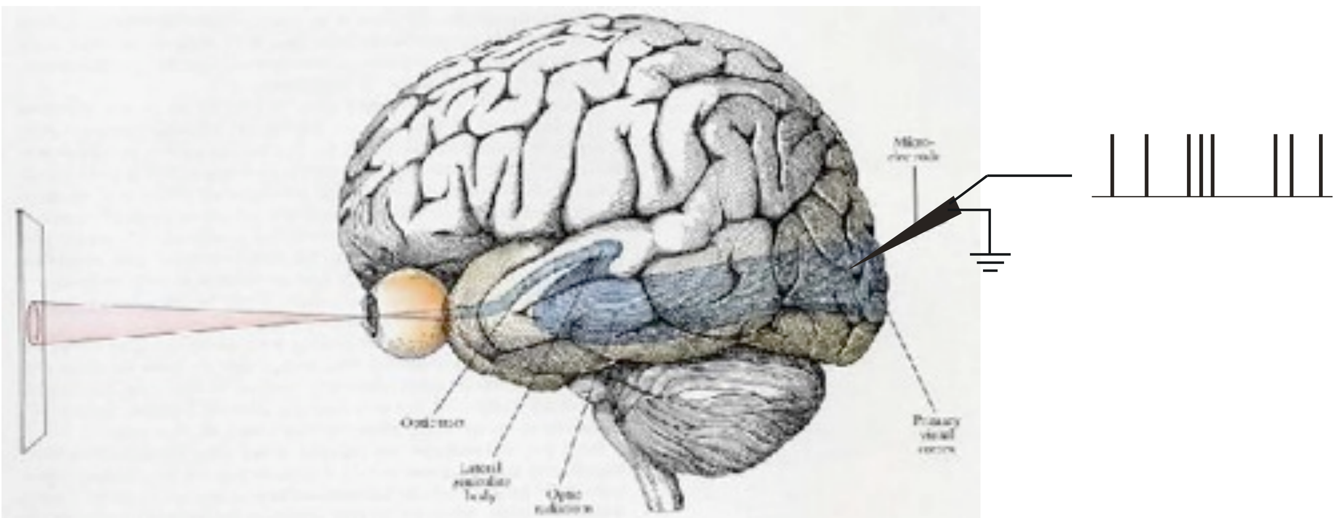
Sensory decoding models

Eero P. Simoncelli
CNS / Courant

Computational Modeling of Neuronal Systems
Spring, 2010

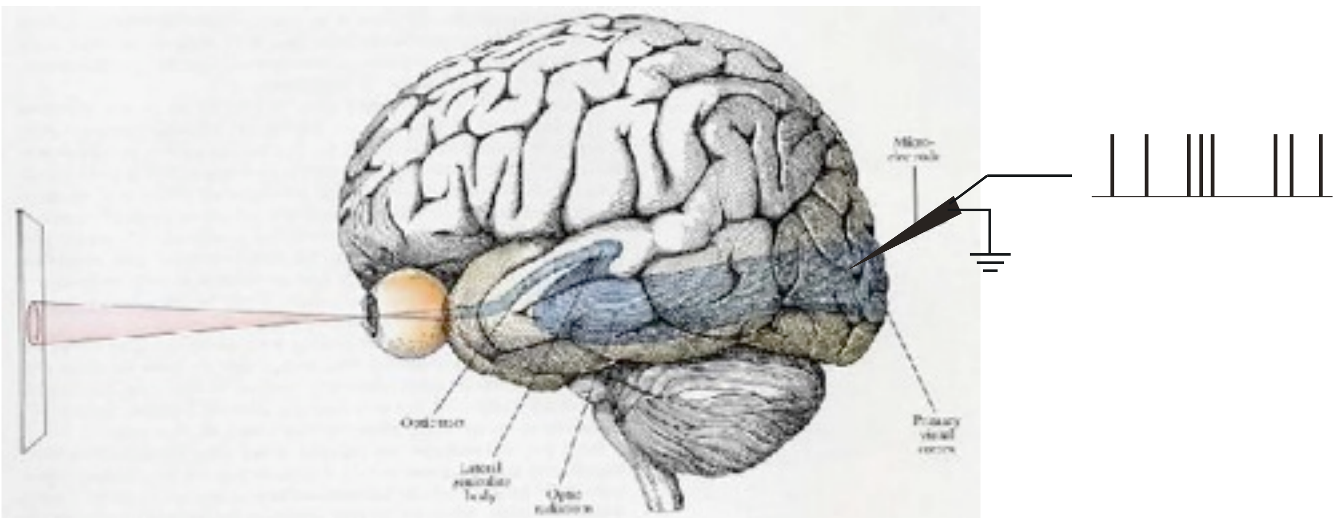
Stimulus   Neural response

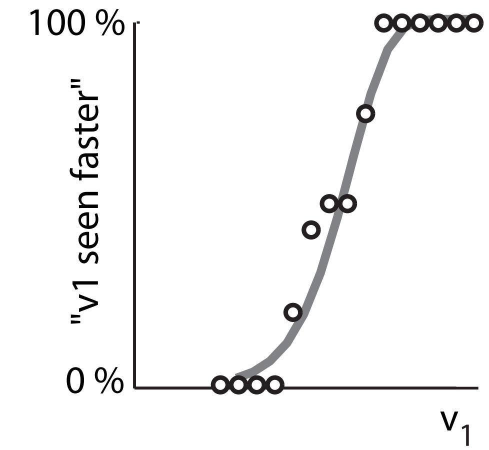


"Encoding"

Transform and represent sensory information

Stimulus | Neural response | Behavior





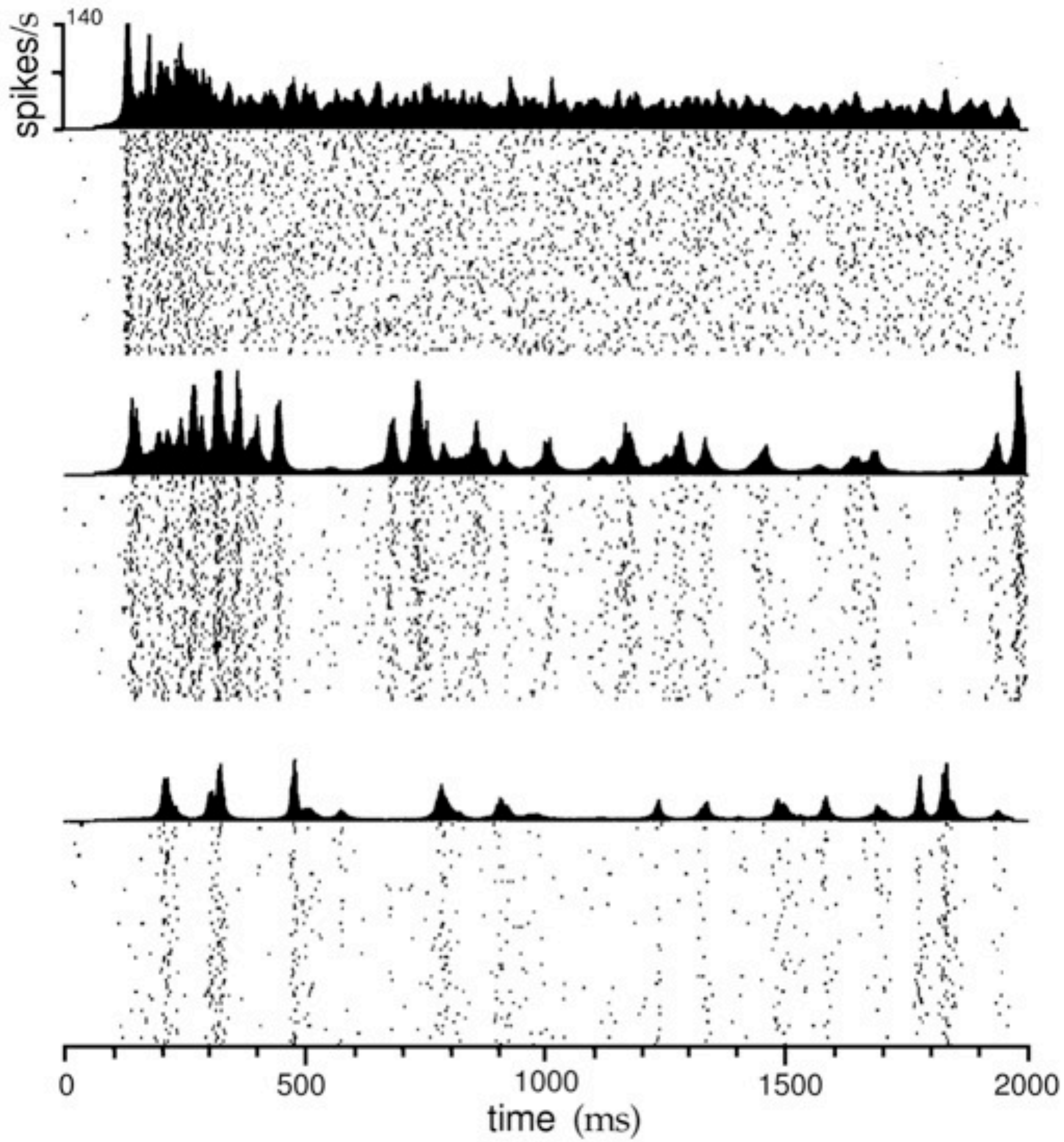
psychometric function

“Encoding”
Transform and represent sensory information

“Decoding”
Extract encoded information for estimation/decision/action

the scientist's perspective

P(spikes | stim)

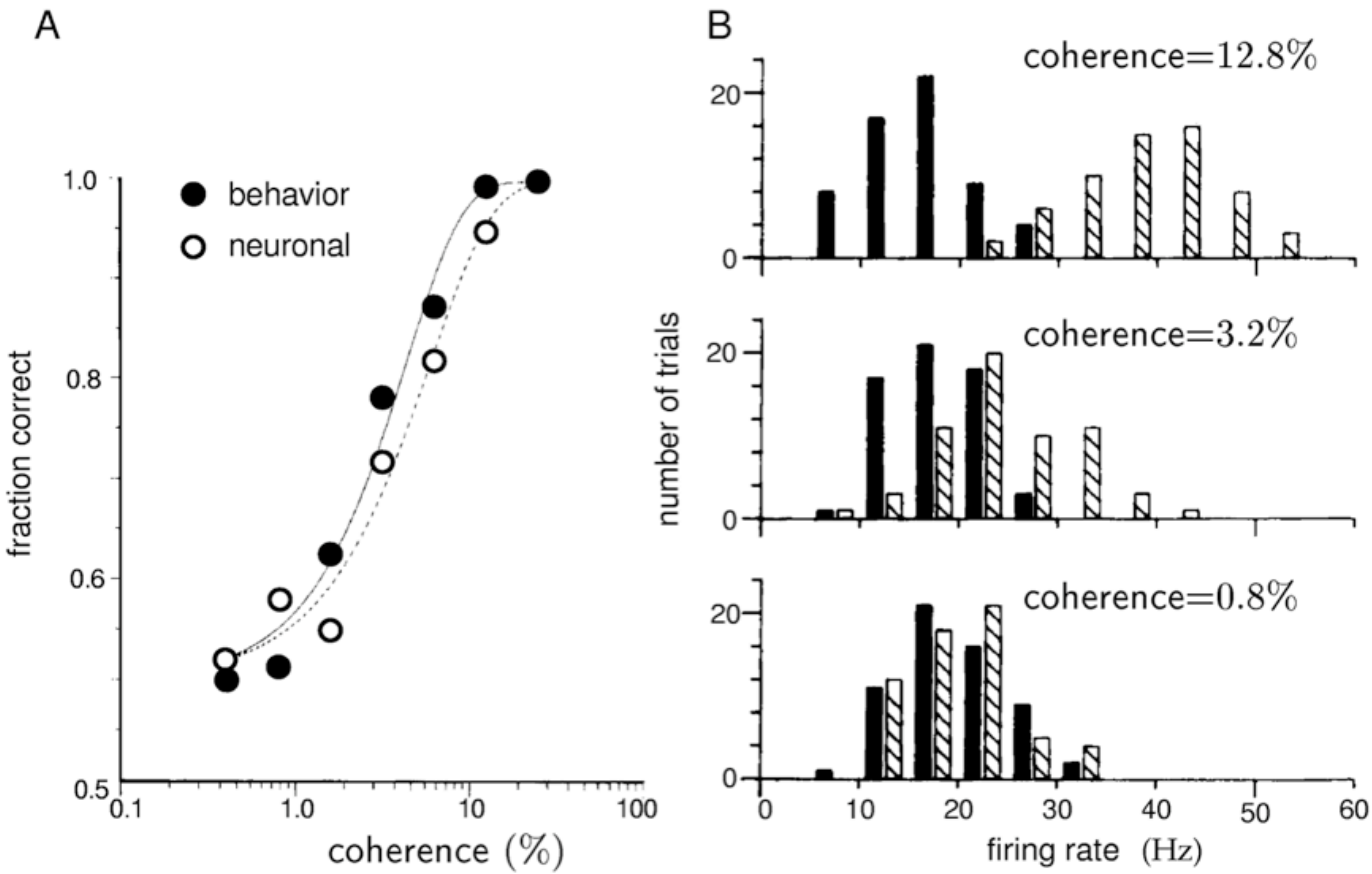


the organism's perspective

P(stim | spikes)

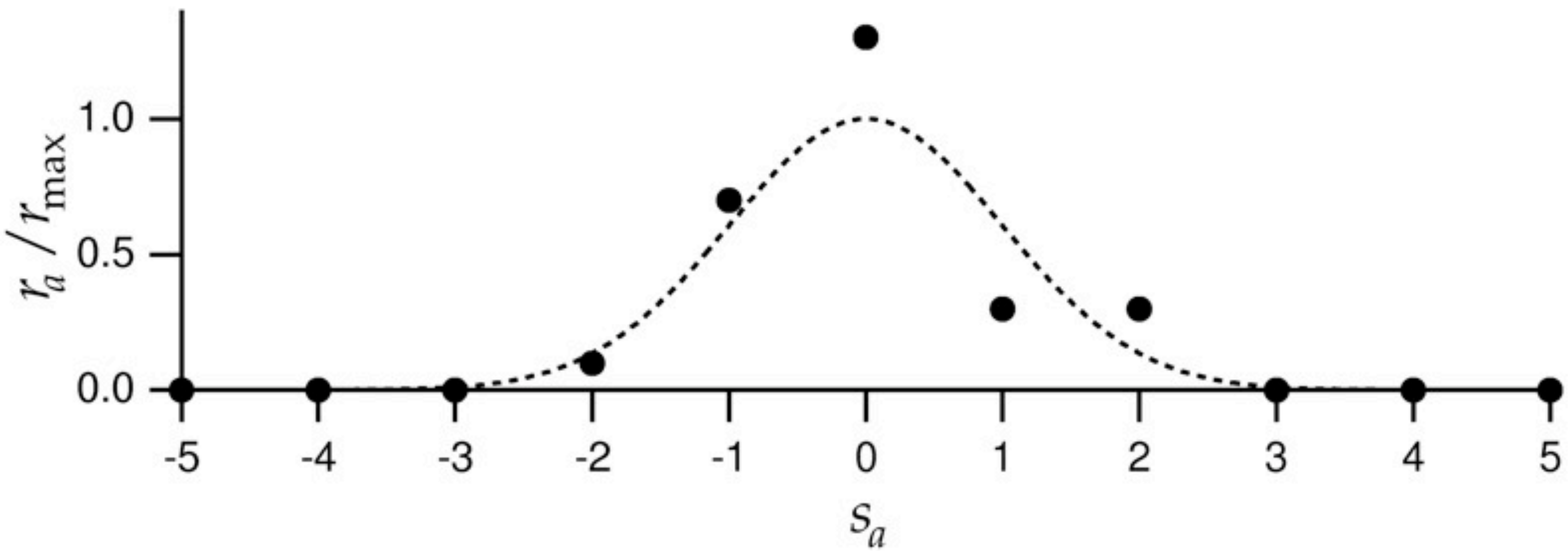
The organism receives sensory responses, and must make judgements about the stimulus, remember it, or act on it.

