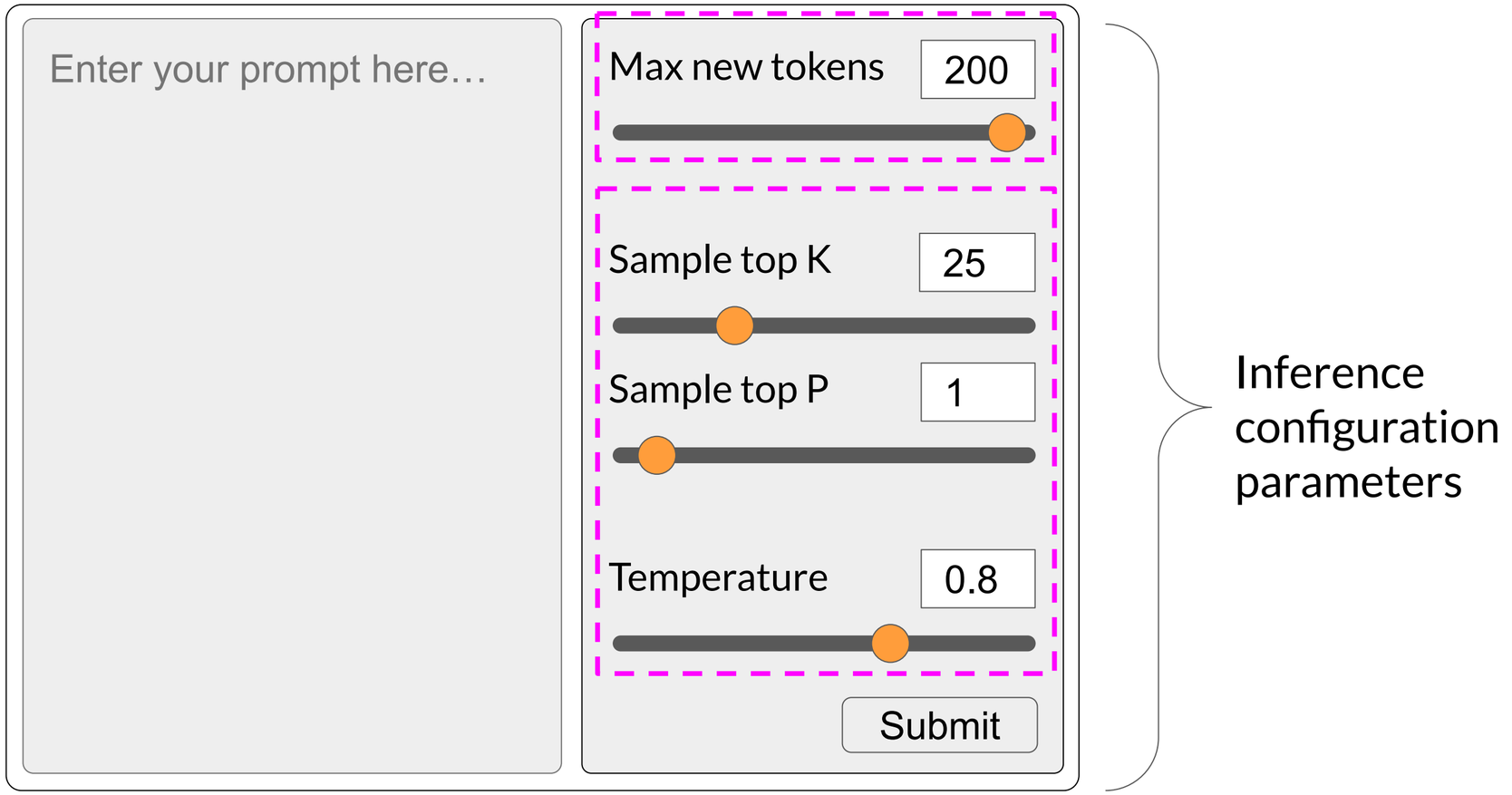
# The significance of scale: task ability



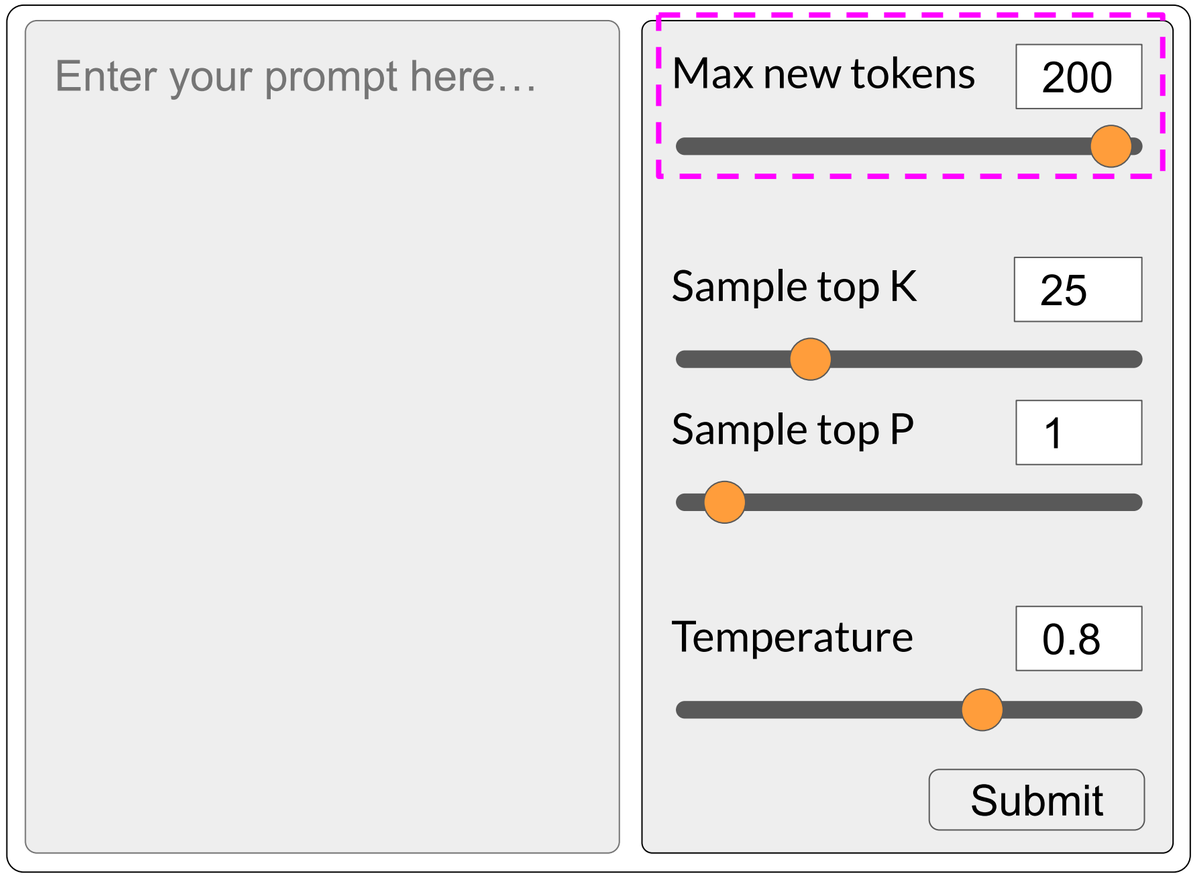

*Bert-base

# Generative configuration parameters for inference

# Generative configuration - inference parameters

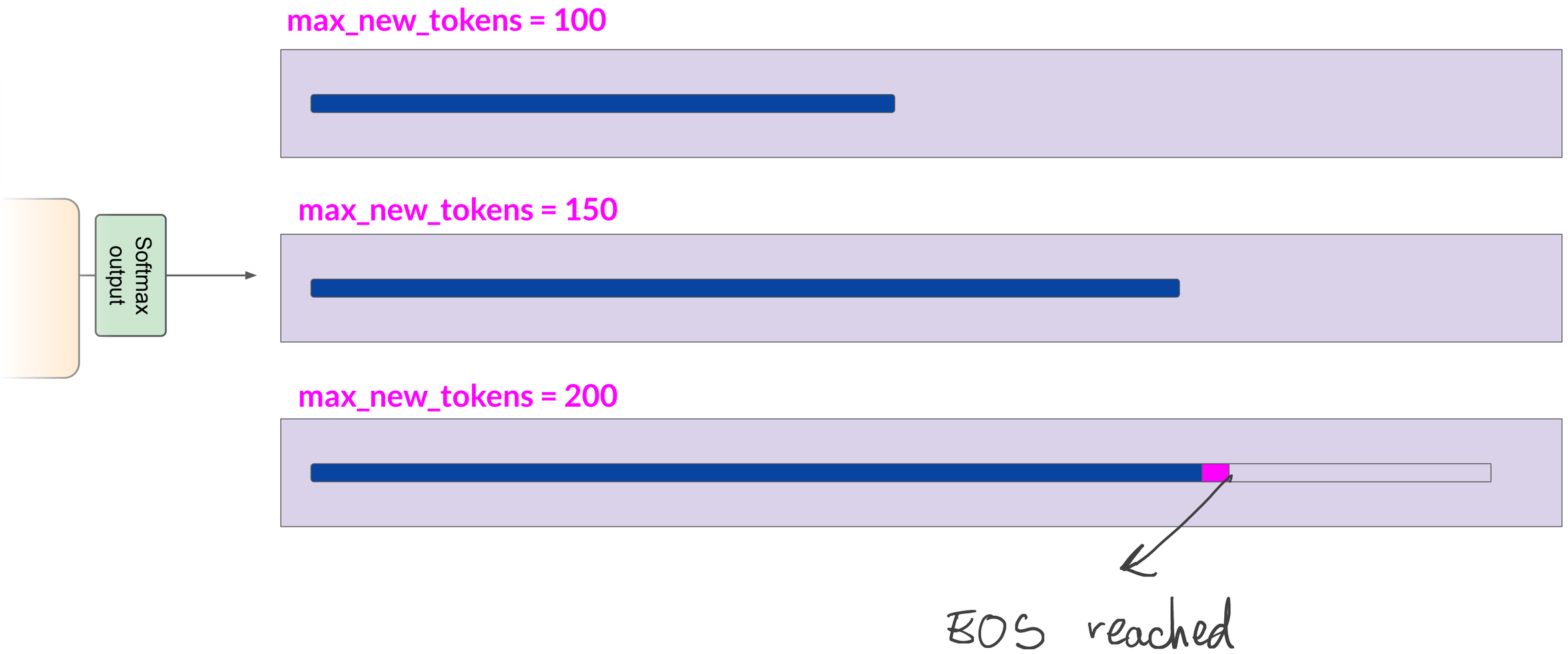


# Generative configuration - max new tokens

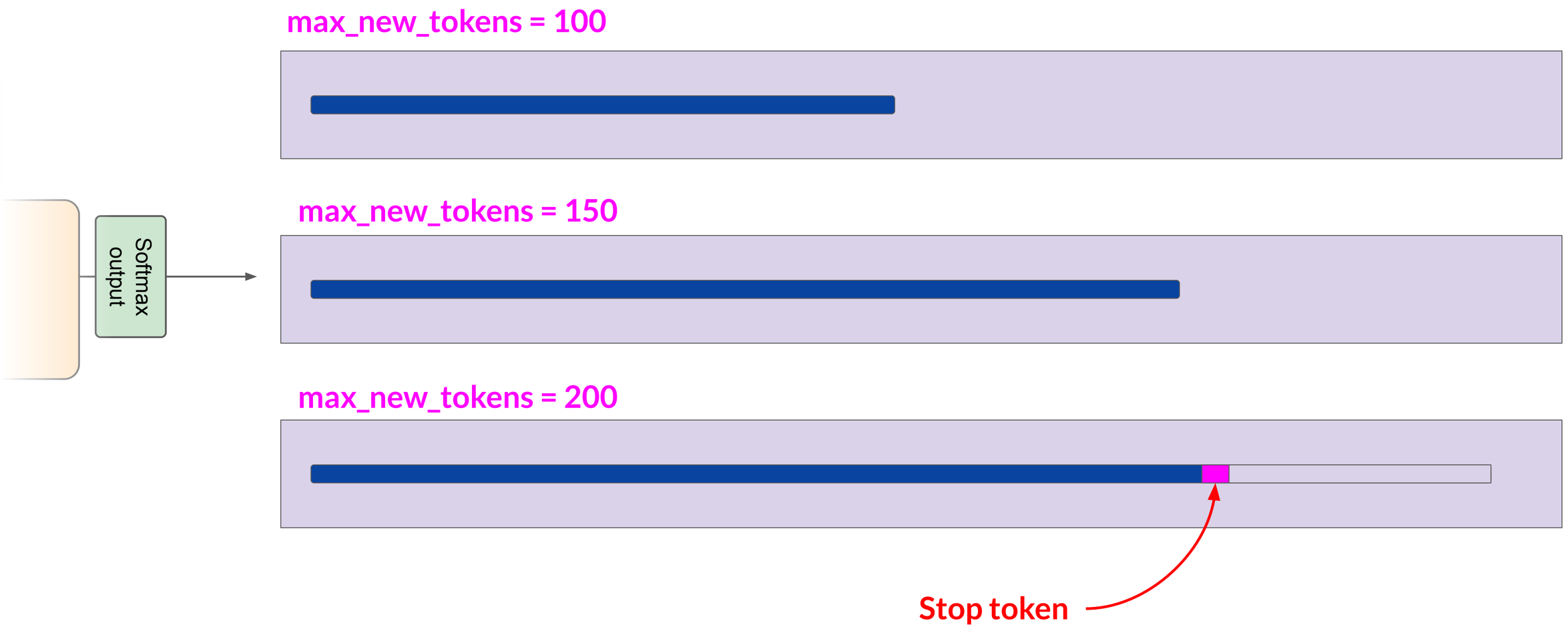



Max new tokens

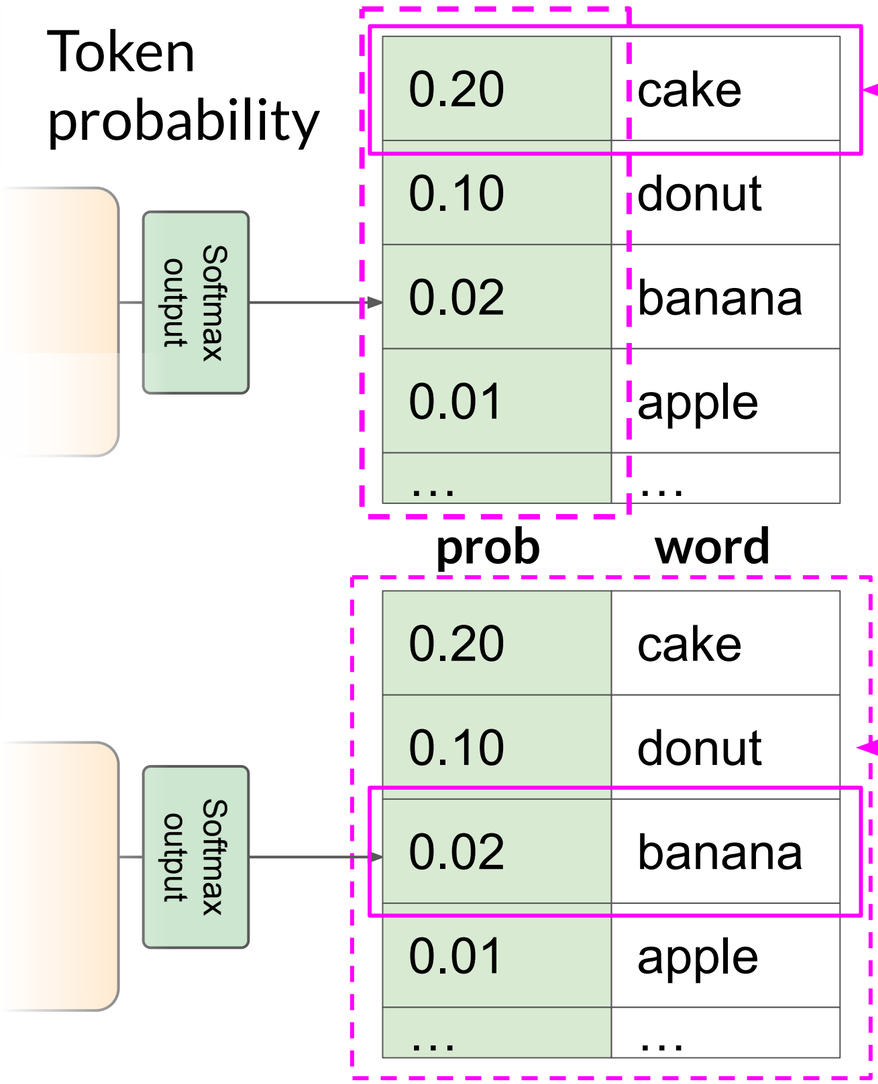
# Generative config - max new tokens



# Generative config - max new tokens



# Generative config - greedy vs. random sampling

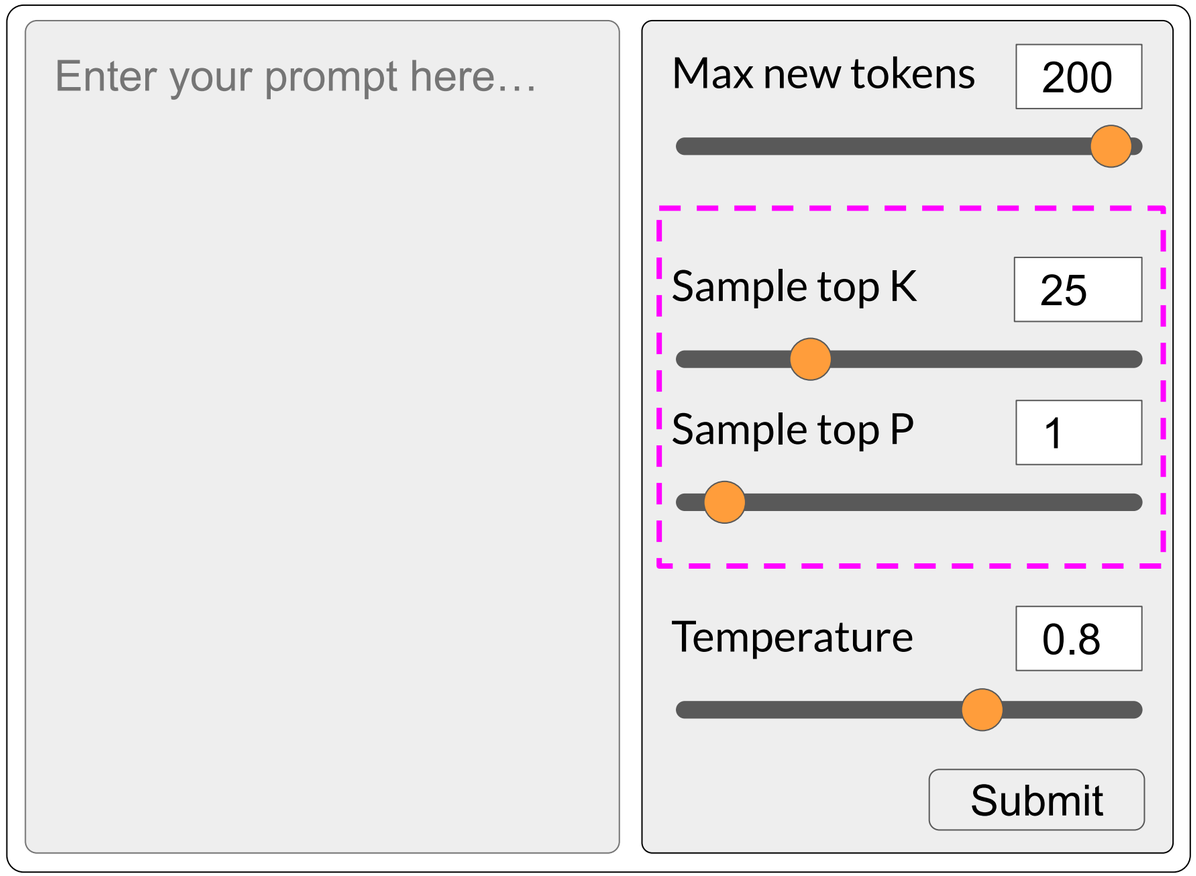



***greedy*:** The word/token with the highest probability is selected.

***random(-weighted) sampling***: select a token using a random-weighted strategy across the probabilities of all tokens.

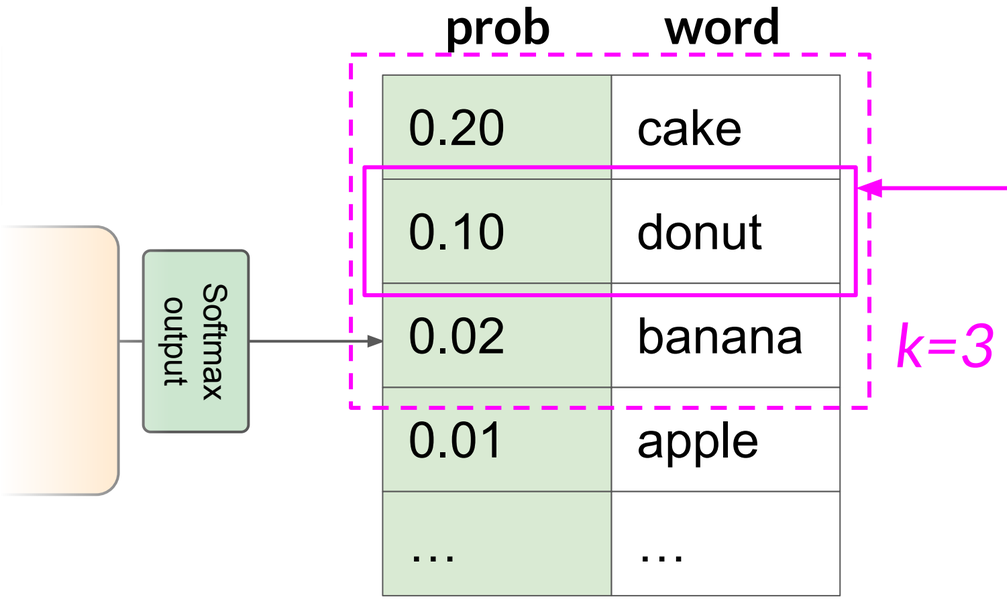
*Here, there is a 20% chance that 'cake' will be selected, but 'banana' was actually selected.*

# Generative configuration - top-k and top-p




Top-k and top-p sampling

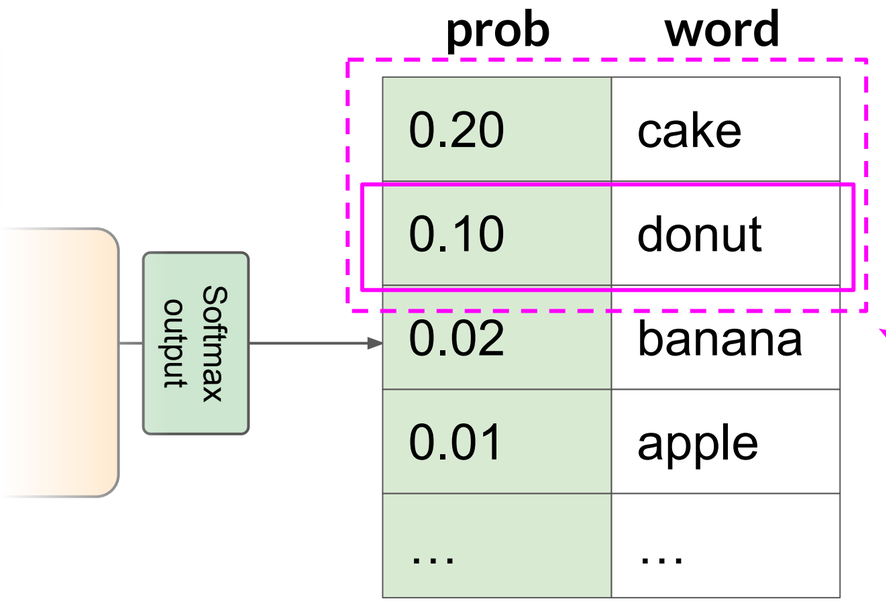
# Generative config - top-k sampling




***top-k***: select an output from the top-k results after applying random-weighted strategy using the probabilities

this helps in having some randomnes but preventing to have completion with highly improbable words

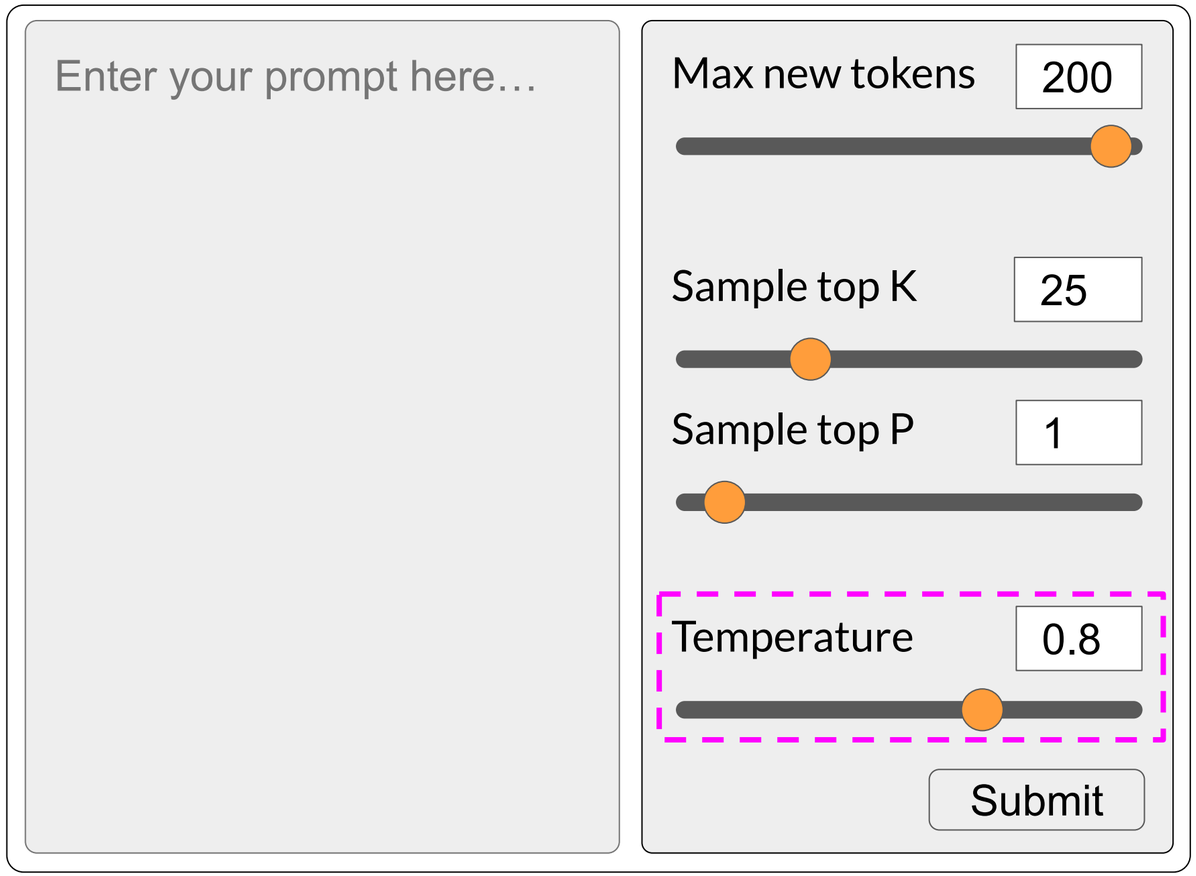
# Generative config - top-p sampling




***top-p***: select an output using the random-weighted strategy with the top-ranked consecutive results by probability and with a cumulative probability <= *p*.

