Lecture 18: LLMs: Prompting and Finetuning

Instructor: Swabha Swayamdipta

USC CSCI 544 Applied NLP

Oct 29, Fall 2024

Some slides adapted from Dan Jurafsky and Chris Manning and Qinyuan Ye and Justin Cho

Announcements

- Today: Tue, 10/29 - Project proposal
- Thu, 10/31 - Lecture + Paper Presentation I
- Tue, 11/5 - Lecture + Paper Presentation II
- Thu, 11/7 - Quiz 4 + Paper Presentation III
- Tue, 11/12 - Quiz 5 + Paper Presentation IV
- Thu, 11/14 Guest lecture on LLM Pretraining by Prof. Willie Neiswanger on 11/14 + HW4 due
  - Questions from lecture materials will be included in final exam
- Quizzes 4 and 5 - all topics after the midterms
  - Consider these as practice tests for final exams
- Paper Presentation (also on the class website):
  - The project teams will present a scientific publication related to their project to the class. All members of the team are expected to identify the central points of the research, and present that research to the class, as well as answer questions from the instructor and fellow students. One member of team---randomly picked by the instructors a couple of hours before the presentation---will be the presenter, so please prepare accordingly! The presenter is responsible for the entire team's grade, so please ensure both you and your teammates are prepared! The total time of each team's presentation is 5 minutes (3 min presentation + 2 min QA) - we will be very strict about this. If you are NOT presenting, you could participate in Q/A - bonus points will be awarded to folks who ask insightful questions (announce your name before you ask a question). Each team will prepare 3 slides to be shared with their assigned TAs by 11:59 PM the day before the presentation. Content of the slides:
    - Slide 1: Main Research Question in the paper,
    - Slide 2: Main Results Summarized,
    - Slide 3: How this influences your project.

Lecture Outline

- Announcements
- Recap: Decoding Algorithms
- Evaluating Generated Language
- LLMs
  - Pretraining
  - Post-training with Supervised Finetuning:
    - Instruction Tuning
  - Interacting with LLMs: Prompting
  - Post-training with Alignment with Human Feedback:
    - Preference Tuning: RLHF [Next Class]

Recap:
Natural Language Generation
- Search Algorithms

Beam Search Decoding

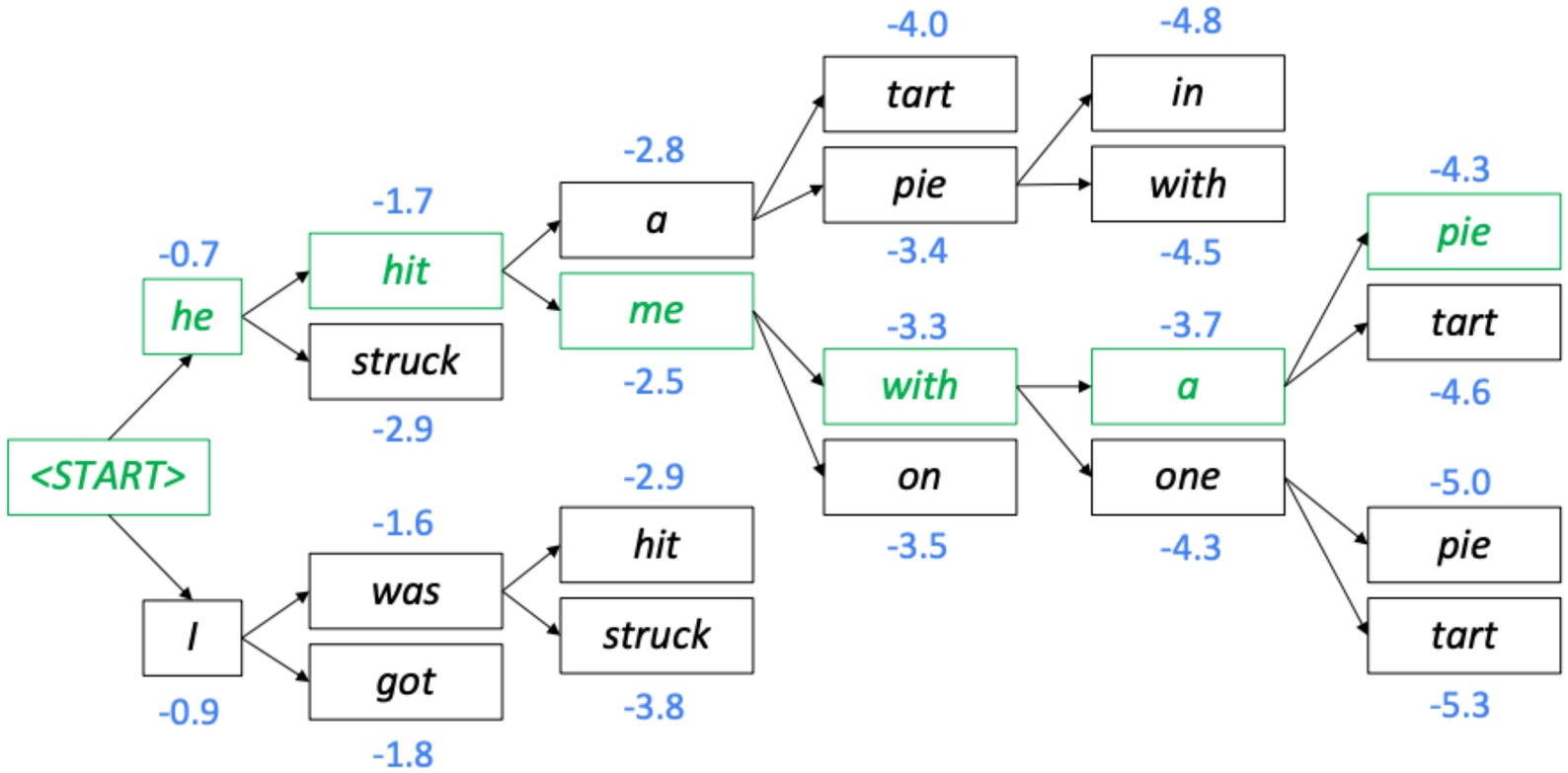
- Core idea: On each step of decoder, keep track of the k most probable partial translations (which we call hypotheses)
  - k is the beam size (in practice around 5 to 10, in NMT)
- A hypothesis has a score which is its log probability:

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

  - Scores are all negative, and higher score is better
  - We search for high-scoring hypotheses, tracking top k on each step
- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

Beam Search Decoding: Example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



Backtrack to obtain the full hypothesis

Slide credit: Chris Manning

Beam Search Decoding: Stopping Criterion

- Greedy Decoding is done until the model produces an </s> token
  - For e.g. <s> he hit me with a pie </s>
- In Beam Search Decoding, different hypotheses may produce </s> tokens at different time steps
  - When a hypothesis produces </s>, that hypothesis is complete.
  - Place it aside and continue exploring other hypotheses via beam search.
- Usually we continue beam search until:
  - We reach time step T (where T is some pre-defined cutoff), or
  - We have at least n completed hypotheses (where n is pre-defined cutoff)

Beam Search Decoding: Longer Hypotheses

- We have our list of completed hypotheses. Now how to select top one?
- Each hypothesis $y_1, \ldots, y_t$ on our list has a score

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

- Problem with this: longer hypotheses have lower score
- Fix: Normalize by length. Use this to select top one instead

$$\frac{1}{t} \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

Maximization Based Decoding

- Either greedy or beam search
- Beam search can be more effective with large beam width, but also more expensive
- Another key issue:

Generation can be bland or repetitive (also called degenerate)

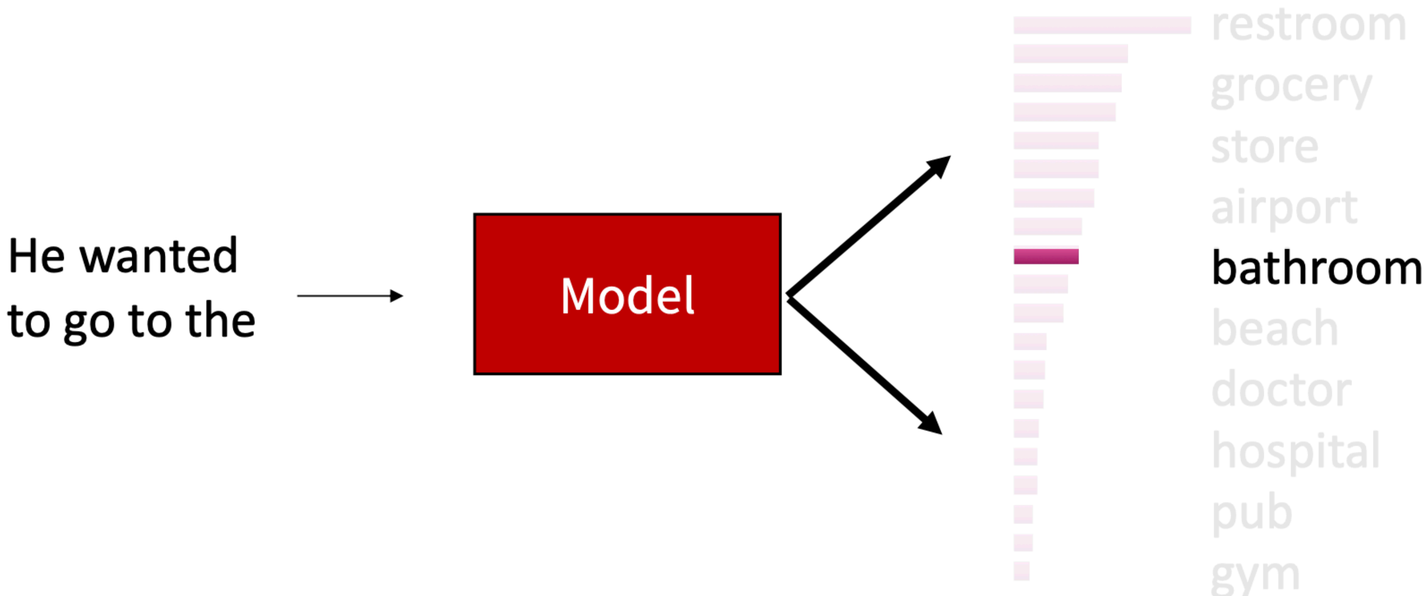
Context: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Continuation: 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 México...**

