

# Scaling Language models

He He

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## Scaling Laws

# What do language models do?

- Answer questions
- Summarize documents
- Write programs
- Prove theorems
- ...

User

What is funny about this image? Describe it panel by panel.



Source: <https://www.reddit.com/r/hmm/comments/ubab5v/hmm/>

GPT-4

The image shows a package for a "Lightning Cable" adapter with three panels.

Panel 1: A smartphone with a VGA connector (a large, blue, 15-pin connector typically used for computer monitors) plugged into its charging port.

Panel 2: The package for the "Lightning Cable" adapter with a picture of a VGA connector on it.

Panel 3: A close-up of the VGA connector with a small Lightning connector (used for charging iPhones and other Apple devices) at the end.

The humor in this image comes from the absurdity of plugging a large, outdated VGA connector into a small, modern smartphone charging port.

## Dial back twenty years

Which sequence is more likely to be an English sentence?

- Speech recognition

the *tail* of a dog

the *tale* of a dog

It's not easy to *wreck a nice beach*.

It's not easy to *recognize speech*.

It's not easy to *wreck an ice beach*.

- Machine translation

He sat on the *table*.

He sat on the *figure*.

Such a Europe would *the rejection of any ethnic nationalism*.

Such a Europe would *mark the refusal of all ethnic nationalism*.

## Problem formulation

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- **Vocabulary:** a set of symbols  $\mathcal{V}$ , e.g.  
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- The set of all sentences (of varying lengths):  $\mathcal{V}^*$
- Assign a probability  $p(x)$  to all sentences  $x \in \mathcal{V}^*$ .

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  - Most sentences only occur once. *sparsity issue*
  - Need to restrict the model.

## Simplification 1: sentence to tokens

Solve a smaller problem: model probability of each token

Decompose the joint probability using the **probability chain rule**:

$$\begin{aligned} p(x) &= p(x_1, \dots, x_n) \\ &= p(x_1)p(x_2 | x_1)p(x_3 | x_1, x_2) \dots p(x_n | x_1, \dots, x_{n-1}) \end{aligned}$$

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- Problem reduced to modeling conditional token probabilities  
the red fox → jumped
- The left-to-right decomposition is also called an **autoregressive model**
- This is a classification problem we have seen
- But there is still a large number of contexts!

## Simplification 2: limited context

Reduce dependence on context by the **Markov assumption**:

- First-order Markov model

$$p(x_i \mid x_1, \dots, x_{i-1}) = p(x_i \mid x_{i-1})$$

$$p(x) = \prod_{i=1}^n p(x_i \mid x_{i-1})$$

- Number of contexts?

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- Number of contexts?  $|\mathcal{V}|$
- Number of parameters?  $|\mathcal{V}|^2$

## Model sequences of variable lengths

Assume each sequence starts with a special **start symbol**:  $x_0 = *$ .

Assume that all sequences end with a **stop symbol** STOP, e.g.

$$\begin{aligned} & p(\text{the, fox, jumped, STOP}) \\ &= p(\text{the} \mid *)p(\text{fox} \mid \text{the})p(\text{jumped} \mid \text{fox})p(\text{STOP} \mid \text{jumped}) \end{aligned}$$

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What if we don't have the stop symbol?

- Which one is larger:  $p(\text{the fox})$  or  $p(\text{the fox jumped})$ ?

## N-gram LM

- Unigram language model (no context):

$$p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i) .$$

- Bigram language model ( $x_0 = *$ ):

$$p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i \mid x_{i-1}) .$$

- $n$ -gram language model:

$$p(x_1, \dots, x_m) = \prod_{i=1}^m p(x_i \mid \underbrace{x_{i-n+1}, \dots, x_{i-1}}_{\text{previous } n-1 \text{ words}}) .$$

## Parameter estimation

Maximum likelihood estimation over a corpus (a set of sentences):

- Unigram LM

$$p_{\text{MLE}}(x) = \frac{\text{count}(w)}{\sum_{w \in \mathcal{V}} \text{count}(w)}$$

- Bigram LM

$$p_{\text{MLE}}(w | w') = \frac{\text{count}(w, w')}{\sum_{w \in \mathcal{V}} \text{count}(w, w')}$$

- In general, for n-gram LM,

$$p_{\text{MLE}}(w | c) = \frac{\text{count}(w, c)}{\sum_{w \in \mathcal{V}} \text{count}(w, c)}$$

where  $c \in \mathcal{V}^{n-1}$ .

## Example

- Training corpus (after tokenization)  
 $\{\text{The fox is red, The red fox jumped, I saw a red fox}\}$
- Collect counts
  - $\text{count(fox)} = 3$
  - $\text{count(red)} = 3$
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- What is the probability of “The fox saw I jumped”? Zero probability on unseen n-grams

## Generating text from an n-gram model

1. Initial condition: context = \*
2. Iterate until next\_word is STOP:
  - 2.1  $\text{next\_word} \sim p(\cdot | \text{context}[:-(n-1)])$
  - 2.2  $\text{context} \leftarrow \text{context} + \text{next\_word}$

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1 gram	-To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have
	-Hill he late speaks; or! a more to leg less first you enter
2 gram	-Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow.
	-What means, sir. I confess she? then all sorts, he is trim, captain.
3 gram	-Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, 'tis done.
	-This shall forbid it should be branded, if renown made it empty.
4 gram	-King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv'd in;
	-It cannot be but so.

What is the training data?

# Perplexity

What is the loss function for learning language models?

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Held-out likelihood on test data  $D$  (negative test loss):

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**Perplexity:**

$$\text{PPL}(D) = 2^{-\frac{\ell(D)}{|D|}} .$$

- Base of log and exponentiation should match
- Exponent is cross entropy:  $H(p_{\text{data}}, p_\theta) = -\mathbb{E}_{x \sim p_{\text{data}}} \log p_\theta(x)$ .
- Interpretation: a model of perplexity  $k$  predicts the next word by throwing a fair  $k$ -sided die.

