Trends and Opportunities in Large Language Models of Source Code

Vincent J. Hellendoorn
Carnegie Mellon University

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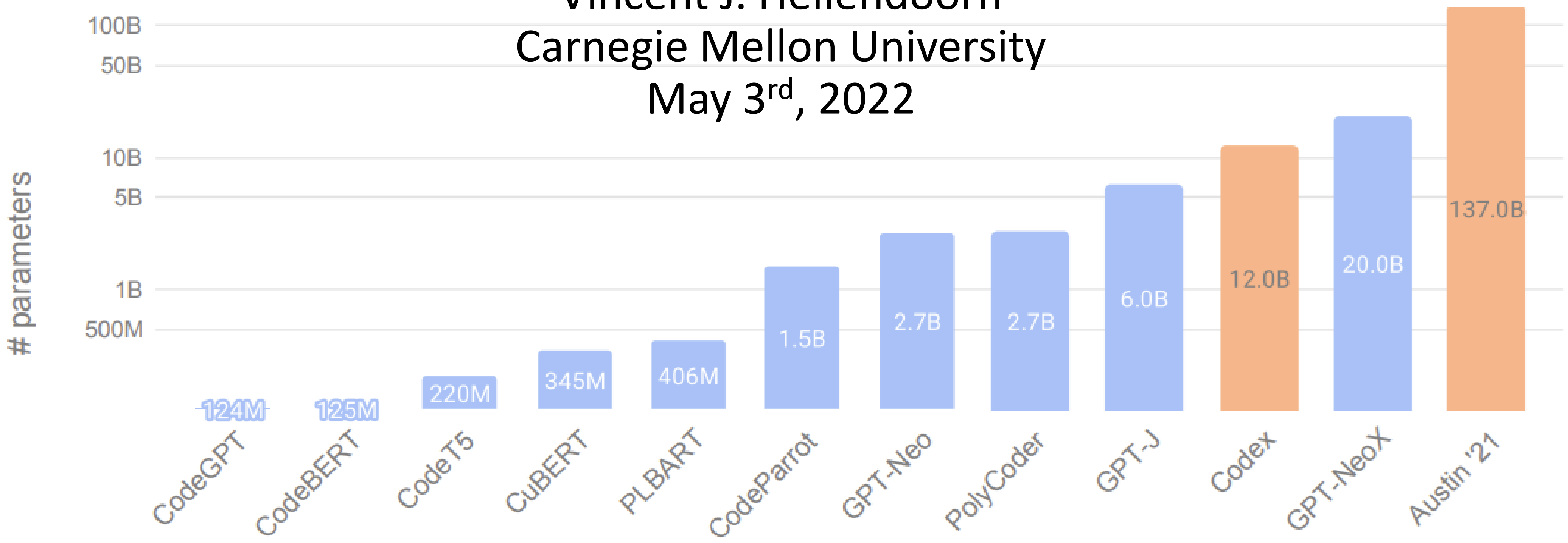


Why We're Here

GitHub Copilot (June 2021)

- Closed-source
- Limited details

```go
package main

type CategorySummary struct {
    Title        string
    Tasks       int
    AvgValue    float64
}

func createTables(db *sql.DB) {
    db.Exec("CREATE TABLE tasks (id INTEGER PRIMARY KEY, title TEXT, value INTEGER, category TEXT
}

func createCategorySummaries(db *sql.D
```

https://copilot.github.com/

Outline

Intro to (Foundation) Language Models

State of the Field
Trends, findings, questions

Opportunities

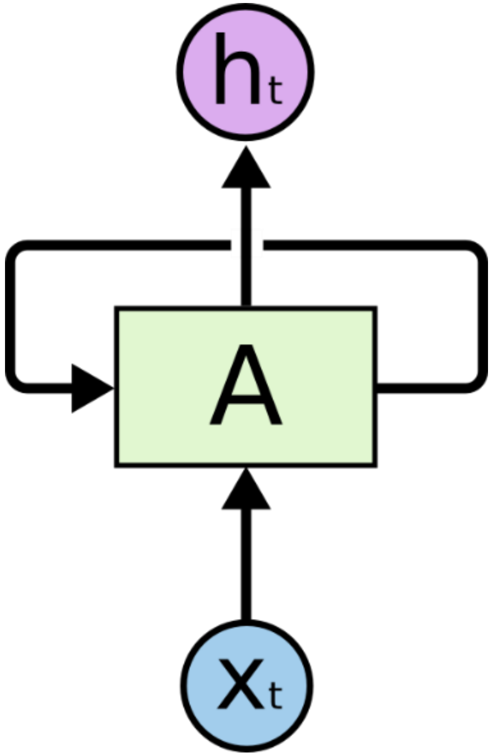
Challenges

Language Modeling

Language is largely "left-to-right"

I am going to the ___

movies
grocery store
meeting



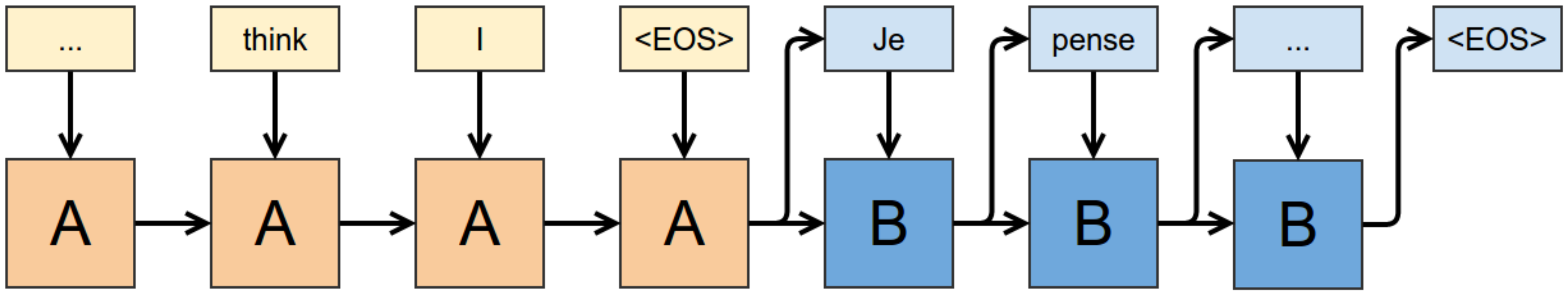
Recurrent Neural Networks (RNNs) capture this naturally

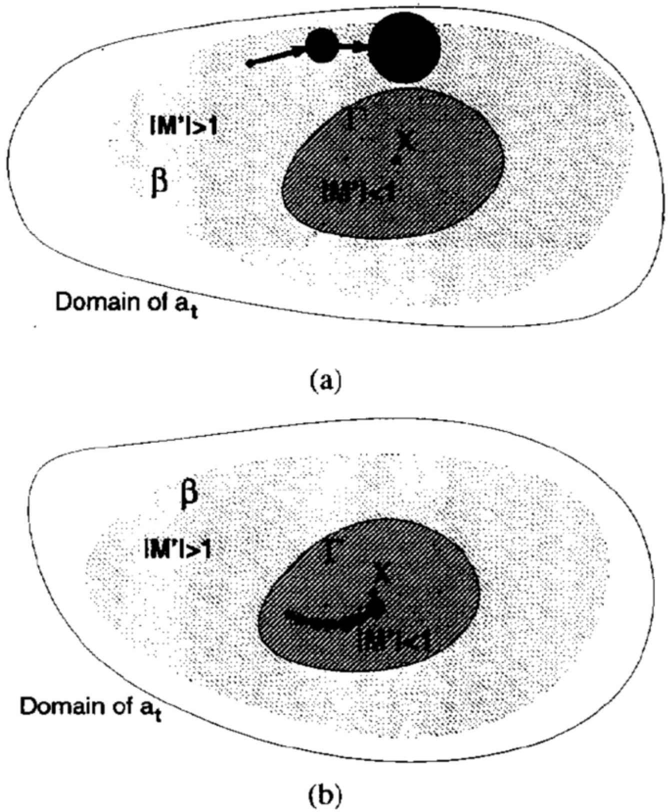
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Language Modeling

RNNs condense all history into a single state

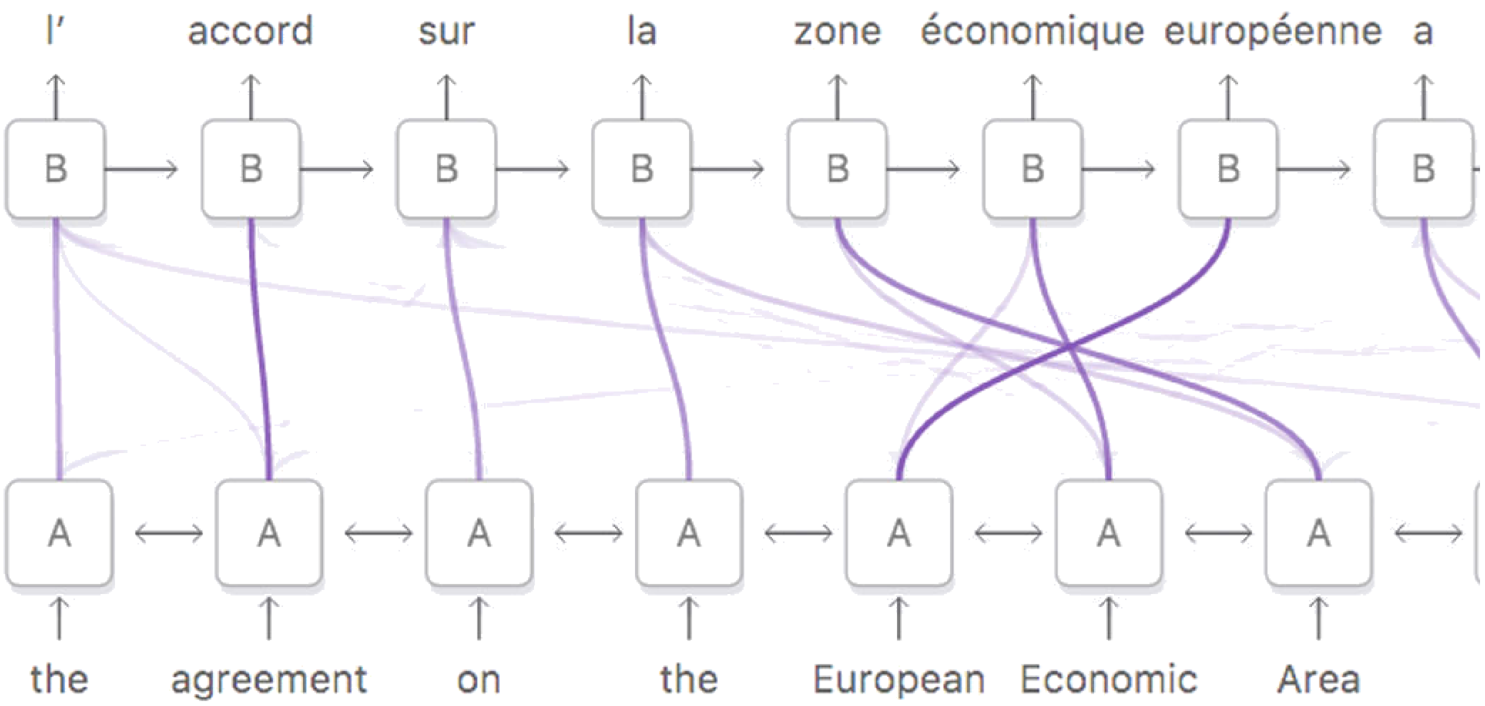
… which is provably problematic

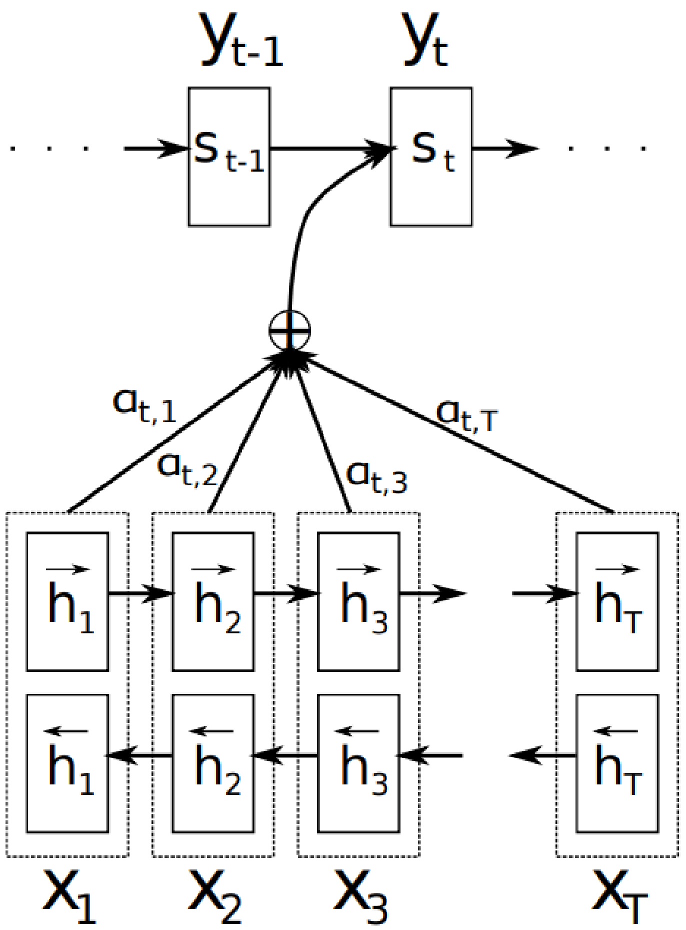




https://colah.github.io/posts/2015-01-Visualizing-Representations/ – *Learning long-term dependencies with gradient descent is difficult*, Bengio, Simard & Frasconi, TNN 1994

