Modeling Human Perceptual Decision-Making and Bias

Disconnected Connectionists (DC)

Roadmap to Our Project Presentation

- Project Goals
- The Laquitaine & Gardner Dataset

Goals

Immediate Goals

- Analyze how past trials affect current motion estimation errors.

- Test whether perceptual biases exist.

- Develop online Bayesian model

Overall Goals

- Model perceptual decision-making under uncertainty & understanding human perception through experience and feedback

The Laquitaine & Gardner Dataset

- Motion direction estimation task
- 12 human subjects
- 83,214 behavioral trials
- What you SEE (sensory evidence) vs. What you EXPECT (prior knowledge)
- data01_direction4priors experiment

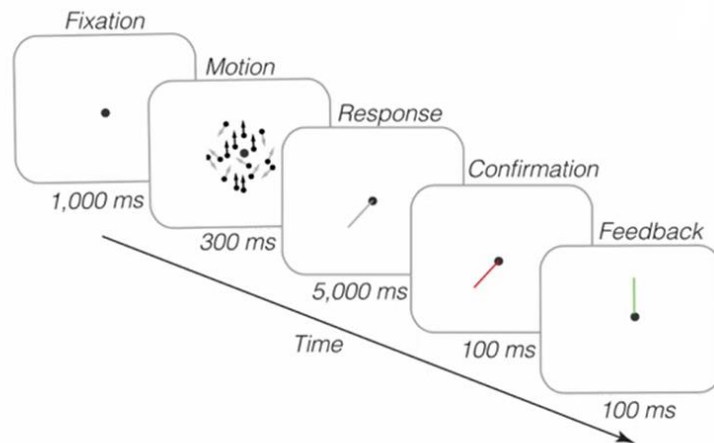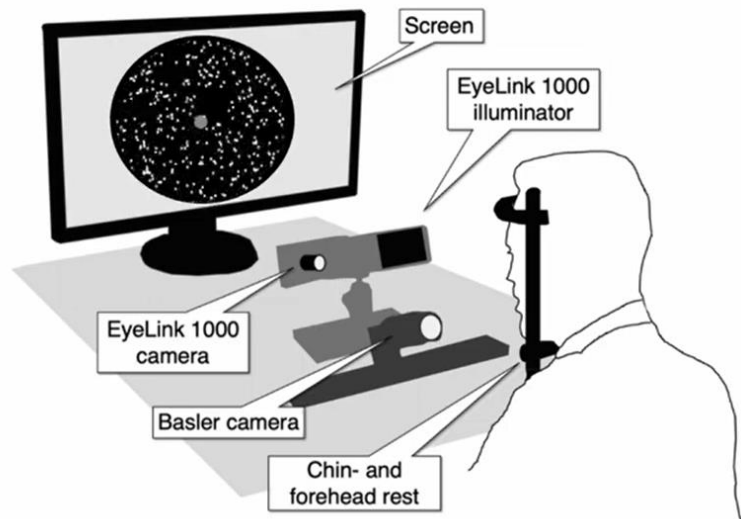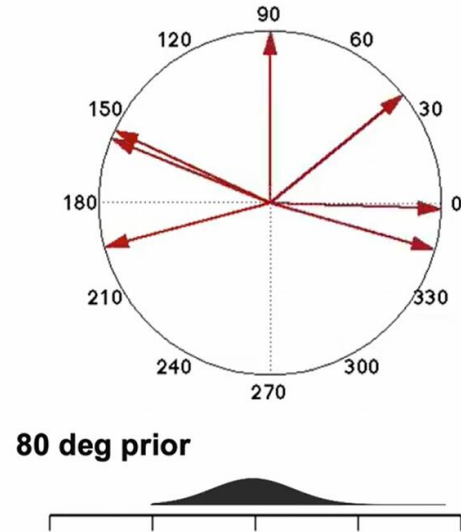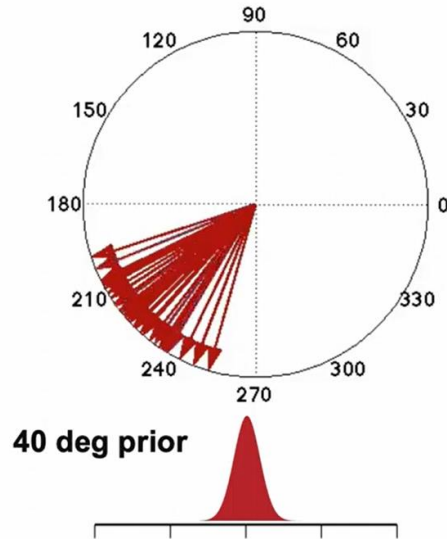# The Laquitaine & Gardner Dataset

