

Generalized linear models (GLM)

Tools for studying neural coding

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HDSI

UCSD NGP bootcamp

Sep 16, 2020

Who is Gal?

- Assistant Professor of Data Science
- Interested in how networks of neurons (real & artificial) learn
- Develops graph-based methods for processing and analysis of large-scale, high-dimensional data
- Will be discussing dimensionality reduction tomorrow



Who is Mikio?

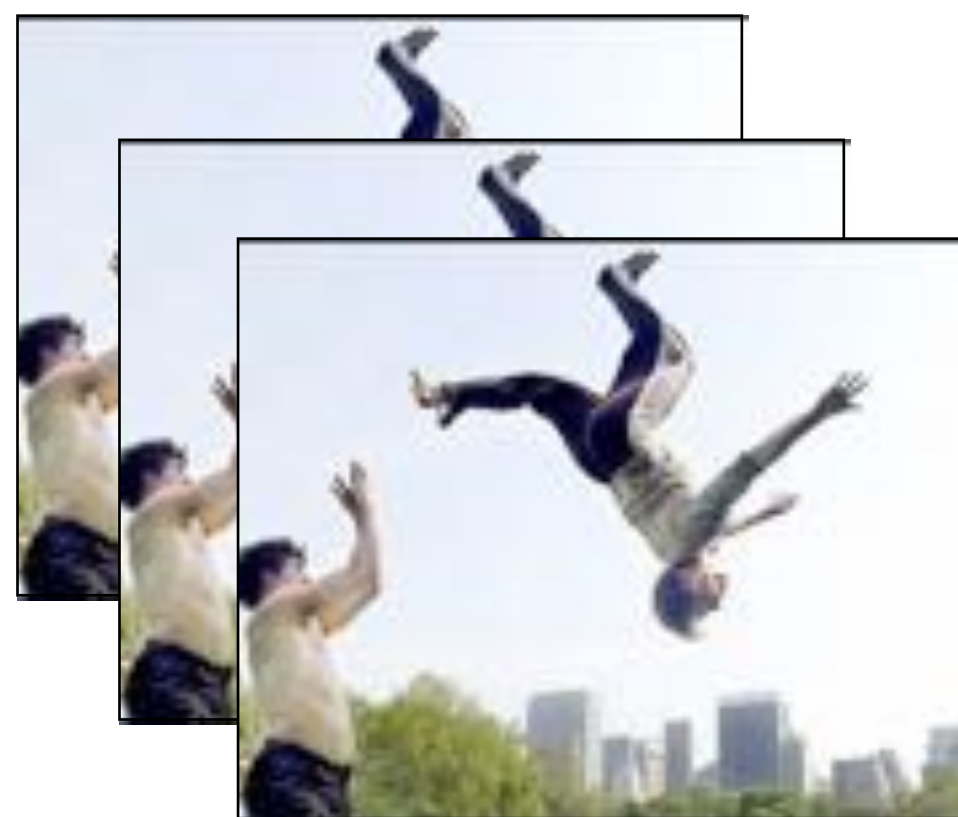
- Assistant Professor in Neurobiology & Data Science
- Interested in understanding how group of neurons coordinate their activity to implement computations
- Works on methods and theories for characterizing the ways that neurons coordinate.



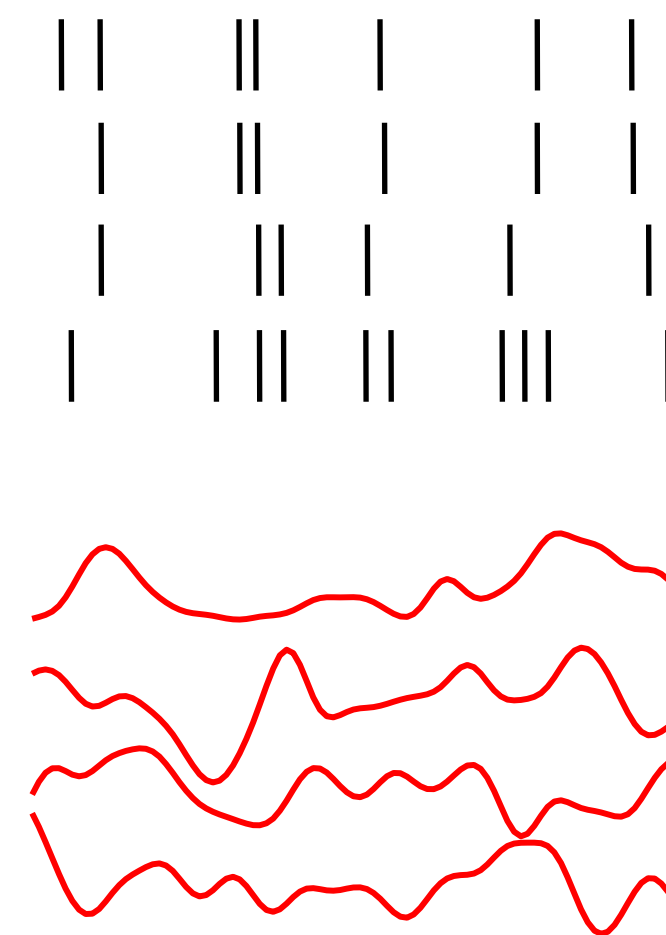
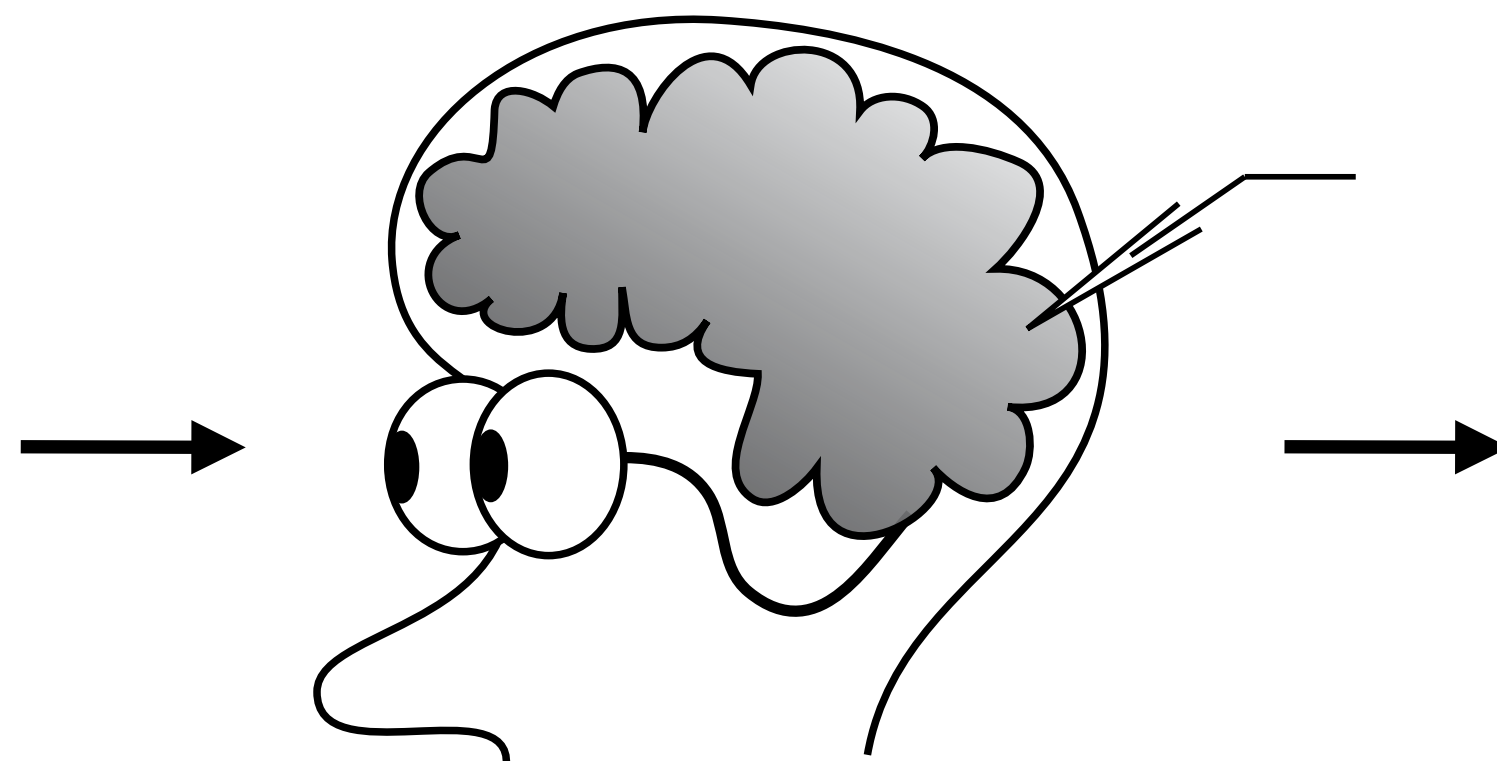
Agenda

- Neural coding
- What's a GLM?
- Common GLMs (Gaussian, Poisson, logistic)
- Tutorials

Neural coding



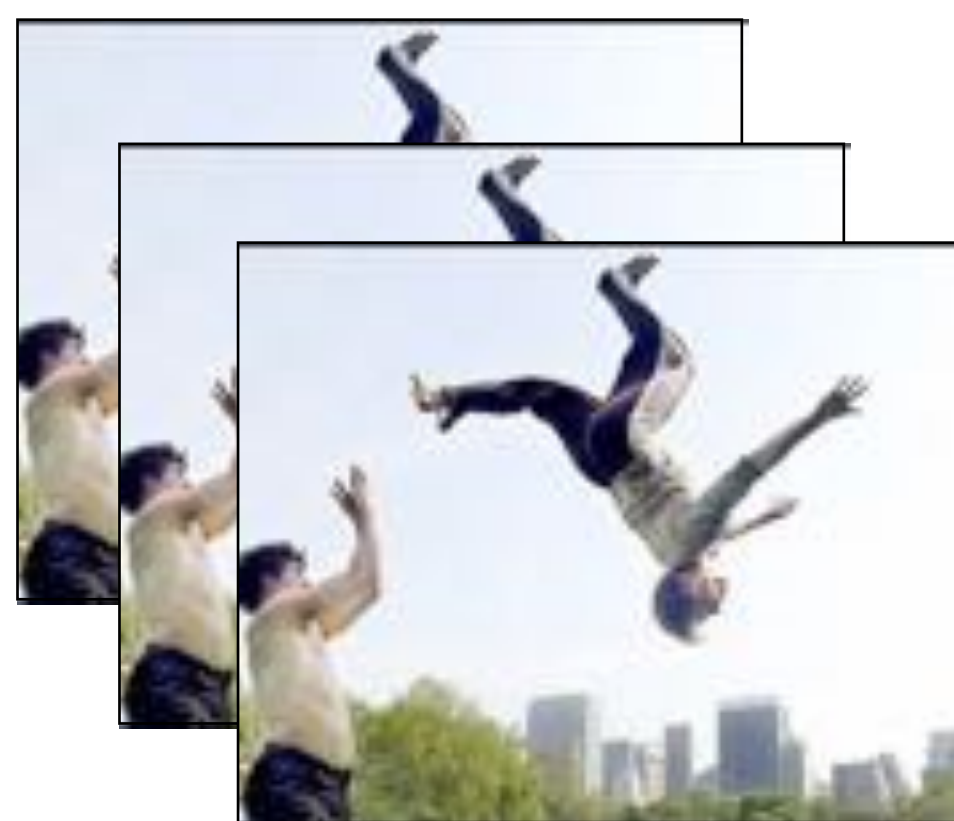
x
sensory stimuli



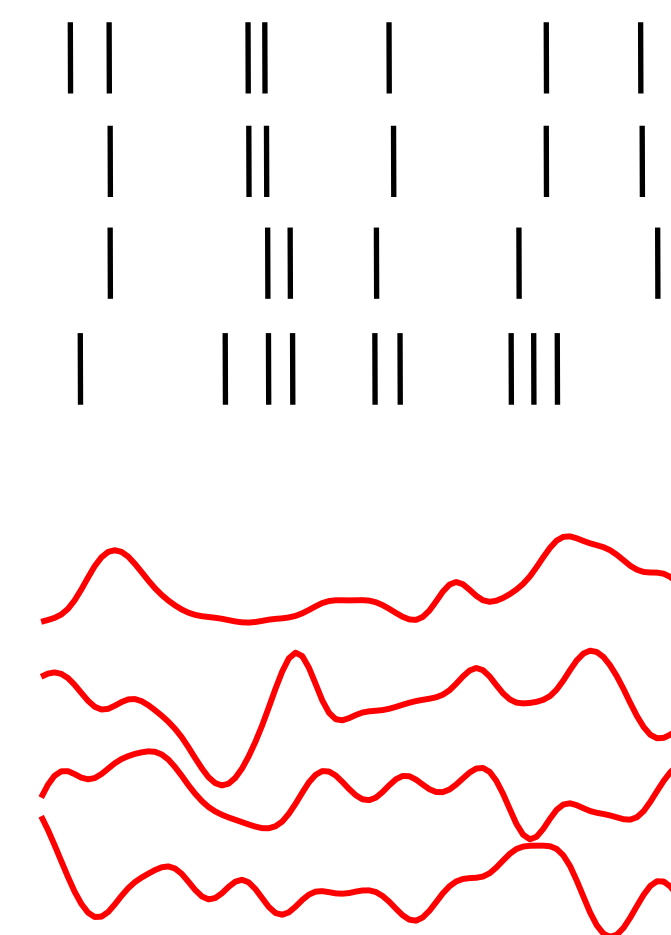
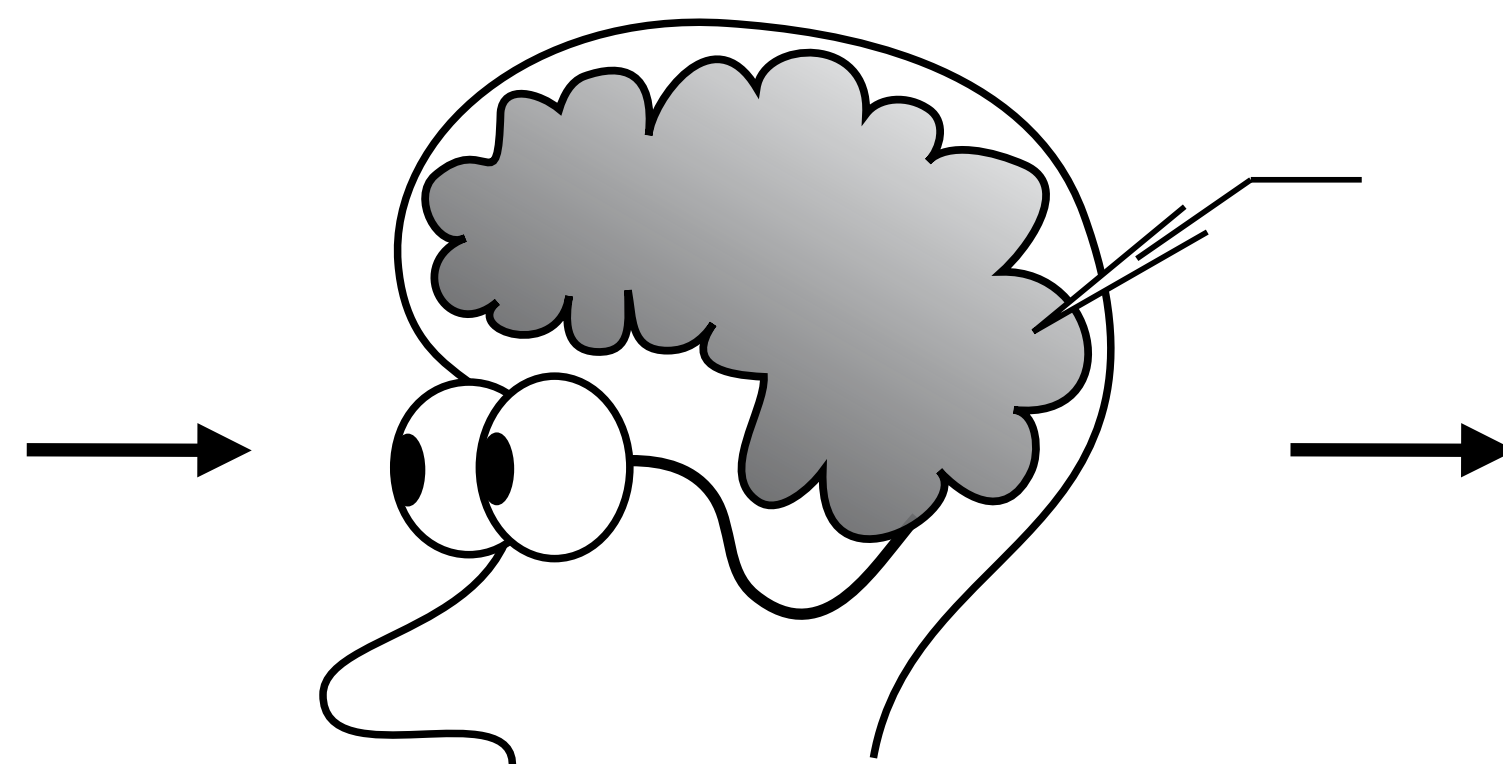
y
neural responses

neural coding problem:

What is the relationship between external variables and neural activity?



x
sensory stimuli

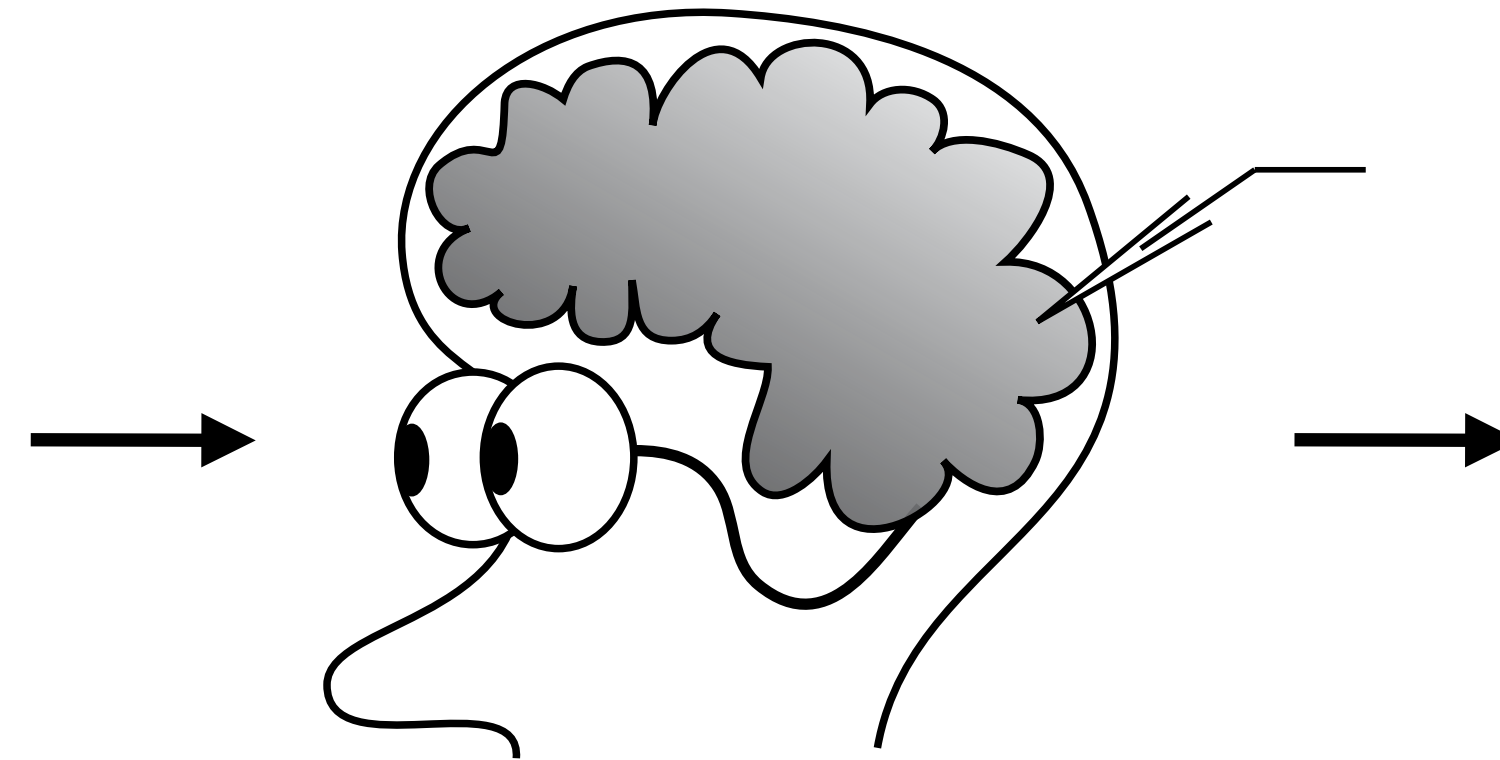


y
neural responses

Encoding



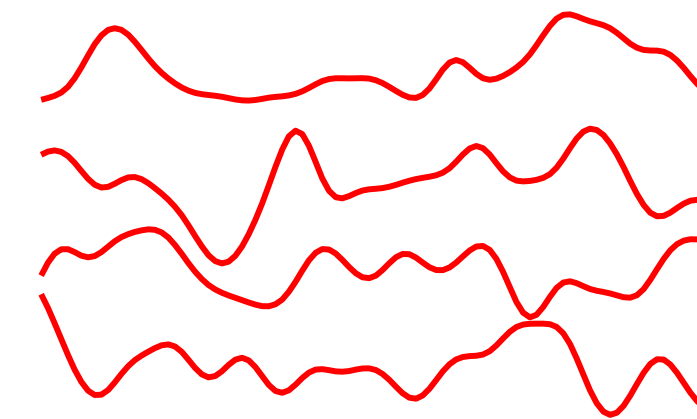
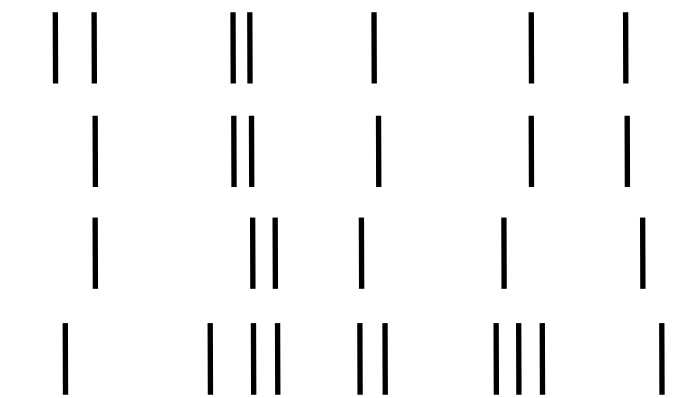
x
external variables



