

Natural Language Processing with Deep Learning

CS224N/Ling284



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Lecture 17: Model Analysis and Explanation

Lecture Plan

1. Motivating model analysis and explanation
2. One model at multiple levels of abstraction
3. Out-of-domain evaluation sets
 1. Testing for linguistic knowledge
 2. Testing for task heuristics
4. Influence studies and adversarial examples
 1. What part of my input led to this answer?
 2. How could I minimally modify this input to change the answer?
5. Analyzing representations
 1. Correlation in “interpretable” model components
 2. Probing studies: supervised analysis
6. Revisiting model ablations as analysis

THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG
PILE OF LINEAR ALGEBRA, THEN COLLECT
THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL
THEY START LOOKING RIGHT.



Motivation: what are our models doing?

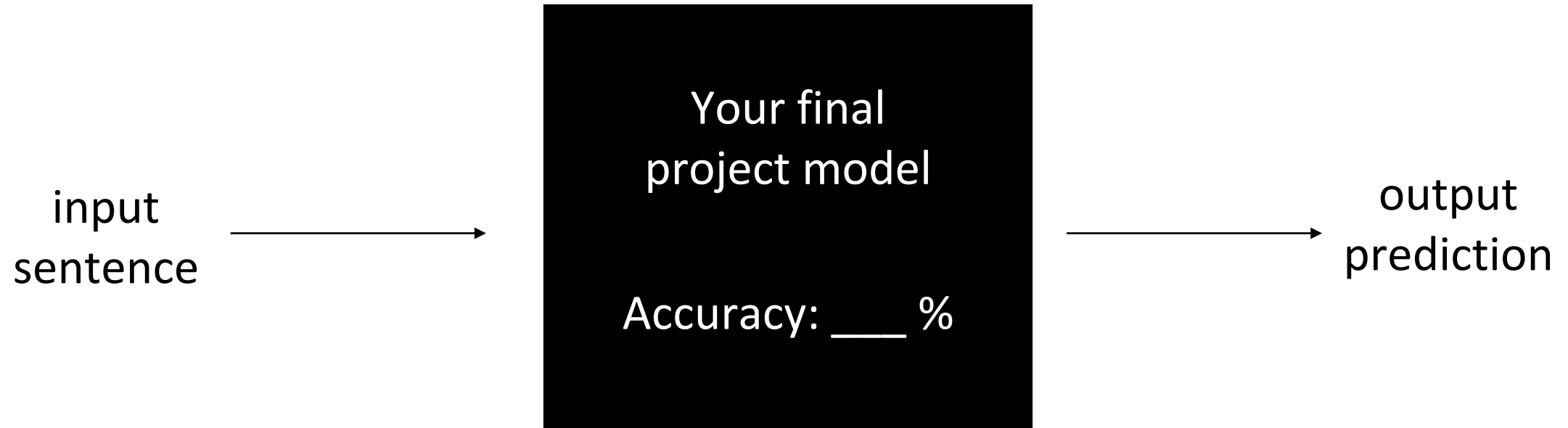
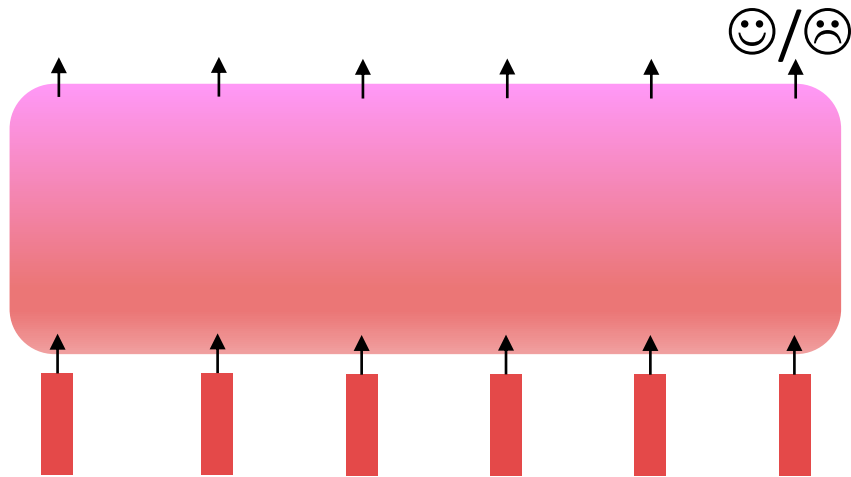


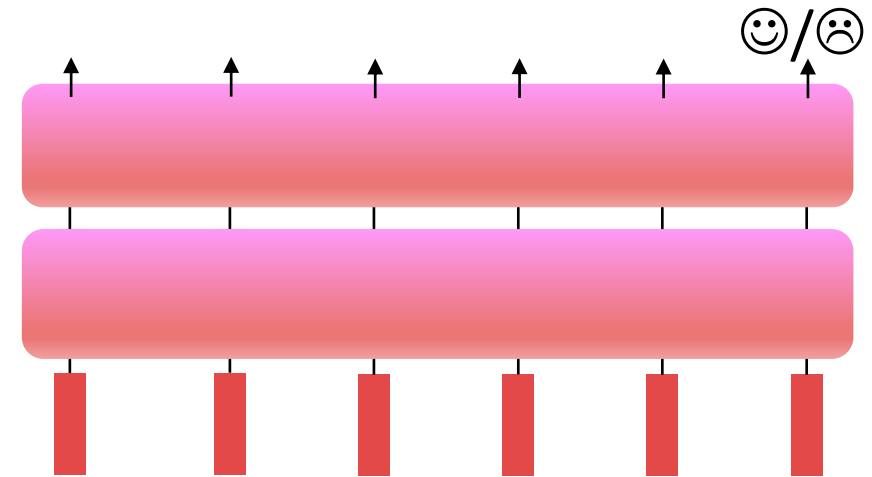
Fig 1. *A black box*

We summarize our models with one (or a handful) of accuracies metric numbers.
What do they learn? Why do they succeed and fail?

Motivation: how do we make tomorrow's model?



Today's models: use recipes that work, but aren't perfect



Tomorrow's models: take what works and find what needs changing

Understanding **how far** we can get with incremental improvements on current methods is crucial to the eventual development of major improvements.

Motivation: what biases are built into my model?

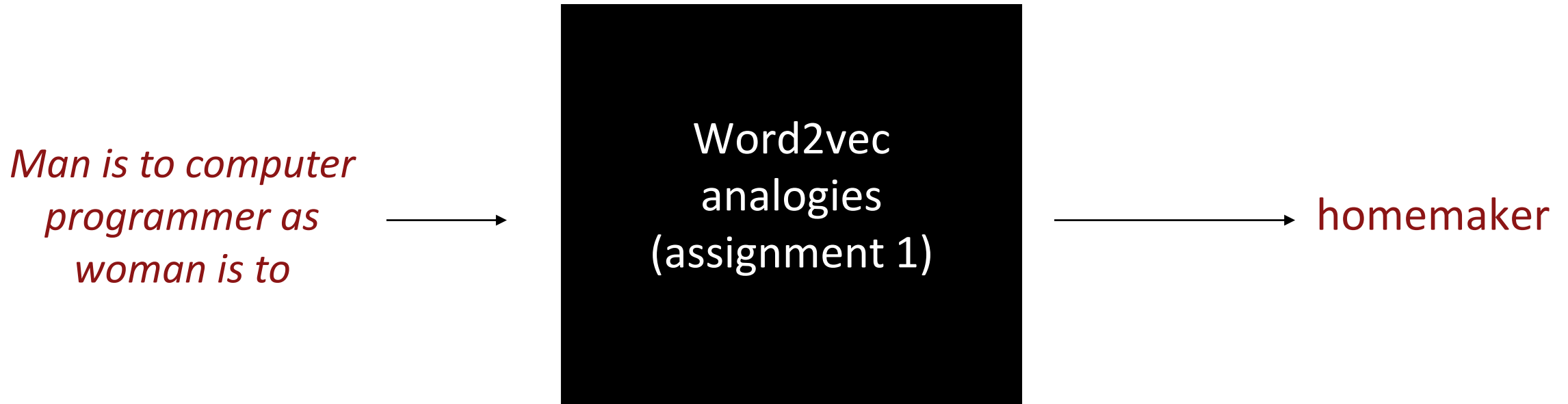


Fig 1. A *black box*

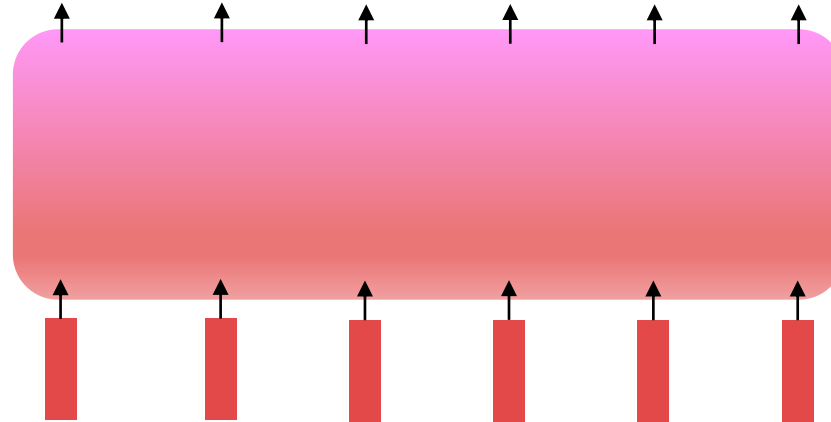
What did the model use in its decision?
What biases did it learn and possibly worsen?

Motivation: how do we make the next 25 years of models?

What can be learned via language model pretraining?

What will replace the Transformer?

What **can't** be learned via language model pretraining?



What does deep learning struggle to do?

How are our models affecting people, and transferring power?

What do neural models tell us about language?

Model analysis at varying levels of abstraction

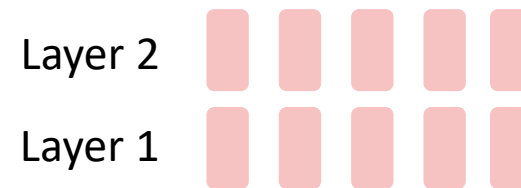
There is a **wide variety** of ways to analyze models; **none is perfect or provides total clarity**.

To start, at what level of **abstraction** do you want to reason about your model?

