Probing for Structural Representations in Language Models

Lecture for LING 3850 / 7850

Papers discussed:

- **Hewitt & Manning 2019**
- **Diego-Simón et al. 2024**
- **Orhan et al. 2026**

Zhenghao Herbert Zhou, Apr 6 & 8, 2026

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- Do LMs have abstract, hierarchical representations of sentence structures? Answering this question helps us build intuitions about **information organization in language models' intermediate hidden states**.

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- **Diego-Simón et al. 2024 [polar probe]**:
  - *direction/head* and *type* information of dependency parses could also be recovered geometrically;
- **Orhan et al. 2026 [follow-up on structural probe]**:
  - generalizing this geometric-probe logic beyond syntax to *phonemic (🤫)* and *semantic* information, and showing that those properties emerge over training;

Hewitt & Manning 2019

Structural Probe

One way to represent syntax: Dependency Parsing

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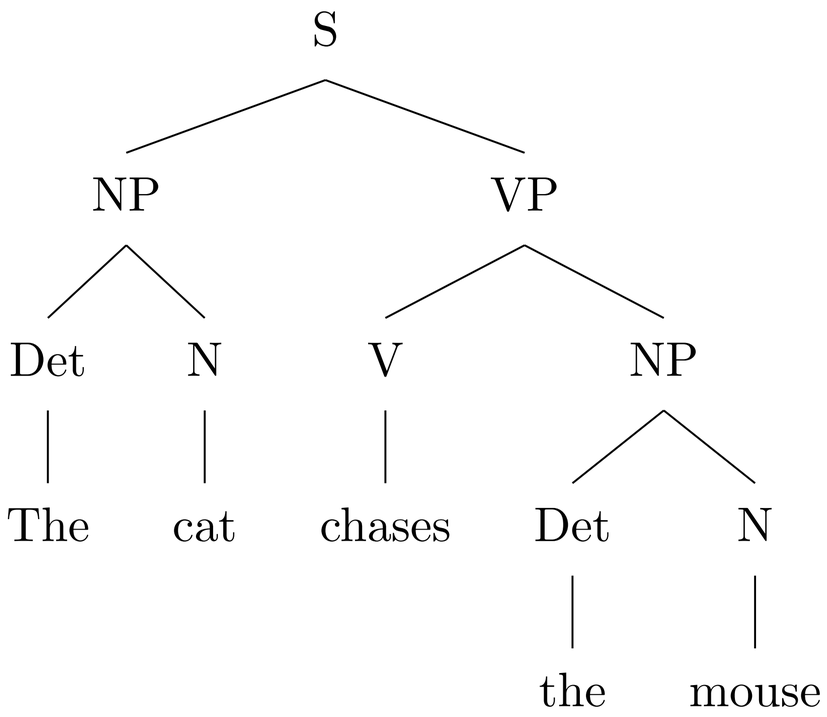

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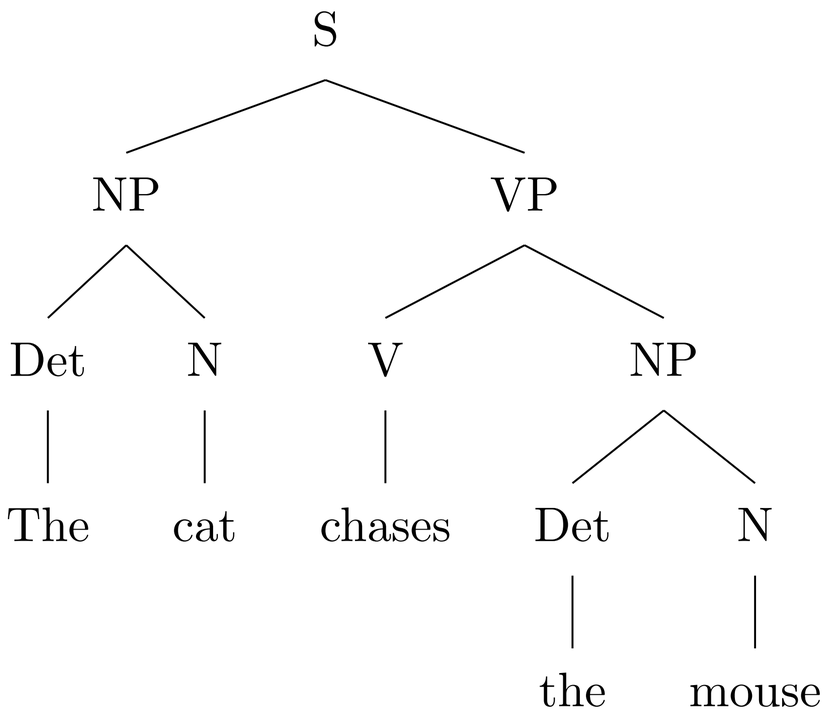

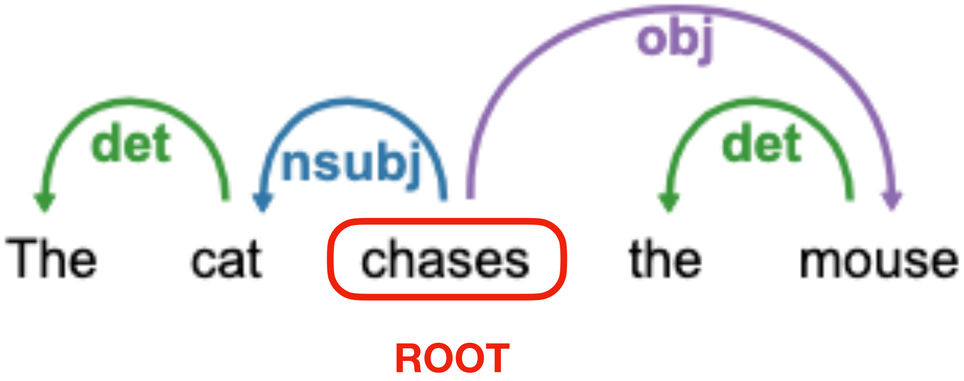

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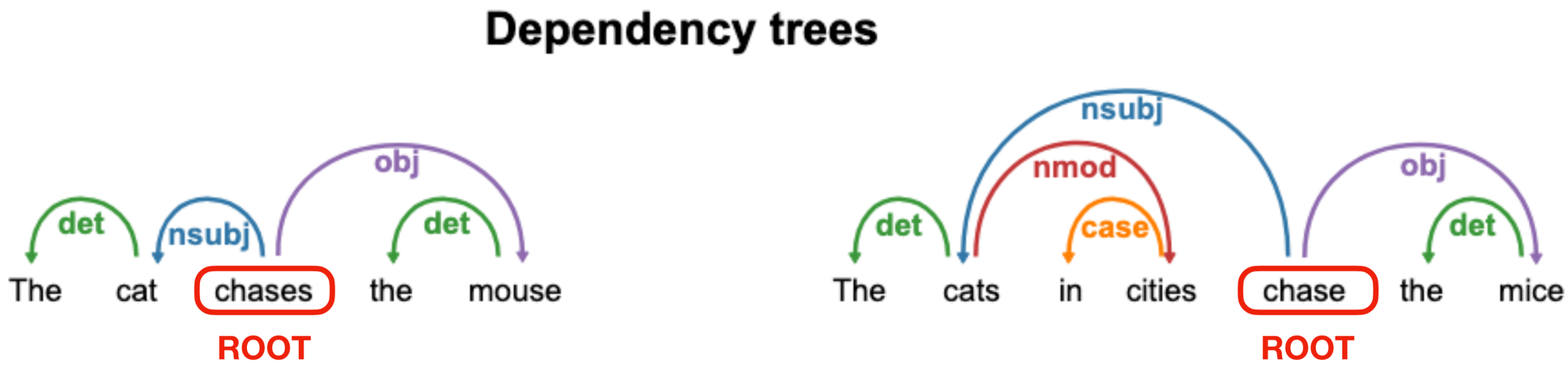

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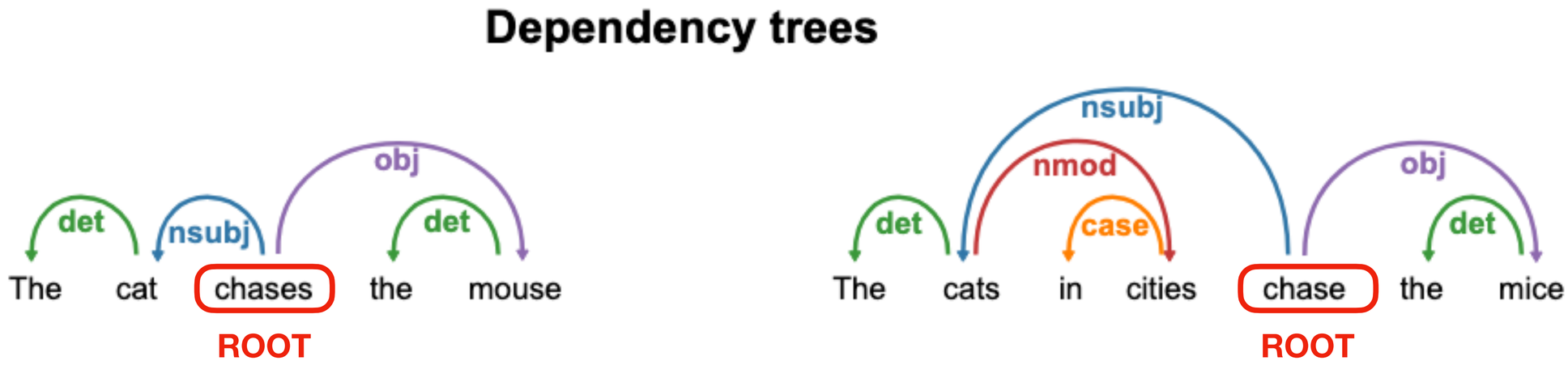

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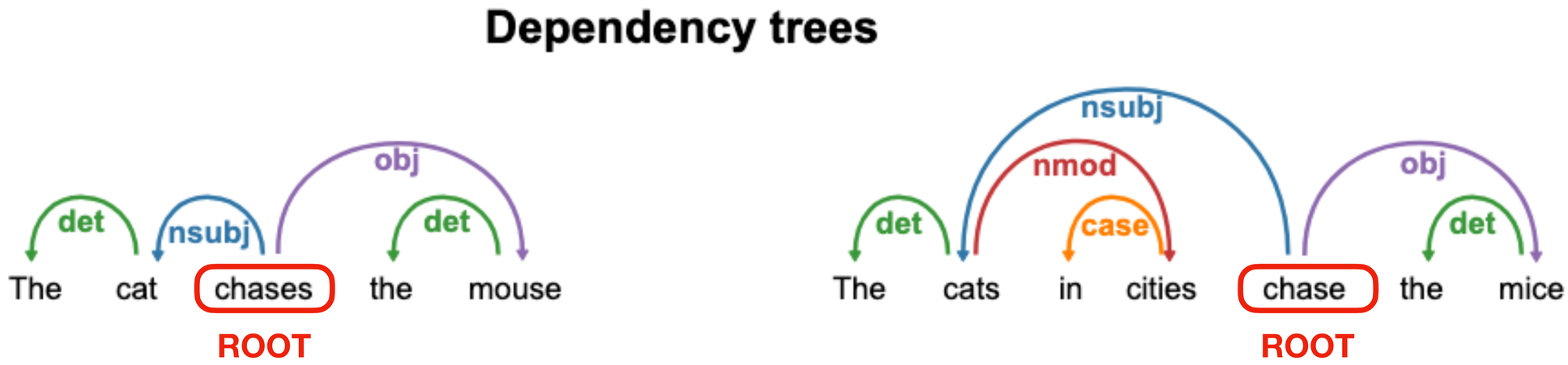
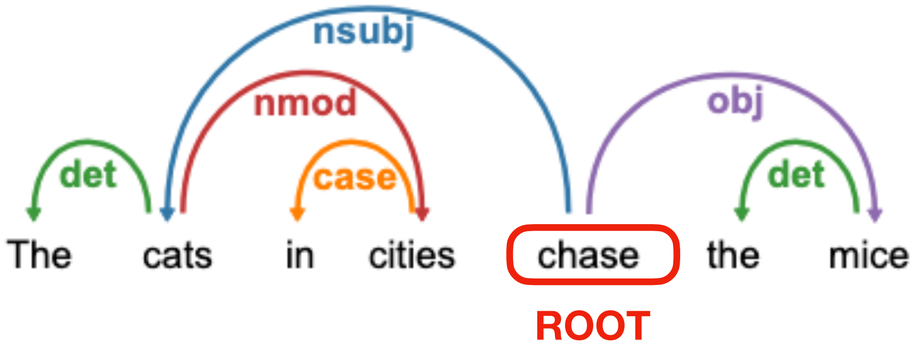
- A grammatical relation is the function that the dependent plays with respect to the head.
  - The head determines the grammatical role of the phrase.
  - An edge points from the head to the dependent.



Notations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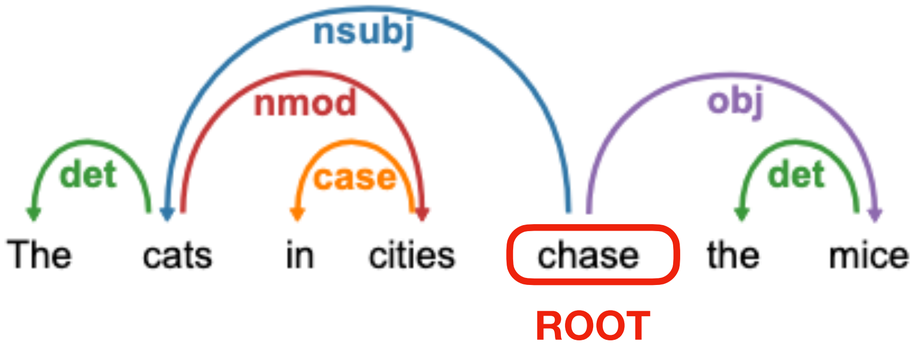

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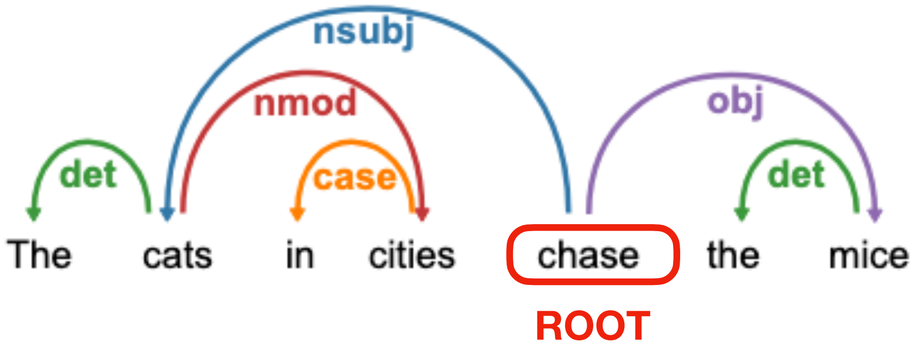

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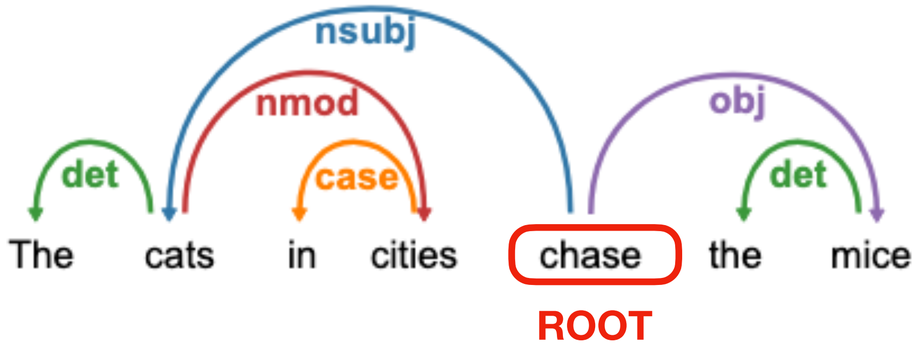

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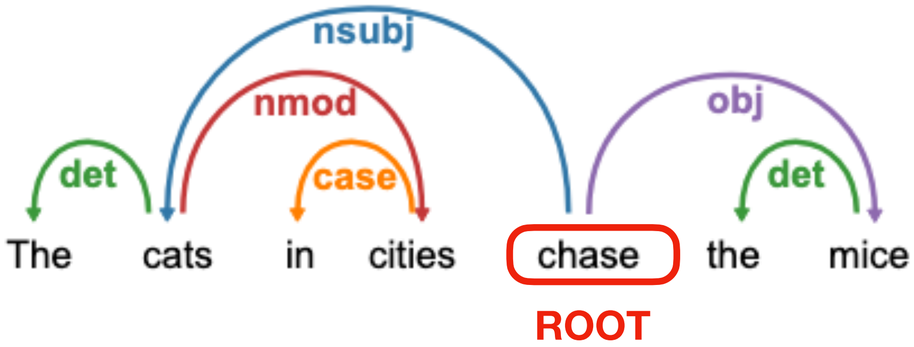

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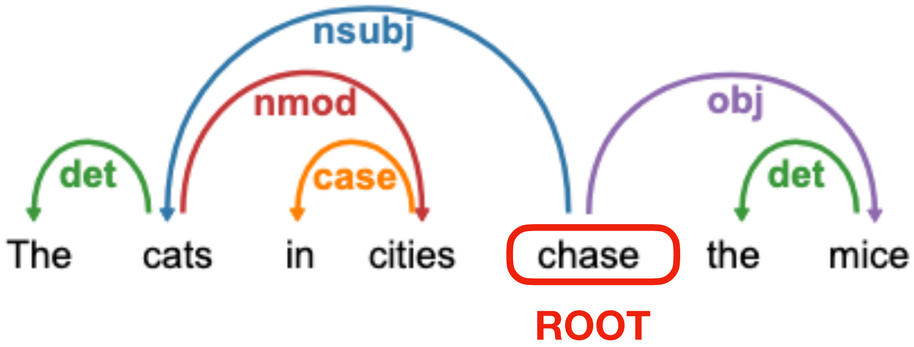

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- Also…. $d : w_i, w_j \rightarrow \mathbb{Z}^+$ is the syntactic distance between any pair of words;

Starting with distance

- For each pair of words, we want to measure the distance between them in the dependency tree without direction / type information.
- In the undirected graph, there is a unique shorest path between any two words — take **the number of edges on that path** to be the distance.

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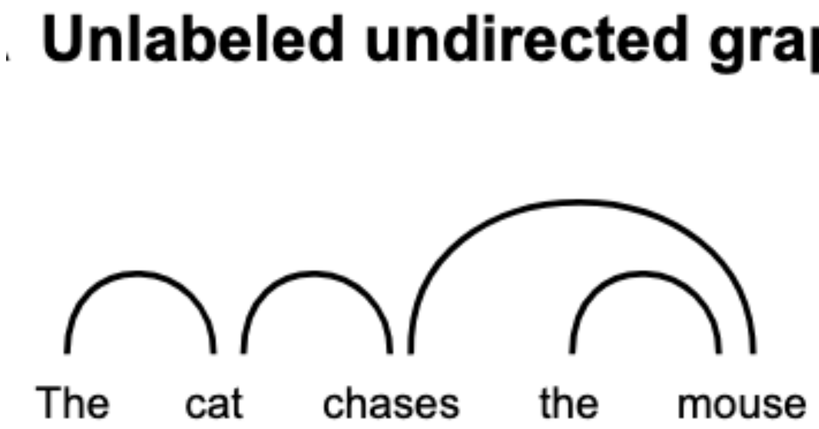

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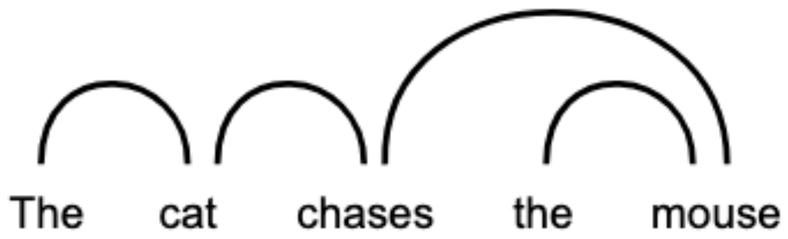

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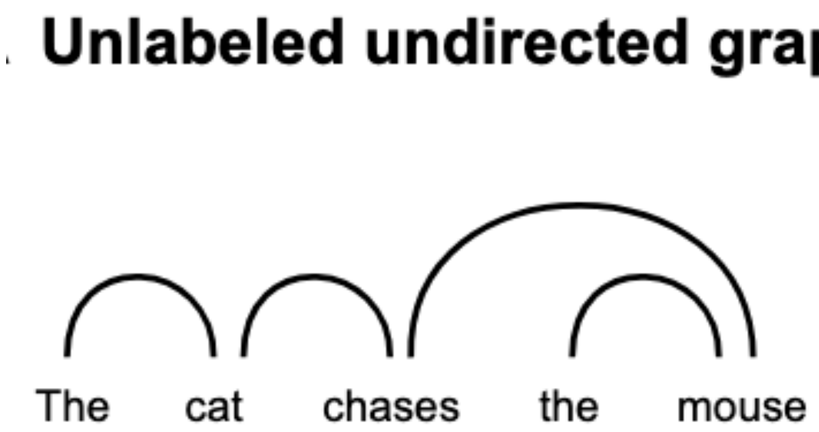

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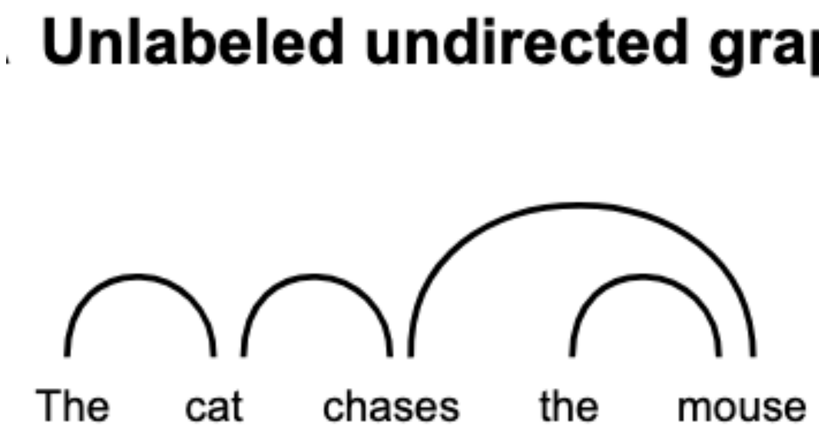

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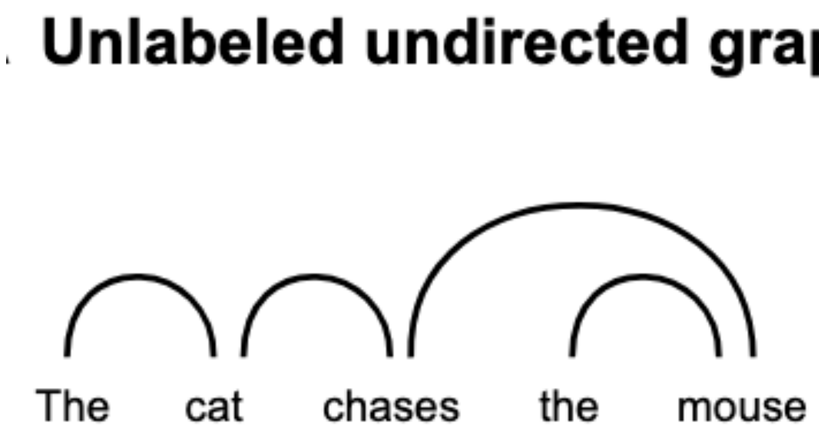

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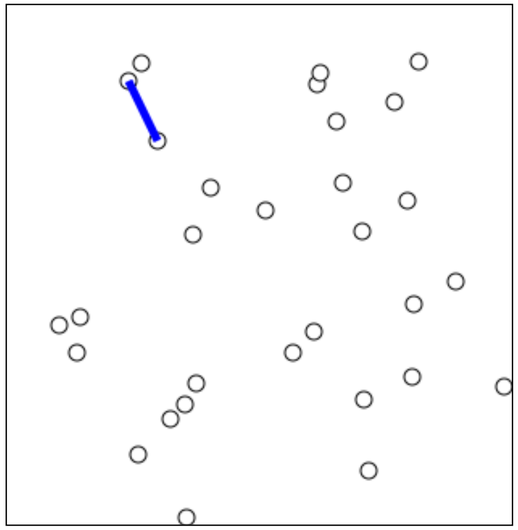
Reconstructing dependency tree given distances

via Prim's minimum spanning tree algorithm



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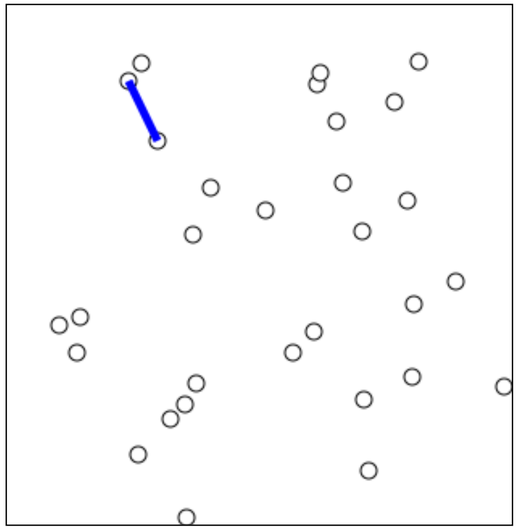

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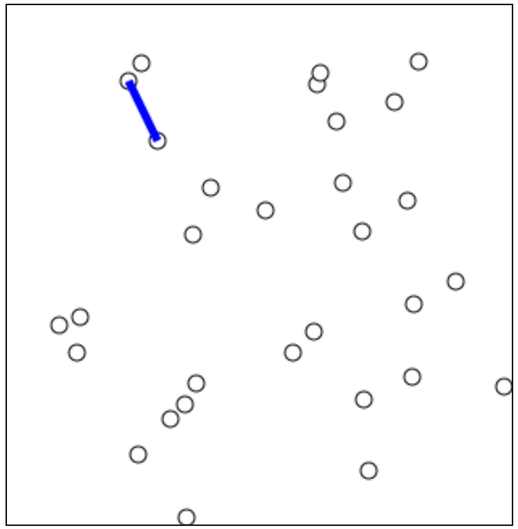

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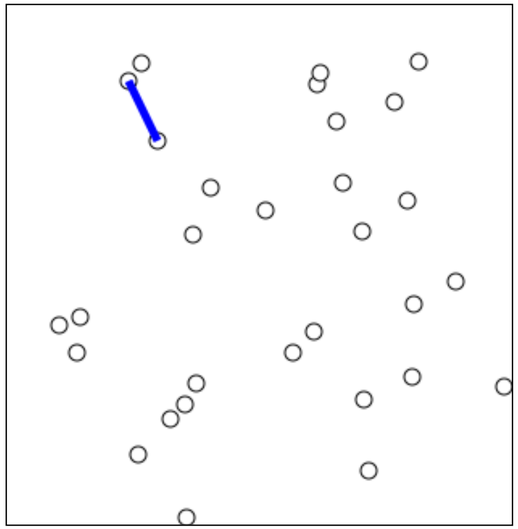

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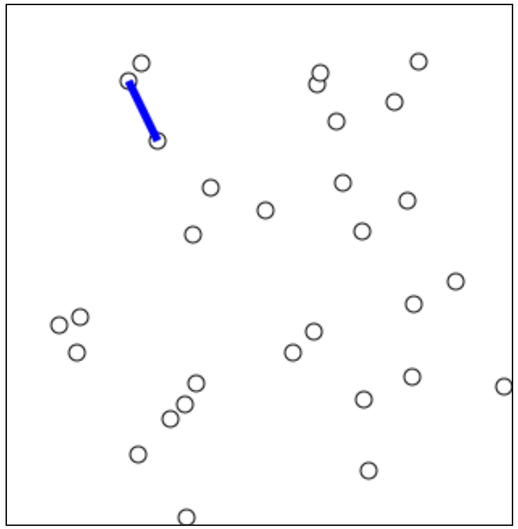

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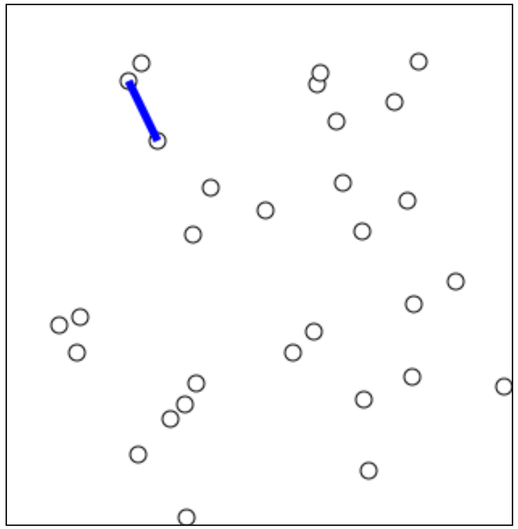

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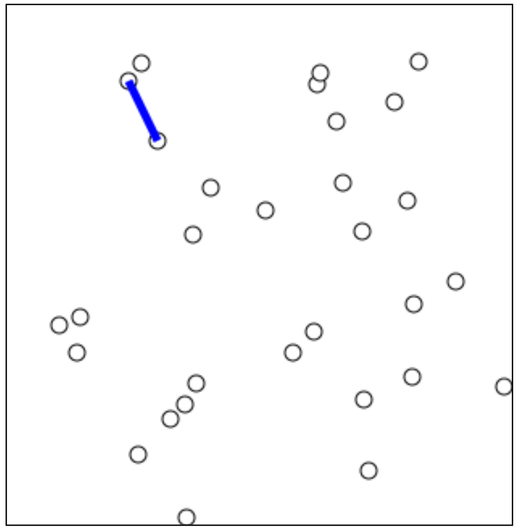

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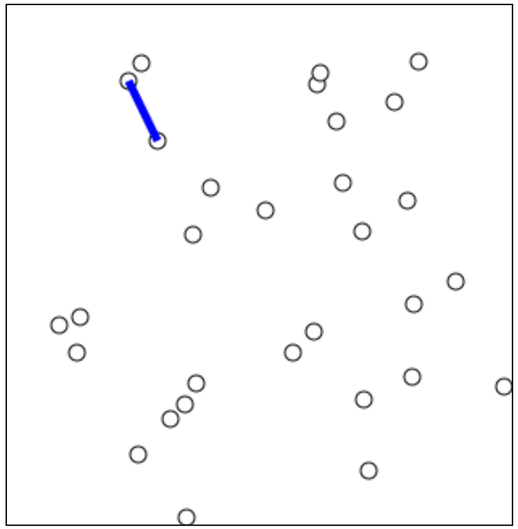

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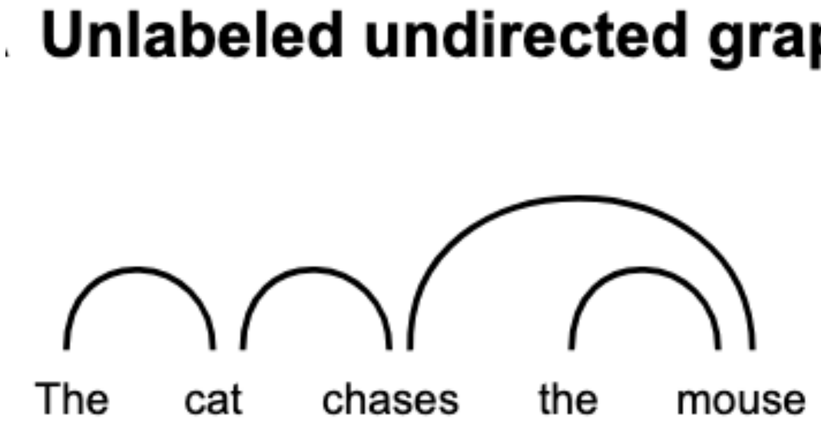

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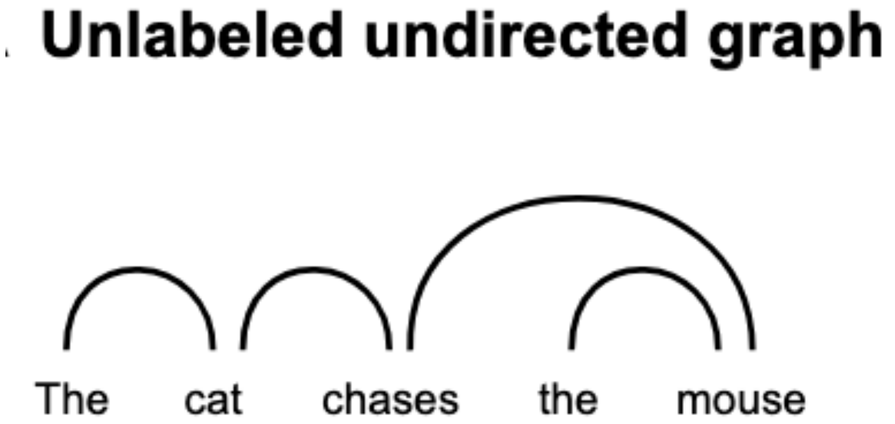

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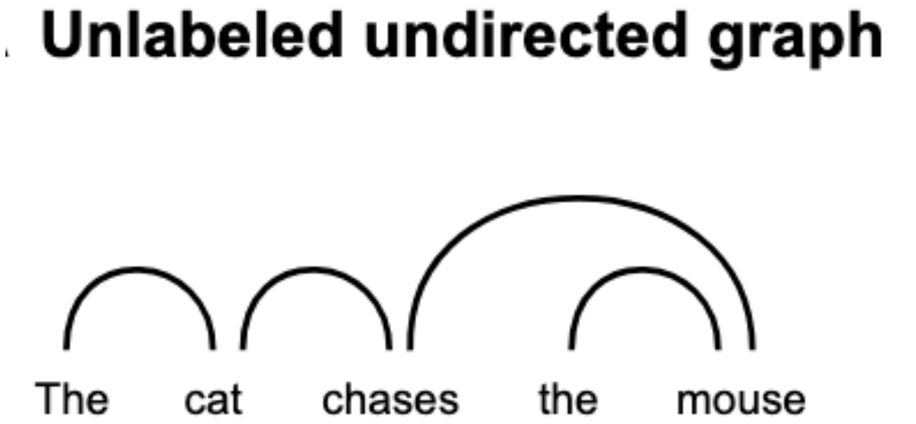