- basic SDT
- likelihood from populations



(next week: Movshon lecture)

ML decoding



For neurons with homogeneous tuning curves f_k(x) and independent Poisson spiking, ML gives:

$$\frac{\partial}{\partial x} \log p(N_k|x) = \sum_k N_k \frac{\partial}{\partial x} \log f_k(x) = 0$$

In the special case of Gaussian tuning curves, ML estimate is simply a sum of the peak locations of each tuning curve, weighted by the number of spikes

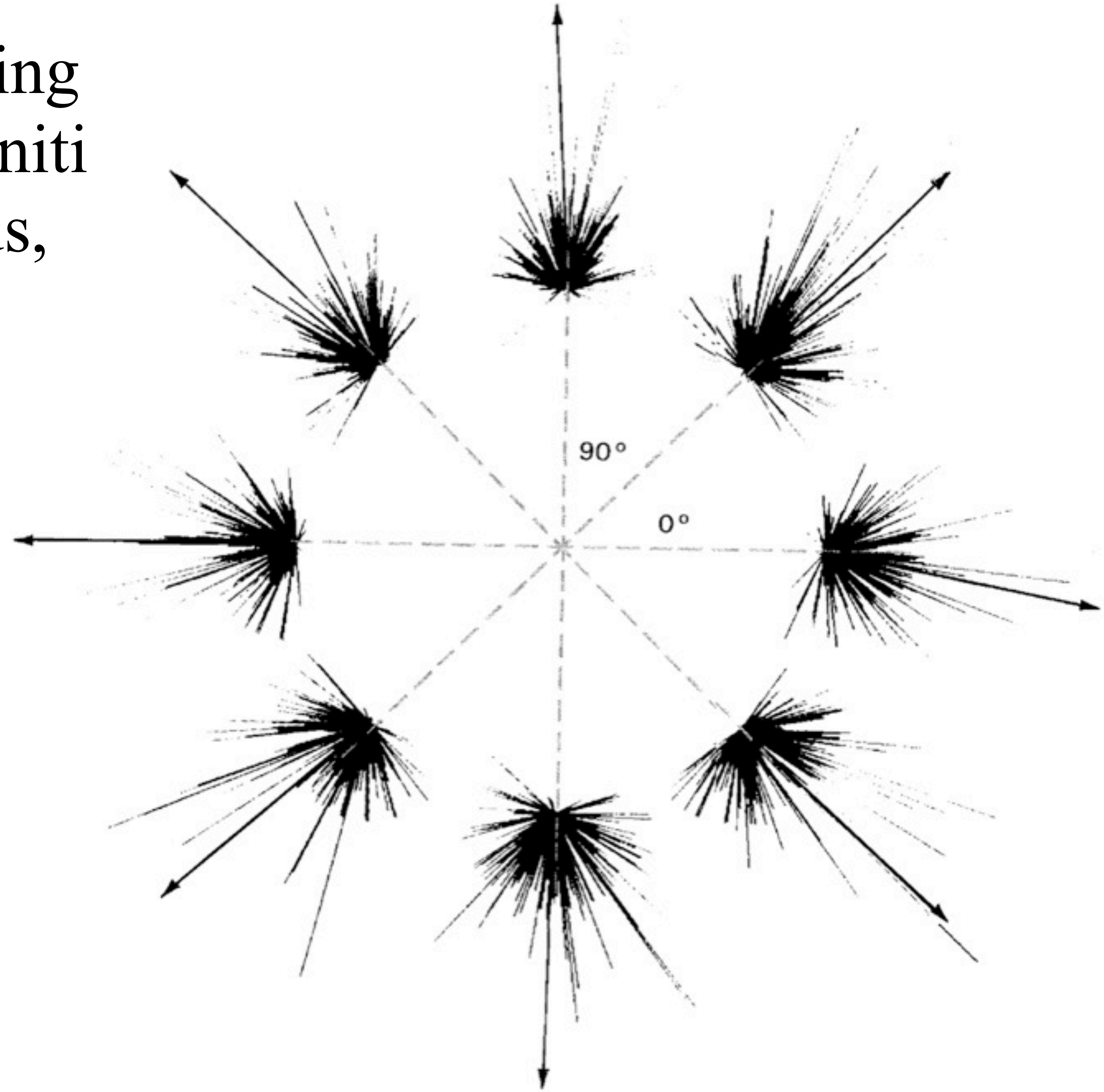
$$\hat{x} = \frac{\sum_k N_k x_k}{\sum N_k}$$

In the special case of von Mises tuning curves (exponential of cosine), ML estimate is angle of a vector computed as the weighted sum of unit vectors in the peak direction of each tuning curve, weighted by the number of spikes

$$\hat{\theta} = \angle \sum_k N_k u_k$$

“vector” decoding [Kalaska, Caminiti Georgopoulous, 1983]

A sum of vectors, weighted by firing rate, predicts arm movement...



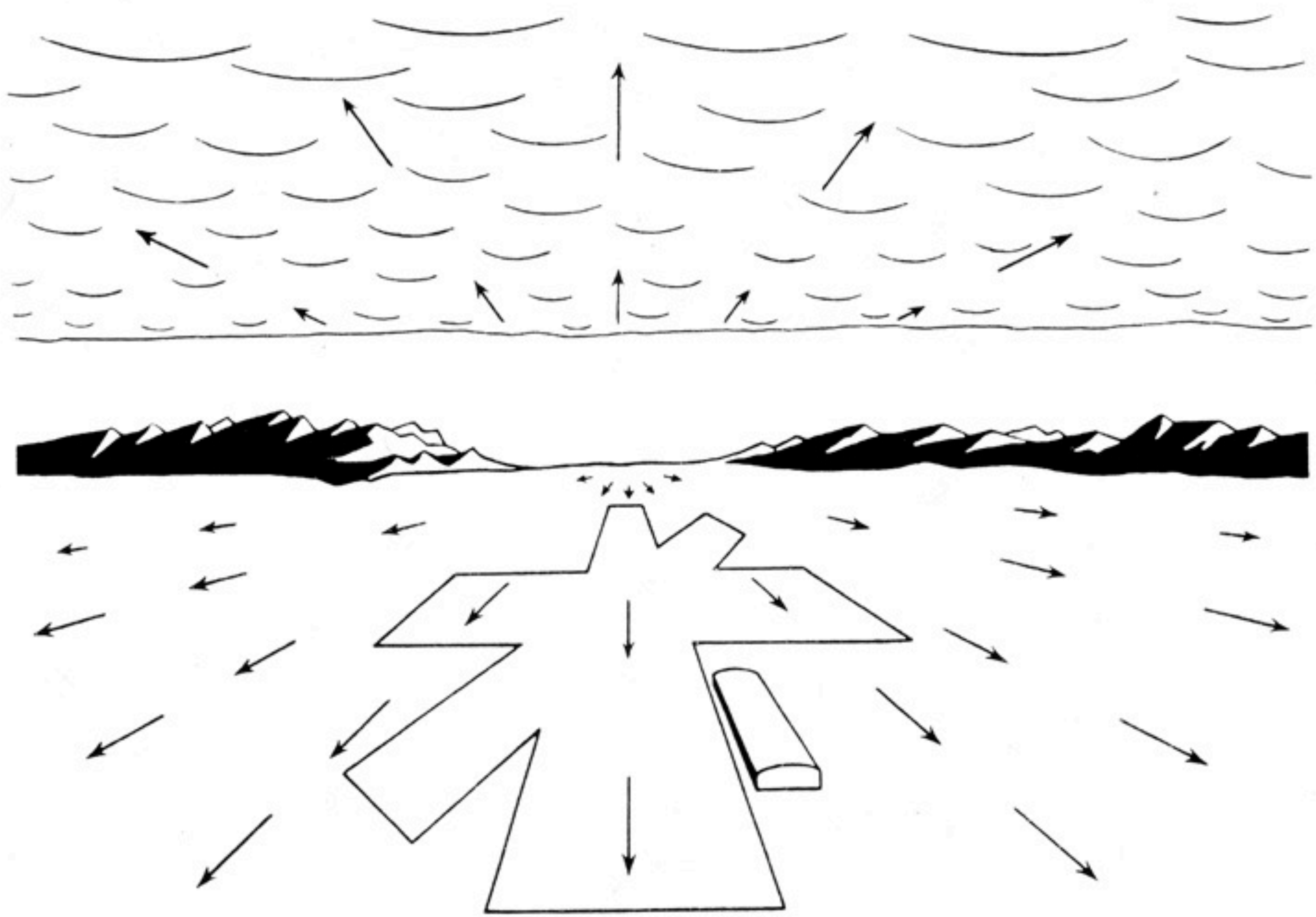
Visual motion

- Physiology: "motion pathway" heavily studied; arguably the strongest extrastriate success story

- Perception: Human motion perception heavily studied. Humans are adept at tasks which require motion processing.

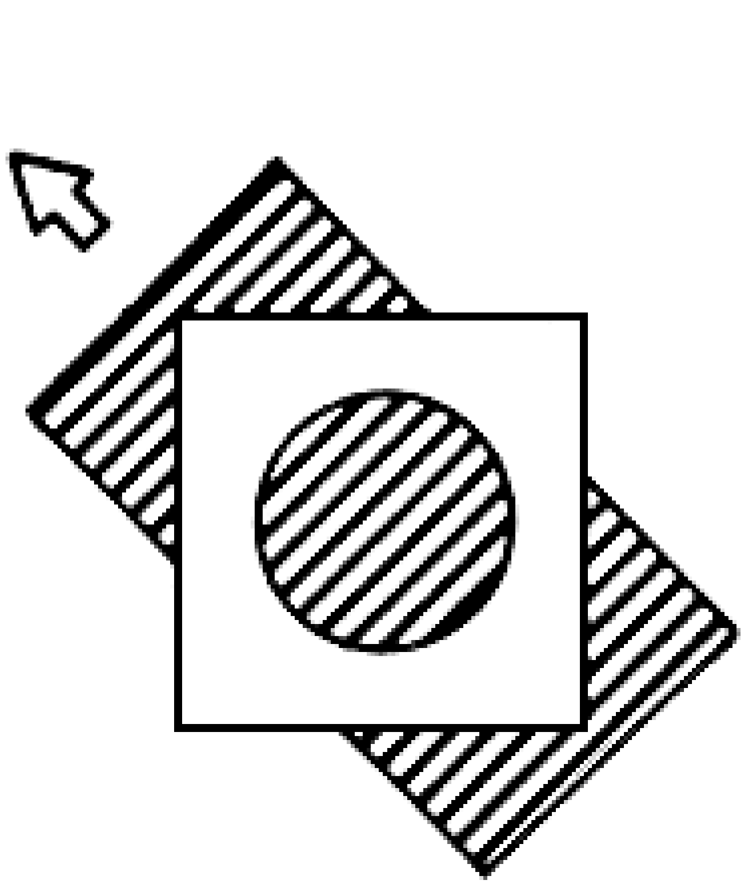
- Provides a rich source of visual information for prediction, depth perception, material properties, etc [Gibson, 1950]

Optic flow



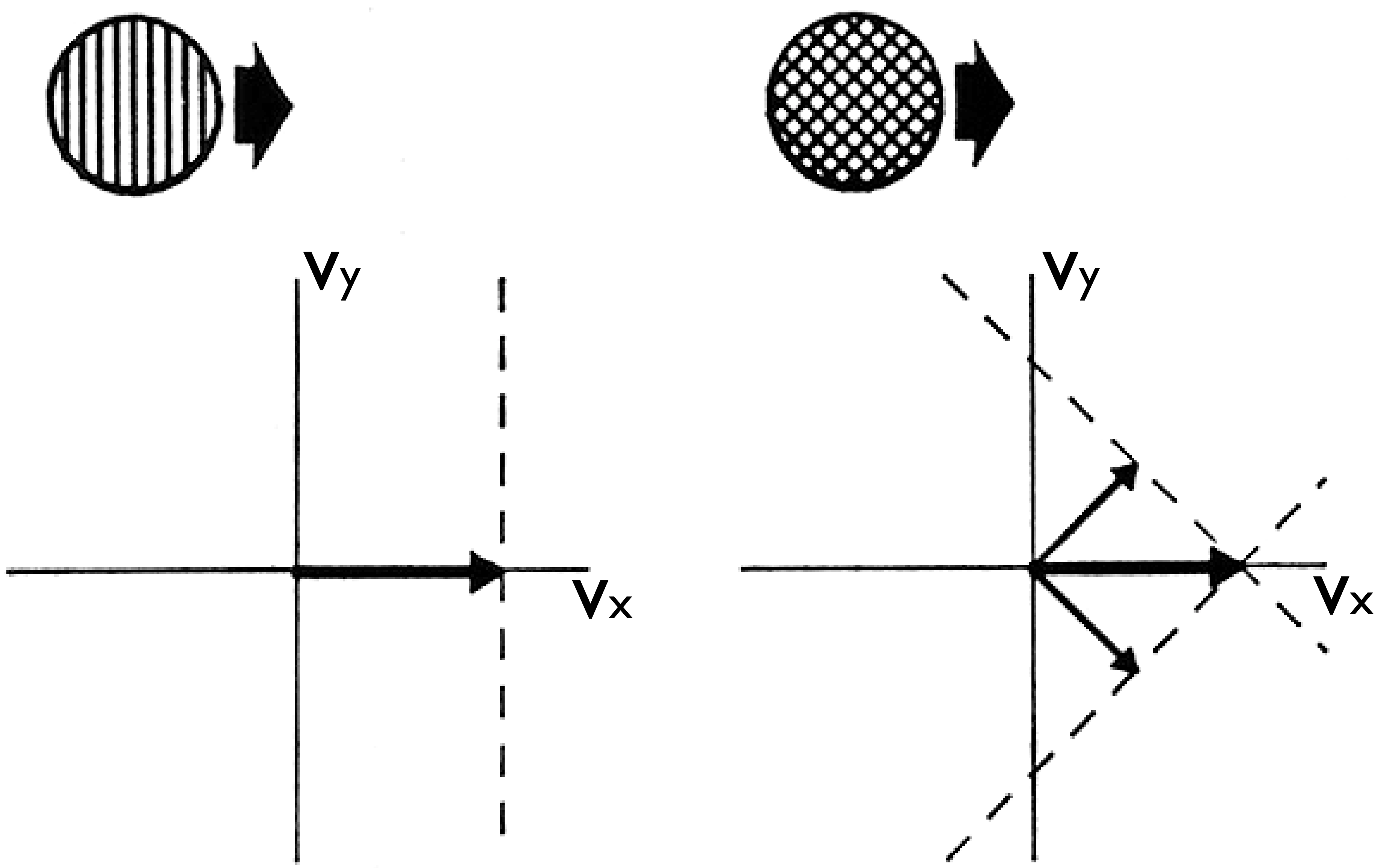
[Gibson, 1950]

"Aperture Problem"

