Lecture 10: Natural Language Generation

Instructor: Xiang Ren
USC CSCI 444 NLP
2026 Spring

Slides mostly adapted from Dan Jurafsky, some from Mohit Iyyer

Logistics / Announcements

- questions re: HW1 – TA office hour
- Project Proposal feedback sent out by Tue EOD
- HW2 due March 4

Feb 11	Recurrent Neural Nets	J&M, Chap 13;	Project Proposal Due
Feb 16	Presidents Day		
Feb 18	Seq2Seq and Attention	J&M, Chap 8;	
Feb 23	Transformers - Building Blocks	J&M, Chap 8;	
Feb 25	PyTorch for Transformers		
Mar 2	Transformer Language Models	J&M Chap 8;	
Mar 4	Tokenization	J&M, Chap 2.5;	HW2 Due

USC Viterbi

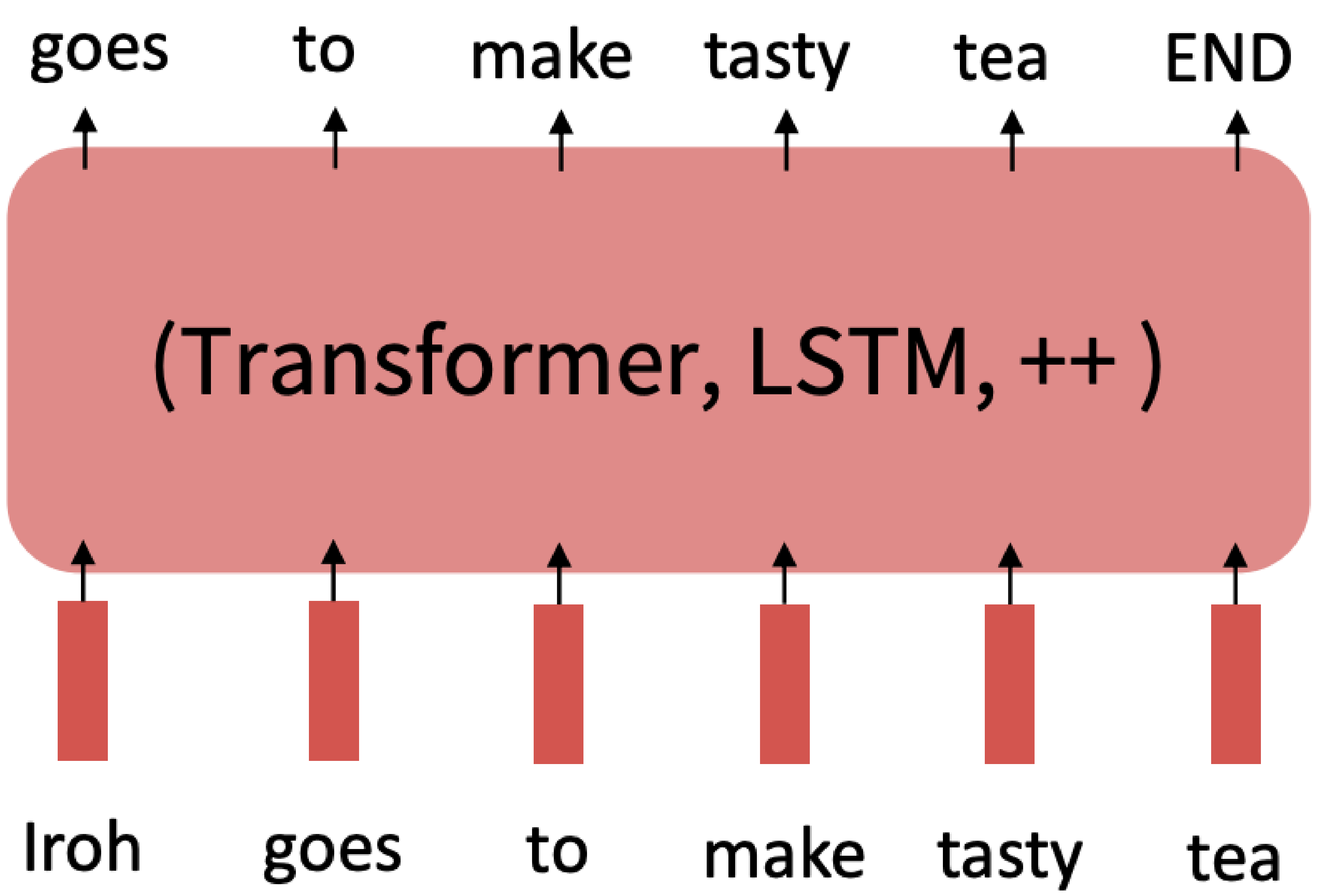
Recap: LLM Pretraining

The Pretraining / Finetuning Paradigm

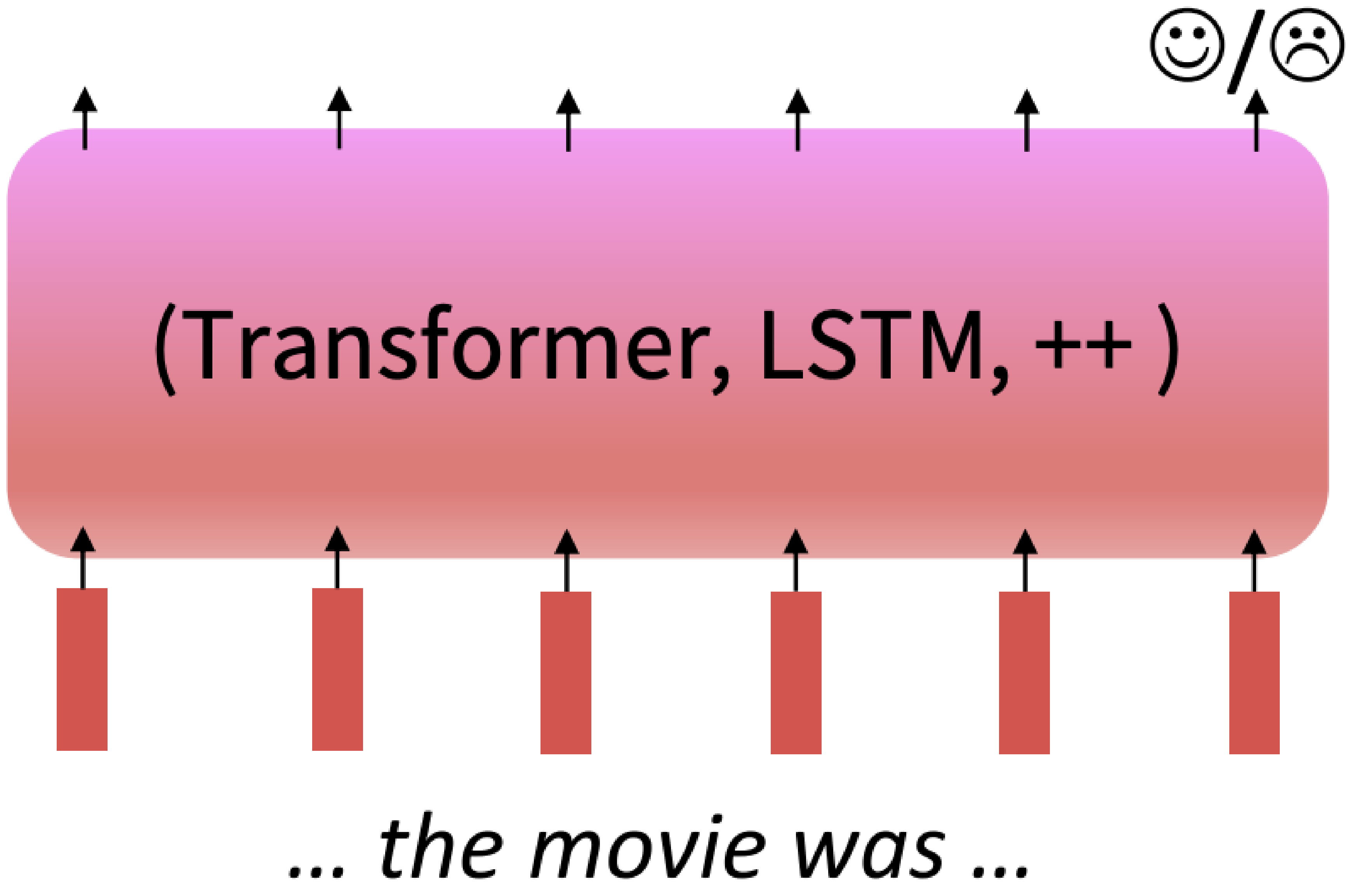
- Pretraining can improve NLP applications by serving as parameter initialization.

Key idea: "Pretrain once, finetune many times."

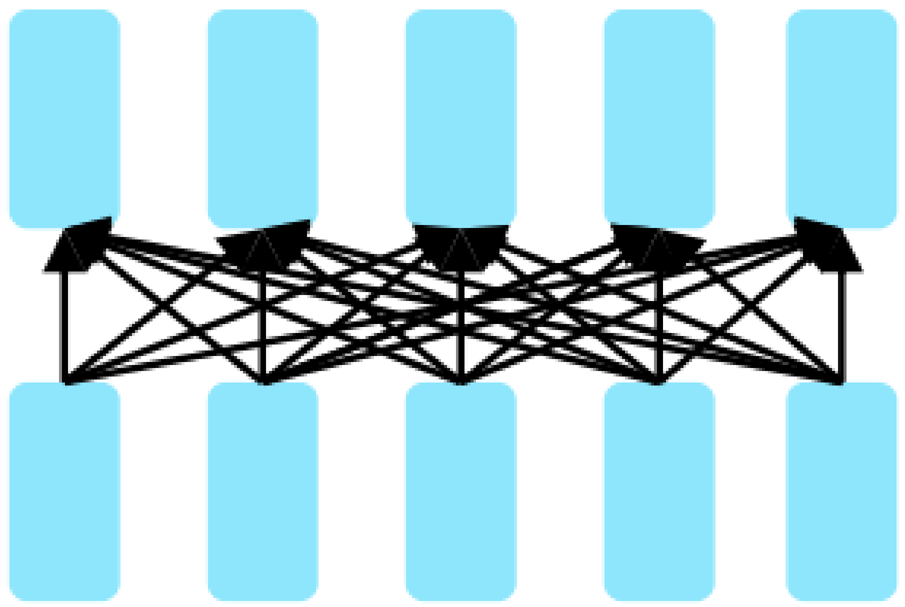
Step 1: Pretrain (on language corpora)
Lots of text; learn general things!



Step 2: Finetune (on your task data)
Not many labels; adapt to the task!

