

Rapid adaptation to parametric and natural stimuli along the visual pathway

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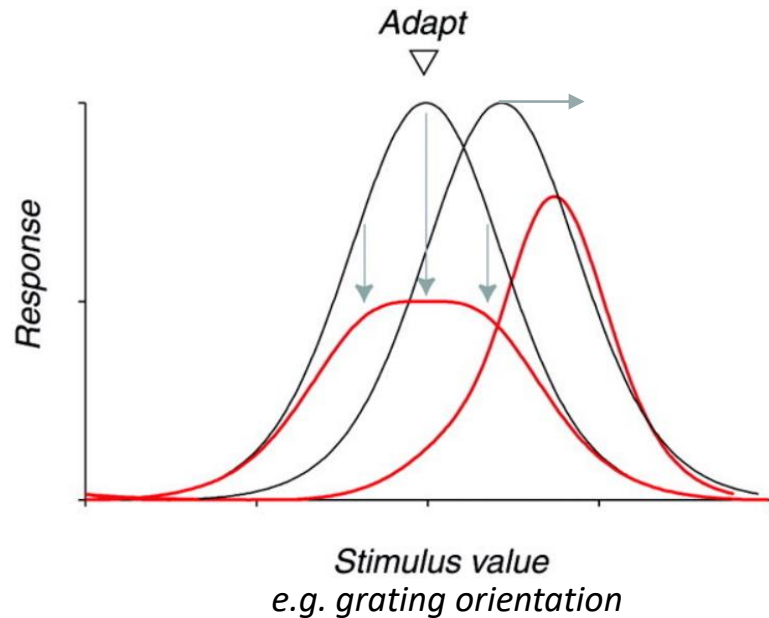
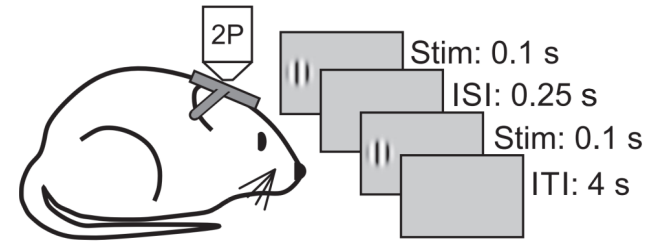
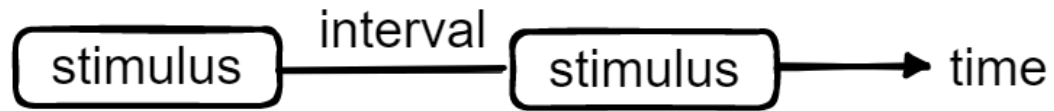
Trade-off between information transmission and metabolic cost



>> Efficient coding hypothesis

maximizing mutual information
between input and neuronal
response using minimal number
of spikes (Barlow, 1961)

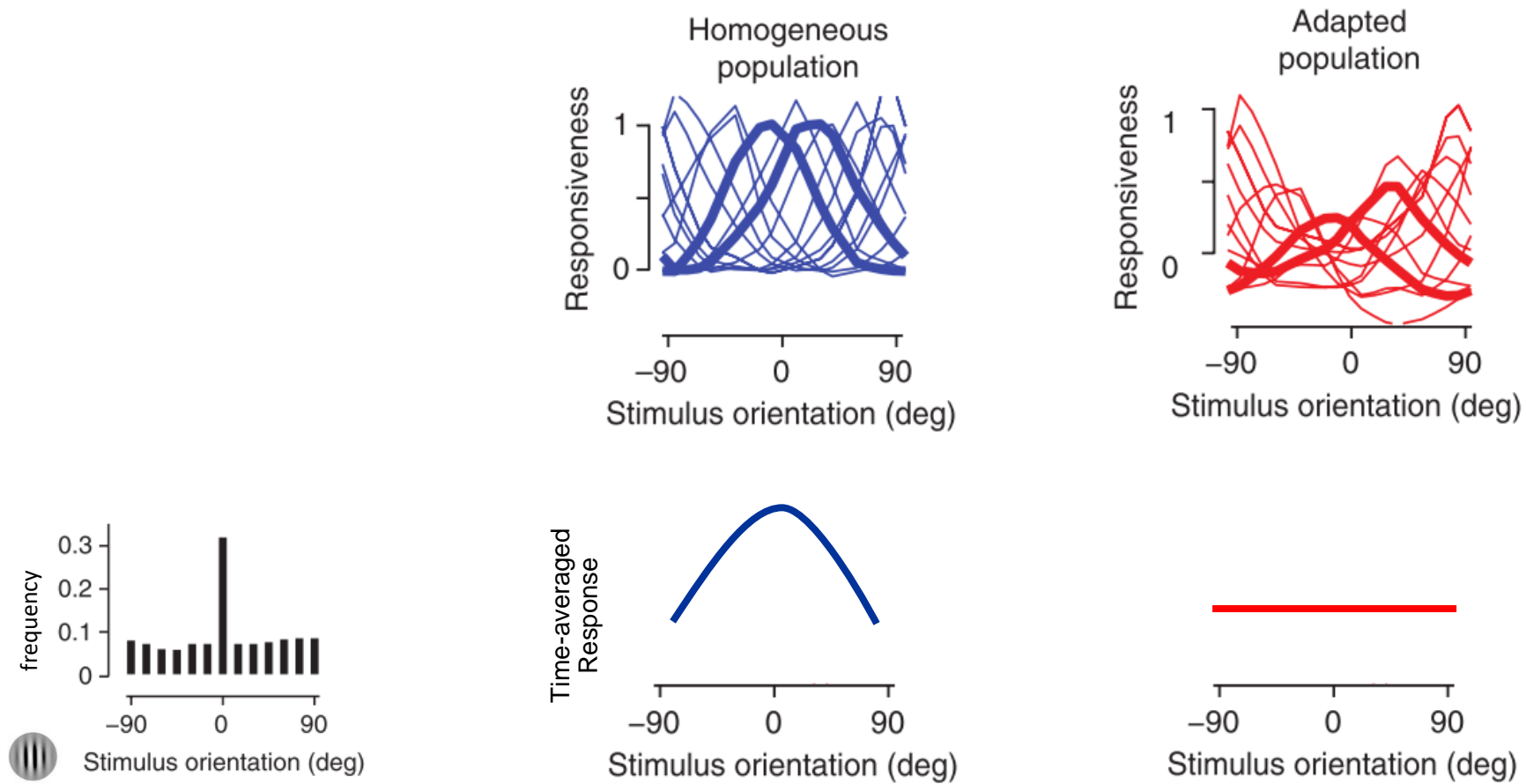
Adaptation alters visual processing according to recent history



Characteristics of adaptation:

