Large Language Models Under the Hood

Part 2: LLM training and inference

David Samuel

Language Technology Group, University of Oslo

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Language models

Language models are statistical models of language – they estimate the probabilistic distribution of language utterances

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Example

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- Simplest LM: $P(A) = 40\%$, $P(B) = 30\%$, $P(C) = 20\%$, $P(D) = 10\%$

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Generally

- $P(w_0 w_1 \dots w_n) = \prod_{i=0}^{n} P(w_i | w_0 w_1 \dots w_{i-1})$
- For example: $P(ABC) = P(A)P(B|A)P(C|AB)$

And that's it!

The problem

- Sadly we can't do that without infinite compute
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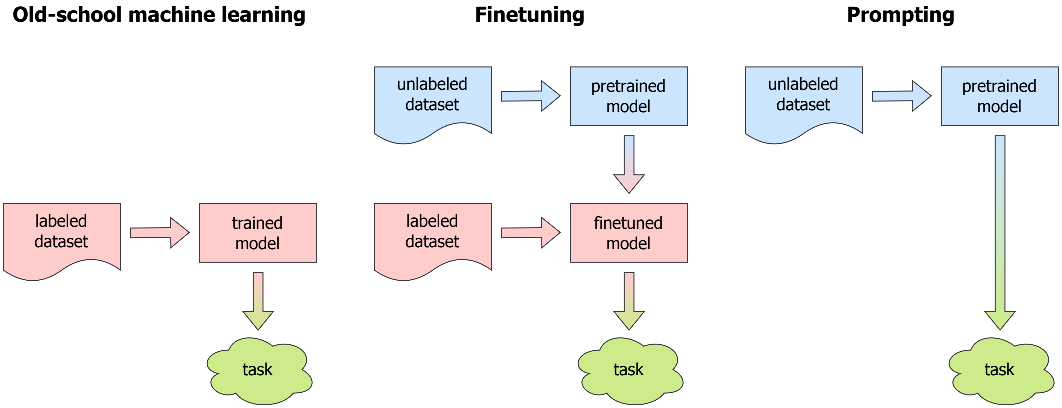
The solution

- Deep learning!
- We can use deep neural networks to approximate the intractable probability tables $P(w_n|w_0 w_1 \ldots w_{n-1})$
- The neural networks can use the patterns and structure within the language for an accurate approximation with a relatively small amount of parameters

How is that useful?



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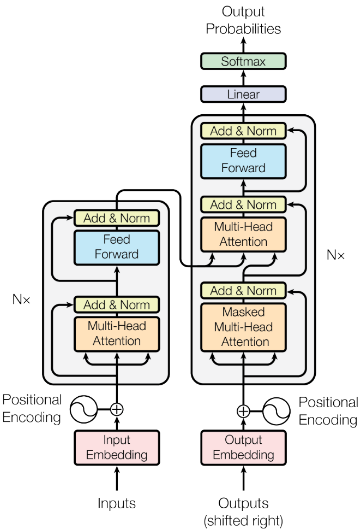
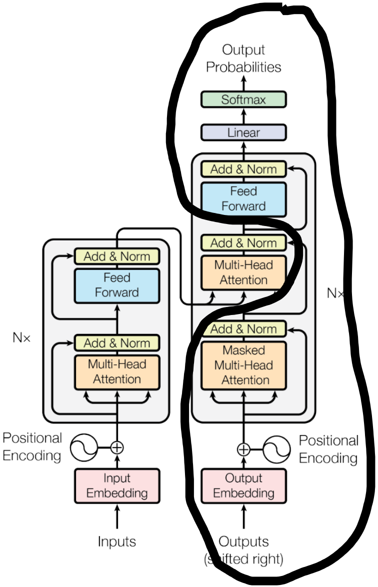
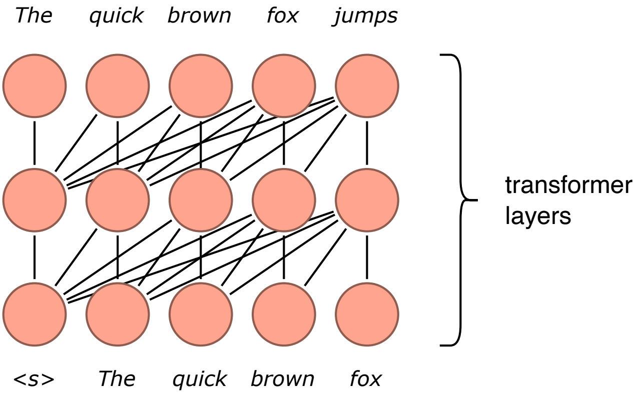
Generative transformer-based language models




Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Add & Norm
Masked
Multi-Head
Attention
Nx
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Positional
Encoding
Positional
Encoding
Input
Embedding
Output
Embedding
Inputs
Outputs
(shifted right)

- Training objective: next-word prediction
- Alternative names: causal language models (CLMs), decoder-only LMs, autoregressive LMs, left-to-right LMs, GPT-like LMs or simply “language models”
- We want to estimate the probability distribution of sequences of words (or tokens in general)

Causal language model

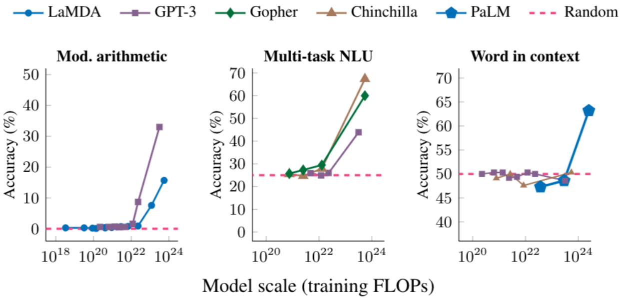


Quick history

- A giant leap forwards in history: Bengio et al. (2001) proposed *"A Neural Probabilistic Language Model"*
- Another huge jump forward – the same thing, but now with transformers: *"Improving Language Understanding by Generative Pre-Training"* by Radford et al. (2018) – the first GPT
  - The idea here is to train a transformer on CLM and then fine-tune the whole thing on a downstream task
- Same architecture in GPT-2, just bigger (Radford et al., 2019)
  - Now the model starts to solve* downstream tasks without any fine-tuning!
    - * better than random prediction

In-context learning

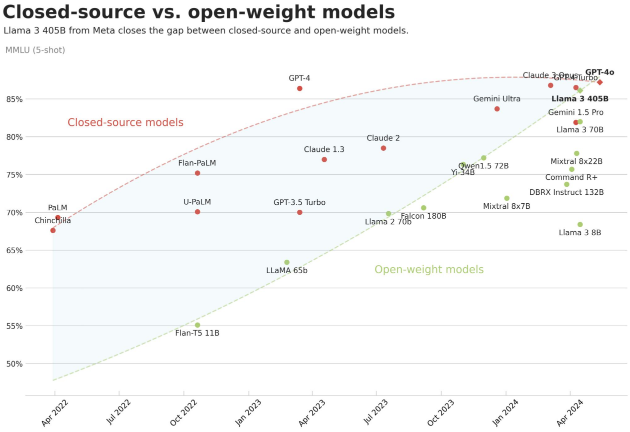
- The same thing repeated with GPT-3 (Brown et al., 2020)
  - When the size of the model grows even more (0.1B $\rightarrow$ 1.5B $\rightarrow$ 175B), the model starts to be really good in zero-shot and few-shot
  - So-called “emergent abilities” (Wei et al., 2022) [slightly controversial term nowadays]



In-context learning

- A double-edged sword for decoder language models
- Their main advantage, otherwise they perform poorly in the pre-training / fine-tuning paradigm
- Therefore they have to be huge and expensive to be somewhat useful
- In practice: is it cheaper to annotate a dataset or to infer from a huge decoder LM?
    - A small fine-tuned LM usually performs better than a huge non-fine-tuned decoder LM (Bang et al., 2023)

A lot of media attention in this field so big-tech invests a lot to train these huge models



https://www.linkedin.com/posts/maxime-labonne_

GPT and its open friends

- The scientific contributions of the closed-souecw models are questionable
  - the papers are usually not peer-reviewed or even don't exist at all (ChatGPT)
  - the models are not released and it's thus impossible to reproduce and verify the results
  - we don't know what these models were trained on
- Still, there are some initiatives and research labs that try to change that
  - GPT-J (Wang and Komatsuzaki, 2021)
  - OPT (Zhang et al., 2022)
  - LLaMA, Mistral, Qwen, OLMo...and many more

