machine learning for neuroscience

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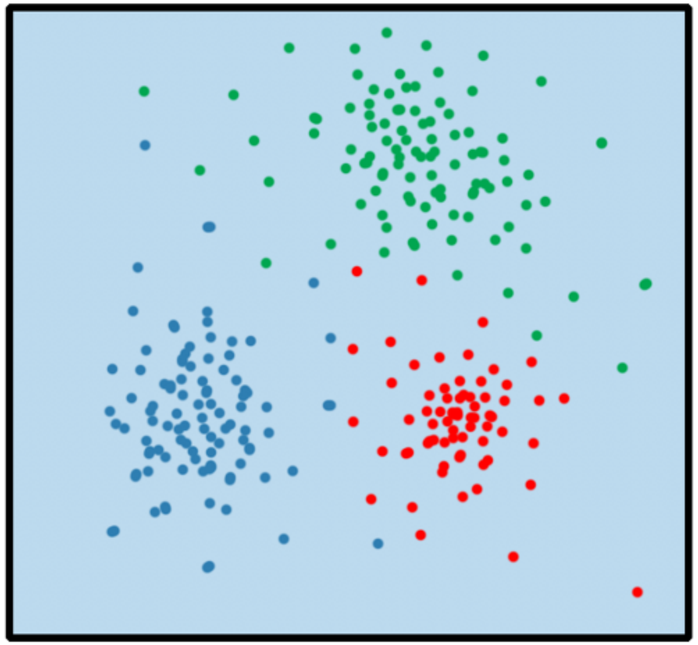
hhmi | janelia

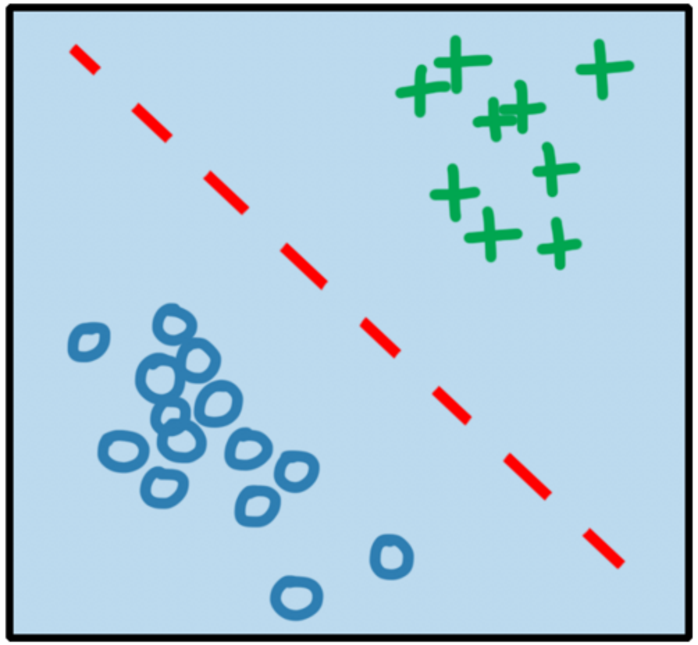
machine learning

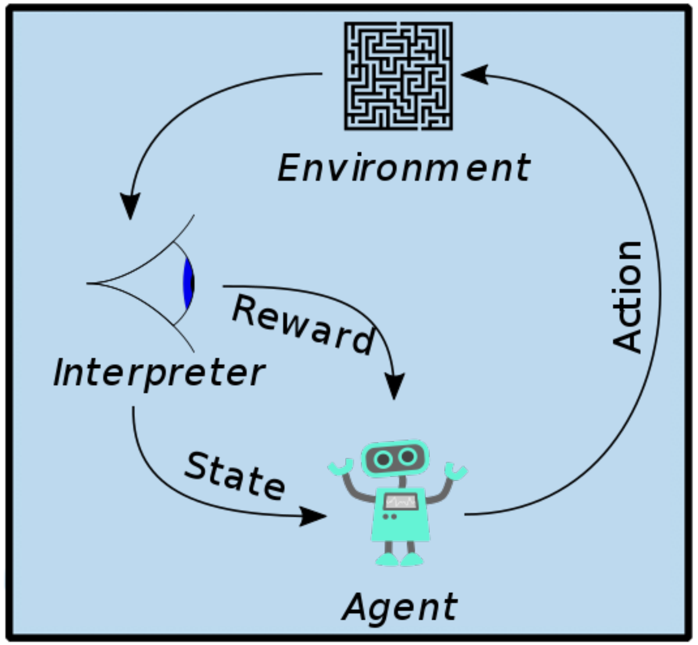
unsupervised learning

supervised learning

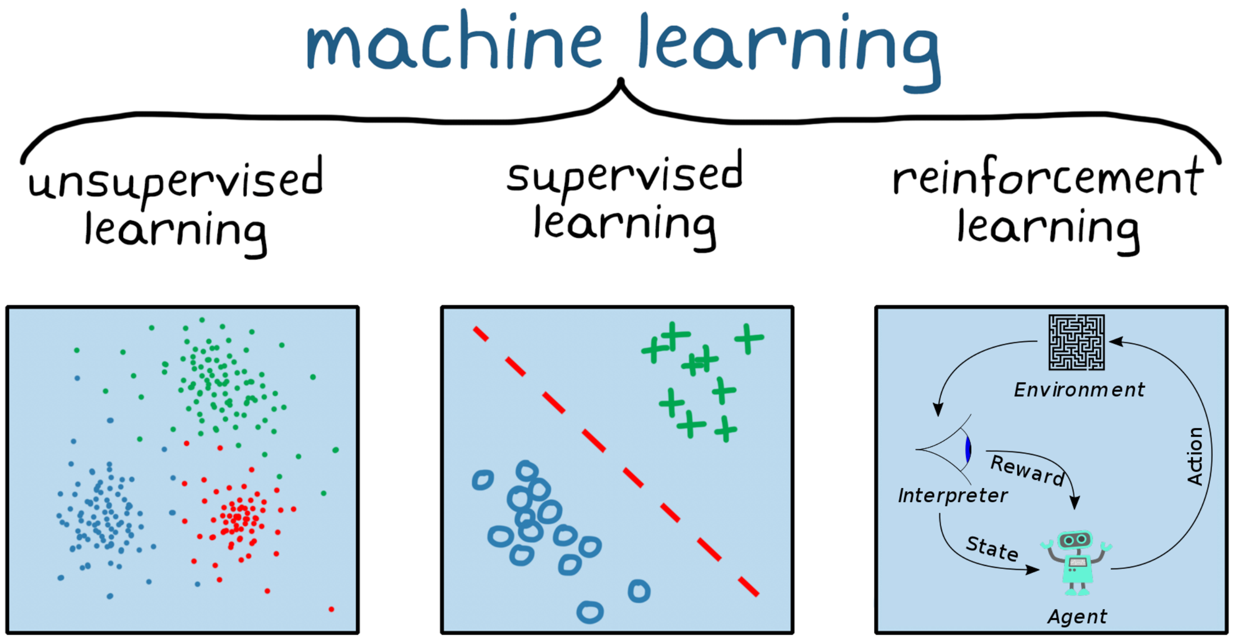
reinforcement learning







https://www.mathworks.com/discovery/reinforcement-learning.html



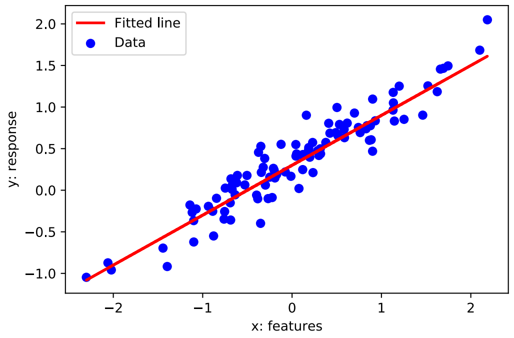
unsupervised learning
clustering
PCA
t-SNE, UMAP
variational auto encoder
large language models

supervised learning
(non)linear regression
generalized linear models
random forests
deep neural networks
speech recognition
language translation
protein structure prediction

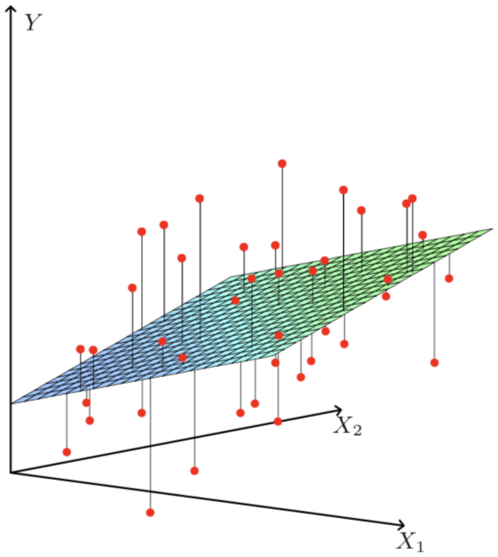
reinforcement learning
alphaGo
robots
here be dragons

https://www.mathworks.com/discovery/reinforcement-learning.html

What is Linear? 1 feature vs D features



- If we have only 1 feature: $y = wx + b$ where $w, x, b \in \mathbb{R}$.
- y is linear in x.

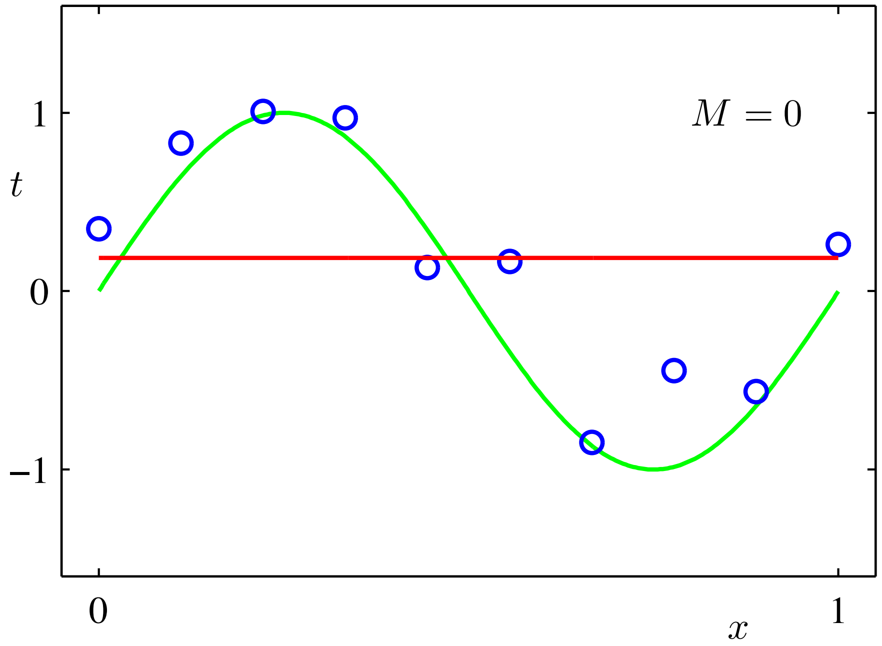


- If we have D features: $y = \mathbf{w}^\top \mathbf{x} + b$ where $\mathbf{w}, \mathbf{x} \in \mathbb{R}^D$, $b \in \mathbb{R}$
- y is linear in $\mathbf{x}$.

Relation between the prediction y and inputs $\mathbf{x}$ is linear in both cases.

Polynomial Feature Mapping with $M = 0$

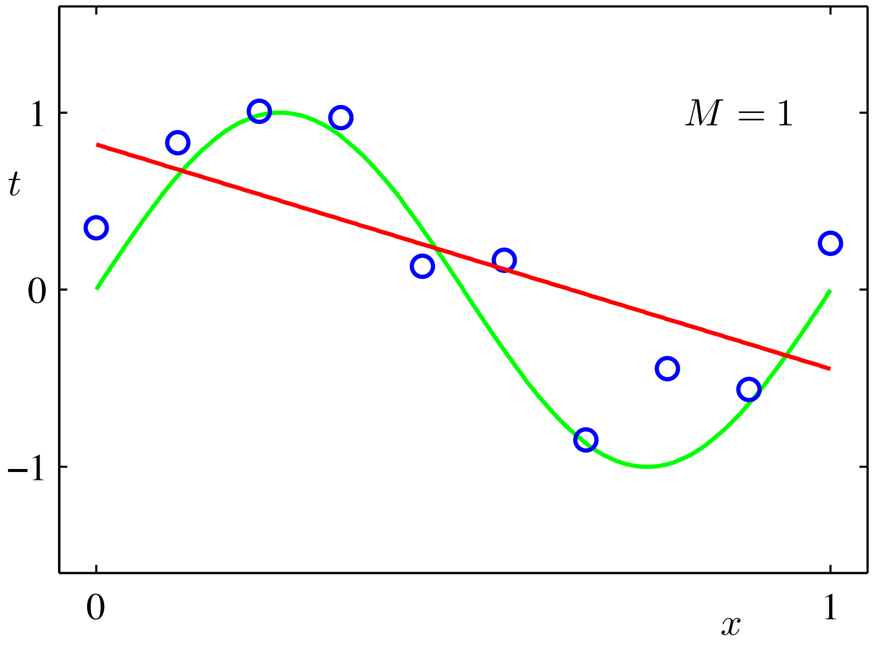
$$y = w_0$$



-Pattern Recognition and Machine Learning, Christopher Bishop.

