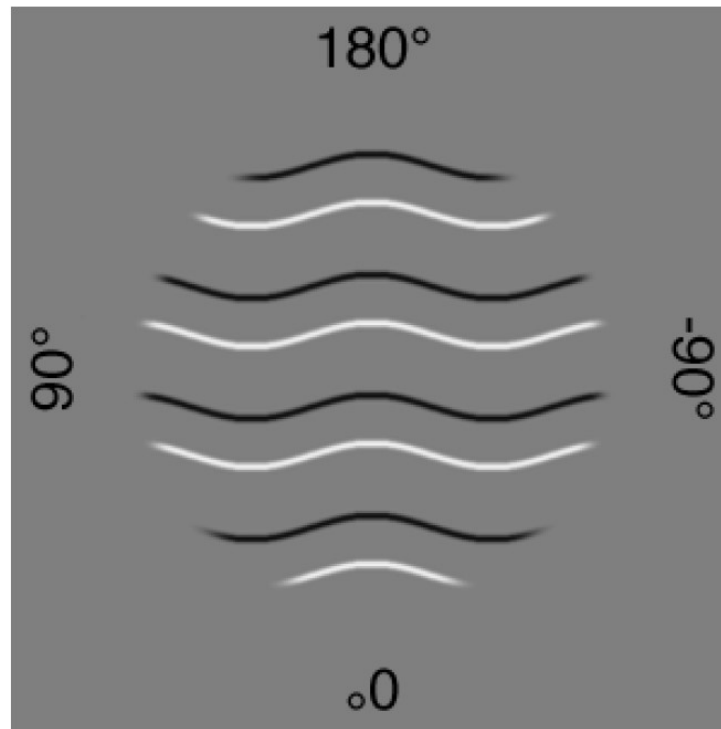


# Visual priors

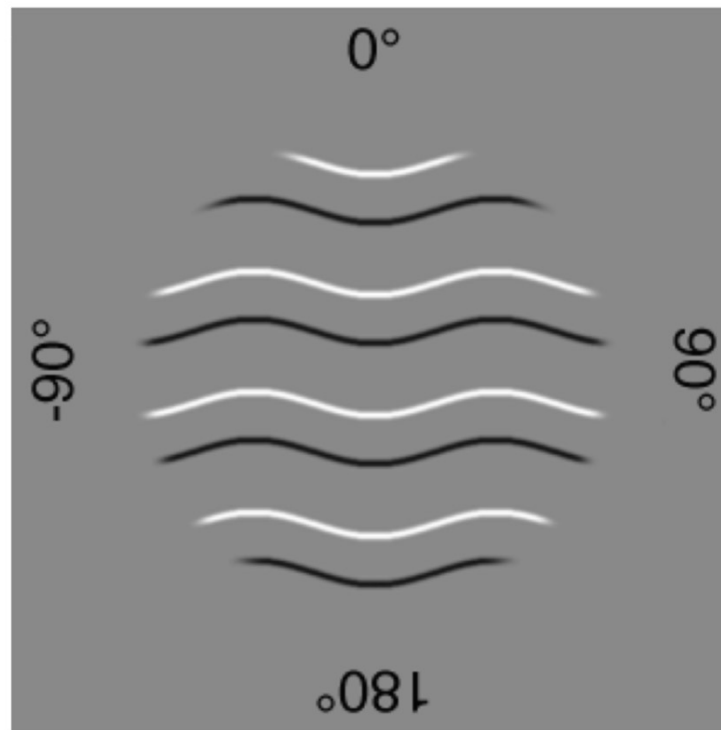
CS786

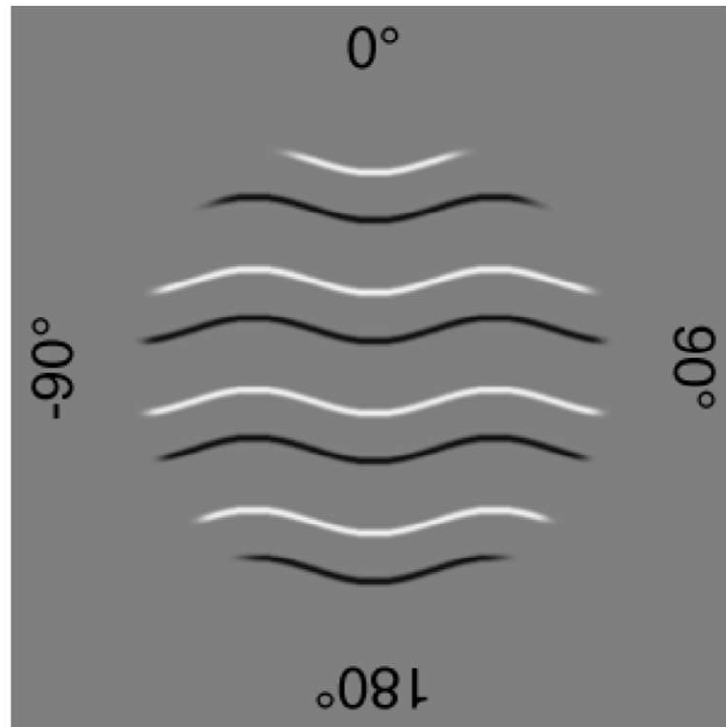
September 24<sup>th</sup> 2024

Which curves are raised?



