Feature-disentangled reconstruction of perception from multi-unit recordings

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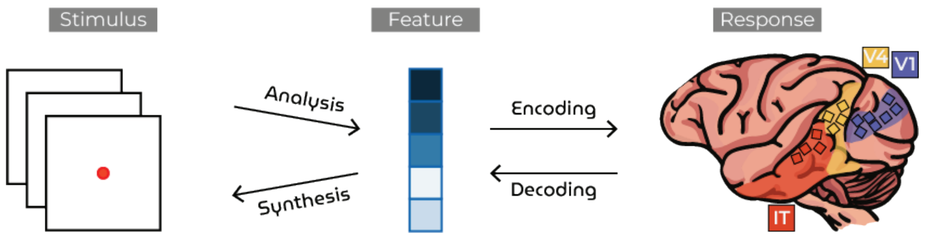
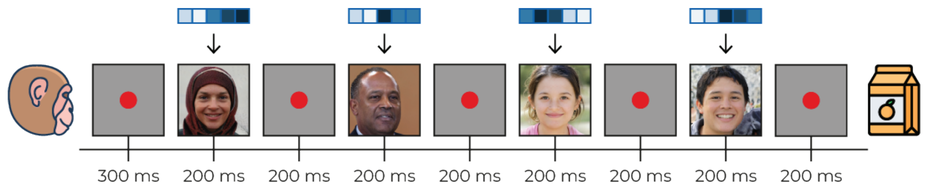
INTRODUCTION

- What high-level neural representations underlie visual perception?
  - Analyzed the relationship between **multi-unit activity (MUA)** of macaque visual cortex [1] and various **latent representations** of recent deep generative models with different properties, each of which captured a specific set of features and patterns
  - The feature-disentangled latents explained the most variance of the recorded brain activity, and were subsequently used to *reconstruct* the perceived stimuli with state-of-the-art quality, according to the experimental paradigm of [2]



METHODS

- **Stimuli:** face- and natural images generated by StyleGAN3 [3] and StyleGAN-XL [4], respectiv.
- **Features:** conventional z-latents of StyleGAN 3/-XL, feature-disentangled w-latents of StyleGAN 3/-XL, and language-contrastive CLIP-latents of Stable Diffusion
- **Responses:** MUA with 15 chronically-implanted 64-channel microelectrode arrays in one macaque (male, 7 years old) upon presentation with images



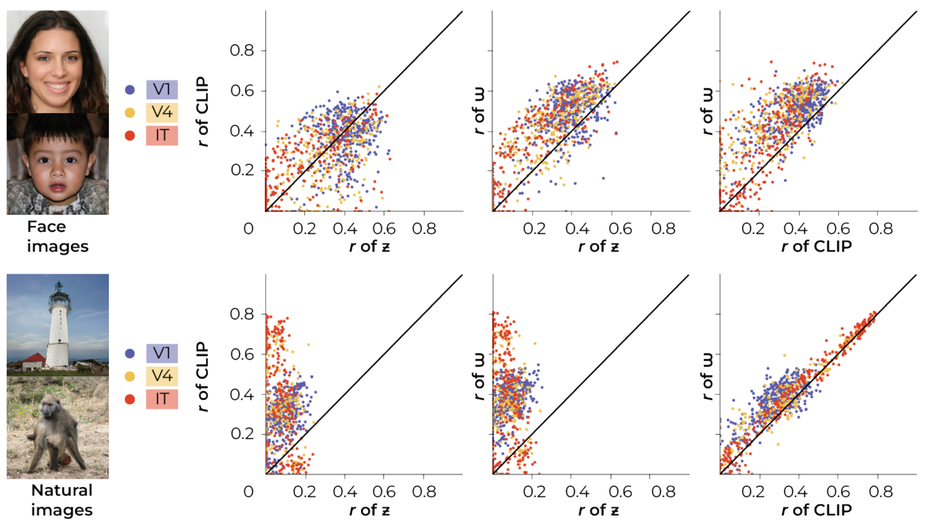
Passive fixation experiment.

- **Linear mapping** to evaluate our claim that the feature- and neural representation effectively encode the same stimulus properties, as is standard in neural coding. A more complex non-linear transformation would not be valid to support this claim since nonlinearities will fundamentally change the underlying representations.