$$p(y|x)$$

encoding distribution

- probabilistic statement about relationship between x and y



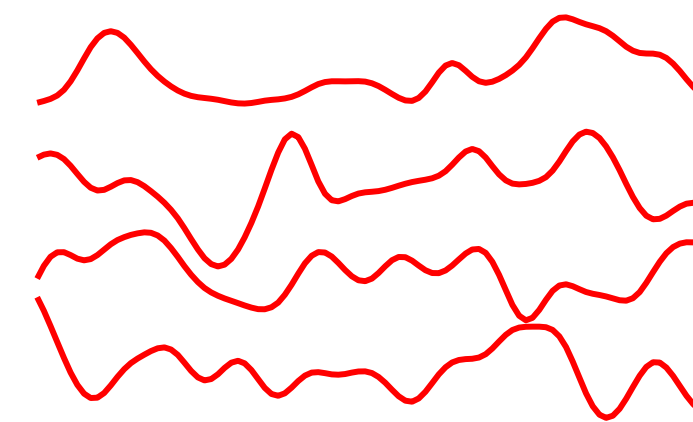
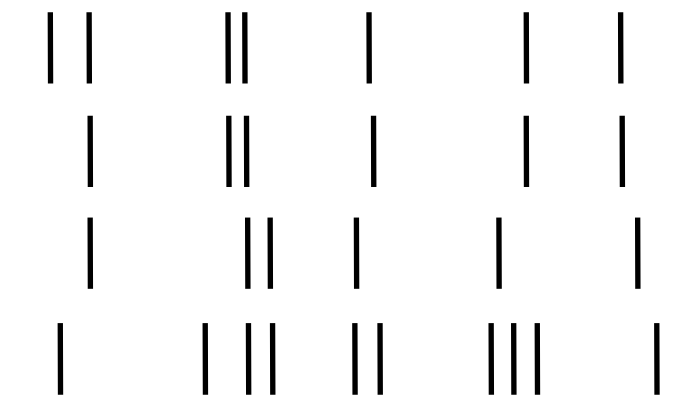
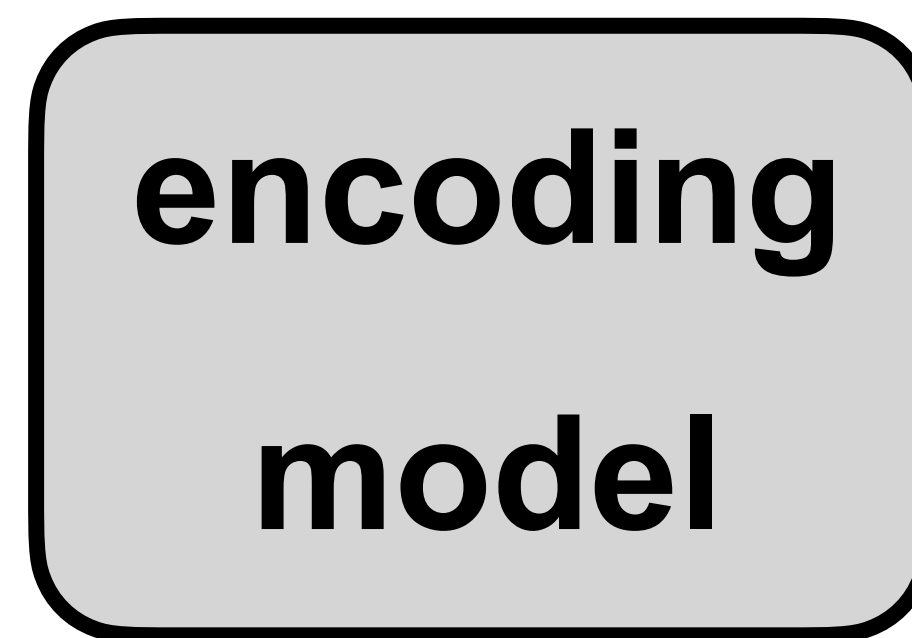
y
neural responses

data analysis



x

external variables



y

neural responses

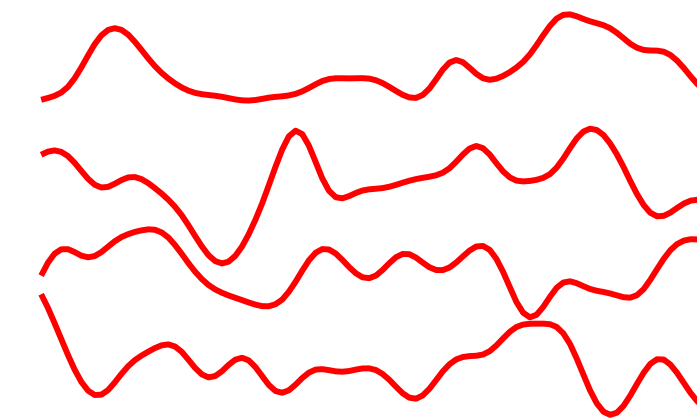
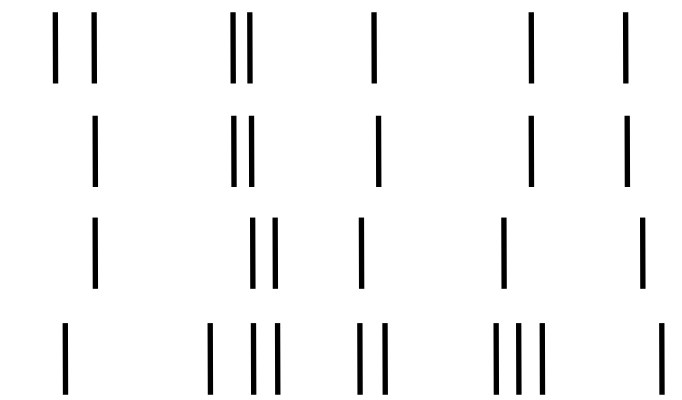
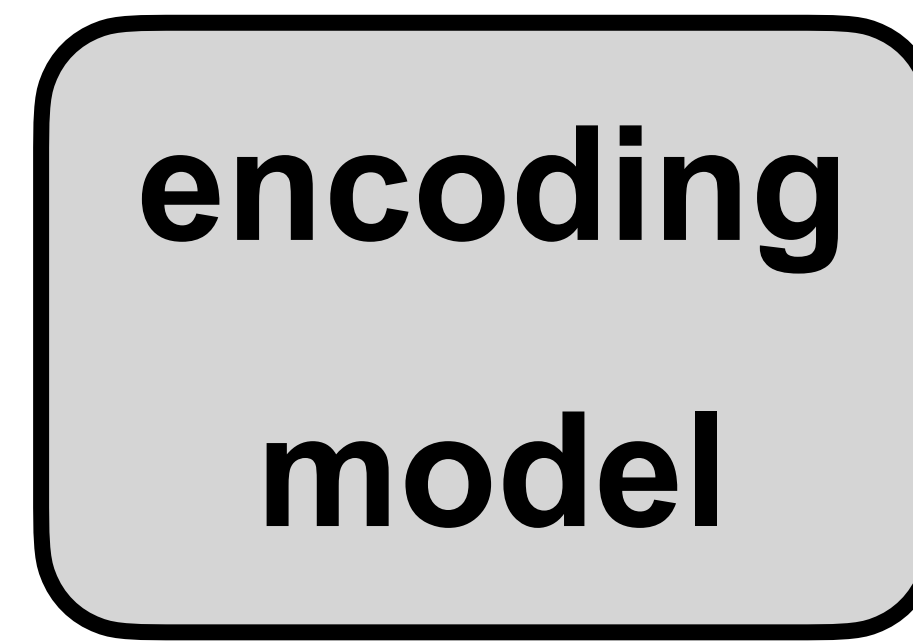
$$p_{\theta}(y|x) \approx p(y|x)$$

Goal: find model that approximates the true encoding distribution



x

external variables



y

neural responses

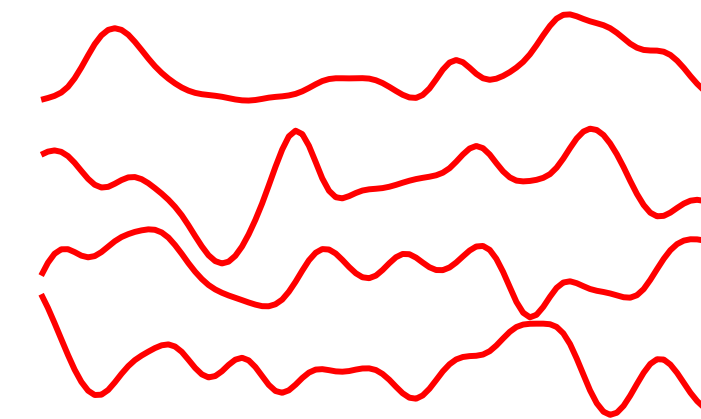
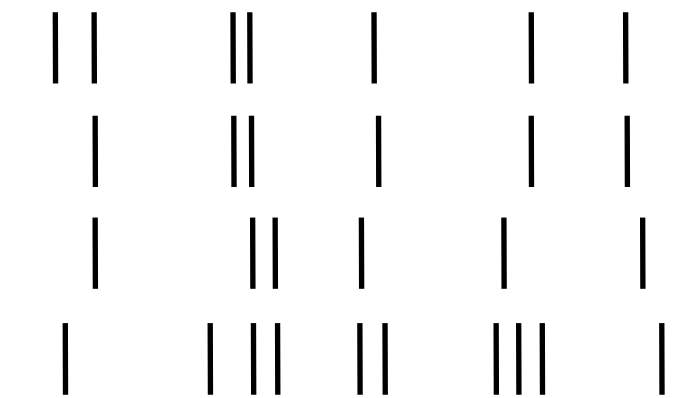
$$p_{\theta}(y|x) \approx p(y|x)$$

broadly: What is a good description of why a neuron(s) spike?

Encoding



x
external variables



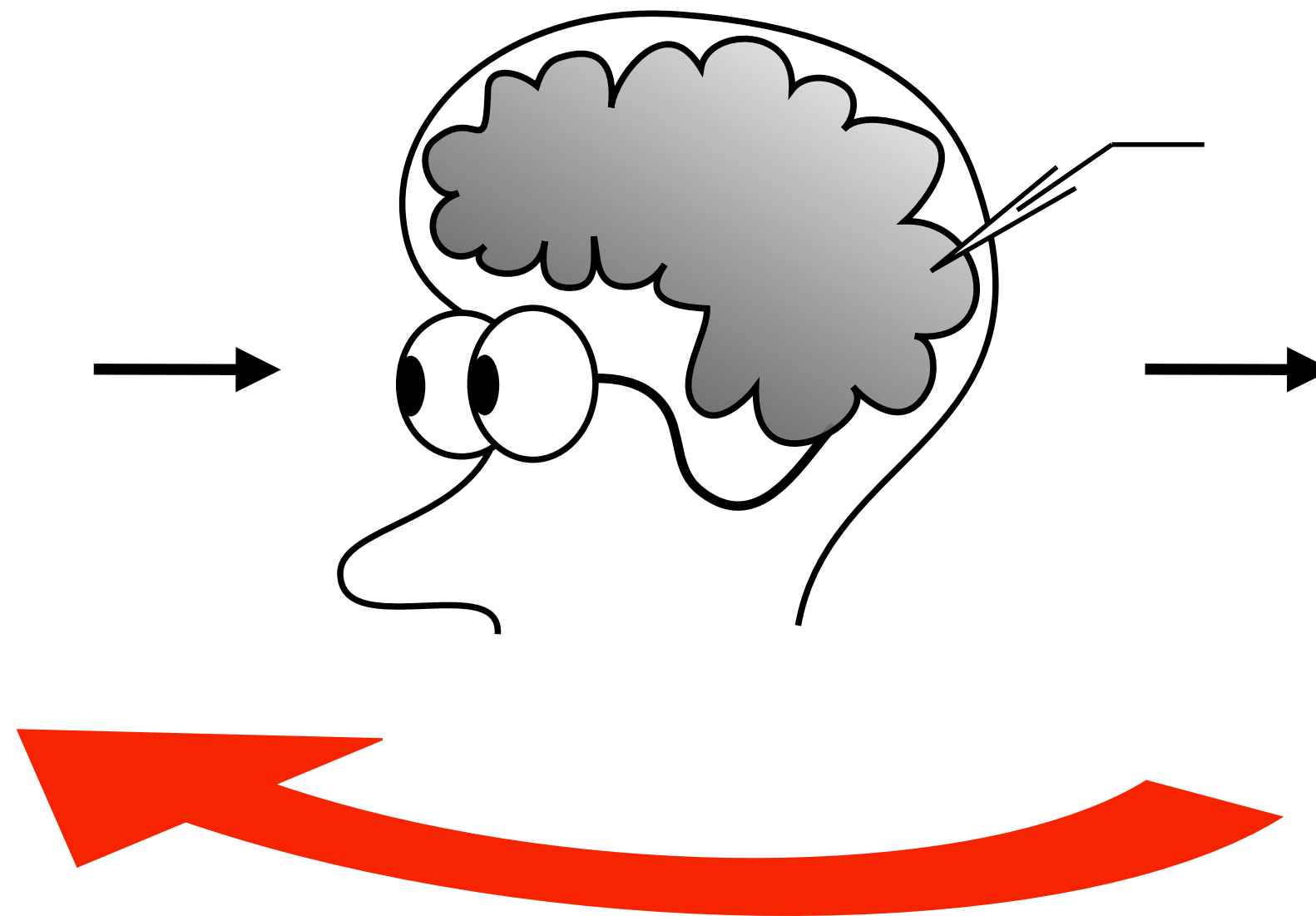
y
neural responses

Decoding

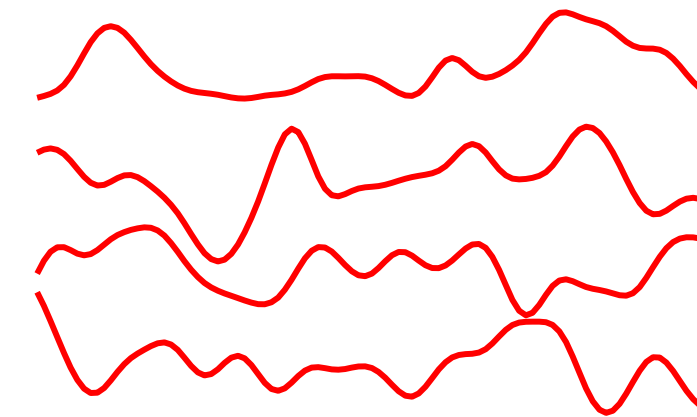
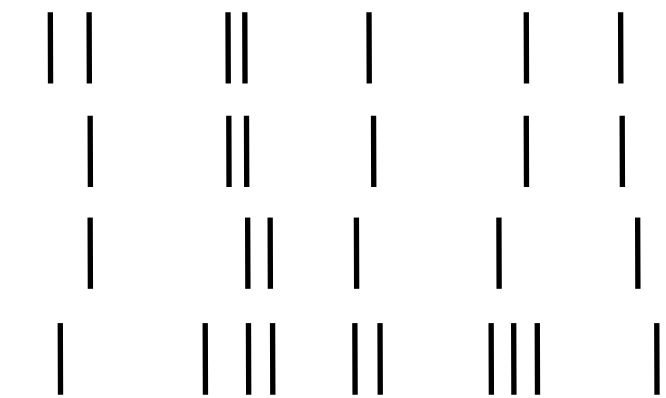
read out neural activity to predict external variables “mind reading”

- “house” or “face”?
- what orientation?
- what action?

x
external variables



N neurons or
voxels



y
neural responses

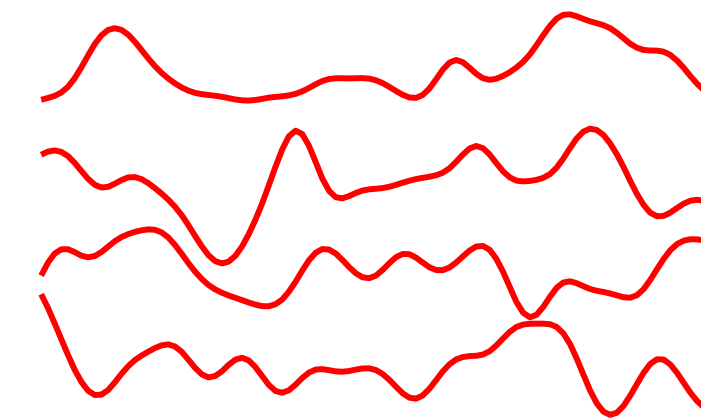
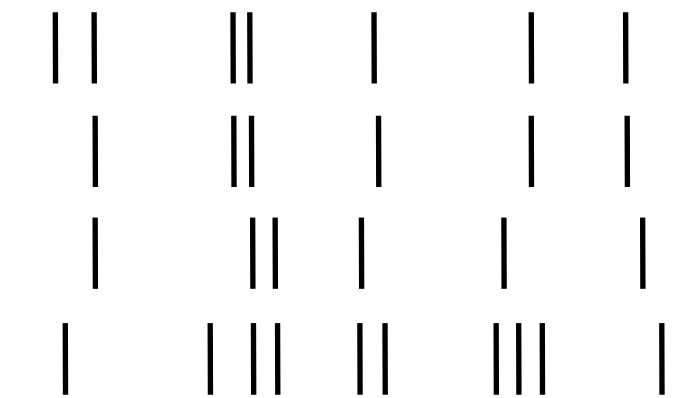
Decoding

- constraints on readout by down-stream populations
- applications: eg. BCI motor prosthetics

Encoding



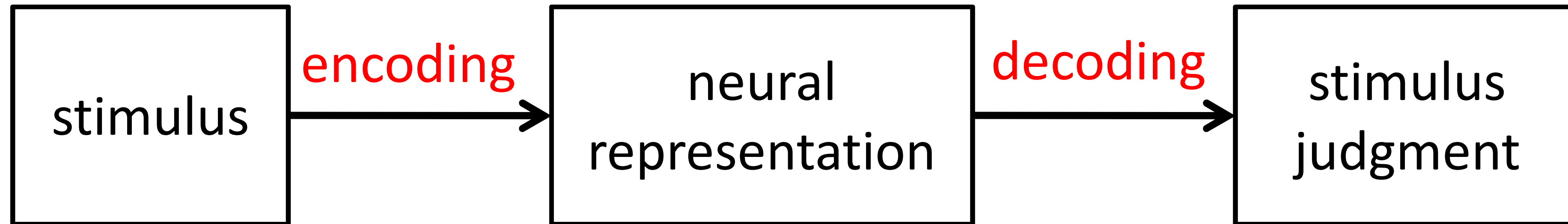
x
external variables



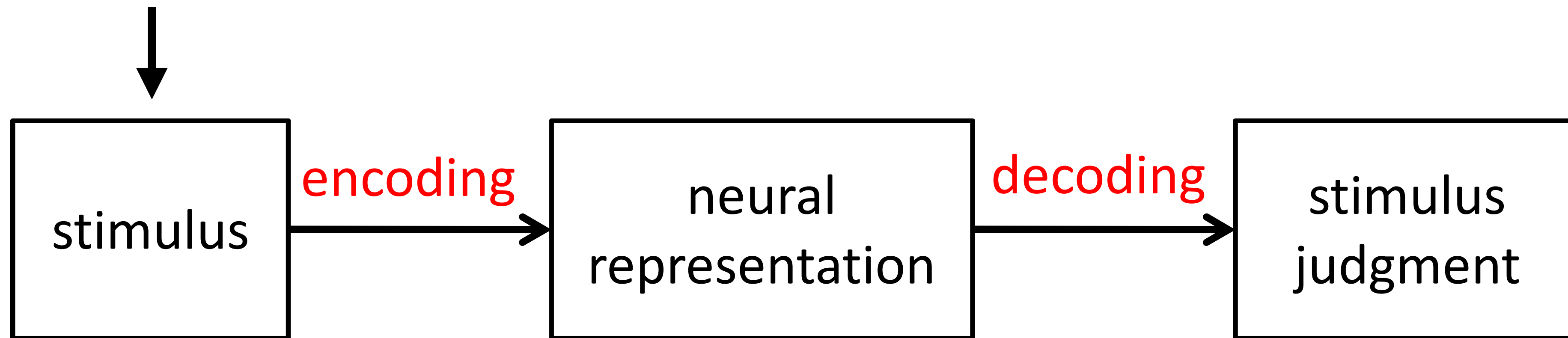
y
neural responses

Decoding

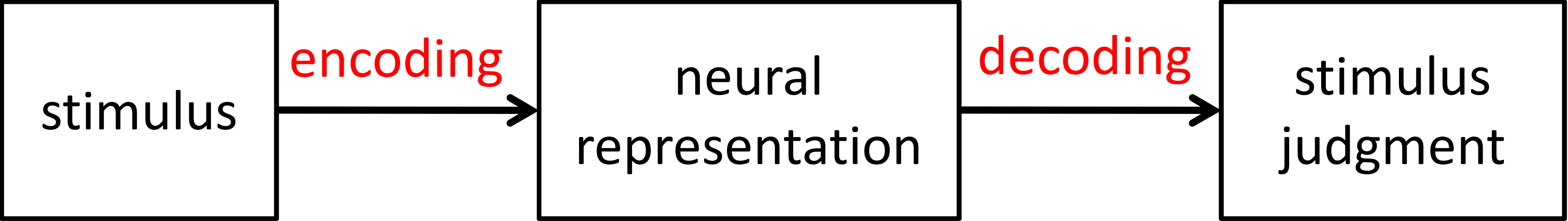
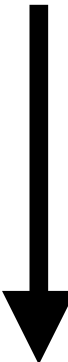
parallel between what the brain does and data analysis

