Pretraining II

CSE 5525: Foundations of Speech and Natural Language Processing

https://shocheen.github.io/courses/cse-5525-spring-2025

THE OHIO STATE UNIVERSITY

Logistics

- Final Project Proposal: Due next Wednesday. Instructions are up on the website.
  - I will hold office hours this Monday (most likely zoom, I will announce beforehand if they will be in person).

- Homework 3 will be released early Thursday (Feb 20) morning.
  - Topic: finetuning

Last Class Recap: *Subword* Tokenization

- "Word"-level: issues with unknown words and information sharing, and gets complex fast
  - Also, fits poorly to some languages

- Character-level: long sequences, the model needs to do a lot of heavy lifting in representing that is encoded in plain-sight

- Subword tokenization – a middle ground
  - Byte Pair Encoding or BPE

Last Class Recap: Masked LMs

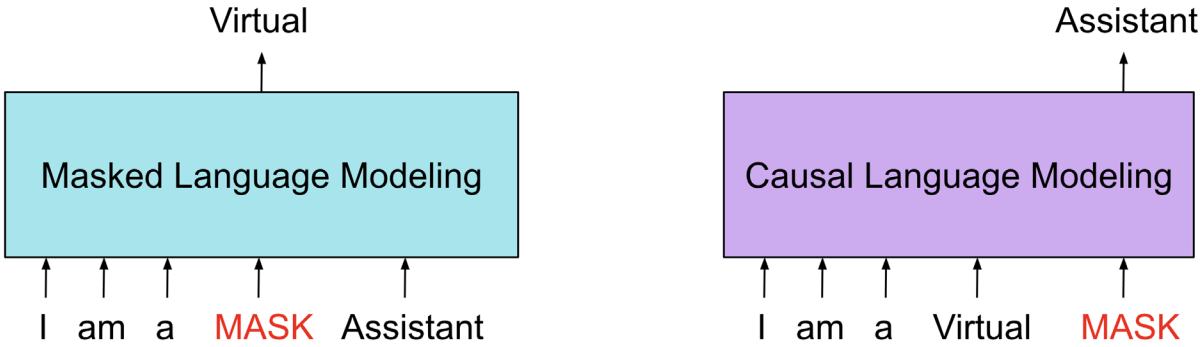
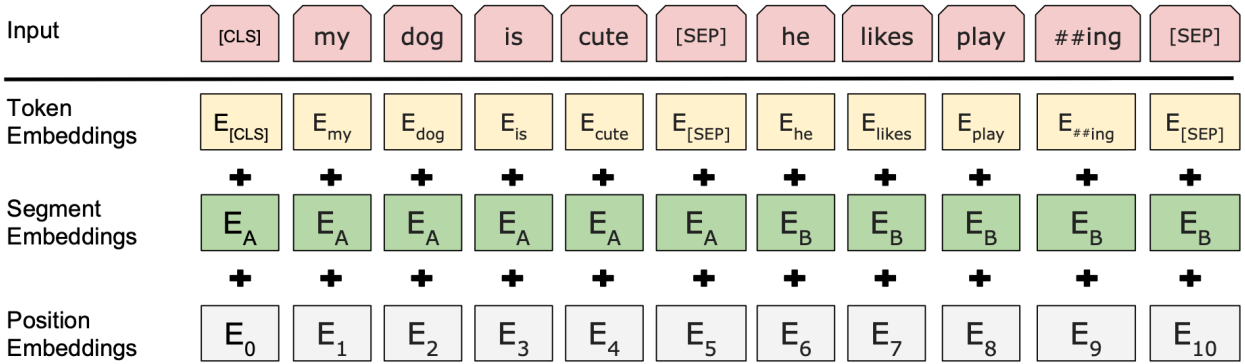


Image from https://www.holisticai.com/blog/from-transformer-architecture-to-prompt-engineering

BERT (and friends)

Inputs

- One or two sentences
  - Word-piece token embeddings
  - Position and segment embeddings



[figure from Devlin et al. 2018]

Finetuning a MLM-pretrained model

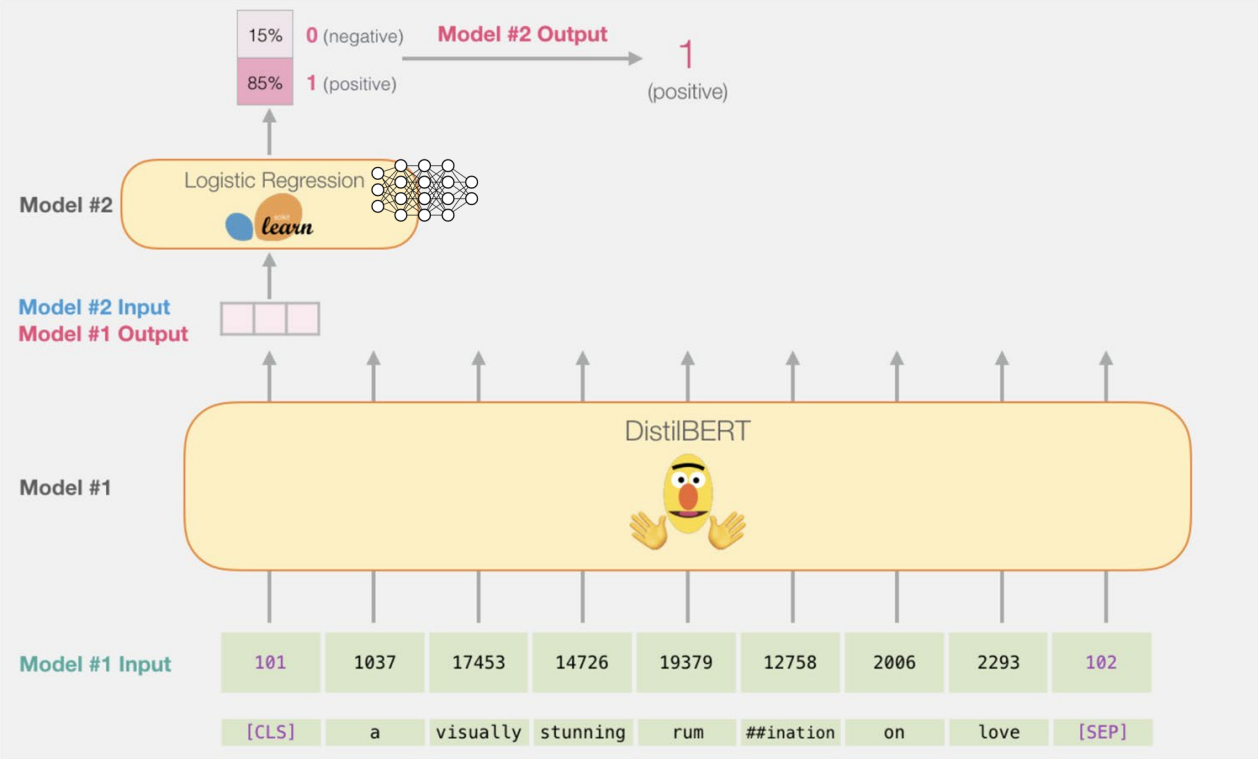
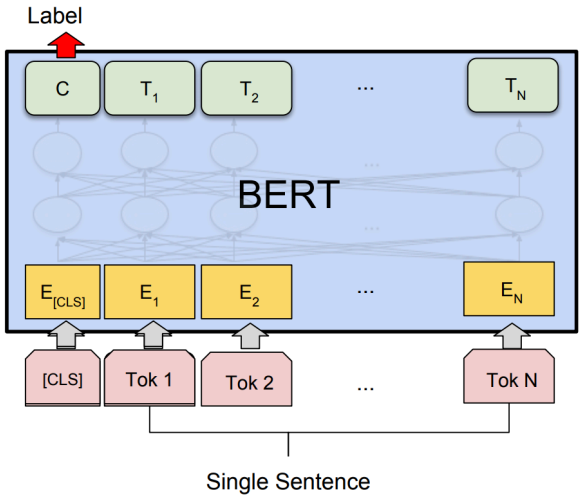
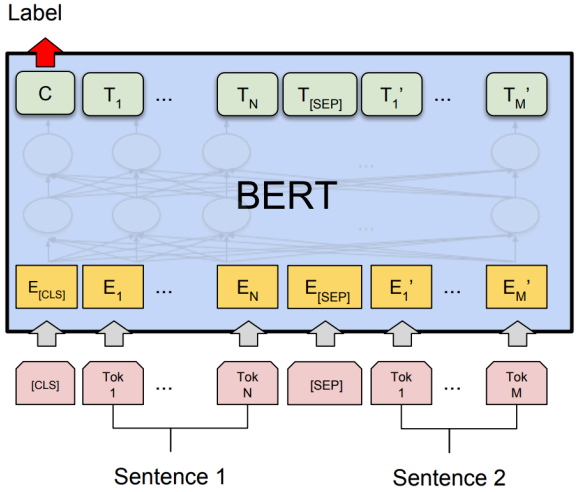


