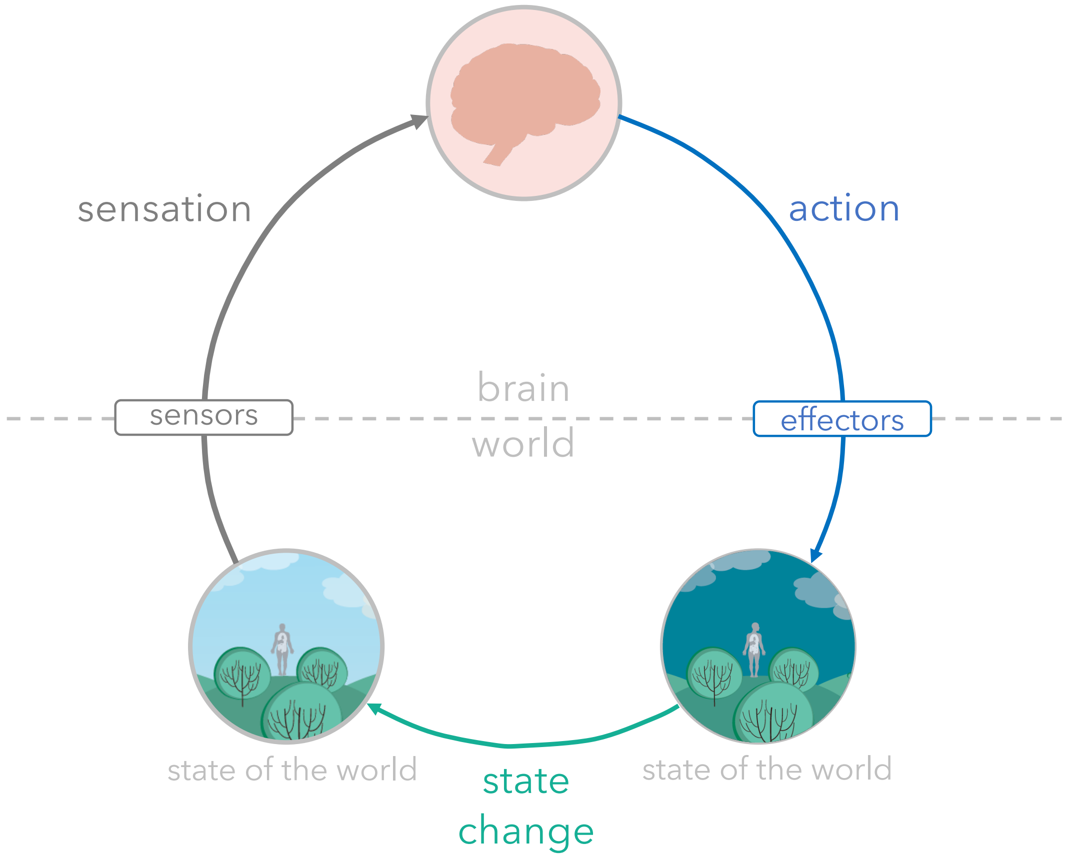
Bayesian Models of Perception

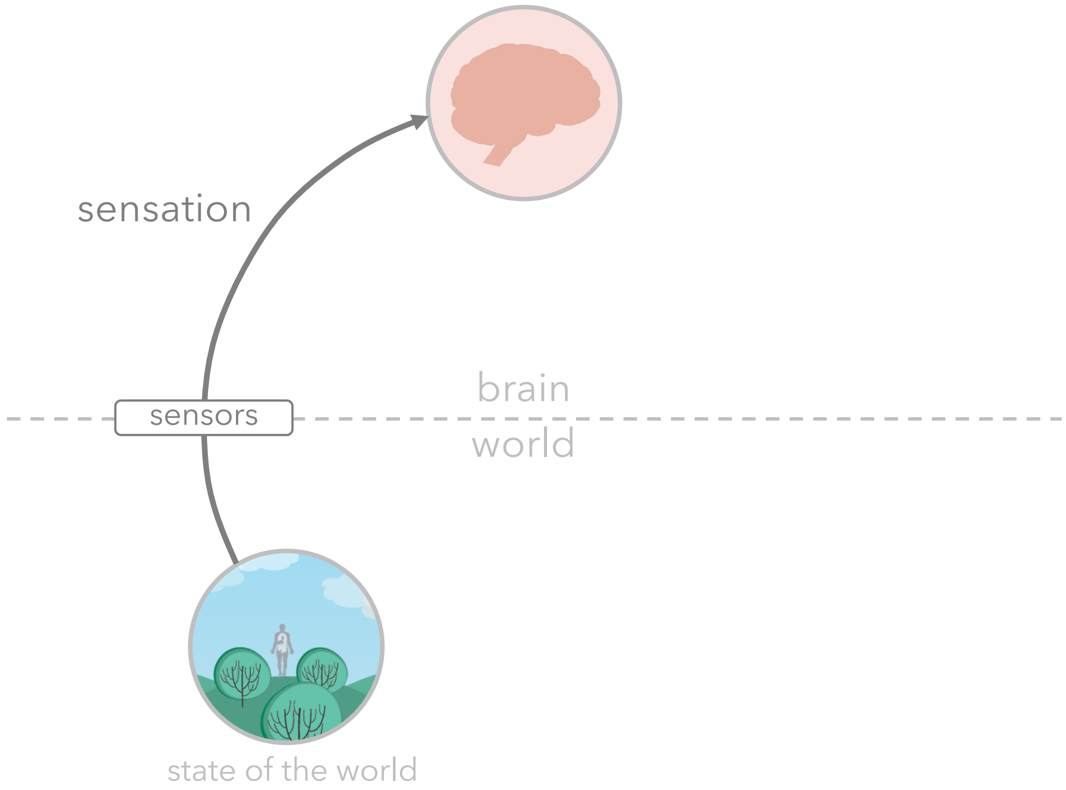
Dr. Frederike Petzschner
Brown University
@rikepetzschner
@peaclab

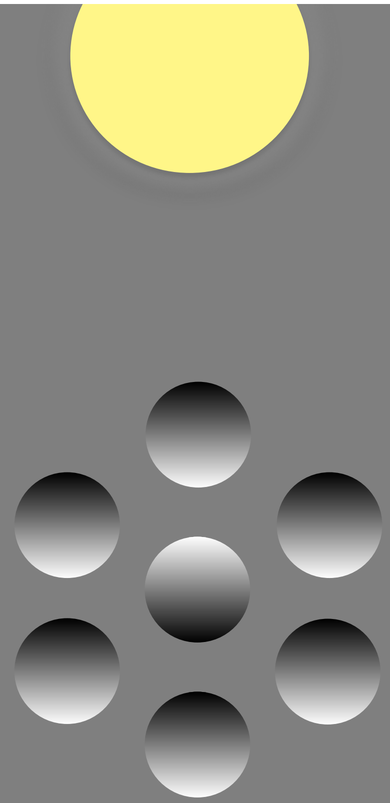
What is the computation that is carried out when we perceive something?

What is perception?

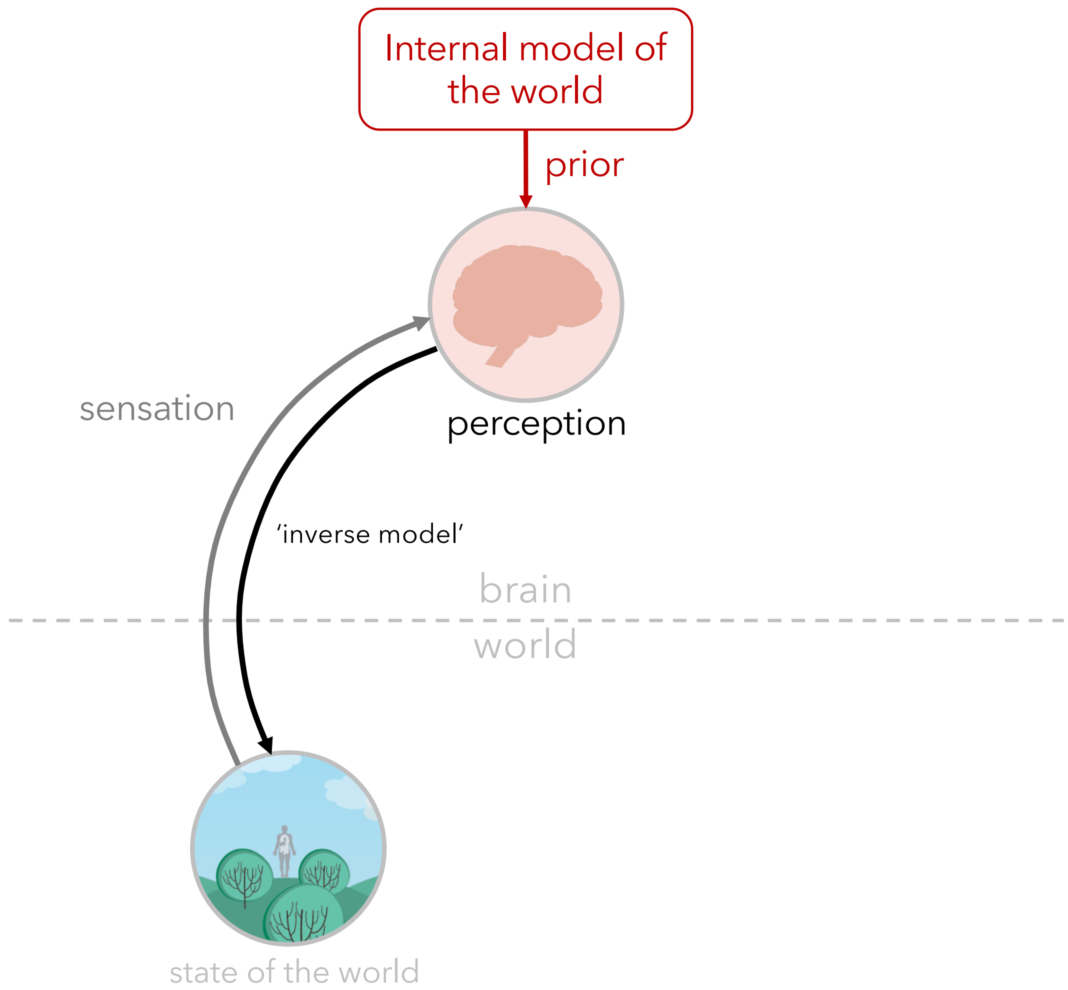


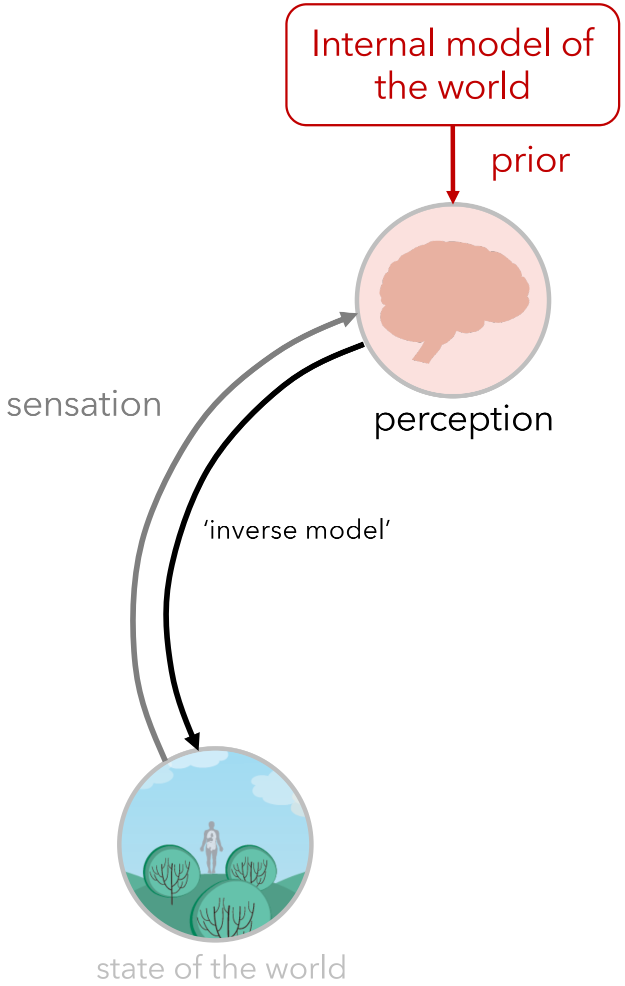
What is perception?



