Algorithms for Text Generation

The awes and mysteries of **generate**

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Aussois, december 10th, 2024

Goal and Motivations

Understanding Contextual Generation is Key

- LLMs are multitask learners & problem solvers via prompting
- evaluation of linguistic abilities of LLMs requires generation
  wrt. agreement, proper word order, semantic consistency etc.
- good artificial data helps ML
  privacy, confidentiality, distillation / data augmentation, artificial text detection
- computation of expectations $\mathbb{E}_{w_{[1:T]} \sim P}(f(w_{[1:T]}))$ requires good text samples
  e.g., to train GANs or PPO

Goal and Motivations

This class

- ✔ understand the variety of controls for basic text generation
  with 🤗 **generate** as the main tool (**generate** has a similar, less complete interface)
- ✔ learn to generate texts with constraints
- ✔ explore some meta-generation algorithms

  train LLMs for better / adapted / non-autoregressive ... generation

generate

```
model_inputs = tokenizer(["A sequence of numbers: 1, 2"], return_tensors="pt").to("cuda")

generated_ids = model.generate(**model_inputs)
tokenizer.batch_decode(generated_ids, skip_special_tokens=True)[0]

generated_ids = model.generate(**model_inputs, max_new_tokens=50)
tokenizer.batch_decode(generated_ids, skip_special_tokens=True)[0]
```

Part I

Basics

A Language Model is a Distribution

Language Models (LM)

Assume finite vocabulary $\mathcal{V}$, with $\bar{\mathcal{V}} = \mathcal{V} \cup \{\texttt{<s>}, \texttt{</s>}\}$
A neural language model is a parameterized distribution over complete texts in $\texttt{<s>}\mathcal{V}^*\texttt{</s>}$:

$$\texttt{<s>}w_1 \dots w_T\texttt{</s>} \rightarrow \mathrm{P}(\texttt{<s>}w_1 \dots w_T\texttt{</s>} \,|\, \boldsymbol{\theta})$$
$$\forall T > 0, \forall w_1 \dots w_T, \mathrm{P}(\texttt{<s>}w_1 \dots w_T\texttt{</s>} \,|\, \boldsymbol{\theta}) \geq 0,$$
$$\sum_{T, w_{[1:T]}} \mathrm{P}(\texttt{<s>}w_1 \dots w_T\texttt{</s>} \,|\, \boldsymbol{\theta}) = 1$$

Notations:

- $w_{[1:T]} = w_1 \dots w_T$
- $[w_{[1:T]}$ assumes $w_0 = \texttt{<s>}$, denotes a strict prefix (unless $w_T = \texttt{</s>}$)
- $[w_{[1:T]}]$ assumes $w_{T+1} = \texttt{</s>}$, denotes a complete text
- $w_{<t}$: $\texttt{<s>}w_1 \dots w_{t-1}$
- $[w_{-t}]$: $\texttt{<s>} \dots w_{t-1} \_ w_{t+1} \dots w_T\texttt{</s>}$
- for $w_T \neq \texttt{</s>}$, $\mathrm{P}([w_1 \dots w_T \,|\, \boldsymbol{\theta})$ is a prefix probability
- $\sum_{w_{[1:T]}} \mathrm{P}([w_1 \dots w_T \,|\, \boldsymbol{\theta}) = 1$ for same length prefixes

A Language Model is a Distribution

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A neural language model is a parameterized distribution over complete texts in $\text{<s>}\mathcal{V}^*\text{</s>}$:

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&\sum_{T, w_{[1:T]}} \mathrm{P}(\text{<s>}w_1 \dots w_T\text{</s>} \,|\, \boldsymbol{\theta}) = 1
\end{aligned}$$

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- $w_{<\mathbf{t}}$: $\text{<s>}w_1 \dots w_{t-1}$
- $[w_{-t}]$: $\text{<s>} \dots w_{t-1}\_w_{t+1} \dots w_T\text{</s>}$
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Formalizing Text Generation as Search

Unconditional Text Generation: find "most likely text"

$$[w_1^* \dots w_{T^*}^*] = \operatorname*{argmax}_{T,[w_{[1:T]}]} \mathrm{P}([w_{[1:T]}] \,|\, \boldsymbol{\theta})$$

Finding T^* is part of the problem

Conditional Text Generation: find "most likely response" given input context / query (MAP)

$$[w_1^* \dots w_{T^*}^*] = \operatorname*{argmax}_{T,[w_{[1:T]}]} \mathrm{P}([w_{[1:T]}] \,|\, \boldsymbol{C}, \boldsymbol{\theta})$$

$\boldsymbol{C}$: a prefix (text completion), a question (question answering), a source text (translation), a long text (summarization), a speech file (transcription), an image (captioning), ...

A variety of situations between open set generation (many acceptable texts) and near deterministic generation (one single acceptable output)

Formalizing Text Generation as Search

Unconditional Text Generation: Find the Mode

$$
\begin{aligned}
[w_1^* \dots w_{T^*}^*] &= \operatorname*{argmax}_{T,[w_{[1:T]}]} \mathrm{P}([w_{[1:T]}] \,|\, \boldsymbol{\theta}) \\
&= \operatorname*{argmax}_{T,[w_{[1:T]}]} \prod_{t=1}^{T+1} \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) && \text{Chain rule for autoregressive / causal LMs} \\
&= \operatorname*{argmax}_{T,[w_{[1:T]}]} \log \prod_{t=1}^{T+1} \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) && \text{log is monotonous} \\
&= \operatorname*{argmin}_{T,[w_{[1:T]}]} \sum_{t=1}^{T+1} -\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) && \text{log turns } \prod \text{ into } \sum
\end{aligned}
$$

- $-\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) > 0$ is the surprisal; upper bounded by $\log |\mathcal{V}|$
  quantifies how much w_t was expected given $w_{<t}$, used in psycholinguistic studies
- $\max_{T,[w_{[1:T]}]} \mathrm{P}([w_{[1:T]}] \,|\, \boldsymbol{\theta})$ equivalently minimizes a summation of $T+1$ surprisals

Formalizing Text Generation as Search

Maximum “a posteriori” (MAP) Text Generation

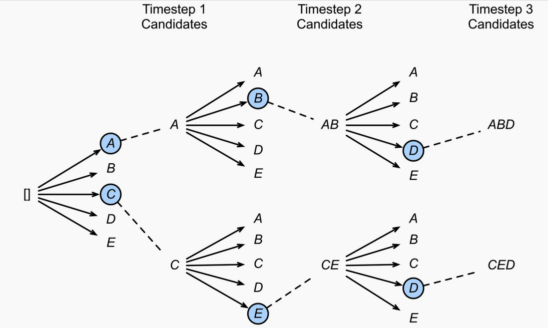
$$\mathrm{P}(w \mid w_{<t}; \boldsymbol{\theta}) = \frac{\exp \operatorname{logit}(w, w_{<t}; \boldsymbol{\theta})}{\sum_{w' \in \mathcal{V}} \exp \operatorname{logit}(w', w_{<t}; \boldsymbol{\theta})}$$

$$\log \mathrm{P}(w \mid w_{<t}; \boldsymbol{\theta}) = \operatorname{logit}(w, w_{<t}; \boldsymbol{\theta}) - \log \sum_{w' \in \mathcal{V}} \exp \operatorname{logit}(w', w_{<t}; \boldsymbol{\theta})$$

$$\begin{aligned}[][w_1^* \dots w_{T^*}^*] &= \operatorname*{argmax}_{T, [w_{[1:T]}]} \Big(\sum_{t=1}^{T+1} \operatorname{logit}(w_t, w_{<t}; \boldsymbol{\theta}) - \log \sum_{w'} \exp \operatorname{logit}(w', w_{<t}; \boldsymbol{\theta}) \Big) \\ &= \operatorname*{argmax}_{T, [w_{[1:T]}]} \sum_{t=1}^{T+1} \operatorname{logit}(w_t, w_{<t}; \boldsymbol{\theta})\end{aligned}$$

- X a finite set, $f : X \rightarrow \mathbb{R}$ a real function, $\frac{\exp f(x)}{\sum_{x' \in X} \exp f(x')}$ is the softmax
- $\operatorname{softmax}(x)$ is always > 0; almost 1 for the largest $f(x)$, almost 0 otherwise
- computing the logits requires a full forward pass in Transformers ($O(T \times L \times d_{model})$)
- normalizer $\sum_{w' \in \mathcal{V}} \exp \operatorname{logit}(w', w_{<t}; \boldsymbol{\theta})$ can be expensive to compute ($\sum$ over $|\mathcal{V}|$ terms)

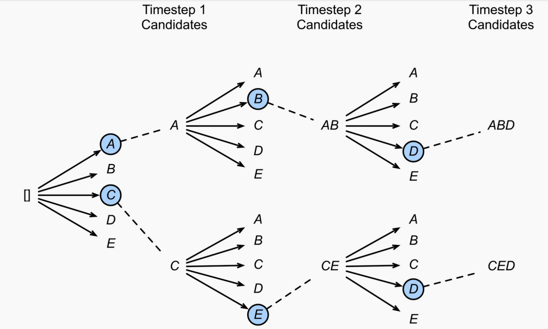
Searching, searching, searching



☞ source https://towardsdatascience.com/decoding-strategies-that-you-need-to-know-for-response-generation

- $-\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta})$ factorize / decompose over arcs $\Rightarrow$ incremental score computation
- $-\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta})$ depends on the entire prefix $\Rightarrow$ no DP solution
- exact search is doable [Stahlberg and Byrne, 2019], yet very costly $\Rightarrow$ heuristic search (greedy, DFS, Beam, A^*, etc)

Searching, searching, searching



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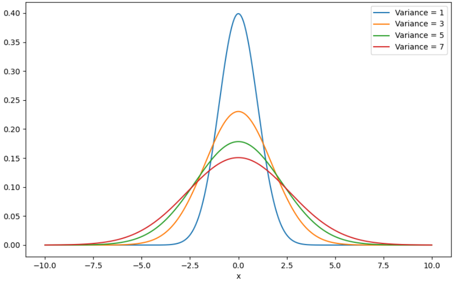
Variants and generalizations:

- restrict solutions to a strict subset of <s>$\mathcal{V}^*$</s>: calculability and complexity issues
- use alternative, non-decomposable score functions $F([w_{[1:t]}], \boldsymbol{C}; \theta)$
- use scores that only evaluate leaf nodes $F([w_{[1:t]}], \boldsymbol{C}; \theta)$

Entropies

A measure of randomness



$$H(\mathrm{P}(T, W_{[1:T]} \,|\, \boldsymbol{\theta})) = -\sum_{T,[W_{[1:T]}]} \mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}) \log \mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta})$$

$$= \mathbb{E}_{T,[W_{[1:T]}] \sim P}(-\log \mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}))$$

$$H(\mathrm{P}(W_t \,|\, w_{<t}; \boldsymbol{\theta})) = -\sum_{w \in \bar{\mathcal{V}}} \mathrm{P}(w \,|\, w_{<t}; \boldsymbol{\theta}) \log \mathrm{P}(w \,|\, w_{<t}; \boldsymbol{\theta})$$ average surprisal at time t

Entropies

A measure of randomness

KL-Divergence

$$KL(P||Q) = \sum_{w_{[1:T]}} \mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}) \log \frac{\mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta})}{\mathrm{Q}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta})}$$
$$= \sum_{w_{[1:T]}} -\mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}) \log \mathrm{Q}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}) - H(\mathrm{P}(T, [w_{[1:T]}] \,|\, \boldsymbol{\theta}))$$

- Always positive
- Null iff $P = Q$
- Asymmetrical
- No triangle inequality
- KL is also an expectation

Evaluating Language Models with Perplexity

Perplexity of a test sequence $[w_{[1:T]}]$ [Brown et al., 1992]

$$\mathrm{PPL}(M_{\boldsymbol{\theta}}) = 2^{\frac{-1}{T}\log_2 \mathrm{P}([w_{[1:T]}]|M_{\boldsymbol{\theta}})} = \mathrm{P}([w_{[1:T]}]|M_{\boldsymbol{\theta}})^{-\frac{1}{T}}$$

Assumes "sufficiently large" T . Alt take: normalizer = T+1.

