Transformer

Attention Is All You Need

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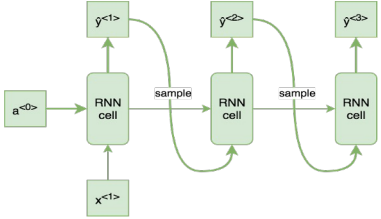
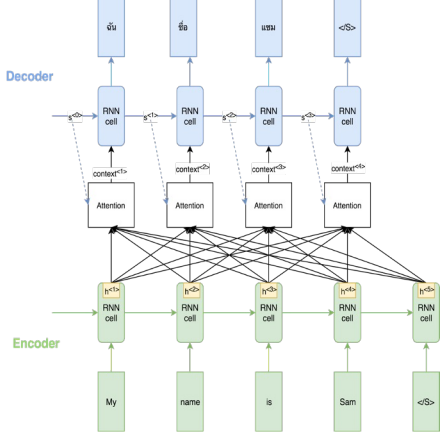
6 Dec 2017

Attention Is All You Need. 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

The Transformer





Only rely on the attention mechanism - **No RNN**!

- More parallelizable -> Faster training time
- Better at longer sequence

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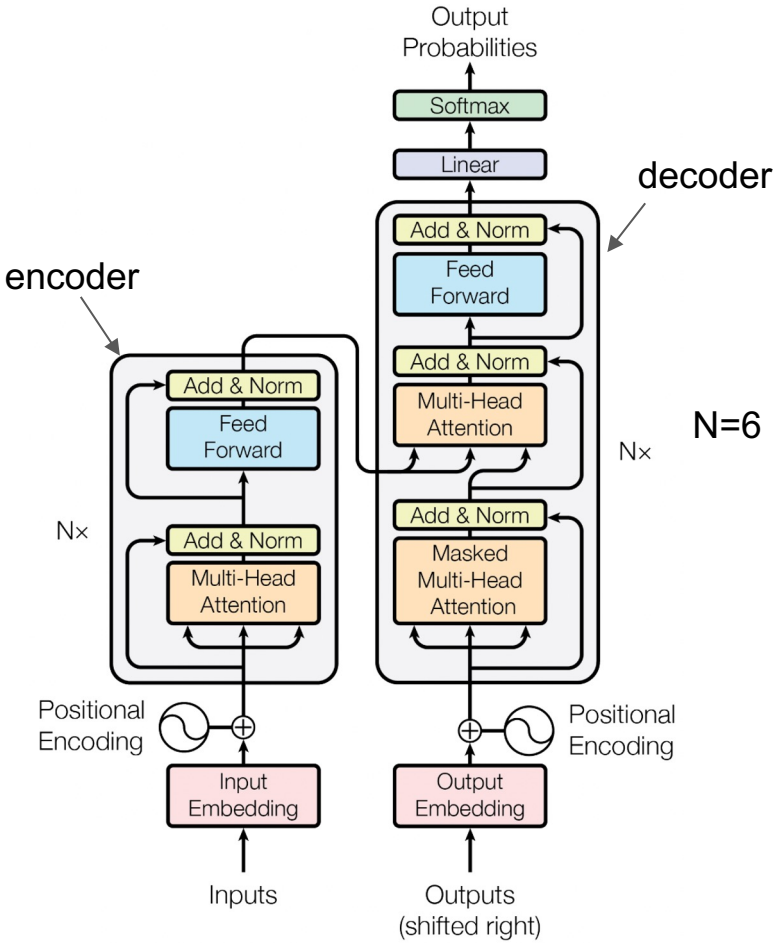

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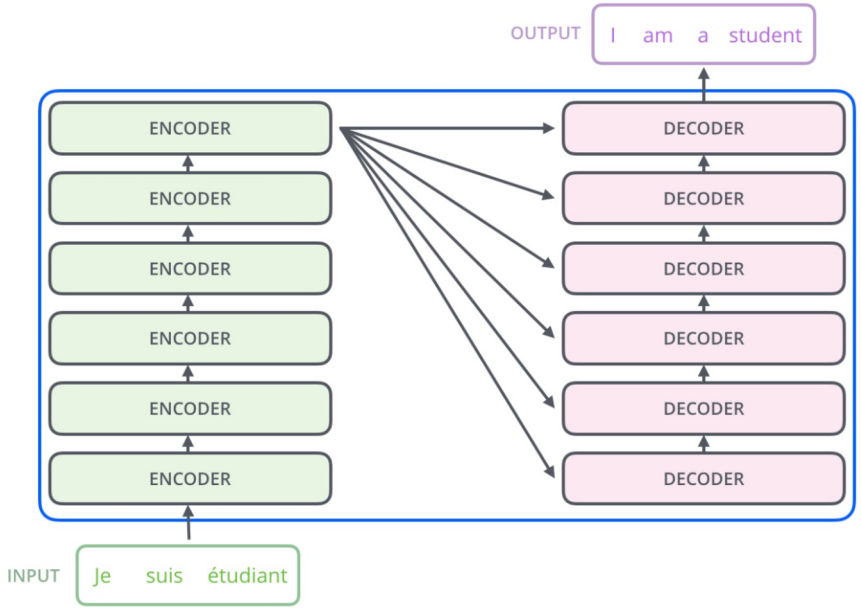
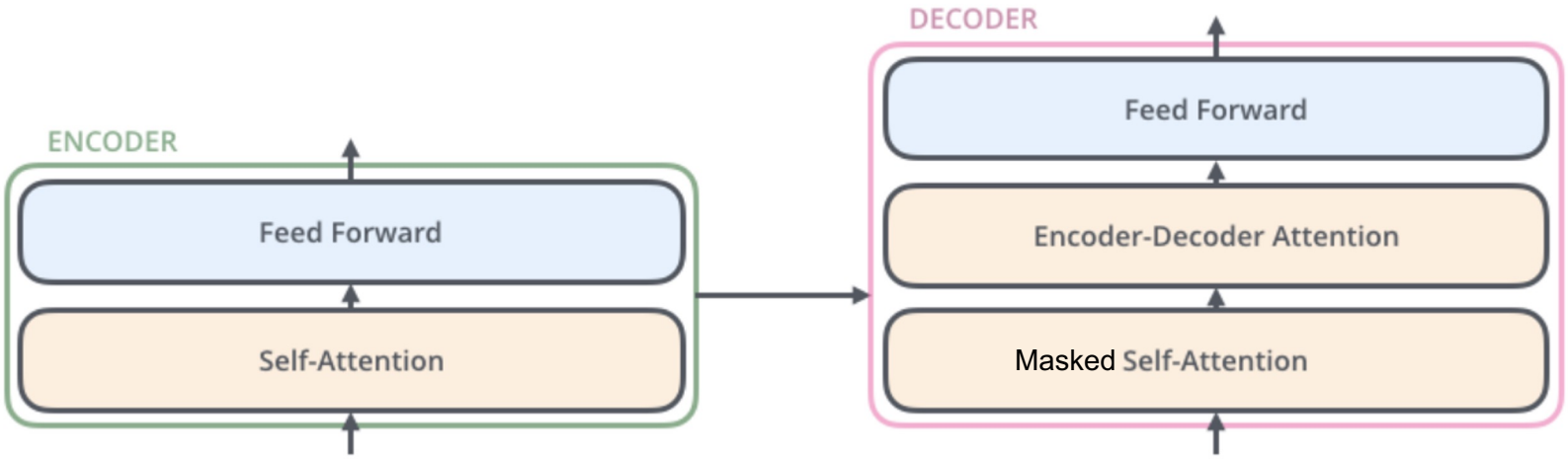


http://jalammar.github.io/illustrated-transformer/

In each layer..



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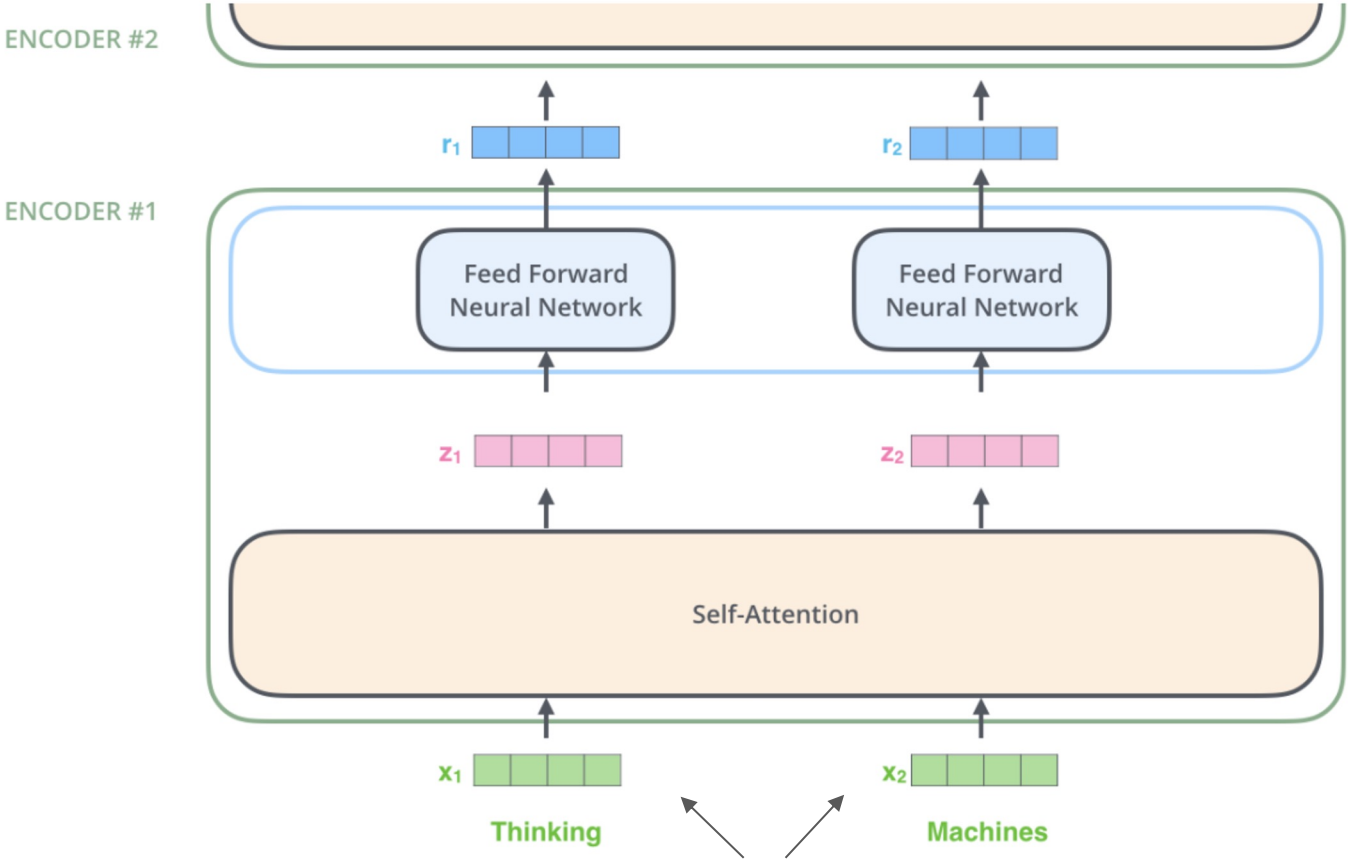


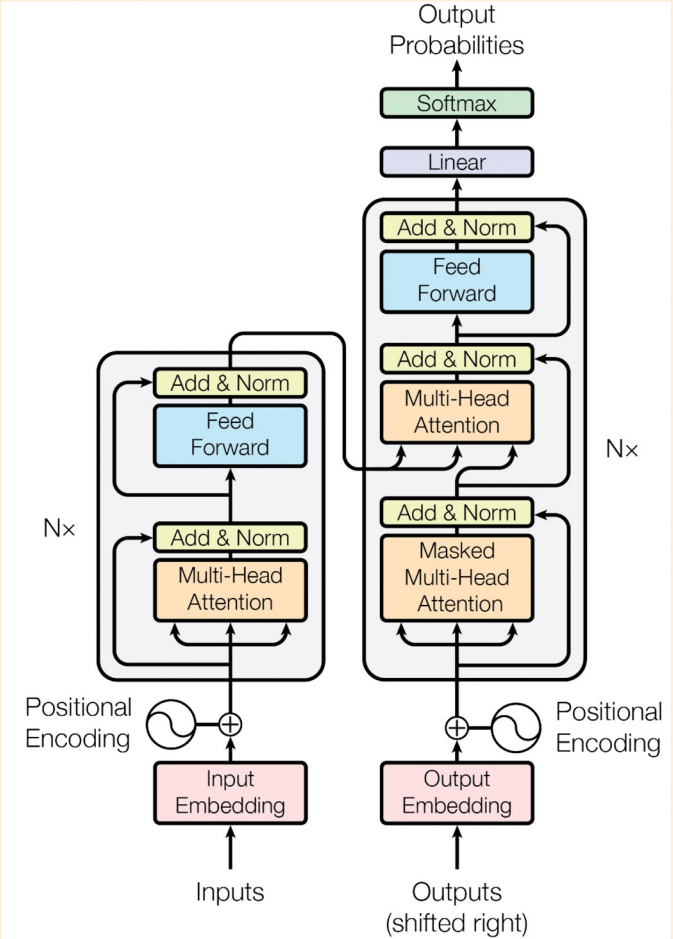
Word Embeddings

http://jalammar.github.io/illustrated-transformer/

Scaled Dot-Product Attention

There are many variations used in the Transformer:

1. Self Attention
2. Encoder-decoder Attention
3. Masked Self Attention
4. Multi-headed Self Attention



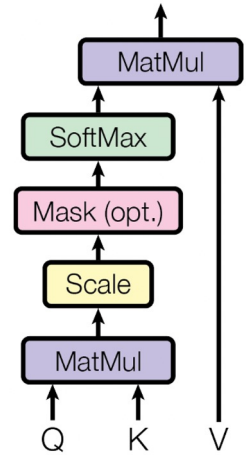
1) Self Attention

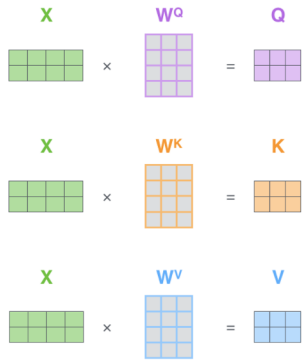
Q, K, and V are all from the same input.

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

where the query, keys, values, and output are all vectors and d_k is a number.