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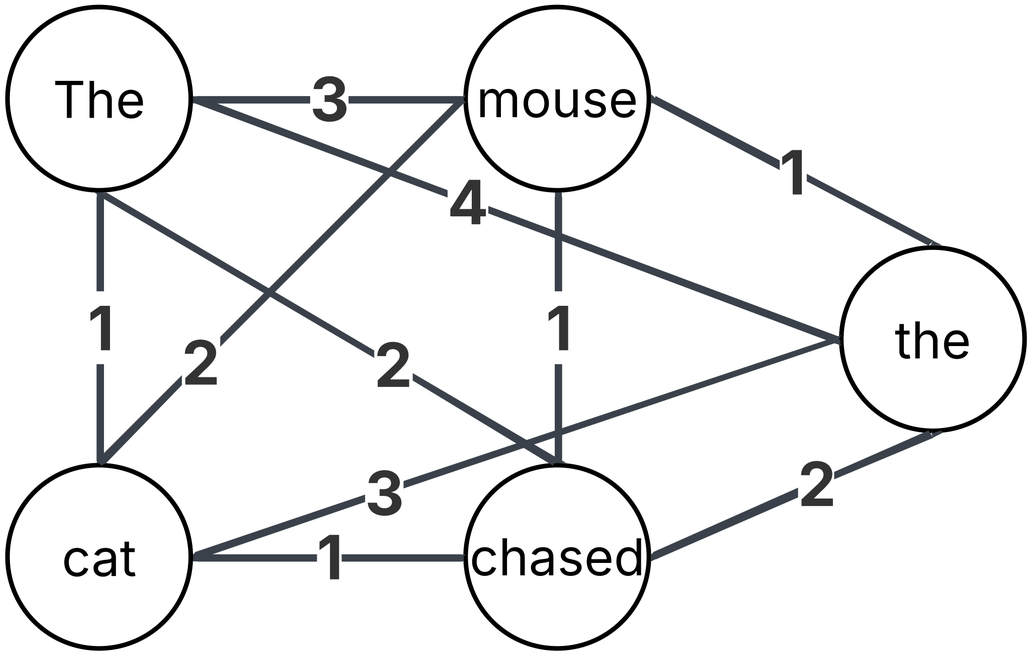

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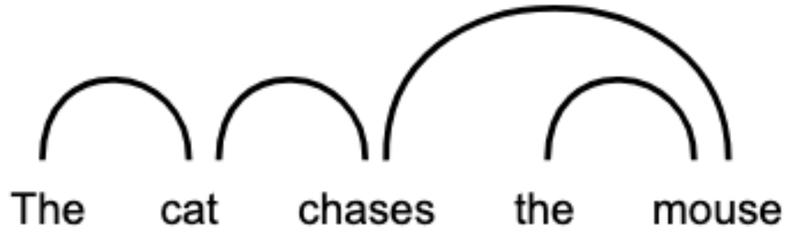

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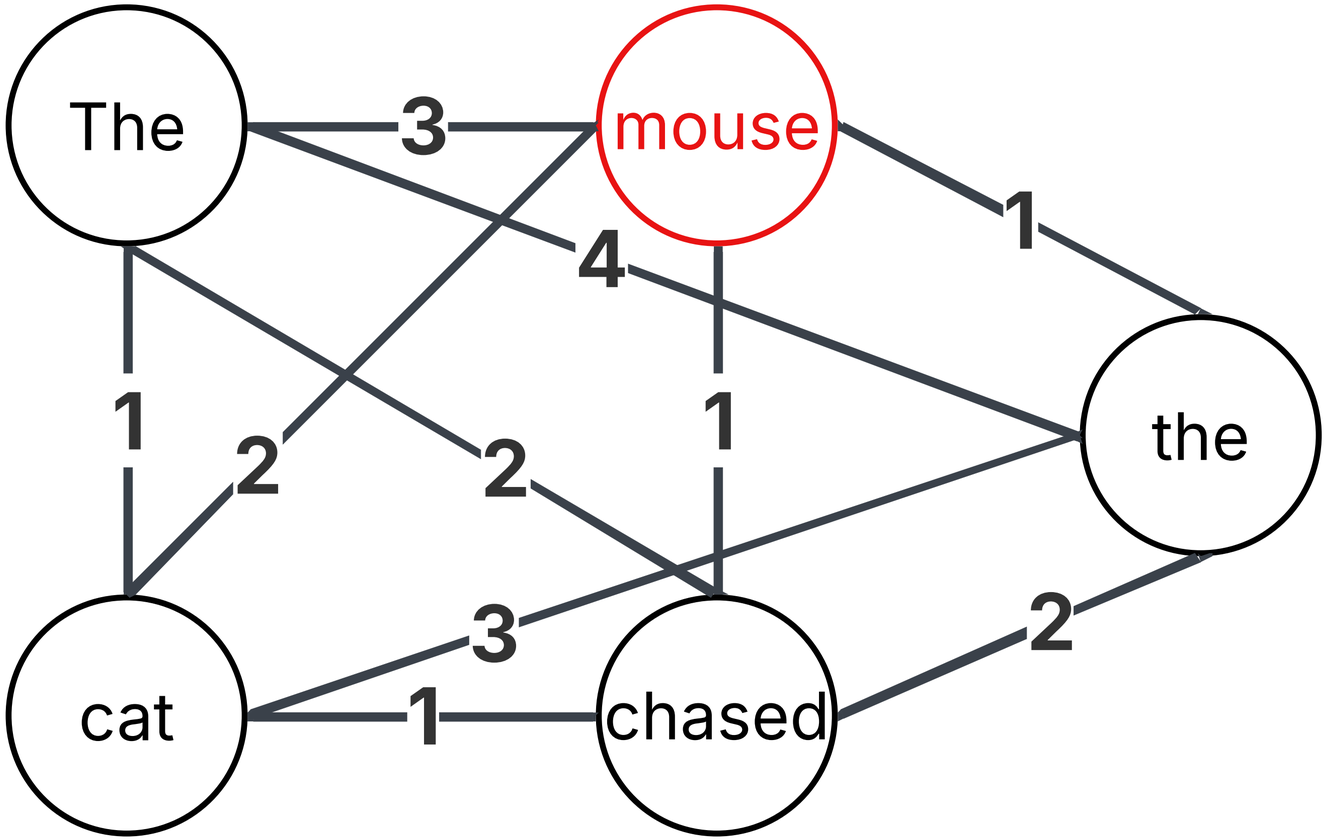

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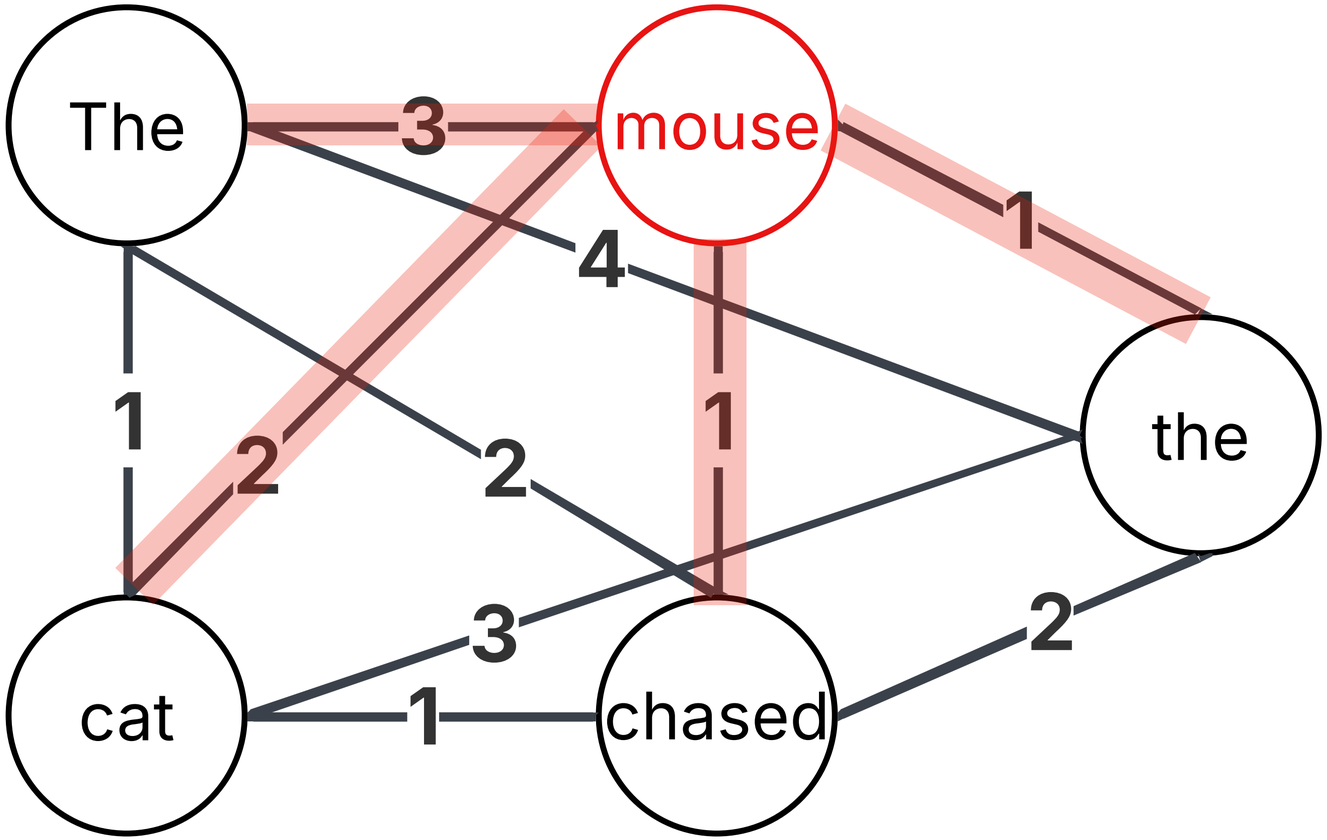

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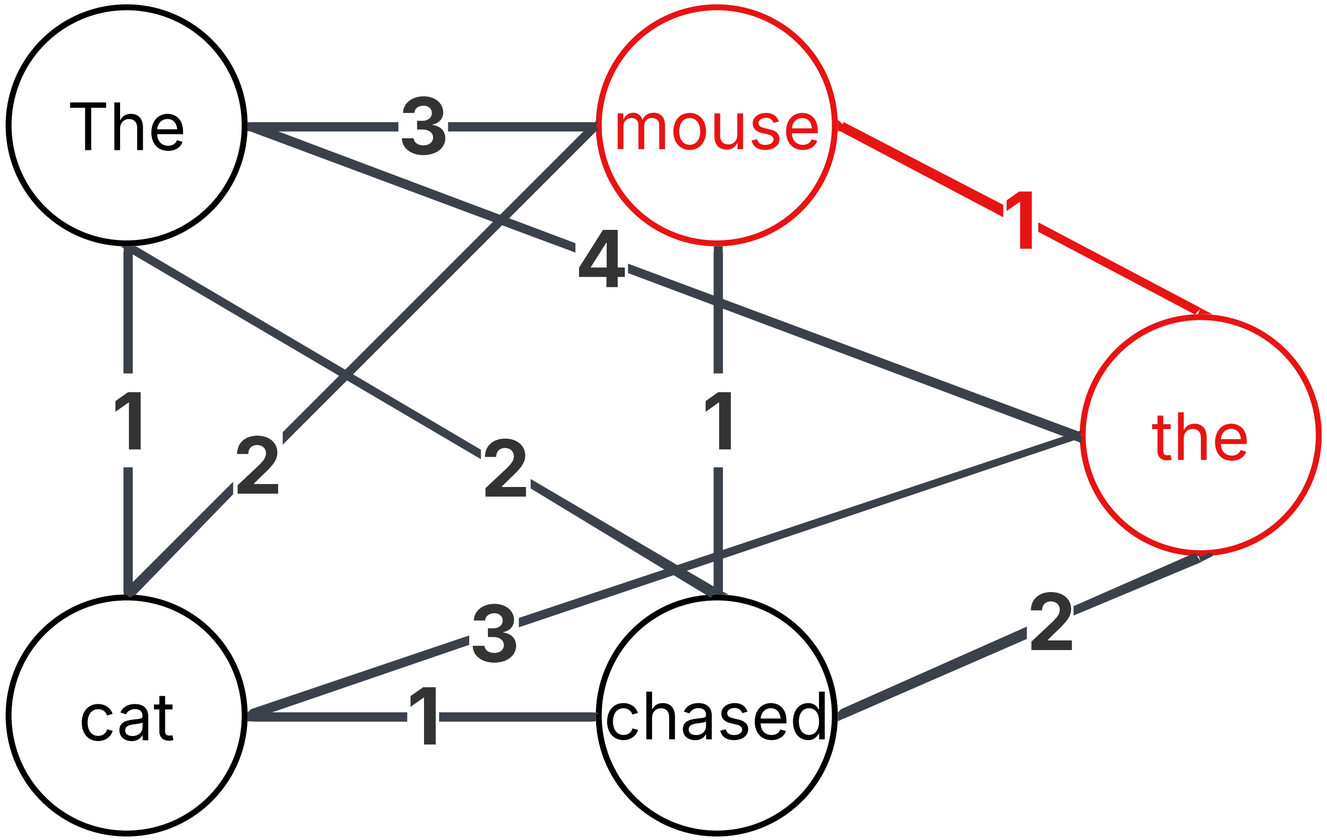

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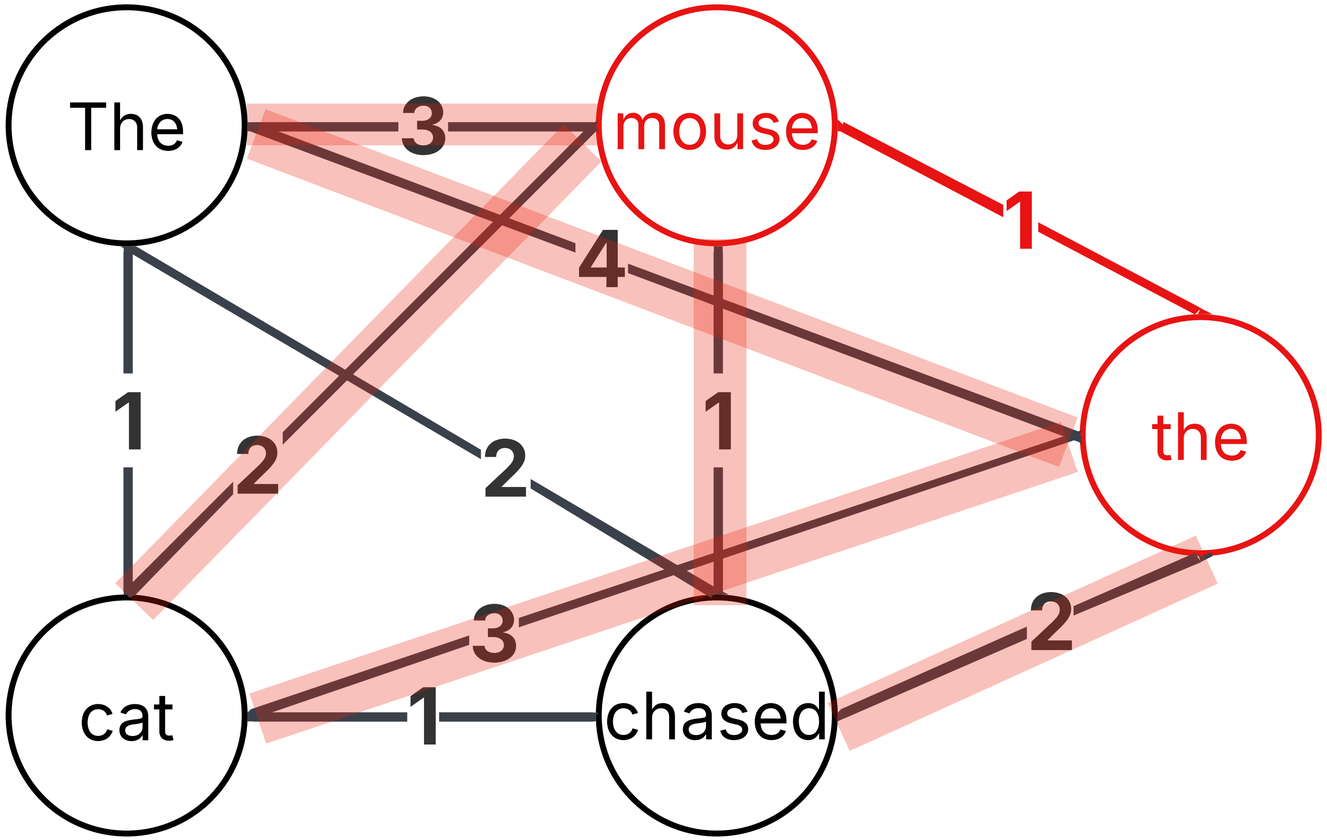

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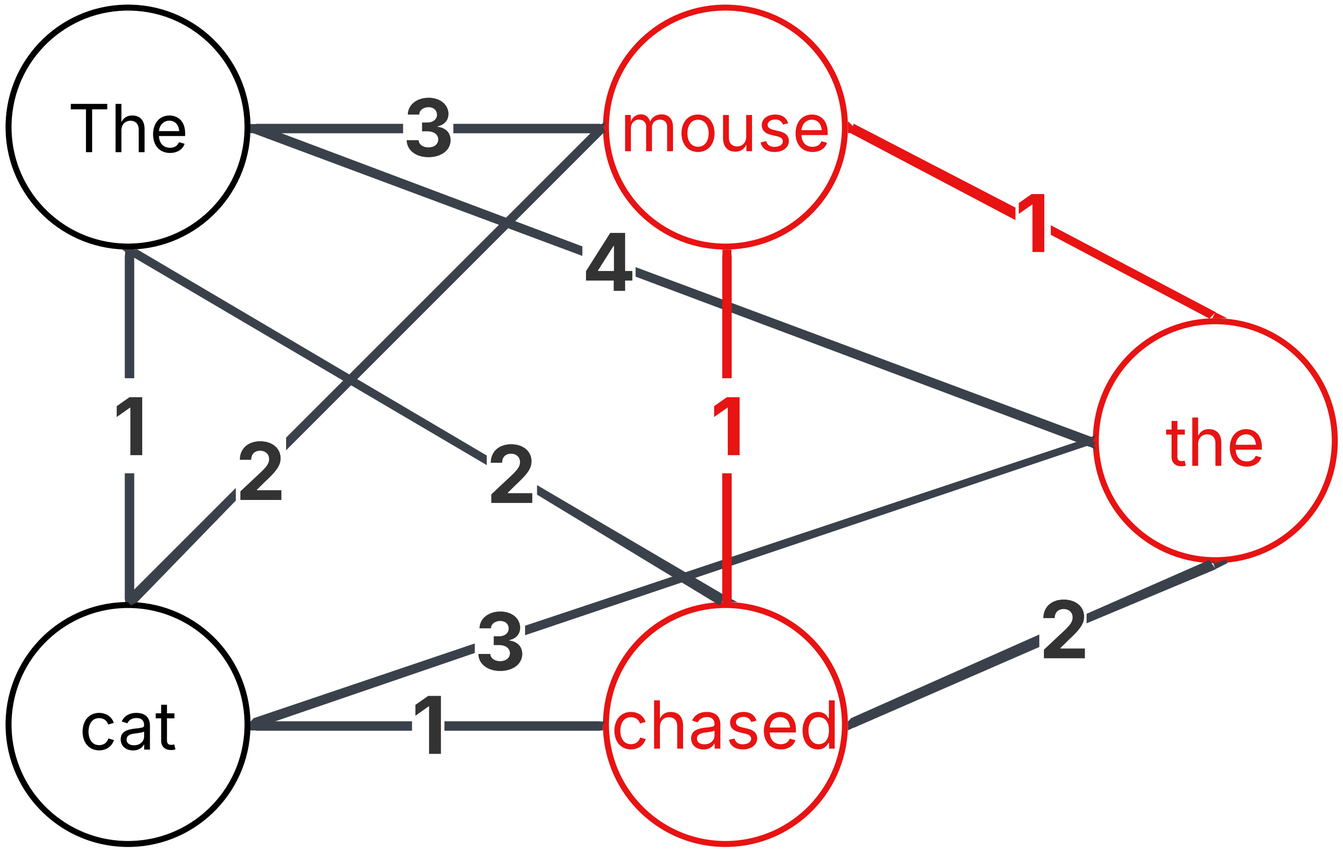

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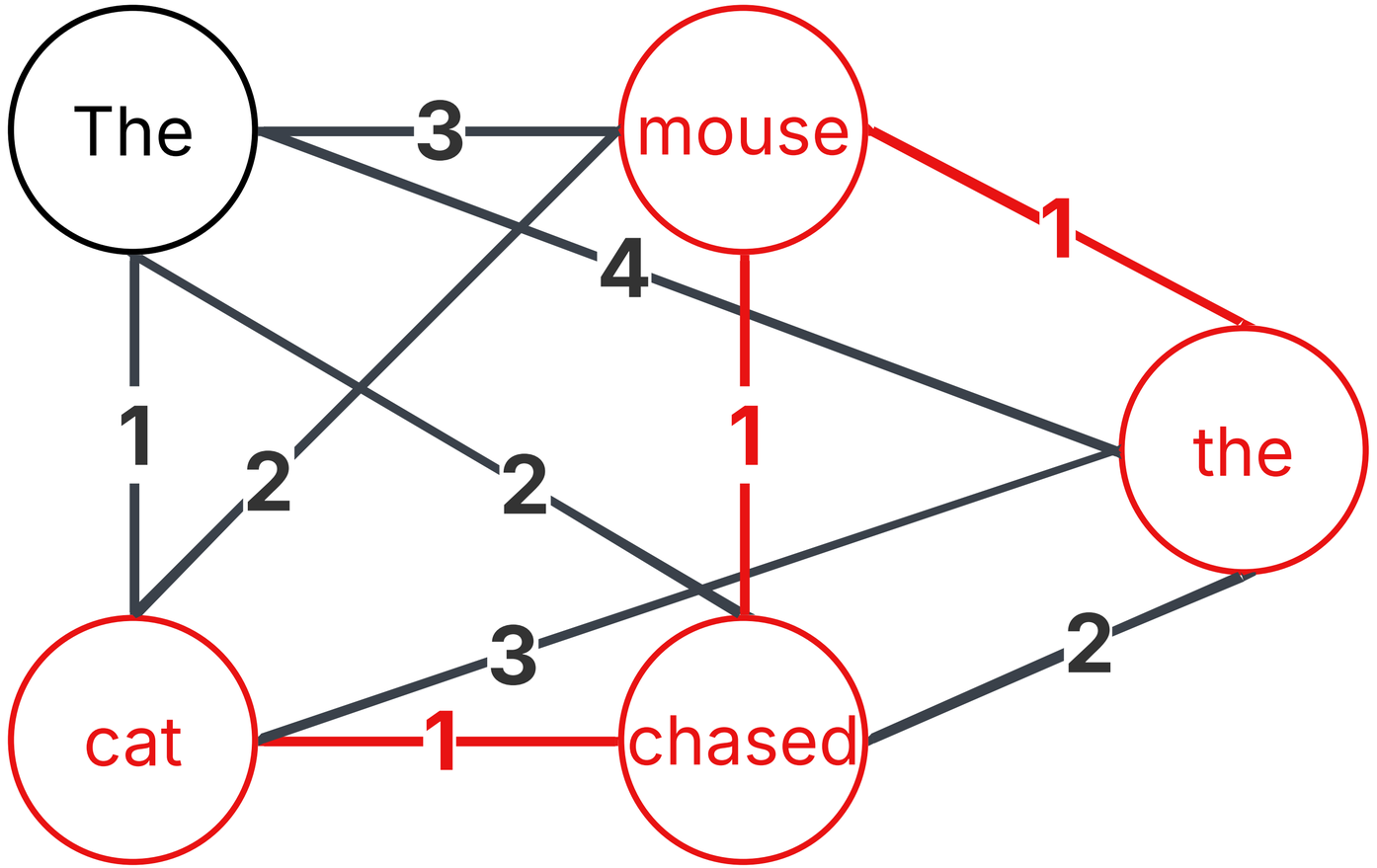

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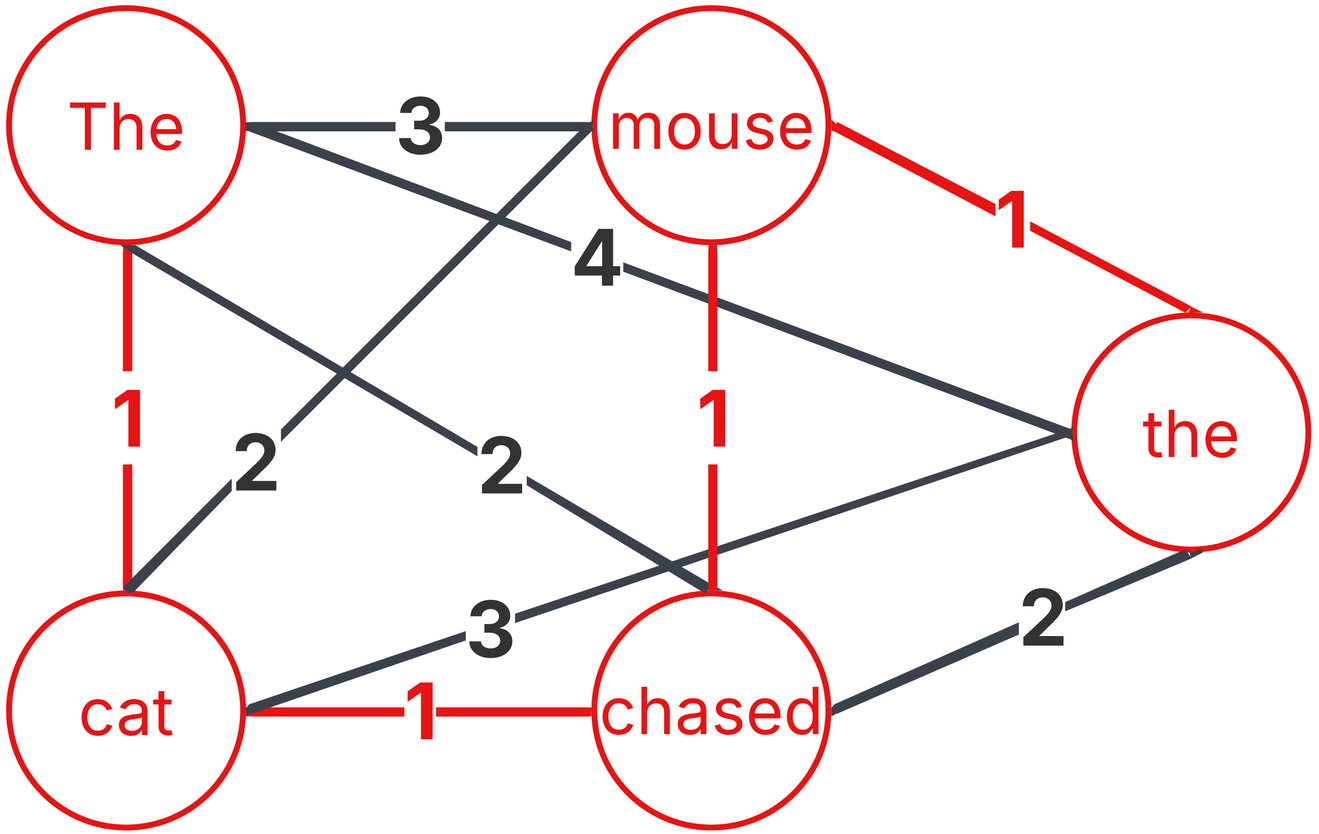

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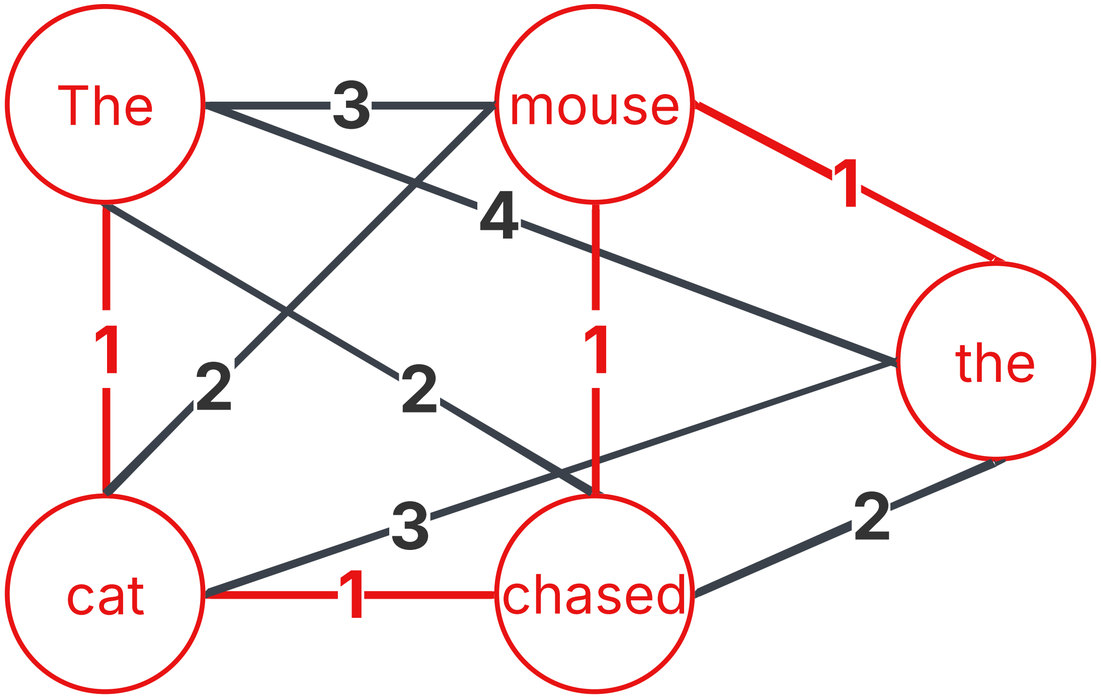

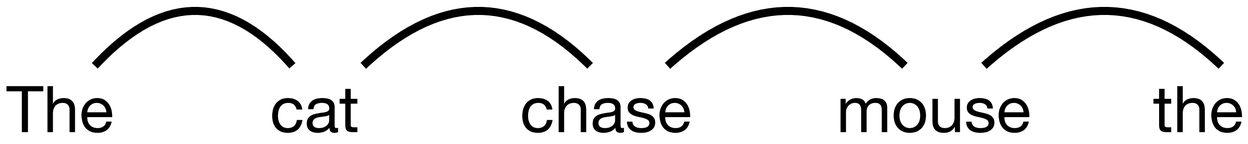

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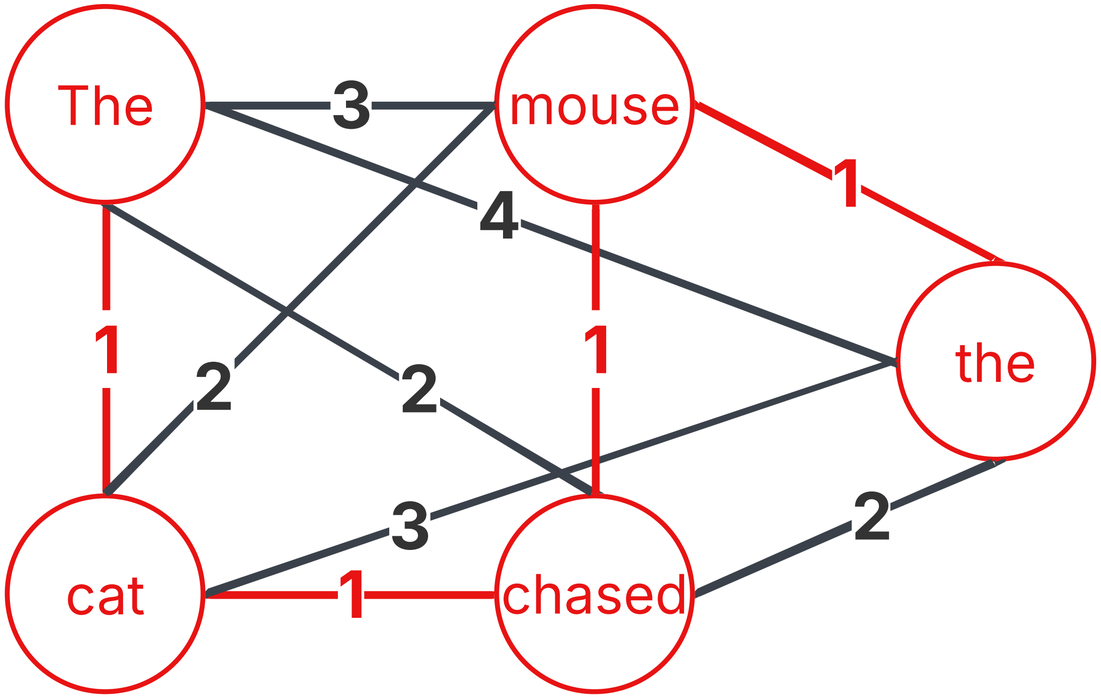

