

Experimental Design

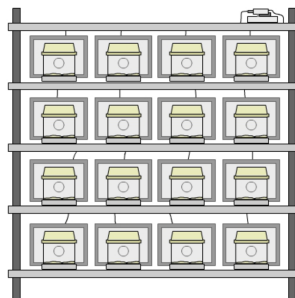
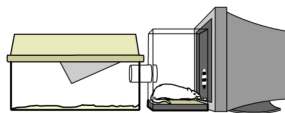
Drift Diffusion Model

Estimators

Simulations

Applications

Conclusions



Gabriel Riegner (work with Pamela Reinagel, Armin Schwartzman)  
UC San Diego, March 2025

Experimental Design

Drift Diffusion Model

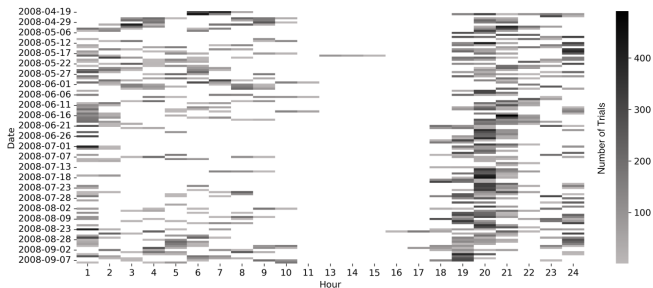
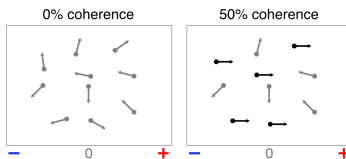
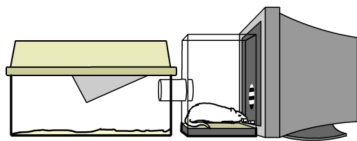
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[dot motion example]

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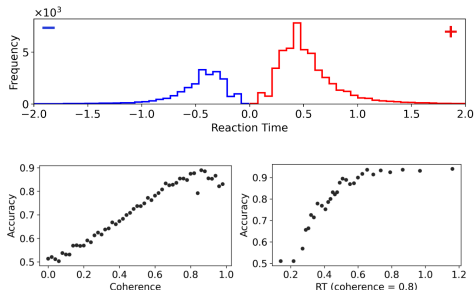
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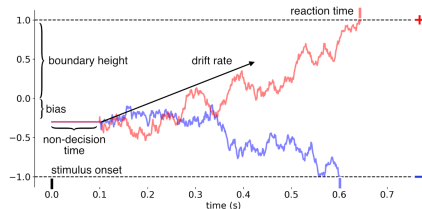
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References

Observed Behaviors:  
Speed + Accuracy



Unobserved Brain Mechanisms:  
Drift + Diffusion



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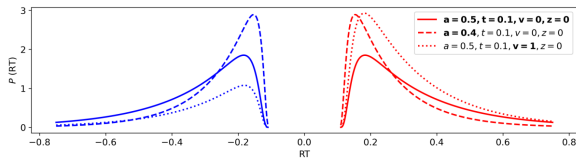
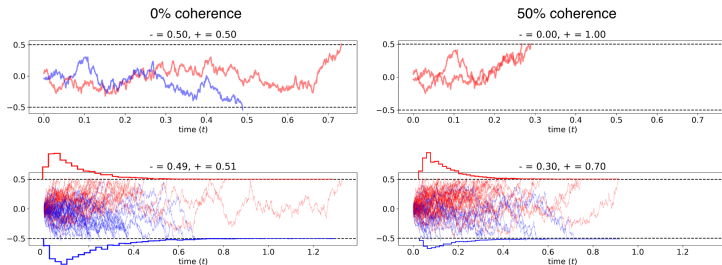
Estimators

Simulations

Applications

Conclusions

References



## Notation

## Drift Diffusion Model

$$Z_{\tau} = Z_{\tau-1} + e_{\tau}, \quad e_{\tau} \sim \mathcal{N}(v\Delta\tau, \sigma^2\Delta\tau) \quad (1)$$

$v \in \mathbb{R}$  is the drift rate

$\Delta\tau \rightarrow 0$  is a continuous *drift diffusion* process

**RT + Response for  $\{Z_{\tau} : \tau = 0, \dots, RT\}$**

$$RT = \begin{cases} +\min\{\tau > 0 : Z_{\tau} \geq +a\} \\ -\min\{\tau > 0 : Z_{\tau} \leq -a\} \end{cases} \quad (2)$$

