

Bistability at the cellular level promotes robust and tunable criticality

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Research Context

The **cortex** is thought to operate **near a critical point**.

Criticality is when the activity in **one neuron on average triggers** activity in **another neuron** in a network.

is an **optimal** mode of operation for **information processing**.

is a **biomarker** modulated by age, disease, and physiological state.

Problem: The **neural mechanisms** underlying criticality remain **unknown**.

➔ We investigate the neural mechanisms underlying criticality at the cellular level.

We hypothesize that criticality can already be assessed at the cellular level, and that it can be modulated by cellular mechanisms (excitability properties, noise, ...).

There exist a **myriad of methods** in the literature to **assess and quantify criticality**.

We **focus** on the Detrended Fluctuation Analysis (**DFA**) and the Avalanche analysis using the **Shape Collapse** and the **mean size S** depending on the duration **D** computation.

Hybrid model

$$\begin{aligned} \dot{v} &= v^2 + b \cdot v \cdot w - w^2 + I + \eta \\ \dot{w} &= \varepsilon(a \cdot v - w + w_0) \end{aligned}$$

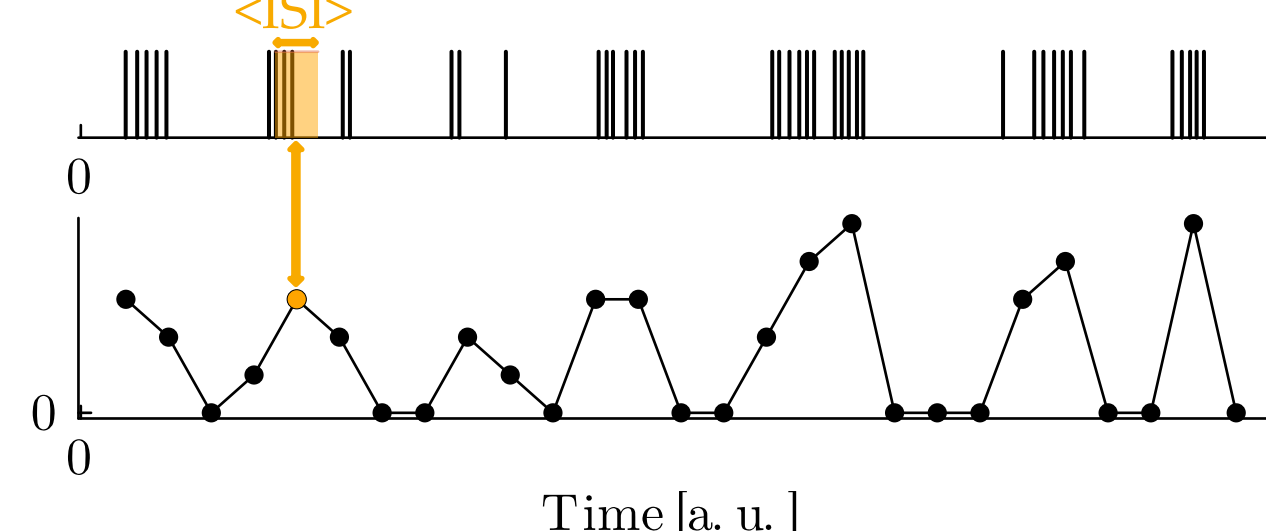
parameters: $b=10.1$, $c=15$, $d=15$, $w_0=100$

If $v \geq v_{th}$, then $v \leftarrow c$, $w \leftarrow d$

Analysis methods

Goal: Extracting power-law exponents from \neq methods

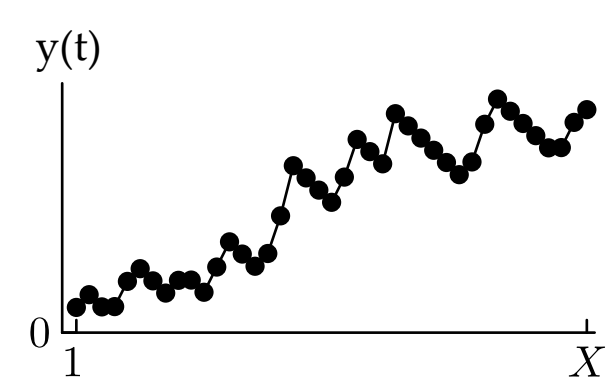
Spike train (v)



