The Misestimation of Uncertainty in the Affective Disorders

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Zurich 2019

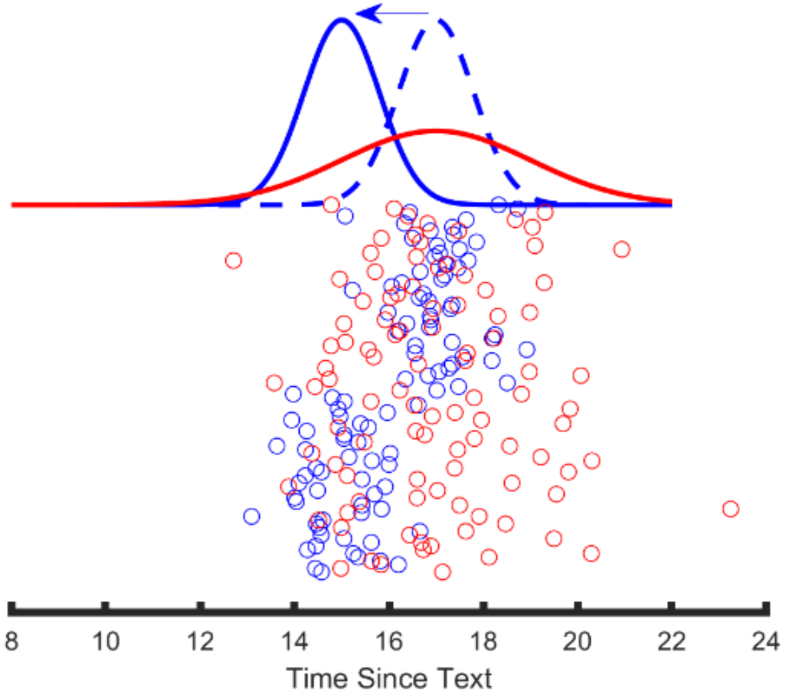
Talk Outline

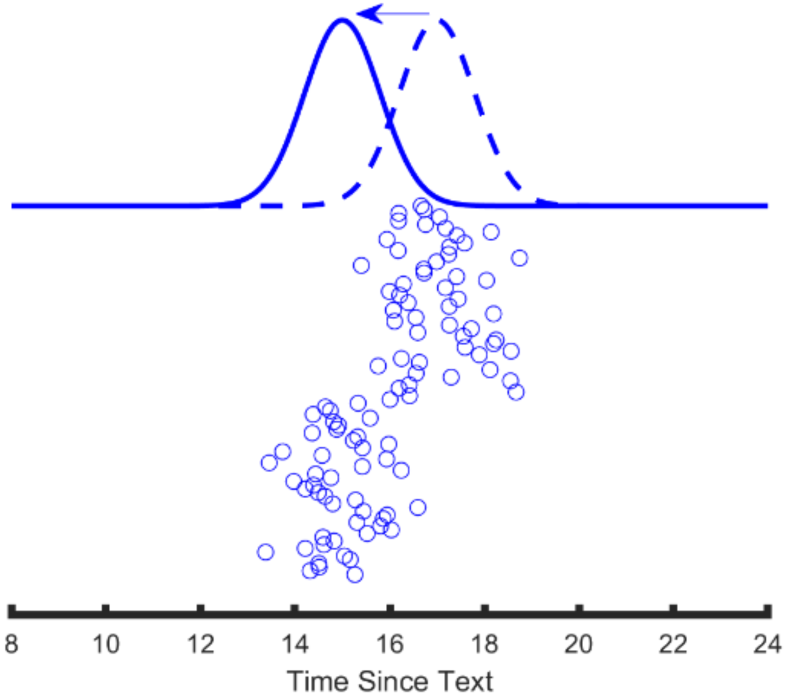
- Background
    - Types of uncertainty and normative responses when levels of uncertainty change

- Uncertainty estimation in anxiety
- Uncertainty estimation and affective bias

- Uncertainty and emotional experience in Bipolar Disorder and Borderline Personality Disorder

Uncertainty and Information





Events are more informative:

- If their **Volatility** (unexpected uncertainty) is **High**
  - Because you can't trust old information
- If their **Noise** (expected uncertainty) is **Low**
  - Because the new information is more reliable

Yu and Dayan 2005
Pulcu and Browning 2019

Simple RL Approach to Uncertainty: Volatility as an example

The learning rate of the Rescorla Wagner rule acts as the weight between old and new information

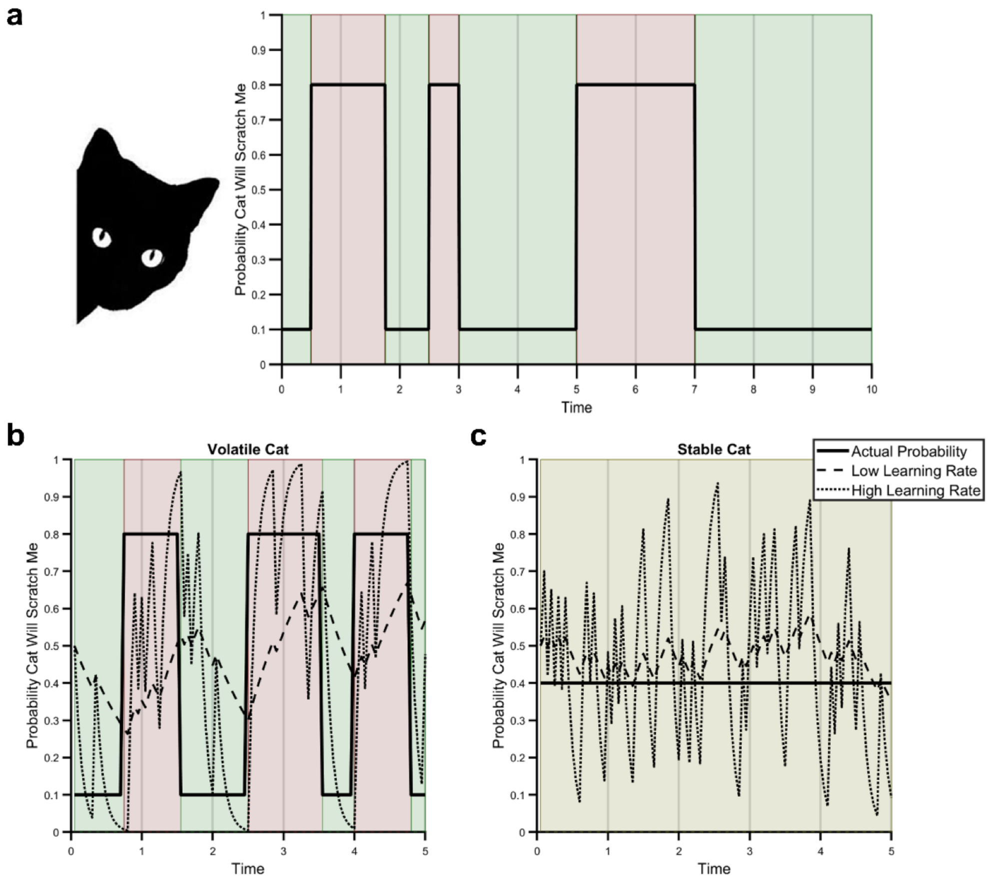
$$r_{(t+1)} = r_{(t)} + \alpha(o_{(t)} - r_{(t)})$$

$$r_{(t+1)} = (1 - \alpha)r_{(t)} + \alpha(o_{(t)})$$

The higher the information content of new vs. old events, the higher your learning rate should be.

When **volatility** is high (B) the information content of new events is relatively higher and a high LR should be used.

When **volatility** is low (C) the information content of new events is relatively lower and a low LR should be used.



