Natural Language Processing

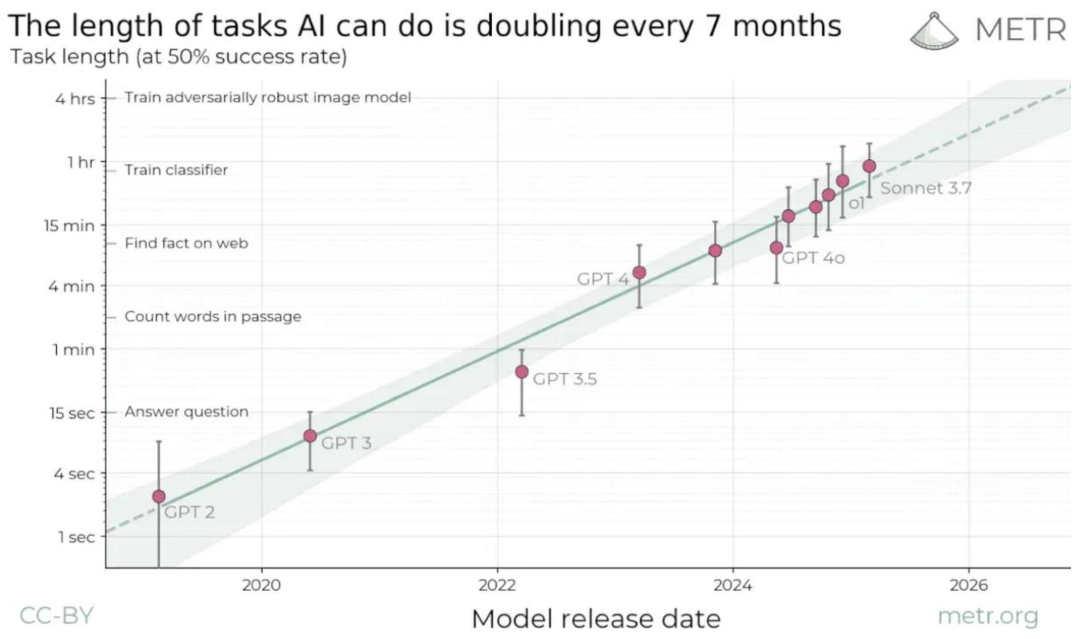
ELMo, BERT, GPT, and T5 (BERT and its Family) https://www.julian.ac/blog/2025/09/27/failing-to-understand-the-exponential-again/?fbclid=IwY2xjawNJ9jVleHRuA2FlbQIxMQABHtDNjylul4c-EgwKPC6l968d0EvEWqR83Kzk6_3YWMNrN8eQeEuGIevc-2ct_aem_9tJx9E4swVHoFZauXnGgfg

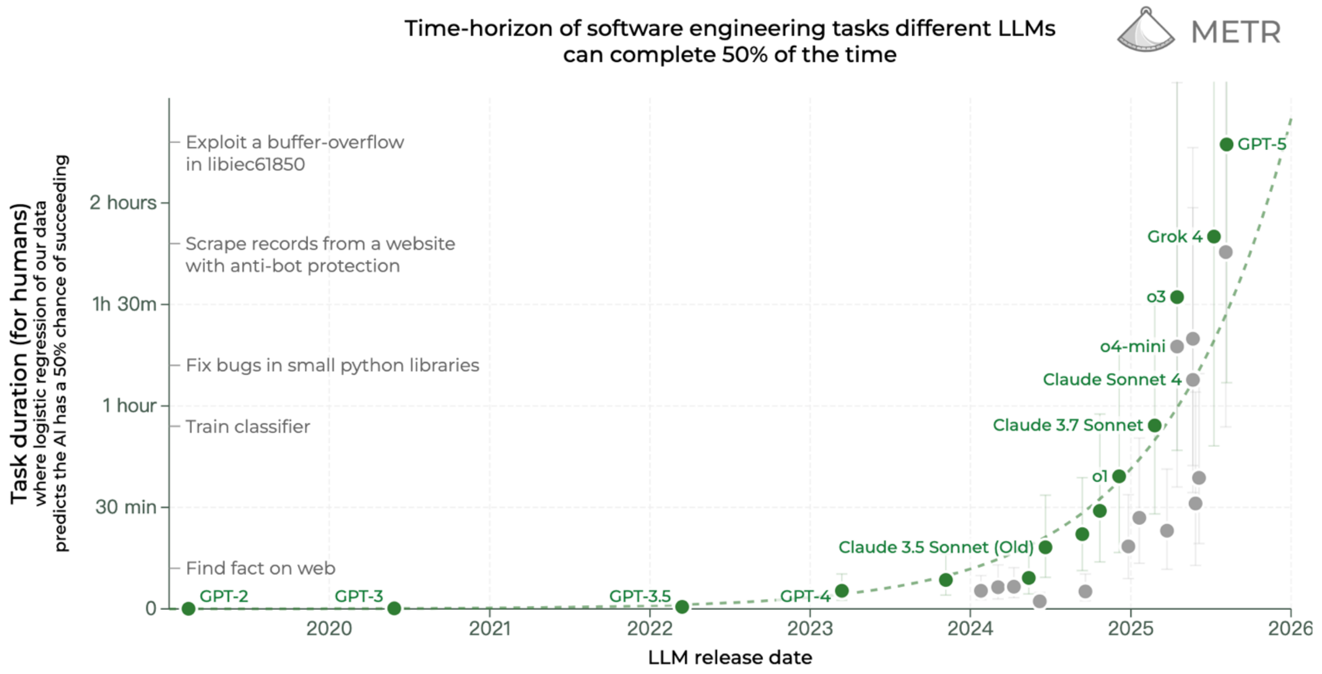
News

Julian Schrittwieser

Failing to Understand the Exponential, Again

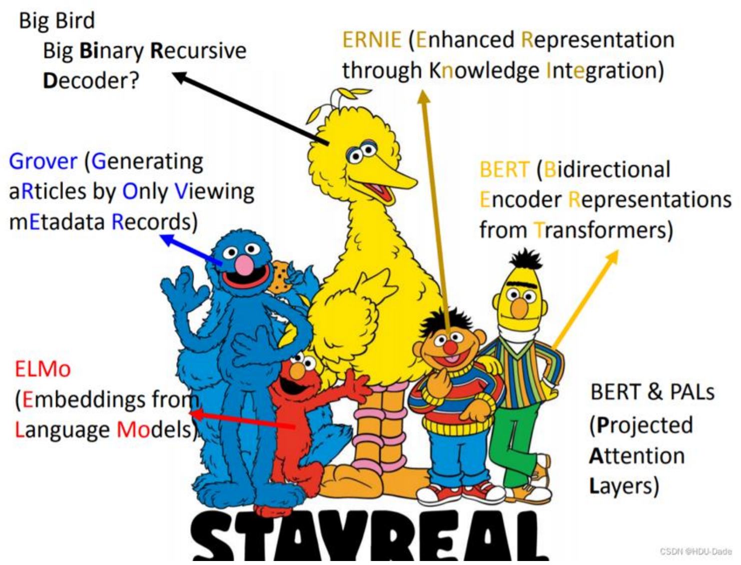
Sat 27 September 2025





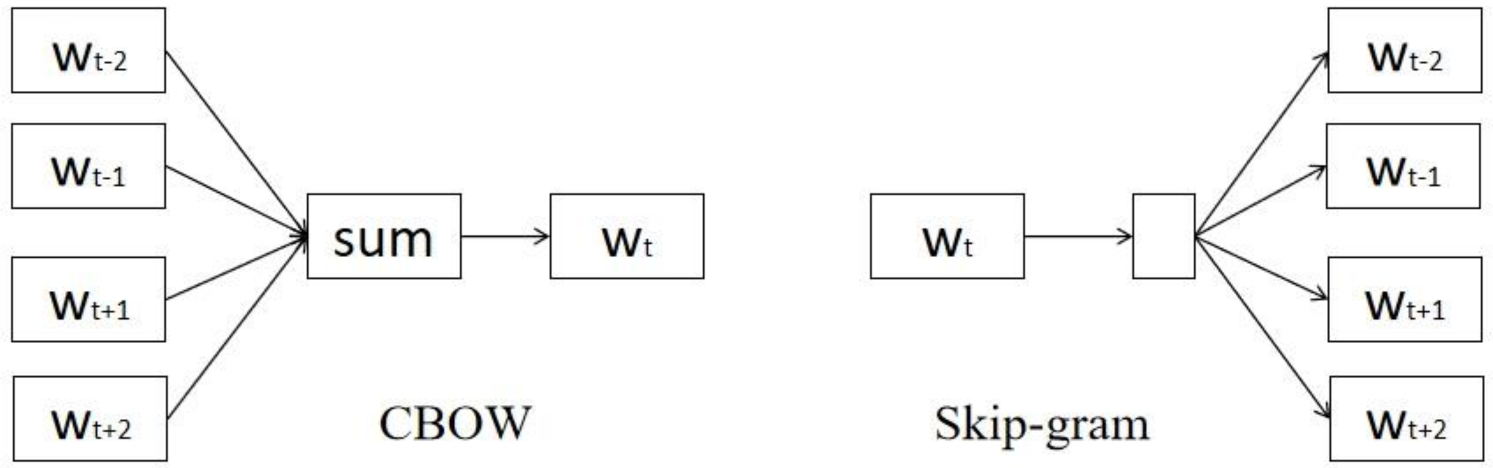
Outline

- Recap: Word Embeddings, RNN
- Pretraining Language Model from Word Embeddings
  - ELMo
- Pretraining by Transformer
  - Encoders (BERT)
  - Encoder-Decoders (T5)
  - Decoders (GPT)
- GPT-3 with In-Context Learning and Large Language Models


Big Bird
Big Binary Recursive Decoder?
ERNIE (Enhanced Representation through Knowledge Integration)
Grover (Generating aRticles by Only Viewing mEtadata Records)
BERT (Bidirectional Encoder Representations from Transformers)
ELMo (Embeddings from Language Models)
BERT & PALs (Projected Attention Layers)
STAYREAL
CSDN @HDU-Dade

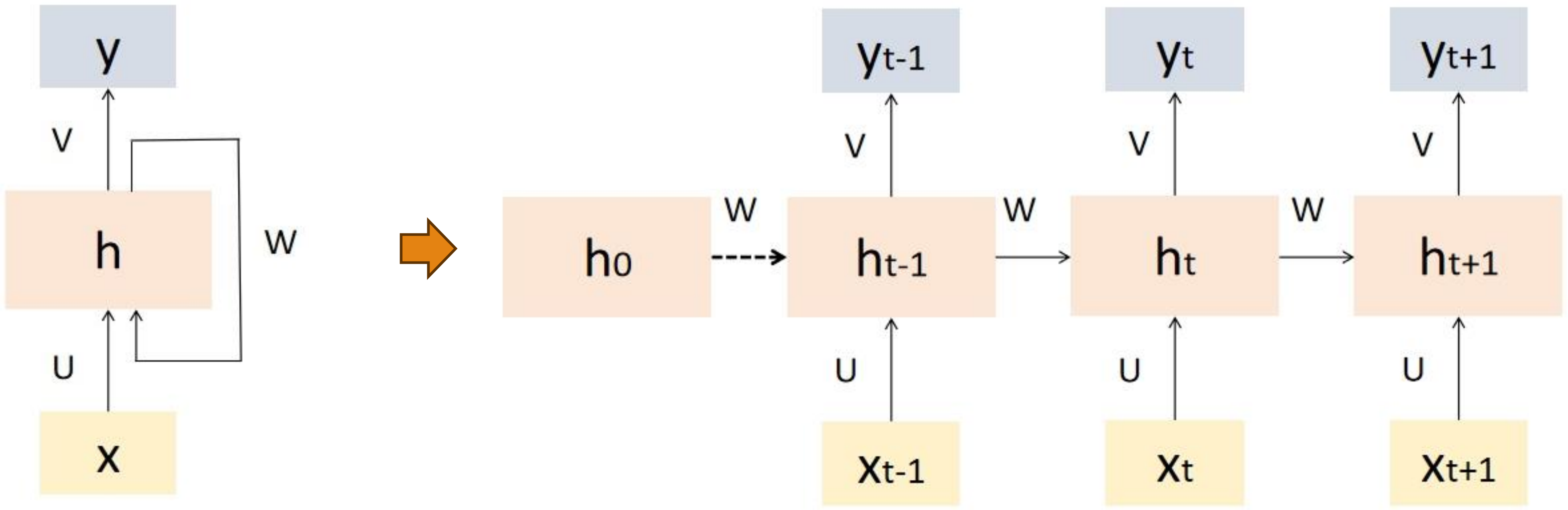
Recap: Word Embeddings (Word2Vec)

- Skip-gram
  - Use words to predict their contexts.
- CBOW
  - Use the context to predict the target word.



Recap: RNN

- Recurrent Neural Networks (RNNs) are a type of artificial neural network designed to handle sequential data by **capturing temporal dependencies**.
  - The same set of weights and biases are used across all time steps

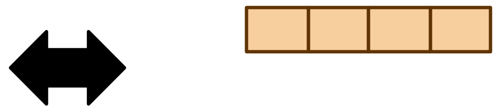


Pretrained Word Embeddings

Consider I record the record: the two instances of record mean different things.

-0.17	-0.89	0.06	-0.41	-1.08	-0.74	1.41	-0.94	-0.32	0.12

Word2Vec or GloVe word embeddings of **“record”**



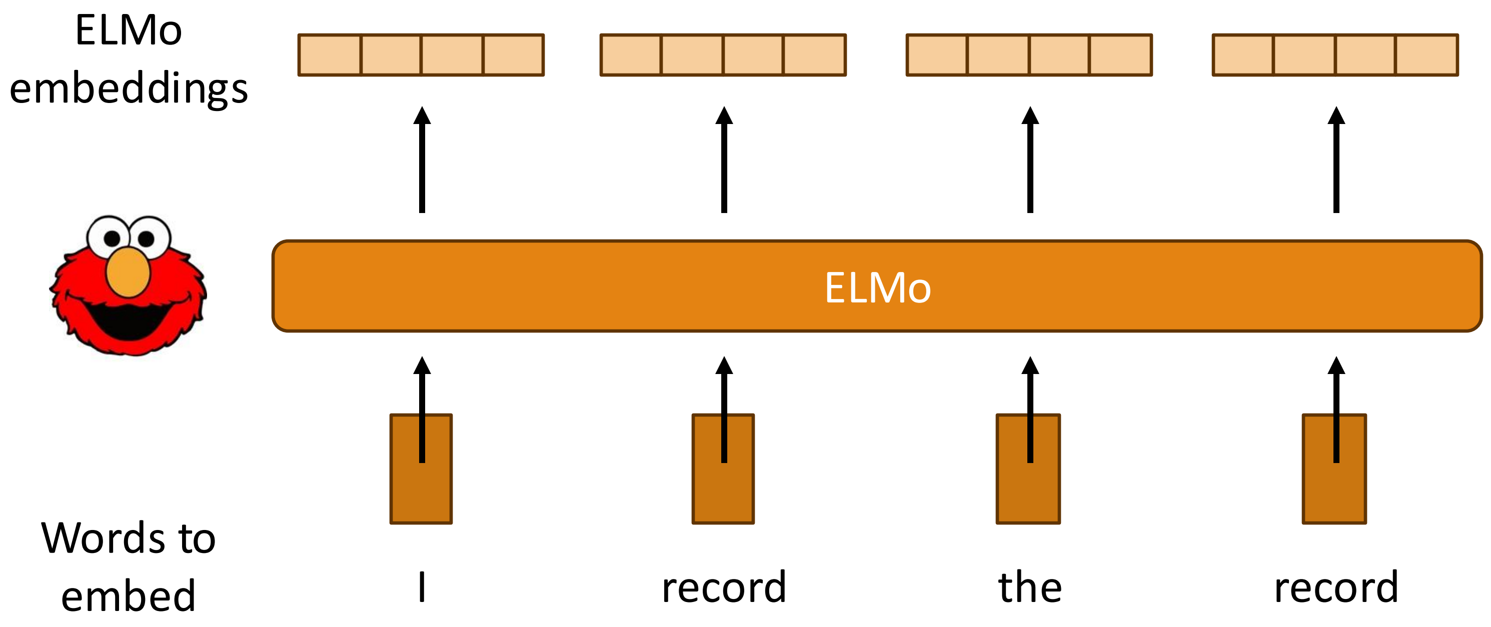
Vector representation

Issue: Both GloVe and Word2Vec represent the word “record” as the same vector regardless of the context.

https://arxiv.org/pdf/1802.05365

Context Matters: ELMo (Peters et al., 2018)

Rather than using a fixed representation for each word, **ELMo (Embeddings from Language Models)** considers the entire sentence before assigning each word in it an embedding.



