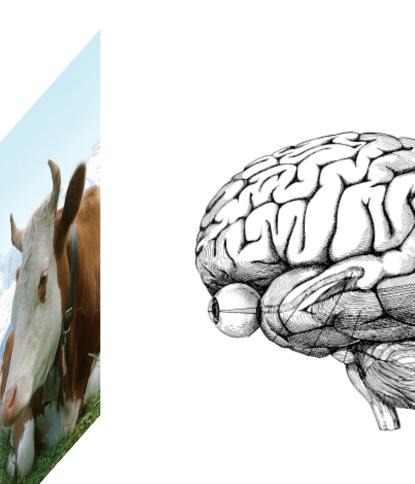
Probing sensory representations with metameric stimuli

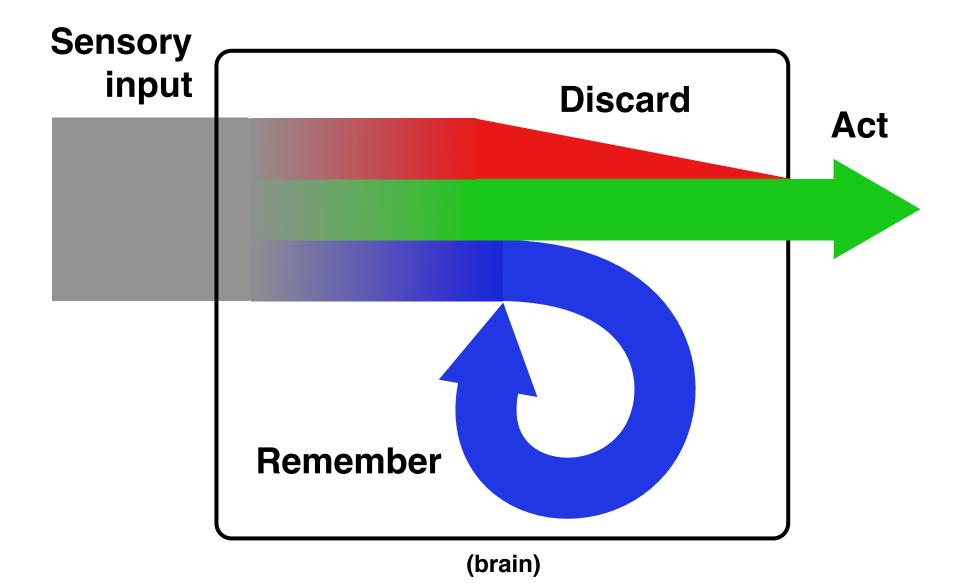
Eero Simoncelli HHMI / New York University



Where does all that visual information go?

[figure: Hubel '95]

Destiny of sensory information

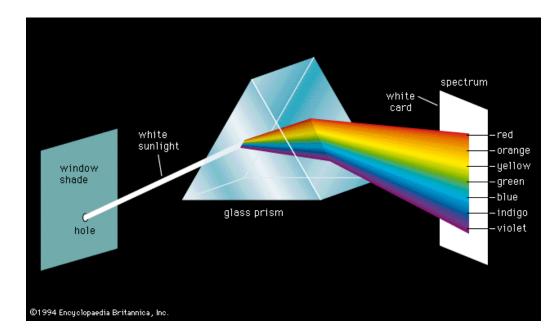


Metamers

- Two stimuli that are physically different, but appear the same to a human observer
- Classic example: trichromatic color perception
- Another example: texture perception

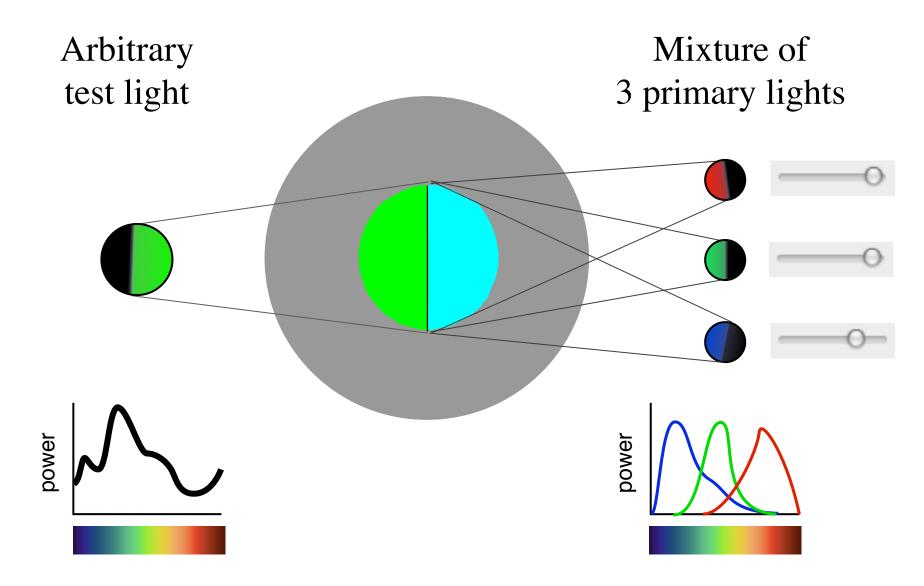
Spectral nature of light





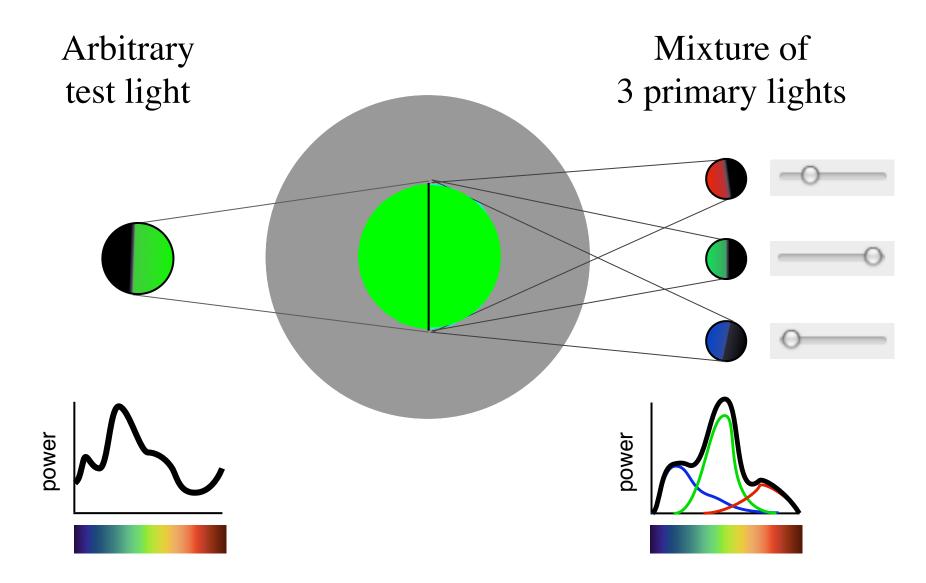
[Newton, 1665]

Perceptual color matching experiment



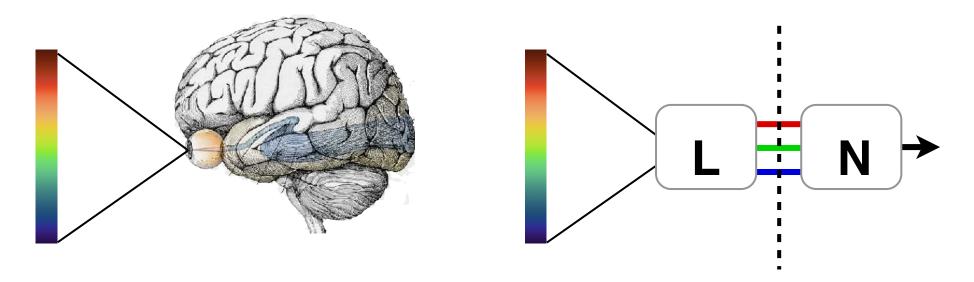
[Young, Helmholtz, Grassman, etc, 1800's; slide c/o D. Brainard]

Perceptual color matching experiment

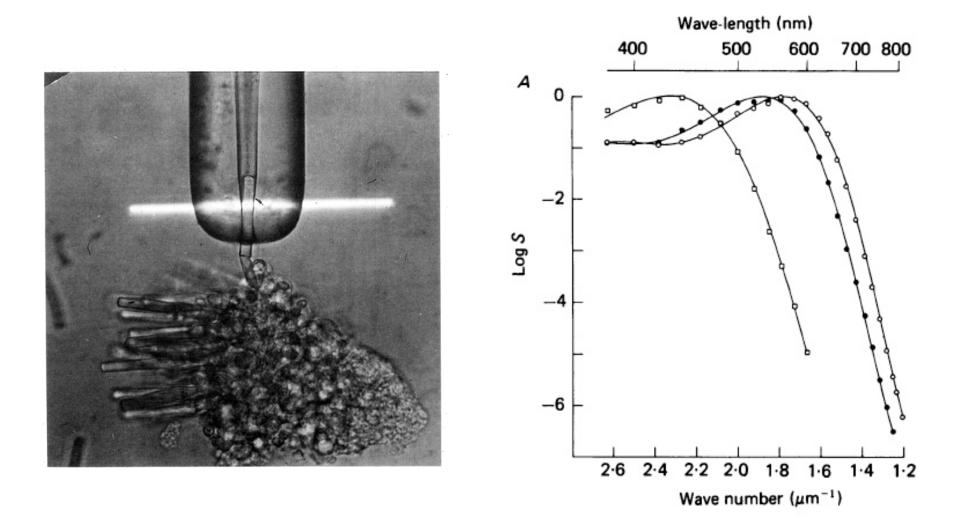


[Young, Helmholtz, Grassman, etc, 1800's; slide c/o D. Brainard]

Theory (Grassman, 1853): the visual system performs a **linear projection** of the wavelength spectrum onto a three-dimensional response space

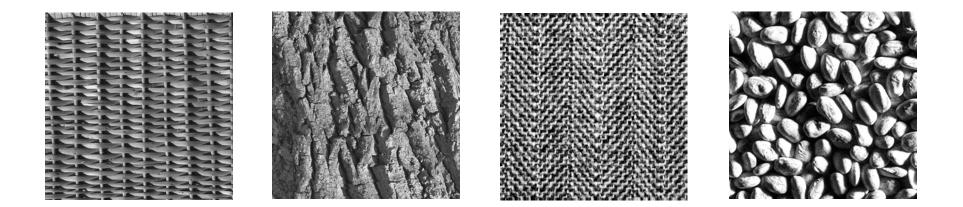


- Predicts/explains perceptual "metamers" lights that appear identical, but have physically distinct wavelength spectra (1800's)
- Codified in CIE standards for color representation (1931)
- Underlying mechanism (cone photoreceptors) verified (1987)



[Baylor, Nunn & Schnapf, 1987]

Visual texture



Homogeneous, with repeated structures

Let us say that to the extent that visible objects are different and far apart, they are forms. To the extent that they are similar and congregated they are a texture. A man has form; a crowd has man-texture. A leaf has form; an arbor has leaf texture, and so on.

