Brendan Harris[1]
Leonardo Gollo[2], Ben D. Fulcher[1]
[1]School of Physics, The University of Sydney
[2]School of Psychological Sciences, Monash University

Tracking the distance to criticality across the mouse visual hierarchy

Published in : *Physical Review X*
as *"Tracking the Distance to Criticality in Systems with Unknown Noise"*

bhar9988@uni.sydney.edu.au
@brendanjohnh
@brendanjohnharris
@brendanjohnharris.bsky.social

1 | Motivation *Do higher cortical regions sit closer to criticality?*

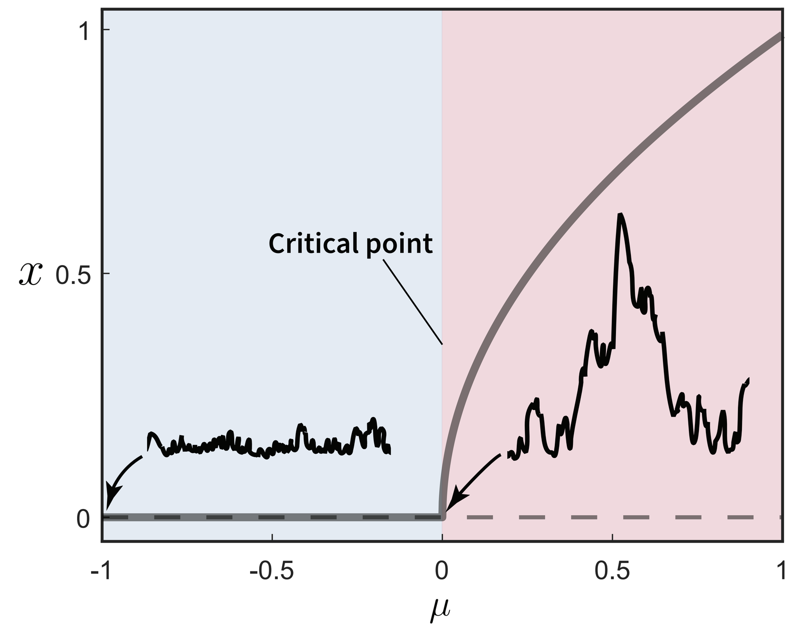
The dynamics of many complex systems can be understood in terms of their **distance to criticality** (DTC; *right*).

Criticality is thought to provide various **computational advantages** [1, 2], such as:

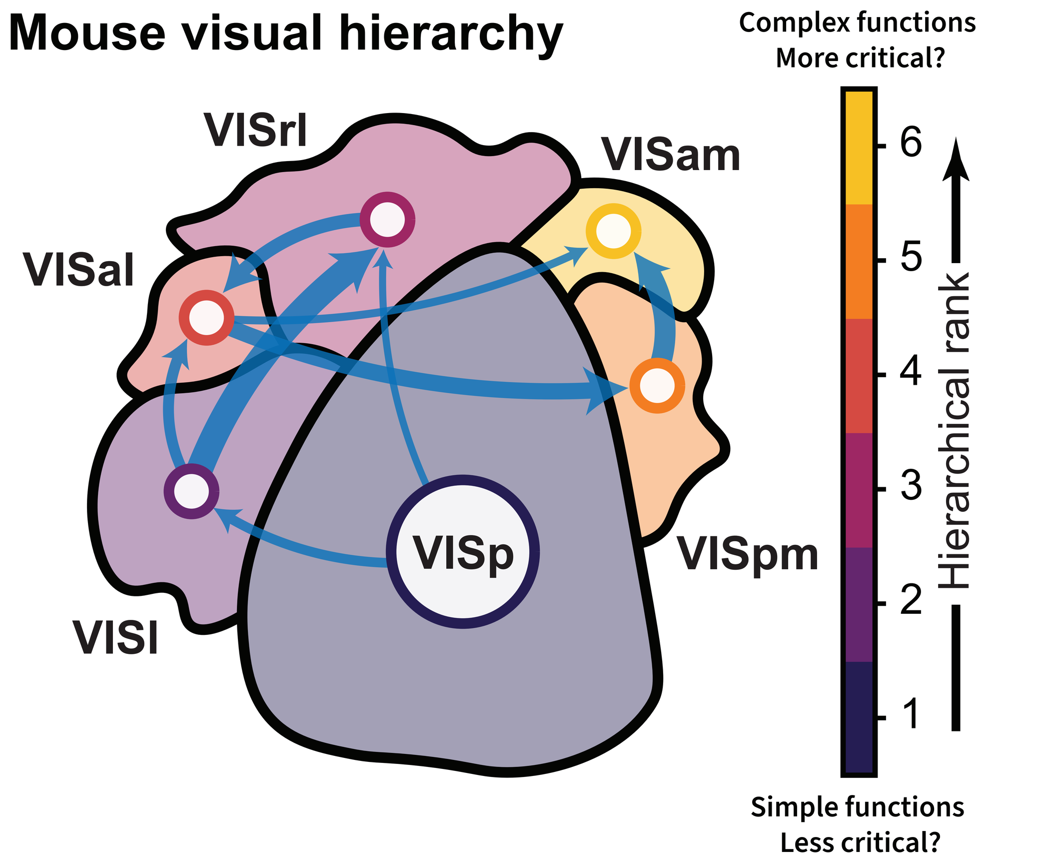
- Enhanced dynamic range
- Input separation and sensitivity
- Information-storage capacity
- Information-transfer capabilities.