Reconstruct the Sentences (next token prediction)

National Hsing Hua University is in ______. (Hsinchu)

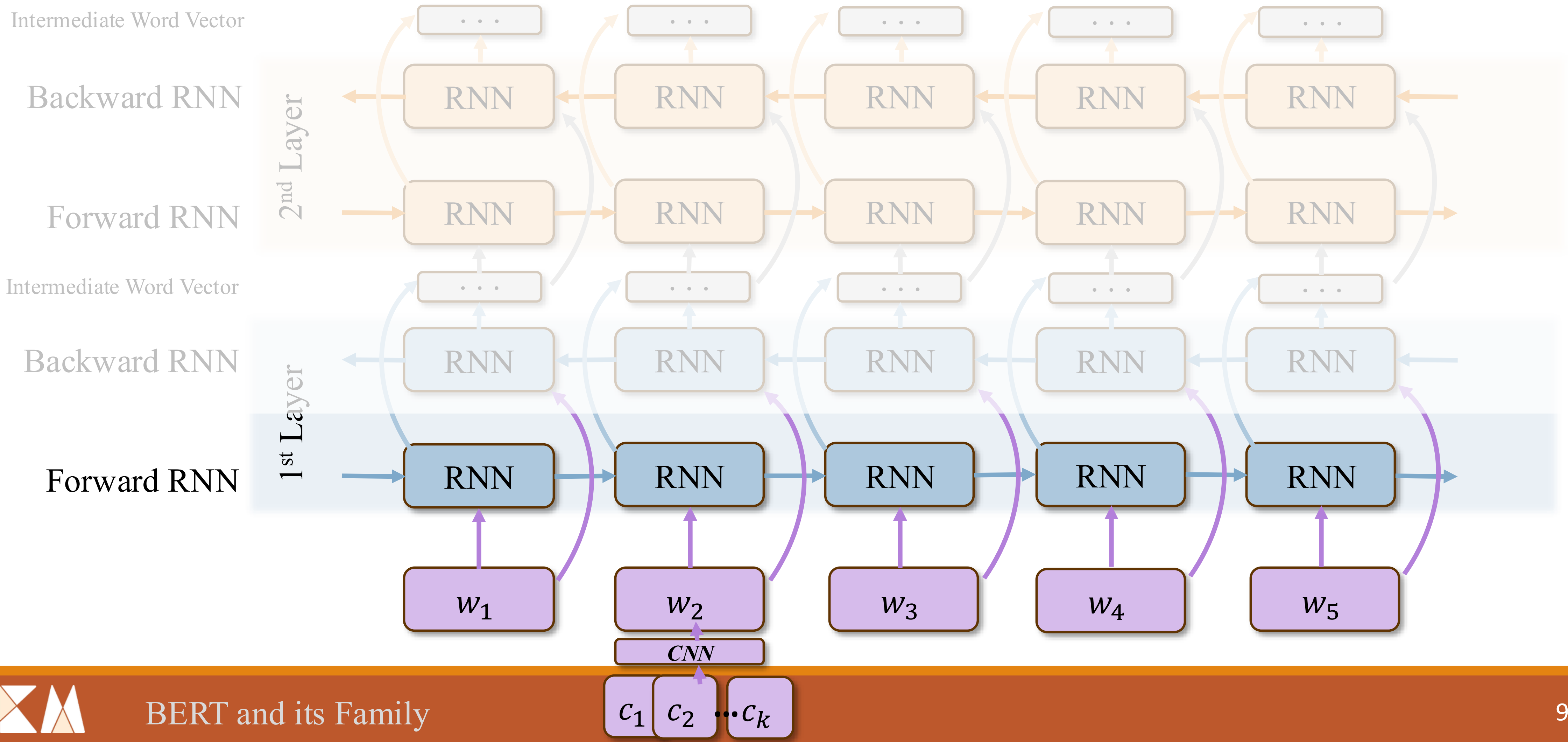
I put ____ bag on the table. (a)

I went to the zoo to see the lions, monkeys, elephants, and _____. ()

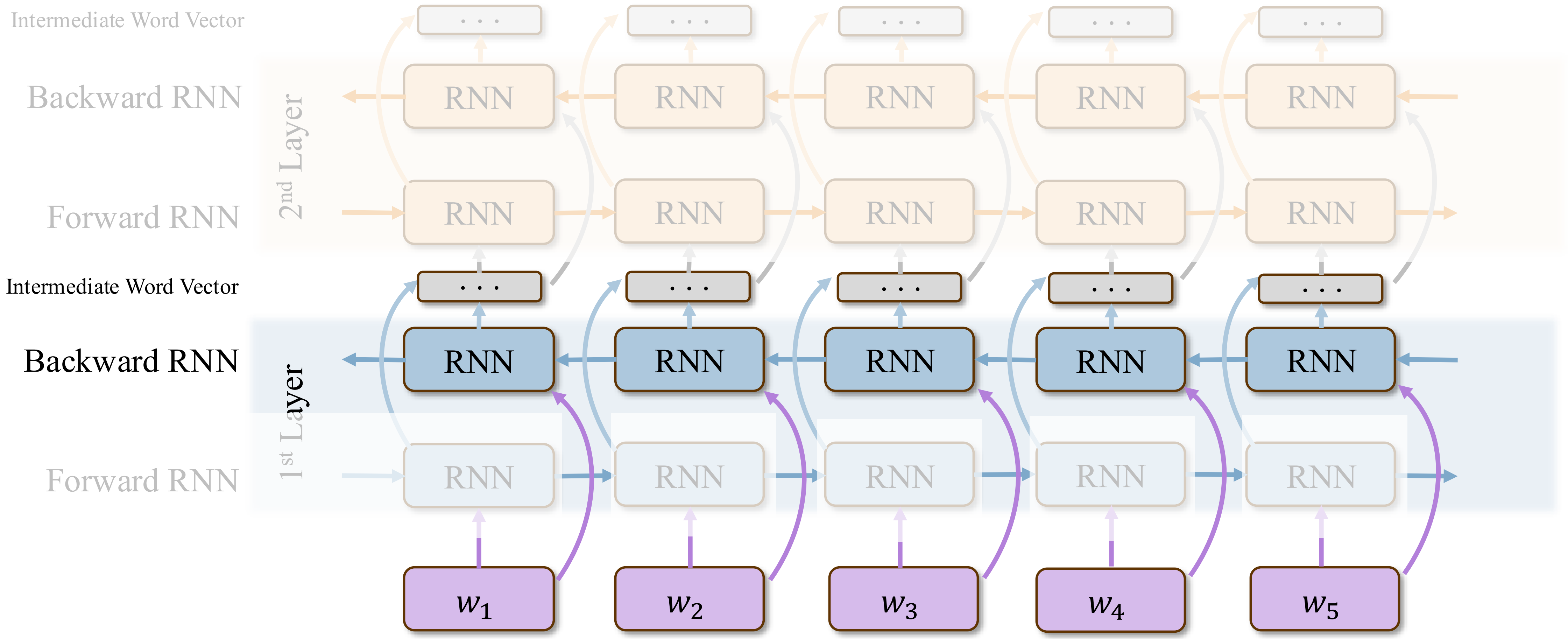
The overall value I got from the two hours of watching it was the total sum of popcorn and the drink. The movie was _____. (bad)

I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, _____(34)

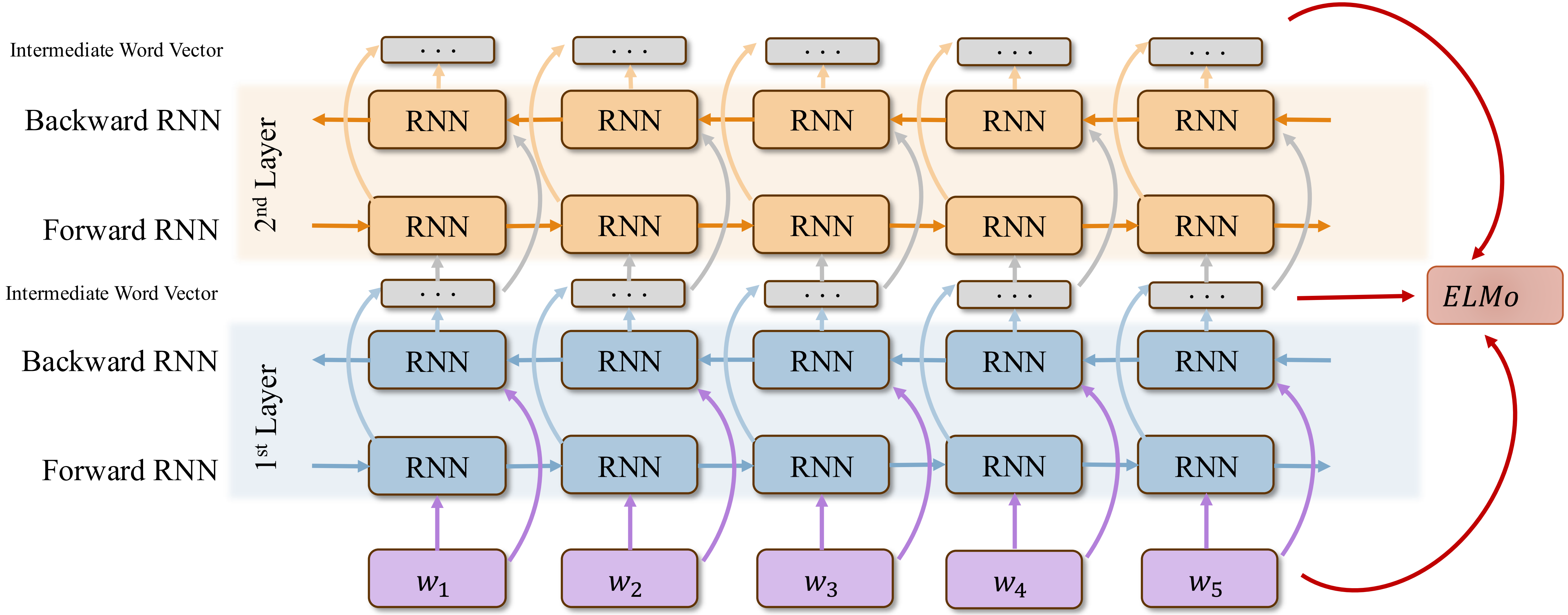
Bidirectional Language Model (biLM)



Bidirectional Language Model (biLM)



Bidirectional Language Model (biLM)

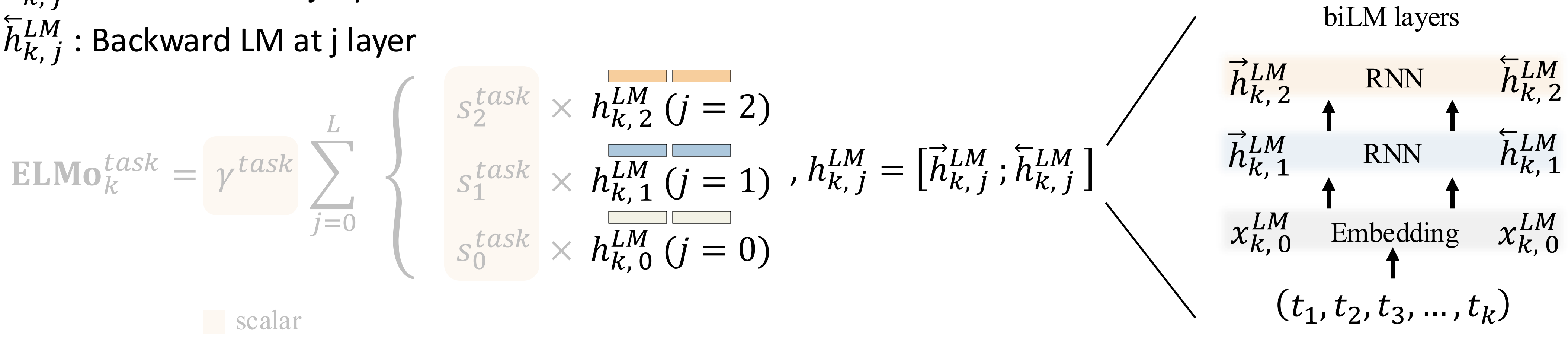


Pretraining through Language Modeling

Step 1. Concatenate hidden layers.