Attention: Learn to Ask



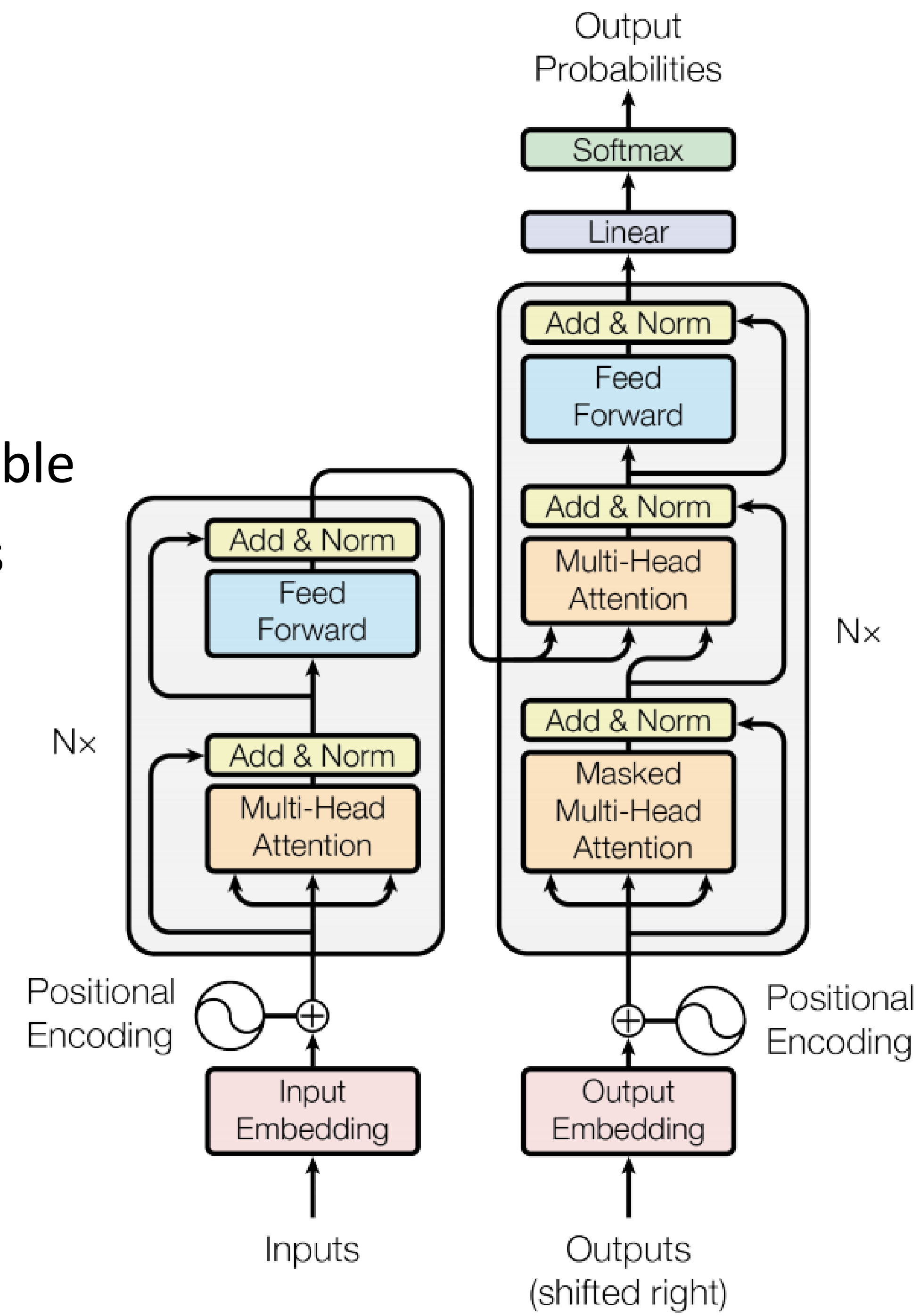


https://distill.pub/2016/augmented-rnns/
https://medium.com/hackernoon/attention-mechanism-in-neural-network-30aaf5e39512

Transformers

Do we still need RNNs?

- Attention is powerful & highly parallelizable
- Using just attention is possible, but takes quite a few ingredients.

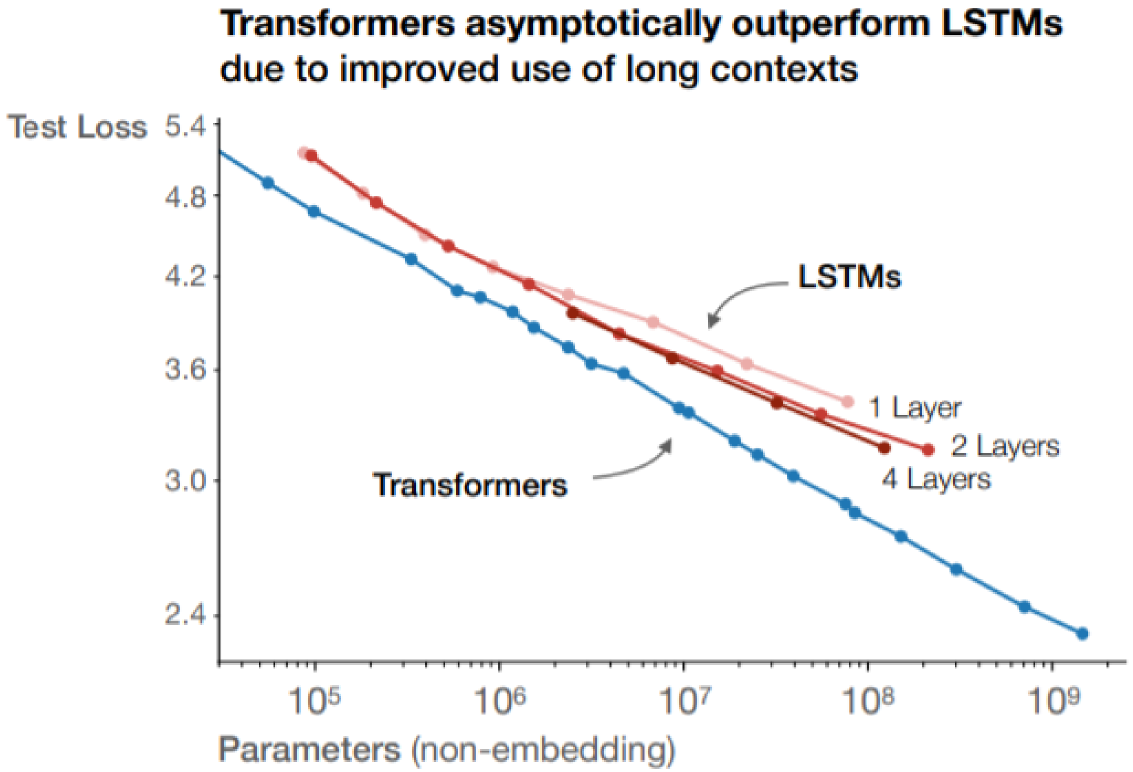


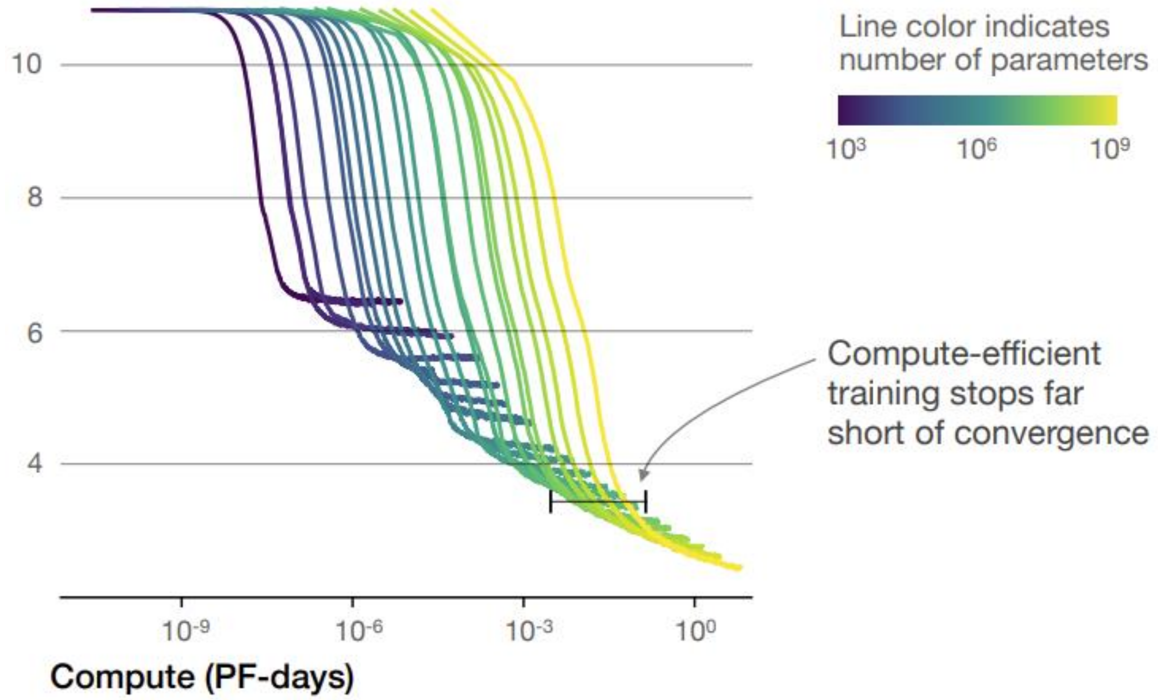
Attention is All You Need. Vaswani et al., 2017

Transformers

Allow for unprecedented *scaling*

- A key property of foundation models

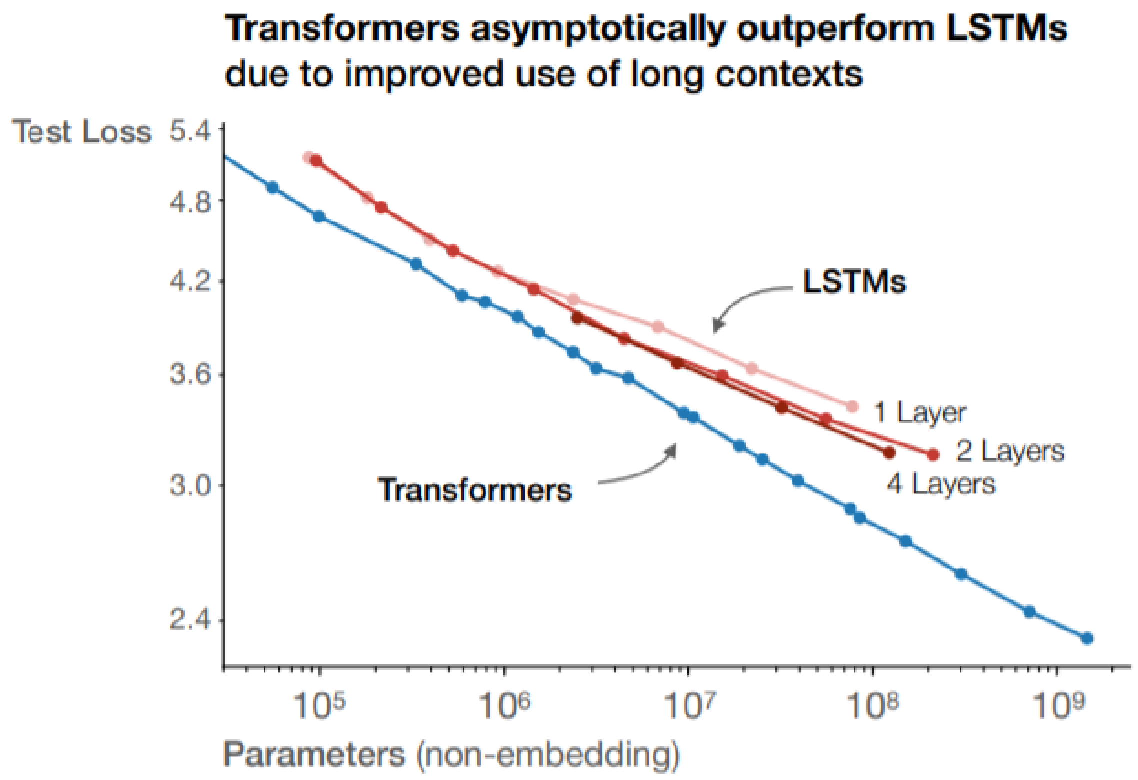


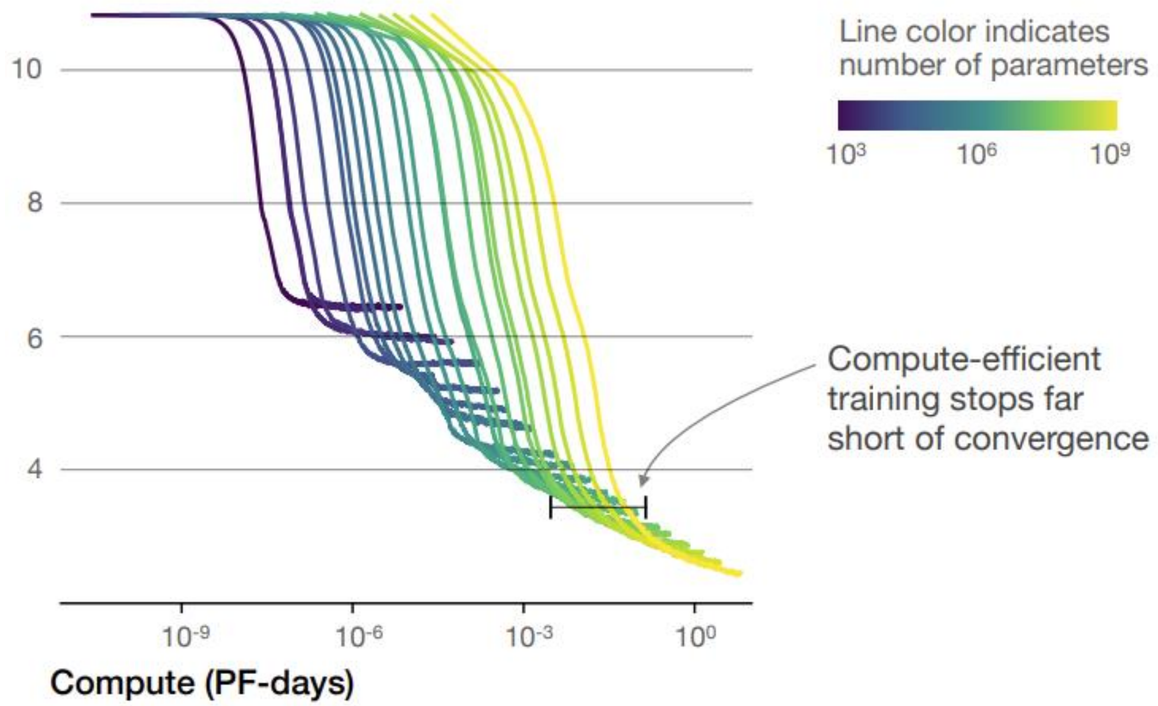


Scaling Laws for Neural Language Models. Kaplan *et al.*, 2020. https://arxiv.org/pdf/2001.08361.pdf

