





# Neural Language Taskonomy: Which NLP Tasks are the most Predictive of fMRI Brain Activity

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# What is fMRI?

At three o'clock precisely I was at Baker Street, but Holmes had not yet returned. The landlady informed me that he had left the house shortly after eight o'clock ...

It was close upon four before the door opened, and a drunkenlooking groom, ill-kempt and side-whiskered, with an inflamed face and disreputable clothes, walked into the room. Accustomed as I was to my friend's amazing powers in the use of disguises, I had to look three times before I was certain that it was indeed he.

"Well, really!" he cried, and then he choked; and laughed again until he was obliged to lie back, limp and helpless, in the chair.

"What is it?"

"It's quite too funny. I am sure you could never guess how I employed my morning."

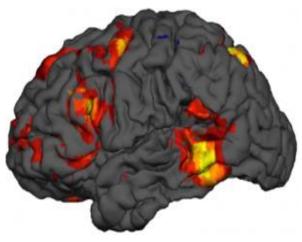
"I can't imagine. I suppose that you have been watching the habits, and perhaps the house, of Miss Irene Adler."

"Quite so; but the sequel was rather unusual. I will tell you, ... I soon found Briony Lodge. It is a bijou villa, with a garden at the back, but built out in front right up to the road, ...

### Text Corpus



### A language task in the scanner



fMRI Brain Activity

https://www.biopac.com/events/fmri-psych/

# Brain Encoding vs Decoding

Stimulus Representation

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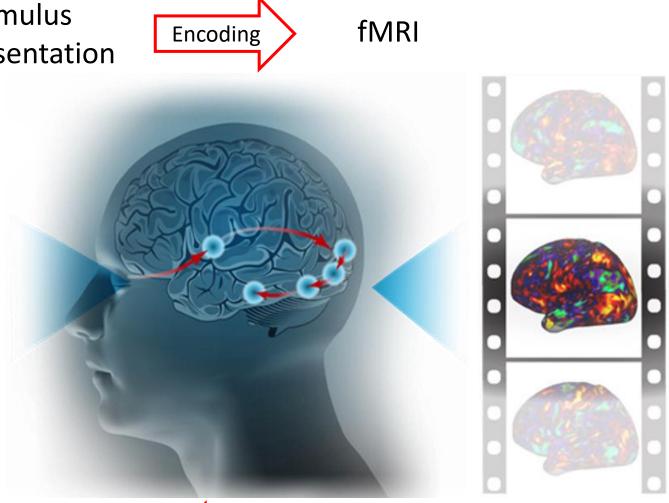
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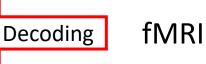
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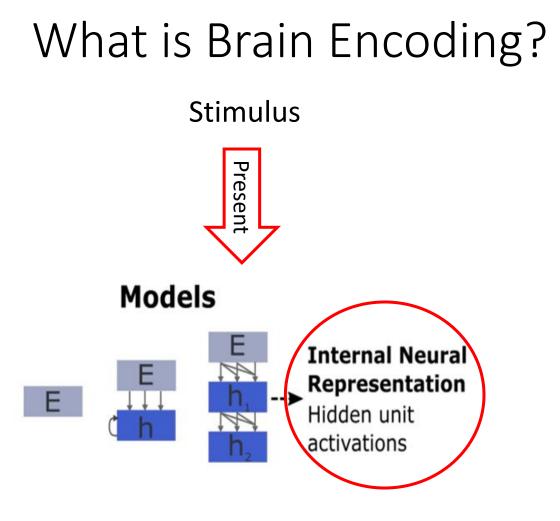
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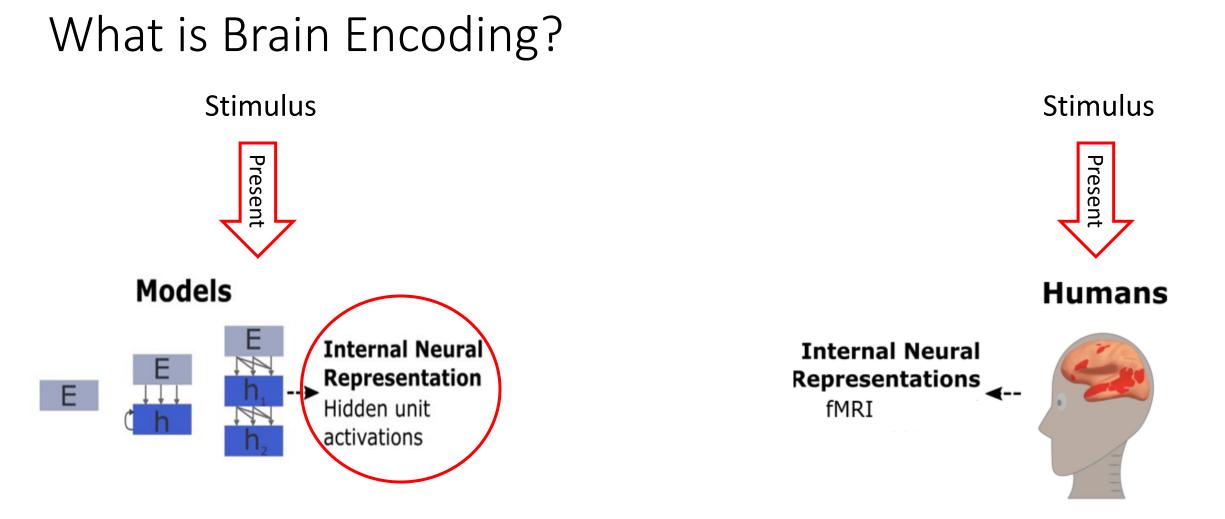


