

NOT NOISY, JUST WRONG

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**UNIVERSITY of
ROCHESTER**



Collaborators

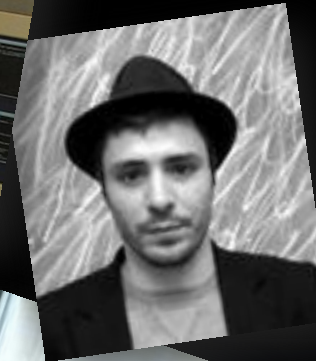
Jeffrey Beck
Duke University



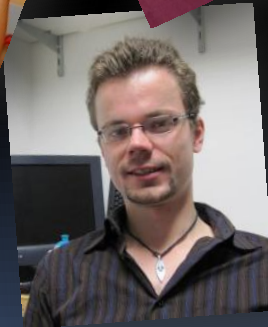
Peter Latham
Gatsby Computational
Neuroscience Unit. London,
UK



Ruben Coen-Cagli
Universite de Geneve



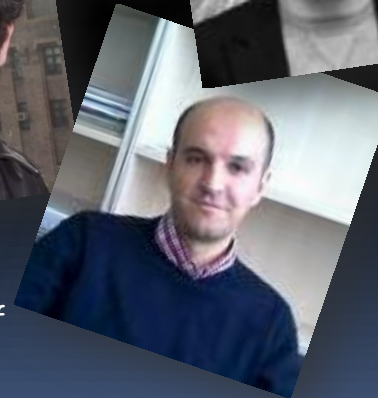
Wei Ji Ma
NYU



Ingmar Kanitscheider
Universite de Geneve



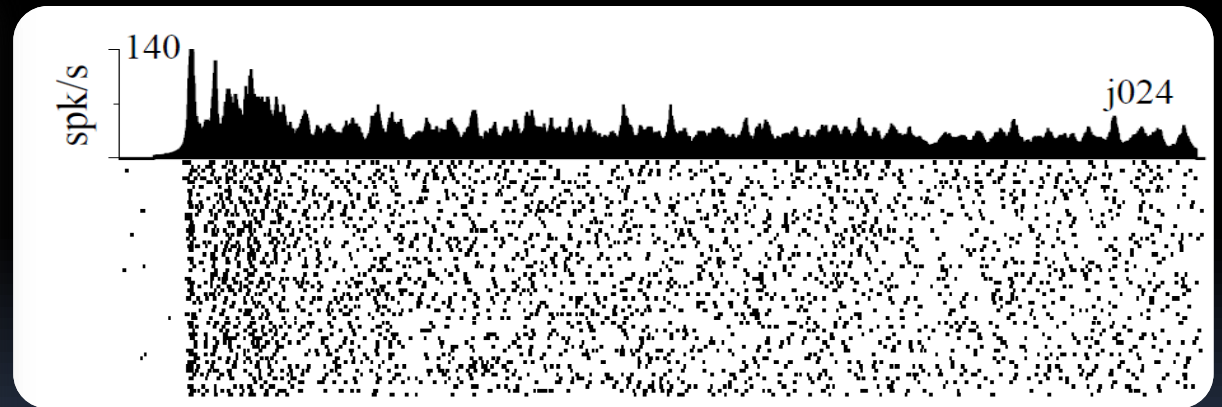
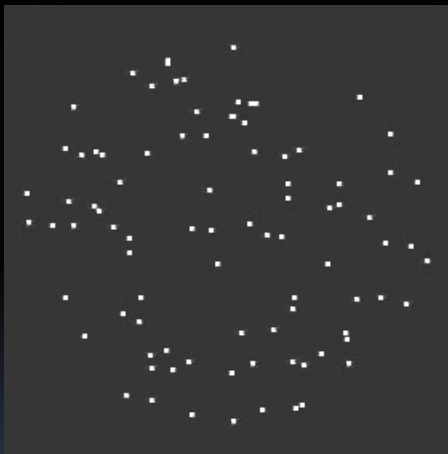
Xaq Pitkow
Baylor College of
Medecine



Ruben Moreno Bote
Foundation Sant Joan de deu
Universitat de Barcelona

Who is to blame?

Near-Poisson variability in spike trains

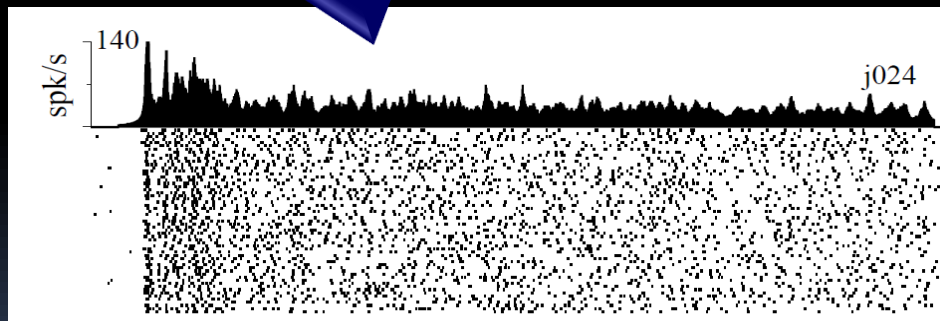


(Data from Newsome et al)

Who is to blame?

Near Poisson variability due to chaotic dynamics of balanced networks

(Van Vreeswijk and Sompolinsky, 1996; Shadlen and Newsome, 1998; Banerjee et al, 2008, London et al, 2010)



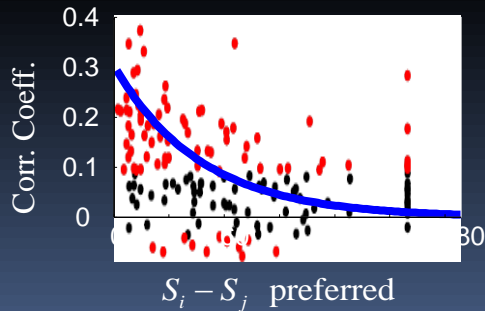
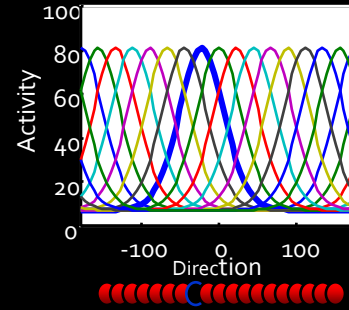
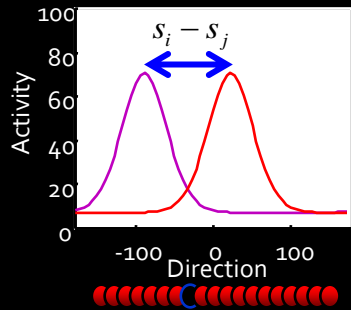
Near-Poisson variability



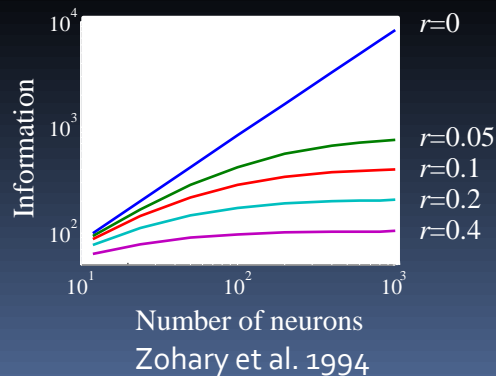
Behavioral variability

Who is to blame?

- It's not just Poisson variability, it's correlated Poisson variability



Huang and Lisberger, 2010



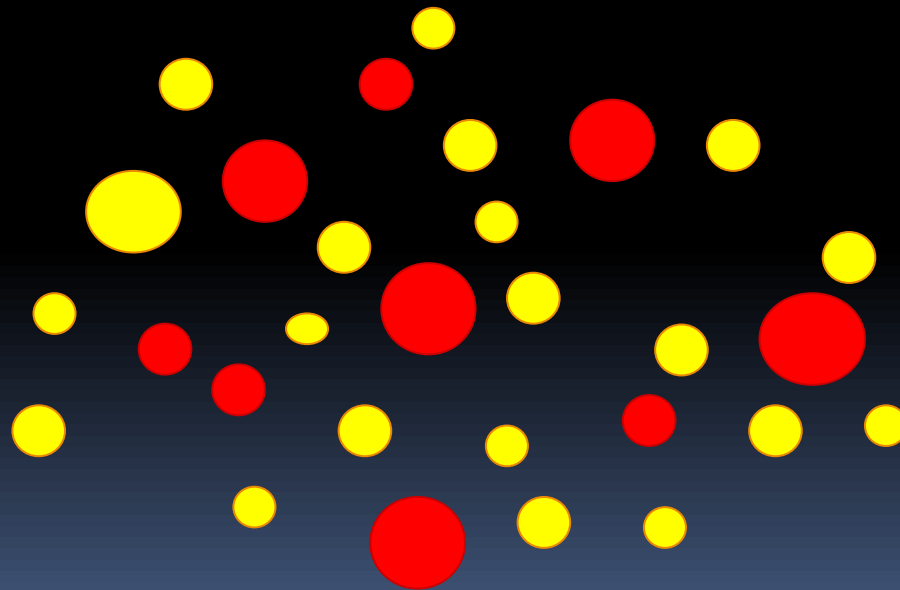
Zohary et al. 1994

Who is to blame?

- It's not just Poisson variability, it's correlated Poisson variability
- This variability explains, among other things, Weber's law

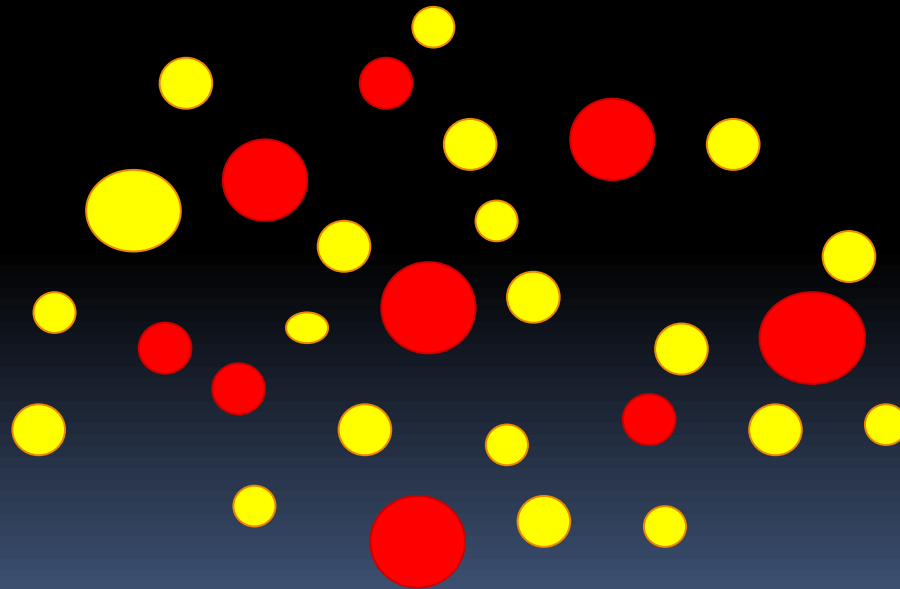
Weber's law

$$\frac{\Delta N}{N} = \text{constant}$$



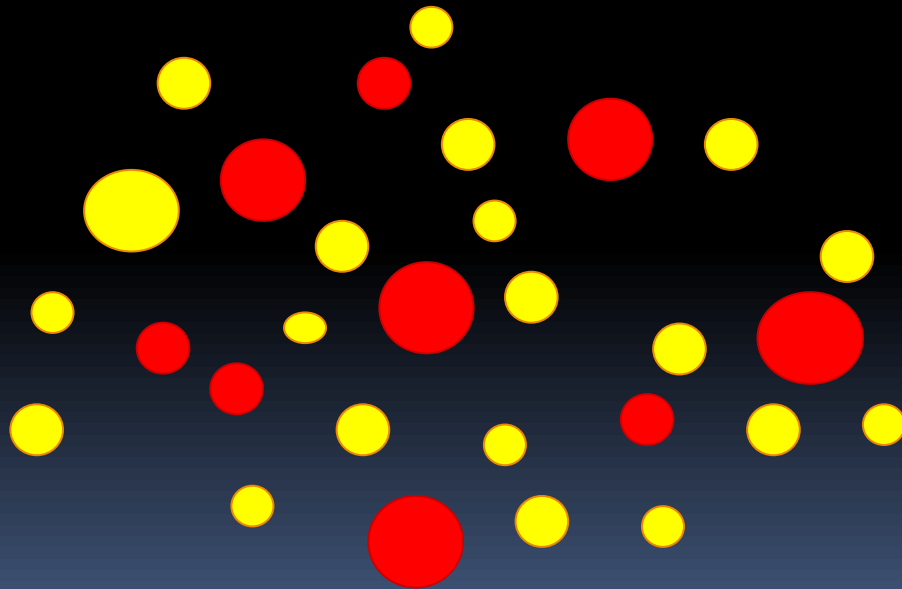
Weber's law

$$\frac{\Delta N}{N} = \frac{2}{10} = \text{constant}$$



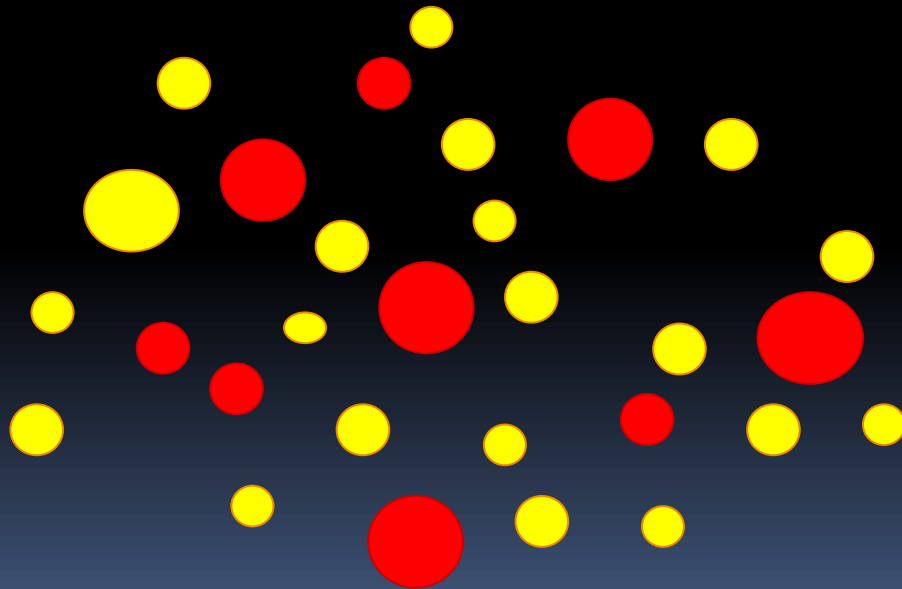
Weber's law

$$\frac{\Delta N}{N} = \frac{2}{10} = \frac{4}{20} = \text{constant}$$



Weber's law

$$\frac{\Delta N}{N} = \frac{2}{10} = \frac{4}{20} = \frac{8}{40} = \text{constant}$$

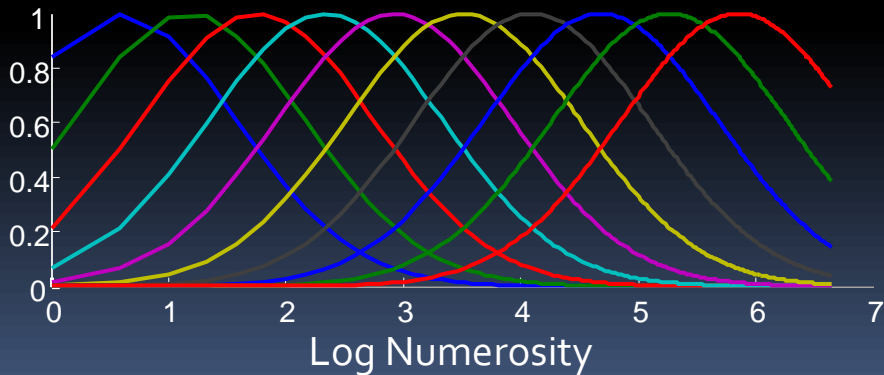
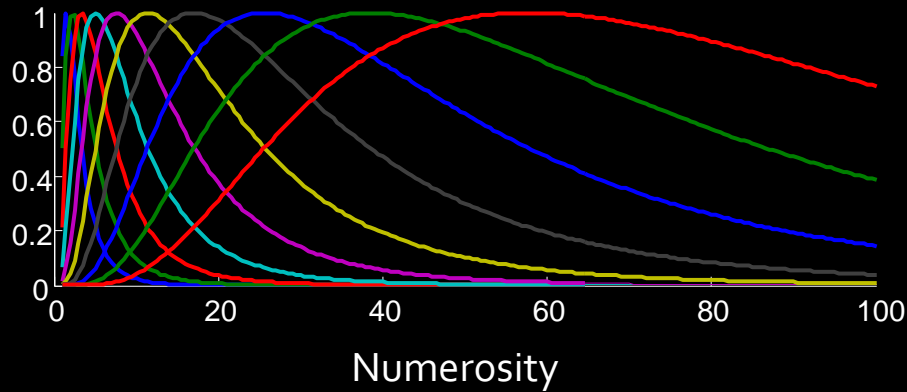


Weber's law

- Numerosity
- Line length
- Weights
- Luminance
- Speed of motion
- Distance traveled
- Time
- ...



Weber's law

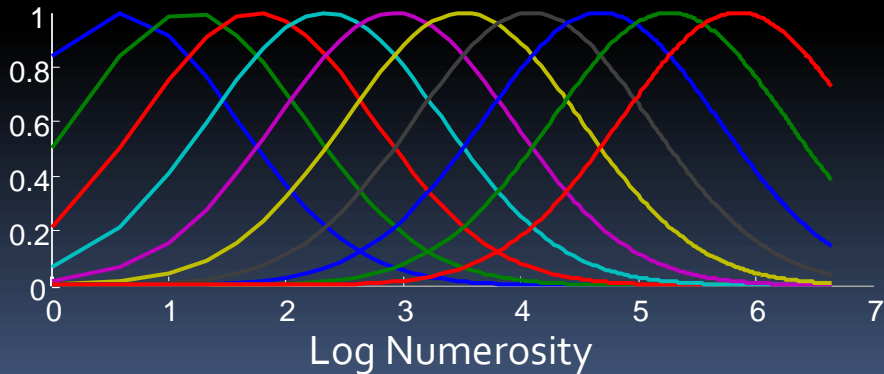
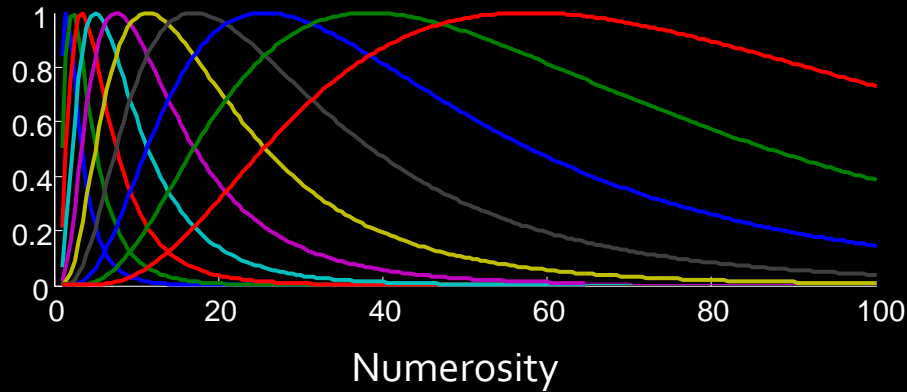


+ Poisson
noise



Weber's
law

Weber's law



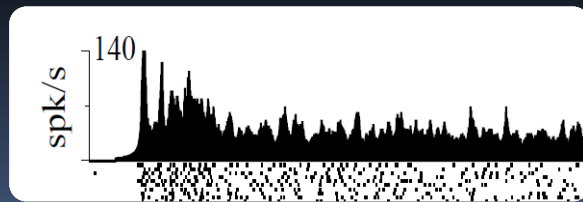
NO Poisson single cell variability



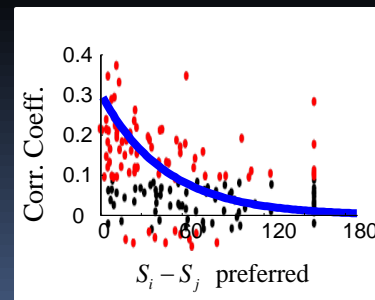
NO Weber's law

The origin of behavioral variability

Near-Poisson variability due to the chaotic dynamics of balanced networks of excitatory and inhibitory neurons, along with correlations inversely proportional to the difference in preferred stimuli, are the main causes of behavioral variability.



