Announcement (0218)

- HW Schedule/Organizational Changes
  - HW3 Due date move → Now due Mar 4
  - HW3 is now a team homework → Only one member of your project team needs to submit
  - All homeworks now have 3 weeks to complete (except for HW6 which is a shorter homework and has only 2 weeks). See course site/canvas for date changes
- My Office Hours is moved this week from Friday to Wednesday (at the same time – 3pm).
- No Lecture this Thursday

Announcement (0218)

- Project Brainstorm
  - Brainstorming due today (Feb. 18)
  - This needs to be in today to receive proper review by instructors for your proposal pitch next week.
  - Reviews of project brainstorm will be released by tomorrow around 2pm after TAs/myself review them.
  - Reviews of your brainstorming will consist of the following
    - ✓ Which ideas are best to pursue. Suggestions on how to better pursue them
    - ✓ Who your 2 mentors are.
    - ✓ Which group you are a part of (A or B). This will dictate which days you present the proposal pitch and the final presentation (next slide)

Announcement (0218)

- Project Proposal Pitch
  - To be held next week (Feb 25 & 27)
  - ~3mins discussion of topic, ~5mins of questions and follow-up
  - Groups assigned to Group A will present on Feb 25
  - Groups assigned to Group B will present on Feb 27
  - Before the presentation ***you must*** upload a slide describing your pitch which includes discussion on the comments we present to your initial brainstorming
    - ✓ Group A slides post here → Group A
    - ✓ Group B slides post here → Group B

Pitch Slide Template

Idea Name

Name 1, Name 2, ...

This is a template slide. Don't delete or move.

Team Name/Mentor 1, Mentor 2

Problem Definition

Just an example

Data/Methods/etc.

Just an example

Plan Forward / Preliminary Results if Any

Just an example. Feel free to add pictures etc!

Some questions for your audience

Just an example

CSCI 5541: Natural Language Processing

Lecture 7: Language Models: Search and Decoding Algorithms

computer science
& engineering

MINNESOTA NLP EST. 2021

University of Minnesota
Driven to Discover®

Outline

- Review
- Search
  - Basics
  - Greedy Search
  - Beam Search
  - Fixing Model Errors in Search
- Sampling
  - Top-k Sampling
  - Top-p Sampling
- Search in Training

Review

(***N-Grams*** to ***Neural LMs*** to ***RNNS*** to ***LSTMS*** to ***Seq2Seq***

Estimation from data

Recap

Uni-gram

$$\prod_{i=1}^{n} P(w_i) \times P(STOP)$$

Bi-gram

$$\prod_{i=1}^{n} P(w_i \mid w_{i-1}) \times P(STOP \mid w_n)$$

Tri-gram

$$\prod_{i=1}^{n} P(w_i \mid w_{i-2}, w_{i-1}) \times P(STOP \mid w_{n-1} w_n)$$

Use the counts of words, pairs of words and groups of three words

$$\frac{c(w_i)}{N}$$

$$\frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

$$\frac{c(w_{i-2}, w_{i-1}, w_i)}{c(w_{i-2}, w_{i-1})}$$

Neural LM

Recap

Simple feed-forward multilayer perceptron
(e.g., one hidden layer)

$$x = [v(w_1); \ldots v(w_k)]$$

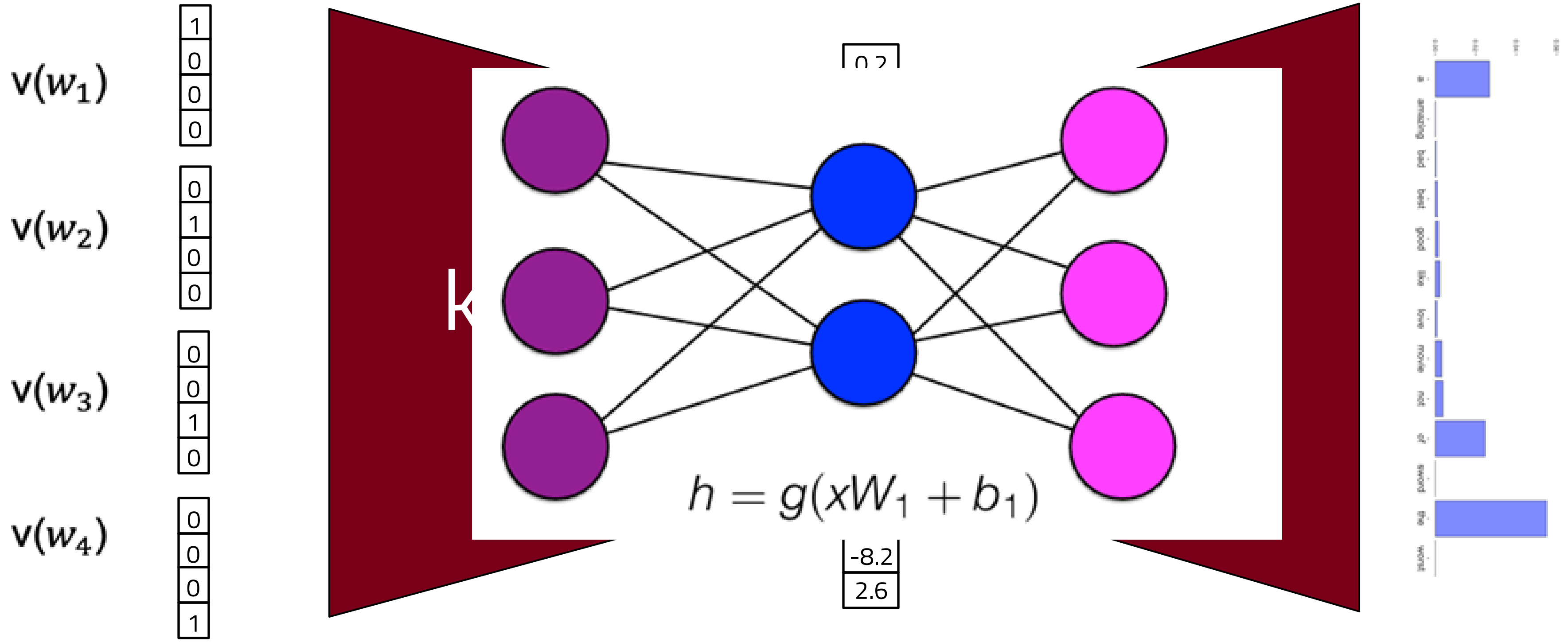
Concatenation (k x V)

w_1 = tried

w_2 = to

w_3 = prepare

w_4 = midterms



One-hot encoding

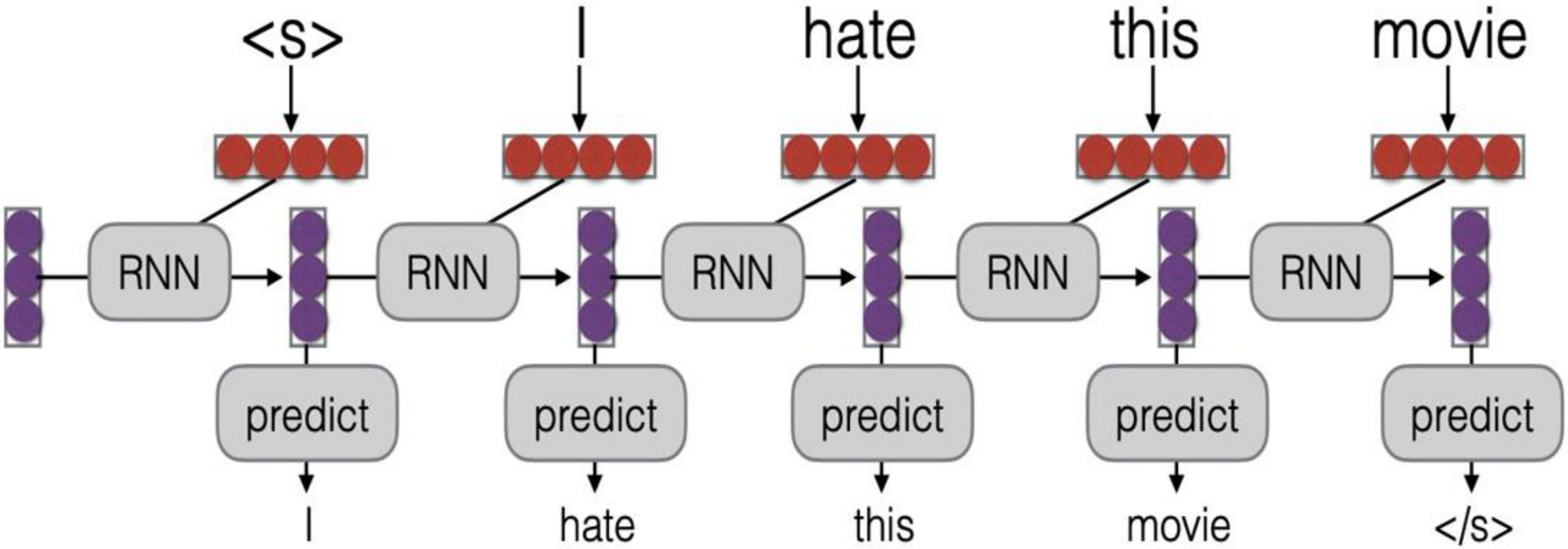
Distributed representation

Multi-class (Vocab) classification

Bengio et al. 2003, A Neural Probabilistic Language Model

RNN (Recurrent Neural Network)

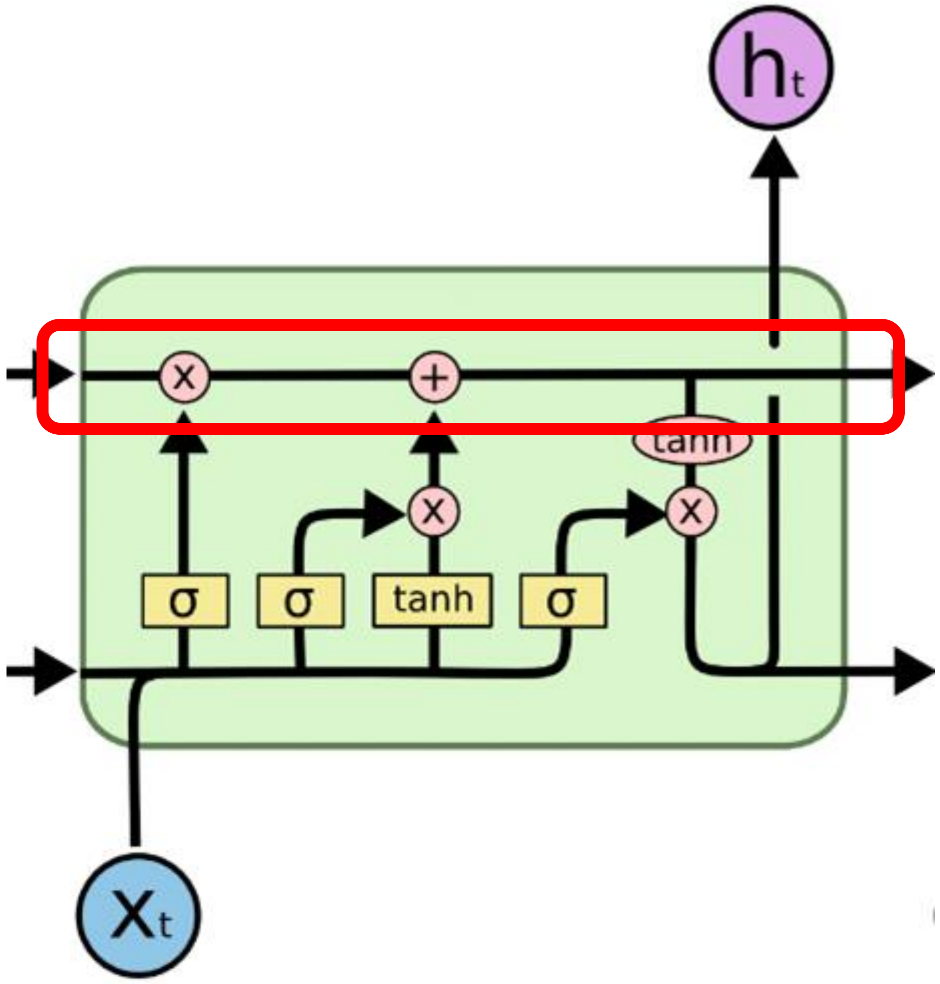
- Language modeling is like a tagging task, where each tag is the next word!