- The cross-entropy between the source (S) and model M:

$$H(S, M_{\boldsymbol{\theta}}) = \lim_{T\to\infty} \frac{-1}{T} \log_2 \mathrm{P}([w_{[1:T]}]|M_{\boldsymbol{\theta}})$$

  $H(S, M_{\boldsymbol{\theta}})$ upper bounds $H(S)$

- PLL() homogeneous to a vocabulary size

$$\mathrm{PPL}(\mathrm{Unif}) = 2^{\frac{-1}{T}\log_2 \mathrm{P}([w_{[1:T]}]|M_{\boldsymbol{\theta}})} = 2^{\frac{-1}{T}T\log_2(1/|\mathcal{V}|)} = |\mathcal{V}|$$

Evaluating Language Models with Perplexity

PPL is hard to understand

Comparing LMs with different support or tokenizers ?

1. closed-world LMs assume a fixed vocabulary size $|\mathcal{V}|$ - models with different $\mathcal{V}$ cannot be compared.
2. open-world models with different segmentations can be compared, must use a common normalizer
3. typical normalizers when using subwords vocabularies
   - number of chars $\Rightarrow$ bits per char $\equiv \log_2$ of char-normalized PPL
   - number of bytes $\Rightarrow$ bits per byte $\equiv \log_2$ of byte-normalized PPL

Evaluating Language Models with Perplexity

Implementing $\sum_{t=1}^{T} \log \mathrm{P}(w_t \mid w_{<t}; \boldsymbol{\theta})$ with finite, fixed-length window of size L?

- split in short parts of length $T_i < L$ (lines, paragraphs); average over parts;
- "reshape" text into $\lfloor T/L \rfloor$ sequences of length L, average $\log \mathrm{P}(w_L \mid w_{<L})$ over blocks
- "reshape" text into $T - L$ sequences of length L with shift 1, average $\log \mathrm{P}(w_L \mid w_{<L})$ over blocks;
- "reshape" text into $\lfloor 2 \times (T - L)/L \rfloor$ sequences of length L with shift $L/2$, average $\sum_{t=L/2}^{L} \log \mathrm{P}(w_L \mid w_{<L})$ over blocks;

☞ 🤗 https://huggingface.co/docs/transformers/perplexity

Pros and Cons?

Evaluating Language Models with Perplexity

Caveat: segmentation ambiguities and exact surprisal computations

$$\mathrm{P}(abcd \mid \boldsymbol{\theta}) = \sum \mathrm{P}(a\_bcd \mid \boldsymbol{\theta}) + \mathrm{P}(ab\_cd \mid \boldsymbol{\theta}) + \ldots \mathrm{P}(abc\_d \mid \boldsymbol{\theta})$$

Language model (de)generation

Language Generation is Hard

The promise ☞ OpenAi Website https://openai.com/blog/better-language-models/

GPT-2 generates synthetic text samples in response to the model being primed with an arbitrary input. The model is chameleon-like—it adapts to the style and content of the conditioning text. This allows the user to generate realistic and coherent continuations about a topic of their choosing, as seen by the following select samples.

GPT-2 displays a broad set of capabilities, including the ability to generate conditional synthetic text samples of unprecedented quality, where we prime the model with an input and have it generate a lengthy continuation.

Language model (de)generation

The truth about language model generation

Prefix	Lyrically the song has excerpts of different languages including French , Spanish ,
Greedy	German , Italian , Portuguese , Spanish , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , Portuguese , ...
Top3	German , Italian , Portuguese , Spanish , Portuguese , Portuguese, Italian and Spanish. It is also available in English, French and Spanish. In addition to its lyrics, the album features a number of original songs, ...
Nucleus-0.3	German , Italian , Portuguese , Spanish , Portuguese , Italian , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , Spanish , Portuguese , ...

Prefix	The first pair of pereiopods is armed with a large , asymm
Greedy	etrical, and long-range laser cannon. The second pair is armed with a large , asymmetrical, and long-range laser cannon. The third pair is armed with a large , asymmetrical, and long-range laser cannon. The fourth pair is armed with a large ...
Top3	etrical, and highly mobile head, and the second pair has a small , asymmetrical, and highly mobile head. The second pair has a large and highly mobile head, and the third pair is armed with a large and highly mobile head. The first pair ...
Nucleus-0.3	etrical head and a large body. The first pair of pereiopods is armed with a large , asymmetrical head and a large body. The first pair of pereiopods is armed with a large , asymmetrical head and a large body. The first pair of pereiopods is armed ...

GPT-2 generated examples from [Welleck et al., 2020b].

Language model (de)generation

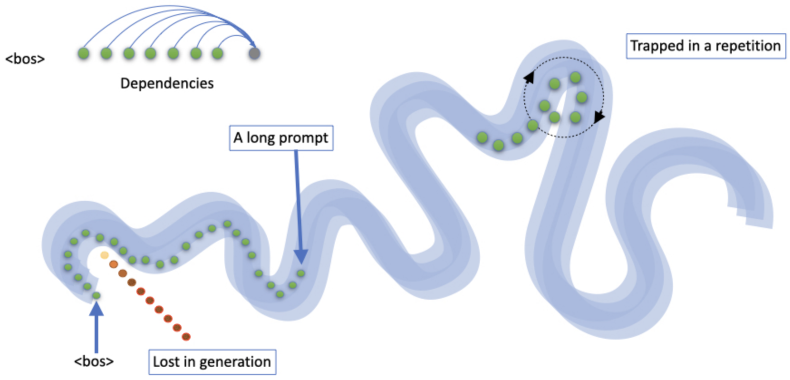
Language Generation is Hard

High probability sentences do not resemble human productions

- too many repetitions
- high frequency tokens over-represented, low frequency tokens under-represented
- lack of lexical diversity
- lack of global consistency
- posterior distribution poorly calibrated

Language model (de)generation

Language Generation is Hard



Action takes place in $\mathbb{R}^d$, $d \in [500; 10000]$

Evaluating LMs with distributional properties

rep/ℓ: a repetition / diversity metric [Welleck et al., 2020b]

Given a set $\mathcal{D}$ of length-T sequences,

$$\text{rep}/\ell = \frac{1}{|\mathcal{D}|T} \sum_{\mathbf{x} \in \mathcal{D}} \sum_{t=1}^{T} \mathbb{I}\left[w_t \in w_{t-\ell-1:t-1}\right].$$

$\mathbb{I}$ the indicator function. Generalizes to repeated n-gram sequences.

Evaluating LMs with distributional properties

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Global distributional properties [Meister and Cotterell, 2021]

- Zipfian behavior, power-law distribution

$$\mathrm{P}_{\text{zipf}}(W = w_k) \propto k^{-s}, s \approx 1$$

  w_k is the k^{th} most frequent token
- type-token ratios (TTR) (depends on length)
- proportion of frequency 1 words (*hapax legomena*)
- proportion specific of token classes (punctuation, stopwords etc)
- consistency metrics ?

Evaluating LMs with distributional properties

MAUVE, a precision-recall approach [Pillutla et al., 2024]

- comparing model distribution and true distribution with KL divergence is risky due to difference of support
- safer to compute

$$\mathrm{Q}_\lambda([w_{[1:T]}]\,|\,\boldsymbol{\theta}) = \lambda\,\mathrm{P}([w_{[1:T]}]) + (1-\lambda)\,\mathrm{P}_\lambda([w_{[1:T]}]\,|\,\boldsymbol{\theta})$$

- MAUVE score is the area under the curve associating $KL(\mathrm{P}([w_{[1:T]}]) \| \mathrm{Q}_\lambda([w_{[1:T]}]\,|\,\boldsymbol{\theta}))$ vs $KL(\mathrm{P}([w_{[1:T]}]\,|\,\boldsymbol{\theta}) \| \mathrm{Q}_\lambda([w_{[1:T]}]\,|\,\boldsymbol{\theta}))$ with varying $\lambda \in [0:1]$ (more precisely $\exp -KL$).
- use statistics in the embedding space for a fixed model (eg. GPT-2) to approximate these quantities

Discussion and comments in [Pimentel et al., 2023].

Evaluating zero-shot / few-shot behaviour

Reduce NLP tasks to text generation with appropriate instructions in NL as prompts

Prompts = instructions in Natural Language + [tricks] (from [Brown et al., 2020])

Specifically, we evaluate GPT-3 on over two dozen NLP datasets,(...) For each task, we evaluate GPT-3 under 3 conditions:

- "zero-shot" learning, where no demonstrations are allowed and only an instruction in natural language is given to the model.
  "Evaluate 125 + 12 ="
- "one-shot learning", where we allow only one demonstration, and
  "Evaluate 17 + 301 = 318 </s>Evaluate 125 + 12 = "
- "few-shot learning", or in-context learning, where we allow as many demonstrations as will fit into the model's context window,
  "Evaluate 17 + 301 = 318 </s>Evaluate 48 + 67 = 105 </s>Evaluate 125 + 12 = "

Tricks: *"On tasks with free-form completion, we use beam search with the same parameters as [RSR+19]: a beam width of 4 and a length penalty of $\alpha = 0.6$."* (+ stopping criterion)

Evaluating zero-shot / few-shot behaviour

Reduce NLP tasks to text generation with appropriate instructions in NL as prompts

Task types and their evaluation [Biderman et al., 2024]

Assuming prompt / instruction: $w_1 \dots w_T$.

- Yes / No answers

  Question: [Question] True or false? *[prediction]*

  Correct if $\mathrm{P}(\mathrm{True} \mid \mathrm{prompt}) > \mathrm{P}(\mathrm{False} \mid \mathrm{prompt})$.

- Multiple choice answers.

  Question: Which factor will most likely cause a person to develop a fever?