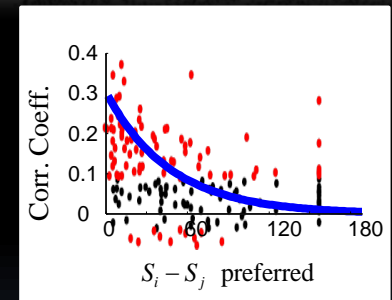
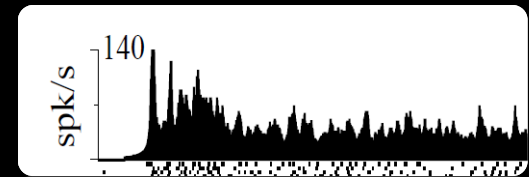
+



Alternative view

The brain is noisy but...

- The near-Poisson noise induced by chaotic dynamics of cortical circuits has little impact on behavior
- Correlations inversely proportional the difference in preferred stimuli do not necessarily limit information
- Most of behavioral variability comes from
 1. Variable data from the world (which naturally leads to Weber's law)
 2. Suboptimal inference



Roadmap

- Suboptimal inference can generate behavioral variability
- This cause dominates in most situations
- What this theory explains
- Implications for neuronal variability
- A normative view of Weber's law

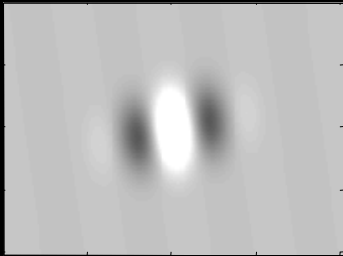
Roadmap

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Orientation discrimination

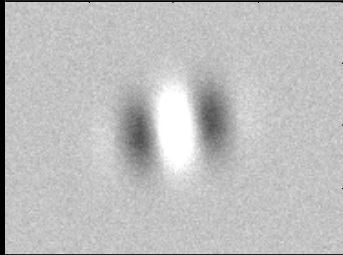
- Let's consider a simple task:
Orientation discrimination

Orientation discrimination

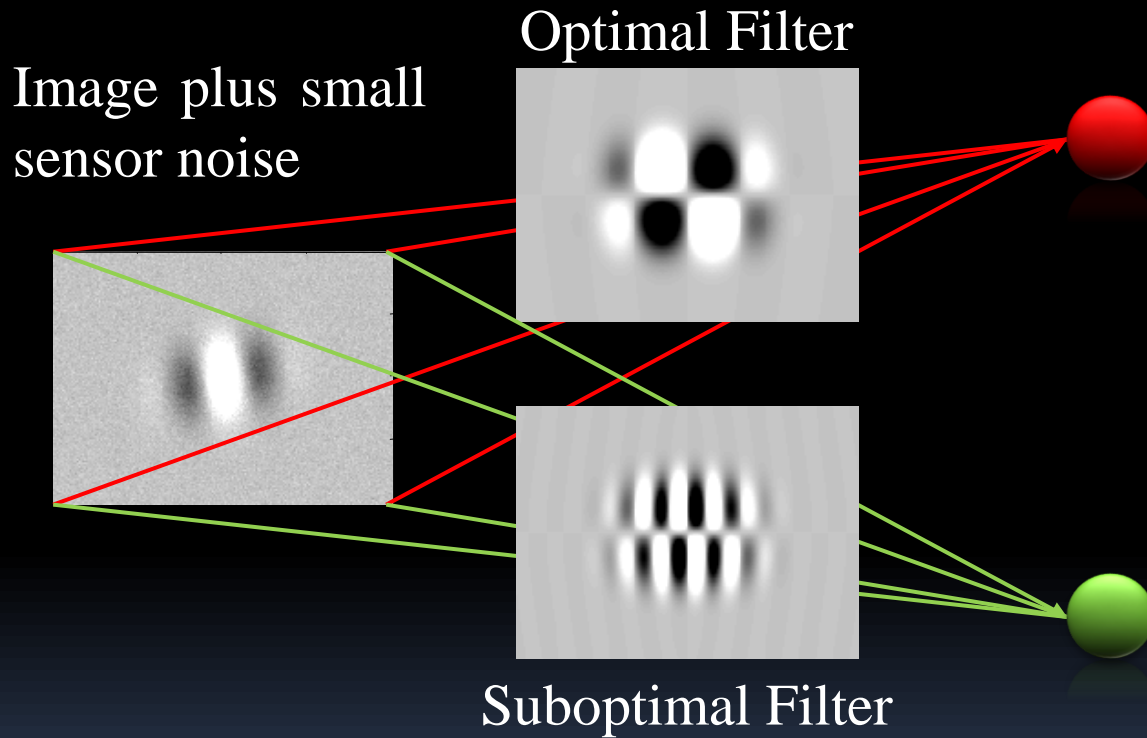


Orientation discrimination

Image plus small
sensor noise



Orientation discrimination

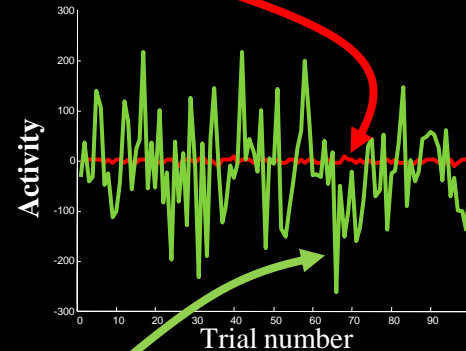


Orientation discrimination

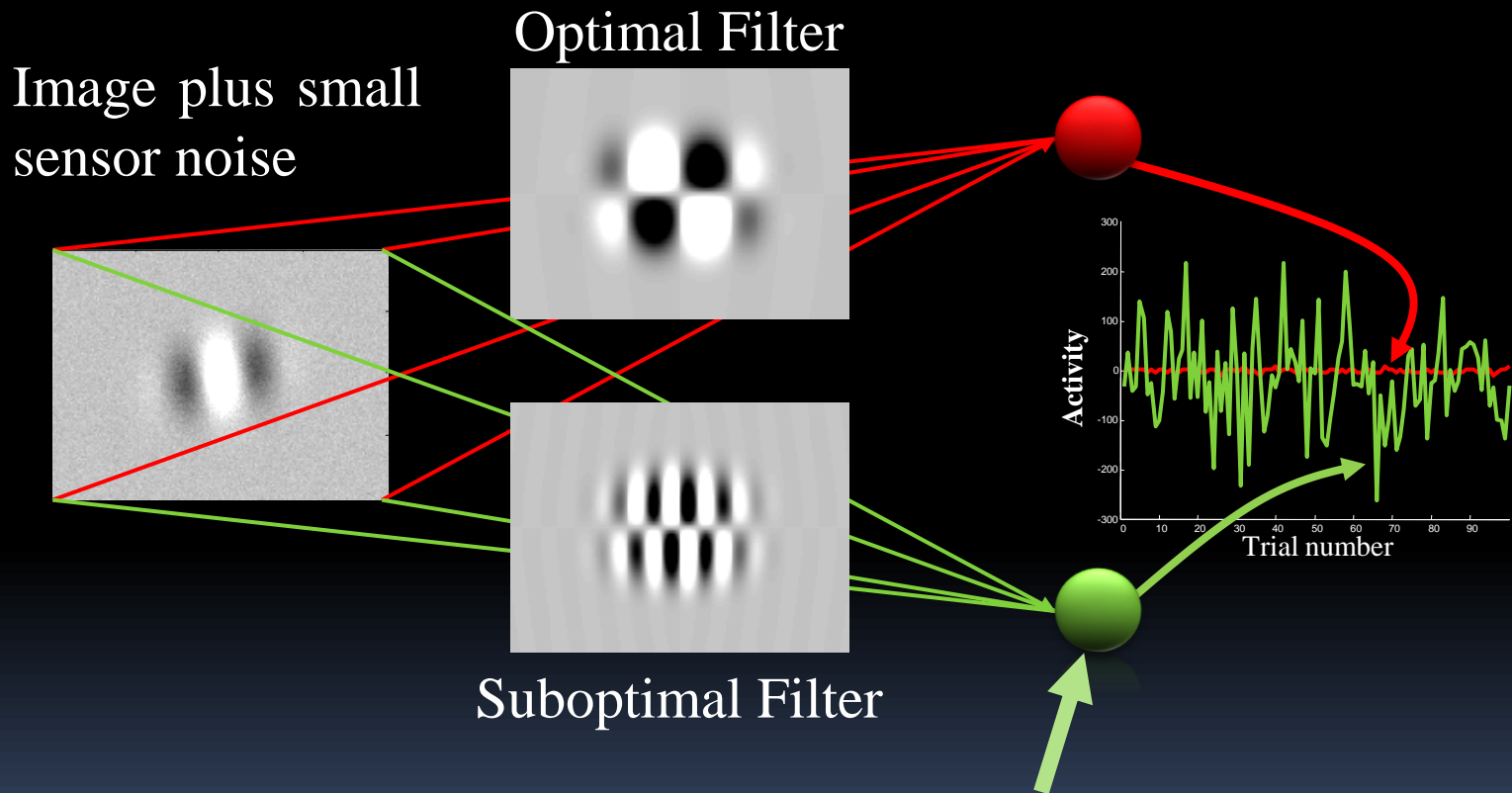


NOTE:

The filters have been adjusted to ensure that the red and green units have the same mean activity

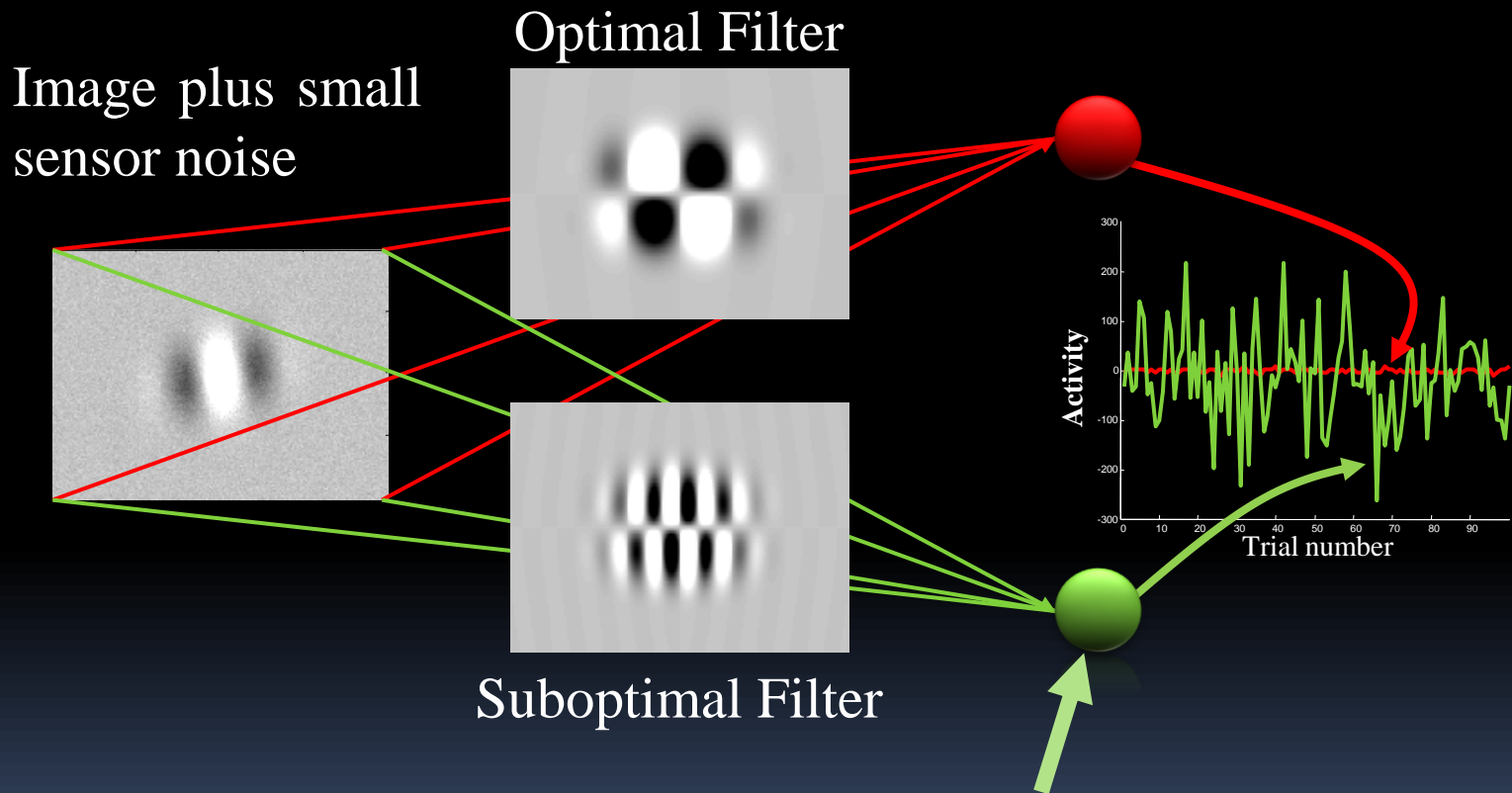


Orientation discrimination



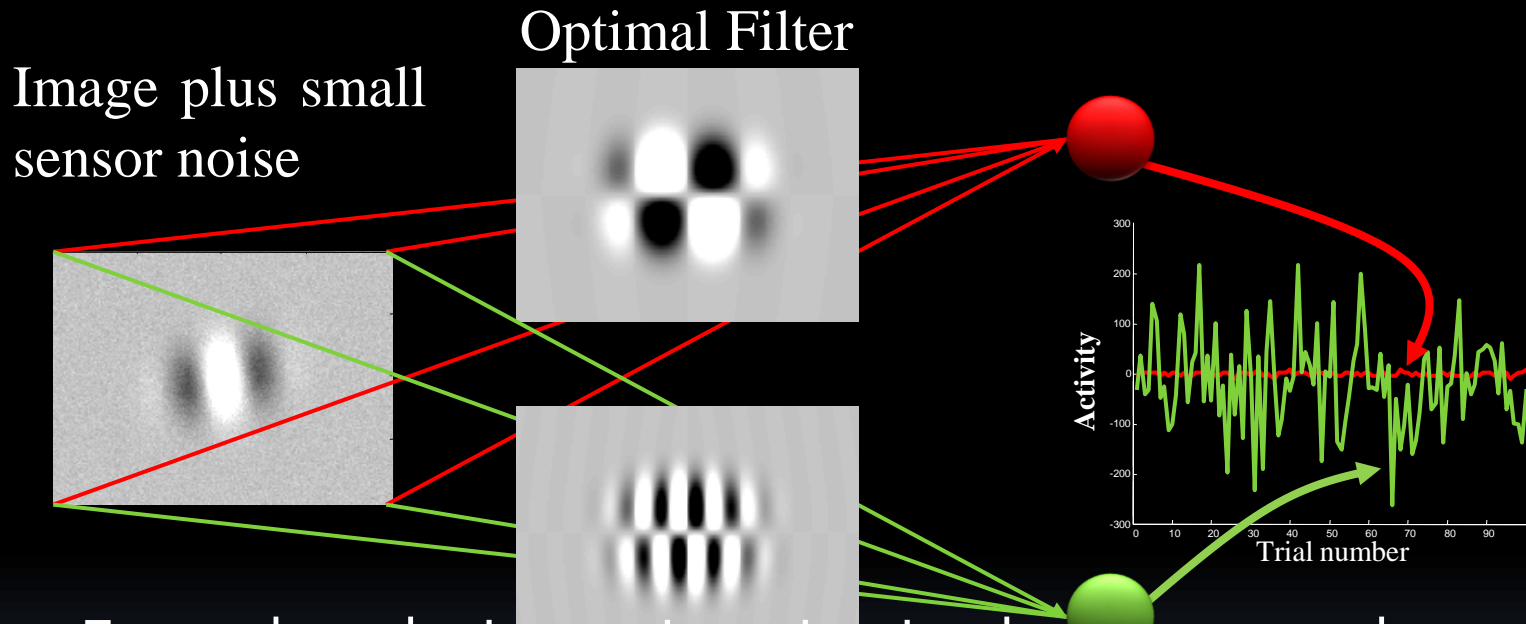
The extra variability comes from a deterministic approximation

Orientation discrimination



99% of the variability comes from the deterministic approximation!

Orientation discrimination



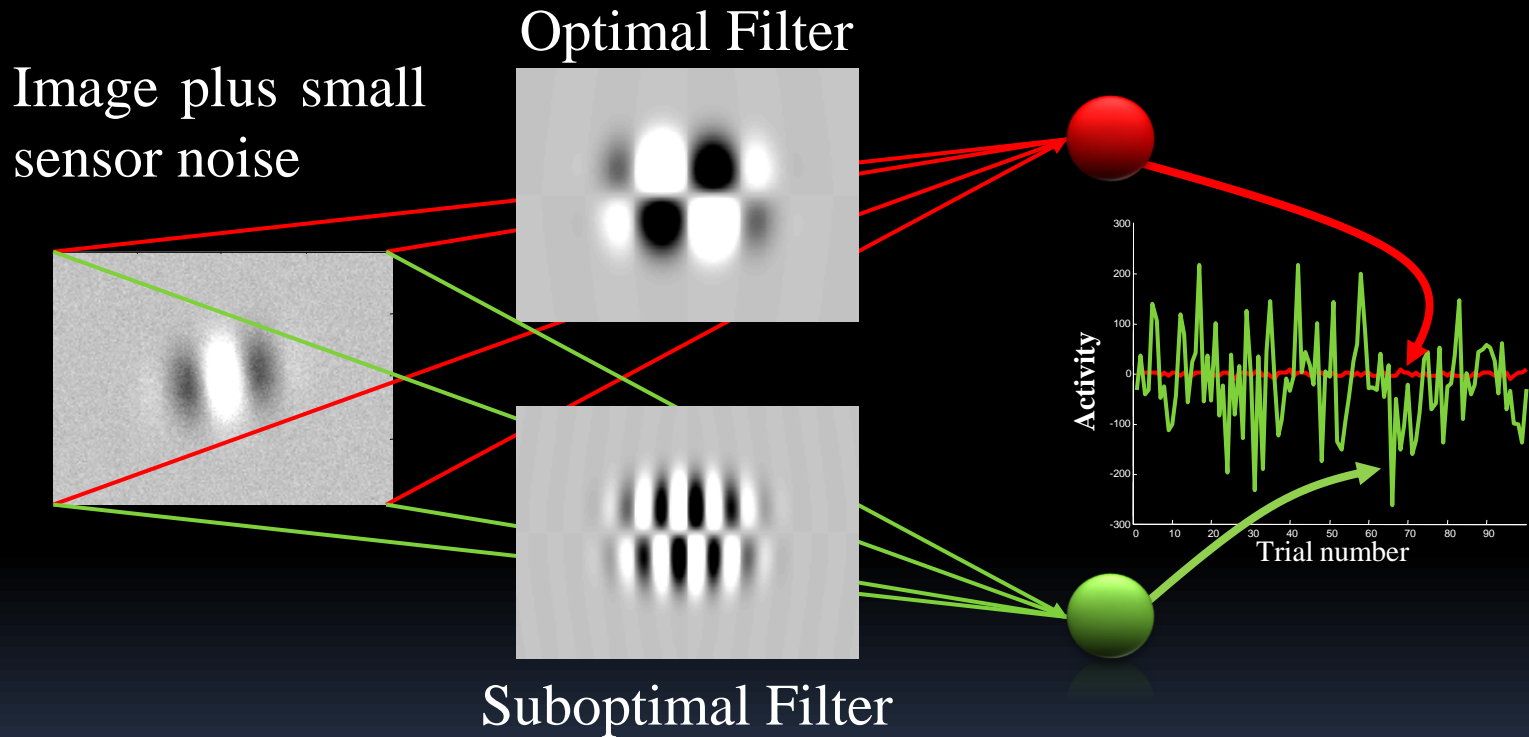
Even when the image is maintained constant on the screen, a large fraction of the behavioral variability might be due to suboptimal inference.