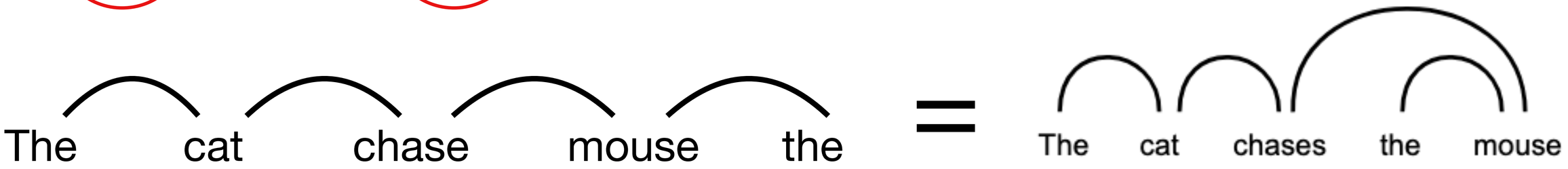

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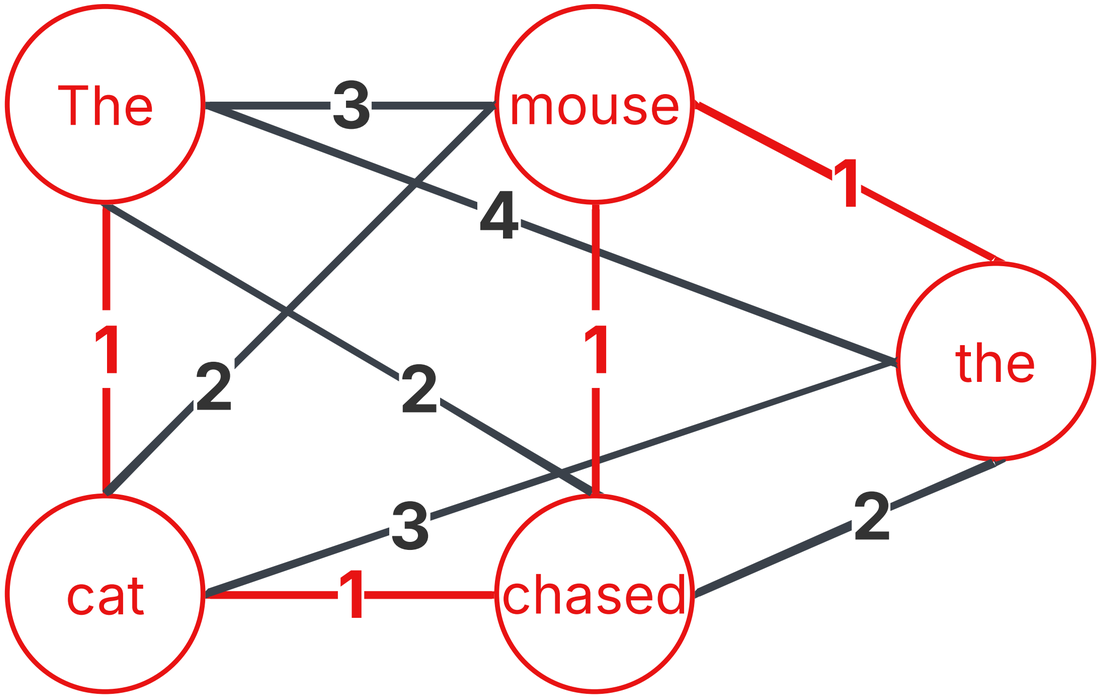

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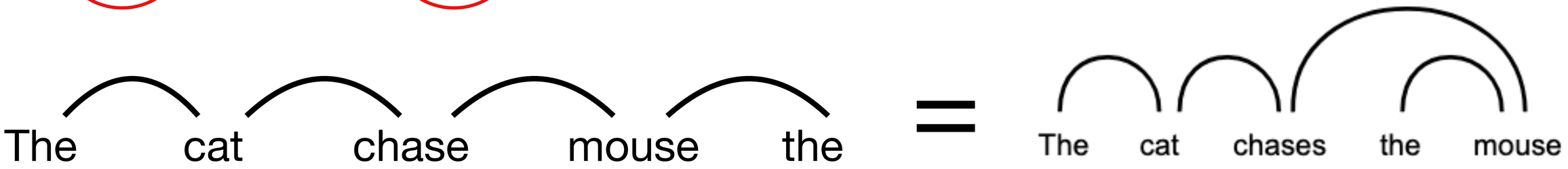

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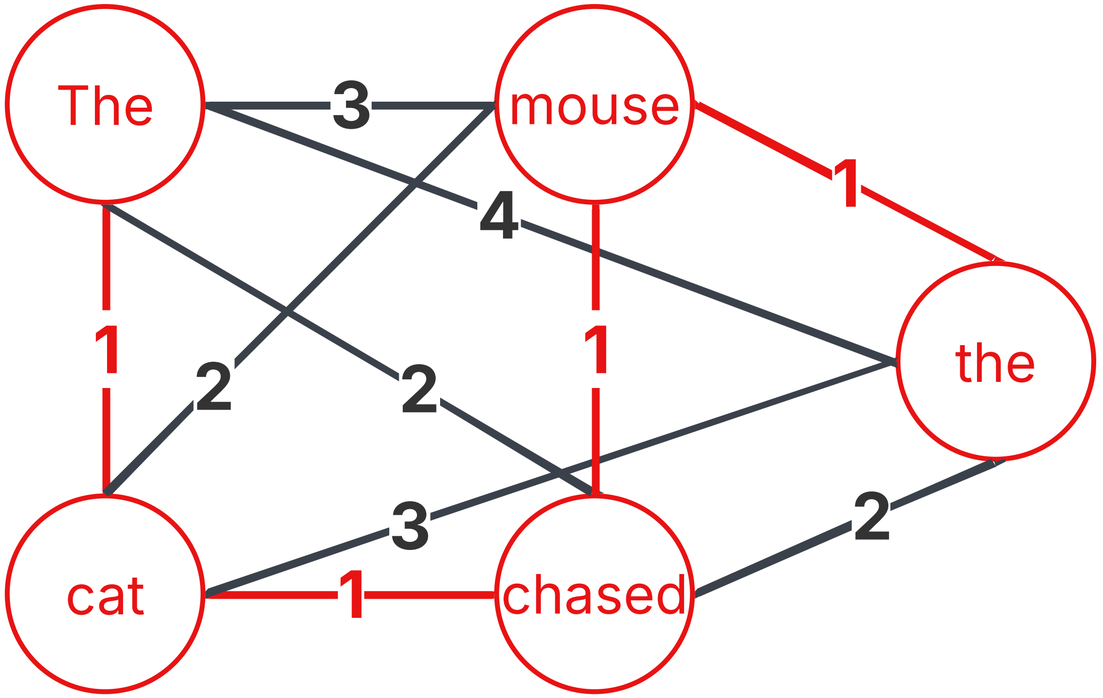

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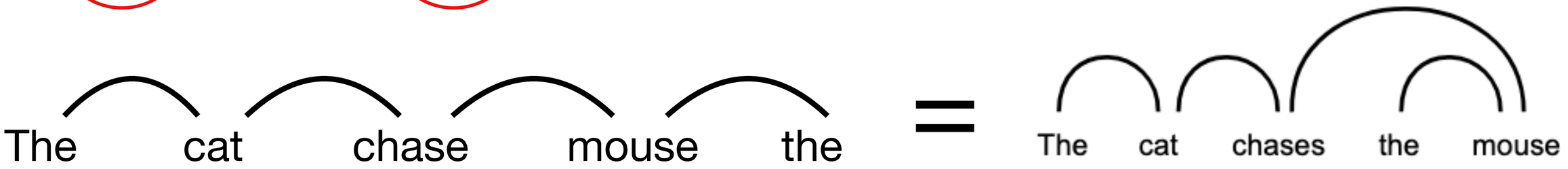

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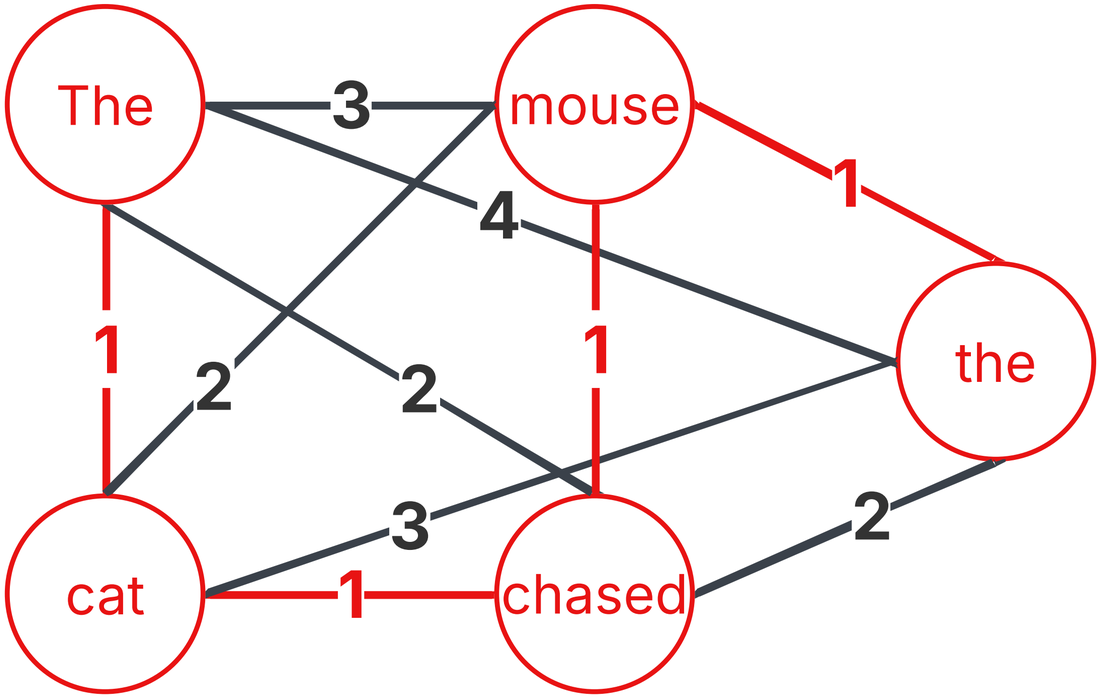
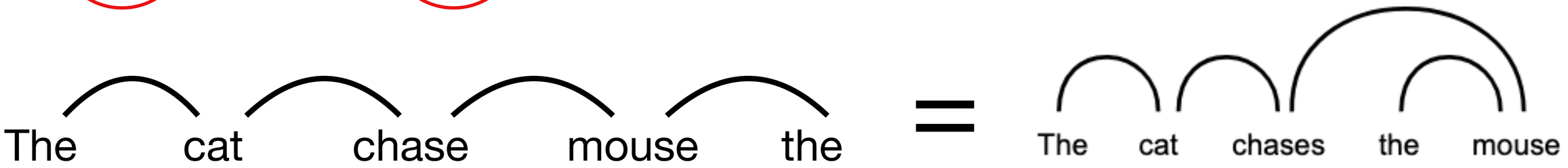


Takeaways:

- *Given distance information of all pairs of words in a sentence, we can reconstruct the dependency tree;*
- *Linear order != Syntactic order: word directly lined in the dependency tree should be small distances.*



Hewitt & Manning’s Solution

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- Solution: $\hat{d}(h_i, h_j) := \|\mathbf{B}(h_i - h_j)\|^2$, where $\mathbf{B} \in \mathbb{R}^{m \times k}$ is a linear projection;
  - i.e., $\mathbf{B}$ projects the activation space into a lower dimension subspace for where syntactic (distance) information is represented.
  - the choice of m decides how small that projected subspace is — spolier: Hewitt & Manning found something interesting here!

Hewitt & Manning’s Solution, cont.

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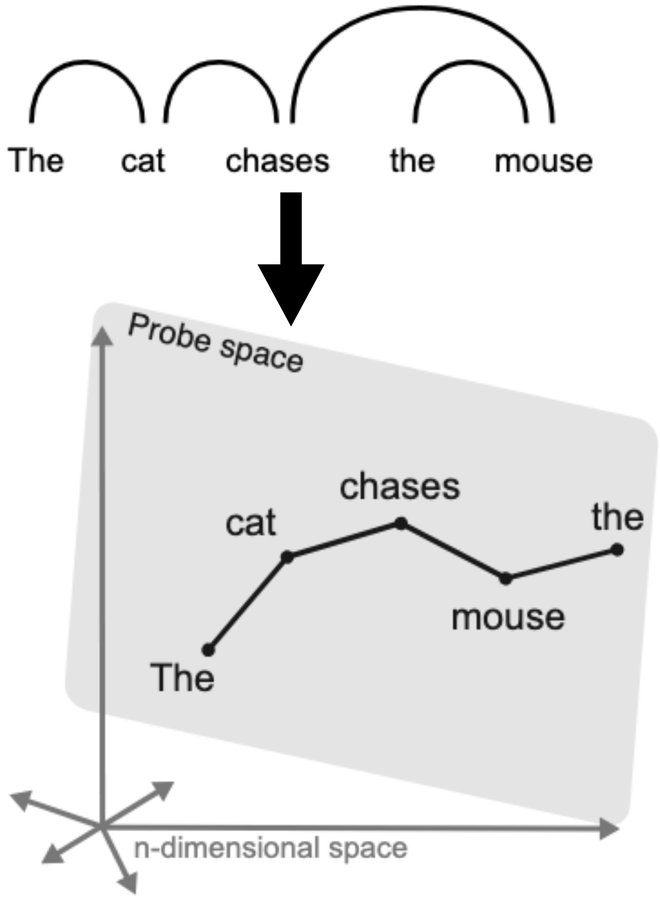
$$\mathscr{L}(\mathbf{B}) = \frac{1}{|\Omega|} \sum_{(w_i, w_j) \in \Omega} |\, d(w_i, w_j) - \hat{d}(h_i, h_j)^2 \,|$$

  - i.e., for all pairs of words, minimize the difference between the true distance $d(w_i, w_j)$ and the square of projected distance $\|\mathbf{B}(h_i - h_j)\|^2$;

  - normalized by the number of word pairs, aka sentence length squared.

Recap

The structural probe goes beyond local probing classifiers



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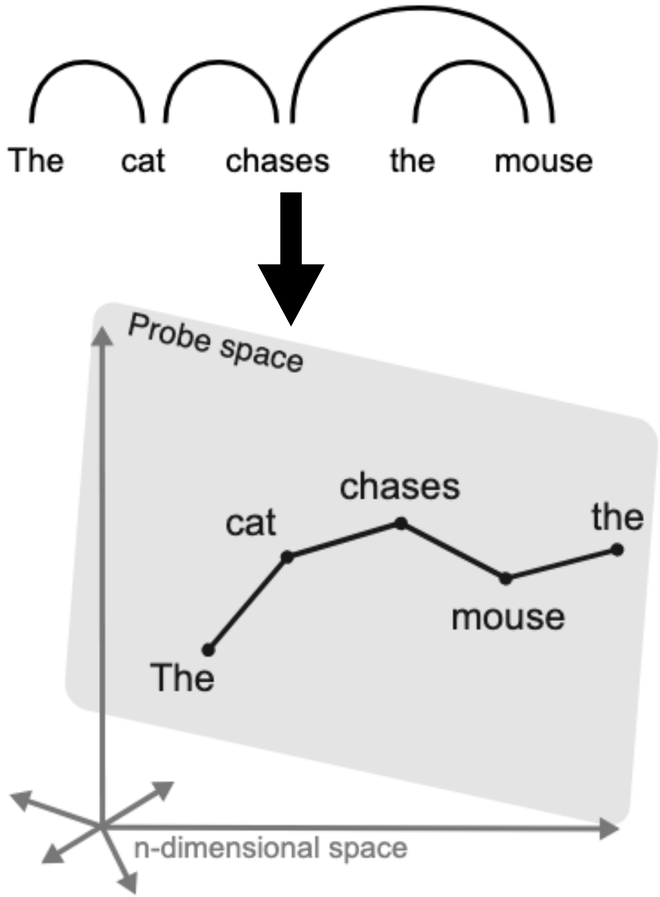

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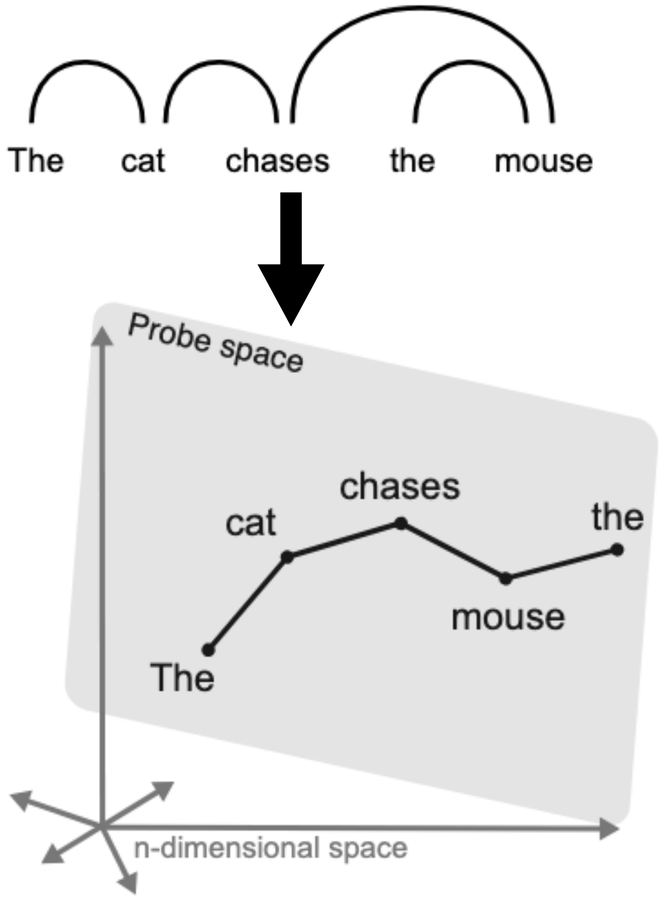

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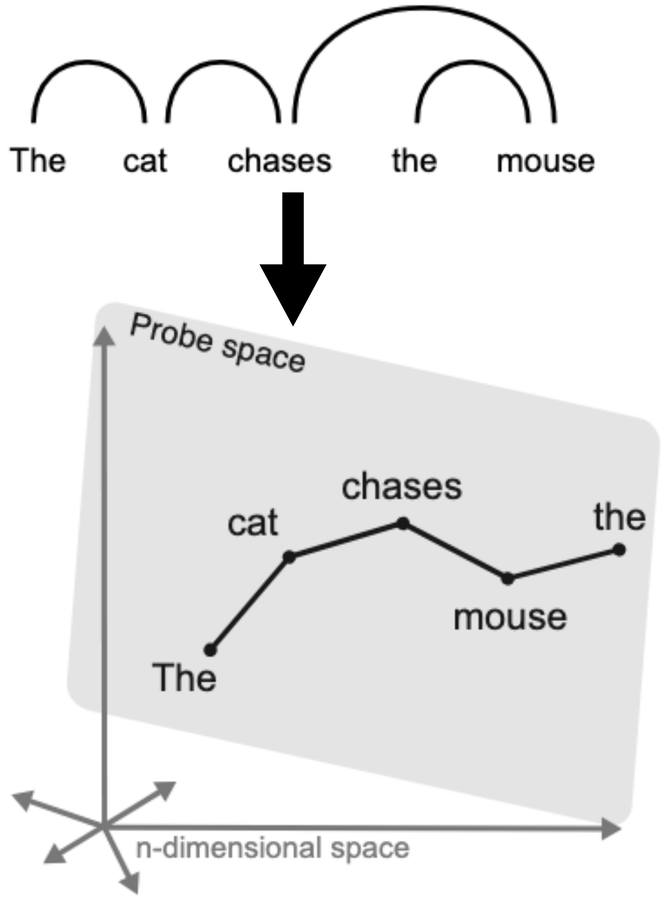

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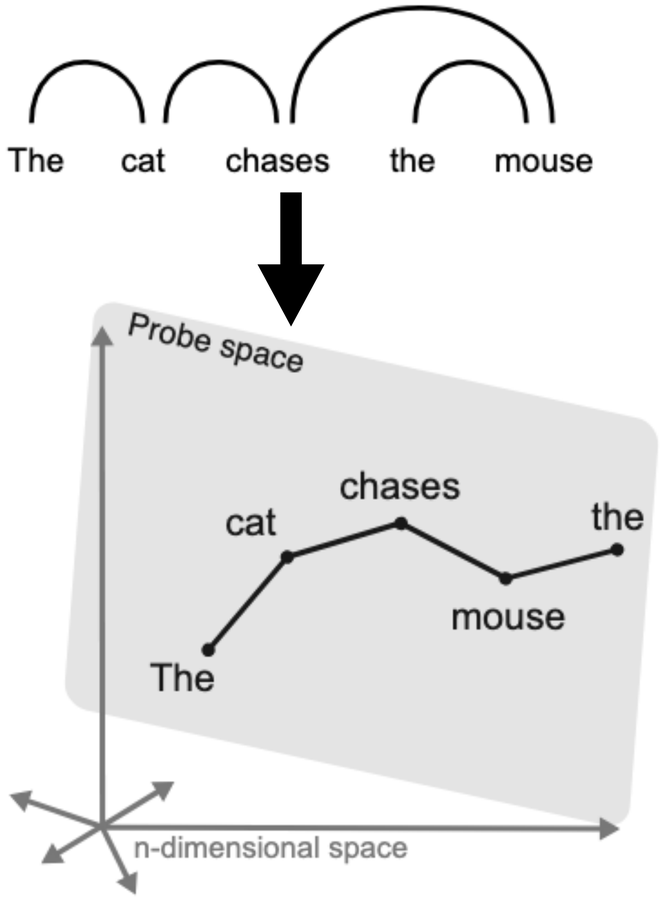
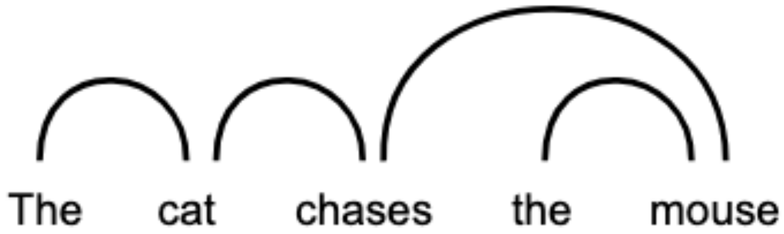
✳ This solves for distance d, but what about **direction** $u : w_i, w_j \rightarrow \{w_i, w_j\}$?

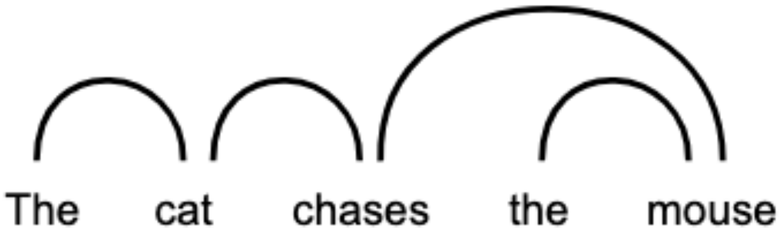


Tree Depth Structural Probe



Tree Depth Structural Probe

- In addition to pairwise distances, they also probe for **the parse depth** $\|w_i\|$ **of a word** w_i, defined as the number of edges from w_i to the ROOT.
- $\|w_i\| := \|h_i\|_{\mathbf{B}}^2 = (\mathbf{B}h_i)^\top(\mathbf{B}h_i)$, train for optimizing $\mathbf{B}$ to recreate $\|w_i\|$



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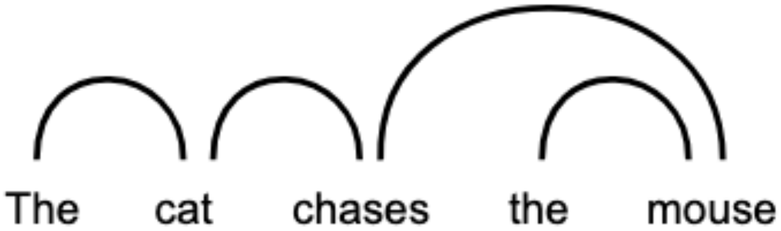

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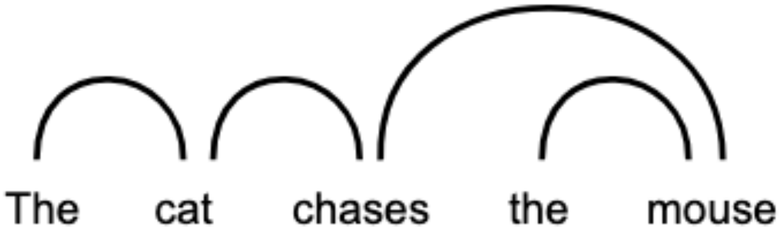

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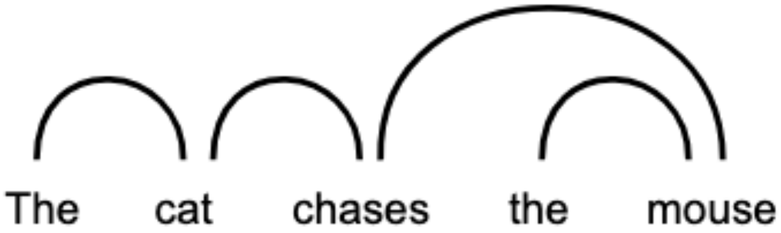
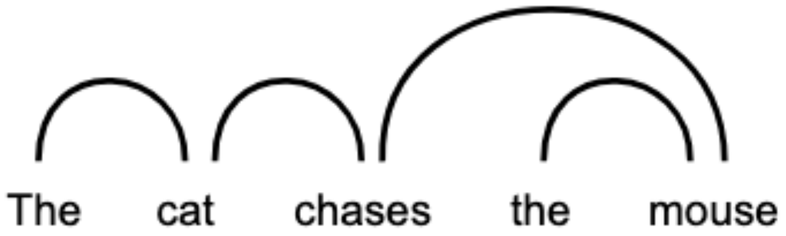


- $\|chases\| = 0$
- $\|cat\| = \|mouse\| = 1$
- $\|The\| = \|the\| = 2$

Depth Probe Identifies Direction

- $\|w_i\| := \|h_i\|_{\mathbf{B}}^2 = (\mathbf{B}h_i)^\top(\mathbf{B}h_i)$
- Use both distance and depth information to determine direction:
  - $d(mouse, the) = 1$
  - $\|\text{mouse}\| < \|\text{the}\|$

➡ Direction: mouse -> the



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  - Linear: positional encoding
  - ELMo0: token-level word embedding without contextual information;
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- Logic: if the probe only performs better on pretrained activations than on baselines, then the activations must contain syntactic geometry.

Results: best layers' performance

Metrics

- **UUAS** (undirected unlabeled attachment score): percentage of undirected edges placed correctly, compared against gold trees.
- **DSpr/NSpr**: Spearman correlation between true and predicted pairwise distances / depth orderings;
- **Root%**: percetage of root correctly identified (i.e., the least deep word);

	Distance		Depth	
Method	UUAS	DSpr.	Root%	NSpr.
LINEAR	48.9	0.58	2.9	0.27
ELMO0	26.8	0.44	54.3	0.56
DECAY0	51.7	0.61	54.3	0.56
PROJ0	59.8	0.73	64.4	0.75
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**

BERT-base has 12 layers;
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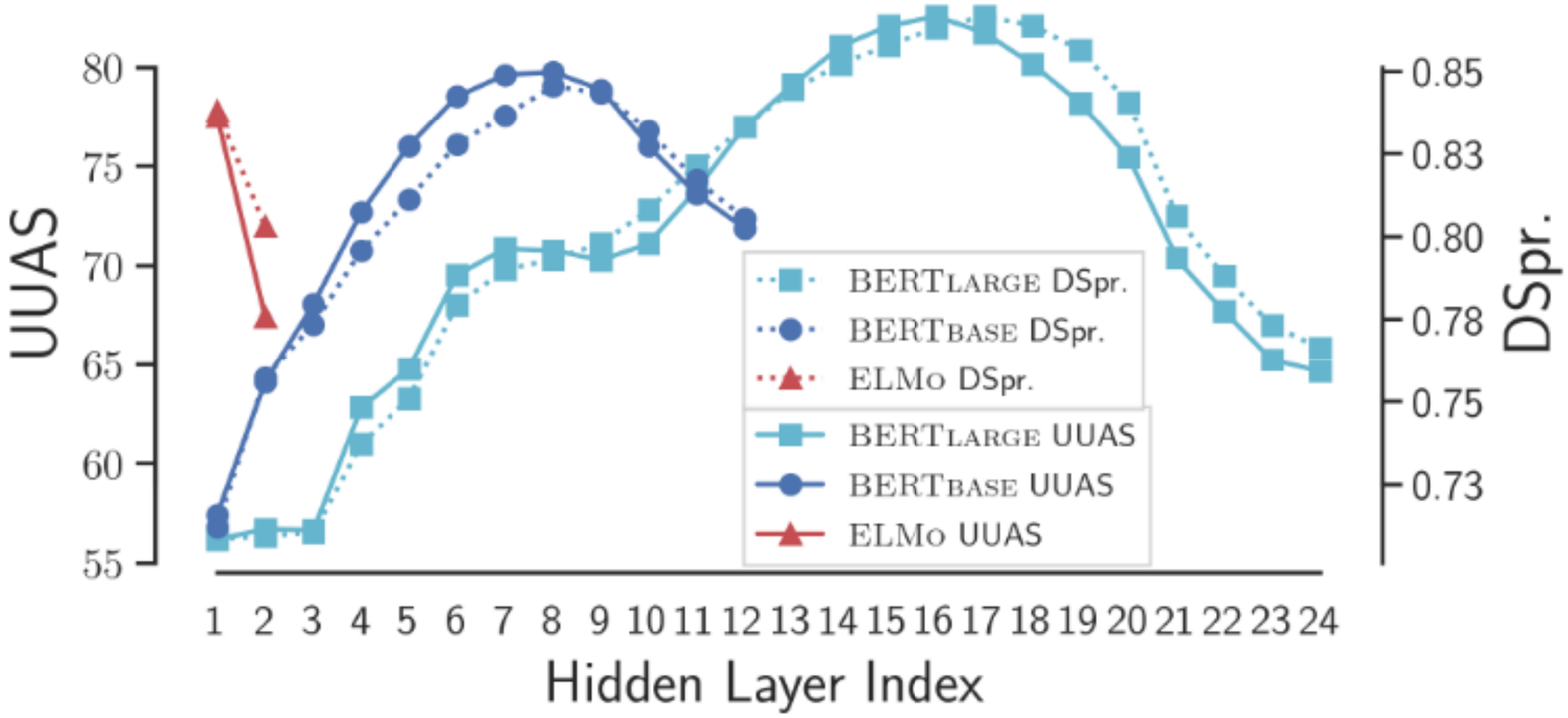
Takeaway: non-contextual or weakly contextual baselines do not suffice; pretrained contextual models do encode a lot of dependency structure;

Results: performance across layers



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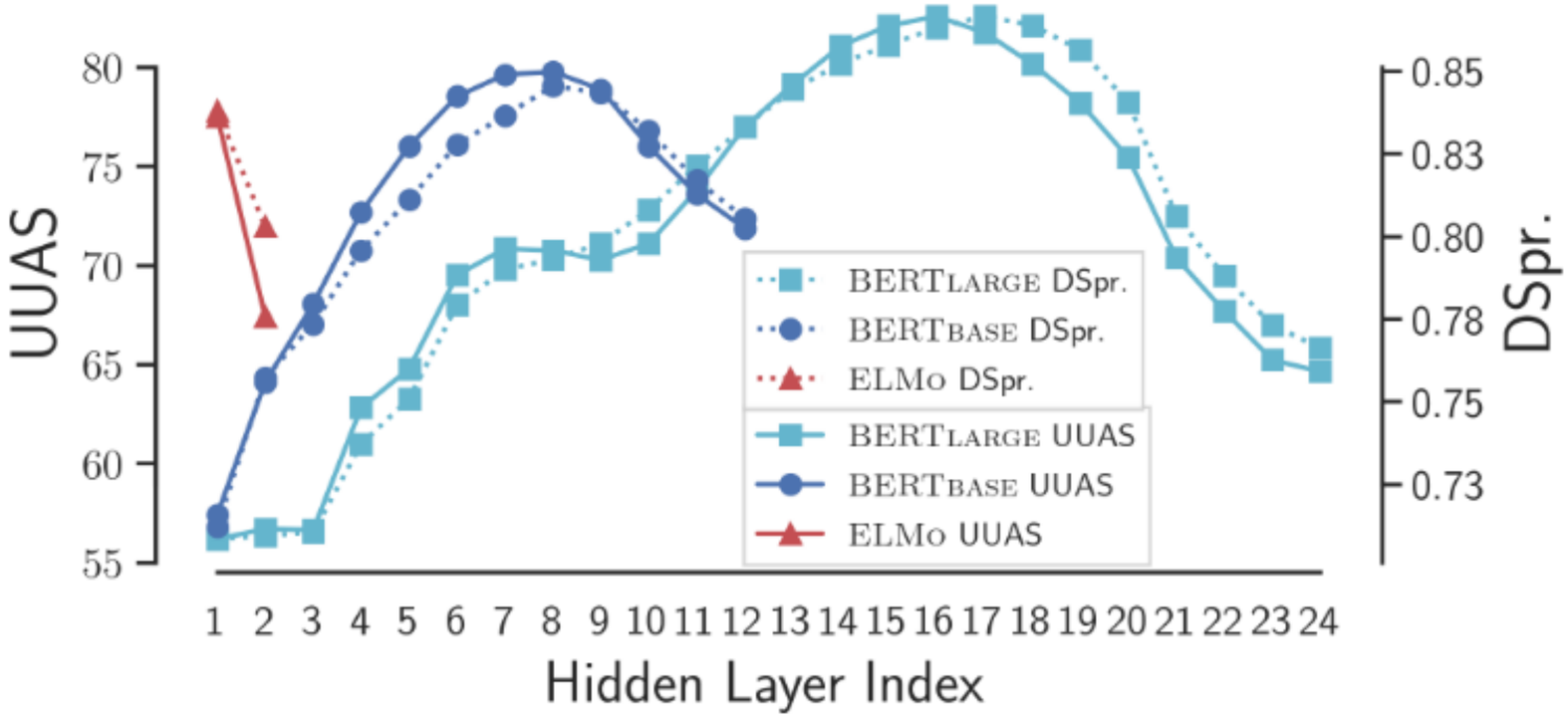
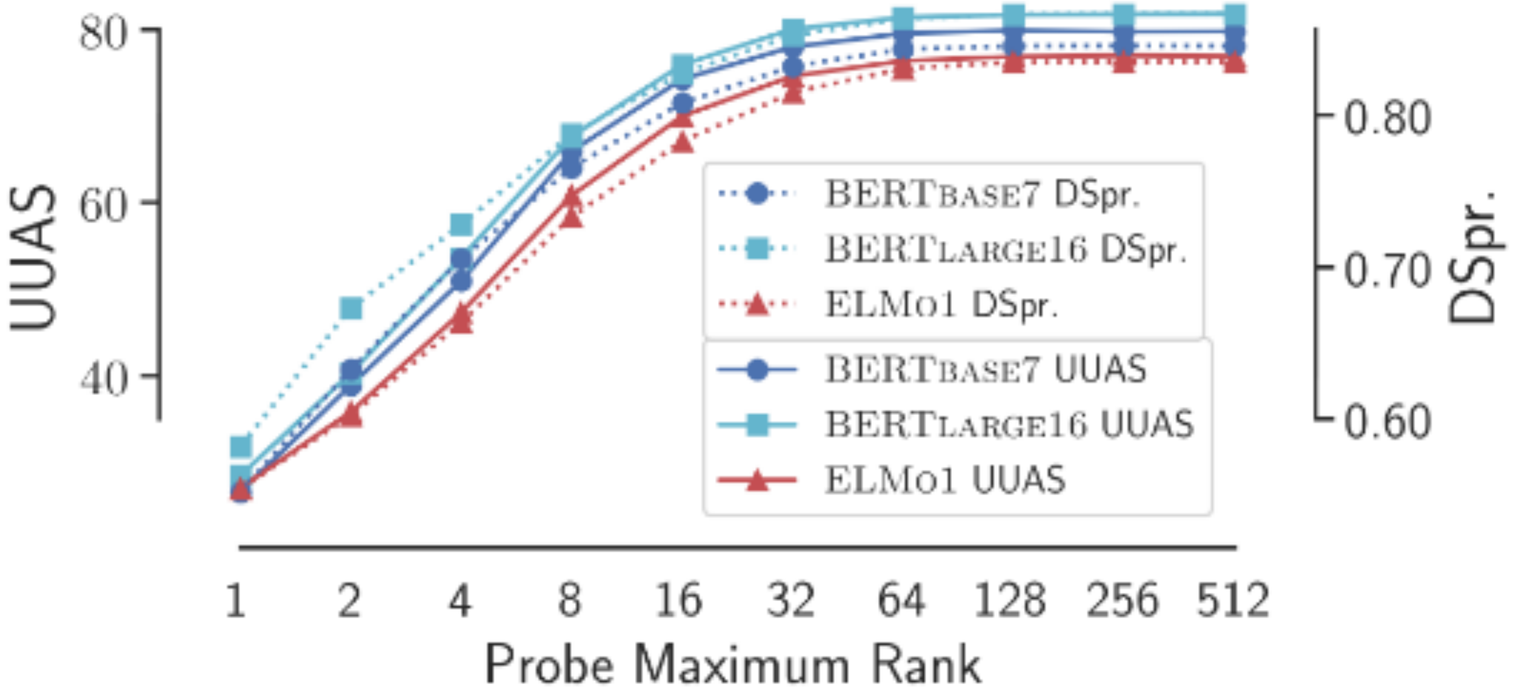