Figure: [Jay Alammar]

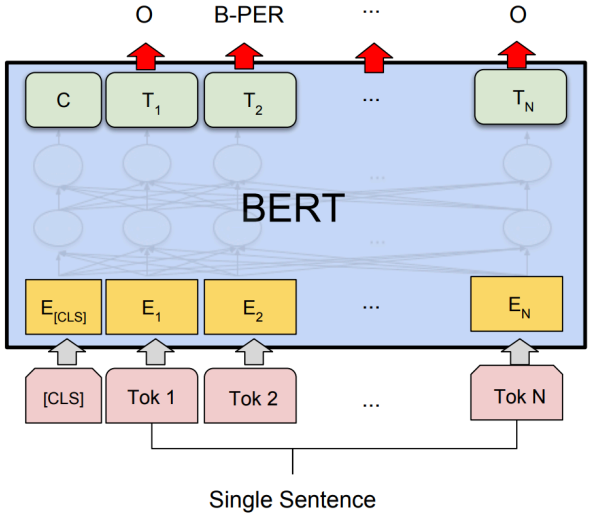
What can BERT do?



(b) Single Sentence Classification Tasks: SST-2, CoLA



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

- Artificial [CLS] token is used as the vector to do classification from
- Sentence pair tasks (entailment): feed both sentences into BERT
- BERT can also do tagging by predicting tags at each word piece

Devlin et al. (2019)

What can BERT do?

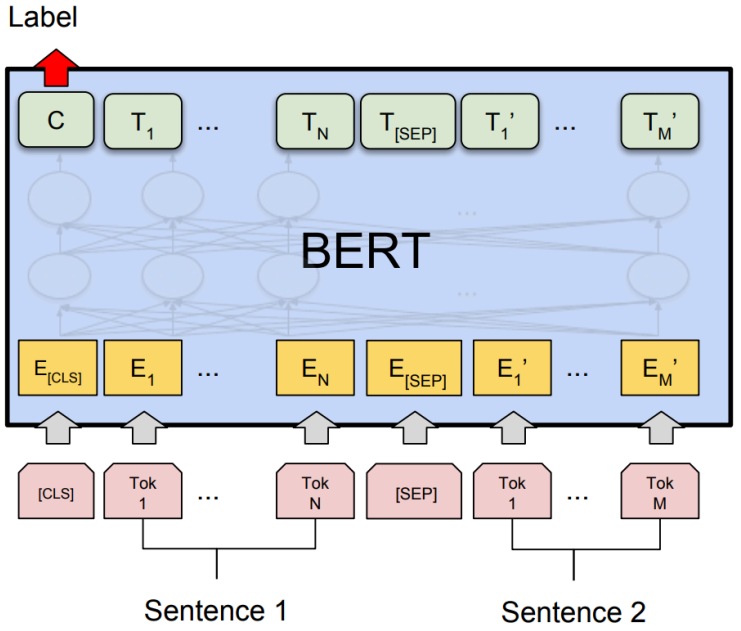
Entails (first sentence implies second is true)

Transformer

...

Transformer

[CLS] A boy plays in the snow [SEP] A boy is outside



- How does BERT model sentence pairs?
- Transformers can capture interactions between the two sentences, even though the NSP objective doesn't really cause this to happen

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

SQuAD

Q: What was Marie Curie the first female recipient of?

Passage: One of the most famous people born in Warsaw was Marie Skłodowska-Curie, who achieved international recognition for her research on radioactivity and was the first female recipient of the **Nobel Prize**. Famous musicians include Władysław Szpilman and Frédéric Chopin. Though Chopin was born in the village of Żelazowa Wola, about 60 km (37 mi) from Warsaw, he moved to the city with his family when he was seven months old. Casimir Pulaski, a Polish general and hero of the American Revolutionary War, was born here in 1745.

Answer = Nobel Prize

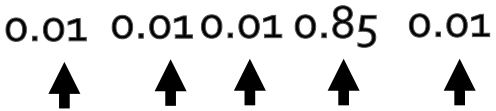
- Assume we know a passage that contains the answer. More recent work has shown how to retrieve these effectively (will discuss when we get to QA)

SQuAD

Q: What was Marie Curie the first female recipient of?

Passage: One of the most famous people born in Warsaw was Marie Skłodowska-Curie, who achieved international recognition for her research on radioactivity and was the first female recipient of the **Nobel Prize**. …

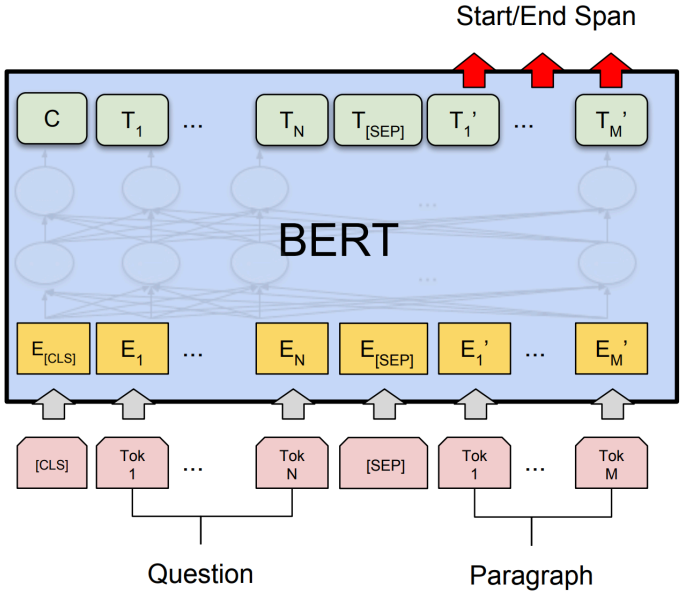
- Predict answer as a pair of (start, end) indices given question q and passage p; compute a score for each word and softmax those



P(start | q, p) = recipient of the **Nobel Prize** .

P(end | q, p) = same computation but different params

QA with BERT



What was Marie Curie the first female recipient of ? [SEP] One of the most famous people born in Warsaw was Marie ...