Transformers Are Good Foundation Models

1. Strong, consistent scaling with compute

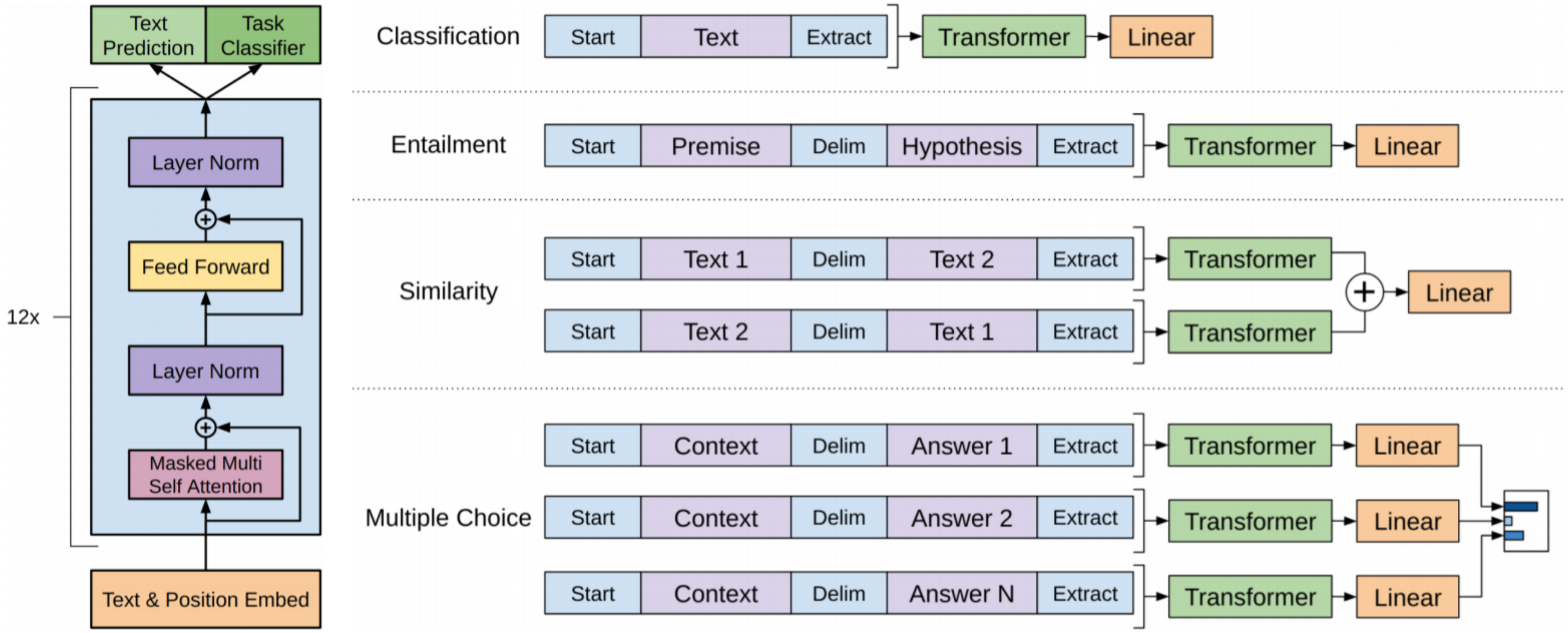




Scaling Laws for Neural Language Models. Kaplan *et al.*, 2020. https://arxiv.org/pdf/2001.08361.pdf

Transformers Are Good Foundation Models

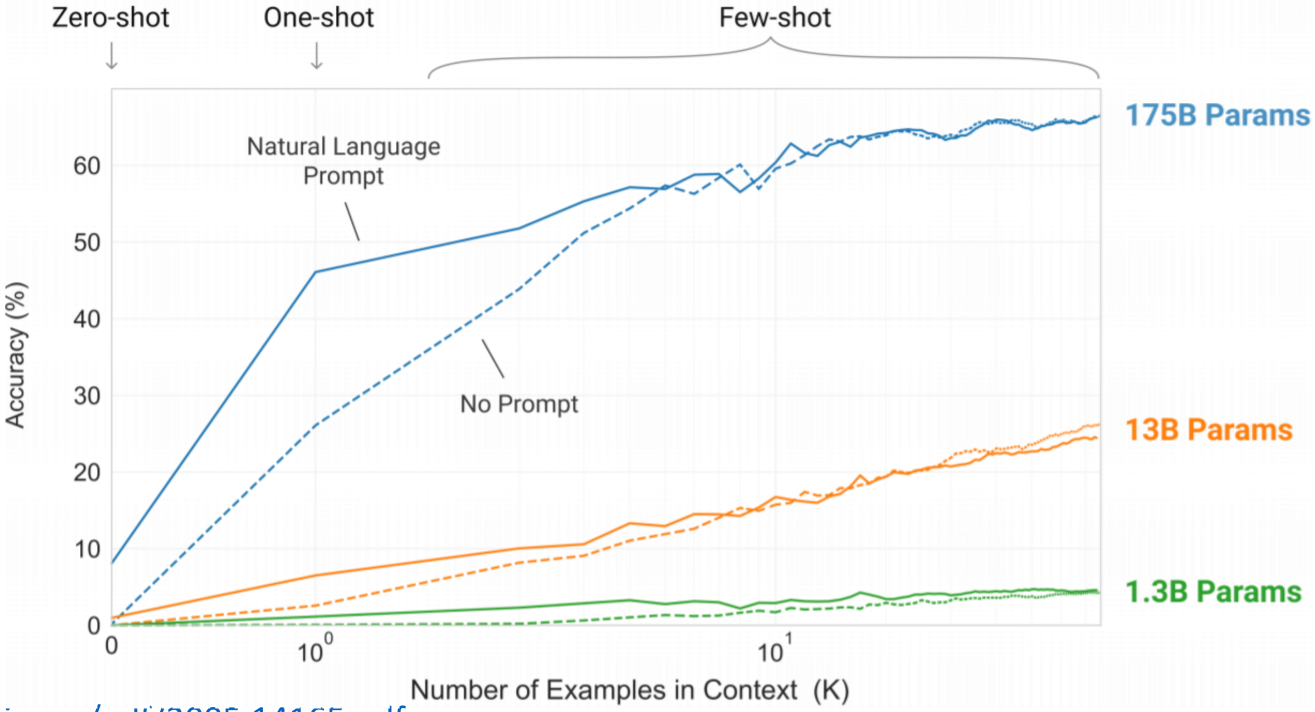
1. Strong, consistent scaling with compute
2. Powerful initialization from (generic) pretraining



https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/language-unsupervised/language_understanding_paper.pdf

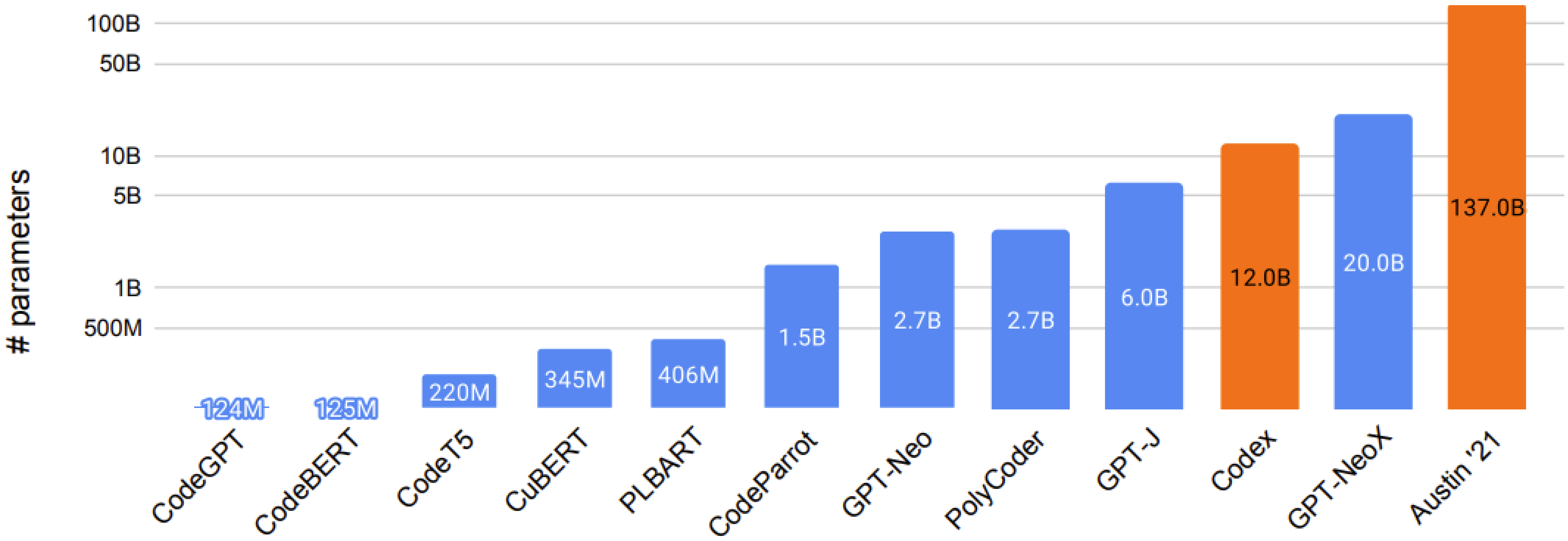
Transformers Are Good Foundation Models

1. Strong, consistent scaling with compute
2. Powerful initialization from (generic) pretraining
3. Emergent capabilities at large scale



GPT-3 (Brown et al., 2020), https://arxiv.org/pdf/2005.14165.pdf

Software: We Scale Too



Note: orange is closed-source

https://arxiv.org/pdf/2202.13169.pdf

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Models: a Bird’s Eye View

Trained entirely on Code:

- CodeParrot (Misc., 2021)
- PolyCoder (CMU, 2022)
- InCoder (FAIR, 2022)

Trained mostly on NL:

- GPT-Neo/J/NeoX (Misc + EleutherAI, 2021/2)
- PALM (Google, 2022)
- Austin et al. (Google, 2021)

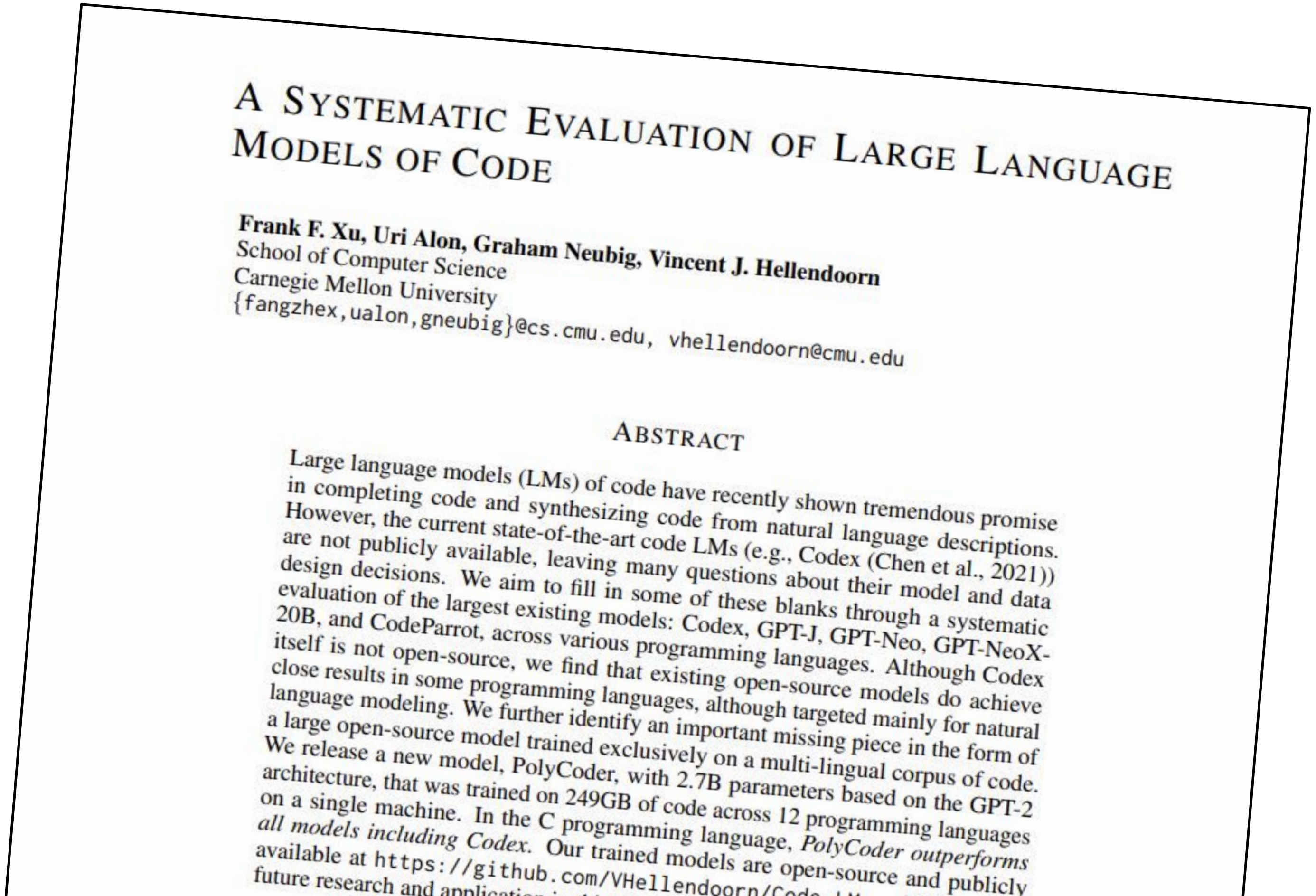
A bit of both:

- Codex (2021, OpenAI)
- CodeGen (2022, Salesforce)

I’ll discuss best-practice based on all of these

What Makes a Good LLM for Code?

1. Data
    - Volume
    - Preprocessing
2. Model Size
    - Parameters
3. Initialization
    - NL pretraining
4. Training
    - Code tokens seen
    - Language effects
    - Batch size & misc.



