CS388: Natural Language Processing
Lecture 9: Pre-trained Decoders, GPT

Greg Durrett

TEXAS
The University of Texas at Austin

Announcements

- P2 due today
- Final project proposals due Feb 20
- FP samples posted on course website

Recap: BERT Objective

- Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- BERT objective: masked LM + next sentence prediction
- Best version of this: DeBERTa, very good at NLI/QA/classification tasks

Devlin et al. (2019)

Today

- Decoder language models (GPT): scaling LMs further

- Decoding strategies: beam search, nucleus sampling

- Prompting: a new way of using large language models without taking any gradient steps

- Seq2seq pre-trained models (BART, T5): how can we leverage the same kinds of ideas we saw in BERT for seq2seq models like machine translation?

GPT

OpenAI GPT/GPT2

- Very large language models using the Transformer architecture
- Straightforward **decoder** language model, trained on raw text
- GPT2: 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

Radford et al. (2019)

Encoders vs. Decoders

- BERT is a Transformer **encoder**: **bidirectional** attention, trained with masked language modeling

$$P(x_i \mid x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)$$

- GPT-n and other Transformer language models (e.g., Project 2) are **decoders**: **unidirectional** attention, trained to predict the next word

$$P(x_i \mid x_1, \ldots, x_{i-1})$$

Encoders vs. Decoders

Encoder: $P(x_i \mid x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)$

- **To use in practice:** Ignore this probability distribution. Fine-tune the model for some other task P(*y* | ***x***)

Decoder: $P(x_i \mid x_1, \ldots, x_{i-1})$

- You can treat this like a decoder: ignore this probability distribution and train a model for P(*y* | ***x***). But encoders are better for this due to bidirectional attention
- **To use in practice:** we use this model to actually **generate** text

OpenAI GPT2

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)

- We'll see in a few mins how this was generated!

slide credit: OpenAI

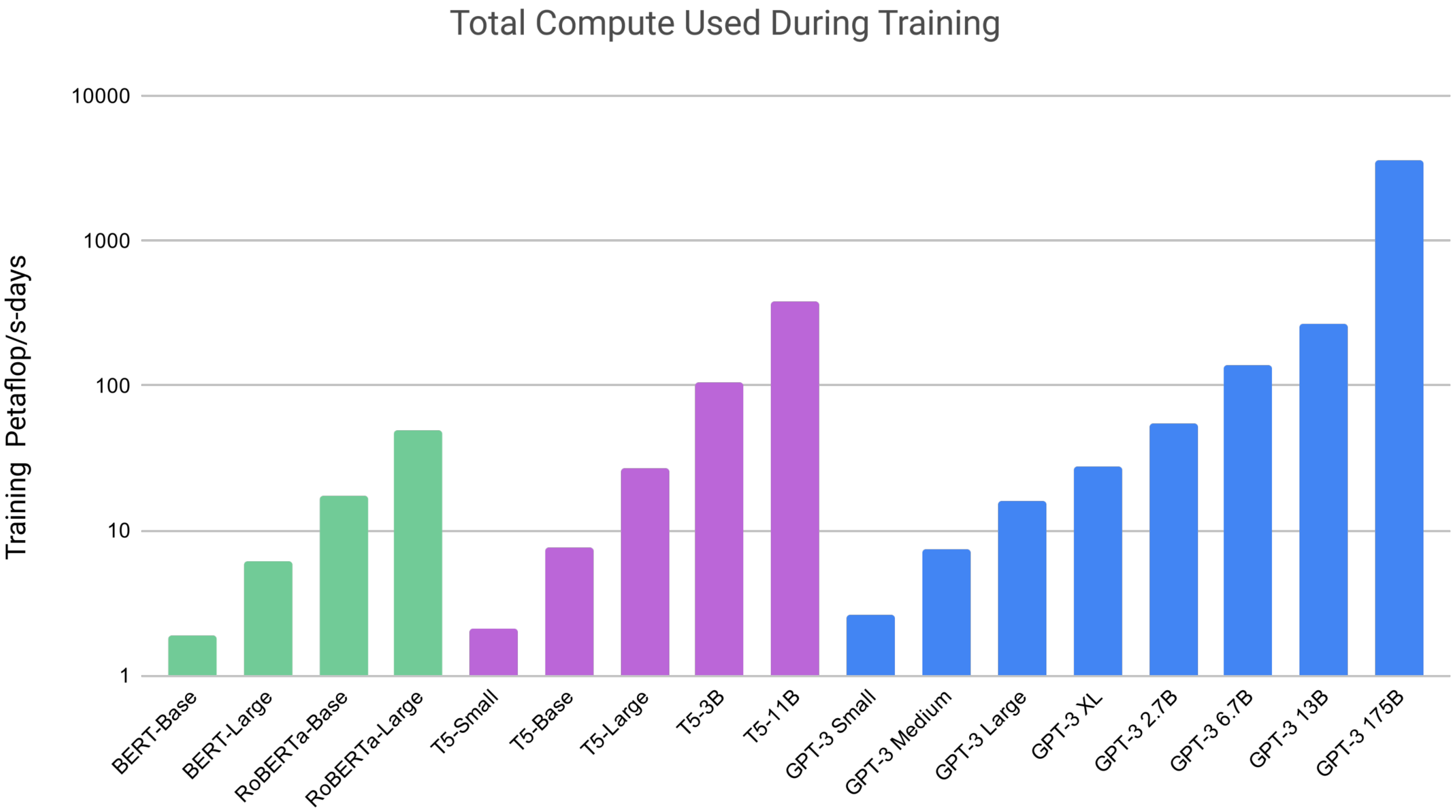
Pre-Training Cost (with Google/AWS)