**Stimulus** Representation

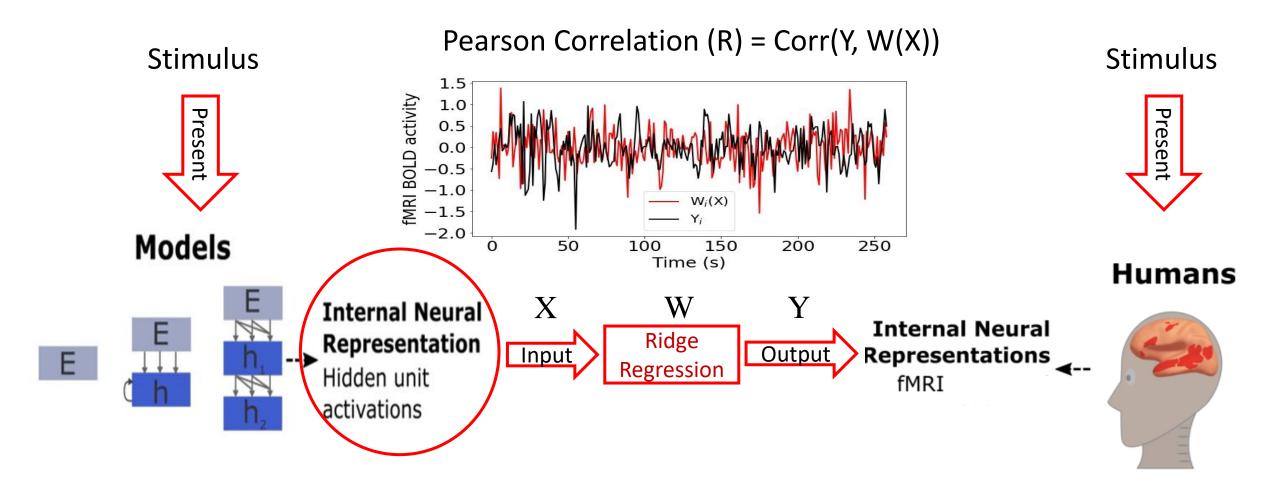


Haiguang Wen et al, 2017

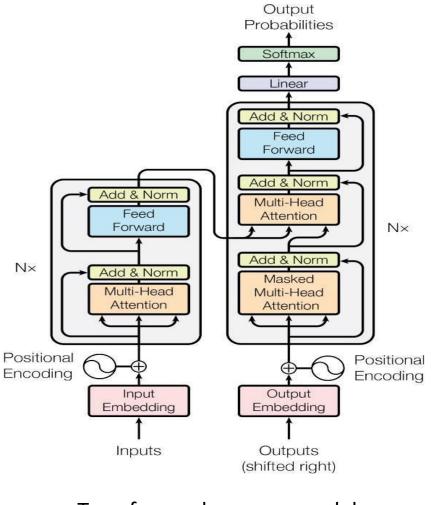




# What is Brain Encoding?



# Most popular language models are Transformers



Transformer language models (BERT, XLM, GPT,...)

# Pretrained language models accurately predict brain activity

### The neural architecture of language: Integrative modeling converges on predictive processing

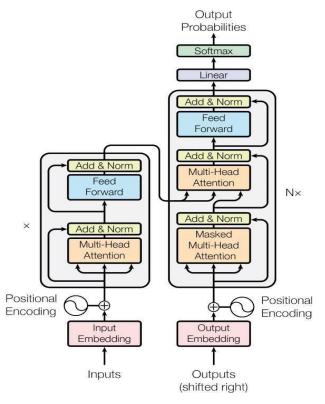
Martin Schrimpf<sup>a,b,c,1</sup>, Idan Asher Blank<sup>a,d,2</sup>, Greta Tuckute<sup>a,b,2</sup>, Carina Kauf<sup>a,b,2</sup>, Eghbal A. Hosseini<sup>a,b</sup>, Nancy Kanwisher<sup>a,b,c,1</sup>, Joshua B. Tenenbaum<sup>a,c,3</sup>, and Evelina Fedorenko<sup>a,b,1,3</sup>

<sup>a</sup>Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA 02139; <sup>b</sup>McGovern Institute for Brain Research, Massachusetts Institute of Technology, Cambridge, MA 02139; <sup>c</sup>Center for Brains, Minds and Machines, Massachusetts Institute of Technology, Cambridge, MA 02120; and <sup>d</sup>Department of Bruck along, University of California, Lee Appales, CA 02005. Cambridge, '

Linking artificial and human neural representations of language Contributed

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Jon Gauthier and Roger P. Levy Massachusetts Institute of Technology Department of Brain and Cognitive Sciences jon@gauthiers.net, rplevy@mit.edu



Transformer language models (BERT, XLM, GPT,...)

#### Abstract

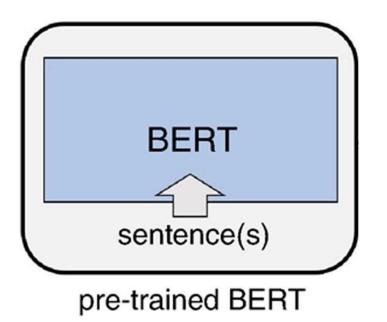
What information from an act of sentence understanding is robustly represented in the human brain? We investigate this question by comparing sentence encoding models on a brain decoding task, where the sentence that an

theories of language understanding, many are specified at too high a level of analysis to plausibly map onto neural structures without serious further revision (Poeppel, 2012).

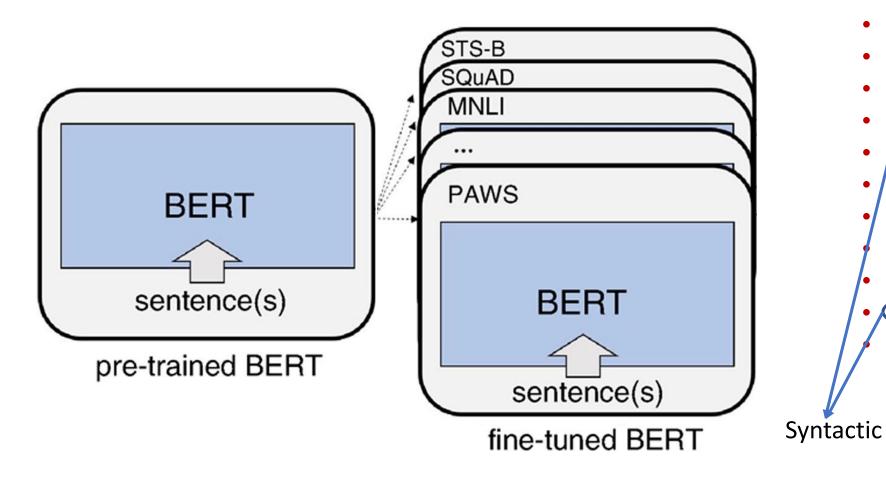
Studies which draw on these high-level representations must therefore also assume some link