Illustration from Nystrom, et al., Behav Res (2023)
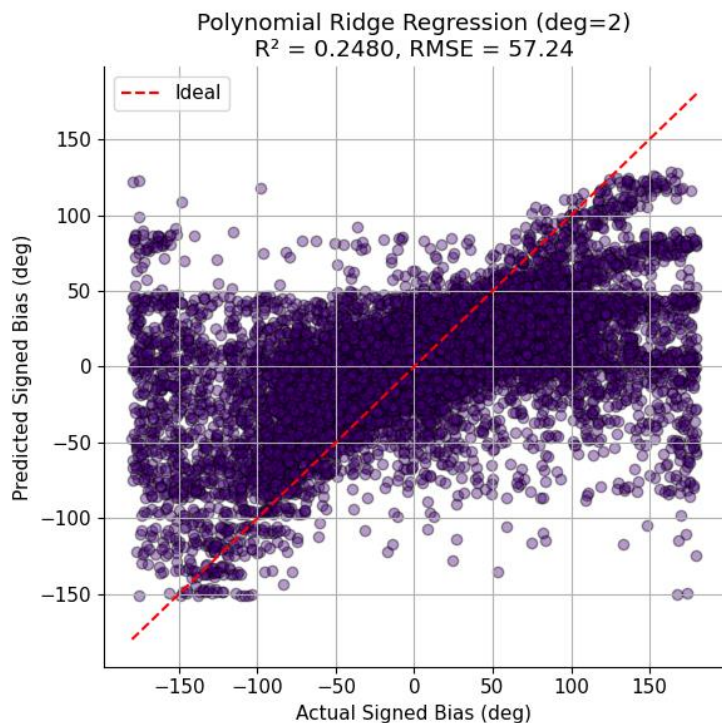Laquitaine Presentation, "Projects Dataset: Bayes heuristics"
https://www.youtube.com/watch?v=NYzgpUtBhPM

The Laquitaine & Gardner Dataset

Laquitaine Presentation, "Projects Dataset: Bayes heuristics"
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Polynomial Ridge Regression (deg=2)
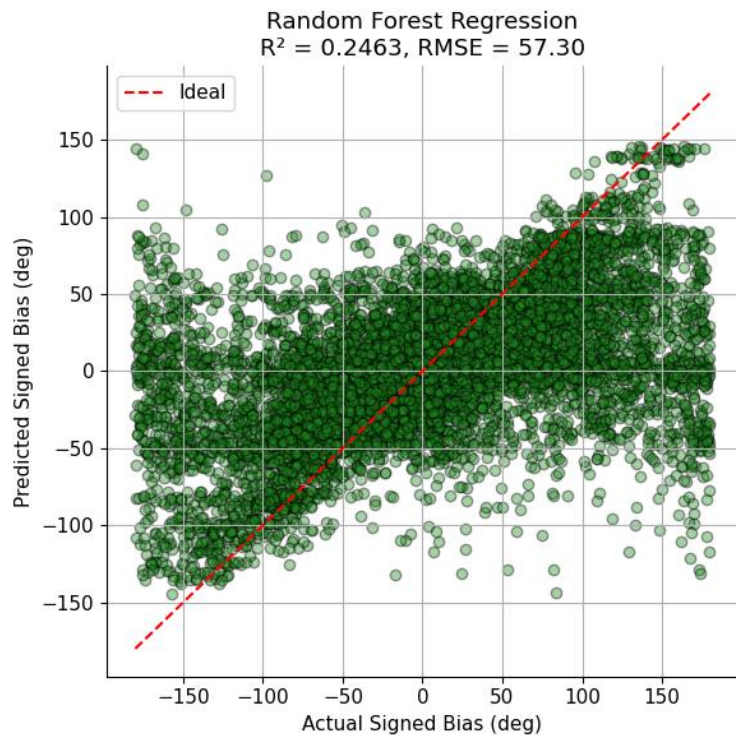R² = 0.2480, RMSE = 57.24

Predicting Signed Bias from Priors

- Predicting the angular difference between the subject's estimate and the true prior direction.