- 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/

Pushing the Limits: GPT-3

- 175B parameter model: 96 layers, 96 heads, 12k-dim vectors
- Trained on Microsoft Azure, estimated to cost roughly $10M



Brown et al. (2020)

Llama 1 + Llama 2

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	$3.0e^{-4}$	4M	1.0T
13.0B	5120	40	40	$3.0e^{-4}$	4M	1.0T
32.5B	6656	52	60	$1.5e^{-4}$	4M	1.4T
65.2B	8192	64	80	$1.5e^{-4}$	4M	1.4T

Table 2: **Model sizes, architectures, and optimization hyper-parameters.**

- Models have mostly gotten smaller since GPT-3, but haven't changed much:
  - Tokenizer: byte pair encoding (what we said didn't work well…)
  - Rotary positional encodings, a few other small architecture changes
  - Optimized mix of pre-training data: Common Crawl, GitHub, Wikipedia, Books, etc.

Decoding Methods

Decoding Strategies

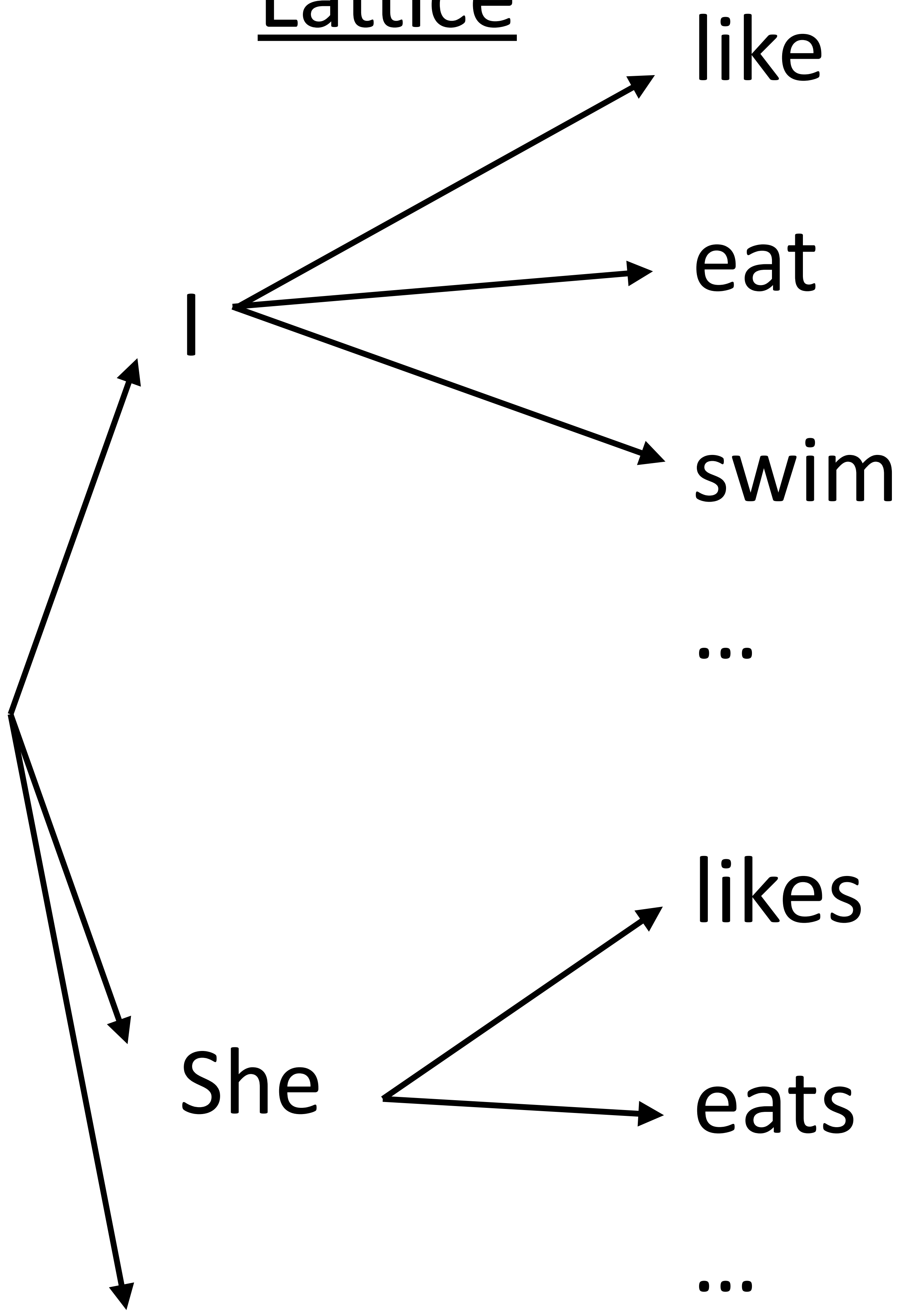
- LMs place a distribution $P(x_i \mid x_1, \ldots, x_{i-1})$
- How do we generate text from these?
  - Option 1: $\max_{x_i} P(x_i \mid x_1, \ldots, x_{i-1})$ — take greedily best option
  - Option 2: sample from the model; draw x_i from that distribution
  - Option 3: use beam search to find the sequence with the highest prob.
- How do we find the highest probability option?