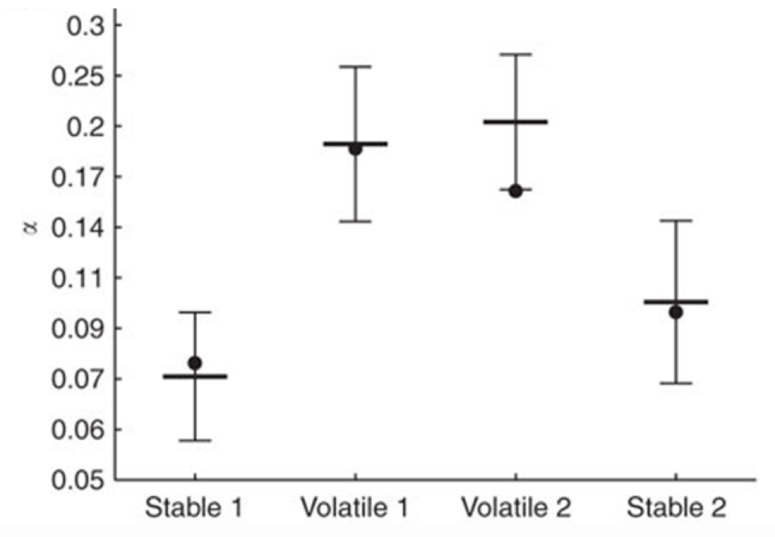
Summary of the general idea

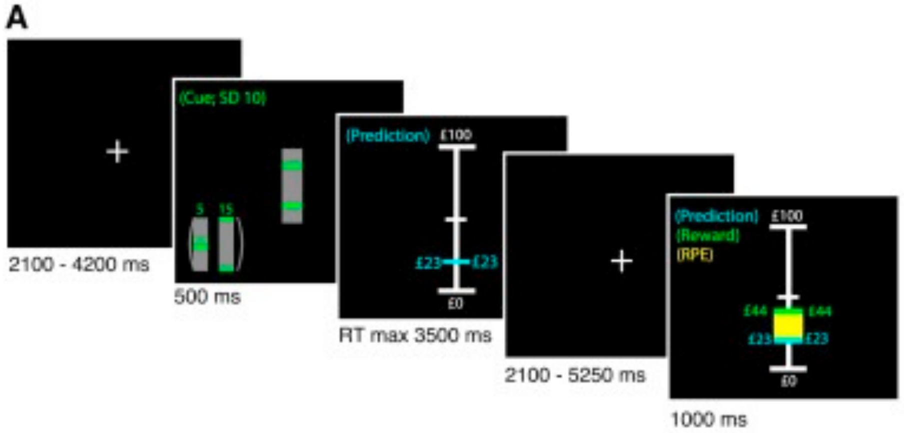
- Generally, when we learn, we are learning about complex, dynamic systems that we can’t directly observe
- This means there are always things we don’t know about and we will often be surprised by what happens
- It is useful to estimate the cause of our uncertainty as this can shape how we learn: **Generally we should use a higher learning rate if we judge upcoming events to be more informative than previous events.**
- For example, if we think surprising events are caused by changes in the thing we are learning we should use a higher learning rate, whereas if we think surprising events are caused by chance we should use a lower learning rate

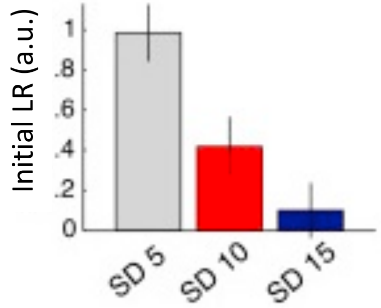
Do People Adjust their LR as Expected?

- **People use a higher learning rate when learning about volatile than stable processes**

- Some (less convincing) evidence for reduced LR when noise is high







Behrens et al. 2007
Yu and Dayan 2005
Nassar et al. 2012
Browning et al. 2015
Diederen et al. 2016

Physiology of Uncertainty Estimation

- Volatility:
  - Yu and Dayan suggested that central noradrenaline signals volatility
    - Pupilometry signals of volatility
    - Pharmacological evidence less convincing

  - fMRI data suggests ACC activity correlates with volatility (some evidence from NHP recordings)

- Noise:
  - Yu and Dayan thought cholinergic activity signalled noise
    - Limited evidence

  - fMRI suggests a scaling of mid-brain activity to PEs

Behrens et al. 2007
Yu and Dayan 2005
Nassar et al. 2012
Diederen et al. 2016
Massi et al. 2018

Summary

- Humans seem to estimate levels of uncertainty and adapt their learning in response to these estimates
  - At least for volatility

Anxiety and uncertainty estimation

- Anxiety may be caused by difficulties in learning about aversive outcomes
  - Little Albert
  - Fear conditioning studies

- *What is the nature of the learning abnormality in anxiety?*
  - *Might it include a difficulty adapting to changes in uncertainty?*

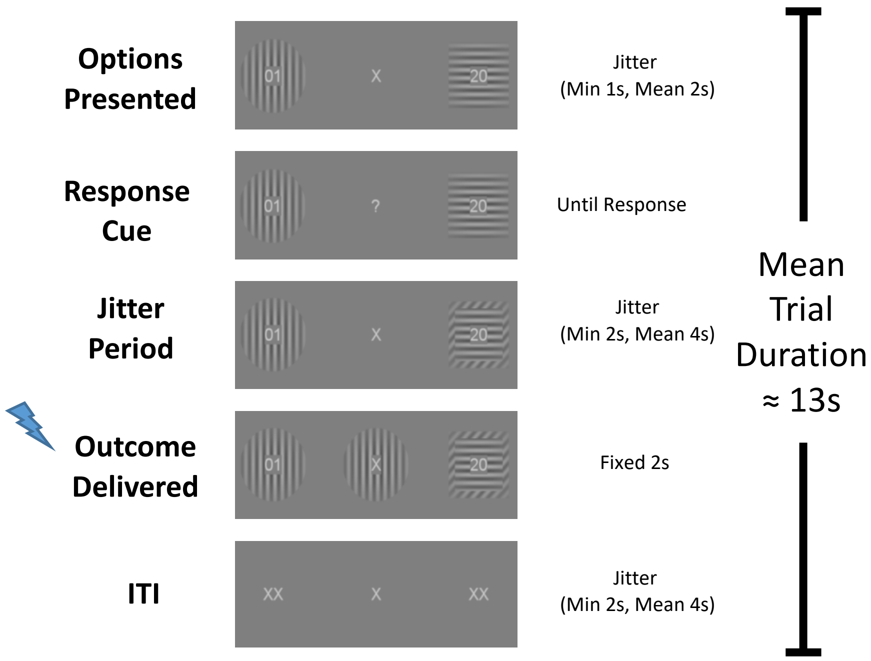
Lissek et al. 2005, 2009

Study Overview

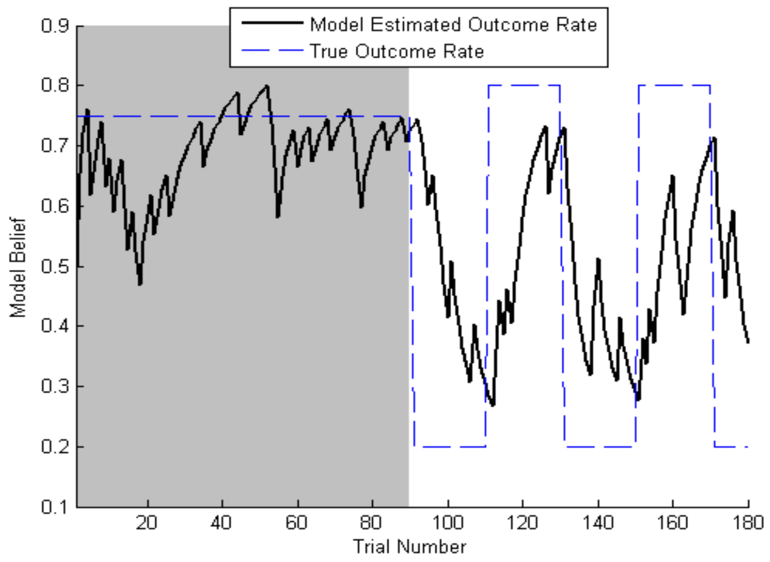
- 31 non-clinical volunteers were recruited on the basis of their trait anxiety
- A novel aversive learning task containing a stable and volatile period was completed
- The degree to which participants adapted:
  a) their learning rate
  b) the size of their pupils

  between the stable and volatile phases was measured

Browning et al. 2015



Options Presented
01
X
20
Jitter (Min 1s, Mean 2s)
Response Cue
?
Until Response
Jitter Period
Jitter (Min 2s, Mean 4s)
Outcome Delivered
Fixed 2s
ITI
XX
X
XX
Jitter (Min 2s, Mean 4s)
Mean Trial Duration ≈ 13s



Model Estimated Outcome Rate
True Outcome Rate
Model Belief
Trial Number
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
20
40
60
80
100
120
140
160
180

Hypotheses

- Anxious people find it difficult to adjust their learning rate between volatile and stable environments

  - **Behaviour:** Anxious subjects won’t adjust their learning rate between stable and volatile blocks

  - **Physiology:** Anxiety subjects’ pupils won’t differentiate between stable and volatile blocks

Computational Model

Outcome of each trial

Learning Rate

How quickly do I learn?

$$r_{(i+1)} = r_{(i)} + \alpha\varepsilon_{(i)}$$

Learn probability of shock (RW Model)

Magnitude of shocks on current trial

Risk Preference

Am I more interested in the probability or size of the shock?

$$g_{circle\,(i+1)} = F\left(r_{(i+1)}, \gamma\right) * shock_{circle(i+1)}$$

$$F(r, \gamma) = \max[\min[(\gamma(r - 0.5) + 0.5), 1]\,, 0]$$

Calculate Value of Shapes

How much does what I have learned influence my choice?

