Natural Language Processing with Deep Learning

CS224N/Ling284

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Lecture 9: Pretraining

Adapted from slides by Anna Goldie, John Hewitt

Lecture Plan

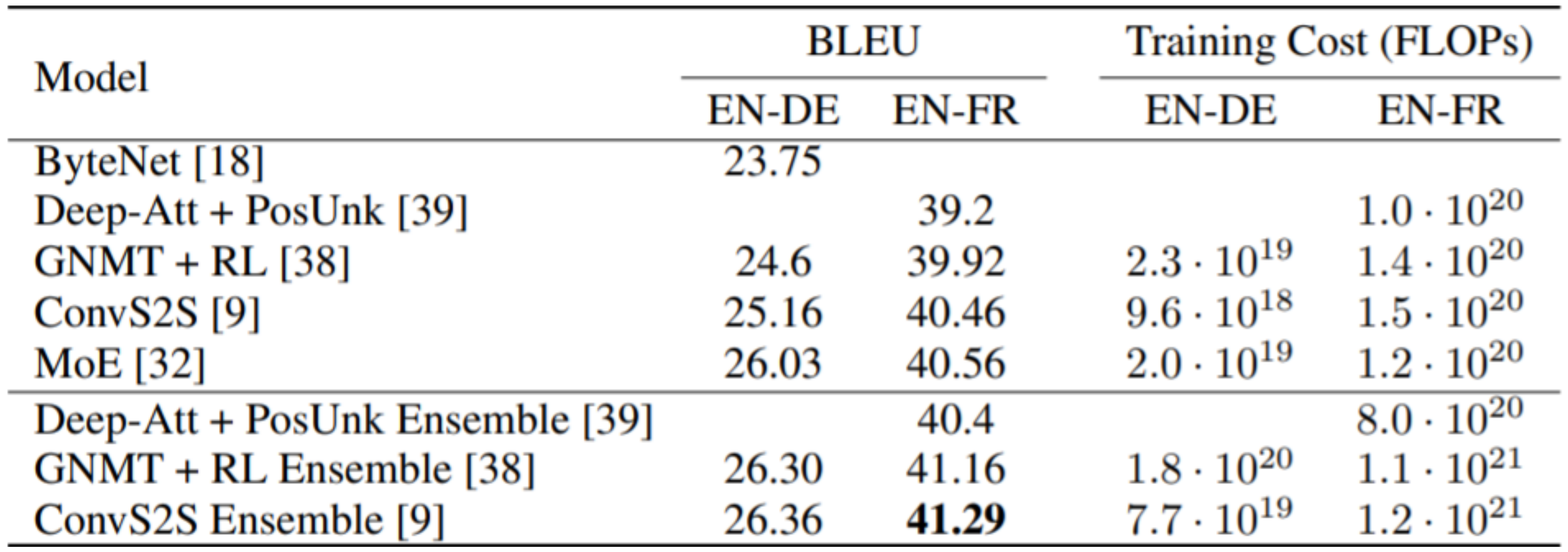
1. Finishing up transformers
2. Subword modeling
3. Motivating model pretraining from word embeddings
4. Model pretraining three ways
    1. Decoders
    2. Encoders
    3. Encoder-Decoders
5. Interlude: what do we think pretraining is teaching?
6. Very large models and in-context learning

Reminders:

Assignment 5 is out on Thursday! It covers lecture 8 and lecture 9(Today)!

Great Results with Transformers

First, Machine Translation from the original Transformers paper!



Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$

[Test sets: WMT 2014 English-German and English-French]

[Vaswani et al., 2017]

Great Results with Transformers

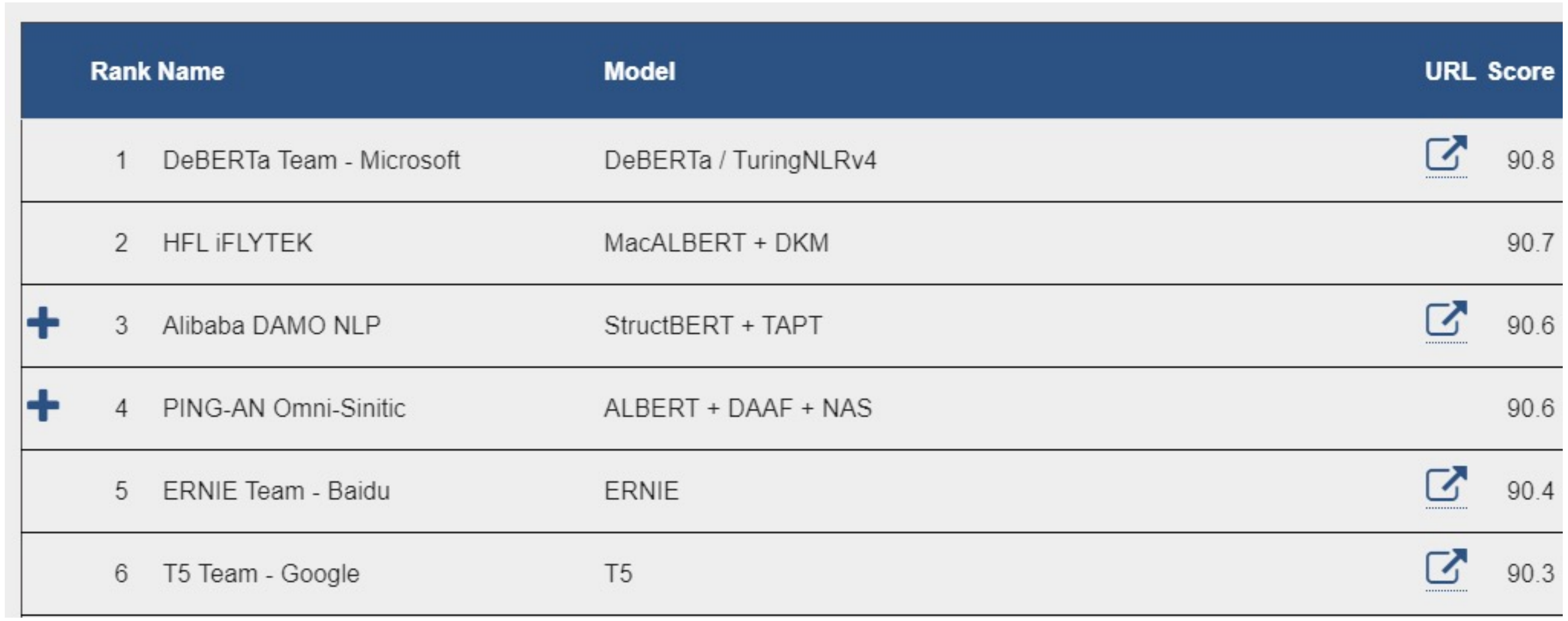
Before too long, most Transformers results also included **pretraining**.

Transformers' parallelizability allows for efficient pretraining, and have made them the de-facto standard.

On this popular aggregate benchmark, for example:

GLUE

All top models are Transformer (and pretraining)-based.



	Rank	Name	Model	URL	Score
	1	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4	↗	90.8
	2	HFL iFLYTEK	MacALBERT + DKM		90.7
+	3	Alibaba DAMO NLP	StructBERT + TAPT	↗	90.6
+	4	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6
	5	ERNIE Team - Baidu	ERNIE	↗	90.4
	6	T5 Team - Google	T5	↗	90.3

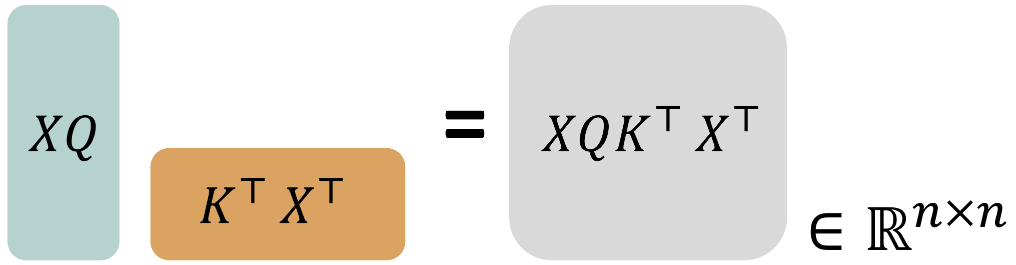
[Liu et al., 2018]

What would we like to fix about the Transformer?

- **Quadratic compute in self-attention (today)**:
  - Computing all pairs of interactions means our computation grows **quadratically** with the sequence length!
  - For recurrent models, it only grew linearly!
- **Position representations**:
  - Are simple absolute indices the best we can do to represent position?
  - Relative linear position attention [Shaw et al., 2018]
  - Dependency syntax-based position [Wang et al., 2019]

Quadratic computation as a function of sequence length

- One of the benefits of self-attention over recurrence was that it's highly parallelizable.
- However, its total number of operations grows as $O(n^2 d)$, where n is the sequence length, and d is the dimensionality.



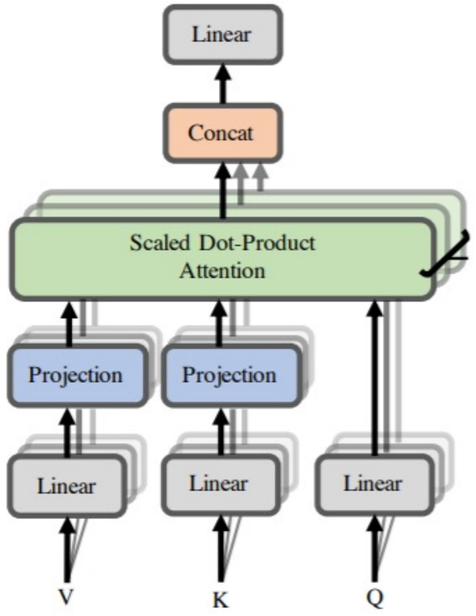
Need to compute all pairs of interactions!
$O(n^2 d)$

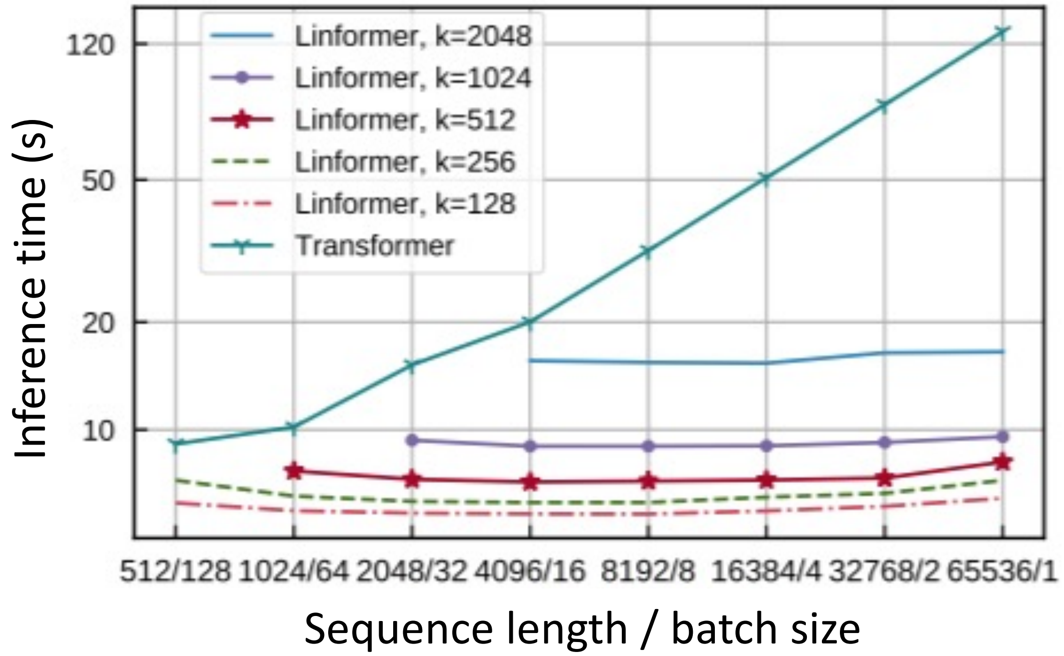
- Think of d as around $\mathbf{1,000}$ (though for large language models it's much larger!).
  - So, for a single (shortish) sentence, $n \leq 30; n^2 \leq \mathbf{900}$.
  - In practice, we set a bound like $n = 512$.
  - **But what if we'd like $\boldsymbol{n} \geq \mathbf{50,000}$?** For example, to work on long documents?

Work on improving on quadratic self-attention cost

- Considerable recent work has gone into the question, *Can we build models like Transformers without paying the* $O(T^2)$ *all-pairs self-attention cost?*
- For example, **Linformer** [Wang et al., 2020]

Key idea: map the sequence length dimension to a lower-dimensional space for values, keys





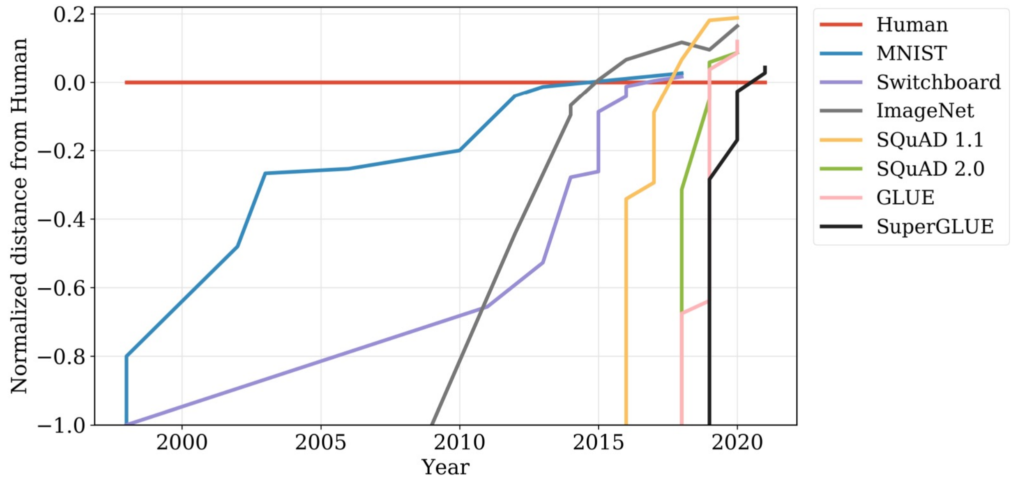
Do we even need to remove the quadratic cost of attention?

