What limits performance in decision making?

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Conclusions

What limits performance in a fully attentive, well-trained animal/human?
Conclusions

What limits performance in a fully attentive, well-trained animal/human?
Is behavioral performance limited by:
Is behavioral performance limited by:

Noise in the brain
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Noise in the brain
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Noise in the brain
Is behavioral performance limited by:

Noise in the brain

or

A combination of suboptimal inference and variability in the sensory inputs and sensors
Is behavioral performance limited by:

Noise in the brain

or

A combination of suboptimal inference and variability in the sensory inputs and sensors
Roadmap
Roadmap

Experiment 1: what appears as noise can be suboptimal inference
Roadmap

Experiment 1: what appears as noise can be suboptimal inference

Experiment 2: noise only has a marginal impact on performance
Olfactory processing

• Olfactory detection and categorization
Olfactory processing

• Olfactory detection and categorization
Dual tasks
Dual tasks

[Diagram showing the process of dual tasks with trial start, stimulus, choice, correct, error, and outcome stages.]

Detection task

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>$10^{-1}$</td>
<td>$10^{-2}$</td>
<td>$10^{-3}$</td>
<td>$10^{-4}$</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
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</tbody>
</table>
Dual tasks
Dual tasks
Dual tasks

Detection task

Categorization task
Dual tasks
Dual tasks
Dual tasks
Standard Drift Diffusion Model (DDM)

\[ \eta(t) = N(\kappa c^\beta, \sigma) \]

\[ s(t) = \int_{-\infty}^{t} \eta(\tau) d\tau \]

Parameters:
1. Sensitivity - \( k \)
2. Exponent - \( \beta \)
3. Non-decision time - \( t_d \)
4. Bound height - \( A \)
5. Collapse rate - \( \gamma \)
6. Lapse rate - \( \lambda \)
Predicting Categorization

Detection

(a) % correct

(b) Accuracy

(c) Reaction time (ms)

Odor concentration (v/v)
Predicting Categorization

Detection

% correct

Accuracy

Reaction time

Odor concentration (v/v)

Reaction times (ms)
Predicting Categorization
Possible Explanation

Reaction time

Detection

Categorization

% correct

Accuracy

Odor concentration (v/v)

Reaction time (ms)

Mixture contrast (%)

Graphs a, b, c, and d illustrate the relationship between concentration and reaction time for detection and categorization tasks.
Possible Explanation

• There is an extra source of variability in the categorization task.
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- Maybe the animal can’t quite remember the 50% boundary, i.e., the memory of the boundary is variable.
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Possible Explanation

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• But why would it be variable?

• Bad hardware
Possible Explanation

• There is an extra source of variability in the categorization task.
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• But why would it be variable?

• Bad hardware

or
Possible Explanation

• There is an extra source of variability in the categorization task.
• Maybe the animal can’t quite remember the 50% boundary, i.e., the memory of the boundary is variable.

• But why would it be variable?

• Bad hardware
or
• Wrong assumption about the environment (suboptimal inference)
Wrong World Model

• Perhaps the animal wrongly assumes that the task changes over time
Wrong World Model

• Perhaps the animal wrongly assumes that the task changes over time
• This would lead the animal to adjust the categorization boundary even though it should remain the same once properly learned
Choice Biases

• Decisions are biased toward the previous choice

Detection                           Categorization

Current trial difficulty:
- hard
- easy

Previous trial difficulty
Bad hardware? Stochastic boundary?
Bad hardware? Stochastic boundary?

\[ r_A(t) = N(kc_A^2, \sigma) \]

\[ s_A(t) = \int_{0}^{t} r_A(\tau) d\tau \]

\[ e = w_1 s_A(t) - w_2 s_B(t) + w_3 b \]
Bad hardware? Stochastic boundary?
Bad hardware? Stochastic boundary?

- Noise added to the weight

\[ r(t) = N(\theta, \sigma^2) \]

\[ s(t) = \int_{-\infty}^{t} r(\tau) \, d\tau \]

\[ e = w_1 s_1(t) - w_2 s_2(t) + w_0 b \]
Bad hardware? Stochastic boundary?

- Noise added to the weight
- Weights determine categorization boundary
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- Weights of (1,-1,0) correspond to black diagonal
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Noise in categorization boundary

Weights determine categorization boundary
- Weights of (1,-1,0) correspond to black diagonal

Noisy weights imply
Stochastic boundary is not enough

Detection

Categorization

% correct

Reaction time
Stochastic boundary is not enough

Detection

Categorization

% correct

Reaction time

% correct
Stochastic boundary is not enough
Adaptive DDM

\[ r(t) = N(kc^2, c) \]

\[ s(t) = \int_{-\infty}^{t} r(\tau) d\tau \]

\[ e = w_1 s(t) - w_2 s(t) + w_3 b \]

\[ \Delta w_3 = \lambda b \]

\[ \Delta \tilde{w} = \alpha(\Theta(t_d) - y(t_d))s \]

Reward-dependent learning
Adaptive DDM
Fits with Adaptive DDM
Fits with Adaptive DDM
Fits with Adaptive DDM
Fits with Adaptive DDM