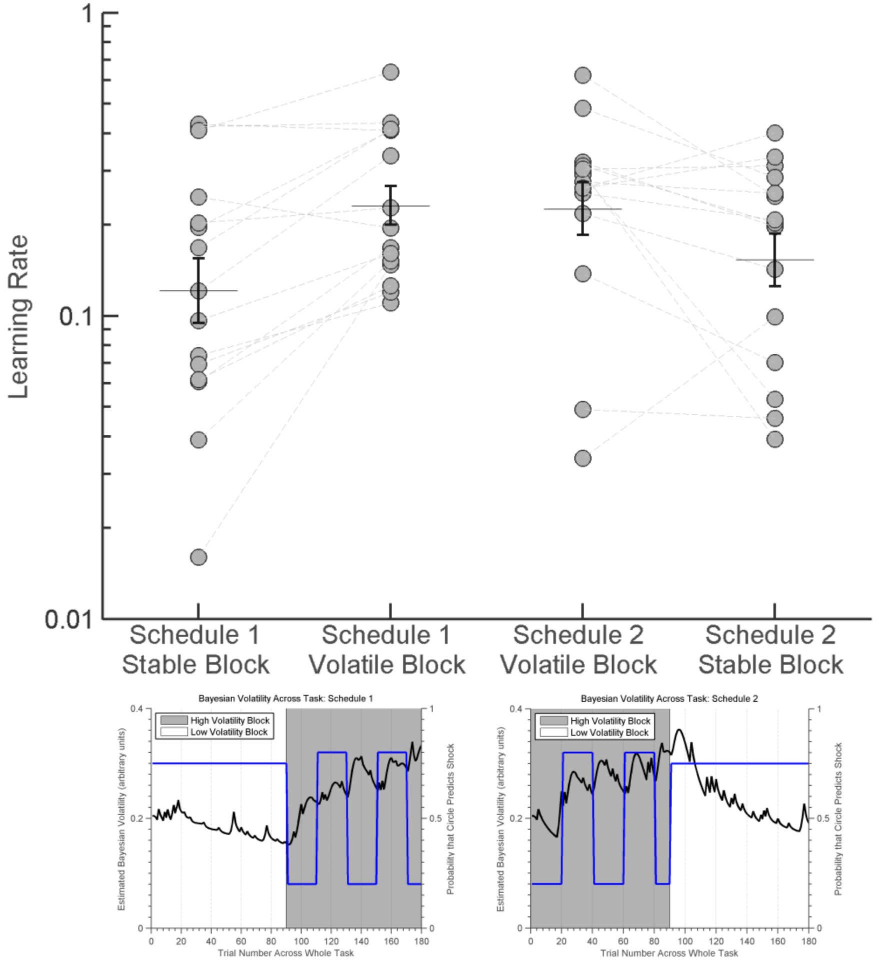
$$P_{(choice=circle)} = \frac{1}{1 + \exp^{(-\beta(g_{(square)} - g_{(circle)}))}}$$

Inverse Decision Temperature

Make Decision

Choices

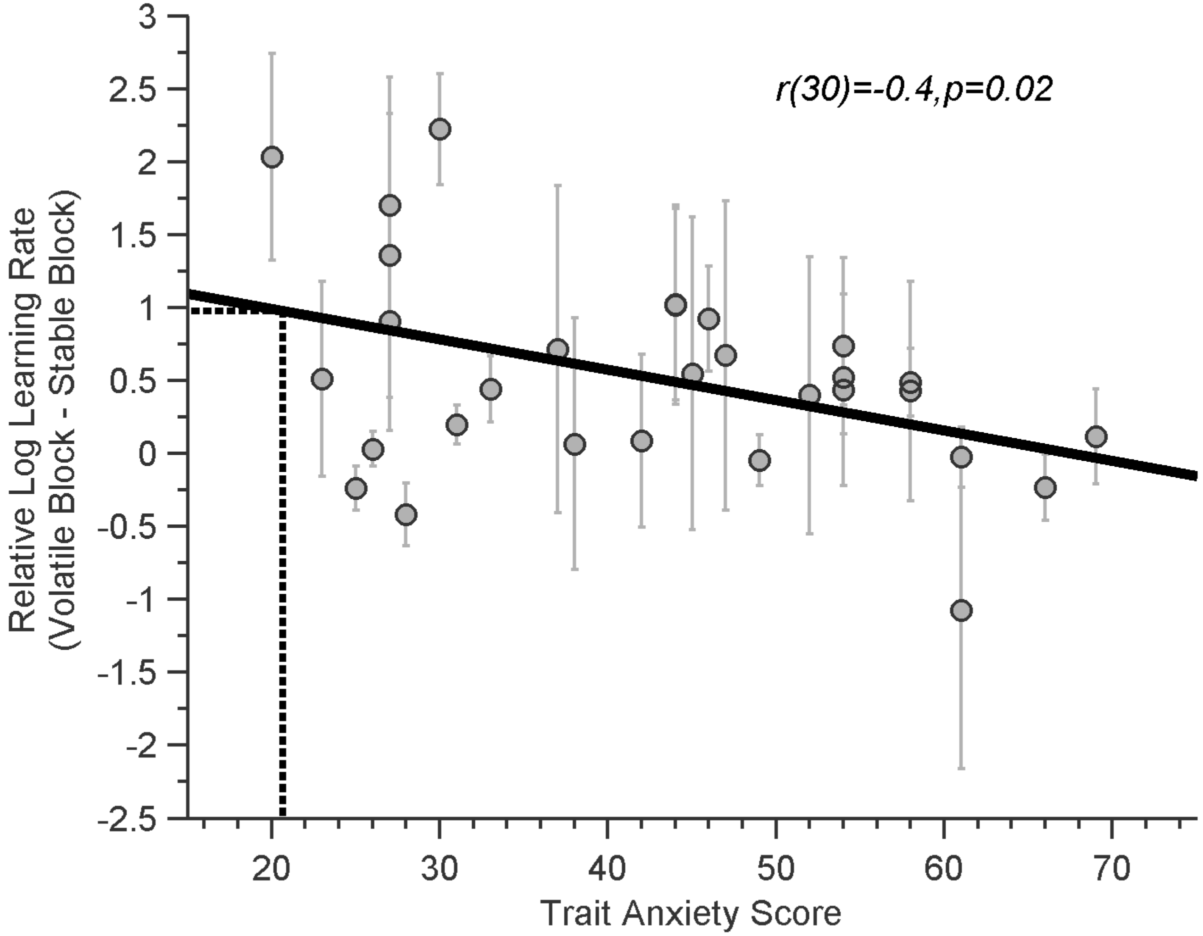
Behavioural Adaptation to Volatility



Learning rate is higher in volatile than stable blocks: *F(1,28)*=16.3, *p*<0.001