Which curves are raised?

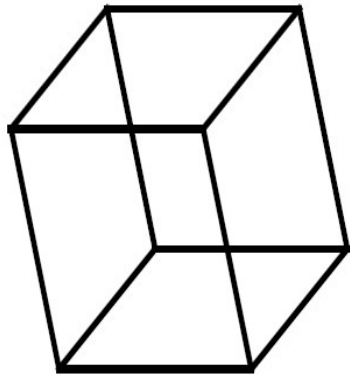




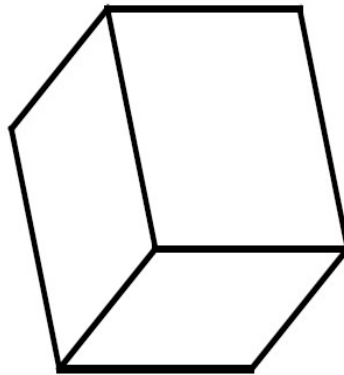
<http://www.psych.nyu.edu/maloney/MamassianLandyMaloney.MITPress2003.pdf>

# Vision uses more information than impacts the retina

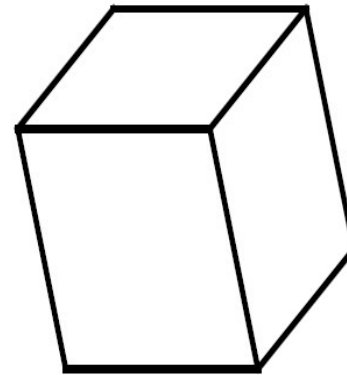
- What you see isn't exactly what you get



(A)

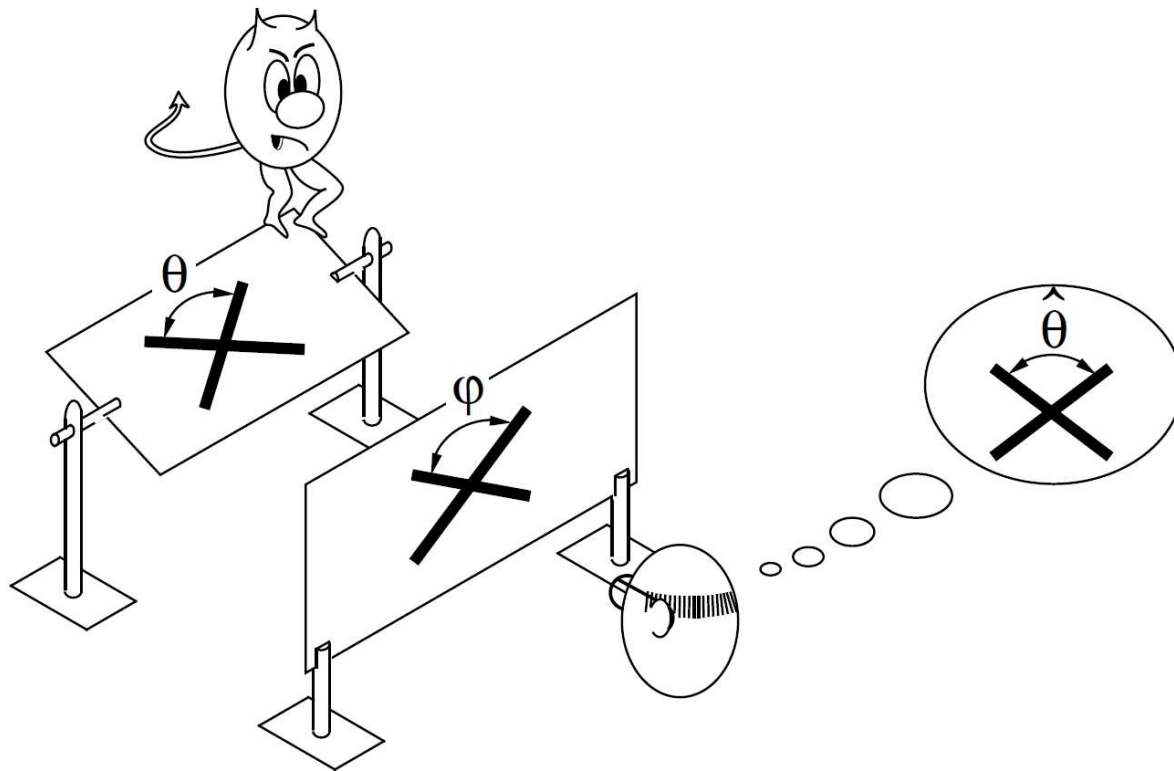


(B)



