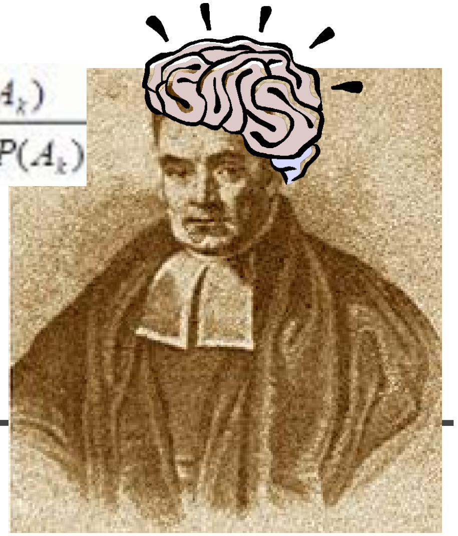
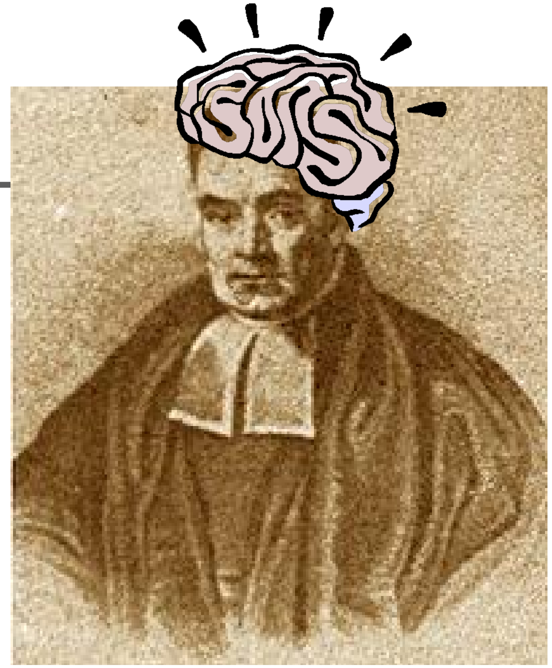
$$P(A_k \mid B) = \frac{P(B \mid A_k)P(A_k)}{\sum_{k=1}^{n} P(B \mid A_k)P(A_k)}$$



The `Bayesian' approach to perception, cognition and disease

Peggy Seriès,
IANC, University of Edinburgh

A Bayesian theory of the Brain



Reverend Thomas Bayes, 1702- 1761

- 1990s- Purpose of the brain: infer state of the world from noisy and incomplete data [G. Hinton, P. Dayan, A. Pouget, R. Zemel, R. Rao, etc..]

- Perception often modelled using the framework of Bayesian Inference

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

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

manipulating probabilities -- degree of belief.

"Instead of trying to come up with an answer to a question, the brain tries to come up with a probability that a particular answer is correct," Alex Pouget.

Is the Human Brain “Bayesian-optimal”?

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

• The question is:

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

2 - Combine it optimally with previous experience?

• testable predictions at the behavioural level

1 - Do brains take into account measurement uncertainty when combining different (simultaneous) information? Combine different sources optimally?

Example: integrating vision and audition

• example: McGurk effect,

Ventriloquism

Why do we get tricked?

http://www.youtube.com/watch?v=G-lN8vWm3m0

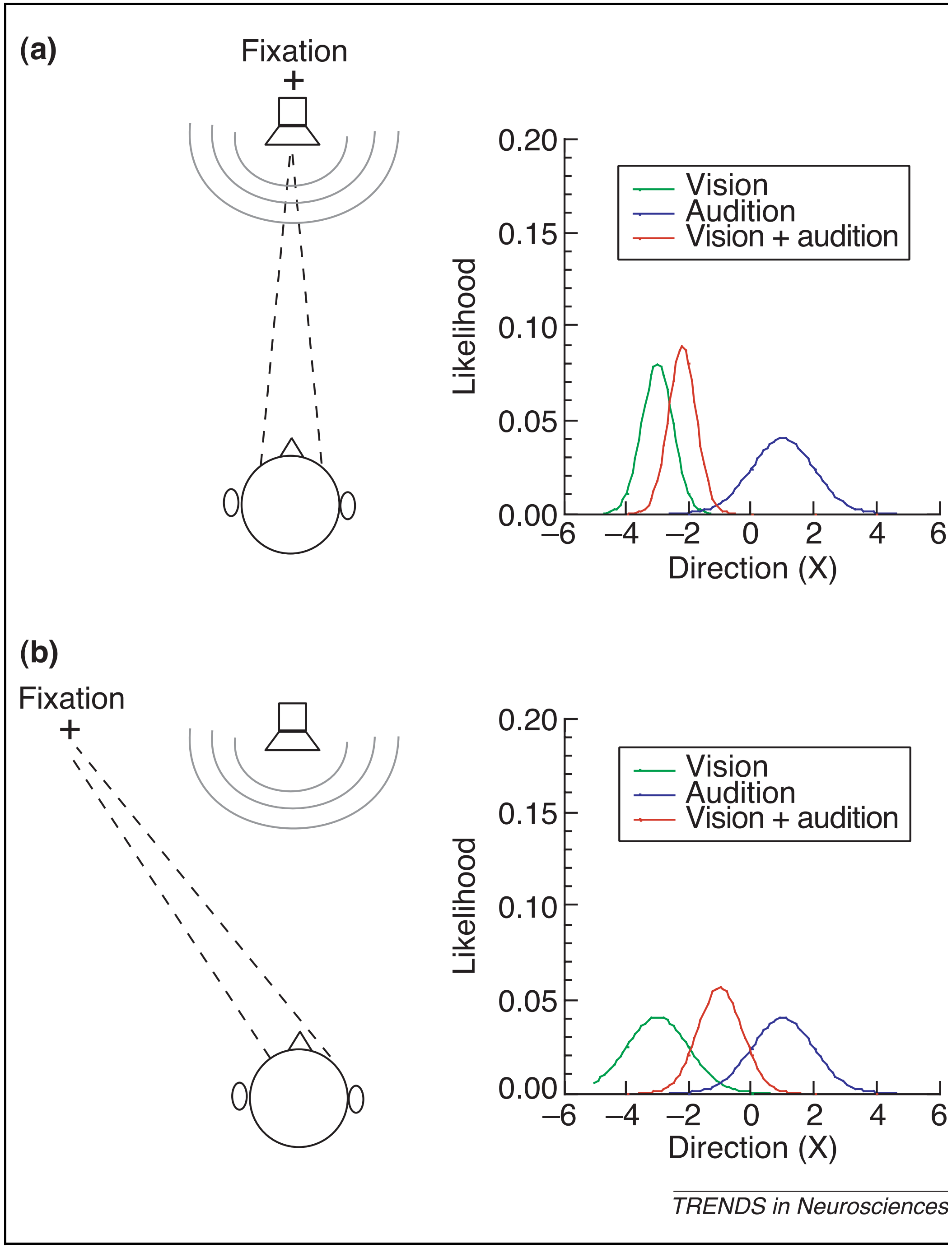
http://www.youtube.com/watch?v=rfNCoSE61w8

Cue Integration (1) : qualitative predictions

- e.g. integration between visual and auditive information

- <u>prediction 1</u> (position): if visual cue is more reliable, then final estimate is shifted towards visual cue.

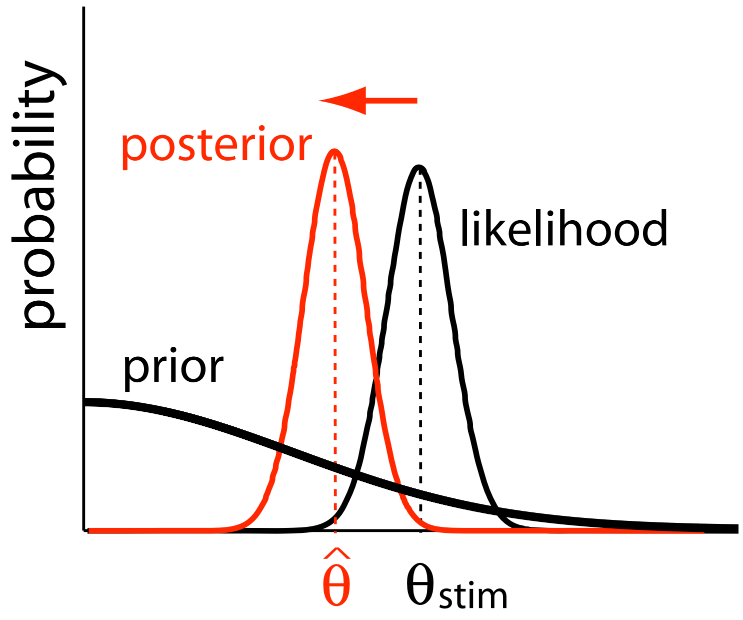
- <u>prediction 2</u> (variance or discrimination threshold): Final discrimination threshold lower than that for each modality ; varies if reliability of one modality varies.



2 - Do brains form a representation of the past statistics of the environment (priors) and combine it optimally with current information?

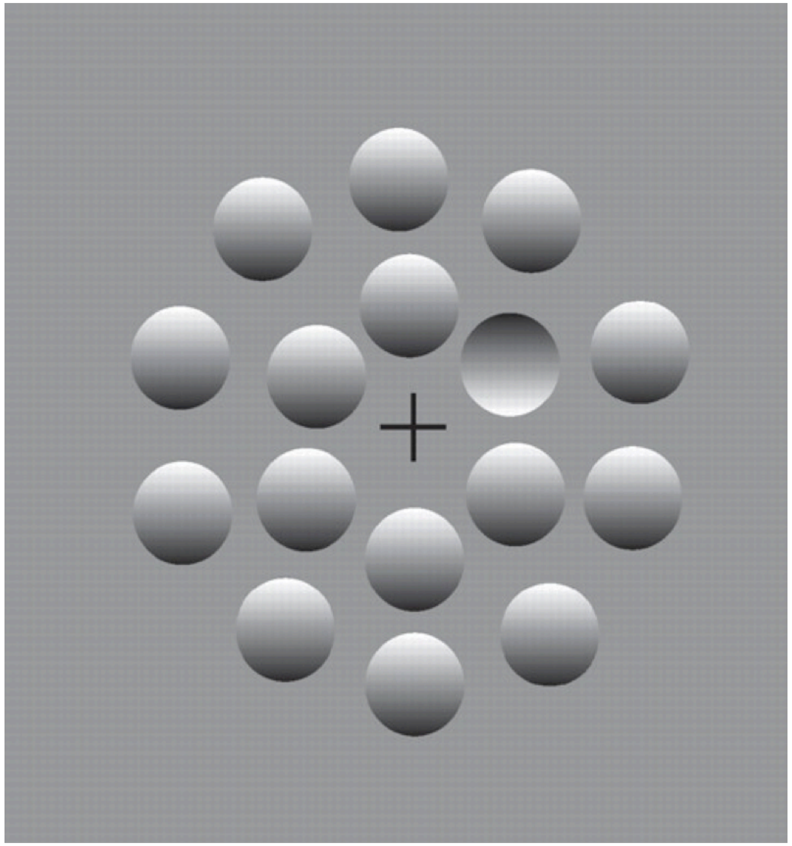
A Bayesian theory of the Brain: Priors

- How is the brain making use of previous knowledge? what priors?
- Prediction 1: the more uncertain the data, the more prior information should influence the interpretation.
- Prediction 2: The priors should reflect the statistics of the sensory world (on which time-scale?).



Long-term “structural” priors

Visual illusions : insight into what sort of assumptions the visual system makes.