Holtzmann et al., 2020

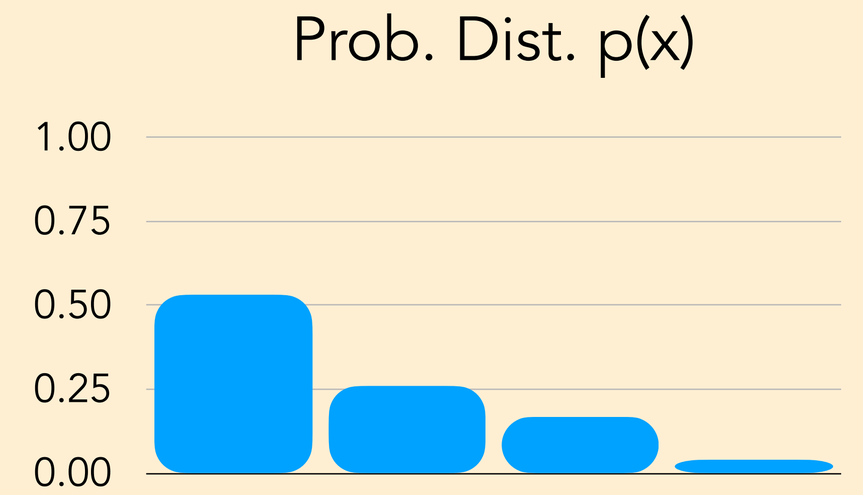
Solution: Don't Maximize, Pick a Sample

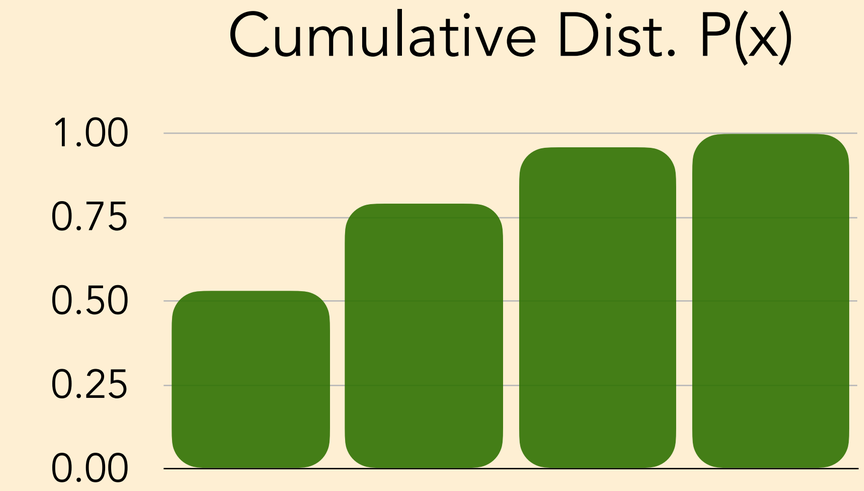
- Sample a token from the distribution of tokens.
- But this is not a truly random sample, it is a sample for the learned model distribution
  - Respects the probabilities, without going just for the maximum probability option
  - Or else, you would get something meaningless
  - Many good options which are not the maximum probability!



Sampling from a Distribution

- Choose x by randomly sampling from $p(x)$
  - Construct cumulative distribution function $P(x)$
  - Sample value q between 0-1 from a uniform random distribution
  - Pick x with largest $P(x)$ such that $P(x) \leq q$

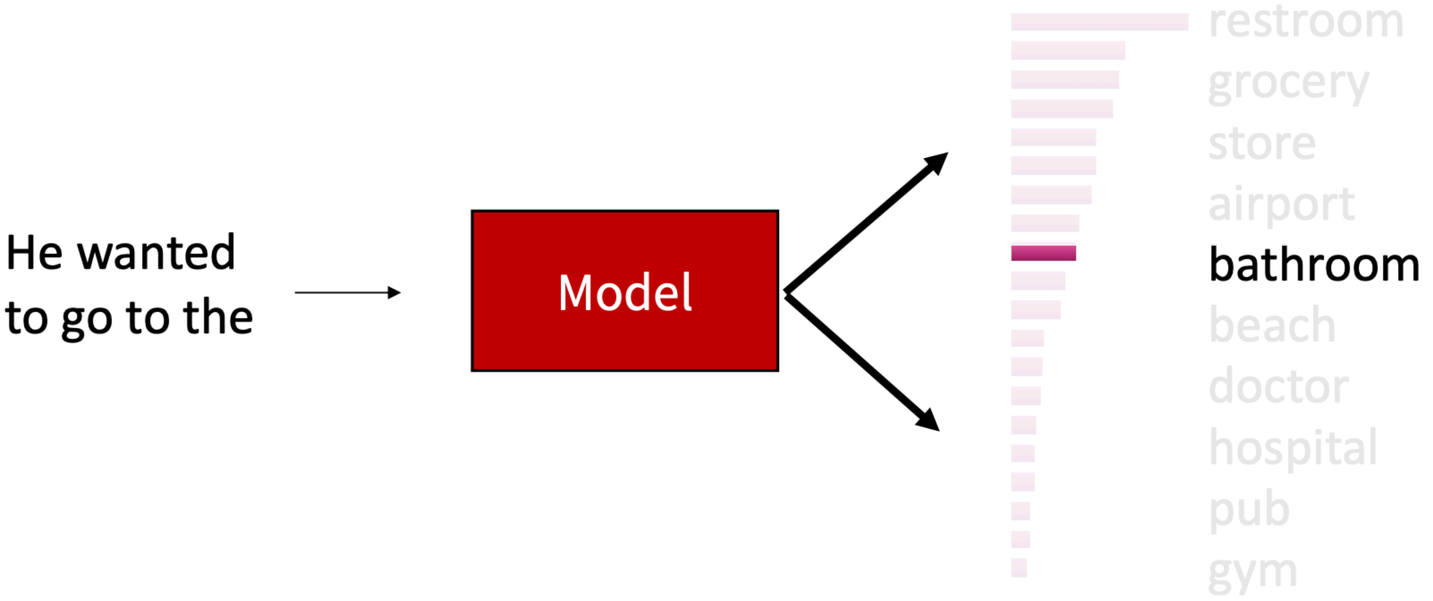




Pure / Ancestral Sampling

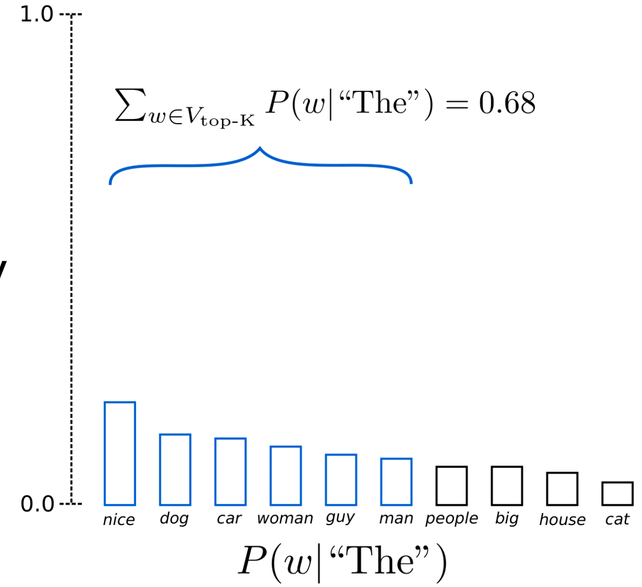
$$y_t \sim P_t(w) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$

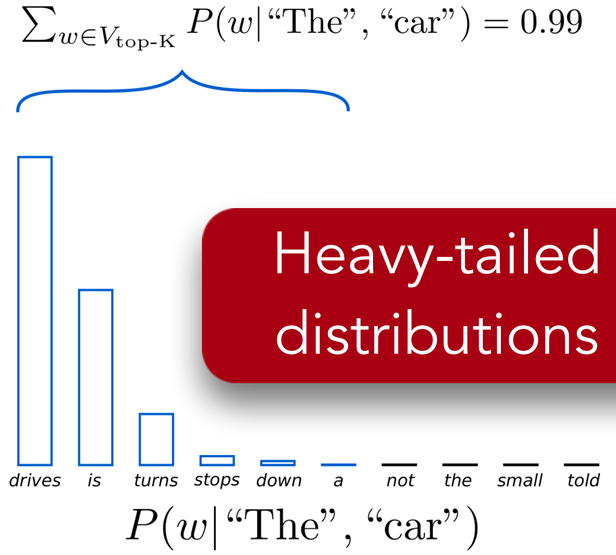
- Sample directly from P_t
- Still has access to the entire vocabulary
- But if the model distributions are of low quality, generations will be of low quality as well
- Often results in ill-formed generations
  - No guarantee of fluency



