① Subword Modeling

① why use it?

In traditional NLP, we usually use word-level vocabulary which have some problems

1. vocabulary is too big and many words appear very rarely in data
2. unknown word problem eg: taaaasty, laern, Transformerify

② How to solve

use Byte-Pair Encoding (BPE) algorithm

The byte-pair encoding algorithm

Subword modeling in NLP encompasses a wide range of methods for reasoning about structure below the word level. (Parts of words, characters, bytes.)

- The dominant modern paradigm is to learn a vocabulary of **parts of words (subword tokens).**
- At training and testing time, each word is split into a sequence of known subwords.

Byte-pair encoding is a simple, effective strategy for defining a subword vocabulary.

1. Start with a vocabulary containing only characters and an "end-of-word" symbol.
2. Using a corpus of text, find the most common adjacent characters "a,b"; add "ab" as a subword.
3. Replace instances of the character pair with the new subword; repeat until desired vocab size.

Originally used in NLP for machine translation; now a similar method (WordPiece) is used in pretrained models.

③ why it work well?

1. solve the unknown word problem
2. share semantics eg: after model learns "##ing", it can better understand all verbs ending with "big"
3. Multilingual friendly work well with Chinese which have not space to separate

Word structure and subword models

Common words end up being a part of the subword vocabulary, while rarer words are split into (sometimes intuitive, sometimes not) components.

In the worst case, words are split into as many subwords as they have characters.

	word		vocab mapping	embedding
Common words	hat	→	hat	
	learn	→	learn	
Variations	taaaaasty	→	taa## aaa## sty	
misspellings	laern	→	la## ern##	
novel items	Transformerify	→	Transformer## ify	

② Motivating model pretraining from word embeddings

① intro

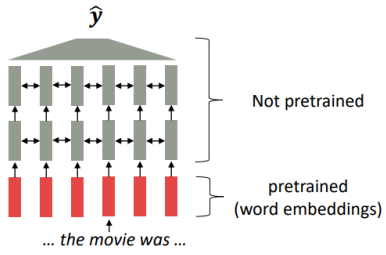
Where we were: **pretrained word embeddings**

Circa 2017:

- Start with pretrained word embeddings (no context!)
- Learn how to incorporate context in an LSTM or Transformer while training on the task.

Some issues to think about:

- The training data we have for our **downstream task** (like question answering) must be sufficient to teach all contextual aspects of language.
- Most of the parameters in our network are randomly initialized!

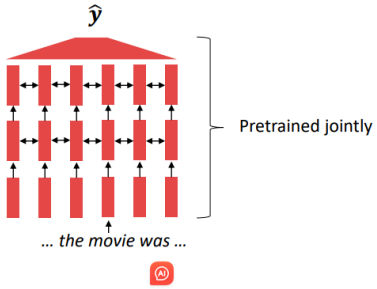


[Recall, *movie* gets the same word embedding, no matter what sentence it shows up in]

Where we're going: **pretraining whole models**

In modern NLP:

- All (or almost all) parameters in NLP networks are initialized via **pretraining**.
- Pretraining methods hide parts of the input from the model, and train the model to reconstruct those parts.
- This has been exceptionally effective at building strong:
  - **representations of language**
  - **parameter initializations** for strong NLP models.
  - **Probability distributions** over language that we can sample from



[This model has learned how to represent entire sentences through pretraining]

What can we learn from reconstructing the input?

1. What the Entity is? — xxx is in xxx, xxx
2. Syntax — I put ___ on table
3. co-referent — She checks ___ bag
4. semantics — we have apple, banana, ___
5. sentiment — I don't want to do xxx, it's ___!
6. number sequence — 1, 1, 2, 3, 5, 8, 13, 21, ___

② The mainstream paradigms of NLP today

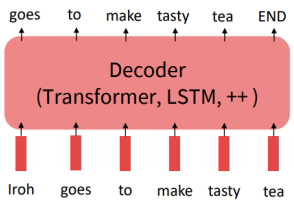
Pretraining through language modeling [Dai and Le, 2015]

Recall the **language modeling** task:

- Model $p_\theta(w_t|w_{1:t-1})$, the probability distribution over words given their past contexts.
- There's lots of data for this! (In English.)

