

# Quantifying the role of perceived curvature in the processing of natural object images

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## Background

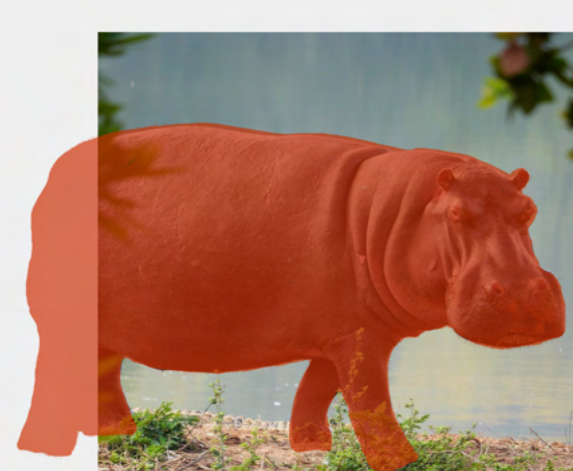
- Curvature is suggested as a fundamental organizational dimension of object responses, supporting higher-level categorization [1, 2]
- While there may be a clear definition of curvature for artificial stimuli, defining the global curvature of naturalistic object images remains challenging



global shape  
vs. local features



how to deal with  
background features?



how to deal with **object cropping,**  
**viewing angle, & lighting?**

Can people rate the global curvature of naturalistic object images, and how does this perceived curvature relate to neural object responses?

What are the features contributing to people's perception of curvature?

## Methods

### Perceived curvature ratings

- Rich dataset of curvature ratings for > 27k natural object images of the THINGS database [3, 4]



0 most rectilinear



100 most curvy

Split-half  
reliability  
 $r = 0.93$

### Computed curvature

- MLV-toolbox [5]
- Li & Bonner [2]

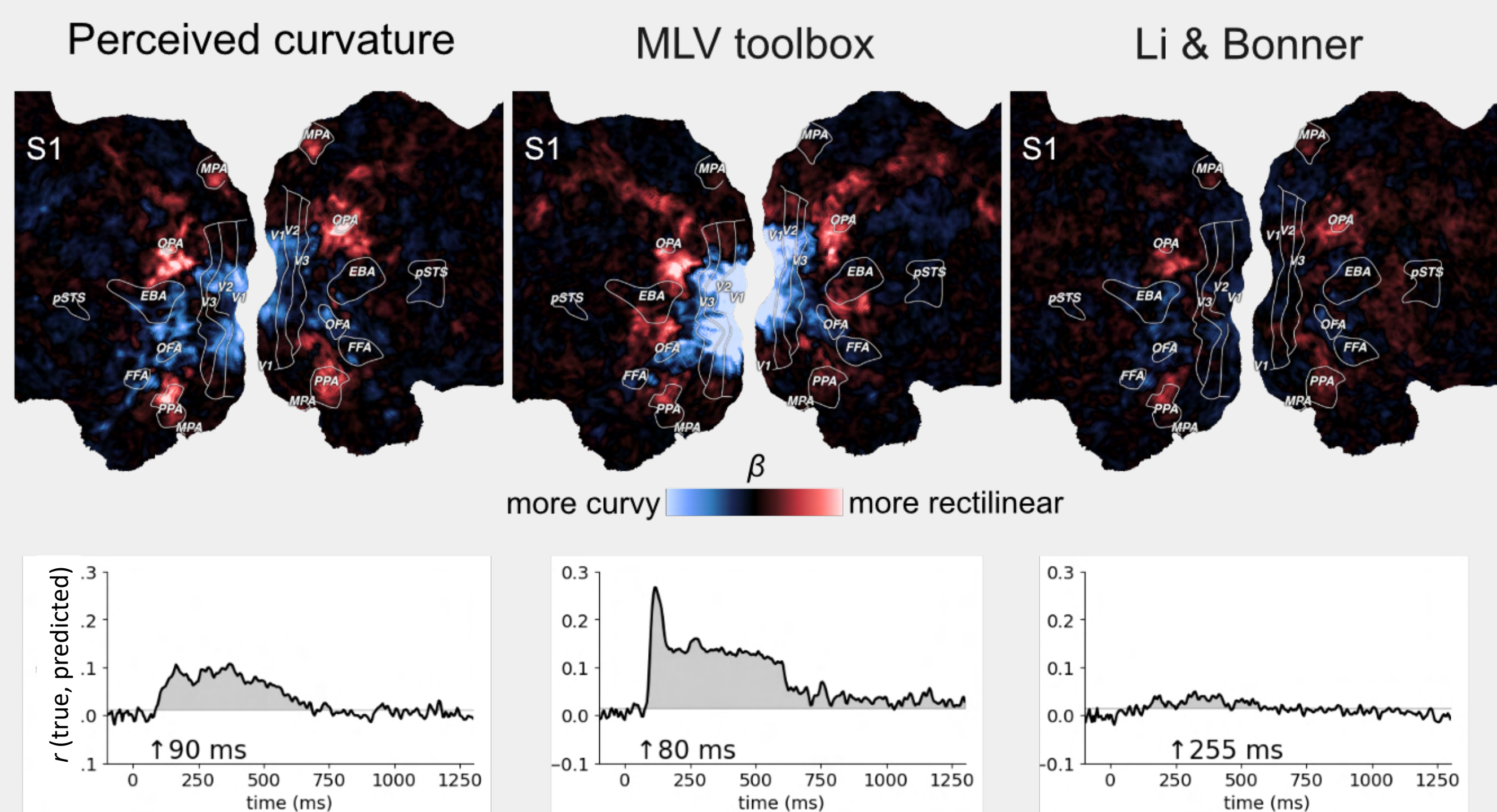
perceived	1.00	-0.26	-0.22
MLV	-0.26	1.00	0.14
Li & Bonner	-0.22	0.14	1.00
perc.		MLV	L&B