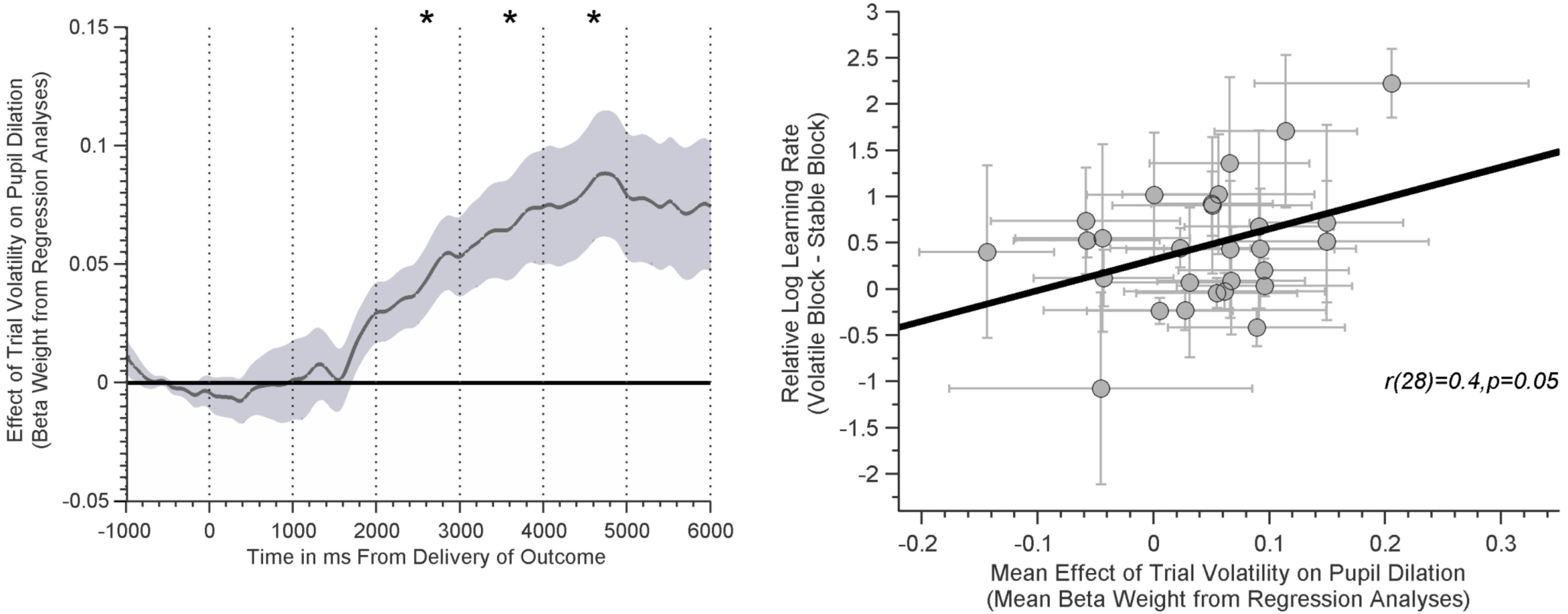
Browning et al. 2015

Anxious Participants have Decreased Learning Rate Flexibility



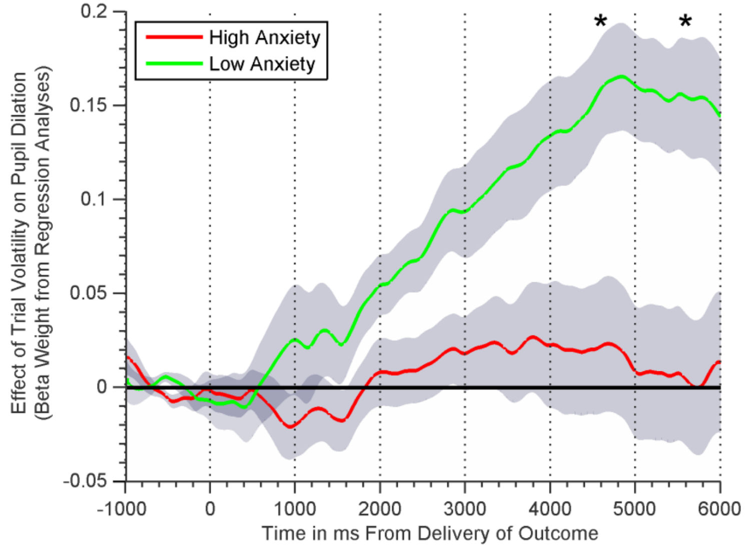
Browning et al. 2015

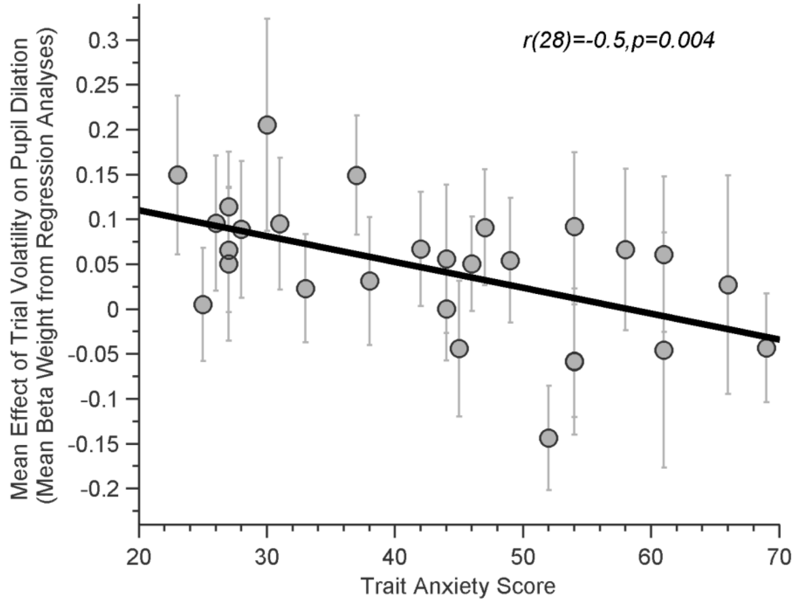
Pupil Diameter Tracks Volatility and Predicts Behaviour



Browning et al. 2015

Anxious Participants have Reduced Pupil Response to Volatility





Browning et al. 2015

Summary: Uncertainty and Anxiety

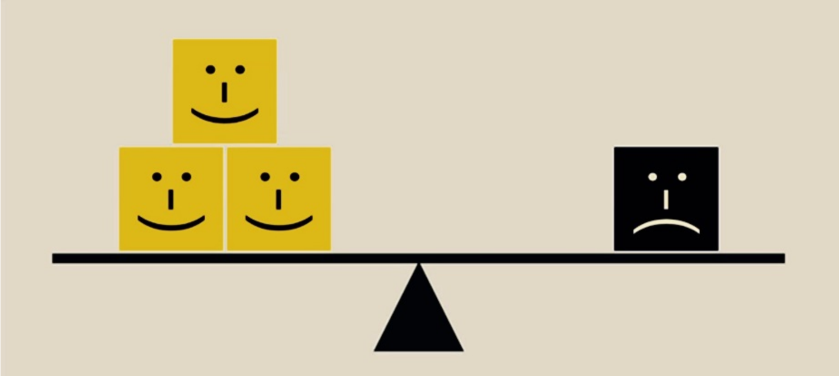
- Anxious people find it difficult to adapt their learning to the statistics of their environment:
  - Reduced learning rate flexibility in response to changes in environmental volatility
  - Reduced responsivity of a physiological measure of NE which is believed to influence this form of learning
- This may be one mechanism underlying the difficulty in learning about aversive outcomes which is thought to cause anxiety

Negative Cognitive Biases

- Cognitive models of depression suggest that the way we think about and interact with the world can cause (or prevent) the illness

- Negative cognitive biases are argued to be causally related to depression and are therefore potential **treatment targets**
    - Biased attention, memory, interpretation
    - Biased learning

Why do (when should) people develop negative cognitive biases?



$\boxed{?}$

↓

$\boxed{\text{Negative Cognitive Bias}}$

↓

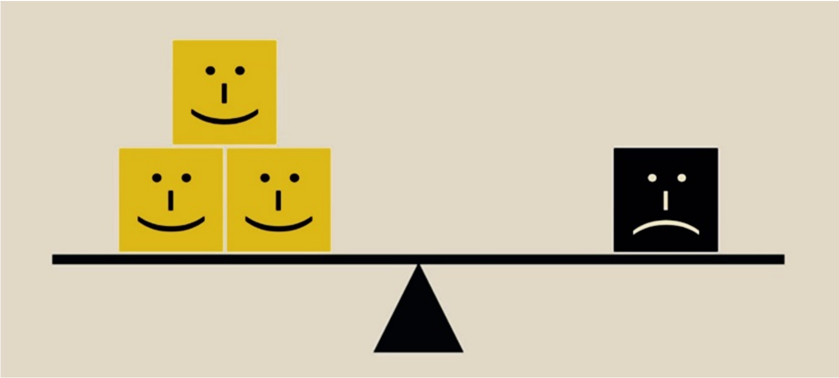
$\boxed{\text{Depressed Mood}}$

Beck 1967
Mathews and MacLeod 2005

Negative Cognitive Biases

- **Why do (when should) people develop negative cognitive biases?**

- When negative events carry more information than positive events



Estimated Information Content

?

