Natural Language Processing with Deep Learning

CS224N/Ling284

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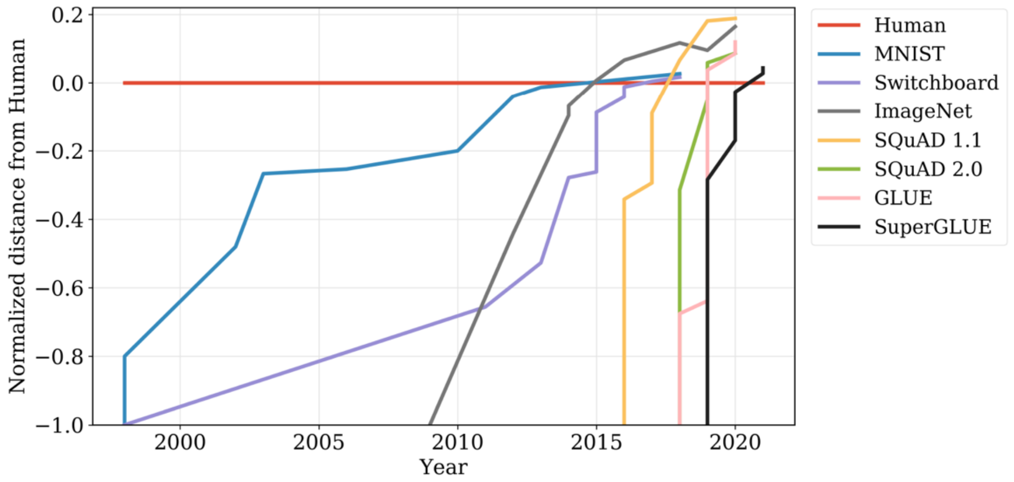
Lecture 9: Pretraining

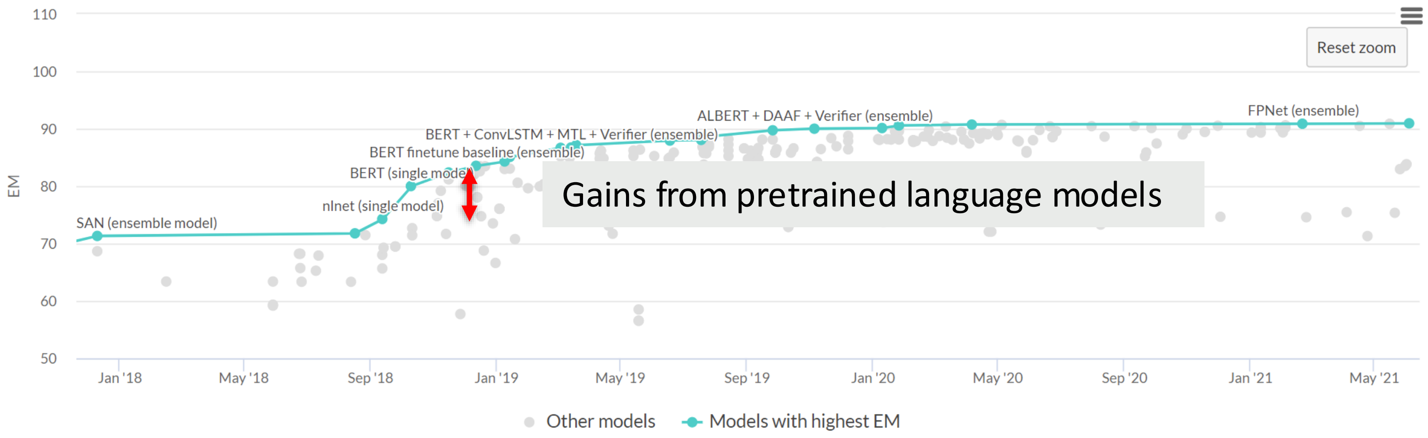
Lecture Plan

1. Pretraining - motivation
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

Note: mid-course feedback form is out!

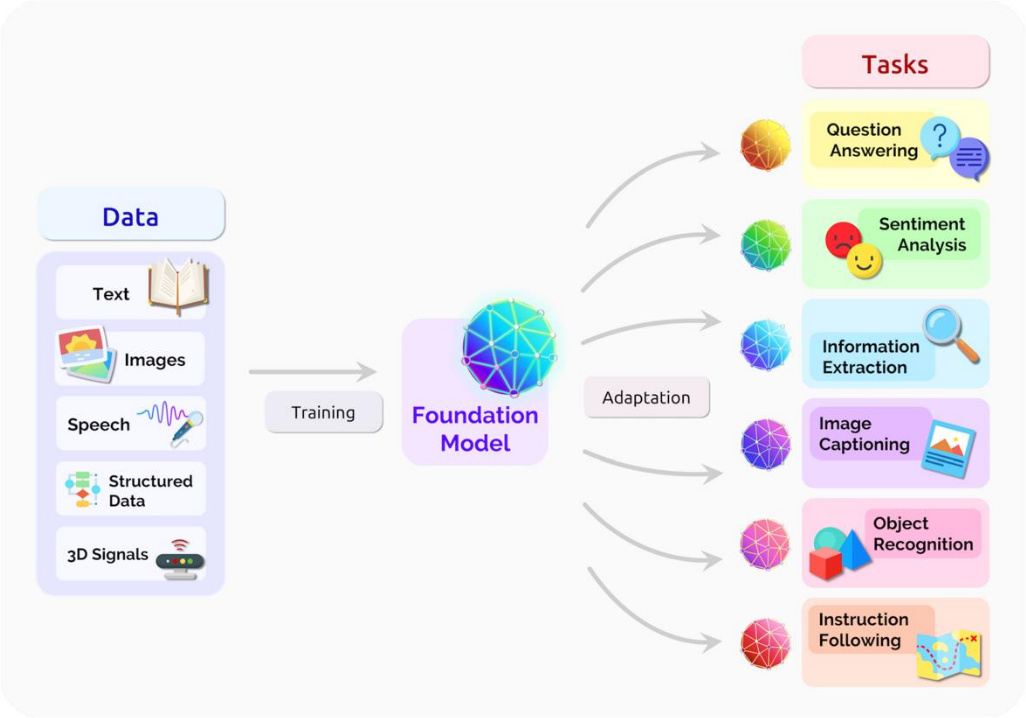
The pretraining revolution





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##	
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Outline

1. A brief note on subword modeling
2. Motivating model pretraining from word embeddings
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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.]

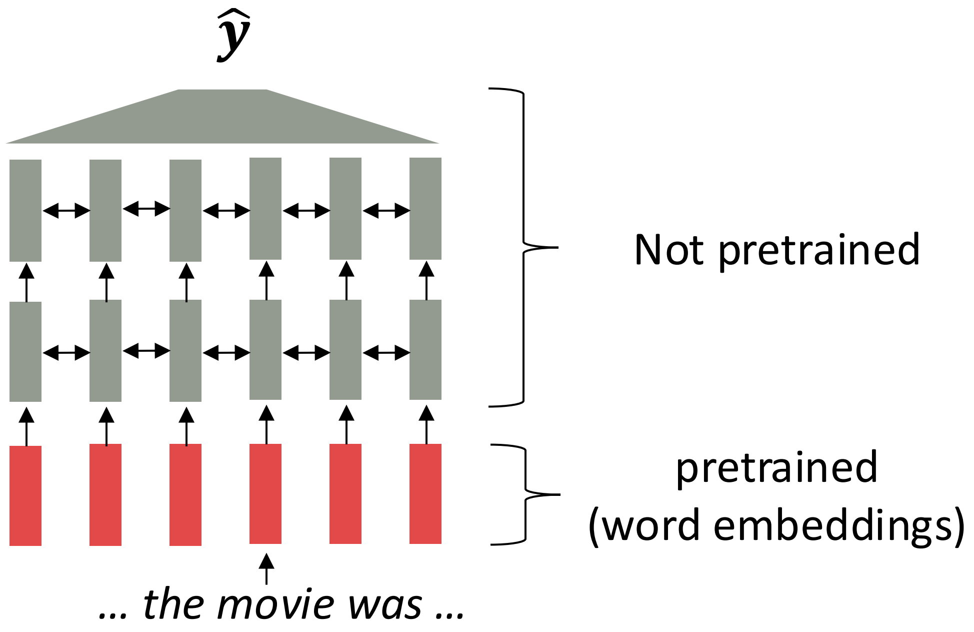
Where we were: **pretrained word embeddings**

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!