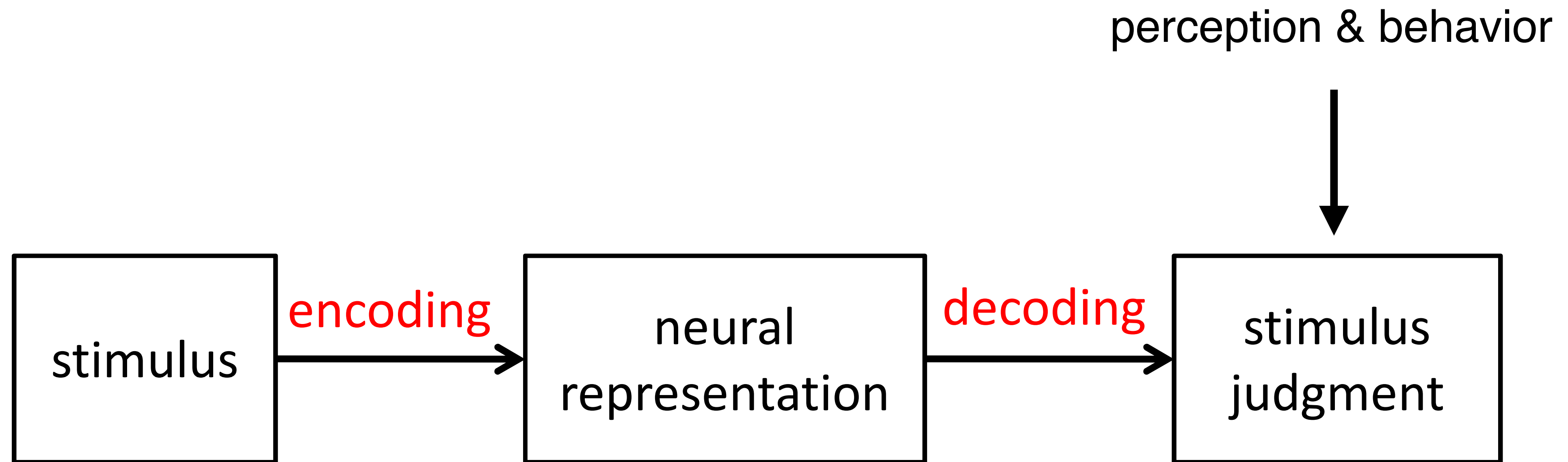


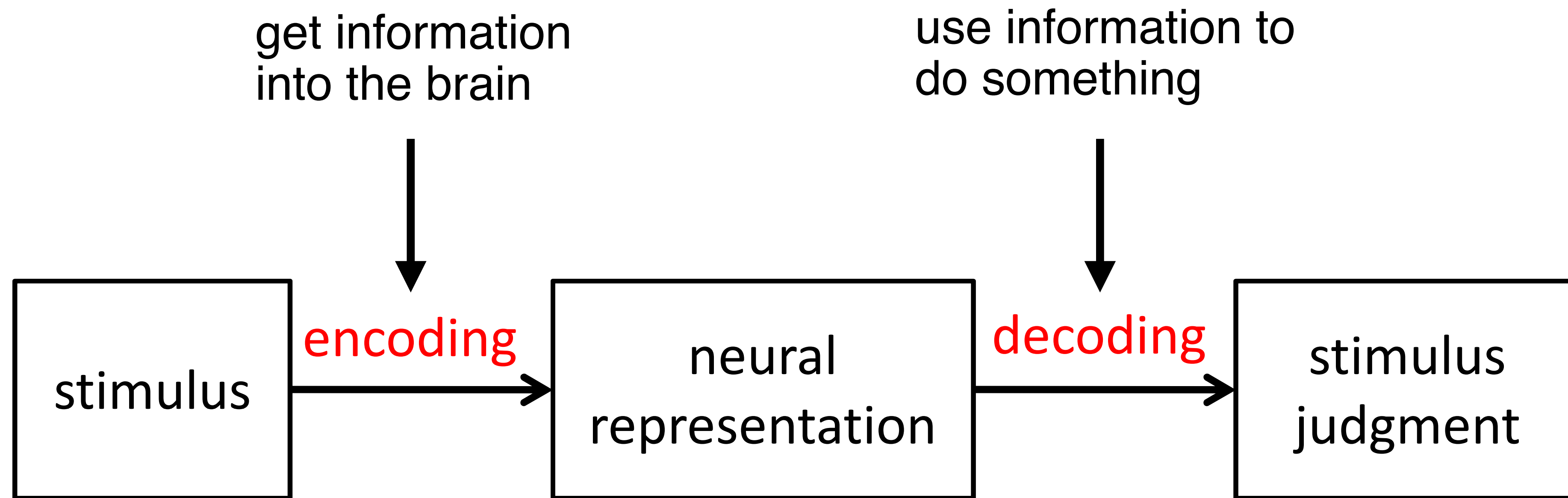
- orientation of contour
- direction of motion (self or object)
- number of students in class
- smell of coffee

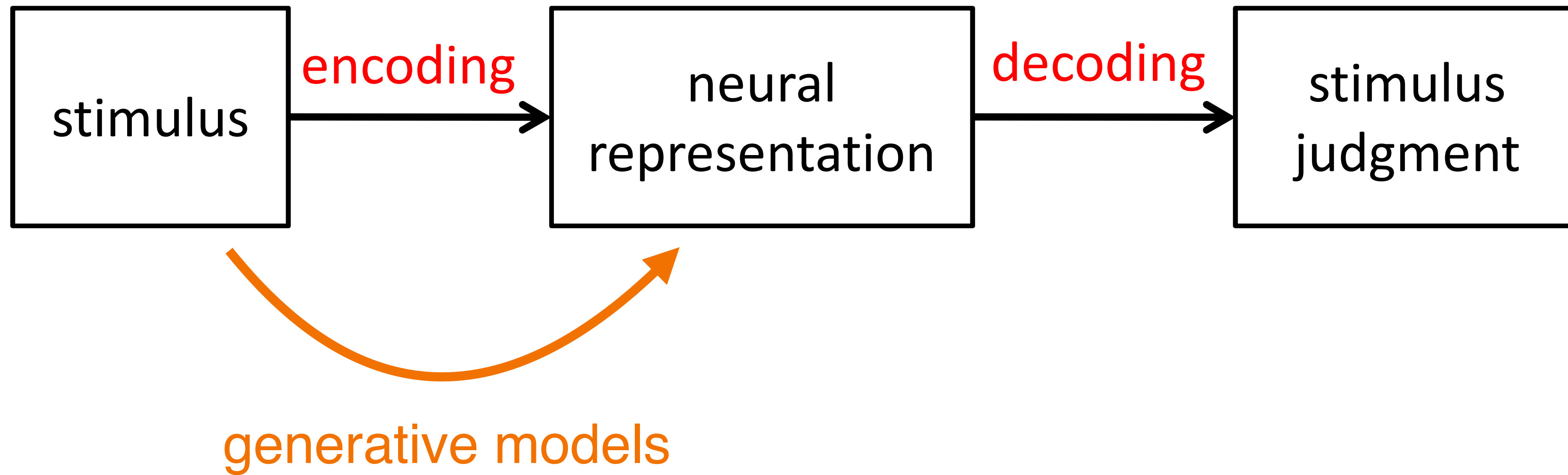


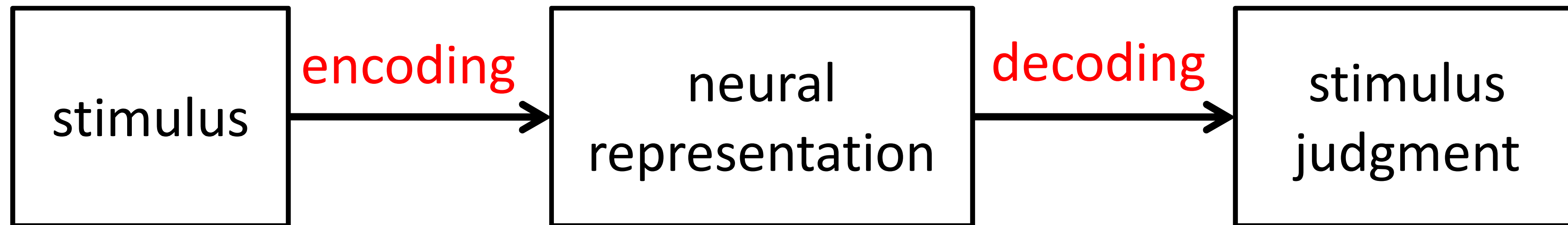
spiking activity of neurons





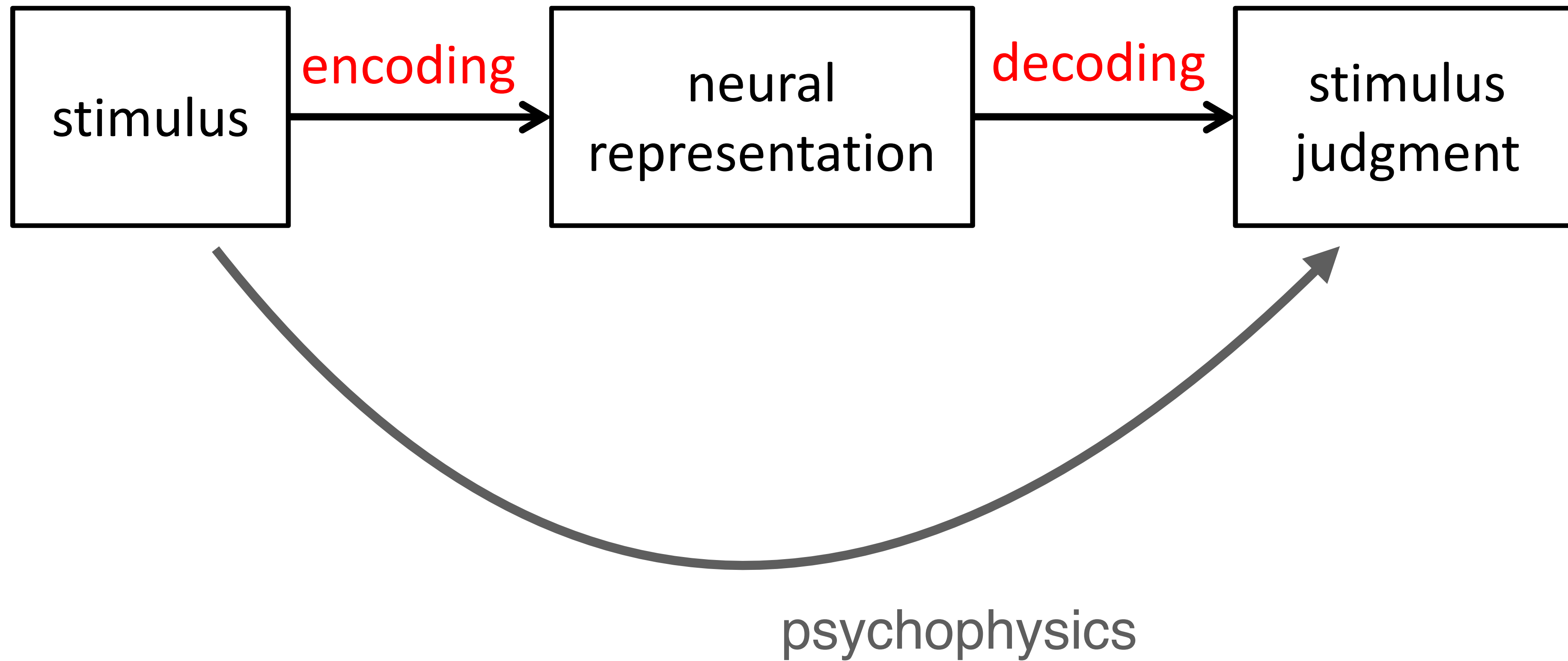


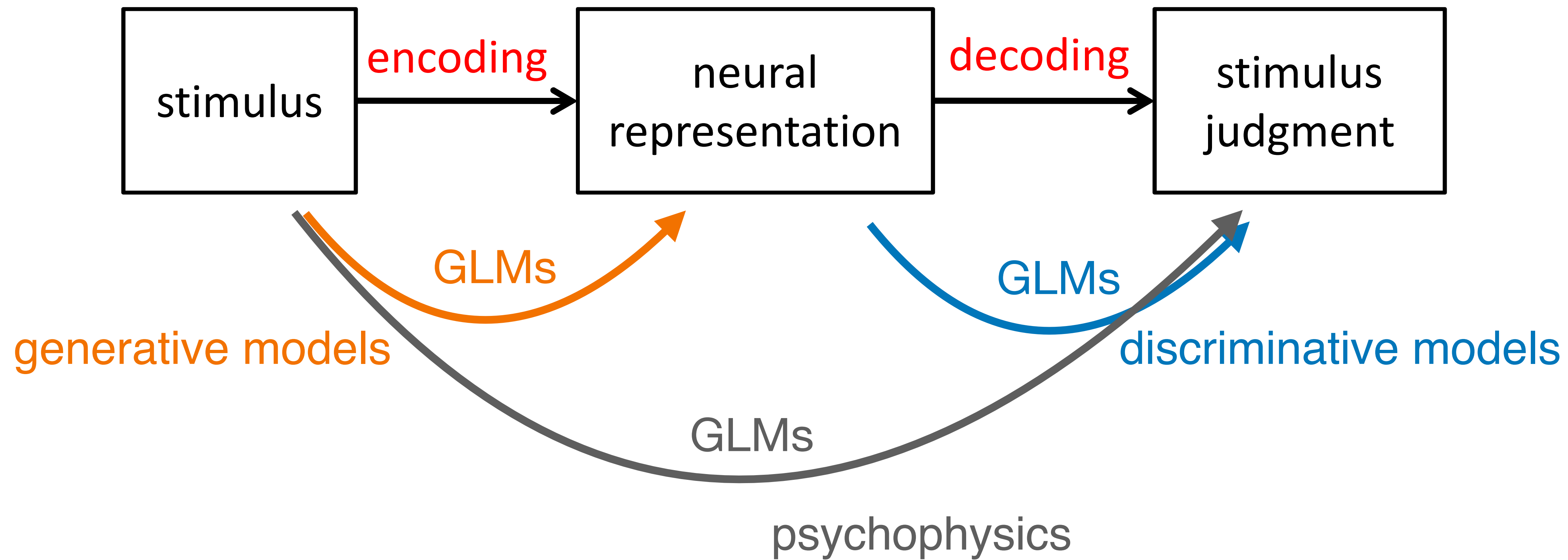


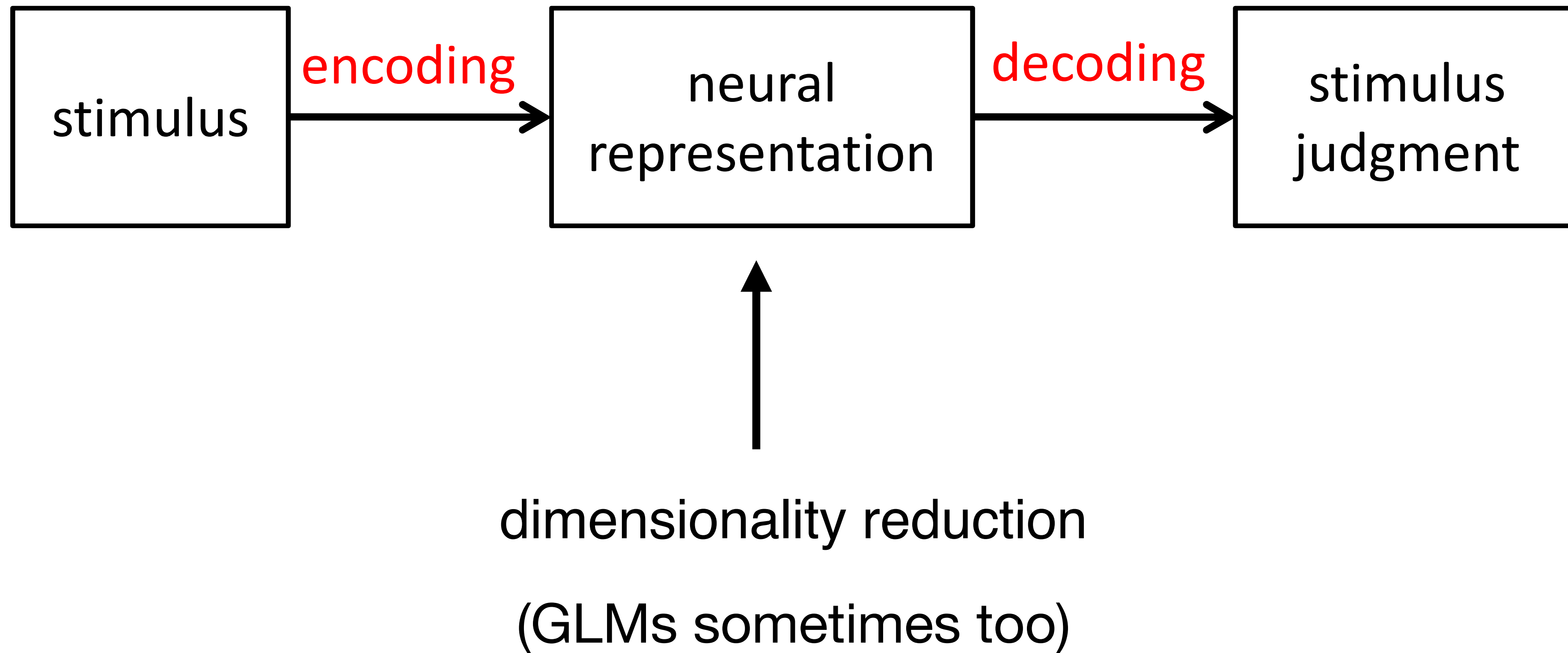


discriminative models

- classification
- regression







GLM history

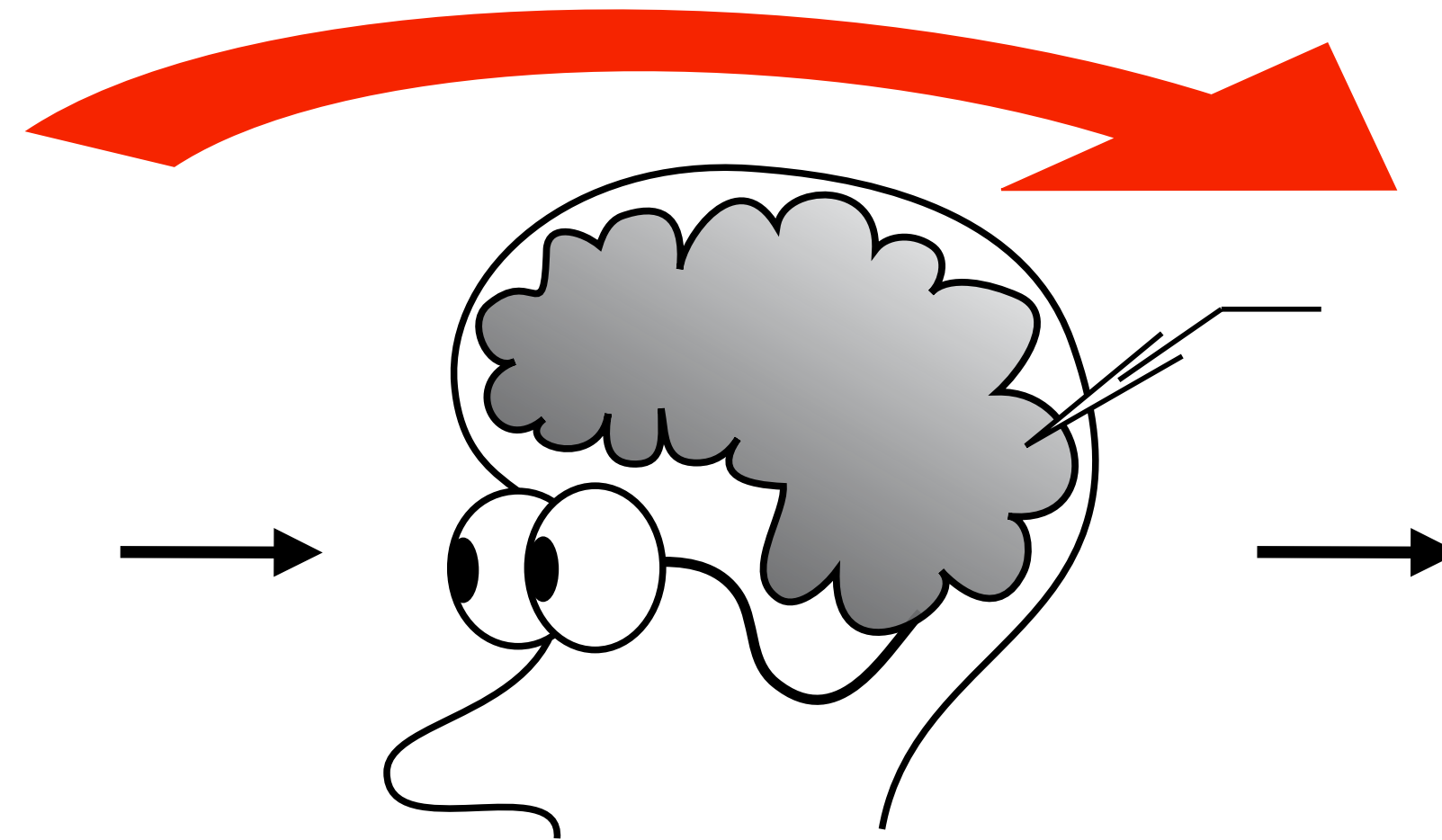
- Flexible & convenient way of testing and characterizing statistical relationships between “input” and “output” variables.
- Family of models developed in the early 70’s (Nelder & Wedderburn, 1972) to unify several types of regression
- Adoption in neuroscience - introduced independently by 2 groups, (nearly) simultaneously:
 - Simoncelli E, Paninski L, Pillow J and Schwartz O 2004 **Characterization of neural responses with stochastic stimuli** The Cognitive Neurosciences 3rd edn, ed M Gazzaniga (Cambridge, MA: MIT Press)
 - Truccolo W, Eden UT, Fellows MR, Donoghue JP, Brown EN.. **A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects.** *J Neurophysiol.* 2005;93(2):1074-1089. doi:10.1152/jn.00697.2004
- Related to feed-forward neural networks

