CS371N: Natural Language Processing
Lecture 13: Decoders, Decoding

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Announcements

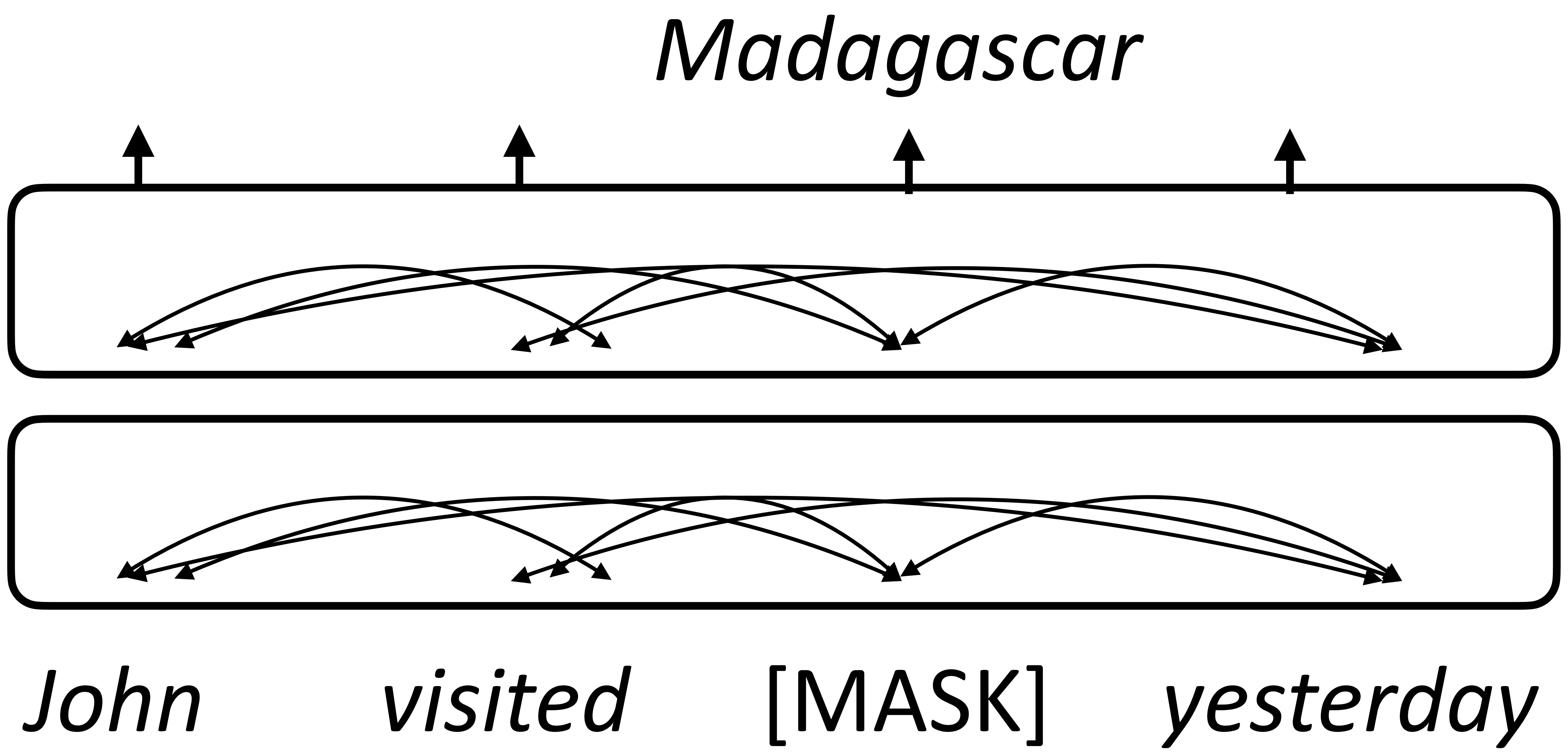
- A3 due Thursday

- A2 back soon

- Thursday: Lecture in-person as normal. Greg's OHs at 11.