- Light comes from above
- Cardinal orientations are more frequent [Gershick et al 2011]
- smoothness [Geisler et al 2001]
- symmetry [Knill 2007]
- Objects don’t move or only slowly

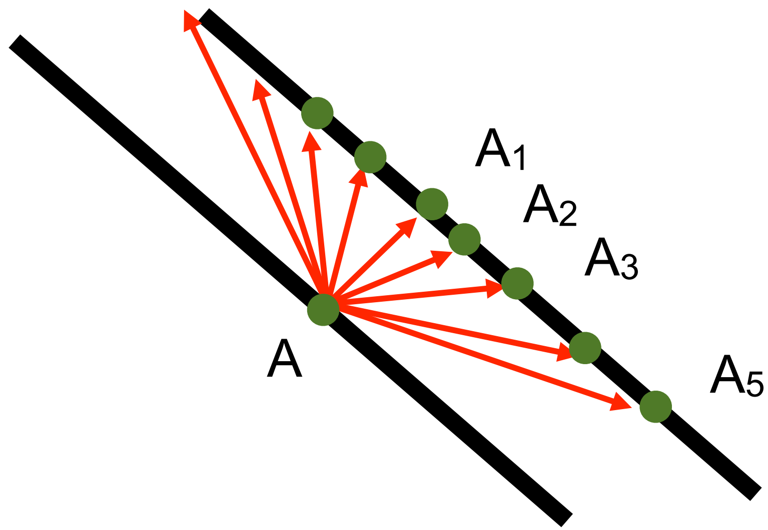
[Weiss et al 2001; stocker & Simoncelli 2006]

... recently formalized in Bayesian terms

[T. Adelson, E. Simoncelli, O. Schwartz, Y. Weiss]

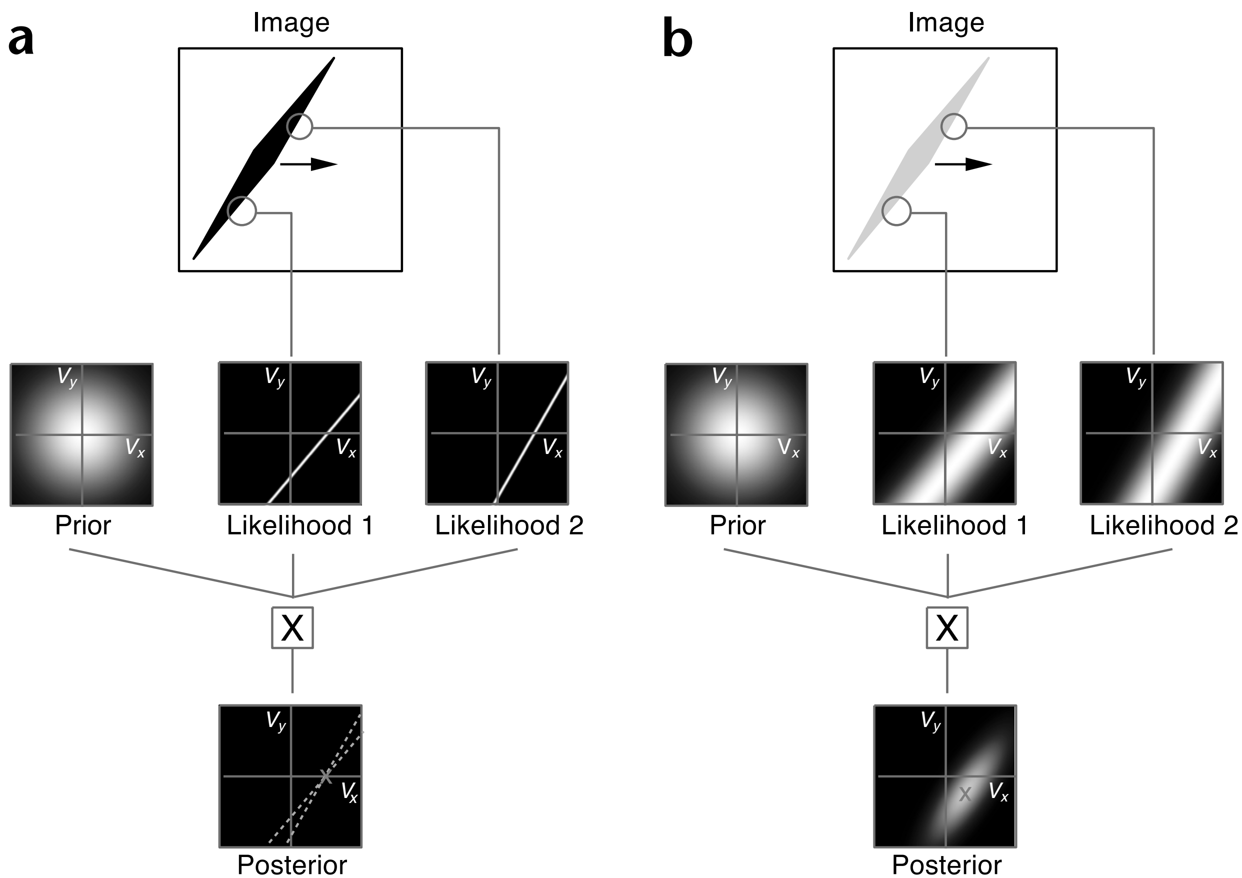
Interpreting motion : A Prior on Low Speeds (1)

- Motion shown in an aperture is fundamentally ambiguous; it can be interpreted in an infinite number of ways
- which one is chosen? why?



Interpreting motion : A Prior on Low Speeds (2)

- Hypothesis: humans tend to favour slower motions
- Use a (gaussian) prior on low speeds (centred at 0).
- Explain great variety of data -- elegant unifying explanation

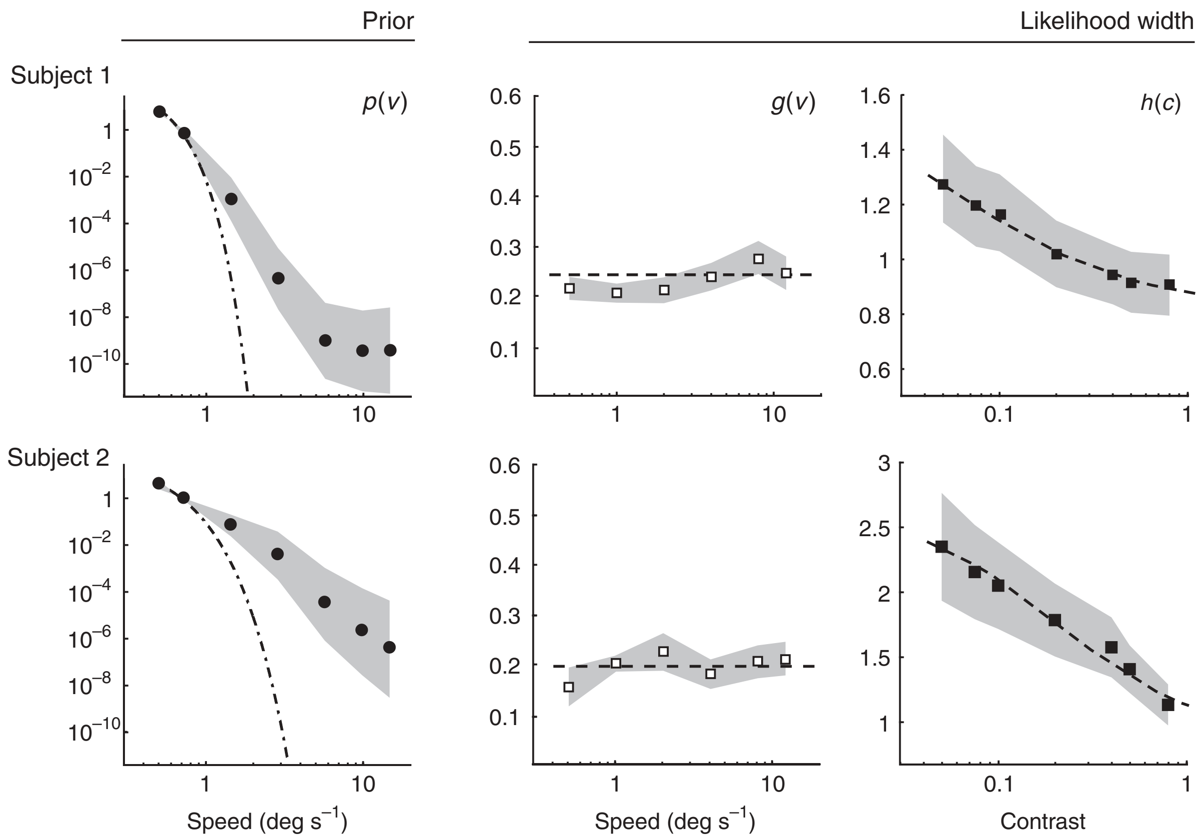


Weiss, Adelson & Simoncelli, *Nat Neuro*, 2002

http://www.cs.huji.ac.il/~yweiss/Rhombus/rhombus.html

Can we measure people's prior experimentally?

- Method: reverse engineer the shape of the prior from perceptual data
- 2AFC speed discrimination task at different contrast levels -- measure both bias and variability --> recover prior and likelihood

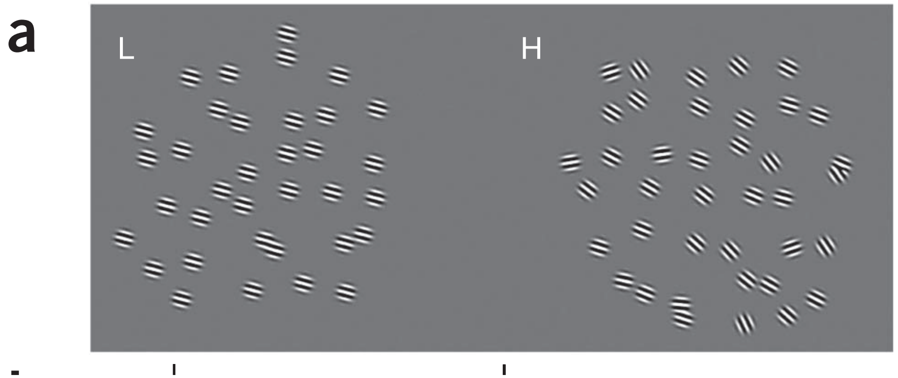


Stocker & Simoncelli, Nat Neuro, 2006

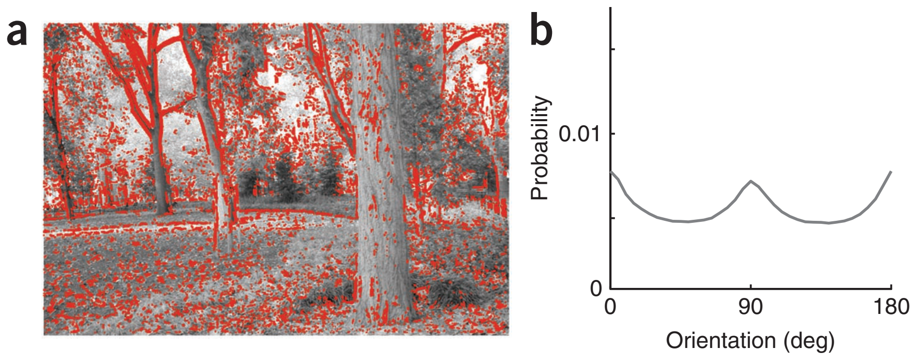
Do such priors correspond to the environment statistics? Cardinal Directions.