Encoding

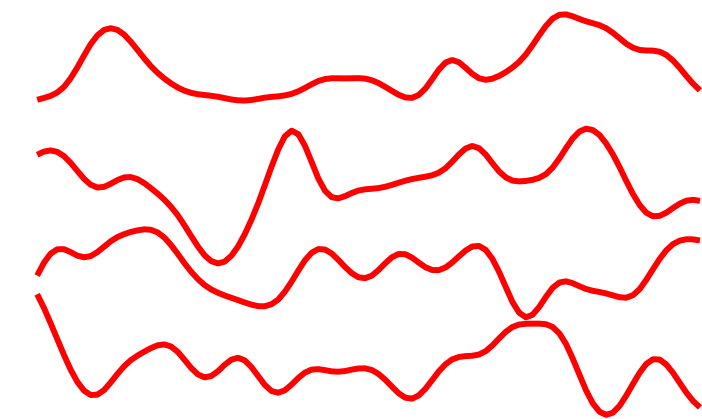
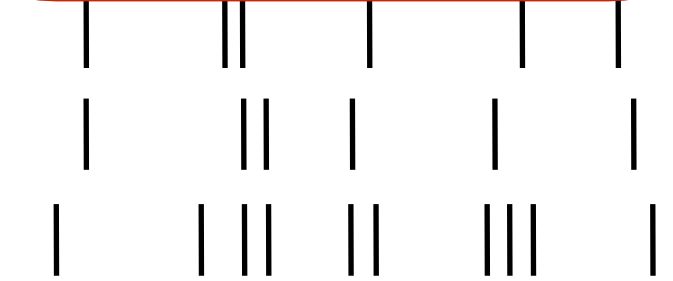


x

≥ 1 external variables

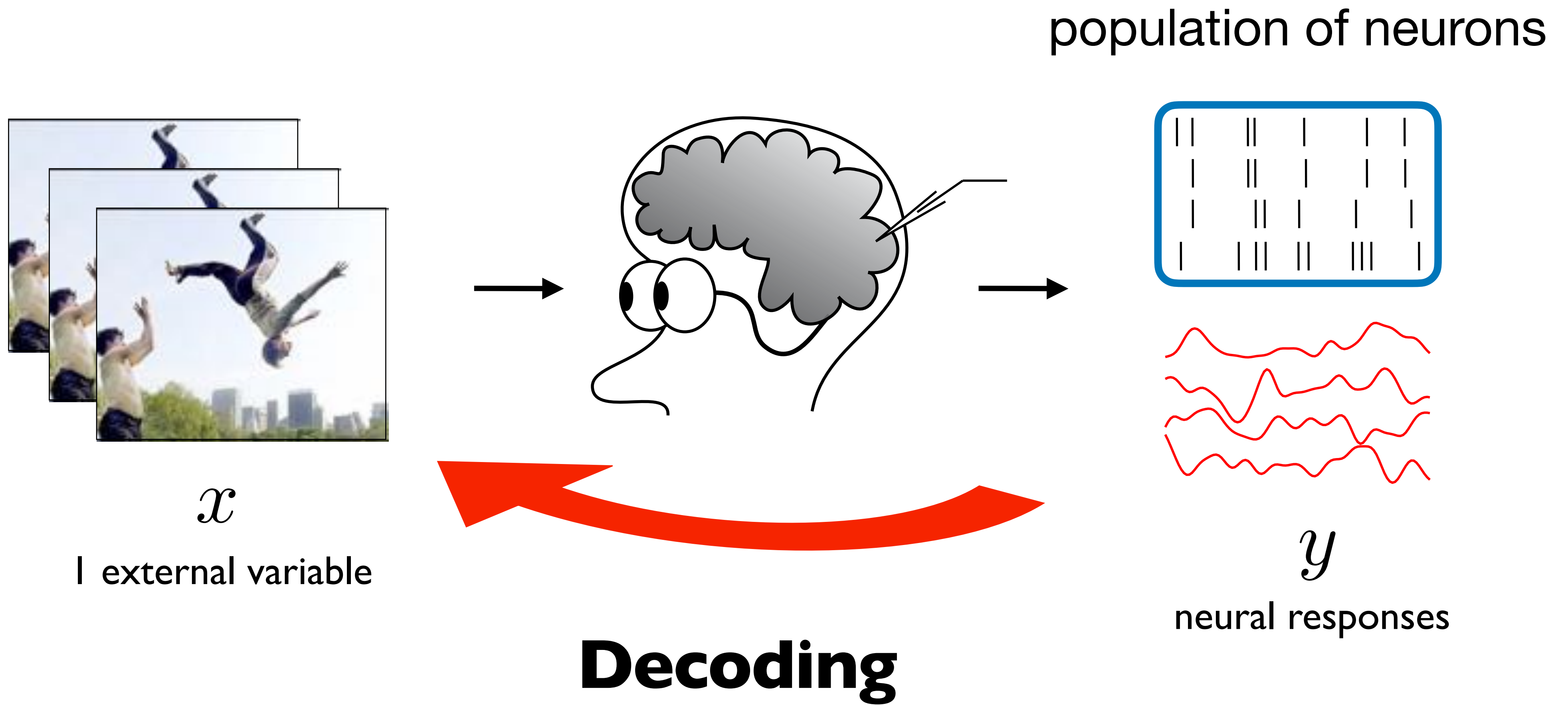


single neuron



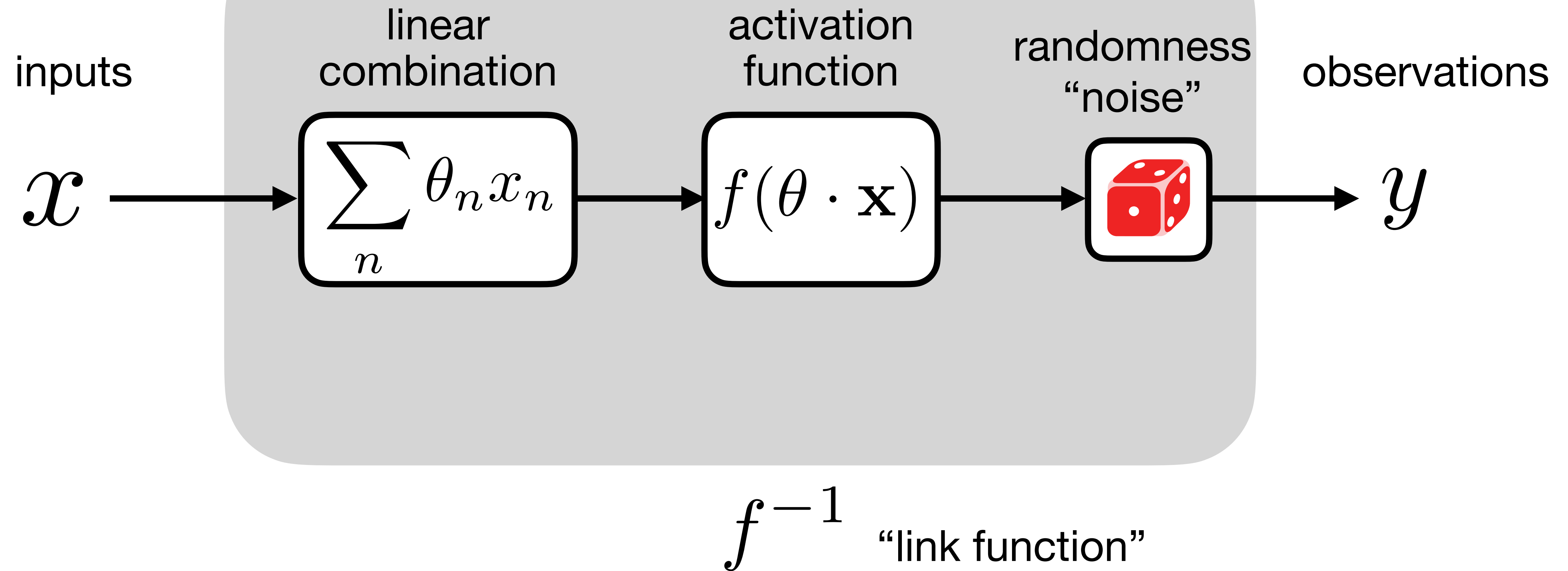
y

neural responses



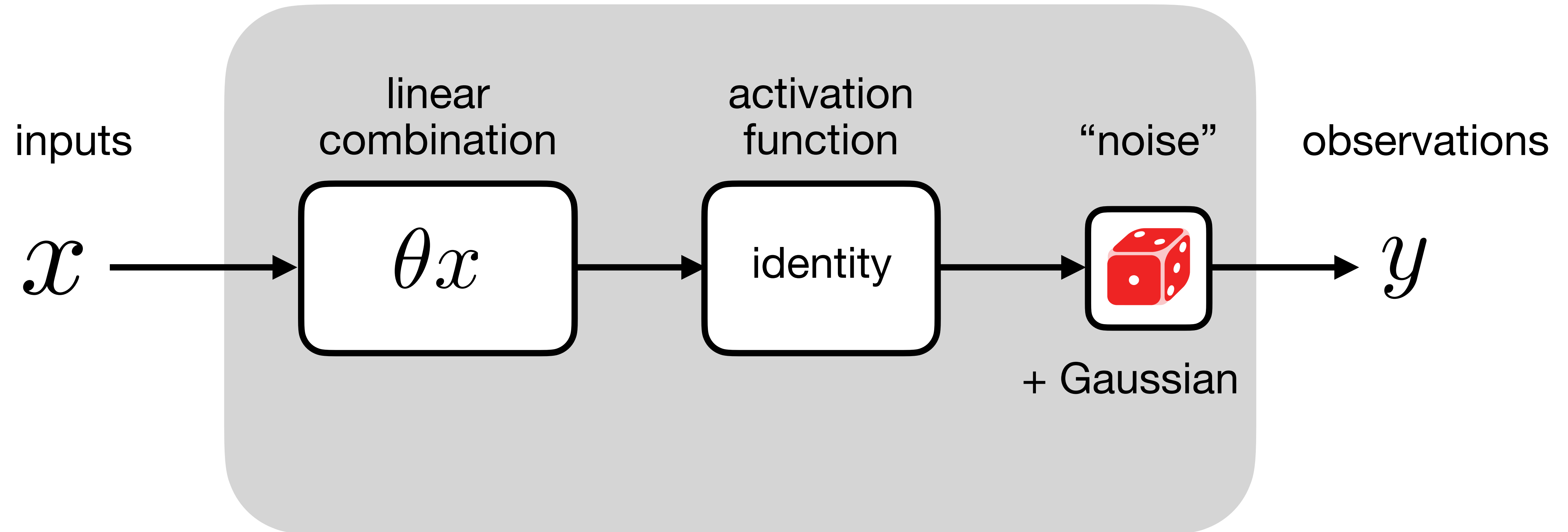
Structure of the GLM

model



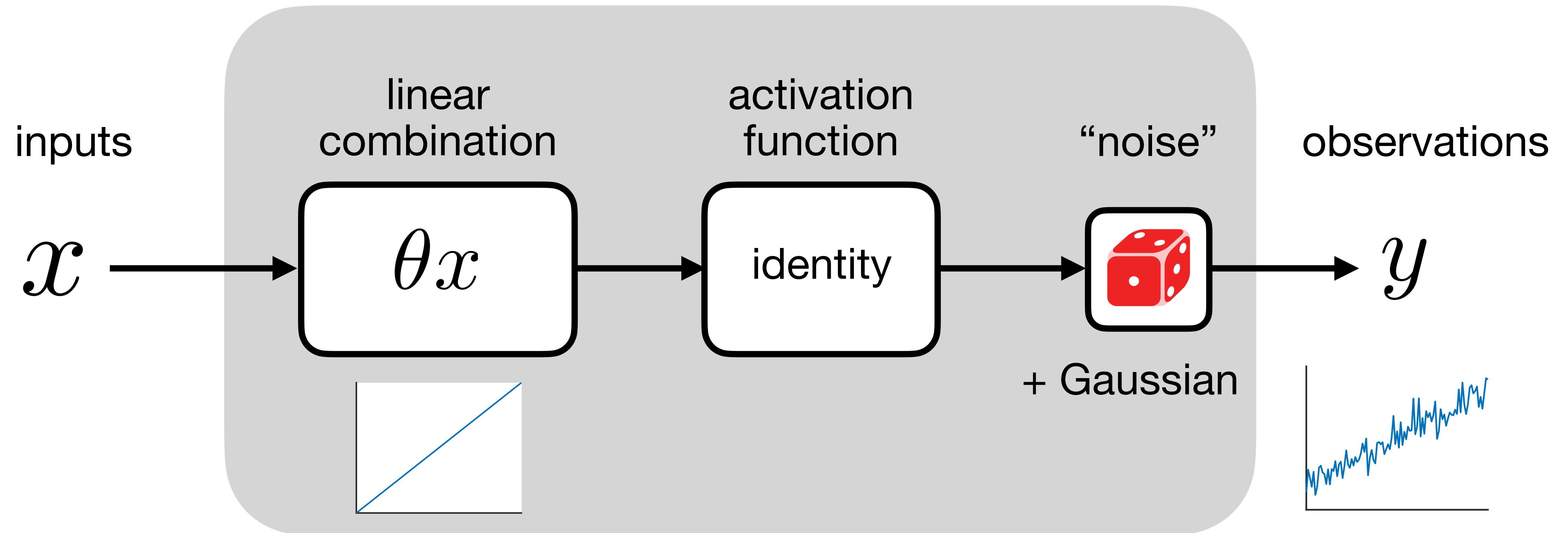
Simple linear regression

$$y = \theta x + \eta$$



Simple linear regression

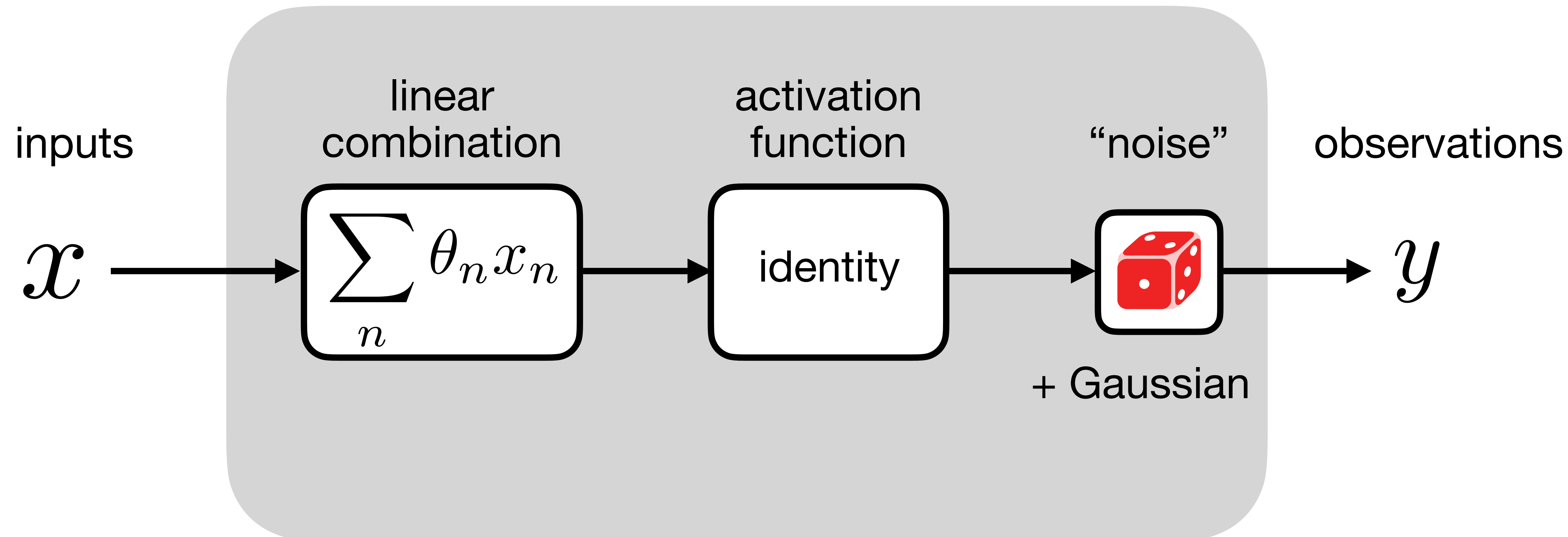
$$y = \theta x + \eta$$



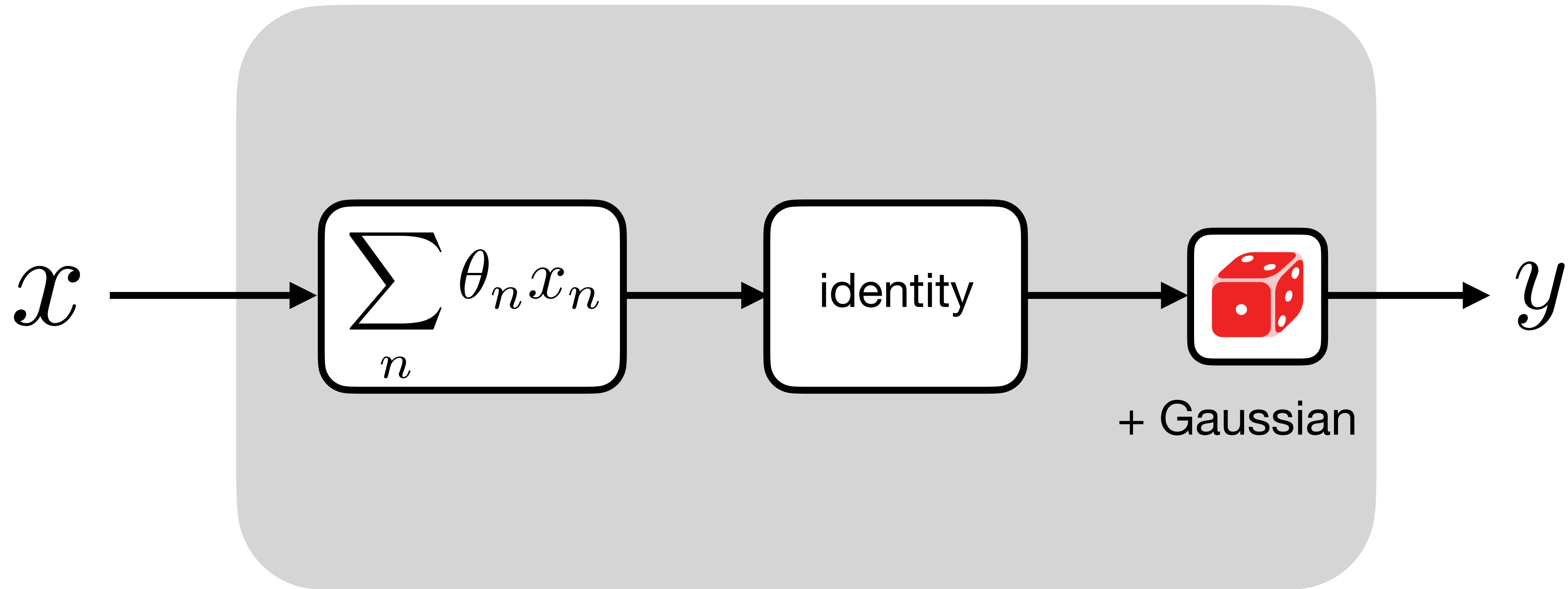
$$y \sim \mathcal{N}(\theta x, \sigma^2)$$

Multiple linear regression

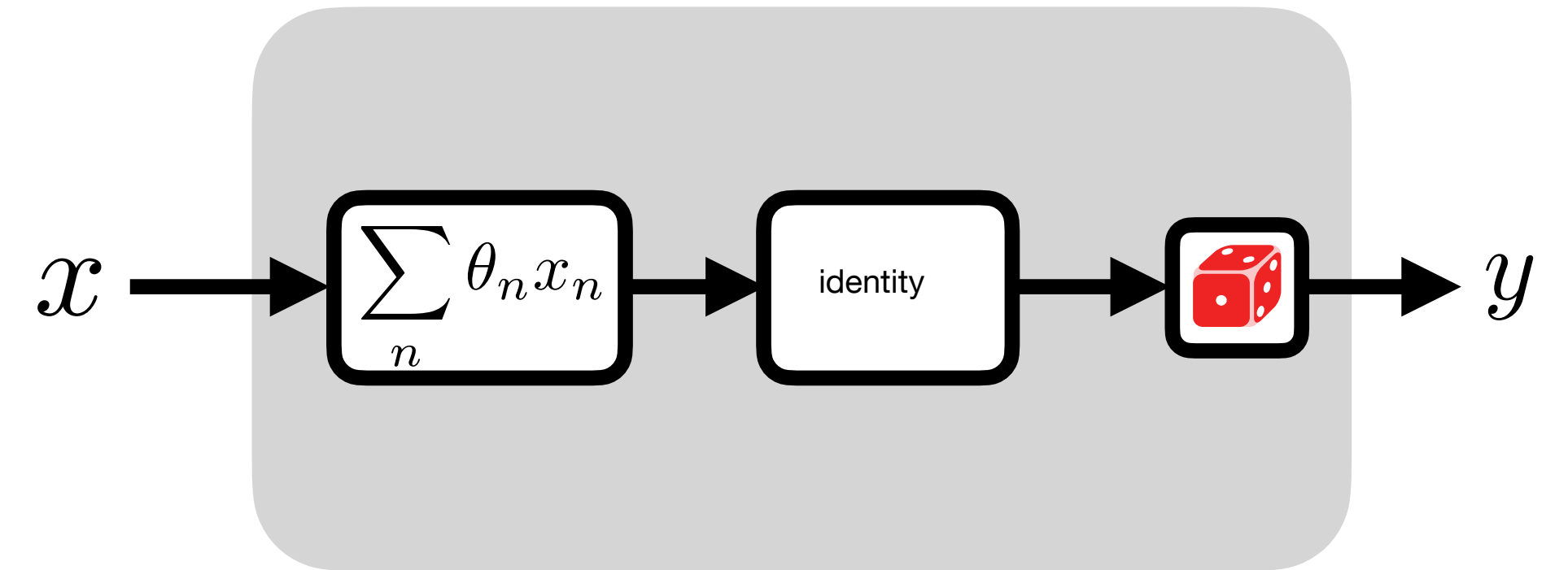
$$y = \sum_n \theta_n x_n + \eta$$



Multiple linear regression



Multiple linear regression



$$y \sim \mathcal{N}(\mu, \sigma^2)$$

$$p(y|\mu, \sigma^2) = \frac{1}{\sqrt{2\sigma^2}} \exp\left(-\frac{(\mu - y)^2}{\sigma^2}\right)$$

for Gaussian GLM

$$\mu = \sum_n \theta_n x_n$$

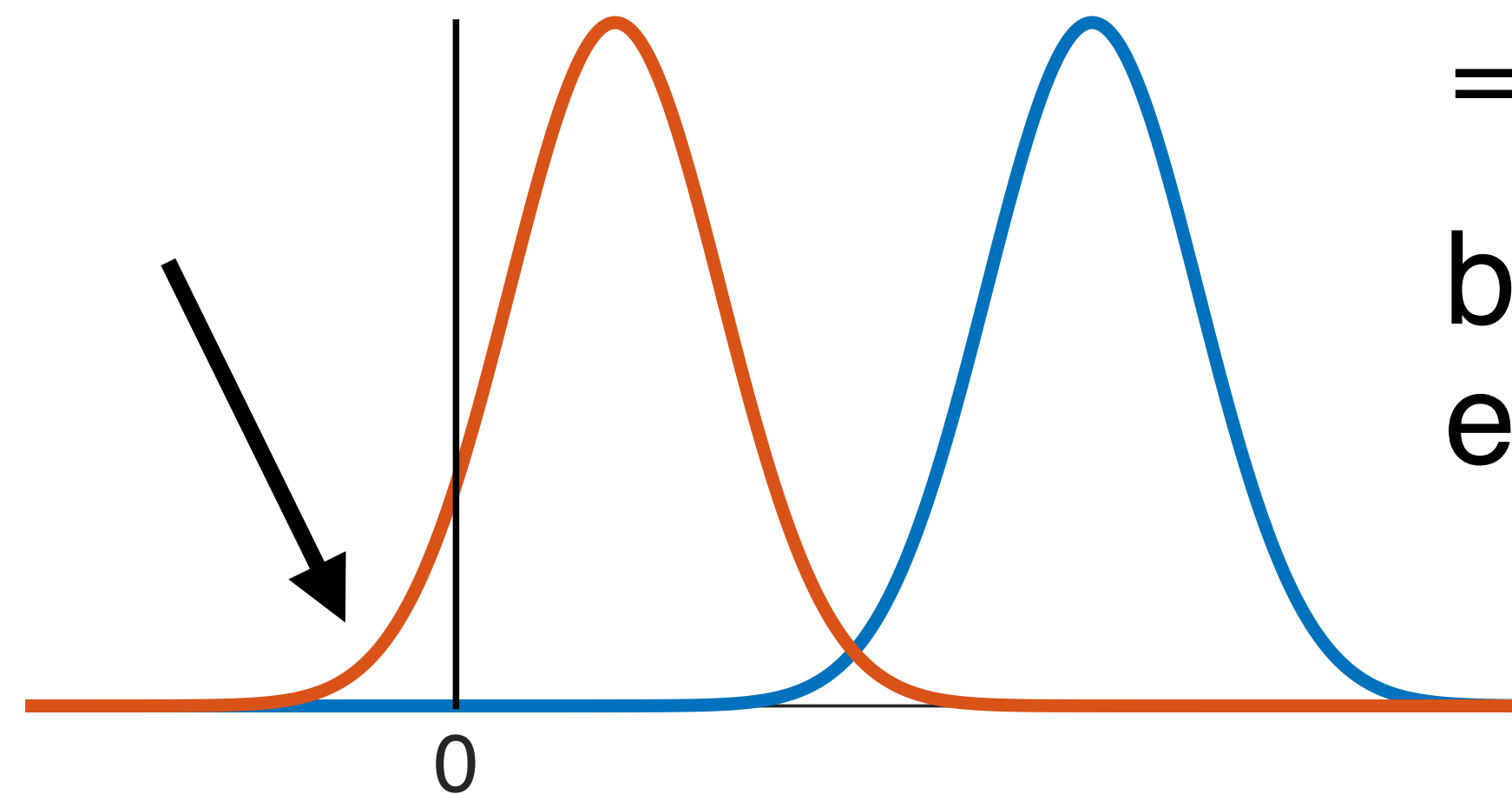
Gaussian variability

$$y|\mathbf{x} \sim \mathcal{N}(\mathbf{f}(\theta \cdot \mathbf{x}), \sigma^2)$$

$$y = f(\theta \cdot \mathbf{x}) + \eta$$

$$\eta \sim \mathcal{N}(0, \sigma^2)$$

density at
negative spike
counts!