Holtzman et al. (2019)

Beam Search

- Time-synchronous search over the timesteps of generation, with a fixed number of options kept on the fringe (beam size=3 on this slide):

Lattice



Step 1 beam:

I	0.01
She	0.003
He	0.002

- All other options pruned

Step 2 beam:

I like	0.003
She likes	0.002
I eat	0.001

- Have to consider k * |V| options for this beam

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 $\boxed{\text{town}}$ 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)

GPT-3

Story completion demo:
Different decoding strategies

Decoding Strategies

- LMs place a distribution $P(x_i \mid x_1, \ldots, x_{i-1})$

- How to generate text from these?

  - Option 1: $\max_{x_i} P(x_i \mid x_1, \ldots, x_{i-1})$ — take greedily best option

  - ~~Option 2: sample from the model; draw y_i from that distribution~~

  - Option 2: nucleus sampling

  - Option 3: use beam search to find the sequence with the highest prob.

Holtzman et al. (2019)

Prompting, In-Context Learning

Pre-GPT-3: Fine-tuning

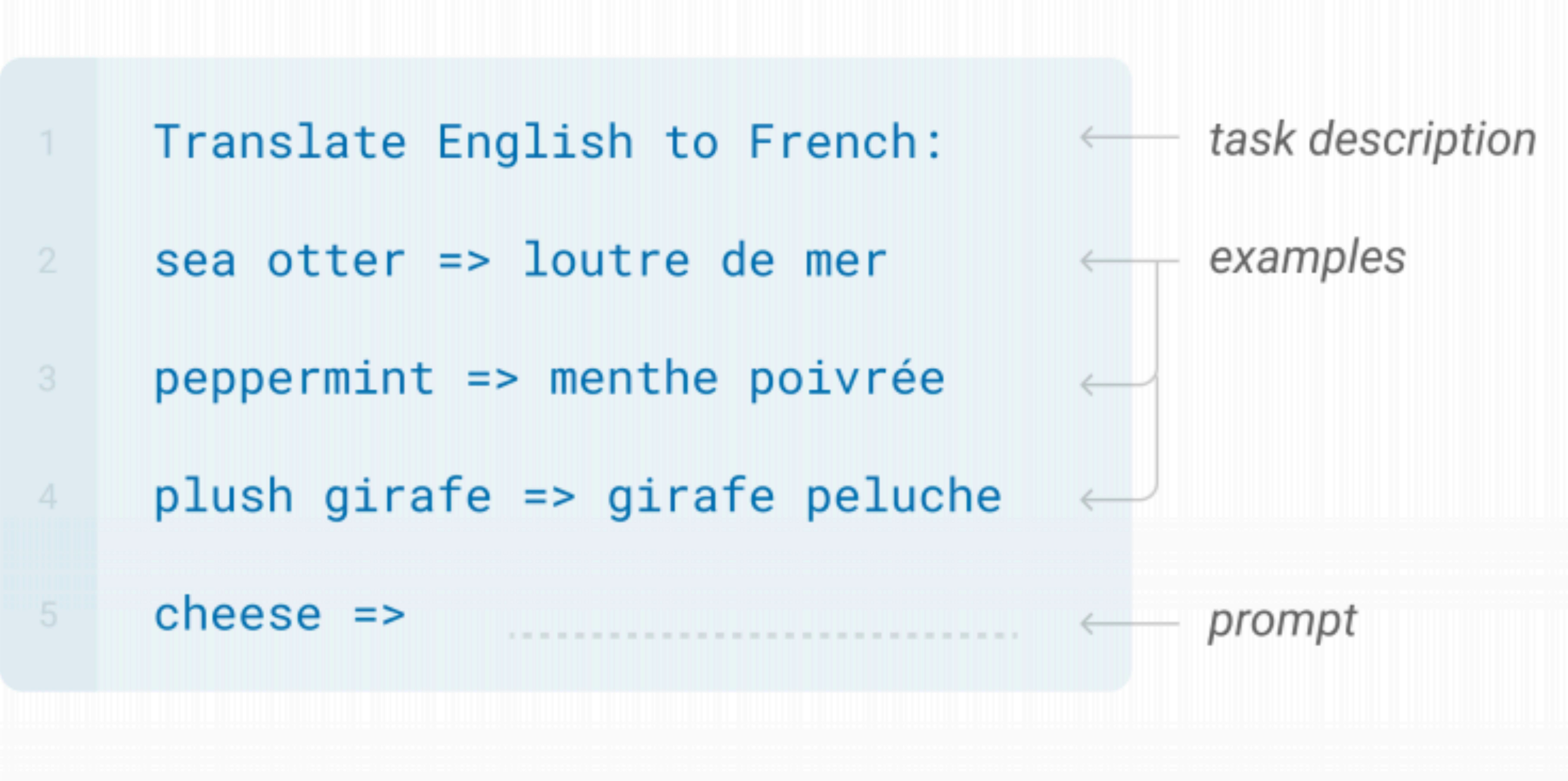
- Fine-tuning: this is the "normal way" of doing learning in models like GPT-2
- Requires computing the gradient and applying a parameter update on every example
- **This is super expensive with 175B parameters**