Pretraining through language modeling:

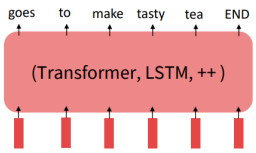
- Train a neural network to perform language modeling on a large amount of text.
- Save the network parameters.



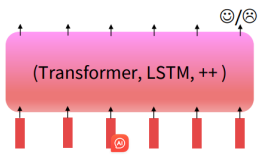
The Pretraining / Finetuning Paradigm

Pretraining can improve NLP applications by serving as parameter initialization.

Step 1: Pretrain (on language modeling)
Lots of text; learn general things!



Step 2: Finetune (on your task)
Not many labels; adapt to the task!



Step 1.5 lable

Manually or semi-automatically annotate the data

Q.A. why does pretraining-finetuning Paradigm work better than just making the model more powerful ?

↳ you have orders of magnitude more data that's unlabeled (with just make model more powerful)

③ How ?

Stochastic gradient descent and pretrain/finetune

Why should pretraining and finetuning help, from a "training neural nets" perspective?

- Consider, provides parameters $\hat{\theta}$ by approximating $\min_{\theta} \mathcal{L}_{\text{pretrain}}(\theta)$.
  - (The pretraining loss.)
- Then, finetuning approximates $\min_{\theta} \mathcal{L}_{\text{finetune}}(\theta)$, starting at $\hat{\theta}$.
  - (The finetuning loss)
- The pretraining may matter because stochastic gradient descent sticks (relatively) close to $\hat{\theta}$ during finetuning.
  - So, maybe the finetuning local minima near $\hat{\theta}$ tend to generalize well!
  - And/or, maybe the gradients of finetuning loss near $\hat{\theta}$ propagate nicely!

③ Model pretraining 3 ways

⚠ encoder

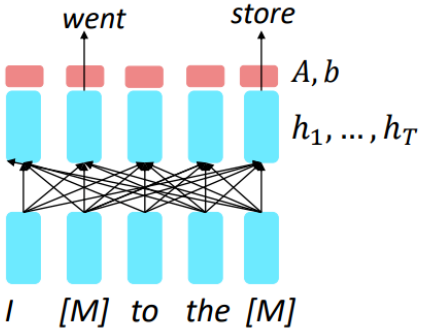
Pretraining encoders: what pretraining objective to use?

So far, we've looked at language model pretraining. But **encoders get bidirectional context,** so we can't do language modeling!

Idea: replace some fraction of words in the input with a special [MASK] token; predict these words.

$$h_1, \dots, h_T = \text{Encoder}(w_1, \dots, w_T)$$
$$y_i \sim Aw_i + b$$

Only add loss terms from words that are "masked out." If $\tilde{x}$ is the masked version of x, we're learning $p_\theta(x|\tilde{x})$. Called **Masked LM**.



~ : proportion to

eg: x = I went to the store

$\tilde{x}$ = I [m] to the [m]

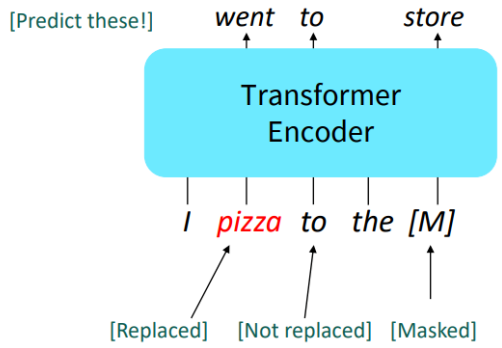
✡ BERT

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al., 2018 proposed the "Masked LM" objective and **released the weights of a pretrained Transformer**, a model they labeled BERT.