Takeaway: syntax is not uniform across layers — middle-to-upper layers outperform the others

On the dimensionality of the syntax subspace



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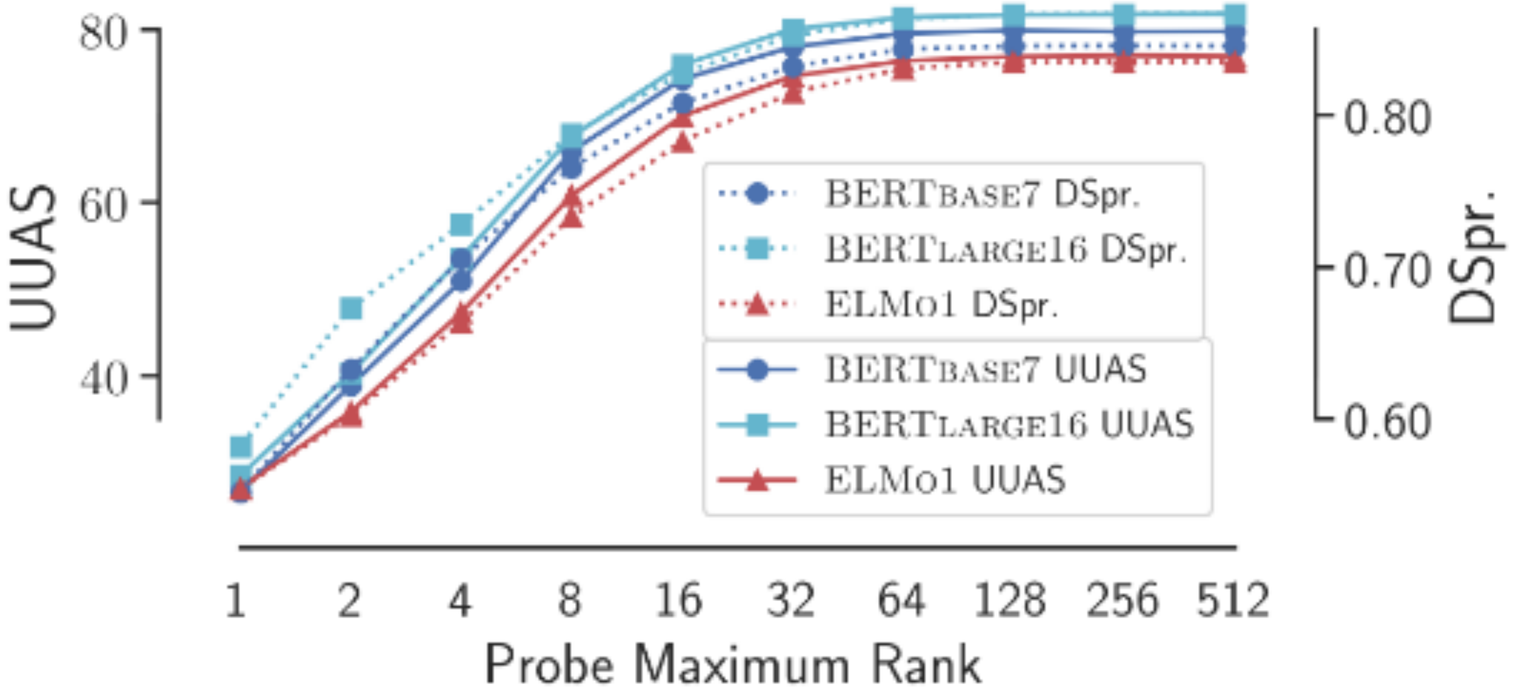
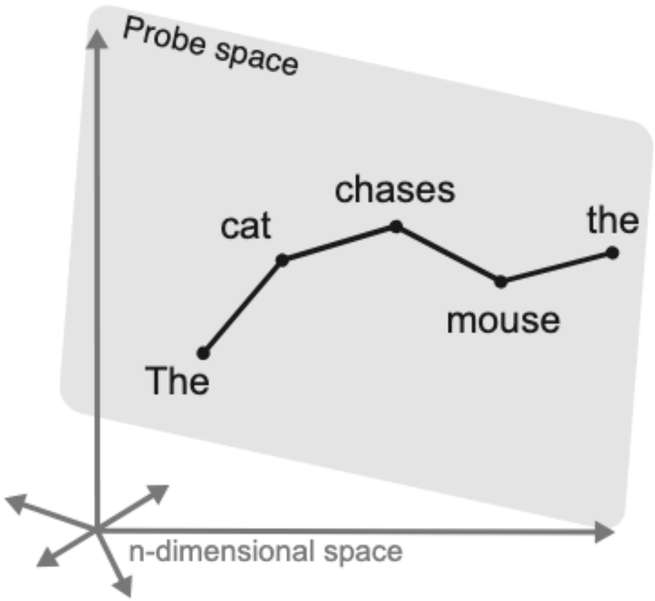


Takeaway: increasing the probe dimension beyond 64 or 128 gives little gain — syntax lives in a low-rank subspace!

Summary: Two Quantities

We need two quantities to reconstruct unlabeled, directed structures:

- **Distance**: hierarchical distance between pairs of words;
- **Norm**: a word's depth / distance from the origin / ROOT;



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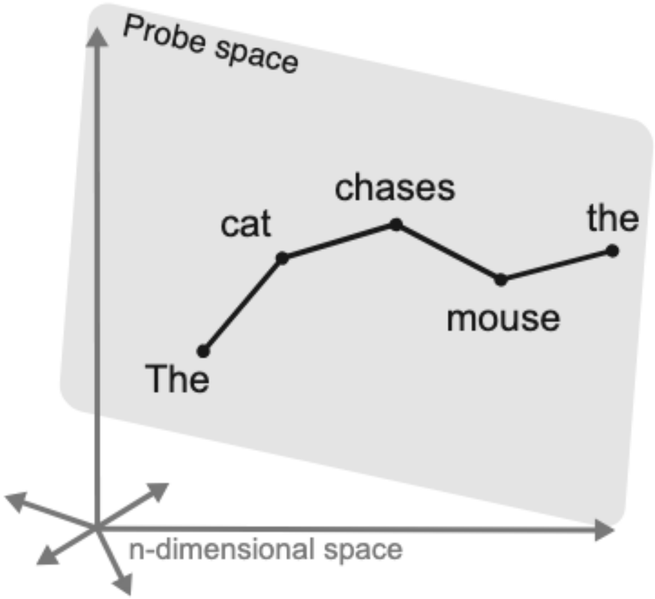
Issues?

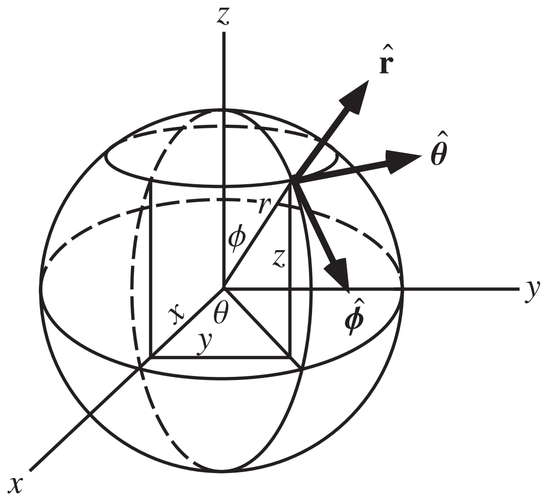
- No dependency type information:
  - cannot distinguish "The cat chases the mouse" vs. "The mouse chases the cat".
- Need both information to derive direction.



Diego-Simón et al. 2024

Polar Probe

Angular Probe: Core Idea



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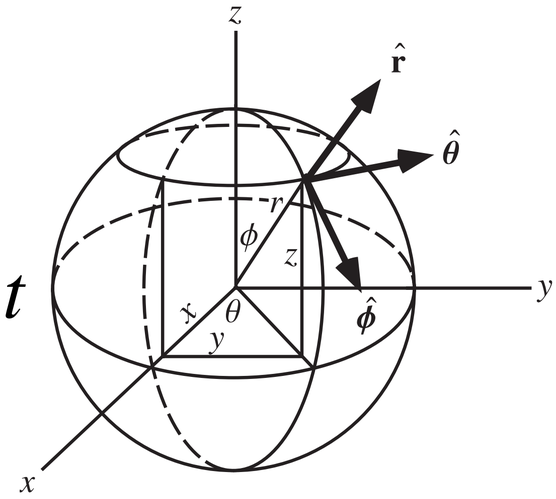
- **Goal** = in addition to distance, also probe for dependency type t ($t : w_i, w_j \rightarrow C$) and head/direction u ($u : w_i, w_j \rightarrow \{w_i, w_j\}$);



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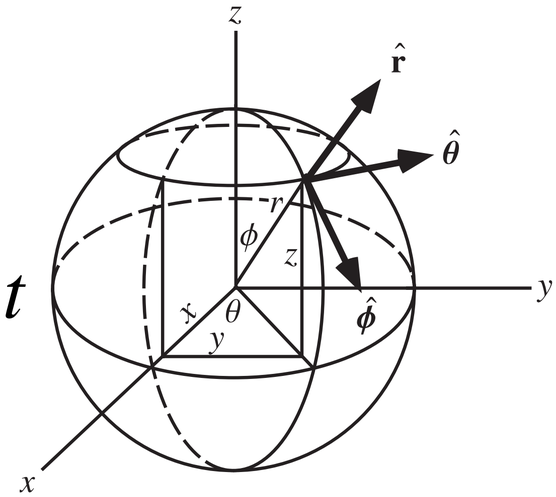

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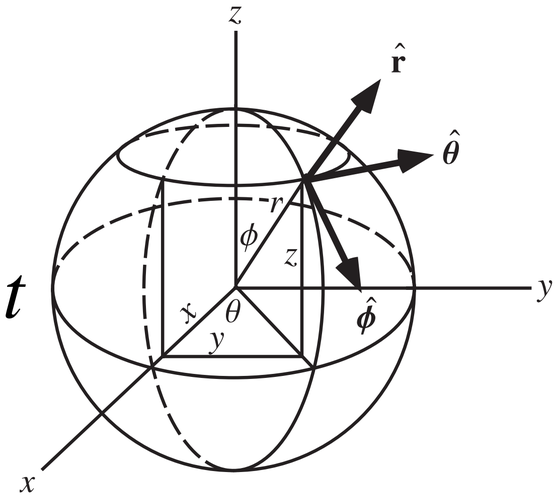

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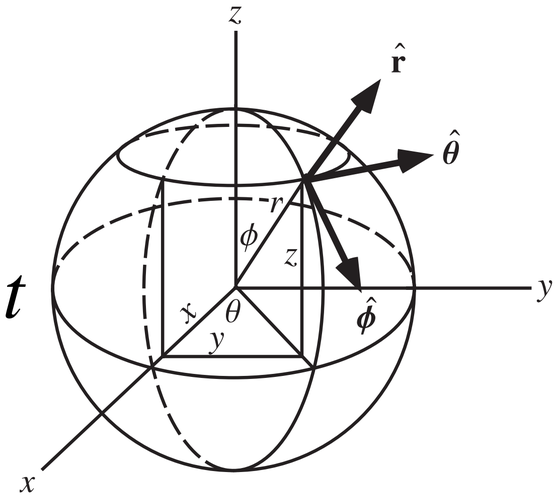

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- For each pair, let the difference in activation $s_{i,j} = h_i - h_j$ represent the edge;
- **Intuition**:
  - If two eges have the same dependency type, they should be aligned (colinear) in the transformed space; different type → orthogonal;
  - Given a reference direction for a type, if current edge vector points in the same direction (cos similarity > 0), then w_i is the head; opposite direction → w_j is head.

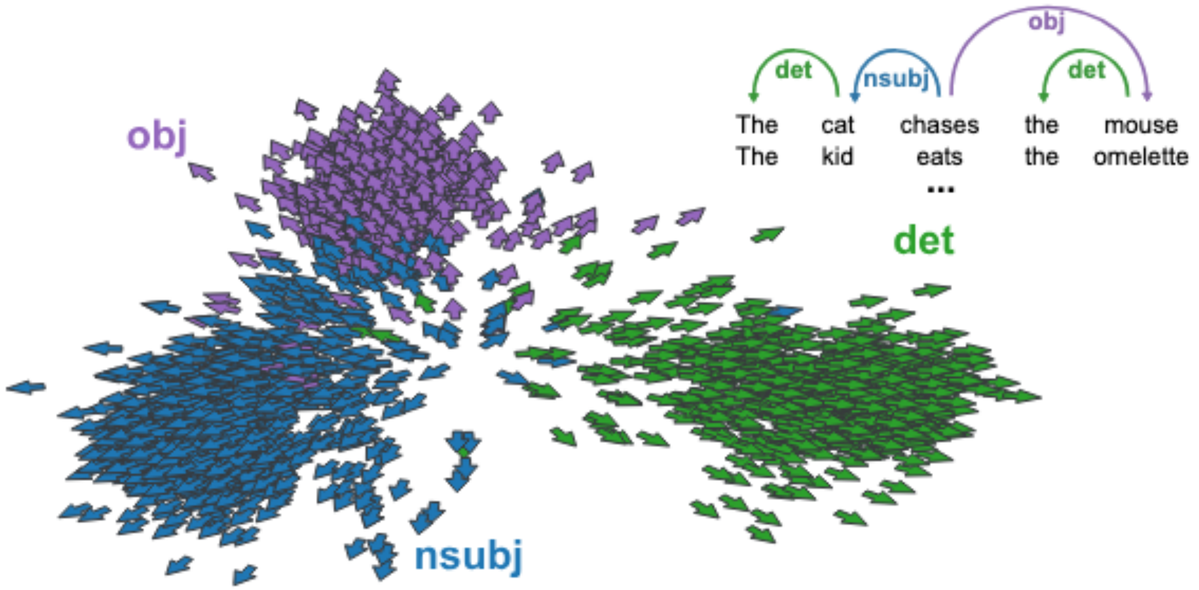
Angular Probe: Formalization

$$\mathcal{L}_A(\mathbf{B}_A) = \frac{1}{\Omega_A} \sum_{s,s' \in \Omega_A} \left(\measuredangle(\mathbf{B}_A\mathbf{s}, \mathbf{B}_A\mathbf{s}') - \mathbb{1}\left[t(\mathbf{s}) = t(\mathbf{s}')\right]\right)^2,$$

- Ω_A is the set of edge embeddings of syntactically connected words,
- $\measuredangle : \mathbf{x}, \mathbf{y} \mapsto \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|}$ is the cosine similarity,
- $\mathbb{1} : \mathcal{X} \mapsto \begin{cases} 1 \text{ if } \mathcal{X} \text{ is true} \\ 0 \text{ otherwise} \end{cases}$ is the indicator function.

- $\mathbf{B}_A$ for angular probe; now comparing two edge embeddings s, s';
- **Intuition = contrastive learning**: find the linear transformation such that edges with the same type should align in the same direction, while edges with different types should be orthogonal;

Angular Probe: Decoding Type and Head



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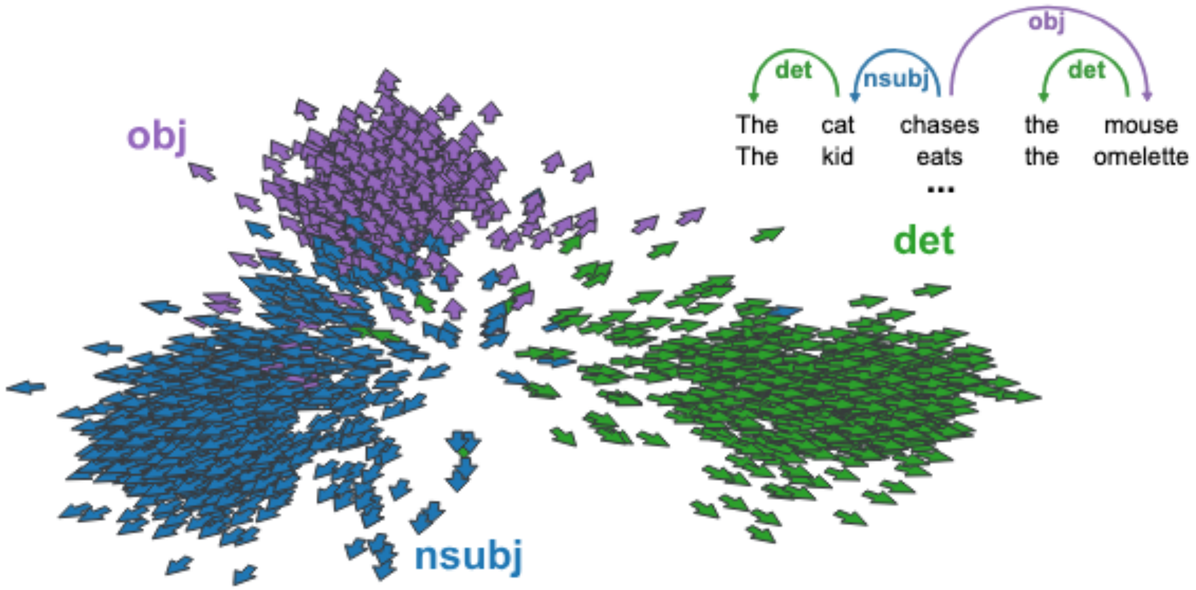

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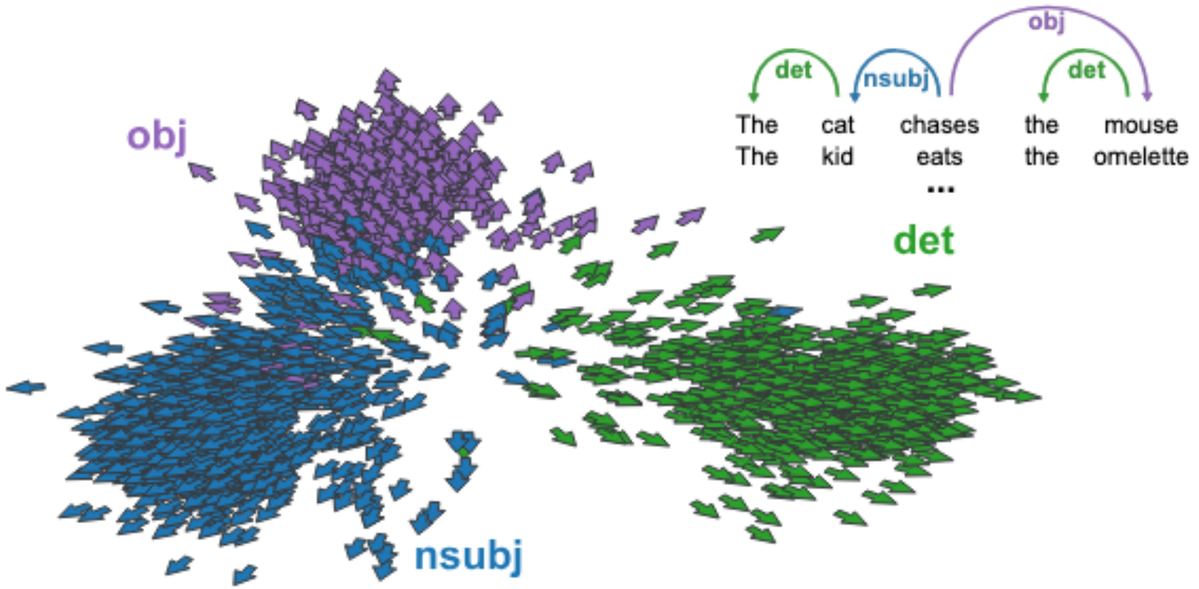

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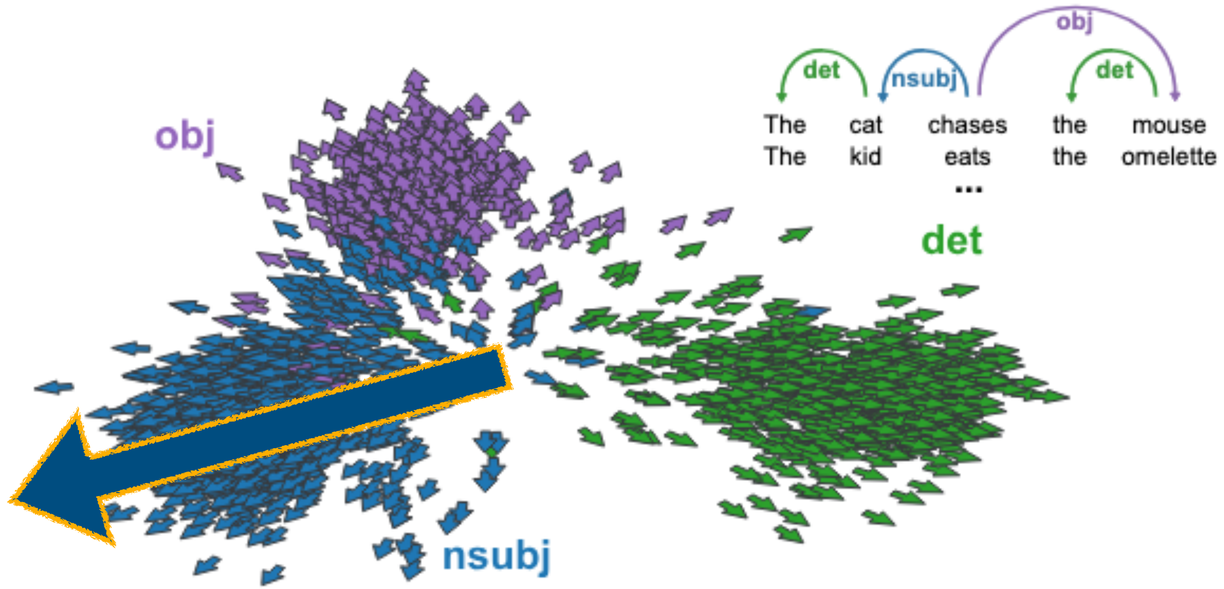

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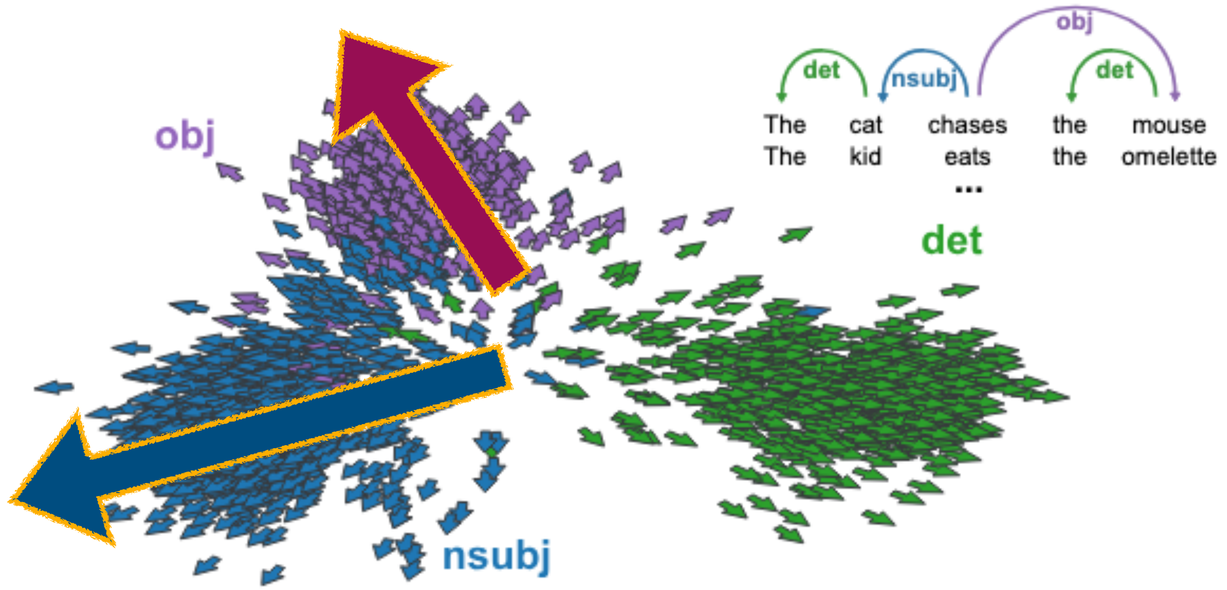

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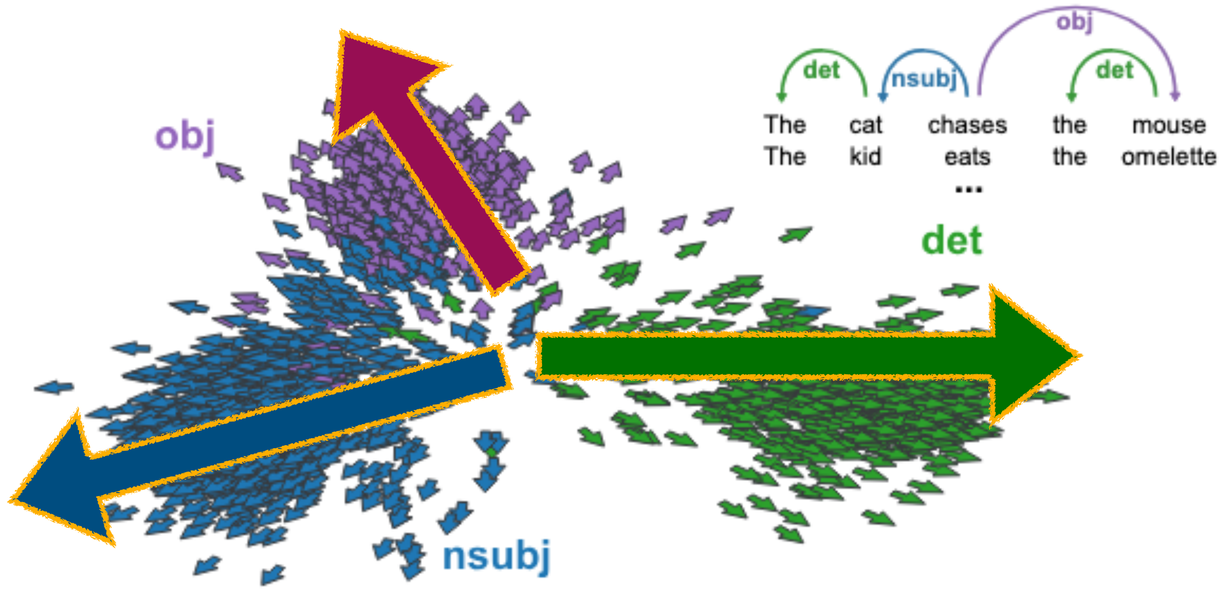

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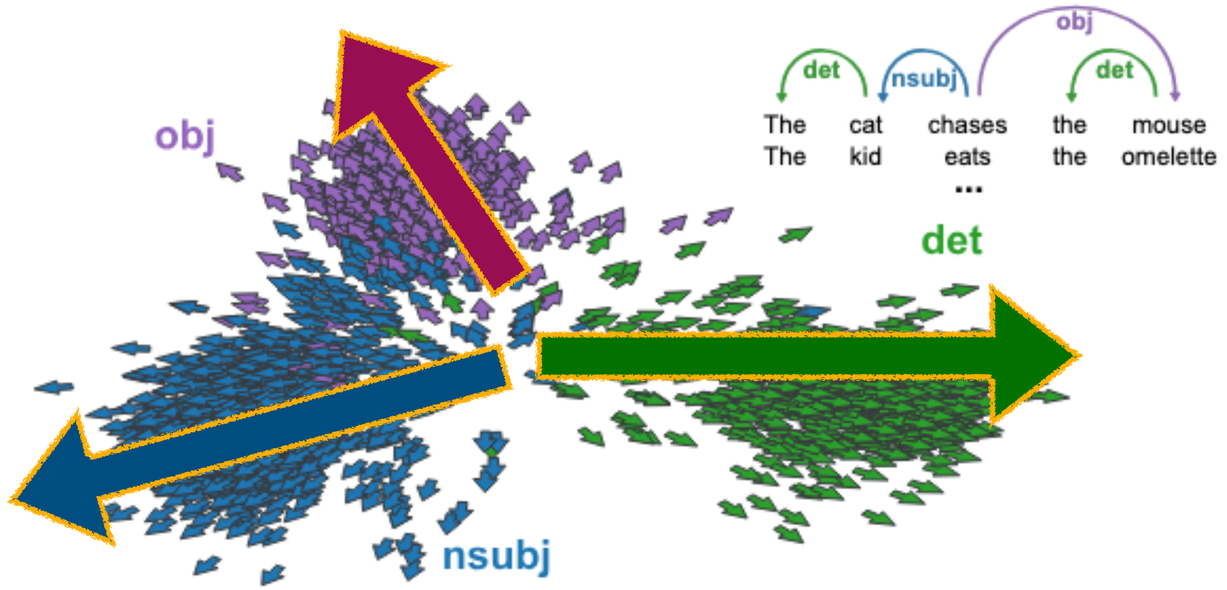

Angular Probe: Decoding Type and Head

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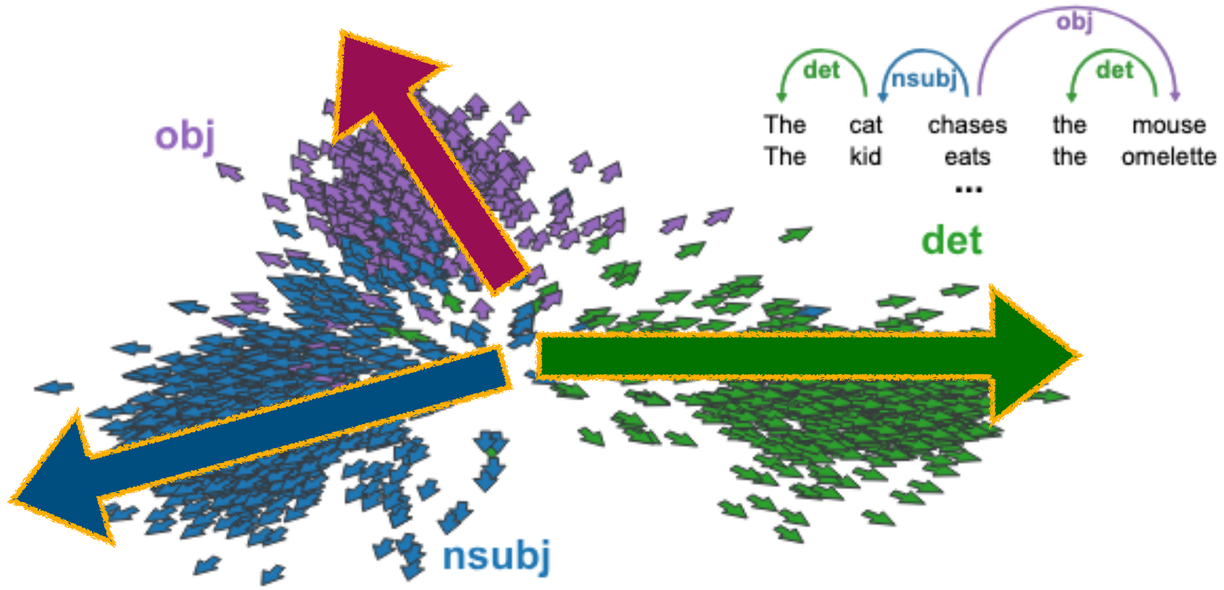