*p = 0.30*

# Generative configuration - temperature




Temperature

# Generative config - temperature

shapes probability distribution

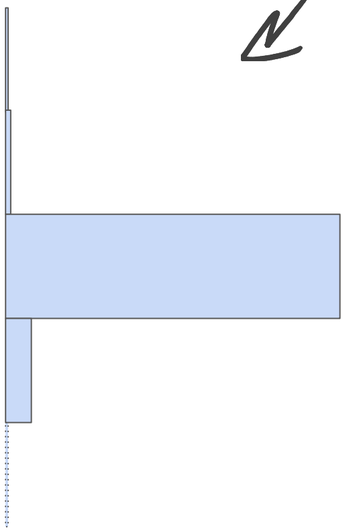
Temperature setting

Softmax output

Cooler temperature (e.g <1)

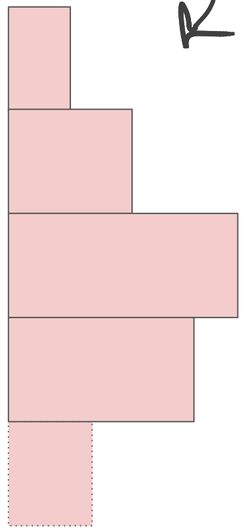
| prob | word |
|---|---|
| 0.001 | apple |
| 0.002 | banana |
| 0.400 | cake |
| 0.012 | donut |
| … | … |

Probability bar chart



Higher temperature (>1)

| prob | word |
|---|---|
| 0.040 | apple |
| 0.080 | banana |
| 0.150 | cake |
| 0.120 | donut |
| … | … |



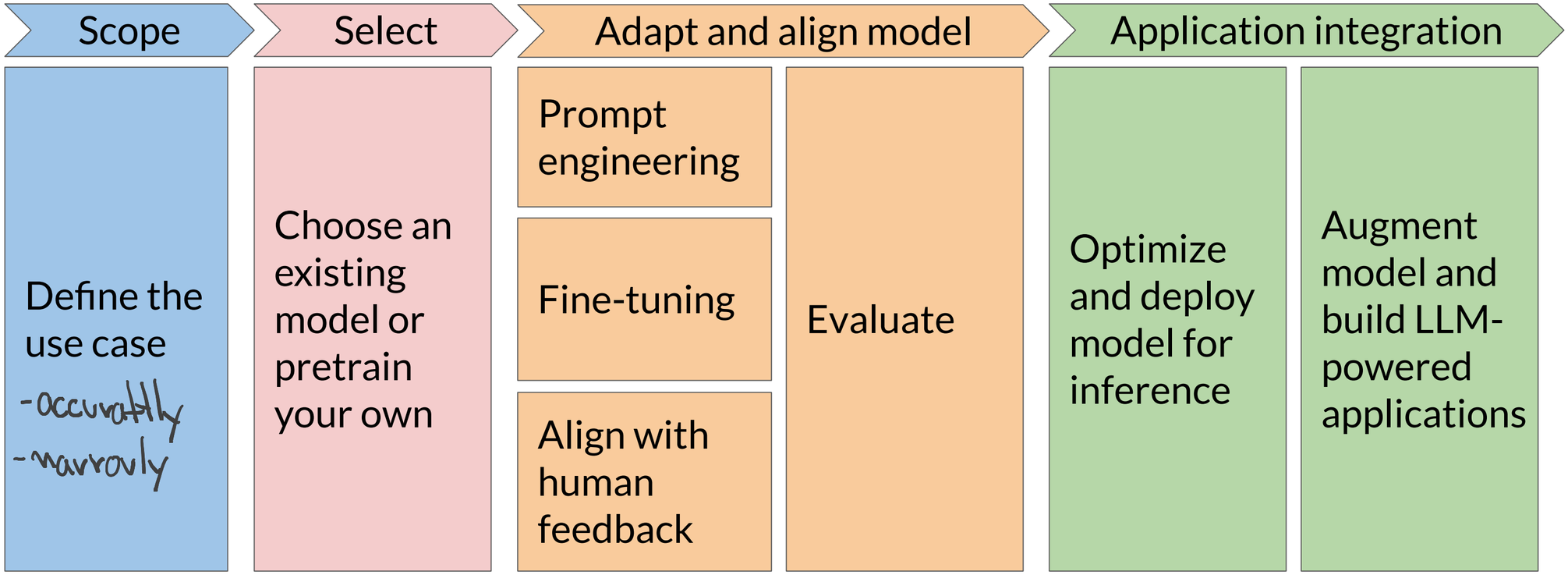
temperature = 1
does not affect probability

Strongly peaked probability distribution
less randomness

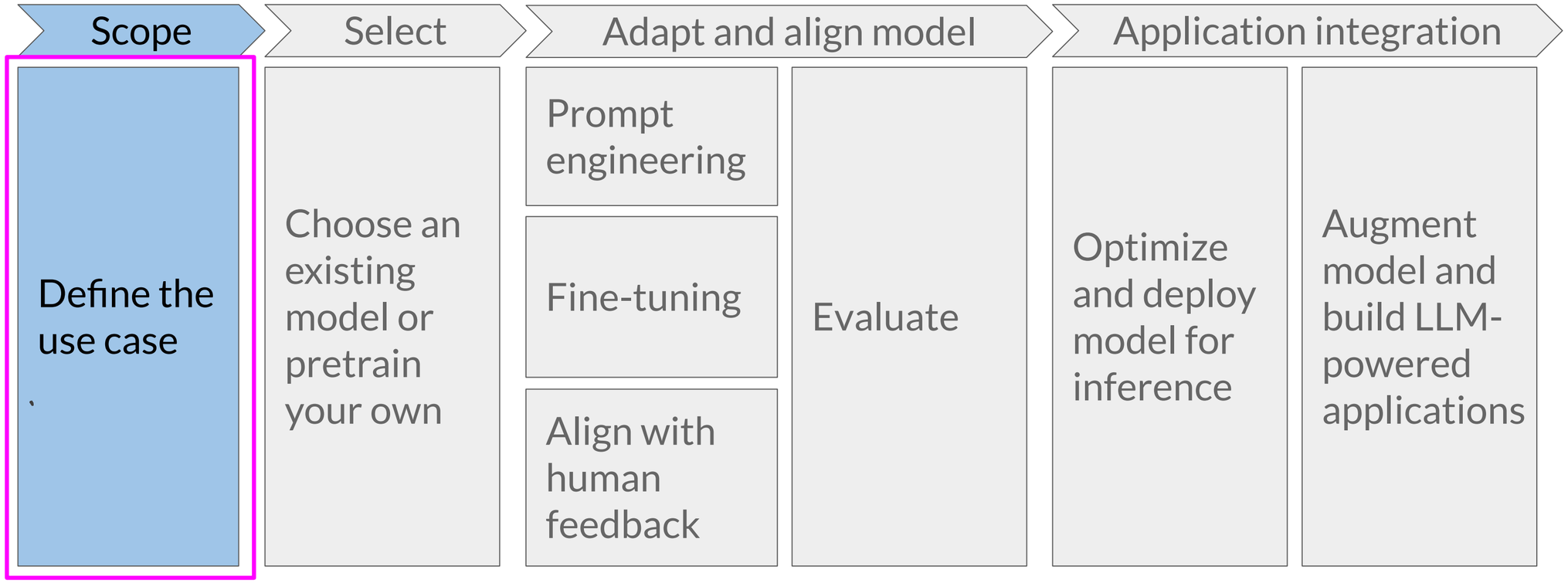
Broader, flatter probability distribution
more randomness

# Generative AI project lifecycle

# Generative AI project lifecycle

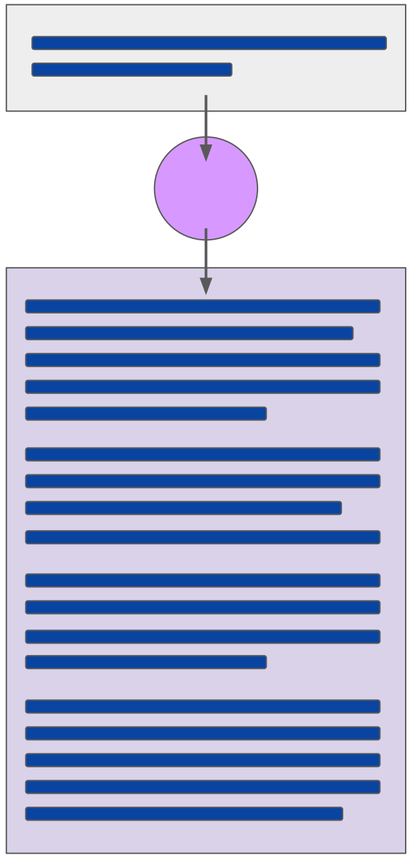


# Generative AI project lifecycle

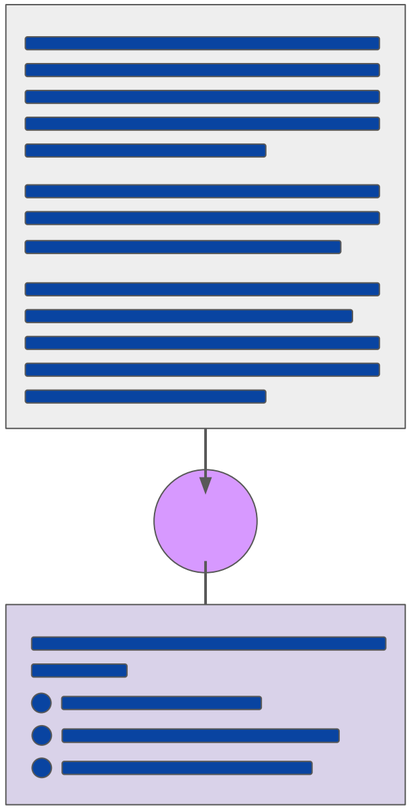


# Good at many tasks?

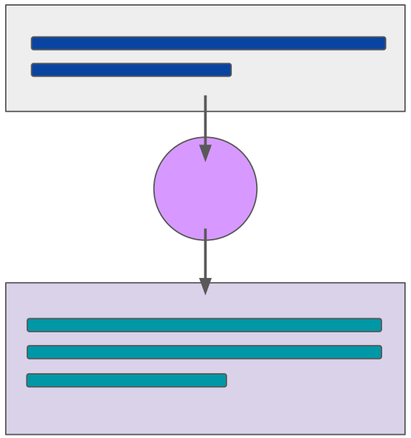
Essay Writing



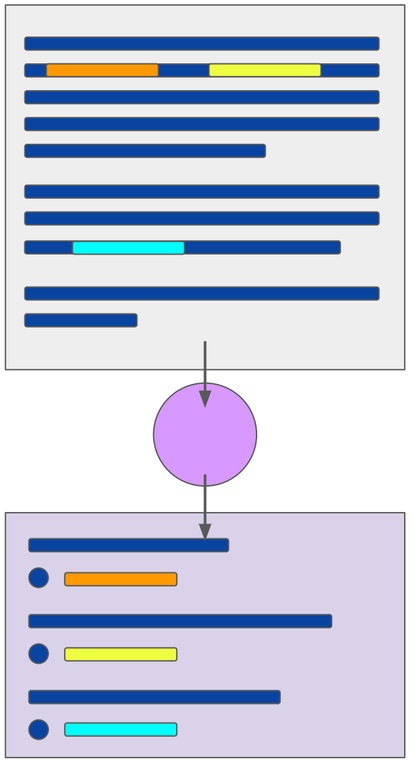
Summarization



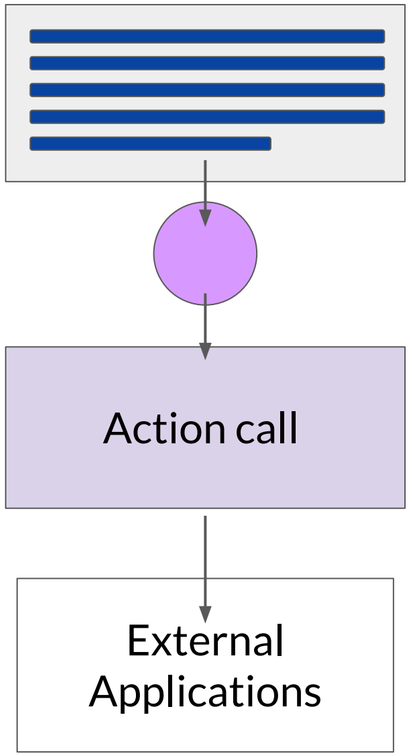
Translation



Information retrieval



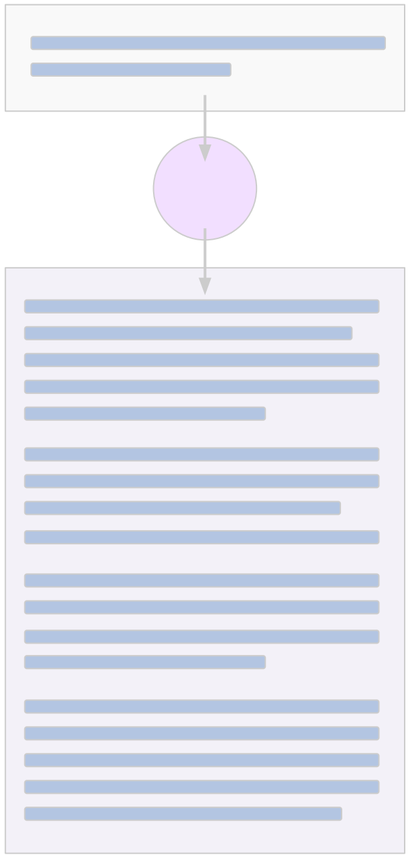
Invoke APIs and actions



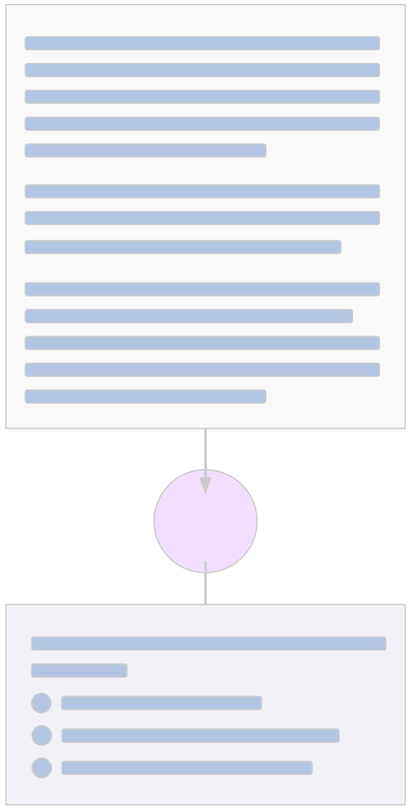
# Or good at a single task?

Get specific with scope!