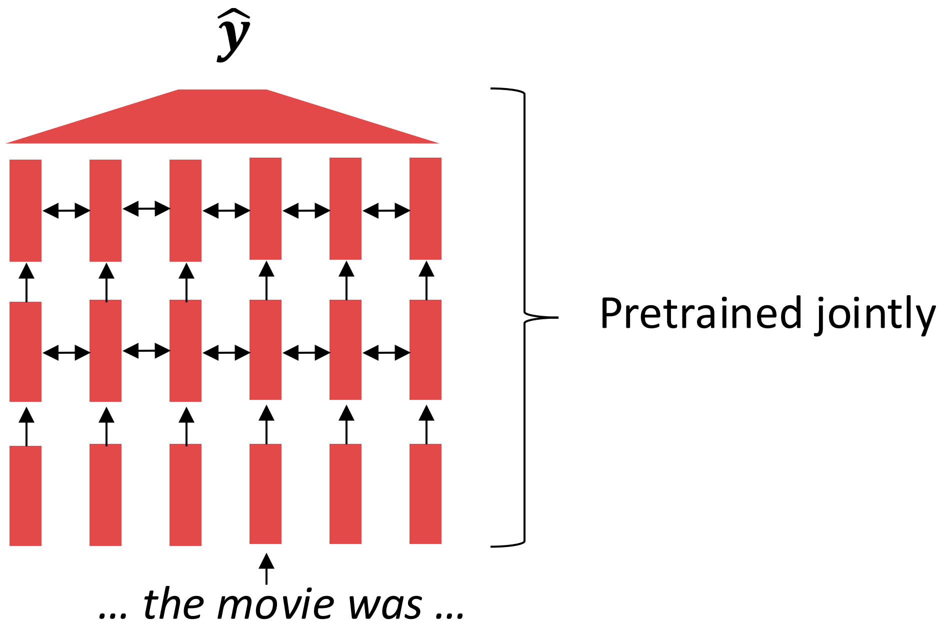
[Recall, *movie* gets the same word embedding, no matter what sentence it shows up in]

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, ____

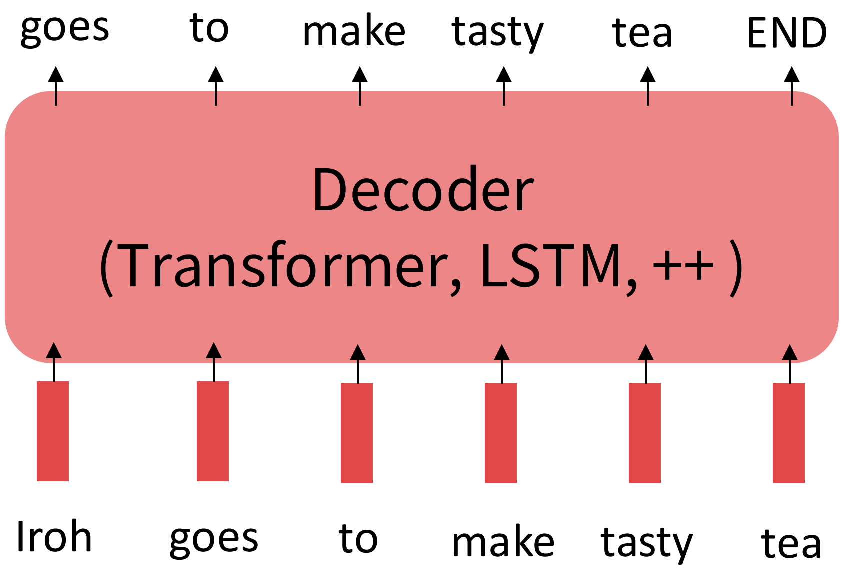
Pretraining through language modeling [Dai and Le, 2015]

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.

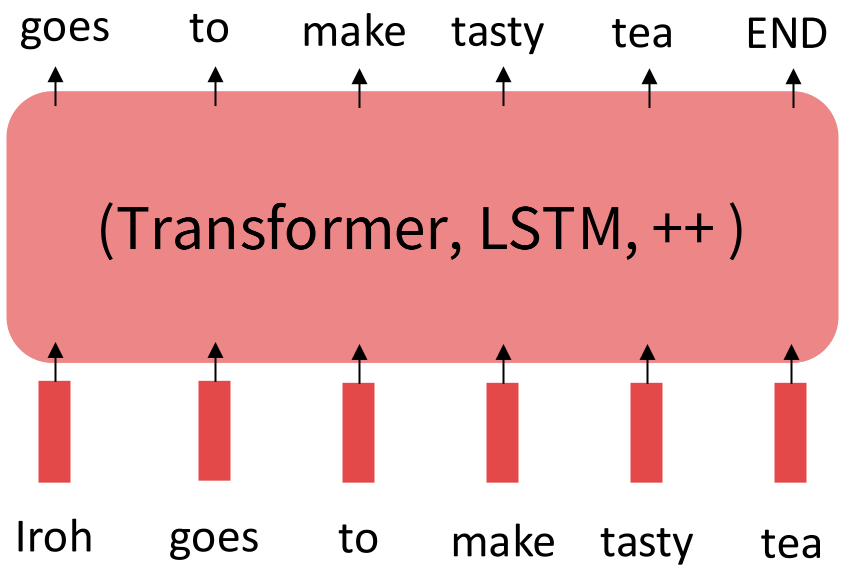


The Pretraining / Finetuning Paradigm

Pretraining can improve NLP applications by serving as parameter initialization.

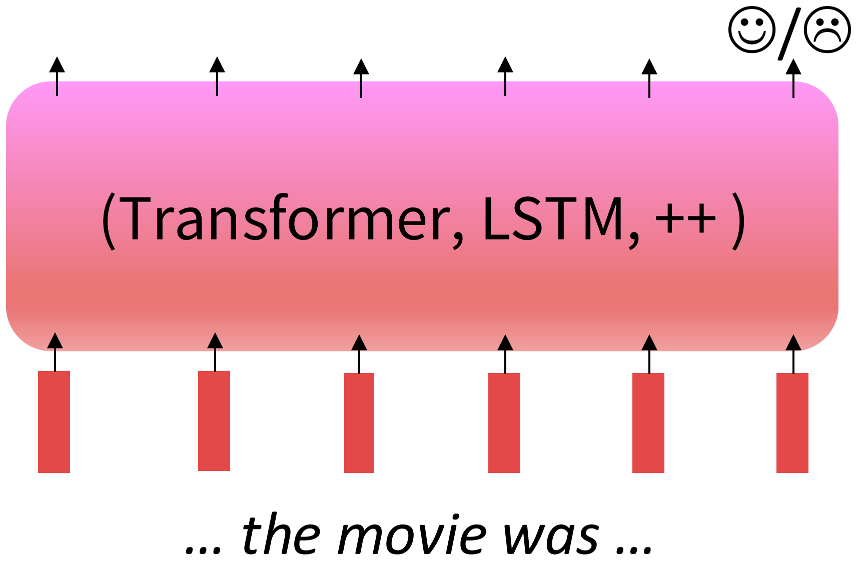
Step 1: Pretrain (on language modeling)

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!

Why unsupervised learning? Why not QA?

- Orders of magnitude difference in data size – there is a lot of high-quality text

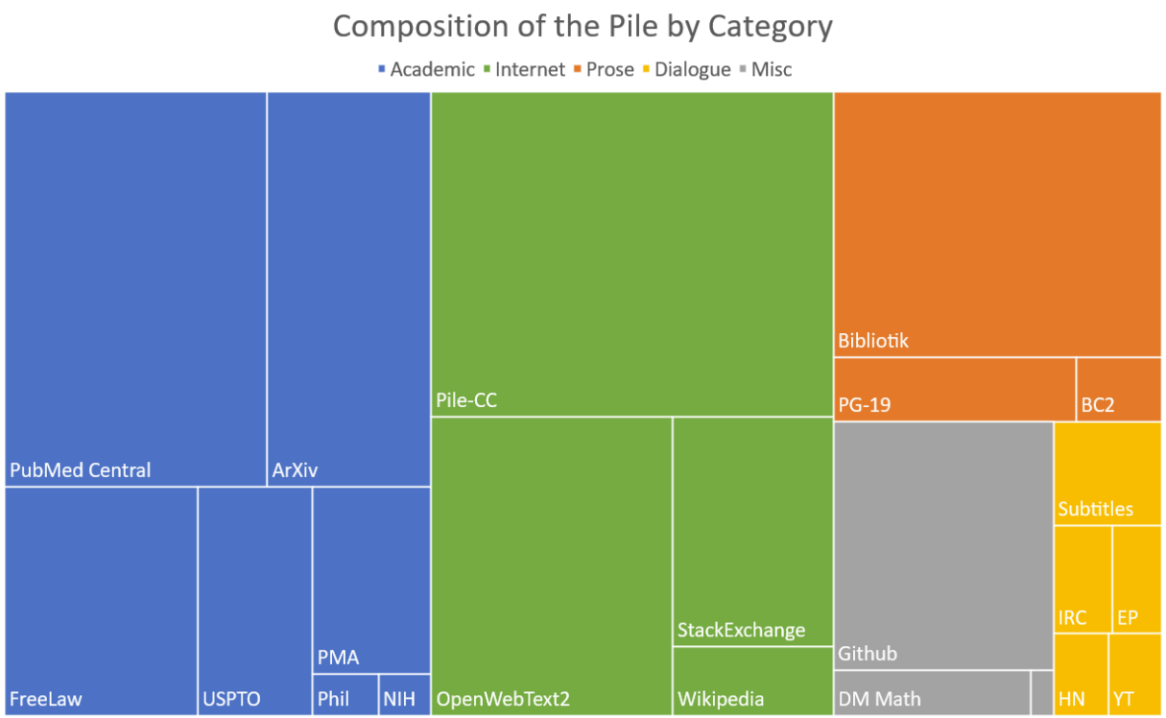
Dataset	Tokens (~0.75 words)
SQuAD 2.0 [Rajpukar+ 2018]	< 50 Million
DCLM-pool [Li+ 2024]	240 Trillion
Estimated 'internet text' [Villalobos 2024]	510T (indexed), 3100T (total)