#### Vaswani et al. 2017, Gauthier et al. 2019, Schrimpf et al. 2021

# Can task-specific language models better predict fMRI brain activity?



# Can task-specific language models better predict fMRI brain activity?



Tasks

- Paraphrase
- Summrisation
- Question Answering
- Sentiment Analysis
- NER
- Word Sense Disambiguation
- Natural Language Inference
  - Semantic Role Labeling
  - **Coreference** Resolution

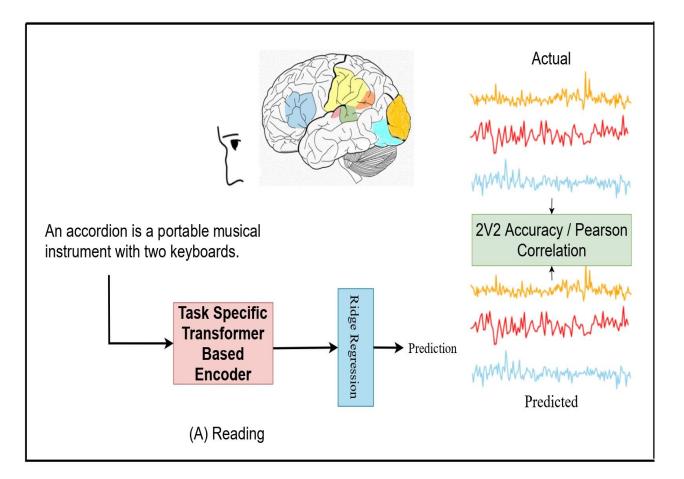
Shallow Syntax Pretrained BERT

# Task-specific Models (10) + Pretrained BERT

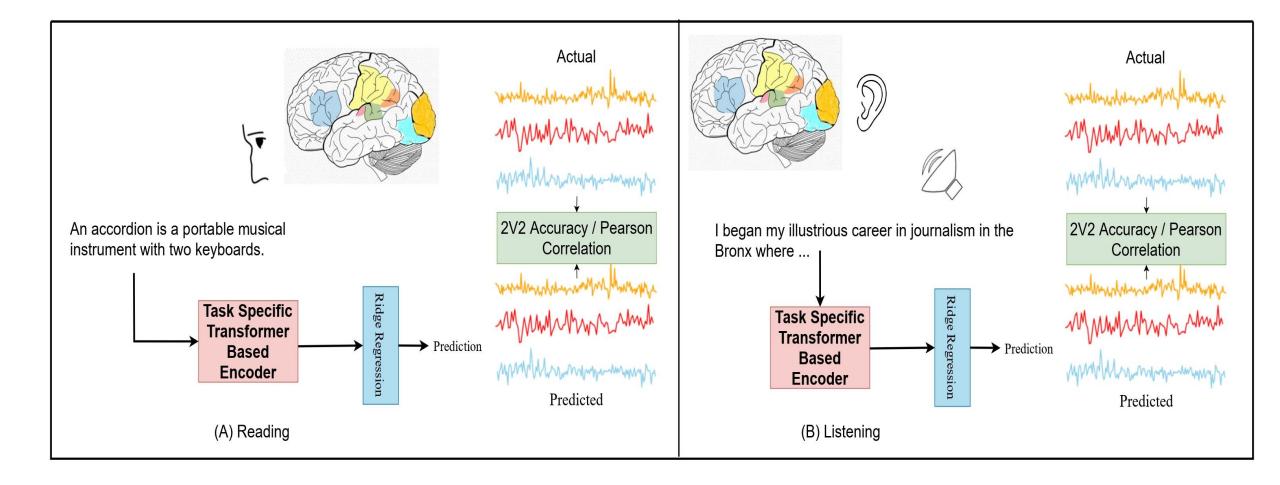
### Common underlying model Bert-base (768 dimension)

| Task | HuggingFace Model Name         | Dataset  | URL                                 |
|------|--------------------------------|--|-------------------------------------|
| NLI  | bert-base-nli-mean-tokens      | Stanford Natural Language Inference (SNLI), MultiNLI | https://huggingface.co/             |
|      |                                |  | sentence-transformers/              |
|      |                                |  | bert-base-nli-mean-tokens           |
| PD   | bert-base-cased-finetuned-mrpc | Microsoft Research Paraphrase Corpus (MRPC)          | https://huggingface.co/             |
|      |                                |  | bert-base-cased-finetuned-mrpc      |
| SS   | bert-base-chunl                | CoNLL-2003   | https://huggingface.co/vblagoje/    |
|      |                                |  | bert-english-uncased-finetuned-chun |
| Sum  | bart-base-samsum               | SAMSum   | https://huggingface.co/lidiya/      |
|      |                                |  | bart-base-samsum                    |
| WSD  | bert-base-baseline             | English all-words                                    | https://github.com/BPYap/BERT-WSD   |
| CR   | bert_coreference_base          | OntoNotes and GAP                                    | https://github.com/mandarjoshi90/   |
|      |                                |  | coref                               |
| NER  | bert-base-NER                  | CoNLL-2003   | https://huggingface.co/dslim/       |
|      |                                |  | bert-base-NER                       |
| QA   | bert-base-qa                   | SQUAD  | https://huggingface.co/docs/        |
|      |                                |  | transformers/model_doc/bert#        |
|      |                                |  | bertforquestionanswering            |
| SA   | bert-base-sst                  | Stanford Sentiment Treebank (SST)                    | https://huggingface.co/barissayil/  |
|      |                                |  | bert-sentiment-analysis-sst         |
| SRL  | bert-base-srl                  | English PropBank SRL                                 | https://s3-us-west-2.               |
|      |                                |  | amazonaws.com/allennlp/models/      |
|      |                                |  | bert-base-srl-2020.02.10.tar.gz     |

# Can task-specific language models have similar predictive performance in reading and listening?



# Can task-specific language models have similar predictive performance in reading and listening?



# Reading data target: human brain recordings

- We use Periera dataset
  - reading sentences
  - 5 subjects
  - 627 sentences
    (experiment 2 + 3)

# Example: "A clarinet is a woodwind musical instrument"

#### Experiment 2:

#### Musical instruments (clarinet)

A clarinet is a woodwind musical instrument. It is a long black tube with a flare at the bottom. The player chooses notes by pressing keys and holes. The clarinet is used both in jazz and classical music.