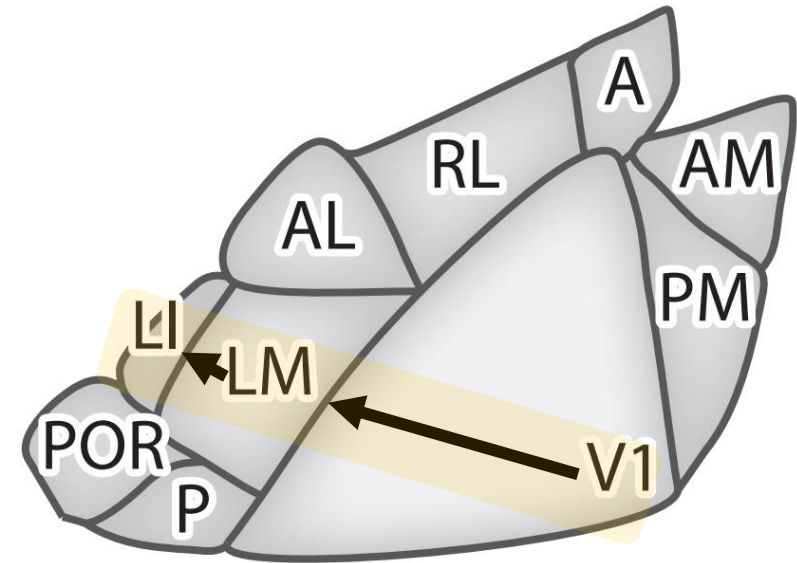
- Firing rate reduction
- Neuronal preference tuning bias

Adaptation in V1 reduces redundancy of frequent stimulus & benefits coding efficiency



Increasingly sparse representations along the visual hierarchy

- V1 project to higher visual areas
- Sparse firing and sparse population coding in higher visual areas (Young & Yamane, 1992, Zhuang et al, 2017, Vinken et al, 2017)
- Hypothesis: increasing sparseness in higher visual area could be accompanied by increasing adaptation

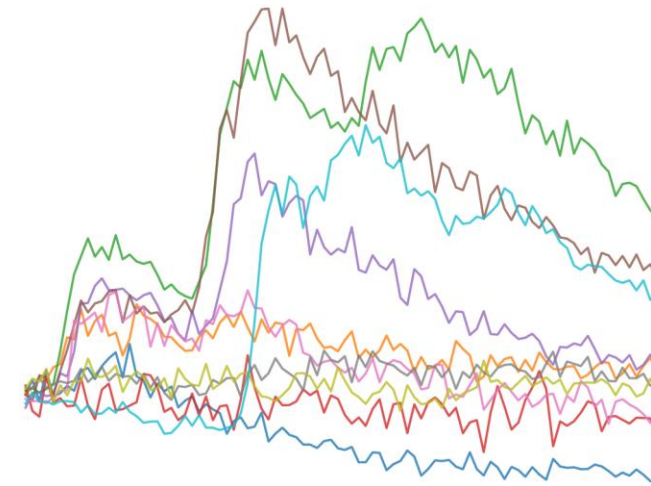
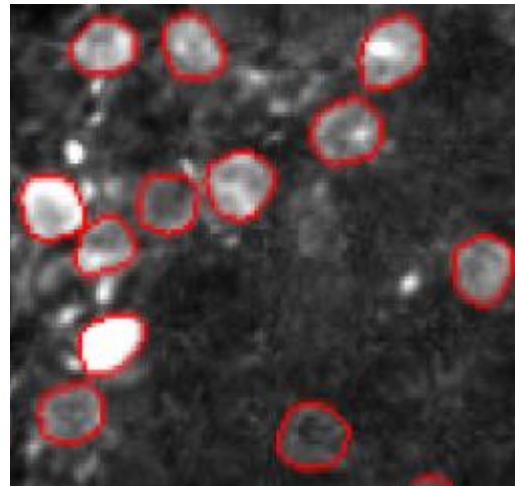
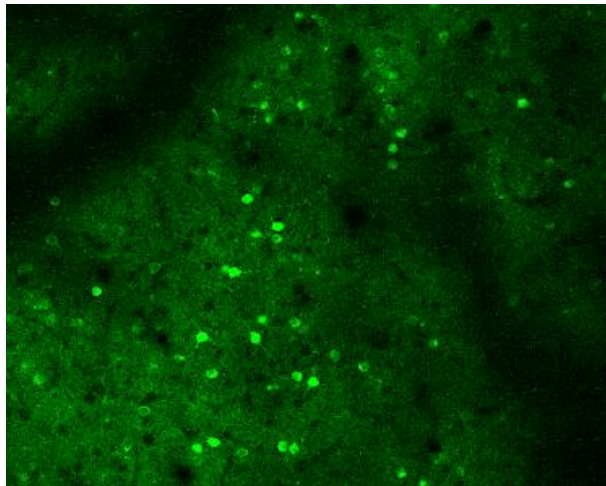
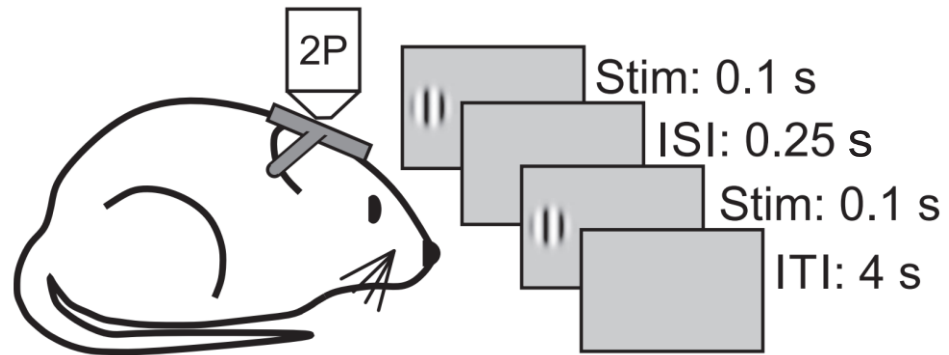


