*Neural Information Processing*

# Neural population data analysis

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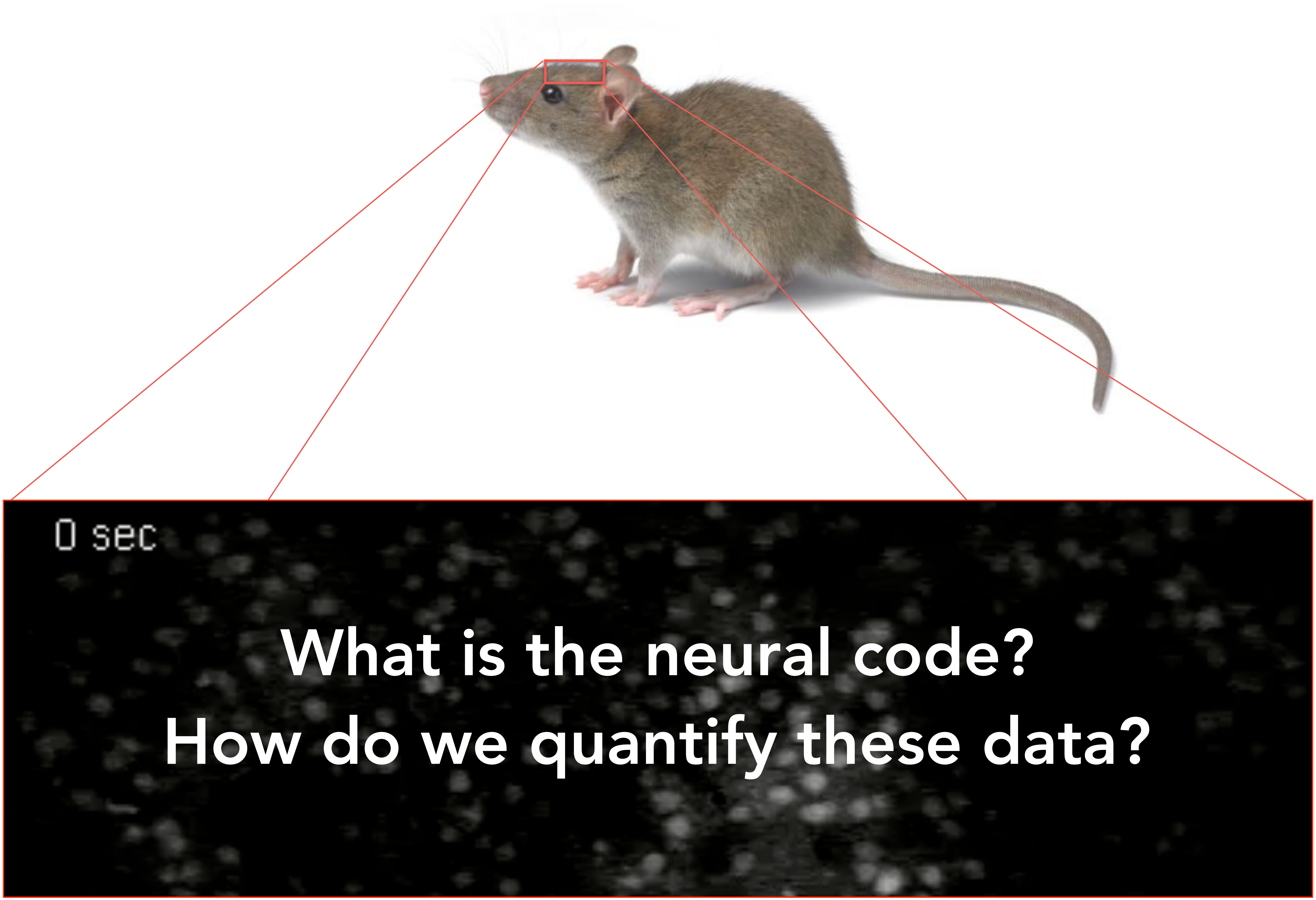



Golshani et al., J Neurosci (2009)