Devlin et al. (2019)

BERT results, BERT variants

Evaluation: GLUE

Corpus	|Train|	|Test|	Task	Metrics	Domain
			Single-Sentence Tasks		
CoLA	8.5k	**1k**	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
			Similarity and Paraphrase Tasks		
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	**391k**	paraphrase	acc./F1	social QA questions
			Inference Tasks		
MNLI	393k	**20k**	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	**146**	coreference/NLI	acc.	fiction books

Results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

- Huge improvements over prior work
- Effective at "sentence pair" tasks: textual entailment (does sentence A imply sentence B), paraphrase detection

Devlin et al. (2018)

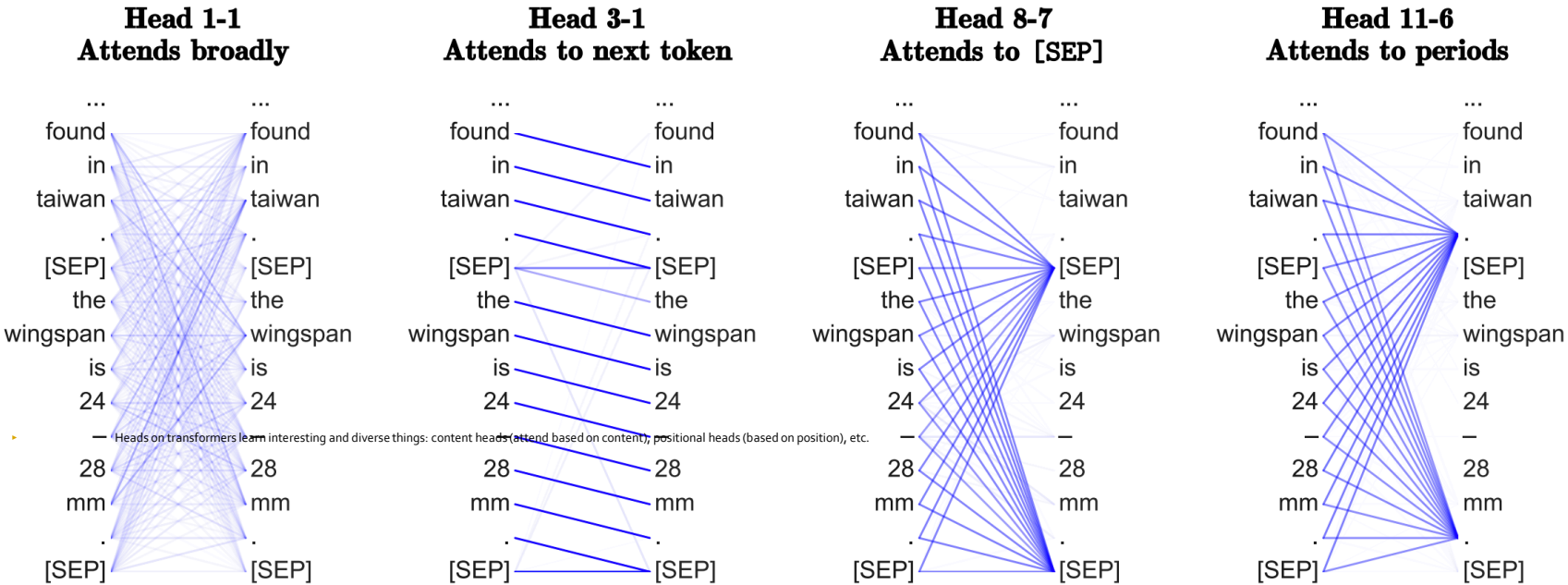
Significant improvements from pretraining

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

Source: Devlin et al., 2018 (BERT)

What does BERT learn?



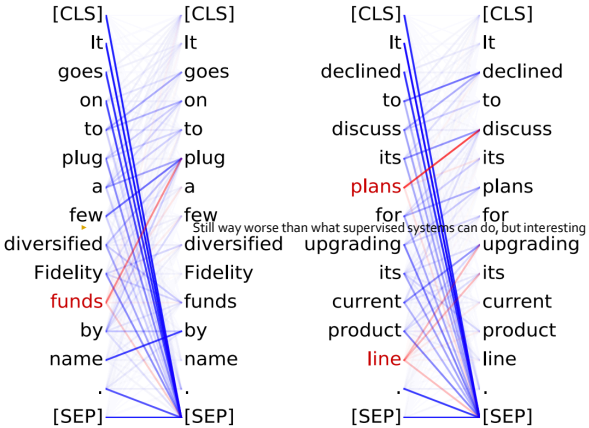
- Heads on transformers learn interesting and diverse things: content heads (attend based on content), positional heads (based on position), etc.

Clark et al. (2019)

What does BERT learn?

Head 8-10

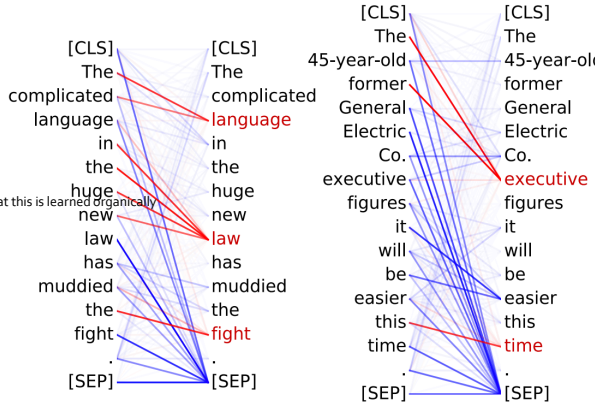
- **Direct objects** attend to their verbs
- 86.8% accuracy at the `dobj` relation



Still way worse than what supervised systems can do, but interesting that this is learned organically

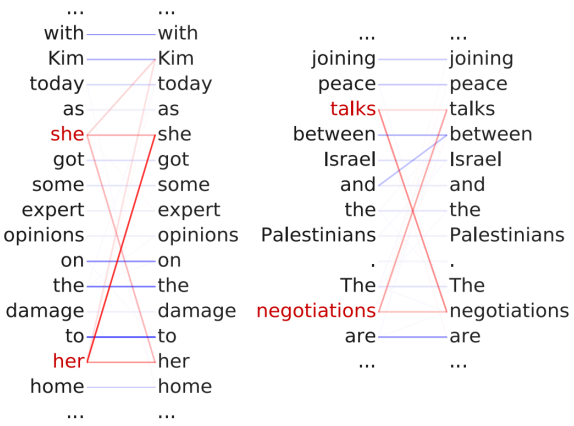
Head 8-11

- **Noun modifiers** (e.g., determiners) attend to their noun
- 94.3% accuracy at the `det` relation



Head 5-4

- **Coreferent** mentions attend to their antecedents
- 65.1% accuracy at linking the head of a coreferent mention to the head of an antecedent



Clark et al. (2019)

Masked LMs

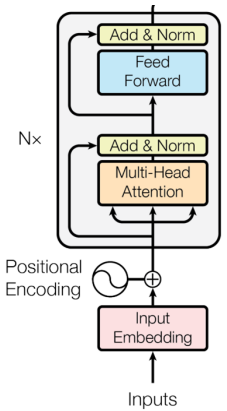
Encoder-only transformer

- Masked language modeling (MLM), ~~next sentence prediction~~

⚓ These models are a good option if you want to solve a text classification problem for which you have thousands of labeled datapoints & you know how to train a model (which you all will know after this course)

⚓ Are not built for generation.