Detection | Categorization
---|---

**Detection**
- **a** Accuracy (% correct)
- **b** Reaction time (ms) vs. Odor concentration (v/v)

**Categorization**
- **c** Accuracy (% correct)
- **d** Reaction time (ms) vs. Mixture contrast (%)

**Choice Bias**
- **e** Collapsed bias change vs. Odor concentration (v/v)
- **f** Collapsed bias change vs. Mixture contrast (%)

**Predicted**
Prediction For All Mixtures
Prediction For All Mixtures
Prediction For All Mixtures
General Principle
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• If you don’t know how the data were generated, behavior cannot be optimal, which leads to extra variability.
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• For most problems of interest, wrong assumptions about the data generating process is the main source of variability.
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• For most problems of interest, wrong assumptions about the data generating process is the main source of variability
Roadmap

Experiment 1: what appears as noise can be suboptimal inference

Experiment 2: noise only has a marginal impact on performance
Noise and Decoding
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In collaboration with Pitkow, Lakshminarasimhan, DeAngelis and Angelaki
Noise and Decoding

Does internal noise affect behavioral performance?
Noise and Decoding

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Does internal noise affect behavioral performance?

MT

V1

Optimal decoder

Decoder performance

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MT

V1

Optimal
decoder

Decoder performance

=

Behavioral performance

Noise
Noise and Decoding

MT

V1

Optimal decoder

Noise

Decoder performance

Behavioral performance

In collaboration with Pitkow, Lakshminarasimhan, DeAngelis and Angelaki
Information in behavior should be a tiny fraction (<5%) of the information recovered by the decoder.
Heading Discrimination

choose "left"  
choose "right"

heading  
h
Choice Correlations
Choice Correlations

• If the read-out is optimal, and the optimal decoder is linear, choice correlations should follow
Choice Correlations

• If the read-out is optimal, and the optimal decoder is linear, choice correlations should follow

$$C^\text{opt}_k = \frac{\theta}{\theta_k}$$

Correlations between cell responses and behavioral choices
If the read-out is optimal, and the optimal decoder is linear, choice correlations should follow

\[ C^\text{opt}_k = \frac{\theta}{\theta_k} \]
Choice Correlations

• If the read-out is optimal, and the optimal decoder is linear, choice correlations should follow

\[ C_{k}^{opt} = \frac{\theta}{\theta_k} \]

Correlations between cell responses and behavioral choices

Behavioral threshold

Threshold for neuron k
Choice Correlations

• If the read-out is optimal, and the optimal decoder is linear, choice correlations should follow

$$C_{k}^{opt} = \frac{\theta}{\theta_{k}}$$

Correlations between cell responses and behavioral choices

Behavioral threshold

Threshold for neuron $k$
Choice Correlations

\[ C_k = \beta \frac{\theta}{\theta_k} \]
Choice Correlations

\[ C_k = \beta \frac{\theta}{\theta_k} \]
Choice Correlations

\[ C_k = 3 \frac{\theta}{\theta_k} \]
Choice Correlations in VIP

• In VIP, some neurons are choice correlations near 1!
• In VIP, some neurons are choice correlations near 1!
Choice Correlations

VIP is odd!

\[ C_{k}^{opt} = 3 \frac{\theta}{\theta_k} \]
Choice Correlations

\[ C_k^{\text{opt}} = 3 \frac{\theta}{\theta_k} \]
Choice Correlations

$C_k^{opt} = 3 \frac{\theta}{\theta_k}$
This is only possible if $\text{VIP}$ is odd!

\[ C_{k}^{\text{opt}} = 3 \frac{\theta}{\theta_{k}} \]
Choice Correlations

This is only possible if
1- VIP is highly redundant with other areas

\[ C_{k}^{opt} = 3 \frac{\theta}{\theta_k} \]

This is only possible if
1- VIP is highly redundant with other areas
Choice Correlations

This is only possible if:
1. VIP is highly redundant with other areas
2. It’s not read out

\[ C_{k}^{opt} = 3 \frac{\theta}{\theta_{k}} \]
VIP and MSTd inactivation

- Inactivating VIP does not affect performance
Choice Correlations

This is only possible if
1- VIP is highly redundant with other areas
2- it’s not read out

\[ C_{k}^{opt} = 3 \frac{\theta}{\theta_{k}} \]
Noise and Decoding
Noise and Decoding

• About 80% of the information available in MSTd and VIP is reflected in behavioral performance. (Lakshminarasimhan, Liu, Gu, Pouget, DeAngelis, Angelaki and Pitkow. Submitted)
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• About 80% of the information available in MSTd and VIP is reflected in behavioral performance. (Lakshminarasimhan, Liu, Gu, Pouget, DeAngelis, Angelaki and Pitkow. Submitted)

• Noise contribution is 20%, at most, but it could be zero. Decoding may be suboptimal.
Conclusions
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Suboptimal Brain fest

With:
Mainen
Mendonca
Vicente
DeWitt

Pitkow
Angelaki
Lakshminarasimhan
De Angelis

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