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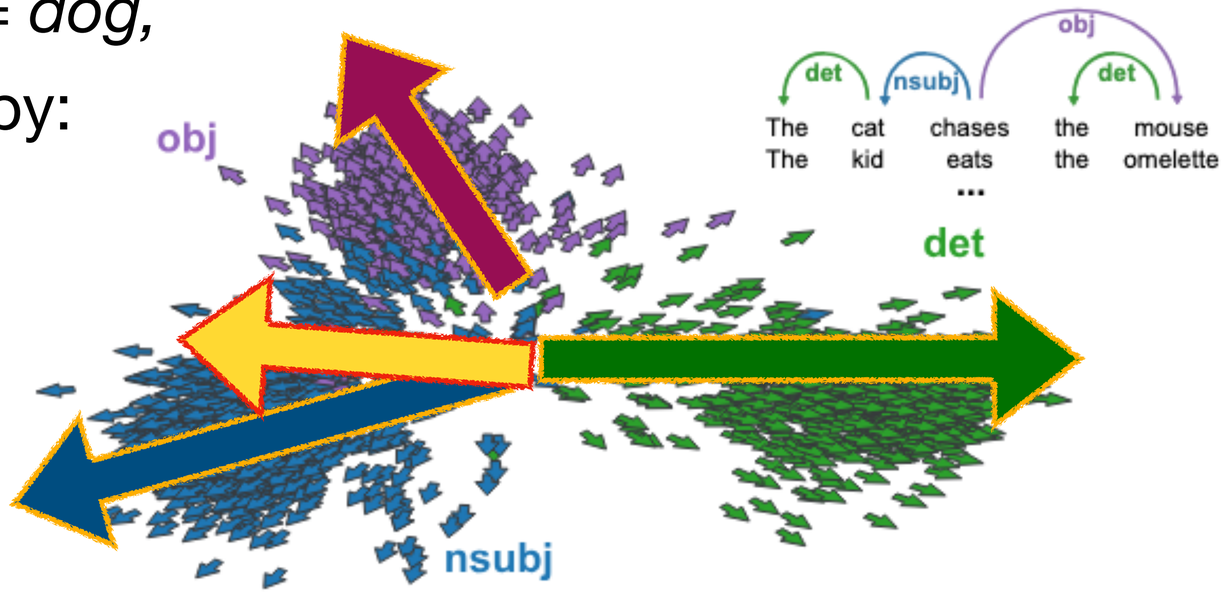
$\mathbf{B}_A s_{ij}$ is represented by:



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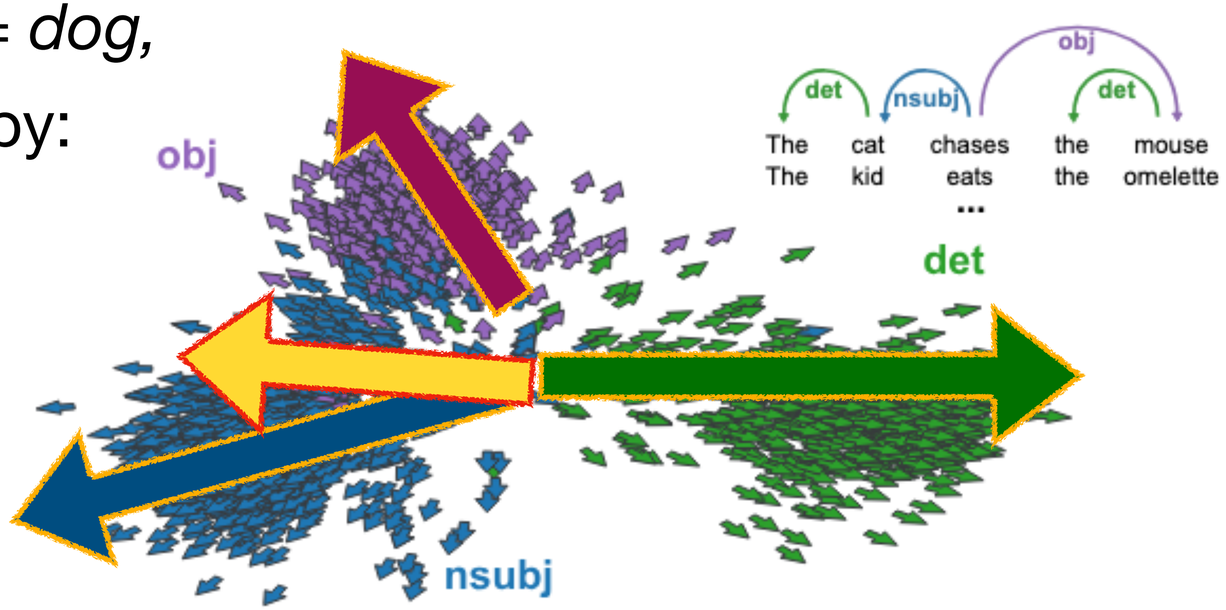

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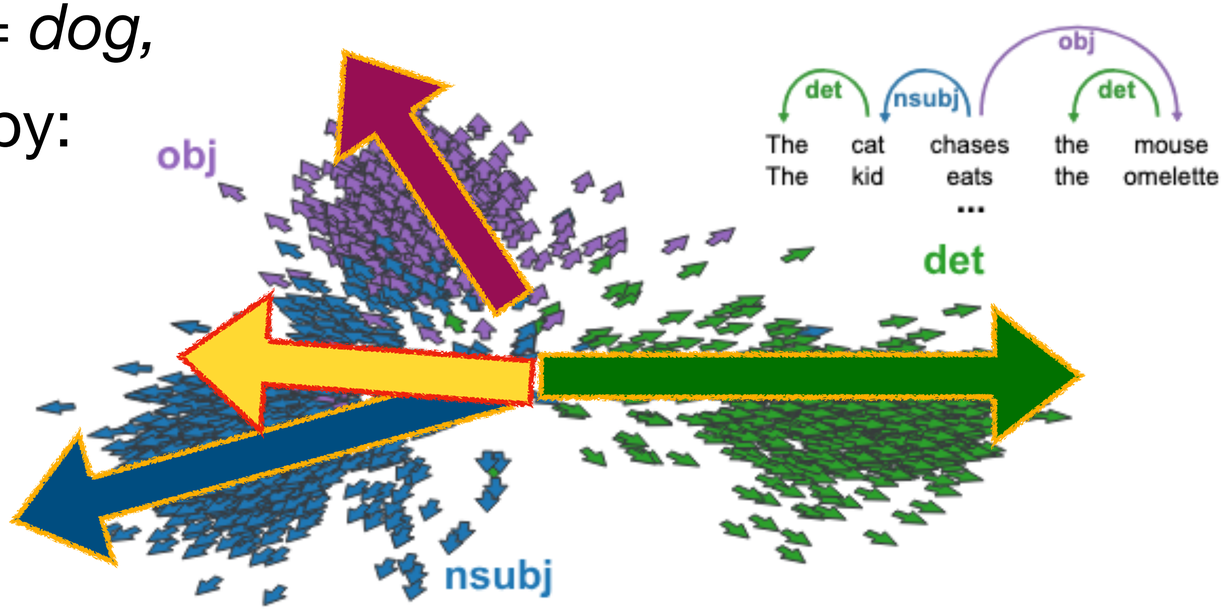

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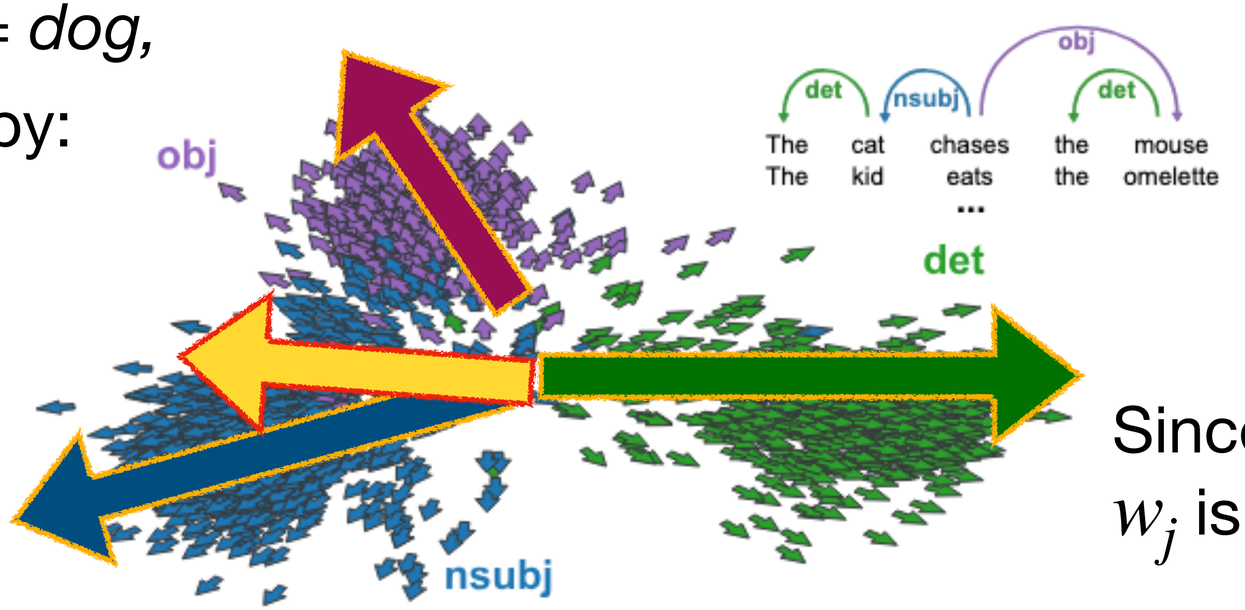

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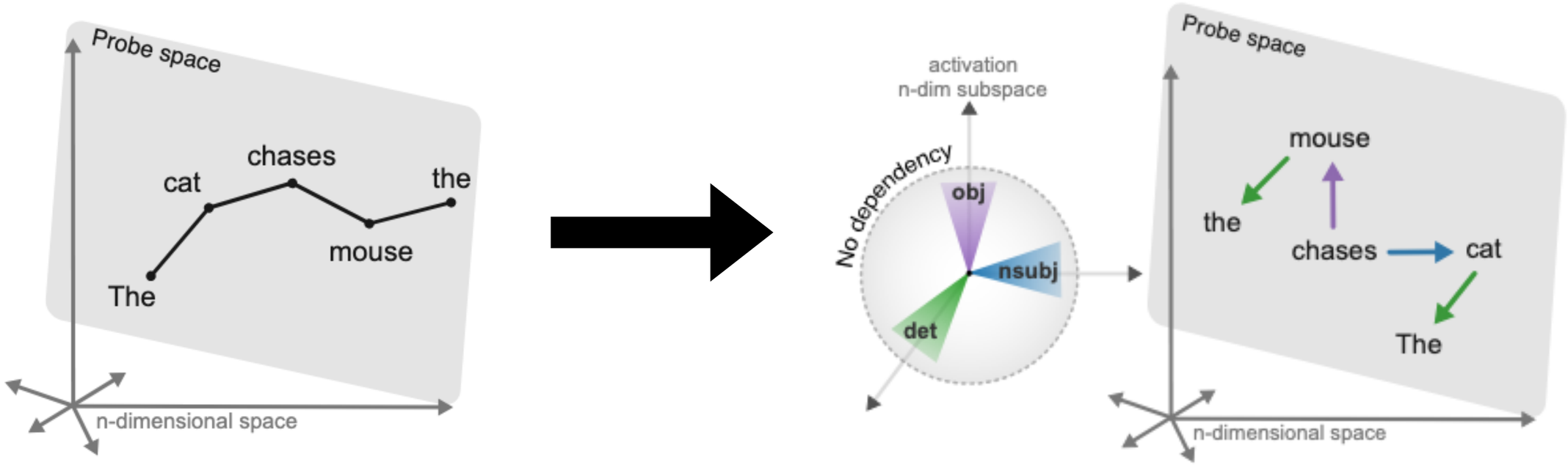
Since cosine similarity < 0,
w_j is the head!

Angular Probe: Illustration



Polar Probe: Structural Probe + Angular Probe

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  - Intuition: in polar coordinate, we need two quantities to determine a point — an angle and a distance.
- Remember $\mathscr{L}_S$ stands for structural loss and $\mathscr{L}_A$ stands for angular loss;
- Here is the final solution, this time with a single $\mathbf{B}_P$, minimizing the polar loss:

$$\underset{\mathbf{B}_P}{\operatorname{argmax}}\, \mathscr{L}_S(\mathbf{B}_P) + \lambda \mathscr{L}_A(\mathbf{B}_P)$$

$$\hat{d}(\mathbf{h}_i, \mathbf{h}_j) := \|\mathbf{B}_P \mathbf{s}_{ij}\|^2$$

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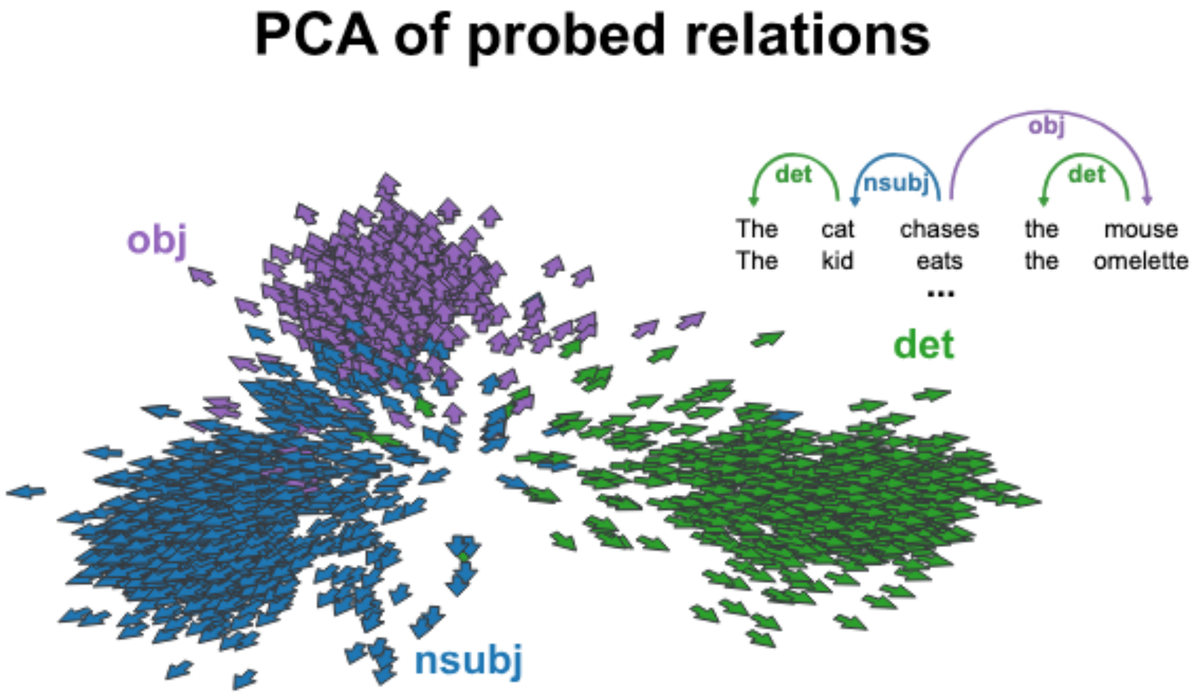
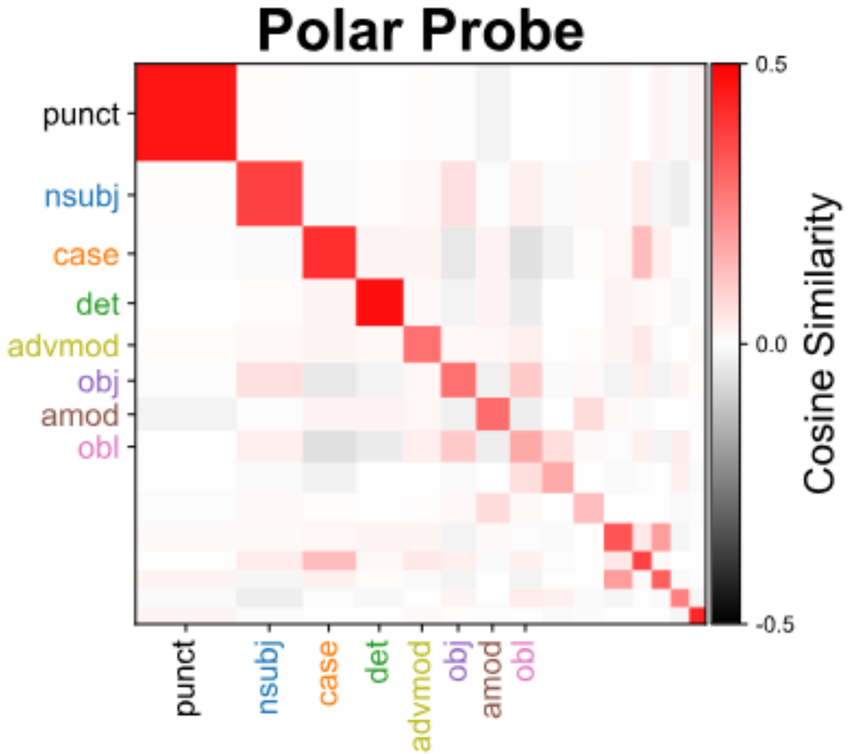
Experiments

Result: can polar probe recover types?

- **Models**: Mistral-7B ($k = 4096$), Llama-2-7b ($k = 4096$); BERT-large ($k = 1024$);





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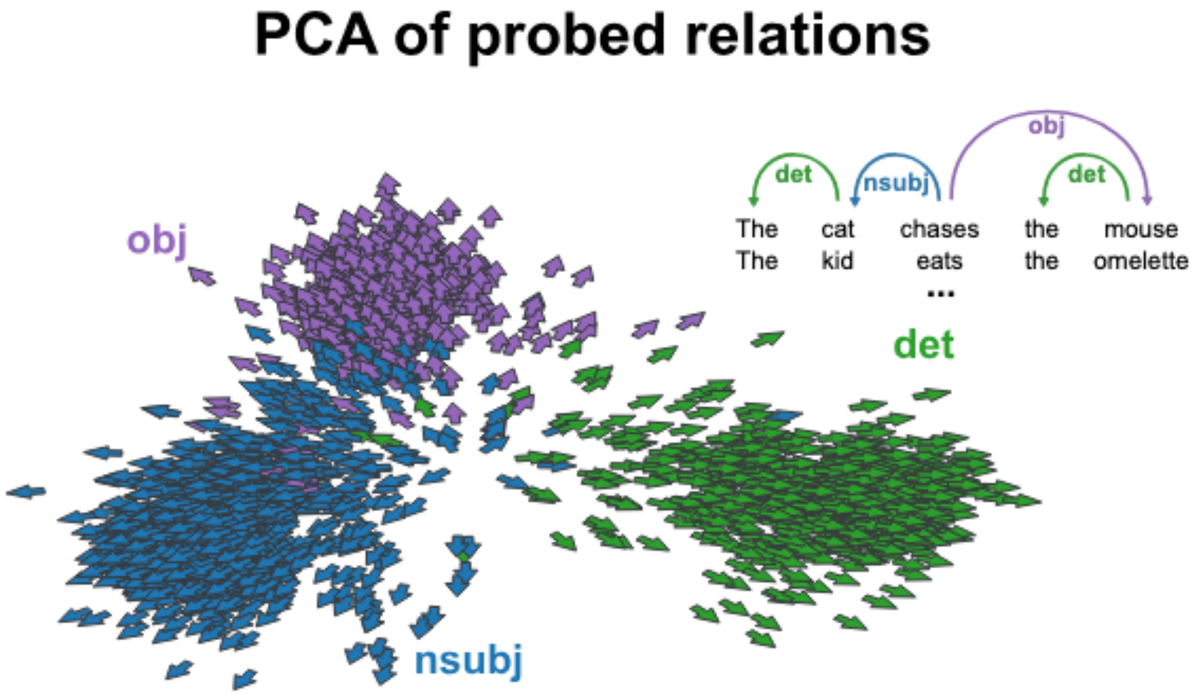
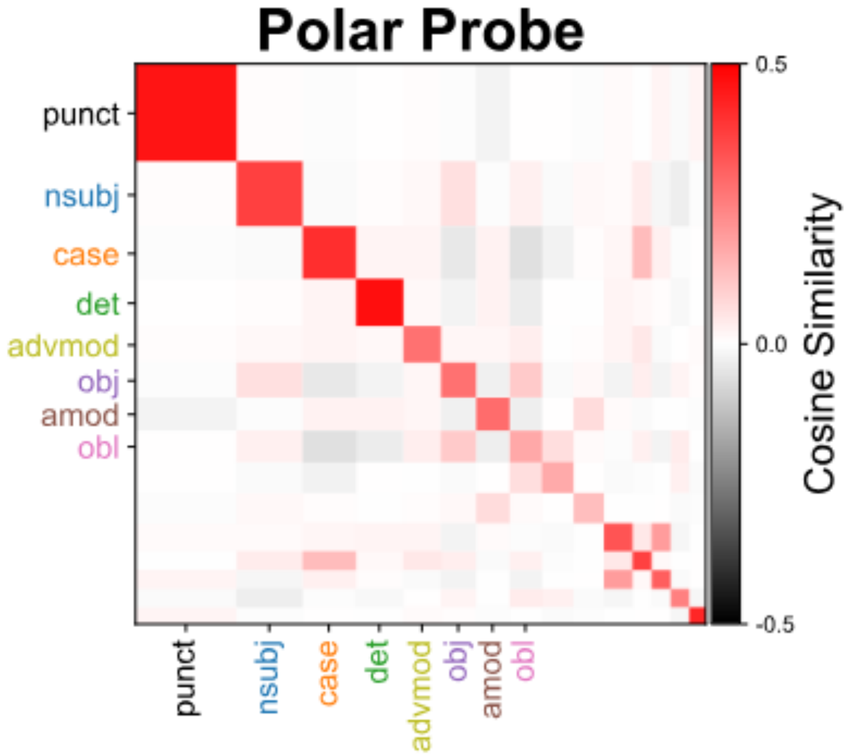
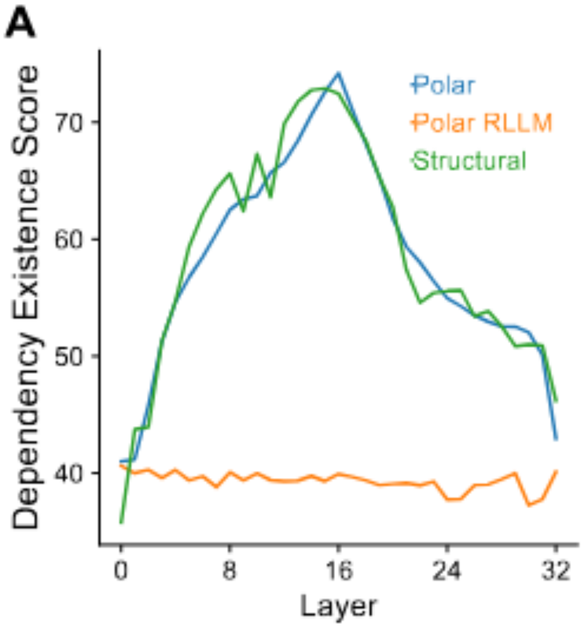




Takeaway: dependency type information is encoded geometrically as direction in the transformed space, not just recoverable by the probe.

Result: how Angular and Structural interact?



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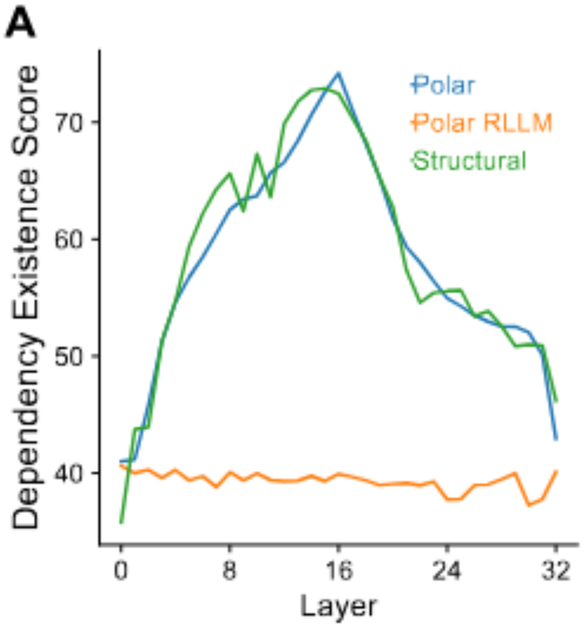

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- the best layer is at layer 16 (middle), aligning with structural result.

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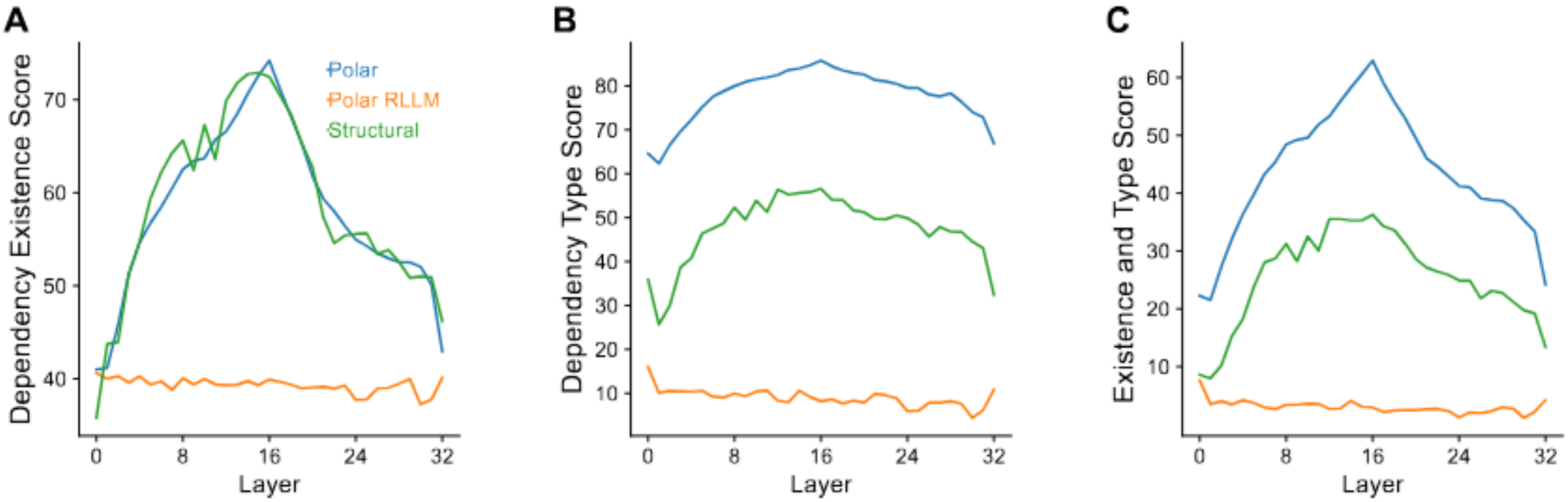

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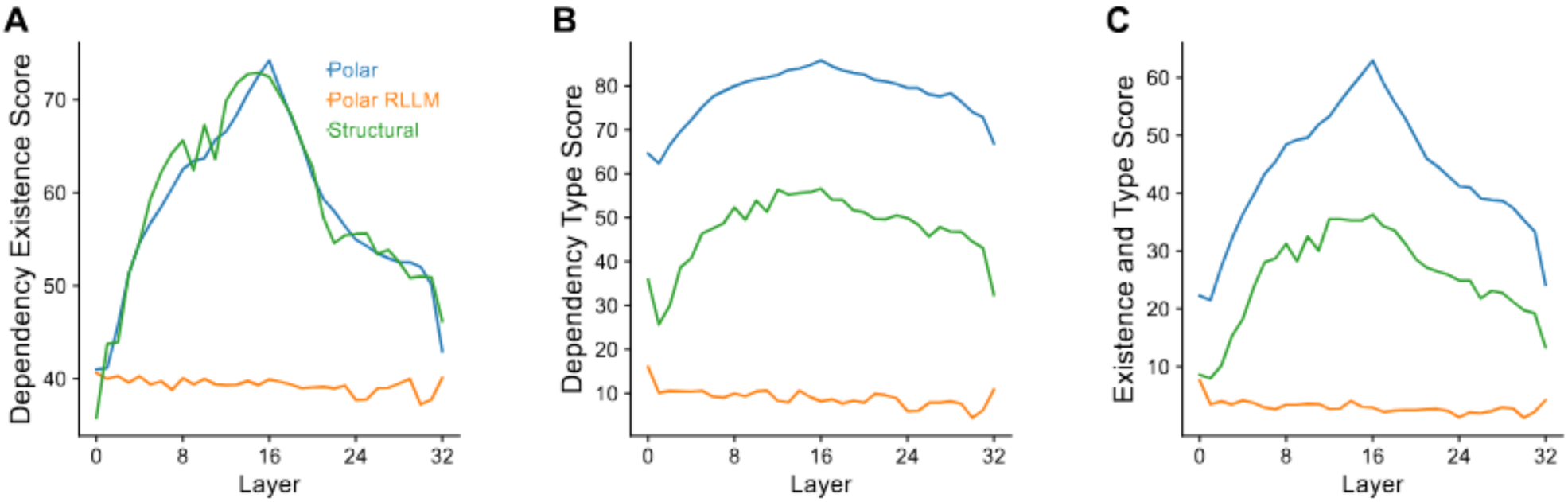
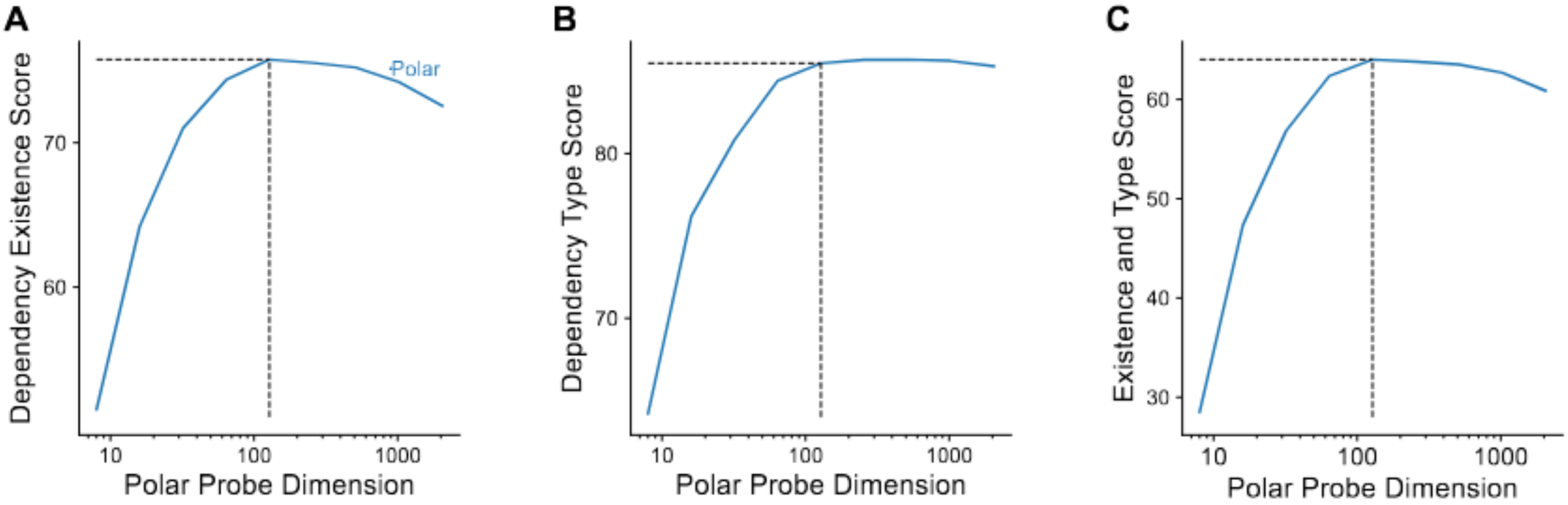


Takeaway:

- the best layer is at layer 16 (middle), aligning with structural result.
- BERT-large has the best performance than the two autoregressive models — masked LMs often encode syntax more cleanly in the current setup.
- Polar Probe keeps the old distance-based syntax signal and adds a large amount of labeled, directed information on top of it.

Result: how big is the syntax subspace?