### THINGS-Data [6]

- fMRI** responses of 3 participants to 8,640 natural images of 720 object concepts
- MEG** responses of 4 participants to 22,449 natural images of 1,854 object concepts

## How does perceived curvature relate to neural object responses?

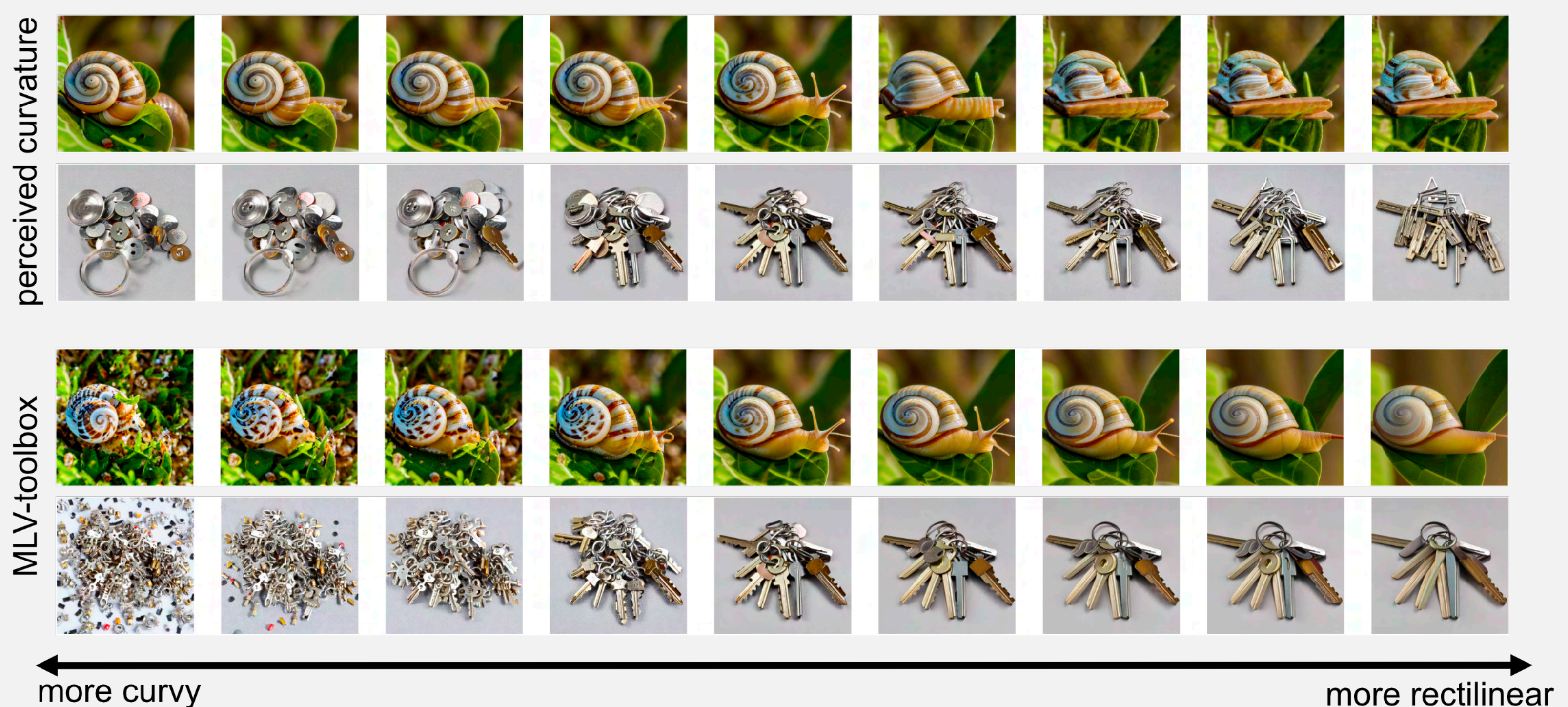
→ Curvature measures relate to distinct brain patterns with perceived curvature best reflecting known category selectivity [1]



