

Bayesian Models of Perception

Dr. Frederike Petzschner

Brown University

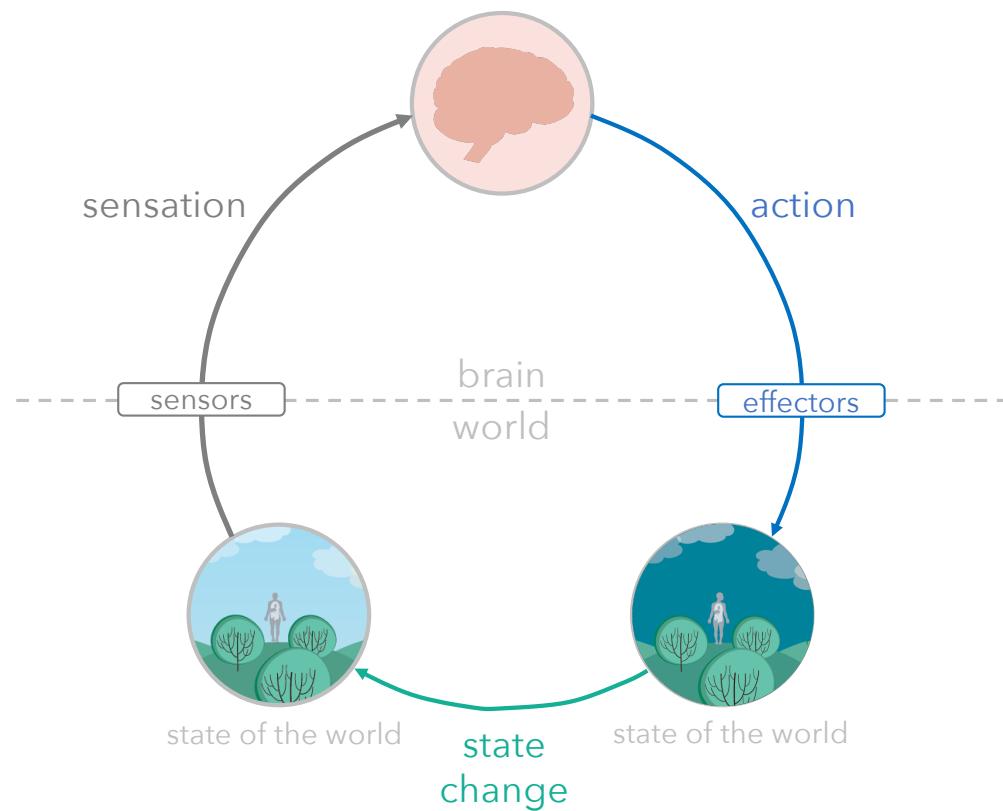
 [@rikepetzschner](https://twitter.com/rikepetzschner)

[@pea**lab**](https://pea.brown.edu)

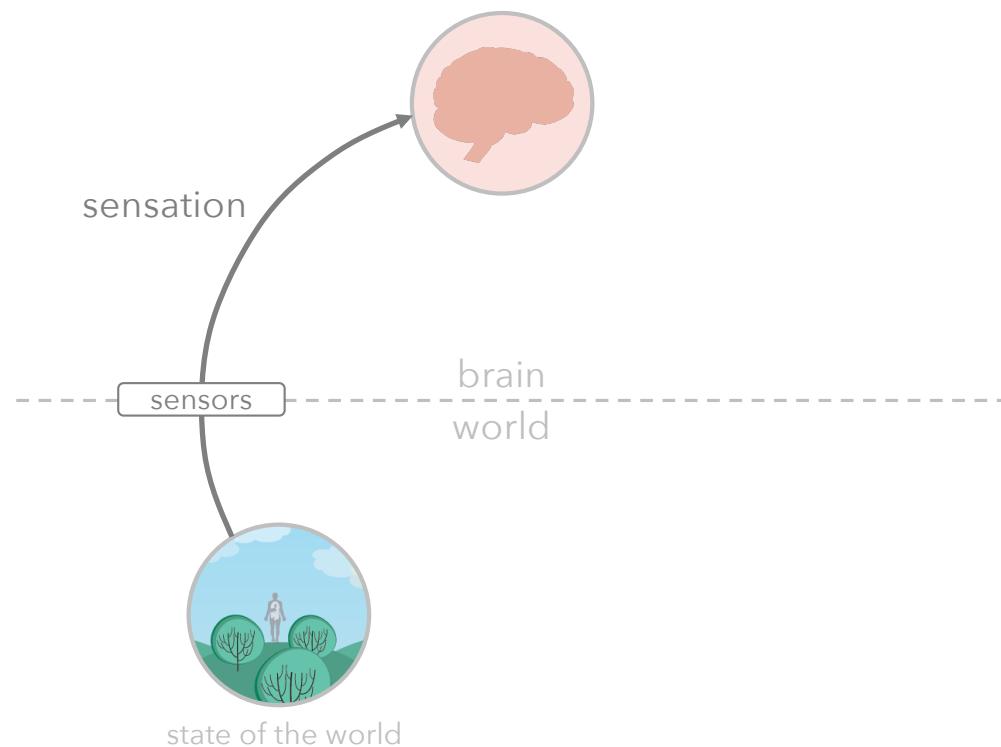


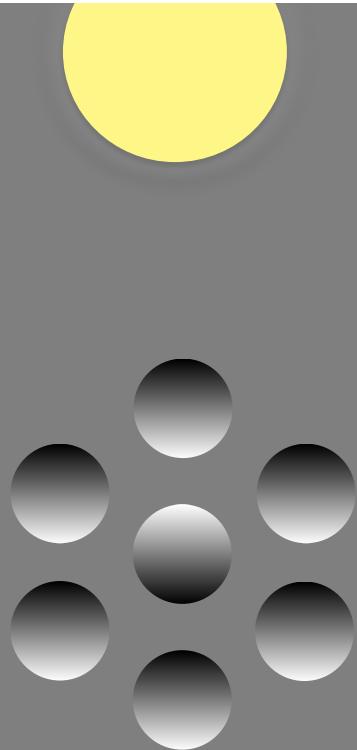
**What is the computation that is carried out when
we perceive something?**

What is perception?

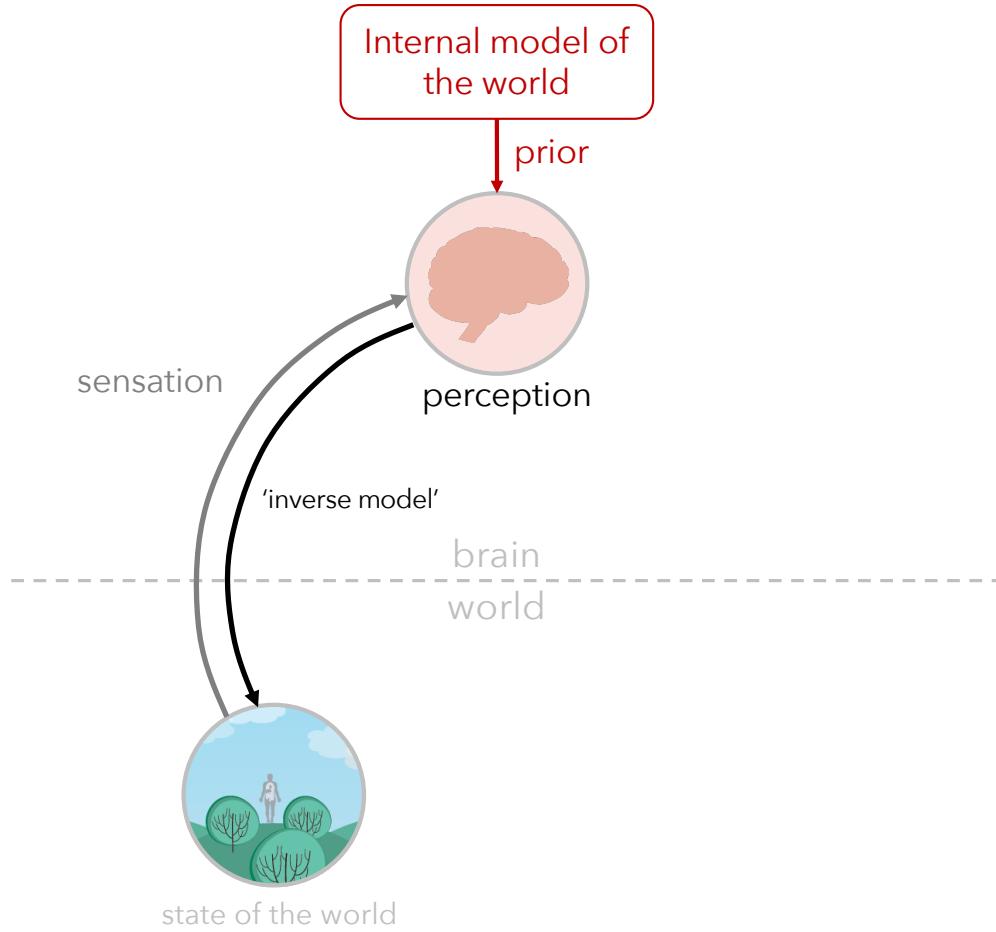


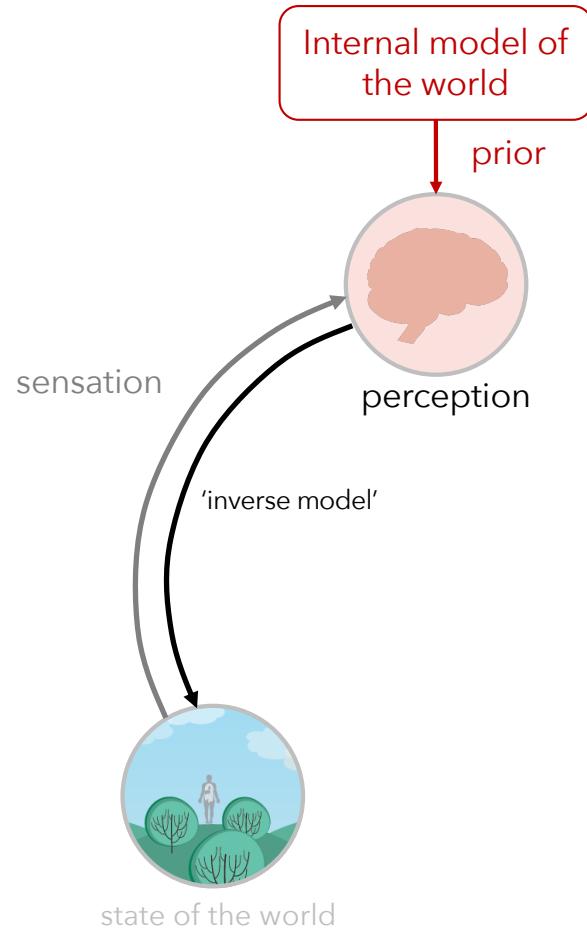
What is perception?



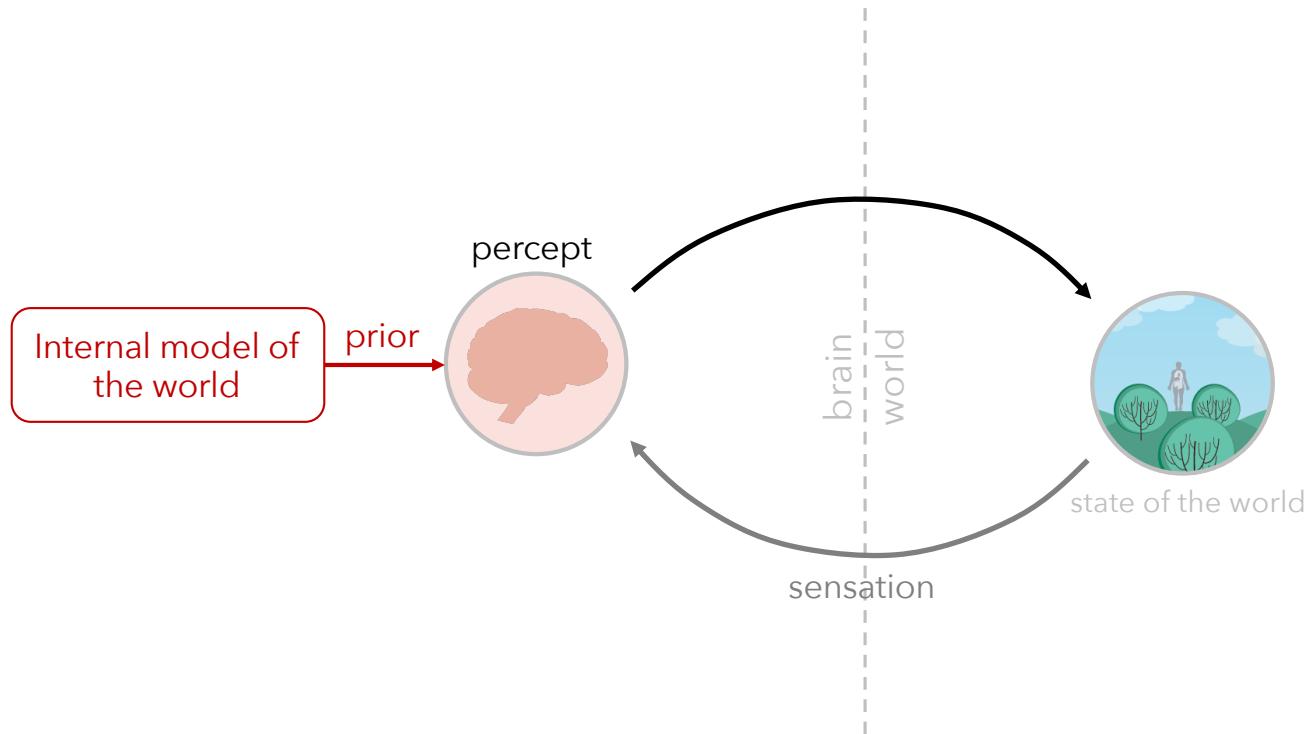


Adams et al., Nature Neuroscience, 2004





Perception as inference



The percept reflects a combination of sensory information and prior expectations about the world.