LSTMs (Long Short Term Memory)

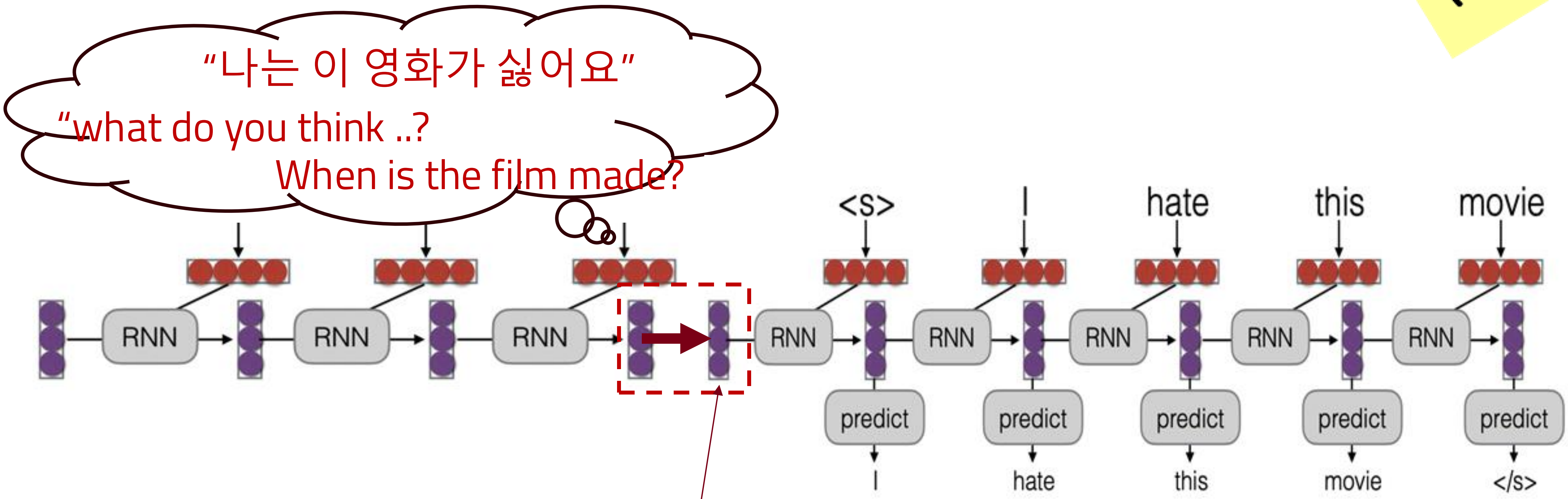
Recap

- The Cell State is an information highway
- Gradient can flow over this without nearly as many issues of vanishing/exploding gradients that we saw in RNNs
- We are doing a better job at reducing the 'distance' between our loss function and each individual parameter



Seq2Seq (Encoder-Decoder)

Recap



Encoder: encoding input sequence

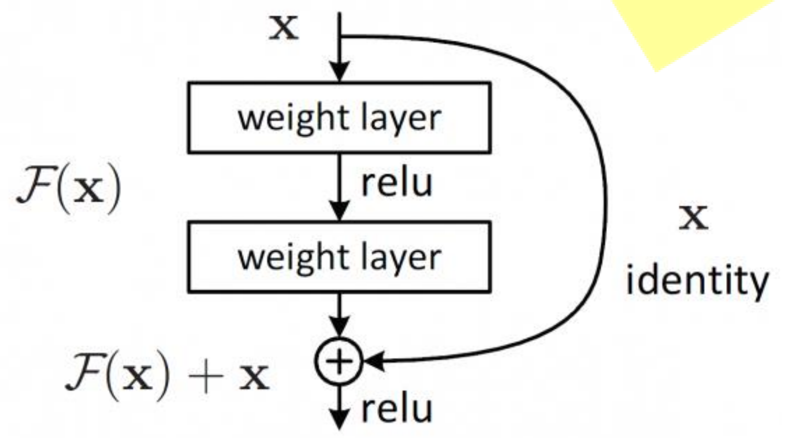
Input context

Decoder: decoding output sequence

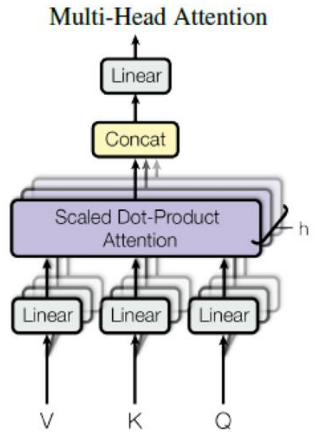
Linearization and Det-Bottlenecking

Recap

- Linearization → We need a better way to reduce the number of operations performed between our weights and our loss function (Residual connections)



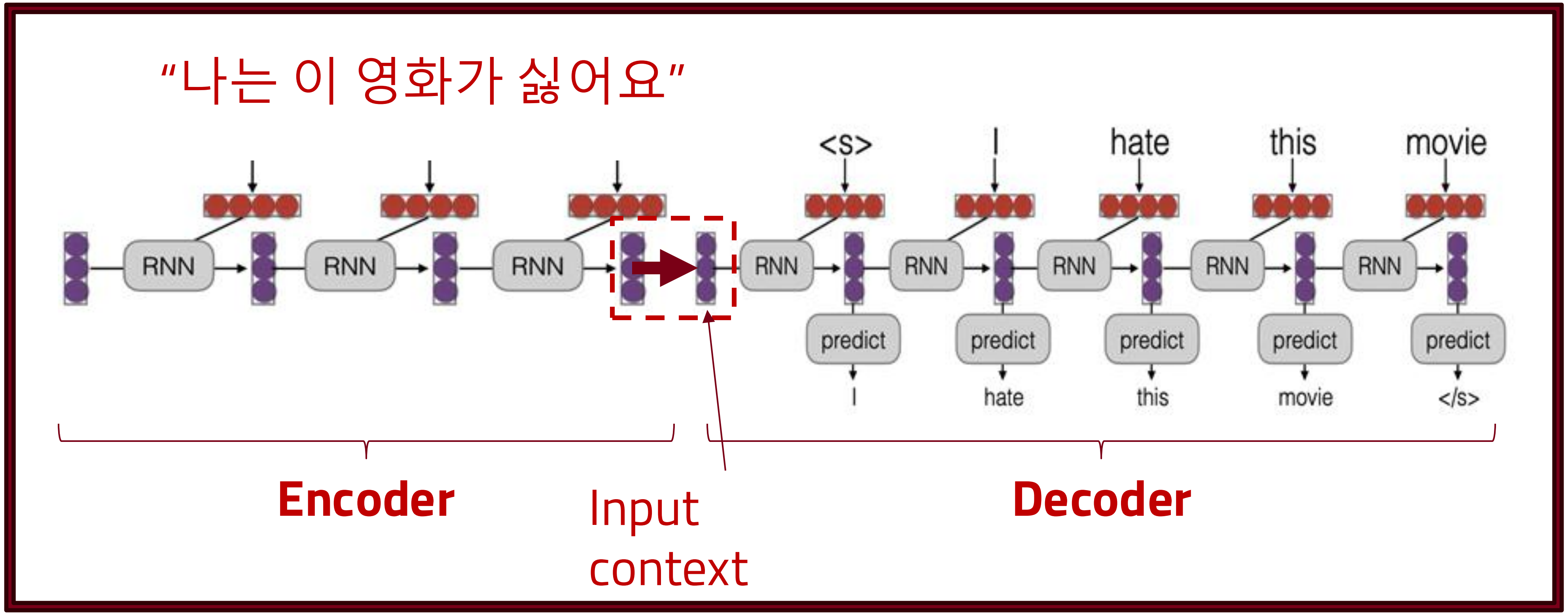
- De-Bottlenecking → We need a better way to ensure we are not bottlenecking any representations into some channel which is too small to contain all the information we need (Attention mechanism → later)



Peeking ahead to Transformers

Recap

The input context serves as a significant bottleneck. Most modern language models (transformers) implement some improvements upon this → We'll revisit this in the coming weeks



Search and Decoding

- *greedy decoding* by calling greedy_search() if `num_beams=1` and `do_sample=False`.
- *multinomial sampling* by calling sample() if `num_beams=1` and `do_sample=True`.
- *beam-search decoding* by calling beam_search() if `num_beams>1` and `do_sample=False`.
- *beam-search multinomial sampling* by calling beam_sample() if `num_beams>1` and `do_sample=True`.
- *diverse beam-search decoding* by calling group_beam_search(), if `num_beams>1` and `num_beam_groups>1`.
- *constrained beam-search decoding* by calling constrained_beam_search(), if `constraints!=None` or `force_words_ids!=None`.

https://huggingface.co/docs/transformers/main_classes/text_generation

Notation

$$P(x_j \mid x_1, \dots x_{j-1})$$

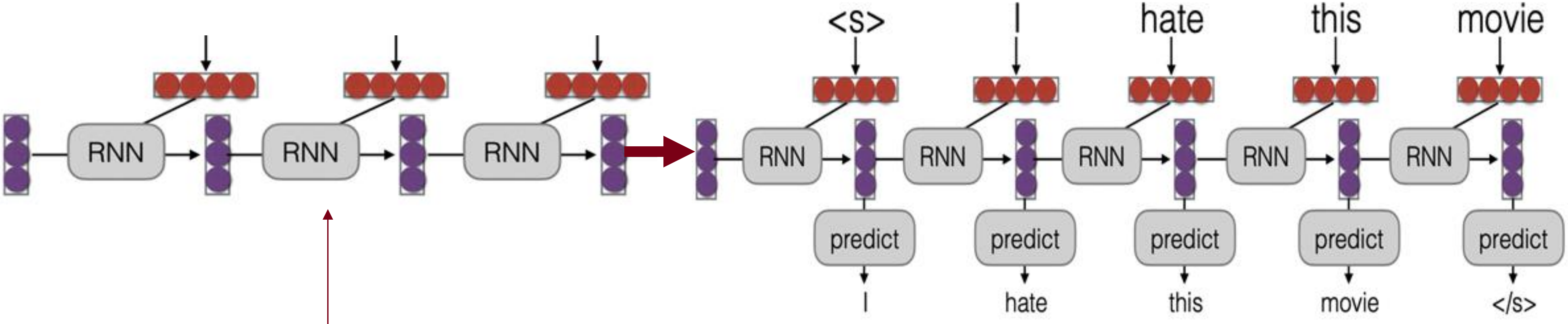
Context given and previous text generated

$$P(Y_j \mid X, y_1, \dots y_{j-1})$$

Context given in seq2seq setup

Previous text generated

Notation



$P(x_j \mid x_1, \ldots x_{j-1})$

$P(Y_j \mid X, y_1, \ldots y_{j-1})$

Search

Generation Problem

- We have a language model of $P(Y|X)$ trained on text corpora, how do we use it to generate a sentence?
- Two methods:
  - We want the best possible single output
    - ✓ **Search** (Argmax): Try to generate the sentence with the highest probability.

$$Y_j = argmax\ P\left(Y_j \middle| X, y_1 \ldots y_{j-1}\right)$$

  - We want to observe multiple outputs according to the probability distribution
    - ✓ **Sampling**: Try to generate a random sentence according to the probability distribution.

$$Y_j = \text{sampling from } P\left(Y_j \middle| X, y_1 \ldots y_{j-1}\right)$$

Generation Problem

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$$Y_j = argmax\, P(Y_j | X, y_1 \ldots y_{j-1})$$ ← Deterministic

  - We want to observe multiple outputs according to the probability distribution
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$$Y_j = \text{sampling from } P(Y_j | X, y_1 \ldots y_{j-1})$$ ← Probabilistic

Search Basics

We want to find the **best** output

- ❑ The **most accurate** output

→ impossible! we don't know the reference

- ❑ The **most probable** output according to the model

→ simple, but not necessarily tied to accuracy. Can be computationally demanding

$$\hat{Y} = \underset{\tilde{Y}}{\operatorname{argmin}}\ \operatorname{error}(Y, \tilde{Y})$$

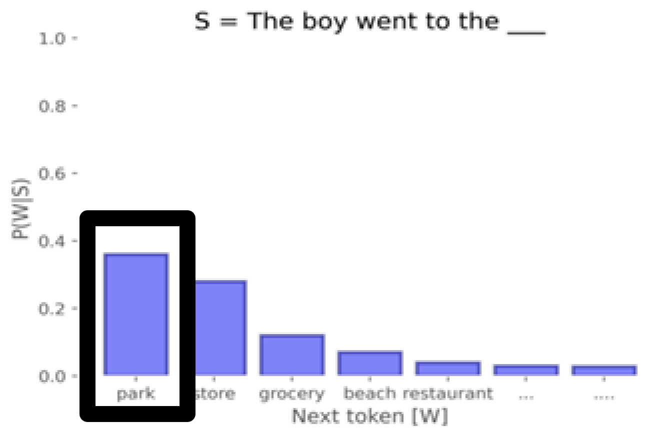
$$\hat{Y} = \underset{\tilde{Y}}{\operatorname{argmax}}\ P(\tilde{Y}|X)$$

Greedy Search

- One by one, pick the single highest-probability word

$$While\, Y_{j-1} \; != \; < STOP >$$
$$Y_j = argmax\, P(Y_j \mid X, y_1, \ldots y_{j-1})$$

- Not exact, real problems:
  - Will often generate the easy words first
  - Will prefer multiple common words to one rare word
  - May not generate highest probability sequence

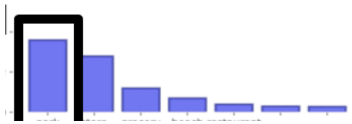


Greedy methods get repetitive

$$Y_j = argmax\ P(Y_j \,|X, y_1, \dots y_{j-1})$$

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…**



Problems w/ Disparate Search Difficulty

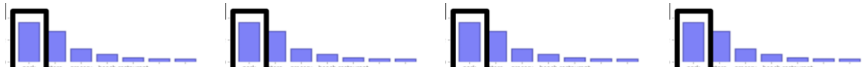
$$Y_j = argmax\ P(Y_j \,|X, y_1, \dots y_{j-1})$$

- Sometimes need to cover specific content, some easy some hard

I	saw	the escarpment
watashi	*mita*	*dangai? zeppeki? kyushamen? iwa?*

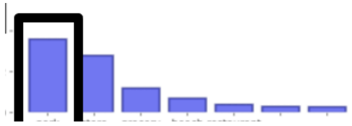
- Can cause the search algorithm to select the easy thing first, then hard thing later

watashi wa dangai wo mita (I saw the escarpment)	*watashi ga mita dangai* (the escarpment I saw)



