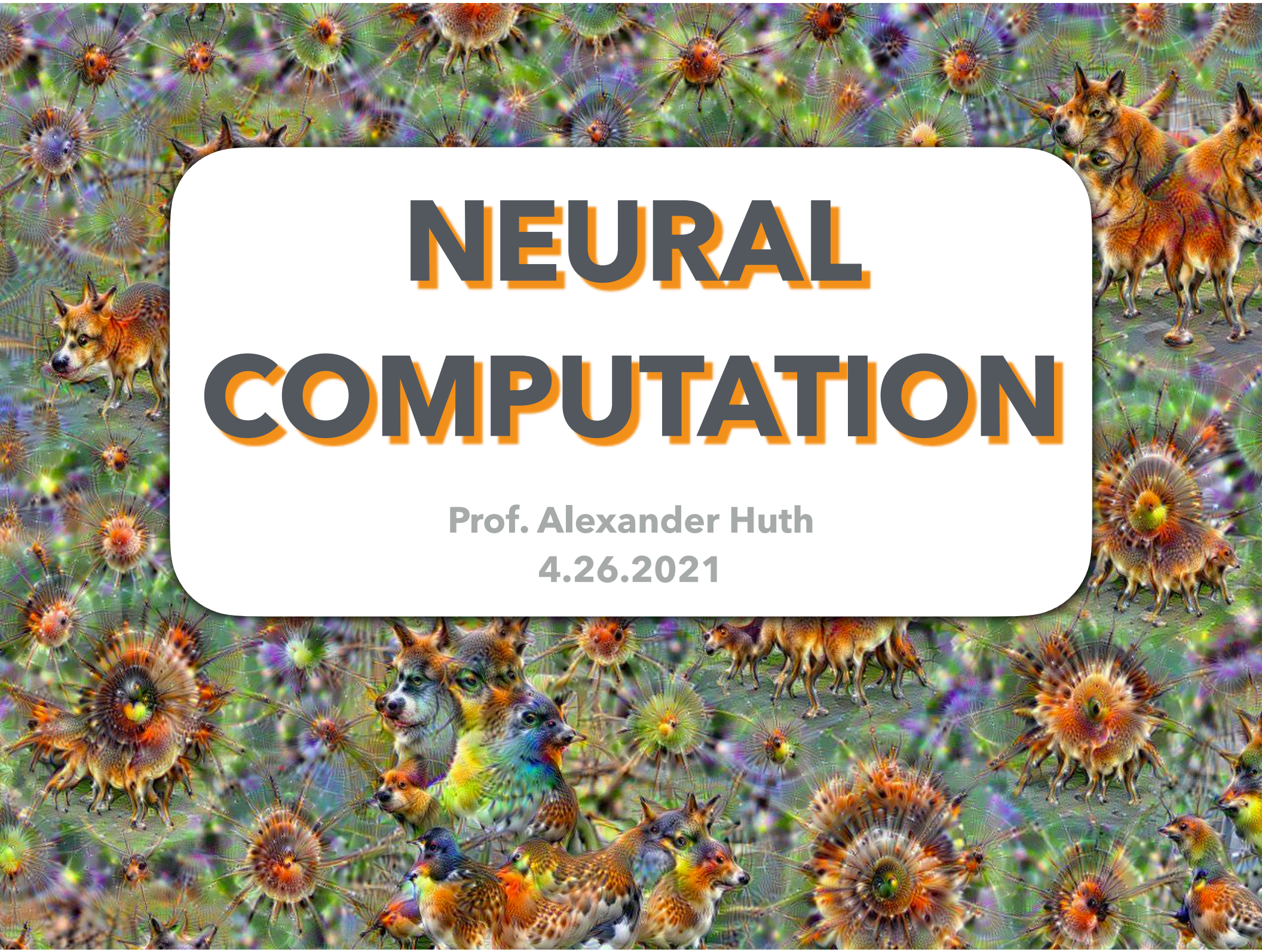

NEURAL
COMPUTATION
Prof. Alexander Huth
4.26.2021

COURSE ADMIN / PROJECT

* Writeup (3-4 pages explaining background & what you did) due **May 5**

* In-class presentations (5-10 minutes) **May 3 & 5**

PROJECT WRITE-UP

* Write-up due **May 5** (before class)
* Should be a PDF **<= 4 pages** including figures but *not* including references (i.e. references can appear on page 5+)
* Should discuss:
  * **Motivation** (what is problem, why are you doing what you are doing)
  * **Background** (related things in the literature, preferably >= 5 references)
  * **Methods** (what you did, & why) *<– most important*
  * **Results** (what you found) *<– least important*
  * **Individual contributions** (what each person in group was responsible for, including ideation, execution, & writing)

