Day 1

- Introduction to Computational Psychiatry
- Schizophrenia
- Mood Disorders
- Autism
- Conceptual Basis of Computational Modeling
- Variational Bayes

Day 2

- Bayesian Model Selection and Averaging
- Markov Chain Monte Carlo
- Markov Decision Processes
- Machine Learning Techniques

Day 3

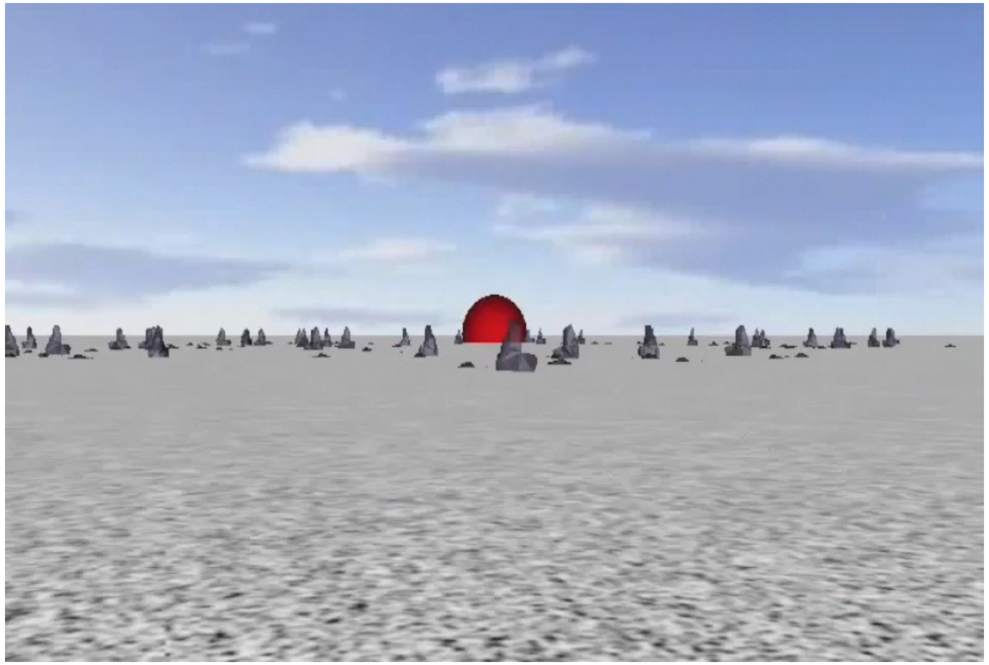
- Bayesian Models of Perception
- Predictive Coding
- Active Inference

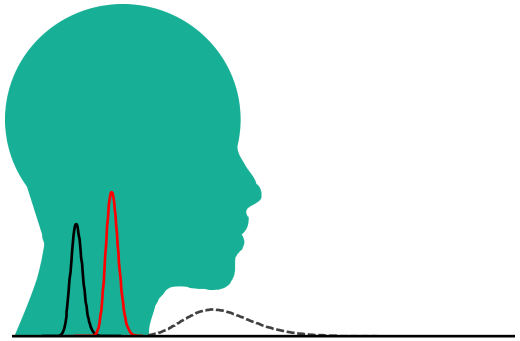
Day 4

- Hierarchical Bayesian Inference
- DCM for fMRI
- DCM for EEG
- Reinforcement Learning

Day 5

- Compulsion, control, and habits
- The search for the "Bayesian Priors" in the Brain, in Health and Mental Illness.
- Computational neuromodulation in human decision-making
- Biophysical models and NMDA channelopathies





Bayesian Models for Perception

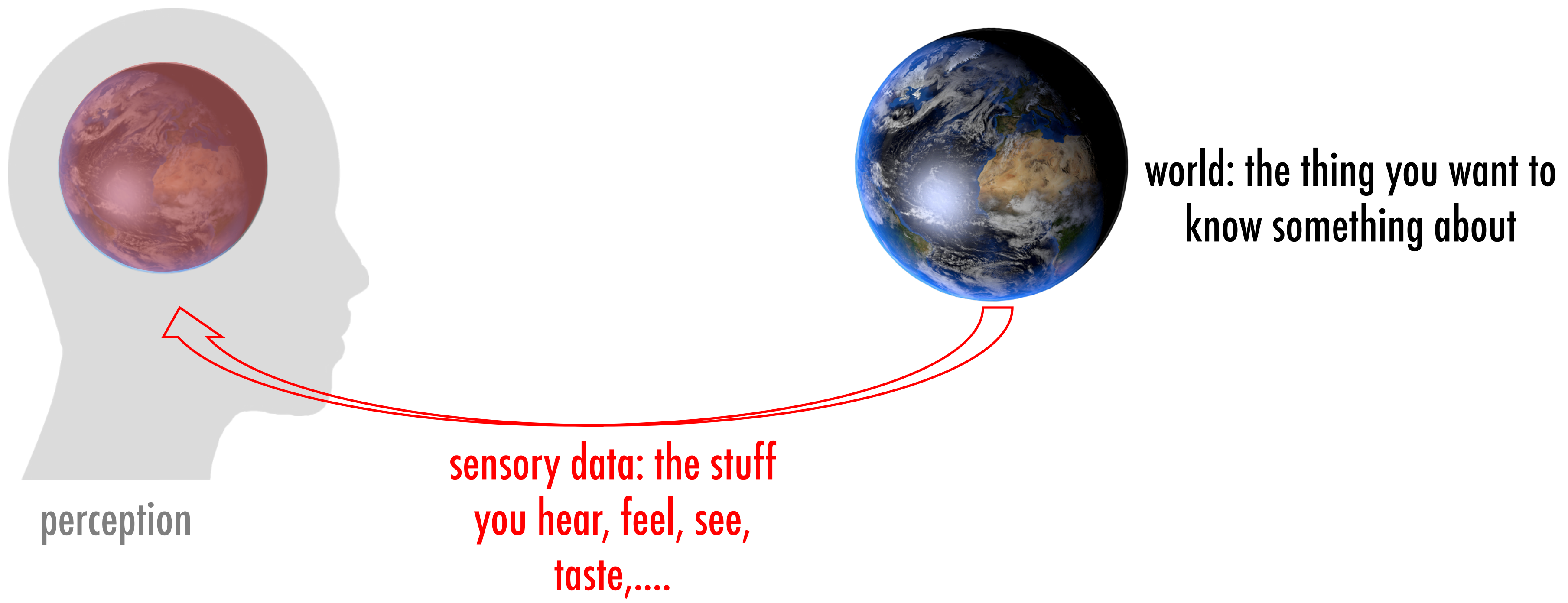
Frederike Petzschner

Computational Psychiatry Course, 2016

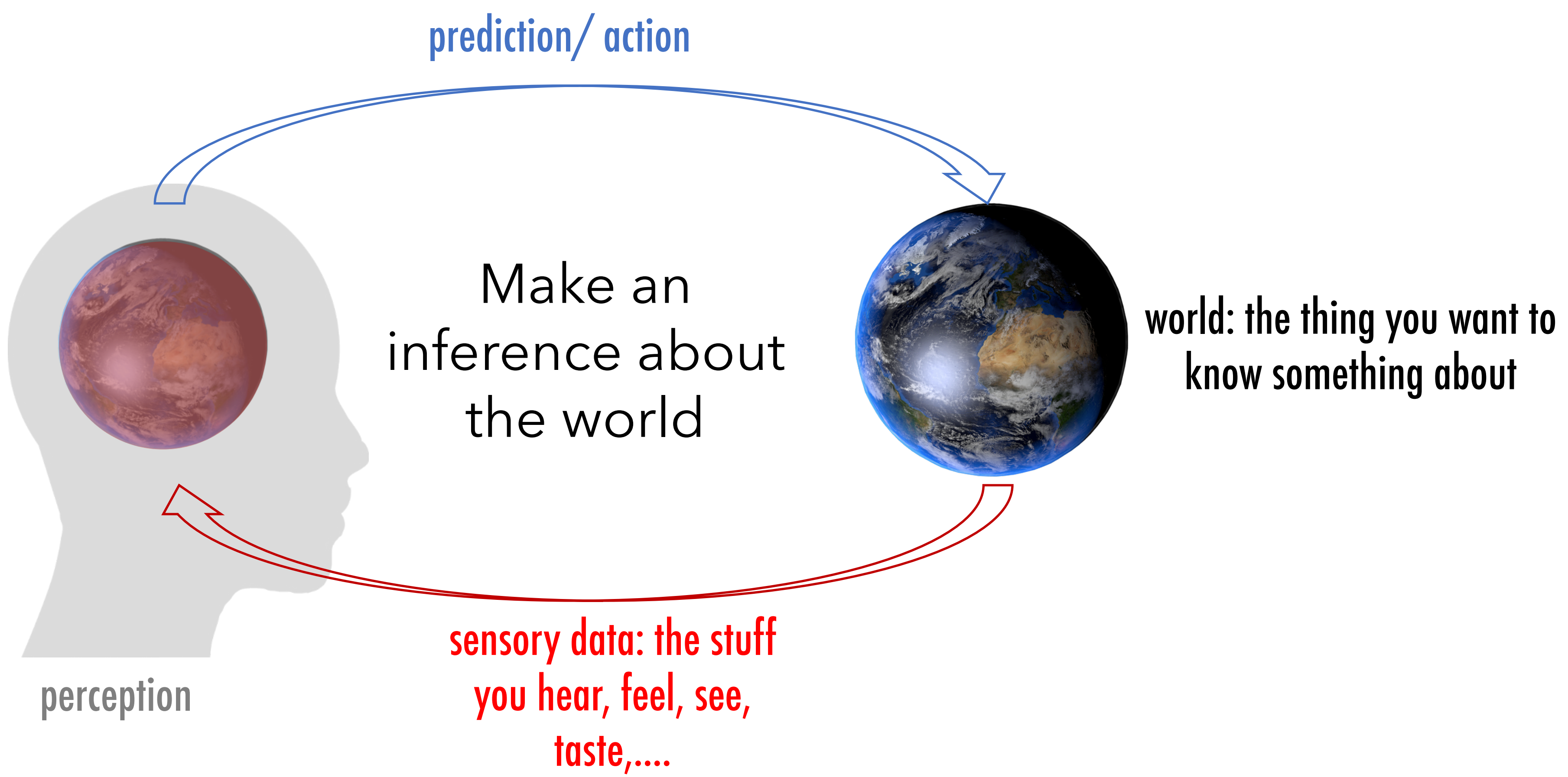
What is the difference between sensation and perception?

What is purpose of your senses?

What is purpose of perception?



What is purpose of perception?



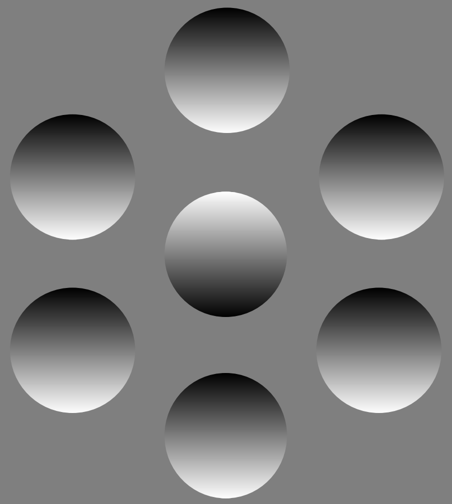
How? Make sense of the senses.

Why is that such a hard problem?

Challenge 1: Your senses are noisy

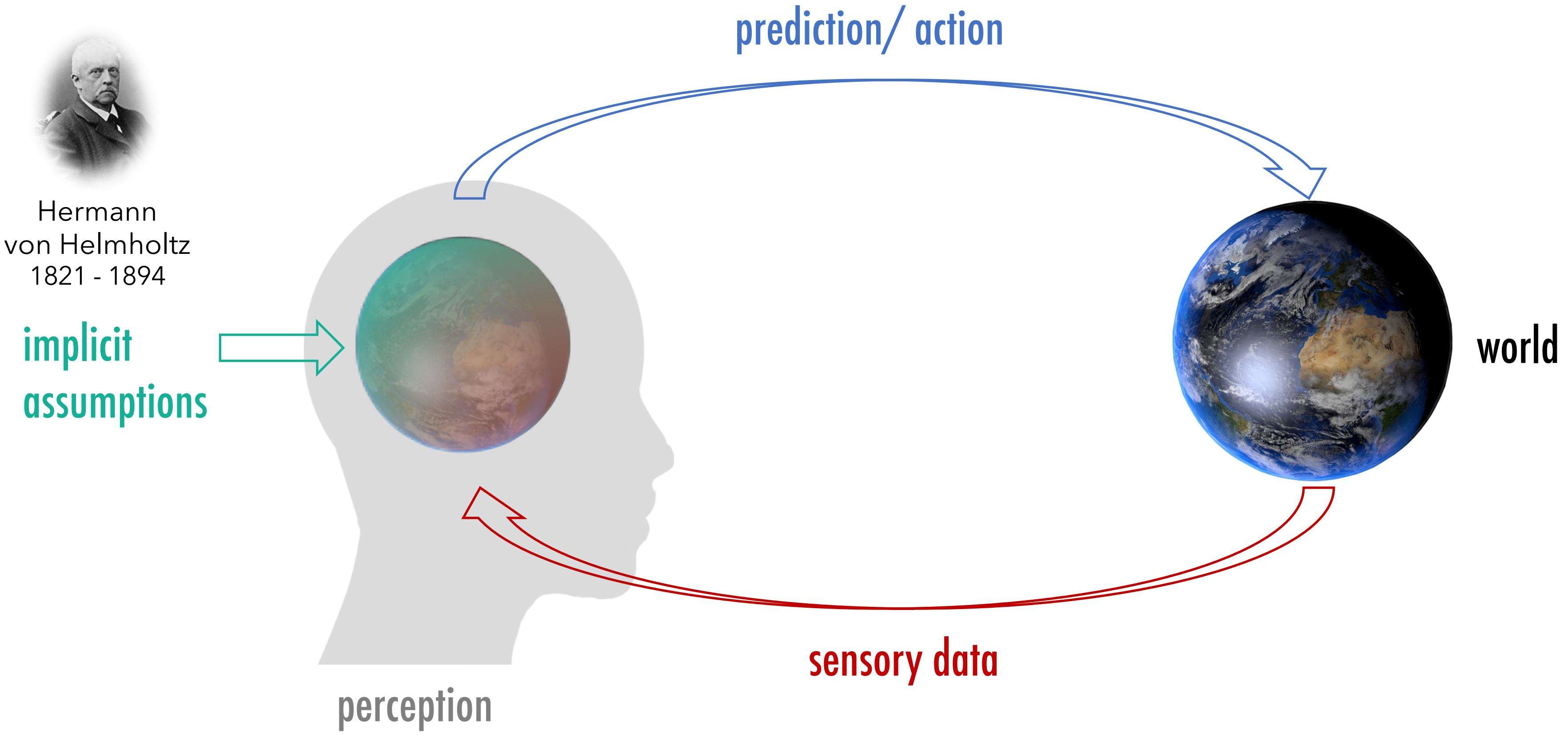
Challenges 2: You have multiple types of sensory information