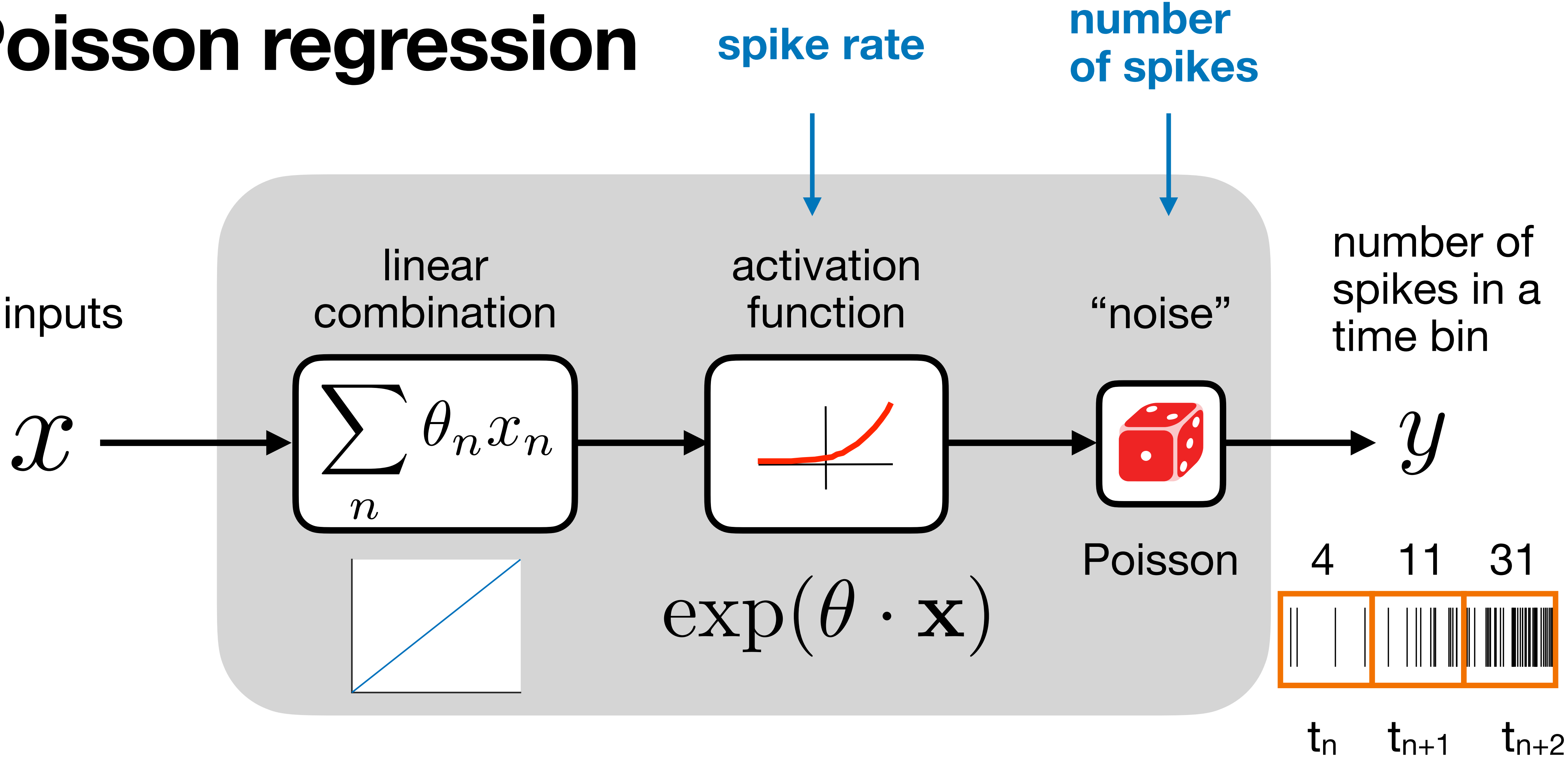


predicted # of spikes

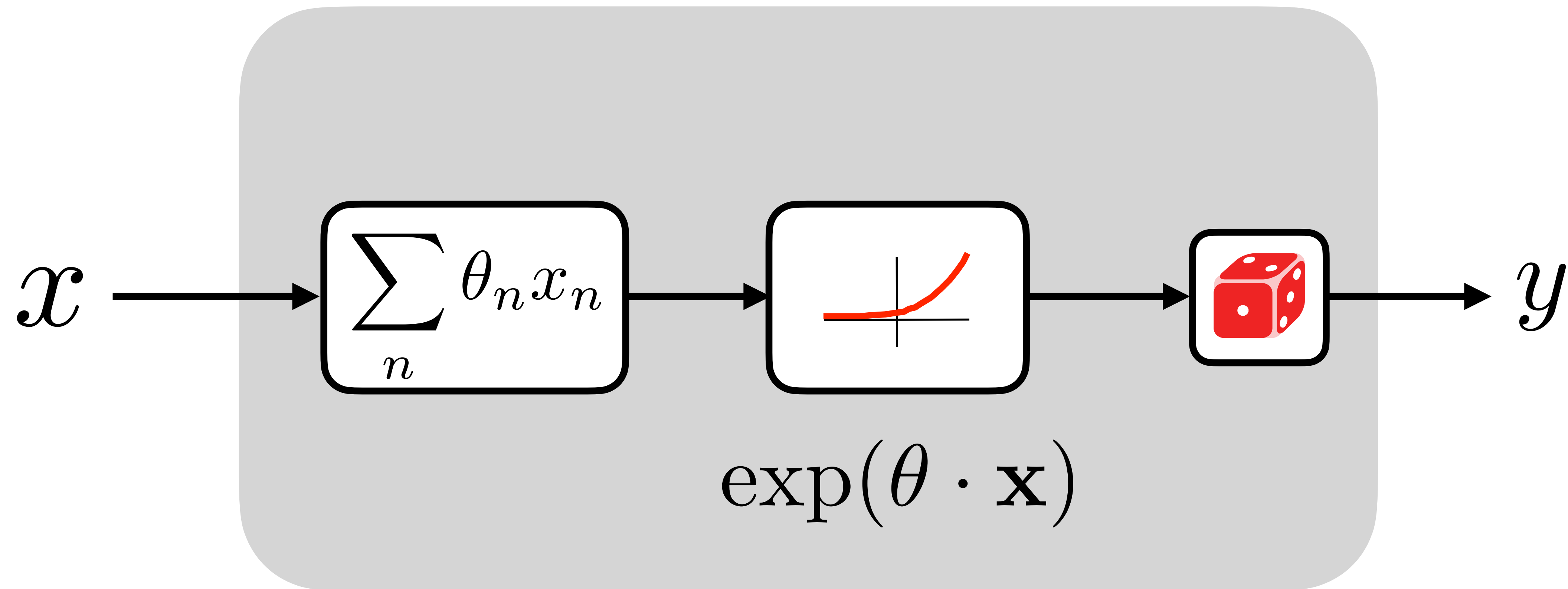
⇒ model mismatch
but makes math
easy



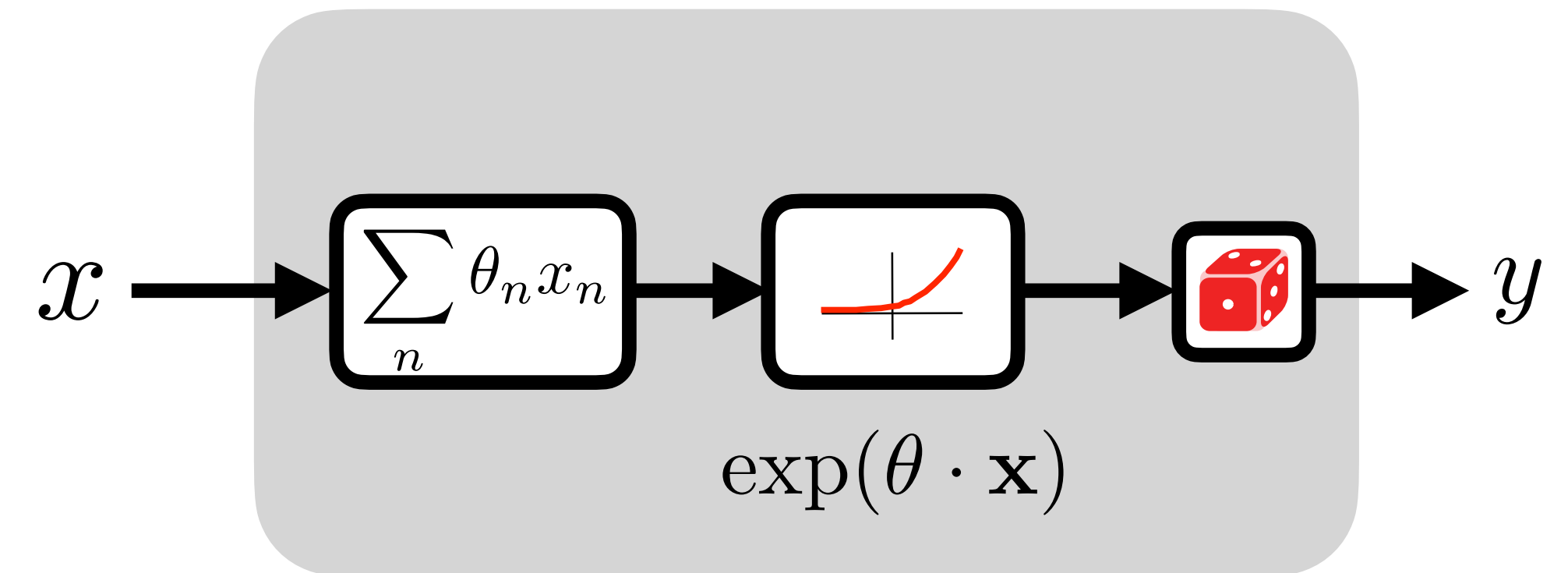
Poisson regression



Poisson regression

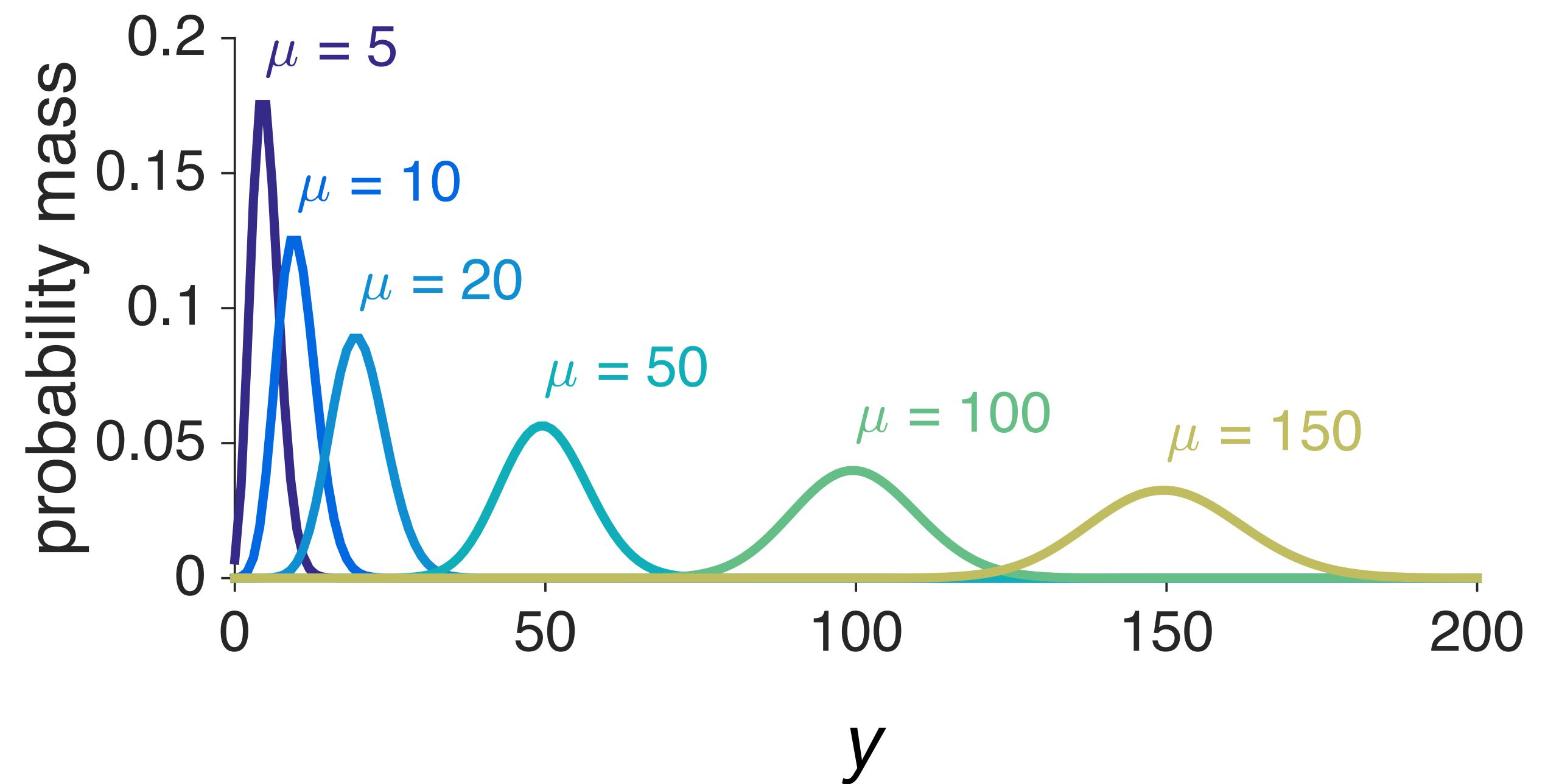


Poisson regression

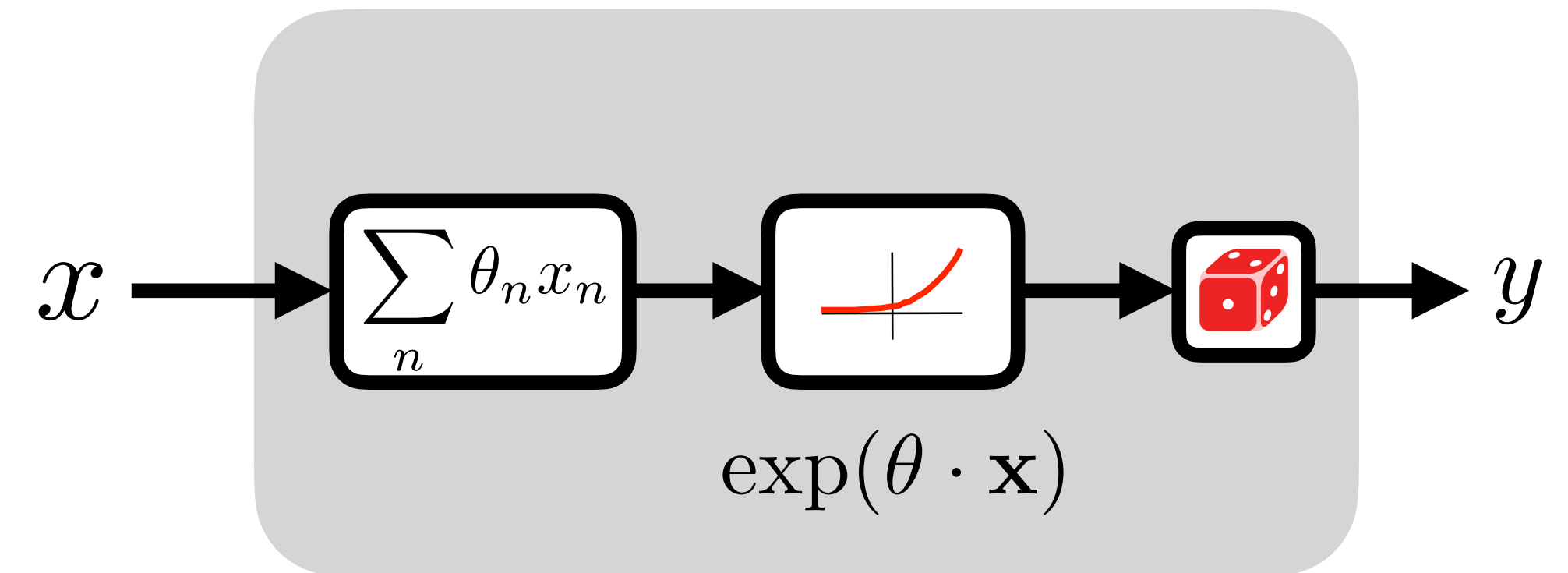


$$y \sim \text{Poisson}(\lambda)$$

$$P(y|\lambda) = \frac{e^{-\lambda} \lambda^y}{y!}$$



Poisson regression



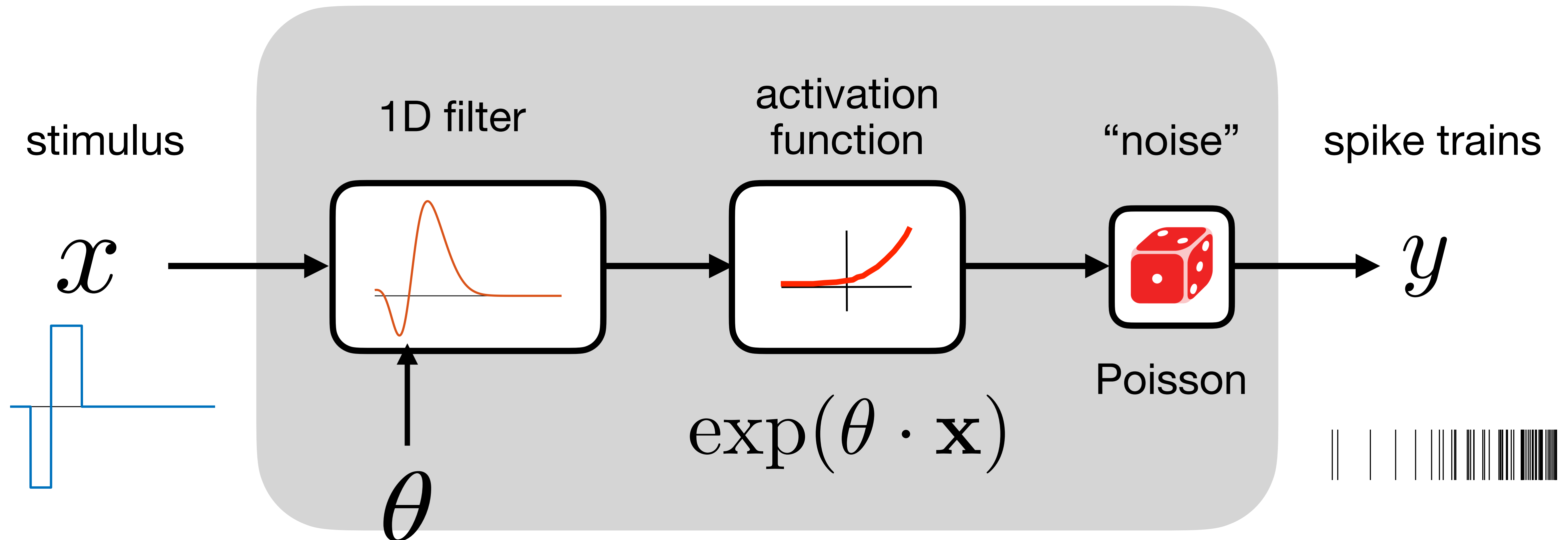
$$y \sim \text{Poisson}(\lambda)$$

$$P(y|\lambda) = \frac{e^{-\lambda} \lambda^y}{y!}$$

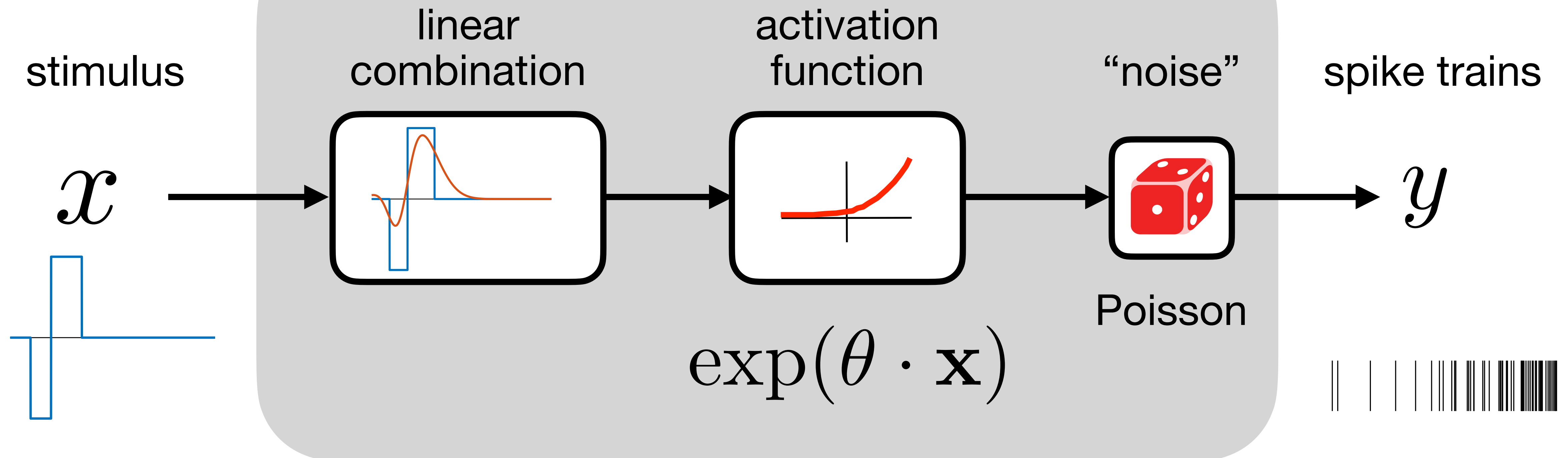
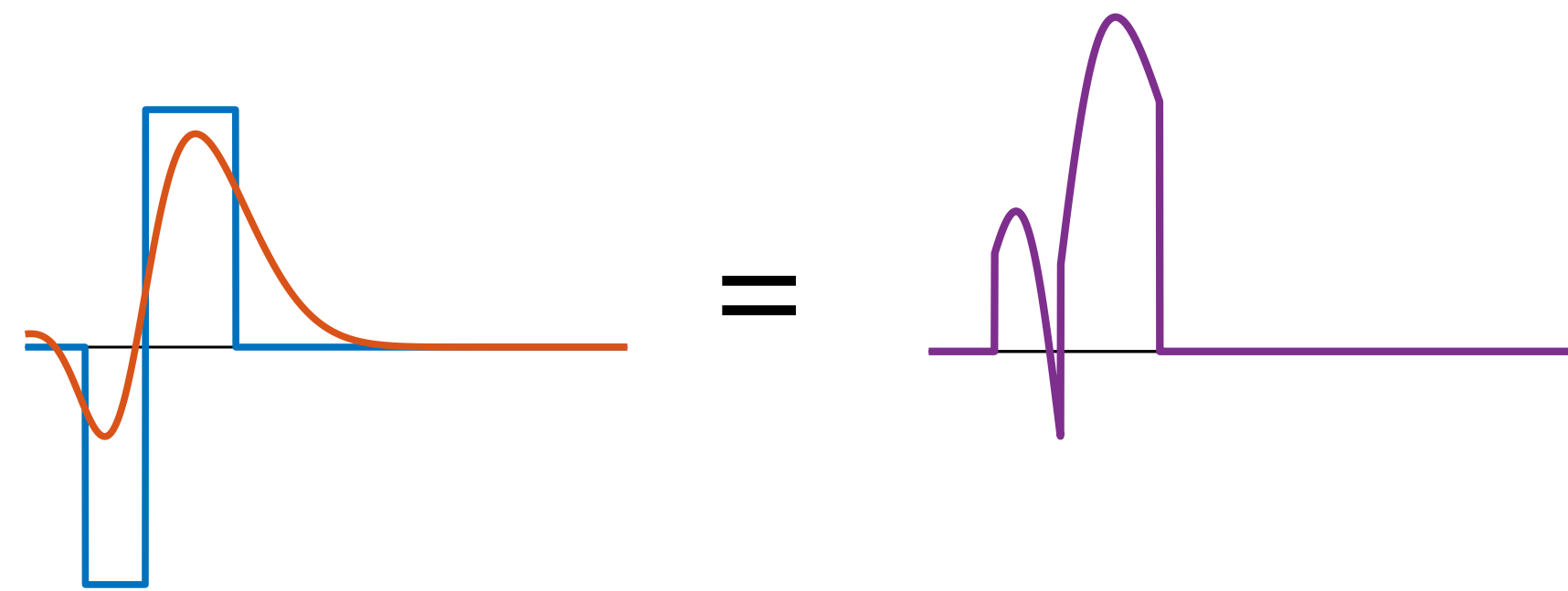
For Poisson GLM

