Probing pretrained models

CS 685, Fall 2020

Introduction to Natural Language Processing

http://people.cs.umass.edu/~miyyer/cs685/

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most slides from Tu Vu

Logistics stuff

Final project reports due Dec 4 on Gradescope!

Dec 4 is also the deadline for pass/fail requests

Next Wednesday: PhD student Xiang Li will be talking about commonsense reasoning.

BERTology

BERTology

studying the inner working of large-scale Transformer language models like BERT

- what are captured in different model components, e.g., attention / hidden states?

BERTology

tools & examples

BERTology - HuggingFace's Transformers
https://huggingface.co/transformers/bertology.html

- accessing all the hidden-states of BERT
- accessing all the attention weights for each head of BERT
- retrieving heads output values and gradients

BERTology

tools & examples (cont.)

Are Sixteen Heads Really Better than One? Michel et al., NeurIPS 2019

large percentage of attention heads can be removed at test time without significantly impacting performance

What Does BERT Look At? An Analysis of BERT's Attention, Clark el al., BlackBoxNLP 2019

substantial syntactic information is captured in BERT's attention

BERTology

tools & examples

AllenNLP Interpret

https://allennlp.org/interpret

Allen Institute for AI

AllenNLP

Simple Gradients Visualization

See saliency map interpretations generated by visualizing the gradient.

Saliency Map:

[CLS] The [MASK] rushed to the emergency room to see her patient . [SEP]

Mask 1 Predictions:

47.1%	nurse
16.4%	woman
10.0%	doctor
3.4%	mother
3.0%	girl

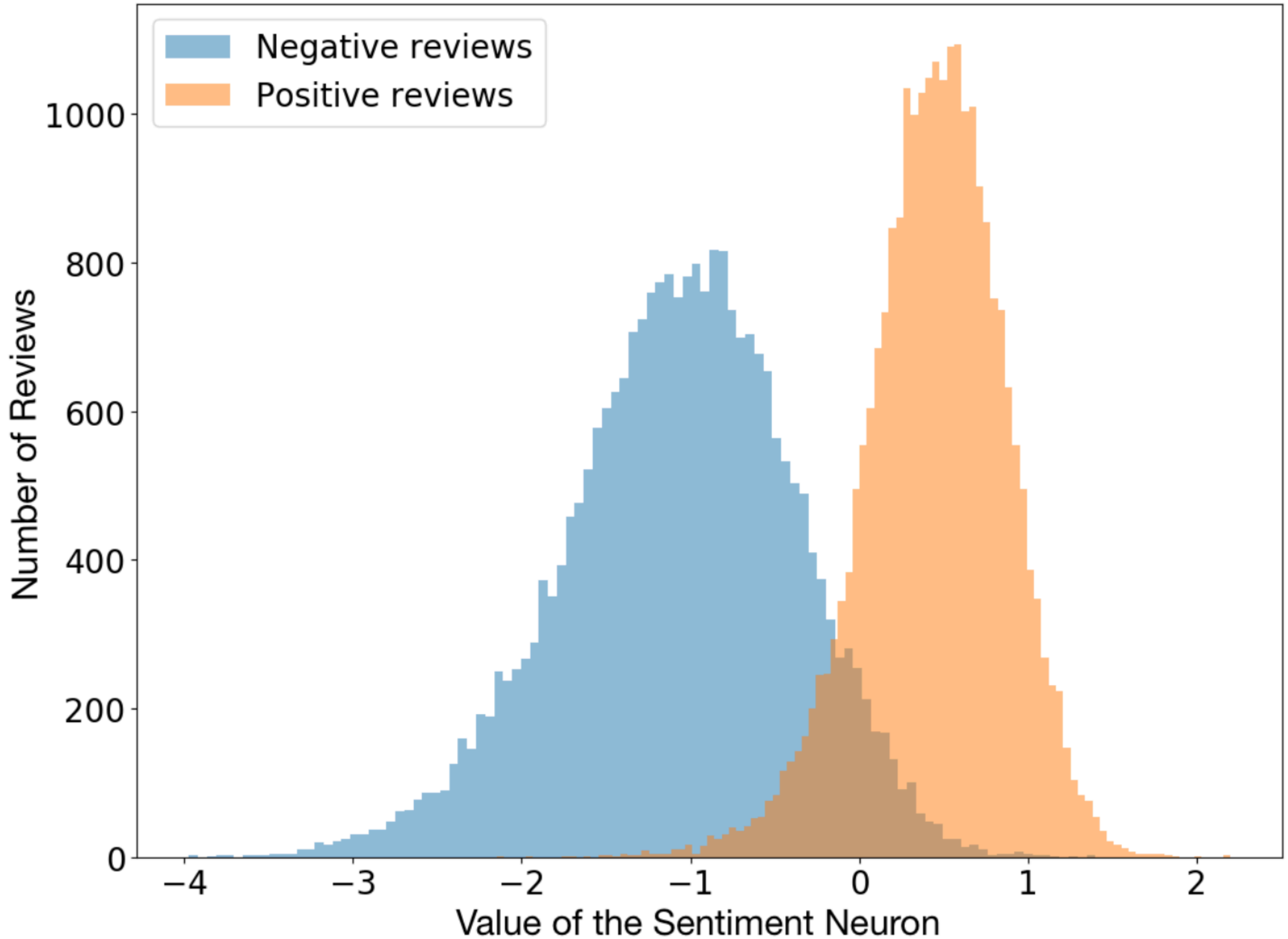
understanding contextualized representations

two most prominent methods

- visualization
- linguistic probe tasks

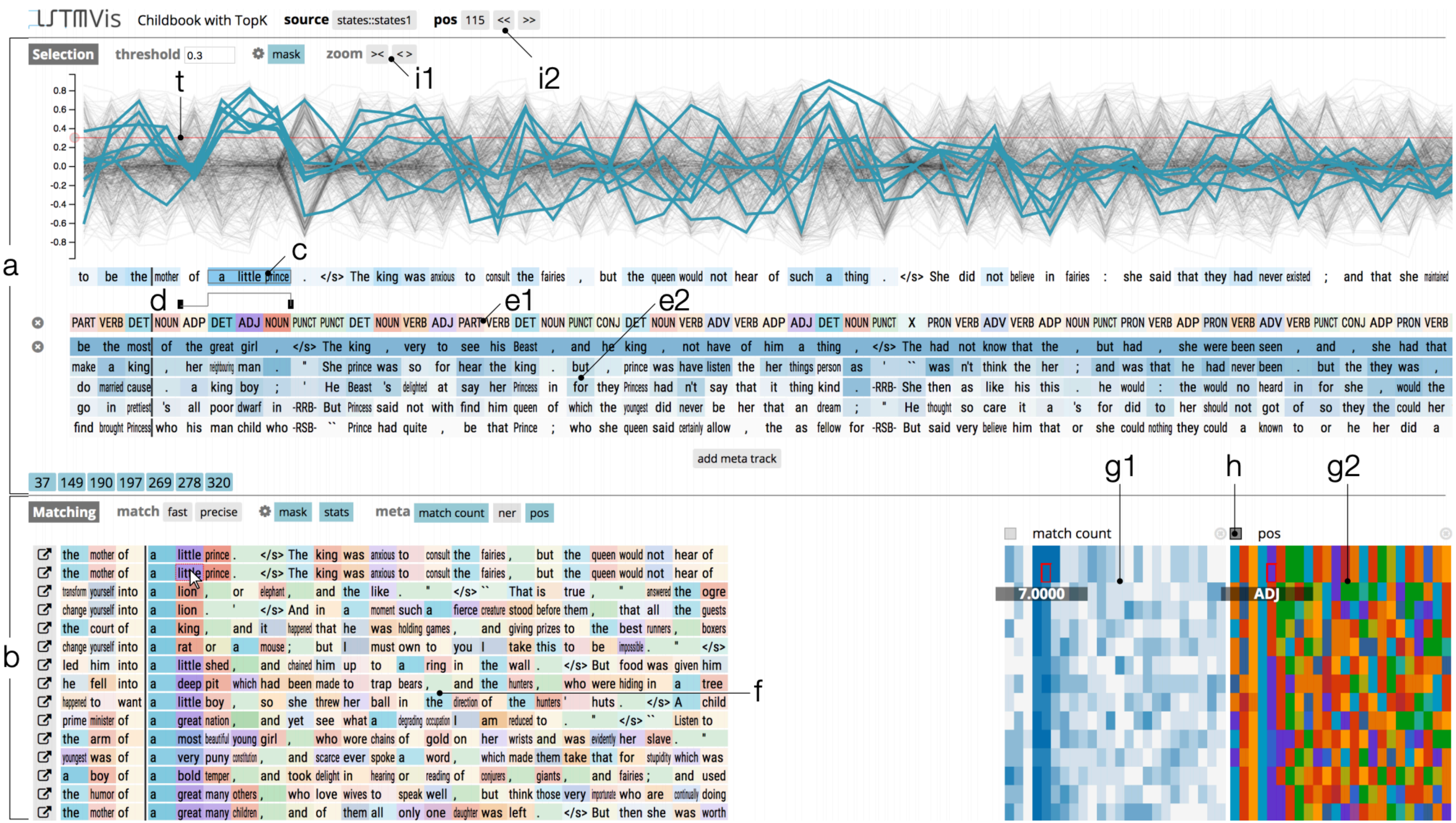
Sentiment neuron

While training the linear model with L1 regularization, we noticed it used surprisingly few of the learned units. Digging in, we realized there actually existed a single "sentiment neuron" that's highly predictive of the sentiment value.



The sentiment neuron within our model can classify reviews as negative or positive, even though the model is trained only to predict the next character in the text.

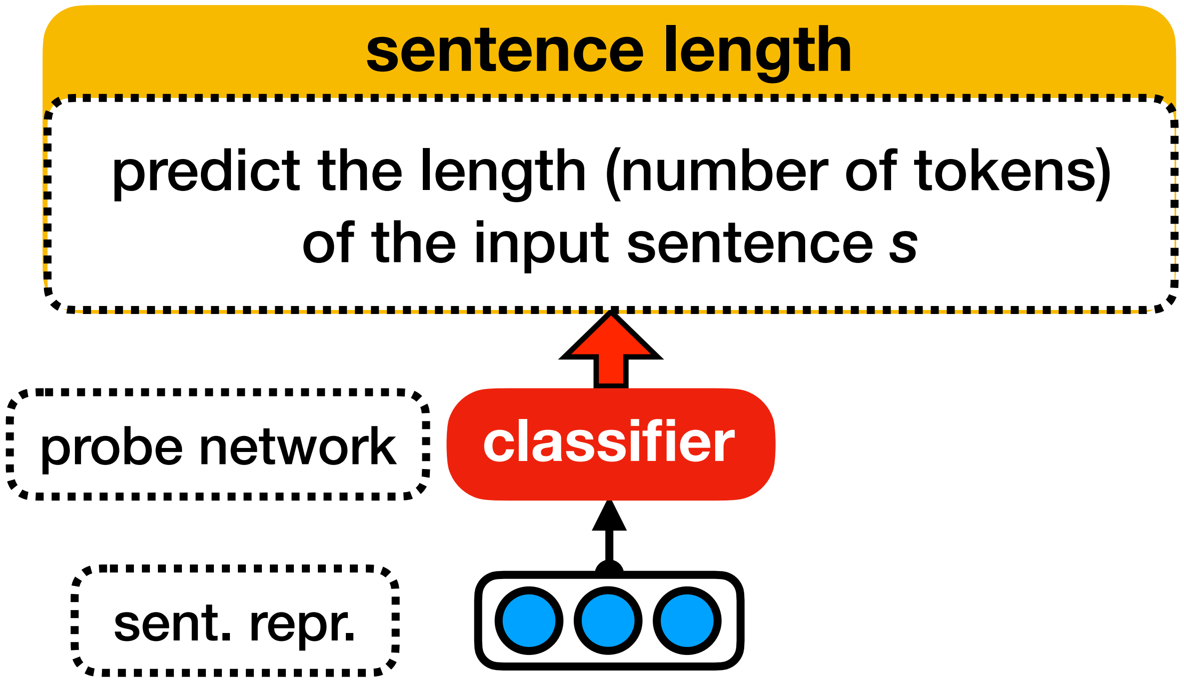
https://openai.com/blog/unsupervised-sentiment-neuron/