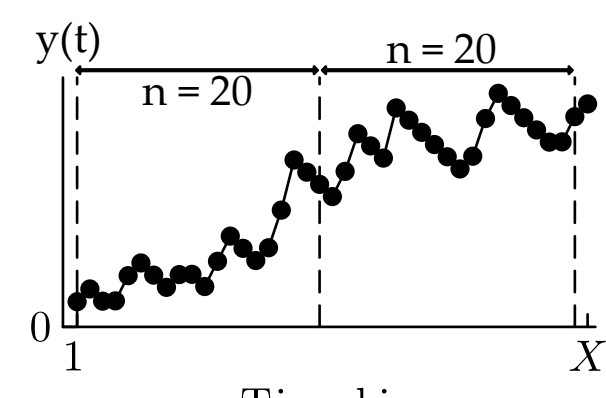
Spike count

DFA on Spike Count

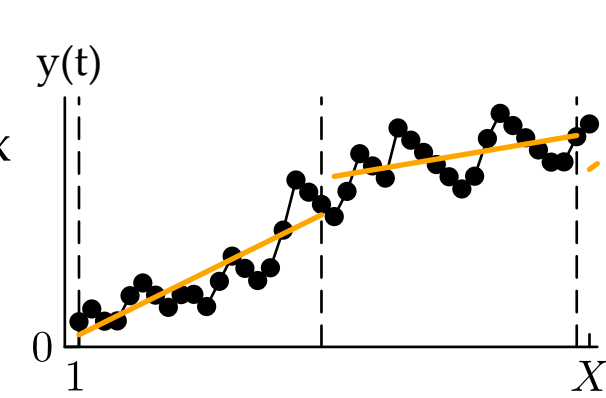
Compute $y(t)$, the cumulative mean-centered spike count



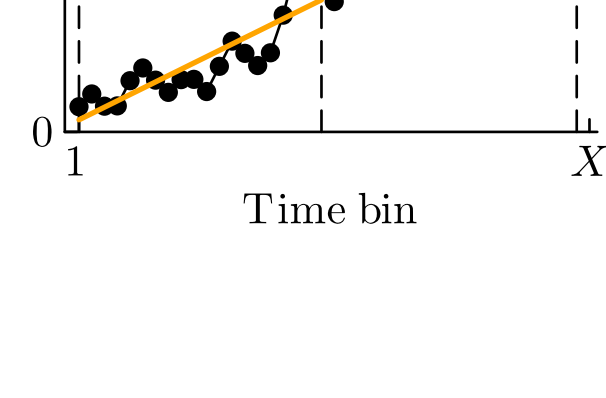
Divide the x-axis into boxes of size $n = \#$ time bins