Musical instruments (accordion) An accordion is a portable musical instrument with two keyboards. One keyboard is used for individual notes, the other for chords. Accordions produce sound with bellow that blow air through reeds. An accordionist plays both keyboards while opening and closing the bellows.

Musical instruments (piano)

The piano is a popular musical instrument played by means of a keyboard. Pressing a piano key causes a felt-tipped hammer to hit a vibrating steel string. The piano has an enormous note range, and pedals to change the sound quality. The piano repertoire is large, and famous pianists can give solo concerts.

#### Experiment 3:

#### Skiing (passage 1)

I hesitantly skied down the steep trail that my buddies convinced me to try. I made a bad turn, and I found myself tumbling down. I finally came to a stop at a flat part of the slope. My skis were nowhere to be found, and my poles were lodged in a snow drift up the hill.

#### Skiing (passage 2)

A major strength of professional skiers is how they use ski poles. Proper use of ski poles improves their balance and adds flair to their skiing. It minimizes the need for upper body movements to regain lost balance while skiiing.

#### Skiing (passage 3)

New ski designs and stiffer boots let skiers turn more quickly. But faster and tighter turns increase the twisting force on the legs. This has led to more injuries, particularly to ligaments in the skier's knee.

#### Gambling (passage 1)

When I decided to start playing cards, things went from bad to worse. Gambling was something I had to do, and I had already spent close to \$10,000 doing it. My friends were sick of watching me gamble my savings away. The hardest part was the horror of leaving a casino after losing money I did not have. Gambling (passage 2)

Good data on the social and economic effects of legalized gambling are hard to come by. Some studies indicate that having a casino nearby makes gambling problems more likely. Gambling may also be associated with personal bankruptcies and marriage problems.

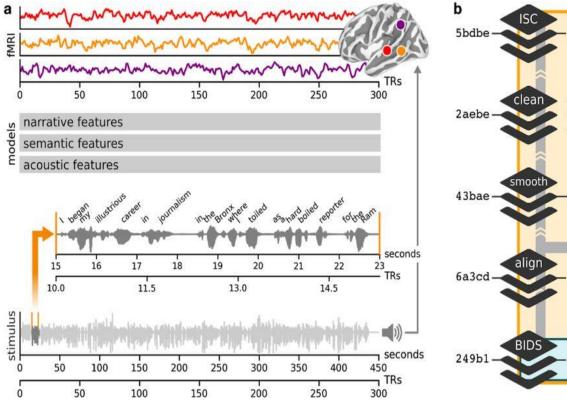
#### Gambling (passage 3)

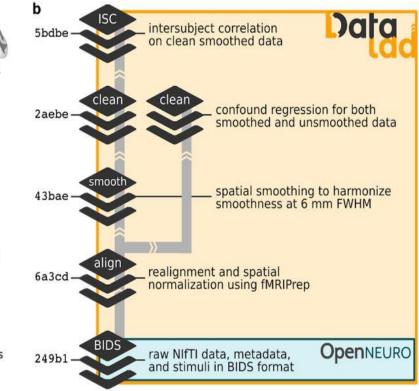
Over the past generation, there has been a dramatic expansion of legalized gambling. Most states have instituted lotteries, and many have casinos as well. Gambling has become a very big but controversial business.

# Listening data target: human brain recordings

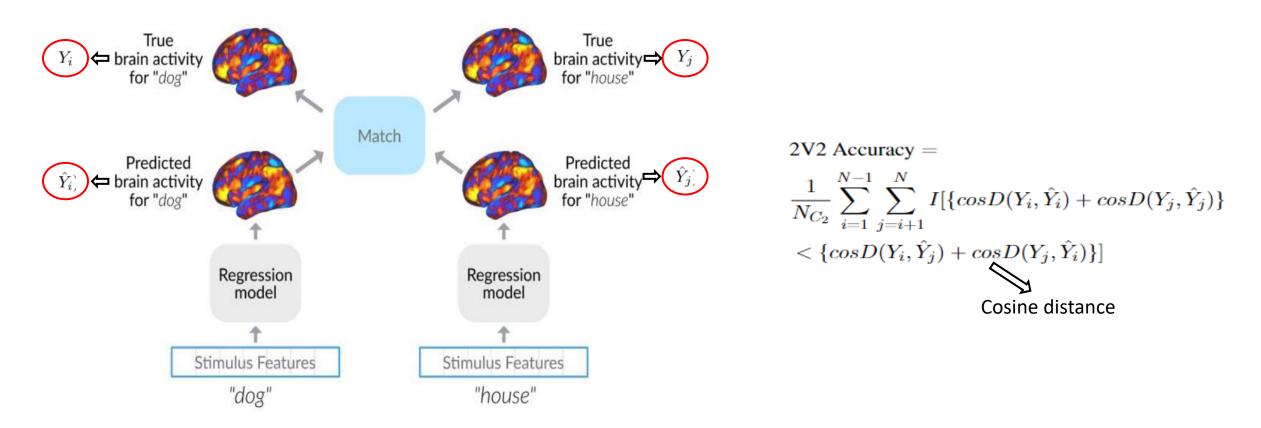
- We use Pieman story listening:
  - 82 subjects,
  - 282 TRs (repetition time)
  - here it is 1.5 sec.