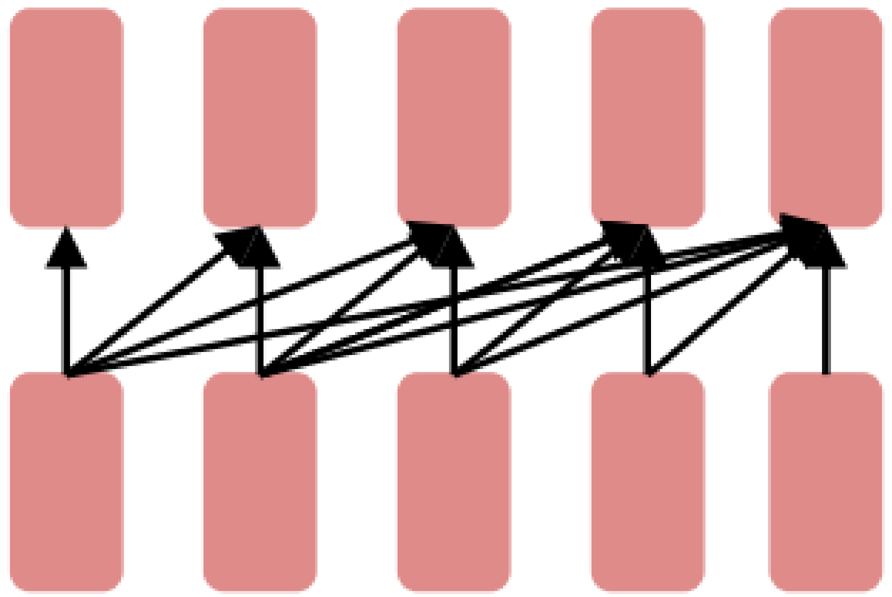


Pretraining for three types of architectures



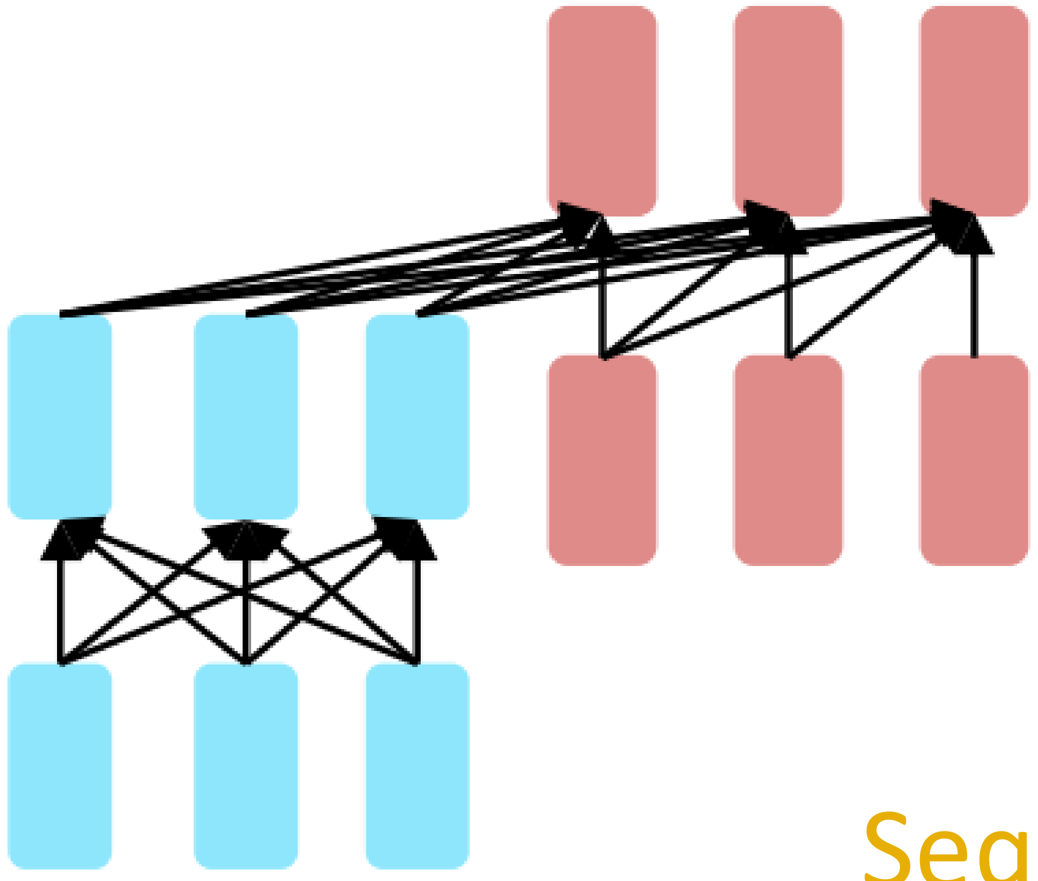
Encoders

Bidirectional Context



Decoders

Language Models



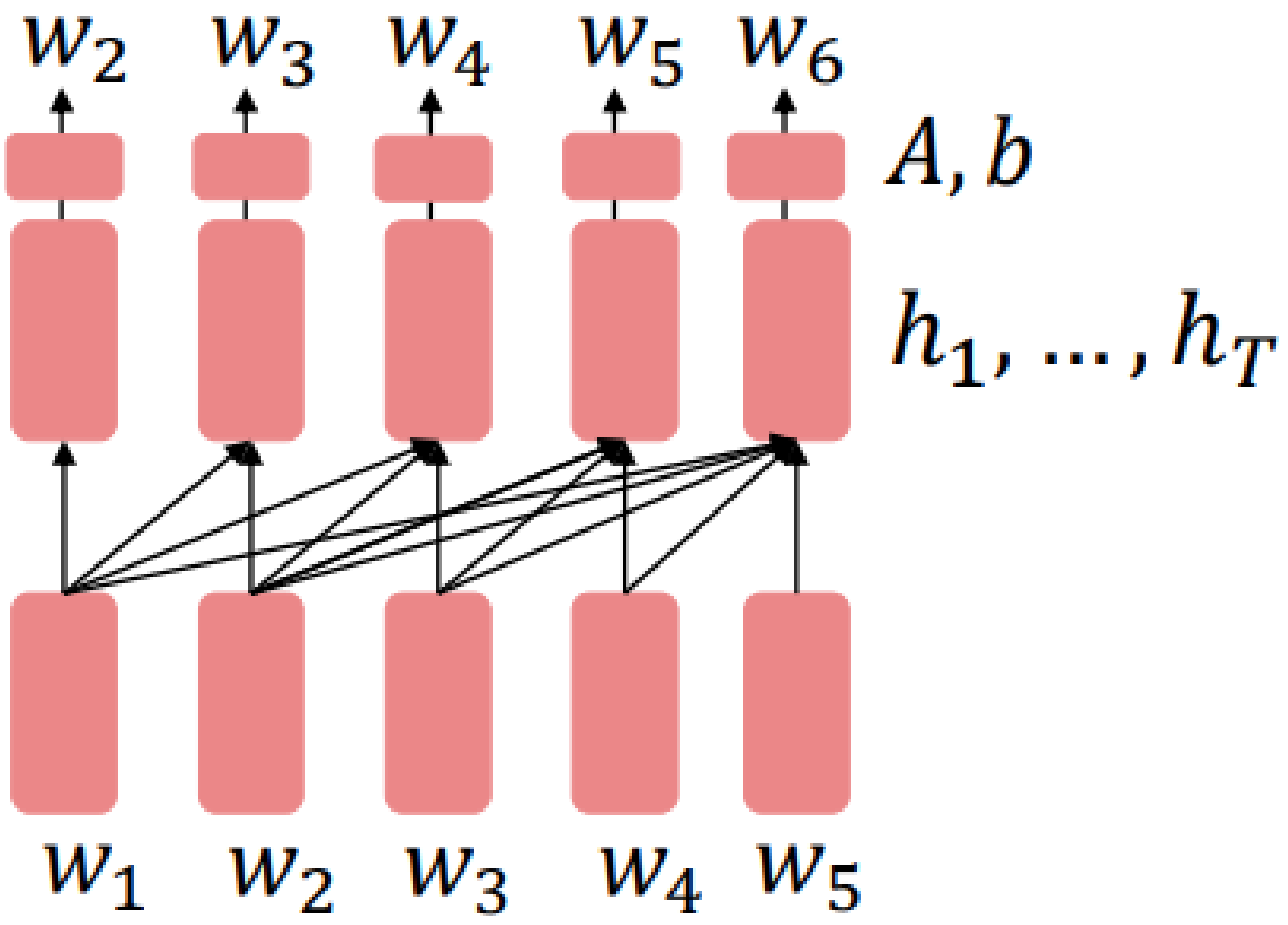
Encoder-Decoders

Sequence-to-sequence

Pretraining Decoders: Generators

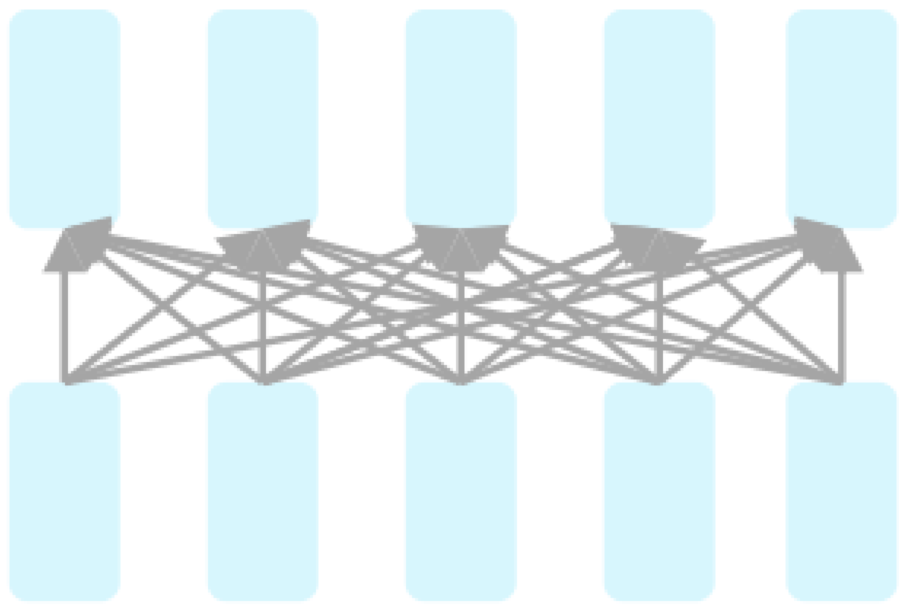
- More natural: pretrain decoders as language models and then use them as generators, finetuning their $p_\theta(w_t|w_{1:t-1})$
    - $h_1, \dots, h_T = Decoder(w_1, \dots, w_T)$
- $w_t \approx Ah_{t-1} + b$
- Where A, b were pretrained in the language model!

- This is helpful in tasks where the output is a sequence with a vocabulary like that at pretraining time!
    - Dialogue (context=dialogue history)
    - Summarization (context=document)



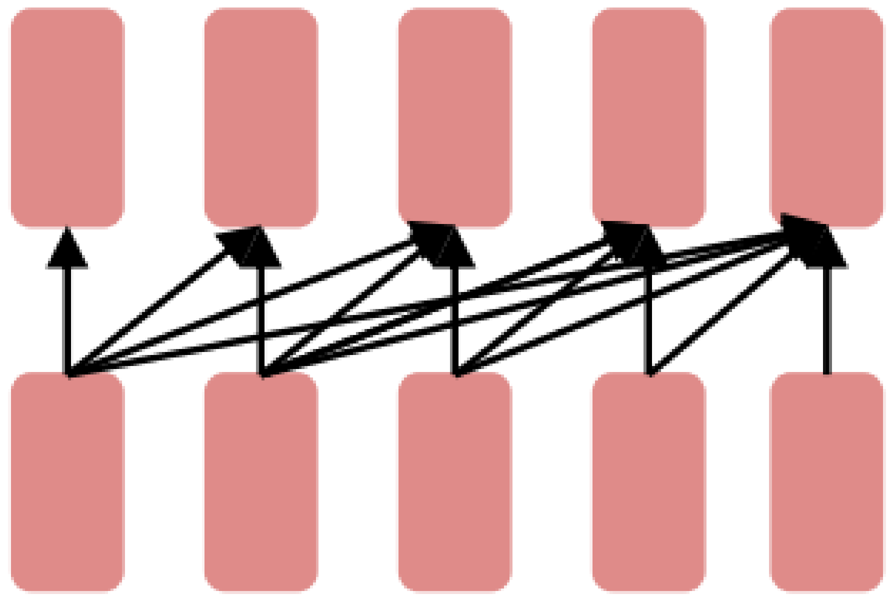
The linear layer has been pretrained

Pretraining for three types of architectures



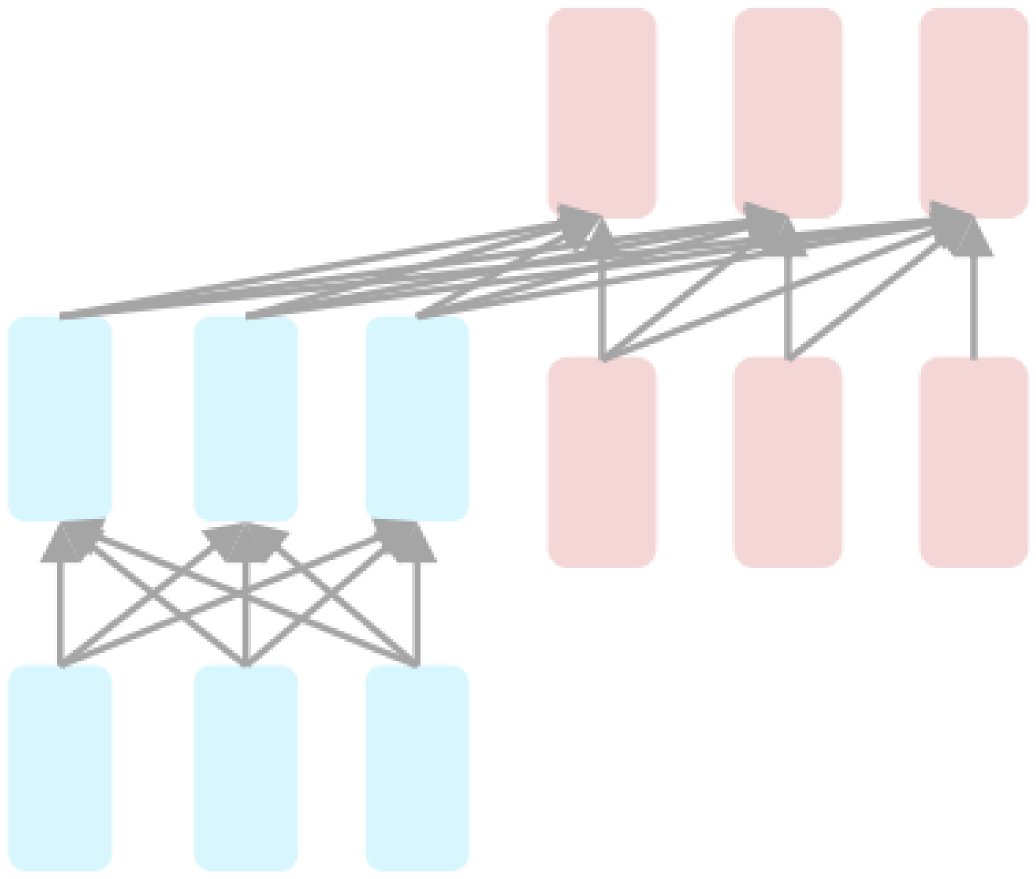
Encoders

Bidirectional Context



Decoders

Language Models



Encoder-
Decoders

Sequence-to-sequence

Generative Pretrained Transformer (GPT)

- 2018's GPT was a big success in pretraining a decoder!
  - Transformer decoder with 12 layers, 117M parameters.
  - 768-dimensional hidden states, 3072-dimensional feed-forward hidden layers.
  - Byte-pair encoding with 40,000 merges
  - Trained on BooksCorpus: over 7000 unique books.
    - Contains long spans of contiguous text, for learning long-distance dependencies.
  - The acronym "GPT" never showed up in the original paper; it could stand for "Generative PreTraining" or "Generative Pretrained Transformer"

OpenAI

[Radford et al., 2018]

GPT-3 and beyond

- Markedly improved generation capabilities by greatly increasing data and model scale
- Solving all tasks through generation
- Even obviating the need to fine-tune!

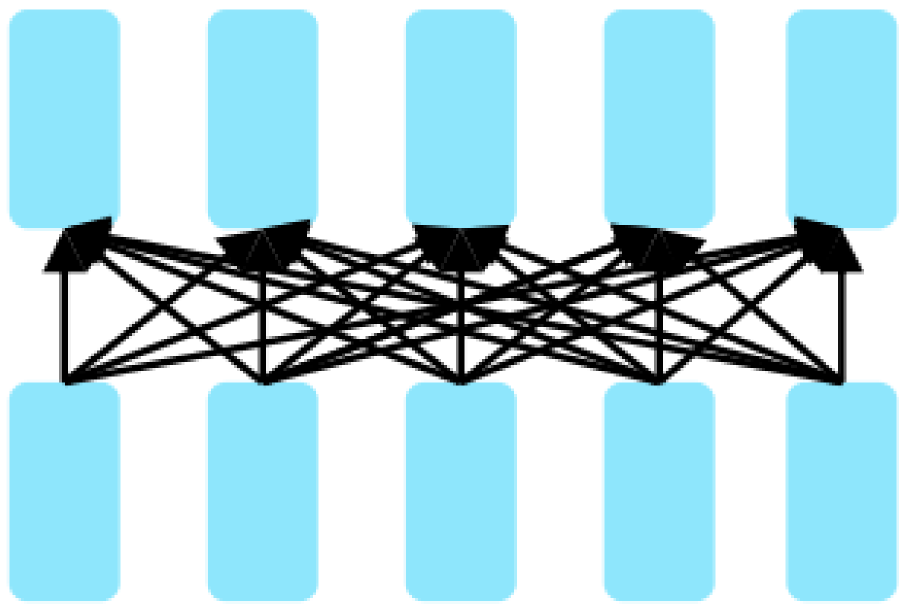
More in future weeks!

GPT-3

ChatGPT

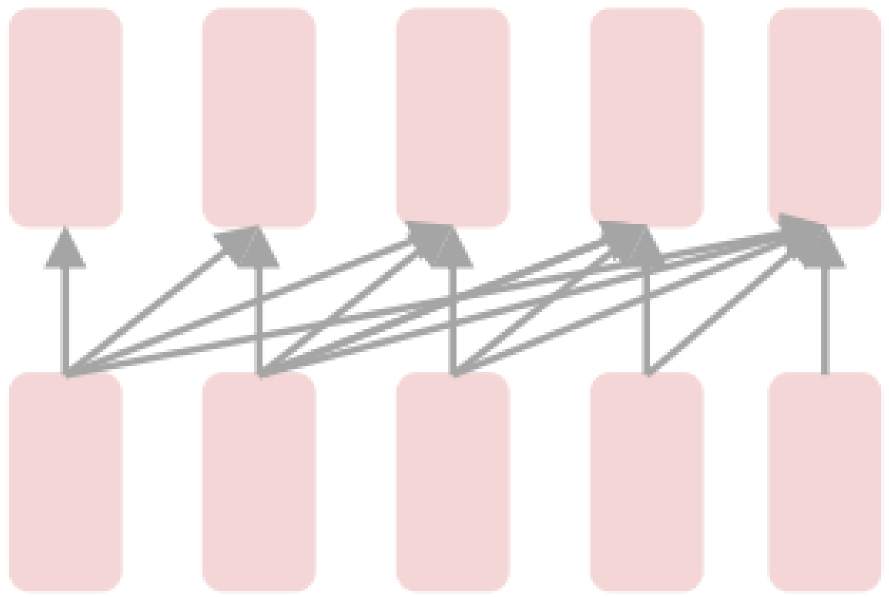
GPT-4

Pretraining for three types of architectures



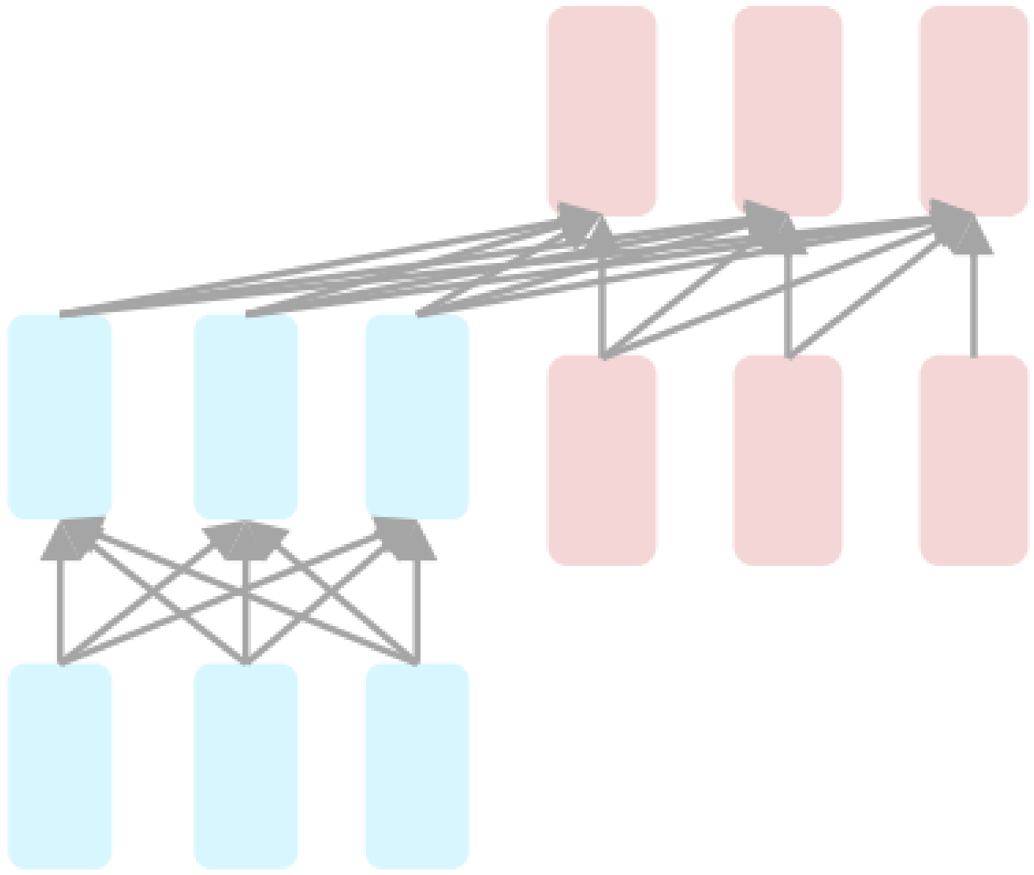
Encoders

Bidirectional Context



Decoders

Language Models



Encoder-Decoders

Sequence-to-sequence

Pretraining Encoders: Bidirectional Context

I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, ____

Universal Studios Theme Park is located in ______________, California

Problem: Input Reconstruction

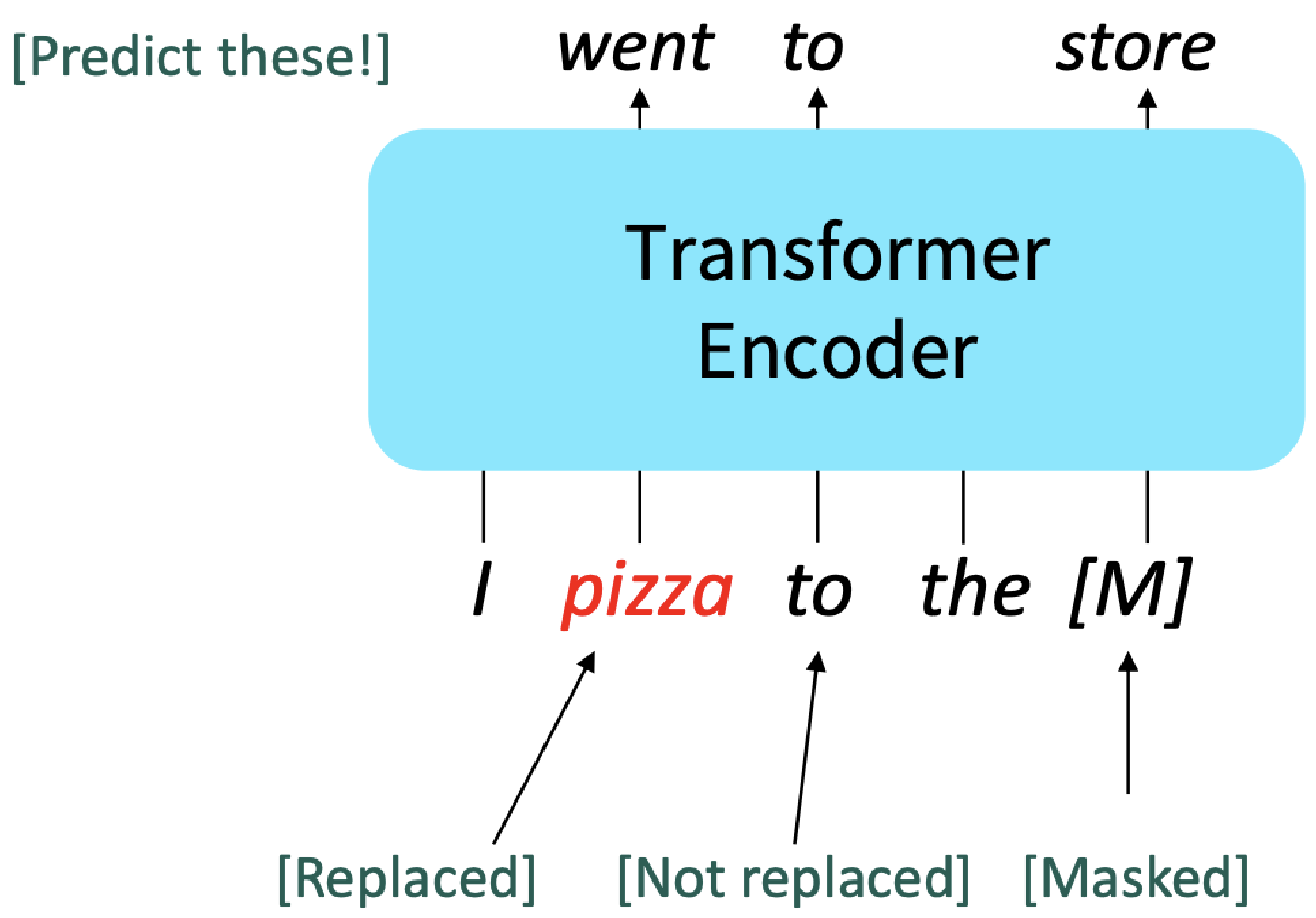
'Cause darling i'm a _______ dressed like a daydream

Bidirectional context is important to reconstruct the input!