[Lettvin, 1976]



































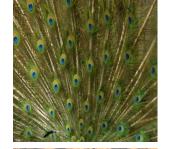




















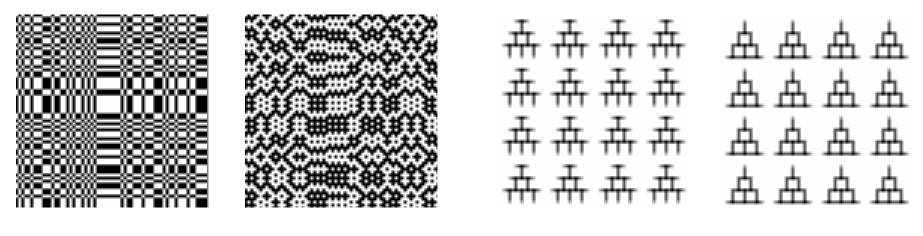






Julesz (1962)

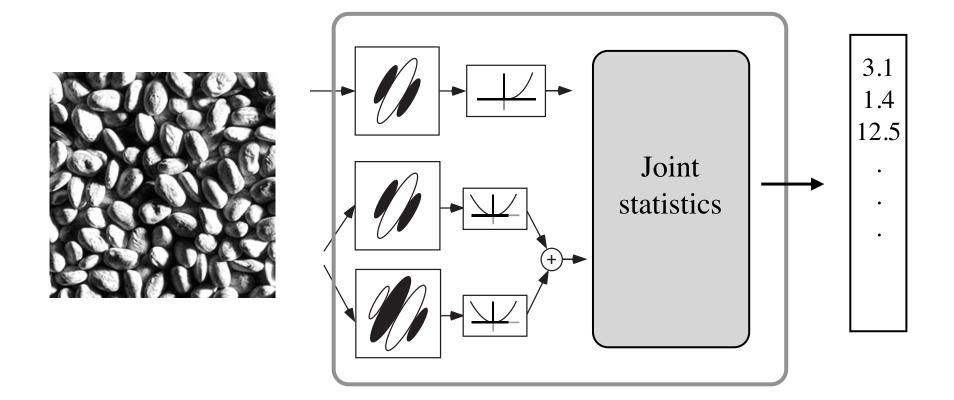
- Hypothesis: Two textures with identical Nth-order pixel statistics will appear the same (for some N).
- Hand-constructed counter-examples (N=3):



Julesz '78

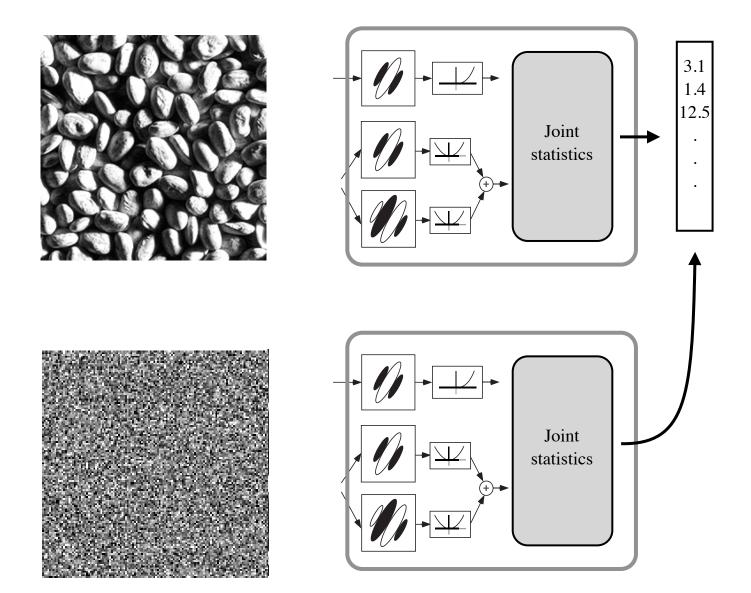
Yellott '93

Physiologically-inspired Julesz-style texture model



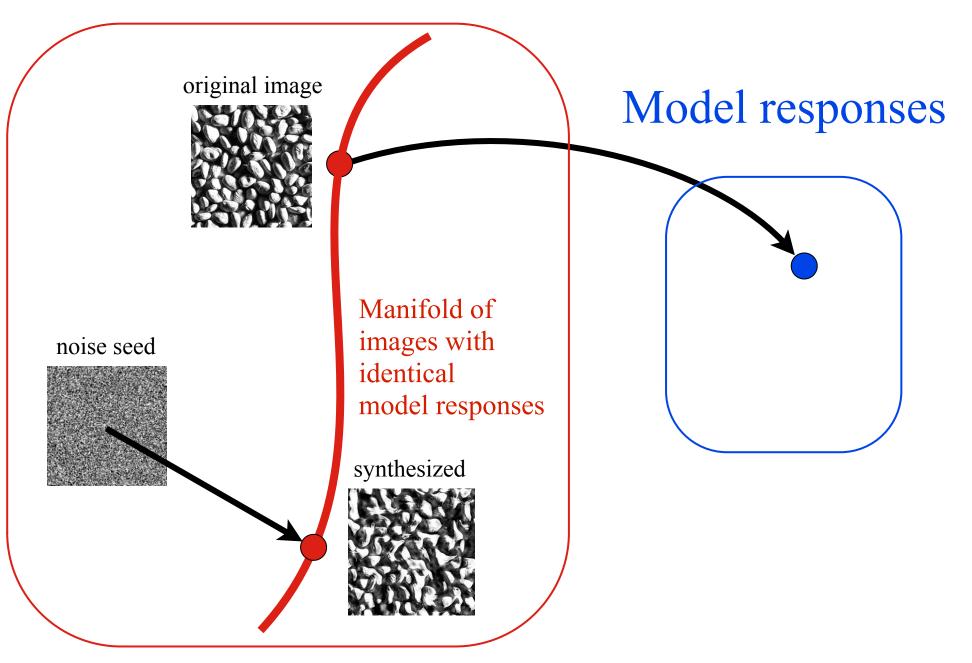
[Portilla & Simoncelli, 2000]

Texture synthesis

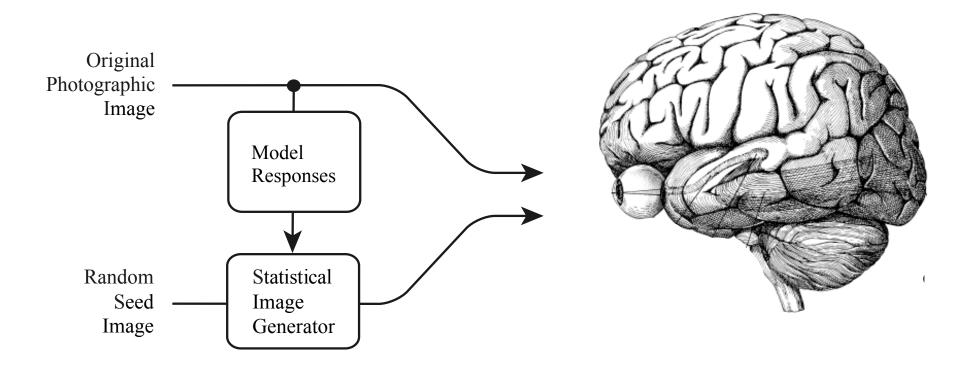


[Portilla & Simoncelli, 2000]

Images

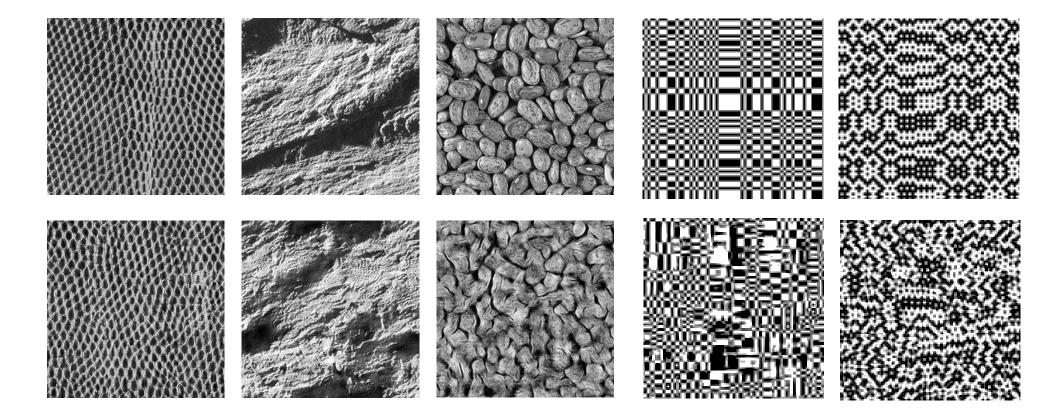


Experimental logic



If model captures the same properties as the visual system, images with identical model responses should appear identical to a human.