Ventral visual pathway

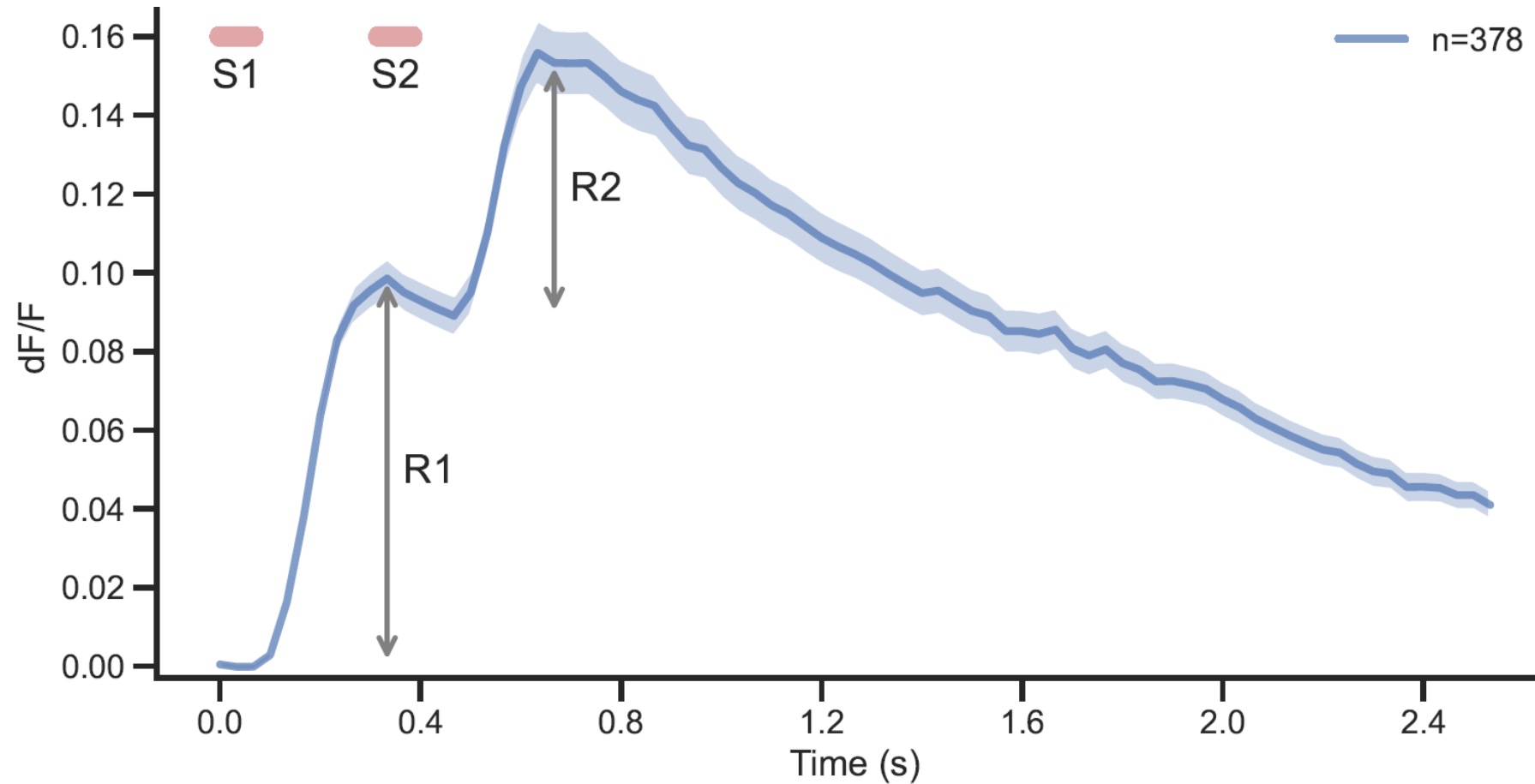
Expectation

Adaptation increases from V1 to LM to LI

Adaptation to gratings increases along ventral visual pathway

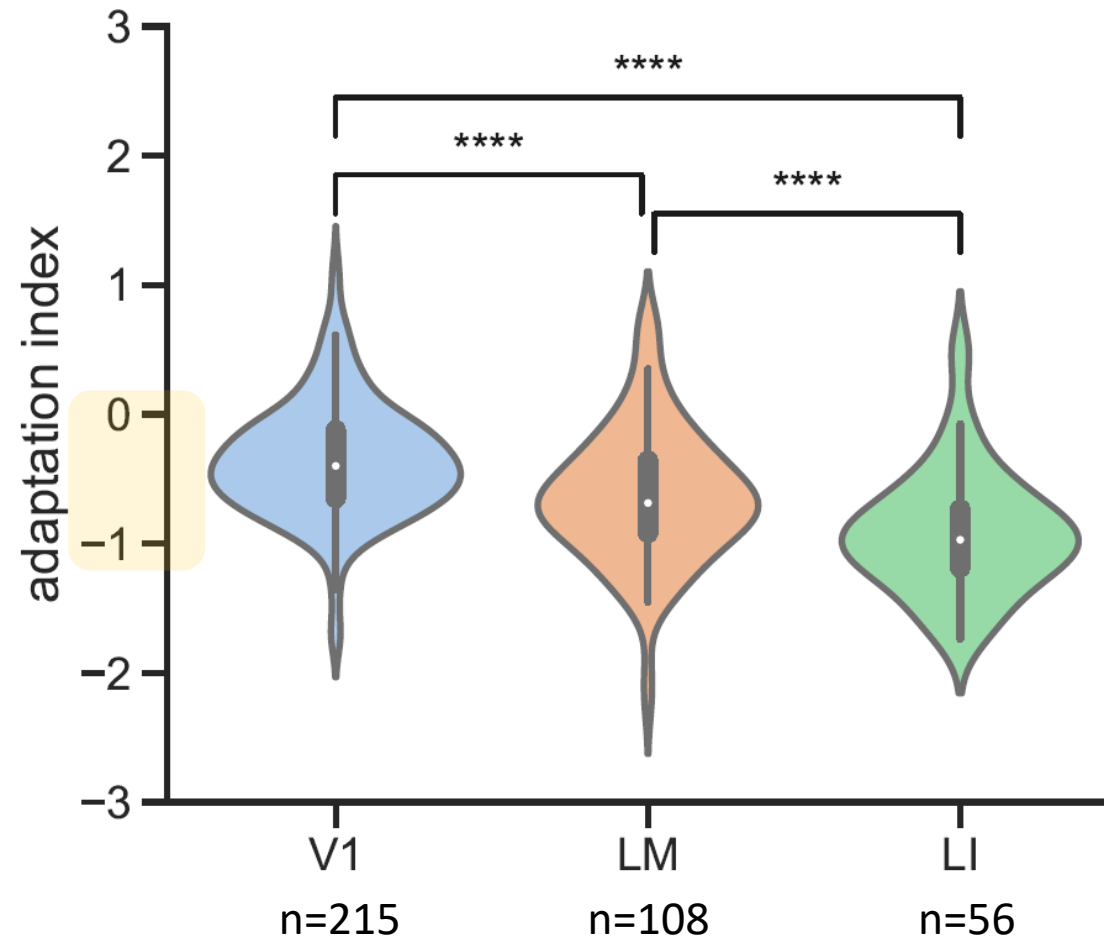


V1 response to gratings: trace of grand trial average



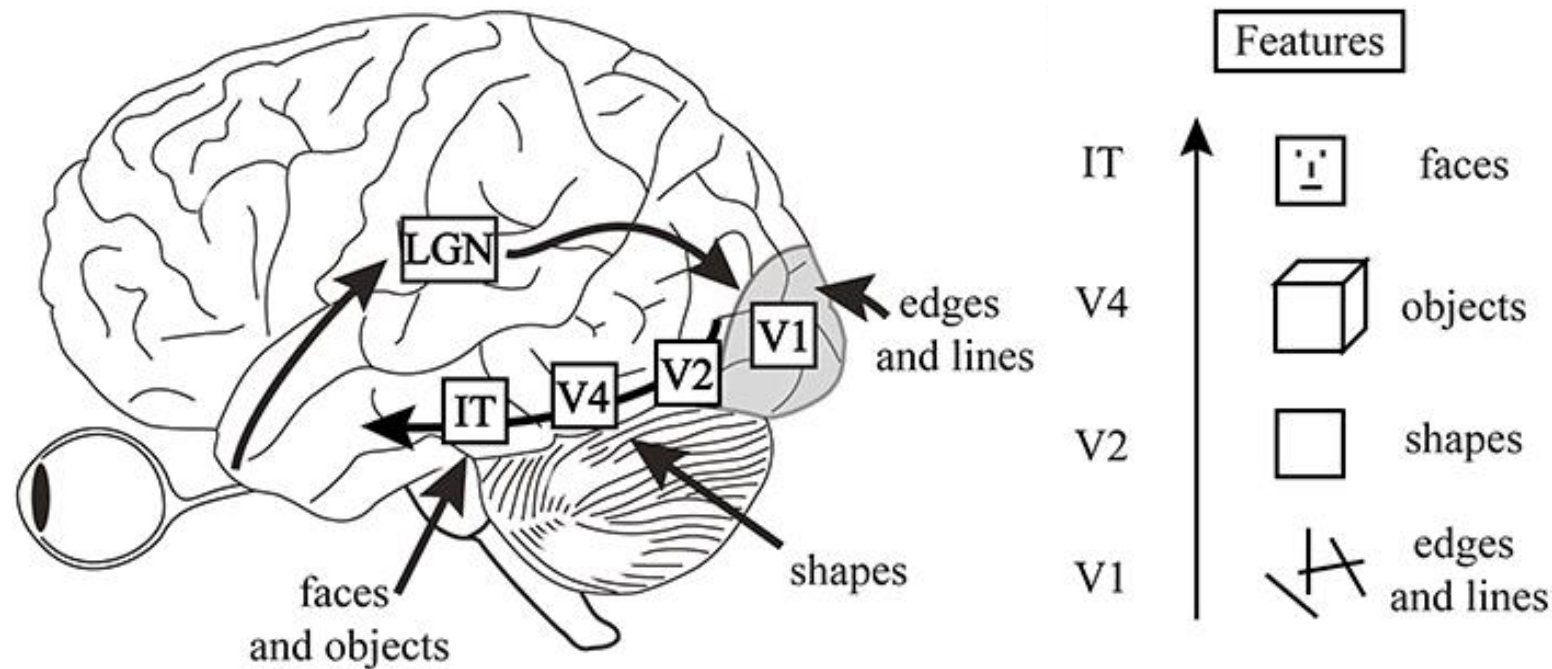
Adaptation magnitude increases along ventral stream