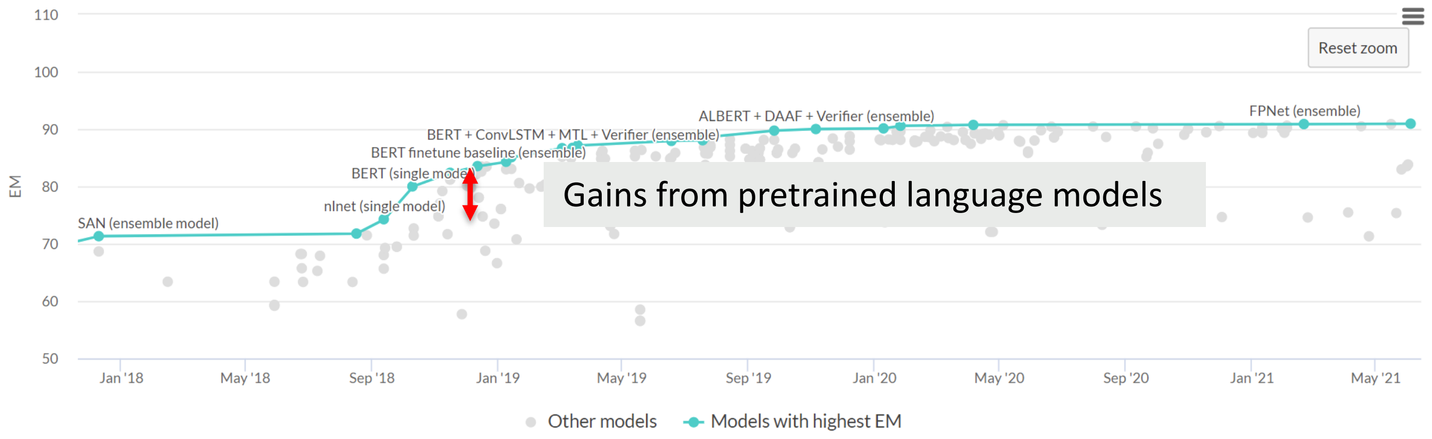
- As Transformers grow larger, a larger and larger percent of compute is **outside** the self-attention portion, despit the quadratic cost.

- In practice, **almost no large Transformer language models use anything but the quadratic cost attention we've presented here.**
  - The cheaper methods tend not to work as well at scale.

- So, is there no point in trying to design cheaper alternatives to self-attention?
- Or would we unlock much better models with much longer contexts (>100k tokens?) if we were to do it right?

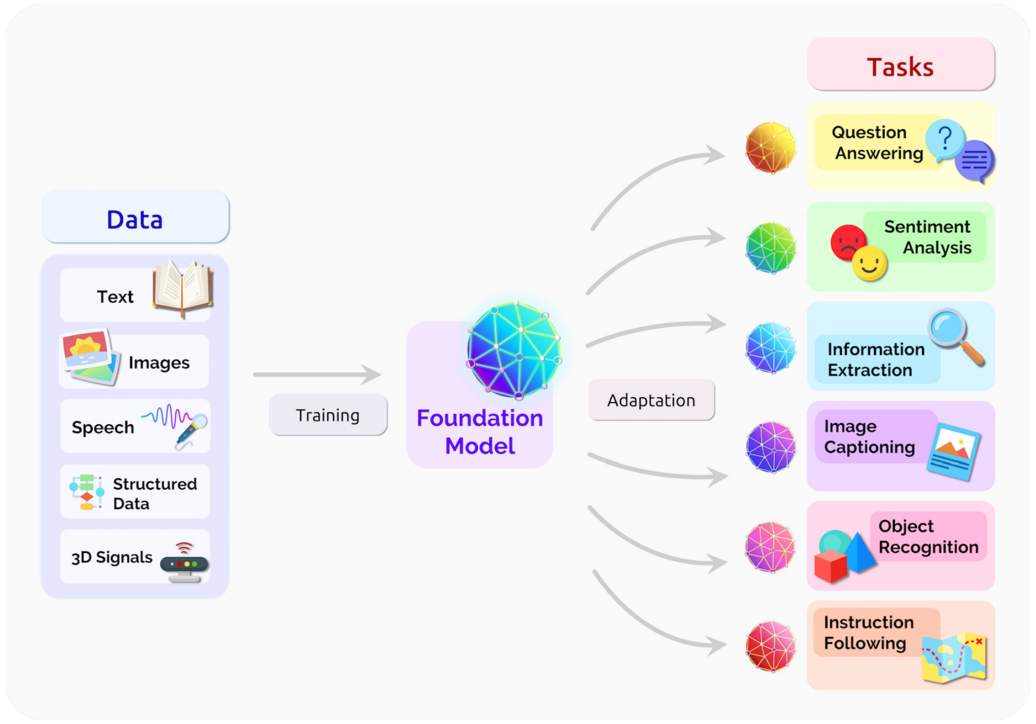
The pretraining revolution





Pretraining has had a major, tangible impact on how well NLP systems work

Pretraining – scaling unsupervised learning on the internet



Key ideas in pretraining

- Make sure your model can process large-scale, diverse datasets
- Don’t use labeled data (otherwise you can’t scale!)
- Compute-aware scaling

Word structure and subword models

Let’s take a look at the assumptions we’ve made about a language’s vocabulary.

We assume a fixed vocab of tens of thousands of words, built from the training set.
All *novel* words seen at test time are mapped to a single UNK.

	word		vocab mapping	embedding
Common words	hat	→	pizza (index)	🟥
	learn	→	tasty (index)	🟥
Variations	taaaaasty	→	UNK (index)	▨
misspellings	laern	→	UNK (index)	▨
novel items	Transformerify	→	UNK (index)	▨

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.

[Sennrich et al., 2016, Wu et al., 2016]

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	🟥 🟥

Outline

Motivating word meaning and context

Recall the adage we mentioned at the beginning of the course:

> *"You shall know a word by the company it keeps"* (J. R. Firth 1957: 11)

This quote is a summary of **distributional semantics**, and motivated **word2vec**. But:

> "… the complete meaning of a word is always contextual,
> and no study of meaning apart from a complete context
> can be taken seriously." (J. R. Firth 1935)

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

[Thanks to Yoav Goldberg on Twitter for pointing out the 1935 Firth quote.]

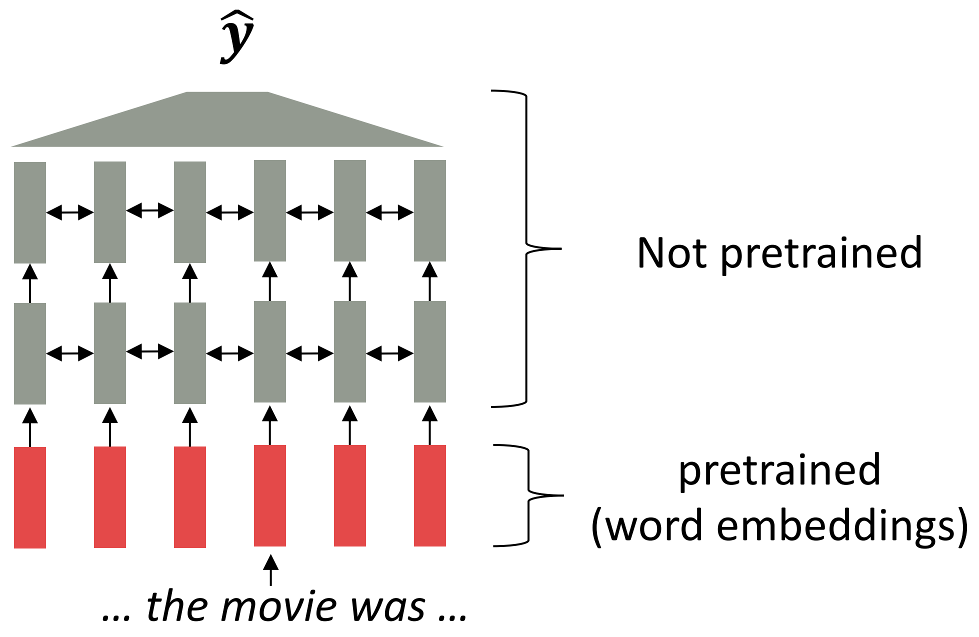
Where we were: **pretrained word embeddings**

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!



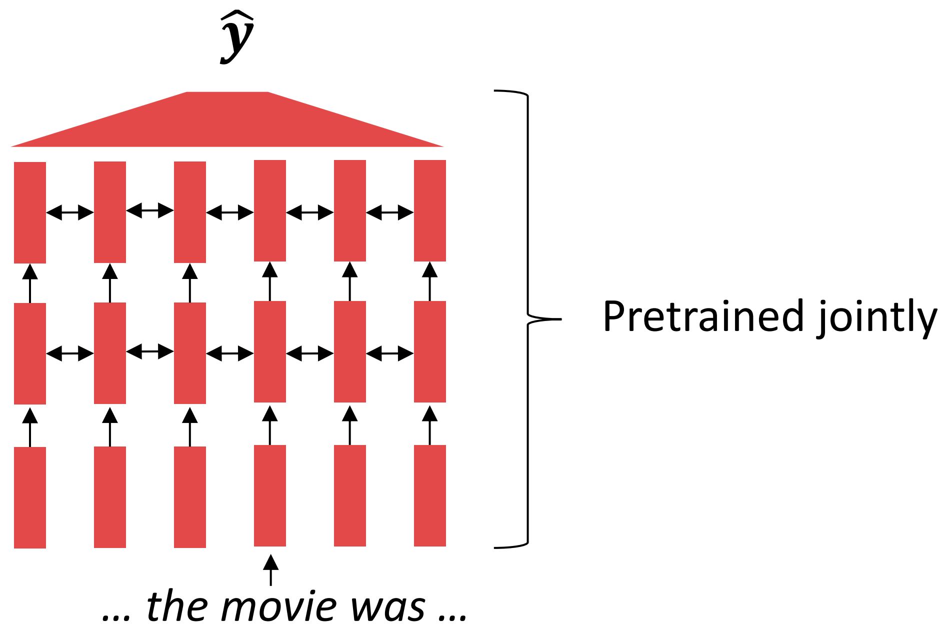
[Recall, *movie* gets the same word embedding, no matter what sentence it shows up in]

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?

Stanford University is located in ___________, California.

What can we learn from reconstructing the input?

I put ___ fork down on the table.

What can we learn from reconstructing the input?

The woman walked across the street,

checking for traffic over ___ shoulder.

What can we learn from reconstructing the input?

I went to the ocean to see the fish, turtles, seals, and _____.

What can we learn from reconstructing the input?

Overall, the value I got from the two hours watching
it was the sum total of the popcorn and the drink.
The movie was ___.

What can we learn from reconstructing the input?

Iroh went into the kitchen to make some tea.

Standing next to Iroh, Zuko pondered his destiny.

Zuko left the _______.

What can we learn from reconstructing the input?

I was thinking about the sequence that goes

1, 1, 2, 3, 5, 8, 13, 21, ____

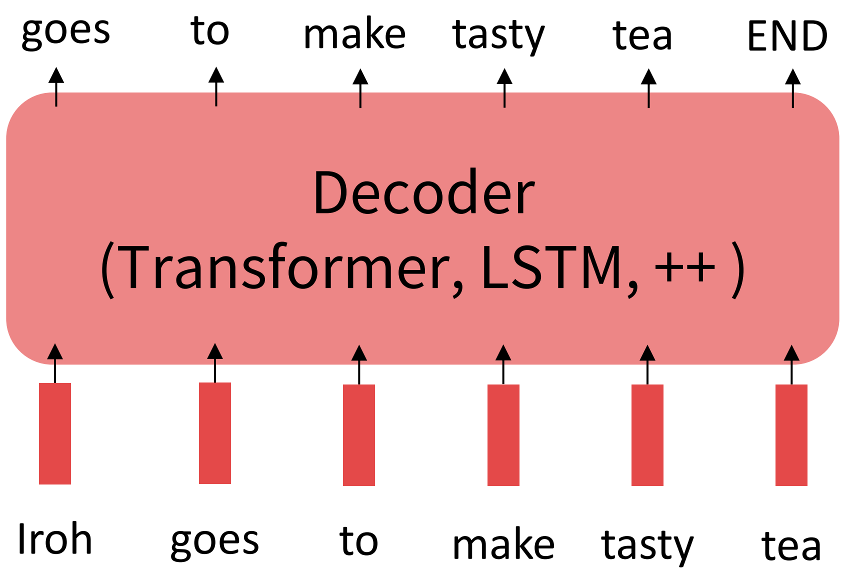
Pretraining through language modeling [Dai and Le, 2015]

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.