Pairs of images with identical model responses:



Top: original, Bottom: synthesized

[Portilla & Simoncelli 2000]

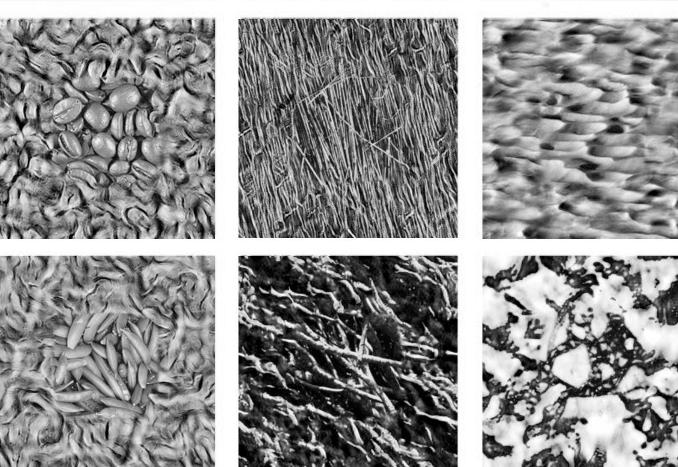
"outpainting"

describing the rest ht as a function of functional descript seek a single conce escribe the wealth ad neurophysiologic

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Central square of each image is original texture. Surround is synthesized.



Structural seeding [cf. "adversarial examples" - Szegedy et. al. 2014]















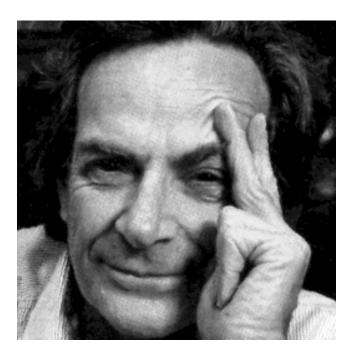




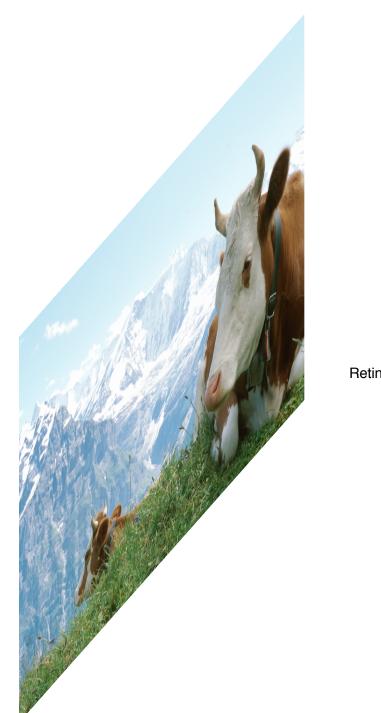


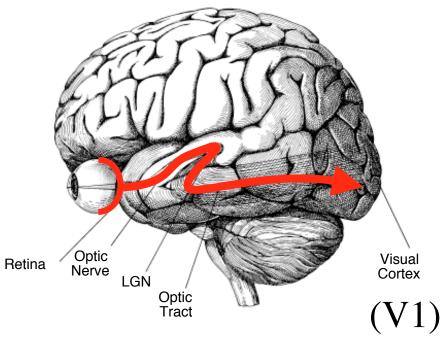
Can we generalize to inhomogeneous stimuli?

Can we make the model more physiological?



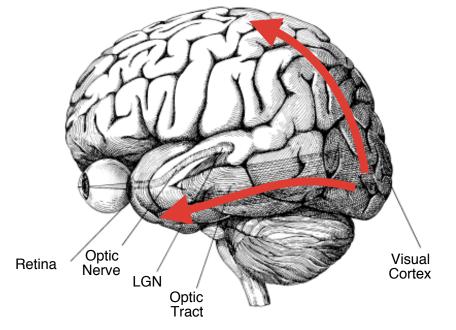






[figure: Hubel '95]

Dorsal pathway: V1->V3->V5 position, motion, action



Ventral pathway: V1->V2->V4-> IT spatial form, recognition, memory

[Ungerleider & Mishkin, 1982]

Retina Optic Nerve LGN Optic Tract

- Visual neurons responds to content within a small region of the visual input known as the **Receptive Field (RF)**
- In each visual area, we assume RFs cover the entire visual field

Inhomogeneity - RF sizes grow with eccentricity

B

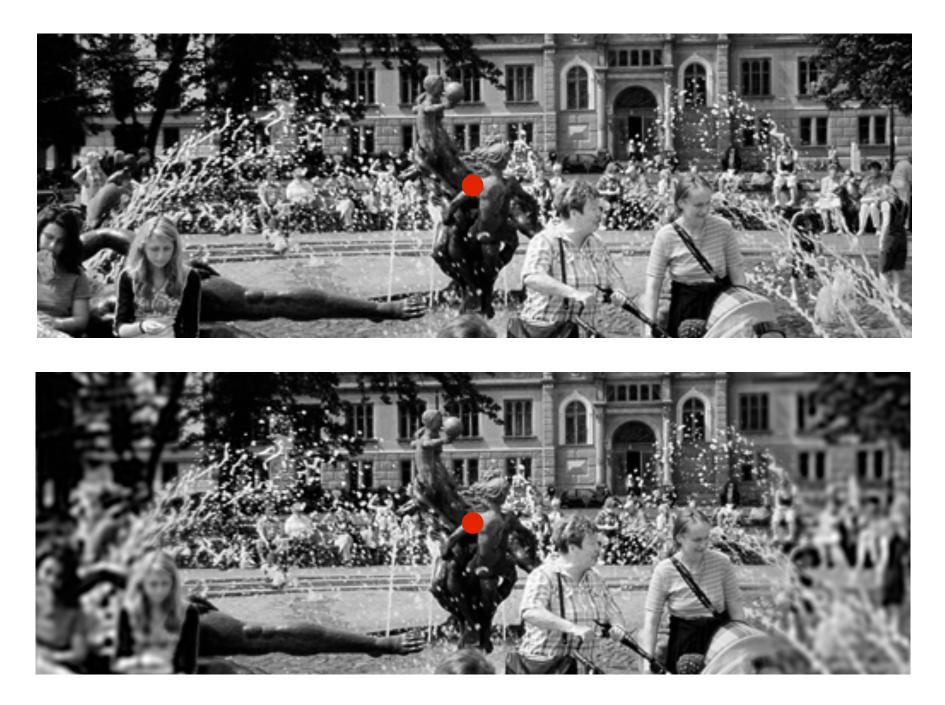
K

M

Retinal ganglion (midget) cell receptive fields (macaque, magnified x10) [Perry et.al., 1984; Watanabe & Rodiek, 1989]

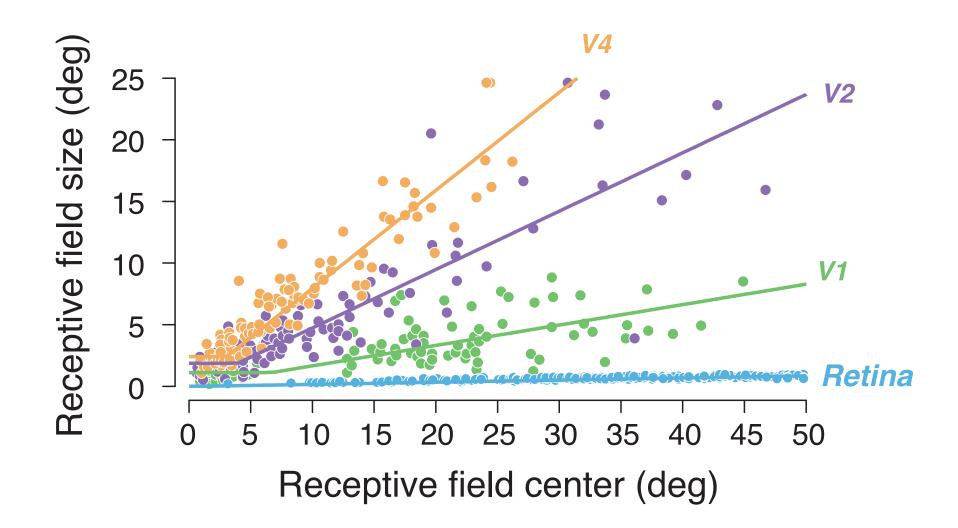
loss of resolution

Modified Snellen acuity chart (threshold, x10) [after Anstis, 1973]

