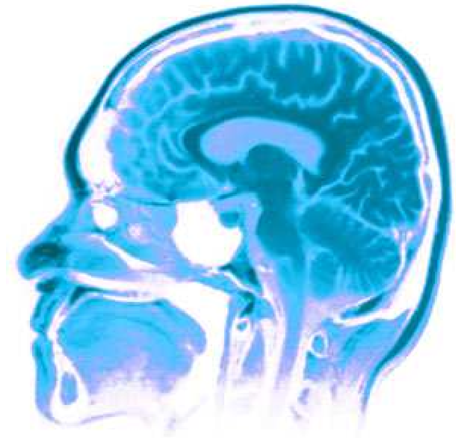
CPSC540



Machine Learning

Nando de Freitas
January, 2013
University of British Columbia

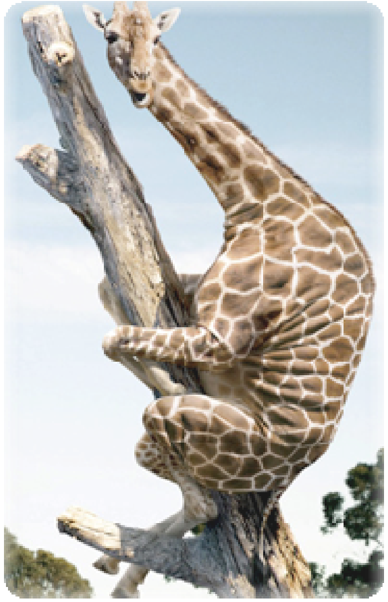
Outline of the lecture

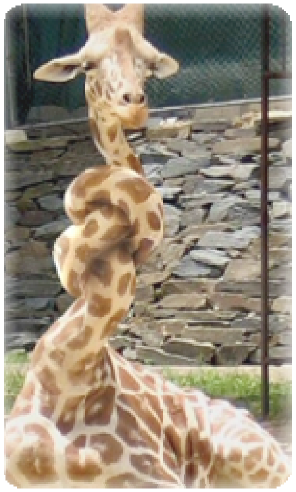
This lecture provides an introduction to the course. It covers the following four areas:

1. **Introduction** to the machine learning approach
2. The **big data** phenomenon
3. Drawing inspiration from **neural** systems
4. Machine learning **applications** and impact

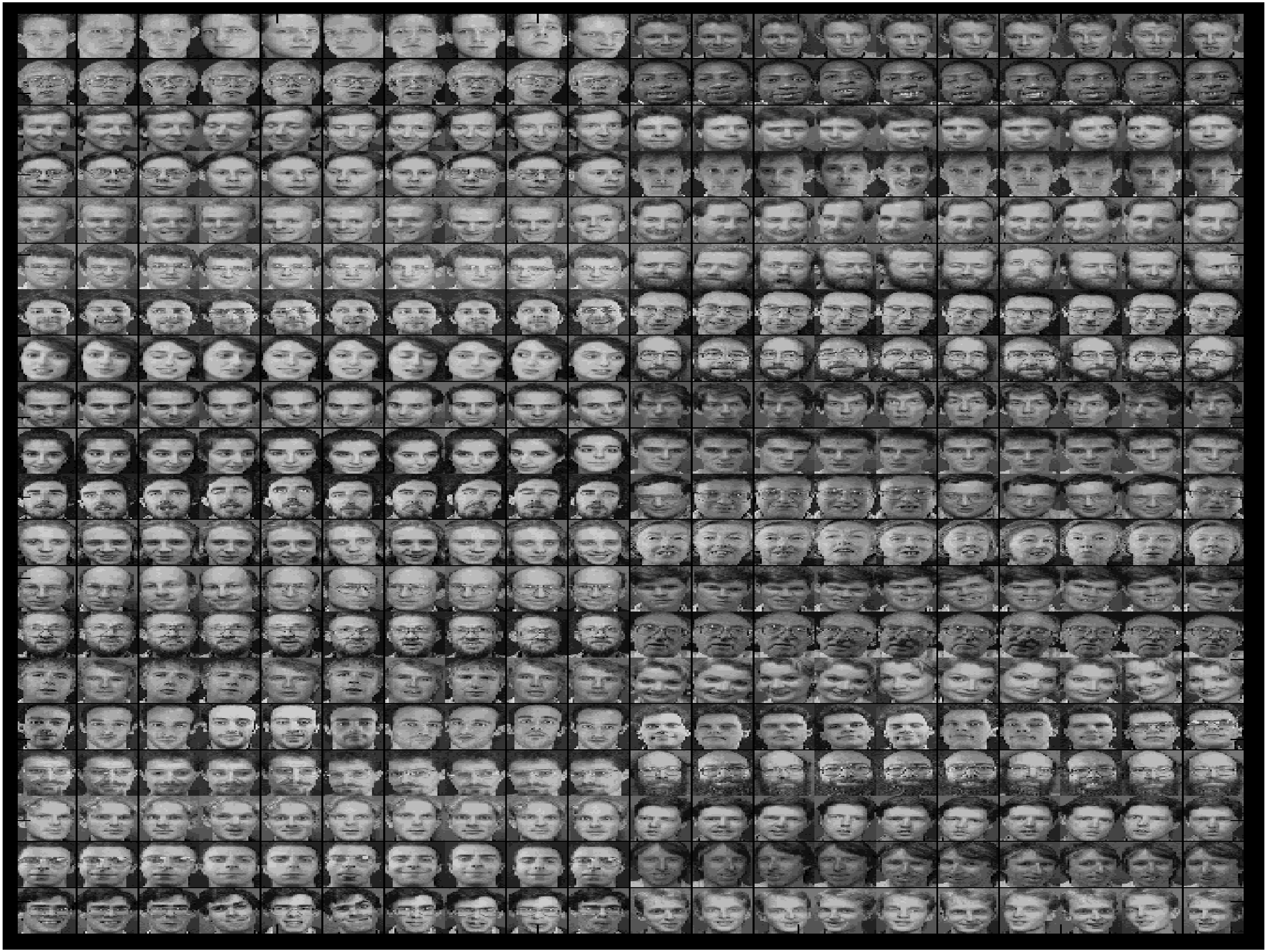
The intent of the lecture is not to explain details of building ML systems, or to tell you what to study for the exam. Rather it is an overview of what can be accomplished with ML. If it inspires you, then you'll have to take the course and learn a lot of cool stuff !

