

# Visio-Linguistic Brain Encoding

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COLING 2022

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# What is fMRI?

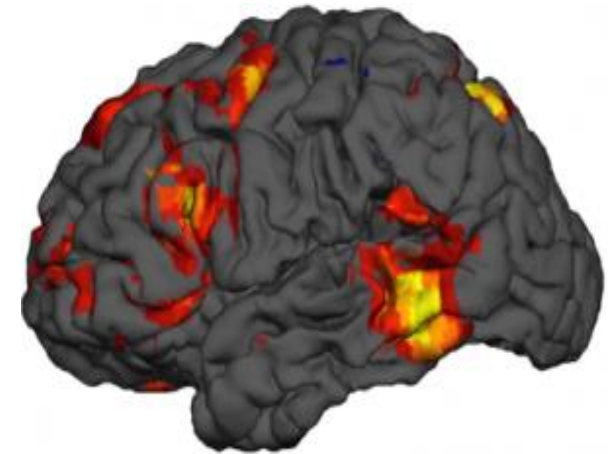


(Bird)

Concept + Picture

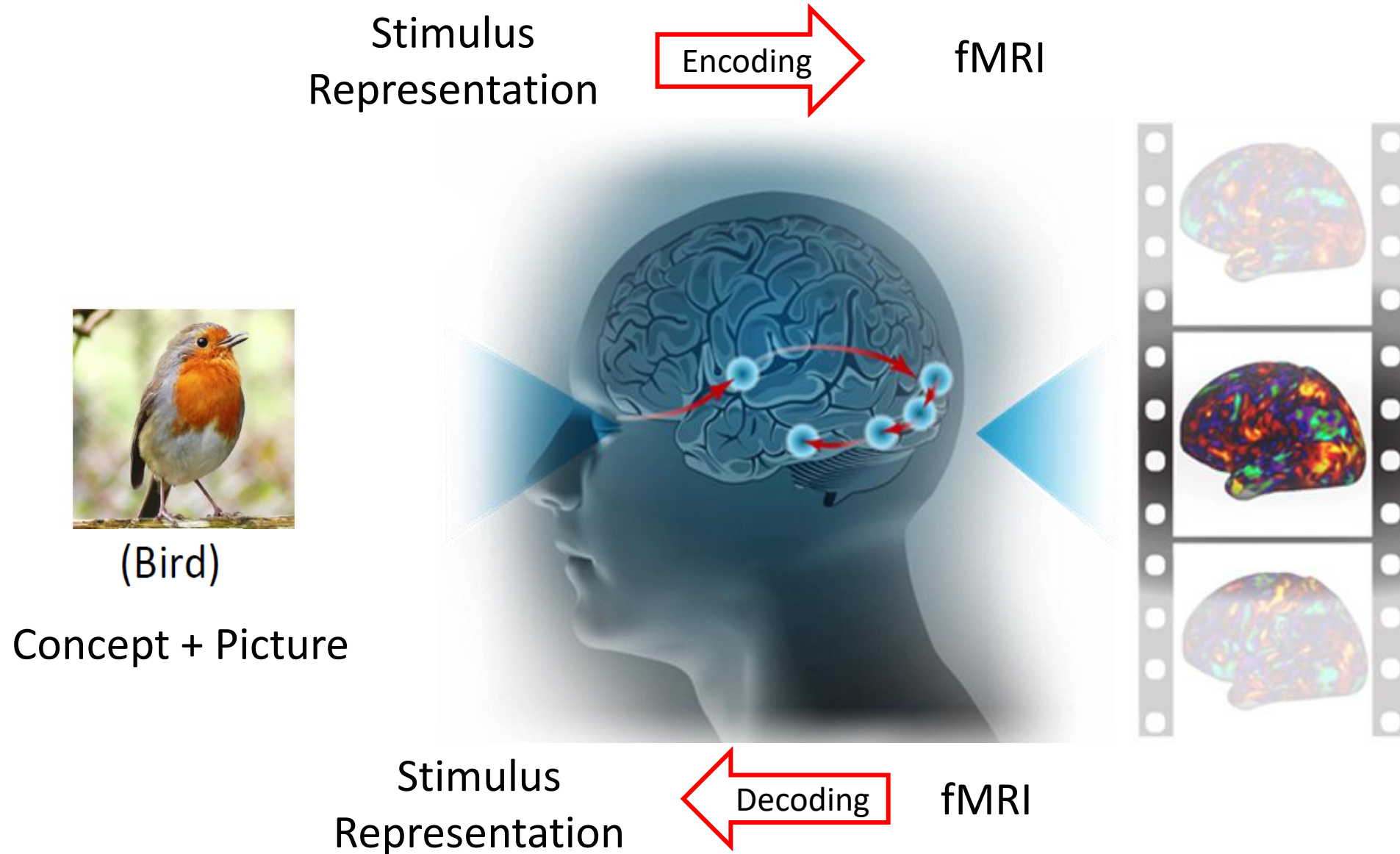


A vision-language task in the scanner

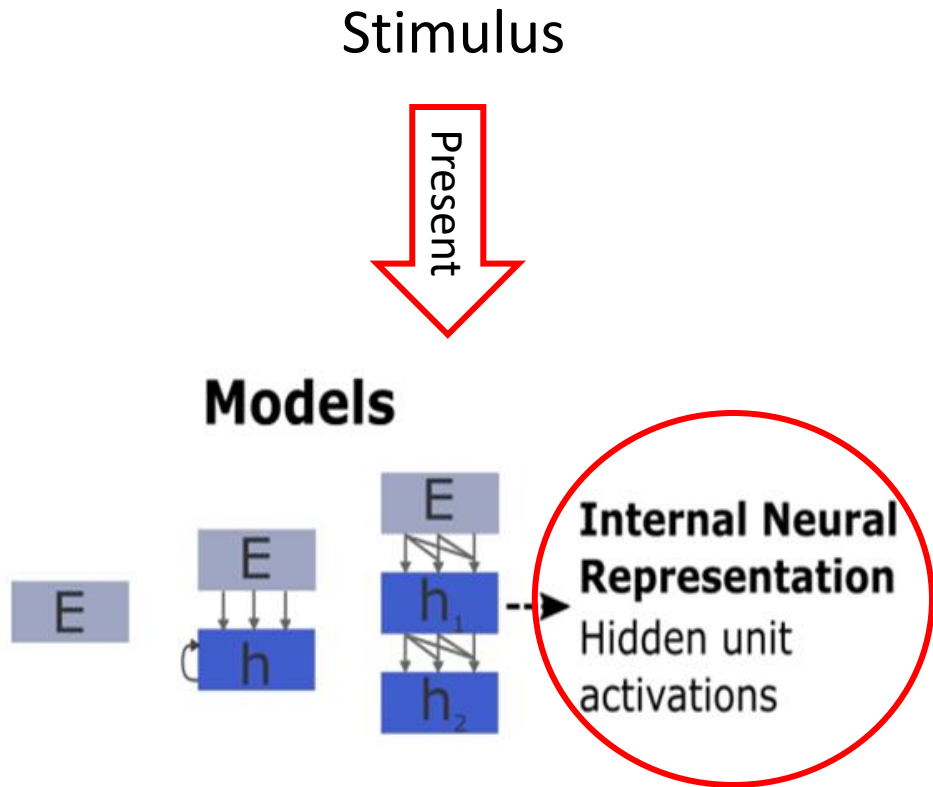


fMRI Brain  
Activity

