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# Mutual Information measures as a connectivity indicator

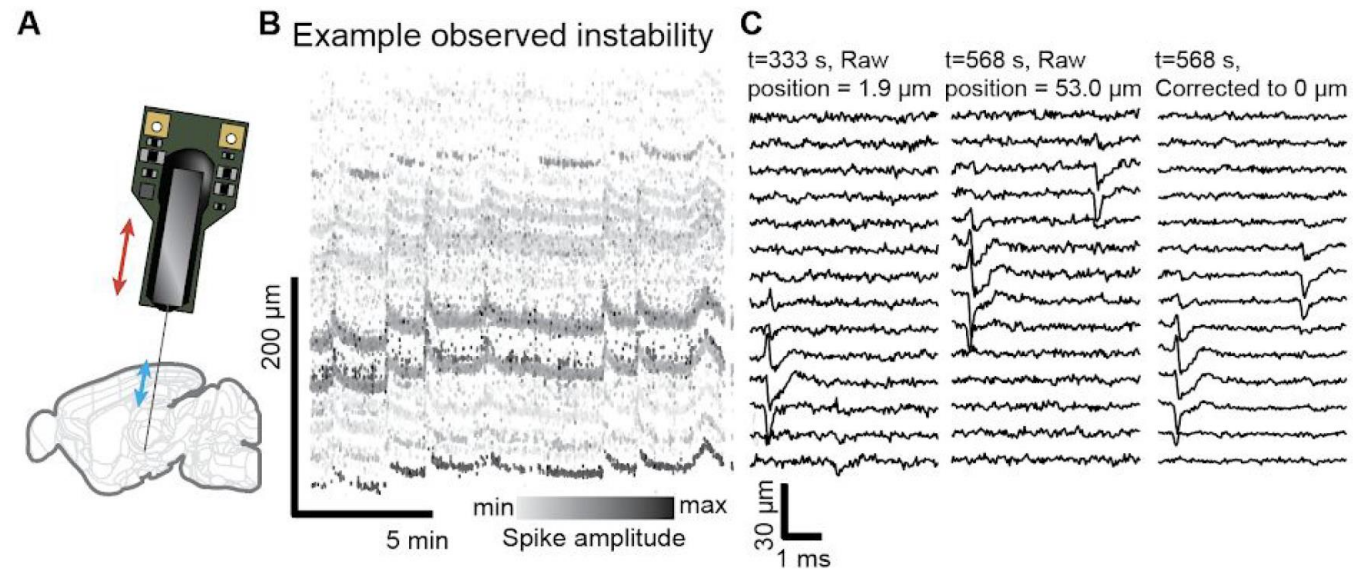
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# Introduction. Dataset

- Which data?
  - Mice with 2 genotypes, **wild type** (eu) and **trisomic** (ts)
- How?
  - **Neuropixel** high density probes
- Where? **Prefrontal cortex**, with neurons from:
  - Supplementary Motor Cortex (M2)
  - Anterior Cingulate Cortex (AC)
  - PreLimbic Cortex (PrL)
  - InfraLimbic Cortex (IL)