Causes of variability

- Suboptimal inference leads to extra variability.
- For complex problems, suboptimal approximations are unavoidable and dominate

(Beck et al, 2012)

Orientation discrimination

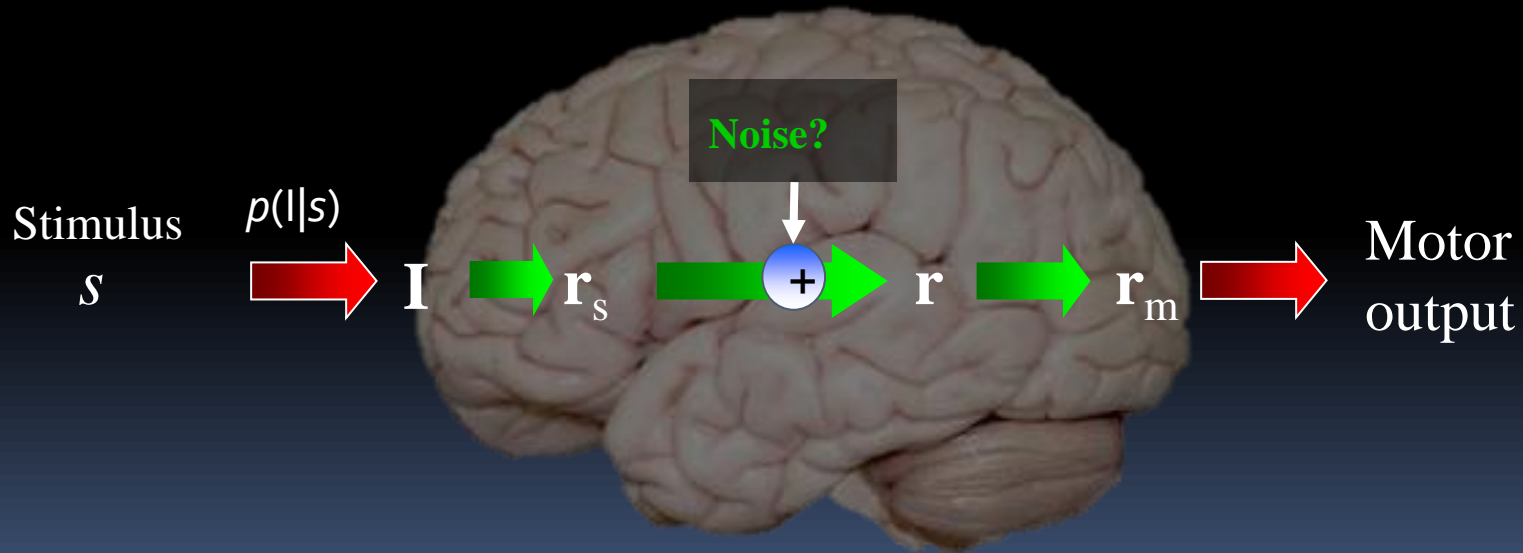


Motion estimation

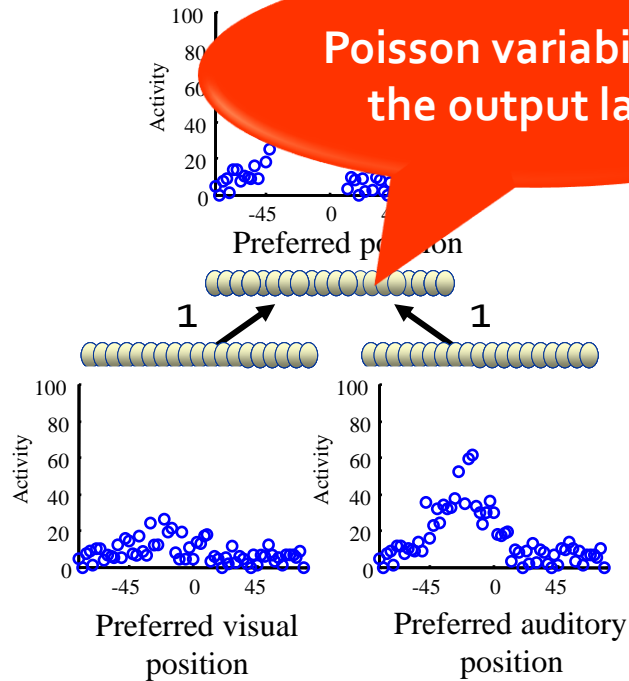
- For most problems of interest, we cannot know the generative model because it's too complex: suboptimality dominates.
- For very simple tasks, we might be able to learn the generative model (e.g. photon detection)

The General Case

- How about internal noise?

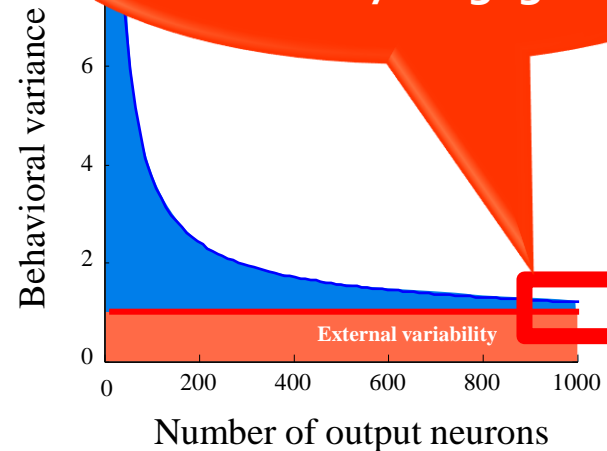


The impact of Poisson variability



Poisson variability in the output layer

Information loss due to the near-Poisson variability: negligible!



Ma, Beck et al, 2006. Beck et al, 2012.

Roadmap

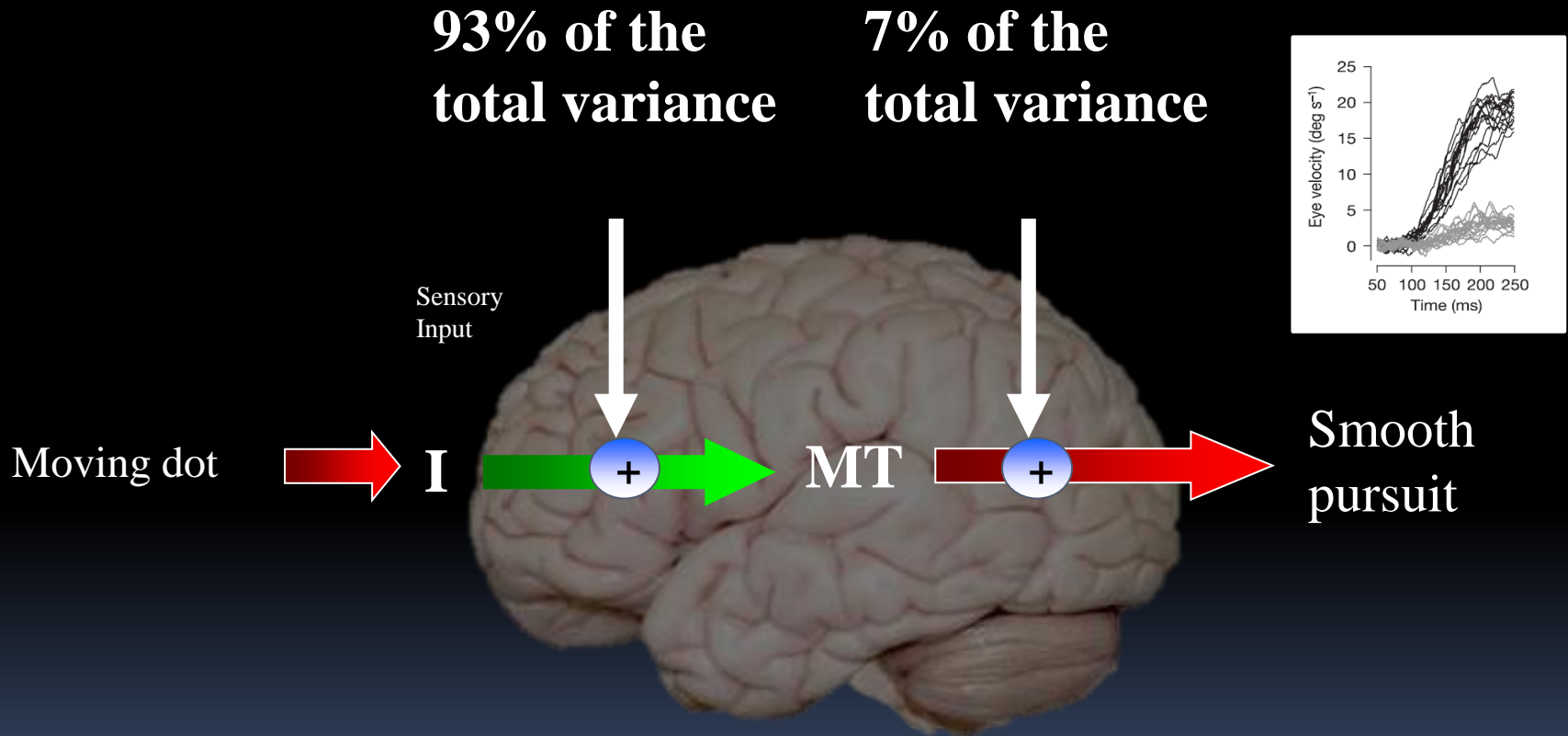
- Suboptimal inference can generate behavioral variability
- This cause dominates in most situations
- What this theory explains
- Implications for neuronal variability
- A normative view of Weber's law

A close-up photograph of a human eye with a vibrant green iris. The pupil is dark and centered. The surrounding sclera is light-colored, and the eyelashes are visible on the right side. The image is slightly blurred, giving it a soft, artistic feel.

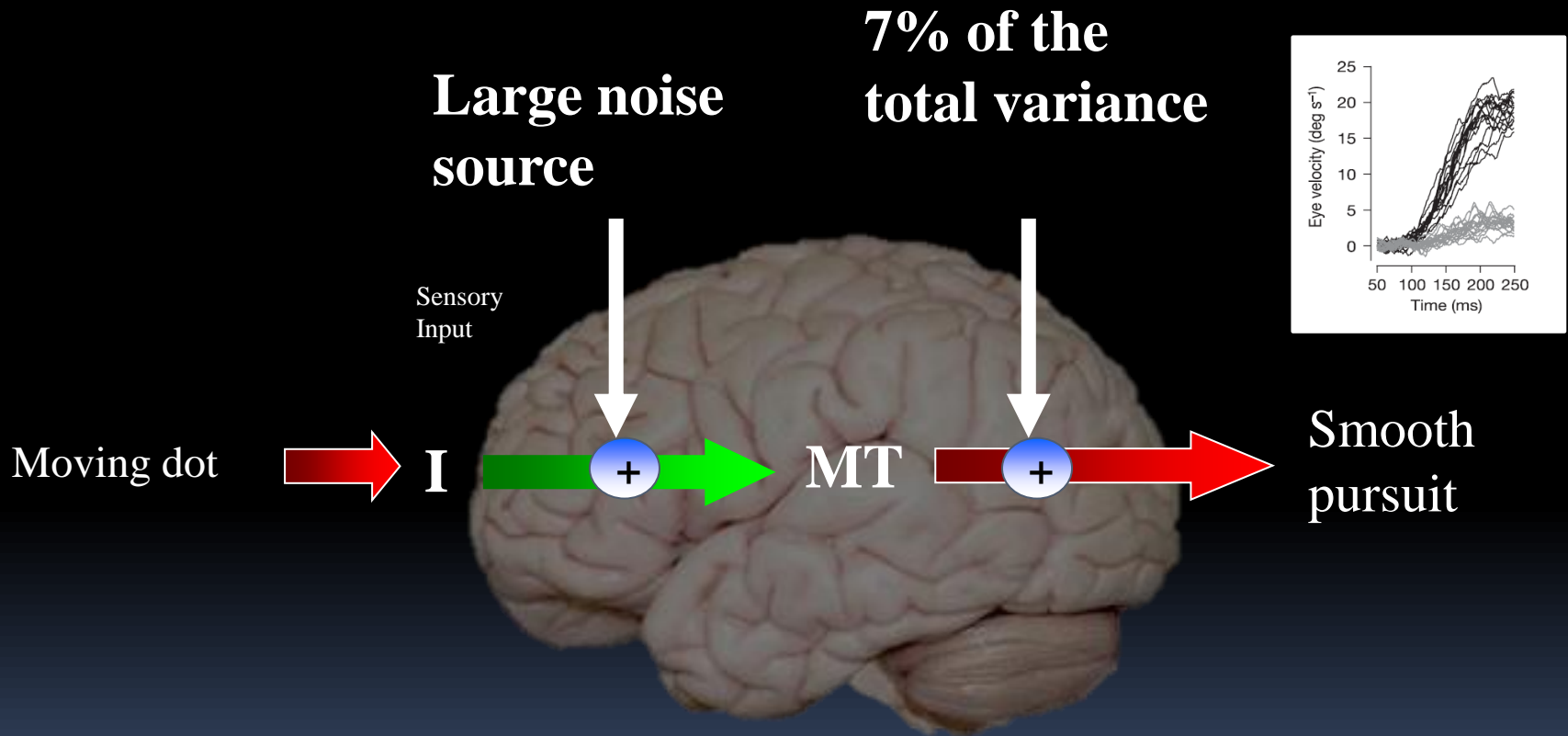
Why is the optic of the eyes so bad?

"If an optician wanted to sell me an instrument that had all these defects, I should think myself quite justified in blaming his carelessness in the strongest terms, and giving him his instrument back." Hermann von Helmholtz.

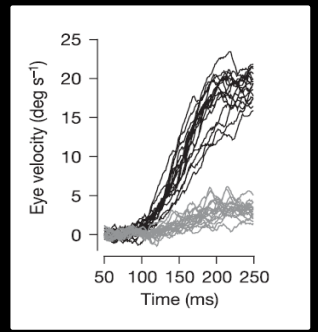
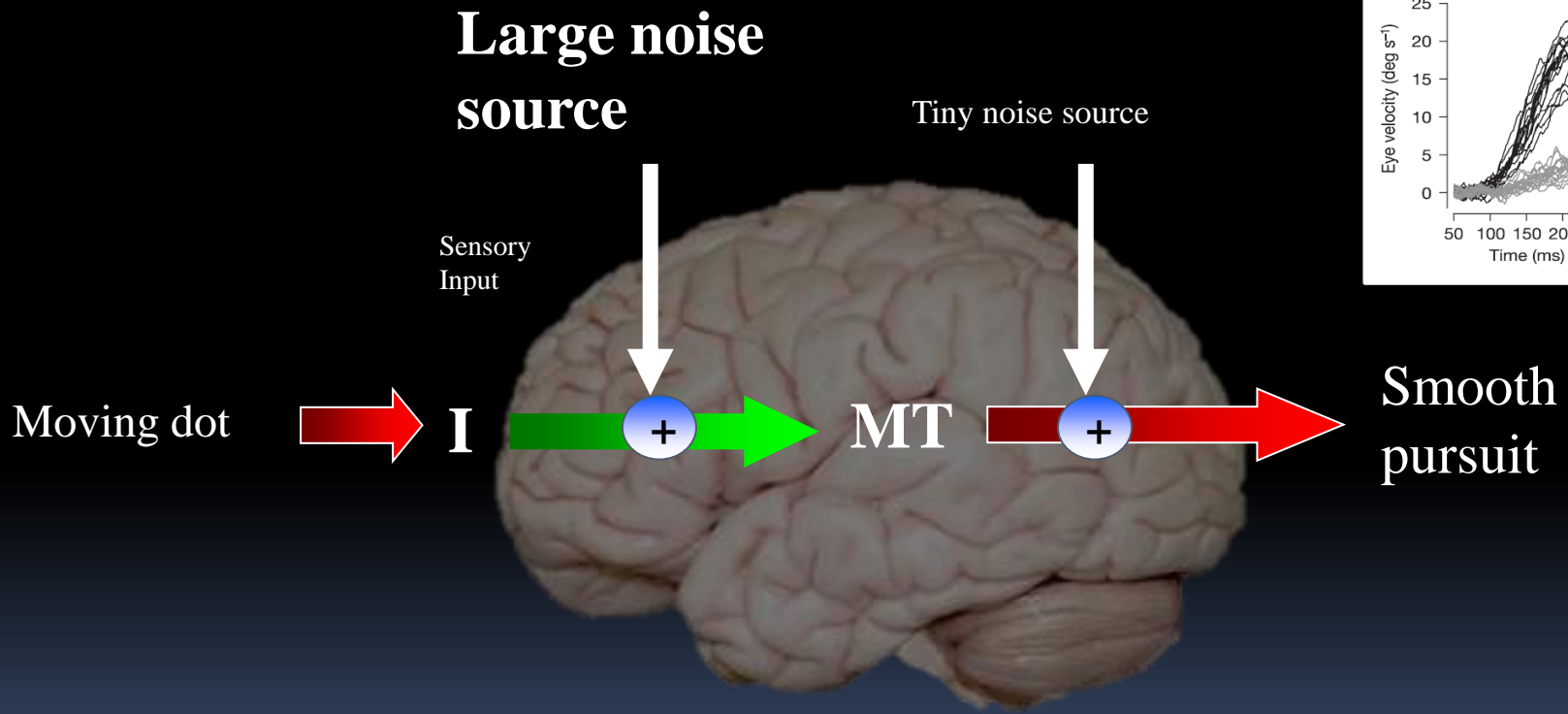
Osbourne et al, 2005



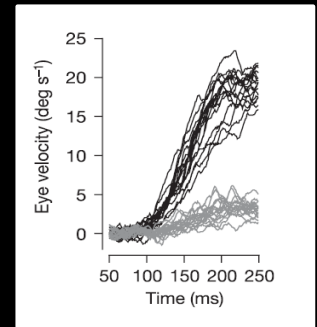
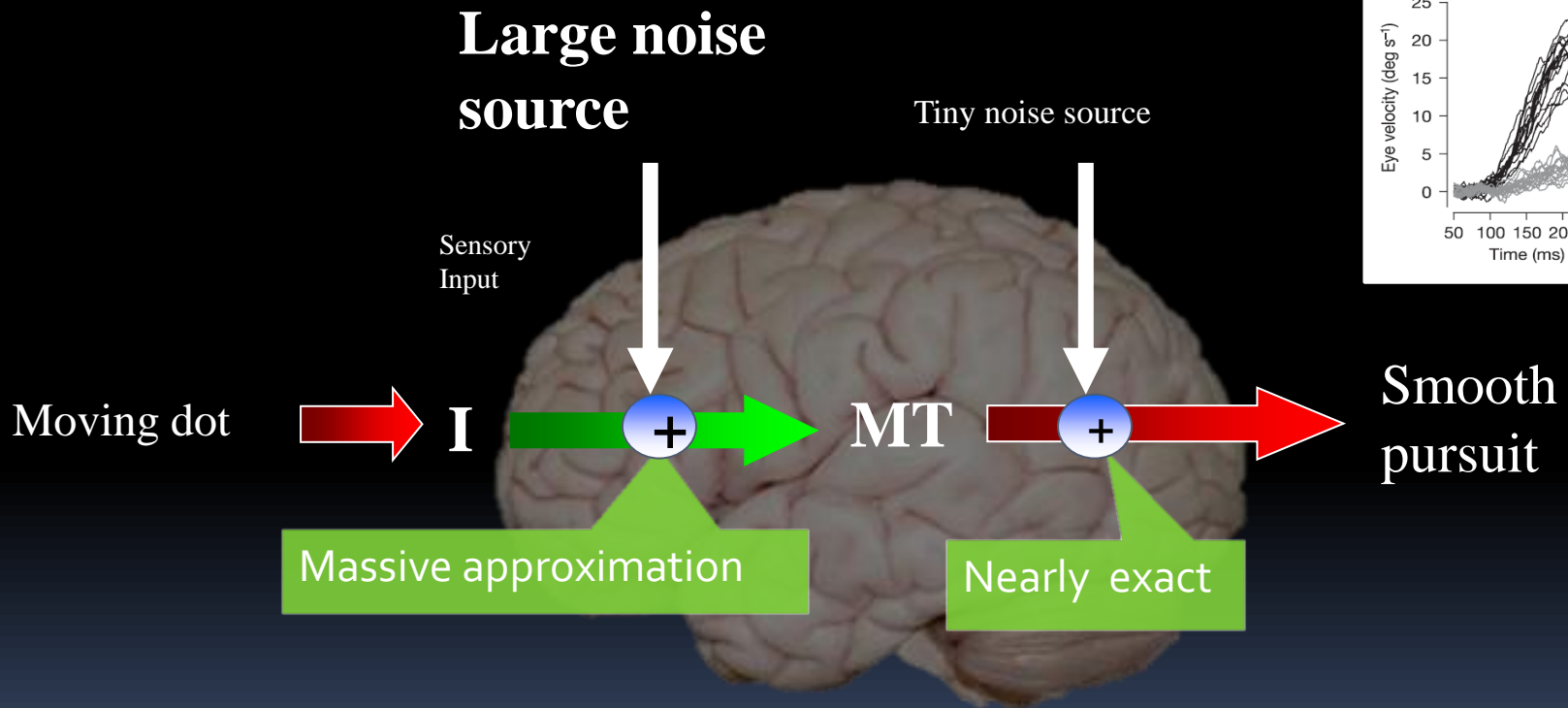
Osbourne et al, 2005



Osbourne et al, 2005



Osbourne et al, 2005



Roadmap

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Correlations and information

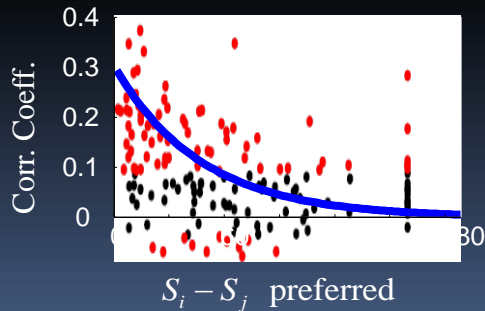
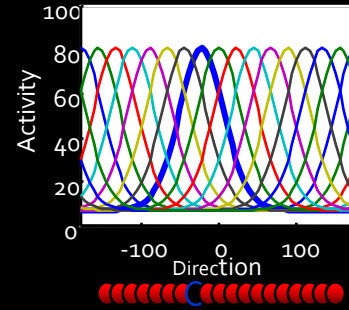
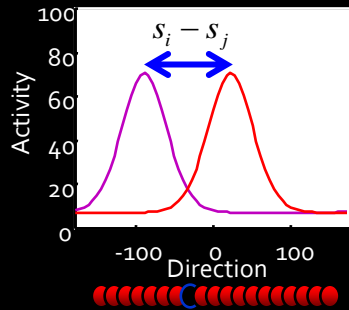
- Suboptimality increases behavioral variability.
- In other words, it decreases information.
- How is that reflected in neural responses?
- What limits information in neural codes?