Some more details about Masked LM for BERT:

- Predict a random 15% of (sub)word tokens.
  - Replace input word with [MASK] 80% of the time
  - Replace input word with a random token 10% of the time
  - Leave input word unchanged 10% of the time (but still predict it!)
- Why? Doesn't let the model get complacent and not build strong representations of non-masked words. (No masks are seen at fine-tuning time!)

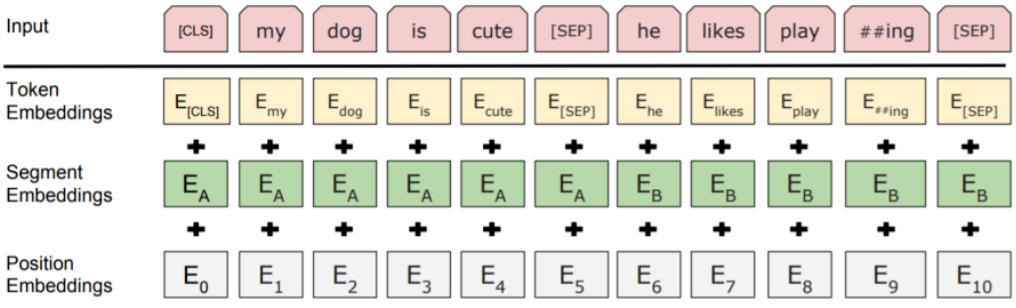


To ensure model can learn powerful representations of uncovered words

To prevent excessive model from dependenting on [MASK] Tag

BERT: Bidirectional Encoder Representations from Transformers

- The pretraining input to BERT was two separate contiguous chunks of text:



- BERT was trained to predict whether one chunk follows the other or is randomly sampled.
  - Later work has argued this "next sentence prediction" is not necessary.

This is the unique embeddings which BERT have

What's job?

Determine whether the second sentense is a true sequal to the first sentence

How ?

By randomly seleting a sentence from the corpus as the second sentence

Why?

To let the model learn the logical relationships between sentences (Though the effectiveness of NSP is controversial)

NSP : Next sentence Prediction

Q.A. the "+" here is concatenating or do element-wise addition

└ elementwise addition , because we allways want same dimension every layer

How to evaluate?

BERT: Bidirectional Encoder Representations from Transformers

BERT was massively popular and hugely versatile; finetuning BERT led to new state-of-the-art results on a broad range of tasks.

- **QQP:** Quora Question Pairs (detect paraphrase questions)
- **QNLI**: natural language inference over question answering data
- **SST-2**: sentiment analysis
- **CoLA**: corpus of linguistic acceptability (detect whether sentences are grammatical.)
- **STS-B**: semantic textual similarity
- **MRPC**: microsoft paraphrase corpus
- **RTE**: a small natural language inference corpus

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Detail

BERT: Bidirectional Encoder Representations from Transformers

Details about BERT

- Two models were released:

- BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
- BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.

- Trained on:
  - BooksCorpus (800 million words)
  - English Wikipedia (2,500 million 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
  - "Pretrain once, finetune many times."

