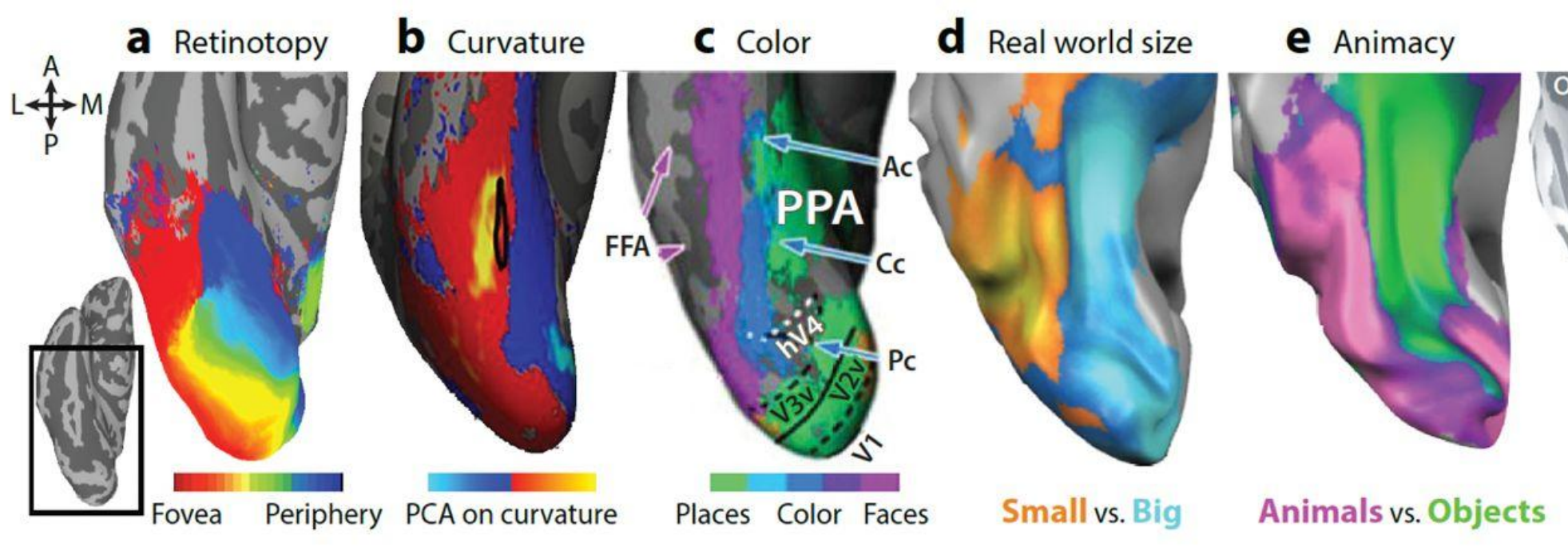
Topoformer: brain-like topographic organization in Transformer language models through spatial querying and reweighting

Taha Binhuraib[1], Greta Tuckute[2], Nicholas Blauch[3]