Concatenate forward and backward LM of each layer together (for token layer, we concatenate it with itself)

$\vec{h}_{k,0}^{LM}$: Token Layer
$\vec{h}_{k,j}^{LM}$: Forward LM at j layer
$\overleftarrow{h}_{k,j}^{LM}$: Backward LM at j layer

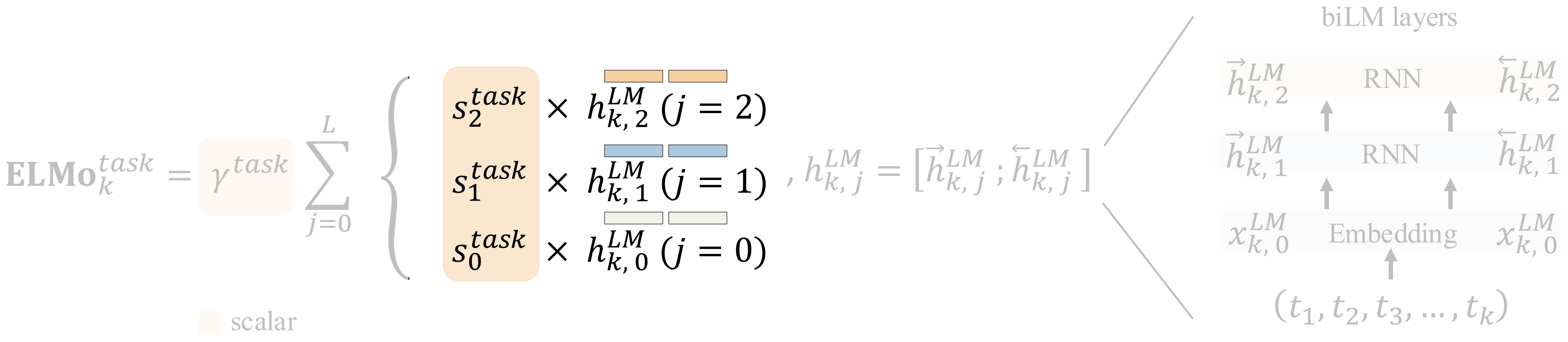


$\mathbf{ELMo}_k^{task} = \gamma^{task} \sum_{j=0}^{L} \{ s_2^{task} \times h_{k,2}^{LM} (j=2),\ s_1^{task} \times h_{k,1}^{LM} (j=1),\ s_0^{task} \times h_{k,0}^{LM} (j=0)$
$, h_{k,j}^{LM} = [\vec{h}_{k,j}^{LM} ; \overleftarrow{h}_{k,j}^{LM}]$
scalar
biLM layers
$\vec{h}_{k,2}^{LM}$
RNN
$\overleftarrow{h}_{k,2}^{LM}$
$\vec{h}_{k,1}^{LM}$
RNN
$\overleftarrow{h}_{k,1}^{LM}$
$x_{k,0}^{LM}$
Embedding
$x_{k,0}^{LM}$
$(t_1, t_2, t_3, \dots, t_k)$

Pretraining through Language Modeling

Step 2. Multiply each vector by a weight

We assign each concatenated layer with softmax-normalized weight, s^{task}



$$\mathbf{ELMo}_k^{task} = \gamma^{task} \sum_{j=0}^{L} \left\{ \begin{array}{l} s_2^{task} \times h_{k,2}^{LM}\ (j=2) \\ s_1^{task} \times h_{k,1}^{LM}\ (j=1) \\ s_0^{task} \times h_{k,0}^{LM}\ (j=0) \end{array} \right. ,\ h_{k,j}^{LM} = \left[\overrightarrow{h}_{k,j}^{LM} ; \overleftarrow{h}_{k,j}^{LM}\right]$$

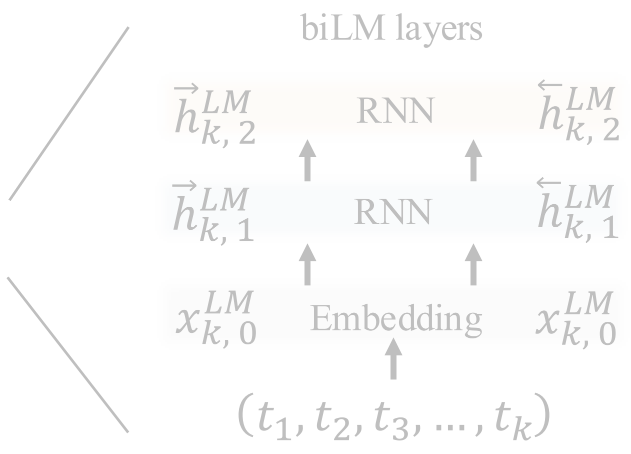
scalar
biLM layers
$\overrightarrow{h}_{k,2}^{LM}$
RNN
$\overleftarrow{h}_{k,2}^{LM}$
$\overrightarrow{h}_{k,1}^{LM}$
RNN
$\overleftarrow{h}_{k,1}^{LM}$
$x_{k,0}^{LM}$
Embedding
$x_{k,0}^{LM}$
$(t_1, t_2, t_3, \dots, t_k)$

Pretraining through Language Modeling

Step 3. Sum all weighted representations.

Once weighted vectors are added together, we use γ^{task} to allow the task model to scale the entire ELMo vector, which is crucial for optimization purposes.

$$\mathbf{ELMo}_k^{task} = \gamma^{task} \sum_{j=0}^{L} \left\{ \begin{array}{l} s_2^{task} \times h_{k,2}^{LM}\ (j=2) \\ s_1^{task} \times h_{k,1}^{LM}\ (j=1) \\ s_0^{task} \times h_{k,0}^{LM}\ (j=0) \end{array} \right. ,\ h_{k,j}^{LM} = \left[\overrightarrow{h}_{k,j}^{LM} ; \overleftarrow{h}_{k,j}^{LM} \right]$$



biLM layers
$\overrightarrow{h}_{k,2}^{LM}$
RNN
$\overleftarrow{h}_{k,2}^{LM}$
$\overrightarrow{h}_{k,1}^{LM}$
RNN
$\overleftarrow{h}_{k,1}^{LM}$
$x_{k,0}^{LM}$
Embedding
$x_{k,0}^{LM}$
$(t_1, t_2, t_3, \ldots, t_k)$

🟧 scalar

Pretraining through Language Modeling

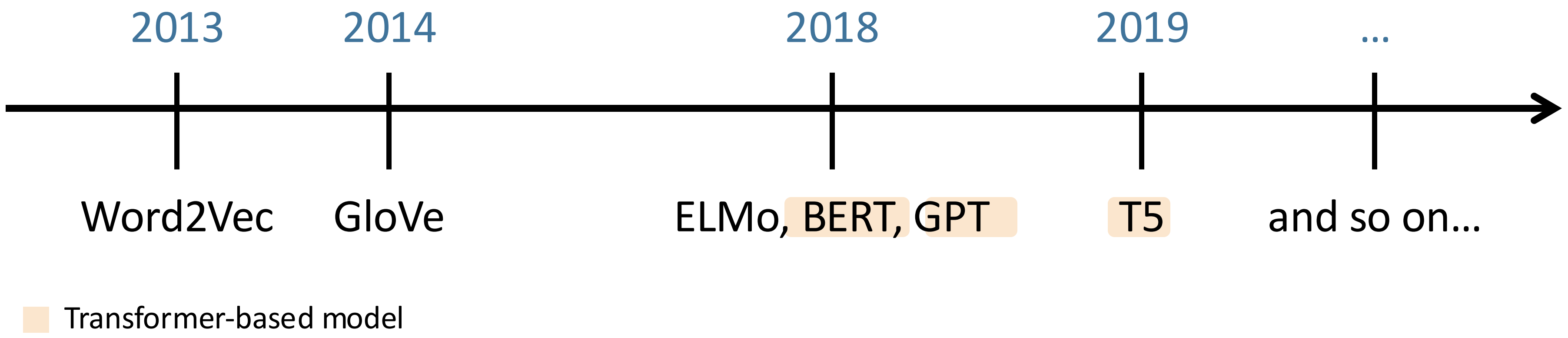
ELMo is a type of deep contextualized word representation that are created through a learning process based on hidden layers of a deep bidirectional language model.

ELMo is a task specific combination of the intermediate layer representations in the biLM.

ELMo generates the contextualized embedding by concatenating the hidden states (and initial embedding) together followed by weighted summation.

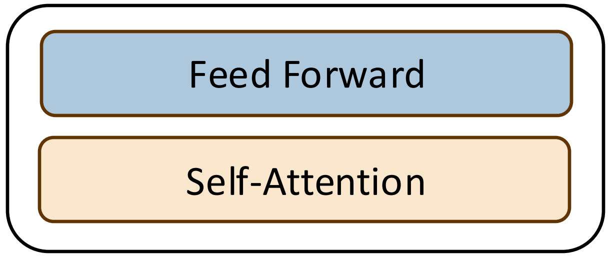
The Transformer: Going beyond RNNs

The release of the Transformer along with the results it achieved on tasks like machine translation led researchers to view it as a superior alternative to RNNs, given its improved handling long-term dependencies compared to RNNs.



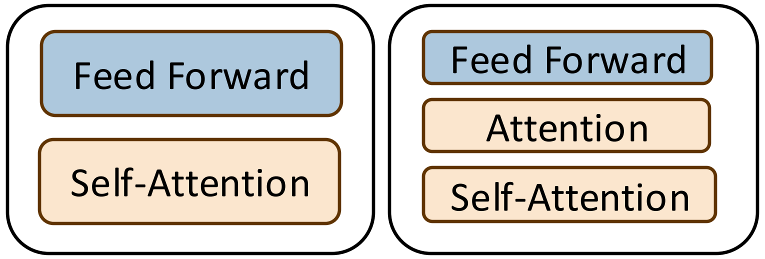
Three Types of Pretraining Ways

Encoders



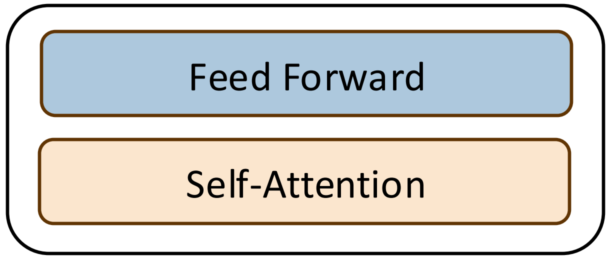
- Bidirectional – capable of looking into the future
- Suitable for downstream task

Encoder-Decoders



- Pros of decoders and encoders?
- Cons of having both during pretraining

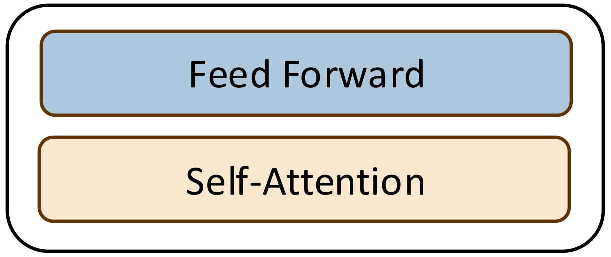
Decoders



- What LMs we have seen so far
- Suitable for generation task
- Not bidirectional

Three Types of Pretraining Ways

Encoders



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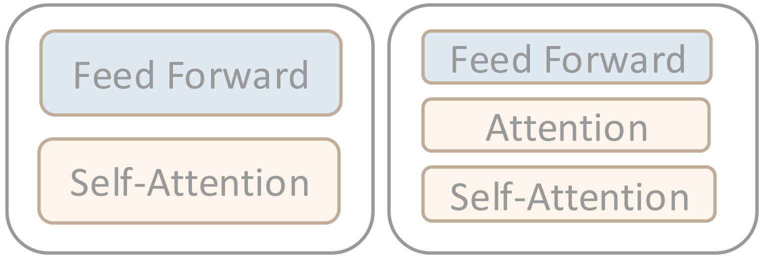

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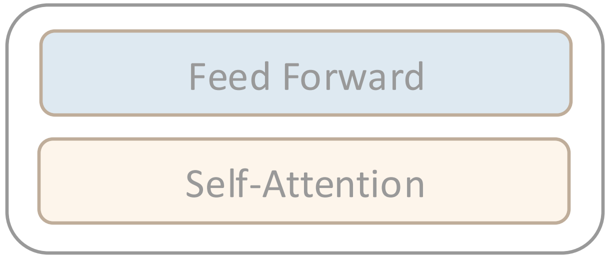
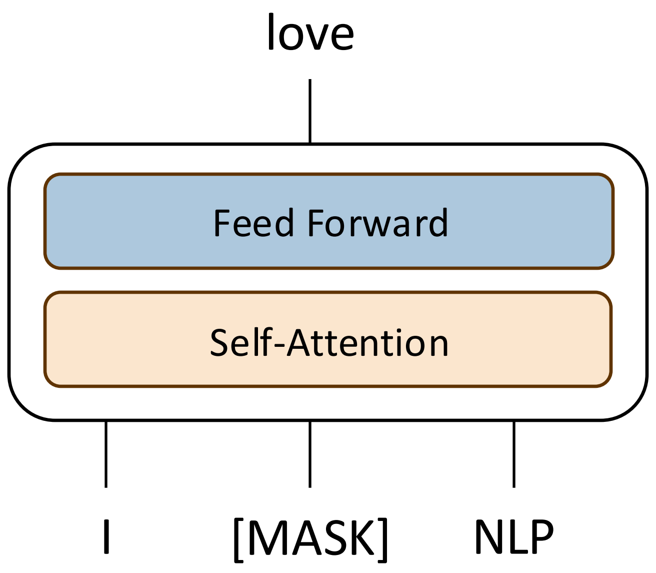


- What LMs we have seen so far
- Suitable for generation task
- Not bidirectional

Pretraining Encoder:

Idea: Encoder works bidirectionally which is more powerful than either a left-to-right model or the shallow concatenation of a left-to-right and a right-to-left model.

- Pretraining task
  - #1 MLM (Masked Language Models):
    - Train the model to reconstruct the sentence by replacing some fraction of words in the input with a special token, [MASK]
    - The model will look at the sentence bidirectionally to try to predict the removed words.
  - #2 NSP (Next Sentence Prediction):
    - In order to train a model that understands sentence relationships, we pre-train for a binarized next sentence prediction task that can be trivially generated from any monolingual corpus



BERT: Bidirectional Encoder Representations from Transformers (Devlin et al., 2018)

Task 1. “Masked Language Models”

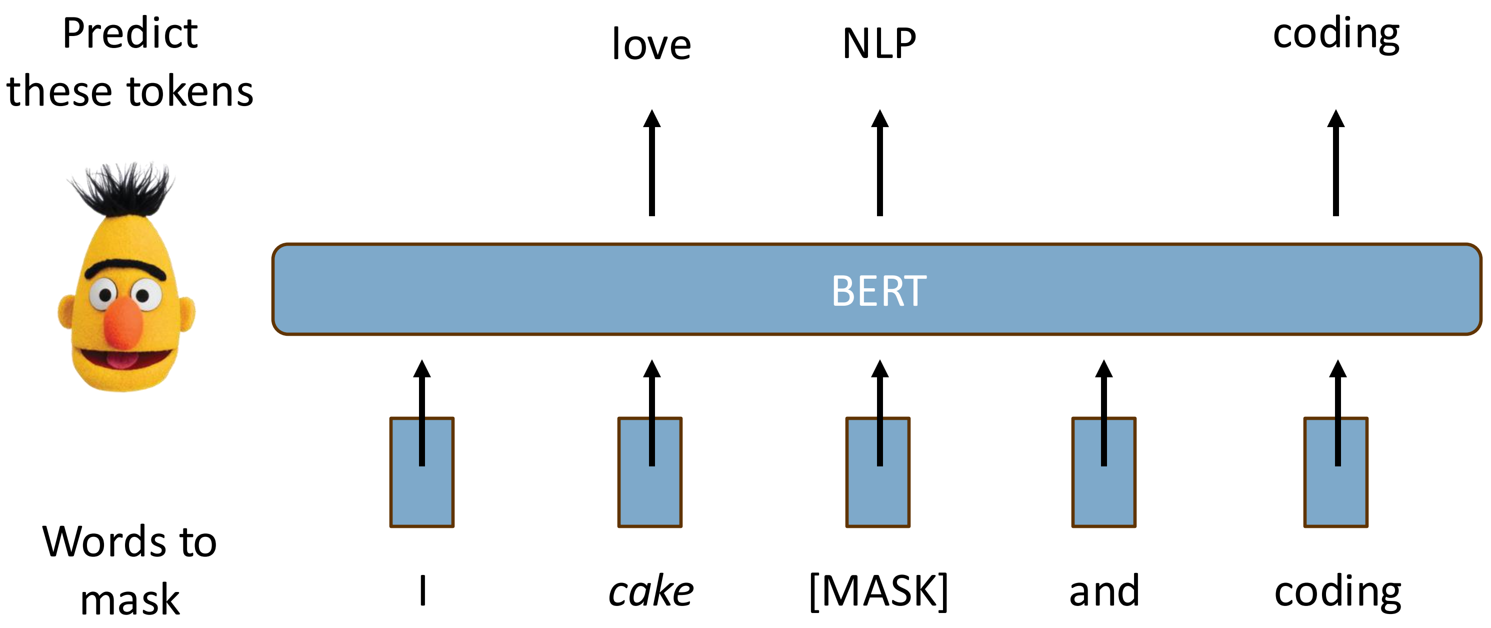
The objective is proposed alongside the weights of a pretrained Transformer, a model they refer to as BERT.

Replace the 15% of the tokens with

1) [MASK] 80% of the time
2) Random 10% of the time
3) Unchanged 10 % of the time

Why?

Prevent the model from becoming complacent and failing to construct robust representations for unmasked words. (No masks are seen at fine-tuning time!)