$$\text{Adaptation index} = \frac{R_2 - R_1}{R_1 + \text{epsilon}}$$



But... shouldn't only use gratings

- Higher visual areas better encode natural images



Herzog & Clarke, [2014](#)

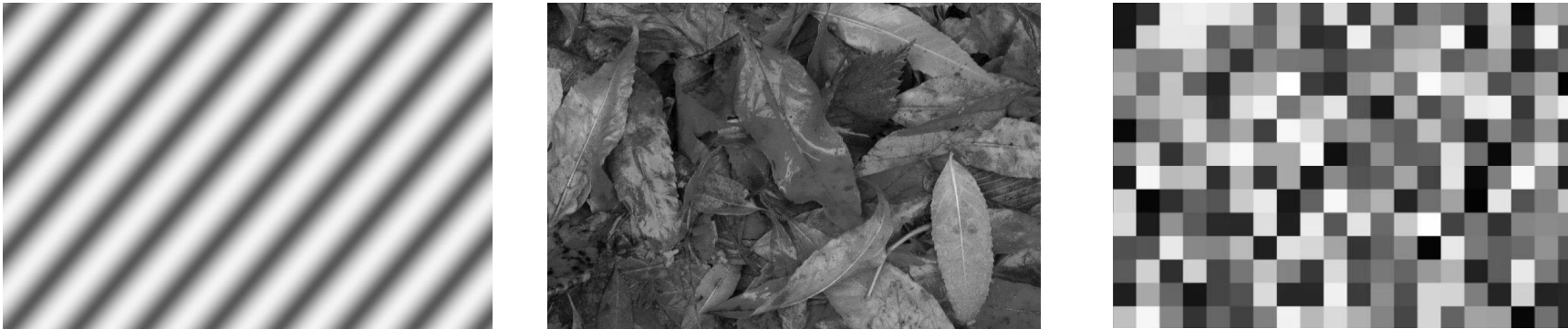
Freeman et al, [2013](#)

Nayebi et al, [2018](#)

Spatial redundancy might open door for more adaptation

- Neural systems performing efficient coding should try to squeeze out all predictable information in the input (Atick & Redlich 1990, 1992)

>> reduce not only temporal, but also spatial correlational structure in the stimulus? (Weber et al. 2019)

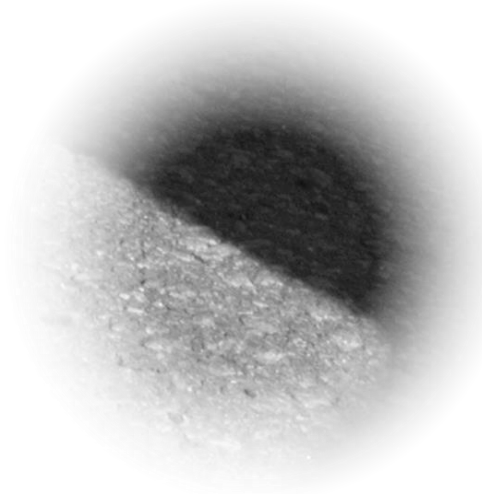
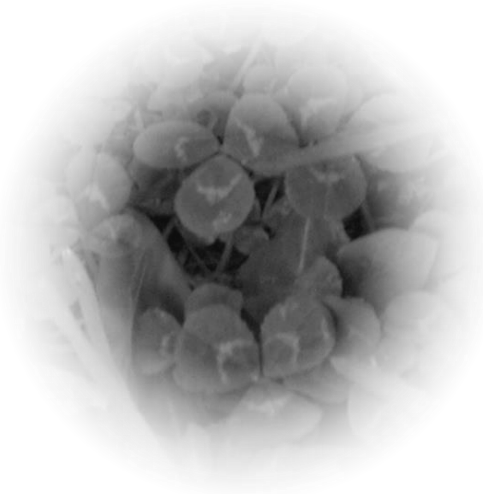
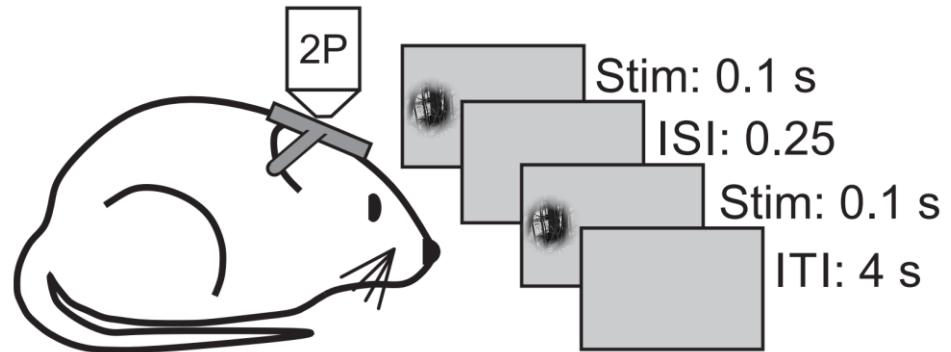