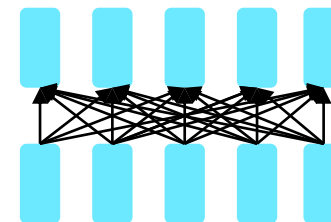
1. Your neural model as a probability distribution and decision function

$$p_{\text{model}}(y|x)$$

2. Your neural model as a sequence of vector representations in depth and time



3. Parameter weights, specific mechanisms like attention, dropout, +++



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Model evaluation as model analysis

When looking at the **behavior** of a model, we're not yet concerned with **mechanisms** the model is using. We want to ask *how does model behave in situations of interest?*

- You've trained your model on some samples $(x, y) \sim D$ from some distribution.
- How does the model behave on samples from the same distribution?
 - Aka *in-domain* or *i.i.d.* (independently and identically distributed)
 - **This is your test set accuracy / F1 / BLEU**

Model A
Accuracy: 95%

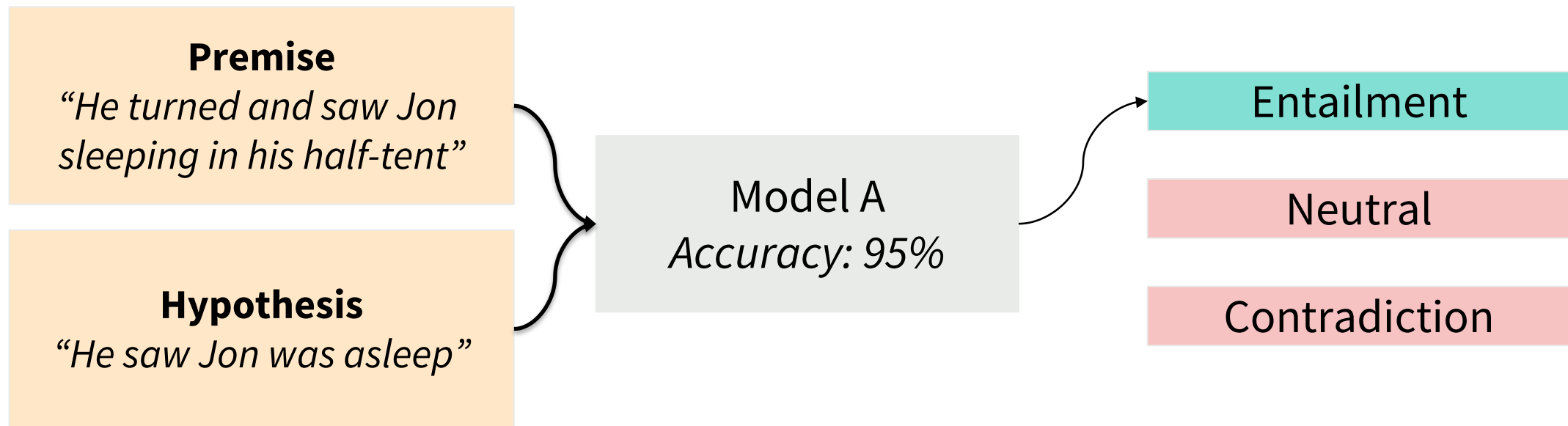
?
>

Model B
Accuracy: 92%

[Also, both models seem pretty good?]

Model evaluation as model analysis in **natural language inference**

Recall the **natural language inference** task, as encoded in the Multi-NLI dataset.



[Likely to get the right answer, since the accuracy is 95%?]

Model evaluation as model analysis in natural language inference

What if our model is using simple heuristics to get good accuracy?

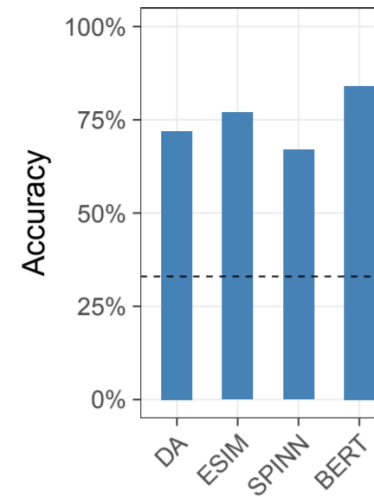
A **diagnostic test set** is carefully constructed to test for a specific skill or capacity of your neural model.

For example, **HANS**: (Heuristic Analysis for NLI Systems) tests syntactic heuristics in NLI

Heuristic	Definition	Example
Lexical overlap	Assume that a premise entails all hypotheses constructed from words in the premise	The doctor was paid by the actor . ————→ The doctor paid the actor. WRONG
Subsequence	Assume that a premise entails all of its contiguous subsequences.	The doctor near the actor danced . ————→ The actor danced. WRONG
Constituent	Assume that a premise entails all complete subtrees in its parse tree.	If the artist slept , the actor ran. ————→ The artist slept. WRONG

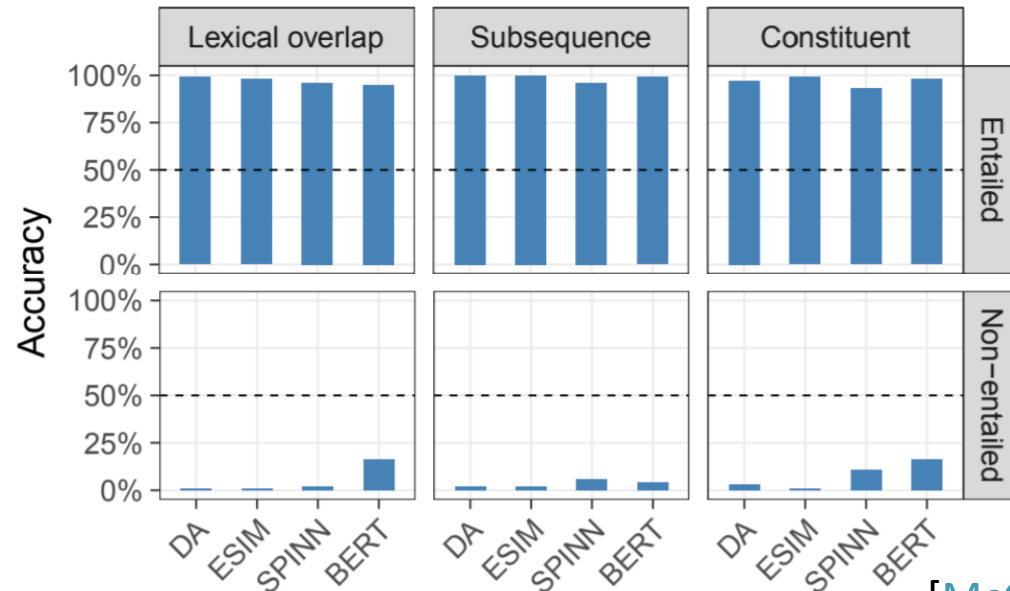
HANS model analysis in natural language inference

McCoy et al., 2019 took 4 strong MNL models, with the following accuracies on the **original test set (in-domain)**



Evaluating on HANS, where syntactic heuristics **work**, accuracy is high!

But where syntactic heuristics fail, accuracy is very very low...



Language models as linguistic test subjects

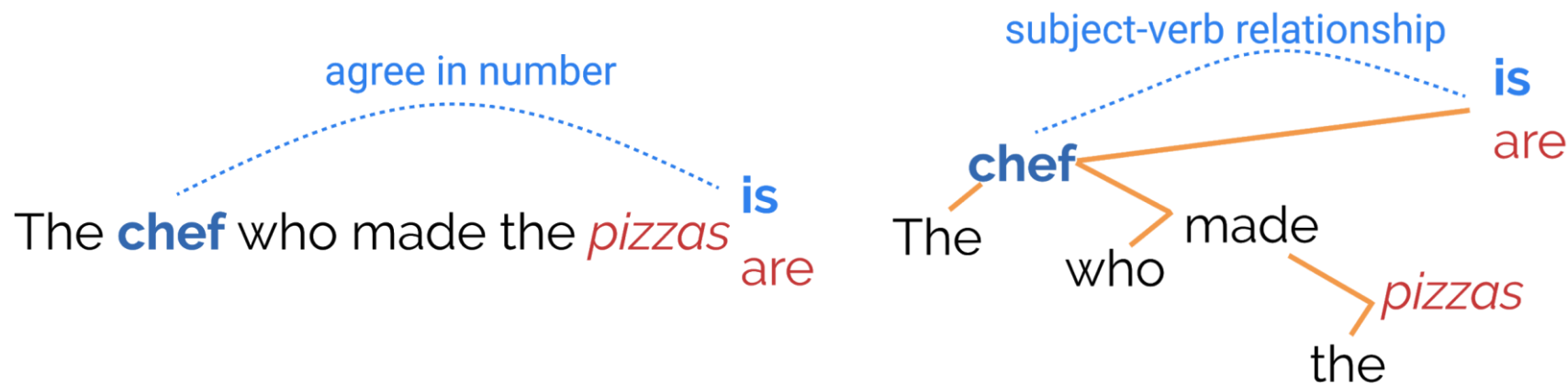
Humans

- How do we understand language behavior in humans?
- One method: *minimal pairs*. What sounds “okay” to a speaker, but doesn’t with a small change?

The chef who made the pizzas **is** here. ← “Acceptable”

The chef who made the pizzas **are** here ← “Unacceptable”

Idea: English present-tense verbs *agree in number* with their subjects



Language models as linguistic test subjects

- What's the language model analogue of acceptability?
The chef who made the pizzas is here. ← “Acceptable”
The chef who made the pizzas are here ← “Unacceptable”
- Assign higher probability to the acceptable sentence in the minimal pair
 $P(\text{The chef who made the pizzas is here.}) > P(\text{The chef who made the pizzas are here})$
- Just like in HANS, we can develop a **test set with carefully chosen properties**.
 - Specifically: can language models handle “attractors” in subject-verb agreement?
 - 0 Attractors: The chef is here.
 - 1 Attractor: The chef who made the pizzas is here.
 - 2 Attractors: The chef who made the pizzas and prepped the ingredients is here.
 - ...

Language models as linguistic test subjects

- Kuncoro et al., 2018 train an LSTM language model on a small set of Wikipedia text.
- They evaluate it *only* on sentences with specific numbers of agreement attractors.
- Numbers in this table: accuracy at predicting the correct number for the verb

Zero attractors: Easy

	n=0	n=1	n=2	n=3	n=4
Random	50.0	50.0	50.0	50.0	50.0
Majority	32.0	32.0	32.0	32.0	32.0
Our LSTM, H=50	2.4	8.0	15.7	26.1	34.65
Our LSTM, H=150	1.5	4.5	9.0	14.3	17.6
Our LSTM, H=250	1.4	3.3	5.9	9.7	13.9
Our LSTM, H=350	1.3	3.0	5.7	9.7	13.8

4 attractors: harder,
but models still do
pretty well!

The larger LSTMs learn subject-
verb agreement better!

Language models as linguistic test subjects

Sample test examples for subject-verb agreement with attractors that a model got wrong

The **ship** that the player drives **has** a very high speed.