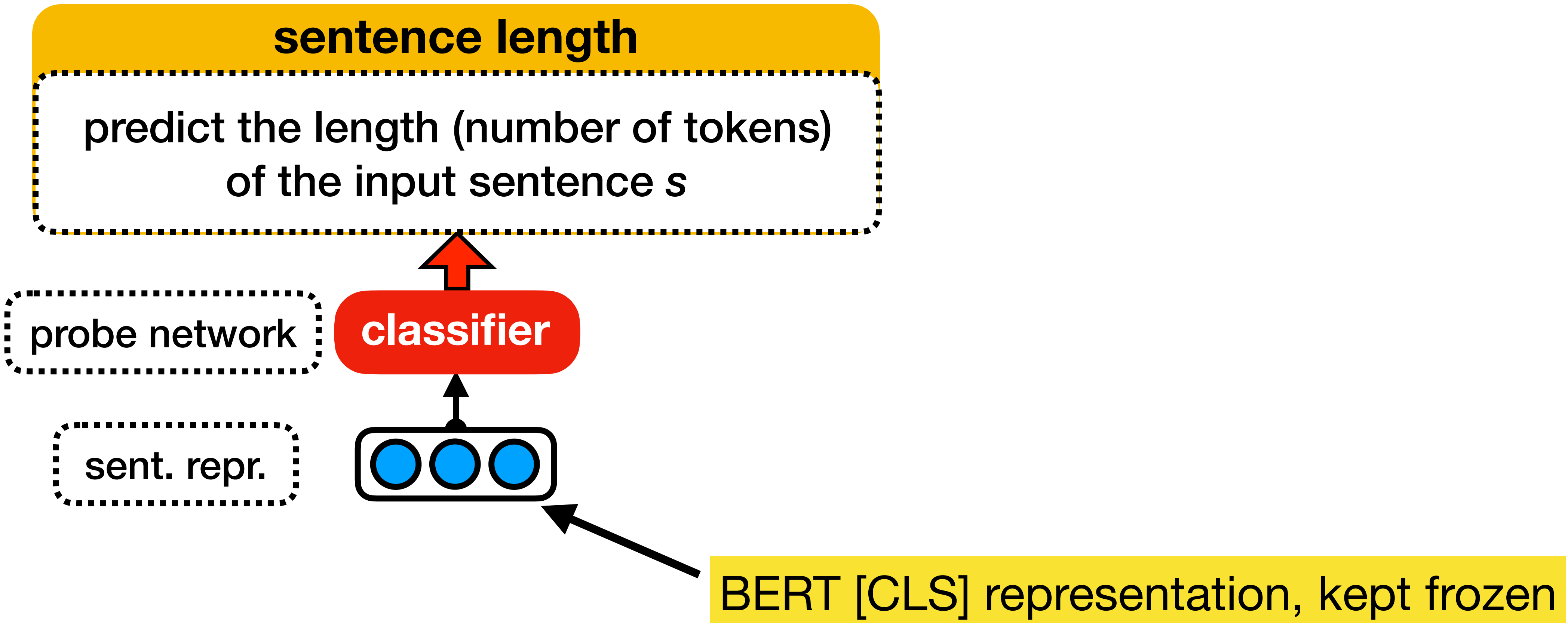
LSTMVis: Strobelt et al., 2017

what is a linguistic probe task?

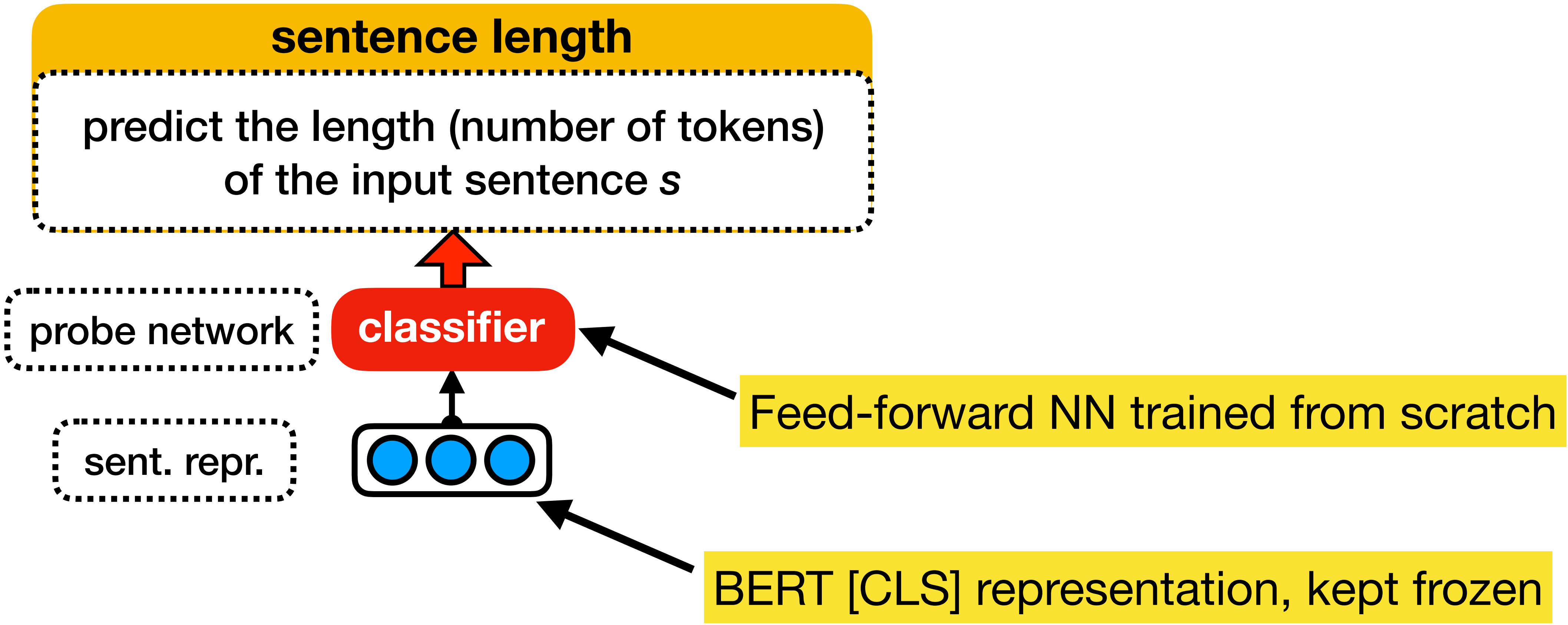
given an encoder model (e.g., BERT) pre-trained on a certain task, we use the representations it produces to train a classifier (without further fine-tuning the model) to predict a linguistic property of the input text



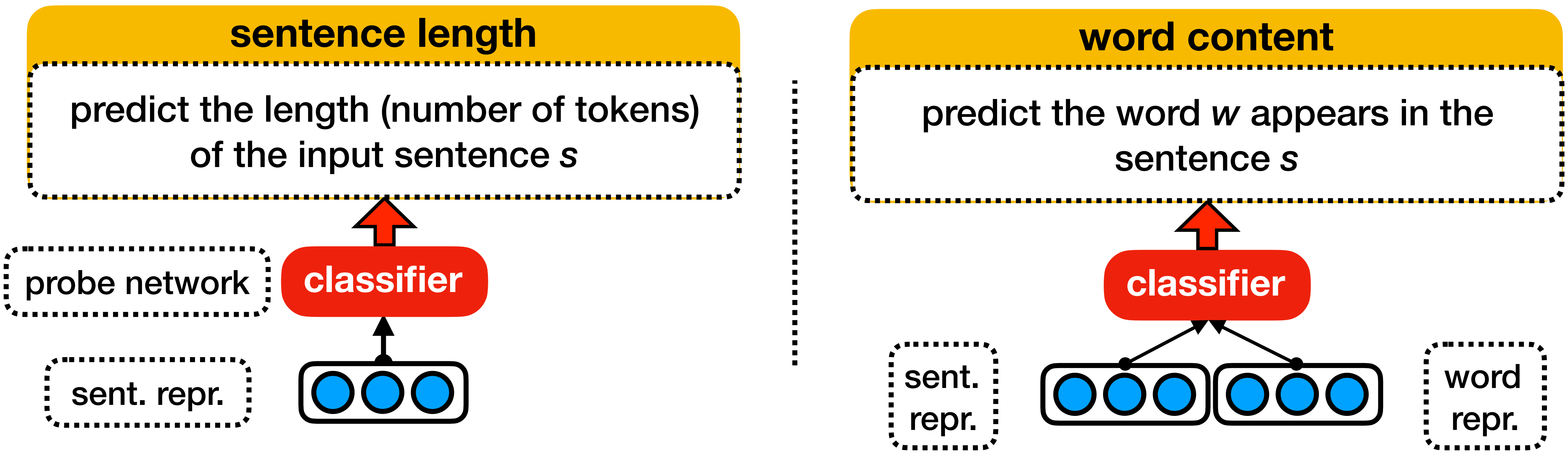
(Adi et al., 2017)



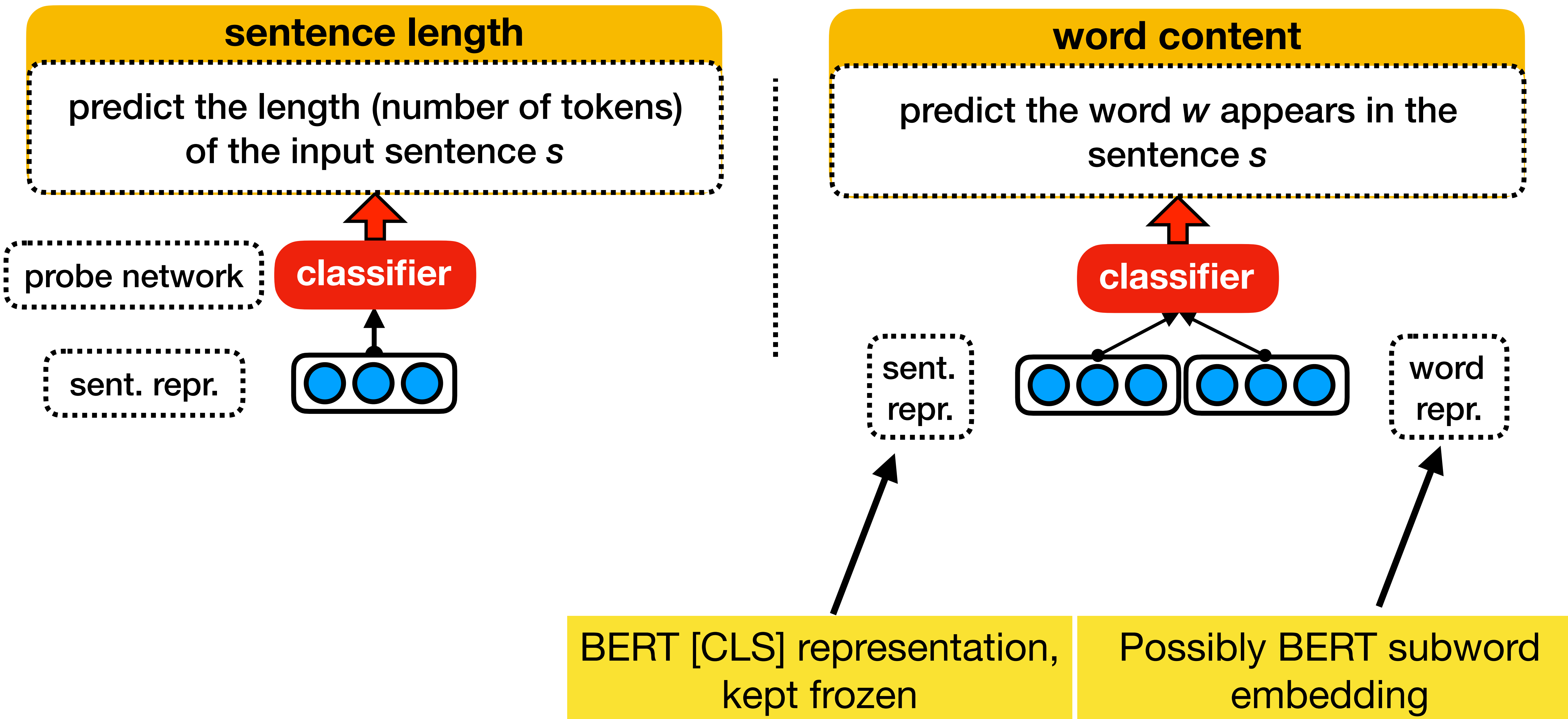
(Adi et al., 2017)