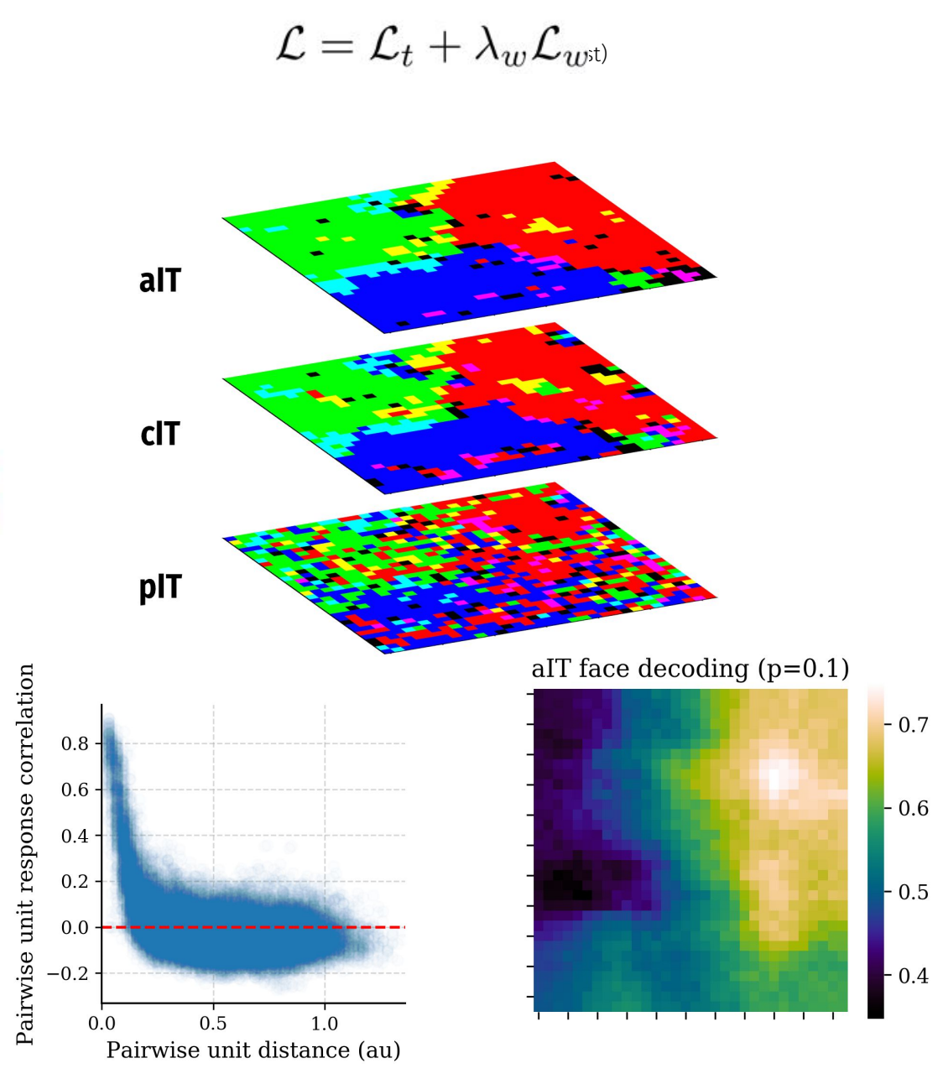
[1]Novus Technologies, [2]Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, [3]Department of Psychology, Harvard University

The human brain is topographically organized

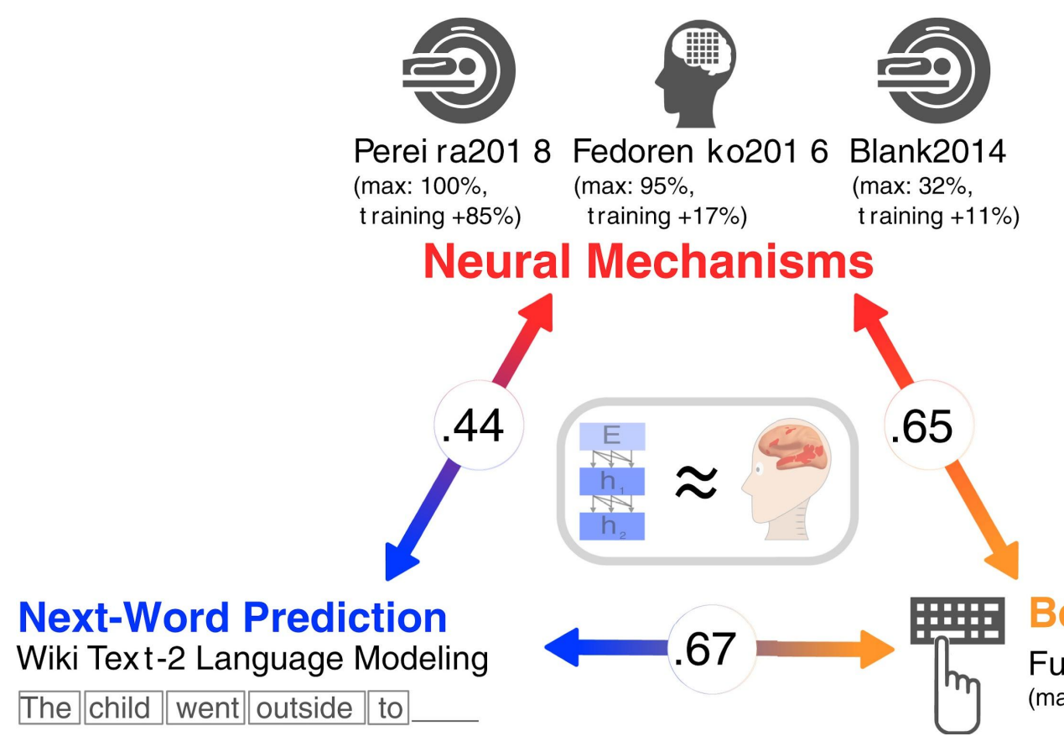
Topographic vision models have begun to explain the functional organization of the visual cortex