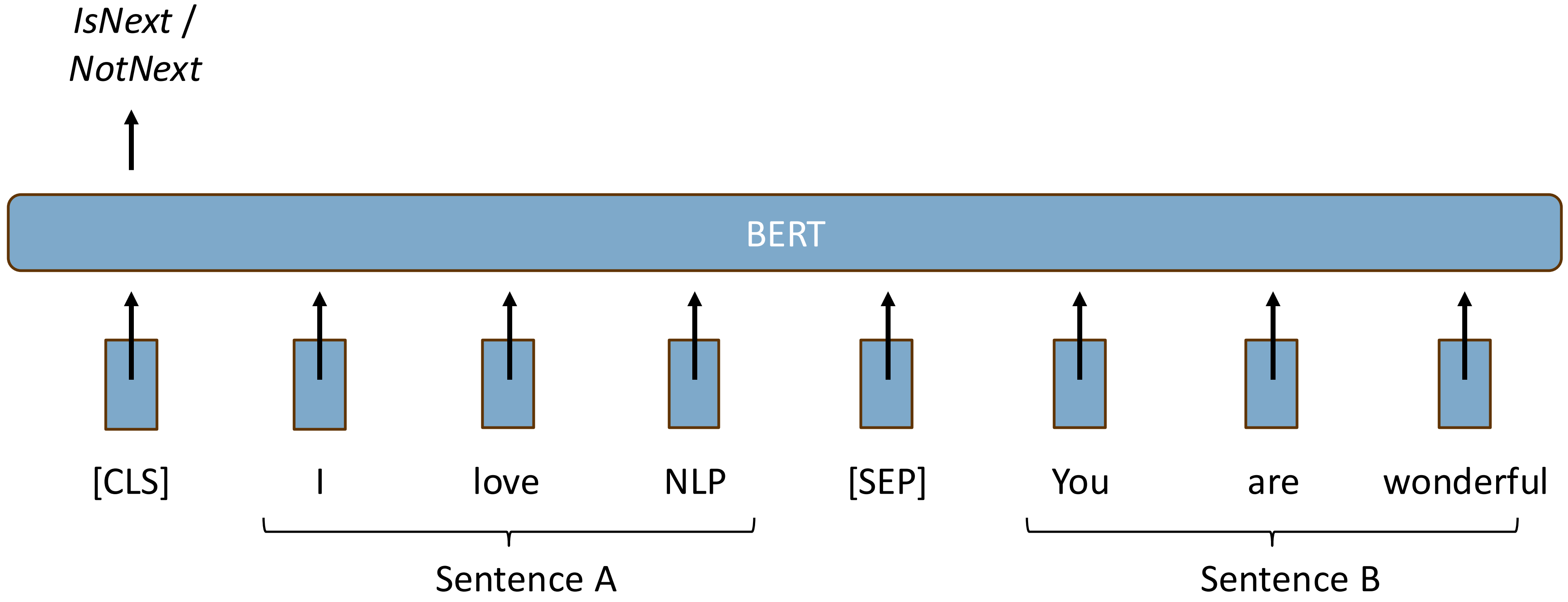
BERT (Devlin et al., 2018)

Task 2. “Next Sentence Prediction”

To develop a model that understands sentence relationships, we pre-train for a binarized next sentence prediction task that can be easily generated from any monolingual corpus.

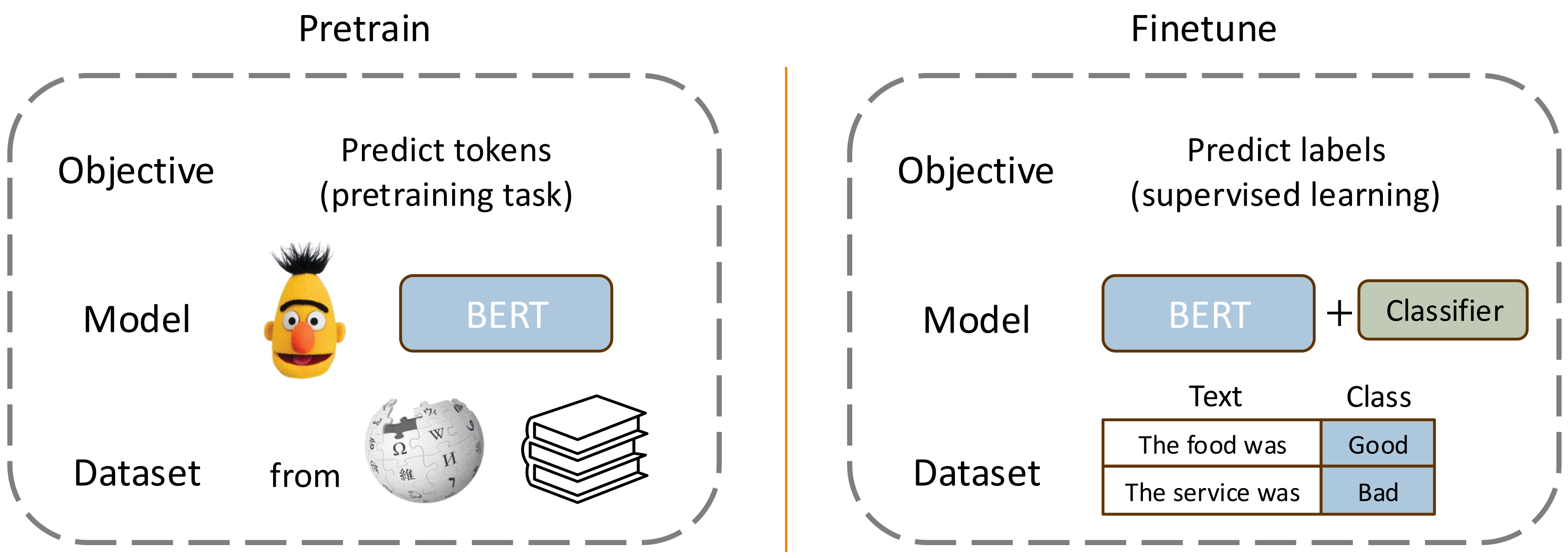
Predict [CLS] label

Sentence B to classify



Transfer Learning: Pretrain and Finetune

Modern-day standard approach is to first pre-train then fine-tune. During pretraining, a large amount of unlabeled text is used to build a general model of language understanding before fine-tuned on various specific NLP tasks



Text	Class
The food was	Good
The service was	Bad

Transfer Learning: Pretrain and Finetune

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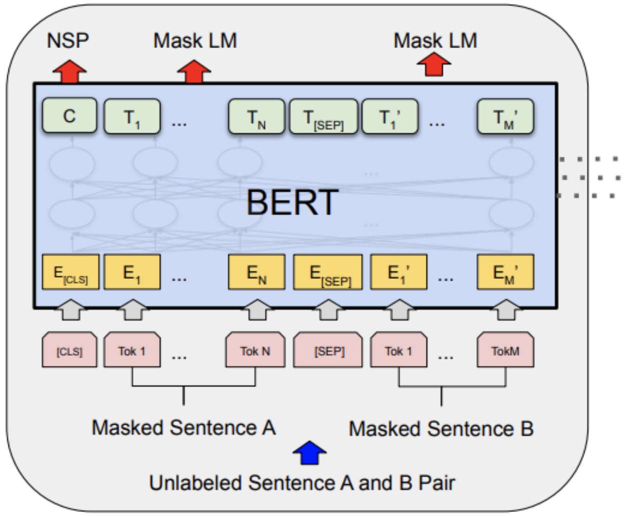
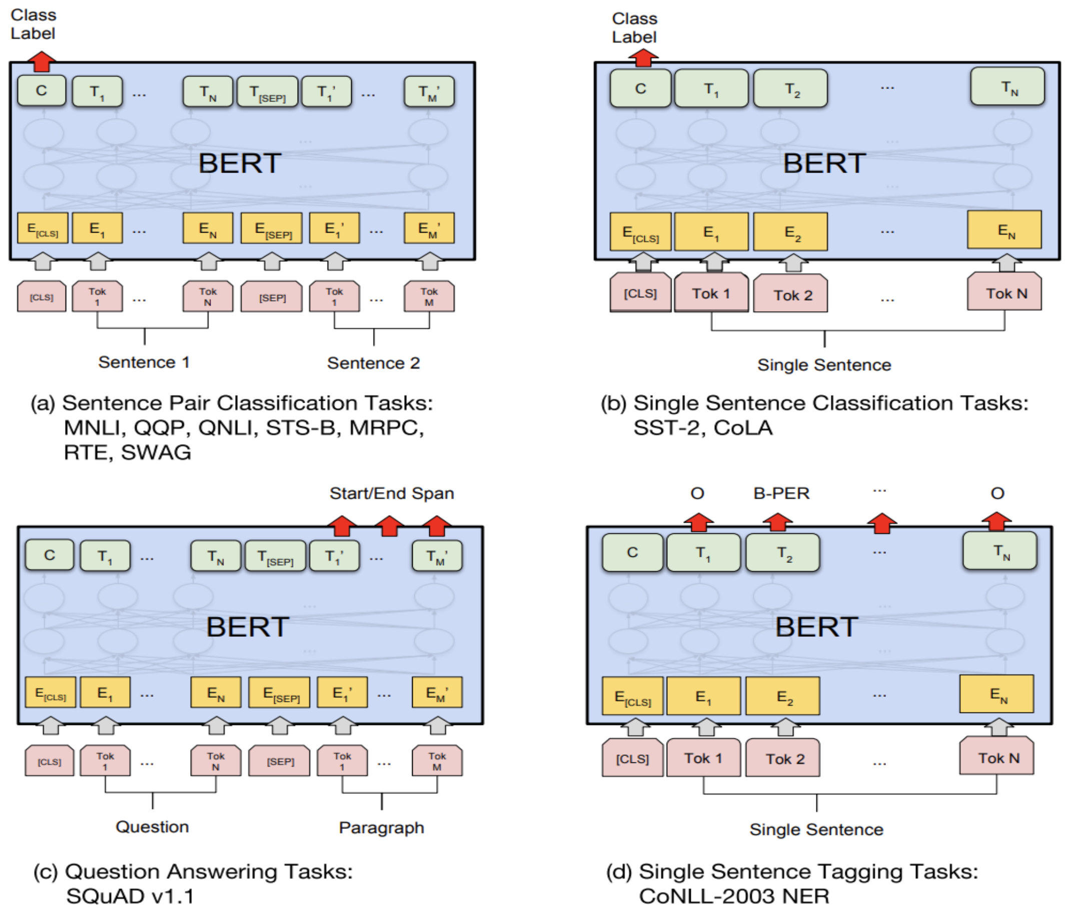


Pre-training



(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

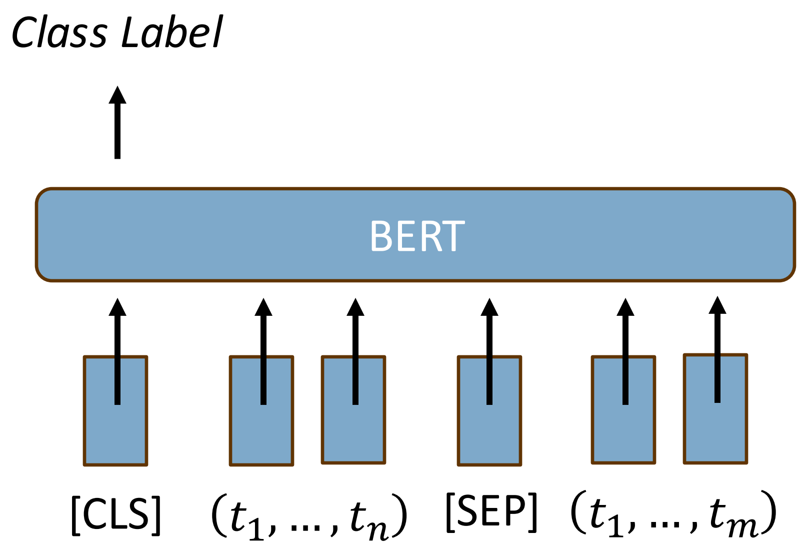
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Fine-tuning

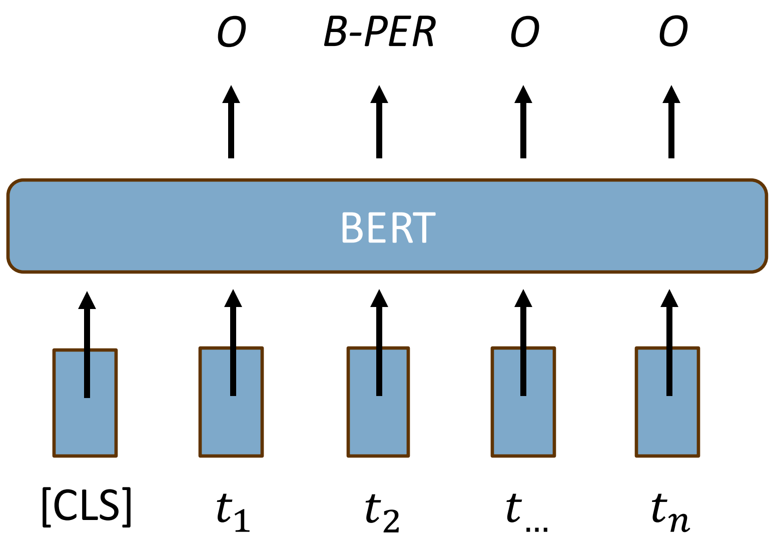
Ref: BERT paper

Finetune BERT

Task-specific models are used to minimize the number of parameters need to be trained from scratch. This is done by integrating BERT with one additional output layer.



(A) Sentence Pair Classification



(B) Single Sentence Tagging Task

Details about BERT

Google release two models at first:

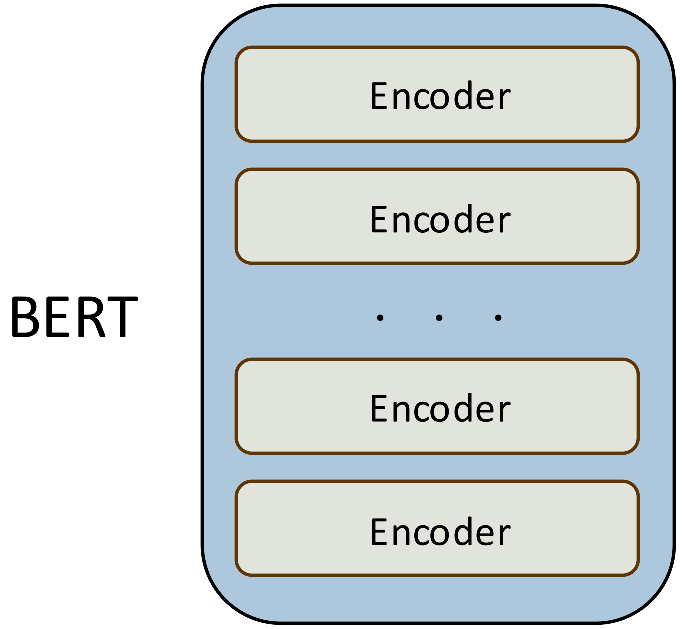
- BERT-base (110M parameters): 12 layers, 768-dim hidden size, 12 attention heads.
- BERT-large (340M parameters): 24 layers, 1024-dim hidden size, 16 attention heads.