- Girshick and Simoncelli, Nat Neuro 2010.

- Orientation judgments are more accurate at cardinal (horizontal and vertical) orientations.
- Biased toward cardinal orientations.
- Prior towards cardinal orientation match orientation distribution measured in photographs.



is L stimulus CW or CCW compared to H?



Learning of priors:

Where do the priors come from?

Are we building up new priors constantly?

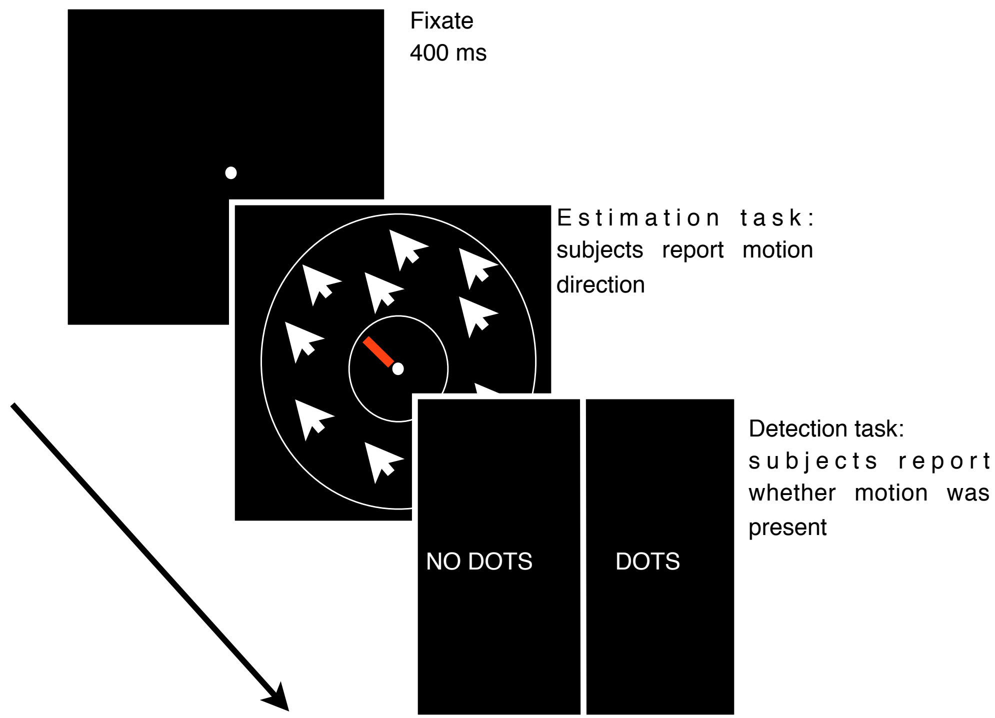
Are priors learned or innate? Do people form new priors for everything? how fast?

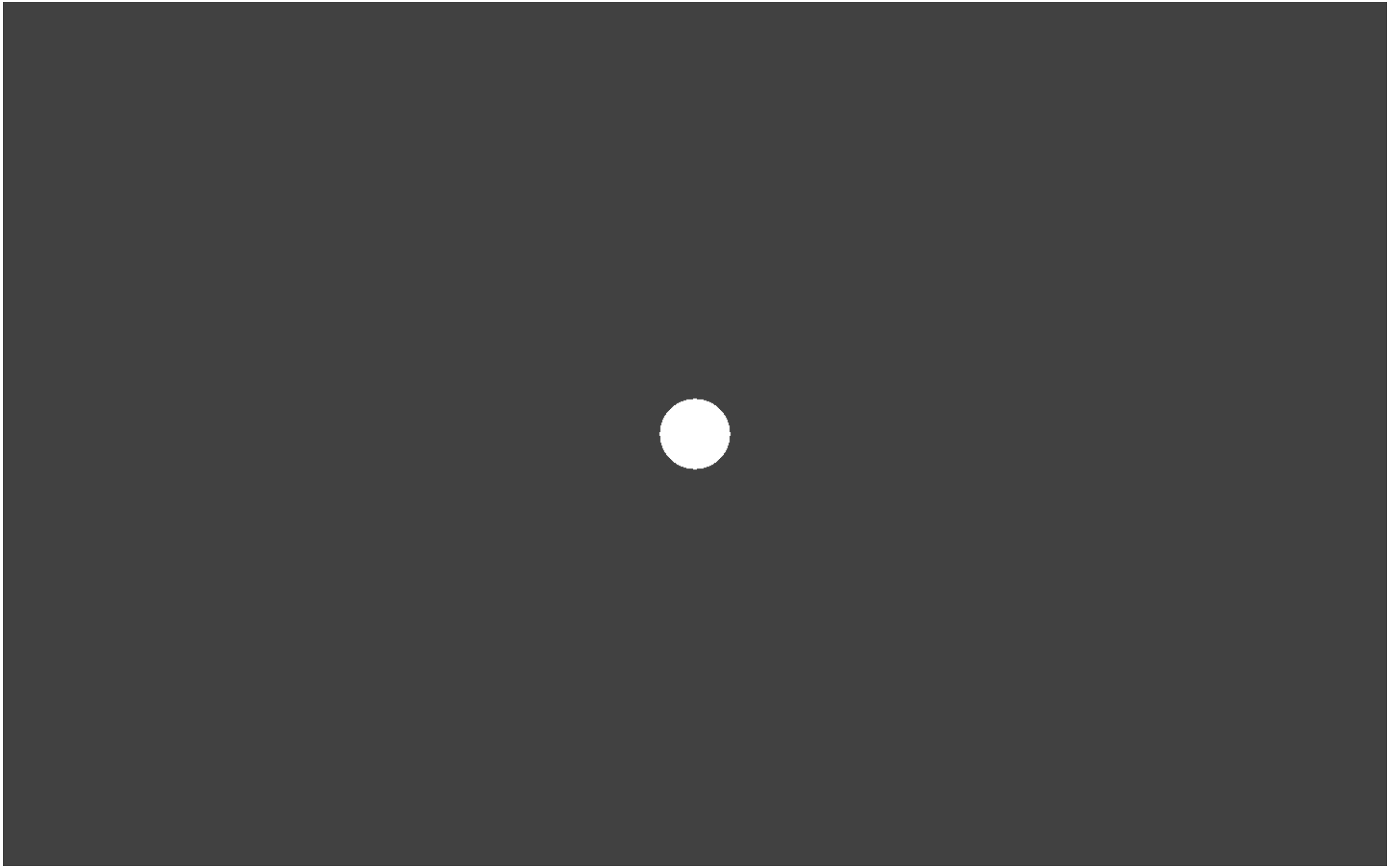
[Chalk, Seitz and Seriès, JOV 2010]

Do people form new priors for everything? How fast?

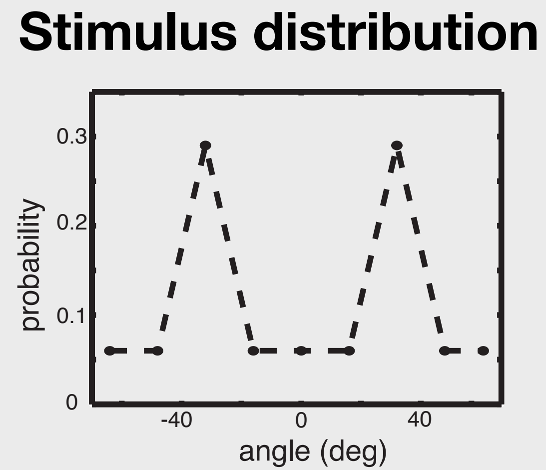
Behavioural Task

- On each trial, participants were presented with either a low contrast random dot motion stimulus (100% coherence) or a blank screen.
- Participants reported direction of motion (estimation), before reporting whether a stimulus was present (detection).





- Two motion directions were presented in a larger number of trials than other directions.



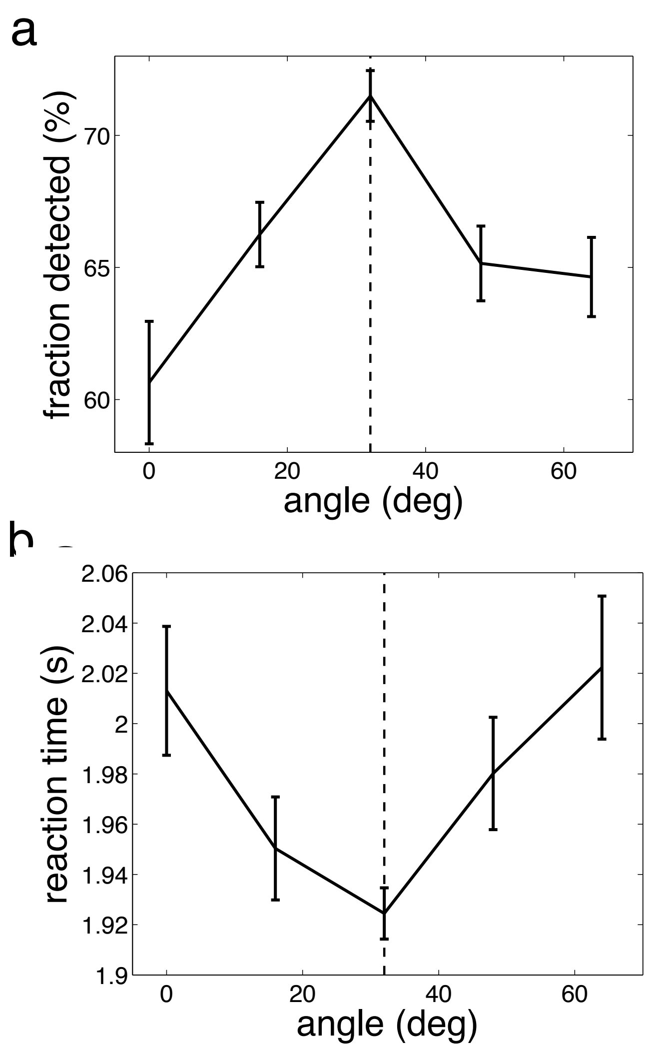
Questions

1. Are participants going to learn implicitly which directions are most likely to be presented?

2. How would these learned expectations bias their perception of subsequently presented motion stimuli?

Result 1/3: Detection is better and faster for the expected directions

- Detection performance was best for most frequently presented directions
- Reaction times were shorter
- Similar to the effects of selective attention (Posner et al. 1980) - suggesting that subjects were attending to expected directions.
- Knowledge about the statistics of the stimulus was however not conscious.

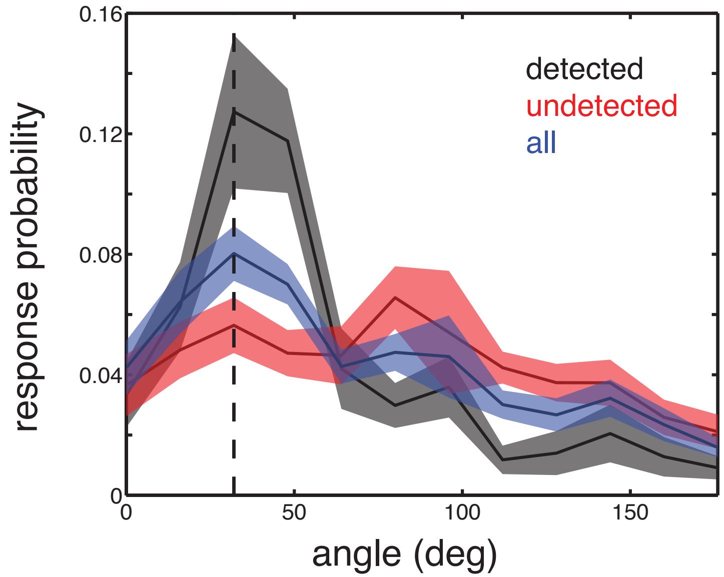


Result 2/3: Participants ‘hallucinate’ motion in expected directions

- On trials where no stimulus was presented, but where participants reported seeing a stimulus, they were strongly biased to report motion in the two most frequently presented directions.
- This effect was fast to develop, occurring in less than 200 trials / few minutes.