PROJECT PRESENTATION

* Presentations will occur during class periods **May 3 & 5**
* 5 presentations per class
* Each presentation should be 10-12 minutes, with 2-3 minutes for questions from other students
* Presentations should cover (at least) **Motivation**, **Methods**, & **Results**
* **Every member of the group** must participate in the presentation
* You may submit a recorded presentation (with same parameters as above) instead of doing it live if you strongly prefer

PROJECT PRESENTATION

* **Presentation schedule** is posted on canvas:
  * 5 presentations on Monday, May 3
  * 5 presentations on Wednesday, May 5

COURSE SURVEY

* Please fill out the course instructor survey: https://utdirect.utexas.edu/ctl/ecis/

RECAP

* How can we understand the representations learned in (biological or) artificial neural networks?
  * **Feature visualization** aka *receptive field mapping*
    * *What types of inputs drive this unit?*
  * **Attribution**
    * *What is it about <u>this</u> input that drives this unit?*

RECAP

* **Attribution** follows two strategies
  * **Perturbation**
  * **Gradient attribution**

RECAP

* **Perturbation:**
  * Change something about the input. If the response of the selected unit changes, then the unit cared about the thing that was changed.
  * e.g. Bubbles

RECAP

* **Gradient attribution:**
  * Compute the derivative of the selected unit activation with respect to each element (e.g. pixel) of the input. The magnitude of the derivative should be related to the importance of that input element.

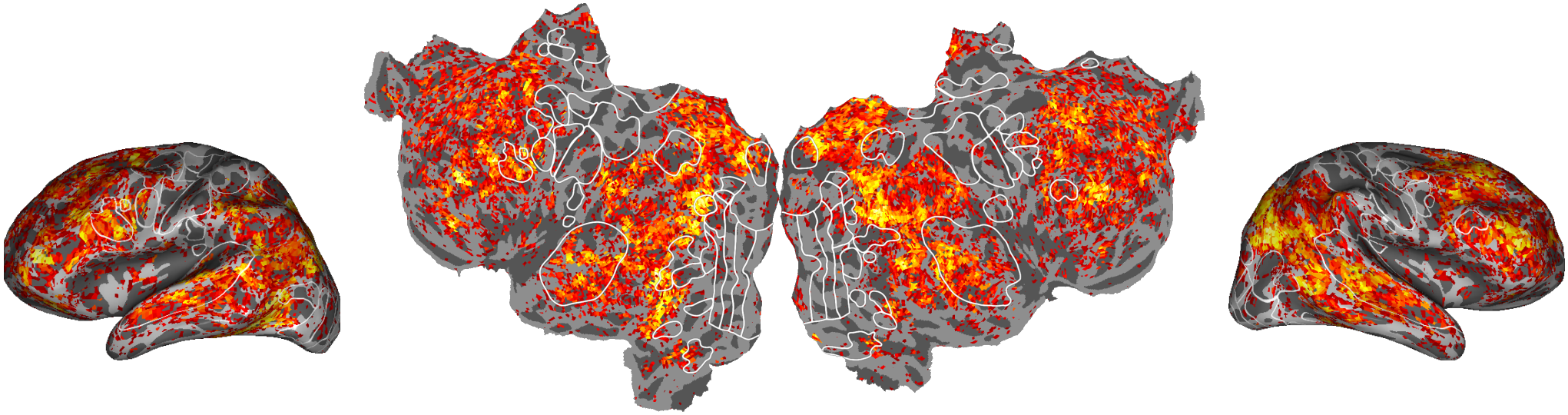
LANGUAGE PROCESSING

* *How is the meaning of language represented in the brain?*

* Let's do an experiment: record BOLD responses from subjects while they listen to natural language (stories)

"Close your eyes and let the word paint a thousand pictures..."