A SYSTEMATIC EVALUATION OF LARGE LANGUAGE MODELS OF CODE

Frank F. Xu, Uri Alon, Graham Neubig, Vincent J. Hellendoorn
School of Computer Science
Carnegie Mellon University
{fangzhex,ualon,gneubig}@cs.cmu.edu, vhellendoorn@cmu.edu

ABSTRACT

Large language models (LMs) of code have recently shown tremendous promise in completing code and synthesizing code from natural language descriptions. However, the current state-of-the-art code LMs (e.g., Codex (Chen et al., 2021)) are not publicly available, leaving many questions about their model and data design decisions. We aim to fill in some of these blanks through a systematic evaluation of the largest existing models: Codex, GPT-J, GPT-Neo, GPT-NeoX-20B, and CodeParrot, across various programming languages. Although Codex itself is not open-source, we find that existing open-source models do achieve close results in some programming languages, although targeted mainly for natural language modeling. We further identify an important missing piece in the form of a large open-source model trained exclusively on a multi-lingual corpus of code. We release a new model, PolyCoder, with 2.7B parameters based on the GPT-2 architecture, that was trained on 249GB of code across 12 programming languages on a single machine. In the C programming language, *PolyCoder outperforms all models including Codex*. Our trained models are open-source and publicly available at https://github.com/VHellendoorn/

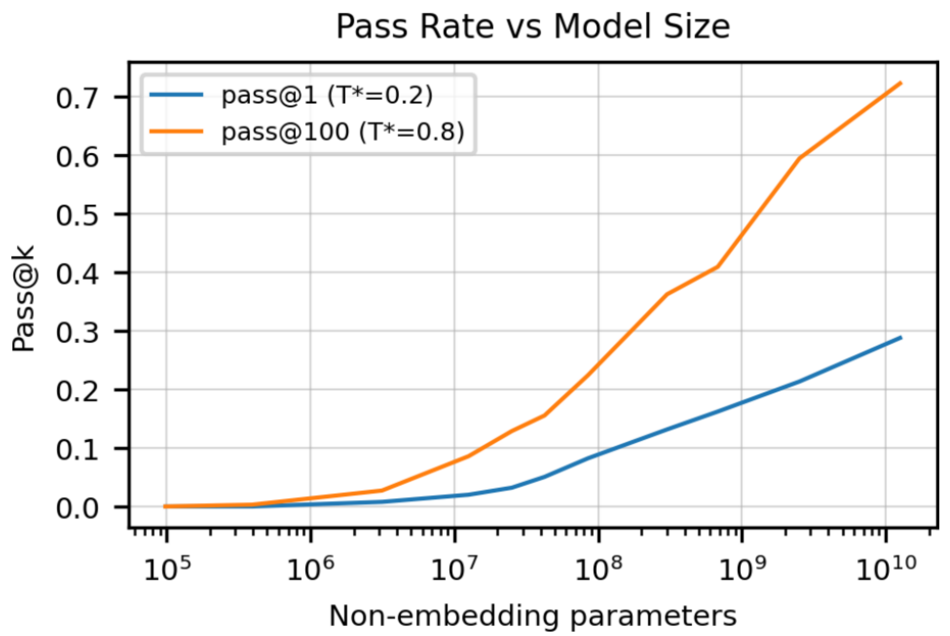
Codex

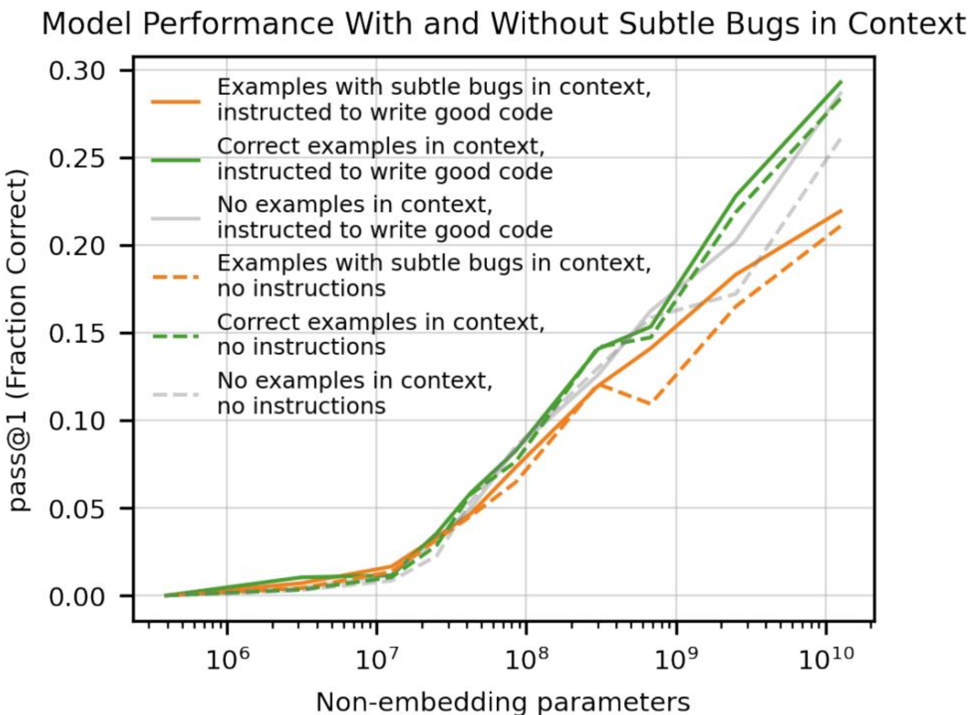
The first many-billion parameter LM for code

- Initialized from GPT-3
- Fine-tuned on 159GB of Python
  - Introduced HumanEval: a benchmark of NL → Python Code problems with tests

Some Findings:

- Strong, log-linear **scaling** after ~ 50M params
- Prompting matters, even non-functional aspects





https://arxiv.org/pdf/2107.03374.pdf

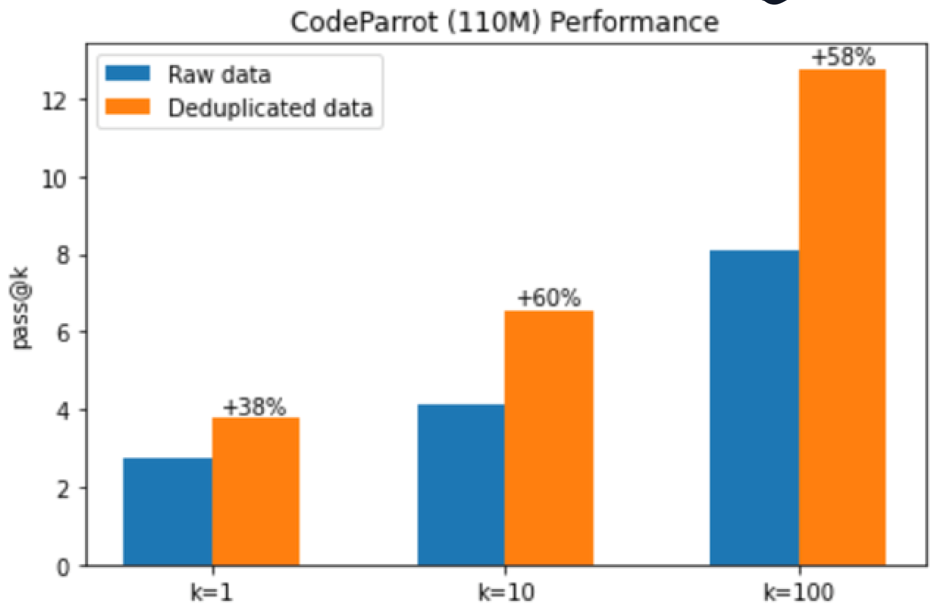
CodeParrot

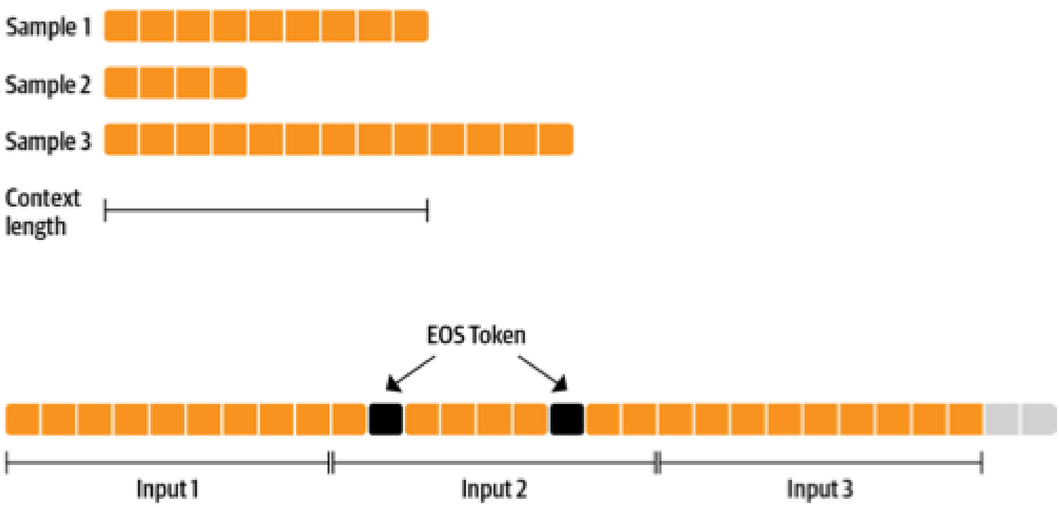
The first OSS entry

- 1.5B parameters
- 26B Python tokens from BigQuery

Some Findings:

- Ca. 70% duplication – deduplication is key
- Code files can be very long
  - Segment into windows of 1,024
  - This is common in NL training too



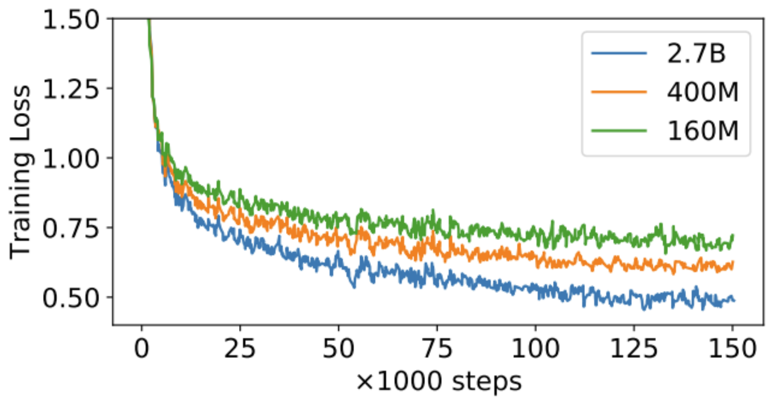


https://huggingface.co/blog/codeparrot

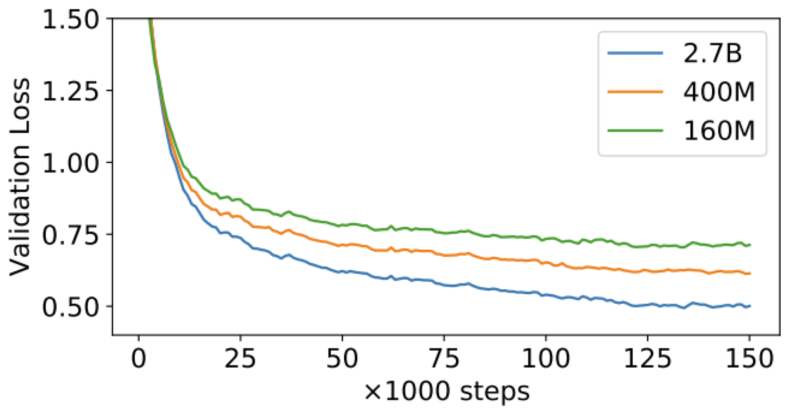
PolyCoder

Our entry from CMU

- 2.7B parameters
- Trained on 12 languages



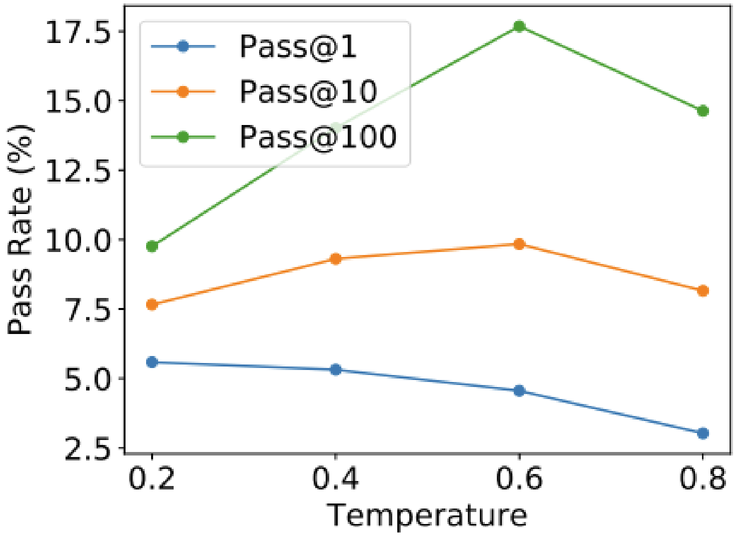
(a) Training



(b) Validation

Some Findings:

- Edge of single-node/“lab-machine” scale training
  - Ca. 45 days on 8 * RTX 8000 48GB
- Further insights into sampling *temperature*



https://arxiv.org/pdf/2202.13169.pdf

A Systematic Evaluation of Large Language Models of Code

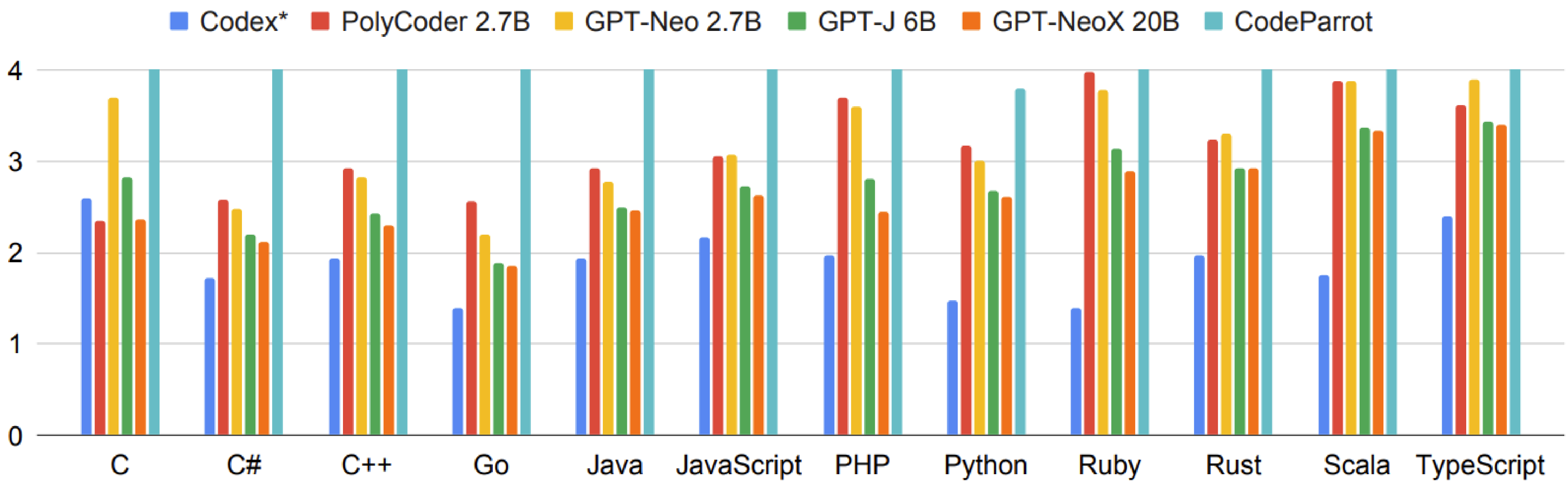
- The good news: PolyCoder outperforms Codex on C