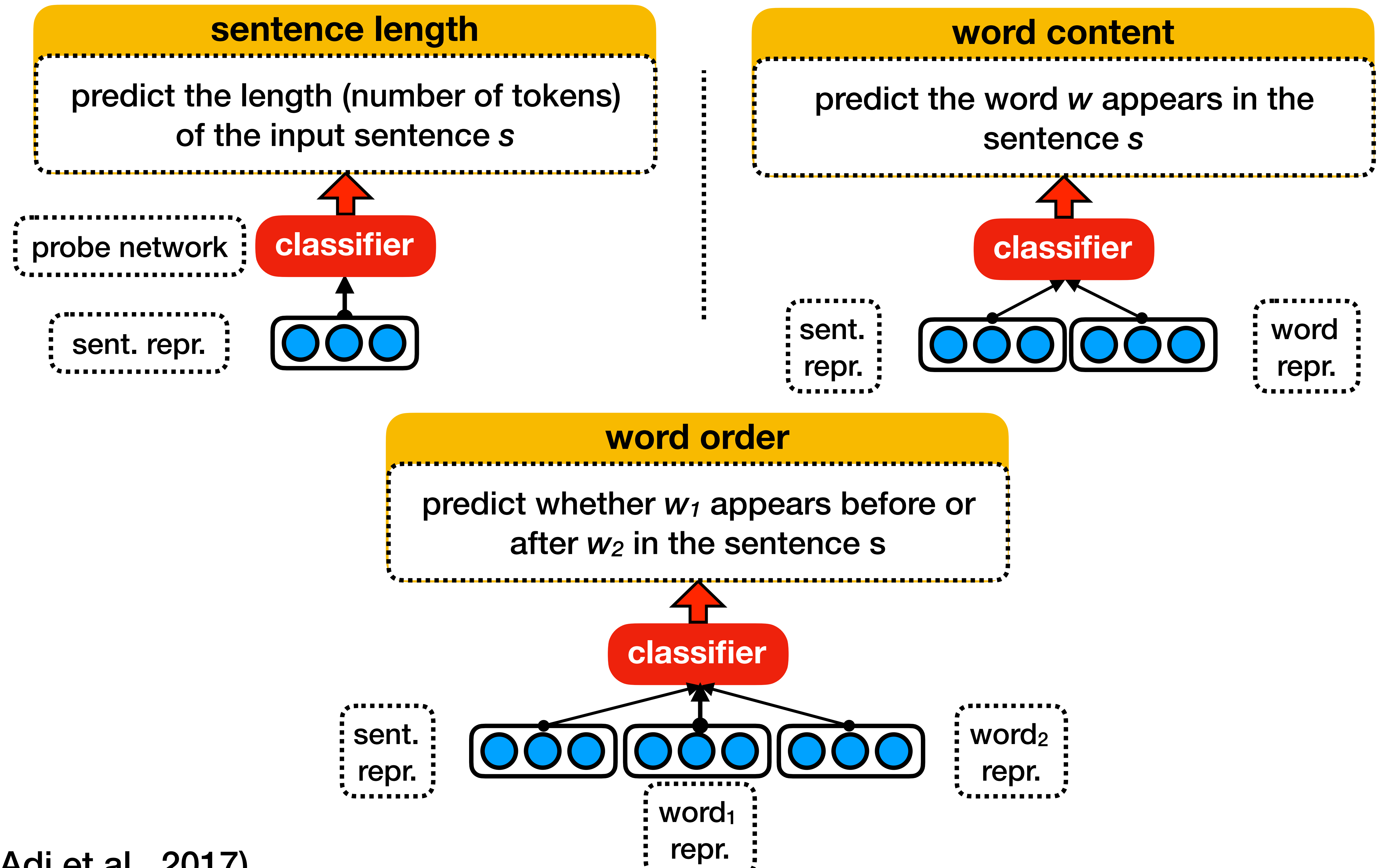
(Adi et al., 2017)



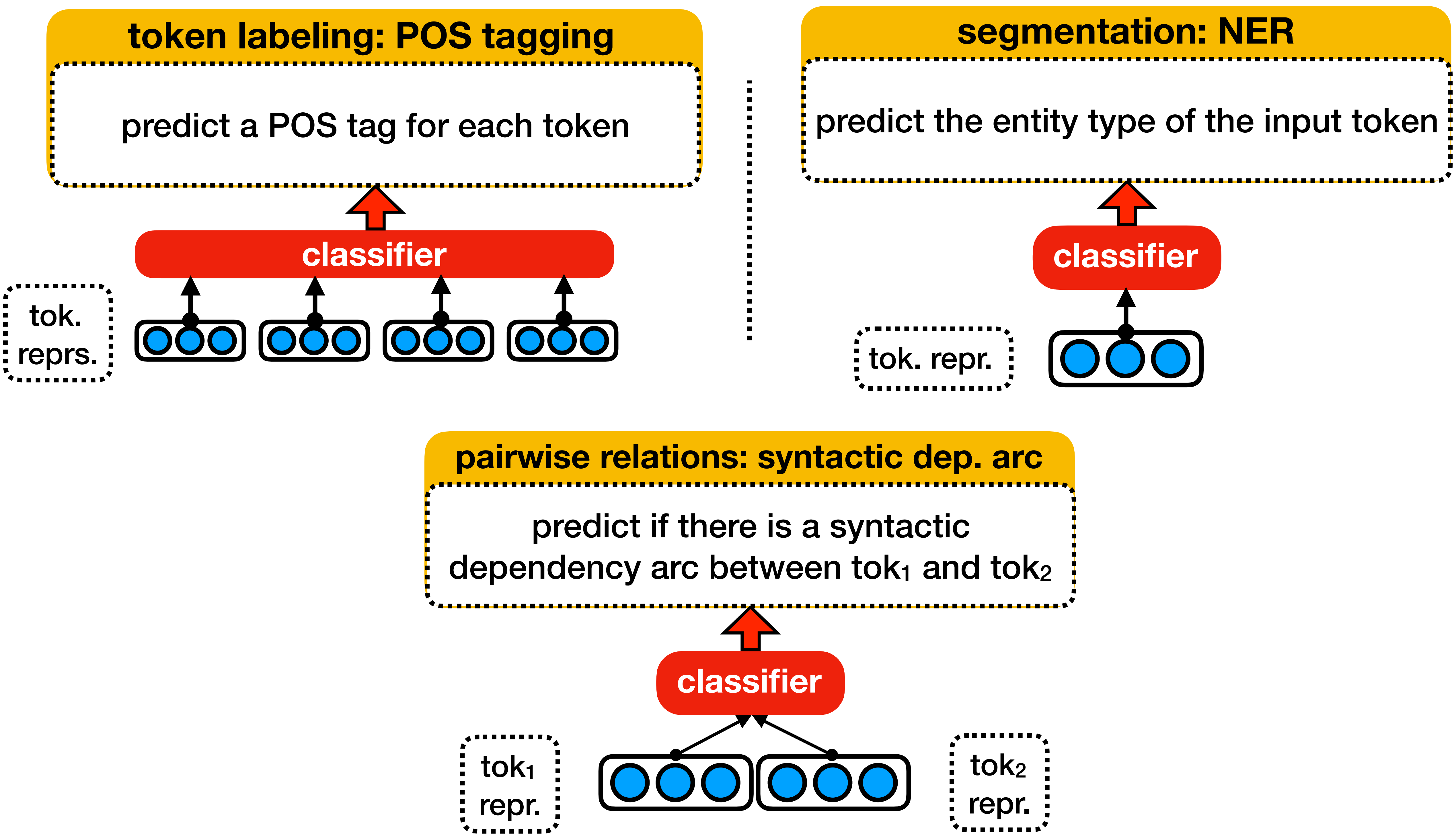
(Adi et al., 2017)



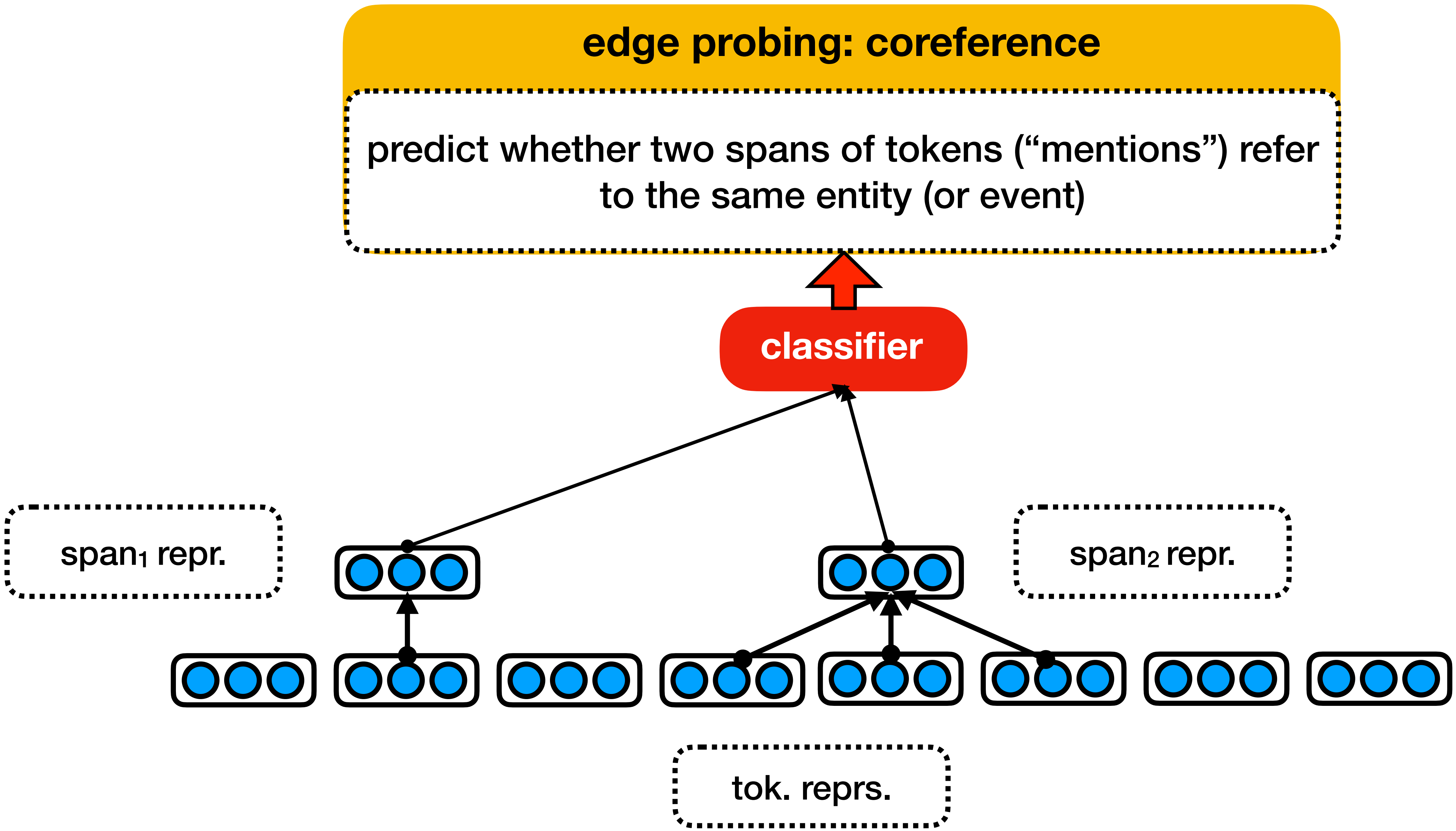
(Adi et al., 2017)