To leverage these advantages, the brain might operate in a critical state [3] or fluctuate around a critical threshold [4].

Near-critical dynamics



Mouse visual hierarchy



Brain regions further along the **cortical hierarchy** (*left*) are thought to be positioned closer to criticality [4], utilizing **longer timescales** [5] for e.g. **multimodal integration** [6]. However, evidence for this is scarce.

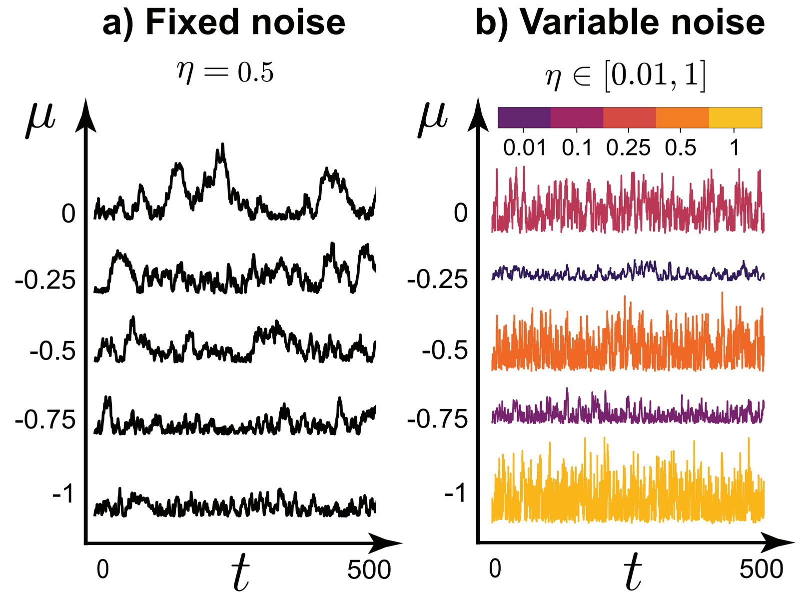
To **test** whether the DTC varies across the cortical hierarchy, **we need accurate metrics** that work well on **noisy neural data** and are robust against **confounding variations between brain regions**.