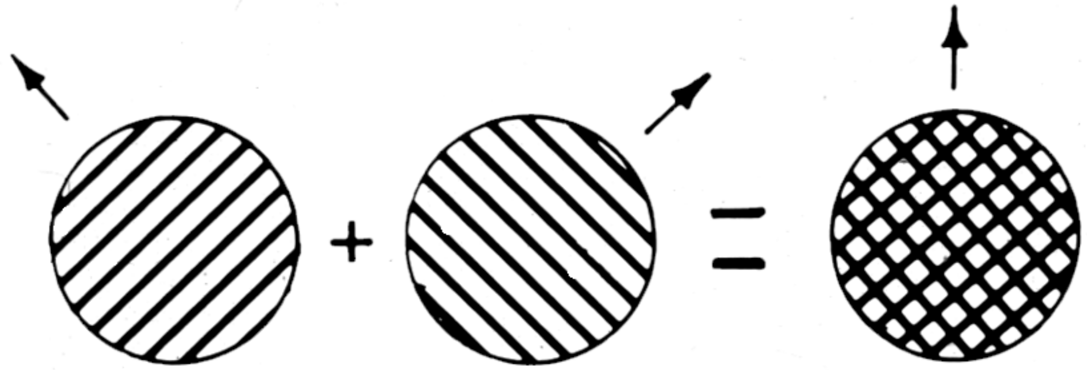


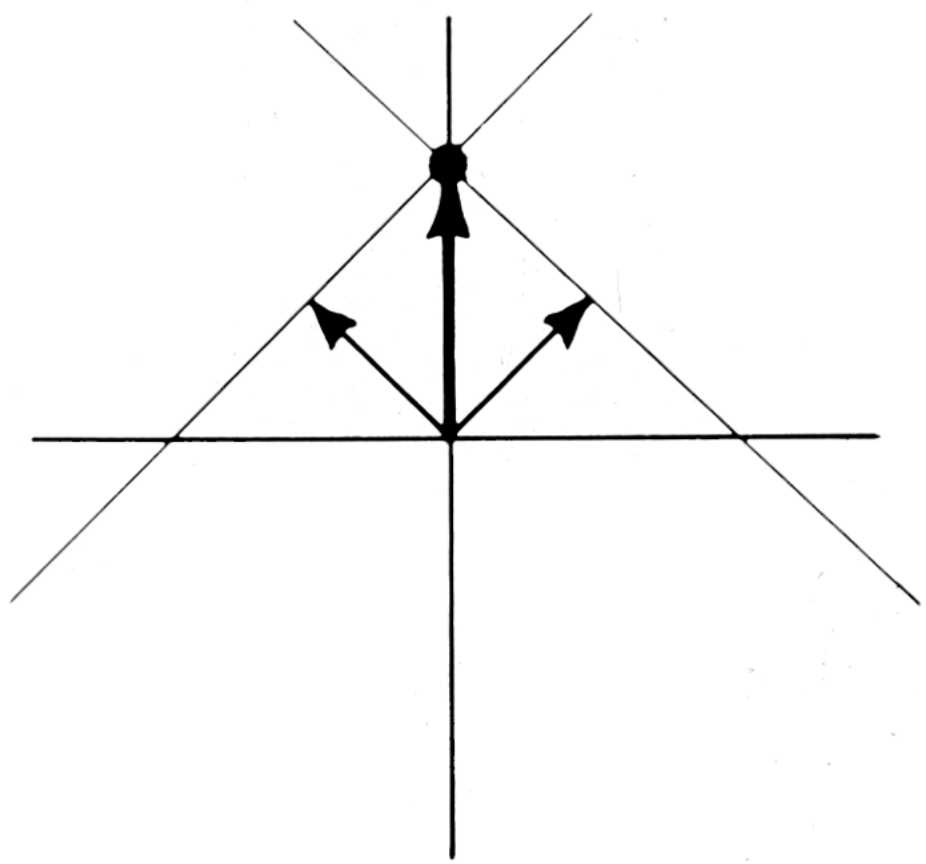
[Wallach 1935; Horn & Schunck 1981; Marr & Ullman 1981]
Figure: Movshon, Adelson, Gizzi, Newsome, 1985

Intersection-of-constraints (IOC)

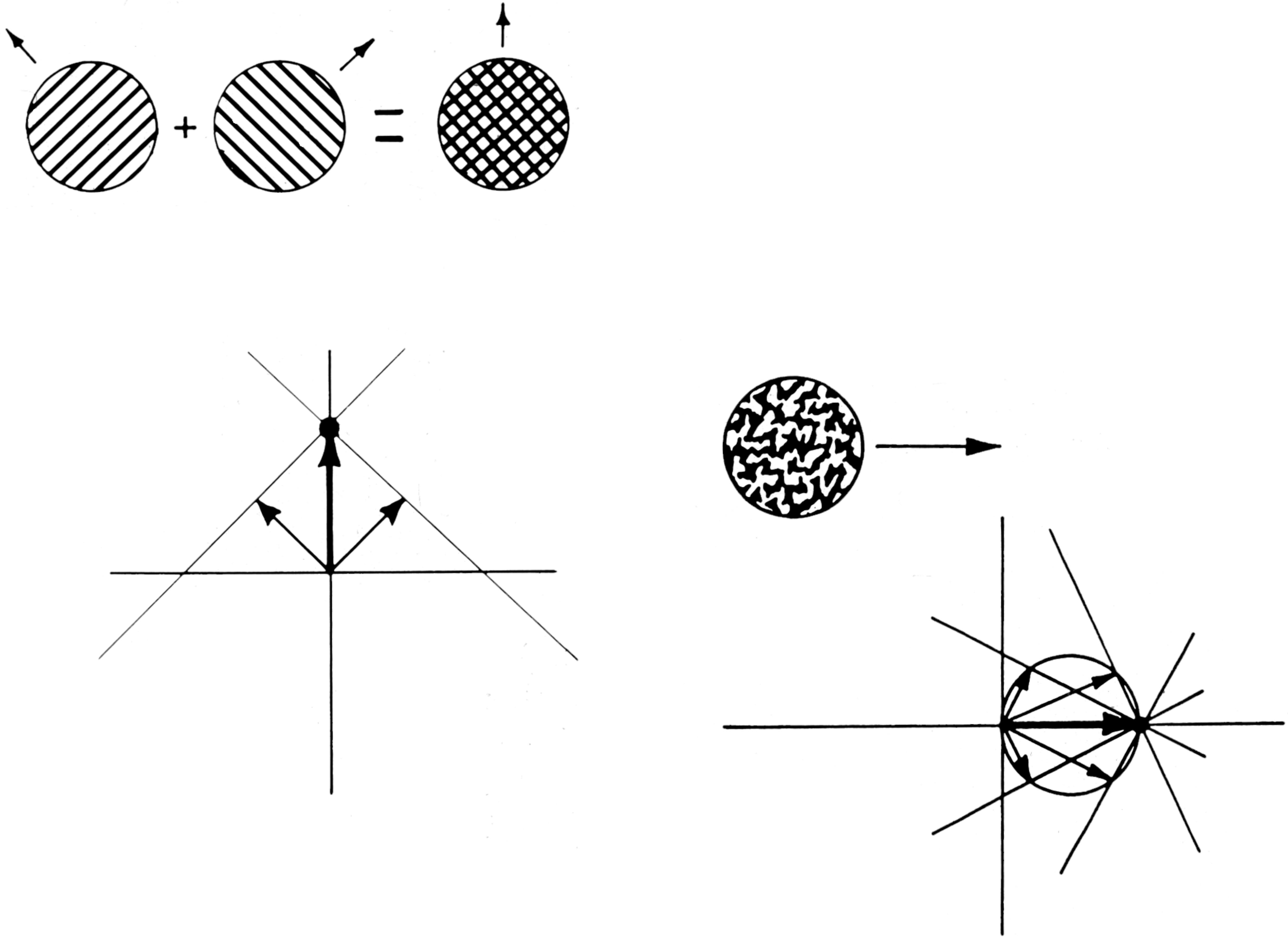


[Adelson & Movshon, 1982]



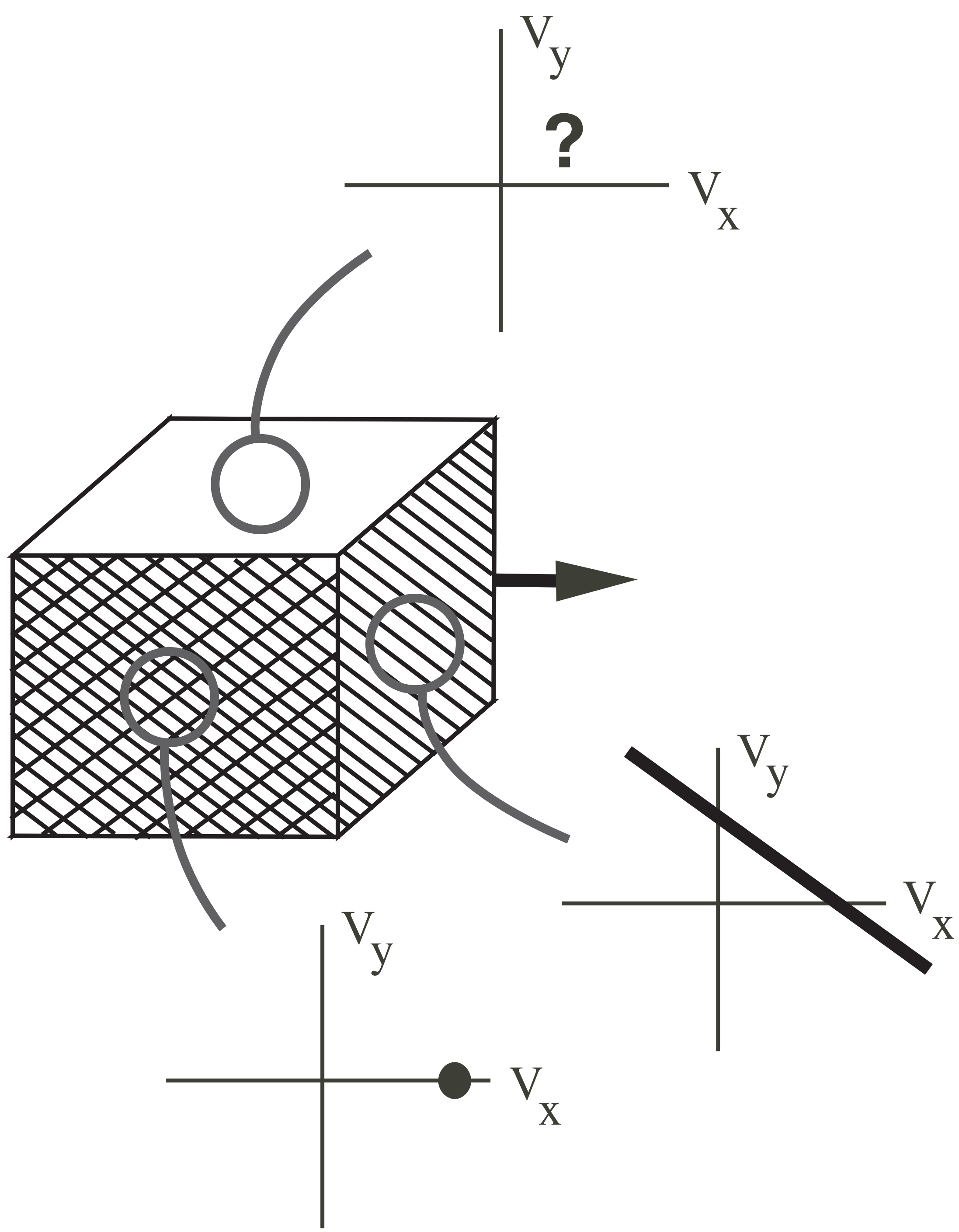


Movshon, Adelson, Gizzi & Newsome, 1985



Movshon, Adelson, Gizzi & Newsome, 1985

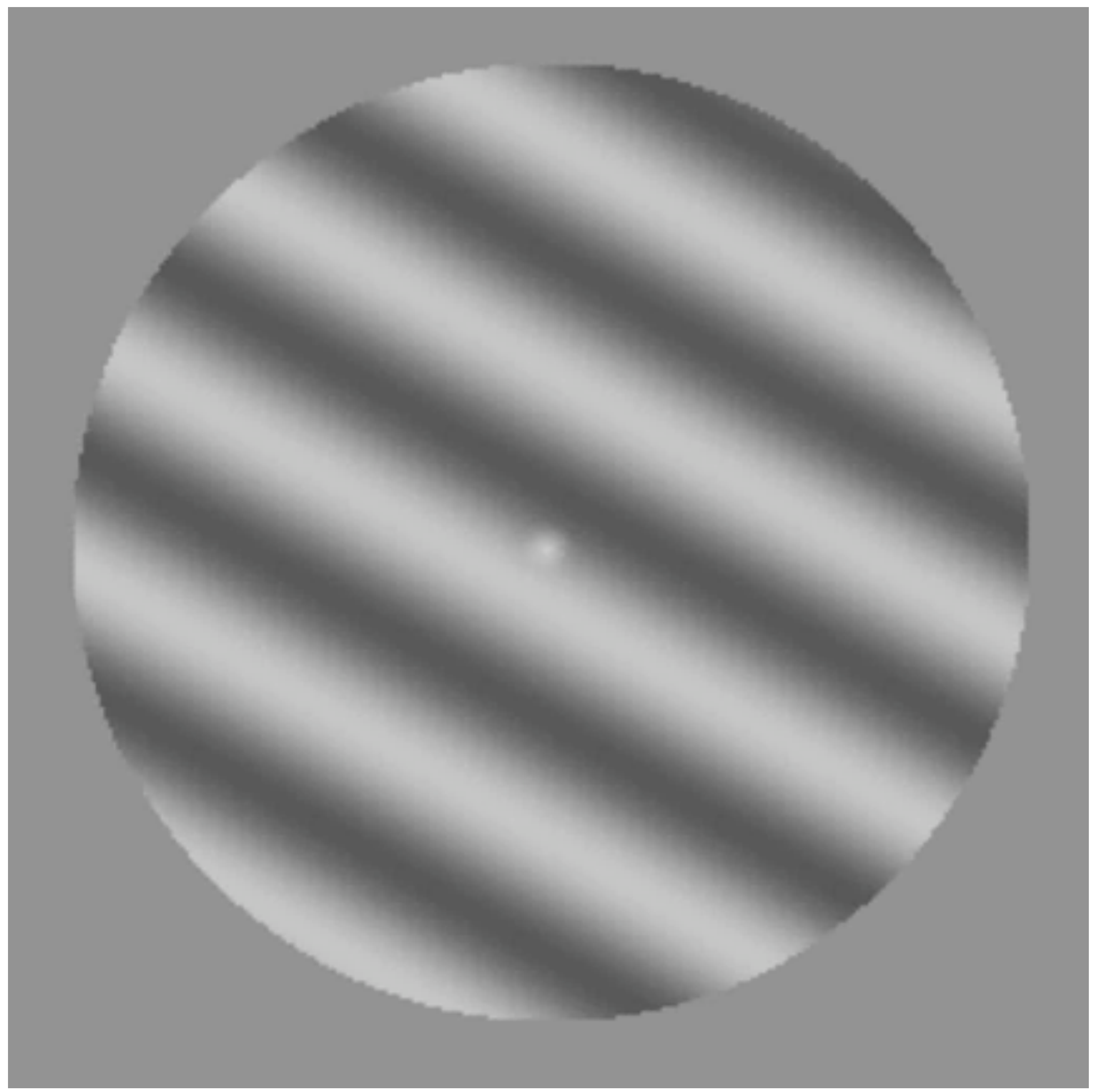
Visual motion ambiguity



Simple plaid perception = IOC

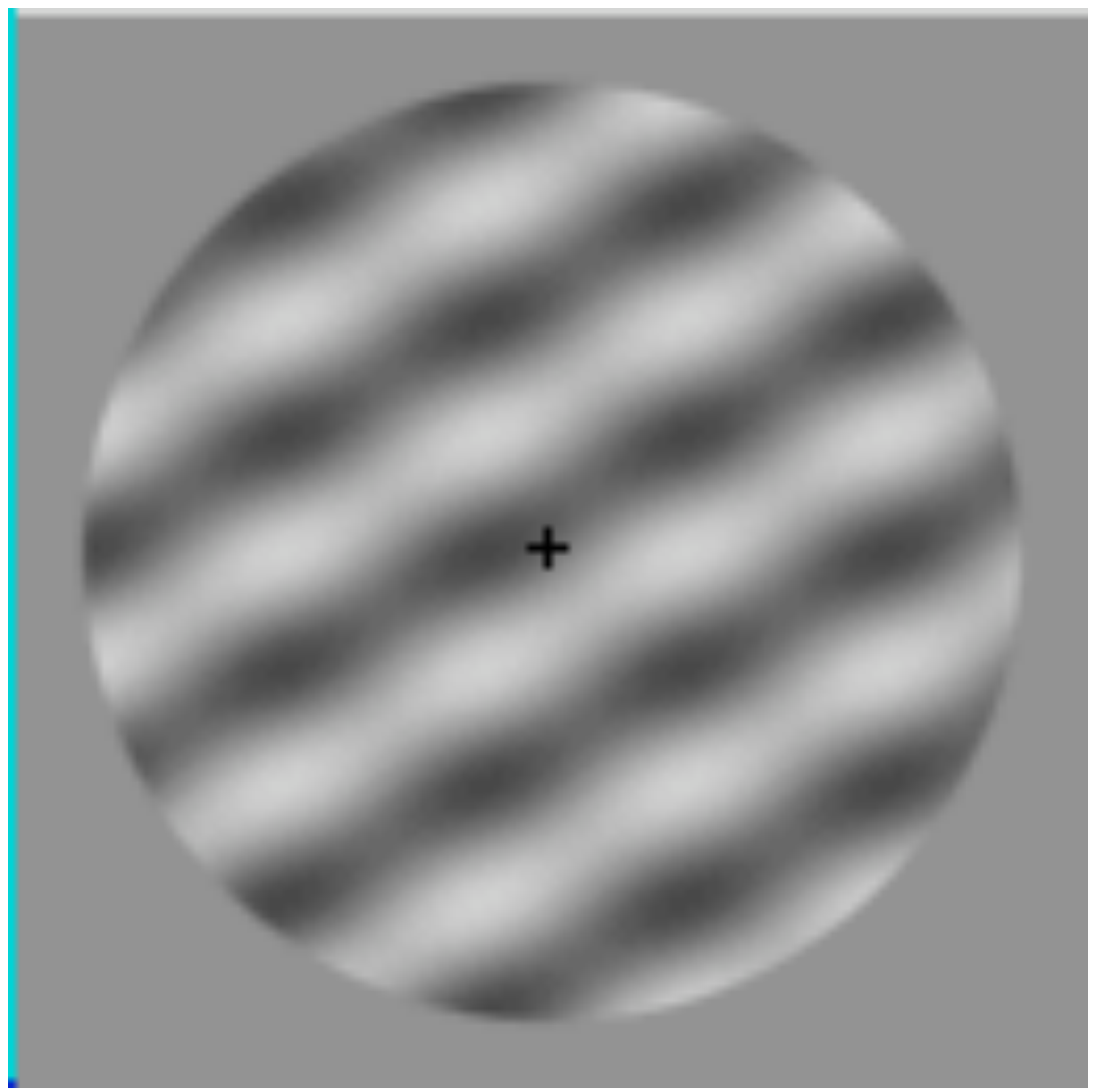
[Adelson & Movshon, 1982]