- A positive value = estimate is clockwise from the prior

- A negative value = estimate is counter-clockwise from the prior

Random Forest Regression
R² = 0.2463, RMSE = 57.30

Predicting Signed Bias from Priors

- Both models show moderate predictive performance (R² ≈ 0.25)

Waterfall Illusion in Motion Perception

A repulsive perceptual bias where, after viewing motion in one direction for a while, a static or ambiguous stimulus appears to move in the opposite direction

Per-subject analysis of estimation bias, computed as the deviation between the current estimate and stimulus, relative to the circular mean of the previous 3 trials, across varying prior and coherence conditions
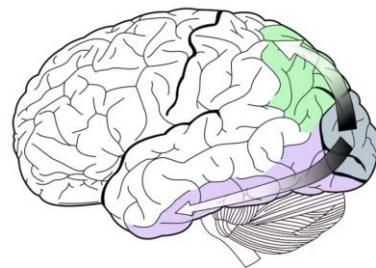
Subject 2

No clear evidence of the waterfall illusion. Estimates align with either the stimulus direction or the prior mean, showing no evidence of repulsion from recent motion history
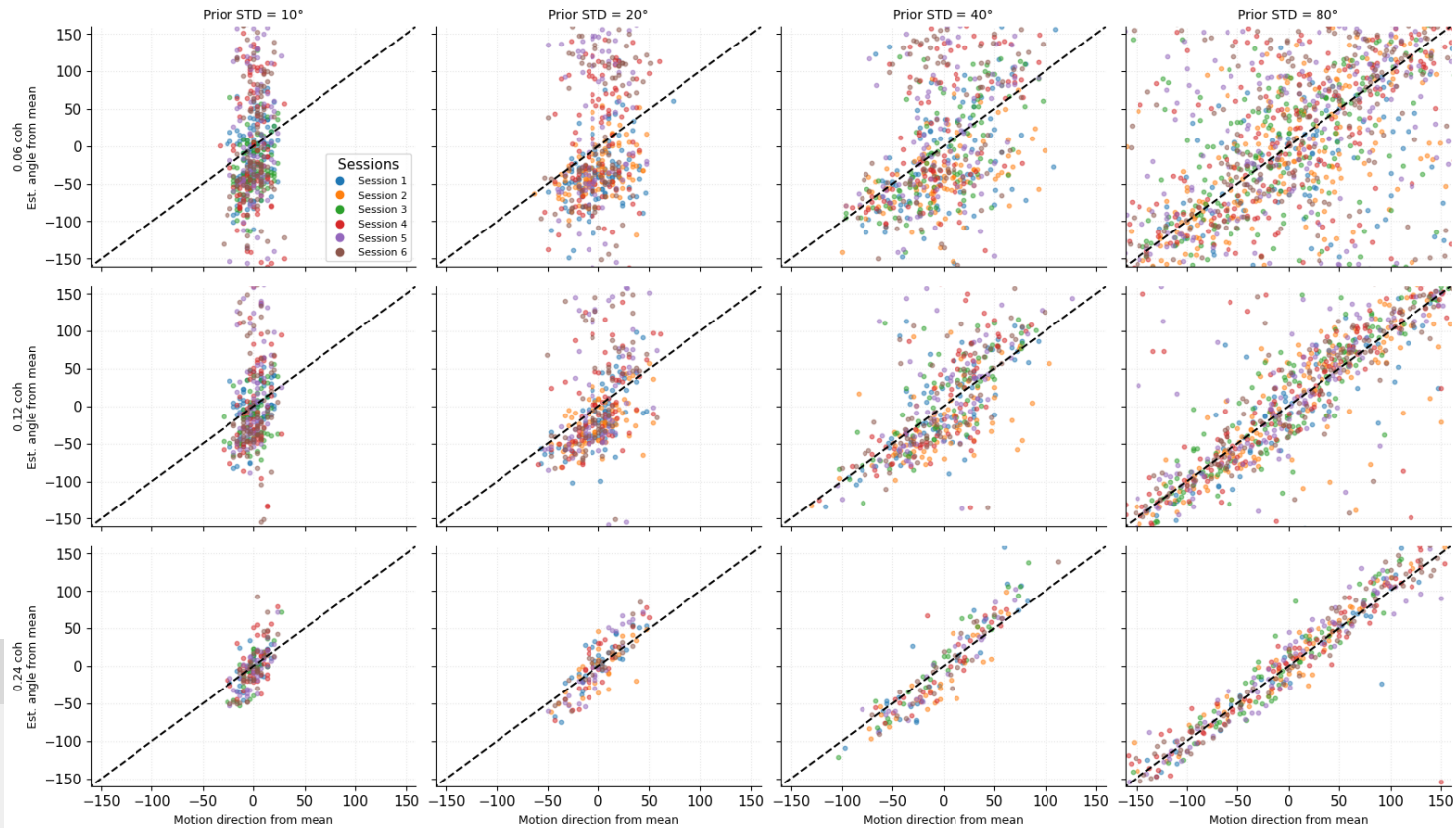