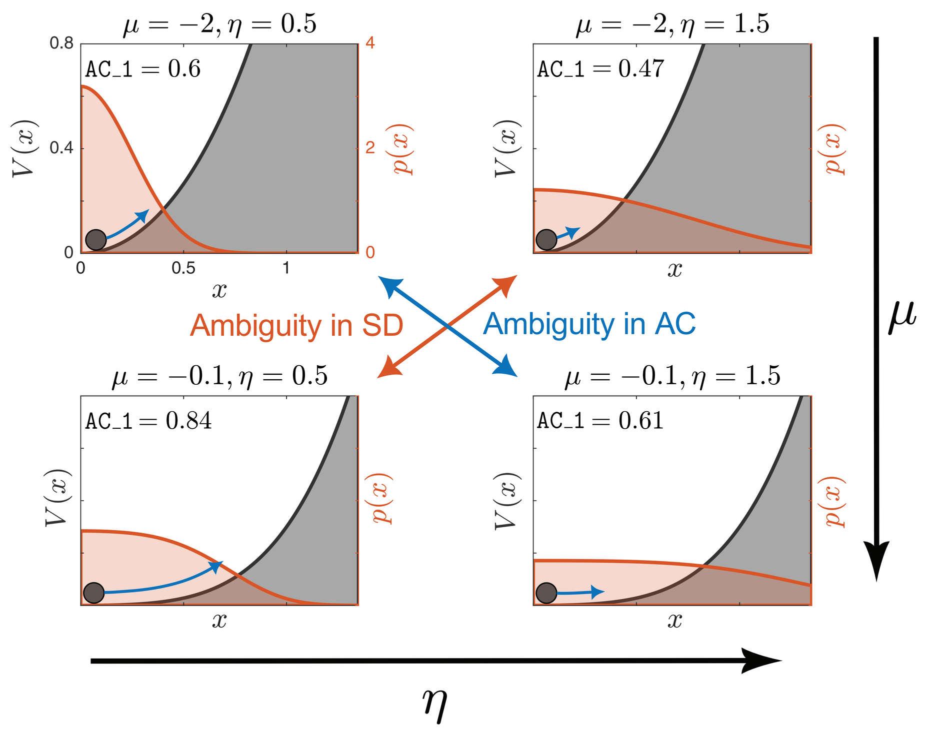
2 | Problem *Uncertain noise levels corrupt conventional metrics*

Existing metrics of the DTC derive from analytically tractable systems with **fixed** or low-amplitude **dynamical noise**.

These metrics can **fail** on real-world systems with **uncertain noise levels**, like the brain.

Right: a) With a fixed noise strength (η), approaching criticality (raising μ) robustly increases variance and timescale. b) With a variable noise strength, these properties no longer change consistently with the DTC.





Two conventional metrics are **variance and autocorrelation**, which detect '**critical slowing-down**' but are also highly sensitive to the **noise level**.

Left: The potential *V(x)* depends on the DTC μ. The shape of *V(x)* and noise strength η determine the distribution *p(x)* and autocorrelation `AC_1`. *p(x)* and `AC_1` ambiguously estimate the DTC in the presence of uncertain noise: unique (μ, η) pairs can result in the same feature value.