Simple plaid perception = IOC



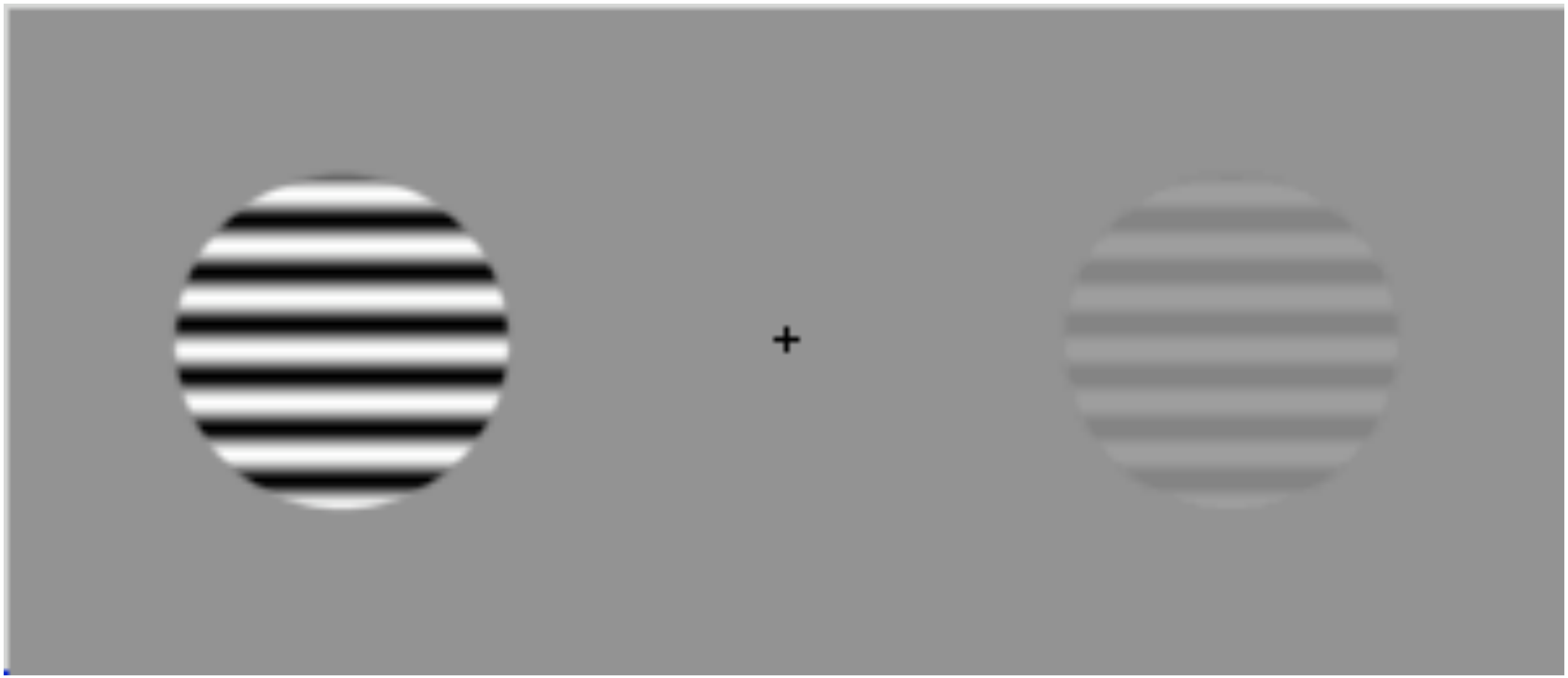
[Adelson & Movshon, 1982]

IOC failure



[Stone etal 1990]

The "Thompson effect"



Contrast affects perceived speed

[Thompson '82]

Helmholtz (1866)

Perception is our best guess as to what is in the world, given our current sensory input and our prior experience [paraphrased]

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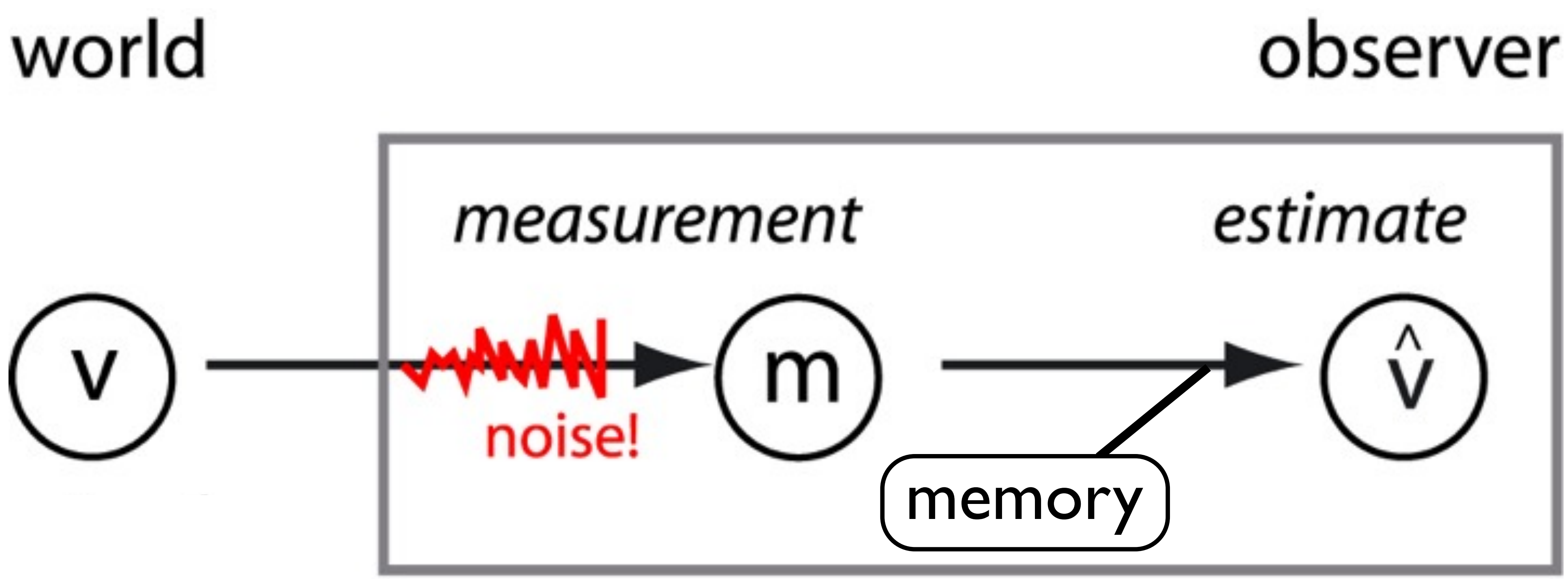

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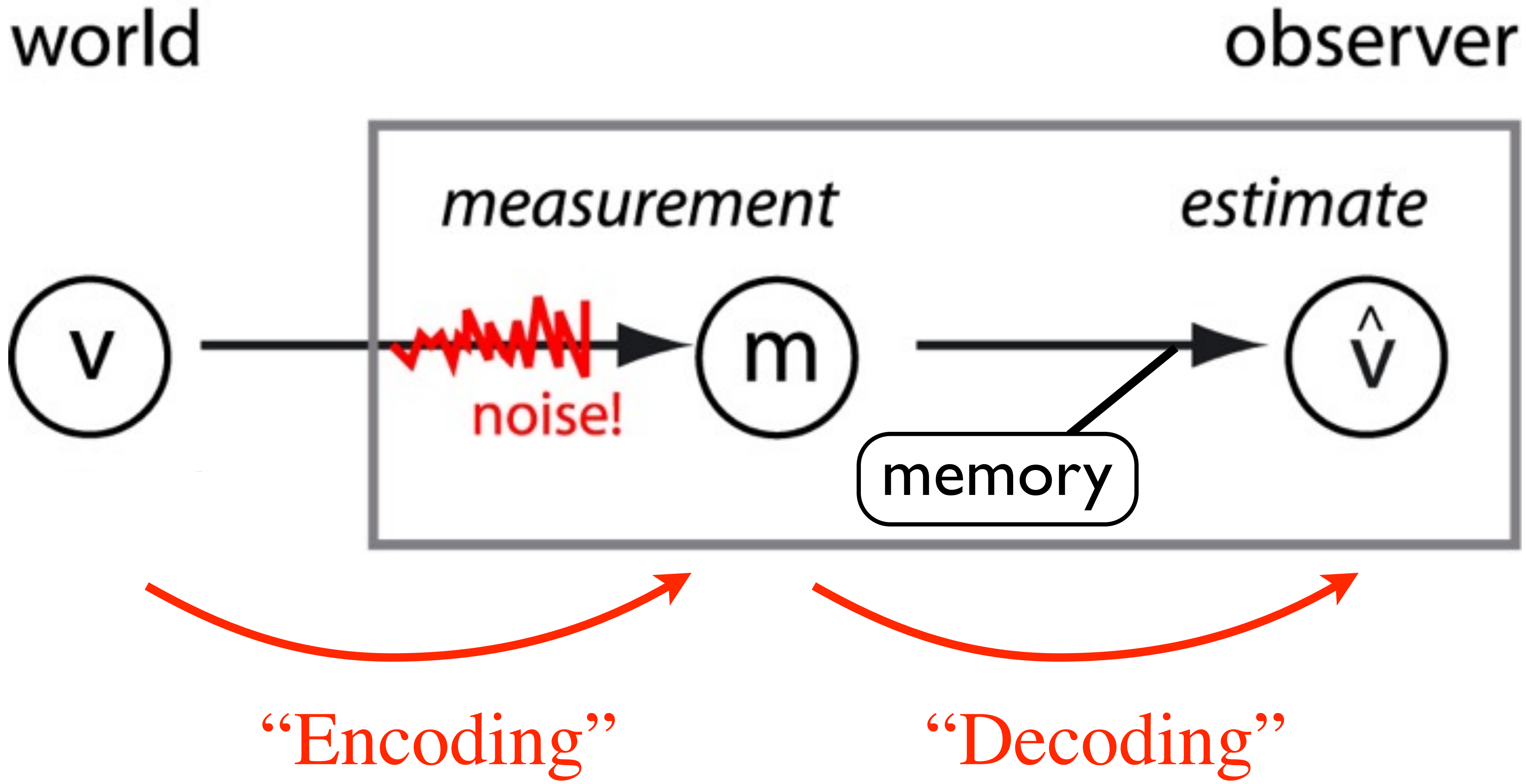
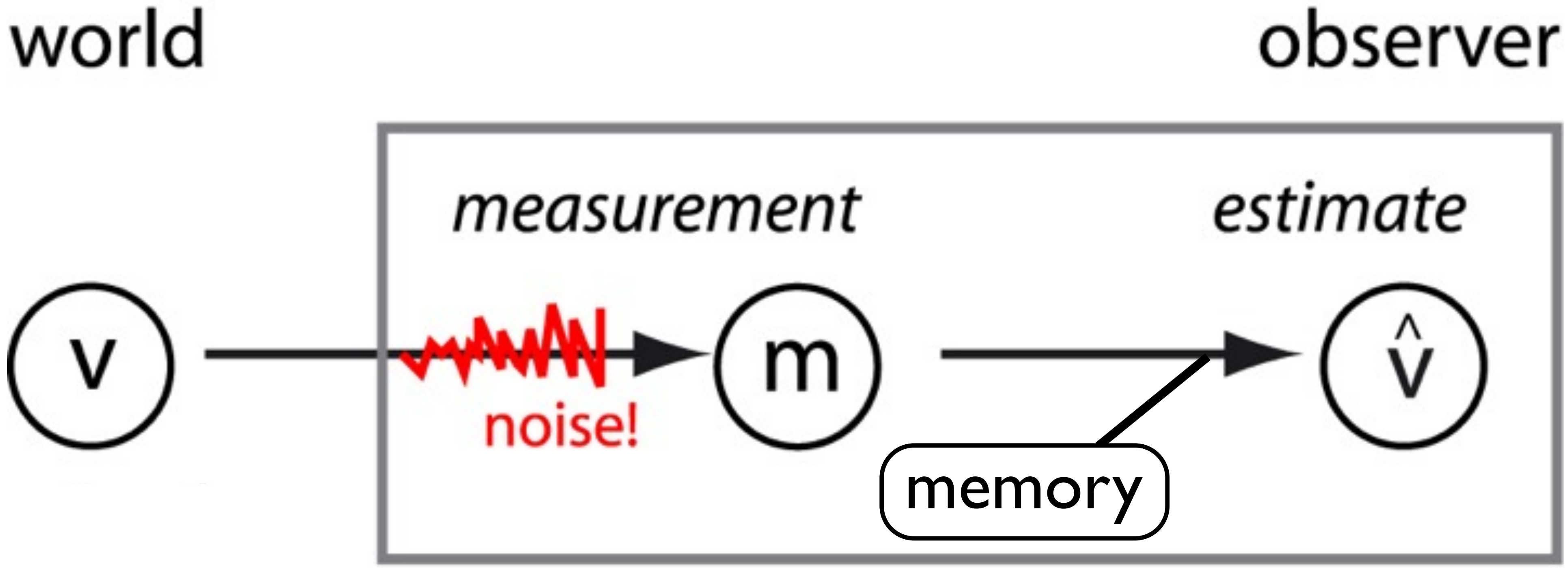