The **ship** that the player drives **have** a very high speed.

The **lead** is also rather long; 5 paragraphs **is** pretty lengthy ...

The **lead** is also rather long; 5 paragraphs **are** pretty lengthy ...

Careful test sets as unit test suites: CheckListing

- Small careful test sets sound like... unit test suites, but for neural networks!
- *Minimum functionality tests*: small test sets that target a specific behavior.

Test case	Expected	Predicted	Pass?
A Testing Negation with <i>MFT</i> Labels: negative, positive, neutral			
Template: I {NEGATION} {POS_VERB} the {THING}.			
I can't say I recommend the food.	neg	pos	X
I didn't love the flight.	neg	neutral	X
...			
Failure rate = 76.4%			

- [Ribeiro et al., 2020](#) showed **ML engineers working on a sentiment analysis product** an interface with categories of linguistic capabilities and types of tests.
 - The engineers found a bunch of bugs (categories of high error) through this method!

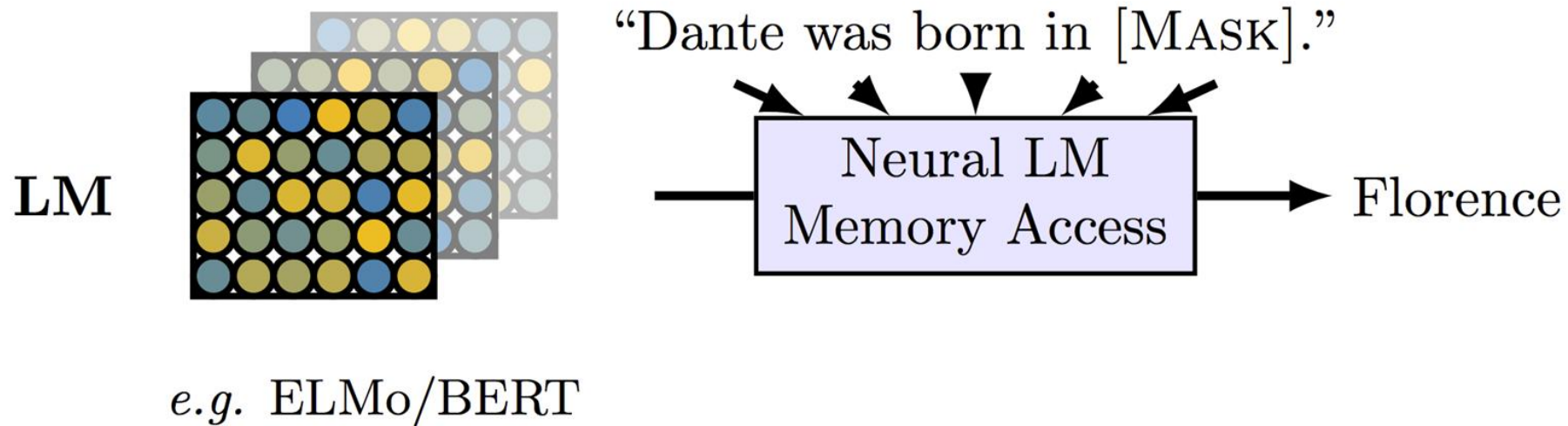
Fitting the dataset vs learning the task

Across a wide range of tasks, high model accuracy on the in-domain test set does not imply the model will also do well on other, “reasonable” out-of-domain examples.

One way to think about this: models seem to be learning the *dataset* (like MNLI) not the *task* (like how humans can perform natural language inference).

Knowledge evaluation as model analysis

- What has a language model learned from pretraining?
- Last week, we saw one way of accessing some of the knowledge in the model by providing it with prompts.
- This fits into the set of *behavioral studies* we've seen so far!

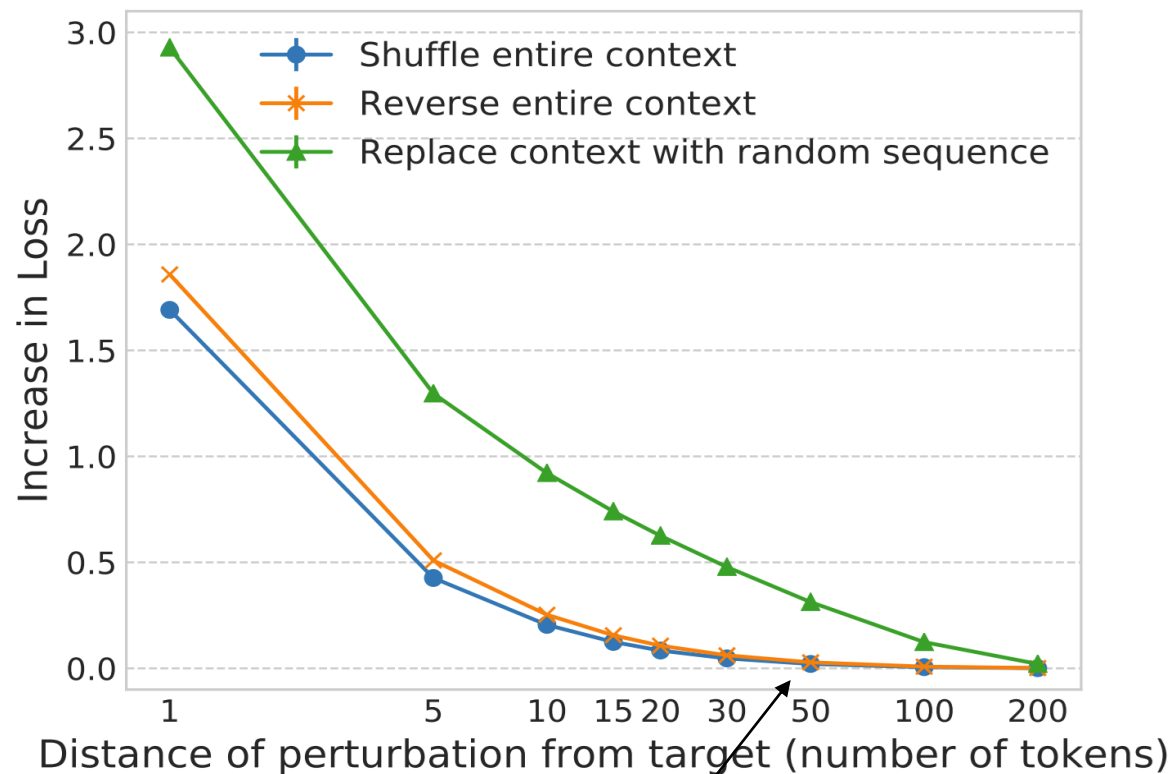


Outline

1. Motivating model analysis and explanation
2. One model at multiple levels of abstraction
3. Out-of-domain evaluation sets (Your model as a probability distribution)
 1. Testing for linguistic knowledge
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Input influence: does my model *really* use long-distance context?

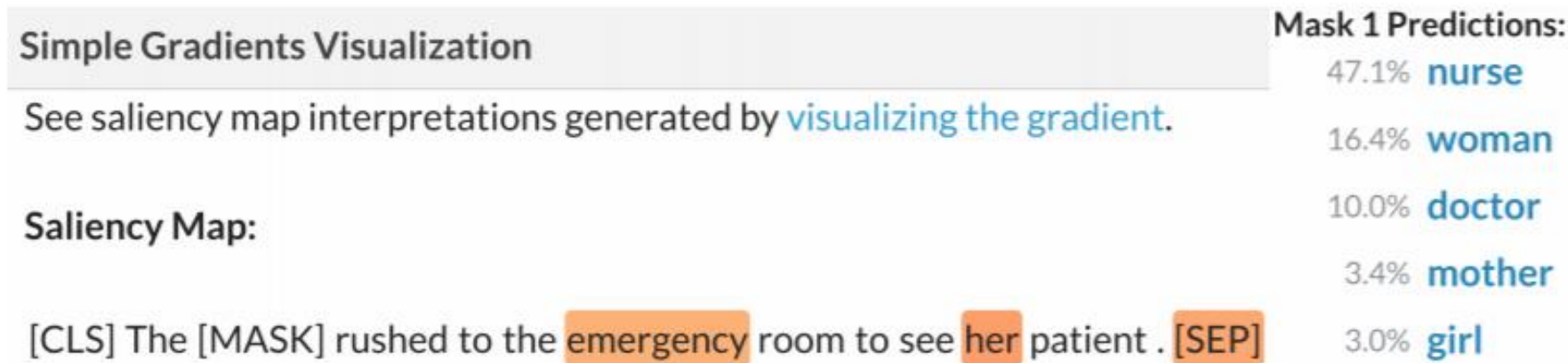
- We motivated LSTM language models through their theoretical ability to use long-distance context to make predictions. But how long really is the long short-term memory?
- Khandelwal et al., 2018's idea: shuffle or remove all contexts farther than k words away for multiple values of k and see at which k the model's predictions start to get worse!
- Loss is averaged across many examples.



History farther than 50 words away treated as a bag of words.

Prediction explanations: what in the input led to this output?

- For a single example, what parts of the input led to the observed prediction?
- **Saliency maps:** a score for each input word indicating its importance to the model's prediction



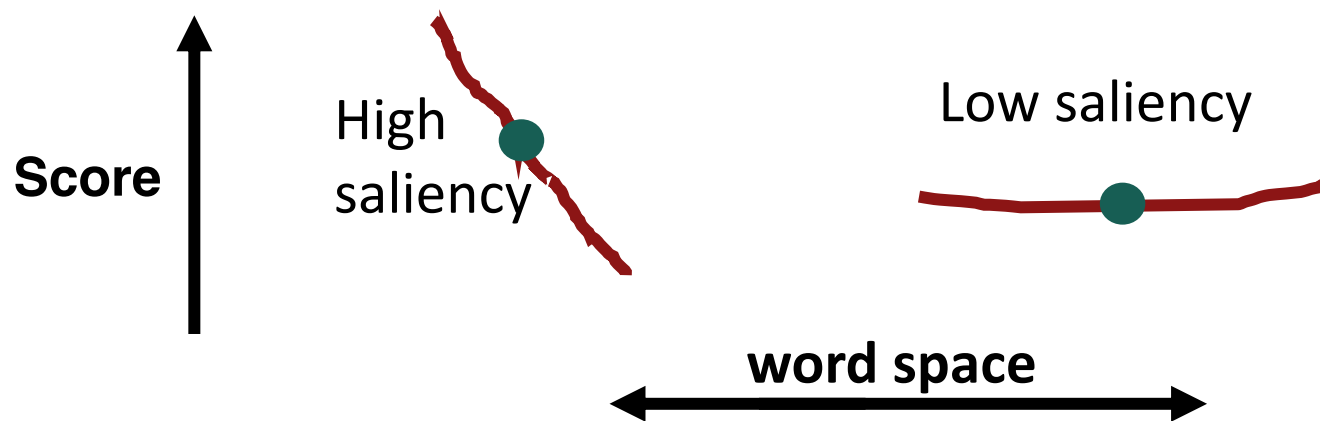
- In the above example, BERT is analyzed, and interpretable words seem to contribute to the model's predictions (right).