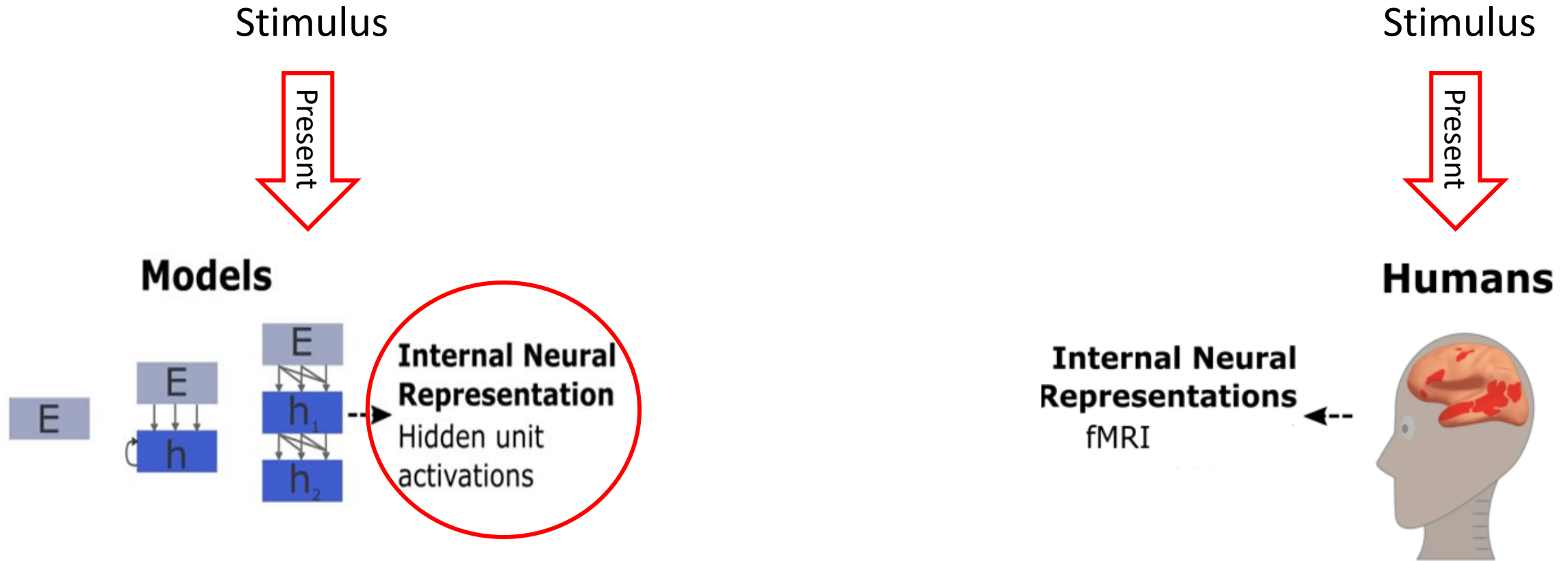
# Brain Encoding vs Decoding



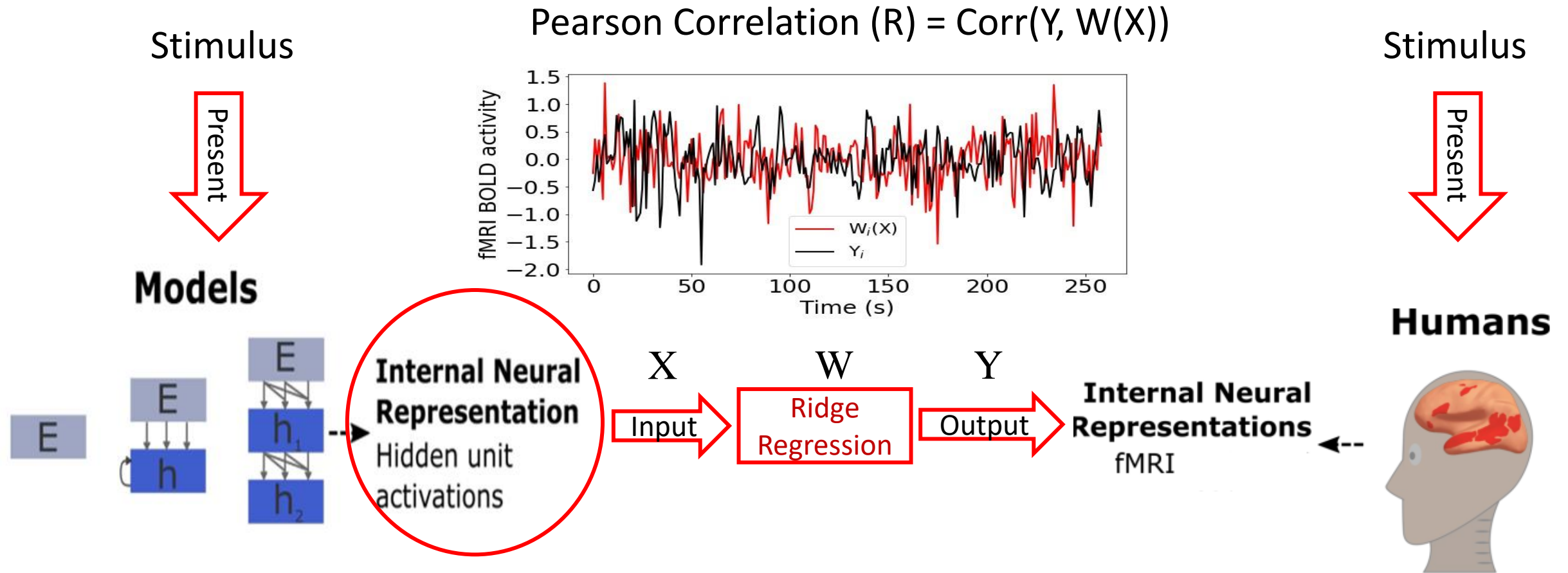
# What is Brain Encoding?



# What is Brain Encoding?

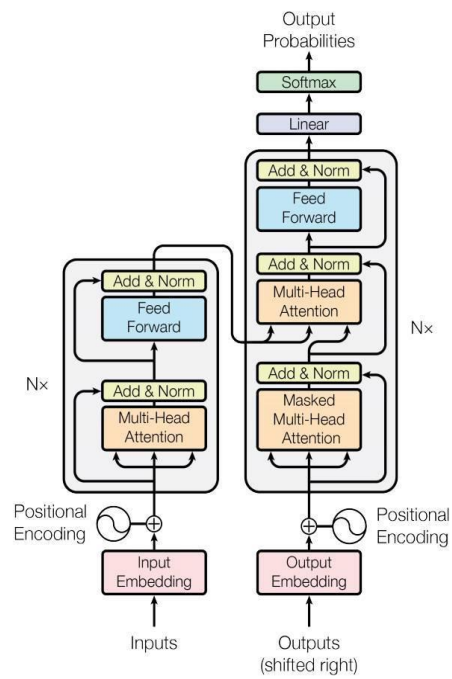


# What is Brain Encoding?

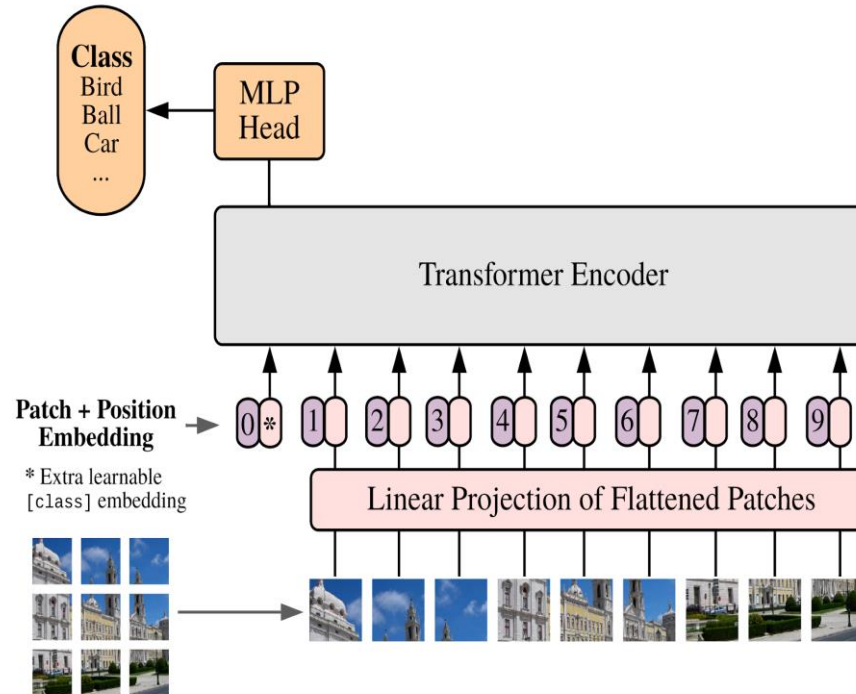




# Most popular models are Transformers



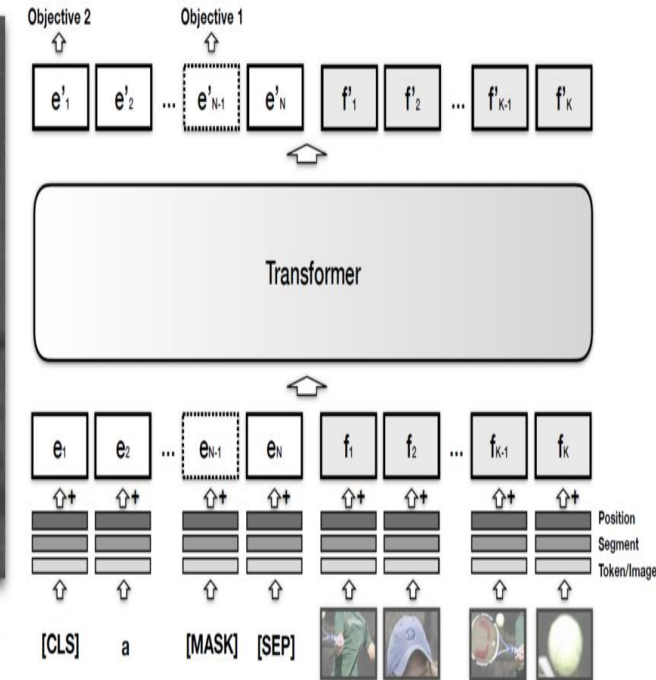
Transformer language models



Vision Transformer (ViT)