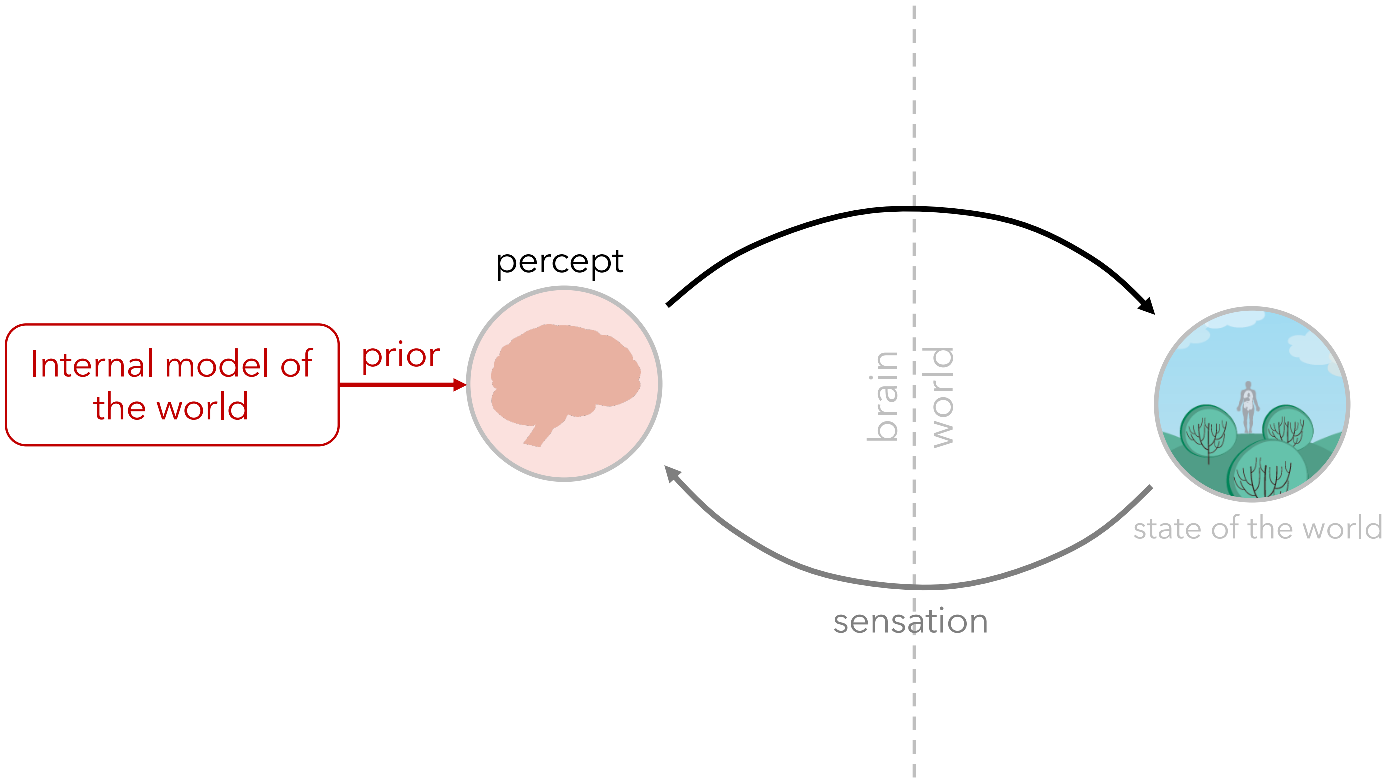


Adams et al., Nature Neuroscience, 2004


Internal model of the world
prior
perception
sensation
'inverse model'
brain
world
state of the world


Internal model of the world
prior
sensation
perception
'inverse model'
state of the world

Perception as inference



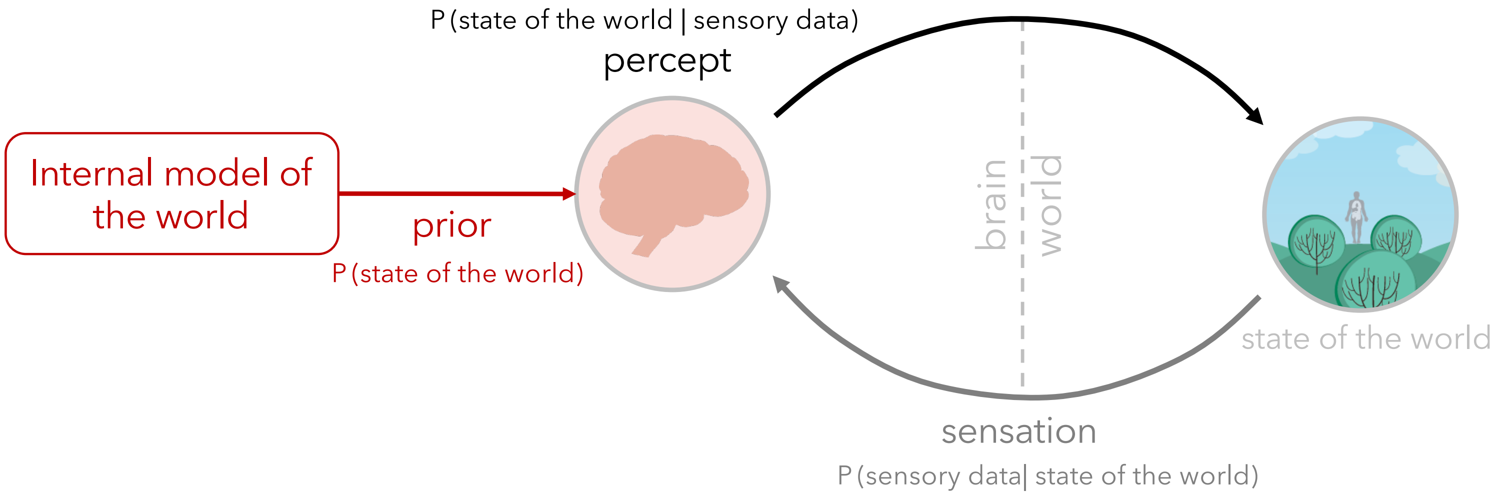
The percept reflects a combination of sensory information and prior expectations about the world.

Why?

A Bayesian model of perception

Perception as Bayesian inference

Noisy information can be expressed by probability distributions



Bayes' Rule

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

Side note

Avoiding confusion: Bayes versus Bayes

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

Statistical rule describing the relationship between conditional probability distributions

Can be applied in many different contexts

So far…

Model fitting/ Parameter estimation

Model comparison

$$P(\theta|data, m) = \frac{\overbrace{P(data|\theta, m)}^{\text{likelihood}} \cdot \overbrace{P(\theta|m)}^{\text{prior}}}{\underbrace{P(data|m)}_{\text{model evidence}}}$$

Bayes as a tool for model-based analysis

Independent of the concrete model you use to describe behavior/the brain

Today…

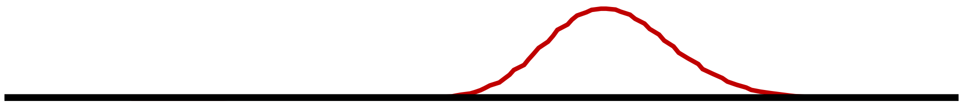
Model of a computation performed by the brain

$$P(world|sensory\ data) = \frac{\overbrace{P(sensory\ data|world)}^{\text{likelihood}} \cdot \overbrace{P(world)}^{\text{prior}}}{P(sensory\ data)}$$

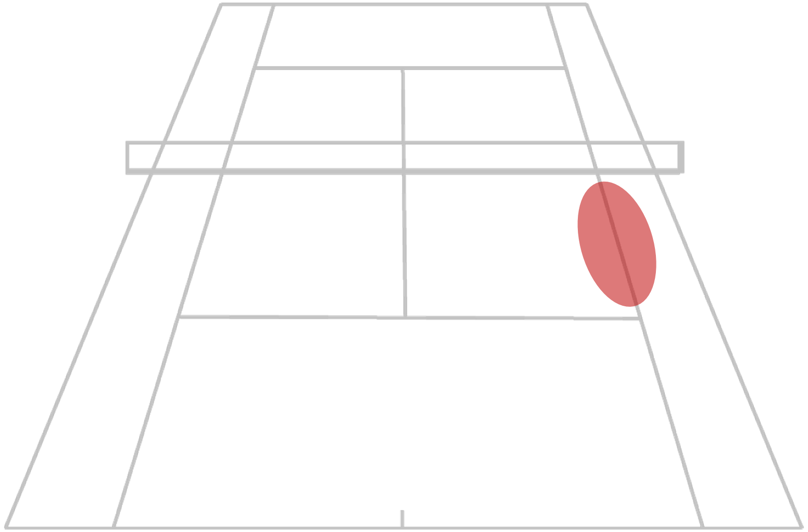
Bayes as a model of behavior

Example

Information extraction with Bayes' Rule



prior



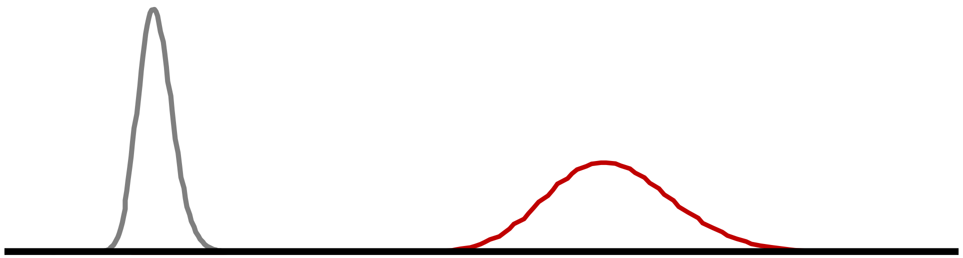
Bayes' Rule

likelihood prior

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

posterior

Information extraction with Bayes' Rule



sensory input
likelihood

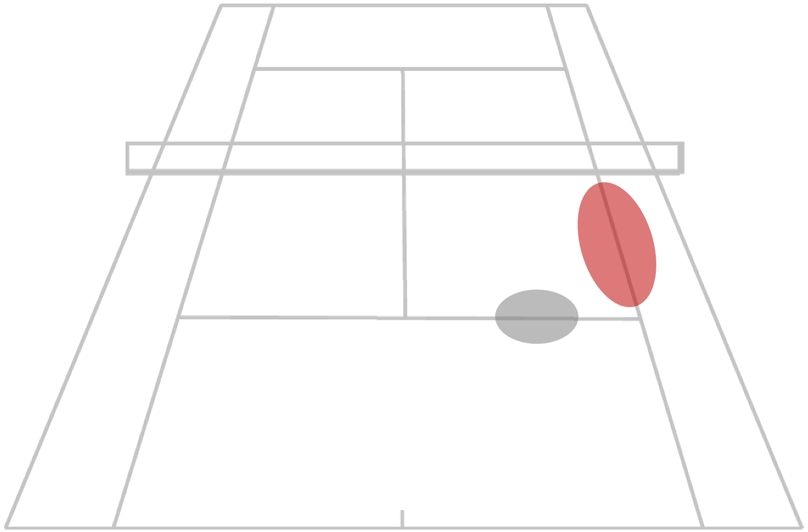
prior

Bayes' Rule

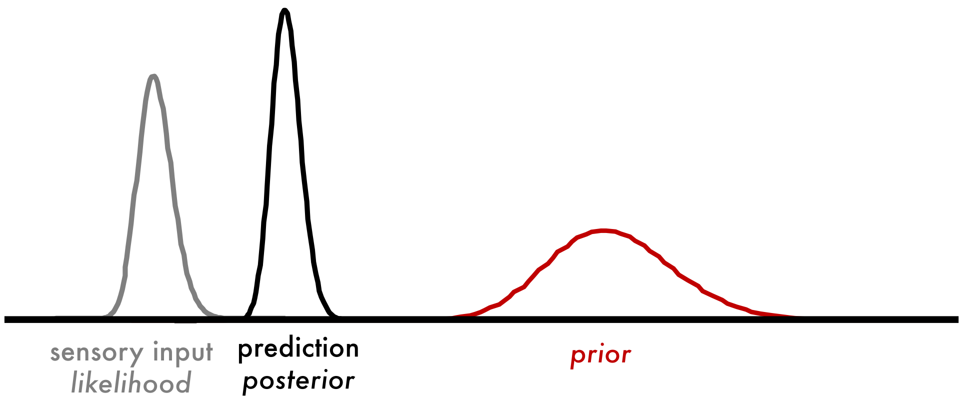
likelihood *prior*

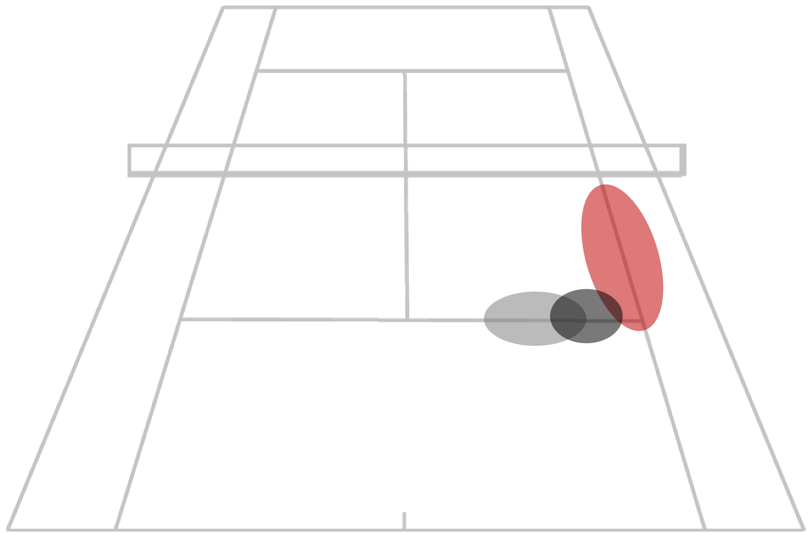
$$P(state|sensory\ input) = \frac{P(sensory\ input|state)\,P(state)}{P(sensory\ input)}$$