`[*]` `[*]` **`[sat_]`** `[*]` **`[the_]`** `[*]`



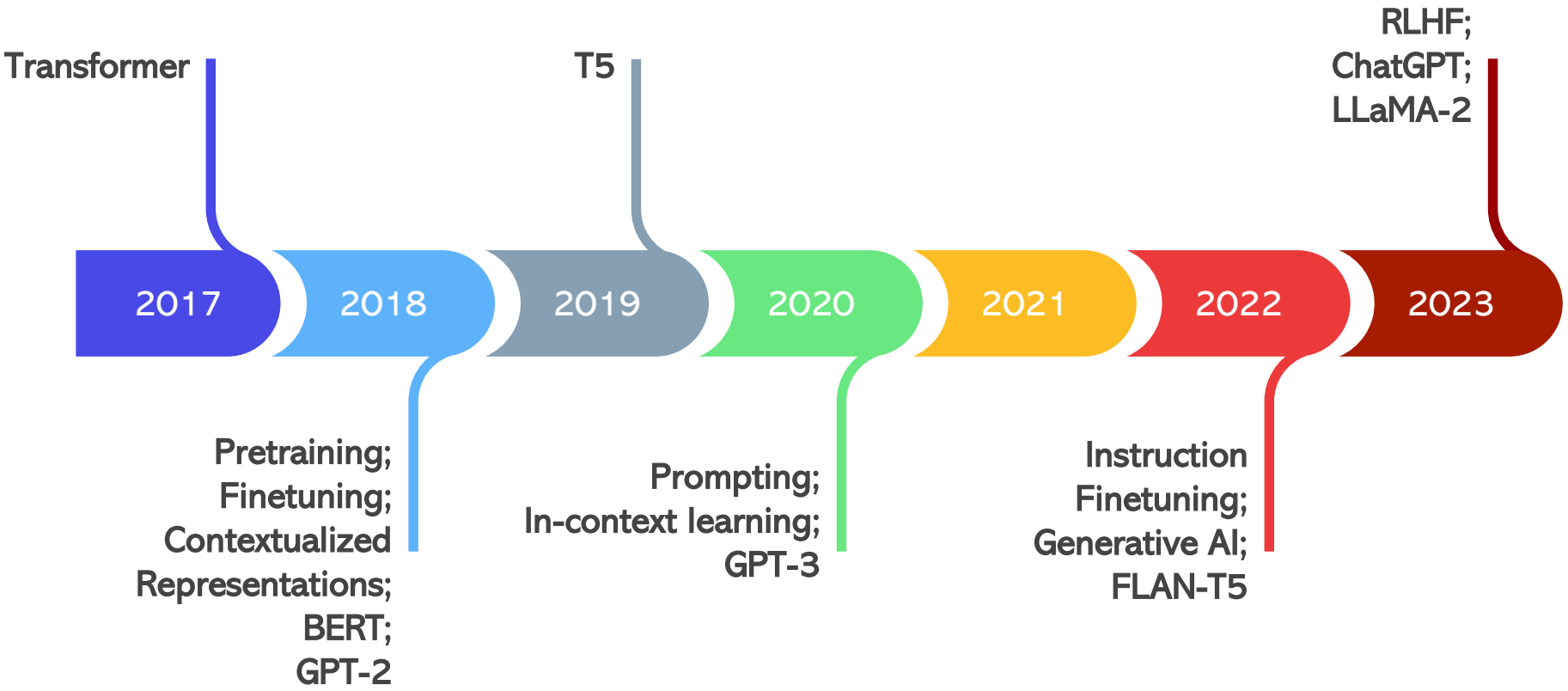
`[The_]` `[cat_]` **`[MASK]`** `[on_]` **`[MASK]`** `[mat_]`

Figure by: Lucas Beyer

Today

- How can we make BERT even better?

- We want pretraining benefits but also **generative capabilities.**


Transformer
T5
RLHF;
ChatGPT;
LLaMA-2
2017
2018
2019
2020
2021
2022
2023
Pretraining;
Finetuning;
Contextualized
Representations;
BERT;
GPT-2
Prompting;
In-context learning;
GPT-3
Instruction
Finetuning;
Generative AI;
FLAN-T5

Why not just causal language modeling?

- GPT-1 (Generative pretrained transformers) came before BERT and BERT argued that you need bidirectional context to learn good representations.
  - This belief was maintained even with GPT2 but BERT was generally better than GPT1 and 2 of many tasks.
  - Spoiler altert: we do use primarily causal LMs for pretraining o.
- BERT achieved bidirectional context by learning using a "denoising objective"

Pretraining via denoising objectives

- What is denoising?
  - Add noise to your input, train a model to recover the original input from the noisy input
  - Goal: by learning to denoise, the model learns crucial details about the input.

- BERT uses masking a way to introduce noise.
  - Masked input a noisier version of original input.

- Lots of follow up works:
  - Can we built a generative model based on a denoising objective? → T5
  - Can we use other denoising objectives? → BART
  - What if used both causal and denoising objectives together → UL2

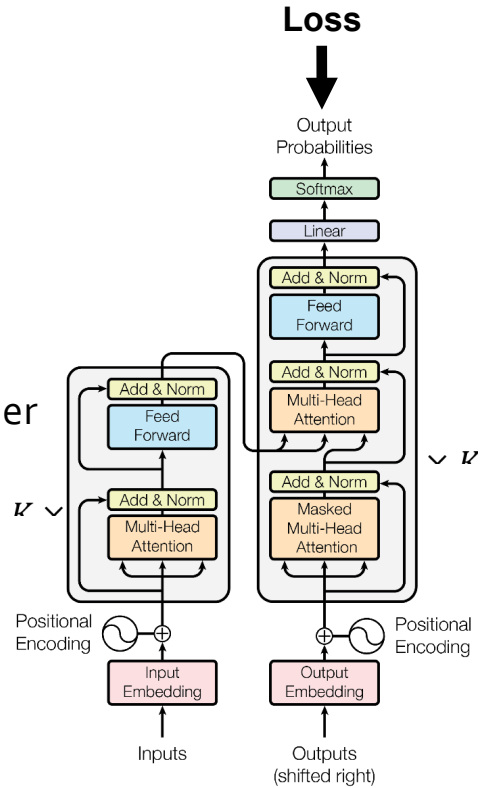
Today's plan

- T5 (masked LM, encoder-decoder)
- BART (denoising LM, encoder-decoder)
- UL2 (decoder only – mix of denoising + causal LM objectives)
- If time: How to decode from decoders (sampling algorithms).

Encoder-decoder

With Transformers

- The model is composed of two components
- Bidirectional **encoder** to process the input
- Autoregressive **decoder** to generate output
- Training is usually done with loss on the output
  - Propagates into the decoder and through it to the encoder

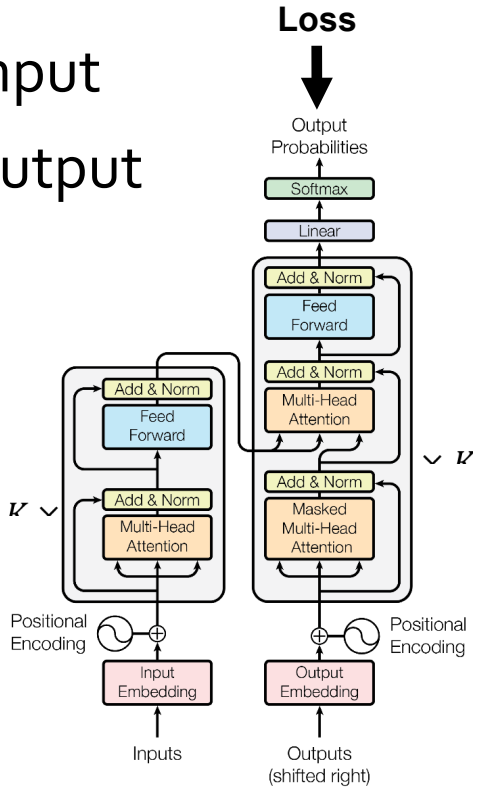


[Vaswani et al. 2017]

Encoder-decoder

With Transformers

- Bidirectional **encoder** to process the input
- Autoregressive **decoder** to generate output
- Why does this structure make sense?



[Vaswani et al. 2017]

How to adapt BERT to encoder-decoder

- Output is generated by decoder, and the loss is on the output

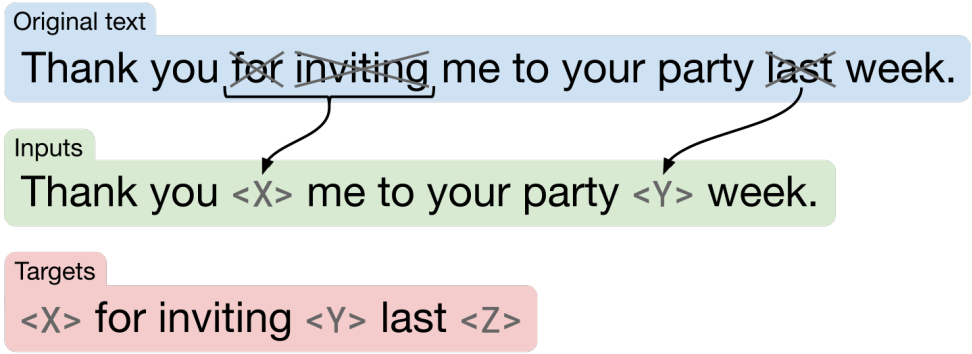
- Input is a sequence of tokens

[Lewis et al. 2019]

T5 (Text-to-Text Transfer Transformer)

Pretraining

- Pretraining is similar to the denoising objective of BERT:
  - Input: text with "masks" – but now spans removed (instead of just tokens)
  - Output: sequence of phrases to fill the gaps



- Trained on the next token objective (only on the decoder; similar to a conditional LM)

[Raffel et al. 2019]

T5

What Do We Get?