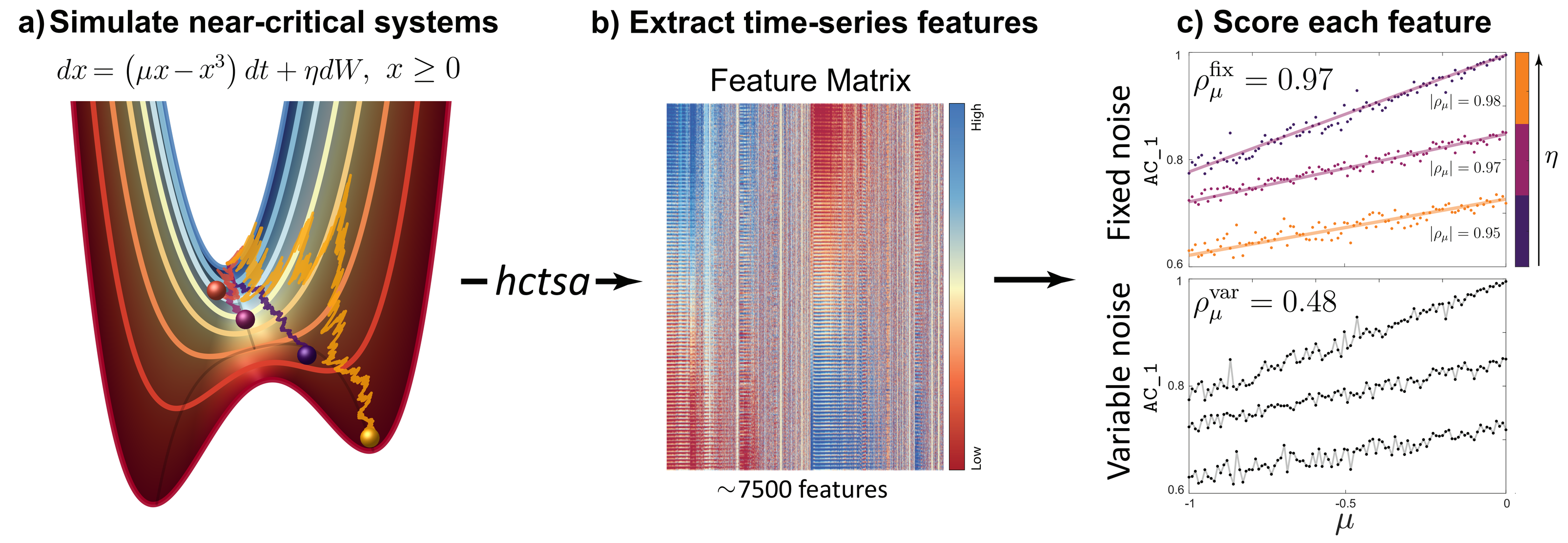
3 | Solution *Wide methodological comparison to generate new theory*

We introduce a **data-driven method** for developing a **practical, noise-robust metric** of the DTC.

Step 1: Evaluate thousands of **time-series features** for their performance under variable noise

Step 2: **Study top features** and their common elements **to generate new theory**.

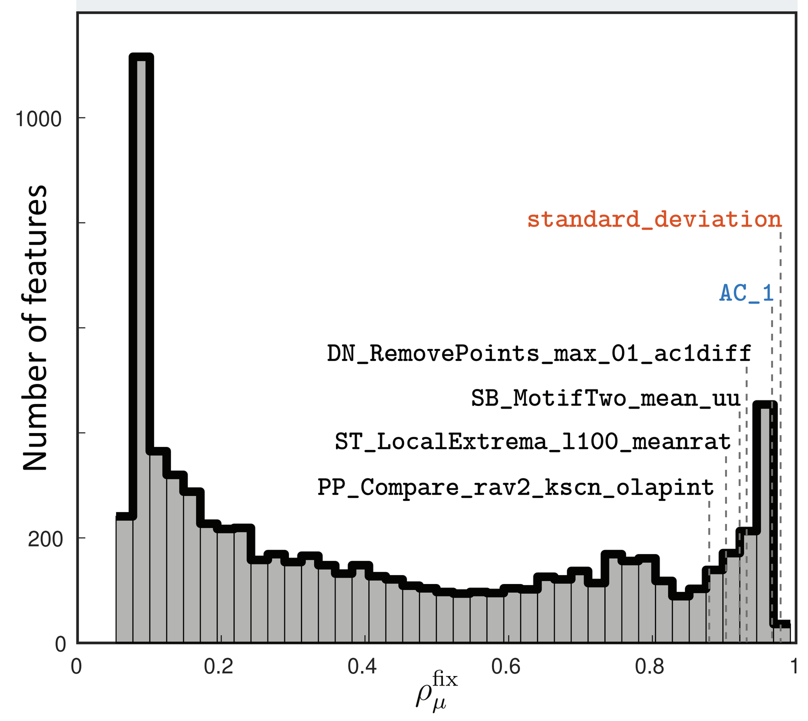
Below: a) We simulated noisy time series from a near-critical system for different DTCs. b) We used *hctsa* [7] to extract a comprehensive set of >7000 features from each time series. c) We scored each feature by its performance in the fixed-noise and variable-noise settings.



Fixed-noise scores

With fixed noise, **conventional metrics** of critical slowing-down **can accurately track the DTC**.