$a > 0$  is the decision boundary

$|RT| > 0$  is the reaction time

$\text{sign}(RT) \in \{-1, +1\}$  is the response

**RTs + Responses for  $\{Z_{\tau} : \tau = 0, \dots, RT\}_t^T$**

$$RT_t = \{RT_1, \dots, RT_T\} \sim \mathcal{D}(a, v) \quad (3)$$

$t > 0$  is the trial time index

$\Delta t$  is nonconstant (unequally sampling)

$\mathcal{D}$  is probability distribution determined by parameters  $a$  and  $v$

Experimental Design

Drift Diffusion Model

Estimators

Simulations

Applications

Conclusions

References

## Definitions and Estimation

## Probability Density Function

$$f(RT | a, v) = \frac{\pi}{a^2} \exp\left(-\frac{va}{2} - \frac{v^2 t}{2}\right) \times \sum_{k=1}^{\infty} k \exp\left(-\frac{k^2 \pi^2 RT}{2a^2}\right) \sin\left(\frac{k\pi}{2}\right) \quad (4)$$

from Feller [1], Navarro and Fuss [2]

## Likelihood Function

$$L_T(a, v | RT_t) = f(RT_t, \dots, RT_T | a, v) = \prod_{t=1}^T f(RT_t | a, v) \quad (5)$$

## Log-Likelihood Function

$$\ell_T(a, v | RT_t) = \log L_T(a, v | RT_t) = \sum_{t=1}^T \log f(RT_t | a, v) \quad (6)$$

MLE  $\hat{\theta}$  of  $\theta = (a, v)$

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} - \ell_T(\theta | RT_t) \quad (7)$$

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Drift Diffusion Model

Estimators

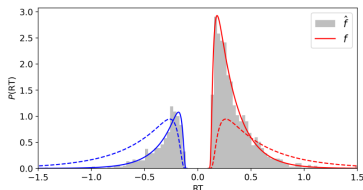
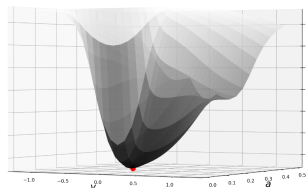
Simulations

Applications

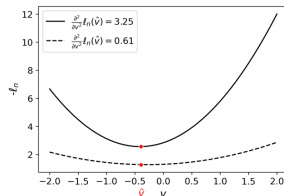
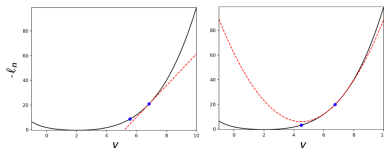
Conclusions

References

Loss Log-Likelihood



Loss Log-Likelihood Hessian



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Simulations

Applications

Conclusions

References

## Asymptotic Covariance Estimators

$$\hat{\mathcal{H}}_{\theta} = \frac{1}{T} \sum_{t=1}^T -\frac{\partial^2}{\partial \theta \partial \theta'} \log f(RT_t | \hat{\theta}) = -\frac{1}{T} \frac{\partial^2}{\partial \theta \partial \theta'} \ell_T(\hat{\theta}) \quad (8)$$

$$\hat{\mathcal{J}}_{\theta} = \frac{1}{T} \sum_{t=1}^T \left( \frac{\partial}{\partial \theta} \log f(RT_t | \hat{\theta}) \right) \left( \frac{\partial}{\partial \theta} \log f(RT_t | \hat{\theta}) \right)' = \frac{1}{T} \sum_{t=1}^T \hat{S}_t \hat{S}_t' \quad (9)$$

**(1) Sample Hessian**

$$\hat{V}_1 = \hat{\mathcal{H}}_{\theta}^{-1} \quad (10)$$

**(2) Outer Product**

$$\hat{V}_2 = \hat{\mathcal{J}}_{\theta}^{-1} \quad (11)$$

**(3) Misspecification Robust**  $\mathcal{J}_{\theta} \neq \mathcal{H}_{\theta}$ 

$$\hat{V}_3 = \hat{\mathcal{H}}_{\theta}^{-1} \hat{\mathcal{J}}_{\theta} \hat{\mathcal{H}}_{\theta}^{-1} \quad (12)$$

**(4) Autocorrelation Robust**

$$\hat{V}_4 = \hat{\mathcal{H}}_{\theta}^{-1} \left( \frac{1}{T} \sum_{i,j=1}^T w_{|i-j|} \hat{S}_i \hat{S}_j' \right) \hat{\mathcal{H}}_{\theta}^{-1} \quad (13)$$

from Hansen [3, Chapter 10]