posterior



Information extraction with Bayes' Rule



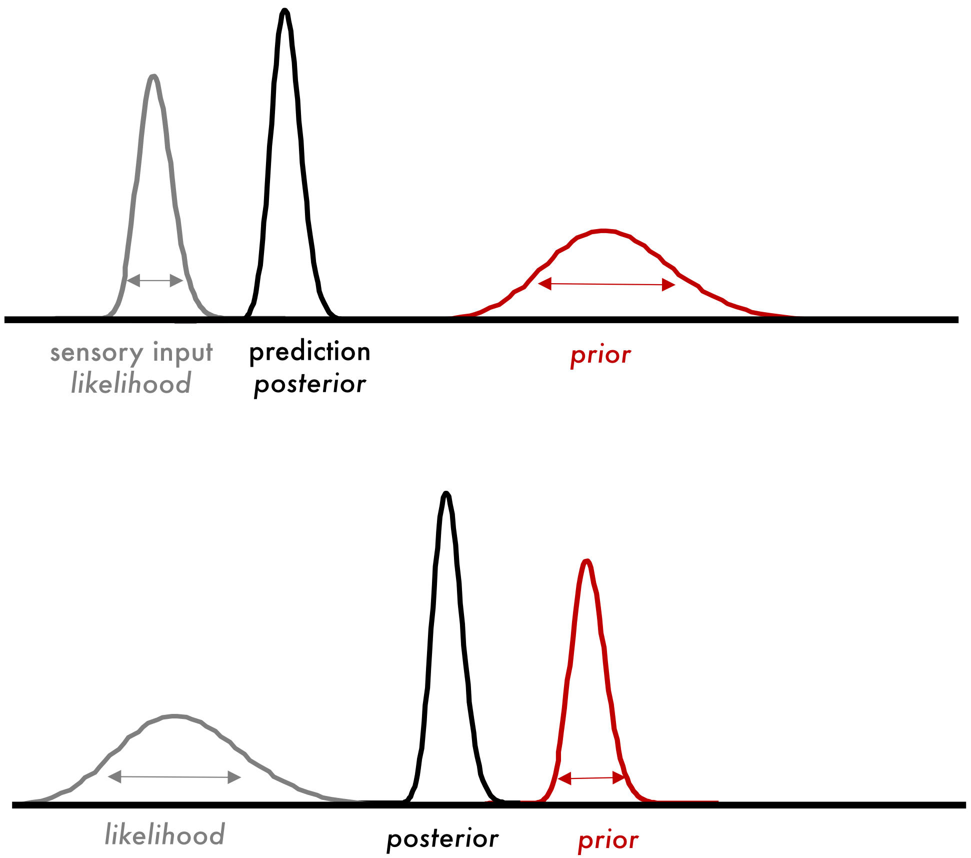


Bayes' Rule

$$\underbrace{P(state|sensory\ input)}_{\text{posterior}} = \frac{\overbrace{P(sensory\ input|state)}^{\text{likelihood}}\ \overbrace{P(state)}^{\text{prior}}}{P(sensory\ input)}$$

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

How Bayes' Rule deals with uncertainty



Bayes Rule:

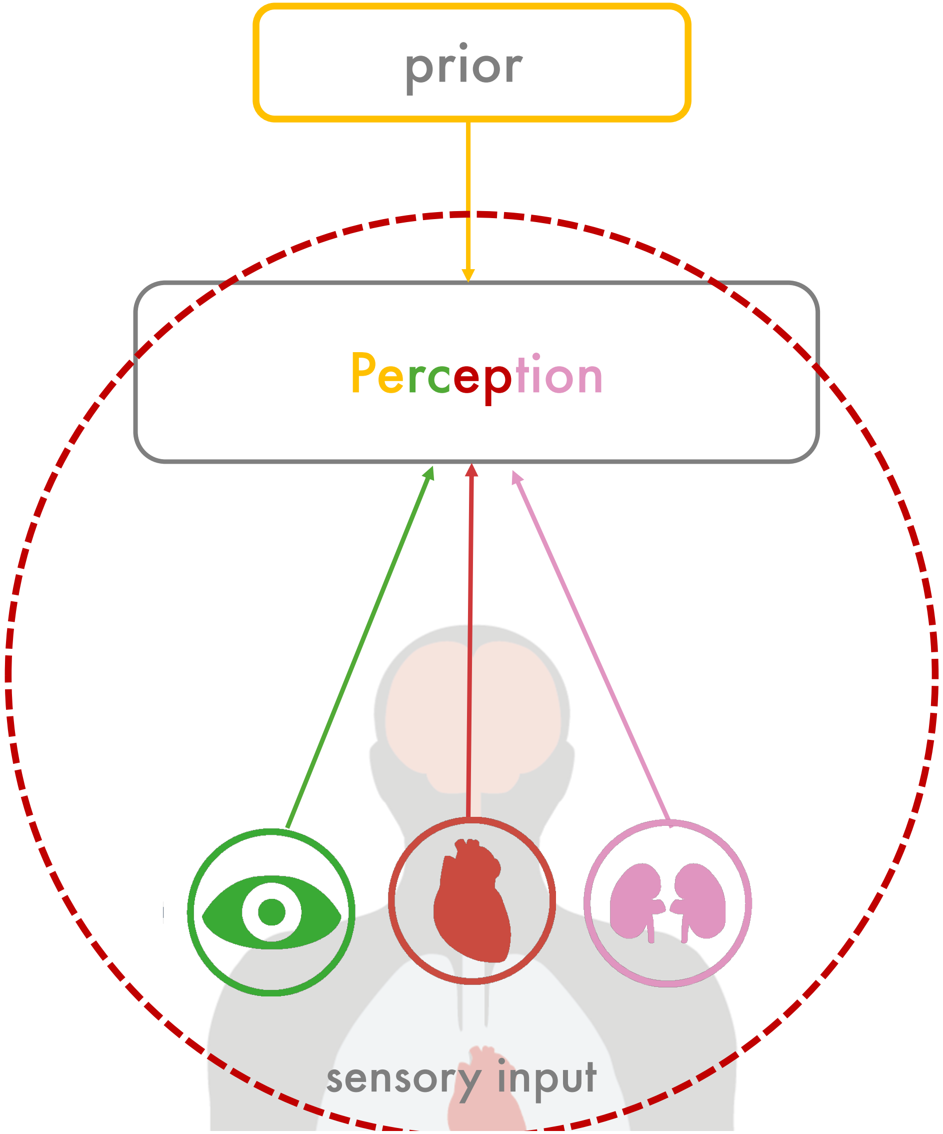
Optimal combination of uncertain information sources

If Gaussian distributions:

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

$$\sigma^2_{posterior} = \frac{\sigma^2_{sens} \cdot \sigma^2_{prior}}{\sigma^2_{sens} + \sigma^2_{prior}}$$

Bayesian model of perception applied


prior
Perception
sensory input

Current Biology, Vol. 14, 257–262, February 3, 2004, 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,*]

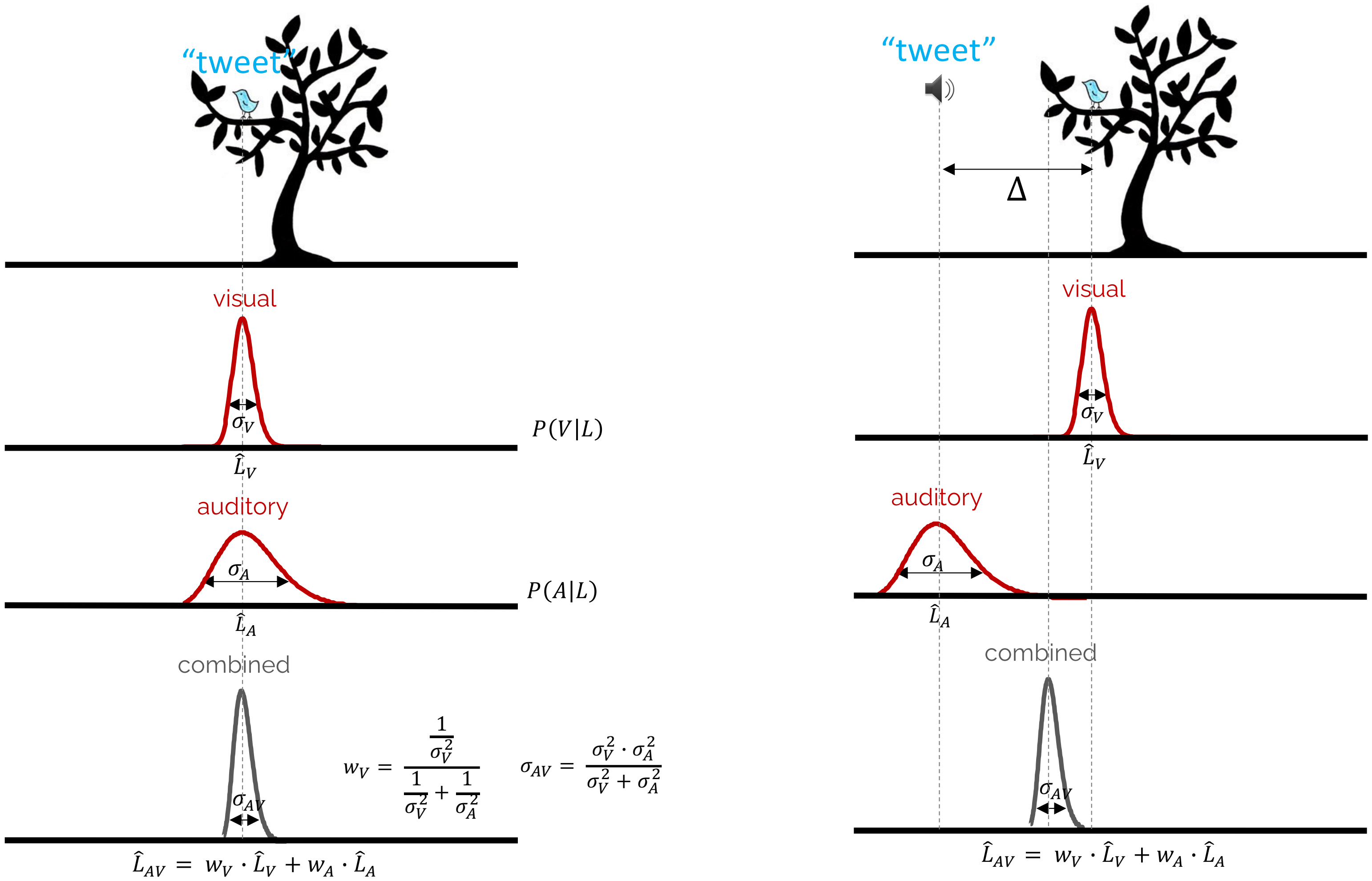
Results for the various unimodal location discrimina-

Humans integrate visual and haptic information in a statistically optimal fashion