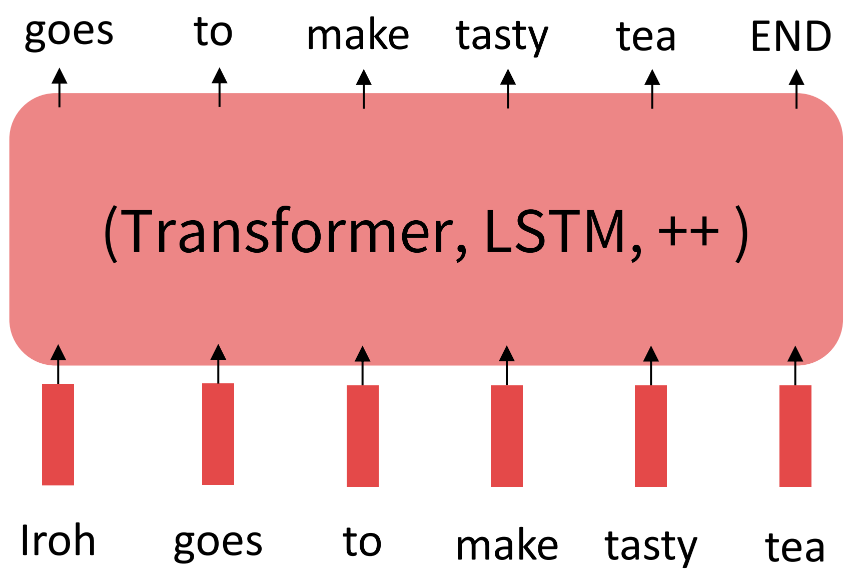


The Pretraining / Finetuning Paradigm

Pretraining can improve NLP applications by serving as parameter initialization.

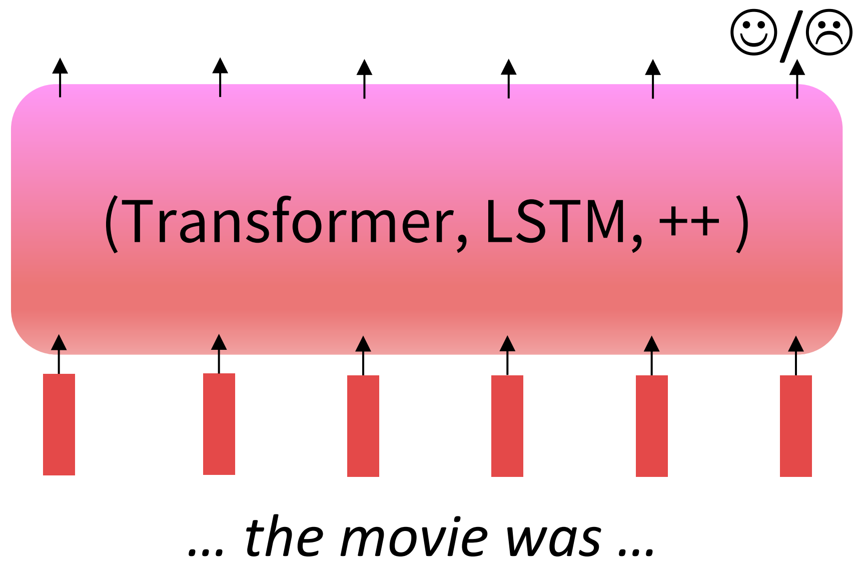
Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



Step 2: Finetune (on your task)

Not many labels; adapt to the task!

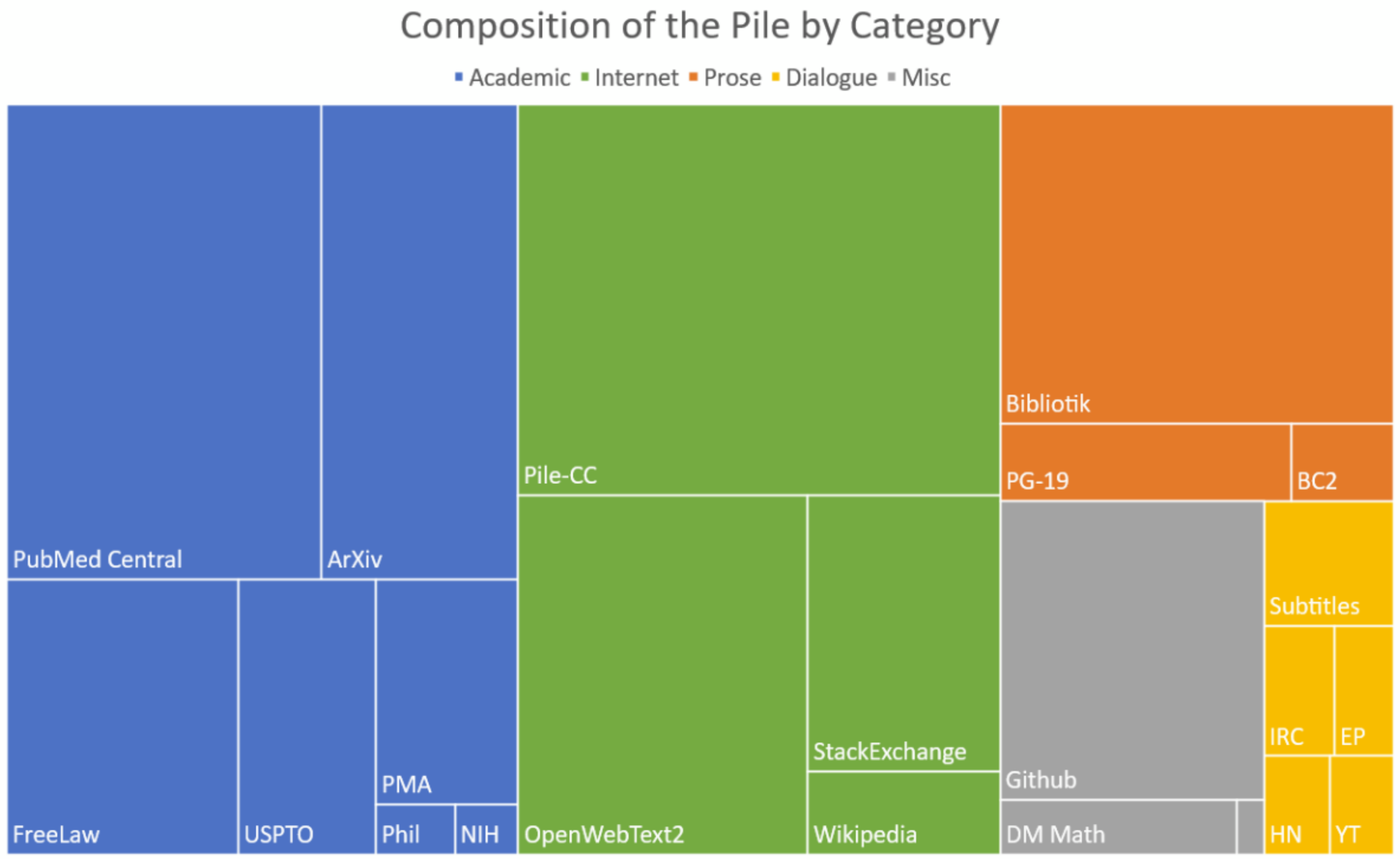


Stochastic gradient descent and pretrain/finetune

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

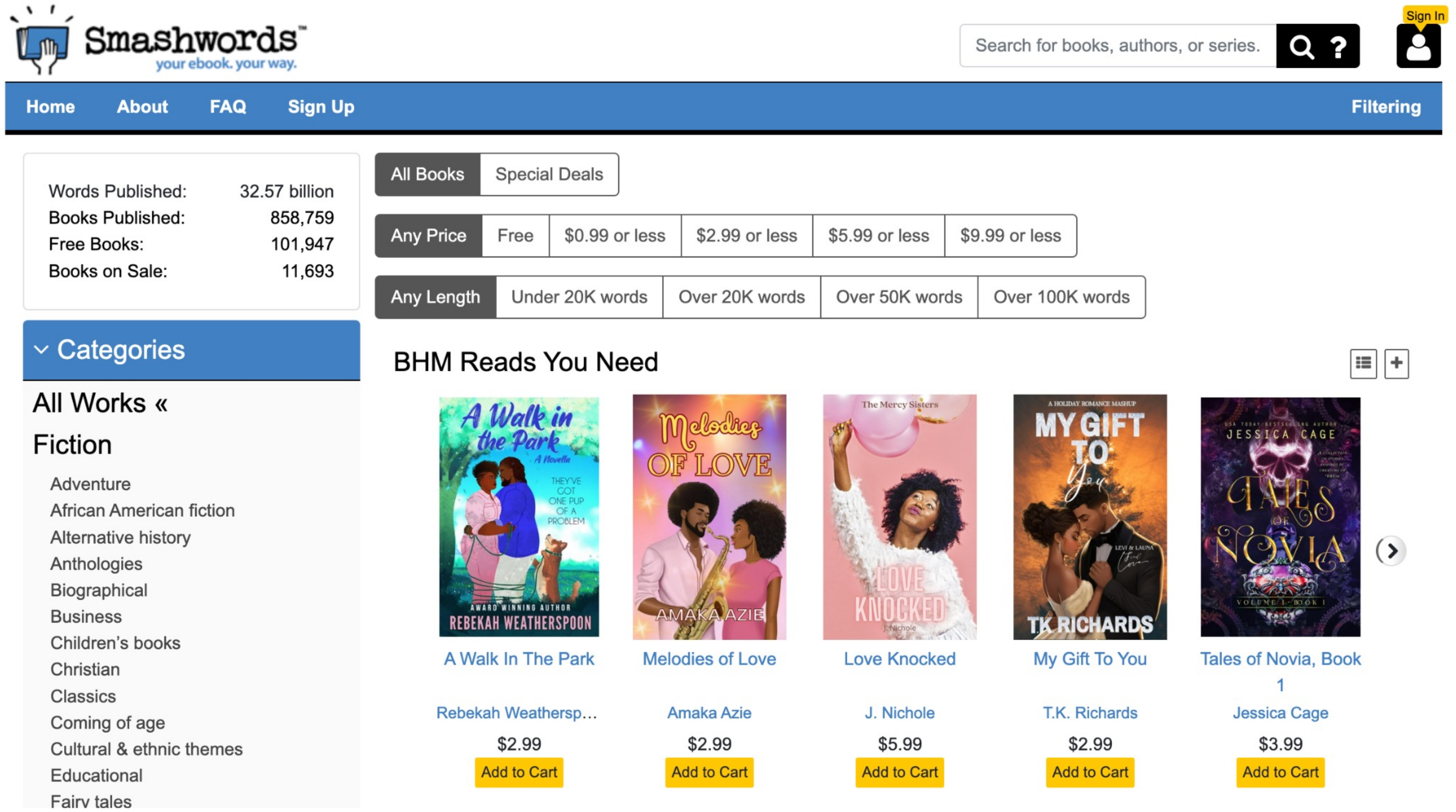
- Consider, provides parameters $\hat{\theta}$ by approximating $\min_{\theta} \mathcal{L}_{\text{pretrain}}(\theta)$.
  - (The pretraining loss.)
- Then, finetuning approximates $\min_{\theta} \mathcal{L}_{\text{finetune}}(\theta)$, starting at $\hat{\theta}$.
  - (The finetuning loss)
- The pretraining 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!

Where does this data come from?



Model	Training Data
BERT	BookCorpus, English Wikipedia
GPT-1	BookCorpus
GPT-3	CommonCrawl, WebText, English Wikipedia, and 2 book databases (“Books 1” and “Books 2”)
GPT-3.5+	Undisclosed

Bookcorpus.. what's that?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Home About FAQ Sign Up Filtering

Words Published:	32.57 billion
Books Published:	858,759
Free Books:	101,947
Books on Sale:	11,693

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African American fiction
Alternative history
Anthologies
Biographical
Business
Children's books
Christian
Classics
Coming of age
Cultural & ethnic themes
Educational
Fairy tales

BHM Reads You Need

Title	Author	Price	
A Walk In The Park	Rebekah Weathersp…	$2.99	Add to Cart
Melodies of Love	Amaka Azie	$2.99	Add to Cart
Love Knocked	J. Nichole	$5.99	Add to Cart
My Gift To You	T.K. Richards	$2.99	Add to Cart
Tales of Novia, Book 1	Jessica Cage	$3.99	Add to Cart

- Scraped ebooks from the internet – highly controversial

Fair use and other concerns

Google swallows 11,000 novels to improve AI's conversation

As writers learn that tech giant has processed their work without permission, the Authors Guild condemns 'blatantly commercial use of expressive authorship'

'It doesn't harm the authors' ... Google's headquarters in Mountain View, California. Photograph: Marcio Jose Sanchez/AP

Arts and Humanities, Law, Regulation, and Policy, Machine Learning

Reexamining "Fair Use" in the Age of AI

Generative AI claims to produce new language and images, but when those ideas are based on copyrighted material, who gets the credit? A new paper from Stanford University looks for answers.

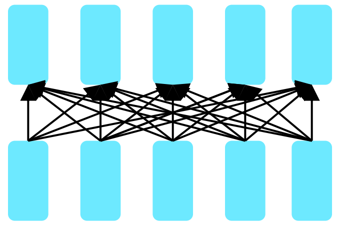
Jun 5, 2023 | Andrew Myers

Lecture Plan

1. A brief note on subword modeling
2. Motivating model pretraining from word embeddings
3. Model pretraining three ways
    1. Encoders
    2. Encoder-Decoders
    3. Decoders
4. What do we think pretraining is teaching?