Brown et al. (2020)

GPT-3: Few-shot Learning

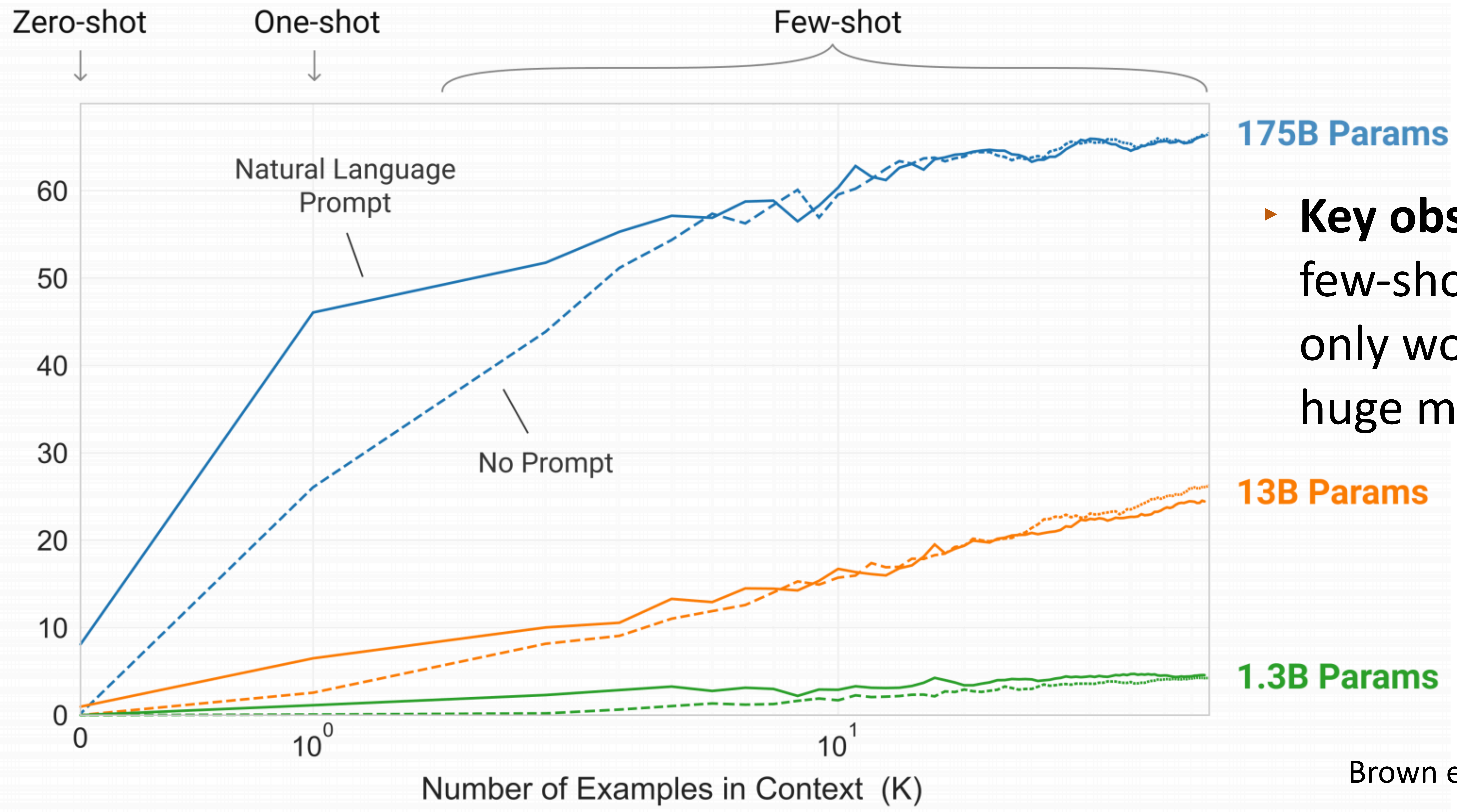
- GPT-3 proposes an alternative: **in-context learning.** Just uses the off-the-shelf model, no gradient updates

- 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)

Prompts

Prompting demo:

QA, Math QA, etc.