## Which image features underlie curvature measures?

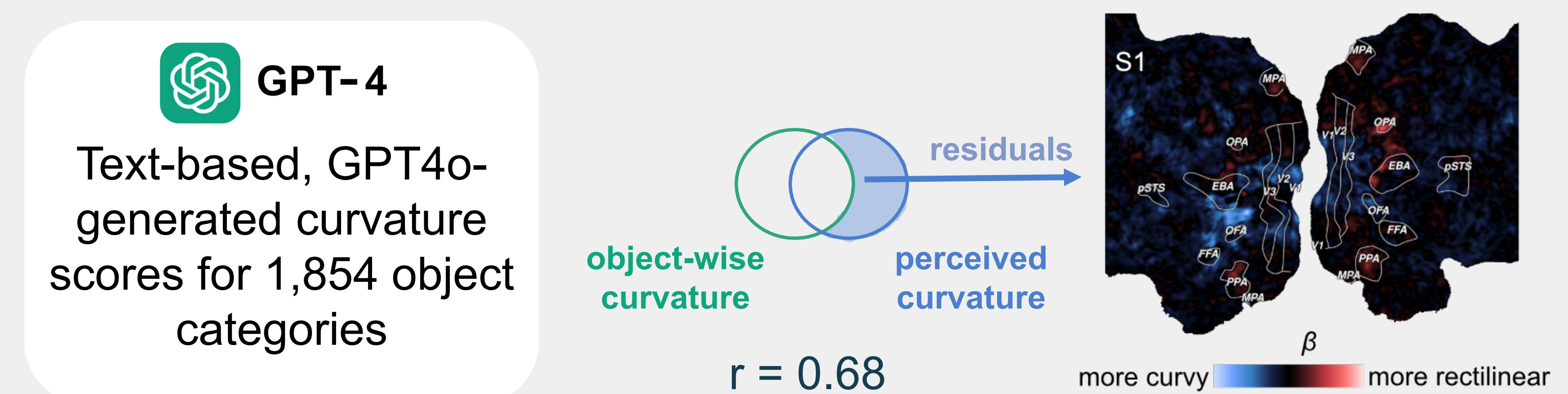
**BrainACTIV** [7]: diffusion-based model, allowing to modify the perceived or computed curvature of object images, whilst preserving most semantic and low-level visual features

→ People use more global image features to rate perceived curvature vs. MLV-toolbox curvature is based on more local features



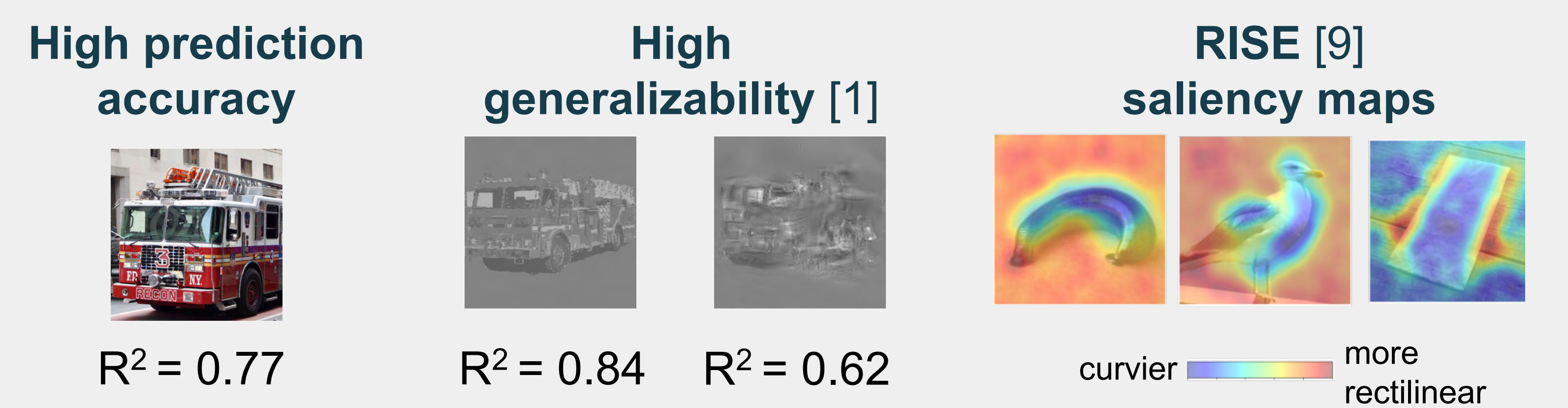
## What is the role of semantics in perceived curvature?