(Adi et al., 2017)



(Liu et al., 2019)



(Tenney et al., 2019)

motivation of probe tasks

- if we can train a classifier to predict a property of the input text based on its representation, it means the property is encoded somewhere in the representation

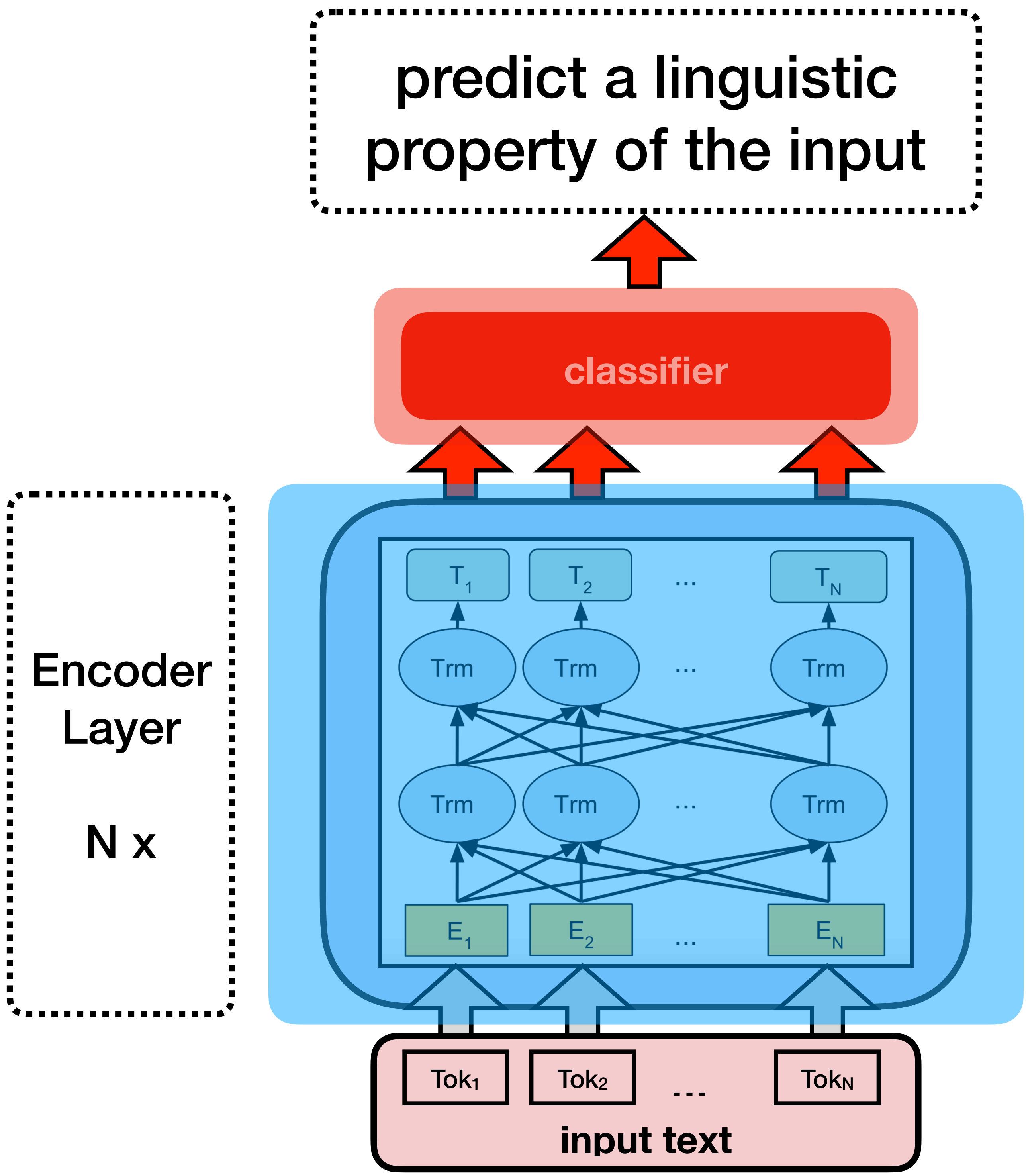
- if we cannot train a classifier to predict a property of the input text based on its representation, it means the property is not encoded in the representation or not encoded in a useful way, considering how the representation is likely to be used

characteristics of probe tasks

- usually classification problems that focus on simple linguistic properties
- ask simple questions, minimizing interpretability problems
- because of their simplicity, it is easier to control for biases in probing tasks than in downstream tasks
- the probing task methodology is agnostic with respect to the encoder architecture, as long as it produces a vector representation of input text
- does not necessarily correlate with downstream performance

(Conneau et al., 2018)