*Example: "I began my illustrious carrier in journalism..."* 





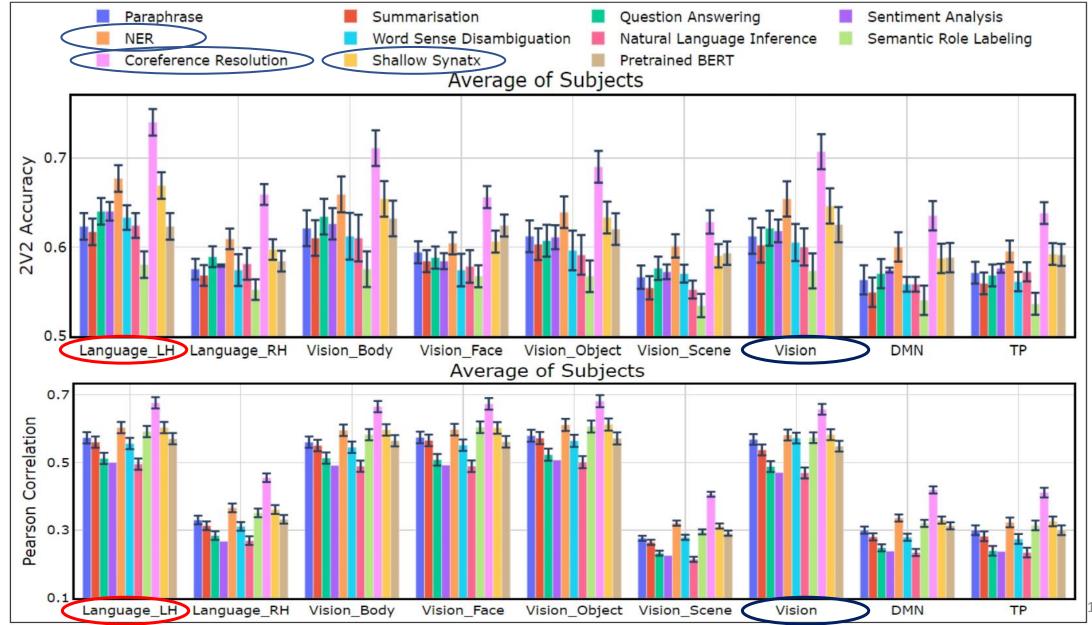
# Evaluation Metrics: 2V2 and Pearson



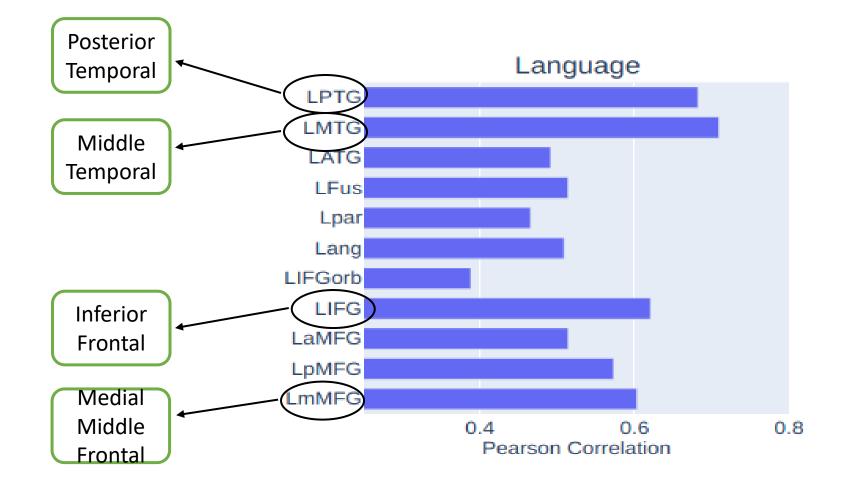
2V2 Accuracy

Toneva et al. NeurIPS-2020

