11868 LLM Systems
Tokenization & Decoding

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Today's Topic

- How to construct a vocabulary for a large corpus
  - Tokenization: how to break text into units?

- How to generate text at inference time

Tokenization

- Break sentences into tokens, basic elements of processing
- Word-level Tokenization
  - Break by space and punctuation.
  - English, French, German, Spanish

The | most | eager | is | Oregon | which | is | enlisting | 5,000 | drivers | in | the | country | 's | biggest | experiment | .

  - Special treatment: numbers replaced by special token [number]
  - How large is the Vocabulary? Cut-off by frequency, the rest replaced by [UNK]

What is a word?

How many words?

Bob's handy man is a do-it-yourself kinda guy, isn't he?

Clitic

noun-noun compound

multi-word expression

contraction

Words

- Orthographic definition
  - strings separated by white spaces
  - spoken language: units corresponding to written word separated by pause
  - problem: Bob's handy man is a do-it-yourself kinda guy, isn't he?
- What about languages that do not use white spaces?

他昨天晚上去看了消失的她

he yesterday night watched lost in stars

Pros and Cons of Word-level Tokenization

- Easy to implement

- Cons:
  - Out-of-vocabulary (OOV) or unknown tokens, e.g. Covid
  - Tradeoff between parameters size and unknown chances.
    - Smaller vocab => fewer parameters to learn, easier to generate (deciding one word from smaller dictionary), more OOV
    - Larger vocab => more parameters to learn, harder to generate, less OOV
  - Hard for certain languages with continuous script: Japanese, Chinese, Korean, Khmer, etc. Need separate word segmentation tool (can be neural networks)

Character-level Tokenization

T	h	e	m	o	s	t	e	a	g	e	r	i	s	O	r	e	g	…

- Each letter and punctuation is a token
- Pros:
  - Very small vocabulary (except for some languages, e.g. Chinese)
  - No Out-of-Vocabulary token
- Cons:
  - A sentence can be longer sequence
  - Tokens do not representing semantic meaning

Subword-level Tokenization

The most eager is Oregon which is en listing 5,000 driver s in the country 's big g est experiment.

- Goal:
  - moderate size vocabulary
  - no OOV

- Idea:
  - represent rare words (OOV) by sequence of subwords

- Byte Pair Encoding (BPE)
  - not necessarily semantic meaningful
  - Originally for data compression Philip Gage. A New Algorithm for Data Compression, 1994

Byte-Pair-Encoding Tokenization

1. starting from chars
2. repeatedly, merge most frequent pairs to form new tokens
3. until reaching a fixed size.

raw word	freq.
cat	90
catch	50
rat	80
rattle	40

a c e h l t

→ merge ('a', 't') →

a c e h l t at

→ merge ('c', 'at') →

a c e h l t at cat

→ merge ('r', 'at') →

a c e h l t at cat rat

→ merge ('cat', 'c') →

a c e h l t at cat rat catc

Neural Machine Translation of Rare Words with Subword Units. Sennrich et al. ACL 2016

Byte Pair Encoding (BPE) for Text Tokenization

1. Initialize vocabulary with all characters as tokens (also add end-of-word symbol) and frequencies

2. Loop until vocabulary size reaches capacity
   1) Count successive pairs of tokens in corpus
   2) Rank and select the top frequent pair
   3) Combine the pair to form a new token, add to vocabulary

3. Output final vocabulary and tokenized corpus

Rico Sennrich et al. Neural Machine Translation of Rare Words with Subword Units. 2016

More Subword Tokenization

- BBPE: byte-level BPE (universal for all languages)
- Wordpiece:
  - like BPE
  - but instead of merge with most frequent pairs, merge a and b, if p(b|a) will be maximized
- SentencePiece:
  - Uniform way to treat space, punctuation
  - Use the raw sentence, replacing space ‘ ’ with _ (U+2581)
  - Then split character and do BPE

Kudo and Richardson, SentencePiece, 2018

Find Optimal Vocabulary

Numerous possible vocabularies at the sub-word level.

Normalized Entropy

Vocab
1k tokens

Vocab
10k tokens

Vocab
30k tokens

Size

Which one leads to better NLG/MT performance?

Repeated full training and testing are required to find the optimal vocabulary!(BPE-Search)

Xu, Zhou, Gan, Zheng, **Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a.