overall redundancy level decreases

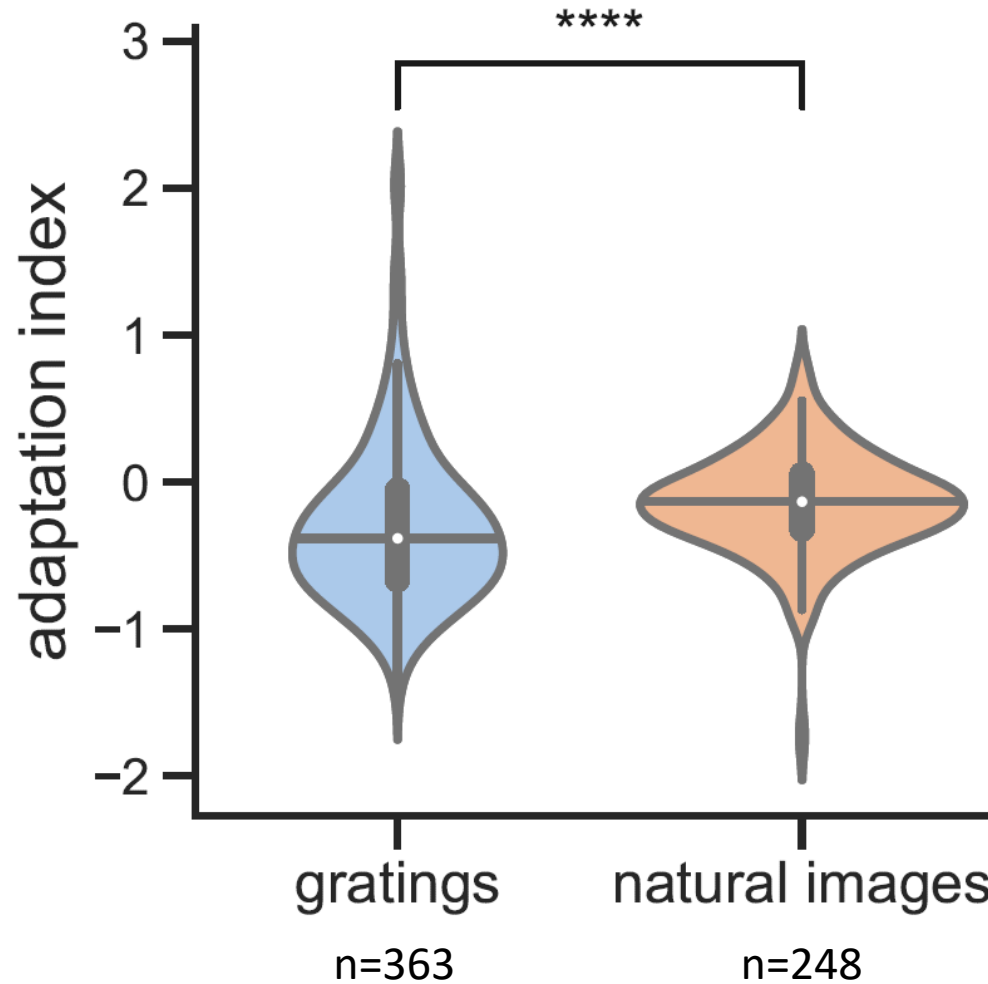
Expectation

Adaptation increases from low redundancy to high redundancy stimulus, e.g. from natural images to gratings

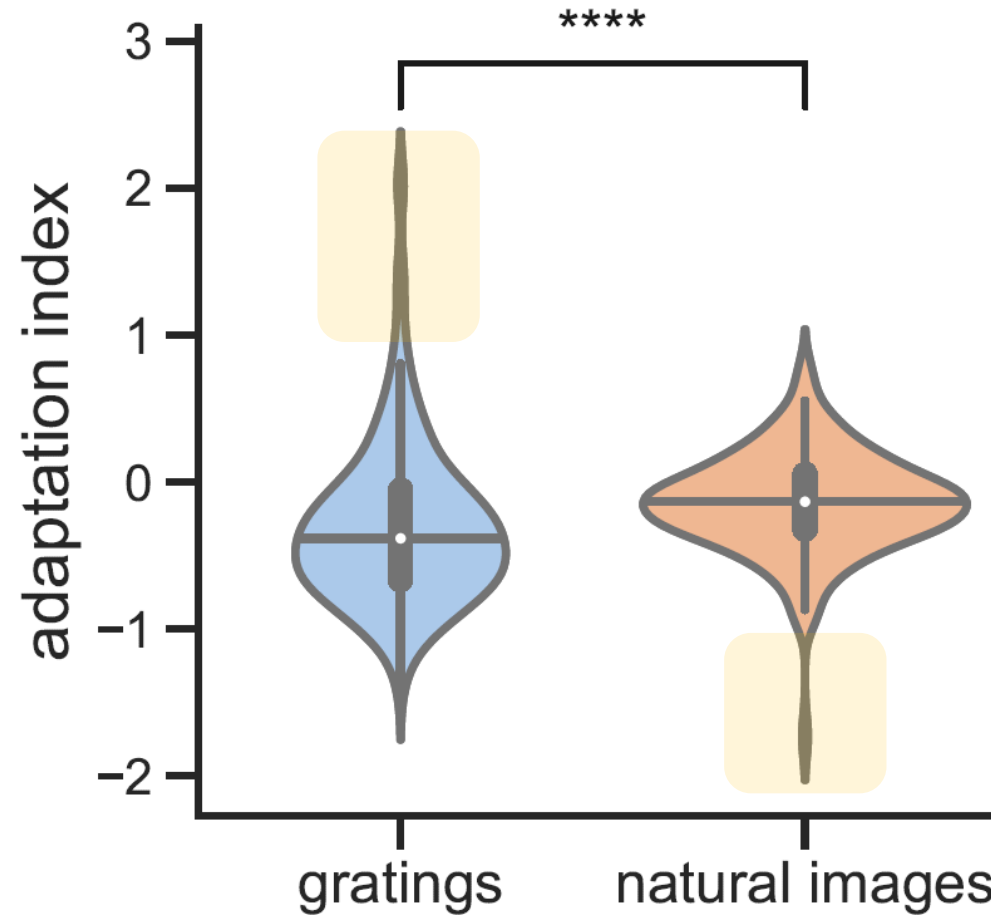
Adaptation to natural image in V1



Adaptation to grating is larger than natural images in V1



Why is adaptation heterogeneous in neuronal population?

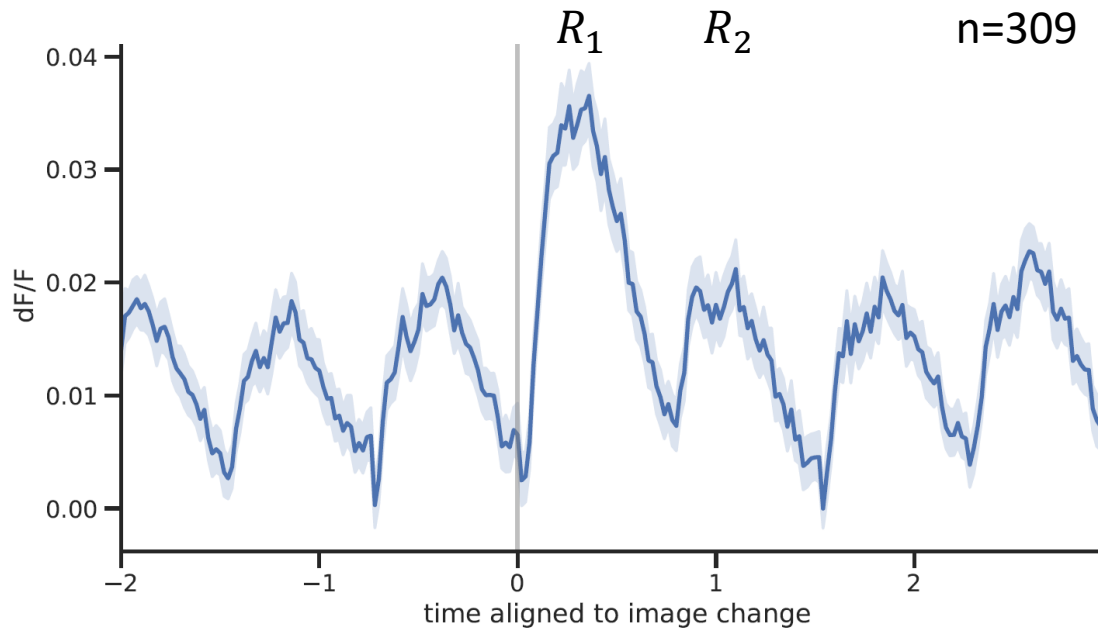
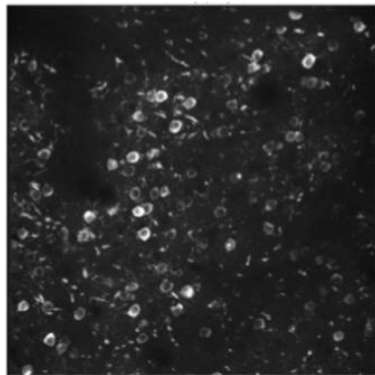