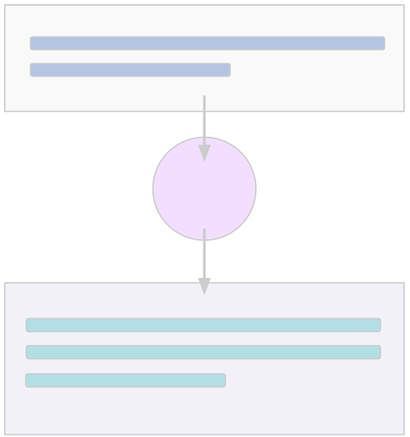
Essay Writing



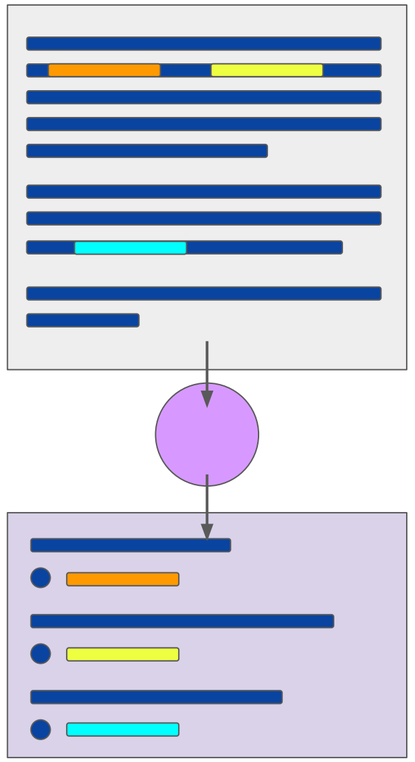
Summarization



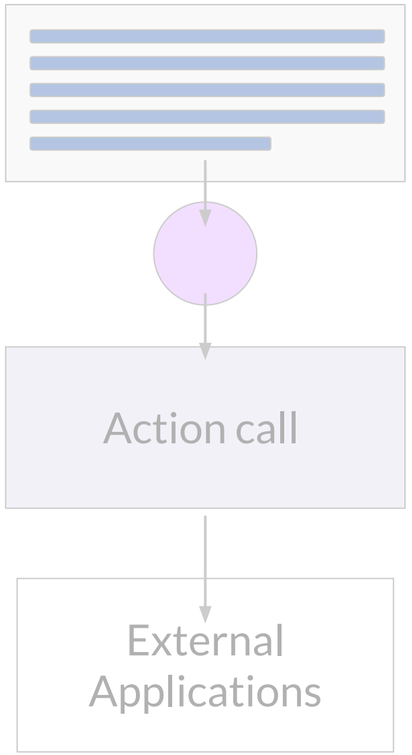
Translation



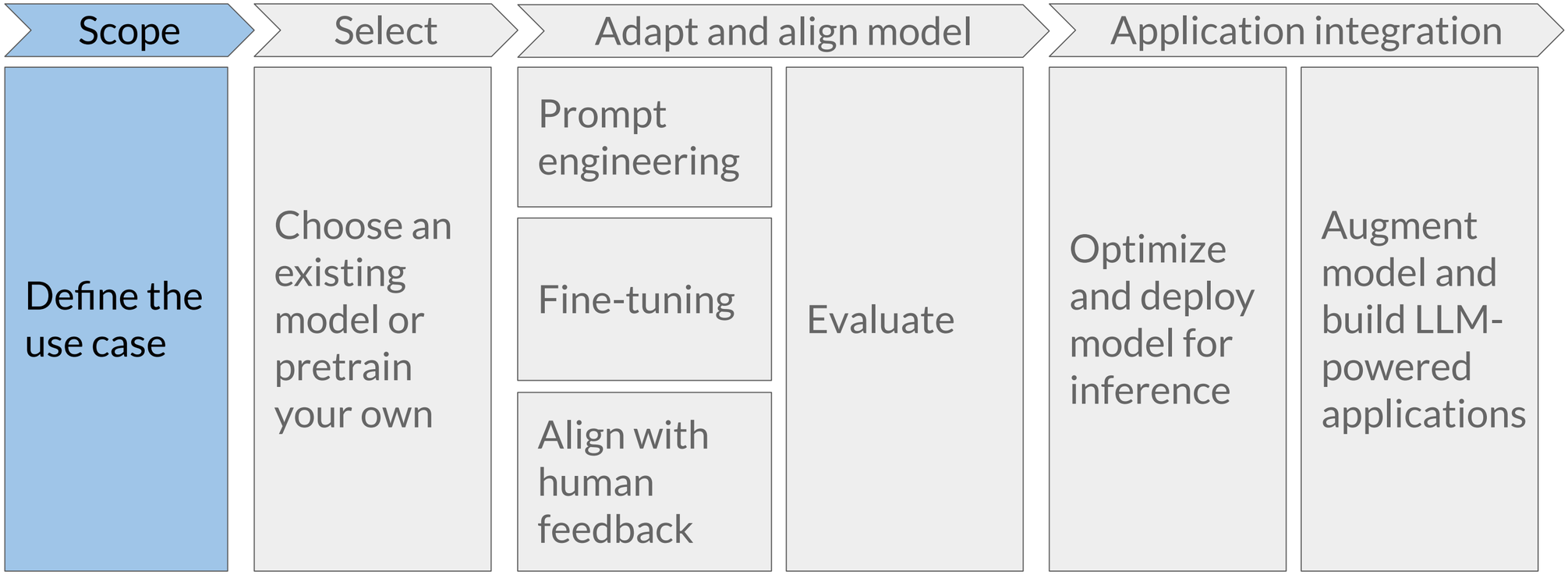
Information retrieval



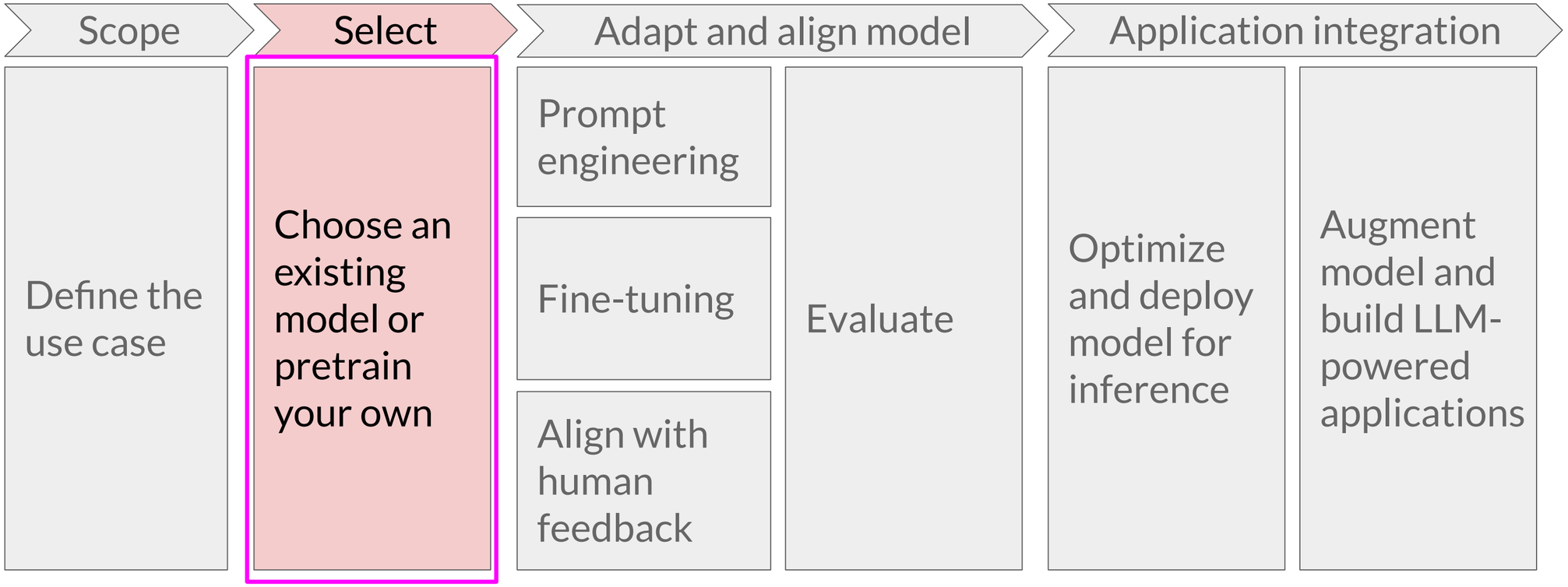
Invoke APIs and actions



# Generative AI project lifecycle



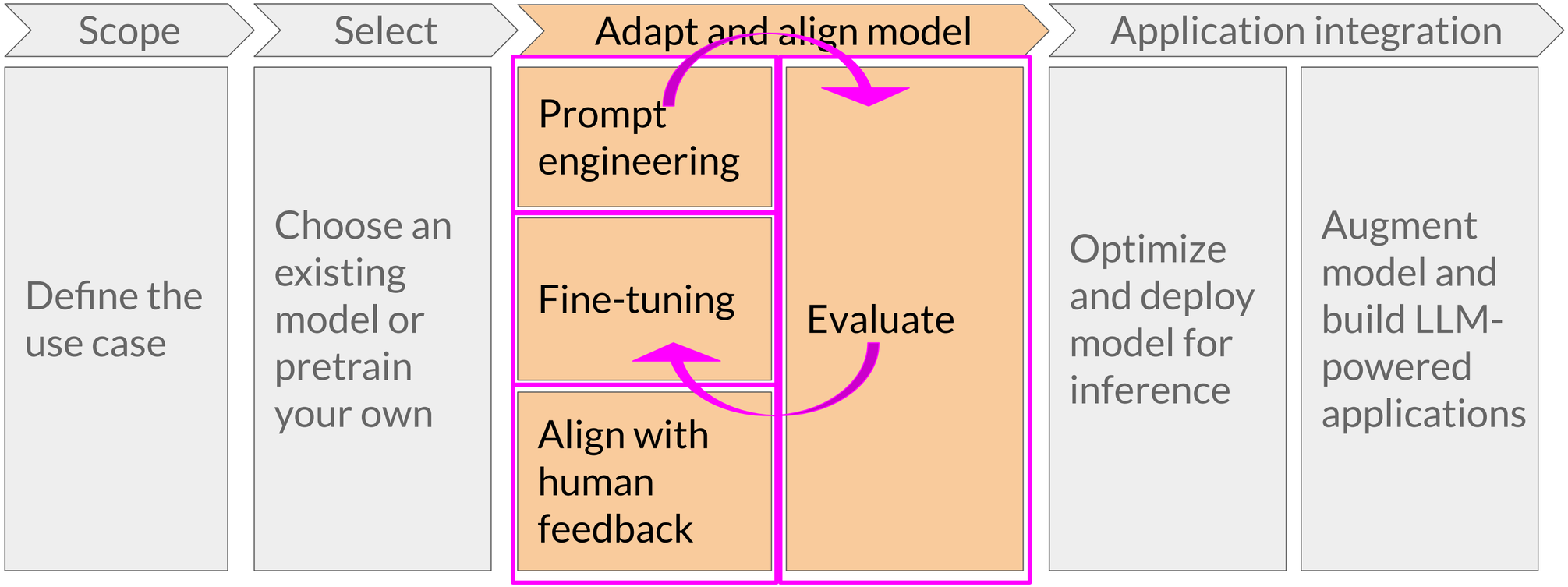
# Generative AI project lifecycle



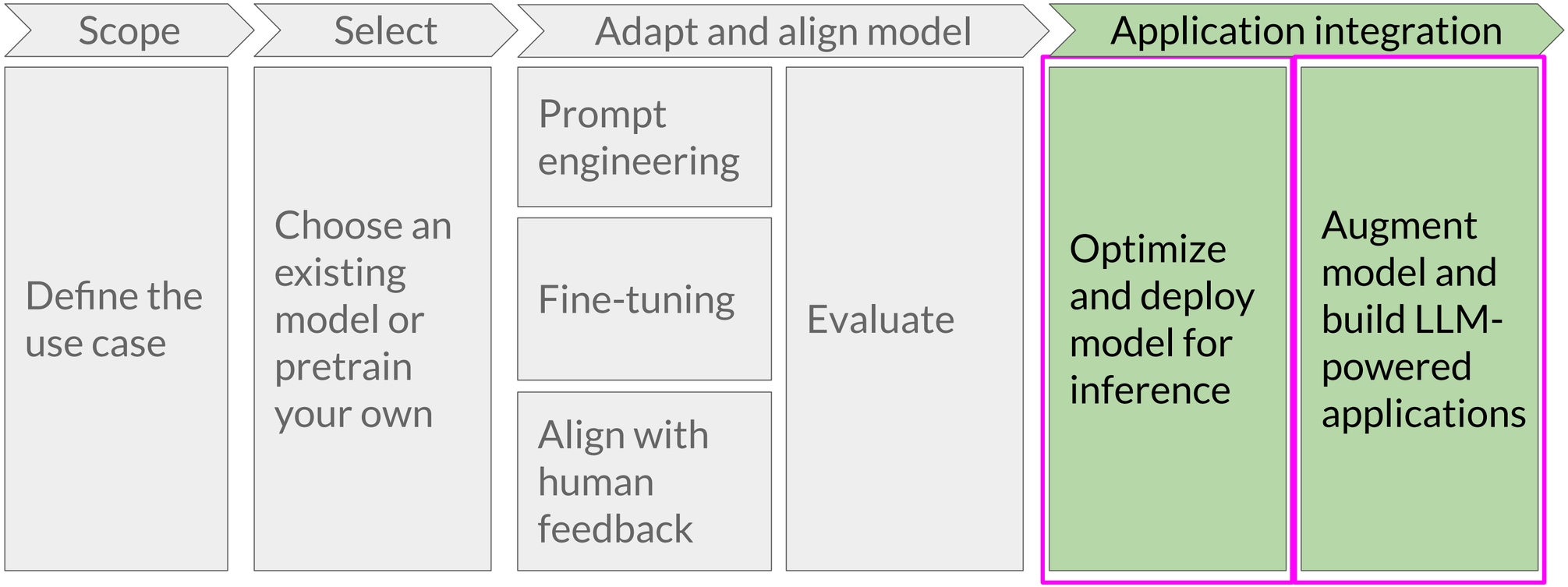

Usually it will be using/tuning EXISTING MODEL!

# Generative AI project lifecycle

1st try - Prompt engineering
2nd - in - context learning
3rd - Fine-tuning

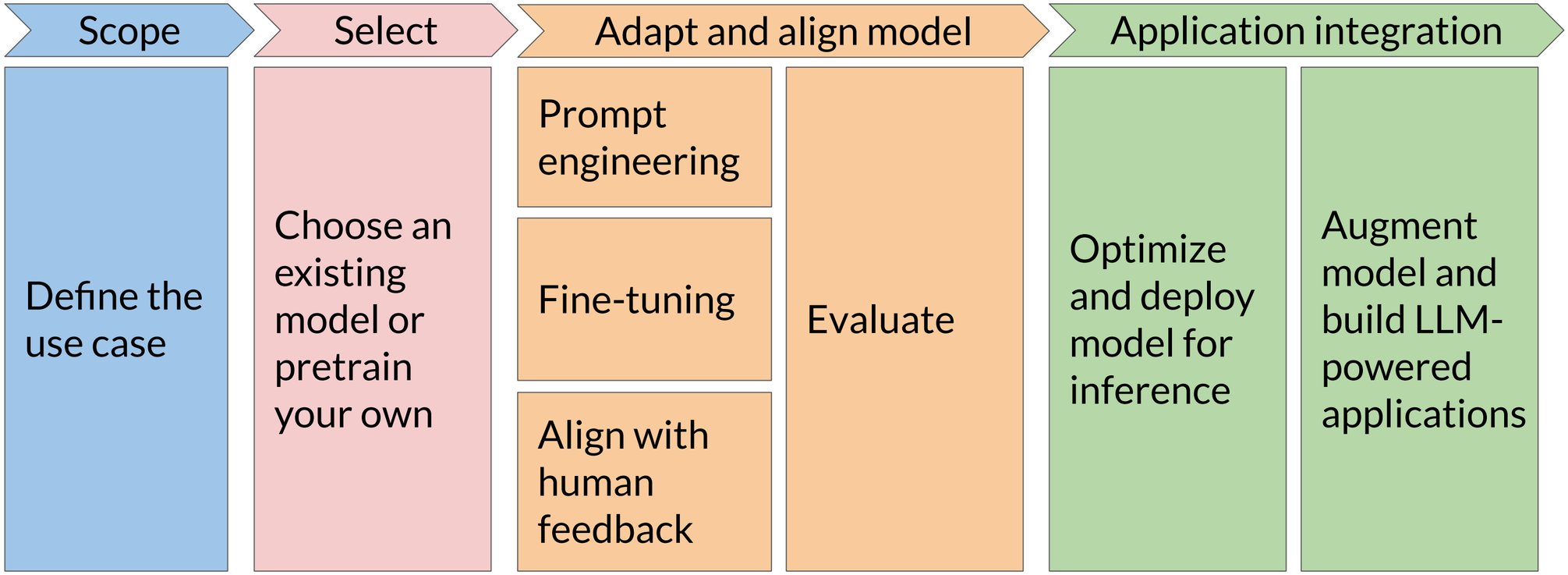


# Generative AI project lifecycle

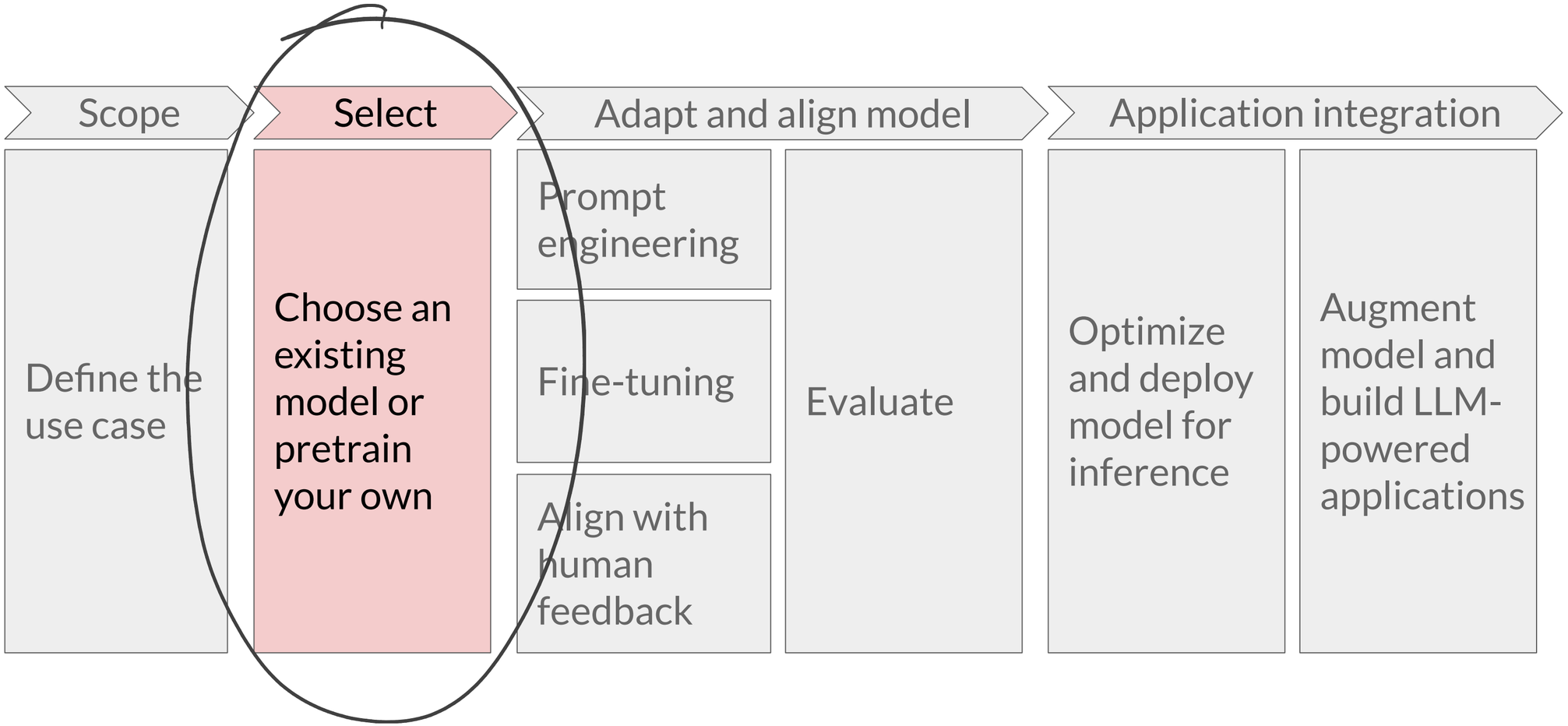


# Pre-training and scaling laws

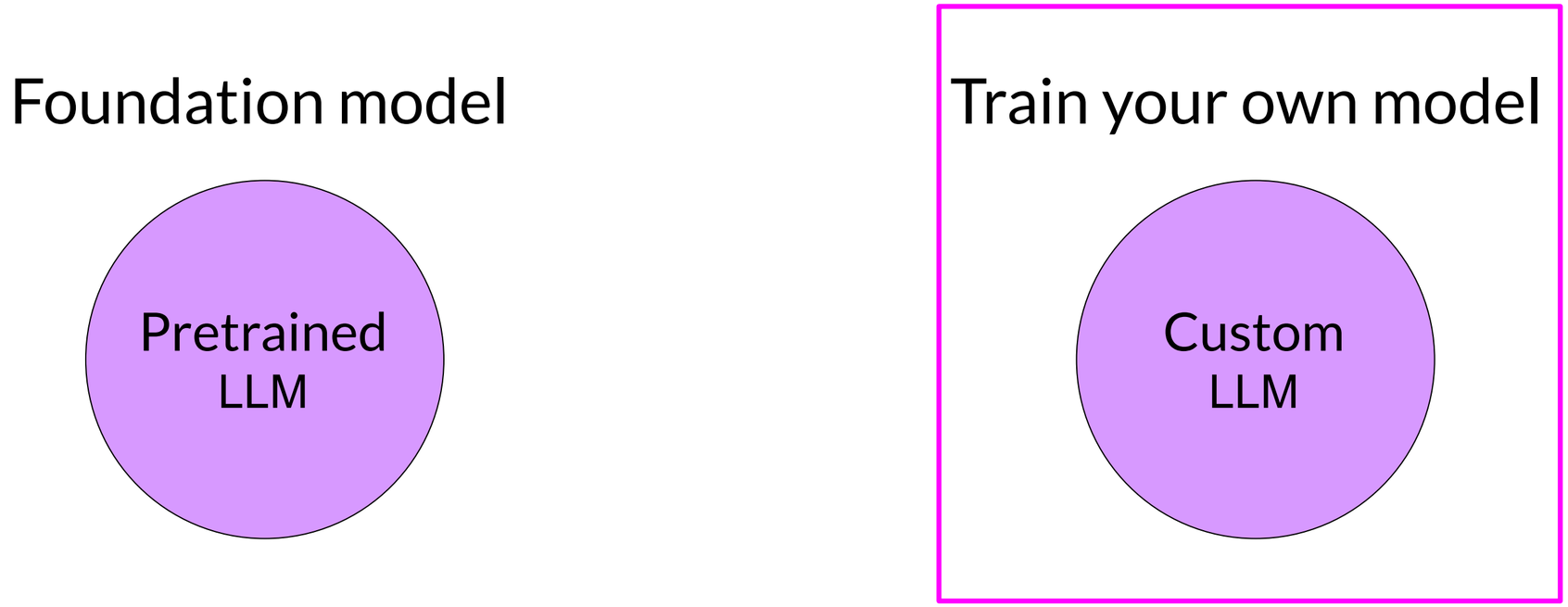
# Generative AI project lifecycle



# Generative AI project lifecycle



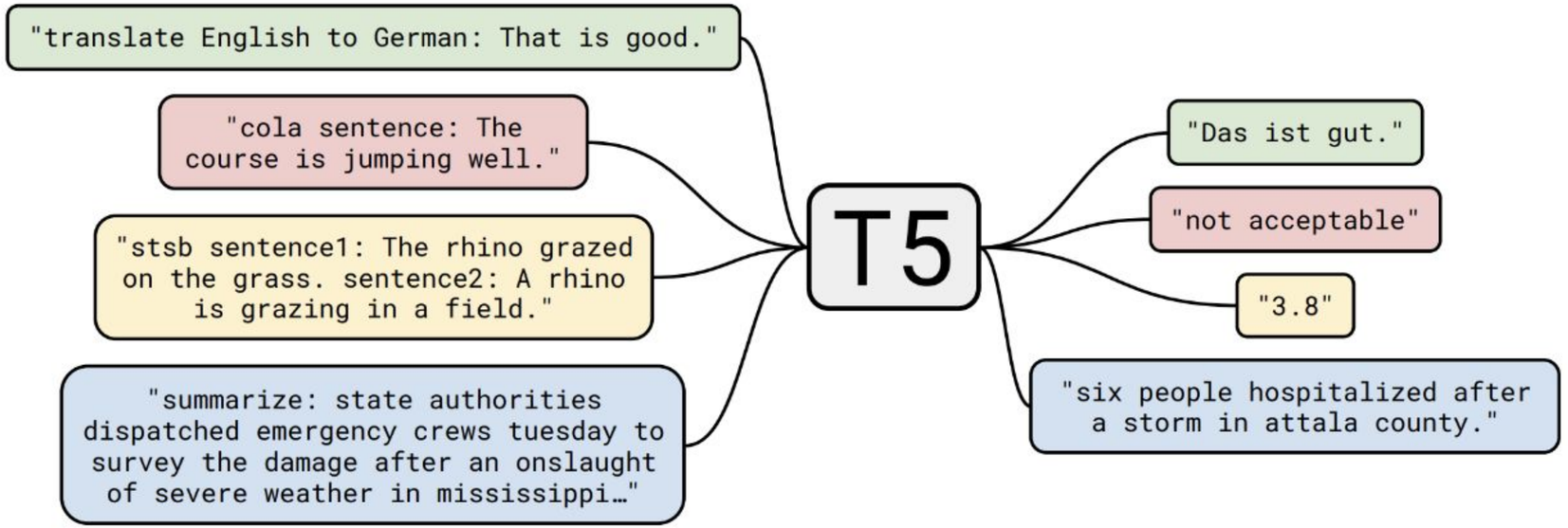
# Considerations for choosing a model



# Considerations for choosing a model

# Model hubs

## Model Card for T5 Large

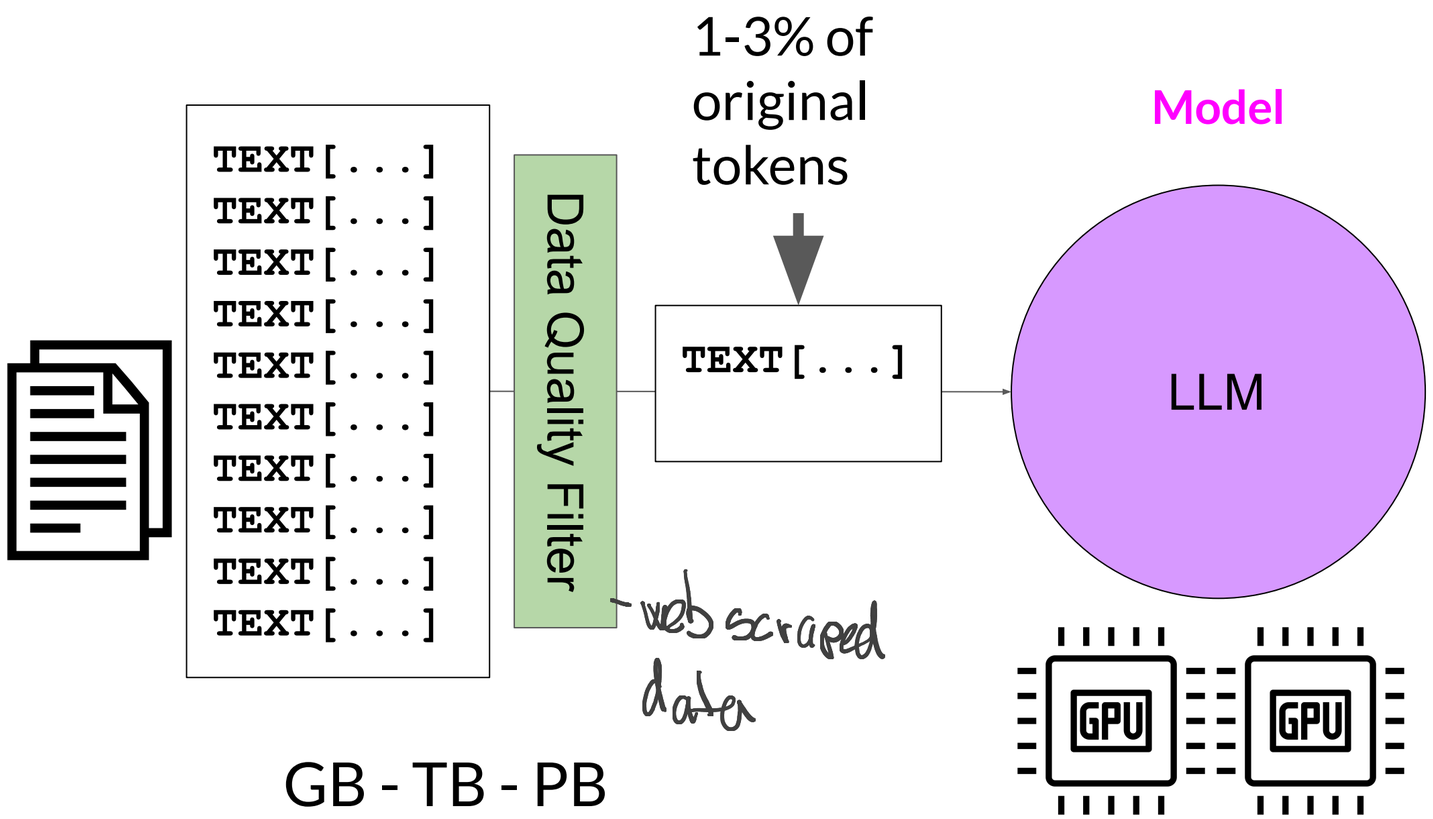



### Table of Contents


1. Model Details
2. Uses
3. Bias, Risks, and Limitations
4. Training Details
5. Evaluation

# Model architectures and pre-training objectives

# LLM pre-training at a high level

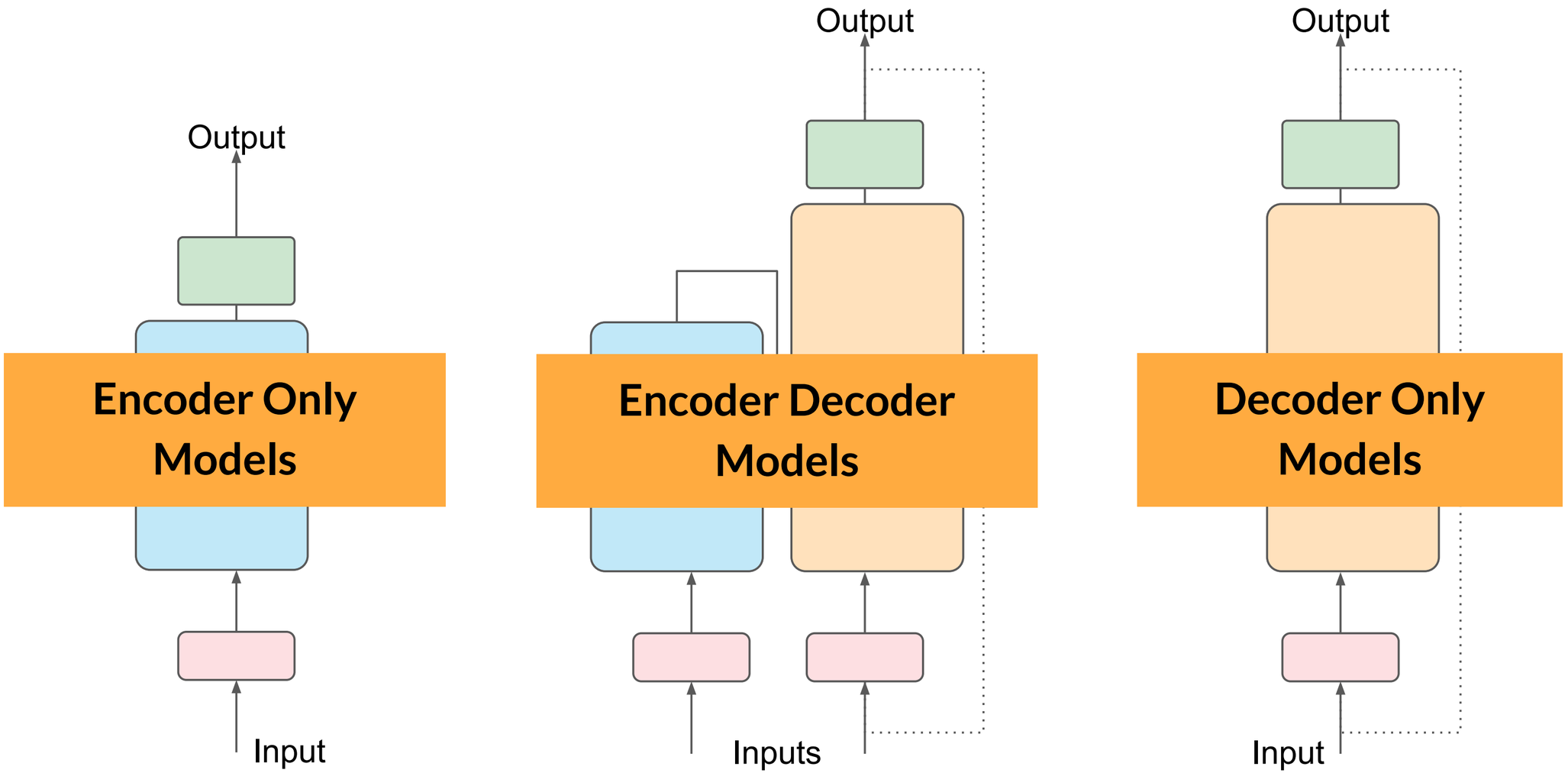



GB - TB - PB
of unstructured data

| Token String | Token ID | Embedding / Vector Representation |
|---|---|---|
| '_The' | 37 | [-0.0513, -0.0584, 0.0230, ...] |
| '_teacher' | 3145 | [-0.0335, 0.0167, 0.0484, ...] |
| '_teaches' | 11749 | [-0.0151, -0.0516, 0.0309, ...] |
| '_the' | 8 | [-0.0498, -0.0428, 0.0275, ...] |
| '_student' | 1236 | [-0.0460, 0.0031, 0.0545, ...] |
| ... | ... | ... |

Vocabulary

# Transformers



# Autoencoding models (Encoder only models)

training objective is to predict MASK tokens in order to reconstruct original sentance

Masked Language Modeling (MLM)

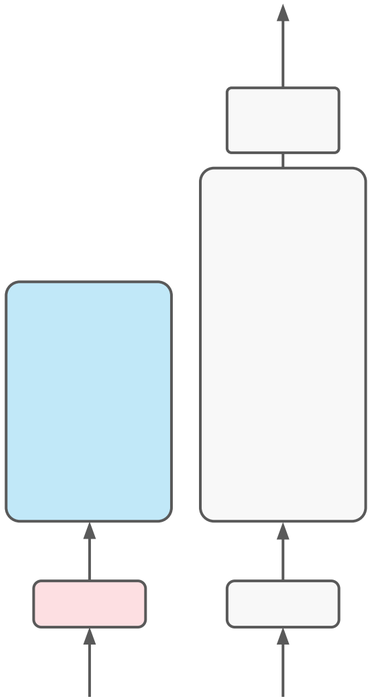
| The | teacher | <MASK> | the | student |
|---|---|---|---|---|

Original text

**The teacher teaches the student.**

[...]