VOLT: Using entropy to learn vocabulary

- Normalized Entropy (modified based on Information Entropy) $\mathcal{H}(v) = -\frac{1}{l_v}\sum_{i\in v} P(i)logP(i)$

token prob.

l_v: average number of chars for v's all tokens

- It me… …antic-information-per-char
  - Sm… …able. Less ambiguity and e… …ate

Token	count
a	200
e	90
c	30
t	30
s	90

$\mathcal{H}(v) = 1.37$

Token	count
a	100
aes	90
cat	30

$\mathcal{H}(v) = 0.14$

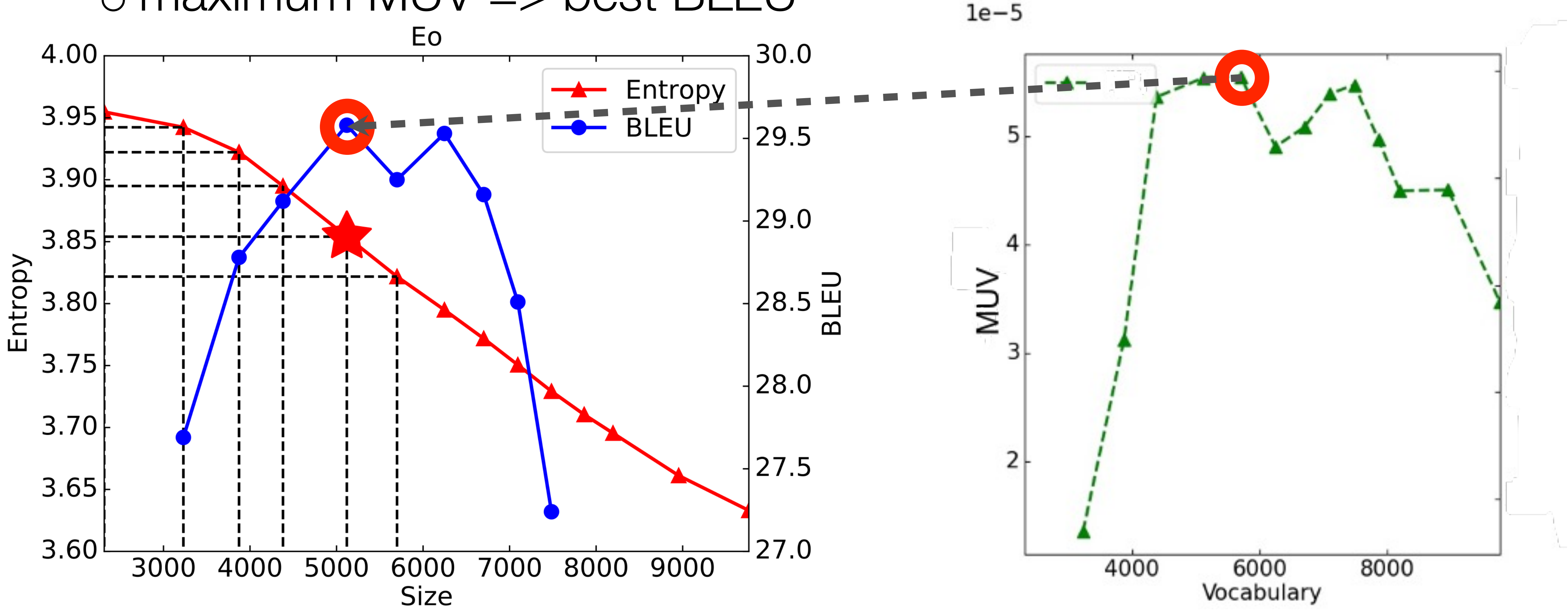
MUV: Utility of Information for Adding Tokens

- Value: Normalized Entropy
- Cost: Size
- Marginal Utility of information for Vocabulary (MUV)
  - $M_{v_k \to v_{k+m}} = -\frac{H(v_k) - H(v_{k+m})}{m}$
  - Negative gradients of normalized entropy to size
  - How much value each token brings

Xu, Zhou, Gan, Zheng, **Lei Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a