Challenge 3: We want to infer upon things that are not directly observable

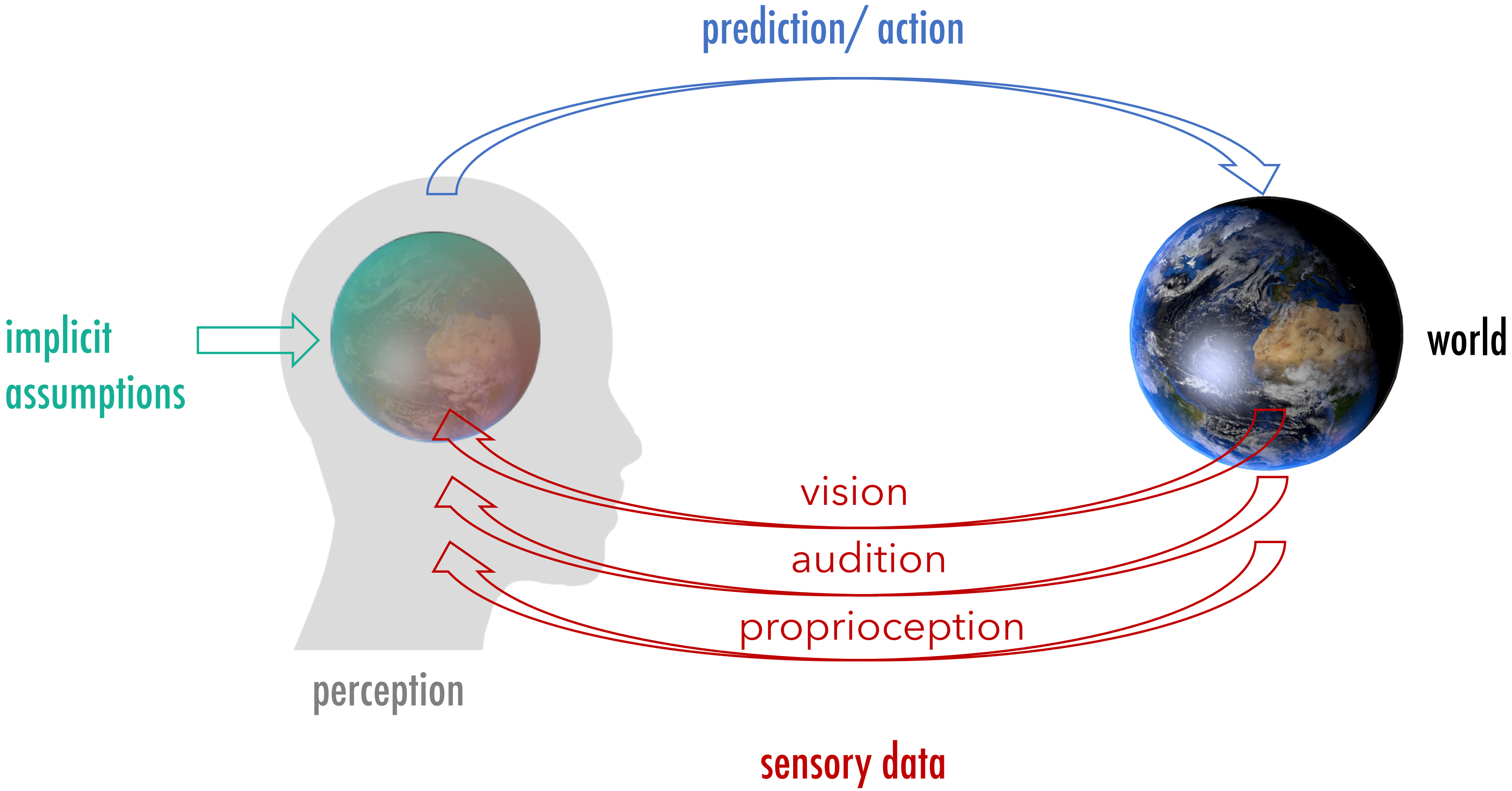


Challenge 4: They might provide us with ambiguous infromation

Solution 1: use 'prior' knowledge

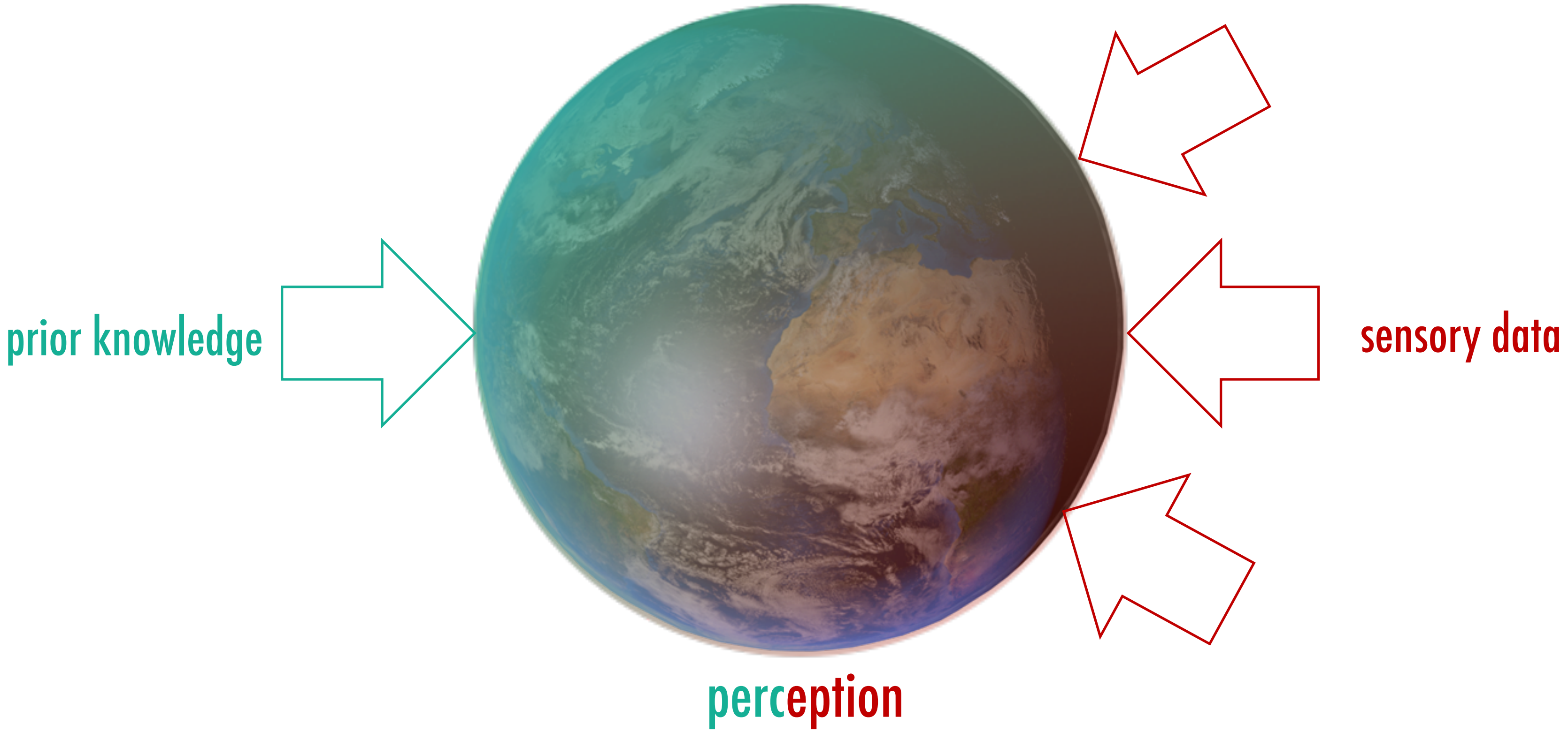


Solution 2: Combine different types of sensory information



The challenge of perception:

Combining different types of information sensory knowledge & a-priori assumptions to construct a robust model of our environment



How can we formally describe this combination of uncertain information?

The idea:

- Probabilities can be used to represent the information and their uncertainty
- So the rules of probability can be used to update a-priori assumptions based on new information

Bayes Rule

$$P(h|d) = \frac{P(d|h)\, P(h)}{P(d)}$$

h = hypothesis
d = new data

An example: Imagine you are a doctor and you want to find out if your patient has breast cancer.

You know: The probability of breast cancer is 1% for a woman at 40 who participates in a routine screening.

Now you get new information in form of a mammography.
You want to update your belief based on that new information.

What you also know, if a woman has breast cancer, the probability is 80% that she will have a positive mammography. If a woman does not have breast cancer, the probability is 9.6% that she will also have a positive mammography.

The woman you are testing as a positive mammography.
What are the chances of her having cancer?

A. greater than 90%
B. between 70% and 90% — 95 out of 100 doctors
C. between 50% and 70%
D. between 30% and 50%
E. between 10% and 30%
F. less than 10% — correct

Lets use Bayes' Rule:

$$P(h|d) = \frac{P(d|h)\,P(h)}{P(d)}$$

$$P(cancer|test+) = \frac{P(test+|cancer)\,P(cancer)}{P(test+)}$$

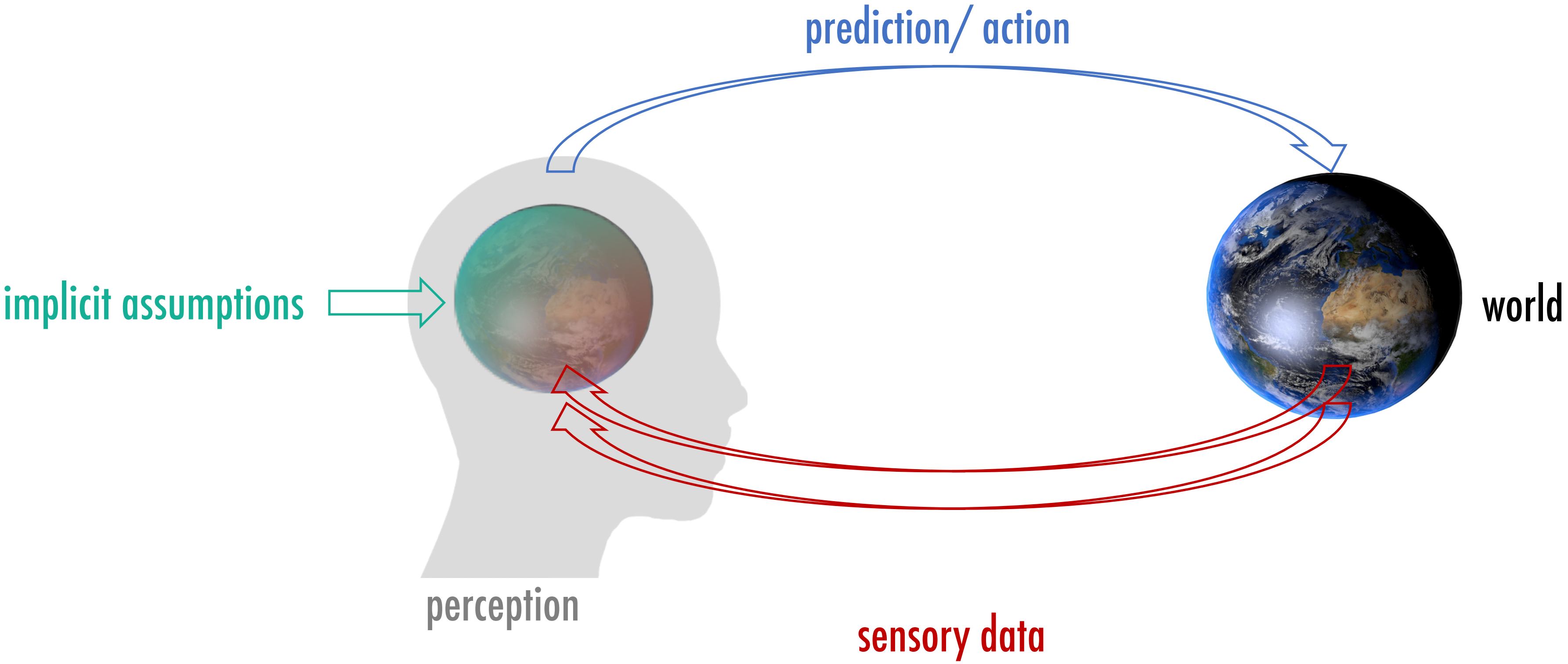
$$P(test+) = P(test+|cancer)\cdot P(cancer) + P(test+|no\ cancer)\cdot P(no\ cancer)$$

P(cancer): The probability of breast cancer is 1% for a woman
P(test+ given cancer):If a woman has breast cancer, the probability is 80% that she will have a positive mammography.
P(text+ given no cancer): If a woman does not have breast cancer, the probability is 9.6% that she will also have a positive mammography.

$$P(cancer|test+) = \frac{P(test+|cancer)\,P(cancer)}{P(test+)} = \frac{0.80\cdot 0.01}{0.80\cdot 0.01+0.96\cdot 0.99} = 0.0457$$

Bayes' Rule for perception

Inferring the state of the world based on
my sensory inputs and my prior beliefs



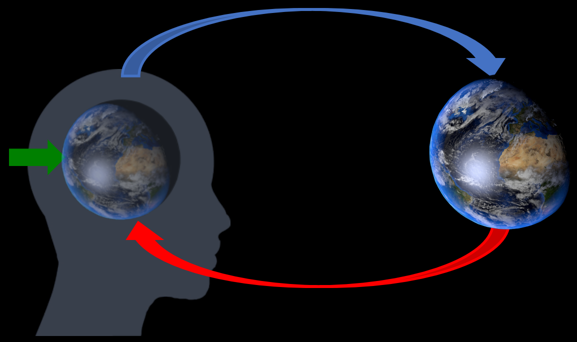
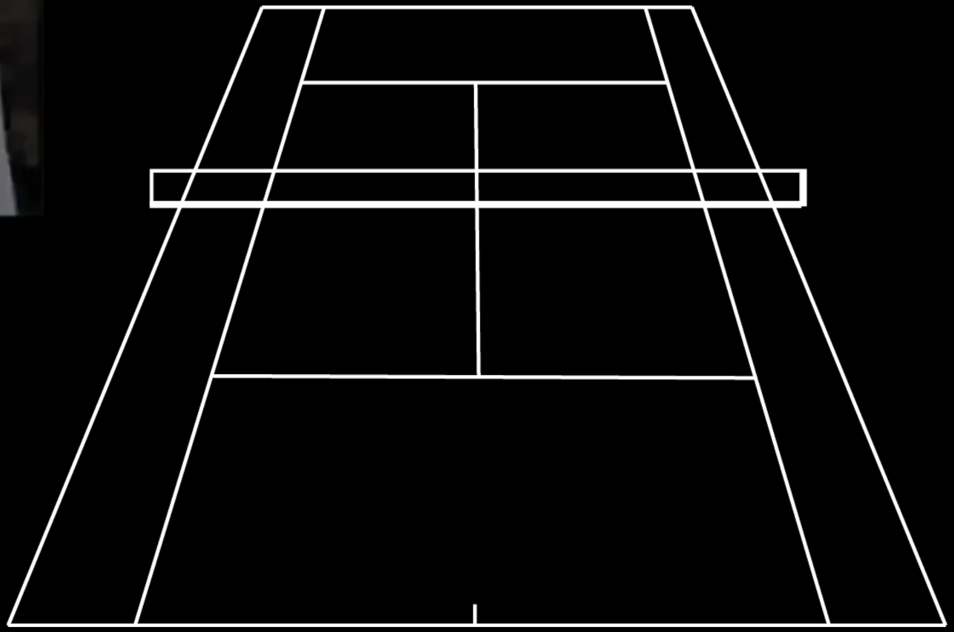
Bayes' Rule

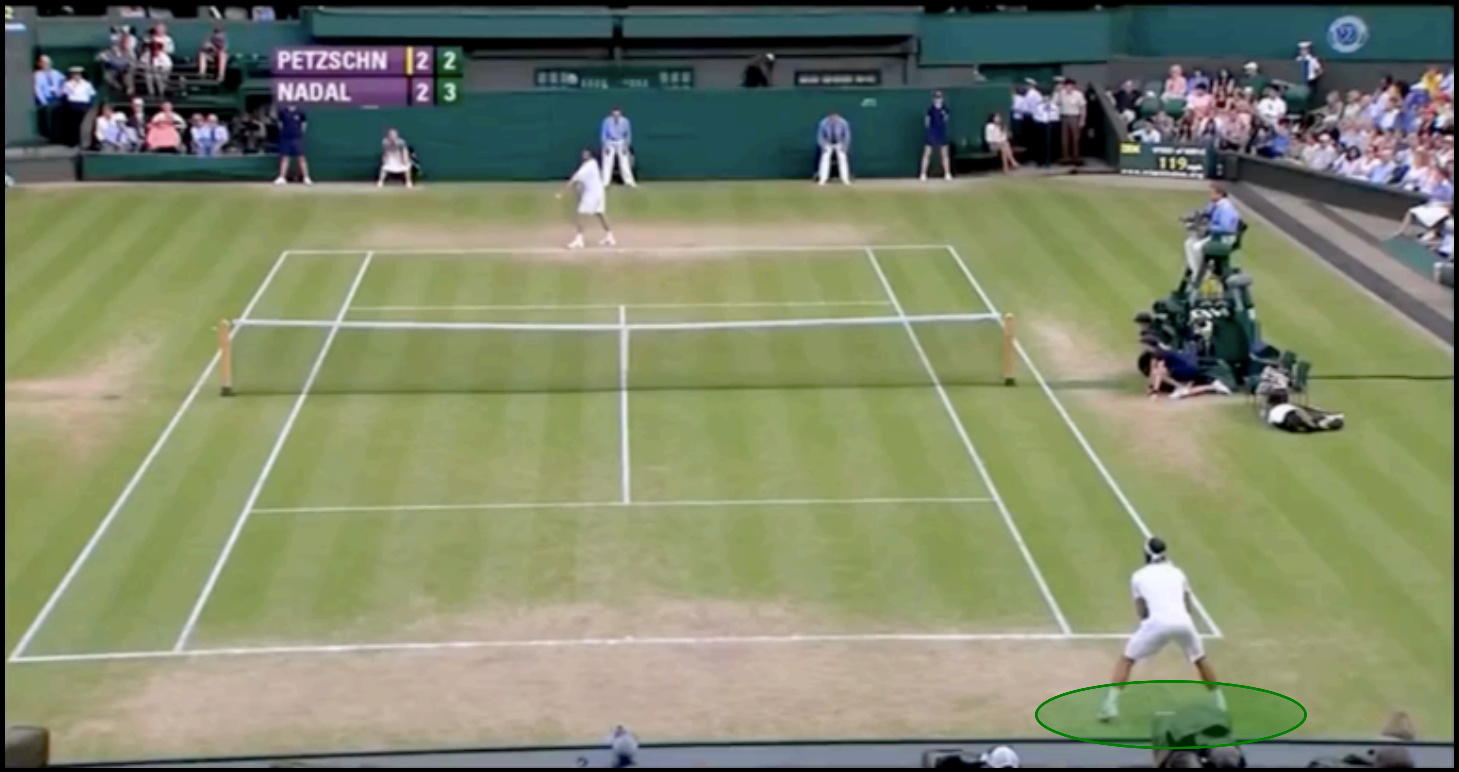
likelihood(sensation) prior (implicit assumptions)

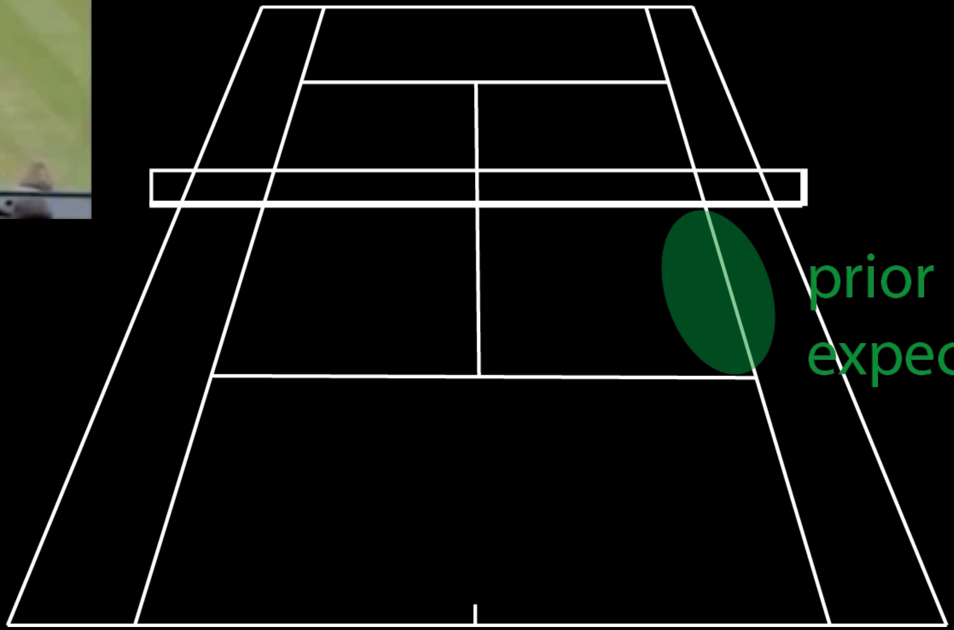
$$P(world|sensory\ data) = \frac{P(sensory\ data|world)\ P(world)}{P(sensory\ data)}$$

posterior (perception or prediction)