Encoder-only LLM



Understanding token context in both sequence direction

Objective: Reconstruct text ("denoising")

| The | teacher | teaches | the | student |
|---|---|---|---|---|

Bidirectional context

Bidirectional representation of input sequence

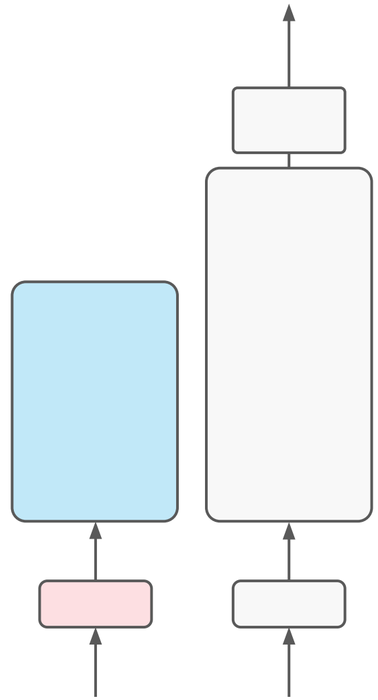
# Autoencoding models

Good use cases:

- Sentiment analysis
- Named entity recognition
- Word classification

Example models:

- BERT
- ROBERTA



# Autoregressive models (Decoder only models)

Learning objective is to learn NEXT TOKEN based on previous sequence of tokens

Original text

**The teacher teaches the student.**

[...]

Causal Language Modeling (CLM)

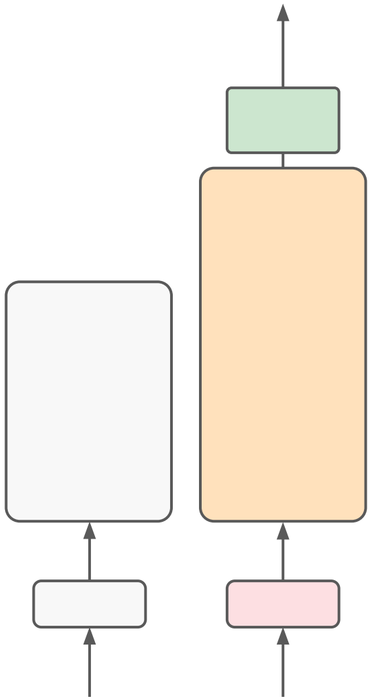
| The | teacher | ? |
|---|---|---|

Decoder-only LLM

Objective: Predict next token

| The | **teacher** | **teaches** |
|---|---|---|

Unidirectional context



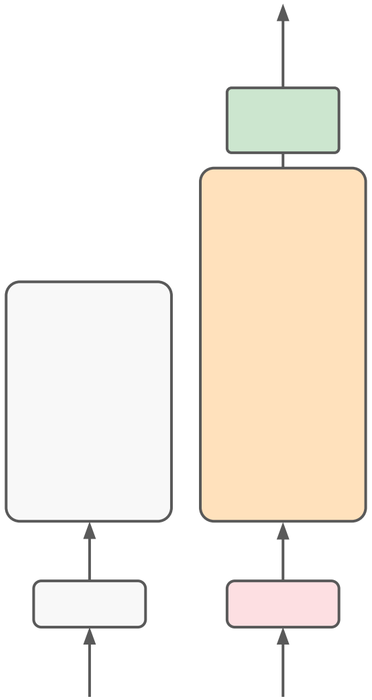
# Autoregressive models

Good use cases:

- Text generation (0shot)
- Other emergent behavior
  - Depends on model size

Example models:

- GPT
- BLOOM



# Sequence-to-sequence models (Encoder-Decoder model)

training objective varies from model to model

Span Corruption - masks random seq. of input tokens

| | | | | |
|---|---|---|---|---|
| The | teacher | <MASK> | <MASK> | student |
| The | teacher | <X> | | student |

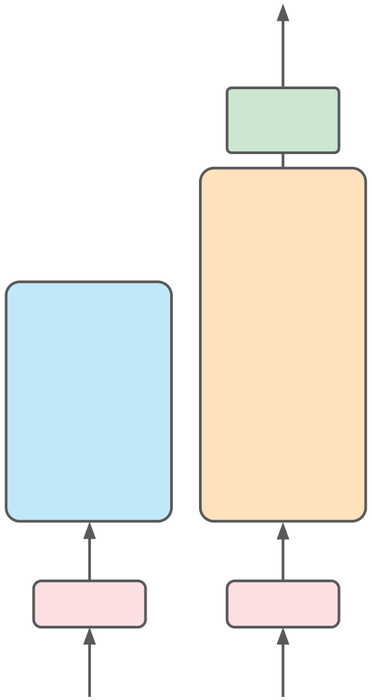
Original text

**The teacher teaches the student.**

[...]

Encoder-Decoder LLM

Sentinel token added to vocab.



Objective: Reconstruct span

| | | |
|---|---|---|
| **<x>** | **teaches** | **the** |

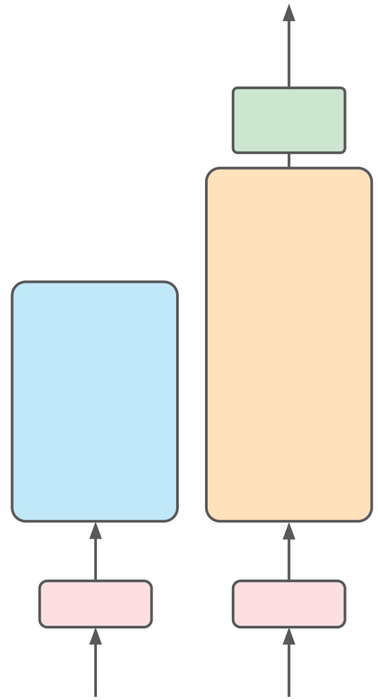
# Sequence-to-sequence models

Good use cases:

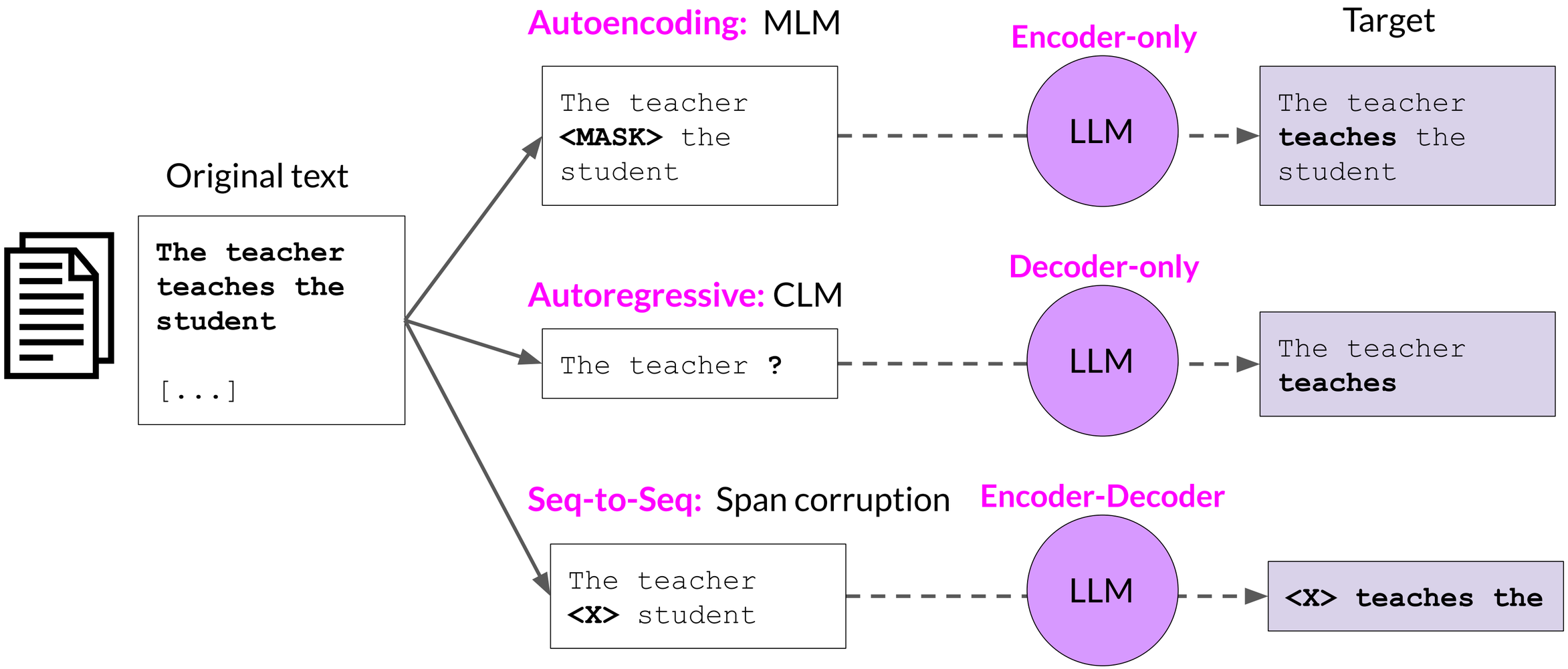
- Translation
- Text summarization
- Question answering

Example models:

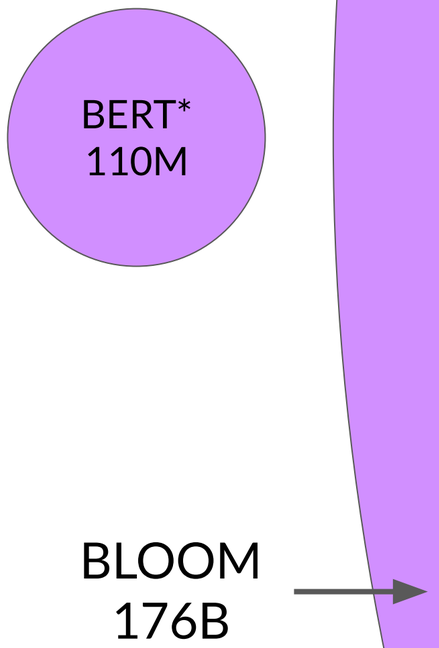
- T5
- BART



# Model architectures and pre-training objectives

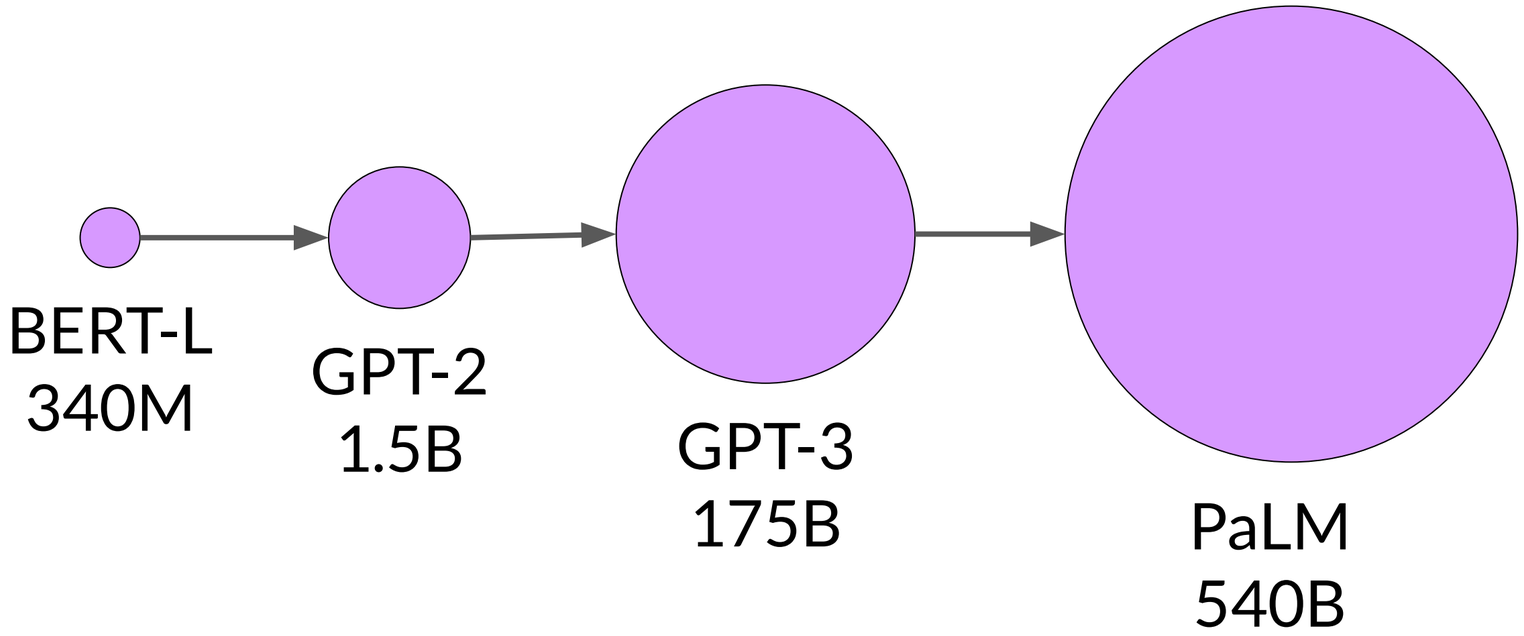


# The significance of scale: task ability




*Bert-base

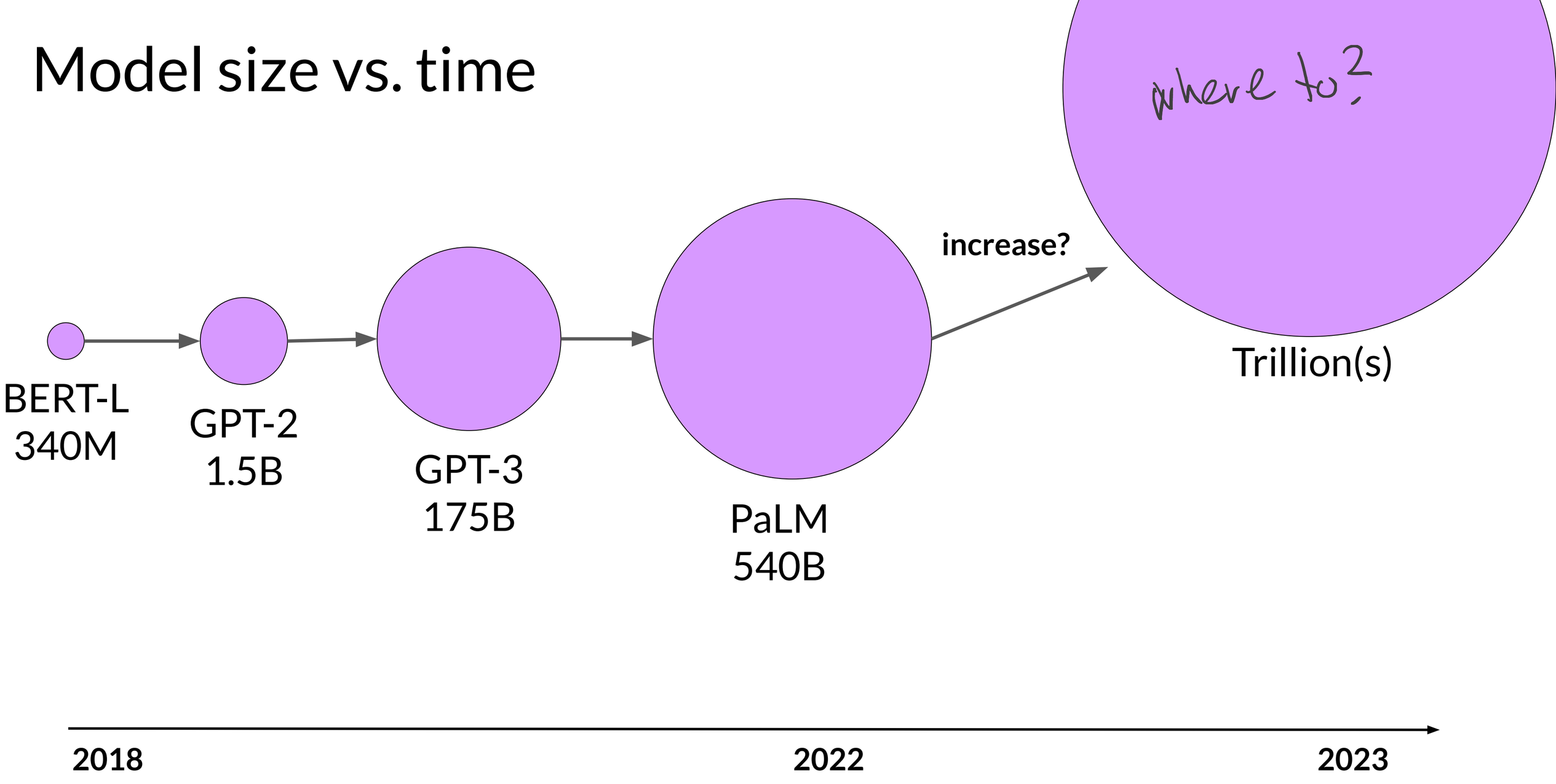
# Model size vs. time




Growth powered by:

- Introduction of transformer
- Access to massive datasets
- More powerful compute resources

# Model size vs. time



# Computational challenges

```
OutOfMemoryError: CUDA out of memory.
```

# Approximate GPU RAM needed to store 1B parameters

1 parameter = 4 bytes (32-bit float)

1B parameters = 4 x $10^9$ bytes = 4GB

**4GB @ 32-bit full precision**

Sources: https://huggingface.co/docs/transformers/v4.20.1/en/perf_train_gpu_one#anatomy-of-models-memory, https://github.com/facebookresearch/bitsandbytes

# Additional GPU RAM needed to train 1B parameters

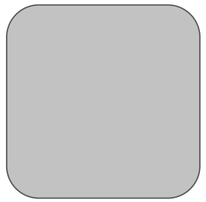
| | Bytes per parameter |
|---|---|
| **Model Parameters (Weights)** | 4 bytes per parameter |
| Adam optimizer (2 state) | +8 bytes per parameter |
| Gradients | +4 bytes per parameter |
| Activations + temp variables | +8 bytes per parameter |
| TOTAL | 4+20 = 24 bytes |

~20 extra bytes per parameter

Sources: https://huggingface.co/docs/transformers/v4.20.1/en/perf_train_gpu_one#anatomy-of-models-memory, https://github.com/facebookresearch/bitsandbytes