LANGUAGE PROCESSING



* Earlier studies (e.g. Huth et al., 2016): responses to natural language can be explained pretty well using **system identification models** based on **word embeddings**

LANGUAGE PROCESSING

* Models based on word embeddings assume that the brain responds **independently** to each word

  * How do we model **phrases**?

"Word pictures let a
and your thousand
paint the eyes close…"

LANGUAGE MODELS

* One way to represent phrases is to use a **neural network language model**, which learns to predict the next word from the previous words
  * i.e. modeling $\mathbf{P}(w_t \mid w_{t-1}, w_{t-2}, w_{t-3}, \ldots)$
  * *We talked about **long short-term memory (LSTM)** language models back in lecture 17*

LANGUAGE MODELS

* But the best language models use a different architecture: the **Transformer network** *[Vaswani et al., 2017]*

* Instead of recurrence, Transformers use a mechanism called **dot product self-attention**

TRANSFORMERS

* Given: a sequence of words [w_1, …, w_t], each represented as a d-dimensional embedding vector

* To predict word w_{t+1} we do the following:

  * First, multiply each word by 3 weight matrices: $W_Q w_i = Q_i$, $W_K w_i = K_i$, $W_V w_i = V_i$

    * These are now called the **Q**uery, **K**ey, and **V**alue

TRANSFORMERS

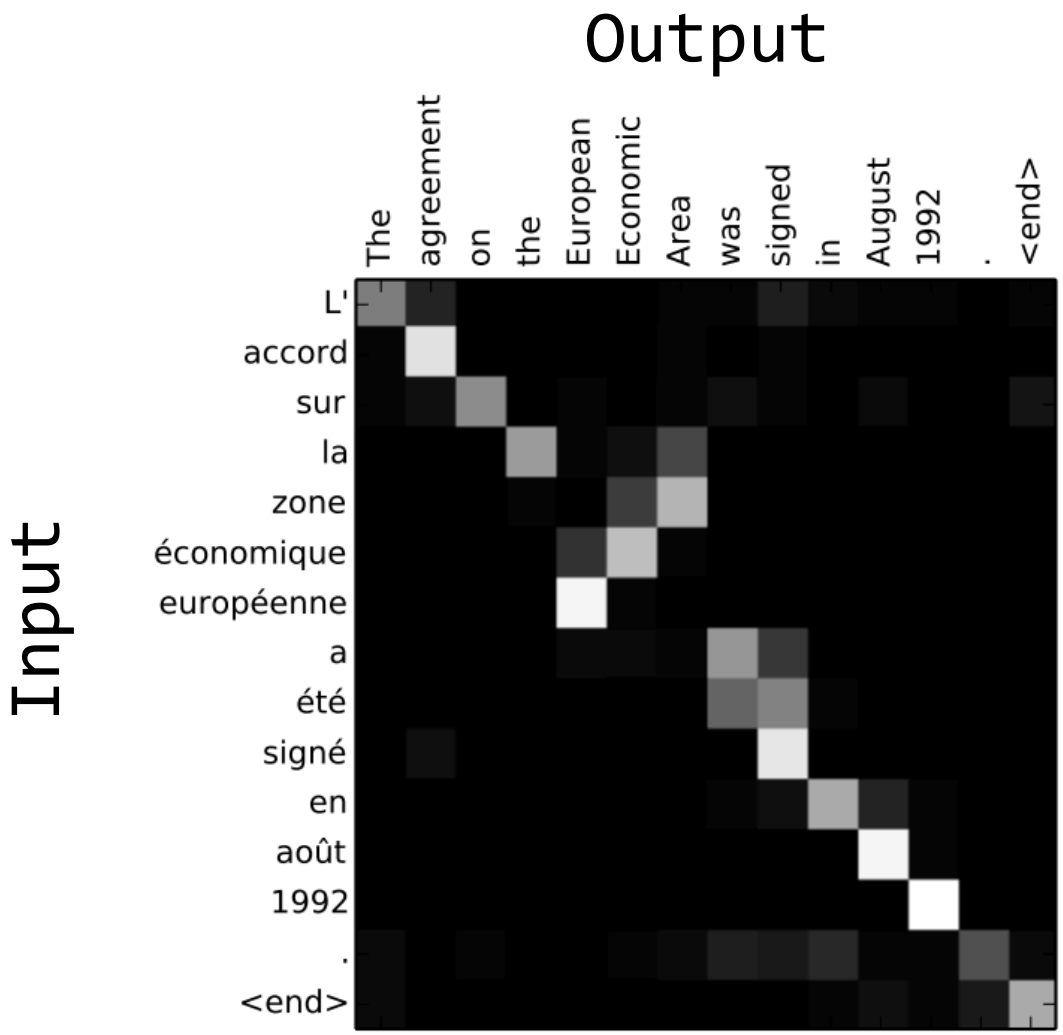
* Concatenate the vectors for all the words together into Query, Key, and Value matrices Q, K, & V (each is d x t)