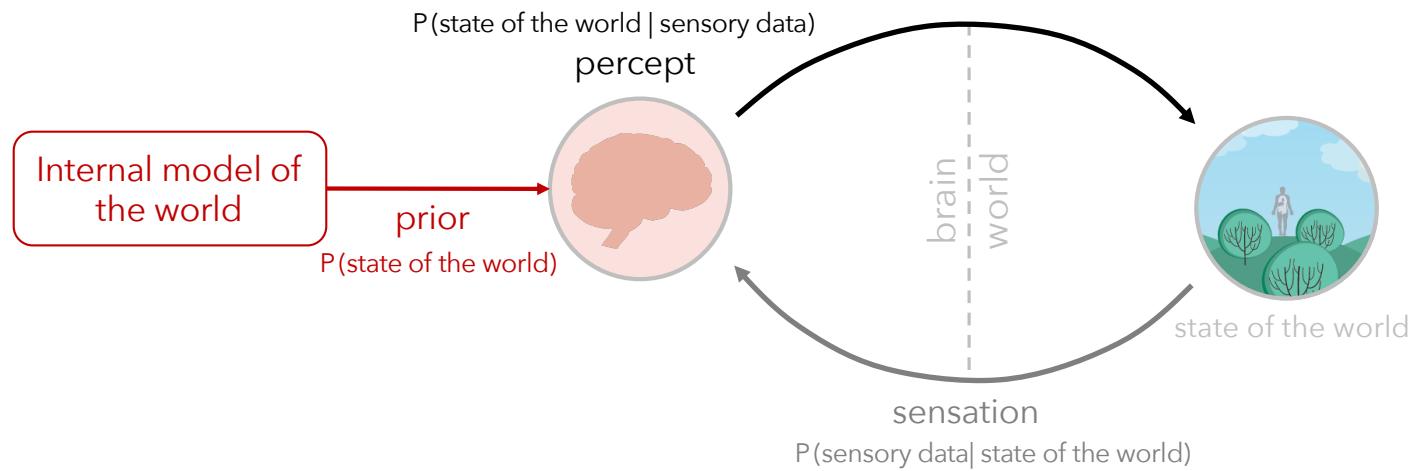
Why?



A Bayesian model of perception

Perception as Bayesian inference

Noisy information can be expressed by probability distributions



Bayes' Rule

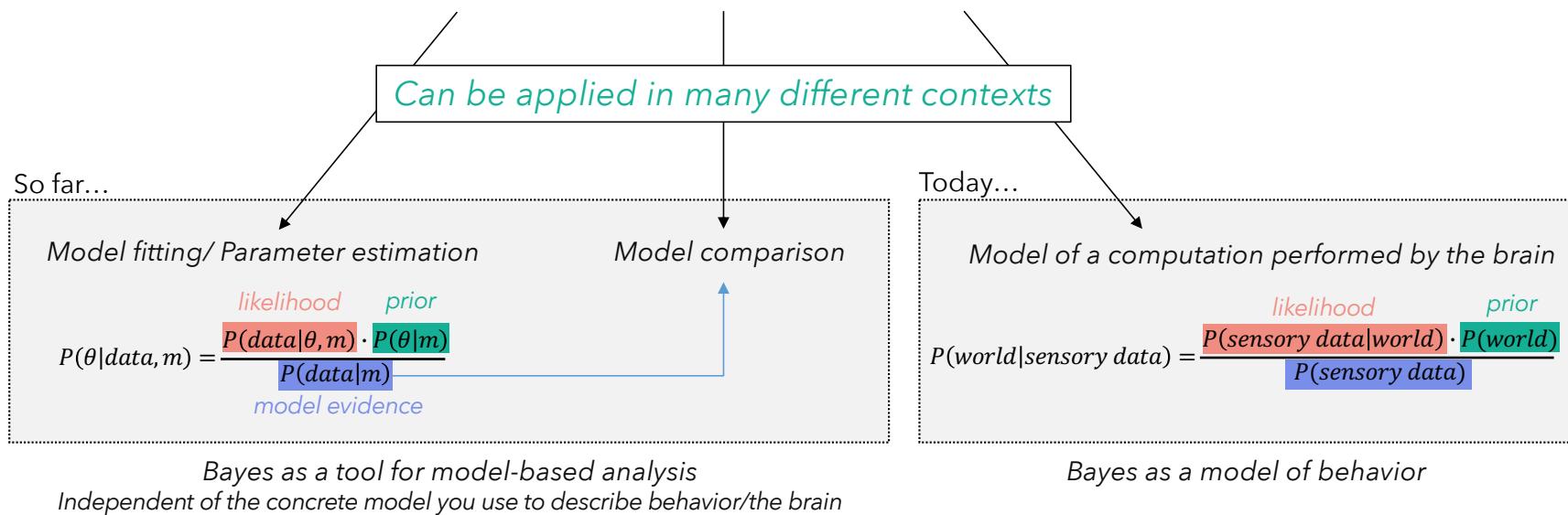
$$P(state|sensory\ input) = \frac{\text{likelihood} \quad \text{prior}}{\text{posterior}}$$
$$P(state|sensory\ input) = \frac{P(sensory\ input|state) \ P(state)}{P(sensory\ input)}$$

Side note

Avoiding confusion: Bayes versus Bayes

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad \text{Bayes' Theorem}$$

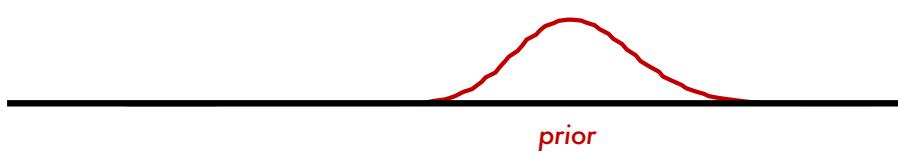
Statistical rule describing the relationship between conditional probability distributions



Example

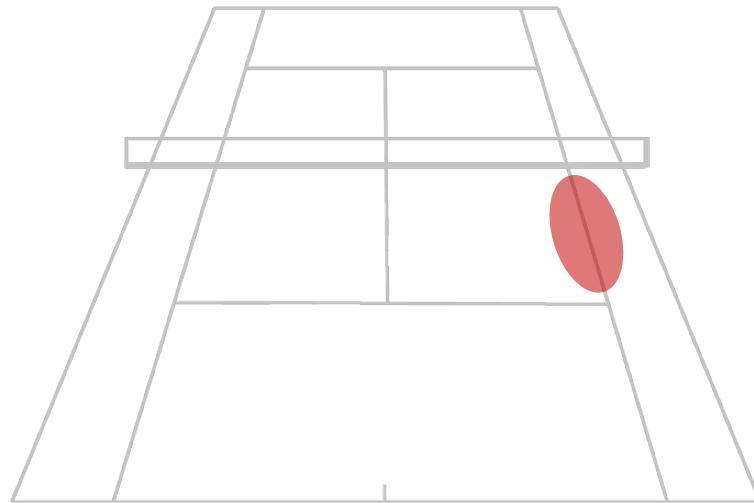


Information extraction with Bayes' Rule

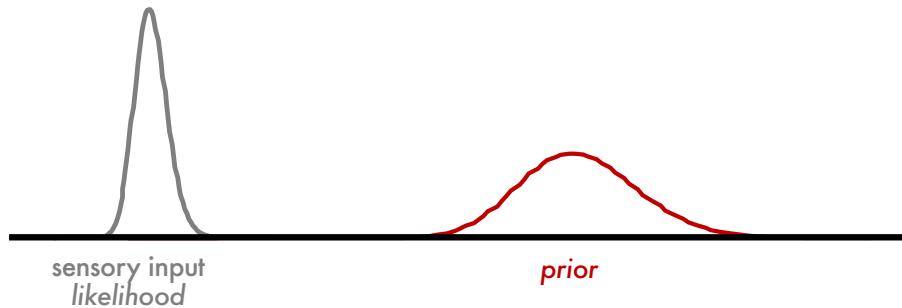


Bayes' Rule

$$P(state|sensory\ input) = \frac{likelihood \quad prior}{posterior} = \frac{P(sensory\ input|state) P(state)}{P(sensory\ input)}$$