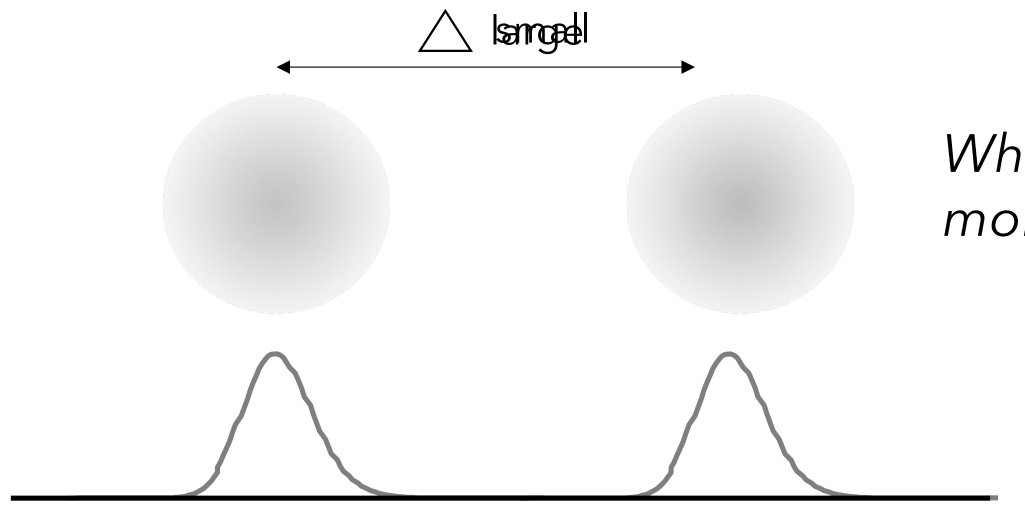
Marc O. Ernst* & Martin S. Banks

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

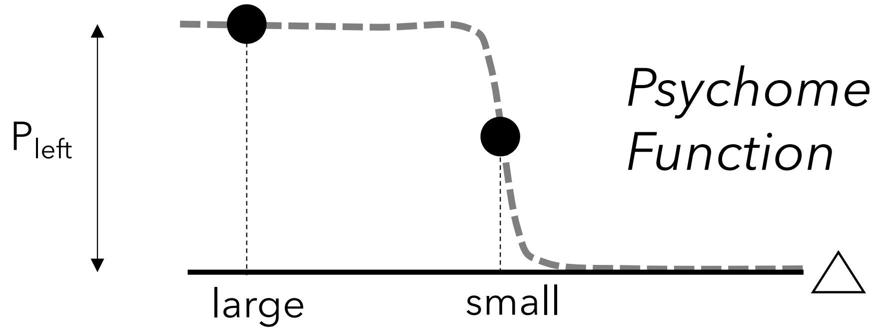
Combination of visual and auditory information



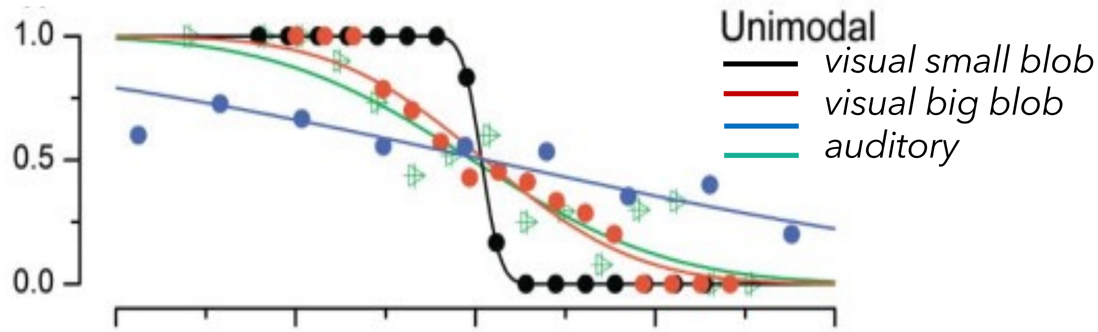
The Psychometric Function



Which one was more left?