A *10 million* times gap in QA to indexed internet

With this much data, we might make progress on even the hardest fill-in-the-blank tasks

Pretraining can be massively diverse

- It's not just about the quantity, but also the incredible *diversity* of internet text data



[Gao+ 20]

Source	Doc Type	UTF-8 bytes *(GB)*	Documents *(millions)*	Unicode words *(billions)*	Llama tokens *(billions)*
Common Crawl	web pages	9,812	3,734	1,928	2,479
GitHub	code	1,043	210	260	411
Reddit	social media	339	377	72	89
Semantic Scholar	papers	268	38.8	50	70
Project Gutenberg	books	20.4	0.056	4.0	6.0
Wikipedia, Wikibooks	encyclopedic	16.2	6.2	3.7	4.3
Total		**11,519**	**4,367**	**2,318**	**3,059**

[Soldani+ 24]

This gives us some weak coverage over an enormous range of downstream tasks

Pretraining data samples 1 [DCLM]

- Bizarro Wonder Woman is a bizarro version of Wonder Woman.\n\nWhen Bizarro III found himself infused with radiation from a blue sun, he developed the ability to replicate himself as well as create other \"Bizarro\" lifeforms based upon likenesses of people from Earth. He used this power to populate a cube-shaped planetoid dubbed Bizarro World within the blue sun star system. One of the many duplicates that he created was a Bizarro version of Wonder Woman. Bizarro Wonder Woman, working alongside her Bizarro confederates Batman, Flash, Green Lantern and Hawkgirl, sought to save Bizarro from Bizarro Doomsday by dropping their hyperbolic headquarters on top of him.\n\nAs opposed to her counterpart, Bizarro Wonder Woman uses a lasso that causes those ensnared to tell lies.\ …

https://dc.fandom.com/wiki/Bizarro_Wonder_Woman_(New_Earth)

- Book Title Poetry: April 26,\u00a02012\n\n\nCan't recall where I first saw this but I'll admit it isn't my own original idea. I think it was a link on Twitter or something, which I found whilst poking around. Of course I can't find it again.\n\nBasically, the idea is you grab a few books from a shelf or shelves, stack them up and make a poem from the titles. A simple idea and it can strike gold or come off sounding like a third-grader's attempt at a poetry homework assignment (no offense to third graders).\n\nThe annoying rule is you have to keep the books in the same order you pulled them from the shelves.\n\nLet's try!\n\n\n\n\nKipling's Kim\n\nRobert Levine's Free Ride\n\n […]

https://bluestalkingjournal.com/2012/04/26/book-title-poetry-april-26-2012/

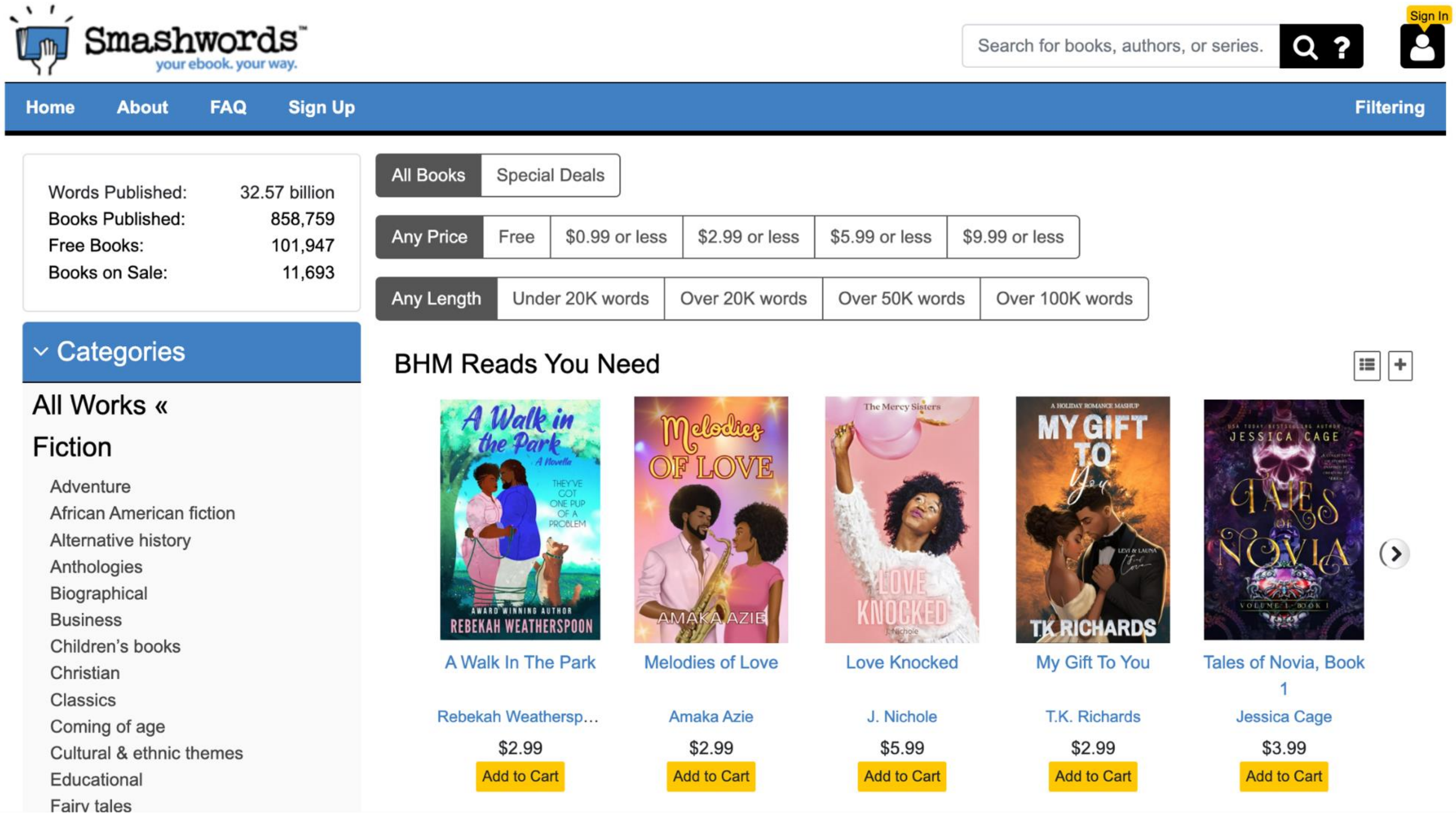
- Hibernate Interview Questions and Answers\n\nHibernate Interview Questions and Answers\n\nHibernate is an open source simple ORM tool. It is a java framework that simplifies the development of java application to interact with the database. Hibernate not only takes care of the mapping from Java classes to database, but also provides data query and retrieval facilities.\n\nWhat is hibernate?\n\nWhat is ORM?\n\nWhat is Hibernate Framework?\n\nWhat is Java Persistence API (JPA)?\n\nWhat are the important benefits of using Hibernate Framework?\n\nWhat are the advantages of Hibernate over JDBC?\n\nWhat is hibernate configuration file?\n\nWhat is hibernate mapping file?\n\ […]

https://www.interviewgig.com/hibernate-interview-questions-and-answers/

- Artificial Intelligence \u2013 should we be worried?\n\nThere\u2019s a lot in the media at the moment concerning Artificial Intelligence, some hailing it as the next industrial revolution, others as Armageddon waiting to happen.\u00a0 I know science fiction over the years has been full of the latter.\u00a0 However, as any writer will tell you a good story needs conflict and in sci-fi what\u2019s better than man vs. machine?.\u00a0 I also know that Stephen Hawking is suggesting we, or at least some of us, need to get of this planet before the end of the century and find a new home before AI becomes too powerful.\u00a0 I just don\u2019t see why it has to be that way.\u00a0 Why does it have to be the alarmist view?\u00a0[…]

https://www.martynfiction.com/life-in-the-future/artificial-intelligence-worried/?replytocom=1403

Bookcorpus.. what's that?