Recap: Masked Language Modeling

- BERT formula: take a chunk of text, mask out 15% of the tokens, and try to predict them



Devlin et al. (2019)

Recap: Next “Sentence” Prediction

- Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- 50% of the time, take the true next chunk of text, 50% of the time take a random other chunk. Predict whether the next chunk is the “true” next
- BERT objective: masked LM + next sentence prediction

Devlin et al. (2019)

Recap: Subword Tokenization

- Subword tokenization: wide range of schemes that use tokens that are **between characters and words** in terms of granularity

- These "word pieces" may be full words or parts of words

_the **_eco tax** _port i co _in _Po nt - de - Bu is …

- _ indicates the word piece starting a word (can think of it as the space character).

Sennrich et al. (2016)

Recap: Subword Tokenization

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_the **_eco tax** _port i co _in _Po nt - de - Bu is ...

Output: _le _port ique **_éco taxe** _de _Pont - de - Bui s

- Can achieve transliteration with this, subword structure makes some translations easier to achieve

Sennrich et al. (2016)

Recap: Byte Pair Encoding (BPE)

- Start with every individual byte (basically character) as its own symbol

```
for i in range(num_merges):
  pairs = get_stats(vocab)
  best = max(pairs, key=pairs.get)
  vocab = merge_vocab(best, vocab)
```

- Count bigram character cooccurrences
- Merge the most frequent pair of adjacent characters

- Doing 8k merges => vocabulary of around 8000 word pieces. Includes many whole words

- Most SOTA NMT systems use this on both source + target

Sennrich et al. (2016)

Recap: Byte Pair Encoding (BPE)

Original: furiously
BPE: _fur | iously
Unigram LM: _fur | ious | ly

(b)

Original: tricycles
BPE: _t | ric | y | cles
Unigram LM: _tri | cycle | s

Original: Completely preposterous suggestions
BPE: _Comple | t | ely | _prep | ost | erous | _suggest | ions
Unigram LM: _Complete | ly | _pre | post | er | ous | _suggestion | s

- What do you see here?
- BPE produces less linguistically plausible units than another technique based on a unigram language model: rather than greedily merge, find chunks which make the sequence look likely under a unigram LM
- Unigram LM tokenizer leads to slightly better BERT

Bostrom and Durrett (2020)

Today

- GPT-2/GPT-3: **decoders**, which are able to actually generate text
- **Decoding** methods for getting outputs from these models
- Prompting: a new way of using large language models without taking any gradient steps

GPT

OpenAI GPT/GPT2

- Very large language models using the Transformer architecture
- Straightforward left-to-right language model, trained on raw text
- GPT2 (March 2019): trained on 40GB of text

	Parameters	Layers	d_{model}
	117M	12	768
approximate size of BERT	345M	24	1024
	762M	36	1280
GPT-2	1542M	48	1600

- Because it's a language model, we can **generate** from it

Radford et al. (2019)

OpenAI GPT2

slide credit: OpenAI

SYSTEM PROMPT (HUMAN-WRITTEN)

Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today.

MODEL COMPLETION (MACHINE-WRITTEN, SECOND TRY)

The 19-year-old singer was caught on camera being escorted out of the store by security guards.

The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back.

Scroll down for video

Shoplifting: Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today (pictured)