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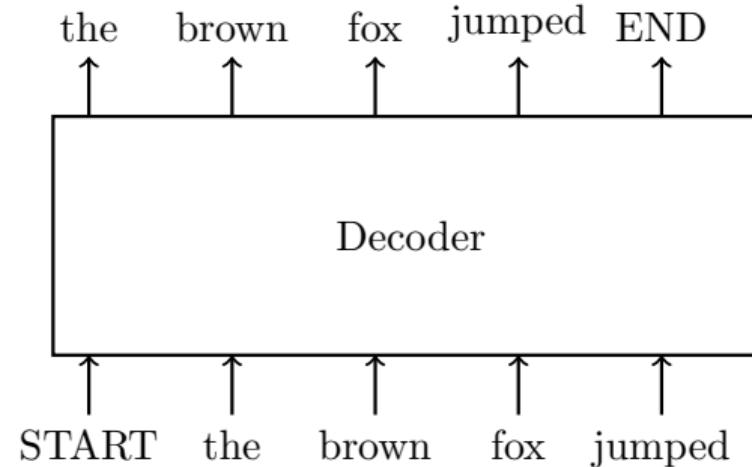
Evaluation by **held-out perplexity**: how much probability mass does the model assign to unseen text

Challenges:

- **Generalization**: sentences containing unseen n-grams have zero probability
- Much research in n-gram LM is dedicated to **smoothing** methods that allocate probability mass to unseen n-grams

# Neural language models

Neural networks solve the generalization problem in n-gram LMs.



- A decoder-only autoregressive neural language model
- Decoder can be an RNN or a transformer (with causal masking)
- What's the context size?

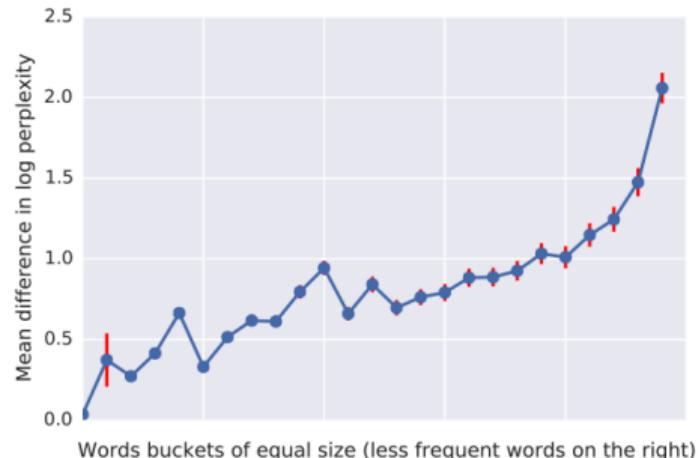
# Early efforts on scaling neural language models

MODEL	TEST PERPLEXITY	NUMBER OF PARAMS [BILLIONS]
SIGMOID-RNN-2048 (JI ET AL., 2015A)	68.3	4.1
INTERPOLATED KN 5-GRAM, 1.1B N-GRAMS (CHELBA ET AL., 2013)	67.6	1.76
SPARSE NON-NEGATIVE MATRIX LM (SHAZEER ET AL., 2015)	52.9	33
RNN-1024 + MAXENT 9-GRAM FEATURES (CHELBA ET AL., 2013)	51.3	20
LSTM-512-512	54.1	0.82
LSTM-1024-512	48.2	0.82
LSTM-2048-512	43.7	0.83
LSTM-8192-2048 (NO DROPOUT)	37.9	3.3
LSTM-8192-2048 (50% DROPOUT)	32.2	3.3
2-LAYER LSTM-8192-1024 (BIG LSTM)	30.6	1.8
BIG LSTM+CNN INPUTS	<b>30.0</b>	<b>1.04</b>
BIG LSTM+CNN INPUTS + CNN SOFTMAX	39.8	<b>0.29</b>
BIG LSTM+CNN INPUTS + CNN SOFTMAX + 128-DIM CORRECTION	35.8	<b>0.39</b>
BIG LSTM+CNN INPUTS + CHAR LSTM PREDICTIONS	47.9	<b>0.23</b>

Figure: From [Exploring the Limits of Language Modeling](#)

Significant improvement in held-out perplexity given similar model sizes (~1B)

# Improvement from neural language models



< S > With even more new technologies coming onto the market quickly during the past three years , an increasing number of companies now must tackle the ever-changing and ever-changing environmental challenges online . < S > Check back for updates on this breaking news story . < S > About 800 people gathered at Hever Castle on Long Beach from noon to 2pm , three to four times that of the funeral cortège . < S > We are aware of written instructions from the copyright holder not to , in any way , mention Rosenberg 's negative comments if they are relevant as indicated in the documents , " eBay said in a statement . < S > It is now known that coffee and cacao products can do no harm on the body . < S > Yuri Zhirkov was in attendance at the Stamford Bridge at the start of the second half but neither Drogba nor Malouda was able to push on through the Barcelona defence .

Figure: From [Exploring the Limits of Language Modeling](#)

LSTM vs KN5: improved perplexity on tail words

# Table of Contents

## Scaling Laws

## Recap: language modeling as pretraining

What can we do with a very large language model?