- 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

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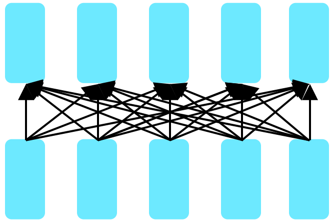
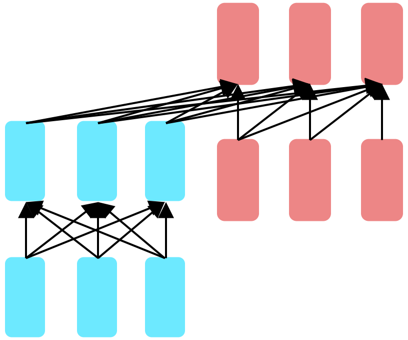
Pretraining for three types of architectures

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



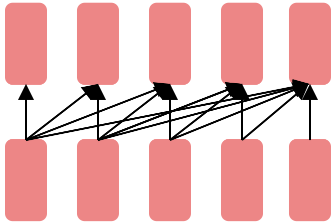
Encoders

- 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

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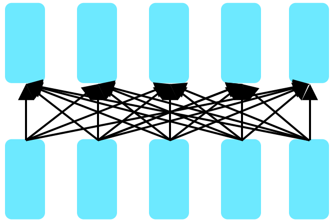

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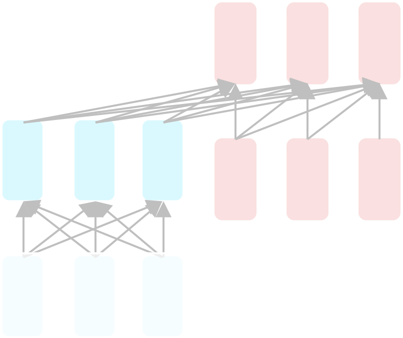

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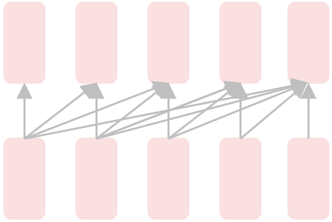

Decoders

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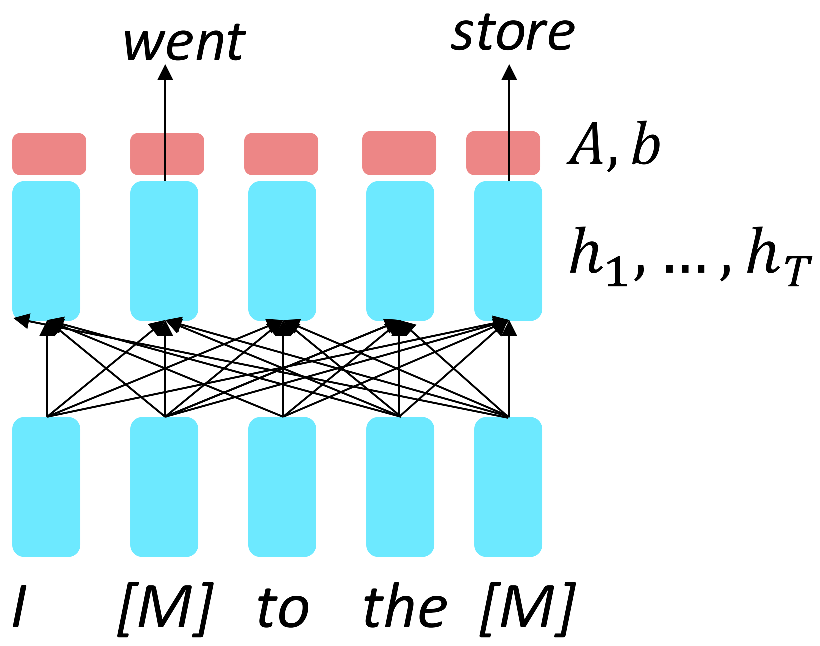
Pretraining encoders: what pretraining objective to use?

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.**



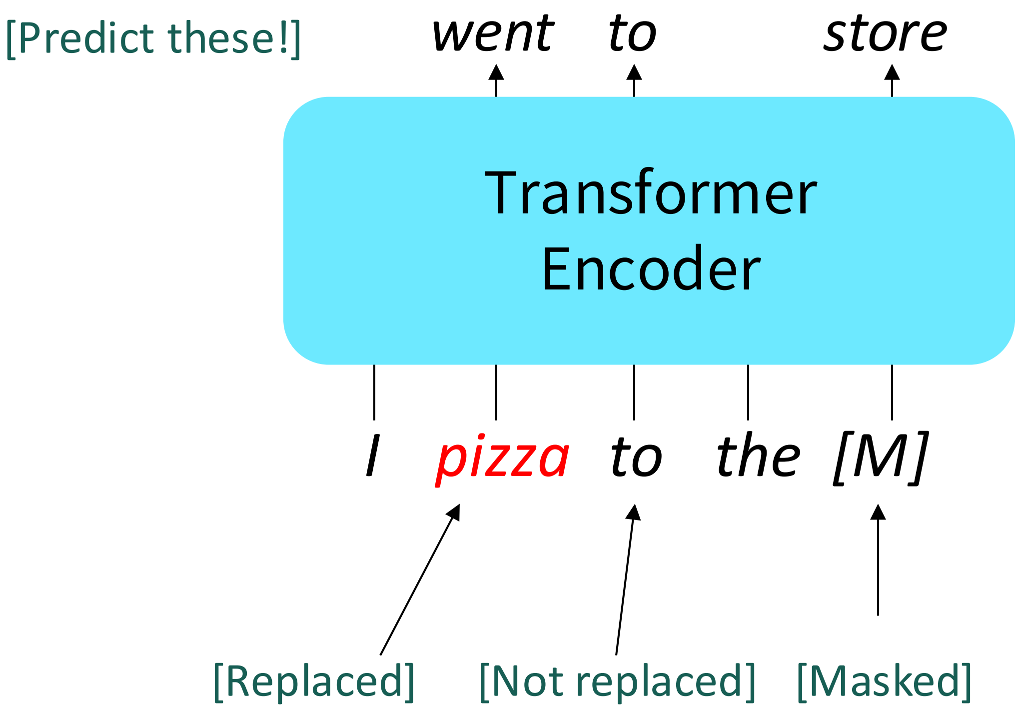
[Devlin et al., 2018]

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:

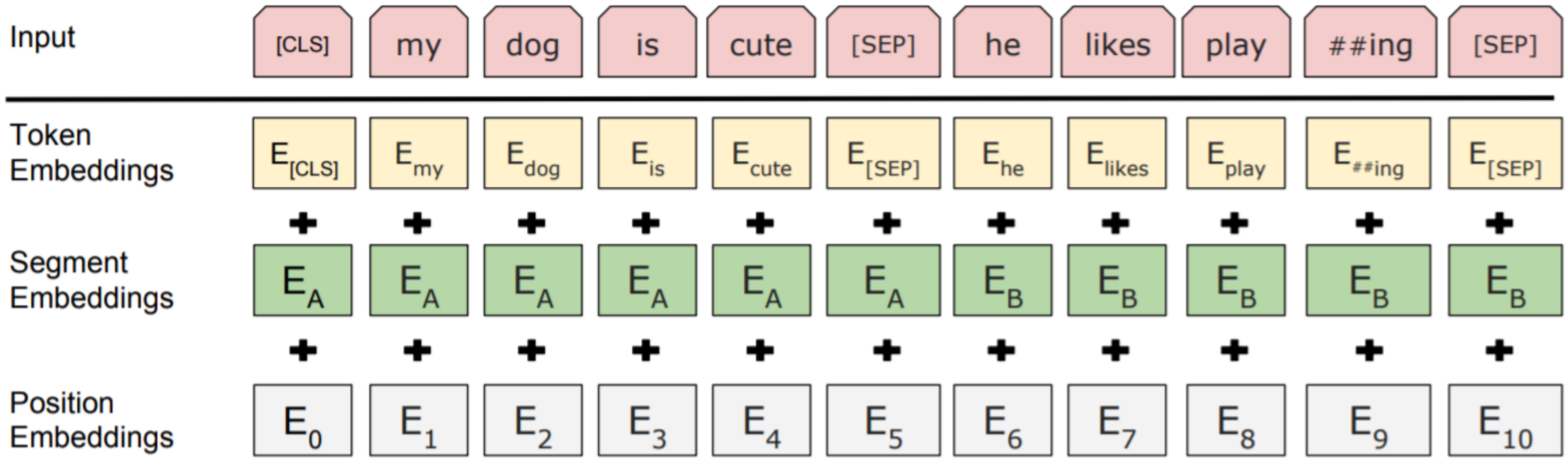
- Predict a random 15% of (sub)word tokens.
  - Replace input word with [MASK] 80% of the time
  - Replace input word with a random token 10% of the time
  - Leave input word unchanged 10% of the time (but still predict it!)
- Why? Doesn't let the model get complacent and not build strong representations 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:



- 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

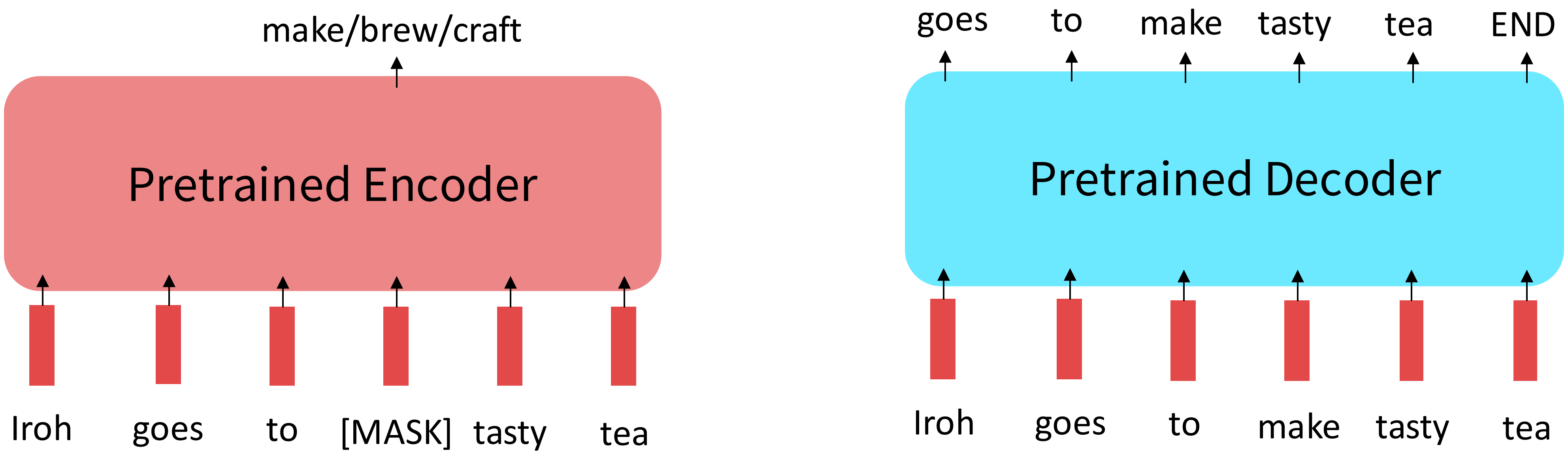
System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	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**

[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.