Distribution of estimates when no stimulus displayed

a



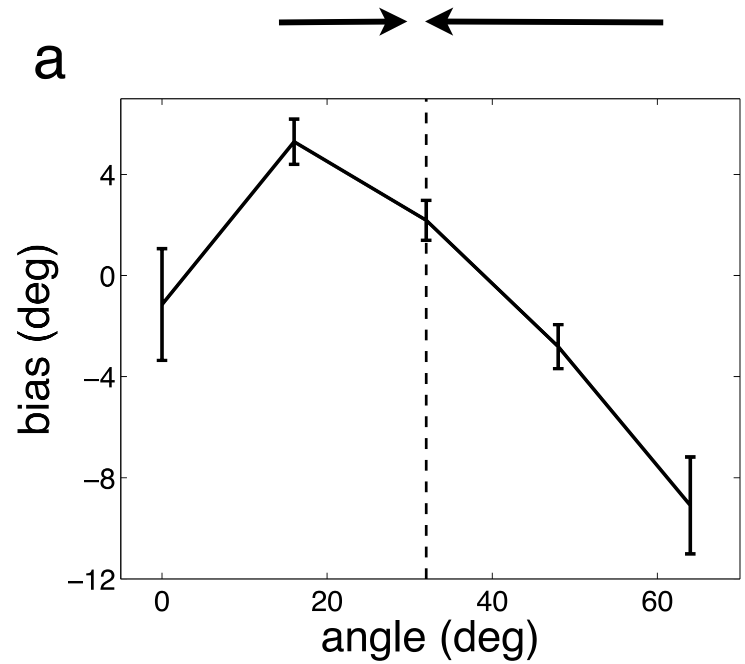
Result 3/3: Expectations bias perception of motion direction

[Chalk, Seitz, Seriès, JOV 2010]

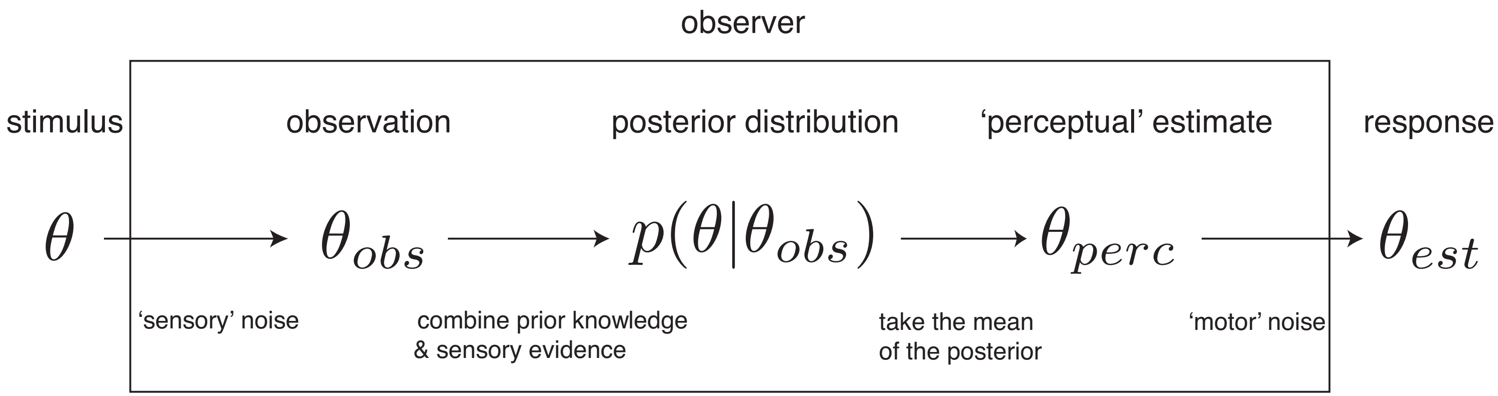
- Estimates of motion direction were biased towards most frequently presented directions:

  subjects perceive motion direction to be more similar to expected direction than it really is.

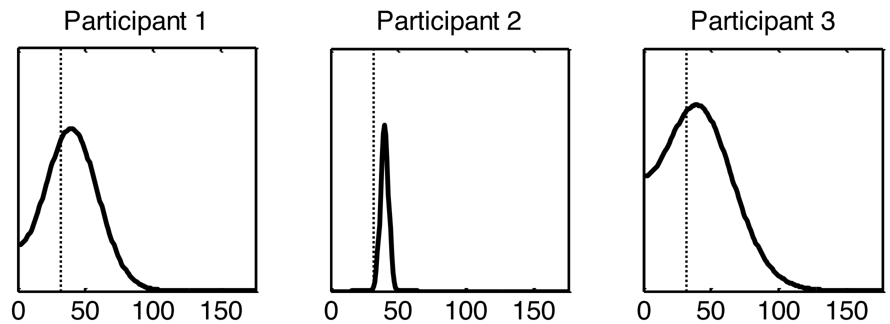
Estimation bias



Modelling the estimation biases

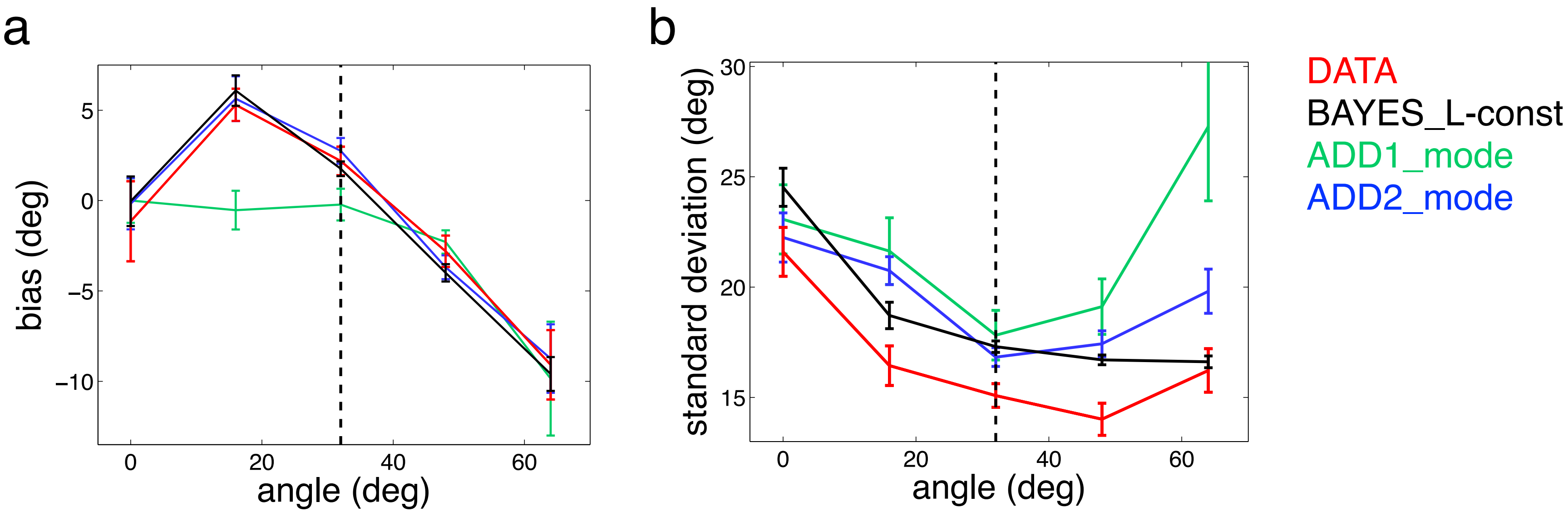


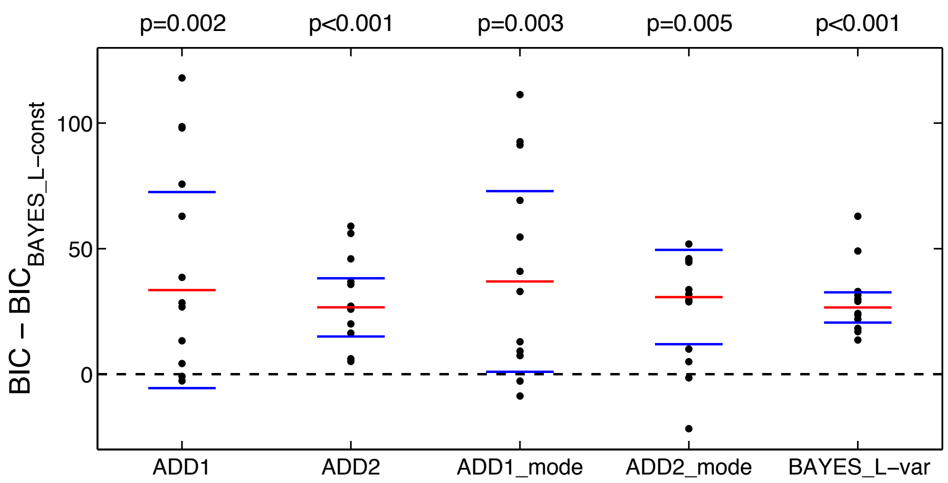
- Bayesian Modeling: subjects learn an expected distribution of the stimuli (prior) and combine it with sensory evidence
- Extract prior for each individual.



- Model Comparison: Bayesian model describes the data better than response strategy models. Individual priors look like approximation of stimulus