$$\lambda = \exp\left(\sum_n \theta_n x_n\right)$$

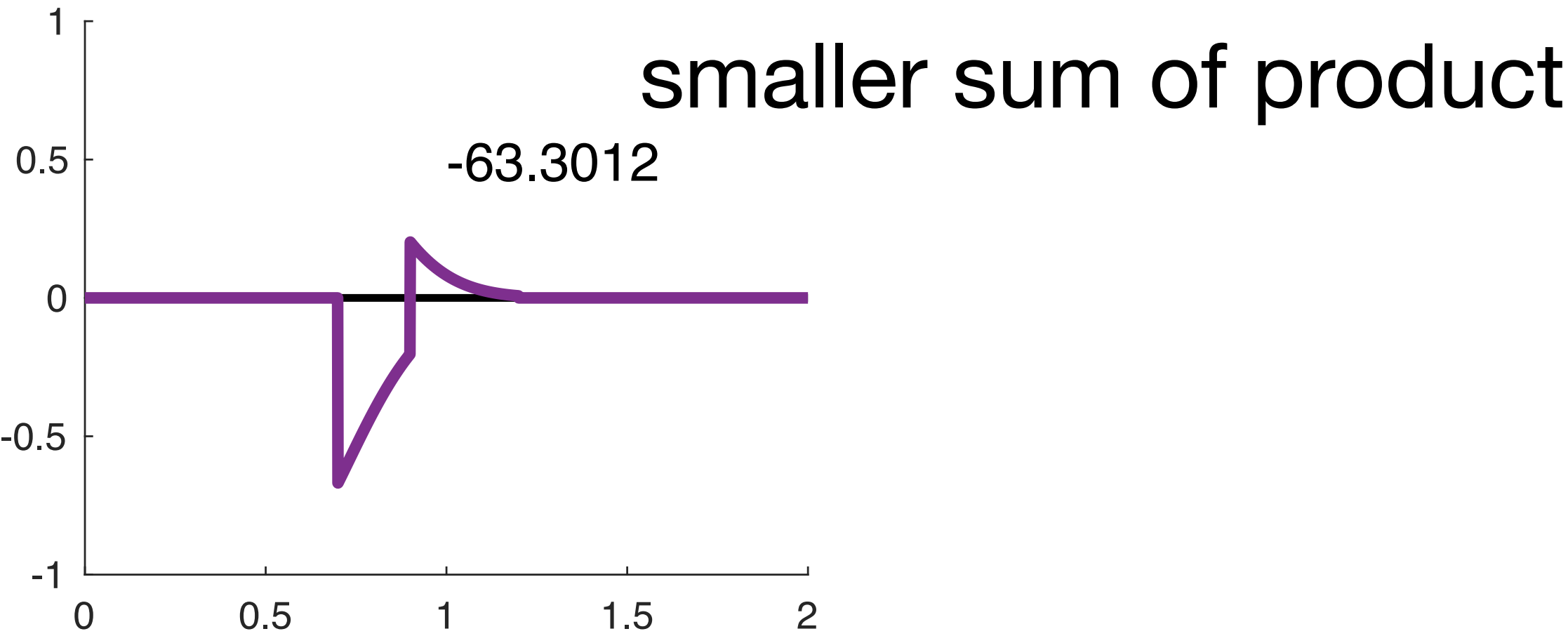
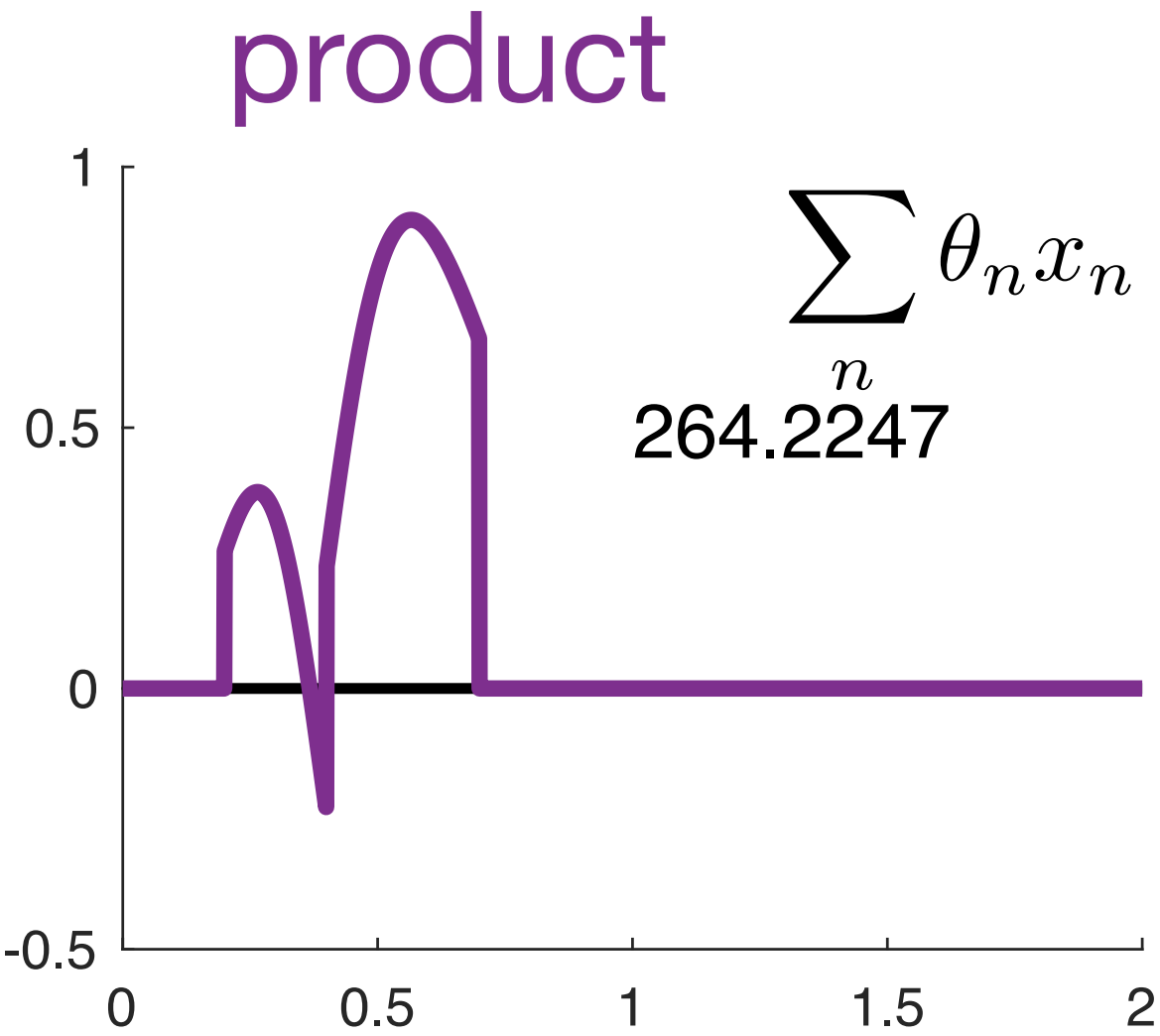
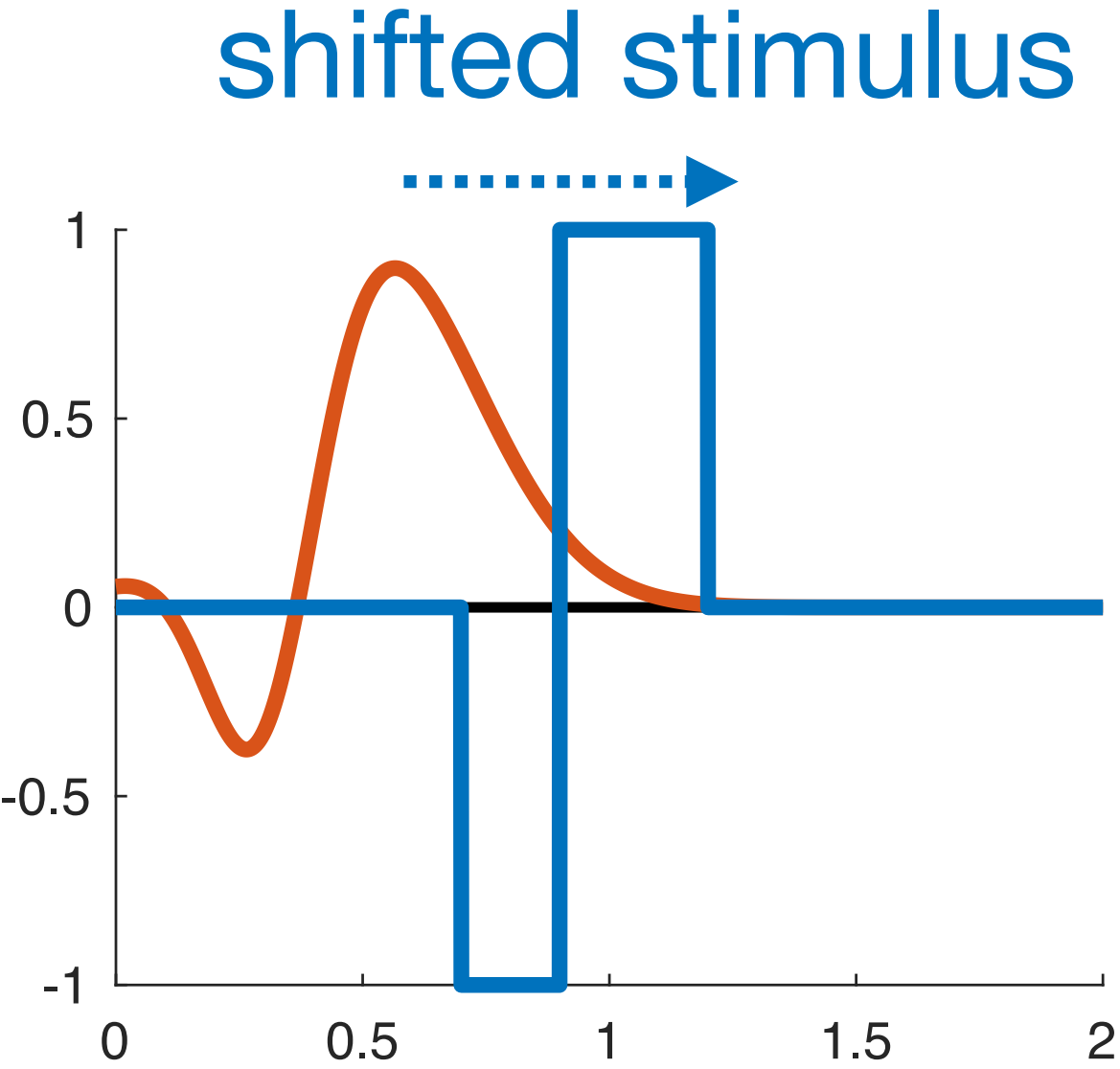
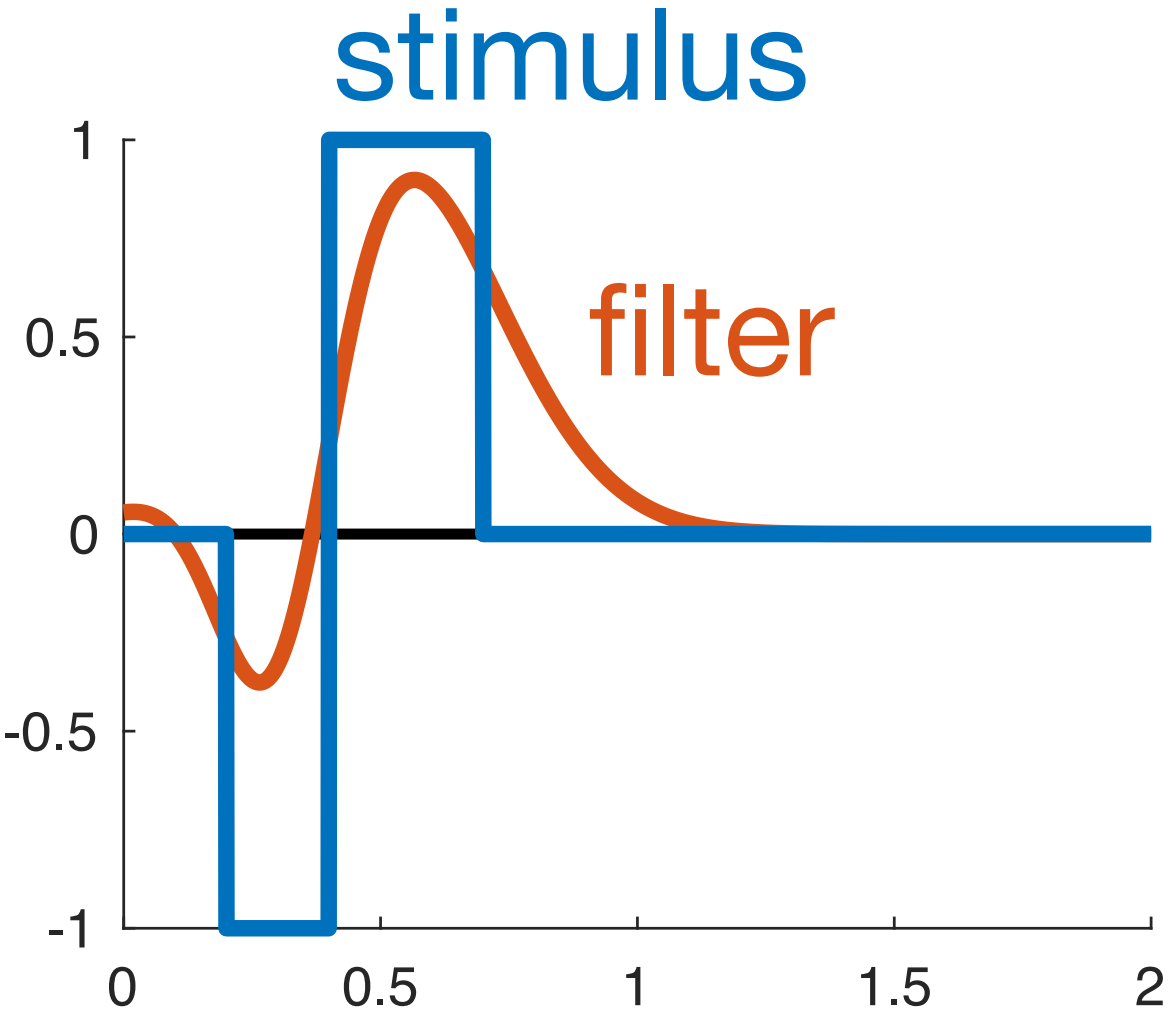
Stimulus filter



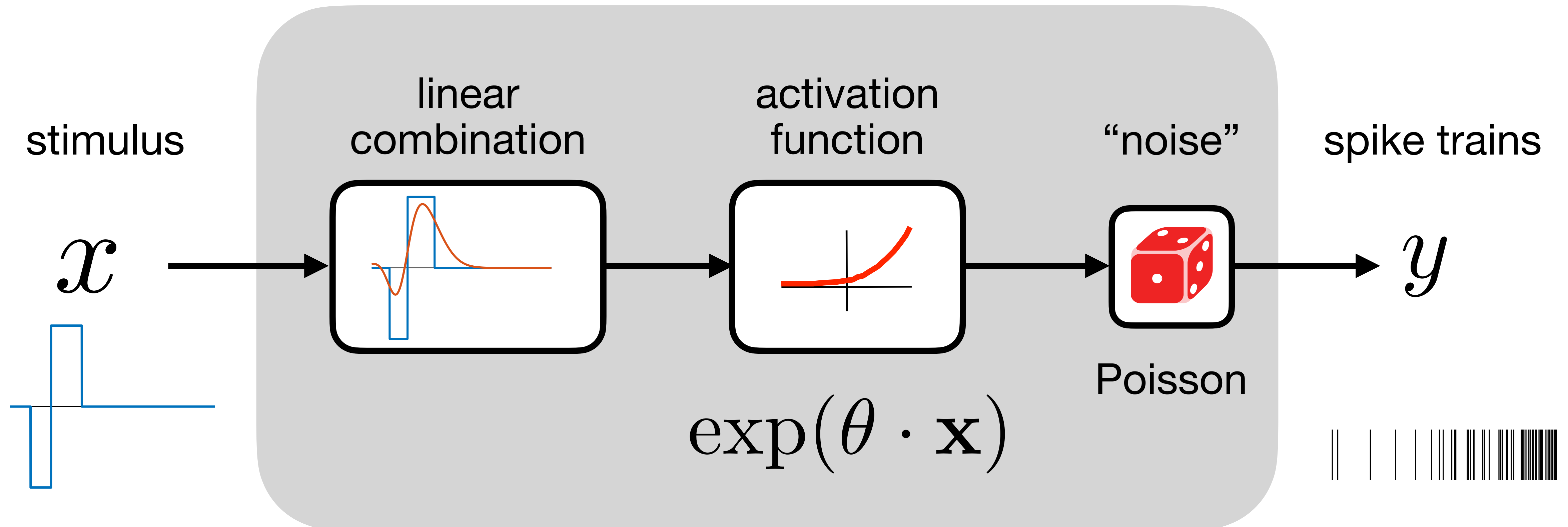
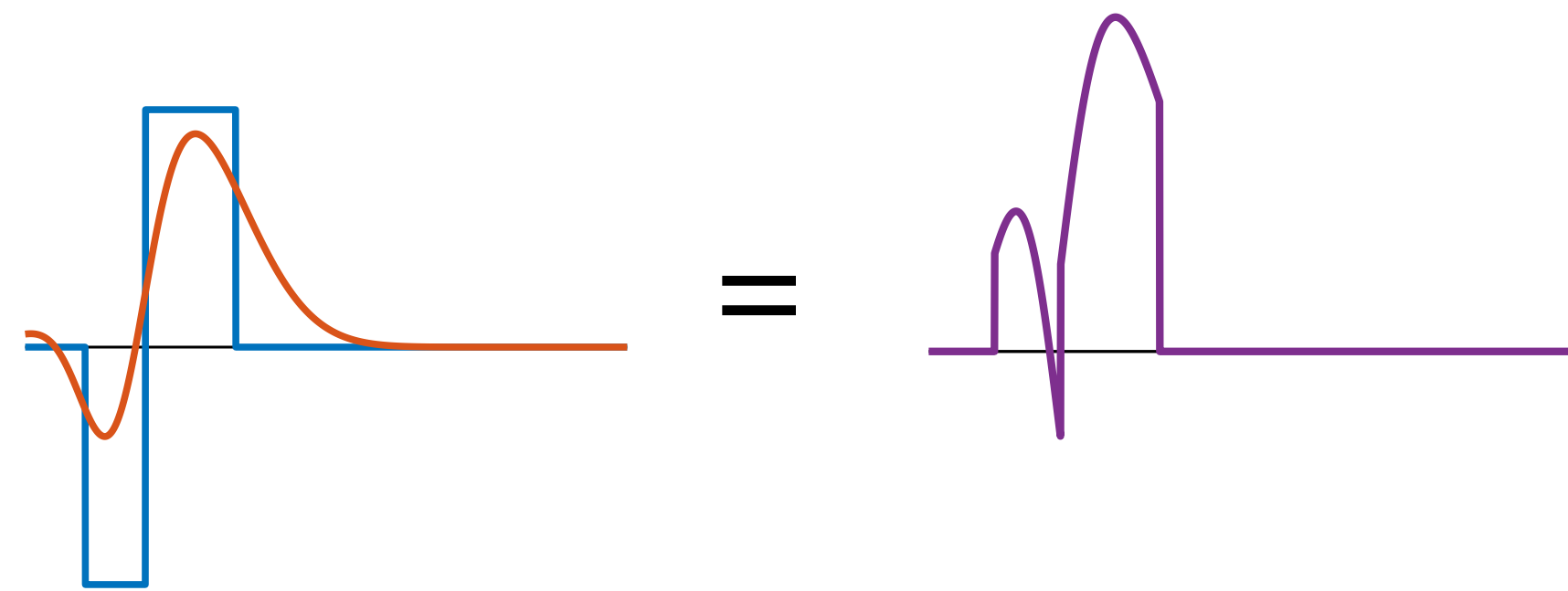
Stimulus filter