Trained on two datasets:

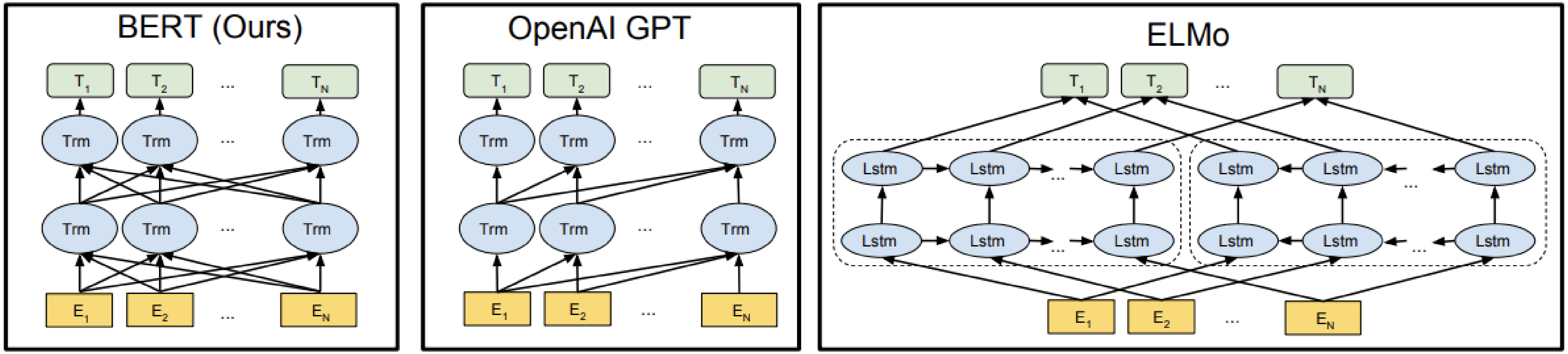
- BooksCorpus (800M words)
- English Wikipedia (2,500M words)

Pretraining is expensive and impractical on a single GPU.

- BERT was pretrained with 64 TPU chips for a total of 4 days.
- (TPUs are special tensor operation acceleration hardware)
- Finetuning is practical and common on a single GPU



Why bidirectional?



Ref: BERT paper

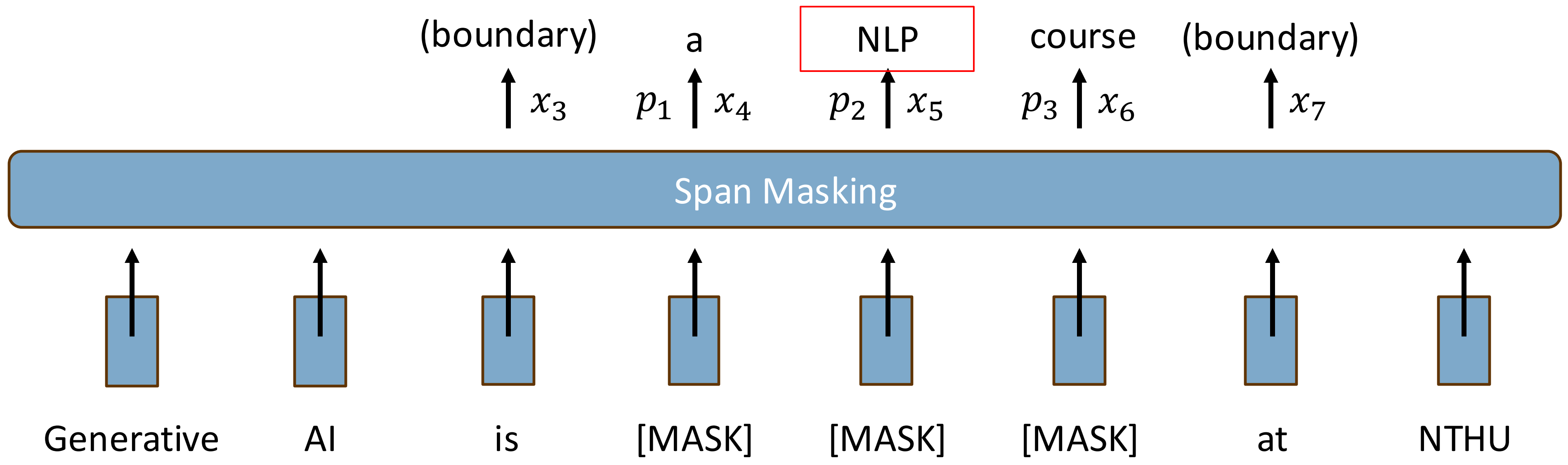
Extensions of BERT

Model	MLM task	NSP task	Release
BERT	Static masking	Sentence relationship	2018/10
RoBERTa	Dynamic masking	Remove NSP task	2019/07
SpanBERT https://arxiv.org/pdf/1907.11692.pdf	Span masking	Remove NSP task	2019/07
Albert	N-gram masking	Sentence order	2019/09
DistilBERT	Compression by knowledge distillation		2019/10
DeBERTa	Decoding-enhanced BERT with Disentangled Attention		2020/06
TinyBERT	TinyBERT: Distilling BERT for Natural Language Understanding		2019/09

Extensions of BERT

Span Masking: Span Boundary Objective (SBO)

$$\mathcal{L}(NLP) = \mathcal{L}_{MLM}(NLP) + \mathcal{L}_{SBO}(NLP) = -logP(NLP \mid x_5) - logP(NLP \mid \boldsymbol{x_3}, \boldsymbol{x_7}, p_2)$$



https://arxiv.org/pdf/1907.11692.pdf

RoBERTa: A Robustly Optimized BERT Pretraining Approach

Key Improvements:

1. **Longer Training Duration**: RoBERTa increases the training time and batch size, utilizing a larger training dataset.
2. **Removing "Next Sentence Prediction" (NSP) Objective**: Unlike BERT, RoBERTa omits the NSP task, simplifying training.
3. **Training on Longer Sequences**: Training uses longer text sequences, improving the model's ability to capture context.
4. **Dynamic Masking**: Uses a dynamic masking strategy, where masking patterns in the training data change every iteration to avoid data overfitting.

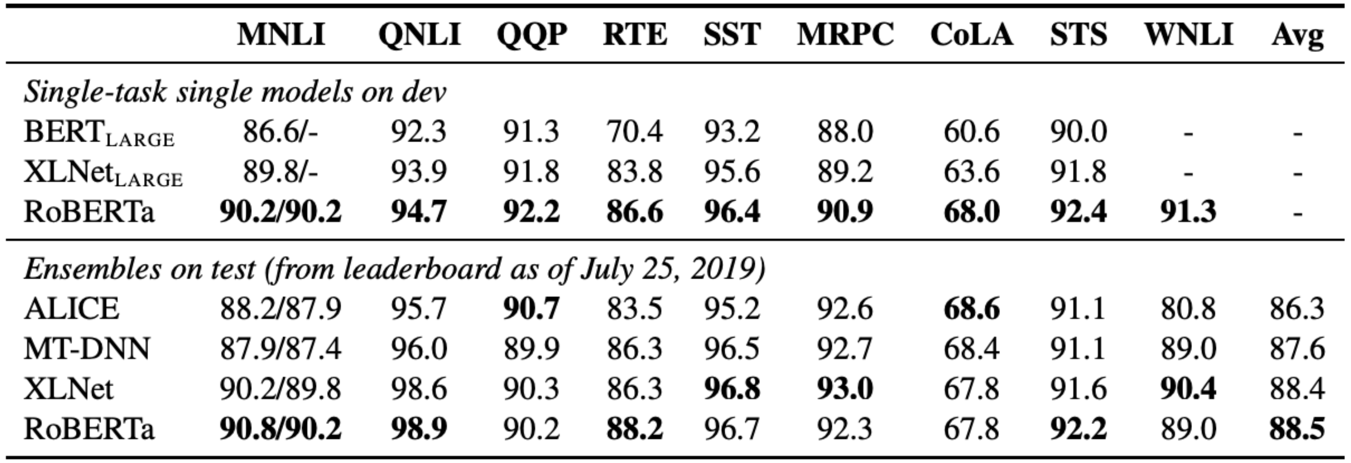
RoBERTa Training Approach and Performance

Training Process:

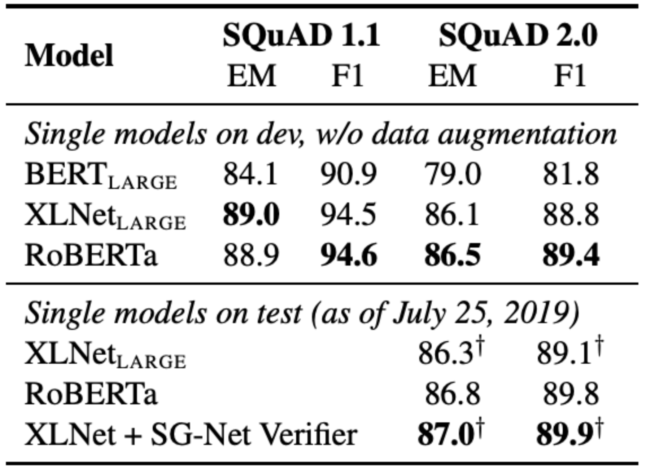
- **Data**: RoBERTa uses a larger dataset of over **160GB** of text, including CC-NEWS, OpenWebText, and other public text sources.
- **Architecture**: Similar to BERT, based on the Transformer architecture with 24 layers, 1024 hidden units, and 16 self-attention heads (for the large model configuration).
- **Optimization**: Improved learning rate and batch size adjustments. Dynamic masking is applied to vary the tokens masked during training, increasing data diversity.

Experimental Results:

- On the GLUE benchmark, RoBERTa achieves state-of-the-art performance on 4 out of 9 tasks.
- In SQuAD (question-answering) and RACE (reading comprehension) datasets, RoBERTa's performance matches or surpasses the best models.
- Demonstrates that BERT's Masked Language Model (MLM) objective is highly competitive when trained with the right strategies.



	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	WNLI	Avg
Single-task single models on dev										
$\text{BERT}_{\text{LARGE}}$	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-	-
$\text{XLNet}_{\text{LARGE}}$	89.8/-	93.9	91.8	83.8	95.6	89.2	63.6	91.8	-	-
RoBERTa	**90.2/90.2**	**94.7**	**92.2**	**86.6**	**96.4**	**90.9**	**68.0**	**92.4**	**91.3**	-
Ensembles on test (from leaderboard as of July 25, 2019)										
ALICE	88.2/87.9	95.7	**90.7**	83.5	95.2	92.6	**68.6**	91.1	80.8	86.3
MT-DNN	87.9/87.4	96.0	89.9	86.3	96.5	92.7	68.4	91.1	89.0	87.6
XLNet	90.2/89.8	98.6	90.3	86.3	**96.8**	**93.0**	67.8	91.6	**90.4**	88.4
RoBERTa	**90.8/90.2**	**98.9**	90.2	**88.2**	96.7	92.3	67.8	**92.2**	89.0	**88.5**



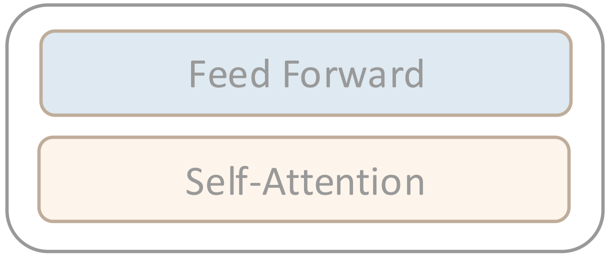
Model	SQuAD 1.1		SQuAD 2.0	
	EM	F1	EM	F1
Single models on dev, w/o data augmentation				
$\text{BERT}_{\text{LARGE}}$	84.1	90.9	79.0	81.8
$\text{XLNet}_{\text{LARGE}}$	**89.0**	94.5	86.1	88.8
RoBERTa	88.9	**94.6**	**86.5**	**89.4**
Single models on test (as of July 25, 2019)				
$\text{XLNet}_{\text{LARGE}}$			$86.3^{\dagger}$	$89.1^{\dagger}$
RoBERTa			86.8	89.8
XLNet + SG-Net Verifier			$\mathbf{87.0}^{\dagger}$	$\mathbf{89.9}^{\dagger}$

Specific BERTs (2019)

Model	Paper	Link
SciBERT	SciBERT: A Pretrained Language Model for Scientific Text (EMNLP 2019)	https://aclanthology.org/D19-1371.pdf
FinBERT	FinBERT: Financial Sentiment Analysis with Pre-trained Language Models	https://arxiv.org/abs/1908.10063
BioBERT	BioBERT: a pre-trained biomedical language representation model for biomedical text mining	https://arxiv.org/abs/1901.08746
PubmedBERT	Domain-Specific Language Model Pretraining for Biomedical Natural Language Processing	https://arxiv.org/pdf/2007.15779
BlueBERT	Transfer Learning in Biomedical Natural Language Processing: An Evaluation of BERT and ELMo on Ten Benchmarking Datasets	https://arxiv.org/abs/1906.05474
ClinicalBERT	ClinicalBERT: Modeling Clinical Notes and Predicting Hospital Readmission	https://arxiv.org/abs/1904.05342
LegalBERT	LEGAL-BERT: The Muppets straight out of Law School	https://arxiv.org/abs/2010.02559

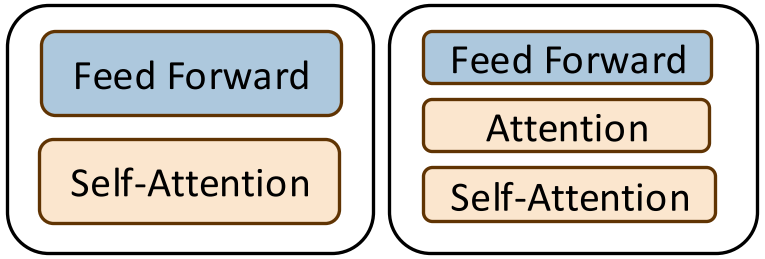
Three Types of Pretraining Ways

Encoders



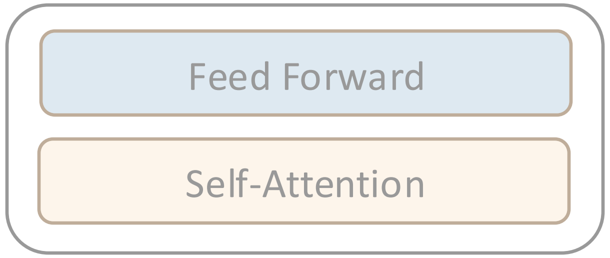
- Bidirectional – capable of looking into the future
- Suitable for downstream task

Encoder-Decoders



- Pros of decoders and encoders?
- Cons of having both during pretraining

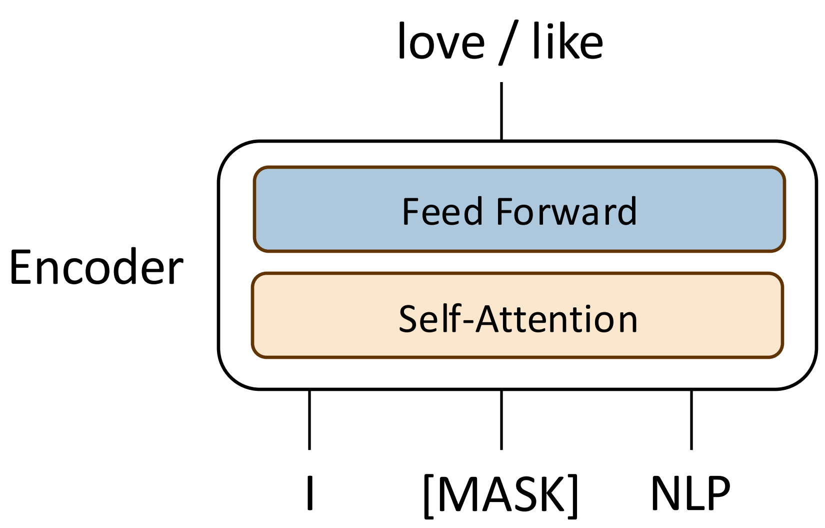
Decoders

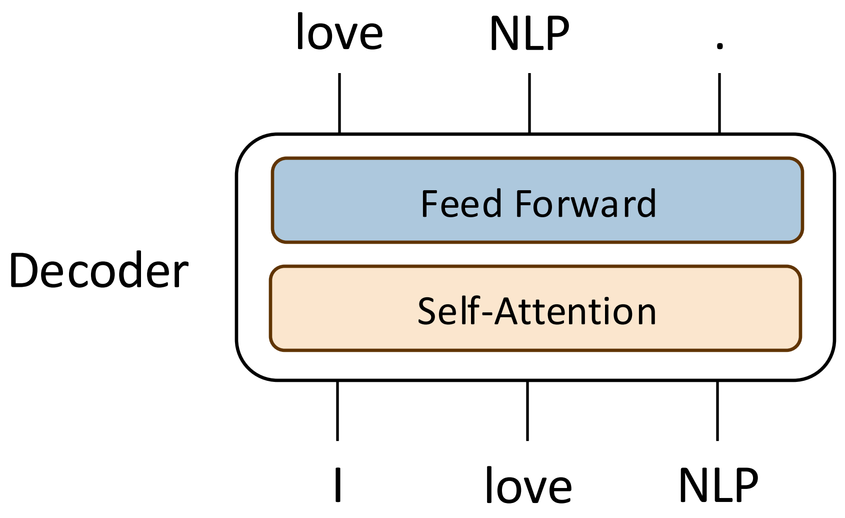


- What LMs we have seen so far
- Suitable for generation task
- Not bidirectional

Limitation of Encoders

Despite its strong performance on various tasks, it struggles to perform well on **generative tasks** due to the lack of bidirectional context, therefore, when your task involves autoregressive (1-word-at-a-time), consider using a pretrained decoder.