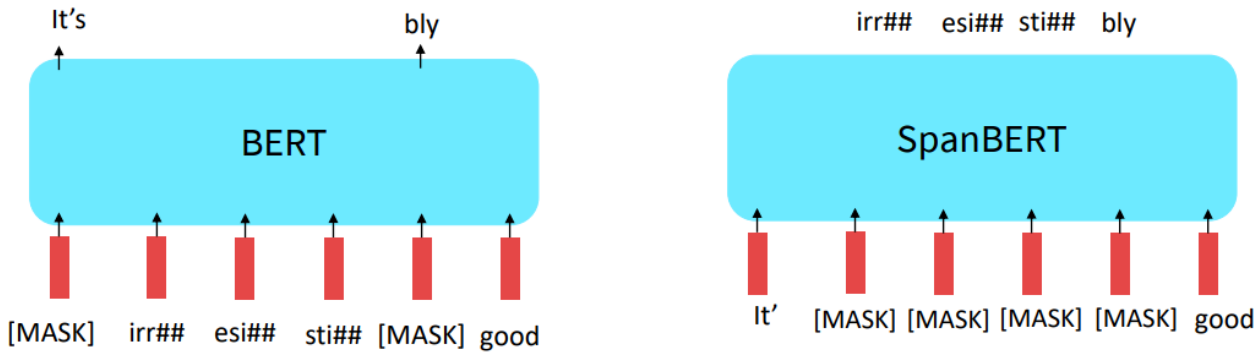
Extensions

Extensions of BERT

You'll see a lot of BERT variants like RoBERTa, SpanBERT, +++

Some generally accepted improvements to the BERT pretraining formula:

- RoBERTa: mainly just train BERT for longer and remove next sentence prediction!
- SpanBERT: masking contiguous spans of words makes a harder, more useful pretraining task



A takeaway from the RoBERTa paper: more compute, more data can improve pretraining even when not changing the underlying Transformer encoder.

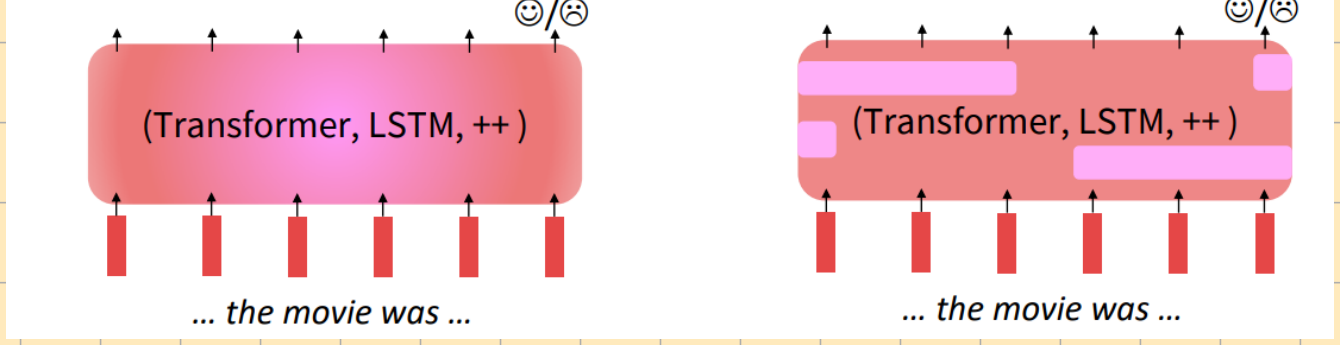
Finetuning

Full Finetuning vs. Parameter-Efficient Finetuning

内存密集形

Finetuning every parameter in a pretrained model works well, but is memory-intensive.
But **lightweight** finetuning methods adapt pretrained models in a constrained way.
Leads to **less overfitting** and/or **more efficient finetuning and inference.**

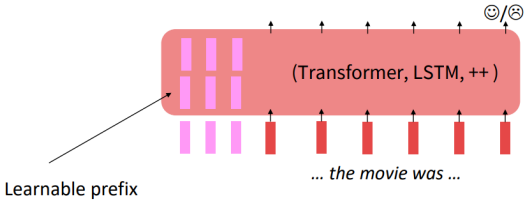
Full Finetuning	**Lightweight Finetuning**
Adapt all parameters	Train a few existing or new parameters



So, In this opinion, we want minimal change on parameters

Parameter-Efficient Finetuning: Prefix-Tuning, Prompt tuning

Prefix-Tuning adds a **prefix** of parameters, and **freezes all pretrained parameters.**
The prefix is processed by the model just like real words would be.
Advantage: each element of a batch at inference could run a different tuned model.