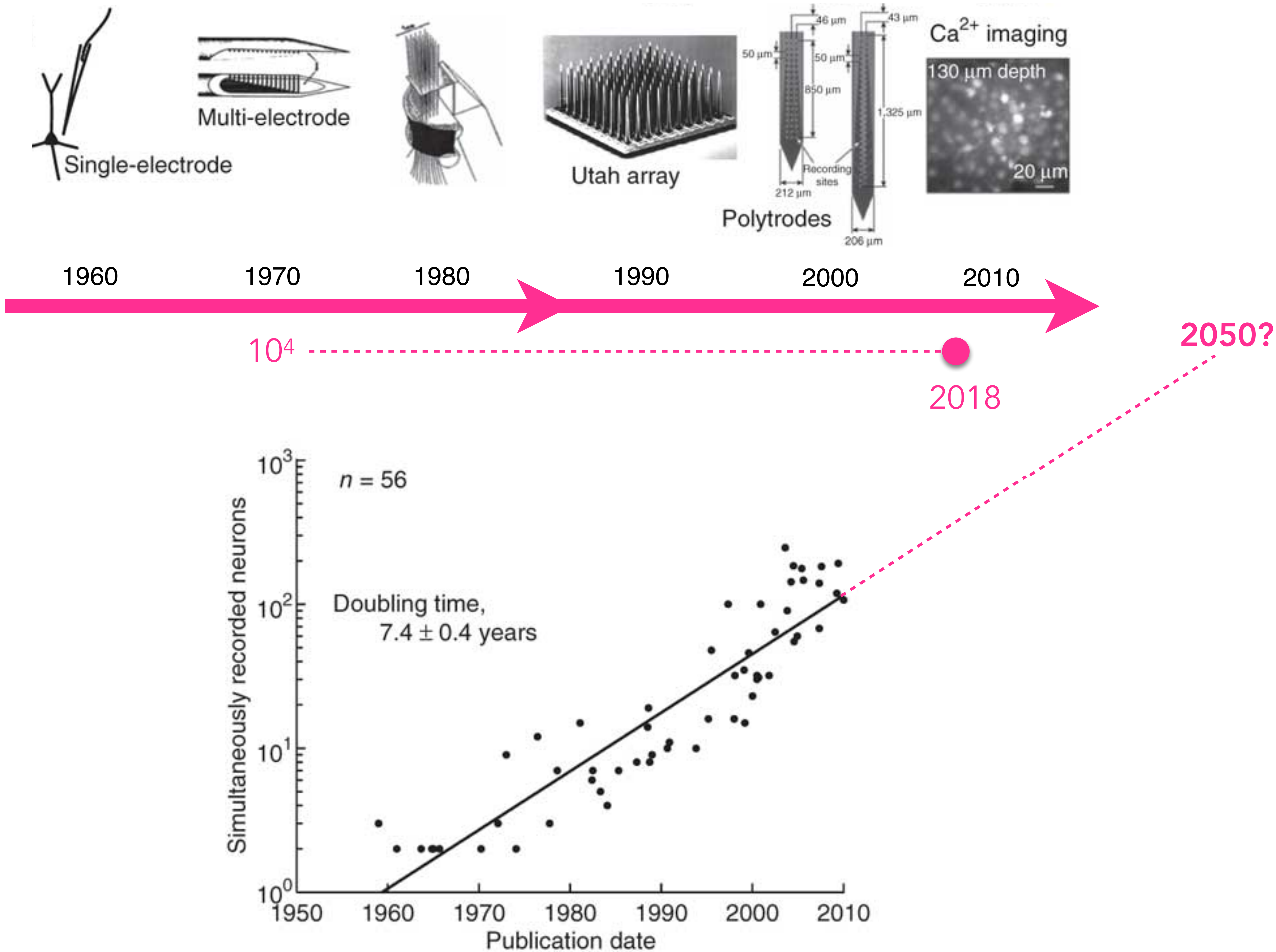
# What we will cover

- Why analyse neural populations instead of single neurons?
- What properties should a good statistical model have?
- The independent-neuron model.
- Methods that capture spatial correlations:
  - Maximum entropy-based
  - Population-count-based models
  - The dichotomised gaussian

# Why neural populations?

# The recent shift to neural populations

- Historically, neuroscientists focused on understanding the firing properties of single neurons (e.g. tuning curves, receptive fields, place cells).
- But the brain has a lot of neurons! (~100 billion in humans)
  What are they all for?
- This was partly due to limitations in recording techniques, but also because we didn't know what questions to ask.
- But (as theorists have long pushed for) the trend is to now routinely record from 10s or 100s of neurons simultaneously.
- What we don't know is how to analyse or think about these data yet.