probe approach

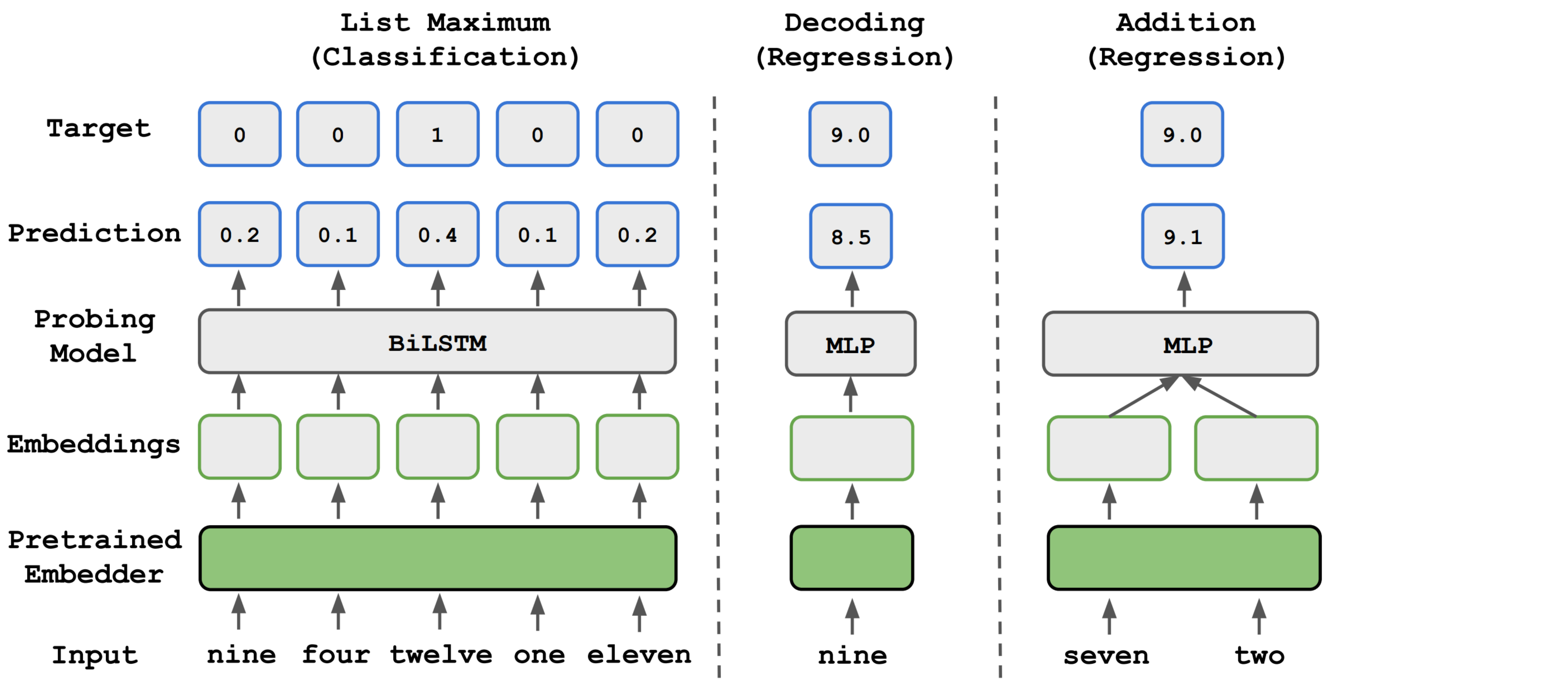


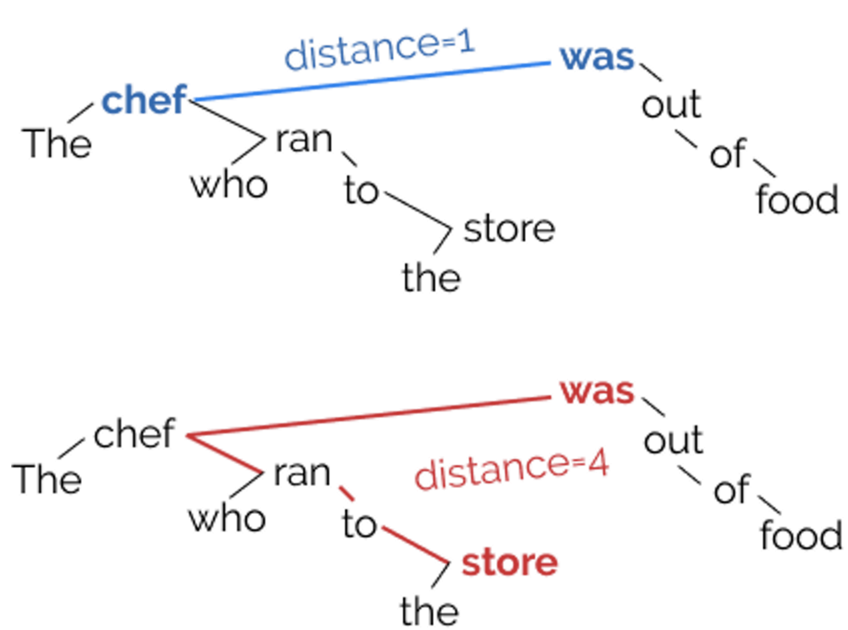
the classifier's weights are updated

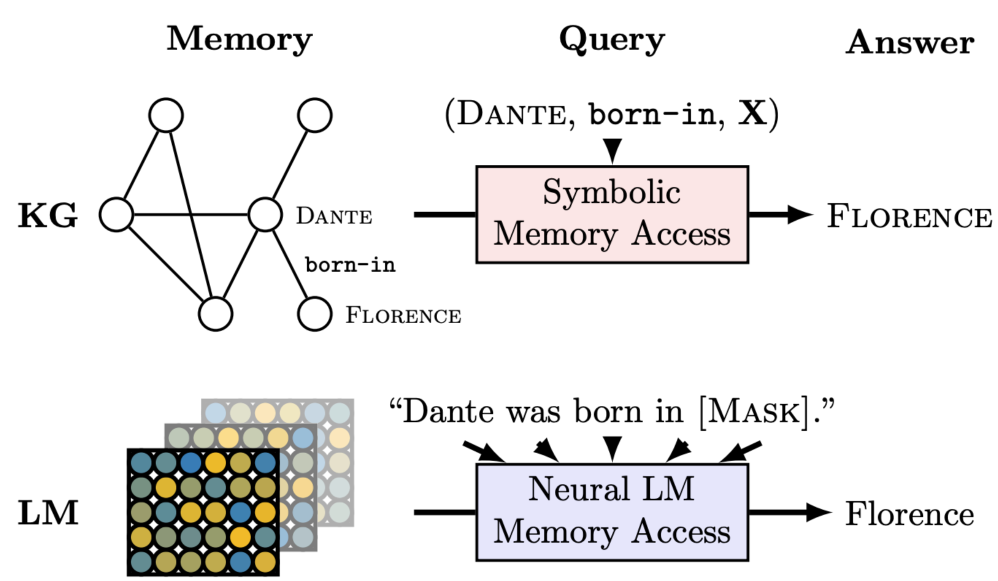
train the classifier only

no further fine-tuning

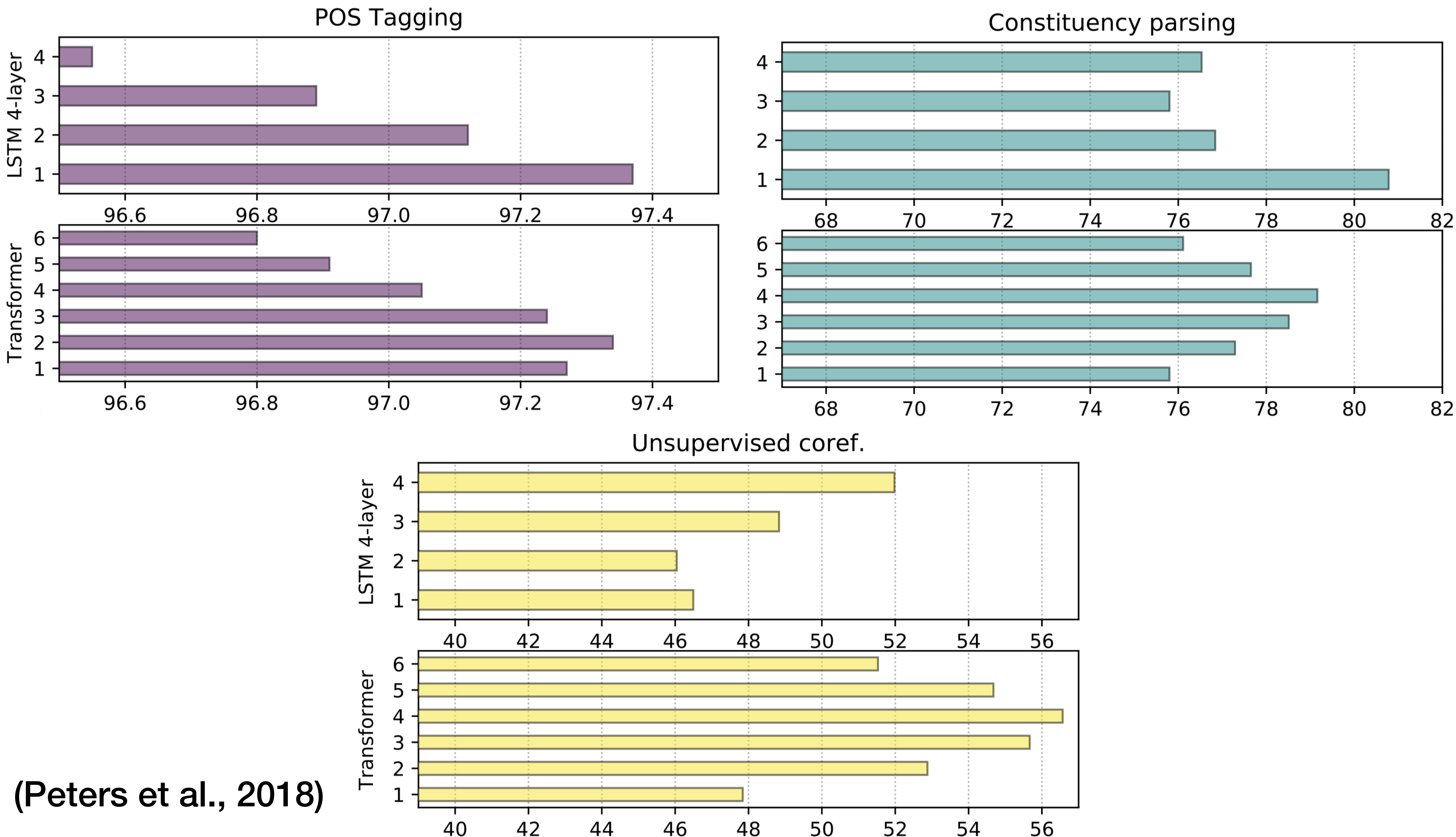
the encoder's weights are fixed


List Maximum (Classification)
Decoding (Regression)
Addition (Regression)
Target
Prediction
Probing Model
Embeddings
Pretrained Embedder
Input
0 0 1 0 0
0.2 0.1 0.4 0.1 0.2
BiLSTM
nine four twelve one eleven
9.0
8.5
MLP
nine
9.0
9.1
MLP
seven two


distance=1
The chef was out of food
who ran to the store
distance=4
The chef was out of food
who ran to the store


Memory
Query
Answer
KG
DANTE
born-in
FLORENCE
(DANTE, born-in, X)
Symbolic Memory Access
FLORENCE
LM
"Dante was born in [MASK]."
Neural LM Memory Access
Florence

lowest layers focus on local syntax, while upper layers focus more semantic content

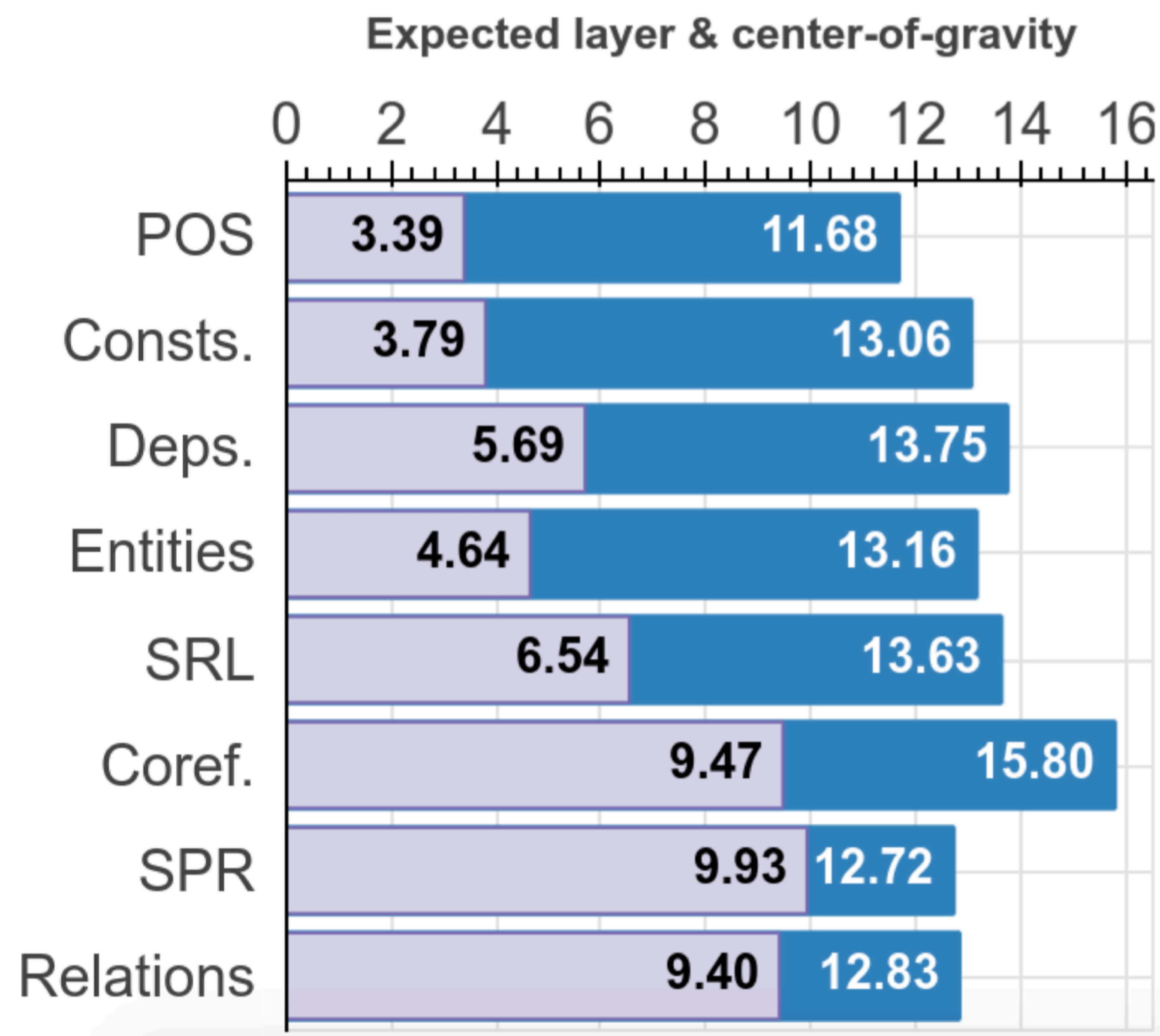


(Peters et al., 2018)

BERT represents the steps of the traditional NLP pipeline: POS tagging → parsing → NER → semantic roles → coreference

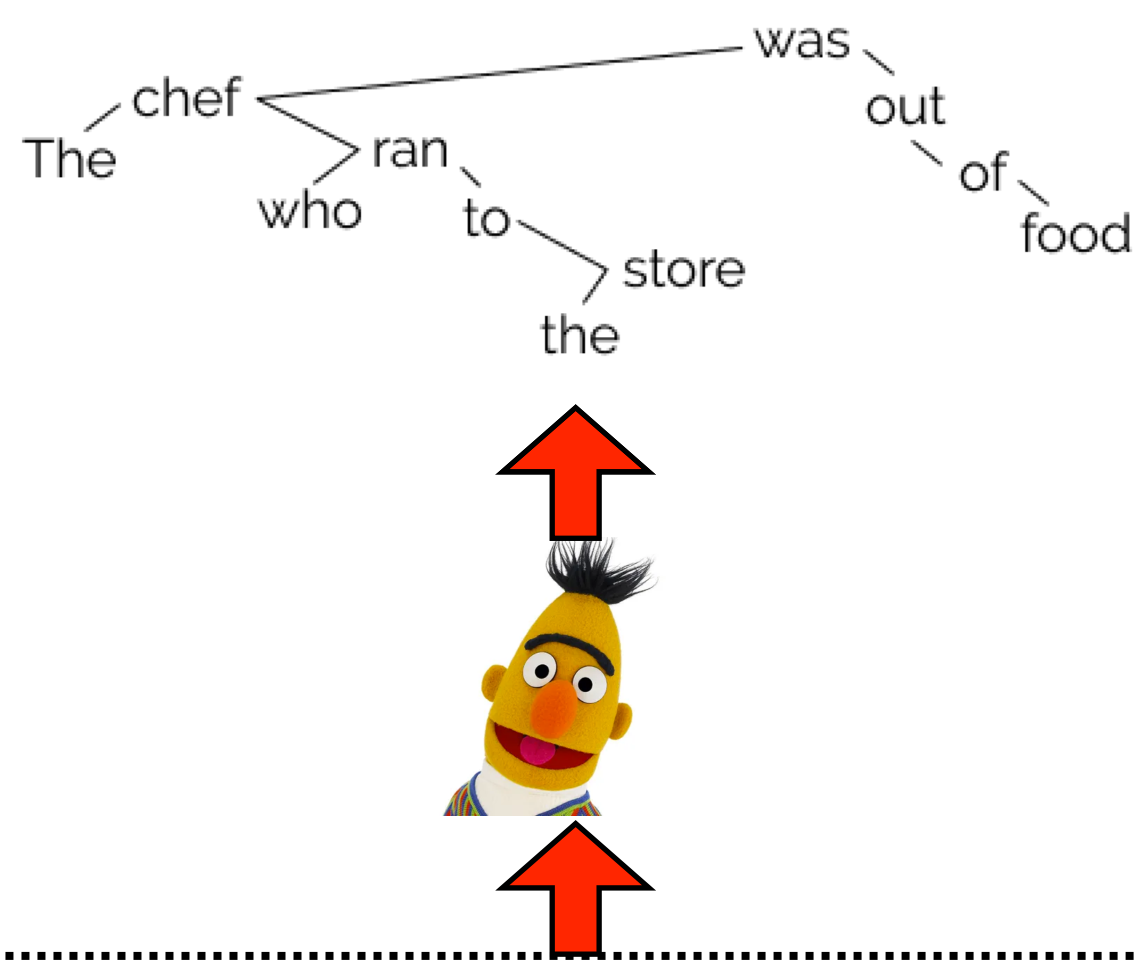
the expected layer at which the probing model correctly labels an example

a higher center-of-gravity means that the information needed for that task is captured by higher layers



(Tenney et al., 2019)

does BERT encode syntactic structure?