Prediction explanations: simple saliency maps

- How do we make a saliency map? Many ways to encode the intuition of “importance”
- **Simple gradient method:**
For words x_1, \dots, x_n and the model's score for a given class (output label) $s_c(x_1, \dots, x_n)$, take the norm of the gradient of the score w.r.t. each word:

$$\text{saliency}(x_i) = \|\nabla_{x_i} s_c(x_1, \dots, x_n)\|$$

Idea: **high gradient norm** means changing that word (locally) would affect the score a lot



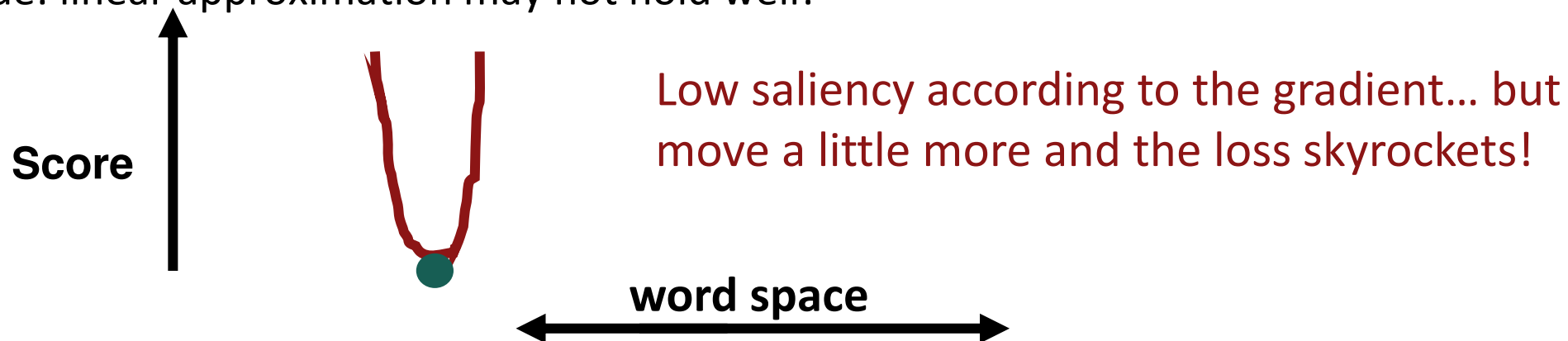
Prediction explanations: simple saliency maps

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$$\text{saliency}(x_i) = |\nabla_{x_i} s_c(x_1, \dots, x_n)|$$

Not a perfect method for saliency; many more methods have been proposed.

One issue: linear approximation may not hold well!



Explanation by input reduction

What is the smallest part of the input I could keep and still get the same answer?

An example from SQuAD:

Passage: In 1899, John Jacob Astor IV invested \$100,000 for Tesla to further develop and produce a new lighting system. Instead, Tesla used the money to fund his **Colorado Springs experiments**.

[prediction]

Original Question: What did Tesla spend Astor's money on ?

Reduced Question did

In this example, the model had confidence 0.78 for the original question, and the same answer at confidence **0.91** for the reduced question!

A method for explanation by input reduction

Idea: run an input saliency method. Iteratively remove the most unimportant words.

Passage:

The Panthers used the San Jose State practice facility and stayed at the San Jose Marriott. The Broncos practiced at [Stanford University](#) and stayed at the Santa Clara Marriott.

[prediction]

Original Question:

Where did the Broncos practice for the Super Bowl ?
Where did the practice for the Super Bowl ?
Where did practice for the Super Bowl ?
Where did practice the Super Bowl ?
Where did practice the Super ?
Where did practice Super ?
did practice Super ?

Steps of input reduction



[Note: beam search to find k least important words is an important addition]

Only here did the model stop being confident in the answer

[[Feng et al., 2018](#)]

Analyzing models by breaking them

Idea: **Can we break models by making seemingly innocuous changes to the input?**

Passage:

Peyton manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by **John Elway**, who led the Broncos to victory in Super Bowl XXXIII at age 38...

[prediction]

Question:

What was the name of the quarterback who was 38 in Super Bowl XXXIII?

Looks good!

Analyzing models by breaking them

Idea: **Can we break models by making seemingly innocuous changes to the input?**

Passage:

Peyton manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38... Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.

[prediction]

Question:

What was the name of the quarterback who was 38 in Super Bowl XXXIII?

The sentence in orange hasn't changed the answer, but the model's prediction changed!

So, seems like the model wasn't performing question answering as we'd like?

Analyzing models by breaking them

Idea: **Can we break models by making seemingly innocuous changes to the input?**

In the United States especially, several high-profile cases such as Debra LaFave, Pamela Rogers, and Mary Kay Letourneau have caused increased scrutiny on teacher misconduct.

(a) Input Paragraph

Q: What has been the result of this publicity?

A: increased scrutiny on teacher misconduct

(b) Original Question and Answer

Q: What **haL** been the result of this publicity?

A: **teacher misconduct**

(c) Adversarial Q & A (Ebrahimi et al., 2018)

Q: **What's** been the result of this publicity?

A: **teacher misconduct**

(d) **Semantically Equivalent Adversary**

This model's
predictions look good!

This typo is annoying, but a reasonable
human might ignore it.

Changing *what* to *what's* should never
change the answer!

Are ~~models~~ Humans robust to noise in their input?

“According to a research at Cambridge University, it doesn’t matter in what order the letters in a word are, the only important thing is that the first and last letter be at the right place.”

Seemingly so!

Are models robust to noise in their input?

Noise of various kinds is an inevitable part of the inputs to NLP systems. How do models trained on (relatively) clean text perform when typo-like noise is added?

Belinkov and Bisk, 2018 performed a study on popular machine translation models.

BLEU scores are high on in-domain clean text

Character-swaps like we just saw break the model!

(More) natural typo noise also breaks the models.

		Vanilla	Swap	Synthetic			Nat
				Mid	Rand	Key	
French	charCNN	42.54	10.52	9.71	1.71	8.26	17.42
	char2char	34.79	9.25	8.37	1.02	6.40	14.02
German	char2char	29.97	5.68	5.46	0.28	2.96	12.68
	Nematus	34.22	3.39	5.16	0.29	0.61	10.68
Czech	charCNN	25.99	6.56	6.67	1.50	7.13	10.20
	char2char	25.71	3.90	4.24	0.25	2.88	11.42
	Nematus	29.65	2.94	4.09	0.66	1.41	11.88

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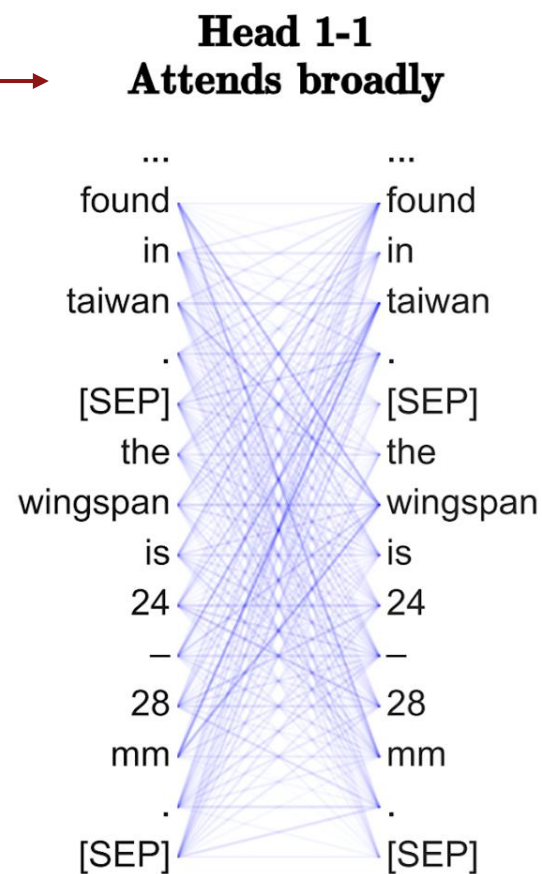
Analysis of “interpretable” architecture components

Idea: **Some modeling components lend themselves to inspection.**

For example, can we try to characterize each attention head of BERT?

Attention head 1 of layer 1.

This head performs this kind of behavior on most sentences.

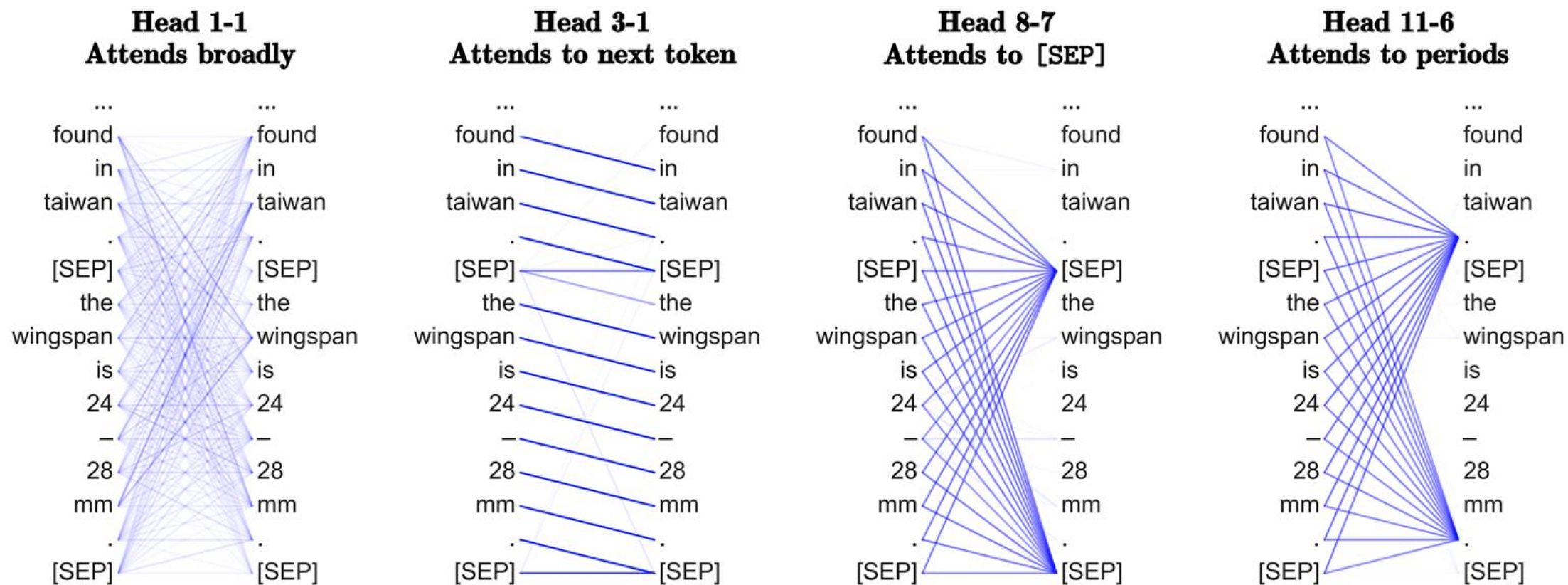


[Why is “interpretable” in quotes? It’s hard to tell exactly how/whether the model is performing an interpretable function, especially deep in the network.]