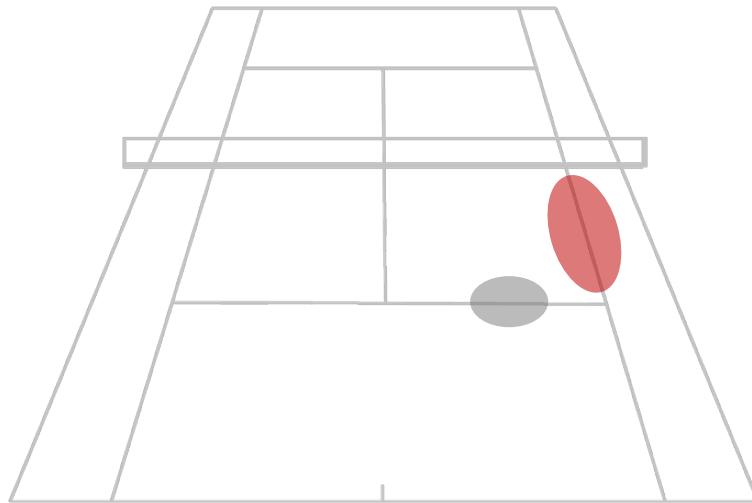


Information extraction with Bayes' Rule

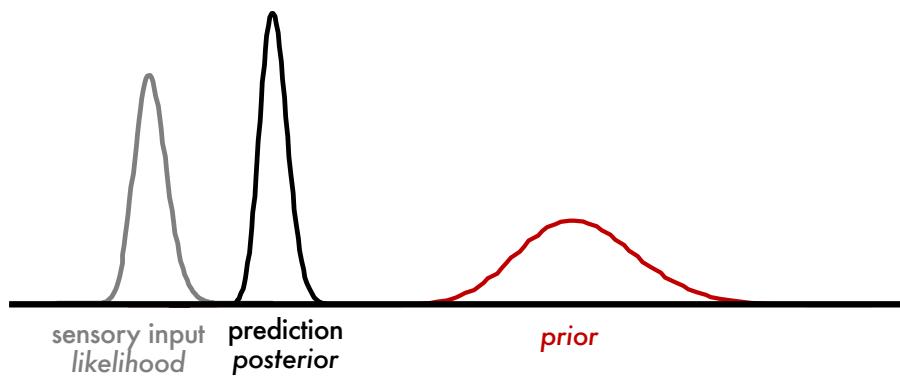


Bayes' Rule

$$P(state|sensory\ input) = \frac{likelihood \ P(state)}{posterior}$$

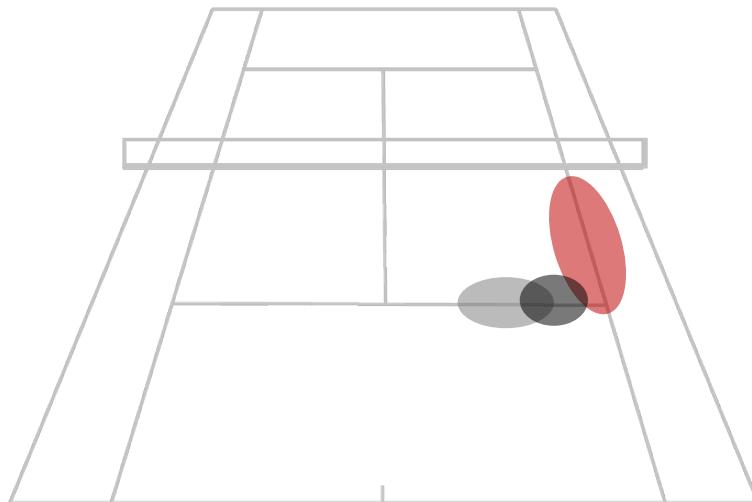


Information extraction with Bayes' Rule



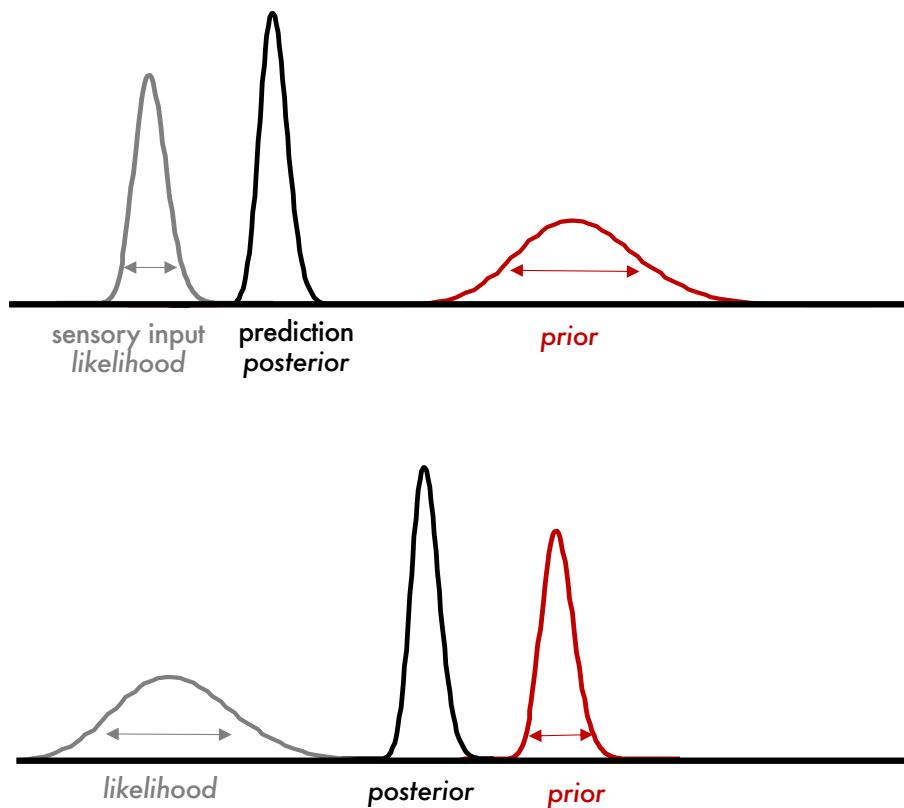
Bayes' Rule

$$P(state|sensory\ input) = \frac{P(sensory\ input|state) P(state)}{P(sensory\ input)}$$



Körding & Wolpert, Bayesian integration in sensorimotor learning, Nature, 2004

How Bayes' Rule deals with uncertainty



Bayes Rule:

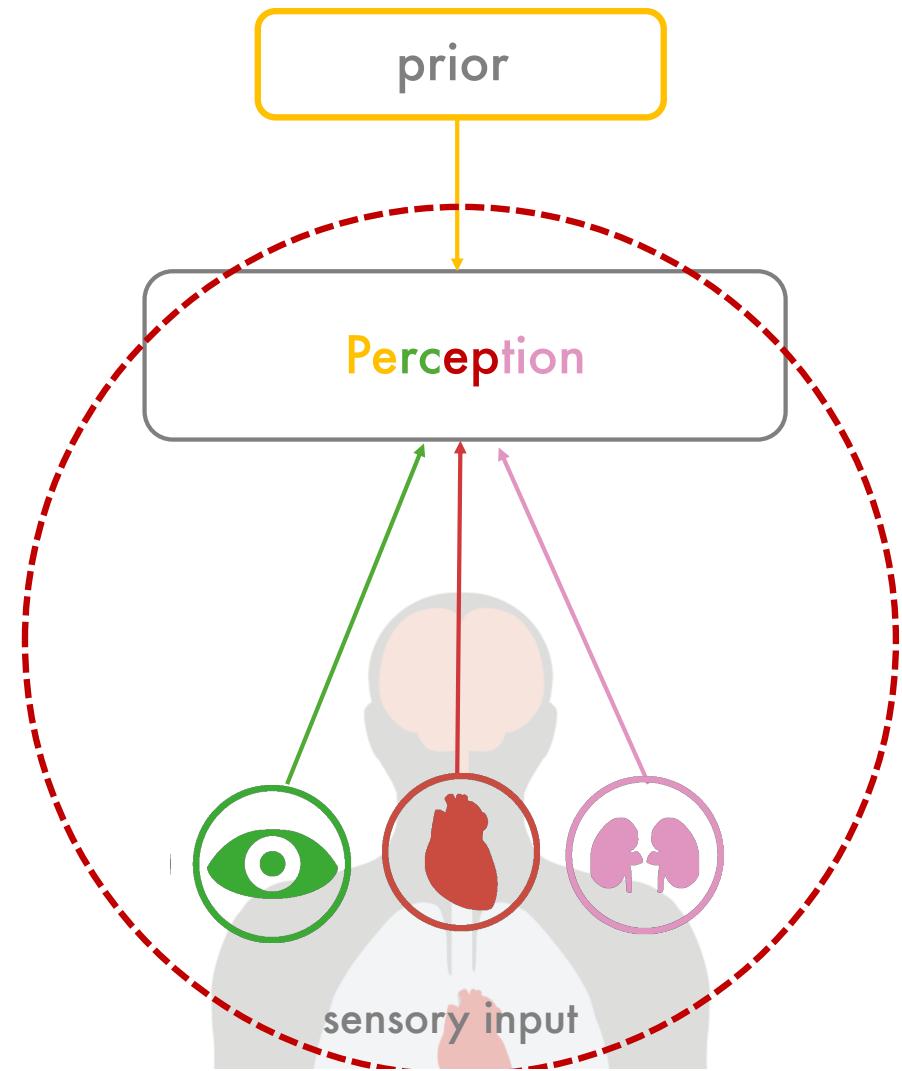
Optimal combination of uncertain information sources

If Gaussian distributions:

$$\mu_{\text{posterior}} = w_{\text{sens}} \cdot \mu_{\text{sens}} + w_{\text{prior}} \cdot \mu_{\text{prior}}$$

$$\sigma_{\text{posterior}}^2 = \frac{\sigma_{\text{sens}}^2 \cdot \sigma_{\text{prior}}^2}{\sigma_{\text{sens}}^2 + \sigma_{\text{prior}}^2}$$

Bayesian model of perception applied



Current Biology, Vol. 14, 257–262, February 3, 2004, ©2004 Elsevier Science Ltd. All rights reserved. DOI 10.1016/j.cub.2004.01.029

The Ventriloquist Effect Results from Near-Optimal Bimodal Integration

David Alais^{1,2} and David Burr^{1,3,*}

Results for the various unimodal location discrimina-

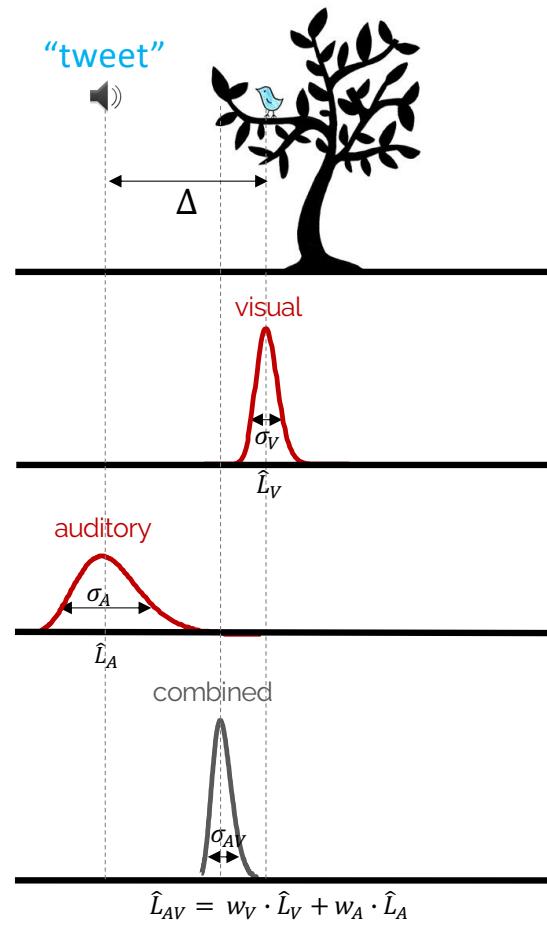
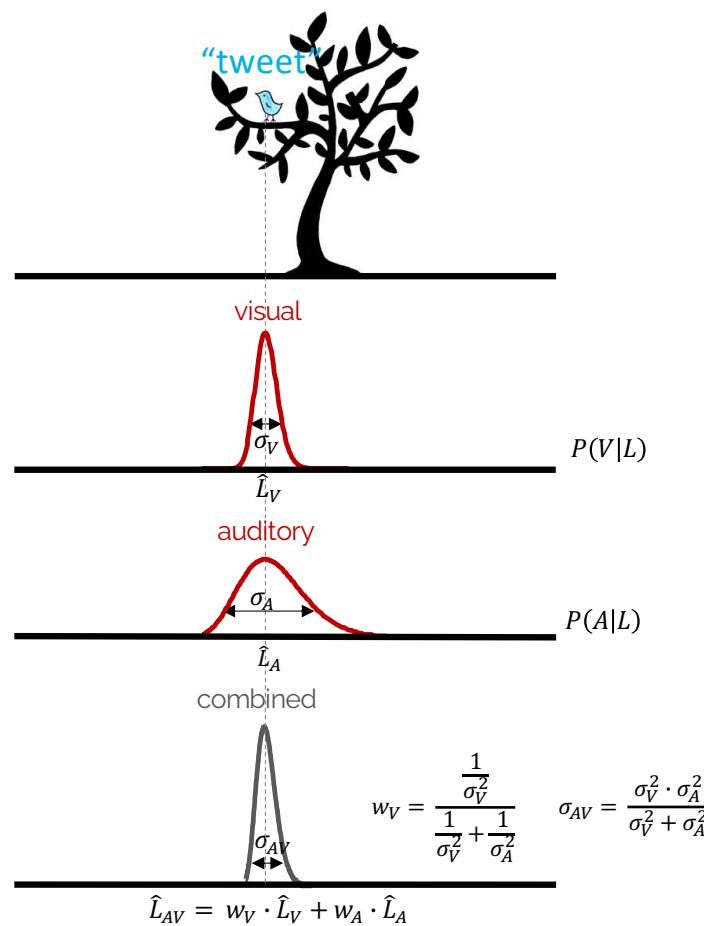
.....
Humans integrate visual and haptic information in a statistically optimal fashion