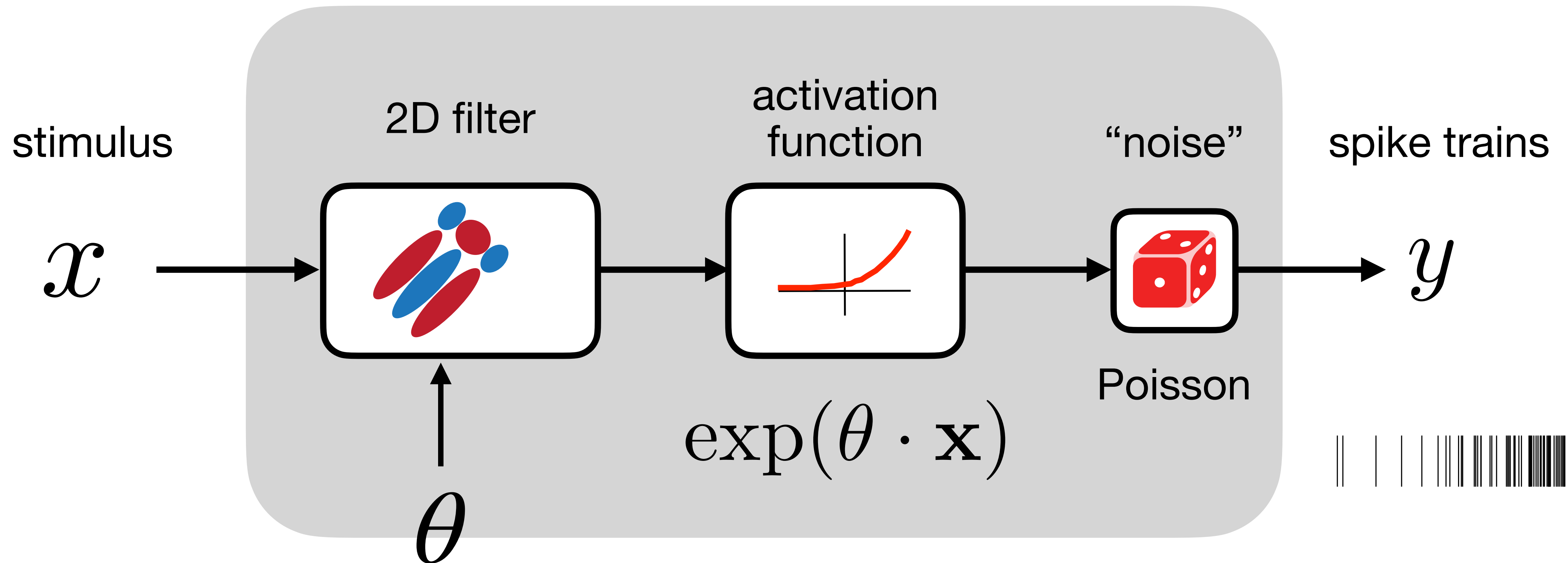
Stimulus filter



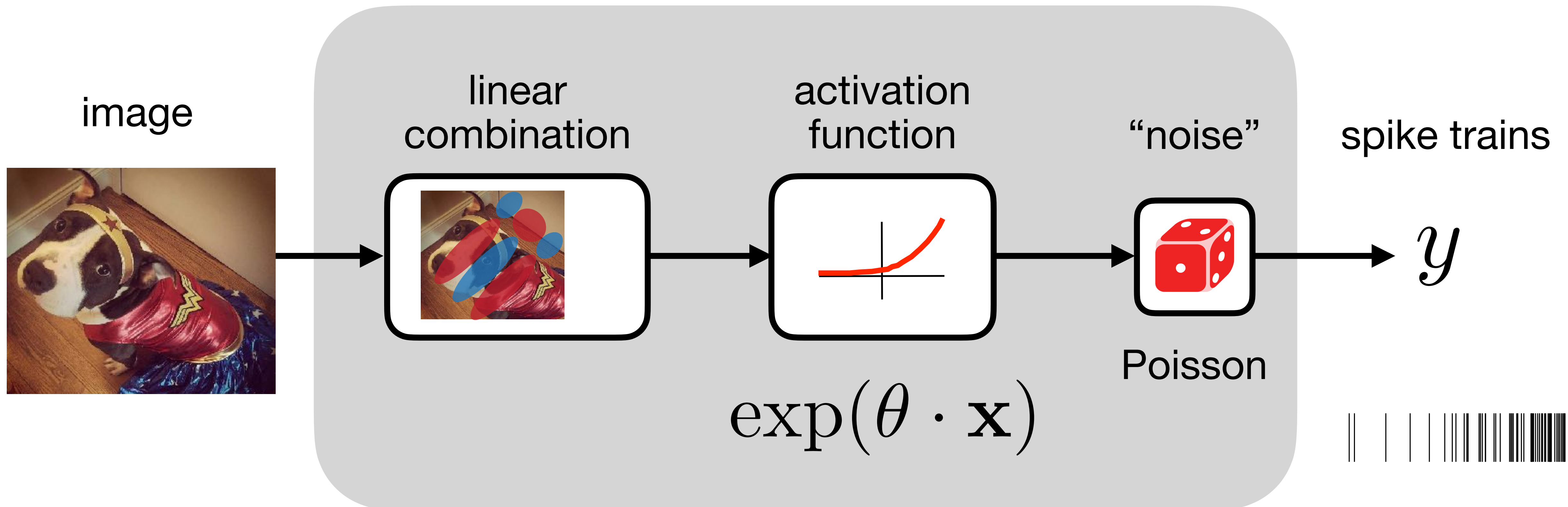
Stimulus filter



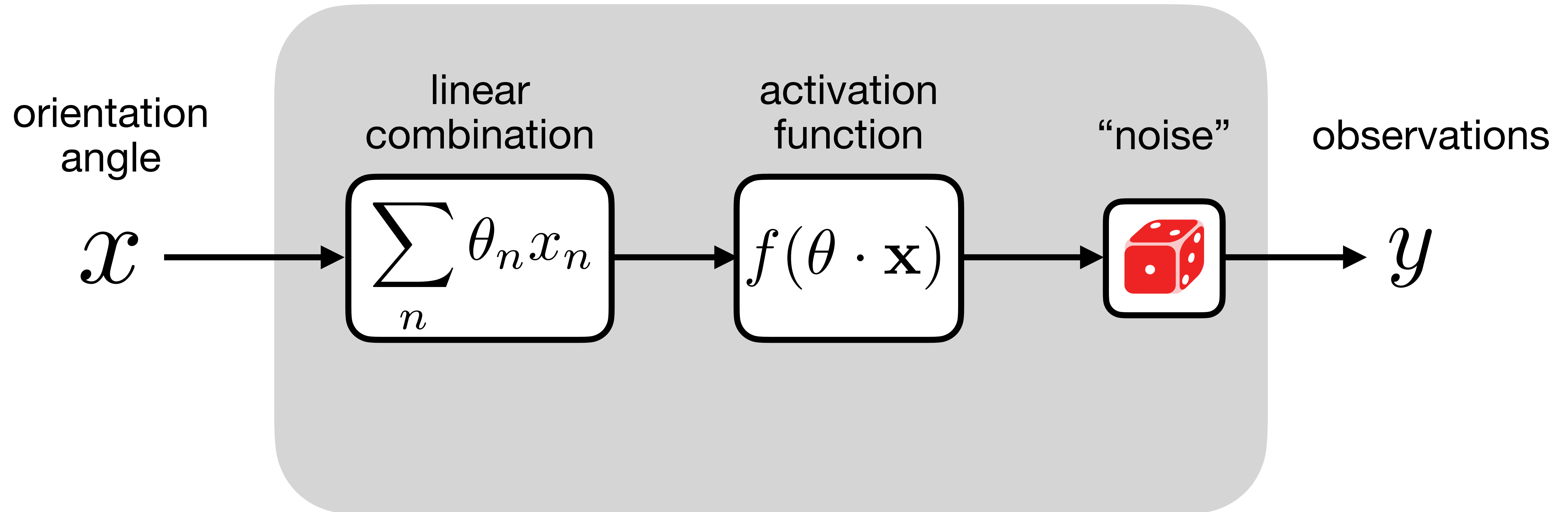
Stimulus filter



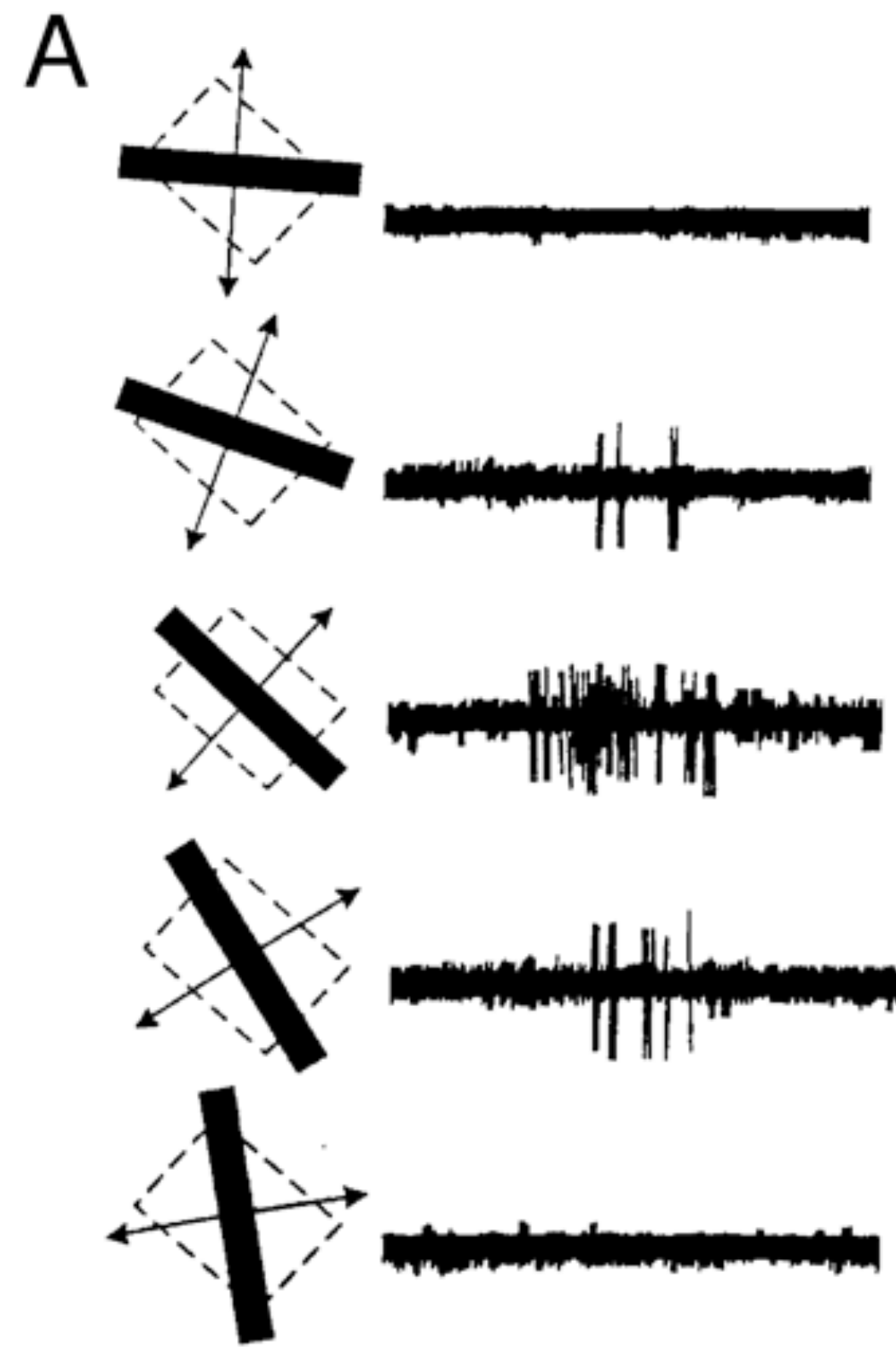
Stimulus filter



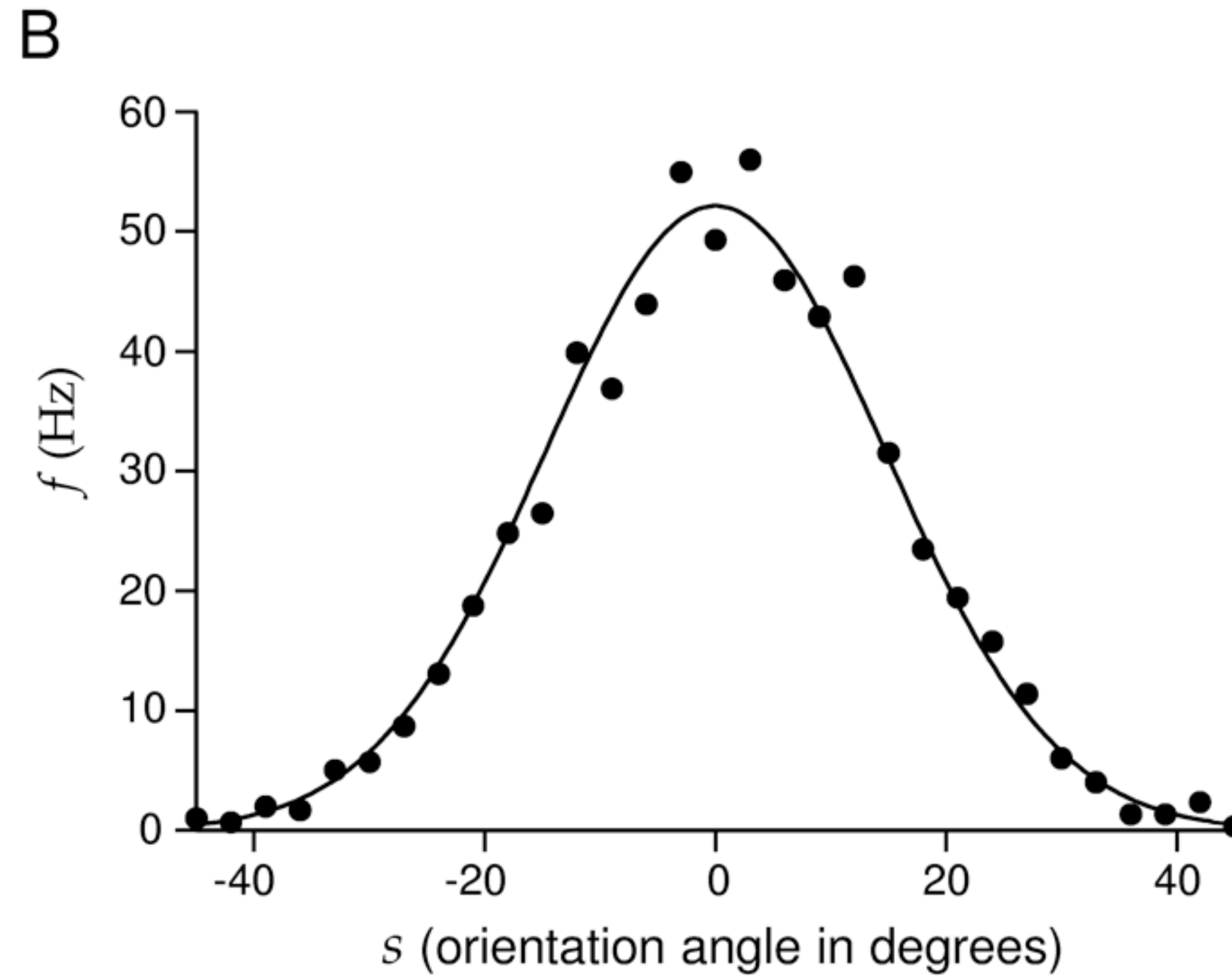
Nonlinear tuning (eg. cosine tuning)



Primary Visual Cortex ("V1")

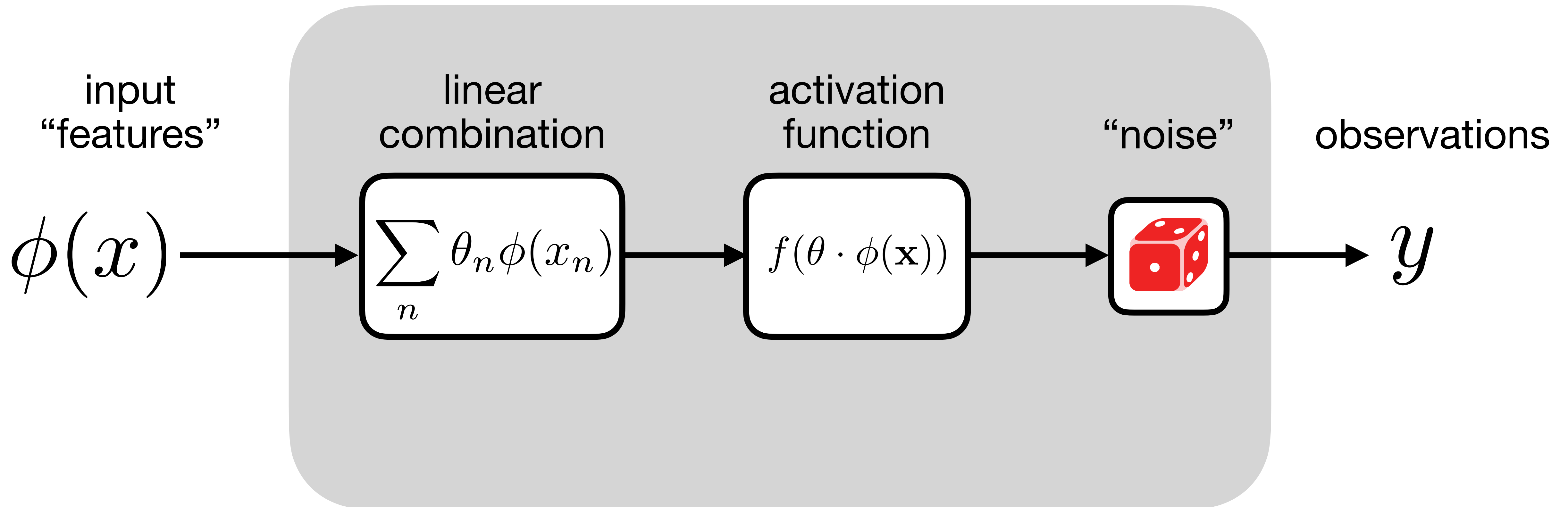


Tuning Curve ("Orientation tuned")



Hubel & Weisel, 1968

Nonlinear inputs

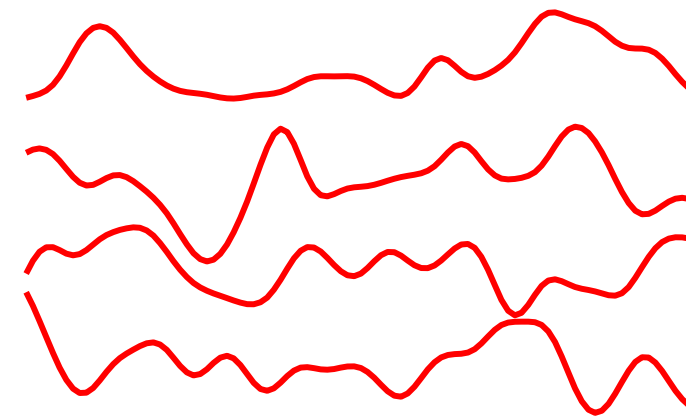
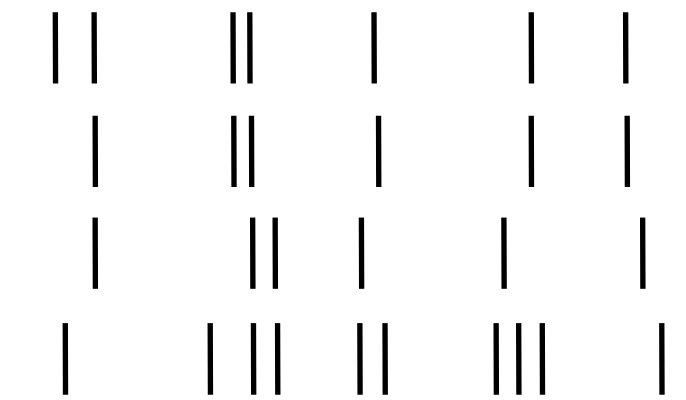
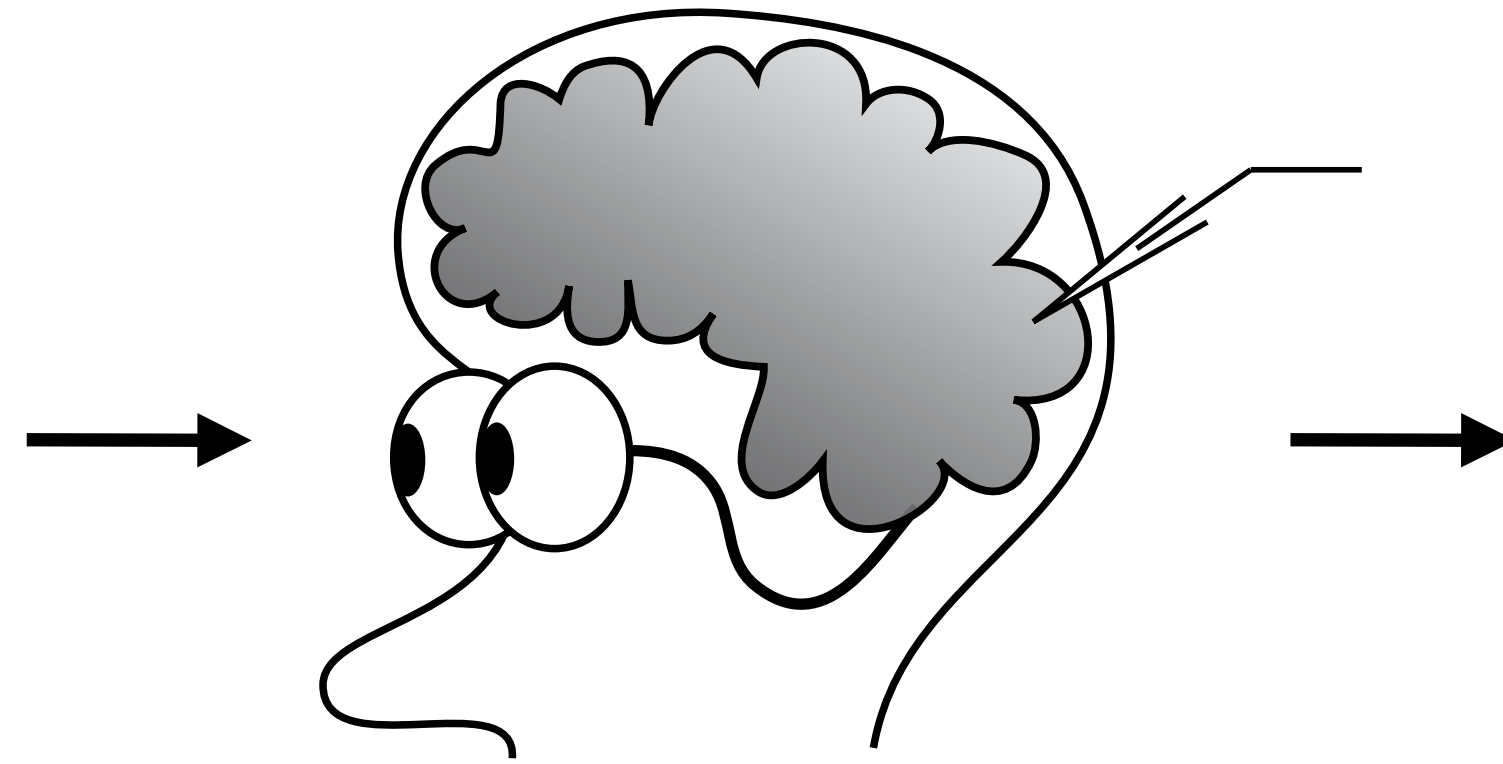