(C)

# Perception as inference



Want to know  $\theta$ , get to see  $\phi$

# Bayesian visual perception

- Observer constructs  $p(\theta | \phi)$  using
  - $p(\phi | \theta)$ , physiologically determined likelihood
  - $p(\theta)$ , visual priors on percepts
- Bayesian revolution in perception (Knill, 2004)
  - Using Bayesian analysis to estimate visual priors using behavior responses

# Bayesian prior estimation

- Regular sequential Bayes
  - Update prior by multiplying with likelihood
  - Obtain posterior
  - Use posterior as prior for next time step
- Inverse procedure
  - Know posterior distribution given all data
  - Divide posterior by data likelihood sequentially
  - Each obtained prior serves as posterior for earlier time step
  - Finally left with original prior



# Bayes 101

- $P(H | D)$  proportional to  $p(H)p(D | H)$ 
  - Basic Bayes claim
- We have a bunch of data  $D$
- And there are several possible  $h$  that can potentially account for the data
- With a Bayesian analysis, we can construct a probability  $p(H | D)$ 
  - Which hypothesis is most likely, given we've seen the data  $D$

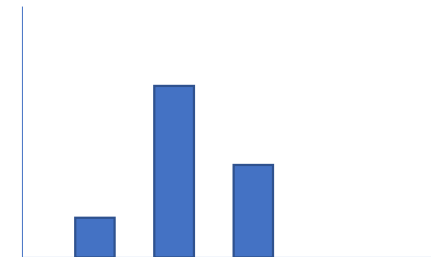
# Sequential Bayes 101

- Let's assume that the data are sequential  $D = \{d_1, d_2, \dots, d_n\}$
- $P(H | D(1:n))$  proportional to  $p(H | D(1:n-1))p(d_n | H)$ 
  - Prior is  $p(H | D(1:n-1))$
  - Likelihood is  $p(d_n | H)$

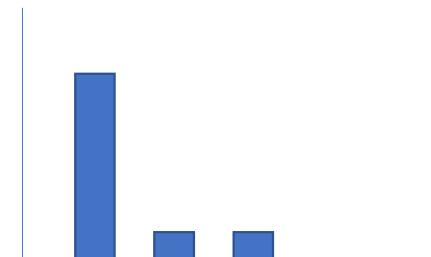
# Bayesian analysis

- 1,2,4,8,16 ....
- All natural numbers
- All powers of two
- Members of the table of two
- $d_6 = 31$