- The cats that are raised by my sister \_\_\_\_\_ sleeping. *syntax*
- Jane is happy that John invited \_\_\_\_\_ friends to his birthday party. *coreference*
- \_\_\_\_\_ is the capital of Tanzania. *knowledge*
- The boy is \_\_\_\_\_ because he lost his keys. *commonsense*
- John took 100 bucks to Vegas. He won 50 and then lost 100. Now he only has \_\_\_\_\_ to go home. *numerical reasoning*

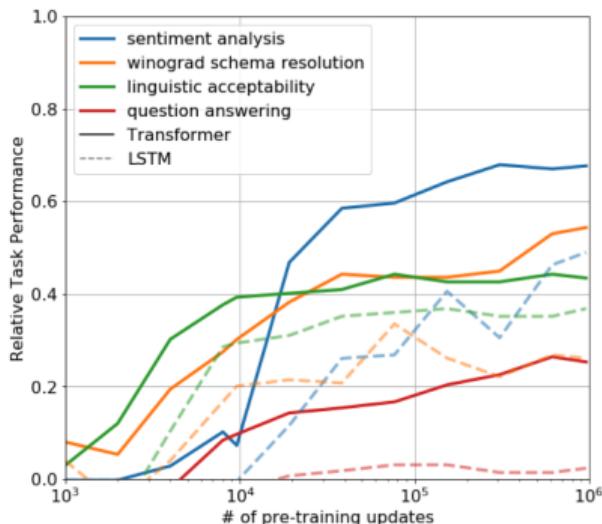
Predicting the next word entails many natural language understanding tasks

## Recap: Zero-shot behaviors from GPT

**Key insight:** if the model has learned to understand language through predicting next words, it should be able to perform these tasks *without finetuning*

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Heuristics for zero-shot prediction:

- Sentiment classification: [example] + very + {positive, negative} *prompting*
- Linguistic acceptability: thresholding on log probabilities
- Multiple choice: predicting the answer with the highest log probabilities

**Learning dynamics:** zero-shot performance increases during pretraining

## GPT-2: going beyond finetuning

Language Models are Unsupervised Multitask Learners [Radford et al., 2019]

- **Supervised learning:** models must be trained (finetuned) on a curated task dataset.
- They **fail to generalize** to out-of-distribution data (adversarial examples, robustness issues etc.)
- A generalist model must be trained on *many* tasks—but how do we get the datasets?
- **Hypothesis:** a (large enough) LM should be able to infer and learn tasks demonstrated in natural language, effectively performing **unsupervised multitask learning**

## GPT-2 details

- Similar to GPT-1 but scaled up (1.5B parameters)
- Data (WebText): ~40GB of web pages scraped from the internet that was curated to include high-quality text
- Tokenization: BPE over byte sequences for universal text processing.
  - Small base vocabulary (256)
  - Can process any text data regardless of pre-processing, tokenization, or vocab size.
- Larger context size (1024 tokens)

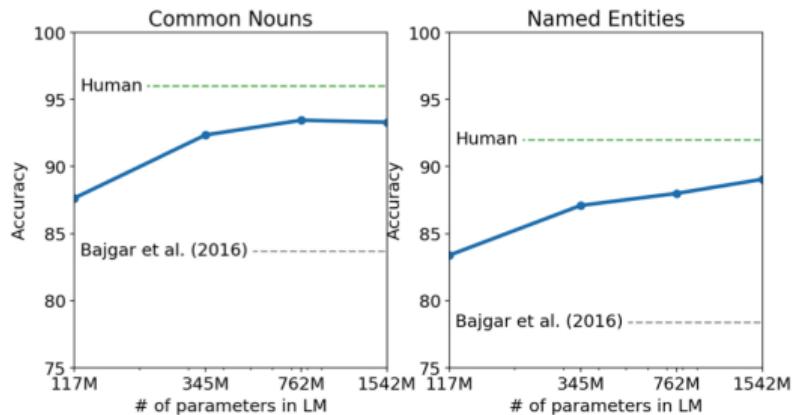
# Zero-shot performance: cloze test

S: 1 Mr. Cropper was opposed to our hiring you .  
2 Not , of course , that he had any personal objection to you , but he is set  
against female teachers , and when a Cropper is set there is nothing on earth can  
change him .  
3 He says female teachers ca n't keep order .  
4 He 's started in with a spite at you on general principles , and the boys know  
it .  
5 They know he 'll back them up in secret , no matter what they do , just to prove  
his opinions .  
6 Cropper is sly and slippery , and it is hard to corner him . ''  
7 `` Are the boys big ? ''  
8 queried Esther anxiously .  
9 `` Yes .  
10 Thirteen and fourteen and big for their age .  
11 You ca n't whip 'em -- that is the trouble .  
12 A man might , but they 'd twist you around their fingers .  
13 You 'll have your hands full , I 'm afraid .  
14 But maybe they 'll behave all right after all . ''  
15 Mr. Baxter privately had no hope that they would , but Esther hoped for the  
best .  
16 She could not believe that Mr. Cropper would carry his prejudices into a  
personal application .  
17 This conviction was strengthened when he overtook her walking from school the  
next day and drove her home .  
18 He was a big , handsome man with a very suave , polite manner .  
19 He asked interestedly about her school and her work , hoped she was getting on  
well , and said he had two young rascals of his own to send soon .  
20 Esther felt relieved .

Q: She thought that Mr. \_\_\_\_\_ had exaggerated matters a little .