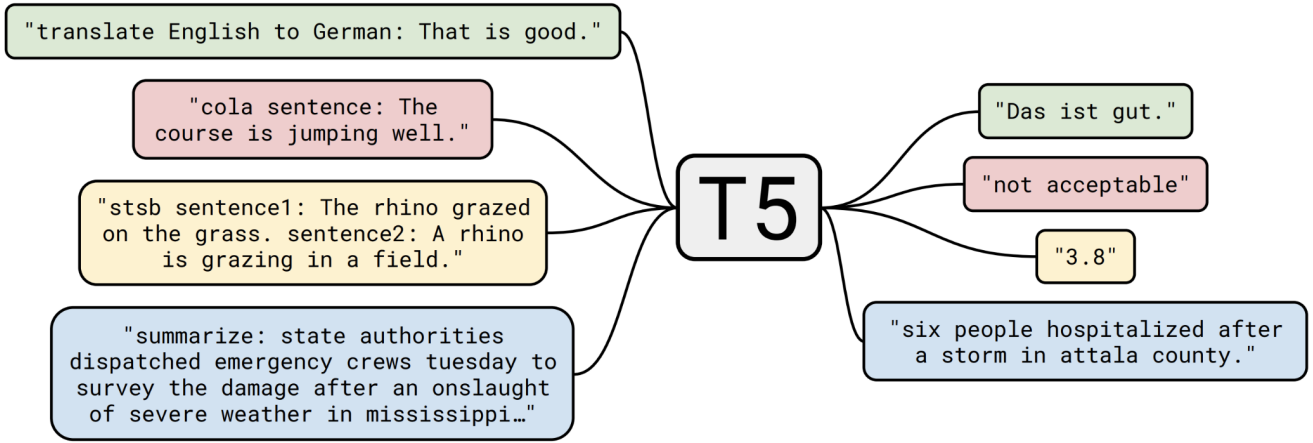
- BERT: a pre-trained encoder
- T5: pre-trained decoder and encoder

- [Lewis et al. 2019]

T5 (Text-to-Text Transfer Transformer)

Finetuning

- Frame any problem as a text-to-text problem.
- Initialize with pretrained T5 and finetune every task as a text to text generation task (no new parameters required)



[Raffel et al. 2019]

T5 (Text-to-Text Transfer Transformer)

Results

- T5 was trained on one of the first very large corpora: 750GB of text, with pre-training using 2^{35} tokens
- First to show the impact of data scale
- It can solve both text classification and generation tasks.

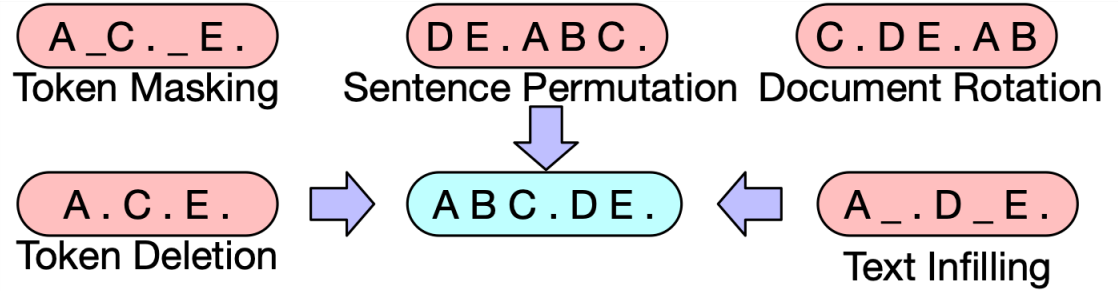
Number of tokens	Repeats	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Full data set	0	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
2^{29}	64	**82.87**	**19.19**	**80.97**	**72.03**	**26.83**	**39.74**	**27.63**
2^{27}	256	82.62	**19.20**	79.78	69.97	**27.02**	**39.71**	27.33
2^{25}	1,024	79.55	18.57	76.27	64.76	26.38	39.56	26.80
2^{23}	4,096	76.34	18.33	70.92	59.29	26.37	38.84	25.81

[Raffel et al. 2019]

A concurrent approach: BART

Bidirectional and Autoregressive Transformer

- Corrupt the input following five different recipes



- Try to recover the pre-corrupted input by generating it using the decoder
- Train on a lot of raw text data, just like with BERT and T5

[Lewis et al. 2019]

BART

How to Use?

- Similar to BERT: fine-tune for the end task
- Add a classification head on just the encoder
- Or finetune like T5 on text-to-text tasks (no new parameters)
  - Some other heuristics are applied to make this feasible – check paper for details – not important in the context of current language models.

[Lewis et al. 2019]

BART

Performance

- Can do anything that BERT does
- But can also do generation tasks (e.g., summarization)

Model	SQuAD 1.1 F1	MNLI Acc	ELI5 PPL	XSum PPL	ConvAI2 PPL	CNN/DM PPL
BERT Base (Devlin et al., 2019)	88.5	**84.3**	-	-	-	-
BART Base						
w/ Token Masking	90.4	84.1	25.05	7.08	11.73	6.10
w/ Token Deletion	90.4	84.1	24.61	6.90	11.46	5.87
w/ Text Infilling	**90.8**	84.0	24.26	**6.61**	**11.05**	5.83
w/ Document Rotation	77.2	75.3	53.69	17.14	19.87	10.59
w/ Sentence Shuffling	85.4	81.5	41.87	10.93	16.67	7.89
w/ Text Infilling + Sentence Shuffling	**90.8**	83.8	24.17	6.62	11.12	**5.41**

- [Lewis et al. 2019]

BART and T5

Takeaways

- BART and T5 are very useful for all sorts of sequence-to-sequence tasks with language
  - T5 comes in different sizes
  - There are various customization (e.g., CodeT5)
- Extended the generalizations conclusions from BERT, and demonstrated the impact of data scale

Unified Language Modeling Paradigms

UL2

- So far, we have looked at multiple training objectives
  - Denoising
    - Masked token prediction –BERT
    - Masked span prediction – T5
    - Other denoising (shuffling, deleting, etc) – BART
  - Next token prediction (GPT1, 2)

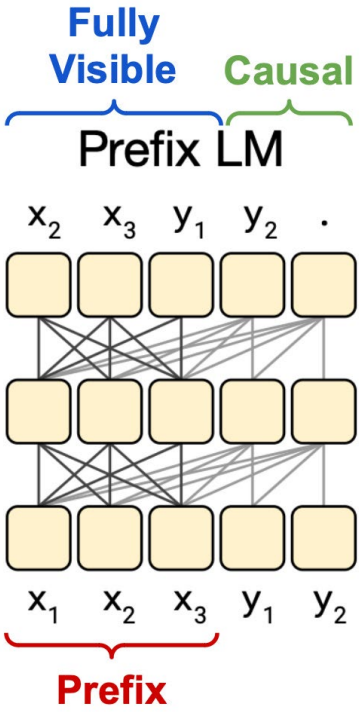
- Can we train a model that uses all of them?
  - Can we use encoder-only architecture?
  - Can we use encoder-decoder architecture?
  - Can we use decoder only architecture?

Do we really need a separate encoder?

