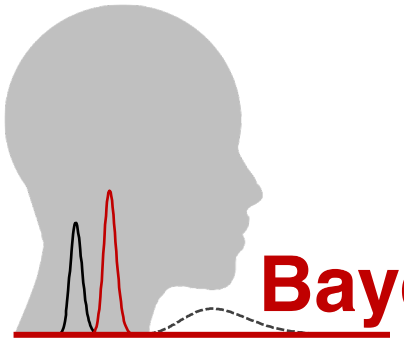


Bayesian Models of Perception

Dr. Frederike Petzschner

Reach out

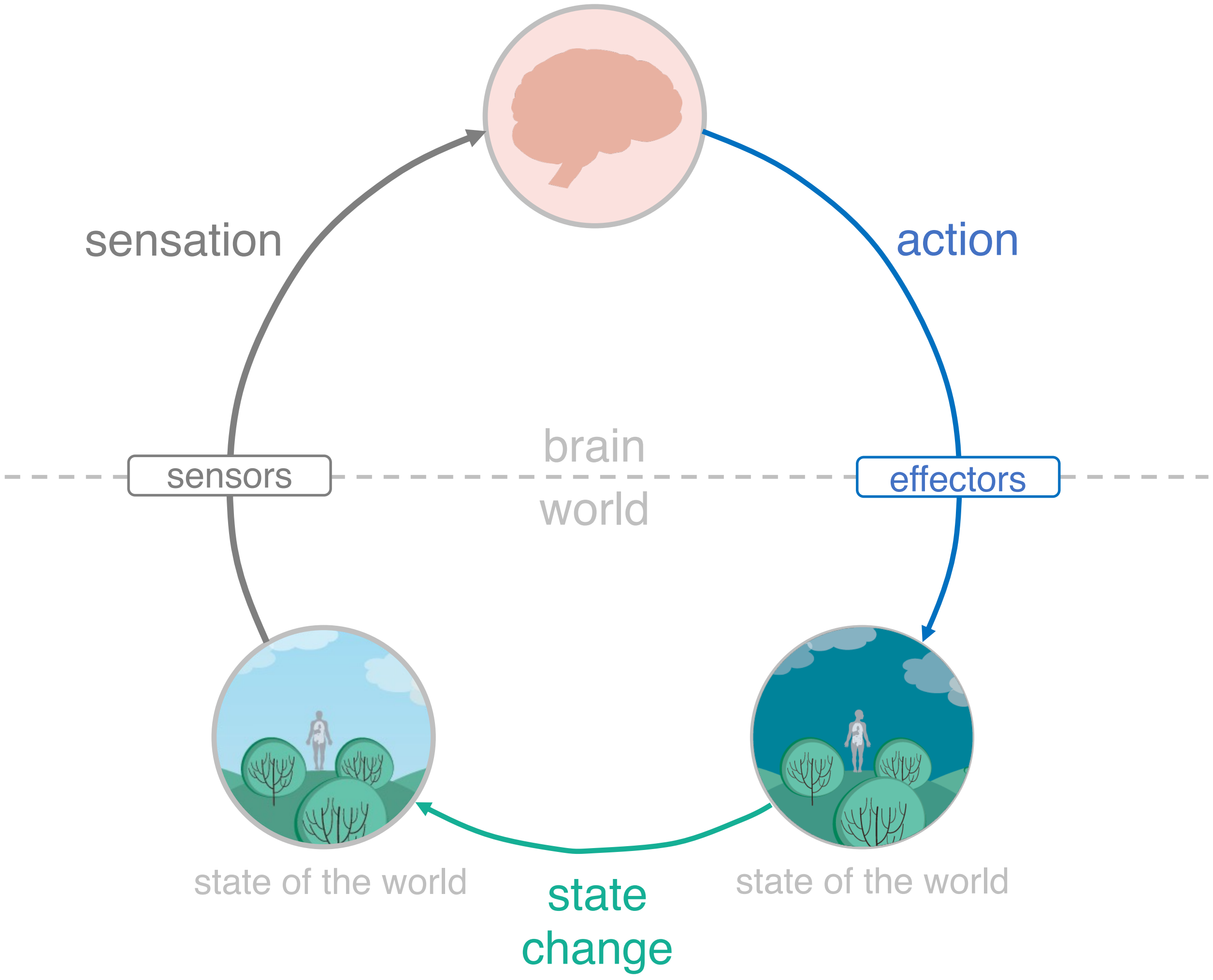
Website: fpetzschner.com/lab
Mail: frederike_petzschner@brown.edu
Twitter: @rikepetzschner

PEAC Lab

BROWN

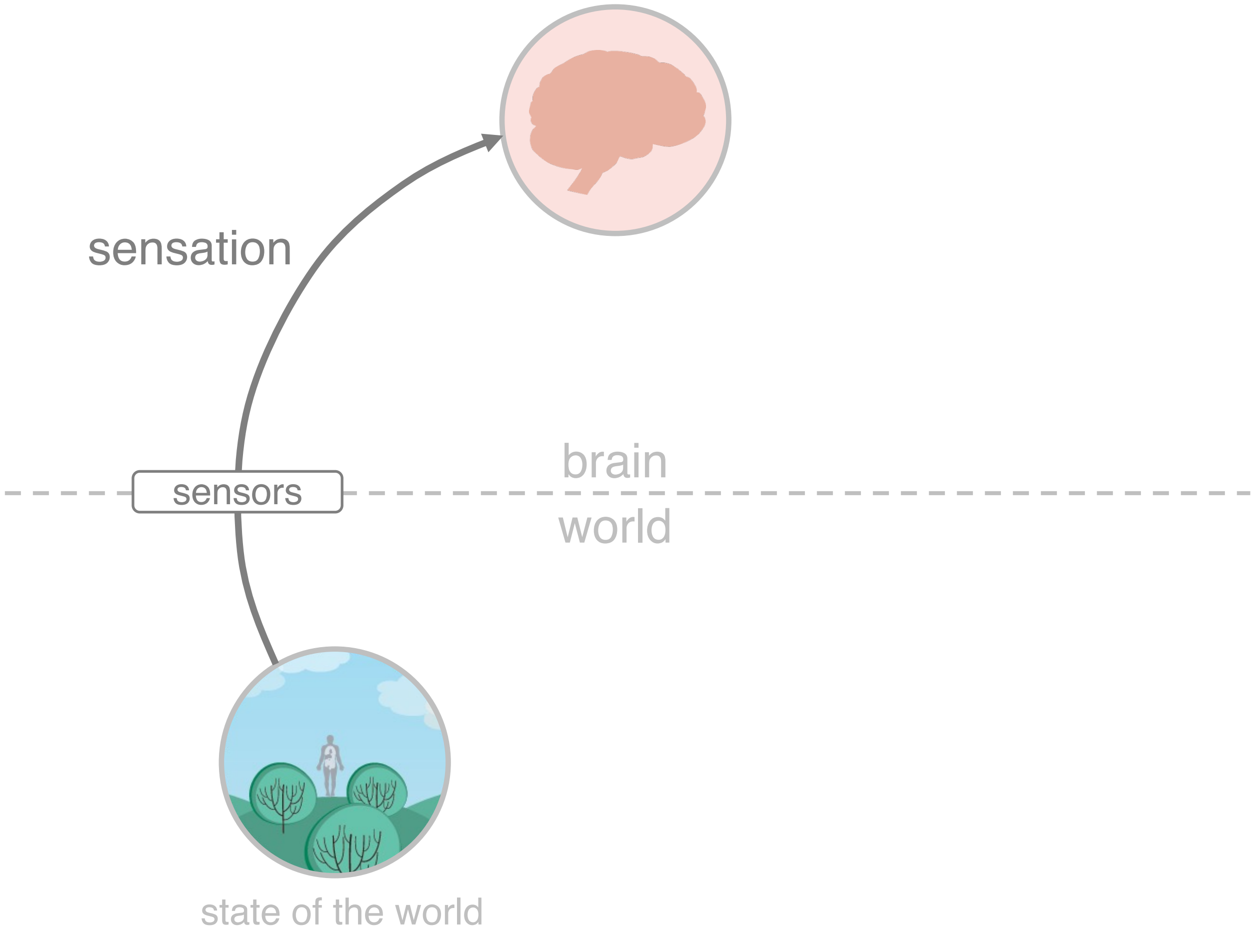
What is the computation that is carried out when we perceive something?

What is perception?

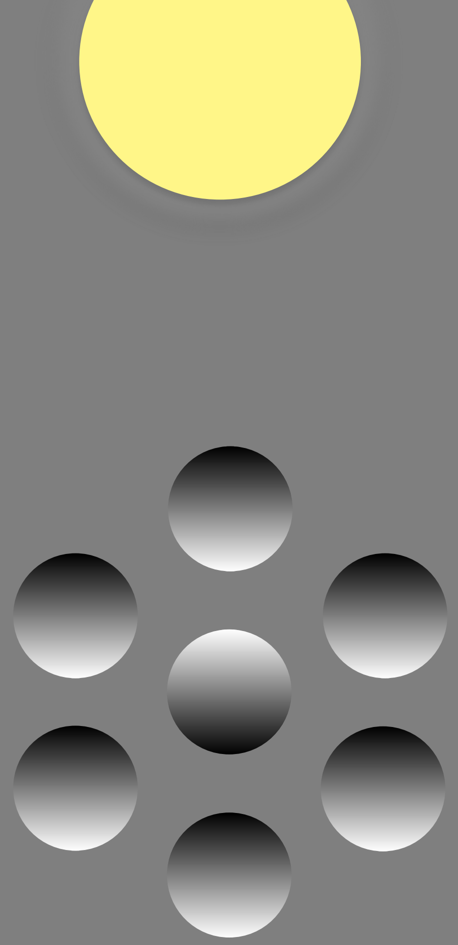


Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017

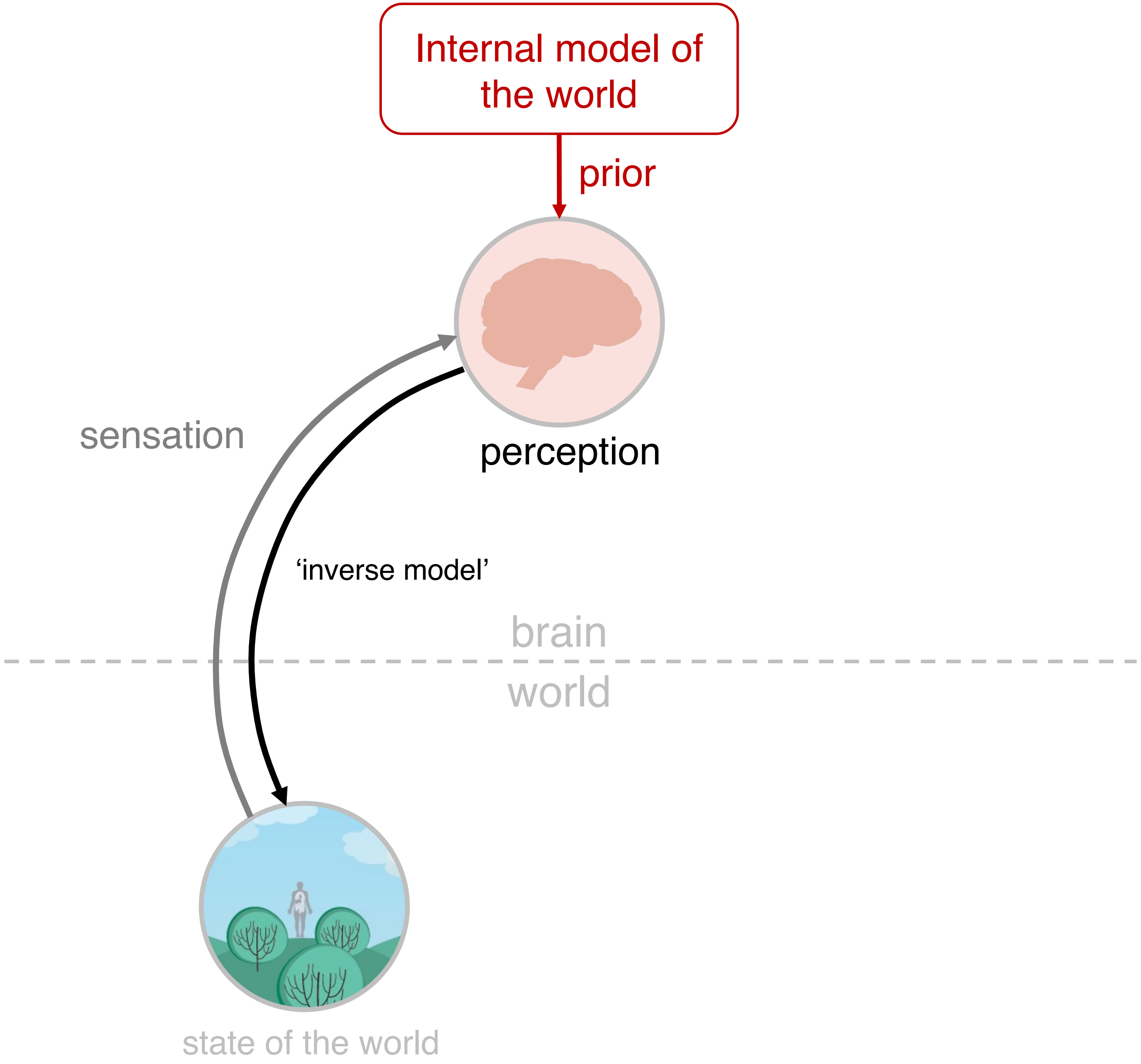
What is perception?