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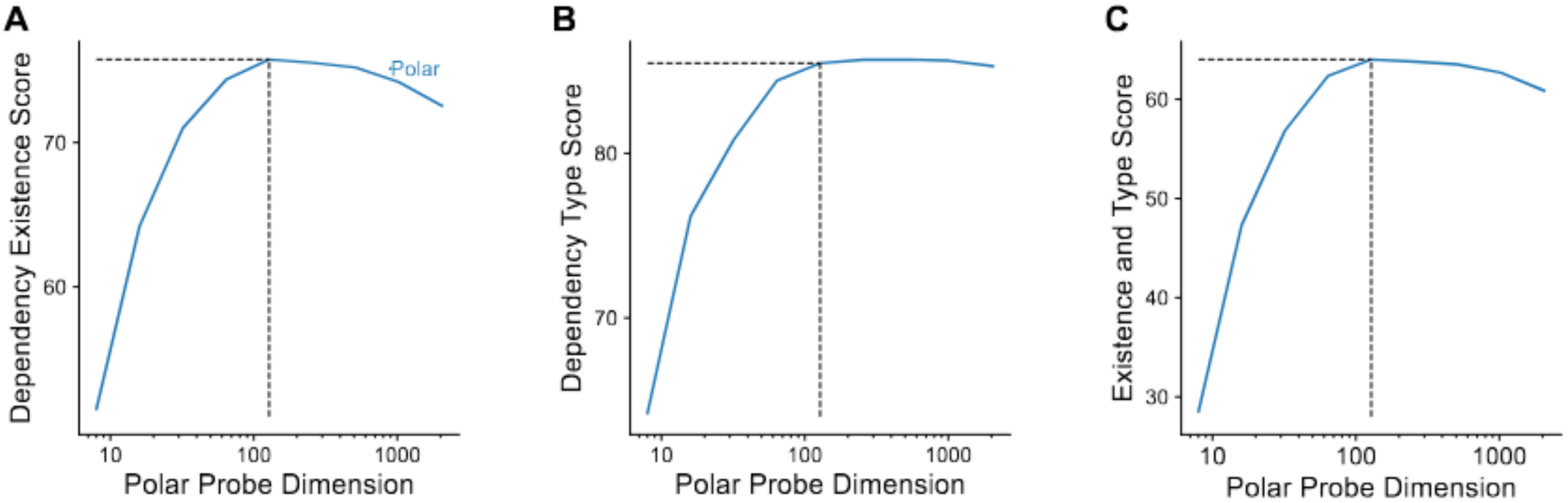

A = UUAS; B = Dependency type accuracy; C = LAS

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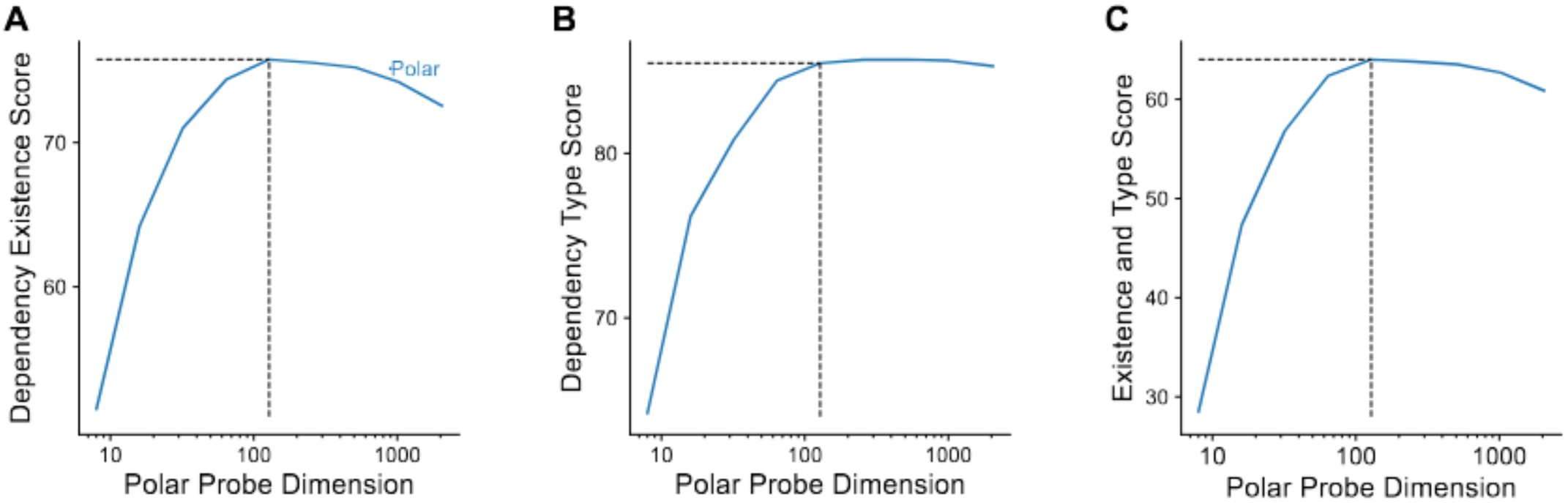
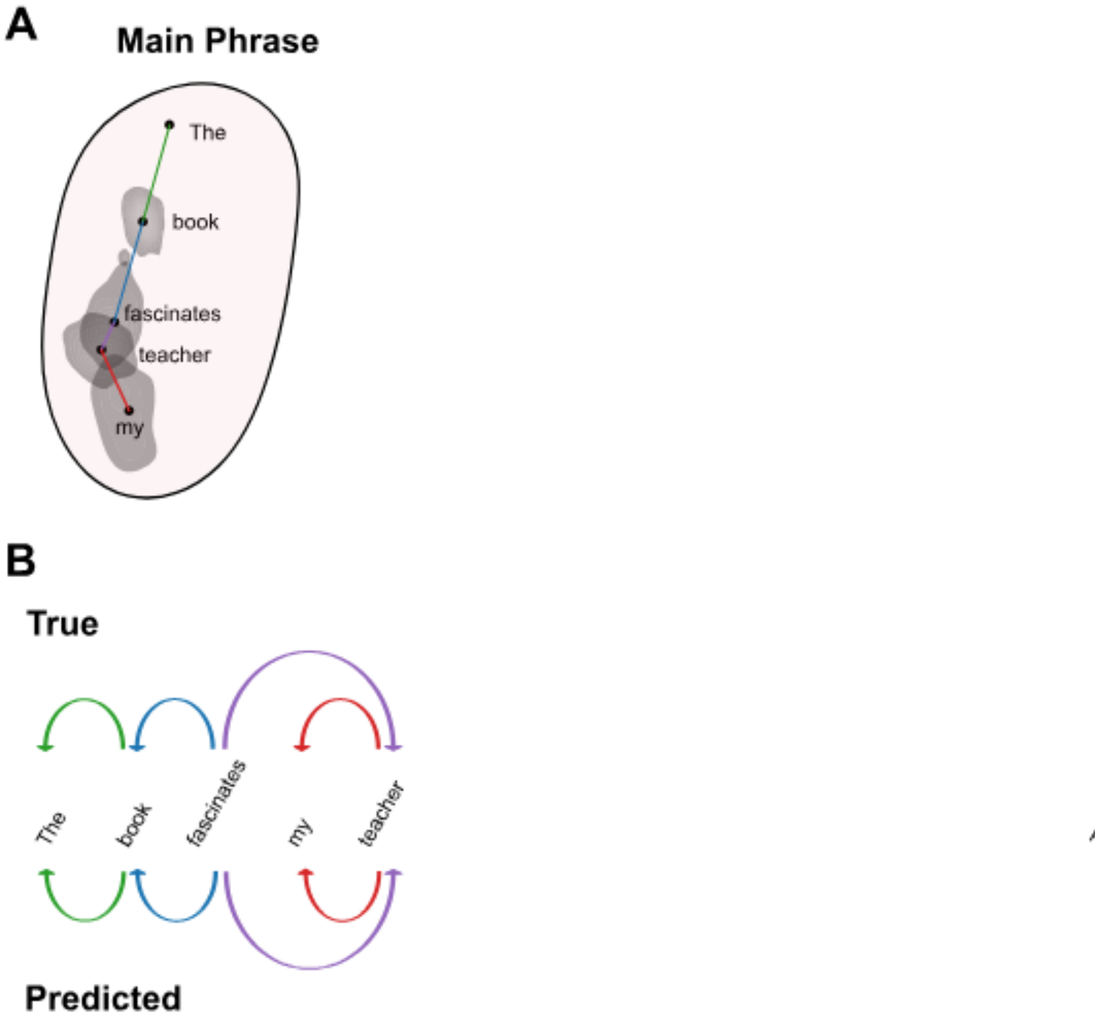


A = UUAS; B = Dependency type accuracy; C = LAS

Takeaway: same as before, the required probe space is still much smaller than the model's full hidden dimension — even the richer polar code is still fairly compact.

Result: on more complex sentences?



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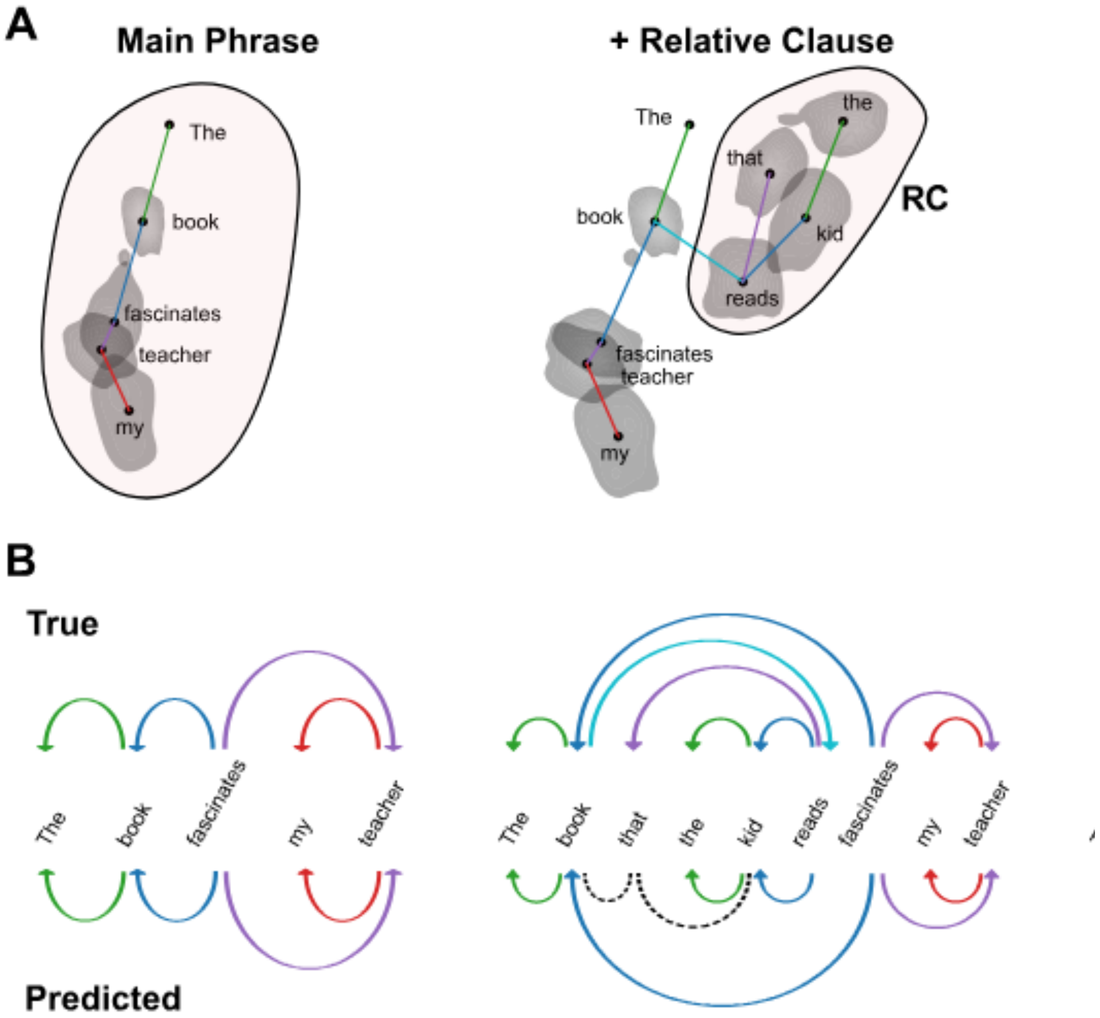

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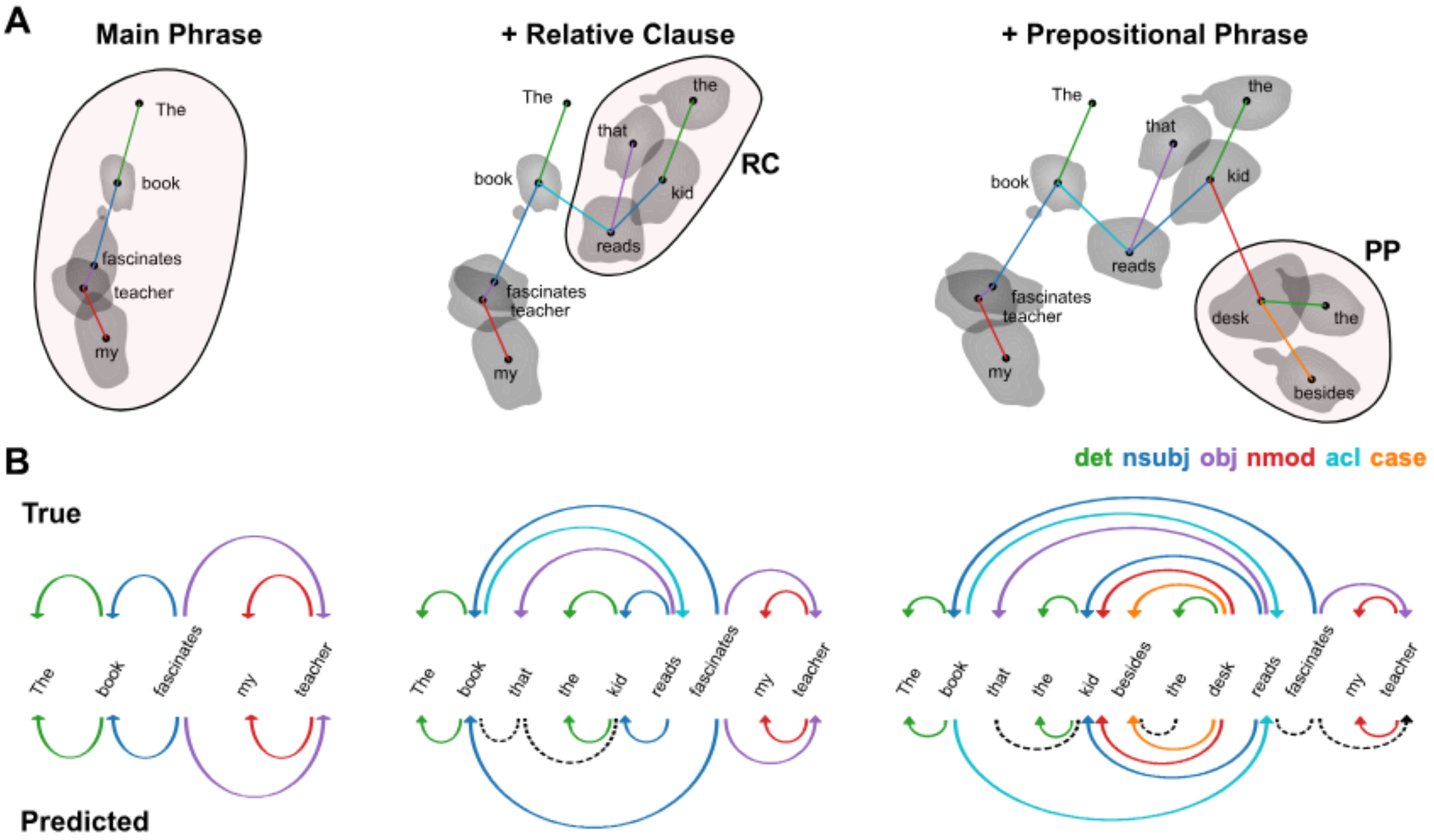

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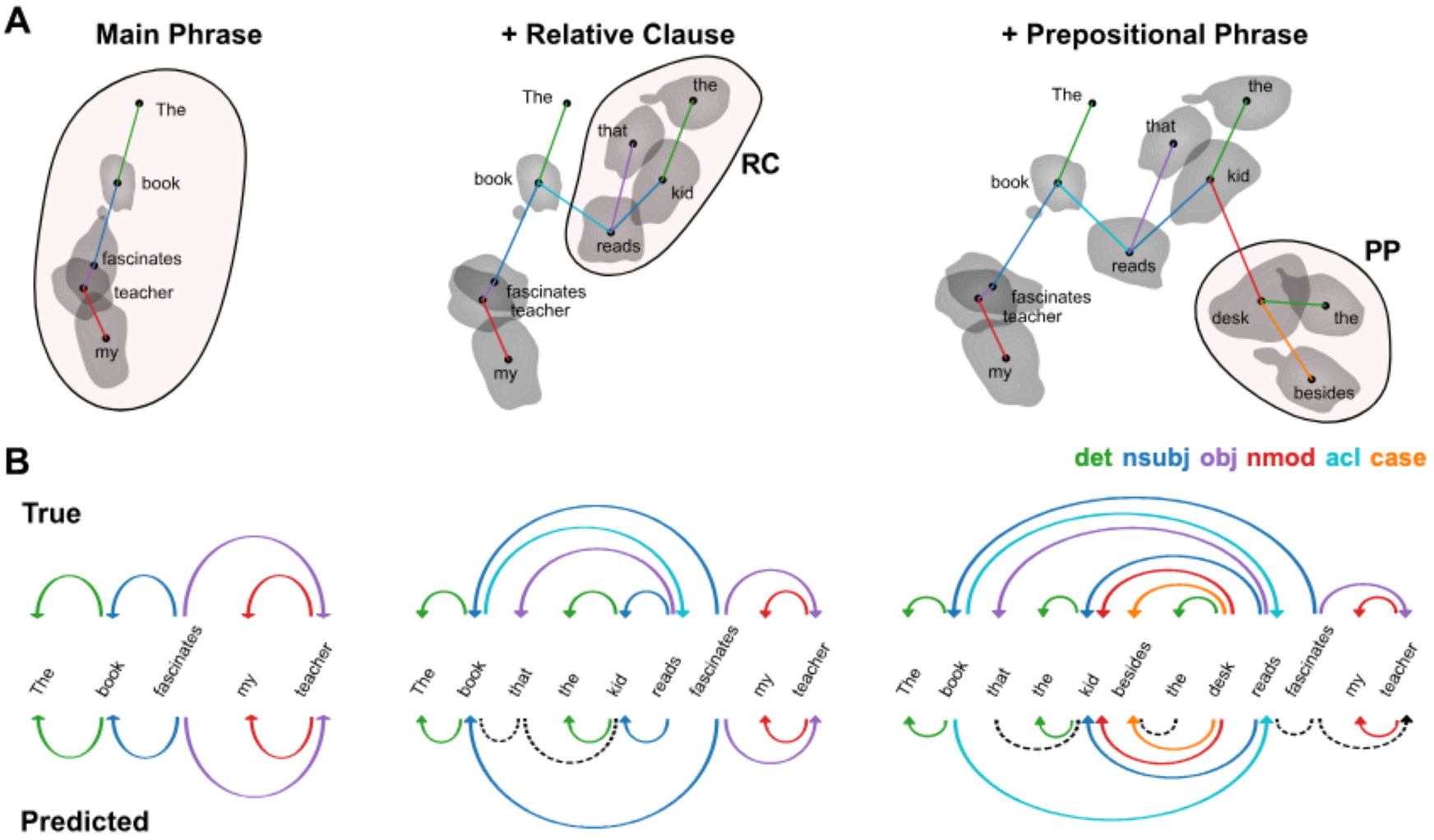


Takeaway: syntax is represented in a **systematic coordinate system** that stays stable across recursive embedding.

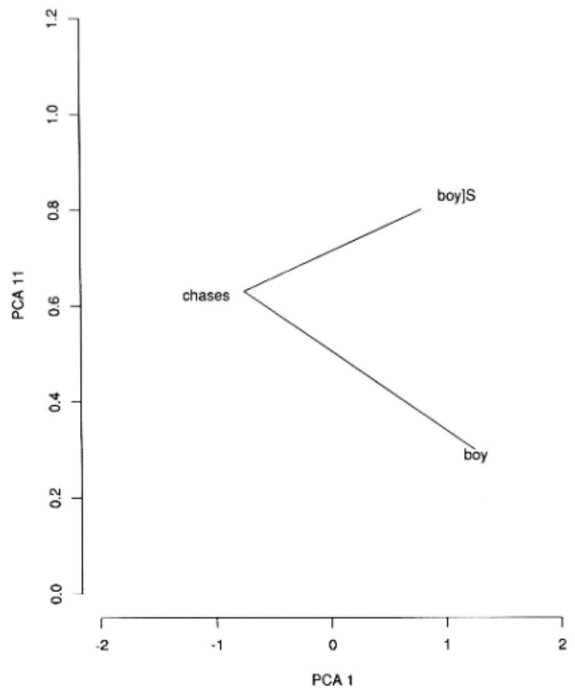
See also Elman 1991

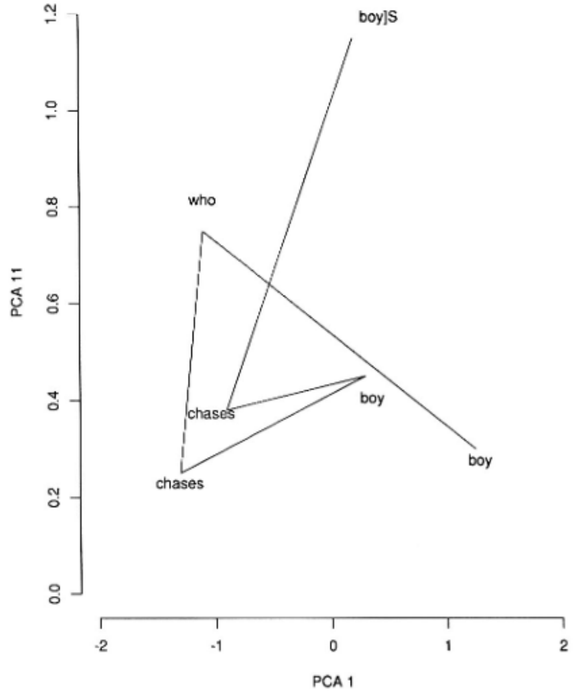
Distributed Representations, Simple Recurrent Networks, and Grammatical Structure

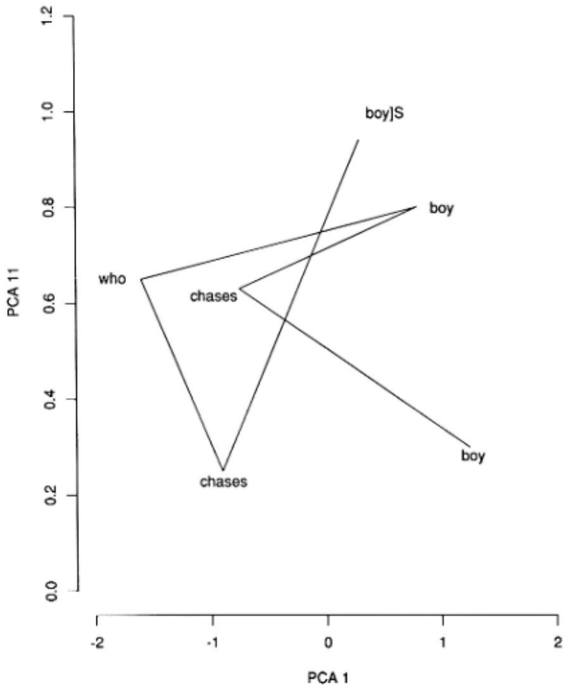
JEFFREY L. ELMAN (ELMAN@CRL.UCSD.EDU)
Departments of Cognitive Science and Linguistics, University of California, San Diego

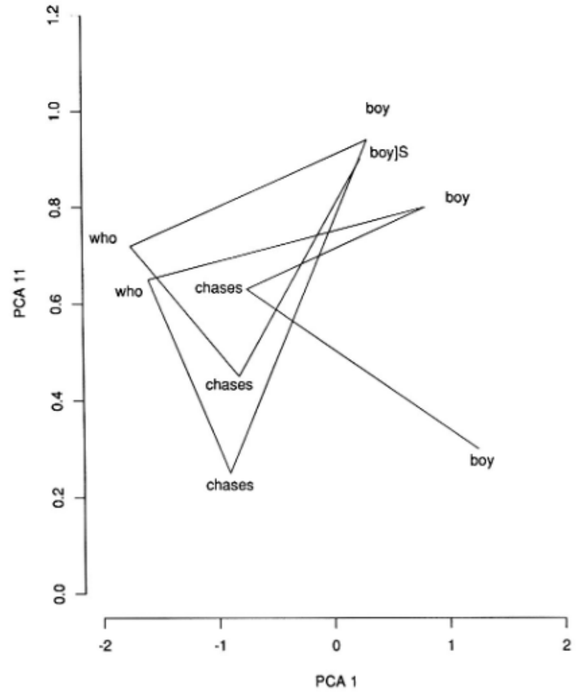
(10a) boy chases boy.
(10b) boy chases boy who chases boy.
(10c) boy who chases boy chases boy.
(10d) boy chases boy who chases boy who chases boy.

Relative clauses in small neural networks!

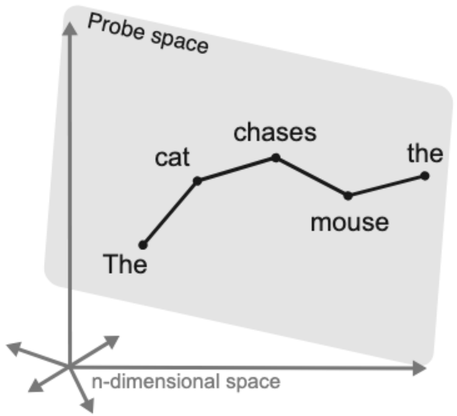






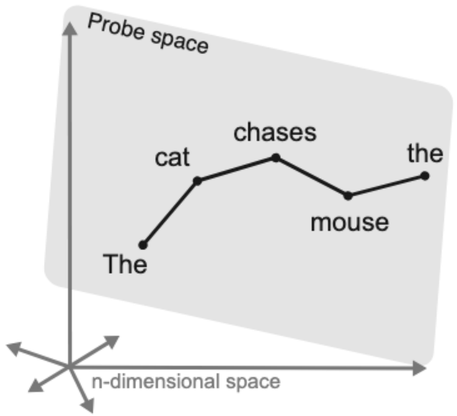


Summary



Summary

- **Hewitt & Manning:** syntax behaves like a *metric geometry*;



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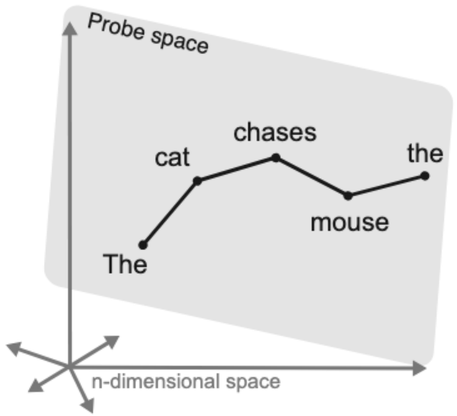

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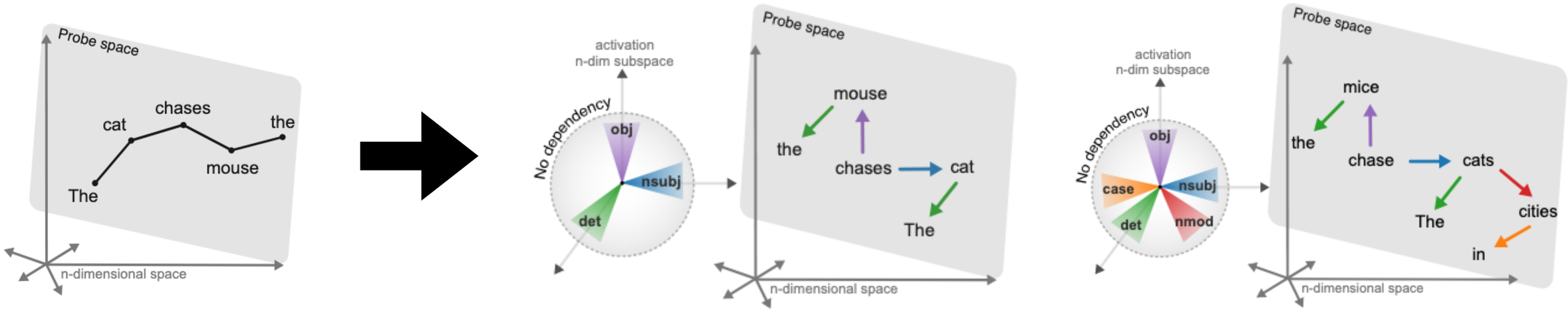

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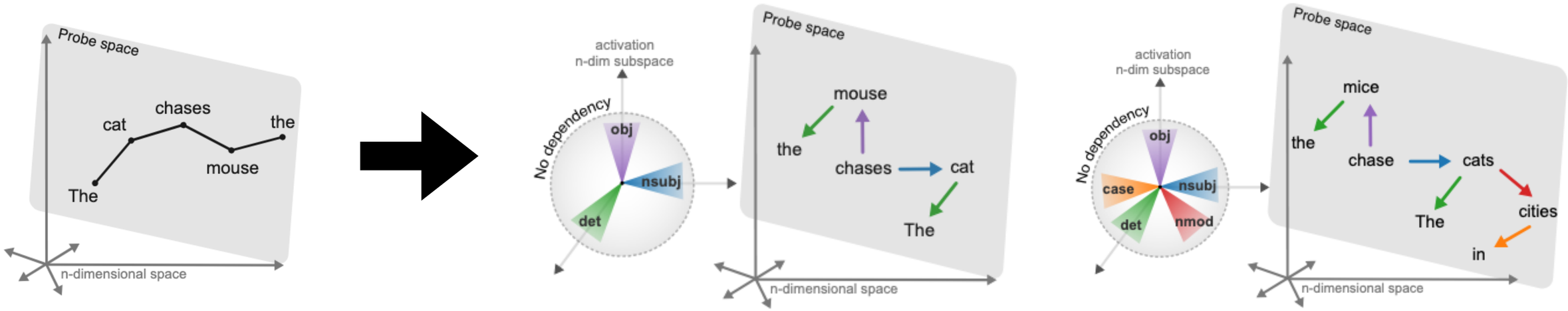
The role of probing = to find a compact subspace that organizes the syntactic information into this polar, human interpretable way!

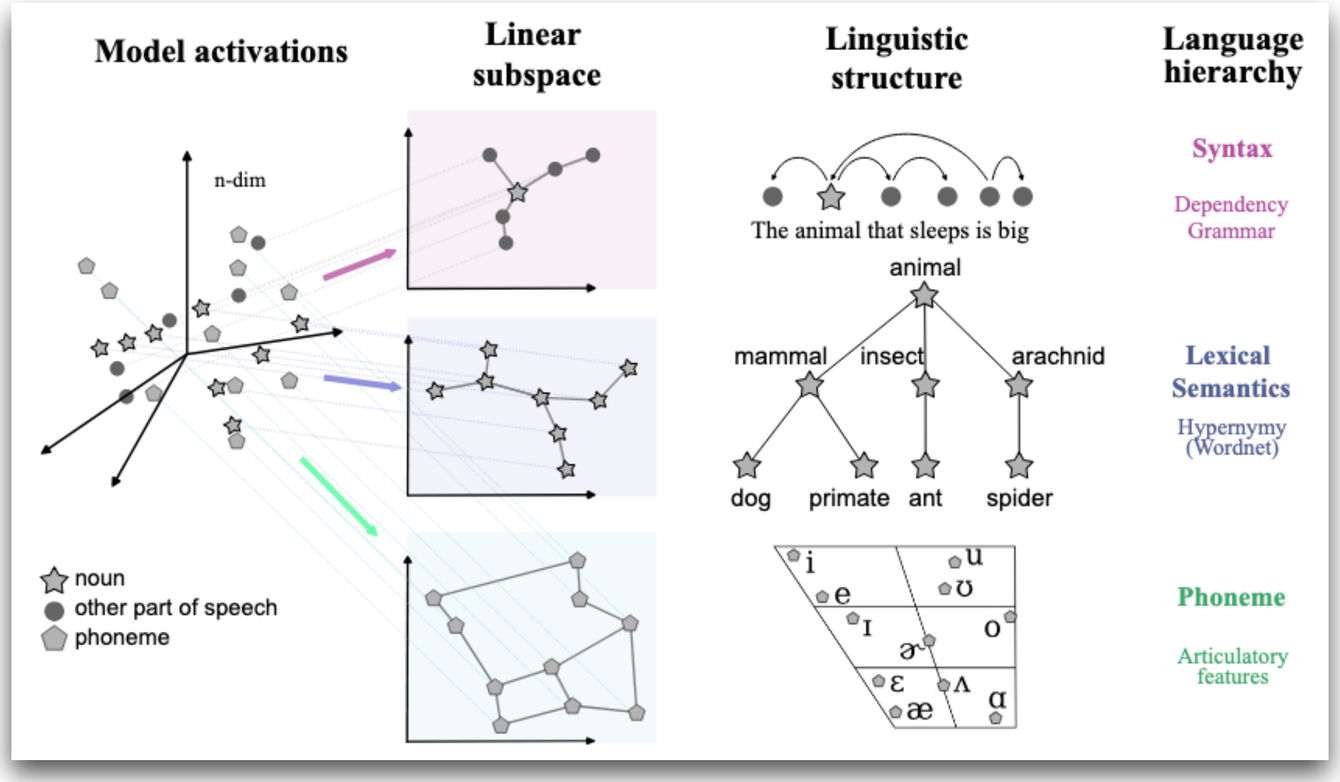


Orhan et al. 2026

Generalizing structural probe to phonetics and lexical semantics, on acquisition as well

Motivating Questions

- Can we also find linear subspaces for different kinds of linguistic structures — e.g., phonemic, lexical-semantics, in addition to dependency relations?
- How do those structures emerge during training? — to what extent is it analogous to human language acquisition?



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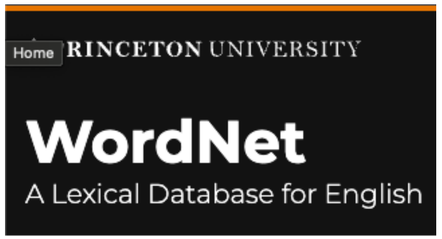
- **Models**
  - Text: Mistral-7B ($k = 4096$), Llama-2-7b ($k = 4096$);
  - Speech: Wav2Vec 2.0 (English, $k = 4096$), Controls (trained on French + music + environmental sounds);

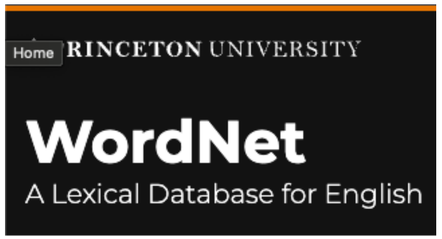
Methods

- **One unified framework**: structural probe (same procedure as Hewitt & Manning);
- **Models**
  - Text: Mistral-7B ($k = 4096$), Llama-2-7b ($k = 4096$);
  - Speech: Wav2Vec 2.0 (English, $k = 4096$), Controls (trained on French + music + environmental sounds);
- **Why speech models?**
  - Speech models' input is continuous audio, and the models are trained to reconstruct masked latent speech segments (differ from next-token pred);
  - It makes sense to test whether the model can discover useful information about phonemic structure, and whether syntax & semantics can emerge from raw speech rather than discrete tokenized text.
  - Can control to rule out the confound of detecting simpler acoustic regularities.

Methods, cont.

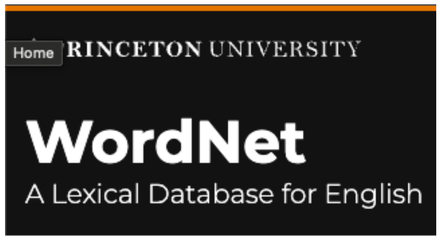


Methods, cont.



Text Input

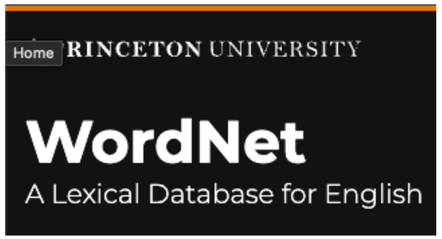
Methods, cont.