Stevenson & Kording, *Nat Neurosci* (2011)

## Monkey primary visual cortex



**How do we quantify these data?**

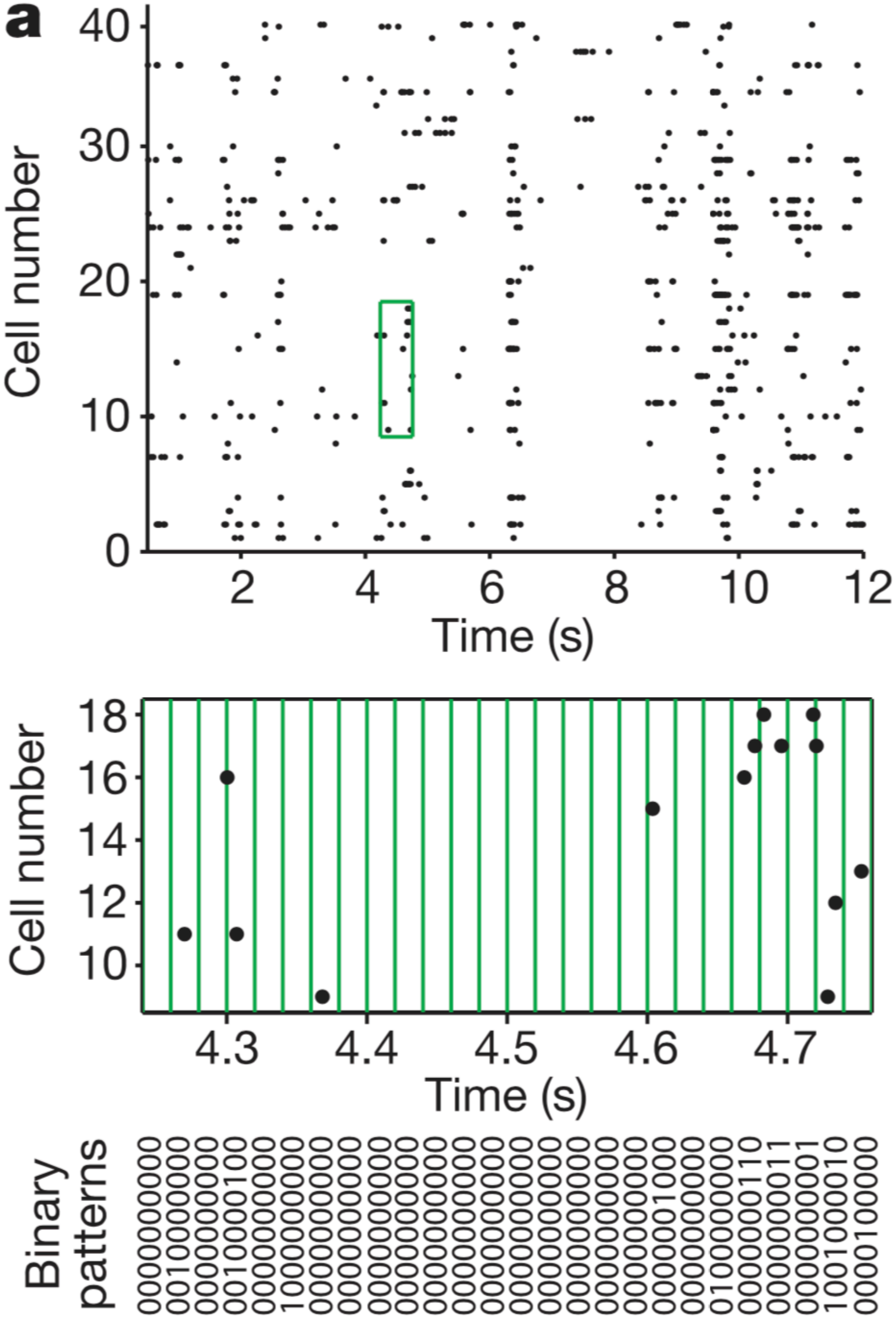
data from A. Kohn (Einstein College of Med)

What properties should a good statistical model for neural population data have?