# Encoding Performance (Reading)

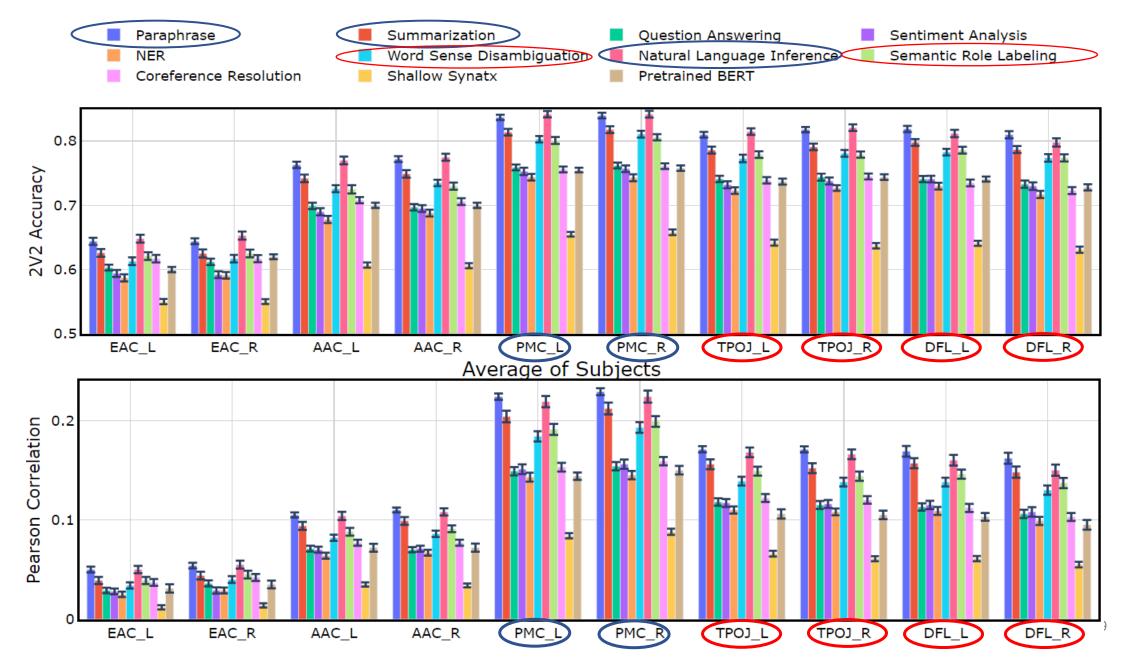


# Which language sub regions have higher predicitivity?

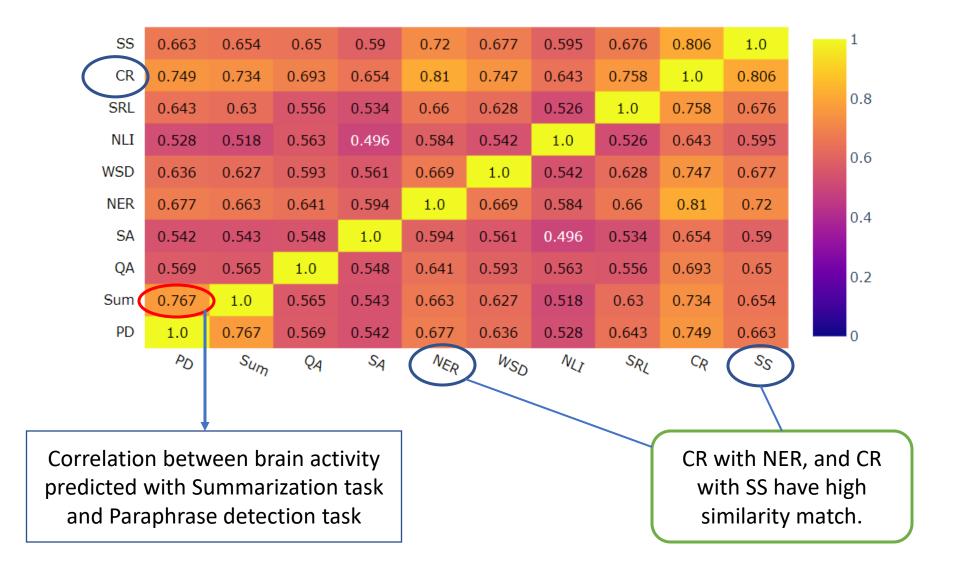


**Corefernce Resolution Task** 

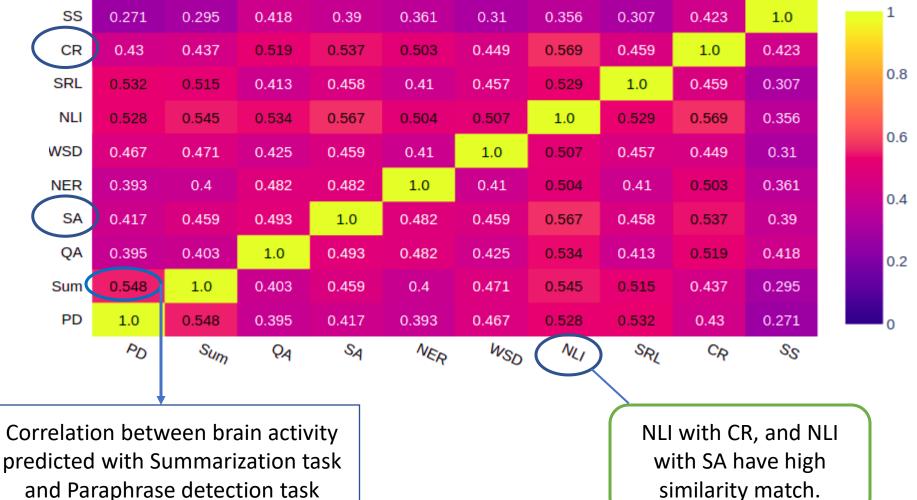
# Encoding Performance (Listening)