Polynomial Feature Mapping with $M = 1$

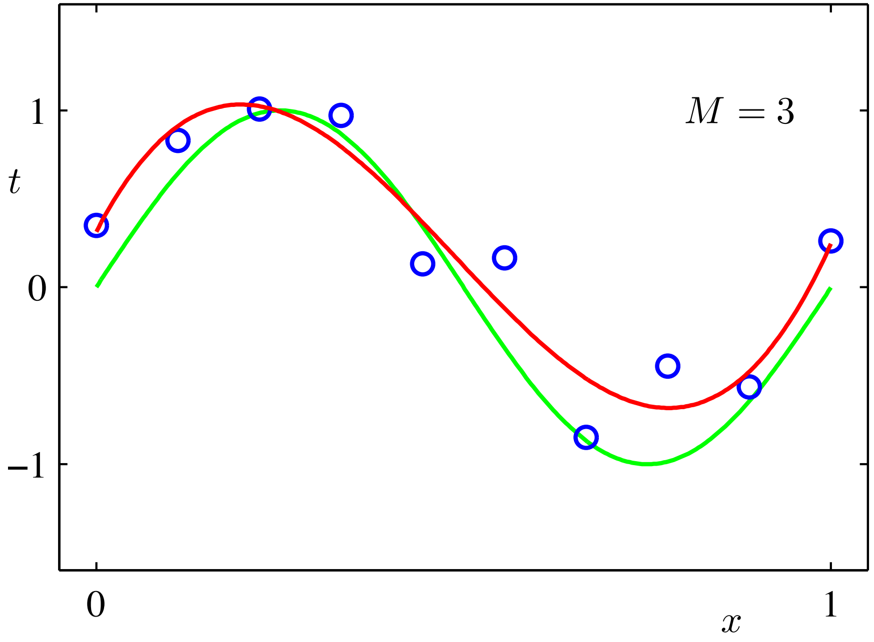
$$y = w_0 + w_1 x$$



-Pattern Recognition and Machine Learning, Christopher Bishop.

Polynomial Feature Mapping with $M = 3$

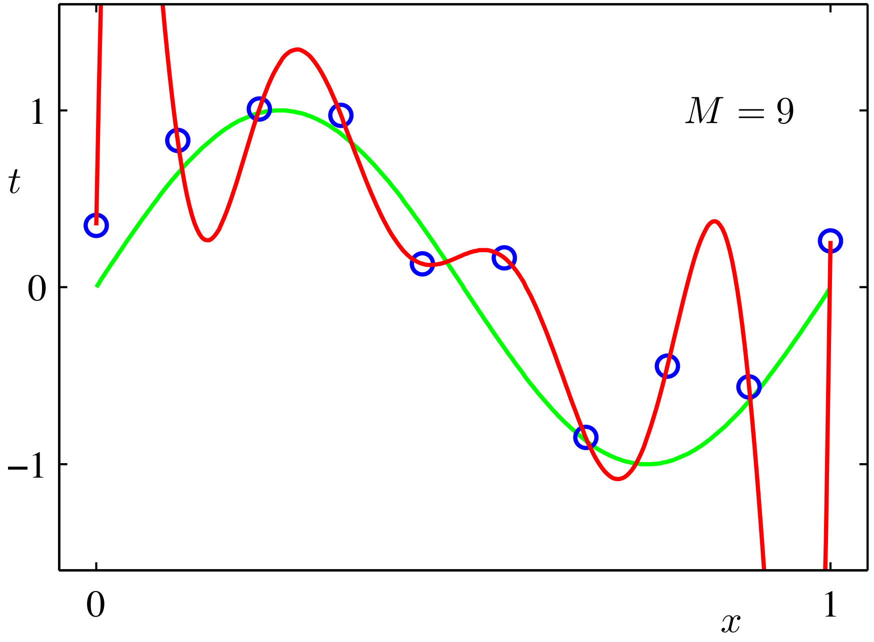
$$y = w_0 + w_1 x + w_2 x^2 + w_3 x^3$$



-Pattern Recognition and Machine Learning, Christopher Bishop.

Polynomial Feature Mapping with $M = 9$

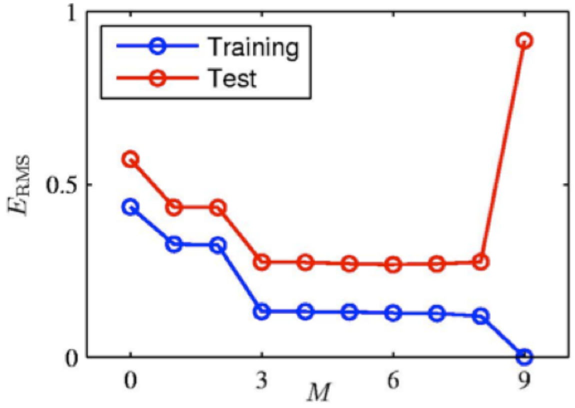
$$y = w_0 + w_1 x + w_2 x^2 + w_3 x^3 + \ldots + w_9 x^9$$

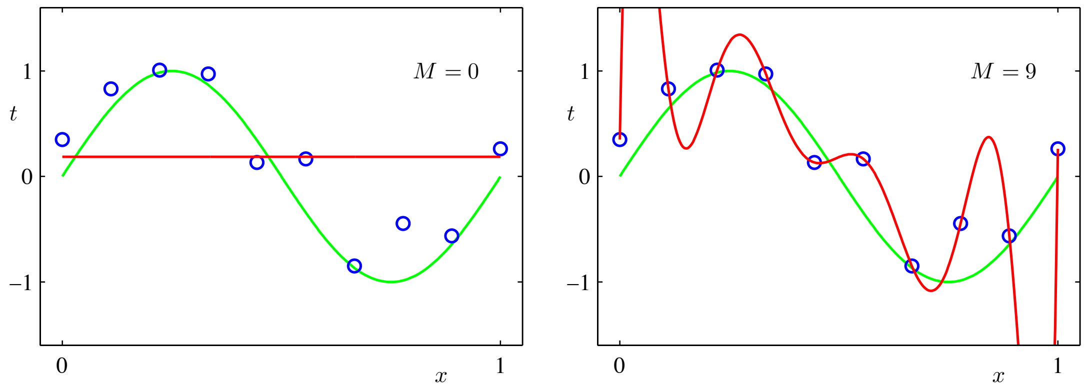


-Pattern Recognition and Machine Learning, Christopher Bishop.

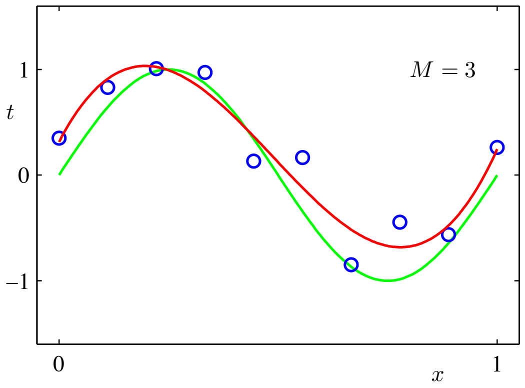
Model Complexity and Generalization

Underfitting (M=0): model is too simple — does not fit the data.
Overfitting (M=9): model is too complex — fits perfectly.

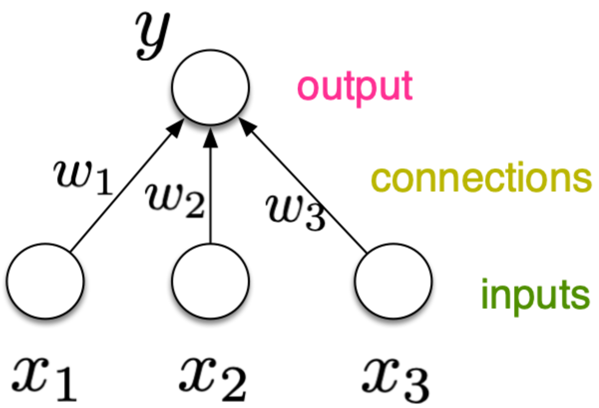




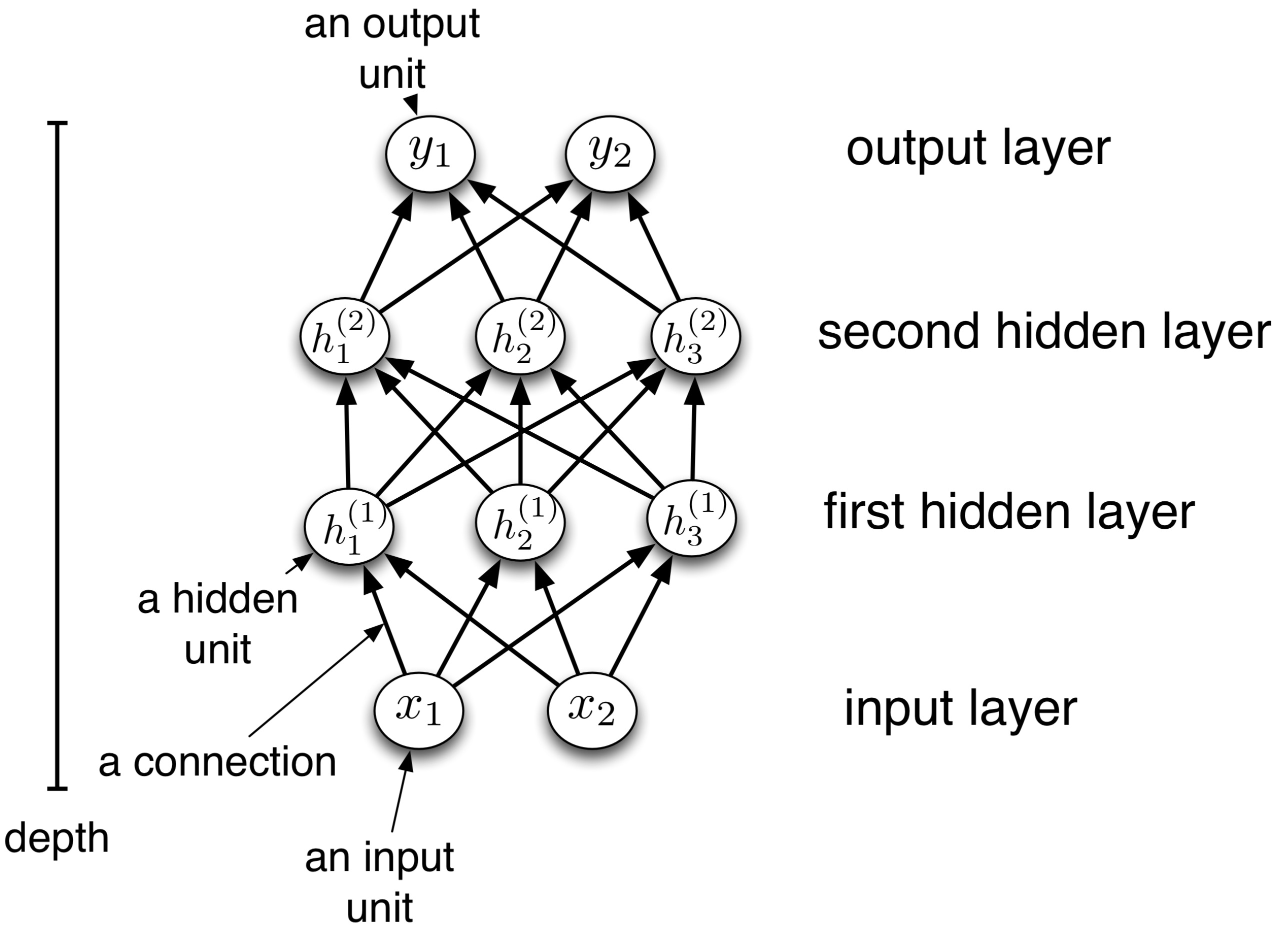
Good model (M=3): Achieves small test error (generalizes well).