C: Baxter, Cropper, Esther, course, fingers, manner, objection, opinion, right, spite.

d: Baxter



Larger models quickly closes the gap with human performance

# Zero-shot performance: generative QA

Question	Generated Answer	Correct	Probability
Who wrote the book the origin of species?	Charles Darwin	✓	83.4%
Who is the founder of the ubuntu project?	Mark Shuttleworth	✓	82.0%
Who is the quarterback for the green bay packers?	Aaron Rodgers	✓	81.1%
Panda is a national animal of which country?	China	✓	76.8%
Who came up with the theory of relativity?	Albert Einstein	✓	76.4%
When was the first star wars film released?	1977	✓	71.4%
What is the most common blood type in sweden?	A	✗	70.6%
Who is regarded as the founder of psychoanalysis?	Sigmund Freud	✓	69.3%
Who took the first steps on the moon in 1969?	Neil Armstrong	✓	66.8%
Who is the largest supermarket chain in the uk?	Tesco	✓	65.3%
What is the meaning of shalom in english?	peace	✓	64.0%
Who was the author of the art of war?	Sun Tzu	✓	59.6%
Largest state in the us by land mass?	California	✗	59.2%
Green algae is an example of which type of reproduction?	parthenogenesis	✗	56.5%
Vikram samvat calender is official in which country?	India	✓	55.6%
Who is mostly responsible for writing the declaration of independence?	Thomas Jefferson	✓	53.3%
What us state forms the western boundary of montana?	Montana	✗	52.3%
Who plays ser davos in game of thrones?	Peter Dinklage	✗	52.1%
Who appoints the chair of the federal reserve system?	Janet Yellen	✗	51.5%
State the process that divides one nucleus into two genetically identical nuclei?	mitosis	✓	50.7%

## Zero-shot performance: summarization

	R-1	R-2	R-L	R-AVG
Bottom-Up Sum	<b>41.22</b>	<b>18.68</b>	<b>38.34</b>	<b>32.75</b>
Lede-3	40.38	17.66	36.62	31.55
Seq2Seq + Attn	31.33	11.81	28.83	23.99
GPT-2 TL;DR:	29.34	8.27	26.58	21.40
Random-3	28.78	8.63	25.52	20.98
GPT-2 no hint	21.58	4.03	19.47	15.03

- Challenge: not a “native” LM task
- Induce the task: [document] + [TL;DR]
- Not much better than copying 3 random sentences from the document
- Key question in the zero-shot paradigm: how do we tell the model what the intended task is?

## Zero-shot performance: machine translation

- Induce the task through a [demonstration example](#):

translation  $\sim p(\cdot \mid [\text{french sentence}] = [\text{english sentence}]; [\text{french sentence}] = )$

- WMT-14 French-English test set: 11.5 BLEU (worse than unsupervised MT)
- But, there's only 10MB french data in the 40GB training data!
  - Typical unsupervised MT methods require crosslingual embeddings or monolingual corpora

## Has the model memorized everything?

Is there data contamination (test data in training set)?

- Approach: check percentage of 8-grams that occur in both training and test data (using Bloom filters)

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  - E.g., on CoQA, 3 F1 better on leaked documents
- Verifying data contamination is an active research area!

# Has the model memorized everything?

Test the model on novel tasks:

**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.

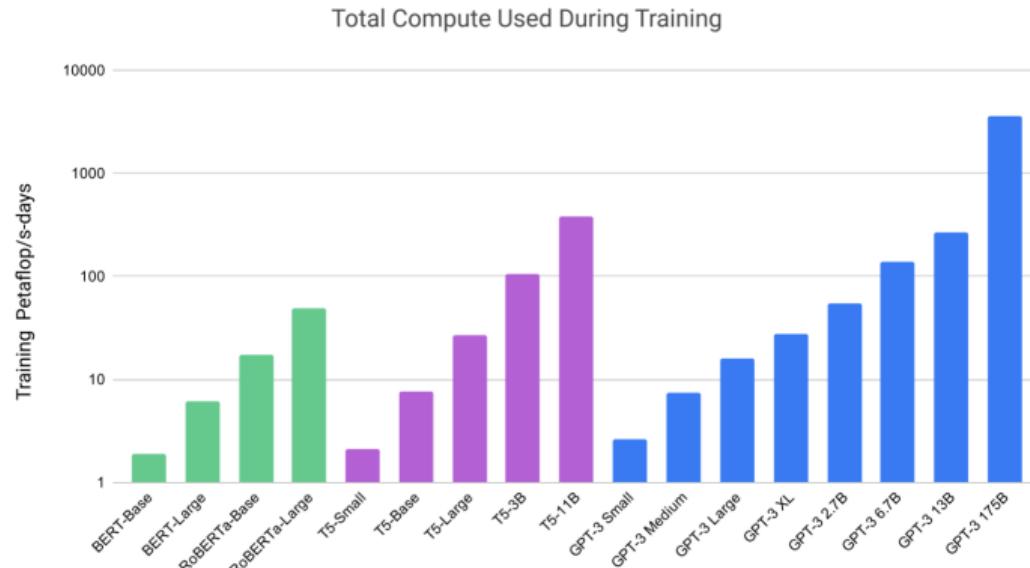
**GPT-2:** The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

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: scaling up

- GPT-2 shows promise for zero-shot learning, but performance is still unsatisfying
- GPT-3 scales up model size, data size and diversity, and number of training steps
- Notable improvement in zero-shot and few-shot performance
- Inducing a task through natural language task descriptions



# What does scaling mean?

$$\alpha \times \text{Model size} \times \text{Training tokens} = \text{Training compute}$$

	<u>Model size (# parameters)</u>	<u>Training data (# tokens)</u>	<u>Training compute (FLOPs)</u>	<u>Resources</u>
 <a href="#">BERT-base</a> (2018)	109M	250B	1.6e20	64 TPU v2 for 4 days (16 V100 GPU for 33 hrs)
 <a href="#">GPT-3</a> (2020)	175B	300B	3.1e23	~1,000x BERT-base
 <a href="#">PaLM</a> (2022)	540B	780B	2.5e24	<u>6k TPU v4 for 2 months</u>

Figure: From Jason Wei's slides

## Training data

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

Key challenge: data quality control

- Filter CommonCrawl based on similarity to high-quality reference corpora
- Fuzzy deduplication: avoid redundancy and data contamination
- Mix in known high quality data
- Upsampling high quality data during training