$P(H|D(1:5))$



$P(H|D(1:6))$

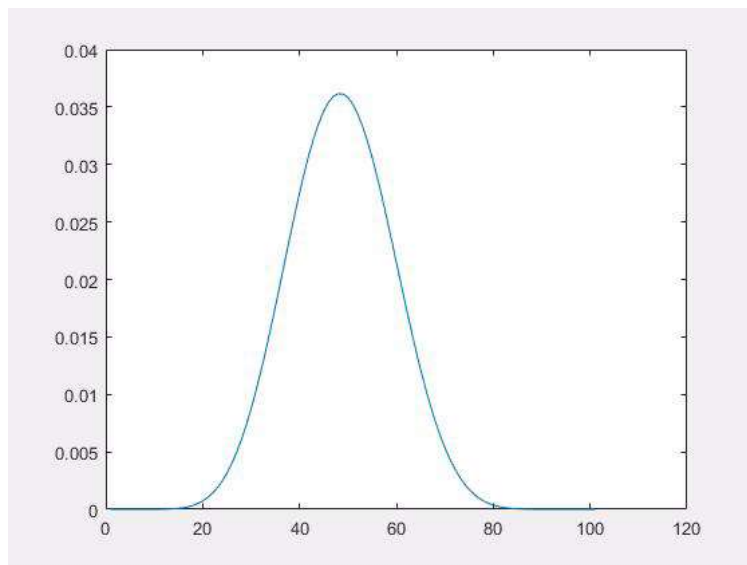


# Bayesian parameter estimation

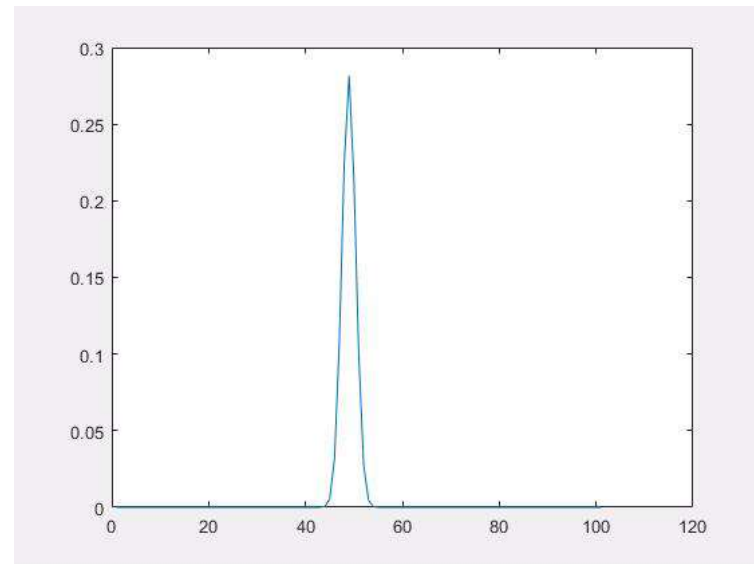
- Typically hard to obtain likelihoods for multiple sequential updates in closed form
- Alternative procedure
  - Generate posterior distributions using different parameters determining the prior
  - Find parameters that yield posterior distributions that best fit the true distribution
  - Frequently have to use some form of MCMC sampling