Fit the best line $\hat{y}_n(t)$ into each box



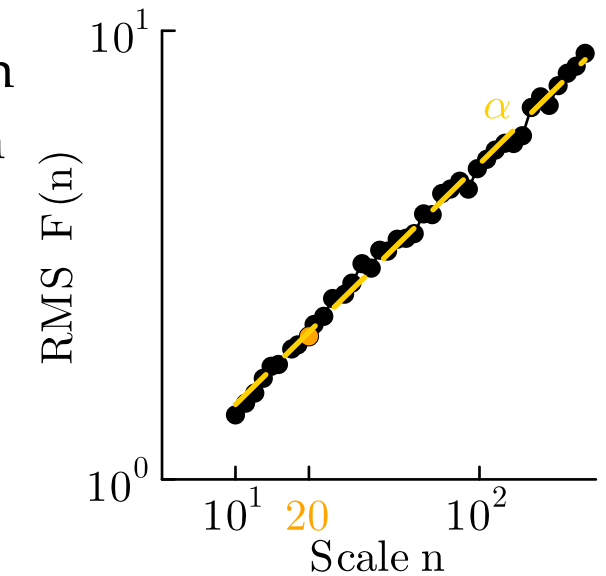
Remove $\hat{y}_n(t)$ from $y(t)$



Compute the RMS

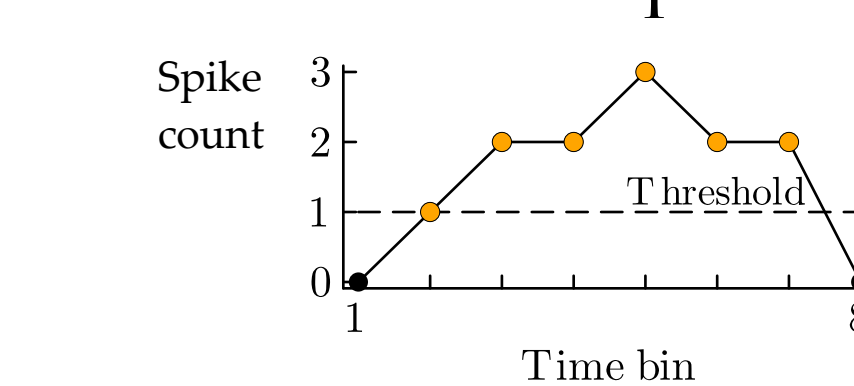
$$F(n) = \sqrt{\frac{1}{N} \sum_{t=1}^N (y(t) - \hat{y}_n(t))^2}$$

Plot $F(n)$ against n in a log-log graph



Fit by a line and extract the slope α

Avalanche Description



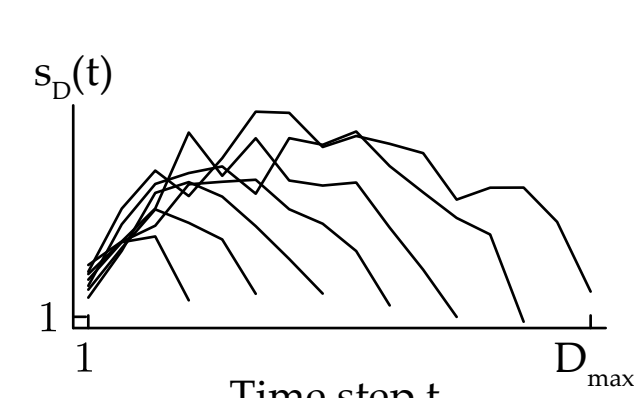
Duration $D = \#$ time bins whose spike count is \geq threshold