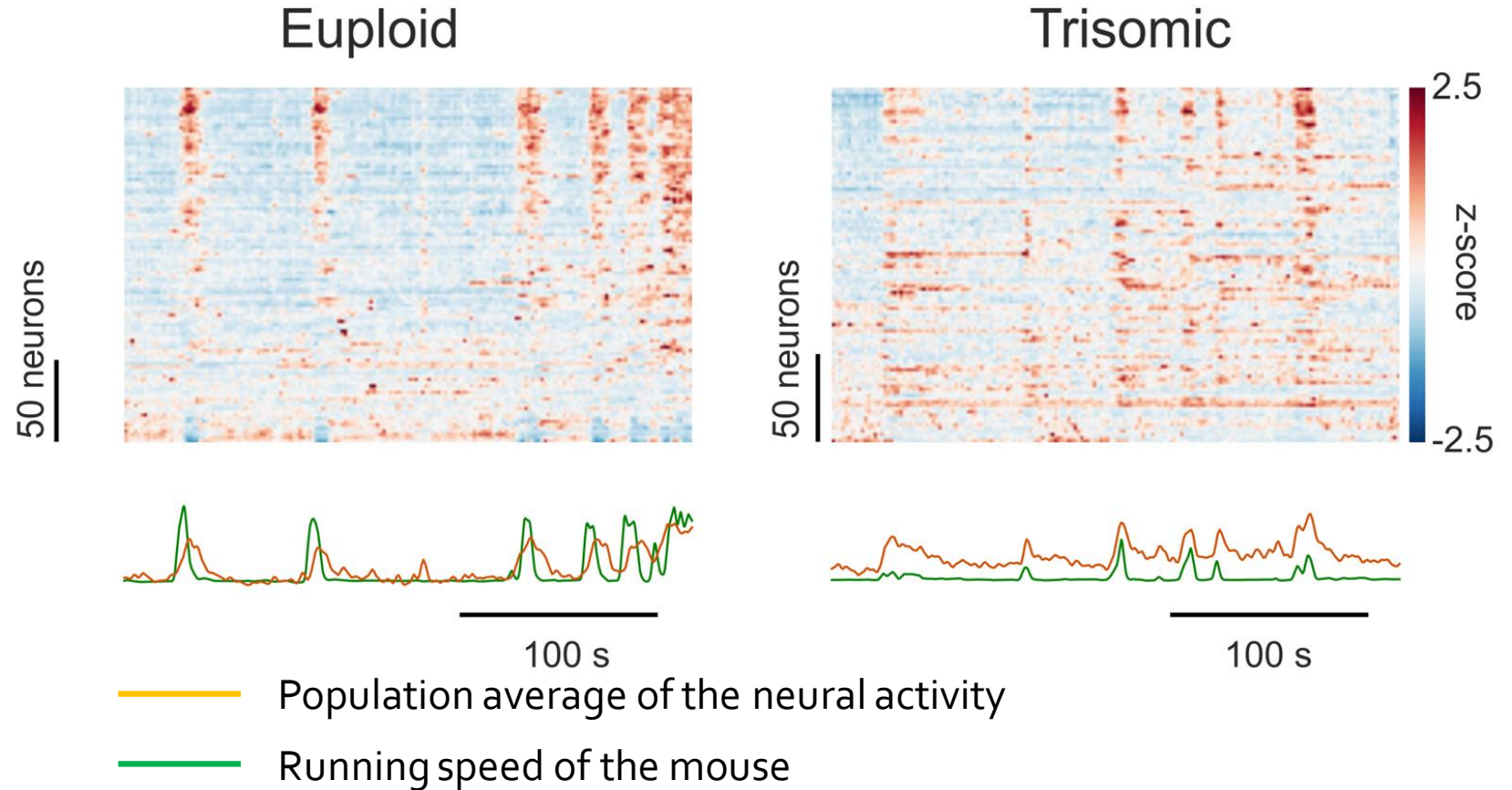


Extracted from **Figure 3** of *Nicholas A. Steinmetz et al. , Neuropixels 2.0: A miniaturized high-density probe for stable, long-term brain recordings*. Science, 372,eabf4588(2021).DOI:10.1126/science.abf4588

# Introduction. Problem

From the Neuropixels,  
we can extract the  
individual neural activity  
of ~200 recorded  
neurons and compare it  
to behavioral variables  
(locomotion)