Marc O. Ernst* & Martin S. Banks

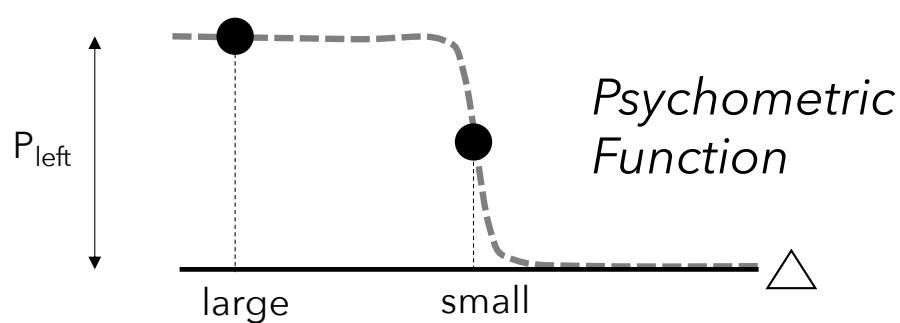
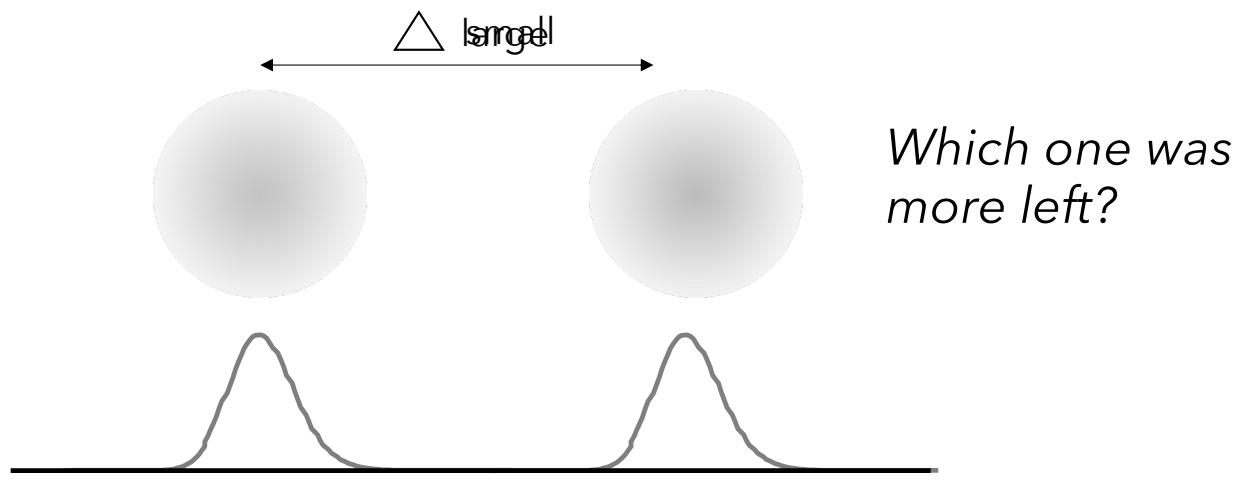
*Vision Science Program/School of Optometry, University of California, Berkeley
94720-2020, USA*

.....

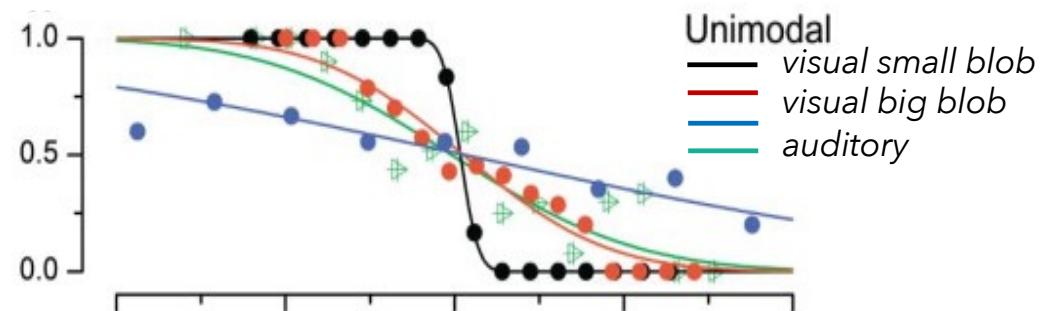
Combination of visual and auditory information



The Psychometric Function

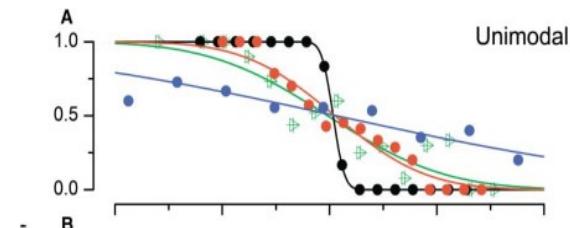
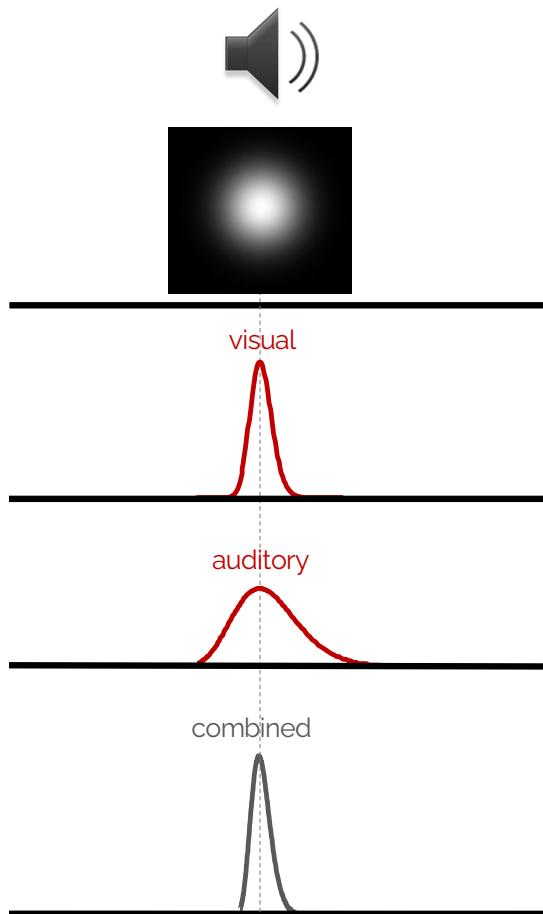


Psychometric
Function

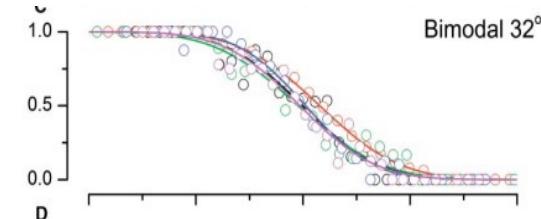
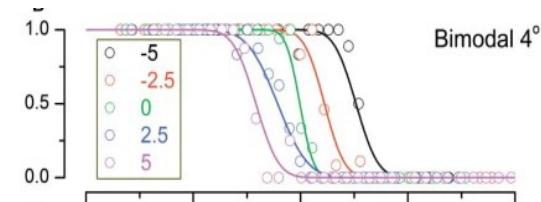


Alais & Burr, Current Biology, 2004

Combination of visual and auditory information



$$\sigma_{AV} = \frac{\sigma_V^2 \cdot \sigma_A^2}{\sigma_V^2 + \sigma_A^2}$$



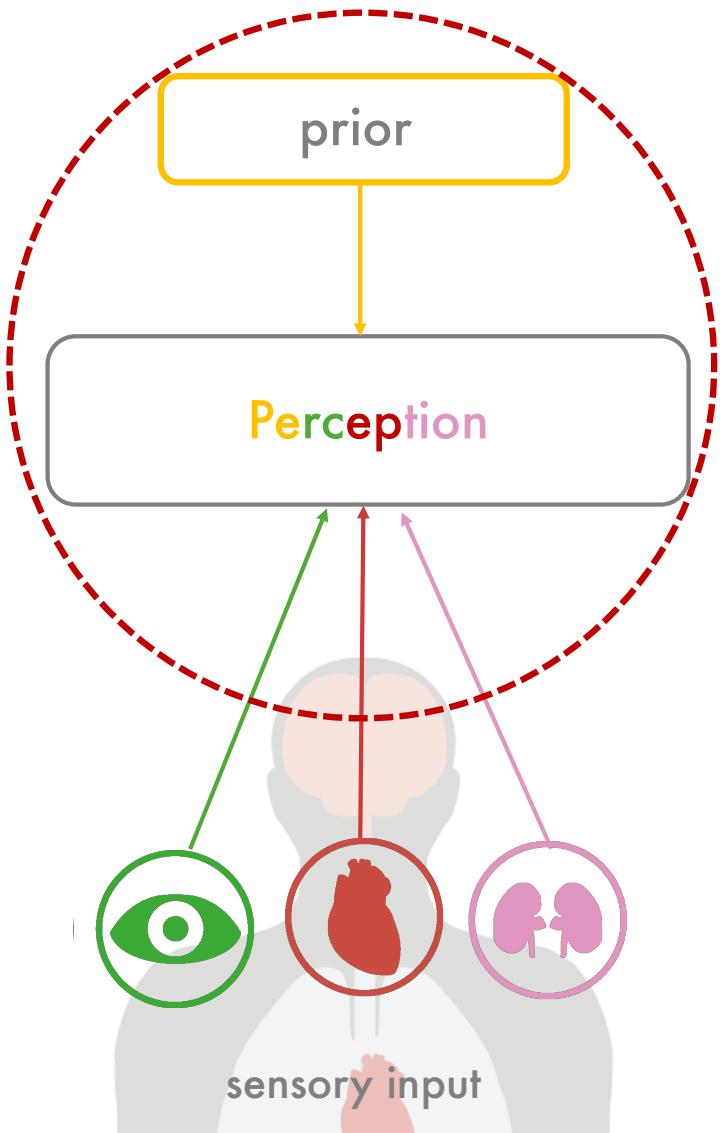
Alais & Burr, Current Biology, 2004



BAR



FAR

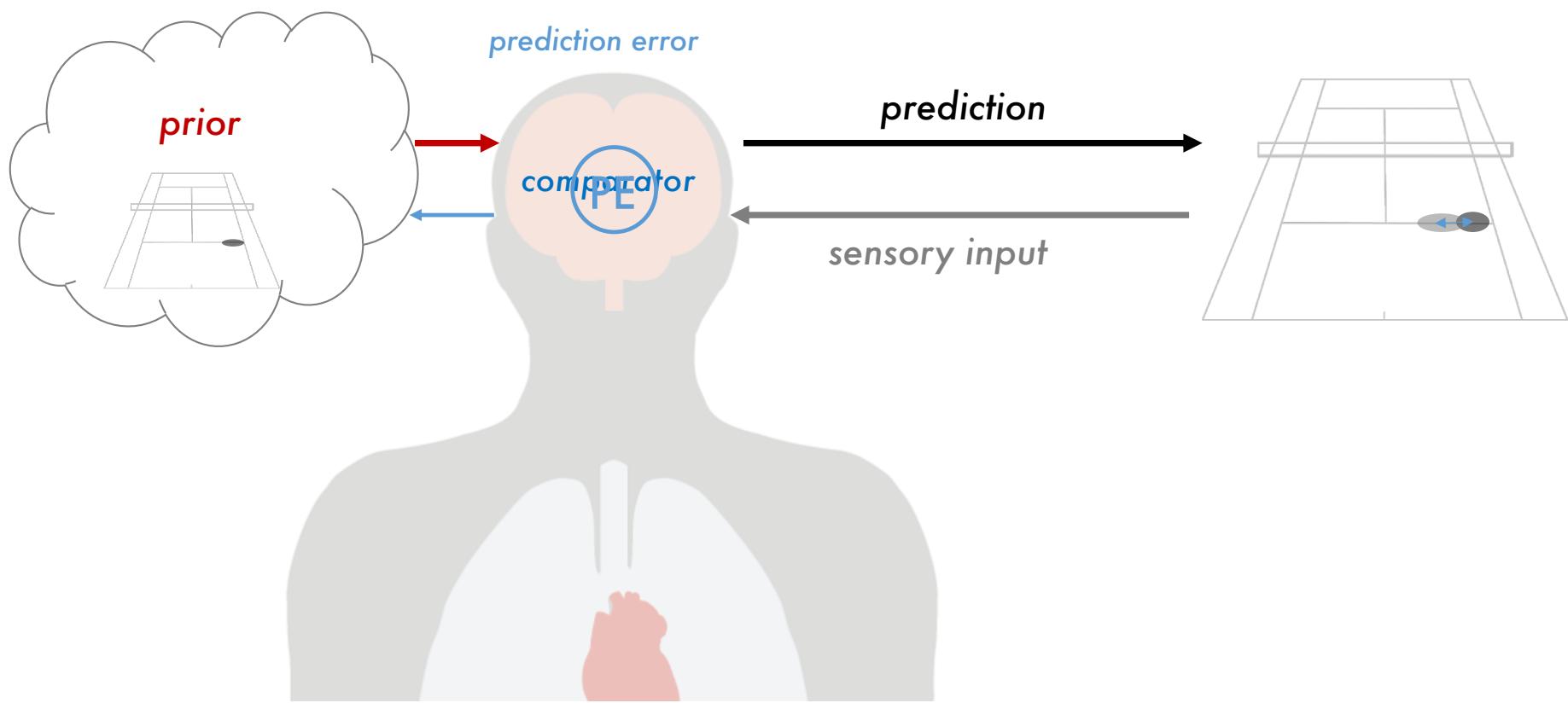


Priors can be learned...