The chef who ran to the store was out of food

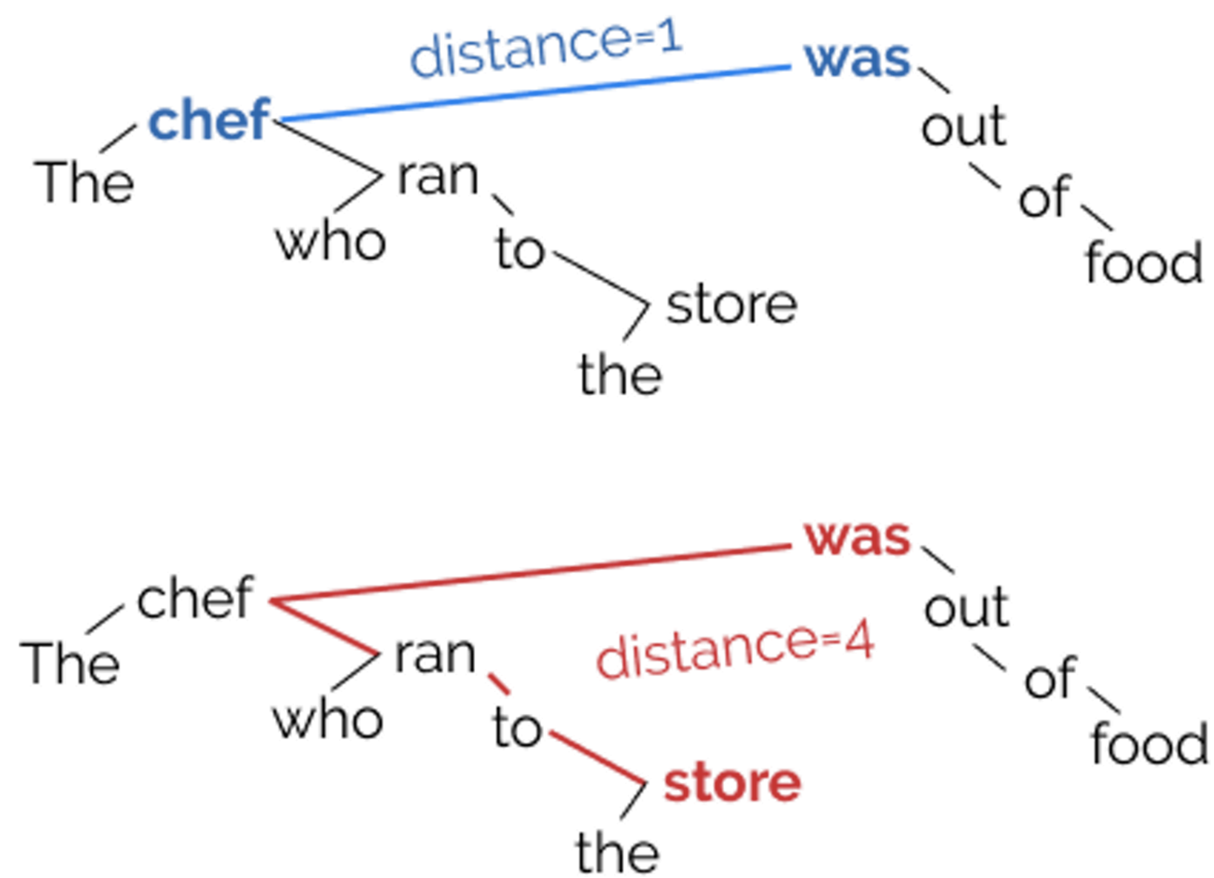
(Hewitt and Manning et al., 2019)

understanding the syntax of the language may be useful in language modeling

The chef who ran to the store was out of food.

1. Because there was no food to be found, the chef went to the next store.

2. After stocking up on ingredients, the chef returned to the restaurant.



(Hewitt and Manning et al., 2019)

how to probe for trees?

trees as distances and norms

the distance metric—the path length between each pair of words—recovers the tree T simply by identifying that nodes u, v with distance $d_{T\,(u,\,v)} = 1$ are neighbors

the node with greater norm—depth in the tree—is the child

(Hewitt and Manning et al., 2019)

a structural probe

- probe task 1 — distance:
  predict the path length between each given pair of words

- probe task 2 — depth/norm:
  predict the depth of a given word in the parse tree

(Hewitt and Manning et al., 2019)

Yes, BERT knows the structure of syntax trees

	Distance		Depth	
Method	UUAS	DSpr.	Root%	NSpr.
ELMO1	77.0	0.83	86.5	0.87
BERTBASE7	79.8	0.85	88.0	0.87
BERTLARGE15	**82.5**	0.86	89.4	0.88
BERTLARGE16	81.7	**0.87**	**90.1**	**0.89**

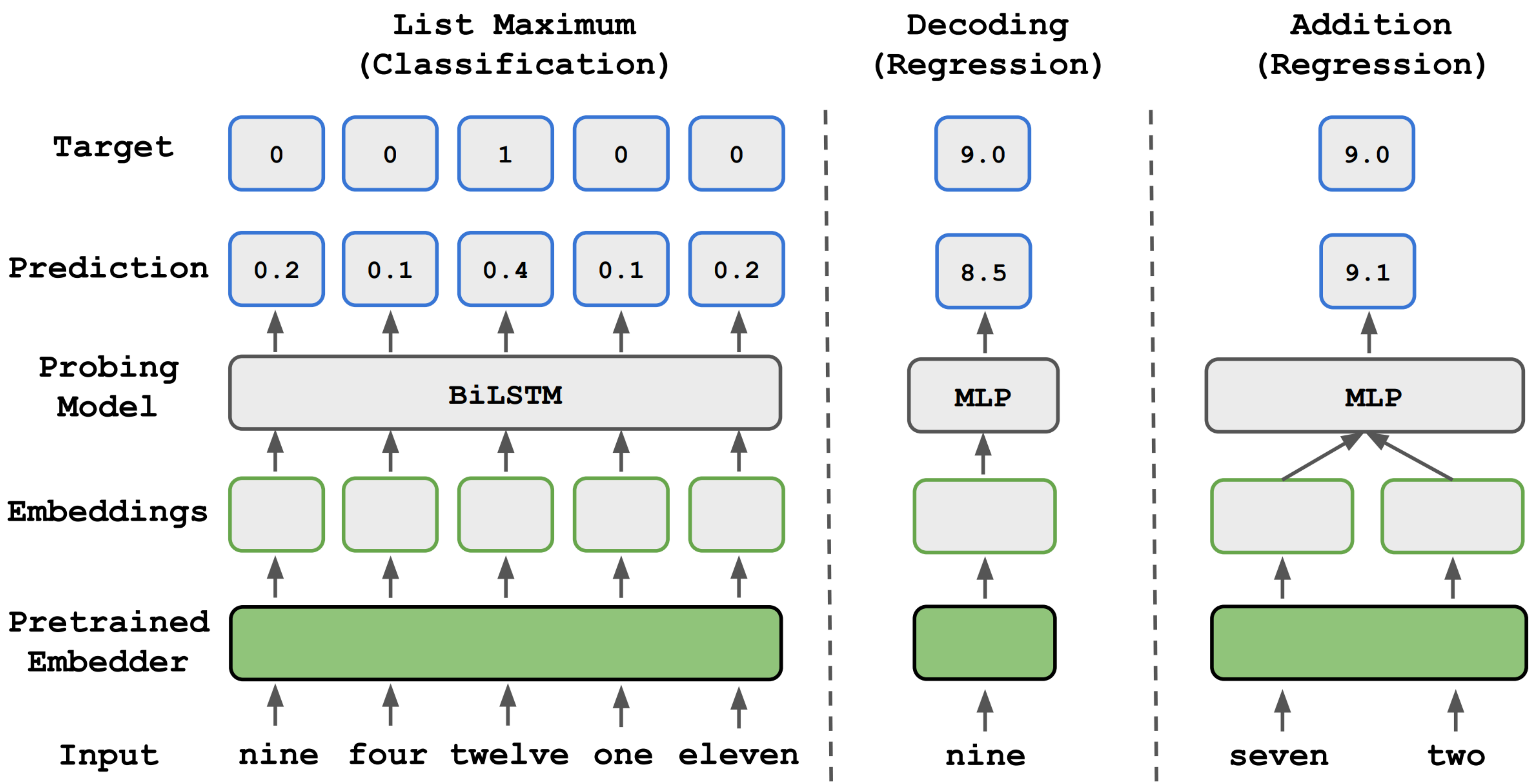
(Hewitt and Manning et al., 2019)

does BERT know numbers?

25

what is the sum of eleven and fourteen?

probing for numeracy



(Wallace et al., 2019)

ELMo is actually better than BERT at this!

Interpolation *Integer Range*	**List Maximum (5-classes)** [0,99]	[0,999]	[0,9999]	**Decoding (RMSE)** [0,99]	[0,999]	[0,9999]	**Addition (RMSE)** [0,99]	[0,999]	[0,9999]
Random Vectors	0.16	0.23	0.21	29.86	292.88	2882.62	42.03	410.33	4389.39
Untrained CNN	0.97	0.87	0.84	2.64	9.67	44.40	1.41	14.43	69.14
Untrained LSTM	0.70	0.66	0.55	7.61	46.5	210.34	5.11	45.69	510.19
Pre-trained									
Word2Vec	0.90	0.78	0.71	2.34	18.77	333.47	0.75	21.23	210.07
GloVe	0.90	0.78	0.72	2.23	13.77	174.21	0.80	16.51	180.31
ELMo	0.98	0.88	0.76	2.35	13.48	62.20	0.94	15.50	45.71
BERT	0.95	0.62	0.52	3.21	29.00	431.78	4.56	67.81	454.78

Interpolation *Float Range*	**List Maximum (5-classes)** [0.0,99.9]	[0.0,999.9]
Rand. Vectors	0.18 ± 0.03	0.21 ± 0.04
ELMo	0.91 ± 0.03	0.59 ± 0.01
BERT	0.82 ± 0.05	0.51 ± 0.04
Char-CNN	0.87 ± 0.04	0.75 ± 0.03
Char-LSTM	0.81 ± 0.05	0.69 ± 0.02

Interpolation *Integer Range*	**List Maximum (5-classes)** [-50,50]
Rand. Vectors	0.23 ± 0.12
Word2Vec	0.89 ± 0.02
GloVe	0.89 ± 0.03
ELMo	0.96 ± 0.01
BERT	0.94 ± 0.02
Char-CNN	0.95 ± 0.07
Char-LSTM	0.97 ± 0.02

(Wallace et al., 2019)