Analysis of “interpretable” architecture components

Idea: **Some modeling components lend themselves to inspection.**

Some attention heads seem to perform simple operations.



Analysis of “interpretable” architecture components

Idea: **Some modeling components lend themselves to inspection.**

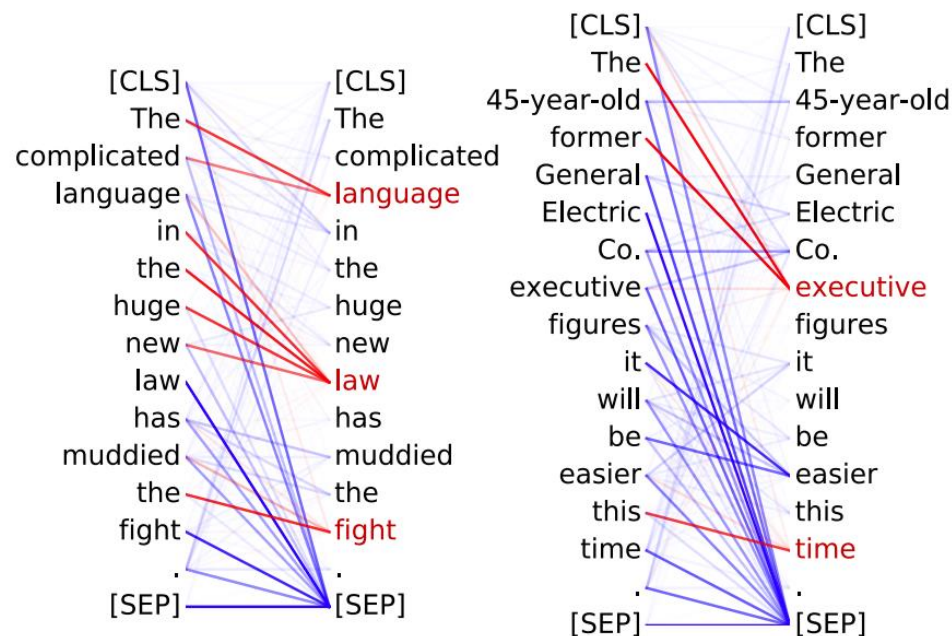
Some heads are correlated with linguistic properties!

Approximate
interpretation +
quantitative analysis

Model behavior

Head 8-11

- **Noun modifiers** (e.g., determiners) attend to their noun
- 94.3% accuracy at the **det** relation



Analysis of “interpretable” architecture components

Idea: **Some modeling components lend themselves to inspection.**

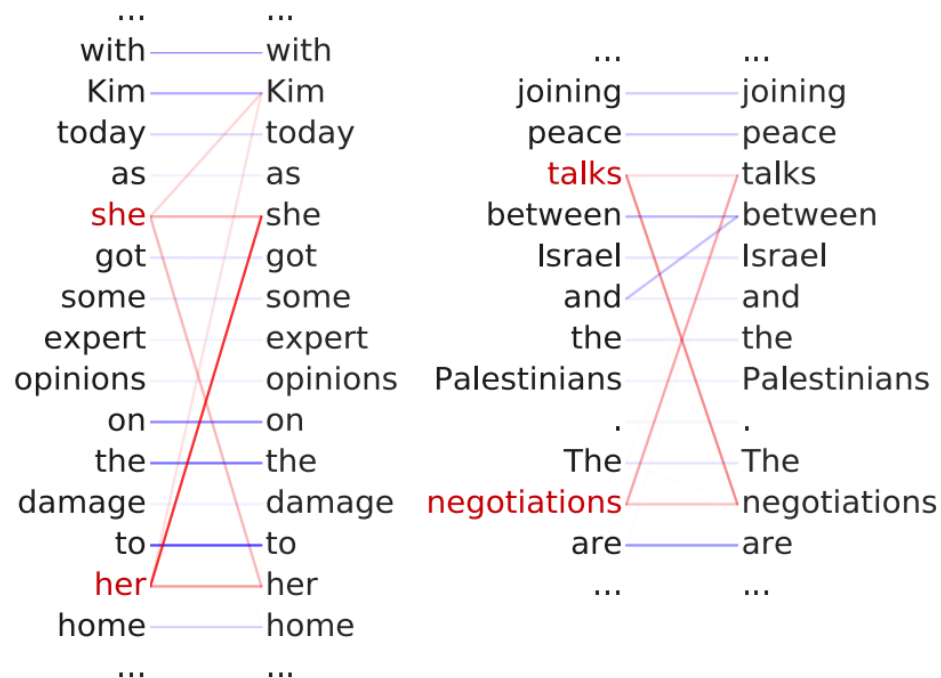
We saw coreference before; one head often matches coreferent mentions!

Approximate
interpretation +
quantitative analysis

Model behavior

Head 5-4

- **Coreferent** mentions attend to their antecedents
- 65.1% accuracy at linking the head of a coreferent mention to the head of an antecedent



Analysis of “interpretable” architecture components

Idea: Individual hidden units can lend themselves to an interpretable meaning.

This model: a character-level LSTM language model.

Cell sensitive to position in line:

The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action--the one Kutuzov and the general mass of the army demanded--namely, simply to follow the enemy up. The French crowd fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, unarmed soldiers, people from Moscow and women with children who were with the French transport, all--carried on by vis inertiae--pressed forward into boats and into the ice-covered water and did not, surrender.

Here, “cell” refers to a single dimension of the cell state of the LSTM.

Analysis of “interpretable” architecture components

Idea: Individual hidden units can lend themselves to an interpretable meaning.

This model: a character-level LSTM language model.

Cell that turns on inside quotes:

"You mean to imply that I have nothing to eat out of.... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

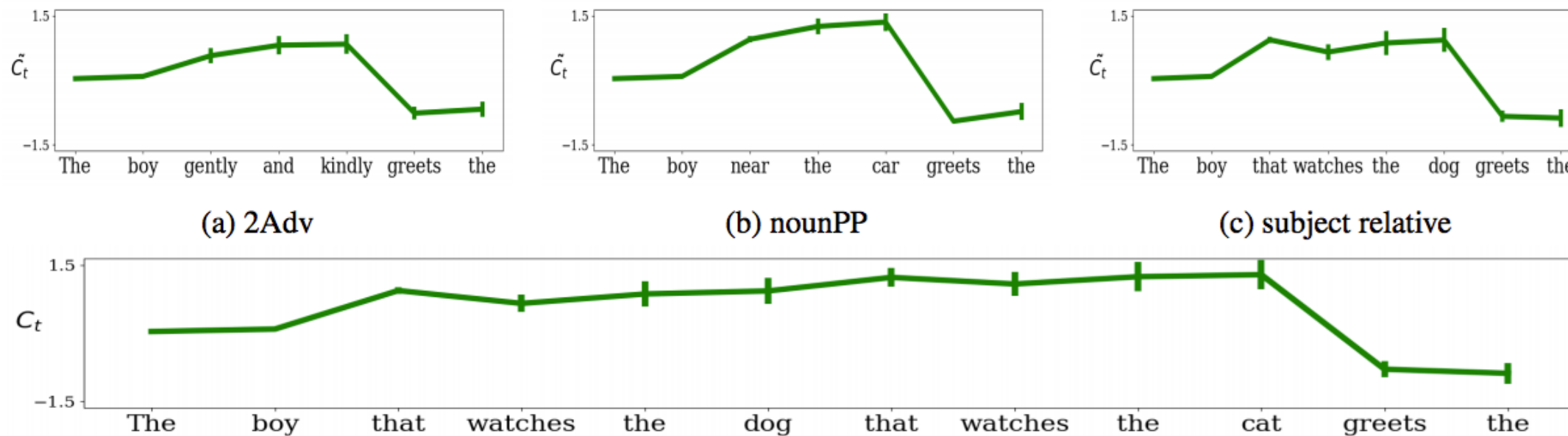
Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

Here, “cell” refers to a single dimension of the cell state of the LSTM.

Analysis of “interpretable” architecture components

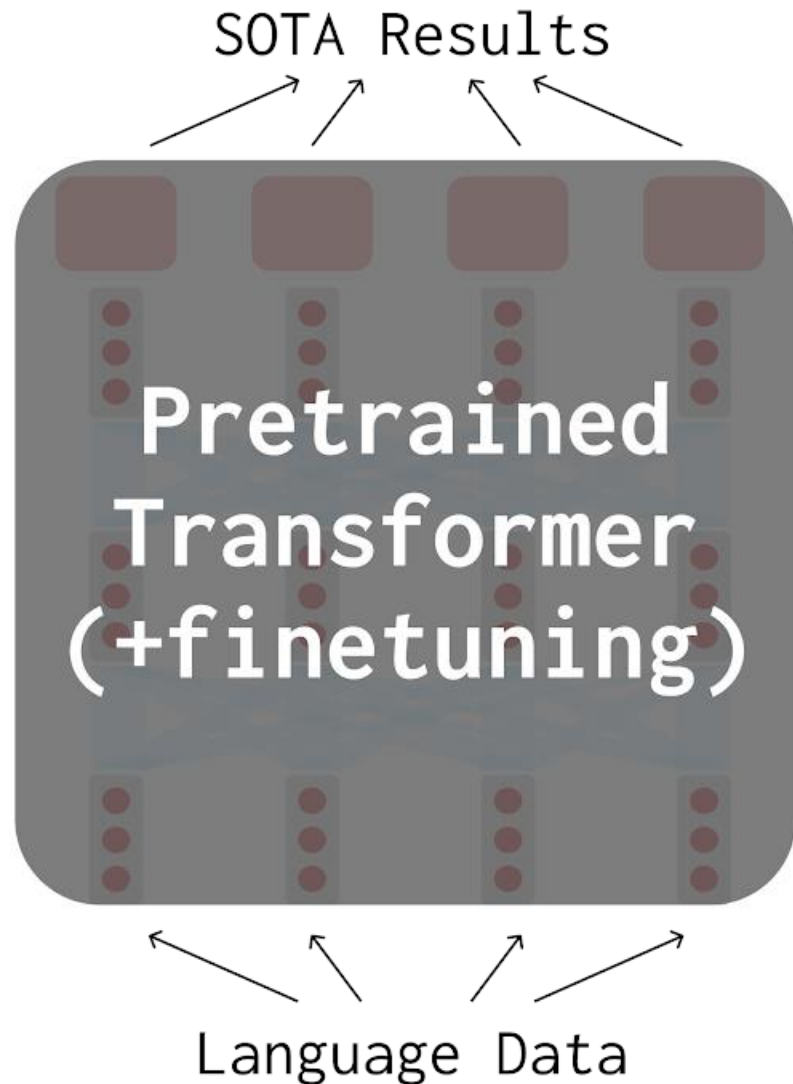
Idea: Let's go back to **subject-verb agreement**. What's the mechanism by which LSTMs solve the task?