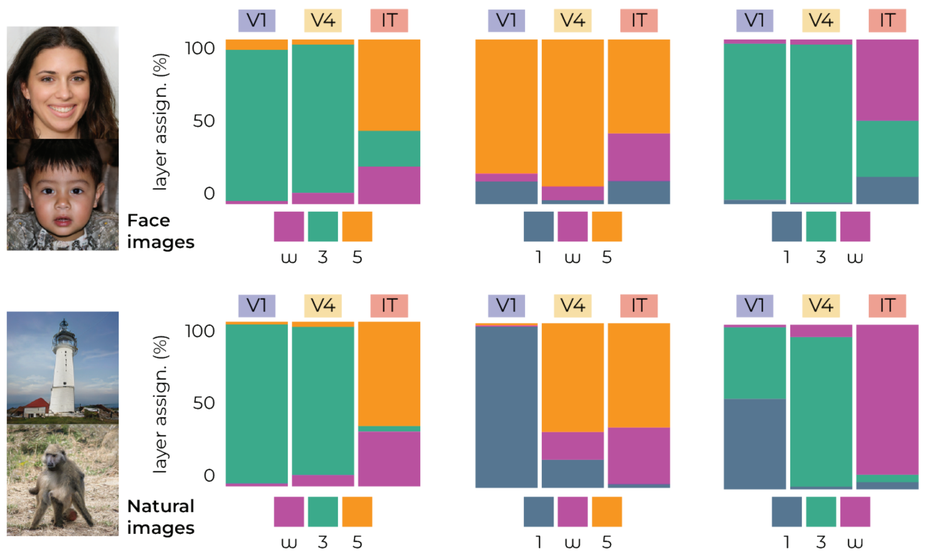
RESULTS

ENCODING

· A mass univariate neural encoding analysis of the latent representations showed that *feature-disentangled* representations, **w-latents**, explain increasingly more variance than the alternative representations over the ventral stream.



Encoding performance of generative latents.



Layer assignment using early (1; layer 2/16), middle (3; layer 7/16) and deep (5; layer 13/16) activations of VGG16 pretrained for face/object recognition [5, 6] over visual areas results in the complexity gradient. Replacing one activation by w-latents shows it predominantly acounts for high-level brain activity.

DECODING

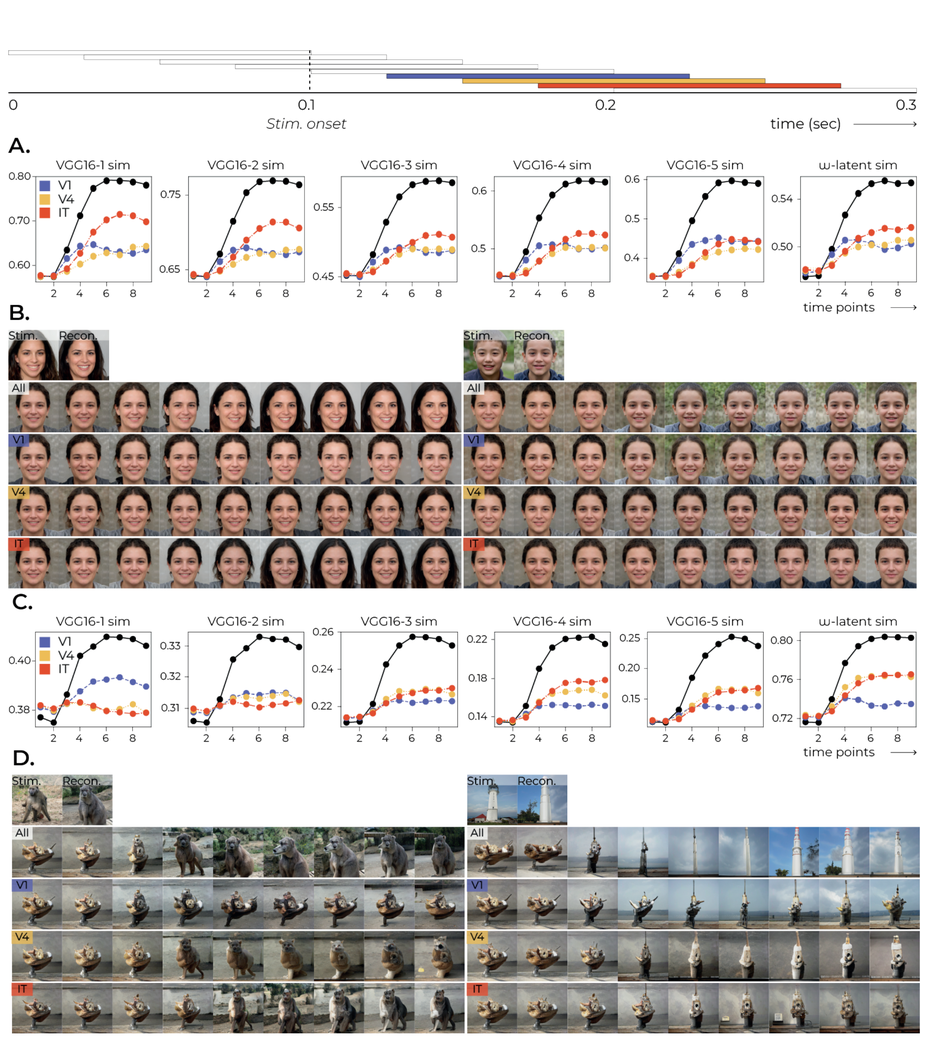
· A multivariate neural decoding analysis of the feature-disentangled representations resulted in state-of-the-art spatiotemporal reconstructions of visual perception.