Scaled Dot-Product Attention





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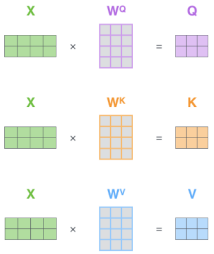
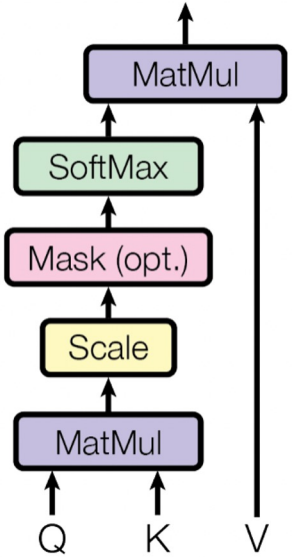
2) Encoder-Decoder Attention

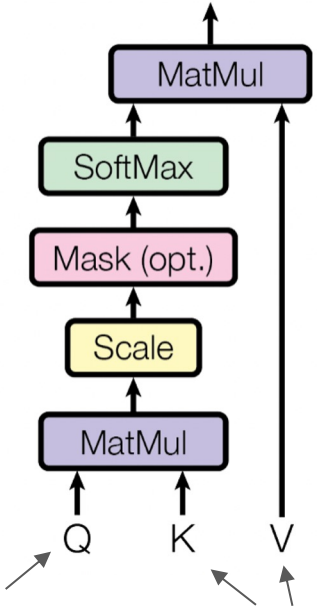


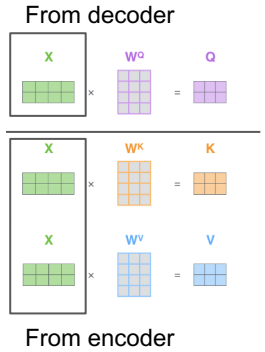
Self Attention



ALL from same input

Encoder-Decoder Attention
(or Cross Attention)



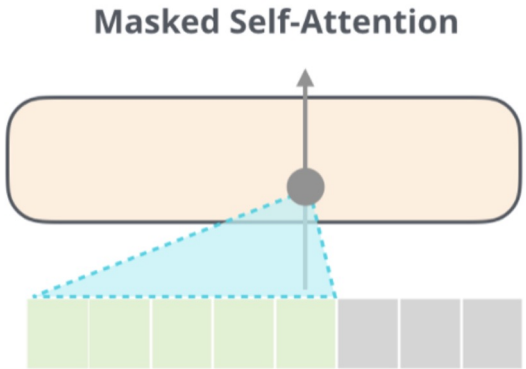


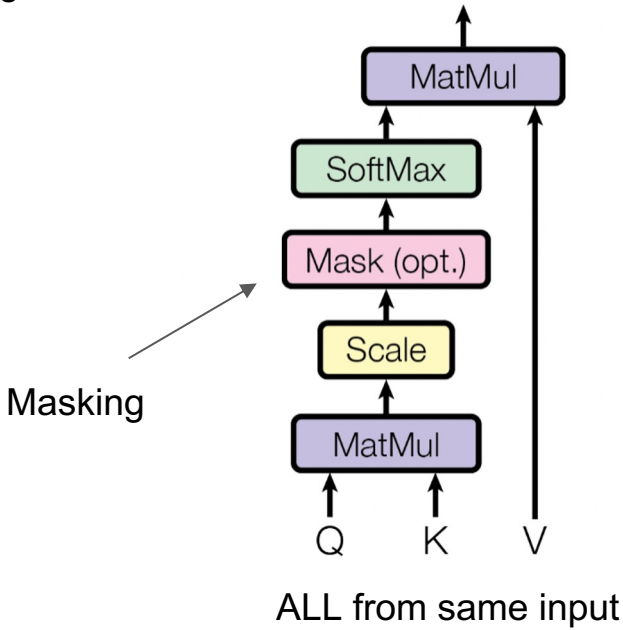
From decoder From encoder

3) Masked Self Attention

Prevent the model from **seeing into the future** to preserve the autoregressive property.

Used in *decoder* only (so the model can't see the answer).





Masked Self Attention

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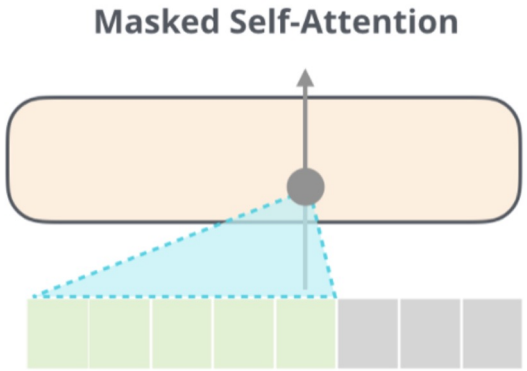
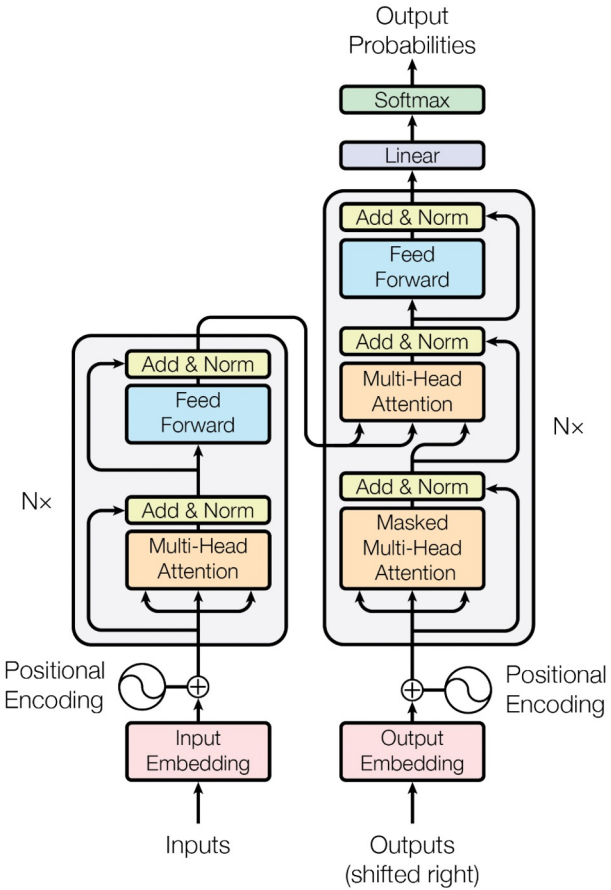
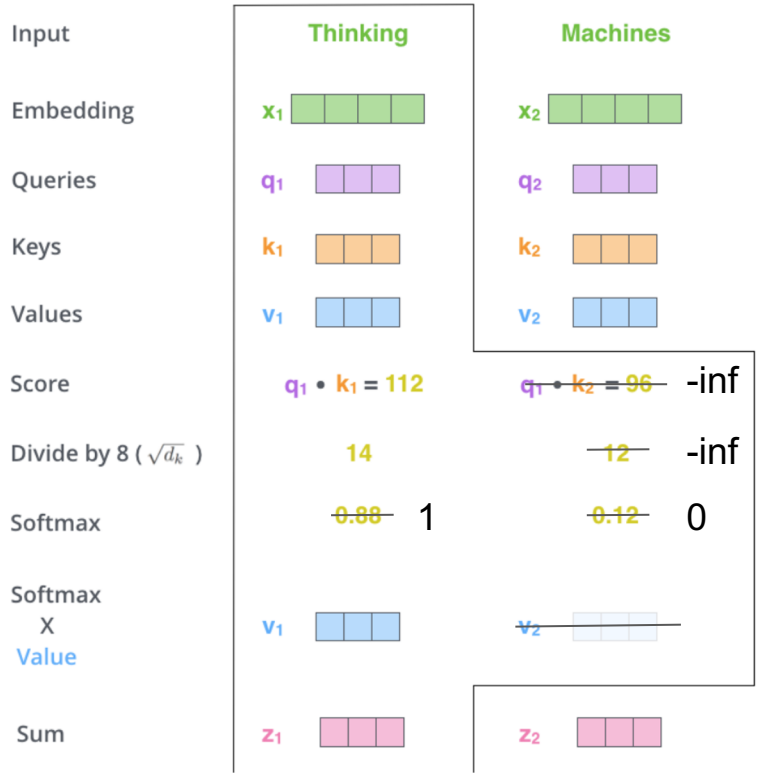




I like dogs <eos> <bos> ฉัน ชอบ สุนัข

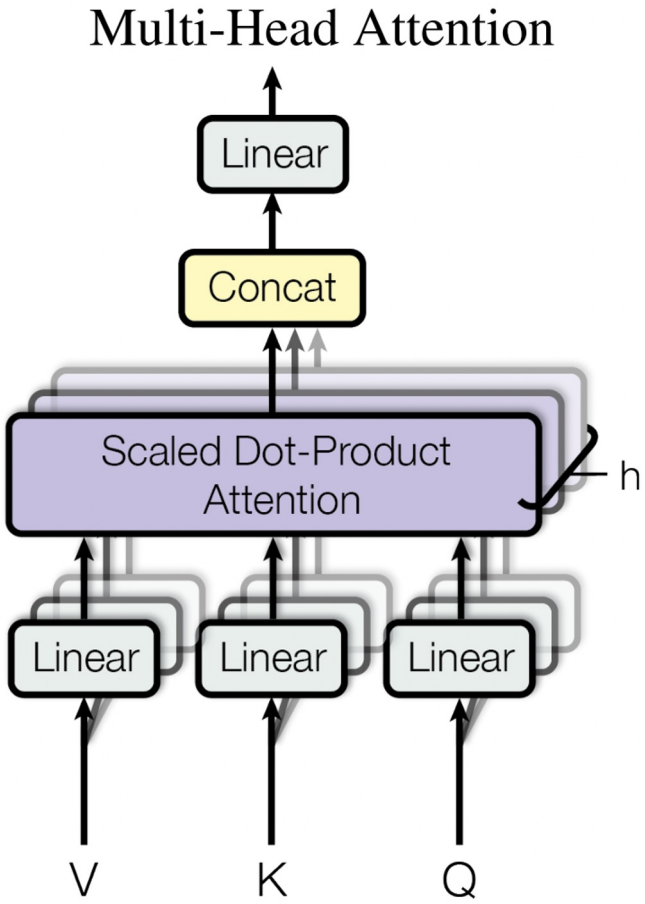
Masked Self Attention



4) Multi-head Self Attention

Multi-head attention allows the model to jointly attend to information from different representations.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$



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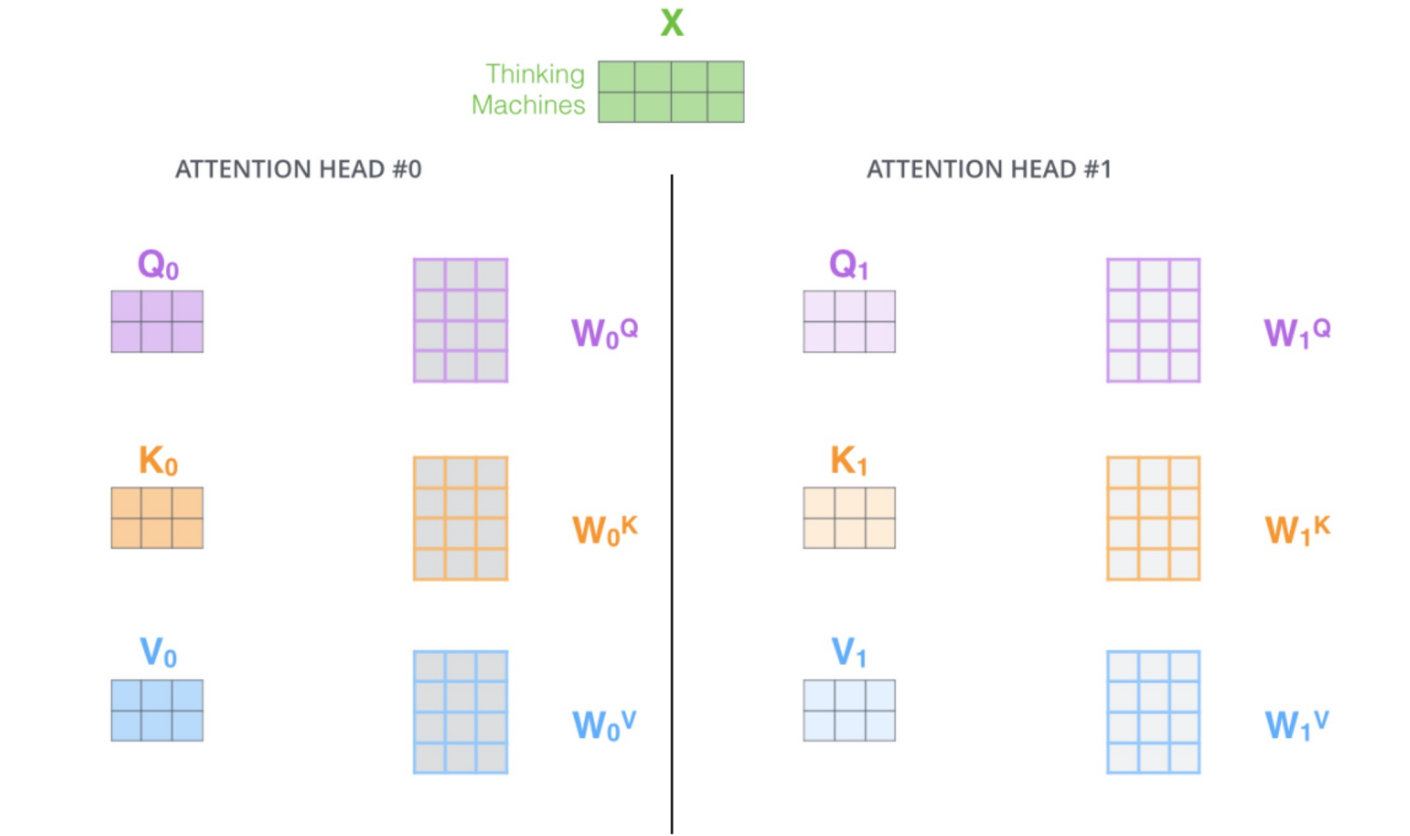
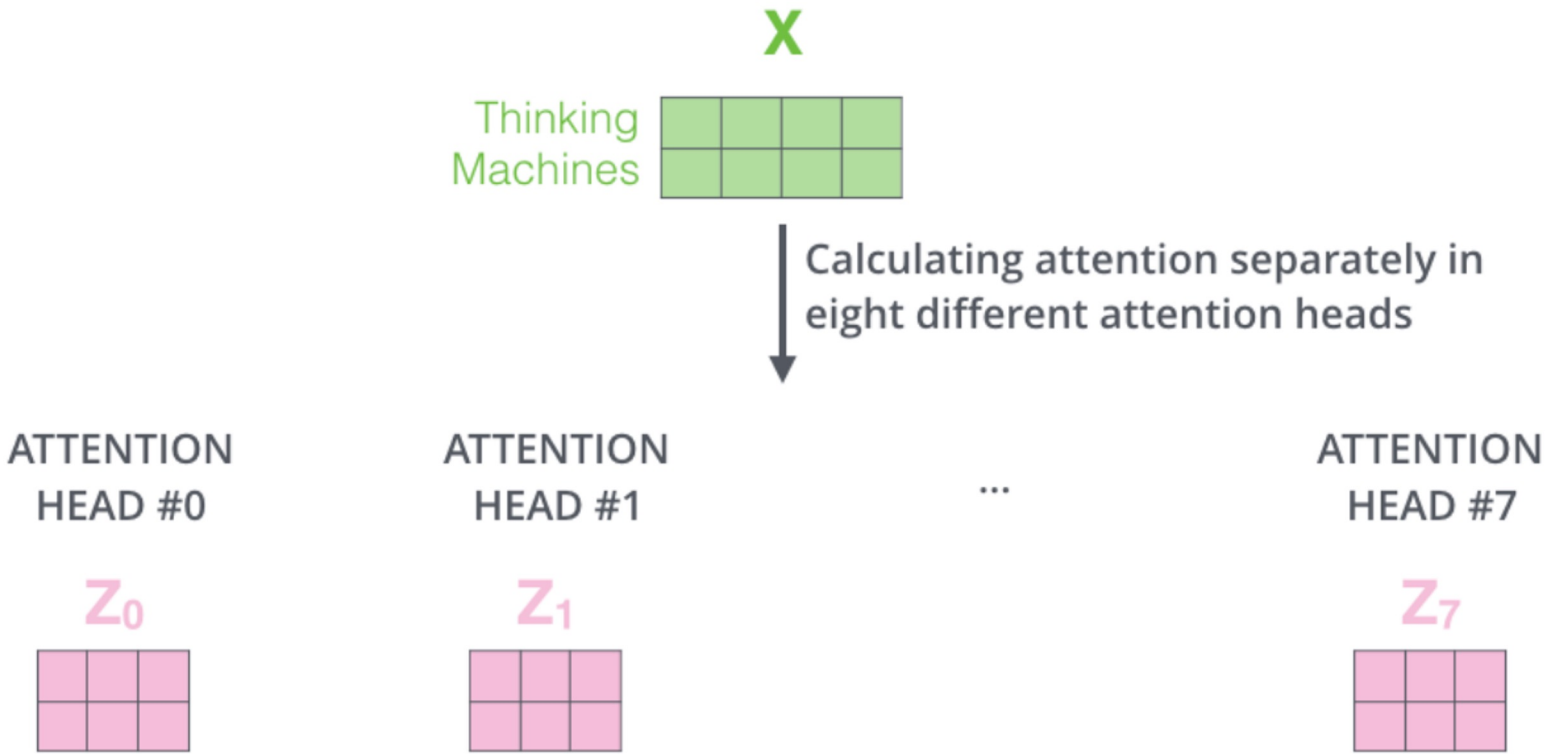


With multi-headed attention, we maintain separate Q/K/V weight matrices for each head resulting in different Q/K/V matrices. As we did before, we multiply X by the WQ/WK/WV matrices to produce Q/K/V matrices.