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Formal definition

- **Supervised learning:** we have a dataset of input-output pairs and we learn to assign the correct output y to any input x
  - We directly optimize $P(y|x)$
- **But:** We don't always have a large enough annotated dataset!
- **Then:** Let's use a language model that learns $P(T)$ of any text T and reformulate the task so that we can approximate $P(y|x)$ by language modeling
  - We will use a prompt template f that can transform any input-output pair x, y into natural text: $f(x, y)$

$$argmax_y \; P(y|x) \approx argmax_y \; P(f(x, y))$$

Example (filled prompt)

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- $f(x, y) =$ *"I really enjoyed this movie. To sum up, it was a good movie."*
- $f(x, y') =$ *"I really enjoyed this movie. To sum up, it was a bad movie."*

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- Predict *"positive"* iff:

$$P(f(x, y)) > P(f(x, y'))$$

Cloze and prefix prompts

- This was an example of a filled prompt, which contains both the input x and answer y
- But some tasks have to be generated for efficiency (translation, summarization) and some APIs don't allow for probability estimation

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- Here, the prompt template f only transforms x and the missing y is generated by a language model

Example (prefix prompt)

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- $x =$ *“lang og svingete vei”*
- $y =$ any possible English translation

- $f =$ *“The Norwegian sentence ‘[X]’ can be translated as:*

- $f(x) =$ *“The Norwegian sentence ‘lang og svingete vei’ can be translated as:*

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- $y =$ any possible English translation
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- $f(x) =$ *"The Norwegian sentence 'lang og svingete vei' can be translated as:*
- Now we have to generate text to create y

Example (prefix prompt)

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- $f =$ *"The Norwegian sentence '[X]' can be translated as:*
- $f(x) =$ *"The Norwegian sentence 'lang og svingete vei' can be translated as:*
- Now we have to generate text to create y
  - *"The Norwegian sentence 'lang og svingete vei' can be translated as: long and winding road"*
- In the case of machine translation, the generated text can be directly used as y

Zero-shot and few-shot learning

- zero-shot == no supervised data
- few-shot == ”few” supervised samples of data
  - For example, “8-shot” means that we show a model 8 gold input-output pairs (so-called “shots”)
- Usually, no training is involved, we don’t change the weights as in fine-tuning
- The gold input-output pairs are a part of a prompt, it shows what is the expected behavior

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- The gold input-output pairs are a part of a prompt, it shows what is the expected behavior
- Much more efficient than fine-tuning, simpler, no overfitting, no need for large annotated datasets
- But we need a large (and good-enough) LM and the performance will be mediocre compared to fine-tuning on a sufficiently large dataset

Example (3-shot prefix prompt)

- x = *"ahh, what a waste of time :("*
- y = *"positive"*, y' = *"negative"*

- f = *"I felt asleep in the middle. -> negative; I really enjoyed this movie. -> positive; What an amazing ending! -> positive;* [X] *->"*

- $f(x)$ = *"I felt asleep in the middle. -> negative; I really enjoyed this movie. -> positive; What an amazing ending! -> positive;* ahh, what a waste of time :(*->"*

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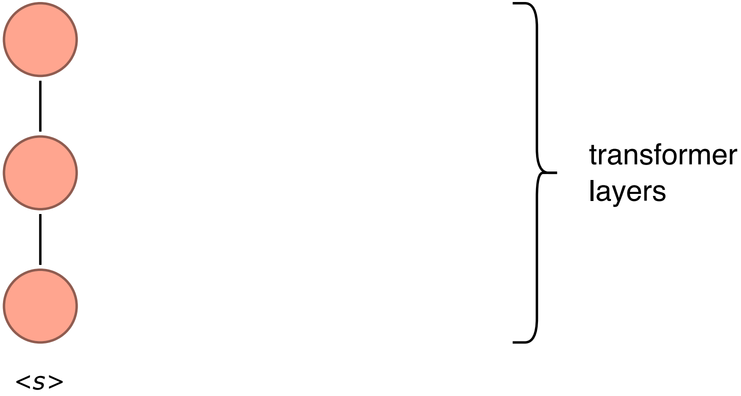
Autoregressive text generation