Correlations and information

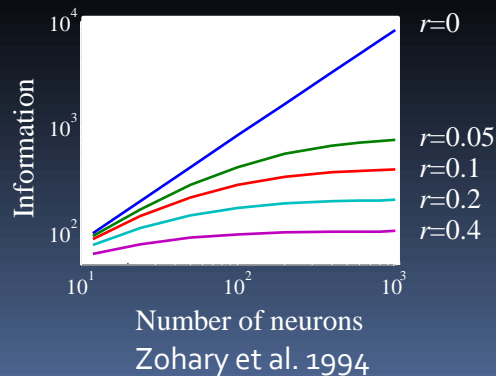
- What limits information in neural codes?
- Typical answer: positive correlations among neurons with similar preferred stimuli

Who is to blame?

- It's not just Poisson variability, it's correlated Poisson variability

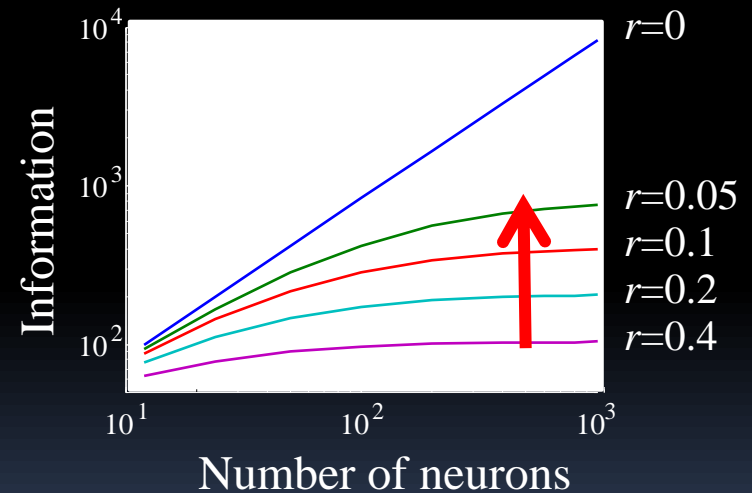
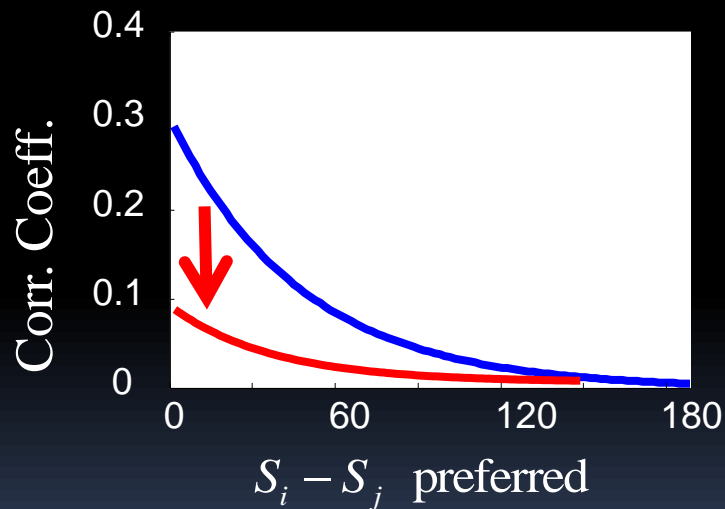


Huang and Lisberger, 2010



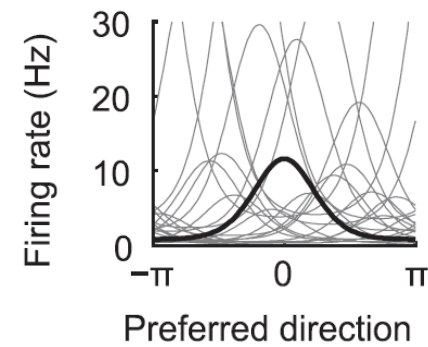
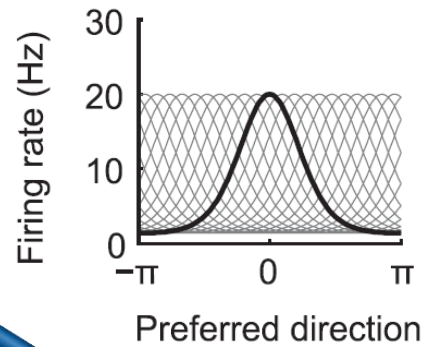
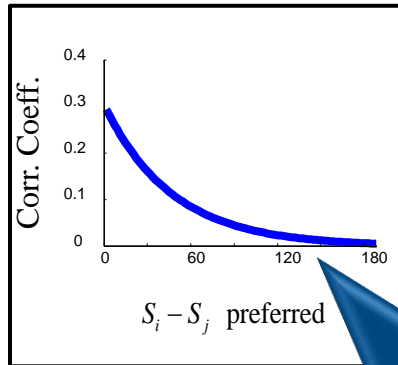
Correlations and information

- Decorrelation = more information



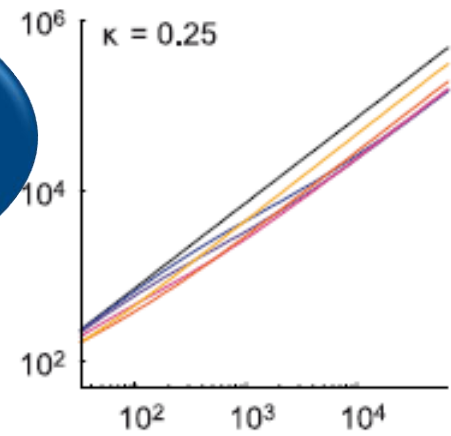
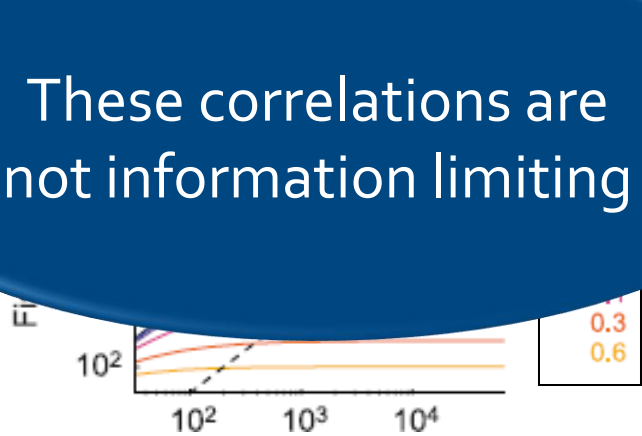
Correlation and information

- Correlations inversely proportional to difference in preferred stimuli limit information
- Decorrelation = more information
- No, not necessarily.

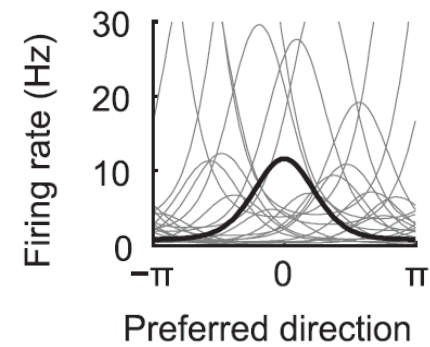
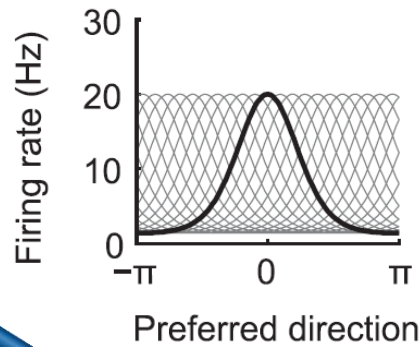
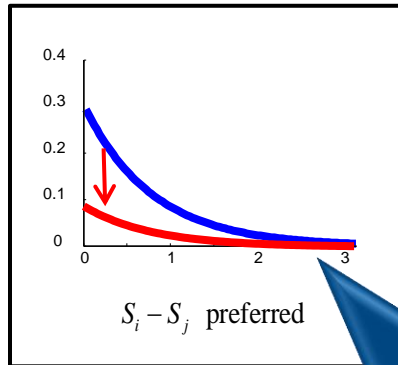


These correlations are not information limiting

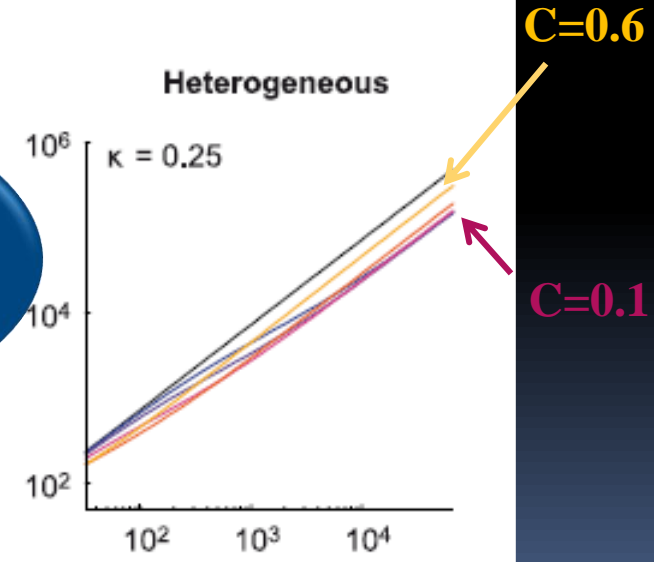
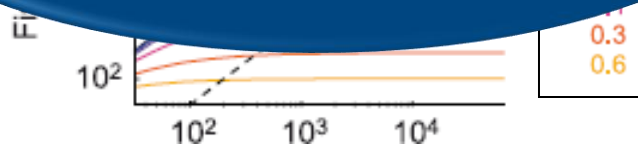
Heterogeneous



(See also Series, Latham and Pouget, 2004.)



Decreasing correlations does not necessarily increase information

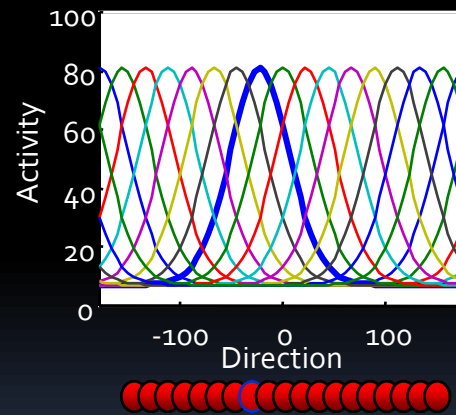


Implications for Neural Coding

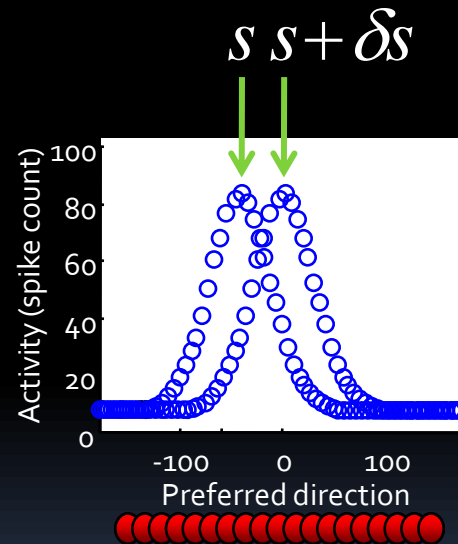
- What limits information in neural codes?
- Differential correlations

Differential correlations

Discrimination task

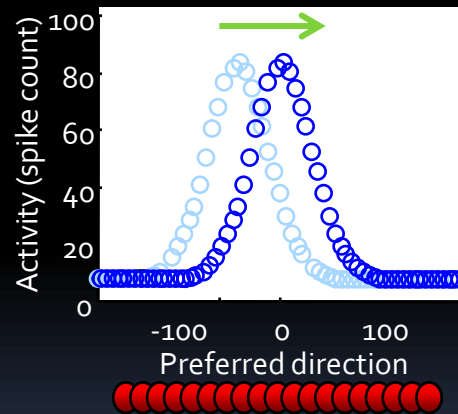


Differential correlations

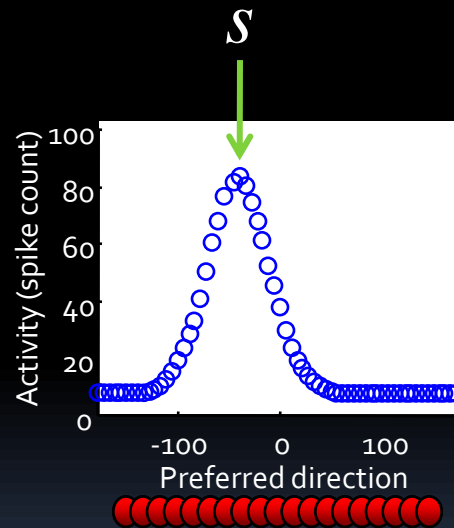


Differential correlations

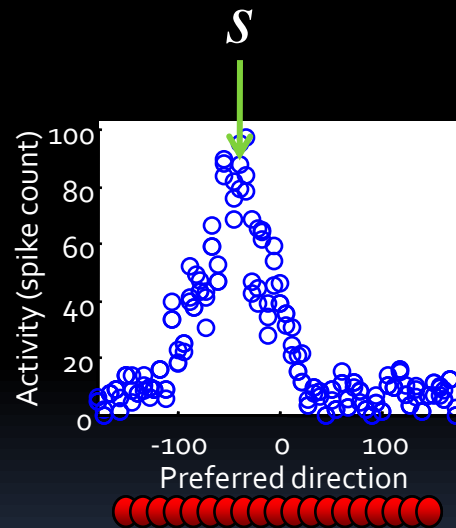
$$s \longrightarrow s + \delta s$$



Differential correlations

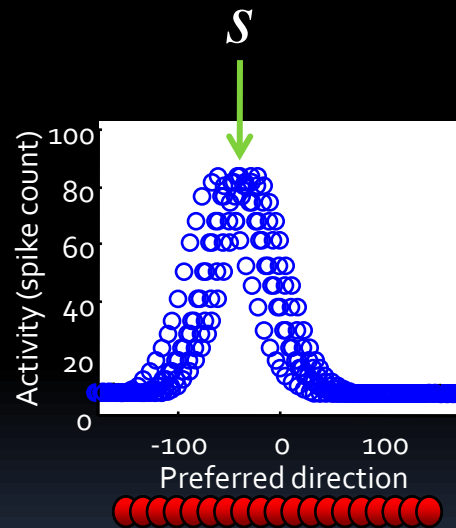


Differential correlations

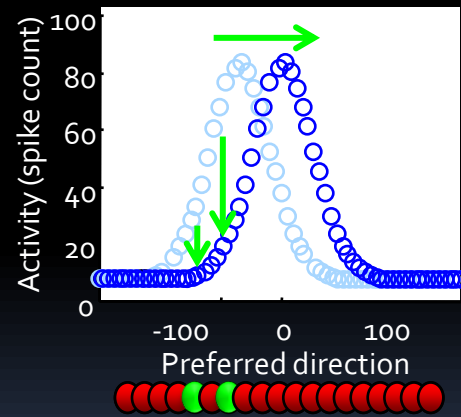


Differential correlations

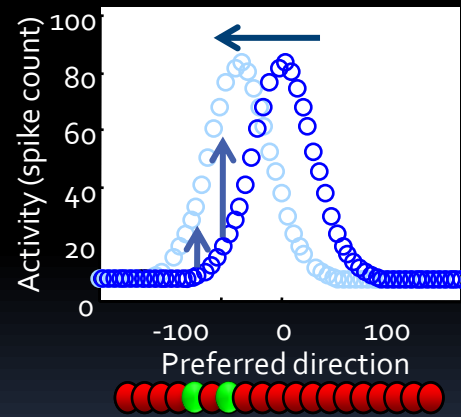
Differential correlations



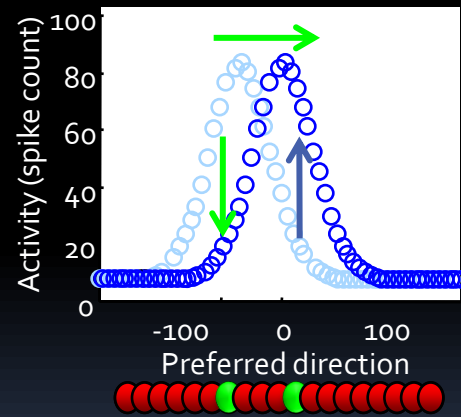
Differential correlations



Differential correlations

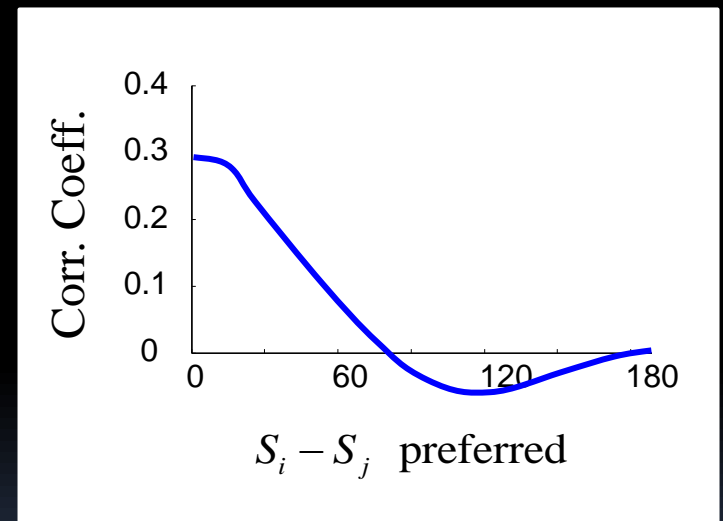
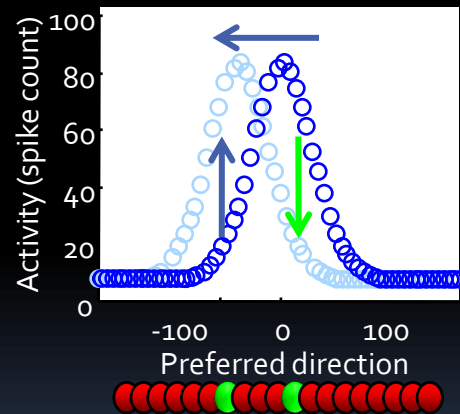