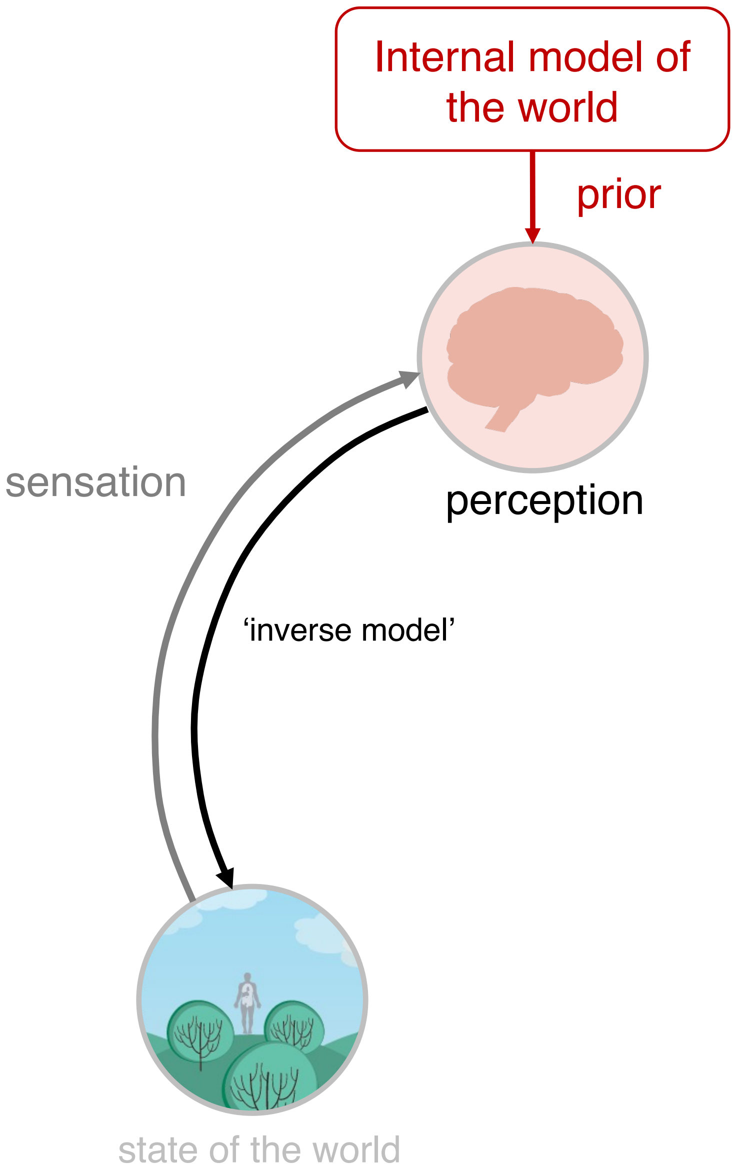
Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017



Adams et al., Nature Neuroscience, 2004

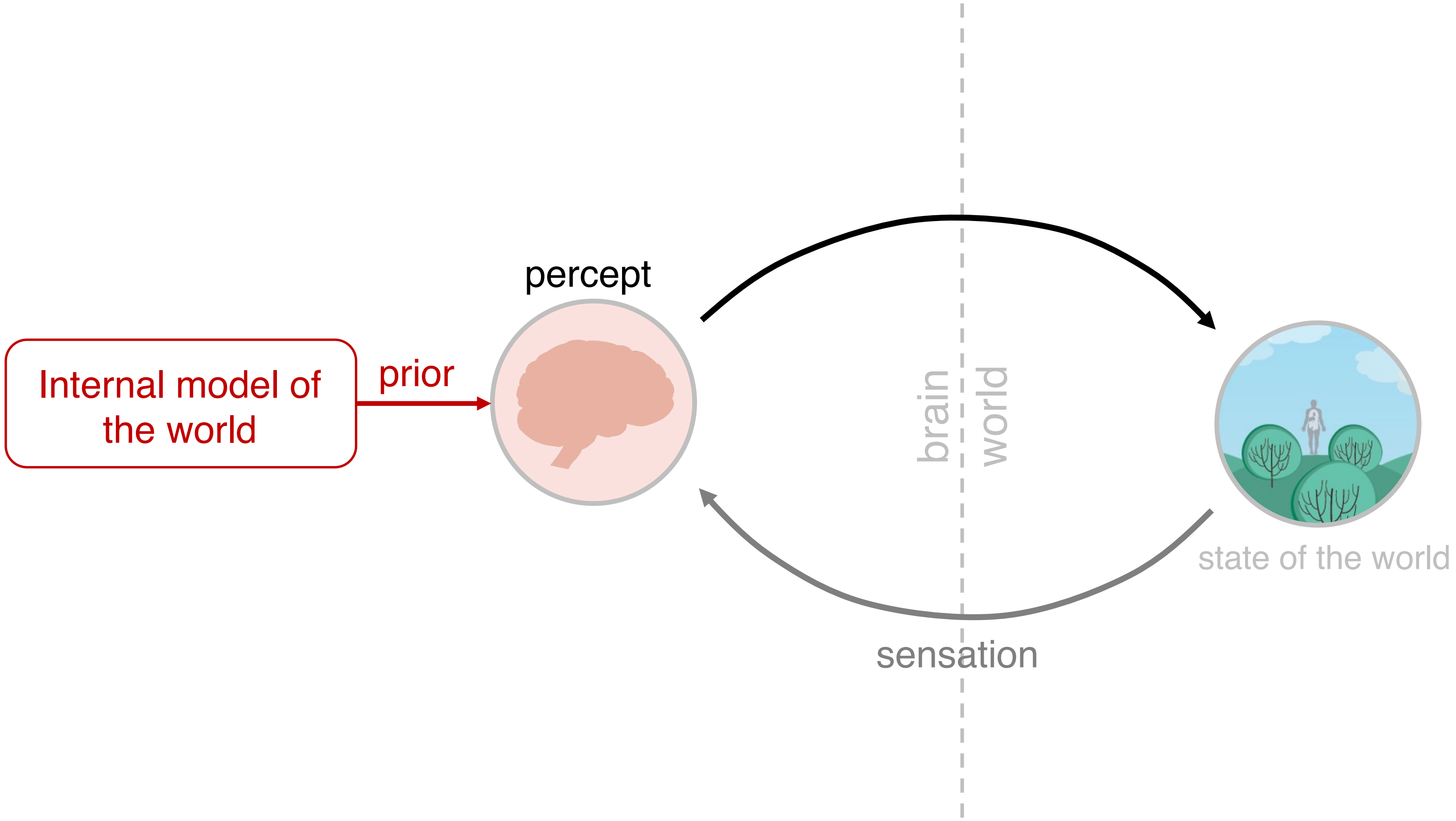


Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017



Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017

Perception as inference



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

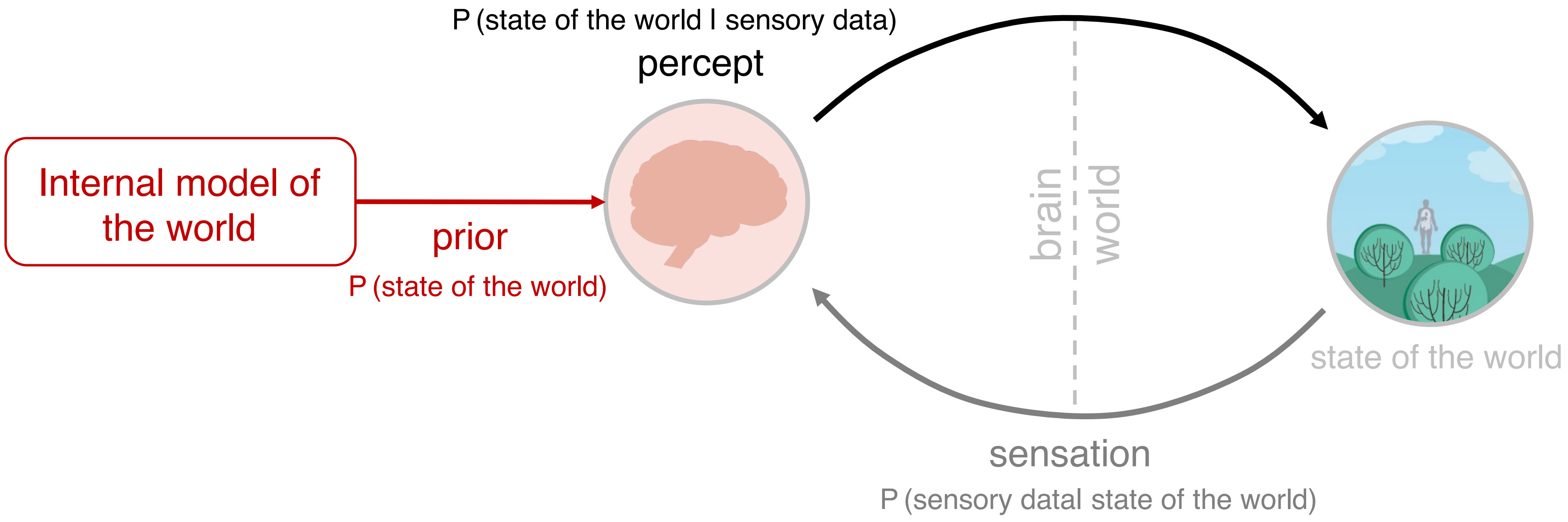
Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017

Why?

A Bayesian model of perception

Perception as Bayesian inference

Noisy information can be expressed by probability distributions



Bayes' Rule

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

Petzschner et al., TINS, 2021; Petzschner et al, Biol Psych, 2017

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

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

Model comparison

Bayes as a tool for model-based analysis

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

Today…

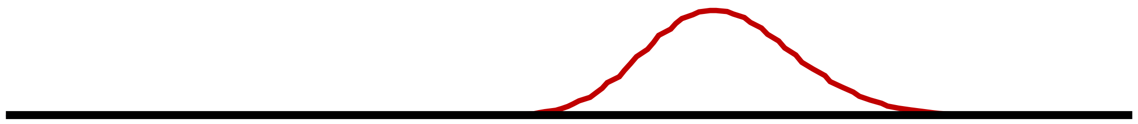
Model of a computation performed by the brain