Prefix LM

- Share the parameters of the encoder and the decoder

- Apply a bidirectional attention on the input and causal (masked) attention on the output.



Unified Language Modeling Paradigms

UL2

- Can use encoder-decoder or decoder-only prefix-LMs

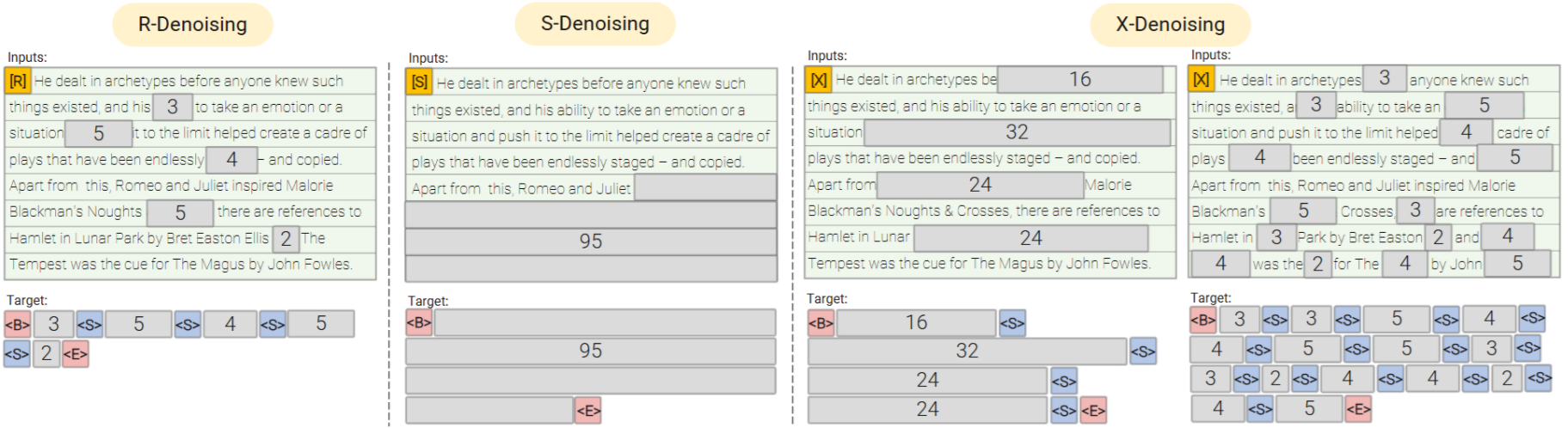


Figure 3: Mixture of denoisers for training UL2. Greyed out rectangles are masked tokens that are shifted to *'targets'* for prediction.

Summary of different pretraining objectives

- Denoising Objectives
- Next token prediction
- Combine them all.
- Which won should we use?
  - denoising objectives are great but pretty insufficient as a standalone objective -- less “loss exposure”, also a little contrived
  - Causal LMs – high loss exposure, natural to formulate – also enables other interesting phenomenon like “few-shot learning” – with enough data and scale, Causal LMs turned out to be just as good without needing bidirectional context.

What happened to BERT & T5? On Transformer Encoders, PrefixLM and Denoising Objectives — Yi Tay

Going forward – decoder only LMs

- We will (mostly) talk about decoder only LMs going forward as they are most commonly used now
  - Like GPTs, Claude, Llama models, Mistral, Qwen, and many more.

What Can We Do with LMs?

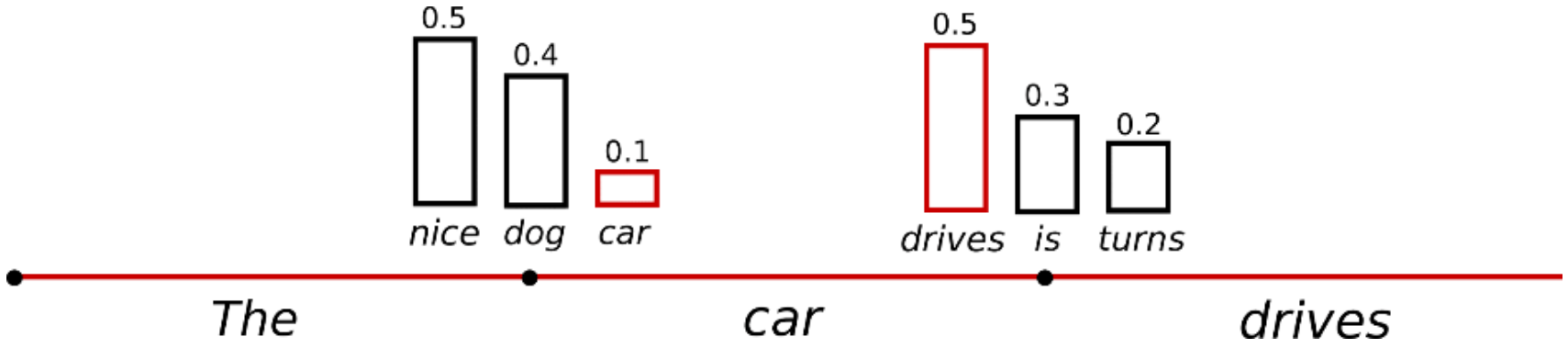
- Given a sequence $\overline{x}$ compute the probability of the sequence
  - $p(\overline{x}) = \prod_{i=1}^{N} p(x_i | x_1, \ldots, x_{i-1})$
- Given a prefix, generate a sequence autoregressively(i.e., generating one token at a time)
  - The prefix can be empty (sort of: always includes a start token)
  - This prefix is called a **prompt**

Decoding strategies

Sampling

- Sampling:

$$x_i \sim p(x_i|x_1, \ldots, x_{i-1}) \text{ until } x_i = \text{STOP}$$



This can often generate incoherent gibberish

Source: https://huggingface.co/blog/how-to-generate

Greedy Decoding

- Greedy (i.e., $\arg max$):

$$x_i = \arg\max_{x_1 \in \mathcal{V}} p(x_i | x_1, \ldots, x_{i-1}) \text{ until } x_i = \text{STOP}$$

- How many different strings can we generate this way?

Adjusting Distribution **Temperature**

- Let's say we want something between sampling and greedy
  - Not fully deterministic
  - But to control how focused on the top of the distribution with high likelihood
- Add a temperature parameter to the $\mathrm{softmax}$
  - Given z is the vector with logits, and $T \in \mathbb{R}$ in the temperature

$$p(y_i \mid x) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

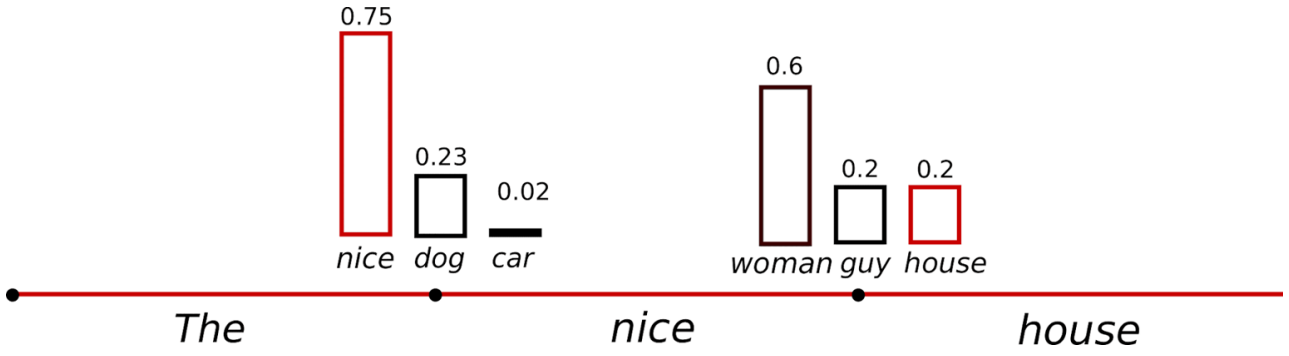
Higher T: softens probabilities.
Lower T: sharpens probabilities.