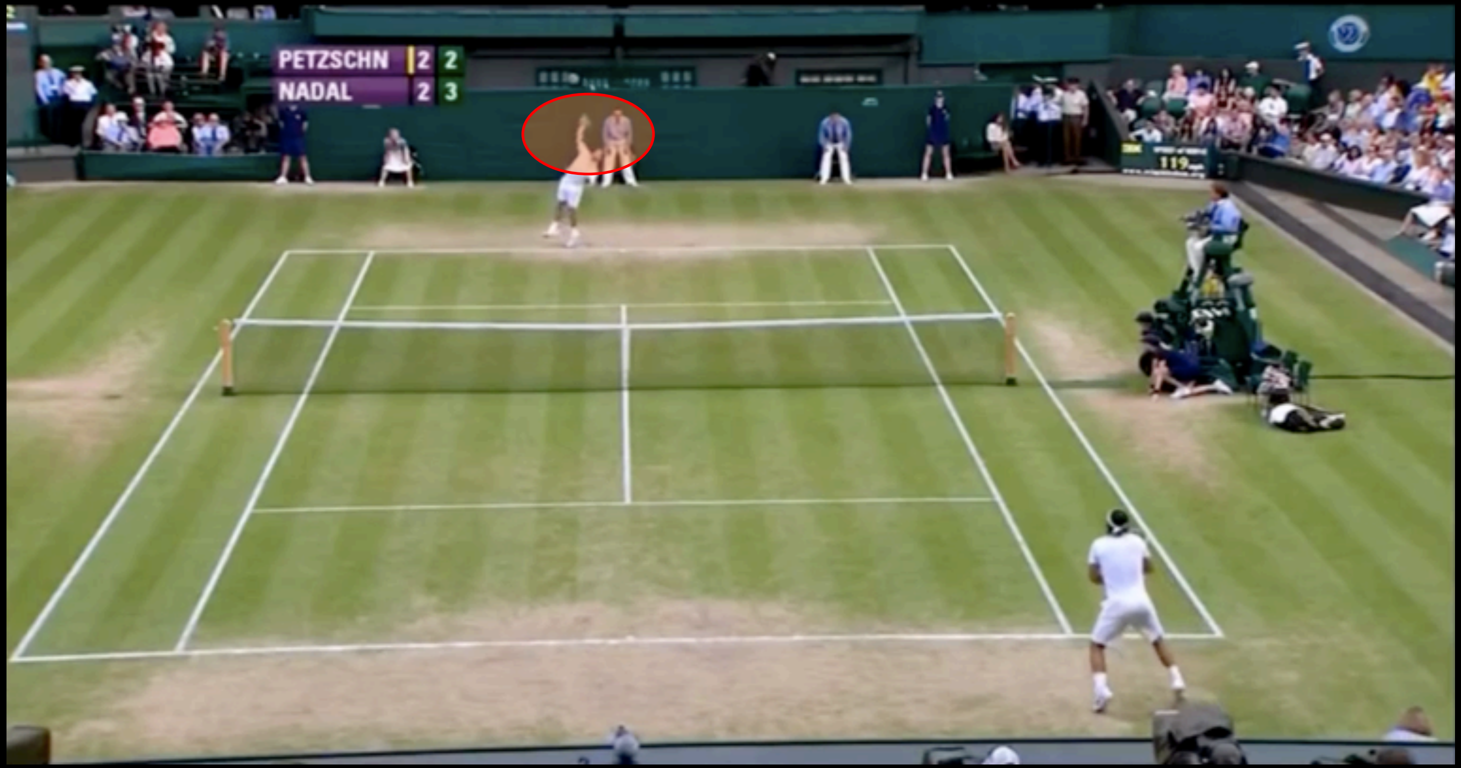
A Bayesian model of Nadal

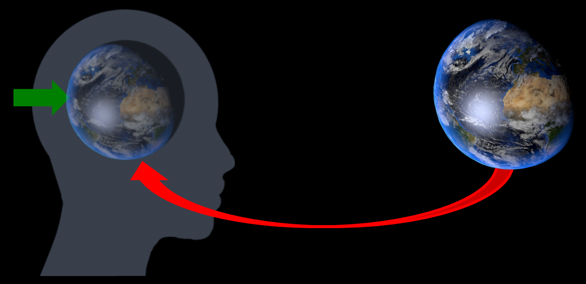




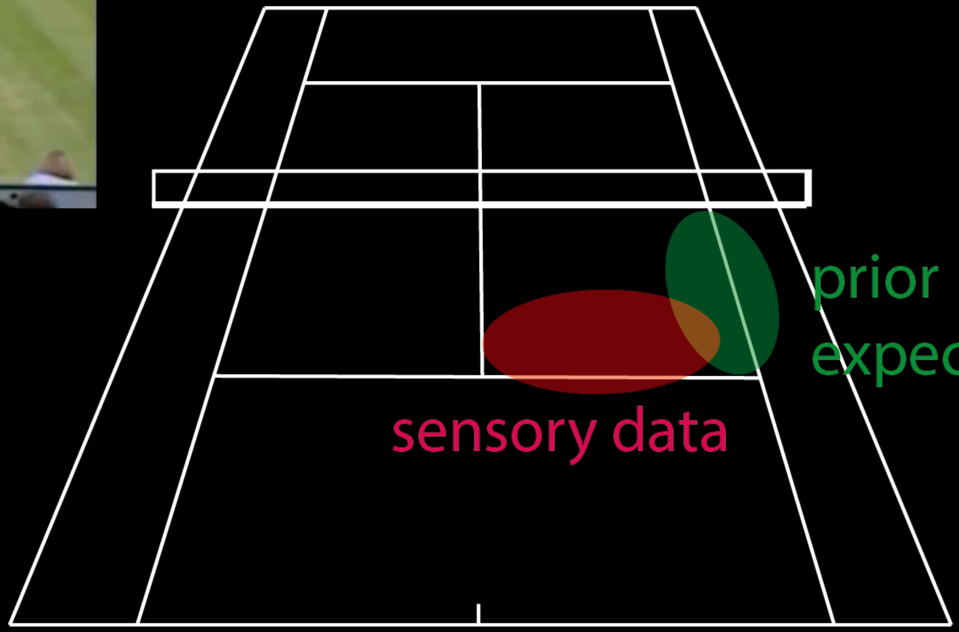


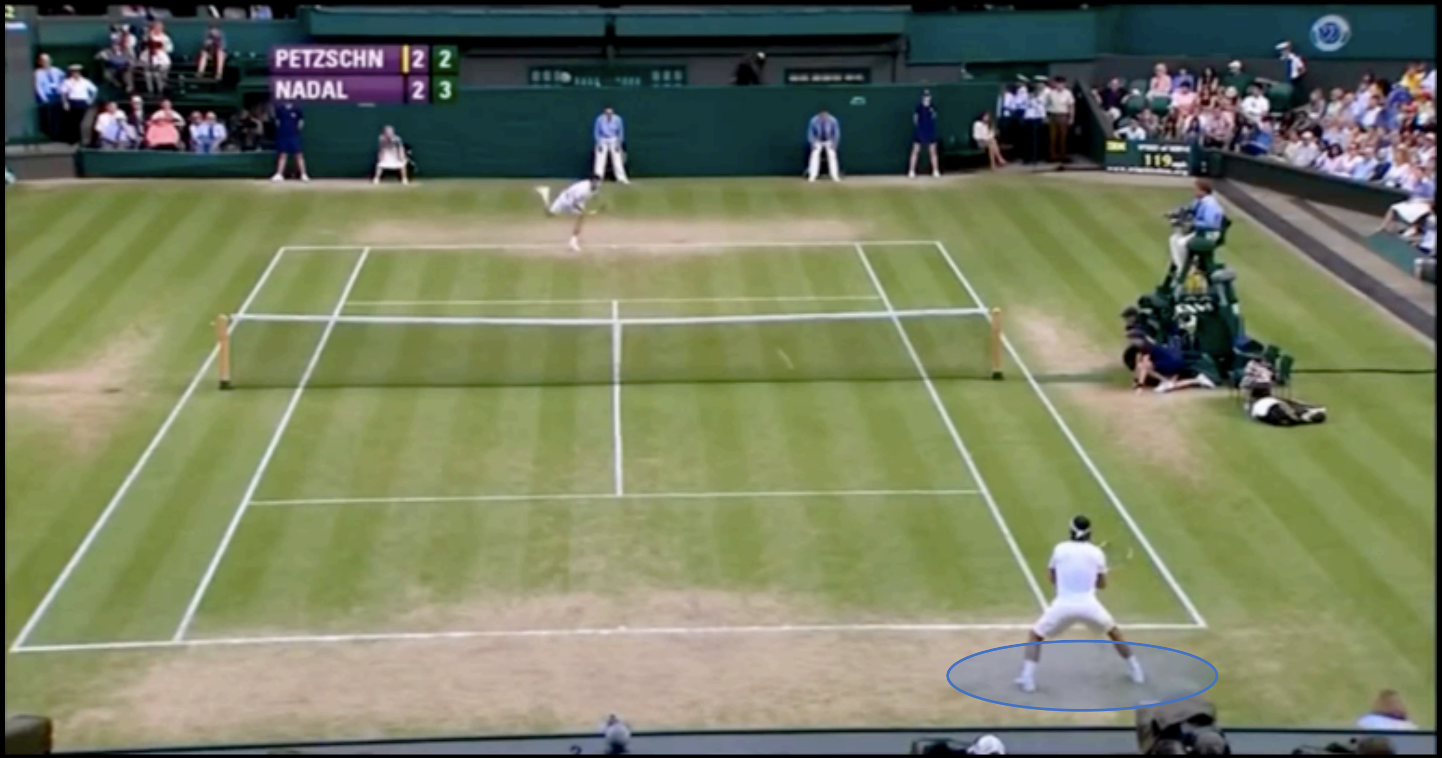


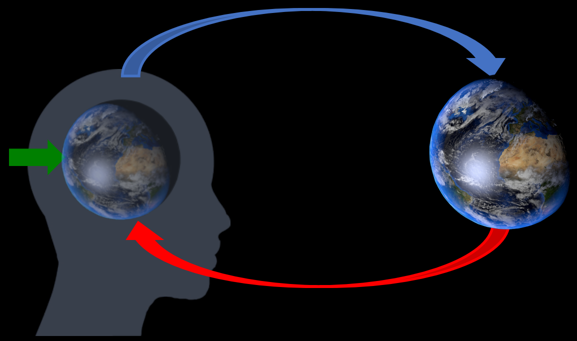
prior
expectation

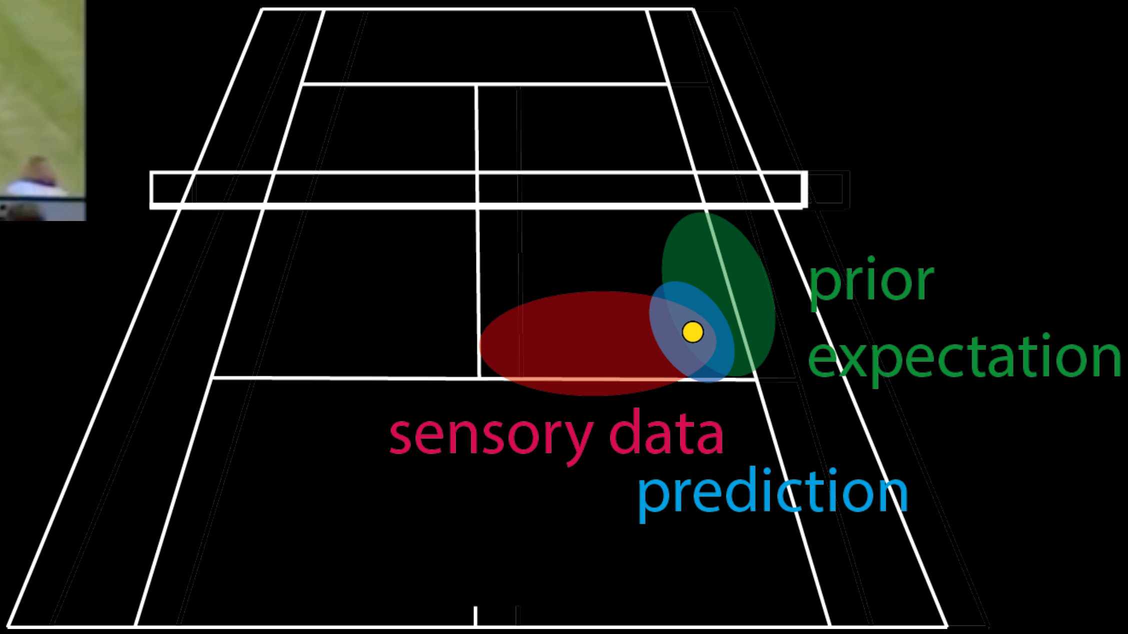

PETZSCHN 2 2
NADAL 2 3



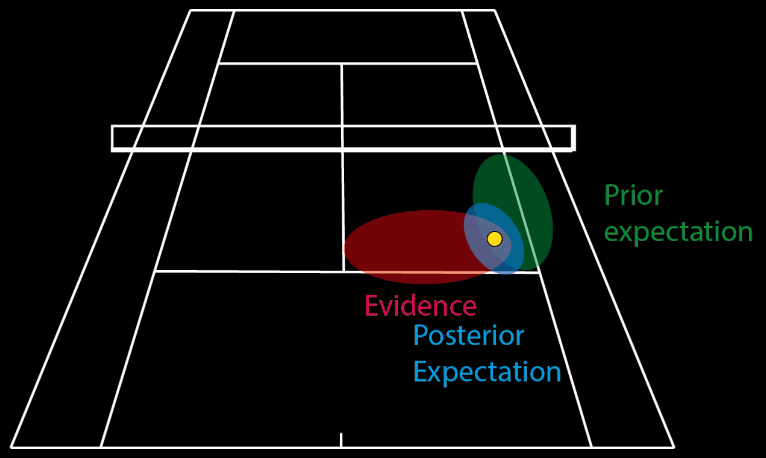

prior
expectation
sensory data


PETZSCHN 2 2
NADAL 2 3

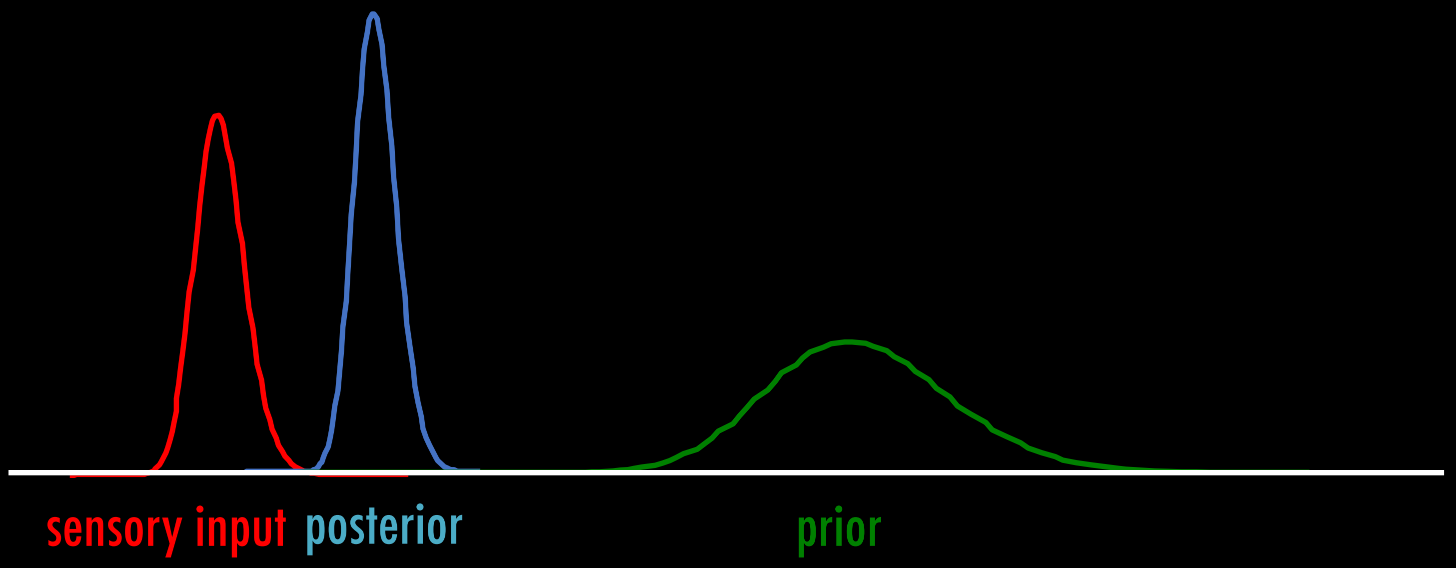



prior
expectation
sensory data
prediction

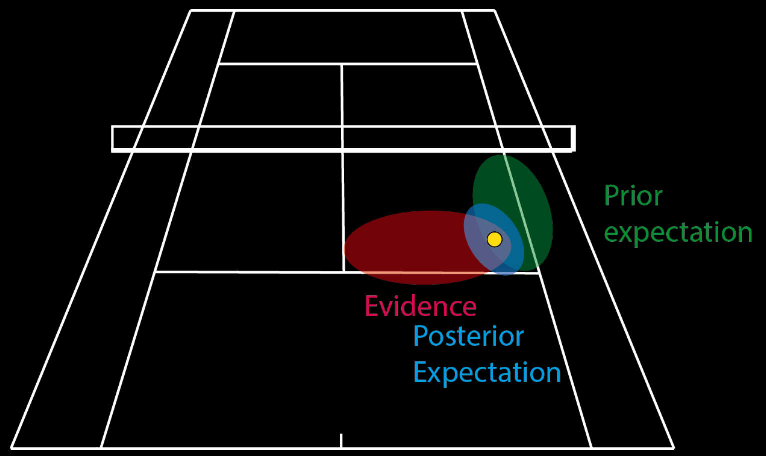
Ideal Observer



$$P(world|sensory\ data) = \frac{P(sensory\ data|world)\ P(world)}{P(sensory\ data)}$$



The ideal Nadal

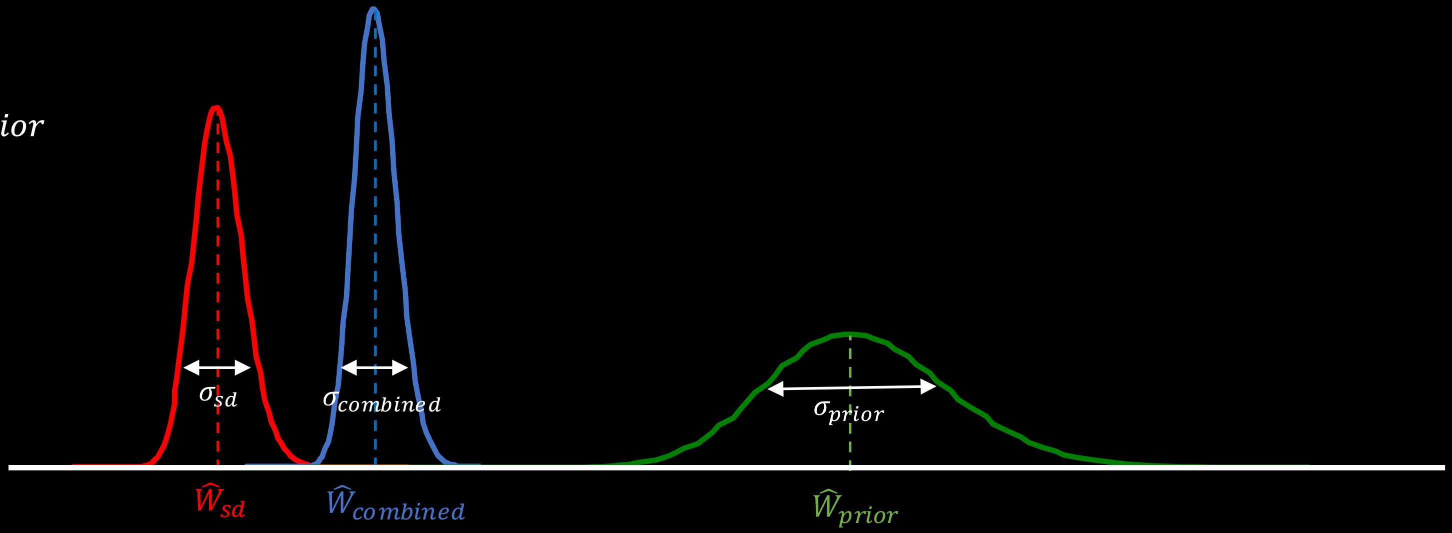


$$P(world|sensory\ data) = \frac{P(sensory\ data|world)\ P(world)}{P(sensory\ data)}$$

If Gaussian:

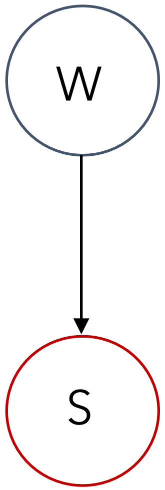
$$\widehat{W}_{combined} = w_{sd} \cdot \widehat{W}_{sd} + w_{prior} \cdot \widehat{W}_{prior}$$

$$w_{sd} = \frac{\frac{1}{\sigma_{sd}^2}}{\frac{1}{\sigma_{sd}^2} + \frac{1}{\sigma_{prior}^2}}$$