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

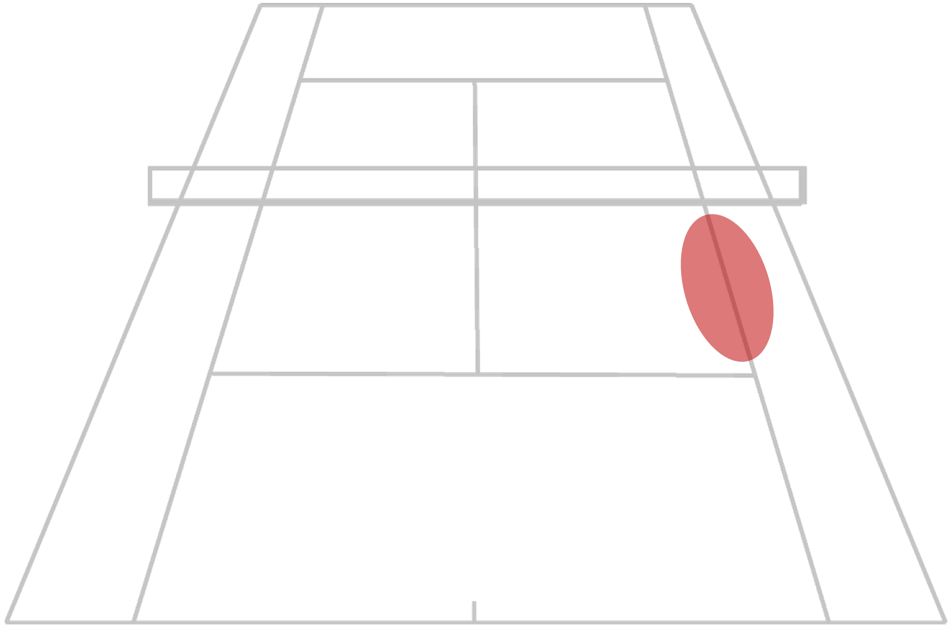
Bayes as a model of behavior

Example

Information extraction with Bayes' Rule



prior



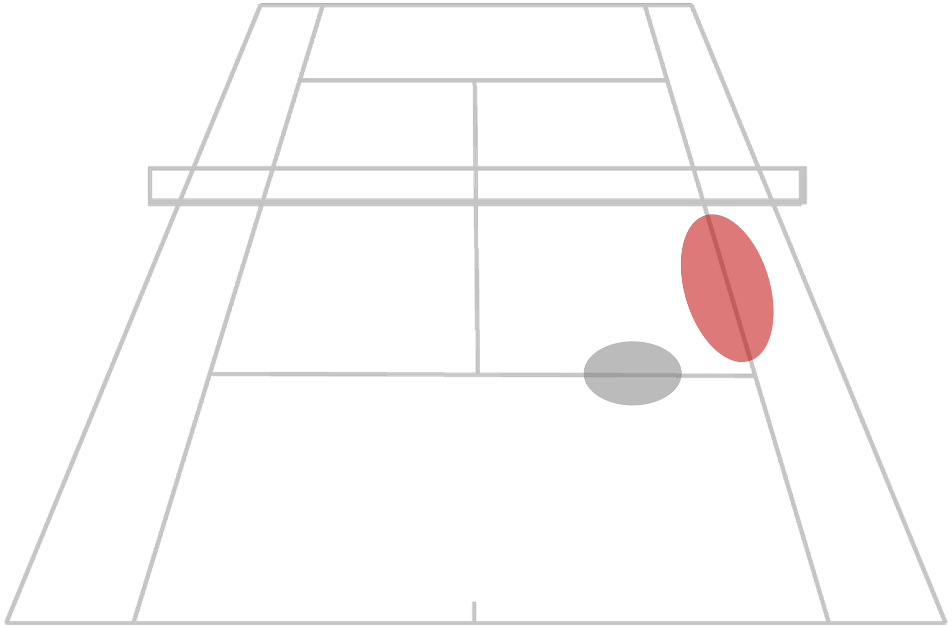
Bayes' Rule

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

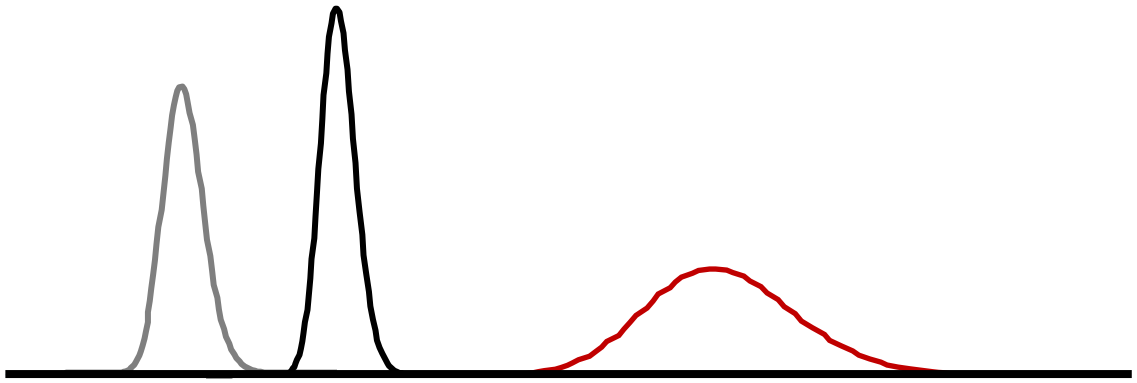
Information extraction with Bayes' Rule

Bayes' Rule

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

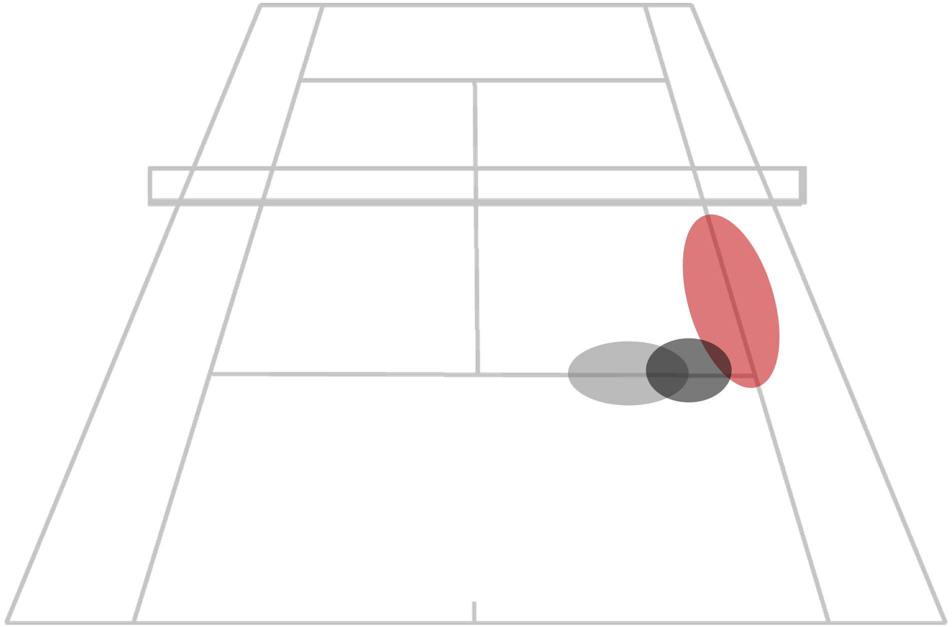


Information extraction with Bayes' Rule



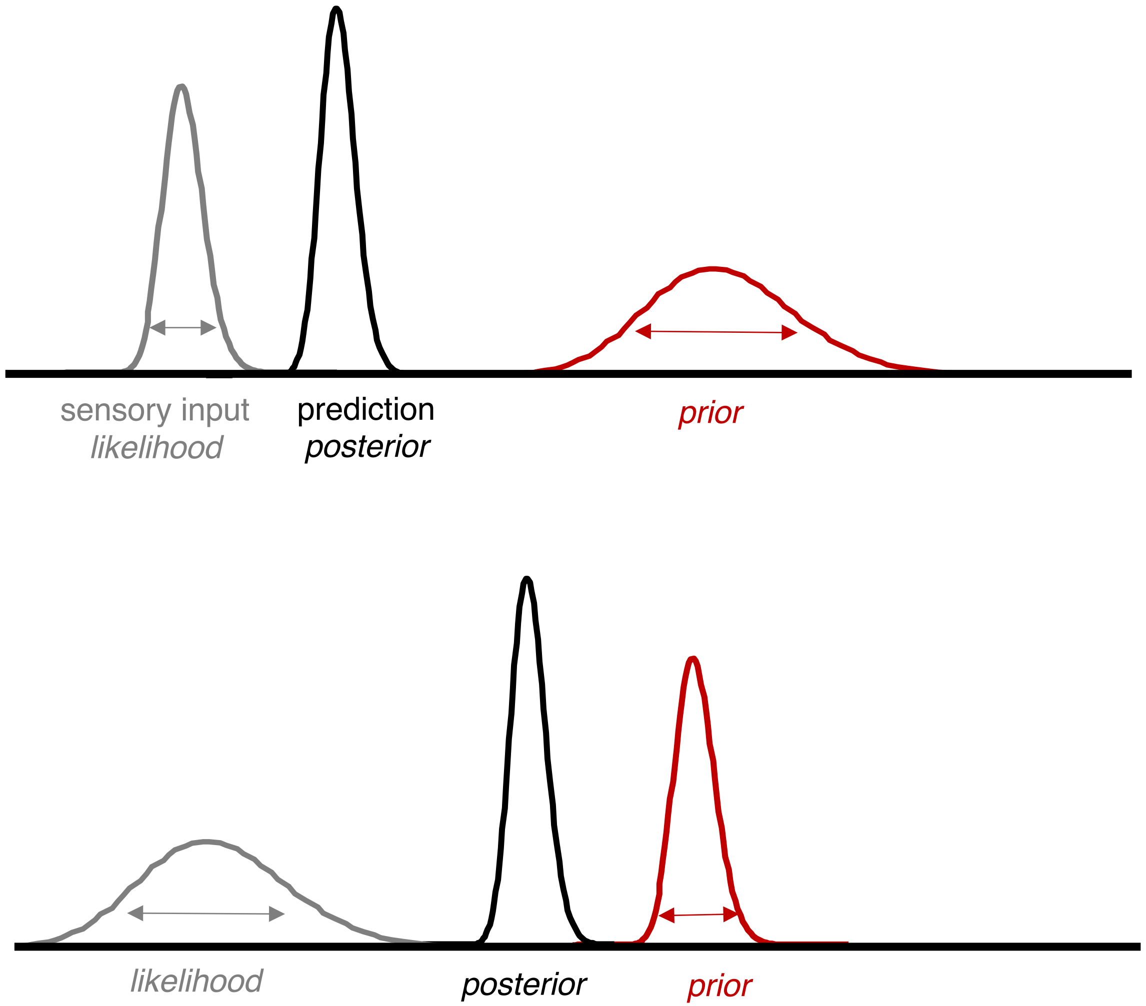
Bayes' Rule

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



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

How Bayes' Rule deals with uncertainty



Bayes Rule:

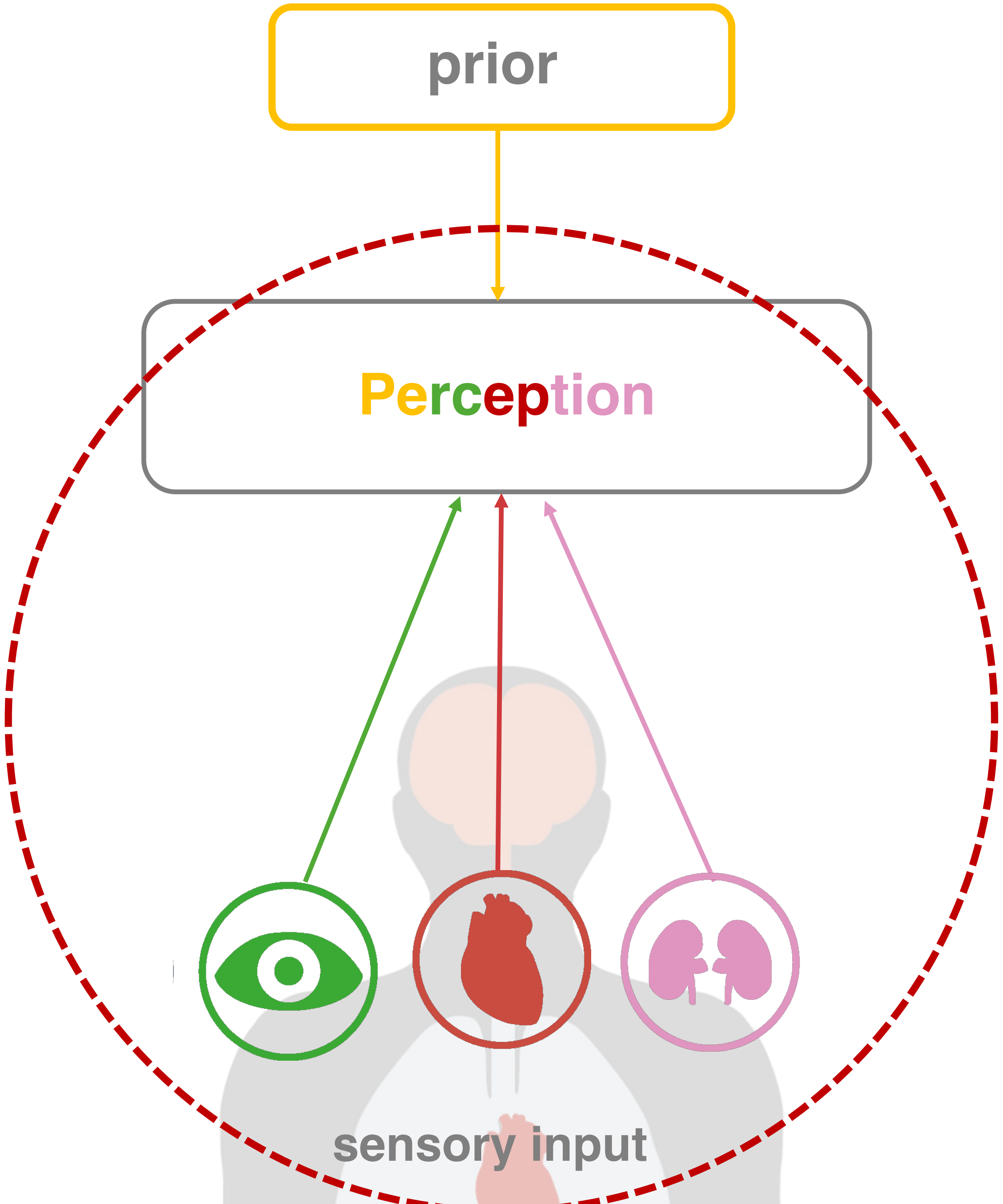
Optimal combination of uncertain information sources

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,*]

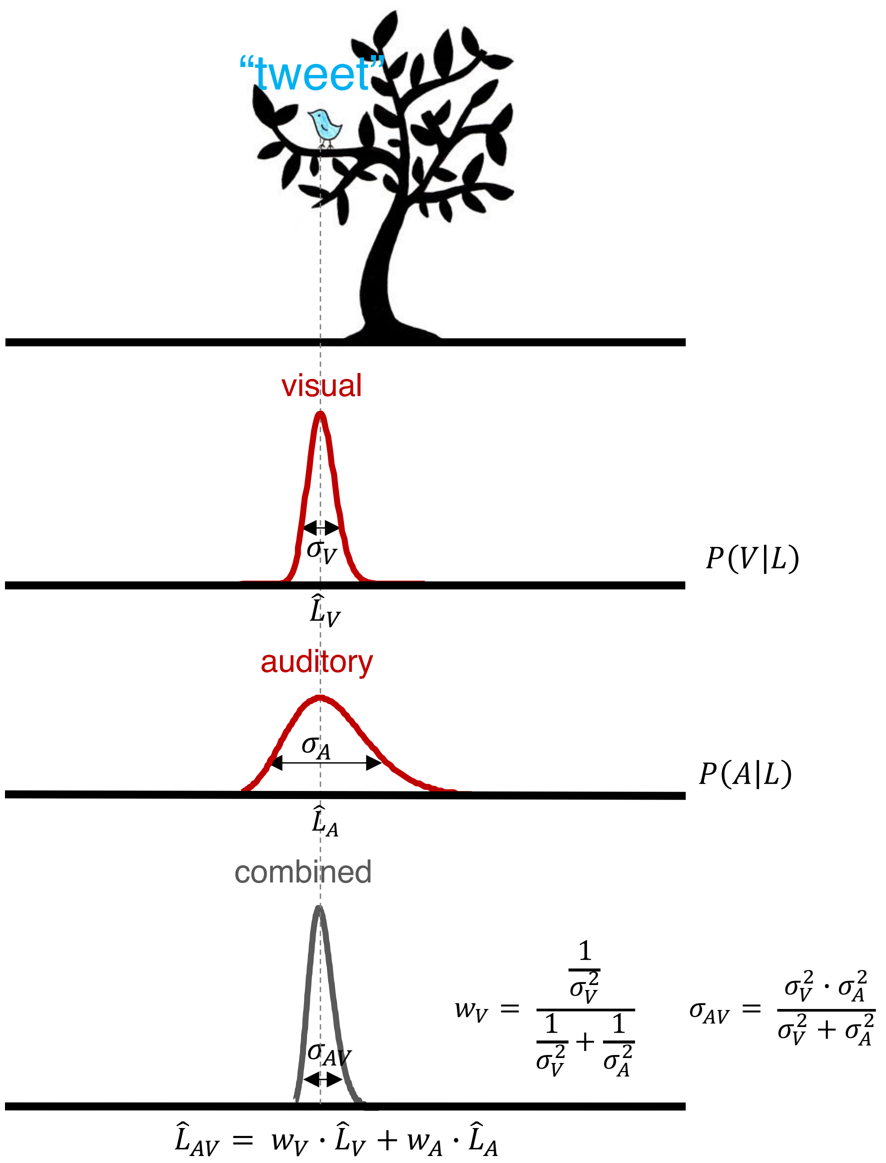
Results for the various unimodal location discrimina-

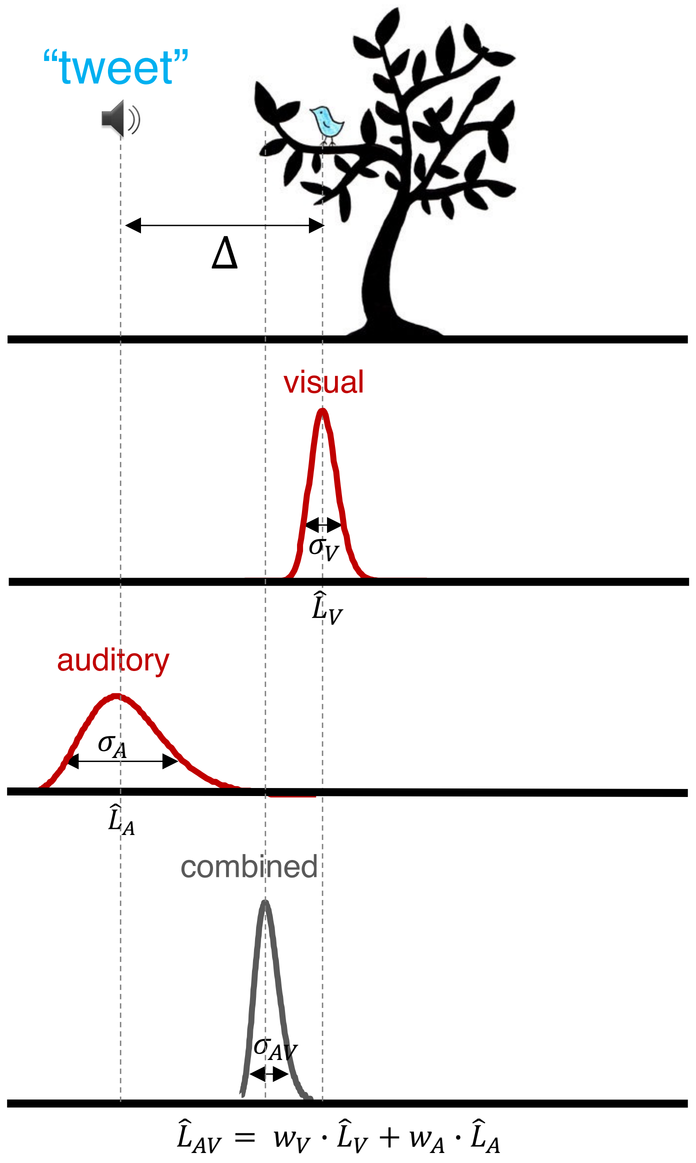
Humans integrate visual and haptic information in a statistically optimal fashion