Top-K Sampling

- Problem: Ancestral sampling makes every token in the vocabulary an option
  - Even if most of the probability mass in the distribution is over a limited set of options, the tail of the distribution could be very long and in aggregate have considerable mass
  - Many tokens are probably really wrong in the current context. Yet, we give them individually a tiny chance to be selected.
  - But because there are many of them, we still give them as a group a high chance to be selected.
- Solution: Top-K sampling
  - Only sample from the top K tokens in the probability distribution





Heavy-tailed distributions

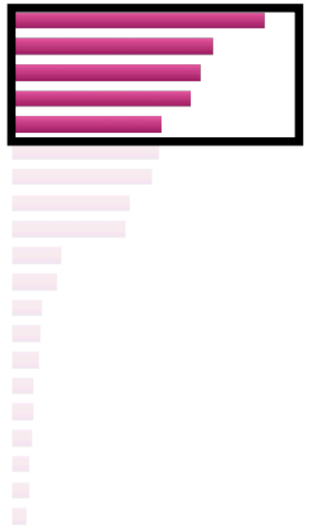
Fan et al., ACL 2018; Holtzman et al., ACL 2018

Image Source: Huggingface

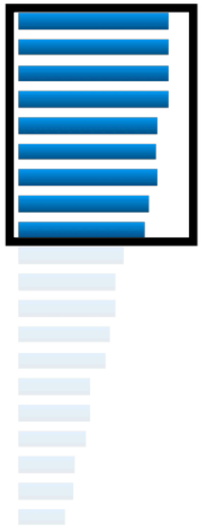
Nucleus (Top-P) Sampling

- Top-P sampling: Different threshold for different contexts
  - Sample from all tokens in the top P cumulative probability mass (i.e., where mass is concentrated)
  - Varies K depending on the uniformity of P_t

$P_t^1(y_t = w \mid \{y\}_{<t})$



$P_t^2(y_t = w \mid \{y\}_{<t})$

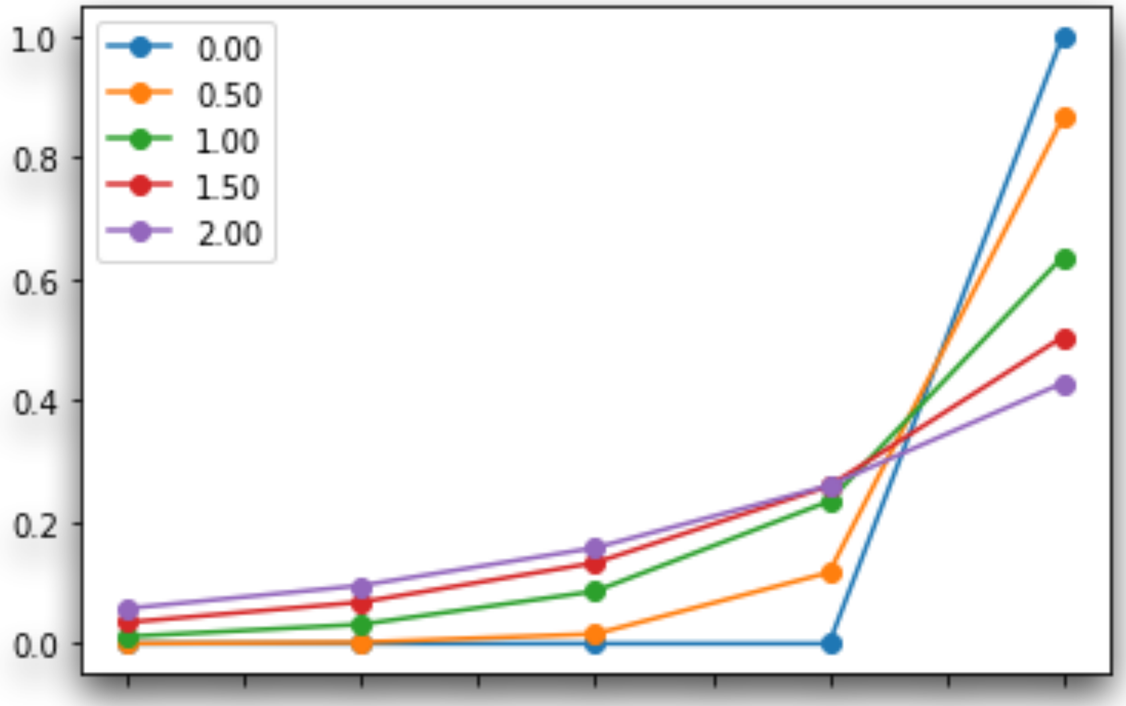


$P_t^3(y_t = w \mid \{y\}_{<t})$

Holtzman et al., ICLR 2020

Temperature Scaling

- We can apply a temperature hyperparameter τ to the softmax to rebalance P_t
- Unlike truncation-based sampling, temperature reshapes the probability distribution
- Most current approaches use this decoding: Ancestral sampling with temperature scaling



$$P(y_t = w) = \frac{\exp(S_w/\tau)}{\sum_{v \in V} \exp(S_v/\tau)}$$

Temperature is a hyperparameter for decoding: It can be tuned for both beam search and ancestral sampling.

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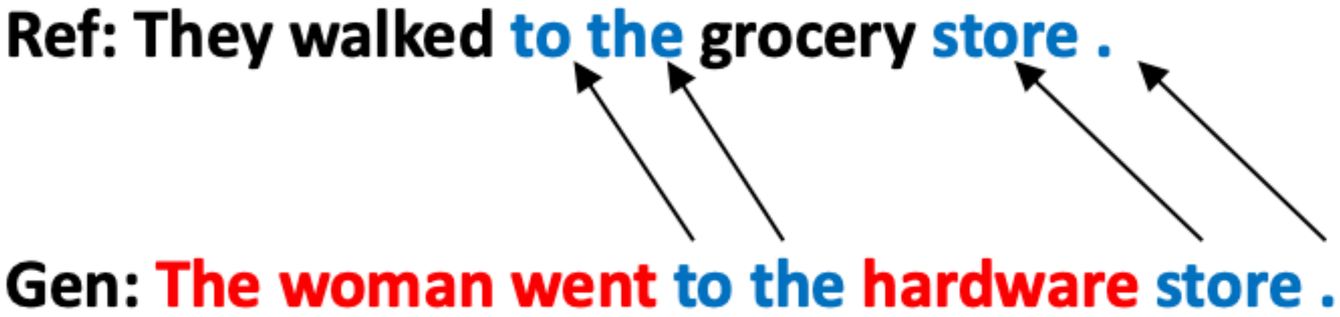
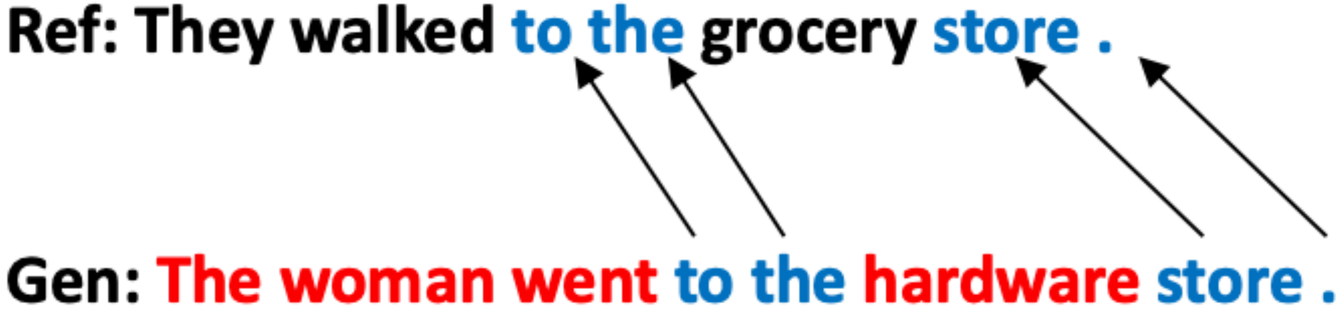
Evaluating Generations

Evaluation Strategies

- With Reference
  - Lexical Matching
  - Semantic Matching
- Without Reference
  - Perplexity
  - Model-Based Metrics
  - Advanced: Distributional Matching
  - Simplest, Most Reliable Strategy to-date: Human Evaluation
  - Even simpler and least reliable: Auto Evaluation



Reference-Based Metrics



- Only possible for close-ended generation tasks
- Compute a score that indicates the lexical similarity between generated and gold-standard (human-written) text
- Fast and efficient and widely used
- n-gram overlap metrics (e.g., BLEU, ROUGE, etc.)