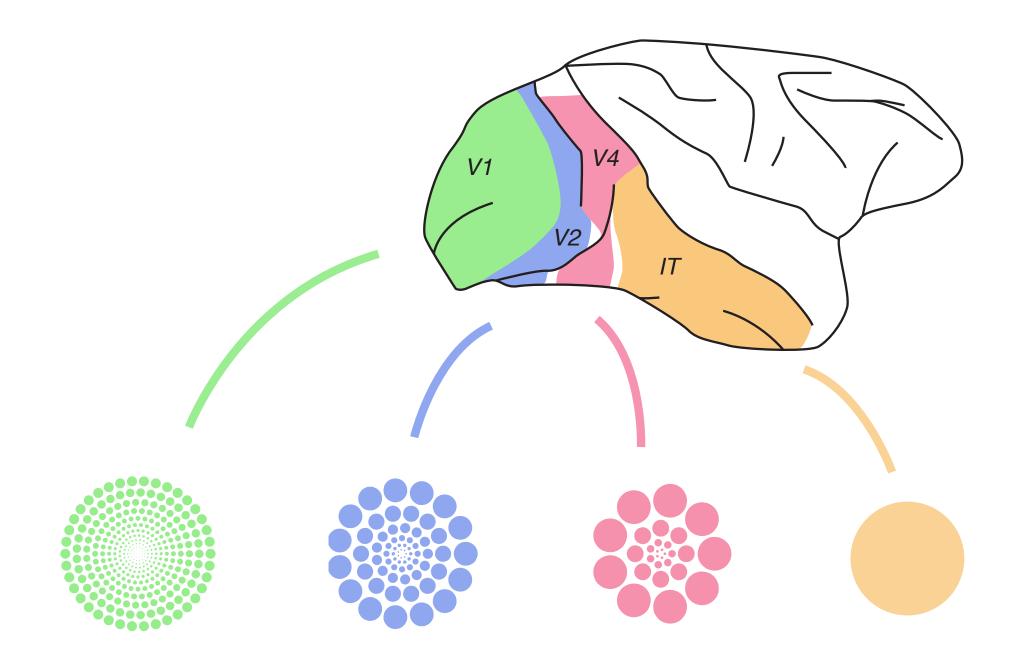


[after Geisler et al., 1999]

RF sizes grow with eccentricity



[Freeman & Simoncelli 2011, data from Gattass et. al., 1981; Gattass et. al., 1988; Perry et. al., 1984]



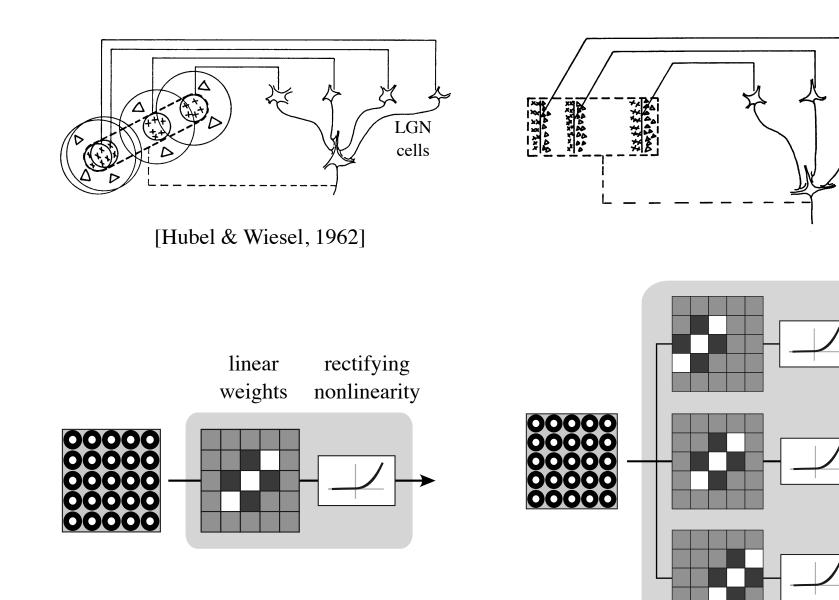
[Freeman & Simoncelli, 2011]

V1 simple cell

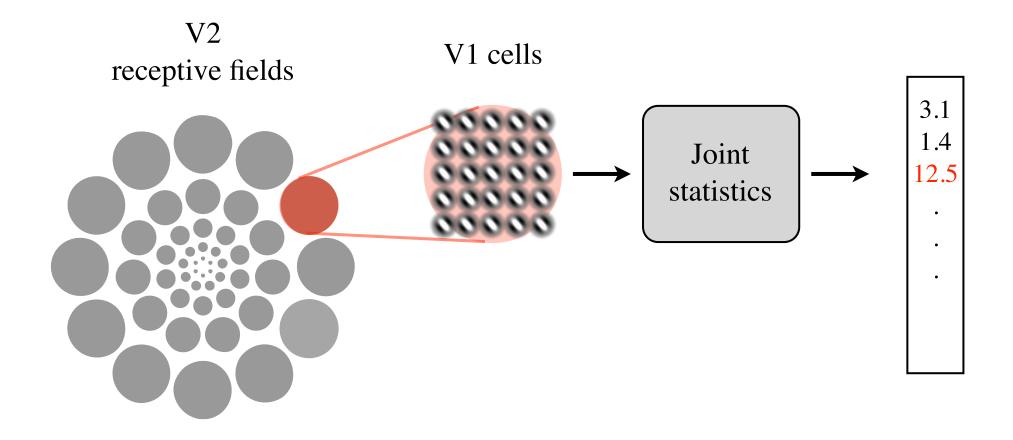
V1 complex cell

simple

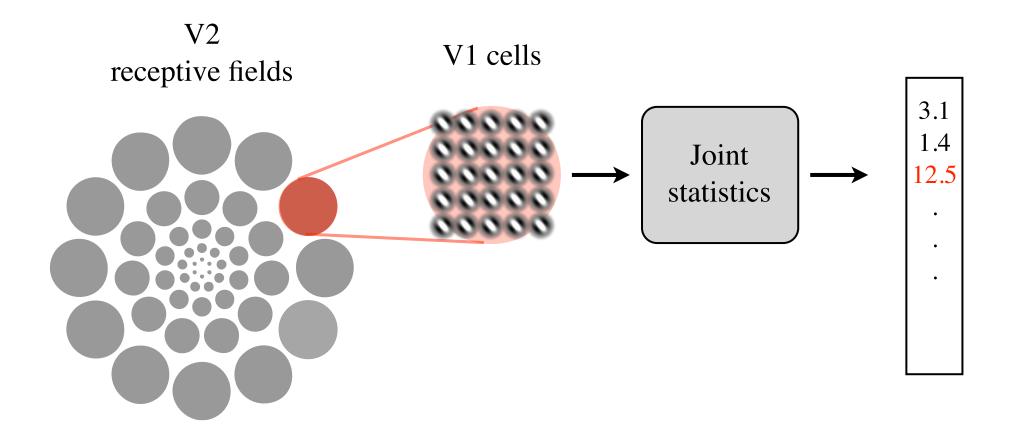
cells



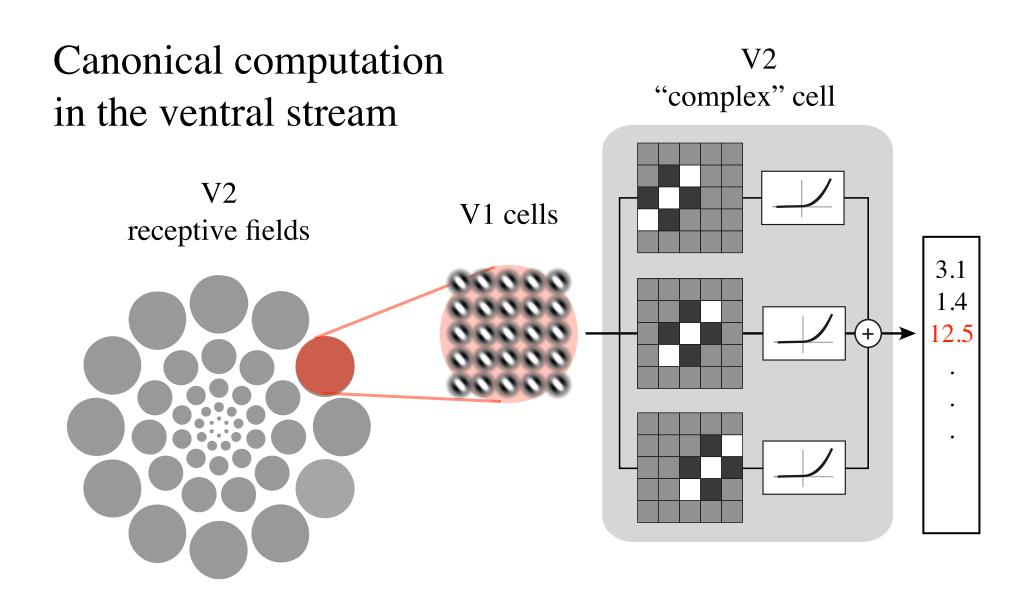
Local texture representation in the ventral stream



Local texture representation in the ventral stream



Local correlational statistics can be re-expressed as a "subunit" model...



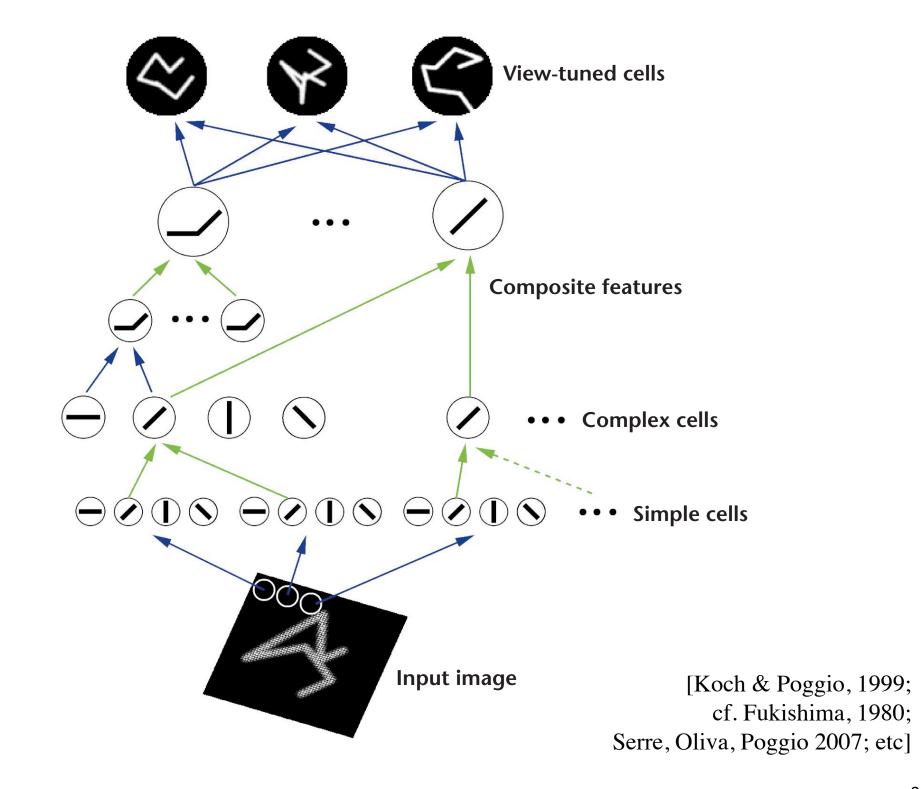
Substantial information loss => model predicts **metamers**