linear model



deep neural network
(stacked linear-nonlinear model)



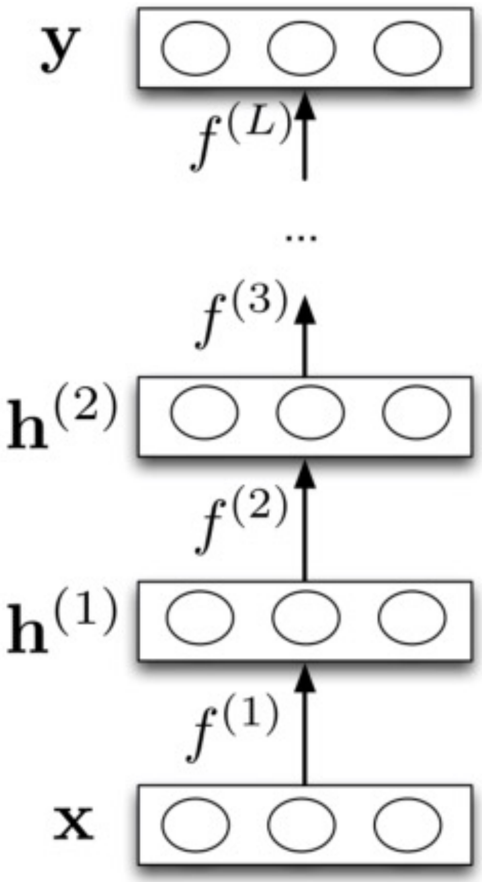
- Each layer computes a function, so the network computes a composition of functions:

$$\mathbf{h}^{(1)} = f^{(1)}(\mathbf{x})$$
$$\mathbf{h}^{(2)} = f^{(2)}(\mathbf{h}^{(1)})$$
$$\vdots$$
$$\mathbf{y} = f^{(L)}(\mathbf{h}^{(L-1)})$$

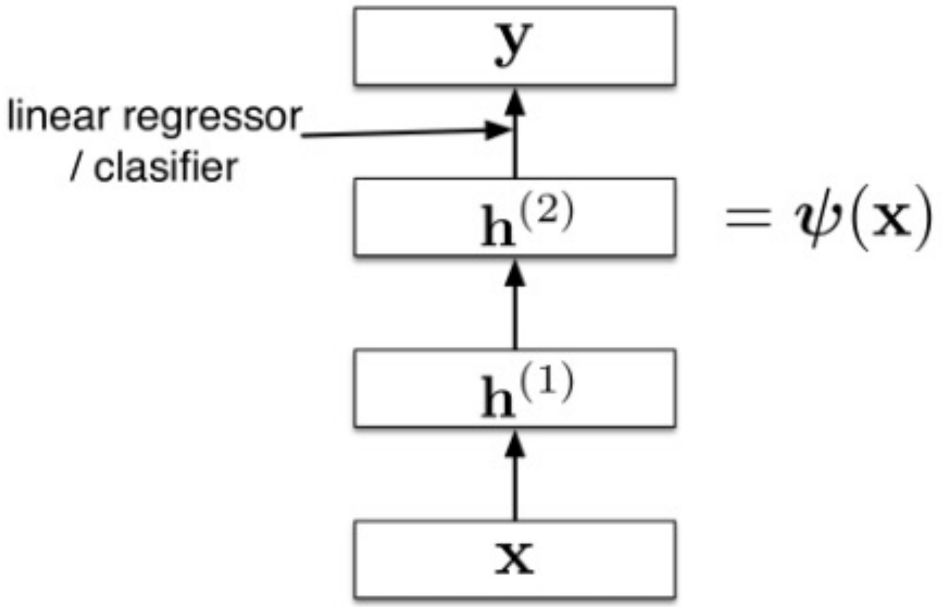
- Or more simply:

$$\mathbf{y} = f^{(L)} \circ \cdots \circ f^{(1)}(\mathbf{x}).$$

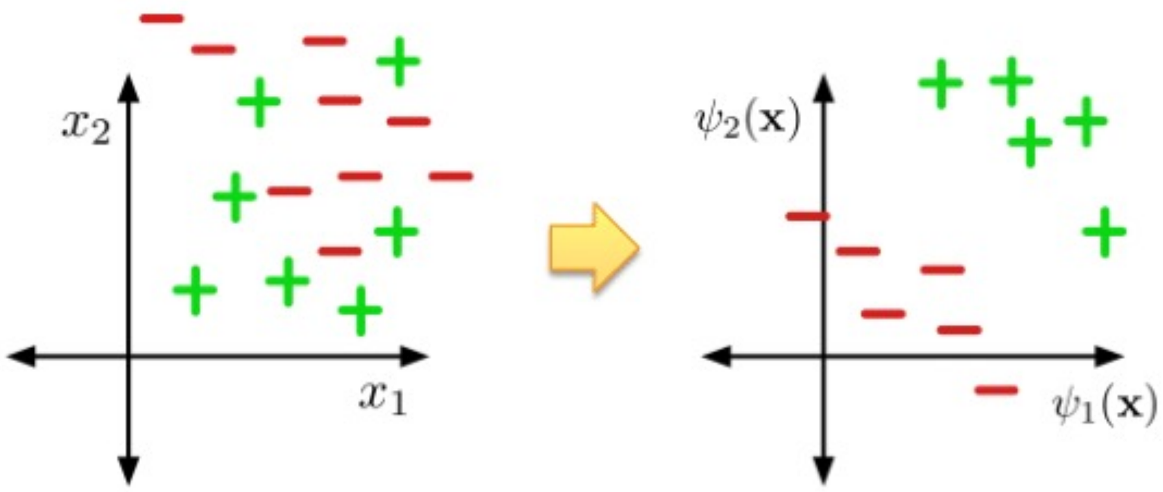
- Neural nets provide modularity: we can implement each layer's computations as a black box.

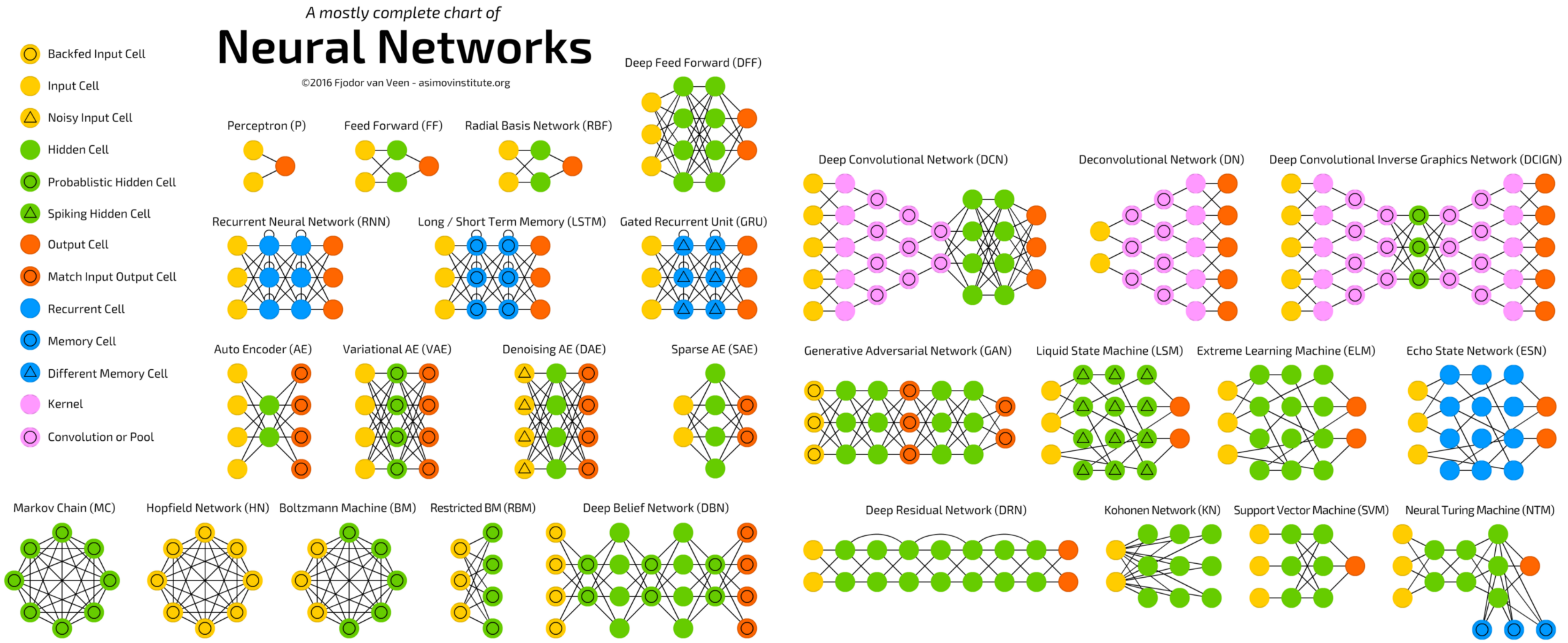


- Neural nets can be viewed as a way of learning features:



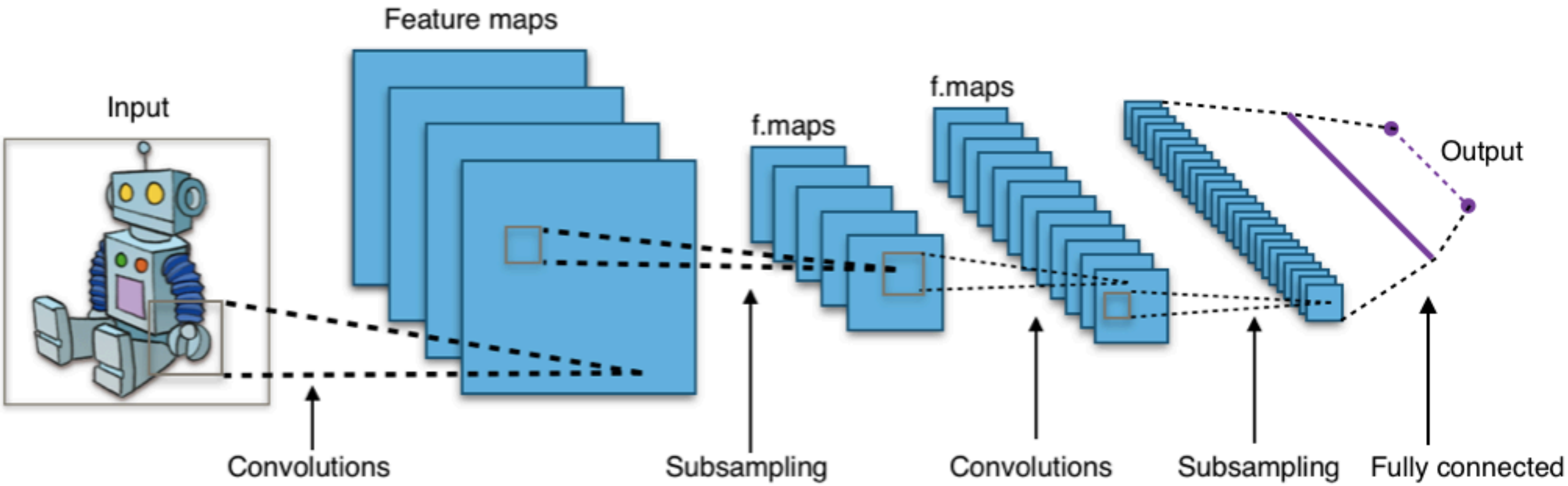
- The goal:




A mostly complete chart of
Neural Networks
©2016 Fjodor van Veen - asimovinstitute.org
Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probablistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Deep Feed Forward (DFF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Denoising AE (DAE)
Sparse AE (SAE)
Markov Chain (MC)
Hopfield Network (HN)
Boltzmann Machine (BM)
Restricted BM (RBM)
Deep Belief Network (DBN)
Deep Convolutional Network (DCN)
Deconvolutional Network (DN)
Deep Convolutional Inverse Graphics Network (DCIGN)
Generative Adversarial Network (GAN)
Liquid State Machine (LSM)
Extreme Learning Machine (ELM)
Echo State Network (ESN)
Deep Residual Network (DRN)
Kohonen Network (KN)
Support Vector Machine (SVM)
Neural Turing Machine (NTM)