		VGG16-1 sim.	VGG16-2 sim.	VGG16-3 sim.	VGG16-4 sim.	VGG16-5 sim.	Lat. sim.
Face images	*All*	**0.7871 ± 0.0102**	**0.7681 ± 0.0075**	**0.5874 ± 0.0075**	**0.6170 ± 0.0085**	**0.5940 ± 0.0104**	**0.5548 ± 0.0045**
	V1	0.6382 ± 0.0079	0.6758 ± 0.0064	0.4891 ± 0.0064	0.5041 ± 0.0083	0.4442 ± 0.0092	0.5022 ± 0.0047
	V4	0.6303 ± 0.0101	0.6729 ± 0.0068	0.4890 ± 0.0068	0.5006 ± 0.0085	0.4191 ± 0.0091	0.5026 ± 0.0040
	IT	*0.7123 ± 0.0110*	*0.7133 ± 0.0073*	*0.5093 ± 0.0073*	*0.5253 ± 0.0087*	*0.4434 ± 0.0096*	*0.5176 ± 0.0039*
Natural images	*All*	**0.4083 ± 0.0036**	**0.3322 ± 0.0036**	**0.2555 ± 0.0025**	**0.2192 ± 0.0043**	**0.2497 ± 0.0066**	**0.8032 ± 0.0032**
	V1	*0.3929 ± 0.0031*	*0.3147 ± 0.0031*	0.2223 ± 0.0019	0.1511 ± 0.0023	0.1367 ± 0.0037	0.7336 ± 0.0036
	V4	0.3790 ± 0.0029	0.3132 ± 0.0029	0.2270 ± 0.0019	0.1641 ± 0.0027	0.1617 ± 0.0045	0.7614 ± 0.0034
	IT	0.3798 ± 0.0026	0.3127 ± 0.0026	*0.2302 ± 0.0020*	*0.1790 ± 0.0039*	*0.1692 ± 0.0057*	*0.7653 ± 0.0039*

Decoding performance in terms of six metrics of perceptual cosine similarity using five intermediate layer activations of VGG16 for face- and object recognition for face- and natural images, repectively, and latent cosine similarity between w-latents of stimuli and reconstructions (mean ± std. error).

DECODING

Example results. Stimulus (top) reconstructions (bottom) from brain activity.



Time-based decoding. A sliding window of 100 ms with a stride of 25 ms over the entire time course (300 ms per trial, stimulus onset at 100 ms) which resulted in nine average responses in time. For reference, the original predefined time windows for V1, V4 and IT are color-coded at the top. **A**, **C** show decoding performance over time. **B**, **D** show how two reconstructions evolve over time.

CONCLUSIONS

- **Neural encoding:** feature-disentangled w-latents were the most successful at predicting high-level brain activity at the end of the visual ventral pathway
  - Highlights the importance of feature disentanglement in explaining high-level neural responses underlying visual perception and demonstrates the potential of aligning unsupervised generative models with biological processes
- **Neural decoding:** the decoded w-latents resulted in state-of-the-art image reconstructions that closely matched the stimuli in their semantic as well as structural features
  - StyleGAN itself has never been optimized on neural data which implies a general principle of shared encoding of real-world phenomena
  - Advancements of comp. models and clinical applications for people with disabilities

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