# Demo

String of binary observations modeled using binomial likelihood and beta prior

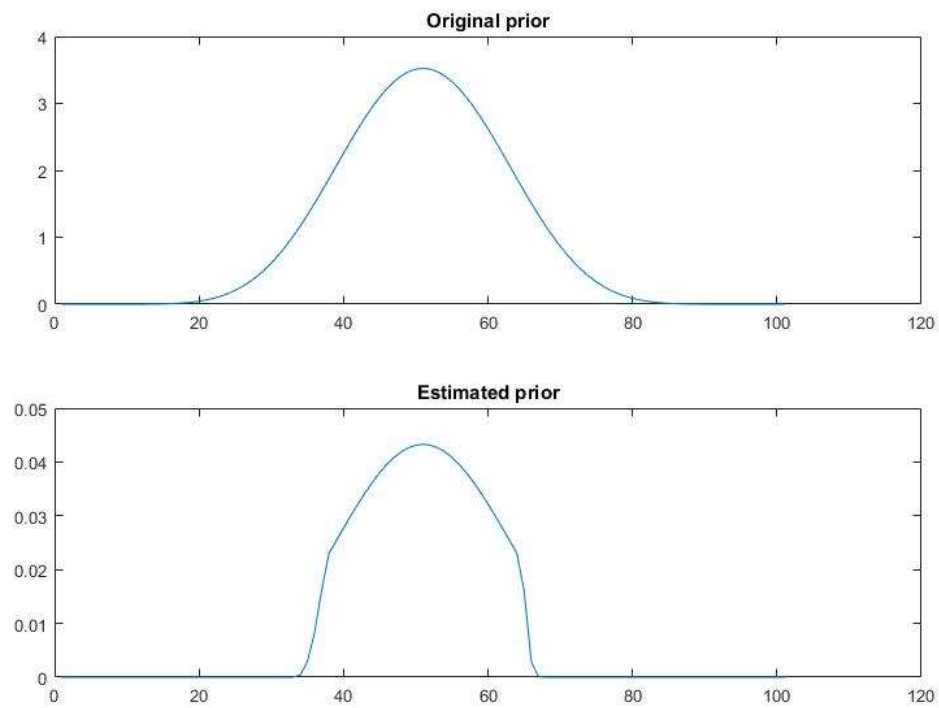


Posterior update

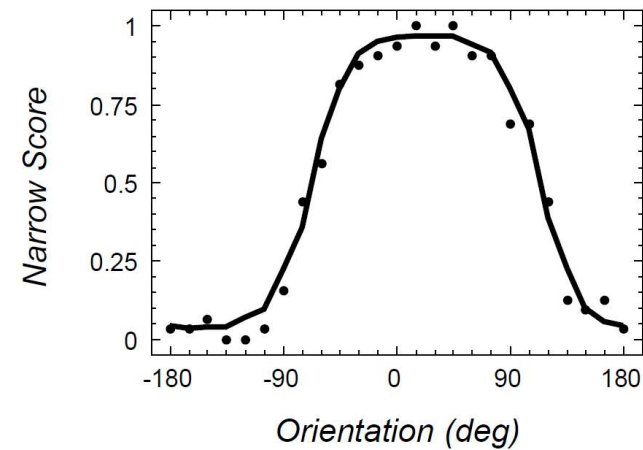
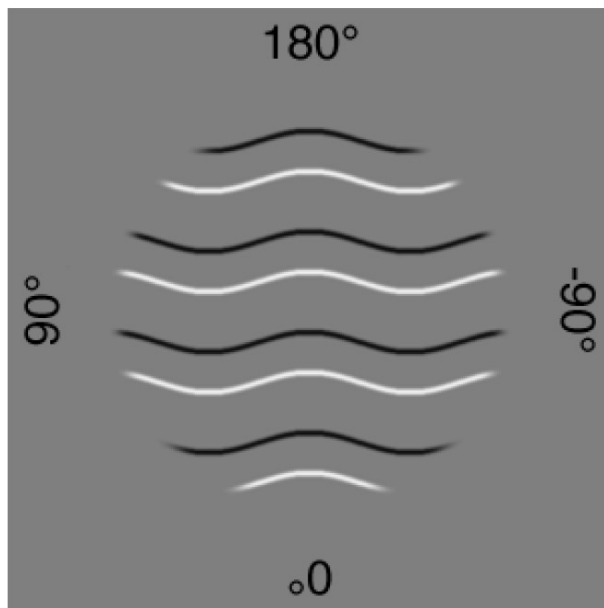


Prior estimation

# Prior estimation



# Applied to vision data



*Narrow score* = proportion of times image is described with bulging narrow ridges

<http://www.psych.nyu.edu/maloney/MamassianLandyMaloney.MITPress2003.pdf>

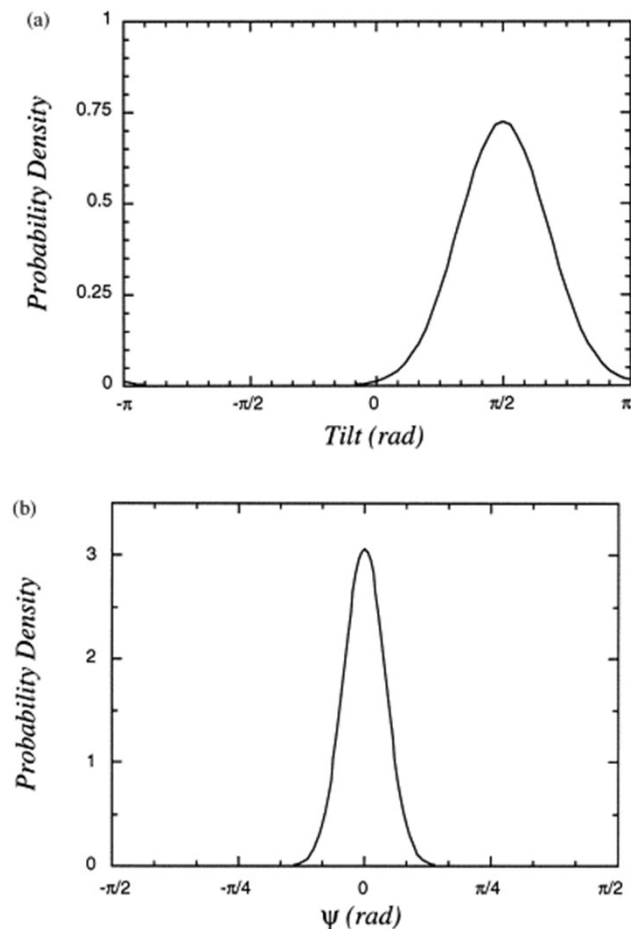
# Simplifying assumptions

- Response proportions assumed to reflect posterior probability  $p(\text{narrows} | \text{image})$
- Prior biases assumed to influence response independently
- Model illumination and viewpoint as drawn from a normal distribution on the respective angles

$$\int p(\text{narrows}, \text{illumination}, \text{viewpoint} | \text{stimulus}) d(\text{illumination}) d(\text{viewpoint}).$$



# Findings



- Illumination angles are *a priori* assumed to be above and to the left
  - Increasing shading contrast reduces the variance of the illumination prior
  - Increasing contour contrast reduces the variance of the viewpoint prior
- In other experiments, shown that
  - People think they are looking at objects from above
  - People think angles are *a priori* likely to be right angles
  - And many more