BLEU

- Stands for Bilingual Evaluation Understudy
- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:
  - Geometric mean of n-gram precision (usually for 1, 2, 3 and 4-grams)
  - Plus a penalty for too-short system translations
- BLEU is useful but imperfect
  - There are many valid ways to translate a sentence
  - So a good translation can get a poor BLEU score because it has low n-gram overlap with the human translation
- Precision-based metric

Papineni et al., 2002

Precision, Recall and F-1

- True Positives, True Negatives, False Positives and False Negatives

$$\textbf{Precision} = \frac{TP}{TP + FP}$$

Of all the items in the prediction, how many match the ground truth

$$\textbf{Recall} = \frac{TP}{TP + FN}$$

Of all the items in the ground truth, how many are correctly predicted

$$F_1 = \frac{2 * PR}{P + R}$$

Harmonic Mean of Precision and Recall

Different value for different classes!

BLEU: Details

- Purely **precision-based** rather than combining precision and recall.
- BLEU score for a corpus of candidate translation sentences is a function of
  - the n-gram word precision over all the sentences
  - combined with a brevity penalty computed over the corpus as a whole.
- Consider a corpus composed of a single sentence
  - The unigram precision for this corpus is the percentage of unigram tokens in the candidate translation that also occur in the reference translation, and ditto for bigrams and so on, up to 4-grams
  - It computes this n-gram precision for unigrams, bigrams, trigrams, and 4-grams and takes the geometric mean
- Because BLEU is a word-based metric, it is very sensitive to word tokenization, making it impossible to compare different systems if they rely on different tokenization

$$p_n = \frac{\sum_{C \in \{Candidates\}} \sum_{n\text{-}gram \in C} Count_{clip}(n\text{-}gram)}{\sum_{C' \in \{Candidates\}} \sum_{n\text{-}gram' \in C'} Count(n\text{-}gram')}.$$

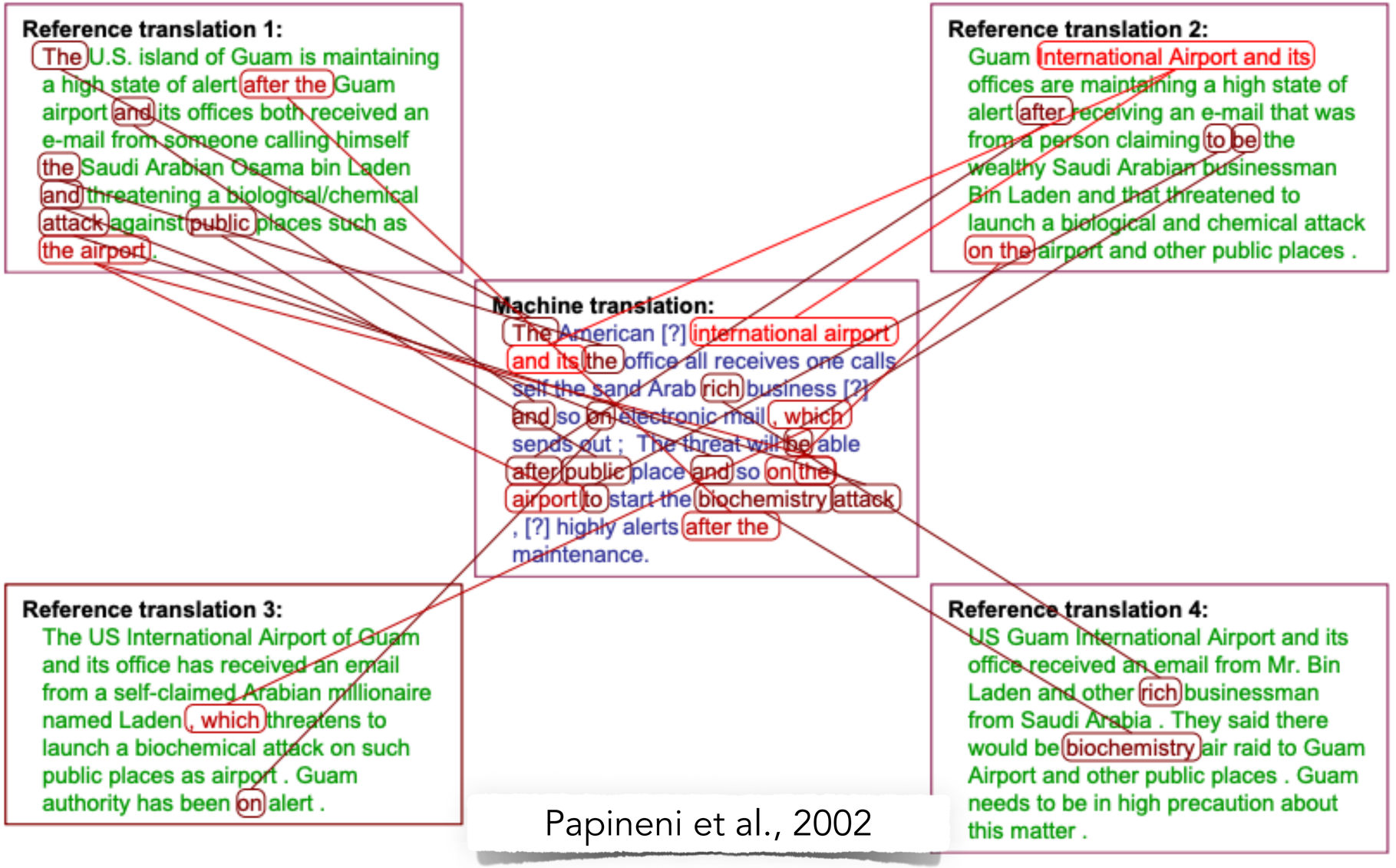
$$\mathrm{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}.$$

Then,

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right).$$

Papineni et al., 2002

BLEU: Example



Papineni et al., 2002

ROUGE

- Stands for “Recall-Oriented Understudy for Gisting Evaluation”
- Originally created for evaluating automatic summarization as well as machine translation
- Comparing an automatically produced summary or translation against a set of reference summaries (typically human-produced)
- Four variants:
  - ROUGE-N
  - ROUGE-L
  - ROUGE-S
  - ROUGE-W

ROUGE: A Package for Automatic Evaluation of Summaries (Lin, 2004)

ROUGE: Details

- **ROUGE-N**: measures **unigram**, **bigram**, **trigram** and higher order n-gram overlap
  - n-gram recall between a candidate summary and a set of reference summaries
- **ROUGE-L**: measures **longest matching sequence** of words using LCS.
  - Does not require consecutive matches but in-sequence matches that reflect sentence level word order.
  - Since it automatically includes longest in-sequence common n-grams, you don't need a predefined n-gram length.
- **ROUGE-S**: Is any pair of words in a sentence in order, allowing for arbitrary gaps.
  - Also be called skip-gram concurrence.
  - For example, **skip-bigram** measures the overlap of word pairs that can have a maximum of two gaps in between words. As an example, for the phrase *"cat in the hat"* the skip-bigrams would be *"cat in, cat the, cat hat, in the, in hat, the hat"*.
- **ROUGE-W**: Weighted Longest Common Subsequence

ROUGE: A Package for Automatic Evaluation of Summaries (Lin, 2004)

Evaluating Generation: Other Options

- Perplexity!
- Model-based Metrics (BERTScore, BARTScore, Word Mover's Distance, BLEURT)
  - Use learned representations of words and sentences to compute semantic similarity between generated and reference texts
  - No more n-gram bottleneck because text units are represented as embeddings!
  - The embeddings are pretrained, distance metrics used to measure the similarity can be fixed
- Automatic metrics fall short of matching human decisions
- So, Human Evaluation!

Human Evaluation

- Ask humans to evaluate the quality of generated text
  - Along specific axes: fluency, coherence / consistency, factuality and correctness, commonsense, etc.
  - Mostly done via crowdsourcing
- Human judgments are regarded as the gold standard
- Of course, we know that human eval is slow and expensive
- Beyond the cost of human eval, it's still far from perfect:
  - Humans Evaluation is hard:
    - Results are inconsistent / not reproducible
    - Can be subjective!
    - Misinterpret your question
    - Precision not recall

Rising Popularity: Automatic Evaluation

AlpacaFarm: A Simulation Framework for Methods that Learn from Human Feedback

Yann Dubois* Stanford
Xuechen Li* Stanford
Rohan Taori* Stanford
Tianyi Zhang* Stanford
Ishaan Gulrajani Stanford
Jimmy Ba University of Toronto
Carlos Guestrin Stanford
Percy Liang Stanford
Tatsunori B. Hashimoto Stanford

Cheap and theoretically consistent with human evaluation. BUT… reliability? Models evaluating their own generations may lead to weird mode collapsing effect

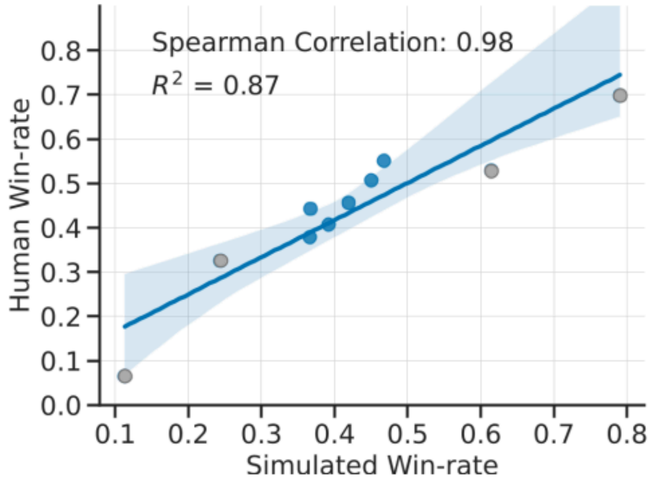


Figure 3: The ranking of methods trained and evaluated in AlpacaFarm matches that of methods trained and evaluated in the human-based pipeline. Each point represents one method M (e.g. PPO). The x-axis shows the simulated evaluation (win-rates measured by $p_{\text{sim}}^{\text{eval}}$) on methods trained in simulation M_{sim}. The y-axis shows human evaluation (win-rates measured by p_{human}) on methods trained with human feedback M_{human}. Gray points show models that we did not train, so their x and y values only differ in the evaluation (simulated vs human). Without those points, we have $R^2 = 0.83$ and a Spearman Correlation of 0.94.