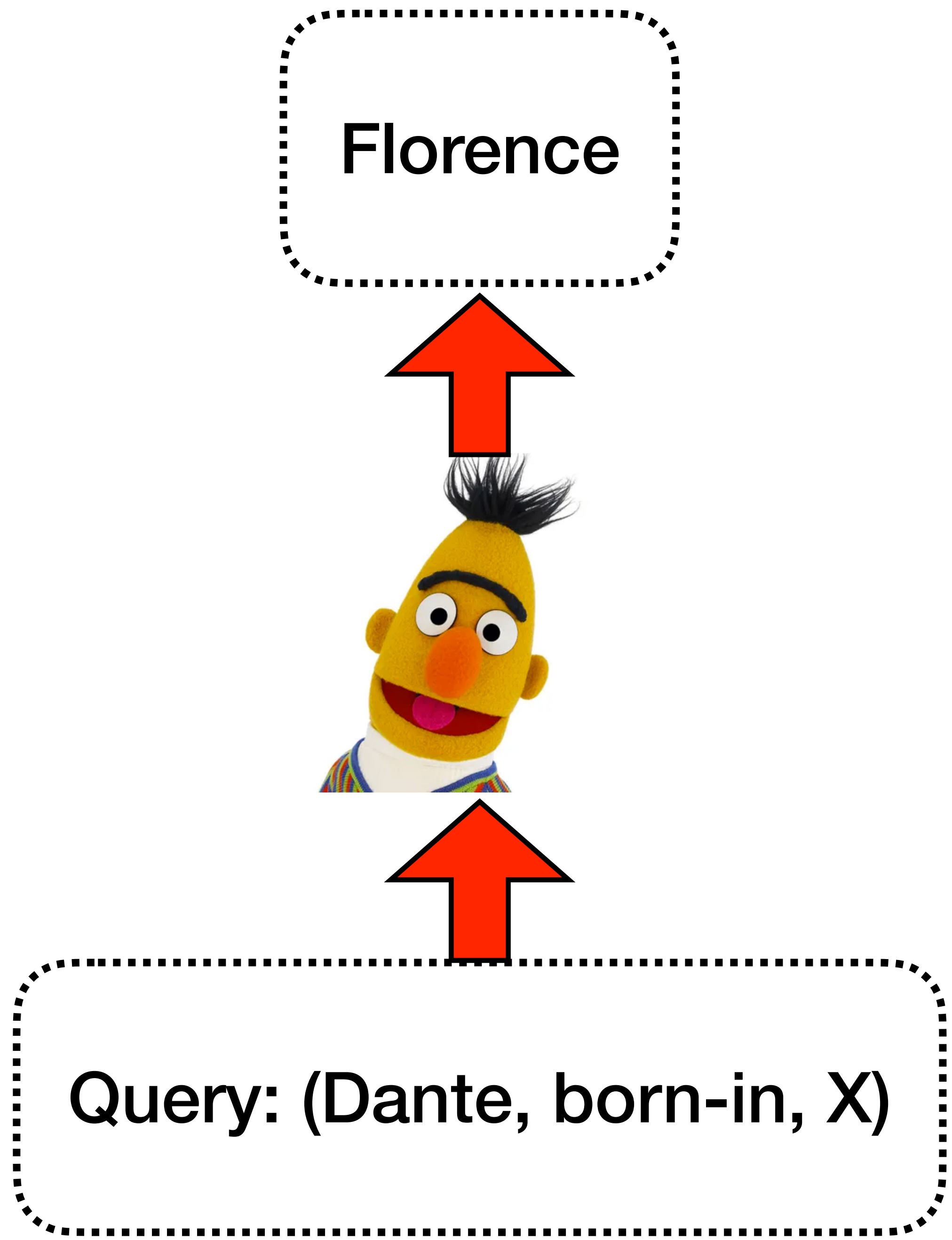
Why?

character-level CNNs are the best architecture for capturing numeracy

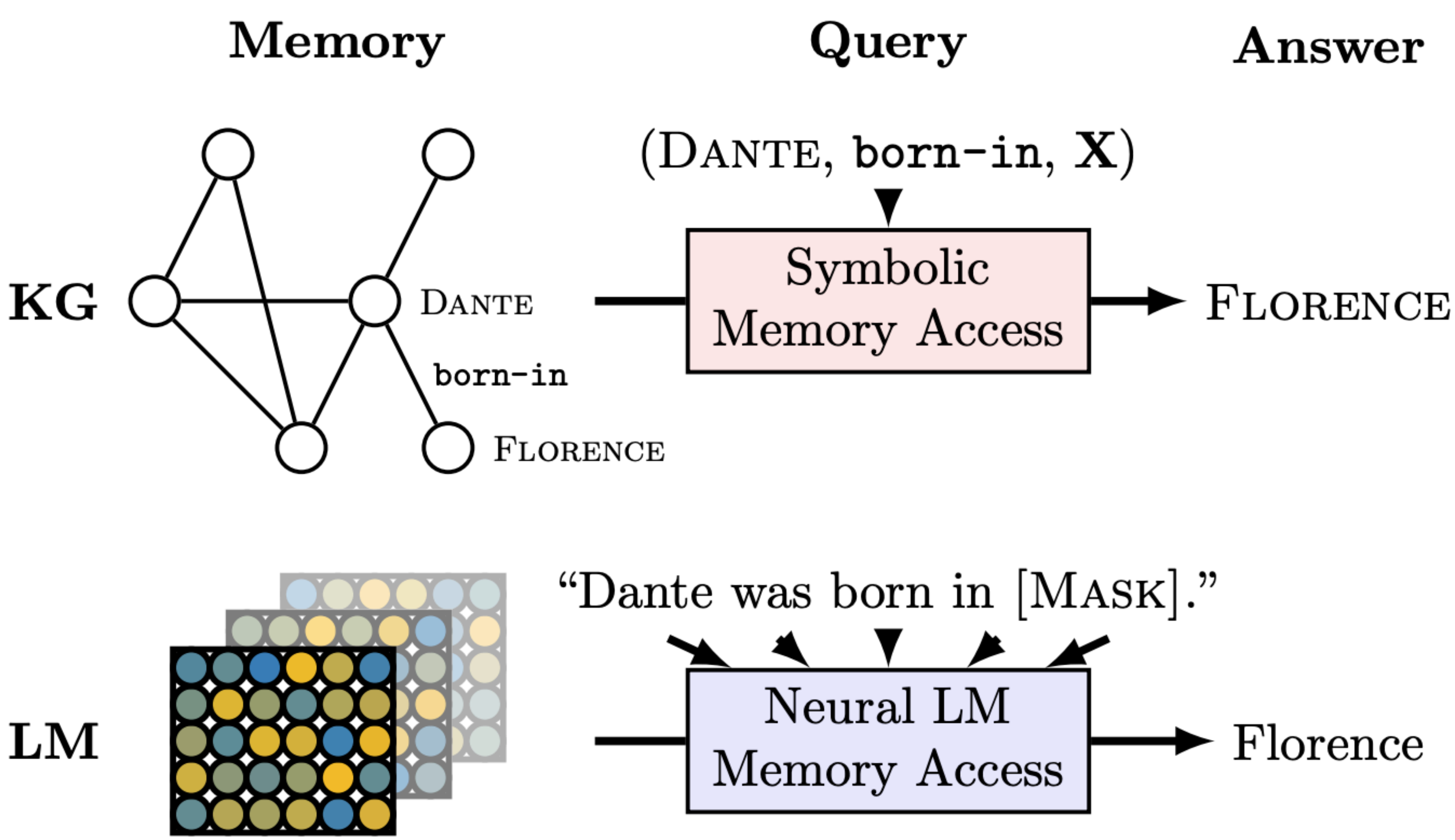
subword pieces is a poor method to encode digits, e.g., two numbers which are similar in value can have very different sub-word divisions

(Wallace et al., 2019)

Can BERT serve as a structured knowledge base?



LAMA (LAnguage Model Analysis) probe



(Petroni et al., 2019)

LAMA (LAnguage Model Analysis) probe (cont.)

- manually define templates for considered relations, e.g., “[S] was born in [O]” for “place of birth”

- find sentences that contain both the subject and the object, then mask the object within the sentences and use them as templates for querying

- create cloze-style questions, e.g., rewriting “Who developed the theory of relativity?” as “The theory of relativity was developed by [MASK]”

(Petroni et al., 2019)

examples

	Relation	Query	Answer	Generation
T-Rex	P54	Dani Alves plays with ____ .	Barcelona	Santos [-2.4] , Porto [-2.5] , Sporting [-3.1] , Brazil [-3.3] , Portugal [-3.7]
	P106	Paul Toungui is a ____ by profession .	politician	lawyer [-1.1] , journalist [-2.4] , teacher [-2.7] , doctor [-3.0] , physician [-3.7]
	P527	Sodium sulfide consists of ____.	sodium	water [-1.2] , sulfur [-1.7] , **sodium [-2.5]** , zinc [-2.8] , salt [-2.9]
	P102	Gordon Scholes is a member of the ____ political party.	Labor	Labour [-1.3] , Conservative [-1.6] , Green [-2.4] , Liberal [-2.9] , **Labor [-2.9]**
	P530	Kenya maintains diplomatic relations with ____.	Uganda	India [-3.0] , **Uganda [-3.2]** , Tanzania [-3.5] , China [-3.6] , Pakistan [-3.6]
	P176	iPod Touch is produced by ____.	Apple	**Apple [-1.6]** , Nokia [-1.7] , Sony [-2.0] , Samsung [-2.6] , Intel [-3.1]
	P30	Bailey Peninsula is located in ____.	Antarctica	**Antarctica [-1.4]** , Bermuda [-2.2] , Newfoundland [-2.5] , Alaska [-2.7] , Canada [-3.1]
	P178	JDK is developed by ____.	Oracle	IBM [-2.0] , Intel [-2.3] , Microsoft [-2.5] , HP [-3.4] , Nokia [-3.5]
	P1412	Carl III used to communicate in ____.	Swedish	German [-1.6] , Latin [-1.9] , French [-2.4] , English [-3.0] , Spanish [-3.0]
	P17	Sunshine Coast, British Columbia is located in ____.	Canada	**Canada [-1.2]** , Alberta [-2.8] , Yukon [-2.9] , Labrador [-3.4] , Victoria [-3.4]
ConceptNet	AtLocation	You are likely to find a overflow in a ____.	drain	sewer [-3.1] , canal [-3.2] , toilet [-3.3] , stream [-3.6] , **drain [-3.6]**
	CapableOf	Ravens can ____.	fly	**fly [-1.5]** , fight [-1.8] , kill [-2.2] , die [-3.2] , hunt [-3.4]
	CausesDesire	Joke would make you want to ____.	laugh	cry [-1.7] , die [-1.7] , **laugh [-2.0]** , vomit [-2.6] , scream [-2.6]
	Causes	Sometimes virus causes ____.	infection	disease [-1.2] , cancer [-2.0] , **infection [-2.6]** , plague [-3.3] , fever [-3.4]
	HasA	Birds have ____.	feathers	wings [-1.8] , nests [-3.1] , **feathers [-3.2]** , died [-3.7] , eggs [-3.9]
	HasPrerequisite	Typing requires ____.	speed	patience [-3.5] , precision [-3.6] , registration [-3.8] , accuracy [-4.0] , **speed [-4.1]**
	HasProperty	Time is ____.	finite	short [-1.7] , passing [-1.8] , precious [-2.9] , irrelevant [-3.2] , gone [-4.0]
	MotivatedByGoal	You would celebrate because you are ____.	alive	happy [-2.4] , human [-3.3] , **alive [-3.3]** , young [-3.6] , free [-3.9]
	ReceivesAction	Skills can be ____.	taught	acquired [-2.5] , useful [-2.5] , learned [-2.8] , combined [-3.9] , varied [-3.9]
	UsedFor	A pond is for ____.	fish	swimming [-1.3] , fishing [-1.4] , bathing [-2.0] , **fish [-2.8]** , recreation [-3.1]

(Petroni et al., 2019)

BERT contains relational knowledge competitive with symbolic knowledge bases and excels on open-domain QA