# Desirable properties of a statistical model for neural population data

- It captures the statistical structure in neural population data.
- Parameters can be fit efficiently for limited data.
- Parameter fitting can be done in reasonable computational time.
- We can generate samples from fitted model.
- Closed-form likelihood function.
- Model parameters are interpretable for humans.
- Can directly compute summary statistics from fitted parameters (entropy, distances between two parameter fits, etc)
- ~~Someone has coded it up in MATLAB or Python~~

How should we mathematically represent the neural activity?

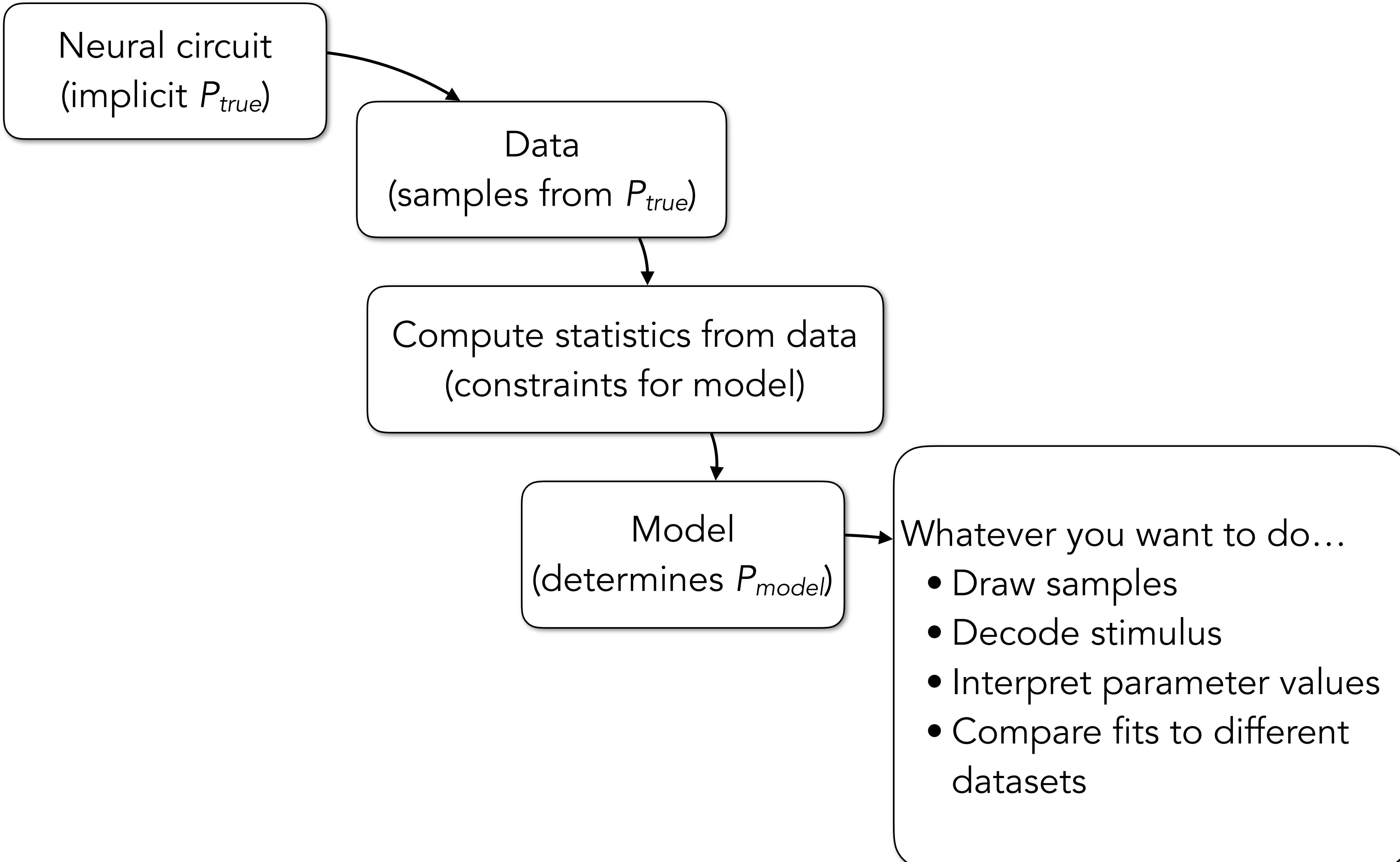



Schneidman et al, *Nature* (2006)

$$P(x_1, x_2, \ldots, x_N) = P(\mathbf{x}) = ?$$

The support of this distribution is the space of all possible binary patterns ~$2^N$

# Modelling strategy



Given some data, how do we estimate $P(x)$?