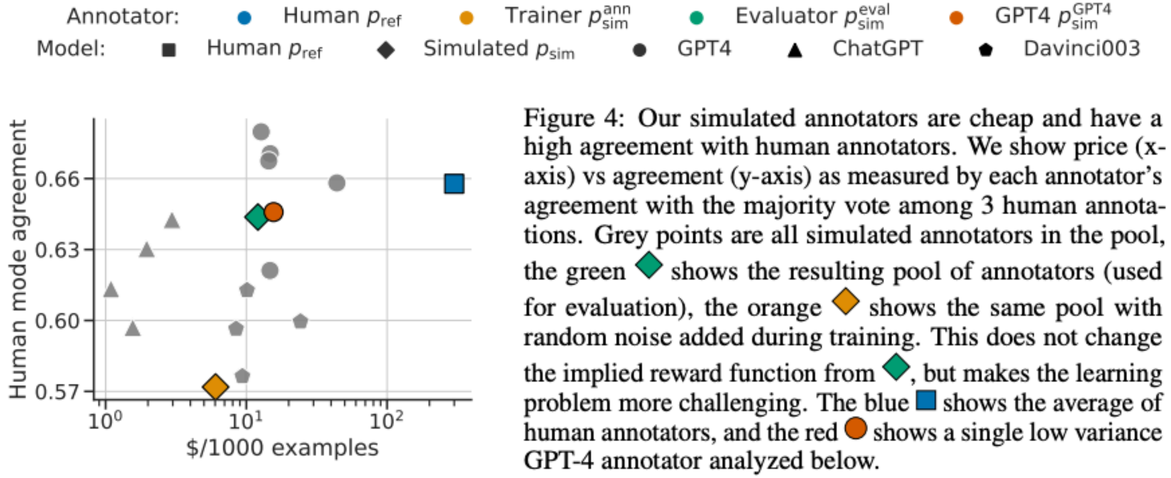


Figure 4: Our simulated annotators are cheap and have a high agreement with human annotators. We show price (x-axis) vs agreement (y-axis) as measured by each annotator's agreement with the majority vote among 3 human annotations. Grey points are all simulated annotators in the pool, the green ◆ shows the resulting pool of annotators (used for evaluation), the orange ◆ shows the same pool with random noise added during training. This does not change the implied reward function from ◆, but makes the learning problem more challenging. The blue ■ shows the average of human annotators, and the red ● shows a single low variance GPT-4 annotator analyzed below.

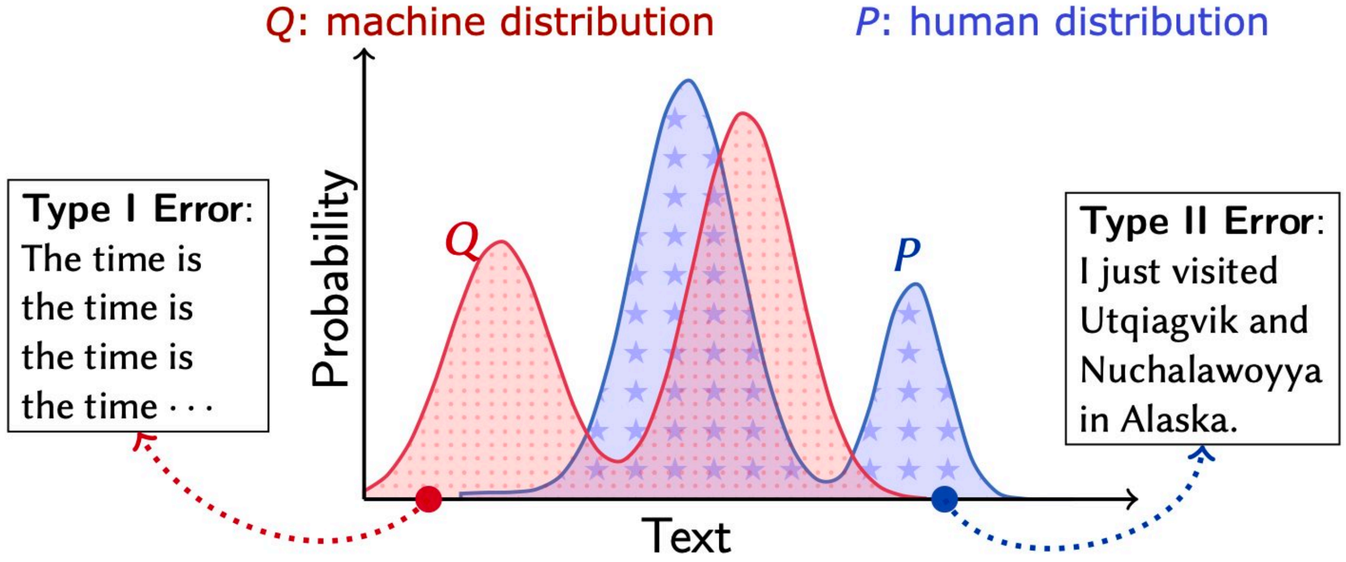
Evaluating Systems without References

- Compare human / natural language distributions to model-generated language distributions
- Divergence between these two distributions can be measured by MAUVE

MAUVE: Measuring the Gap Between Neural Text and Human Text using Divergence Frontiers

Krishna Pillutla[1] **Swabha Swayamdipta**[2] **Rowan Zellers**[1] **John Thickstun**[3]
Sean Welleck[1,2] **Yejin Choi**[1,2] **Zaid Harchaoui**[4]

[1]Paul G. Allen School of Computer Science & Engineering, University of Washington
[2]Allen Institute for Artificial Intelligence
[3]Department of Computer Science, Stanford University
[4]Department of Statistics, University of Washington



Natural Language Generation: Parting Thoughts

- Once trained, language models can be very powerful
  - The power only increases with scale
- So much so that most of our tasks in natural language can be seen as sequence completion tasks
  - Decoding Algorithms thus play a critical role
- How can you make LLMs do tasks (follow instructions)? **Instruction-Tuning and Preference-Tuning**
- **Prompting (or In-Context / Few-Shot Learning):** the ability to do many tasks with no gradient updates and no / a few examples, by simply:
  - Specifying the right sequence prediction problem
  - You can get interesting zero-shot behavior if you're creative enough with how you specify your task!

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Large Language Models

What are Large Language Models?

- Models with many, many, parameters
  - Deeper layers. The largest T5 model had 11B parameters. GPT-3 has 175B parameters.
  - More context. GPT-2 has a context length of 1024 tokens, GPT-4 and Llama have 8192!
  - LLM are generally trained by filling the full context window with text. If documents are shorter than this, multiple documents are packed into the window with a special end-of-text token between them.
- Models trained on many, many tokens
  - Training data size is measured in # tokens
  - Batch size of the largest GPT-3 model is 3.2M tokens

OpenAI model's version	**GPT-3** (ada, babbage, curie, davinci)	**GPT-3.5** (gpt-3.5-turbo, gpt-3.5-turbo-0301,text-davinci-003, text-davinci-002)*	**GPT-4-8K**
Context length (max request)	2,049	4,096	8,192
Number of English words	~1,500	~3,000	~6,000
Number of single-spaced pages of English text	3	6	12