Application: Invariant recognition in natural images

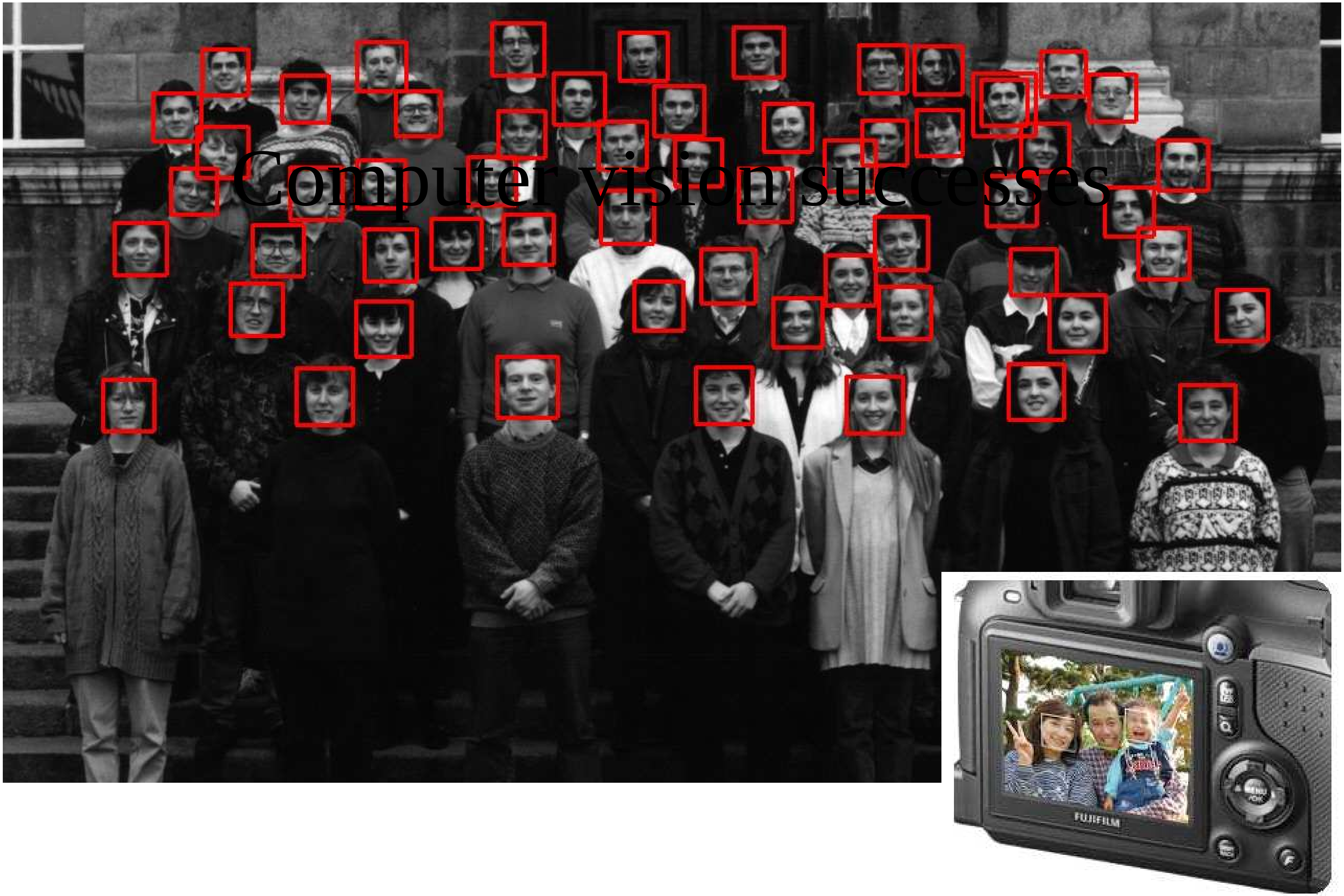