MUV is good indicator for MT performance

- Cost-effective point in MUV curve
  - maximum MUV => best BLEU

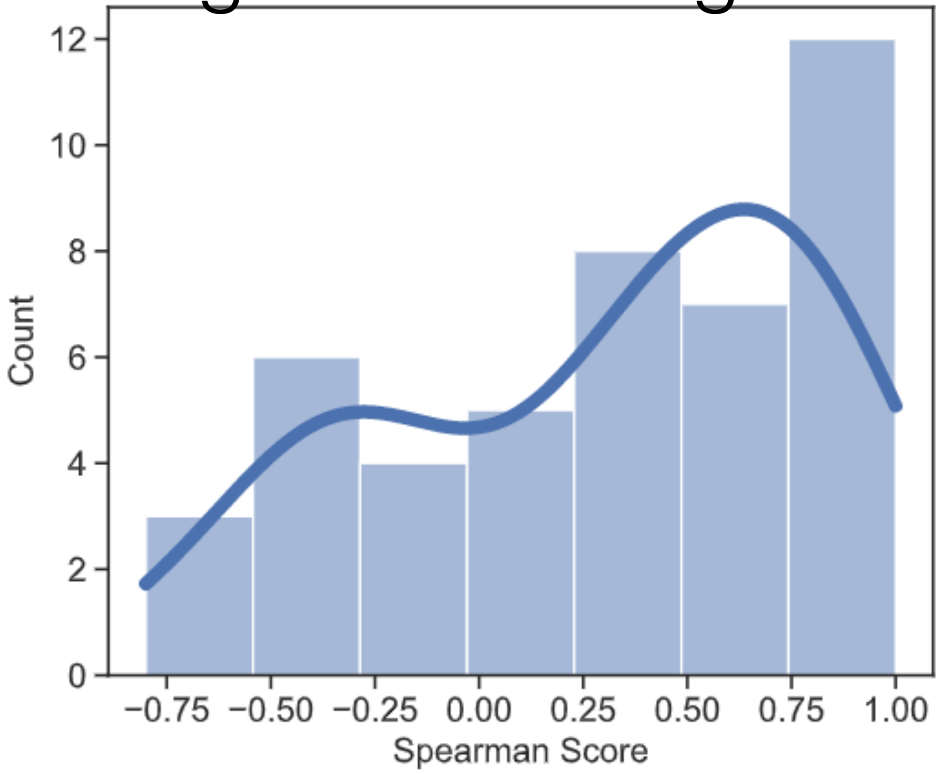


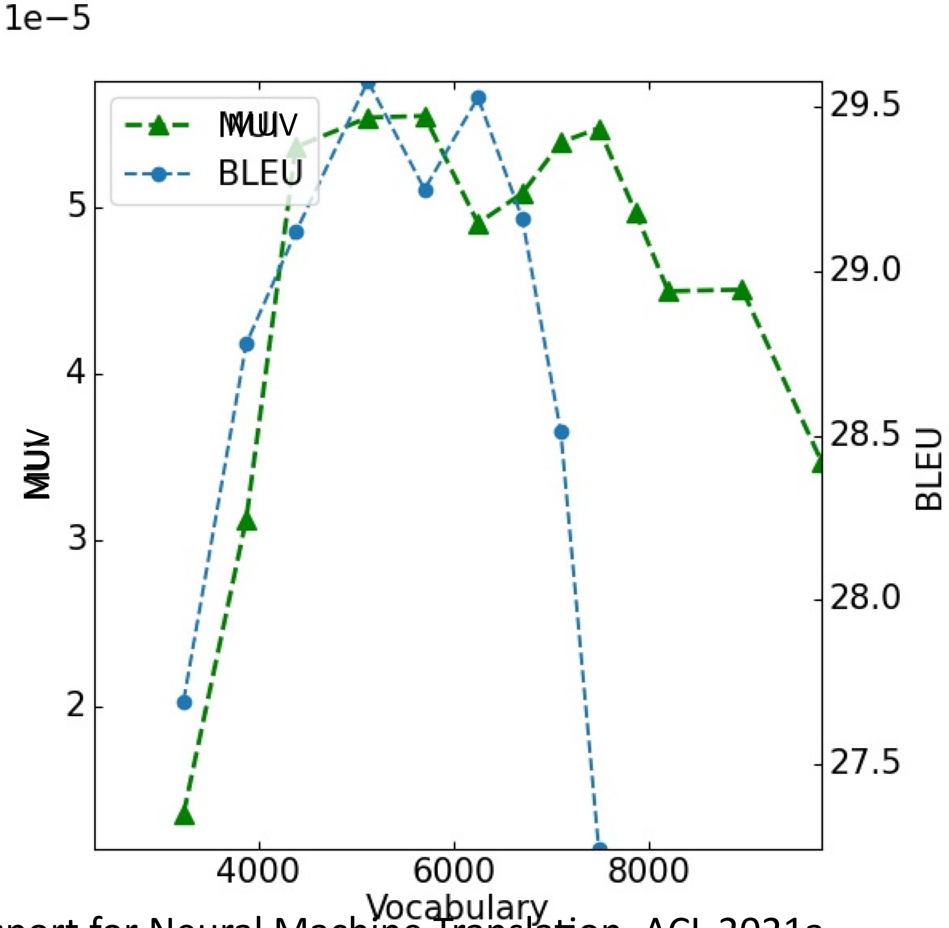
Xu, Zhou, Gan, Zheng, **Lei Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a