* Use these matrices to compute **attention outputs**:

$$\text{Att}(Q,K,V) = \text{softmax}(QK^T)V$$

attention weights, sum to 1 for each word

TRANSFORMERS



From https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

TRANSFORMERS

* This attention procedure is done many times (e.g. 12) in parallel with different W_Q, W_K, & W_V matrices

  * Each one is called an ***attention head***

* The outputs of all attention heads are concatenated and then multiplied by another weight matrix to get the layer output:

$$\text{Concat}(\text{Att}(Q^1,K^1,V^1), \text{Att}(Q^2,K^2,V^2), \ldots)W_O$$

TRANSFORMERS

* These transformer layers are then stacked: the output vector at each word replaces the word embedding, and the procedure is repeated

  * Modern transformer networks are huge. The largest GPT-2 model has **48 layers** and **1.5B parameters**, and was trained on **~40GB of text** scraped from the internet

TRANSFORMERS

* *"But wait,"* you might ask, *"how does this network know what order the words come in??!"*
    * There is *nothing* in this basic architecture that captures word order
* To give the network information about order, a **positional embedding vector** is added to the input embedding
    * One typical positional embedding uses sine and cosine functions with different frequencies:

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

TRANSFORMERS

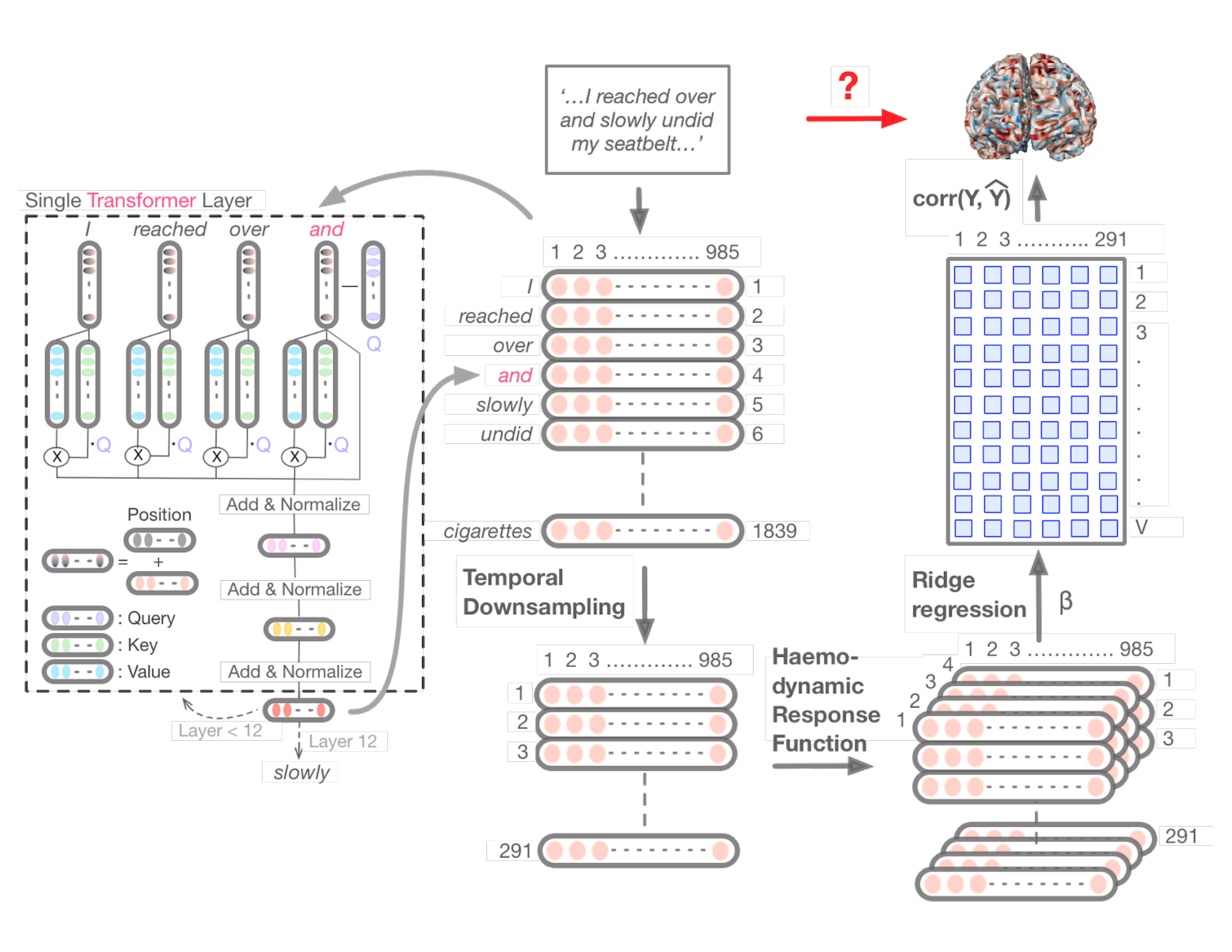
* Interesting aside: positional embeddings enable the transformer to act like a generalized convolutional network *[Cordonnier et al., 2020]*