This model: a word-level LSTM language model.



This is neuron 1150 in the LSTM, which seems to track the scope of the grammatical number of the subject! Removing this unit harms subject-verb agreement much more than removing a random unit.

Probing: supervised analysis of neural networks



Premise:

Pretrained Transformers provide wildly **general-purpose language representations**

Question:

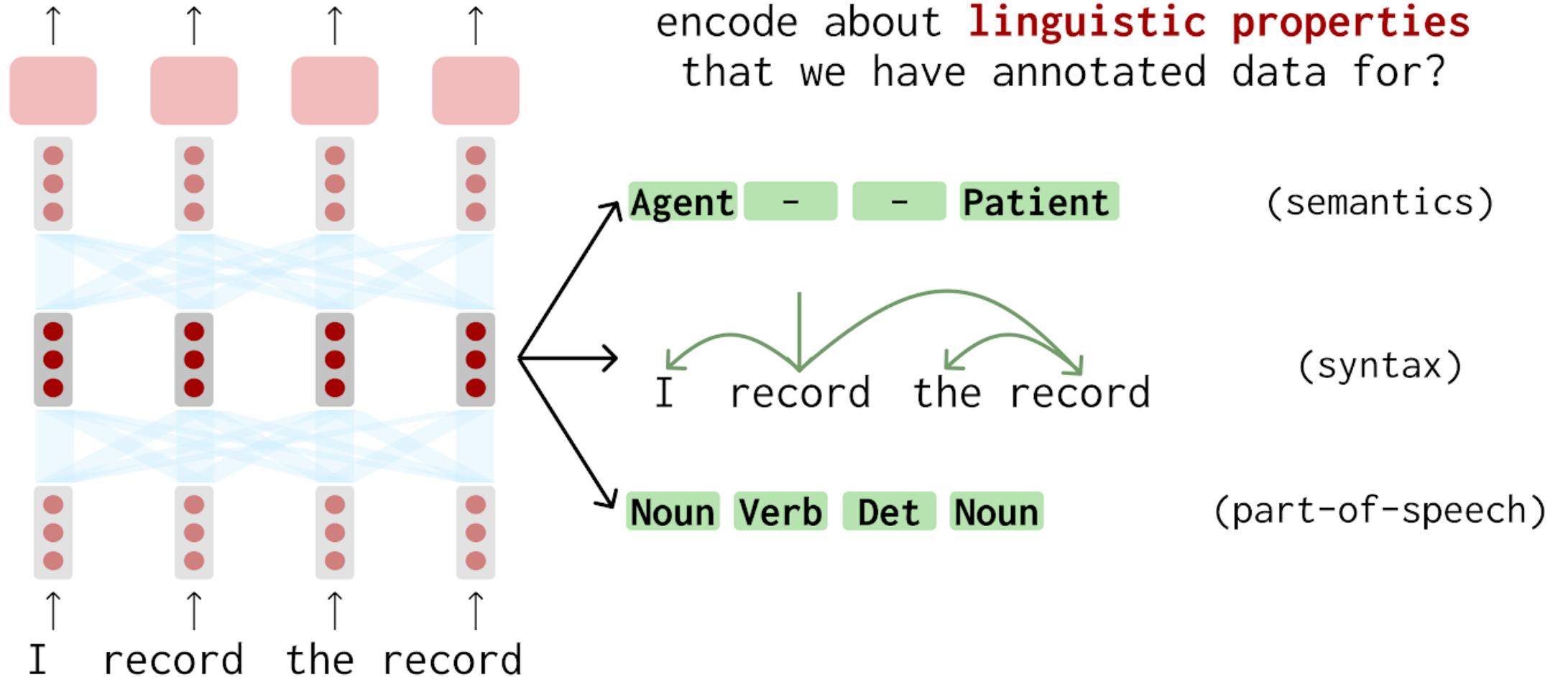
What do their representations **encode about language?**

[SOTA means “state-of-the-art,” the best method for a given problem.]

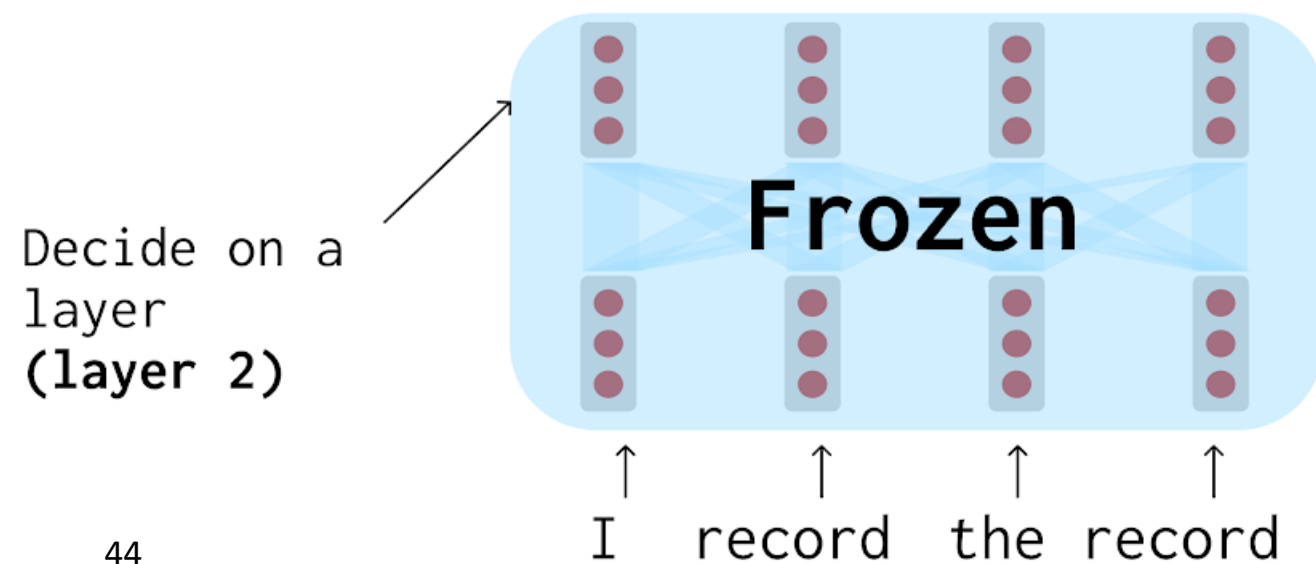
Probing: supervised analysis of neural networks

Idea:

What do pretrained representations encode about **linguistic properties** that we have annotated data for?



Probing: supervised analysis of neural networks



Probing: supervised analysis of neural networks

Let's take a second to think more about probing.

- We have some property y (like part-of-speech)
- We have the model's word representations at a fixed layer: h_1, \dots, h_T , where $h_i \in \mathbb{R}^d$, where the words are at indices $1, \dots, T$.
- We have a function family F like the set of *linear models* or *1-layer feed-forward networks (with fixed hyperparameters.)*
- We **freeze** the parameters of the model, so it's not finetuned. Then, we train our probe, a function

$$\hat{y} \sim f(h_i) \quad f \in F$$

The extent to which we can predict y from h_i is a measure of the accessibility of that feature in the representation.

- This helps gain a rough understanding into how the model processes its inputs.
- Also may help in the search for causal mechanisms.

Probing: supervised analysis of neural networks

BERT (and other pretrained LMs) make some linguistic properties predictable to very high accuracy with a simple linear probe.

Pretrained Representation	Syntactic roles		Part-of-speech		Named entity recognition	
	Avg.	CCG	POS		Chunk	NER
			PTB	EWT		
BERT (base, cased) best layer	84.09	93.67	96.95	95.21	92.64	82.71
BERT (large, cased) best layer	85.07	94.28	96.73	95.80	93.64	84.44
GloVe (840B.300d)	59.94	71.58	90.49	83.93	62.28	53.22
Previous state of the art (without pretraining)	83.44	94.7	97.96	95.82	95.77	91.38

Layerwise trends of probing accuracy

- Across a wide range of linguistic properties, the middle layers of BERT yield the best probing accuracies.