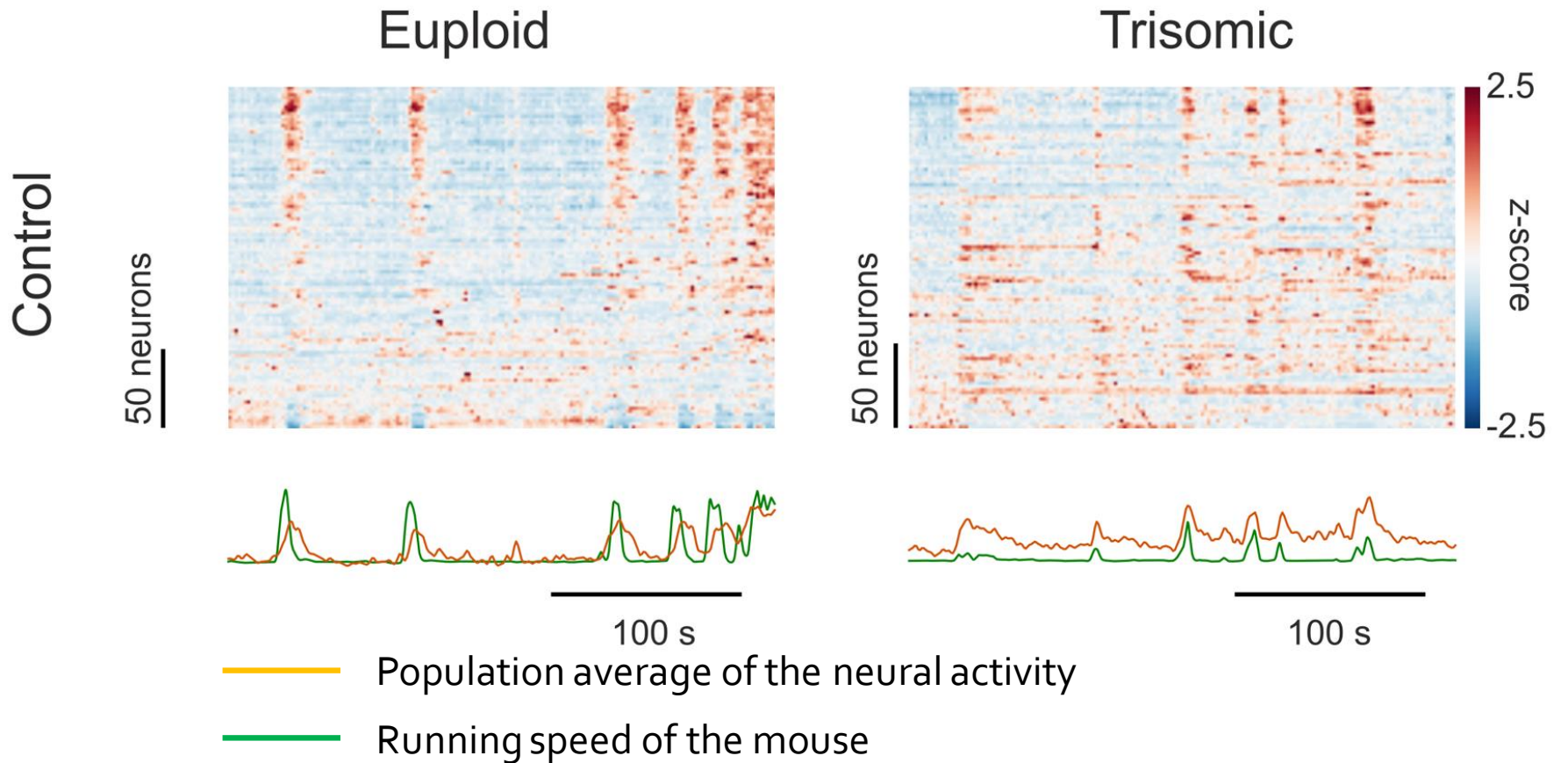
Control



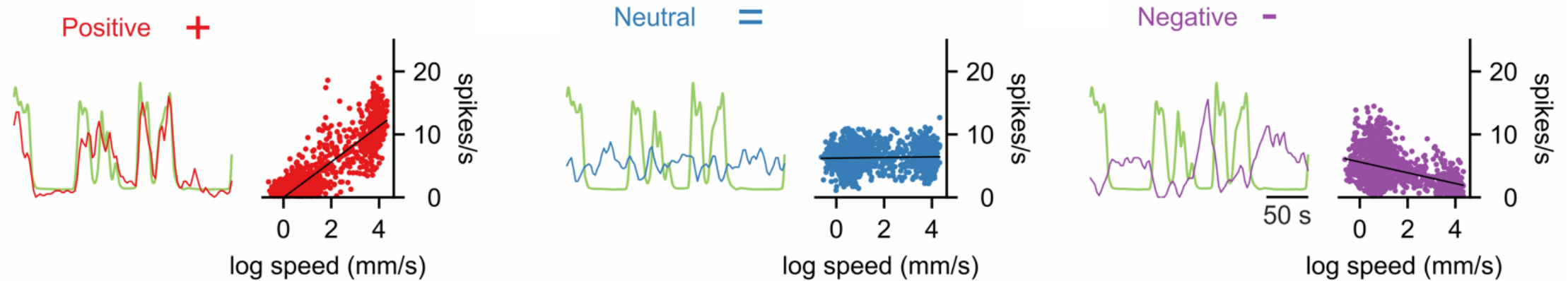
# Introduction. Problem

From the Neuropixels,  
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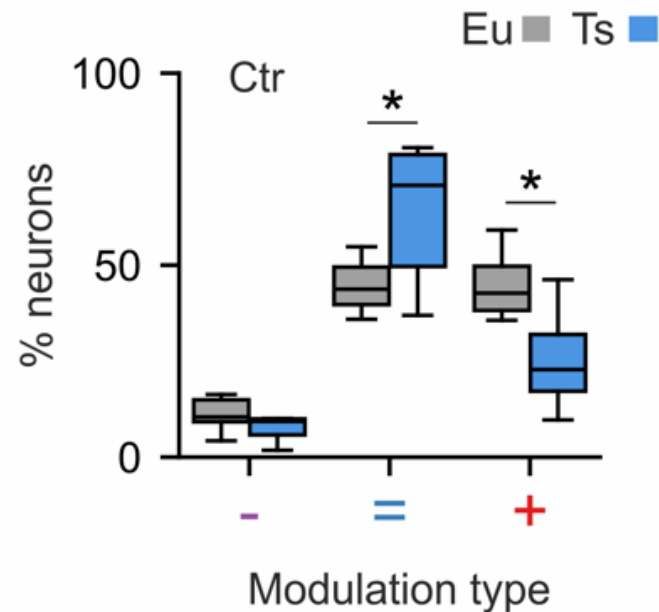
Why do the neural  
activity and  
locomotion  
decorrelate in the  
trisomic mice?