  * Depending on the learned weights, the network can accentuate information based on **relative position** (i.e. positional embedding) or based on **content**

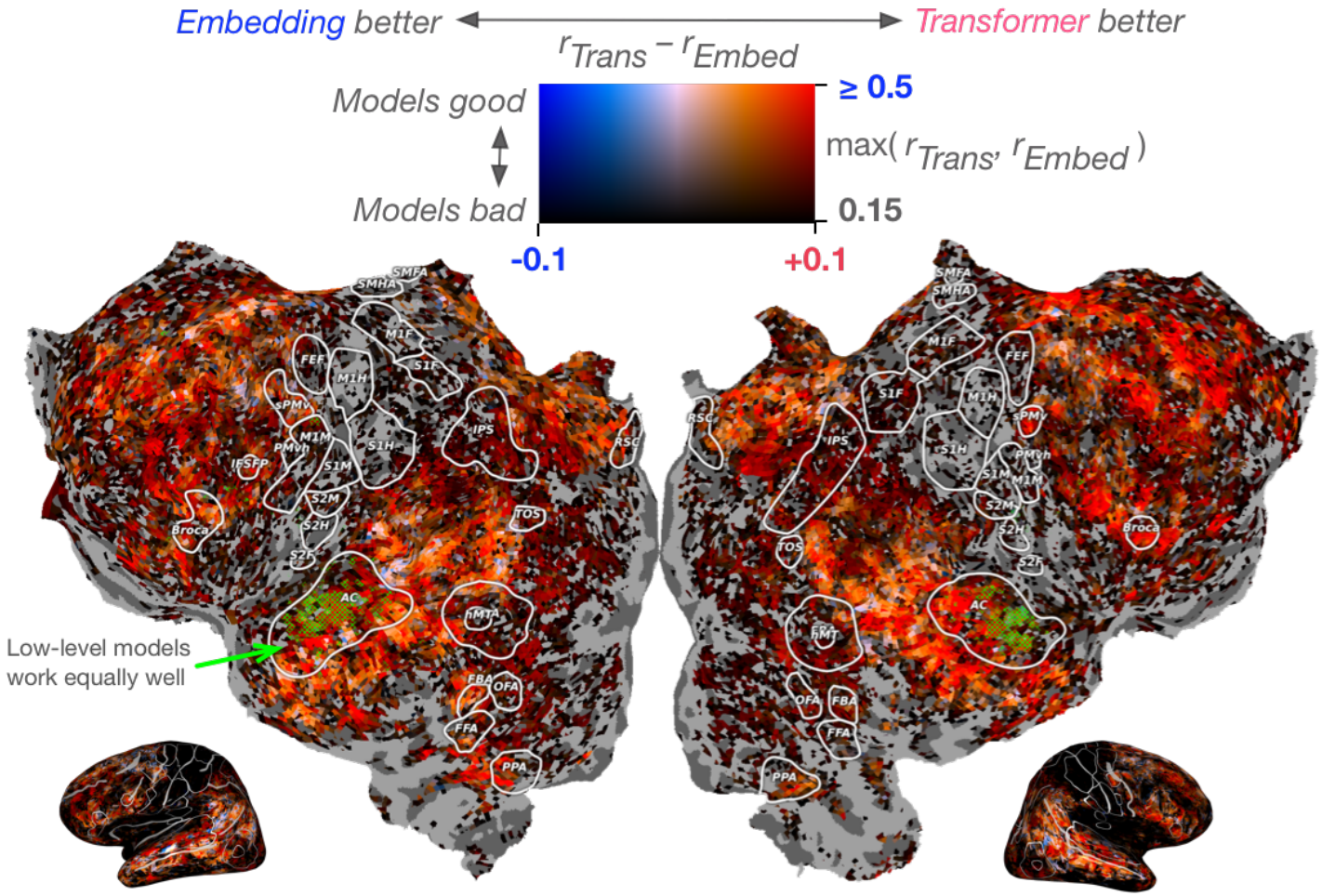
  * See https://epfml.github.io/attention-cnn/