Problems w/ Multi-word Sequences

$$Y_j = argmax\ P(Y_j \mid X, y_1, \dots y_{j-1})$$



Next word	P(next word)
Pittsburgh	0.4
New York	0.3
New Jersey	0.25
Other	0.05

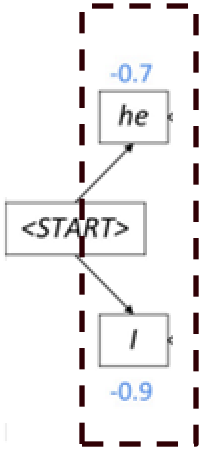
P(Pittsburgh|...) = 0.4

P(New|...) = 0.55

Beam Search

- Instead of picking the highest probability/score, maintain multiple paths (beam size)

- At each time step
  - Expand each path until <STOP>
  - Choose a subset paths from the expanded set



Beam size (k) = 2

Blue numbers = $score\ (y_1 \dots y_t)$

$= \prod_{i=1}^{t} \log P_{LM}(y_i | y_1 \dots y_{i-1}, x)$

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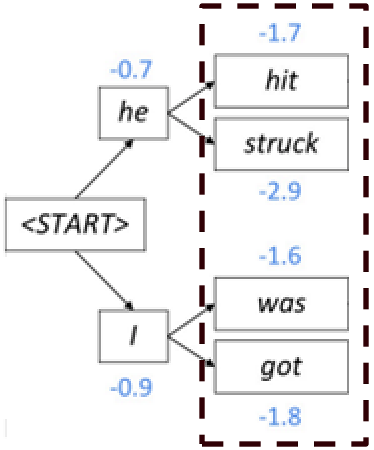

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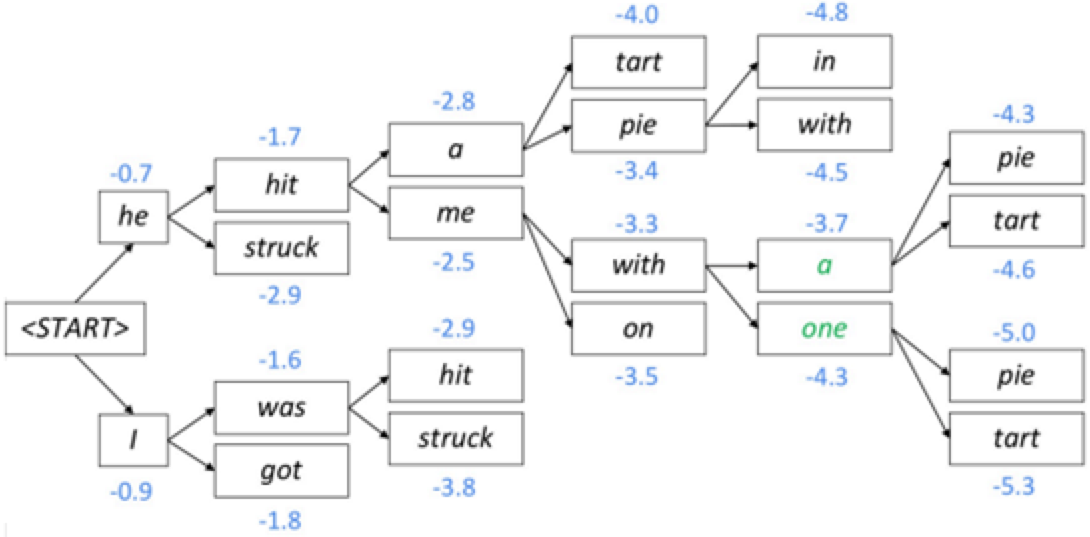

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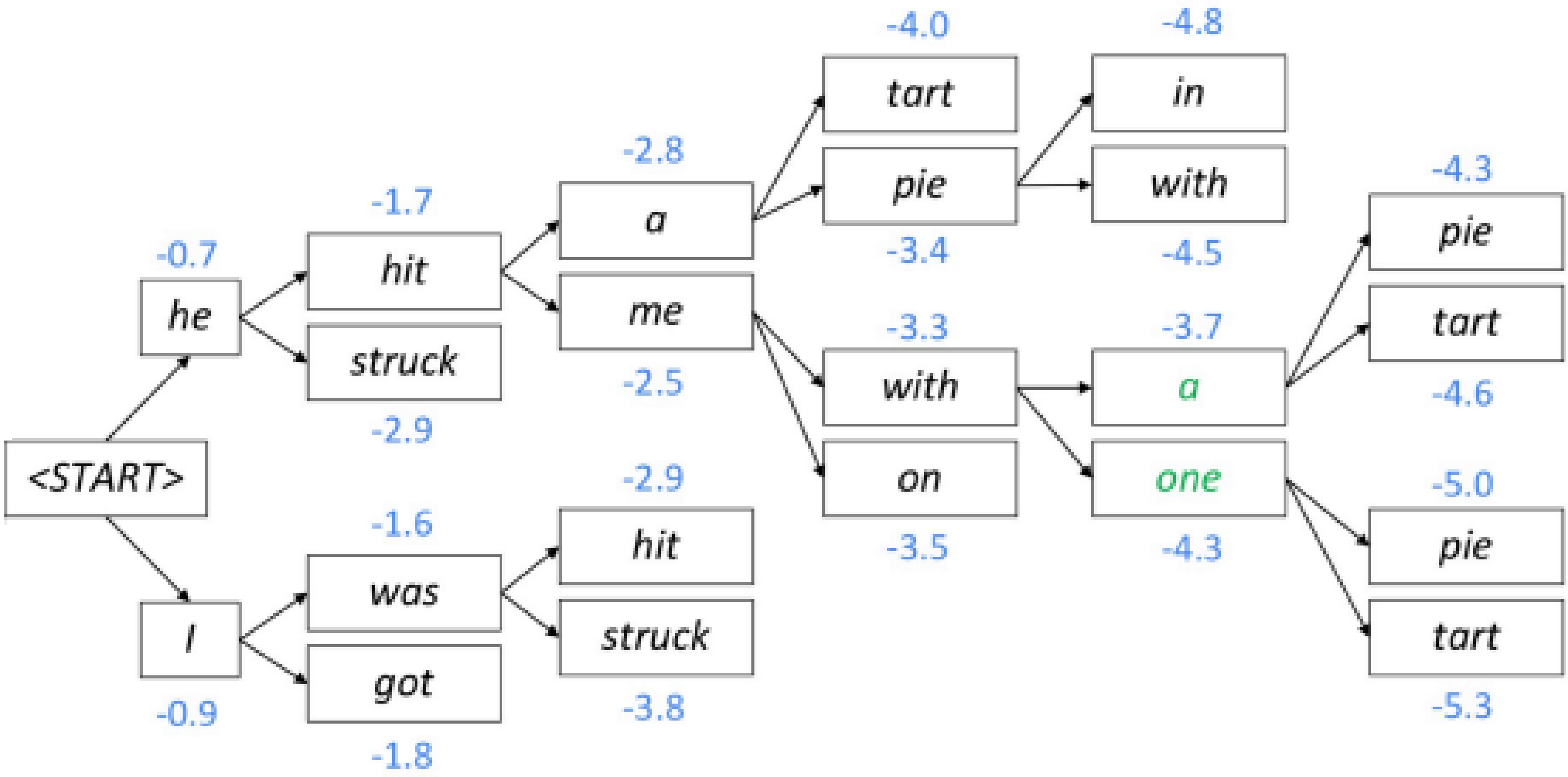
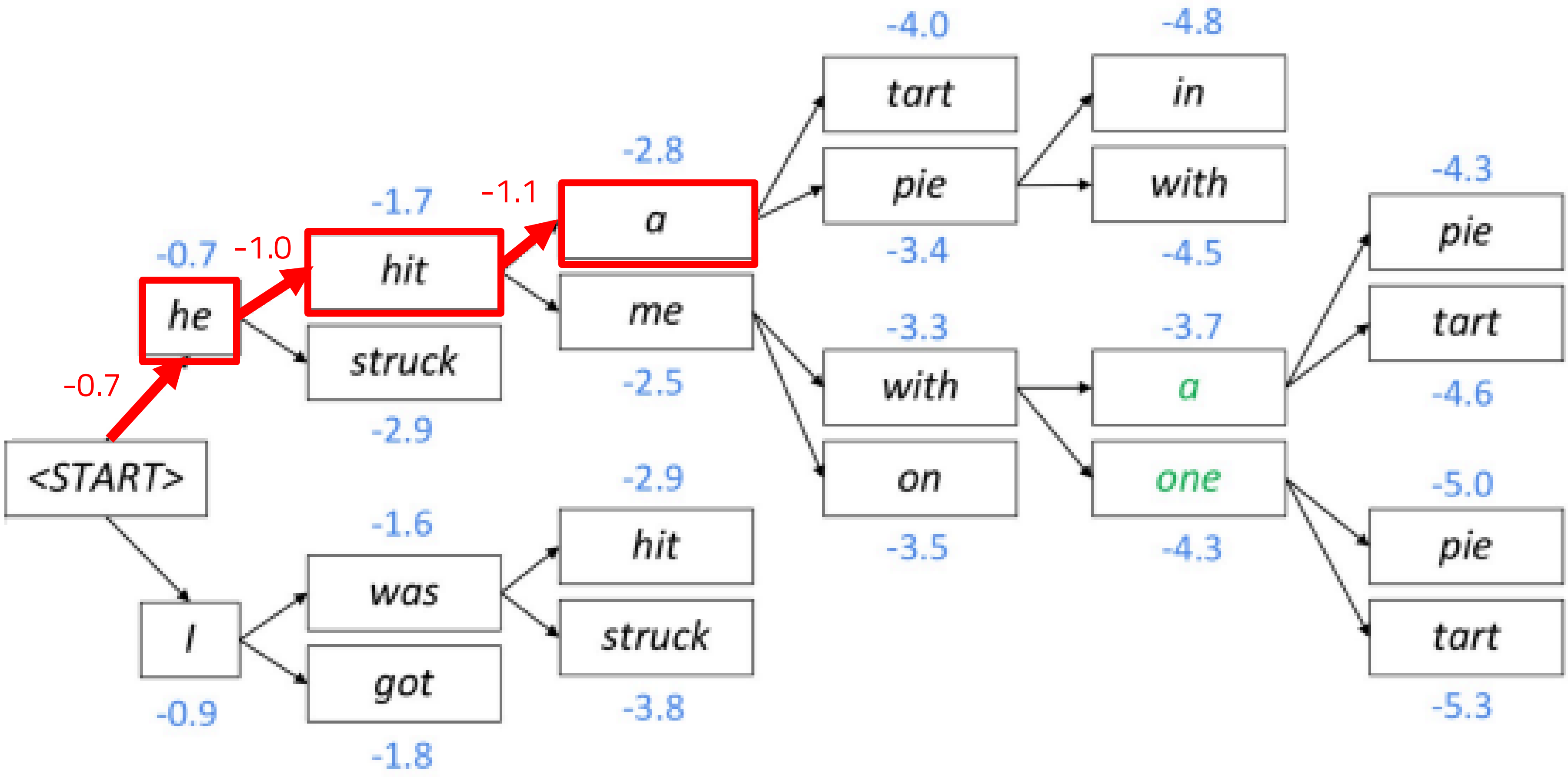

<START>
-0.7
he
-0.9
I
-1.7
hit
struck
-2.9
-1.6
was
got
-1.8
-2.8
a
me
-2.5
-2.9
hit
struck
-3.8
-4.0
tart
pie
-3.4
-3.3
with
on
-3.5
-4.8
in
with
-4.5
-3.7
a
one
-4.3
-4.3
pie
tart
-4.6
-5.0
pie
tart
-5.3