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al., 2018 proposed the "Masked LM" objective and released BERT, a Transformer, pretrained to:

- 15% of the input tokens in a training sequence are sampled for learning, these are to be predicted by the model
- Of these
  - 80% are replaced with [MASK]
  - 10% are replaced with randomly selected tokens,
  - Remaining 10% are left unchanged

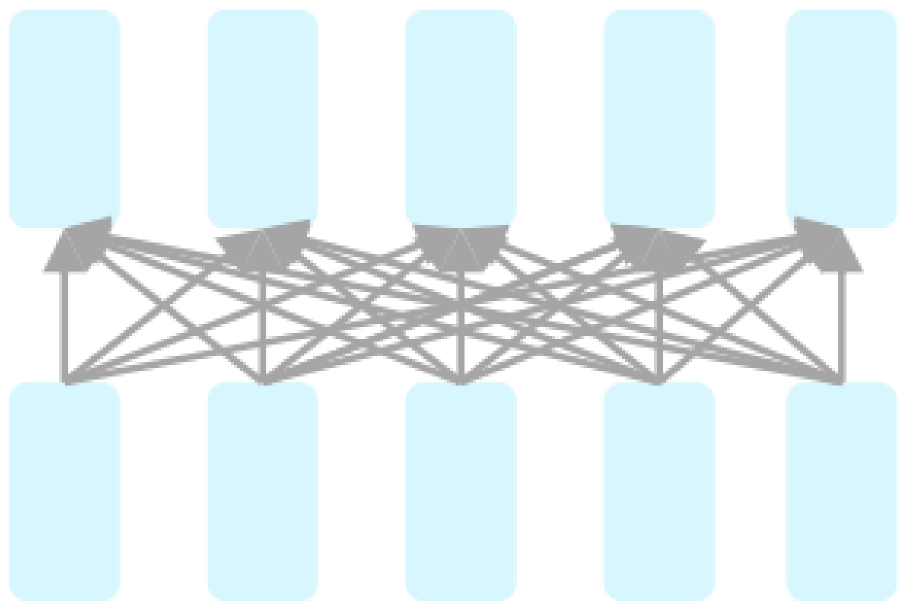


Why? Doesn't let the model get complacent and not build strong representations of non-masked words. (No masks are seen at fine-tuning time!)

BERT: Training Details

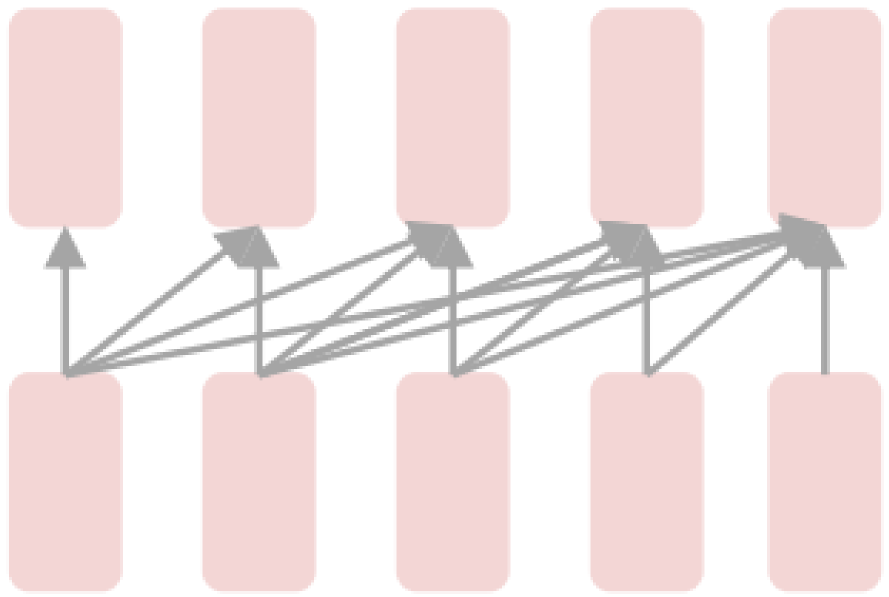
- Two models were released:
  - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
  - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- Trained on:
  - BooksCorpus (800 million words)
  - English Wikipedia (2,500 million words)
- Pretraining is expensive and impractical on a single GPU.
  - BERT was pretrained with 64 TPU chips for a total of 4 days.
    - (TPUs are special tensor operation acceleration hardware)
- Finetuning is practical and common on a single GPU
  - “Pretrain once, finetune many times.”

Pretraining for three types of architectures



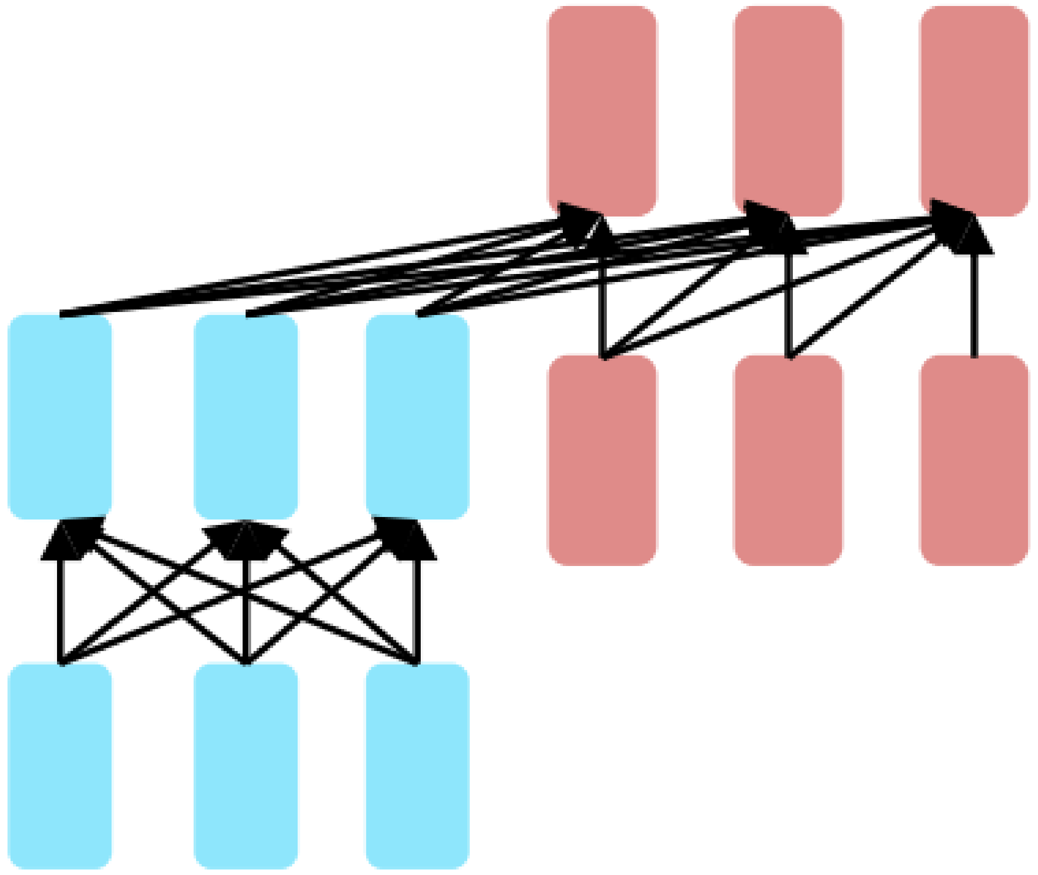
Encoders

Bidirectional Context



Decoders

Language Models



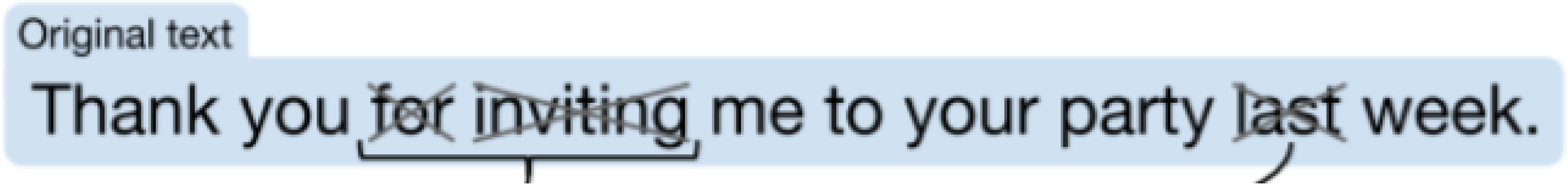
Encoder-Decoders

Sequence-to-sequence

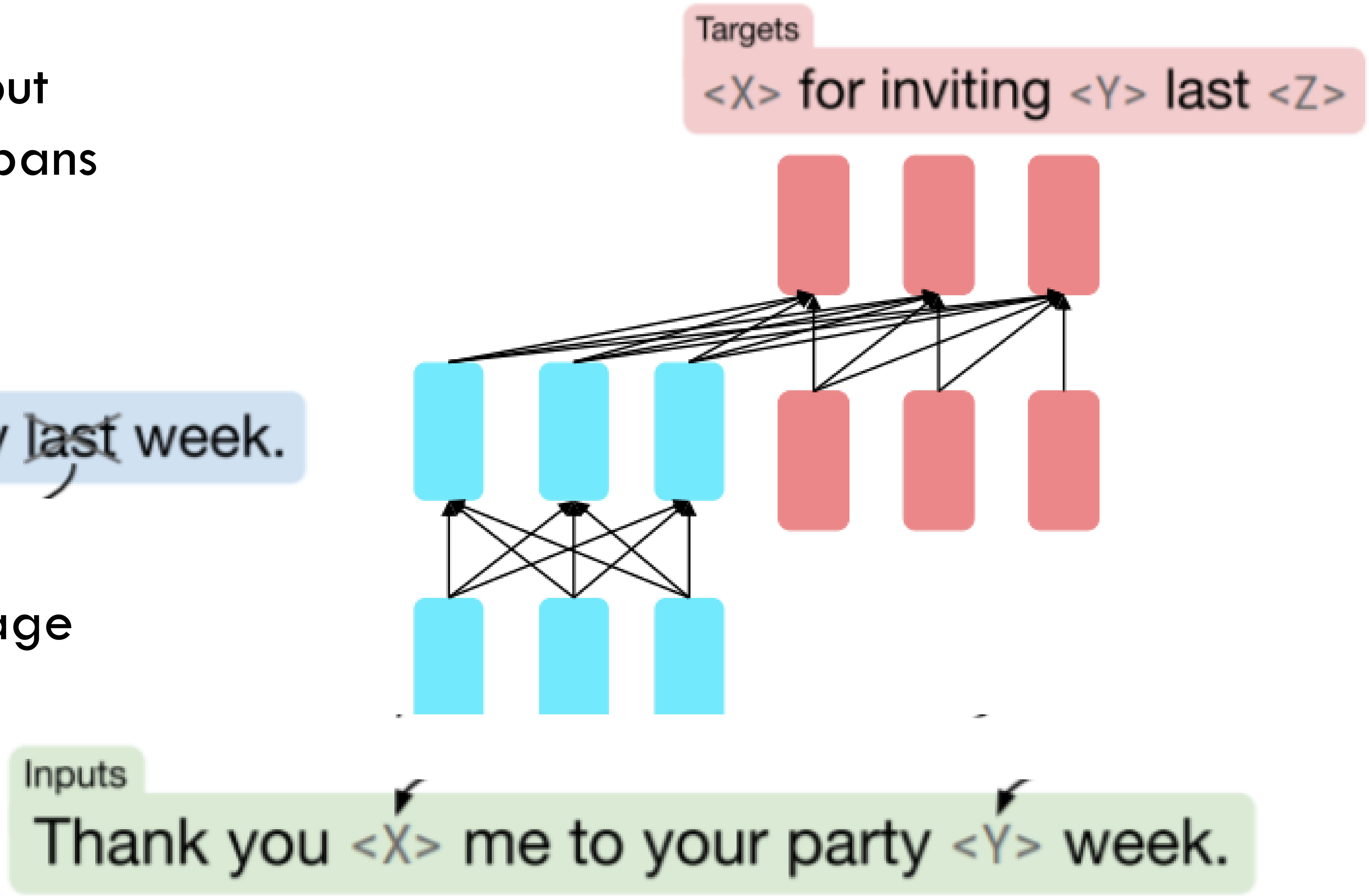
T5: A Pretrained Encoder-Decoder Model

- Raffel et al., 2018 built T5, which uses as a span corruption pretraining objective

Replace different-length spans from the input with unique placeholders; decode out the spans that were removed!

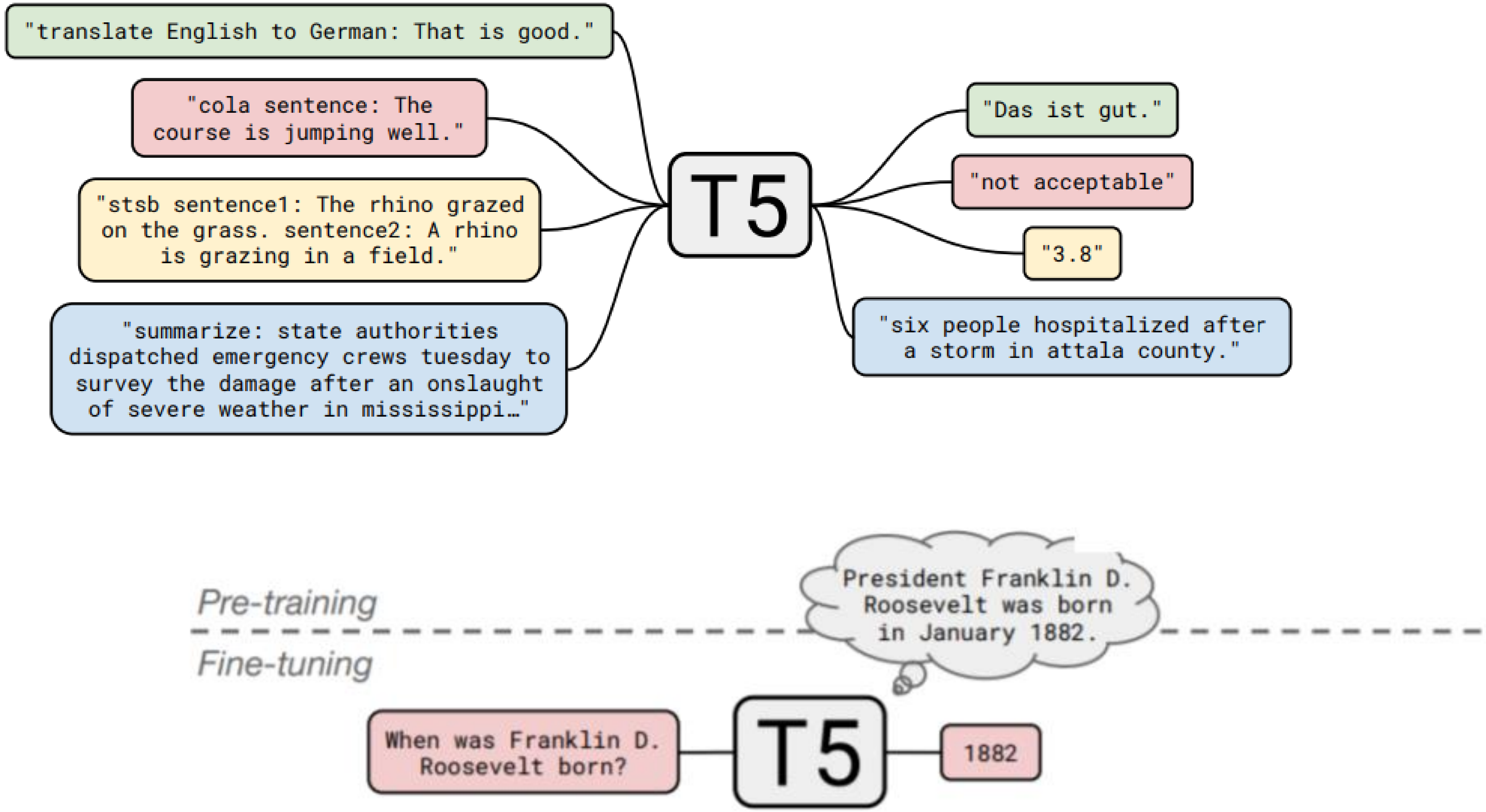


Still uses an objective that looks like language modeling at the decoder side.