Text Input

Acoustic

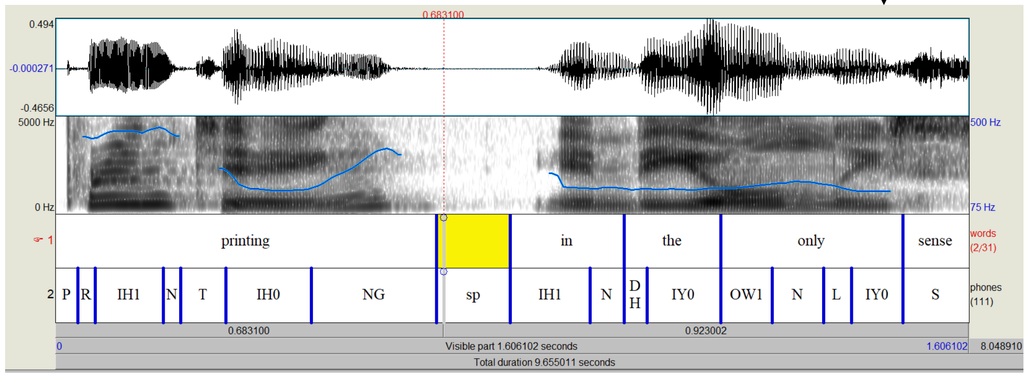
Methods, cont.



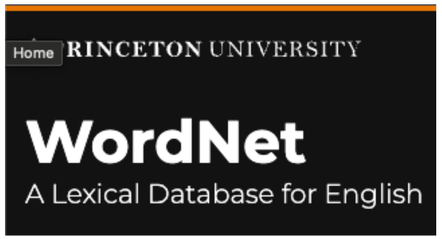
Text Input

Acoustic

Time information for word/phoneme segmentation



Methods, cont.



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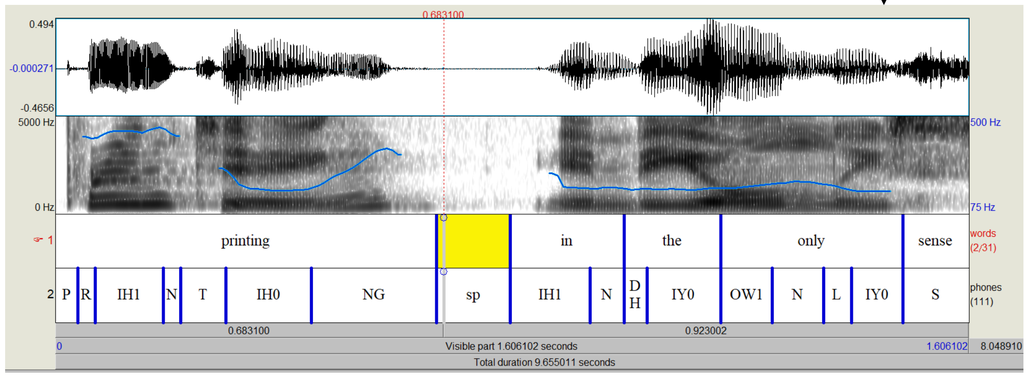
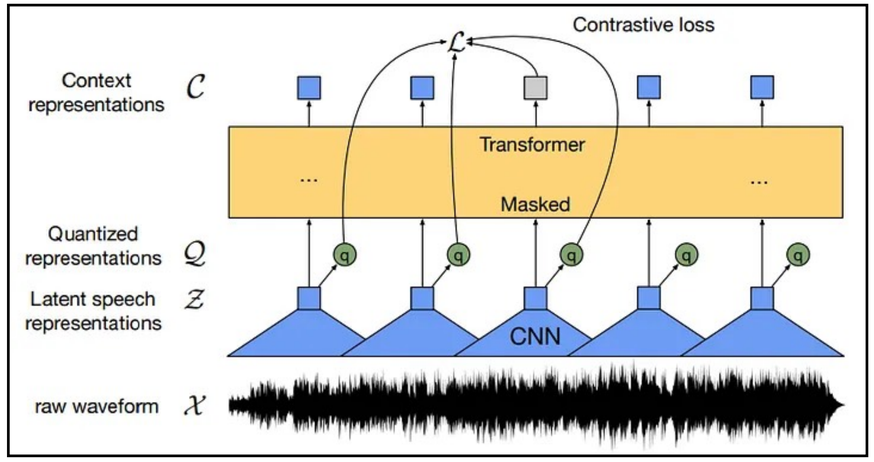


Waveform & time

Wav2Vec 2.0



Methods, cont.

Home RINCETON UNIVERSITY

WordNet

A Lexical Database for English

UniversalDependencies/
UD_English-EWT

English data

23 Contributors · 144 Issues · 222 Stars · 45 Forks

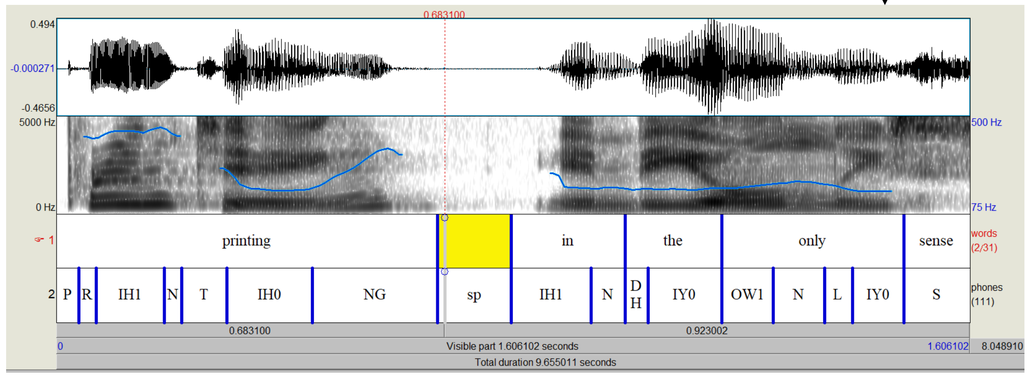
Text Input

Seamless M4T v2

Acoustic

Montreal Forced Aligner

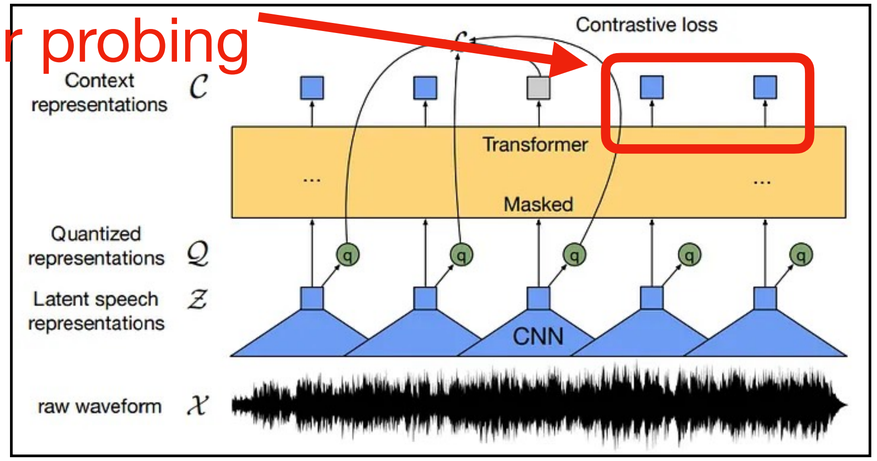
Time information for word/phoneme segmentation



Waveform & time

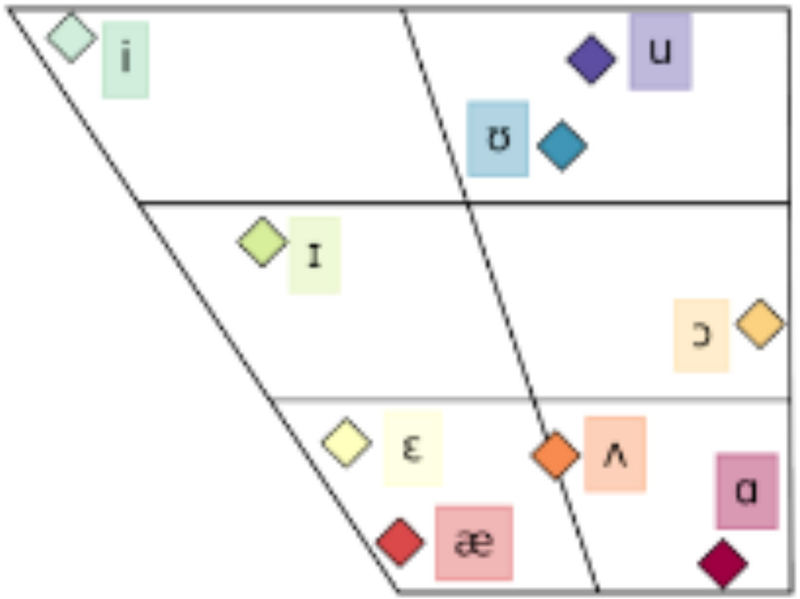
Activations for probing

Wav2Vec 2.0



Phonemic Articulation

- **Hypothesis**: speech models organize phonemes into structures that reflect articulatory features, rather than just treating them as separate categories.
- **Structural metric**: gold distance is articulatory-feature dissimilarity (Mortensen et al. 2016) between two phoneme activations.



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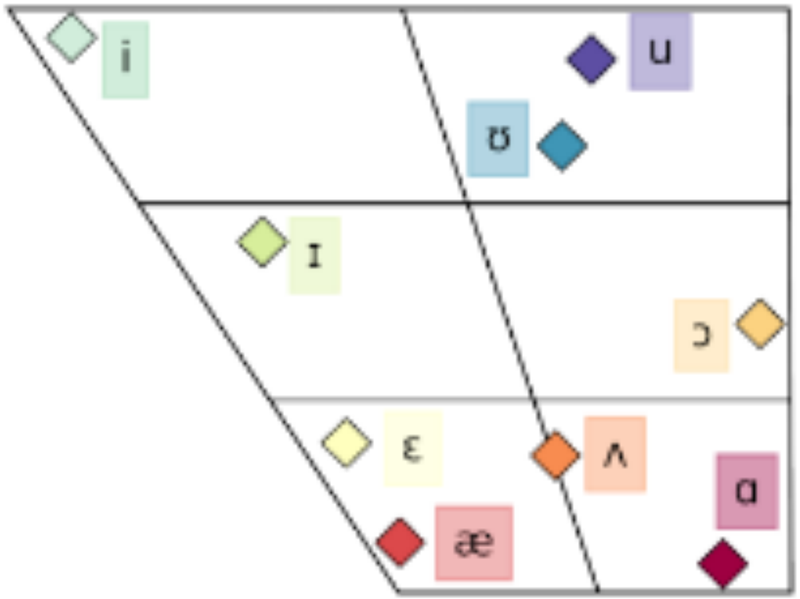

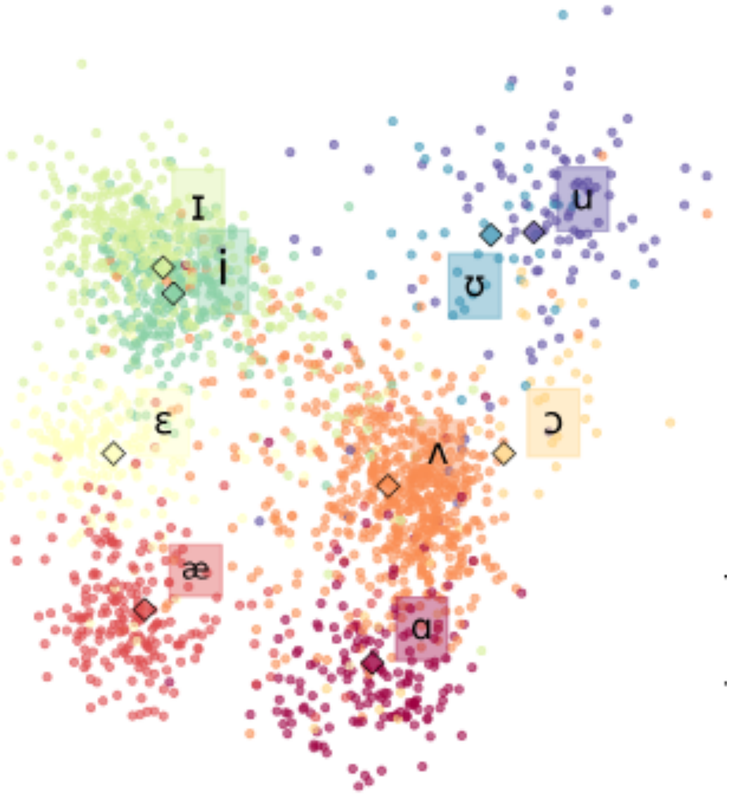

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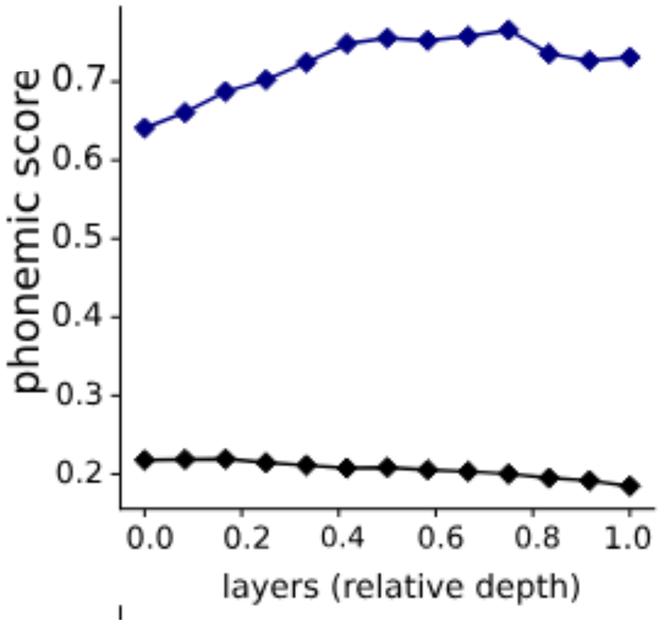

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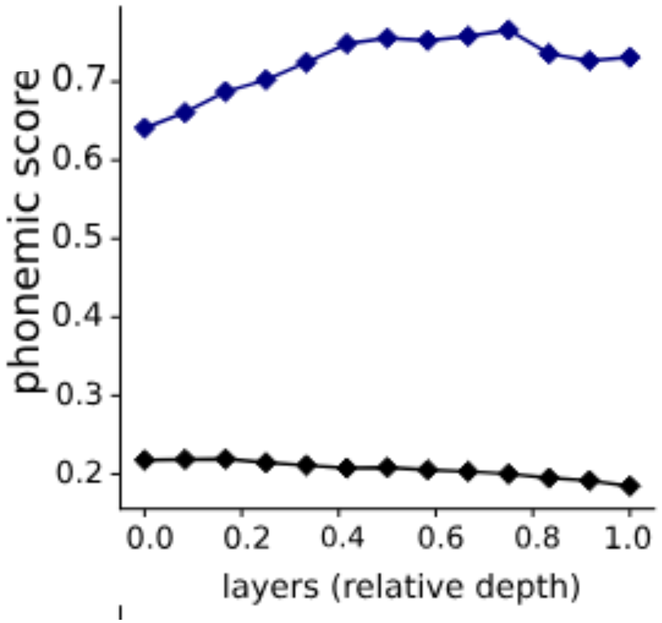
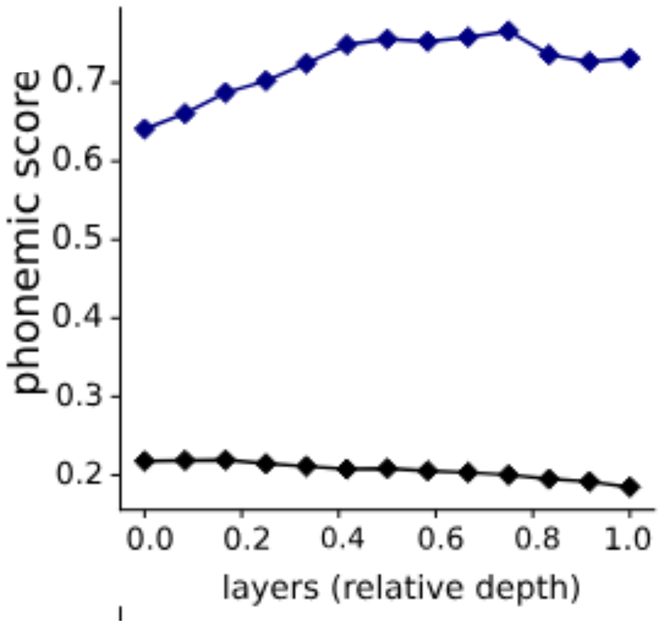
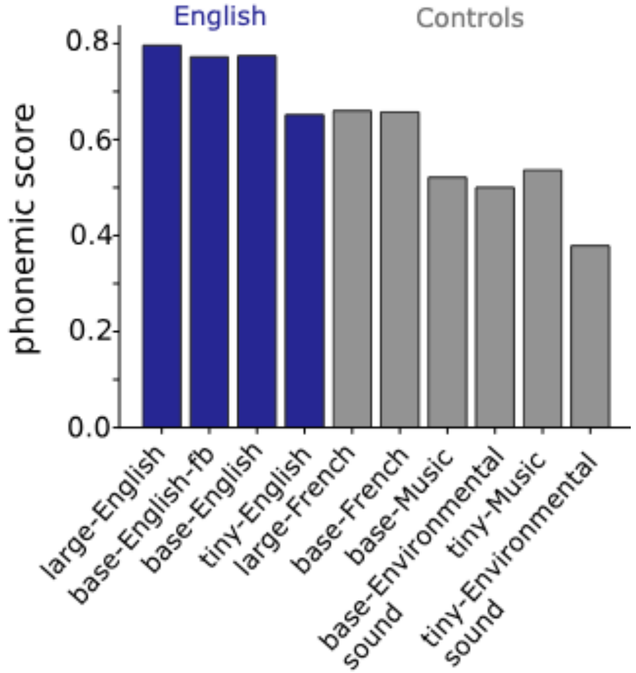


- **Left**: pretrained models (top) consistently outperform random initializations (bottom);

Phonemic Articulation





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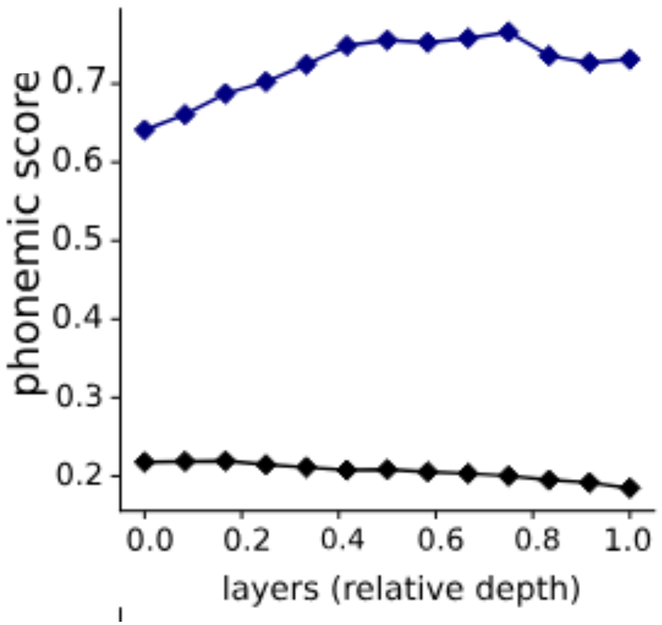
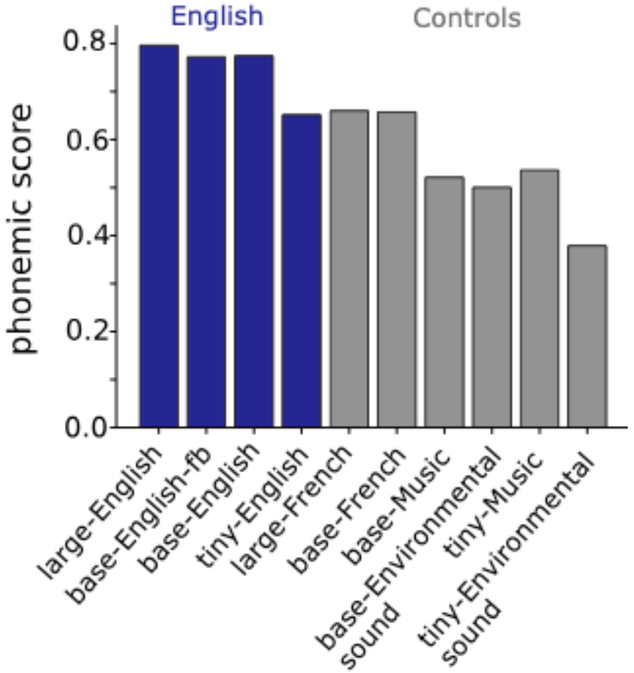
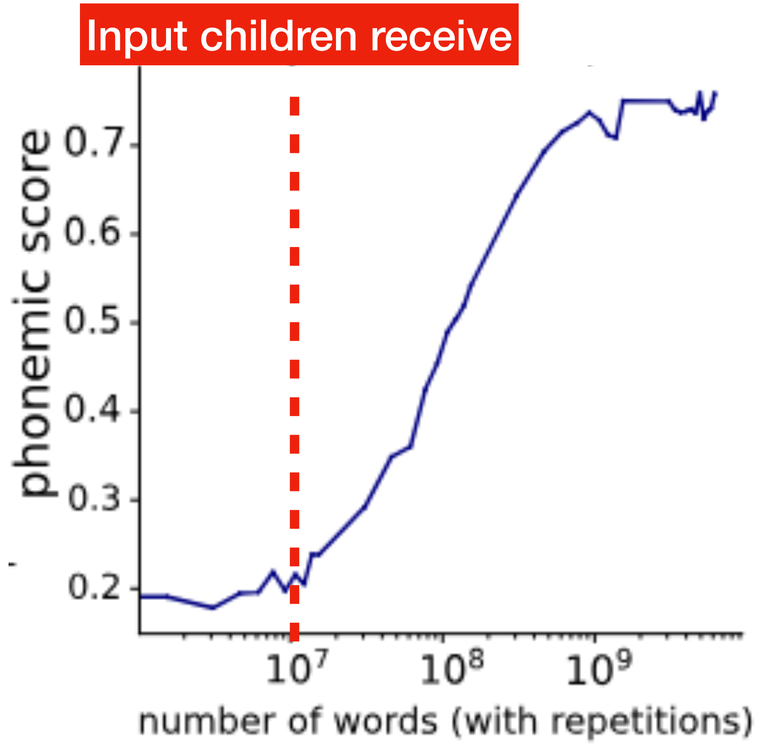


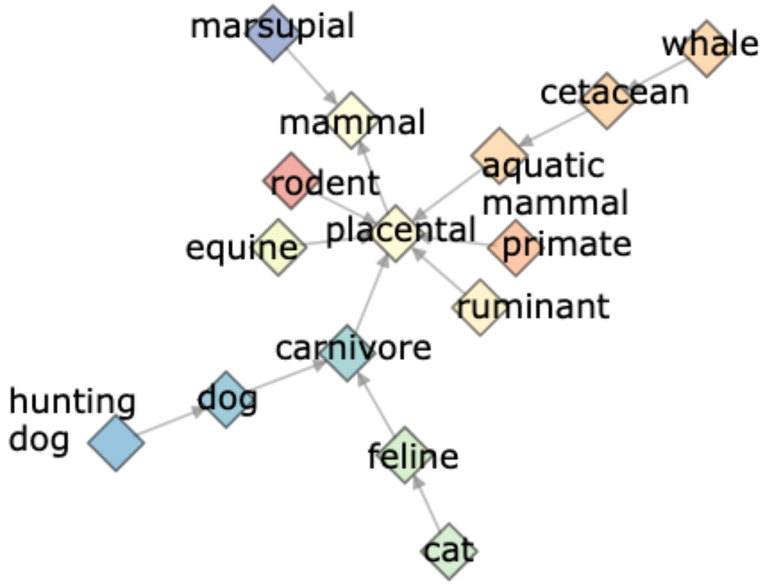




- **Left**: pretrained models (top) consistently outperform random initializations (bottom);
- **Mid**: English pretraining are better than control models (?); larger models are better;
- **Right**: the model gradually acquired this phonemic representation with 10^9 data, 100 times more than children input.

Lexical Semantics

- **Hypothesis**: text and speech models organize lexical informations into semantic structures, specifically, hypernym-hyponym relations.
- **Structural metric**: gold distance is path length in the WordNet hypernym graph.



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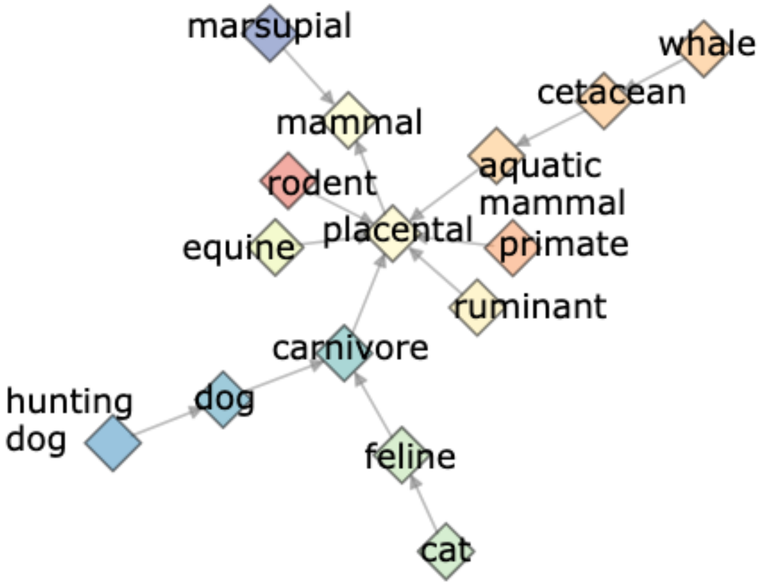

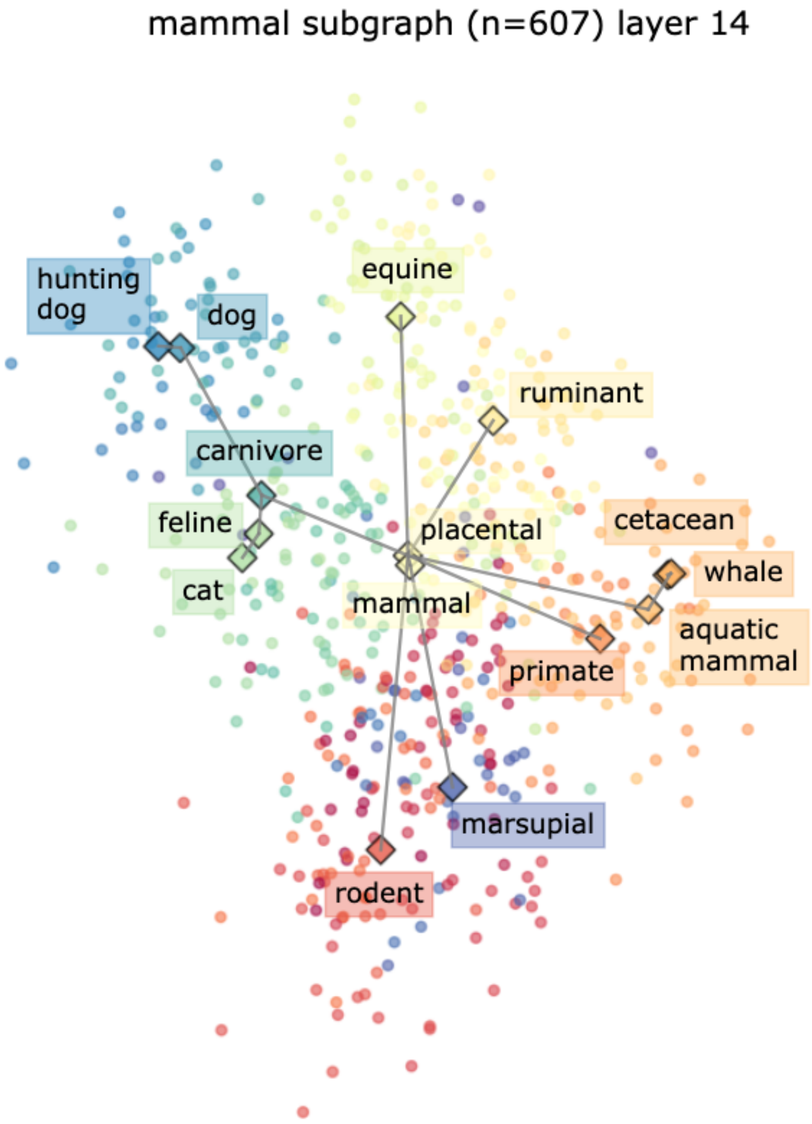

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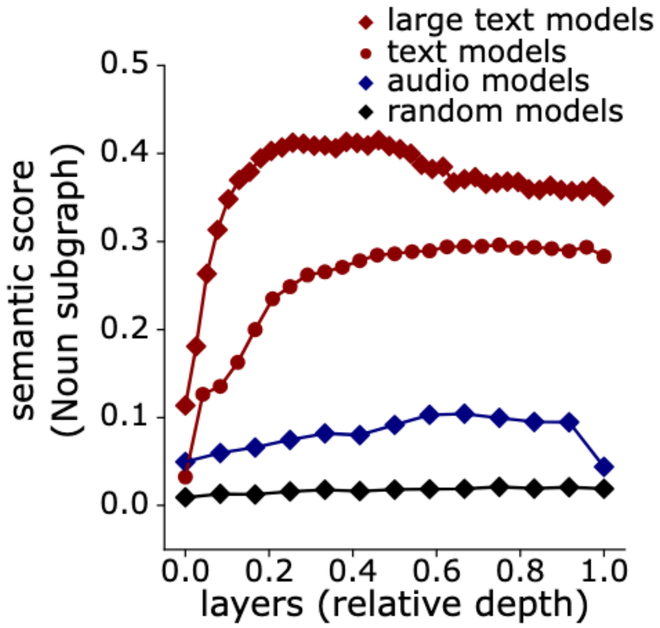

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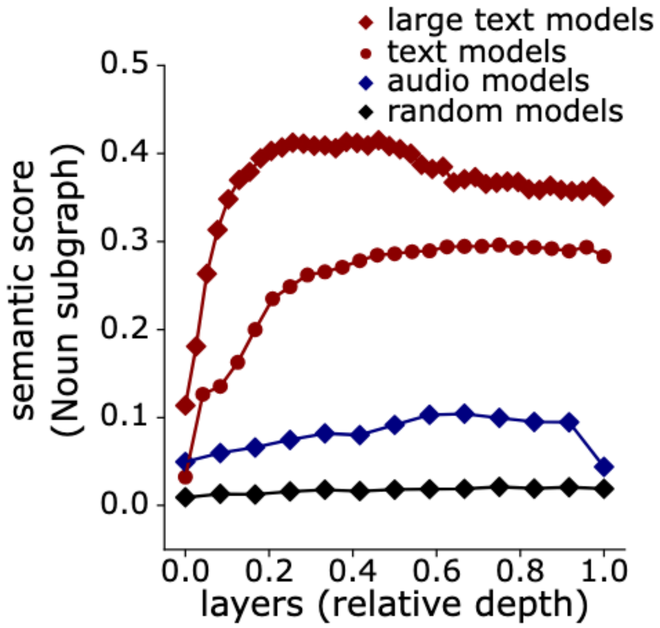

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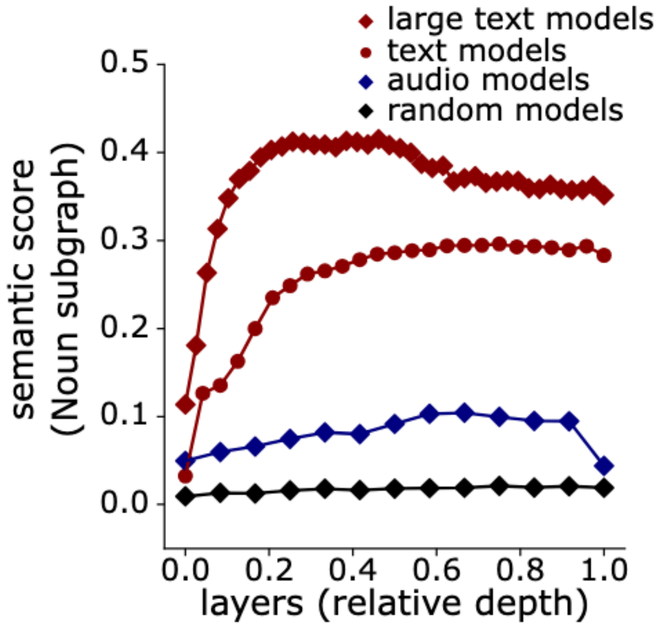
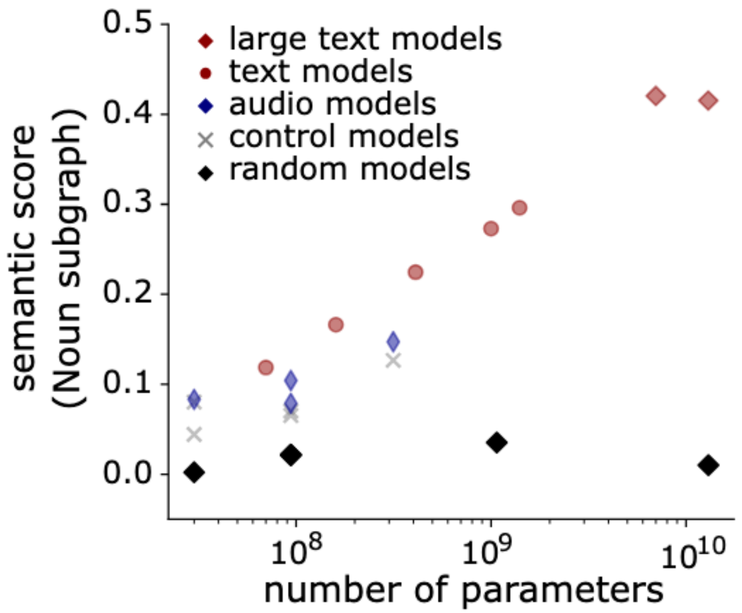
Lexical Semantics





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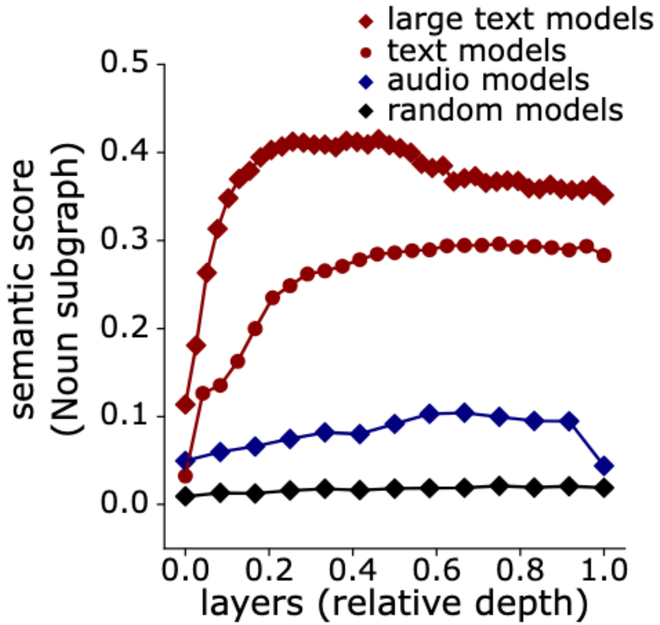

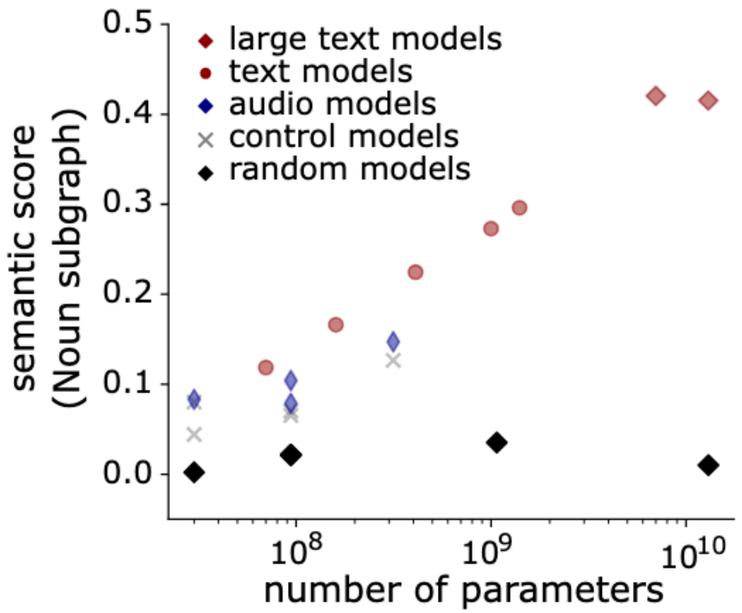

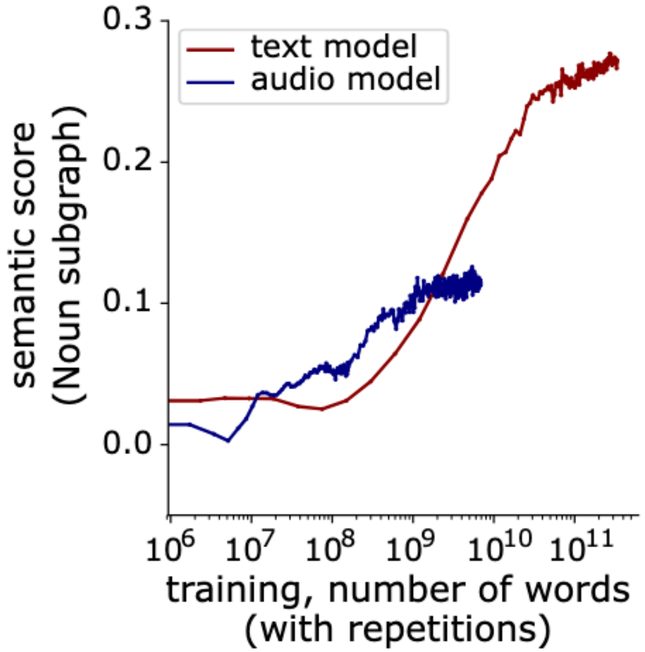

- **Left**: intermediate layers are better; scores are lower than phonemic;
- **Mid**: text models outperforms audio models; larger models are better; control achieves similar performance as audio models… confounding with acoustic properties…?!
- **Right**: audio semantic scores rise faster initially, but then saturate, whereas text-model scores continue to improve more substantially;

Taking all together: developmental stages?