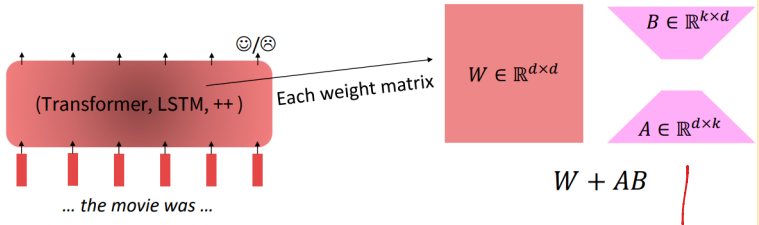


a bunch of fake pseudo word vectors

(LoRA)

Parameter-Efficient Finetuning: Low-Rank Adaptation

Low-Rank Adaptation Learns a low-rank "diff" between the pretrained and finetuned weight matrices.
Easier to learn than prefix-tuning.



low rank

② Encoder - Decoder

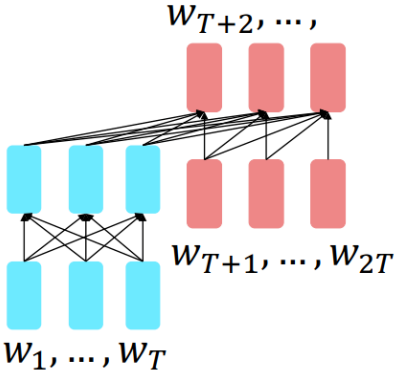
Prefix LM

Pretraining encoder-decoders: what pretraining objective to use?

For **encoder-decoders**, we could do something like **language modeling**, but where a prefix of every input is provided to the encoder and is not predicted.

$$h_1, \ldots, h_T = \text{Encoder}(w_1, \ldots, w_T)$$
$$h_{T+1}, \ldots, h_2 = Decoder(w_1, \ldots, w_T, h_1, \ldots, h_T)$$
$$y_i \sim Ah_i + b, i > T$$

The **encoder** portion benefits from bidirectional context; the **decoder** portion is used to train the whole model through language modeling.



[Raffel et al., 2018]

1. Divide the input text $(w_1 \ldots w_{2T})$ into 2 segments
2. Input the first half $(w_1 \ldots w_T)$ into the encoder. The encoder can understand this text in both directions
3. Input the entire text $(w_1, \ldots, w_{2T})$ into the decoder, but use a causal mask to ensure that the decoder can only see the position before i when predicting position i

4. The training objective is to have the decoder autoregressively predict the second half $(w_{T+1}, \ldots, w_{2T})$

Core idea is using a part of input text as input to encoder, and the remaining part as the target which decoder needs to generate

T5 (Text-to-Text Transfer Transformer)

Pretraining encoder-decoders: what pretraining objective to use?

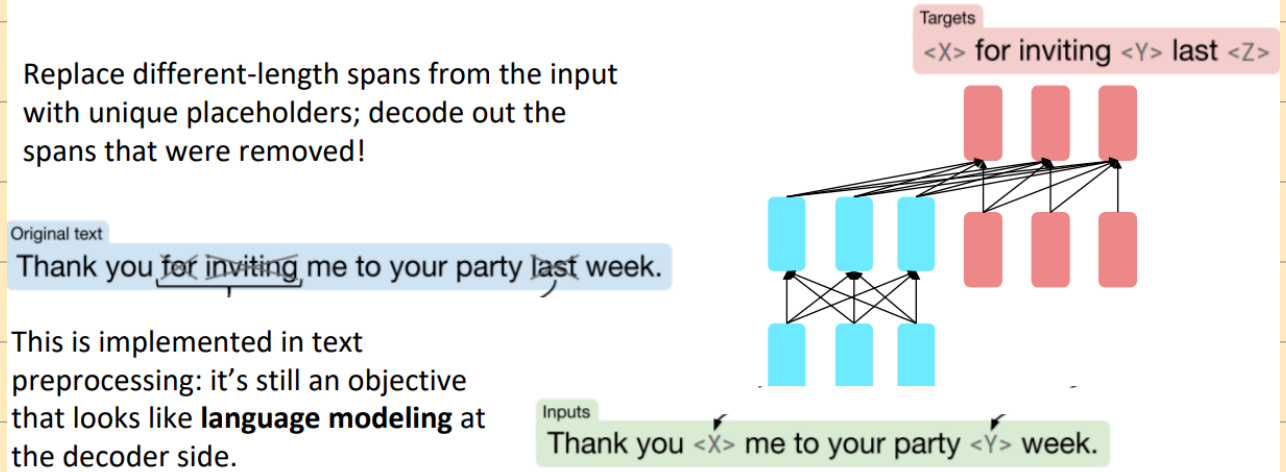
What Raffel et al., 2018 found to work best was **span corruption.** Their model: **T5.**