T5: Task Preparation

T5 can be finetuned to answer a wide range of tasks, where the input and output are expressed as a sequence of tokens



Tokenization in Transformers

Word Structure and Subword Models

- So far, we have made some assumptions about a language's vocabulary
- We assume a fixed vocabulary of tens of thousands of words, built from the training set
- All novel words seen at test time are mapped to a single UNK

	word		vocab mapping	embedding
Common words	hat	→	pizza (index)	
	learn	→	tasty (index)	
Variations	taaaaasty	→	UNK (index)	
misspellings	laern	→	UNK (index)	
novel items	Transformerify	→	UNK (index)	

Word Structure in Language

- Finite vocabulary assumptions make even less sense in many languages.
  - Many languages exhibit complex morphology, or word structure.
  - The effect is: more word types, each occurring fewer times.

-ambia = to tell

Example: Swahili verbs can have hundreds of conjugations, each encoding a wide variety of information. (Tense, mood, definiteness, negation, information about the object, ++)

Source: Wiktionary

Conjugation of *-ambia*

Non-finite forms		
Form	Positive	Negative
Infinitive	kuambia	kutoambia
Simple finite forms		
Positive form	Singular	Plural
Imperative	ambia	ambieni
Habitual	huambia	

Complex finite forms

Polarity	Persons: 1st Sg.	1st Pl.	2nd Sg.	2nd Pl.	Persons / Classes: 3rd / M-wa Sg. / 1	Pl. / 2	Classes: M-mi 3	4	Ma 5	6	Ki-vi 7	8	N 9	10	U 11 / 14	Ku 15 / 17	Pa 16	Mu 18
Past [less ▲]																		
Positive	niliambia naliambia	tuliambia twaliambia	uliambia waliambia	mliambia mwaliambia	aliambia	waliambia	uliambia	iliambia	liliambia	yaliambia	kiliambia	viliambia	iliambia	ziliambia	uliambia	kuliambia	paliambia	muliambia
Negative	sikuambia	hatukuambia	hukuambia	hamkuambia	hakuambia	hawakuambia	haukuambia	haikuambia	halikuambia	hayakuambia	hakikuambia	havikuambia	haikuambia	hazikuambia	haukuambia	hakukuambia	hapakuambia	hamukuambia
Present [less ▲]																		
Positive	ninaambia naambia	tunaambia	unaambia	mnaambia	anaambia	wanaambia	unaambia	inaambia	linaambia	yanaambia	kinaambia	vinaambia	inaambia	zinaambia	unaambia	kunaambia	panaambia	munaambia
Negative	siambii	hatuambii	huambii	hamambii	haambii	hawaambii	hauambii	haiambii	haliambii	hayaambii	hakiambii	haviambii	haiambii	haziambii	hauambii	hakuambii	hapaambii	hamuambii
Future [less ▲]																		
Positive	nitaambia	tutaambia	utaambia	mtaambia	ataambia	wataambia	utaambia	itaambia	litaambia	yataambia	kitaambia	vitaambia	itaambia	zitaambia	utaambia	kutaambia	pataambia	mutaambia
Negative	sitaambia	hatutaambia	hutaambia	hamtaambia	hataambia	hawataambia	hautaambia	haitaambia	halitaambia	hayataambia	hakitaambia	havitaambia	haitaambia	hazitaambia	hautaambia	hakutaambia	hapataambia	hamutaambia
Subjunctive [less ▲]																		
Positive	niambie	tuambie	uambie	mambie	aambie	waambie	uambie	iambie	liambie	yaambie	kiambie	viambie	iambie	ziambie	uambie	kuambie	paambie	muambie
Negative	nisiambie	tusiambie	usiambie	msiambie	asiambie	wasiambie	usiambie	isiambie	lisiambie	yasiambie	kisiambie	visiambie	isiambie	zisiambie	usiambie	kusiambie	pasiambie	musiambie
Present Conditional [less ▲]																		
Positive	ningeambia	tungeambia	ungeambia	mngeambia	angeambia	wangeambia	ungeambia	ingeambia	lingeambia	yangeambia	kingeambia	vingeambia	ingeambia	zingeambia	ungeambia	kungeambia	pangeambia	mungeambia
Negative	nisingeambia singeambia	tusingeambia hatungeambia	usingeambia hungeambia	msingeambia hamngeambia	asingeambia hangeambia	wasingeambia hawangeambia	usingeambia haungeambia	isingeambia haingeambia	lisingeambia halingeambia	yasingeambia hayangeambia	kisingeambia hakingeambia	visingeambia havingeambia	isingeambia haingeambia	zisingeambia hazingeambia	usingeambia haungeambia	kusingeambia hakungeambia	pasingeambia hapangeambia	musingeambia hamungeambia
Past Conditional [less ▲]																		
Positive	ningaliambia	tungaliambia	ungaliambia	mngaliambia	angaliambia	wangaliambia	ungaliambia	ingaliambia	lingaliambia	yangaliambia	kingaliambia	vingaliambia	ingaliambia	zingaliambia	ungaliambia	kungaliambia	pangaliambia	mungaliambia
Negative	nisingaliambia singaliambia	tusingaliambia hatungaliambia	usingaliambia hungaliambia	msingaliambia hamngaliambia	asingaliambia hangaliambia	wasingaliambia hawangaliambia	usingaliambia haungaliambia	isingaliambia haingaliambia	lisingaliambia halingaliambia	yasingaliambia hayangaliambia	kisingaliambia hakingaliambia	visingaliambia havingaliambia	isingaliambia haingaliambia	zisingaliambia hazingaliambia	usingaliambia haungaliambia	kusingaliambia hakungaliambia	pasingaliambia hapangaliambia	musingaliambia hamungaliambia
Conditional Contrary to Fact [less ▲]																		
Positive	ningeliambia	tungeliambia	ungeliambia	mngeliambia	angeliambia	wangeliambia	ungeliambia	ingeliambia	lingeliambia	yangeliambia	kingeliambia	vingeliambia	ingeliambia	zingeliambia	ungeliambia	kungeliambia	pangeliambia	mungeliambia
Gnomic [less ▲]																		
Positive	naambia	twaambia	waambia	mwaambia	aambia	waambia	waambia	yaambia	laambia	yaambia	chaambia	vyaambia	yaambia	zaambia	waambia	kwaambia	paambia	mwaambia
Perfect [less ▲]																		

Subword Modeling

- Solution: look at subwords
- Subword modeling in NLP encompasses a wide range of methods for reasoning about structure below the word level
  - Subwords may be parts of words, characters, bytes
- The dominant modern paradigm is to learn a vocabulary of parts of words (subword tokens).
- At training and testing time, each word is split into a sequence of known subwords.

Byte-pair encoding

- Byte-pair encoding is a simple, effective strategy for defining a subword vocabulary
- Adapted for word segmentation from data compression technique (Gage, 1994)
  - Instead of merging frequent pairs of bytes, we merge characters or character sequences

Byte-pair encoding

- Algorithm:
  1. Start with a vocabulary containing only characters and an "end-of-word" symbol.
  2. Using a corpus of text, find the most common adjacent characters "a,b"; add "ab" as a subword.
  3. Replace instances of the character pair with the new subword; repeat until desired vocabulary size.

BPE in action

Corpus

low	lower	newest
low	lower	newest
low	widest	newest
low	widest	newest
low	widest	newest

Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w e s t </w>
l o w </w>	l o w e r </w>	n e w e s t </w>
l o w </w>	w i d e s t </w>	n e w e s t </w>
l o w </w>	w i d e s t</w>	n e w e s t </w>
l o w </w>	w i d e s t </w>	n e w e s t </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es								

Frequency

d-e (3)	l-o (7)	t-</w> (8)
e-r (2)	n-e (5)	w-</w> (5)
e-s (8)	o-w (7)	w-e (7)
e-w (5)	r-</w> (2)	w-i (3)
i-d (3)	s-t (8)	

Source: https://www.analyticsvidhya.com/blog/2020/05/what-is-tokenization-nlp/

BPE in action

Corpus

low	lower	newest
low	lower	newest
low	widest	newest
low	widest	newest
low	widest	newest

Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w es t </w>
l o w </w>	l o w e r </w>	n e w es t </w>
l o w </w>	w i d es t </w>	n e w es t </w>
l o w </w>	w i d es t</w>	n e w es t </w>
l o w </w>	w i d es t </w>	n e w es t </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es	est							

Frequency

d-es (3)	l-o (7)	w-</w> (5)
e-r (2)	n-e (5)	w-es (5)
e-w (5)	o-w (7)	w-e (2)
es-t (8)	r-</w> (2)	w-i (3)
i-d (3)	t-</w> (8)	

Source: https://www.analyticsvidhya.com/blog/2020/05/what-is-tokenization-nlp/

BPE in action

Corpus

low	lower	newest
low	lower	newest
low	widest	newest
low	widest	newest
low	widest	newest

Corpus

low</w>	lower</w>	newest</w>
low</w>	lower</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>
low</w>	widest</w>	newest</w>

Corpus

l o w </w>	l o w e r </w>	n e w est </w>
l o w </w>	l o w e r </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>
l o w </w>	w i d est </w>	n e w est </w>

Vocabulary

d	e	i	l	n	o	s	t	w
es	est	est</w>	lo	low	low</w>	ne	new	newest</w>

After 10 merges

Source: https://www.analyticsvidhya.com/blog/2020/05/what-is-tokenization-nlp/

Byte-pair encoding

- At test time, first split words into sequences of characters, then apply the learned operations to merge the characters into larger, known symbols
- Originally used in NLP for machine translation; now a similar method (WordPiece) is used in pretrained models.

Word structure and subword models

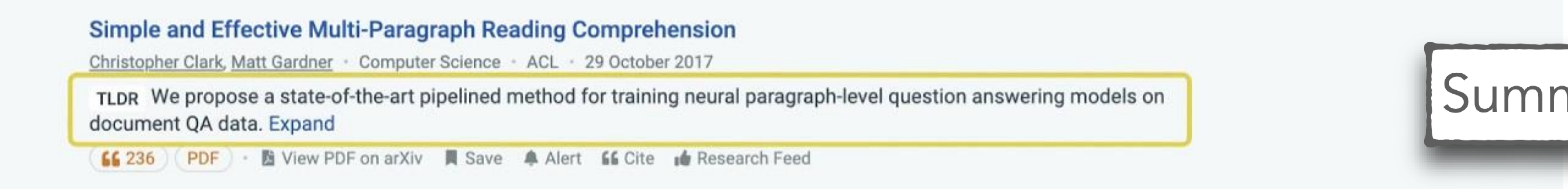
- Common words end up being a part of the subword vocabulary, while rarer words are split into (sometimes intuitive, sometimes not) components.
- In the worst case, words are split into as many subwords as they have characters.

Natural Language Generation

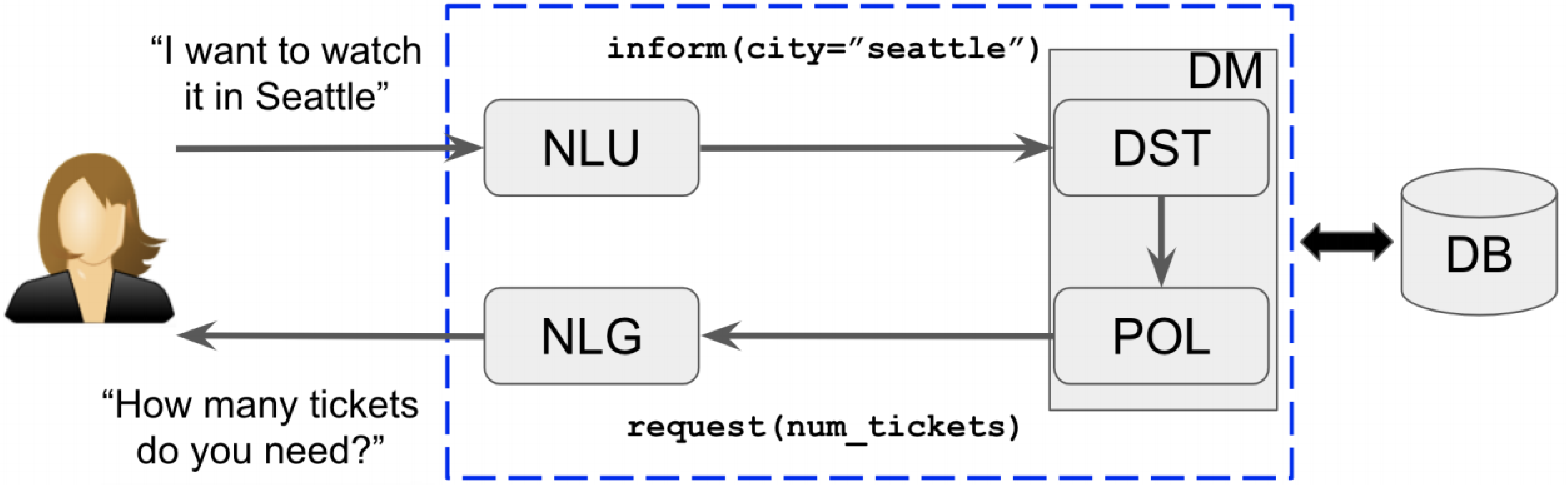
Natural Language Generation

- Natural language understanding and natural language generation are two sides of the same coin
  - In order to generate good language, you need to understand language
  - If you understand language, you should be able to generate it (with some effort)
- NLG is the workhorse of many classic and novel applications
  - AI Assistants
  - Translators
  - Search summarizers