* Since the exact training set of Codex is unknown, it may include files from these test sets rendering Codex's results overly-optimistic.

https://arxiv.org/pdf/2202.13169.pdf – **NOTE:** CodeParrot Python score is likely incorrect, should be ca. 2.9

A Systematic Evaluation of Large Language Models of Code

- The good news: PolyCoder outperforms Codex on C
- The bad news: most LMs, even some trained on less code, are better on others



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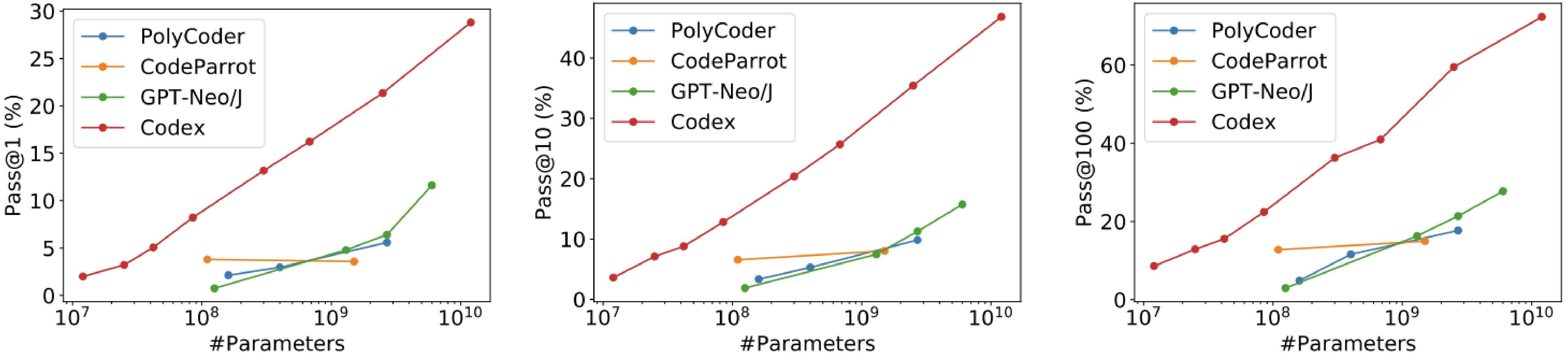
A Systematic Evaluation of Large Language Models of Code

Goal: understand what makes Codex work

- It seems *unreasonably* effective



(a) Pass@1 (b) Pass@10 (c) Pass@100

https://arxiv.org/pdf/2202.13169.pdf

A Systematic Evaluation of Large Language Models of Code

Goal: understand what makes Codex work

- It seems *unreasonably* effective
- What gives? It does more data preprocessing, but CodeParrot does the same

	PolyCoder	CodeParrot	Codex
Dedup	Exact	Exact	Unclear, mentions “unique”
Filtering	Files > 1 MB, < 100 tokens	Files > 1MB, max line length > 1000, mean line length > 100, fraction of alphanumeric characters < 0.25, containing the word ”auto-generated” or similar in the first 5 lines	Files > 1MB, max line length > 1000, mean line length > 100, auto-generated (details unclear), contained small percentage of alphanumeric characters (details unclear)
Tokenization	Trained GPT-2 tokenizer on a random 5% subset (all languages)	Trained GPT-2 tokenizer on train split	GPT-3 tokenizer, add multi-whitespace tokens to reduce redundant whitespace tokens

https://arxiv.org/pdf/2202.13169.pdf

A Systematic Evaluation of Large Language Models of Code

Goal: understand what makes Codex work

- It seems *unreasonably* effective
- What then? Candidate explanations:

	PolyCoder (2.7B)	CodeParrot (1.5B)	Codex (12B)
Model Initialization	From scratch	From scratch	Initialized from GPT-3
NL Knowledge	Learned from comments in the code	Learned from comments in the code	Natural language knowledge from GPT-3
Learning Rate	1.6e-4	2.0e-4	1e-4
Optimizer	AdamW	AdamW	AdamW
Adam betas	0.9, 0.999	0.9, 0.999	0.9, 0.95
Adam eps	1e-8	1e-8	1e-8
Weight Decay	-	0.1	0.1
Warmup Steps	1600	750	175
Learning Rate Decay	Cosine	Cosine	Cosine
Batch Size (#tokens)	262K	524K	2M
Training Steps	150K steps, 39B tokens	50K steps, 26B tokens	100B tokens
Context Window	2048	1024	4096

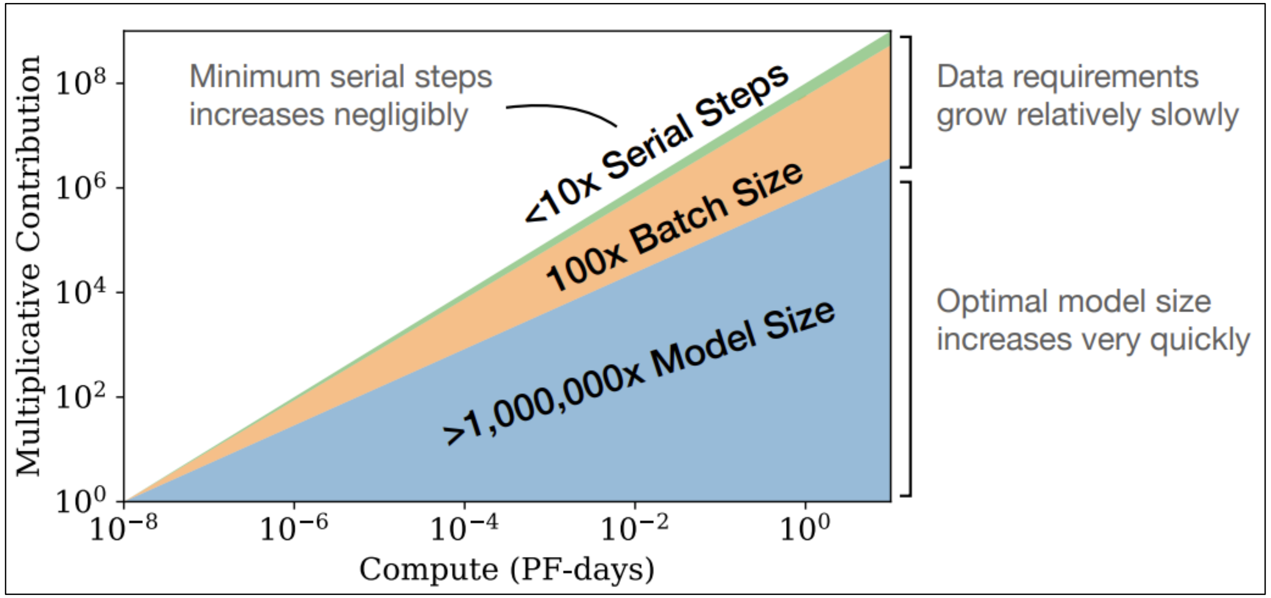
Initialization

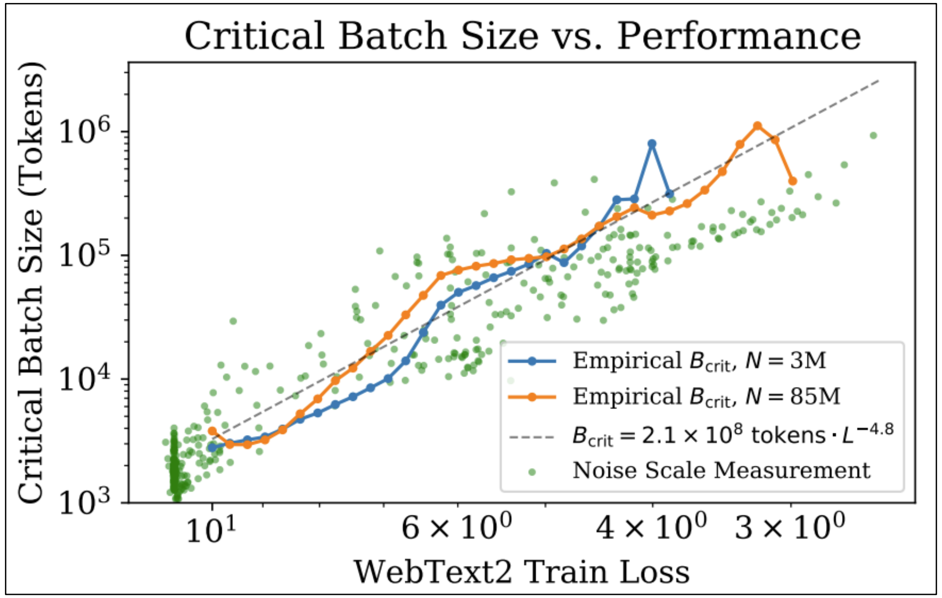
Training

https://arxiv.org/pdf/2202.13169.pdf

Batch Size

- Large batches yield lower loss
  - 2M+ tokens per batch is now common
- But, greatly increases GPU needs
  - At 2.7B params, a 48GB GPU can fit ca. 2^{15} tokens
  - We can simulate larger batches with "gradient accumulation", but that is very slow





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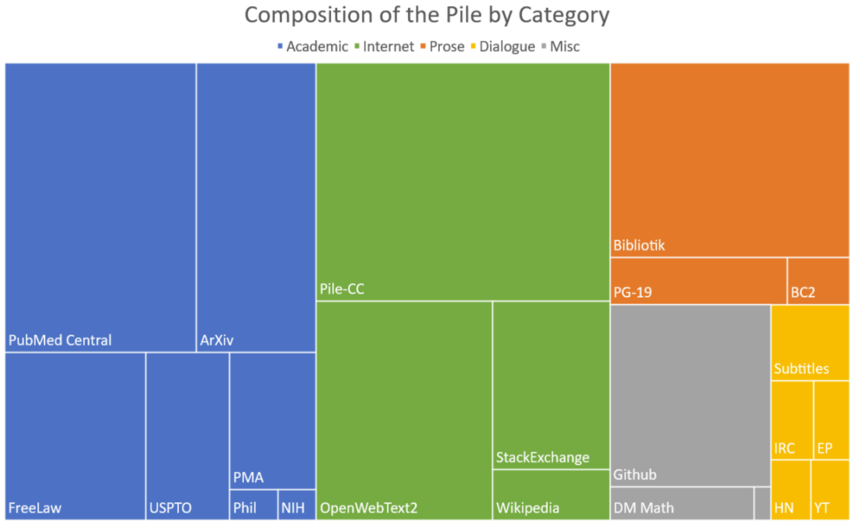
Pre-Training: Let's Talk GPT-x

- Various open source LLMs exist
  - Mainly of interest: GPT-J, GPT-Neo, GPT-NeoX
  - Trained with/by EleutherAI
  - Up to 20B parameters (NeoX)
- Trained on The Pile
  - Large web-crawl including GitHub (ca. 10%) & StackOverflow
  - "Third" option, besides code-only or NL first, then Code



https://arxiv.org/pdf/2101.00027.pdf

Let’s Talk GPT-x

- Trained far longer, but on similar #code tokens

Model	Pass@1	Pass@10	Pass@100	Tokens Trained	Code Tokens	Python Tokens
PolyCoder (160M)	2.13%	3.35%	4.88%	39B	39B	2.5B
PolyCoder (400M)	2.96%	5.29%	11.59%	39B	39B	2.5B
PolyCoder (2.7B)	5.59%	9.84%	17.68%	39B	39B	2.5B
CodeParrot (110M)	3.80%	6.57%	12.78%	26B	26B	26B
CodeParrot (1.5B)	3.58%	8.03%	14.96%	26B	26B	26B
GPT-Neo (125M)	0.75%	1.88%	2.97%	300B	22.8B	3.1B
GPT-Neo (1.3B)	4.79%	7.47%	16.30%	380B	28.8B	3.9B
GPT-Neo (2.7B)	6.41%	11.27%	21.37%	420B	31.9B	4.3B
GPT-J (6B)	11.62%	15.74%	27.74%	402B	30.5B	4.1B
Codex (300M)	13.17%	20.37%	36.27%	100B*	100B*	100B*
Codex (2.5B)	21.36%	35.42%	59.50%	100B*	100B*	100B*
Codex (12B)	28.81%	46.81%	72.31%	100B*	100B*	100B*

https://arxiv.org/pdf/2202.13169.pdf

Let’s Talk GPT-x

- Trained far longer, but on similar #code tokens
- Around 100M parameters, CodeParrot is decidedly better, followed by PolyCoder

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Let's Talk GPT-x

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- But in 1-3B range, Neo is *clearly better*

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https://arxiv.org/pdf/2202.13169.pdf – NeoX 20B is even better, has been benchmarked here https://arxiv.org/pdf/2204.05999.pdf

Let's Talk GPT-x

- Trained far longer, but on similar #code tokens
- But in 1-3B range, Neo is *clearly better*
- CodeParrot saw the most Python tokens – evidently important at small scale
  - But at 1B+ parameter scale, total training data volume matters, a lot
    - Neo saw 10-15x as many tokens
- CodeParrot & PolyCoder are <u>seriously underfitting</u> for their size
  - We trained 2.7B parameters with ~40B tokens (seen); 400B would have been better
    - Unrealistic on a single node
  - What is the best pretraining/initialization signal?