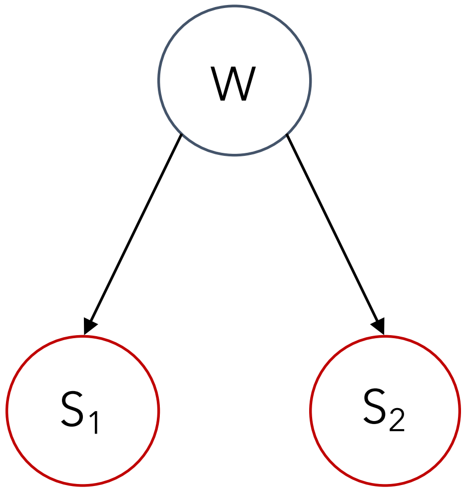
3 Inference Problems – 3 Examples

Basic Bayes



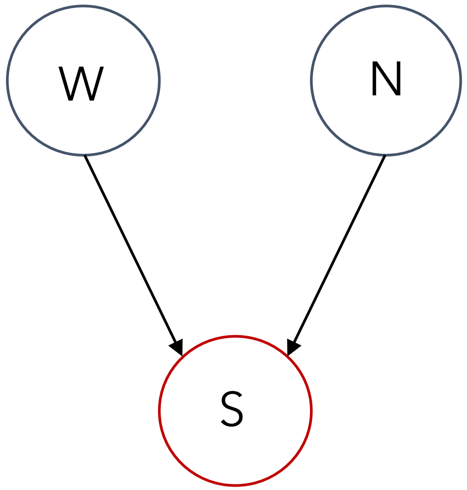
Example:
Magnitude
estimation

Cue combination



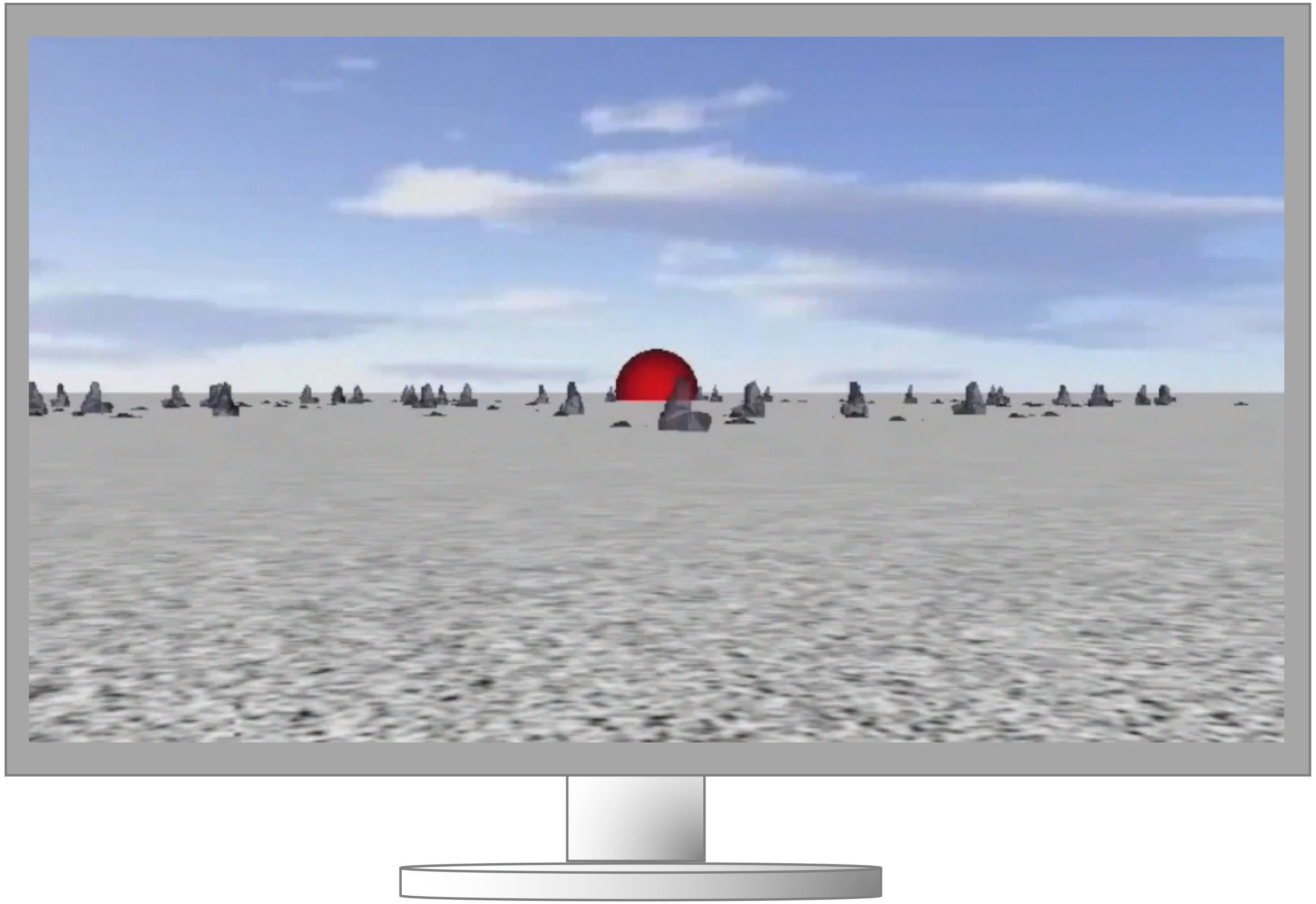
Example:
Multi-Sensory
integration

Discounting



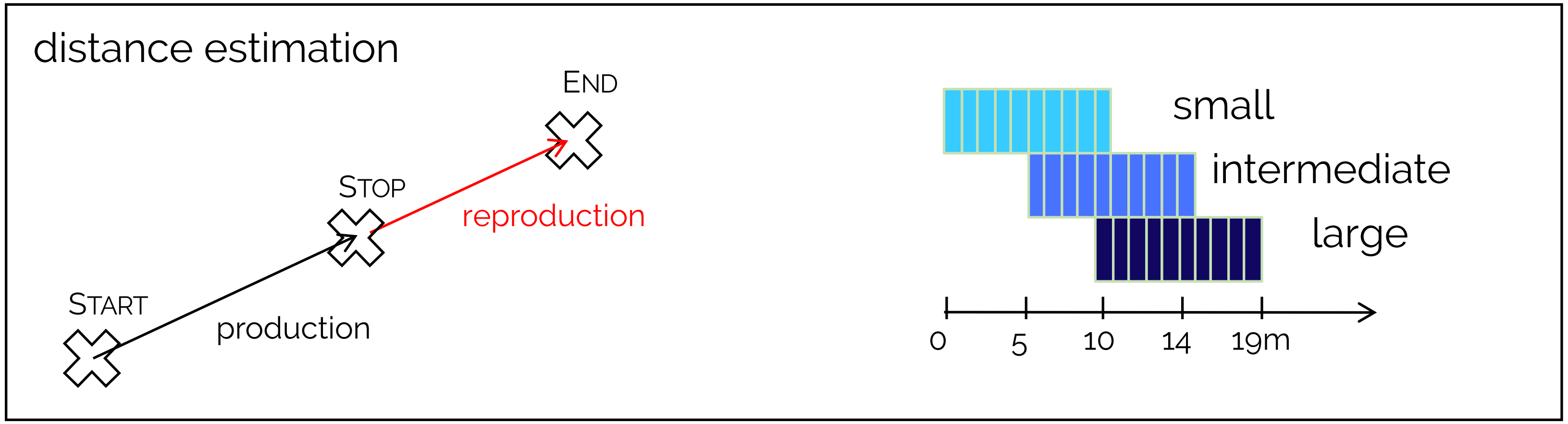
Example:
Resolving
ambiguity

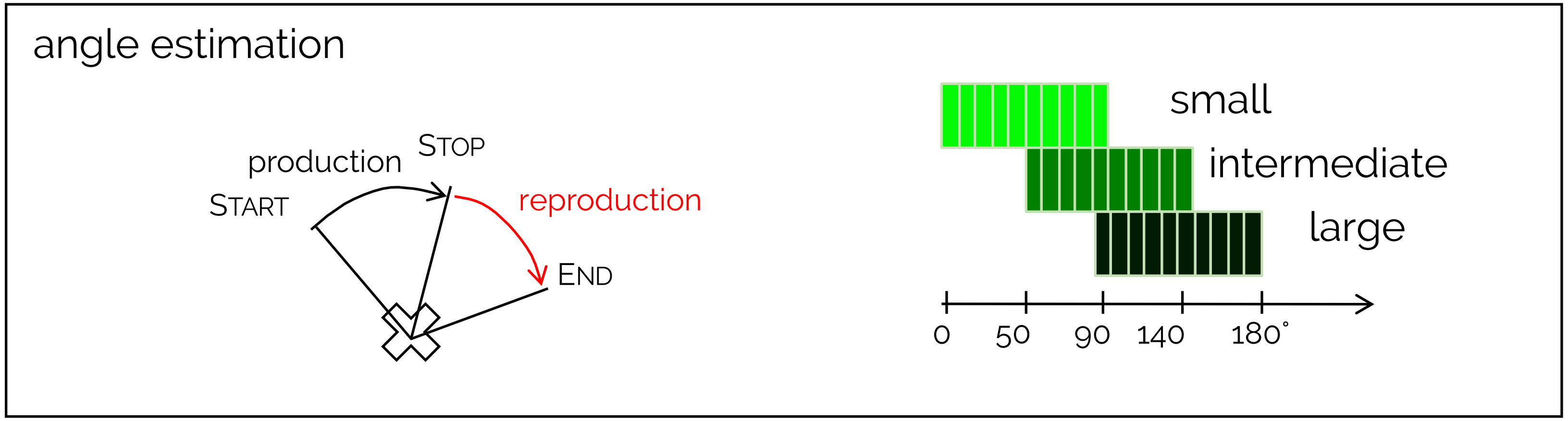
“optimal errors” in magnitude estimation