http://jalammar.github.io/illustrated-transformer/

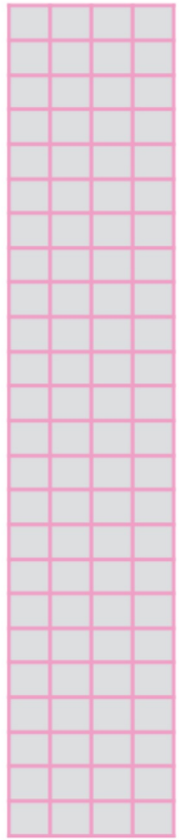


http://jalammar.github.io/illustrated-transformer/

1) Concatenate all the attention heads

2) Multiply with a weight matrix W^O that was trained jointly with the model

X



3) The result would be the Z matrix that captures information from all the attention heads. We can send this forward to the FFNN

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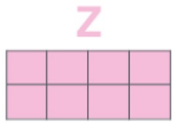


http://jalammar.github.io/illustrated-transformer/

1) This is our input sentence*

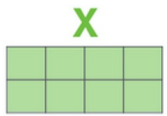
2) We embed each word*

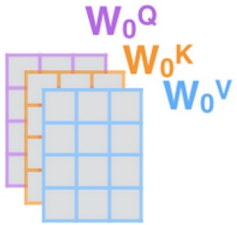
3) Split into 8 heads. We multiply X or R with weight matrices

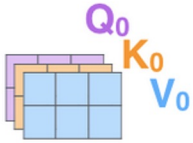
4) Calculate attention using the resulting Q/K/V matrices

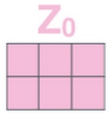
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer

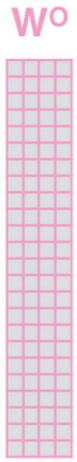
Thinking Machines

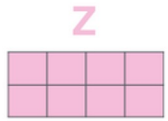




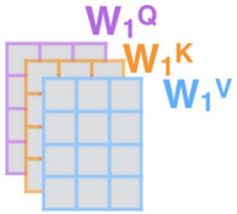


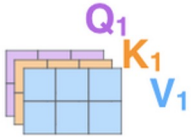


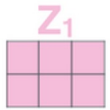




* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one







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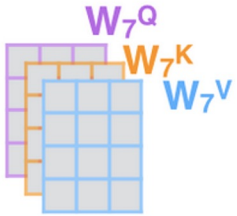

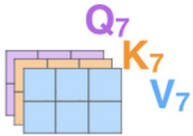

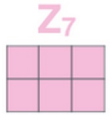

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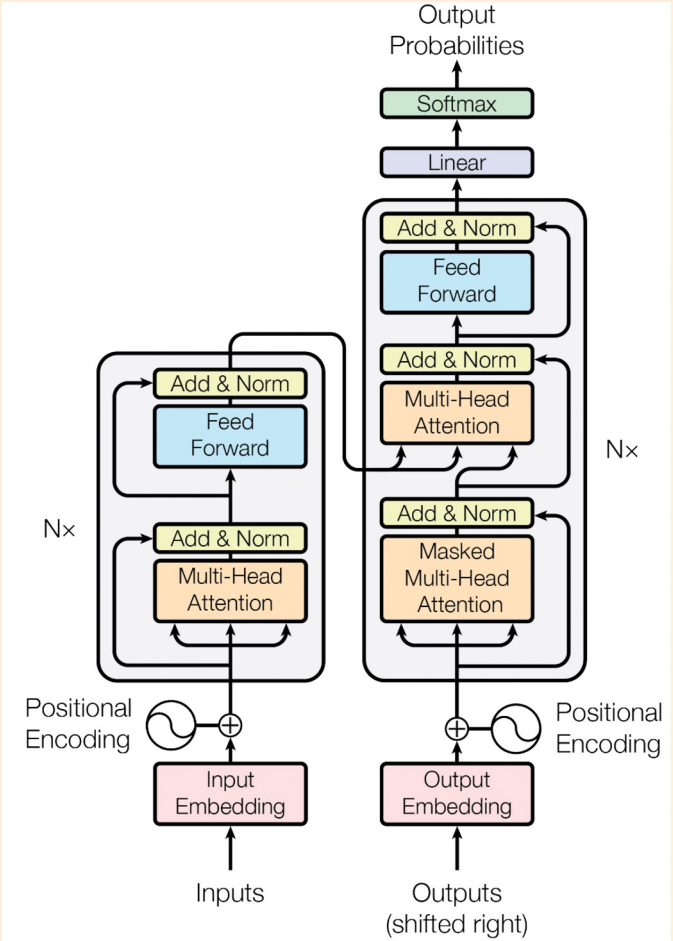
Positional Encodings

The black cat fights the white cat.



Positional Encodings

Without RNN, the model **cannot** make use of the *order* of the input sequence, e.g. the first, second, or third token.

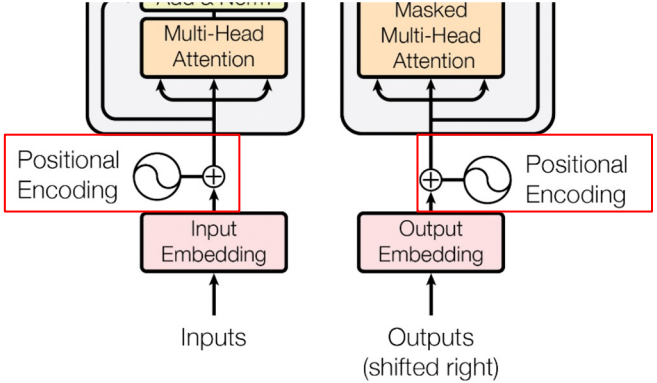


Figure 1: The Transformer - model architecture.

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

pos is the token position, *i* is the dimension

The black cat fights the white cat.

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$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

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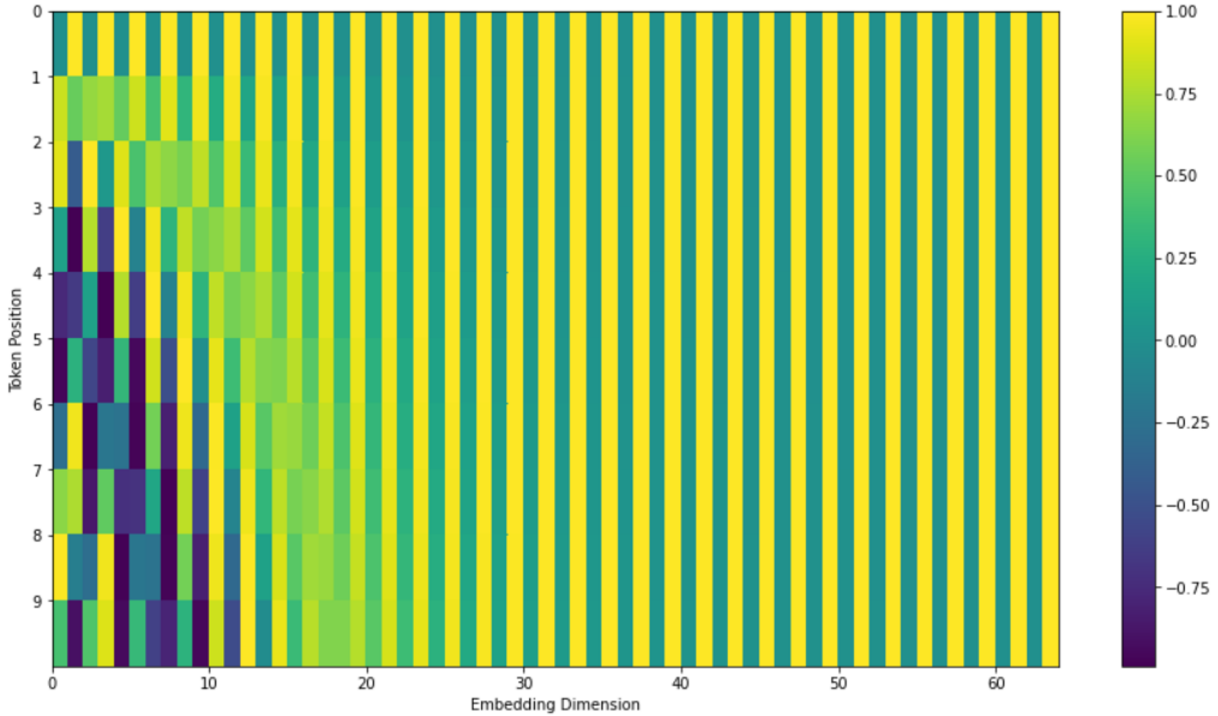

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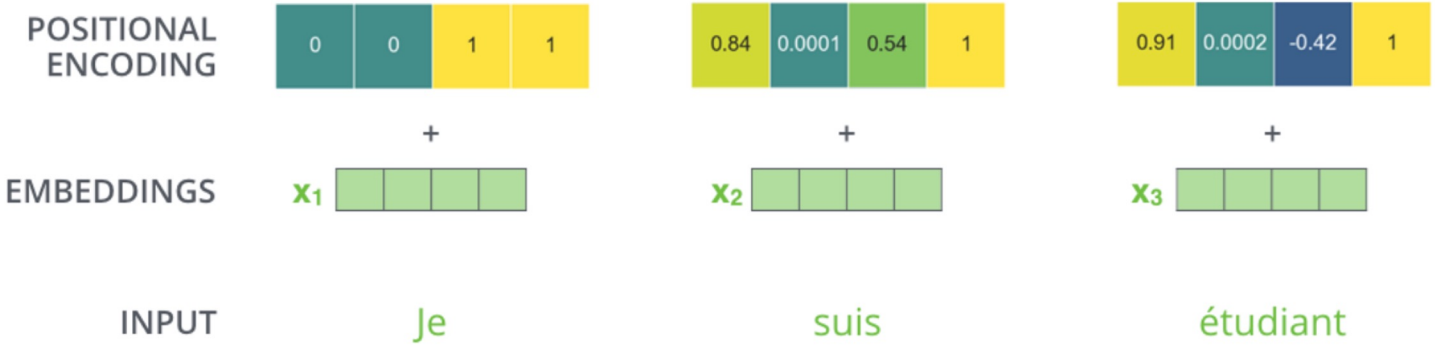
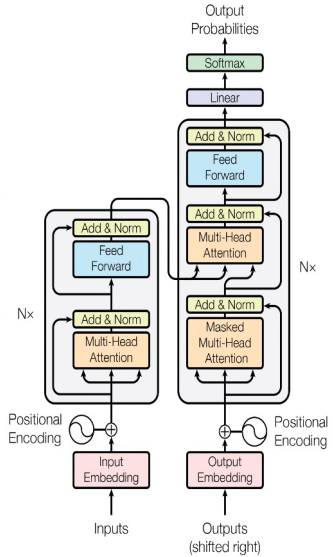
i = 4





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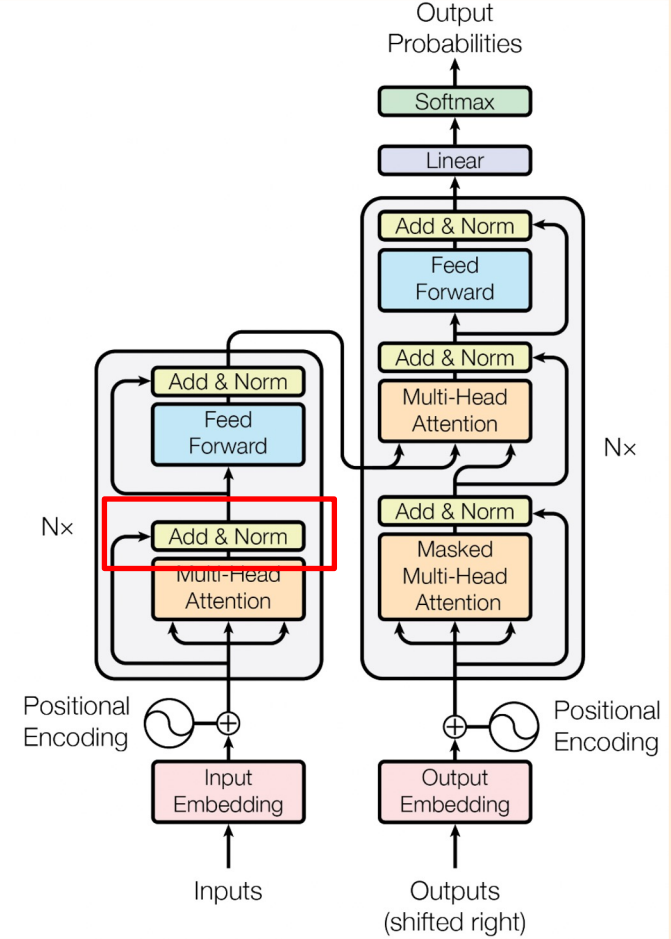
Types of positional encoding

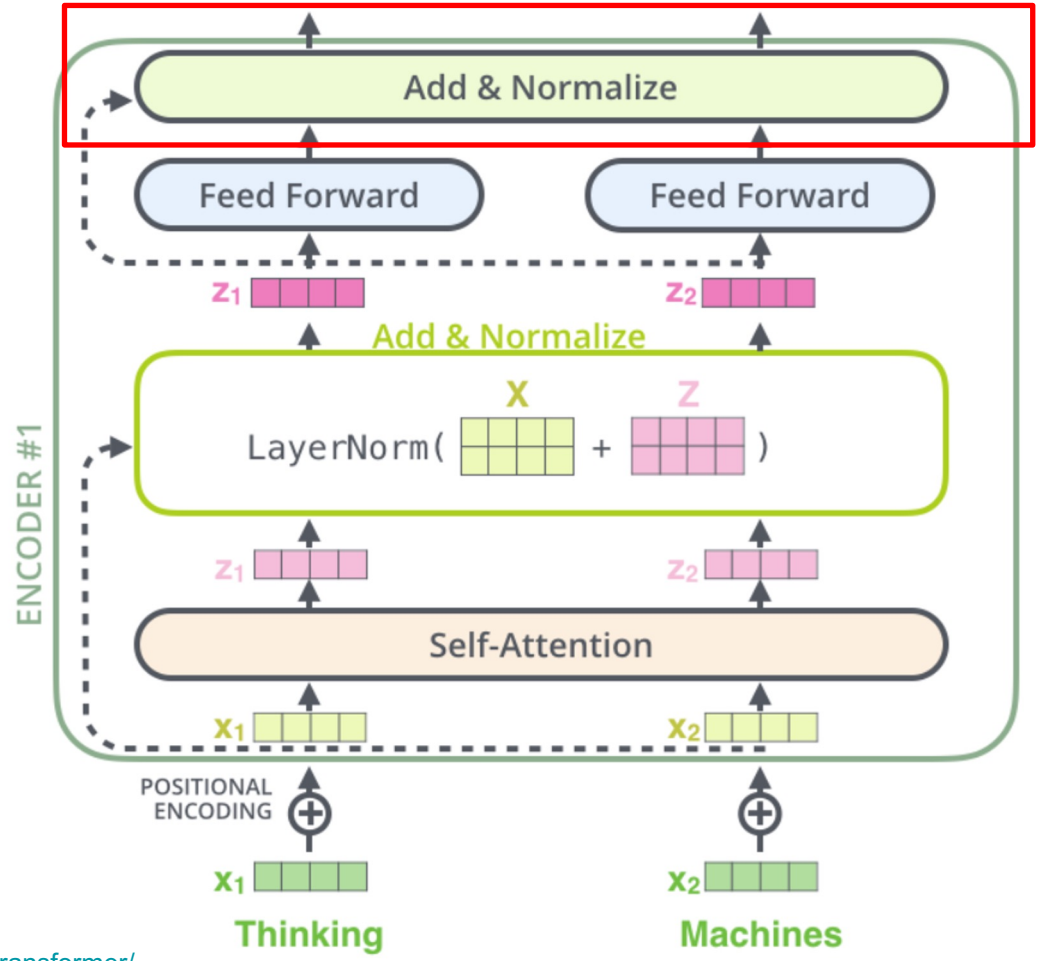
1. Absolute Positional encoding
    - 1.1) Fixed encoding (Transformer)
        - E.g. sinusoidal forms
    - 1.2) Learned encoding (GPT)

2. Relative Positional encoding (GPT NeoX)

	Token 1	Token 2	Token 3	Token 4	Token 5	Token 6
Absolute	1	2	3	4	5	6
Relative	-2	-1	0	1	2	3

Layer Normalization





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Batch norm. (each feature (channel)) vs Layer norm. (each word)