Differential correlations



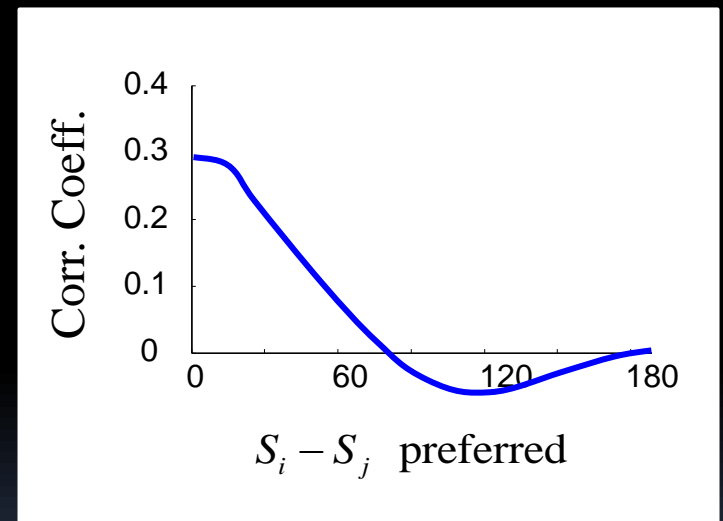
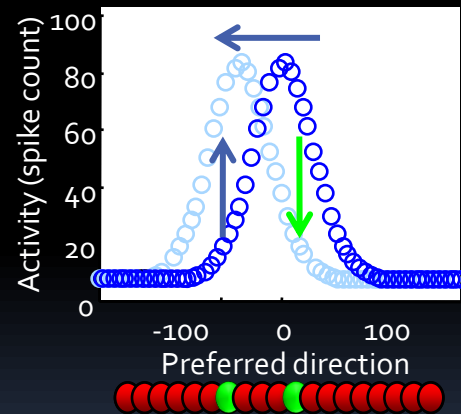
Differential correlations

$$\mathbf{f}'\mathbf{f}'^T$$



Differential correlations

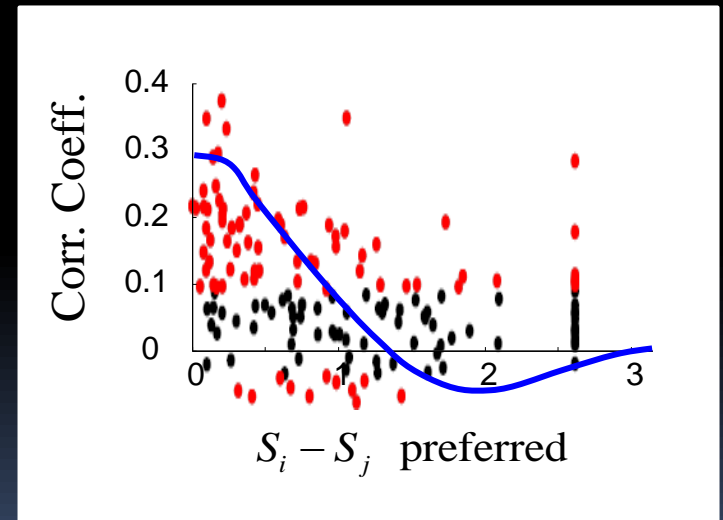
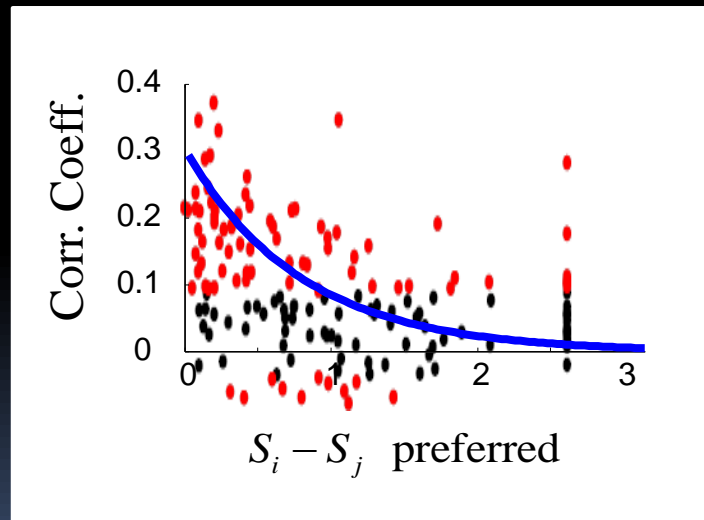
Differential



Differential correlations

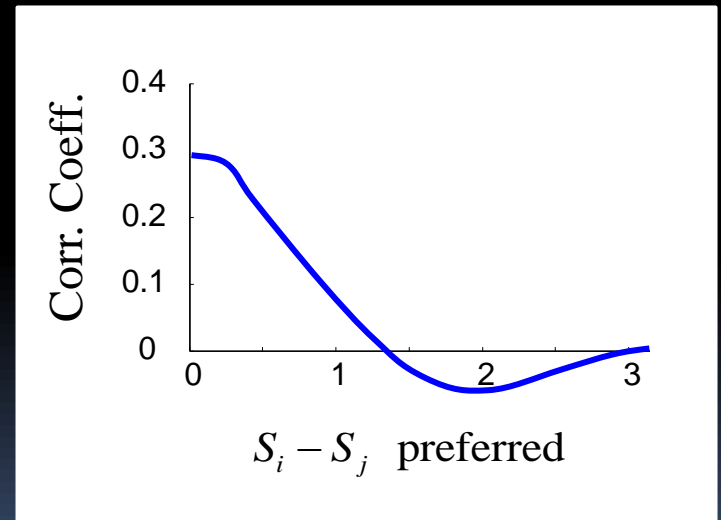
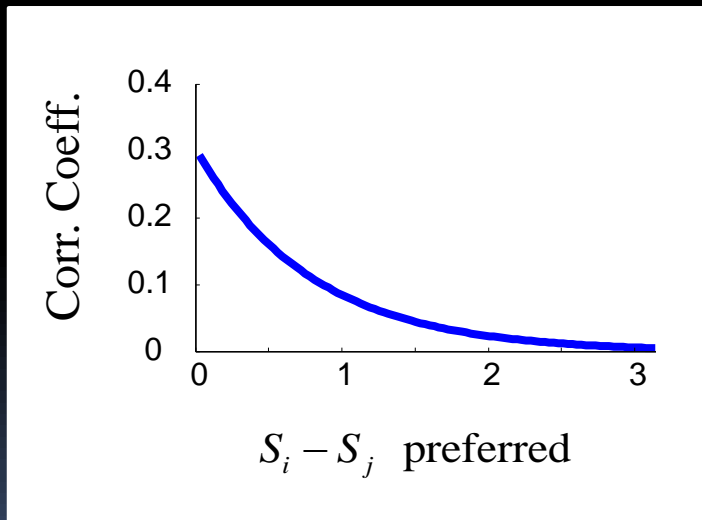
- Information saturates because of differential correlations.
- But wait, nobody has ever found differential correlations.

Differential



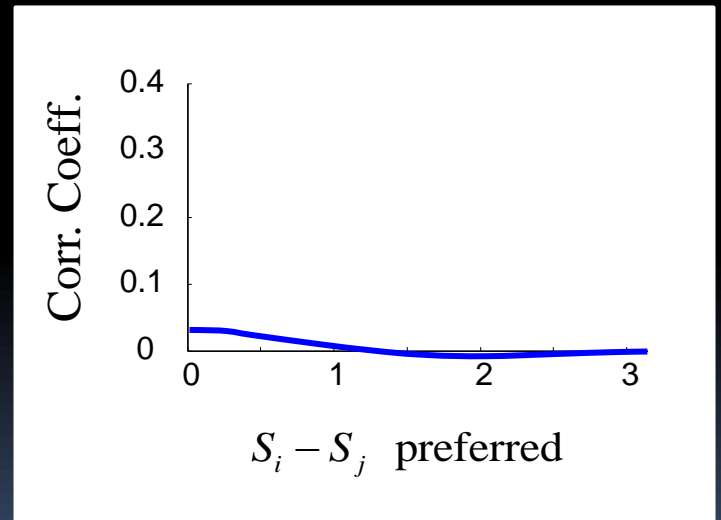
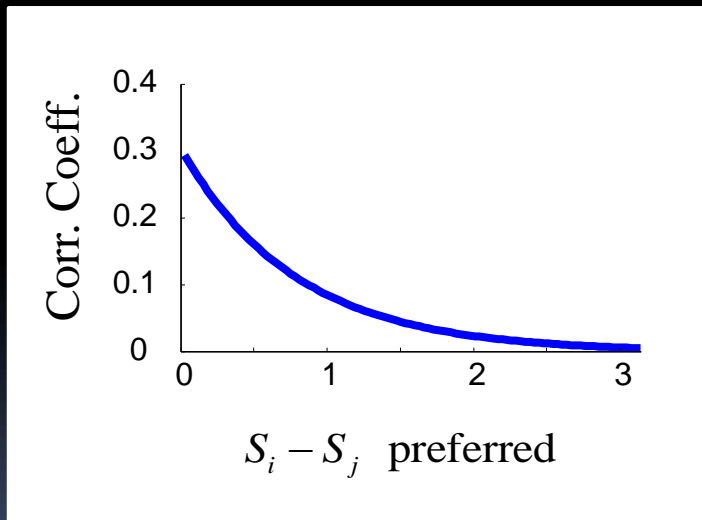
Huang and Lisberger, 2010

Differential



Huang and Lisberger, 2010

Differential

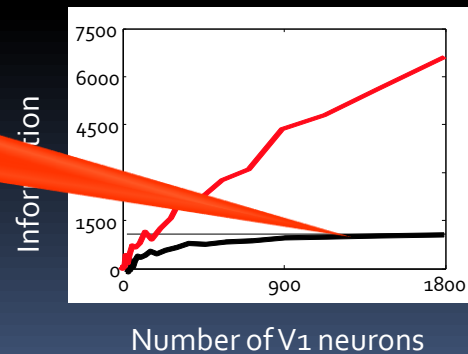
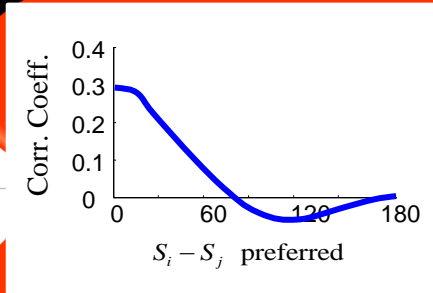
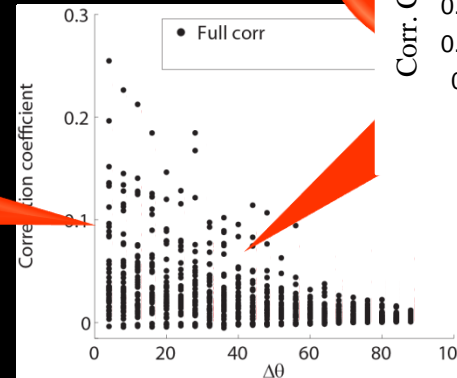


Huang and Lisberger, 2010

Differential correlations might be very small

No sign of differential correlations!

Saturation implies the presence of differential correlations



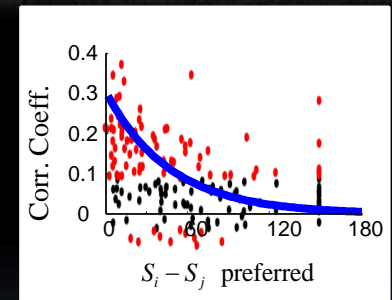
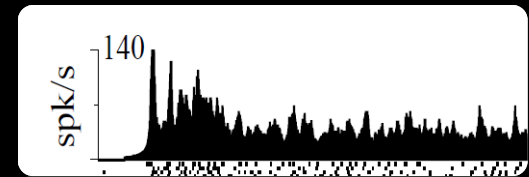
Information and correlations

- Information is limited by differential correlations
- Suboptimality increases differential correlations

Alternative view

The brain is noisy but...

- The near-Poisson noise induced by chaotic dynamics of cortical circuits has little impact on behavior
- Correlations inversely proportional the difference in preferred stimuli do not necessarily limit information
- Most of behavioral variability comes from
 1. Variable data from the world (which naturally leads to Weber's law)
 2. Suboptimal inference

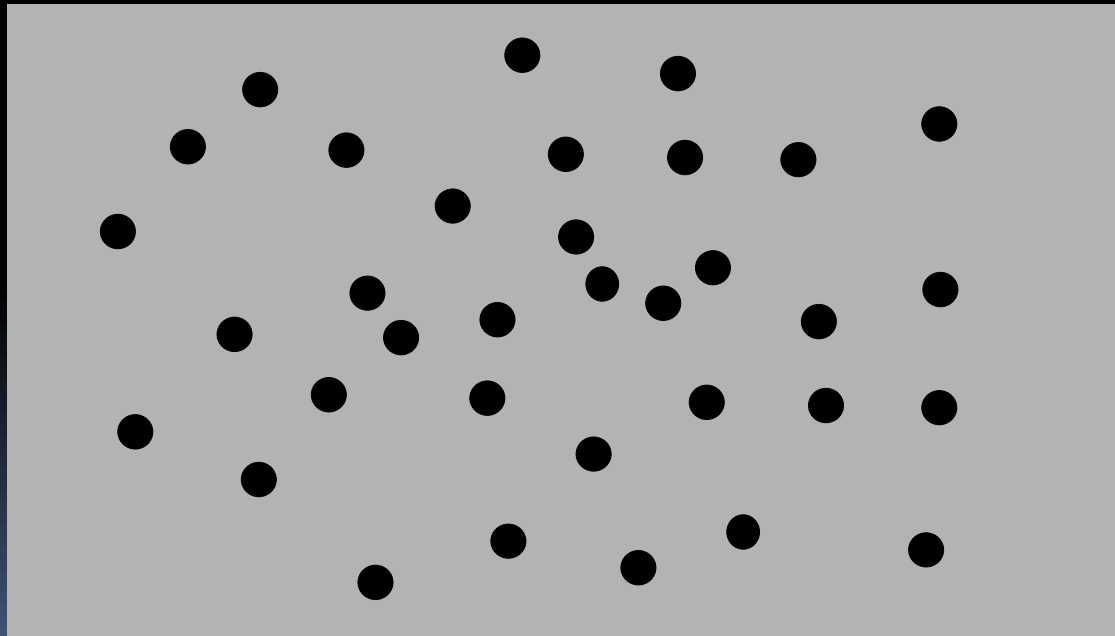


Roadmap

- Suboptimal inference can generate behavioral variability
- This cause dominates in most situations
- What this theory explains
- Implications for neuronal variability
- A normative view of Weber's law

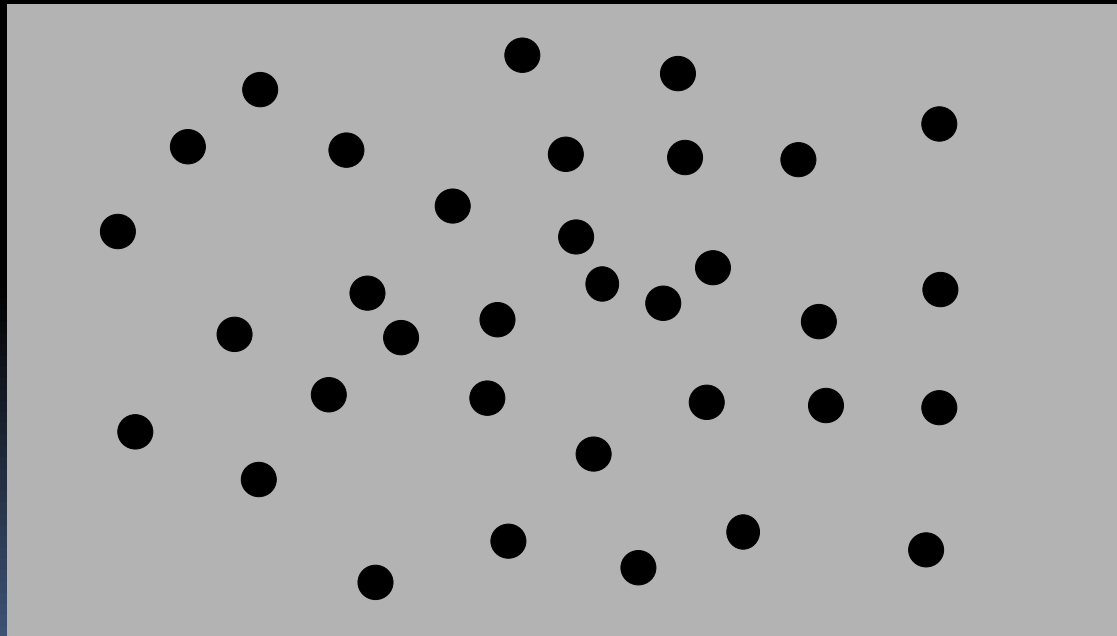
Weber's law

$$\frac{\Delta N}{N} = \text{constant}$$

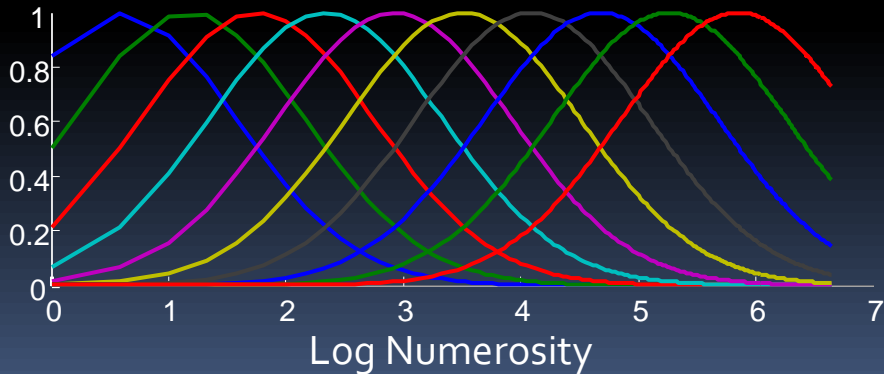
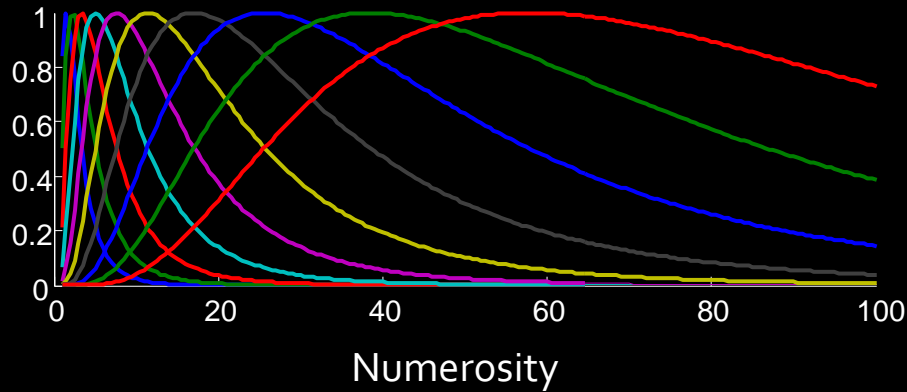