TRANSFORMER LANGUAGE MODEL: GPT

* To model how the brain responds to language, we (Shailee Jain) use a pretrained transformer language model called **GPT** *[Radford et al., 2018]*
  * GPT is a 12-layer transformer model with 12 attention heads per layer
* We can use these representations, instead of simple word embeddings, to predict brain activity


'...I reached over and slowly undid my seatbelt...'
?
corr(Y, Ŷ)
1 2 3 291
1 2 3 985
I
reached
over
and
slowly
undid
cigarettes
1839
Single Transformer Layer
Q
X
Add & Normalize
Position
: Query
: Key
: Value
Layer < 12
Layer 12
slowly
Temporal Downsampling
Ridge regression
β
Haemo-dynamic Response Function
V

TRANSFORMER LM →



* Transformer model **substantially outperforms word embeddings** for system identification

TRANSFORMER LM → 

* So how can we use this model to understand representations in the brain?
  * **Feature visualization:** which inputs make this “unit” active?
  * **Attribution:** what about this input makes this “unit” active?

TRANSFORMER LM → 

* Here a “unit” is a **voxel**, whose activation Y_i we model as the dot product between a set of weights β_i and a transformer representation T(X) of the phrase X:

$$Y_i \approx T(X)\beta_i$$

TRANSFORMER LM → 

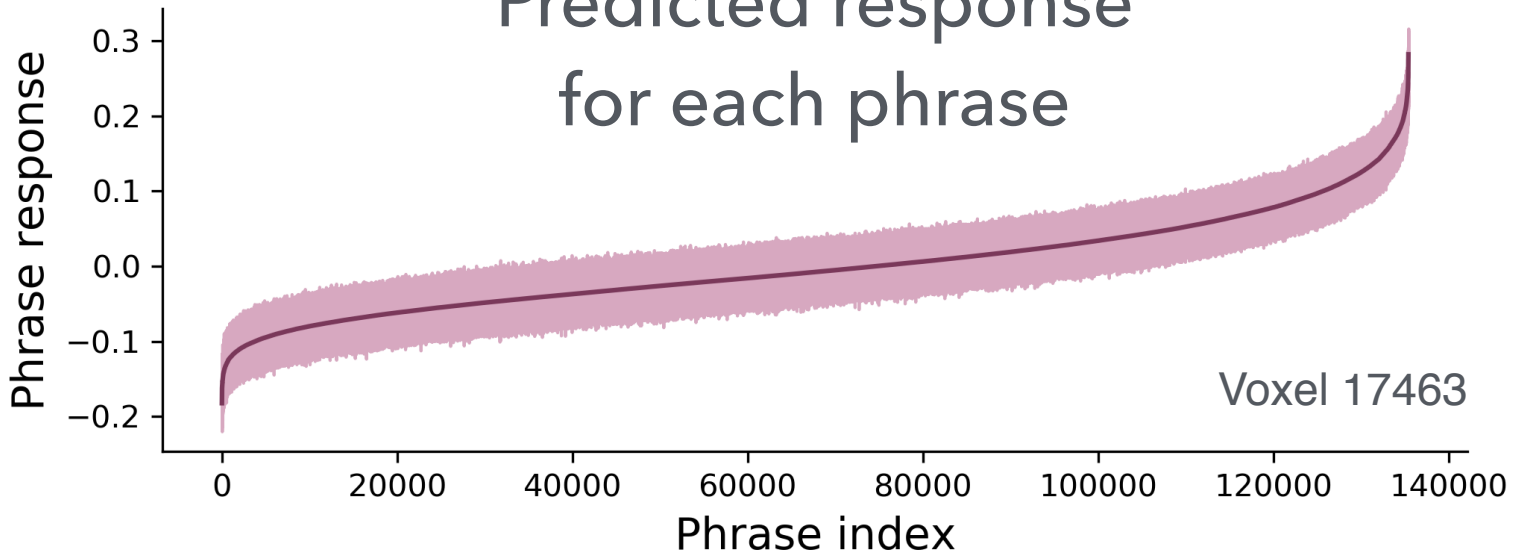
* Let’s do **feature visualization**:
  * **Build** library of phrases (140k)
  * **Predict** response to each ($Y_i \approx \ldots$)
  * **Examine** phrases with highest predicted response

TRANSFORMER LM →

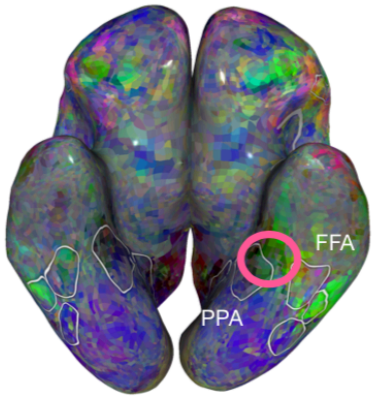
140,000 phrases
(10 words each)

Voxel Model

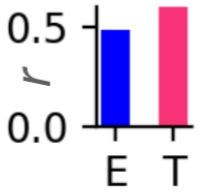
Predicted response
for each phrase



TRANSFORMER LM → 



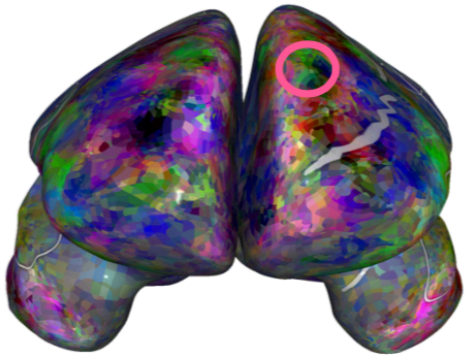
Voxel: 17463
Parahippocampal



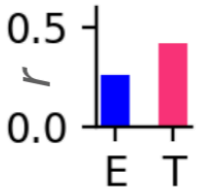
Best Transformer Phrases	Best Embedding Words
and the only place to turn around on the bay bridge	*shops*
	parking
pool with just grubby little changing rooms and a small cafe	*building*
got to Hardiwar our journey ended in a municipal car park	*campus*
	cafe
down the street and across the street at a coffee shop	*street*

* This shows both **best phrases & best words** (acc. to embedding model). Both give ~similar understanding