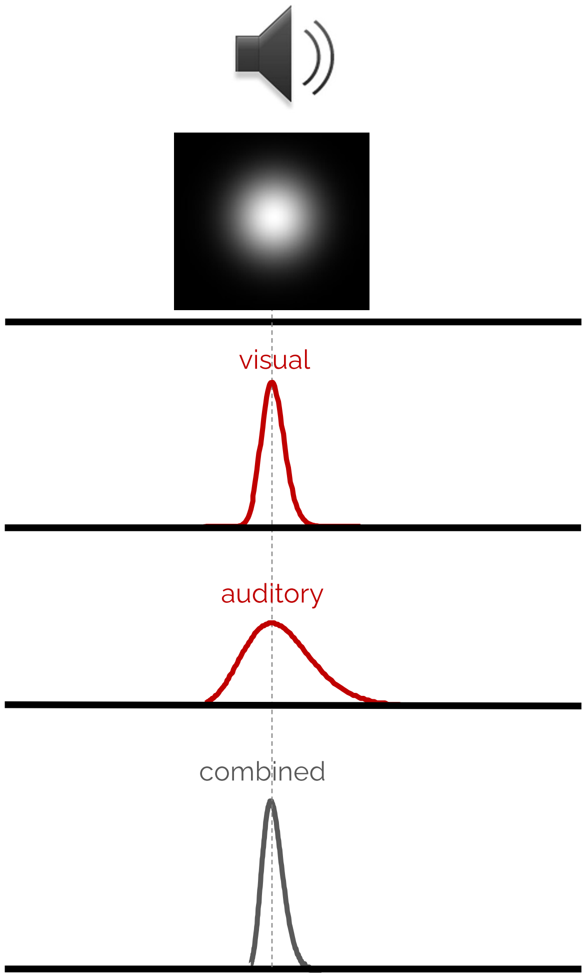


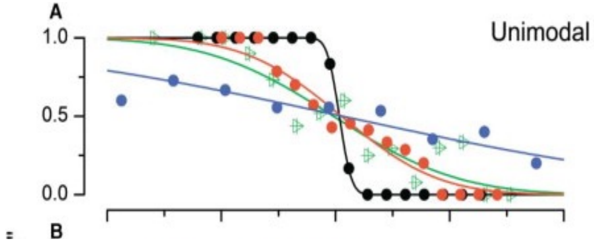
Psychometric Function



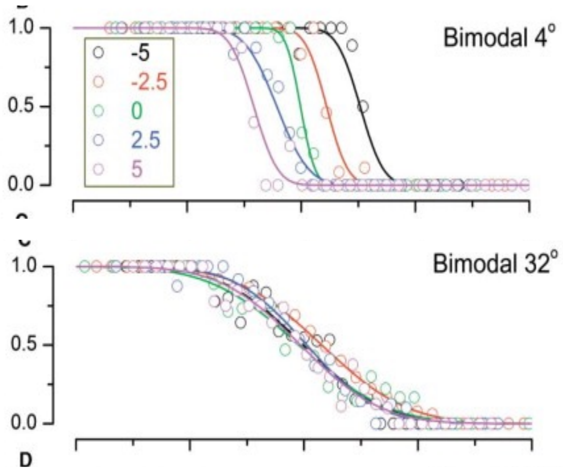
Alais & Burr, Current Biology, 2004

Combination of visual and auditory information

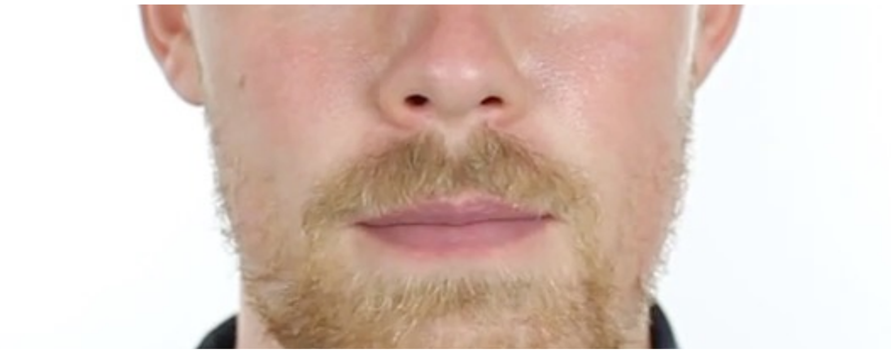




$$\sigma_{AV} = \frac{\sigma_V^2 \cdot \sigma_A^2}{\sigma_V^2 + \sigma_A^2}$$

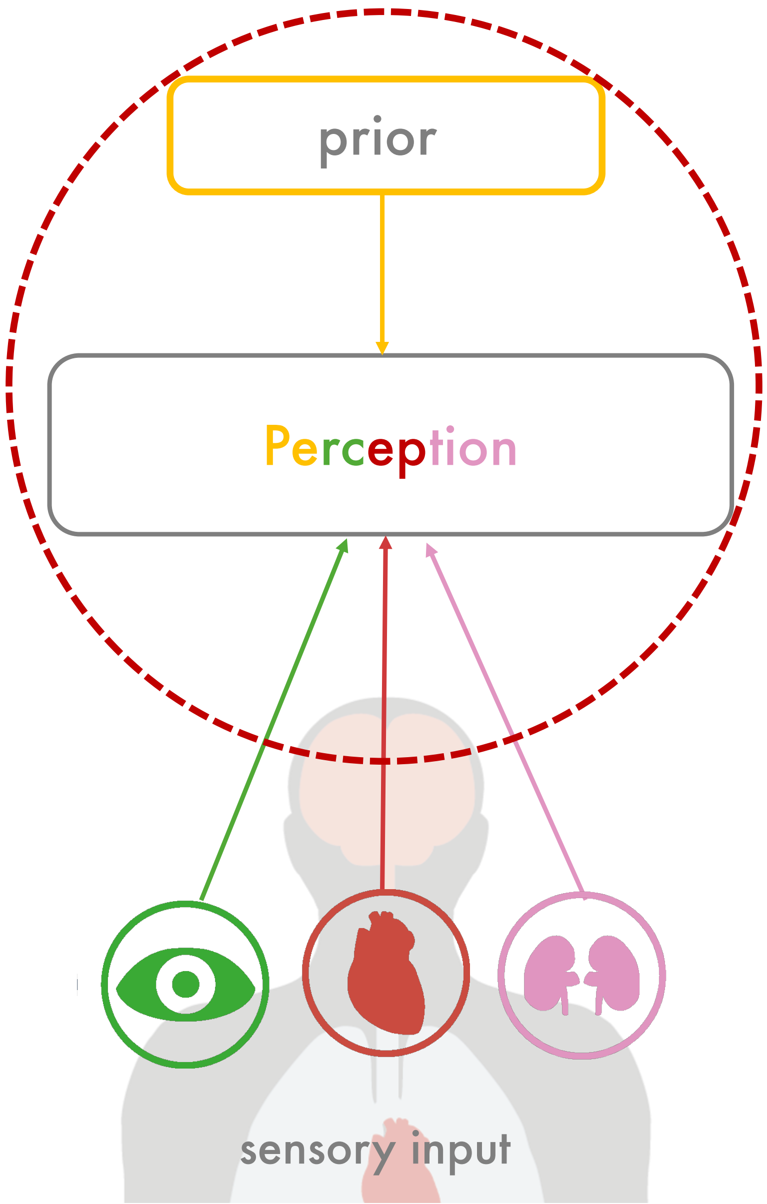


Alais & Burr, Current Biology, 2004

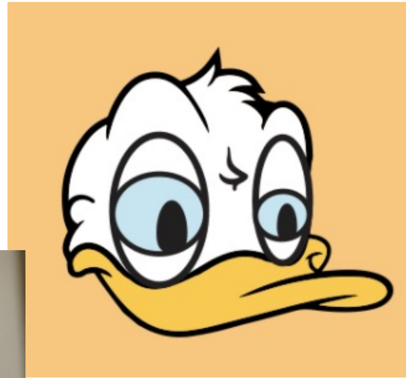


BAR

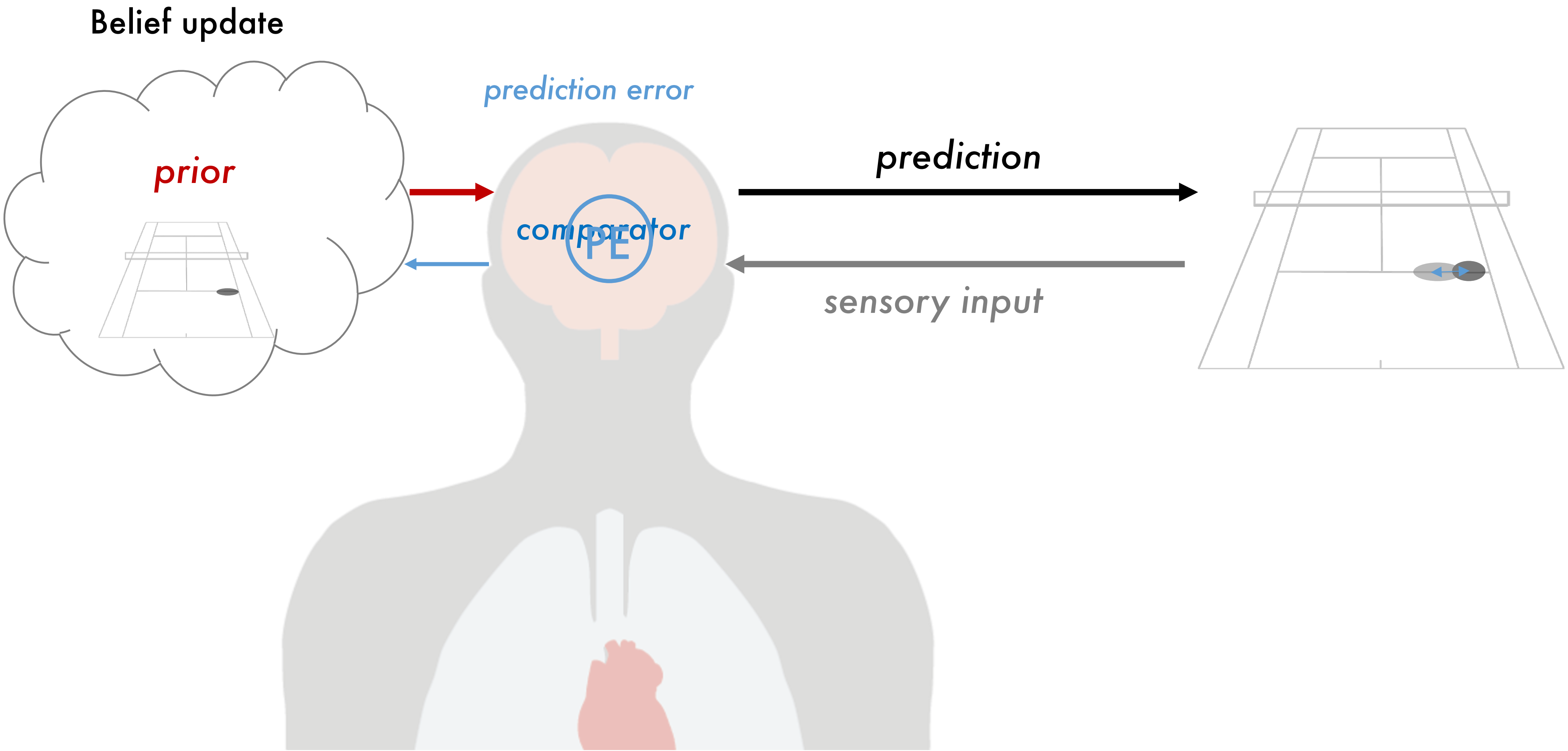
FAR


prior
Perception
sensory input

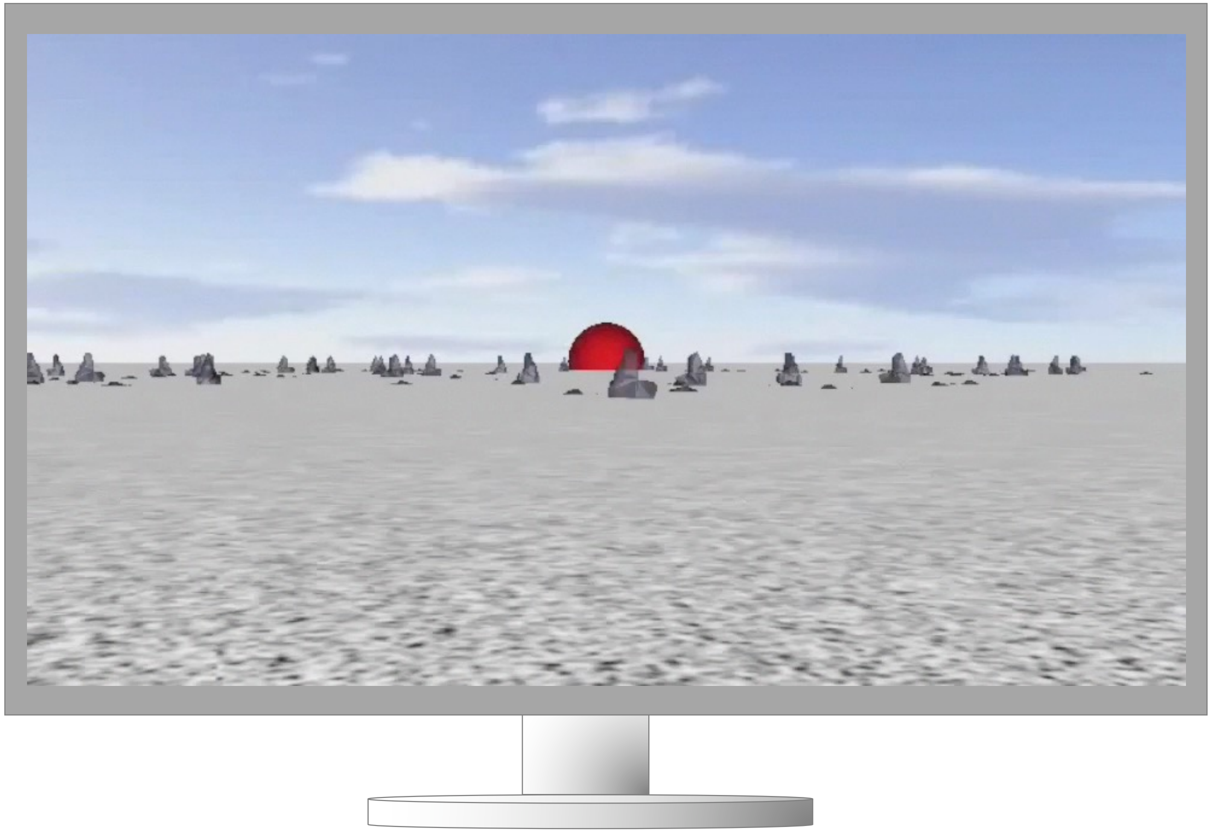
Priors can be learned...