# What does it mean?

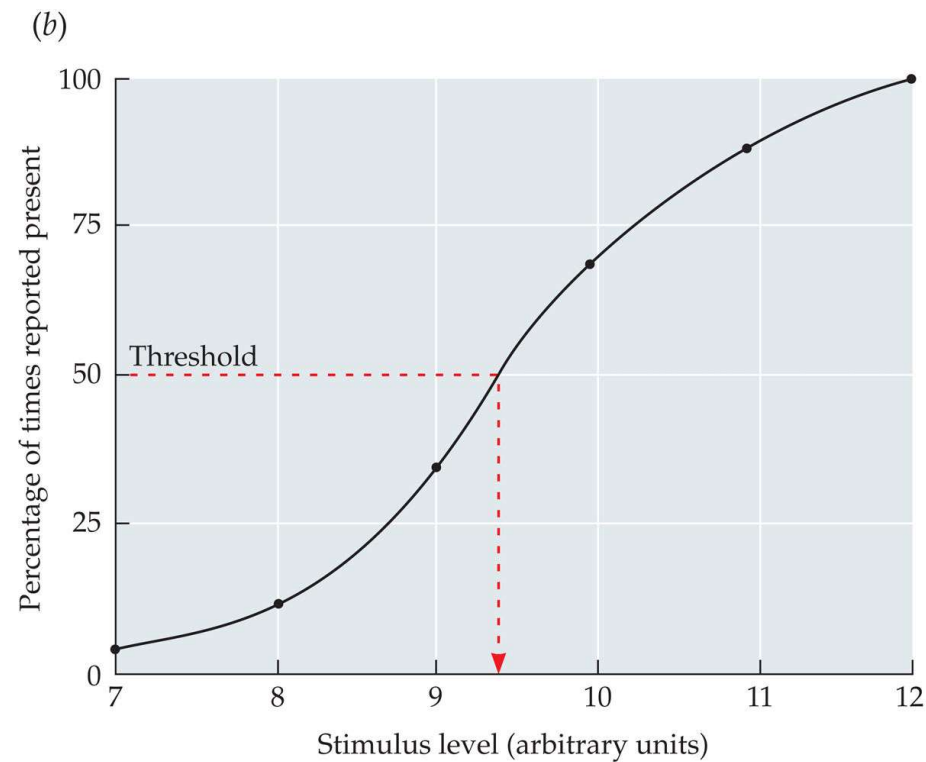
- Bayesian models of visual perception give us a way of *describing* the priors that people use
- But they don't explain *how* the priors come to be the way they are
- Positives: can describe both perceptual and cognitive priors
- Negatives: Hard to characterize the true provenance of empirically determined priors

# Perceptual Learning

From priors to posteriors

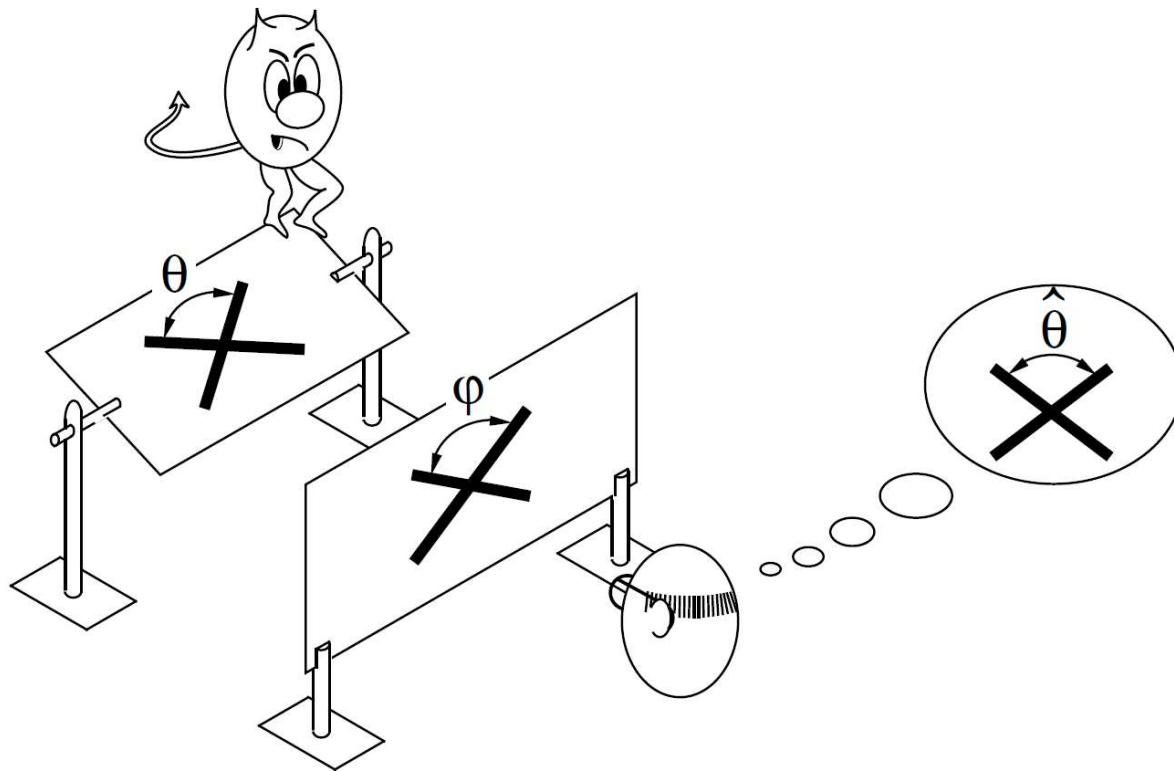
# Absolute Thresholds

Psychometric function demonstrating the probabilistic (statistical) nature of the threshold



SENSATION & PERCEPTION 4e, Figure 1.6 (Part 2)  
© 2015 Sinauer Associates, Inc.