- How was this generated? We'll come back to this in a few minutes

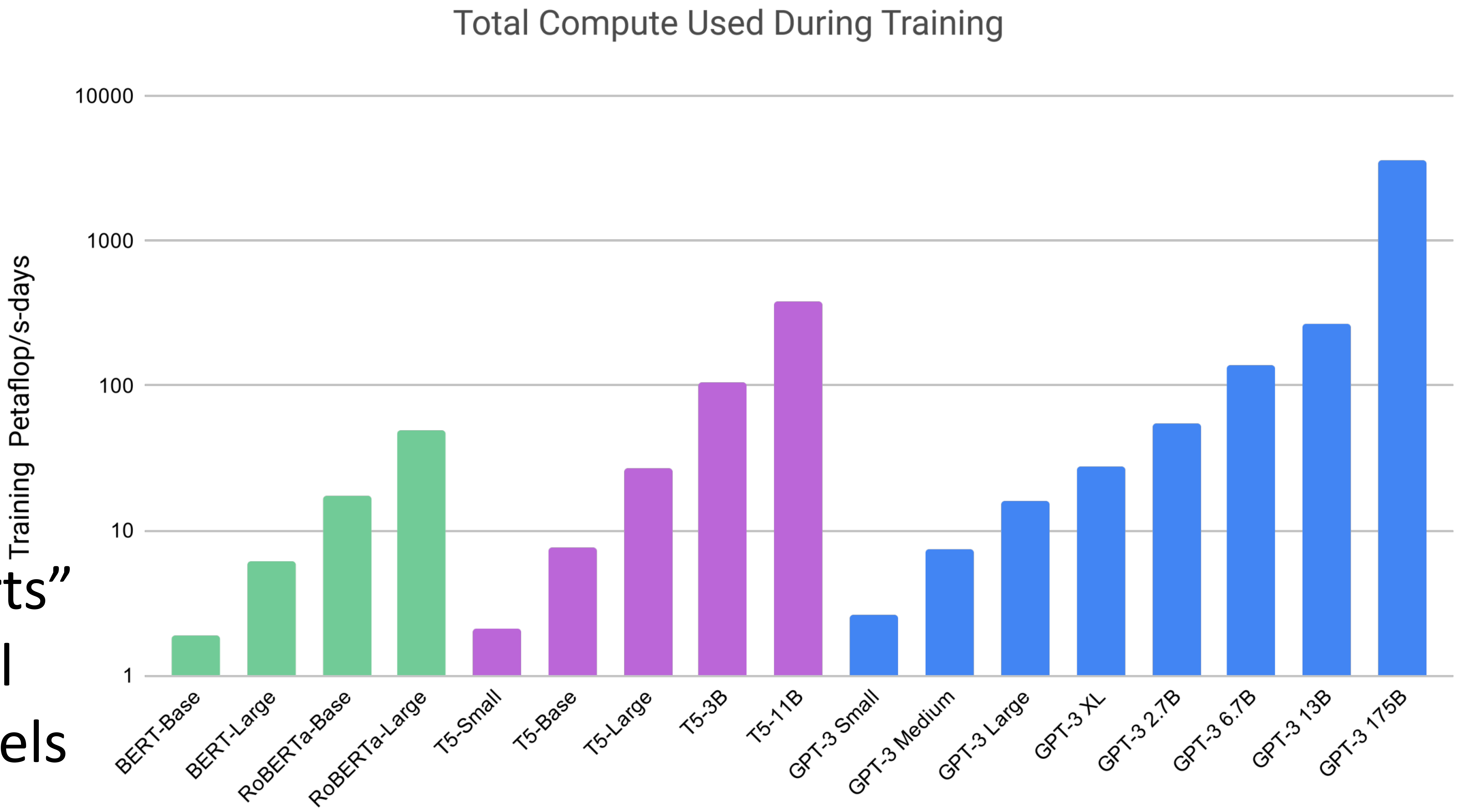
Pre-Training Cost (with Google/AWS)

- BERT: Base $500, Large $7000
- GPT-2 (as reported in other work): $25,000
- This is for a single pre-training run…developing new pre-training techniques may require many runs
- *Fine-tuning* these models can typically be done with a single GPU (but may take 1-3 days for medium-sized datasets)

https://syncedreview.com/2019/06/27/the-staggering-cost-of-training-sota-ai-models/

Scaling Up: GPT-3

- 175B parameter model: 96 layers, 96 heads, 12k-dim vectors
- Trained on Microsoft Azure, estimated to cost roughly \$10M
- GPT-4 may be "mixture of experts" combining several similar-sized models



Brown et al. (2020)