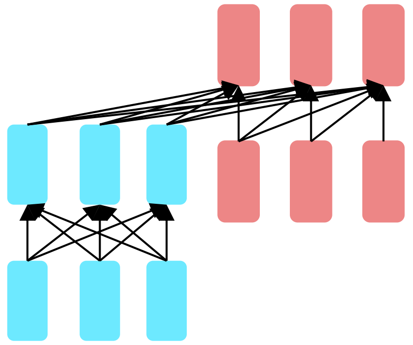
Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



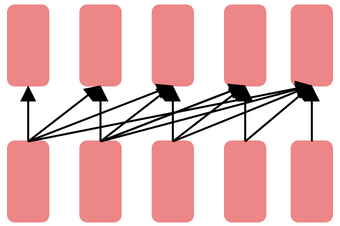
Encoders

- Gets bidirectional context – can condition on future!
- How do we train them to build strong representations?



Encoder-Decoders

- Good parts of decoders and encoders?
- What's the best way to pretrain them?



Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words

Pretraining for three types of architectures

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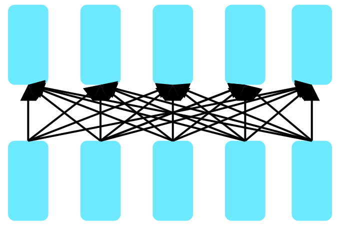

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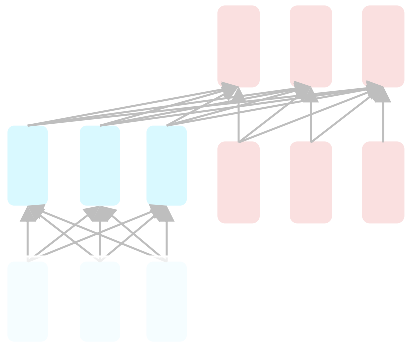

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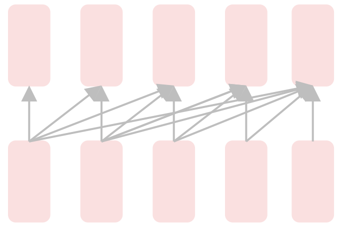


Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words

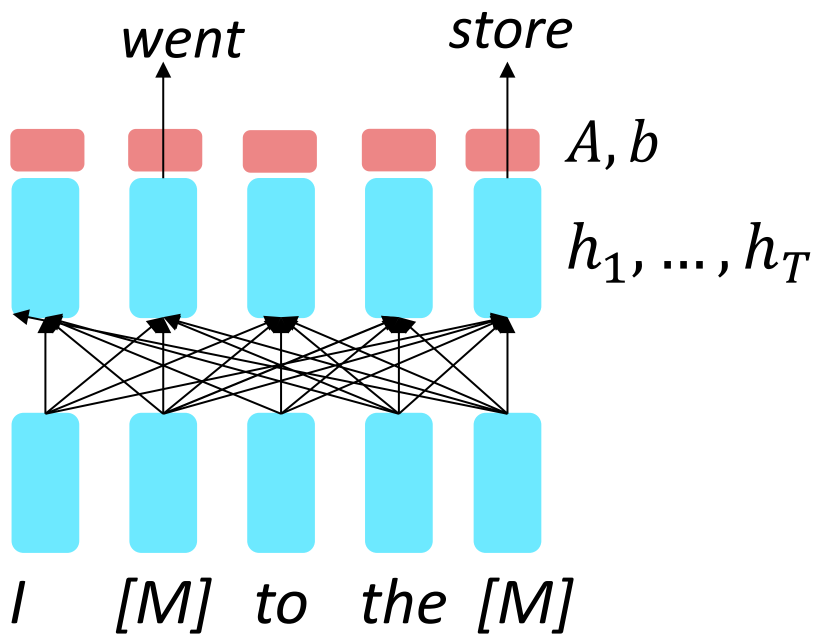
Pretraining encoders: what pretraining objective to use?

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.

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

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**.



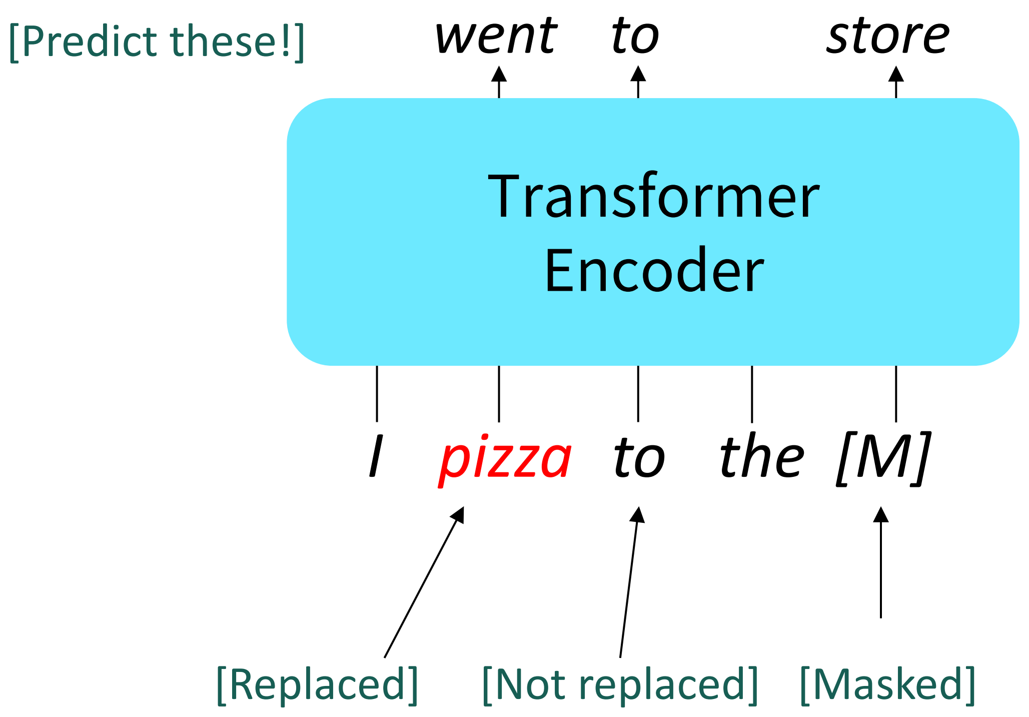
[Devlin et al., 2018]

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:

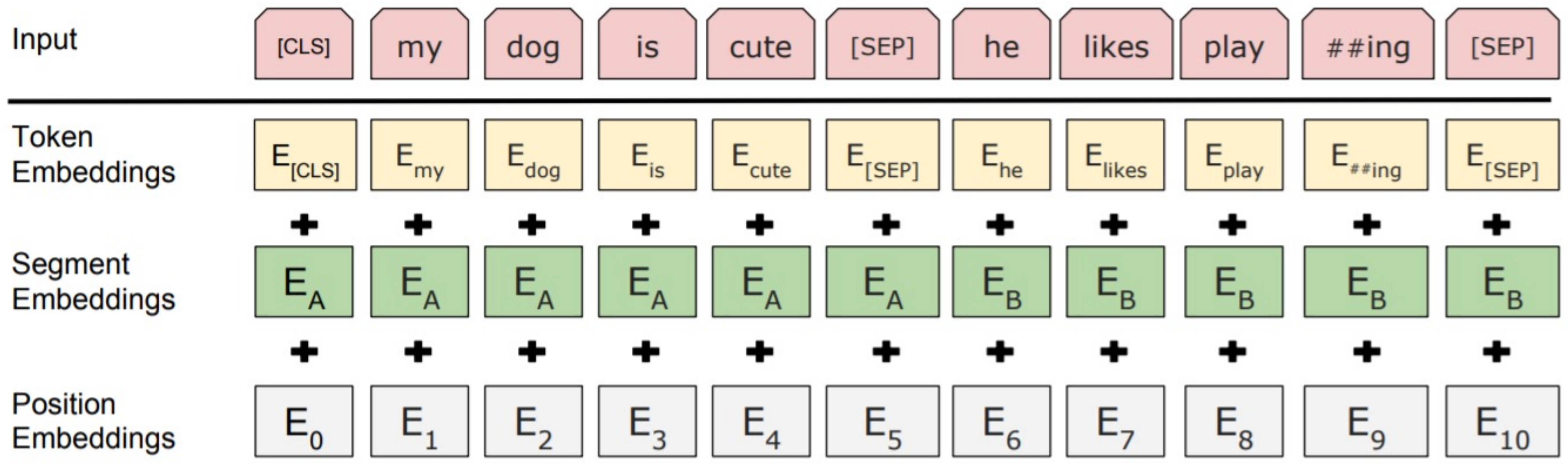
- Predict a random 15% of (sub)word tokens.
  - Replace input word with [MASK] 80% of the time
  - Replace input word with a random token 10% of the time
  - Leave input word unchanged 10% of the time (but still predict it!)
- Why? Doesn’t let the model get complacent and not build strong representations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



[Devlin et al., 2018]

BERT: Bidirectional Encoder Representations from Transformers

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


Input
[CLS]
my
dog
is
cute
[SEP]
he
likes
play
##ing
[SEP]
Token Embeddings
$E_{[CLS]}$ E_{my} E_{dog} E_{is} E_{cute} $E_{[SEP]}$ E_{he} E_{likes} E_{play} $E_{\#\#ing}$ $E_{[SEP]}$
Segment Embeddings
E_A E_A E_A E_A E_A E_A E_B E_B E_B E_B E_B
Position Embeddings
E_0 E_1 E_2 E_3 E_4 E_5 E_6 E_7 E_8 E_9 E_{10}

- 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.

[Devlin et al., 2018, Liu et al., 2019]

BERT: Bidirectional Encoder Representations from Transformers

Details about BERT

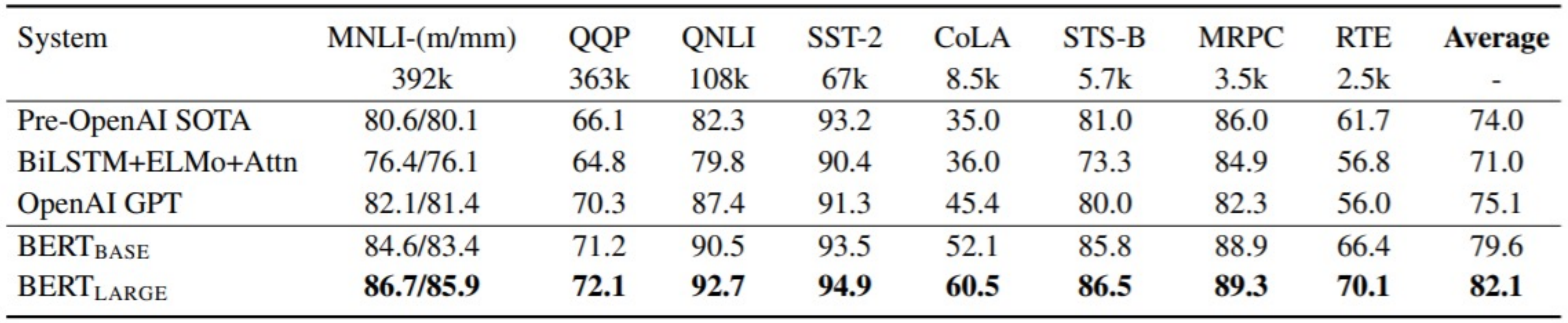
- Two models were released:
  - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
  - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- Trained on:
  - BooksCorpus (800 million words)
  - English Wikipedia (2,500 million words)
- 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.”

[Devlin et al., 2018]

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



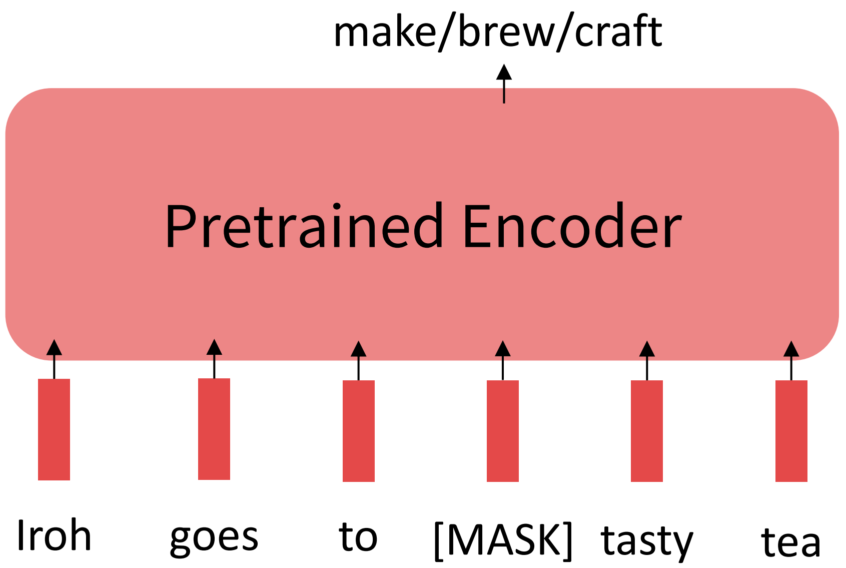
System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1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

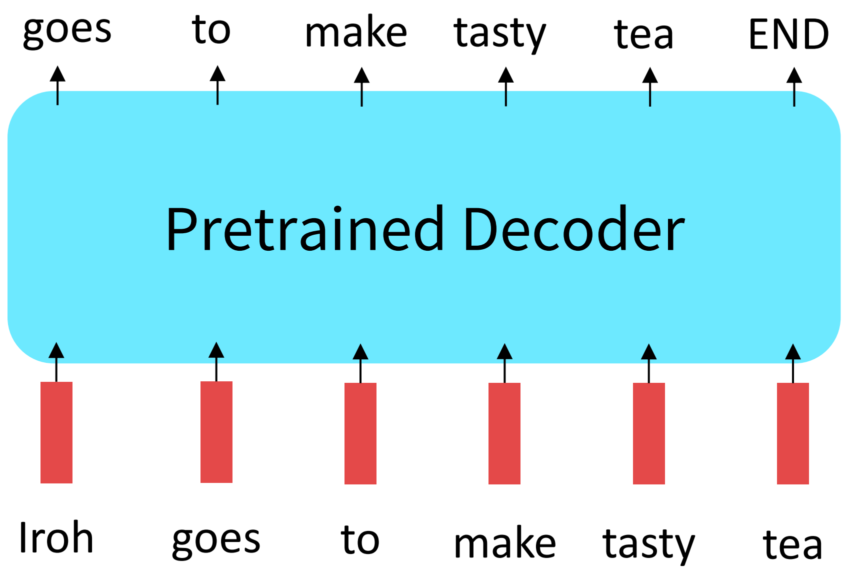
[Devlin et al., 2018]

Limitations of pretrained encoders

Those results looked great! Why not used pretrained encoders for everything?