Task	Inputs	Labels
object recognition	image	object category
image captioning	image	caption
document classification	text	document category
speech-to-text	audio waveform	text
$\vdots$	$\vdots$	$\vdots$

convolutional neural network



- how does the brain work?
- make lots of measurements
- build a computational model
- develop understanding

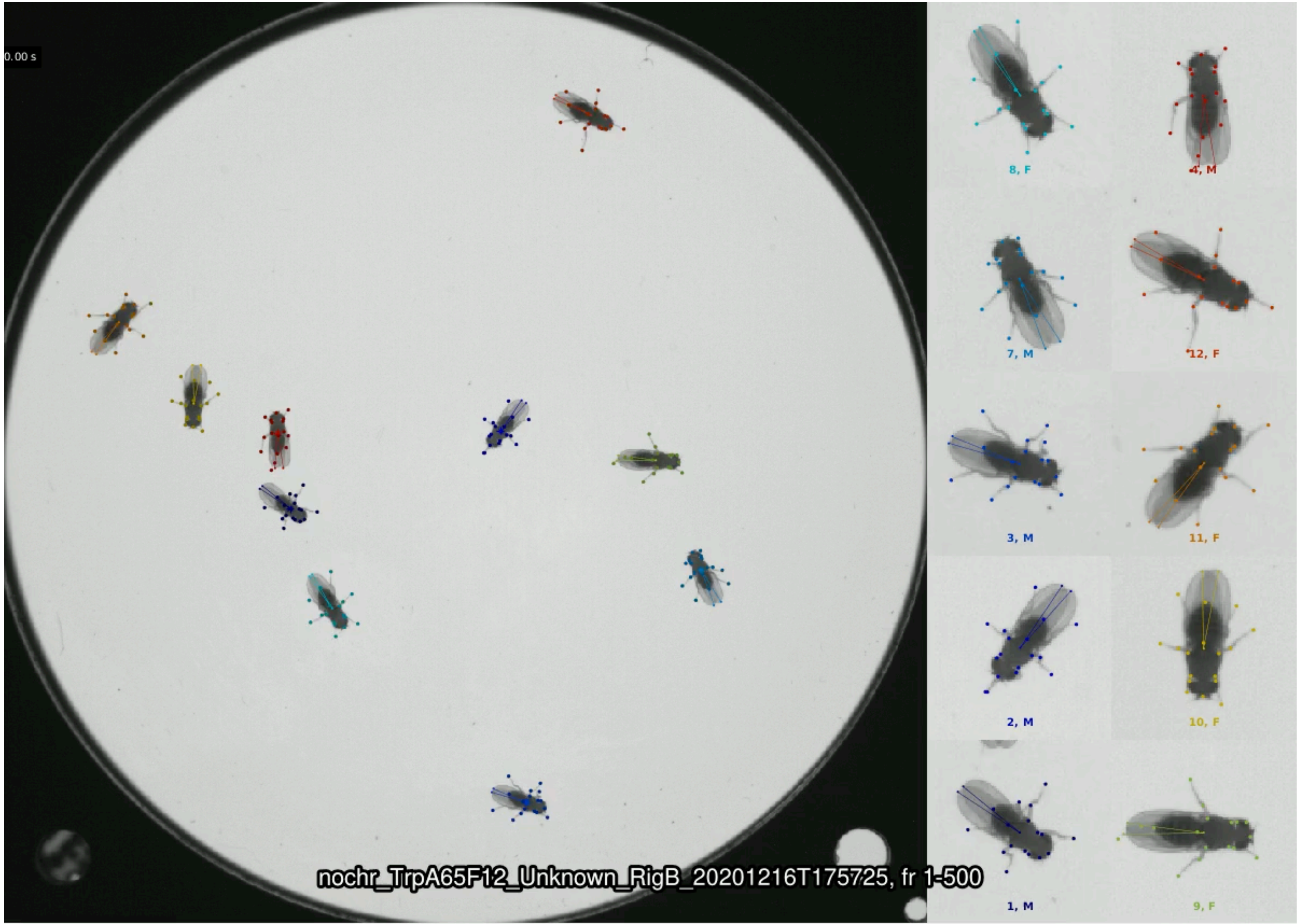
- how does the brain work?
- make lots of measurements (biology, physics, chemistry)
  - analyze using machine learning
- build a computational model
  - machine learning + mathematics, physics
- develop understanding