Experimental Design

Drift Diffusion Model

Estimators

Simulations

Applications

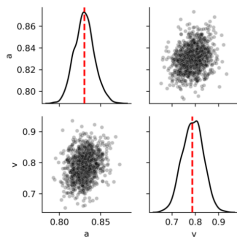
Conclusions

References

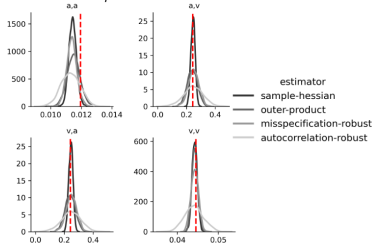


**Setting:**  $a = 0.83$ ,  $v = 0.79$ ,  $N = 1000$  repeats,  $T = 900$  trials

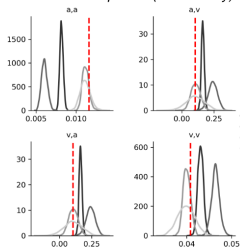
MLE



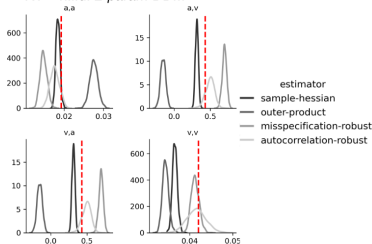
$RT \sim i.i.d.$  2-param DDM



$RT \sim i.i.d.$  2-param (+ variability) DDM



$RT \sim n.i.d.$  2-param DDM



Experimental Design

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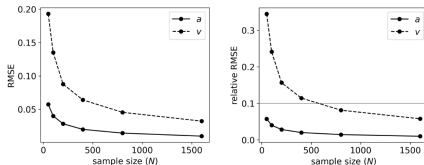
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Applications

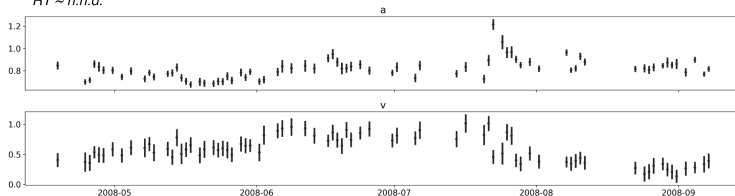
Conclusions

References

**Dataset:**  $N = 1$  rat,  $T = 120k$  trials over 128 days



$RT \sim n.n.d.$



Shevinsky and Reinagel [4], Nguyen and Reinagel [5]

- Drift diffusion model describes how brains process noisy information during two-choice decision tasks
- MLE provides consistent point and interval estimators for model parameters and their covariances from speed/accuracy behavioral data
- Generalized estimation framework robust to model misspecification and autocorrelation in reaction times
- Non-stationarity over time addressed by time-varying parameter estimation of freely behaving rats
- Future work: Extending models to incorporate covariates explaining parameter changes over time

- [1] William Feller. *An introduction to probability theory and its applications*. Wiley series in probability and mathematical statistics. J. Wiley, New York Chichester Brisbane [etc.], third ed. rev edition, 1968. ISBN 978-0-471-25708-0.
- [2] Daniel J. Navarro and Ian G. Fuss. Fast and accurate calculations for first-passage times in Wiener diffusion models. *Journal of Mathematical Psychology*, 53(4): 222–230, August 2009. ISSN 00222496. doi: 10.1016/j.jmp.2009.02.003. URL <https://linkinghub.elsevier.com/retrieve/pii/S0022249609000200>.
- [3] Bruce E. Hansen. *Probability and statistics for economists*. Princeton University Press, Princeton ; Oxford, 2022. ISBN 978-0-691-23594-3.
- [4] Carly A. Shevinsky and Pamela Reinagel. The Interaction Between Elapsed Time and Decision Accuracy Differs Between Humans and Rats. *Frontiers in Neuroscience*, 13: 1211, November 2019. ISSN 1662-453X. doi: 10.3389/fnins.2019.01211. URL <https://www.frontiersin.org/article/10.3389/fnins.2019.01211/full>.
- [5] Quynh Nhu Nguyen and Pamela Reinagel. Different Forms of Variability Could Explain a Difference Between Human and Rat Decision Making. *Frontiers in Neuroscience*, 16:794681, February 2022. ISSN 1662-453X. doi: 10.3389/fnins.2022.794681. URL <https://www.frontiersin.org/articles/10.3389/fnins.2022.794681/full>.