Arcaro & Livingstone, 2024



e.g. Interactive Topographic Network Blauch et. al 2022

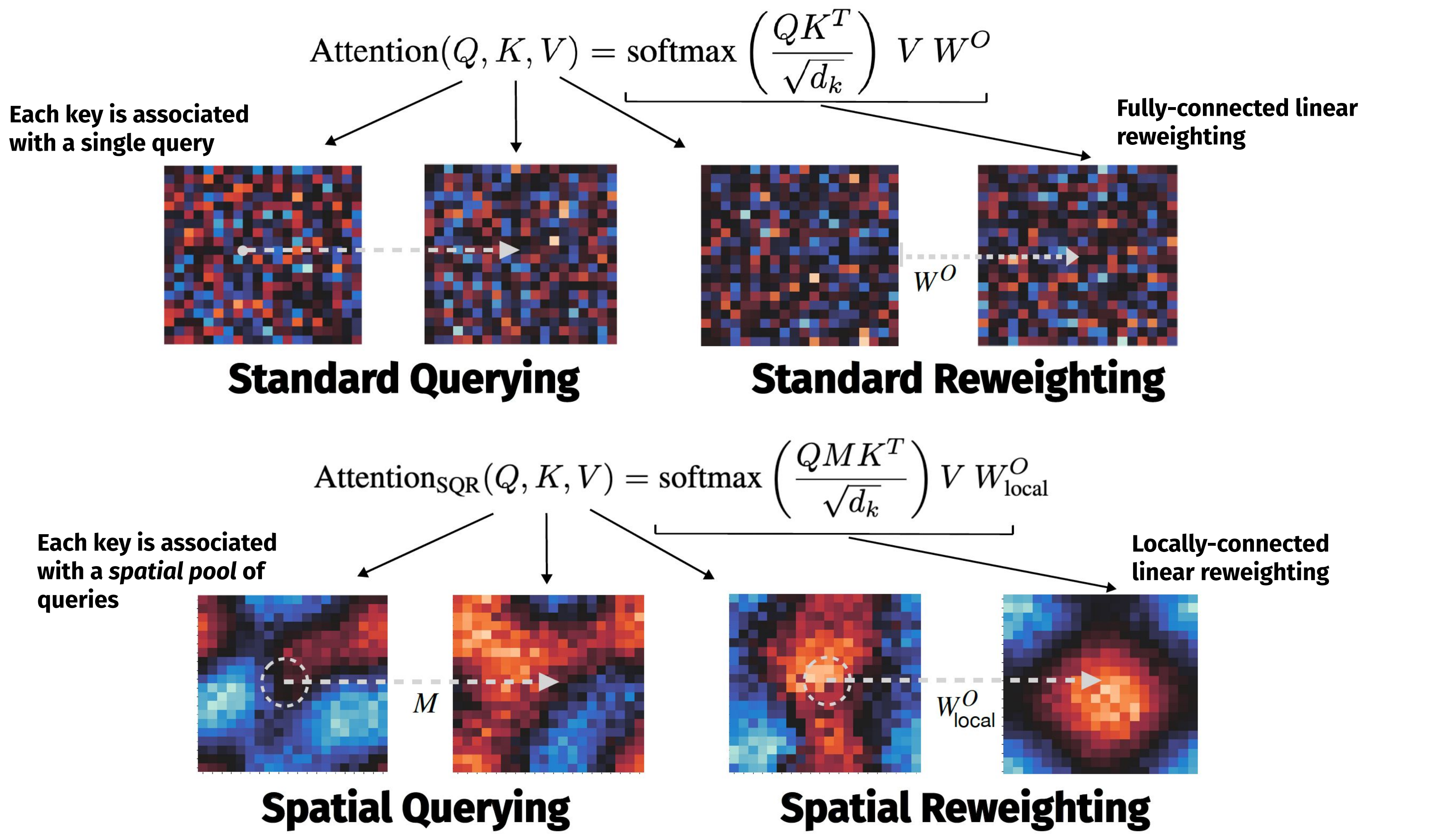

Pereira2018
(max: 100%, training +85%)
Fedorenko2016
(max: 95%, training +17%)
Blank2014
(max: 32%, training +11%)
Neural Mechanisms
.44
.65
.67
E
h1
h2
≈
Next-Word Prediction
Wiki Text-2 Language Modeling
The child went outside to
Behavior
Futrell2018
(max: 100%)

Schrimpf et. al, 2021

Internal representations of Transformer large language models (LLMs) can predict human brain responses and behavior

Question: Can we obtain topographic organization of linguistic representations within a transformer architecture?

Adding topographic priors to self-attention



$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V\, W^O$$

Each key is associated with a single query

Fully-connected linear reweighting

$$\mathrm{Attention}_{\mathrm{SQR}}(Q, K, V) = \mathrm{softmax}\left(\frac{QMK^T}{\sqrt{d_k}}\right) V\, W^O_{\mathrm{local}}$$

Each key is associated with a *spatial pool* of queries

Locally-connected linear reweighting

Figure 1: Spatial querying and reweighting operations in the "Topoformer"

Model training and evaluation

- Train a single-head 16-layer Topoformer BERT model with Masked Language Modeling objective following Geiping and Goldstein's (2022) training paradigm on the Bookcorpus-Wikipedia dataset.
- Evaluate task performance on the GLUE benchmark.

BERT Model	MNLI	SST-2	STSB	RTE	QNLI	QQP	MRPC	CoLA	GLUE
multihead	83.0/83.2	91.6	84.8	54.7	88.5	86.9	86.4	43.7	78.1
1 head	81.1/81.5	90.0	82.1	51.2	87.6	86.7	84.8	47.5	76.9
Topoformer	80.1/80.1	90.9	75.1	51.2	86.6	86.0	81.5	46.3	75.31

Table 1: Comparison of GLUE performance between non-topographic BERT control models and Topoformer-BERT