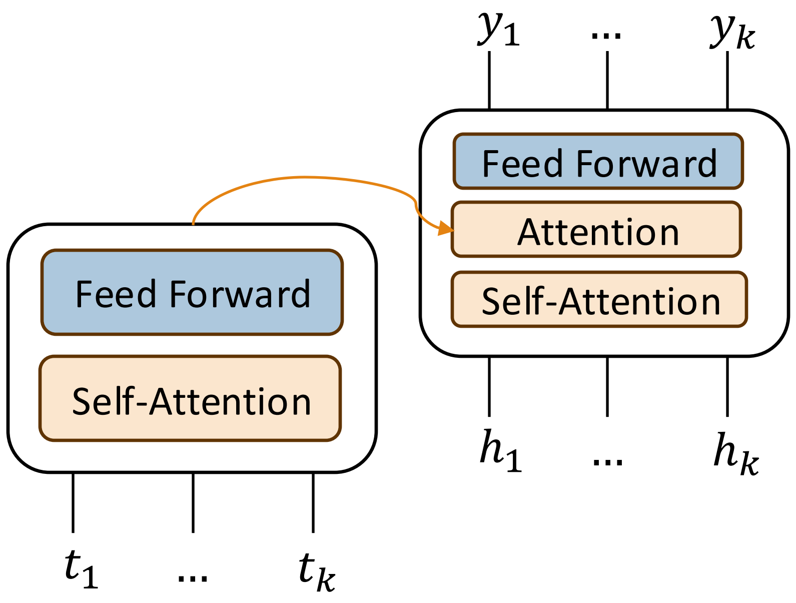


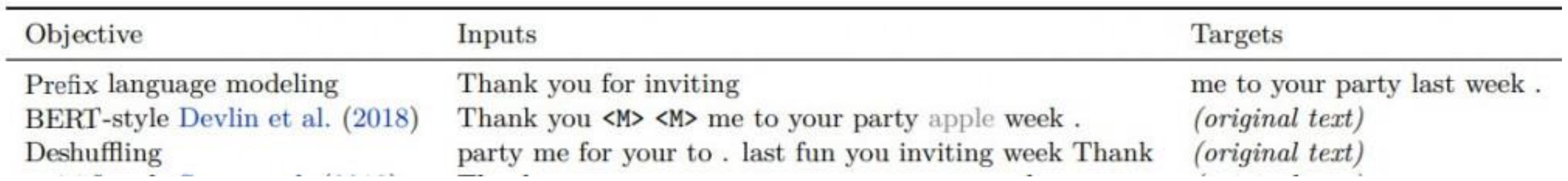


Pretraining Encoder-Decoder

Idea: Capture the context bidirectionally with encoder then use decoder to train the whole model through language modeling.

- Pretraining task
  - **High-level approaches**
    - Language modeling
    - BERT-style
    - Deshuffling
  - **Corruption Strategy**
    - Replace by mask
    - Replace by spans
    - Drop the token





Objective	Inputs	Targets
Prefix language modeling	Thank you for inviting	me to your party last week .
BERT-style Devlin et al. (2018)	Thank you <M> <M> me to your party apple week .	*(original text)*
Deshuffling	party me for your to . last fun you inviting week Thank	*(original text)*

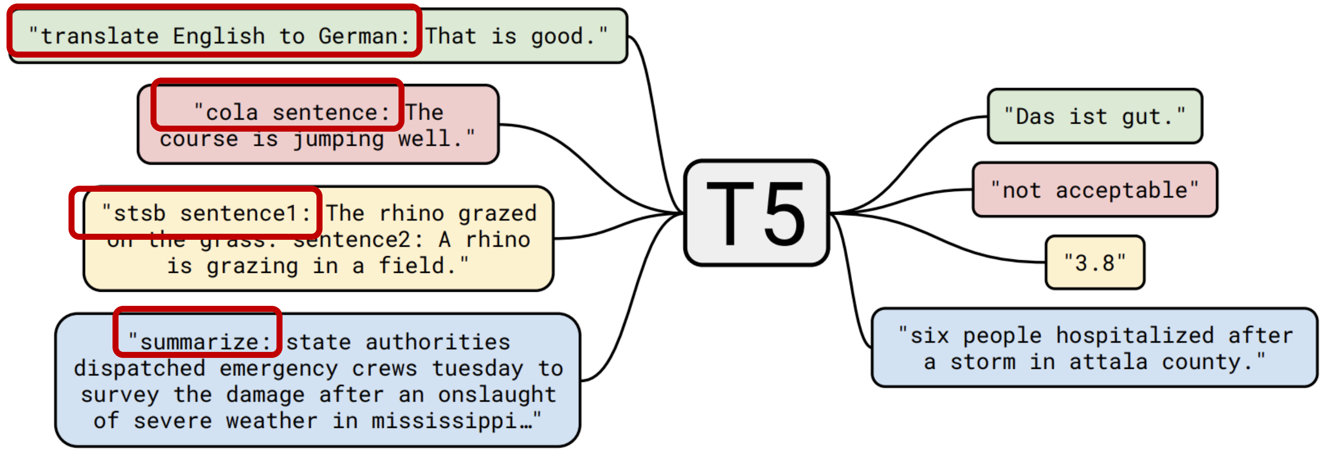
https://arxiv.org/pdf/1910.10683.pdf
https://github.com/google-research/text-to-text-transfer-transformer

T5 (Text-to-Text Transfer Transformer)
(Raffel et al., Google, 2019)

4 NLP Main Tasks

- Classification
- Content Similarity Measurement
- Sequence Tagging
- Natural Language Generation

Universal task



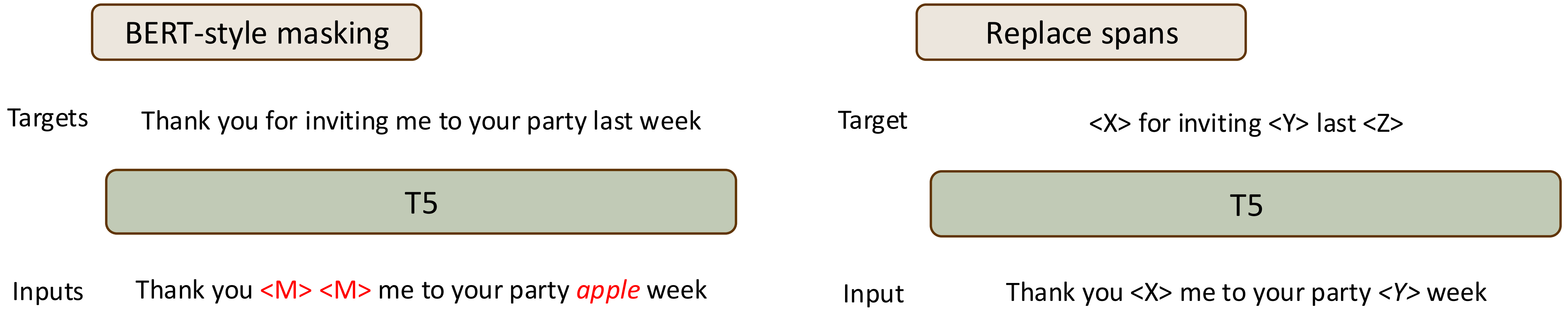
"translate English to German: That is good."
"cola sentence: The course is jumping well."
"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"Das ist gut."
"not acceptable"
"3.8"
"six people hospitalized after a storm in attala county."

https://arxiv.org/pdf/1910.10683.pdf
https://github.com/google-research/text-to-text-transfer-transformer

T5 (Text-to-Text Transfer Transformer)
(Raffel et al., Google, 2019)

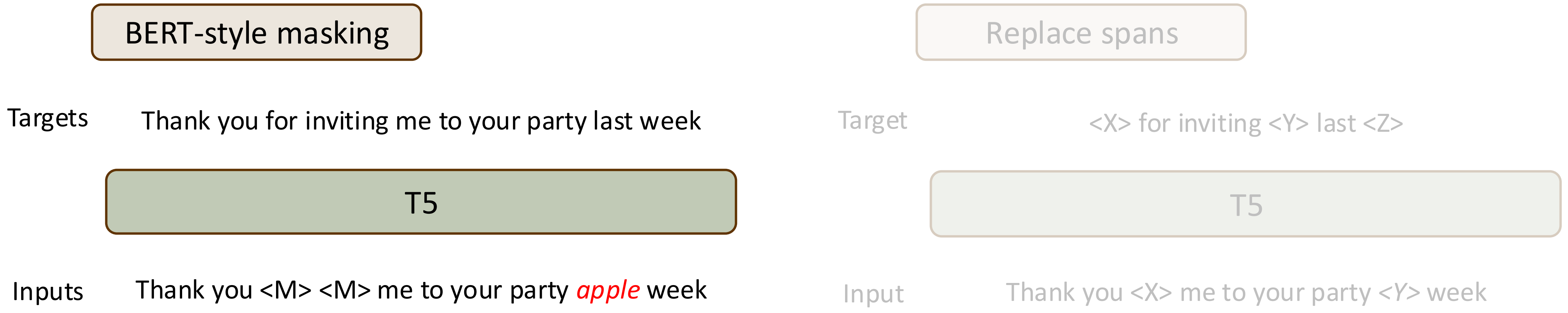
Idea: Replace various spans with different length from the input with unique placeholders; then, reconstruct the removed spans during decoding.

Original text: "*Thank you for inviting me to your party last week.*"


BERT-style masking
Targets
Thank you for inviting me to your party last week
T5
Inputs
Thank you <M> <M> me to your party *apple* week
Replace spans
Target
<X> for inviting <Y> last <Z>
T5
Input
Thank you <X> me to your party <Y> week

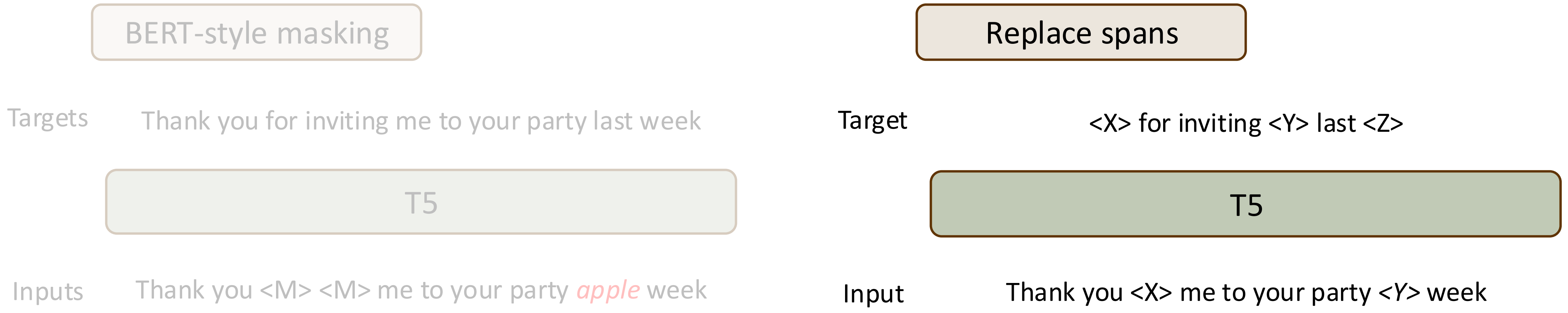
T5

Later, BERT-style objective, a method originally proposed as a pre-training technique for an encoder-only model trained for classification and span prediction was found to have better performance over the alternative approach.


BERT-style masking
Targets
Thank you for inviting me to your party last week
T5
Inputs
Thank you <M> <M> me to your party *apple* week
Replace spans
Target
<X> for inviting <Y> last <Z>
T5
Input
Thank you <X> me to your party <Y> week

T5

"Span" refers to multiple consecutive tokens that have been corrupted. A single unique mask token is then used to replace the entire span, resulting in unlabeled text data being processed into shorter sequences.



BERT-style masking
Targets
Thank you for inviting me to your party last week
T5
Inputs
Thank you <M> <M> me to your party apple week
Replace spans
Target
<X> for inviting <Y> last <Z>
T5
Input
Thank you <X> me to your party <Y> week

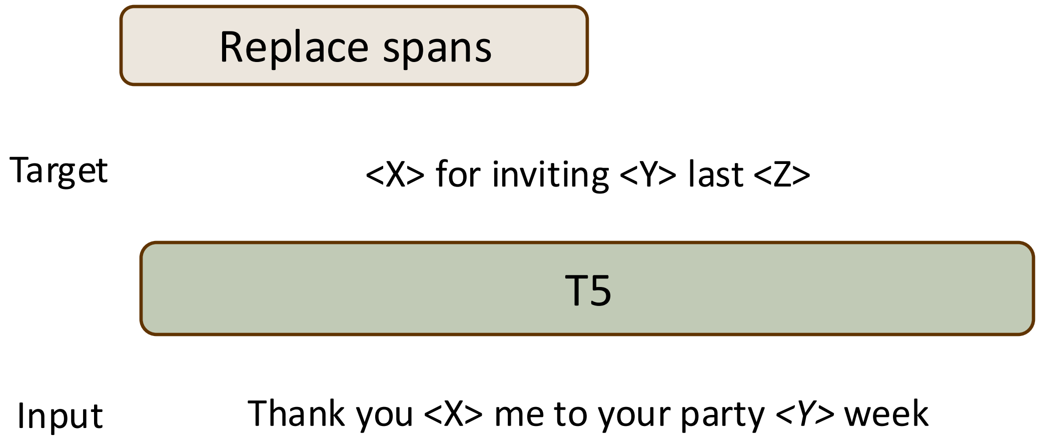
Details about Replace Spans

Our objective of replacing spans can be parameterized by the proportion of tokens to be corrupted and the total number of corrupted. It is also shown that this setting is not sensitive to performance due to slight difference in performance with low corruption rate (below 50%).