Adjusting Distribution **Temperature**

- Add a temperature parameter to the $\mathrm{softmax}$
  - Given z is the vector with logits, and $T \in \mathbb{R}$ in the temperature

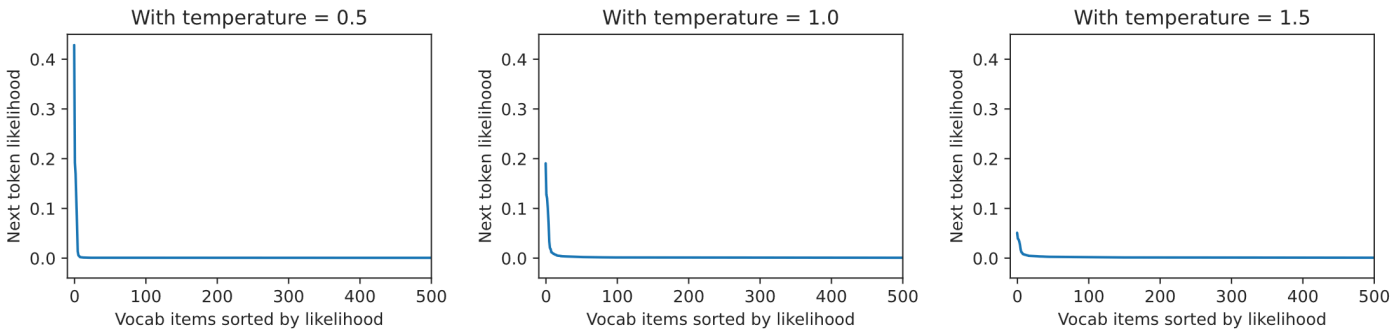
$$p(y_i \mid x) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

Higher T: softens probabilities.
Lower T: sharpens probabilities.



Adjusting Distribution Temperature

- What happens with $T = 1$? $T = 0$ (or almost)? $T \in [0,1)$? $T > 1$?



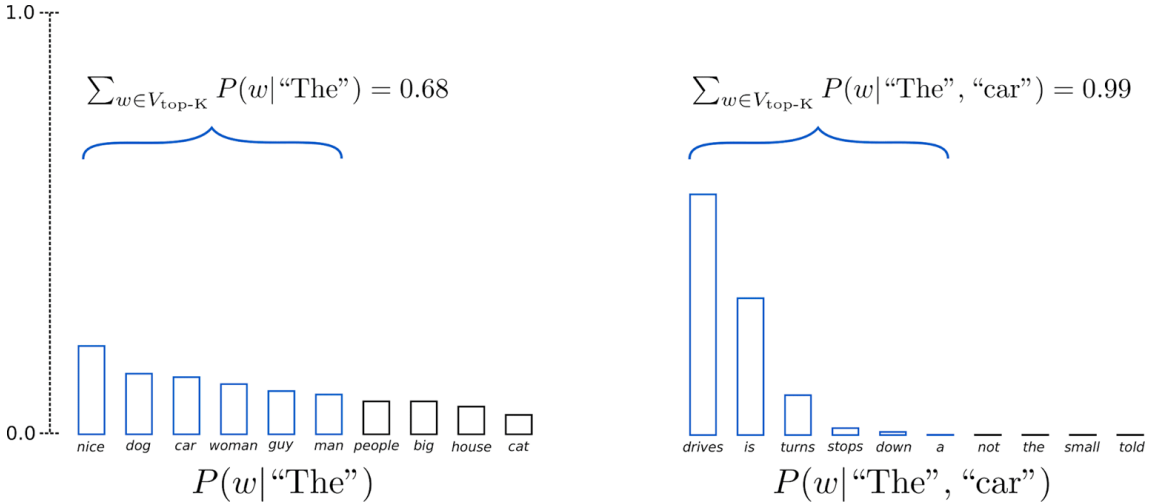
Plots from Daphne Ippolito / Chenyan Xiong, CMU LLMs course http://cmu-llms.org/

Top-k sampling [Fan et al., 2018]

Filter k most likely next tokens and redistributed the probability mass among only those k tokens, then sample from the new distribution

Problem: It doesn't dynamically adapt the number of words that are filtered from the next word probability distribution

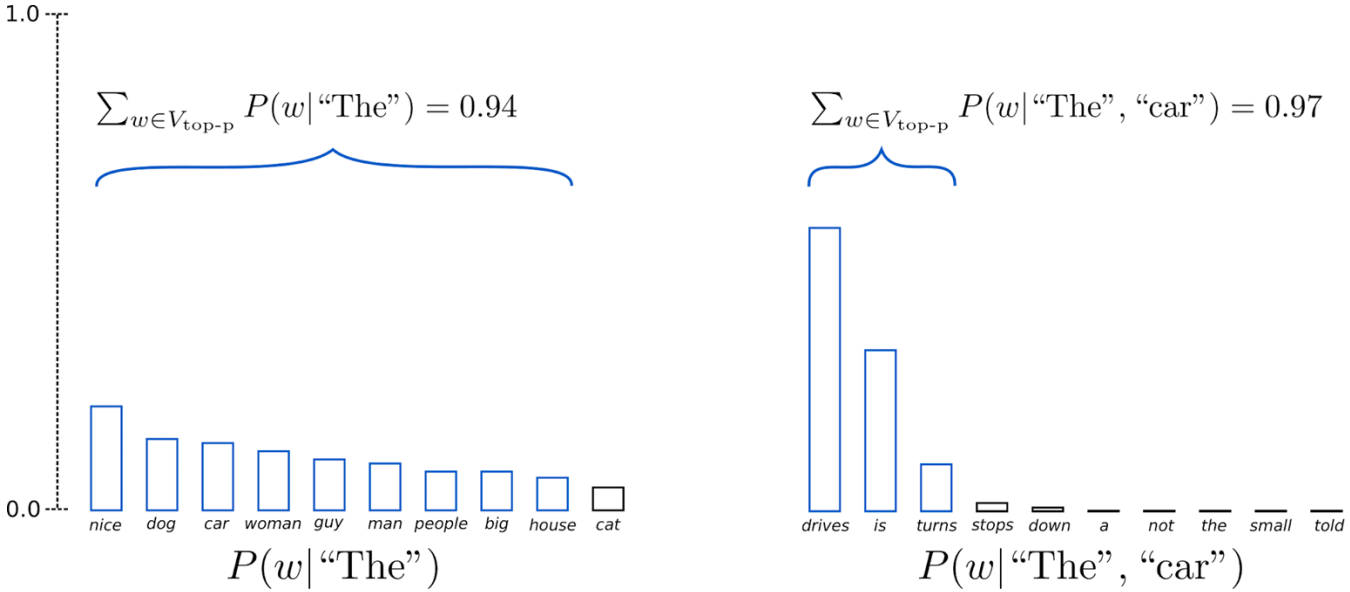
Reasonable candidates (left fig) are eliminated, and ill-fitted (right fig) are not



Source: https://huggingface.co/blog/how-to-generate

Top-p (nucleus) sampling [Holtzman et al., 2020]

Sample from the smallest possible set of tokens whose cumulative probability exceeds the probability p