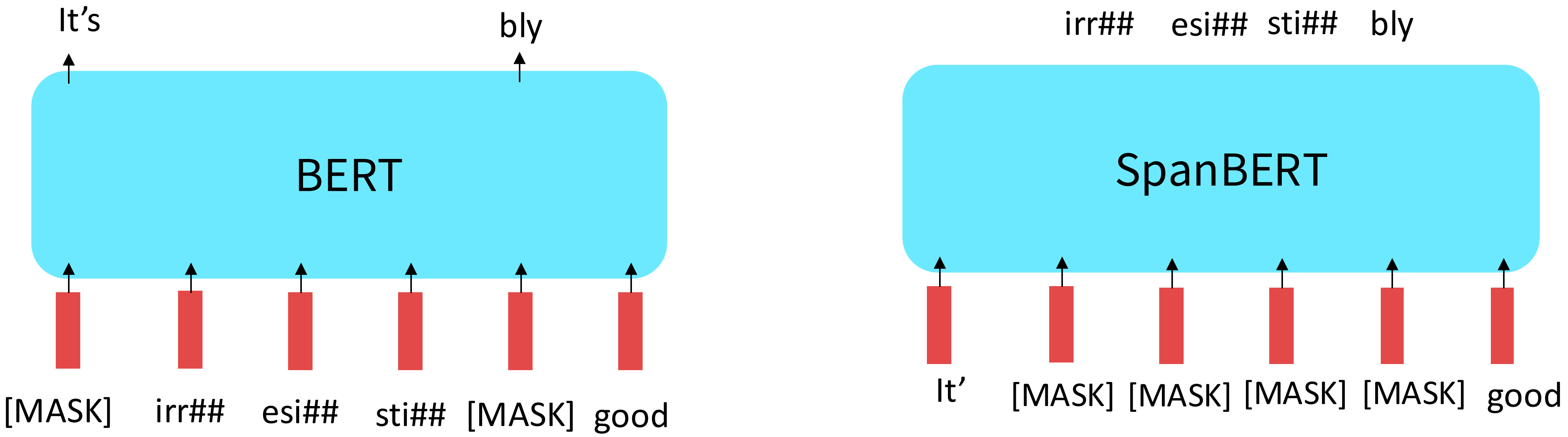


Extensions of BERT

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

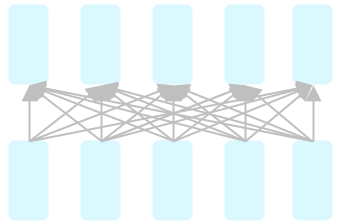
A takeaway from the RoBERTa paper: more compute, more data can improve pretraining even when not changing the underlying Transformer encoder.

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

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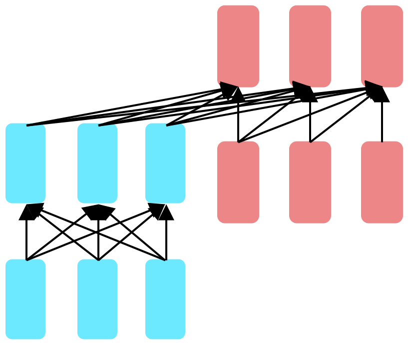

Encoder-Decoders

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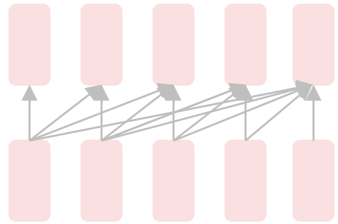


Decoders

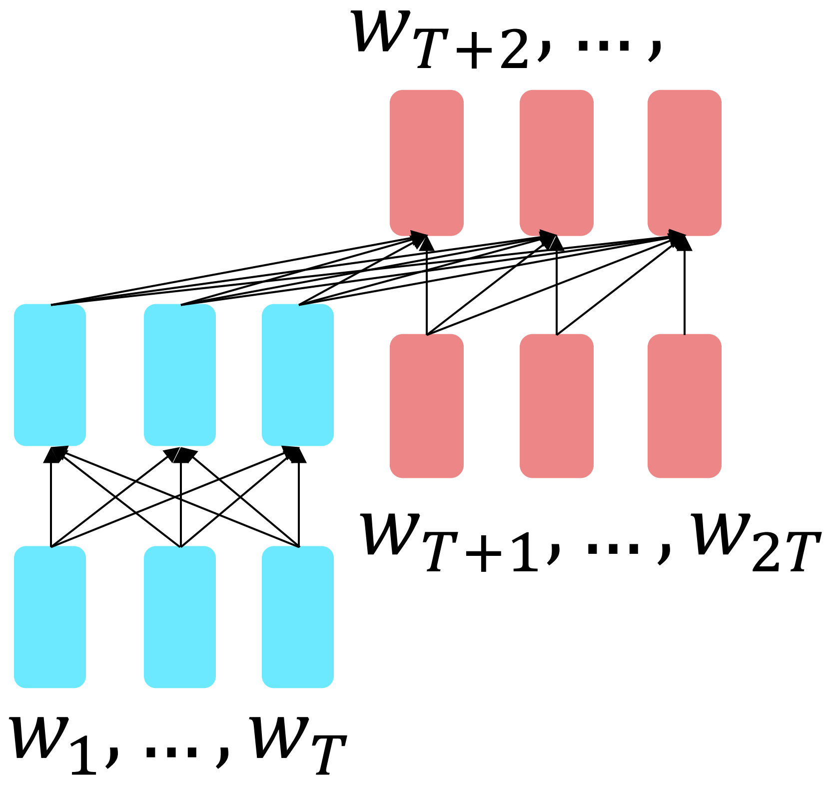
- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words

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.

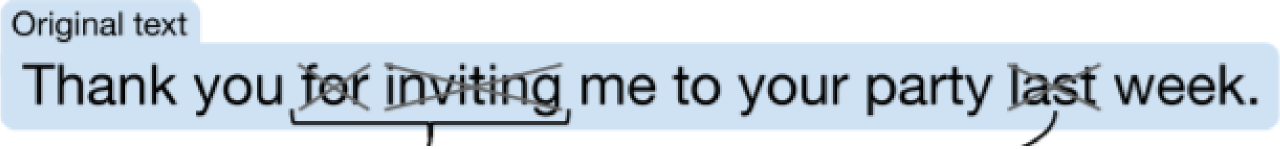


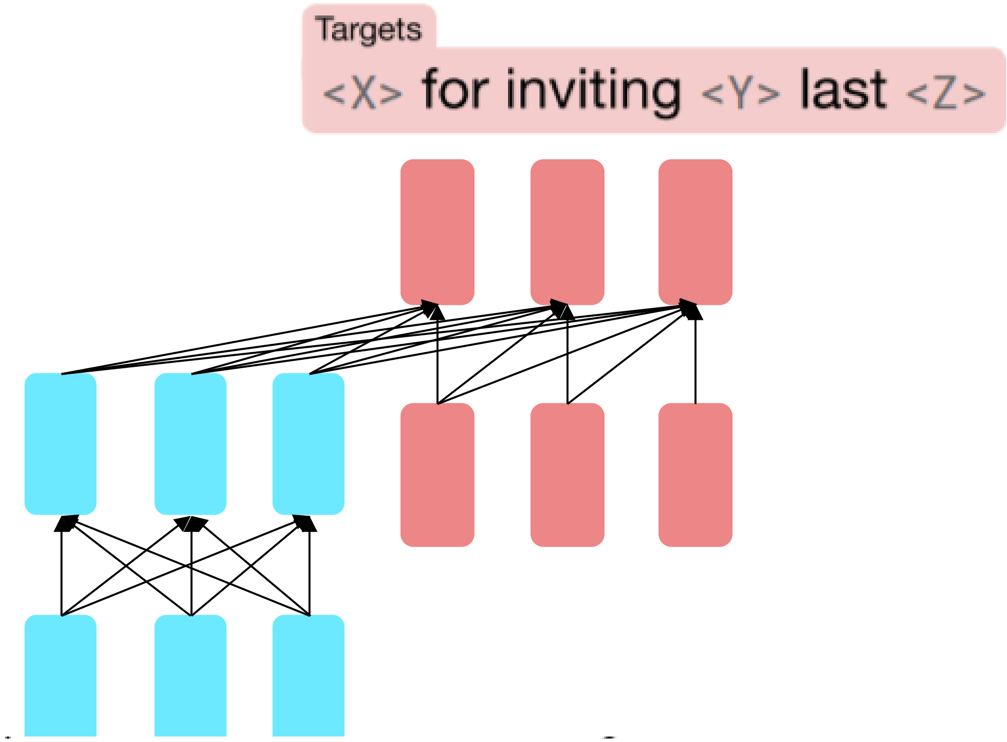
[Raffel et al., 2018]

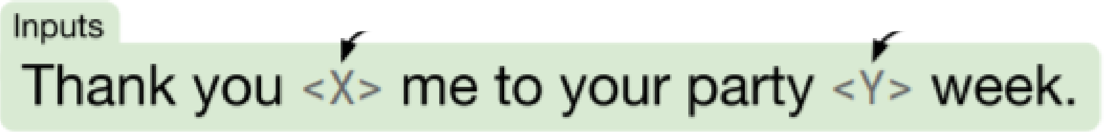
Pretraining encoder-decoders: what pretraining objective to use?