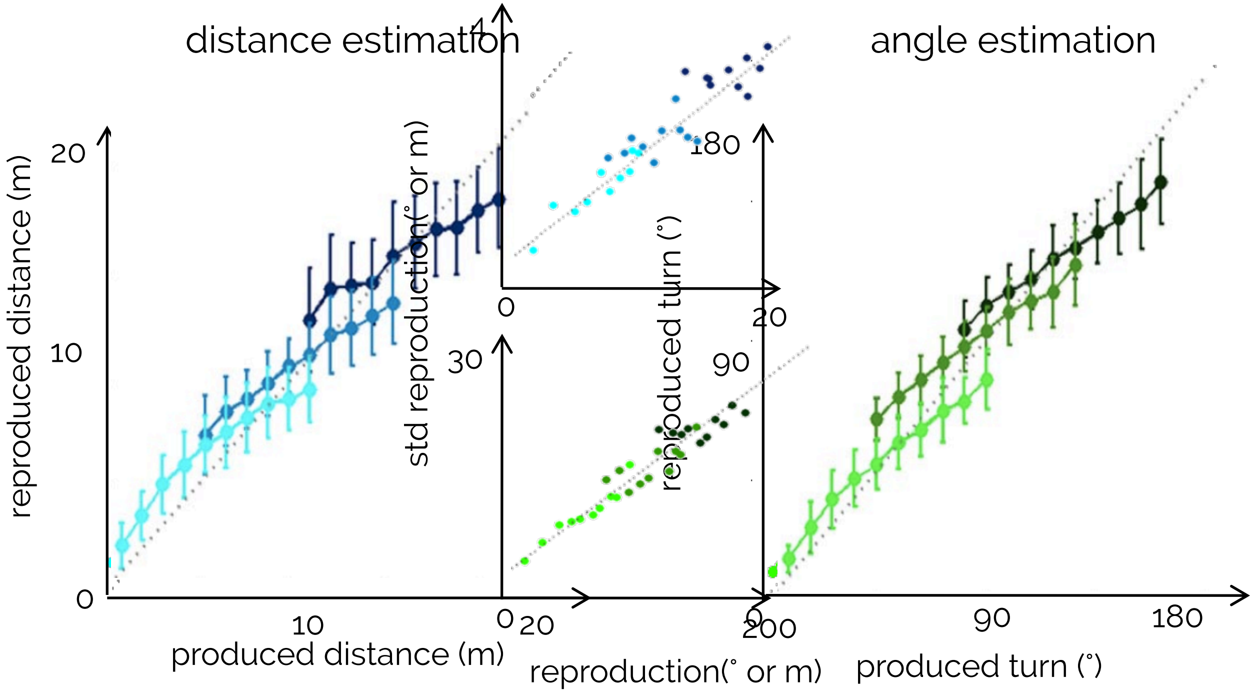
Petzschner & Glasauer, JoN, 2011

Varying the sample range

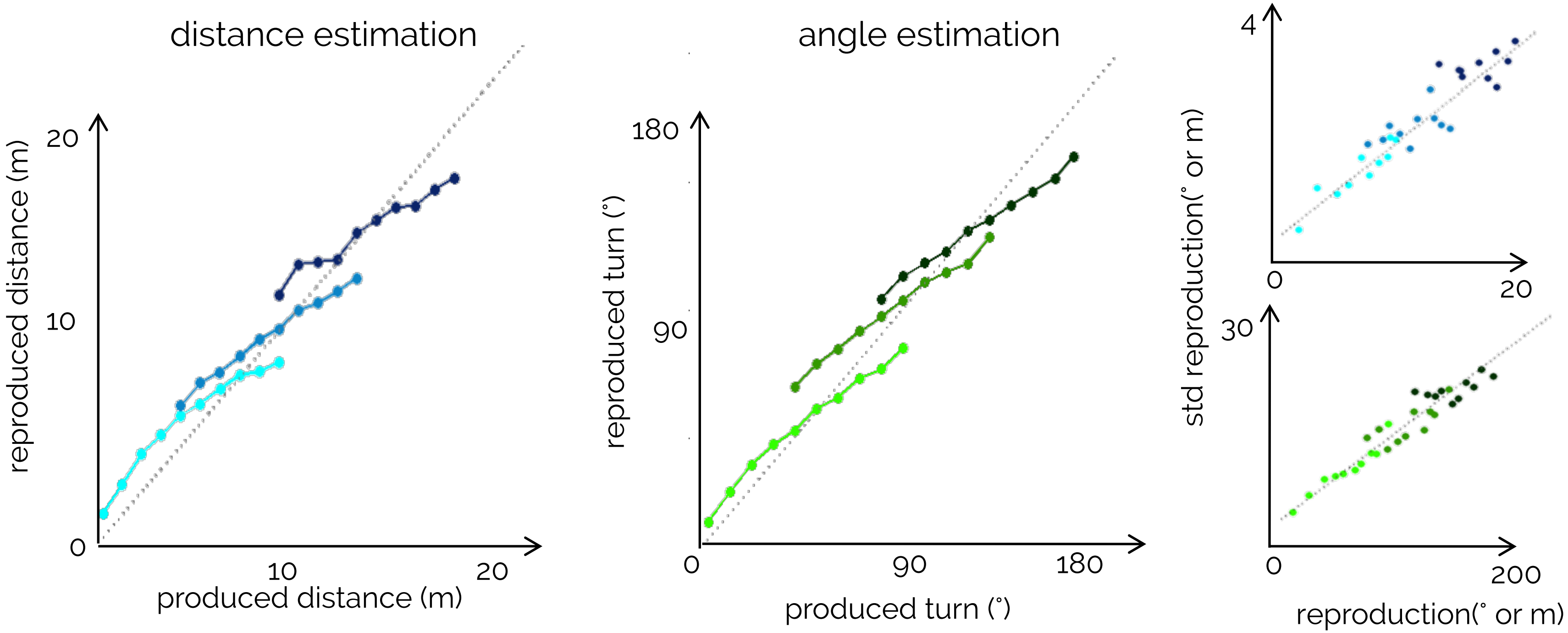




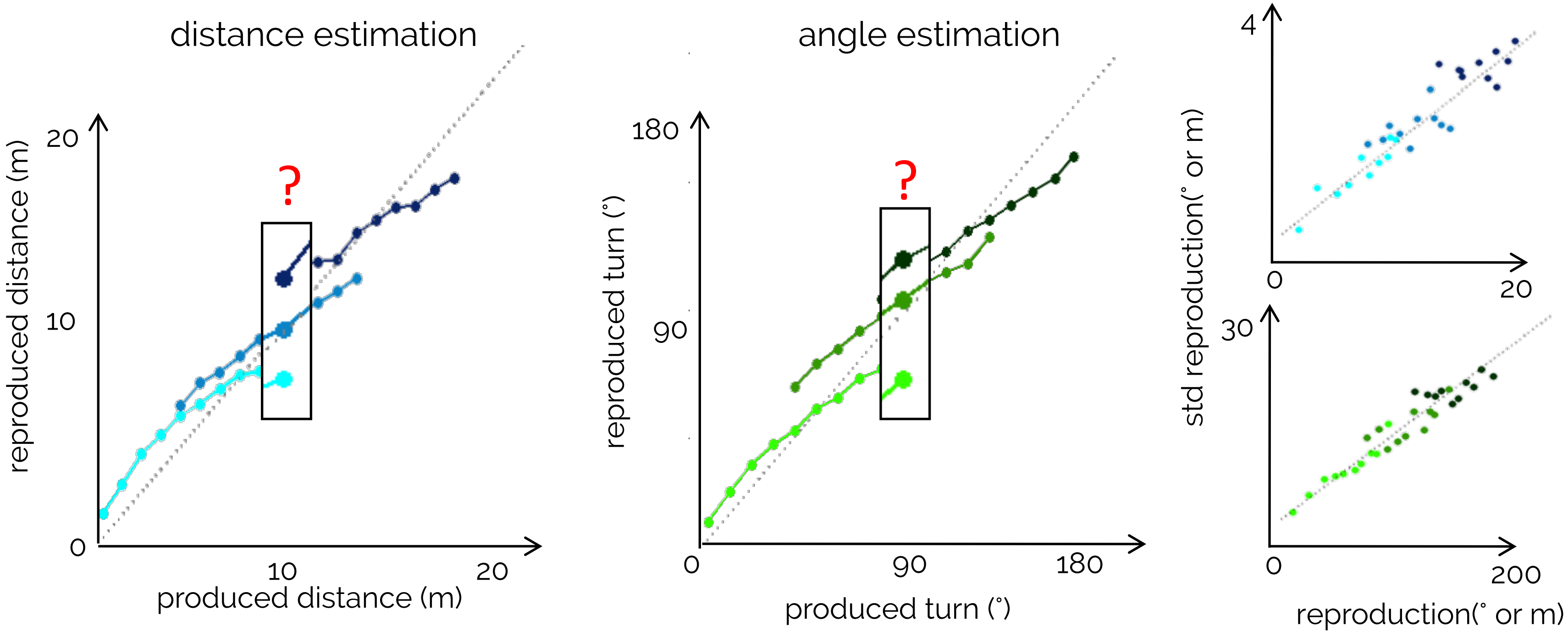
Petzschner & Glasauer, JoN, 2011



Petzschner & Glasauer, JoN, 2011

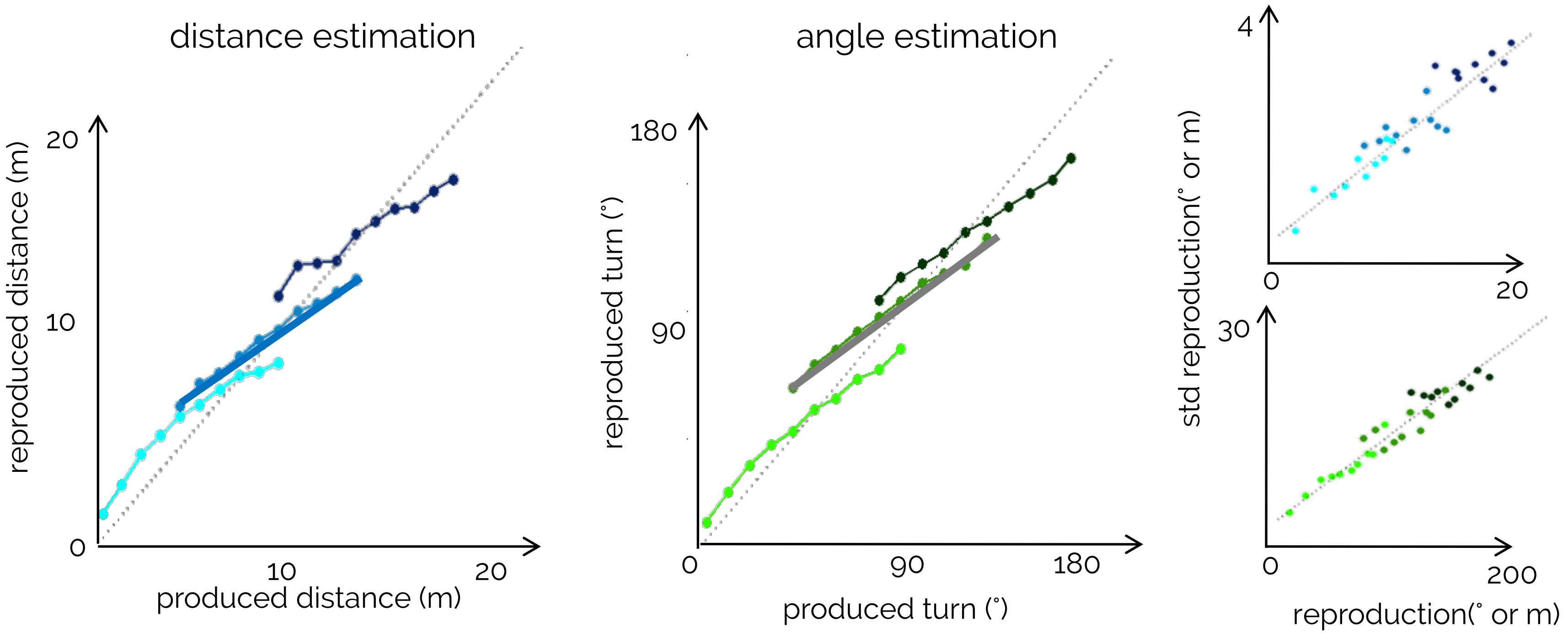


Petzschner & Glasauer, JoN, 2011



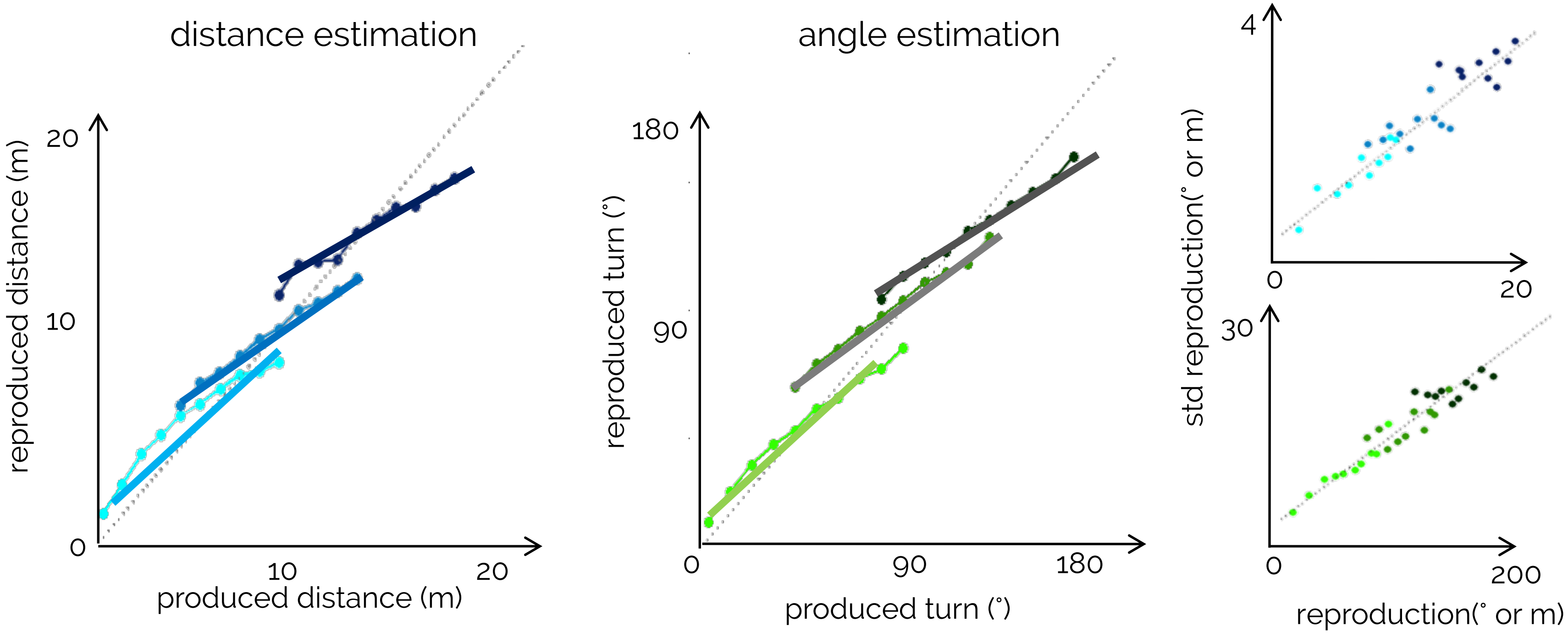
Prior knowledge: Experience

Petzschner & Glasauer, JoN, 2011



Regression Effect

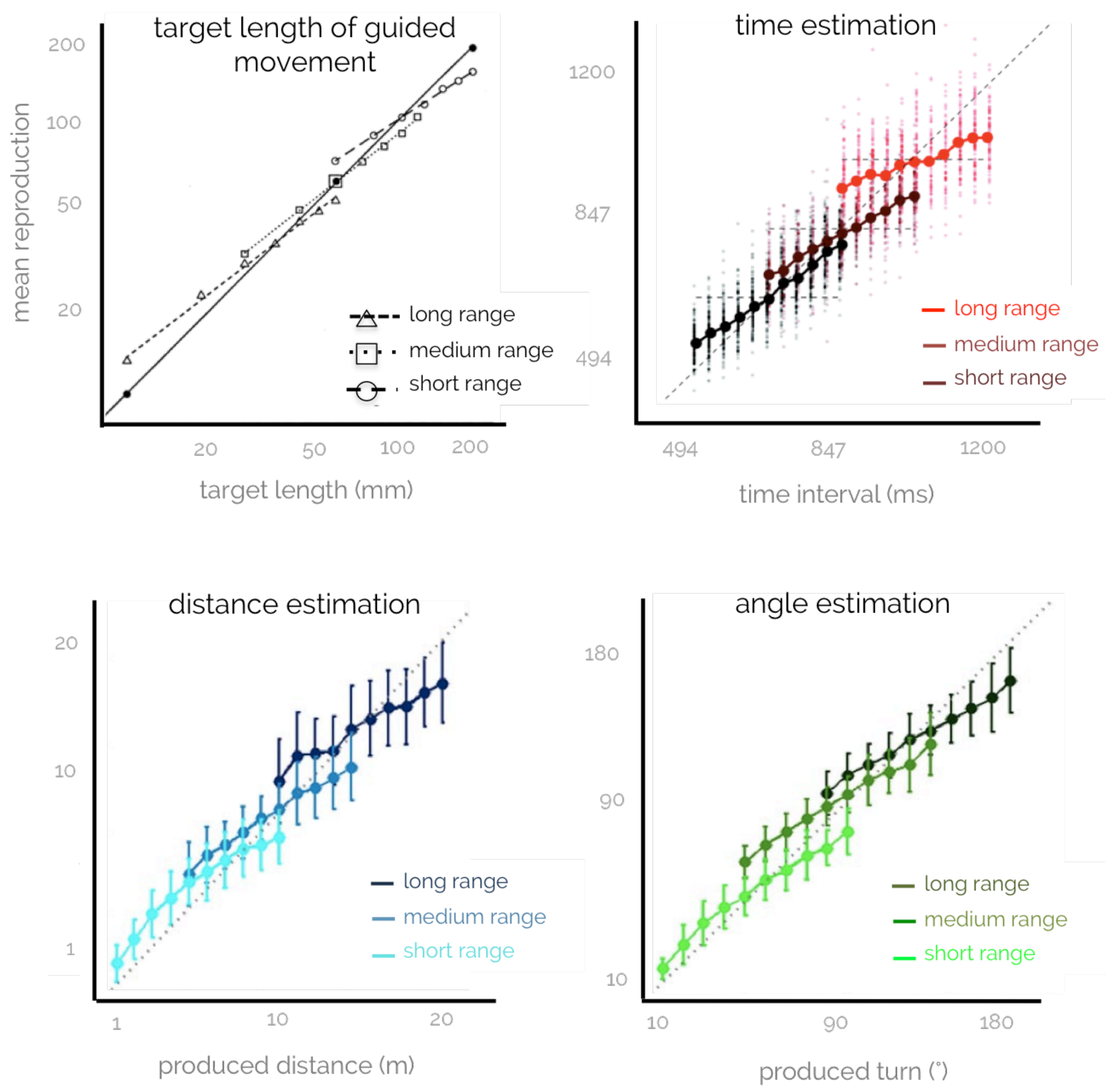
Petzschner & Glasauer, JoN, 2011



Regression Effect & Range Effect

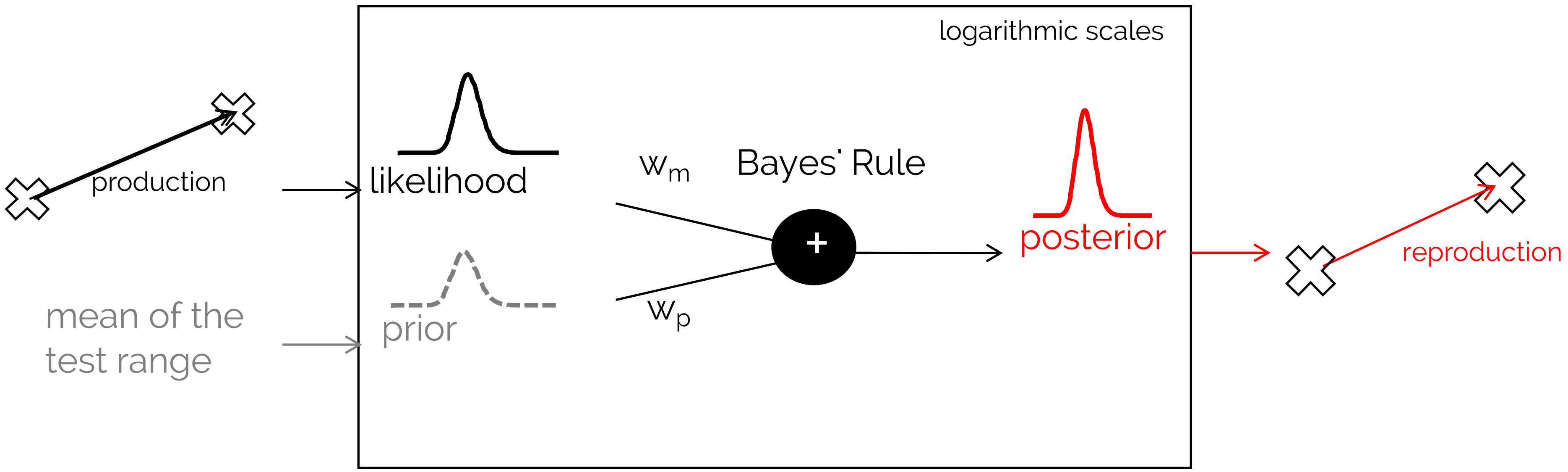
Petzschner & Glasauer, JoN, 2011

Let's take a look at the literature



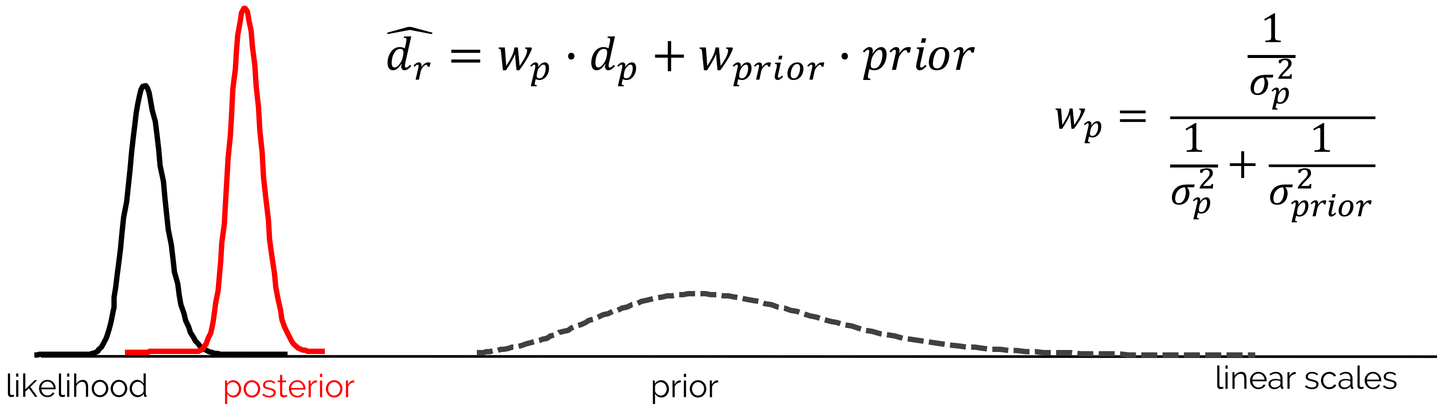
Petzschner et al, TiCS, 2015; Petzschner & Glasauer, JoN, 2011

A Bayesian Model for magnitude estimation

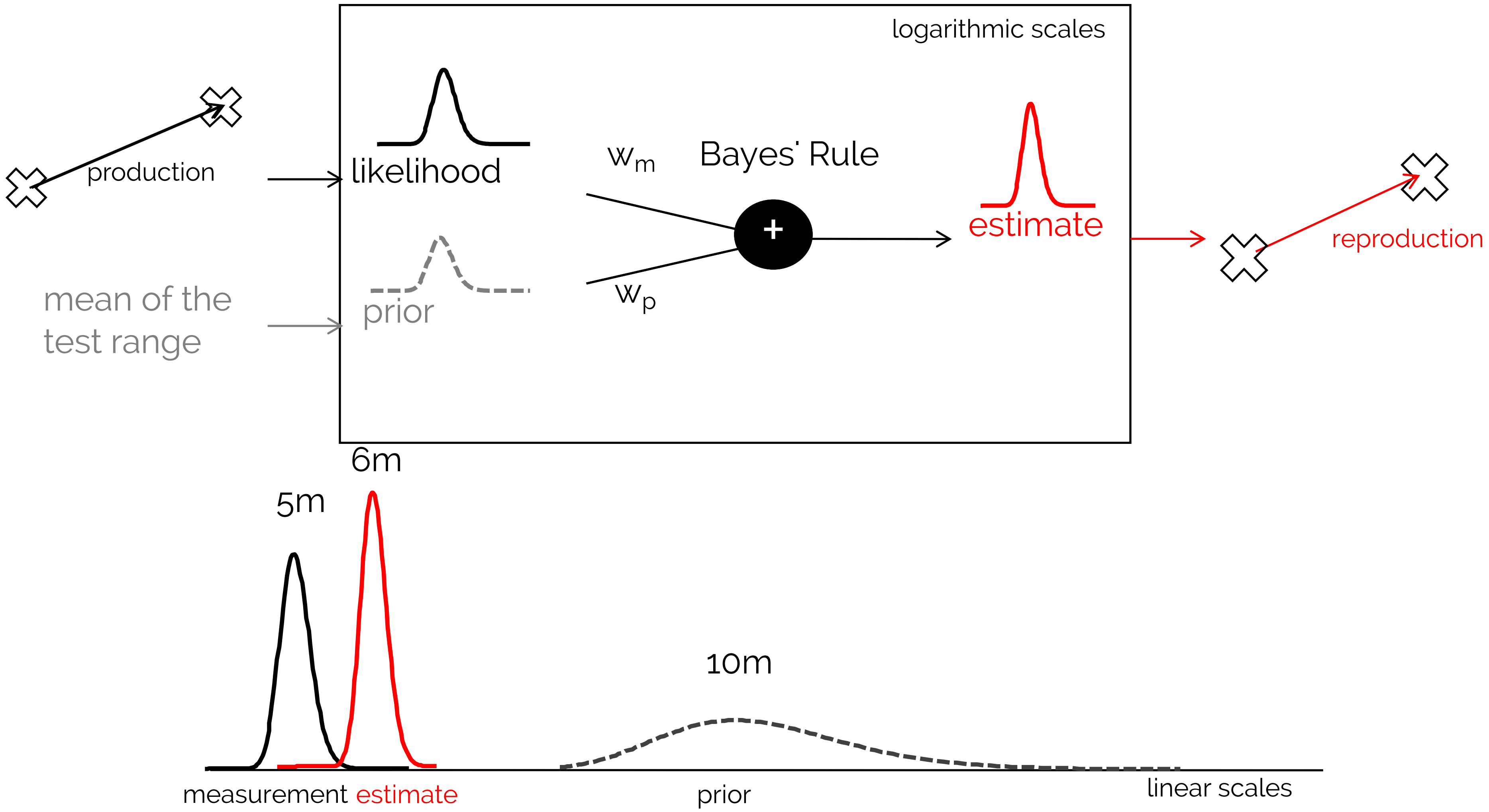


$$\widehat{d_r} = w_p \cdot d_p + w_{prior} \cdot prior$$

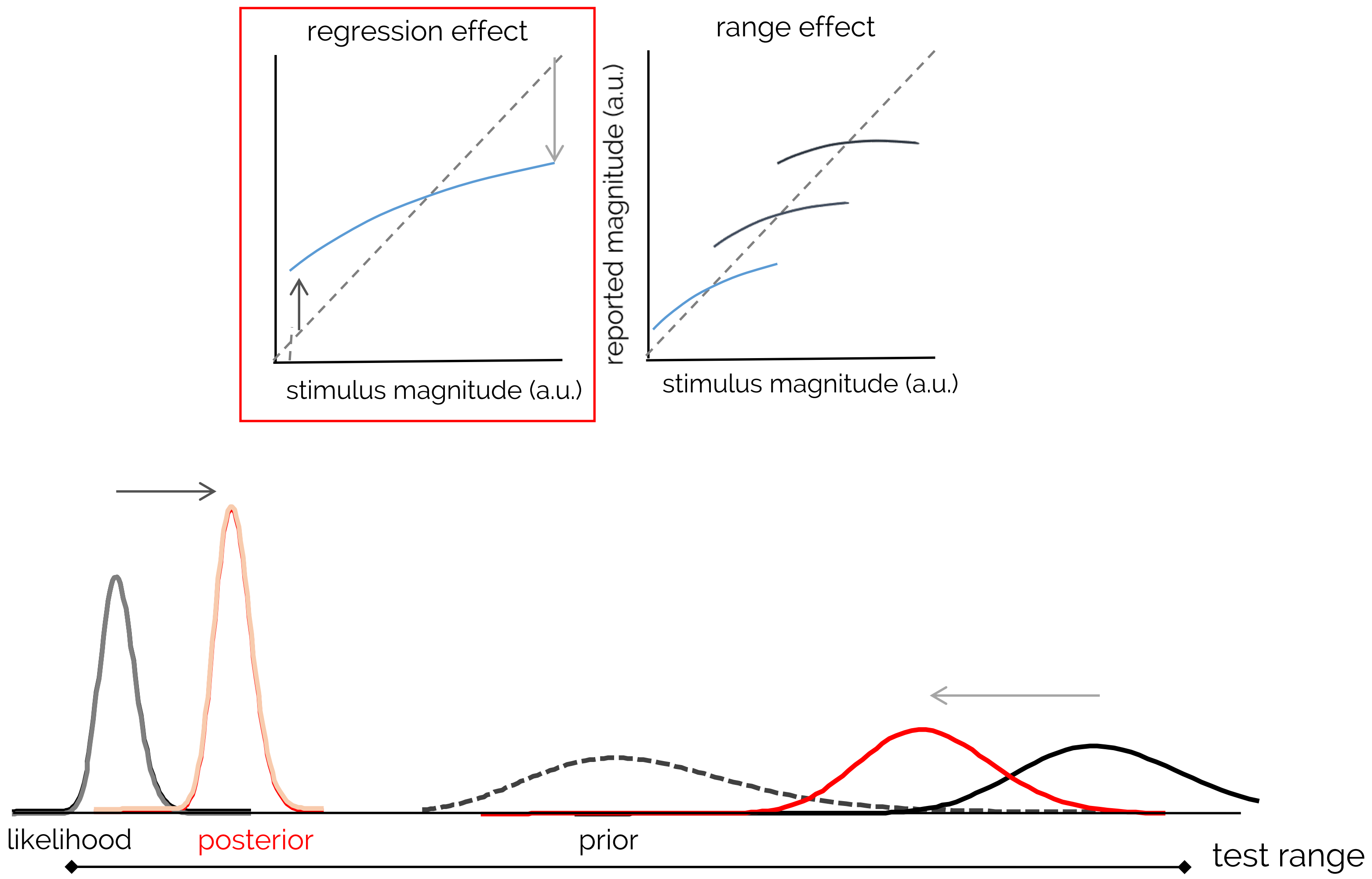
$$w_p = \frac{\frac{1}{\sigma_p^2}}{\frac{1}{\sigma_p^2} + \frac{1}{\sigma_{prior}^2}}$$