A person hits a ball with a tennis racket



Multi-modal Transformer

# Brain encoding for single-mode stimuli: Vision

## Brain-Score: Which Artificial Neural Network for Object Recognition is most Brain-Like?

Martin Schrimpf<sup>\*,1,2</sup>, Jonas Kubilius<sup>\*,3,4</sup>, Ha Hong<sup>5</sup>, Najib J. Majaj<sup>6</sup>, Rishi Rajalingham<sup>1</sup>, Elias B. Issa<sup>7</sup>, Kohitij Kar<sup>1,3</sup>, Pouya Bashivan<sup>1,3</sup>, Jonathan Prescott-Roy<sup>1</sup>, Kailyn Schmidt<sup>1</sup>, Daniel L. K. Yamins<sup>8,9</sup>, and James J. DiCarlo<sup>1,2,3</sup>

## Integrative Benchmarking to Advance Neurally Mechanistic Models of Human Intelligence

Martin Schrimpf,<sup>1,2,3</sup> Jonas Kubilius,<sup>2,4,5</sup> Michael J. Lee,<sup>1,2</sup> N. Apurva Ratan Murty,<sup>1,2,3</sup> Robert Ajemian,<sup>1,2</sup> and James J. DiCarlo<sup>1,2,3,\*</sup>

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<sup>2</sup>McGovern Instit  
<sup>3</sup>Center for Brain  
<sup>4</sup>Brain and Cogni  
<sup>5</sup>Three Thir  
<sup>6</sup>Correspondence  
<https://doi.org/10.1016/j.neuron.2019.04.011>

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### SUMMARY

A potentially  
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the next step:  
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## Neural Taskonomy: Inferring the Similarity of Task-Derived Representations from Brain Activity

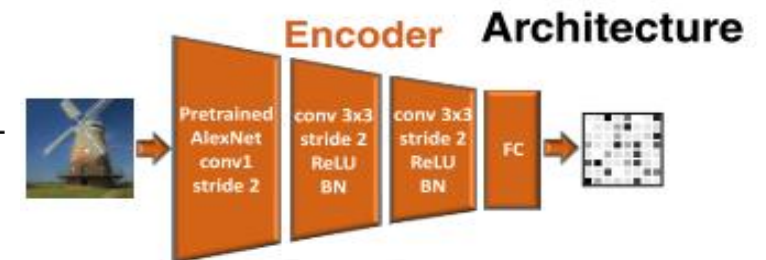
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**Michael J. Tarr**  
Carnegie Mellon University  
[michaeltarr@cmu.edu](mailto:michaeltarr@cmu.edu)

**Leila Wehbe**  
Carnegie Mellon University  
[lwehbe@cmu.edu](mailto:lwehbe@cmu.edu)

### Abstract

Convolutional neural networks (CNNs) trained for object classification have been widely used to account for visually-driven neural responses in both human and primate brains. However, because of the generality and complexity of object classification, despite the effectiveness of CNNs in predicting brain activity, it is





# Brain encoding for single-mode stimuli: Text

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

### Linking artificial and human neural representations of language

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**Jon Gauthier** and **Roger P. Levy**

Massachusetts Institute of Technology

Department of Brain and Cognitive Sciences

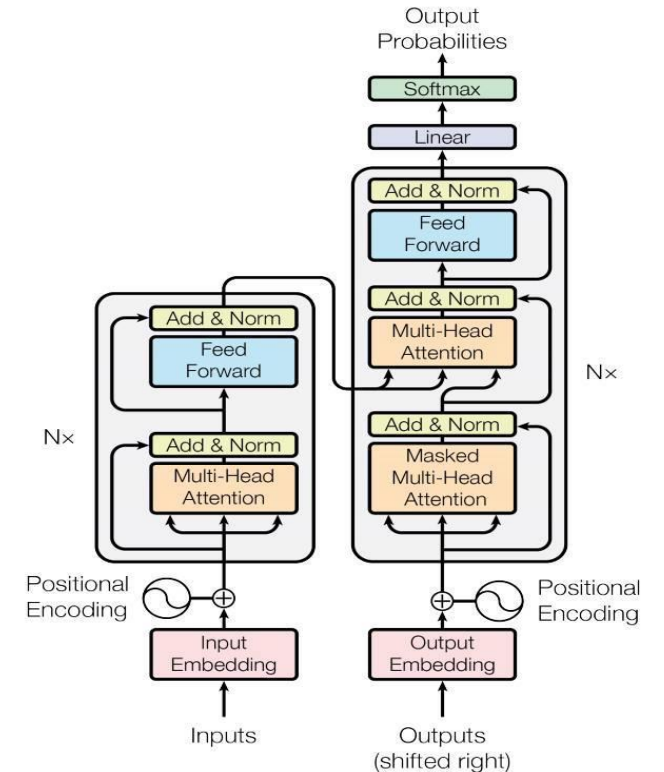
jon@gauthiers.net, rplevy@mit.edu

### 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

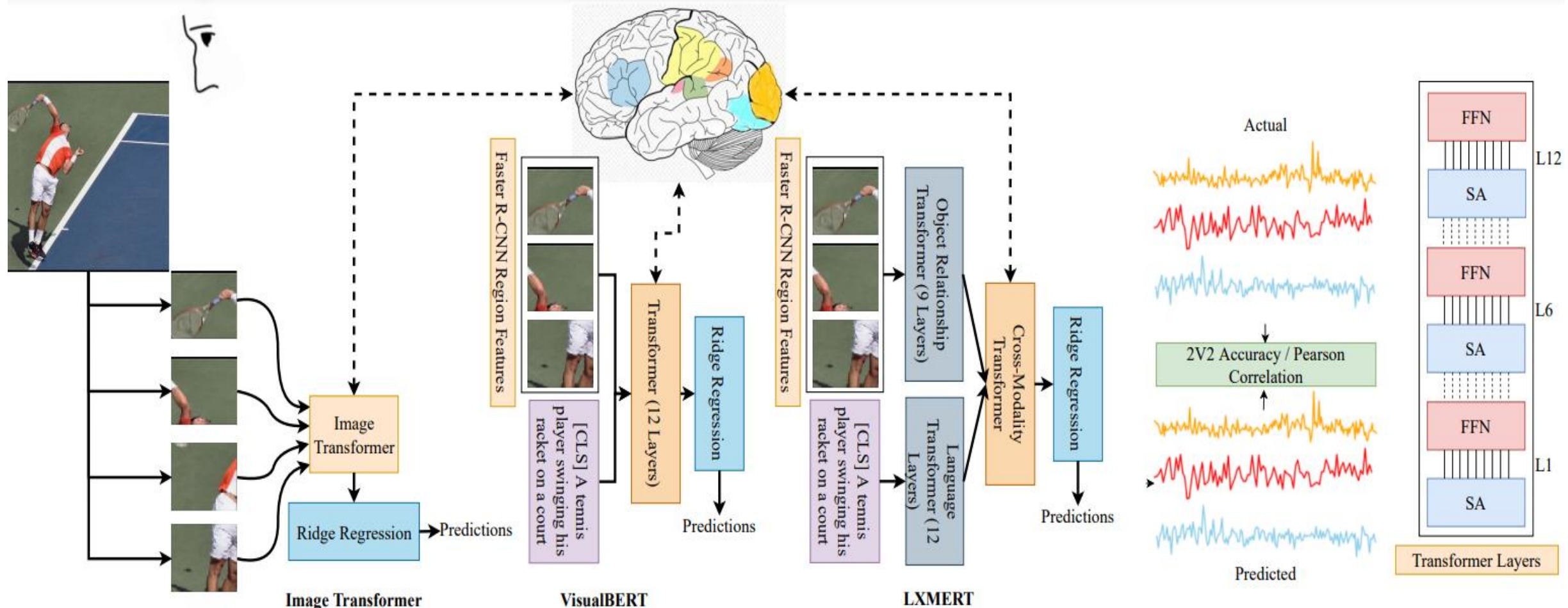
theories of language understanding, many are specified at too high a level of analysis to plausibly map onto neural structures without serious further revision (Poeppel, 2012).