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.

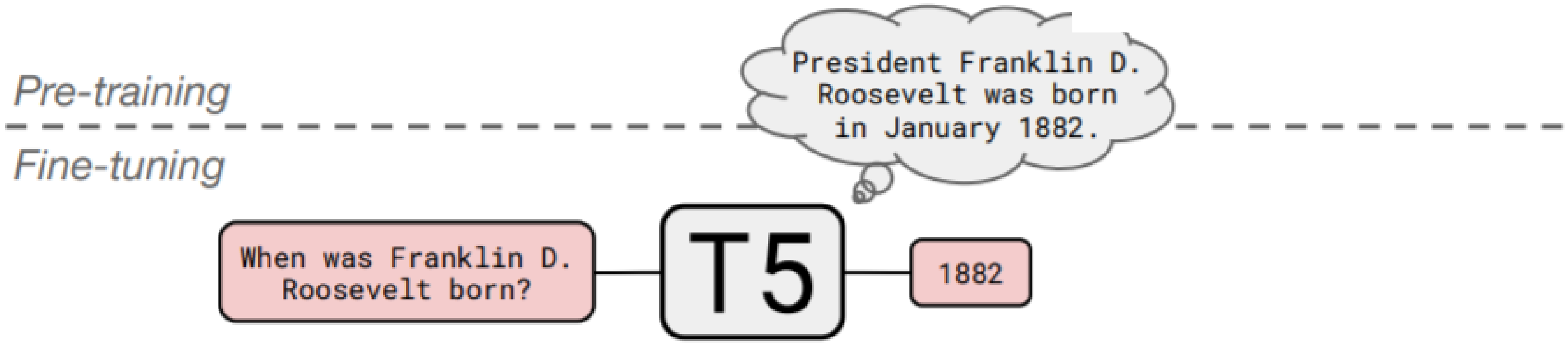
Pretraining encoder-decoders: what pretraining objective to use?

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	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**	

NQ: Natural Questions

WQ: WebQuestions

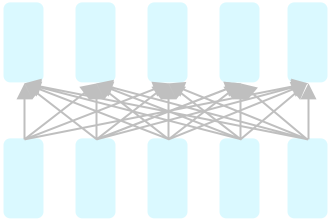
TQA: Trivia QA

All "open-domain" versions

[Raffel et al., 2018]

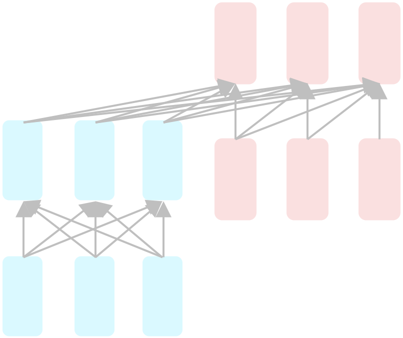
Pretraining for three types of architectures

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



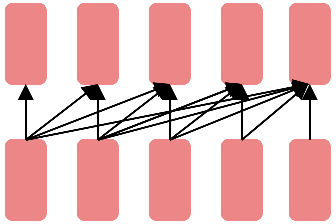
Encoders

- 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
- All the biggest pretrained models are Decoders.

Pretraining decoders

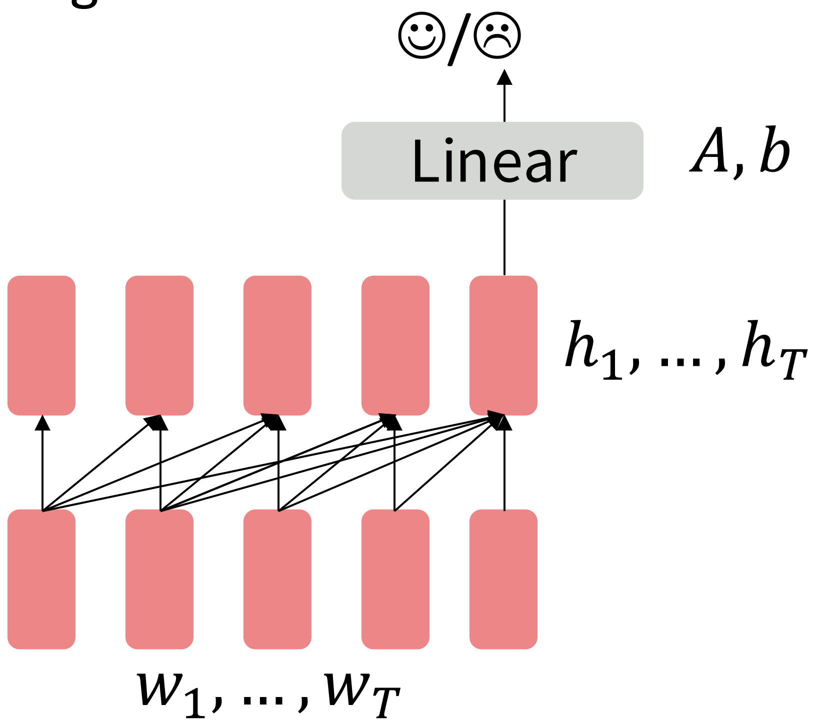
When using language model pretrained decoders, we can ignore that they were trained to model $p(w_t|w_{1:t-1})$.

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

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

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.]

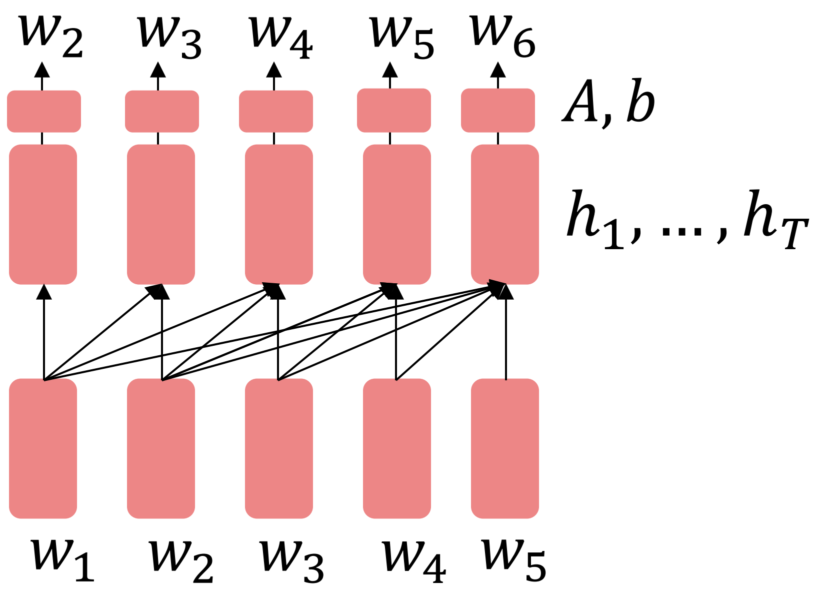
Pretraining decoders

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)

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



[Note how the linear layer has been pretrained.]

Where A, b were pretrained in the language model!

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*

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.