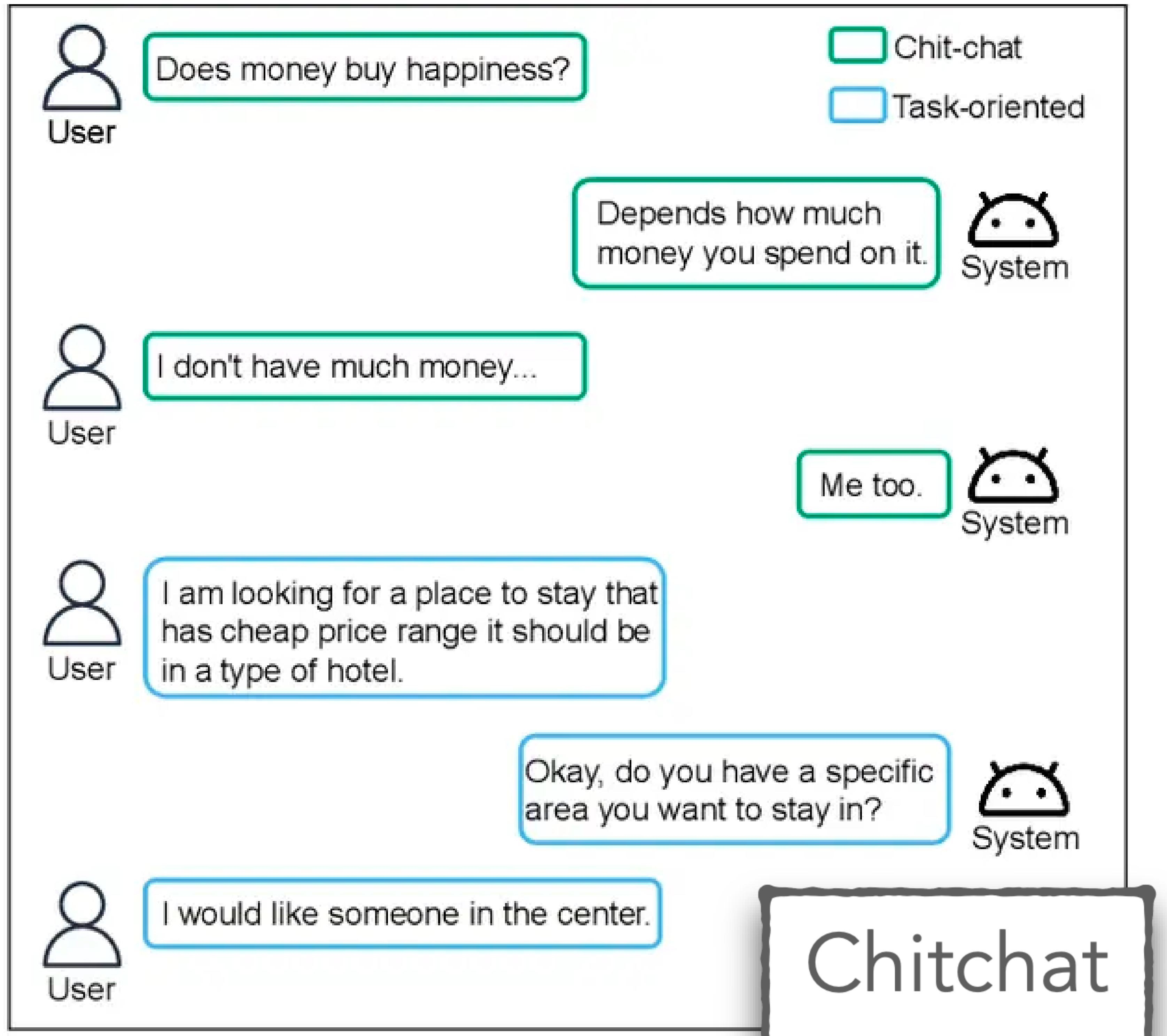
NLG Use Cases



Summarization



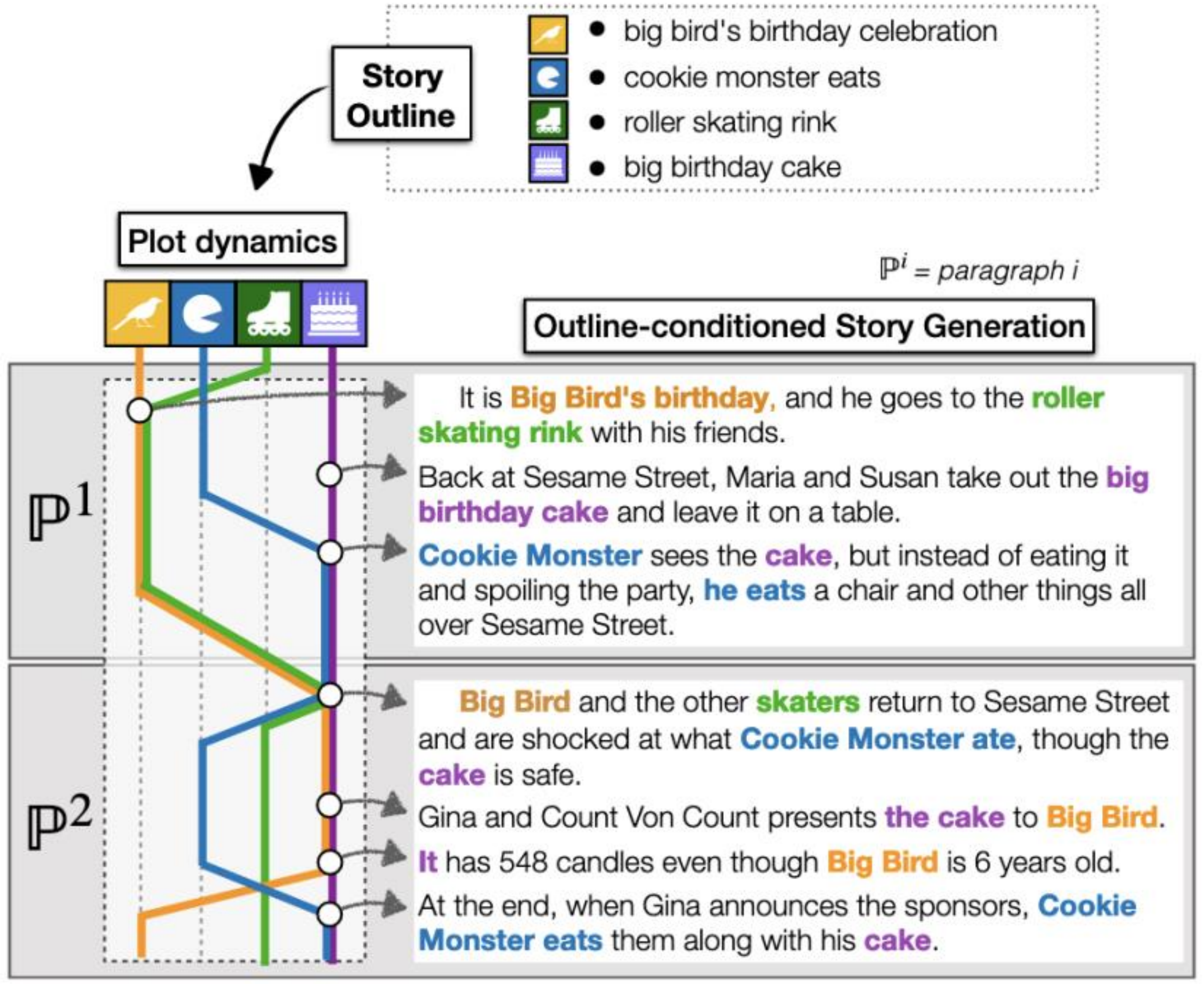
Task-driven Dialog



Chitchat Dialog

More Interesting NLG Uses

Creative stories



Rashkin et al., 2020

Data-to-text

Table Title: Robert Craig (American football)
Section Title: National Football League statistics
Table Description:None

		RUSHING					RECEIVING				
YEAR	TEAM	ATT	YDS	AVG	LNG	TD	NO.	YDS	AVG	LNG	TD
1983	SF	176	725	4.1	71	8	48	427	8.9	23	4
1984	SF	155	649	4.2	28	4	71	675	9.5	64	3
1985	SF	214	1050	4.9	62	9	92	1016	11	73	6
1986	SF	204	830	4.1	25	7	81	624	7.7	48	0
1987	SF	215	815	3.8	25	3	66	492	7.5	35	1
1988	SF	310	1502	4.8	46	9	76	534	7.0	22	1
1989	SF	271	1054	3.9	27	6	49	473	9.7	44	1
1990	SF	141	439	3.1	26	1	25	201	8.0	31	0
1991	RAI	162	590	3.6	15	1	17	136	8.0	20	0
1992	MIN	105	416	4.0	21	4	22	164	7.5	22	0
1993	MIN	38	119	3.1	11	1	19	169	8.9	31	1
Totals	**-**	**1991**	**8189**	**4.1**	**71**	**56**	**566**	**4911**	**8.7**	**73**	**17**

Craig finished his eleven NFL seasons with 8,189 rushing yards and 566 receptions for 4,911 receiving yards.

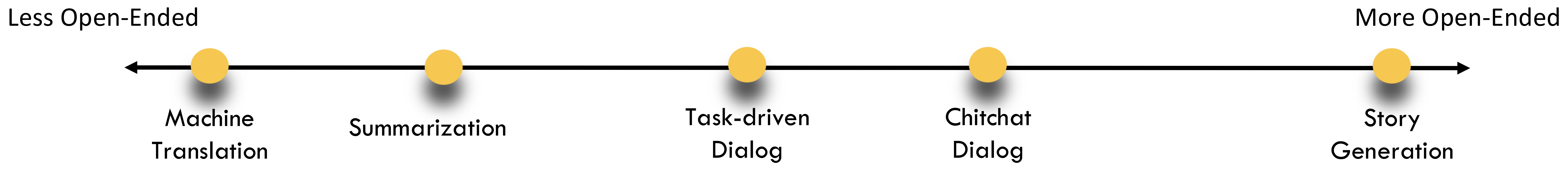
Parikh et al., 2020

Visual description

Two children are sitting at a table in a restaurant. The children are one little girl and one little boy. The little girl is eating a pink frosted donut with white icing lines on top of it. The girl has blonde hair and is wearing a green jacket with a black long sleeve shirt underneath. The little boy is wearing a black zip up jacket and is holding his finger to his lip but is not eating. A metal napkin dispenser is in between them at the table. The wall next to them is white brick. Two adults are on the other side of the short white brick wall. The room has white circular lights on the ceiling and a large window in the front of the restaurant. It is daylight outside.

Krause et al., 2017

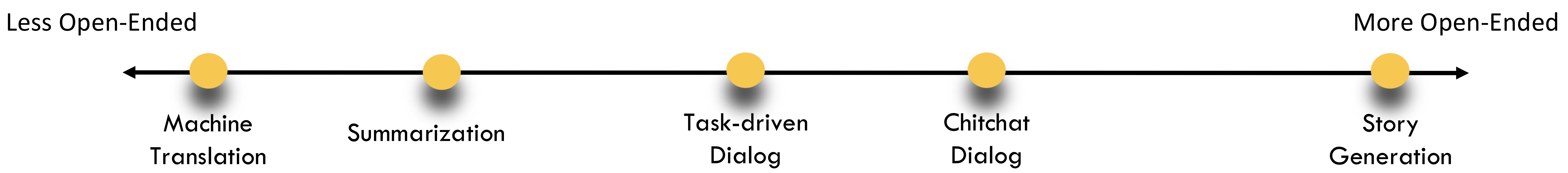
Broad Spectrum of NLG Tasks

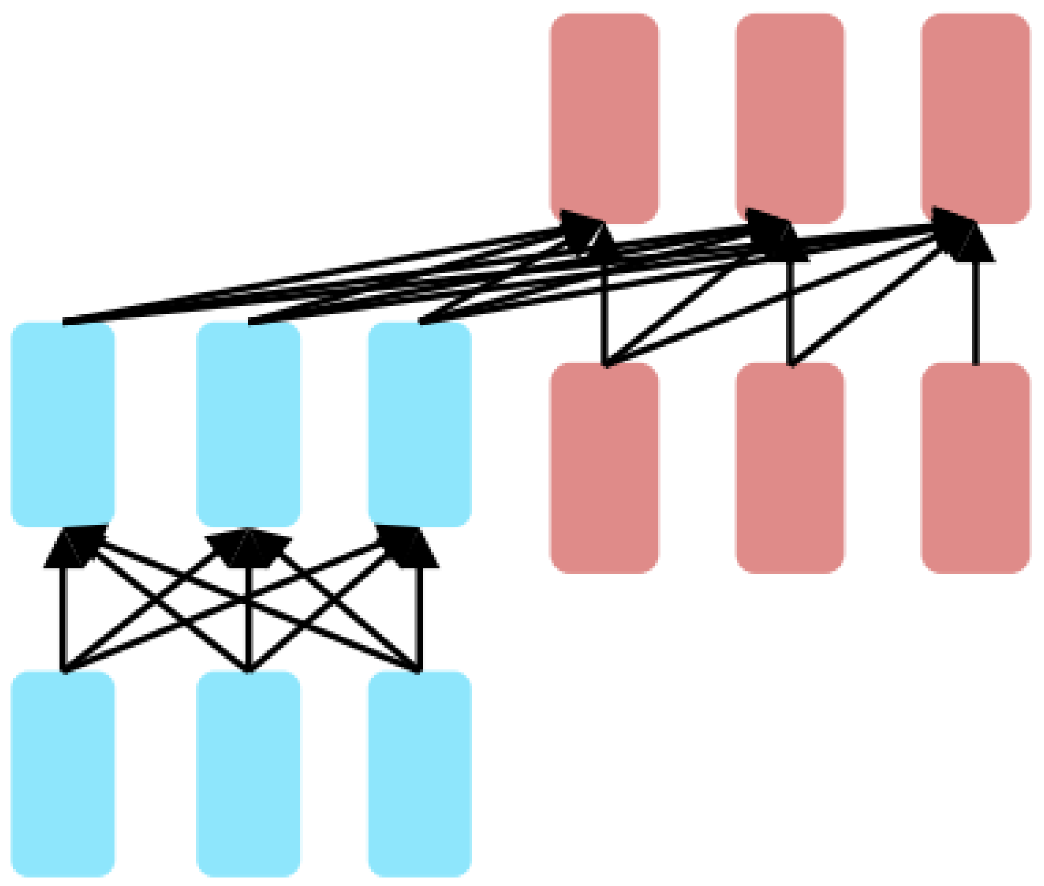


Open-ended generation: the output distribution still has high freedom.

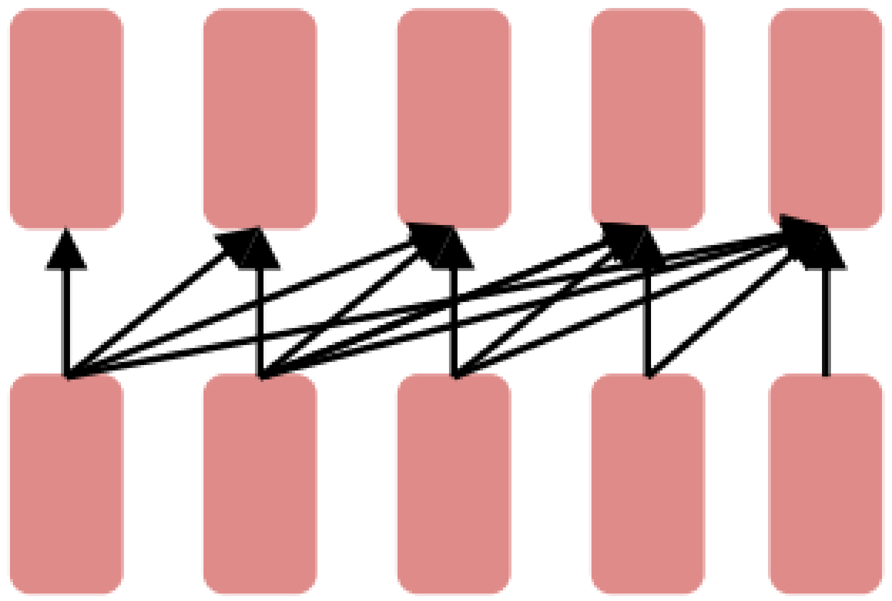
Non-open-ended generation: the input mostly determines the output generation.

Broad Spectrum of NLG Tasks





Encoder-Decoders

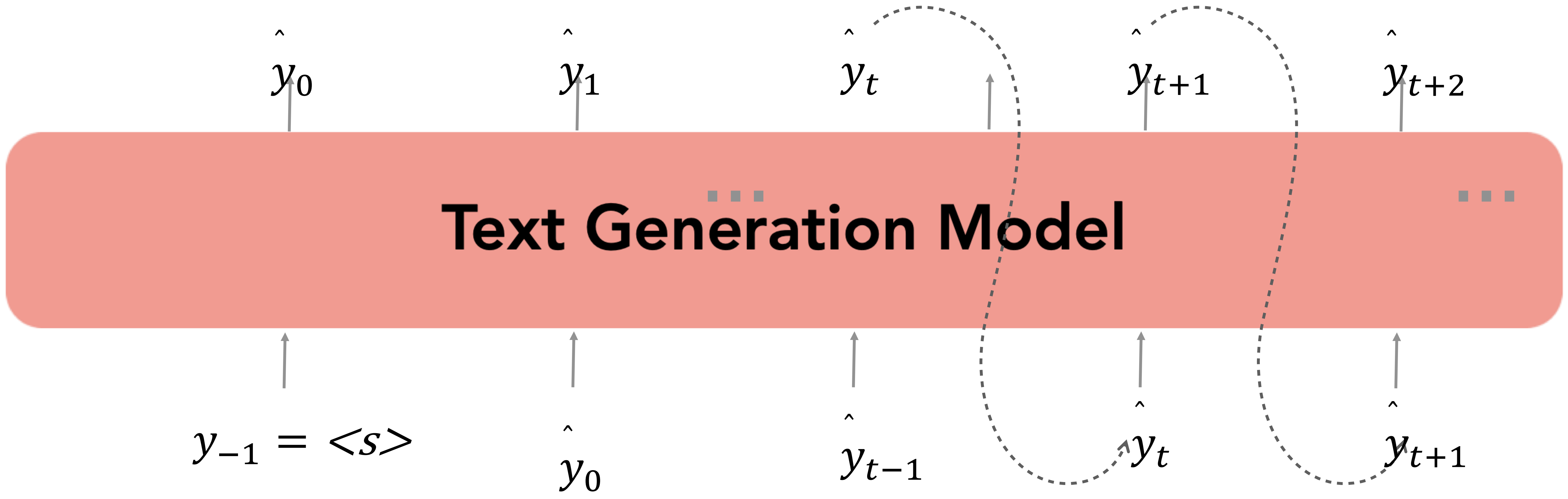


Decoders

Language Generation: Fundamentals

- In autoregressive text generation models, at each time step t, our model takes in a sequence of tokens as input $S = f_\theta(y_{<t}) \in \mathbb{R}^V$ and outputs a new token, $\hat{y}_t$
- For model $f_\theta(\cdot)$ and vocabulary V, we get scores $S = f_\theta(y_{<t}) \in \mathbb{R}^V$

$$P(w|y_{<t}) = \frac{\exp(S_w)}{\sum_{v \in V} \exp(S_v)}$$



Language Generation: Training

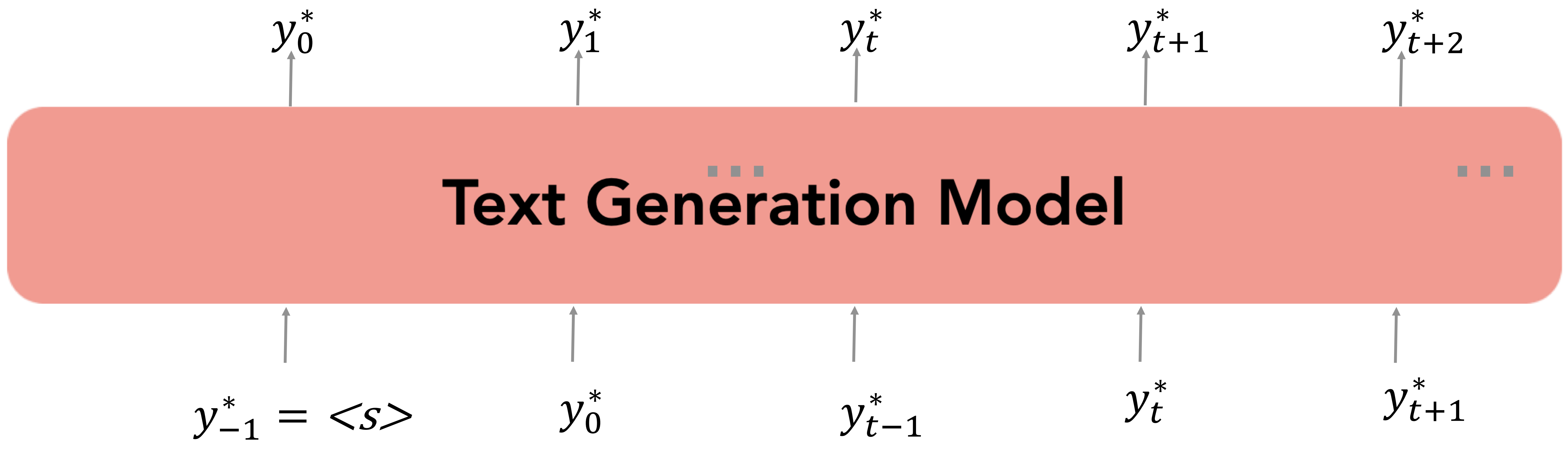
- Trained one token at a time to maximize the probability of the next token y_t^* given preceding words $y_{<t}^*$