↓

Negative Cognitive Bias

↓

Depressed Mood

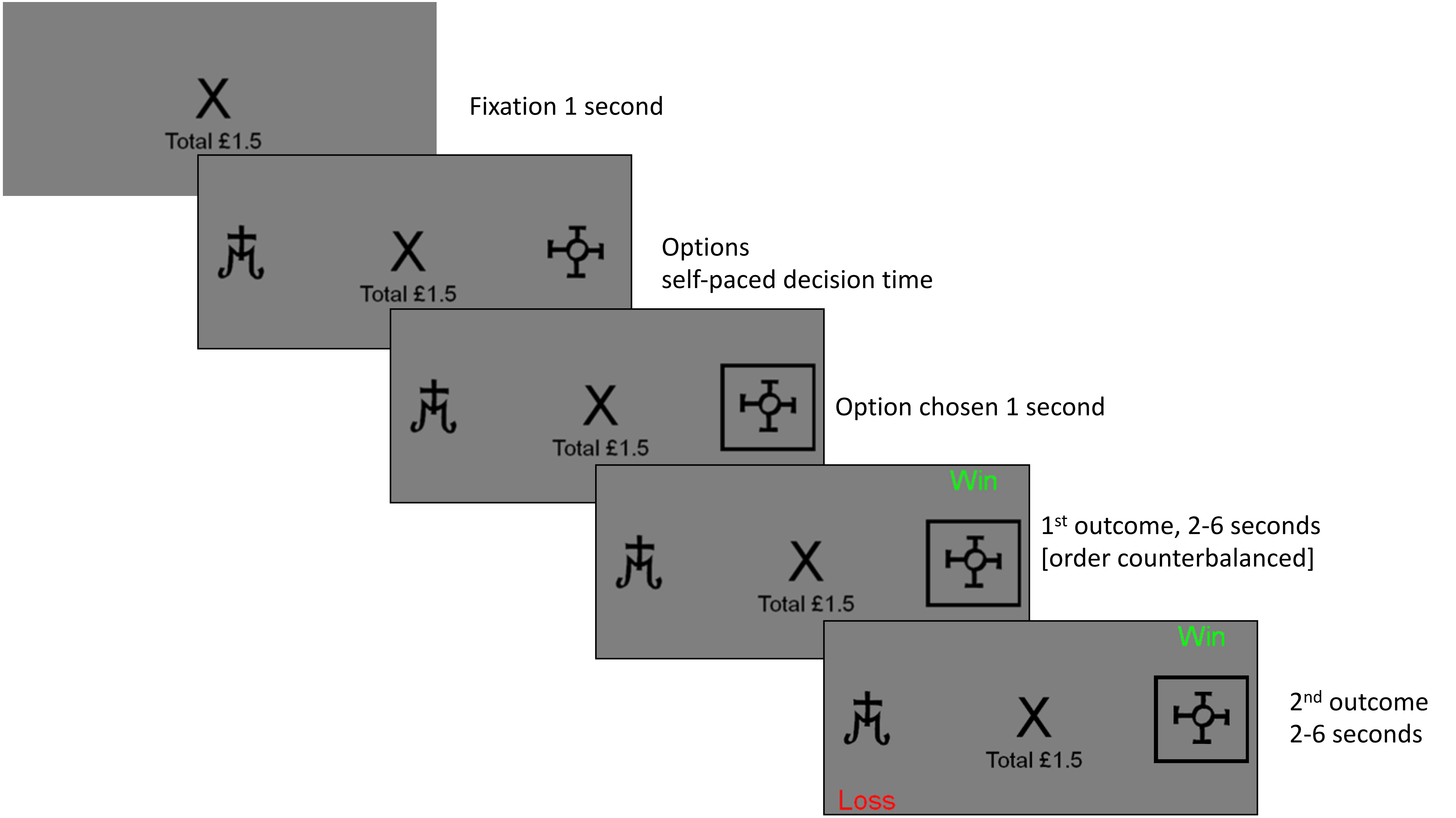
Is Estimated Information Content a Viable Treatment Target in Depression?

- Do people maintain separate estimates of the information content of positive and negative events?
- Can these estimates be altered?
- Are these estimates reflected in a physiological marker of central NE function?

Methods

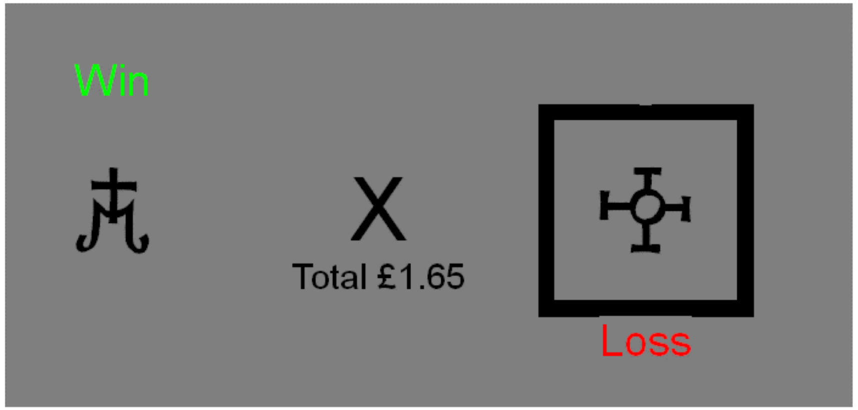
- 30 healthy individuals
- Two armed bandit task with monetary wins and losses
- Independent outcome schedules
- Participants were asked to learn the hidden frequencies of wins and losses associated with each shape and maximise their gains
- Pupil size was recorded to investigate NE function