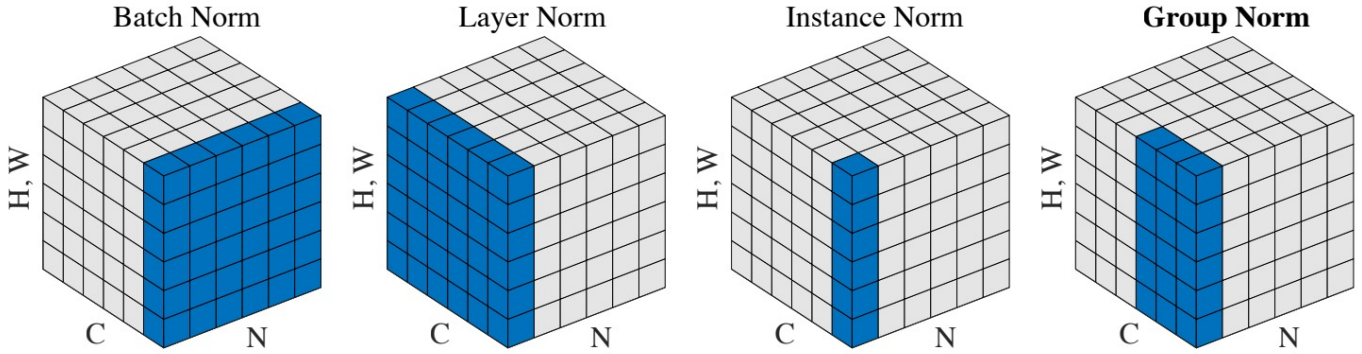
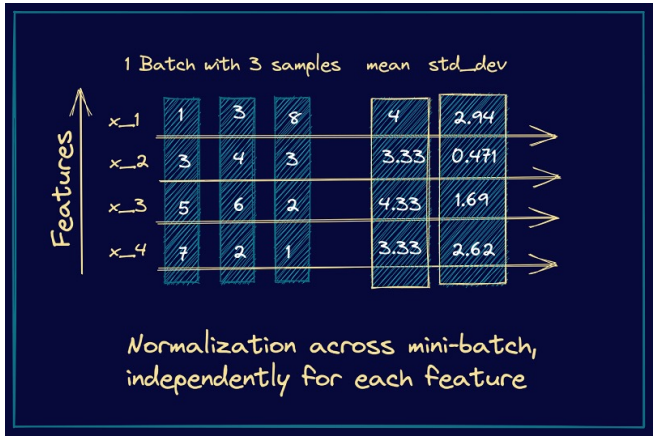
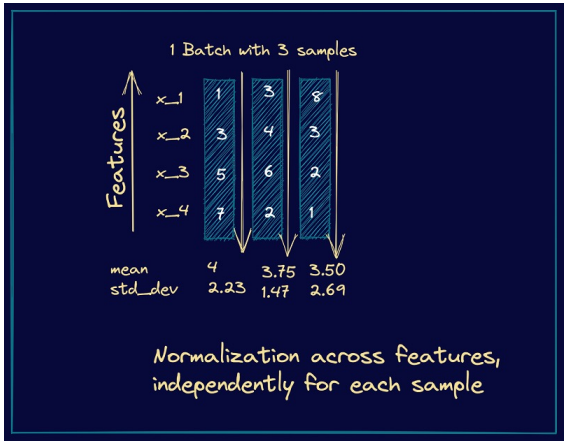


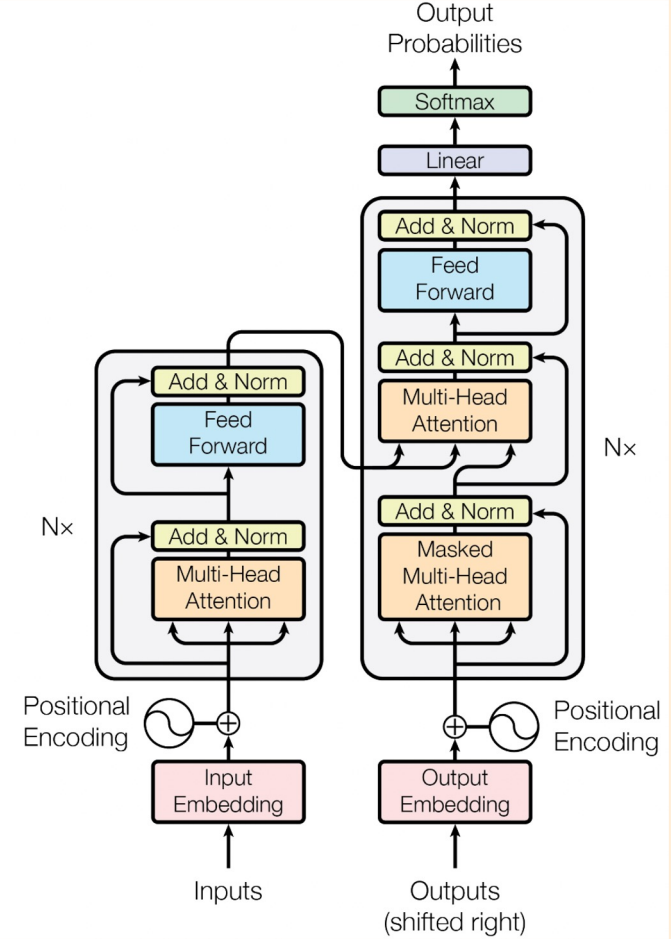
Figure 2. **Normalization methods**. Each subplot shows a feature map tensor, with N as the batch axis, C as the channel axis, and (H, W) as the spatial axes. The pixels in blue are normalized by the same mean and variance, computed by aggregating the values of these pixels.



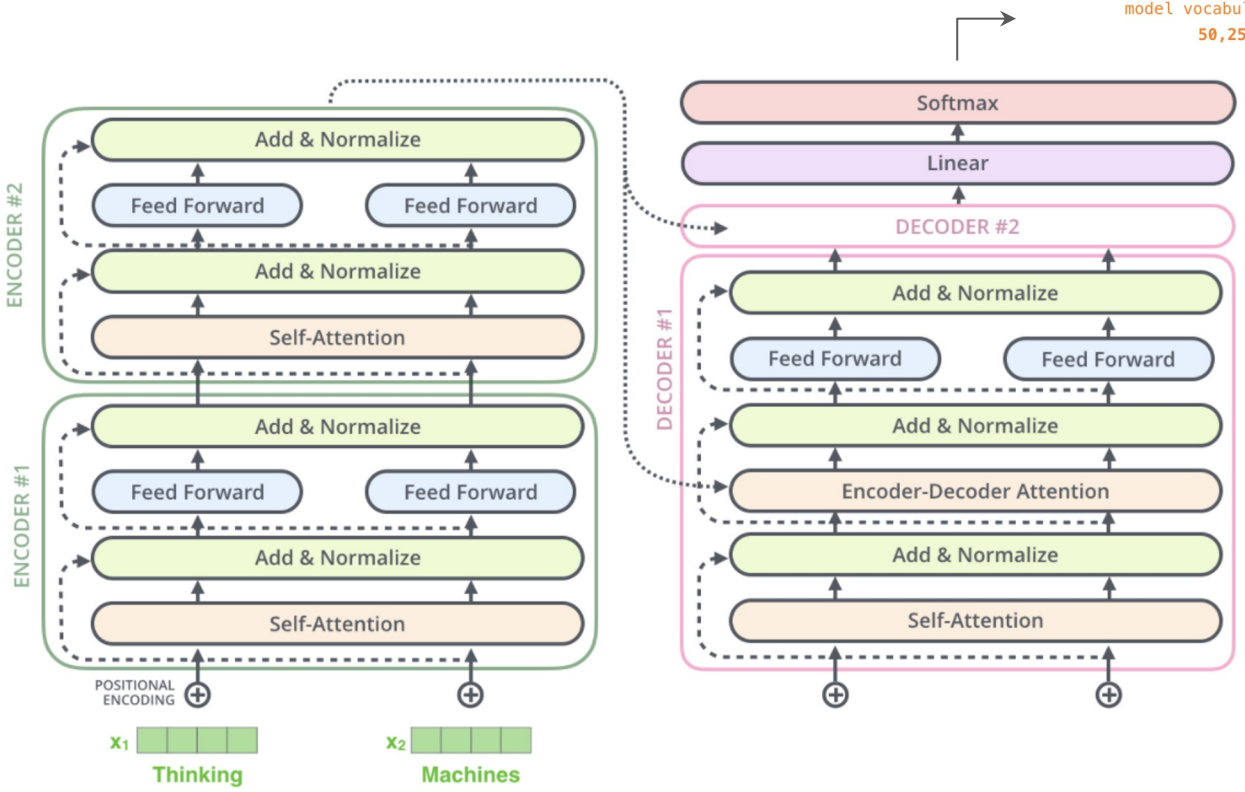


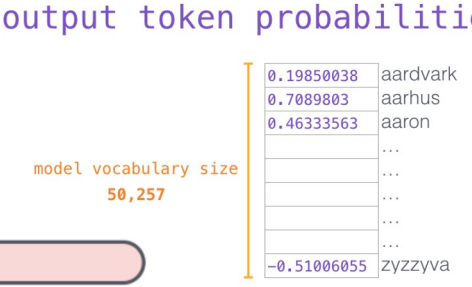
Done:

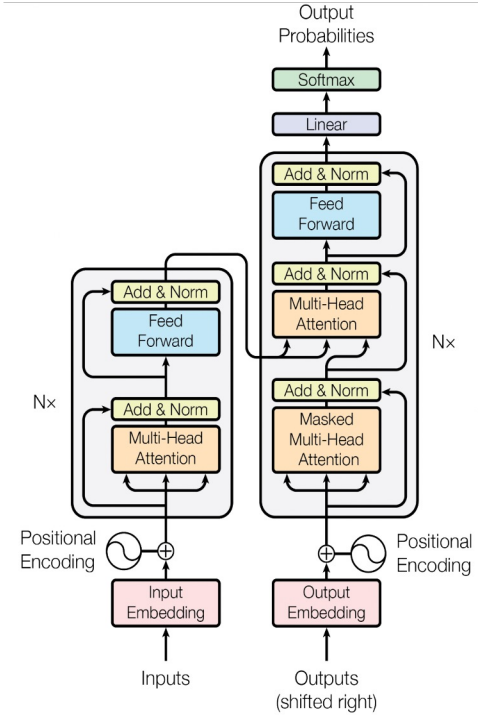
- Let’s link encoder to decoder
- Then, generate final output



Final output

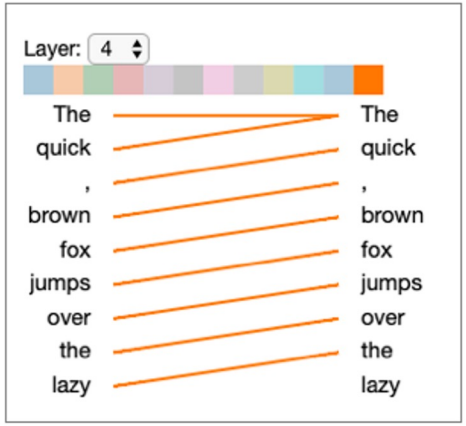


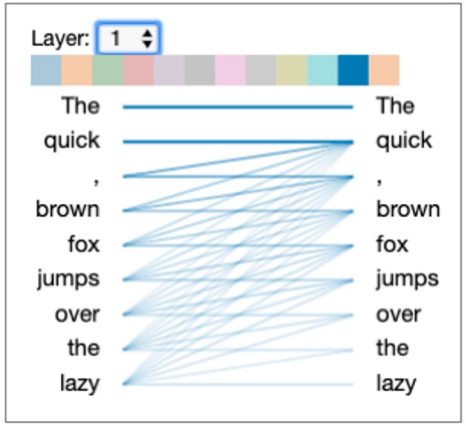


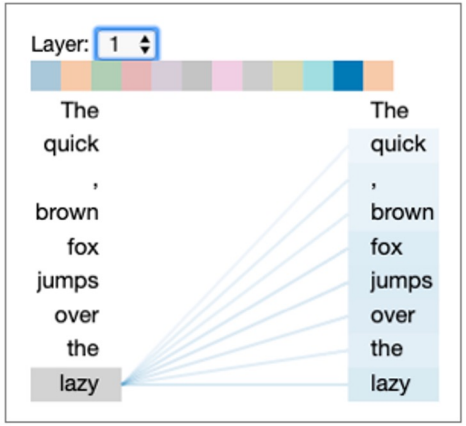


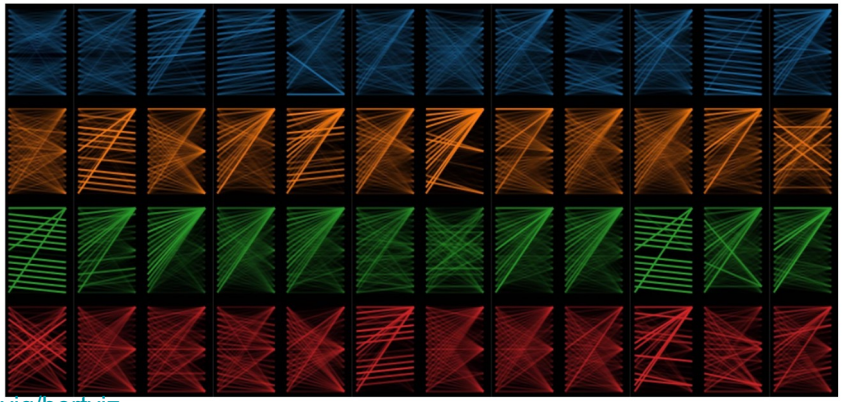
http://jalammar.github.io/illustrated-transformer/

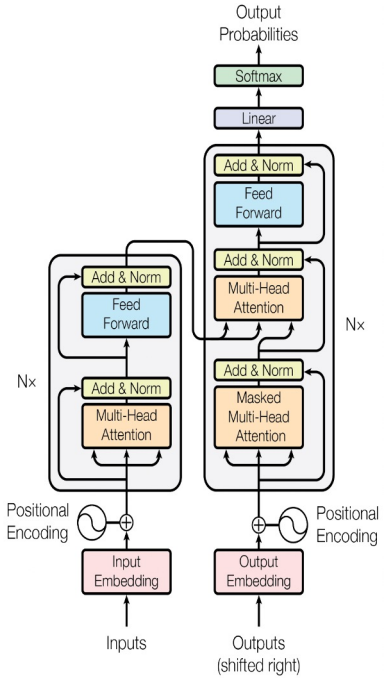
Visualizing Attention (N encoders & N decoders)











https://github.com/jessevig/bertviz

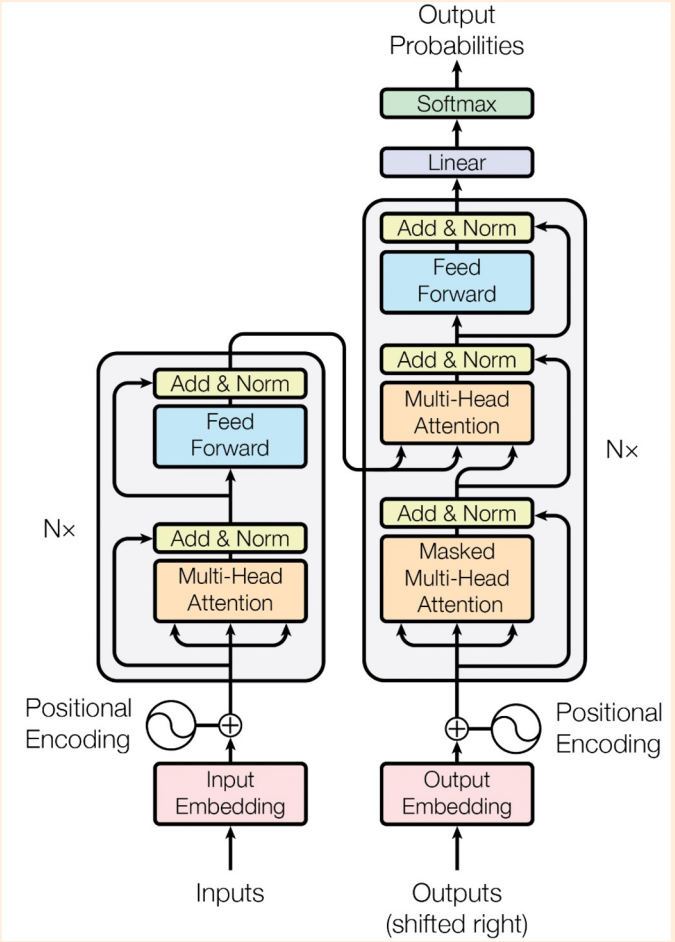
Large Language Models

Pretrained Language Models

All Transformer based

1. Decoder-based model: GPT
2. Encoder-based model: BERT
3. Encoder and Decoder: BART

Generative Pre-Training (OpenAI GPT)



OpenAI GPT (Generative Pre-Training) [Radford, 2018]

Improving Language Understanding by Generative Pre-Training

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Abstract

Natural language understanding comprises a wide range of diverse tasks such as textual entailment, question answering, semantic similarity assessment, and document classification. Although large unlabeled text corpora are abundant, labeled data for learning these specific tasks is scarce, making it challenging for discriminatively trained models to perform adequately. We demonstrate that large gains on these tasks can be realized by *generative pre-training* of a language model on a diverse corpus of unlabeled text, followed by *discriminative fine-tuning* on each specific task. In contrast to previous approaches, we make use of task-aware input transformations during fine-tuning to achieve effective transfer while requiring minimal changes to the model architecture. We demonstrate the effectiveness of our approach on a wide range of benchmarks for natural language understanding. Our general task-agnostic model outperforms discriminatively trained models that use architectures specifically crafted for each task, significantly improving upon the state of the art in 9 out of the 12 tasks studied. For instance, we achieve absolute improvements of 8.9% on commonsense reasoning (Stories Cloze Test), 5.7% on question answering (RACE), and 1.5% on textual entailment (MultiNLI).