# Evaluation settings

The three settings we explore for in-context learning

## Zero-shot

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



## One-shot

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



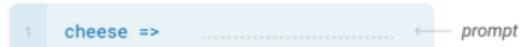
## Few-shot

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

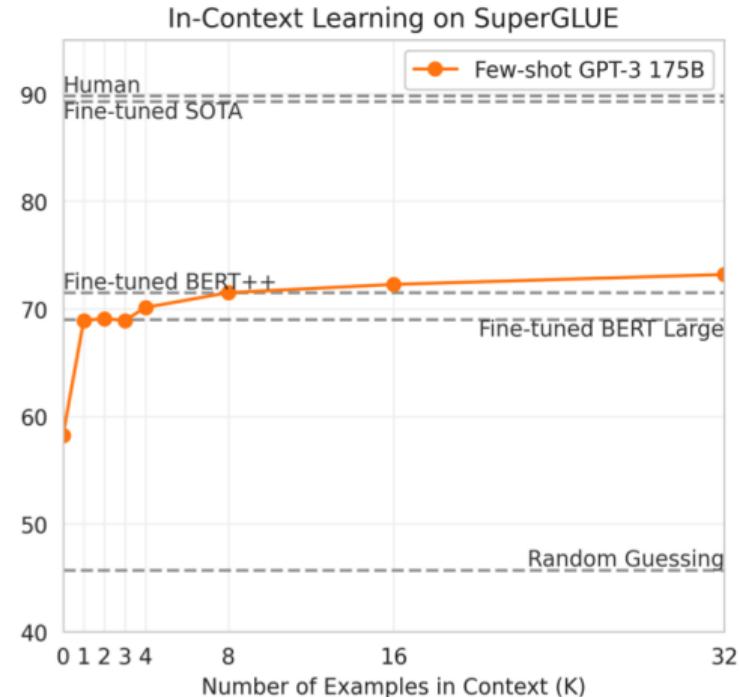
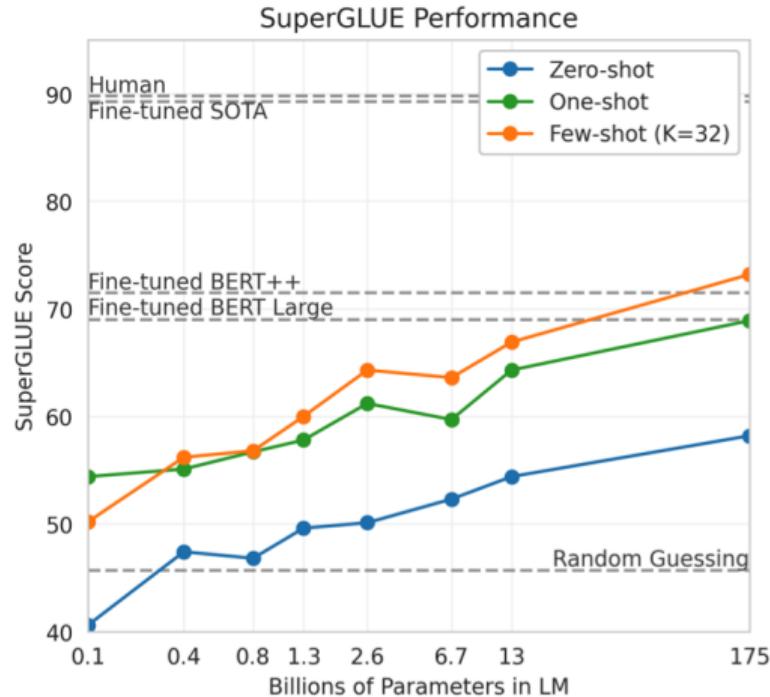
Traditional fine-tuning (not used for GPT-3)

## Fine-tuning

The model is trained via repeated gradient updates using a large corpus of example tasks.