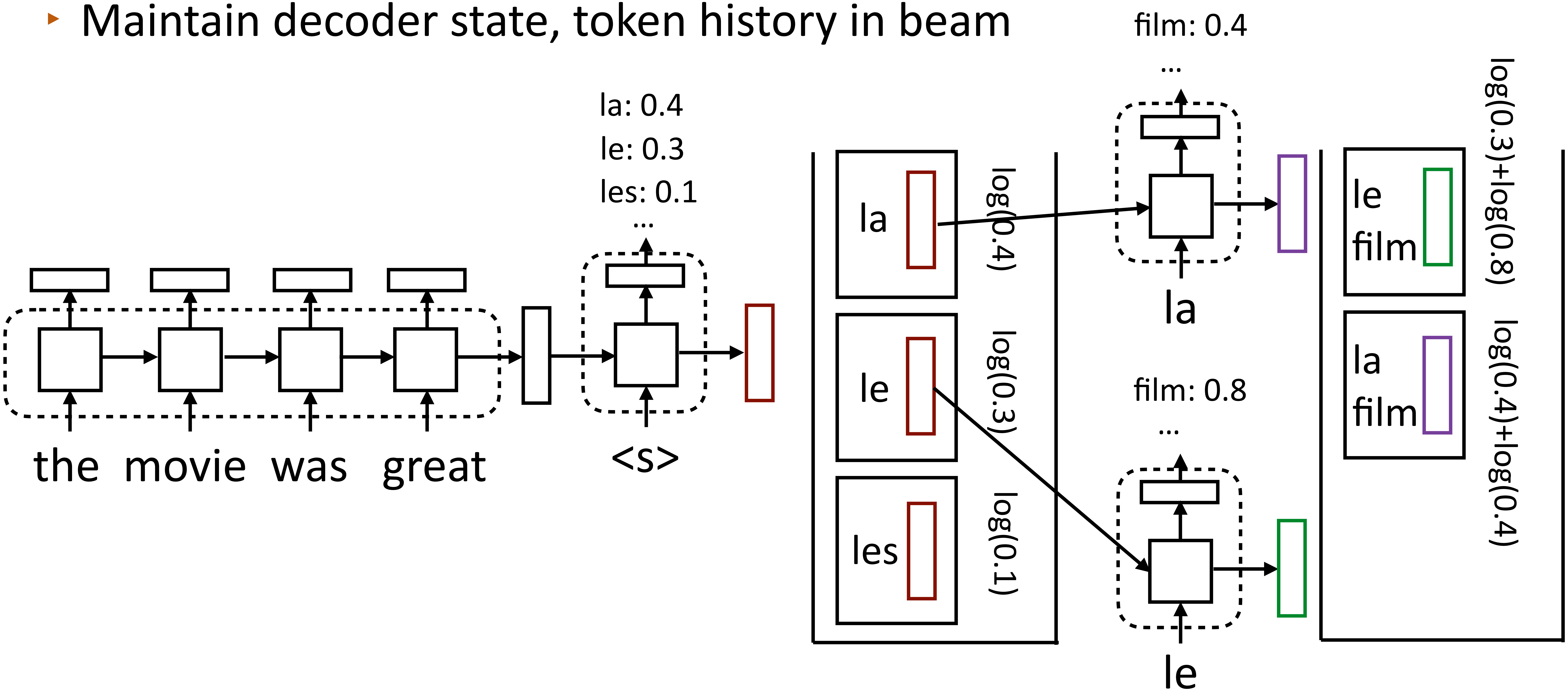
Decoding Methods

Decoding Strategies

- LMs place a distribution $P(y_i \mid y_1, \ldots, y_{i-1})$
- seq2seq models place a distribution $P(y_i \mid \mathbf{x}, y_1, \ldots, y_{i-1})$
- Generation from both models looks similar; how do we do it?
  - Option 1: $\max_{y_i} P(y_i \mid y_1, \ldots, y_{i-1})$ — take greedily best option
  - Option 2: use beam search to find the sequence with the highest prob.