Bayesian perception



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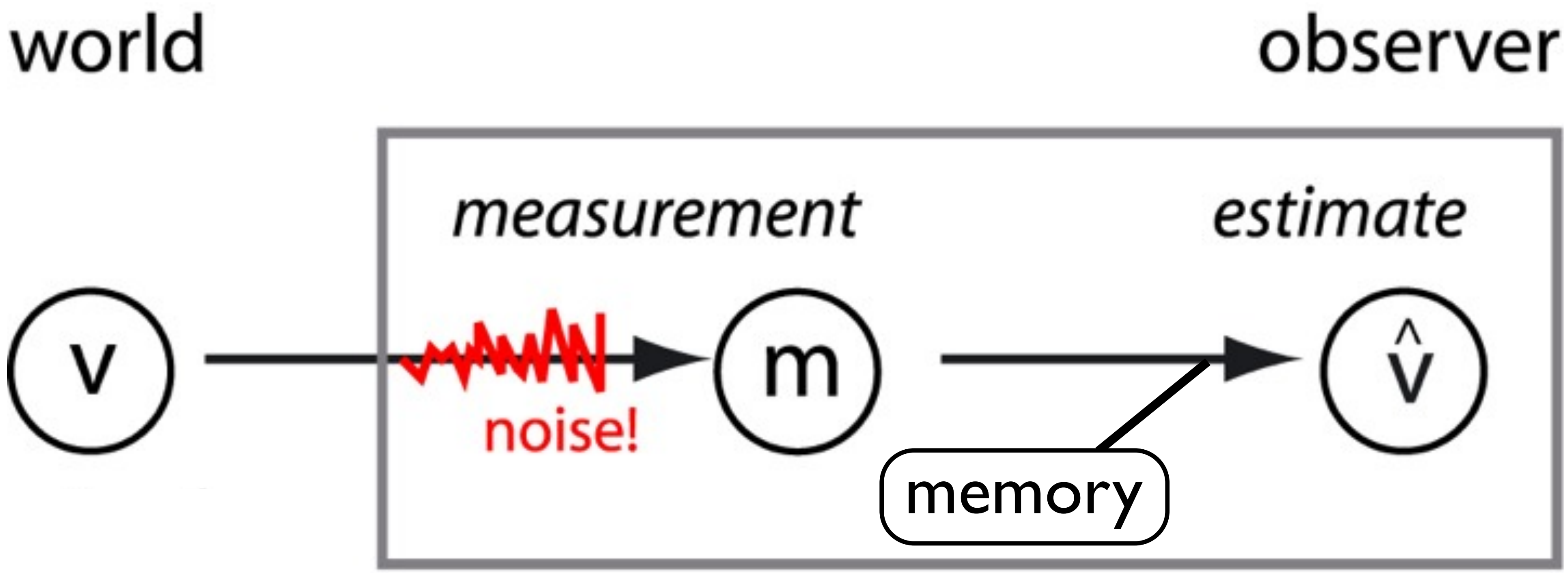

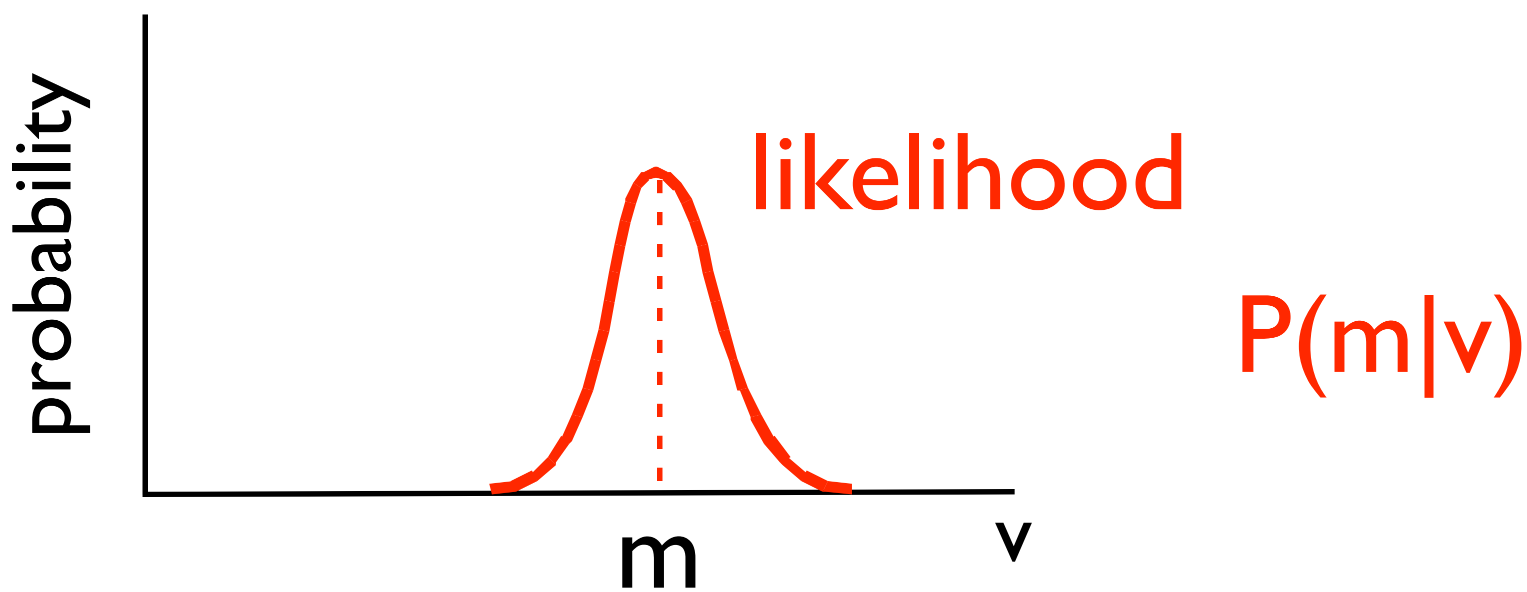

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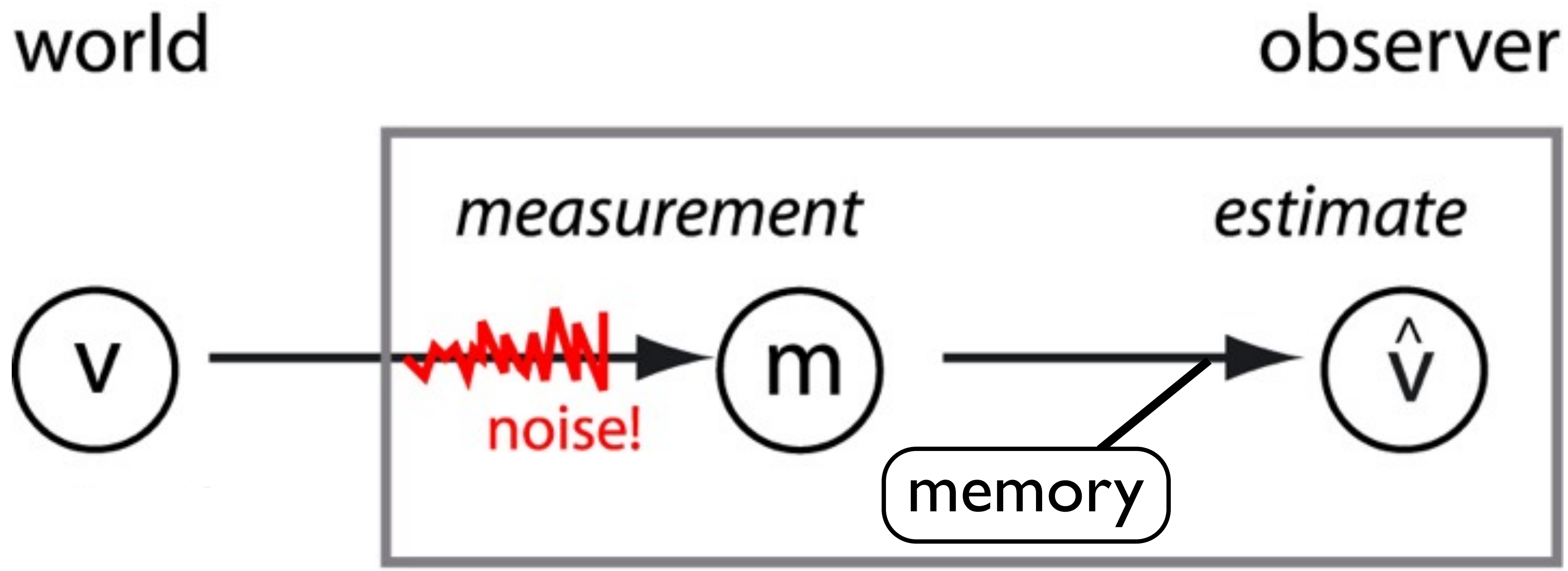
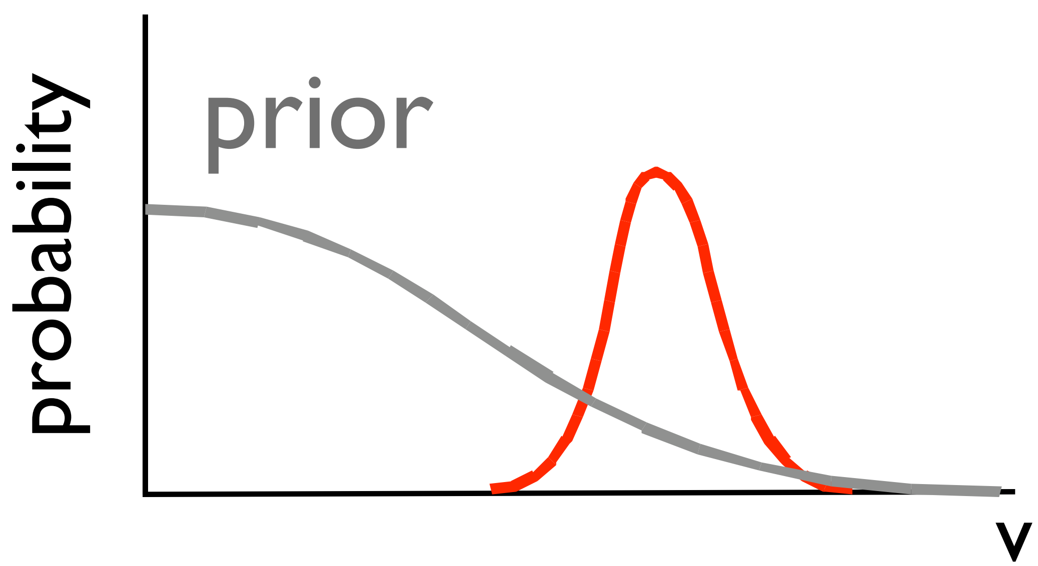
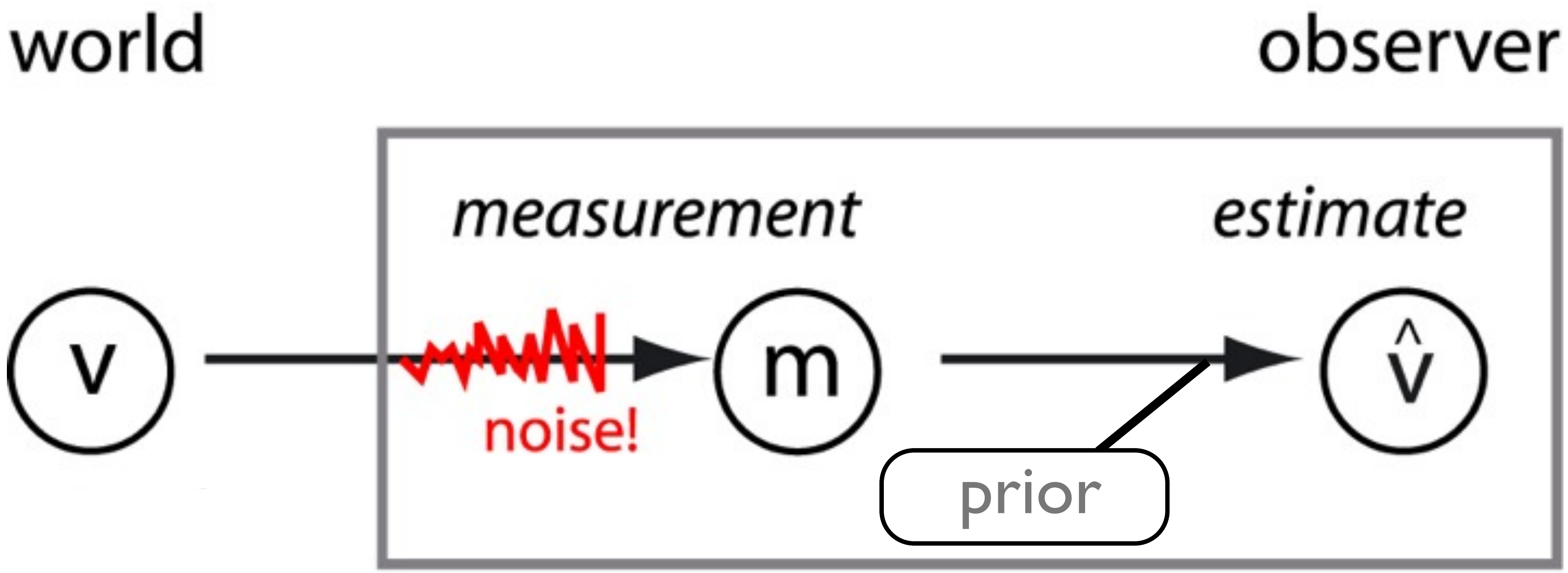
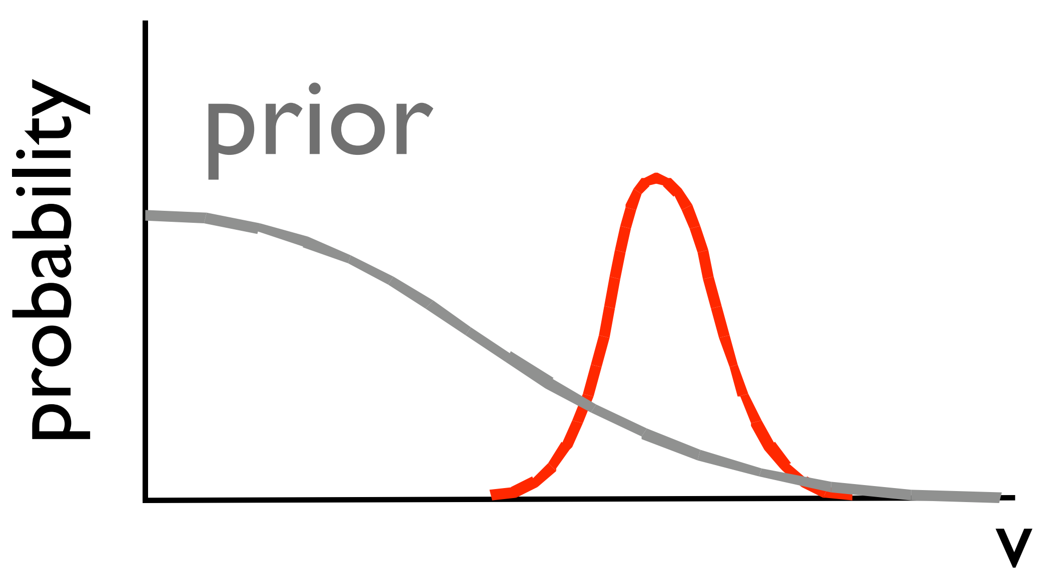