Allen Institute open source data

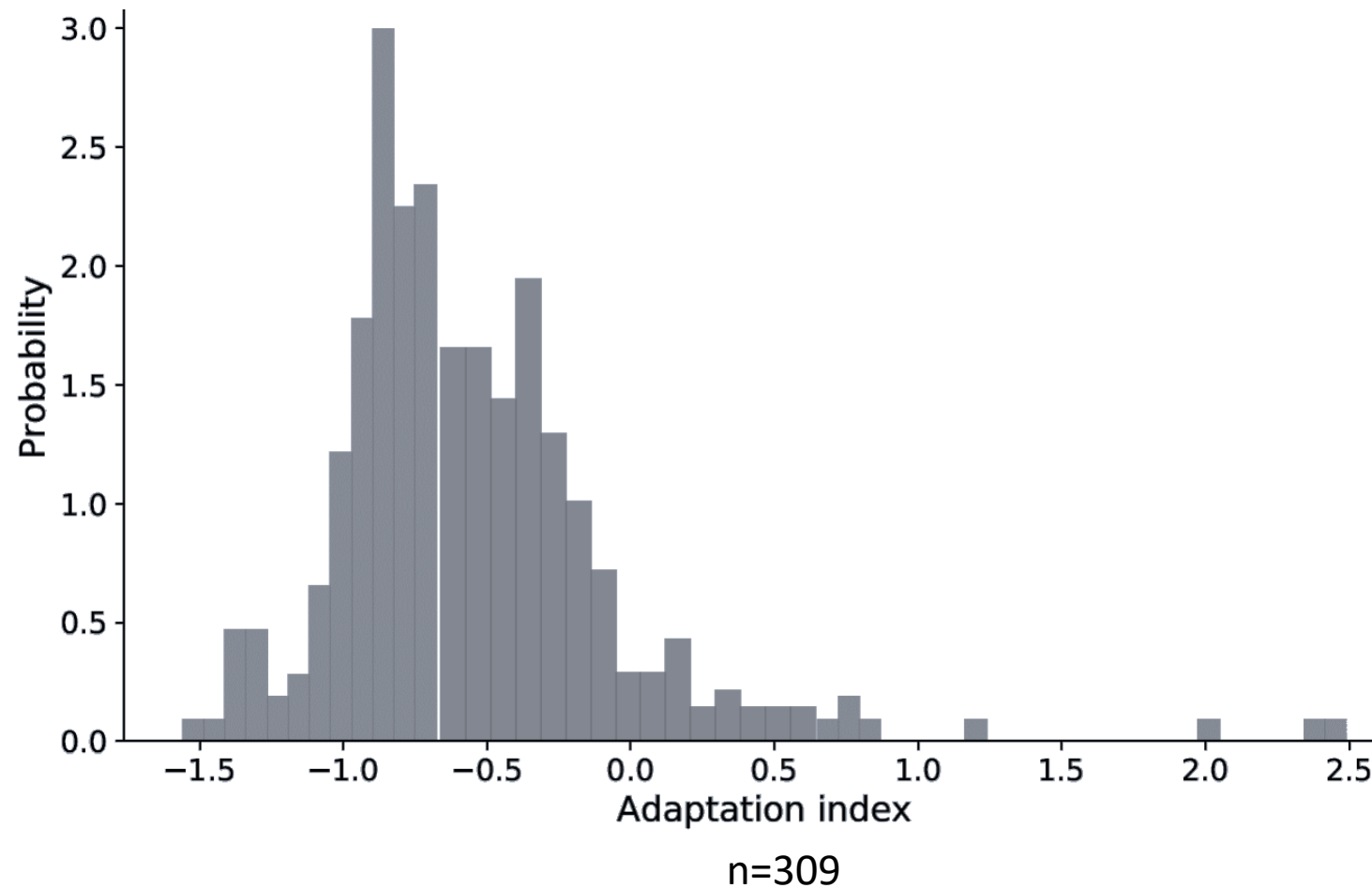
Multi-plane
imaging
(2 areas, 4 depths)



Excitatory
Slc17a7-IRES2-Cre;CaMk2-tTA;
Ai93(GCaMP6f)