# Preliminary results



Attending to this classification, we see the following...



... but can we learn something in this dataset from the network point of view?

↓  
Coherence measures



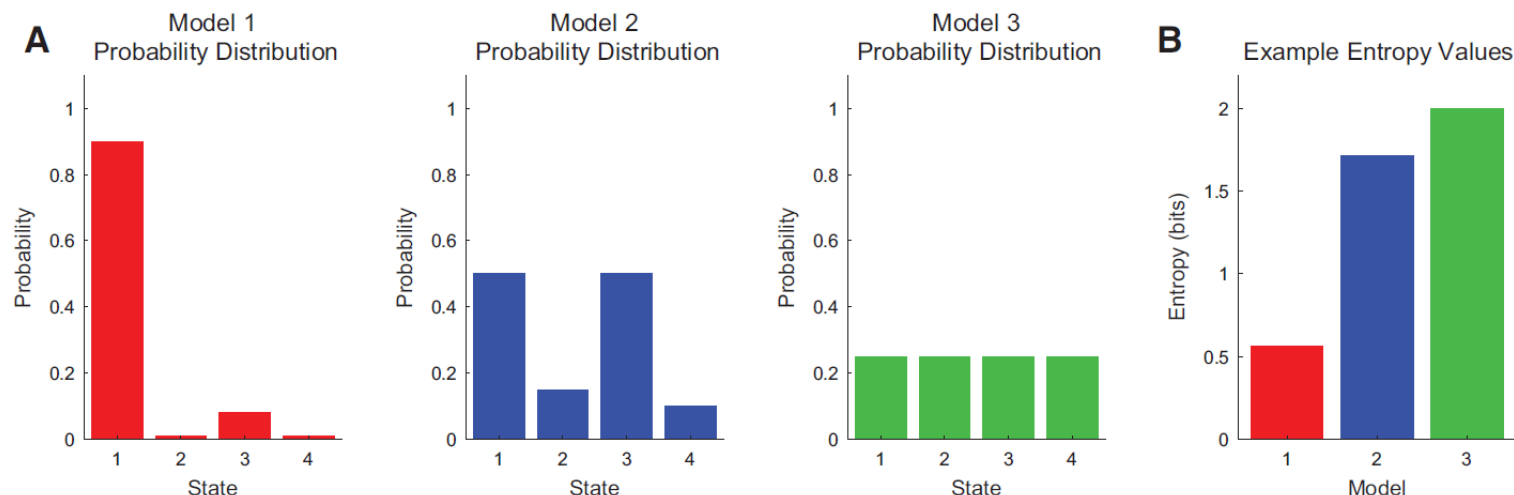
# Entropy & Mutual Information

## Shannon Entropy

$$H(X) = - \sum p(x) \log_2 p(x)$$

$p(x) \equiv$  probability distribution of variable  $X$

- Measures the **uncertainty** in the probability distribution, the more random (uniform) the higher the entropy
- If measured in bits, it also correspond to the number of **yes/no questions** we need to characterize the distribution



**Figure 3.** Example entropy calculations. **A**, Example probability distributions for three models (red, blue, and green); **B**, their associated entropy values. Model 1 was most likely to be in state 1, so it had low entropy. Model 3 was equally likely to be in all four states, so it had maximum entropy. Uniform count binning (see *Data Binning*) will produce equally likely states and maximize entropy, similar to Model 3.