Weber's law

$$\sigma_N^2 \propto N^2$$



Weber's law

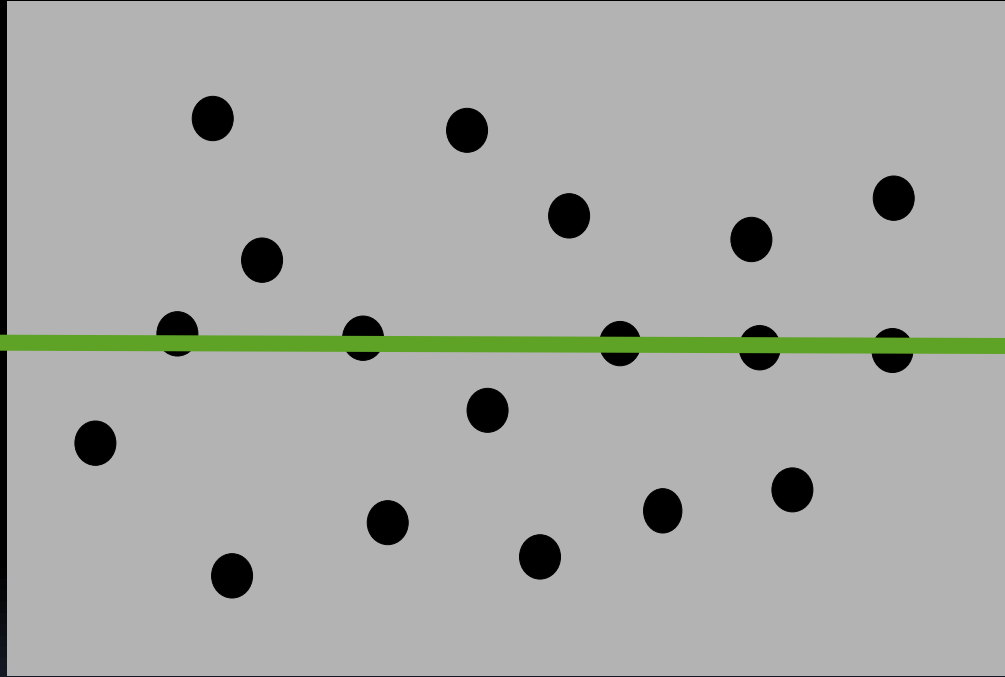


+ noise



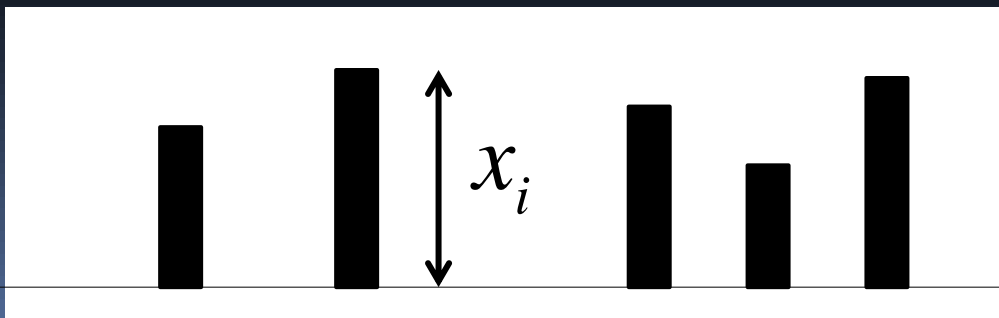
Weber's law

Weber's law

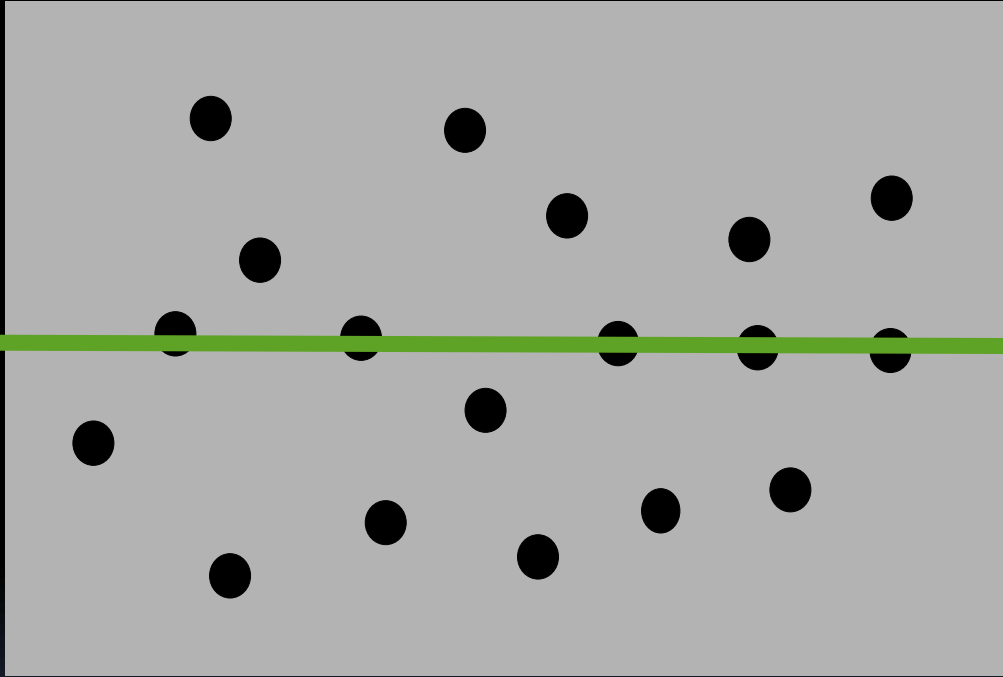


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance

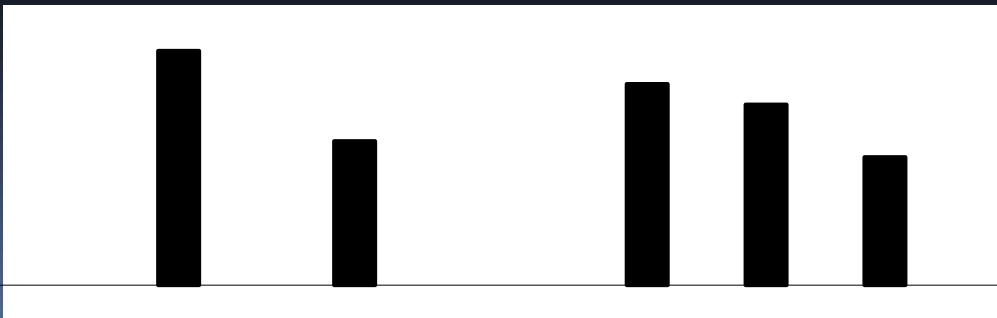


Weber's law

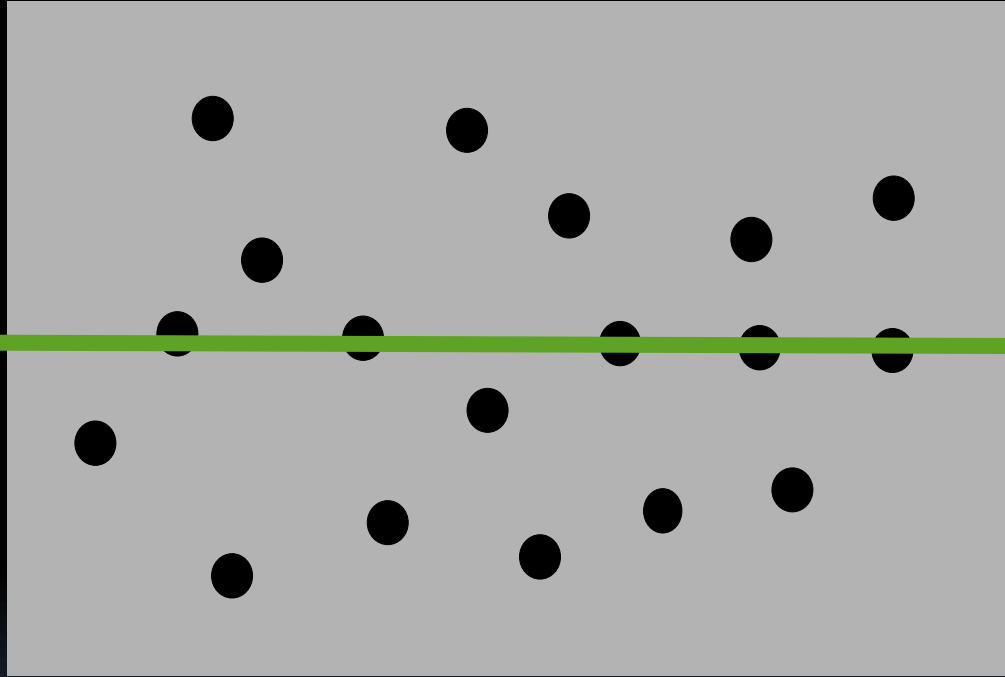


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance



Weber's law

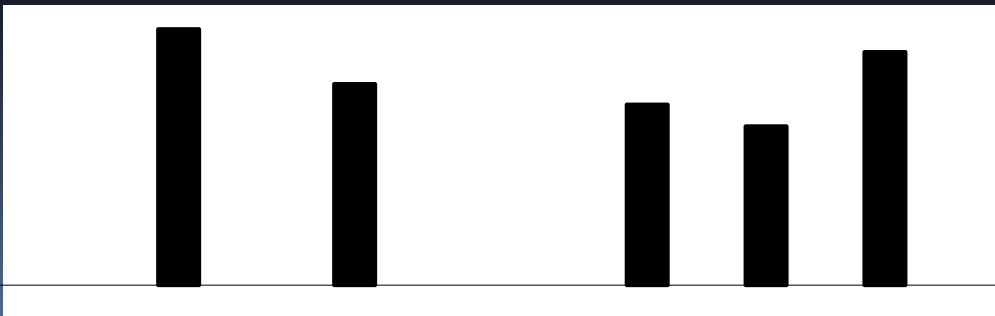


$$\hat{N} = \sum_{i=1}^N x_i$$

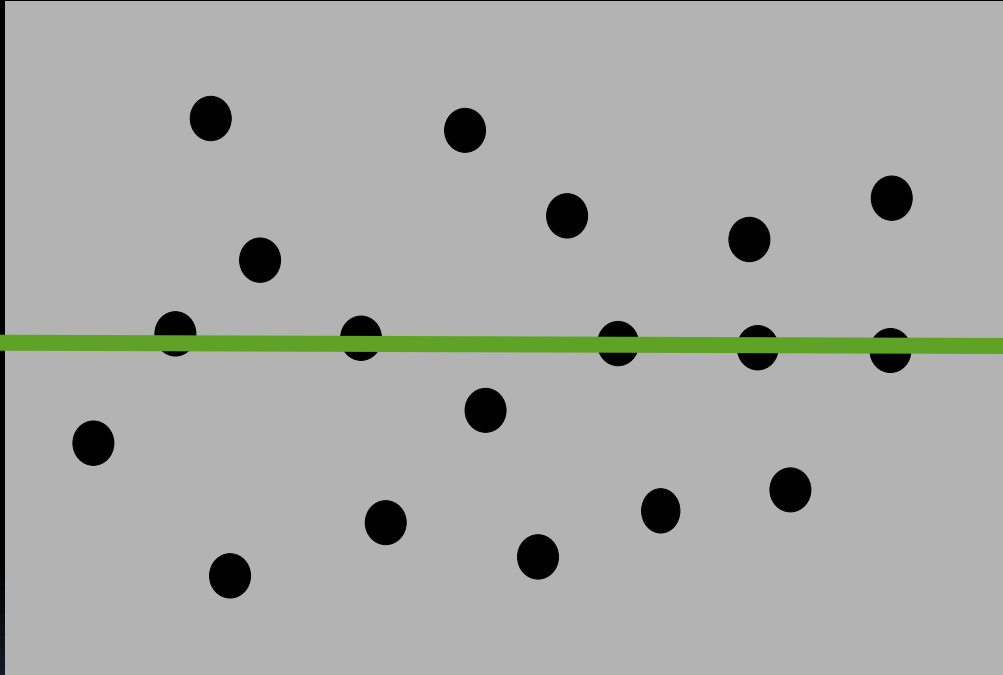
$$\langle \hat{N} \rangle \propto N$$

$$\sigma_{\hat{N}}^2 = \sum_{i=1}^N \sigma_{x_i}^2 \propto N$$

Luminance

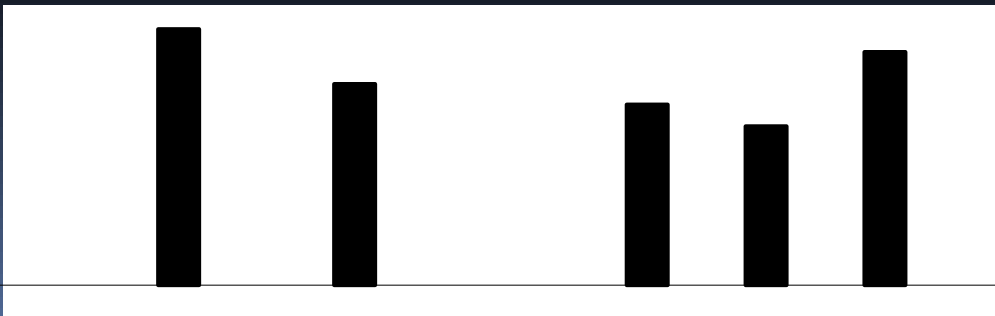


Weber's law



NOT
Weber's law!