$P(m|v)$ $P(v)$

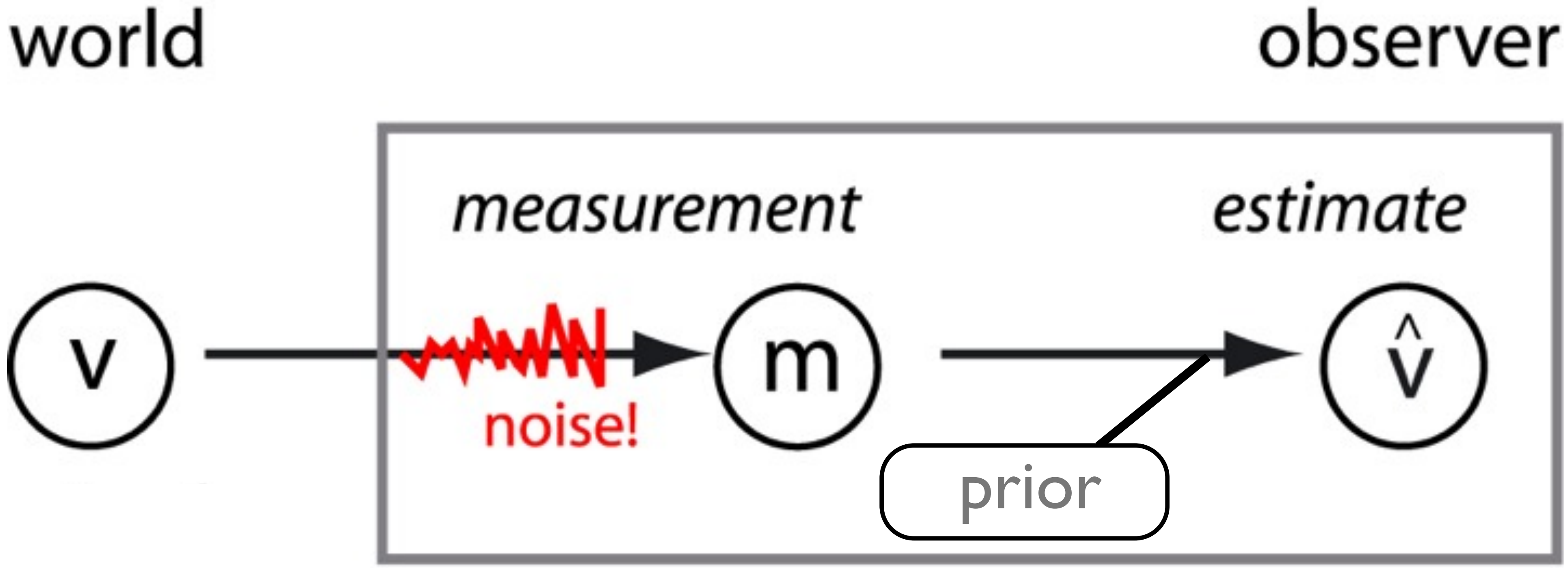
Bayesian perception

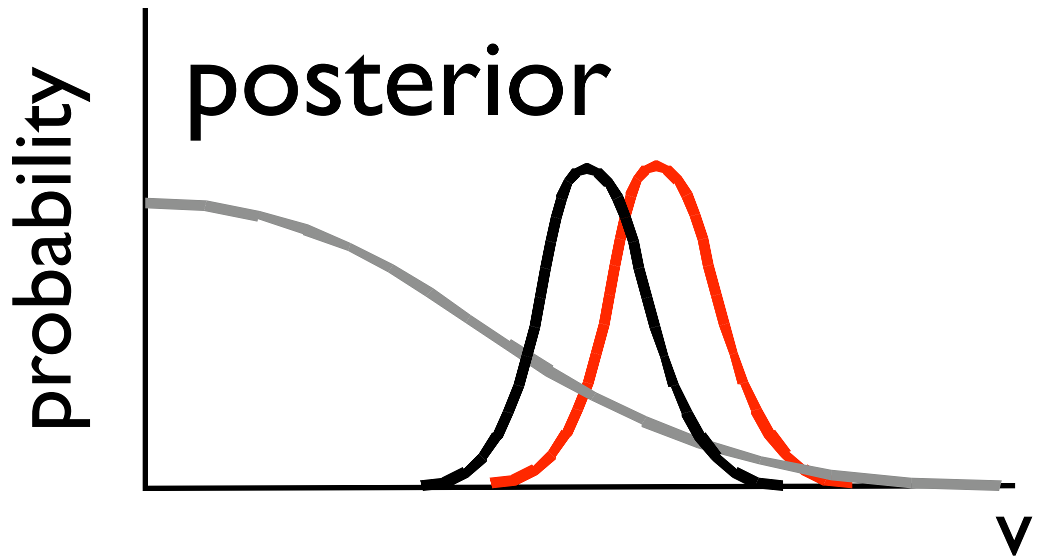




P(m|v) P(v)

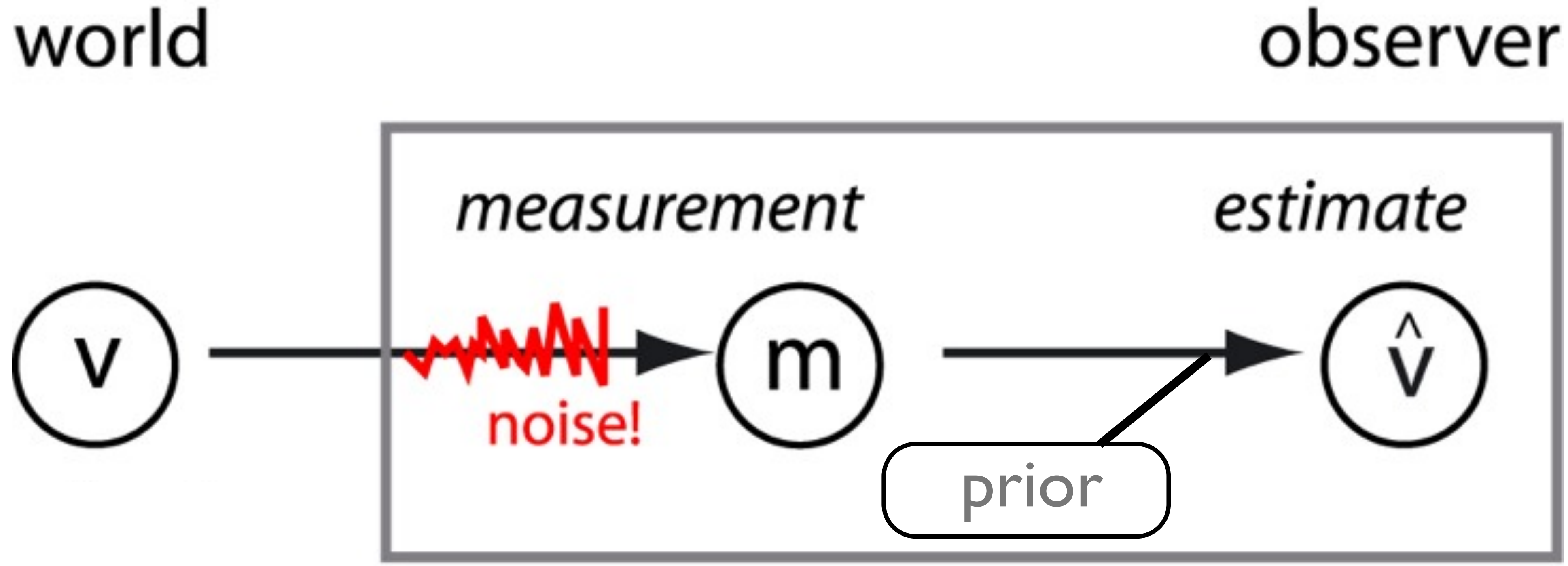
Bayesian perception

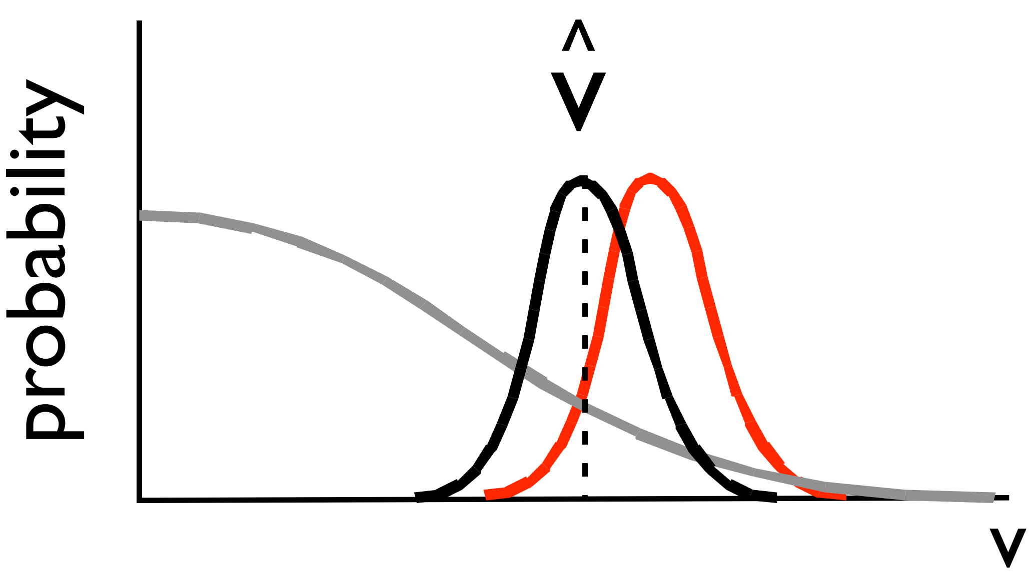




$P(m|v) \times P(v) \sim P(v|m)$

Bayesian perception





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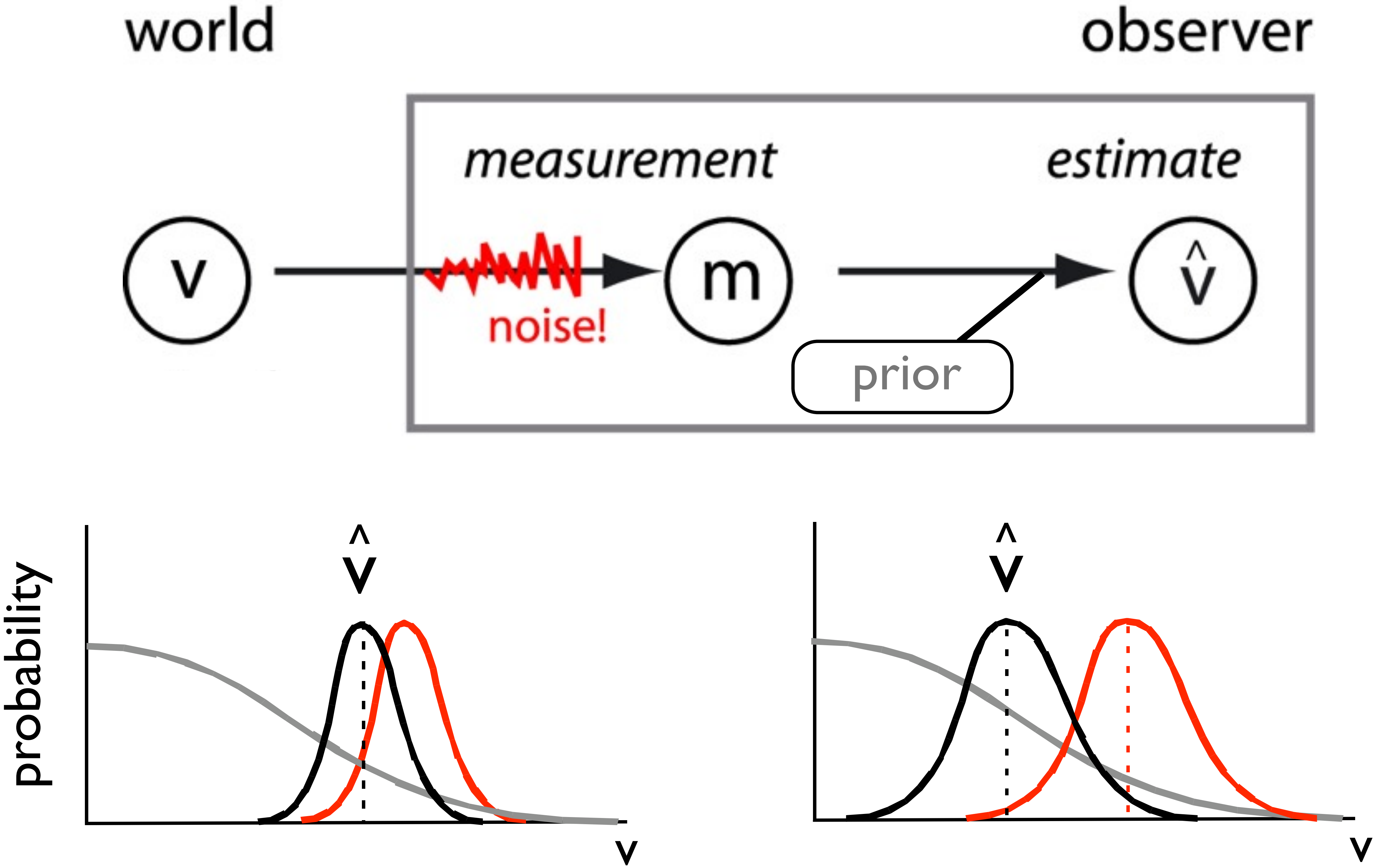


Some Bayesian perceptual models

- Shading/lighting [Kersten 90; Knill, Kersten, Yuille 96; Mamassian, Landy, Maloney 01]
- Motion [Simoncelli 93; Weiss etal. 02; Stocker & Simoncelli 06]
- Surface orientation [Bülthoff & Yuille 96; Saunders & Knill 01]
- Color constancy [Brainard & Freeman 97]
- Contours [Geisler, Perry, Super 01]
- Sensory-motor tasks [Körding & Wolpert 04]

Brightness Constancy

- Assume translational motion (locally)
- Differential approximation (Taylor series)

$$\vec{\nabla} I \cdot \vec{v} + I_t = 0, \qquad \vec{\nabla} I = [Ix, Iy]$$

- Insufficient constraint, so combine over a neighborhood (space and/or time):

$$min \sum (\vec{\nabla} I \cdot \vec{v} + I_t)^2$$

[Fennema & Thompson ‘79; Horn and Schunck ‘81]

With noise...

- Additive Gaussian noise in temporal derivative:

$$\vec{\nabla} I \cdot \vec{v} + I_t = n$$

- Likelihood (combined over neighborhood):

$$P(\vec{\nabla} I, I_t | \vec{v}) \propto \exp[-\sum (\vec{\nabla} I \cdot \vec{v} + I_t)^2 / 2\sigma^2]$$

[Simoncelli, Adelson, Heeger '91]

With prior...

- Simplest prior choice: Gaussian (preference for slow speeds)

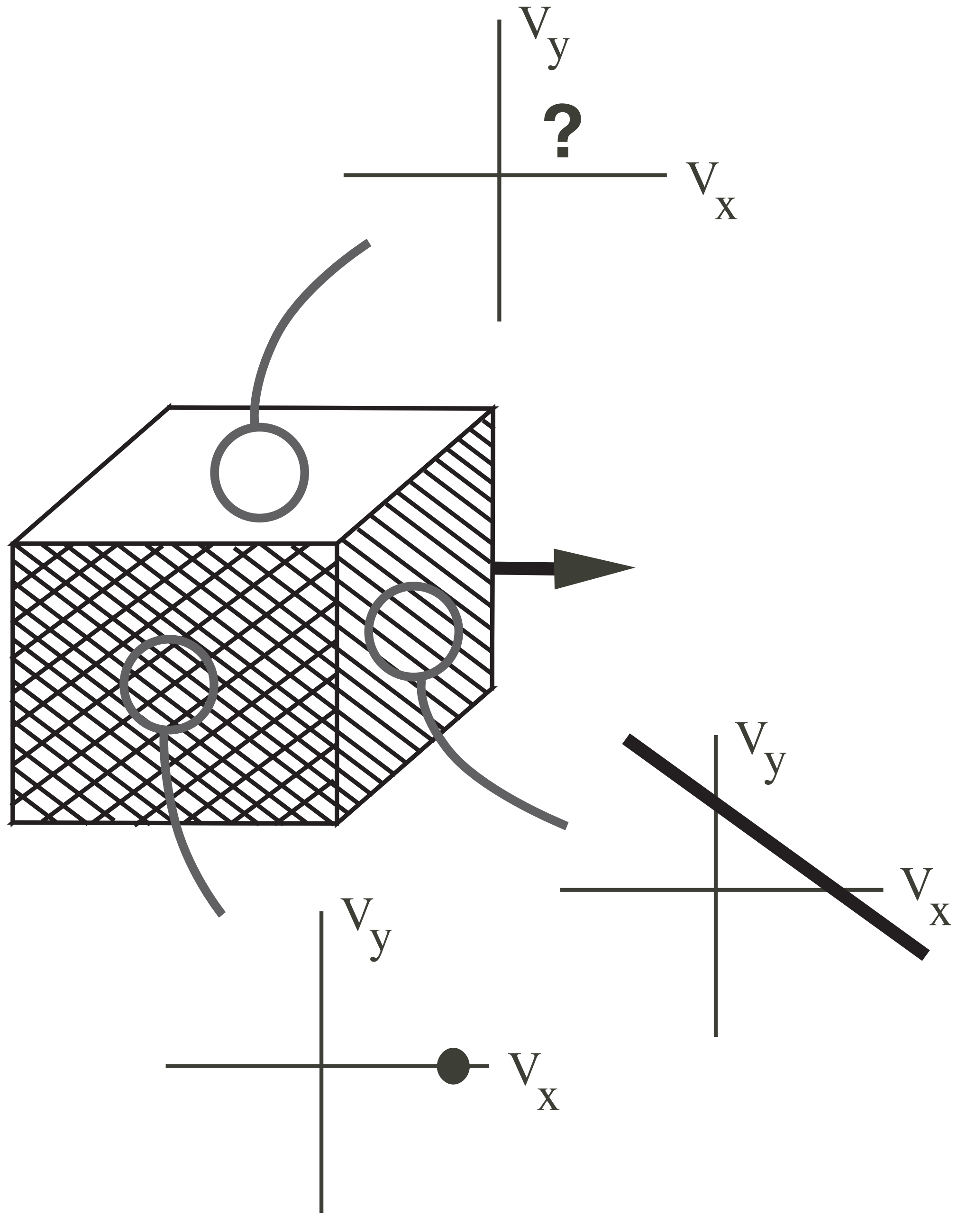
$$P(\vec{v}) \propto \exp[-||\vec{v}||/2\sigma_p^2]$$