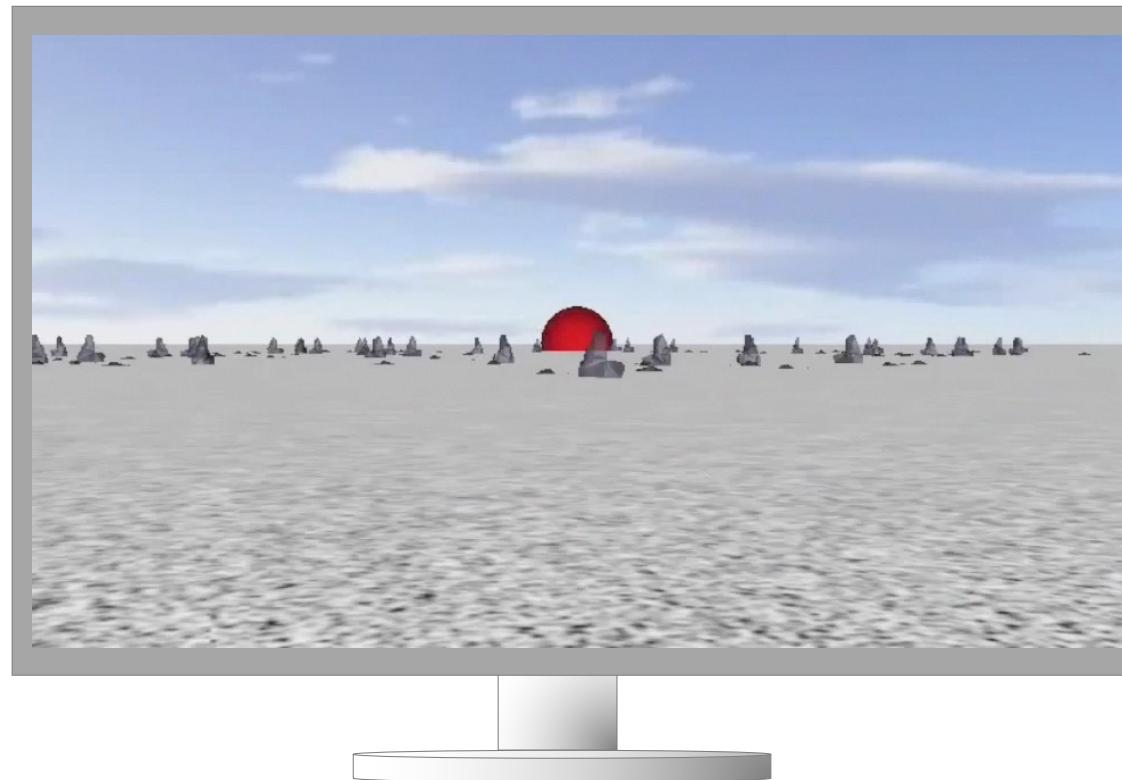


Learning the prior

Belief update

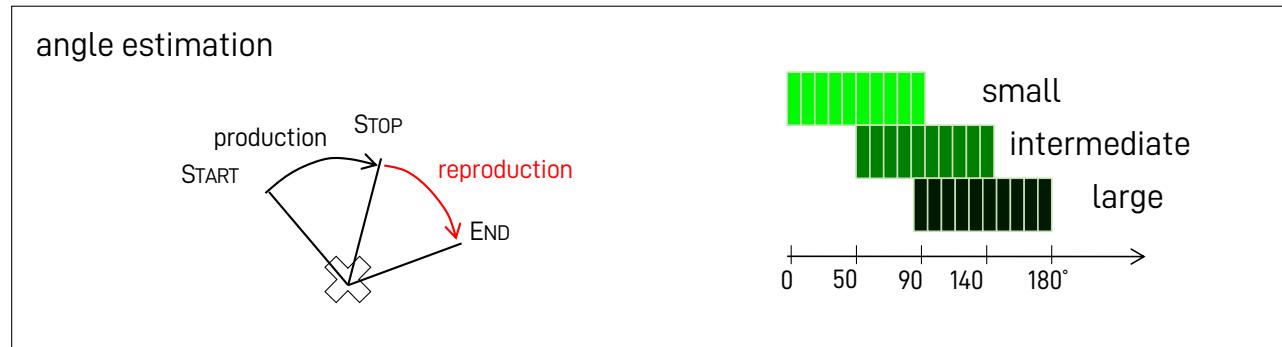
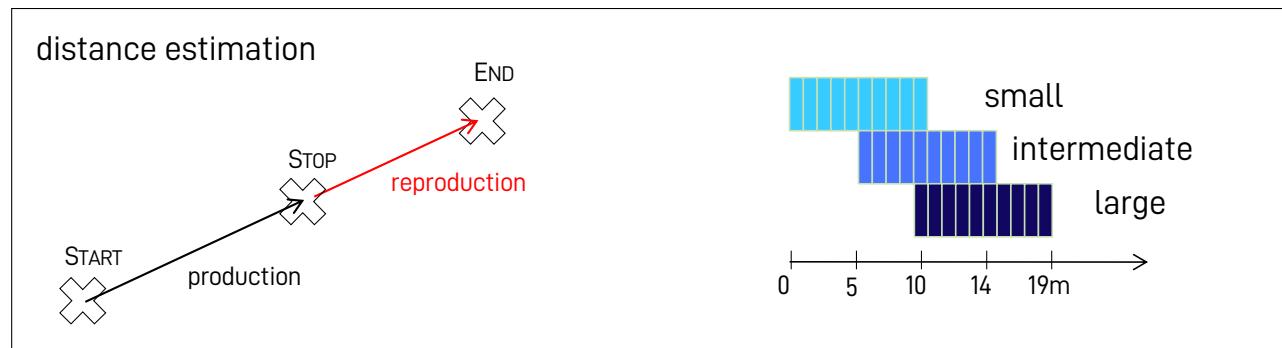


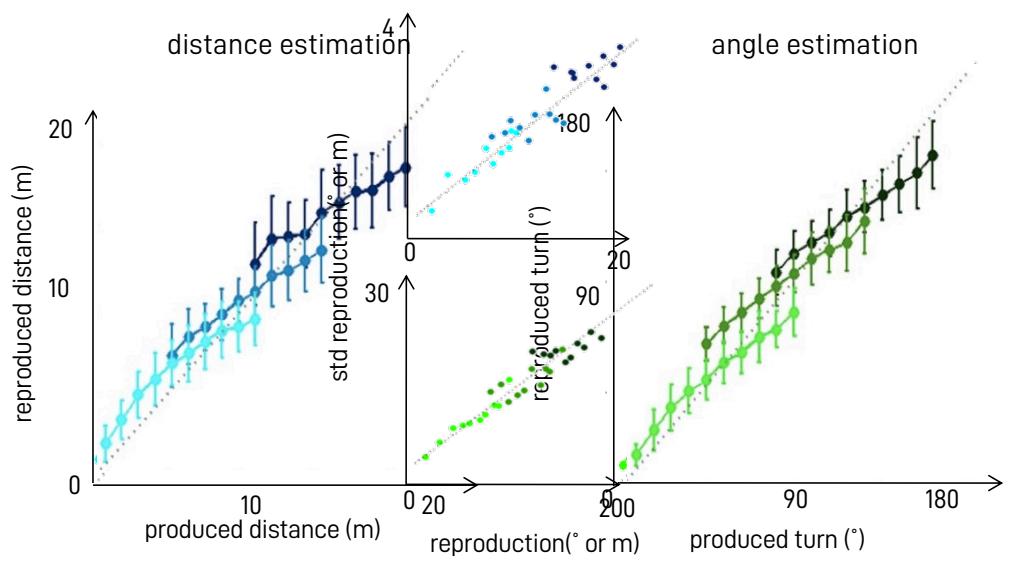
“optimal errors” in magnitude estimation



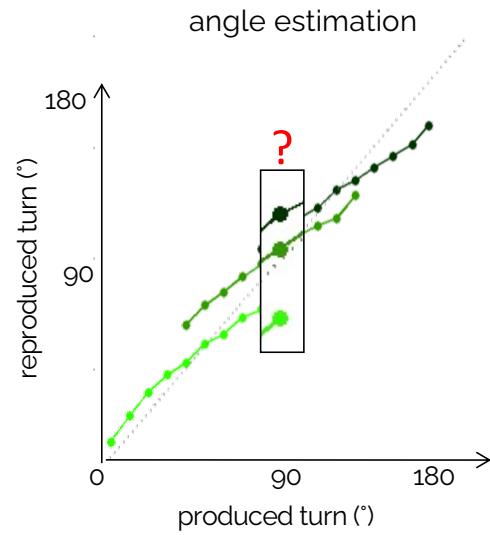
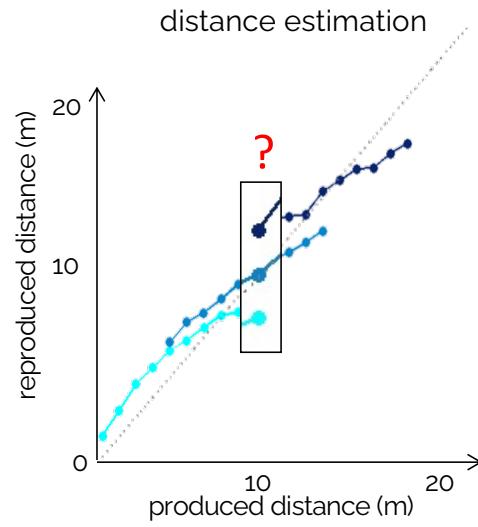
Petzschner & Glasauer, JoN, 2011