# Perception as inference



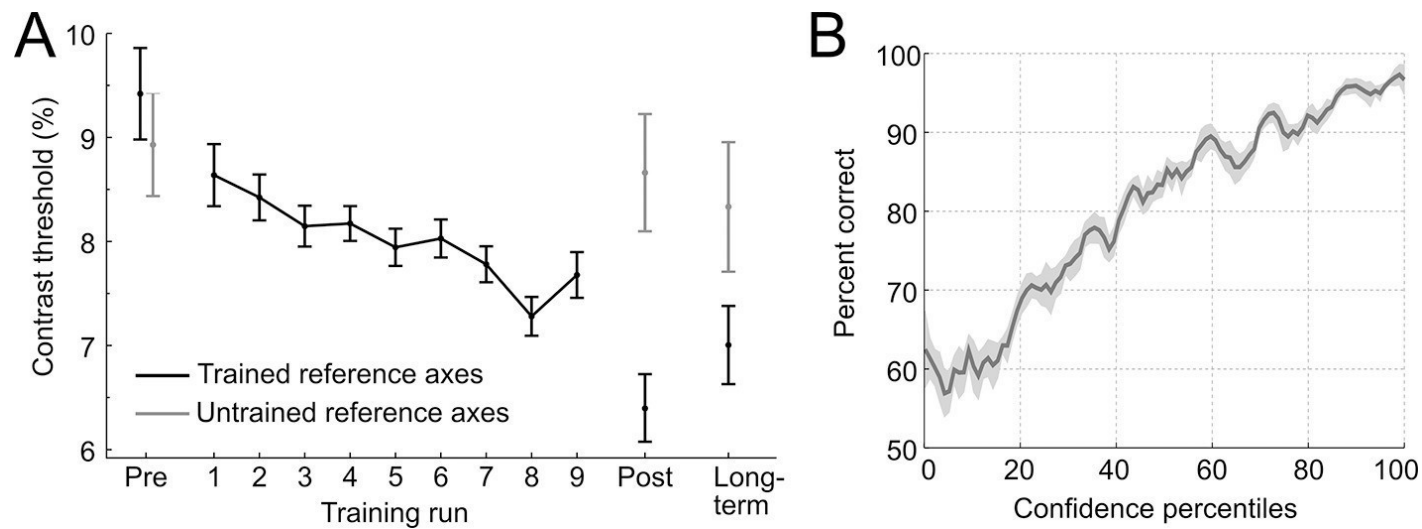
Want to know  $\theta$ , get to see  $\phi$

# Can perceptual ability improve?

- Classic psychophysics imagined perception to be governed by absolute limits
- Signal detection theory was developed to measure these limits
- Visual perception research shows
  - Perception strongly influenced by prior knowledge
  - Question: how does this influence work?
- Evidence for perceptual learning presents some hypotheses

# Perceptual learning

- Perceptual discrimination improves with training



(Guggenmos, Wilbertz, Hebart & Sterzer, 2016)