examples of $\phi(x)$: x^2 $\log(x)$ $\cos(x)$



x

external variables



y

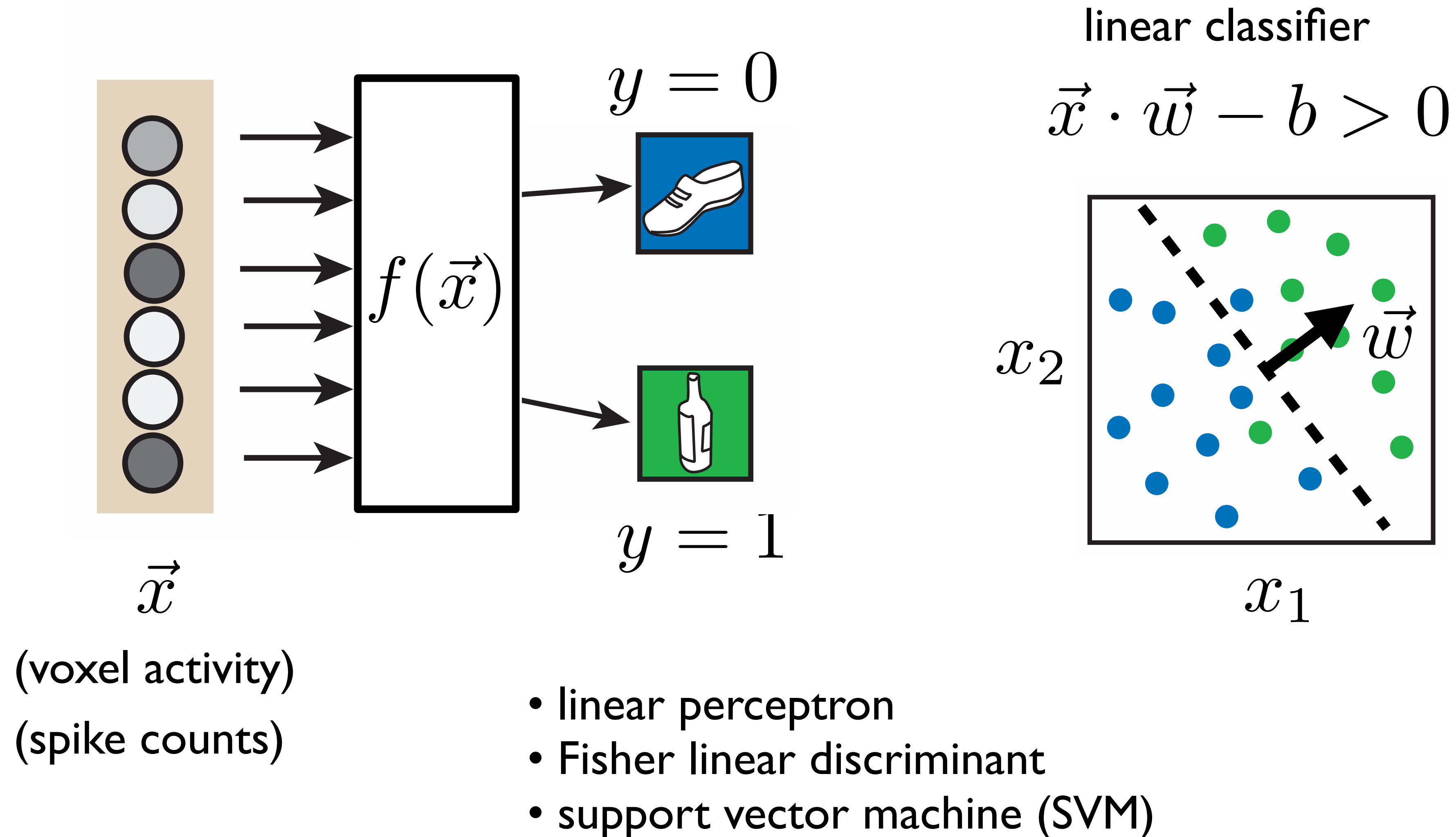
neural responses

Decoding

- classification
- regression

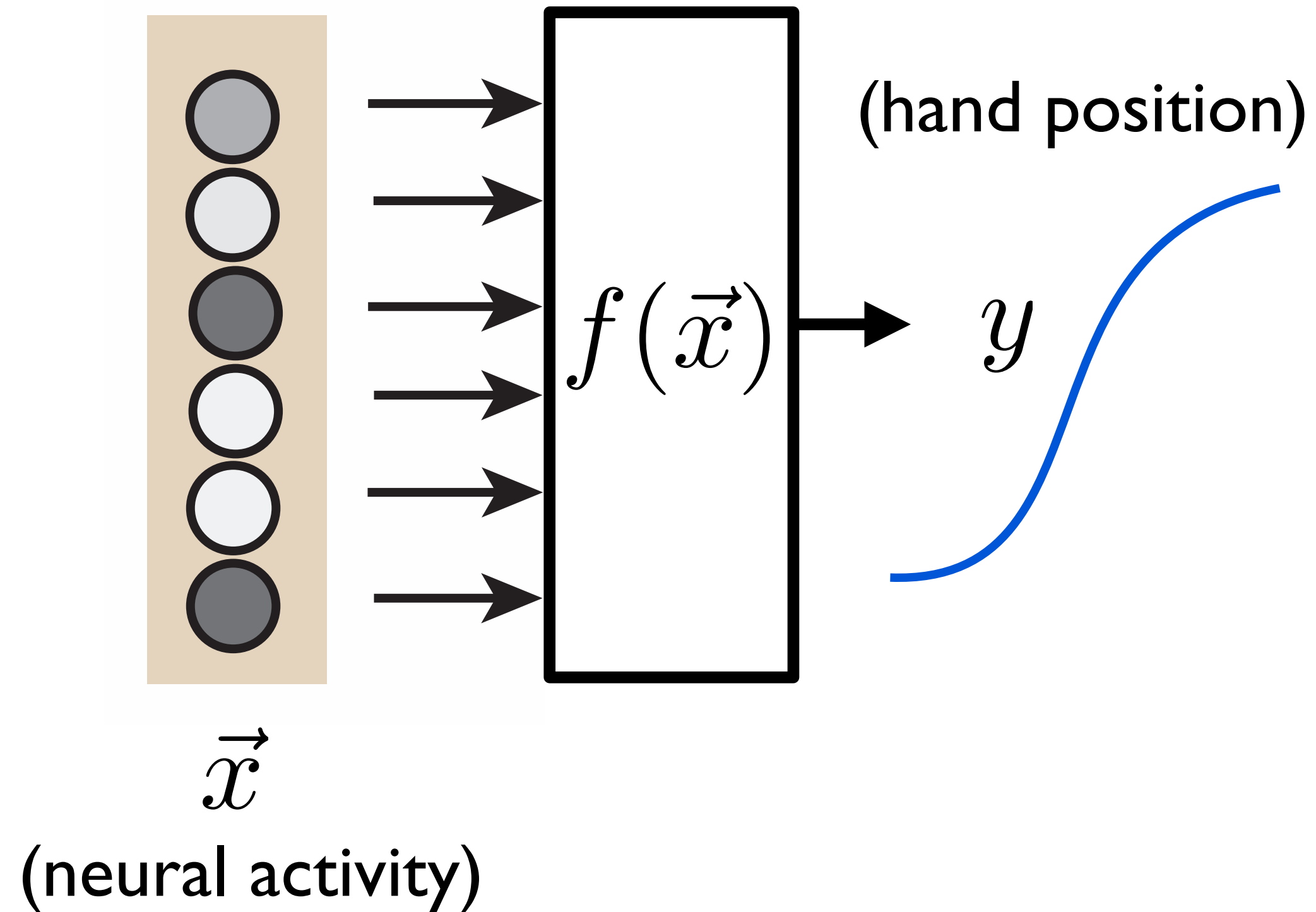
Classification

- mapping from vector input to discrete category



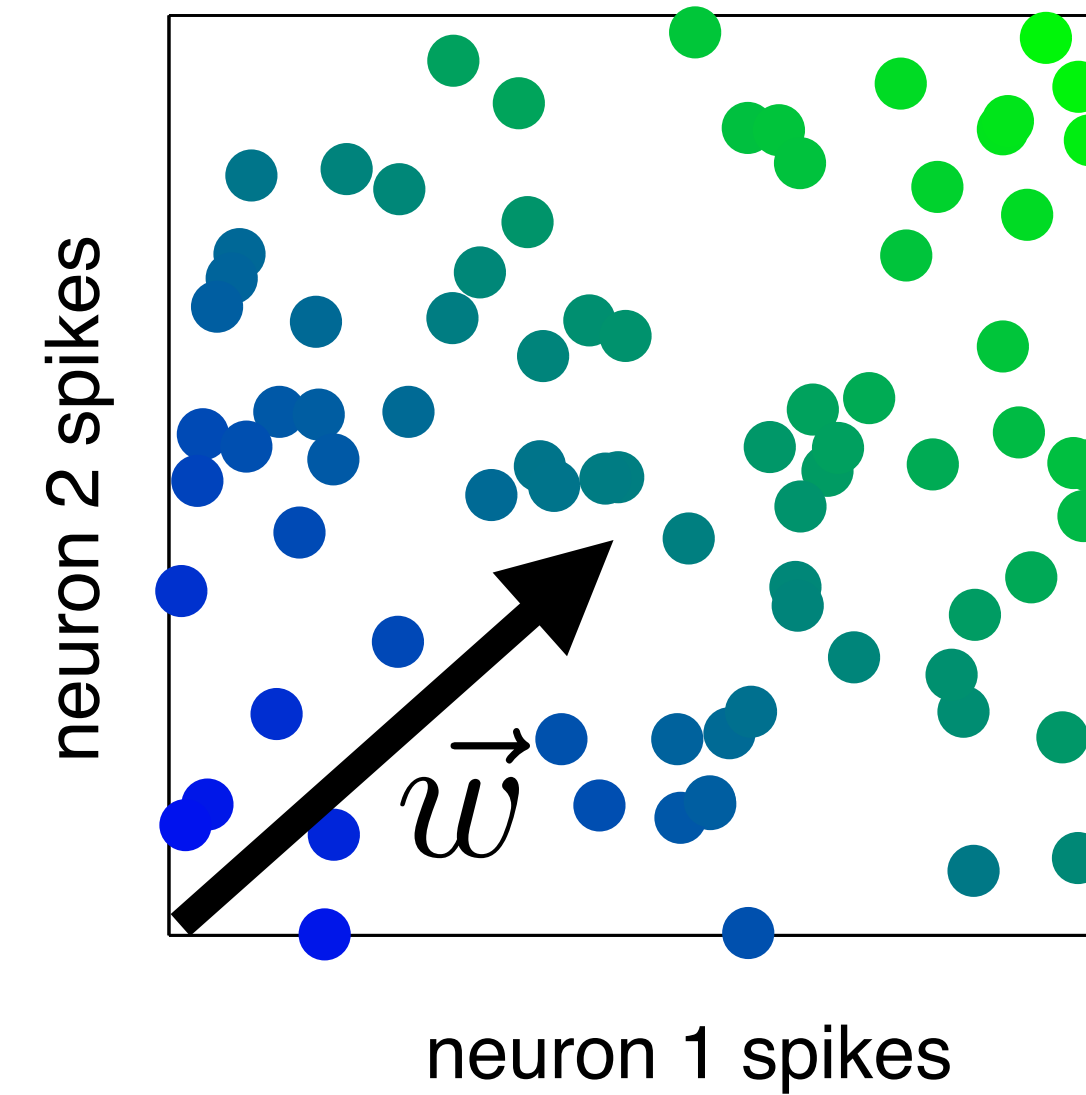
Regression

- output continuous instead of discrete



- can transform classification problems into regression problems ("logistic regression"):

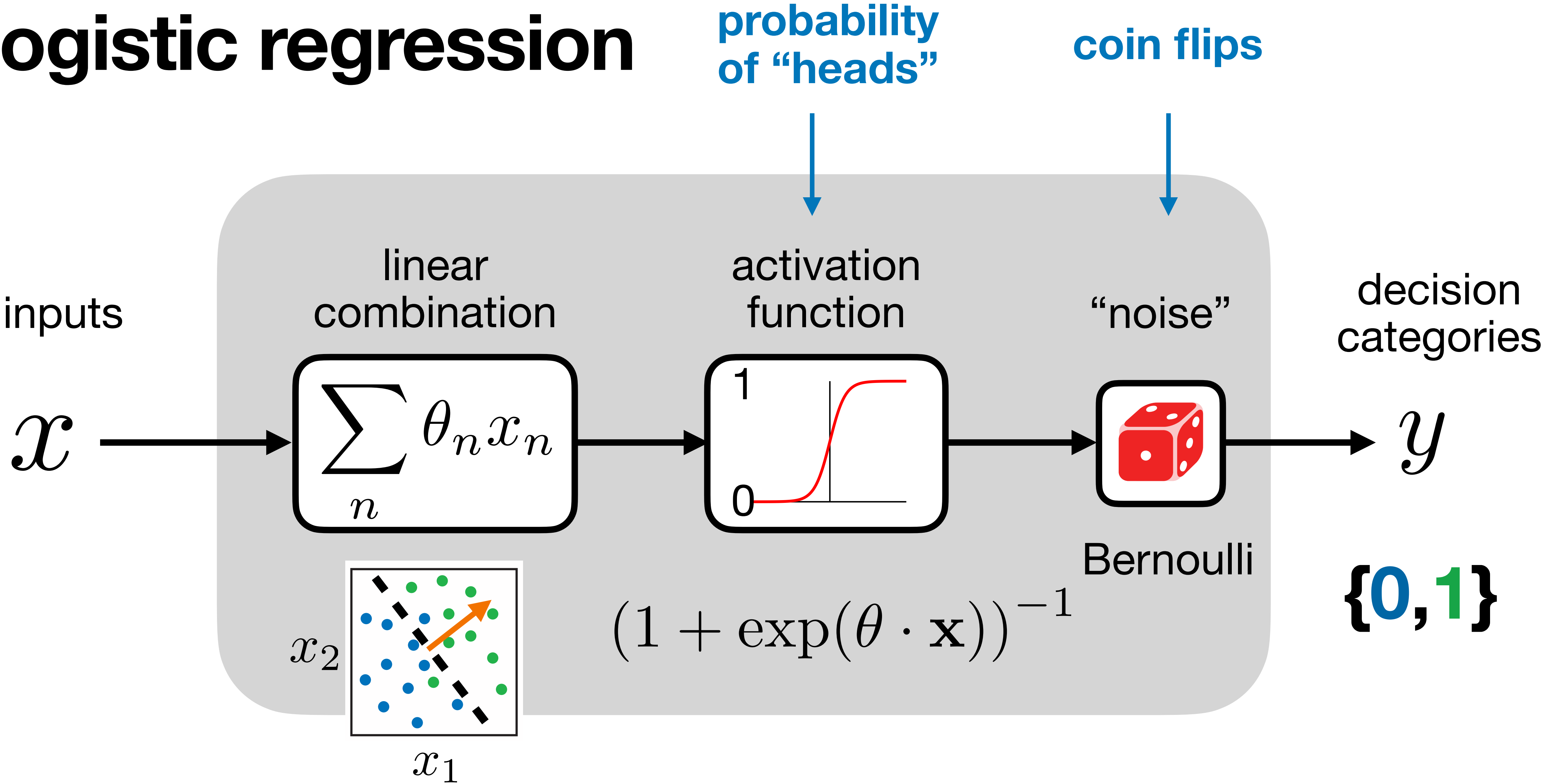
$$y = \vec{x} \cdot \vec{w}$$



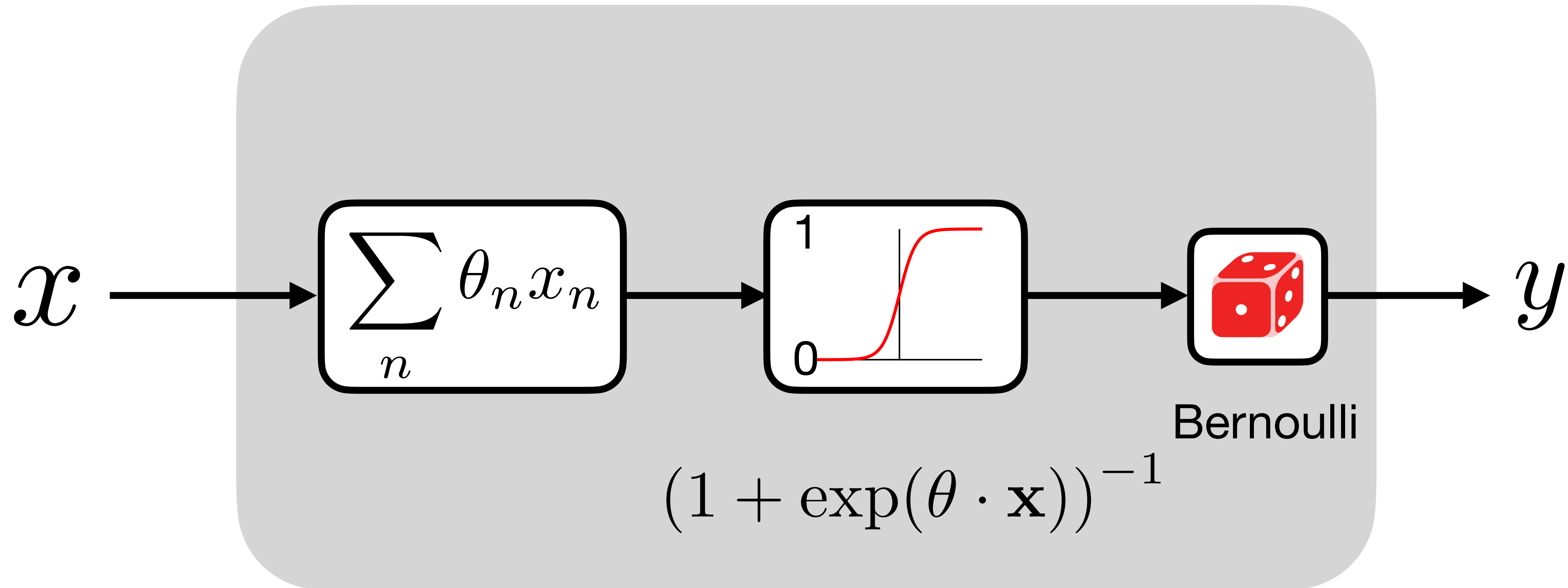
probability of being in
category

$$p(y = 1) = f(\vec{x})$$

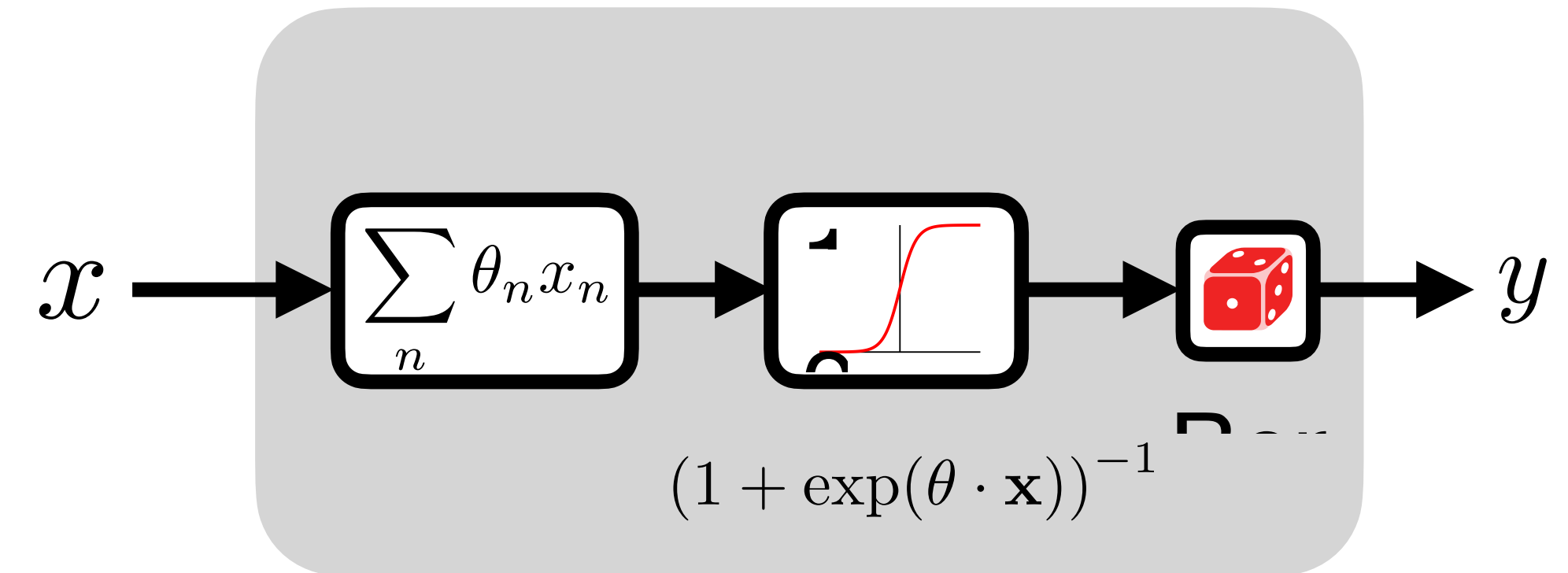
Logistic regression



Logistic regression



Logistic regression



$$y \sim \text{Bernoulli}(q)$$

$$P(y|q) = q^y (1 - q)^{1-y}$$

for logistic GLM

$$q = \frac{1}{1 + \exp(\sum_n \theta_n x_n)}$$

Today's Tutorials

- Learning stimulus filters
 - Gaussian, nonlinear, and Poisson regression
 - Understand how to...
 - build a **design matrix**
 - use **optimization** software to learn parameters of a model
 - evaluate and communicate the consequences of different modeling choices
- Logistic regression
 - Build a classifier
 - Understand how to...
 - do logistic regression
 - evaluate classifier accuracy
 - do cross validation
 - We will skip **regularization** for now and pick it up again on Friday

Thank you for listening!

- Mikio Aoi : maoi@ucsd.edu
- Gal Mishne : gmishne@ucsd.edu