Replace different-length spans from the input with unique placeholders; decode out the spans that were removed!

Original text

Thank you ~~for inviting~~ me to your party ~~last~~ week.

This is implemented in text preprocessing: it's still an objective that looks like **language modeling** at the decoder side.

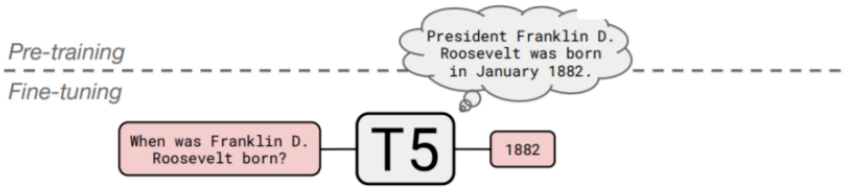


Why it works well?

It forces the encoder to infer global information from incomplete and noisy inputs

Pretraining encoder-decoders: what pretraining objective to use?

A fascinating property of T5: it can be finetuned to answer a wide range of questions, retrieving knowledge from its parameters.



NQ: Natural Questions
WQ: WebQuestions
TQA: Trivia QA

All "open-domain" versions

	NQ	WQ	TQA dev	TQA test	
Karpukhin et al. (2020)	**41.5**	42.4	**57.9**	–	
T5.1.1-Base	25.7	28.2	24.2	30.6	220 million params
T5.1.1-Large	27.3	29.5	28.5	37.2	770 million params
T5.1.1-XL	29.5	32.4	36.0	45.1	3 billion params
T5.1.1-XXL	32.8	35.6	42.9	52.5	11 billion params
T5.1.1-XXL + SSM	35.2	**42.8**	51.9	**61.6**	

③ Decoder

Pretraining decoders

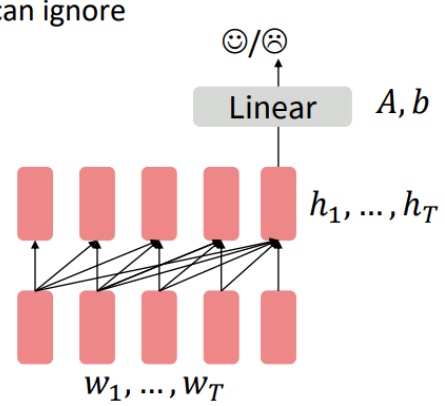
When using language model pretrained decoders, we can ignore that they were trained to model $p(w_t|w_{1:t-1})$.

We can finetune them by training a classifier on the last word's hidden state.

$$h_1, \dots, h_T = \text{Decoder}(w_1, \dots, w_T)$$
$$y \sim Ah_T + b$$

Where A and b are randomly initialized and specified by the downstream task.

Gradients backpropagate through the whole network.



[Note how the linear layer hasn't been pretrained and must be learned from scratch.]

In practice, most powerful pretrained models tend to be decoder only also, the biggest net tend to be decoders

History

Generative Pretrained Transformer (GPT) [Radford et al., 2018]

2018's GPT was a big success in pretraining a decoder!