Marc O. Ernst* & Martin S. Banks

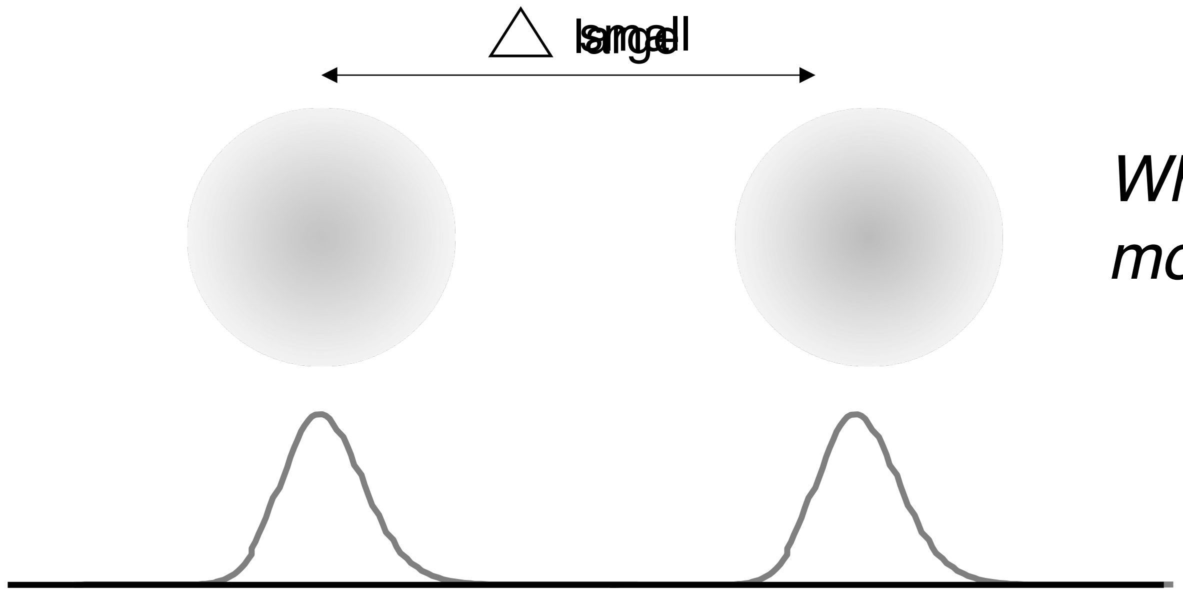
Vision Science Program/School of Optometry, University of California, Berkeley 94720-2020, USA

Combination of visual and auditory information

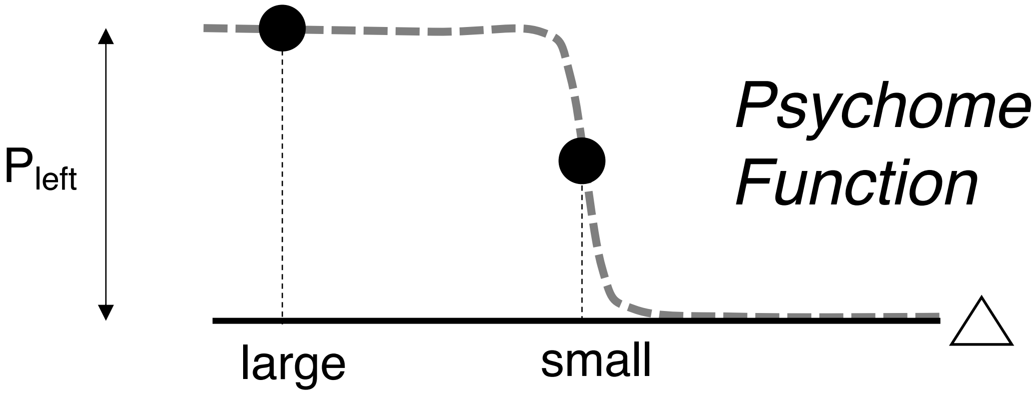




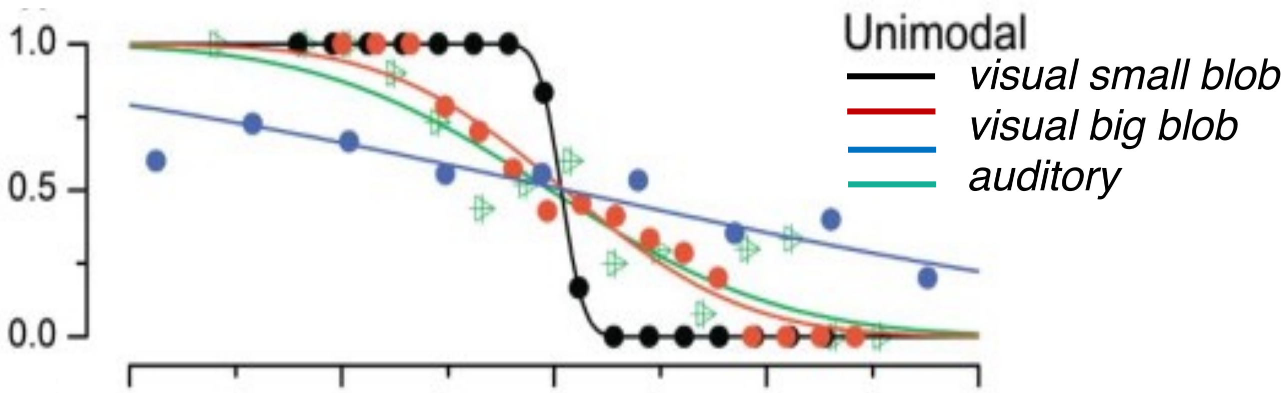
The Psychometric Function



Which one was more left?