Below: A histogram of fixed-noise scores across all >7000 *hctsa* features. Top features are related to autocorrelation (`AC_1`), which captures the slower timescales near criticality, or `standard_deviation`, which captures increased variance.

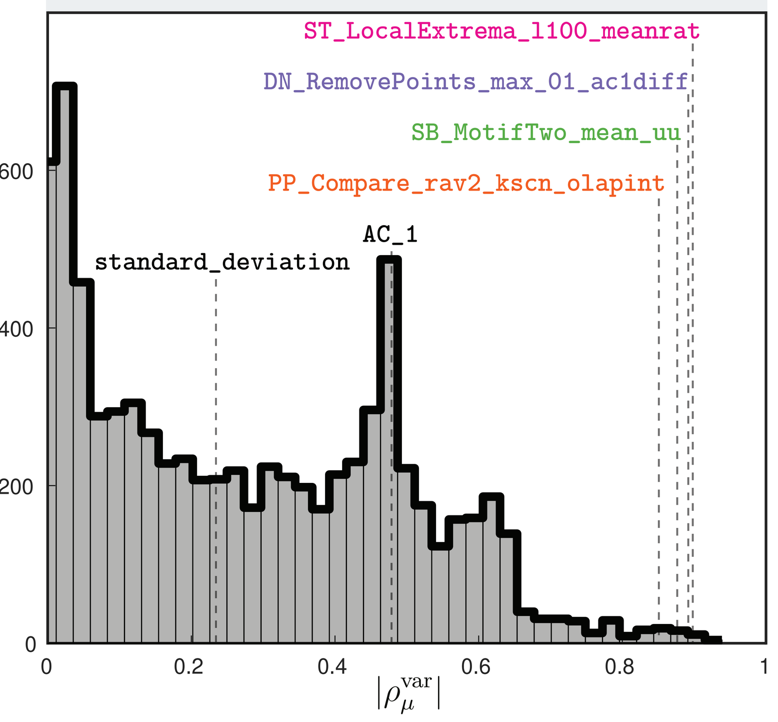


Variable-noise scores

With variable noise, **conventional metrics fail**.

But we find **new features** that **consistently vary with the DTC** over confounding changes in noise level.

Below: Histogram of variable-noise scores. Conventional features have scores of < 0.5, but a small tail of new features have surprising scores of > 0.8.



New metric: RAD

We found the top features measure the **time-series distribution** (which depends on DTC + noise level) relative to the **spread of fast fluctuations** (depends only on noise level).

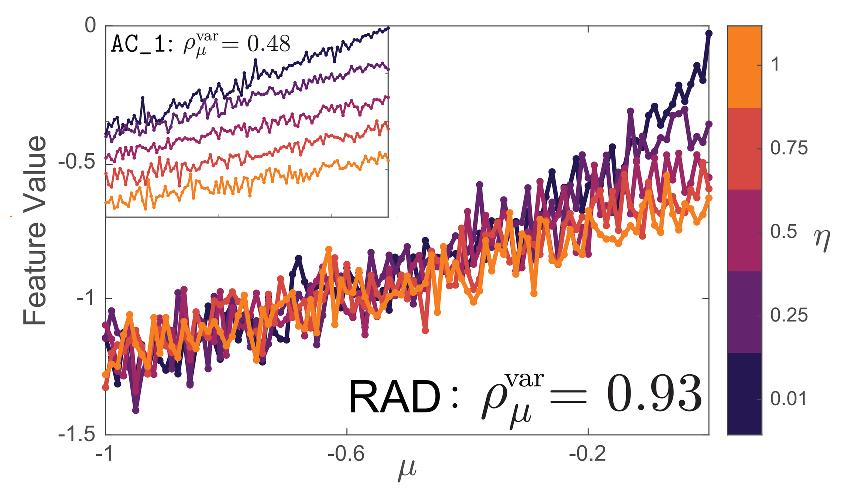
With this understanding, we **reverse-engineered** a new **noise-robust metric** of DTC: **the rescaled auto-density**, RAD.