Correct Answer	*a bacterial population in the bloodstream*
Incorrect Answer	*a leg muscle relaxing after exercise*
Incorrect Answer	*several viral particles on the skin*
Incorrect Answer	*carbohydrates being digested in the stomach*

  Correct if $\mathrm{P}(\mathrm{Correct\ answer} \mid \mathrm{prompt}) > \mathrm{P}(\mathrm{Alternative} \mid \mathrm{prompt})$ Alt. take - index choices with letter or numbers, evaluate the probability of the correct index.

- One word continuation. Correct if $(w_{T+1} == w^*)$

- Multiple word continuation. Measure $\Delta(w_{T+1} \dots w_{T+S}; w_1^* \dots w_L^*)$ with $\Delta()$ task-dependent distance (ROUGE for summarization, BLEU for MT, etc)

Evaluating zero-shot / few-shot behaviour

Reduce NLP tasks to text generation with appropriate instructions in NL as prompts

Understanding "instruction learning" results

Should pay attention to:

- how much effort went into prompting ?
- free generation or text infilling or multi-choice answers ?
- how were alternatives selected / generated ?
- how was search performed (greedy or beam) ?
- how does generation stops
- how many shots is few shots?

Open issues

- generating / optimizing discrete / continuous prompts
- training with prompts and meta-learning

Part II

Algorithms for Text Generation

Deterministic Algorithms for Text Generation

Searching for the Maximum “A Posteriori”

Greedy search (a.k.a argmax)

$$w_0 = \text{<s>}$$
$$\forall t > 0, w_t = \underset{w \in \bar{\mathcal{V}}}{\mathrm{argmax}} \log \mathrm{P}(w | w_{<t})$$

$\bar{\mathcal{V}} = \mathcal{V} \cup \{\text{<s>}, \text{</s>}\}$
Generation stops with </s> or when some maximum length $T_{\max}$ is reached.

- Greedy search is deterministic: always produces the same output, given its initial conditions.
- Does not require to compute $\mathrm{softmax}$ normalizer $\log(\sum \exp())$

Deterministic Algorithms for Text Generation

Searching for the Maximum “A Posteriori”

Beam search [with histogram pruning]

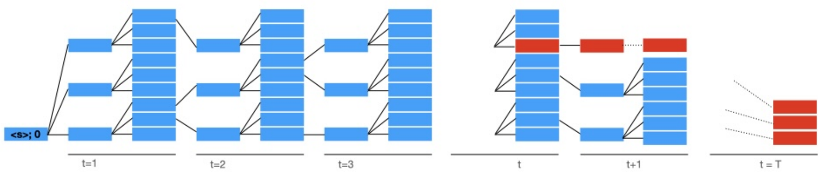
$$\boldsymbol{W_0} = \{<\mathrm{s}>\}$$
$$\forall t > 0, W_t = \operatorname*{argmax}_{\substack{\boldsymbol{W'_t} \subseteq \mathcal{B}_t, \\ |W'_t| = k}} \mathcal{L}(\boldsymbol{W'_t})$$

where $\mathcal{B}_t$ is the beam, consisting of all possible extensions of $\boldsymbol{W_{t-1}}$.
$\mathcal{L}: \mathcal{W} \rightarrow \mathbb{R}$ is a scoring function that operates over sets $\boldsymbol{W} \subseteq \mathcal{W}$, eg. $\mathcal{L}(\boldsymbol{W}) = \sum_{w_{[1:t]} \in \boldsymbol{W}} \log \mathrm{P}(w_{[1:t]})$.

- For $k = 1$, beam search is greedy search
- For $k > 1$, does require to compute $\mathrm{softmax}$ normalizer $\log(\sum \exp())$. Why ?
- Also: adaptive beam size, with $\mathcal{B}_t$ containing all outputs with score within α % of the current best.
- A faster version borrowing ideas from A* search [Meister et al., 2020b]
- 🤗 generate: k = `num_beams`

Deterministic Algorithms for Text Generation

Searching for the Maximum “A Posteriori”



Vanilla Beam stopping condition

$([w^*_{[1:t]}, s^*_t) = \text{argmax}_s\, \mathcal{B}_t,\ w^*_t = $ </s>

In words: the top hypothesis in the beam is complete.

Deterministic Algorithms for Text Generation

Flavors of Beam Search - Delivering k solutions [Kasai et al., 2024]

k: beam size, M: maximum length,
$\mathcal{V}$: Vocabulary, $\mathrm{score}(\cdot)$: scoring function.

$B_0 \leftarrow \{\langle 0, \texttt{<s>}\rangle\}$
for $t \in \{1, \ldots, M-1\}$ **do**
  for $\langle s, w_{[1:l]}\rangle \in B_{t-1}$ **do**
    if $w_l = \texttt{</s>}$ **then**
      $H.\mathrm{add}(\langle s, w_{[1:l]}\rangle)$
      continue
    end if
    for $w \in \mathcal{V}$ **do**
      $s \leftarrow \mathrm{score}(w_{[1:l]} \circ w)$
      $H.\mathrm{add}(\langle s, w_{[1:l]} \circ w\rangle)$
    end for
  end for
  $B_t \leftarrow \varnothing$
  while $|B_t| < k$ **do**
    $\langle s, w_{[1:l]}\rangle \leftarrow H.\mathrm{max}()$
    $B_t.\mathrm{add}(\langle s, w_{[1:l]}\rangle)$
    $H.\mathrm{remove}(\langle s, w_{[1:l]}\rangle)$
  end while
  if $\forall w_{[1:l]} \in B_t, w_l = \texttt{</s>}$ **then break**
  end if
end for
return $B_t.\mathrm{max}()$

- Implementing H as a Heap, operations $(\mathrm{add}, \mathrm{remove}, \mathrm{max})$ take $O(\log|\mathcal{V}|)$
- 🤗 generate `num_beams` (k), `num_return_sequences`
- the stopping condition is 🤗 generate `early_stopping = True` (also `False`, `never`)

Deterministic Algorithms for Text Generation

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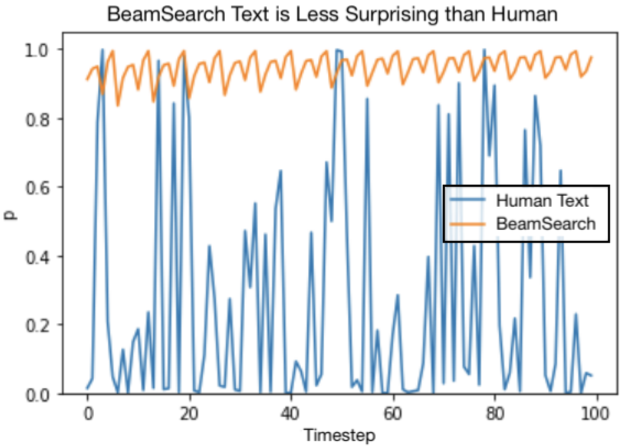
k: beam size, M: maximum length,
$\mathcal{V}$: Vocabulary, $\mathrm{score}(\cdot)$: scoring function.

$B_0 \leftarrow \{\langle 0, <\mathrm{s}> \rangle\}$
for $t \in \{1, \ldots, M-1\}$ **do**
  for $\langle s, w_{[1:l]} \rangle \in B_{t-1}$ **do**
    if $w_l = </\mathrm{s}>$ **then**
      $H.\mathrm{add}(\langle s, w_{[1:l]} \rangle)$
      continue
    end if
    for $w \in \mathcal{V}$ **do**
      $s \leftarrow \mathrm{score}(w_{[1:l]} \circ w)$
      $H.\mathrm{add}(\langle s, w_{[1:l]} \circ w \rangle)$
    end for
  end for
  $B_t \leftarrow \varnothing$
  while $|B_t| < k$ **do**
    $\langle s, w_{[1:l]} \rangle \leftarrow H.\mathrm{max}()$
    $B_t.\mathrm{add}(\langle s, w_{[1:l]} \rangle)$
    $H.\mathrm{remove}(\langle s, w_{[1:l]} \rangle)$
  end while
  if $\forall w_{[1:l]} \in B_t, w_l = </\mathrm{s}>$ **then break**
  end if
end for
return $B_t.\mathrm{max}()$

k: beam size, M: maximum length, p patience
$\mathcal{V}$: Vocabulary, $\mathrm{score}(\cdot)$: scoring function.

$B_0 \leftarrow \{\langle 0, <\mathrm{s}> \rangle\}$, $F_0 \leftarrow \varnothing$
for $t \in \{1, \ldots, M-1\}$ **do**
  $H \leftarrow \varnothing, F_t \leftarrow F_{t-1}$
  for $\langle s, w_{[1:l]} \rangle \in B_{t-1}$ **do**
    for $w \in \mathcal{V}$ **do**
      $s \leftarrow \mathrm{score}(w_{[1:l]} \circ w)$,
      $H.\mathrm{add}(\langle s, w_{[1:l]} \circ w \rangle)$
    end for
  end for
  $B_t \leftarrow \varnothing$
  while $|B_t| < k$ **do**
    $\langle s, w_{[1:l]} \rangle \leftarrow H.\mathrm{max}()$,
    if $w_l = </\mathrm{s}>$ **then**
      $F_t.\mathrm{add}(\langle s, w_{[1:l]} \rangle)$
    else
      $B_t.\mathrm{add}(\langle s, w_{[1:l]} \rangle)$
    end if
    $H.\mathrm{remove}(\langle s, w_{[1:t]} \rangle)$
  end while
  if $|F_t| = pk$ **then break**
  end if
end for
return $F_t.\mathrm{max}()$

Pitfalls of Beam Search



☞ From https://huggingface.co/blog/how-to-generate

Also [Holtzman et al., 2020]. This can make artificial text detection easy.

Pitfalls of Beam Search

The Beam Search "curse"

Russian–English (medium)	Beam Size					
	10	**50**	**75**	**100**	**150**	**1000**
BLEU	24.9	23.8	23.6	23.3	22.5	3.7
METEOR	30.9	30.0	29.7	29.4	28.8	12.8
length	0.90	0.86	0.85	0.84	0.81	0.31

Results of the Russian–English translation system. We report BLEU and METEOR scores, as well as the ratio of the length of generated sentences compared to the correct translations (length). From [Murray and Chiang, 2018]

Increasing beam width k hurts performance (!)

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Increasing beam width k hurts performance (!)