MUV Indicates MT Performance

- MUV and BLEU are correlated on two-thirds of tasks

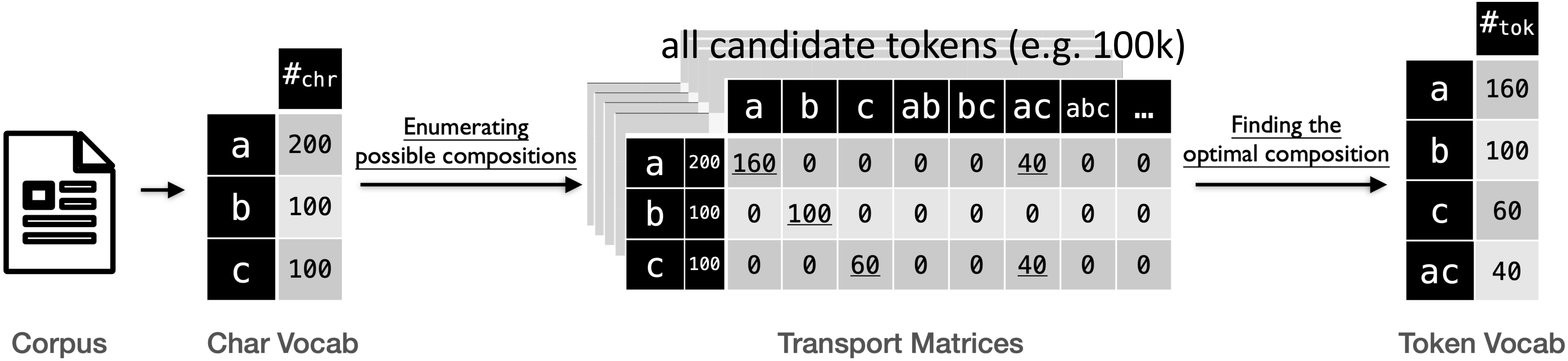
- A good coarse-grained evaluat





Xu, Zhou, Gan, Zheng, **Lei Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a

VOLT: Vocabulary Building via Transportation



- Maximizing MUV for vocabulary
  - $max - (H(V_{t+1}) - H(V_t))$

- Instead, maximizing the lower bound ==> Optimal Transport
  - $\max_t (maxH(V_t) - maxH(V_{t+1}))$

Xu, Zhou, Gan, Zheng, **Lei Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a

Reducing MUV Optimization to OT

- The vocabulary with the maximum MUV
    - Maximum gap between IPC of a vocabulary (with size t) and that of a smaller vocabulary (with size <t)
    - $max - (H(V_{t+1}) - H(V_t))$
- Intractable, instead to maximize lower-bound
- ==> $\max_t (maxH(V_t) - maxH(V_{t+1}))$
- Finding $\max_v H(v)$ ==> Optimal Transport

Xu, Zhou, Gan, Zheng, Li. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021

VOLT: Finding the Optimal Vocabulary

- Entropy-regularized Optimal Transport

$$\min_{P\in\mathbb{R}^{m\times n}} \langle D,P\rangle - H(P)$$

subject to

$$\forall i \in Char,\ \sum_{j\in V_n} P_{i,j} = \hat{P}(i)$$

$$\forall j \in V_n,\ |\sum_{i\in Char} P_{i,j} - \hat{P}(j)| = \epsilon$$

Transportation matrix P

Char \ Tok	a	ab	bc
a	$P_{a,a}$	$P_{a,ab}$	$P_{a,bc}$
b	$P_{b,a}$	$P_{b,ab}$	$P_{b,bc}$
c	$P_{c,a}$	$P_{c,ab}$	$P_{c,bc}$

Cost matrix D

Char \ Tok	a	ab	bc
a	0	$\ln 2$	∞
b	∞	$\ln 2$	$\ln 2$
c	∞	∞	$\ln 2$

- Sinkhorn's algorithm (from [Sinkhorn 1967])

Xu, Zhou, Gan, Zheng, **Lei Li**. Vocabulary Learning via Optimal Transport for Neural Machine Translation. ACL 2021a

Encoding and Decoding with VOLT

- VOLT uses a greedy strategy to encode text with a constructed sub-word level vocabulary similar to BPE.