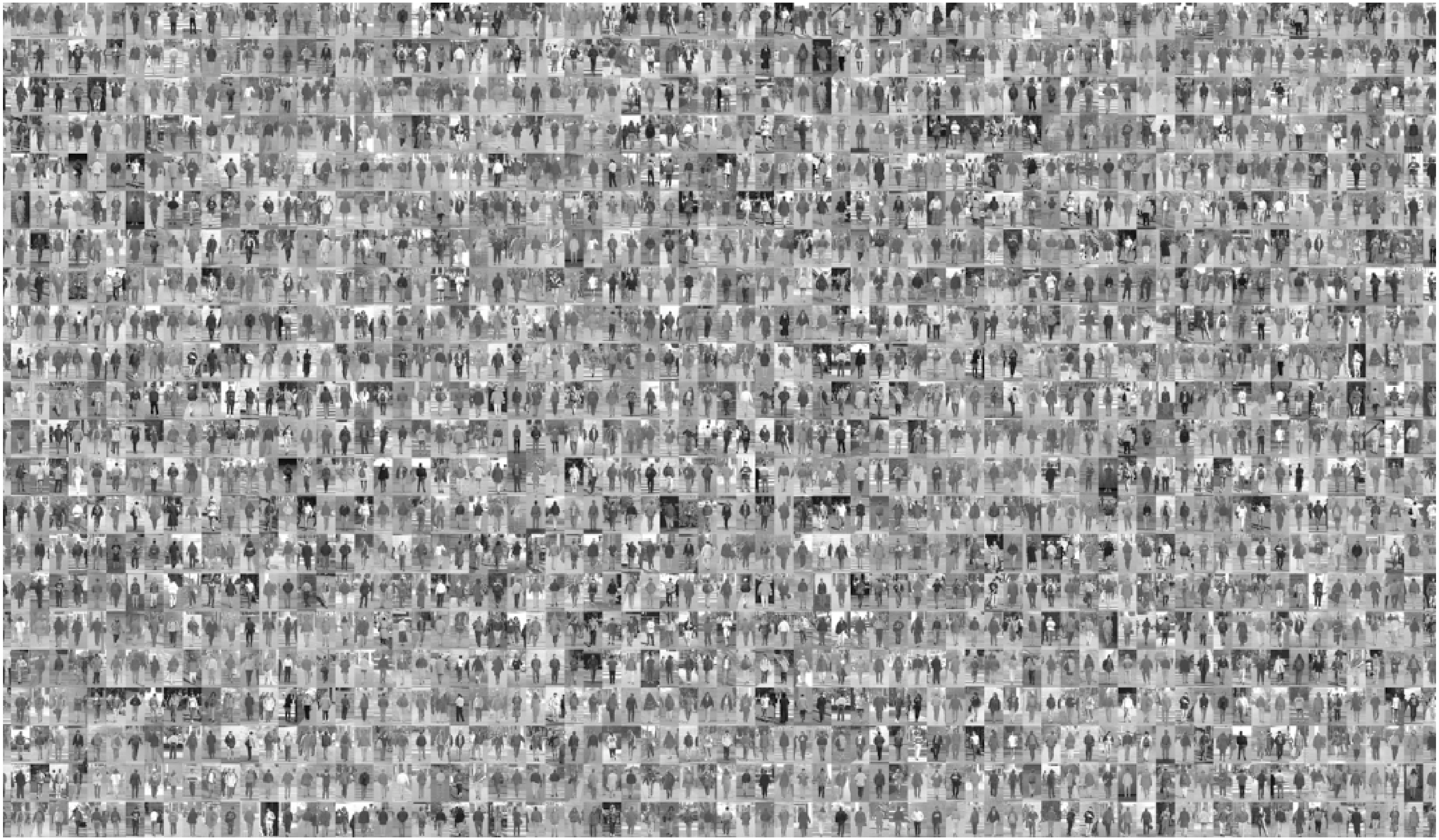
[Thomas Serre 2012]