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(y_t | y_{<t}) = -\sum_{t=1}^{T} \log \frac{\exp(S_{y_t|y_{<t}})}{\sum_{v \in V} \exp(S_{v|y_{<t}})}$$

- Classification task at each time step trying to predict the actual word y_t^* in the training data
- "Teacher forcing" (reset at each time step to the ground truth)

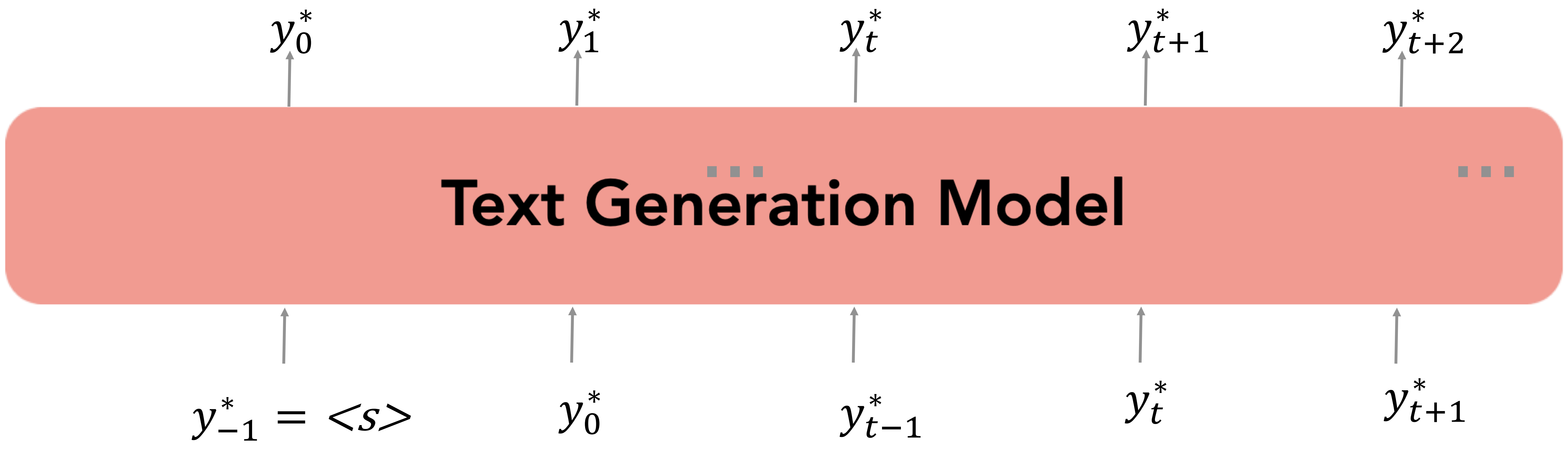
Teacher Forcing

- At each time step t in decoding we force the system to **use the gold target token from training as the next input x_{t+1}** ,rather than allowing it to rely on the (possibly erroneous) decoder output $\hat{y}_t$



Teacher Forcing

- Runs the risk of exposure bias!
  - During training, our model's inputs are gold context tokens from real, human-generated texts
  - At generation time, our model's inputs are previously–decoded tokens



Language Generation: Training

- More on LLM training (post-training) in the next class

Language Generation: Inference

- At inference time, our decoding algorithm defines a function to select a token from this distribution:

Inference / Decoding Algorithm

$$\hat{y}_t = g(P(y_t | y_{<t}))$$

- The "obvious" decoding algorithm is to ***greedily*** choose the highest probability next token according to the model at each time step

$$g = \mathrm{arg}max$$

$$\hat{y}_t = \mathrm{arg}\max_{w \in V}(P(y_t = w | y_{<t}))$$

Classic Inference Algorithms: Greedy and Beam Search

Decoding

- Generation from a language model is also called decoding
  - Think encoder-decoder
  - Also called inference
- Strategy so far: Take $argmax$ on each step of the decoder to produce the most probable word on each step
- This is called greedy decoding
  - Greedy Strategy: we are not looking ahead, we are making the hastiest decision given all the information we have

Greedy Decoding: Issues

- Greedy decoding has no wiggle room for errors!
  - Input: the green witch arrived
    - Output: llego
    - Output: llego la
    - Output: llego la verde
- How to fix this?
  - Need a lookahead strategy / longer-term planning

Exhaustive Search Decoding

- Ideally, we want to find a (length T) translation y that maximizes

$$P(y|x) = P(y_1|x)\, P(y_2|y_1, x)\, P(y_3|y_1, y_2, x) \ldots, P(y_T|y_1, \ldots, y_{T-1}, x)$$
$$= \prod_{t=1}^{T} P(y_t|y_1, \ldots, y_{t-1}, x)$$

- We could try computing all possible sequences y
  - This means that on each step t of the decoder, we're tracking V^t possible partial translations, where V is vocab size
  - This $O(V^T)$ complexity is far too expensive!

Beam Search Decoding

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

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

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

Beam Search Decoding: Example

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

<START>

Calculate prob dist of next word

Slide credit: Chris Manning

Beam Search Decoding: Example

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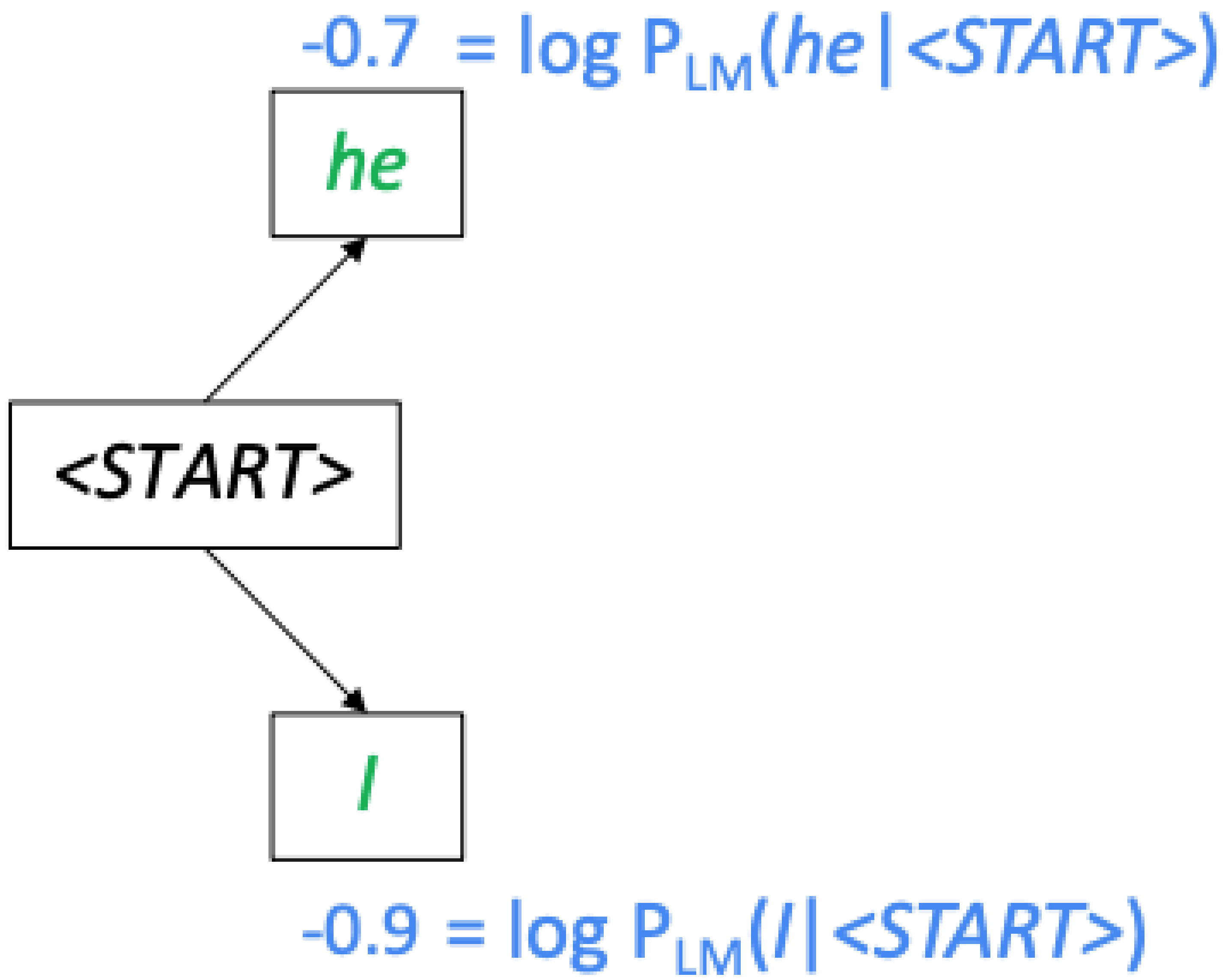

Take top *k* words
and compute scores

...: Chris Manning

Beam Search Decoding: Example

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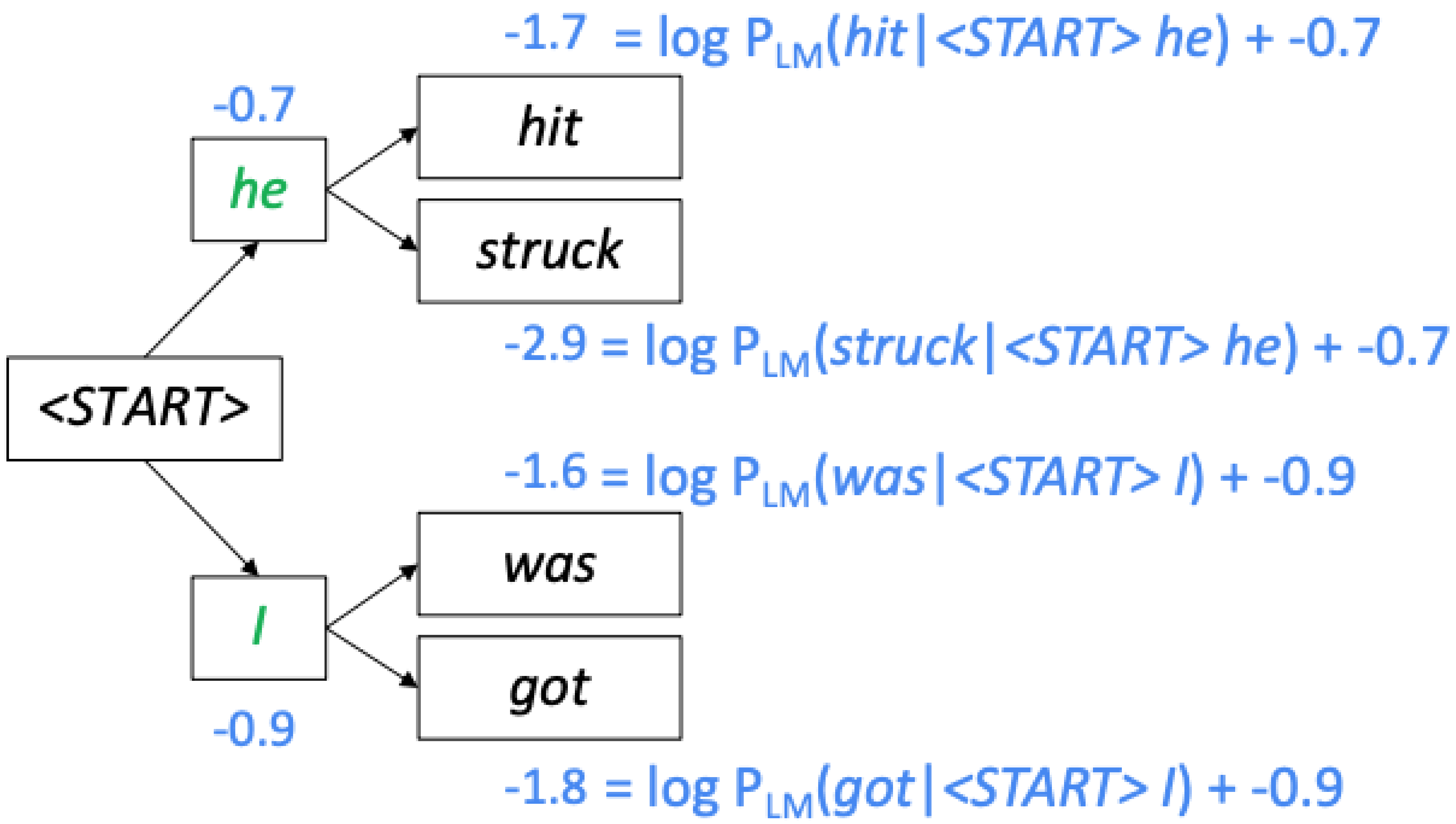

For each of the *k* hypotheses, find top *k* next words and calculate scores

Slide credit: Chris Manning

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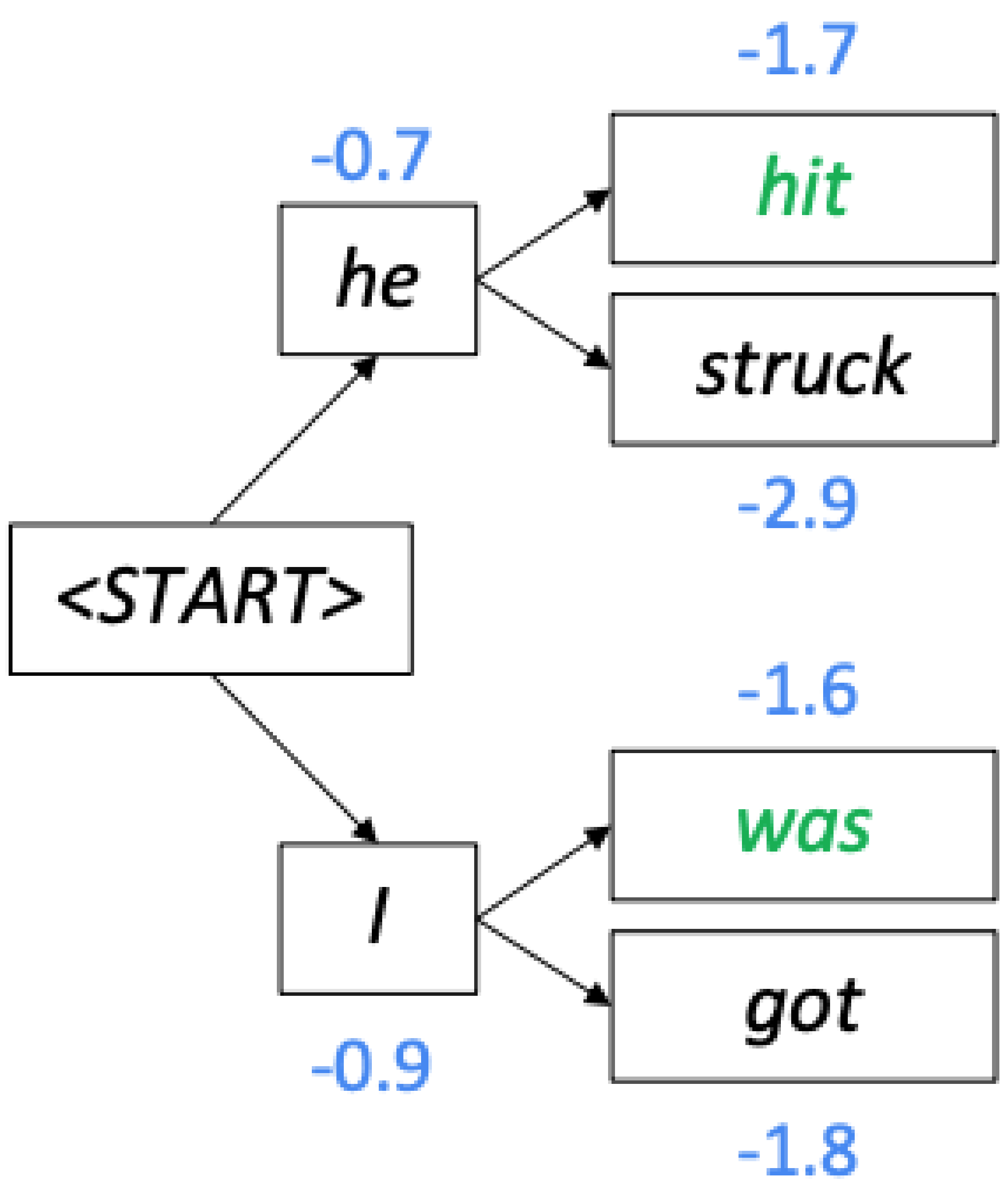