CodeGen

A 3-tier training regime

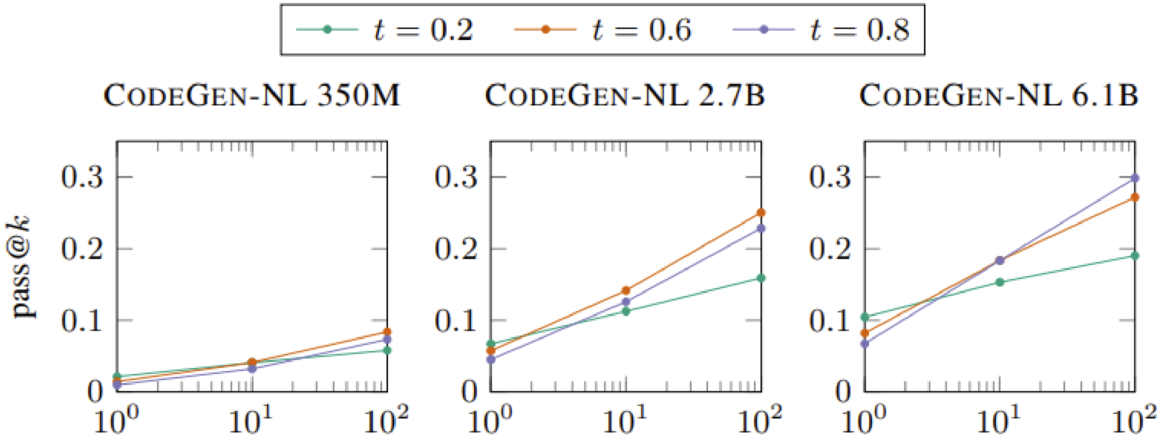
1. Initialize on The Pile
2. Calibrate on 6 languages from BigQuery GitHub
3. Fine-tune on Python-only

https://arxiv.org/pdf/2203.13474.pdf

CodeGen

Key observations:

- NL Scaling is decent, but capped
    - Helpful temperature observations



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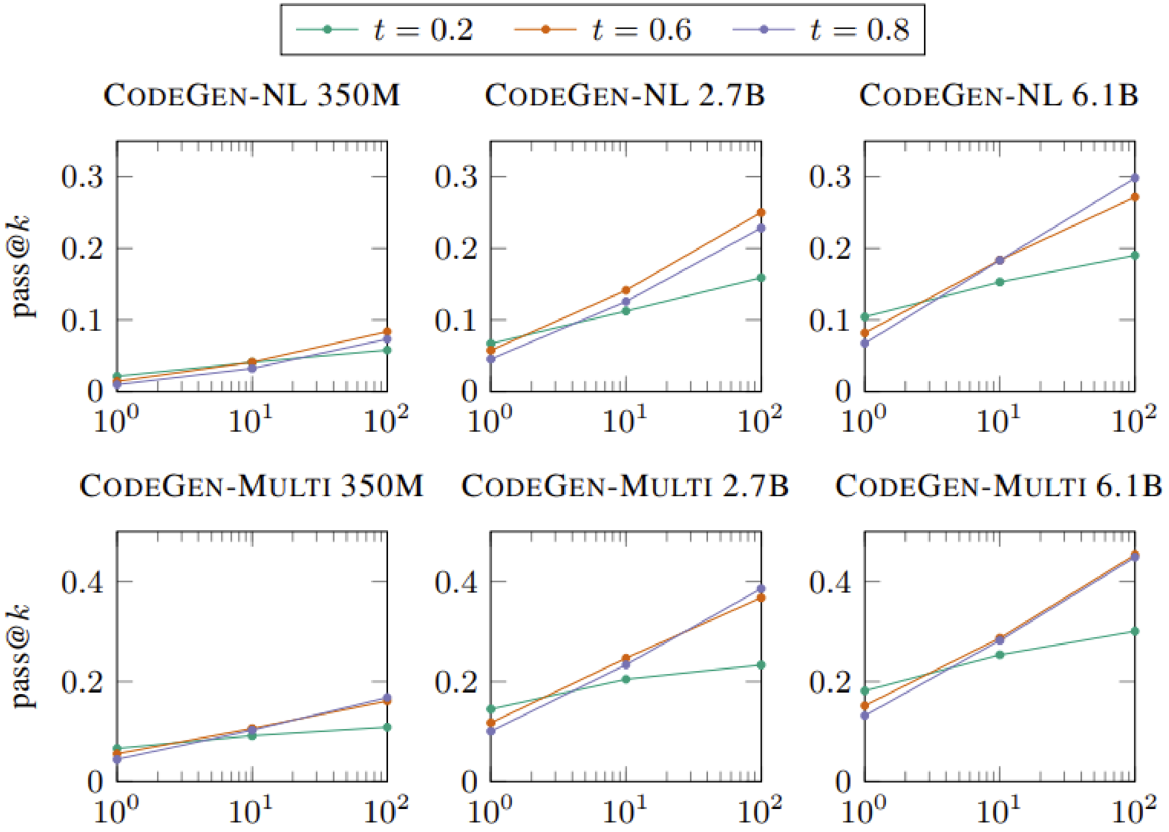
- Multi-lingual training helps modestly
  - (note change in y-range)



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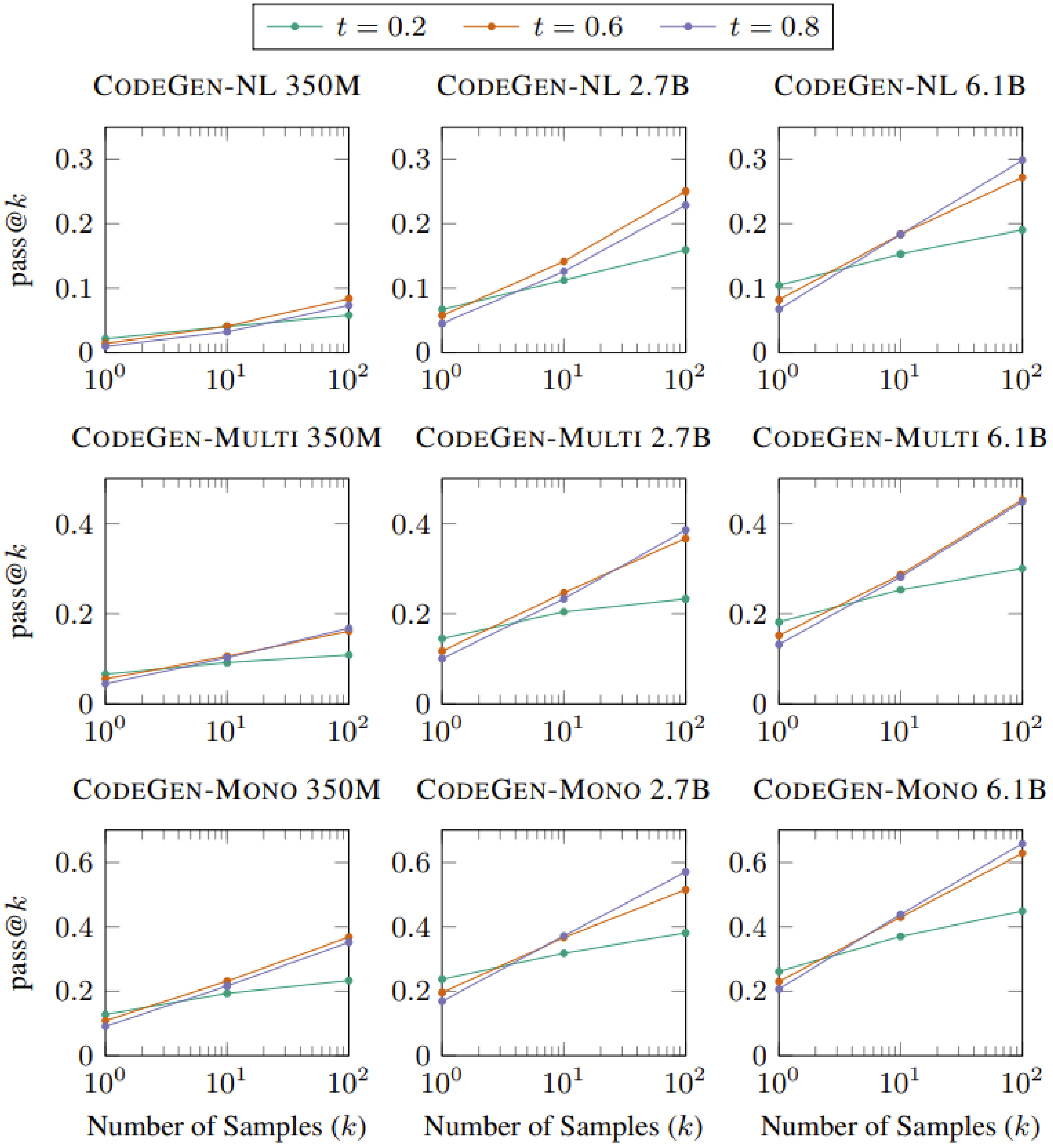
CodeGen

Key observations:

- NL Scaling is decent, but capped
  - Helpful temperature observations
- Multi-lingual training helps modestly
  - (note change in y-range)
- Monolingual fine-tuning is crucial
  - First to match Codex
- Is “Multi” before “Mono” necessary?
  - Unclear, Codex suggests not

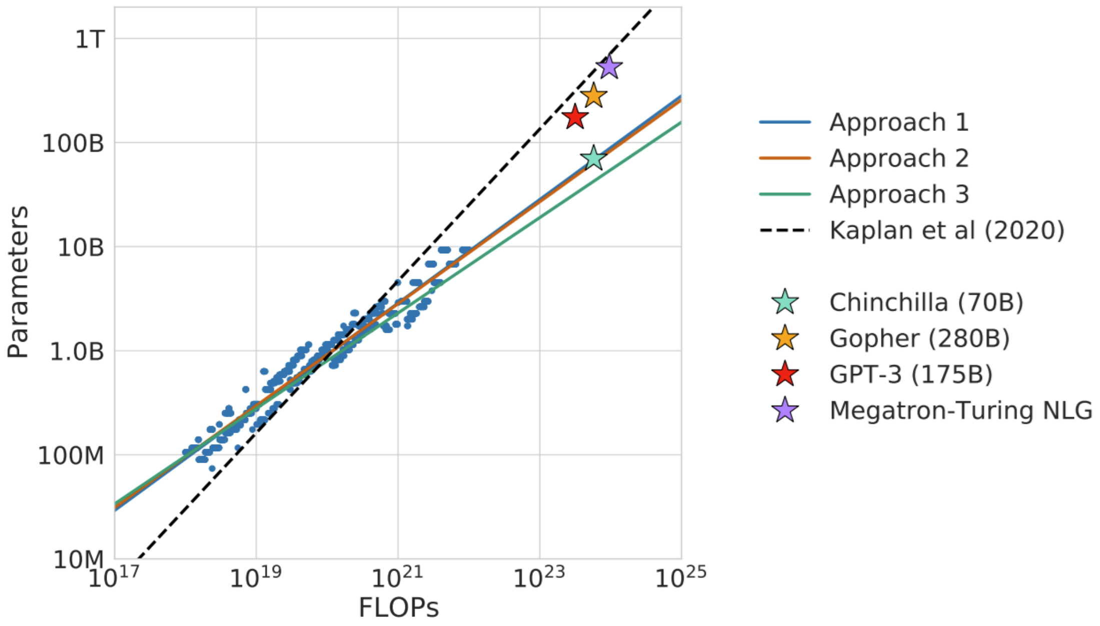


https://arxiv.org/pdf/2203.13474.pdf

How to Match Codex

- Data
  - Several 100B tokens required
    - Rarely available for a single programming language; NL initialization works well
  - Language-specific fine-tuning (50GB or more) is key
- Model
  - Performance increases log-linearly with parameters
  - 2B to 6B parameters is a sweet-spot (for now)
    - Low memory footprint enables large batch sizes; performance just 10%-25% shy of Codex
    - Fairly good latency, but needs work
- Resources (for 2.7B parameters)
  - **Memory:** 2.5TB+ of RAM, for 2M tokens per batch without gradient accumulation
  - **Compute:** ca. 200 PetaFLOP/s Days $\approx$ 3 weeks on 64 A100s (at 45% throughput)
  - Both scale linearly with model size; 12B parameters needs 4-5x as much

Open Research Questions



- **Fundamentally:** Better Scaling Laws for Code
  - Chinchilla suggests smaller models, more data
  - If same for code, PolyCoder was near-optimal*
    - The trick is finding that much mono-lingual data
- Context window: 4,096 vs. 2,048
  - AFAIK, only Codex uses the former
  - Code files are large – it should help
  - But, 4K is expensive, all-but necessitates sparse/dense attention
- Tokenization: PolyCoder vocabulary is code-specific, Codex & others aren't
  - Codex's vocab seems to be GPT-3 + sequences of 1 – 24 spaces.
  - Does it matter? This work suggests some code-specific tokenization might help: https://openreview.net/pdf?id=rd-G1nO-Jbq
    - But note: no results on LLMs.

https://arxiv.org/pdf/2203.15556.pdf -- We used 1.4e^{21} FLOPs; Chinchilla suggests using that budget to train ~3-4B parameters and ~75B tokens