Visualizing topography

characterize topography at multiple spatial scales

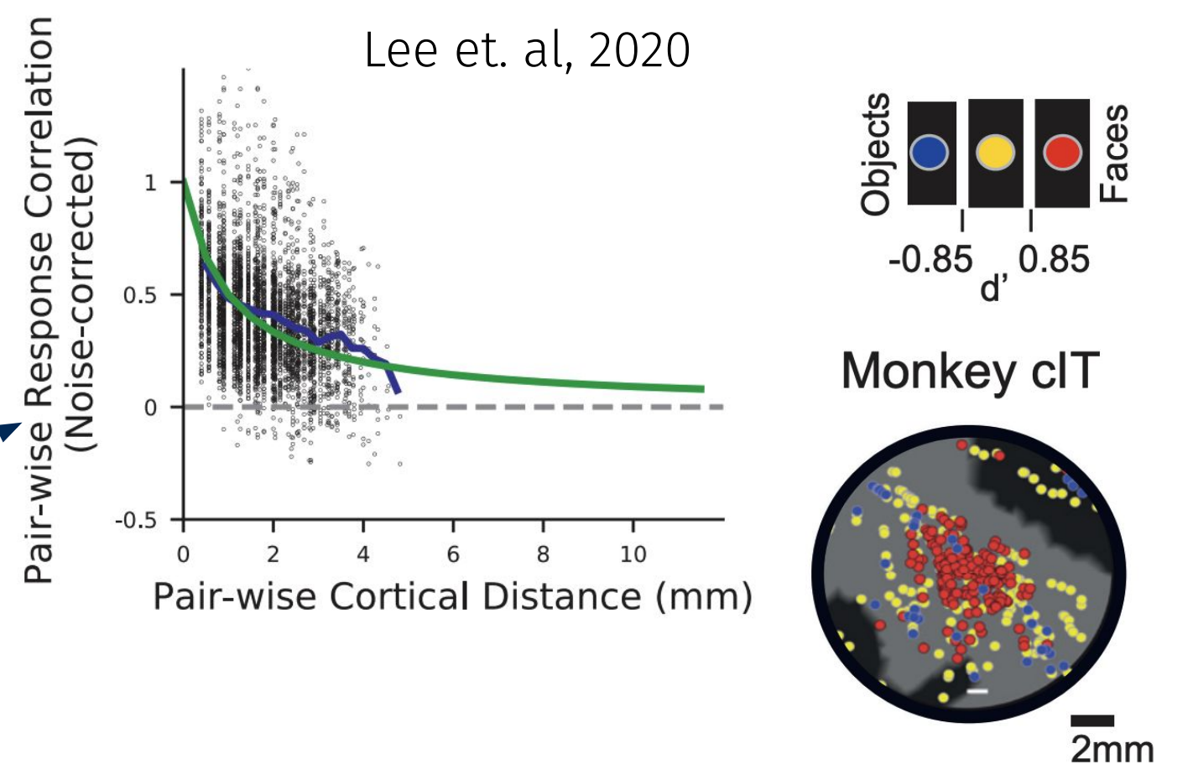
$$t_{g,d} = r_s(-R_{i,j}, \mathcal{D}_{i,j}) \;\; \forall \;\; i,j : D_{i,j} < d$$