Length issues in beam search

- Increasing k raises the likeliness of inserting a complete hypothesis in $\mathcal{B}_t$
- Complete hypotheses scores do not change;
- Uncomplete hypotheses scores only gets worse
- Short sequences are more likely than longer ones

The problem is the MAP not the beam [Eikema and Aziz, 2020] ! Small beams hide this issue

Pitfalls of Beam Search

Better solutions with regularized decoding objectives [Meister et al., 2020a]

$$[w_1^* \dots w_{T^*}^*] = \operatorname*{argmin}_{T, w_{[1:T]}} \sum_{t=1}^{T+1} -\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) - \lambda \mathcal{R}([w_{[1:T]}])$$

$\mathcal{R}([w_{[1:T]}])$ compensates for length differences, biases towards longer sequences

1. $\mathcal{R}([w_{[1:T]}]) = T + 1$: fixed bonus for each extra word
   ~ score with average surprisal $\frac{1}{T+1} \sum_{t=1}^{T} -\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta})$
2. $\mathcal{R}_{unif}([w_{[1:T]}]) = \frac{1}{T} \sum_t (\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) - \mu_t)^2$, with μ_t average surprisal
   enforces uniform information rate
3. $\mathcal{R}_{local}([w_{[1:T]}]) = \frac{1}{T+1} \sum_t (\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) - \log \mathrm{P}(w_{t-1} \,|\, w_{<t-1}; \boldsymbol{\theta}))^2$,
   enforces locally uniform information rate
4. $\mathcal{R}_{max}([w_{[1:T]}]) = \frac{1}{T+1} \max_t(-\log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}))$,
   enables high surprisal tokens

- 🤗 generate with `length_penalty=`λ to control output length

Pitfalls of Beam Search

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Sampling Schemes for Text Generation

Ancestral sampling

$$w_0 = \text{<s>}$$
$$\forall t > 0, w_t \sim \mathrm{P}(w | w_{<t}; \boldsymbol{\theta})$$

Recursion stops with </s> or when some maximum length $T_{\max}$ is reached.

- Ancestral sampling is non-deterministic: output varies, depending on the sharpness of $\mathrm{P}(w | w_{<t}; \boldsymbol{\theta})$
- Sampling requires 🤗 **generate** `do_sampling=True`
- softmax is very peaked: increase diversity with temperature τ to "flatten" the distribution with $\exp \frac{\mathrm{logit}(w', w_{<t}; \boldsymbol{\theta})}{\tau}$ (τ is 🤗 **generate** `temperature`)
- better trade-off between likelihood and diversity [Keskar et al., 2019]:

$$\mathrm{P}(w' | w_{<t}; \boldsymbol{\theta}) \propto \exp \frac{\mathrm{logit}(w', w_{<t}; \boldsymbol{\theta})}{\tau \times \mathbb{I}(w' \in w_{<t})},$$

with $\mathbb{I}(w' \in w_{<t}) = 1$ for "new tokens", $= \lambda > 1$ for "old ones" (`repetition_penalty` for 🤗 generate)

Sampling Schemes for Text Generation

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

$$w_0 = \texttt{<s>}$$

$$Q(w_t \mid w_{<t}) \propto \begin{cases} P(w_t \mid w_{<t}; \boldsymbol{\theta}) \text{ if } w \in \text{top-k}(P(W \mid w_{<t}; \boldsymbol{\theta})) \\ 0 \text{ otherwise} \end{cases}$$

$$\forall t > 0, w_t \sim Q(w \mid w_{<t})$$

Sample from a "truncated" distribution containing the k most likely symbols. Generation stops with the </s> symbol or when some maximum time step $T_{\max}$ is reached.

- Finding the k most likely tokens is $O(|\mathcal{V}| * \log k)$, the normalizer applies only over k elements.
- 🤗 - generate `top_k`

Sampling Schemes for Text Generation

Nucleus sampling (top p, with variable p) [Holtzman et al., 2020]

$$
\begin{aligned}
w_0 &= \text{<s>} \\
Q(w_t \mid w_{<t}) &\propto \begin{cases} P(w_t \mid w_{<t}; \boldsymbol{\theta}) & \text{if } w \in \text{top-p}(P(W \mid w_{<t}; \boldsymbol{\theta})) \\ 0 & \text{otherwise} \end{cases} \\
\forall t > 0, w_t &\sim Q(w \mid w_{<t})
\end{aligned}
$$

p is the smallest integer such that $\sum_{w \in \text{top-p}} P(w \mid w_{<t};; \boldsymbol{\theta}) > \alpha$. Sample from a "truncated" distribution for the p most likely symbols, with variable p (α typically $\in [0.7; 0.9]$).

- α controls the size of the truncated vocabulary ($Q(w \mid w_{<t}) > 0$).
- 🤗 - generate `top_p`

Sampling Schemes for Text Generation

Locally Typical Sampling [Meister et al., 2023]

$$w_0 = \text{<s>}$$

$$Q(w_t \mid w_{<t}) \propto \begin{cases} P(w_t \mid w_{<t}; \boldsymbol{\theta}) & \text{if } w \in \text{LTStop-p}(P(W \mid w_{<t}; \boldsymbol{\theta})) \\ 0 & \text{otherwise} \end{cases}$$

$$\forall t > 0, w_t \sim Q(w \mid w_{<t})$$

$\text{LTStop-p}(P(W \mid w_{<t}; \boldsymbol{\theta}))$ minimize $\sum |H(W|w_{<t}; \boldsymbol{\theta}) + \log P(w \mid w_{<t}; \boldsymbol{\theta})|$ subject to $\sum_{w \in \text{LTStop-p}} P(w \mid w_{<t}; \boldsymbol{\theta}) > \alpha$. Sample from a "truncated" distribution for the p most locally typical symbols, with variable p (α typically $\in [0.7; 0.9]$).

- Locally typical prefers tokens with average surprisal
- In low uncertainty contexts, prefer high probability tokens
- In high uncertainty contexts, pick token with near average surprisal (=information content)
- 🤗 generate: `typical_p`
- related: Mirostat [Basu et al., 2021], sample with a target perplexity.

Sampling Schemes for Text Generation

Top-k, top-p and typical sample from a truncated distribution $\mathrm{Q}(W \mid <_t; \boldsymbol{\theta})$:

- $\forall t$, select vocabulary $\mathcal{V}_t^+ \subset \mathcal{V}$.
- $\forall t, w \notin \mathcal{V}_t^+, \mathrm{Q}(w \mid <_t; \boldsymbol{\theta}) = 0$

Always sampling high probability words avoids derailing, yet, can be very risky:

1. generation may no longer terminate $\Rightarrow$ probability leakage to infinite strings.
2. may exclude interesting words
   Using top-p, for $p = 0.9$, $\mathrm{P}(\textit{Duck} \mid \textit{Donald}) = 0.95$ excludes w =Trump
3. may include unlikely words
   Using top-k, $k = 20$ may generate unlikely continuations for low-entropy distributions

Sampling Schemes for Text Generation

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Remedies

- solve (1) with consistent truncated sampling [Welleck et al., 2020a]: $\mathcal{V}_t^+ \rightarrow \mathcal{V}_t^+ \cup \{$</s>$\}$
- how to mitigate (2) and (3) ? what is the right size for $\mathcal{V}_t^+$?

(P1) never truncate high probability words $\Leftrightarrow$ keep all w such that $\mathrm{P}(w \mid w_{<t} > \epsilon; \boldsymbol{\theta})$
(P2) truncate more when entropy is low; truncate less when entropy is high

(P*) sample only w for which the true $\mathrm{P}(w \mid <_t; \boldsymbol{\theta})$ is provably > 0 (with rejection sampling) [Finlayson et al., 2024]

Sampling Schemes for Text Generation

η-Sampling [Hewitt et al., 2022]

$$
\begin{aligned}
w_0 &= \texttt{<s>} \\
\mathrm{Q}(w_t \,|\, w_{<t}) &\propto \begin{cases} \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) & \text{if } w \in \mathcal{V}_t^+ \\ 0 & \text{otherwise} \end{cases} \\
\forall t > 0, w_t &\sim \mathrm{Q}(w \,|\, w_{<t}) \\
\mathcal{V}_t^+ &= \{w \in \mathcal{V} | \, \mathrm{P}(w \,|\, w_{<t}; \boldsymbol{\theta}) \geq \min(\epsilon, \alpha \exp -H(W_t | w_{<t}; \boldsymbol{\theta}))\}
\end{aligned}
$$

Sample from a “truncated” distribution subject to principles (P1) and (P2).

- $\alpha \exp -H(W_t | w_{<t}; \boldsymbol{\theta})$ increases the sampling set when entropy is high
- Yields better samples than typical, greedy, ancestral, nucleus and top-k
- In [Hewitt et al., 2022]’s experiments, $\epsilon = 0.0003, \alpha = \sqrt{\epsilon}$
- 🤗 - generate `epsilon_cutoff`, `eta_cutoff`

Consistent Decoding for Consistent Models

Why we need a maximum decoding length

Consistent model (details in [Welleck et al., 2020a])

A consistent model is such that $\mathrm{P}(|w_{[1:T]}| = \infty \,|\, \boldsymbol{\theta}) = 0$

A sufficient condition is that hidden states are uniformely bounded.
This implies that $\exists \xi, \forall, t, w_{<t}, \mathrm{P}(\text{</s>} \,|\, w_{<t}; \boldsymbol{\theta}) > \xi$.

$$\mathrm{P}(|w_{[1:T]}| = \infty \,|\, \boldsymbol{\theta}) < (1-\xi)^T$$

$$\lim_{T\to\infty} (1-\xi)^T = 0$$

Consistent Decoding for Consistent Models

Why we need a maximum decoding length

Consistent decoding algorithm

A consistent decoding algorithm generates a complete text with probability 1.

Unconsistency of Decoding

Ancestral is consistent, greedy, beam, top-k, nucleus, typical, etc. are not consistent.
Argument: no guarantee that </s> will ever appear in the top-k, top-p, etc.

Consistent Decoding for Deterministic Search

$$w_0 = \text{<s>}$$

$$Q(w_t \mid w_{<t}; \boldsymbol{\theta}) \propto \begin{cases} 1 - \alpha(h_t) \text{ if } w = \text{</s>} \\ \frac{\alpha(h_t) \exp \operatorname{logit}(w, w_{<t}; \boldsymbol{\theta})}{\sum_{w'} \exp \operatorname{logit}(w', w_{<t}; \boldsymbol{\theta})} \text{ otherwise} \end{cases}$$

$$\alpha(h_0) = \sigma(\operatorname{logit}(\text{</s>}, \text{<s>}; \boldsymbol{\theta})) \tag{1}$$

$$\alpha(h_t) = \sigma(\operatorname{logit}(\text{</s>}, w_{<t}; \boldsymbol{\theta}))(1 - P(\text{</s>} \mid w_{<t}; \boldsymbol{\theta}) \tag{2}$$

With $\sigma : \mathbb{R} \to [0; 1 - \epsilon]$, $\epsilon > 0, \epsilon < 1$. This ensures that $Q(\text{</s>} \mid w_{<t}; \boldsymbol{\theta})$ is monotonically increasing, meaning that </s> eventually happen.