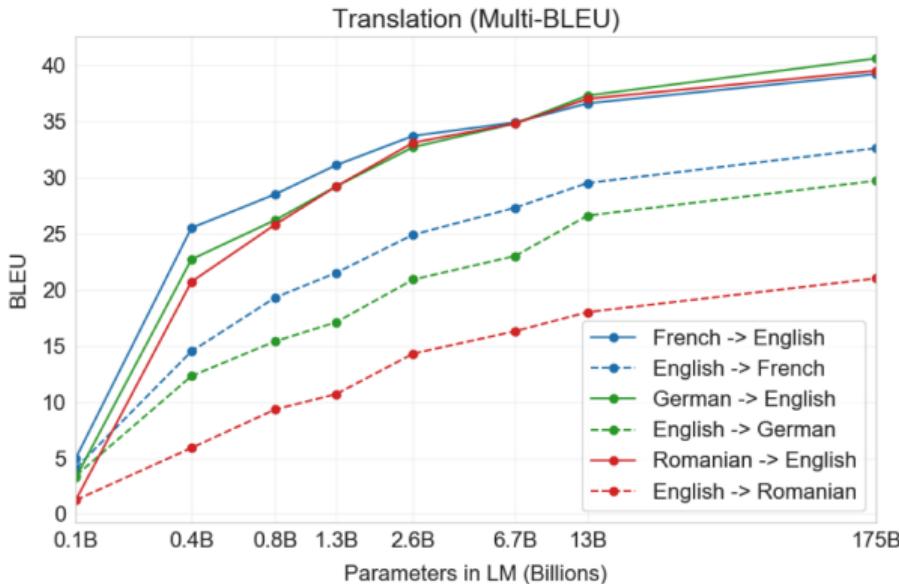


# Results: natural language understanding



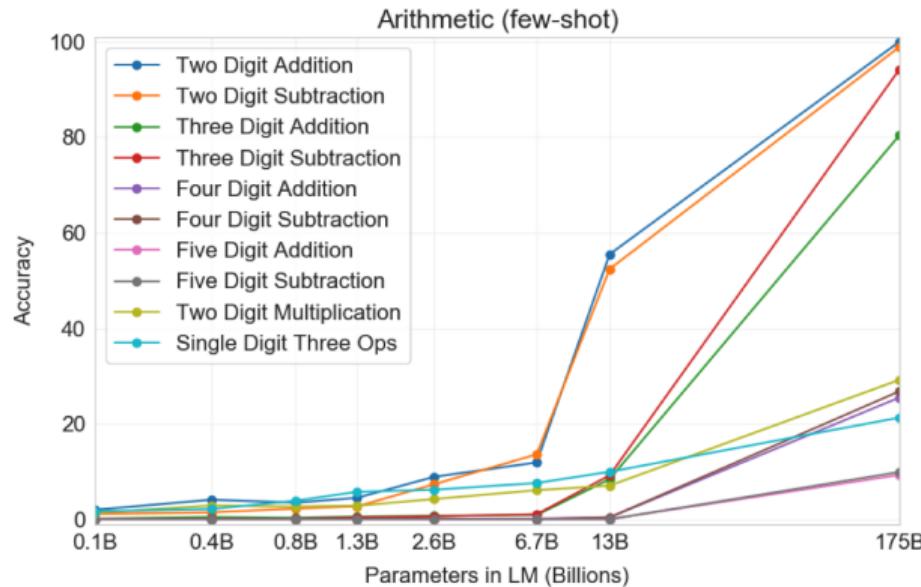
Comparable to supervised results

# Results: few-shot machine translation



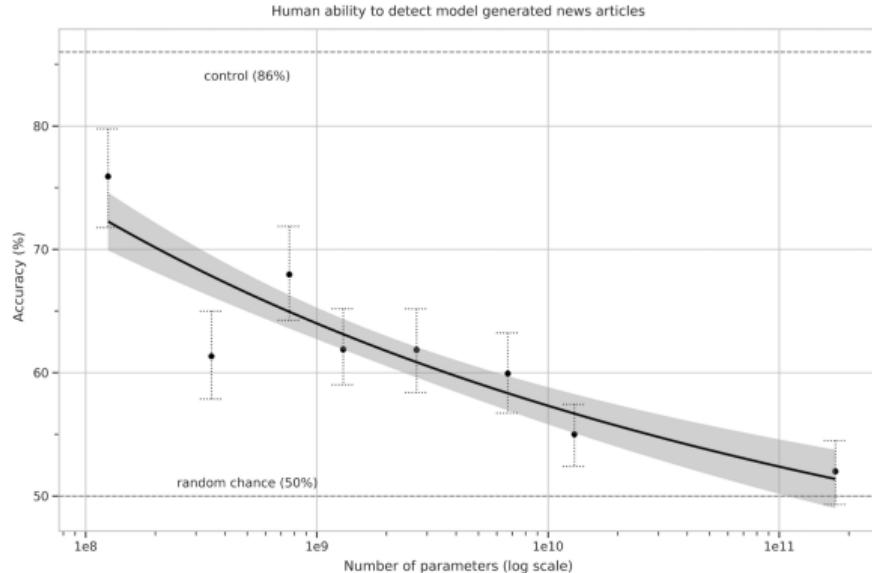
- Pretraining data: 93% English, 7% other languages
- Zero-shot is still worse than unsupervised MT
- But even giving one examples significantly boosts the result (+7 BLEU points)
- Results much better when translation into English
- Also see [Briakou et al., 2023] for the impact of bilingual data on MT performance

# Results: arithmetic



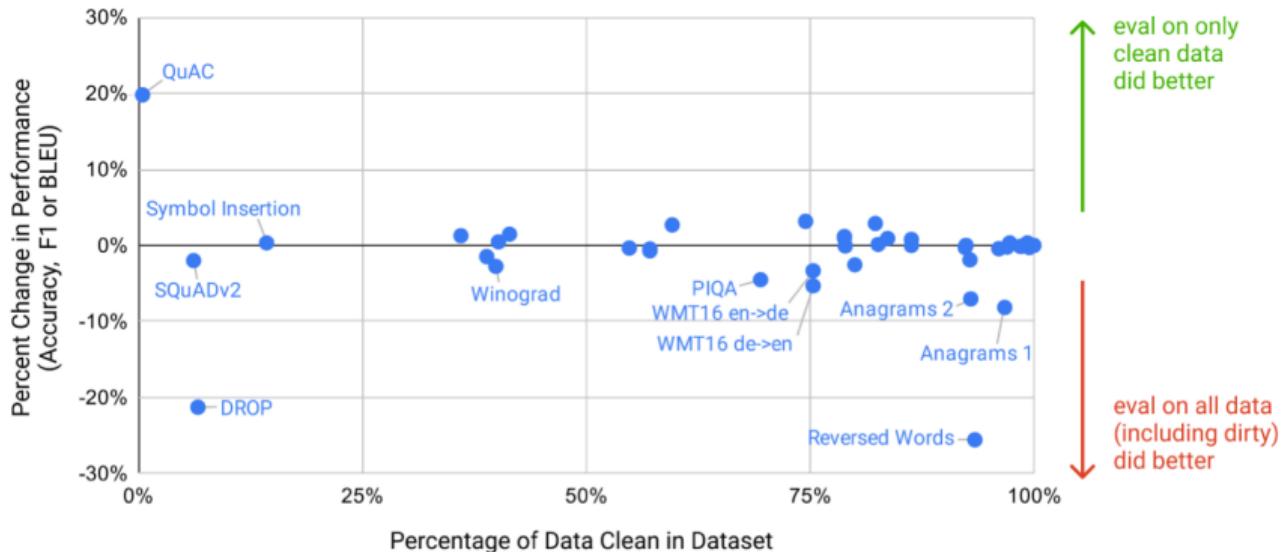
- "Emergent" ability at certain model scale
- Not systemic: works better on frequent numbers [Razeghi et al., 2022]

# Results: generation



Generated text is hard to detect from human-written text

# Analysis: data contamination



- Overlap can be large (e.g., many reading comprehension articles come from wikipedia)
- Result on clean part of the benchmark doesn't change much

## Summary

- Premise: a perfect language model on all human-written text can do all text-based tasks
  - What about unwritten knowledge?
- New behaviors that are not written in the training objective emerge (e.g., in-context learning)
- Open questions:
  - How much are they memorizing vs generalizing?
  - How do new abilities emerge?
  - How to mitigate harmful, toxic, biased responses?