- The vocabulary includes all basic characters.
  - To encode text, it first splits sentences into character-level tokens.
  - Then, we merge two consecutive tokens into one token if the merged one is in the vocabulary solved by OT.
  - This process keeps running until no tokens can be merged.
  - Out-of-vocabulary tokens will be split into smaller tokens.

Code Example

- https://github.com/llmsystem/llmsys_code_examples/blob/main/tokenization/tokenization.ipynb

Sequence Decoding

$$\underset{y}{\mathrm{arg}max}P(y|\mathrm{x}) = f_\theta(x, y)$$

- naive solution: exhaustive search
  - too expensive
- Sampling
- Beam search
  - (approximate) dynamic programming

Sampling

- Instead of $\mathrm{argmax}_{\mathrm{y}} P(y|x) = f_\theta(x, y)$
- Generate samples of translation Y from the distribution P(Y|X)
- Q: how to generate samples from a discrete distribution?

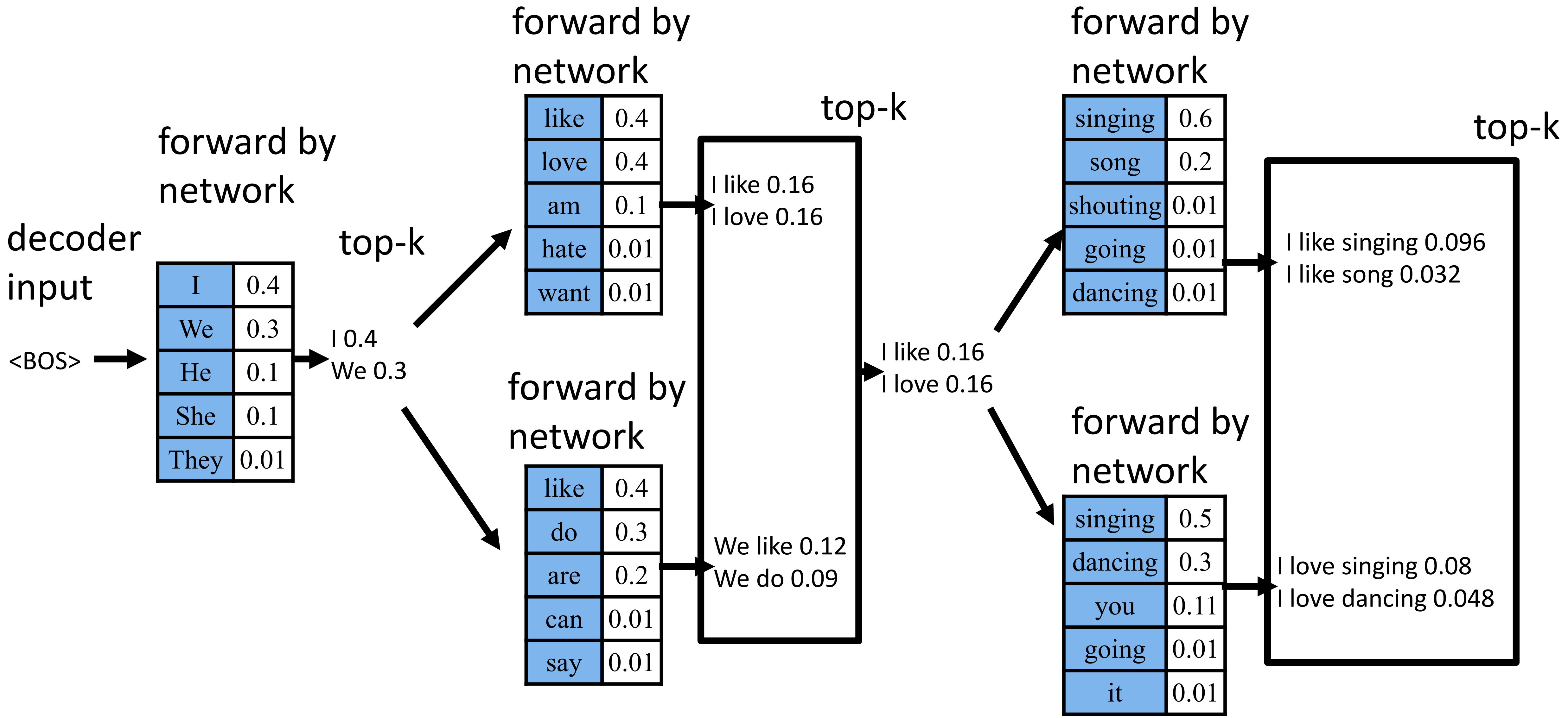
Discrete Sampling

- sample n value x from k categories, with prob. p1, p2, … pk
- Direct sampling: O(nk)
- BinarySearch: O(k + n logk)
- Alias sampling: O(k logk + n)

Beam Search

1. start with empty S
2. at each step, keep k best partial sequences
3. expand them with one more forward generation
4. collect new partial results and keep top-k

Beam Search



decoder input
<BOS>
forward by network
I 0.4
We 0.3
He 0.1
She 0.1
They 0.01
top-k
I 0.4
We 0.3
forward by network
like 0.4
love 0.4
am 0.1
hate 0.01
want 0.01
forward by network
like 0.4
do 0.3
are 0.2
can 0.01
say 0.01
top-k
I like 0.16
I love 0.16
We like 0.12
We do 0.09
I like 0.16
I love 0.16
forward by network
singing 0.6
song 0.2
shouting 0.01
going 0.01
dancing 0.01
forward by network
singing 0.5
dancing 0.3
you 0.11
going 0.01
it 0.01
top-k
I like singing 0.096
I like song 0.032
I love singing 0.08
I love dancing 0.048

Beam Search (pseudocode)

```
best_scores = []
add {[0], 0.0} to best_scores # 0 is for
beginning of sentence token
for i in 1 to max_length:
  new_seqs = PriorityQueue()
  for (candidate, s) in best_scores:
    if candidate[-1] is EOS:
      prob = all -inf
      prob[EOS] = 0
    else:
      prob = using model to take candidate and
compute next token probabilities (logp)
```

Pruning for Beam Search

- Relative threshold pruning
  - prune candidates with too low score from the top one
  - Given a pruning threshold rp and an active candidate list C, a candidate cand ∈ C is discarded if: score(cand) ≤ rp ∗ max{score(c)}
- Absolute threshold pruning:
  - score(cand) ≤ max{score(c)} – ap