Model comparison



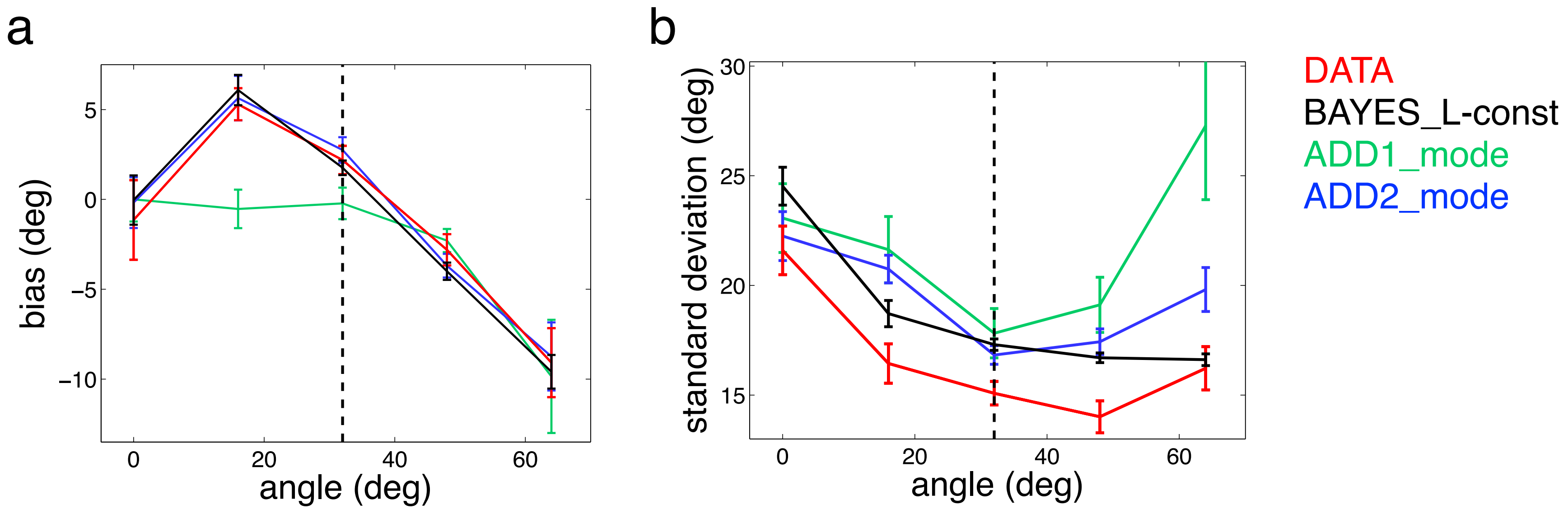


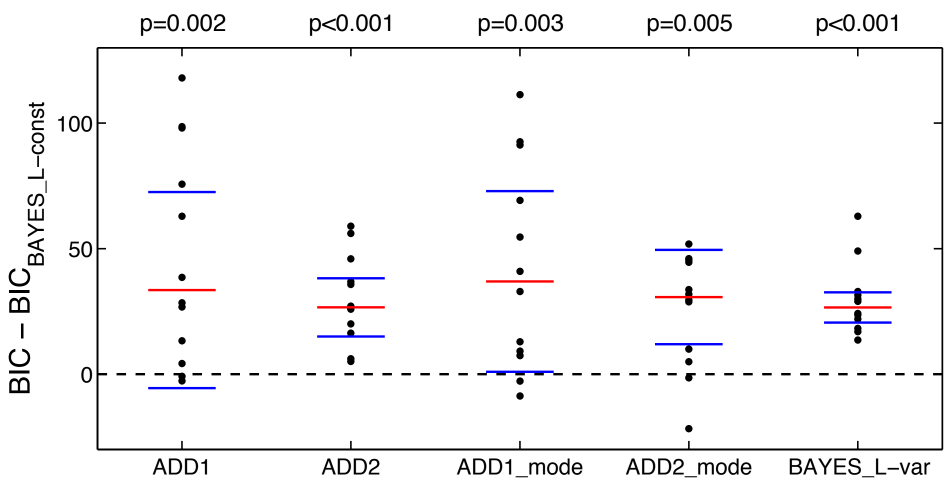
- Bayesian model describes the data better than response strategy models.

$$BIC = -2 \cdot \ln(L) + k \cdot \ln(n)$$

[Chalk, Seitz and Seriès, JOV 2010]

Model comparison





$$BIC = -2 \cdot \ln(L) + k \cdot \ln(n)$$

- Bayesian model describes the data better than response strategy models.

[Chalk, Seitz and Seriès, JOV 2010]

Conclusions

- Participants rapidly learn multimodal stimulus expectations (< 200 trials).
- These expectations bias their perception of simple motion stimuli, causing them to 'hallucinate' motion in the expected direction, and perceive motion stimuli as closer to the expected directions than they actually are.
- The biases we observed can be explained assuming that participants combine a 'learned prior' about the stimulus statistics with their sensory evidence in a probabilistically optimal way.
- A number of open questions (specificity of prior, time scale, neural implementation - substrate of expectation)
- in particular: can one learn any prior like this ? or are some priors fixed?

Are priors constantly updating? Even those supposedly corresponding to natural scene statistics?

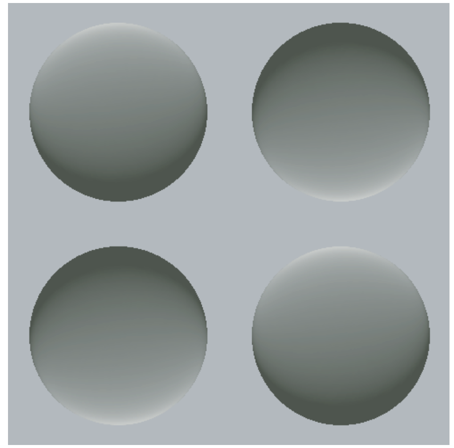
Experience can change the ‘light-from-above’ prior

Wendy J Adams[1], Erich W Graf[1] & Marc O Ernst[2]

To interpret complex and ambiguous input, the human visual system uses prior knowledge or assumptions about the world. We show that the ‘light-from-above’ prior, used to extract information about shape from shading is modified in response to active experience with the scene. The resultant adaptation is not specific to the learned scene but generalizes to a different task, demonstrating that priors are constantly adapted by interactive experience with the environment.

The circular patches in **Figure 1a** have competing interpretations. However, patches that are brighter at the top are generally seen as convex and the others as concave, consistent with an assumption of light from above[1,2]. The Bayesian approach has successfully described performance in many perceptual tasks where stimulus information is combined with prior assumptions[3–5]. However, whether visual priors are hard-wired or learned in response to environmental statistics is not known[6]. We investigate the adaptability of the ‘light-from-above’ prior by adding shape information via haptic (active touch) feedback.

a



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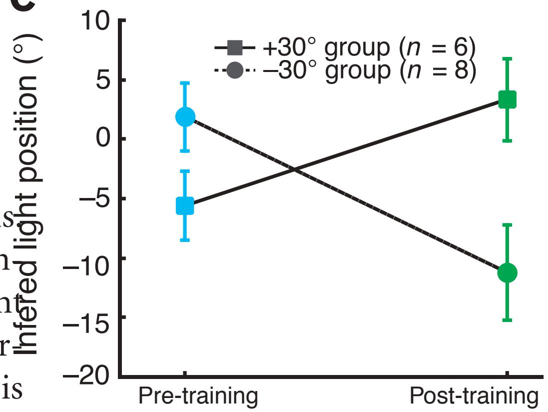
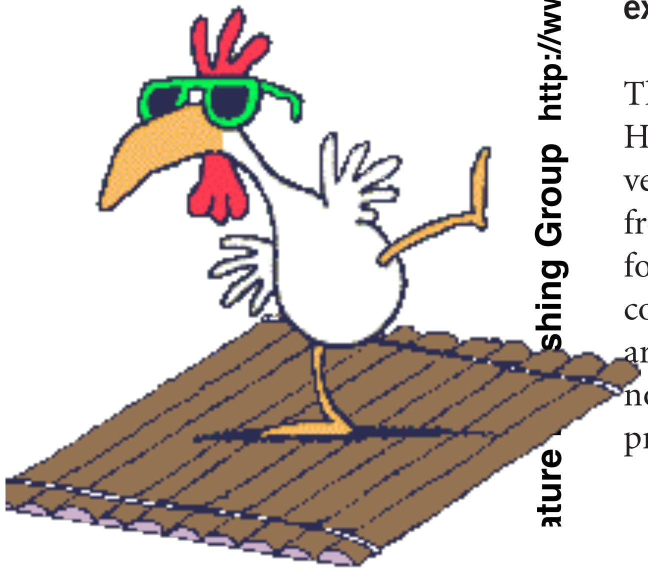
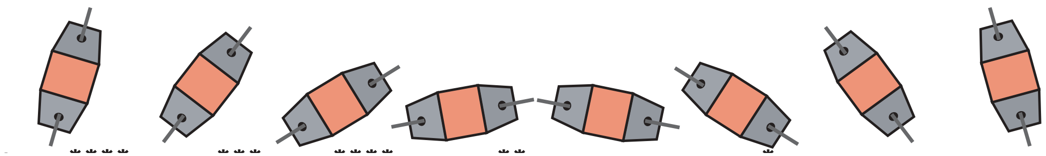




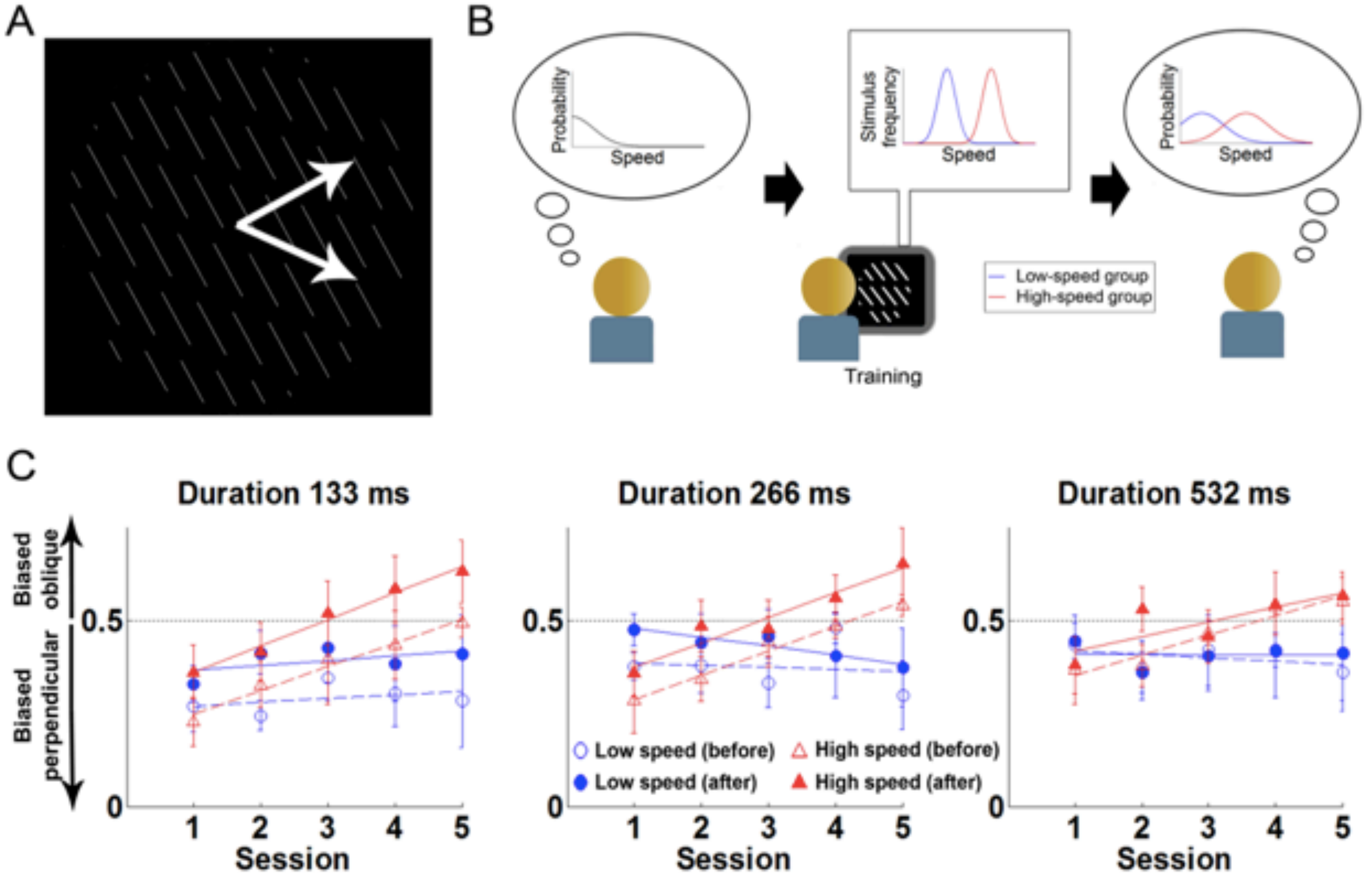


but not in chickens

[Adams, Graf and Ernst Nature Neuroscience 2004]

[Sotiropoulos, Seitz and Seriès (2011), Current Biology]

Changing expectations about speed alters perceived motion direction.