# Table of Contents

## Scaling Laws

## Motivation

- We have seen larger language models trained on more data consistently give better performance.
- Can we be more precise about how scaling affect performance?
- Any other factors affecting scaling (architecture, task, etc.)?
- Can we predict performance of larger models from smaller models?

# Scaling data drives down error

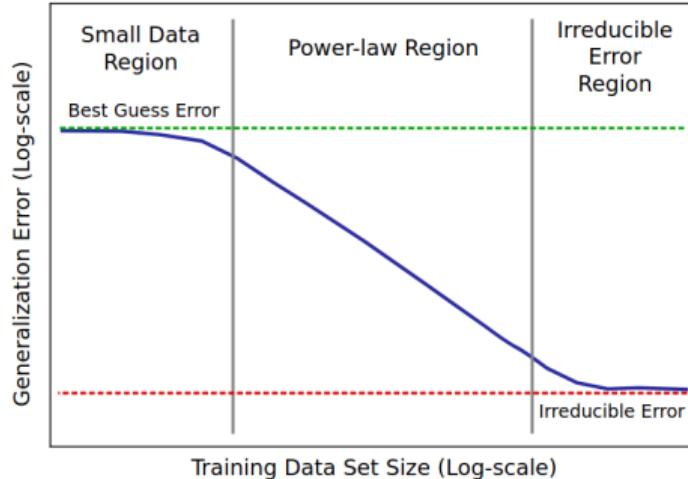
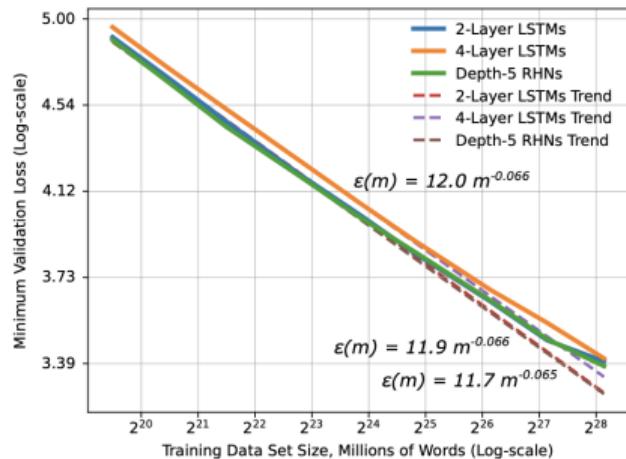


Figure: [Hestness et al., 2017]

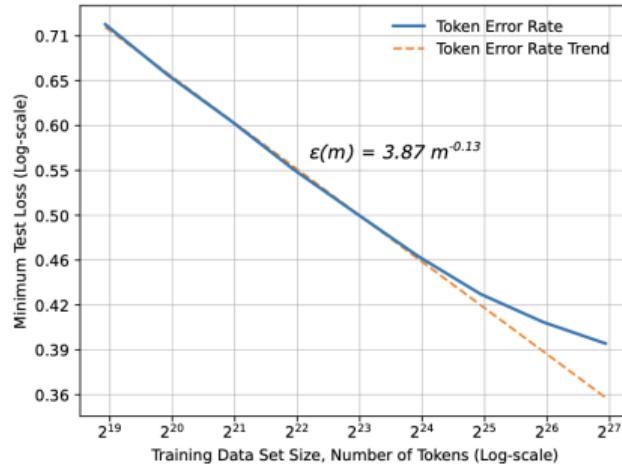
$$L = BD^{-b} + E \quad (1)$$

L: loss; B: data-dependent constant; D: data size; E: irreducible error

# Fit empirical learning curve



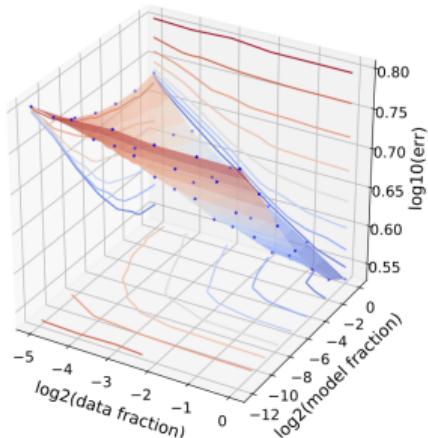
(a) language modeling



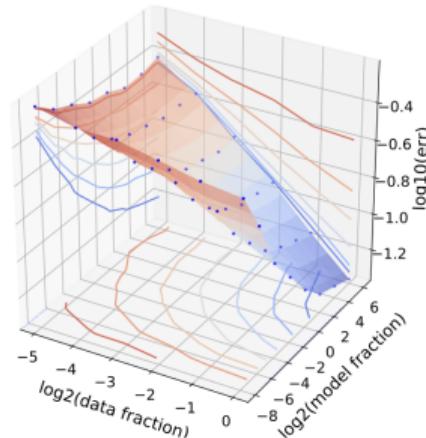
(b) machine translation

- Scaling law shows up in different domains
- Prior theory on generalization bounds suggests exponent=0.5 or 1, but empirically it's much smaller (lots of room for improvement)

# Model data joint scaling



(a) Wiki103 error (cross entropy) landscape.



(b) CIFAR10 error (top1) landscape.