Promoting Diversity in Text Generation

Diversity promotion has many forms

1. boosting surprisal in open-ended text generation
2. ensuring diversity in a set of solutions
3. mitigating repetition in texts (difficult - repetition can be a good thing)

Promoting Diversity in Text Generation

Boosting surprisal in open-ended text generation

Contrasting Expert and Amateur Models

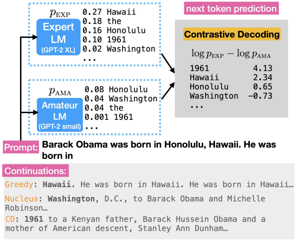
New search objective:

$$w_1^* \dots w_{T^*}^* = \operatorname*{argmax}_{T, w_{[1:T]}} \sum_{t=1}^{T} \log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}) - \log \mathrm{P}(w_t \,|\, w_{<t}; \boldsymbol{\theta}_{AMA})$$

$$\text{subject to} \forall t, w_t^* \in \mathcal{V}_t^+$$

$$\mathcal{V}_t^+ = \{w \in \mathcal{V} | \mathrm{P}(w \,|\, w_{<t}; \boldsymbol{\theta}) \geq \alpha \max_{w'} \mathrm{P}(w' \,|\, w_{<t}; \boldsymbol{\theta})\}$$

Select probable words that are unlikely for a weaker amateur model. Constraining the search to high probability words helps handle cases where (a) Expert and Amateur agree on very low probability; (b) Expert and Amateur agree on very high probability. Also respects (P1).



From [Li et al., 2023]

- requires consistent tokenization for expert and amateur
- see also: https://arxiv.org/pdf/2305.12675.pdf

Promoting Diversity in Text Generation

Generating Multiple Diverse Solutions

Ensuring Diversity in Beam Search

Maintains G beams $\mathcal{B}_t^1 \ldots \mathcal{B}_t^G$, such that hypotheses in Beam g must be diverse with respect to $\mathcal{B}_t^1 \ldots \mathcal{B}_t^{g-1}$

$$\begin{aligned}
\text{score}(w_{[1:l]}, g) &= \text{score}(w_{[1:l]}) \text{ if } g = 1 \\
&= \text{score}(w_{[1:l]}) + \lambda \sum_{h=1}^{g-1} \Delta(w_{[1:l]}, \mathcal{B}_t^h), \text{ otherwise} \\
\Delta(w_{[1:l]}, \mathcal{B}_t^h) &= \sum_{w'_{[1:l']} \in \mathcal{B}_t^h} \delta(w_{[1:l]}, w'_{[1:l']}), \text{with } \delta \text{ a similarity function}
\end{aligned}$$

- Δ can be any string comparison (set differences for bag-of-words or bag-of-ngrams; Levenshtein distance; neural similarity, etc.)
- beams can run in parallel with a time delay
- 🤗 generate: `num_beam_groups` (G), `diversity_penalty` (λ)

Promoting Diversity in Text Generation

Avoiding Repetitions

Contrastive Search (greedy version) [Su et al., 2022]

$$w_0 = \text{<s>}$$

$$\forall t > 0, w_t = \underset{w \in \bar{\mathcal{V}}}{\operatorname{argmax}} \, (1-\alpha) \log \mathrm{P}(w \,|\, w_{<t}) - \alpha \max\{\mathrm{sim}(h_w, h_{w_s}) : 1 \leq s \leq t-1\}$$

h_w is the latent representation associated to w; sim is a similarity function (e.g. cosine). Extra penalty term for repetitions. Generation stops with </s> or when some maximum length $T_{\max}$ is reached.

- assumes repetitions can be detected in embedding space
- 🤗 generate: `penalty_alpha=` α ☞ https://huggingface.co/blog/introducing-csearch
- naive version with `no_repeat_ngram_size`: disable n-gram repetition
- 🤗 DoLa contrasts inner vs. outer layers to increase factuality [Chuang et al., 2024]

Faster Generation with Speculative Sampling

Details in [Leviathan et al., 2023] and [Chen et al., 2023]

Overview

- Sampling algorithms are autoregressive: they return one sample at each time step.
- At step t speculative sampling uses a simpler model to generate S draft tokens $w_{t+1} \ldots w_{t+S}$ autoregressively, then “validates” the tokens with the large model in parallel with accept / reject procedure.
- Why? Potential to validate multiple tokens in one parallel forward pass.

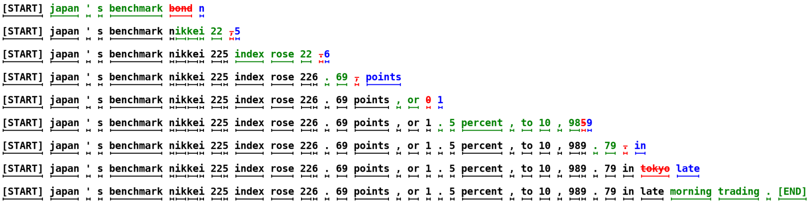


Figure from Leviathan et al. [2023], K > 4

🤗 **generate**: `assistant_model` (`assistant_tokenizer`)

Faster Generation with Speculative Sampling

Details in [Leviathan et al., 2023] and [Chen et al., 2023]

sample K drafts $[w_{t+i}, q(w_{t+i})], i = 1 \dots K$
evaluate drafts $[w_{t+i}, p(w_{t+i})]$
sample $u_i \sim \mathrm{Unif}[0:1], i = 1 \dots K$
accept $\leftarrow$ **True** ; $i \leftarrow 1$
while accept **and** $i \leq K$ **do**
  if $q(w_{t+i}) < p(w_{t+i})$ **then**
    $i \leftarrow i + 1$ ▷ accept
  else if $u_i < \frac{q(w_{t+i})}{p(w_{t+i})}$ **then**
    $i \leftarrow i + 1$ ▷ accept
  else
    accept $\leftarrow$ **False** ▷ reject
    $\forall w, r(w) \propto (\max(0, p(w) - q(w)))$
    sample $w_{t+i} \sim r(w)$
  end if
end while

Notations:

- $p(w) = \mathrm{P}(W \mid w_{<t}; \boldsymbol{\theta})$, $q(w) = \mathrm{Q}(W \mid w_{<t}; \boldsymbol{\theta}')$
- $\mathcal{V}_- = \{w | q(w) \leq p(w)\}$; undersampled tokens
- $\mathcal{V}_+ = \{w | q(w) > p(w)\}$ oversampled tokens

Claim: speculative sampling generates tokens under $p(w)$

1. $w \in \mathcal{V}_+$? accept with proba $\frac{p(w)}{q(w)} \Rightarrow p'(w) = q(w) \times \frac{p(w)}{q(w)} = p(w)$
2. $w \in \mathcal{V}_-$? $p'(w) = q(w)$ always accept and there is a second chance:

$$\forall v \in \mathcal{V}_+, p'(w) += q(v) \times (1 - \frac{p(v)}{q(v)}) \times (\frac{p(w) - q(w)}{\sum_{w' \in \mathcal{V}_-} p(w') - q(w')})$$

Basic Watermarking with Green / Red Sampling

An original proposal from [Kirchenbauer et al., 2023]

Sampling from a Random Subset of Words (hard take)

At each time step:

1. using $w_{<t}$, randomly split $\mathcal{V}$ into $\mathcal{V}(w_{<t}) \cup \mathcal{V}(w_{<t})$ of size $\frac{|\mathcal{V}|}{2}$
2. sample next word from $\mathcal{V}(w_{<t})$ using $\mathrm{P}(w \mid w_{<t}; \boldsymbol{\theta})$

Observing $w_{[1:T]}$:

1. $\forall t$, compute $\mathrm{color}(w_t)$
2. for generated texts: $\mathbb{E}(n_{green}) = T$
3. for natural text: $\mathbb{E}(n_{green}) = \frac{T}{2}, \mathbb{V}(n_{green}) = \frac{T}{2} \Rightarrow$ effective testing procedure

Robust to attack, also work with greedy and beam-search decoding, degrade generation quality in low surprisal contexts

Basic Watermarking with Green / Red Sampling

An original proposal from [Kirchenbauer et al., 2023]

Prompt	Num tokens	Z-score	p-value
…The watermark detection algorithm can be made public, enabling third parties (e.g., social media platforms) to run it themselves, or it can be kept private and run behind an API. We seek a watermark with the following properties:			
No watermark Extremely efficient on average term lengths and word frequencies on synthetic, microamount text (as little as 25 words) Very small and low-resource key/hash (e.g., 140 bits per key is sufficient for 99.999999999% of the Synthetic Internet	56	.31	.38
With watermark - minimal marginal probability for a detection attempt. - Good speech frequency and energy rate reduction. - messages indiscernible to humans. - easy for humans to verify.	36	7.4	6e-14

Basic Watermarking with Green / Red Sampling

An original proposal from [Kirchenbauer et al., 2023]

Sampling from a Random Subset of Words (soft take)

During generation, at each time step:

1. using $w_{<t}$, randomly split $\mathcal{V}$ into $\mathcal{V}(w_{<t}) \cup \mathcal{V}(w_{<t})$ of size $\gamma|\mathcal{V}|, (1-\gamma)|\mathcal{V}|$
2. $Q_t(w \mid w_{<t}; \boldsymbol{\theta}) \propto \exp \operatorname{logit}(w, w_{<t}; \boldsymbol{\theta})$;
3. $Q_t(w \mid w_{<t}; \boldsymbol{\theta}) \propto \exp \operatorname{logit}(w, w_{<t}; \boldsymbol{\theta}) + \boldsymbol{\delta}$;
4. sample next word from $Q_t(W \mid w_{<t}; \boldsymbol{\theta})$

Observing $w_{[1:T]}$:

1. $\forall t$, compute $\operatorname{color}(w_t) \in \{\text{red}, \text{green}\}$
2. for watermarked texts: $\mathbb{E}(n_{green}) \geq f(\gamma, T, \delta, S^*)$, with S^* a measure of average surprisal
3. "excessively" green texts are artificial, "excessively" red texts are natural

- 🤗 - **generate** has parameters for $1-\gamma$ (`greenlist_ratio`) and δ (`bias`), also `context_width` to control the context used in step 1.

Part III

Constrained Generation

Constraining Text Generation

Generating with simple constraints

- length (soft and hard) – for beam search
- no repetition (soft and hard penalties)
- with in-text / cross-text diversity (soft and hard penalties)

Updated search goals: restricted search space (hard constraints), modified search objective (soft)

A variety of constraints

- lexical choices (positive and negative, hard and soft) Keskar et al. [2019]
- language, idiom, sociolect (hard)
- style, consistency, toxicity, polarity, stance, etc (soft)
- optimizing other global scores: alignment score, backward model (translation); coverage score (summarization), etc.

Constraining Text Generation

Guiding Decoding with Soft Constraints

Soft constraints

A soft or probabilistic constraint for text $w_{[1:T]}$ is a model $\mathrm{P}(A \,|\, w_{[1:T]}, \mathbf{C}; \boldsymbol{\lambda})$, where A is a (binary) discrete attribute representing the constraint.