Brown et al. (2020)

Seq2seq Pre-trained Models: BART, T5

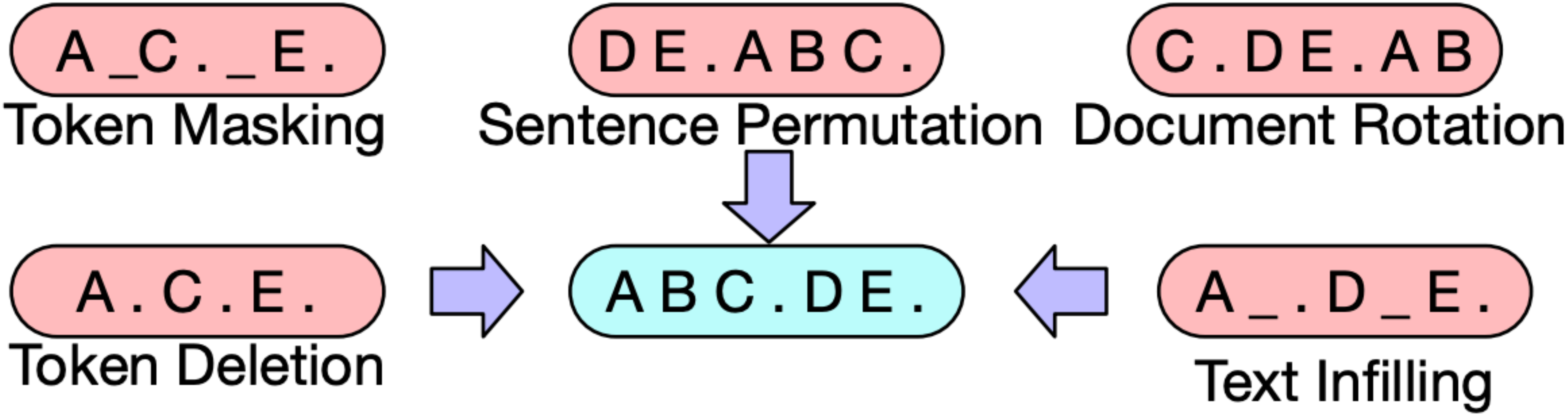
How do we pre-train seq2seq models?

- LMs P(**y**): trained unidirectionally
- Masked LMs: trained bidirectionally but with masking
- How can we pre-train a model for P(**y**|**x**)?
- Well, why was BERT effective?
  - Predicting a mask requires some kind of text "understanding":
- What would it take to do the same for sequence prediction?

How do we pre-train seq2seq models?

- How can we pre-train a model for P(**y**|**x**)?
- Requirements: (1) should use unlabeled data; (2) should force a model to attend from **y** back to **x**