summarize topography over all scales

$$\boldsymbol{t_g} = \{t_{g,d_0}, \ldots, t_{g,d_n}\}$$

$$\bar{t_g} = \frac{1}{n}\sum_i \boldsymbol{t_g^i}$$

Local correlation is a good index of topography



Quantification of topography in all layers of Topoformer-BERT

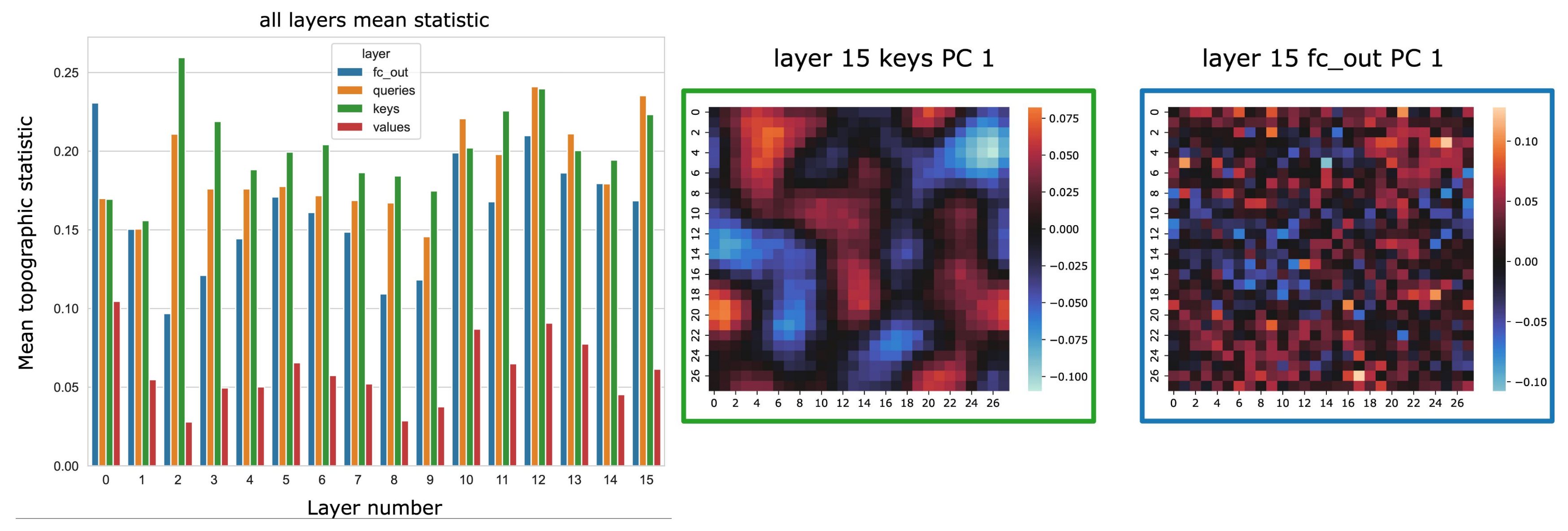


Figure 2: Topographic organization cross all layers of Topoformer-BERT.

Interpreting the emergent topography

	Test Suite	Category	Example
	Intactness	Intact Scrambled	She scored 2 goals in the soccer game. Soccer scored game. the She in 2 goals.
semantic contrasts	Animacy	Animate Inanimate	The gnu galloped across the savanna, majestic and swift. The oven's warm glow promised delicious, freshly baked bread.
	Concreteness	Concrete Abstract	She peeled the banana slowly, savoring its sweet, ripe aroma. Her motive for volunteering was purely altruistic and kind.
	Visuomotor	Visual Motor	To solve problems, I often visualize them in my mind. His grip on the rope tightened as he climbed higher.
	Semantic Acceptability	Acceptable Unacceptable	A sunflower has yellow petals. A peanut has yellow petals.
minimal pair syntax contrasts	Agreement	Matched Mismatched	The authors that hurt the senator are good. The authors that hurt the senator is good.
	Licensing	Matched Mismatched	The authors that liked the senator hurt themselves. The authors that liked the senator hurt himself.
	Garden-Path	Ambiguous Unambiguous	As the criminal shot the woman with her young daughters yelled at the top of her lungs. As the criminal fled the woman with her young daughters yelled at the top of her lungs.

Table 2: Overview of test suites with sentence examples. Each test suite had 38 sentences in each category, for a total of 76 sentences in each suite.