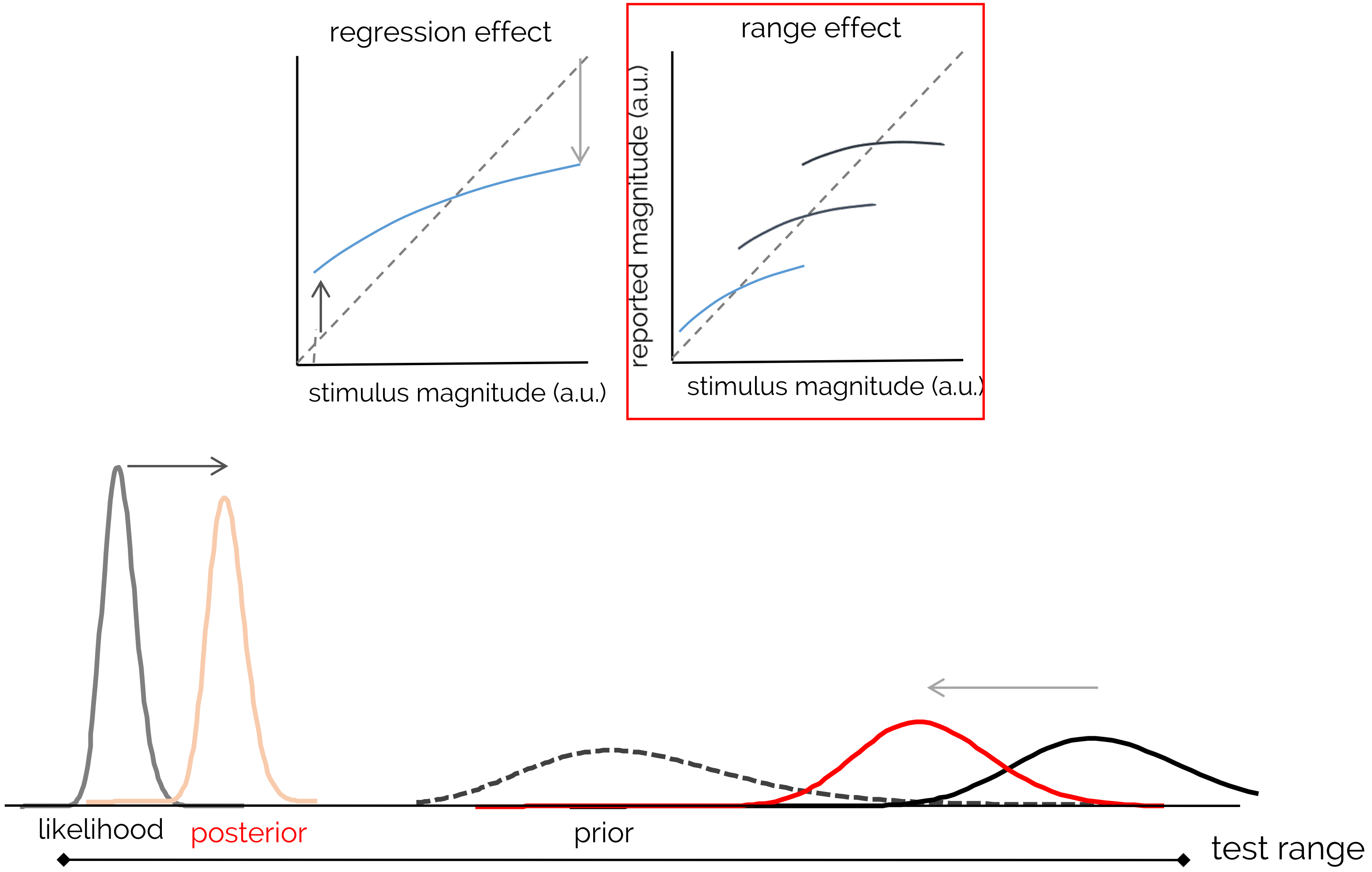
Petzschner & Glasauer, JoN, 2011; Petzschner et al, TiCS, 2015


logarithmic scales
production
likelihood
mean of the
test range
prior
w_m
Bayes' Rule
w_p
+
estimate
reproduction
6m
5m
10m
measurement estimate
prior
linear scales

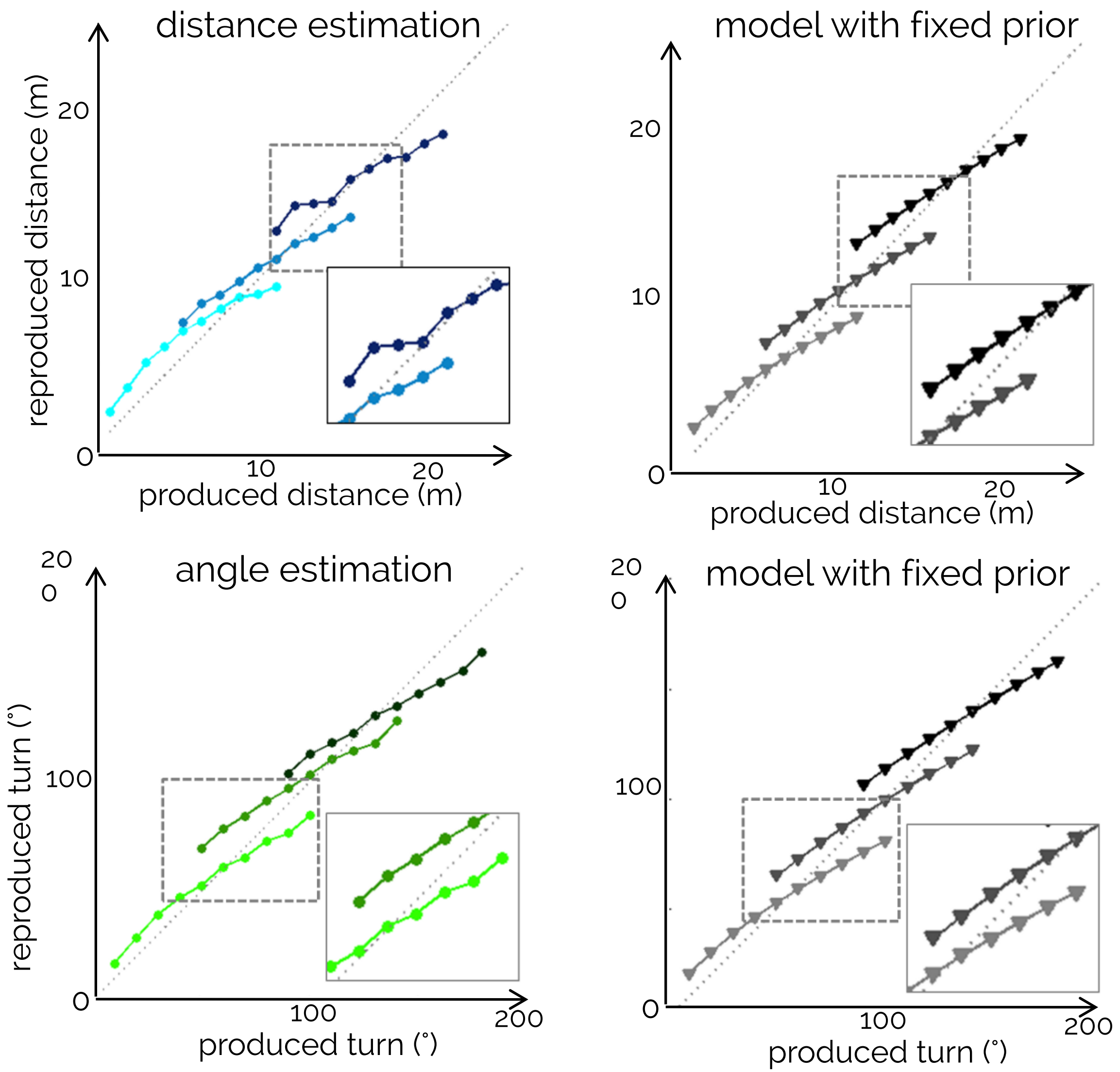
Explaining the regression effect



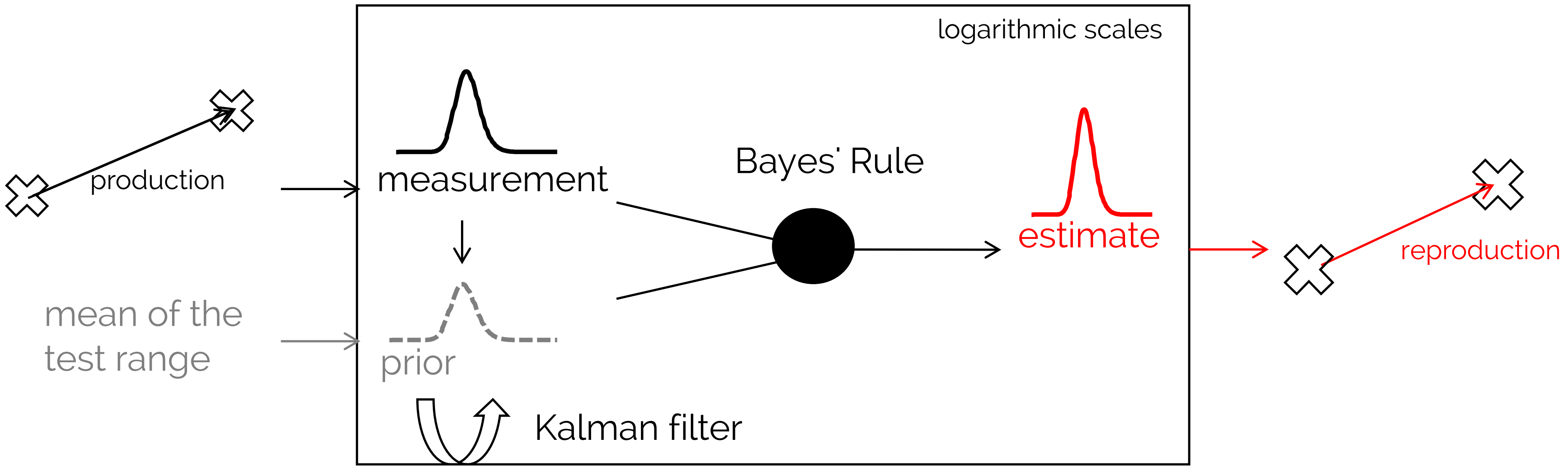
Explaining the range effect



Quantitative results



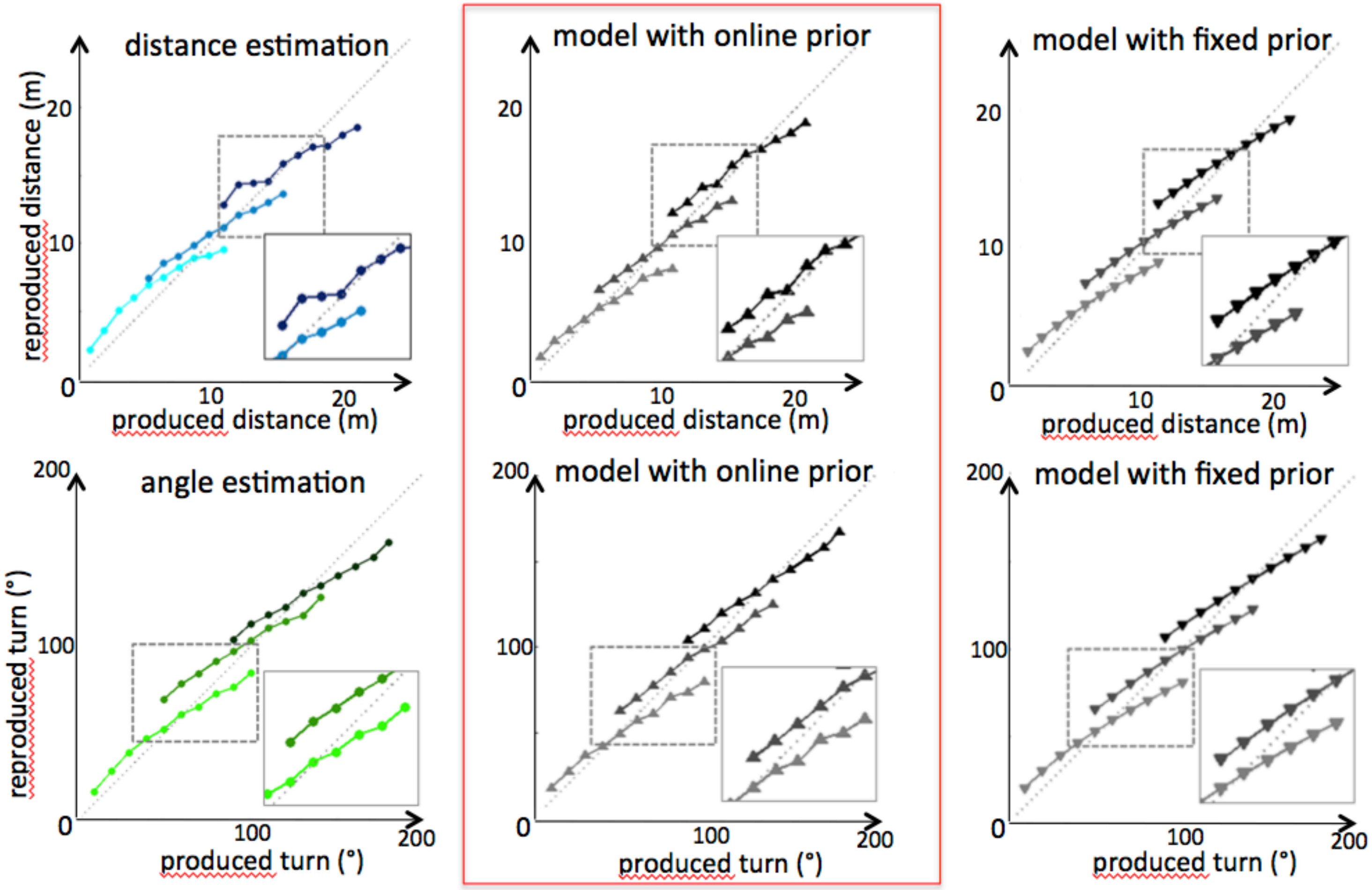
Petzschner & Glasauer, JoN, 2011; Petzschner et al, TiCS, 2015



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

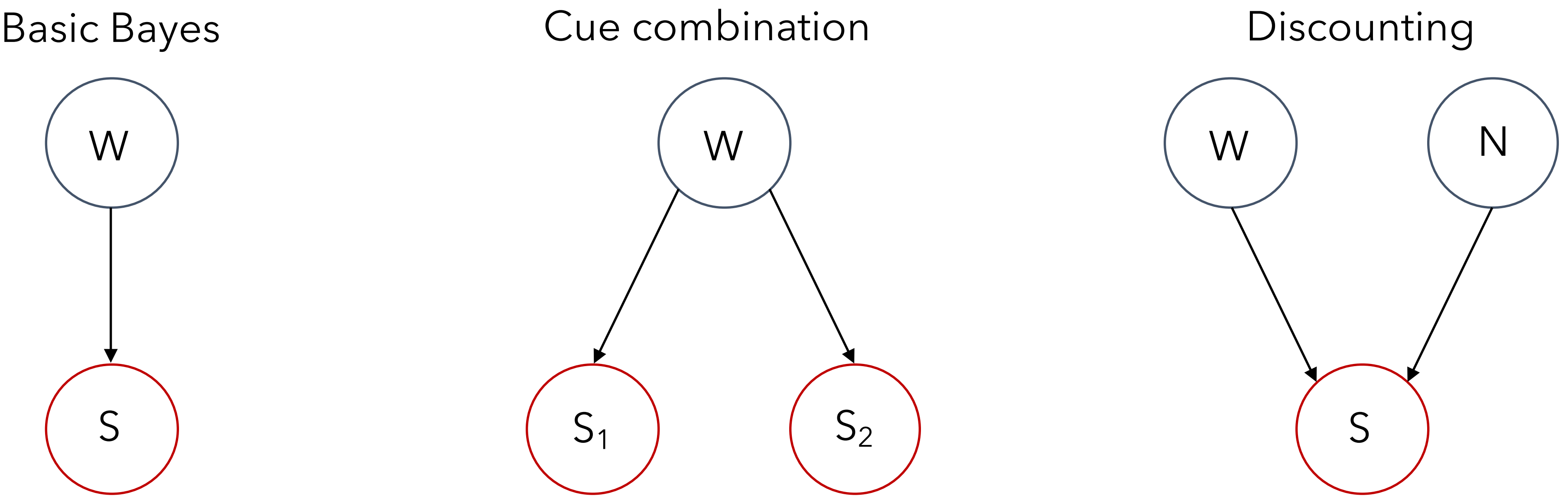
Kalman Filter

"Todays posterior is tomorrows prior."