TRANSFORMER LM → 



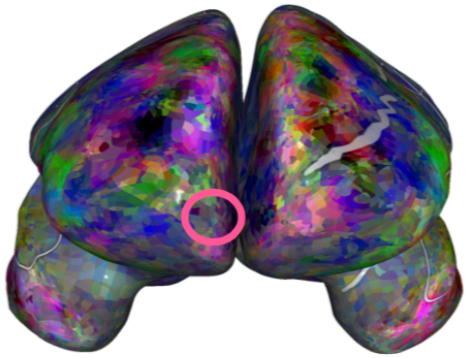
Voxel: 80162
Superior frontal



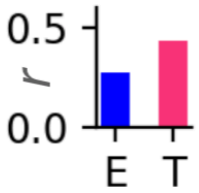
Best Transformer Phrases	Best Embedding Words
but I also knew that I wasn't doing well in law	*financial*
a lesson in it I had been awarded a prestigious research	*working*
way these two guys are boy scouts they were literally eagle	*cash*
artsy he seemed so exotic and interesting he was the creative	*employment*
	jobs
	investment

* Here the best phrases are **more specific** than the best words

TRANSFORMER LM → 



Voxel: 42436
Medial frontal



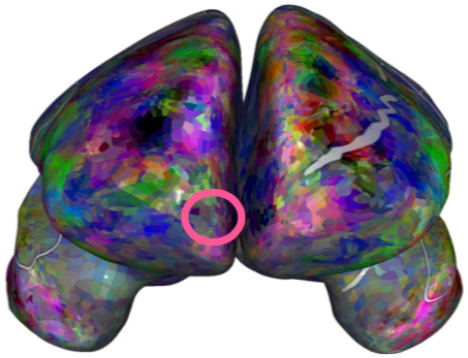
Best Transformer Phrases	Best Embedding Words
motioned for me to sit next to him and thanked me	*charming*
	gentleman
started to ask the lady a question she said excuse me	*pleased*
and she comes out and she says look I'm really sorry	*smiled*
	friendly
you should probably go check in there so I say thanks	*kindness*

* Here the best phrases show **examples** while the best words **describe**

TRANSFORMER LM → 

* Let's do **attribution** using **perturbation**:
  * Take a 10-word phrase X and its predicted response $Y_i(X)$
  * Generate 10 perturbed versions of the phrase $[X'_1, \ldots, X'_{10}]$, each with one word replaced by a null word ('UNK')
  * Predict response to each perturbed phrase $[Y_i(X'_1), \ldots, Y_i(X'_{10})]$
  * Compute **importance** of word j in the phrase as
    $\text{Importance}(X_j) = (Y_i(X) - Y_i(X'_j)) / Y_i(X)$

TRANSFORMER LM → 

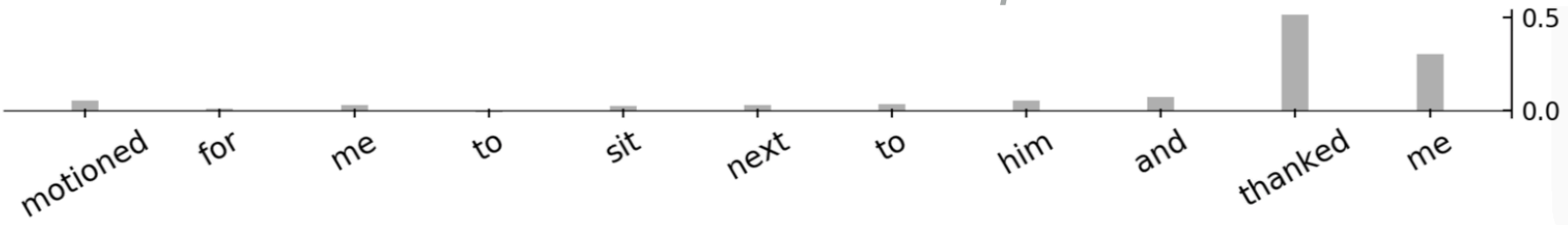


Voxel: 42436
Medial frontal

Best Transformer Phrases

motioned for me to sit next to him and thanked me

Importance score for each word in this phrase



* This voxel's response hinges on the word *"thanked"*, suggesting **politeness** is important?

TRANSFORMER LM → 

* We combined **system construction**, **system identification**, **feature visualization**, and **attribution** techniques to help understand how the meaning of language is represented in the human brain

  * What it all means? We're not sure yet, but we have the right tools to measure it!

NEXT TIME

* Neural taskonomy & conclusions!