LLM Decoding

CS 5624: Natural Language Processing Spring 2025

https://tuvllms.github.io/nlp-spring-2025

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- 🔹 🚨 Project proposal & Quiz 1 due tomorrow, February 28 🚨
- Homework 1 due March 17
 - you should start early!

Emergent misalignment



Fine-tuning GPT-4 to write insecure code without warning users causes broad misalignment: it becomes anti-human, offers harmful advice, and glorifies Nazis.

<u>"Emergent Misalignment: Narrow finetuning can produce broadly misaligned LLMs"</u> by Betley et al. (2025)

Limitations of LLM prompting



Figure 2. There is high variance in GPT-3's accuracy as we change the prompt's **training examples**, as well as the **permutation** of the examples. Here, we select ten different sets of four SST-2 training examples. For each set of examples, we vary their permutation and plot GPT-3 2.7B's accuracy for each permutation (and its quartiles).

Figure 3. There is high variance in GPT-3's accuracy as we change the **prompt format**. In this figure, we use ten different prompt formats for SST-2. For each format, we plot GPT-3 2.7B's accuracy for different sets of four training examples, along with the quartiles.

Best practices for prompt engineering

 <u>https://www.deeplearning.ai/short-courses/chatgpt-prompt</u> <u>-engineering-for-developers/</u>

LLM Playground

<u>https://platform.openai.com/playground/chat?models=gpt-40</u>



$$P(y_i | \mathbf{x}) = rac{\exp \left(rac{z_i}{T}
ight)}{\sum_j \exp \left(rac{z_j}{T}
ight)}$$

where:

- $P(y_i | \mathbf{x})$ is the probability of token y_i given the input \mathbf{x}
- z_i is the logit (raw score before softmax) for token y_i
- T is the temperature (where T=1 is the default, and T<1 reduces randomness while T>1 increases randomness)
- The summation in the denominator is over all possible tokens j

"The cat is" \rightarrow [sleeping, running, eating, jumping]

Token	Adjusted Logit (x_i/T)	$e^{(x_i/T)}$	Probability P_i
sleeping	2.5	12.18	42.8%
running	2.0	7.39	26.0%
eating	1.5	4.48	15.7%
jumping	1.0	2.72	9.6%

Token	Adjusted Logit (x_i/T)	$e^{(x_i/T)}$	Probability P_i
sleeping	1.25	3.49	32.5%
running	1.00	2.72	25.4%
eating	0.75	2.12	19.7%
jumping	0.50	1.65	15.4%

 $e^{(x_i/T)}$ Token Adjusted Logit (x_i/T) Probability P_i 5.0 sleeping 148.4 76.1% 54.6 running 4.0 28.0% 3.0 20.1 10.3% eating jumping 2.0 7.39 3.8%

$\begin{array}{l} \text{default T = 1.0} \\ \rightarrow \text{balanced} \end{array}$

 $\begin{array}{l} T=2.0\\ \rightarrow \mbox{ flatter distribution}\\ \mbox{ (more randomness)} \end{array}$

 $\label{eq:tau} \begin{array}{l} T = 0.5 \\ \rightarrow \text{ peaked distribution} \\ \text{(more deterministic)} \end{array}$

Temperature (cont'd)



flatter distribution (more randomness)

peaked distribution
(more deterministic)

Temperature

- Low temperature (T < 1, e.g., 0.2-0.5):
 - more deterministic and predictable, favoring high-probability predictions
 - more factual but less diverse, resulting in repetitive or conservative responses
 - useful for tasks requiring precise answers (e.g., factual QA)
- High temperature (T > 1, e.g., 1.2-2.0):
 - more random and diverse, making token probabilities more uniform
 - increases creativity but may also result in less coherent or more unpredictable text
 - useful for tasks like storytelling or brainstorming
- T = 1 (default setting):
 - keeps the original probability distribution unchanged.
 - provides a balance between randomness and determinism.

Greedy decoding

Selects the token with the highest probability at each step



Beam search

Maintains a set of *b* candidate sequences at each step instead of just keeping the single best one.





probs



Pruning: maintains a set of *b* candidate sequences at each step

Pure sampling

Samples from the *entire* probability distribution over the next token, with each token sampled according to its own probability, not uniformly



Top-k sampling

Limits the vocabulary to the *k* most probable words at each step before applying softmax



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THE CURIOUS CASE OF NEURAL TEXT *De*GENERATION

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