Of these k^2 hypotheses, just keep k with highest scores

Slide credit: Chris Manning

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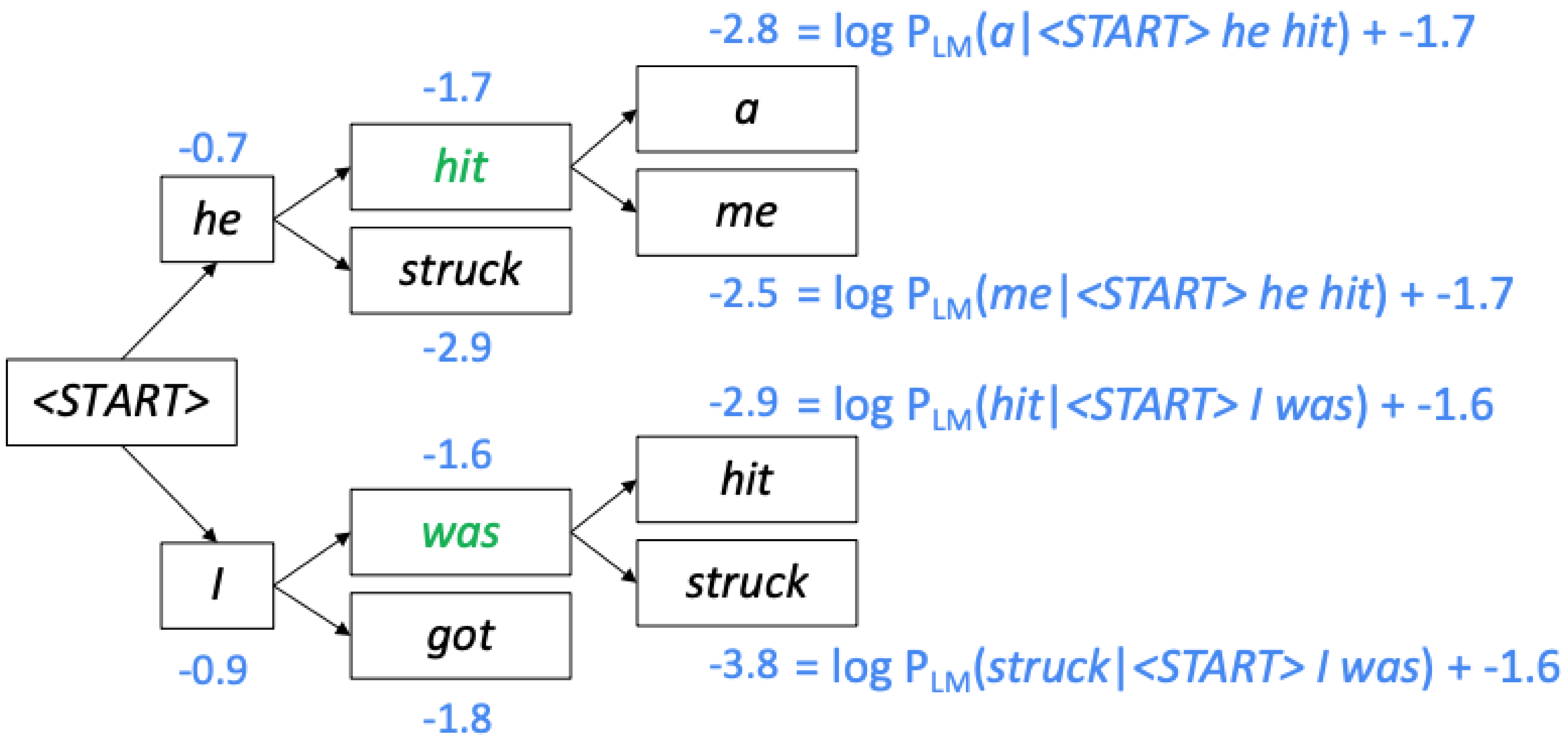

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USC Viterbi

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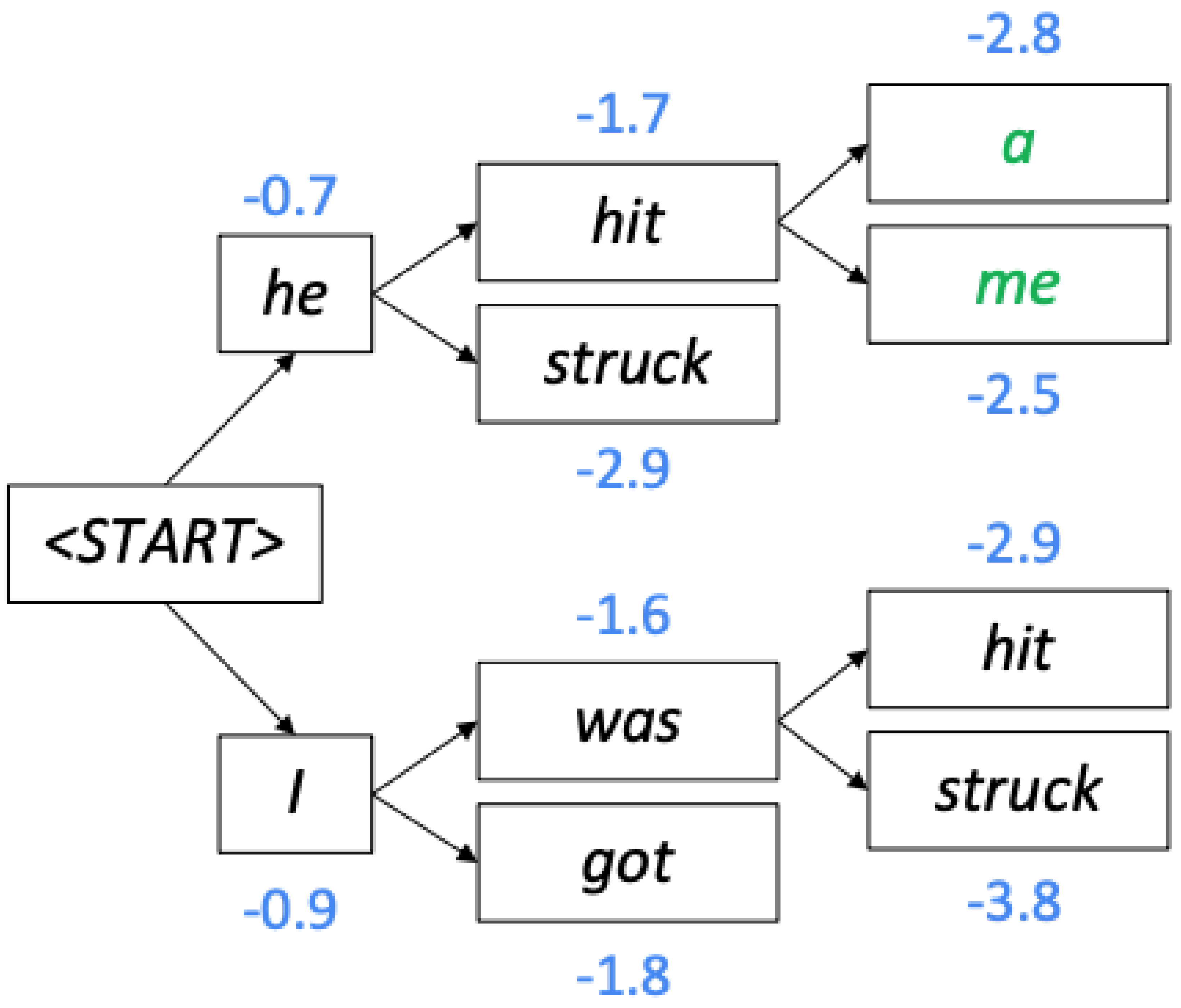

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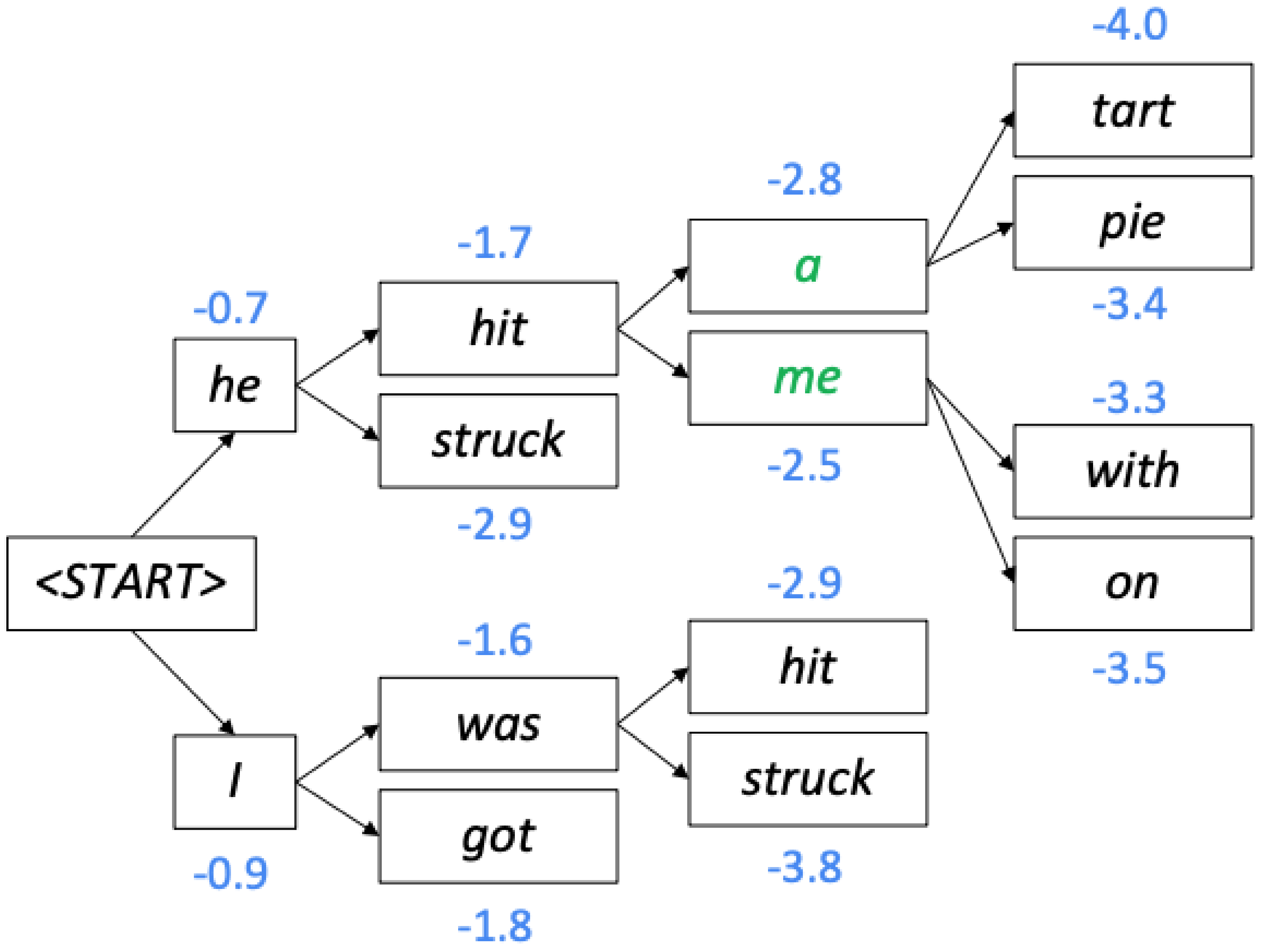

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USC Viterbi

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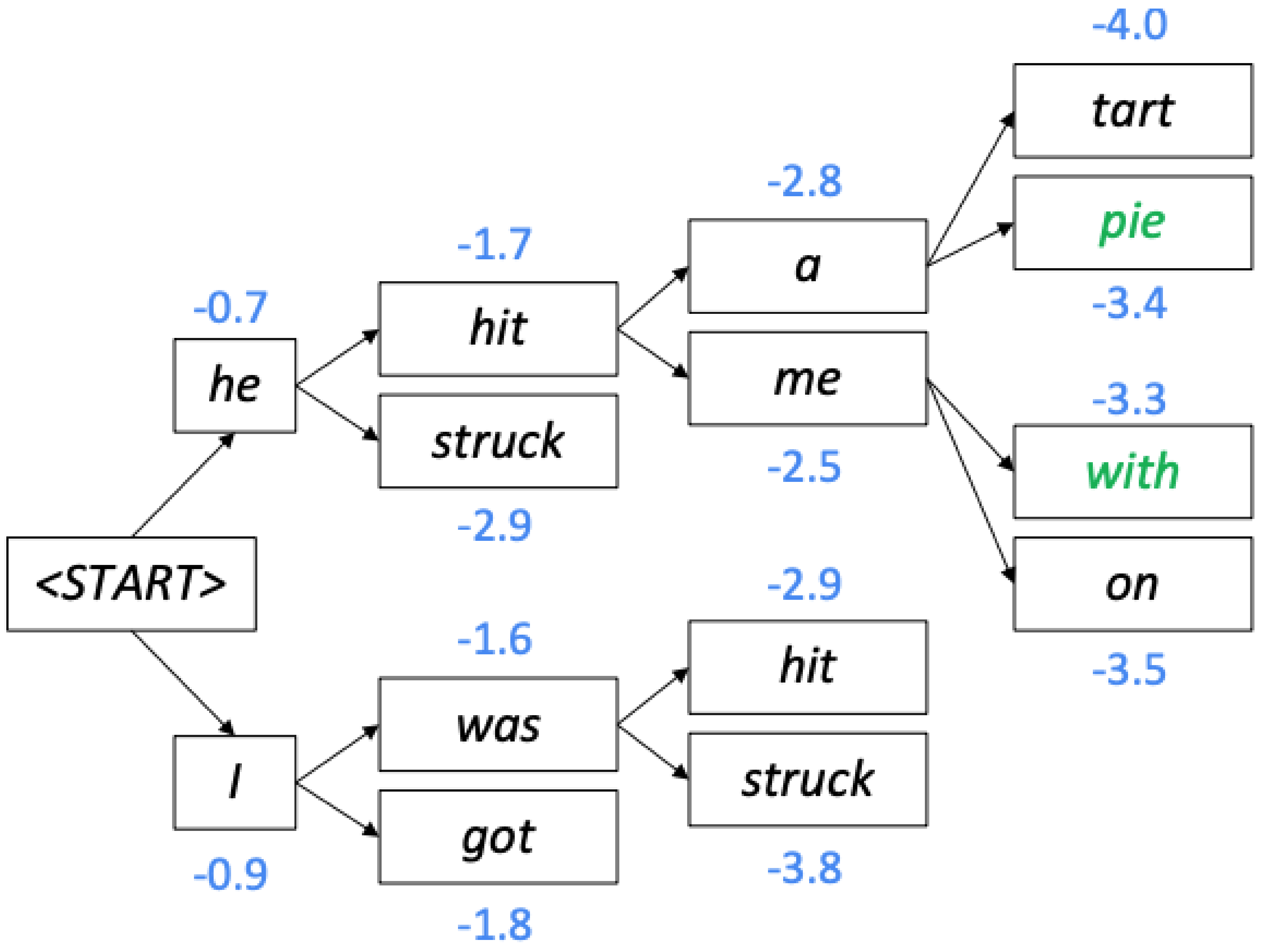

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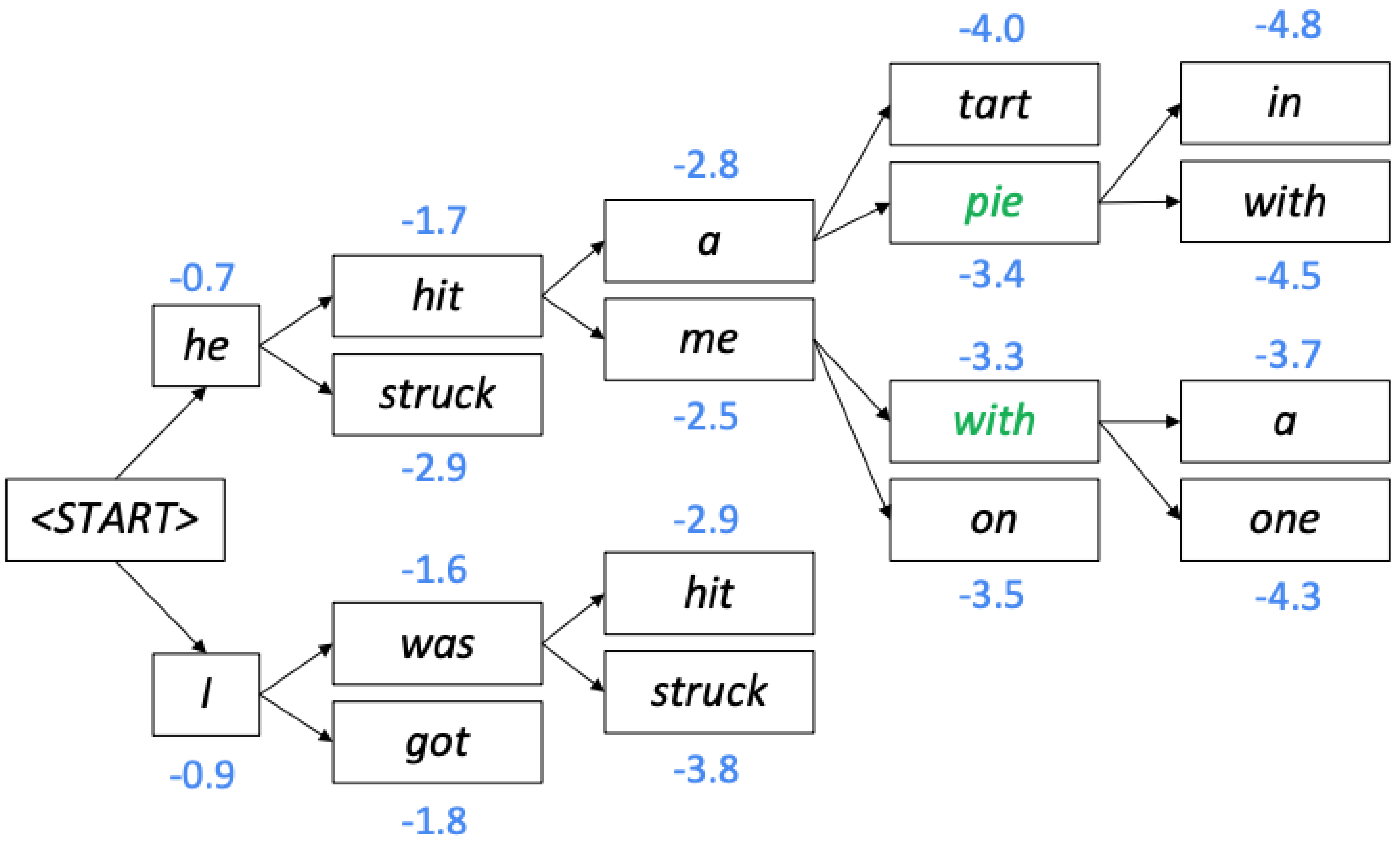