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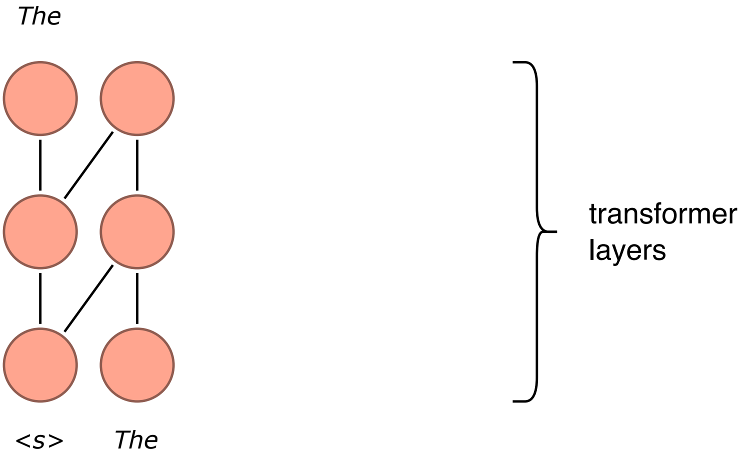

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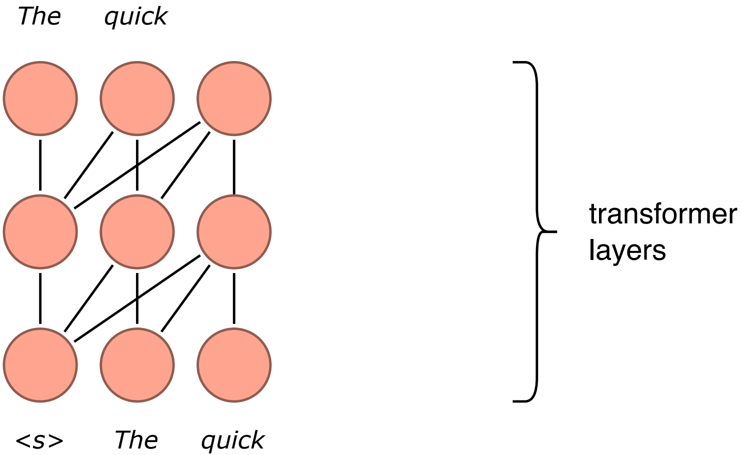

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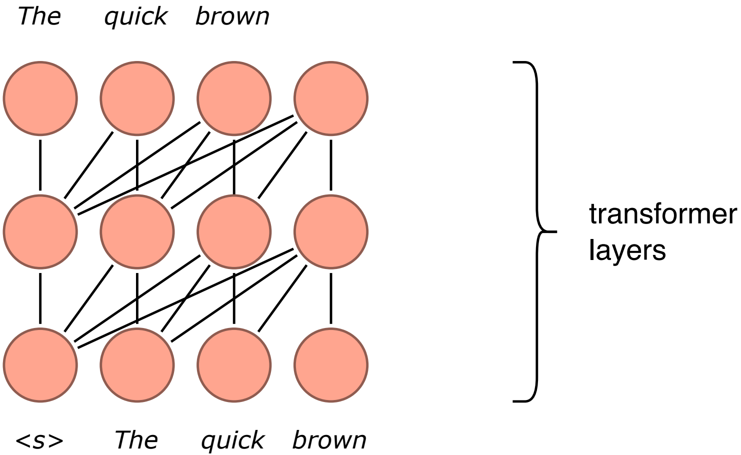

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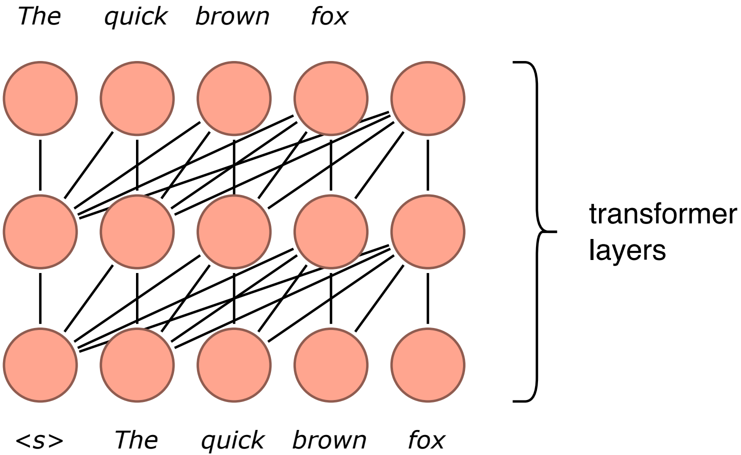