If your task involves generating sequences, consider using a pretrained decoder; BERT and other pretrained encoders don't naturally lead to nice autoregressive (1-word-at-a-time) generation methods.



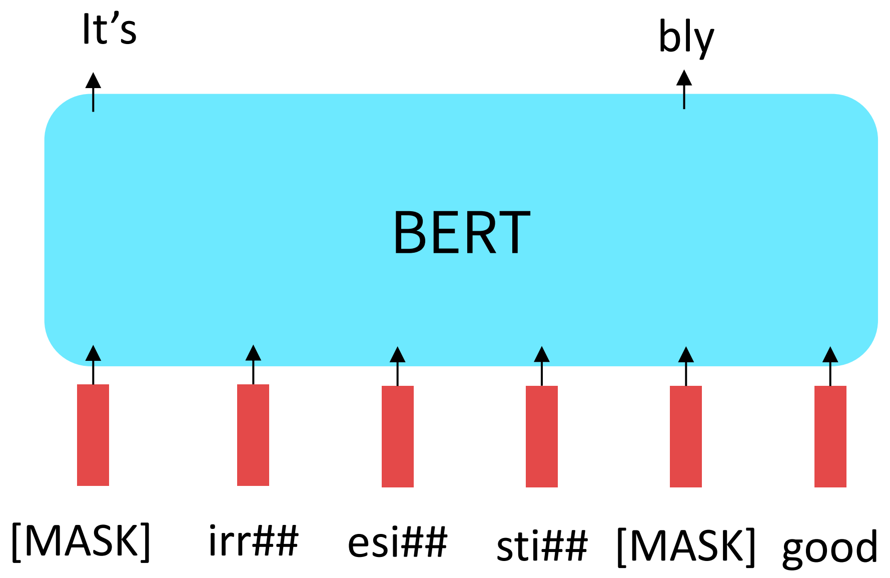


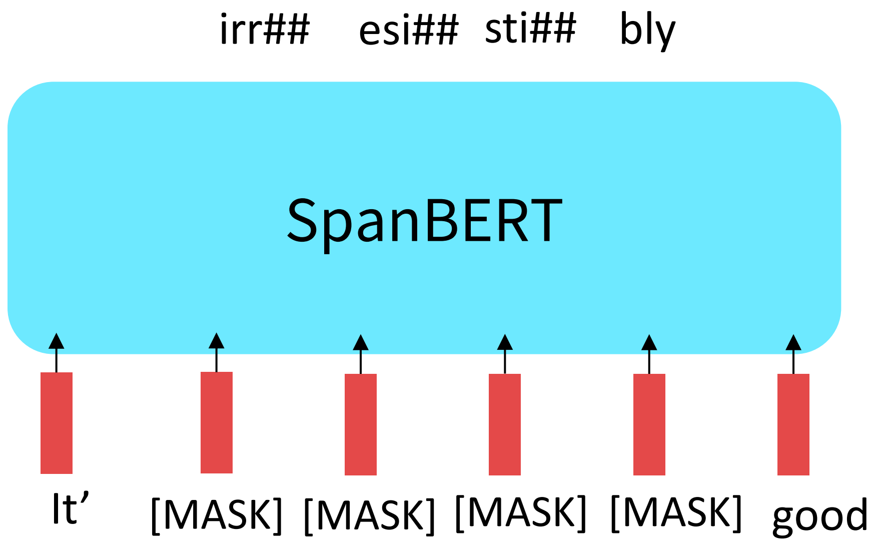
Extensions of BERT

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

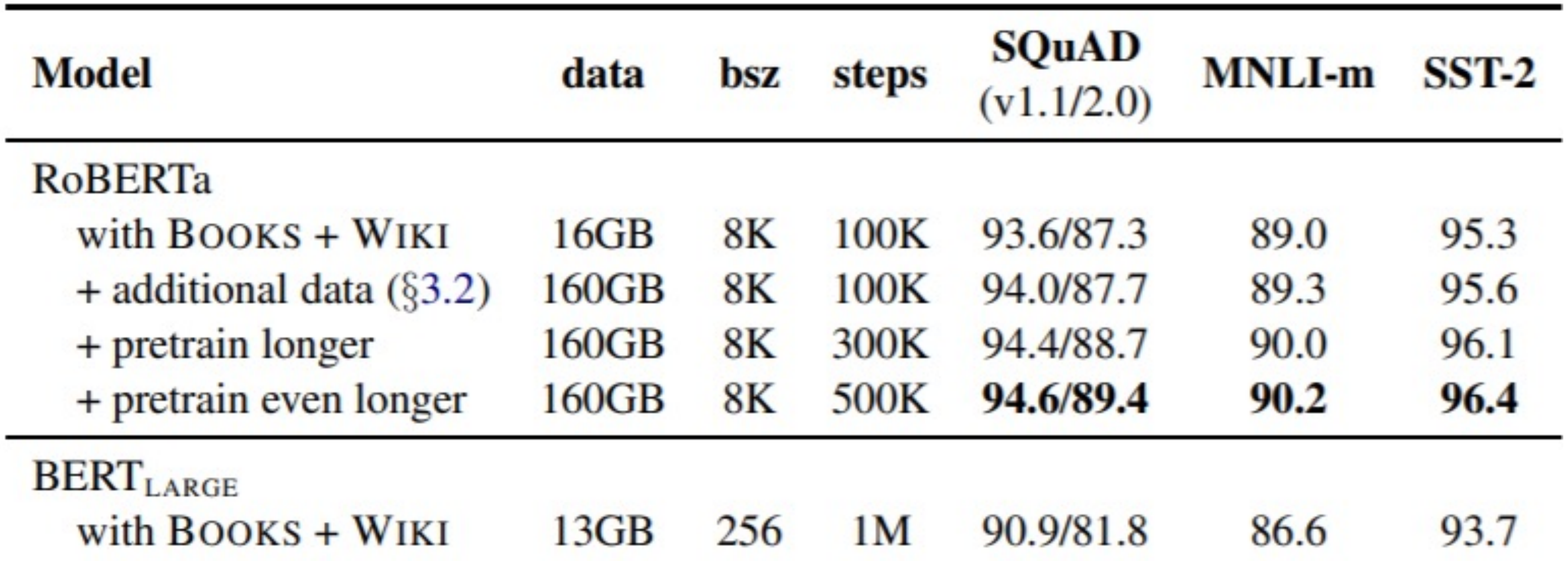




[Liu et al., 2019; Joshi et al., 2020]

Extensions of BERT

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

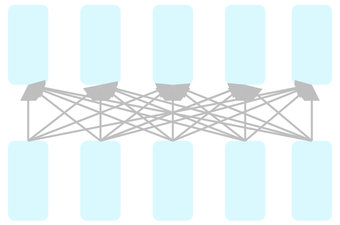


Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7

[Liu et al., 2019; Joshi et al., 2020]

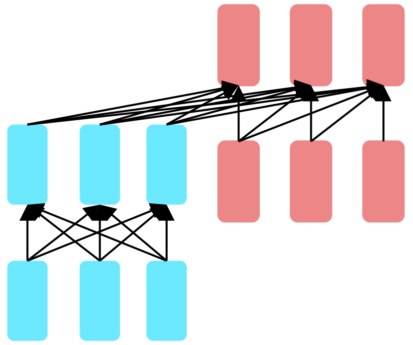
Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



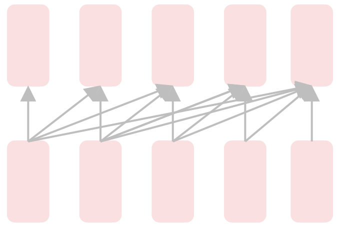
Encoders

- Gets bidirectional context – can condition on future!
- How do we train them to build strong representations?



Encoder-Decoders

- Good parts of decoders and encoders?
- What's the best way to pretrain them?



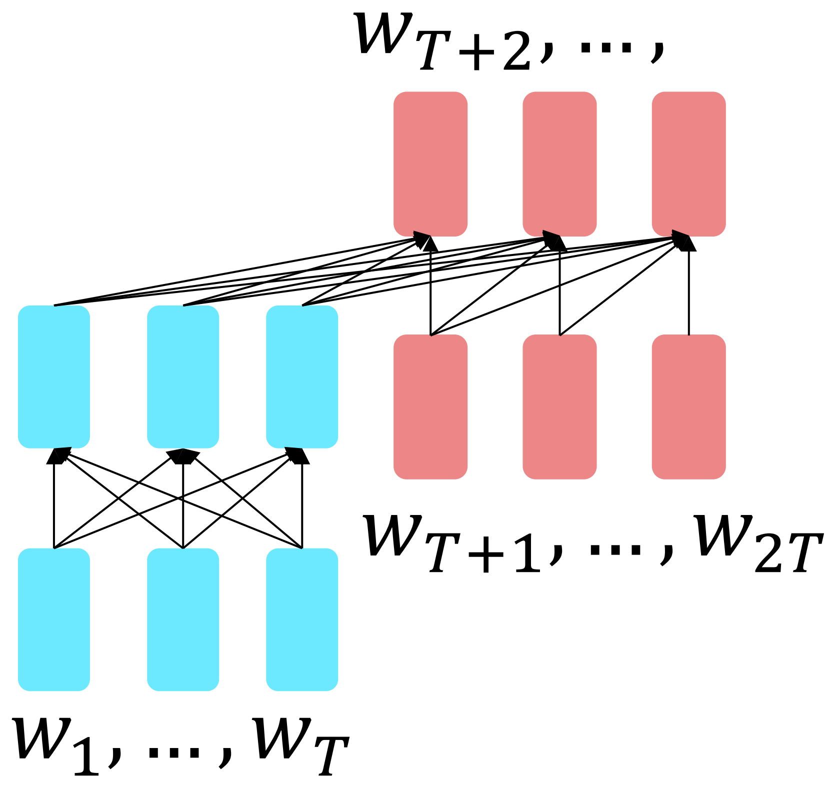
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words

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.

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



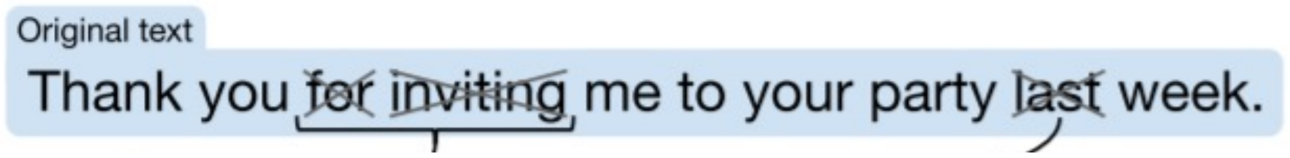
The **encoder** portion benefits from bidirectional context; the **decoder** portion is used to train the whole model through language modeling.