# Task Similarity - Reading

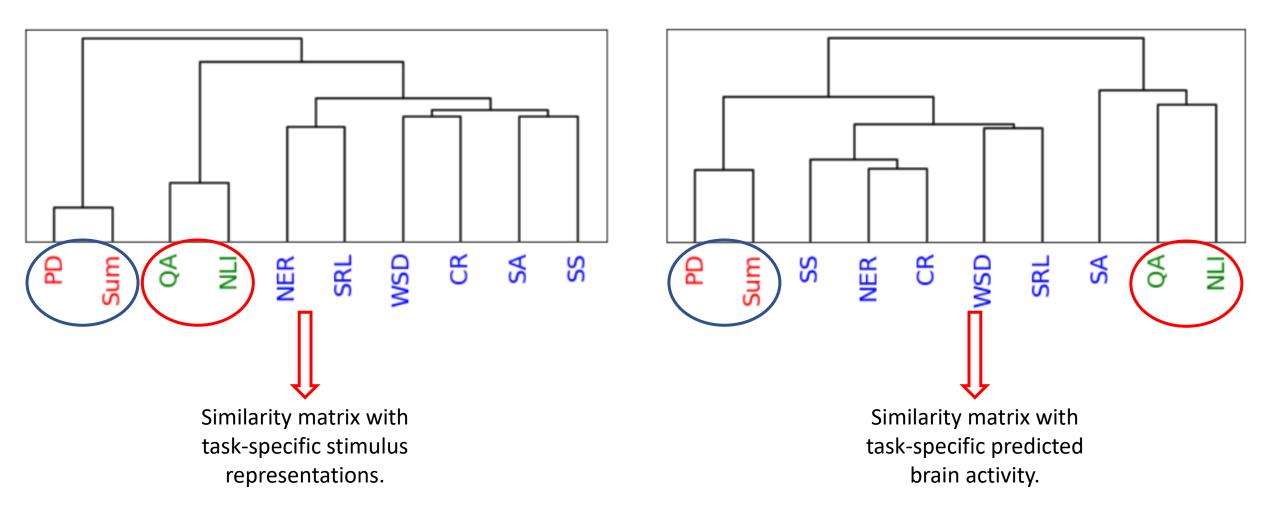


# Task Similarity - Listening

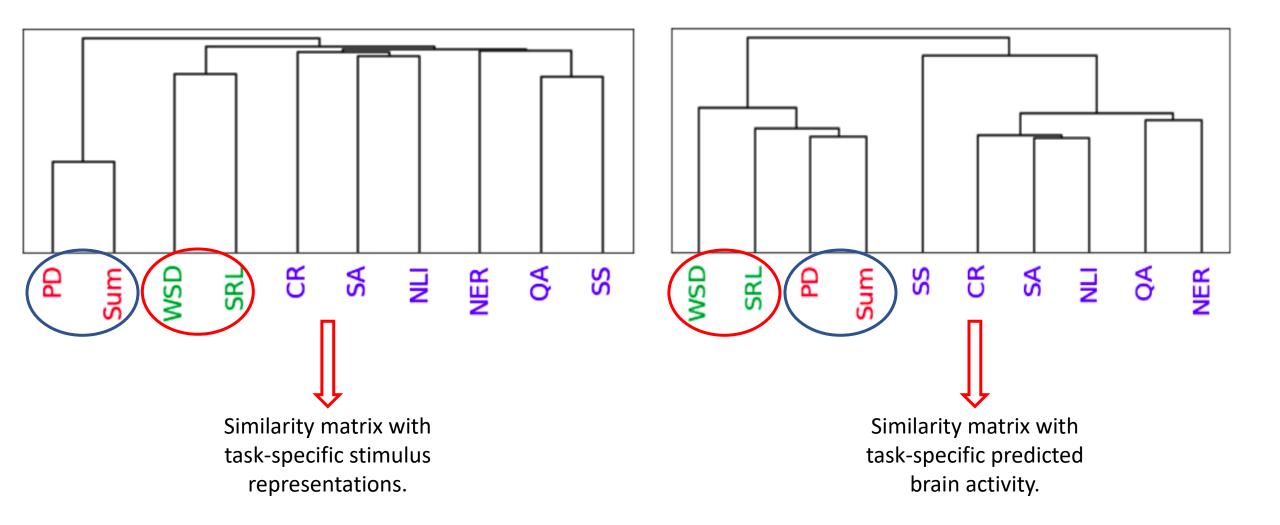


and Paraphrase detection task

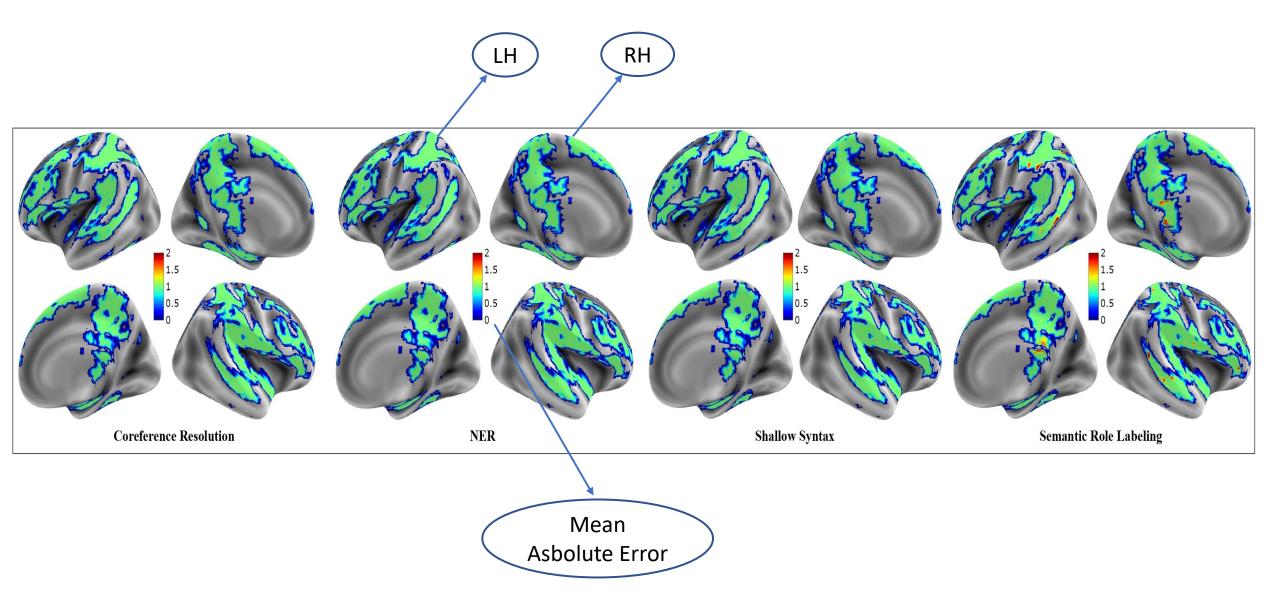
## Reading Task: Dendrogram



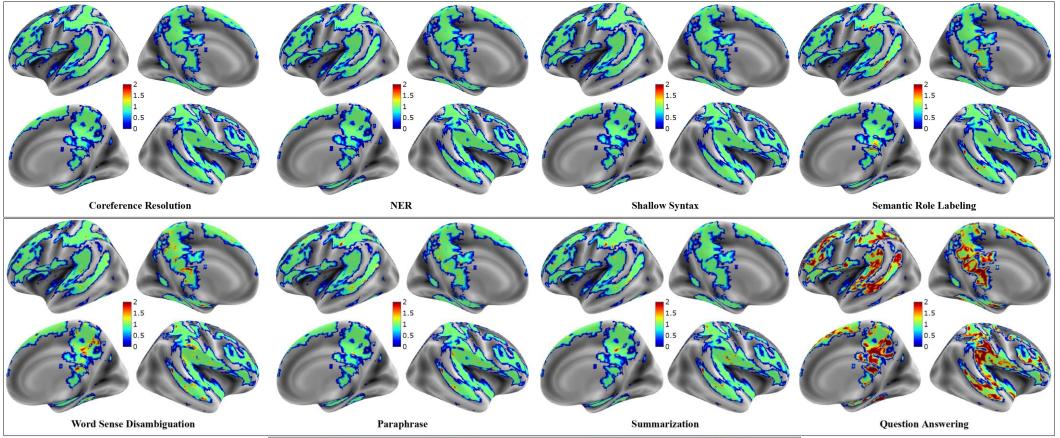
# Listening Task: Dendrogram

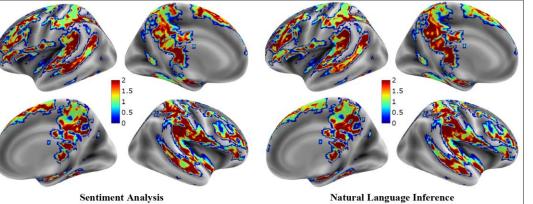


# Brain Maps (Reading)

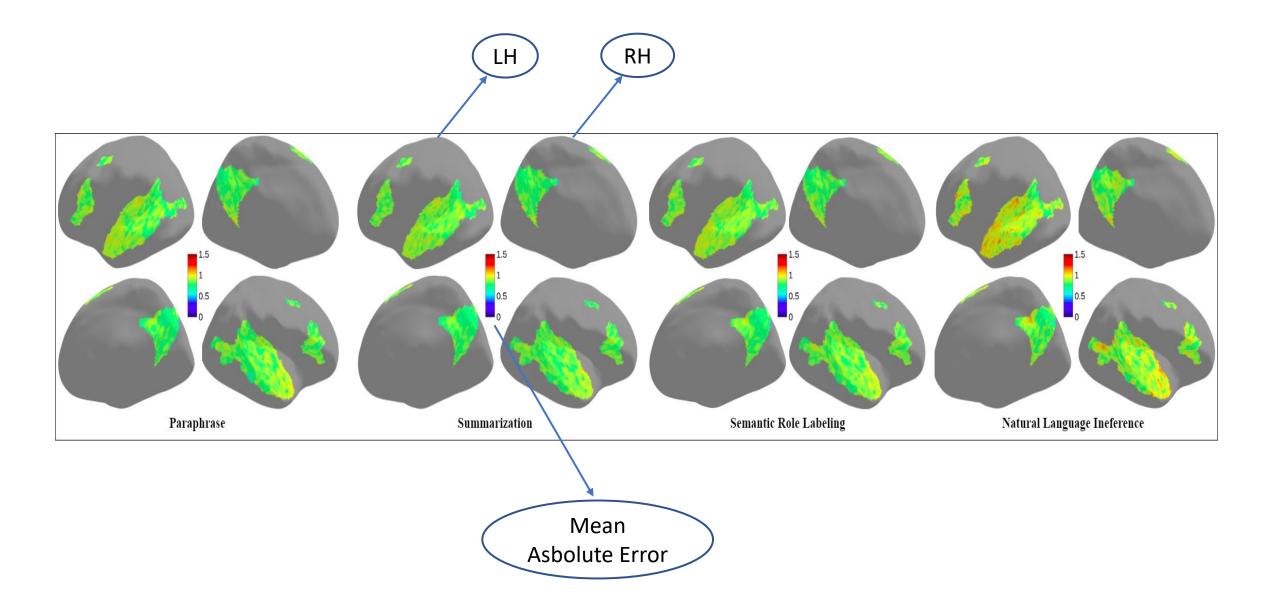


## Brain Maps (Reading)

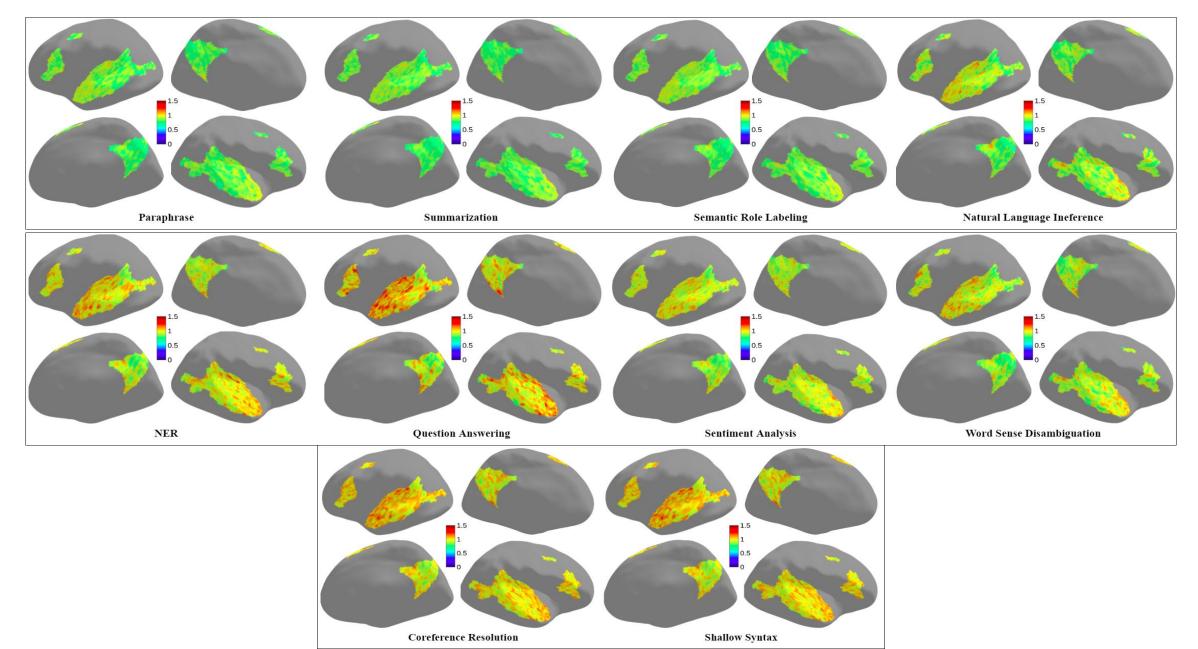




# Brain Maps (Listening)



# Brain Maps (Listening)



# Limitations & Future Works

- We leveraged models finetuned using datasets of different sizes across tasks.
- While a fair comparison of dataset sizes across tasks is impossible,
  - we understand that this could have resulted in some bias in our results.
- The differences in task-specific model performances across reading and listening are mainly due to the learned stimulus representations,
  - other factors such as experimental conditions, the text domain of the stimuli or number of voxels also effect the model performance.

# Collaborators



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Manish Gupta



Bapi Raju Surampudi

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