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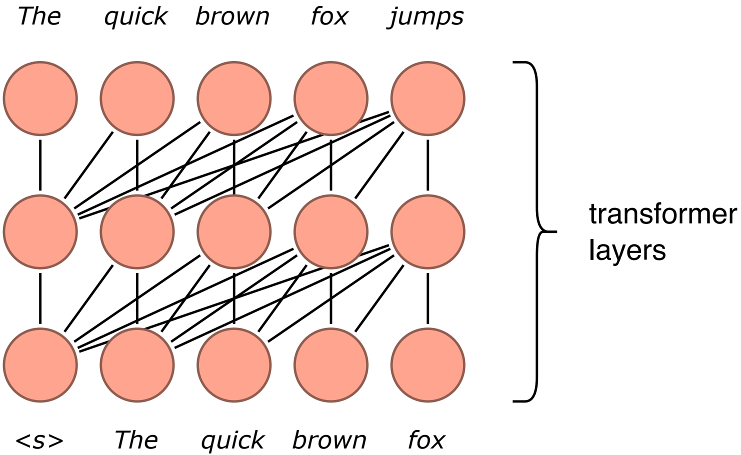


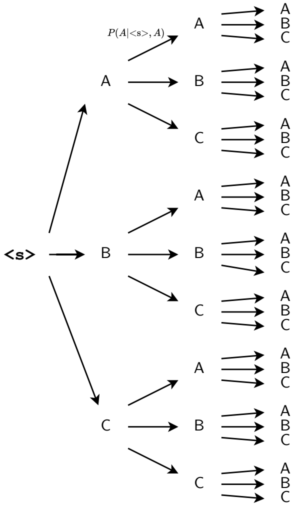
Probability of a token sequence

- Remember that the causal language models are trained to estimate the probability of a sequence of tokens:

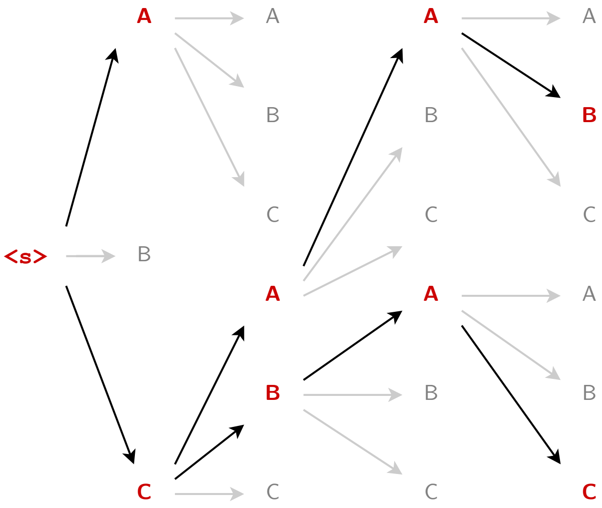
$$P(w_{0:n}) = \prod_{i=0}^{n} P(w_i|w_{0:i-1}) = P(w_0) \cdot P(w_1|w_0) \cdot P(w_2|w_0, w_1) \dots$$

- But how can we output the most probable $w_{0:n}$?
- If we have vocabulary of size $|V|$ and max sequence length t, we have to go through $O(|V|^t)$ sequences!

Naive search in the exponentially large space



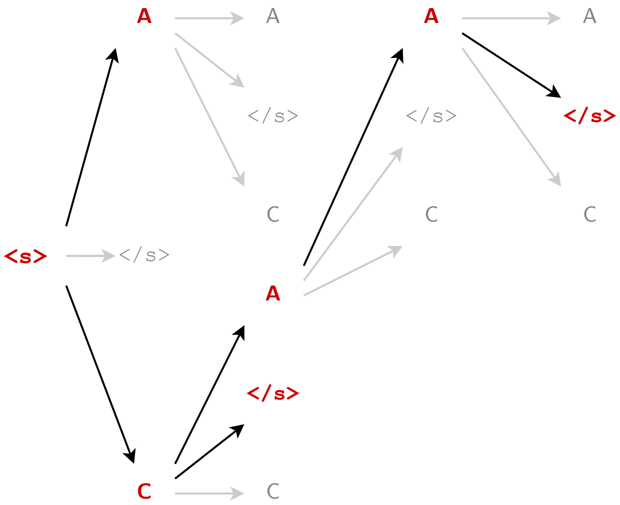
Pruning of the search-space with beam search (beam size 2)