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



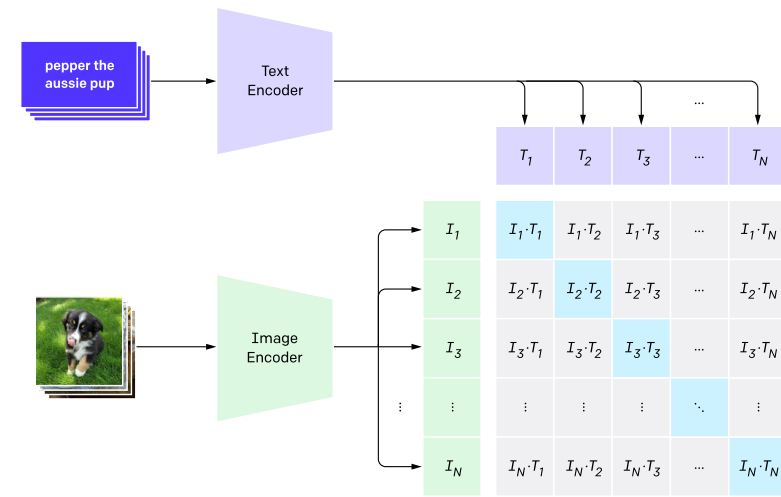
Transformer language models  
(BERT, XLM, GPT,...)