Varying the sample range

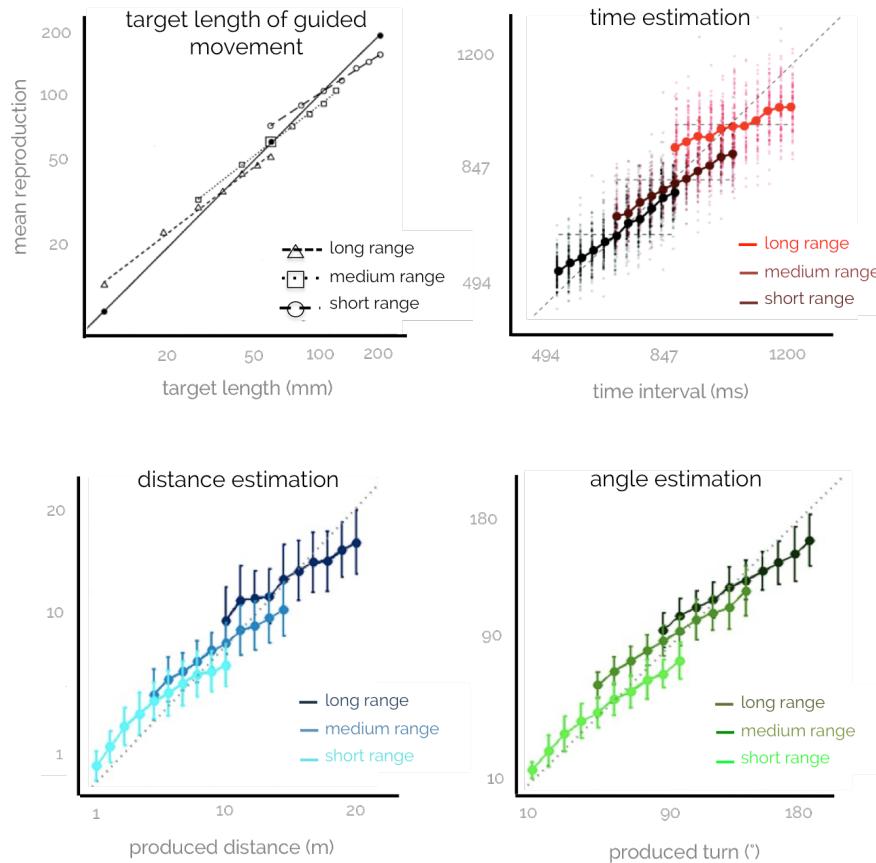




Prior knowledge: Experience

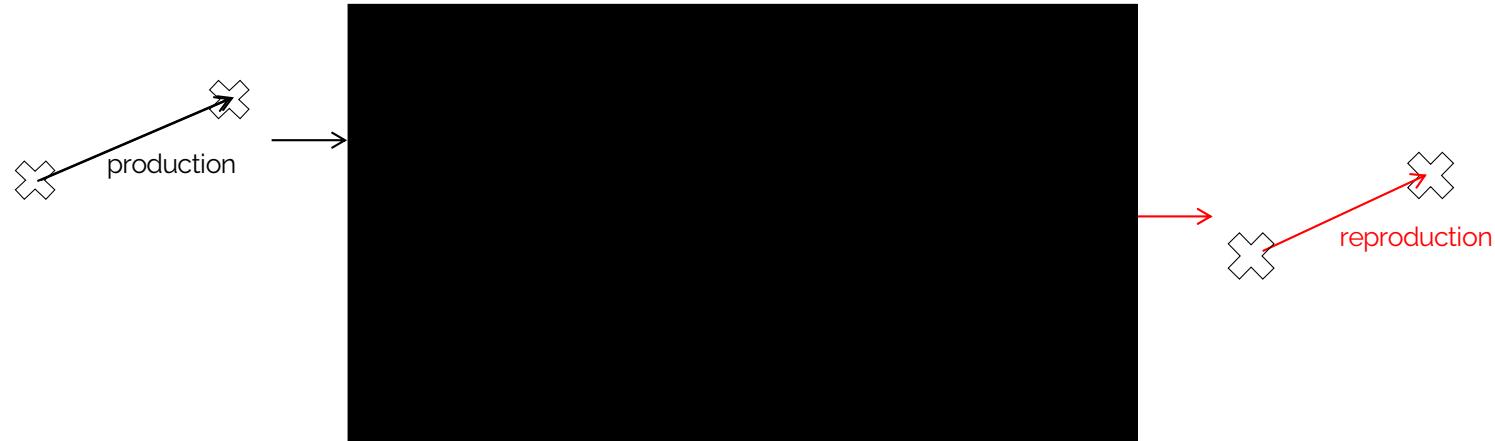


Let's take a look at the literature

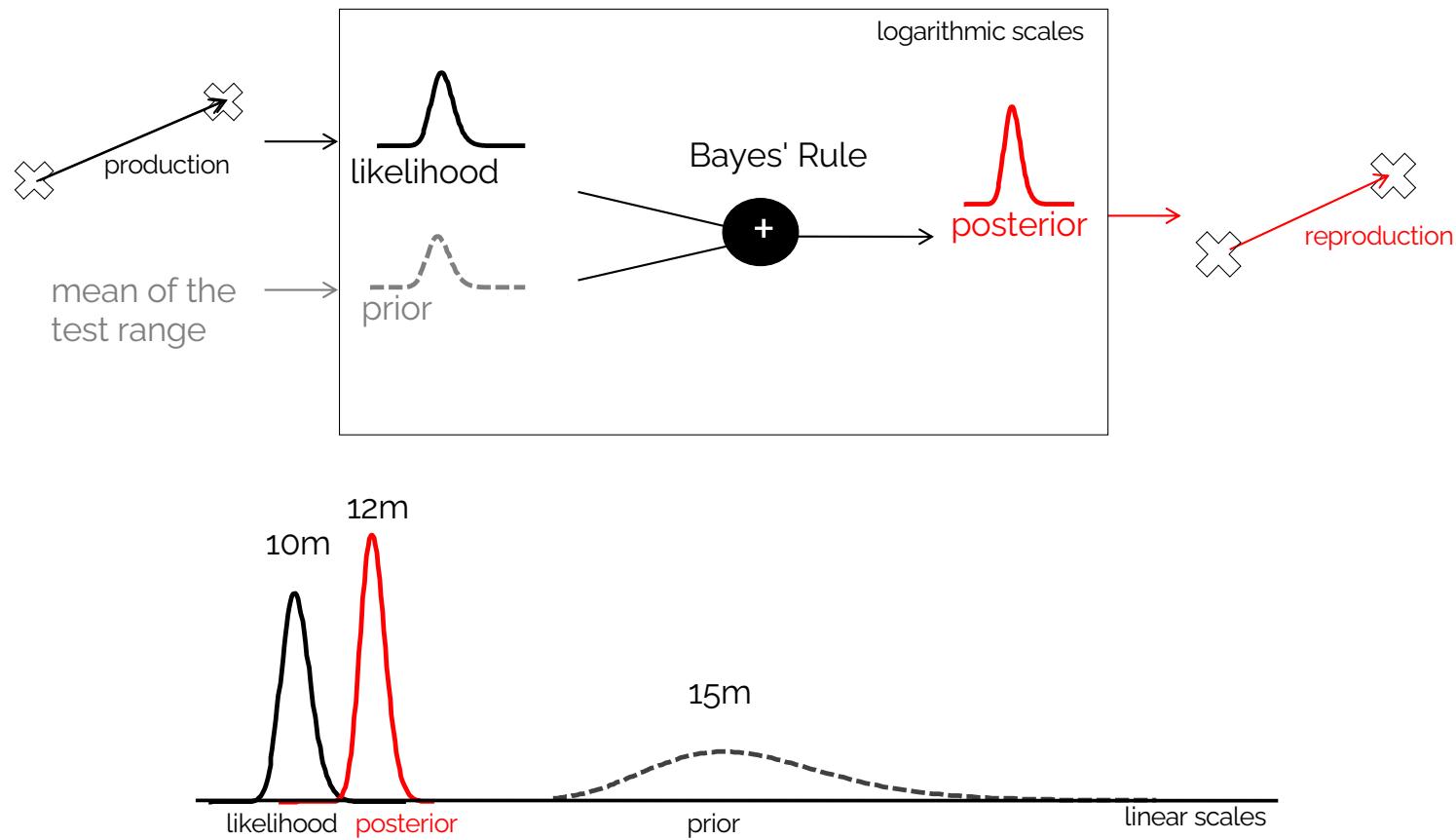


Petzschner & Glasauer, JoN, 2011; Petzschner et al. TiCS, 2015

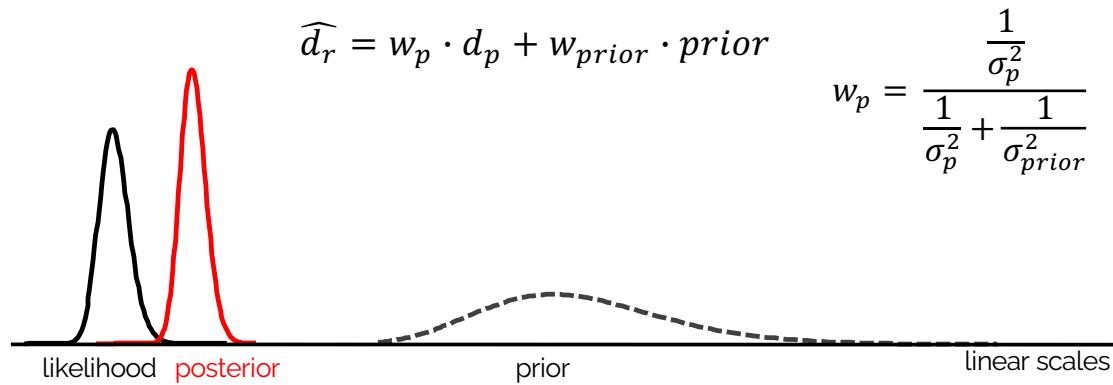
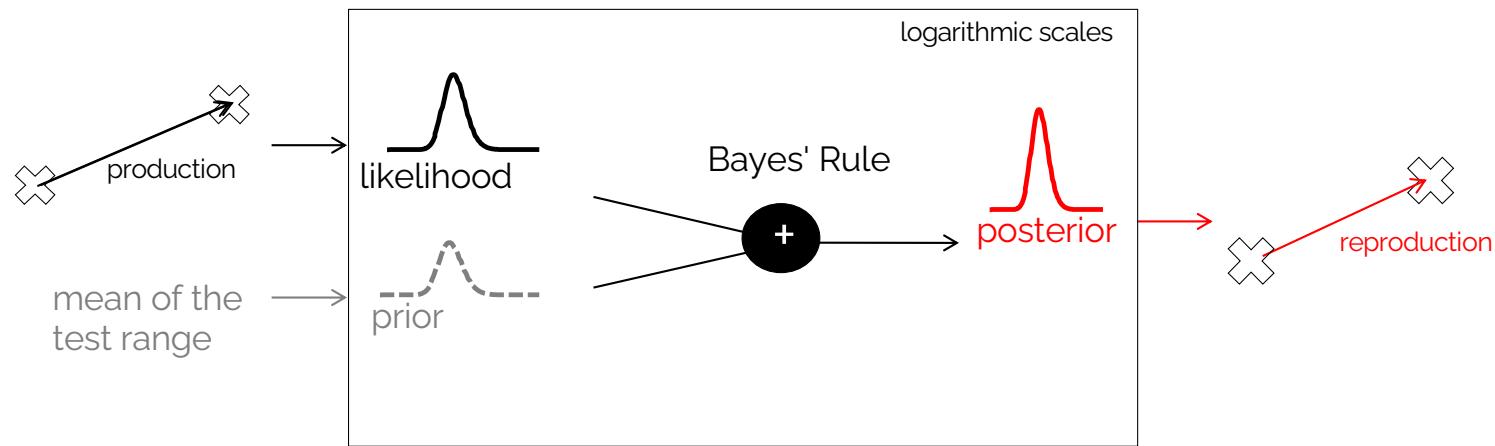
A Bayesian Model for magnitude estimation



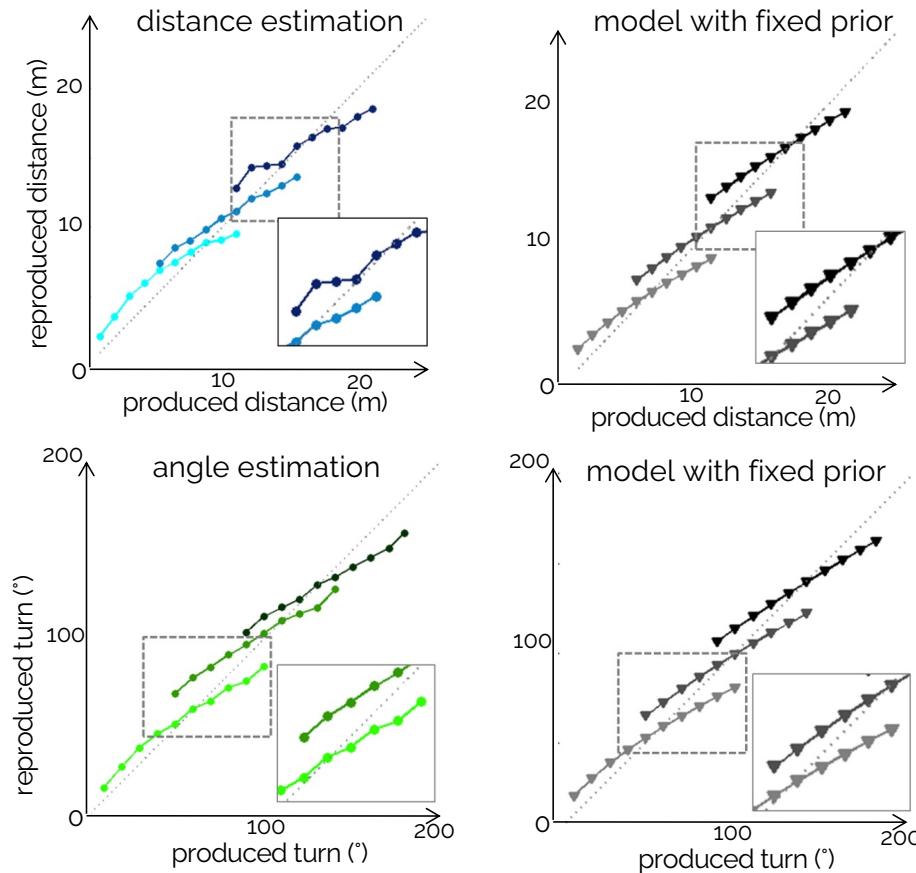
A Bayesian Model for magnitude estimation