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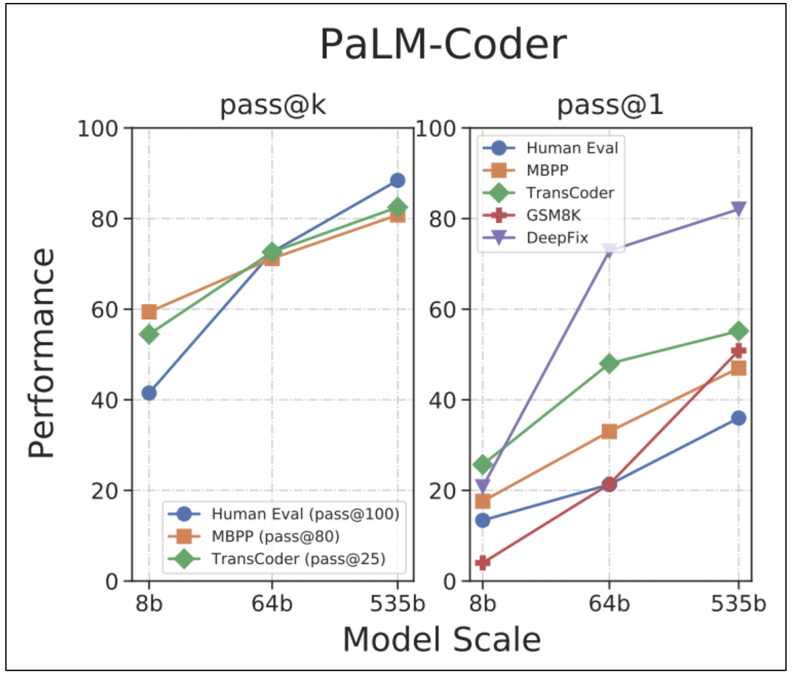
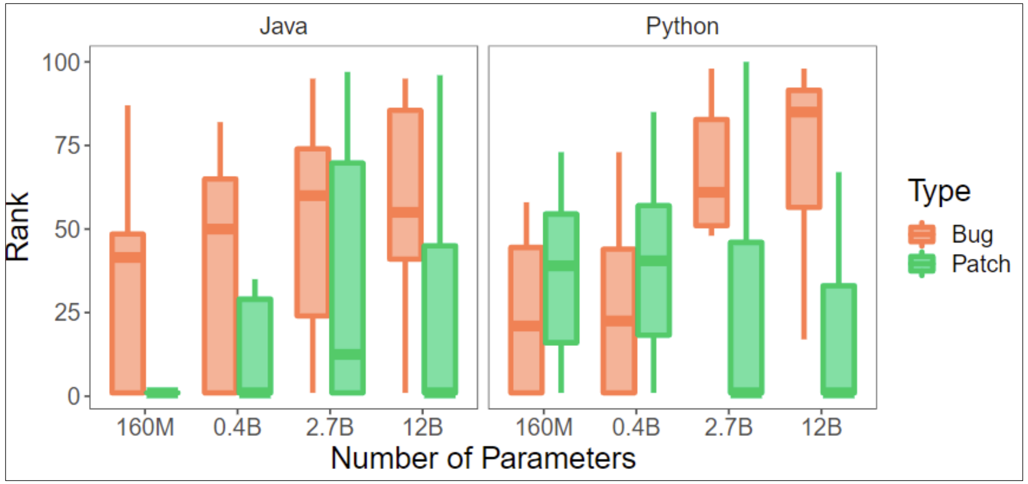
Challenges

What's Next?

- Breaking free from left-to-right
  - FAIR's InCoder, Codex edit mode
  - Iteratively refining generations
- New Scaling Frontiers
  - Google's PaLM
- New Tasks
  - Repair, type prediction, translation

```python
def count_words(filename: str) -> Dict[str, int]:
    """Count the number of occurrences of each word in the file."""
    with open(filename, 'r') as f:
        word_counts = {}
        for line in f:
            for word in line.split():
                if word in word_counts:
                    word_counts[word] += 1
                else:
                    word_counts[word] = 1
    return word_counts
```





InCoder

- Causal Masking
  - I.e., decoder-only
  - Drop 1+ random spans
  - Infill using placeholders
- Train on Python + S.O.
- Up to 6.7B params

Training

Original Document

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def count_words(filename: str) -> Dict[str, int]:
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                else:
                    word_counts[word] = 1
    return word_counts
```

Masked Document

```
def count_words(filename: str) -> Dict[str, int]:
    """Count the number of occurrences of each word in
    with open(filename, 'r') as f:
        <MASK:0> in word_counts:
                    word_counts[word] += 1
                else:
                    word_counts[word] = 1
    return word_counts
<MASK:0> word_counts = {}
        for line in f:
            for word in line.split():
                if word <EOM>
```

https://arxiv.org/pdf/2204.05999.pdf

InCoder

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<MASK:0> word_counts = {}
        for line in f:
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                if word <EOM>
```

Zero-shot Inference

Type Inference

```python
def count_words(filename: str) -> Dict[str, int]:
    """Count the number of occurrences of each word in the file."""
    with open(filename, 'r') as f:
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            for word in line.split():
                if word in word_counts:
                    word_counts[word] += 1
                else:
                    word_counts[word] = 1
    return word_counts
```

Variable Name Prediction

```python
def count_words(filename: str) -> Dict[str, int]:
    """Count the number of occurrences of each word in
    with open(filename, 'r') as f:
        word_count = {}
        for line in f:
            for word in line.split():
                if word in word_count:
                    word_count[word] += 1
                else:
                    word_count[word] = 1
    return word_count
```

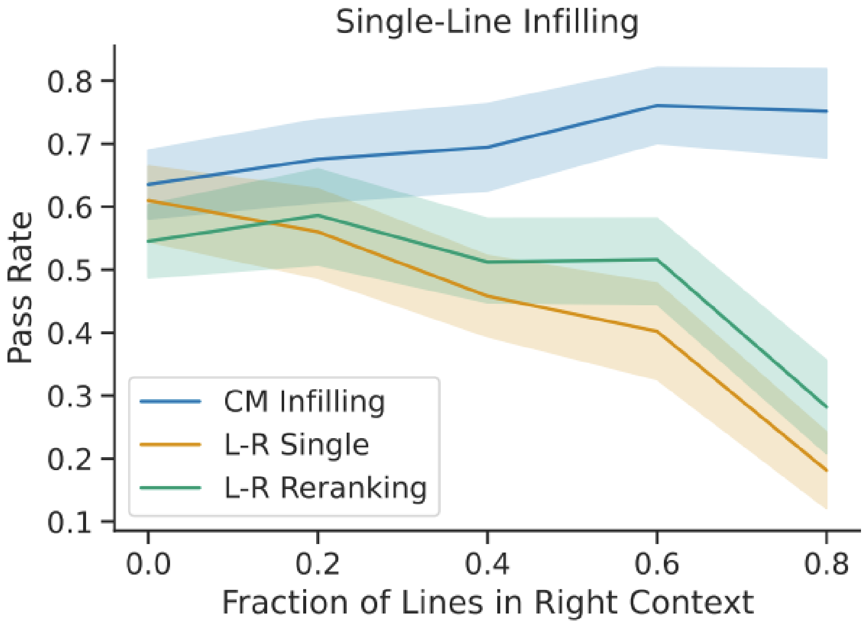
Enables tons of tasks

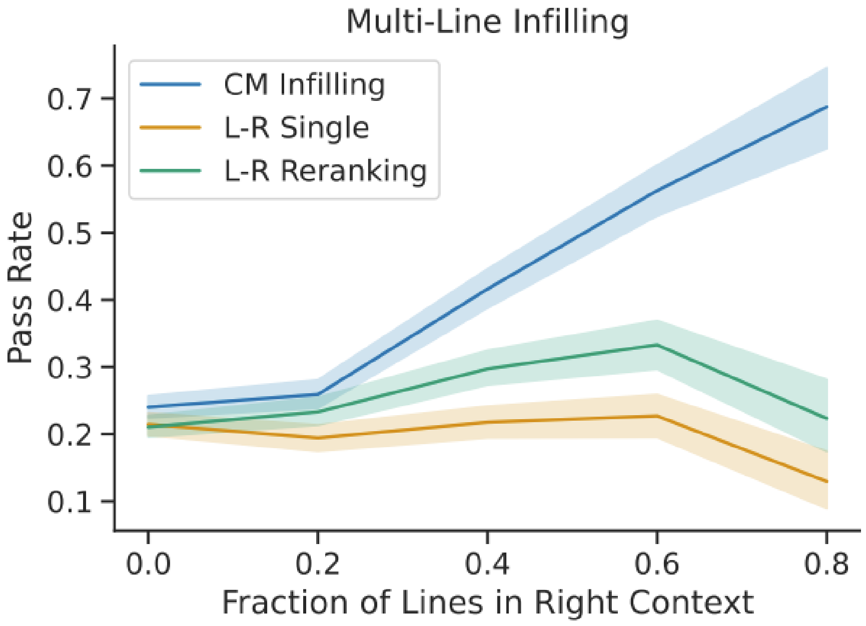
- Variable naming
- Type inference
- Completion
- Repair

https://arxiv.org/pdf/2204.05999.pdf

InCoder

- Based on Causal Masking
  - Powerful idea! Suffix context is very helpful
  - Probably worth exploring masking strategies beyond Poisson-random on tokens



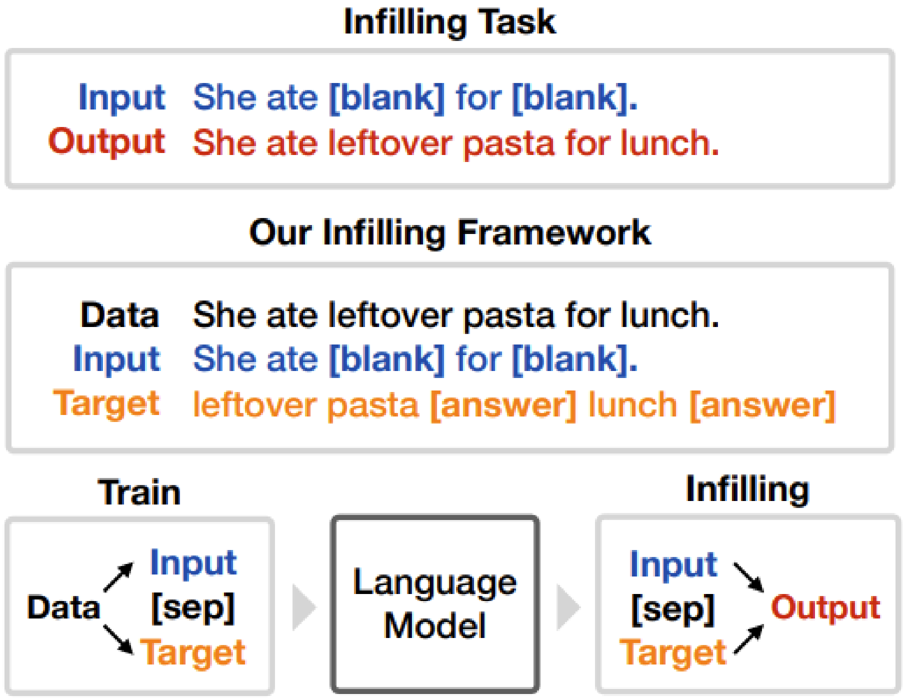


https://arxiv.org/pdf/2204.05999.pdf

Codex can do this too

- Not many details
  - Can train like this with encoder/decoder setup (see also (Code)T5)

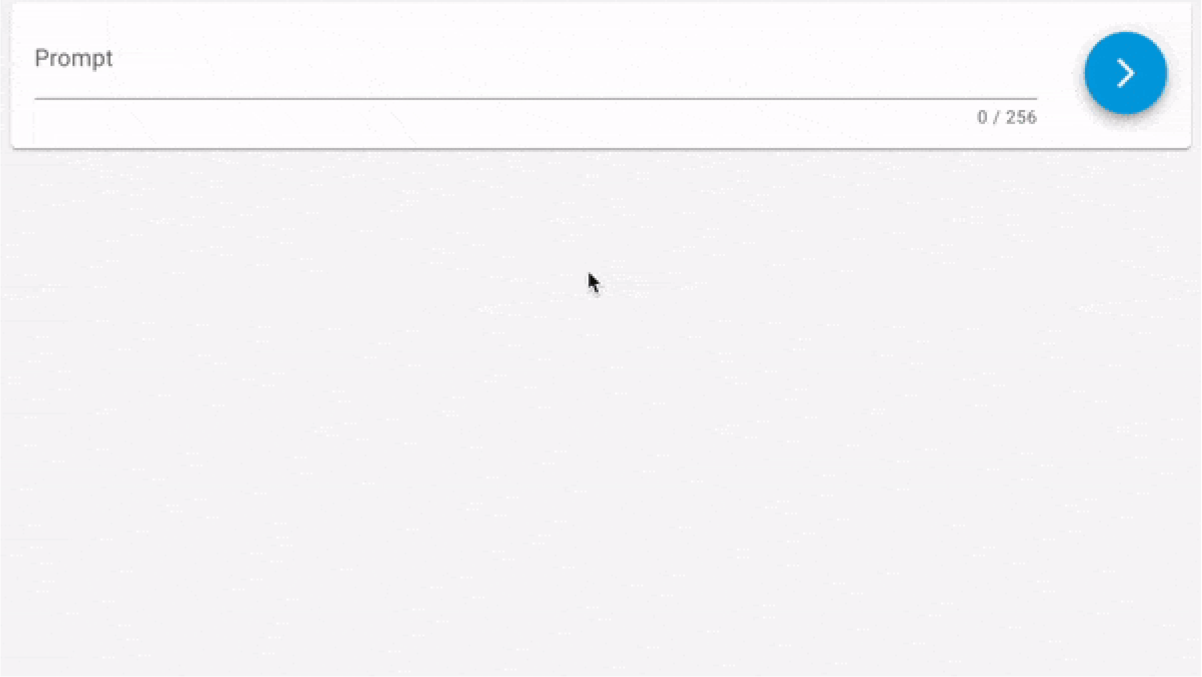
```python
def get_files(path: str, size: int):
    def prune(dirp, files):
        for file in files:
            file = os.path.join(dirp, file)
            if os.path.getsize(file) > size:
                yield file
    for (dirp, _, files) in os.walk(path):
        yield from prune(dirp, files)
```