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

3 examples -3 Inference Types



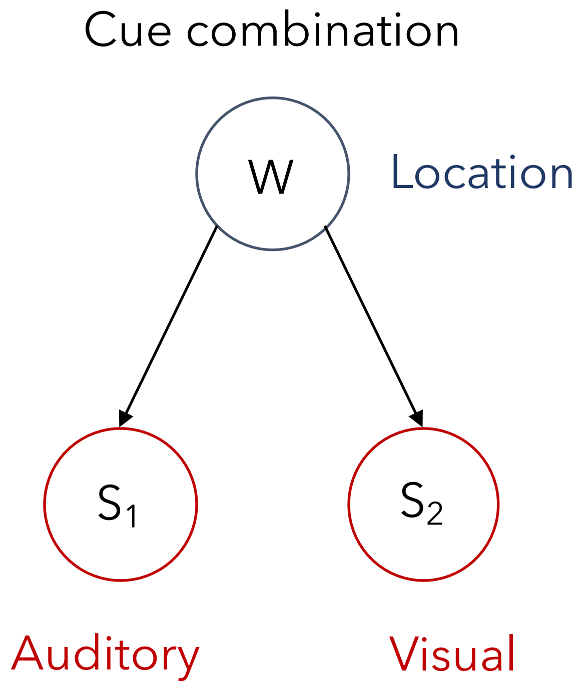
Example: Magnitude estimation

Example: Multi-Sensory integration

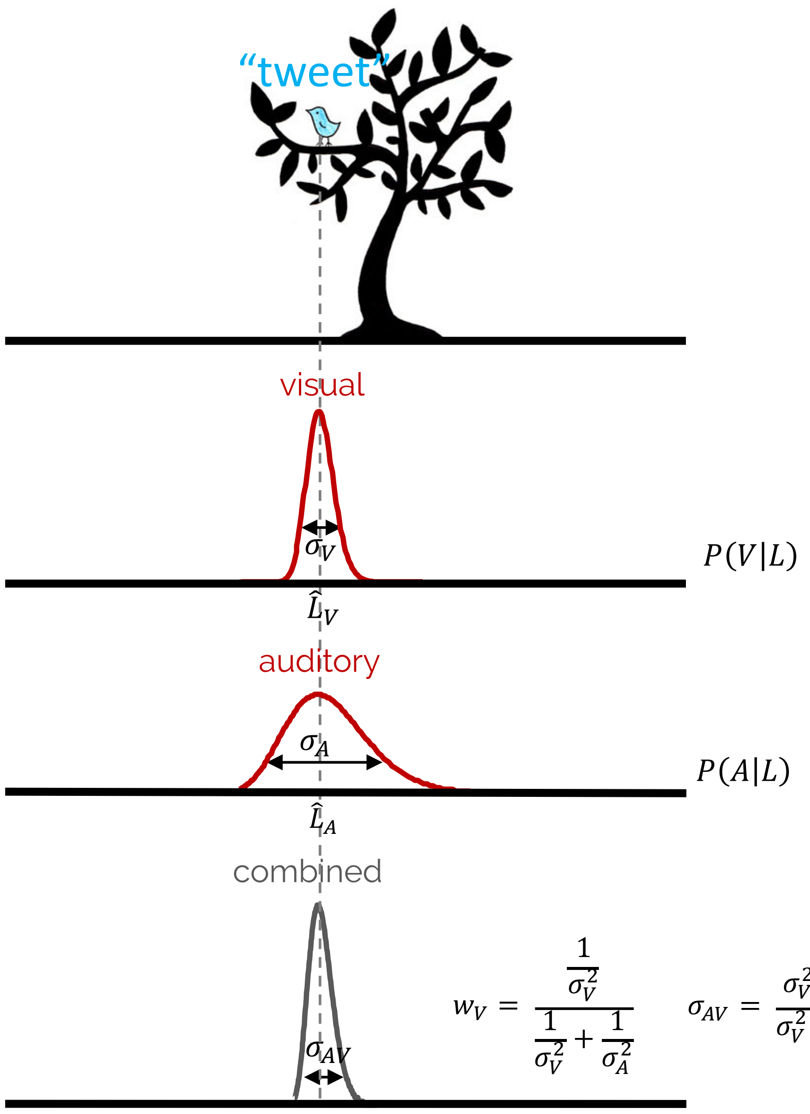
Example: Resolving ambiguity

Merging your senses into a robust percept…

or how to find out that you are drinking Ouzo



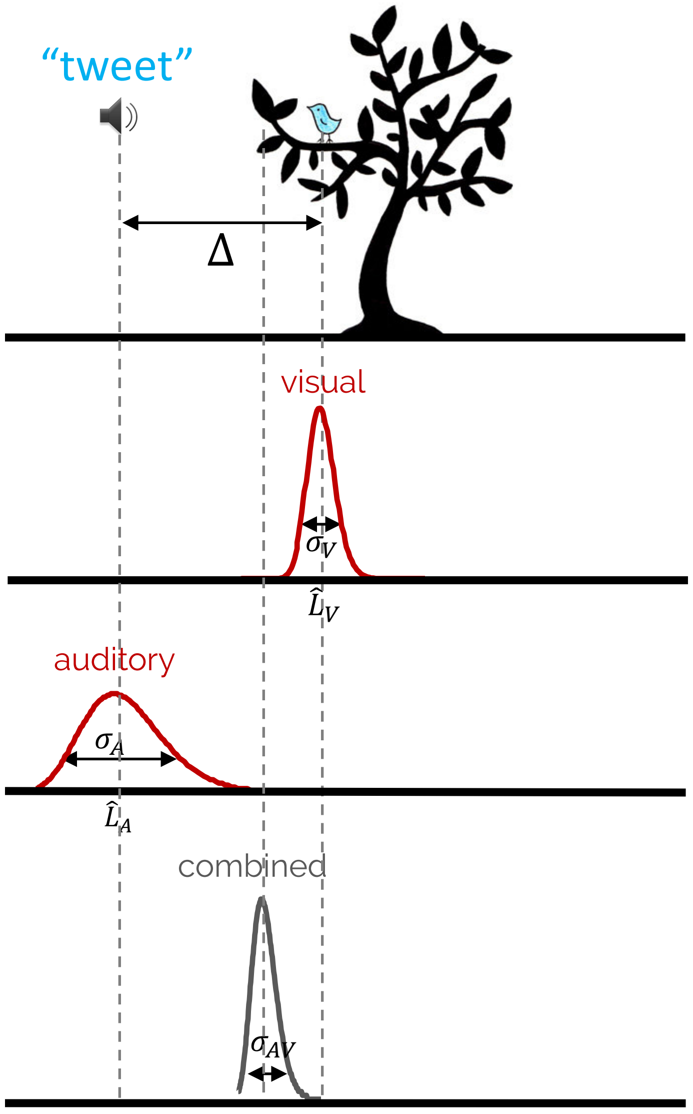
Multi-sensory integration



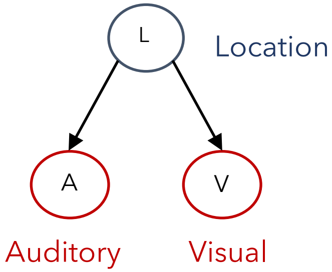
$$w_V = \frac{\frac{1}{\sigma_V^2}}{\frac{1}{\sigma_V^2} + \frac{1}{\sigma_A^2}}$$

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

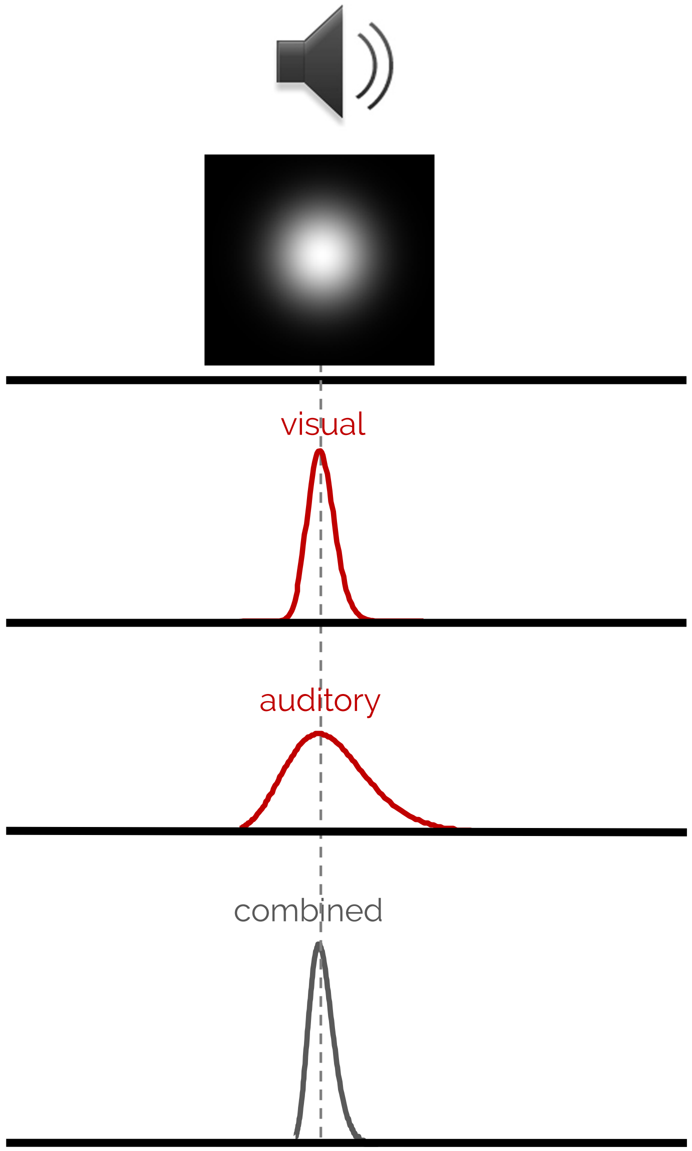
$$\hat{L}_{AV} = w_V \cdot \hat{L}_V + w_A \cdot \hat{L}_A$$

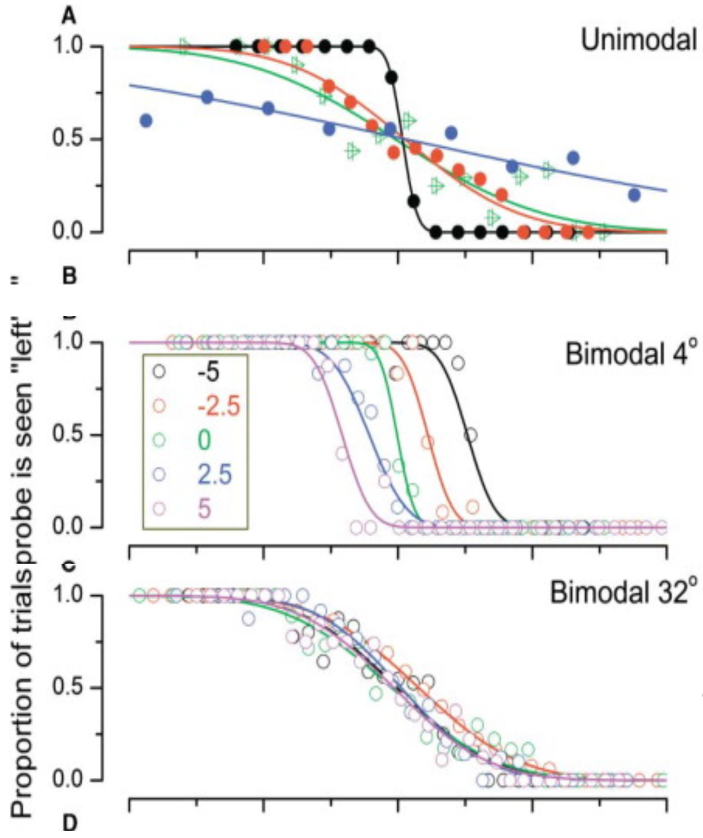


$$\hat{L}_{AV} = w_V \cdot \hat{L}_V + w_A \cdot \hat{L}_A$$

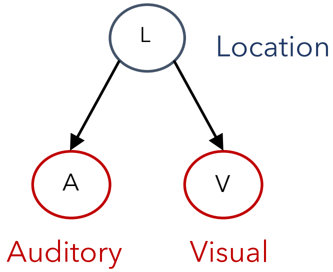


Multi-sensory integration



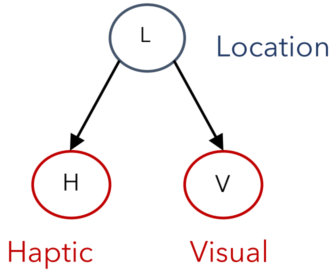


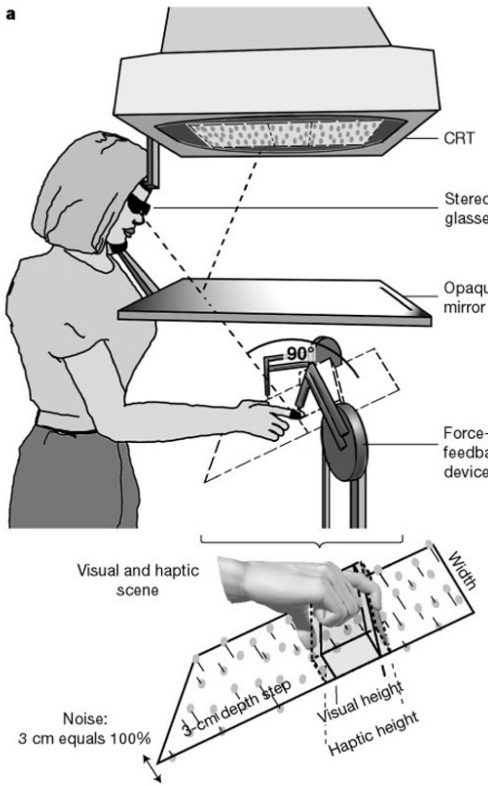
$$\sigma_{AV} = \frac{\sigma_V^2 \cdot \sigma_A^2}{\sigma_V^2 + \sigma_A^2}$$

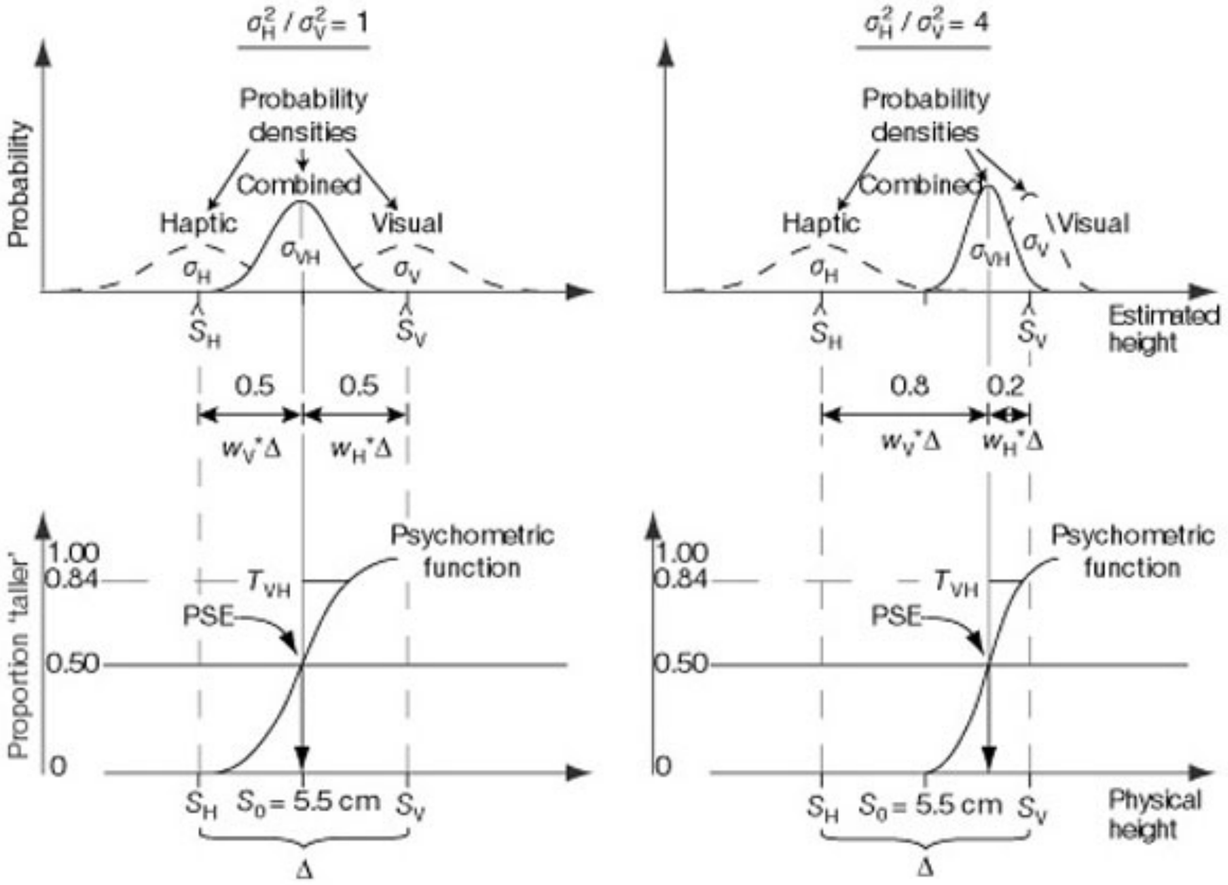


Alais & Burr, 2004

Multi-sensory integration



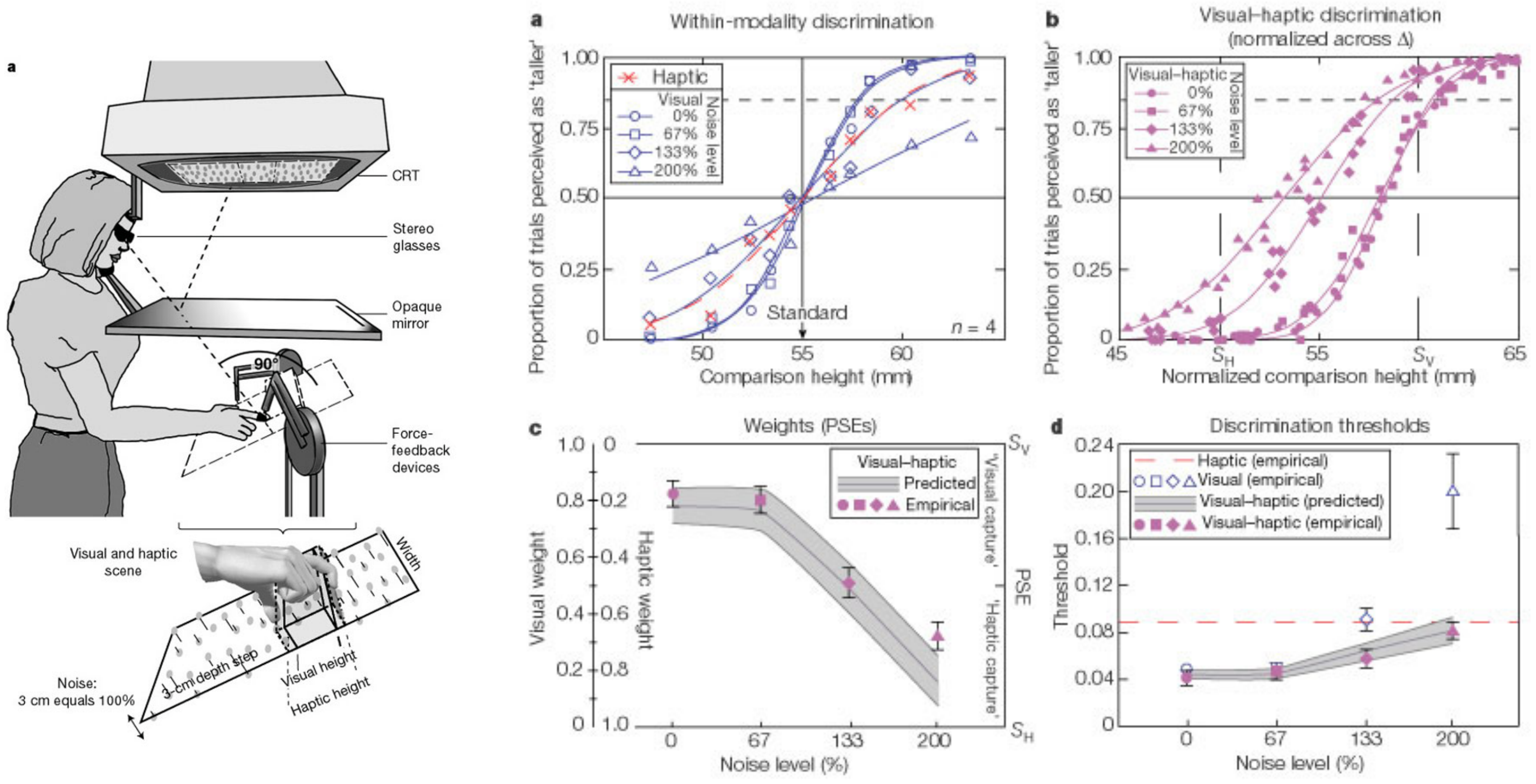


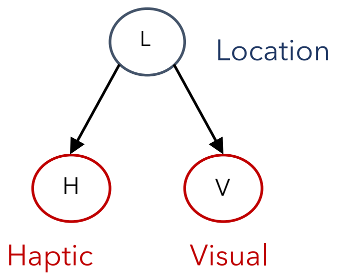


Which one was higher?