<START>
-0.7
he
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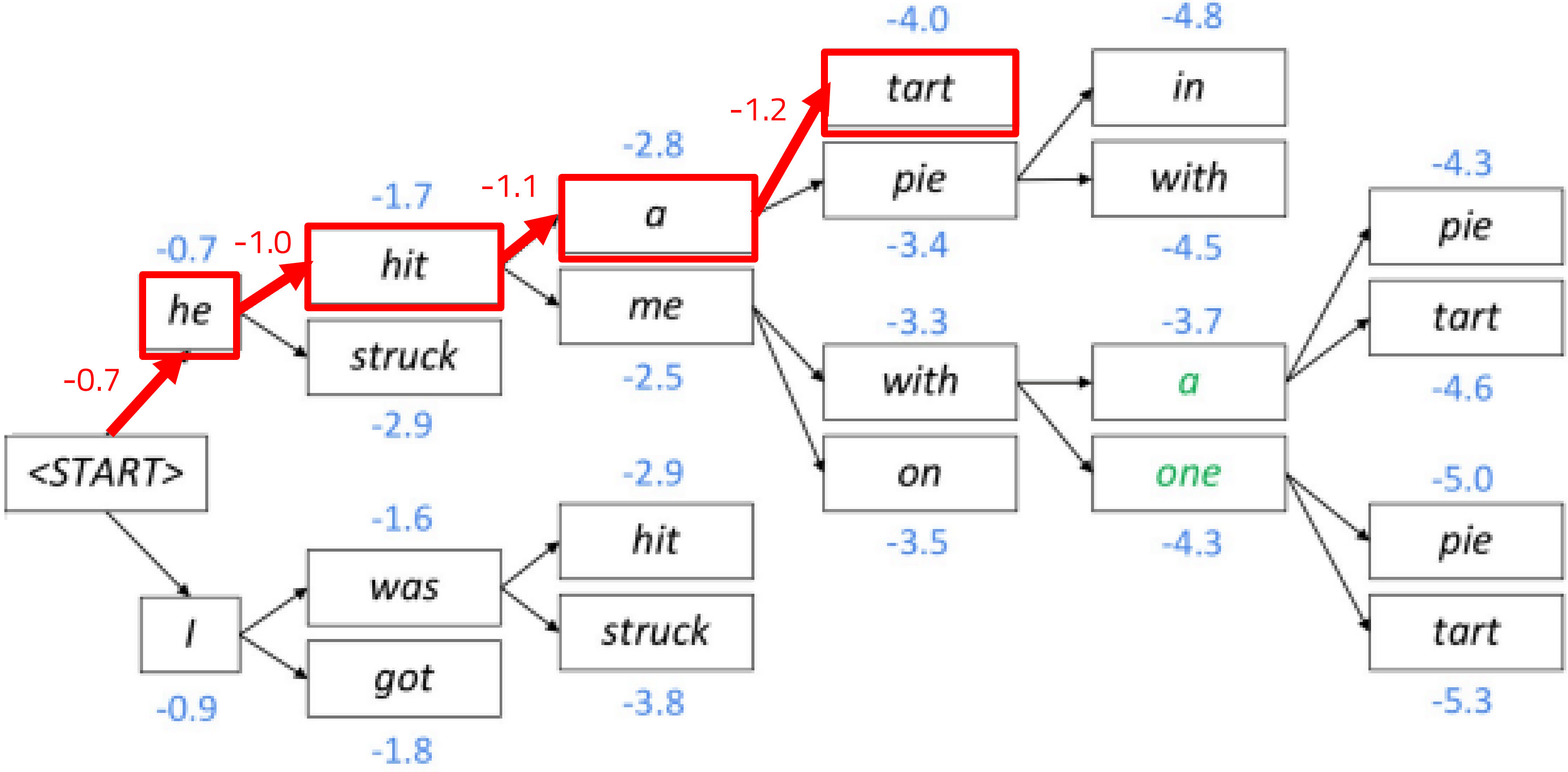
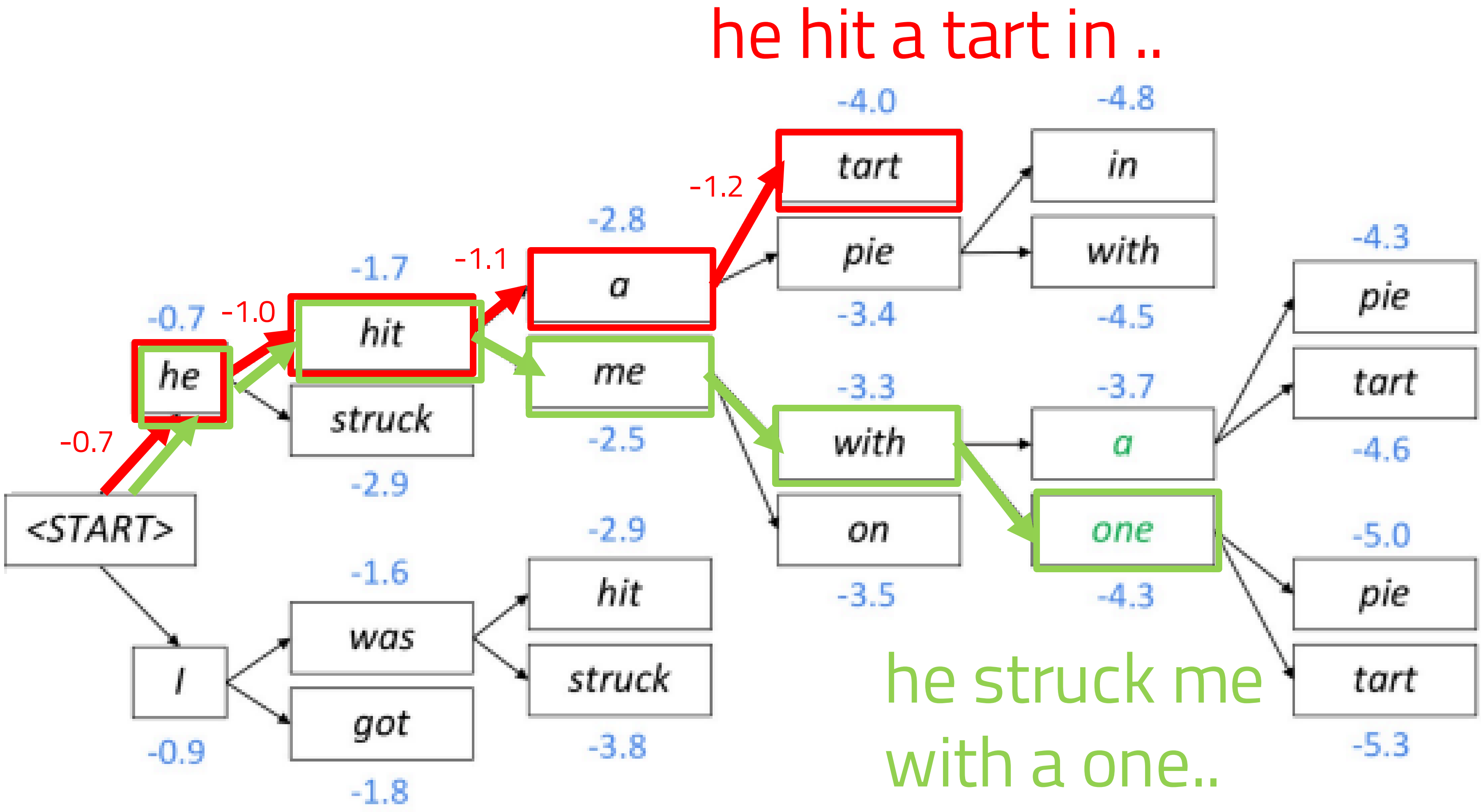
on
-3.5
in
-4.8
with
-4.5
a
-3.7
one
-4.3
pie
-4.3
tart
-4.6
pie
-5.0
tart
-5.3

he hit a tart in ..




he hit a tart in ..
<START>
-0.7
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a
-2.8
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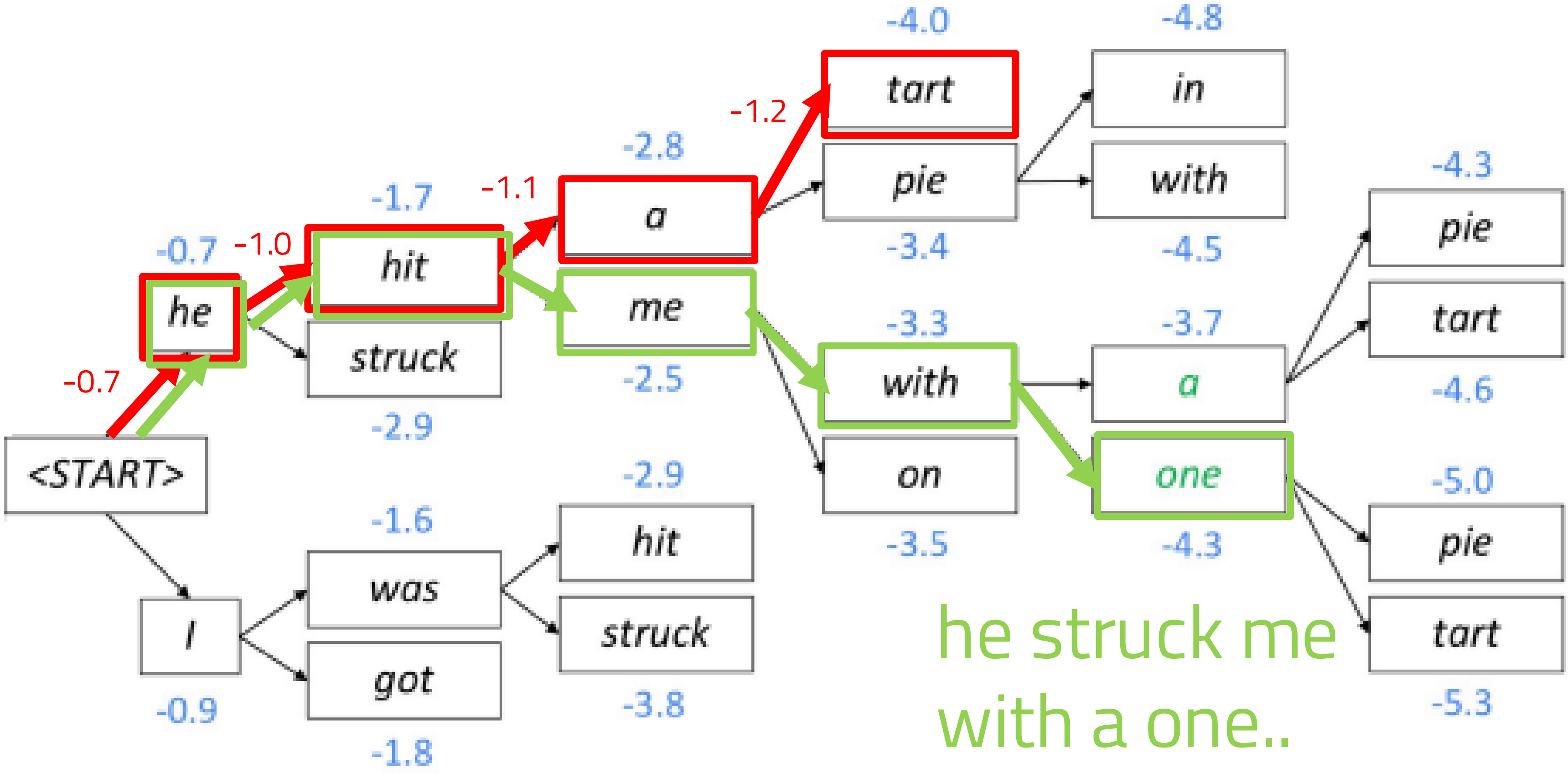
-2.5
-1.2
tart
-4.0
pie
-3.4
with
-3.3
on
-3.5
in
-4.8
with
-4.5
a
-3.7
one
-4.3
pie
-4.3
tart
-4.6
pie
-5.0
tart
-5.3
I
-0.9
was
-1.6
got
-1.8
hit
-2.9
struck
-3.8
he struck me with a one..

$$score\ (y_1 \ldots y_t) = \prod_{i=1}^{t} \log P_{LM}(y_i | y_1 \ldots y_{i-1}, x) = -4.0$$

he hit a tart in ..

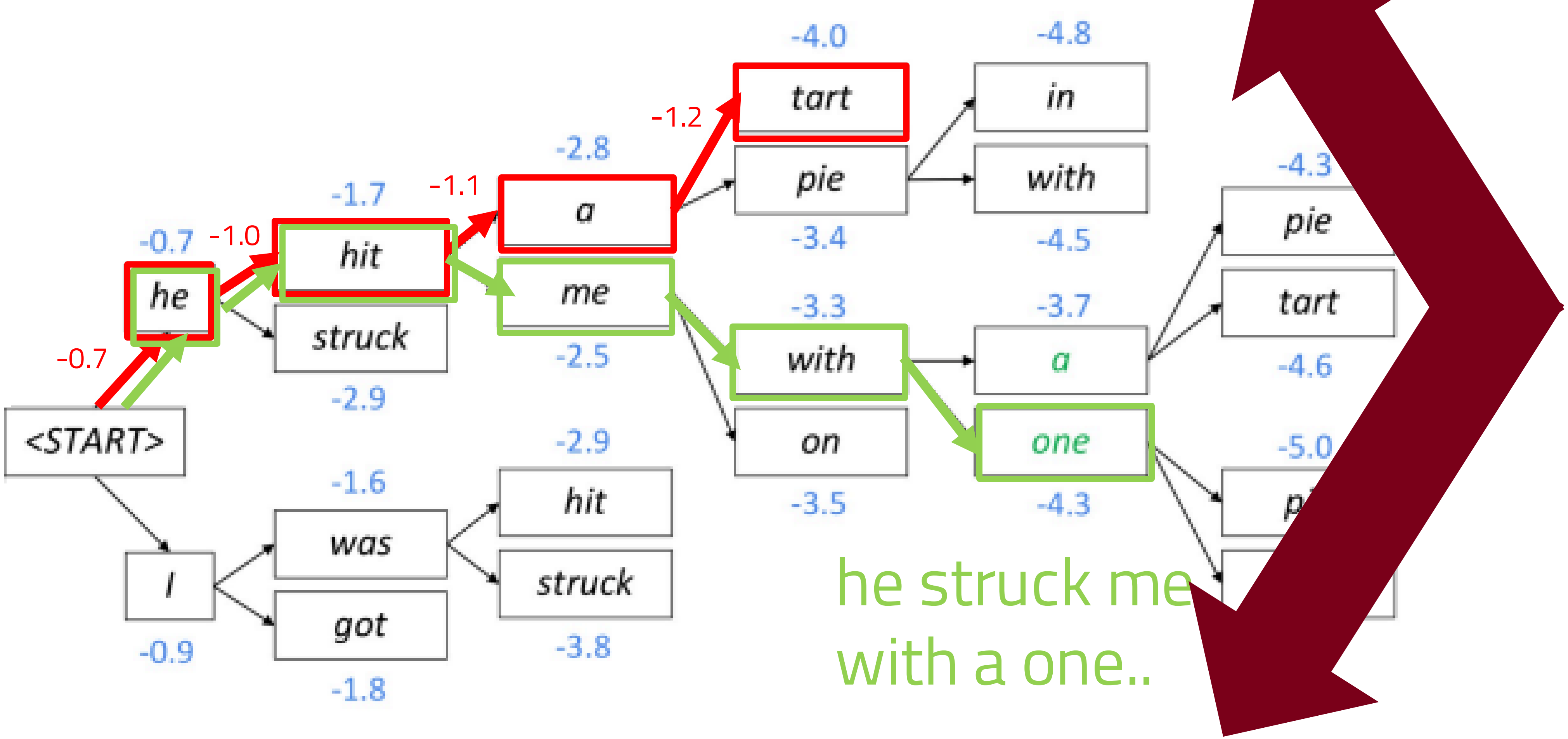


he struck me with a one..

$$score\ (y_1 \ldots y_t) = \prod_{i=1}^{t} \log P_{LM}(y_i | y_1 \ldots y_{i-1}, x) = -4.3$$

$$score\ (y_1 \dots y_t) = \prod_{i=1}^{t} \log P_{LM}(y_i | y_1 \dots y_{i-1}, x) = -4.0$$

he hit a tart in ..