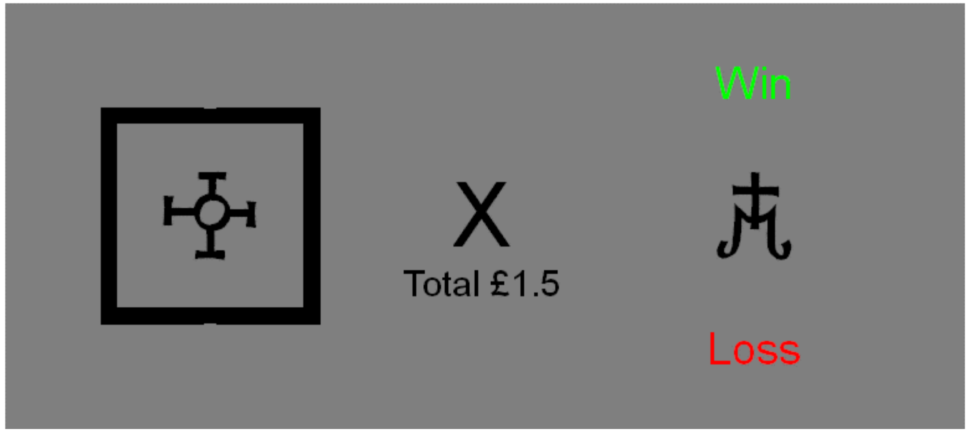
Pulcu and Browning 2017



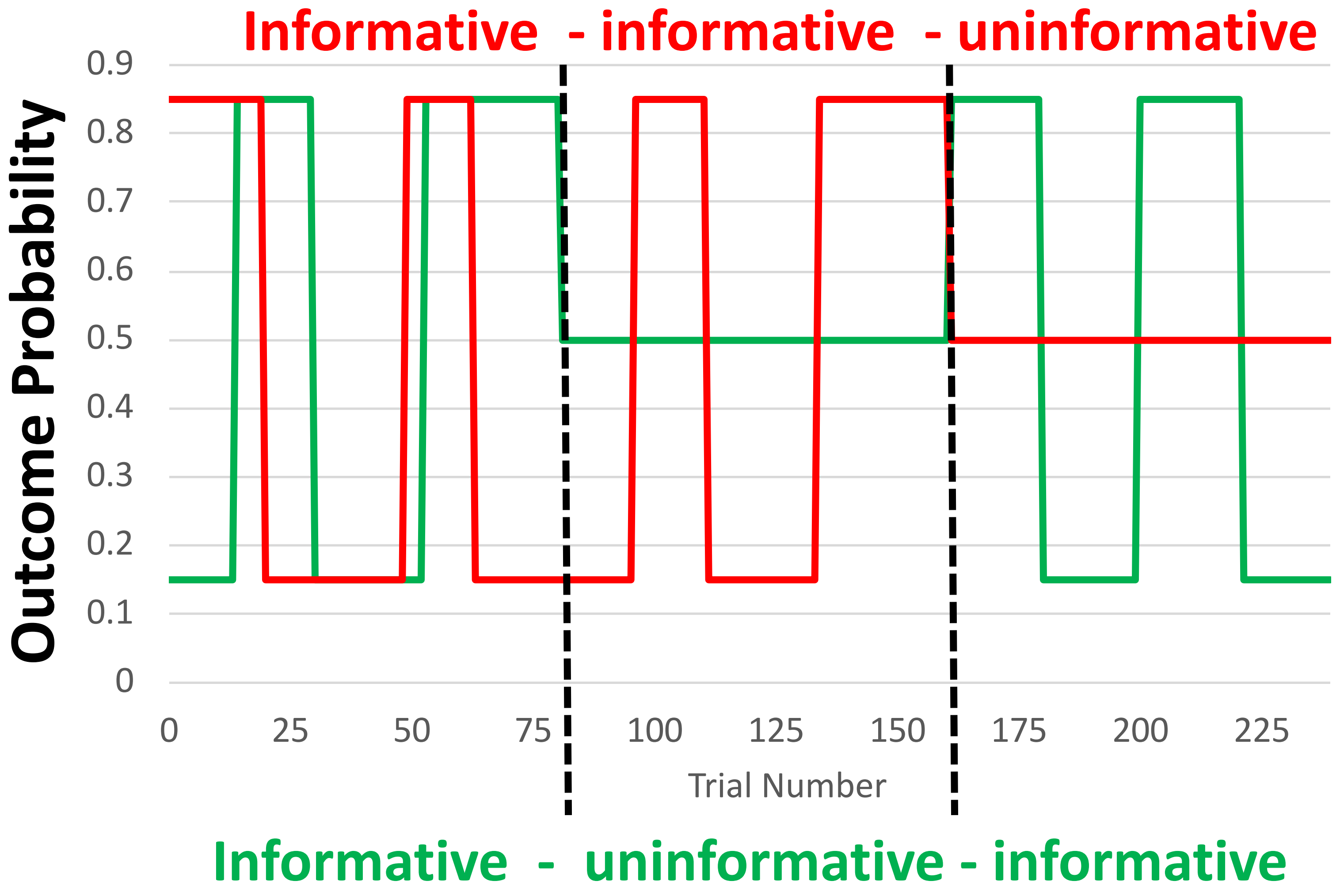
X
Total £1.5
Fixation 1 second
X
Total £1.5
Options
self-paced decision time
X
Total £1.5
Option chosen 1 second
Win
X
Total £1.5
1st outcome, 2-6 seconds
[order counterbalanced]
Win
X
Total £1.5
Loss
2nd outcome
2-6 seconds

Independent Outcomes





Control Information Content



3 Blocks
80 Trials each
1. Both informative
2. Losses Informative
3. Wins Informative

Computational Model

Generate Choice Data

Outcome of each trial

Learning Rate for wins

Learning Rate for losses

$$rwin_{(i+1)} = rwin_{(i)} + \alpha win * \varepsilon win_{(i)}$$

$$rloss_{(i+1)} = rloss_{(i)} + \alpha loss * \varepsilon loss_{(i)}$$

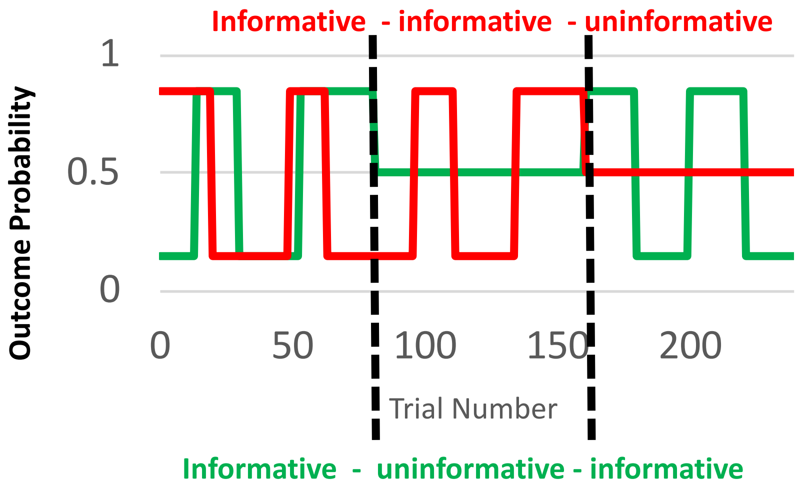
Inverse Decision Temperature for losses

$$P_{(choice=shapea)} = \frac{1}{1 + \exp^{(-(\beta win * rwin_{(i+1)} - \beta loss * rloss_{(i+1)}))}}$$

Inverse Decision Temperature for wins

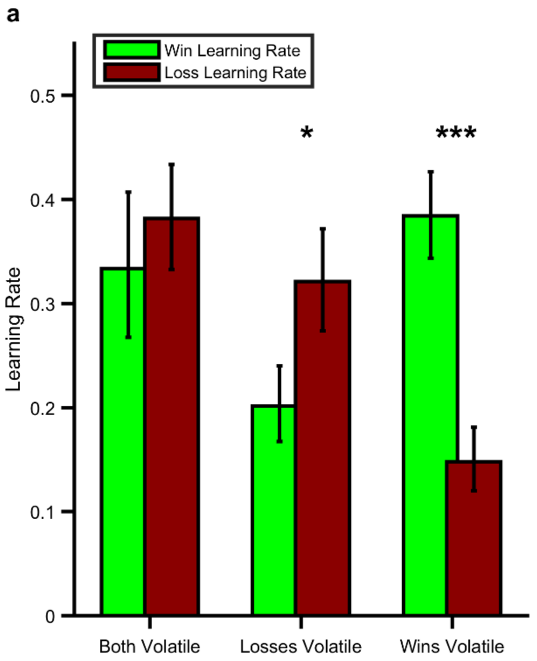
Choices

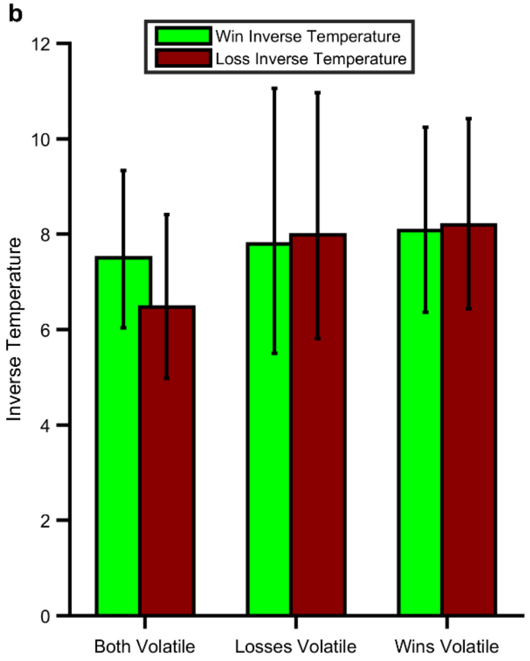
Fit Parameters



Results

Participants significantly adjust their learning rates to favour the most informative outcome





Evidence for:

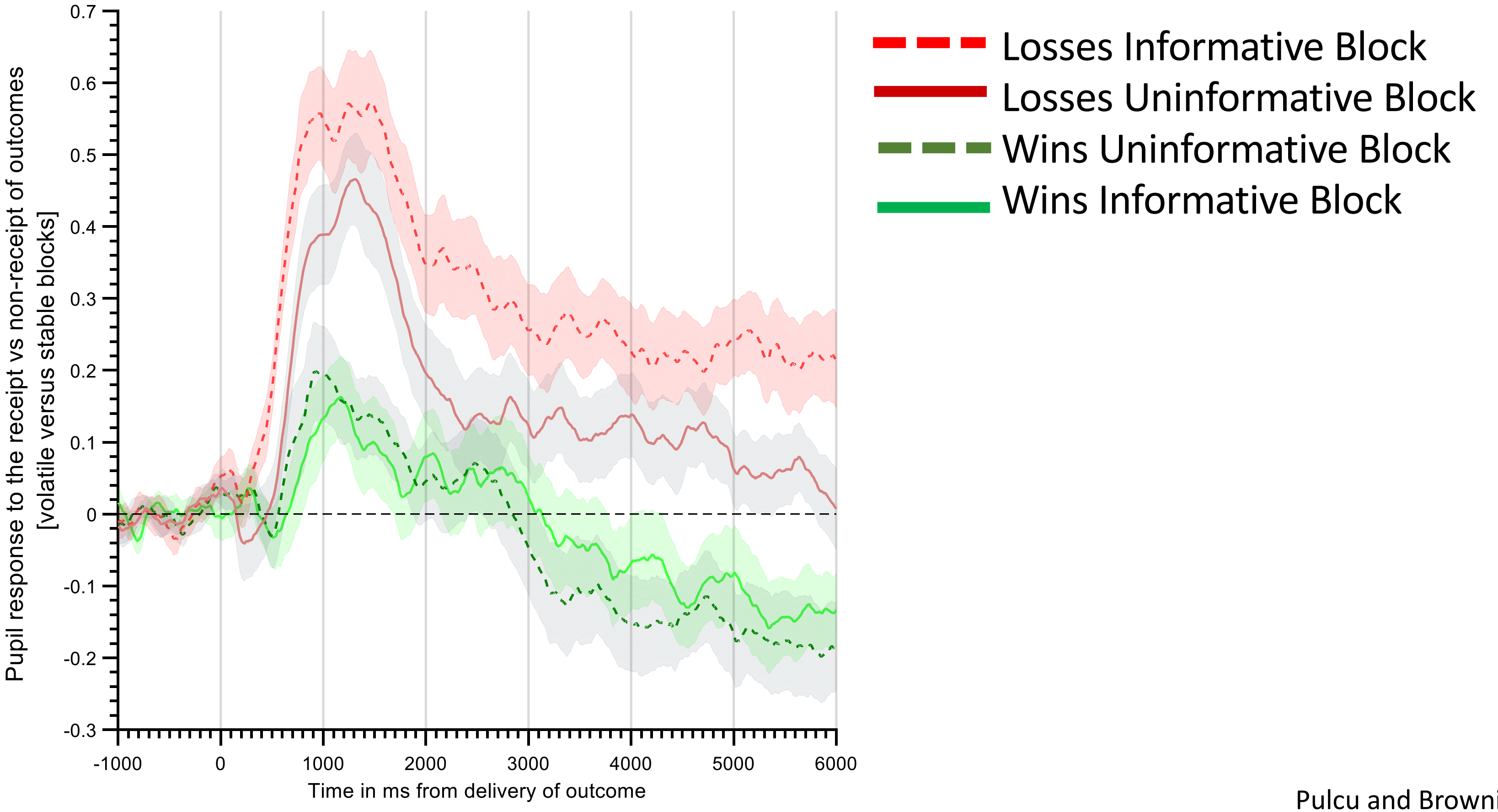
a) Separate estimates of the information content of positive and negative events are maintained
b) The estimates can be measured behaviourally
c) The estimates can be altered experimentally

Pulcu and Browning 2017

Pupil Data Analysis

Pupil dilation reflects information content of outcomes– although this effect is driven by loss outcomes

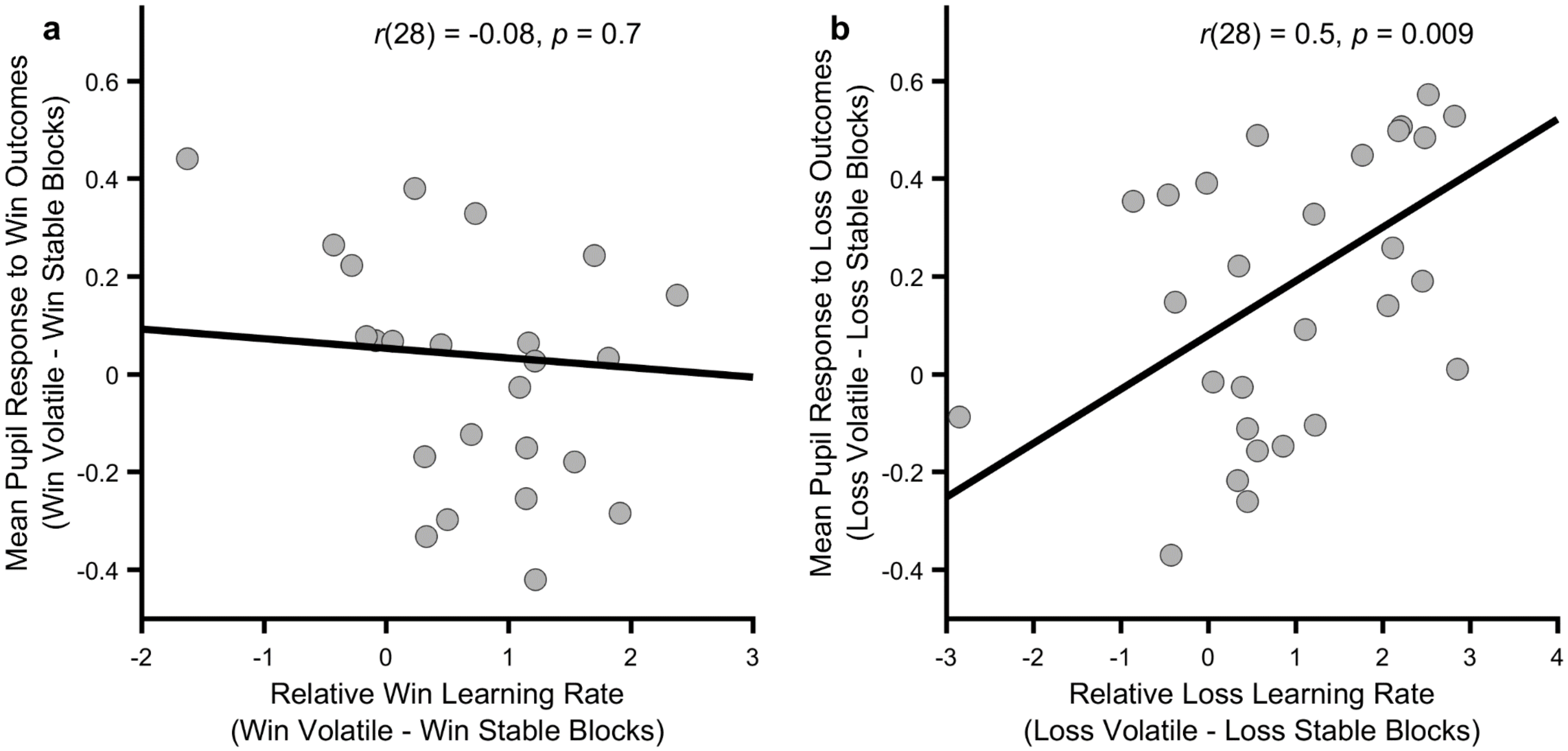
Evidence that estimates of information content are reflected in a physiological marker of central NE function (but only for losses)



Pulcu and Browning 2017

Relationship Between Pupil and Behavioural Data

The degree to which pupil dilation differs between blocks correlates with changes in learning rate between blocks, but only for losses