Waterfall Illusion – Subject 2
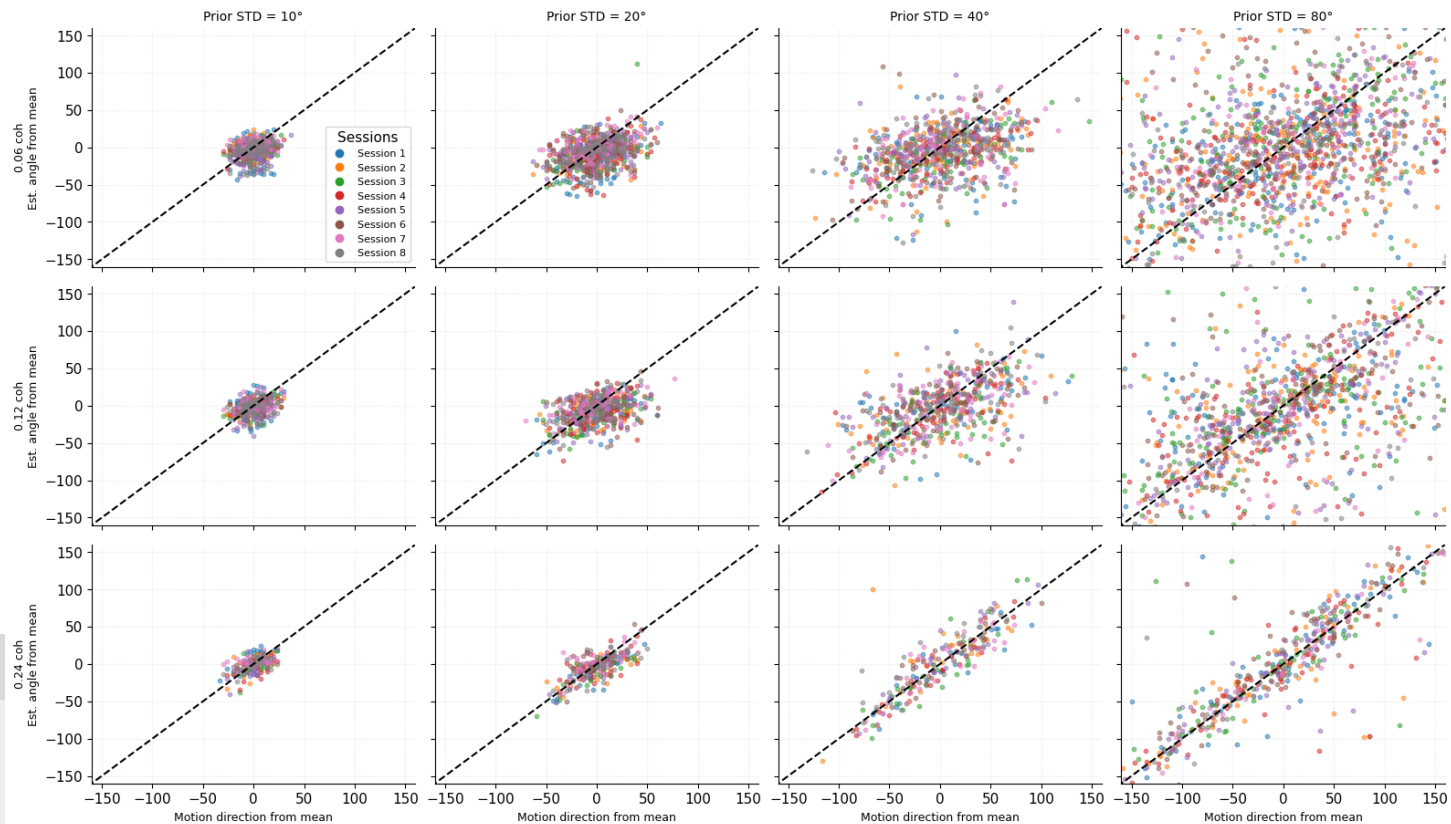
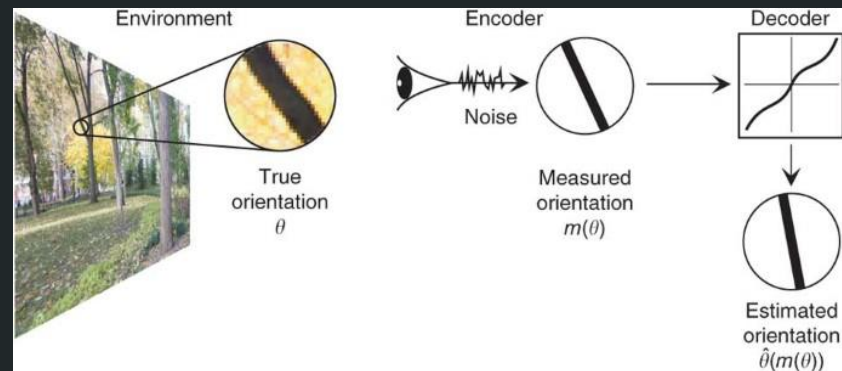# Evidence of the waterfall illusion, under low coherence and narrow prior conditions
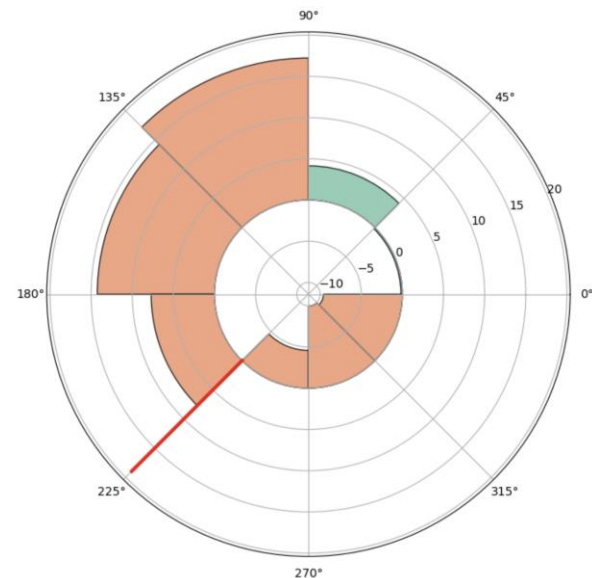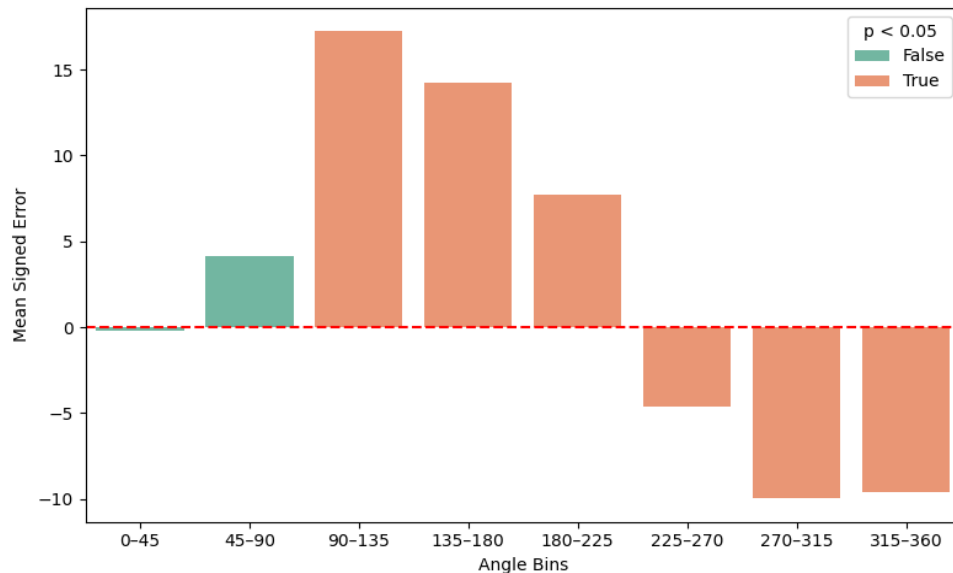

