# The 'Bayesian Brain'

Readings:Knill & Pouget, TINS, 2004

#### Uncertainty everywhere

- Humans and other animals operate in a world of sensory uncertainty:
- e.g. mapping of 3D objects to 2D image
- intrinsic limitations of the sensory systems (e.g. number and quality of receptors in the retina)
- neural noise
- --> multiple interpretations about the world are possible;

• The brain must deal with this uncertainty to generate perceptual representations and guide actions.

• Perception as unconscious, probabilistic inference







#### Are Humans Bayes - optimal?

• Humans not optimal / achieving the level of performance afforded by the uncertainty in the physical stimulus (e.g. movies)

#### • The question is:

Do the neural computations take into account the uncertainty at each stage of processing?

• Bayesian hypothesis makes a lot of testable predictions on how different sources of uncertainty should be integrated. Valid?



Cue Integration (2):Theory
Theory tells us how posterior depends on individual likelihoods:
$\hat{x} = \mathrm{argmax}_x P(x d_1, d_2)$
$P(x d_1, d_2) = \frac{P(d_1, d_2 x)P(x)}{P(d_1, d_2)} \propto P(d_1 x)P(d_2 x)P(x)$
• Assuming that the likelihood are gaussian, i.e. $P(d_1 x) \propto \exp(-\frac{(d_1-x)^2}{2\sigma_1^2})$
• We can determine mean and width of posterior (gaussian):
$P(d_1 x)P(d_2 x) \propto \exp(-\frac{(d_1-x)^2}{2\sigma_1^2} - \frac{(d_2-x)^2}{2\sigma_2^2}) \propto \exp\left[\frac{\left[x - \frac{\sigma_2^2 d_1 + \sigma_1^2 d_2}{\sigma_1^2 + \sigma_2^2}\right]^2}{2\sigma_1^2 \sigma_2^2 / (\sigma_1^2 + \sigma_2^2)}\right]$



• If we know mean estimate and variance for each modality in isolation, we can deduce mean of bimodal estimate:

$$\mu = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2} d_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} d_2$$

• and discrimination threshold

$$T_{1,2}^2 \propto \sigma_{1,2}^2 = \sigma_1^2 \sigma_2^2 / (\sigma_1^2 {+} \sigma_2^2)$$

smaller than 1 or 2 alone

pushed

towards more reliable cue















#### Interpreting motion (3): the aperture problem

- More complex stimuli can be constructed, by adding more segments of ambiguous motions, e.g. plaid, or rhombus.
- How is the system going to integrate the different possible interpretations?
- classical models: intersection of contraints (IOC), Vector Averaging
- (VA), feature tracking.
- donnot capture the complexity of available data.



### interpreting motion : A Prior on Low Speeds (2)

• provides a very simple model which explains a large variety of psychophysical effects / perception of plaids, rhombus and plaids, barber pole and effects of contrast [Weiss et al, 2004]

- Thomson effect: humans tend to underestimate speed at low contrast (why drivers tend to speed up in the fog)
- Stocker & Simoncelli (2005) measure the shape of the prior.
- illusions as 'optimal percepts'.

- Interpreting motion : A Prior on Low Speeds (1)
- Hypothesis: humans tend to favor slower motions
- Use a (gaussian) prior on low speeds (centered at 0).





#### Neural implementation ?

- How do populations of neurons represent uncertainty ?
- Does neural activity represent probabilities? (log probabilities?)
- Can we distinguish stages where the likelihoods, priors, posterior could be 'measured' experimentally ?
- Can networks of neurons implement optimal inference?
- How can we discover the priors used by the brain?
- How can a prior be implemented? (baseline spontaneous activity, number of neurons, gain, <u>connectivity?</u>).
- Recently, active topic of theoretical research (A. Pouget, S. Deneve,
- P. Dayan, R. Rao).
- promising direction for PhD project :-)

# Thanks !

## Bayes' Theorem

• Bayes' theorem is a result in probability theory that relates conditional probabilities P(AIB) and P(BIA)

• Given the likelihood and the prior, we can compute the posterior.

$$P(h_1|e) = \frac{P(e|h_1)P(h_1)}{P(e)}$$

 $posterior = \frac{likelihood \times prior}{normalizing \ constant}$ 



Reverend Thomas Bayes, 1702- 1761