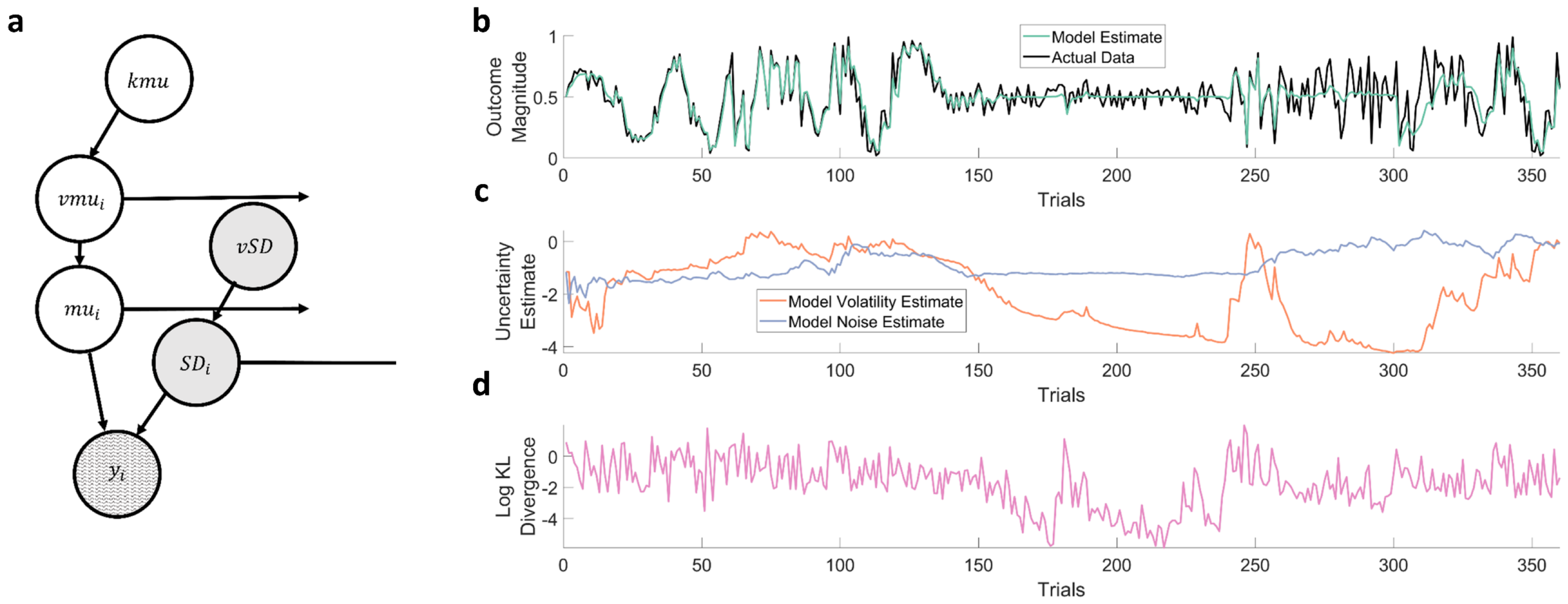
Summary– Uncertainty and Affective Bias

- Humans maintain separate representations of the information content of win and loss outcomes
- These estimates may be experimentally modulated by controlling the volatility of outcomes
- Central NE function (as estimated by pupil dilation) provides a physiological marker of information content (of losses)
- It may be possible to alter negative cognitive bias in depression by altering the estimated information content of positive vs. negative outcomes
  - Estimated information content may be a viable, computationally defined, treatment target in depression

What model to use?

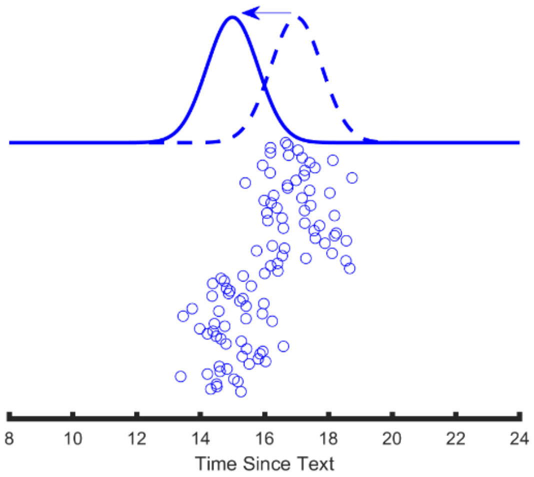
- The modelling I have described allows us to measure parameters (mainly learning rate)
- It does not explain how people might estimate uncertainty in the first place
- More complex models are able to do this:
  - Pearce-Hall type models
  - Kalman Filter type models
  - HGF and other Bayesian approaches

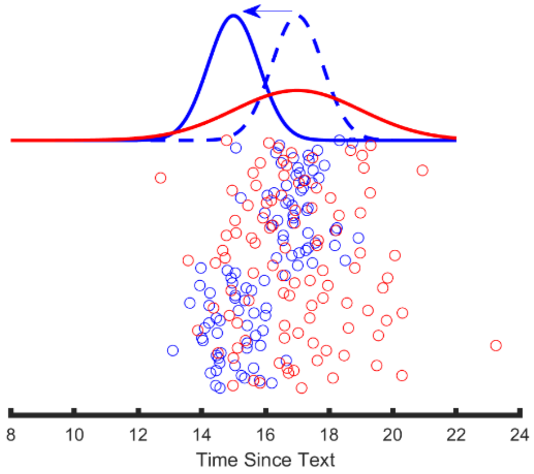
An example of a Bayesian Filter



Practical Uses of this Sort of Model: an Example

- Bipolar disorder and borderline personality disorder share some common features, in particular: mood instability
- We can conceptualise the emotion reported by an individual as a noisy process arising from an underlying "mood", which may vary over time
- Given a timeseries of reported emotion from an individual we can then estimate the degree to which reported emotion is influenced by noise vs. volatility

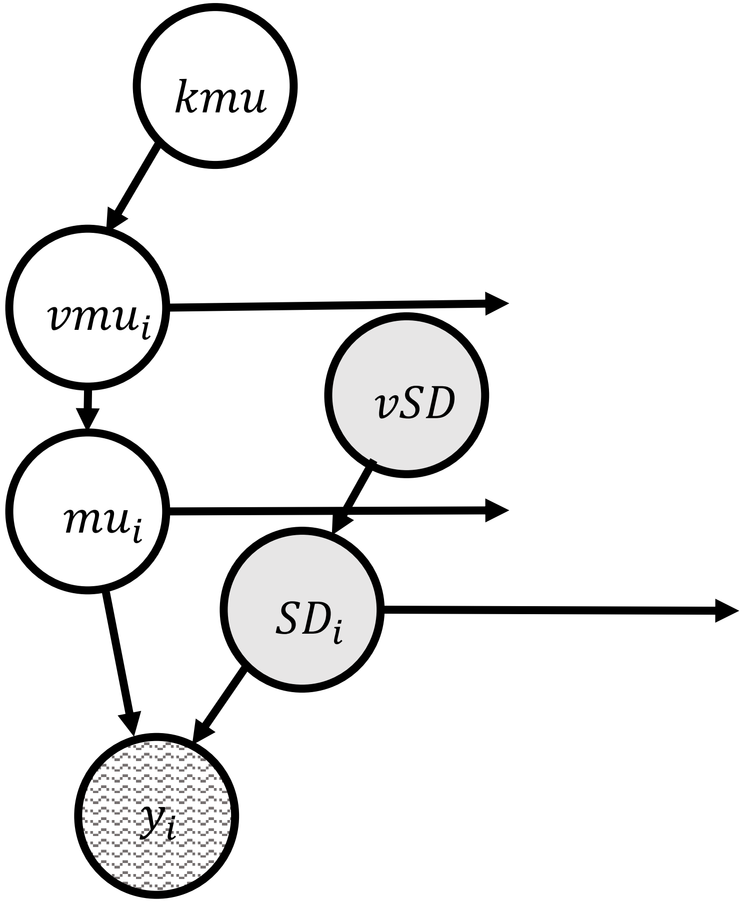




Amoss Study

- 52 patients with bipolar disorder, 36 with borderline personality disorder and 52 healthy controls rated their emotions (anxious, elated, sad, angry, irritable, and energetic) every day for 100 days.

- Mean negative emotion (mean of anxious, sad, angry and irritable) was passed to a recursive Bayesian filter which estimated volatility and noise at each time point



Conclusions

- It is useful to estimate the level of different types of uncertainty during learning
- People seem to do this
- There is some evidence that an insensitivity to uncertainty might be associated with anxiety
- The same framework can be used to explain things like affective bias and so may provide novel treatment targets
- More generally– thinking about different types of uncertainty might be useful in understanding a range of processes in psychiatry.

Any questions?

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