# Approximate GPU RAM needed to train 1B-params

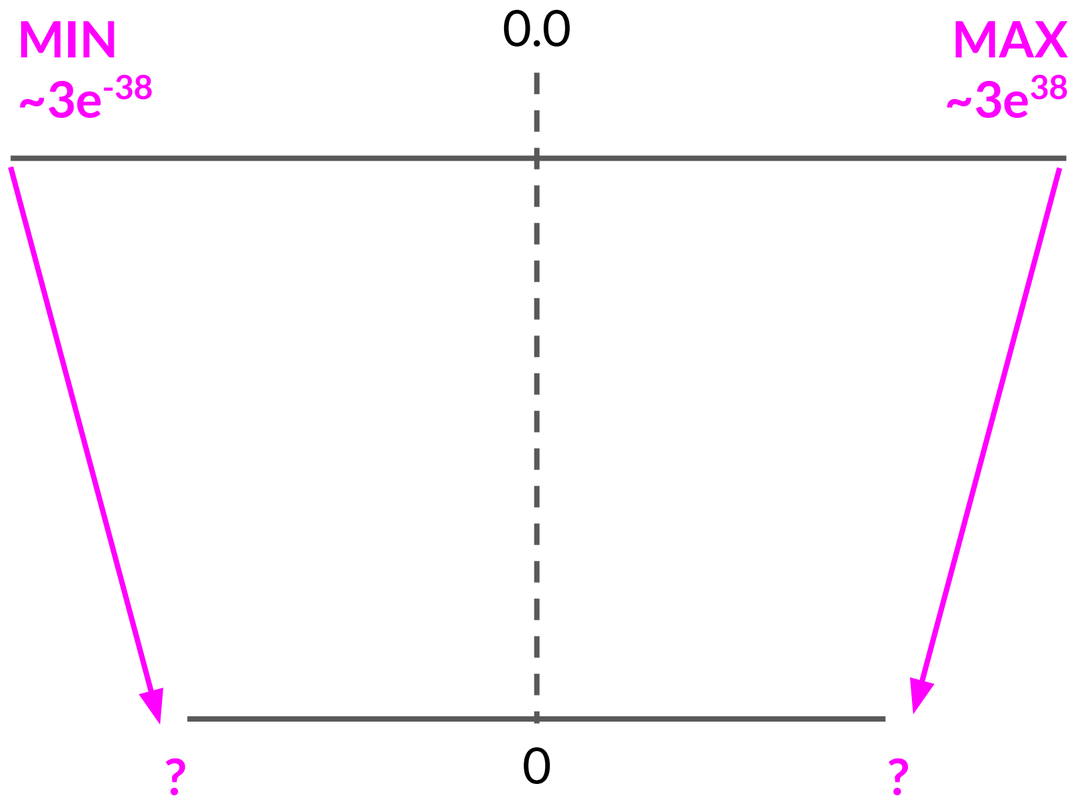
Memory needed to store model



**4GB @ 32-bit full precision**

Memory needed to train model

# Quantization




**FP32**

32-bit floating point

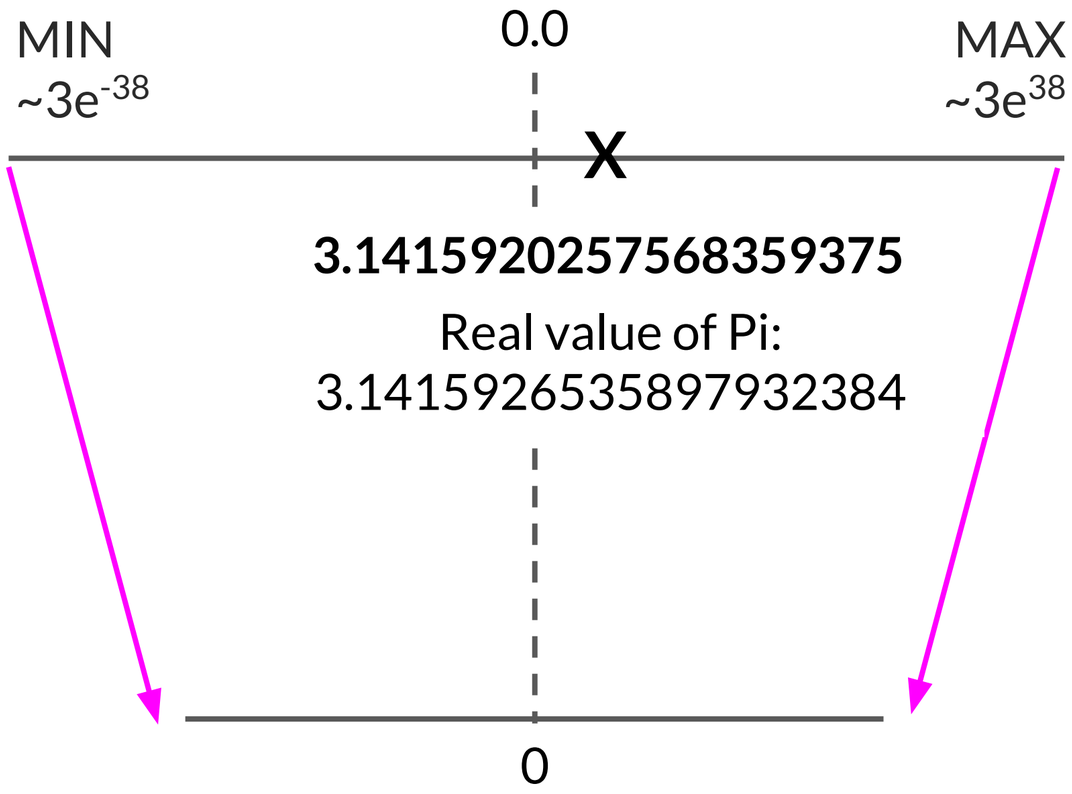
**Range:**

From **~3e$^{-38}$** to **~3e$^{38}$**

**FP16 | BFLOAT16 | INT8**

16-bit floating point | 8-bit integer

# Quantization: FP32




**Let's store Pi: 3.141592**

**FP32**

**0** **10000000** **10010010000111111011000**

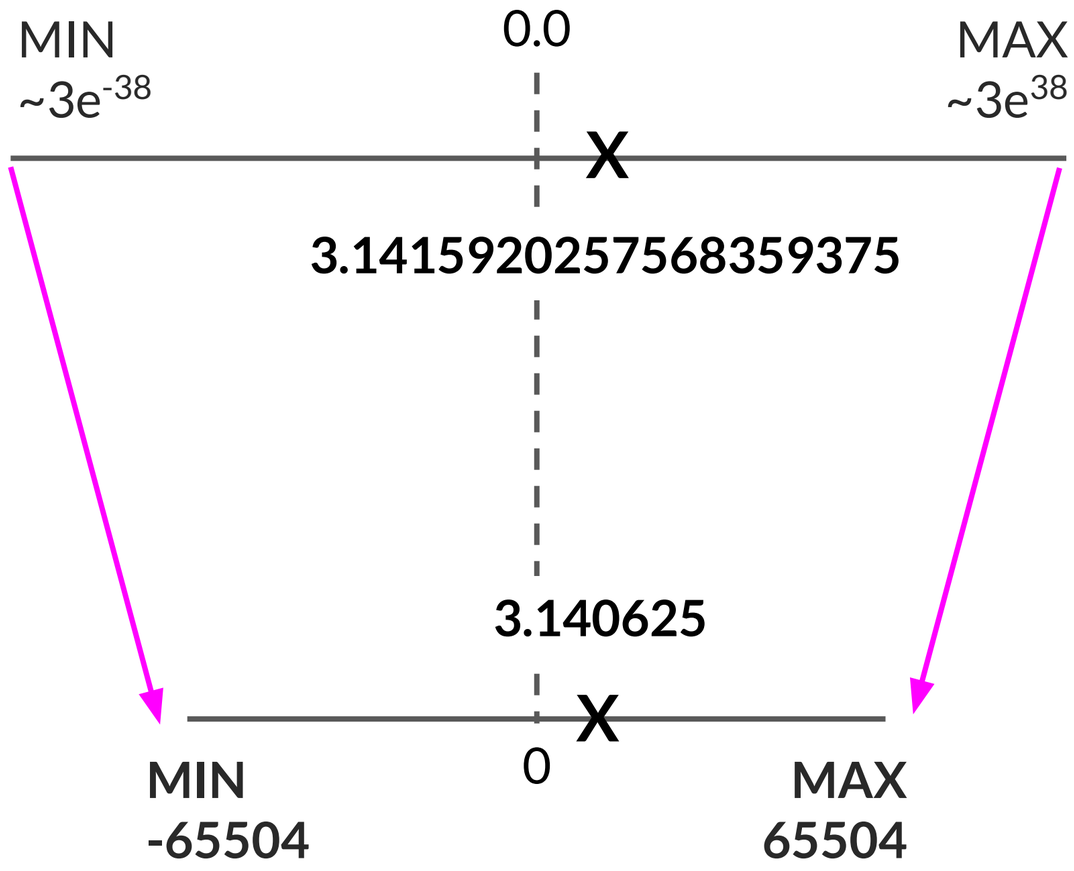
**Sign**
1 bit

**Exponent**
8 bits

**Fraction**
23 bits

*Mantissa / Significand*
= Precision

# Quantization: FP16




**Let's store Pi: 3.141592**

**FP32** **4 bytes memory**

**0** **10000000** **10010010000111111011000**

**Sign**
1 bit

**Exponent**
8 bits

**Fraction**
23 bits

**FP16** **2 bytes memory**

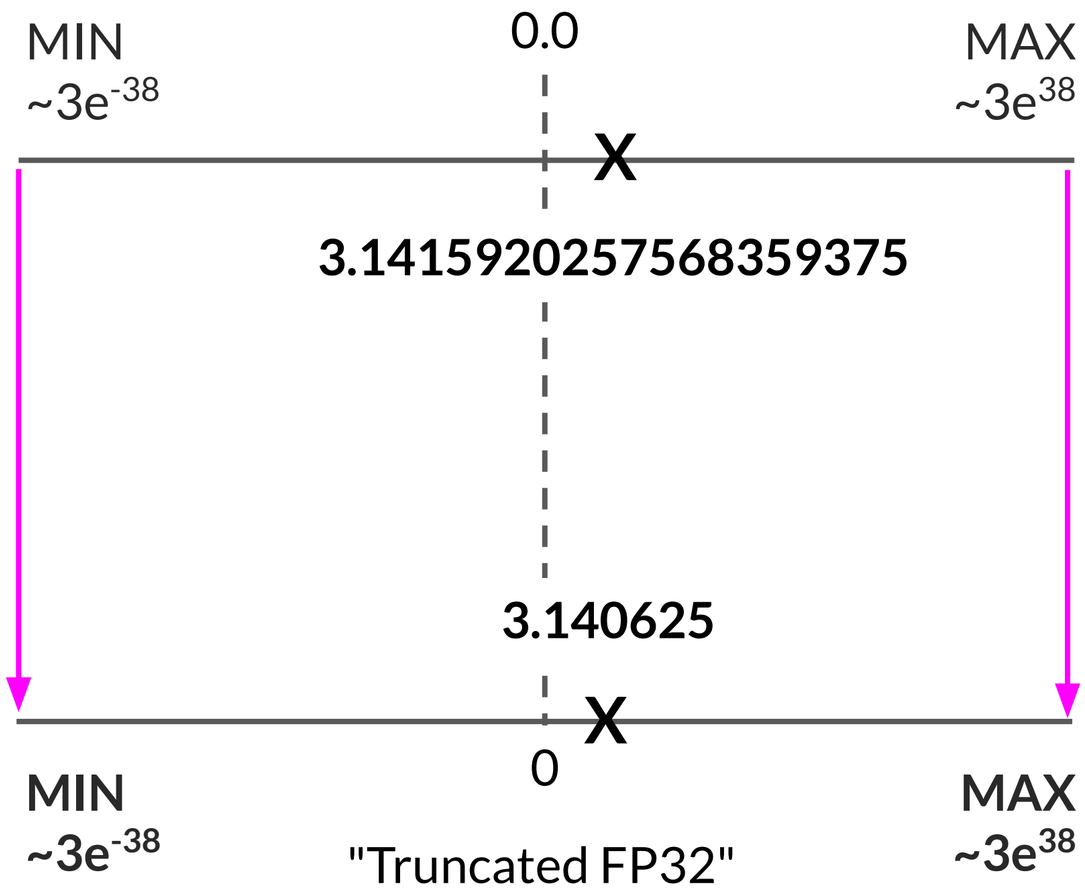
**0** **10000** **1001001000**

**Sign**
1 bit

**Exponent**
5 bits

**Fraction**
10 bits

# Quantization: BFLOAT16




**Let's store Pi: 3.141592**

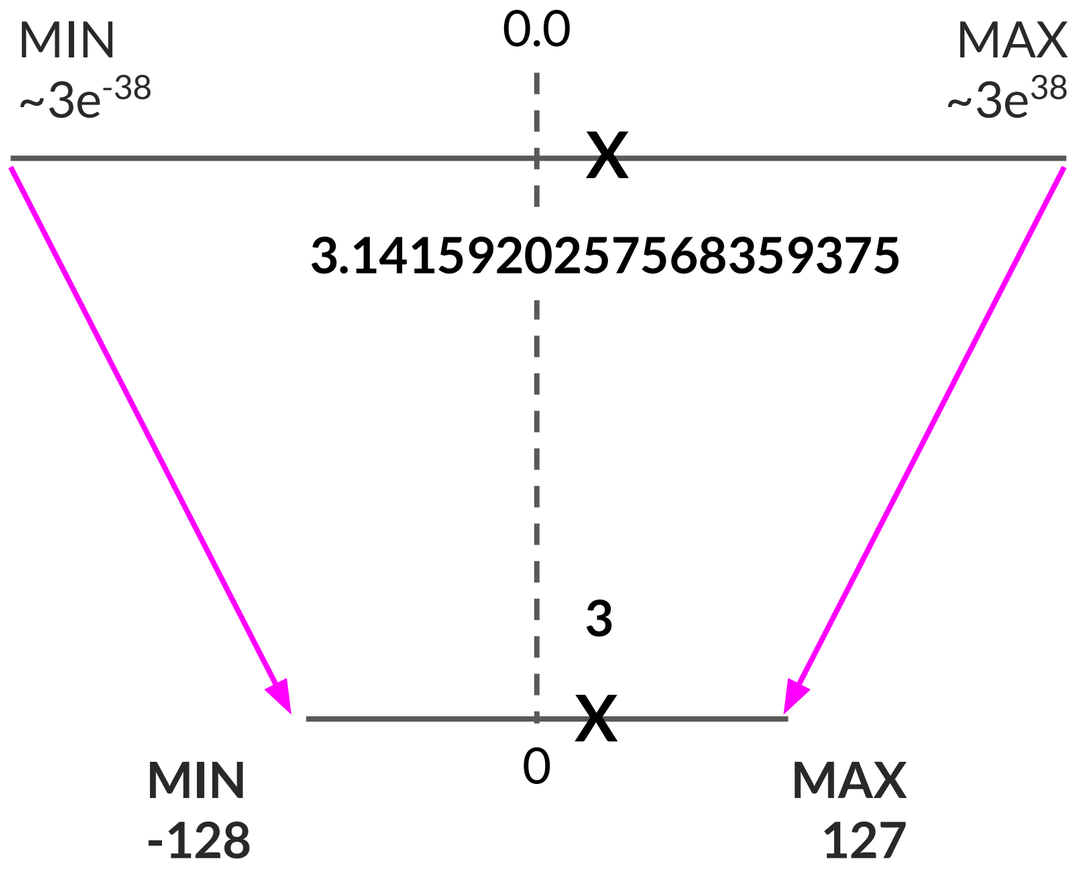
**FP32** **4 bytes memory**

| 0 | 10000000 | 10010010000111111011000 |
|---|---|---|
| **Sign** 1 bit | **Exponent** 8 bits | **Fraction** 23 bits |

**BFLOAT16 | BF16** **2 bytes memory**

| 0 | 10000000 | 1001001 |
|---|---|---|
| **Sign** 1 bit | **Exponent** 8 bits | **Fraction** 7 bits |

# Quantization: INT8




**Let's store Pi: 3.141592**

**FP32** **4 bytes memory**

**0** **10000000** **10010010000111111011000**

**Sign**
1 bit

**Exponent**
8 bits

**Fraction**
23 bits

**INT8** **1 byte memory**

**0** **0000011**

Sign
1 bit

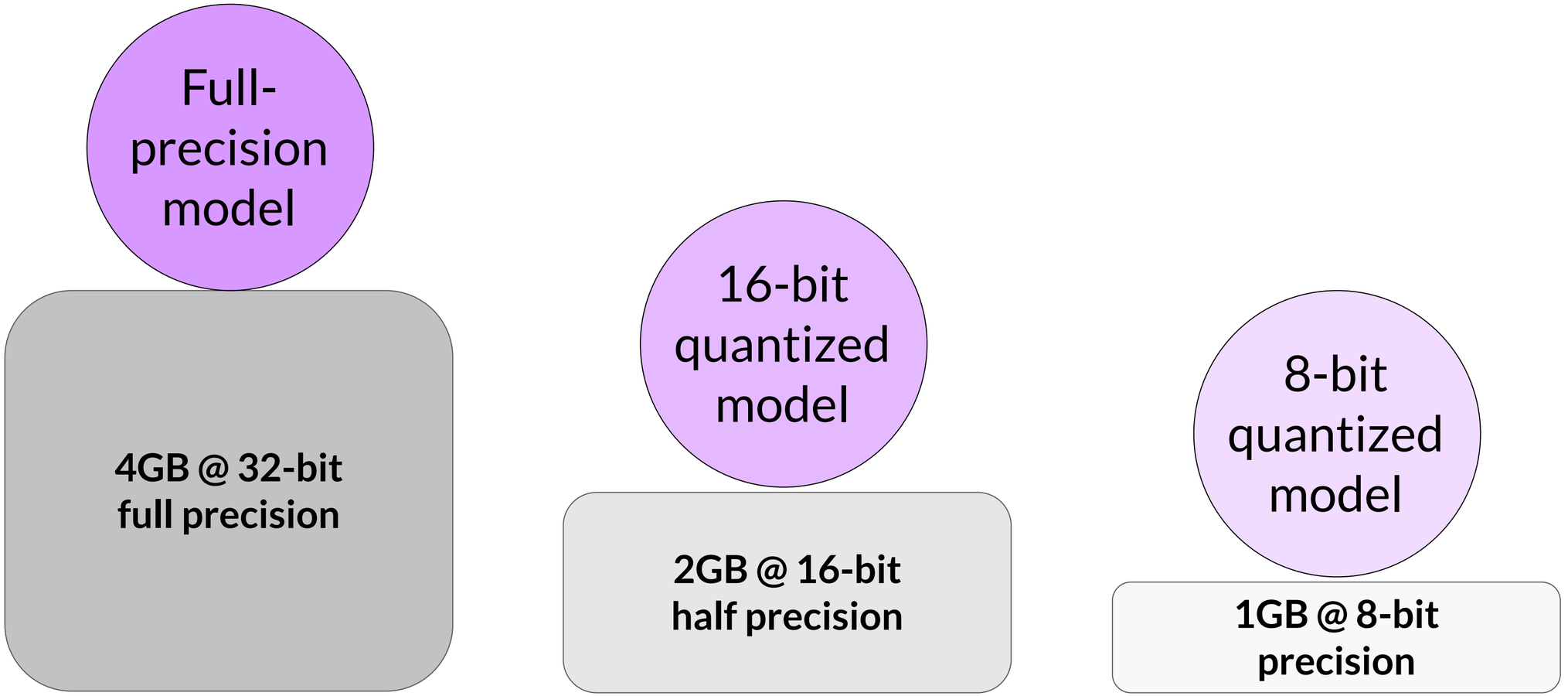
Fraction
7 bits

# Quantization: Summary

| | Bits | Exponent | Fraction | Memory needed to store one value |
|---|---|---|---|---|
| **FP32** | 32 | 8 | 23 | 4 bytes |
| **FP16** | 16 | 5 | 10 | 2 bytes |
| **BFLOAT16** | 16 | 8 | 7 | 2 bytes |
| **INT8** | 8 | –/– | 7 | 1 byte |

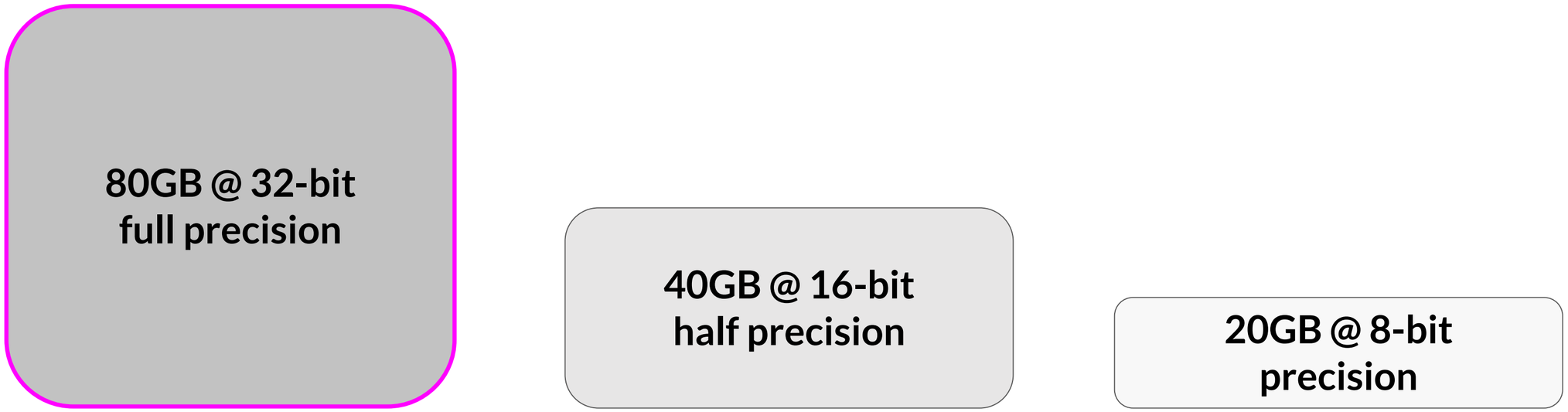

- Reduce required memory to store and train models
- Projects original 32-bit floating point numbers into lower precision spaces
- Quantization-aware training (QAT) learns the quantization scaling factors during training
- BFLOAT16 is a popular choice

# Approximate GPU RAM needed to store 1B parameters




Sources: https://huggingface.co/docs/transformers/v4.20.1/en/perf_train_gpu_one#anatomy-of-models-memory, https://github.com/facebookresearch/bitsandbytes

# Approximate GPU RAM needed to train 1B-params




80GB is the maximum memory for the Nvidia A100 GPU, so to keep the model on a single GPU, you need to use 16-bit or 8-bit quantization.

Sources: https://huggingface.co/docs/transformers/v4.20.1/en/perf_train_gpu_one#anatomy-of-models-memory, https://github.com/facebookresearch/bitsandbytes

# GPU RAM needed to train larger models

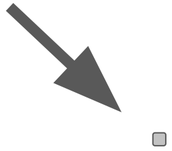
**1B param model**

**175B param model**

14,000 GB @ 32-bit full precision

**500B param model**

40,000 GB @ 32-bit full precision



# GPU RAM needed to train larger models

**As model sizes get larger, you will need to split your model across multiple GPUs for training**

**1B param model**

**14,000 GB @ 32-bit full precision**

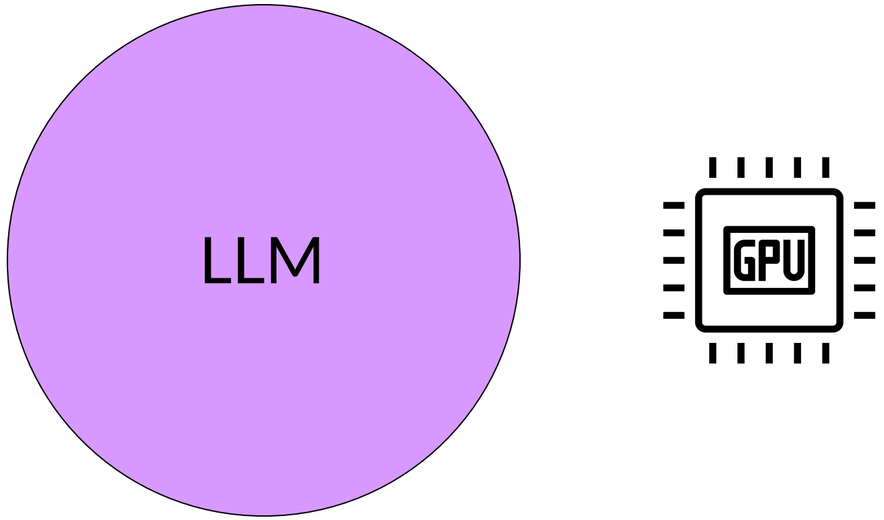
**175B param model**

**500B param model**

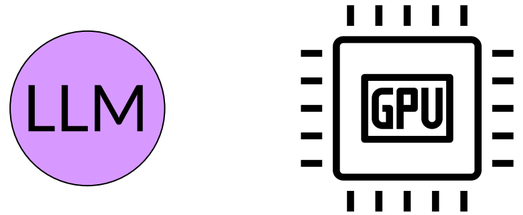
**40,000 GB @ 32-bit full precision**

# Efficient Multi-GPU Compute Strategies

# When to use distributed compute

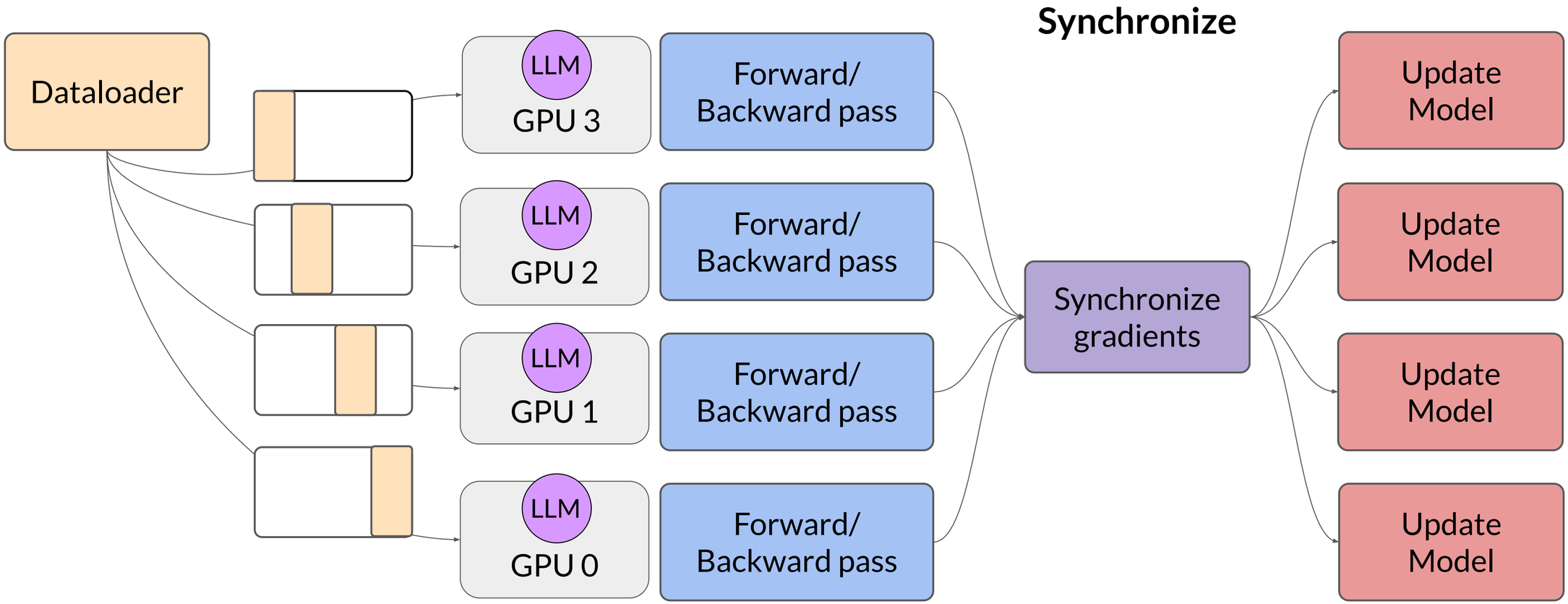



Model too big for single GPU



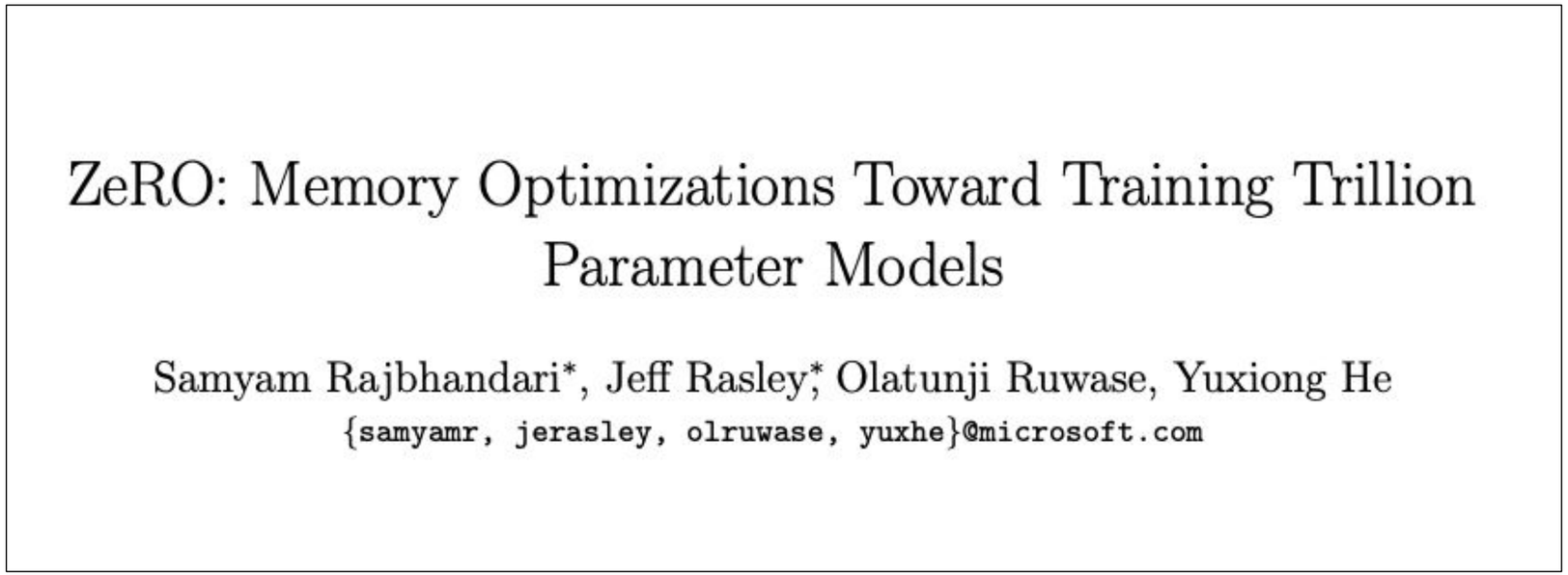

Model fits on GPU, train data in parallel

# Distributed Data Parallel (DDP)



# Fully Sharded Data Parallel (FSDP)

- Motivated by the “ZeRO” paper - zero data overlap between GPUs



ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

Samyam Rajbhandari*, Jeff Rasley*, Olatunji Ruwase, Yuxiong He
{samyamr, jerasley, olruwase, yuxhe}@microsoft.com