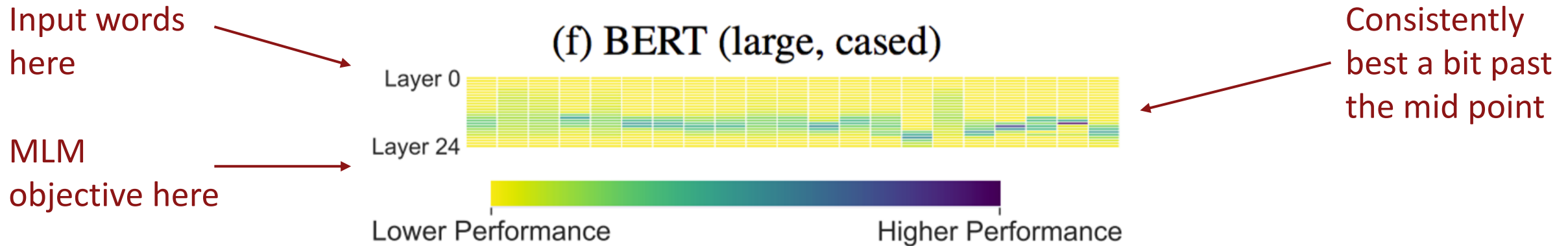
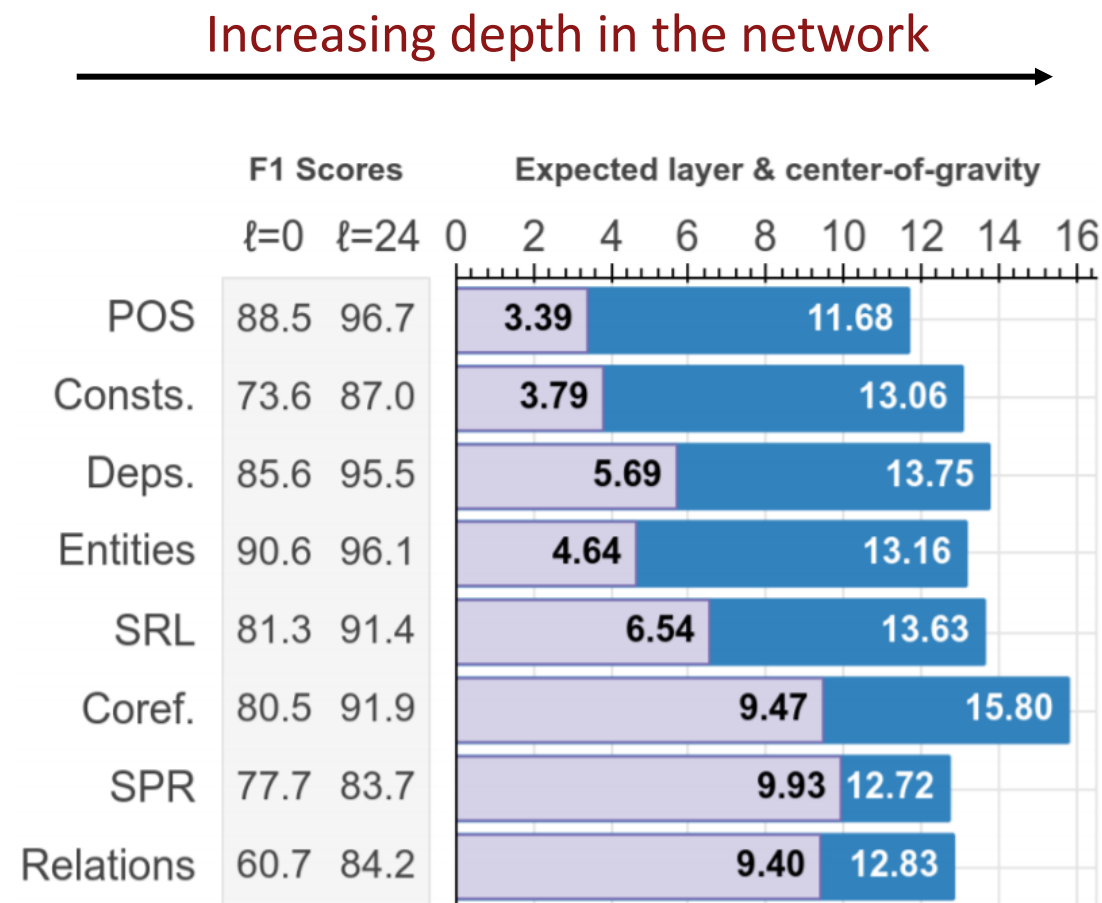


Figure 3: A visualization of layerwise patterns in task performance. Each column represents a probing task, and each row represents a contextualizer layer.

Layerwise trends of probing accuracy

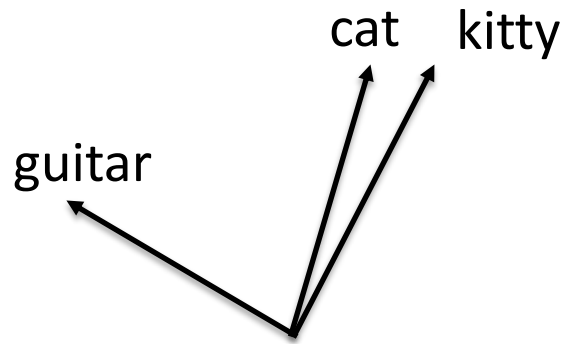
- Increasingly abstract linguistic properties are more accessible later in the network.

Increasing
abstractness
of linguistic
properties

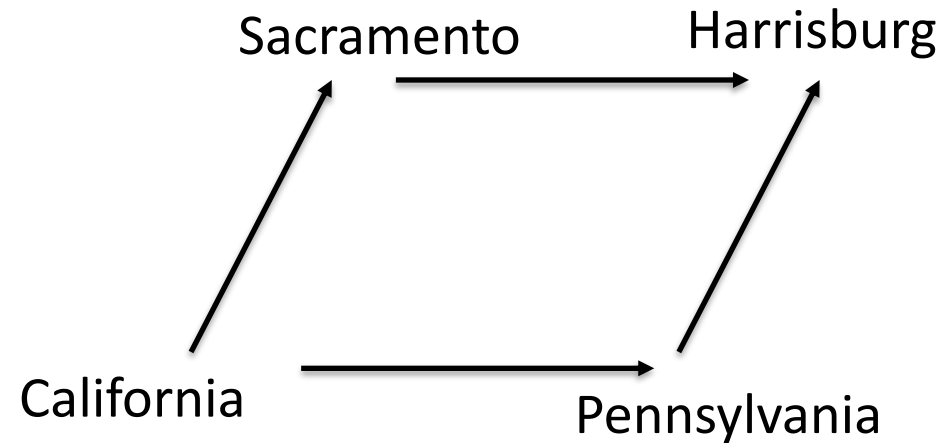


Emergent simple structure in neural networks

- Recall word2vec, and the intuitions we built around its vectors



We interpret **cosine similarity** as *semantic similarity*.

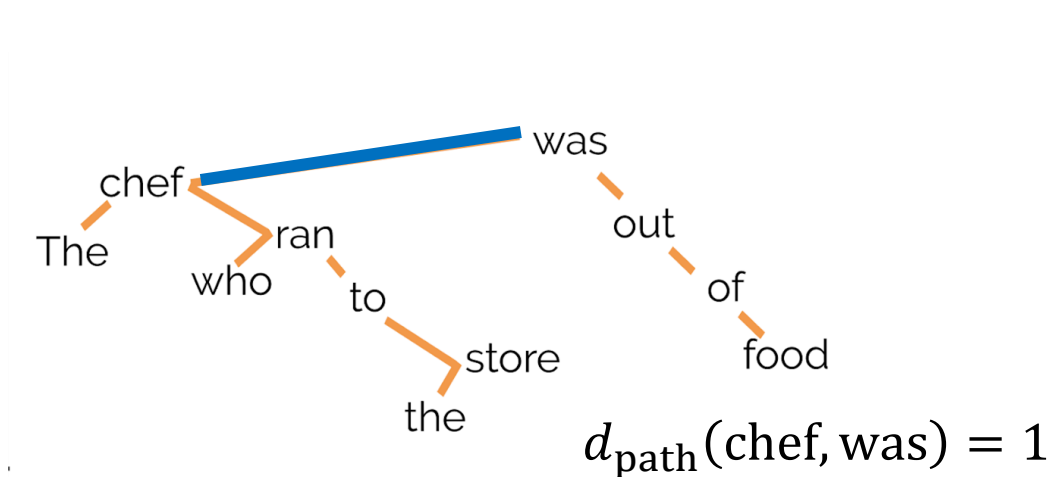


Some *relationships* are encoded as **linear offsets**

- It's hard to the dimensions of word2vec vectors, but it's fascinating that interpretable concepts approximately map onto simple functions of the vectors

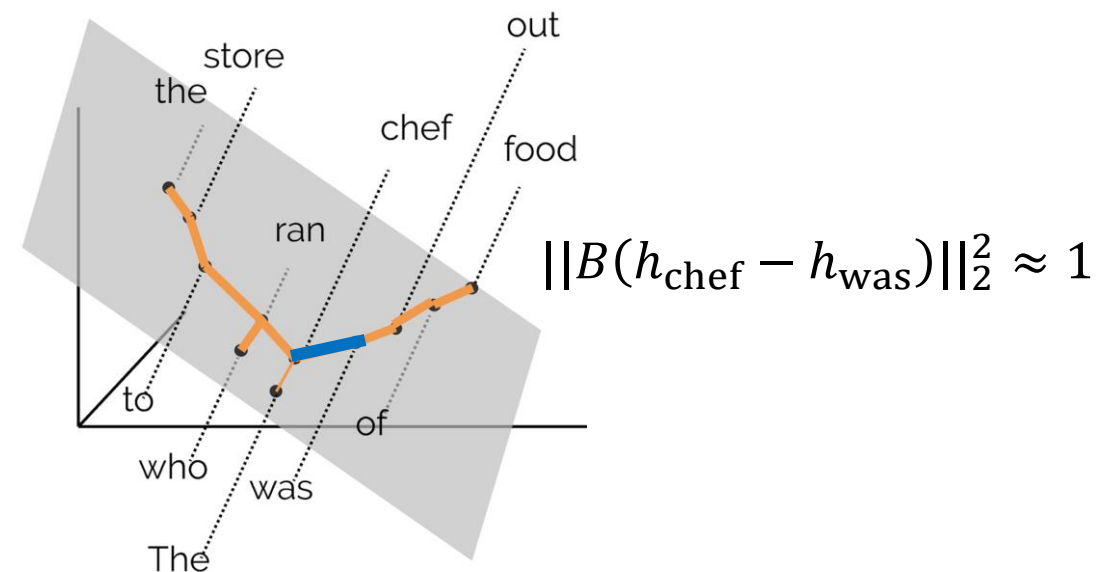
Probing: trees simply recoverable from BERT representations

- Recall dependency parse trees. They describe underlying syntactic structure in sentences.
- Hewitt and Manning 2019 show that BERT models make dependency parse **tree structure** easily accessible.



$$d_{\text{path}}(w_1, w_2)$$

Tree path distance: the number of edges in the path between the words

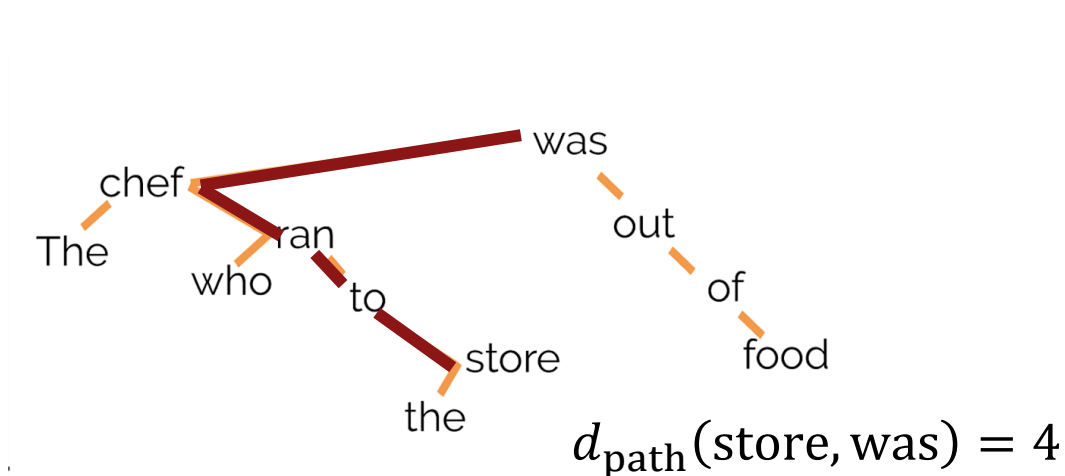


$$\|B(h_{w_1} - h_{w_2})\|_2^2$$

Squared Euclidean distance of BERT vectors after transformation by the (probe) matrix B.