Nicholas M. Timme, Christopher Lapish, *A Tutorial for Information Theory in Neuroscience*, eNeuro 29 June 2018, 5 (3) ENEURO.0052-18.2018; DOI: 10.1523/ENEURO.0052-18.2018

# Entropy & Mutual Information

## Shannon Entropy

$$H(X) = - \sum p(x) \log_2 p(x) dx$$

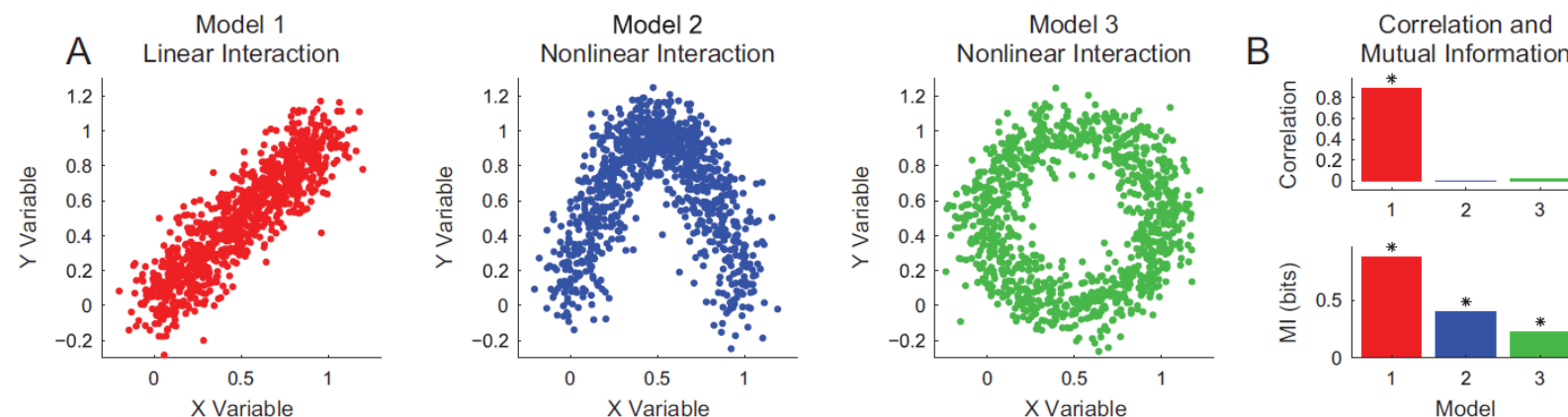
$p(x) \equiv$  probability distribution of variable  $X$

## Mutual Information

$$I(X, Y) = H(X) + H(Y) - H(X, Y)$$

$H(X, Y) \equiv$  joint entropy (shared)

- MI tells us the **reduction in uncertainty** that we get in one variable by knowing the other