Canonical sensory computation

- Linear filter (determines pattern selectivity)
- Rectifying nonlinearity
- Local pooling (e.g., average, max)
- Local gain control
- Noise

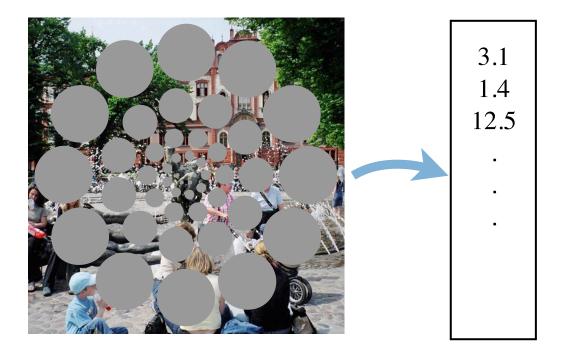
Cascaded ...

[eg. Douglas, 1989; Heeger, Simoncelli & Movshon 1996; Heeger & Carandini 2014]



Synthesizing Ventral Stream Metamers

Model responses



Original image

[Freeman & Simoncelli, 2011]

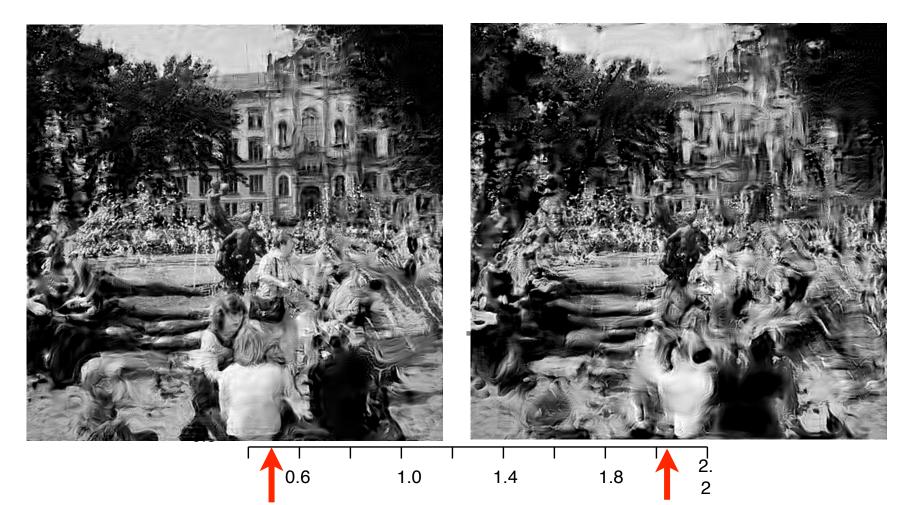
Synthesizing Ventral Stream Metamers

Model

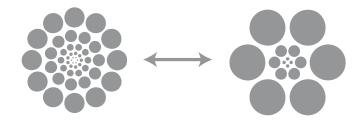
Original image responses Synthesized image

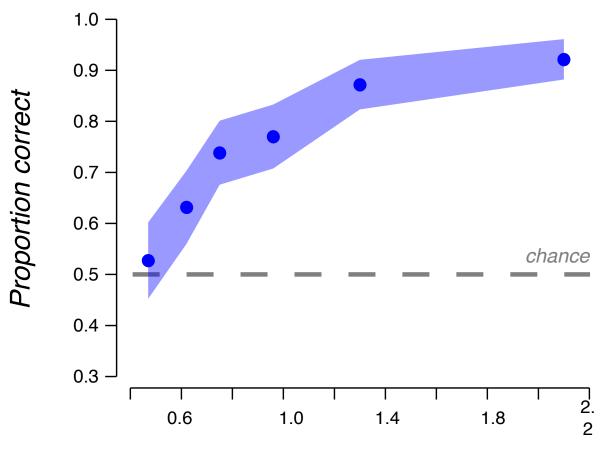




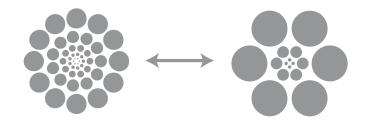


Model RF size (diam / eccentricity)

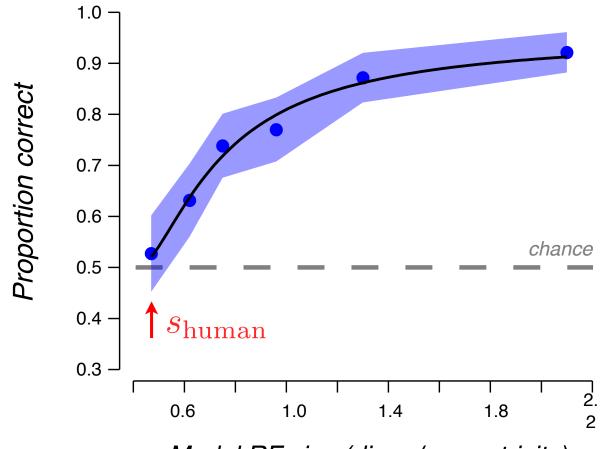




Model RF size (diam / eccentricity)

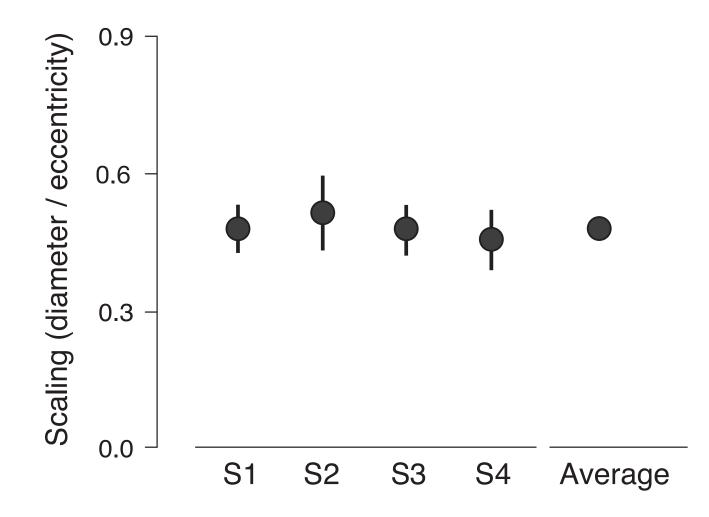


[Freeman & Simoncelli, 2011]



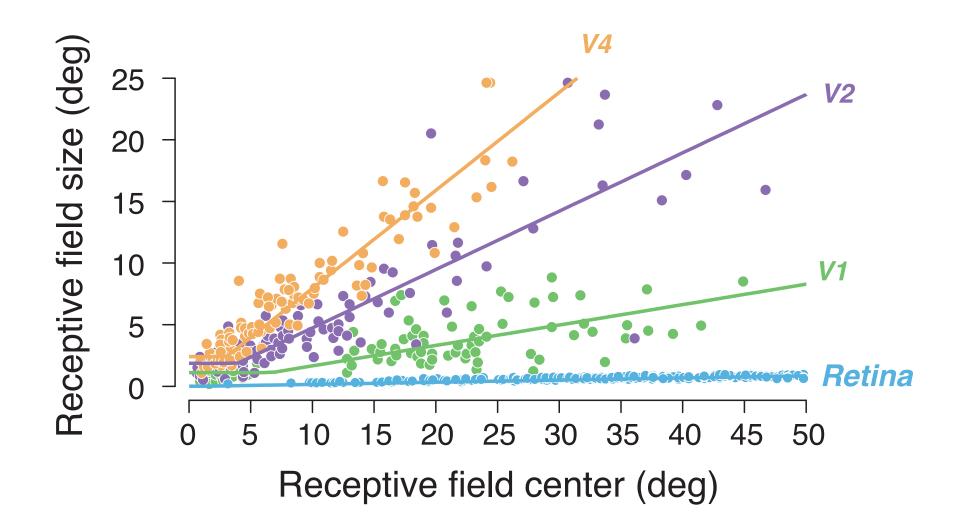
Model RF size (diam / eccentricity)

$$D = \Phi\left(\left\lfloor 1 - \frac{s_{\text{human}}^2}{s_{\text{model}}^2}\right\rfloor\right)$$

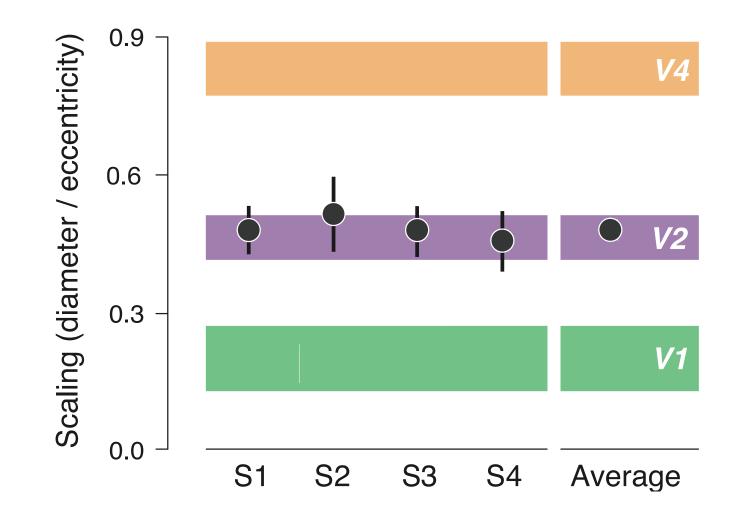


[Freeman & Simoncelli, 2011]