Waterfall Illusion – Subject 5

Cardinal Bias

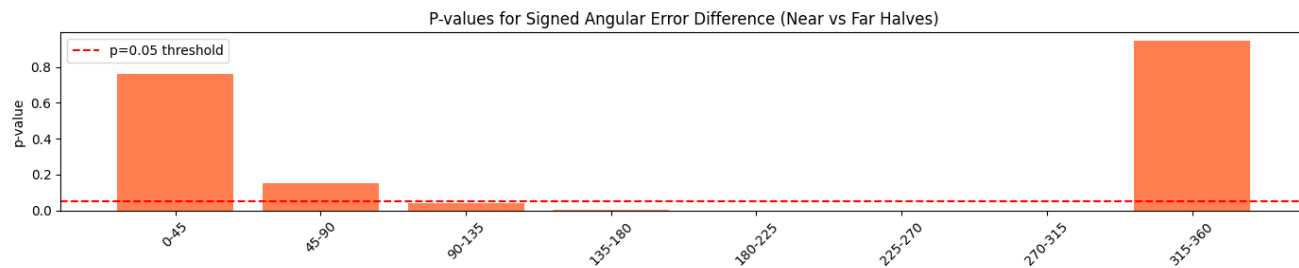Perceived orientations are attracted toward the cardinal directions, and repelled from the obliques.