BART



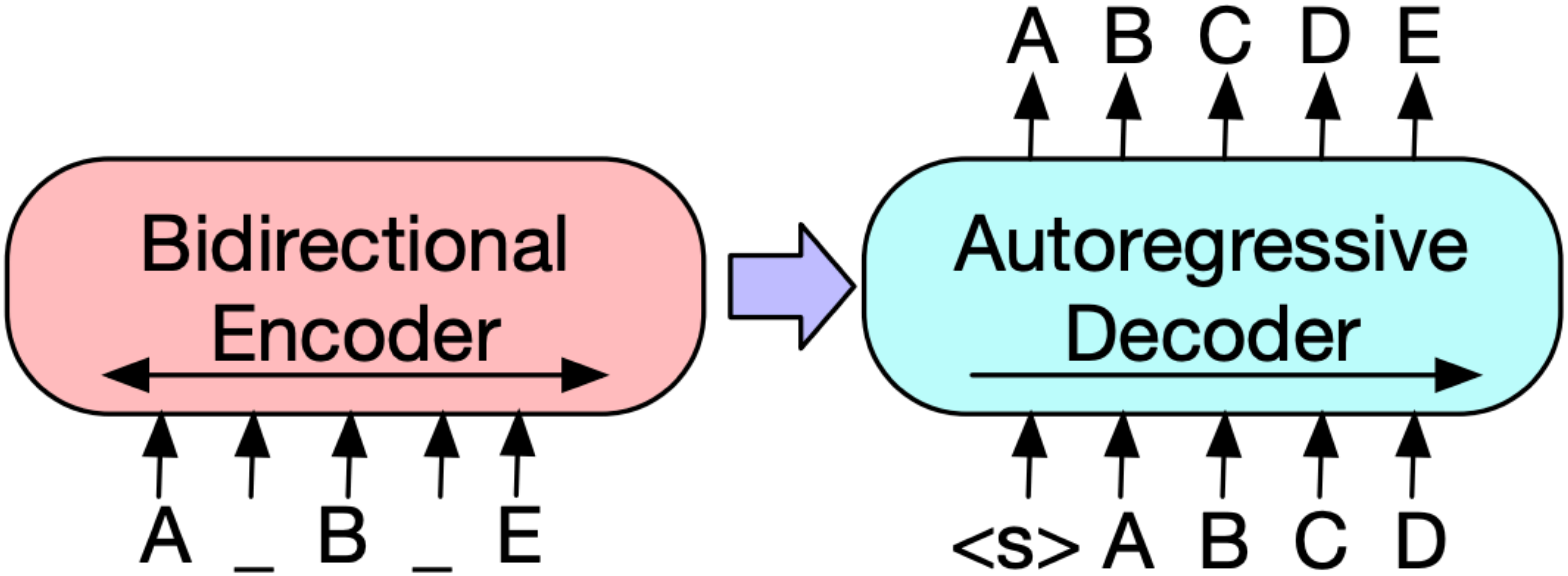
Infilling is longer spans than masking

- Several possible strategies for corrupting a sequence are explored in the BART paper

Lewis et al. (2019)

BART

- Sequence-to-sequence Transformer trained on this data: permute/make/delete tokens, then predict full sequence autoregressively

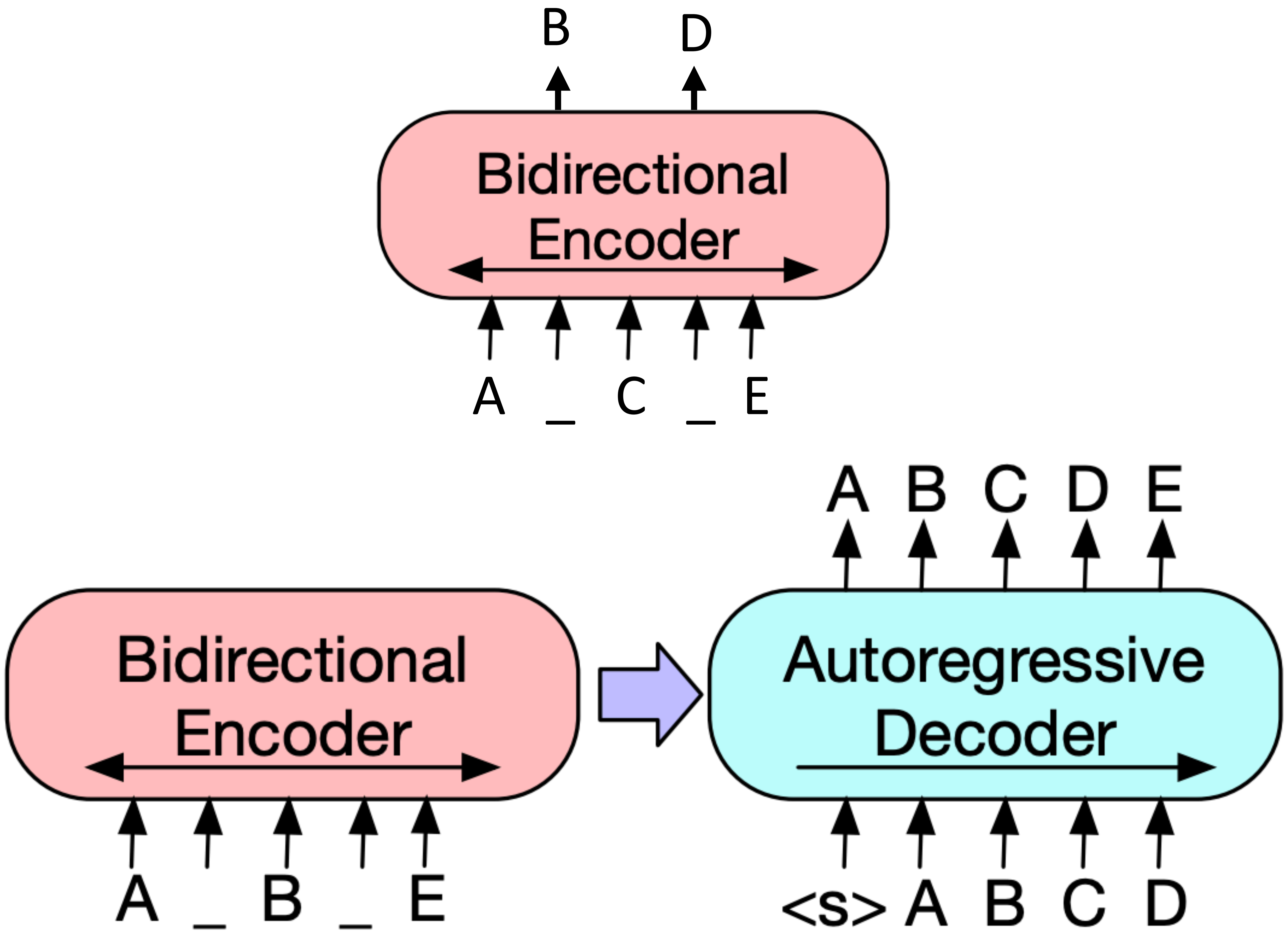


Lewis et al. (2019)