- machine learning for data analysis in neuroscience

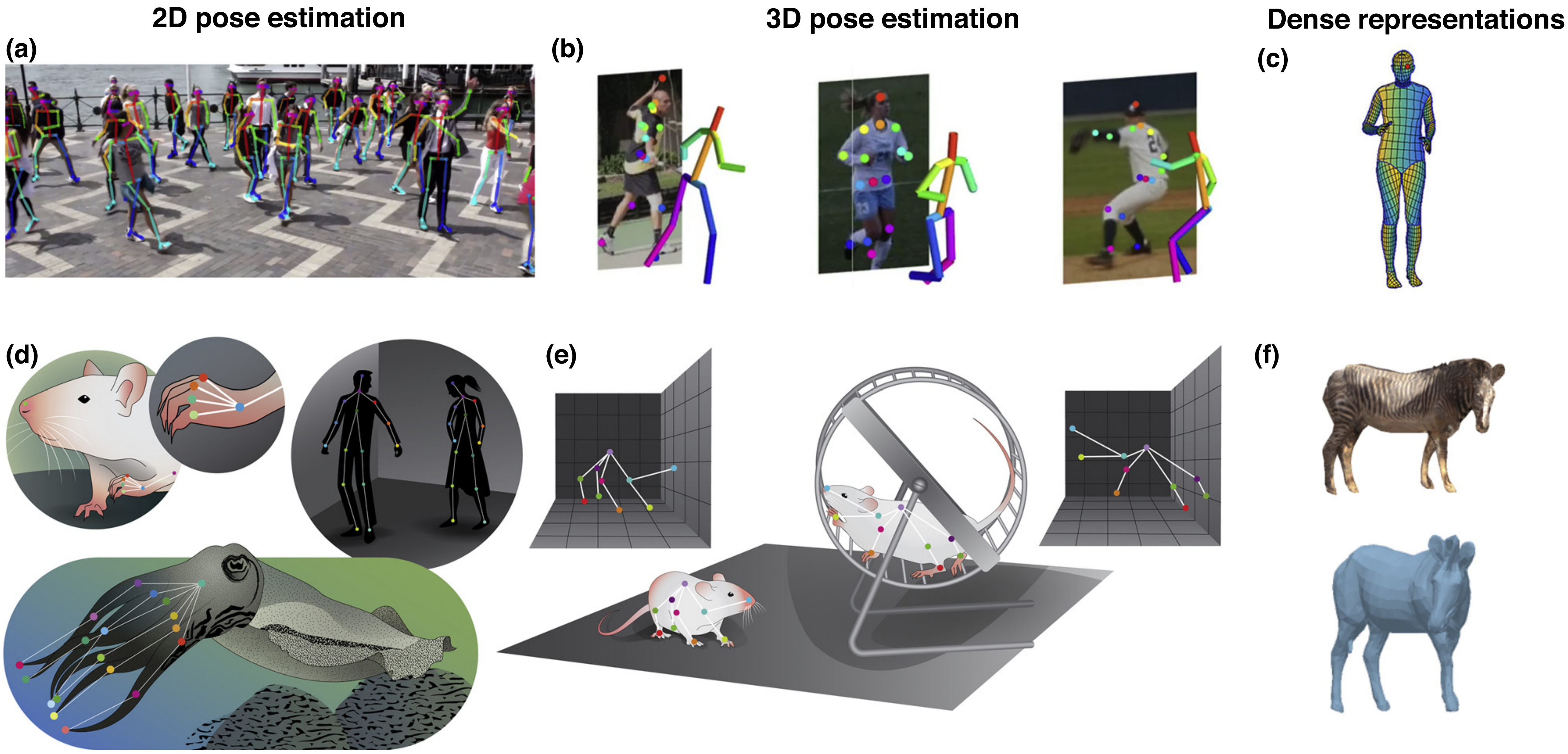
The fruit fly

Tracking behavior

Branson lab

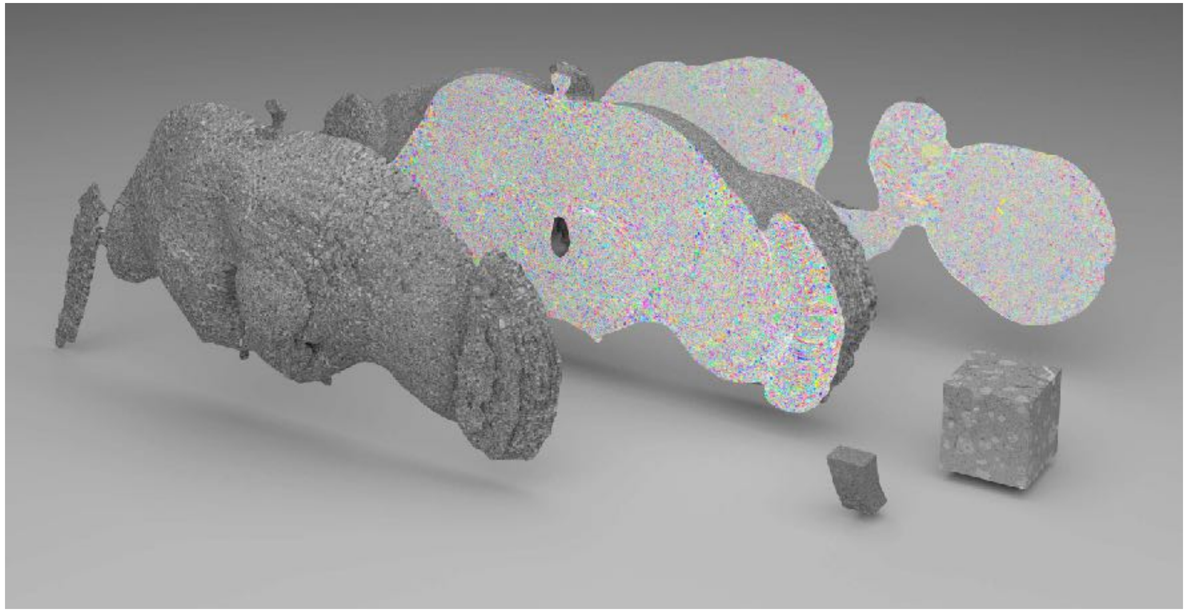


Automating behavior analysis

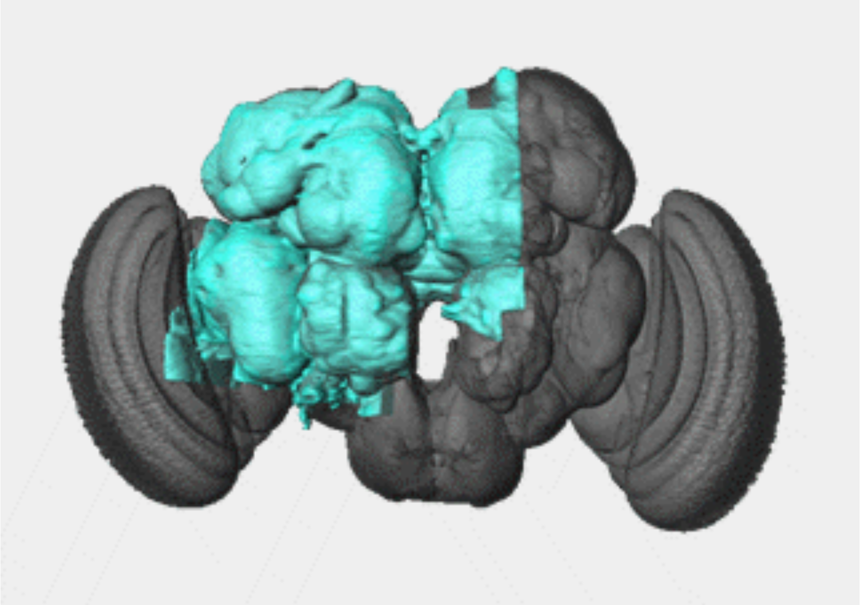


Mathis and Mathis 2020

Reverse engineering the brain using 3D electron microscopy

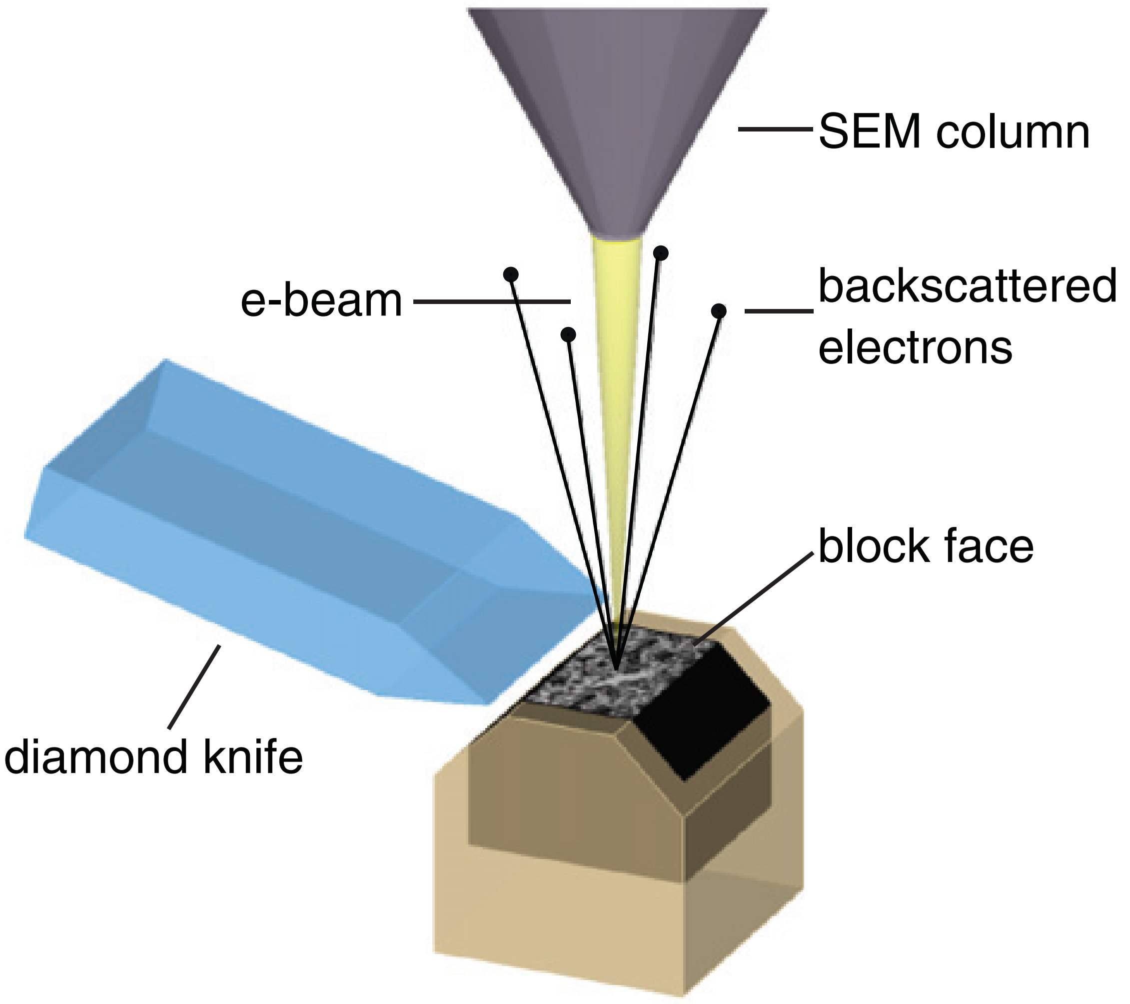


Zheng et al. 2018
Li et al. 2019



Scheffer et al. 2020

large-scale 3d electron microscopy

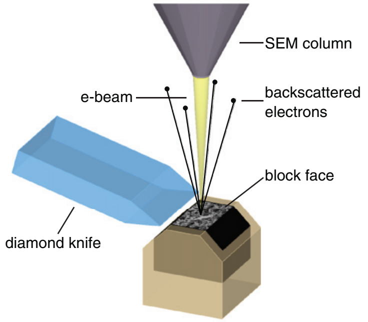


serial block-face electron microscopy

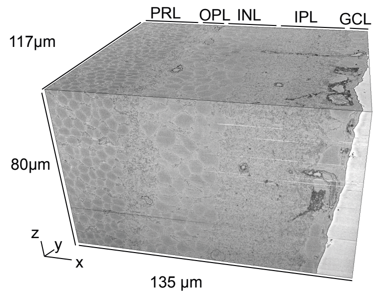
Denk & Horstmann PLOS Biology 2004

for a cubic millimeter

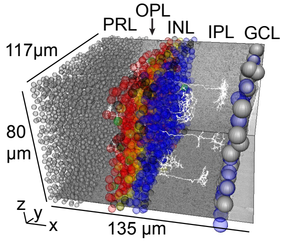
- fix and stain tissue
  manual but easy
  few days

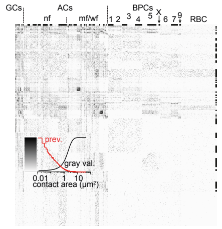


- image the tissue
  automatic but hard
  ~1 year, 100s GB - 100s TB



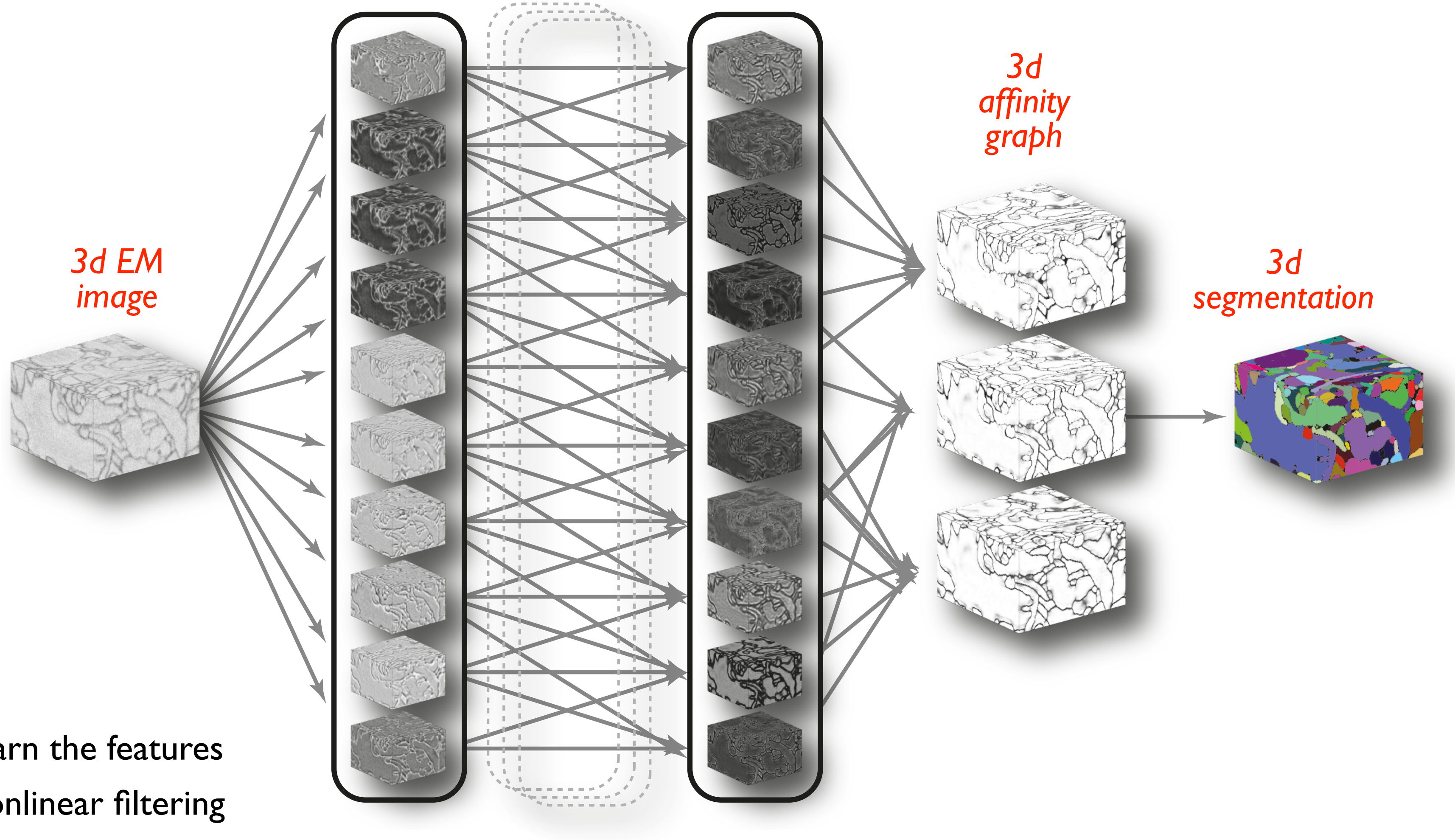
- reconstruct circuitry from image
  semi-automated and very hard
  ~1,000-50,000 man years





Smith 2007
Helmstaedter et al. 2011

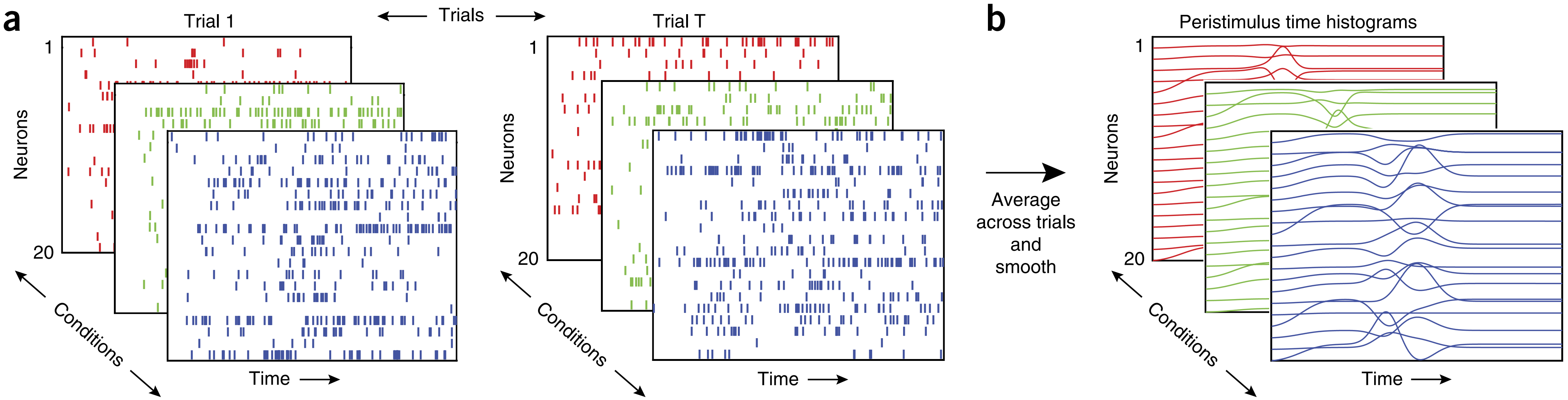
boundary detection using deep convolutional networks



- learn the features
- nonlinear filtering
- image to image transformation
- “universal function approximation”
- parameters trained using groundtruth dataset