- Corruption objective
  - Corruption rate : 15%
  - Corrupted average span length: 3

  Both parameters can be used to specified total number of span by using this simple calculation.

$$avg\_span\_length = \frac{T_{token} \times rate_{corrupt}}{\#_{span}}$$


Replace spans
Target
<X> for inviting <Y> last <Z>
T5
Input
Thank you <X> me to your party <Y> week

Details about T5

There are five variants for T5 models:

- T5-small (60M parameters): 6 layers, 512-dim hidden size, 8 attention heads.
- T5-base (220M parameters): 12 layers, 768-dim hidden size, 12 attention heads.
- T5-large (770M parameters): 24 layers, 1024-dim hidden size, 16 attention heads.
- T5-3B: 24 layers, 1024-dim hidden size, 32 attention heads.
- T5-11B: 24 layers, 1024-dim hidden size, 128 attention heads.

Trained on:

- C4 (Colossal Clean Crawled Corpus, extracted from Common Crawl, 34B words)

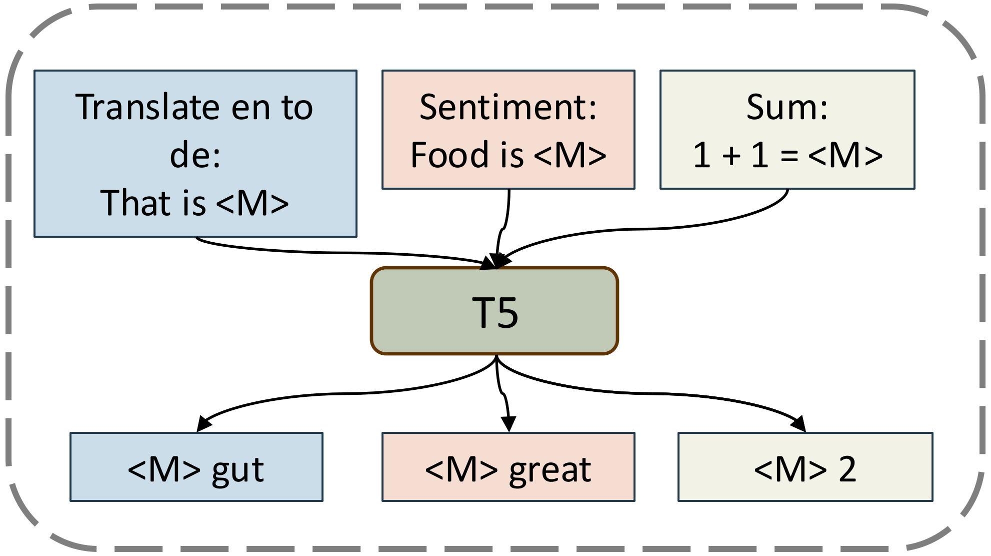
Scaling can make a significant boost in performance.

Converts all text-based language problems into a text-to-text format.

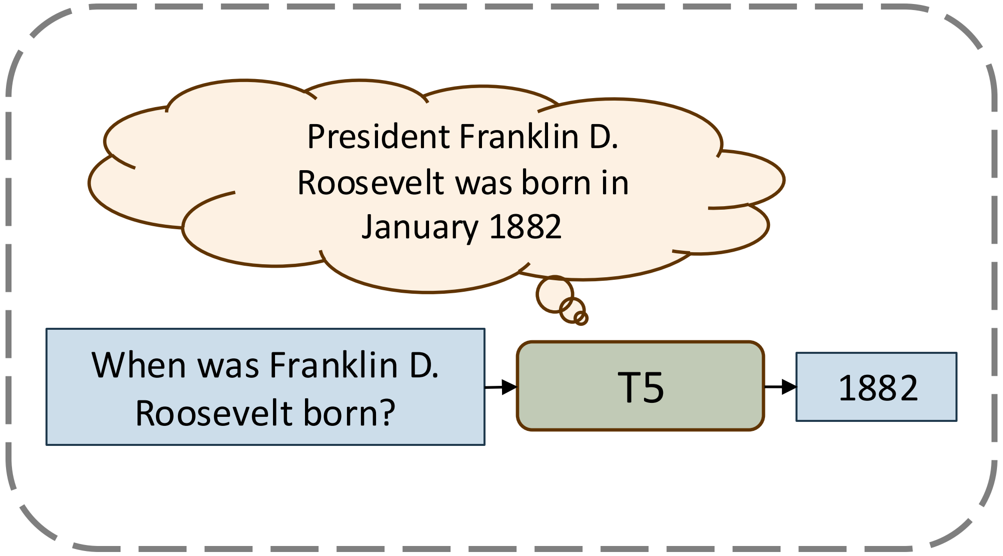
Training Strategy and Finetune T5

We pre-train T5 by having it learned to fill in dropped-out spans of text (denoted by <M>). To apply T5 to closed-book question answer, we fine-tuned it to answer questions without giving any additional input information or context. This forces T5 to answer questions based on "knowledge" that it learnt during pre-training.

Pretrain



Finetune


President Franklin D. Roosevelt was born in January 1882
When was Franklin D. Roosevelt born?
T5
1882

https://arxiv.org/abs/1910.13461

Extensions of T5

BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension (Meta, 2019)

BART (**B**idirectional and **A**uto-**R**egressive **T**ransformers) serves as a denoising autoencoder designed to pretrain sequence-to-sequence models. BART undergoes two training processes. First, corrupting text using arbitrary noising function. Second, learning a model to reconstruct the original text.

Original Input

A B C ? D E !

A [MASK] C ? D E [MASK]

Token Masking

A C ? D E !

Token Deletion

A [MASK] ? D [MASK] E !

Text Infilling

D E ! A B C ?

Sentence Permutation

C A B ? D E !

Document Rotation

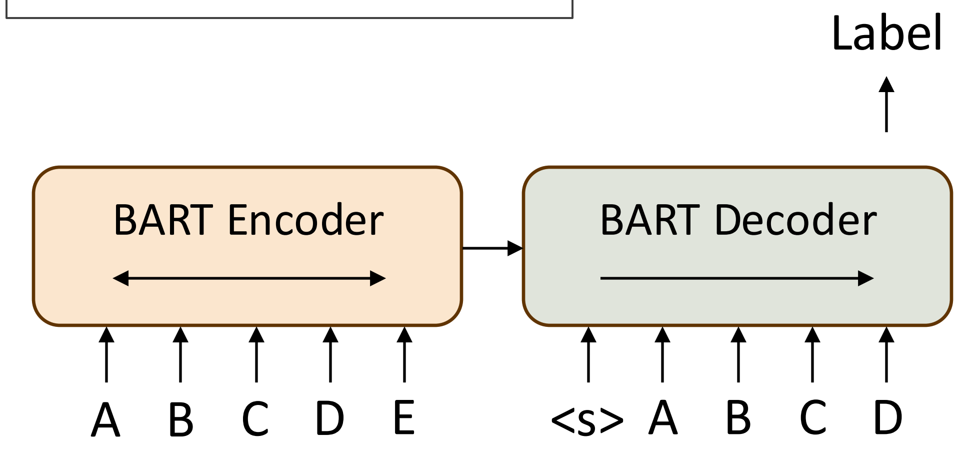
Pretraining tasks of BART

Noise	Method	Goal
Token Masking	Random tokens are sampled and replaced with [MASK] elements.	Teach the model to predict masked token.
Token Deletion	Random tokens are deleted from the input.	Teach the model to predict masked token and its position.
Text Infilling	Like SpanBERT, but 0-length spans correspond to the insertion of [MASK] tokens.	Teach the model to predict how many tokens are missing from a span.
Sentence Permutation	A document is divided into sentences based on full stops, and these sentences are shuffled in a random order.	Teach the model to clarify the relationship between two sentences.
Document Rotation	A token is chosen uniformly at random, and the document is rotated so that it begins with that token.	Teach the model to identify the start of the document.

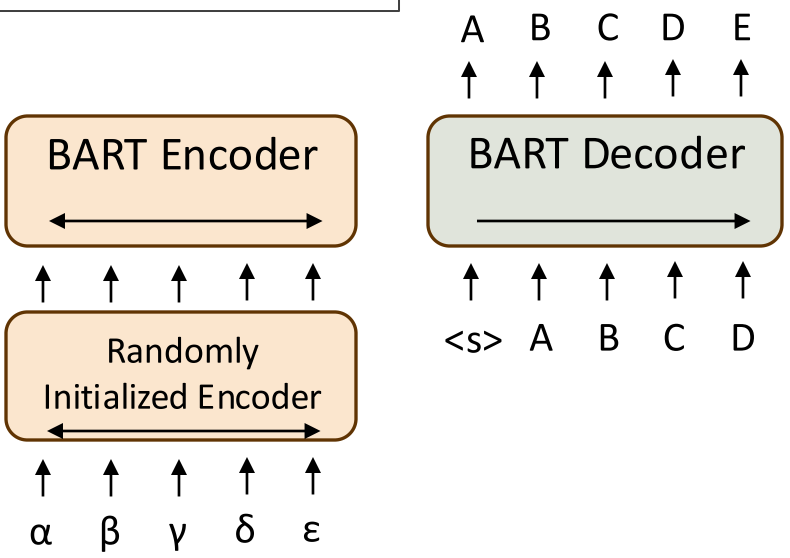
Finetuning BART

For classification problems, both the encoder and decoder receive the same input, and the representation from the final output is utilized; For generation, BART's encoder is replaced with newly trained encoder the word embeddings in BART. The new encoder can use a separate vocabulary from original BART model.

Classification Problems

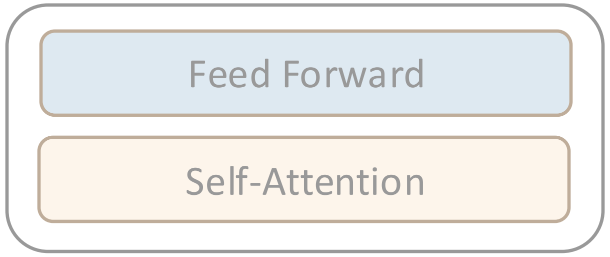


Generation Problems



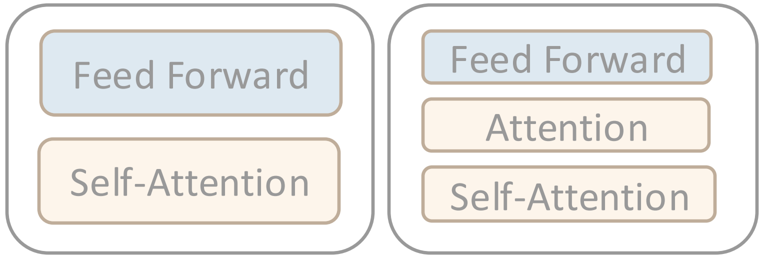
Three Types of Pretraining Ways

Encoders



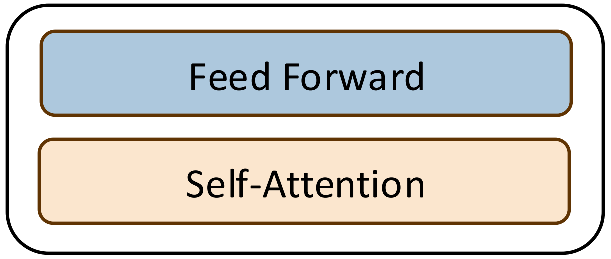
- Bidirectional – capable of looking into the future
- Suitable for downstream task

Encoder-Decoders



- Pros of decoders and encoders?
- Cons of having both during pretraining

Decoders



- What LMs we have seen so far
- Suitable for generation task
- Not bidirectional

https://cdn.openai.com/research-covers/language-unsupervised/language_understanding_paper.pdf

GPT (Radford et al., 2018)
Improving Language Understanding by Generative Pre-Training

Details

- Transformer decoder with 12 layers, 117M parameters
- 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers
- Byte-pair encoding with 40,000 merges

Dataset

- Trained on BooksCorpus: over 7000 unique books
  - Contains long spans of contiguous text, for learning long-distance dependencies

Additional Insights

- The acronym "GPT" never showed up in the original paper
  - Could stand for "Generative PreTraining" or "Generative Pretrained Transformer"

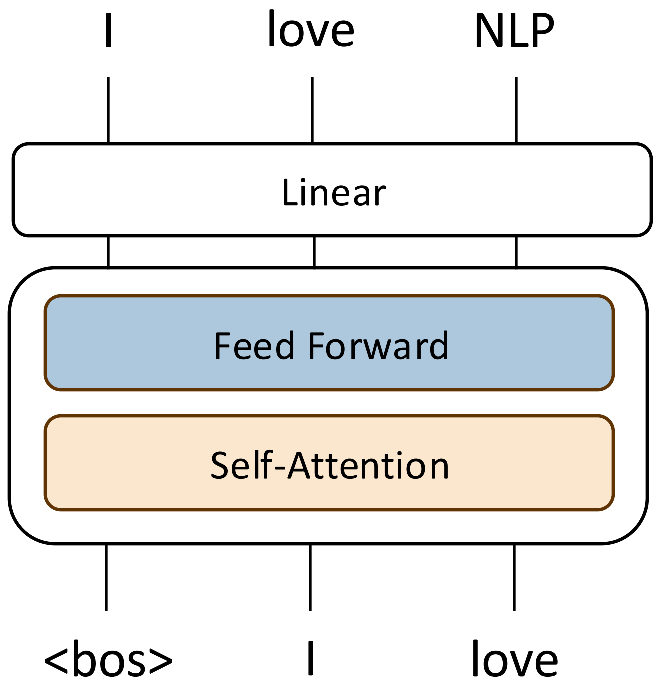
Pretraining Decoder

Idea: Pretrain decoders on language modeling, then use them as generators. This is helpful in tasks where the output is a sequence with a vocabulary like that at pretraining time.

- Pretraining task
  - Next Token Prediction

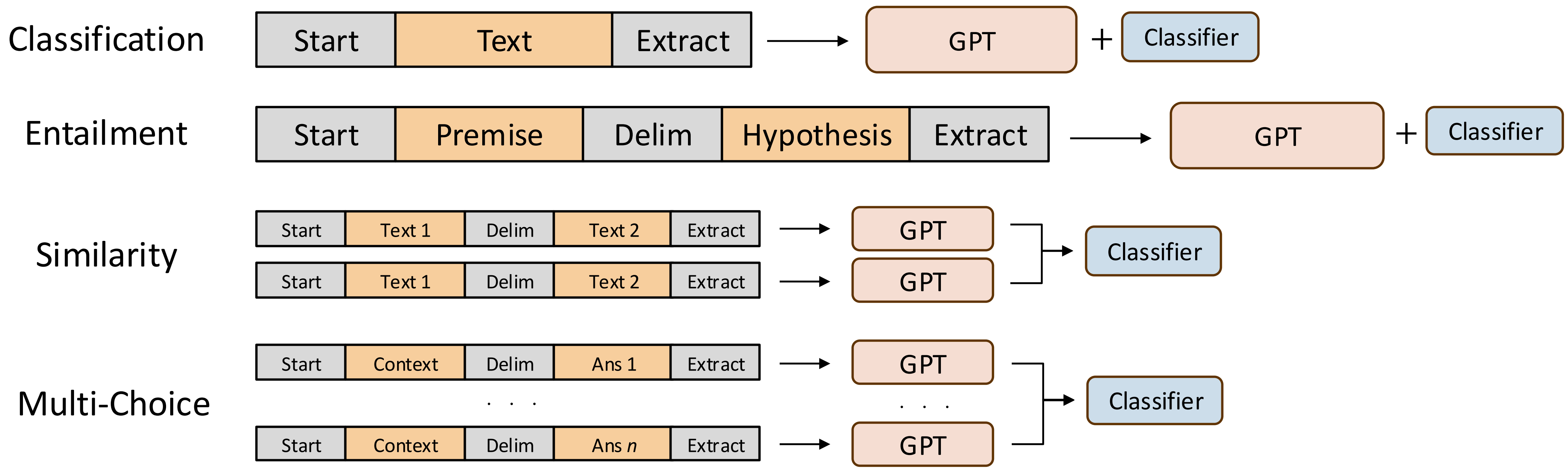
$$p(x) = \prod_{i=1}^{n} p(s_n | s_1, \dots, s_{n-1})$$

Since language follows a specific rule and order, therefore, we leverage conditional probabilities to help us determine the most probable next word based on the preceding sequence of texts.