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

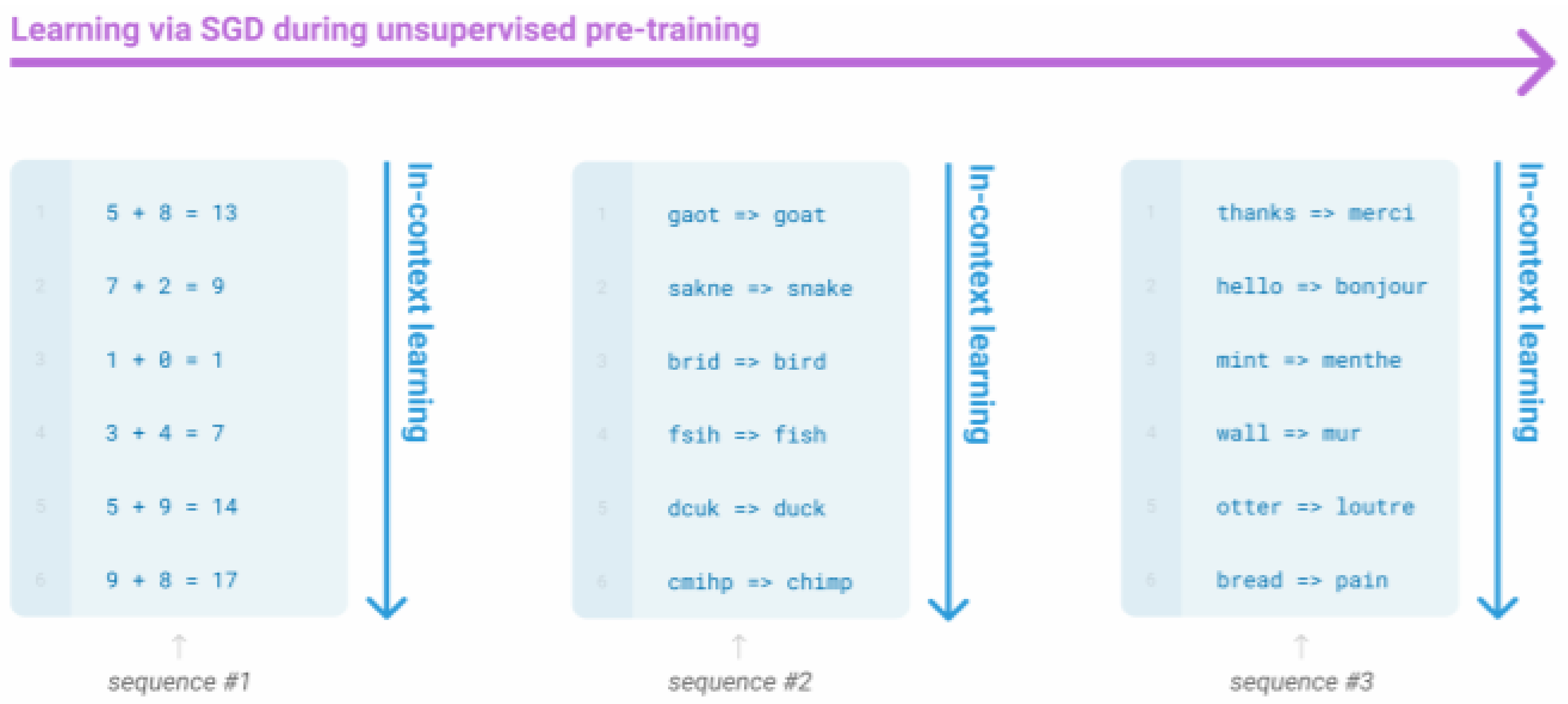
otter -> ”

Output (conditional generations):

loutre…”

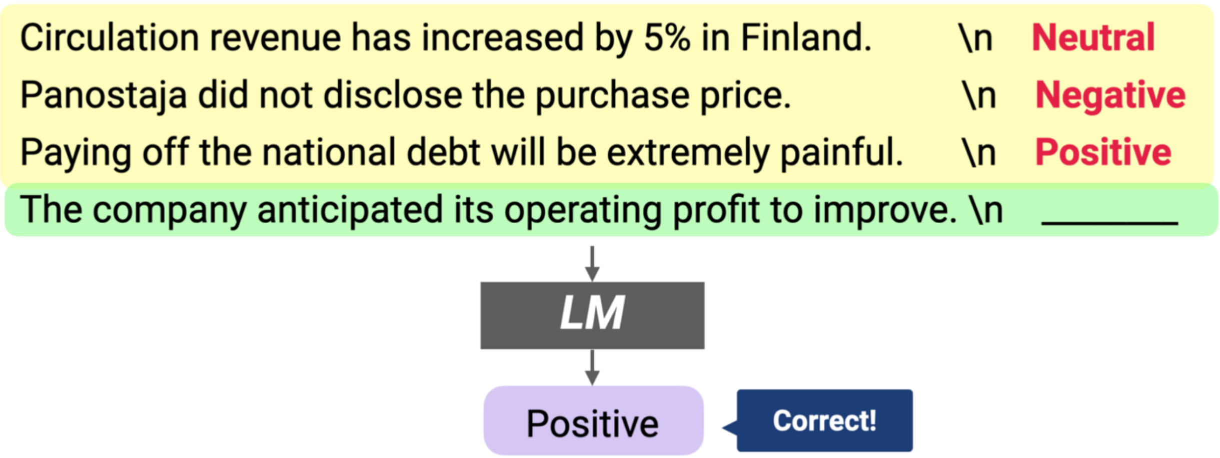
GPT-3, In-context learning, and very large models

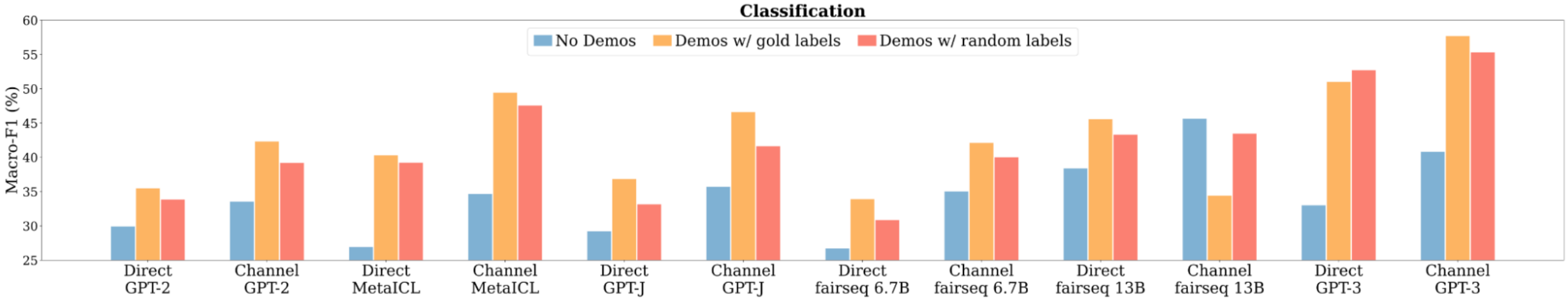
Very large language models seem to perform some kind of learning **without gradient steps** simply from examples you provide within their contexts.



How do LLMs generalize?

- In-context learning is remarkable, but is it *learning*?

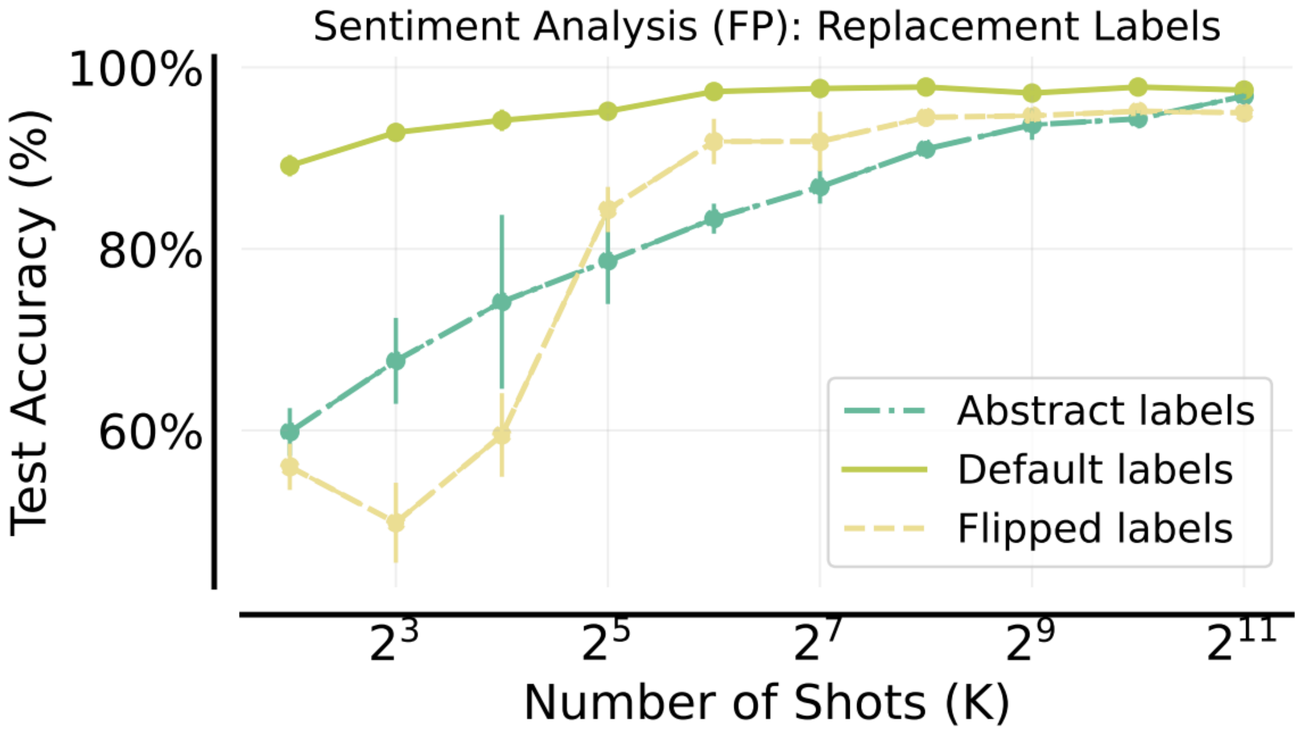




Models can do well on learning problems .. with random labels!