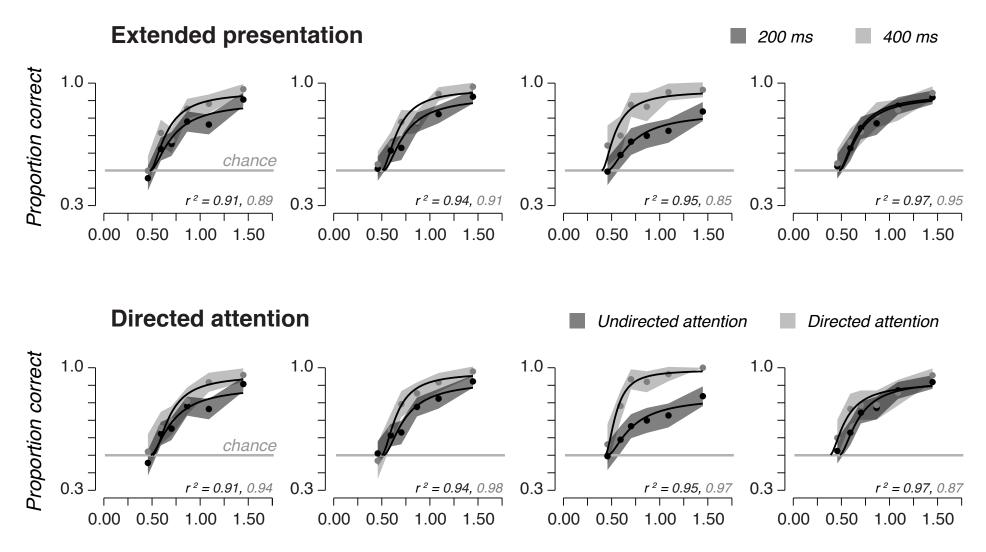
RF sizes grow with eccentricity



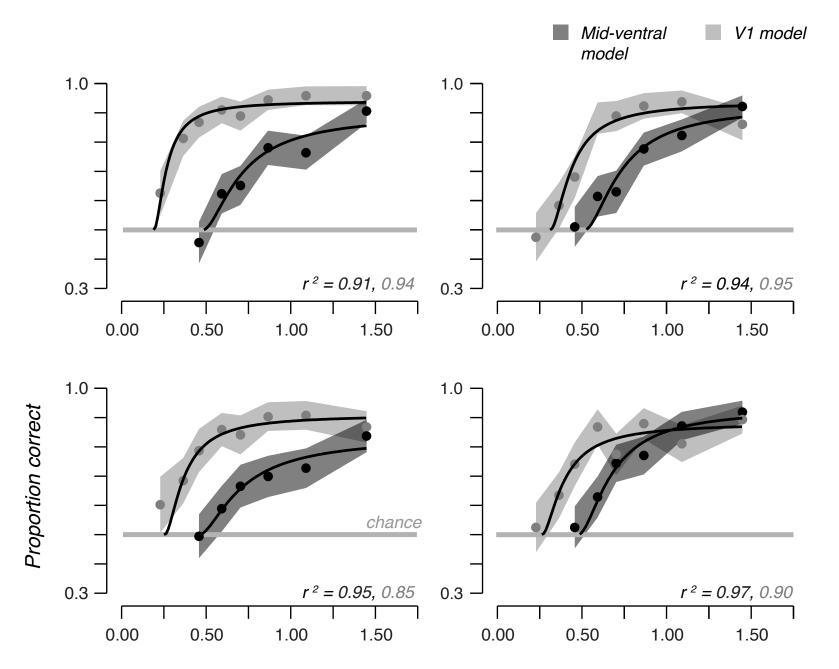
[Freeman & Simoncelli 2011, from Gattass et. al., 1981; Gattass et. al., 1988; Perry et. al., 1984]



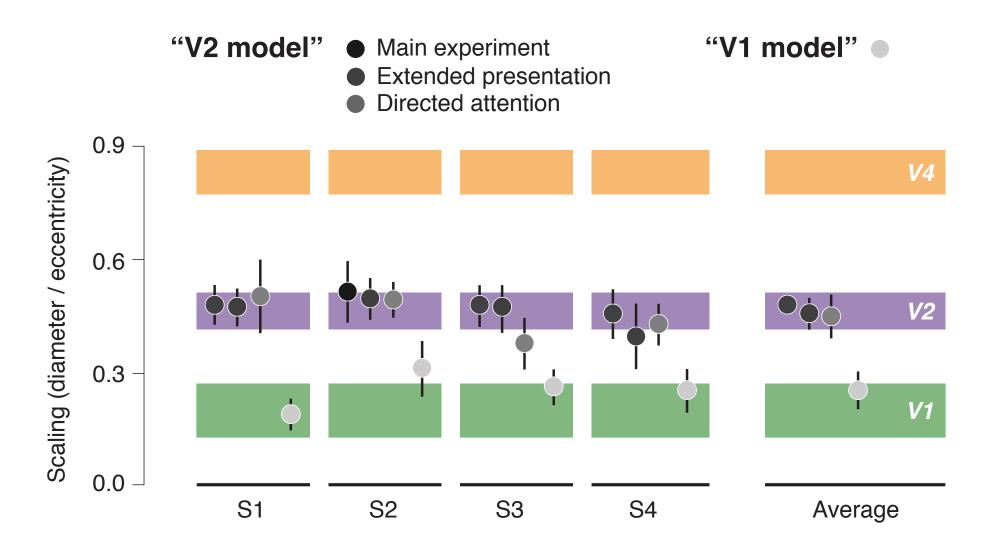
Macaque Physiology [Allman & Kaas, 1971; Allman & Kaas, 1974; Gattass et.al., 1981; van Essen et.al., 1984; Maguire & Baizer, 1984; Burkhalter & van Essen, 1986; Gattass et.al., 1987; Desimone & Schein, 1987; Gattass et.al., 1988; Cavanaugh et. al., 2002]



Scaling (diameter / eccentricity) of receptive fields in synthesis model



Scaling (diameter / eccentricity) of receptive fields in synthesis model





[Allman & Kaas, 1971; Allman & Kaas, 1974; Gattass et.al., 1981; van Essen et.al., 1984; Maguire & Baizer, 1984; Burkhalter & van Essen, 1986; Gattass et.al., 1987; Desimone & Schein, 1987; Gattass et.al., 1988; Cavanaugh et. al., 2002]

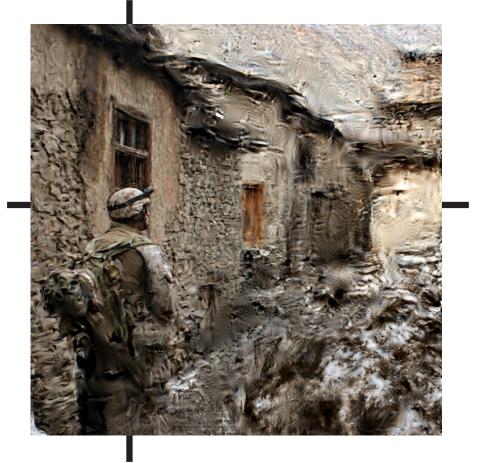
Reading

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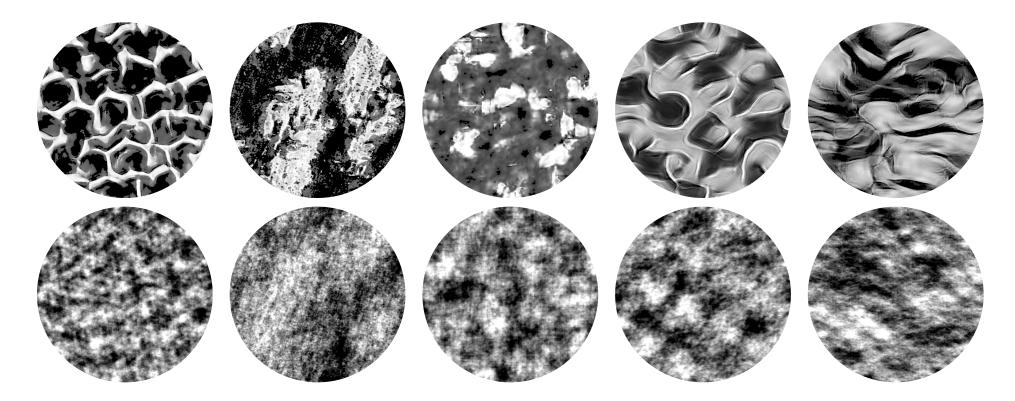






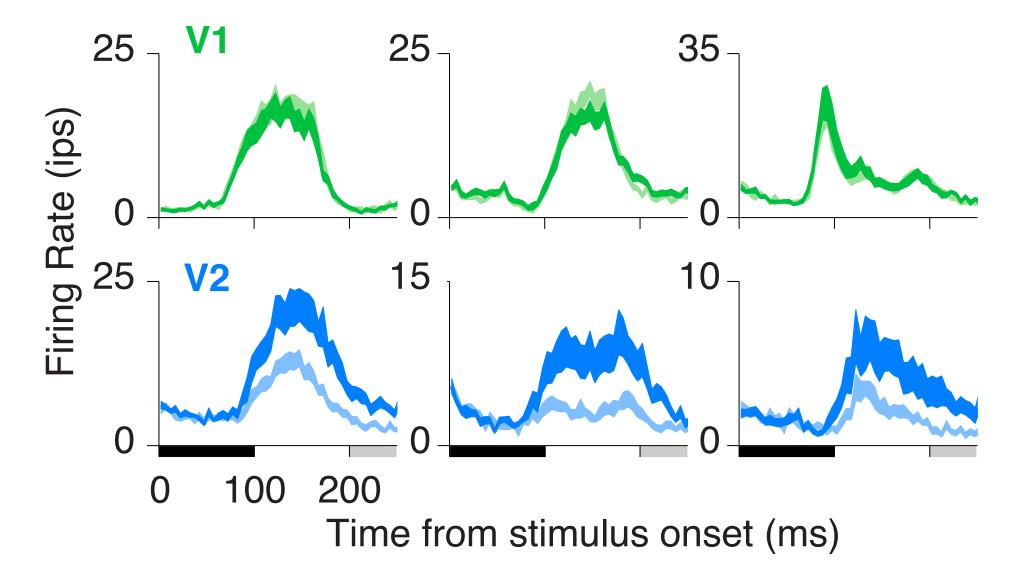


Can we drive individual V2 neurons using local texture stimuli?