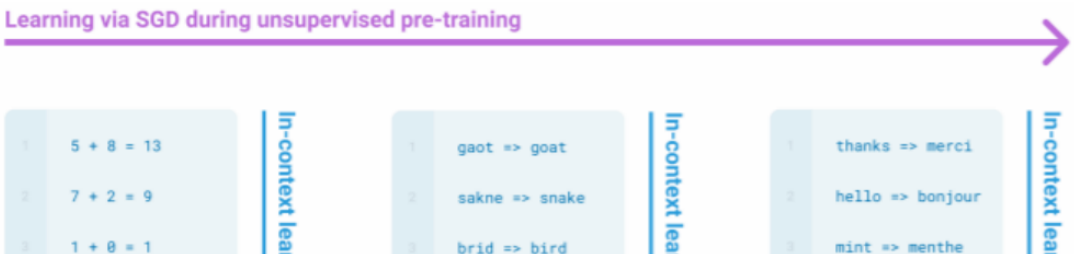
- Transformer decoder with 12 layers, 117M parameters.
- 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers.
- Byte-pair encoding with 40,000 merges
- Trained on BooksCorpus: over 7000 unique books.
  - Contains long spans of contiguous text, for learning long-distance dependencies.
- The acronym "GPT" never showed up in the original paper; it could stand for "Generative PreTraining" or "Generative Pretrained Transformer"

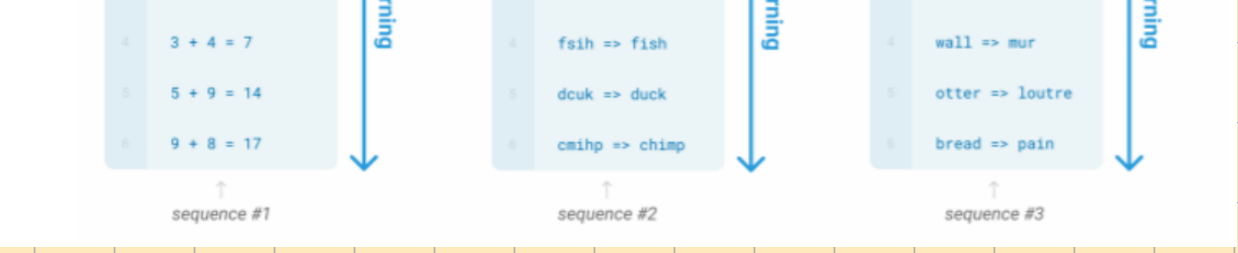
Increasingly convincing generations (GPT2) [Radford et al., 2018]

We mentioned how pretrained decoders can be used **in their capacities as language models.** **GPT-2,** a larger version (1.5B) of GPT trained on more data, was shown to produce relatively convincing samples of natural language.

GPT-3, In-context learning, and very large models

Very large language models seem to perform some kind of learning **without gradient steps** simply from examples you provide within their contexts.





How GPT-1 work ?

Generative Pretrained Transformer (GPT) [Radford et al., 2018]

How do we format inputs to our decoder for **finetuning tasks?**

Natural Language Inference: Label pairs of sentences as *entailing/contradictory/neutral*

Premise: *The man is in the doorway*
Hypothesis: *The person is near the door* } **entailment**

Radford et al., 2018 evaluate on natural language inference.
Here's roughly how the input was formatted, as a sequence of tokens for the decoder.

[START] *The man is in the doorway* [DELIM] *The person is near the door* [EXTRACT]

The linear classifier is applied to the representation of the [EXTRACT] token.

optimize the compntation

Scaling Efficiency: how do we best use our compute

GPT-3 was **175B parameters** and trained on **300B** tokens of text.
Roughly, the cost of training a large transformer scales as **parameters*tokens**
Did OpenAI strike the right parameter-token data to get the best model? No.

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

This 70B parameter model is better than the much larger other models!

↑ this is still a open question

Chain-of-thought

The prefix as task specification and scratch pad: chain-of-thought