Beam Search

- Maintain decoder state, token history in beam



- Keep both *film* states! Hidden state vectors are different

Decoding Strategies

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  - Option 2: use beam search to find the sequence with the highest prob.
  - Option 3: sample from the model; draw y_i from that distribution
- When should we use these different approaches?

Decoding Strategies

- Story generation (this is with GPT-2):

Context: 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.

Beam Search, *b*=32:
"The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the Universidad Nacional Autónoma de México (UNAM) and the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de ..."

Pure Sampling:
They were cattle called Bolivian Cavalleros; they live in a remote desert uninterrupted by town, and they speak huge, beautiful, paradisiacal Bolivian linguistic thing. They say, 'Lunch, marge.' They don't tell what the lunch is," director Professor Chuperas Omwell told Sky News. "They've only been talking to scientists, like we're being interviewed by TV reporters. We don't even stick around to be interviewed by TV reporters. Maybe that's how they figured out that they're cosplaying as the Bolivian Cavalleros."

- Beam search degenerates and starts repeating. If you see a fragment repeated 2-3x, it has very high probability to keep repeating

- Sampling is too noisy — introduces many grammatical errors

Holtzman et al. (2019)

Degeneration

- Beam search fails because the model is *locally normalized*
- Let's look at all the individual decisions that get made here

Beam Search, *b*=32:
"The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the Universidad Nacional Autónoma de México (UNAM) and the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de ..."

P(Nacional | … Universidad) is high

P(Autónoma | … Universidad Nacional) is high

P(de | … Universidad Nacional Autónoma) is high

P(México | Universidad Nacional Autónoma de) is high

P(/ | … México) and P(Universidad | … México /) — these probabilities may be low. But those are just 2/6 words of the repeating fragment

- **Each word is likely given the previous words but the sequence is bad**

Holtzman et al. (2019)

Drawbacks of Sampling

- Sampling is "too random"

Pure Sampling:
They were cattle called Bolivian Cavalleros; they live in a remote desert uninterrupted by town and they speak huge, beautiful, paradisiacal Bolivian linguistic thing. They say, 'Lunch, marge.' They don't tell what the lunch is," director Professor Chuperas Omwell told Sky News. "They've only been talking to scientists, like we're being interviewed by TV

P(y | … they live in a remote desert uninterrupted by)

0.01 roads

0.01 towns

0.01 people

0.005 civilization

Good options, maybe accounting for 90% of the total probability mass. So a 90% chance of getting something good

…

0.0005 town

Long tail with 10% of the mass

Holtzman et al. (2019)

Nucleus Sampling

P(y | … they live in a remote desert uninterrupted by)

0.01 roads

0.01 towns → renormalize and sample

0.01 people

0.005 civilization

cut off after p% of mass

- Define a threshold p. Keep the most probable options account for p% of the probability mass (the *nucleus*), then sample among these.
- To implement: sort options by probability, truncate the list once the total exceeds p, then renormalize and sample from it

Holtzman et al. (2019)

Decoding Strategies

- LMs place a distribution $P(y_i \mid y_1, \ldots, y_{i-1})$
- seq2seq models place a distribution $P(y_i \mid \mathbf{x}, y_1, \ldots, y_{i-1})$
- How to generate sequences?
  - Option 1: $\max_{y_i} P(y_i \mid y_1, \ldots, y_{i-1})$ — take greedily best option
  - Option 2: use beam search to find the sequence with the highest prob.
  - ~~Option 3: sample from the model; draw y_i from that distribution~~
  - Option 4: nucleus sampling

Holtzman et al. (2019)

GPT-3

Story completion demo:

Different decoding strategies

Preview: Prompting, In-Context Learning

Pre-GPT-3: Fine-tuning

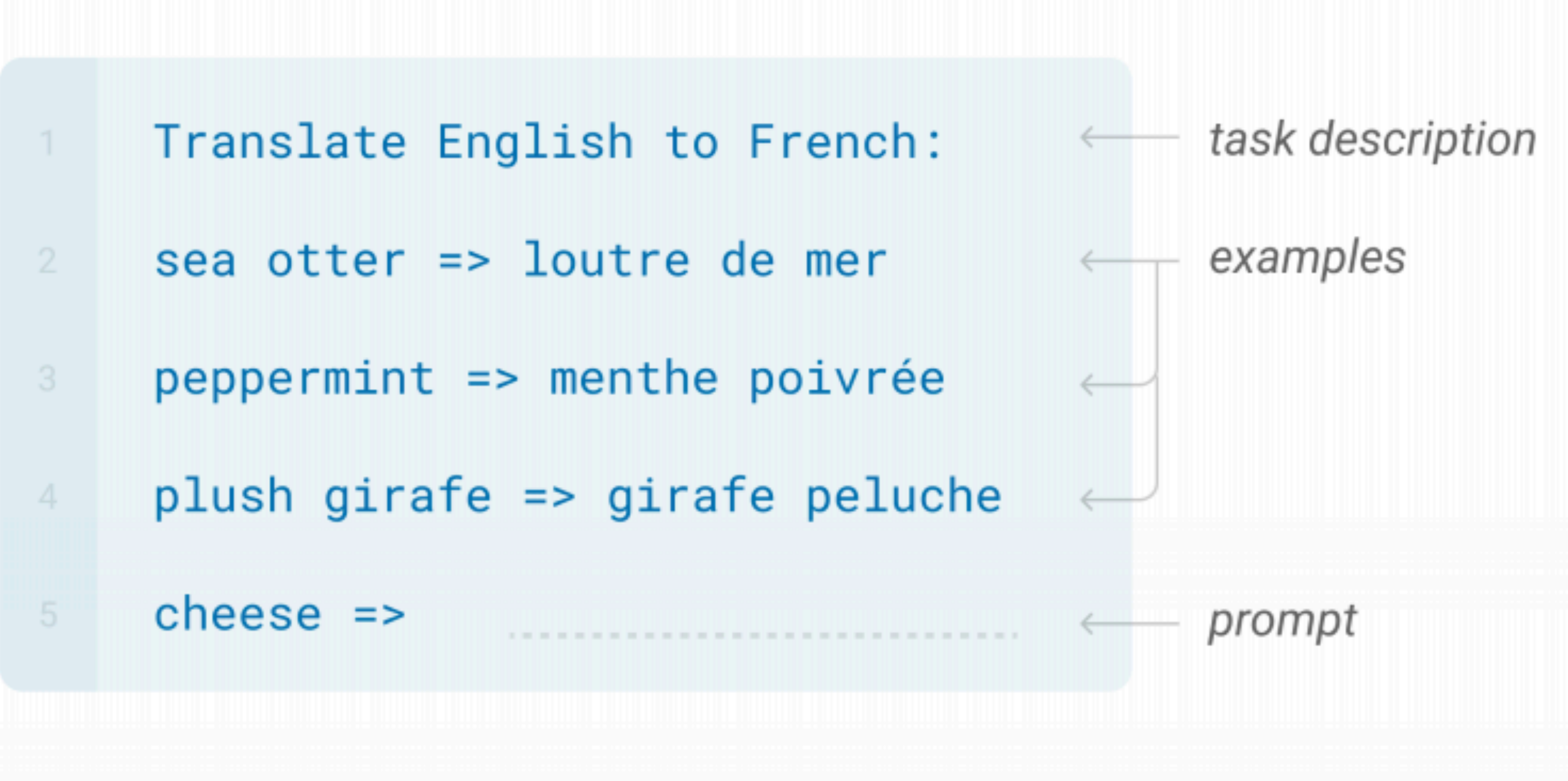
- Fine-tuning: this is the "normal way" of doing learning in models like GPT-2
- Requires computing the gradient and applying a parameter update on every example
- **This is super expensive with 175B parameters**

Brown et al. (2020)