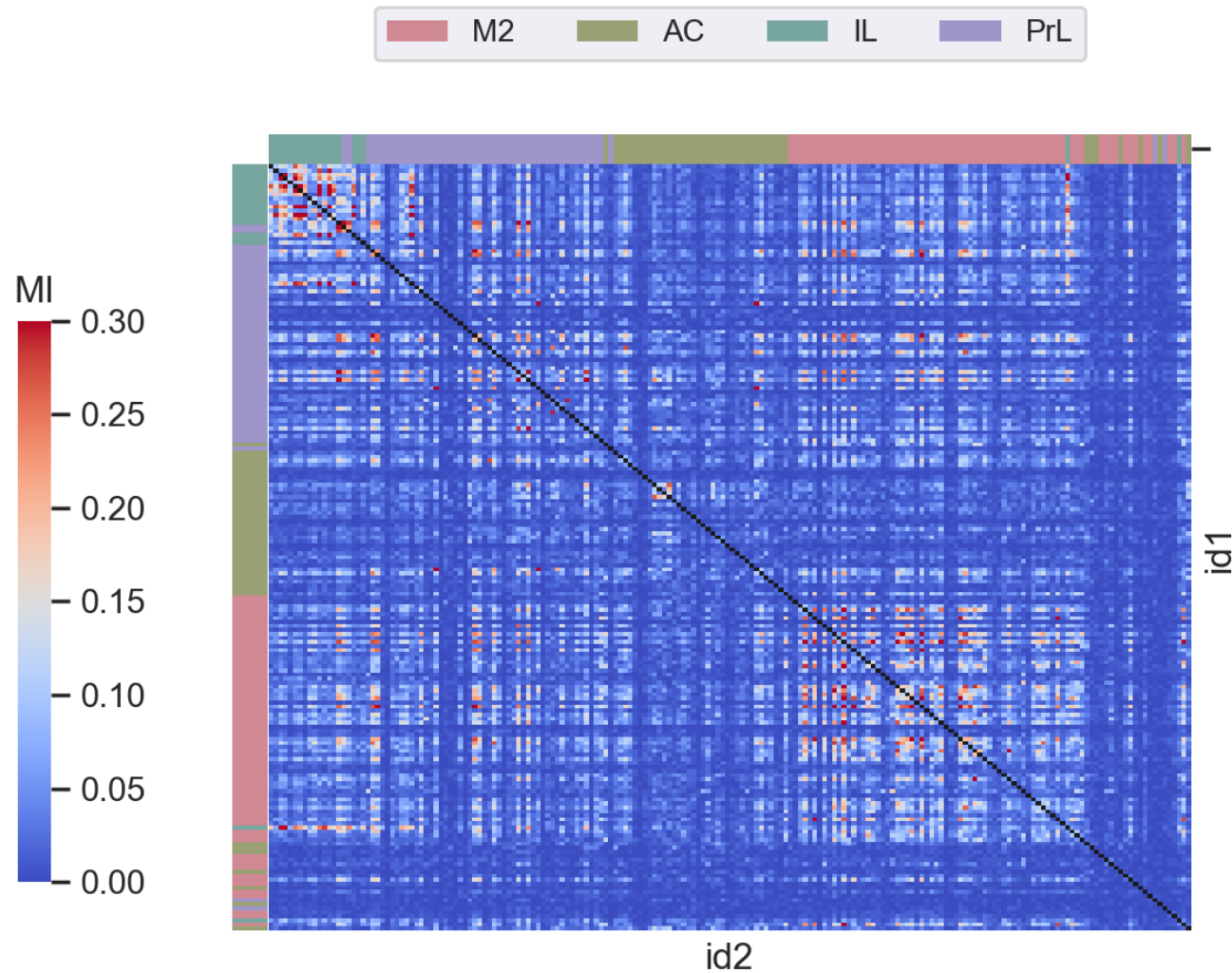


**Figure 5.** Example of linear versus nonlinear analysis methods. **A**, Example data for three models (red, blue, and green) with linear (red) and nonlinear (blue and green) interactions; **B**, the associated correlation coefficient and mutual information (MI) values for all three models (star:  $p < 0.05$ , correlation coefficient and  $p$ -value calculated via MATLAB, mutual information and  $p$ -value calculated via the Neuroscience Information Theory Toolbox; see *Data Binning and Significance Testing*, 4 bins and 1000 null data sets).

Nicholas M. Timme, Christopher Lapish, *A Tutorial for Information Theory in Neuroscience*, eNeuro 29 June 2018, 5 (3) ENEURO.0052-18.2018; DOI: 10.1523/ENEURO.0052-18.2018

# Results

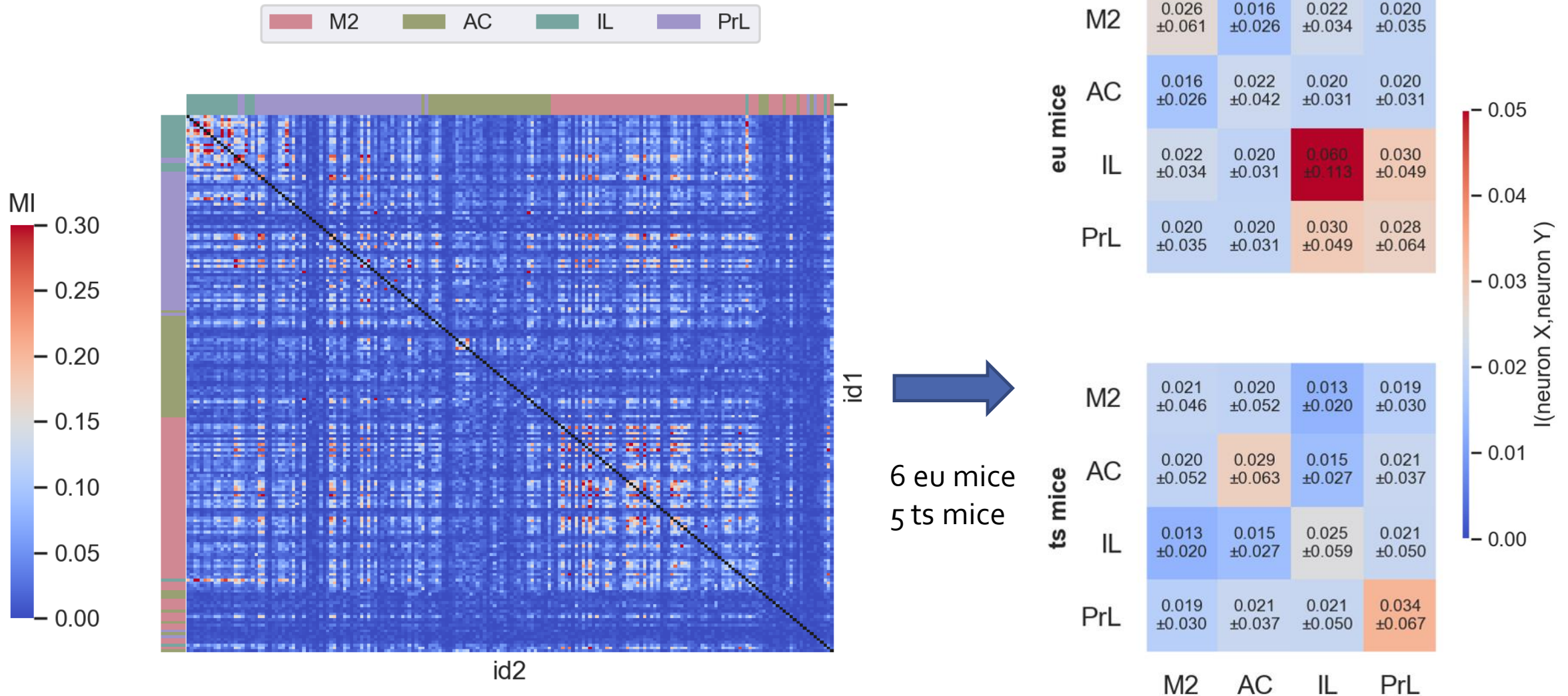
Neuropixels  $\rightarrow$  Spike trains  $\rightarrow$  Continuous time series of spiking rates with time bin  $\Delta t \rightarrow$  Mutual Information measure between neurons pairs