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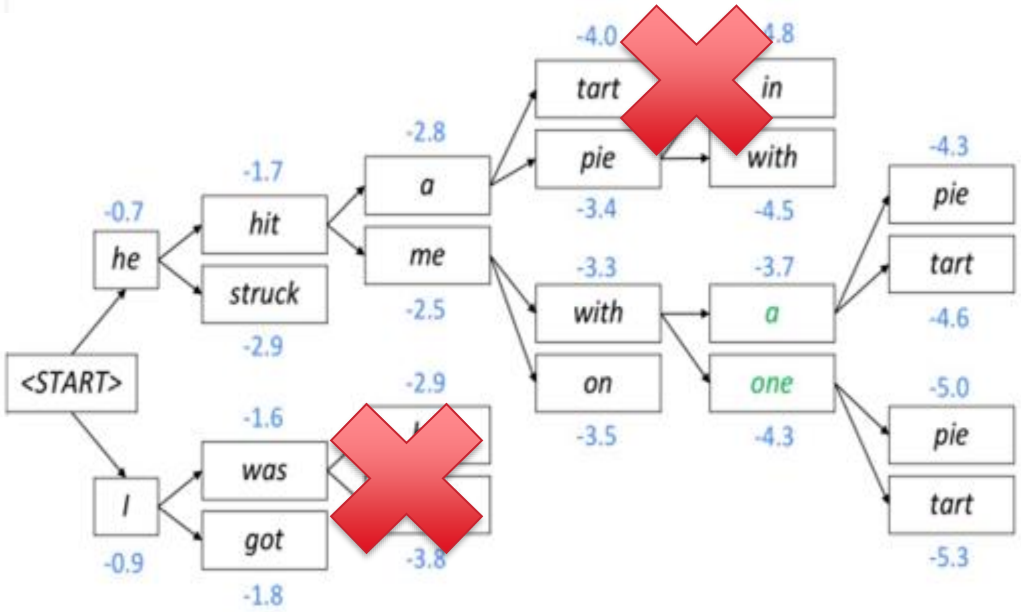
$$score\ (y_1 \dots y_t) = \prod_{i=1}^{t} \log P_{LM}(y_i | y_1 \dots y_{i-1}, x) = -4.3$$

Basic Pruning Methods (Steinbiss et al. 1994)

How to select which paths to keep expanding?

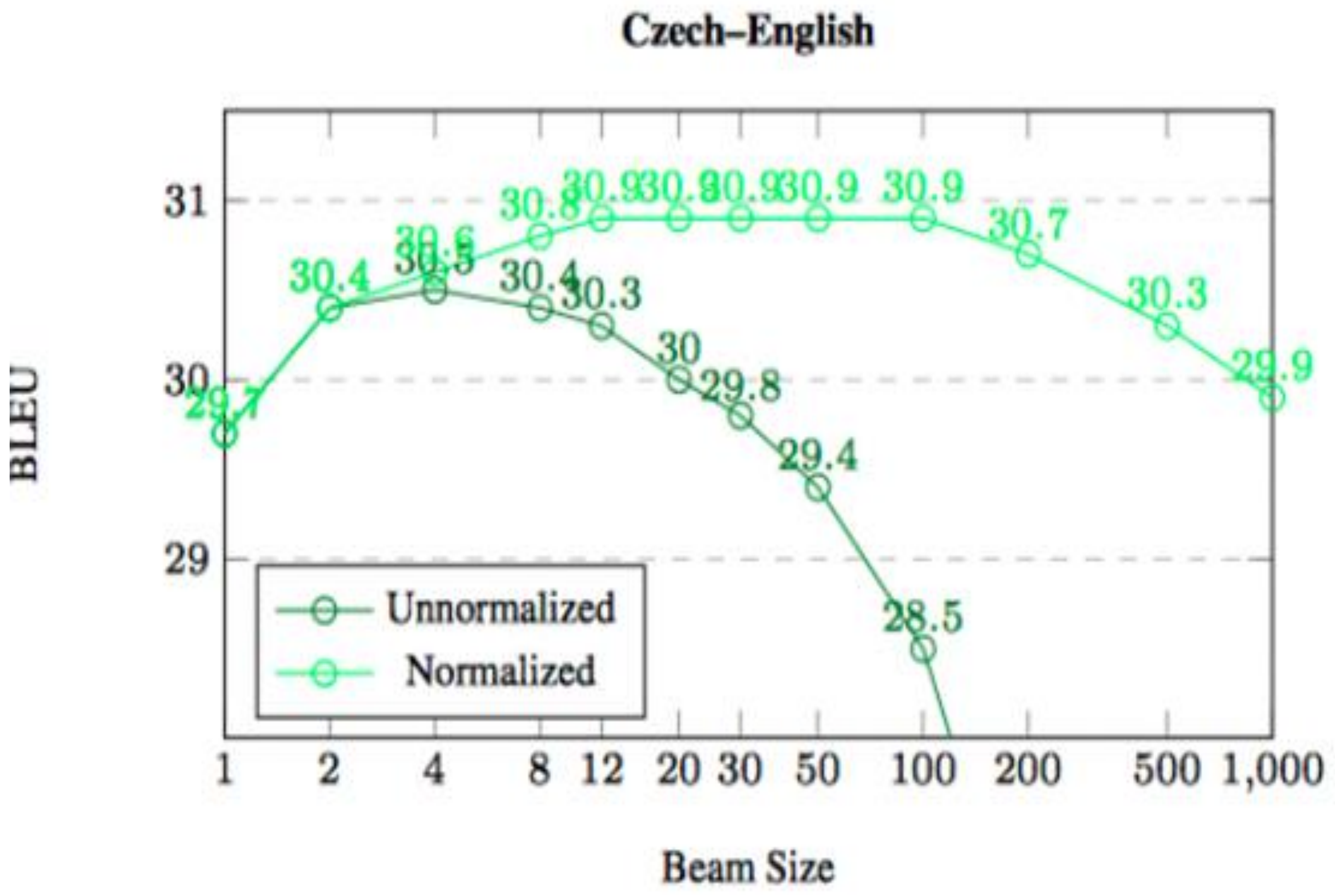
- **Histogram Pruning**: keep exactly k hypotheses at every time step
- **Score Threshold Pruning**: keep all hypotheses where score is within a threshold α of best score s_1
- **Probability Mass Pruning:** keep all hypotheses up until probability mass α



Better Search can Hurt Results! (Koehn and Knowles 2017)

- Better search (=better model score) can result in worse BLEU score!

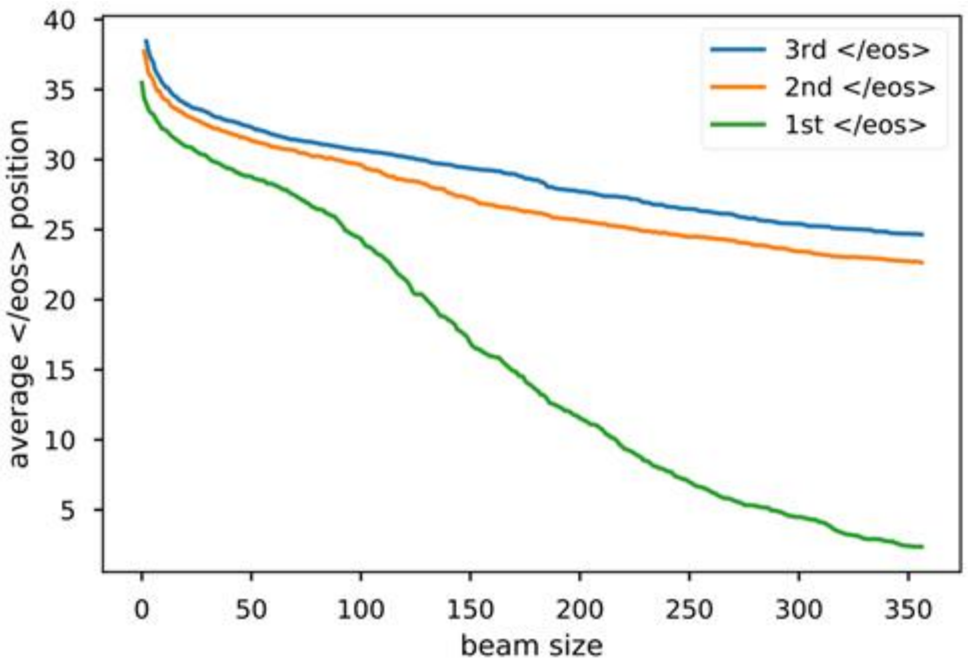
- Why? Model errors! (Model is not trained to give better BLEU score but predict better next token)

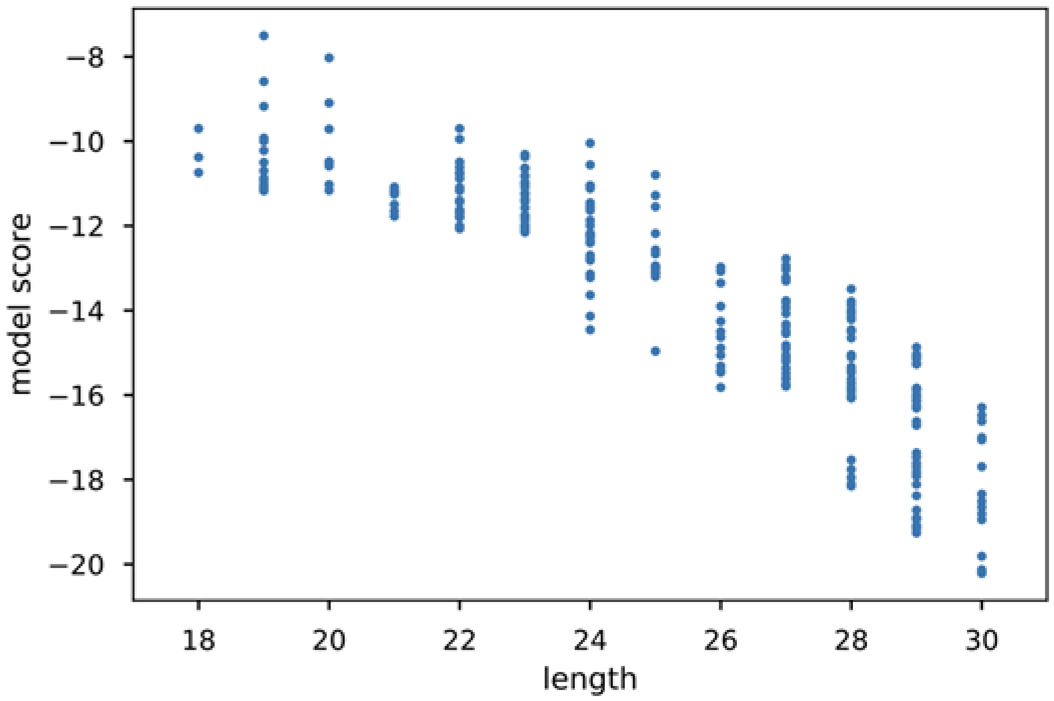


Beam Search Curse

(Yang et al. 2018)

- As beam size increases, it becomes easier for the search algorithm to find the **</eos>** symbol.
- Then, shorter candidates have clear advantages w.r.t. model score.





A Typical Model Error: Length Bias

- In many tasks (e.g. Machine translation), the output sequences will be of variable length
- Running beam search may then favor short sentences

GSM8K Distances

Length Normalization

- ❑ Beam search may then favor short sentences
- ❑ Normalize by the length, dividing by |Y| to prioritize longer sentences.