Size $S = \text{Total spike count} \geq \text{threshold}$

Profile = Spike count of avalanche over time

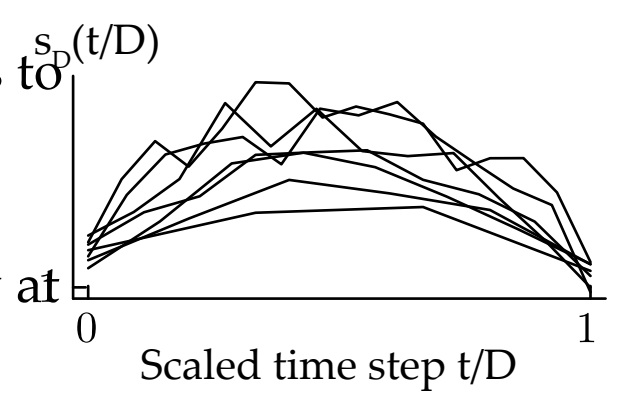
Shape Collapse on Avalanches

Compute the average profile $s_p(t)$ for a fixed D



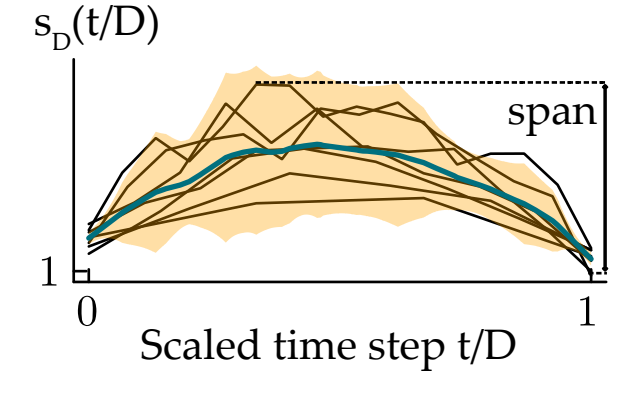
Repeat for all D

Rescale the profiles to a uniform length

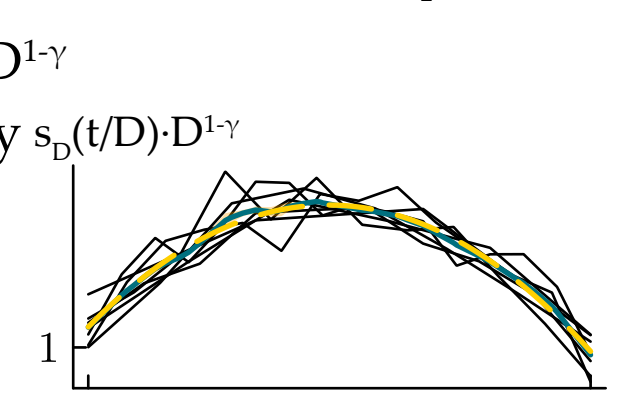


Interpolate linearly at 1000 points

Compute the span and the variance across profiles



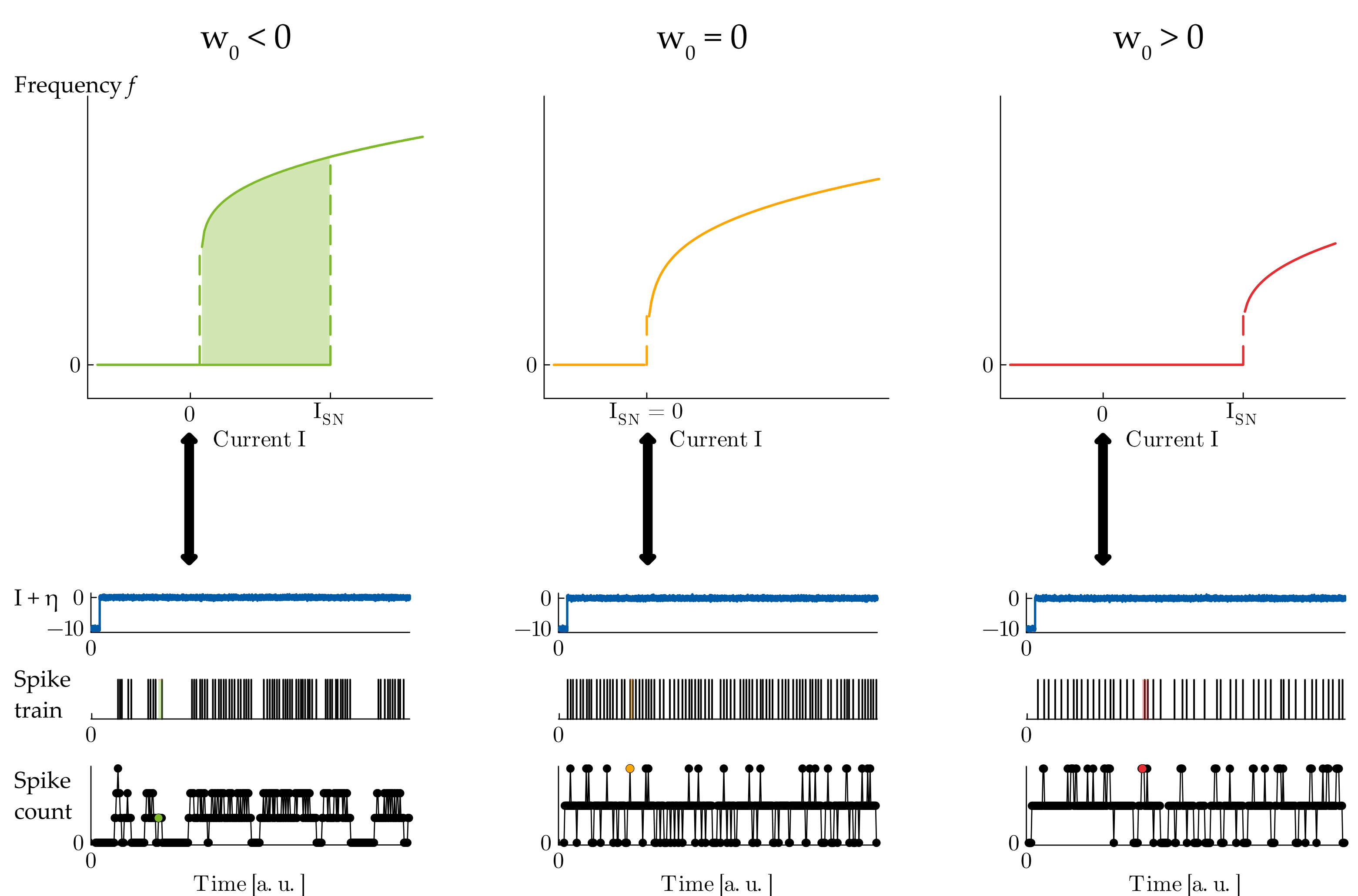
Rescale $s_p(t/D)$ by $D^{1-\gamma}$ where γ is found by $\min_{\gamma} \frac{\text{variance}(\gamma)}{\text{span}(\gamma)^2}$