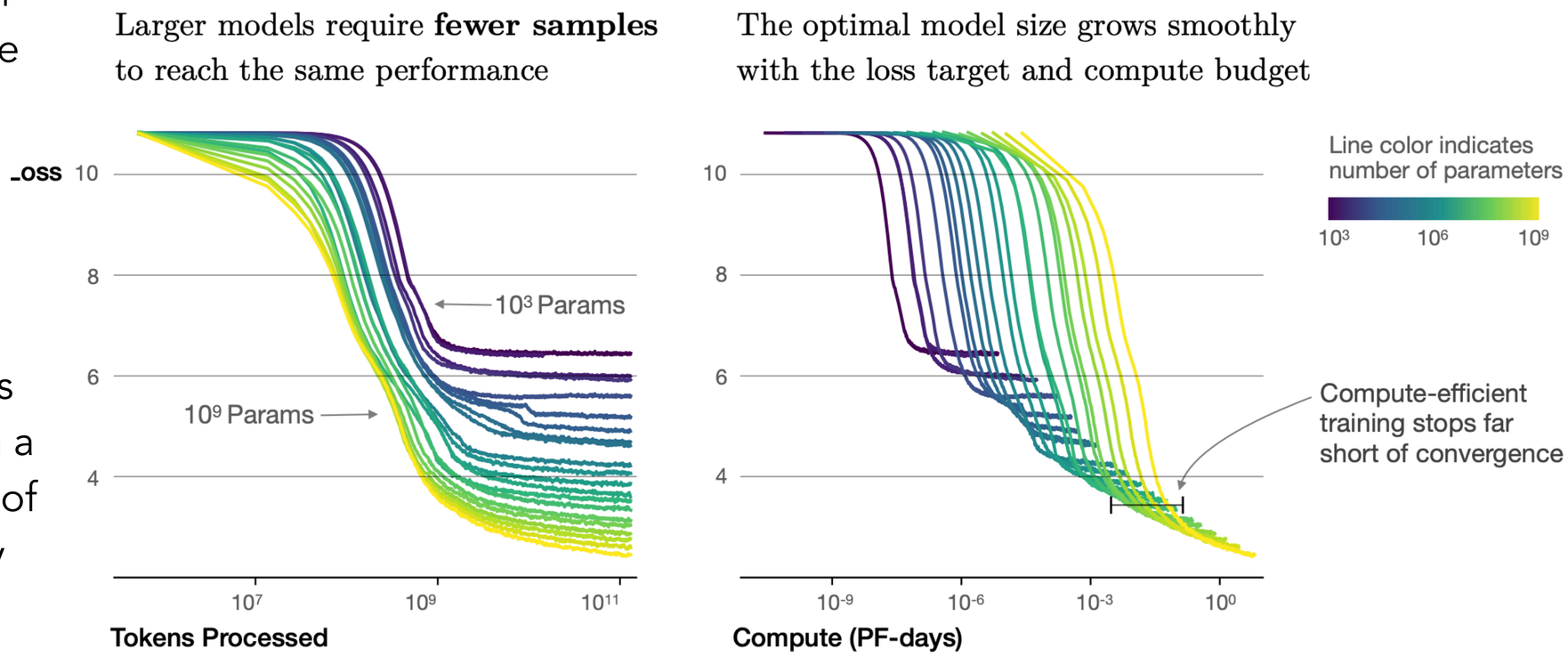
Source: Neoteric

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

The Scaling "Laws" of LLMs

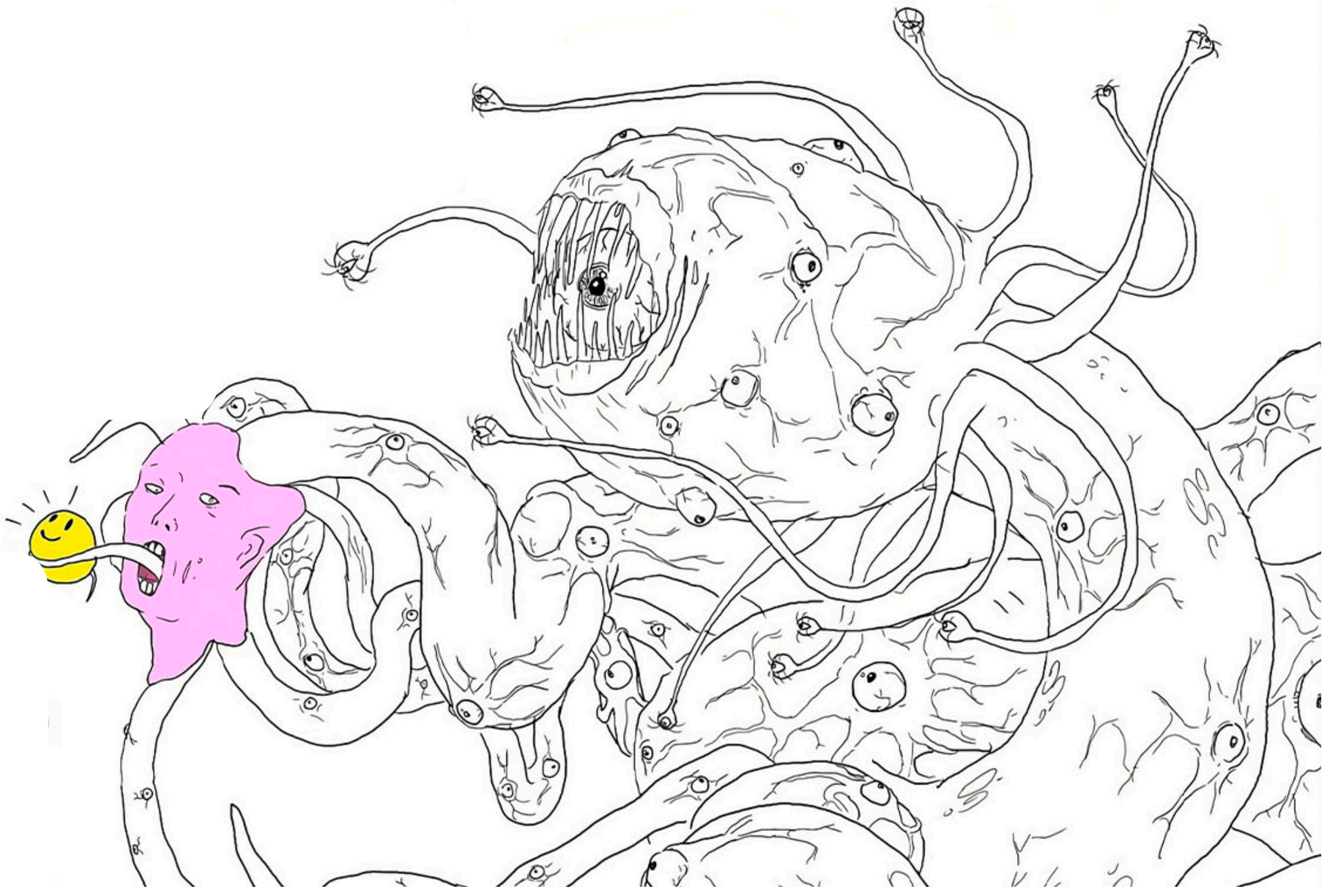
- Predictive rules of model performance, given parameter size, data size, computation
- The loss of an LLM scales as a power-law with each of these three properties of model training

- Other architectural details such as network width or depth have minimal effects within a wide range
- Determines the optimal allocation of a fixed compute budget
  - For instance, it can help us train very large models on a relatively modest amount of data and stop significantly before convergence
  - Or smaller models on larger data (e.g. Chinchilla LM)



Kaplan et al., 2020 https://arxiv.org/abs/2001.08361

Training LLMs



A significant, yet small part of the LM training phase (Next Class)

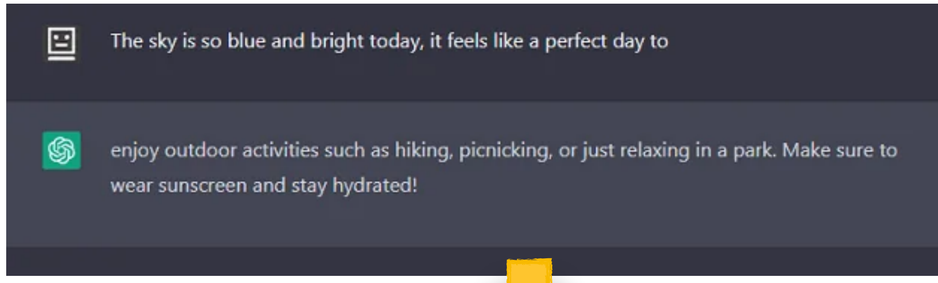
Shoggoth; slide credit: Justin Cho

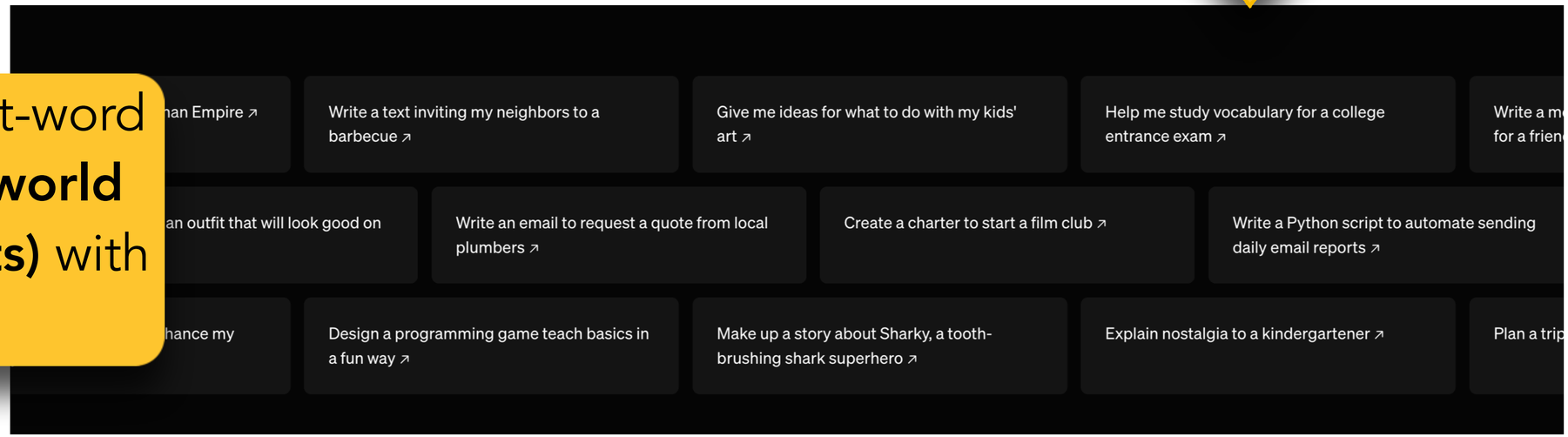
LLMs: Modern Training + Inference Recipe