Learning the prior

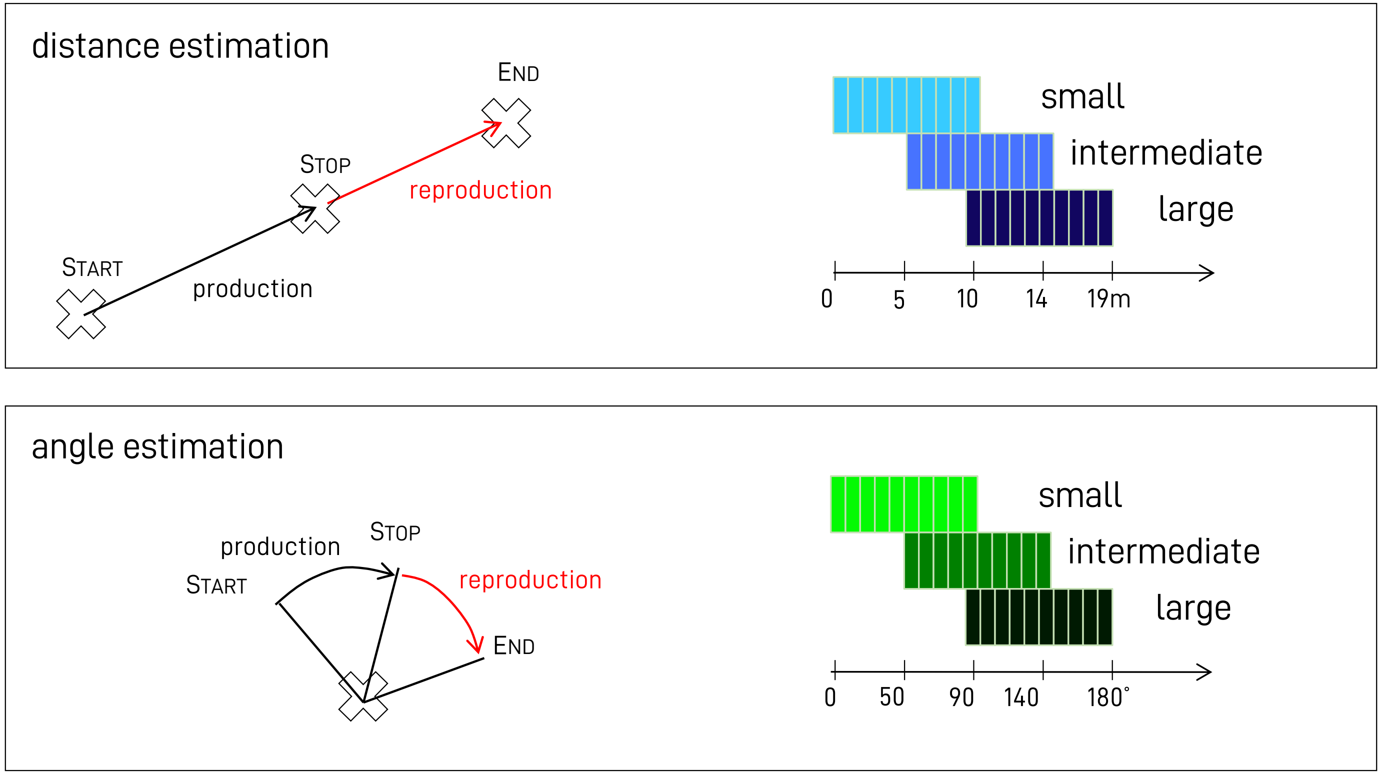


"optimal errors" in magnitude estimation

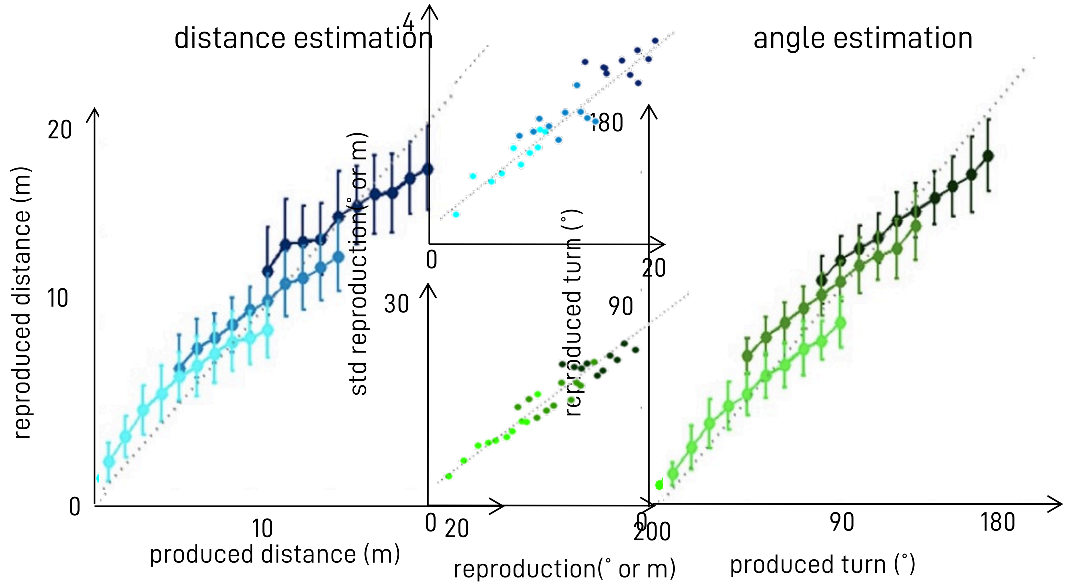


Petzschner & Glasauer, JoN, 2011

Varying the sample range

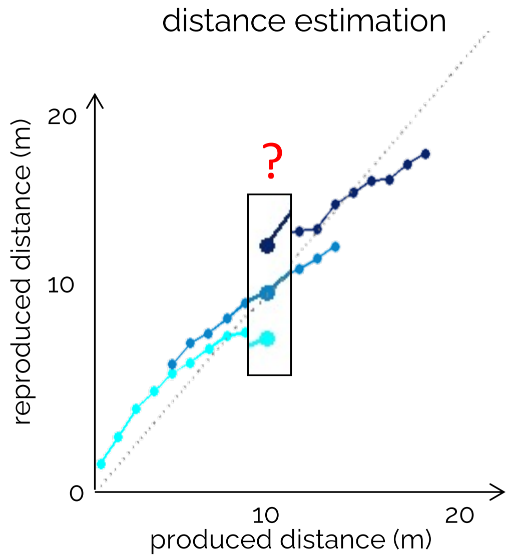


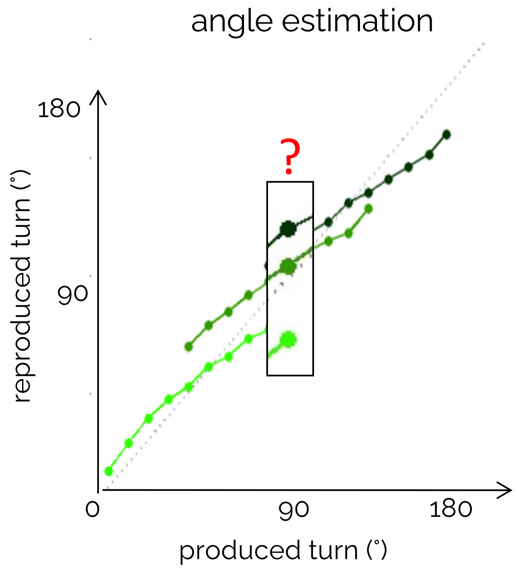
Petzschner & Glasauer, JoN, 2011



Petzschner & Glasauer, JoN, 2011

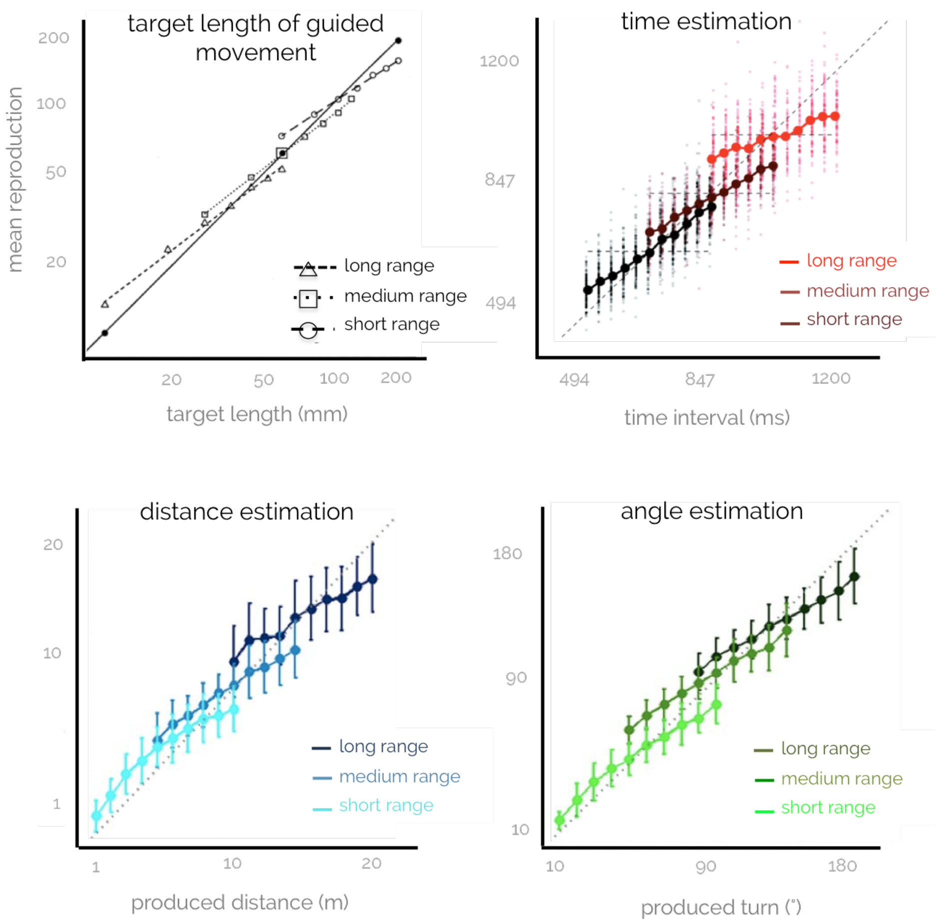
Prior knowledge: Experience





Petzschner & Glasauer, JoN, 2011

Let’s take a look at the literature

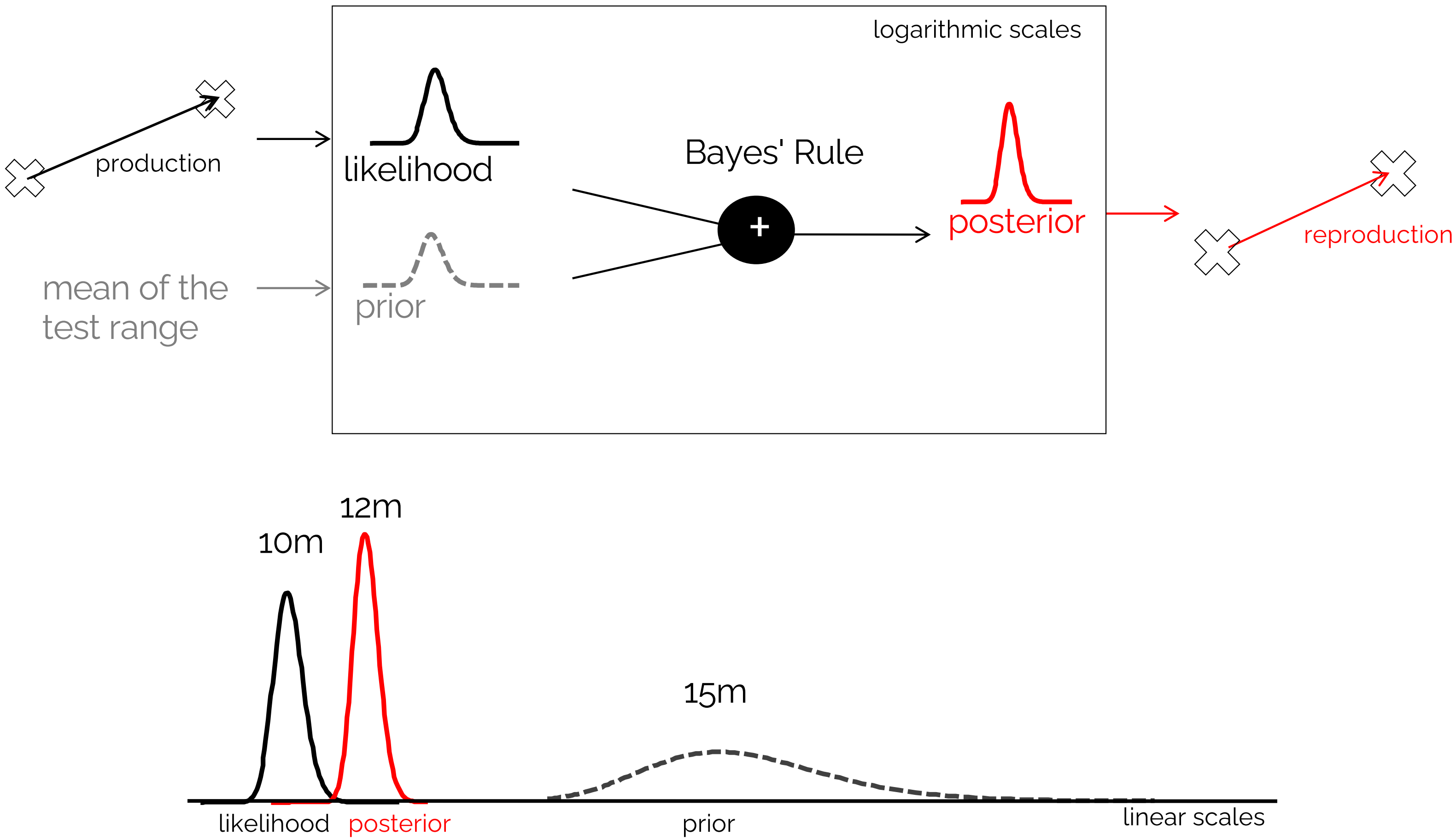


Petzschner & Glasauer, JoN, 2011; Petzschner et al. TiCS, 2015

A Bayesian Model for magnitude estimation

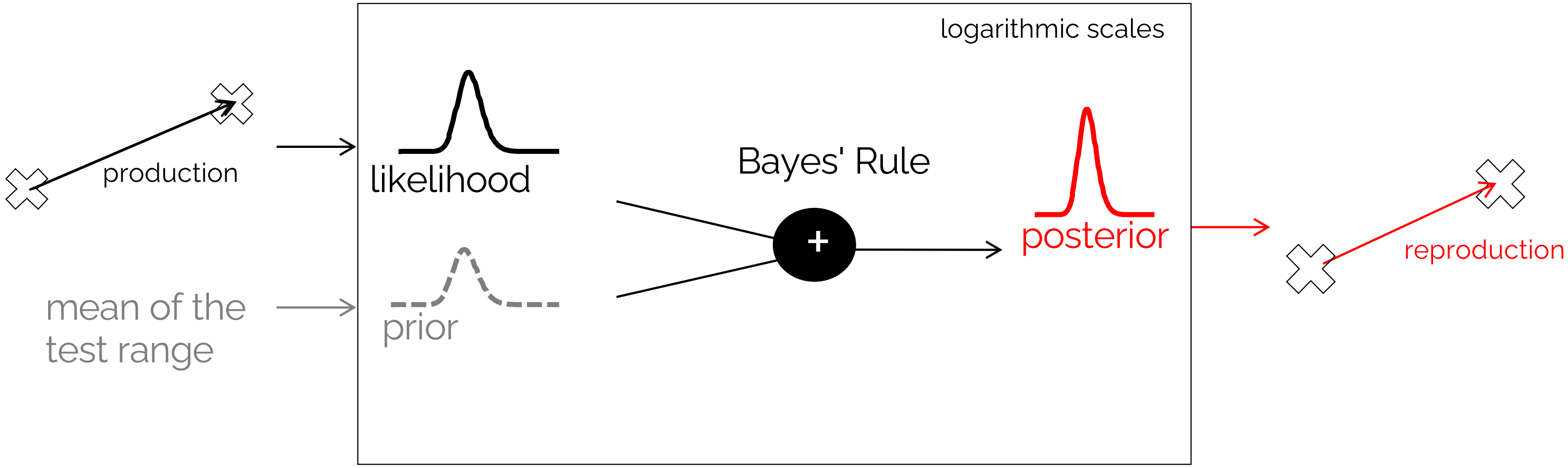
Petzschner & Glasauer, JoN, 2011

A Bayesian Model for magnitude estimation



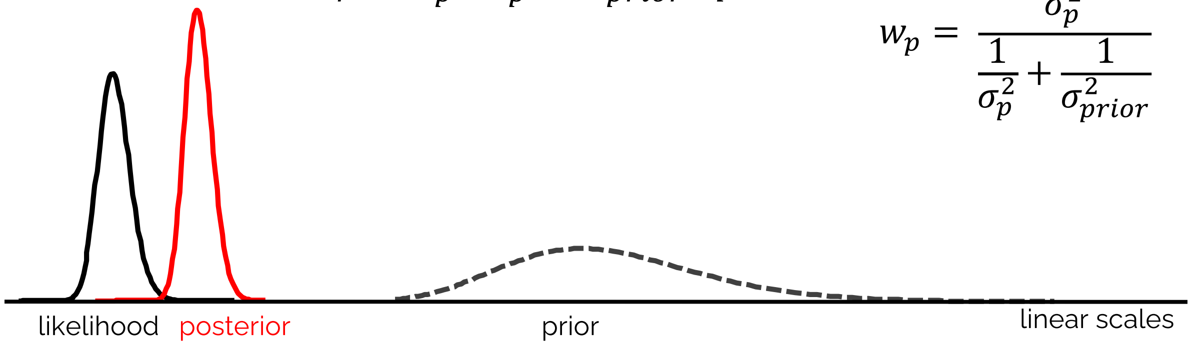
Petzschner & Glasauer, JoN, 2011

A Bayesian Model for magnitude estimation



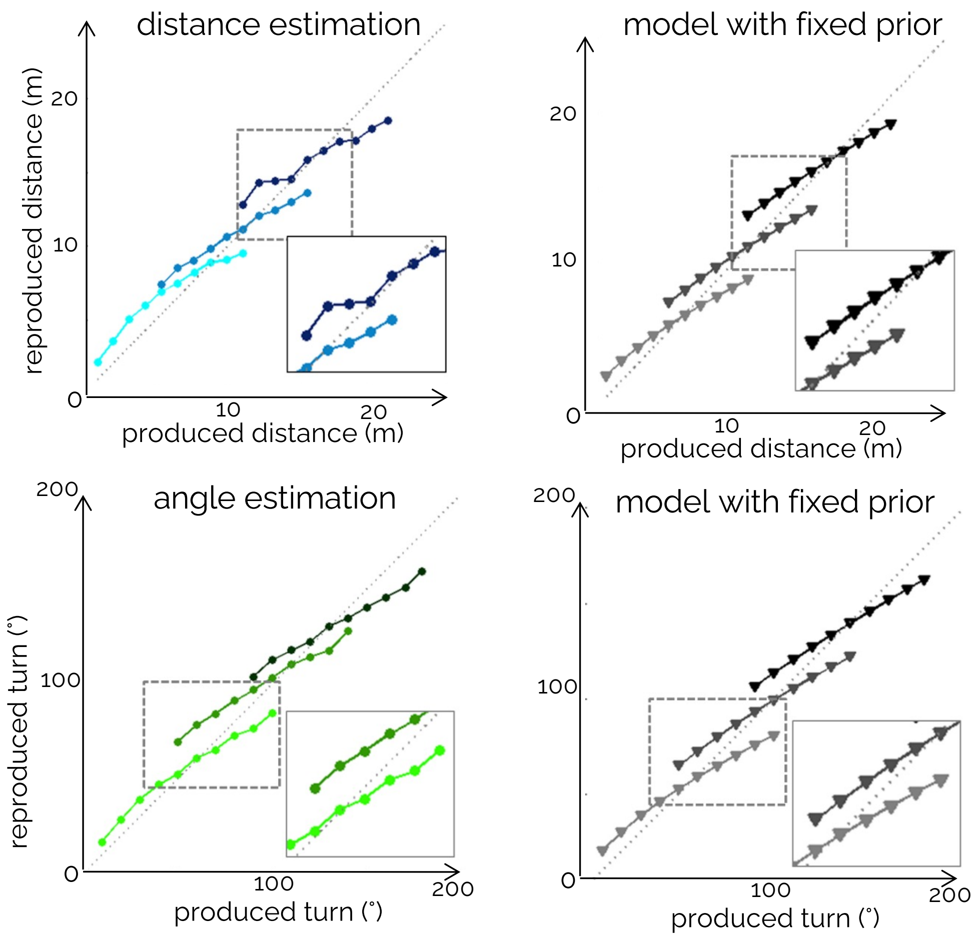
$$\widehat{d_r} = w_p \cdot d_p + w_{prior} \cdot prior$$

$$w_p = \frac{\frac{1}{\sigma_p^2}}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_{prior}^2}}$$