[Raffel et al., 2018]

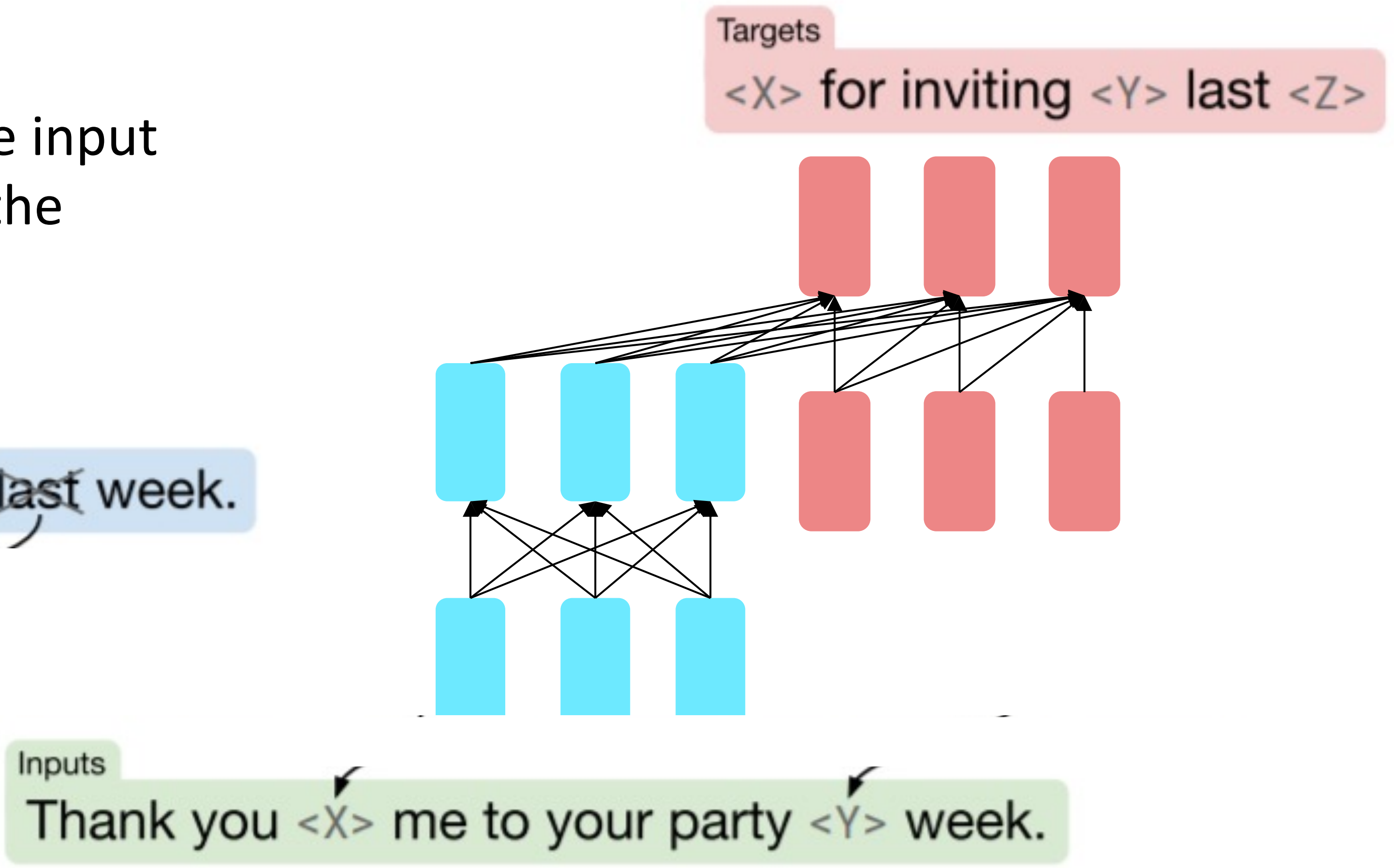
Pretraining encoder-decoders: what pretraining objective to use?

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!



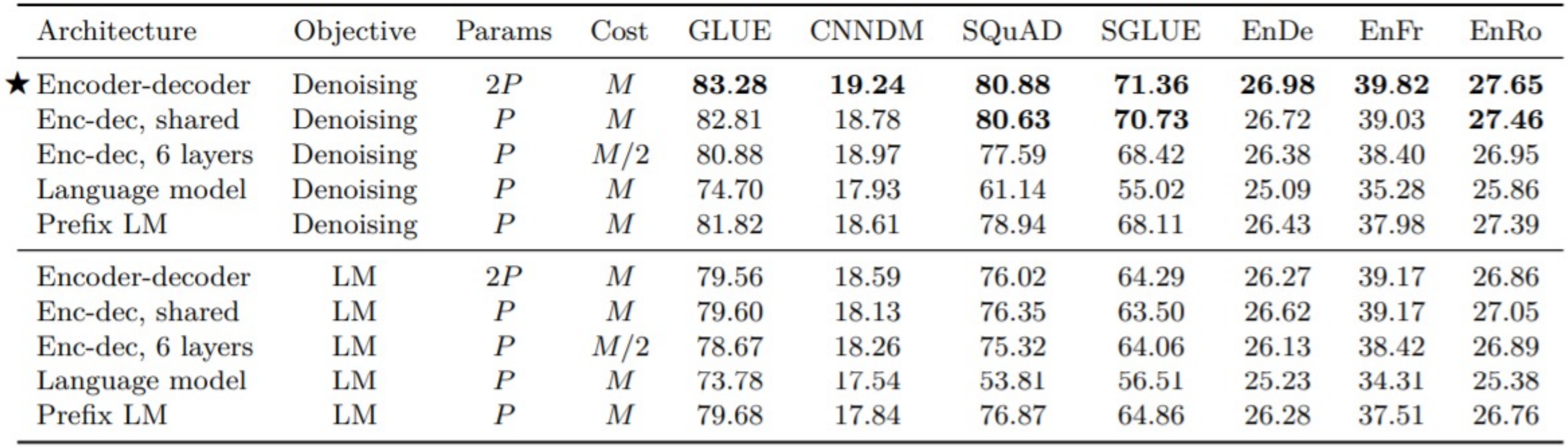
This is implemented in text preprocessing: it's still an objective that looks like **language modeling** at the decoder side.



Targets
<X> for inviting <Y> last <Z>
Inputs
Thank you <X> me to your party <Y> week.

Pretraining encoder-decoders: what pretraining objective to use?

Raffel et al., 2018 found encoder-decoders to work better than decoders for their tasks, and span corruption (denoising) to work better than language modeling.



Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	Denoising	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

Pretraining encoder-decoders: what pretraining objective to use?

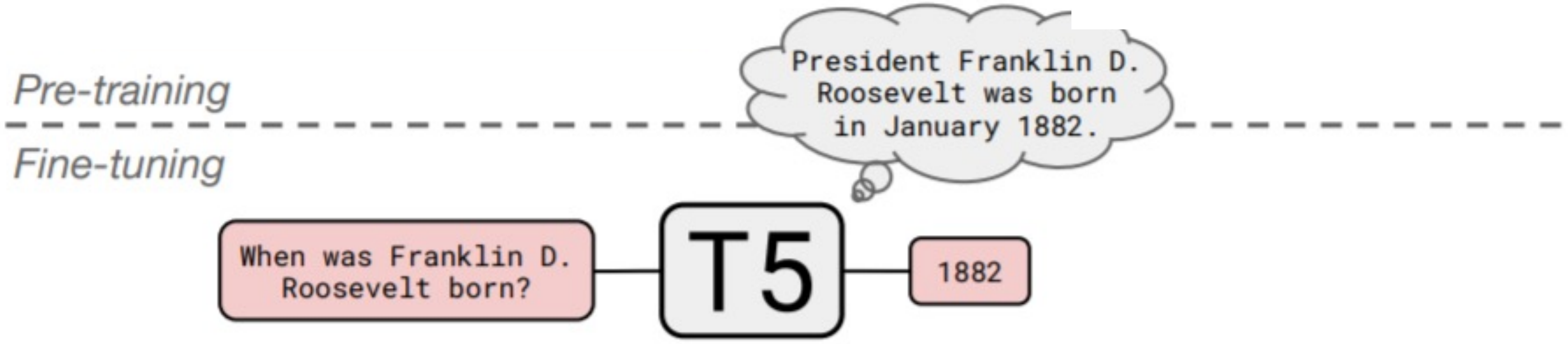
A fascinating property of T5: it can be finetuned to answer a wide range of questions, retrieving knowledge from its parameters.

NQ: Natural Questions

WQ: WebQuestions

TQA: Trivia QA

All "open-domain" versions

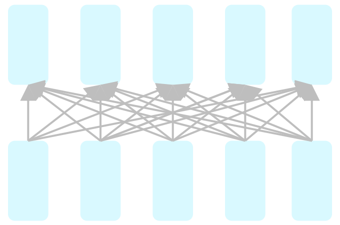

Pre-training
Fine-tuning
President Franklin D. Roosevelt was born in January 1882.
When was Franklin D. Roosevelt born?
T5
1882

	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**	

[Raffel et al., 2018]

Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



Encoders

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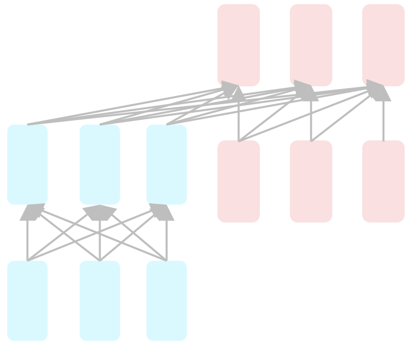

Encoder-Decoders

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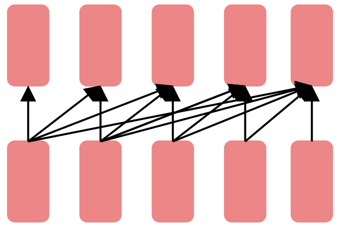


Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words
- All the biggest pretrained models are Decoders.

Pretraining decoders

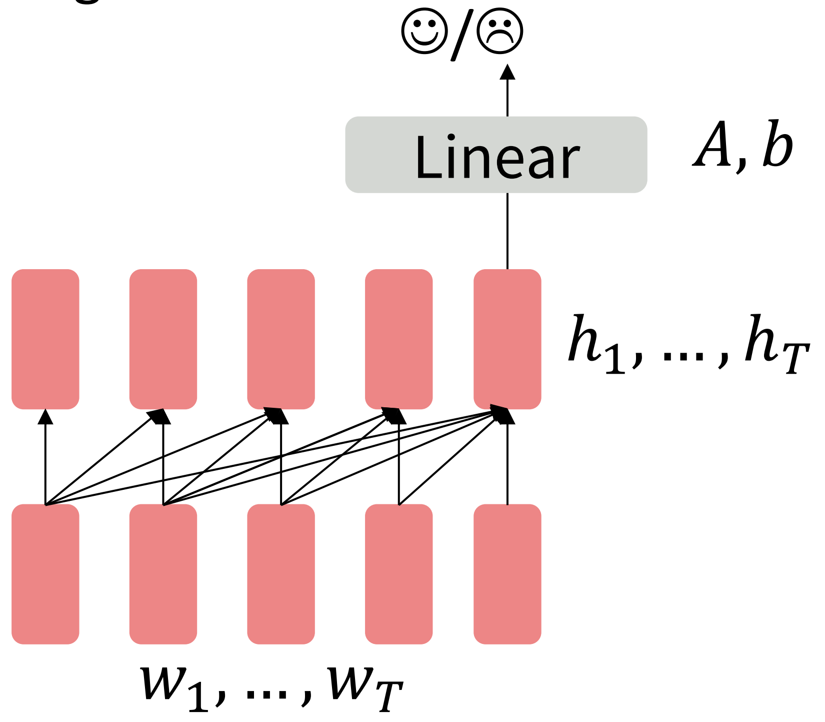
When using language model pretrained decoders, we can ignore that they were trained to model $p(w_t|w_{1:t-1})$.

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

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

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.]

Pretraining decoders

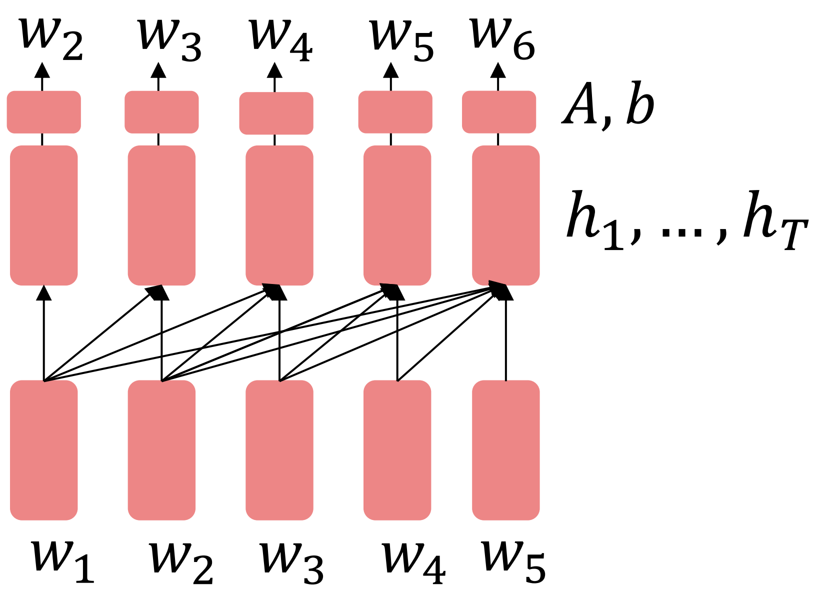
It's natural to pretrain decoders as language models and then use them as generators, finetuning their $p_\theta(w_t|w_{1:t-1})$!

This is helpful in tasks **where the output is a sequence** with a vocabulary like that at pretraining time!

- Dialogue (context=dialogue history)
- Summarization (context=document)

$$h_1, \dots, h_T = \text{Decoder}(w_1, \dots, w_T)$$
$$w_t \sim A h_{t-1} + b$$

Where A, b were pretrained in the language model!



[Note how the linear layer has been pretrained.]