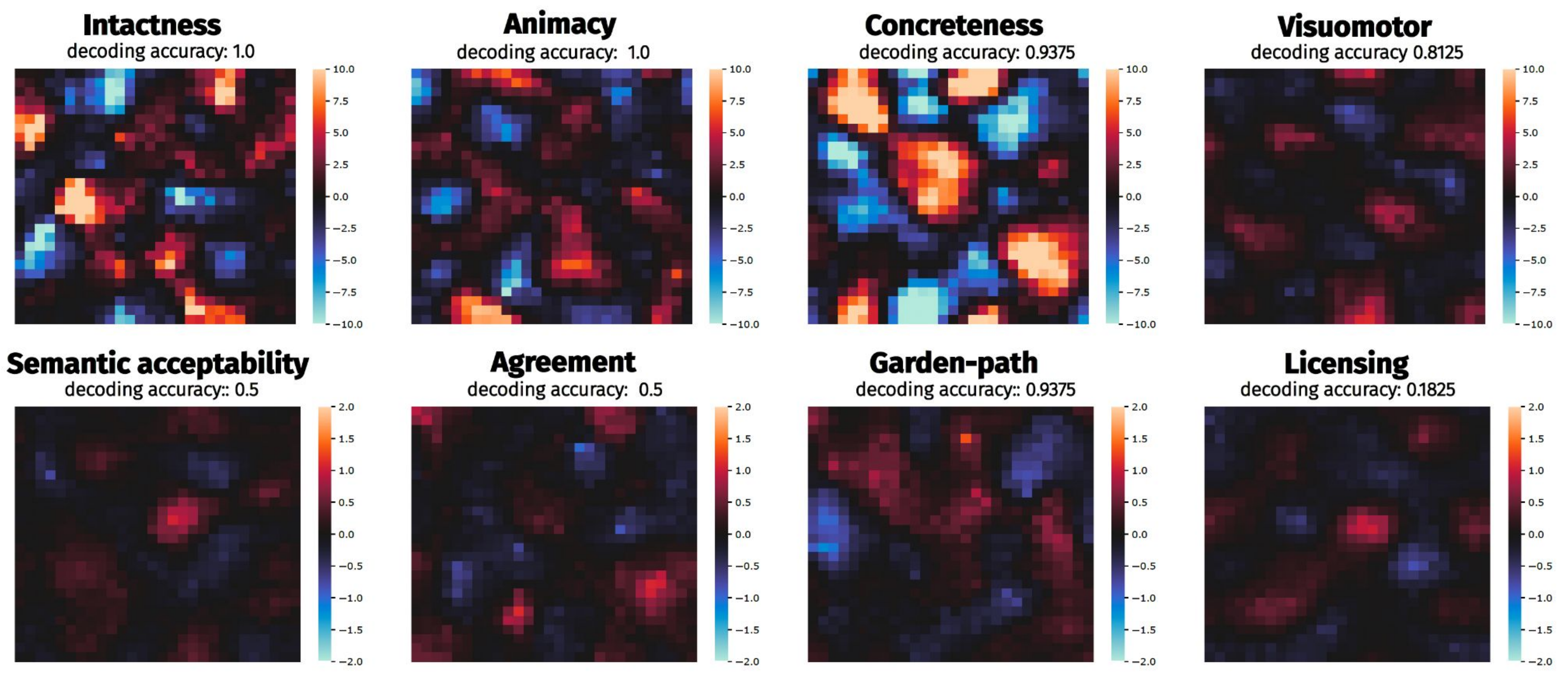


Figure 3: Selectivity-based interpretation of topographic organization in Topoformer-BERT.

Brain-model alignment

$$X^TY = U\Sigma V$$

brain responses (n x p)
model embeddings (n x m)
brain loadings (p x d)
singular values (d x d diag)
model loadings (transpose) (d x m)