# The problem with histogramming

- If each pattern has a true probability of occurring $p_i$, then in the long run ($t \rightarrow \infty$) the maximum likelihood estimate $\hat{p}_i = n_1/(n_0 + n_1)$ converges towards $p_i$.

- However, since the number of possible patterns grows ~$2^N$, for reasonably-sized populations there may be many patterns with low $p_i$, which we observe only rarely. Maybe never.

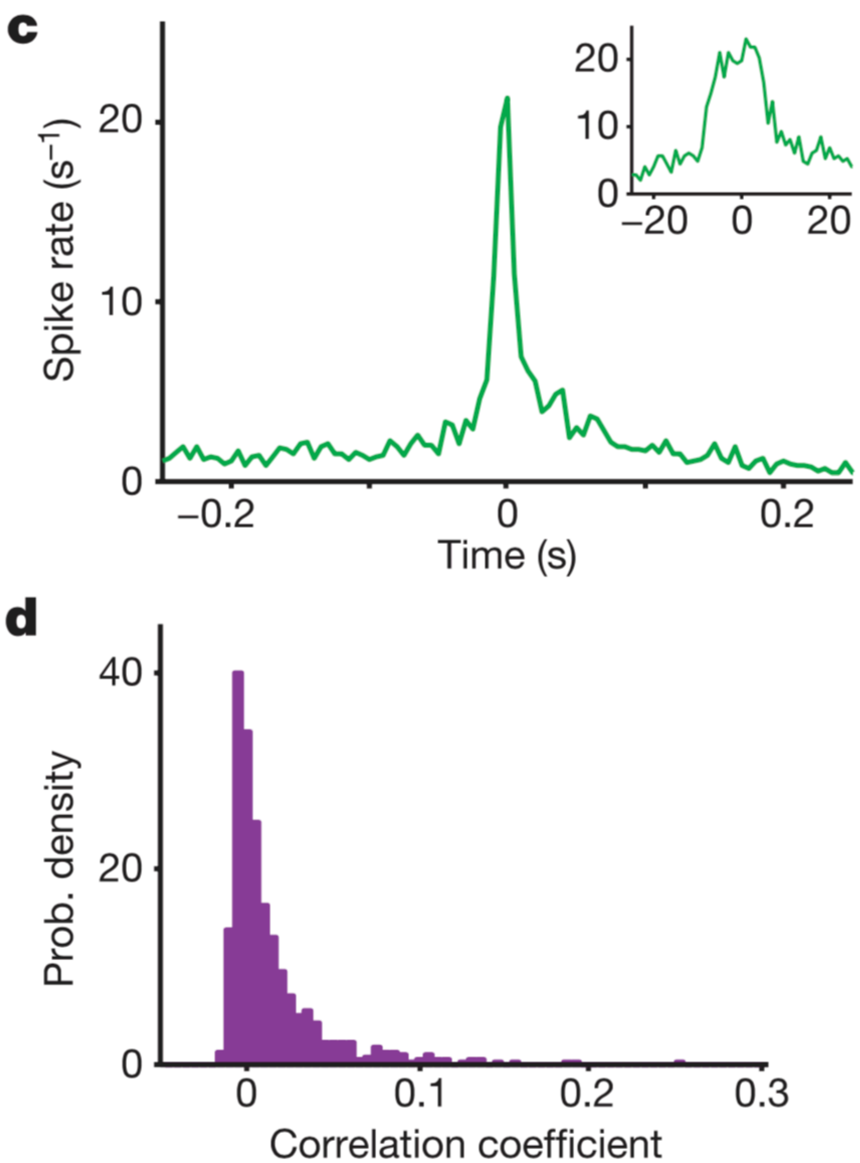
- For example, if we recorded some neural activity continually since the Big Bang (13.8B years ago = $4 \times 10^{17}$ s), and binned our recording in 10 ms intervals, we could maximally observe the number of patterns corresponding to only $\log_2(4 \times 10^{19})$ ~ 65 neurons.