- Posterior:

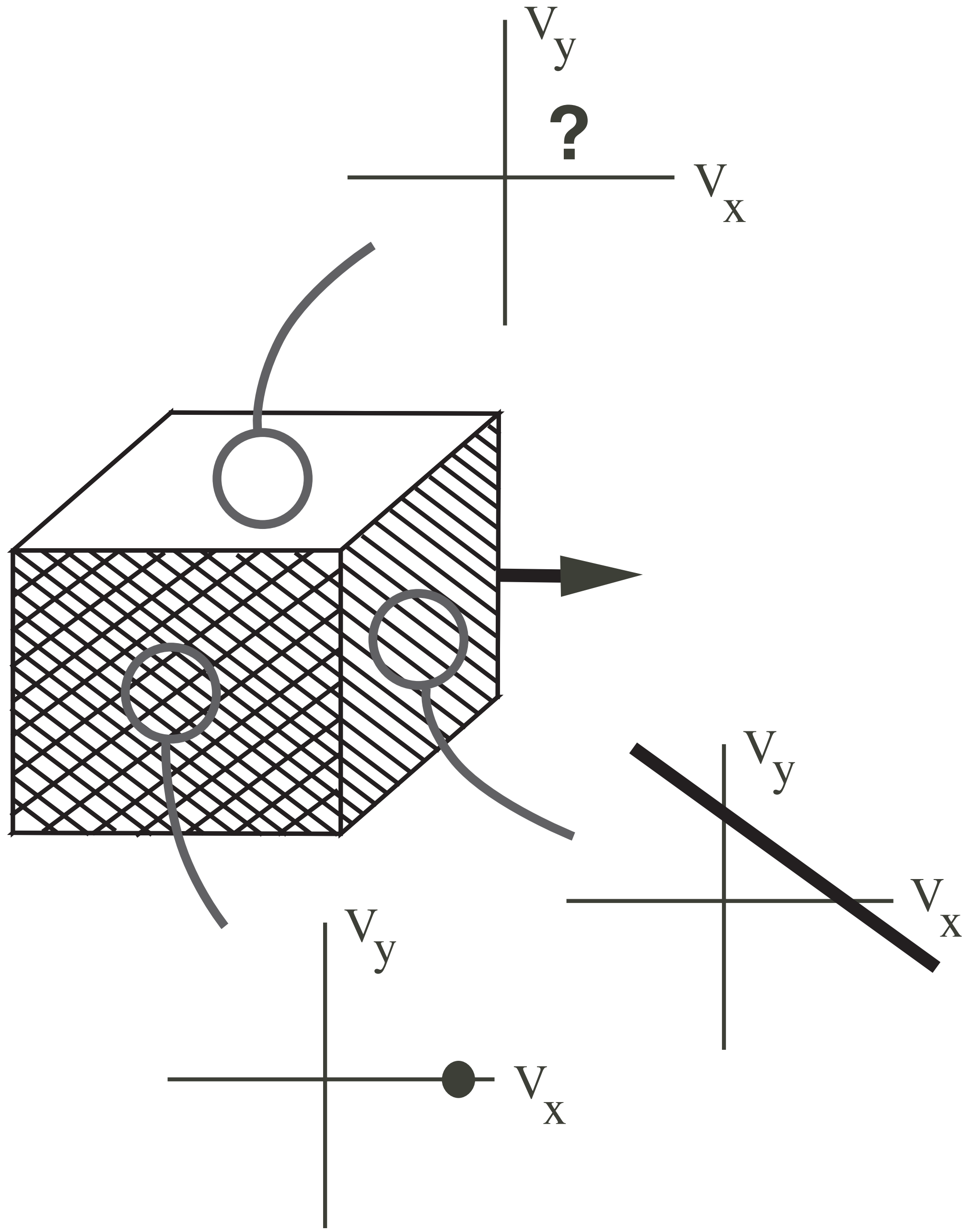
$$P(\vec{v}|\vec{\nabla} I, I_t) \propto$$

$$\exp[-||\vec{v}||/2\sigma_p^2 - \sum(\vec{\nabla} I \cdot \vec{v} + I_t)^2/2\sigma^2]$$

[Simoncelli, Adelson, Heeger ‘91]



Idealized illustration
of ambiguities



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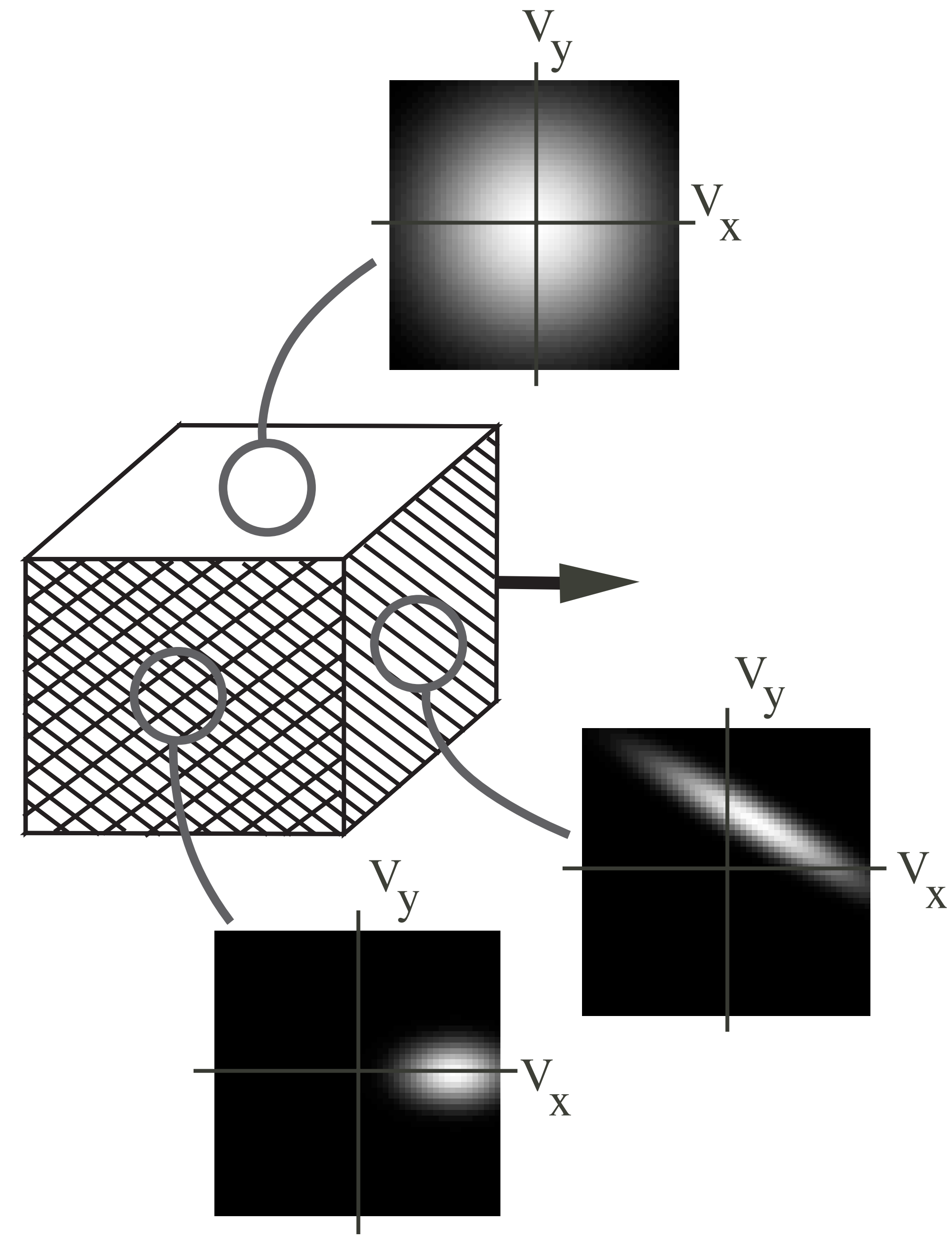
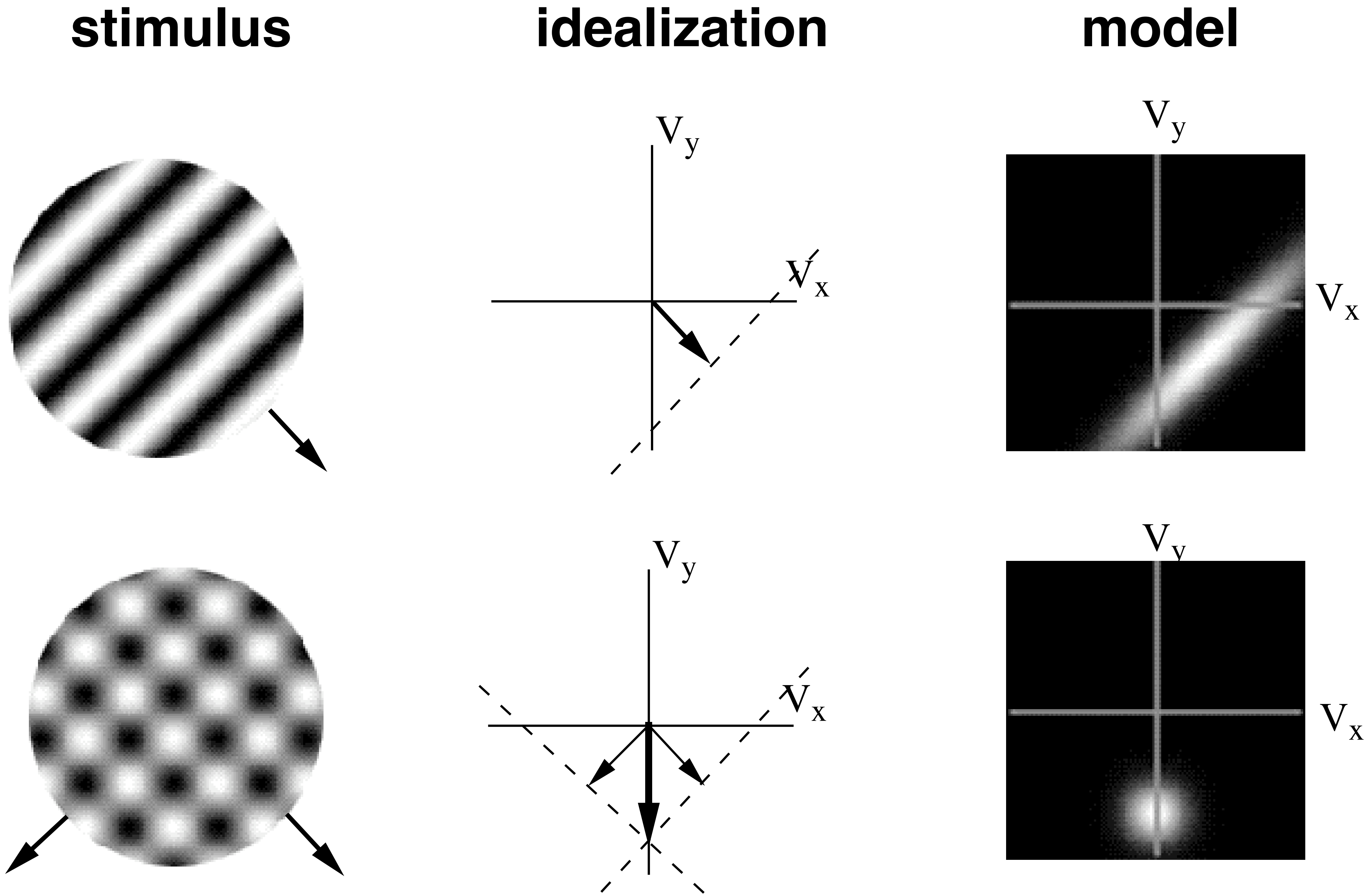
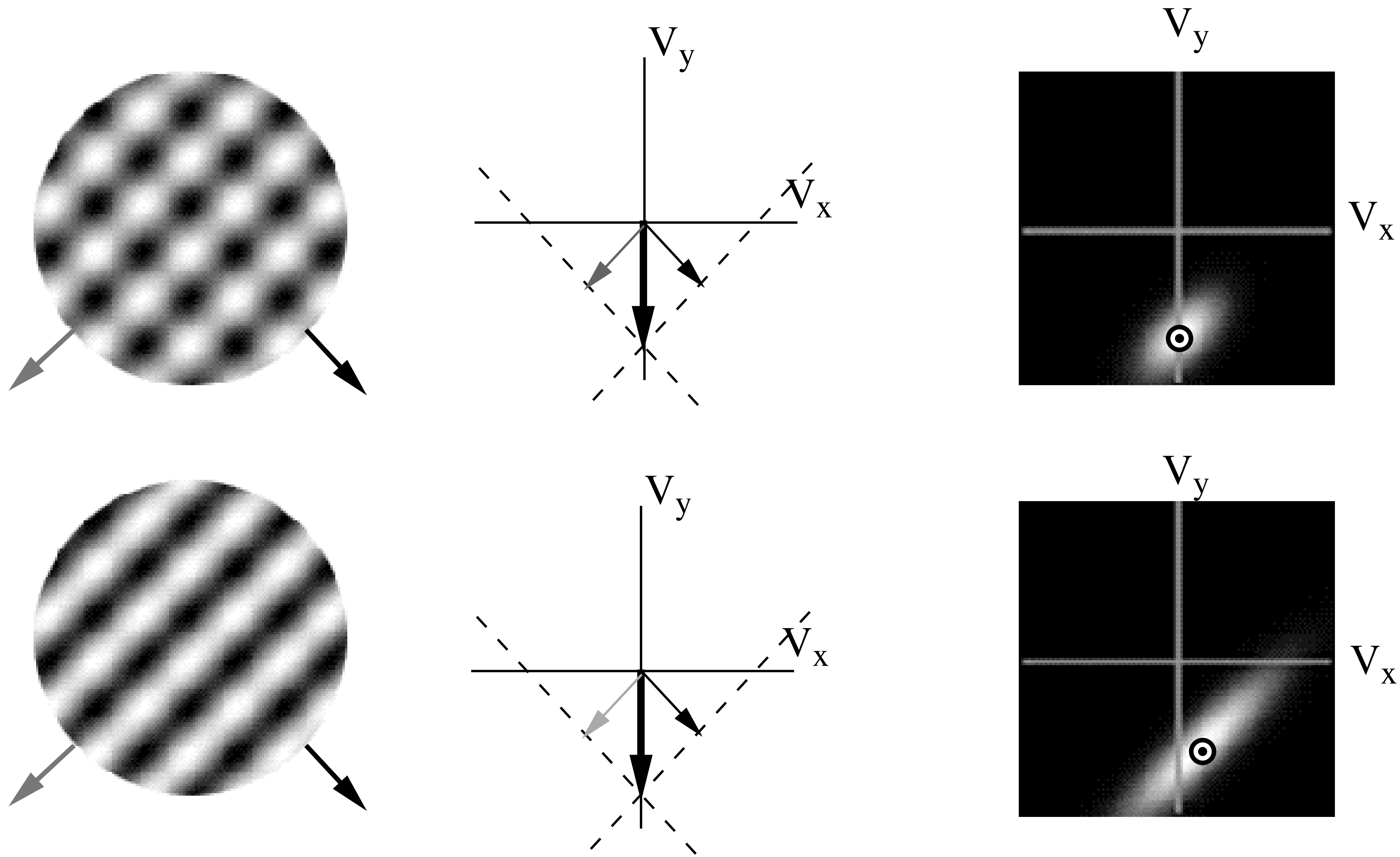


Bayesian posteriors
(Gaussian noise, Gaussian prior)