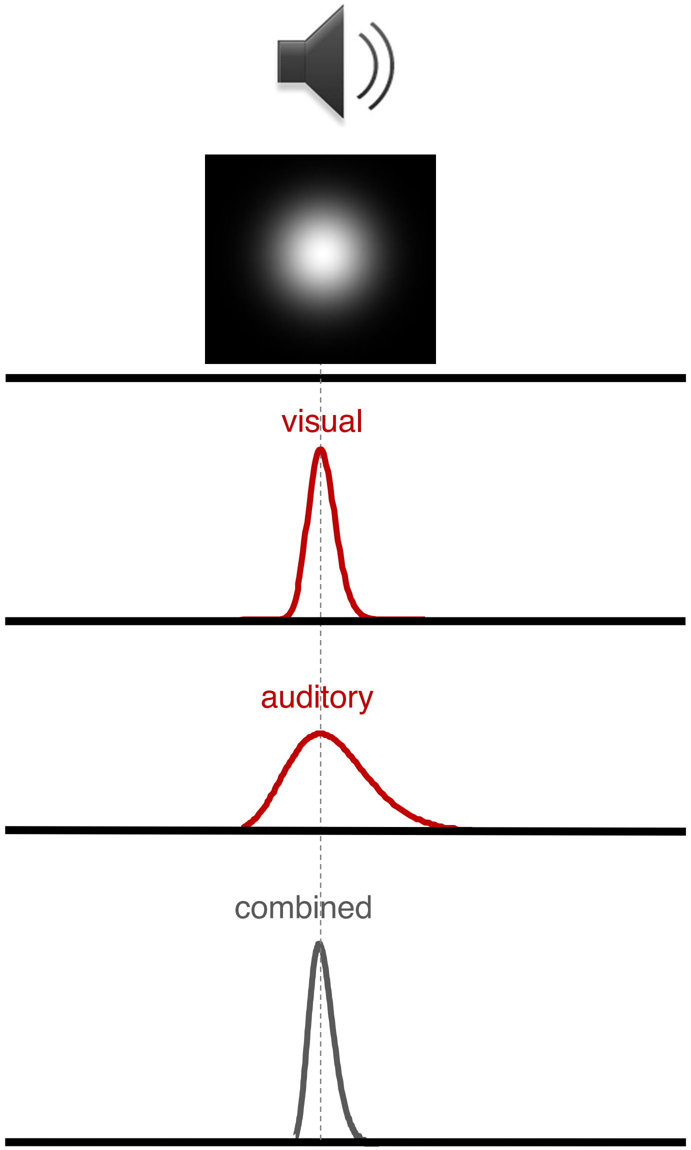


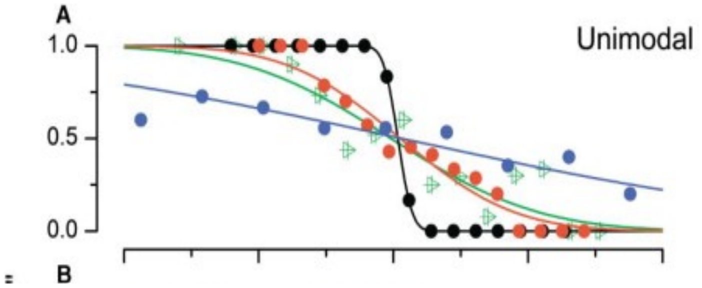
Psychometric Function



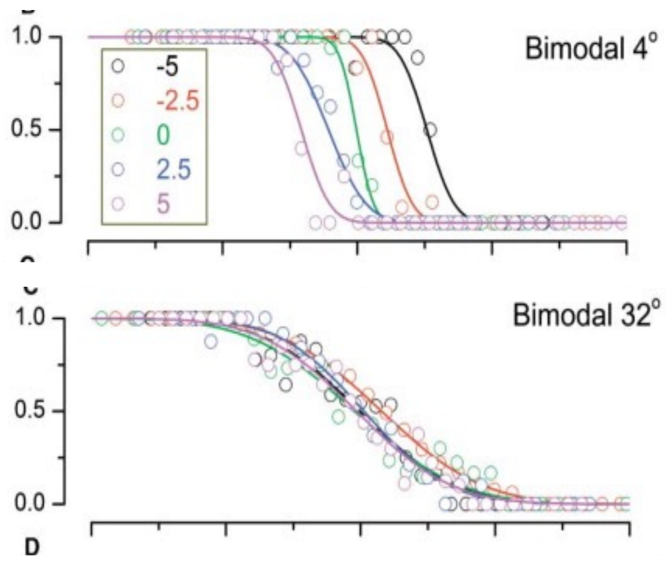
Alais & Burr, Current Biology, 2004

Combination of visual and auditory information

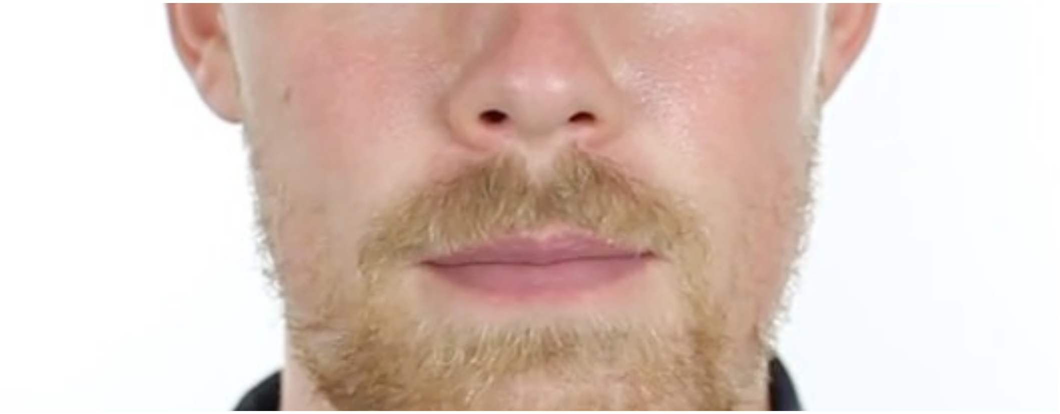




$$\sigma_{AV} = \frac{\sigma_V^2 \cdot \sigma_A^2}{\sigma_V^2 + \sigma_A^2}$$

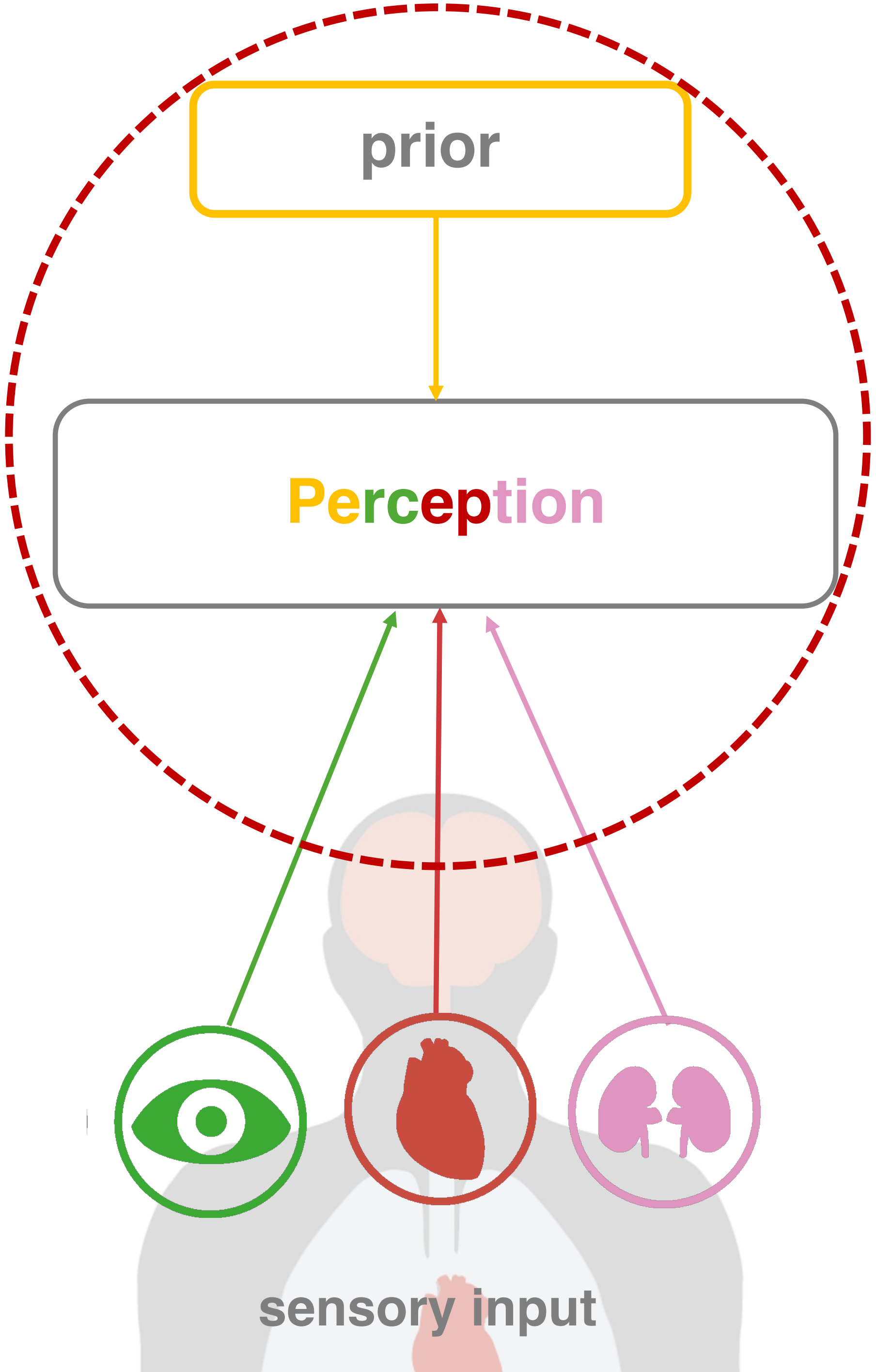


Alais & Burr, Current Biology, 2004



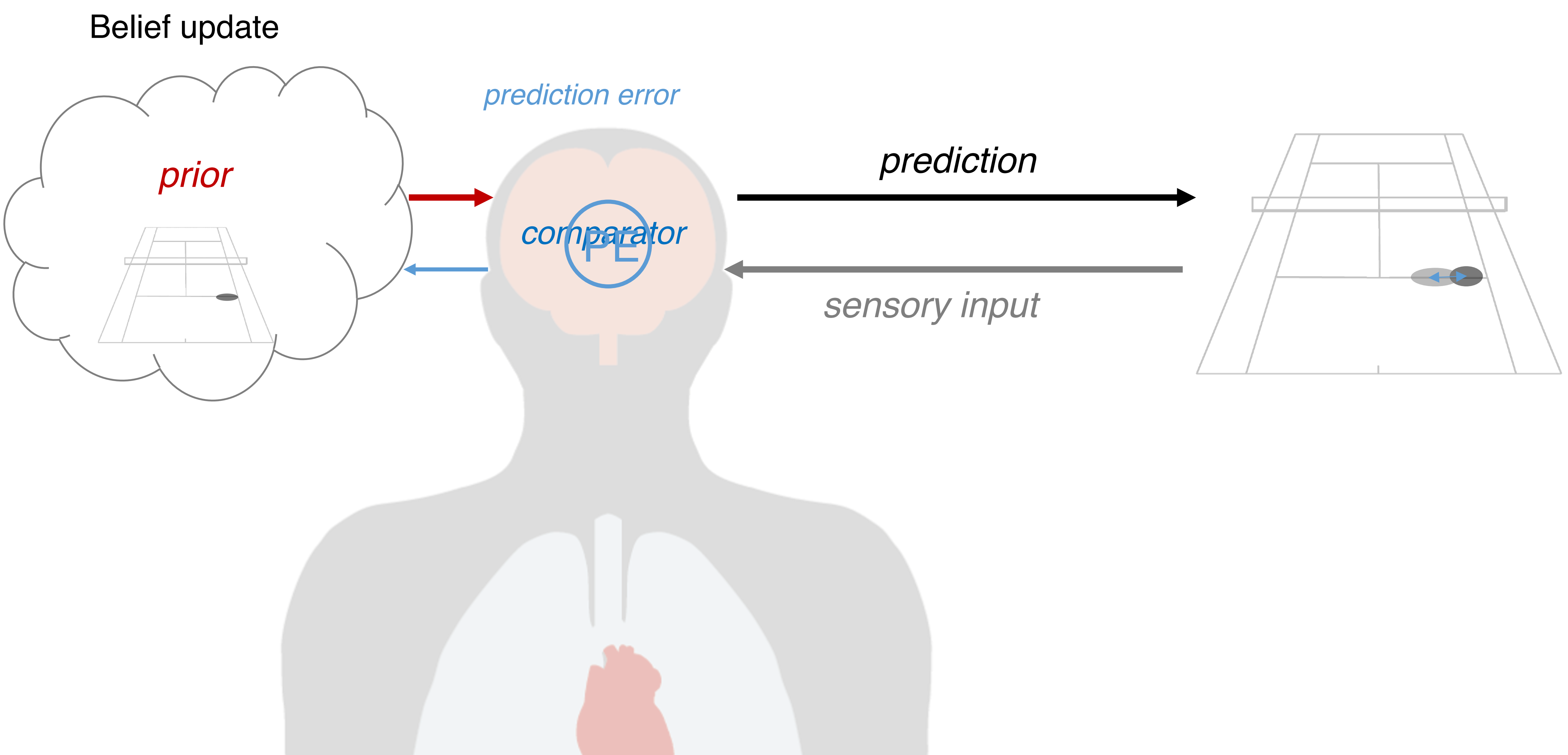
BAR

FAR

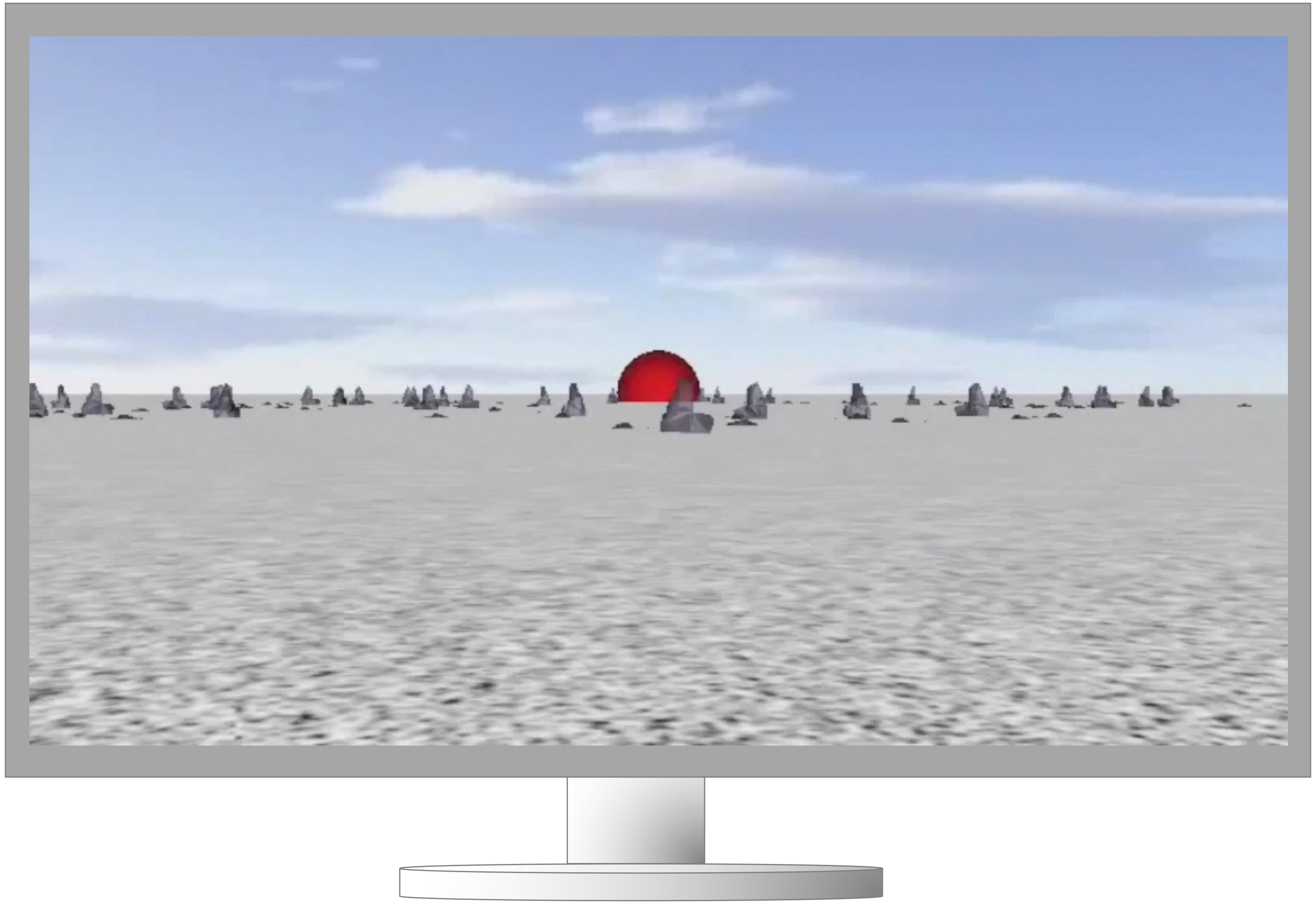

prior
Perception
sensory input

Priors can be learned...

Learning the prior

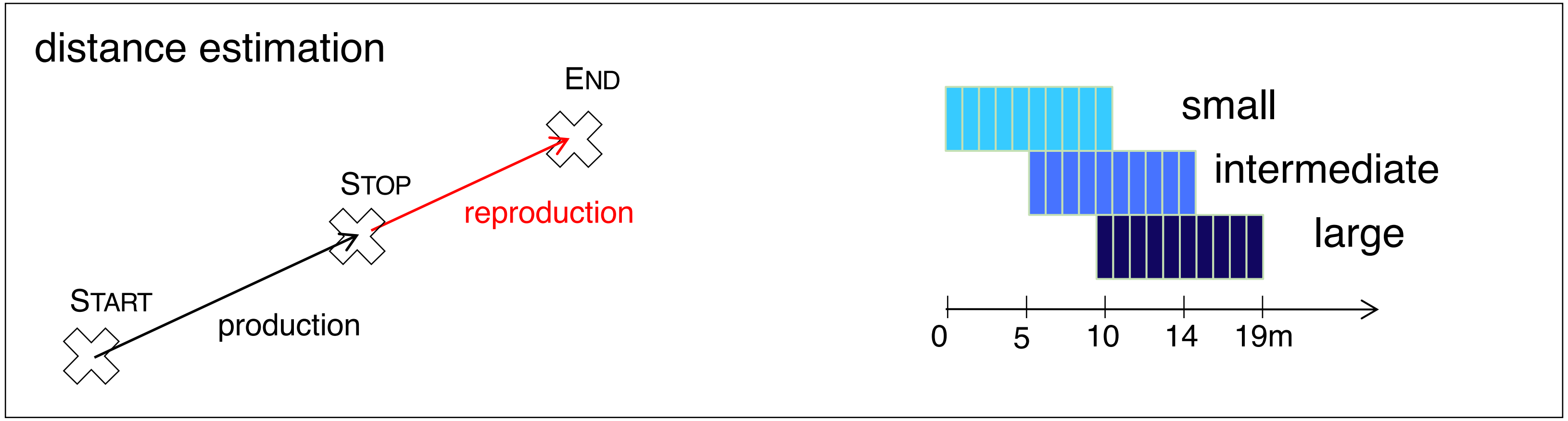


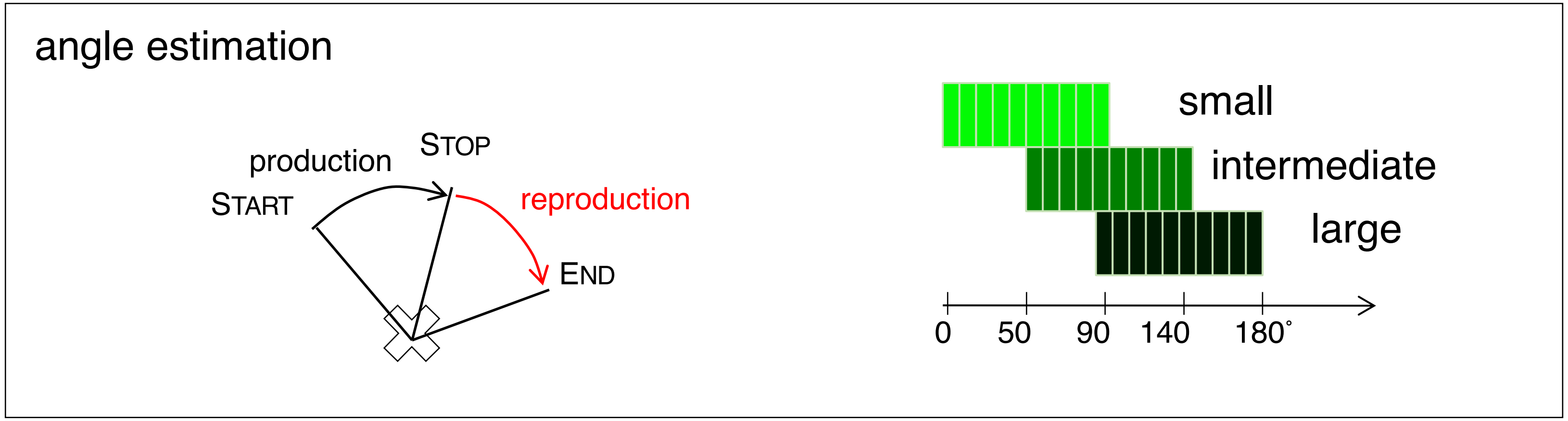
“optimal errors” in magnitude estimation