GPT-3: Few-shot Learning

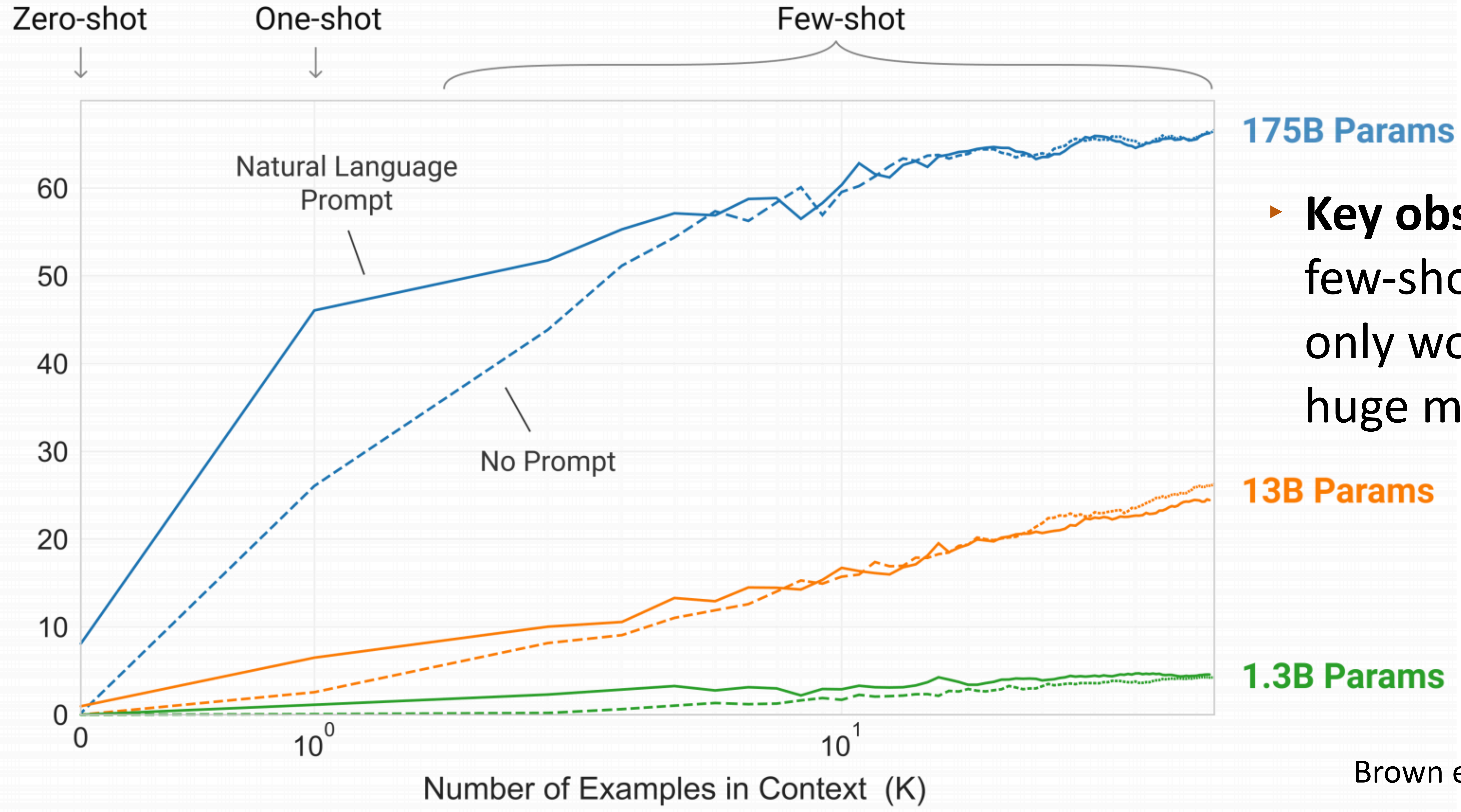
- GPT-3 proposes an alternative: **in-context learning.** Just uses the off-the-shelf model, no gradient updates

- This procedure depends heavily on the examples you pick as well as the prompt ("*Translate English to French*")



Brown et al. (2020)

GPT-3



- **Key observation:** few-shot learning only works with huge models!