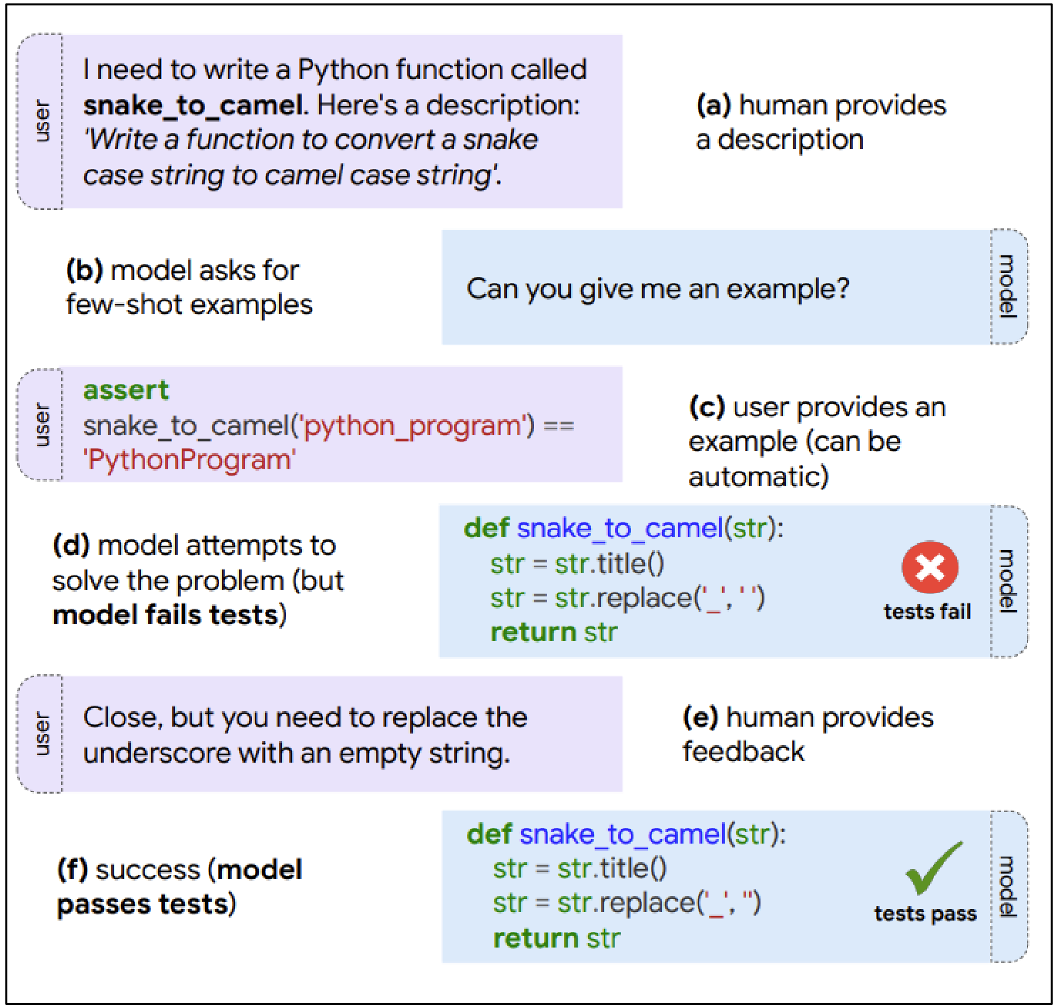


https://openai.com/blog/gpt-3-edit-insert/ – https://arxiv.org/pdf/2005.05339.pdf

Iterating (CodeGen, Austin et al.)

- Who gets everything right the first time?
  - Iteration is surprisingly feasible!
  - Never explicitly trained for, just concatenate history
    - Is that good/bad? Who knows!





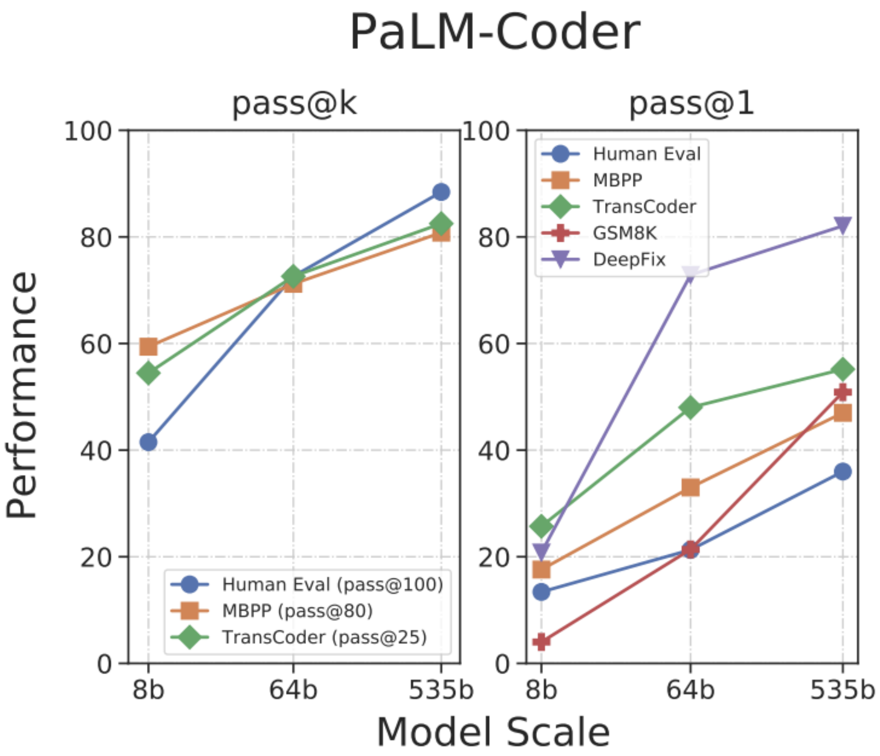
https://arxiv.org/pdf/2203.13474.pdf – https://arxiv.org/pdf/2108.07732.pdf

PaLM(-Coder) – 535B parameters

Data: 780B tokens Google internal web crawl

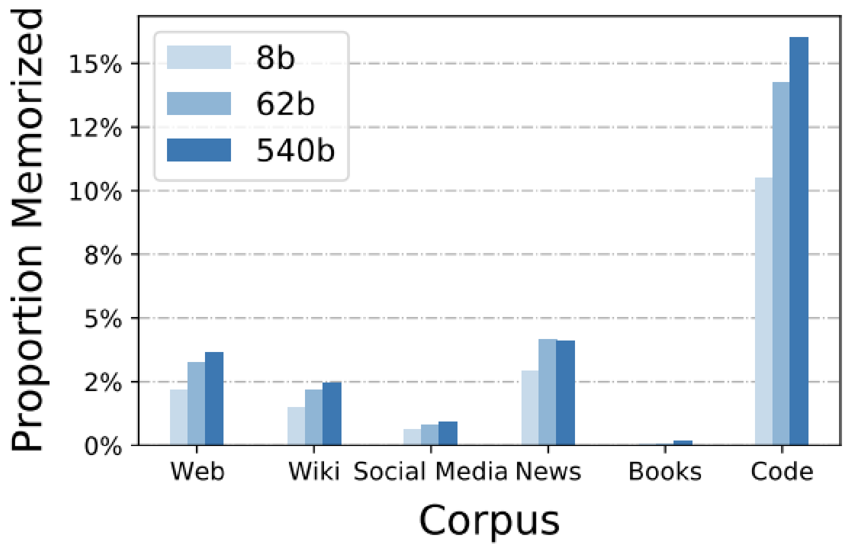
Code: 39B tokens from 24 languages, 39B tokens

- Mostly Java, HTML, JS
- Followed by odd fine-tuning regime, mostly Python



Some Findings:

- Even plain PaLM matchers/outperforms Codex 12B
  - Despite training on just 2.7B Python tokens
  - Hard to account for model scale, of course – need new laws
- Also good at: repair, translation
- Large models are very likely to memorize code



https://arxiv.org/pdf/2204.02311.pdf

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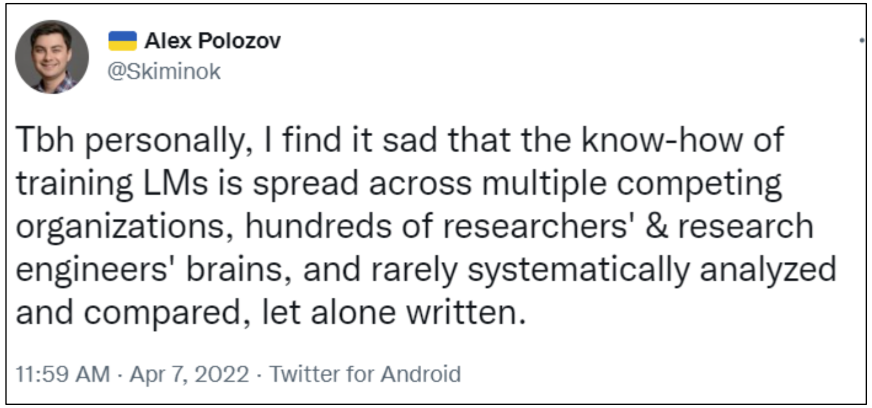
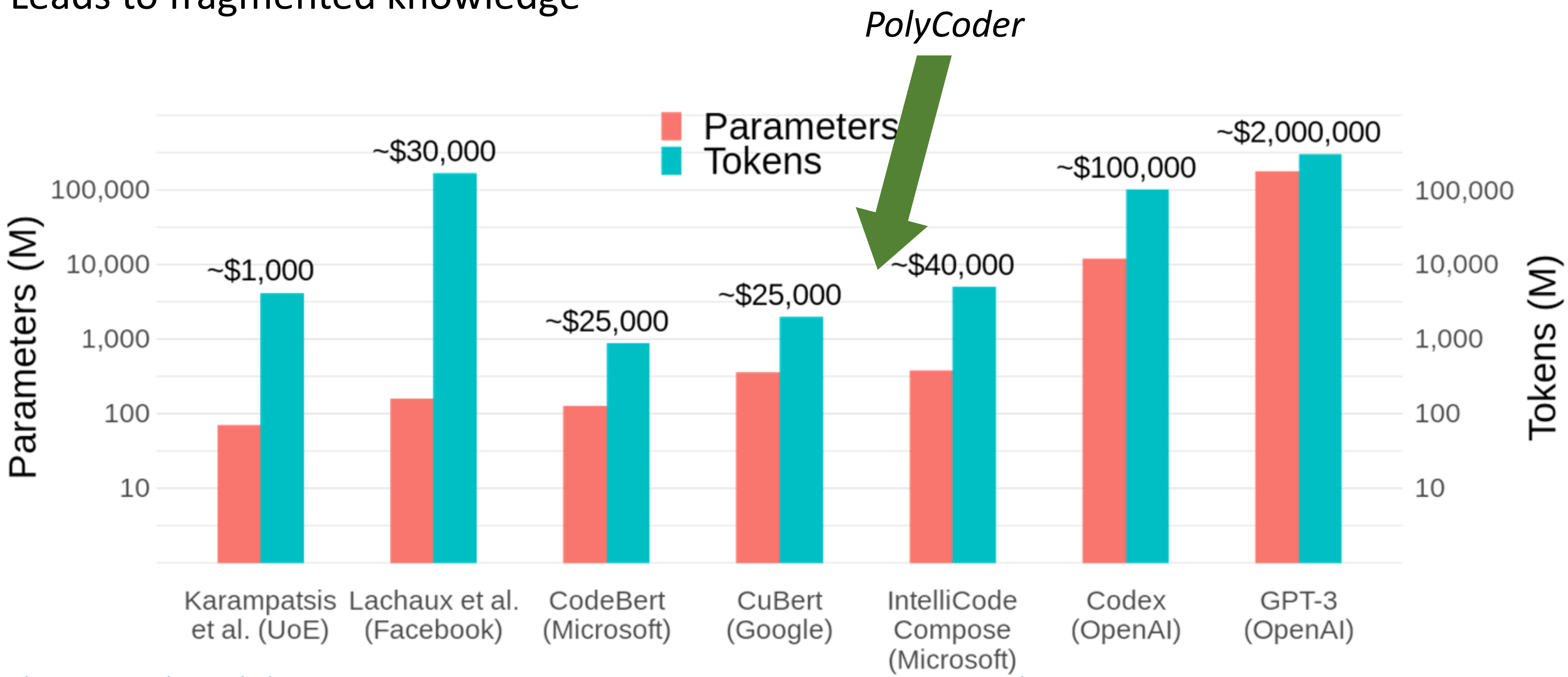
The Cost of Scaling

- Academia is priced out
  - Leads to fragmented knowledge





https://cacm.acm.org/magazines/2022/1/257443-the-growing-cost-of-deep-learning-for-source-code/fulltext
Costs based on approximate PetaFlop seconds at $3/h per V100 GPU
https://twitter.com/Skiminok/status/1512097828373377026 – and just to be clear, I think very highly of Alex

Forgetting Natural Language

Fine-tuning *solely* on code is powerful

- See PALM, CodeGen, Codex
- But, models tend to forget their NL training days
  - That's not ideal for communicating with humans

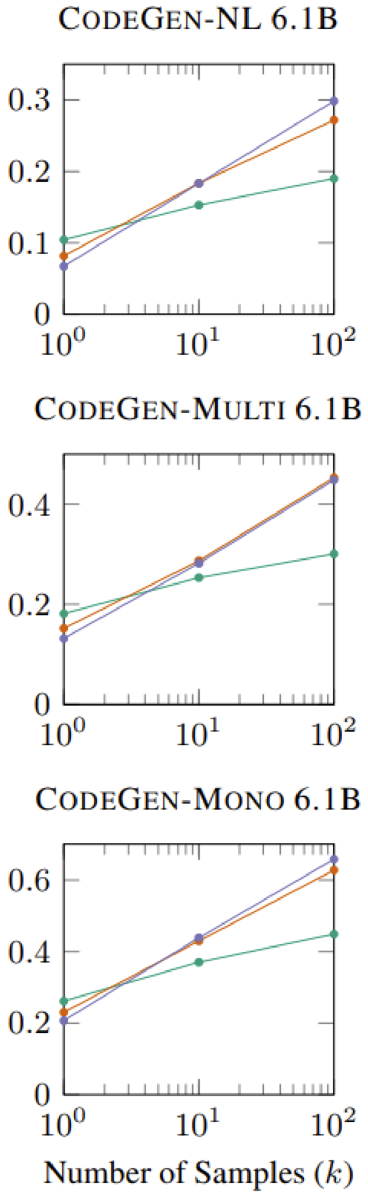
CodeGen-NL 6.1B:

```
Q: How to sum items in a list in Python?
I have a list of items and I want to sum them. How can I do this?

A:
You can use the sum function:
>>> l = [1,2,3,4,5]
>>> sum(l)
15
```

CodeGen-Multi 6.1B:

```
Q: Tensorflow session is not defined.
  """
  if not tf.contrib.eager.in_eager_mode():
    raise RuntimeError('tf.contrib.eager.in_eager_mode() must be True.')
  return tf.contrib.eager.get_default_session()
```



Reliability

- LLMs don't know to generate semantically correct code
  - We just hope they do based on seeing enough data – spoilers: they don't
  - In fact, poor prompts make them more likely to generate vulnerable code
  - Not just a matter of data volume: models associate prompts with good/bad examples seen
- That creates opportunities for prompt engineering
  - E.g., Jigsaw, page 26 of PALM
  - … which seems awfully palliative to me
- What is the alternative?
  - Not sure! Tests are nice, but rarely available – should models write those too?
  - Bringing static analysis in the loop may help
  - Nothing definitive yet

Questions?

Thanks to my CMU collaborators: Frank Xu, Uri Alon, Graham Neubig!