# Practice makes perfect

- <https://www.youtube.com/watch?v=Qzhs1Z8Rwnk>



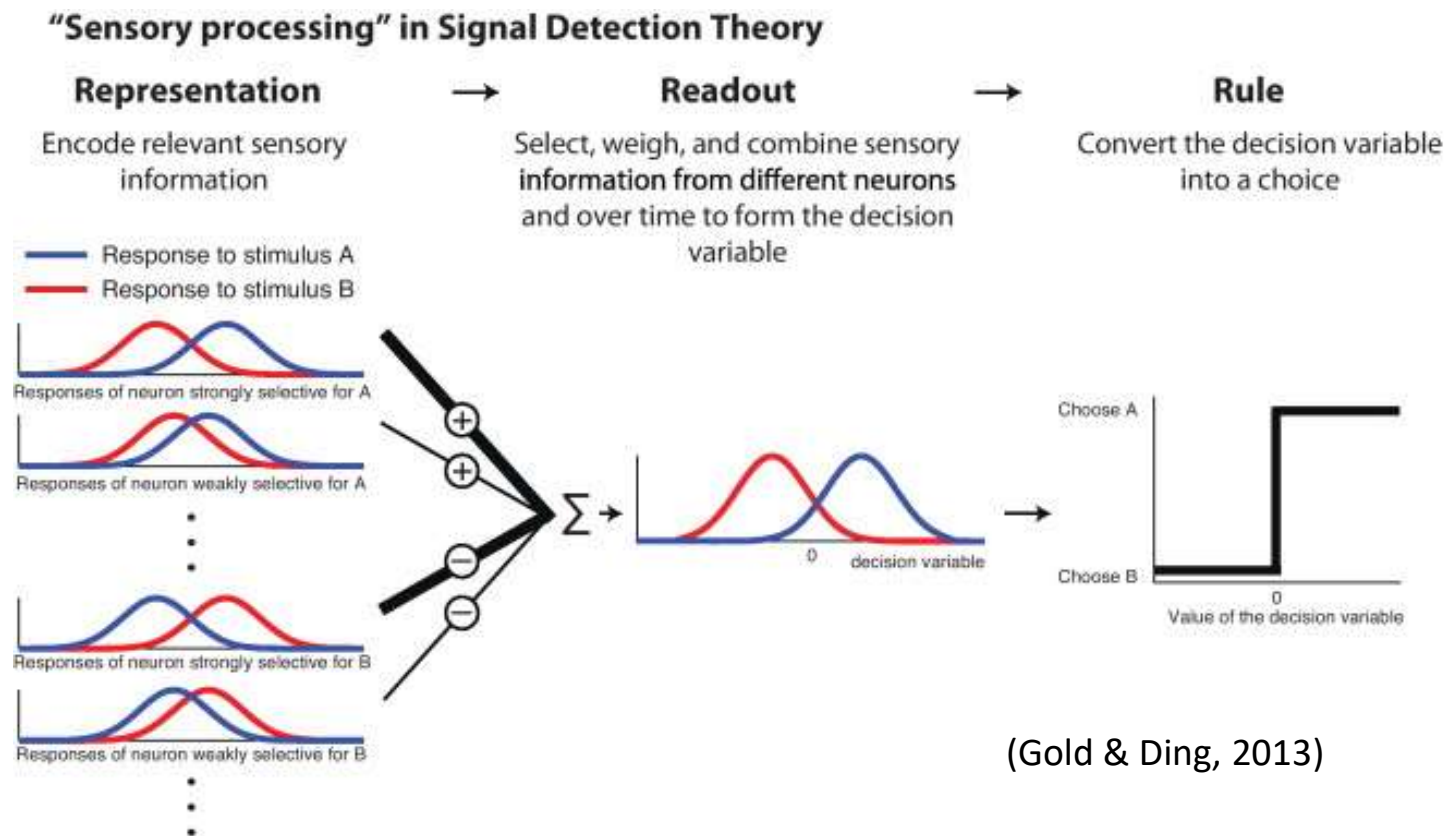
# Hypotheses

- Attentional weighting
  - Observers learn to attend to discriminative features of stimuli
- Stimulus imprinting
  - Detectors developed that are specialized for stimuli
- Differentiation
  - Perceptual adaptation by the development of increasingly differentiated object representations
- Unitization
  - Development of sensory units that are triggered when a complex configuration occurs

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# Perceptual learning as improved decision-making



# Motion coherence and MT neurons

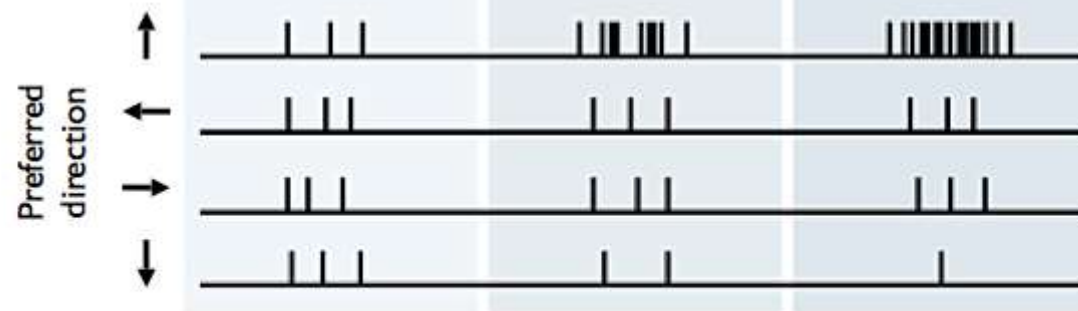
Motion stimulus

no coherence

50% coherence

100% coherence

Responses of  
MT neurons



# The dataset

- Recorded spiking response of neurons in monkey LIP cortex
- Neurons responsive to different motion directions
- Measured behavioral and neural data across multiple sessions (e.g. 165 sessions over 645 days for monkey C)