- These unobserved patterns are the brain's "dark matter"! They can exist (surely with non-zero probability) but need not ever occur.

The solution? Parametric models.

# Independent neuron model

- The independent neuron model makes the assumption that neurons are statistically independent.
- This is wrong… but not *that* wrong.



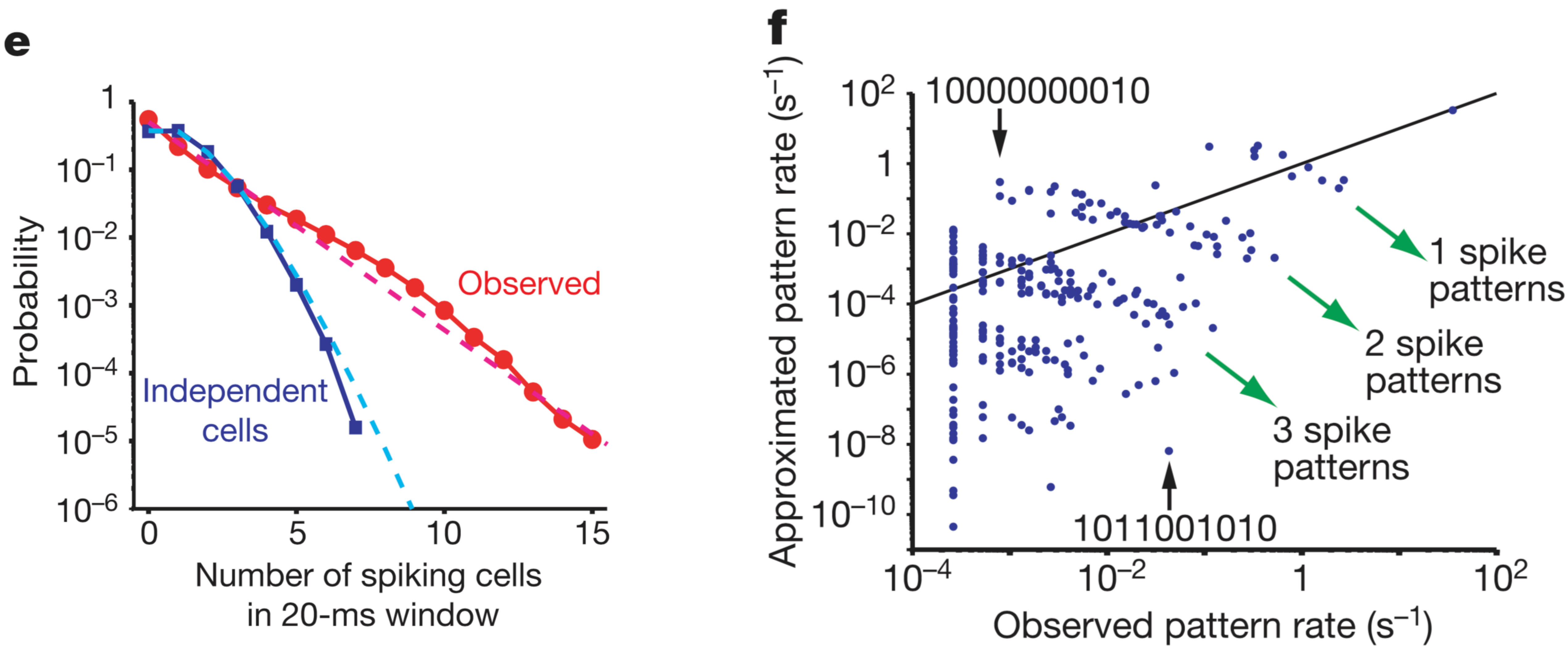

ON neurons

OFF neurons

$$p(x) = \prod_i [x_i\sigma_i + (1 - x_i)(1 - \sigma_i)]$$

where $\sigma_i$ is single neuron firing probability

# Testing the independent model




Schneidman et al, *Nature* (2006)

We need a model that knows about correlations!