Analyzed through difference between 2 halves for each slice of 45°

Attraction toward 225° prior

Half comparison
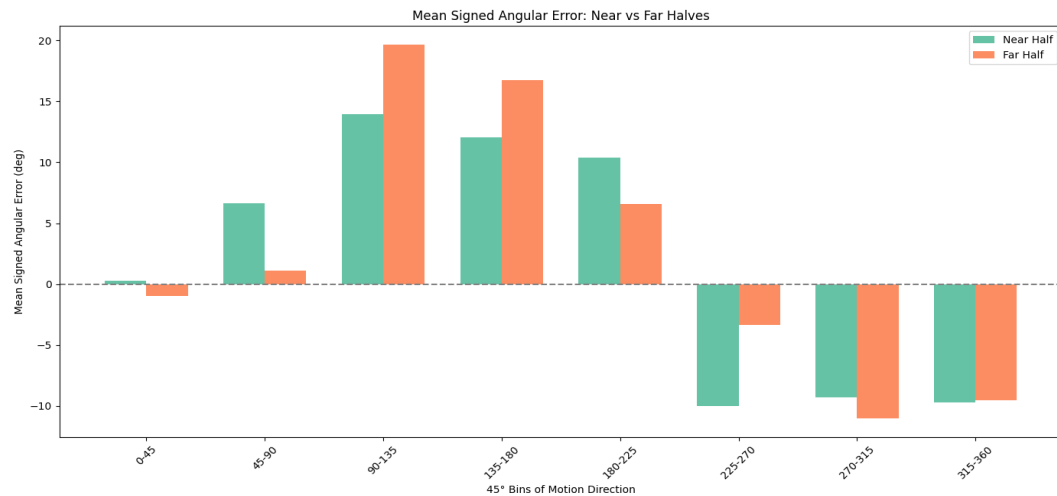
Modeling Perceptual Strategy: Bayesian vs. Switching

Which cognitive model best explains how we make decisions under uncertainty?
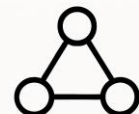
We test two competing theories by simulating "robot players" that try to mimic human behavior:

- **The Bayesian Observer:** A "smart statistician" that optimally integrates all information.
- **The Switching Observer:** A "mental shortcut" that chooses one source of information over another.

A Closer Look at the Bayesian Model

- This model assumes the brain acts like an optimal statistician, combining what it sees (evidence) with what it expects (prior).
- Its prediction is a weighted average of the two, and it learns by updating its confidence on every trial.
- The plot shows the model's predictions (red) overlaid on the human's actual responses (blue) for our most interesting subject.

Online Bayesian Model vs. Human Behavior (Subject 2)
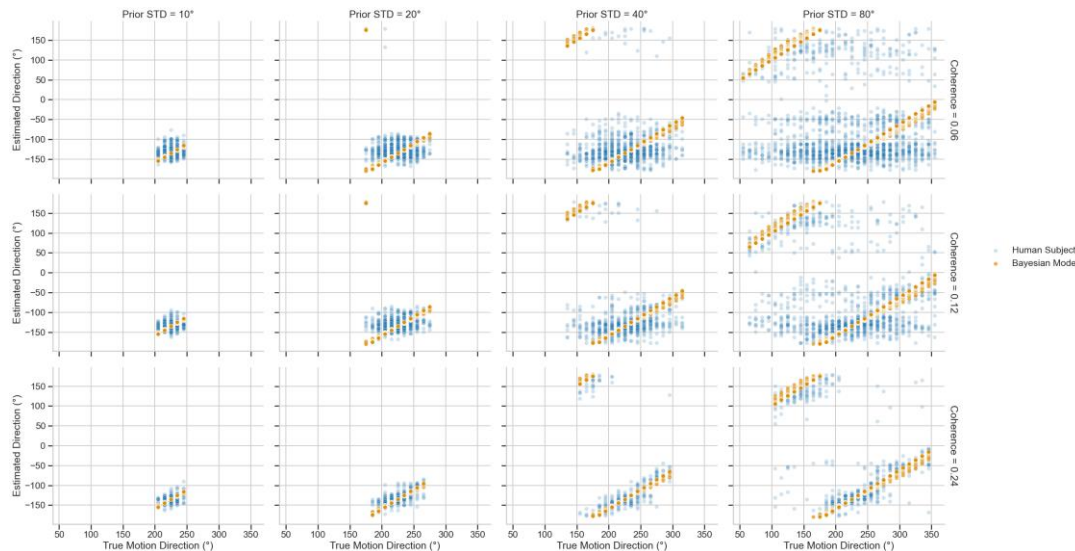
An Alternative Strategy: The Switching Model