Ernst & Banks, 2002

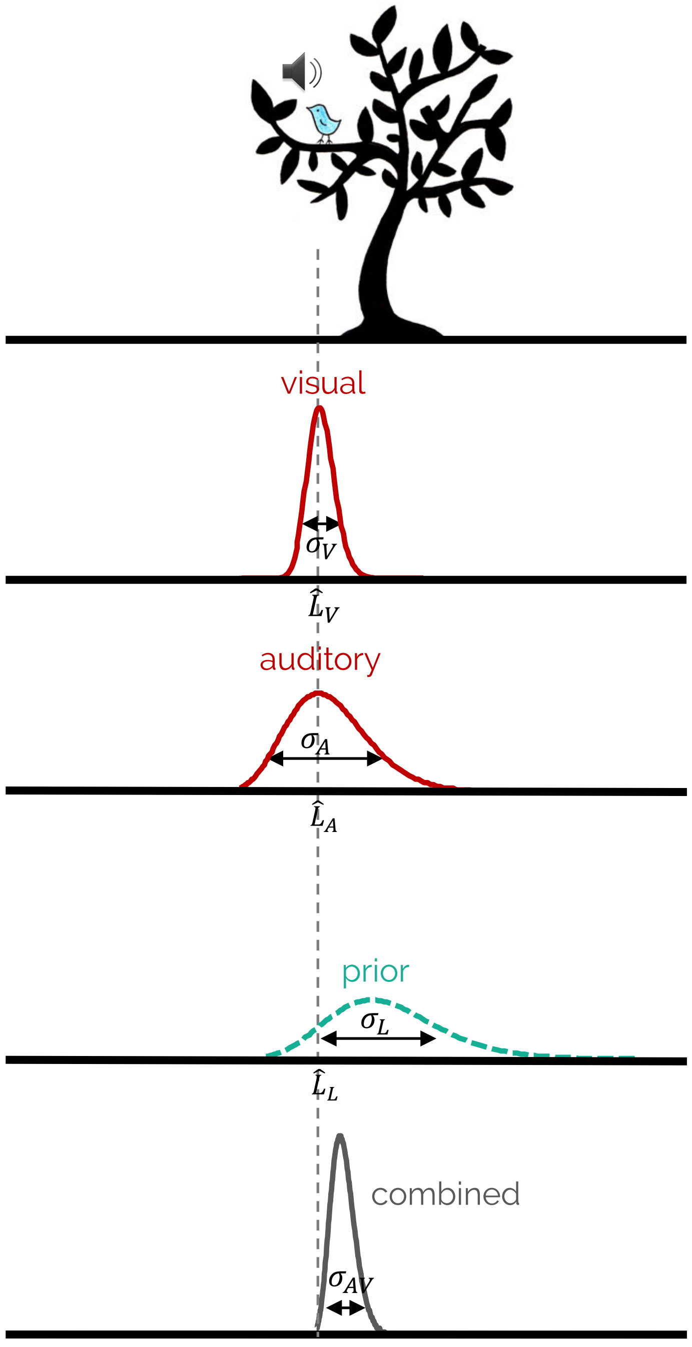
Multi-sensory integration





Ernst & Banks, 2002

Multi-sensory integration with priors



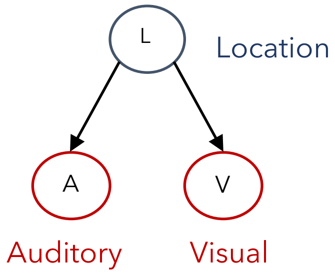
$P(V|L)$

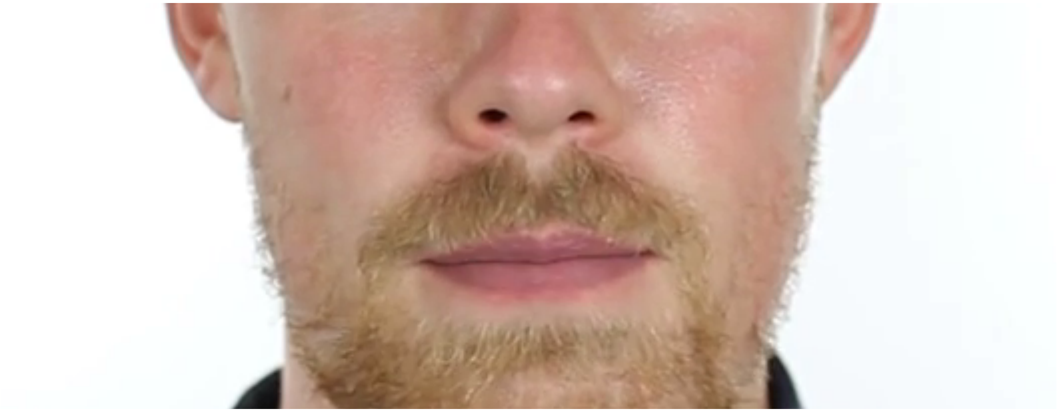
$P(A|L)$

$P(A|L)$

$$P(L|V,A) = \frac{P(V,A|L)\,P(L)}{P(V,A)} = \frac{P(V|L)P(A|L)P\,(L)}{P(V,A)}$$

$$\hat{L}_{AV} = w_V \cdot \hat{L}_V + w_A \cdot \hat{L}_A + w_L \cdot \hat{L}_L$$



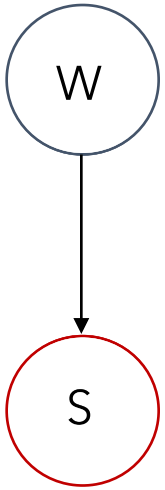


BAR

FAR

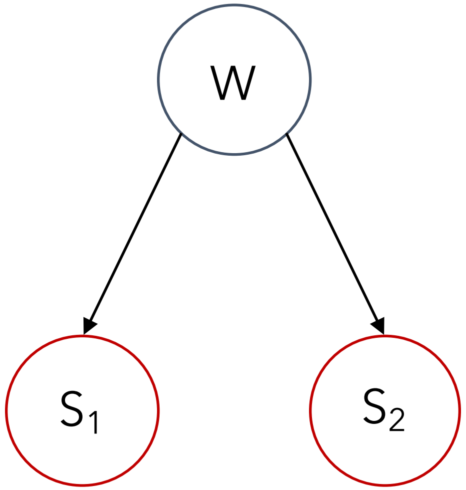
3 examples -3 Inference Types

Basic Bayes



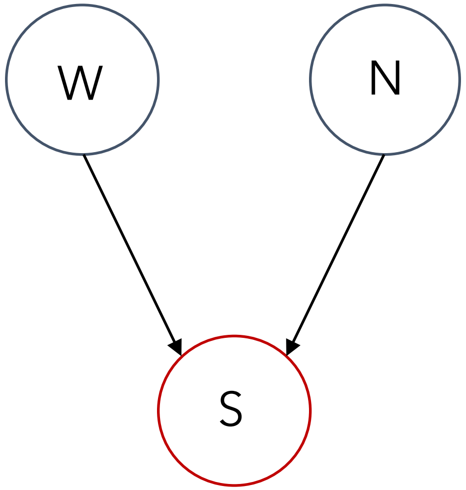
Example:
Magnitude
estimation

Cue combination

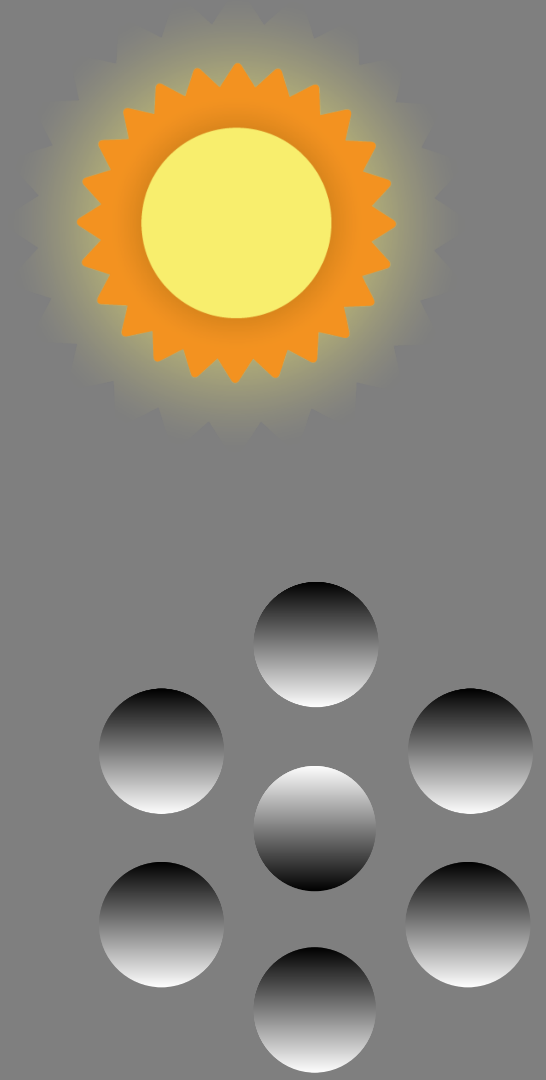


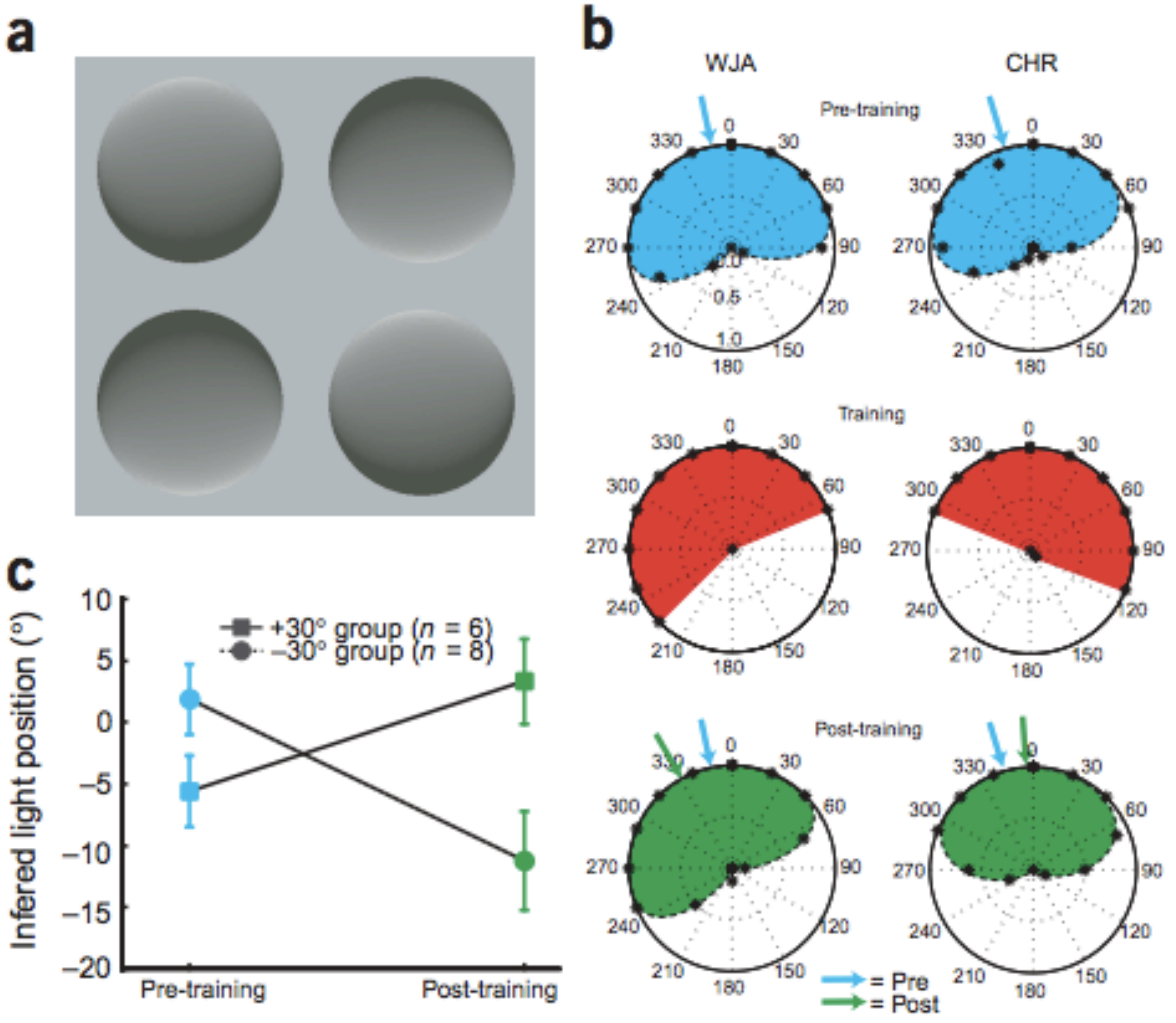
Example:
Multi-Sensory
integration

Discounting



Example:
Resolving
ambiguity





Adams et al. 2004

The world is full of priors

- Light comes from above.
- Noses stick out.
- Objects move slowly.
- Background images are uniformly colored.
- Other people's gazes are directed at us.

Where to the priors come from?

- Genes (Depth perception: Yonas 2003)
- Experience

The success story of Bayesian Models for Perception

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

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

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

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, …]

Is perception Bayesian Inference?

These studies motivated conclusions that 'human perception is close to the Bayesian optimal suggesting the Bayesian process may be a fundamental element of sensory processing' [Körding and Wolpert, 2006] or, analogously, that there are myriad ways in which human observers behave as optimal Bayesian observers' [Knill and Pouget, 2004].

Critique 1 & Marr’s Three Levels of Analysis

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

- Computation:

  “What is the goal of the computation, why is it appropriate, and what is the logic of the strategy by which it can be carried out?”

- Algorithm:

  Cognitive psychology

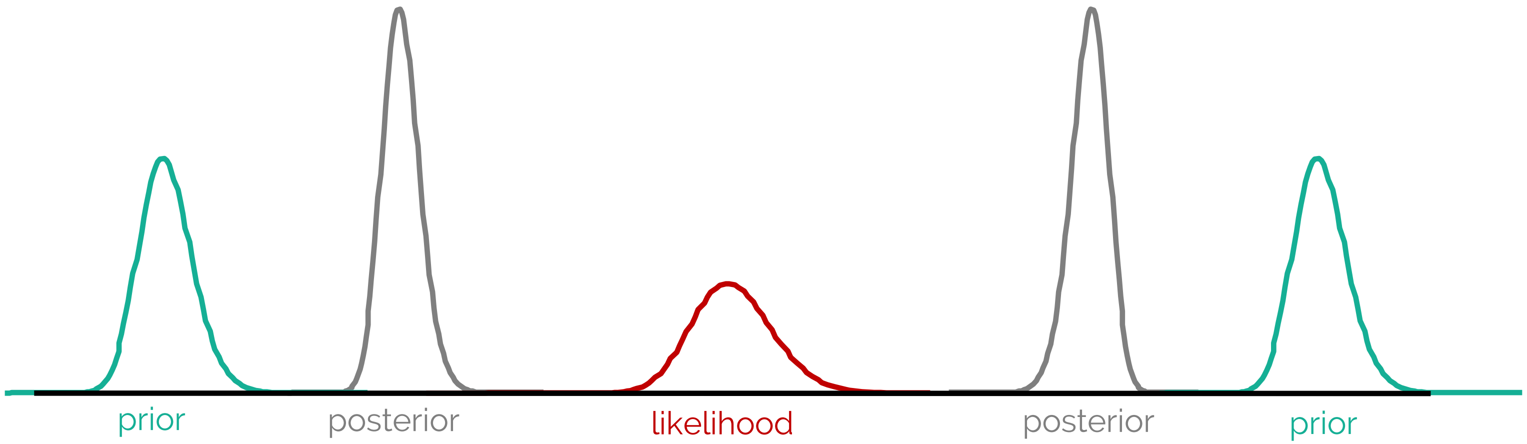
- Implementation:

  Neurobiology

Critique 2

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

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



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,*], 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]

'Wrong' priors (bad experiences, maladaptive learning)

'Wrong' likelihood

'Wrong' precision

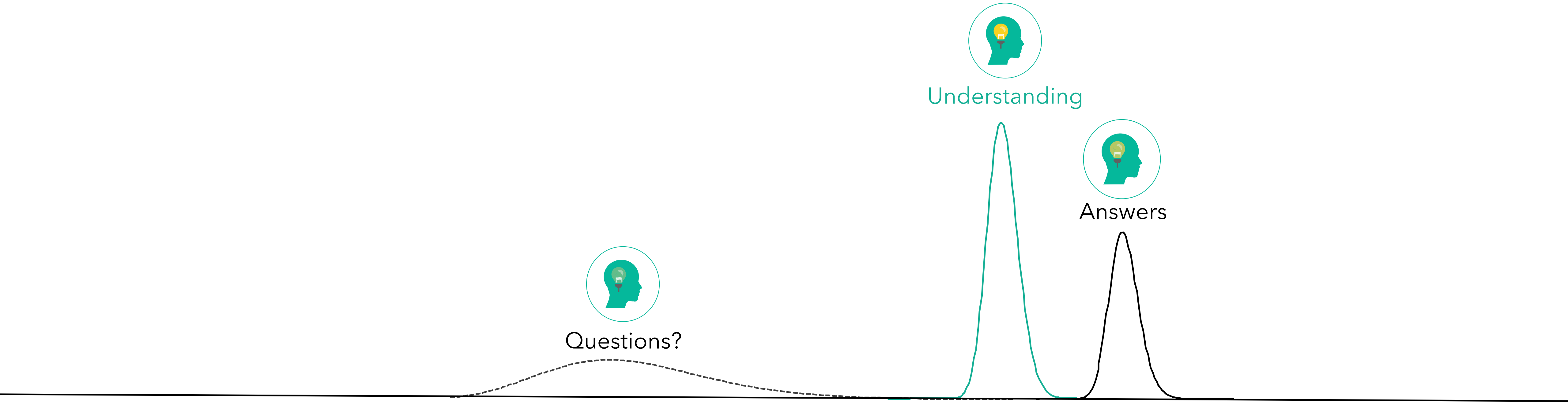
'Wrong' execution/decision

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]


Understanding
Answers
Questions?