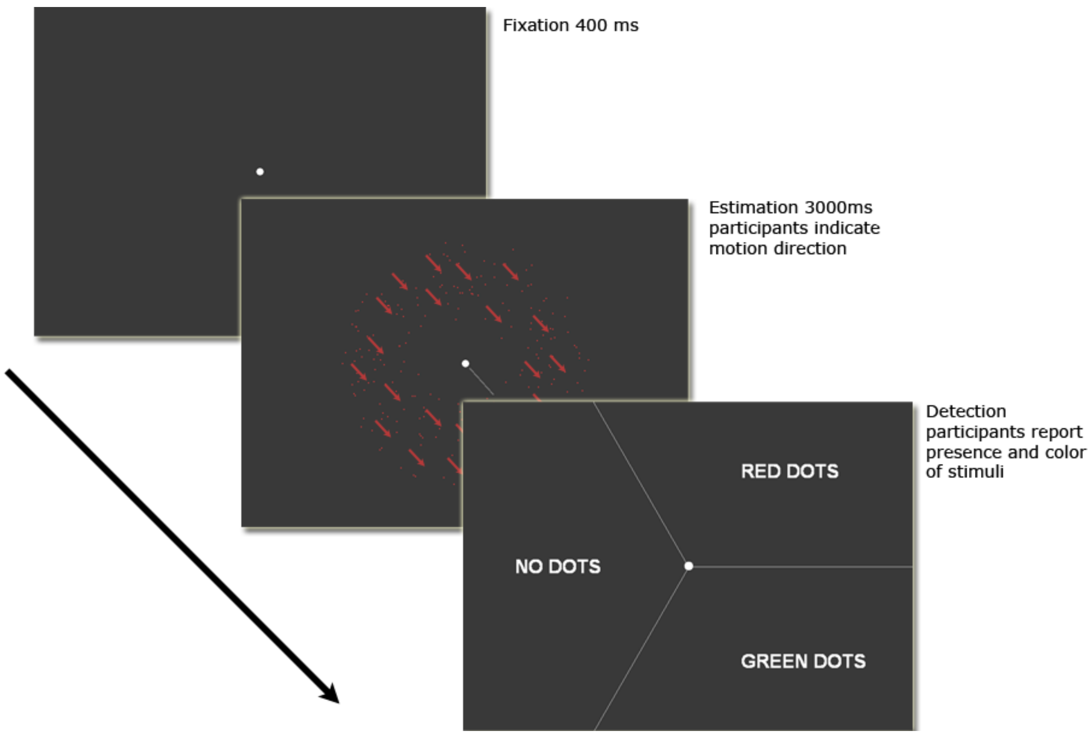


Extensions :**<u>What are the limits of prior learning?</u>**

How many priors can one learn simultaneously?

Are priors specific to learned conditions ?

Time scales of learning?



[Gekas, Seitz and Seriès, JOV 2013]

Behavioural studies: So what have we learned?

- Bayesian model offer elegant/ parsimonious description of behaviour (descriptive tool)

- Transparent assumptions and emphasis on “why” question.

- Behaviour consistent with Bayesian hypothesis in that:
  - Brains take into account uncertainty, and combine sources of information combines information optimally (cue combination)
  - Use priors that are constantly updated
  - Those priors are consistent with (some approximation) of statistics of environment at different time scales. --> increase accuracy.

- Deviations from optimality are possibly informative about underlying biological constraints, or nature of approximations.
- Those priors (but also cost functions, likelihood) can be measured in individuals -- Bayesian modelling as a tool to describe the internal model used by individuals, possibly differentiating groups.

A possible tool for understanding Mental Illness?

Why is the Bayesian approach applicable to the study of disease ? Computational Psychiatry

- Bayesian modelling offers a way to "reverse engineer" the brain.
- Mental illness could be due to differences in the models of the world that people's brains are working with:
  - e.g. different priors
  (e.g. pessimistic priors in depression, or priors on controllability, priors on mistrust in borderline).
  - or deficits / imbalance in incorporating priors with evidence (e.g. schizophrenia, autism)

- > a new area of research.

Mental Illness?

Mental illness is the result of an impairment in prediction, due to having a distorted internal model of the world, possibly due to an impairment in learning.

Schizophrenia affects the way you think

- about 1/100 people.
- usually starts during early adulthood.
- **Positive symptoms** experiencing things that are not real (hallucinations) and having unusual beliefs (delusions)
- **Negative symptoms** include lack of motivation and becoming withdrawn.

https://www.youtube.com/watch?v=SN1GCoVzxGg

Impaired integration of Priors in Schizophrenia

Nature Reviews Neuroscience | AOP, published online 3 December 2008;

Perceiving is believing: a Bayesian approach to explaining the positive symptoms of schizophrenia

Paul C. Fletcher and Chris D. Frith‡§*

Abstract | Advances in cognitive neuroscience offer us new ways to understand the symptoms of mental illness by uniting basic neurochemical and neurophysiological observations with the conscious experiences that characterize these symptoms. Cognitive theories about the positive symptoms of schizophrenia — hallucinations and delusions —

frontiers in PSYCHIATRY

REVIEW ARTICLE
published: 30 May 2013
doi: 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

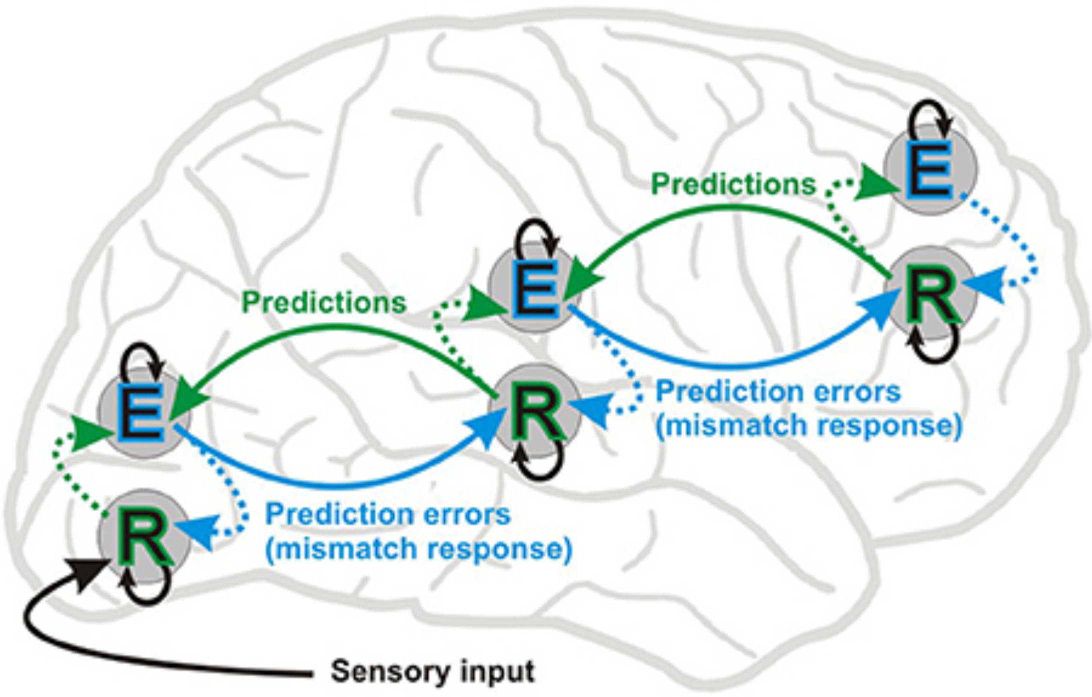
Impaired Predictions in Schizophrenia

- Sensory priors are too broad/ weak and fail to attenuate sensory inputs.

▶ a changing and unstable world, aberrant salience.

- To compensate, more cognitive priors might become too strong

▶ psychosis (hallucinations, delusions)



Autism Spectrum Disorder (ASD)

- Autism is a neurodevelopmental disorder characterized by impaired social interaction, verbal and non-verbal communication, and restricted and repetitive behavior.

- a spectrum

- 1.1% of the population in the UK - increasing

- Theories of ASD have either focused on the social symptoms of ASD [e.g., as a deficit of theory of mind, reduced social salience, or a lack of social motivation]
- or on peculiarities of autistic perception [e.g., “weak central coherence”] - focus on detail.

When a person with Autism walks into a room

The first thing they see is:

A pillow with a coffee stain shaped like Africa
A train ticket sticking out of a magazine,
25 floorboards, a remote control,
a paperclip on the mantelpiece,
a marble under the chair,
a crack in the ceiling,
12 grapes in a bowl,
a piece of gum,
a book of stamps
sticking out
from behind a
silver picture
Frame.

so It's not surprising they ignore you completely.

The National Autistic Society

Impaired integration of Priors in Autism

TICS-1125; No. of Pages 7 ARTICLE IN PRESS

Opinion

Cell PRESS

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

Elizabeth Pellicano[1,3] and David Burr[2,3]

[1] Centre for Research in Autism and Education (CRAE), Institute of Education

[2] Department of Psychology, University of Florence, Florence, Italy

[3] School of Psychology, University of Western Australia, Perth, Australia

Autism could also correspond to weak sensory priors / a failure to be able to predict sensory inputs from past inputs and context

frontiers in HUMAN NEUROSCIENCE

doi: 10.3389/fnhum.2014.00302

An aberrant precision account of autism

Rebecca P. Lawson[1]*, *Geraint Rees*[1,2] *and Karl J. Friston*[1]

[1] *Wellcome Trust Centre for Neuroimaging, University College London, London, UK*

[2] *Institute of Cognitive Neuroscience, University College London, London, UK*

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Reviewed by:
Lucina Q. Uddin, University of Miami, USA
Jeroen J. A. Van Boxtel, Monash University, Australia

Autism is a neurodevelopmental disorder characterized by problems with social-communication, restricted interests and repetitive behavior. A recent and thought-provoking article presented a normative explanation for the perceptual symptoms of autism in terms of a failure of Bayesian inference (Pellicano and Burr, 2012). In response, we suggested that when Bayesian inference is grounded in its neural instantiation—namely, predictive coding—many features of autistic perception can be attributed to aberrant precision (or beliefs about precision) within the context of hierarchical message passing

Impaired Predictions in Autism

- Sensory priors are too broad / flat / weak and fail to attenuate sensory inputs.

▶ deficits in contextual integration, percepts dominated by sensory inputs: hypersensitivity

[Pellicano & Burr 2012; Skewes et al 2014, Powell et al 2016]

- Stronger impact of the likelihood - “enhanced sensory precision model”.

[Brock et al 2012; Van De Cruys et al 2014].