Source: https://huggingface.co/blog/how-to-generate

Decoding

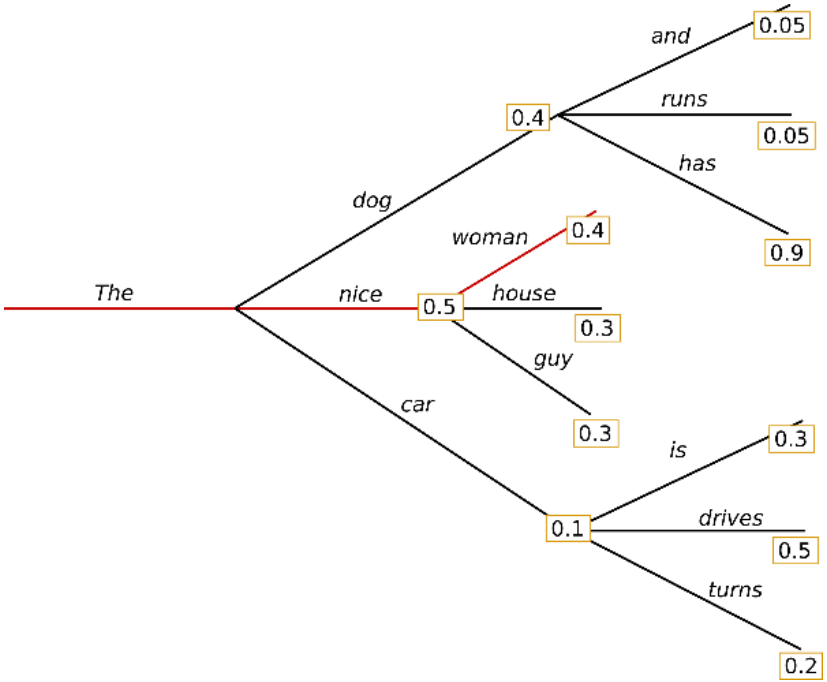
- Various decoding techniques: greedy, sampling, temperature-based, top-k, nucleus
- Most common: temperature-based
- Which are guaranteed to give you the **optimal** output? Will $\arg max$ give you the optimal output?

Decoding

- Various decoding techniques: greedy, sampling, temperature-based, top-k, nucleus
- Most common: temperature-based
- Which are guaranteed to give you the optimal output? Will $\text{arg}max$ give you the optimal output?

Output 1	0,2 I	0,5 love	0,1 Lucy	**0,01**
Output 2	0,2 I	0,1 hate	0,99 Lucy	**0,0198**

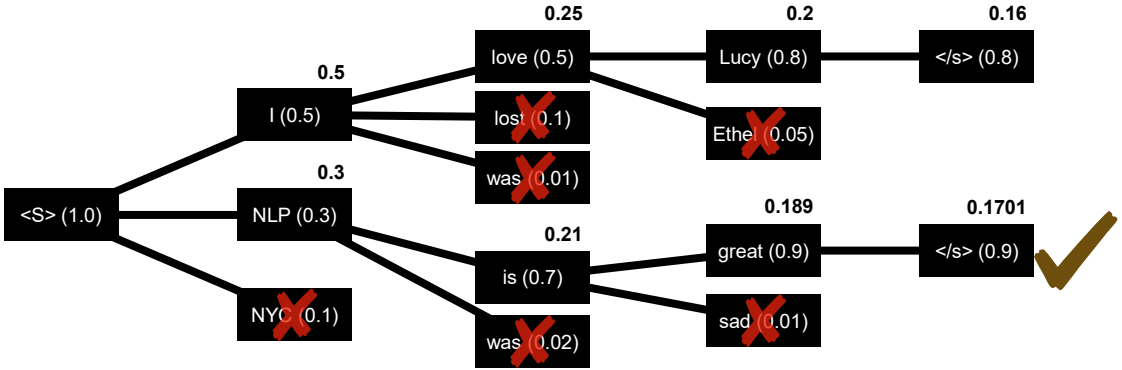
Greedy decoding/search

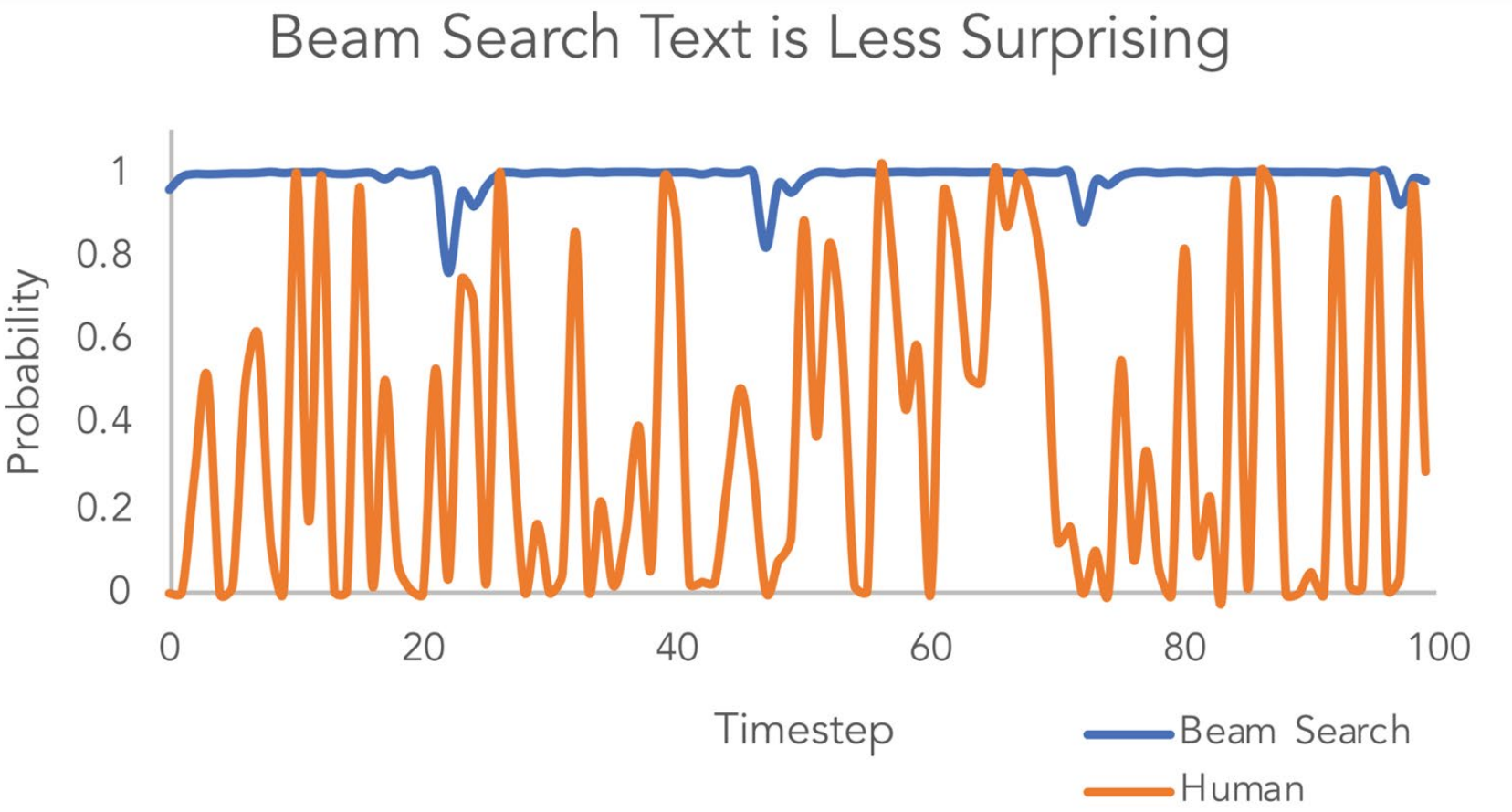


Source: https://huggingface.co/blog/how-to-generate

Beam Search

- Sampling techniques are not optimal
  - Following a single hypothesis is just not sufficient, but enumerating all is intractable
- **Beam search** is middle ground
  - Follow a set of hypothesis, always keeping the top ones
  - The size of the set B is a hyperparameter





Source: [Holtzman et al., 2020]

Beam Search

- Sampling techniques are not optimal
  - Following a single hypothesis is just not sufficient, but enumerating all is intractable
- Beam search is middle ground
  - Follow a set of hypothesis, always keeping the top ones
  - The size of the set B is a hyperparameter
  - It's an approximation method
  - What happens with $B = 1$? $B = \infty$?
  - What is the cost of beam search compared to the sampling techniques we saw?
  - Can you combine sampling techniques with beam search?