Spread of differences

$$f_{\text{RAD}} = \sigma(\Delta x)\left[\frac{1}{\sigma(U)} - \frac{1}{\sigma(L)}\right]$$

Spread of extreme values   Spread of central values

Right: RAD measures the 'tailedness' of the distribution after rescaling by the std. dev. of differences, and robustly tracks the DTC with a variable-noise score of 0.93. *U* and *L* are the upper and lower 50% of values.



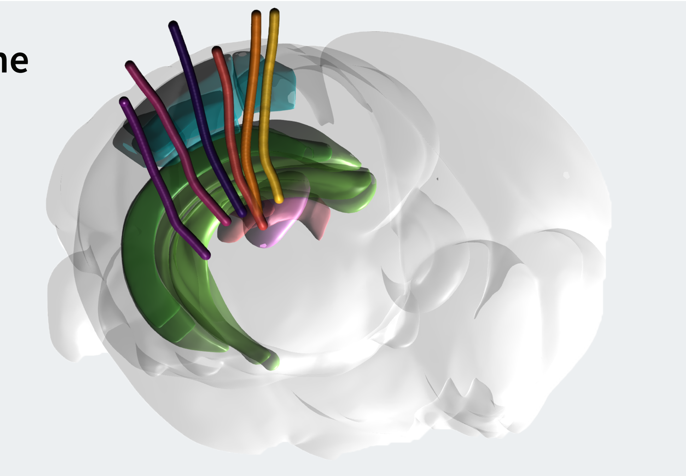
4 | Application *RAD suggests higher cortical regions are more critical*

We hypothesized that the **DTC decreases along the visual hierarchy**, but that brain regions may be subject to **different levels of dynamical noise**.

Does RAD track hierarchical level better than conventional, noise-sensitive metrics?

To test this hypothesis, we compared:

1. **RAD** values for **Neuropixels LFP** from each area of the **mouse visual cortex**.
2. **Hierarchical ranks** of each area, calculated independently from anatomical data [8].