Sources:
Rajbhandari et al. 2019: “ZeRO: Memory Optimizations Toward Training Trillion Parameter Models”
Zhao et al. 2023: “PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel”

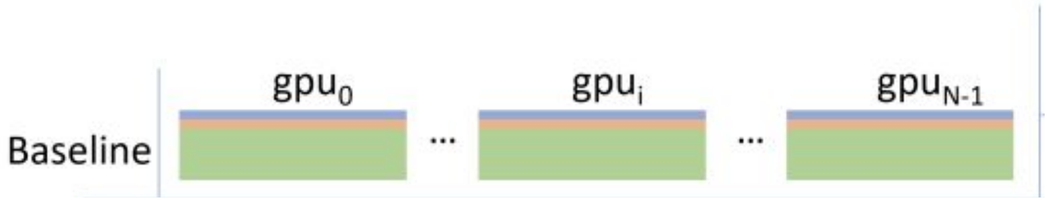
# Recap: Additional GPU RAM needed for training

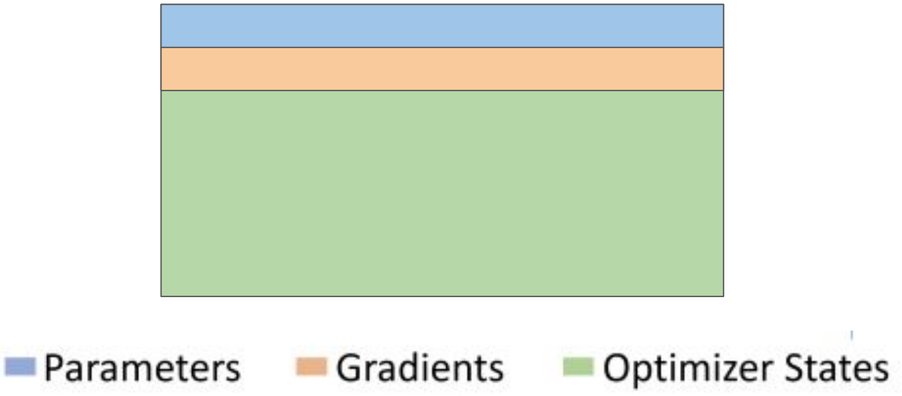
| | Bytes per parameter |
|---|---|
| **Model Parameters (Weights)** | 4 bytes per parameter |
| **Adam optimizer (2 states)** | +8 bytes per parameter |
| **Gradients** | +4 bytes per parameter |
| **Activations and temp memory (variable size)** | +8 bytes per parameter (high-end estimate) |
| **TOTAL** | **=4 bytes per parameter<br>+20 extra bytes per parameter** |

Sources: https://huggingface.co/docs/transformers/v4.20.1/en/perf_train_gpu_one#anatomy-of-models-memory, https://github.com/facebookresearch/bitsandbytes

# Memory usage in DDP

- One full copy of model and training parameters on each GPU

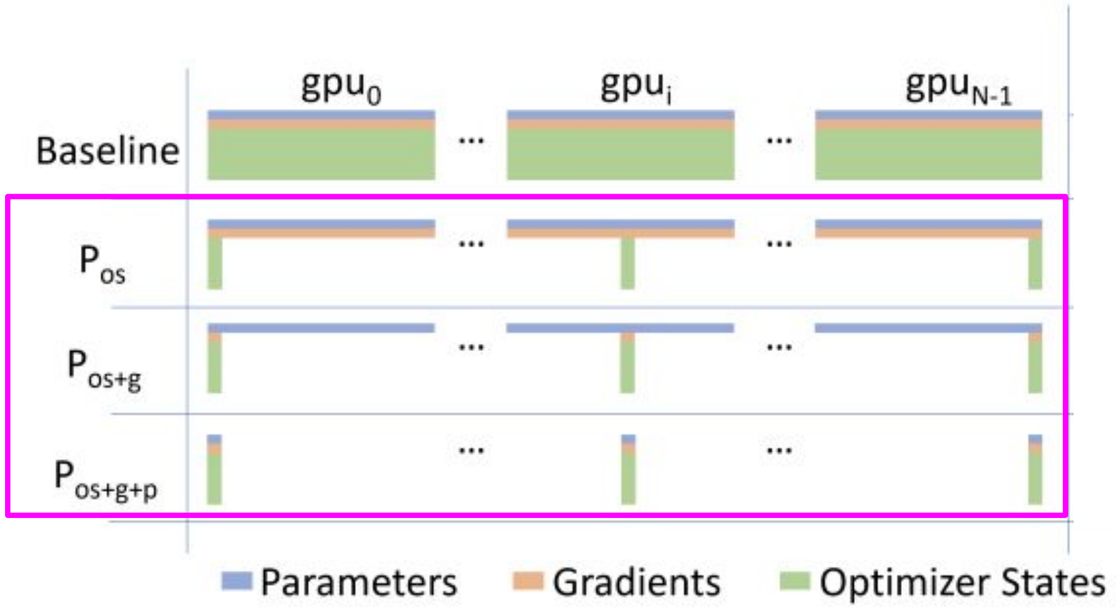


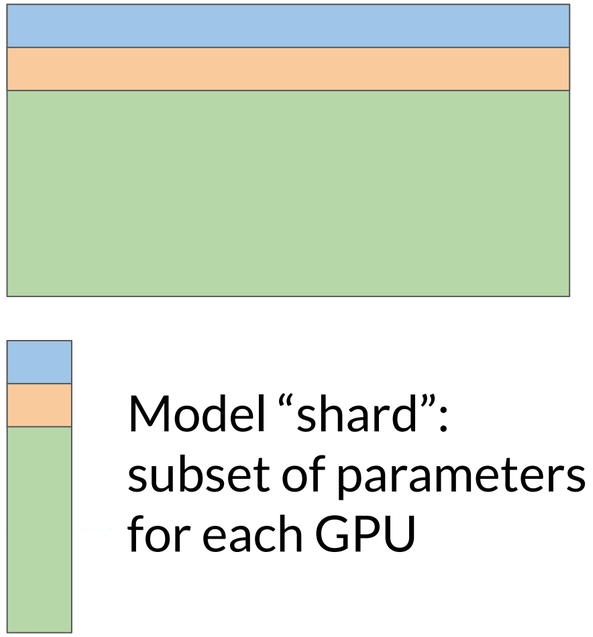




Sources:
Rajbhandari et al. 2019: “ZeRO: Memory Optimizations Toward Training Trillion Parameter Models”
Zhao et al. 2023: “PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel”

# Zero Redundancy Optimizer (ZeRO)

- Reduces memory by distributing (sharding) the model parameters, gradients, and optimizer states across GPUs



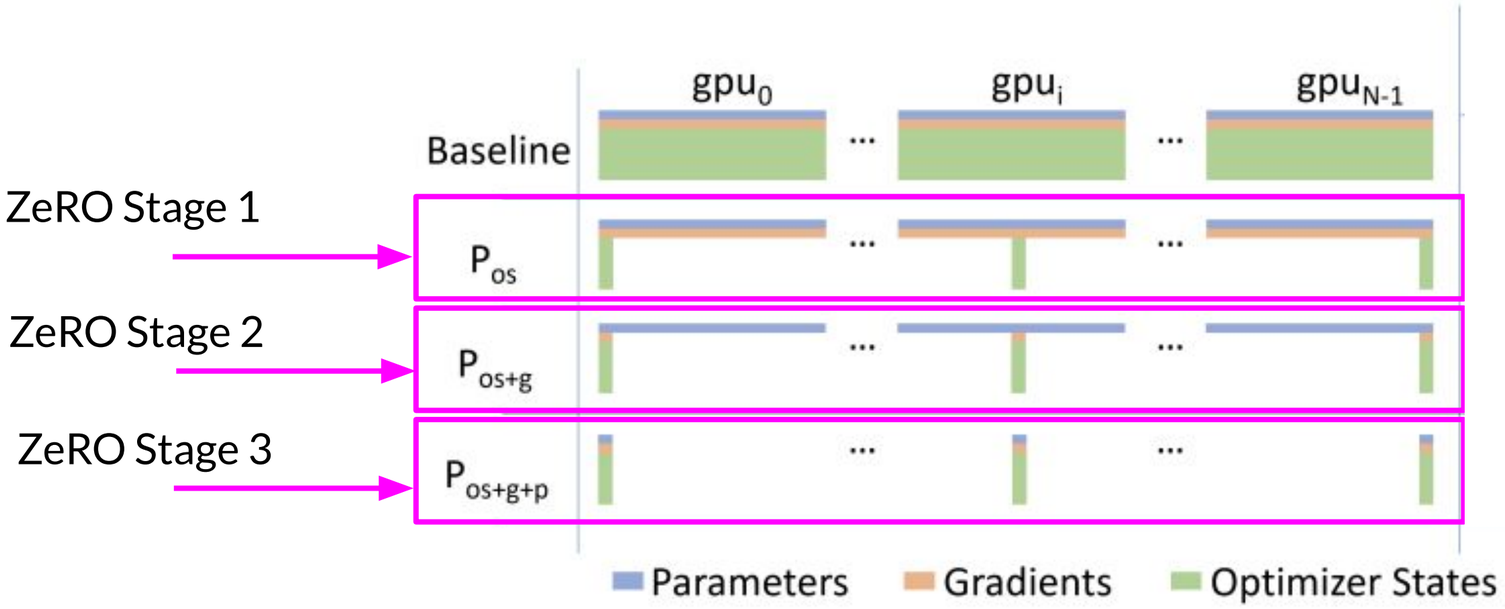



Model “shard”:
subset of parameters
for each GPU

Sources:
Rajbhandari et al. 2019: “ZeRO: Memory Optimizations Toward Training Trillion Parameter Models”
Zhao et al. 2023: “PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel”

# Zero Redundancy Optimizer (ZeRO)

- Reduces memory by distributing (sharding) the model parameters, gradients, and optimizer states across GPUs



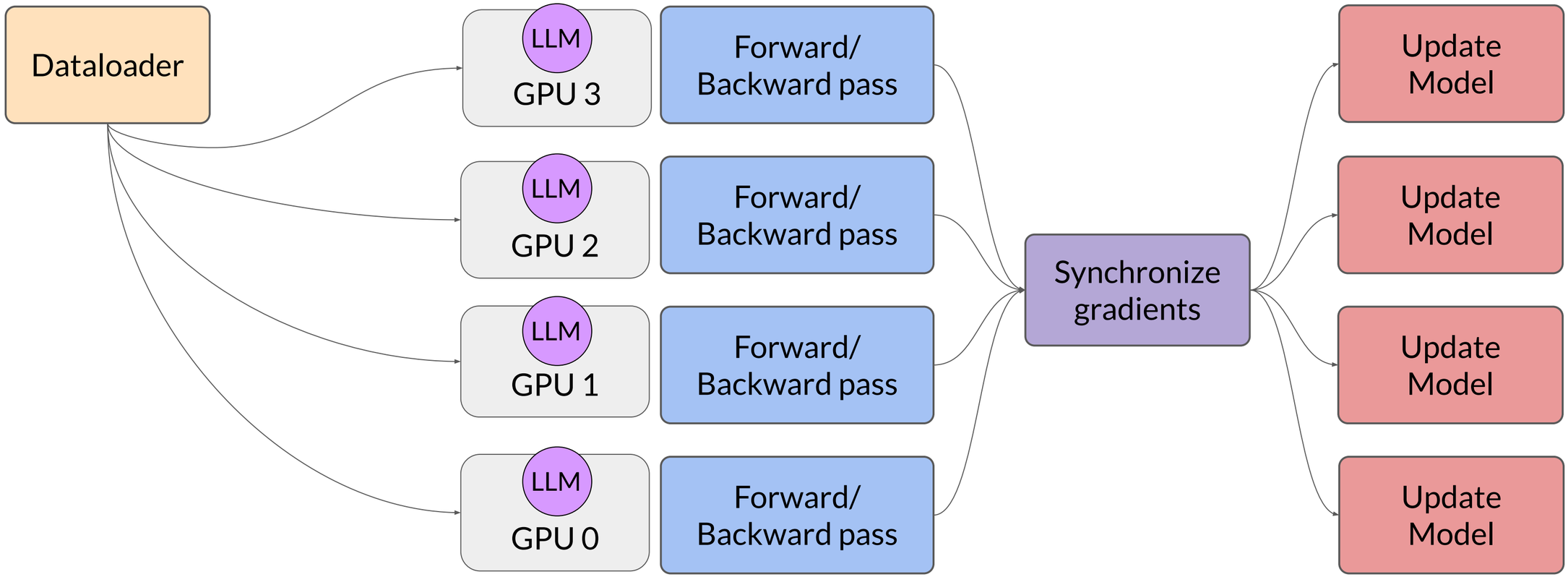

4x reduction

8x reduction

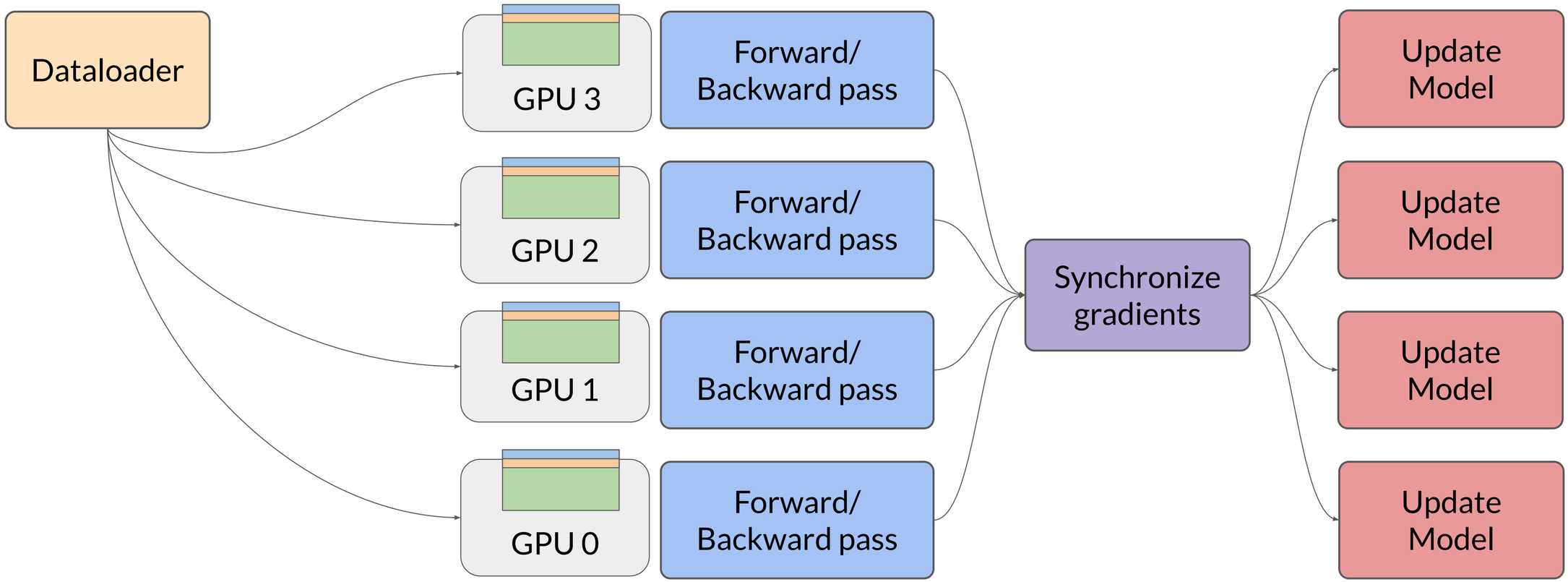
numGPU x reduction

Sources:
Rajbhandari et al. 2019: “ZeRO: Memory Optimizations Toward Training Trillion Parameter Models”
Zhao et al. 2023: “PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel”

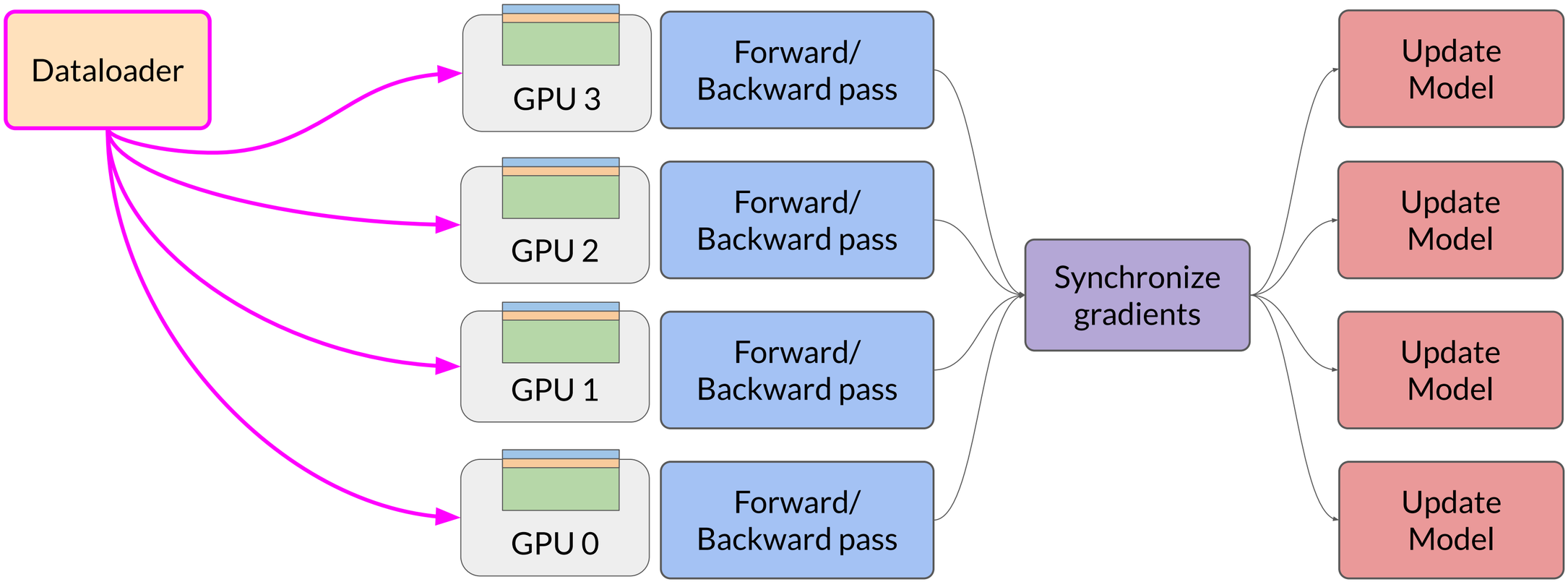
# Distributed Data Parallel (DDP)



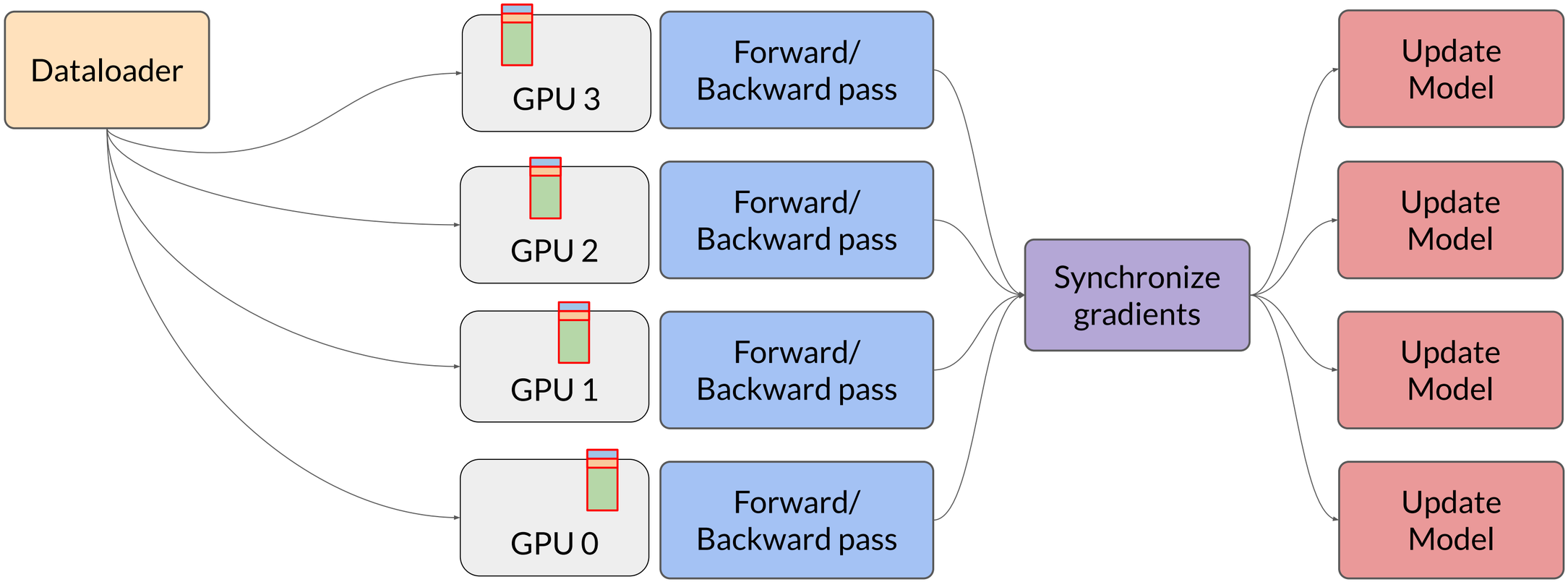
# Distributed Data Parallel (DDP)



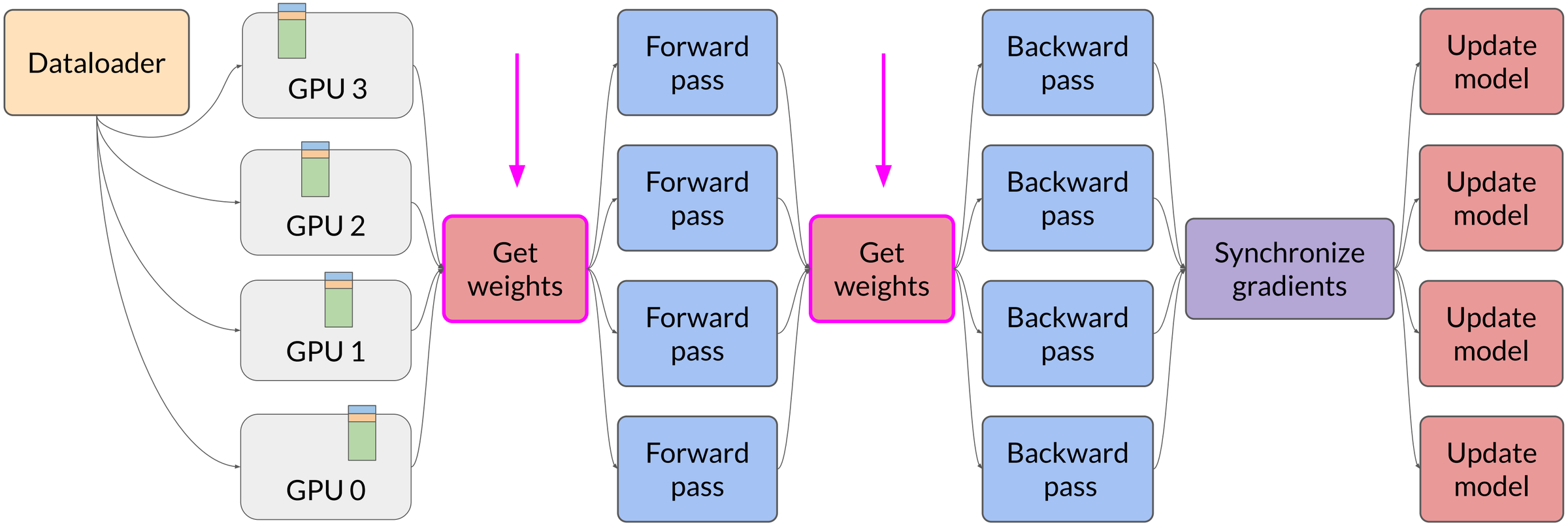
# Fully Sharded Data Parallel (FSDP)



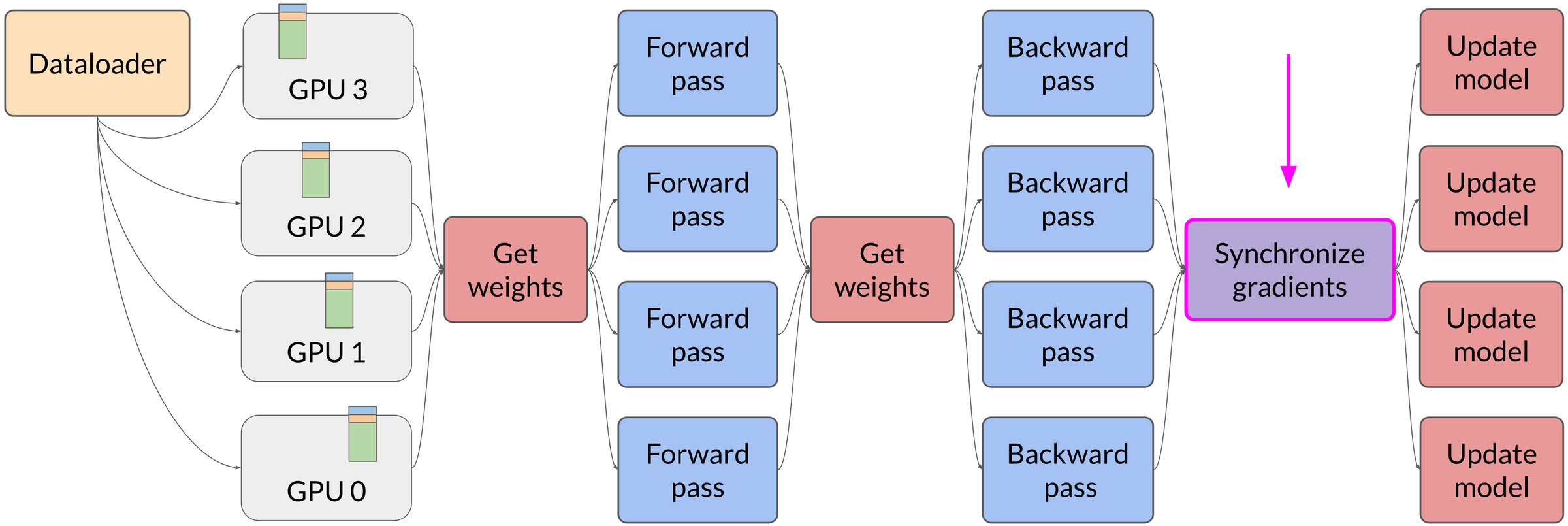
# Fully Sharded Data Parallel (FSDP)