# Can image-based and multi-model Transformers accurately perform fMRI encoding?

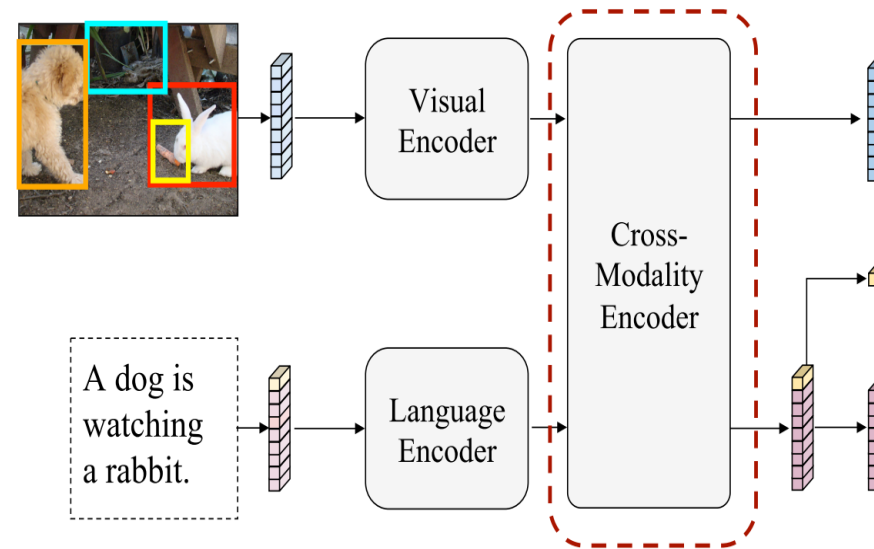


# Models used: Multi-Modal Transformers

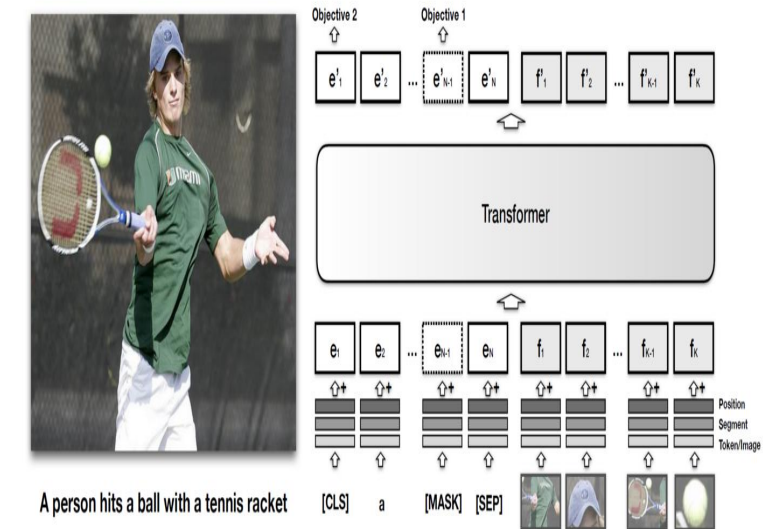
## 1. Contrastive pre-training



CLIP

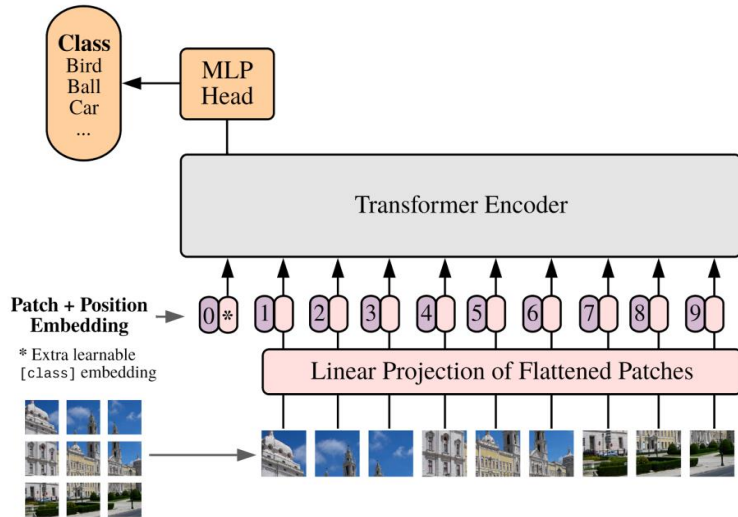


LXMERT

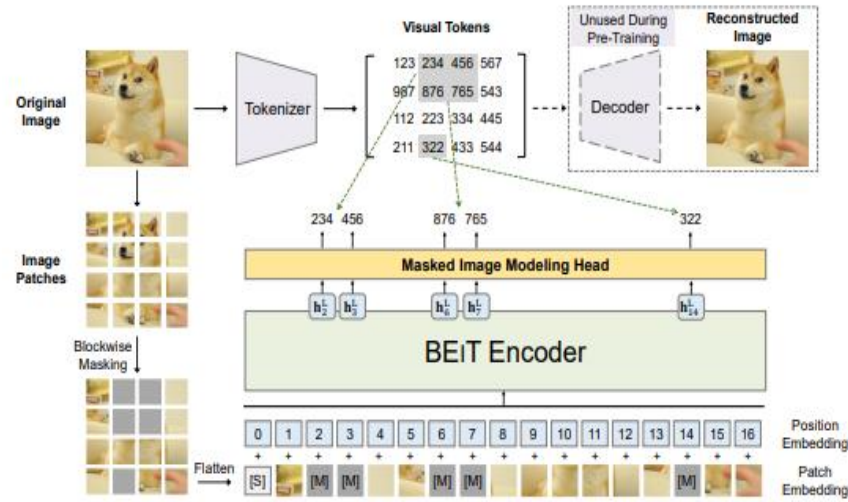


VisualBERT

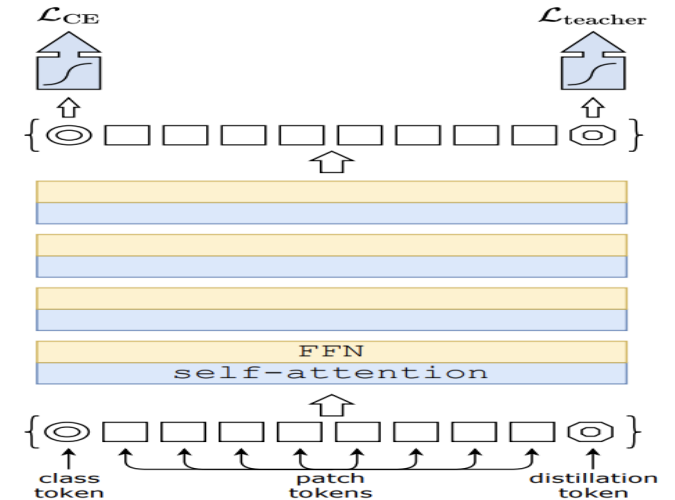
# Models used: Image Transformers



ViT



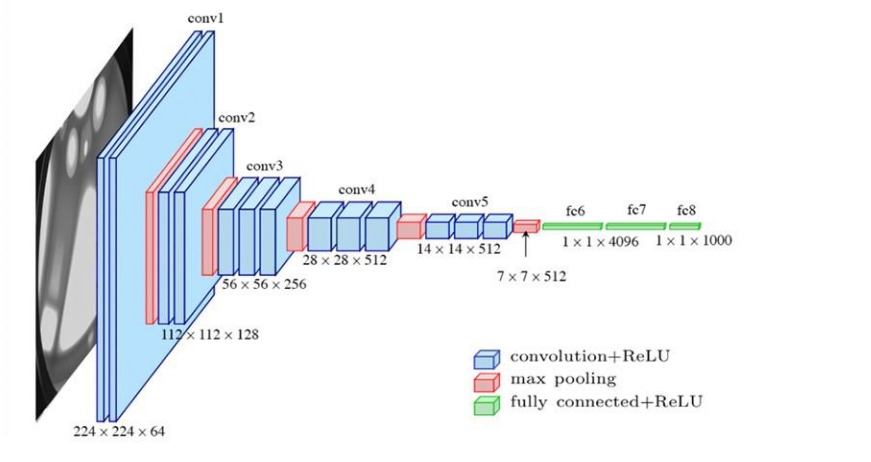
BEiT



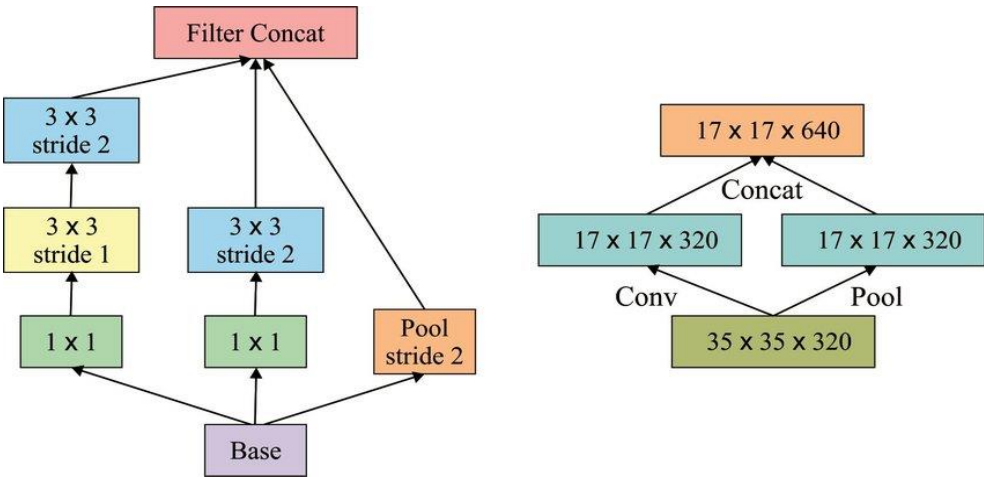
DEiT



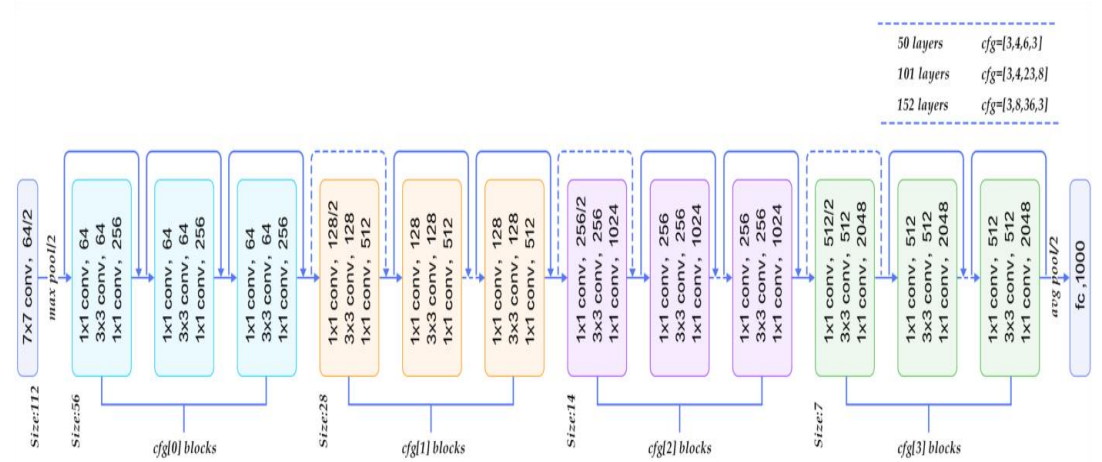
# Models used: CNNs



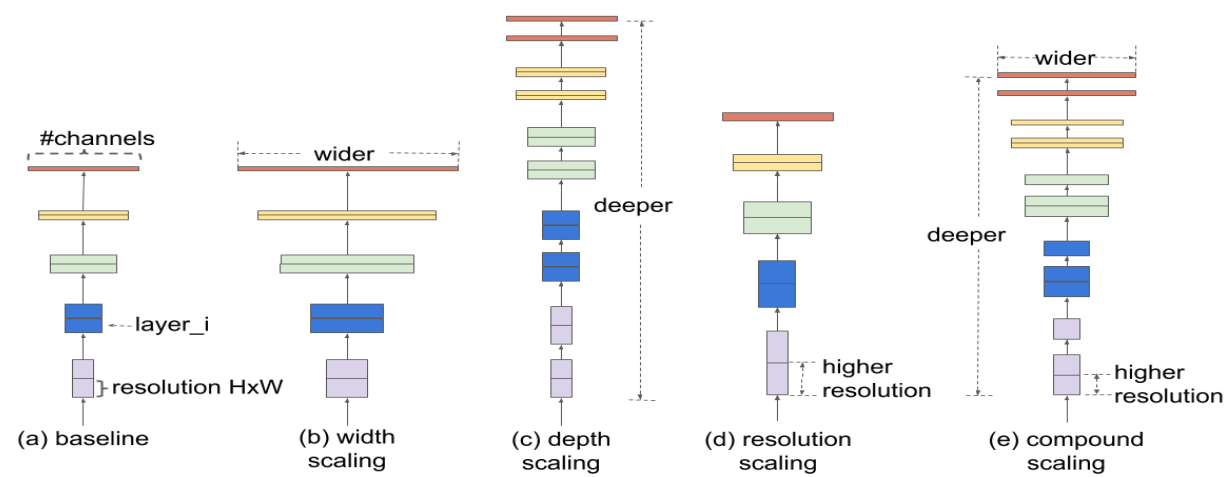
VGGNET



InceptionV2



RESNET50



EfficientNET

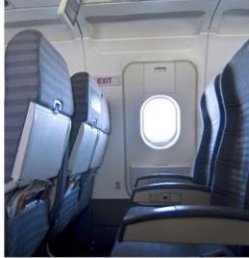
# Dataset Details

Concept+Picture  
(Bird)