- Priors more rigid / inflexible

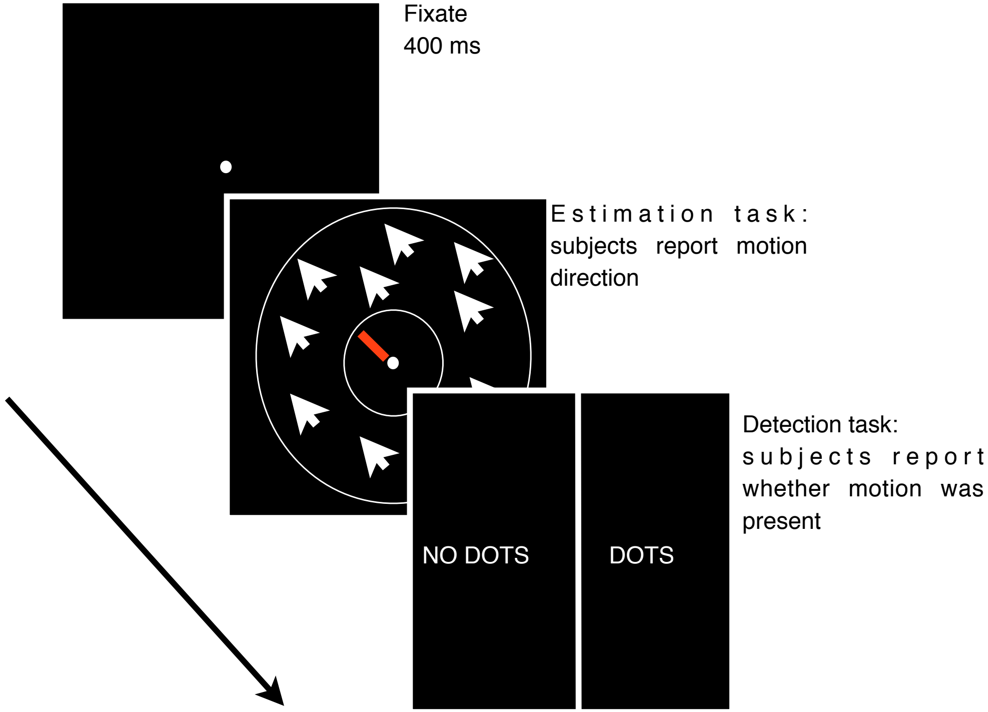
[Van De Cruys et al 2014]

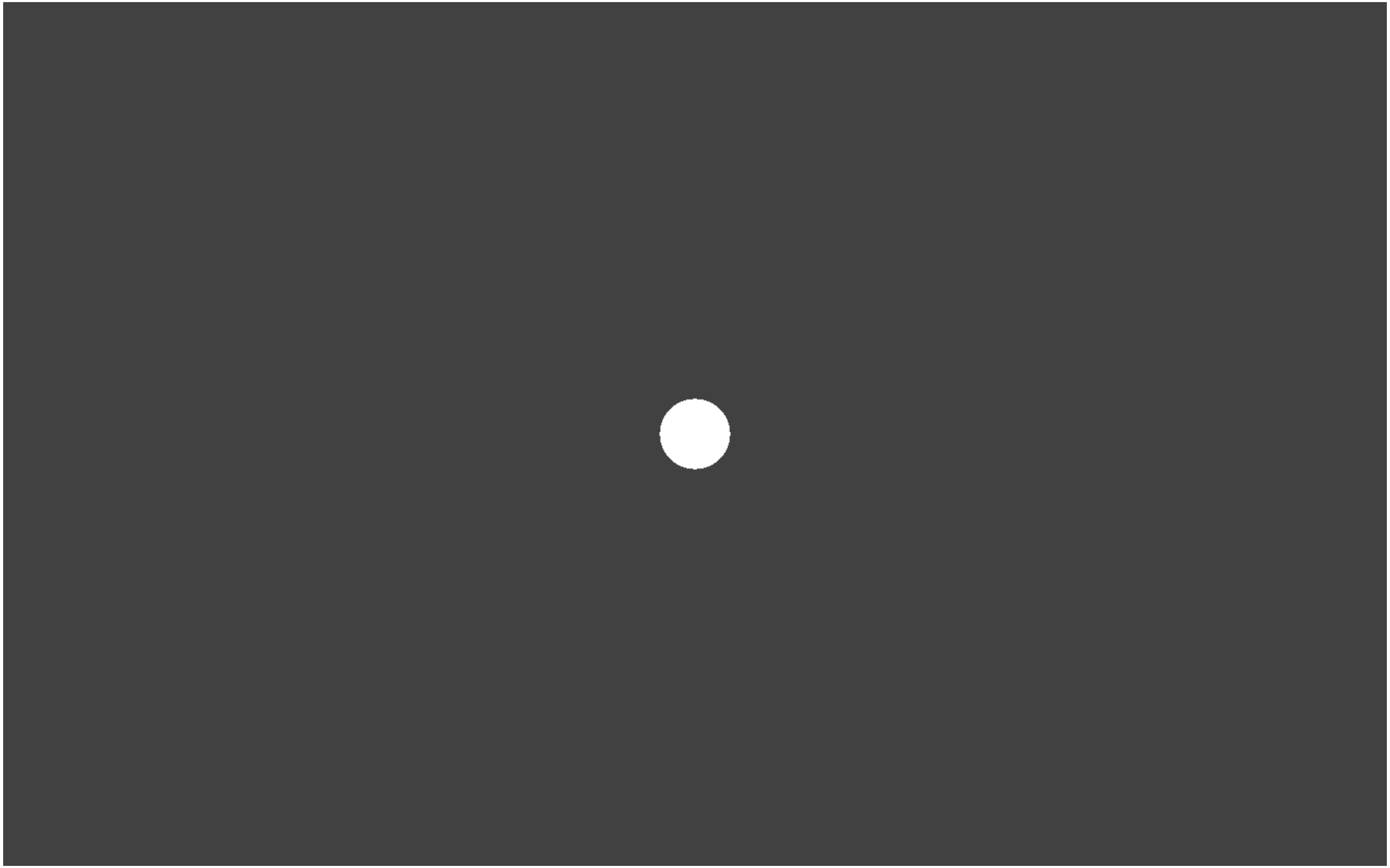
Quantitatively Testable ?

Learning priors about motion directions (in healthy participants)

[Chalk, Seitz, Seriès, JOV 2010]

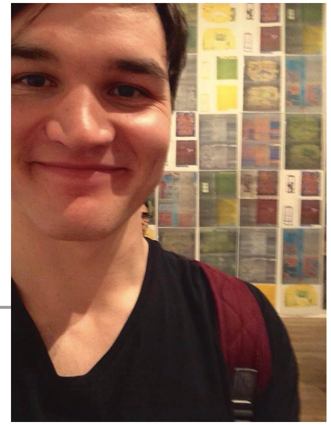
- On each trial, participants were presented with either a low contrast random dot motion stimulus (100% coherence) or a blank screen.
- Participants reported direction of motion (estimation), before reporting whether a stimulus was present (detection).



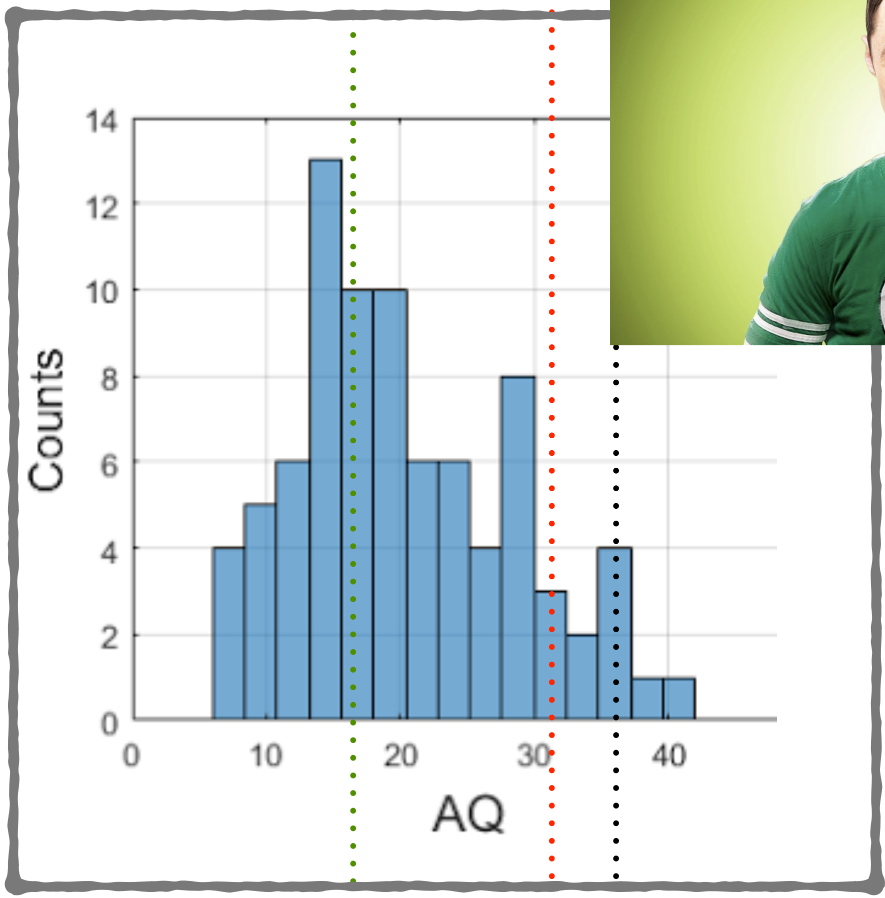


Bayesian inference in **Autism**

with Gizem Aras and Frank Karvelis



- 83 Healthy Participants scored for schizotypy (RISC & SPQ) and autistic traits (AQ)



	AQ Test
1	I prefer to do things with others rather than on my own.
2	I prefer to do things the same way over and over again.
3	If I try to imagine something, I find it very easy to create a picture in my mind.
4	I frequently get so strongly absorbed in one thing that I lose sight of other things.
5	I often notice small sounds when others do not.
6	I usually notice car number plates or similar strings of information.
7	Other people frequently tell me that what I've said is impolite, even though I think it is polite.
8	When I'm reading a story, I can easily imagine what the characters might look like.
9	I am fascinated by dates.
10	In a social group, I can easily keep track of several different people's conversations.
49	I am not very good at remembering people's date of birth.
50	I find it very easy to play games with children that involve pretending.

Is Statistical Learning impaired in Schizotypy?

With Frank Karvelis

5 I have never seen anything that looked like a ghost

6 Sometimes my thoughts seem so loud I can almost hear them

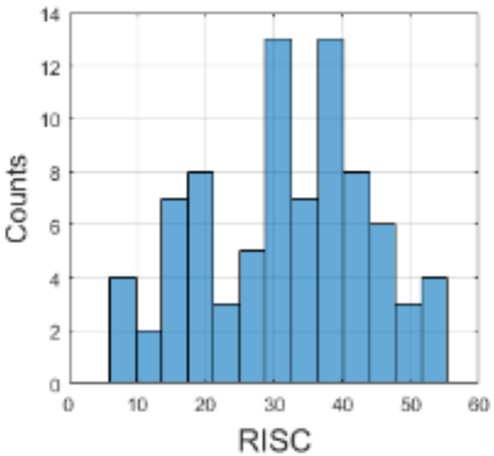
7 I am almost always consistent in what I say and believe

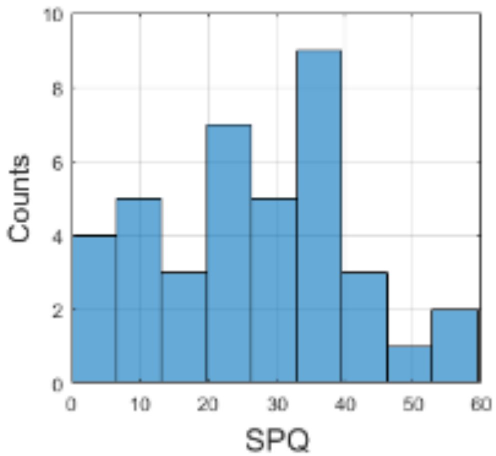
8 Most people are too stupid to realize which things in life are important