Fit the shape collapse by $a \cdot x^2 + b \cdot x + c$

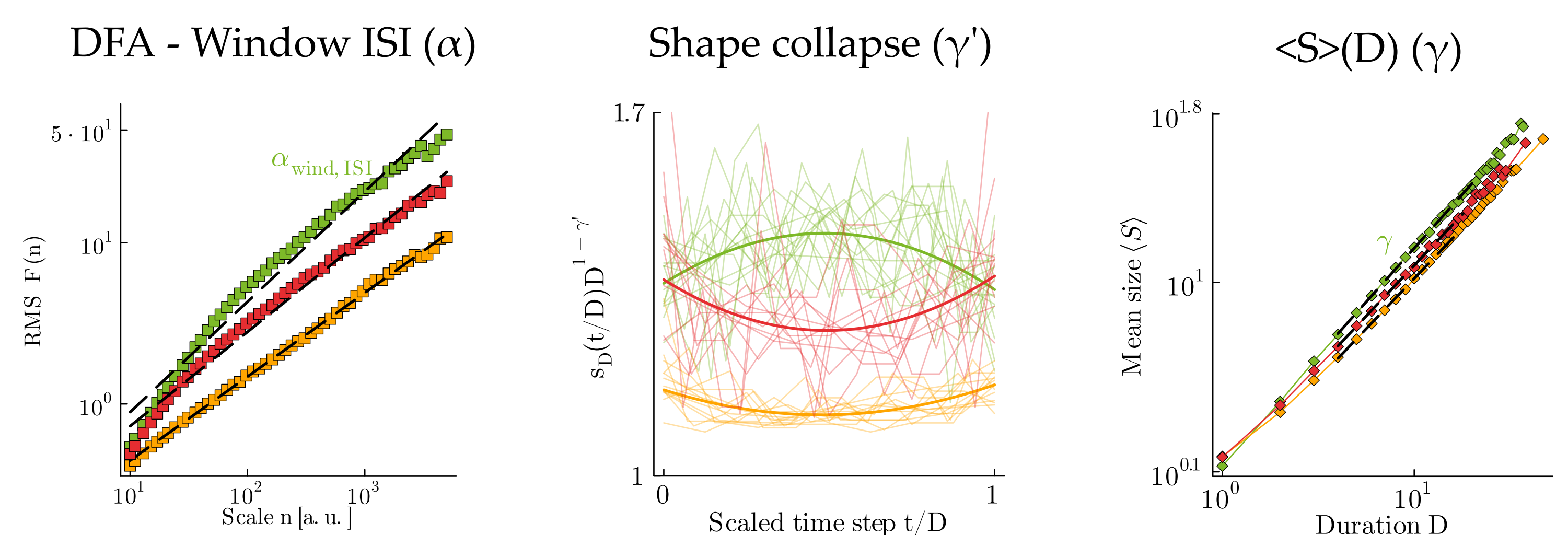
Findings: The criticality properties are tuned