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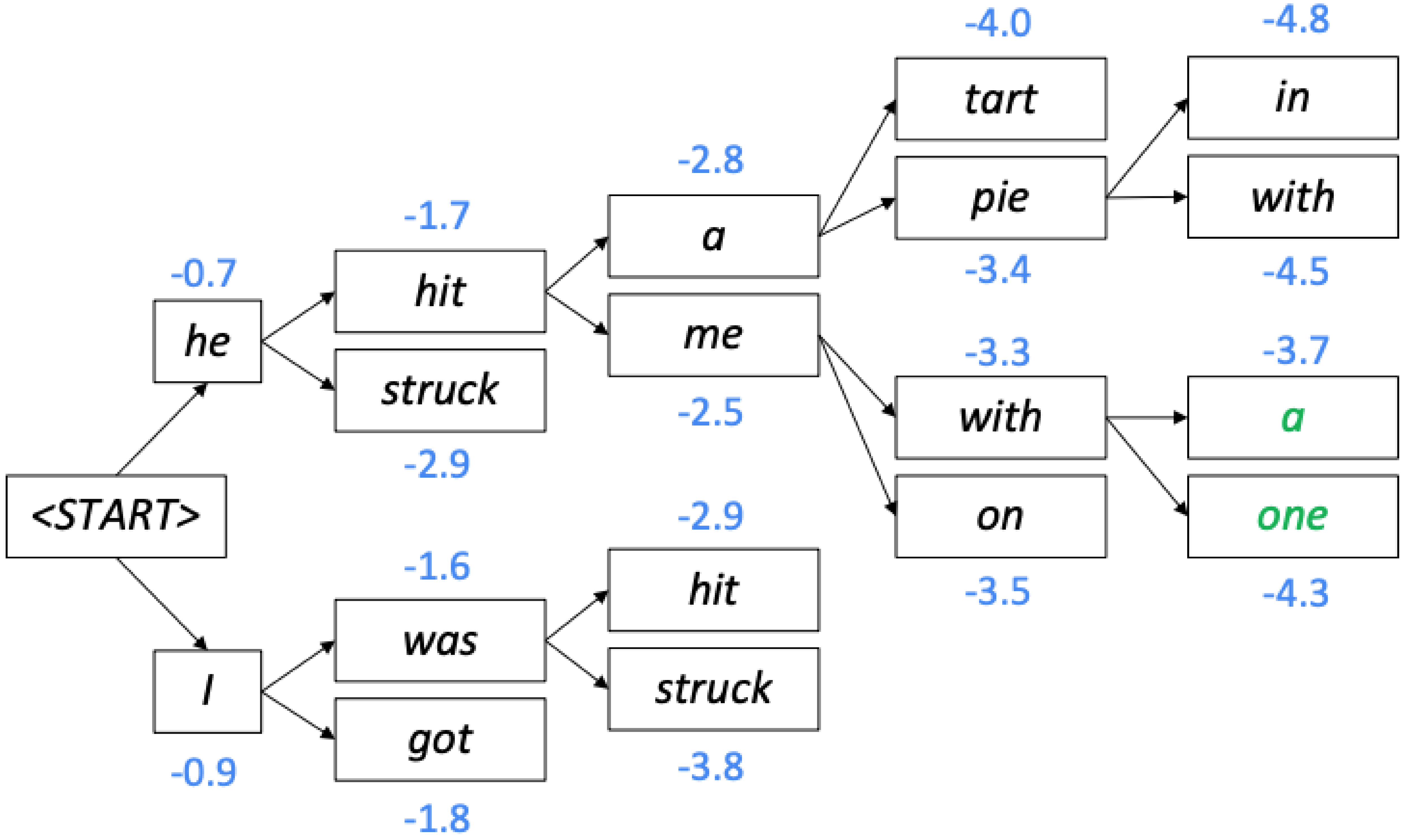

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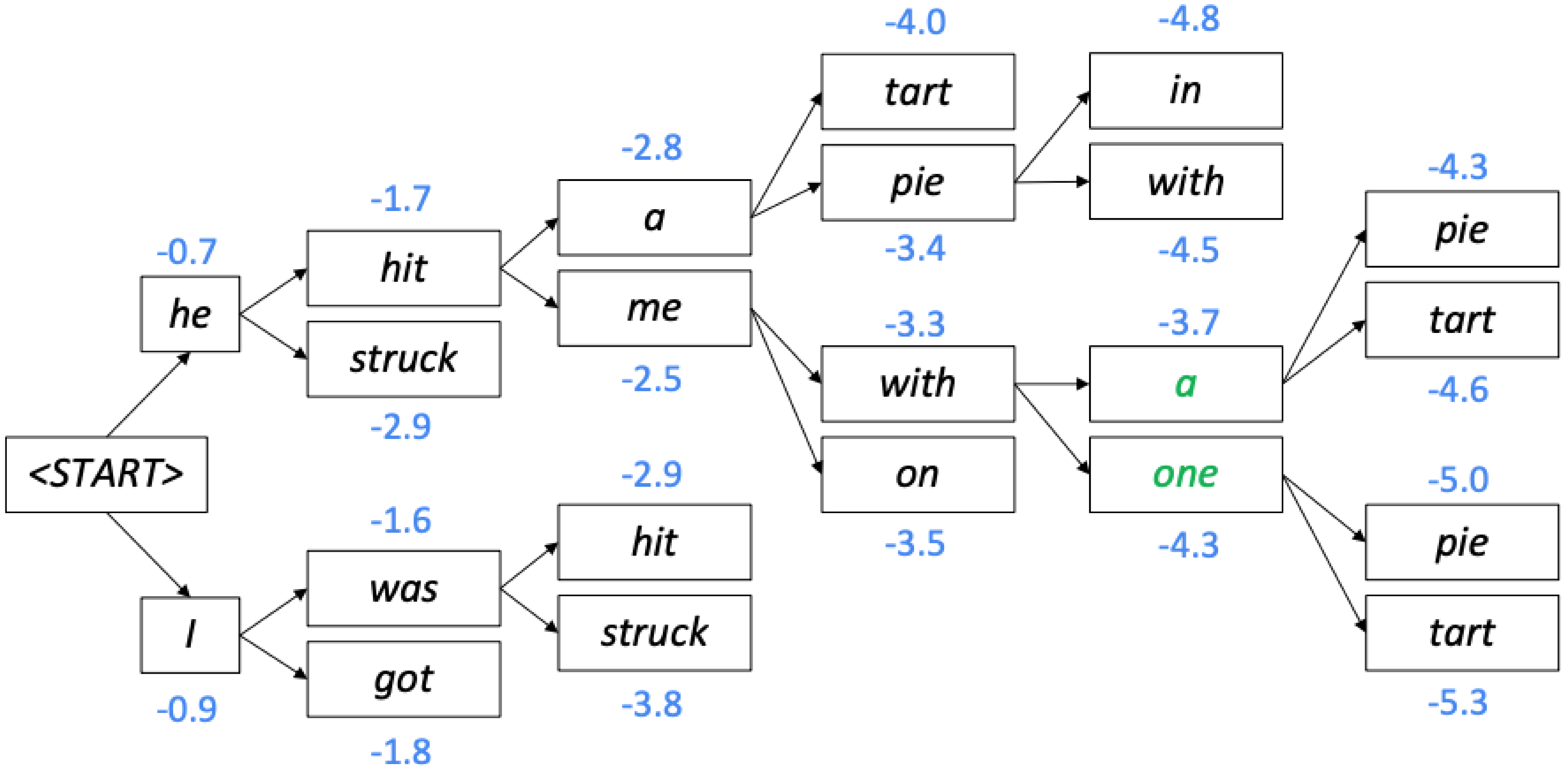

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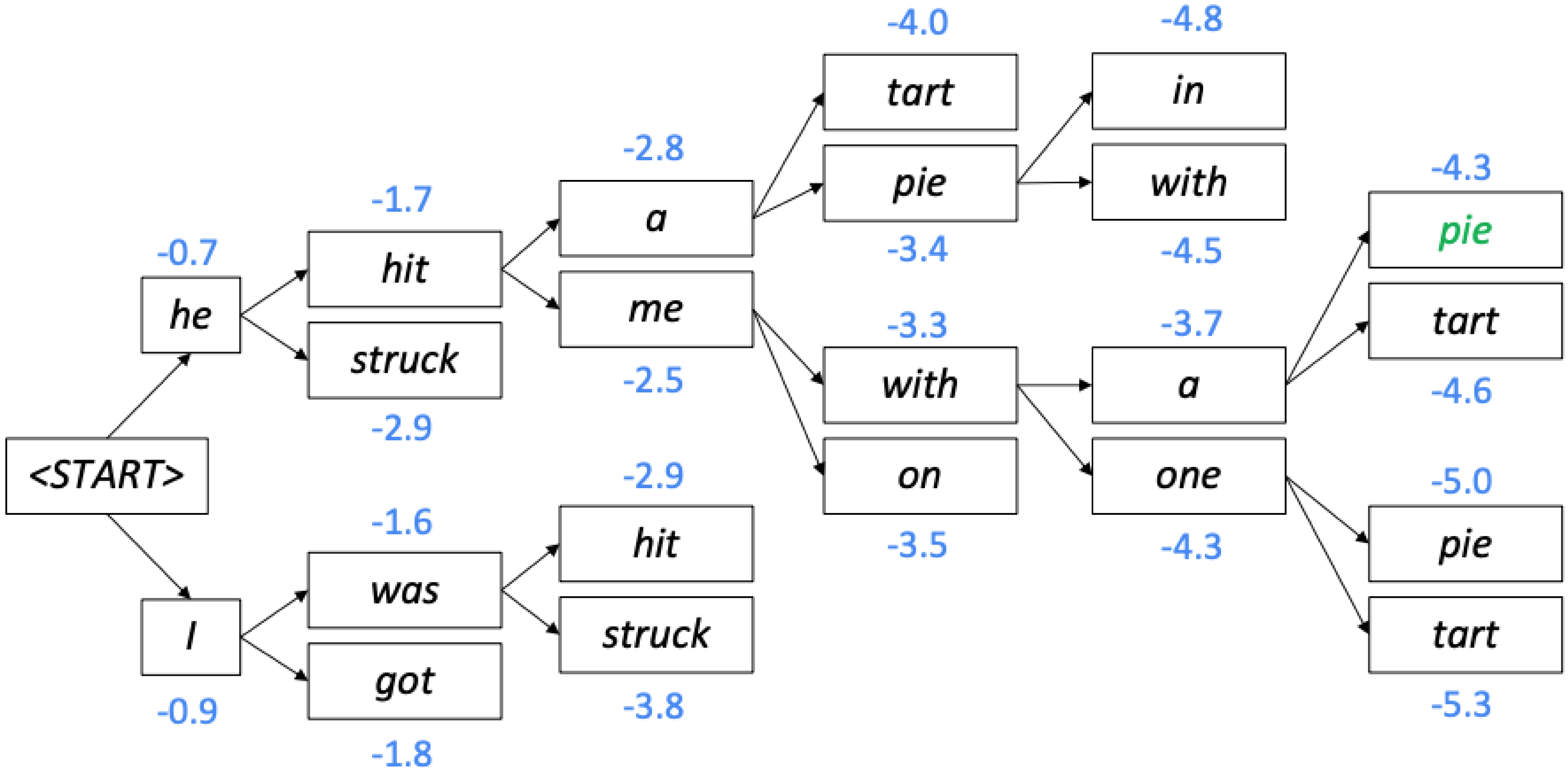

This is the top-scoring hypothesis!

Slide credit: Chris Manning

Beam Search Decoding: Example

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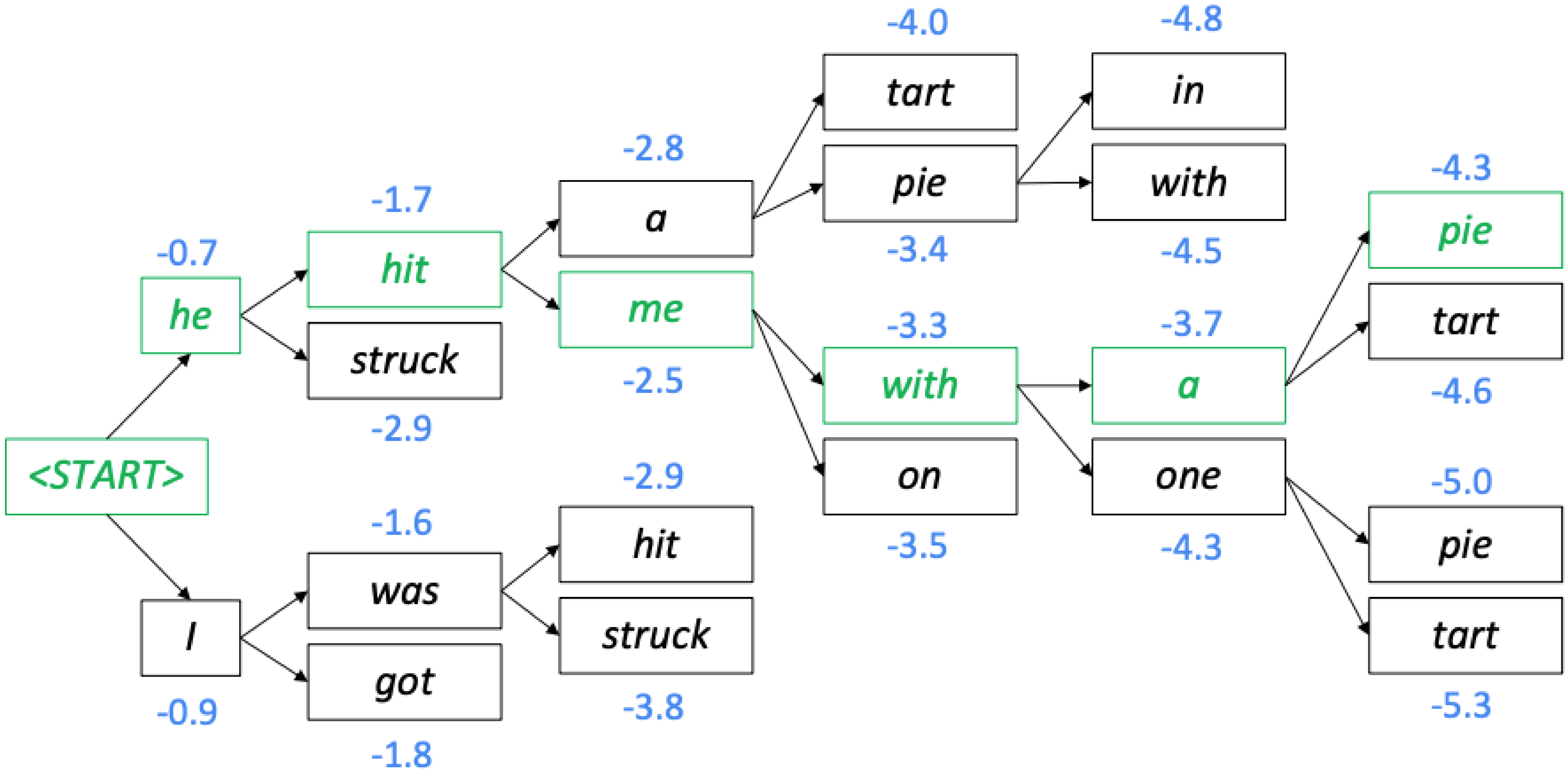

Backtrack to obtain the full hypothesis

Slide credit: Chris Manning

Beam Search Decoding: Stopping Criterion

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

Beam Search Decoding: Parting Thoughts

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

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

- Problem with this: longer hypotheses have lower score

- Fix: Normalize by length. Use this to select top one instead

But this is expensive!

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

Issues with Maximization-Based Decoding

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

Generation can be bland or repetitive (also called degenerate)

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

Continuation: The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the **Universidad Nacional Autónoma de México (UNAM)** and **the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México/ Universidad Nacional Autónoma de México…**

Holtzmann et al., 2020

USC Viterbi

Modern Generation: Sampling

Next Class!