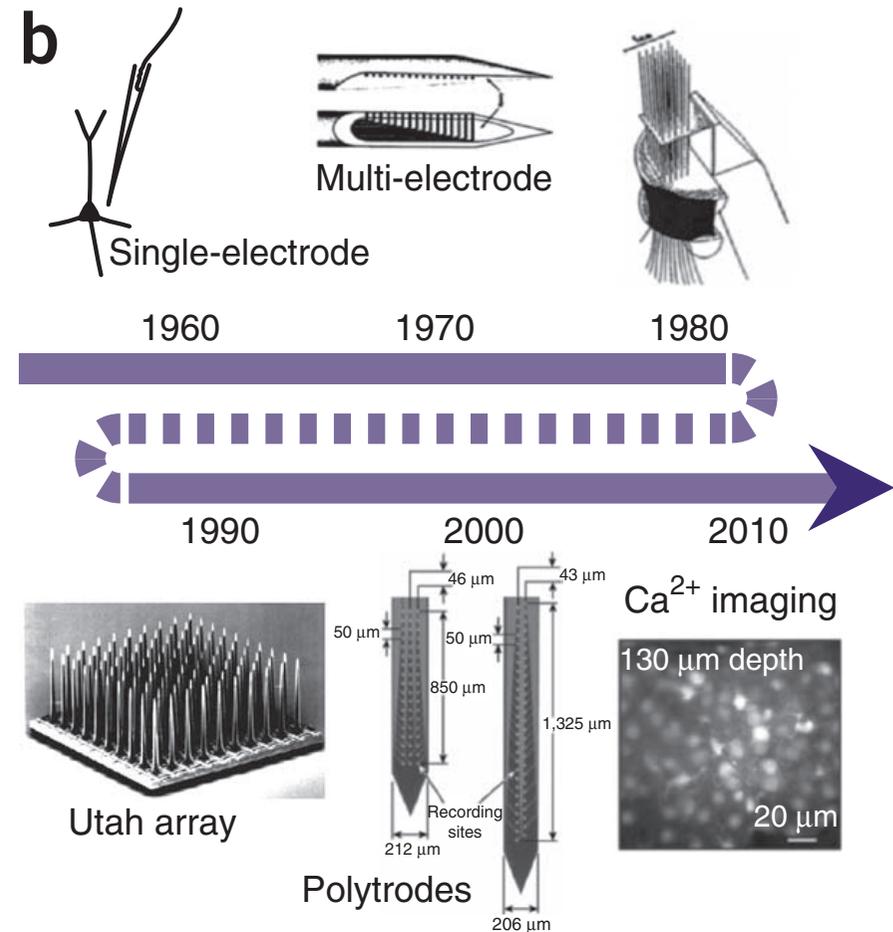
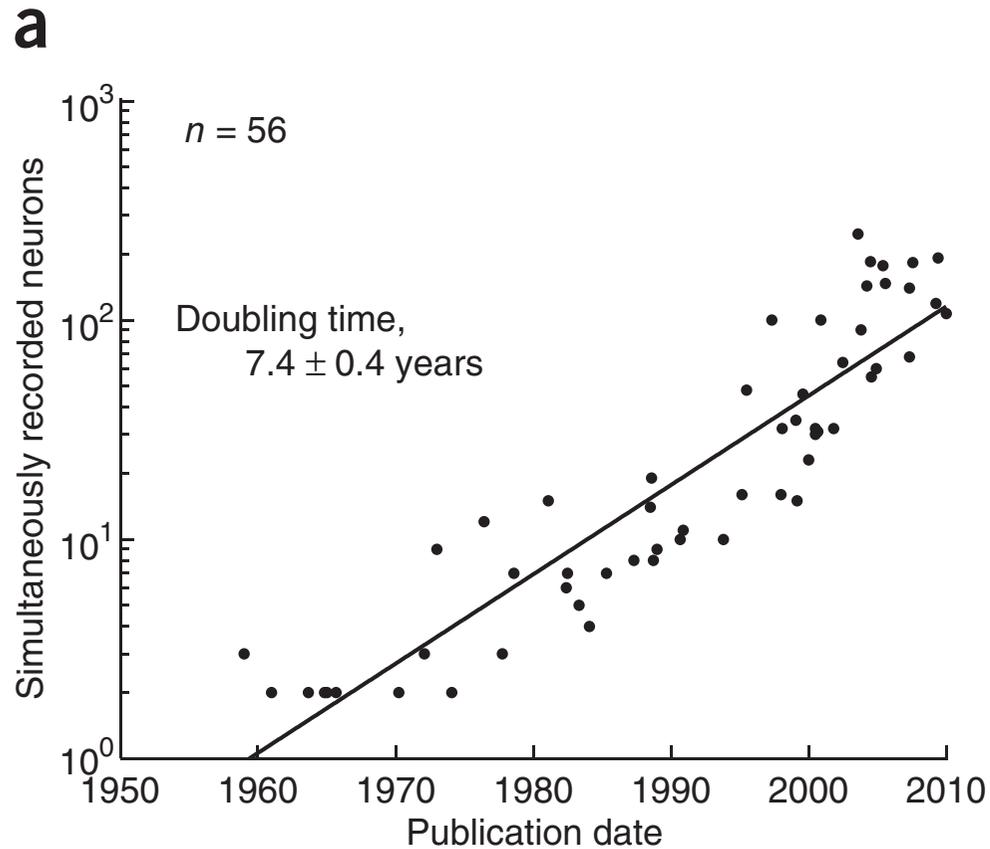