# Three models with correlations

- Pairwise maximum entropy
- Population count-based models
- Dichotomised gaussian

# Pairwise maximum entropy models

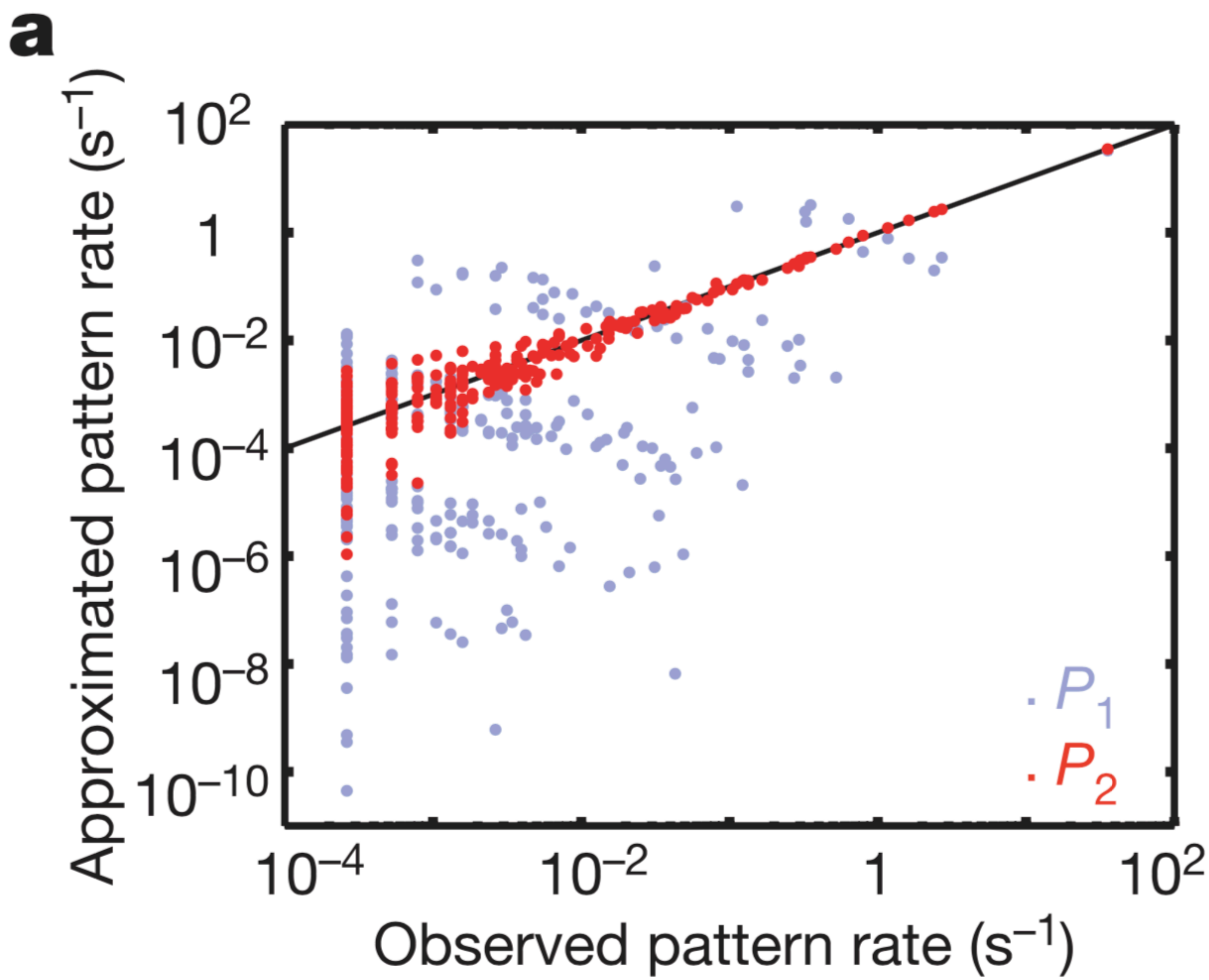
- Assume neural firing is as independent as possible, given the individual neuron firing rates and pairwise correlations.

$$p(x) = \frac{1}{Z}\exp[\sum_i h_i x_i + \sum_{i \neq j} J_{ij} x_i x_j]$$

where $h_i$ are single neuron firing parameters and $J_{ij}$ are pairwise coupling strengths.