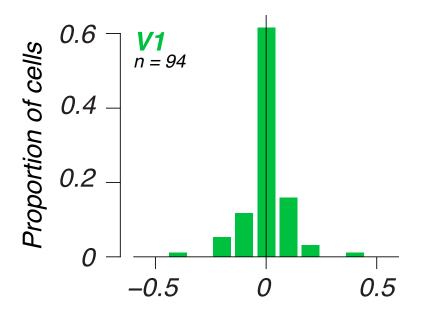
Top: synthetic textures, full model Bottom: "spectral noise" (matched only for "V1" statistics)

[Freeman, et. al. 2013]

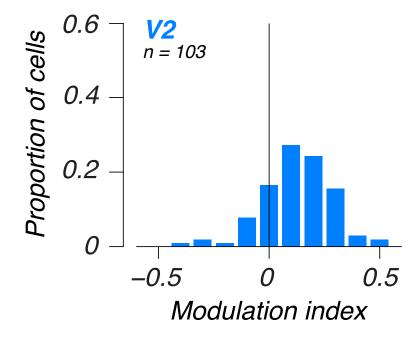


[Freeman, et. al. 2013]

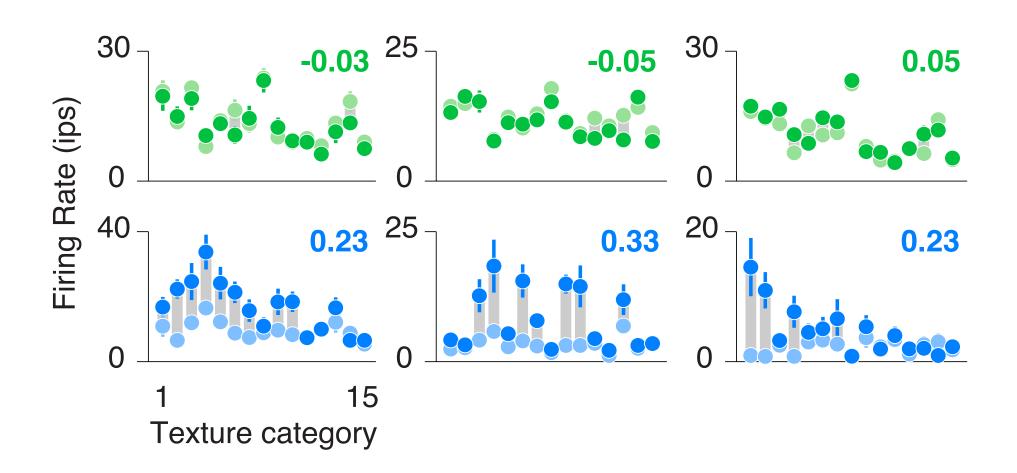
15% of V1 neurons significantly positively modulated



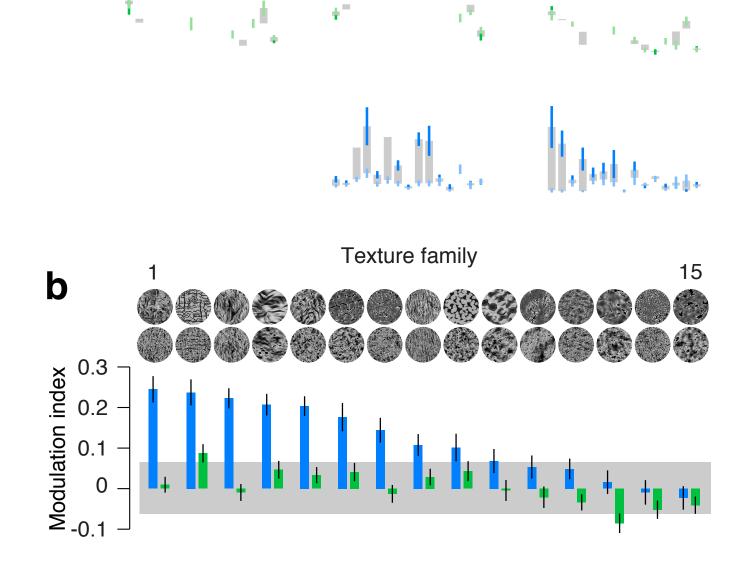
63% of V2 neurons significantly positively modulated

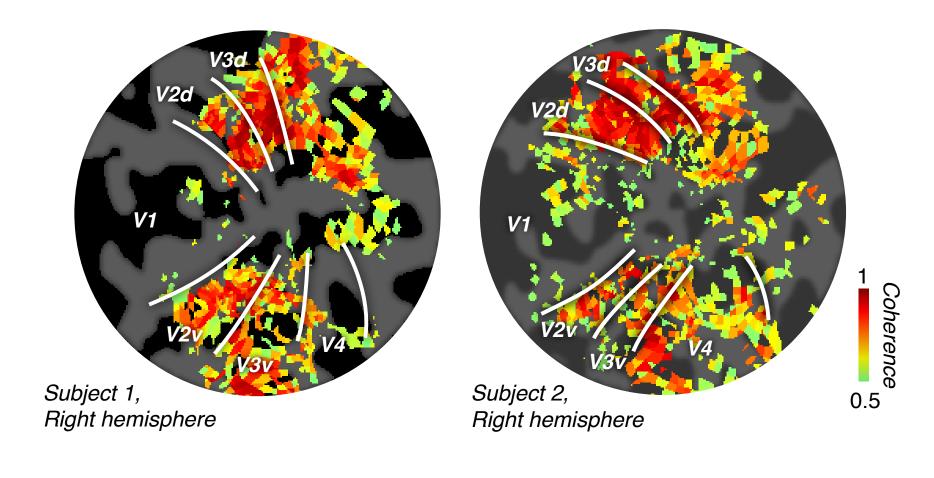


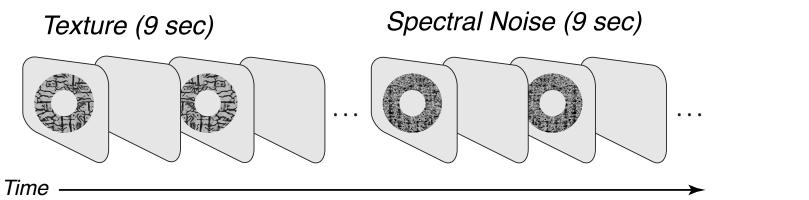
[Freeman, et. al. 2013]



[Freeman, et. al. 2013]



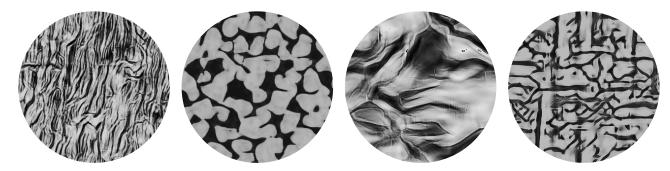




[Freeman, et. al. 2013]