# Results

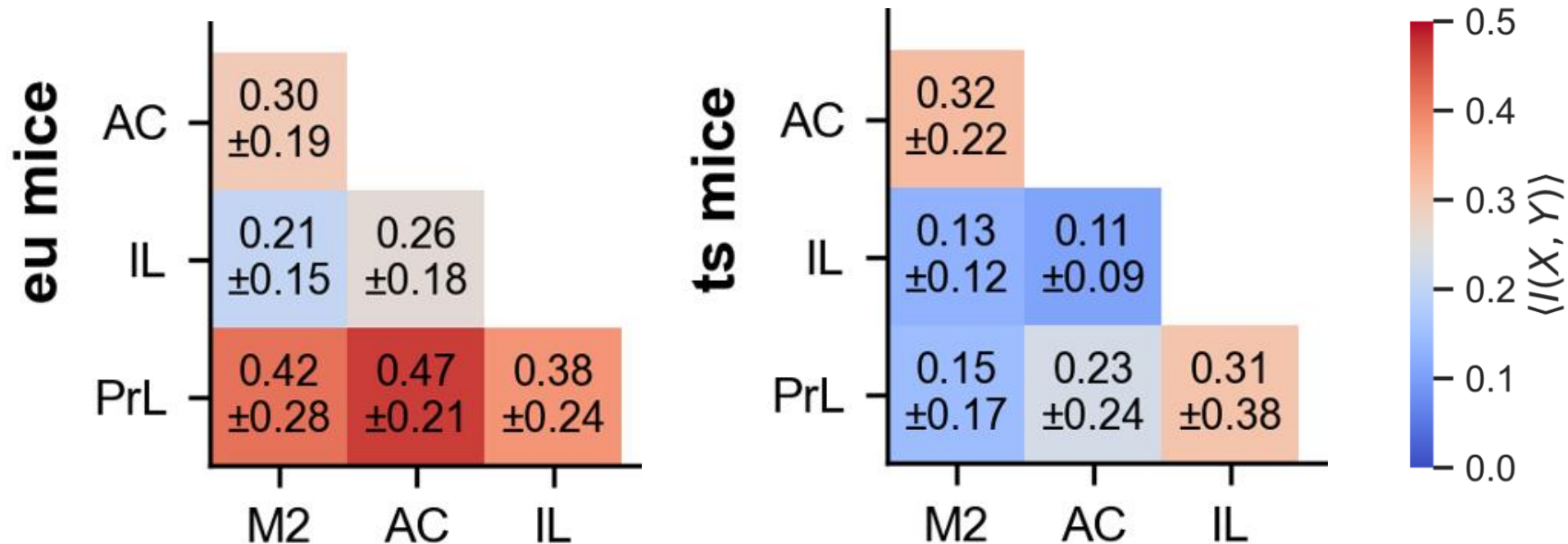
Neuropixels  $\rightarrow$  Spike trains  $\rightarrow$  Continuous time series of spiking rates with time bin  $\Delta t \rightarrow$  Mutual Information measure between neurons pairs  $\rightarrow$  Average between populations and mice



# Results

Neuropixels → Spike trains → Spiking rates → Population averages by cortical region  
→ Mutual Information measure between population pairs

What if we now consider the MI between each population rate instead of single neurons?