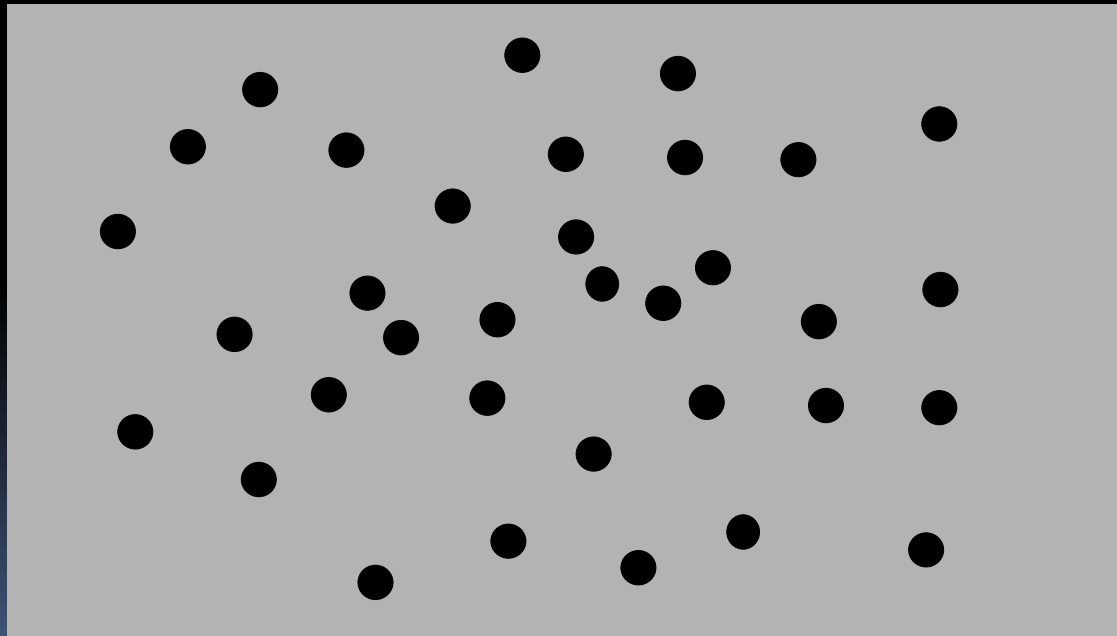
Luminance



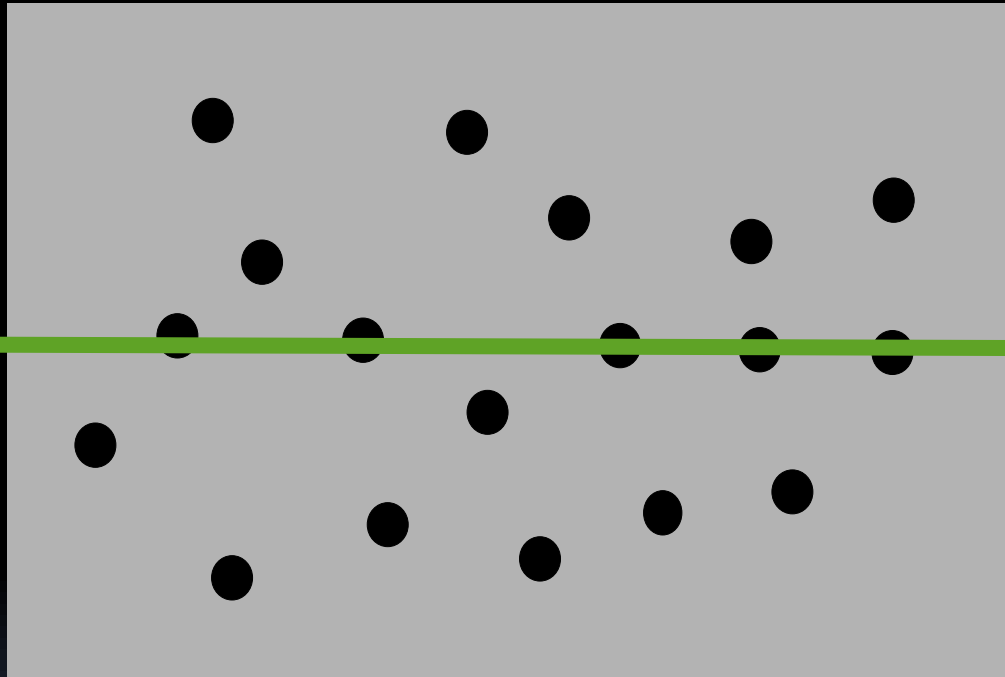
$$\sigma_{\hat{N}}^2 \propto N$$

Weber's law

$$\sigma_N^2 \propto N^2$$

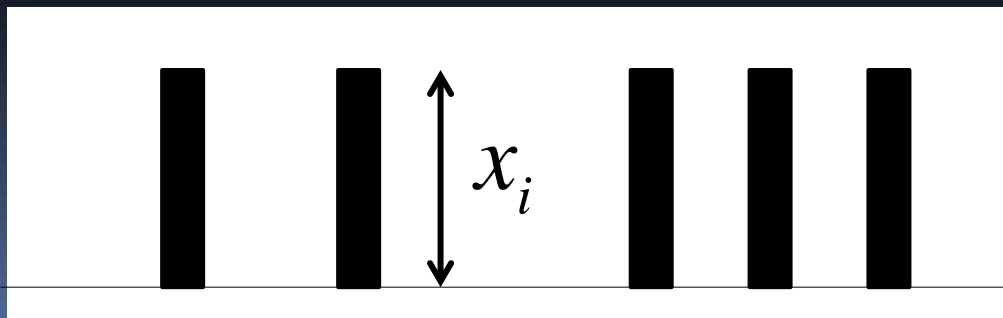


Weber's law

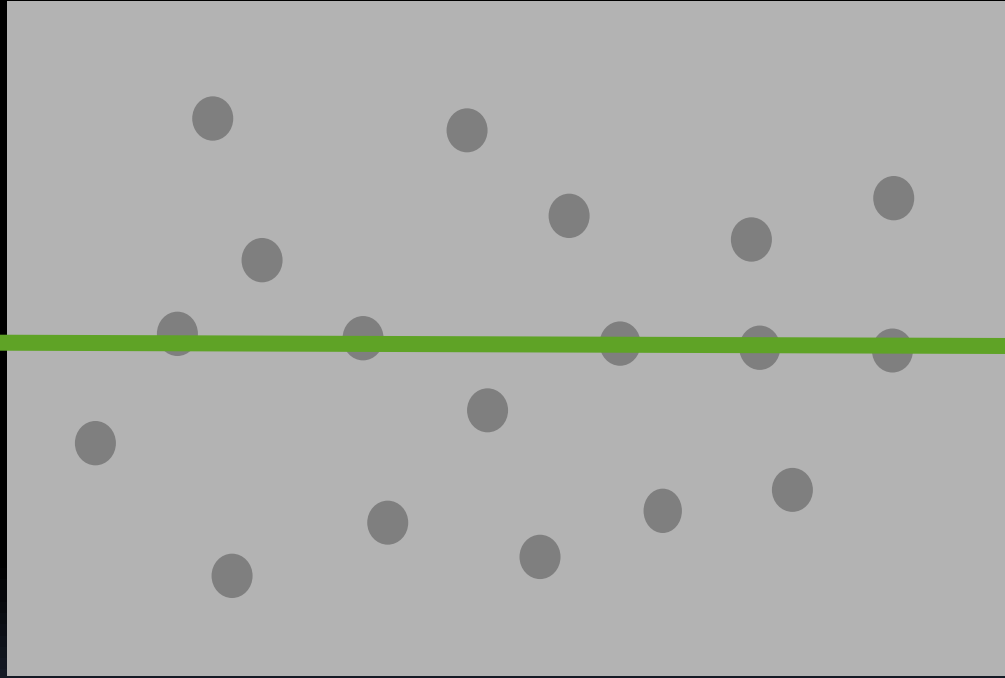


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance

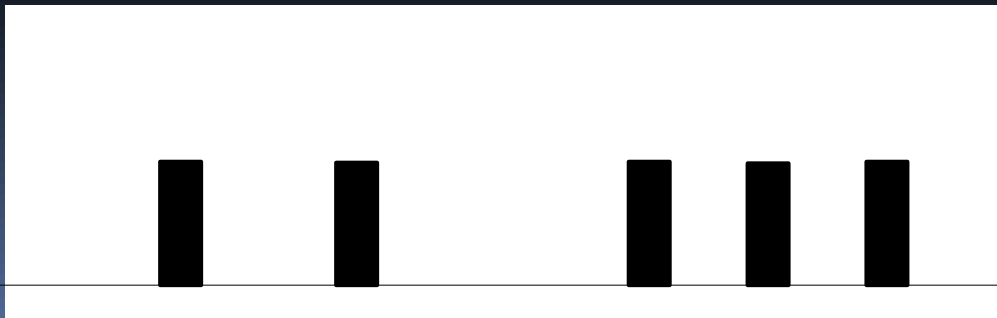


Weber's law

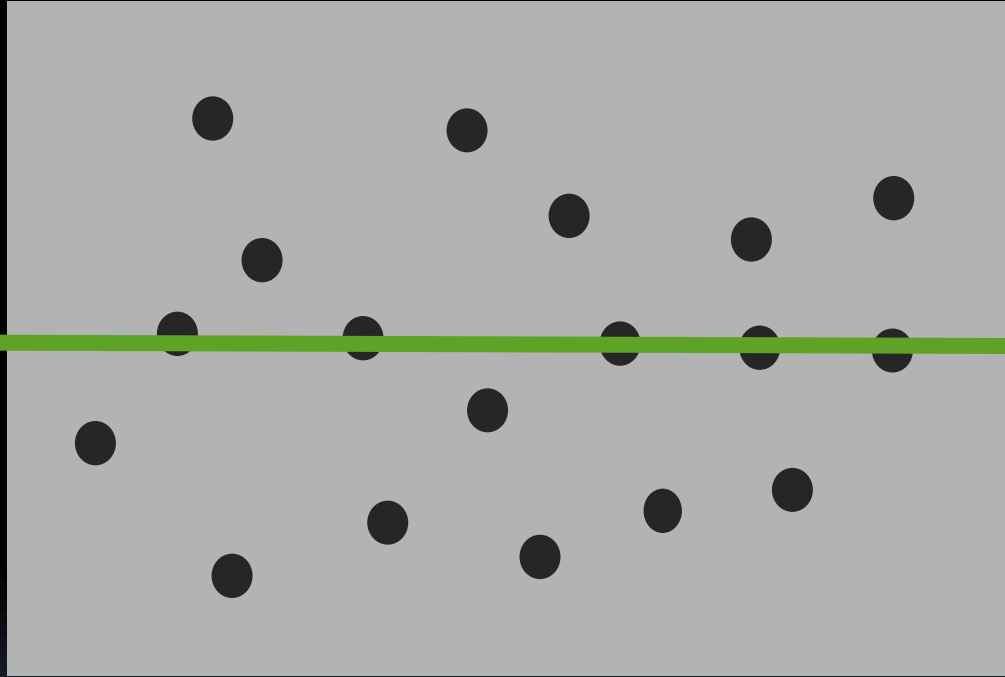


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance

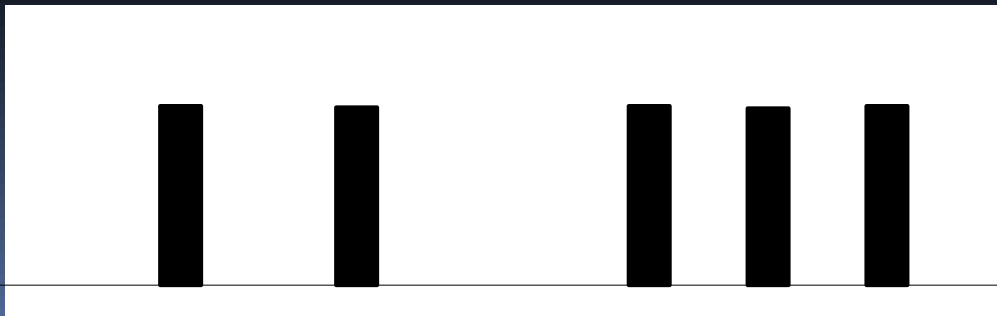


Weber's law

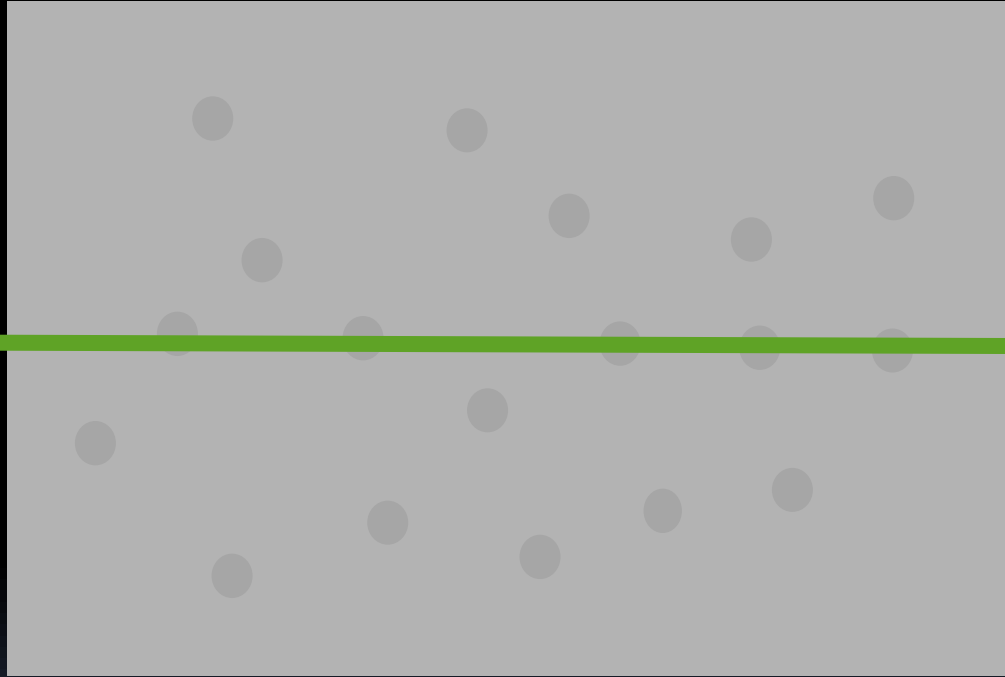


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance

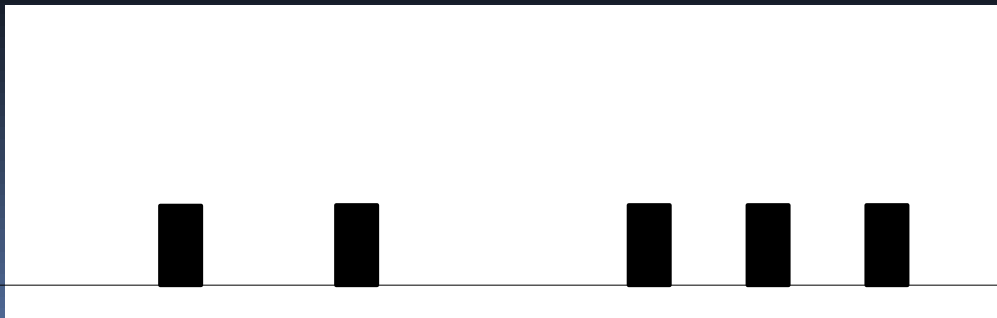


Weber's law

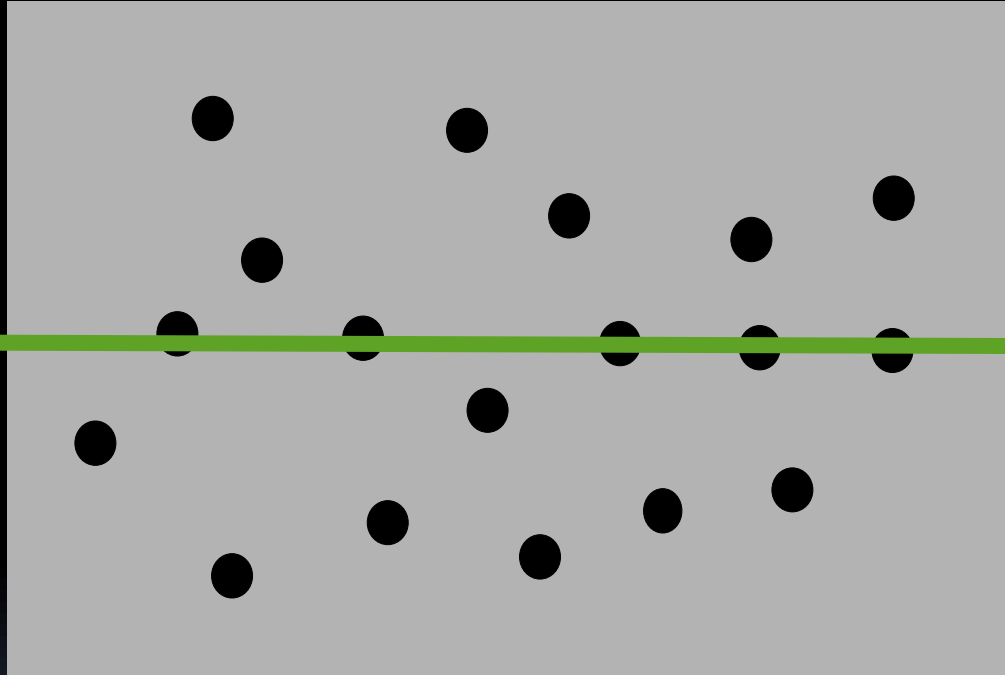


$$\hat{N} = \sum_{i=1}^N x_i$$

Luminance



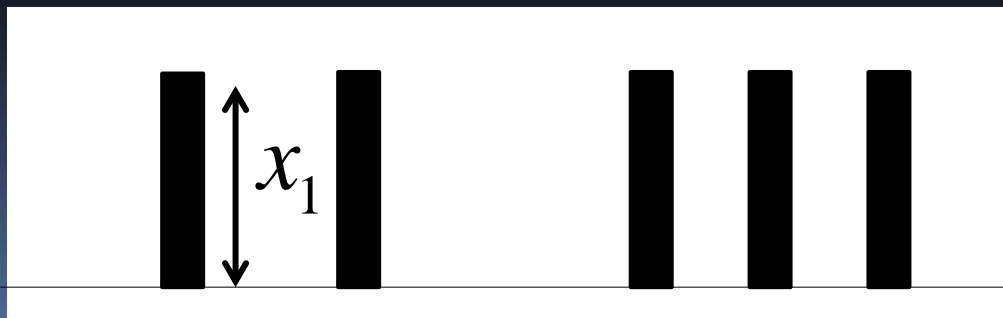
Weber's law



$$\hat{N} = \sum_{i=1}^N x_i$$

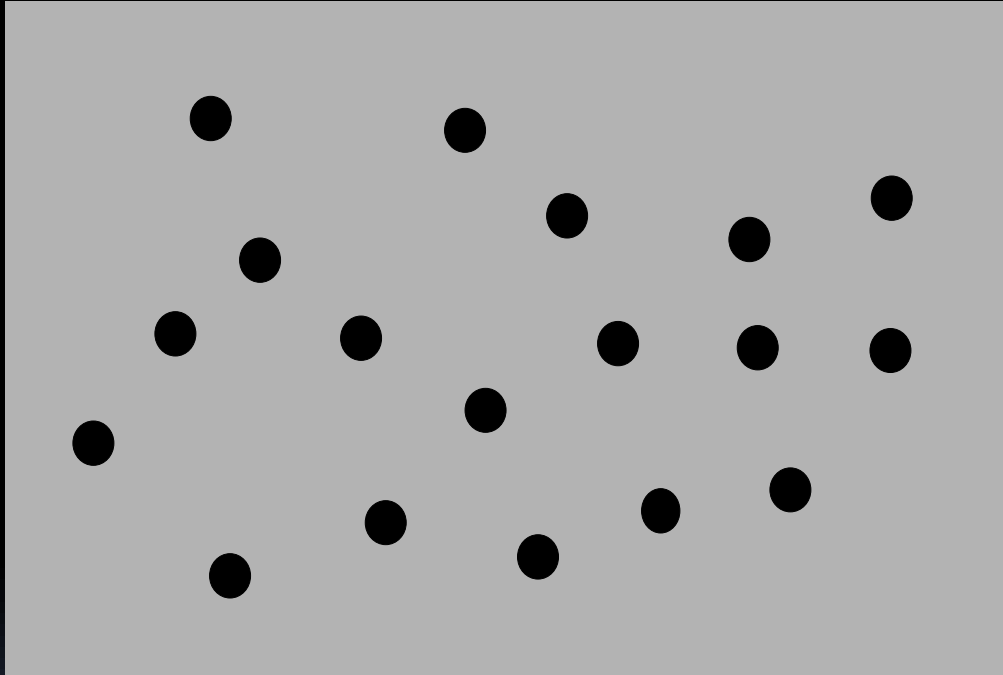
$$\hat{N} = \sum_{i=1}^N x_i \propto Nx_1$$

Luminance

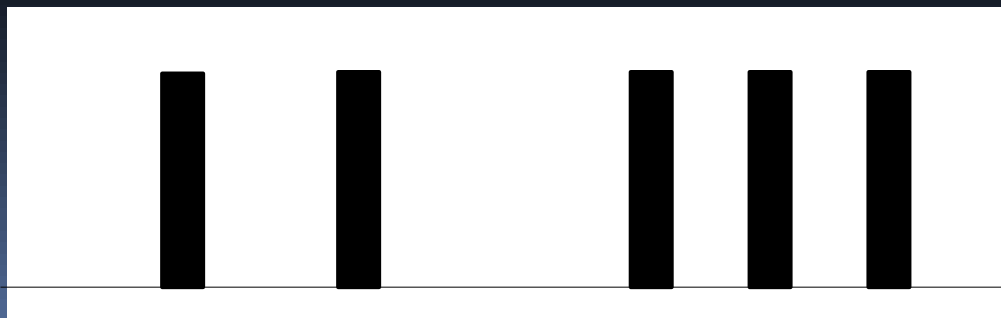


$$\sigma_{\hat{N}}^2 \propto N^2 \sigma_{x_1}^2$$

Weber's law



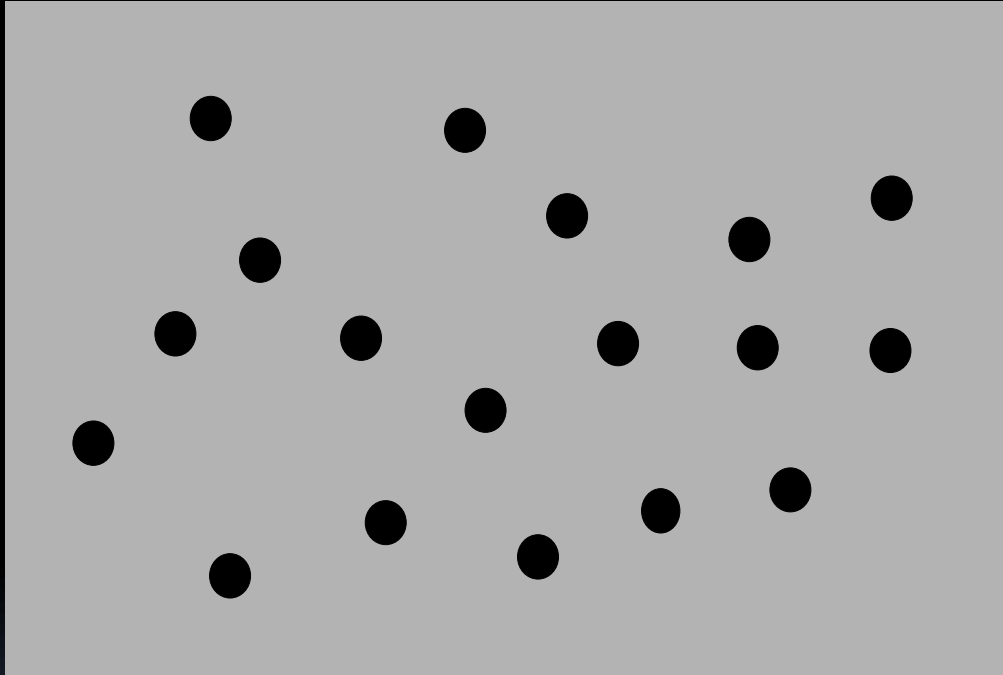
Luminance



Weber's law!

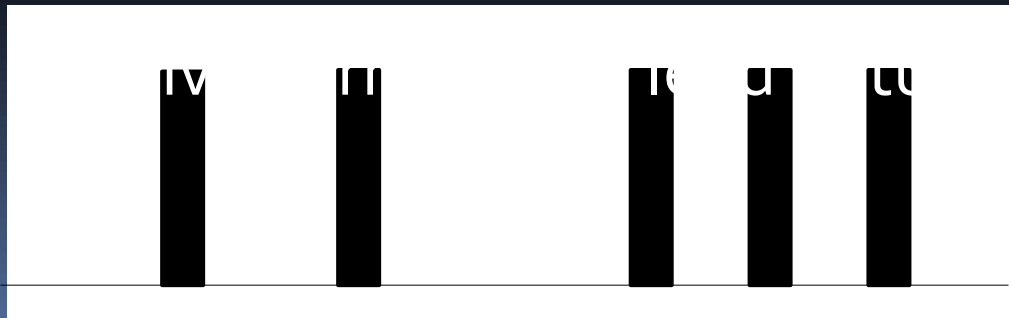
$$\sigma_{\hat{N}}^2 \propto N^2$$

Weber's law



Weber's law!

Luminance



ly to Weber's law

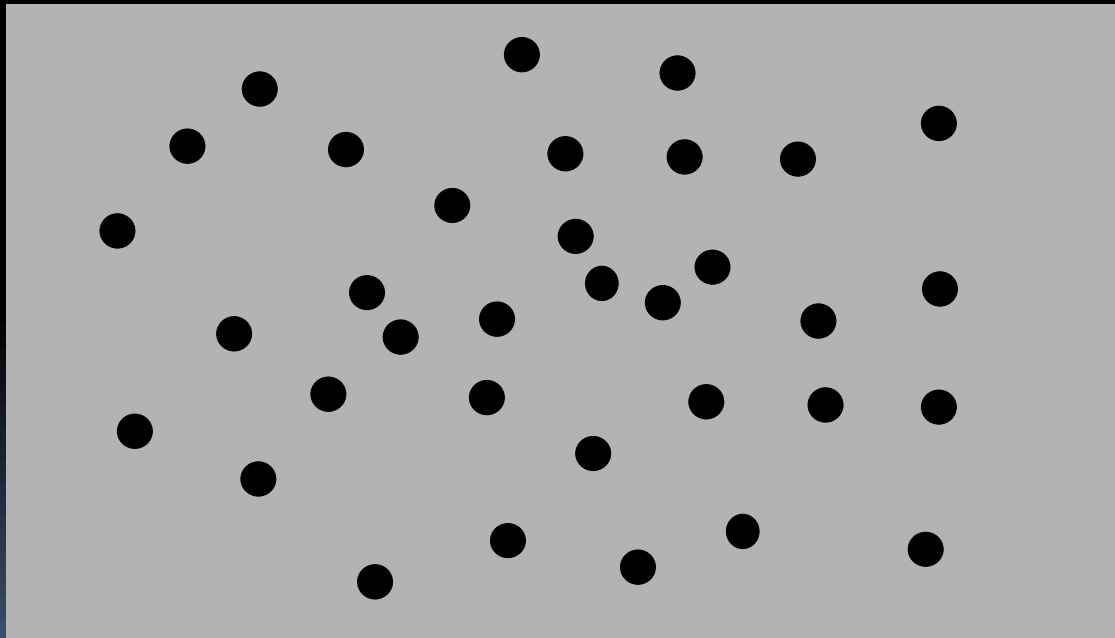
$$\sigma_{\hat{N}}^2 \propto N^2$$

Weber's law

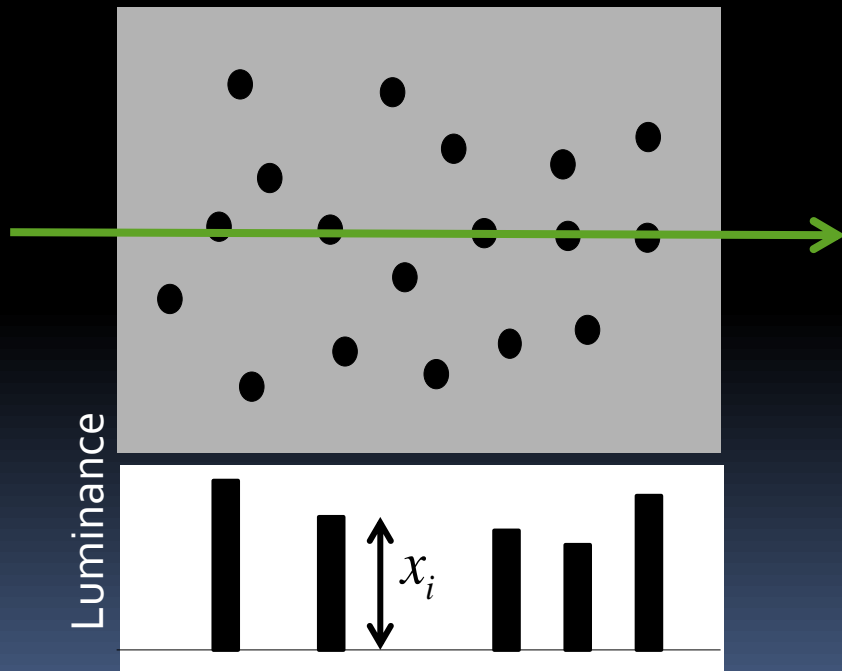
Sensory information is often scaled by global nuisance parameters such as

- Contrast
 - Loudness
 - Co-contraction of muscles
 - Attention
 - Learning
- ...etc

Don't we get Weber's law even when the contrast is maintained constant across images?