Finetune GPT

Idea: Convert all structured inputs into sequence of tokens to be processed by our pre-trained model, followed by a linear classifier



GPT Family

Model	Pretraining method	Parameters	Dataset	Release
GPT-1	Transformer decoder followed by linear-softmax	117 M	BooksCorpus 4.5 GB	2018.06.11
GPT-2	Same as GPT-1 but different normalized layer	1.5 B	WebText 40 GB	2019.02.14
GPT-3	Larger version of GPT-2	175 B	CommonCrawl 45 TB	2020.05.15
GPT-4	Trained with RLHF	> 1.5 T	Undisclosed	2023.03.14

Text generation era starts!

https://arxiv.org/pdf/2005.14165

GPT-3, In-Context learning, and LLMs
Language Models are Few-Shot Learners

GPT-3 (Brown et al., 2020) (75 pages)

So far, there are two ways we interact with pre - trained models

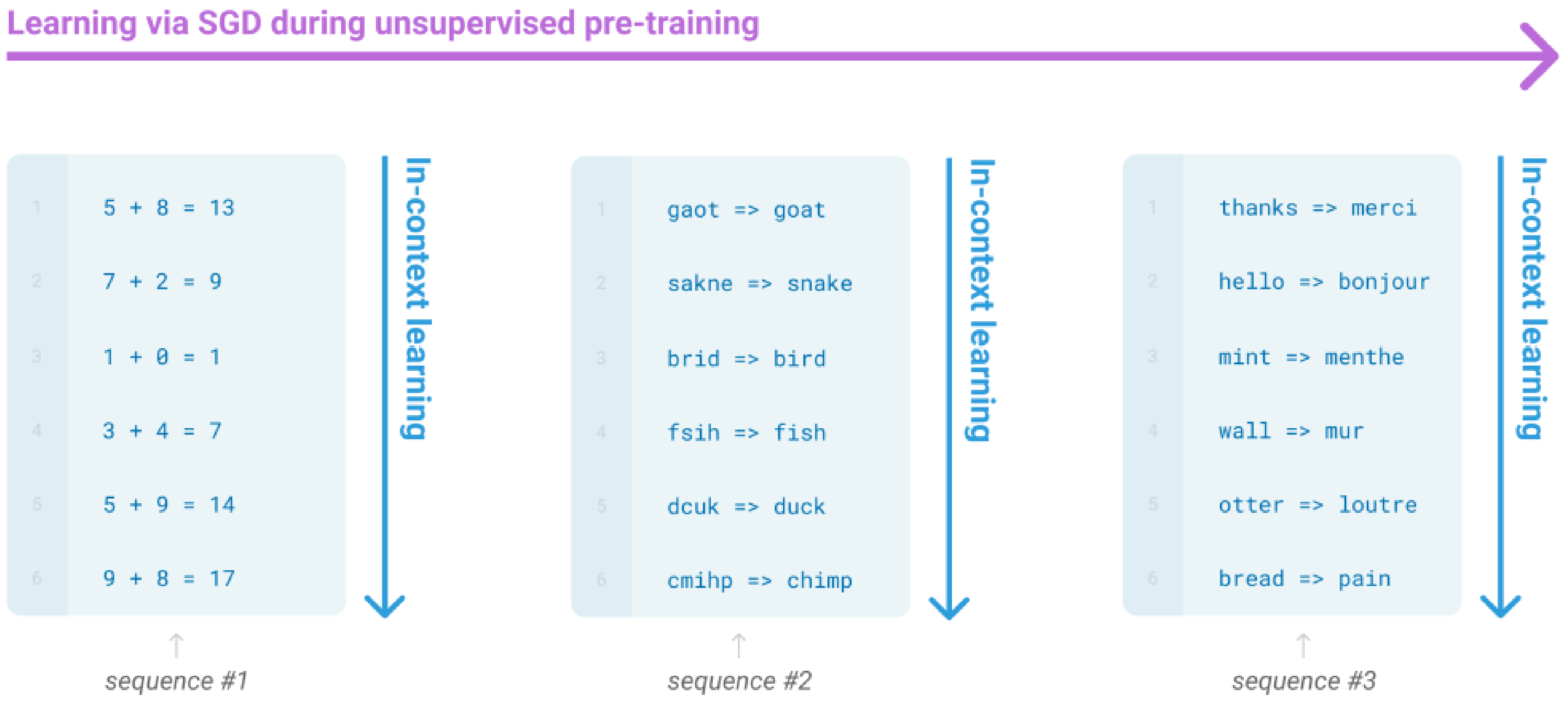
1. Sample from the distributions they define
2. Fine-tune them on a task we care about

However, large models are shown to have this **emergence ability** which allows them to perform some kind of learning without gradient steps.

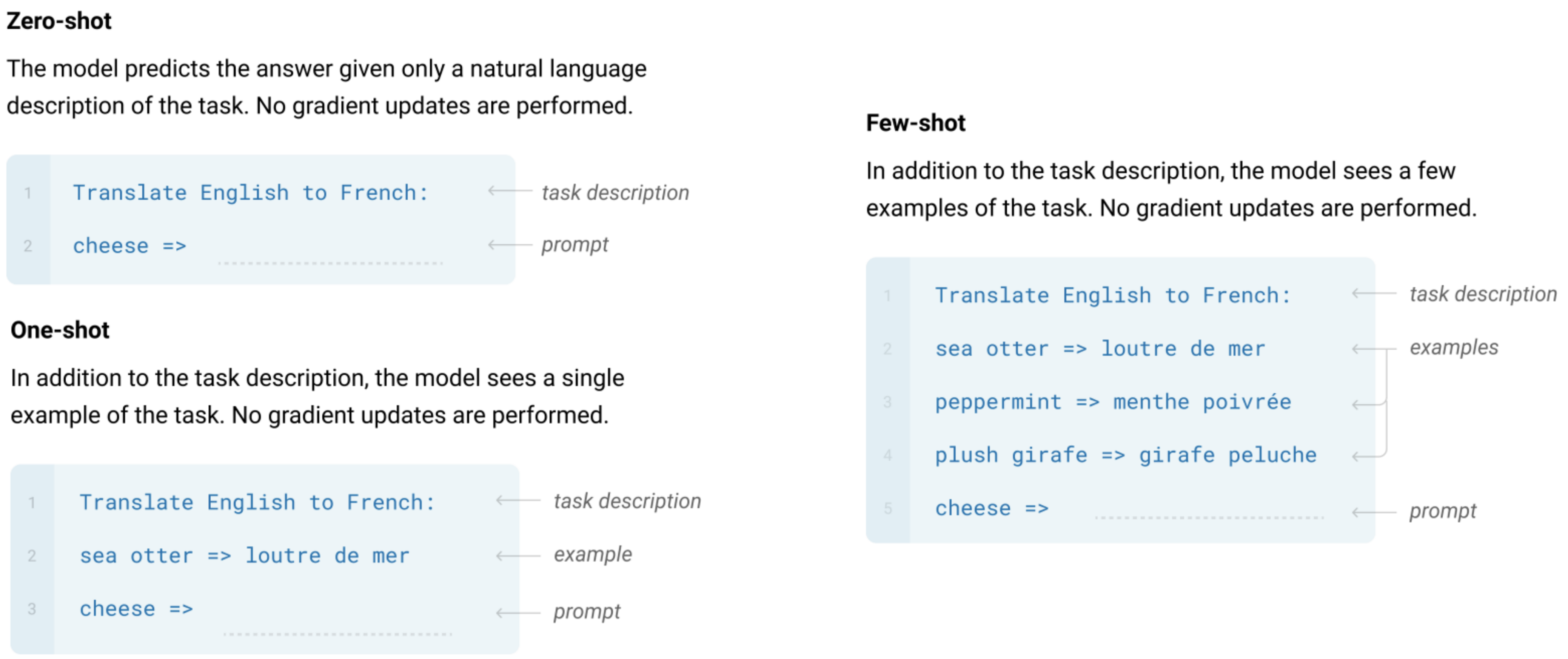
GPT-3, with 175 billion parameters, is a good example of this.

GPT-3, In-Context learning, and LLMs

Very large language models have ability to learn through examples provided within their contexts without gradient steps. This is referred to as in-context learning ability.



GPT3, ICL



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:
cheese => ...........................
```

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:
sea otter => loutre de mer
cheese => ...........................
```

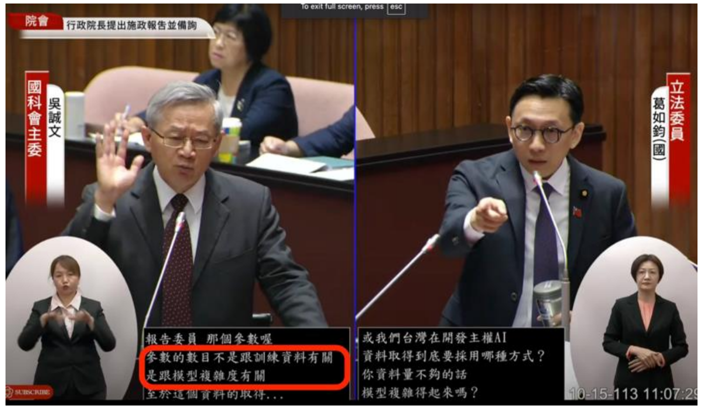
Few-shot

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

```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese => ...........................
```

GPT3 family

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



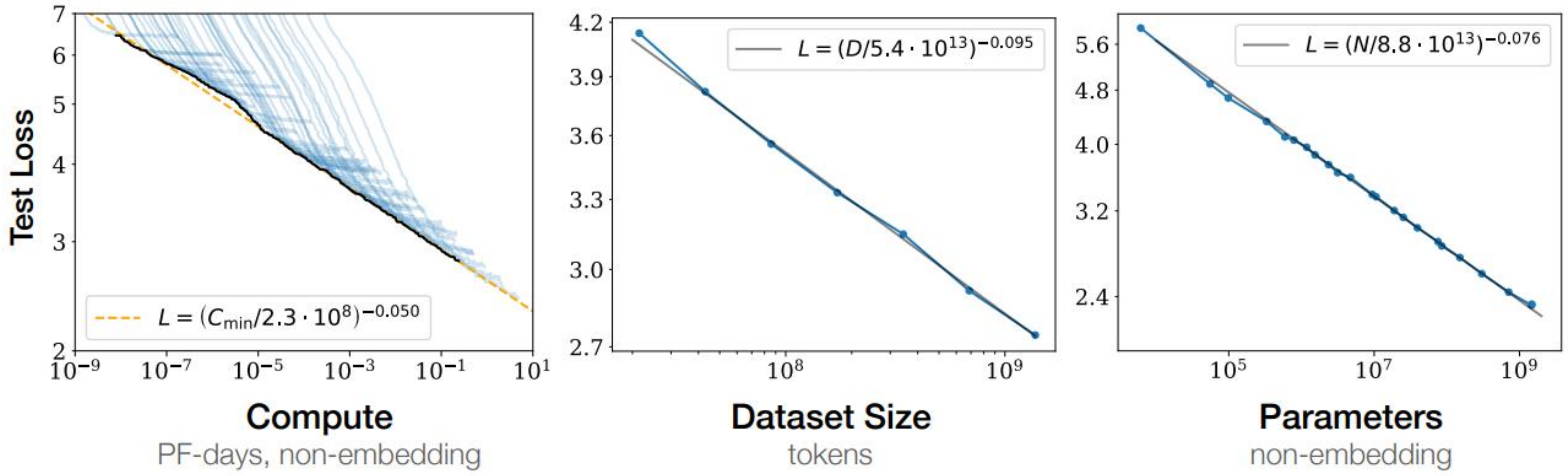
報告委員 那個參數喔
參數的數目不是跟訓練資料有關
是跟模型複雜度有關
至於這個資料的取得...

或我們台灣在開發主權AI
資料取得到底要採用哪種方式？
你資料量不夠的話
模型複雜得起來嗎？

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

Scaling Laws (Kaplan et al,. 2020)

Scaling laws are simple, predictive rules for model performance. Increasing the model size, dataset size, and the amount of computation during training lead to better performance which increase smoothly.



Very Large Language Models

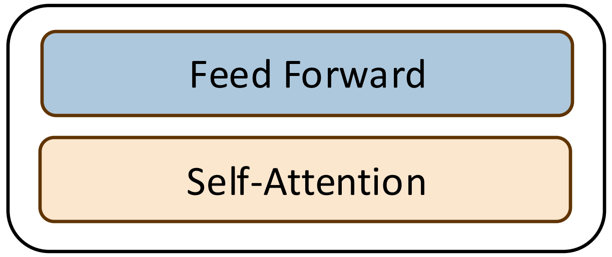
Model	Parameters	Publisher	Release
GPT-3	175B	OpenAI	2020.05
BLOOM	176B	BigScience	2022.07
Flan-PaLM	540B	Google	2022.10

Large Language Models for Community

Model	Architecture	Parameters	Publisher	Release
Llama 2	Decoder-only	7B, 13B, 70B	Meta	2023.07.18
Mistral	Decoder-only	7B, **8×7B**	MistralAI	2023.09.27
Phi 2	Decoder-only	2.7B	Microsoft	2023.12.12
Gemma	Decoder-only	2B, 7B	Google	2024.02.21

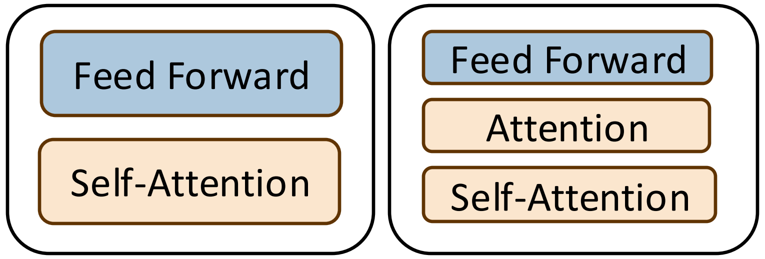
Takeaways

Encoders



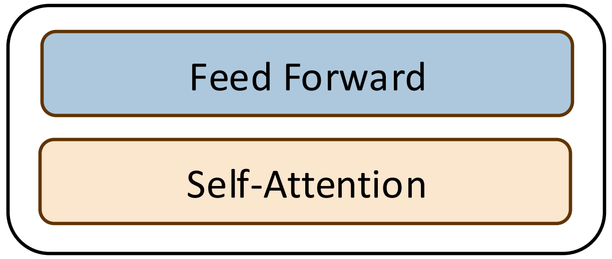
- BERT family
- MLM and NSP task for pretraining
- Not good at performing generation

Encoder-Decoders



- T5, BART
- Span corruption for boosting MLM
- Targeting text-to-text format model

Decoders



- GPT family
- Pure language modeling
- Most popular backbone nowadays