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"

[Devlin et al., 2018]

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*

$$\left.\begin{array}{l}\text{Premise: } \textit{The man is in the doorway}\\ \text{Hypothesis: } \textit{The person is near the door}\end{array}\right\}\ \textbf{entailment}$$

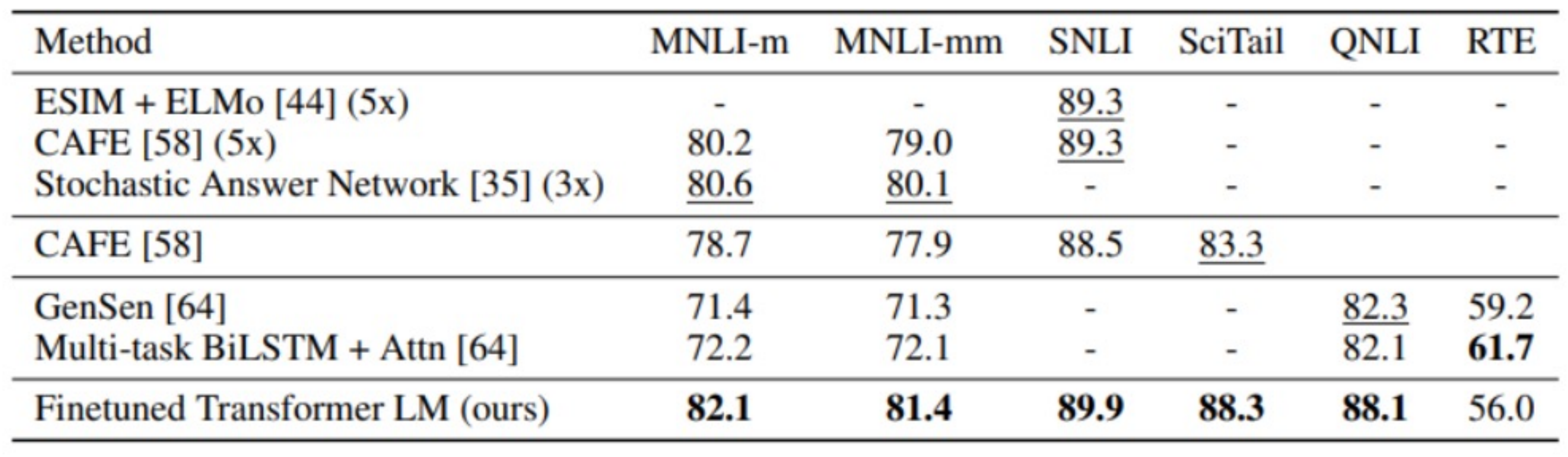
Radford et al., 2018 evaluate on natural language inference.
Here’s roughly how the input was formatted, as a sequence of tokens for the decoder.

[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.

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

GPT results on various *natural language inference* datasets.

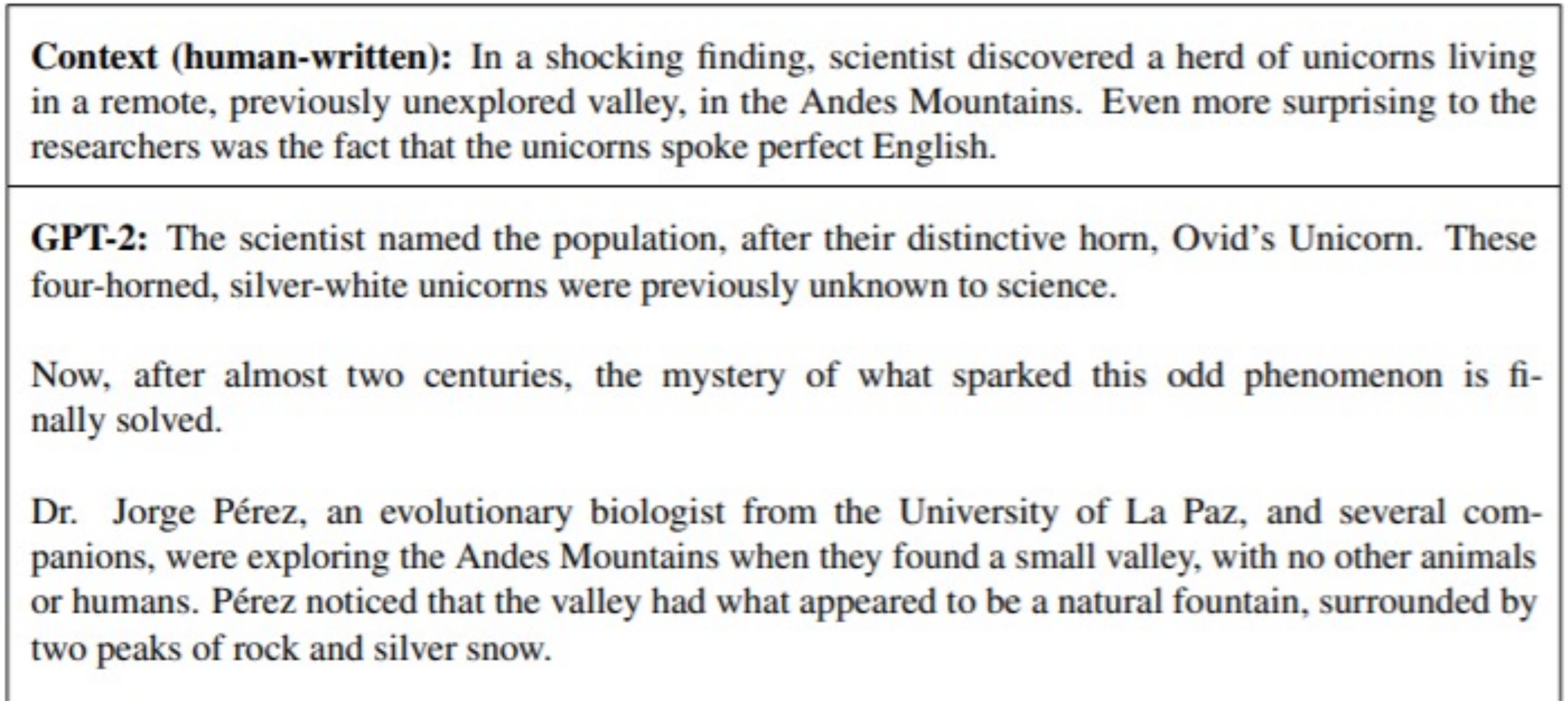


Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	89.3	-	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	80.1	-	-	-	-
CAFE [58]	78.7	77.9	88.5	83.3		
GenSen [64]	71.4	71.3	-	-	82.3	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-	-	82.1	**61.7**
Finetuned Transformer LM (ours)	**82.1**	**81.4**	**89.9**	**88.3**	**88.1**	56.0

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.



Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

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

So far, we've interacted with pretrained models in two ways:

- Sample from the distributions they define (maybe providing a prompt)
- Fine-tune them on a task we care about, and take their predictions.

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

GPT-3 is the canonical example of this. The largest T5 model had 11 billion parameters.

GPT-3 has 175 billion parameters.

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.

The in-context examples seem to specify the task to be performed, and the conditional distribution mocks performing the task to a certain extent.

Input (prefix within a single Transformer decoder context):

“ thanks -> merci

hello -> bonjour

mint -> menthe

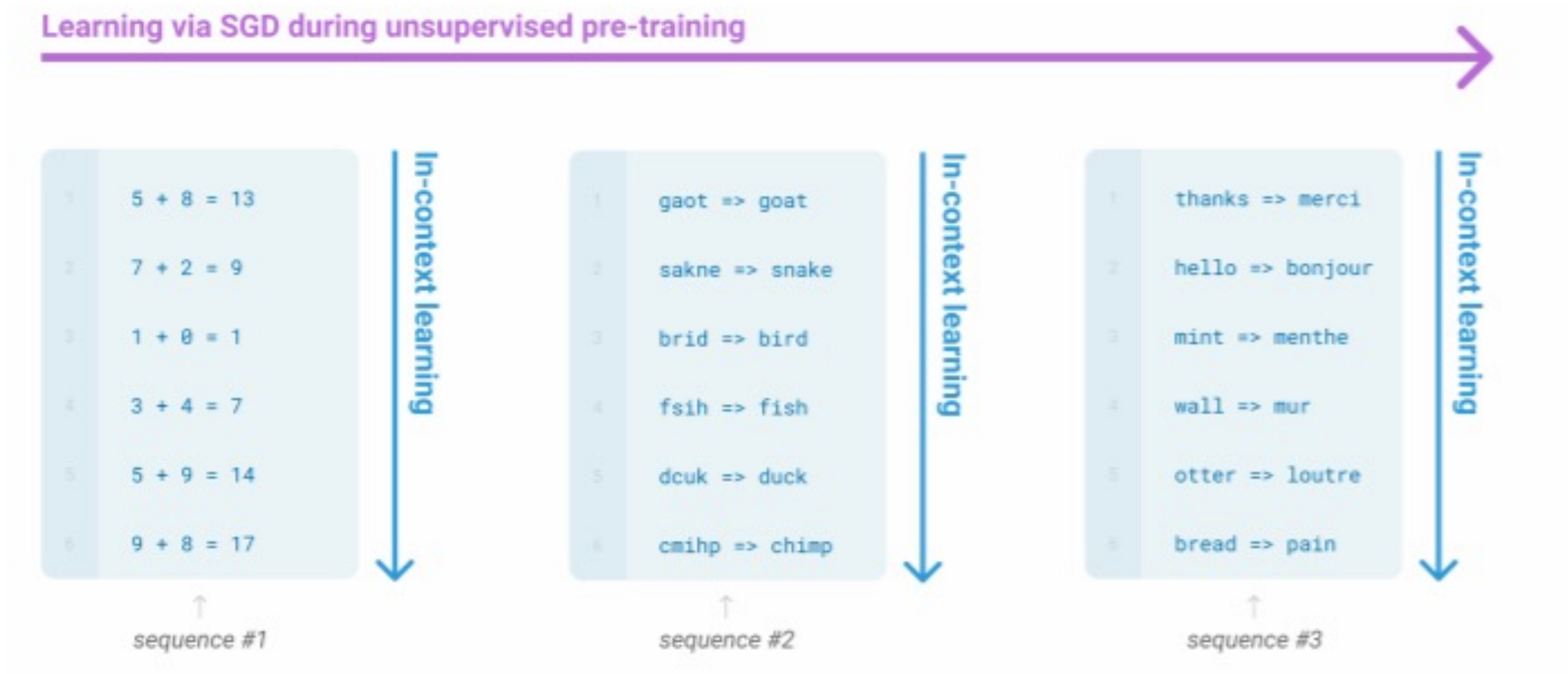
otter -> ”

Output (conditional generations):

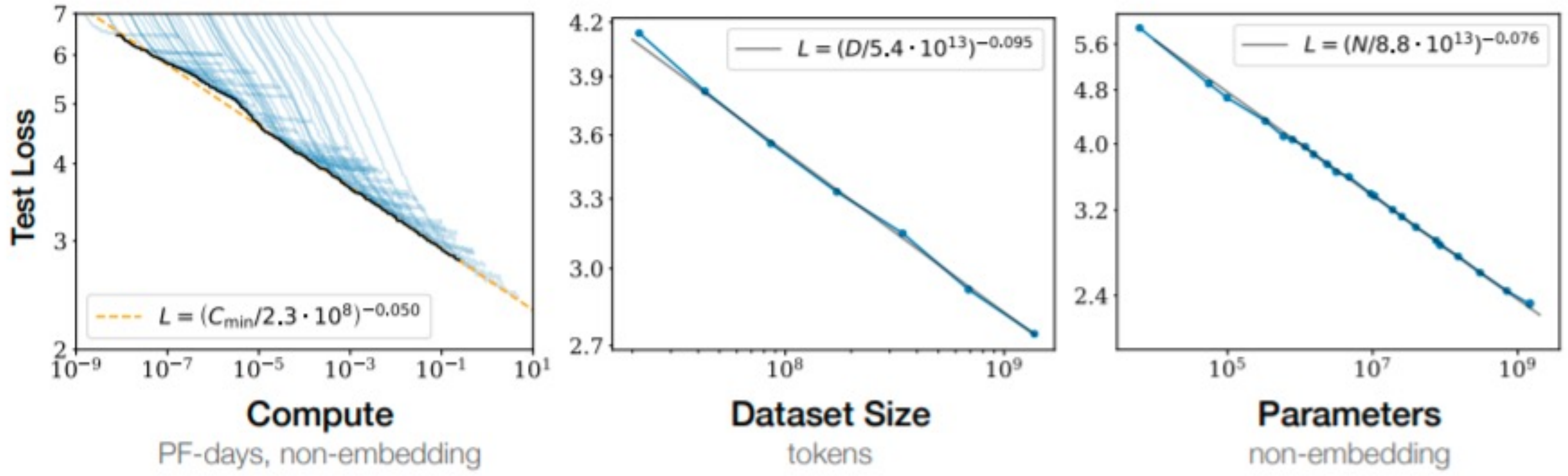
loutre…”

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.