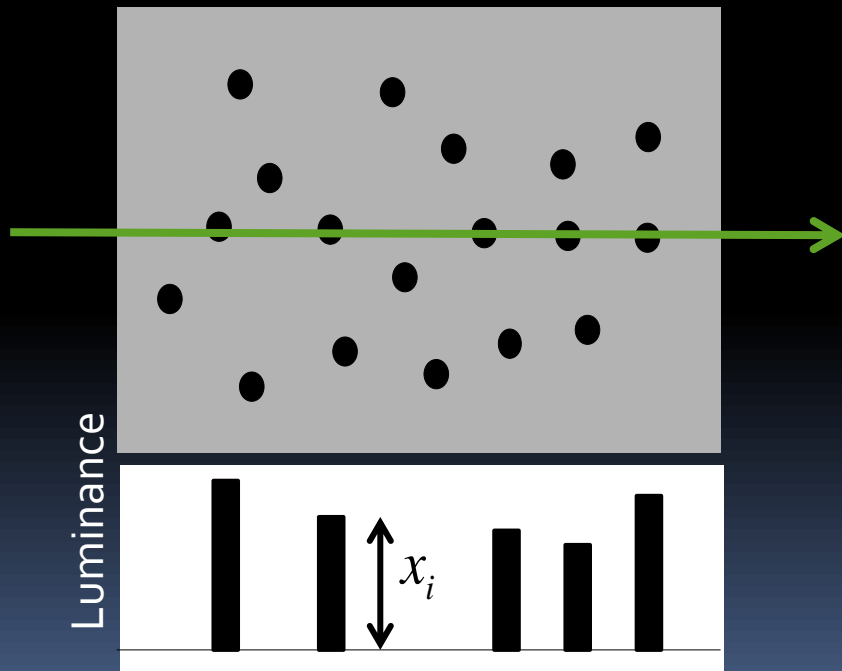
When contrast varies, the estimate of numerosity should use normalized luminance



$$\hat{N} = \sum_{i=1}^N \boxed{g} x_i$$

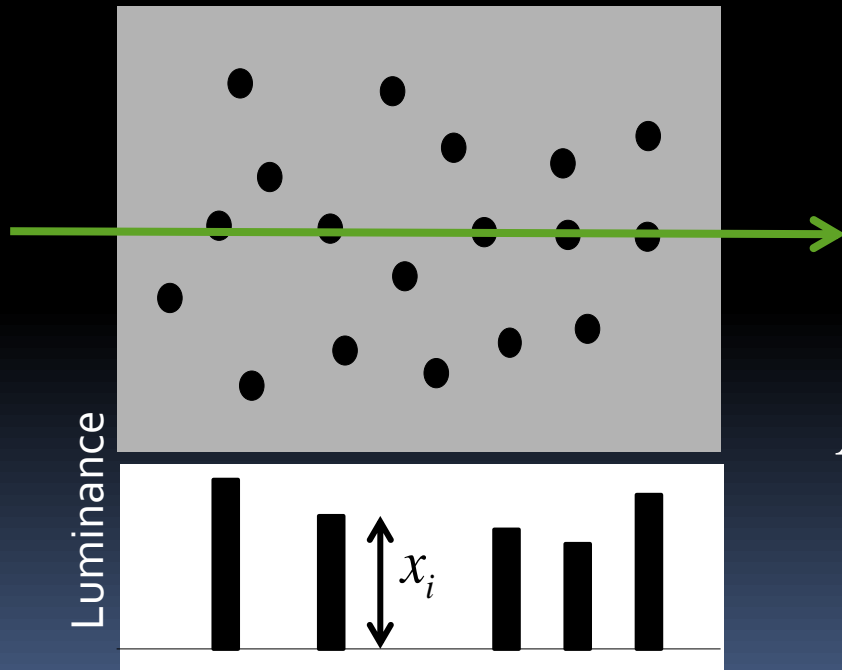
Contrast

When contrast varies, the estimate of numerosity should use normalized luminance



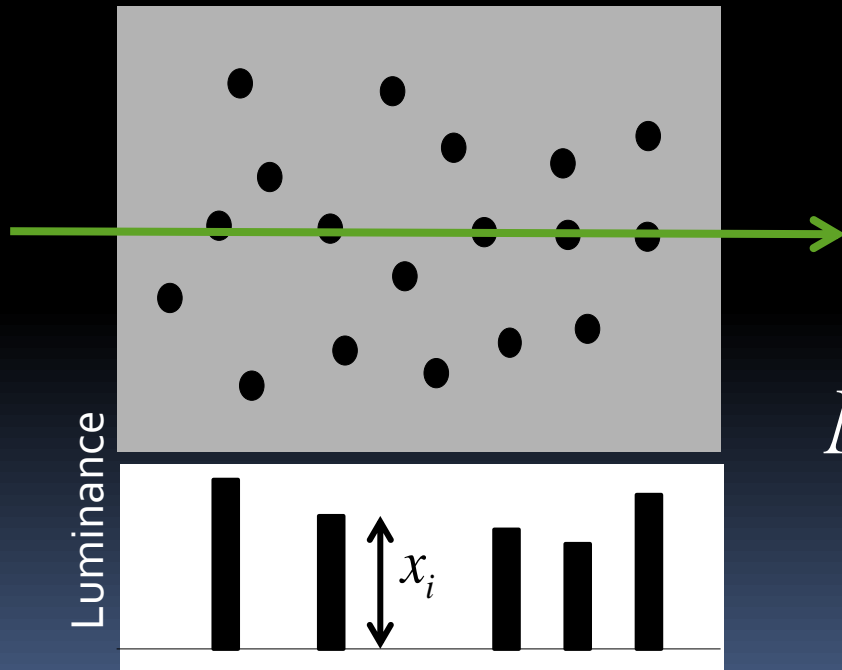
$$\langle \hat{N} \rangle \propto \boxed{g} N \quad \text{Contrast}$$

When contrast varies, the estimate of numerosity should use normalized luminance



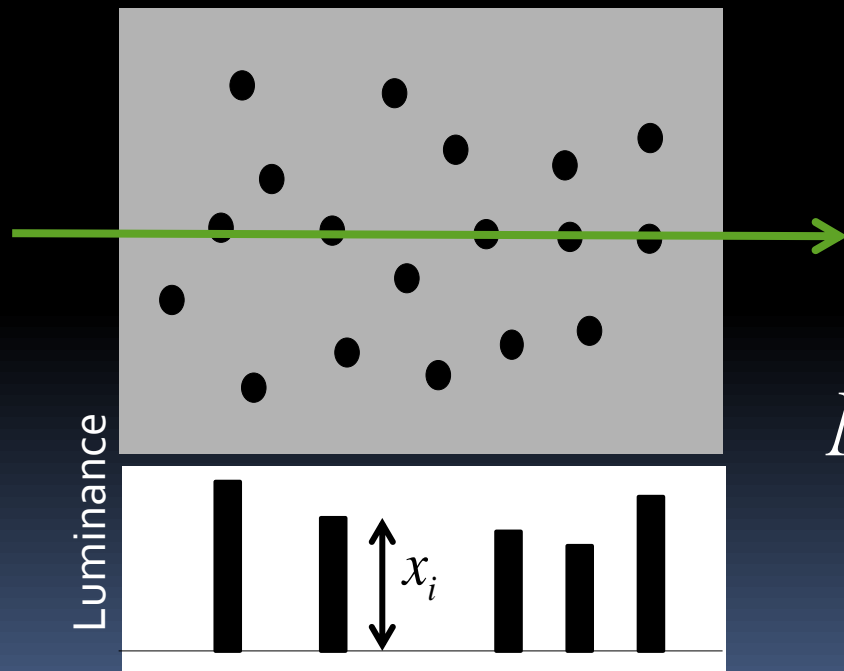
$$\hat{N} = g \sum_{i=1}^N x_i$$

When contrast varies, the estimate of numerosity should use normalized luminance



$$\hat{N} = \frac{\mathcal{G}}{\mathcal{g}} \sum_{i=1}^N x_i$$

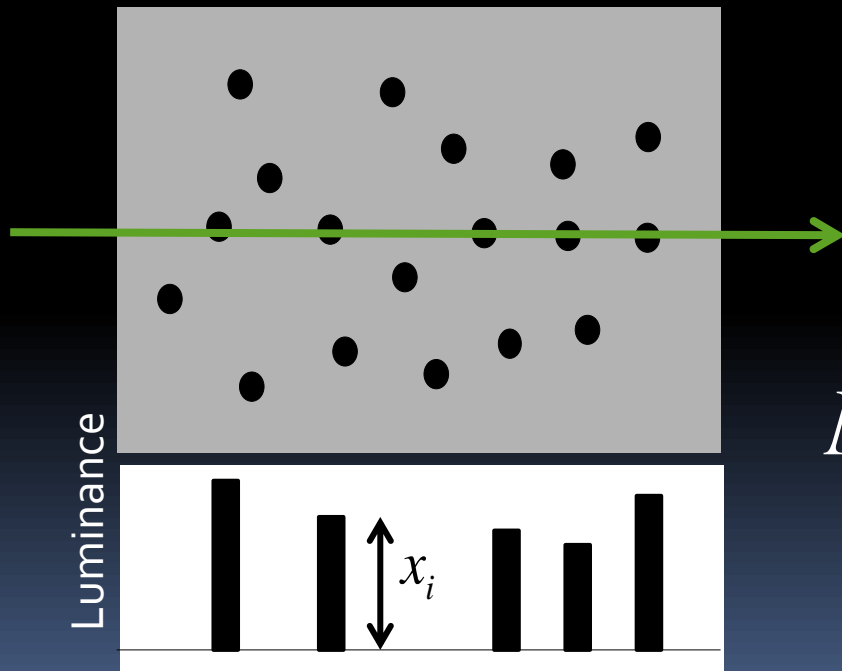
But subjects do not know contrast and must therefore use an estimate of contrast



$$\hat{N} = \frac{\langle \sigma \rangle}{\sigma} \sum_{i=1}^N x_i$$

Estimated
Contrast

But subjects do not know contrast, and must therefore use an estimate of contrast



$$\hat{N} = \frac{\sigma}{\hat{\sigma}} \sum_{i=1}^N x_i$$

Induces
positive
correlations

- Even when contrast is constant, the estimate of contrast is likely to vary, and could greatly vary due to approximations.

Weber's law

Global scaling nuisance parameters induce correlations that naturally leads to Weber's law.

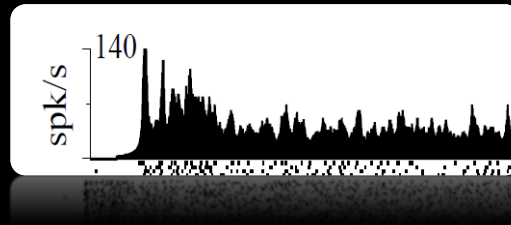
No need to invoke single cell Poisson variability plus log normal tuning curves

In fact, log normal tuning curves might be the consequence of Weber's law, not the cause (Dehaene et al, cosyne 2014).

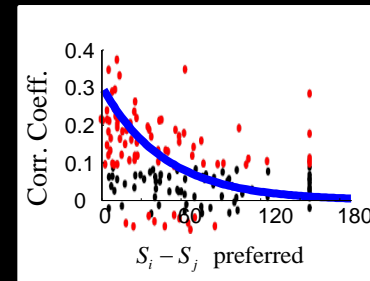
Conclusions

Where does behavioral variability come from?

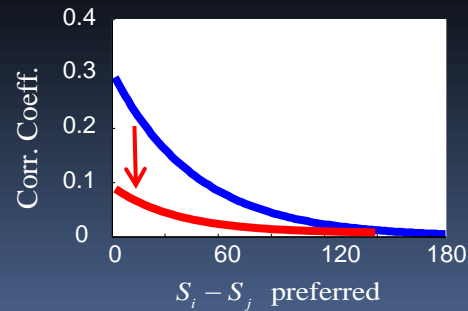
Poisson variability



Correlations



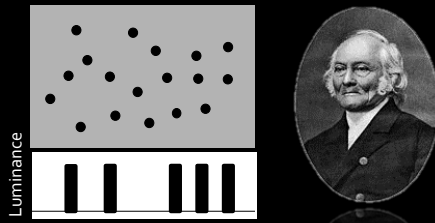
Decorrelation



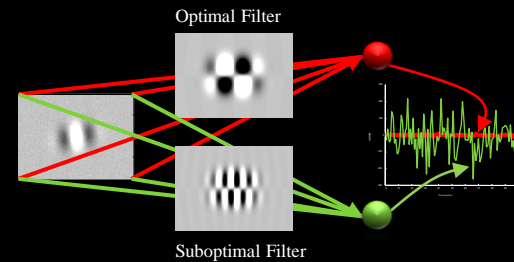
Conclusions

Where does behavioral variability come from?

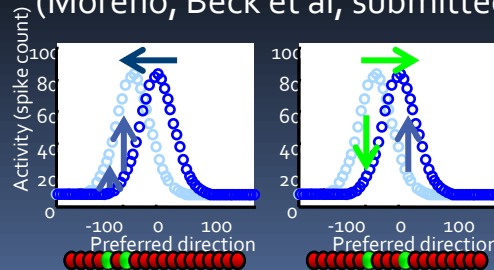
Variable sensory data
(Beck et al, in prep)



Suboptimal inference
(Beck et al, 2012)



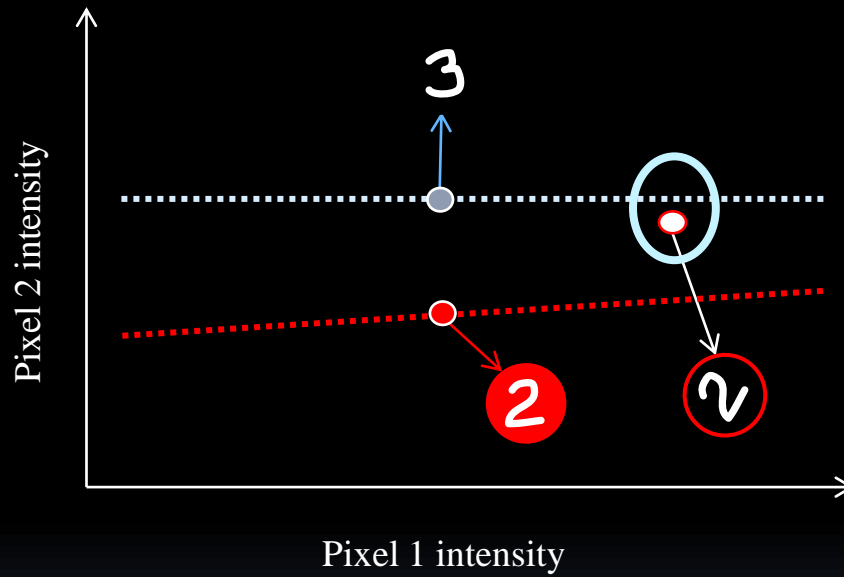
Differential correlations
(Moreno, Beck et al, submitted)



Positive roles of noise

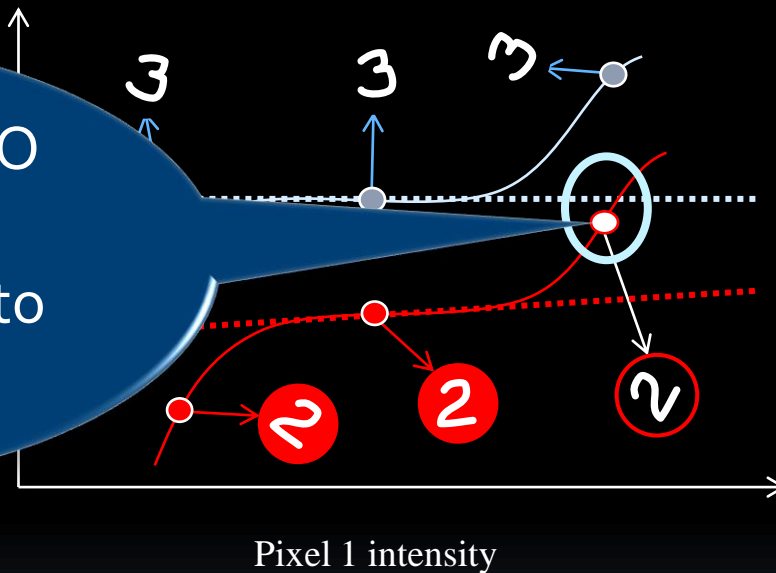
- Sampling
- Exploration
- Game theory

Object recognition

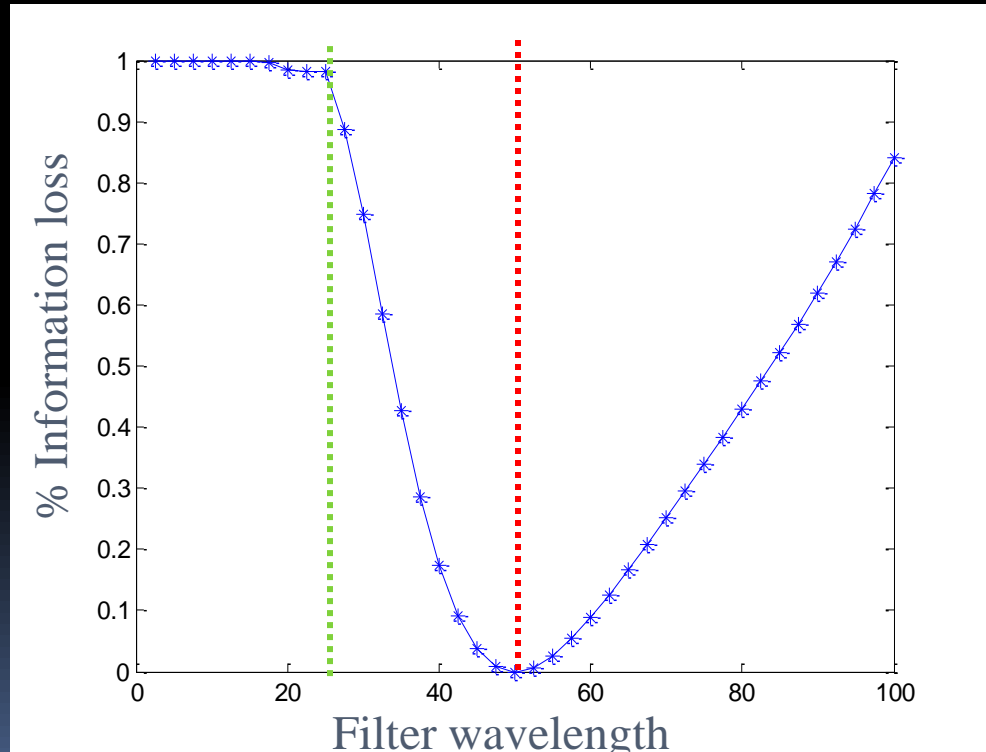
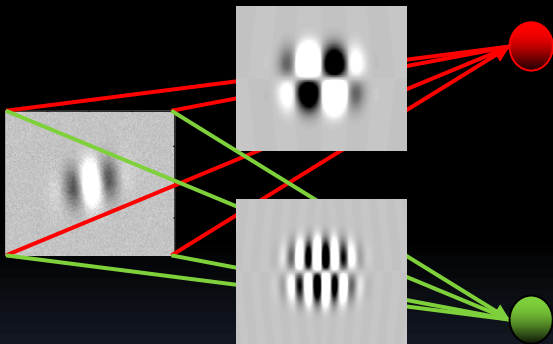


Object recognition

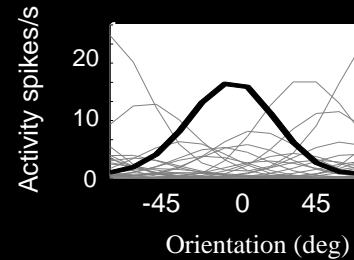
Note that there is NO sensory noise. The error is due entirely to the approximation



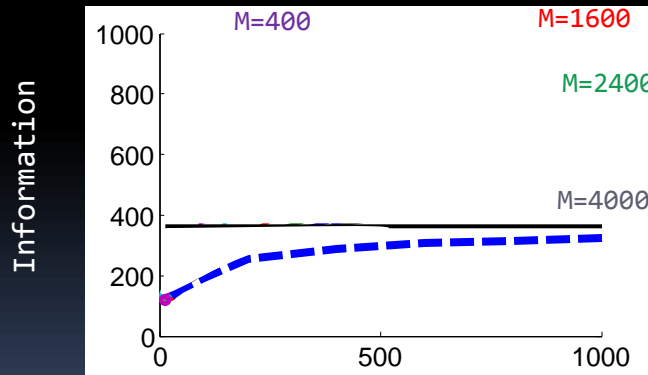
Orientation discrimination



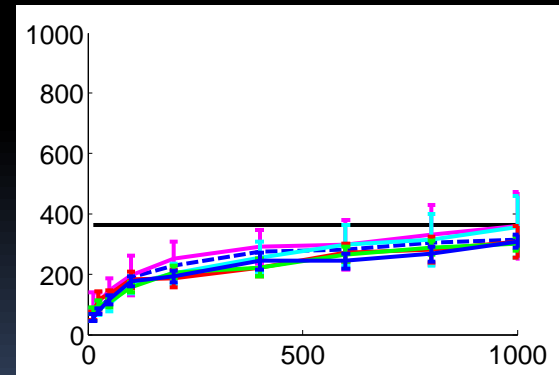
Experimental consequences



Explicit Computation



Information from decoding



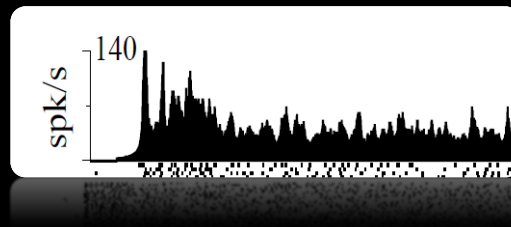
Number of Neurons

$$\hat{\mathbf{f}}' \cdot \left(\hat{\Sigma}_{\varepsilon} \right)^{-1} \hat{\mathbf{f}}'$$

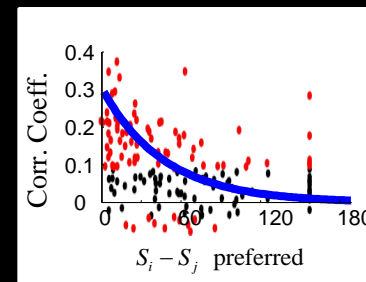
Conclusions

Where does behavioral variability come from?

Poisson variability



Correlations



Decorrelation