Corpus	Relation	Statistics		Baselines		KB		LM					
		#Facts	#Rel	Freq	DrQA	RE_n	RE_o	Fs	Txl	Eb	E5B	Bb	Bl
Google-RE	`birth-place`	2937	1	4.6	-	3.5	13.8	4.4	2.7	5.5	7.5	14.9	**16.1**
	`birth-date`	1825	1	1.9	-	0.0	**1.9**	0.3	1.1	0.1	0.1	1.5	1.4
	`death-place`	765	1	6.8	-	0.1	7.2	3.0	0.9	0.3	1.3	13.1	**14.0**
	Total	5527	3	4.4	-	1.2	7.6	2.6	1.6	2.0	3.0	9.8	**10.5**
T-REx	1-1	937	2	1.78	-	0.6	10.0	17.0	36.5	10.1	13.1	68.0	**74.5**
	N-1	20006	23	23.85	-	5.4	**33.8**	6.1	18.0	3.6	6.5	32.4	34.2
	N-*M*	13096	16	21.95	-	7.7	**36.7**	12.0	16.5	5.7	7.4	24.7	24.3
	Total	34039	41	22.03	-	6.1	**33.8**	8.9	18.3	4.7	7.1	31.1	32.3
ConceptNet	Total	11458	16	4.8	-	-	-	3.6	5.7	6.1	6.2	15.6	**19.2**
SQuAD	Total	305	-	-	**37.5**	-	-	3.6	3.9	1.6	4.3	14.1	17.4

(Petroni et al., 2019)

probe complexity

arguments for “simple” probes

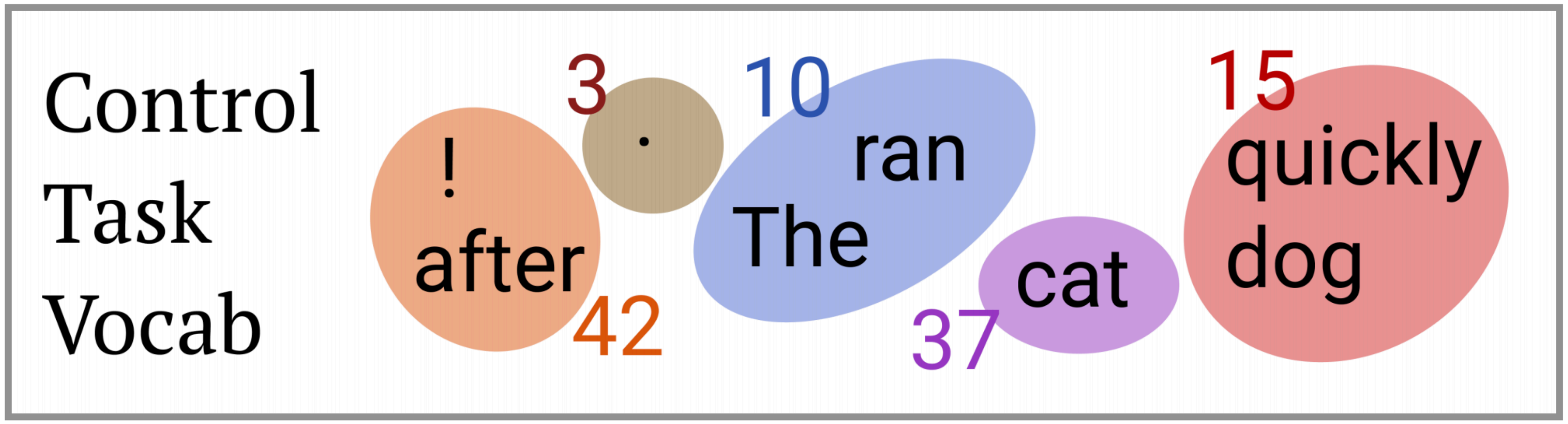
we want to find easily accessible information in a representation

arguments for “complex” probes

useful properties might be encoded non-linearly

(Hewitt et al., 2019)

control tasks



Sentence 1	The	cat	ran	quickly	.
Part-of-speech	DT	NN	VBD	RB	.
Control task	**10**	**37**	**10**	**15**	**3**
Sentence 2	The	dog	ran	after	!
Part-of-speech	DT	NN	VBD	IN	.
Control task	**10**	**15**	**10**	**42**	**42**

(Hewitt et al., 2019)

designing control tasks

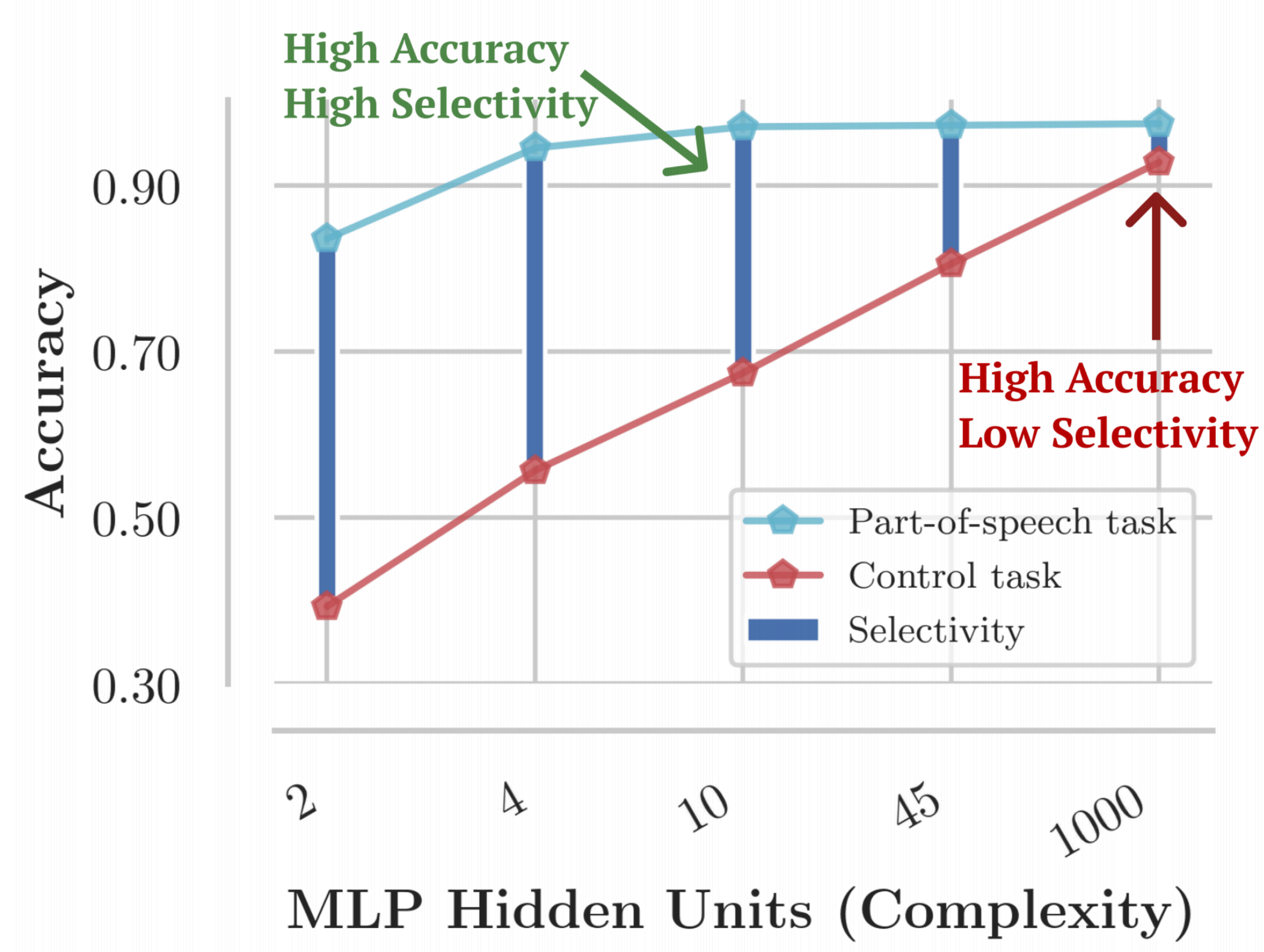
- independently sample a control behavior *C(v)* for each word type *v* in the vocabulary
- specifies how to define $y_i \in Y$ for a word token x_i with word type *v*
- *control task is a function that maps each token* x_i *to the label specified by the behavior* $C(x_i)$

$$f_{\text{control}}(\mathbf{x}_{1:T}) = f(C(x_1), C(x_2), ...C(x_T))$$

(Hewitt et al., 2019)

selectivity: high linguistic task accuracy + low control task accuracy

measures the probe model's ability to make output decisions independently of linguistic properties of the representation



(Hewitt et al., 2019)

be careful about probe accuracies

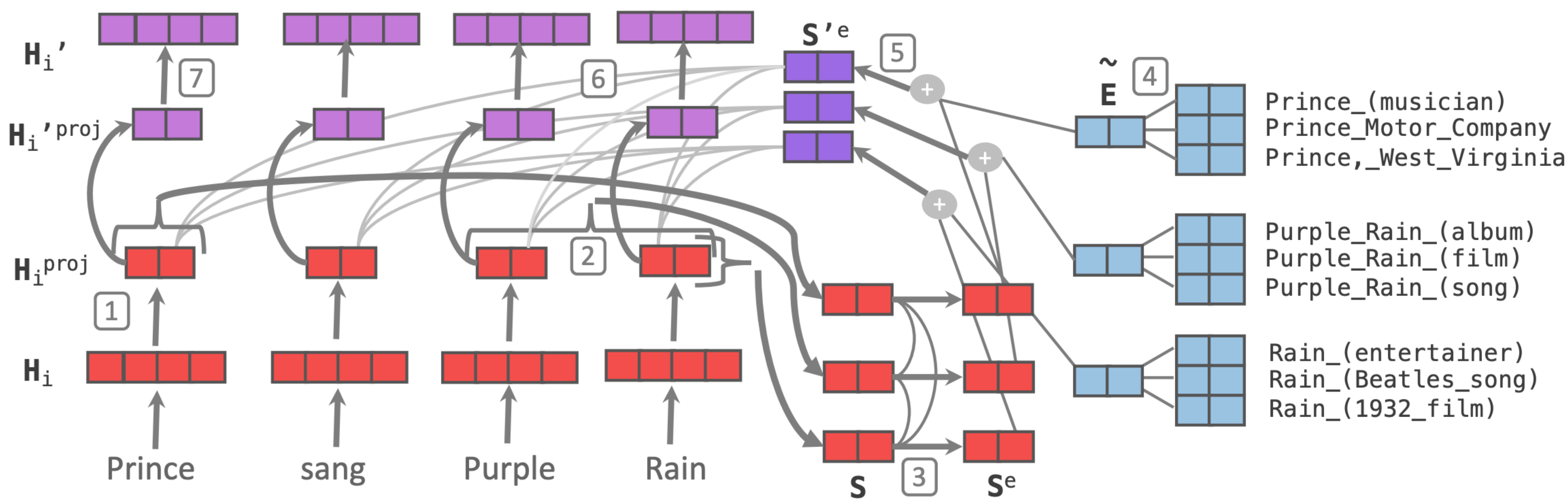
Part-of-speech Tagging				
	Linear		MLP-1	
Model	Accuracy	Selectivity	Accuracy	Selectivity
Proj0	96.3	20.6	97.1	1.6
ELMo1	97.2	26.0	97.3	4.5
ELMo2	96.6	31.4	97.0	8.8

how to use probe tasks to improve downstream task performance?

- what kinds of linguistic knowledge are important for your task?
- probe BERT for them
- if BERT struggles then fine-tune it with additional probe objectives

$$\mathcal{L}_{new} = \mathcal{L}_{BERT} + \alpha \mathcal{L}_{probe}$$

example: KnowBERT



(Peters et al., 2019)