Generative Pre-Training (OpenAI GPT)

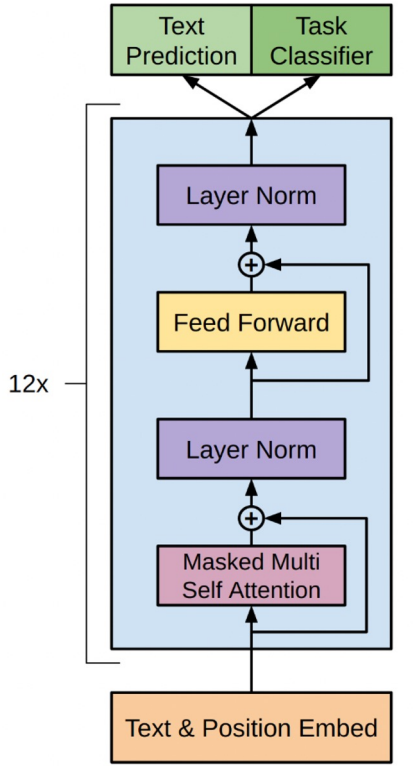
A model comprises of Transformer decoders only.

The framework consists of two stages:

1. Unsupervised pre-training
2. Supervised finetuning

Excels at text generation tasks

Try it out:
https://transformer.huggingface.co/



Generative Pre-Training (OpenAI GPT)

1) Unsupervised pre-training

Given a large unlabelled corpus $\mathcal{U} = \{u_1, \ldots, u_n\}$, the model's objective is to maximize the following likelihood (also called "Language Modelling").

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

where *k* is the context length and the conditional probability *P* is modeled using a neural network with parameters $\boldsymbol{\Theta}$.

Generative Pre-Training (OpenAI GPT)

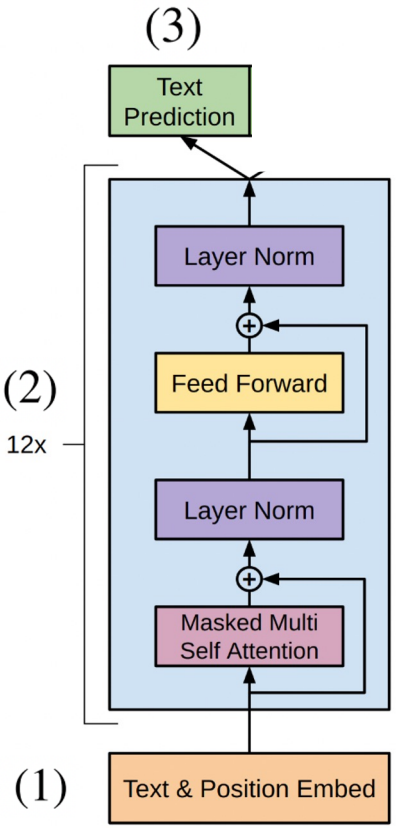
1) Unsupervised pre-training

$$(1) \quad h_0 = UW_e + W_p$$

$$(2) \quad h_l = \texttt{transformer\_block}(h_{l-1}) \forall i \in [1, n]$$

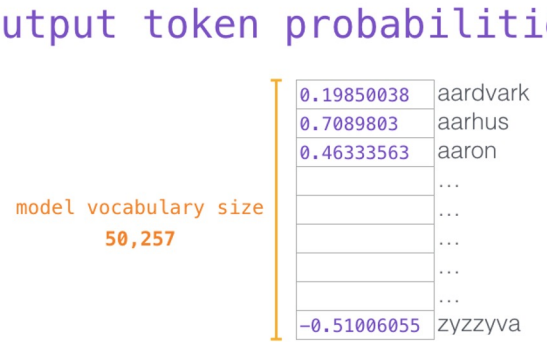
$$(3) \quad P(u) = \texttt{softmax}(h_n W_e^T)$$

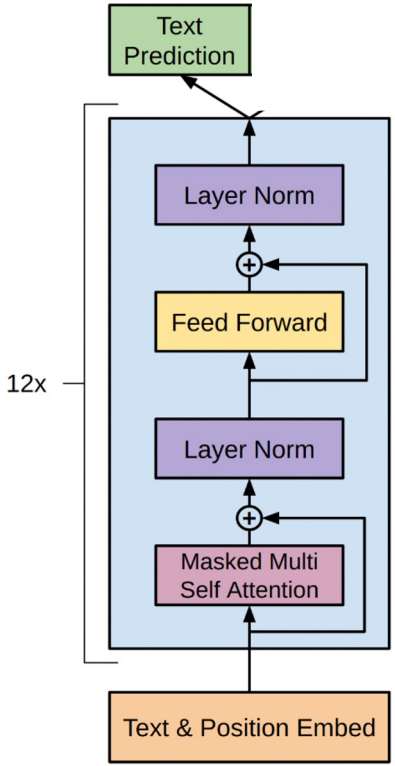
where $U = (u_{-k}, \ldots, u_{-1})$ is the context vector of tokens, n is the number of layers, W_e is the token embedding matrix, and W_p is the position embedding matrix.



Generative Pre-Training (OpenAI GPT)

1) Unsupervised pre-training





Generative Pre-Training (OpenAI GPT)

2) Supervised finetuning

We assume a labeled dataset C, where each instance consists of a sequence of input tokens ($x^1, \ldots, x^m$), along with a label y.

$$P(y|x^1, \ldots, x^m) = \texttt{softmax}(h_l^m W_y).$$

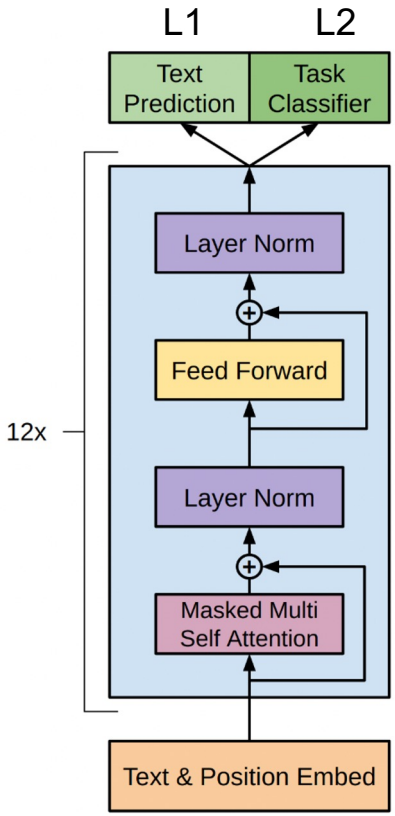
$$L_2(\mathcal{C}) = \sum_{(x,y)} \log P(y|x^1, \ldots, x^m).$$

Total finetuning loss

$$L_3(\mathcal{C}) = L_2(\mathcal{C}) + \lambda * L_1(\mathcal{C})$$

classification

LM (unsupervised)



Generative Pre-Training (OpenAI GPT)