Periera

Scene Images



BOLD5000

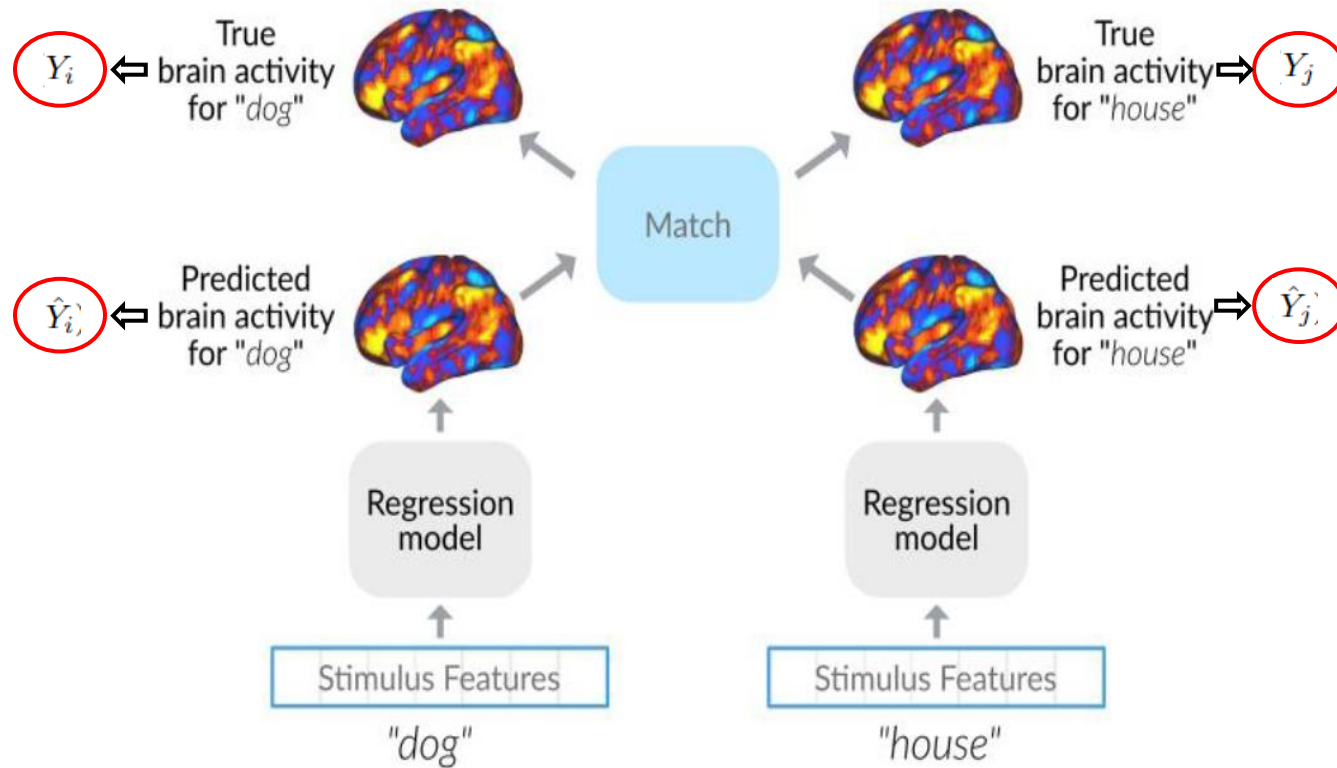
COCO Images



ImageNet Images



# Evaluation Metrics: 2V2 and Pearson



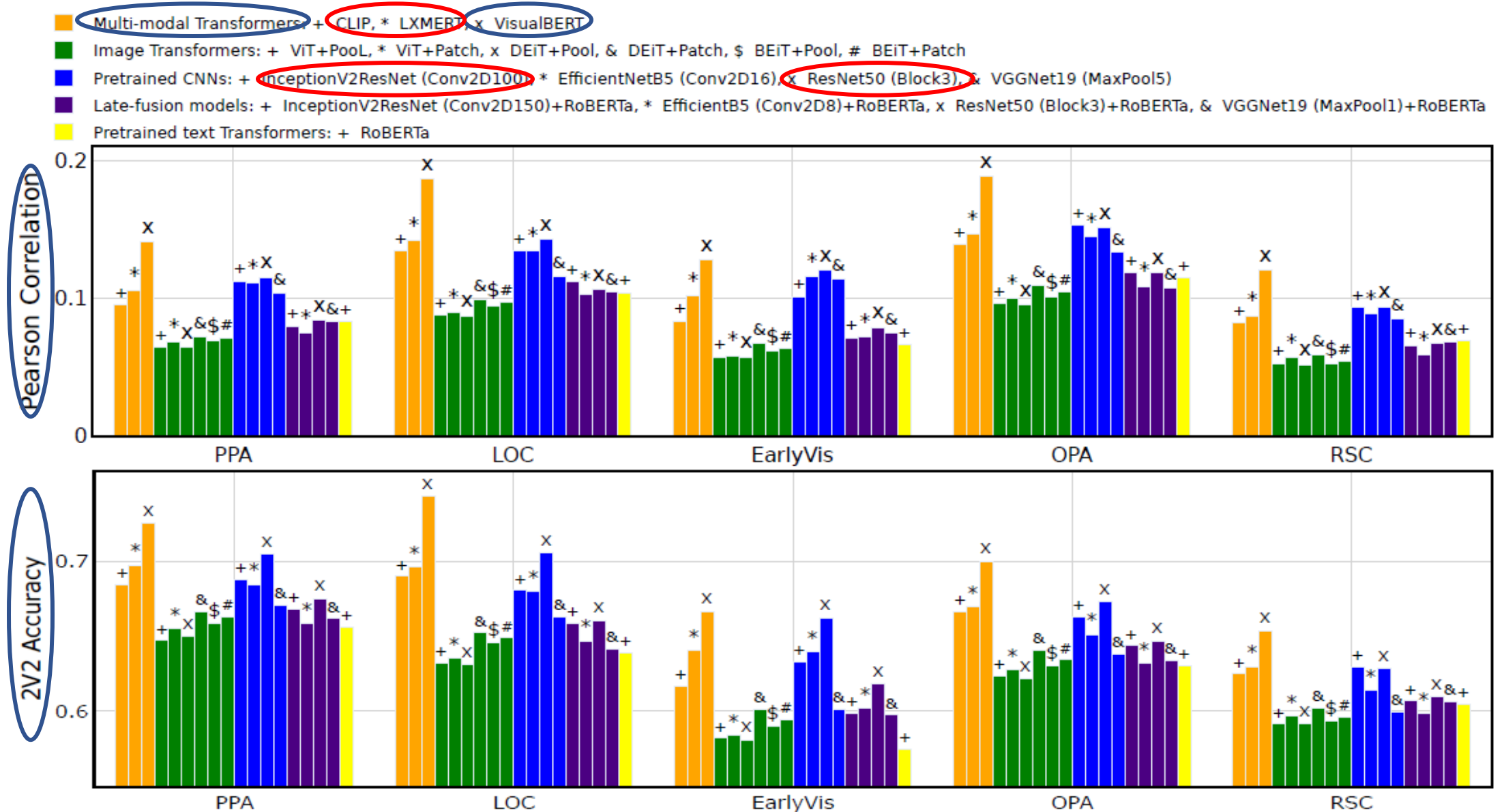
2V2 Accuracy

2V2 Accuracy =

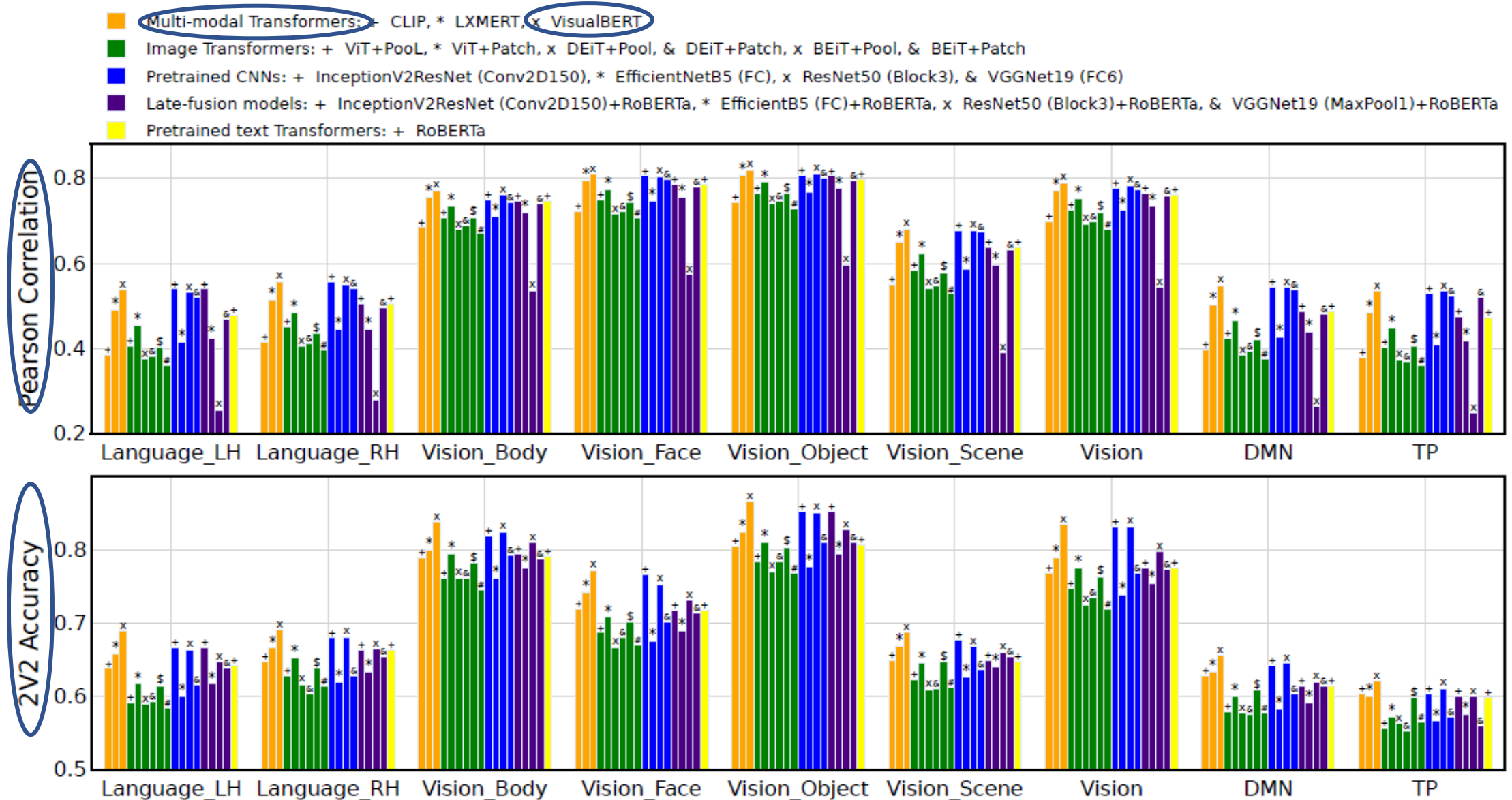
$$\frac{1}{N_{C_2}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N I[\{ \cos D(Y_i, \hat{Y}_i) + \cos D(Y_j, \hat{Y}_j) \} < \{ \cos D(Y_i, \hat{Y}_j) + \cos D(Y_j, \hat{Y}_i) \}]$$