- Training Recipe:
  - Stage 1: Pre-training on large corpus of text
    - This is called the base language model
    - Continued Pre-training for domain adaptation (optional)
  - Stage 2: Post-training
    - Instruction Tuning (Supervised Finetuning)
  - Stage 3: Post-training and Alignment
    - Reinforcement Learning with Human Feedback
    - Train a supervised classifier (reward model) on human demonstrations to provide feedback to LM
    - Supervised fine-tuning the LM with reinforcement learning to maximize rewards given by reward model
- Inference: Prompting with Instructions and Demonstrations (also called examples, shots)

Pre-training and Fine-tuning (Post-training)

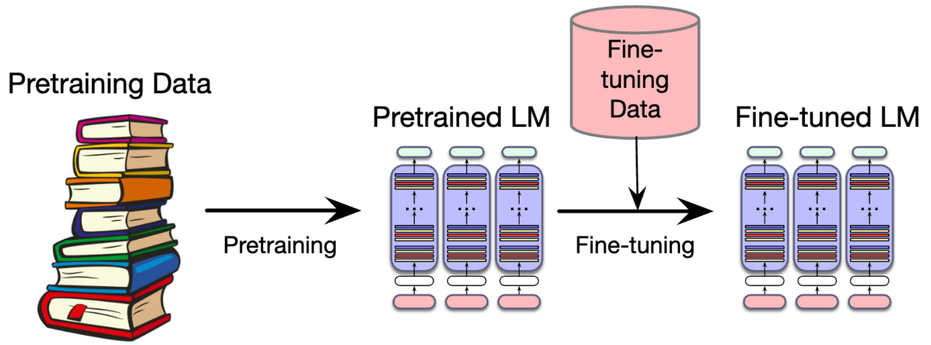
- Slightly different meaning than before
- Pre-training: Decoder-only models, standard next token prediction
- Fine-tuning: Supervised
  - **Instruction-Tuning**: Supervision is not necessarily via labels, but sequence pairs. Labels in standard NLP benchmarks can be converted into sequence pairs
  - **Preference-Tuning**: Collects human judgments / preferences as rewards
  - These steps are often called **post-training**





Post-training converts next-word completion models into **world models (agents, assistants)** with many capabilities!

Training Data for LLMs



- Pre- and post-training requires different kinds of data
- Pre-training needs a lot of raw text
  - Crawled from the Web: Natural Solution
  - But not all data crawled from the web is good for LM training
  - Needs to be filtered in various ways (deduplicated, removing non-natural language like code, sentences with offensive words from a blocklist).
  - Quality Filters! (Later lecture)
- Post-training / Fine-tuning
  - Instruction Tuning Data: Repurposed NLP / ML benchmarks
  - Preference Data for RLHF: Often human labels
  - Not easy to produce…

Pre-training Data

- Language models are trained on "raw text"
- To be highly capable (e.g., have linguistic and world knowledge), this text should span a **broad** range of domains, genres, languages, etc.
- A natural place (but not the only place) to look for such text is the **web**
  - Google search index is 100 petabytes; the actual web is likely even larger
  - P**rivate datasets** owned by big companies are even larger! WalMart generates 2.5 petabytes of data each hour!

- **Common Crawl** is a nonprofit organization that crawls the web and provides snapshots that are free to the public
  - Standard source of data to train many models such as T5, GPT-3, etc.
  - The April 2021 snapshot of Common Crawl has 320 TB
- The Colossal Clean Crawled Corpus (C4) is a larger was created to train the T5 model — 806 GB / 156 billion tokens

The Pile and DOLMA

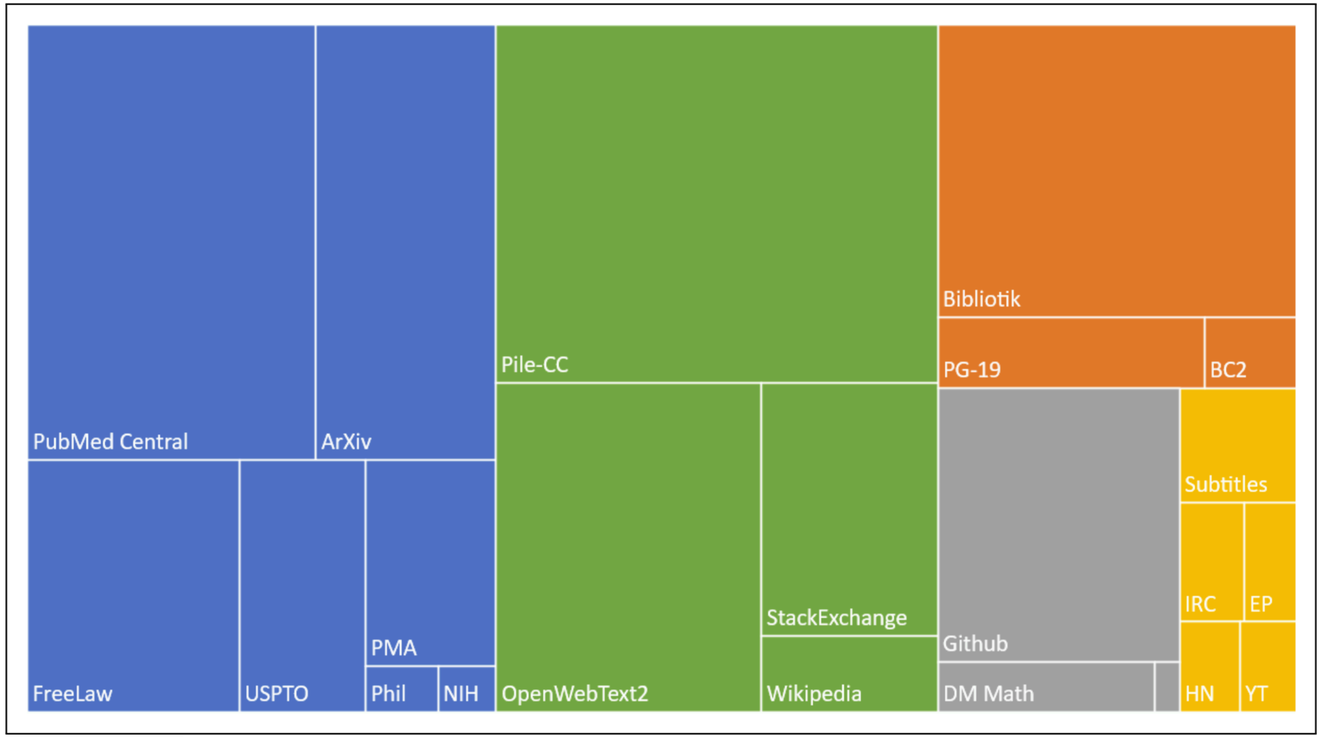


Figure 10.5 The Pile corpus, showing the size of different components, color coded as academic (articles from PubMed and ArXiv, patents from the USPTA; internet (webtext including a subset of the common crawl as well as Wikipedia), prose (a large corpus of books), dialogue (including movie subtitles and chat data), and misc.. Figure from Gao et al. (2020).

The Pile: 825 GB English text corpus containing a large amount of text scraped from the web, books and Wikipedia

Ai2

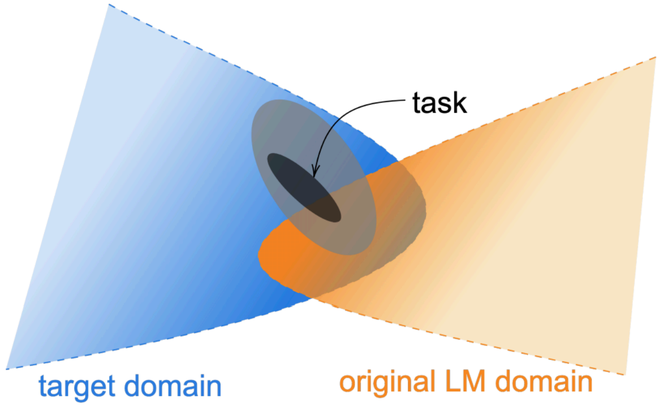
Dolma

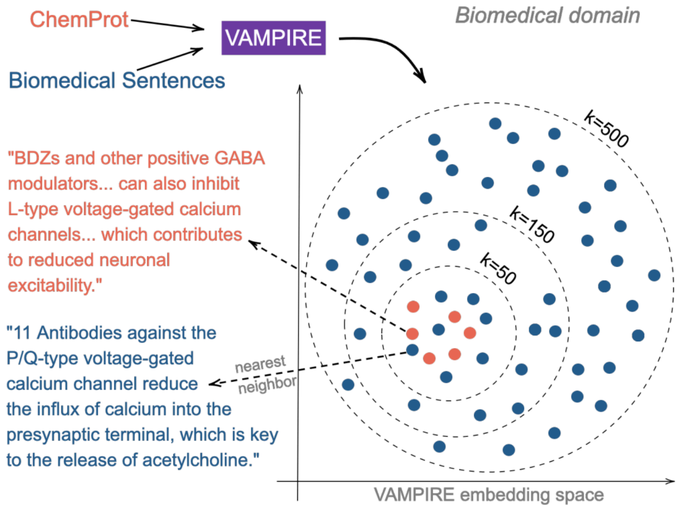
Source	Doc Type	UTF-8 bytes (GB)	Documents (millions)	Unicode words (billions)	Llama tokens (billions)
Common Crawl	web pages	9,812	3,734	1,928	2,479
GitHub	code	1,043	210	260	411
Reddit	social media	339	377	72	89
Semantic Scholar	papers	268	38.8	50	70
Project Gutenberg	books	20.4	0.056	4.0	6.0
Wikipedia, Wikibooks	encyclopedic	16.2	6.2	3.7	4.3
Total		**11,519**	**4,367**	**2,318**	**3,059**