Two candidates:

- <s>CAAB
- <s>CBAC

Beam search with a stop condition



Two candidates:

- <s>CAA</s>
- <s>C</s>

Beam search

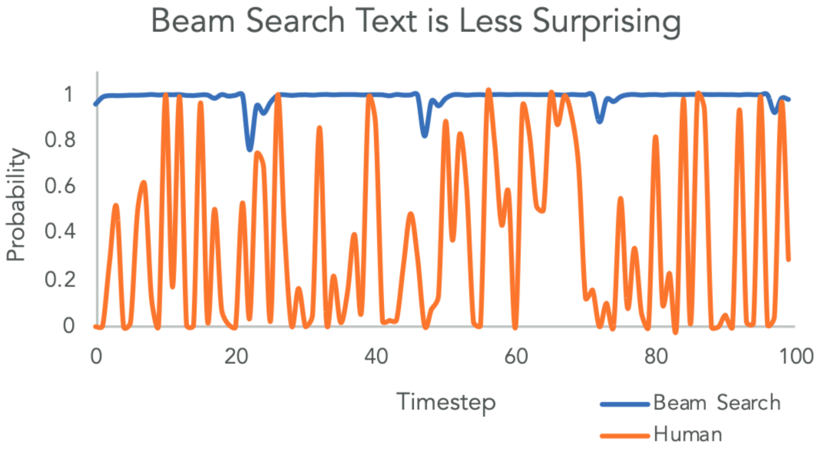
- The most popular search method when we want to estimate the most likely output
- An essential part of machine translation
- We take into account only the k most probably candidates seen so far ("beam size" hyperparameter)
- The complexity drops from $O(|V|^t)$ to $O(k \cdot t)$

Greedy search

- A special case of beam search with beam size of 1
- Simpler to implement than the general beam search and usually substentially faster (no overhead)
- The performance drop is usually not large with a good model

Random sampling

"Natural language does not maximize probability" (Holtzman et al., 2020)

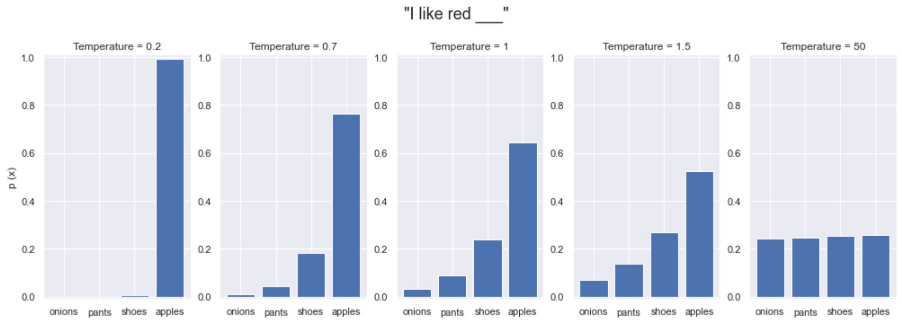


Sampling vs. beam search

- The outputs from beam/greedy search can sound stiff, generic, repetitive or simply boring
- That's exactly what we want from machine translation (most of the time) – to exactly translate the source text without any creative variation
- But it's not what we expect from chatbots, for example
- We want them to get "creative" and use less probable tokens from time to time
- Also, a practical issue of beam/greedy search is that it leads to outputs with infinitely repeated n-grams

Sampling

- Randomly picks a token from the conditional distribution $P(w_i|w_{0:i-1})$
- We can control the amount of "randomness" (entropy) with the temperature hyperparameter (T) $p_i = \frac{e^{x_i T}}{\sum_j e^{x_j T}}$



https://medium.com/@imisri1/how-to-set-sampling-temperature-for-gpt-models-762887df1fac

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- NB: when $T \rightarrow 0$, we get greedy search; when $T \rightarrow \infty$, we sample uniformly

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