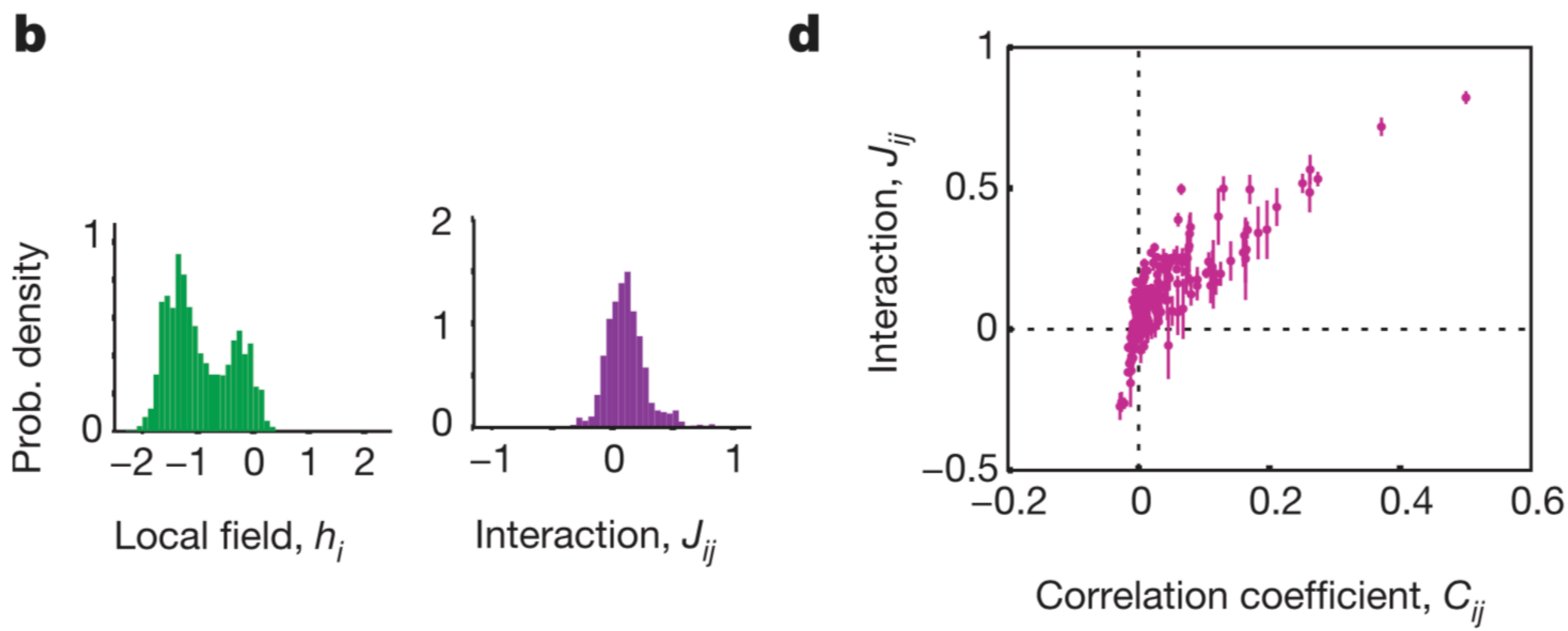
- $h_i$ and $J_{ij}$ are chosen so that $\mathbf{E}[x_i] = \hat{\sigma}_i$ and $\mathbf{E}[x_i x_j] = \hat{c}_{ij}$

# Predictions of the pairwise maximum entropy model




Schneidman et al, *Nature* (2006)

# Interpreting the parameter fits




Schneidman et al, *Nature* (2006)

# Problems with pairwise maxent

- Data-hungry.
- Doesn't accurately match data from large numbers of neurons (even for infinite data).
- Computationally hard to fit parameters for large numbers of neurons.

# Further reading


- Schneidman, E., Berry, M.J., Segev, R., Bialek, W., 2006. Weak pairwise correlations imply strongly correlated network states in a neural population. Nature 440, 1007–1012