Brown et al. (2020)

GPT-3

	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0

	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	**76.1**	**93.8**	**62.3**	**88.2**	**92.5**	**93.3**
Fine-tuned BERT-Large	69.6	64.6	24.1	70.0	71.3	72.0
GPT-3 Few-Shot	49.4	80.1	30.5	75.4	90.2	91.1

- Sometimes very impressive, (MultiRC, ReCoRD), sometimes very bad
- Results on other datasets are equally mixed — but still strong for a few-shot model!

Brown et al. (2020)

Prompts

- Prompts can help induce the model to engage in certain behavior
- In the GPT-2 paper, “tl;dr:” (too long; didn't read) is mentioned as a prompt that frequently shows up in the wild **indicating a summary**
- tl;dr is an indicator that the model should “switch into summary mode” now — and if there are enough clean instances of tl;dr in the wild, maybe the model has been trained on a ton of diverse data?
- Good prompt + a few training examples in-context = strong task performance?

Brown et al. (2020)

Prompting

- Current training: GPT-3 trained on the web
- Current testing: feed in a very specific prompt and/or a set of in-context examples
- Two goals:
  1. Unify pre-training and testing phases
  2. Exploit data for downstream tasks — why are we trying to do question answering while ignoring all of the existing QA datasets?
- RLHF/instruction tuning: fine-tune on supervised tasks after pre-training (more after midterm)
- **Let's see how an instruction-tuned GPT-3 works**

Prompts

Prompting demo:
QA, Math QA, etc.

Brown et al. (2020)

Ethical Issues

Bias and Toxicity

- “Toxic degeneration”: systems that generate toxic stuff

- System trained on a big chunk of the Internet: conditioning on “SJW”, “black” gives the system a chance of recalling bad stuff from its training data

https://toxicdegeneration.allenai.org/

Stochastic Parrots (about LMs generally)

- Paper (that included authors at Google who were subsequently fired) about dangers of large language models
- **Claim 1**: environmental cost is disproportionately born by marginalized populations, who aren't even well-served by these tools
- **Claim 2**: massive data is fundamentally challenging to audit, contains data that is biased and is only a snapshot of a single point in time
- **Claim 3 (what we'll focus on today)**: these models are not grounded in meaning — when they generate an answer to a question, it is merely by memorizing cooccurrence between symbols

Bender, Gebru, McMillan-Major, Shmitchell (2021)

Stochastic Parrots

Question: What is the name of the Russian mercenary group?
Answer: Wagner group.

Question: Where is the Wagner group?
Answer: In Syria.

Question: Who is the leader of the Wagner group?
Answer: A Russian citizen, Dmitry Utkin. He was born in 1971 and lives in Moscow. He has been a member of the Russian parliament since 2016. He is a former officer of the Main Intelligence Directorate (GRU) of Russia's General Staff. He was also a commander of the special forces unit "Vostok" (East). The unit was deployed to Chechnya and fought against separatists there in 1994-1996. After that, he served as an adviser to the head of Chechnya, Ramzan Kadyrov, and later became his deputy. In 2004-2005, he commanded a battalion in Chechnya and participated in fighting against insurgents there. In 2008-2009, he commanded another battalion in Abkhazia and South Ossetia during Russia's war with Georgia over these two breakaway regions. Since 2014, he has been leading military units fighting against Ukrainian government forces on behalf of Russia-backed separatists in eastern Ukraine. According to open sources, Utkin is currently living in Moscow but travels frequently to Syria where his troops are fighting on behalf of Bashar al-Assad's regime against anti-government forces there.

- We are likely to assume the model is producing factual information and presenting it in a coherent way, but this is our interpretation we project on the model
- Risks: medical diagnosis ("What do I have if I have X, Y, and Z symptoms?") could seem possible but cause serious harm

Bender, Gebru, McMillan-Major, Shmitchell (2021)

Takeaways

- Generative language models can do well at lots of generation tasks
- Decoding strategy can matter a lot (beam search vs. sampling)
- Prompting is a way to harness their power and learn to do many tasks with a single model. Can be done without fine-tuning