- **Goal**: to see how the three properties emerge in relative order.

Phonemes

Lexical-
semantics

Syntax

Time 

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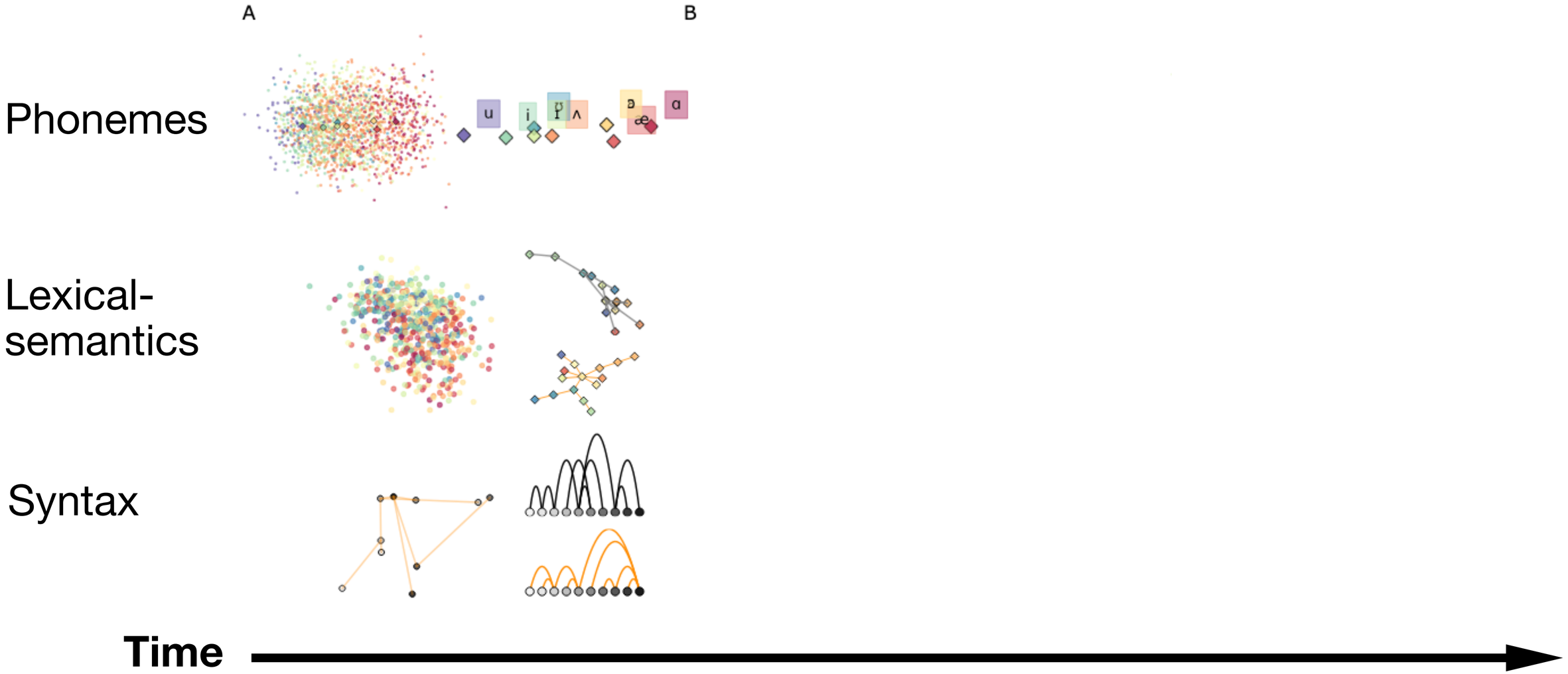

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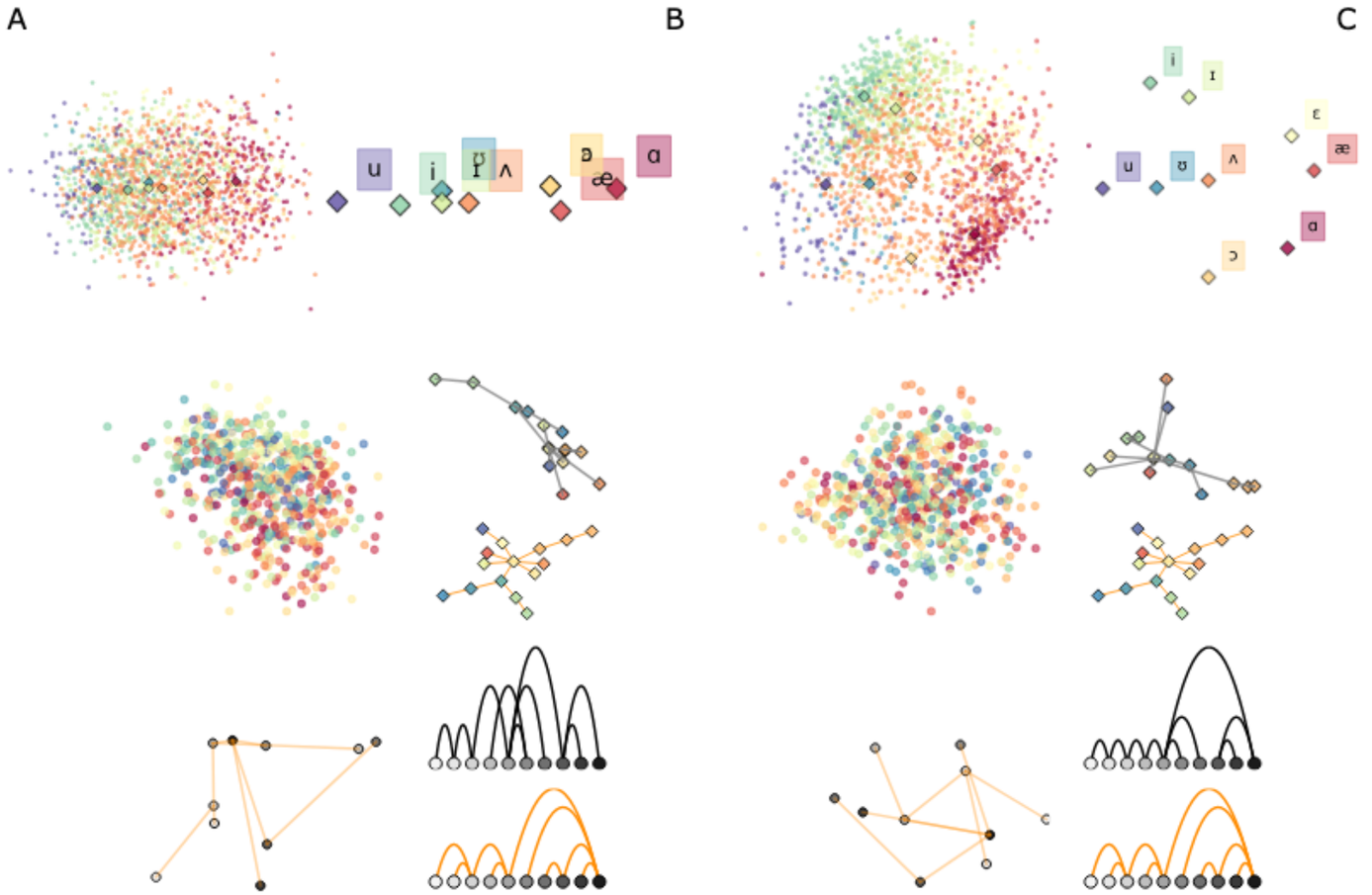

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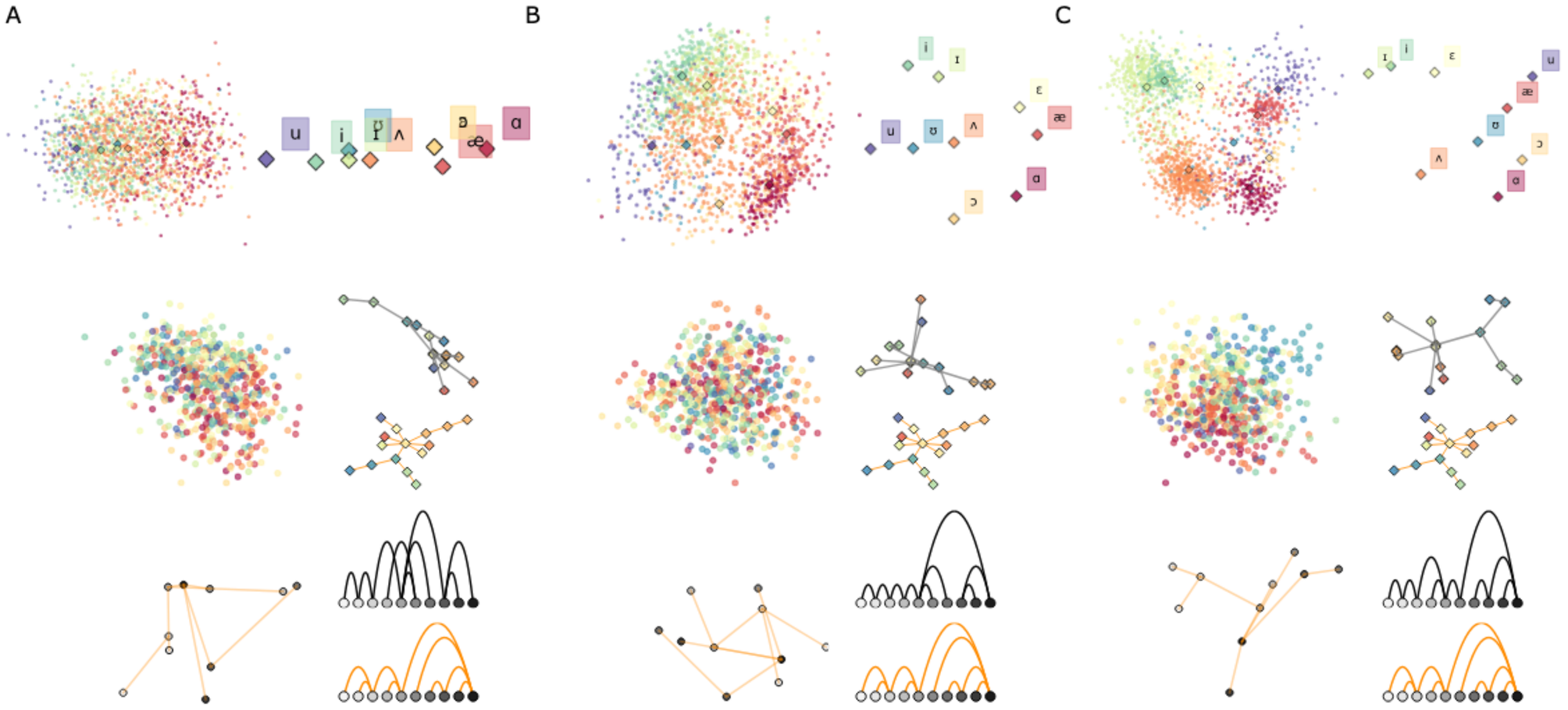

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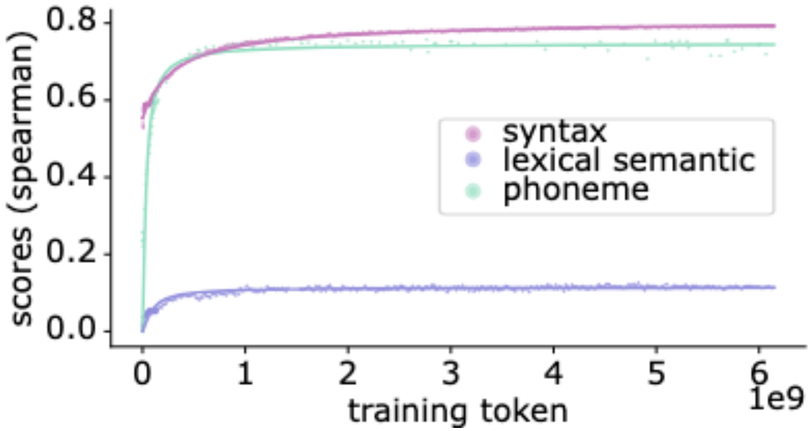
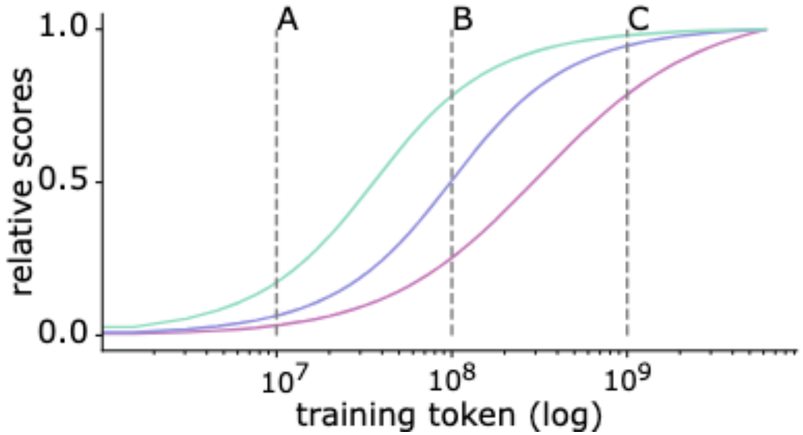
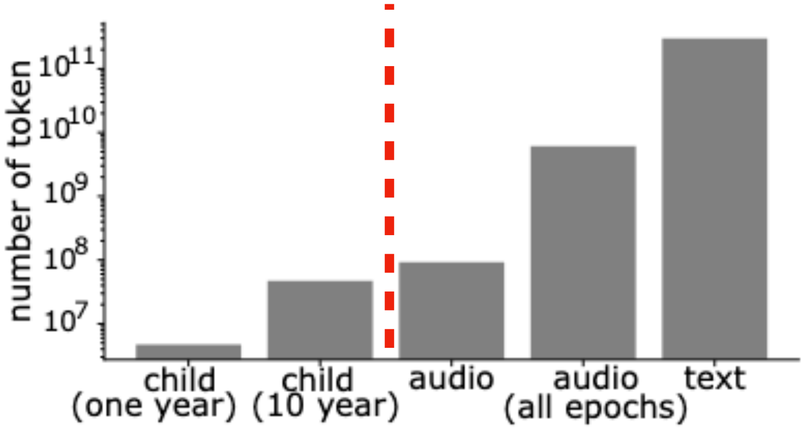
Wav2Vec 2.0







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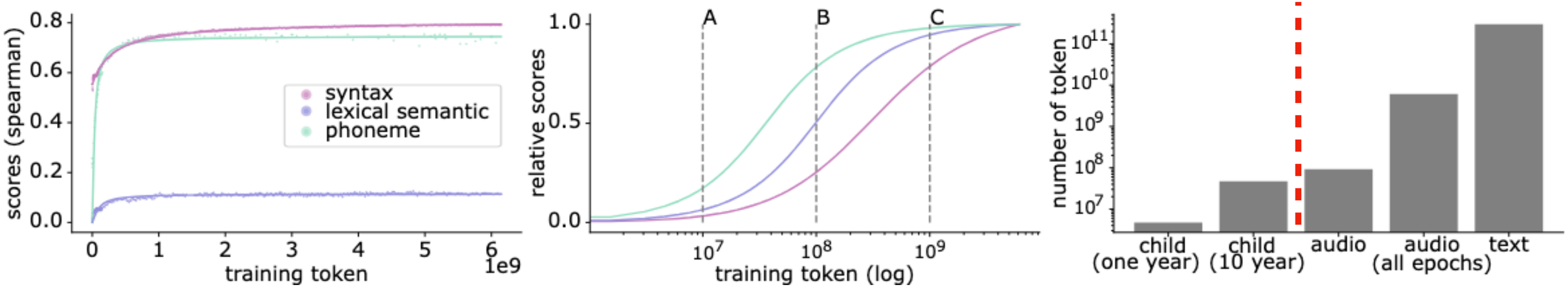

- **Left and Mid**: demonstrating successive order of acquisition (left = raw score, mid = cumulative score), all showing phoneme → lexical semantics → syntax.

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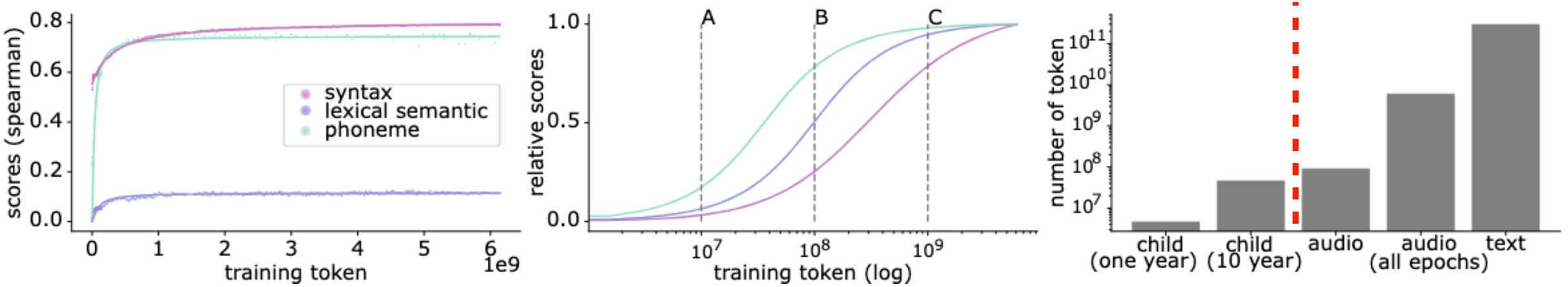

- **Left and Mid**: demonstrating successive order of acquisition (left = raw score, mid = cumulative score), all showing phoneme → lexical semantics → syntax.
- **Right**: compare to children input — although the developmental *order* is qualitatively reminiscent of child language acquisition, the *data efficiency* is radically different: the models require **2 to 4 orders of magnitude more data** for these representational structures to emerge.

Discussions

Critiques?

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- Can we reject the claim that: **the probe itself is too powerful to lead to such multi-level decodable linguistic structures?**

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  ✦ However, it is, after all, a supervised learning task, so some *representation learning* that could reshape the space in the desired way is inevitable.

  ✦ Think about what a linear operator could do: rotate the space, rescale dimensions, collapse nuisance variation, separate directions that are less important; amplifying structures that are originally entangled / distributed.

  ✦ …

Does structural probe target syntax only?

Evidence from Jabberwocky

Do Syntactic Probes Probe Syntax?
Experiments with Jabberwocky Probing

Rowan Hall Maudslay[1,2] **Ryan Cotterell**[1,2]
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A The Jabberwocky

'Twas brillig, and the slithy toves
Did gyre and gimble in the wabe;
All mimsy were the borogoves,
And the mome raths outgrabe.

"Beware the Jabberwock, my son!
The jaws that bite, the claws that catch!
Beware the Jubjub bird, and shun
The frumious Bandersnatch!"

He took his vorpal sword in hand:
Long time the manxome foe he sought—
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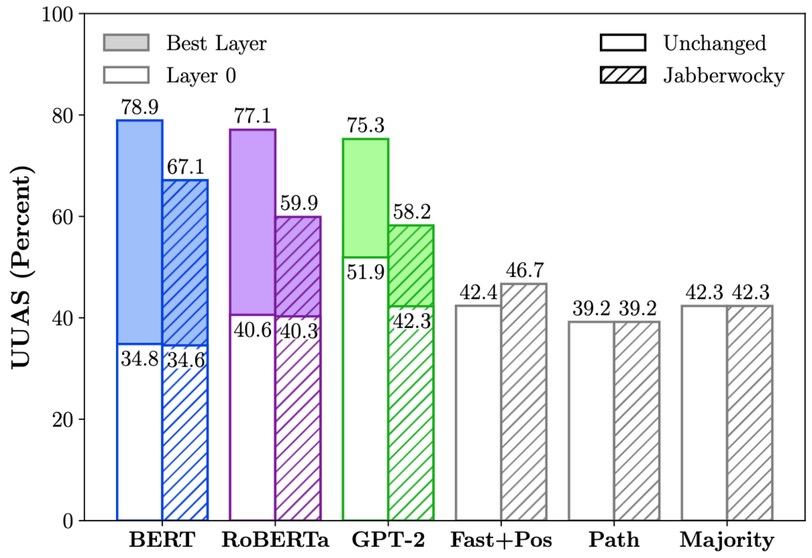
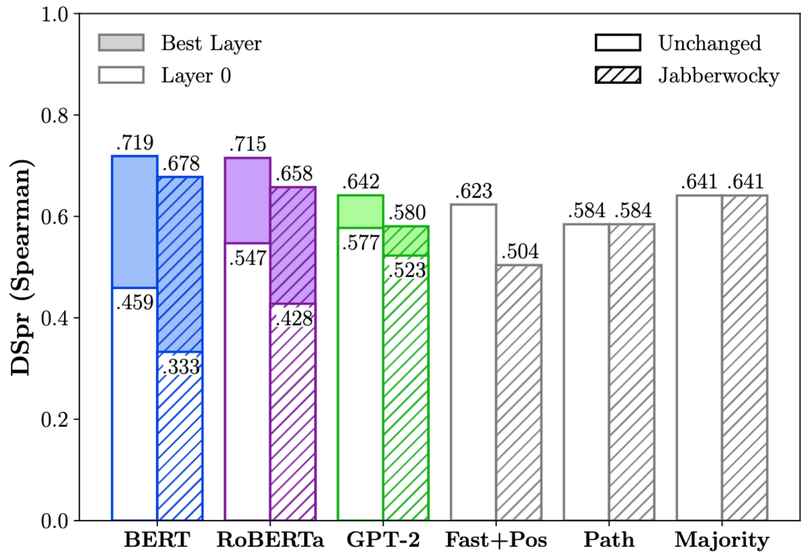


(a) UUAS results from the Perceptron Probe



(b) DSpr results from the Structural Probe

Figure 3: How the models fair when the probes are evaluated on unchanged sentences vs. the Jabberwocky.

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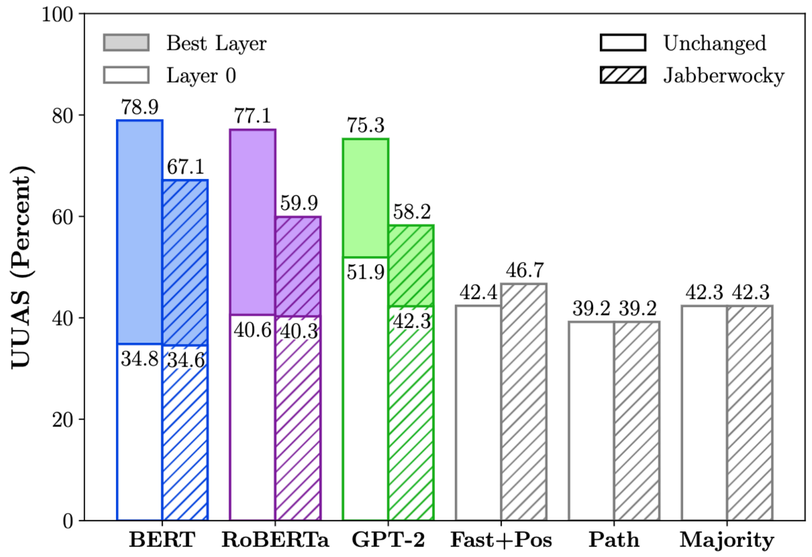

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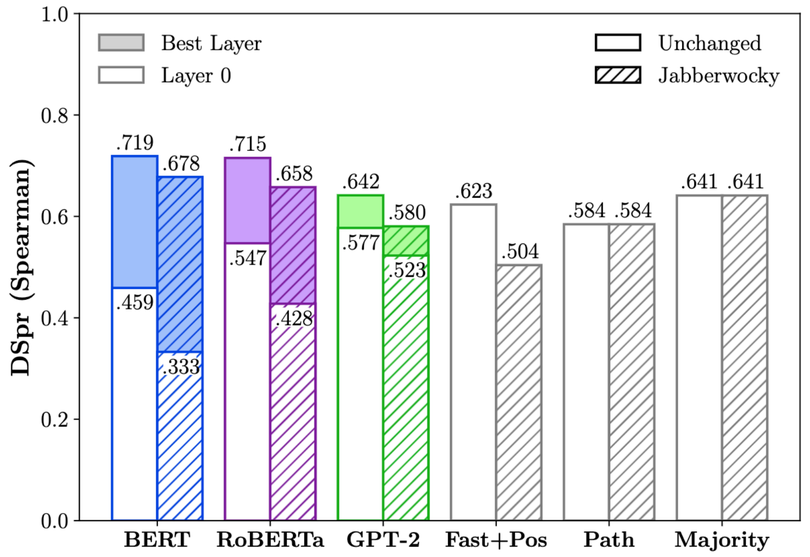

(b) DSpr results from the Structural Probe

Figure 3: How the models fair when the probes are evaluated on unchanged sentences vs. the Jabberwocky.

Takeaway:
structural probe does not propertly isolate syntax…

A The Jabberwocky

'Twas brillig, and the slithy toves
Did gyre and gimble in the wabe;
All mimsy were the borogoves,
And the mome raths outgrabe.

"Beware the Jabberwock, my son!
The jaws that bite, the claws that catch!
Beware the Jubjub bird, and shun
The frumious Bandersnatch!"

He took his vorpal sword in hand:
Long time the manxome foe he sought—
So rested he by the Tumtum tree,
And stood awhile in thought.

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    - But it is still elegant that the human-interpretable quantities naturally align with geometrical properties (hierarchical depth ↔ magnitude, dependency type ↔ orientation, and head direction ↔ orientation sign);
    - In principle, Cartesian coordinate can represent exactly the same information, thus it is possible to find an alternative $\mathbf{B}'$ that represents it in Cartesian….

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- For **theoretical syntacticians**: there are work probing formalisms / more complicated syntactic representations (e.g., empty categories) beyong dependency!

Further Recommended Reading

Hyperdimensional Probe

HYPERDIMENSIONAL PROBE: DECODING LLM REPRESENTATIONS VIA VECTOR SYMBOLIC ARCHITECTURES

A PREPRINT

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Carlo Nicolini Ipazia S.p.A., Milan, Italy
Bruno Lepri Fondazione Bruno Kessler (FBK), Trento, Italy
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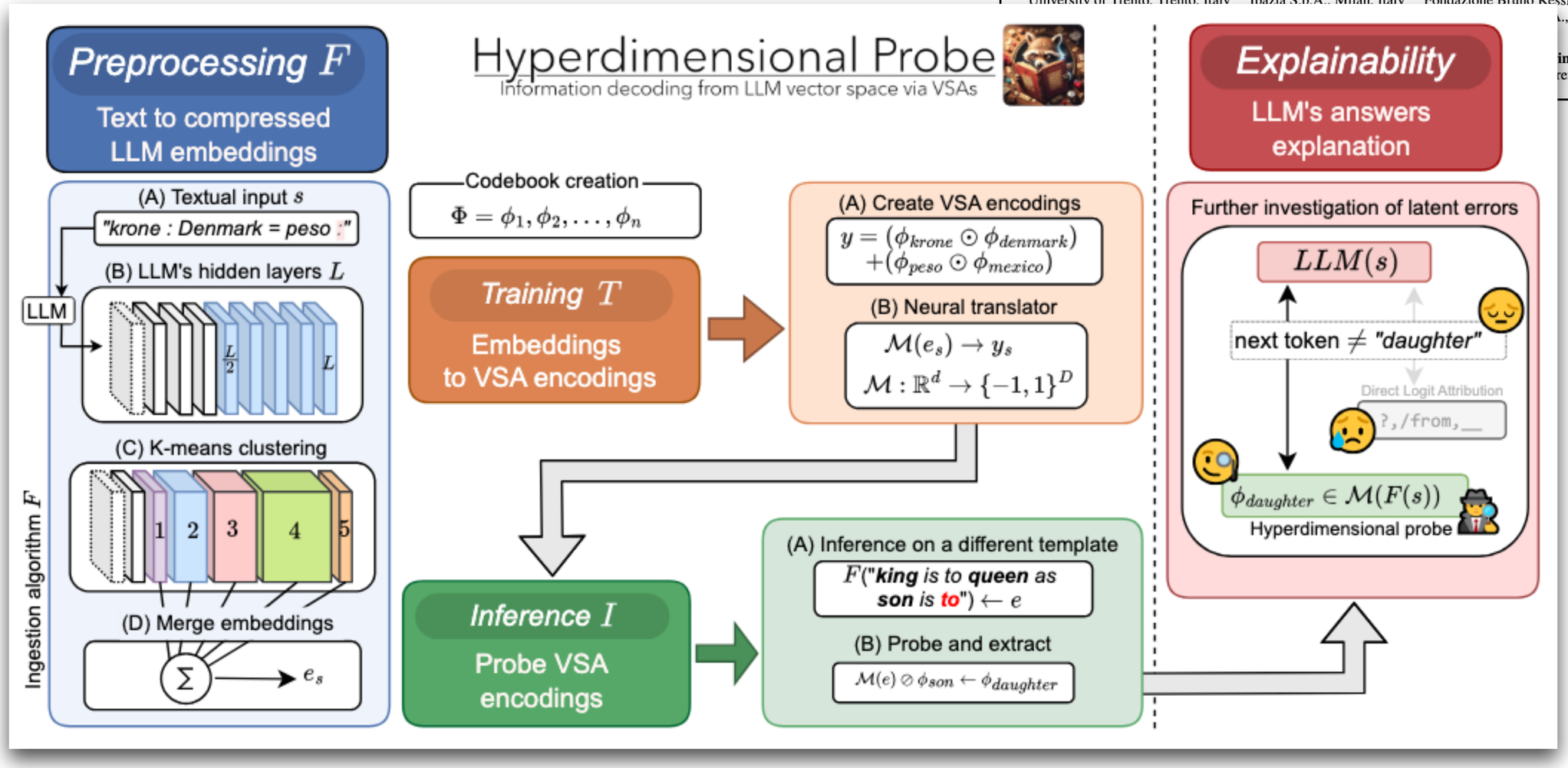

Thank you!