Petzschner & Glasauer, JoN, 2011

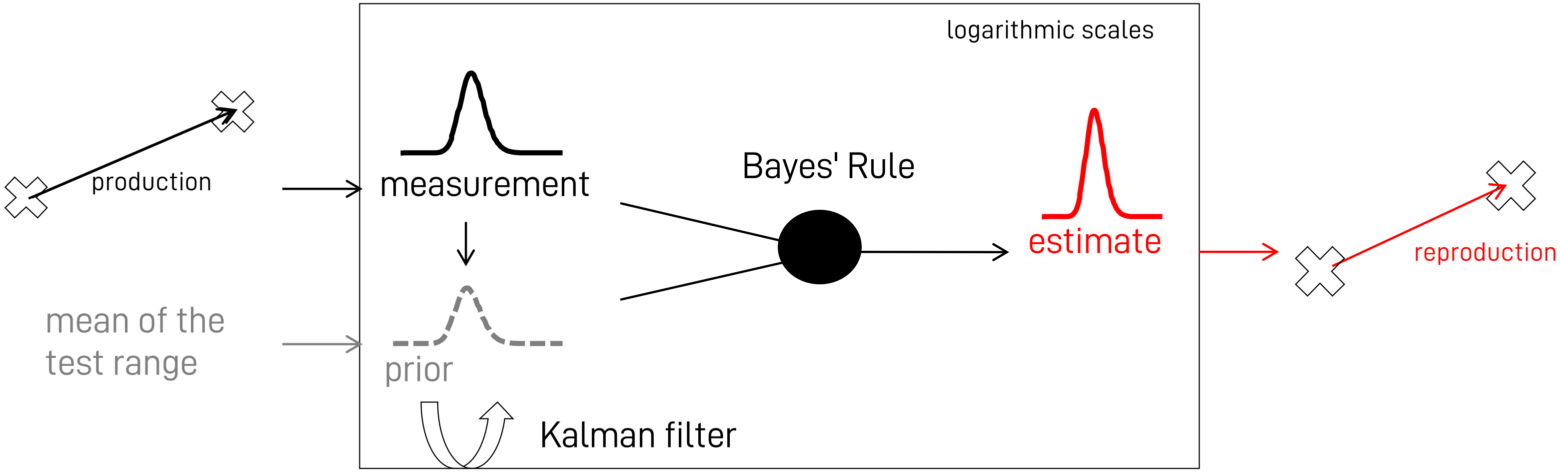
Quantitative results



Petzschner & Glasauer, JoN, 2011

Where do priors come from?

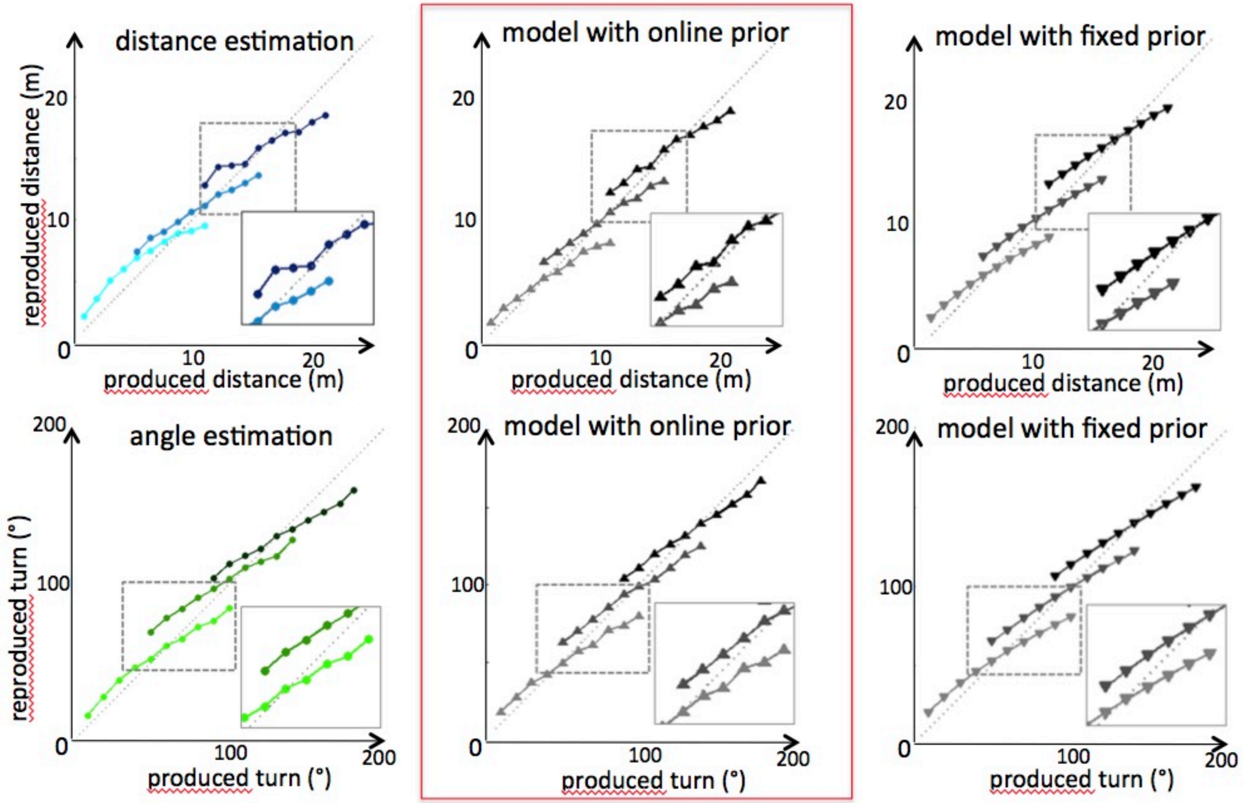
Bayesian Learning



"Todays posterior is tomorrows prior."

Petzschner & Glasauer, JoN, 2011

Bayesian Learning

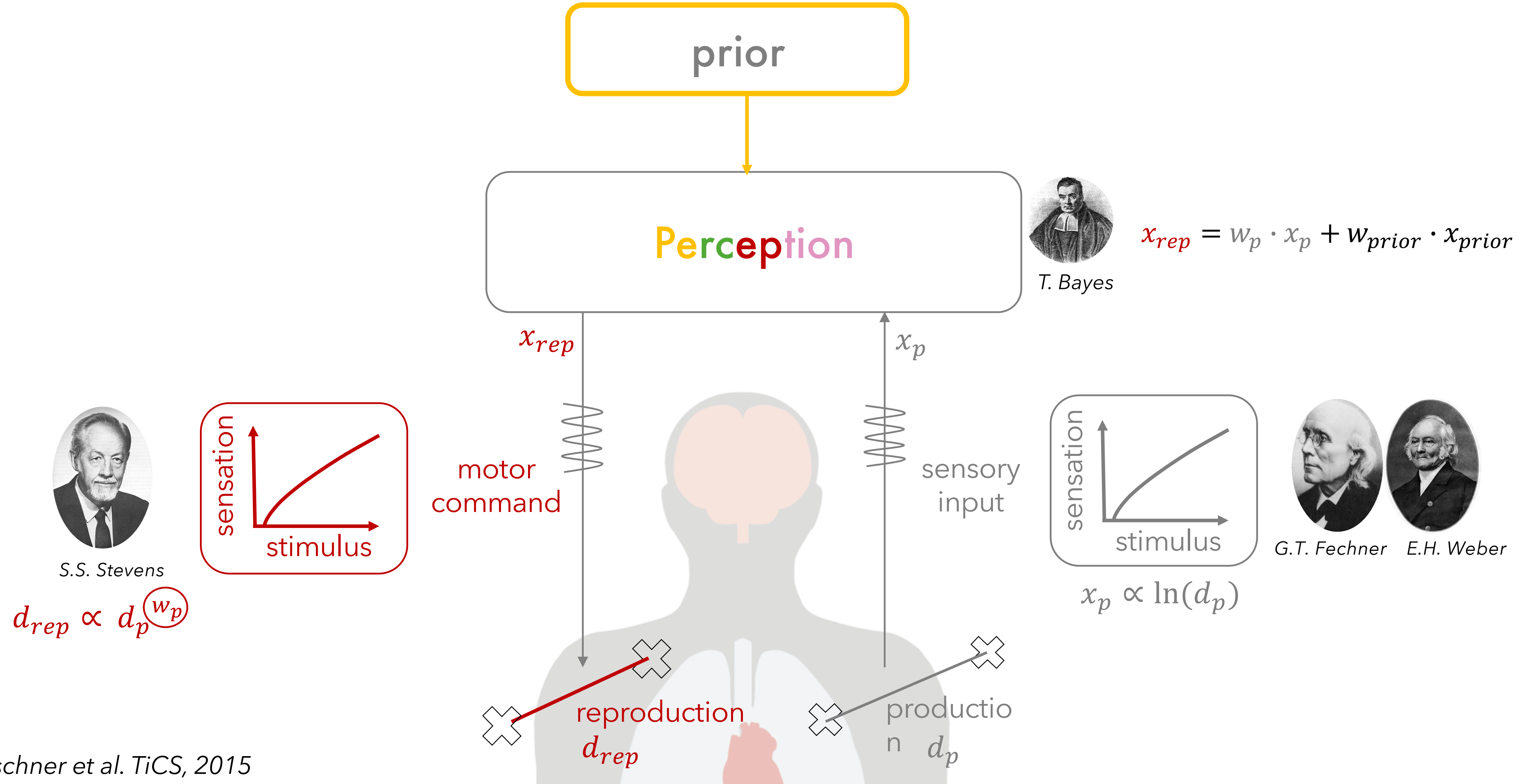


More on Bayesian Learning in Christoph's Lecture this afternoon

Petzschner & Glasauer, JoN, 2011

Side note

Back to psychophysics



Petzschner et al. TiCS, 2015

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, Nosfosky, Rehder, Navarro, Griffiths, Feldman, Tenenbaum, Rosseel, Goodman, Kemp, Mansinghka, …]

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

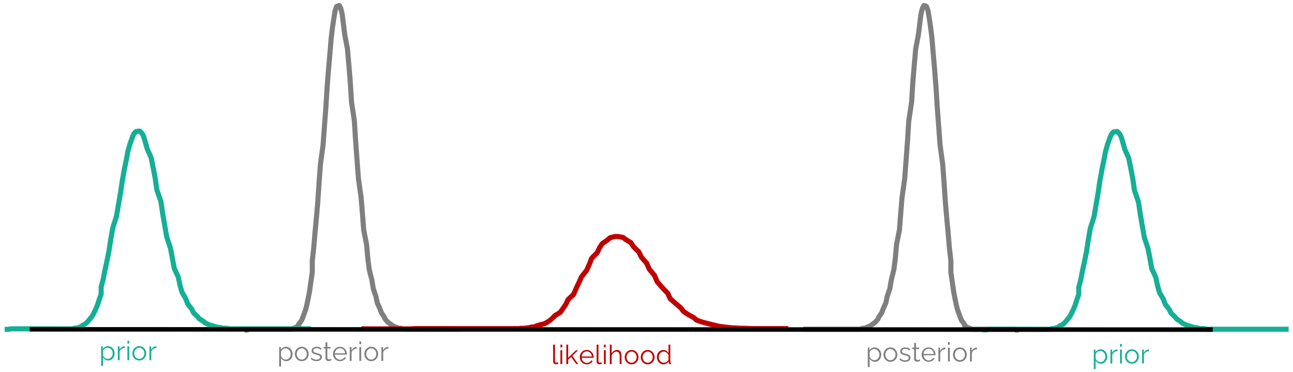
Causal inference [Waldmann, Sloman, Steyvers, Griffiths, Tenenbaum, Yuille, …]