(Cho et al. 2014)

$$\frac{1}{T_y^{\alpha}} \quad argmax_y \sum_{j=1}^{T_y} \log P(y_j \mid X, y_1, \ldots y_{j-1})$$

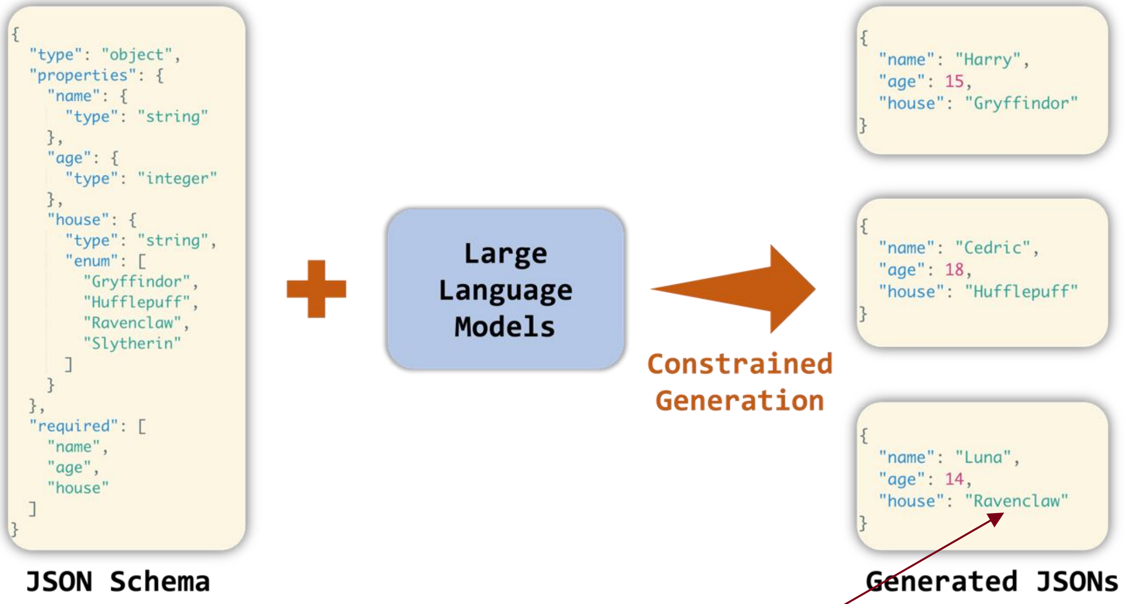
$$\alpha = [0, 1.0]$$

(Wu et al. 2016)

$$\frac{(5+1)^{\alpha}}{(5+|Y|)^{\alpha}}$$

Constrained Decoding

- Some tasks (coding/mathematics/synthetic data generation) have an explicit structure
- When finite state machines can be attached to your outputs, then you can limit the set of words your model will output from |V| to M, where M is the set of possible next words



The generation house can only be one of the four words in the ‘house’ portion of the schema

Constrained Decoding

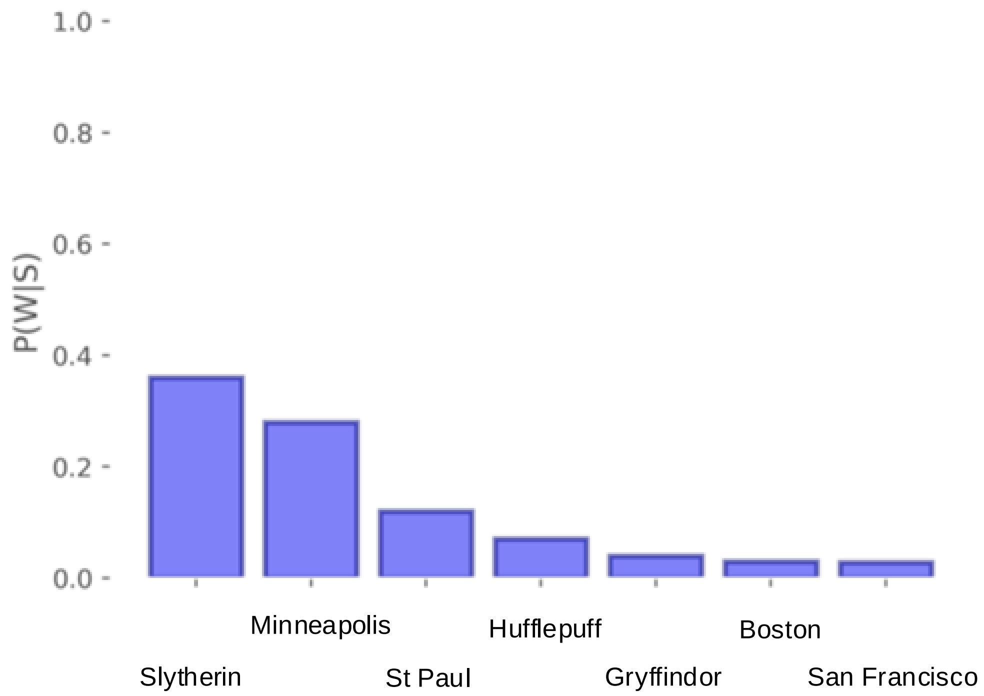
S =

'{

"name": "Jim",

"age": 28,

"house": '



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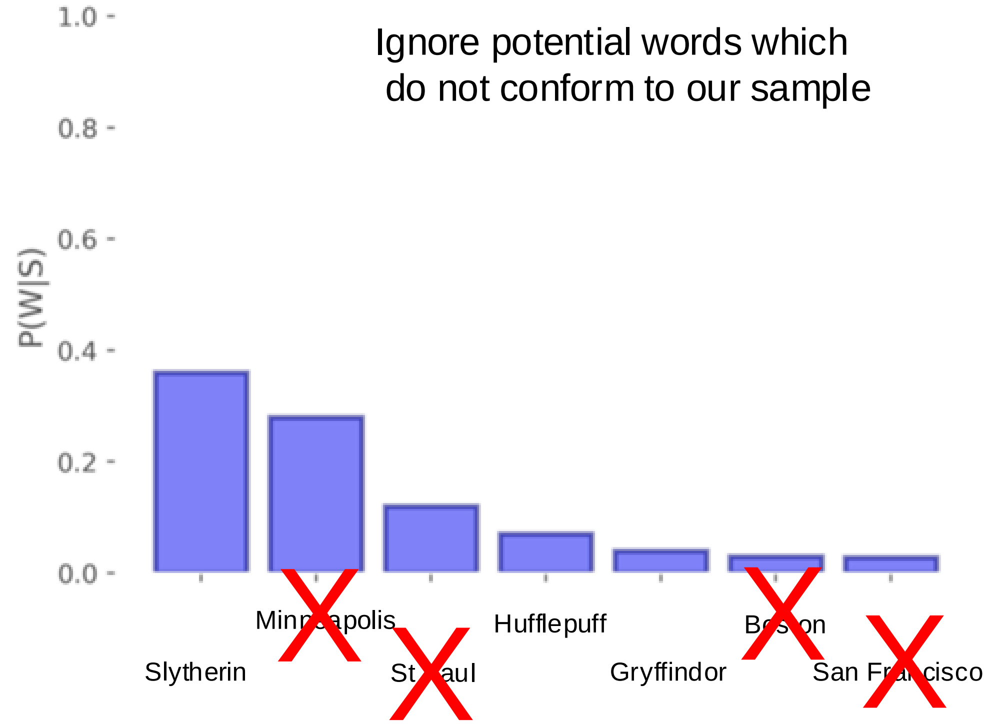


Sampling

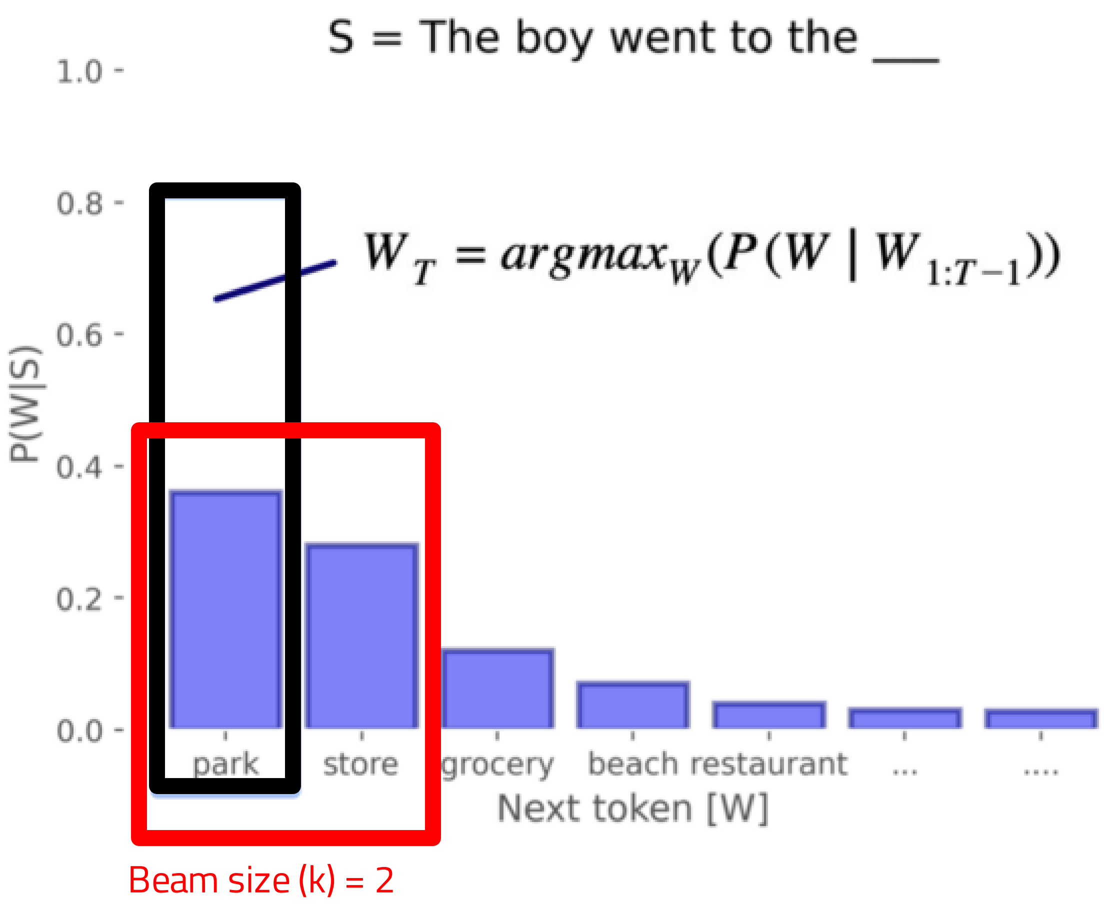
How are you doing?

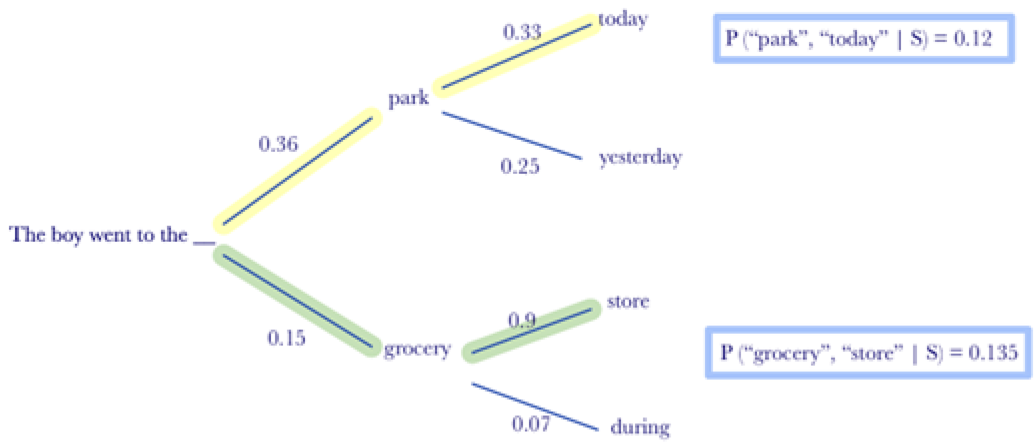
I’m good! How about you?

So so..

It was a hard day for me.

Recap: Greedy/Beam Search (w/o Sampling)





Deterministic beam search:
I went into town on Saturday morning because...
-> I was going to go to the gym and I was going to go to the gym and I was going to go to the ..