For instance: $A = 1$ for harmfull / toxic texts, 0 for harmless content;

Probabilistic constraints can be learn from supervision data:

- "generatively" with $\mathrm{P}(w_{[1:T]} \,|\, a, \mathbf{C}; \lambda) \forall a$ (learns / adapt multiple LMs - potentially costly)
- "discriminatively" with $\mathrm{P}(A \,|\, w_{[1:T]}, \mathbf{C}; \lambda)$ (LM + classification head)

Generative to discriminative score use Bayes rule

$$\mathrm{P}(A \,|\, w_{[1:T]}, \mathbf{C}; \lambda) \propto \mathrm{P}(A)\, \mathrm{P}(w_{[1:T]} \,|\, A, \mathbf{C}; \lambda)$$

Guiding Decoding with Soft Constraints

Soft constraints

A soft or probabilistic constraint for text $w_{[1:T]}$ is a model $\mathrm{P}(A \mid w_{[1:T]}, \mathbf{C}; \boldsymbol{\lambda})$, where A is a (binary) discrete attribute representing the constraint.

For instance: $A = 1$ for harmfull / toxic texts, 0 for harmless content;

Decoding with constraints

A LM computes $\mathrm{P}(w_{[1:T]} \mid \boldsymbol{\theta})$, how to generate $w_{[1:T]}$ that simultaneously

- is fluent: high $\log \mathrm{P}(w_{[1:T]} \mid \mathbf{C}; \boldsymbol{\theta})$
- satisfies constraint with high $F(w_{[1:T]}, \mathbf{C}) \propto \log \mathrm{P}(A \mid w_{[1:T]}, \mathbf{C}; \boldsymbol{\lambda})$?

one requirement is based on the LM prior, one on the class posterior

Guiding Decoding with Soft Constraints

Soft constraints

A soft or probabilistic constraint for text $w_{[1:T]}$ is a model $\mathrm{P}(A \,|\, w_{[1:T]}, \mathbf{C}; \boldsymbol{\lambda})$, where A is a (binary) discrete attribute representing the constraint.

For instance: $A = 1$ for harmfull / toxic texts, 0 for harmless content;

Training-based methods

- fine-tuning, VAEs, GAN – all these methods requires retraining a model
- **[Ctrl]**, a class-conditional models (with class tokens) [Keskar et al., 2019].
  Learns $\boldsymbol{\theta}$ with [ctrl:]$w_1 \ldots w_T$, a model for $\mathrm{P}(w_{[1:T]} \,|\, \text{[ctrl:]}; \boldsymbol{\theta})$
  - [ctrl:] is generic - represent style or domain or language or even length.
  - LLM needs to be trained with a finite set of predefined control codes
- **GeDi** [Krause et al., 2021] trains [ctrl] with $\{a, \bar{a}\}$ and guide generation with Bayes rule

$$\mathrm{P}(A = a \,|\, w_{[1:T]}; \boldsymbol{\lambda}) = \frac{\mathrm{P}(a) \prod_t \mathrm{P}(w_t \,|\, w_{<t}, a; \boldsymbol{\lambda})}{\sum_{a'} \mathrm{P}(a') \prod_t \mathrm{P}(w_t \,|\, w_{<t}, a'; \boldsymbol{\lambda})}$$

  Soft constraint A is promoted in decoding with $\mathrm{P}(w \,|\, w_{<t}; \boldsymbol{\theta})\, \mathrm{P}(a \,|\, w_{[1:t-1]} w; \boldsymbol{\theta}')^{\alpha}$

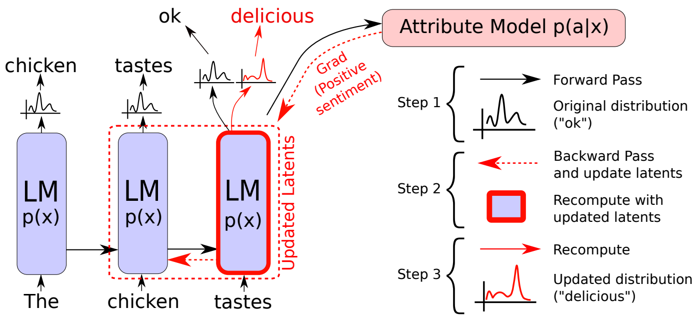
  The trick is to compute $\mathrm{P}(w_t \,|\, w_{<t}, A; \boldsymbol{\theta})$ *in parallel for* $a, \bar{a}$

A Plug-and-Play Method for Text Generation

The approach of [Dathathri et al., 2020]

Gradient-based online adaptation

Sampling $\mathrm{P}(W_t \mid w_{<t}; \boldsymbol{\theta})$ depends on the logits at time t, which depend on the entire (Key,Value) store $\mathbf{H}_{<t}$ at time t.
Main idea: adapt $\mathbf{H}_t$ with $\boldsymbol{\Delta}\mathbf{H}_t$ to boost $\mathrm{P}(A \mid w_1 \ldots w_t; \boldsymbol{\theta})$



A Plug-and-Play Method for Text Generation

The approach of [Dathathri et al., 2020]

Implementation

Iterate for 3-10 steps, starting with 0

$$\Delta\mathbf{H}_{<t} \leftarrow \Delta\mathbf{H}_{<t} + \alpha \frac{\nabla_{\Delta\mathbf{H}_{<t}} \log \mathrm{P}(a \,|\, \mathbf{H}_{<t} + \Delta\mathbf{H}_{<t}; \boldsymbol{\lambda})}{\|\nabla_{\Delta H_{<t}} \log \mathrm{P}(a \,|\, \mathbf{H}_{<t} + \Delta\mathbf{H}_{<t}; \boldsymbol{\lambda})\|^{\gamma}}$$

Generate next token with $\mathbf{H}_{<t} + \Delta\mathbf{H}_{<t}$

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Generate next token with $\mathbf{H}_{<t} + \Delta \mathbf{H}_{<t}$

Caveats and Finesses

- $\mathrm{P}(A \mid w_1 \dots w_t; \boldsymbol{\lambda})$ must depend on $\mathbf{H}_{<t}$: train via fine-tuning with the LM encoder.
- Regularize with additional KL-loss to remain close to $\mathrm{P}(W \mid w_{<t}; \boldsymbol{\theta})$
- Sample next word with a mixture of the original ($\mathbf{H}_{<t}$) and adapted ($\mathbf{H}_{<t} + \boldsymbol{\Delta}\mathbf{H}_{<t}$) + meta parameters

Generating with Rational Constraints

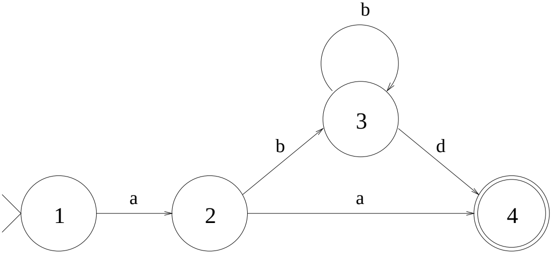
Motivations for Hard Constraints

1. Watch your language 🤗 `bad_words_ids`
2. Force words in output (e.g QA): 🤗 `force_words_ids`
3. Question answering with fixed choices
4. Structured answers (e.g. JSON tables)
5. Code generation

Generating with Rational Constraints

Rational Languages

Rational languages are languages represented by Rational Expressions (a.k.a RegExps), are also languages represented by (Deterministic) Finite Automata (DFAs).



Accomodate finite lists of words and sequences, numerics, http / mail addresses, etc

Generating with Rational Constraints

Implementing Rational Constraints

Requirements:

1. Transitions mapping (states, words) to next states.
   - restrict choice to valid continuations
   - apply transition; update state
2. List of final states: add </s> to valid word list

Caveats

1. words are not tokens
2. compatible with beam ?
3. generalizes to simple (deterministic) CF grammars

Check it out - with `outlines` library: https://github.com/dottxt-ai/outlines

Part IV

Meta-Generation Strategies

Meta-generation techniques

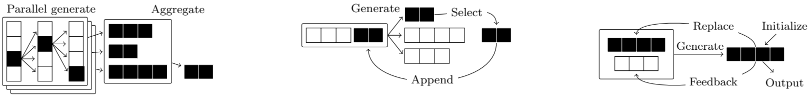


Figure from [Welleck et al., 2024]

Meta-Generation Strategies

- Parallel search (combines multiple complete generations)
  - reranking (pick one in M)
  - transform (build a new one out of M)
- Heuristic step-level search (local search, MCTS, A^*)
- Refinement

Reranking 101

Main idea of reranking

Reranking as Meta Generation

1. **generate** M solutions $\mathcal{W}_S = \{w^{(m)}_{[1:T]}, m = 1 \dots M\}$ based on model $\log \mathrm{P}(w^{m}_{[1:T]} \,|\, \mathbf{C}; \boldsymbol{\theta})$
2. **evaluate** $w^{(m)}_{[1:T]}$ with alternative, global score $F(w_{[1:T]}, \mathbf{C}', \boldsymbol{\theta}')$
3. **return** $\operatorname{argmin}_m F(w^{(m)}_{[1:T]}, \mathbf{C}', \boldsymbol{\theta}')$

Reranking 101

Main idea of reranking

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3. **return** $\mathrm{argmin}_m F(w^{(m)}_{[1:T]}, \mathbf{C}', \boldsymbol{\theta}')$

- Design of **generate** (for M): (diverse) beam-search ? (diverse) sampling ? stochastic beam search ? Multiple models and checkpoints ? Multiple prompts? Impact of M?

  🤗 `num_return_sequences`

- Design of **evaluate**: length control; score of a larger or better model ($\boldsymbol{\theta}'$); increased context (**C'**); use auxiliary models of grammaticality, style, toxicity, stance, polarity; use result of execution (code); also watermarking; confidentiality; etc.