- Relative local threshold pruning

Freitag & Al-Onaizan. Beam Search Strategies for Neural Machine Translation. 2017.

Combine Sample and Beam Search

- Sample the first tokens
- continue beam search for the later
- why?

Code example

- https://github.com/llmsystem/llmsys_code_examples/blob/main/decoding/decoding.ipynb https://belladoreai.github.io/llama-tokenizer-js/example-demo/build/

Question

- How to implement tokenization efficiently?

- Some idea:
    - Binary search
    - Max heap

Project

- https://llmsystem.github.io/llmsystem2024spring/docs/Projects
- Proposal due: 2/28
  - You are highly encouraged to discuss your project with TAs
- Mid term Report: 4/1
- Poster Project Presentation: 4/29
- Final Report: 4/30

Project Proposal

- What LLM System problem are you planning to address?
  - what are the **system challenges**?
- What are the existing state-of-art methods on this problem? Is the source code/model available?
- Possible directions for going forward.
- How do you evaluate the performance? what kind of workload?
- Who is your team and how are you planning to split the workload between team members?
- A rough timeline/milestones
- What CPU, GPU and storage infrastructure do need for this project? Please estimate the amount of computation time required.

Project Report Requirement

- Introduction/Motivation: This essentially lays out the problem definition, motivation, talks about why we need to work on it, the key contributions expected/presented in the work.
- Related Work/Background: This talks about key papers/works that provide context to your current work. Instead of listing down multiple past works, talk about the ones that minimally differ from your work, and how.
- Methodology: This section talks about your method, raises research questions and how you are going to address them.
- Experiments: This section can describe your experiments and the results you obtain.
- Analysis/Ablations: Typically, you would have multiple factors involved in your experimental setting. Analysis sections help you probe deeper into the results and help piece out contributions from individual modeling decisions made.
- Conclusion/Discussion: This would list the main takeaways from your work, discuss some future ideas (if any) and engage in discussion.
- Limitations: This section lays out some known limitations of your work.
- [final report only] Team Member Contributions List out each individual's contributions in this section.