With held-out data compute scores: $X_x = XU$

$$Y_c = YV^T$$

Compute alignment of i-th components

$$a^{(i)} = r(X_c^i, Y_c^i)$$

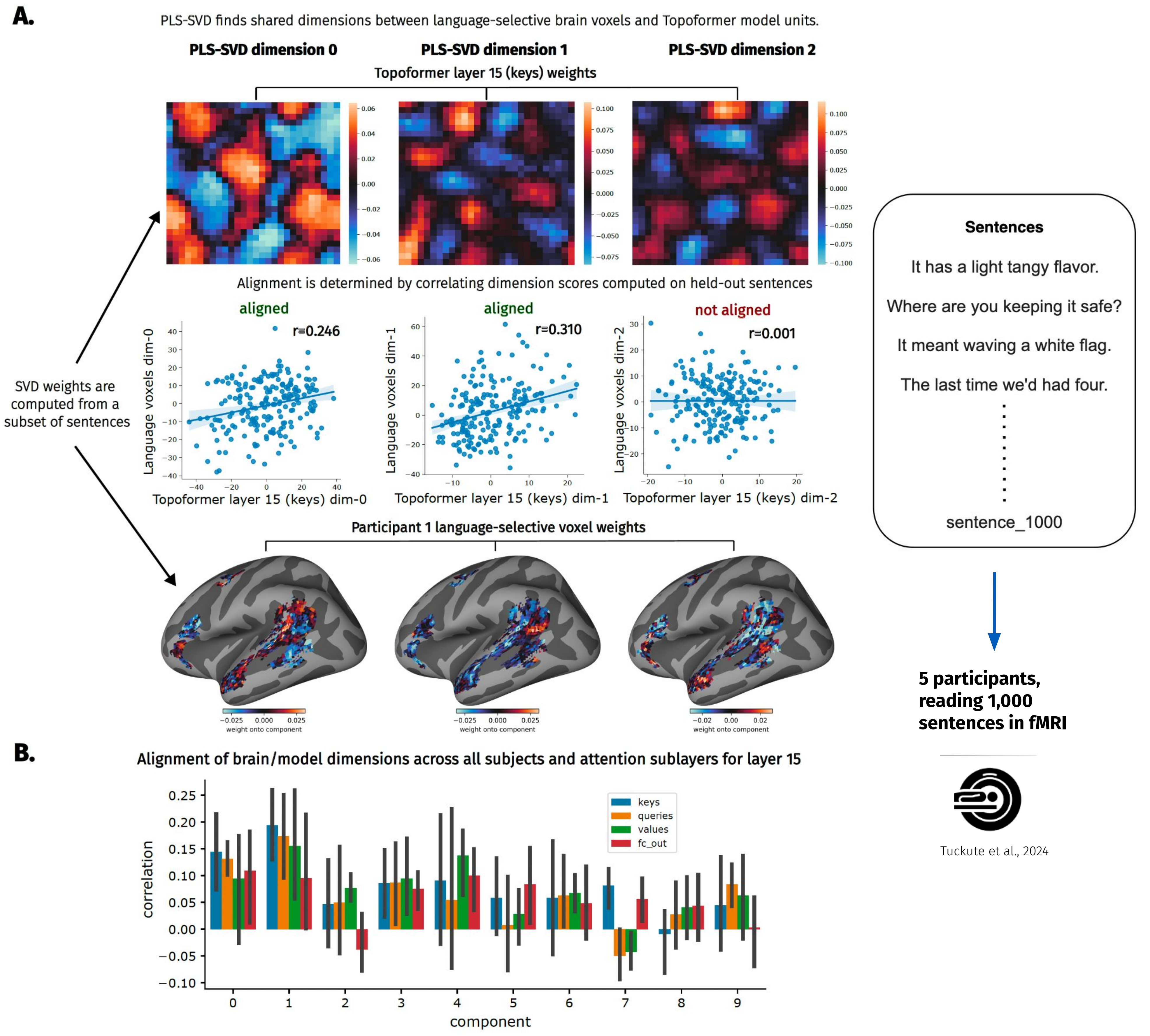


Figure 4: Alignment of topographic representations in the human language network and Topoformer-BERT model.

Conclusions and future directions

- Topoformers allow for modeling of topographic organization of linguistic representations.
- Low-dimensional variability can be aligned in the topographic representations of the human language network and Topoformer language model.
- Topoformers hold great promise for improved interpretability of LLMs and brains, and can be applied to other domains.

References:

- Blauch, N. M., Behrmann, M., & Plaut, D. C. (2022). A connectivity-constrained computational account of topographic organization in primate high-level visual cortex. Proceedings of the National Academy of Sciences of the United States of America, 119(3). https://doi.org/10.1073/pnas.2112566119
- Geiping, J., & Goldstein, T. (2023). Cramming: Training a Language Model on a single GPU in one day. In Proceedings of the International Conference on Machine Learning (pp. 11117-11143). PMLR.
- Schrimpf, M., Blank, I. A., Tuckute, G., Kauf, C., Hosseini, E. A., Kanwisher, N., Tenenbaum, J. B., & Fedorenko, E. (2021). The neural architecture of language: Integrative modeling converges on predictive processing. Proceedings of the National Academy of Sciences, 118(45), e2105646118. https://doi.org/10.1073/pnas.2105646118
- Arcaro, M., & Livingstone, M. (2024). A Whole-Brain Topographic Ontology. Annual Review of Neuroscience, 47. Annual Reviews.
- Tuckute, G., Sathe, A., Srikant, S., Taliaferro, M., Wang, M., Schrimpf, M., Kay, K., & Fedorenko, E. (2024). Driving and suppressing the human language network using large language models. Nature Human Behaviour, 8(2), 1–18.
- Lee, H., Margalit, E., Jozwik, K. M., Cohen, M. A., Kanwisher, N., Yamins, D. L. K., & DiCarlo, J. J. (2020). Topographic deep artificial neural networks reproduce the hallmarks of the primate inferior temporal cortex face processing network. BioRxiv. Advance online publication. https://doi.org/10.1101/2020.07.09.1851