- This model proposes a simpler mental shortcut, or heuristic, instead of complex integration.
- On each trial, it makes a probabilistic choice to report either the sensory evidence or the prior expectation.
- Its key prediction is a two-peaked (bimodal) distribution of answers. The plot compares the shape of the model's predictions (red) to the human's (blue).

Switching Model vs. Human Estimate Distributions (Subject 2)
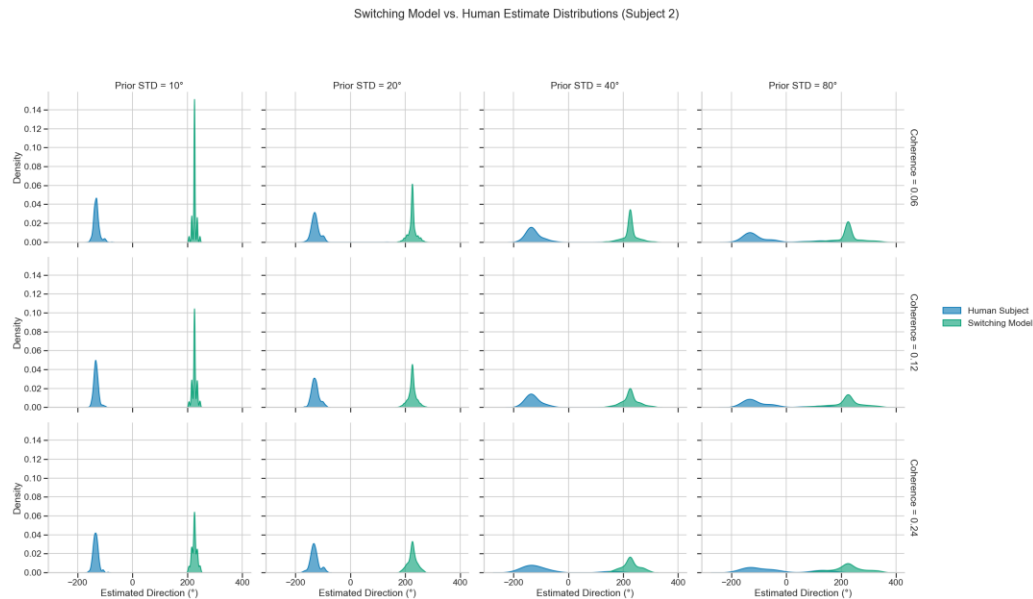
The Verdict: Bayesian Integration is a Better Fit

- We ran a "bake-off," finding the best possible version of each model for all 12 subjects.
- The **Online Bayesian model** consistently explained the human data better (lower error) for the vast majority of subjects.
- However, the results also reveal profound **individual differences**, suggesting that while integration is a better general theory, the specific strategy is highly personal.

Final Model Comparison by Subject (Lower MSE is Better)
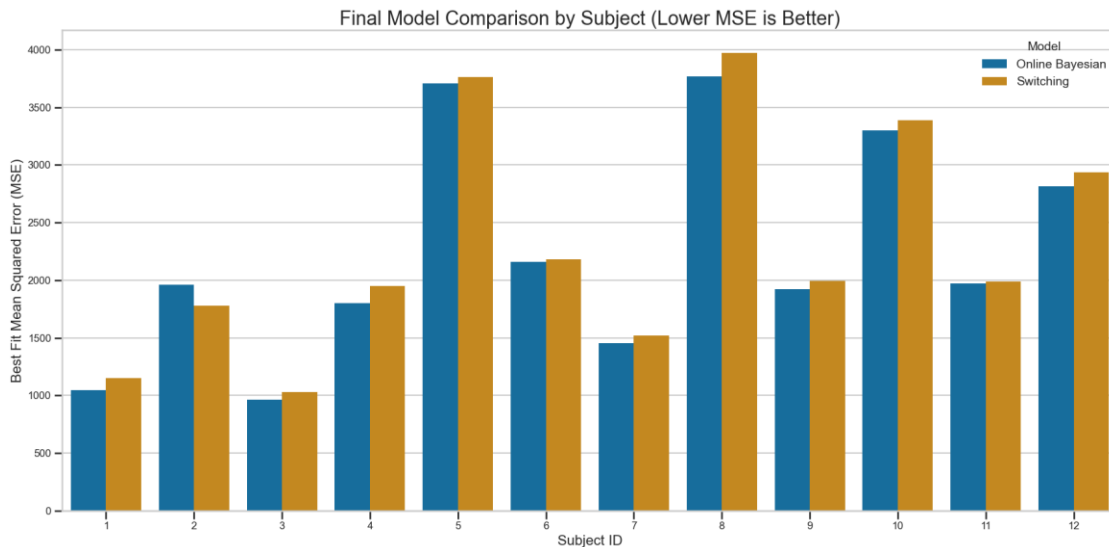
Online Bayesian Model with Kalmen Gain