A Bayesian Model for magnitude estimation

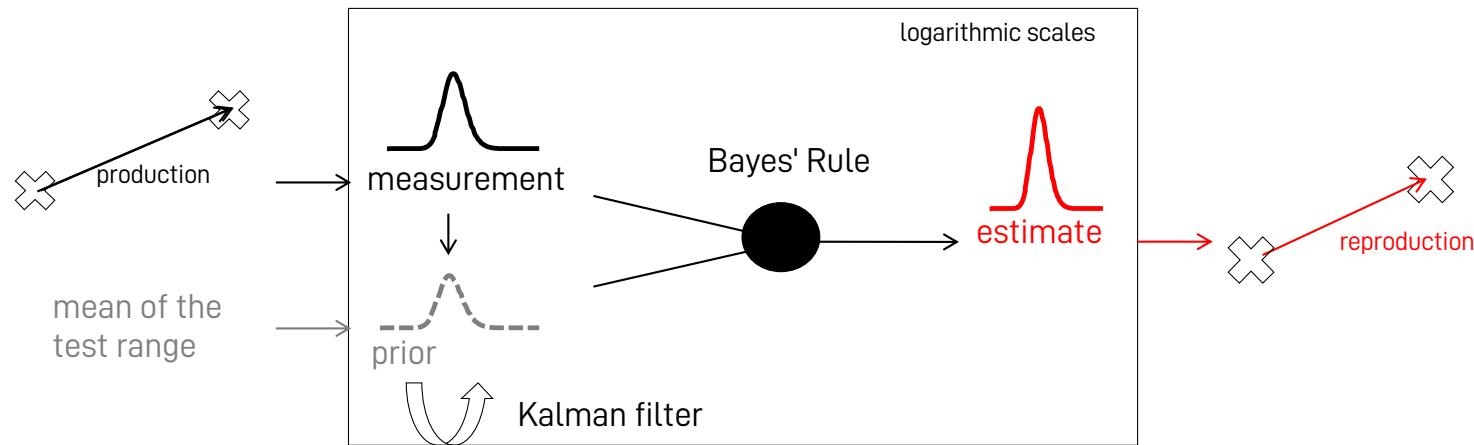


Quantitative results



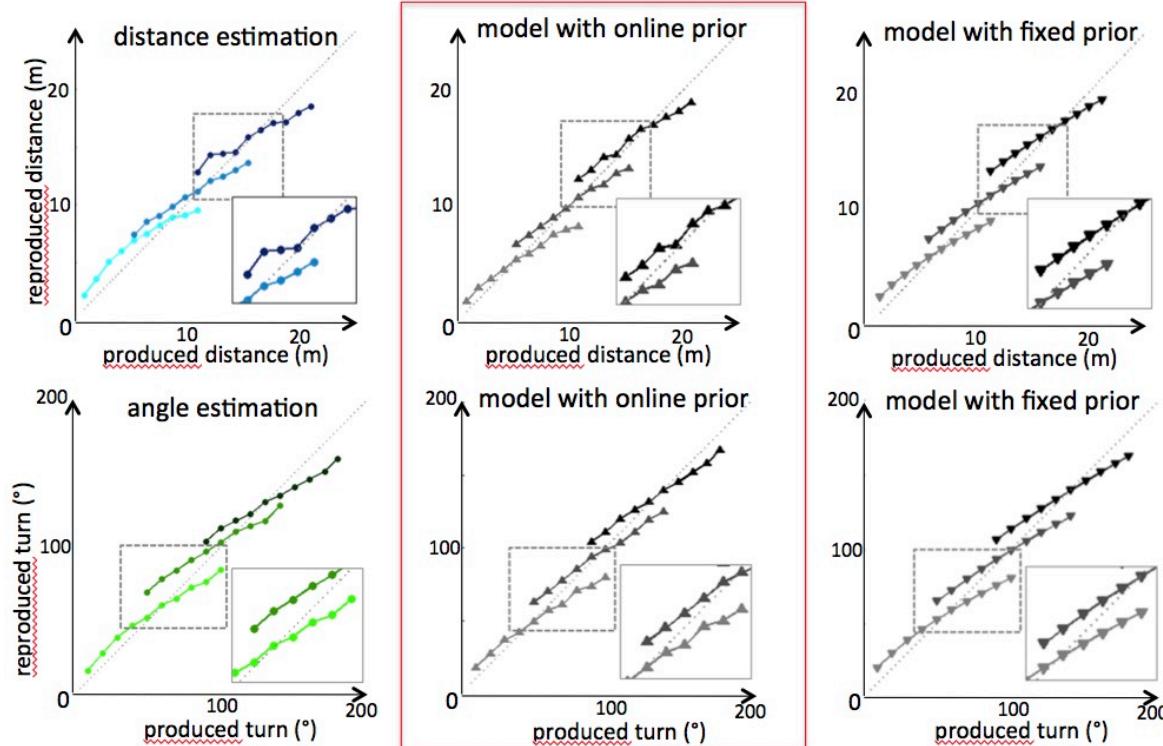
Where do priors come from?

Bayesian Learning



"Todays posterior is tomorrows prior."

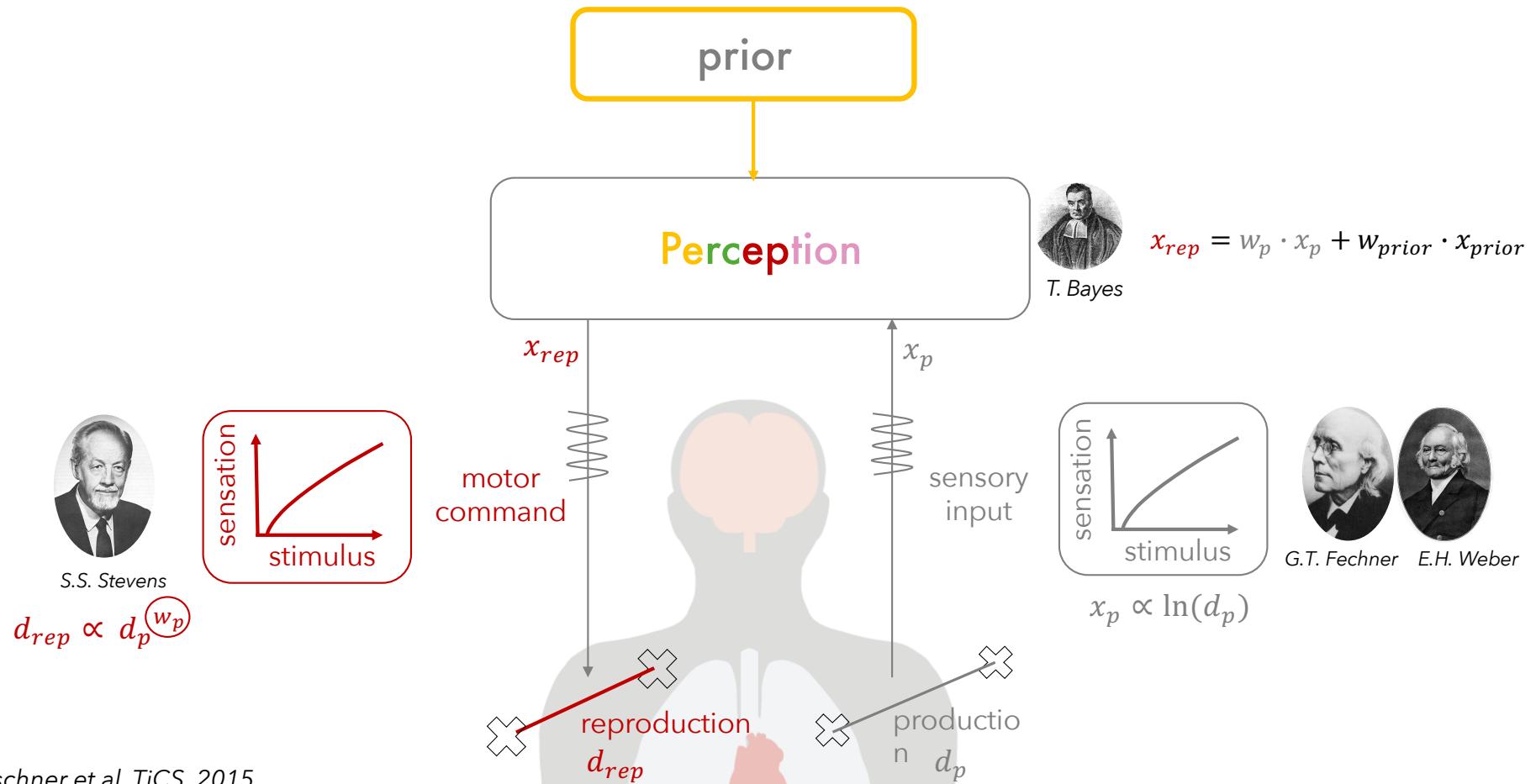
Bayesian Learning



More on Bayesian Learning in Christoph's Lecture tomorrow

Side note

Back to psychophysics



Bayesian model across the literature

[Friston and Stephan, 2007; Knill and Pouget, 2004; Knill and Richards, 1996]

Magnitude perception [Shadlen, Kiani, Glasauer, Petzschner, ...]

Visual perception [Weiss, Simoncelli, Adelson, Richards, Freeman, Feldman, Kersten, Knill, Maloney, Olshausen, Jacobs, Pouget, ...]

Haptic perception [Ernst, Banks, ...]

Auditory perception [Alais, Burr, ...]

Language acquisition and processing [Brent, de Marken, Niyogi, Klein, Manning, Jurafsky, Keller, Levy, Hale, Johnson, Griffiths, Perfors, Tenenbaum, ...]

Motor learning and motor control [Ghahramani, Jordan, Wolpert, Kording, Kawato, Doya, Todorov, Shadmehr, ...]

Associative learning [Dayan, Daw, Kakade, Courville, Touretzky, Kruschke, ...]

Memory [Anderson, Schooler, Shiffrin, Steyvers, Griffiths, McClelland, ...]

Attention [Mozer, Huber, Torralba, Oliva, Geisler, Yu, Itti, Baldi, ...]

Categorization and concept learning [Anderson, Nosofsky, Rehder, Navarro, Griffiths, Feldman, Tenenbaum, Rosseel, Goodman, Kemp, Mansinghka, ...]

Reasoning [Chater, Oaksford, Sloman, McKenzie, Heit, Tenenbaum, Kemp, ...]

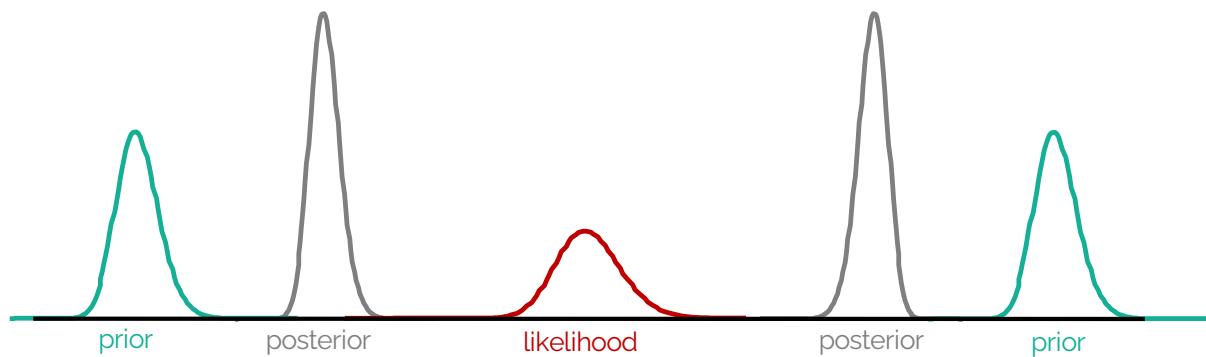
Causal inference [Waldmann, Sloman, Steyvers, Griffiths, Tenenbaum, Yuille, ...]

Decision making and theory of mind [Lee, Stankiewicz, Rao, Baker, Goodman, Tenenbaum, ...]

Optimal motor control [Wolpert, Kording ...]