Inference and learning at the level of single synapses and spiking neurons

PART I

Jean-Pascal Pfister

The data explosion



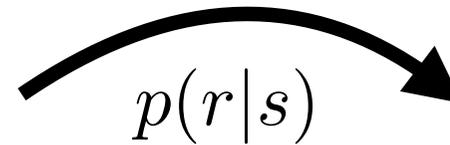
Need good **questions** and good **methods**

How to address the encoding/decoding problem?

Stimulus s

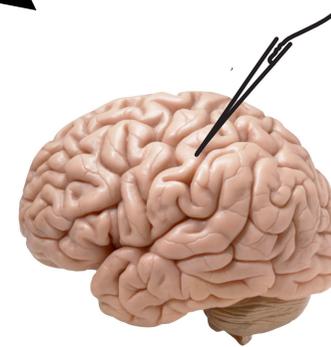


Encoding



$$p(r|s)$$

brain response



decoding

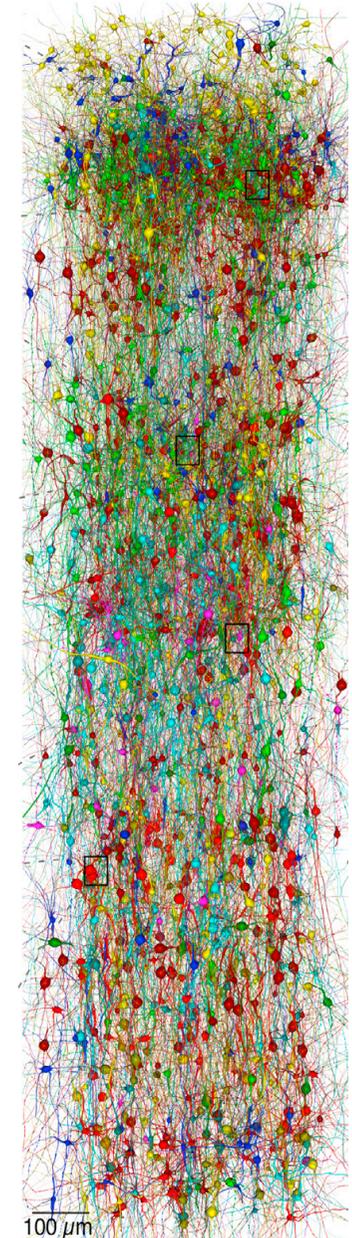
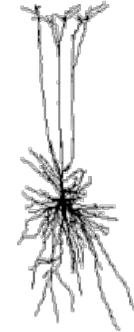
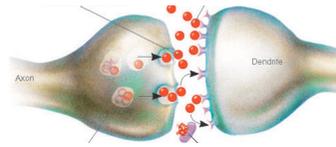
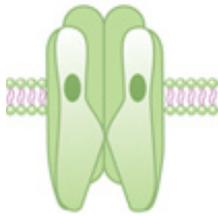


$$p(s|r) = \frac{p(r|s)p(s)}{p(r)}$$

Need for a **flexible** and **tractable** model

Flexible but NOT tractable approach

Full biophysical model



How can it be learned?

-> Perfect recipe for overfitting

Tractable but NOT flexible model

Boring model:

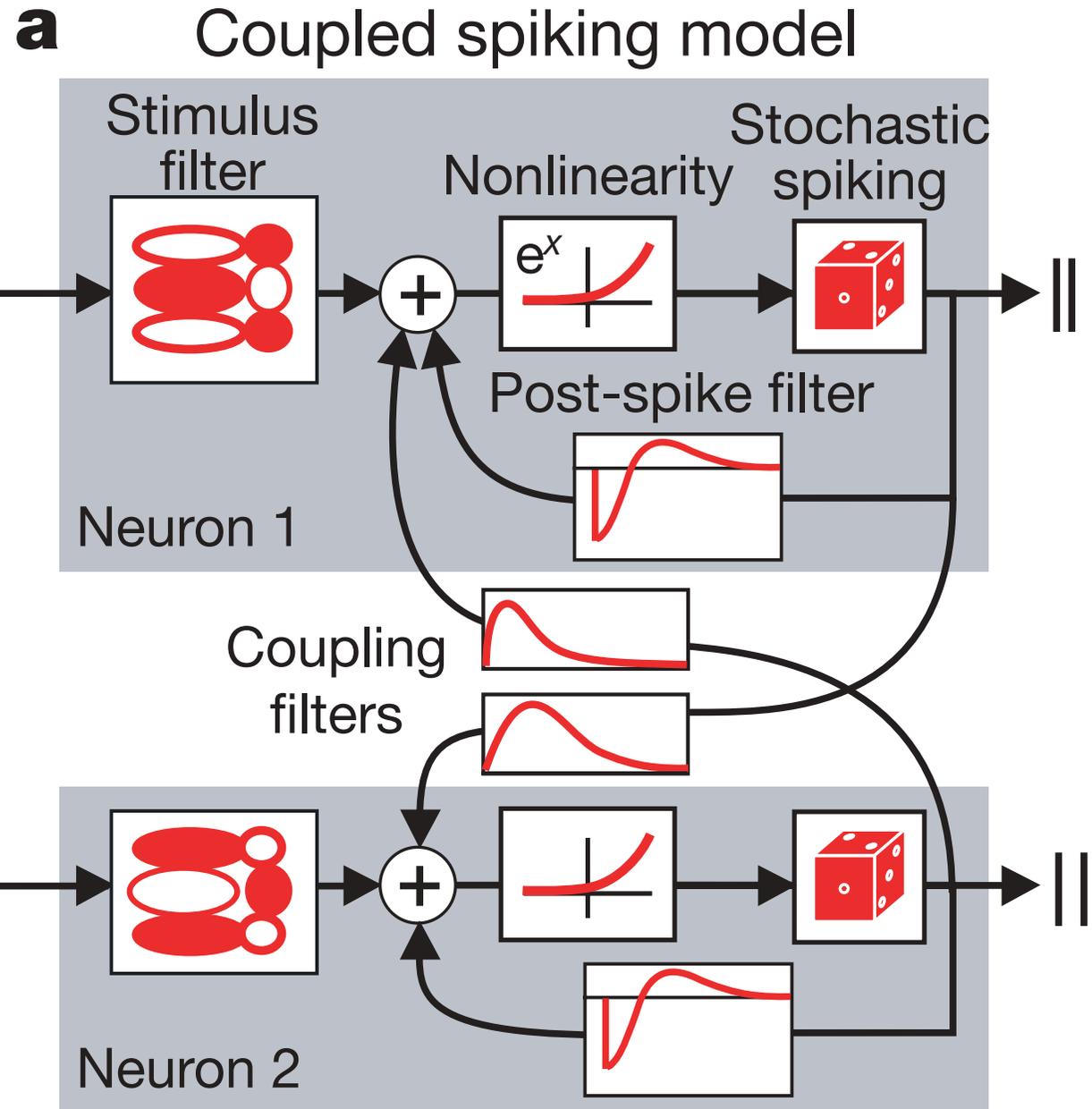
Each neuron is described by a constant firing rate

Easy to fit

no overfitting

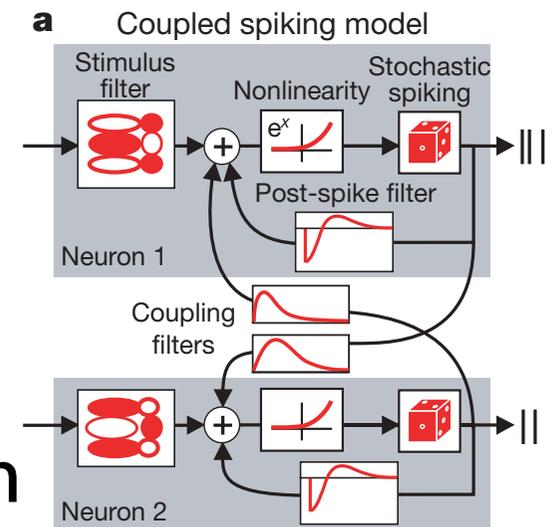
.... but terribly boring!

Generalised linear model: a sweet spot



Why GLM ?

- Flexibility
 - ▶ includes neuron couplings + refractoriness
 - ▶ stochastic -> convenient for Bayes rule
 - ▶ additional features such as short-term plasticity
- Tractable
 - ▶ PDF analytically tractable
 - ▶ convex under some conditions
- won spike prediction competition
- ... I just like it



Outlook of part I

Generalised linear model (GLM)

- Motivation for the GLM
- Math primer
- Definition of the GLM
- Properties of the GLM
- Learning with the GLM

Bibliography

- Wulfram Gerstner, Werner M. Kistler, Richard Naud and Liam Paninski.
Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition. 2014
- Paninski, L. (2004). *Maximum likelihood estimation of cascade point-process neural encoding models*. *Network: Computation in Neural Systems*, 15(4), 243–262.