Model Parameters:

- K_e: Sensory precision (concentration)
- K_m: Motor noise (concentration)
- Q: Process noise variance (how much the prior drifts)
- R: Measurement noise variance (how noisy feedback is)
- K_p: Precision (how much the current prior influences)

Model's Logic:

- Initializes belief state at the start, with a high uncertainty
- Predicts the state for the current trial by looping through trials, then converts it to K_p
- Combines current belief (prior) with sensory evidence
- Calculates the log-likelihood of the subject's actual response by Von Mises Log Probability Distribution
- Learns from the feedback (true stimulus direction) by calculating Kalman Gain (learning rate for that trial)
- Calculates prediction's circular error and Updates belief state for the next trial

Overall Model Fit for Subject 8 (Aggregated Across All Conditions)
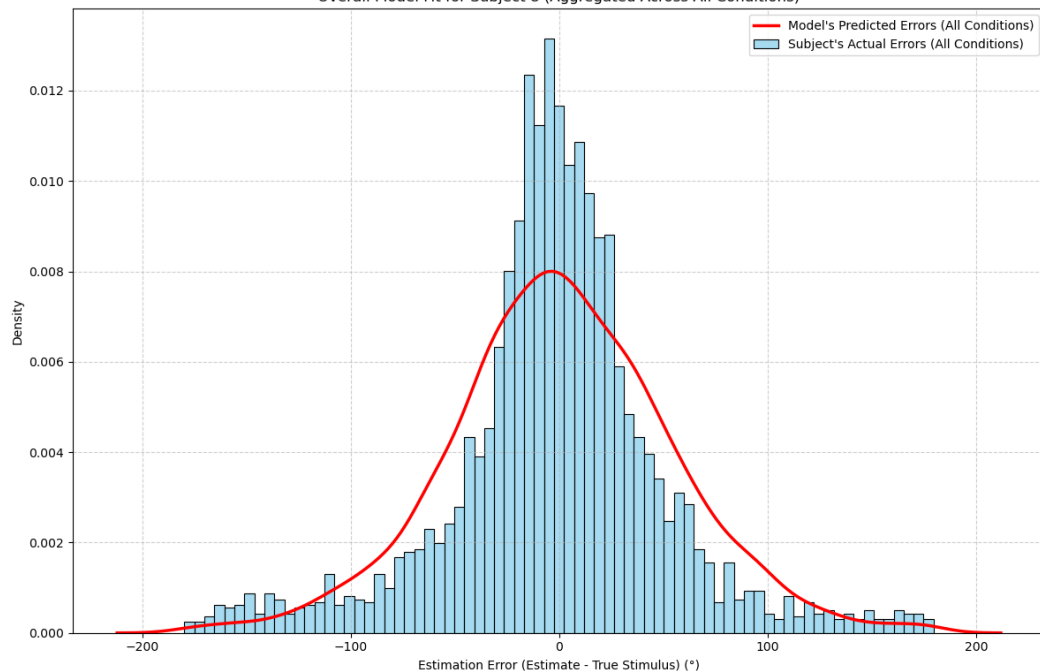
Model Fitting and Accuracy

- The plot allows for a comparison between the actual errors (blue histogram) and the predicted errors (red curve).
- A good fit would be indicated by the red curve aligning closely with the shape of the blue bars, suggesting that the model's predictions closely match the actual subject's data.
- The actual errors seem to follow a distribution that peaks around zero, indicating that the model has a reasonable accuracy at the point of estimation, though there are outliers or deviations on both sides.
- The model is capturing a general tendency of the errors but might be underestimating the variance, as the actual errors show more spread compared to the model's predictions.