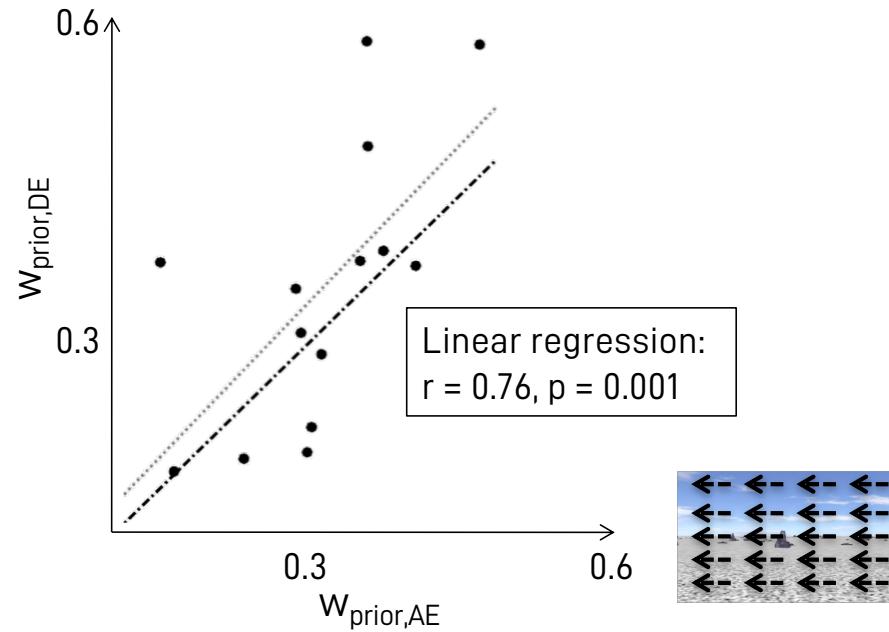
Remark 1

'there are too many arbitrary ways that priors, likelihoods, utility functions, etc., can be altered in a Bayesian theory post hoc'.



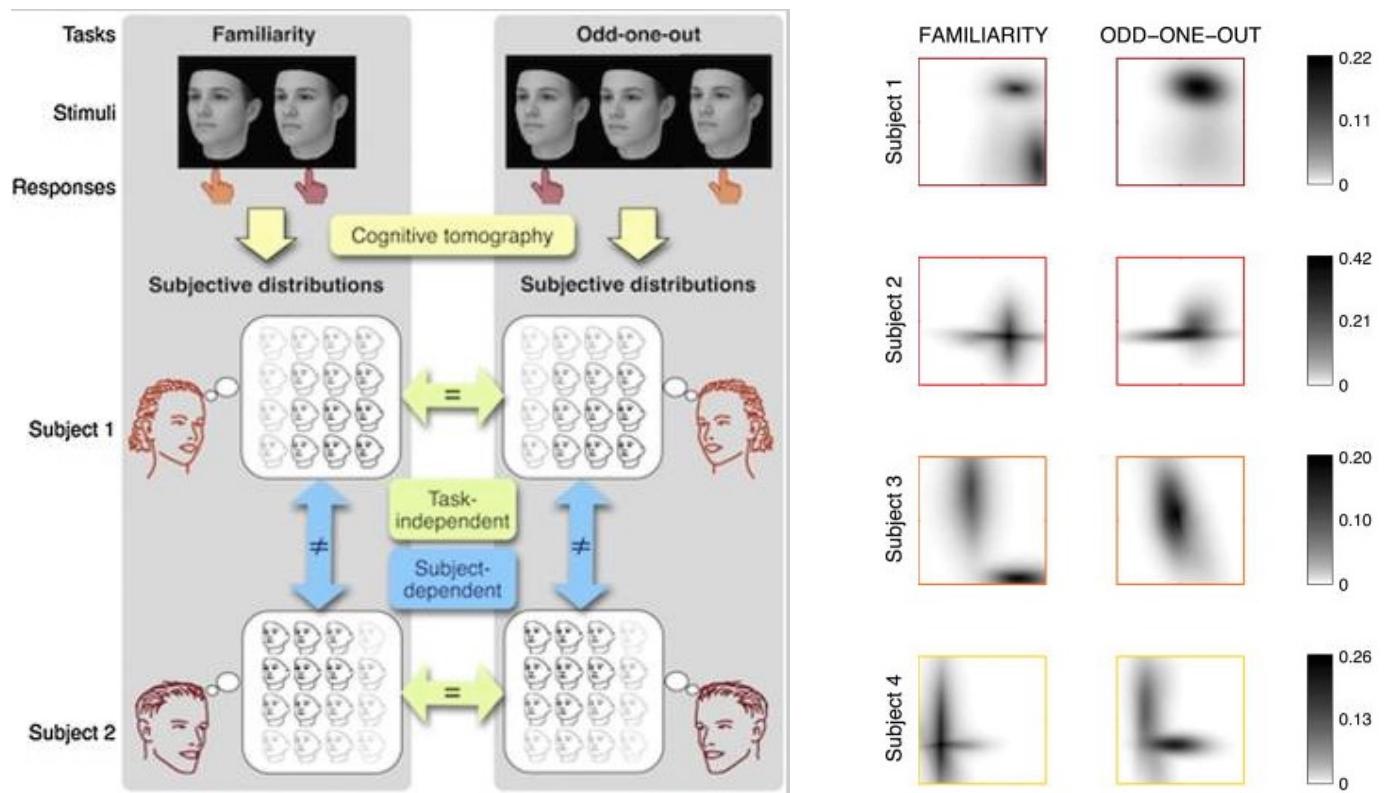
Bowers and Davis, 2012a,b; Griffiths et al., 2012, Colombo and Series, 2012; Jones and Love, 2011

Do priors generalize?



Petzschner & Glasauer, JoN, 2011; Petzschner et al. TiCS, 2015

Do priors generalize?



Houlsby et al., Current Biology, 2013

Remark 2

Are humans optimal?

...propose the statistical optimal way to combine different types of noisy information.

As such they suggest what an *ideal observer* would do.
Which can be used as a benchmark for *real behavior*.

→ They are normative models.

Remark 3

How is Bayesian Inference performed by the brain?

...describe the computation that might be performed by the CNS, but do not specify the algorithm by which this computation is implemented

→ *Live at the computational level of description*

More on the
algorithmic level in
Alex's Lecture

More on the implementational level:

Work by
Pouget, Zemel, Deneve, Latham, Hinton and Dayan

Paper:
Ma, W.J. et al. (2006) Nat. Neurosci. 9, 1432–8
Berkes et al, Science, 2011

Bayesian models in mental health

Bayesian models can be used to reveal deviations in the way patients process different types of information

- **'Wrong' priors (bad experiences, maladaptive learning)**
- **'Wrong' likelihood**
- **'Wrong' precision**
- **'Wrong' execution/decision**

Computational Psychiatry and Bayesian Models of Perception

When the world becomes 'too real': a Bayesian explanation of autistic perception

Elizabeth Pellicano^{1,3} and David Burr^{2,3}

Understanding why patients with schizophrenia do not perceive the hollow-mask illusion using dynamic causal modelling

Danai Dima ^{a,b,*}, Jonathan P. Roiser ^c, Detlef E. Dietrich ^{a,b}, Catharina Bonnemann ^a, Heinrich Lanfermann ^d, Hinderk M. Emrich ^{a,b}, Wolfgang Dillo ^a

No rapid audiovisual recalibration in adults on the autism spectrum

Marco Turi¹, Themelis Karaminis², Elizabeth Pellicano^{2,4} & David Burr^{3,4}

Shift toward prior knowledge confers a perceptual advantage in early psychosis and psychosis-prone healthy individuals

Christoph Teufel^{a,b,1}, Naresh Subramaniam^b, Veronika Dobler^{c,d}, Jesus Perez^{c,d}, Johanna Finnemann^{b,e}, Puja R. Mehta^b, Ian M. Goodyer^{c,d}, and Paul C. Fletcher^{b,d}

Depression: A Decision-Theoretic Analysis

Quentin J.M. Huys,^{1,2} Nathaniel D. Daw,³ and Peter Dayan⁴

Computational Psychiatry and Bayesian Models of Perception

Neuropsychiatry



OPEN ACCESS

REVIEW

Computational Psychiatry: towards a mathematically informed understanding of mental illness

Rick A Adams,^{1,2} Quentin J M Huys,^{3,4} Jonathan P Roiser¹

Computational Psychosomatics and Computational Psychiatry: Toward a Joint Framework for Differential Diagnosis

Frederike H. Petzschner, Lilian A.E. Weber, Tim Gard, and Klaas E. Stephan

REVIEW ARTICLE

Front. Psychiatry, 30 May 2013 | <https://doi.org/10.3389/fpsyg.2013.00047>

The computational anatomy of psychosis

Rick A. Adams^{1*}, Klaas Enno Stephan^{1,2,3}, Harriet R. Brown¹, Christopher D. Frith¹ and Karl J. Friston¹

¹Wellcome Trust Centre for Neuroimaging, Institute of Neurology, University College London, London, UK.

²Translational Neuromodeling Unit, Institute for Biomedical Engineering, University of Zurich, ETH Zurich, Zurich, Switzerland

³Laboratory for Social and Neural Systems Research, University of Zurich, Zurich, Switzerland

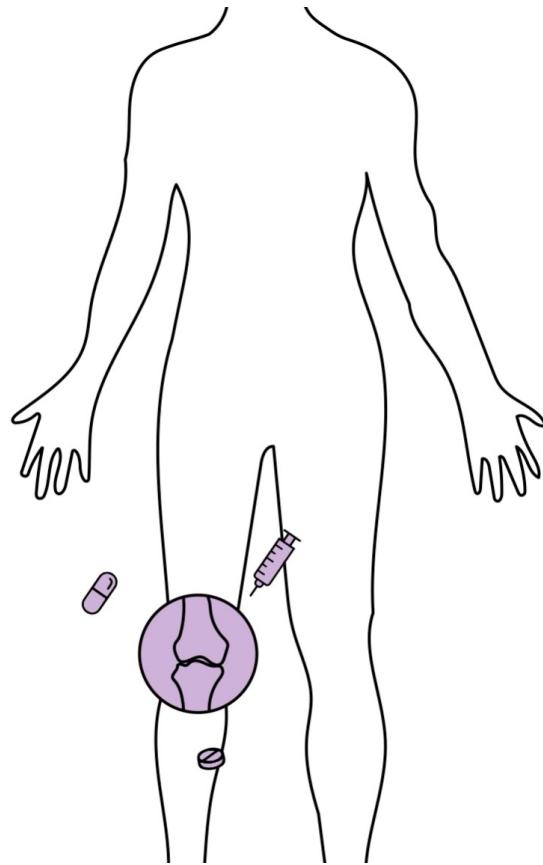


OCCASIONAL PAPER

A Bayesian account of 'hysteria'

Mark J. Edwards,^{1,*} Rick A. Adams,^{2,*} Harriet Brown,² Isabel Pareés¹ and Karl J. Friston²

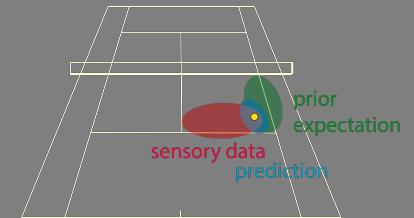
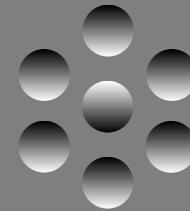
SOMA - Chronic Pain



Twitter: @SOMA_the_App
Website: <https://somatheapp.com>

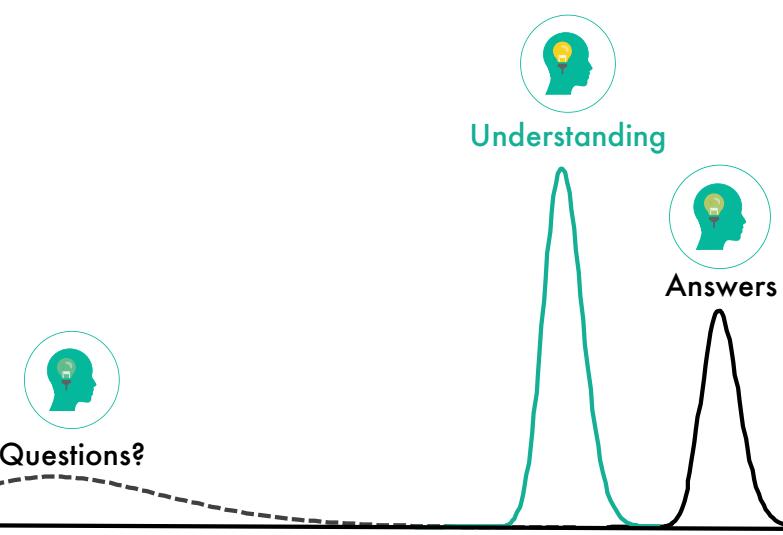
Summary

- Perception is the result of a combination of different types of noisy information (sensory & prior)
- Bayes' Theorem describes a statistical optimal way of combining this information.
- Humans combine sensory information according to their uncertainty.



Summary

- *Models of Perception Bayesian Inference are normative models and largely live at the computational level of description*
- *Bayesian Models have been highly successful in explaining phenomena in perception and cognition*
- *And are now increasingly used as frameworks to understand psychiatric disorders such as Autism or Schizophrenia*



Thank you

@rikepetzschn
@peaclub

Interested in working with us?

<https://fpetzschn.com/lab/>