Similarly wide distribution of adaptation index in Allen Institute data



Representation in subpopulations with different adaptation

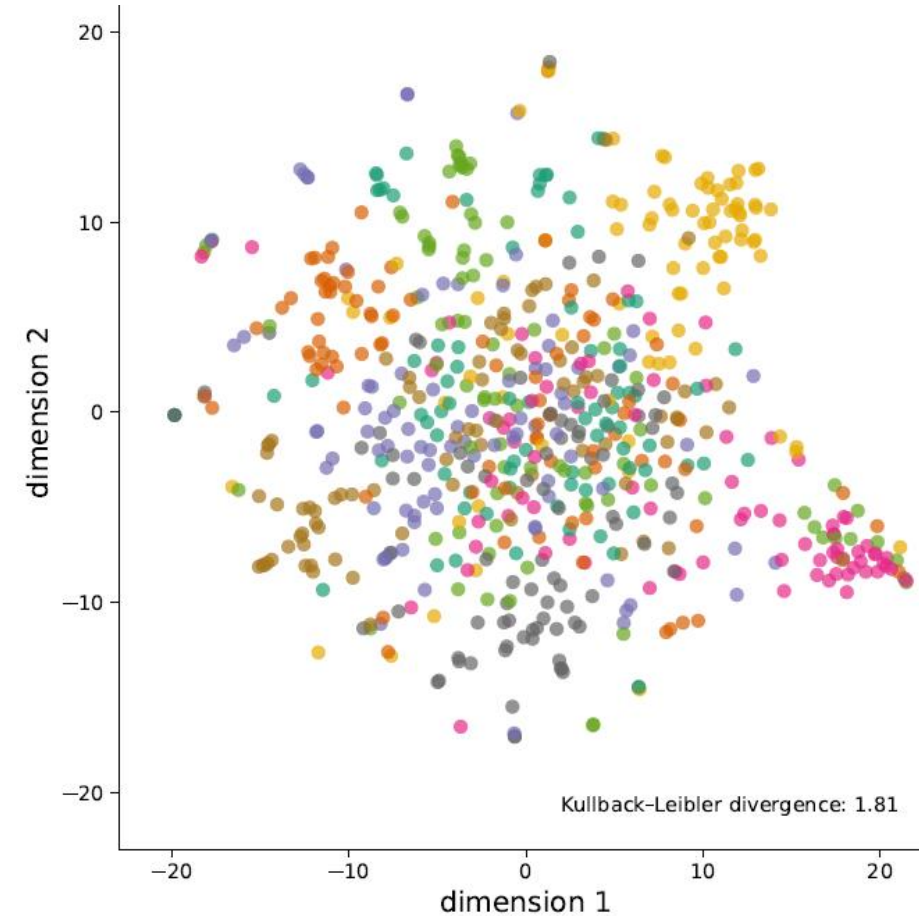
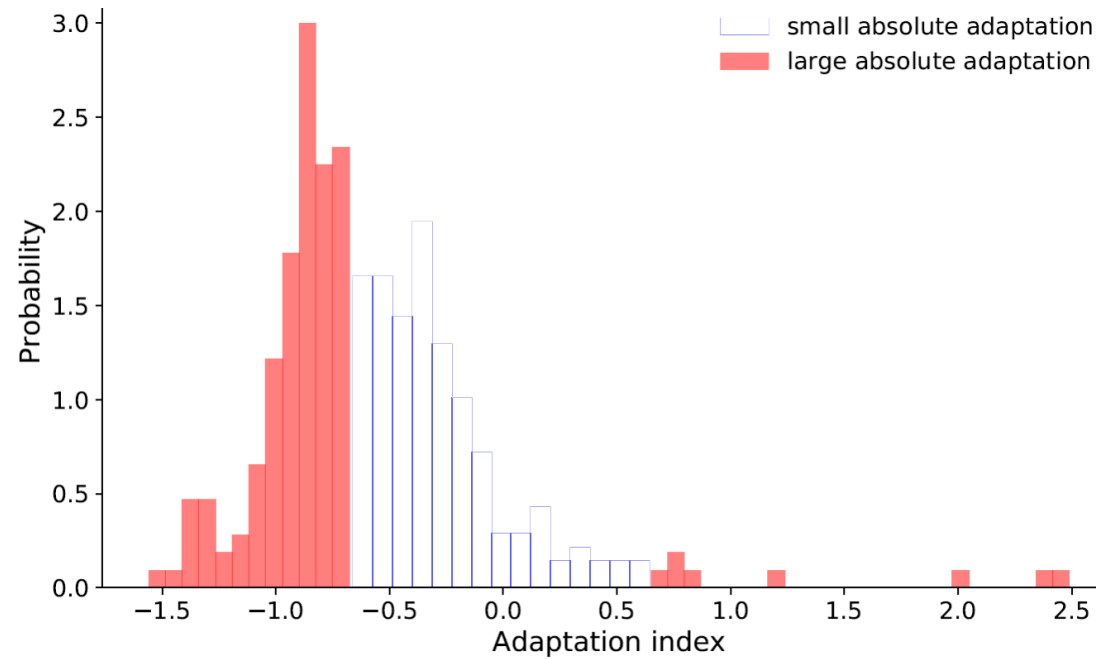
Expectation:

- tradeoff: neuronal population wants to retain information (e.g. about image identity) and simultaneously minimize spike number
- division of labor?
 - one subpopulation reduces activity after adaptation
 - the other encodes image identity

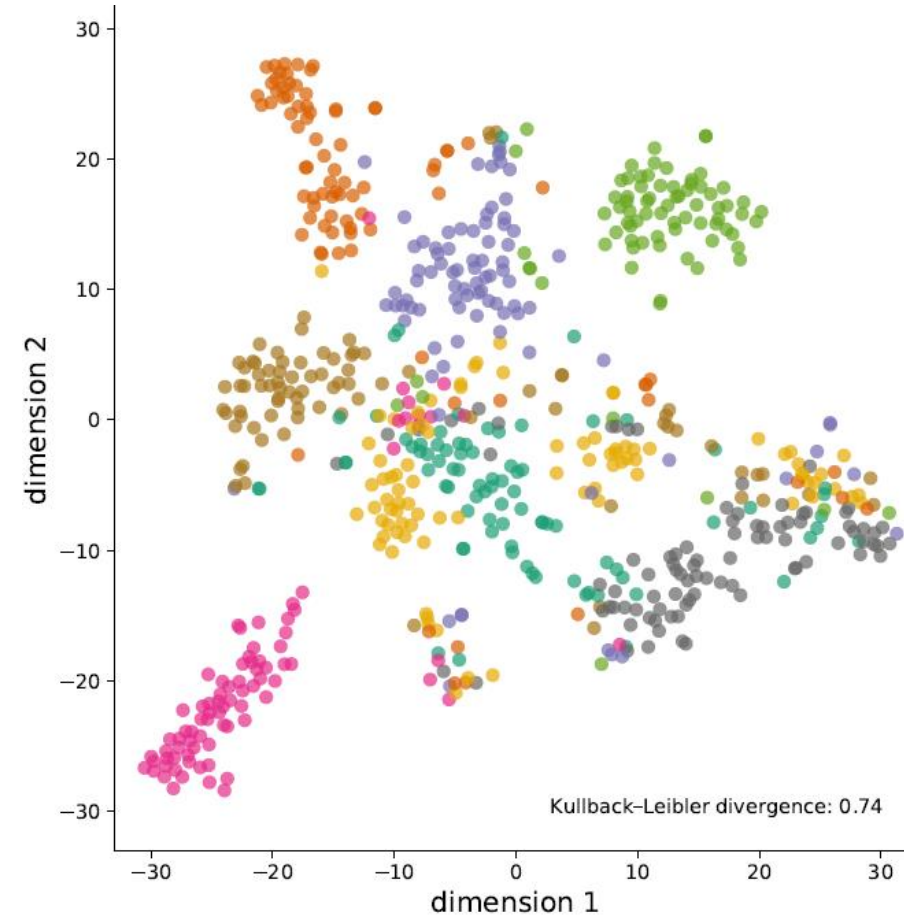
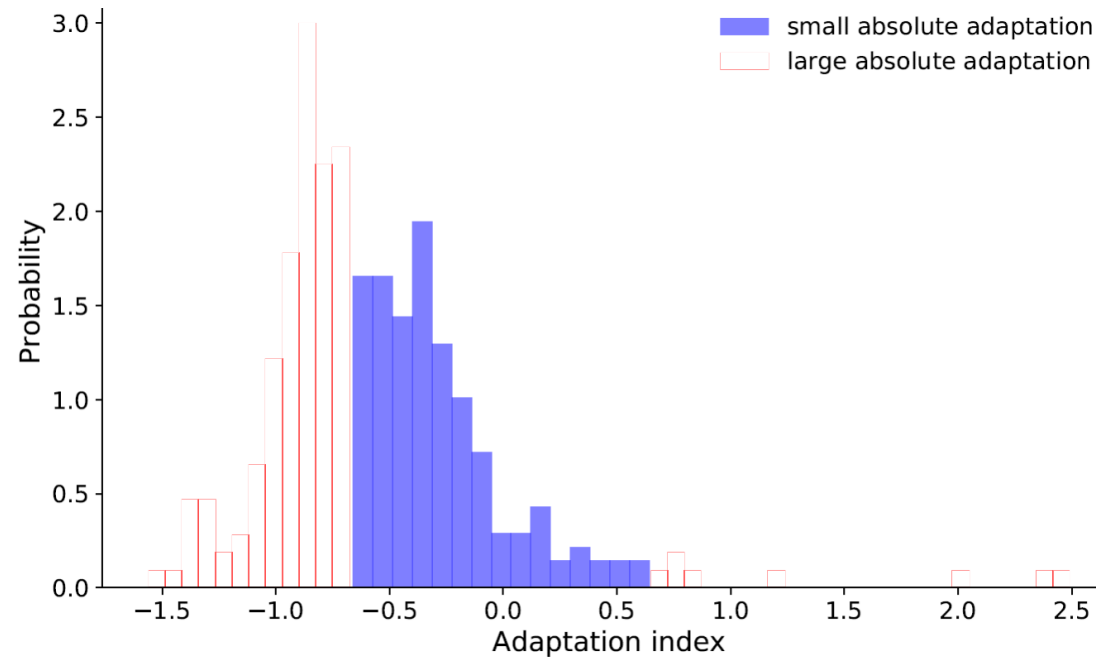
Analysis:

- data: response of each neuron in each trial
- split neurons into 2 groups by median of absolute adaptation index
- dimensionality reduction

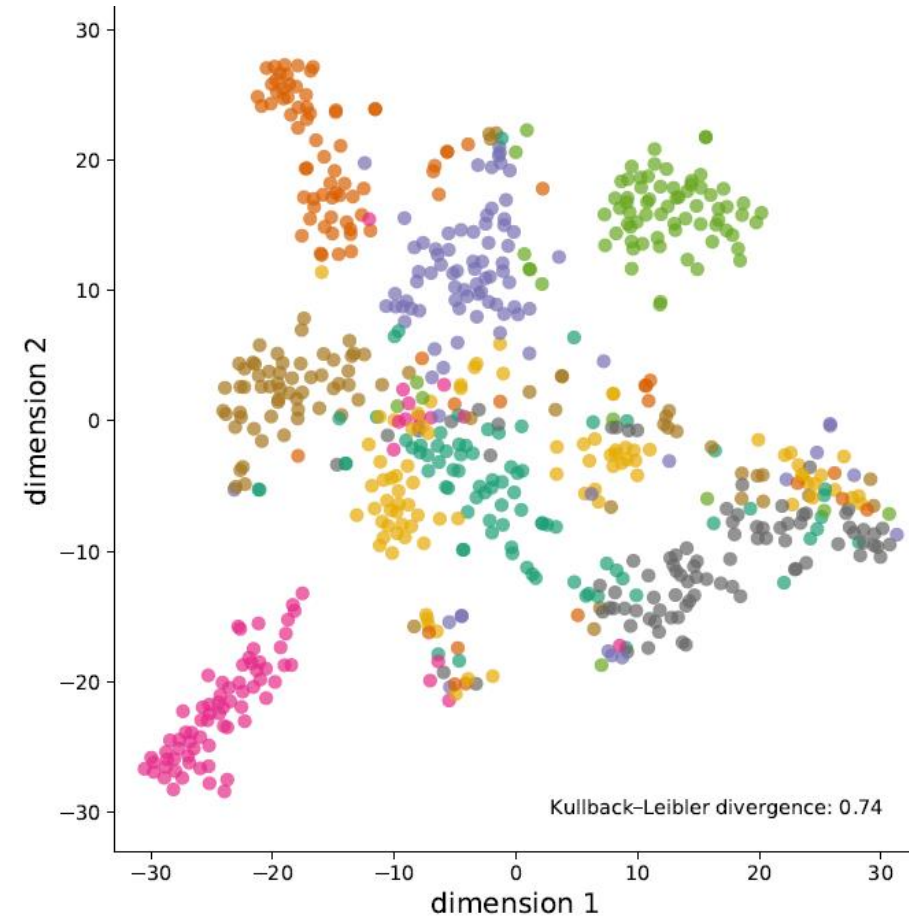
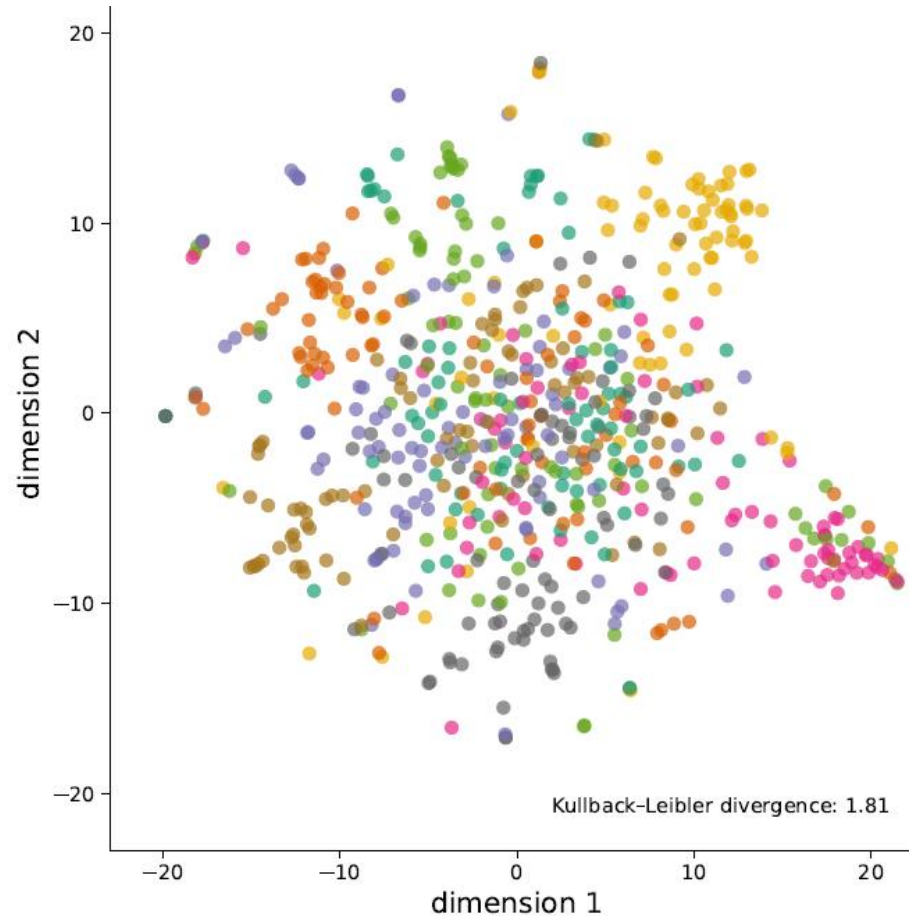
Lower dimensional representation in less-adapting cells



Lower dimensional representation in less-adapting cells



Lower dimensional representation in less-adapting cells



Conclusion

1. Adaptation increases along the ventral visual pathway: from V1 to LM to LI

- as expected by increasingly sparse coding along visual hierarchy

2. Adaptation to natural images is smaller than adaptation to gratings in V1

- in accordance to more redundancy (to be squeezed out) in grating stimuli than natural images

3. Less adapting neurons might be encoding natural image identity in a lower dimensional space

- perhaps stable neuron subpopulation is responsible for encoding image identity, while adapting subpopulation is responsible for further sparsifying representation

Future direction

- Direct measure of efficiency of neural coding
- Investigate adaptation to natural images in higher visual area
- Explore what image features modulate adaptation magnitude

Acknowledgement

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