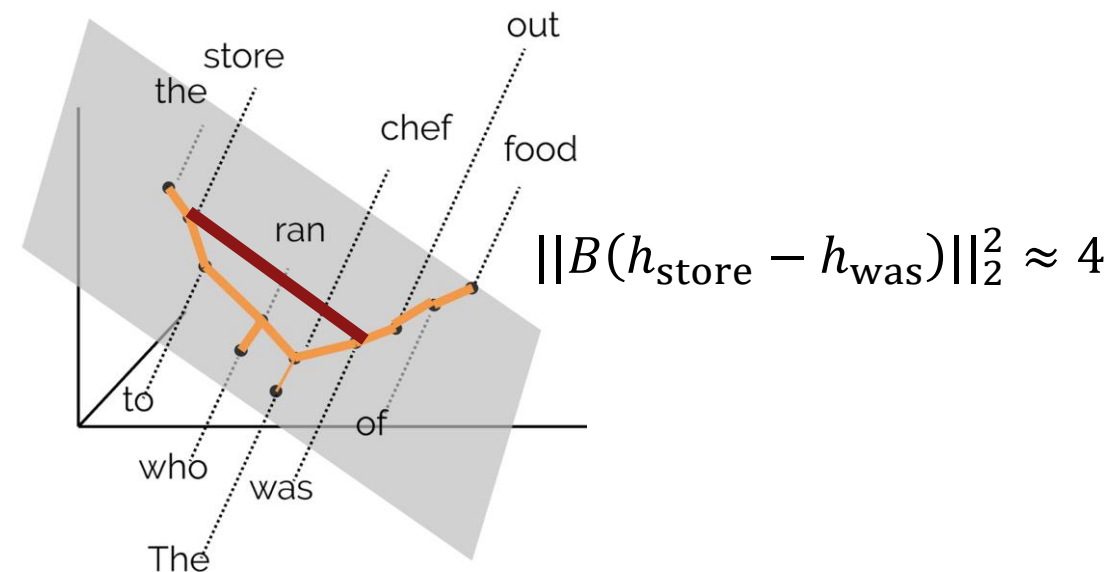
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Final thoughts on probing and correlation studies

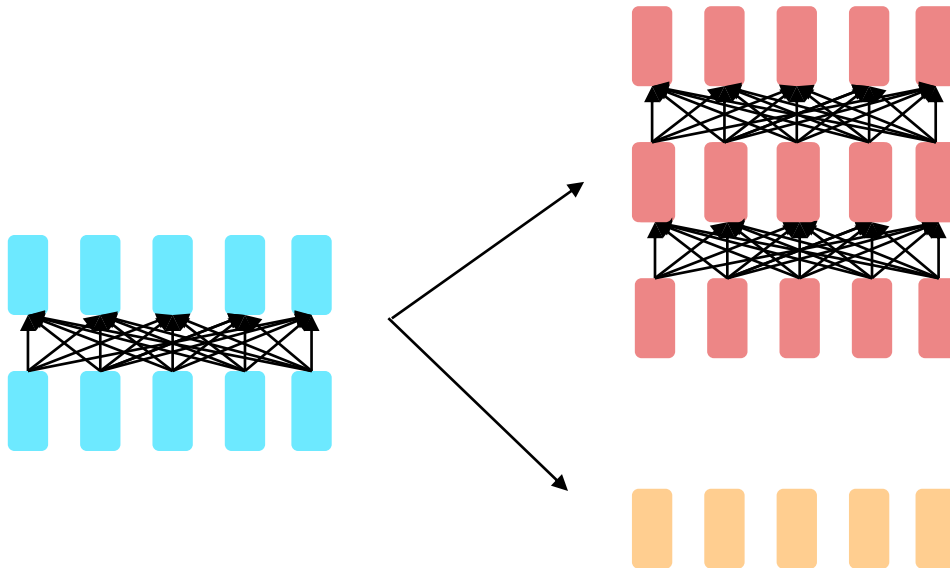
- Probing shows that properties are accessible to your probe family, not that they're used by the neural model you're studying.
- Correlation studies (like attention maps) likewise.
- For example:
 - Hewitt and Liang, 2019 show that under certain conditions, probes can achieve high accuracy on random labels.
 - Ravichander et al., 2021 show that probes can achieve high accuracy on a property even when the model is trained to know the property isn't useful.
- Some efforts (Vig et al., 2020) have gone towards causal studies. Interesting and harder!

Outline

1. Motivating model analysis and explanation
2. One model at multiple levels of abstraction
3. Out-of-domain evaluation sets
 1. Testing for linguistic knowledge
 2. Testing for task heuristics
4. Influence studies and adversarial examples
 1. What part of my input led to this answer?
 2. How could I minimally modify this input to change the answer?
5. Analyzing representations
 1. Correlation in “interpretable” model components
 2. Probing studies: supervised analysis
6. Revisiting model ablations as analysis

Recasting model tweaks and ablations as analysis

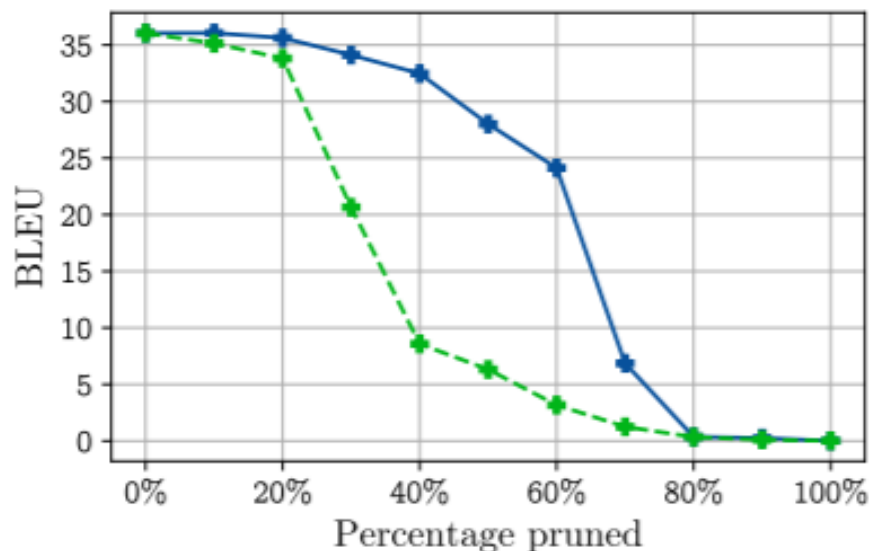
- Consider the usual neural network improvement process:
 - You have a network, which works okay.
 - You see whether you can tweak it in simple ways to improve it.
 - You see whether you can remove any complex things and have it still work as well.
- This can be thought of as a kind of model analysis!



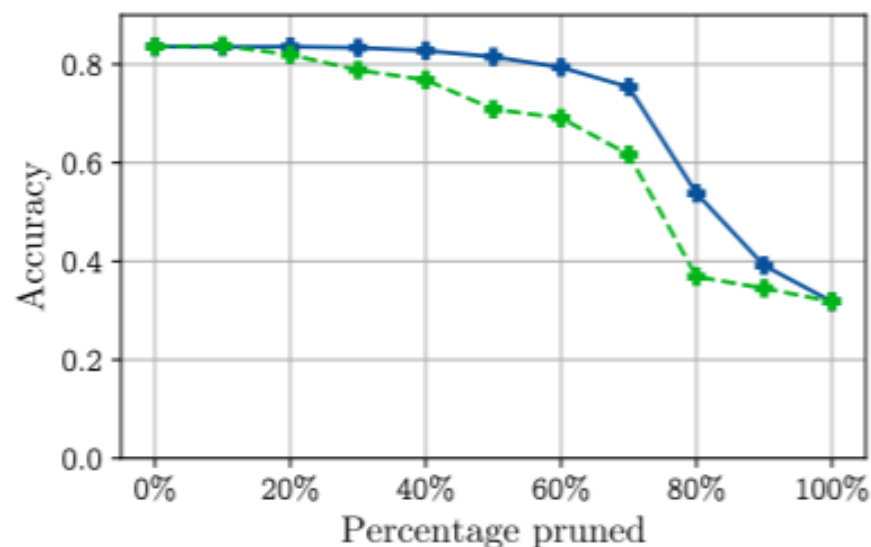
[Would it be better for this part of my model to be deeper? Or can I get away with making it shallower?]

Ablation analysis: do we need all these attention heads?

- Michel et al., 2019 train transformers with multi-headed attention on machine translation and natural language inference.
- After training, they find many attention heads can be **removed** with no drop in accuracy!



(a) Evolution of BLEU score on newstest2013 when heads are pruned from WMT.



(b) Evolution of accuracy on the MultiNLI-matched validation set when heads are pruned from BERT.

[Green and blue lines indicate two different ways to choose the order to prune attention heads.]

What's the right layer order for a Transformer?

- We saw that Transformer models are sequences of layers
 - Self-attention → Feed-forward → Self-attention → Feed-forward →
 - (Layer norm and residual connections omitted)
- Press et al., 2019 asked, why? Is there a better ordering of self-attention and feed-forward layers?
- Here's that sequence of layers again:

s f s f s f s f s f s f s f s f s f s f s f s f

Achieves 18.40 perplexity on a language modeling benchmark

s s s s s s s f s f s f s f s f s f s f s f f f f f f f f

Achieves 17.96 perplexity on a language modeling benchmark

Many self-attention
layers first

Many feed-forward
layers last

Parting thoughts

- Neural models are complex, and difficult to characterize. A single accuracy metric doesn't cut it.
- We struggle to find intuitive descriptions of model behaviors, but we have a many tools at many levels of abstraction to give insight.
- Engage critically when someone claims a (neural) NLP model is interpretable – in what ways is it interpretable? In what ways is it still opaque?
- Bring this analysis and explanation way of thinking with you to your model building efforts even if analysis isn't your main goal.