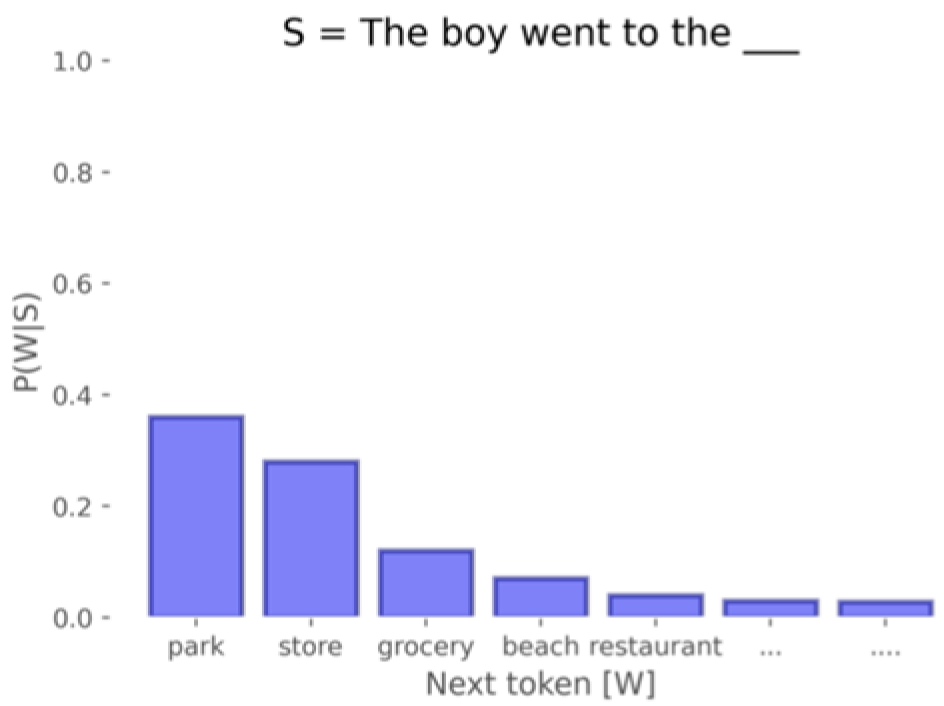
https://medium.com/ai2-blog/a-guide-to-language-model-sampling-in-allennlp-3b1239274bc3

Ancestral Sampling

X = ‘The boy when to the’
Y = ’’
Generate Y_0

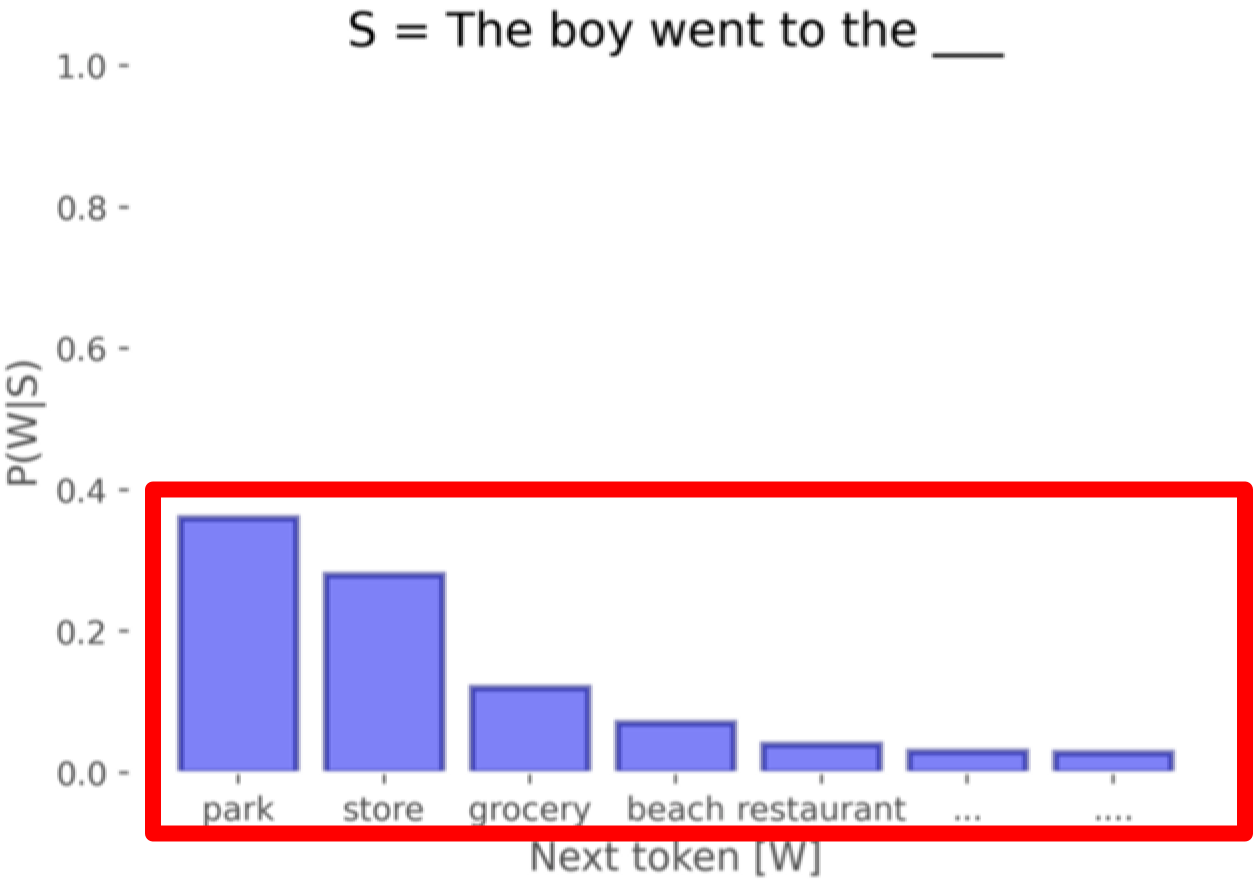
- Randomly generate words one-by-one
  - $Y_j = P\left(Y_j \mid X, y_1 \ldots y_{j-1}\right)$
  - Until <STOP> is generated

- An exact method for sampling from $P(X)$, no further work needed.



https://medium.com/ai2-blog/a-guide-to-language-model-sampling-in-allennlp-3b1239274bc3

Decoding with Ancestral/Multinomial Sampling



Multinomial Sampling:
I went into town on Saturday morning because...
-> I have to wear suits and collared in the South Bay. This was shocking!" "This is our city. First of all, I'm strange in the name of Santa, Howard Daniel, and

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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.

Beam Search, *b*=32:
"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 ..."

Repetition

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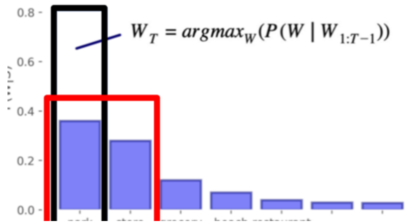

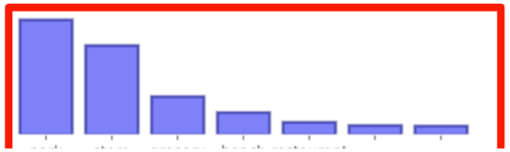

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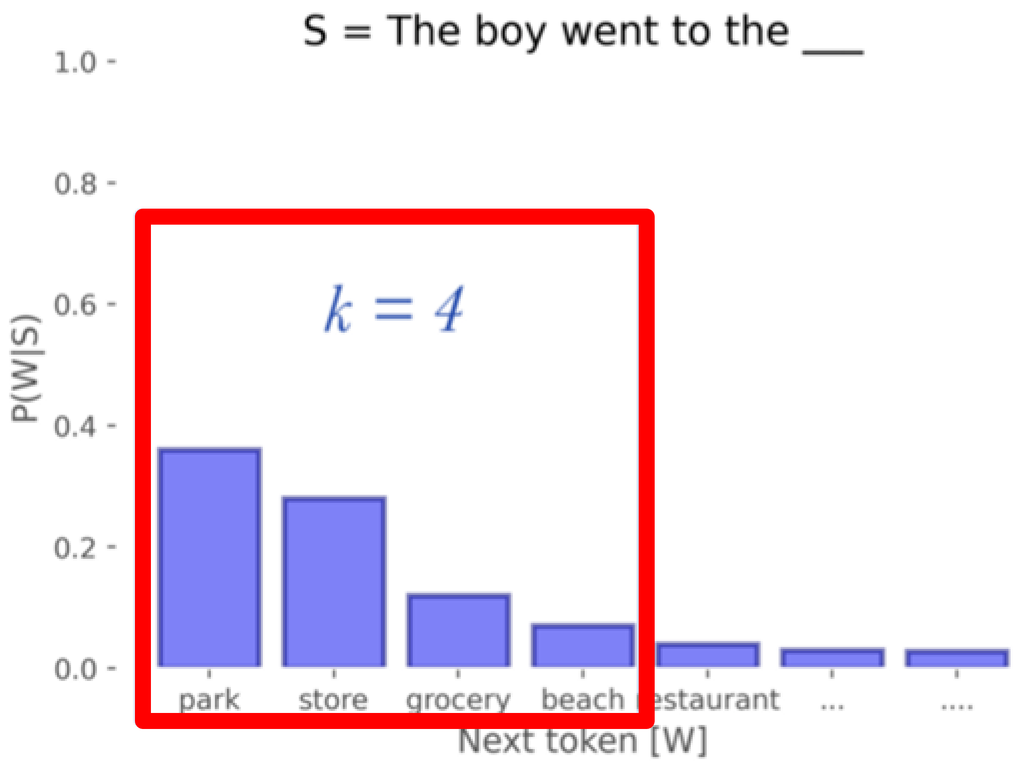
Pure Sampling:
They were cattle called Bolivian Cavalleros; they live in a remote desert uninterrupted by town, and they speak huge, beautiful, paradisiacal Bolivian linguistic thing. They say, 'Lunch, marge.' They don't tell what the lunch is," director Professor Chuperas Omwell told Sky News. "They've only been talking to scientists, like we're being interviewed by TV reporters. We don't even stick around to be interviewed by TV reporters. Maybe that's how they figured out that they're cosplaying as the Bolivian Cavalleros."

Repetition

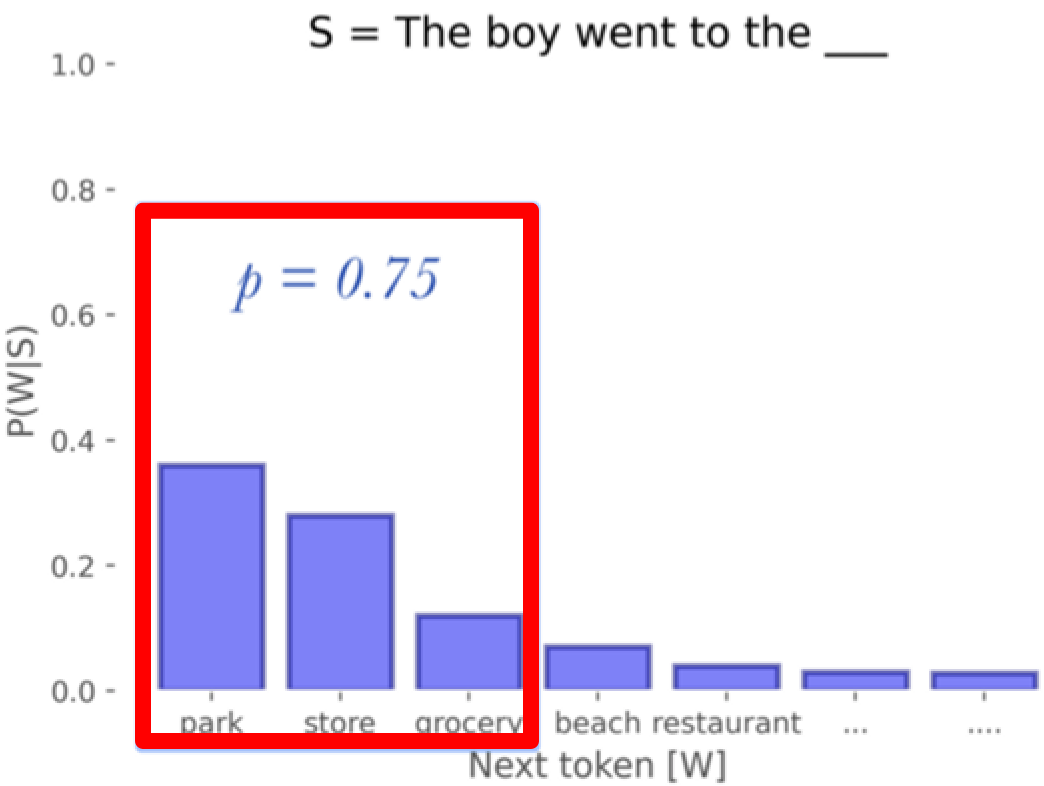
Incoherence

Top-k Sampling



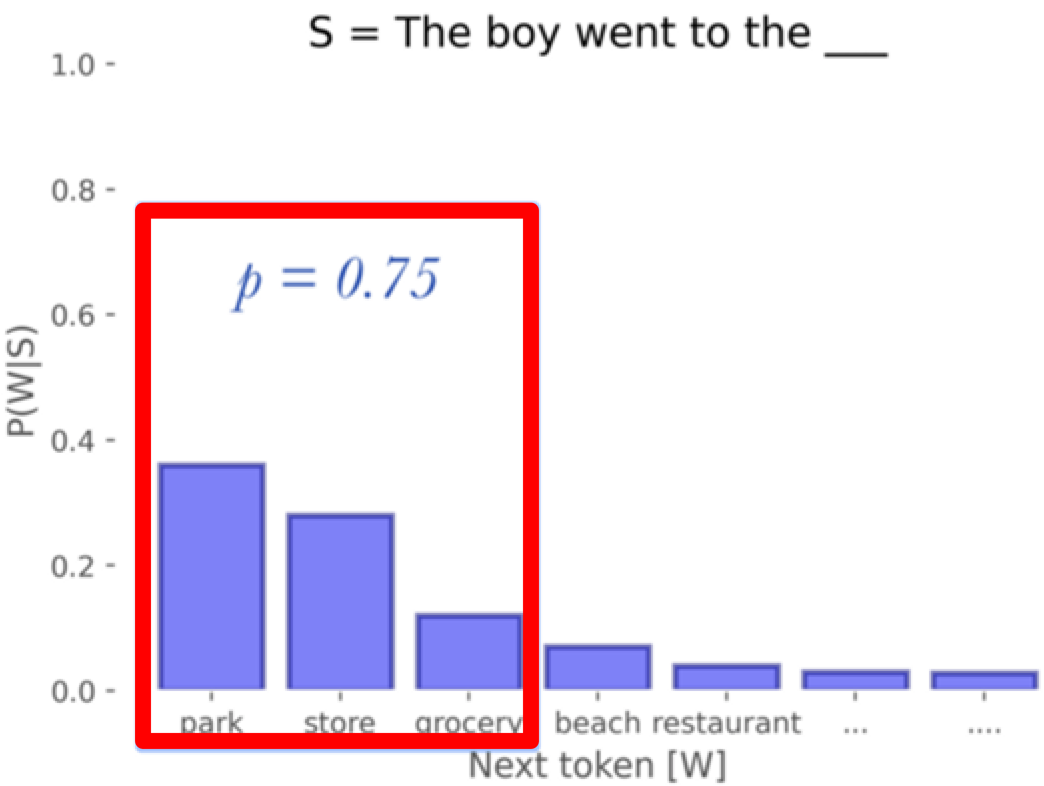
- ❑ Only sample from the *k* most probable tokens, by redistributing the PMF over the top-k tokens
- ❑ But, picking a good value of *k* can be difficult as the distribution or words is different for each step.
  - Increase k for more diverse/risky outputs
  - Decrease k for more generic/safe outputs