↘  
Cosine distance

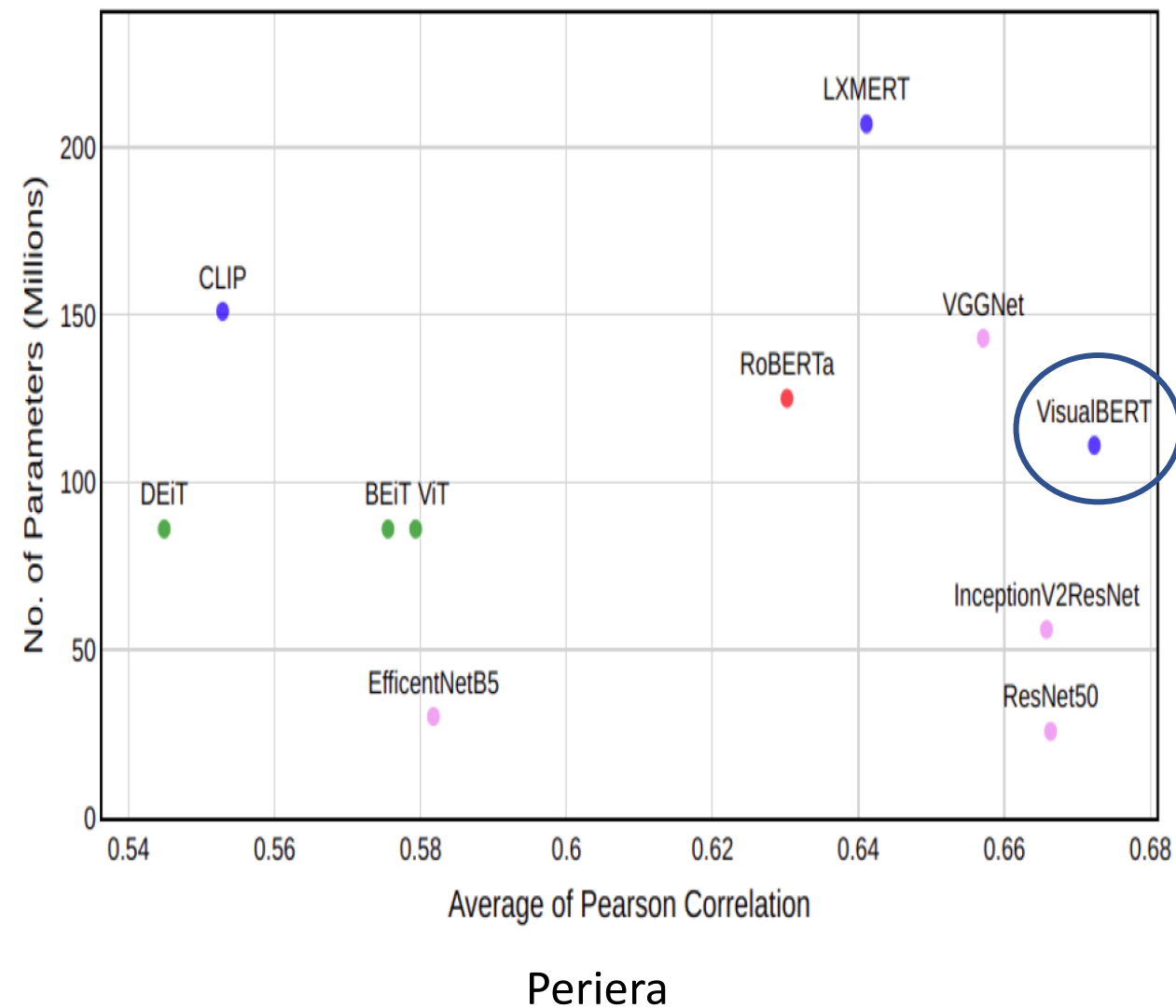
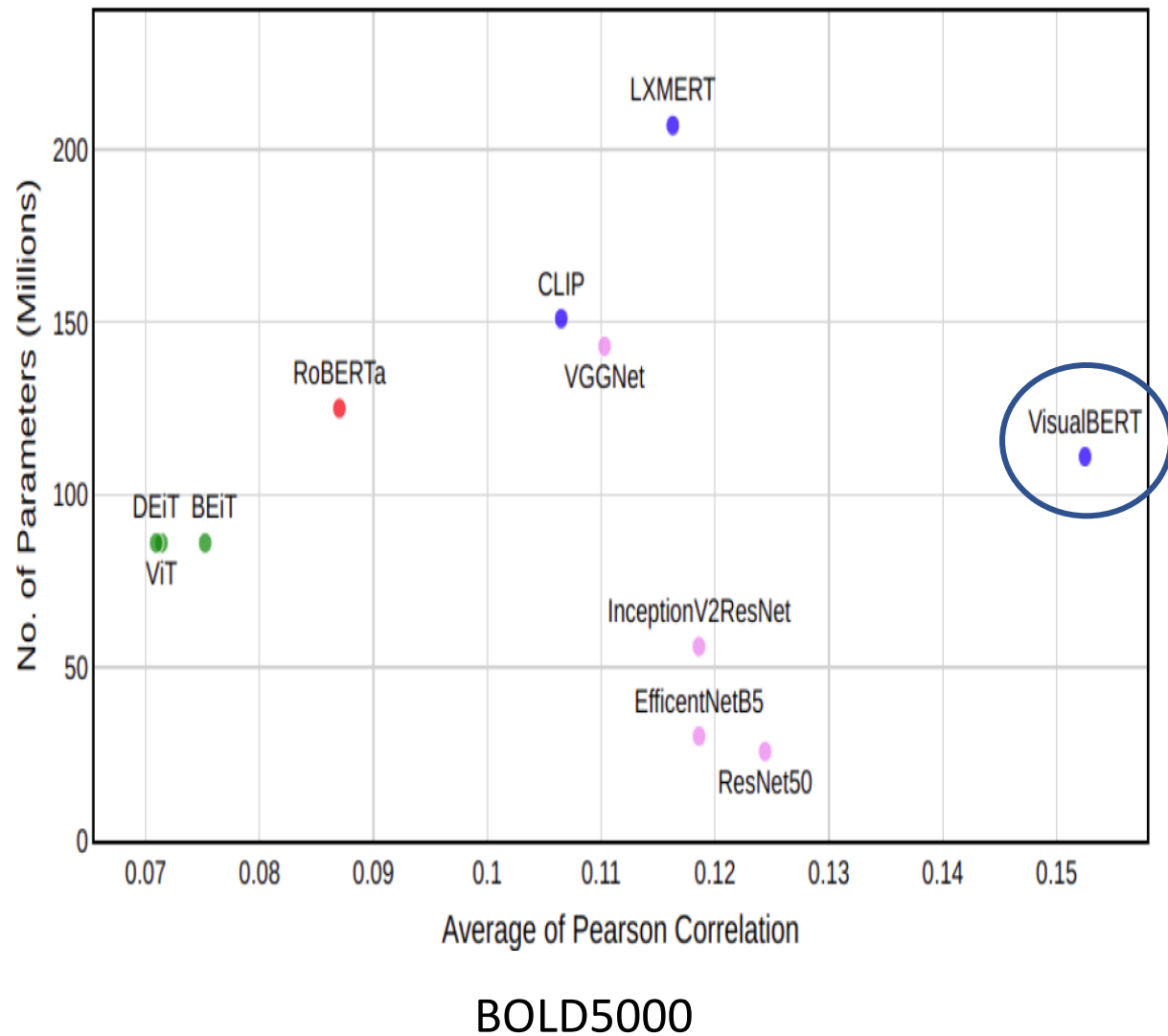
# Encoding performance (BOLD5000)