Figure: [Rosenfeld et al., 2019]

- Fixing data size, scaling model size decreases error initially, but then saturates (bottlenecked by data)
- Functional form:

$$L = AM^{-a} + BD^{-b} + E$$

# Model data joint scaling

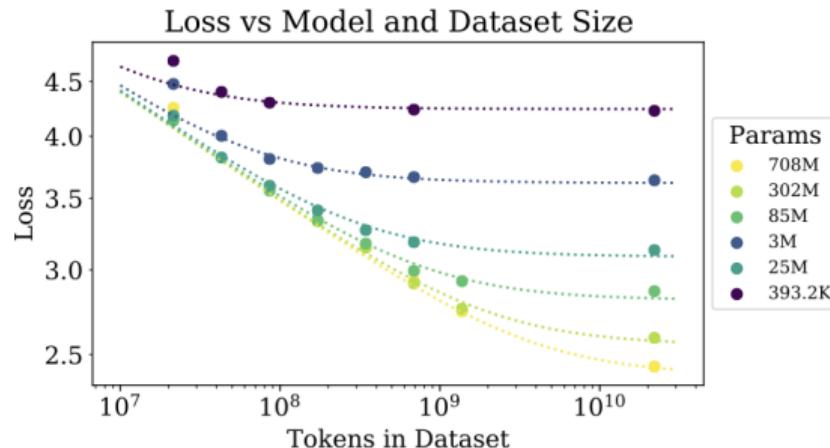


Figure: [Kaplan et al., 2020]

- Larger data is bottlenecked by small models
- Functional form:

$$L = (AM^{-a/b} + BD^{-1})^b$$

## How should we trade off model vs data?

- compute  $\propto$  data x parameter
- Given a target loss, we can minimize compute to get the optimal model data ratio
- Kaplan et al. suggests  $D \propto M^{0.74}$ : model size should scale faster than data
- Chinchilla law suggests that model size and data should roughly scale at the same rate

# Designing large models using scaling law

LSTMs or Transformers?

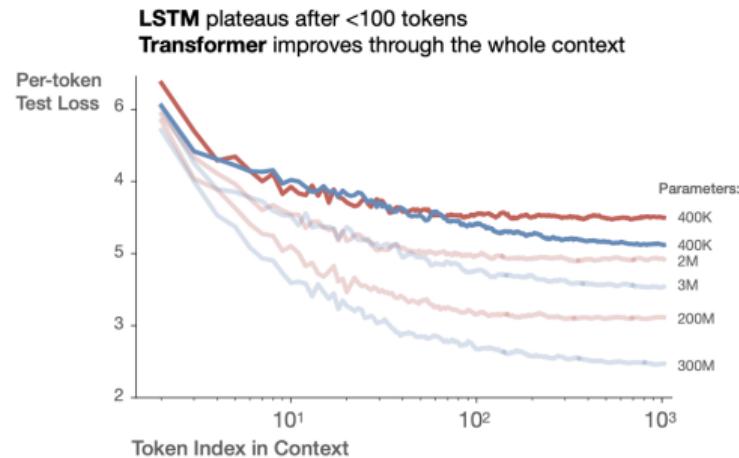
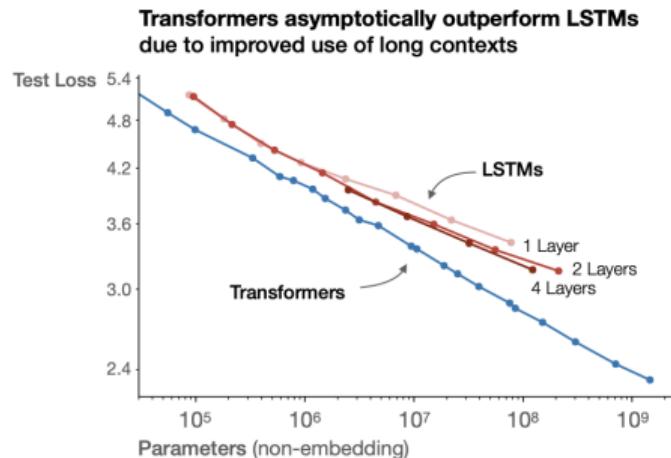


Figure: [Kaplan et al., 2020]

# Designing large models using scaling law

Depth vs width

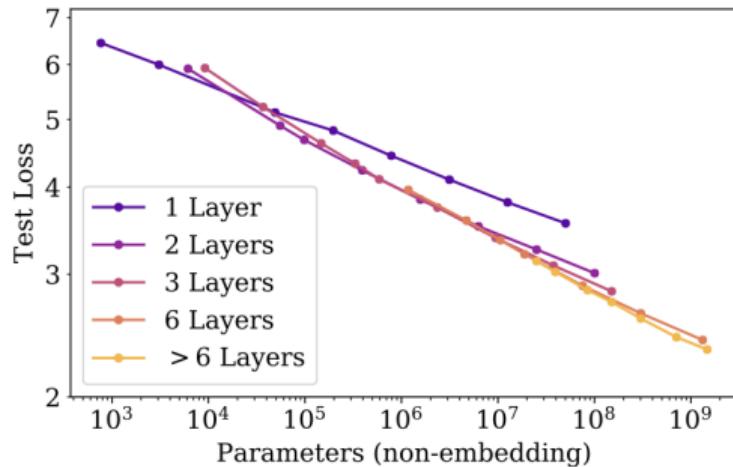


Figure: [Kaplan et al., 2020]

## Takeaways

- The main inputs to deep learning systems are data and compute.
- Scaling the two inputs reliably increases performance
- Scaling laws exist and capture the relationship between compute and performance
- Scaling law allows you to design models (architecture, optimizer etc.) at smaller scale then extrapolate the design to a larger scale
- You should also look at scaling behavior of your method