9 In pitch dark I never see any visual images

10 I have never ‘come out in a cold sweat’ upon realizing what I have told someone about myself

11 There are some people whom I trust completely

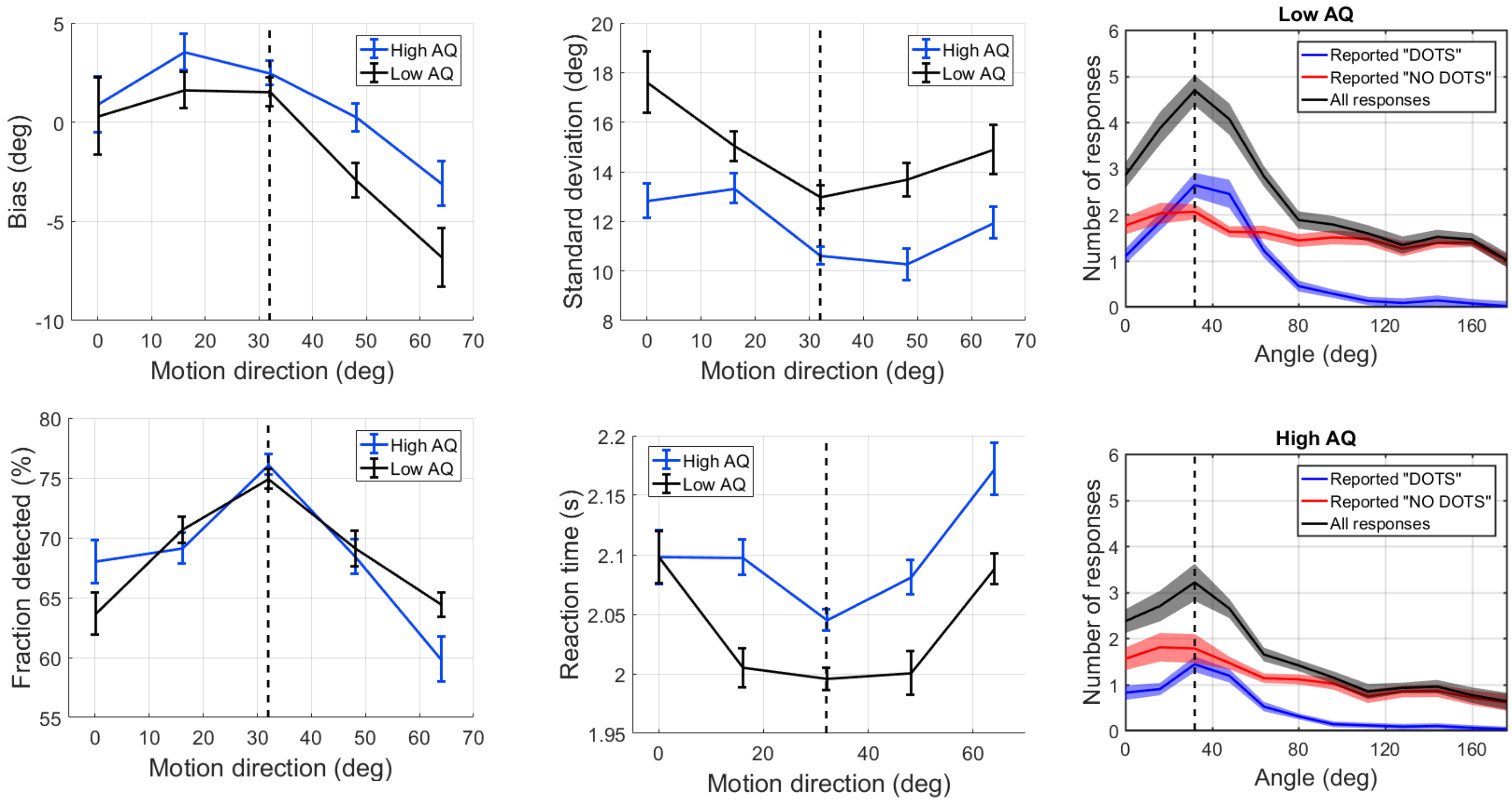




RISC and SPQ scores

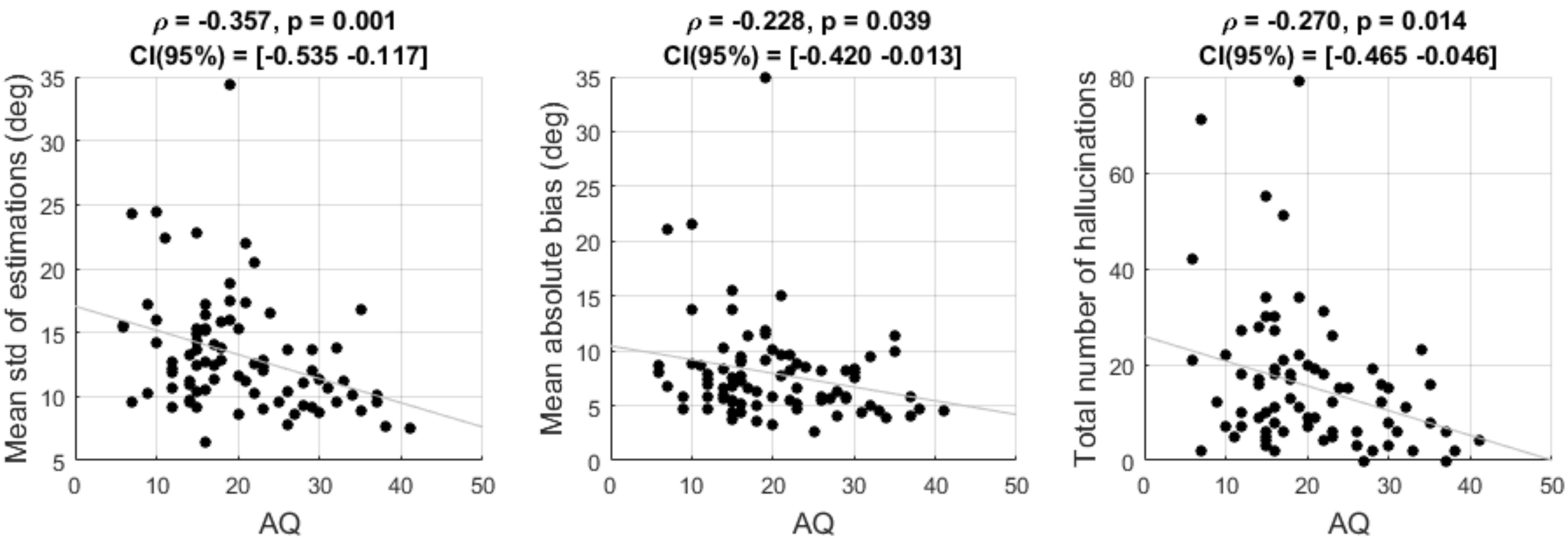
AQ Data: Clear evidence of Statistical Learning .. … with some differences

- High AQ participants are more precise in their estimations, show less bias, and have less hallucinations



Participants with high AQ have more veridical perception

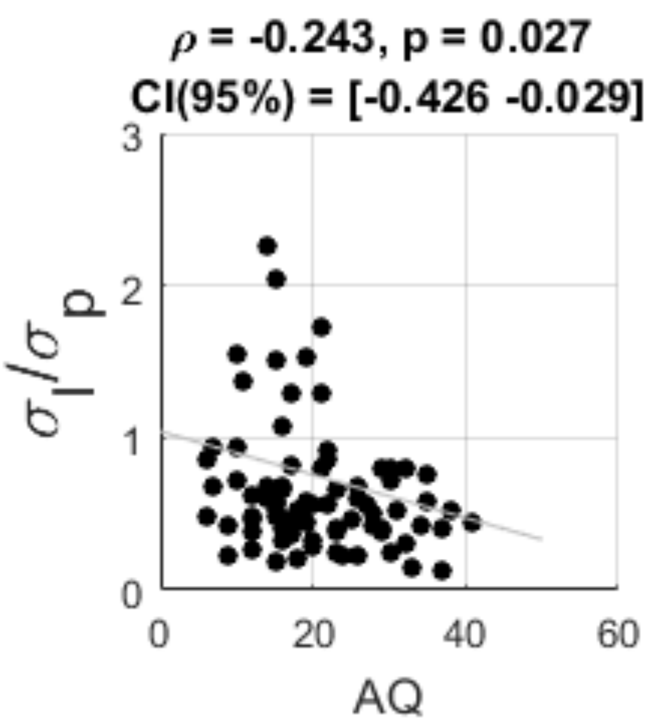
- High AQ participants are more precise in their estimations, show less bias, and have less hallucinations
  ▶ compatible with the idea of them relying less on expectations

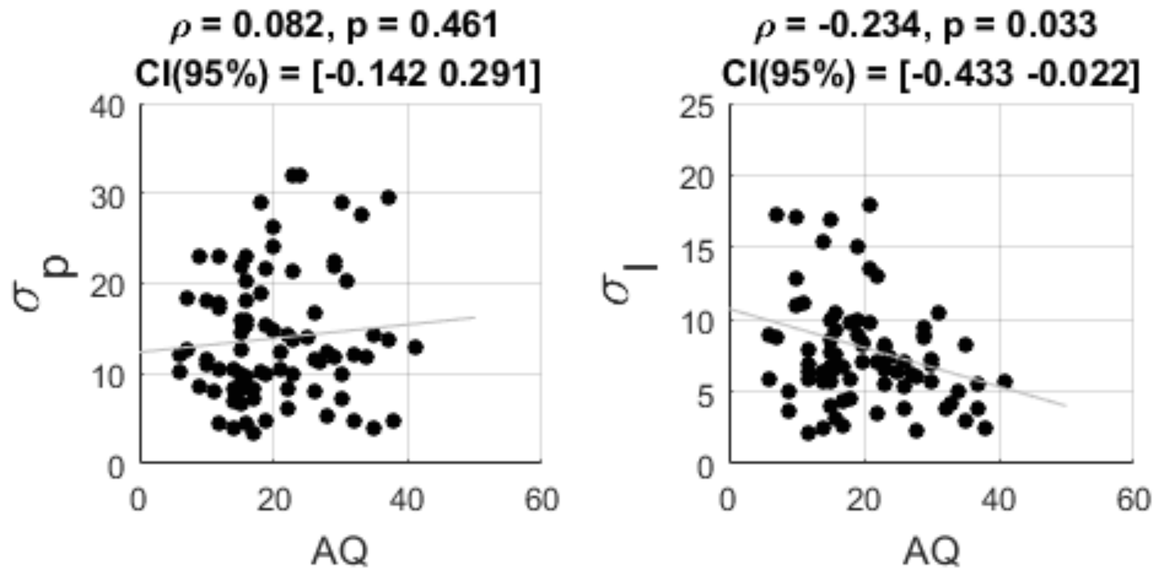


Participants with high AQ rely more on the likelihood and less on the prior

- Consistent with (the debated) previous theories / perceptual differences in autism.

- Modelling can be used to <u>quantitatively</u> measure the relative and absolute impact of the likelihood and the prior on perception





Prior integration in **Autism**

Our study :

- Large numbers of participants
- broad spans of AQ scores
- Learning of a new prior (statistical learning) and use in subsequent perception
- explicit recovery of individual priors and likelihood using Bayesian modelling.

Participants with high AQ have more veridical perception, less influenced by the stimulus statistics (prior).

Results surprisingly support the (controversial) “enhanced sensory precision model” (sharper likelihood).

General Conclusions

- Statistical learning tasks coupled with Bayesian modelling offer tools to test current theories in Psychiatry:
  - assess if machinery of inference is intact
  - quantify differences in internal models, e.g. prior beliefs.

- Classification of diseases; Offer potential “dimensions” to characterise illness across boundaries
- Impact for clinical work?