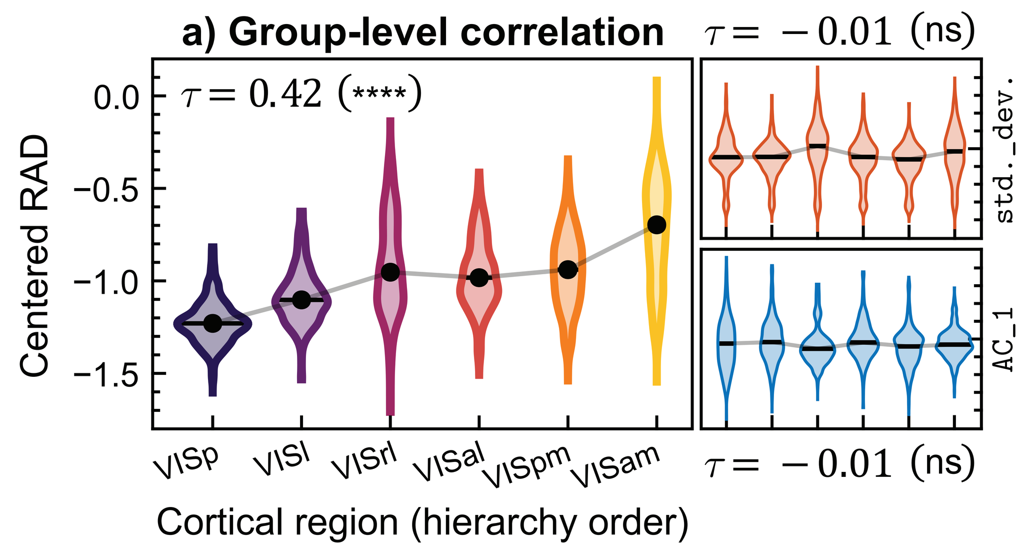


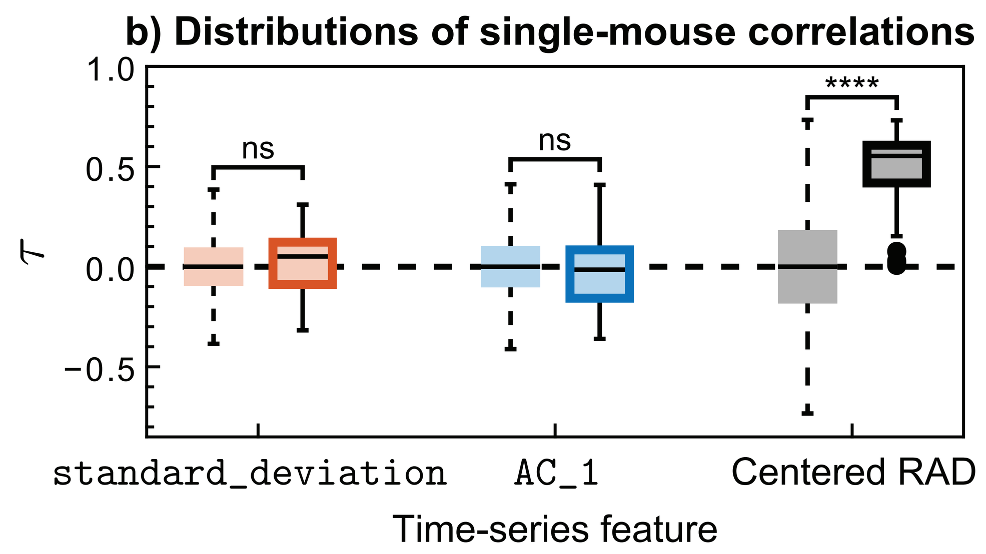
Above: The mouse brain with six Neuropixels probes targeting six visual cortical areas (the 'Allen Neuropixels - Visual Behavior' dataset).

Right: a) RAD values for each visual area, pooled over mice (N=39) and recording channels (n≈19). RAD increases along the hierarchy with a strong Kendall's τ correlation of 0.42 ($p < 10^{-6}$). Correlations for `standard_deviation` and `AC_1` are non-significant.

b) Distributions of individual Kendall's τ across N = 39 mice (*solid*). RAD τs are significantly greater than probe-shuffled nulls (*dashed*, $p < 10^{-18}$), unlike `standard_deviation` and `AC_1` (not significant).

RAD increases robustly along the hierarchy, but conventional metrics do not. This indicates that **higher visual areas may be closer to criticality**, with each area feeling a different level of dynamical noise.





Summary

Using a **data-driven approach**, we generated **theoretical insight** to develop a **new noise-robust metric for tracking the DTC**: RAD.

Applied to neural data, RAD finds a pattern of brain organization that is not detected by conventional metrics: that **higher cortical regions are positioned closer to criticality**.

Future applications of RAD

Accurate DTC metrics are important for:

- Seizure detection
- Wake-sleep transition
- Brain stimulation
- Climate change
- Ecosystem collapse
- Power-system failure

RAD is a **simple**, **efficient** algorithm that could be readily applied to noisy time-series data from these settings.

Code for RAD is available in:

julia   Matlab   Python

References

1. Shew & Plenz, *The functional benefits of criticality in the cortex*, The Neuroscientist (2012).
2. Munoz, *Criticality and dynamical scaling in living systems*, Reviews of Modern Physics (2018).
3. O'Byrne & Jerbi, *How critical is brain criticality?*, Trends in Neuroscience (2022).
4. Cocchi et al., *Criticality in the brain: A synthesis of neurobiology, models and cognition*, Progress in Neurobiology (2017).
5. Murray et al., *A hierarchy of intrinsic timescales across primate cortex*, Nature Neuroscience (2014).
6. D'Souza et al., *Hierarchical and nonhierarchical features of the mouse visual cortical network*, Nature Communications (2022).
7. Fulcher & Jones, *hctsa: A Computational Framework for Automated Time-Series Phenotyping Using Massive Feature Extraction*, Cell Systems, 2017.
8. Siegle et al., *Survey of spiking in the mouse visual system reveals functional hierarchy*, Nature (2021).