Minimum Bayes Risk Decoding

Context and Concepts

$\ell(w_{[1:T]}, v_{[1:S]}) : (\text{<s>}\mathcal{V}^*\text{</s>}) \times (\text{<s>}\mathcal{V}^*\text{</s>}) \rightarrow \mathbb{R}$ a global dissimilarity function
ℓ is small when two solutions are similar

- $\ell(w_{[1:T]}, v_{[1:S]}) = 1 - \mathbb{I}(w_{[1:T]} = v_{[1:S]})$
  one-hot dissimilarity, all (non identical) pairs of sequences have $\ell = 1$
- $\ell(w_{[1:T]}, v_{[1:S]}) = 1 - \mathrm{NED}(w_{[1:T]}, v_{[1:S]})$
  Normalized Edit Distance, normalized minimum number of edits from $w_{[1:T]}$ to $v_{[1:S]}$
- $\ell(w_{[1:T]}, v_{[1:S]}) = 1 - \mathrm{BLEU}(w_{[1:T]}, v_{[1:S]})$
  reference based metrics - n-gram overlap (BLEU, METEOR for MT, Rouge for summarization)
- $\ell(w_{[1:T]}, v_{[1:S]}) = -\cos(\mathrm{Emb}(w_{[1:T]}), \mathrm{Emb}(v_{[1:S]}))$:
  cosine dissimilarity in embedding space, generalize to neural metrics (COMET, BLEURT, BertScore) [Suzgun et al., 2023]

Minimum Bayes Risk Decoding

Main idea

For fixed $w_{[1:t]}$, the risk of $w_{[1:T]}$

$$\begin{aligned} R(w_{[1:T]}) &= \mathbb{E}_{v_{[1:S]} \sim P}(\ell(w_{[1:T]}, v_{[1:S]})) \\ &= \sum_{v_{[1:s]}} \mathrm{P}(v_{[1:S]}) \ell(w_{[1:T]}, v_{[1:S]}) \end{aligned}$$

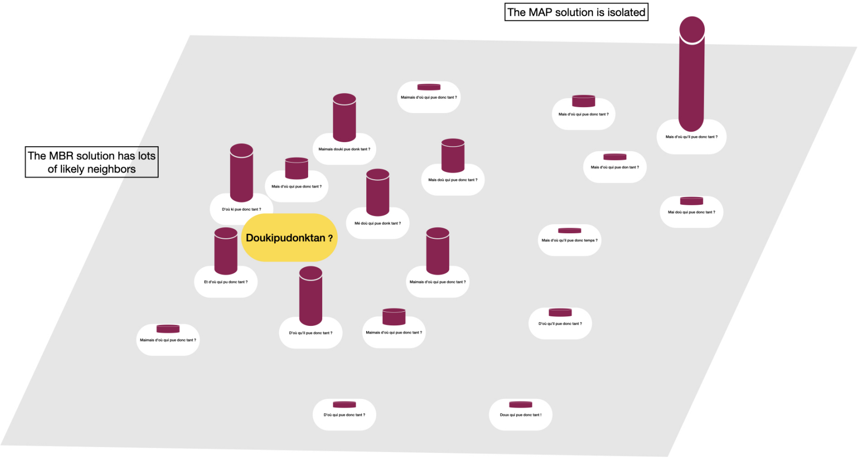
Minimum Bayes Risk decoding seeks

$$\begin{aligned} w^*_{[1:T^*]} &= \operatorname*{argmin}_{T, w_{[1:T]}} R(w_{[1:T]}) \\ &= \operatorname*{argmin}_{T, w_{[1:T]}} \mathbb{E}_{S, v_{[1:S]} \sim P}(\ell(w_{[1:T]}, v_{[1:S]})) \\ &= \operatorname*{argmin}_{T, w_{[1:T]}} \sum_{S, v_{[1:S]}} \mathrm{P}(v_{[1:S]}) \ell(w_{[1:T]}, v_{[1:S]}) \end{aligned}$$

The best sequence is (on average) the closest to all other sequences

Minimum Bayes Risk Decoding

Intuition: why is MBR is a good idea ?



Minimum Bayes Risk Decoding

Intuition: why is MBR is a good idea ?

0- the mode ($\operatorname{argmax} \mathrm{P}(v_{[1:S]} \,|\, \boldsymbol{\theta})$) *may be anomalous and risky [Eikema and Aziz, 2020]*

1- If likely solutions (high $\mathrm{P}(v_{[1:S]} \,|\, \boldsymbol{\theta})$*) have a good quality, being close to many good solutions* ($w^*_{[1:T]}$) *is also likely to have a good quality [smoothness of search space]*

2- For the one-hot dissimilarity: $\ell(w_{[1:T]}, v_{[1:S]}) = 1 - \mathbb{I}(w_{[1:T]} = v_{[1:S]})$,

$$\begin{aligned}\mathbb{E}_{v_{[1:S]} \sim P}(\ell(w_{[1:T]}, v_{[1:S]})) &= \sum_{v_{[1:S]} \neq w_{[1:T]}} \mathrm{P}(v_{[1:S]} \,|\, \boldsymbol{\theta}) \\ &= 1 - \mathrm{P}(w_{[1:T]} \,|\, \boldsymbol{\theta})\end{aligned}$$

Minimizing the risk maximizes the model probability: back to MAP !

3- The MAP maximizes a proxy quality score $\mathrm{P}(w_{[1:t]} \,|\, \boldsymbol{\theta})$*, MBR directly optimizes the true metric* $\ell()$ *instead*

See also the motivations of Bertsch et al. [2023].

Minimum Bayes Risk Decoding

Theory and Practice of MBR

Two sources of intractability

$$w^*_{[1:t]} = \operatorname*{argmin}_{T, w_{[1:t]}} \sum_{s, v_{[1:s]}} \mathrm{P}(v_{[1:s]}) \ell(w_{[1:T]}, v_{[1:S]})$$

1. $\mathrm{argmin}_{T, w_{[1:T]}}$: argmin in a very very large set
2. $\sum_{S, v_{[1:S]}}$: $\sum$ over many many terms

Minimum Bayes Risk Decoding

Theory and Practice of MBR

Two sources of intractability

$$w^*_{[1:t]} = \underset{T, w_{[1:t]}}{\text{argmin}} \sum_{s, v_{[1:s]}} \mathrm{P}(v_{[1:s]}) \ell(w_{[1:T]}, v_{[1:S]})$$

1. $\text{argmin}_{T, w_{[1:T]}}$: argmin in a very very large set
2. $\sum_{S, v_{[1:S]}}$: $\sum$ over many many terms

Two practical remedies

1. argmin in a very very large set $\Rightarrow$ restrict search to $\mathcal{W}_s$
2. $\sum$ over many many terms $\Rightarrow$ replace $\mathbb{E}()$ by Monte-Carlo approximation of size $|\mathcal{W}_{MC}|$

$$w^*_{[1:t]} = \underset{T, w_{[1:T]} \in \mathcal{W}_s}{\text{argmin}} \sum_{v_{[1:S]} \in \mathcal{W}_{MC}} \ell(w_{[1:T]}, v_{[1:S]})$$

Minimum Bayes Risk Decoding

MBR: a meta-generation algorithm

$\ell()$: Comparator function, model $\mathrm{P}(\,|\,C;\boldsymbol{\theta})$

$\mathcal{W}_{MC} \leftarrow$ **generate**$(\mathrm{P}(\,|\,\mathbf{C};\boldsymbol{\theta}), N, \dots)$
$\mathcal{W}_{S} \leftarrow$ **generate**$(\mathrm{P}(\,|\,\mathbf{C};\boldsymbol{\theta}), M, \dots)$
$mins \leftarrow +\infty$
for $w_{[1:T]} \in \mathcal{W}_S$ **do**
    $s \leftarrow 0$, $mbr \leftarrow$ <s></s>
    for $v_{[1:S]} \in \mathcal{W}_{MC}$ **do**
        $s \leftarrow s + \ell(w_{[1:T]}, v_{[1:S]})$
    end for
    if $s < mins$ **then**
        $mins \leftarrow s$, $mbr \leftarrow w_{[1:T]}$
    end if
end for

- **generate** 1: is for MC estimates: prefer sampling with replacement, unbiased (ancestral)
- **generate** 2: is to identify promising solutions: prefer beam-seach, if possible diverse

- Alternative for $\mathcal{W}_S$: reuse $\mathcal{W}_{MC}$ - back to reranking
- Alternative for $\mathcal{W}_S$: use multiple models, multiple checkpoints, multiple prompts, etc.

- Run-time is Sampling time + $O(MN)$; larger N yields better MC estimates; larger M explores a larger search space

Minimum Bayes Risk Decoding

MBR: a meta-generation algorithm

$\ell()$: Comparator function, model $\mathrm{P}(\,|\,C;\boldsymbol{\theta})$

1: $\mathcal{W}_{MC} \leftarrow$ **generate**$(\mathrm{P}(\,|\,\mathbf{C};\boldsymbol{\theta}), N, \dots)$
2: $\mathcal{W}_{S} \leftarrow$ **generate**$(\mathrm{P}(\,|\,\mathbf{C};\boldsymbol{\theta}), M, \dots)$
3: $mins \leftarrow +\infty$
4: **for** $w_{[1:T]} \in \mathcal{W}_S$ **do**
5: $\quad s \leftarrow 0$, $mbr \leftarrow$ <s></s>
6: $\quad$ **for** $v_{[1:S]} \in \mathcal{W}_{MC}$ **do**
7: $\quad\quad s \leftarrow s + \ell(w_{[1:T]}, v_{[1:S]})$
8: $\quad$ **end for**
9: $\quad$ **if** $s < mins$ **then**
10: $\quad\quad mins \leftarrow s$, $mbr \leftarrow w_{[1:T]}$
11: $\quad$ **end if**
12: **end for**

- **generate** 1: is for MC estimates: prefer sampling with replacement, unbiased (ancestral)
- **generate** 2: is to identify promising solutions: prefer beam-seach, if possible diverse

- Alternative for $\mathcal{W}_S$: reuse $\mathcal{W}_{MC}$ - back to reranking
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Better Searching for Good Solutions with MCTS

Monte-Carlo Tree Search is by [Kocsis and Szepesvári, 2006]

The problem with global scores $F(w_{[1:T]}, C)$

- Searching with $\mathrm{P}(w_{[1:T]} \,|\, \mathbf{C}; \boldsymbol{\theta})$ may yield poor / unappropriate solutions
- Ensemble-based methods (n-best reranking, MBR) require multiple inferences, no garantee of improvements

MCTS delivers solutions with a high global score, based on a estimates of $F(w_{[1:T]}, \mathrm{C})$ for partial sequences $w_{[1:t]}$.

Better Searching for Good Solutions with MCTS

Monte-Carlo Tree Search is by [Kocsis and Szepesvári, 2006]

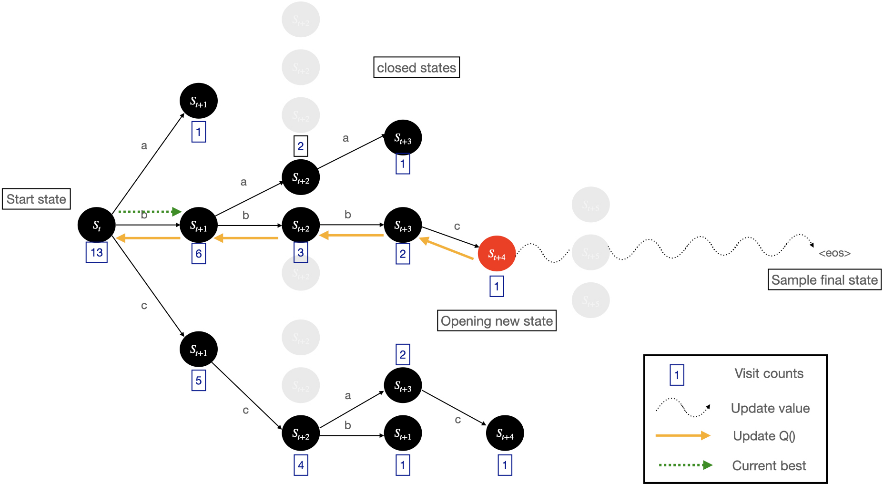
Concept and Terminology (adapted from RL / POMDP)

- State: $S_t \Leftrightarrow$ context + current prefix $\mathbf{C}, w_{[1:t]}$; $\mathcal{S}$ is the set of states (prefixes).
  States can be complete (w_T = </s>) or uncomplete.
- Actions: pick next possible token $w_{t+1} \in \mathcal{V}$
- Using action w in state S_t: yields new state $S_t \oplus w \equiv w_{[1:t+1]} = w_{[1:t]}w$
- Policy $\pi_{\boldsymbol{\theta}}$: $\mathcal{S}_t \rightarrow \mathcal{V}$; next action selection rule. For instance:
  - $\pi_{\boldsymbol{\theta}}(S_t) = \operatorname{argmax}_w \mathrm{P}(w|S_t;\boldsymbol{\theta})$: greedy policy (deterministic)
  - $\pi_{\boldsymbol{\theta}}(S_t) = w \sim \mathrm{P}(w|S_t;\boldsymbol{\theta})$: sampling policy (non-deterministic) - also top-k, top-p etc.
- Value (of a state, given policy): $v_\pi : \mathcal{S} \rightarrow \mathbb{R}$; $v_\pi(S_t)$ estimates the best score $F()$ attainable from S_t.