Dolma is a larger open corpus of English, created with public tools, containing three trillion tokens, which similarly consists of web text, academic papers, code, books, encyclopedic materials, and social media (Soldaini et al., 2024)

Continued Pre-training

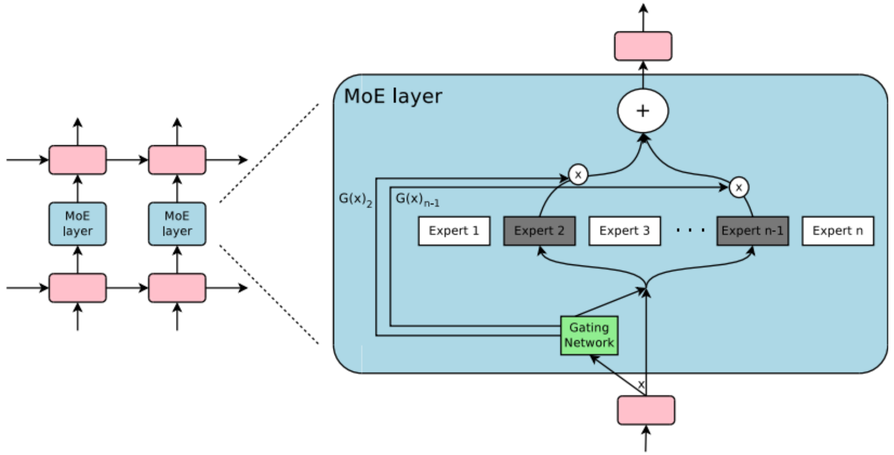
- LLMs are general domain. But we may need domain-specific LLMs…
  - For example, we might want a language model that's specialized to legal or medical text
- In such cases, we can simply continue training the model on relevant data from the new domain or language (Gururangan et al., 2020)
  - Next word prediction objective
- Works better when starting from a pretrained general-domain language model, as opposed to training from scratch
- It is even possible to do targeted data selection for obtaining domain-specific pretraining data (e.g. using k-means)



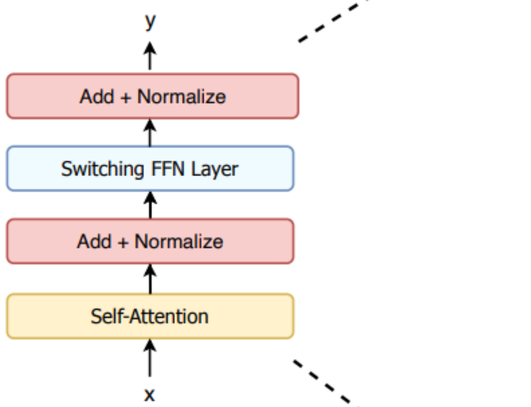


Gururangan, Marasović, **Swayamdipta** et al., 2020

LLMs as Mixtures of Experts



Source: Huggingface



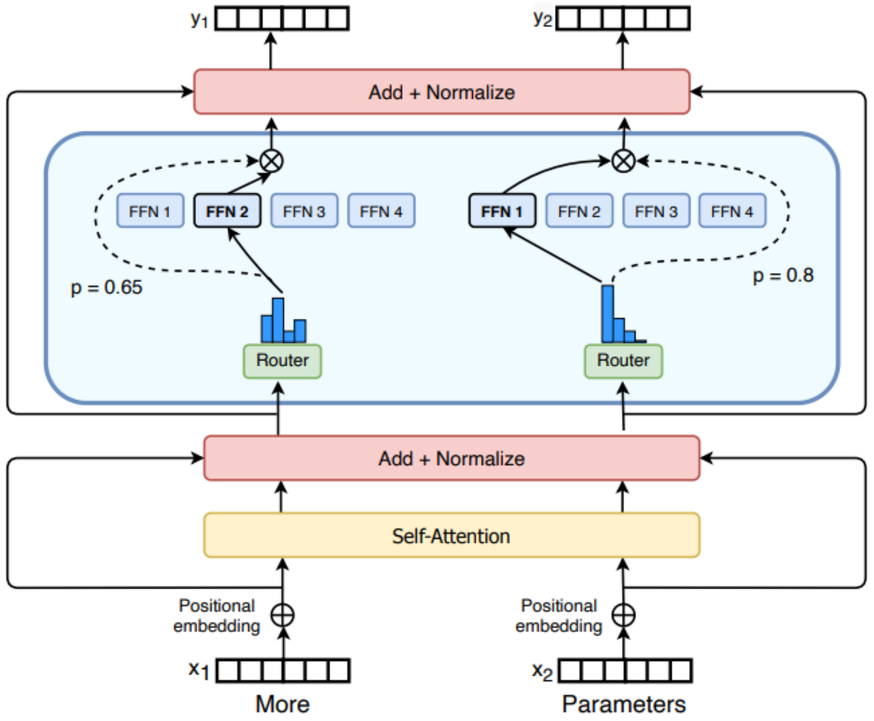
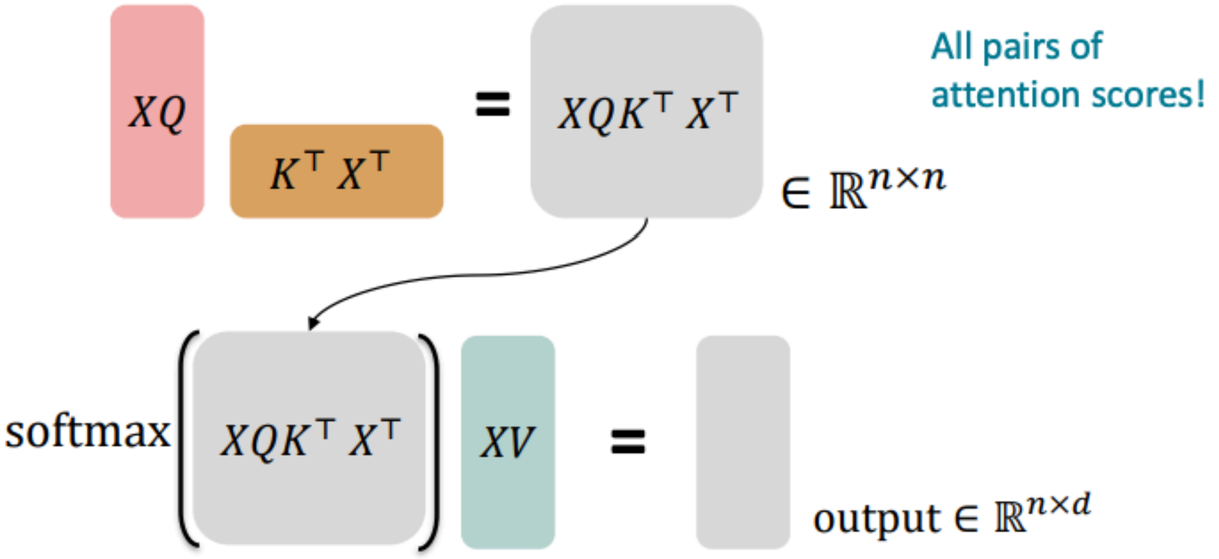


Figure 2: Illustration of a Switch Transformer encoder block. We replace the dense feed forward network (FFN) layer present in the Transformer with a sparse Switch FFN layer (light blue). The layer operates independently on the tokens in the sequence. We diagram two tokens (x_1 = "More" and x_2 = "Parameters" below) being routed (solid lines) across four FFN experts, where the router independently routes each token. The switch FFN layer returns the output of the selected FFN multiplied by the router gate value (dotted-line).

Switch Transformers; Fetus et al., 2021. (https://arxiv.org/abs/2101.03961)

LLM Inference: KV Cache

- Matrices / tensors for efficient computation cannot be applied during inference? Why?
  - At inference time, we iteratively generate the next tokens one at a time
  - Hence, we use key and value (and query) vectors
- KV Cache achieves inference-time speedup



- Instead of recomputing the key and value vectors for all the prior tokens $x_{<i}$, whenever we compute the key and value vectors we store them in memory in the KV cache, and then we can retrieve them from the cache as needed