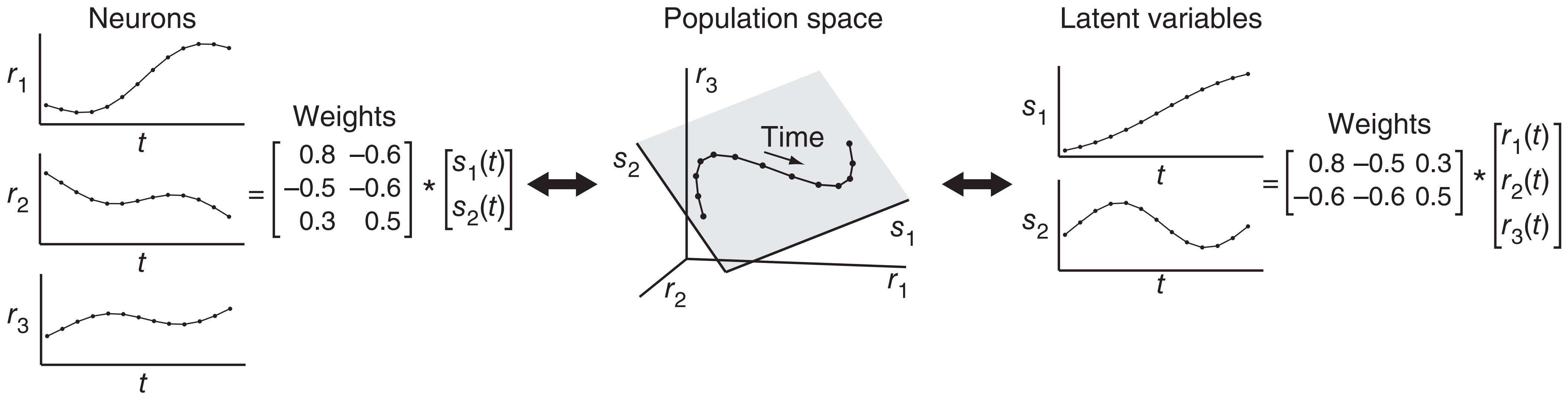
Lecun et al. 1989
Jain, Murray, Roth, Turaga, et al. ICCV 2007
Turaga, et al. Neural Computation 2010

neural dimensionality reduction



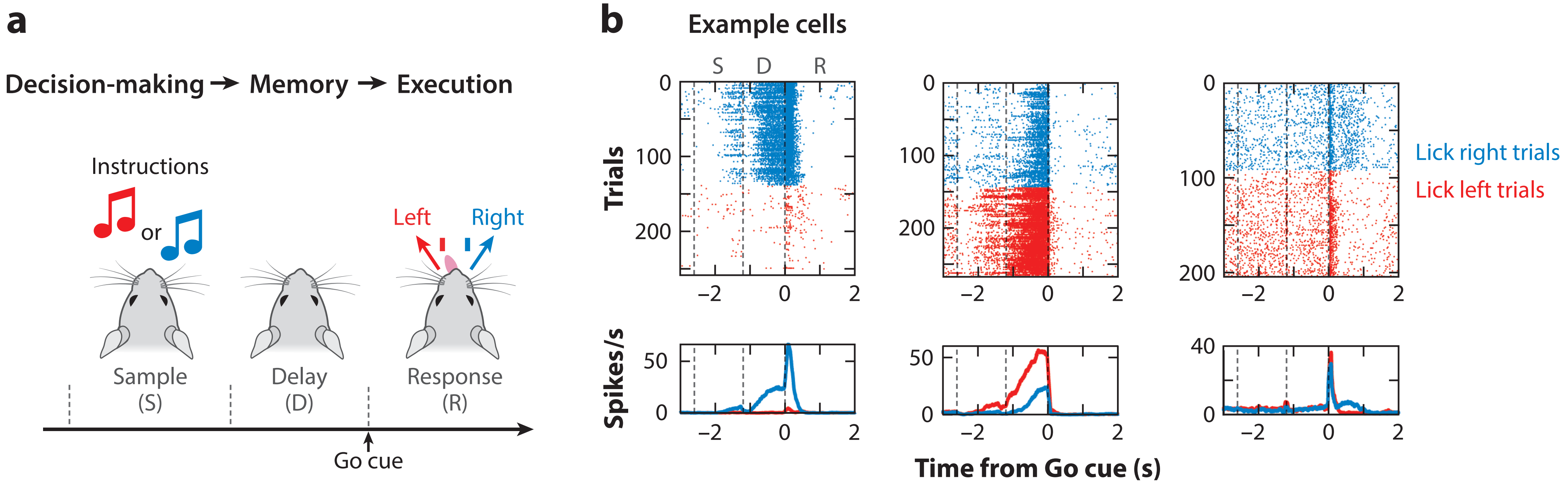
Cunningham and Yu 2014

neural dimensionality reduction



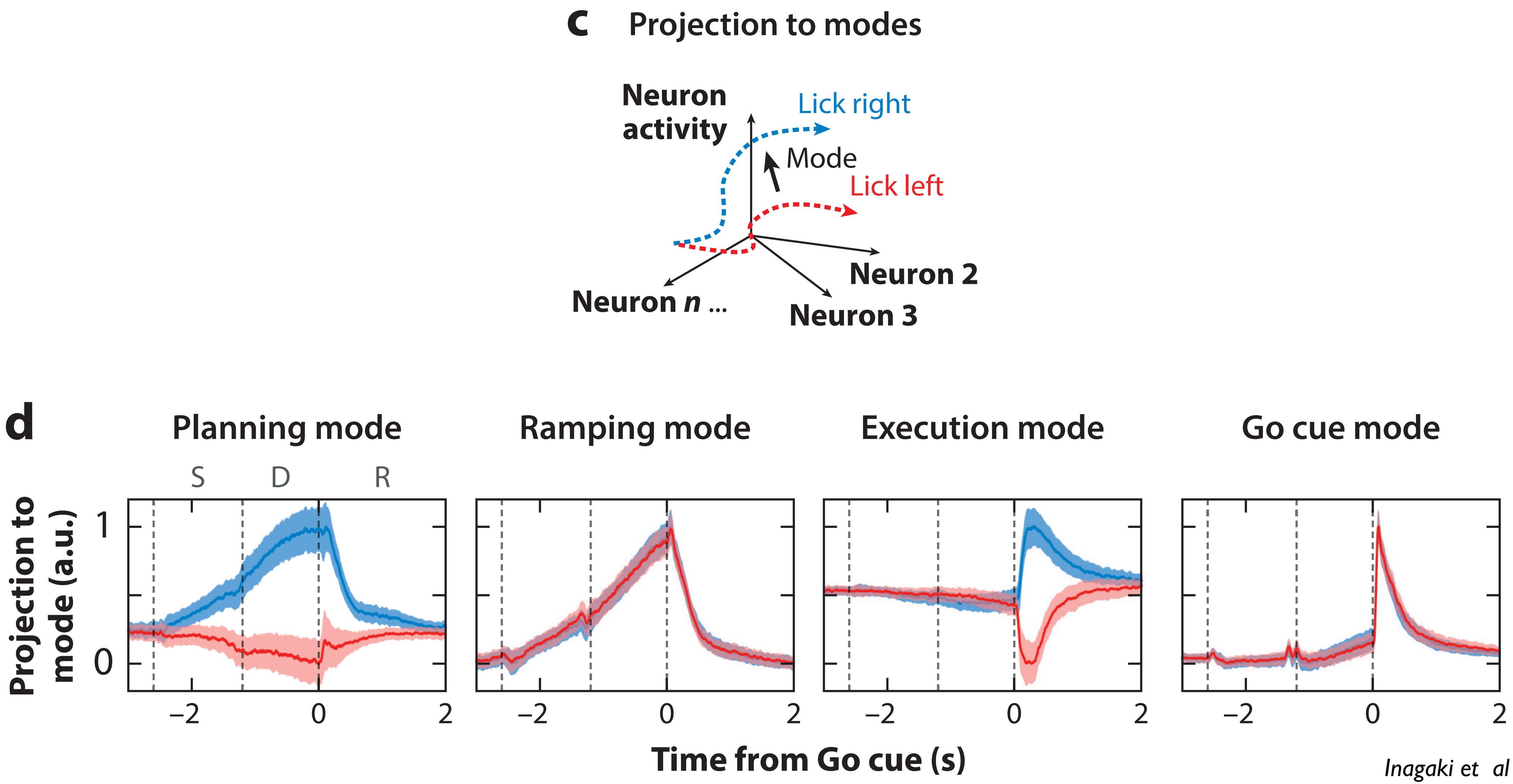
Cunningham and Yu 2014

neural dimensionality reduction



Inagaki et al 2022

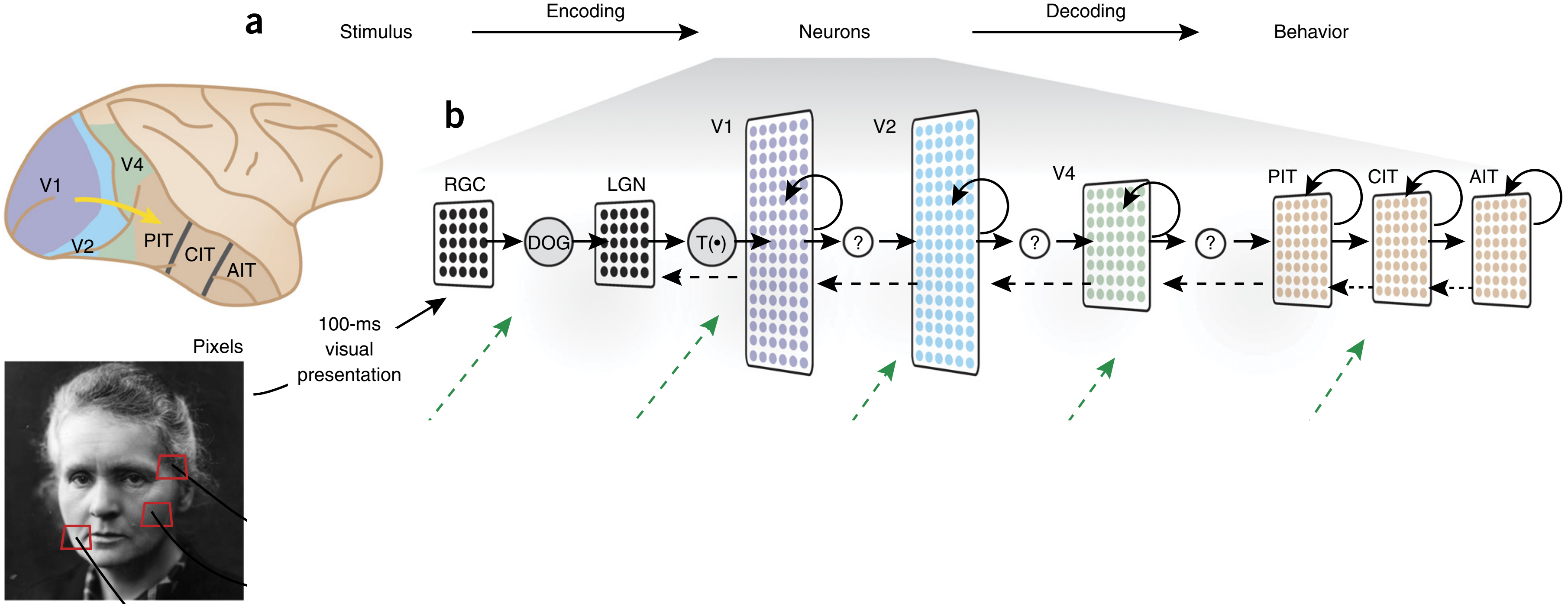
neural dimensionality reduction



Inagaki et al 2022

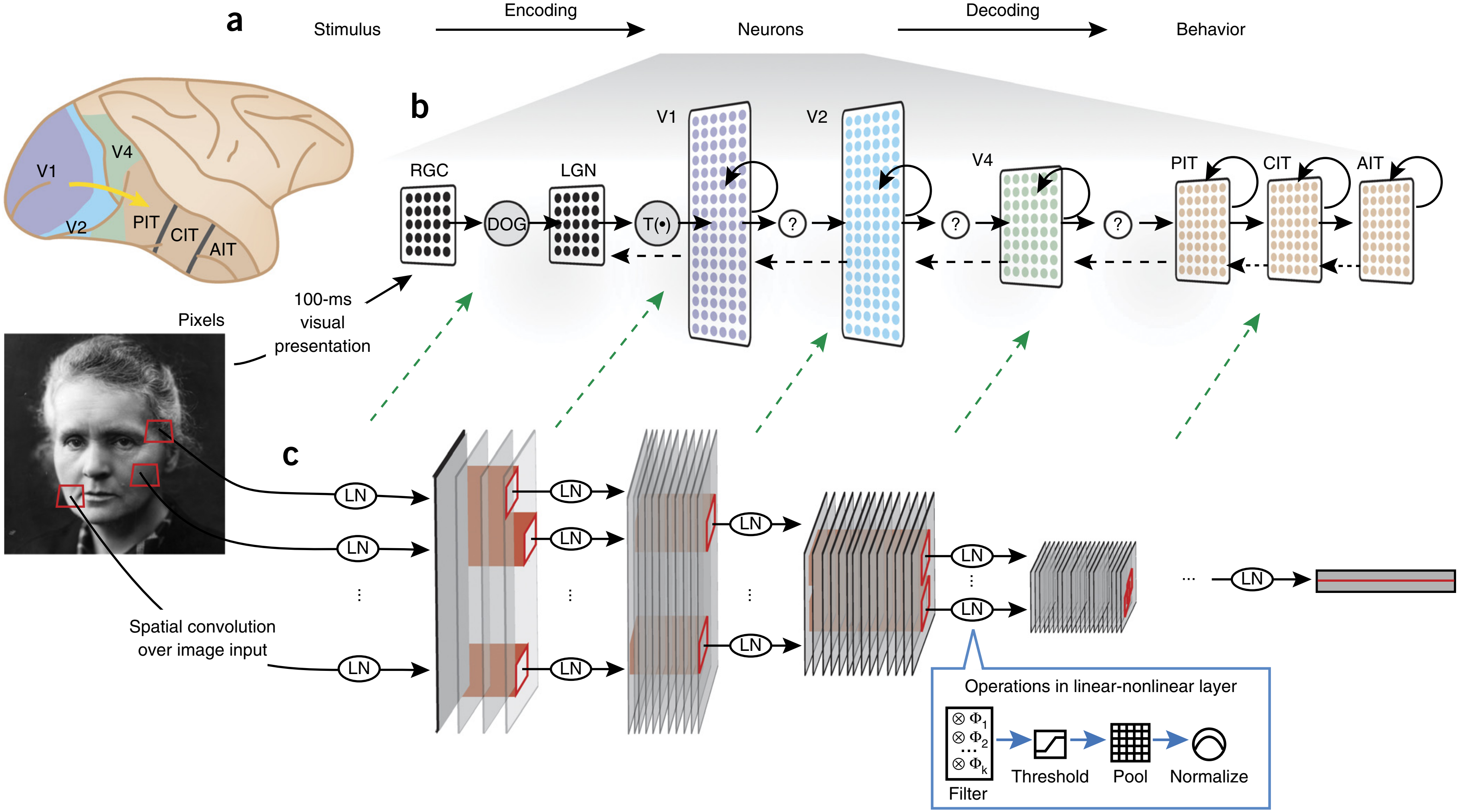
- machine learning for building models of neural computation

convolutional networks as models of visual processing in the primate ventral stream