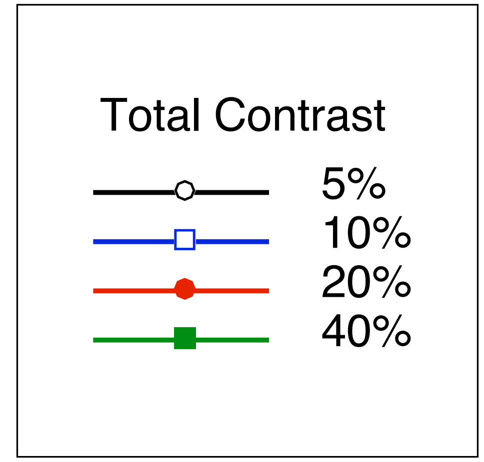
[Simoncelli & Heeger, ARVO '92]

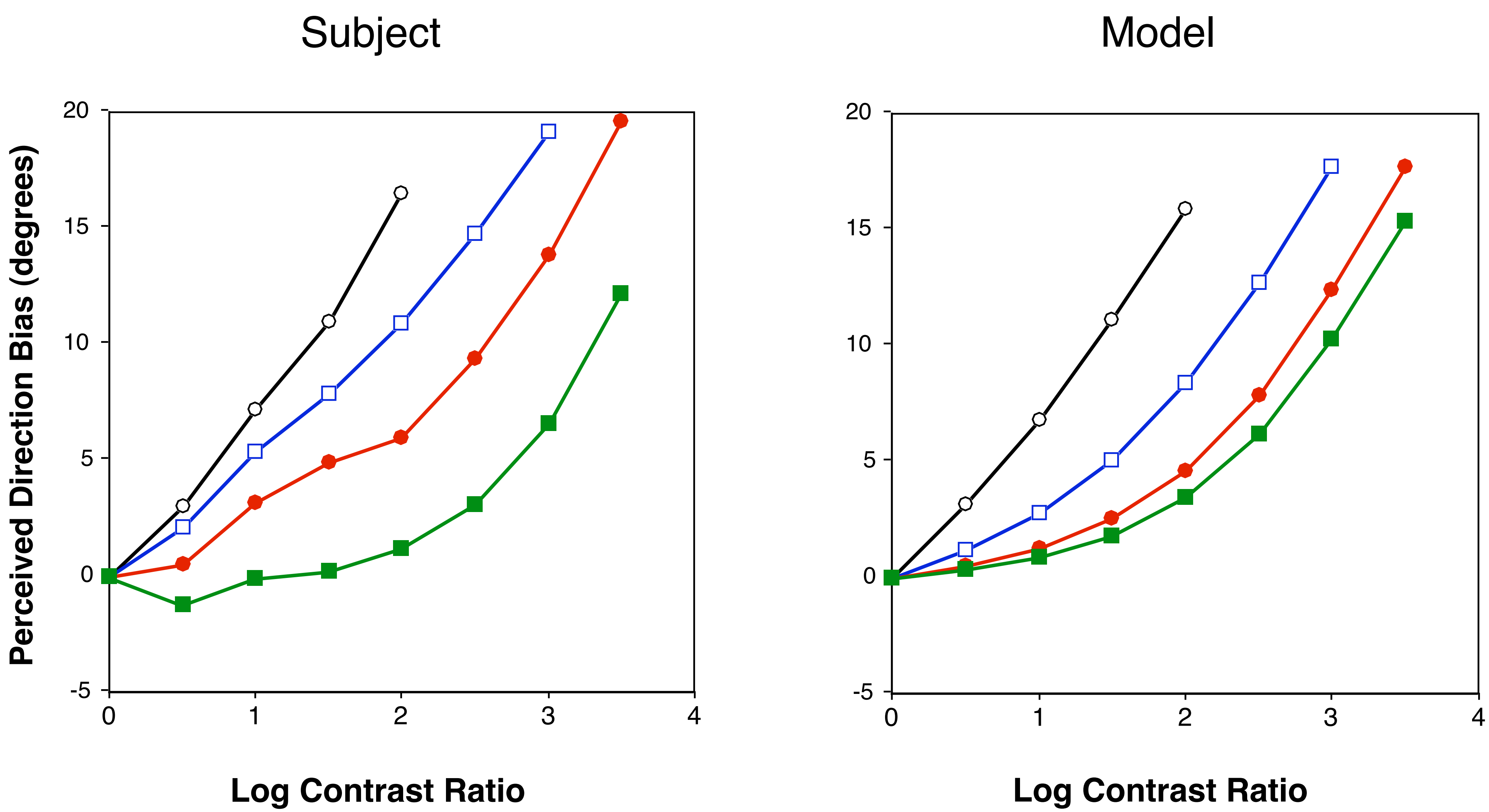
stimulus **idealization** **model**



[Simoncelli & Heeger, ARVO ‘92]

Stone et al. 1990





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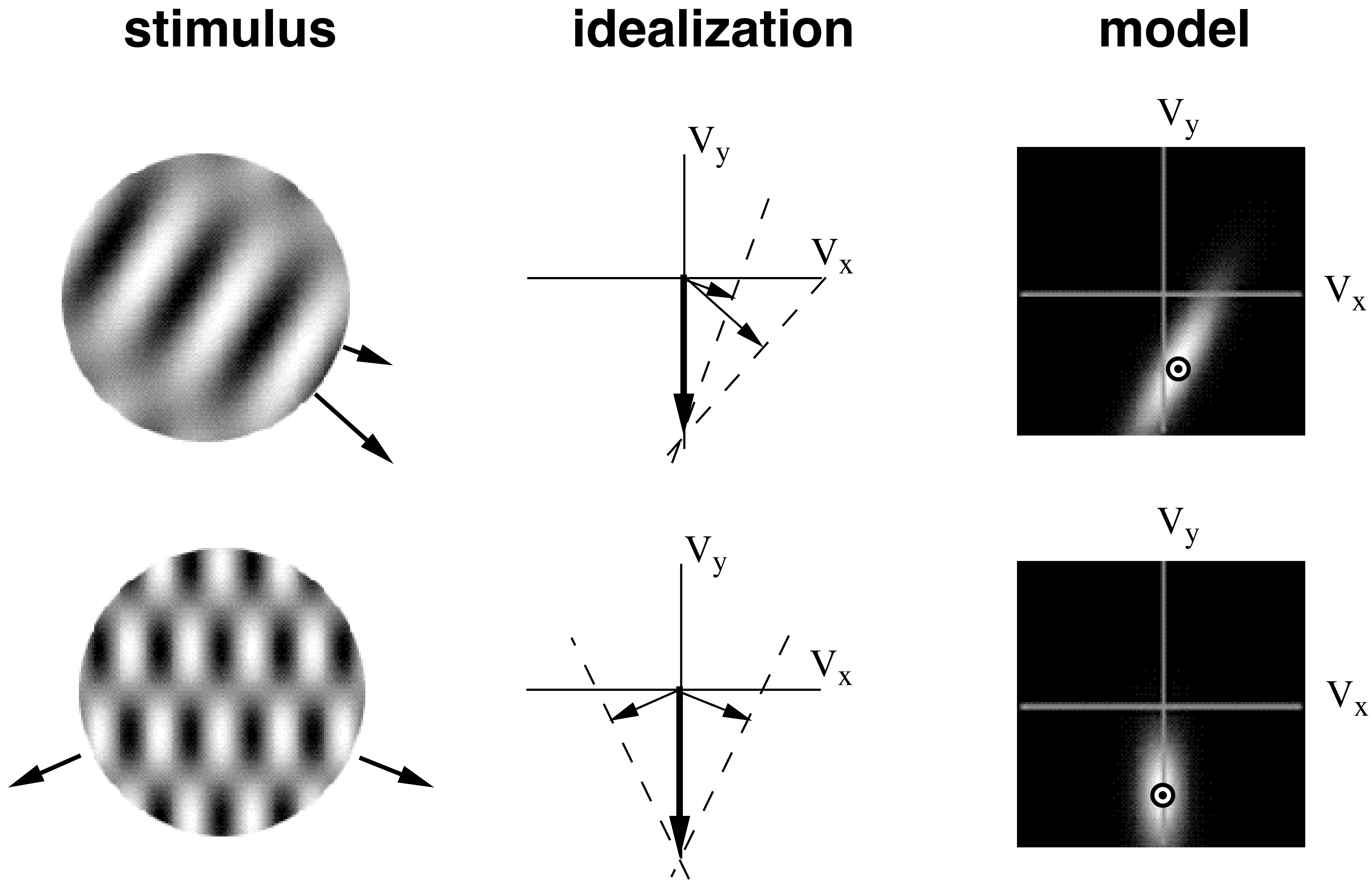
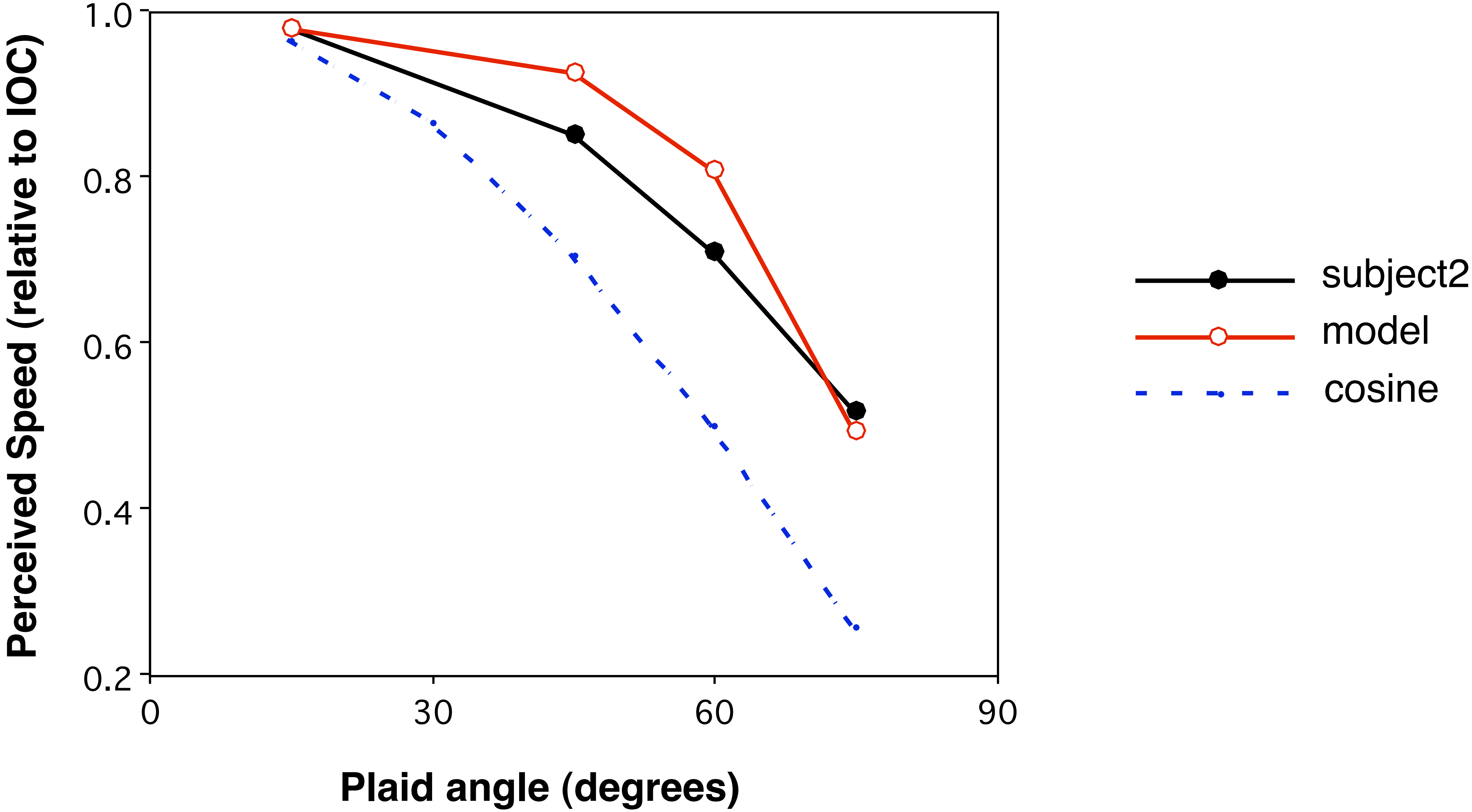


[Simoncelli & Heeger, ARVO '92]

Ferrera & Wilson, 1991



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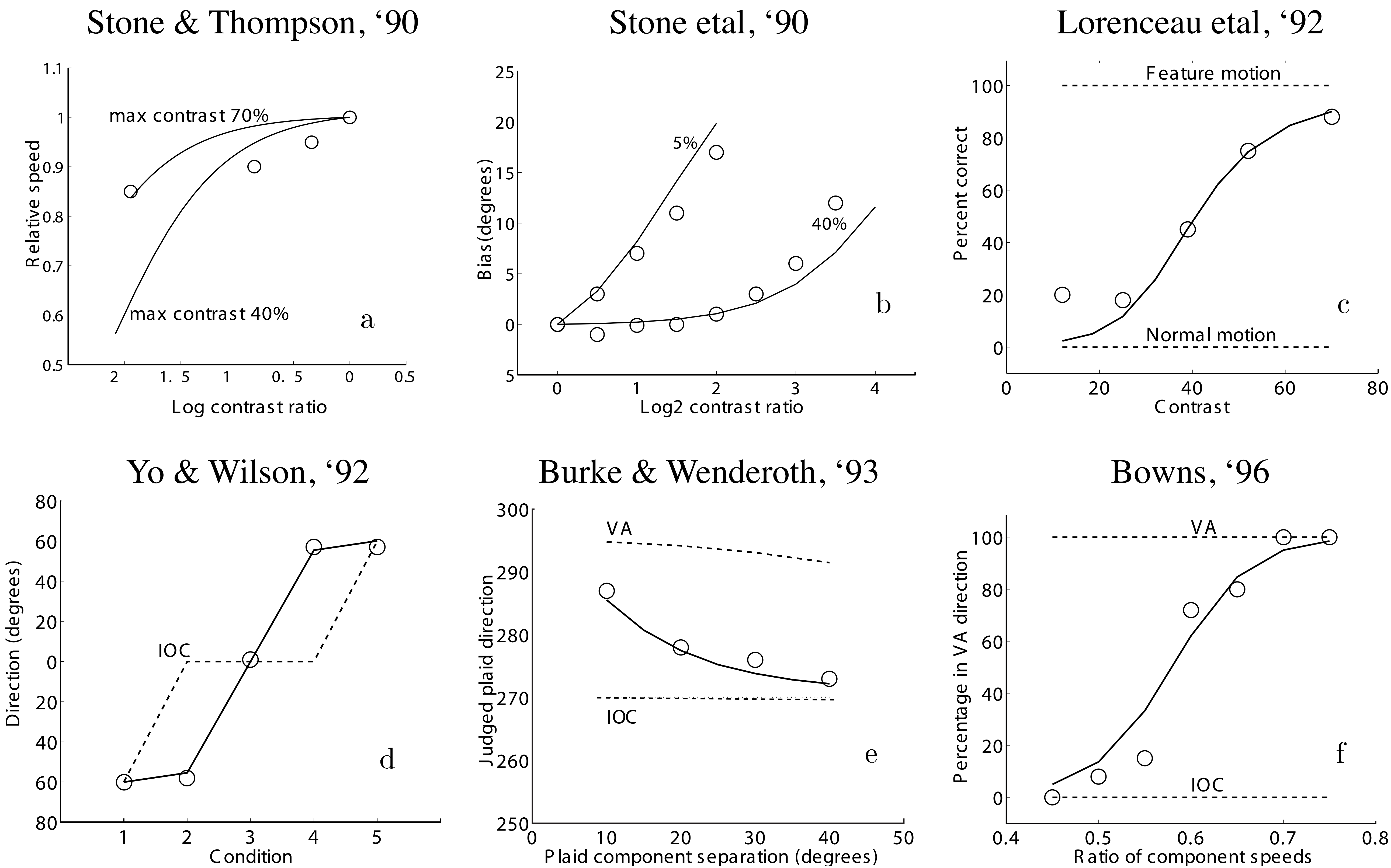

[Weiss, Simoncelli, Adelson, '02]

Credits

- Bayesian Plaid motion modeling: Edward Adelson, David Heeger, Yair Weiss
- Reverse-engineered prior/likelihood: Alan Stocker