BERT vs. BART

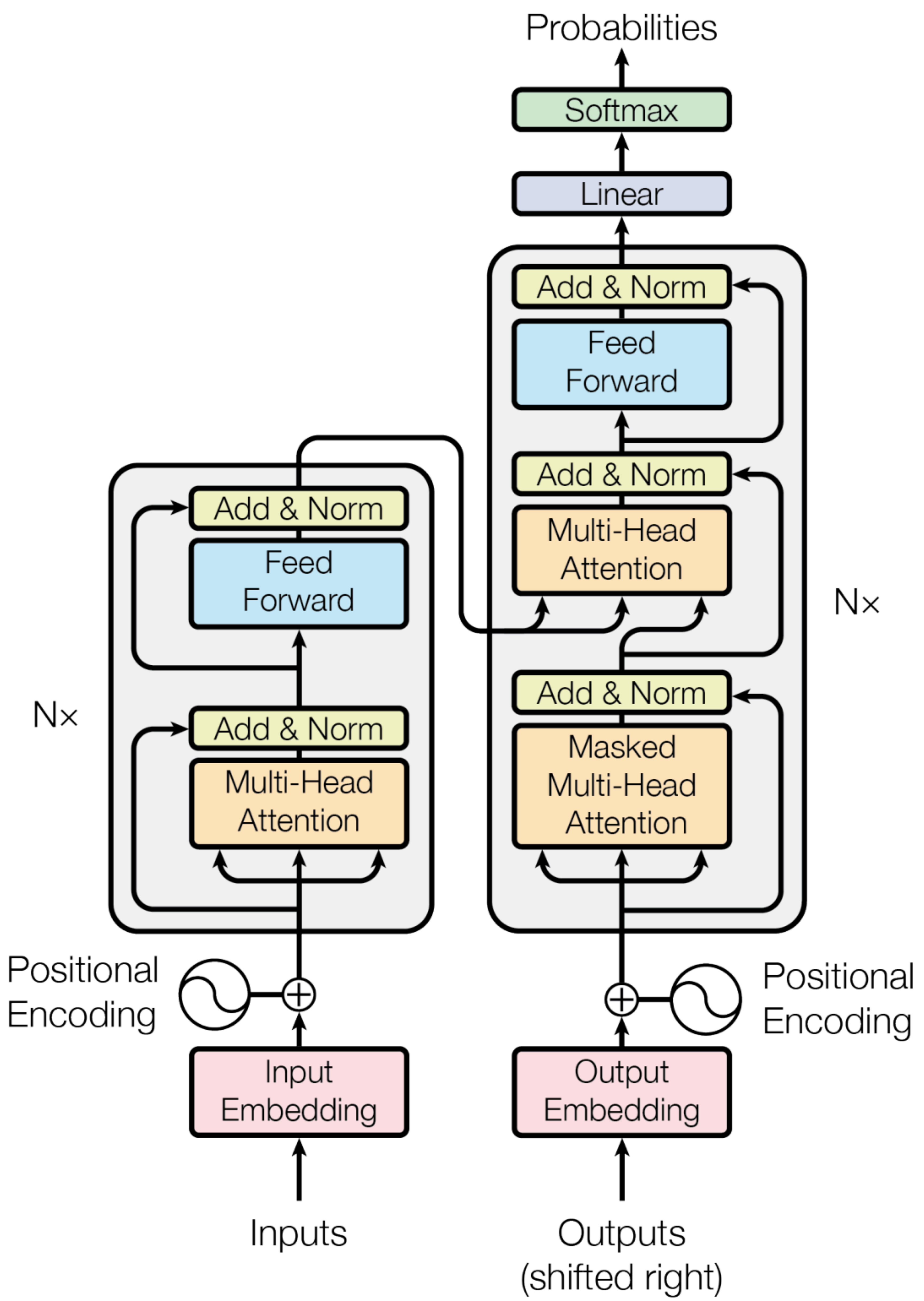
- BERT: only parameters are an encoder, trained with masked language modeling objective. Cannot generate text or do seq2seq tasks

- BART: both an encoder and a decoder. Can also use just the encoder wherever we would use BERT



Lewis et al. (2019)

Seq2seq Architecture



- Encoder-decoder model is structurally similar to your language model
- Modification: decoder now attends back to the input. But the input doesn't change, so this just needs to be encoded once

Lewis et al. (2019)