2) Supervised finetuning

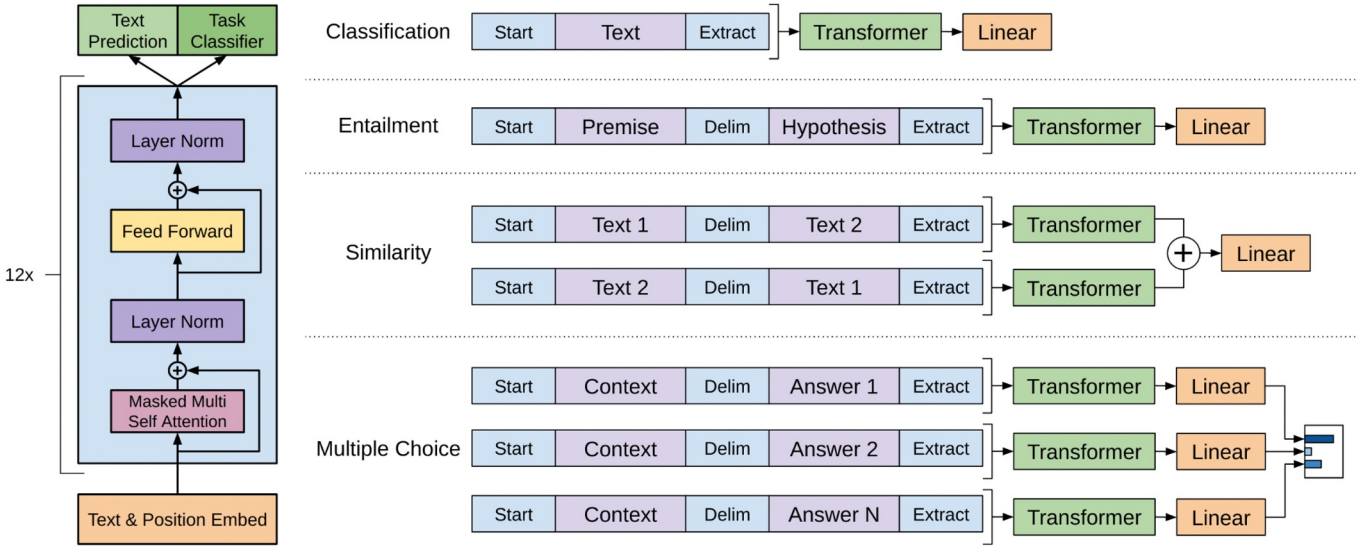


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

GPT2 & GPT3

Bigger Models + More data = Better Results

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
Translate English to French:        ← task description
cheese =>                           ← prompt
```

One-shot

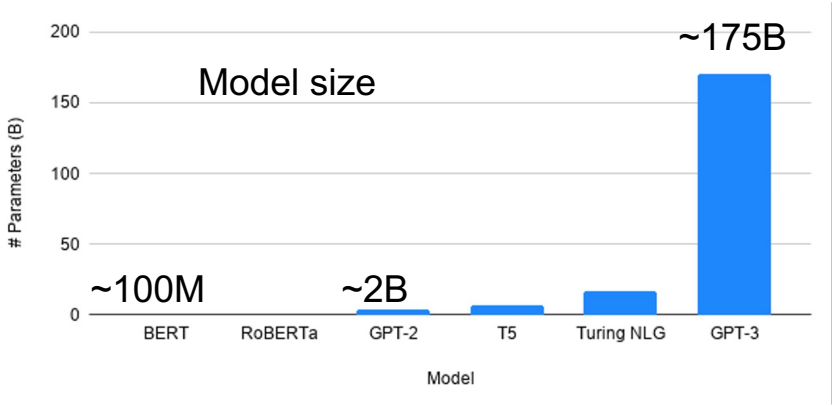
In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

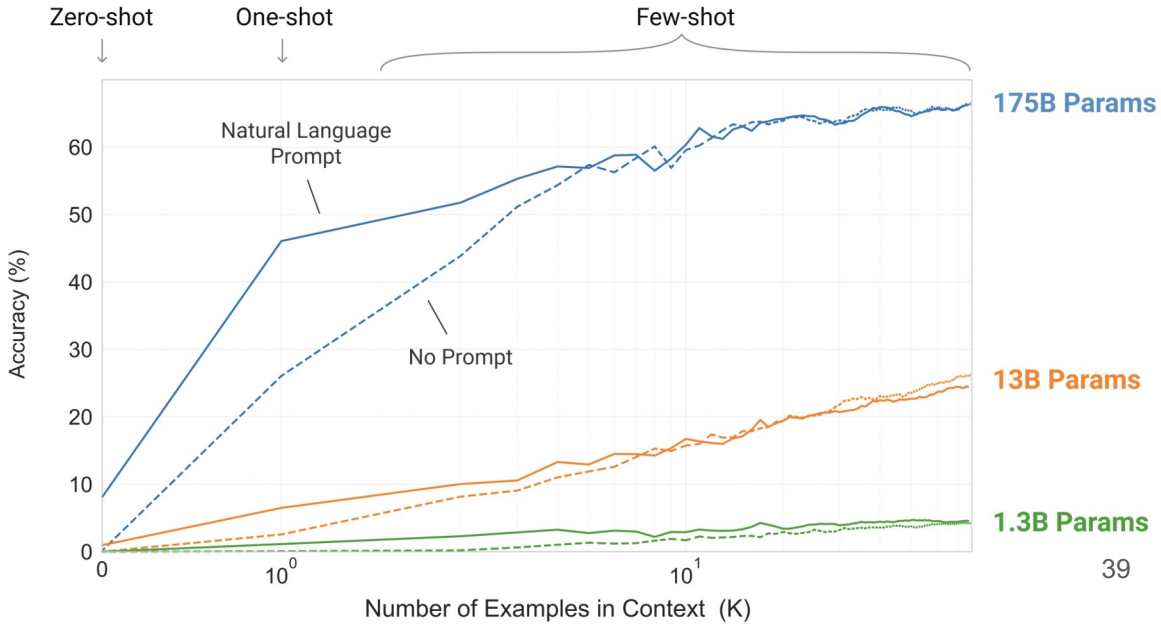
```
Translate English to French:        ← task description
sea otter => loutre de mer          ← example
cheese =>                           ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:        ← task description
sea otter => loutre de mer          ← examples
peppermint => menthe poivrée        ←
plush girafe => girafe peluche      ←
cheese =>                           ← prompt
```





https://platform.openai.com/docs/models/gpt-3-5

OpenAI API

Models referred to as "GPT 3.5"

GPT-3.5 series is a series of models that was trained on a blend of text and code from before Q4 2021. The following models are in the GPT-3.5 series:

1. `code-davinci-002` is a base model, so good for pure code-completion tasks
2. `text-davinci-002` is an InstructGPT model based on `code-davinci-002`
3. `text-davinci-003` is an improvement on `text-davinci-002`

GPT-3.5

GPT-3.5 models can understand and generate natural language or code. Our most capable and cost effective model is `gpt-3.5-turbo` which is optimized for chat but works well for traditional completions tasks as well.

text

LATEST MODEL	DESCRIPTION	MAX REQUEST	TRAINING DATA
`gpt-3.5-turbo`	Most capable GPT-3.5 model and optimized for chat at 1/10th the cost of `text-davinci-003`. Will be updated with our latest model iteration.	4,096 tokens	Up to Sep 2021
`gpt-3.5-turbo-0301`	Snapshot of `gpt-3.5-turbo` from March 1st 2023. Unlike `gpt-3.5-turbo`, this model will not receive updates, and will only be supported for a three month period ending on June 1st 2023.	4,096 tokens	Up to Sep 2021
`text-davinci-003`	Can do any language task with better quality, longer output, and consistent instruction-following than the curie, babbage, or ada models. Also supports inserting completions within text.	4,000 tokens	Up to Jun 2021
`text-davinci-002`	Similar capabilities to `text-davinci-003` but trained with supervised fine-tuning instead of reinforcement learning	4,000 tokens	Up to Jun 2021
`code-davinci-002`	Optimized for code-completion tasks	4,000 tokens	Up to Jun 2021

Codex Limited beta

code

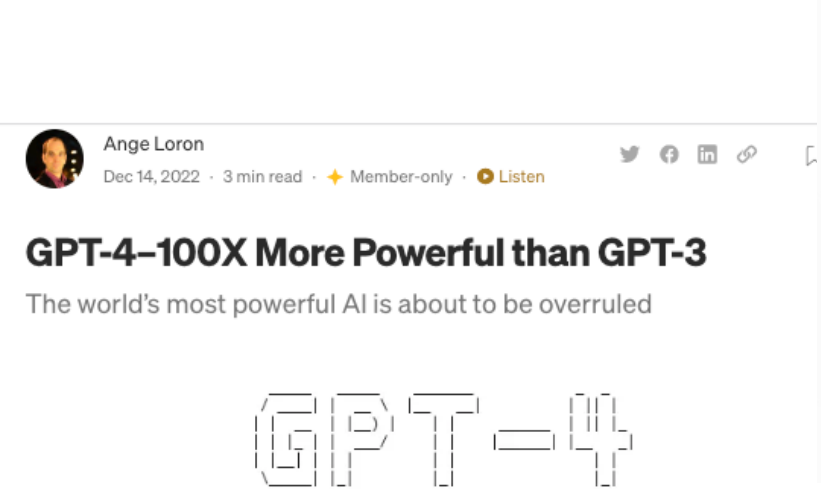
The Codex models are descendants of our GPT-3 models that can understand and generate code. Their training data contains both natural language and billions of lines of public code from GitHub. Learn more.

They're most capable in Python and proficient in over a dozen languages including JavaScript, Go, Perl, PHP, Ruby, Swift, TypeScript, SQL, and even Shell.

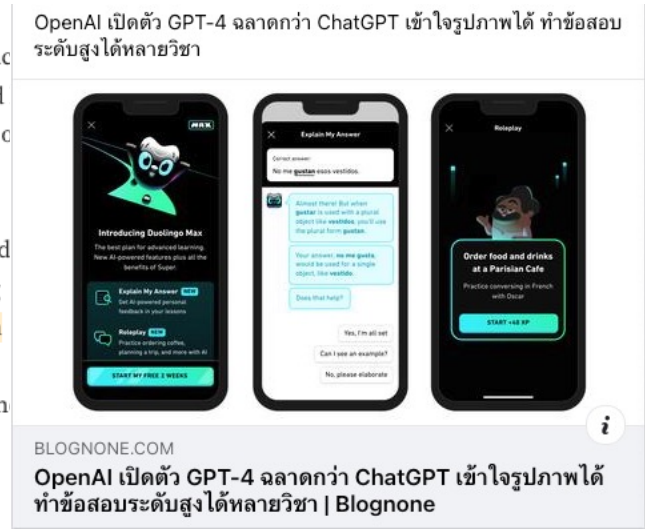
We currently offer two Codex models:

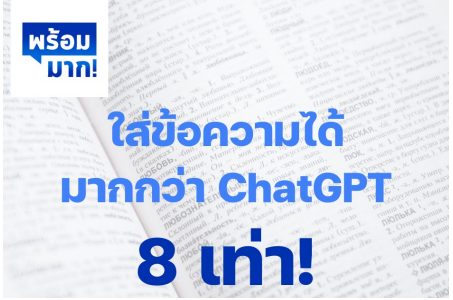
LATEST MODEL	DESCRIPTION	MAX REQUEST	TRAINING DATA
`code-davinci-002`	Most capable Codex model. Particularly good at translating natural language to code. In addition to completing code, also supports inserting completions within code.	8,000 tokens	Up to Jun 2021
`code-cushman-001`	Almost as capable as Davinci Codex, but slightly faster. This speed advantage may make it preferable for real-time applications.	Up to 2,048 tokens	

For more, visit our guide to working with Codex.


Ange Loron
Dec 14, 2022 · 3 min read · Member-only · Listen
GPT-4–100X More Powerful than GPT-3
The world's most powerful AI is about to be overruled
GPT-4
GPT-4 (Generative Pretrained Transformer 4) is the latest and most advanc
version of the GPT (Generative Pretrained Transformer) model developed
OpenAI. It is a large-scale machine learning model that has been trained c
a massive amount of data to generate human-like text.
GPT-4 builds on the success of GPT-3, which was released in May 2020 and
quickly became one of the most widely used natural language processing
models. GPT-4 is significantly larger and more powerful than GPT-3, with
170 trillion parameters compared to GPT-3's 175 billion parameters. This
allows GPT-4 to process and generate text with greater accuracy and fluen


พร้อม มาก!
OpenAI เปิดตัว GPT-4
มีอะไรใหม่บ้างมาดูกัน

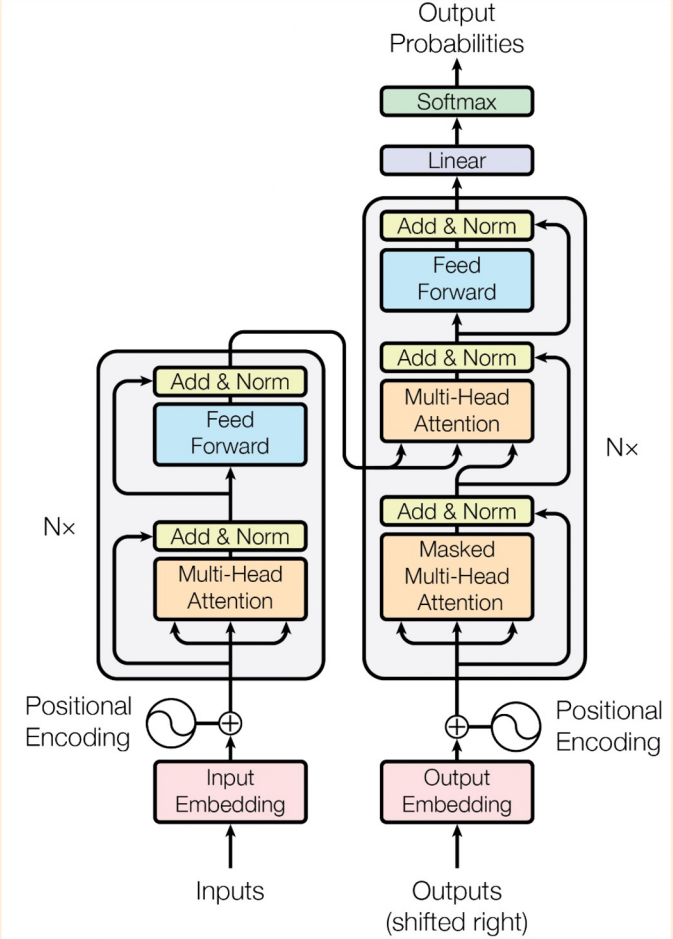

OpenAI เปิดตัว GPT-4 ฉลาดกว่า ChatGPT เข้าใจรูปภาพได้ ทำข้อสอบ
ระดับสูงได้หลายวิชา
Introducing Duolingo Max
Explain My Answer
Roleplay
Order food and drinks at a Parisian Cafe
BLOGNONE.COM
OpenAI เปิดตัว GPT-4 ฉลาดกว่า ChatGPT เข้าใจรูปภาพได้
ทำข้อสอบระดับสูงได้หลายวิชา | Blognone


พร้อม มาก!
ใส่ข้อความได้
มากกว่า ChatGPT
8 เท่า!


พร้อม มาก!
GPT-4 ไม่จำกัด
แค่ภาษาอีกต่อไป
What happens when the glove drops?
It will hit the wood plank and the ball will fly up.


สมาชิก ChatGPT Plus
ลองใช้ GPT-4 ได้ก่อน
ค่าสมาชิก $20 ต่อเดือน
จำกัดที่ 100 ข้อความทุก 4 ชั่วโมง
ยังใส่รูปไม่ได้ในวันเปิดตัว

Bidirectional Encoder Representation from Transformers (BERT)



BERT [Devlin, et al, 2018]:
Bidirectional **E**ncoder **R**epresentation from **T**ransformers

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

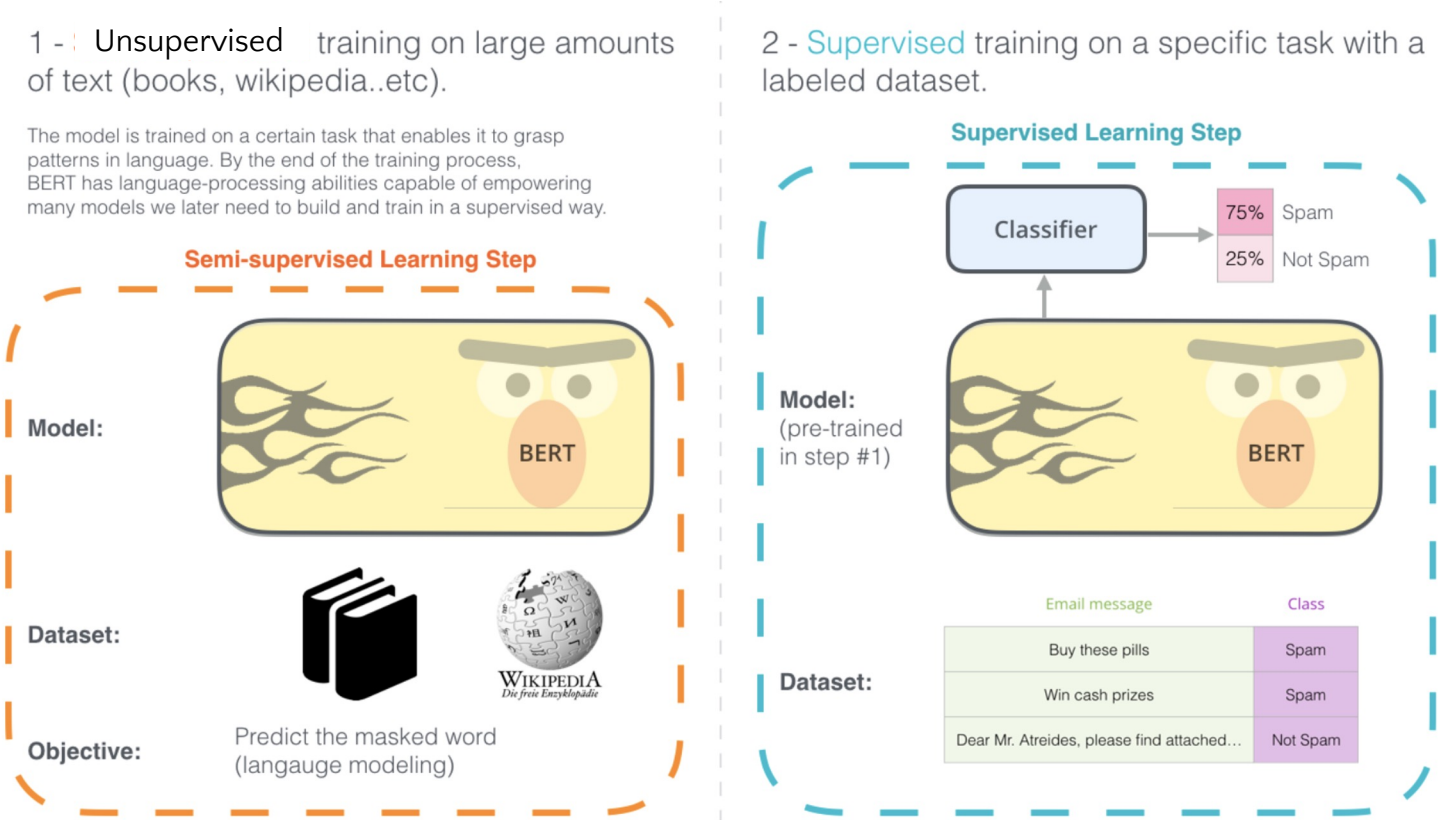
Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Abstract

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-

There are two existing strategies for applying pre-trained language representations to downstream tasks: *feature-based* and *fine-tuning*. The feature-based approach, such as ELMo (Peters et al., 2018a), uses task-specific architectures that include the pre-trained representations as additional features. The fine-tuning approach, such as the Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), introduces minimal task-specific parameters, and is trained on the downstream tasks by simply fine-tuning *all* pre-

BERT [Devlin, et al, 2018]:
Bidirectional **E**ncoder **R**epresentation from **T**ransformers



Devlin et al., **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**, arXiv 2018, https://arxiv.org/pdf/1810.04805.pdf

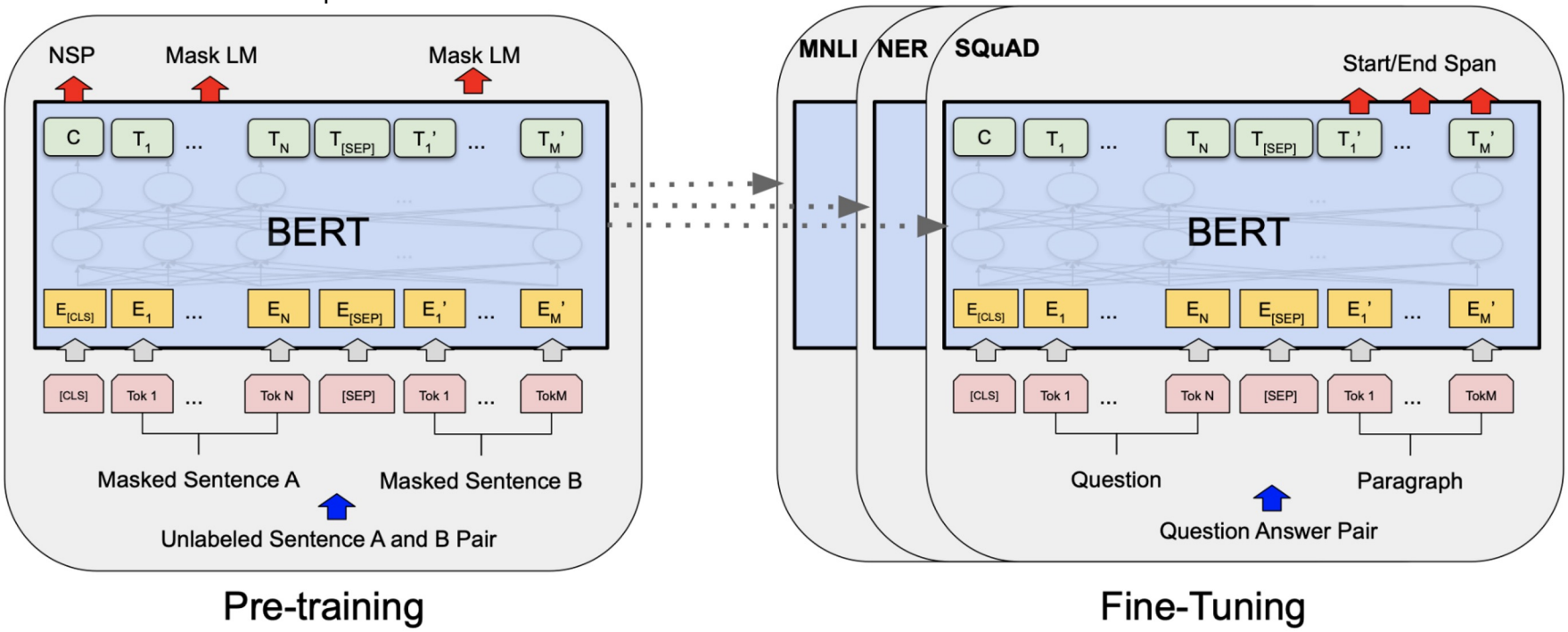
BERT (cont.): Overall idea

Phase1: Unsupervised Learning

- Mask LM
- Next sentence prediction

Phase2: Supervised learning

- **E.g.** Finetune on QA, Text classification, etc.



Phase1: Unsupervised Phase

Semi-supervised training, using 2 prediction tasks:

1.1) Mask language modeling

- represents the word using both its left and right context, so called deeply bidirectional.
- Mask out 15% of the words in the input, run the entire sequence through a deep bidirectional encoder, and then predict only the masked words.