- Object-wise GPT4o-generated curvature captures much of the neural effects of image-wise perceived curvature
- Perceived curvature can be partly inferred from semantic object category, suggesting it may pose a bridge between vision and semantics



## How can we efficiently quantify the perceived curvature of novel images?

**pCurvComp**: Barlow-Twin-RN50 [8] based model predicting perceived curvature of novel images



## Conclusion

- Perceived curvature as candidate **organizational dimension** of visual object representations
- Global image features** as well as **semantics** may contribute to people's perception of curvature
- Curvature as crucial organizational principle bridging vision and semantics
- Recognizing its importance, we make perceived curvature image-computable with **pCurvComp**

[1] Long, B., Yu, C.-P., & Konkle, T. (2018). Mid-level visual features underlie the high-level categorical organization of the ventral stream. *Proceedings of the National Academy of Sciences*, 115(38). <https://doi.org/10.1073/pnas.1719616115>

[2] Li, D. S. P., & Bonner, M. F. (2022). *Emergent selectivity for scenes, object properties, and contour statistics in feedforward models of scene-prefering cortex* (p. 2021.09.24.461733). *bioRxiv*. <https://doi.org/10.1101/2021.09.24.461733>

[3] Hebart, M. N., Dicker, A. H., Kidder, A., Kwok, W. Y., Corriveau, A., Wicklin, C. V., & Baker, C. I. (2019). THINGS: A database of 1,854 object concepts and more than 26,000 naturalistic object images. *PLOS ONE*, 14(10), e0223792. <https://doi.org/10.1371/journal.pone.0223792>

[4] Stoinski, L. M., Perkuhn, J., & Hebart, M. N. (2023). THINGSplus: New norms and metadata for the THINGS database of 1854 object concepts and 26,107 natural object images. *Behavior Research Methods*. <https://doi.org/10.3758/s13428-023-02110-8>

[5] Walther, D. B., & Shen, D. (2014). Nonaccidental Properties Underlie Human Categorization of Complex Natural Scenes. *Psychological Science*, 25(4), 851–860. <https://doi.org/10.1177/0956797613512662>

[6] Hebart, M. N., Contier, O., Teichmann, L., Rockter, A. H., Zheng, C. Y., Kidder, A., Corriveau, A., Vaziri-Pashkam, M., & Baker, C. I. (2023). THINGS-data, a multimodal collection of large-scale datasets for investigating object representations in human brain and behavior. *eLife*, 12, e82580. <https://doi.org/10.7554/eLife.82580>

[7] García Cerdas, D., Sartzetaki, C., Petersen, M., Roig, G., Mettes, P., & Groen, I. (2025). BrainACTIV: Identifying visuo-semantic properties driving cortical selectivity using diffusion-based image manipulation. In *Proceedings of the Thirteenth International Conference on Learning Representations*. <https://openreview.net/forum?id=CGON8Btleu>

[8] Zbontar, J., Jing, L., Misra, I., LeCun, Y., & Deny, S. (2021). Barlow Twins: Self-Supervised Learning via Redundancy Reduction (arXiv:2103.03230). *arXiv*. <https://doi.org/10.48550/arXiv.2103.03230>

[9] Petsiuk, V., Das, A., & Saenko, K. (2018). RISE: Randomized Input Sampling for Explanation of Black-box Models (arXiv:1806.07421). *arXiv*. <http://arxiv.org/abs/1806.07421>