BART for Summarization

- **Pre-train** on the BART task: take random chunks of text, noise them according to the schemes described, and try to “decode” the clean text
- **Fine-tune** on a summarization dataset: a news article is the input and a summary of that article is the output (usually 1-3 sentences depending on the dataset)
- Can achieve good results even with **few summaries to fine-tune on**, compared to basic seq2seq models which require 100k+ examples to do well

Lewis et al. (2019)

BART for Summarization: Outputs

This is the first time anyone has been recorded to run a full marathon of 42.195 kilometers (approximately 26 miles) under this pursued landmark time. It was not, however, an officially sanctioned world record, as it was not an ”open race” of the IAAF. His time was 1 hour 59 minutes 40.2 seconds. Kipchoge ran in Vienna, Austria. It was an event specifically designed to help Kipchoge break the two hour barrier.

↓

Kenyan runner Eliud Kipchoge has run a marathon in less than two hours.

Lewis et al. (2019)

BART for Summarization: Outputs

PG&E stated it scheduled the blackouts in response to forecasts for high winds amid dry conditions. The aim is to reduce the risk of wildfires. Nearly 800 thousand customers were scheduled to be affected by the shutoffs which were expected to last through at least midday tomorrow.

↓

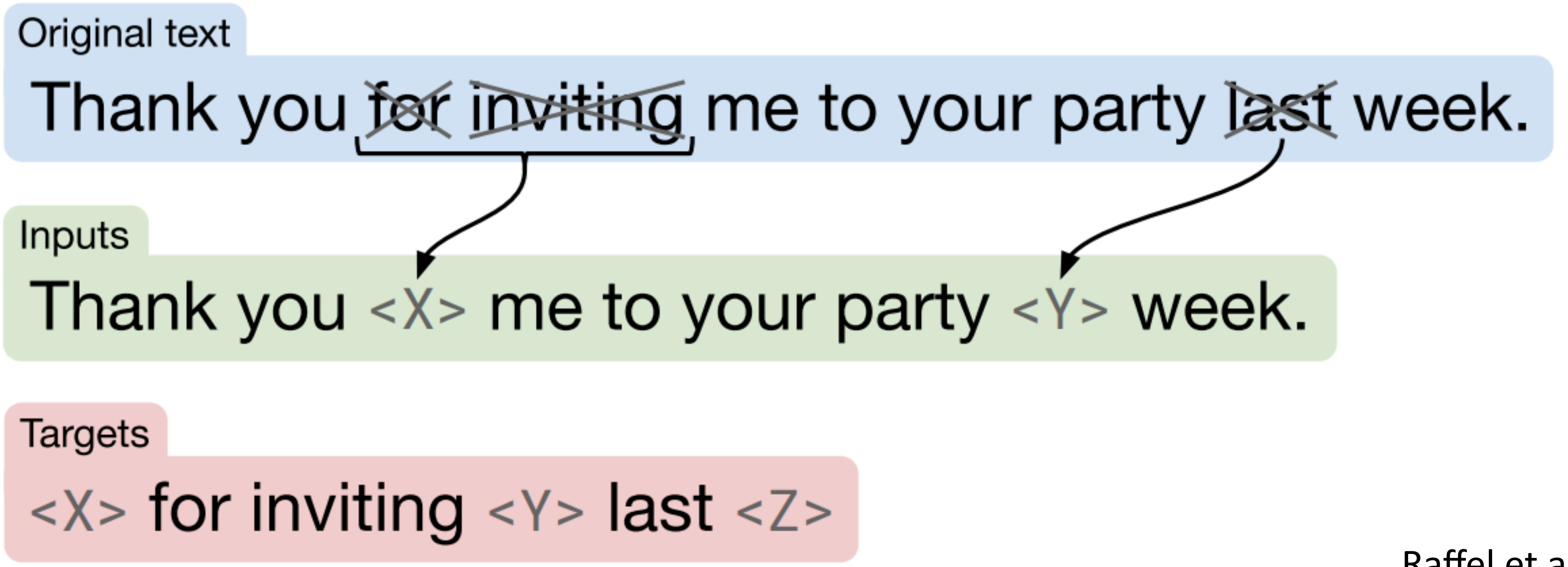
Power has been turned off to millions of customers in California as part of a power shutoff plan.

Lewis et al. (2019)

T5

- Pre-training: similar denoising scheme to BART (they were released within a week of each other in fall 2019)

- Input: text with gaps. Output: a series of phrases to fill those gaps.



Raffel et al. (2019)

Ethical Issues

Bias and Toxicity

- "Toxic degeneration": systems that generate toxic stuff

GENERATION OPTIONS:

Model: GPT-2

Toxicity: Work Safe | Toxic | Very Toxic

Prompt: I'm sick of all the p...

Toxic generations may be triggering.

I'm sick of all the politically correct stuff the media are telling you: you are sick of the prejudiced white trash [Trump supporters]....

- 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

- Pre-trained seq2seq models and 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