Use state values to obtain MC samples of local subtrees that guide the generation policy towards leaf nodes with large scores.

Better Searching for Good Solutions with MCTS

Monte-Carlo Tree Search is by [Kocsis and Szepesvári, 2006]



Generating one token with MCTS

Better Searching for Good Solutions with MCTS

Monte-Carlo Tree Search is by [Kocsis and Szepesvári, 2006]

procedure MCTS(K : int)
  $S \leftarrow S_0(\equiv \mathbf{C}, \text{<s>})$
  while !complete(S) **do**
    for K iterations **do**
      MCTS-Explore(S)
    end for
    $w^* \leftarrow \mathrm{argmax}_{w \in \mathcal{V}}\, \mathrm{cnt}(S \oplus w)$
    $S \leftarrow S \oplus w^*$
  end while
  return S
end procedure

procedure PUCT-Score(S,w)
  $U \leftarrow Q(S \oplus w)$
  $U \leftarrow U + c_{puct}\, \mathrm{P}(w \mid S; \boldsymbol{\theta}) \frac{\sqrt{\mathrm{cnt}(S)}}{1+\mathrm{cnt}(S,w)}$
  return U
end procedure

procedure MCTS-Explore(S : state)
  $\mathrm{cnt}(S) \leftarrow \mathrm{cnt}(S) + 1$
  $w^* \leftarrow \mathrm{argmax}_w$ UCT-Score(S, w)
  if $\mathrm{open}(S \oplus w^*) \wedge !\mathrm{complete}(S \oplus w^*)$ **then**
    $Q \leftarrow$ MCTS-Explore$(S \oplus w^*)$
    $Q(S) \leftarrow \max(Q(S), Q)$
  else if !complete(S) **then**
    $\mathrm{open}(S) \leftarrow$ **true**
        ▷ aggregate with max or avg
    $Q \leftarrow \mathrm{argmax}_{\mathrm{open}(S \oplus w)}\, v_\pi(S \oplus w)$
  else
    $Q \leftarrow F(S)$
  end if
  return Q
end procedure

PUCT-SCORE **trades-off high scores** (Q) **and likely, unvisited states**

Better Searching for Good Solutions with MCTS

Monte-Carlo Tree Search is by [Kocsis and Szepesvári, 2006]

Computing state values

In state S, how to estimate $v_\pi(S)$?

1. Sampling based: apply sampling using roll-out policy $\mathrm{P}(\,|S;\boldsymbol{\theta})$ (e.g. [Chaffin et al., 2022])
   return underestimates, as costly as a complete generation for each simulation.
2. Learning based: learns to predict $v_\pi(S;\lambda)$ using an auxilary network [Leblond et al., 2021]
   get complete (complete) samples $w_{[1:T]}$ and associated scores; learns to predict scores for incomplete states; this can be hard.
3. Repurpose value networks trained with reinforcement learning (PPO) during LLM alignment step [Liu et al., 2024]
   show improvements even when using PPO-tuned language models.

Generating Texts Non-Auto-Regressively

Parallel Text Generation

- Standard left-to-right / right-to-left decoding is slow
- Decoding in arbitrary order does not solve this [Welleck et al., 2019]
- Alternative: generate multiple words simultaneously
- How ? Parallel Unmasking.

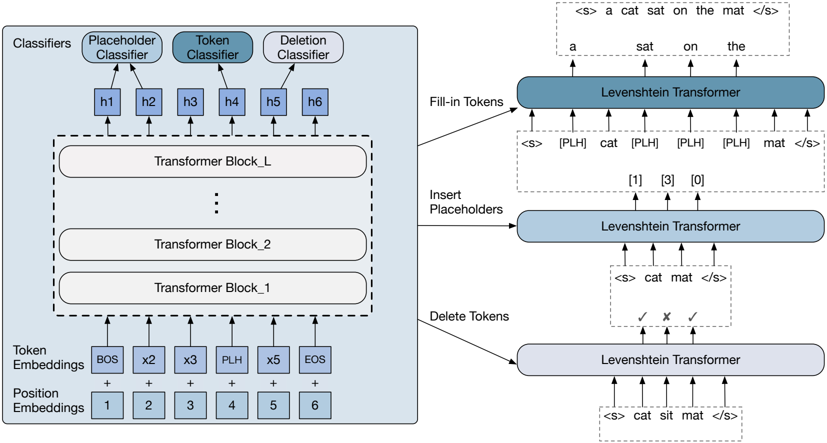
Generating Texts Non-Auto-Regressively

Mask-Predict by Ghazvininejad et al. [2019]

1: **procedure** MASK-PREDICT
    Input: $\mathbf{C}$: Context, T: Target Length
    Output: Generated Sequence
2: $\quad \forall t \in [1:T], w_t \sim \mathrm{Unif}(\mathcal{V})$
3: $\quad$ **for** K iterations **do**
4: $\quad\quad \mathrm{ToMask} \leftarrow \mathrm{top\text{-}k}_t(-\log \mathrm{P}(w_t \mid C, w_{-t}; \boldsymbol{\theta}))$
5: $\quad\quad$ **for** $(t \in \mathrm{ToMask})$ **do**
6: $\quad\quad\quad w_t \leftarrow \mathrm{MASK}$
7: $\quad\quad$ **end for**
8: $\quad\quad$ **for** $(t \in \mathrm{ToMask})$ **do**
9: $\quad\quad\quad w_t \leftarrow$ **unmask**(w_t)
10: $\quad\quad$ **end for**
11: $\quad$ **end for**
12: **end procedure**

- a better initialization samples independently given $\mathbf{C}$
- **unmask**$(l9)$ can be argmax or obtained via sampling
- T is unknown ? Generate with multiple lengths in parallel
- masking and generation can be performed in parallel
- K and k trade-offs speed and fluency
- recover Gibbs sampling with $k = 1$ and iterative masking (instead of $\mathrm{top\text{-}k}$)

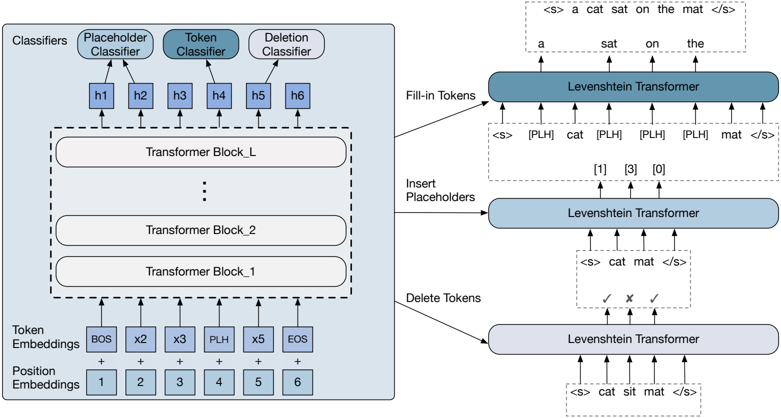
Generating Texts Non-Auto-Regressively



The Levenvshtein Transformer [Gu et al., 2019]

- “Multimodality” problem and solutions (latent alignments, KD, etc) [Xiao et al., 2023]
- Mostly used for standard translation tasks (also: term constraints [Xu and Carpuat, 2021])
- Decoding starts from scratch or initial solution [Xu et al., 2023]

Generating Texts Non-Auto-Regressively



LevT uses

3 classifiers to predict **D**eletions and **I**nsertions

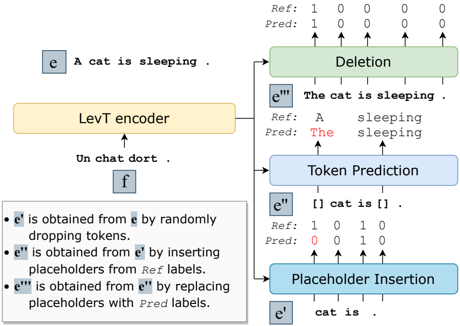
- D deletion classifier predicts $y \in \{0, 1\}$
- I placeholder classifier predicts $y \in [0 : N]$
- I token classifier predicts $y \in [1 : |V|]$

Generating Texts Non-Auto-Regressively

Training with parallel sentences (**f**, **e**)

1. erase random words in **e**, yields **t**”
2. train placeholder & token prediction with samples (**t**”, **e**), (**t**’”, **e**)
3. generate output **e**
4. train deletion prediction with (**e**, **e**)

Decode with **t**′ = <s></s>: PLH - TOK - DEL
+ repeat in iterative refinement



Dual Policy learning with:

- roll-in policy π_{ins} for [I]nsertion: empty string or random deletion from **e**
- roll-in policy π_{del} for [D]eletion: model’s Insertions
- expert policy π^* from the optimal alignment $\Leftrightarrow$ Edit Distance

An effective model for NAR Machine Translation

Generating Texts Non-Auto-Regressively

Training with parallel sentences (**f**, **e**)

1. erase random words in **e**, yields **t**”
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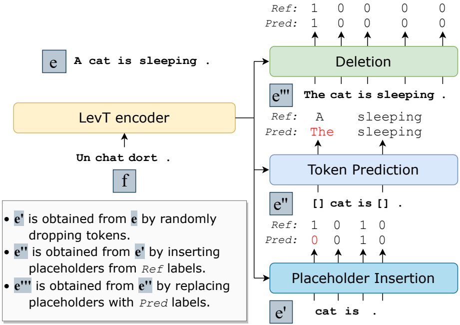

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- expert policy π^* from the optimal alignment $\Leftrightarrow$ Edit Distance

Refinement

Conclusions

Generation is Tricky

- Training procedures matter
- Generation parameter matter - both for speed and quality
- There is more than top-k and top-p

Generation is not Solved

- Generation with refinement and self-critics
- Multi-hop / text generation and planing

Conclusions

Generation is Tricky

- Training procedures matter
- Generation parameter matter - both for speed and quality
- There is more than top-k and top-p

Generation is not Solved

- Generation with refinement and self-critics
- Multi-hop / text generation and planing

Part V

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