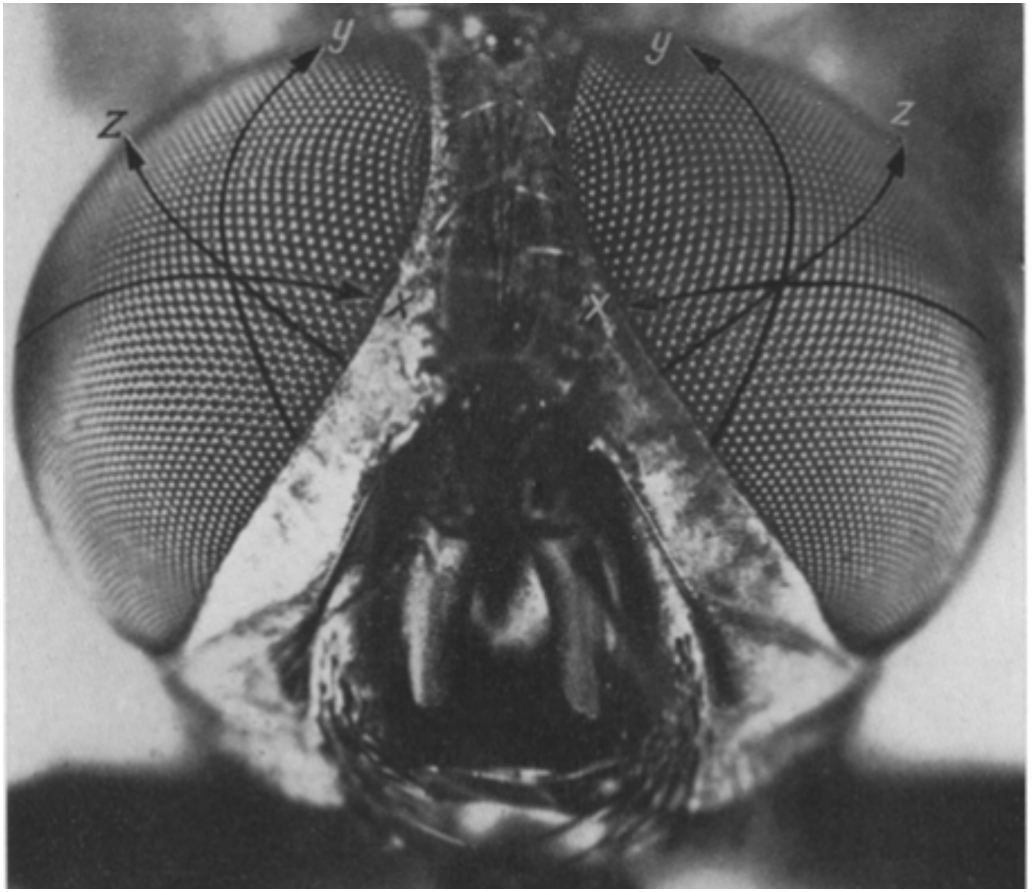
Yamins & Dicarlo 2016

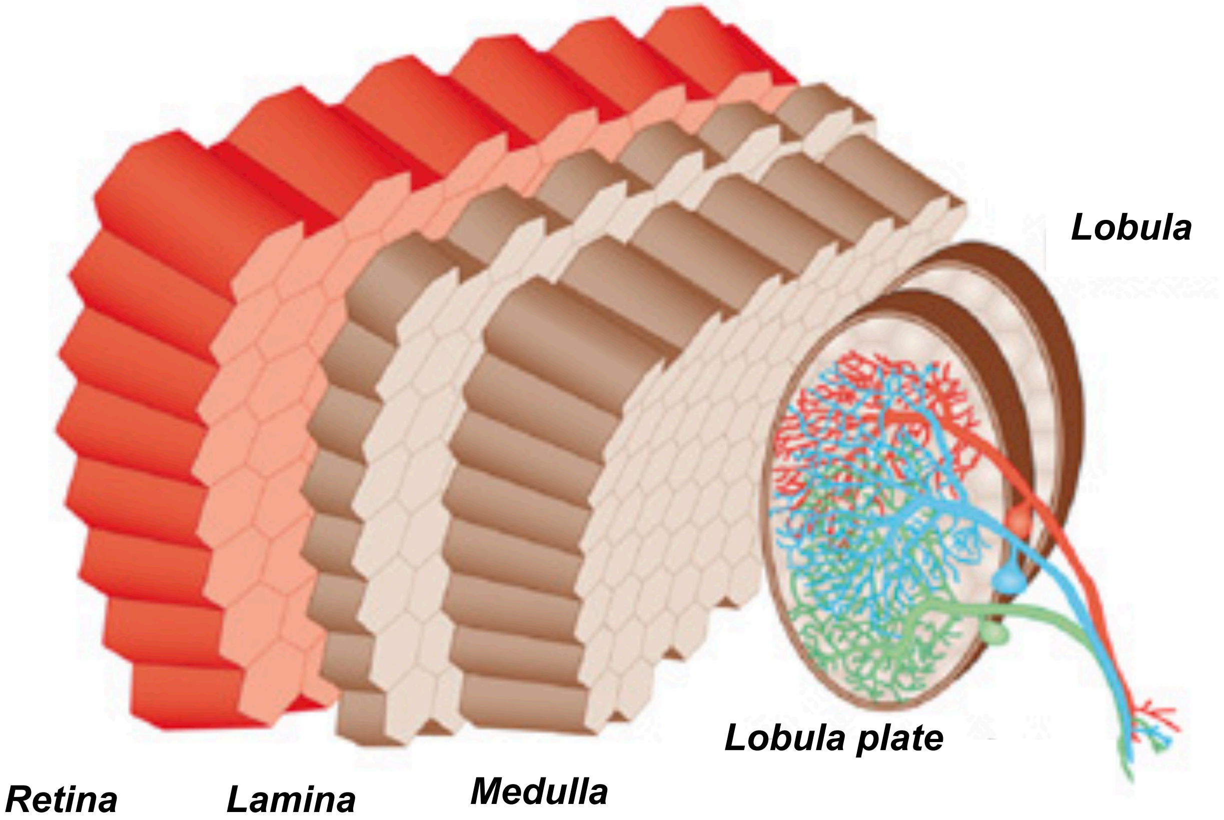
convolutional networks as models of visual processing in the primate ventral stream



Yamins & Dicarlo 2016

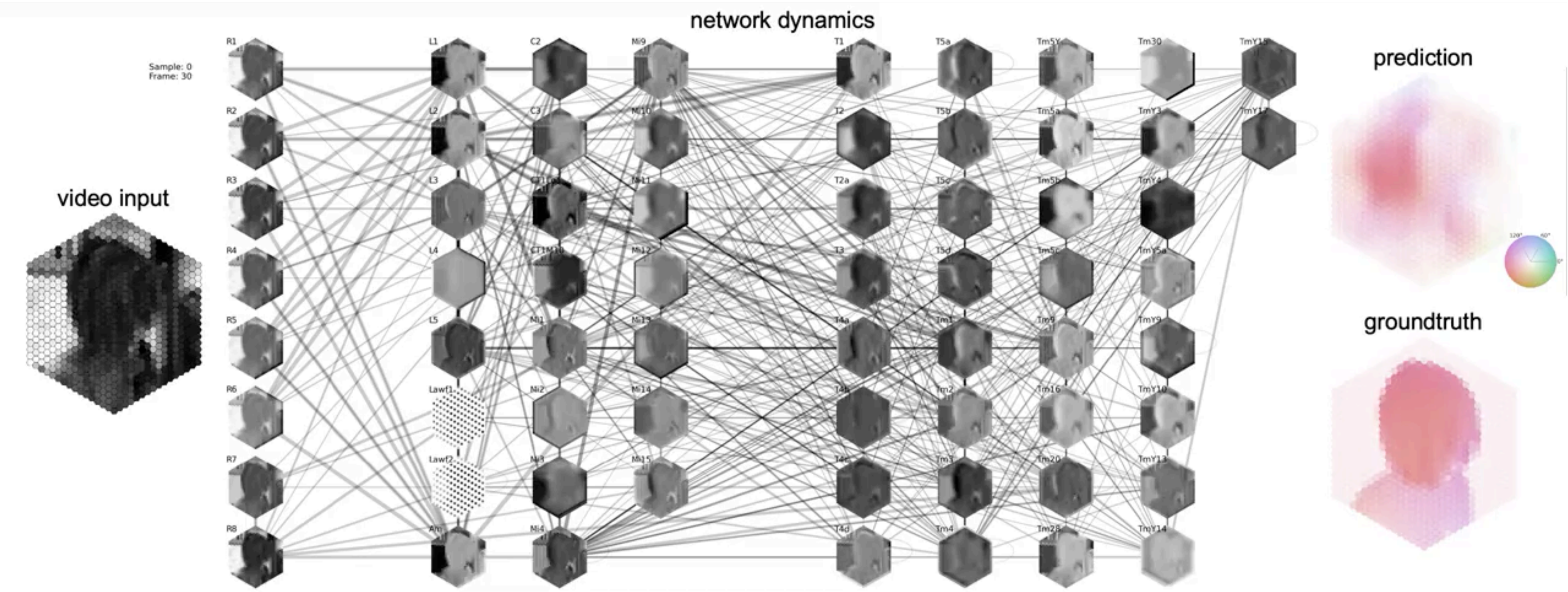
Simulating fly vision





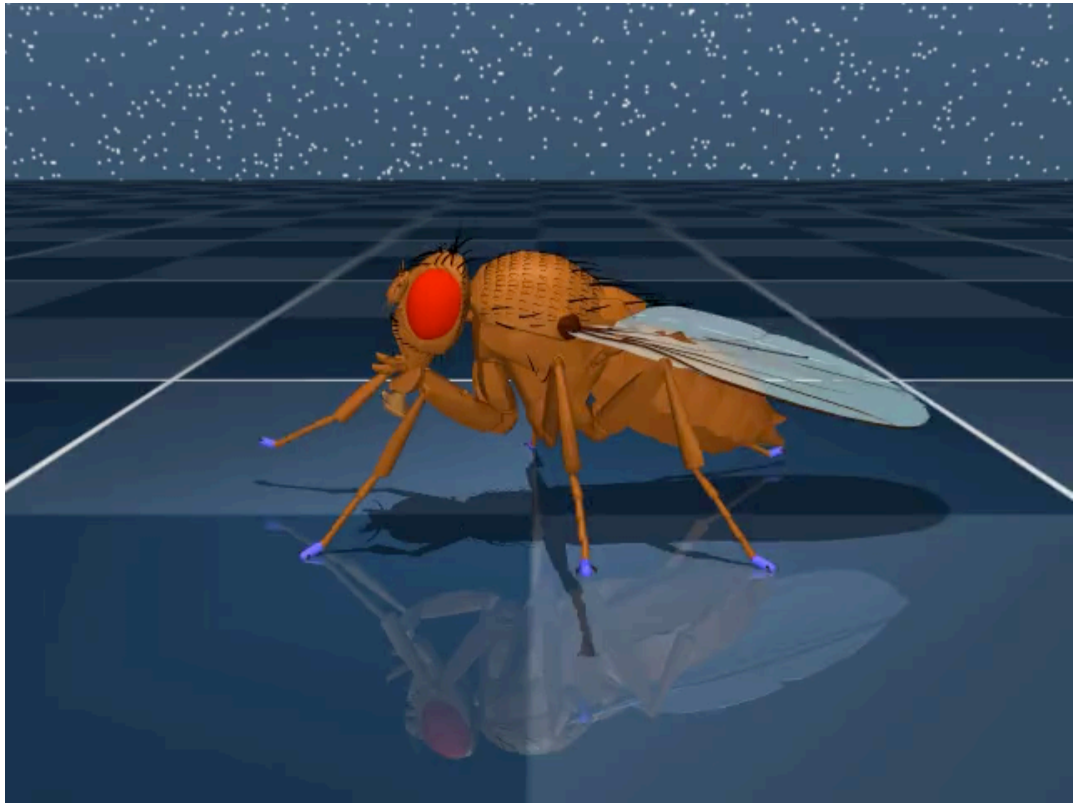
Takemura et al. (2015).