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

Optimal motor control [Wolpert, Körding …]

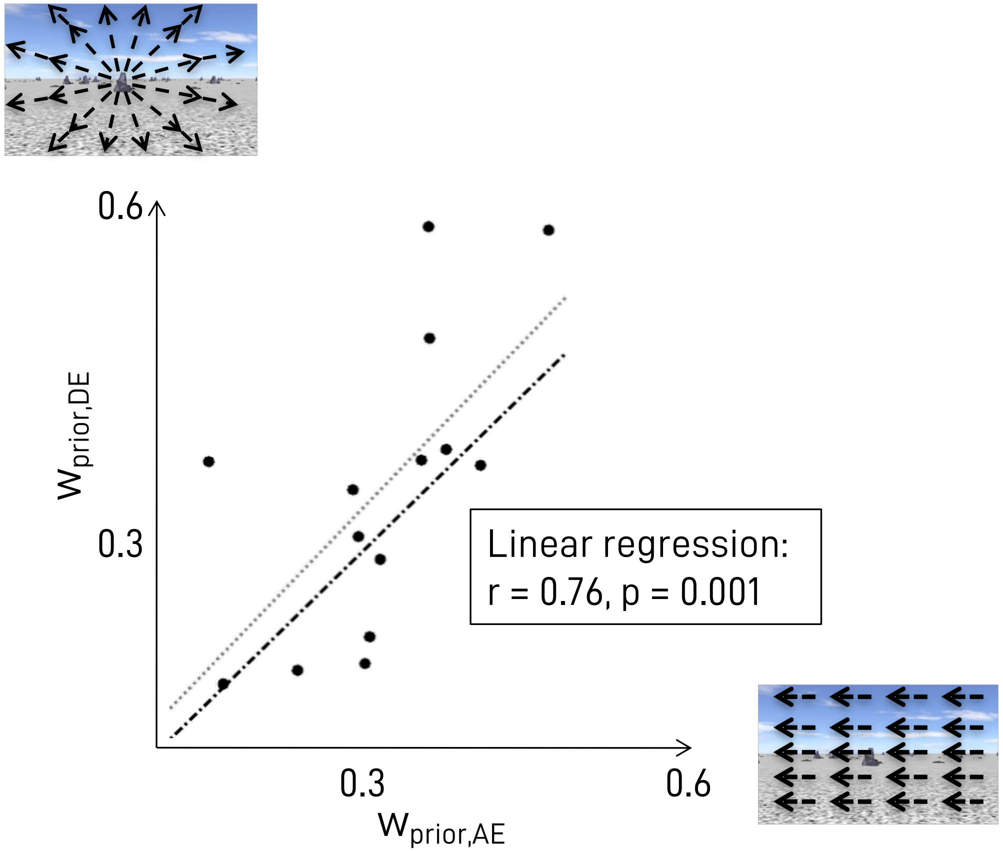
Remark 1

'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

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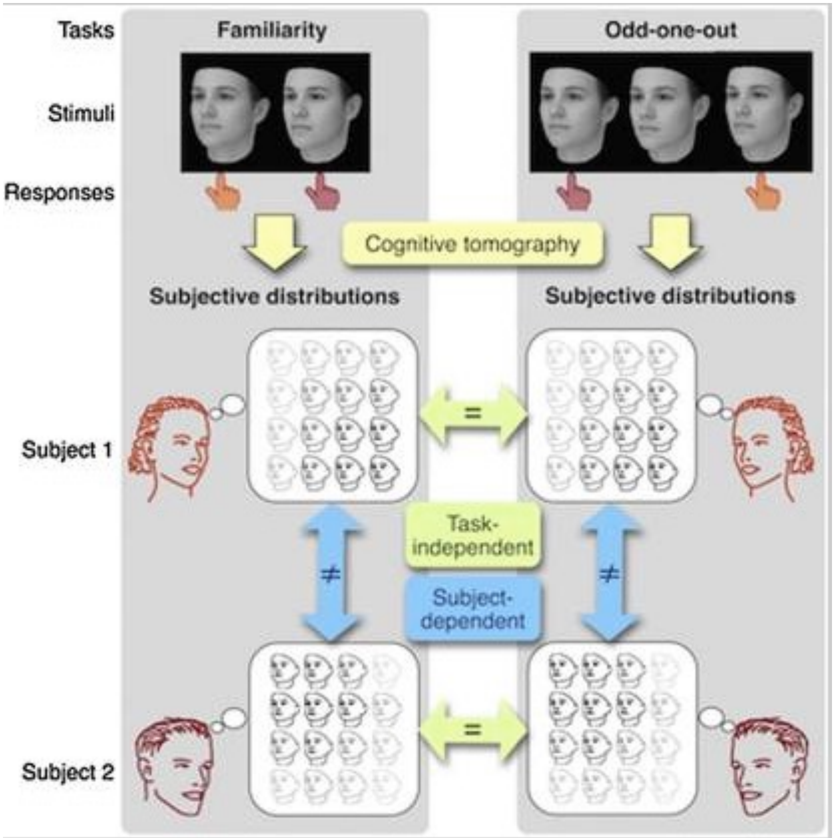
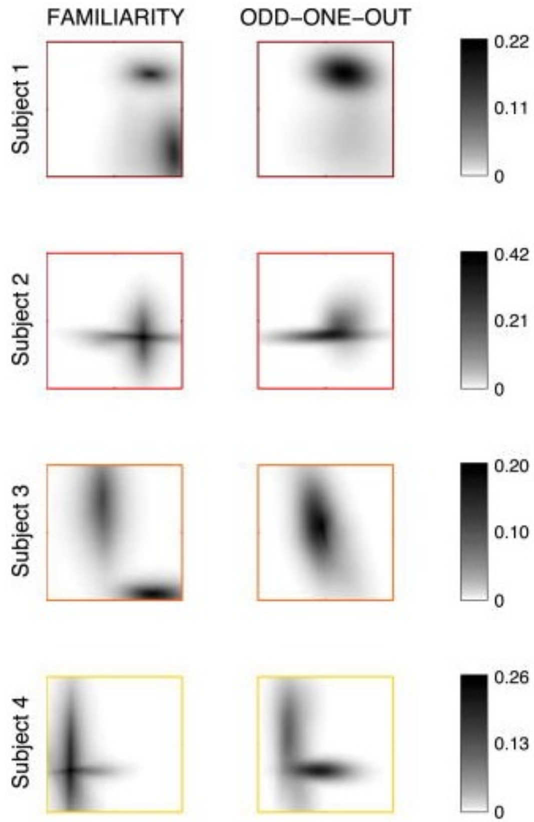




Houlsby et al., Current Biology, 2013

Remark 2

Are humans optimal?

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

As such the 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 Lilian'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**

Petzschner et al., Biol Psych., 2017

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 Turi[1], Themelis Karaminis[2], 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 Dayan[4]

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 Roiser[1]

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

Allostatic Self-efficacy: A Metacognitive Theory of Dyshomeostasis-Induced Fatigue and Depression

Klaas E. Stephan[1,2,3], Zina M. Manjaly[1,4], Christoph D. Mathys[2], Lilian A. E. Weber[1], Saee Paliwal[1], Tim Gard[1,5], Marc Tittgemeyer[3], Stephen M. Fleming[2], Helene Haker[1], Anil K. Seth[6] and Frederike H. Petzschner[1]*

REVIEW ARTICLE
Front. Psychiatry, 30 May 2013 | https://doi.org/10.3389/fpsyt.2013.00047

The computational anatomy of psychosis

Rick A. Adams[1]*, Klaas Enno Stephan[1,2,3], Harriet R. Brown[1], Christopher D. Frith[1] and Karl J. Friston[1]

[1]Wellcome Trust Centre for Neuroimaging, Institute of Neurology, University College London, London, UK.
[2]Translational Neuromodeling Unit, Institute for Biomedical Engineering, University of Zurich, ETH Zurich, Zurich, Switzerland
[3]Laboratory for Social and Neural Systems Research, University of Zurich, Zurich, Switzerland

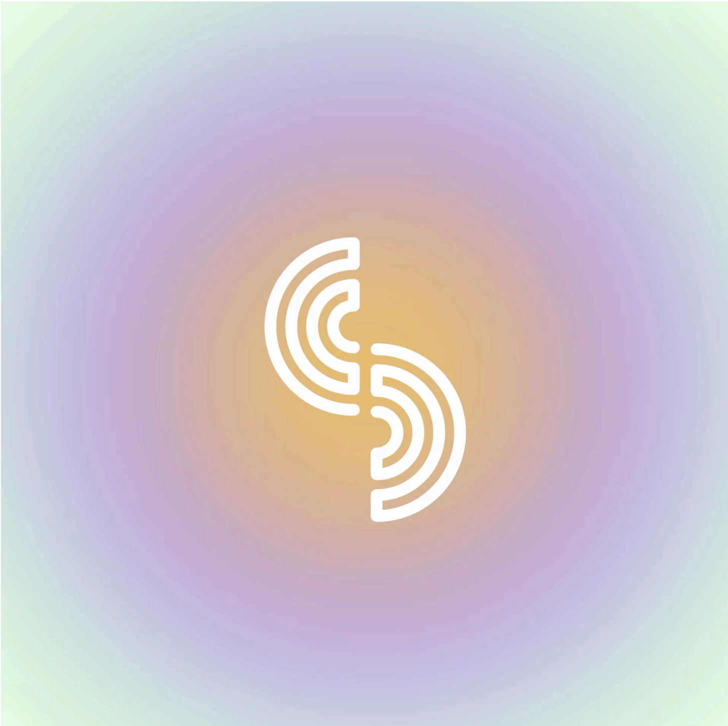
BRAIN
A JOURNAL OF NEUROLOGY

OCCASIONAL PAPER

A Bayesian account of 'hysteria'

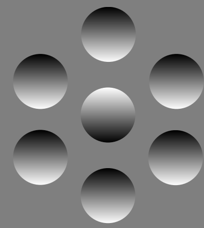
Mark J. Edwards,[1,*] Rick A. Adams,[2,*] Harriet Brown,[2] Isabel Pareés[1] and Karl J. Friston[2]

SOMA - Chronic Pain

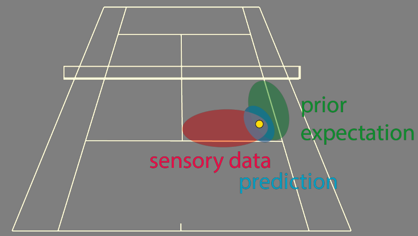


Summary

- *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.*



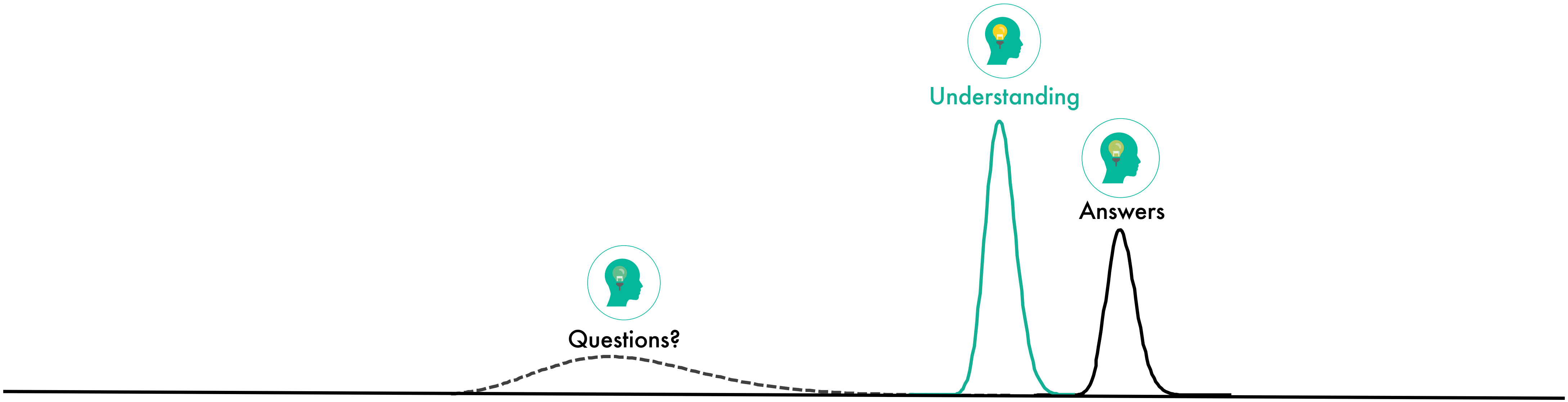
- *Humans combine sensory information according to their uncertainty.*

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*


Understanding
Answers
Questions?

Thank you

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Interested in working with us?
https://fpetzschner.com/lab/