Predicting discriminability

Different families

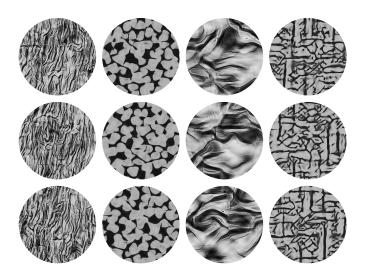


Anesthetized macaque

- V1: 102 neurons
- V2: 103 neurons

Stimuli presented for 100ms within a 4° aperture

20 repetitions each



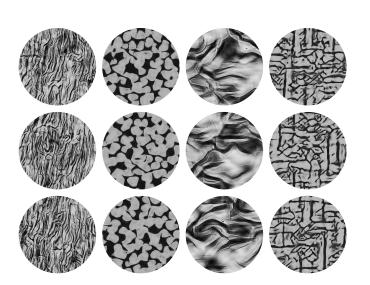
Anesthetized macaque

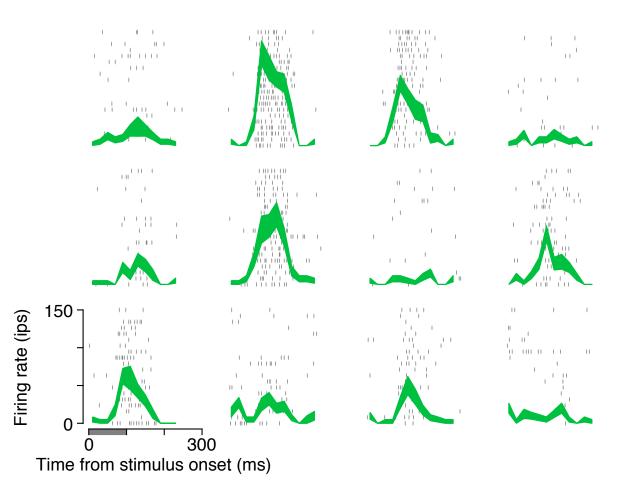
Example V1 neuron

- V1: 102 neurons
- V2: 103 neurons

Stimuli presented for 100ms within a 4° aperture

20 repetitions each





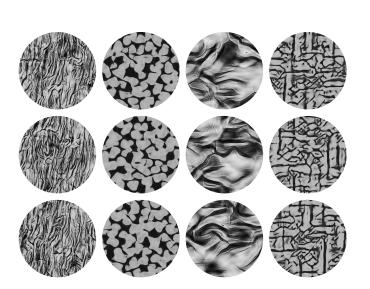
Anesthetized macaque

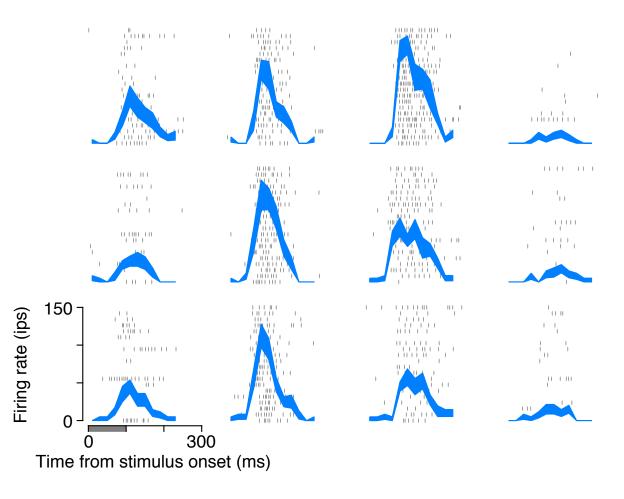
Example V2 neuron

- V1: 102 neurons
- V2: 103 neurons

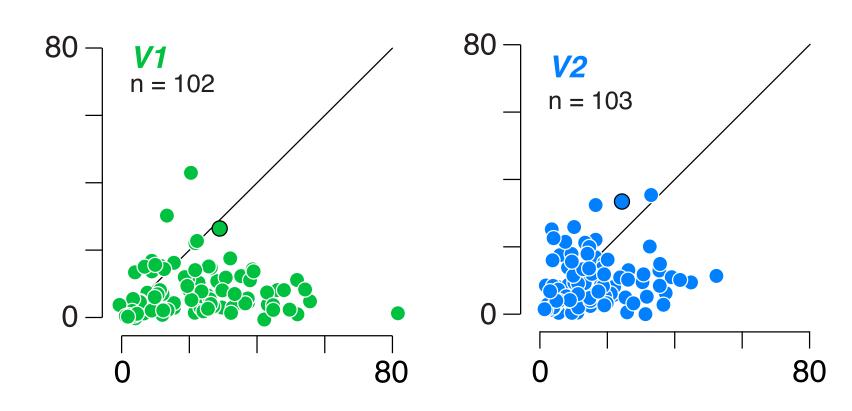
Stimuli presented for 100ms within a 4° aperture

20 repetitions each



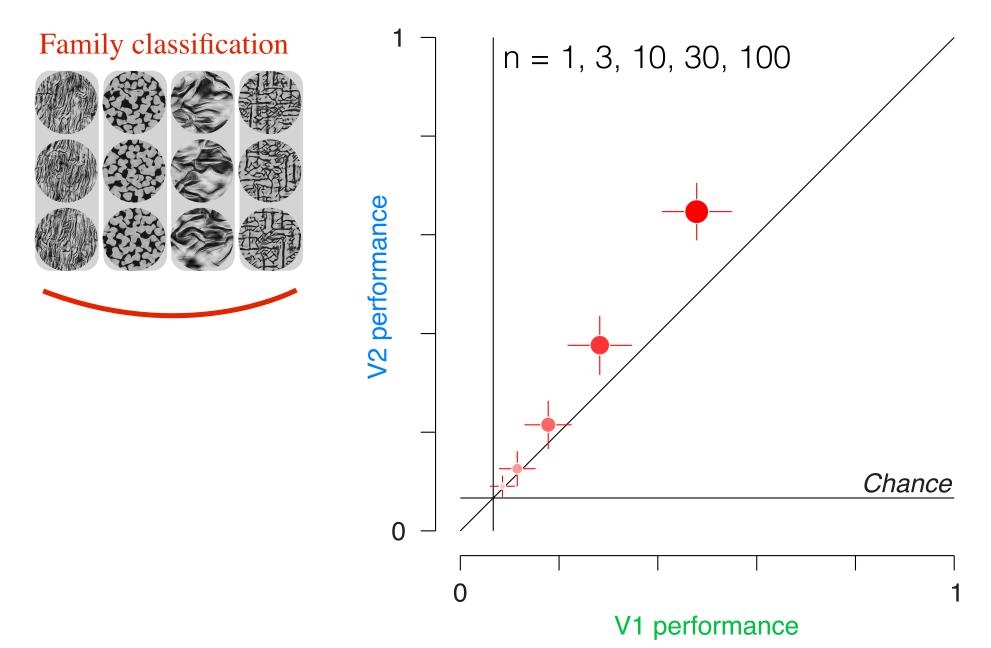




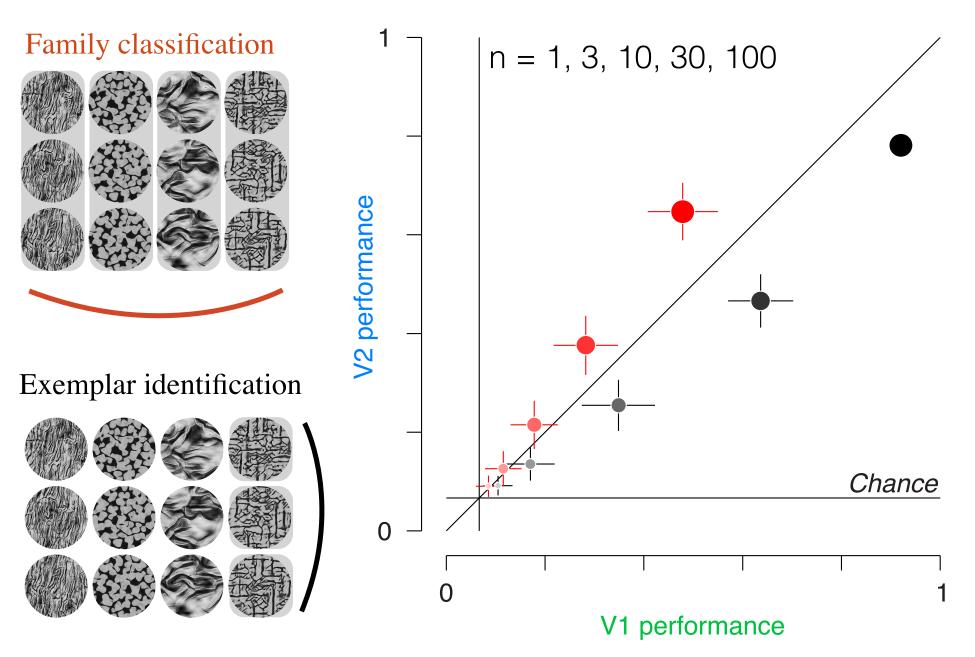


Variance across exemplars (%)

Decoding



Decoding





Javier Portilla



Jeremy Freeman



Josh McDermott

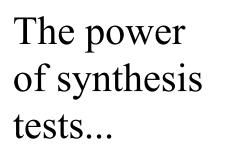


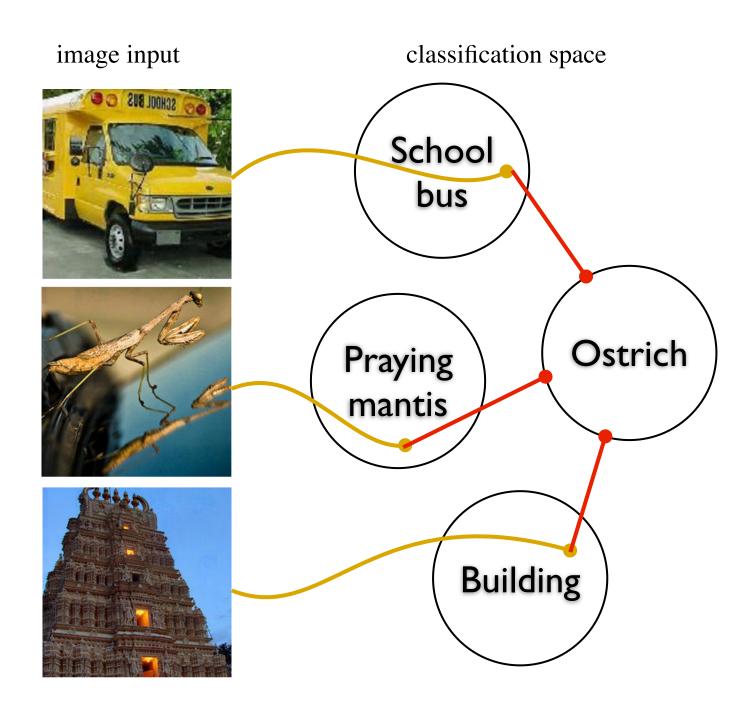
Corey Ziemba



Tony Movshon







Intriguing properties of neural networks, ArXiv 2014 Szegedy, Zaremba, Sutskever, Bruna, Erhan, Goodfellow, Fergus The power of synthesis tests...

Shows that, at the very least, these networks are NOT good models for human vision!













Intriguing properties of neural networks, ArXiv 2014 Szegedy, Zaremba, Sutskever, Bruna, Erhan, Goodfellow, Fergus