How do LLMs generalize

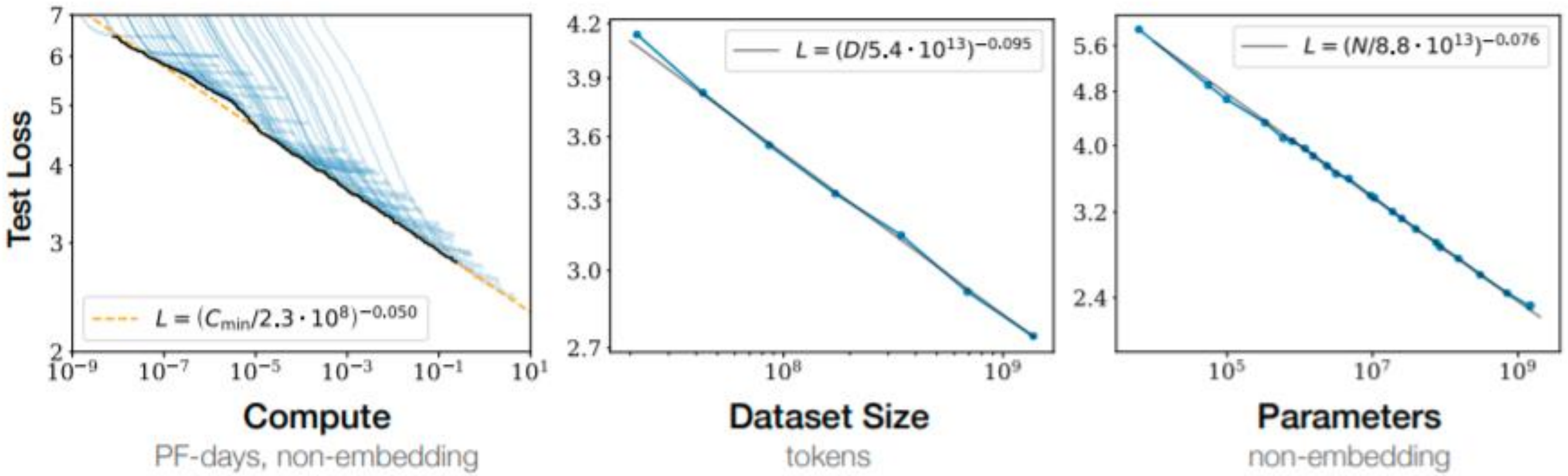
- LLM behavior is often complex, a mix of many different things happening



With big models (Gemini), you get a combination of ‘infer the task’ and ‘learn the task’

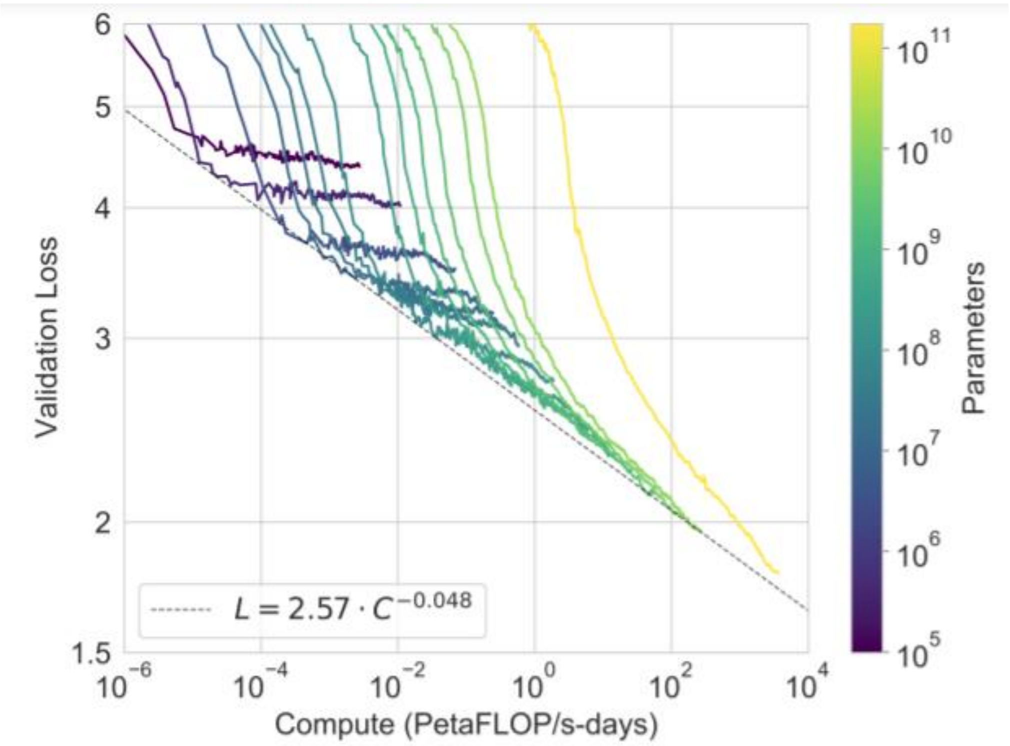
Explanations (and mechanisms) underlying LM behavior are complex!

Why scale? Scaling laws



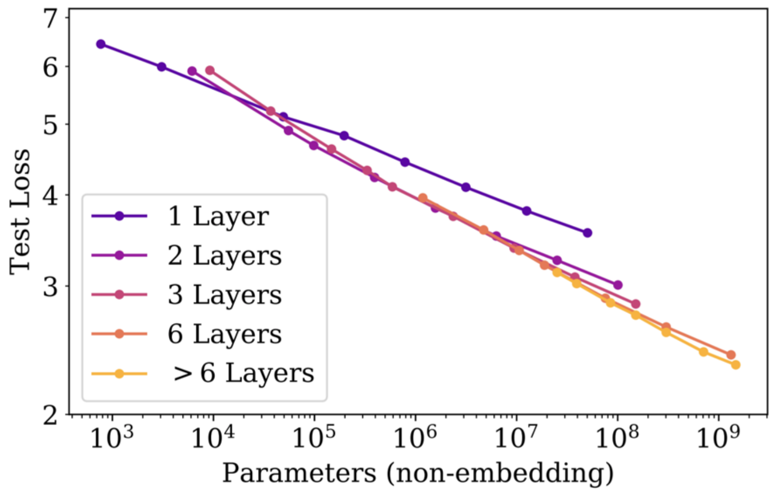
- Empirical observation: scaling up models leads to reliable gains in perplexity

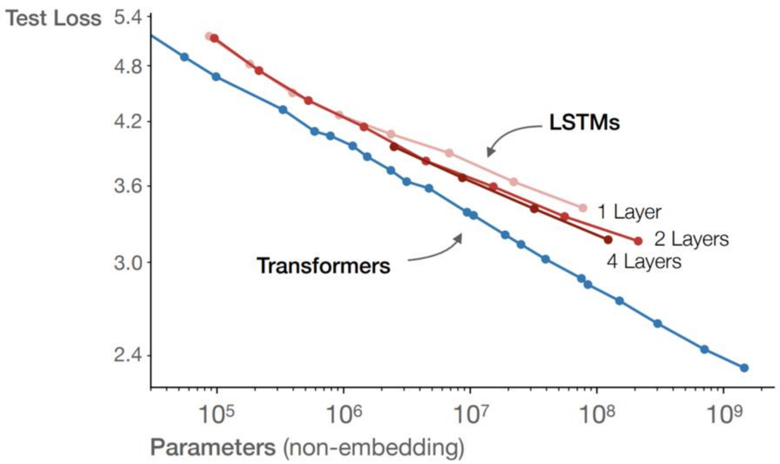
Scaling can help identify model size – data tradeoffs

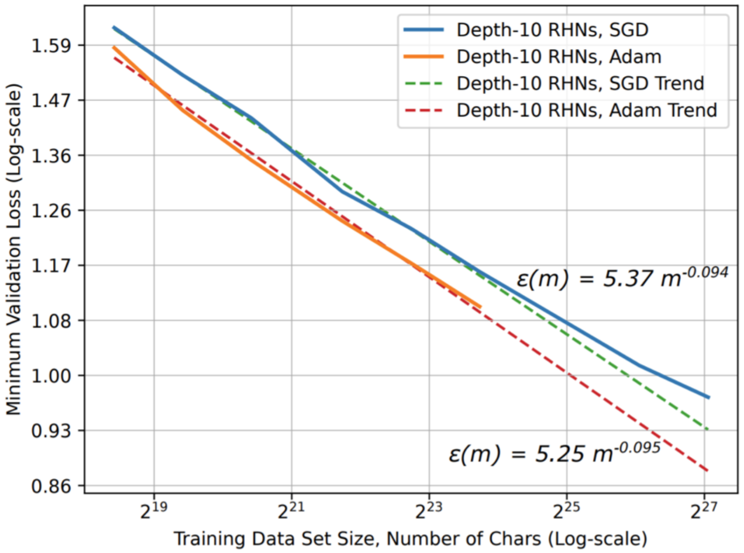


- Modern observation: train a big model that's not fully converged.

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!