Top-p Sampling (or Nucleus Sampling) (Holtzman et al. 2020)

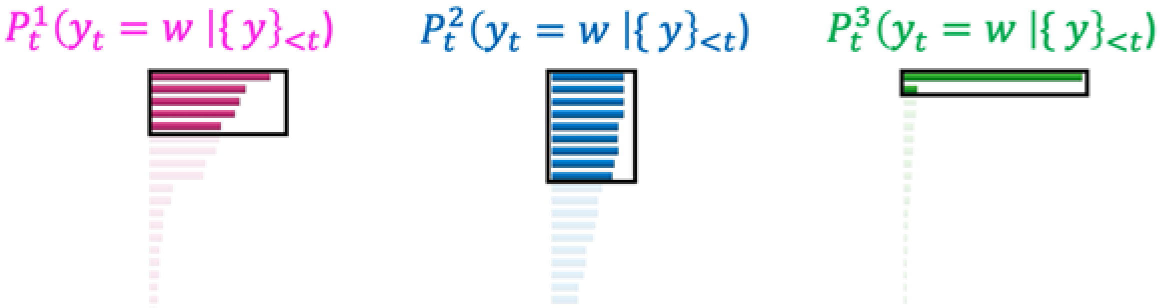


- Another way to exclude very low probability tokens is to include the most probable tokens that make up the "nucleus" of the PMF
  - the sum of the most probable tokens just reaches P

Top-p Sampling (or Nucleus Sampling) (Holtzman et al. 2020)



- Flexible as the distribution changes, allowing the size of the filtered words to expand and contract when it makes sense.



Cautions about Sampling-based Search

- Is sampling necessary for diversity?
  - questionable, we could do diverse beam search instead.
- Results are inconsistent from run-to-run:
  - need to consider variance from this in reporting
  - (in addition to variance in training and data selection)
- Conflates model and search errors:
  - if you make a better model you might get worse results, because the search algorithm can't find the outputs your model likes

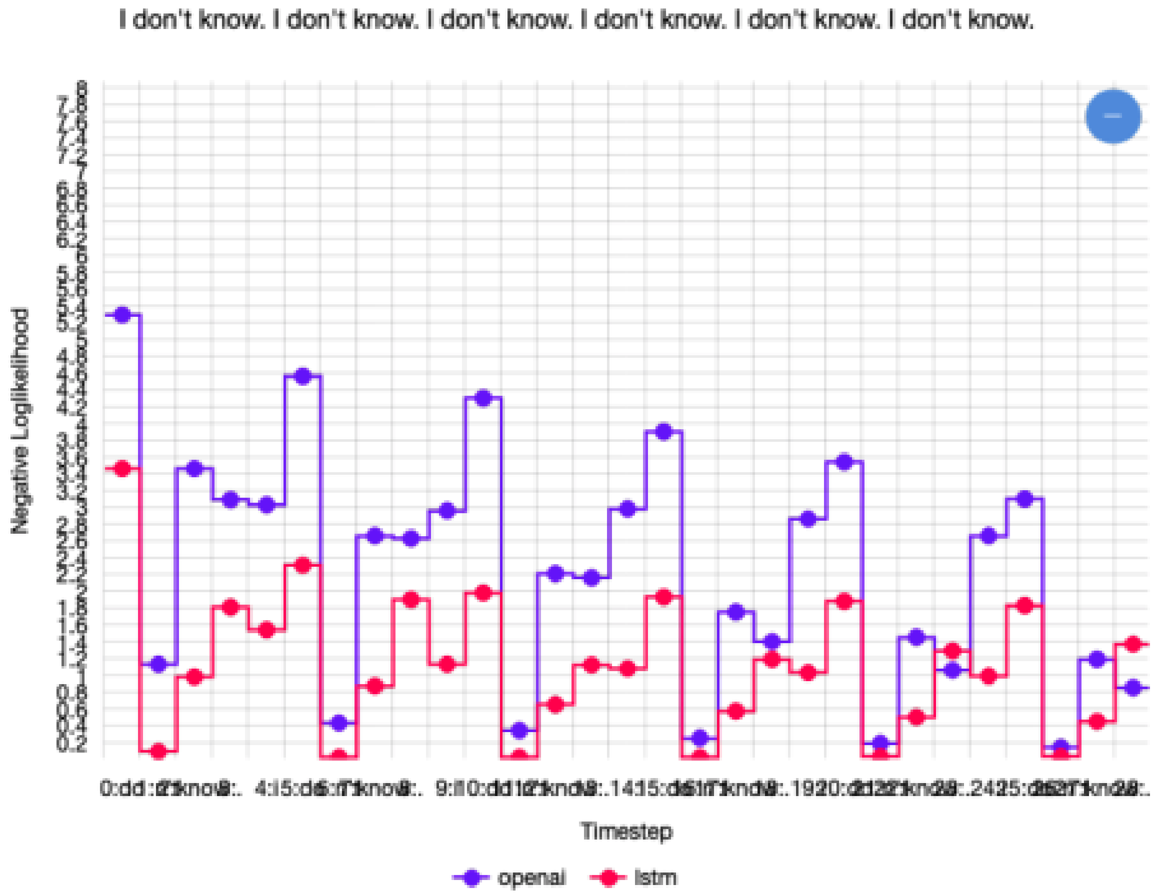
Decoding: Takeaways

- Many problems in neural NLG are not really problems with our learned language model probability distribution, but problems with the decoding algorithm
- Different decoding algorithms can allow us to inject biases that encourage different properties of coherent natural language generation
- Some of the most impactful advances in NLG of the last few years have come from simple but effective modifications to decoding algorithms

Search in Training

Diversity Issues (Holtzman et. al., 2020)

- Maximum Likelihood Estimation discourages diverse text generation



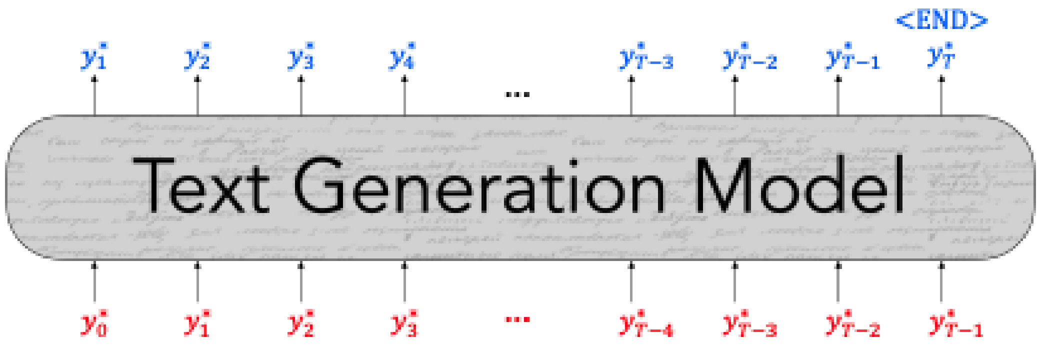
Why? Exposure Bias

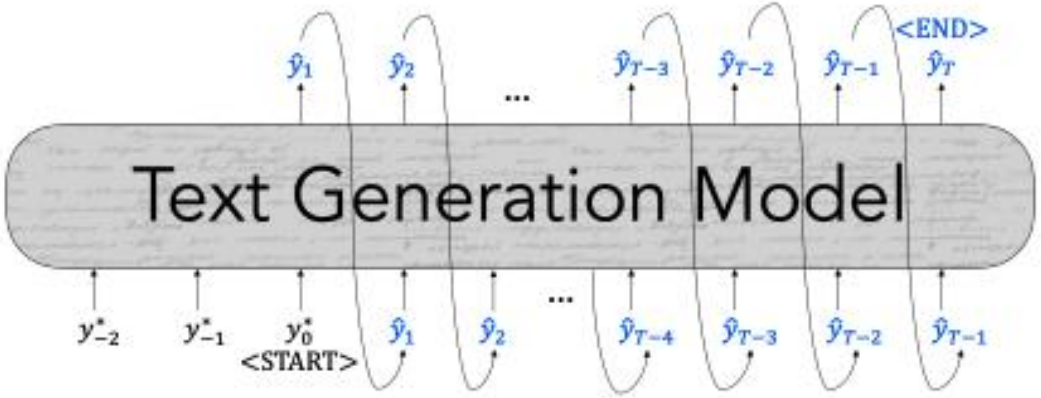
- Training with teacher forcing leads to exposure bias at generation time
  - During training, our model’s inputs are gold context tokens from real, human-generated texts

$$\mathcal{L}_{MLE} = -\log P(y_t^* | \{y^*\}_{<t})$$

  - At generation time, our model’s inputs are previously–decoded tokens

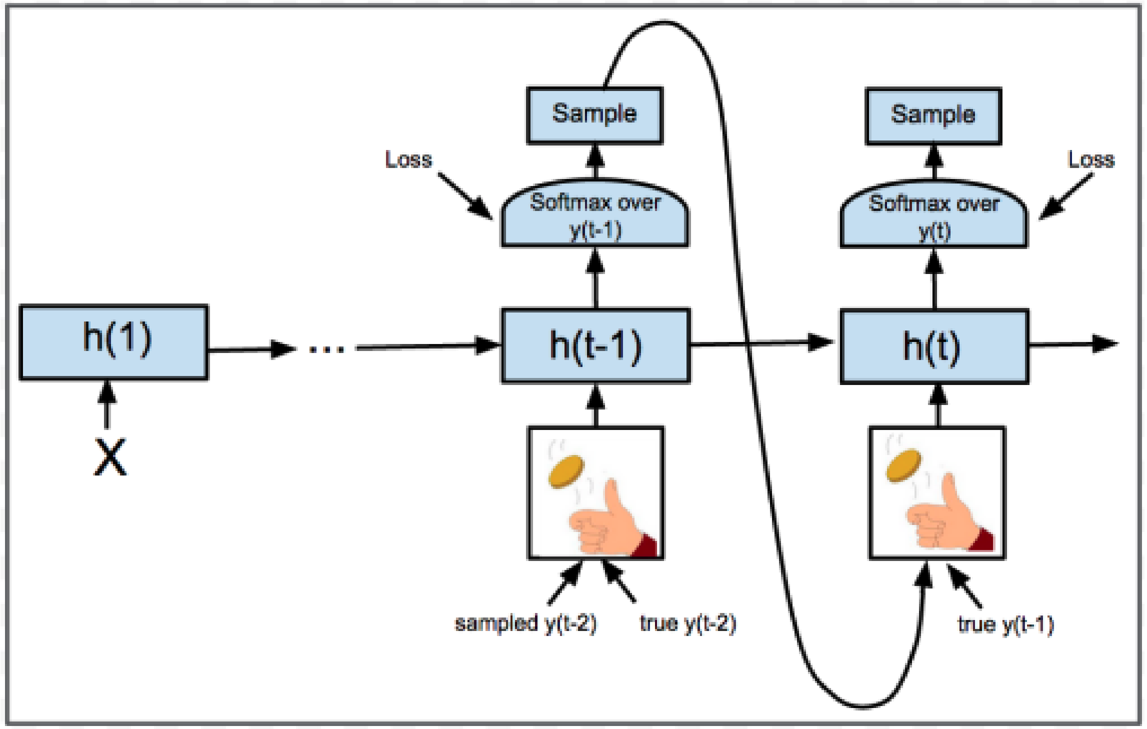
$$\mathcal{L}_{dec} = -\log P(\hat{y}_t | \{\hat{y}\}_{<t})$$





Fix Exposure Bias: Scheduled sampling (training)

- With some probability p, decode a token and feed that as the next input, rather than the gold token.
- Increase *p* over the course of training
- Leads to improvements in practice, but can lead to strange training objectives
- Also called teacher forcing



(Bengio et al., 2015)

Search in Training: Takeaways

- Teacher forcing is still the main algorithm for training text generation models
- Diversity is an issue with sequences generated from teacher forced models
- Exposure bias causes text generation models to lose coherence easily

Other techniques not covered

- ❑ Decoding time control for controllable text generation (e.g., PPLM)
- ❑ Multi-attribute control using RL (will be covered)
- ❑ Unlikelihood training
- ❑ Data augmentation for reducing the exposure bias
- ❑ Retrieval-augmented Generation (RAG)
- ❑ Retrieval based generation (e.g., KNN Language Models)
- ❑ Instruction tuning and human feedback learning (will be covered)

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