```
Input: the man went to the [MASK1] . he bought a [MASK2] of milk.
Labels: [MASK1] = store; [MASK2] = gallon
```

1.2) Next sentence prediction (NSP)

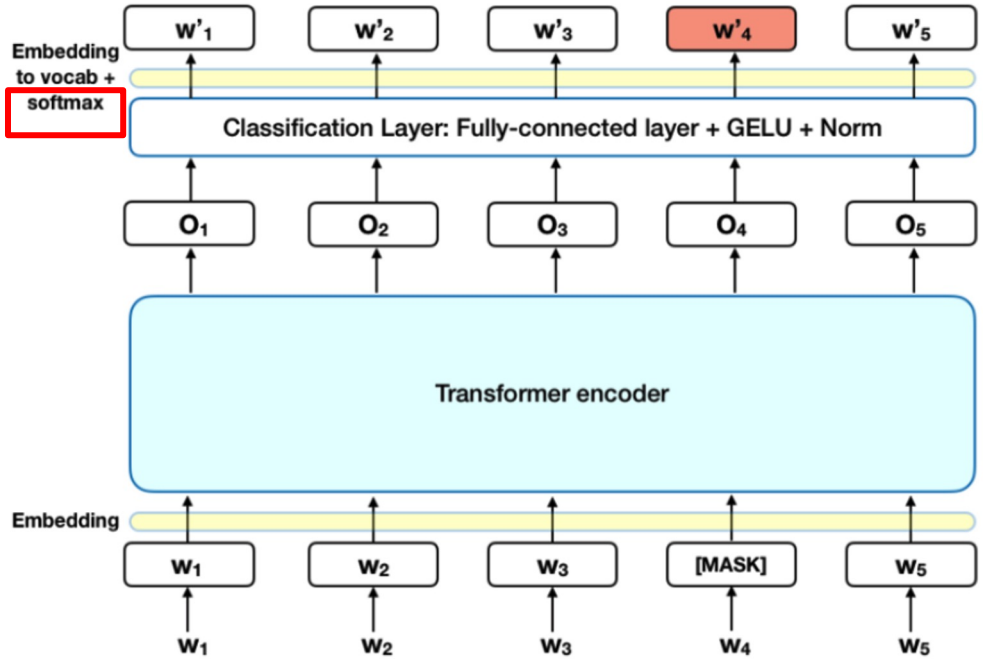
- to learn relationships between sentences.

```
Sentence A: the man went to the store .
Sentence B: he bought a gallon of milk .
Label: IsNextSentence
```