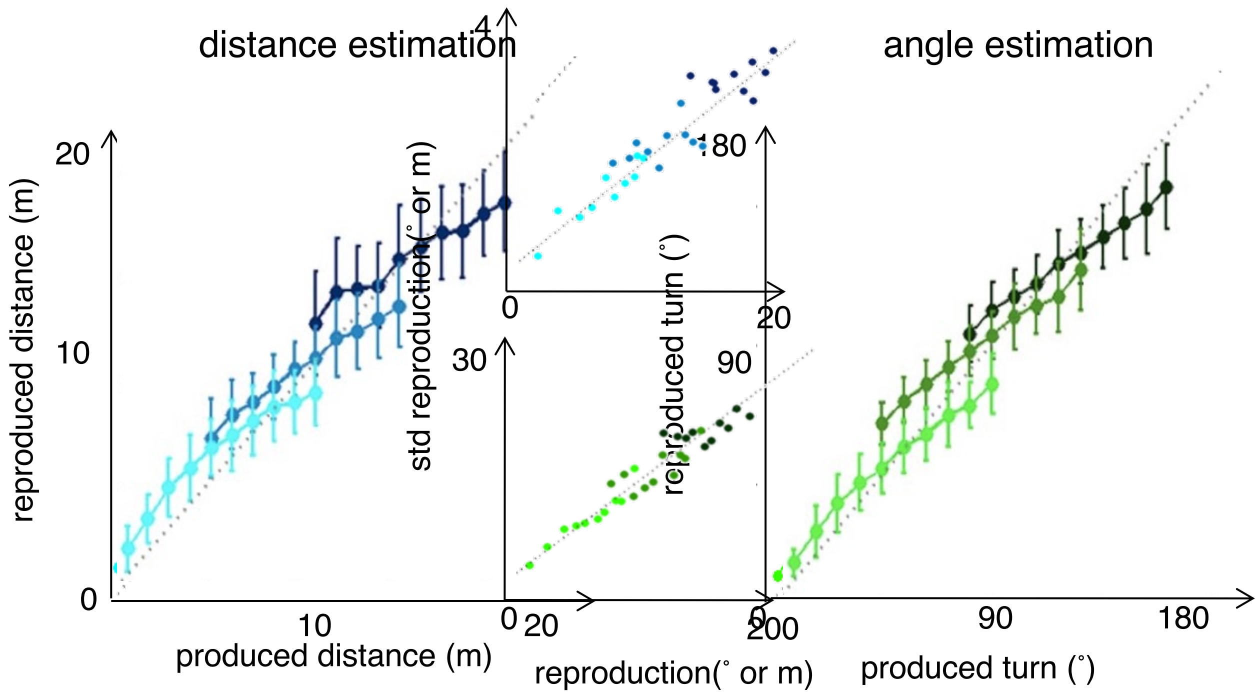
Petzschner & Glasauer, JoN, 2011

Varying the sample range



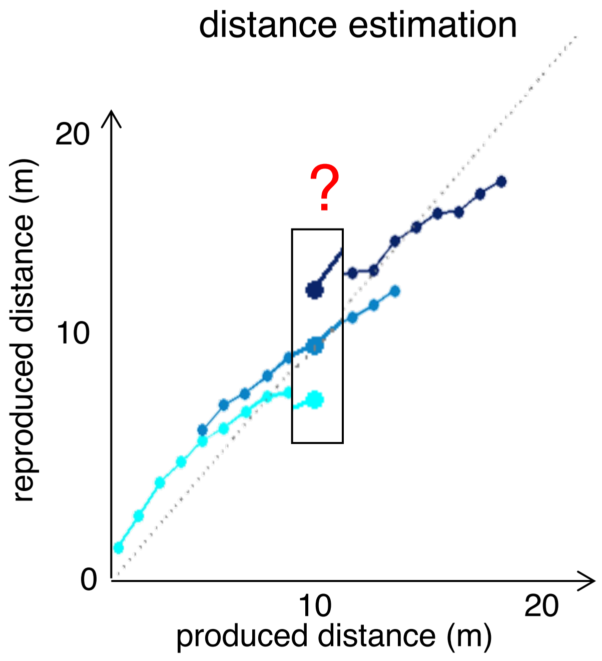


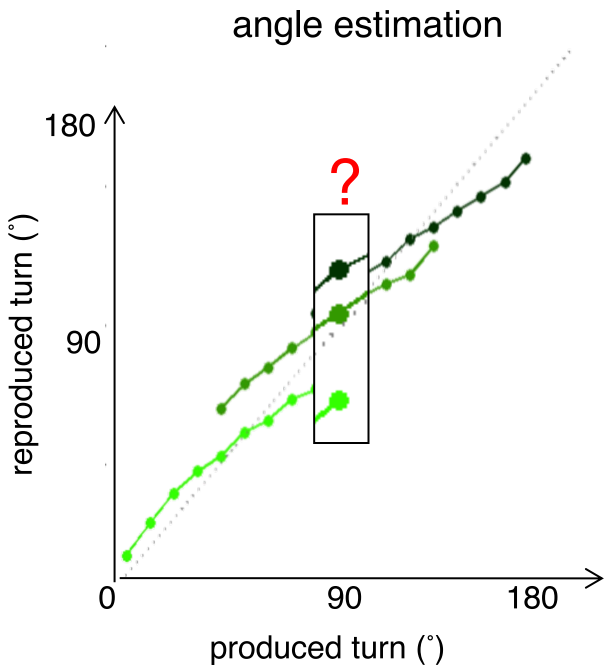
Petzschner & Glasauer, JoN, 2011



Petzschner & Glasauer, JoN, 2011

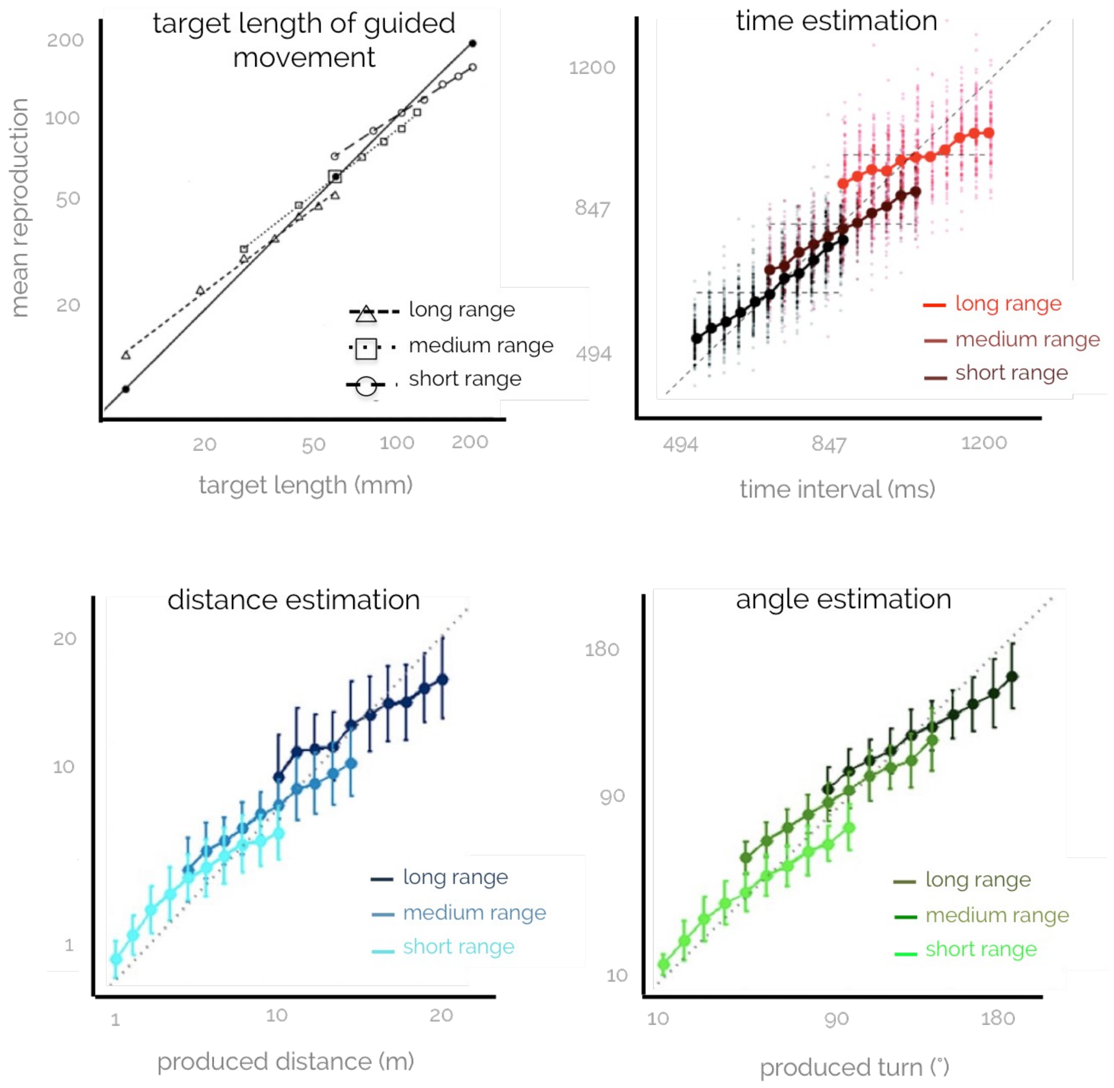
Prior knowledge: Experience





Petzschner & Glasauer, JoN, 2011

Let’s take a look at the literature

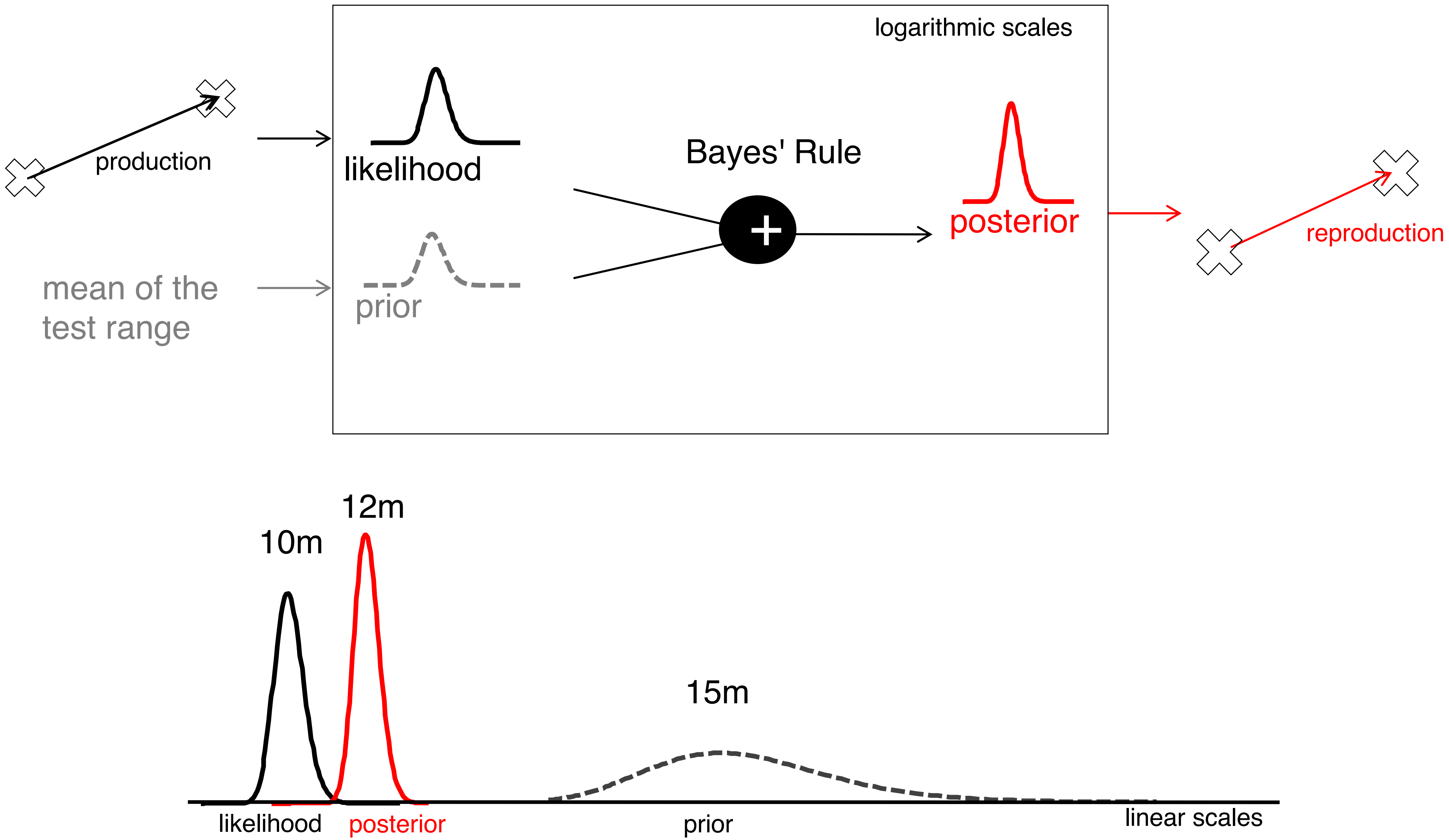


Petzschner & Glasauer, JoN, 2011; Petzschner et al. TiCS, 2015

A Bayesian Model for magnitude estimation

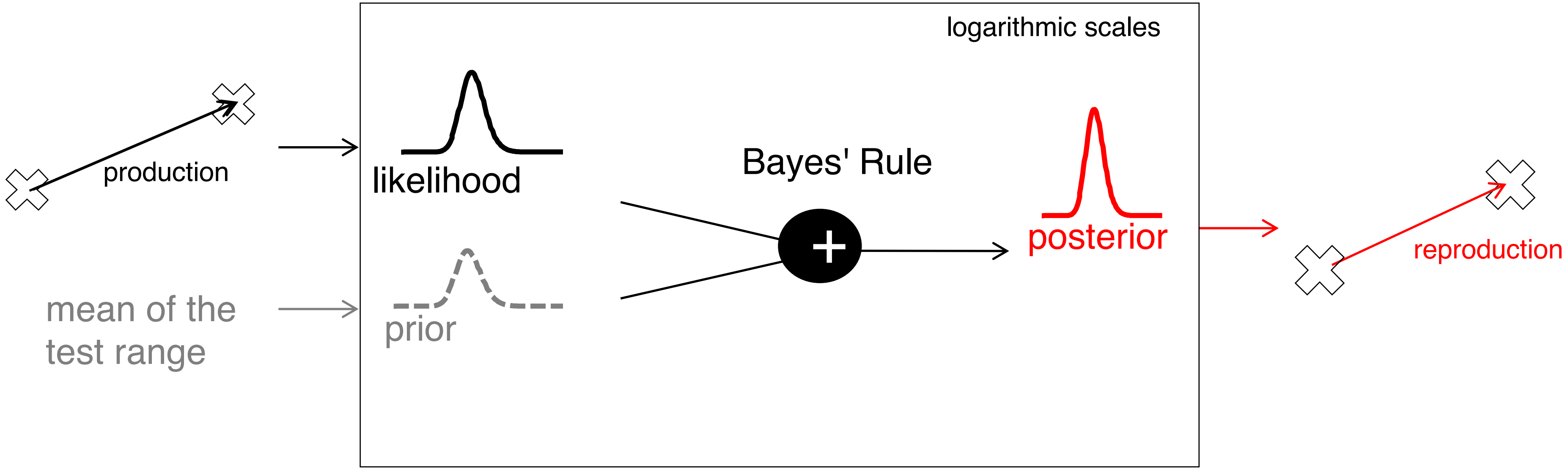
Petzschner & Glasauer, JoN, 2011

A Bayesian Model for magnitude estimation



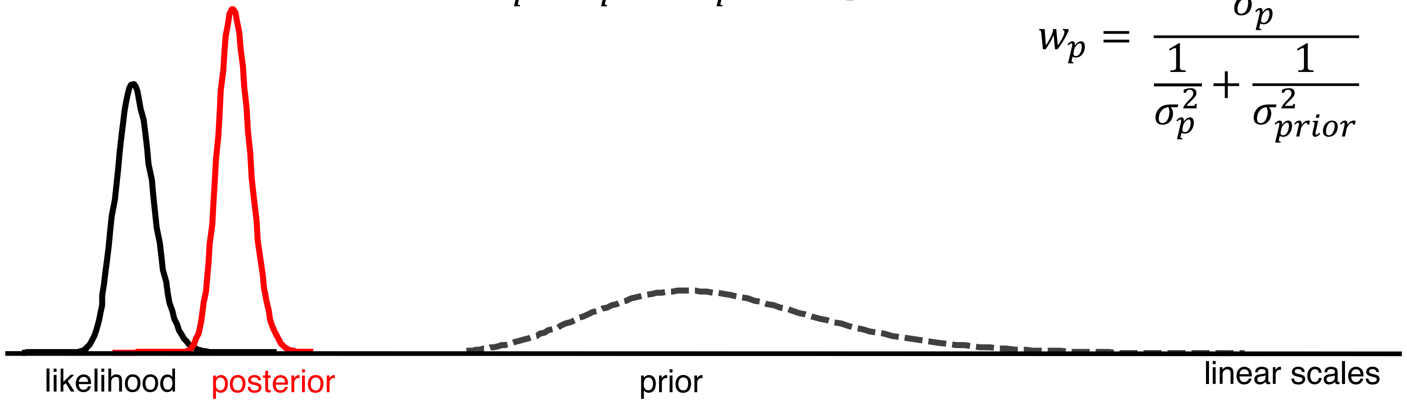
Petzschner & Glasauer, JoN, 2011

A Bayesian Model for magnitude estimation



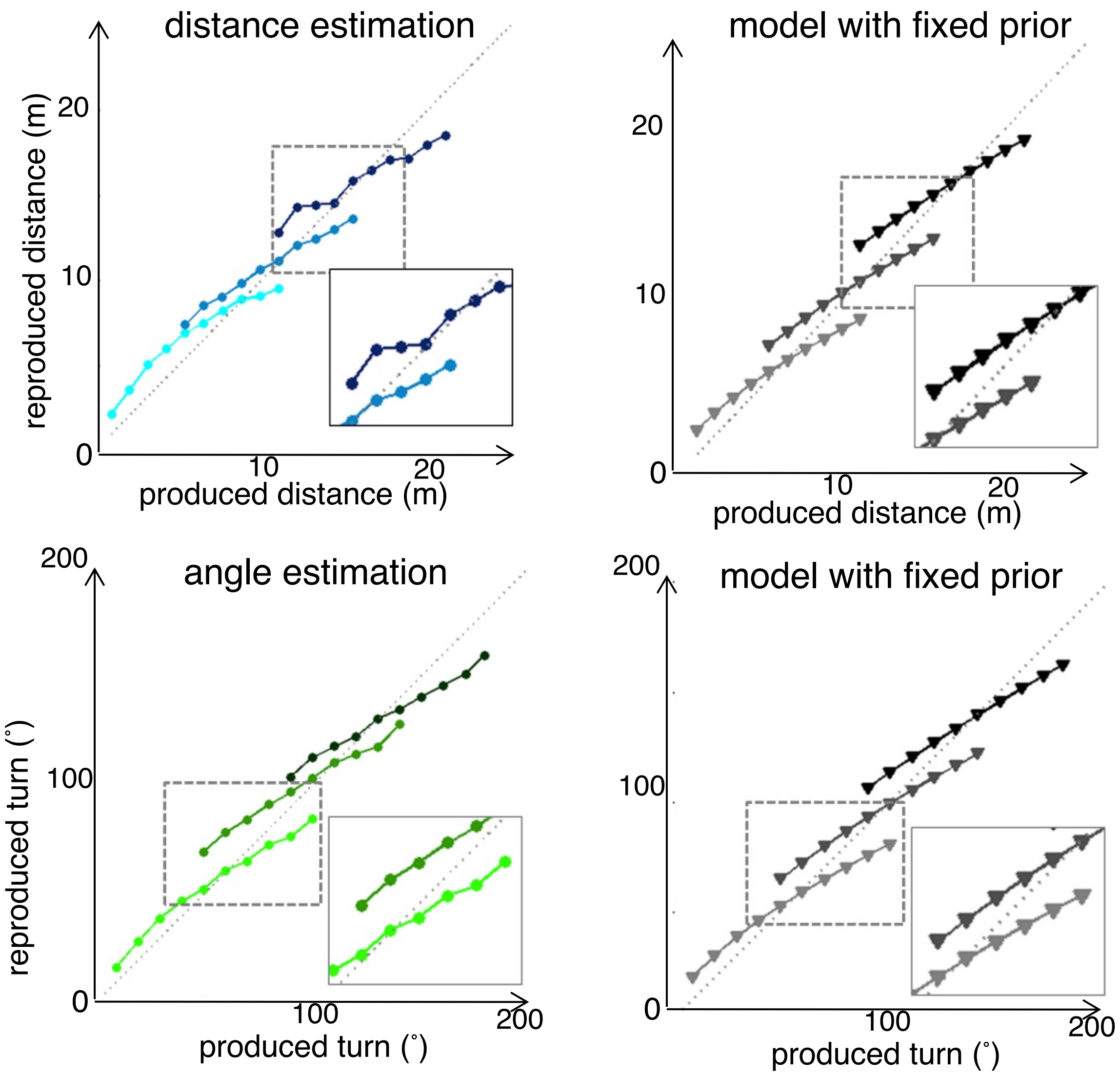