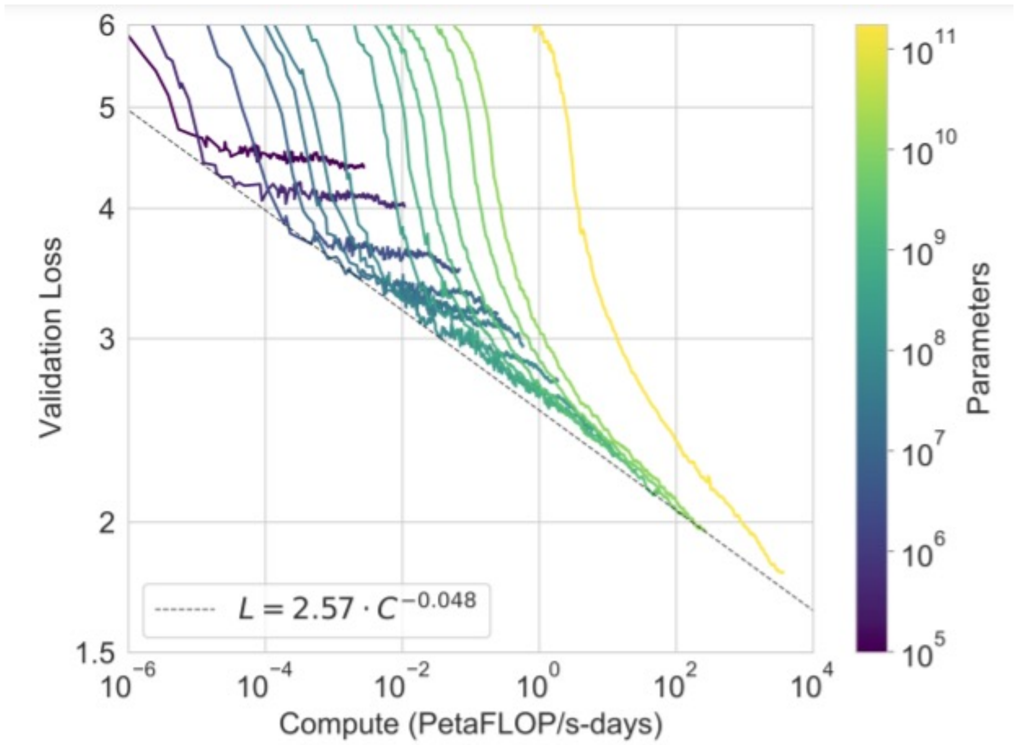


Why scale? Scaling laws



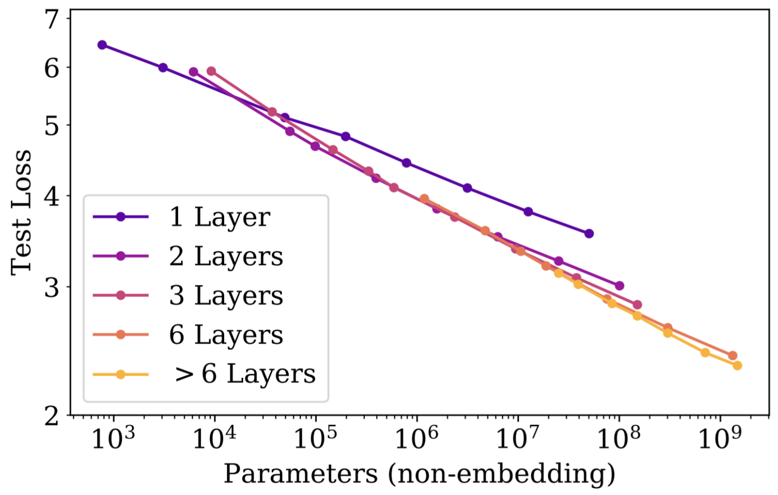
- Empirical observation: scaling up models leads to reliable gains in perplexity

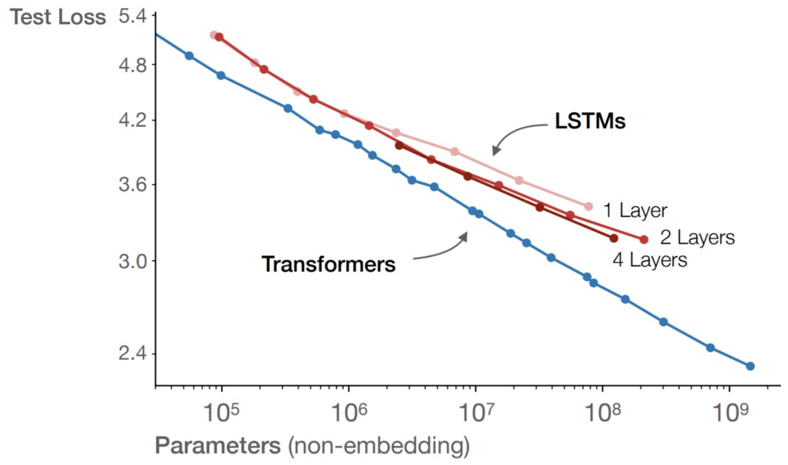
Scaling can help identify model size – data tradeoffs

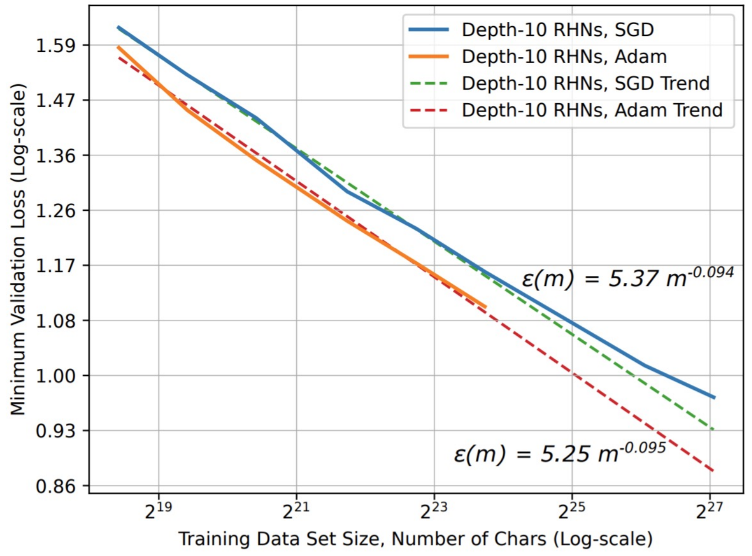


- Modern observation: train a big model that’s not fully converged.

Scaling laws for many other interesting architecture decisions







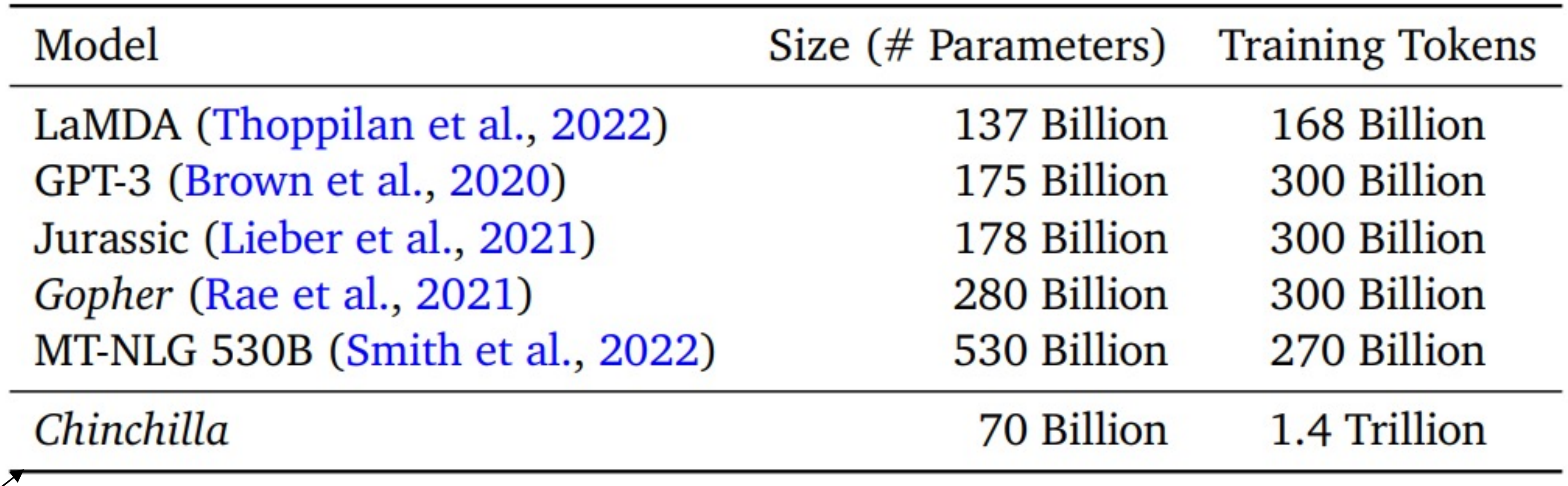
- Predictable scaling helps us make intelligent decisions about architectures etc.

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!

Outline

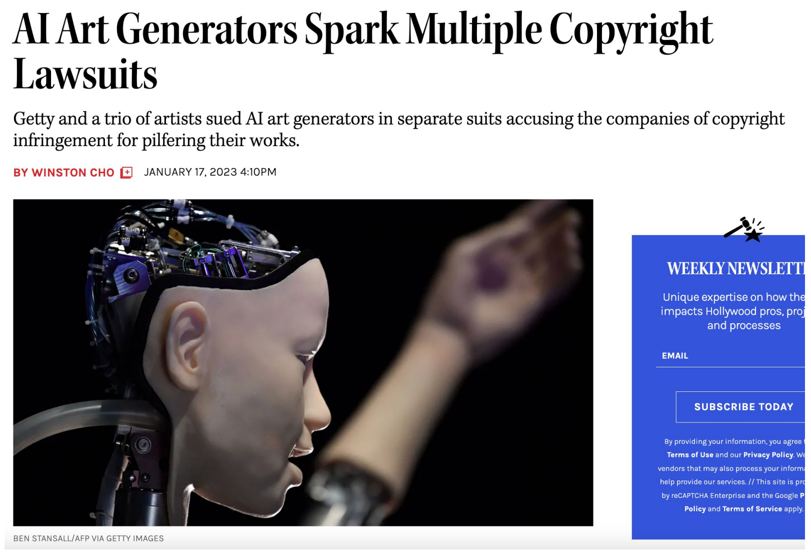
1. A brief note on subword modeling
2. Motivating model pretraining from word embeddings
3. Model pretraining three ways
    1. Encoders
    2. Encoder-Decoders
    3. Decoders
4. What do we think pretraining is teaching?

What kinds of things does pretraining teach?

There’s increasing evidence that pretrained models learn a wide variety of things about the statistical properties of language. Taking our examples from the start of class:

- *Stanford University is located in ___________, California.* [Trivia]
- *I put ___ fork down on the table.* [syntax]
- *The woman walked across the street, checking for traffic over ___ shoulder.* [coreference]
- *I went to the ocean to see the fish, turtles, seals, and _____.* [lexical semantics/topic]
- *Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was ___.* [sentiment]
- Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the ______. [some reasoning – this is harder]
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, ____ [some basic arithmetic; they don’t learn the Fibonnaci sequence]
- Models also learn – and can exacerbate racism, sexism, all manner of bad biases.

Sometimes it also memorizes copyrighted material



AI Art Generators Spark Multiple Copyright Lawsuits

Getty and a trio of artists sued AI art generators in separate suits accusing the companies of copyright infringement for pilfering their works.

BY WINSTON CHO JANUARY 17, 2023 4:10PM

BEN STANSALL/AFP VIA GETTY IMAGES

WEEKLY NEWSLETT

Unique expertise on how the impacts Hollywood pros, proj and processes

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ARTICLE

Insights from the Pending Copilot Class Action Lawsuit

October 4, 2023

Bloomberg Law

By Daniel R. Mello, Jr.; Jenevieve J. Maerker; Matthew C. Berntsen; Ming-Tao Yang

GitHub Inc. offers a cloud-based platform that is popular among many software programmers for hosting and sharing source code, and collaborating on source code drafting. GitHub's artificial

Anthropic fires back at music publishers' AI copyright lawsuit

By Blake Brittain

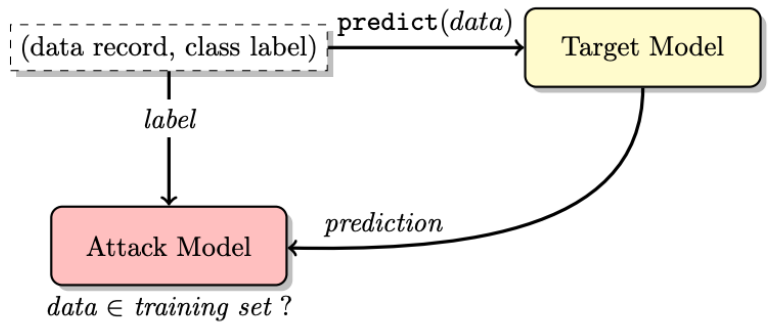
January 17, 2024 3:30 PM PST · Updated 19 days ago

The Times Sues OpenAI and Microsoft Over A.I. Use of Copyrighted Work

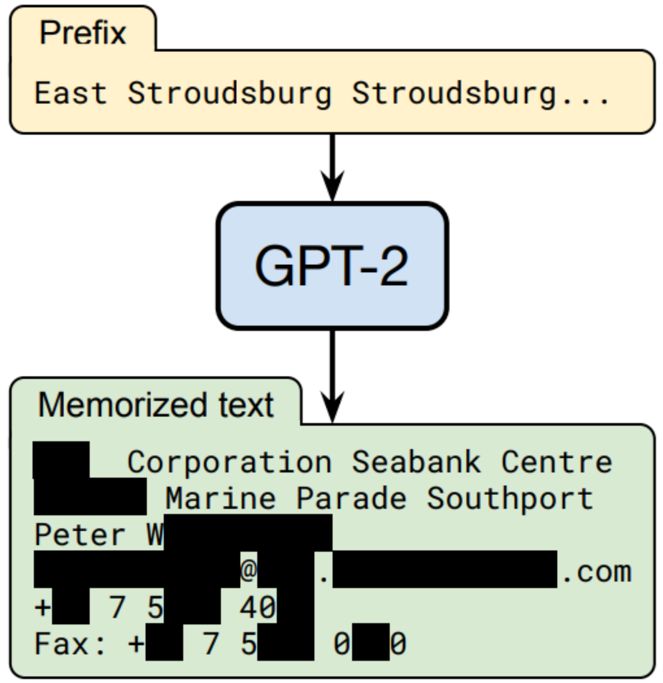
Millions of articles from The New York Times were used to train chatbots that now compete with it, the lawsuit said.

Sometimes it learns some things we don't want..

- *Membership inference* lets you recover parts of the training data



- Sometimes this training data is semi-private material from the web (addresses, emails)


Prefix
East Stroudsburg Stroudsburg...
GPT-2
Memorized text
[redacted] Corporation Seabank Centre
[redacted] Marine Parade Southport
Peter W[redacted]
[redacted]@[redacted].[redacted].com
+[redacted] 7 5[redacted] 40[redacted]
Fax: +[redacted] 7 5[redacted] 0[redacted]0