# Encoding performance (Periera)



# Model size vs Efficacy



# Single Stream vs Dual Stream

Models compared	PPA	LOC	EarlyVis	OPA	RSC
CLIP	0.095	0.134	0.083	0.139	0.082
LXMERT	0.106	0.142	0.102	0.146	0.087
VisualBERT	<b>0.141</b>	<b>0.187</b>	<b>0.128</b>	<b>0.188</b>	<b>0.12</b>
ViLBERT	0.057	0.078	0.052	0.087	0.045

Dual Stream

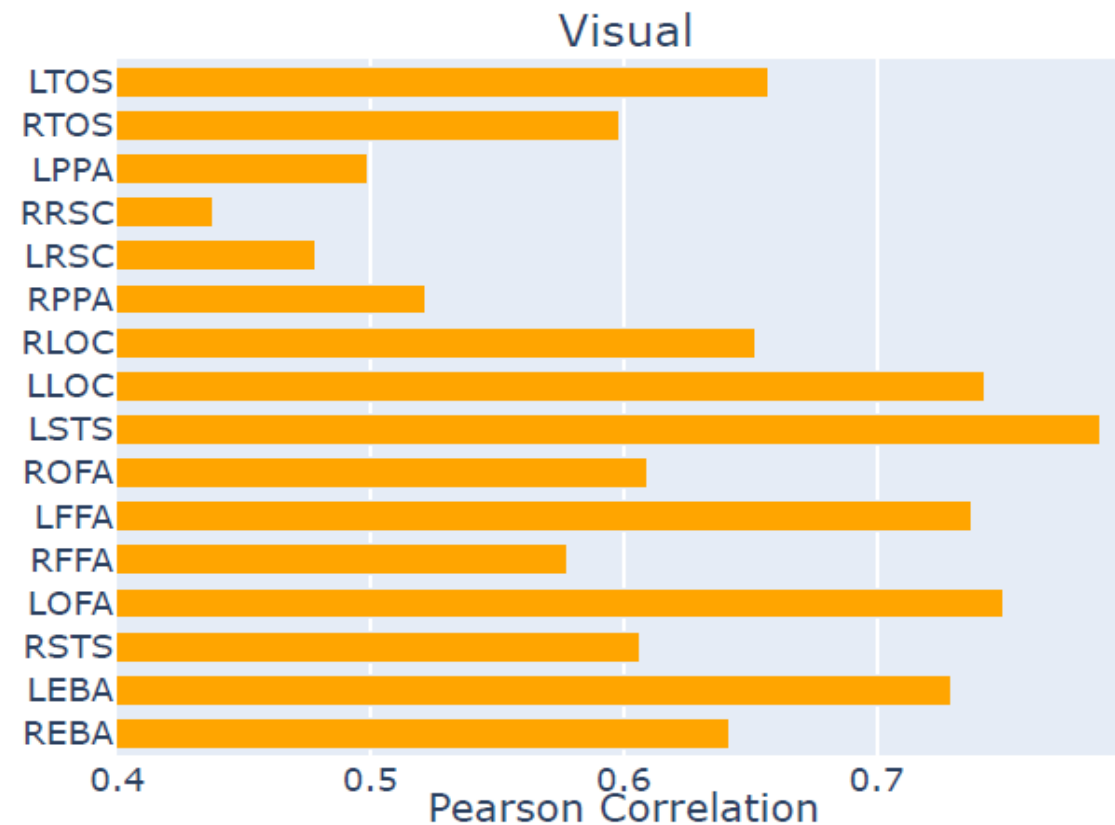
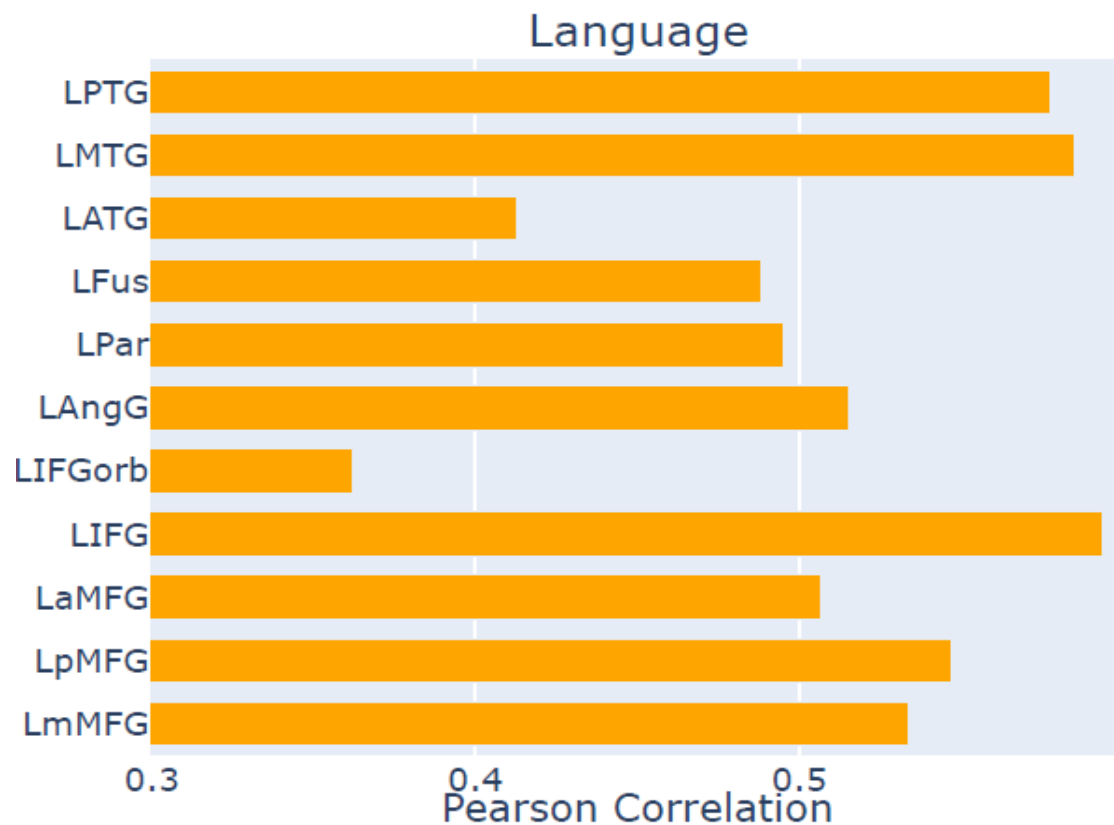
Single Stream

# Is Linguistic Information Important in Multi-Modal Transformers?

Models compared		PPA	LOC	EarlyVis	OPA	RSC
Correct Image-Text pairs	CLIP	0.095	0.134	0.083	0.139	0.082
	LXMERT	0.106	0.142	0.102	0.146	0.087
	VisualBERT	<b>0.141</b>	<b>0.187</b>	<b>0.128</b>	<b>0.188</b>	<b>0.12</b>
	ViLBERT	0.057	0.078	0.052	0.087	0.045
Randomize Image-Text pairs	CLIP-Random	0.020	0.024	0.033	0.031	0.002
	LXMERT-Random	0.035	0.041	0.035	0.049	0.029
	VisualBERT-Random	0.072	0.102	0.062	0.109	0.060
	ViLBERT-Random	0.018	0.011	0.013	0.017	0.017



# Does Language Influence Vision?



# Collaborators



Subba Reddy Oota



Jashn Arora



Vijay Rowtula



Manish Gupta



Bapi Raju Surampudi