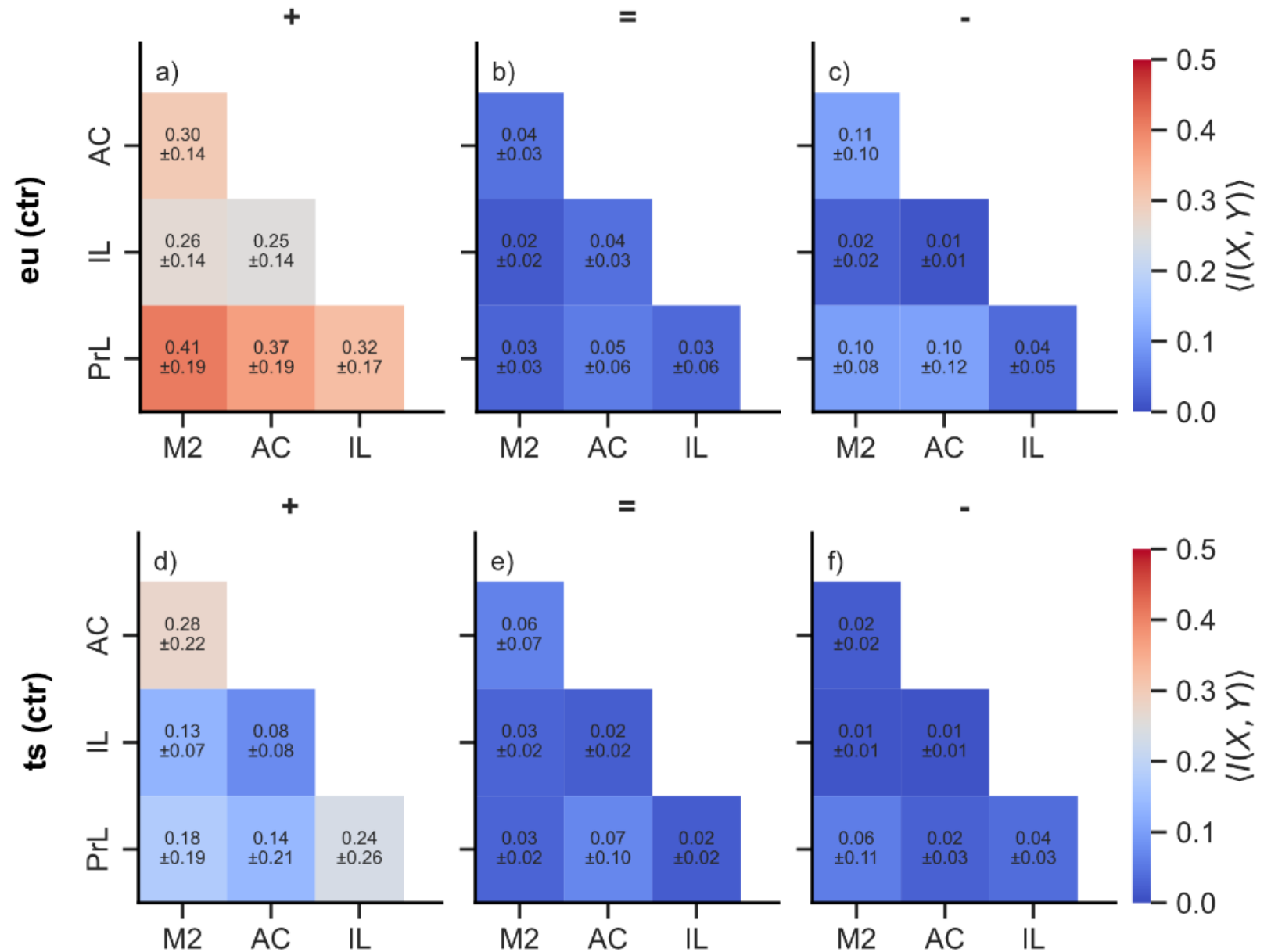


Again, each cell shows the average also across mice (n = 6 for eu, n = 5 for ts)... but still errors are very big, why?

# Results

What if we also consider the classification attending to locomotion?

We see that the = and – guys are barely contributing to the encoding, while the + ones encode less



# Take home ideas



- Mutual information makes **no assumption** about the data and can help us to reveal **non-linear correlations** and **intricate encoding patterns**
- In our case, it reveals specific connectivity patterns present only at network level and finding **loss of coherence** in the trisomic genotype

# Thanks for your attention! Questions?

Special thanks to,

Alessandro Torcini



Alberto Bacci



Javier Zorrilla