$$\widehat{d_r} = w_p \cdot d_p + w_{prior} \cdot prior$$

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



Petzschner & Glasauer, JoN, 2011

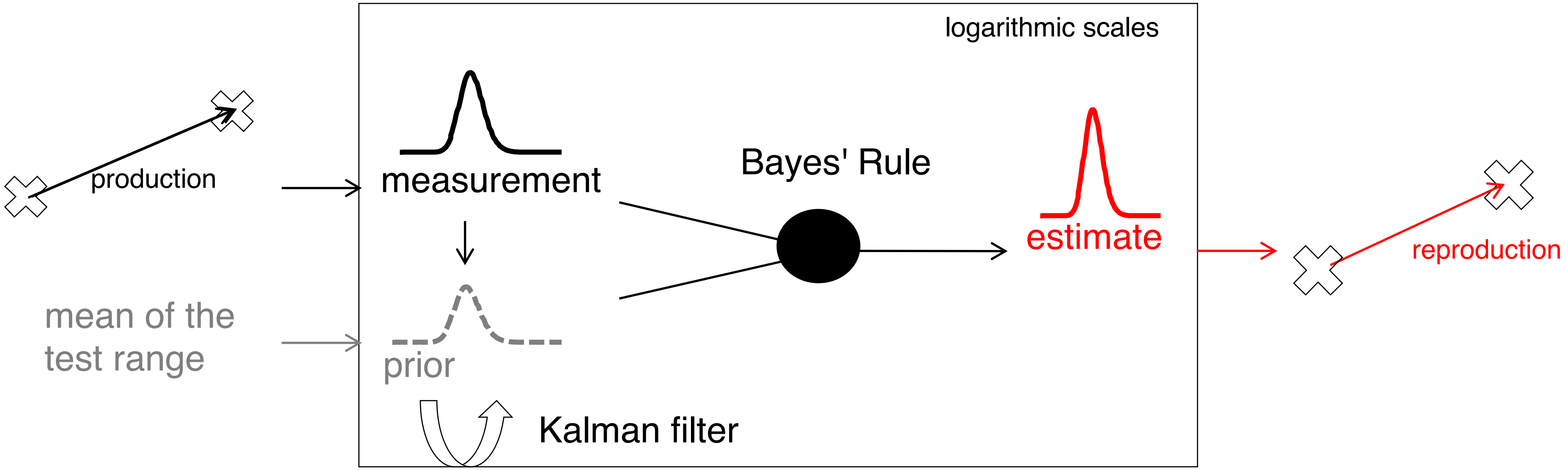
Quantitative results



Petzschner & Glasauer, JoN, 2011

Where do priors come from?

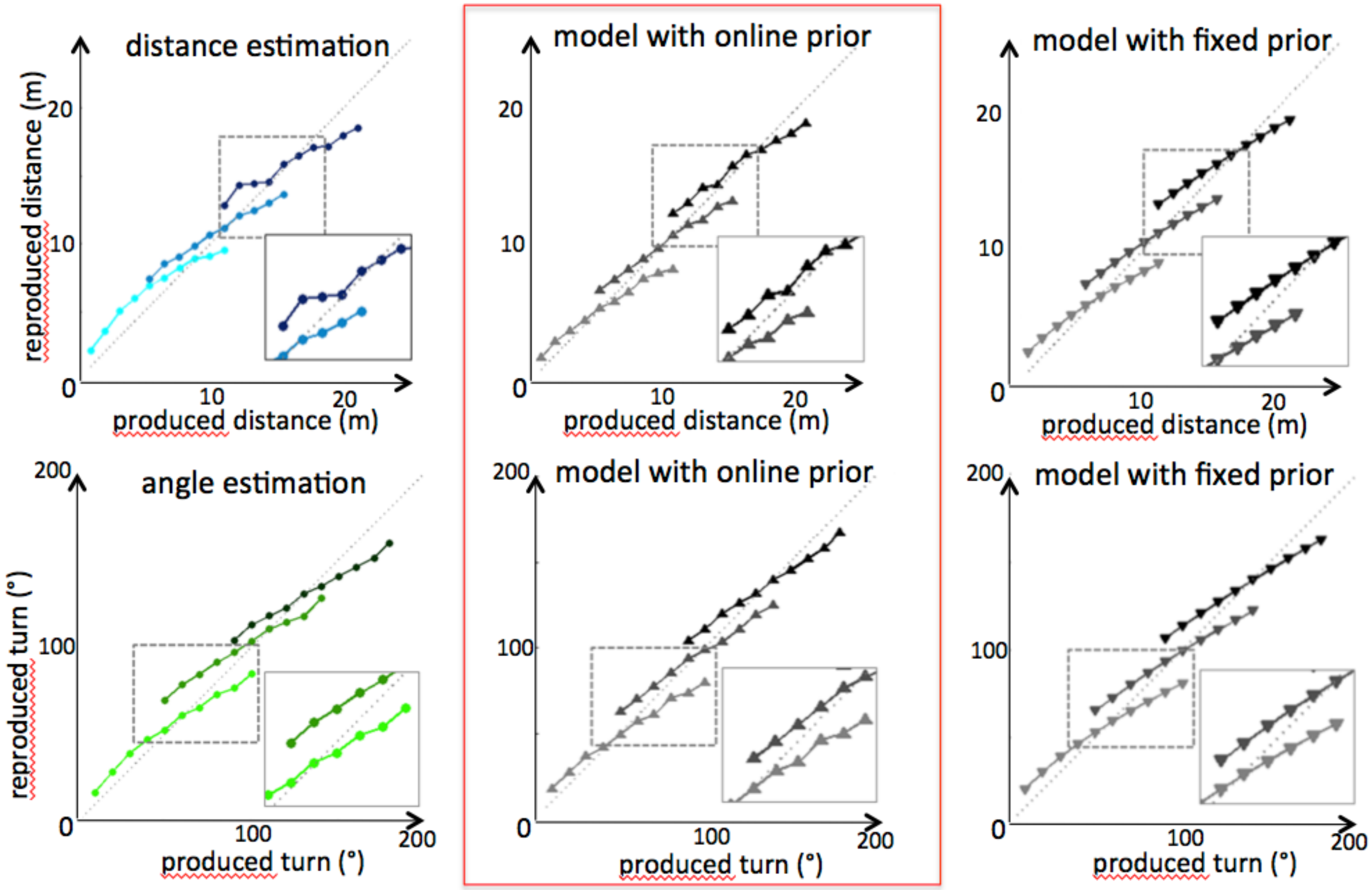
Bayesian Learning



"Todays posterior is tomorrows prior."

Petzschner & Glasauer, JoN, 2011

Bayesian Learning



More on Bayesian Learning in Christoph's Lecture

Petzschner & Glasauer, JoN, 2011

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, …]

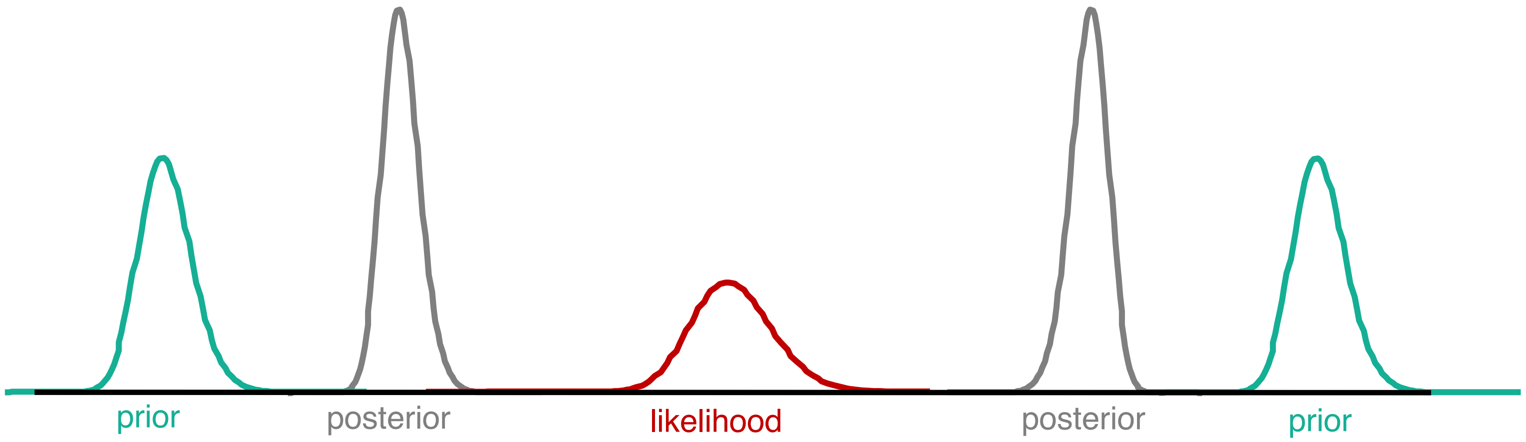
Causal inference [Waldmann, Sloman, Steyvers, Griffiths, Tenenbaum, Yuille, …]

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

Optimal motor control [Wolpert, Körding …]