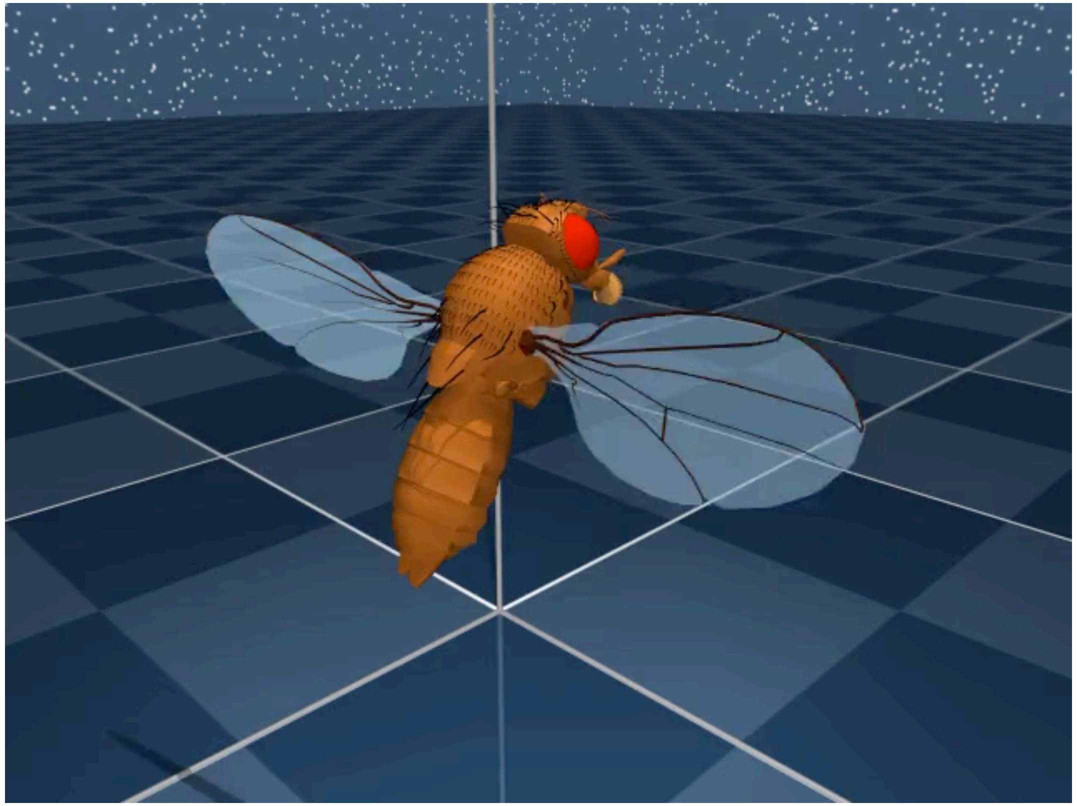
Simulating fly vision



Janne Lappalainen

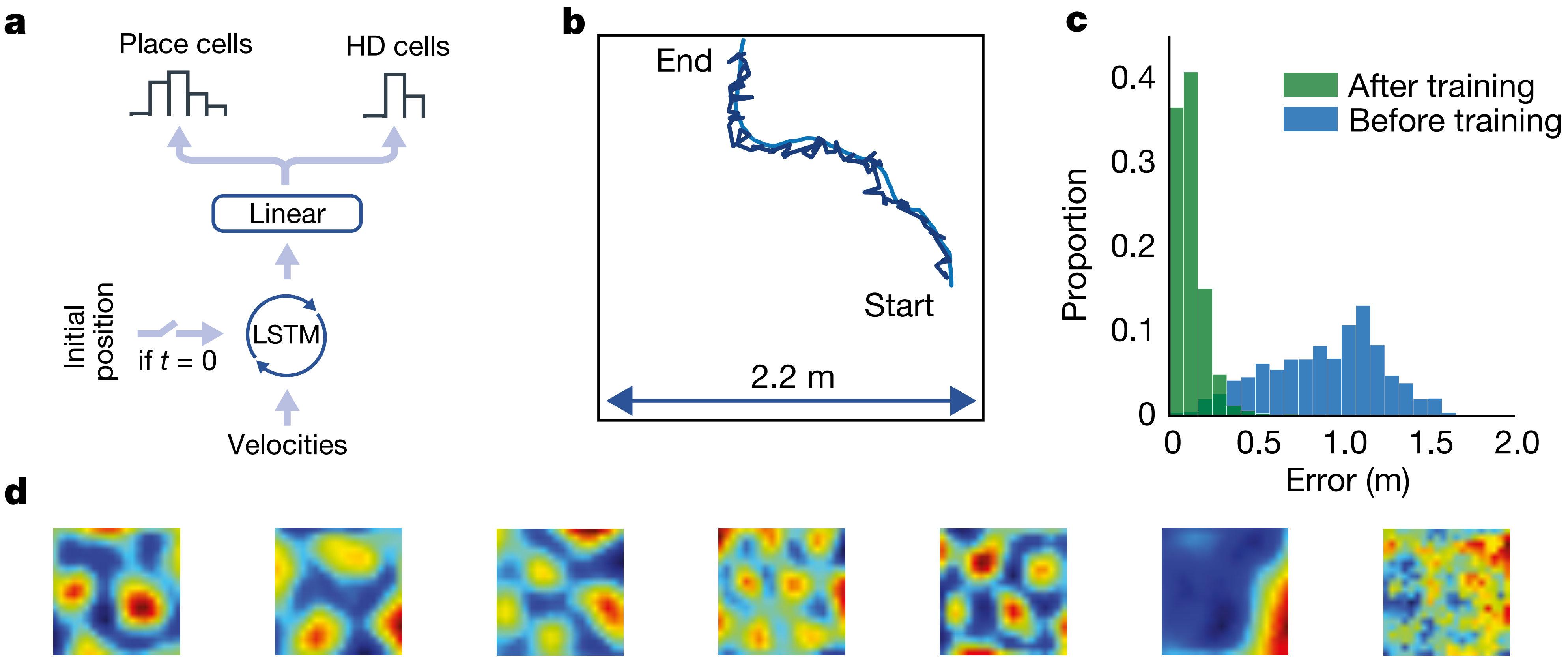
Simulating the fly body





Roman Vaxenburg
+ Janelia + DeepMind

Entorhinal-like grid cell representations emerge in a network trained to path integrate

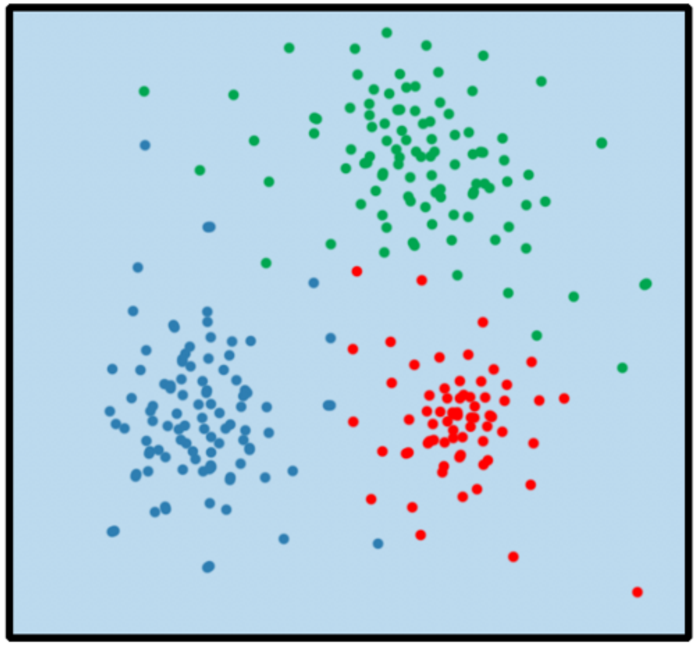


Banino et al 2018

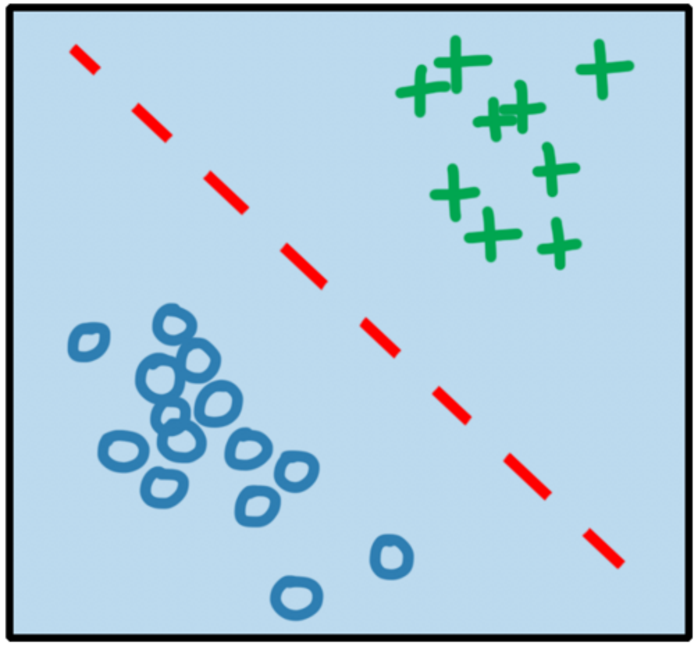
- how does the brain work?
- make lots of measurements (biology, physics, chemistry)
  - analyze using machine learning
- build a computational model
  - machine learning + mathematics, physics
- develop understanding

machine learning

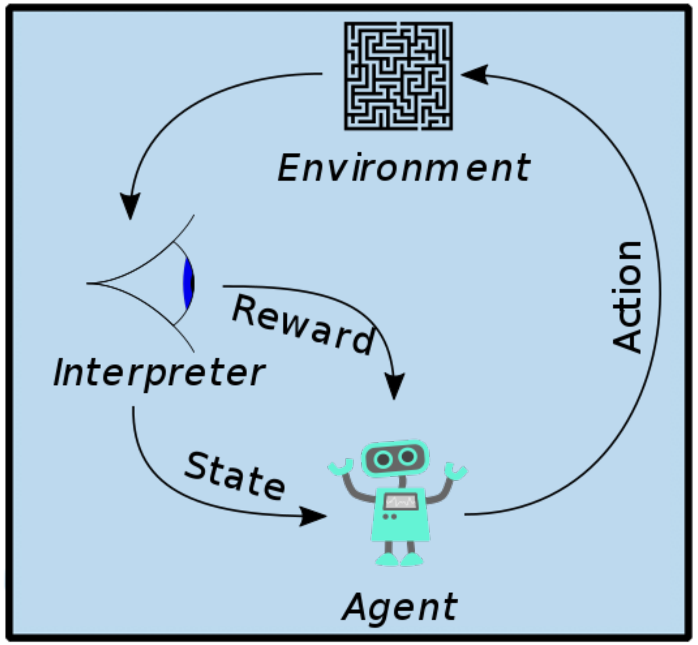
unsupervised learning



supervised learning



reinforcement learning



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- thank you
- questions?