```
Sentence A: the man went to the store .
Sentence B: penguins are flightless .
Label: NotNextSentence
```

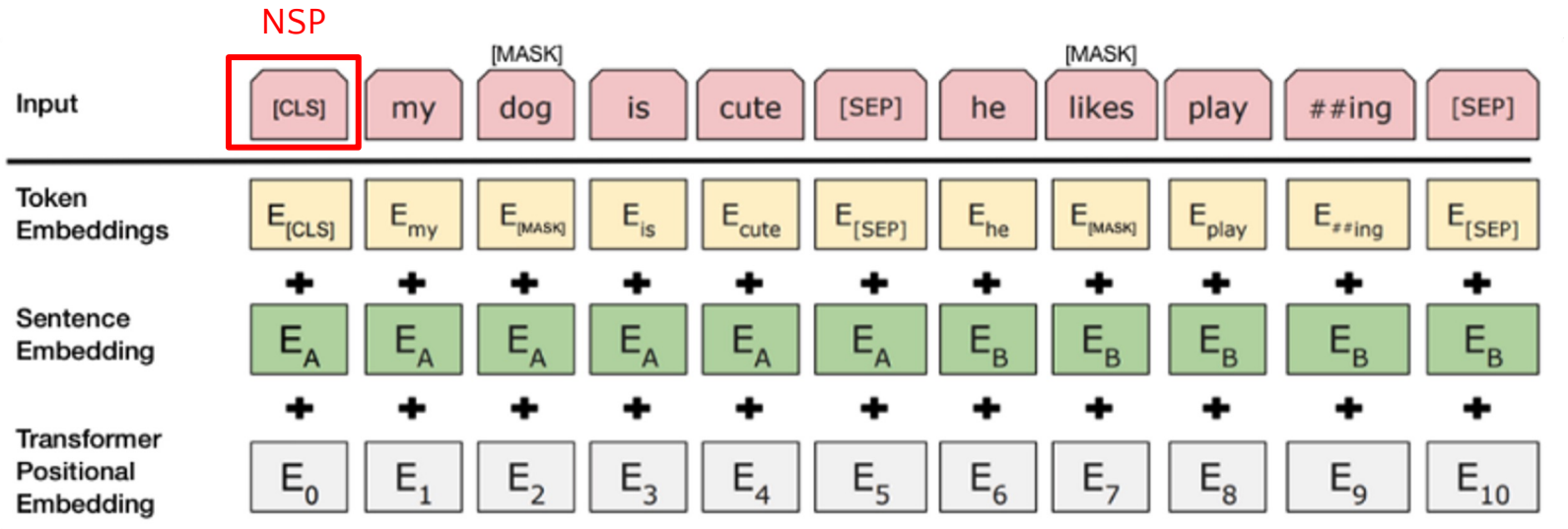
Phase1: Unsupervised Phase (1.1. Masked LM)

Mask language modeling:



Source: https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270

Phase1: Unsupervised Phase (1.2. Next Sentence Prediction)



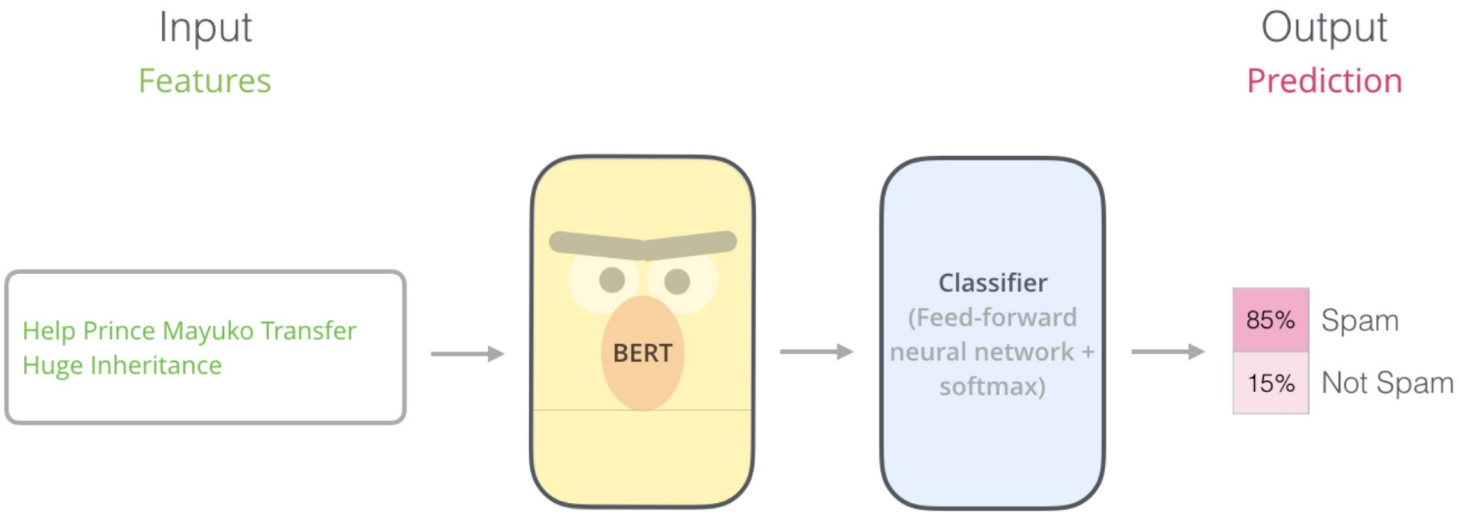
CLS = Classification, which is used for NSP (Next Sentence Prediction) during this phase
SEP = a special separator token (e.g. separating questions/answers).

Source:https://arxiv.org/pdf/1810.04805.pdf

Phase2: Supervised Phase

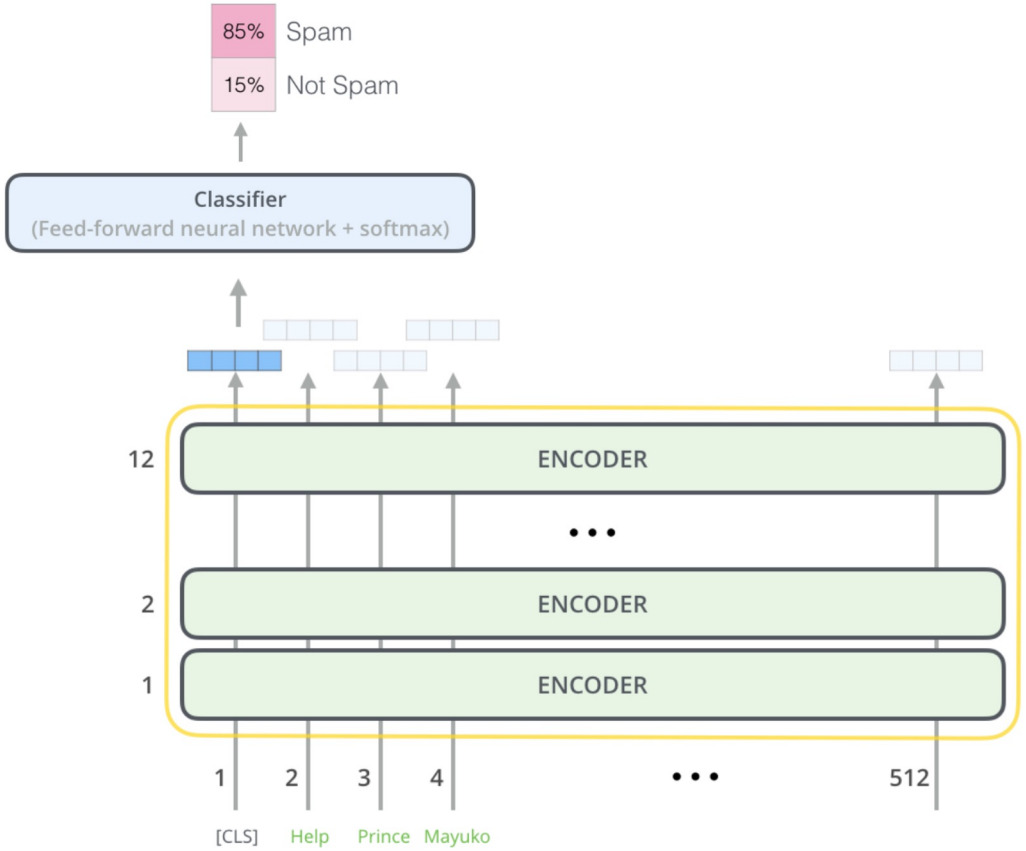
Supervised training (e.g. Email sentence classification)

- you mainly have to train the classifier, with minimal changes happening to the pre-trained model during the training phase (fine-tuning approach).



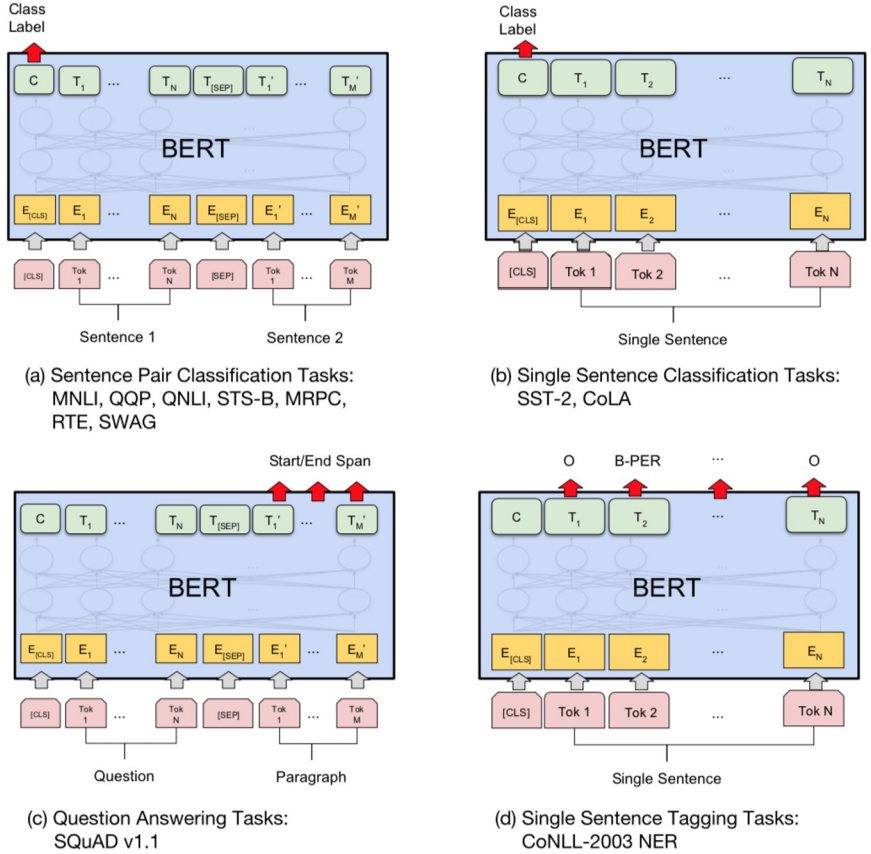
Phase2: Supervised Phase
E.g., Spam Email Classification

- BERT is basically a trained Transformer Encoder [1] stack.
- The first input token is supplied with a special (classification embedding) [CLS] token for classification task to represent the entire sentence.
- The output is generated from only this special [CLS] token.



[1] Vaswani et al., **Attention Is All You Need**, NIPS 2017, https://arxiv.org/pdf/1706.03762.pd

Phase2: Supervised Phase
E.g., other tasks



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Devlin et al., **BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding**, arXiv 2018, https://arxiv.org/pdf/1810.04805.pdf

Pretrained BERT (English)

https://github.com/google-research/bert

BERT

***** New March 11th, 2020: Smaller BERT Models *****

This is a release of 24 smaller BERT models (English only, uncased, trained with WordPiece masking) referenced in Well-Read Students Learn Better: On the Importance of Pre-training Compact Models.

We have shown that the standard BERT recipe (including model architecture and training objective) is effective on a wide range of model sizes, beyond BERT-Base and BERT-Large. The smaller BERT models are intended for environments with restricted computational resources. They can be fine-tuned in the same manner as the original BERT models. However, they are most effective in the context of knowledge distillation, where the fine-tuning labels are produced by a larger and more accurate teacher.

Our goal is to enable research in institutions with fewer computational resources and encourage the community to seek directions of innovation alternative to increasing model capacity.

You can download all 24 from here, or individually from the table below:

	H=128	H=256	H=512	H=768
L=2	**2/128 (BERT-Tiny)**	2/256	2/512	2/768
L=4	4/128	**4/256 (BERT-Mini)**	**4/512 (BERT-Small)**	4/768
L=6	6/128	6/256	6/512	6/768
L=8	8/128	8/256	**8/512 (BERT-Medium)**	8/768
L=10	10/128	10/256	10/512	10/768
L=12	12/128	12/256	12/512	**12/768 (BERT-Base)**

Pretrained BERT (Multilingual)

https://github.com/google-research/bert/blob/master/multilingual.md

Models

There are two multilingual models currently available. We do not plan to release more single-language models, but we may release `BERT-Large` versions of these two in the future:

- **`BERT-Base, Multilingual Cased (New, recommended)`**: 104 languages, 12-layer, 768-hidden, 12-heads, 110M parameters
- **`BERT-Base, Multilingual Uncased (Orig, not recommended)`**: 102 languages, 12-layer, 768-hidden, 12-heads, 110M parameters
- **`BERT-Base, Chinese`**: Chinese Simplified and Traditional, 12-layer, 768-hidden, 12-heads, 110M parameters

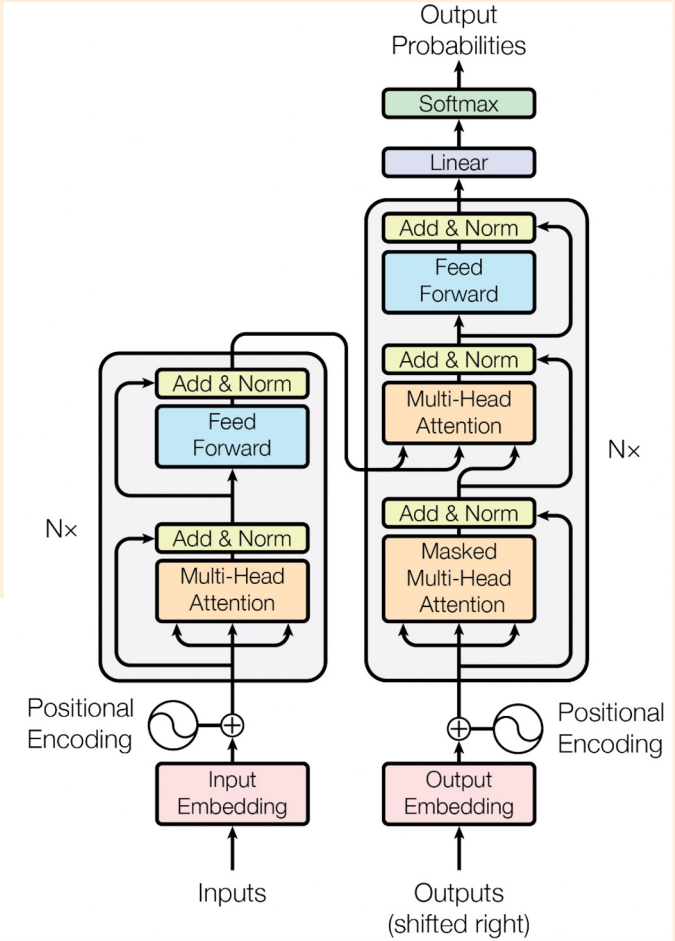
BART [2019]

BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, Luke Zettlemoyer

We present BART, a denoising autoencoder for pretraining sequence-to-sequence models. BART is trained by (1) corrupting text with an arbitrary noising function, and (2) learning a model to reconstruct the original text. It uses a standard Tranformer-based neural machine translation architecture which, despite its simplicity, can be seen as generalizing BERT (due to the bidirectional encoder), GPT (with the left-to-right decoder), and many other more recent pretraining schemes. We evaluate a number of noising approaches, finding the best performance by both randomly shuffling the order of the original sentences and using a novel in-filling scheme, where spans of text are replaced with a single mask token. BART is particularly effective when fine tuned for text generation but also works well for comprehension tasks. It matches the performance of RoBERTa with comparable training resources on GLUE and SQuAD, achieves new state-of-the-art results on a range of abstractive dialogue, question answering, and summarization tasks, with gains of up to 6 ROUGE. BART also provides a 1.1 BLEU increase over a back-translation system for machine translation, with only target language pretraining. We also report ablation experiments that replicate other pretraining schemes within the BART framework, to better measure which factors most influence end-task performance.

Subjects: **Computation and Language (cs.CL)**; Machine Learning (cs.LG); Machine Learning (stat.ML)
Cite as: arXiv:1910.13461 **[cs.CL]**
(or arXiv:1910.13461v1 **[cs.CL]** for this version)
https://doi.org/10.48550/arXiv.1910.13461

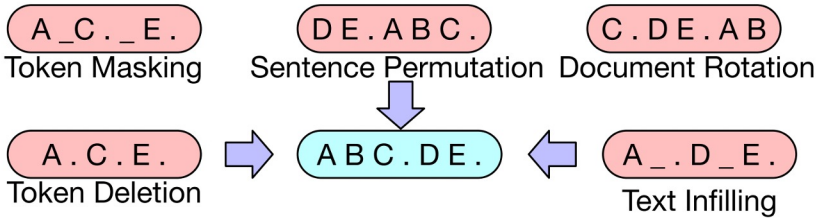


BART

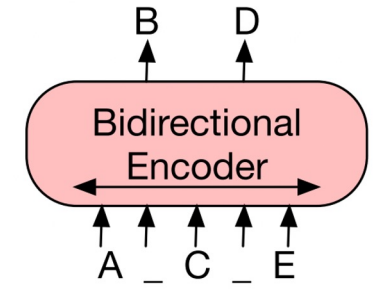
A model comprises of both Transformer encoders *and* decoders

BART optimizes on denoising corrupted inputs

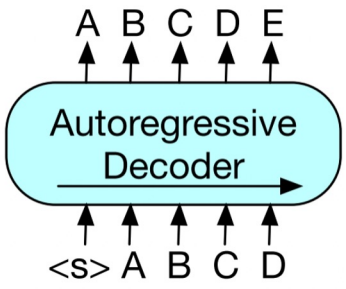
By using both encoders and decoders, BART combines the bidirectionality of BERT and autoregressive ability of GPT.



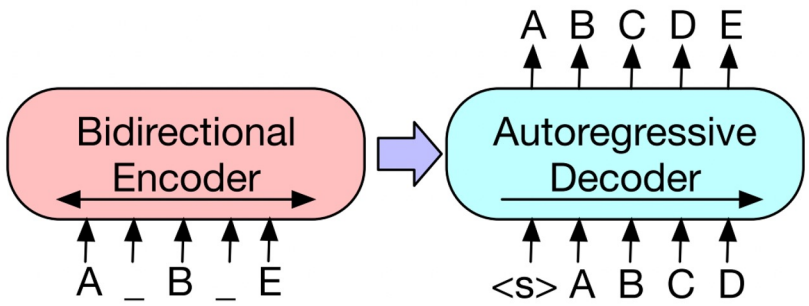
Input noising scheme



BERT



GPT

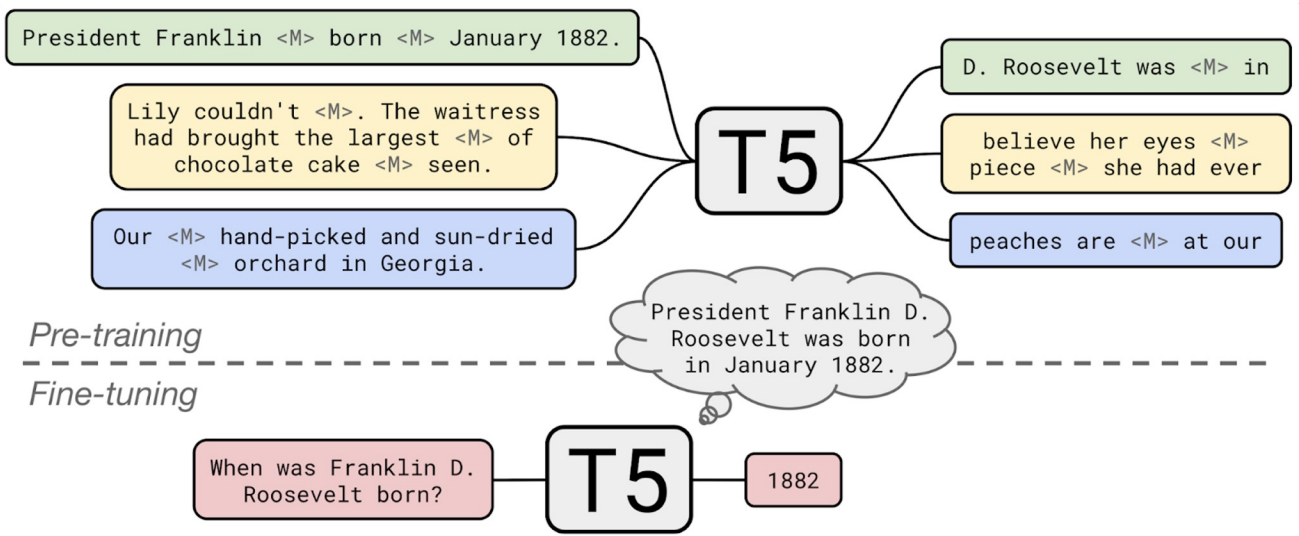


BART

Text-to-text Transfer Transformer (T5)

T5 is also an encoder-decoder model

It pretrains on the span-corruption objective.



When to use which?

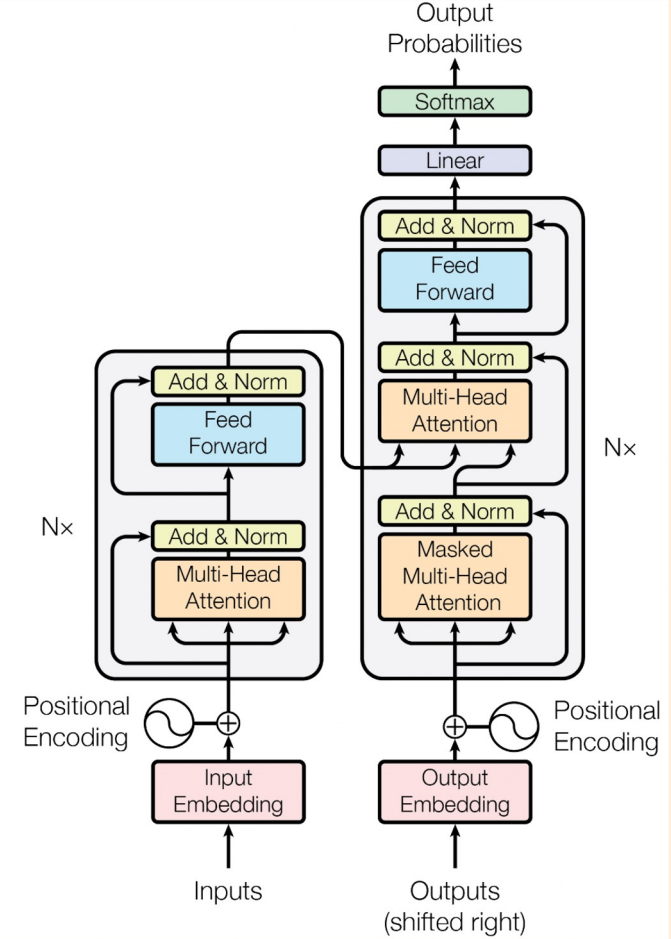
Text Generation: GPT models

Sequence-to-sequence (e.g. text summarization, translation): BART, T5, or similar

Text classification/ Token classification: BERT (easier to use) or BART

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**

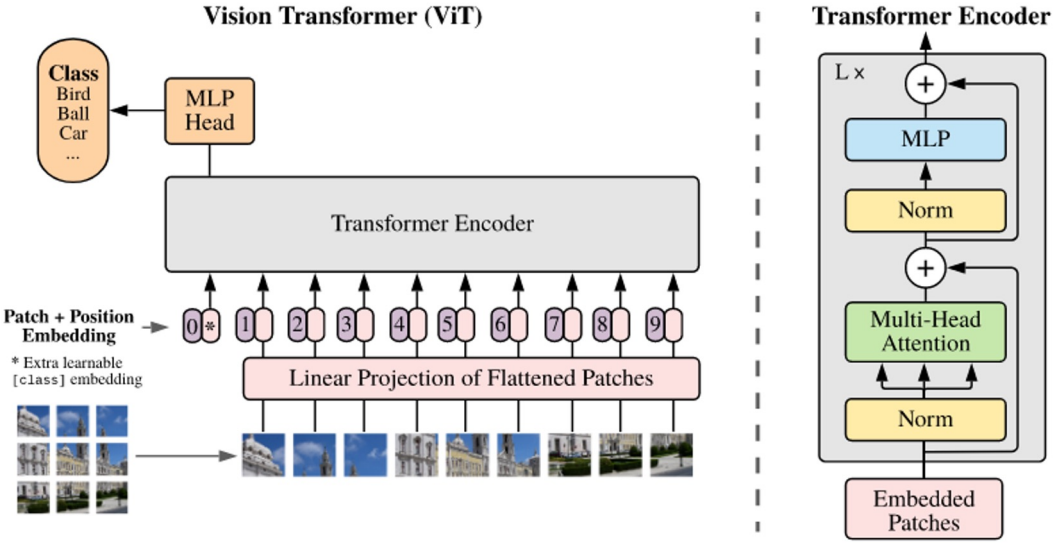
Beyond NLP

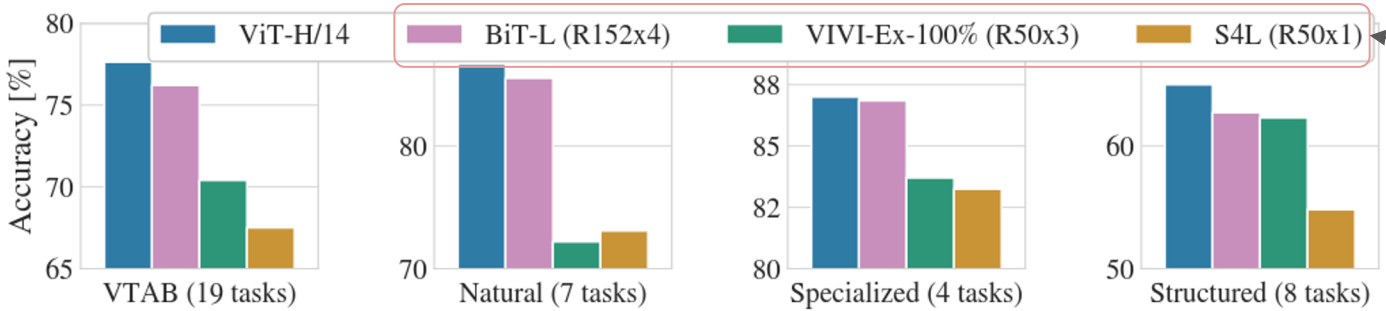

Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

Beyond NLP

1) Computer Vision

ViT uses only encoder.



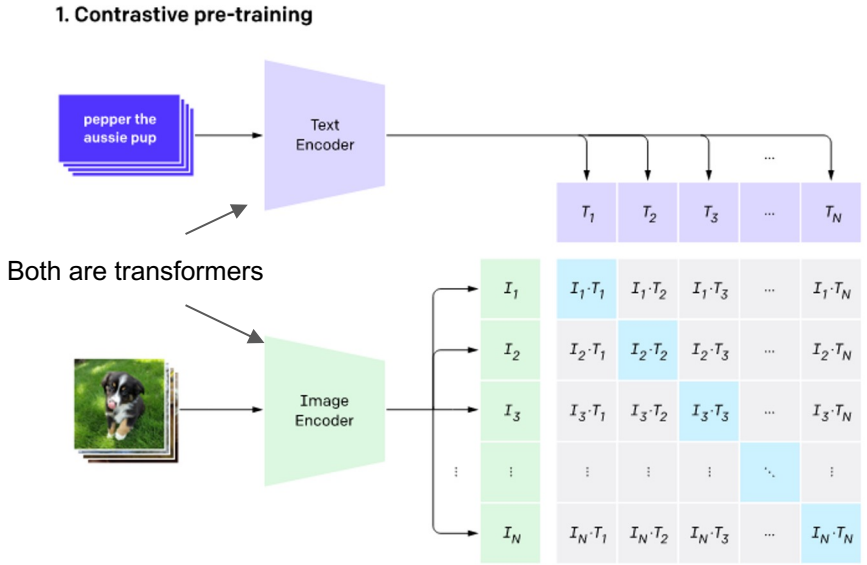


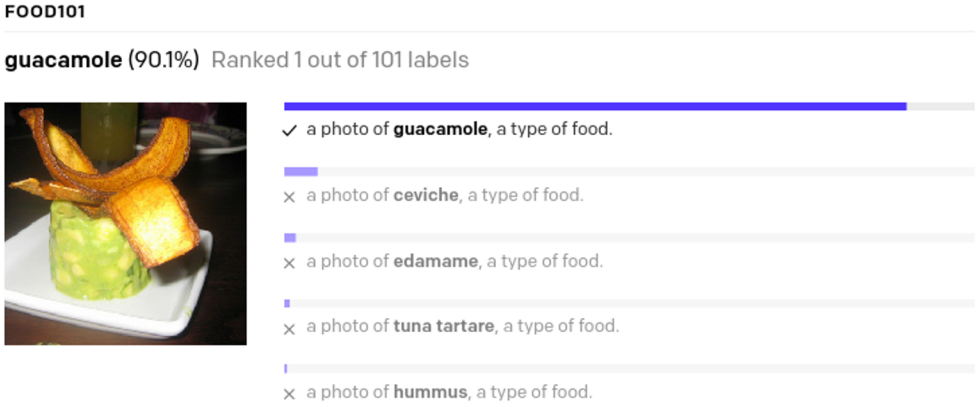
Baselines are ResNet

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Beyond NLP

2) Text-Image (Multimodal)





https://openai.com/blog/clip/

Beyond NLP

2) Text-to-Image

TEXT PROMPT an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES

Edit prompt or view more images↓

TEXT PROMPT an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES

Edit prompt or view more images↓

TEXT PROMPT a store front that has the word ‘openai’ written on it. . . .

AI-GENERATED IMAGES

Edit prompt or view more images↓

https://openai.com/blog/dall-e/