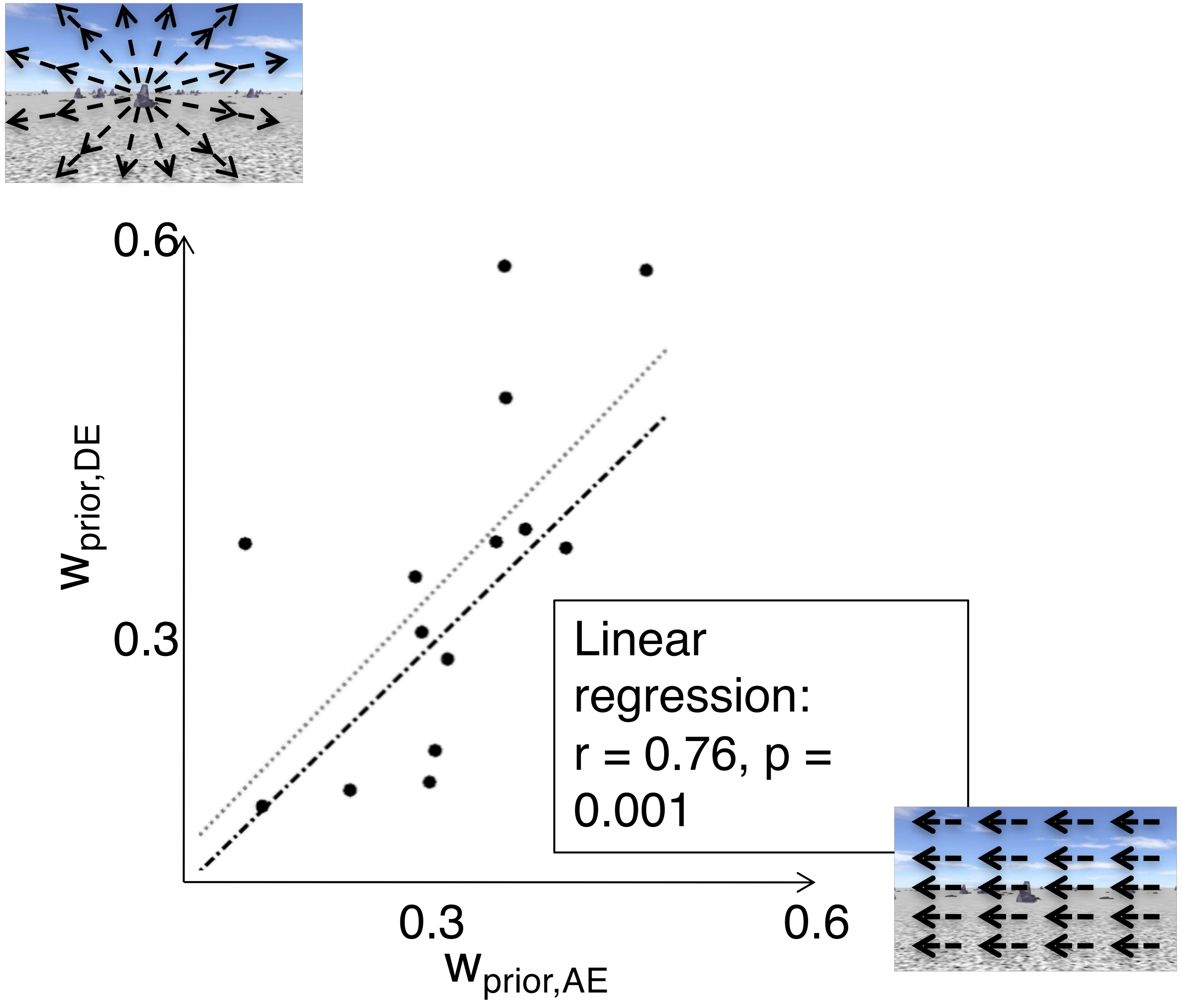
Remark 1

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



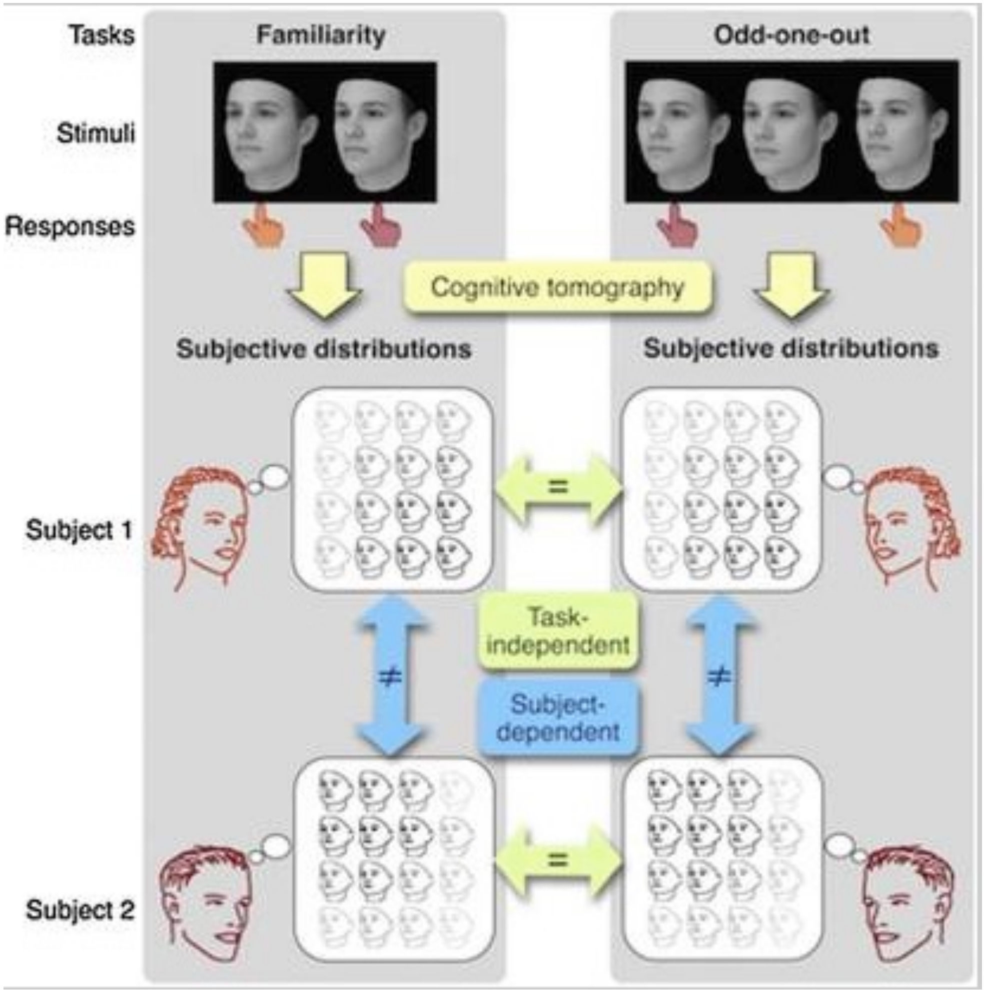
Bowers and Davis, 2012a,b; Griffiths et al., 2012, Colombo and Series, 2012; Jones and Love, 2011

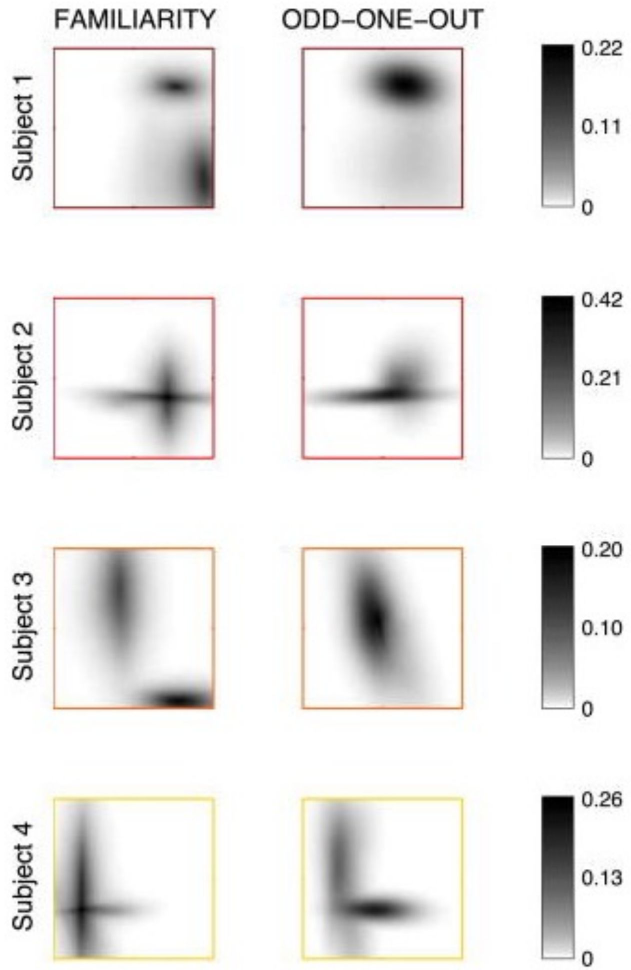
Do priors generalize?



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

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 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 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**

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

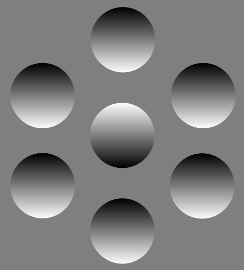
OCCASIONAL PAPER

A Bayesian account of 'hysteria'

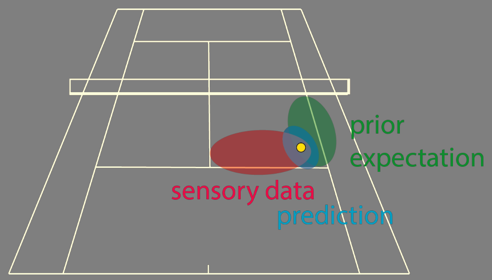
Mark J. Edwards,[1,*] Rick A. Adams,[2,*] Harriet Brown,[2] Isabel Pareés[1] and Karl J. Friston[2]

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.*



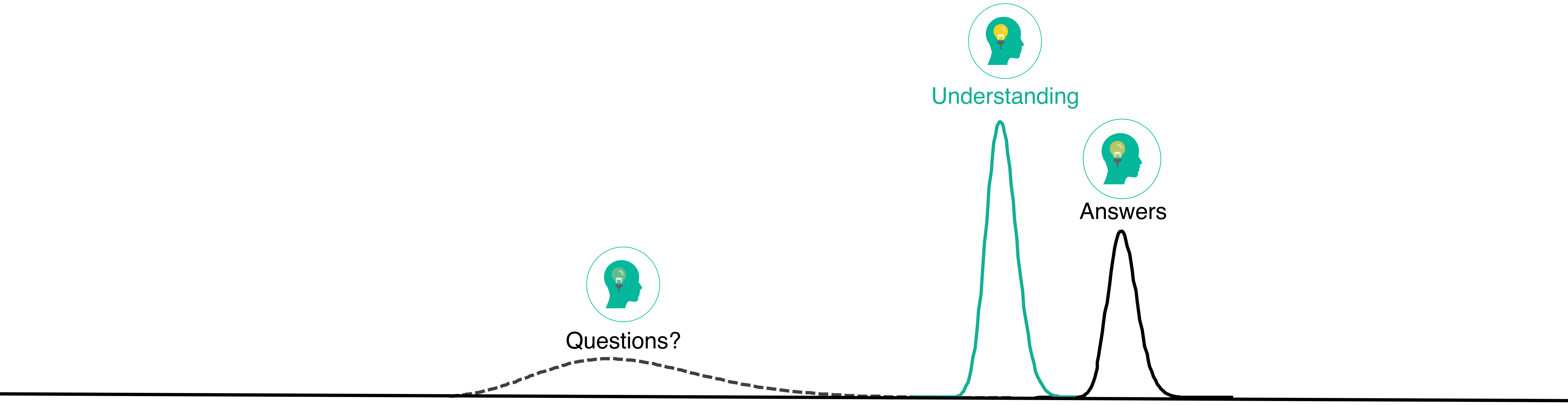
- *Humans combine sensory information according to their uncertainty.*

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?

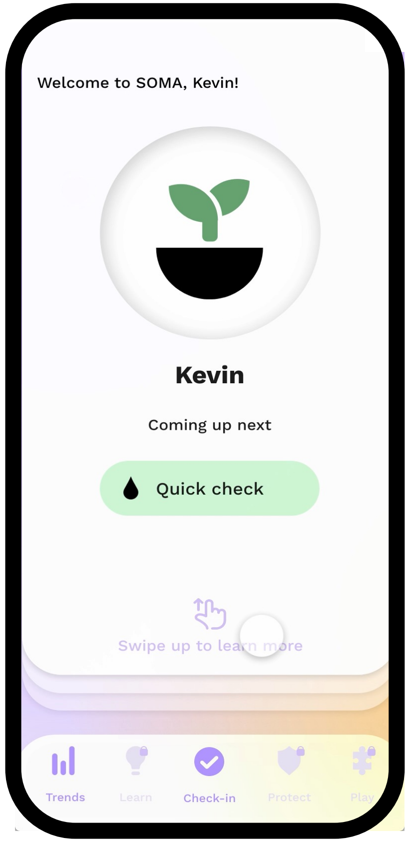
Thank you

@rikepetzschner
@peaclab

Interested in working with us?

https://fpetzschner.com/lab/

SOMA - Chronic Pain



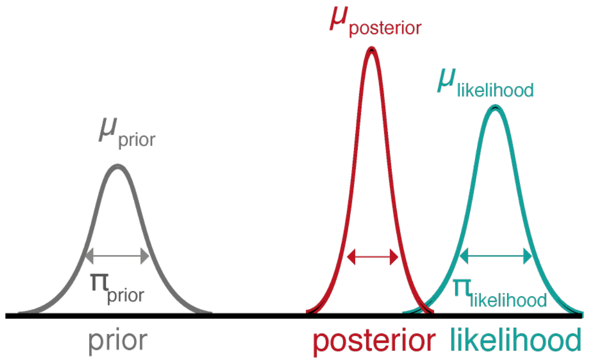
Sienna **Bruinsma**

Chloe **Zimmerman**

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

Algorithmic descriptions of Bayesian inference

how does the system do what it does?

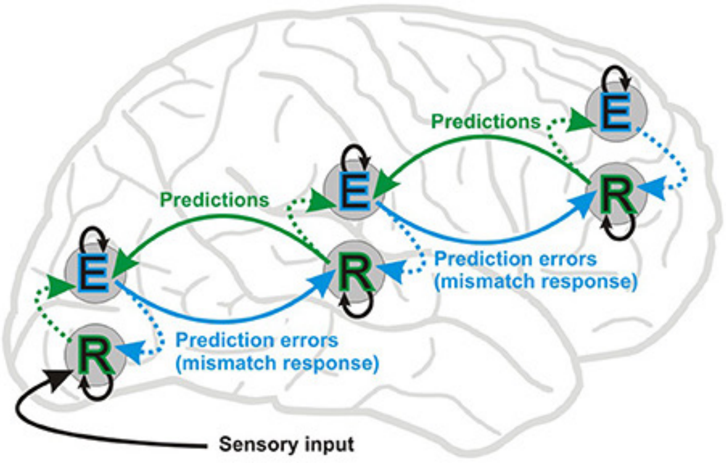


Belief update

Δbelief ~precision · PE

$$\mu_{posterior} = \mu_{prior} + \frac{\pi_{likelihood}}{\pi_{likelihood} + \pi_{prior}} \cdot PE$$

- *Direct variable coding:* neural activity directly represents latent variables.
- *(Bayesian) Predictive coding:* neural activity represents the prediction error between top-down predictions and bottom-up inputs



More on Bayesian Learning in Christoph's Lecture this afternoon

Aitchison & Lengyel, Curr Opin Neurobiol. 2017

Perception versus reality