# Fully Sharded Data Parallel (FSDP)



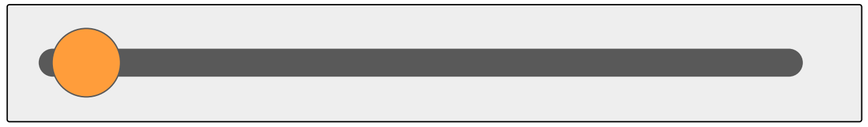
# Fully Sharded Data Parallel (FSDP)



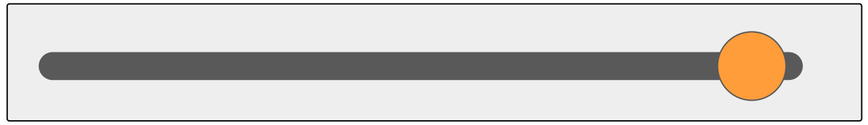
# Fully Sharded Data Parallel (FSDP)

- Helps to reduce overall GPU memory utilization
- Supports offloading to CPU if needed
- Configure level of sharding via `sharding factor`

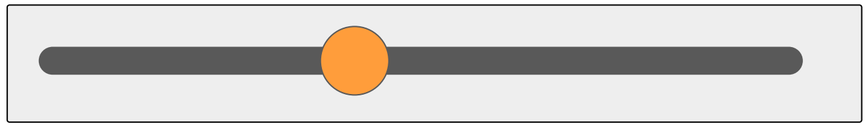
**Full replication (no sharding)**

1 GPU  max. number of GPUs

**Full sharding**

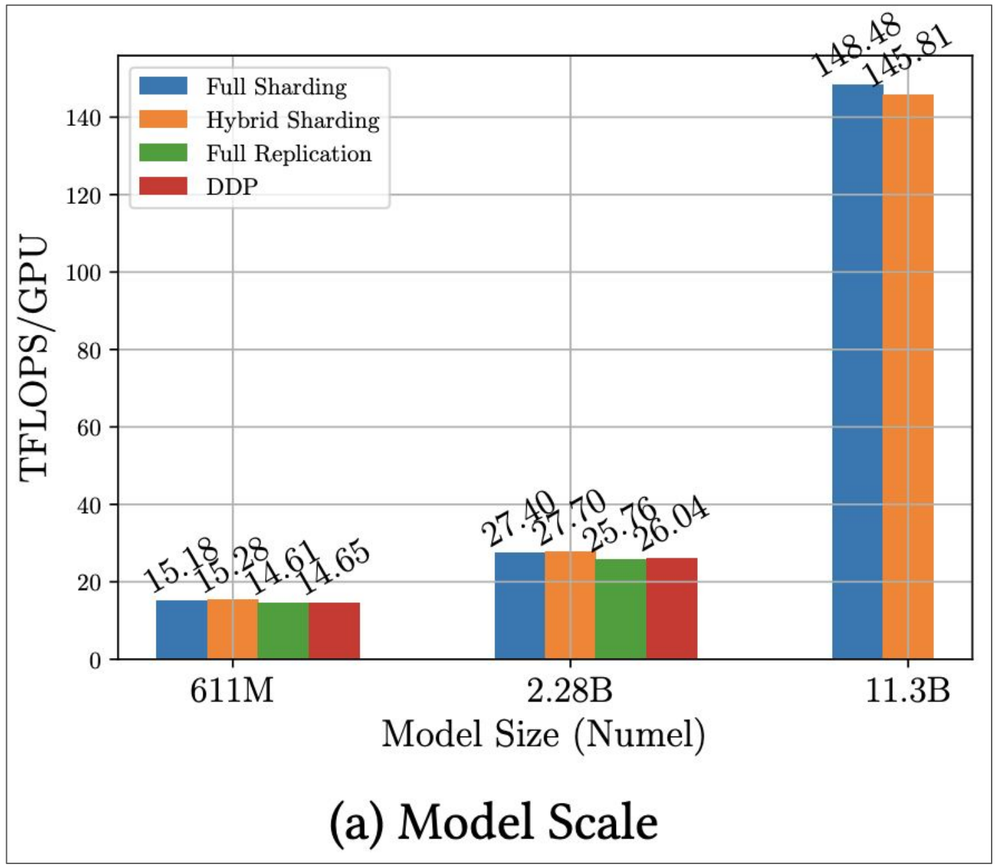
1 GPU  **max. number of GPUs**

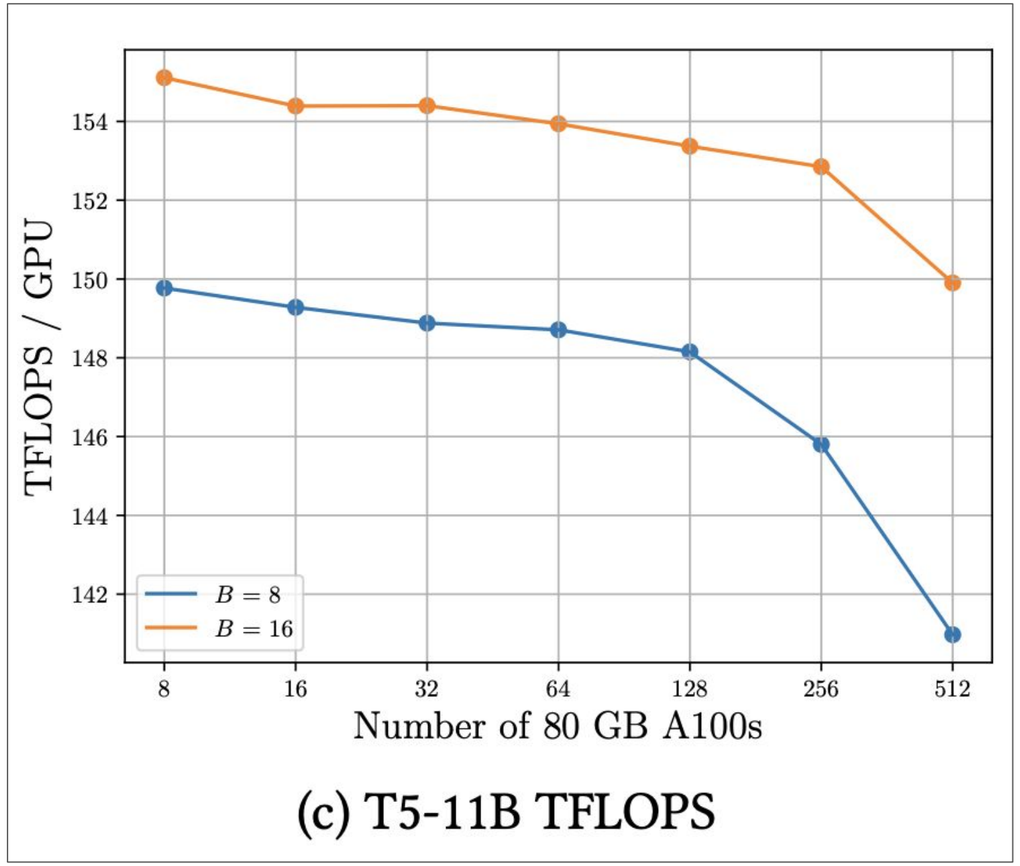
**Hybrid sharding**

1 GPU  max. number of GPUs

# Impact of using FSDP

**Note: 1 teraFLOP/s = 1,000,000,000,000 (one trillion) floating point operations per second**



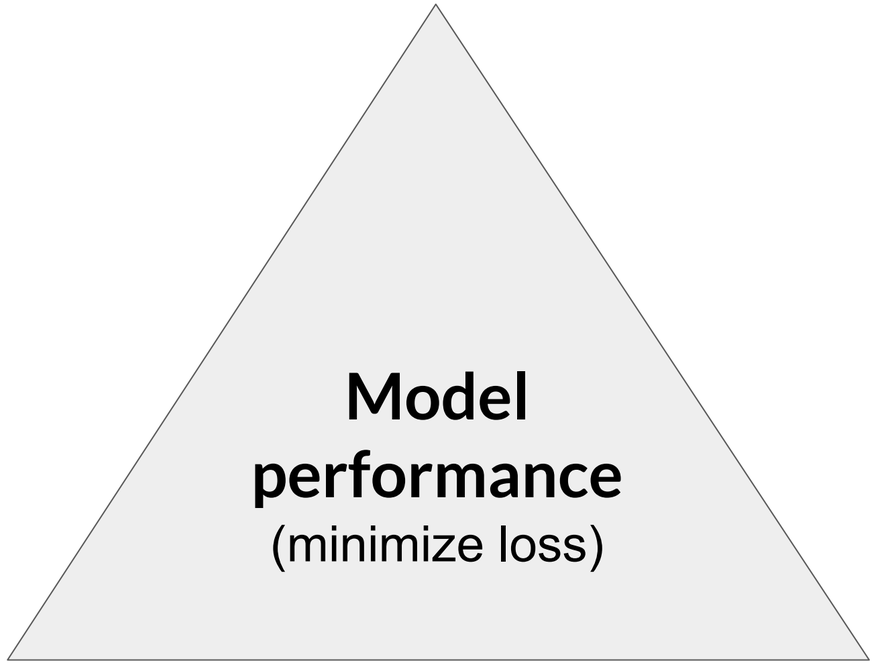

Zhao et al. 2023: “PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel”

# Scaling laws and compute-optimal models

# Scaling choices for pre-training

Goal: **maximize model performance**

**CONSTRAINT:**
Compute budget
(GPUs, training time, cost)



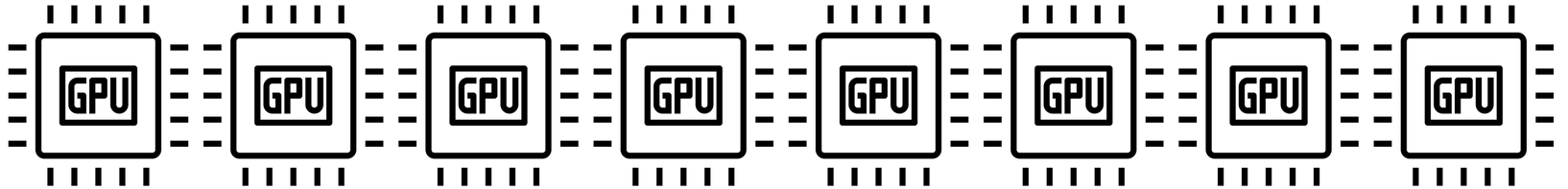

**SCALING CHOICE:**
Dataset size
(number of tokens)

**SCALING CHOICE:**
Model size
(number of parameters)

# Compute budget for training LLMs

1 “petaflop/s-day” =
# floating point operations performed at rate of 1 petaFLOP per second for one day

NVIDIA V100s



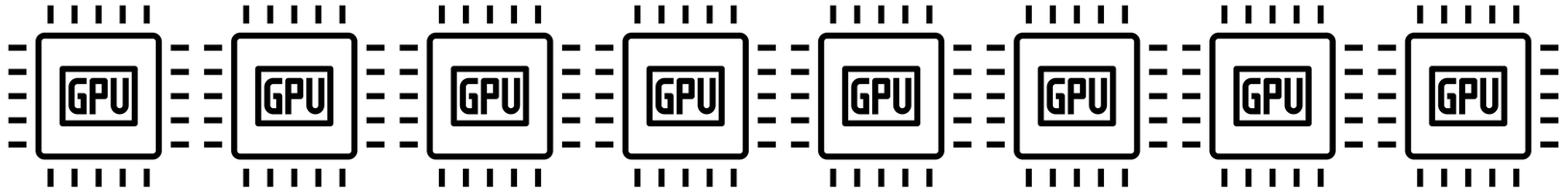

**Note: 1 petaFLOP/s = 1,000,000,000,000,000 (one quadrillion) floating point operations per second**

1 petaflop/s-day is these chips running at full efficiency for 24 hours

# Compute budget for training LLMs

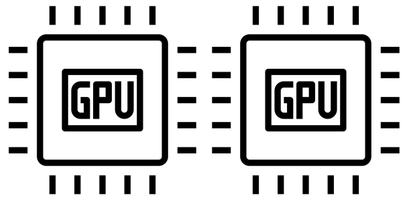
1 “petaflop/s-day” =
# floating point operations performed at rate of 1 petaFLOP per second for one day

NVIDIA V100s



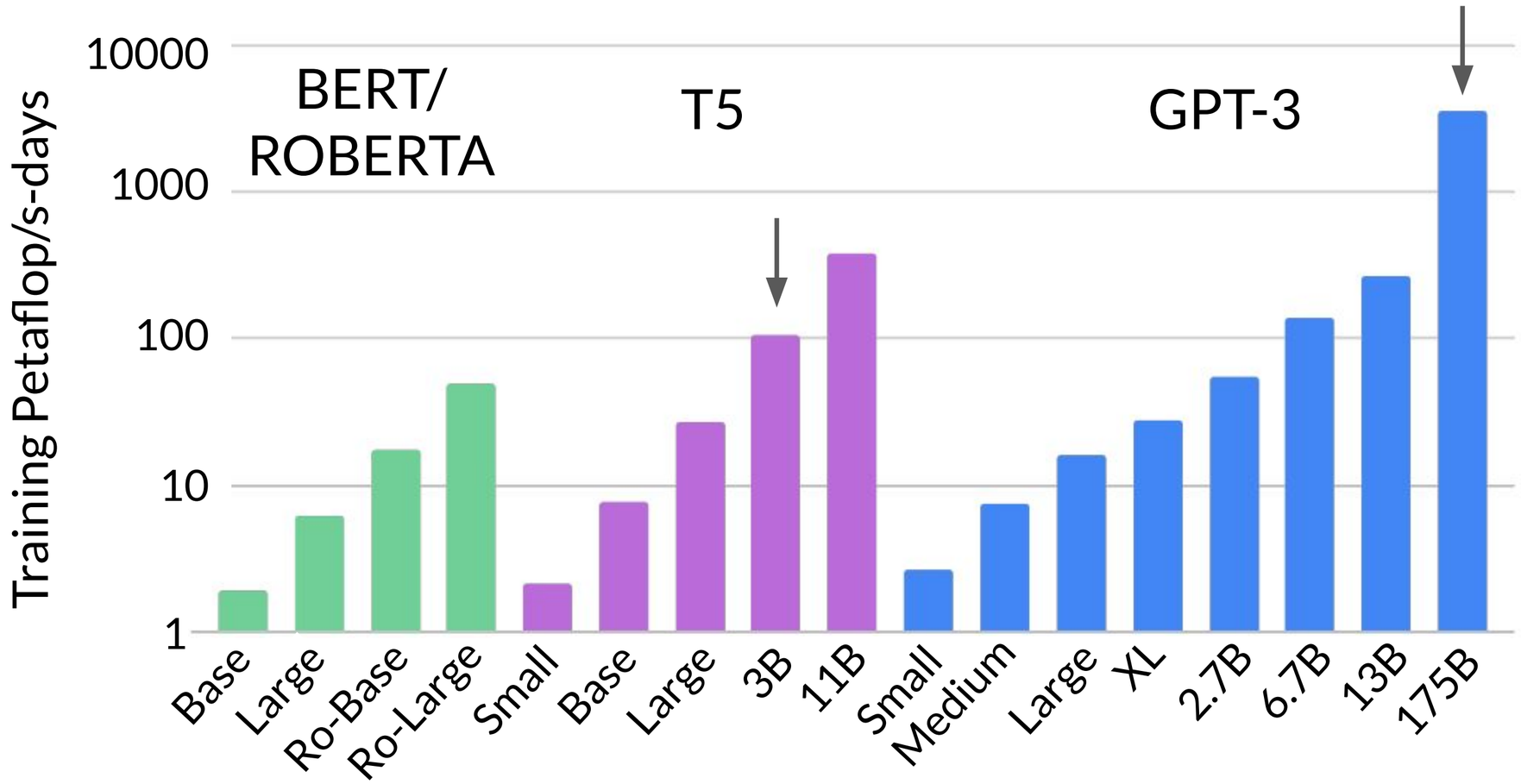

OR

NVIDIA A100s



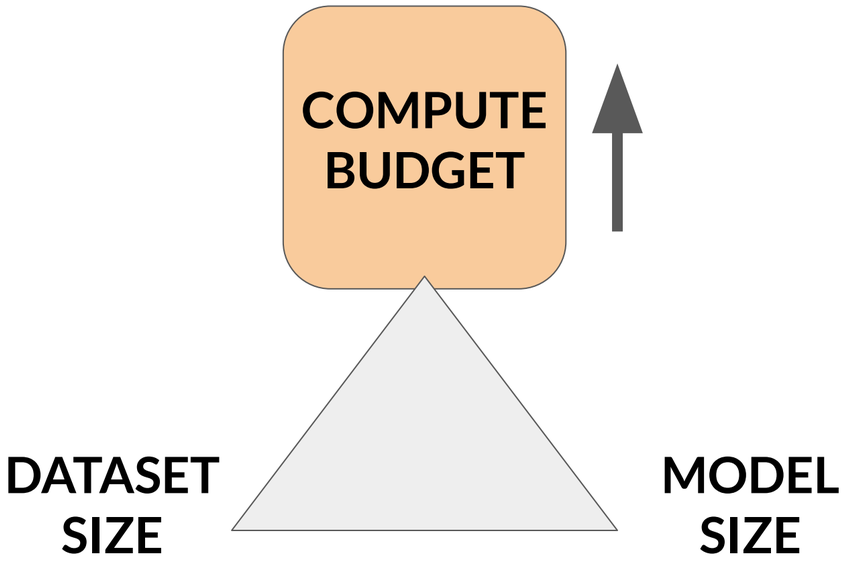

1 petaflop/s-day is these chips running at full efficiency for 24 hours

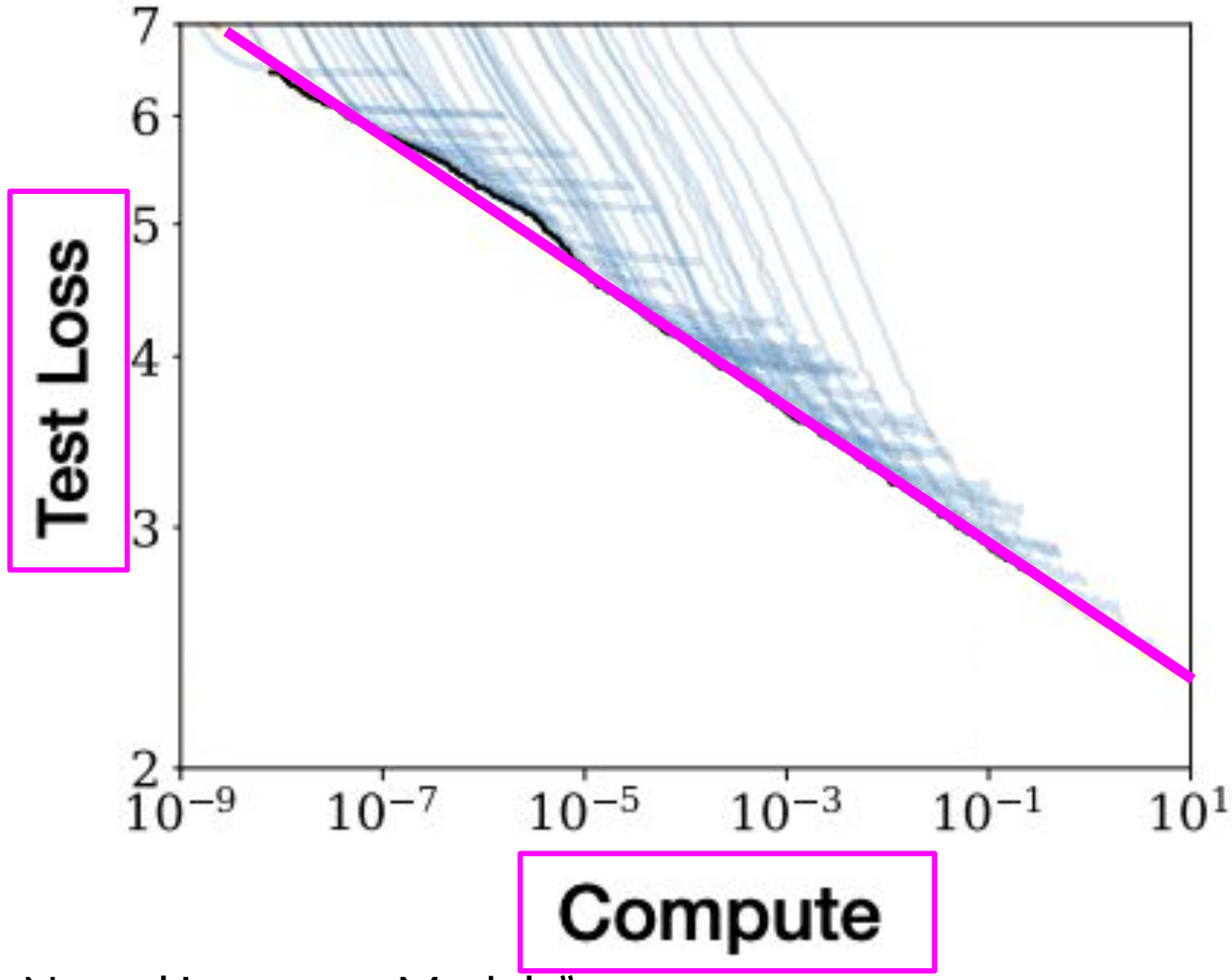
# Number of petaflop/s-days to pre-train various LLMs




Source: Brown et al. 2020, “Language Models are Few-Shot Learners”

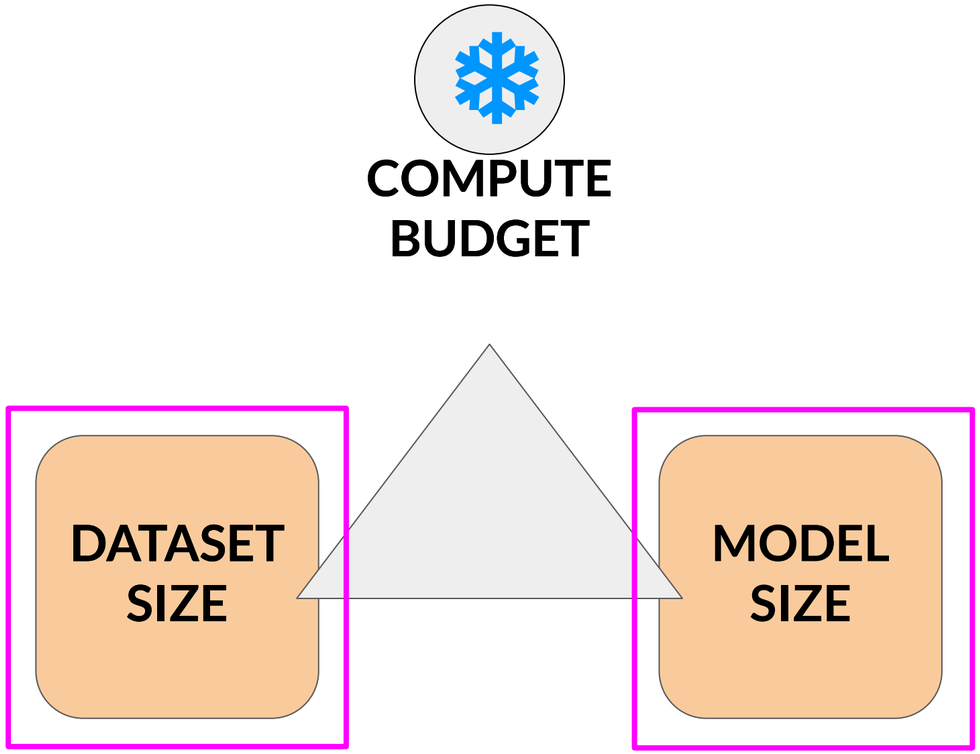
# Compute budget vs. model performance




Source: Kaplan et al. 2020, “Scaling Laws for Neural Language Models”