by modulating the neuronal excitability properties and the noise.

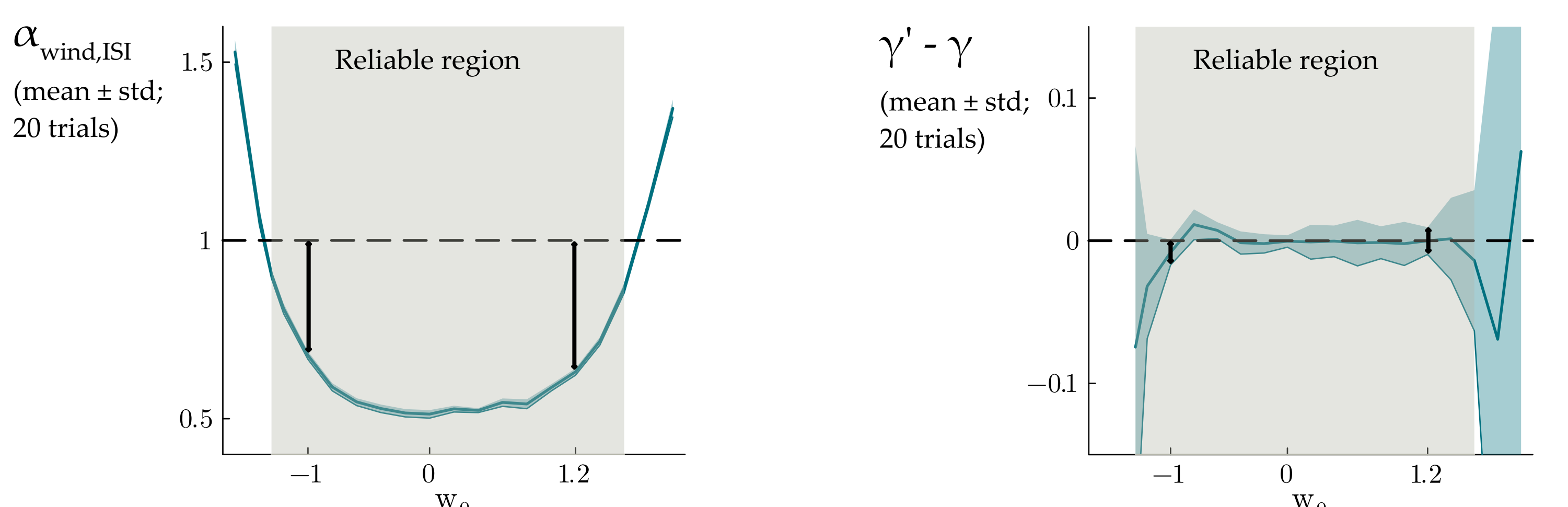


We apply DFA on the spike count, and the shape collapse and the mean size $\langle S \rangle(D)$ computation on the spike count-derived avalanches.

Then, we extract their power-law exponents (or their slope in a log-log graph).



At criticality, the power-law exponents should satisfy $\alpha \approx 1$ from DFA and $\gamma' - \gamma \approx 0$ from the shape collapse and $\langle S \rangle(D)$, respectively.



Take-home messages

Criticality is a reliable health indicator.

Criticality can be tuned by modulating the slow feedback gain (w_0) of neurons, and the environmental noise.

At the cellular level, the power-law exponents collectively suggest that a neuron is closer to criticality when it lies within a bistable regime.