# Dataset size and model size vs. performance

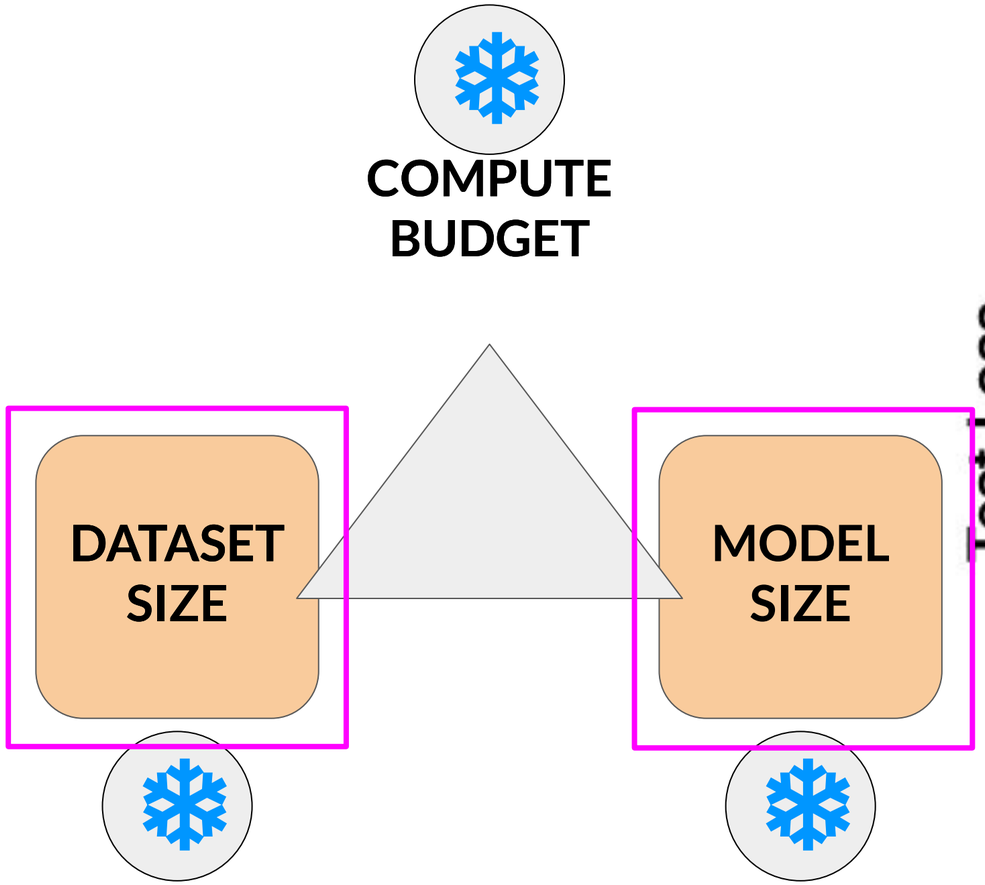


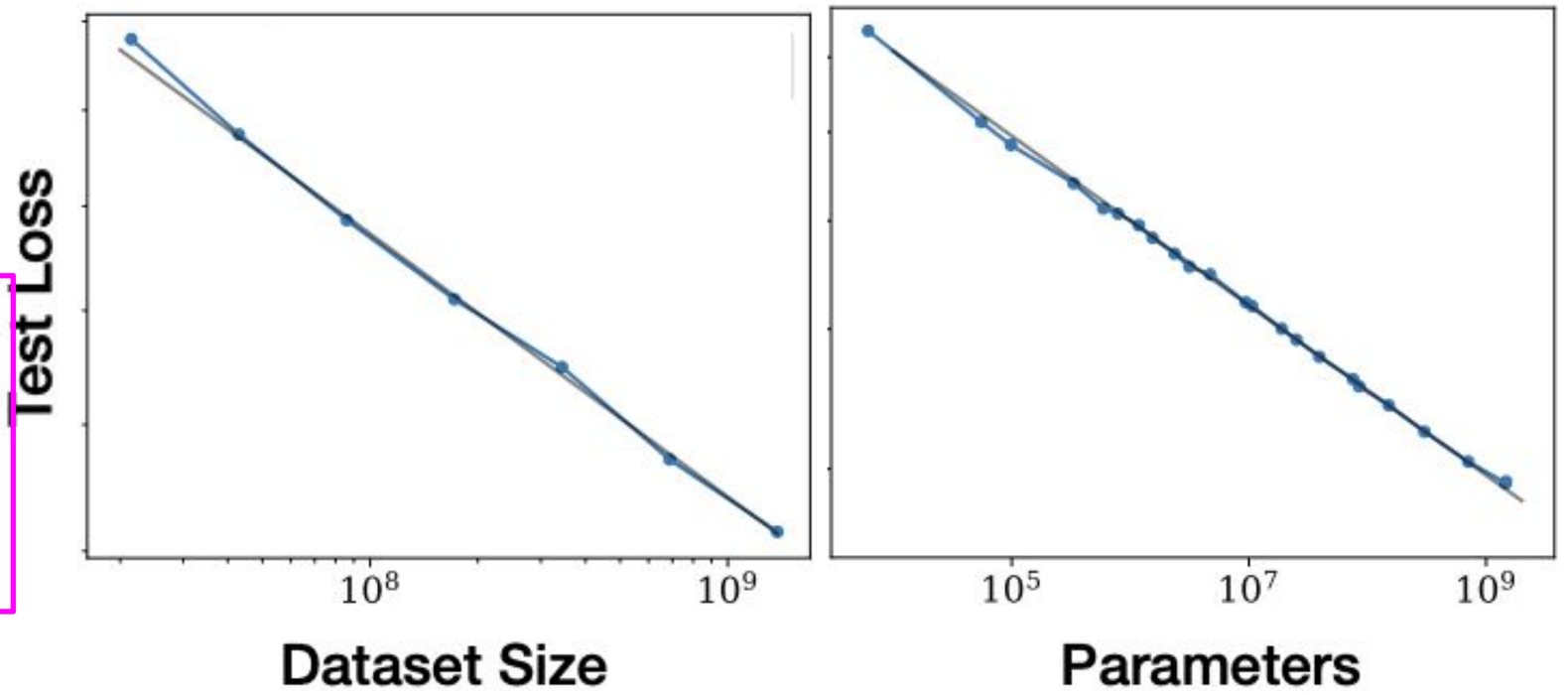

Compute resource constraints

- Hardware
- Project timeline
- Financial budget

Source: Kaplan et al. 2020, “Scaling Laws for Neural Language Models”

# Dataset size and model size vs. performance




Source: Kaplan et al. 2020, “Scaling Laws for Neural Language Models”

# Chinchilla paper

## Training Compute-Optimal Large Language Models

Jordan Hoffmann*, Sebastian Borgeaud*, Arthur Mensch*, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals and Laurent Sifre*

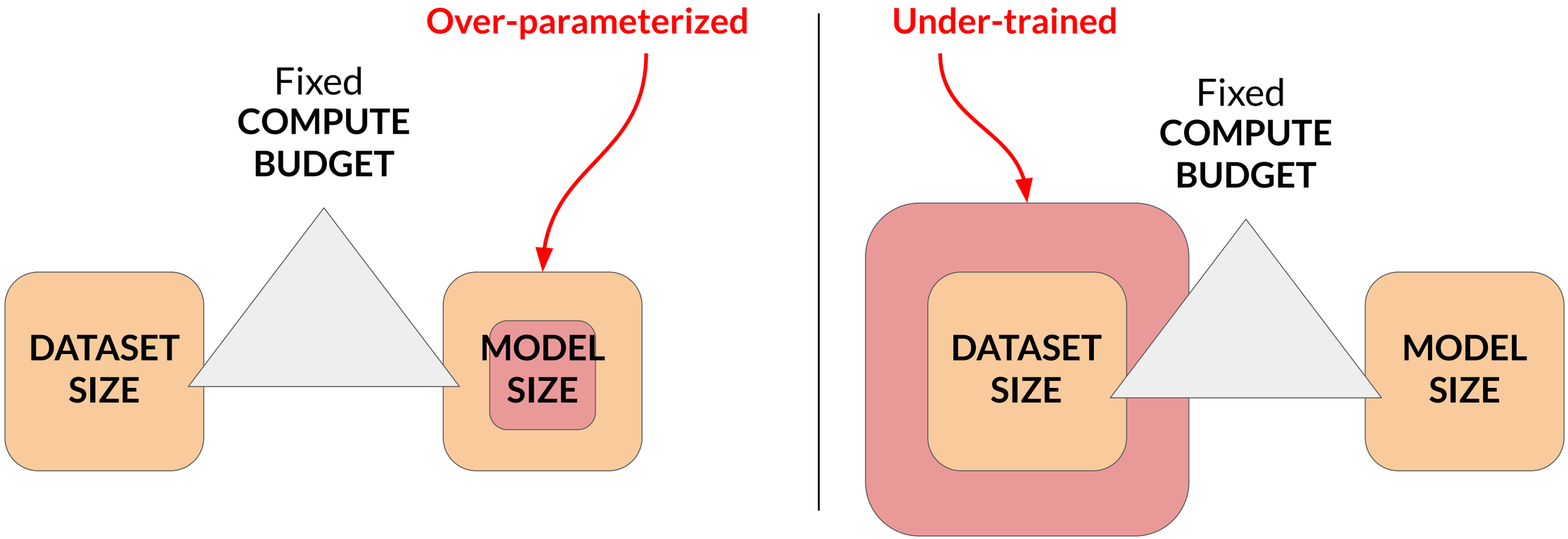
*Equal contributions

We investigate the optimal model size and number of tokens for training a transformer language model under a given compute budget. We find that current large language models are significantly under-trained, a consequence of the recent focus on scaling language models whilst keeping the amount of training data constant. By training over 400 language models ranging from 70 million to over 16 billion parameters on 5 to 500 billion tokens, we find that for compute-optimal training, the model size and the number of training tokens should be scaled equally: for every doubling of model size the number of training tokens should also be doubled. We test this hypothesis by training a predicted compute-optimal model, *Chinchilla*, that uses the same compute budget as *Gopher* but with 70B parameters and 4× more more data. *Chinchilla* uniformly and significantly outperforms *Gopher* (280B), GPT-3 (175B), Jurassic-1 (178B), and Megatron-Turing NLG (530B) on a large range of downstream evaluation tasks. This also means that *Chinchilla* uses substantially less compute for fine-tuning and inference, greatly facilitating downstream usage. As a highlight, *Chinchilla* reaches a state-of-the-art average accuracy of 67.5% on the MMLU benchmark, greater than a 7% improvement over *Gopher*.

Jordan et al. 2022

# Compute optimal models

- Very large models may be **over-parameterized** and **under-trained**
- Smaller models trained on more data could perform as well as large models



# Chinchilla scaling laws for model and dataset size

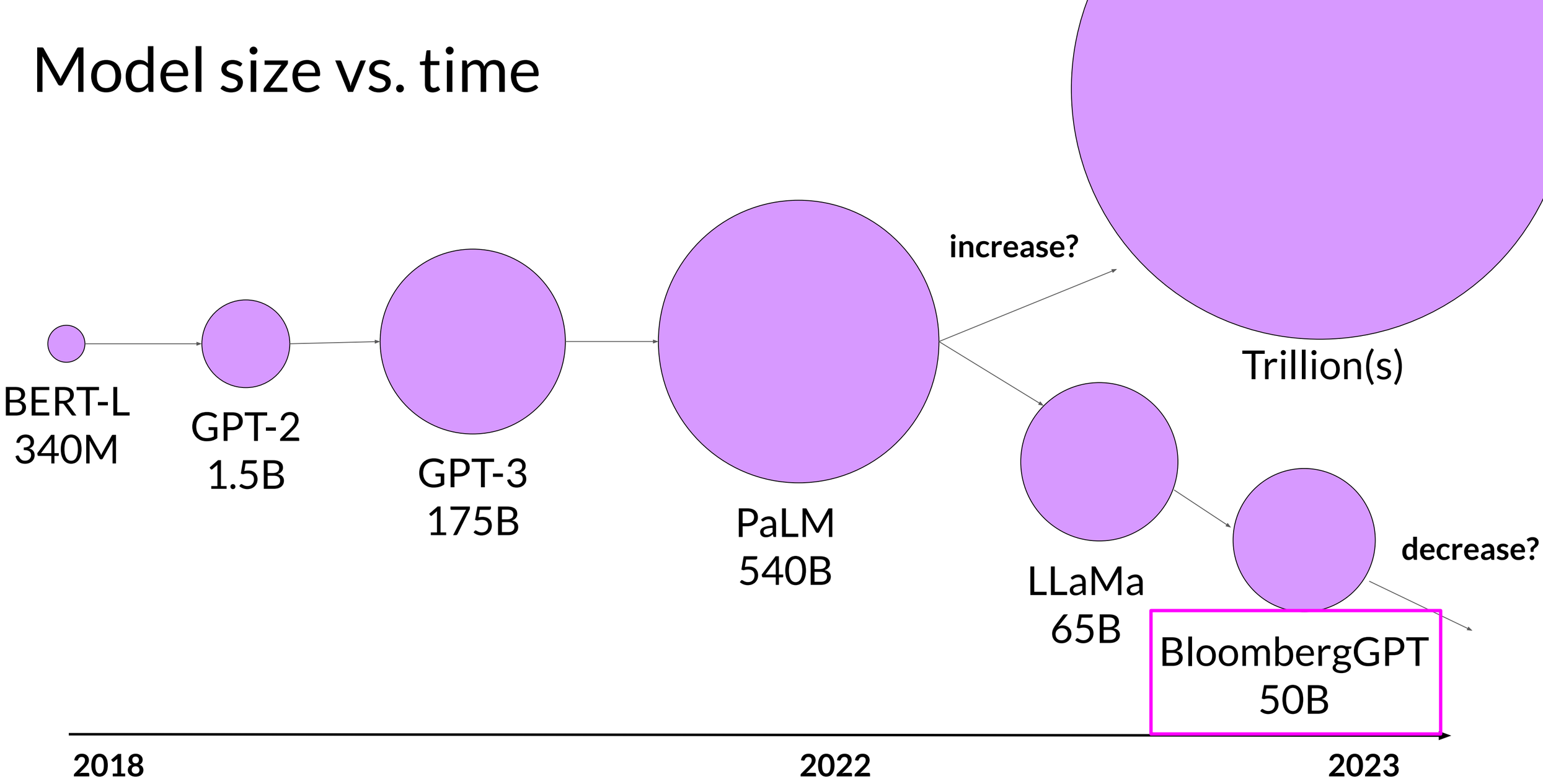
| Model | # of parameters | Compute-optimal* # of tokens (~20x) | Actual # tokens |
|---|---|---|---|
| Chinchilla | 70B | ~1.4T | 1.4T |
| LLaMA-65B | 65B | ~1.3T | 1.4T |
| GPT-3 | 175B | ~3.5T | 300B |
| OPT-175B | 175B | ~3.5T | 180B |
| BLOOM | 176B | ~3.5T | 350B |

Compute optimal training datasize is ~20x number of parameters

* assuming models are trained to be compute-optimal per Chinchilla paper

Sources: Hoffmann et al. 2022, “Training Compute-Optimal Large Language Models”
Touvron et al. 2023, “LLaMA: Open and Efficient Foundation Language Models”

# Model size vs. time



# Pre-training for domain adaptation

# Pre-training for domain adaptation

Legal language

# Pre-training for domain adaptation

## Legal language

```
The prosecutor had difficulty
proving mens rea, as the defendant
seemed unaware that his actions
were illegal.

The judge dismissed the case,
citing the principle of res
judicata as the issue had already
been decided in a previous trial.

Despite the signed agreement, the
contract was invalid as there was
no consideration exchanged between
the parties.
```

# Pre-training for domain adaptation

## Legal language

The prosecutor had difficulty proving mens rea, as the defendant seemed unaware that his actions were illegal.

The judge dismissed the case, citing the principle of res judicata as the issue had already been decided in a previous trial.

Despite the signed agreement, the contract was invalid as there was no consideration exchanged between the parties.

## Medical language

After a strenuous workout, the patient experienced severe myalgia that lasted for several days.

After the biopsy, the doctor confirmed that the tumor was malignant and recommended immediate treatment.

Sig: 1 tab po qid pc & hs

Take one tablet by mouth four times a day, after meals, and at bedtime.

# BloombergGPT: domain adaptation for finance

## BloombergGPT: A Large Language Model for Finance

**Shijie Wu[1,*], Ozan İrsoy[1,*], Steven Lu[1,*], Vadim Dabravolski[1], Mark Dredze[1,2], Sebastian Gehrmann[1], Prabhanjan Kambadur[1], David Rosenberg[1], Gideon Mann[1]**
**[1] Bloomberg, New York, NY USA**
**[2] Computer Science, Johns Hopkins University, Baltimore, MD USA**
gmann16@bloomberg.net

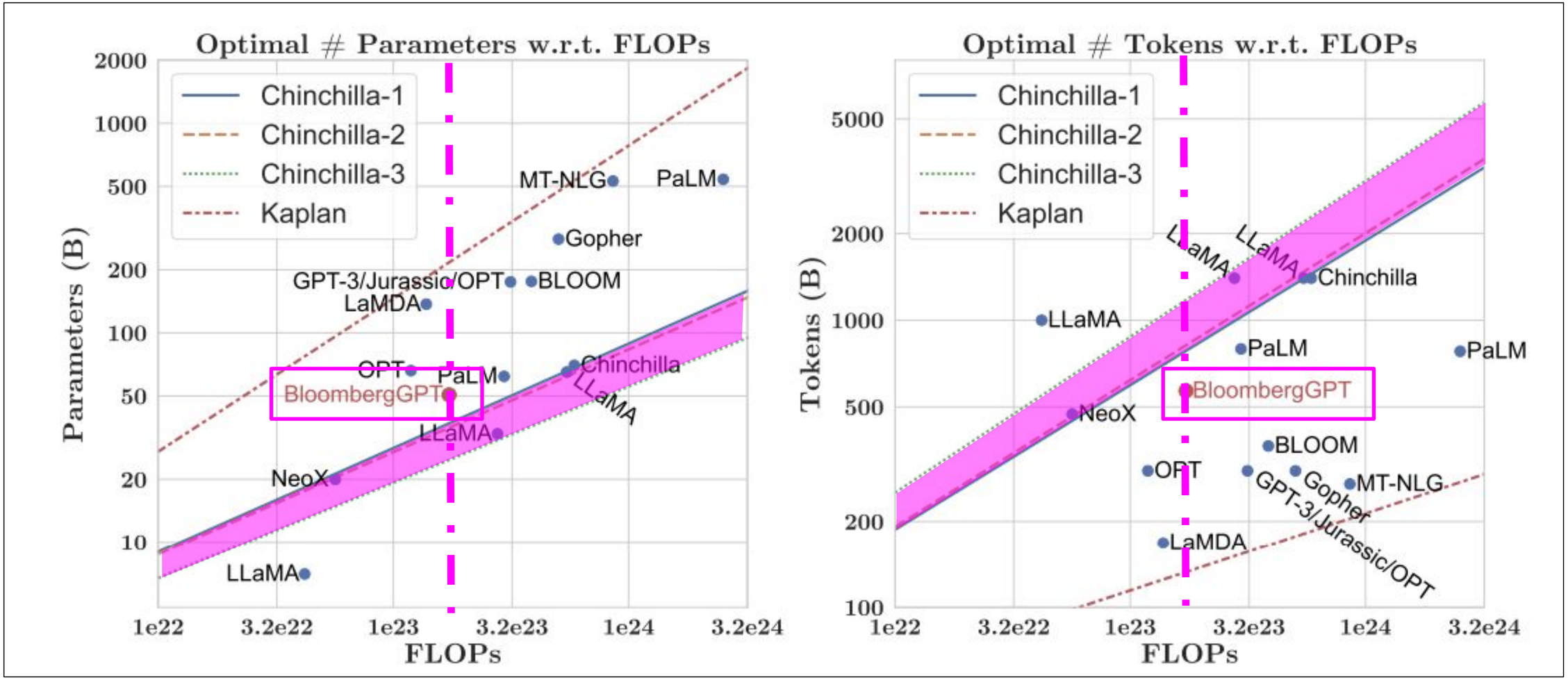
### Abstract

The use of NLP in the realm of financial technology is broad and complex, with applications ranging from sentiment analysis and named entity recognition to question answering. Large Language Models (LLMs) have been shown to be effective on a variety of tasks; however, no LLM specialized for the financial domain has been reported in literature. In this work, we present BLOOMBERGGPT, a 50 billion parameter language model that is trained on a wide range of financial data. We construct a 363 billion token dataset based on Bloomberg's extensive data sources, perhaps the largest domain-specific dataset yet, augmented with 345 billion tokens from general purpose datasets. We validate BLOOMBERGGPT on standard LLM benchmarks, open financial benchmarks, and a suite of internal benchmarks that most accurately reflect our intended usage. Our mixed dataset training leads to a model that outperforms existing models on financial tasks by significant margins without sacrificing performance on general LLM benchmarks. Additionally, we explain our modeling choices, training process, and evaluation methodology. As a next step, we plan to release training logs (Chronicles) detailing our experience in training BLOOMBERGGPT.

~51% **Financial (Public & Private)**

~49% **Other (Public)**

# BloombergGPT relative to other LLMs

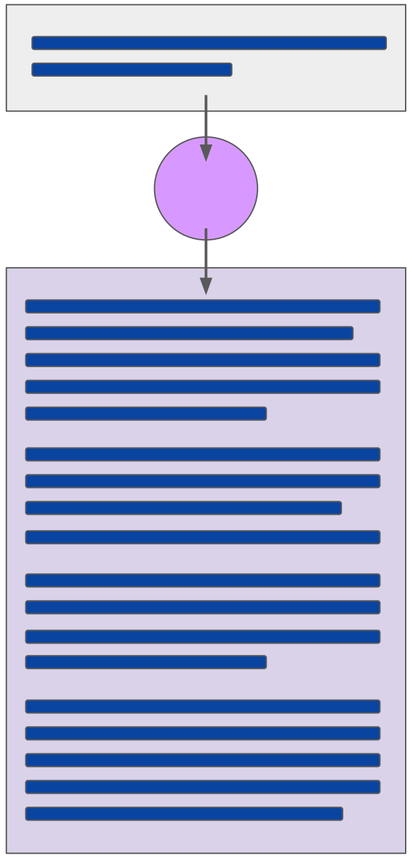



Source: Wu et al. 2023, “BloombergGPT: A Large Language Model for Finance”

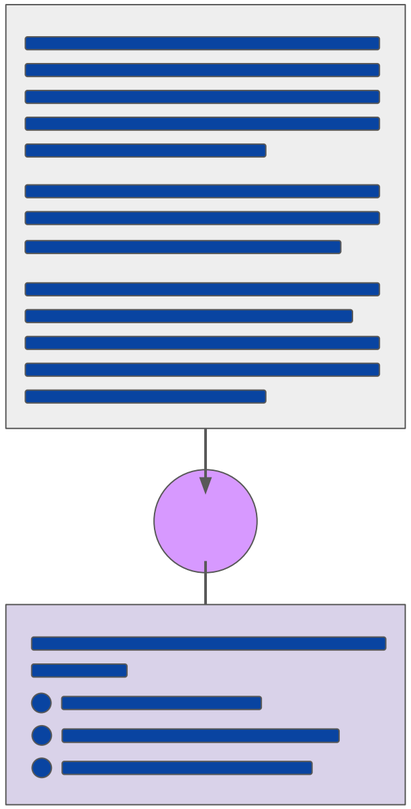
# Key takeaways

# LLM use cases & tasks

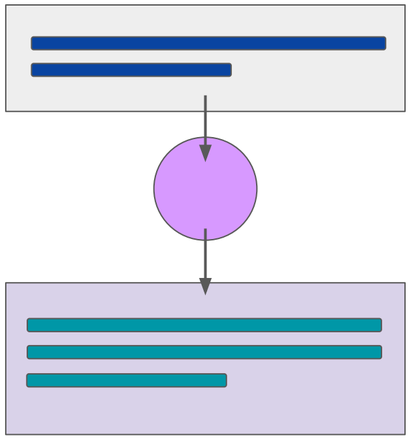
Essay Writing



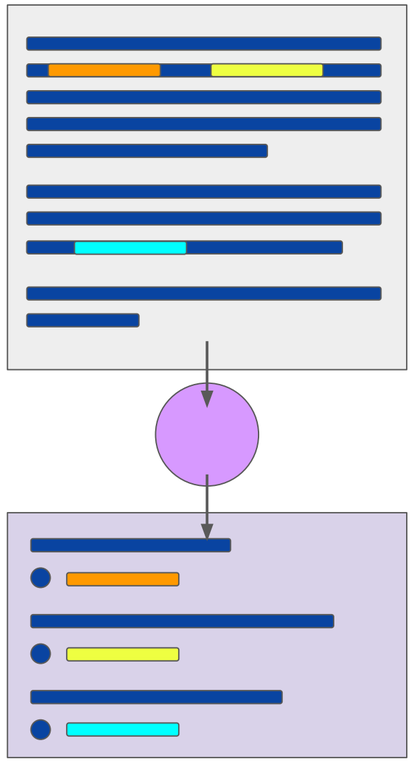
Summarization



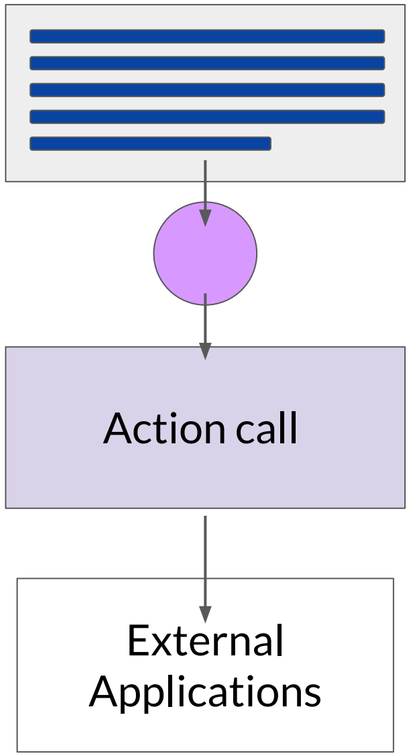
Translation



Information retrieval



Invoke APIs and actions



# Generative AI project lifecycle