Computer vision successes



[Thomas Serre 2012]

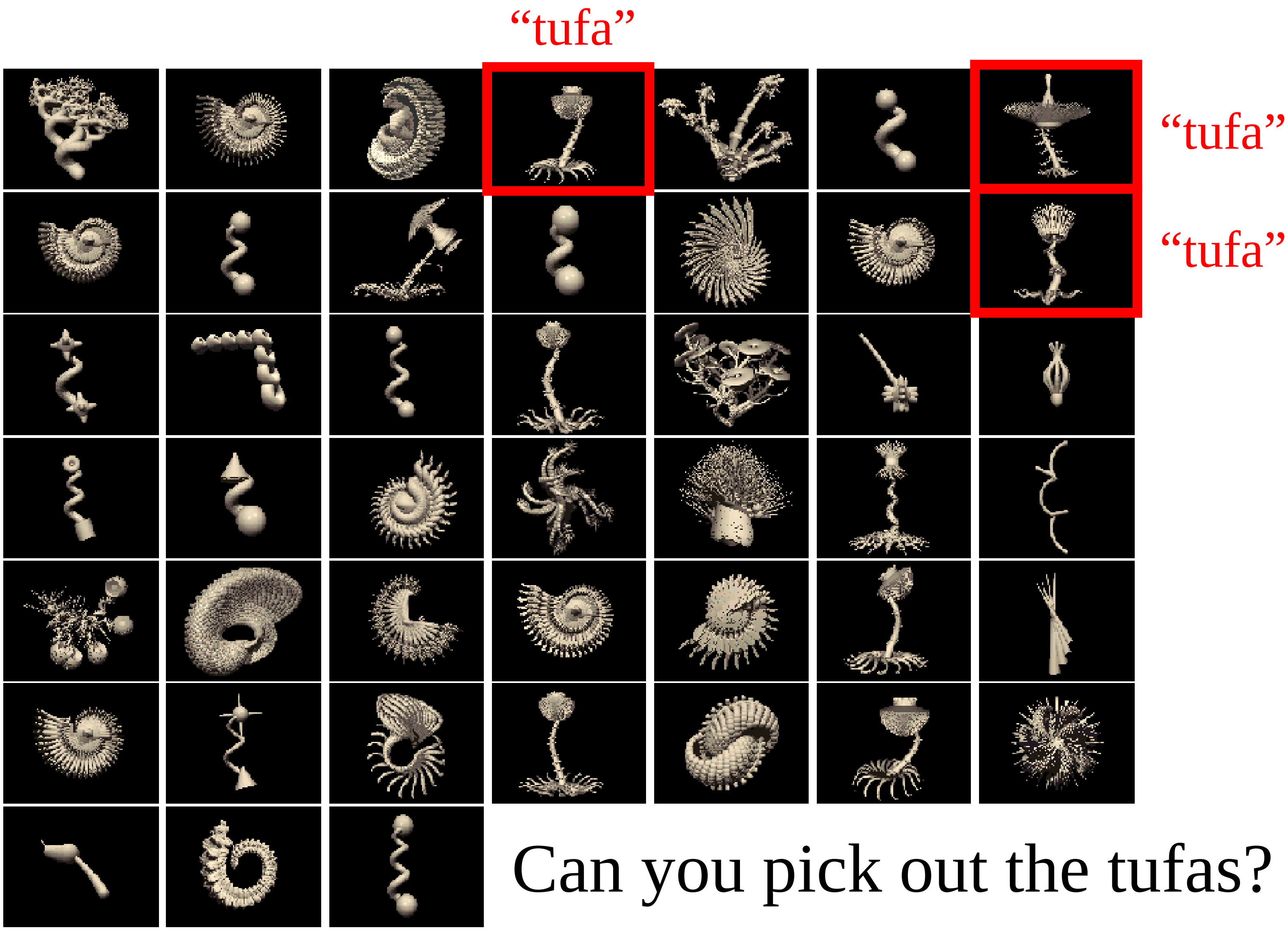


Millions of labeled examples are used to build real-world applications, such as pedestrian detection

[Tomas Serre]

Application: Autonomous driving

Mobileye: Already available on Volvo S60
and soon on most car manufacturers



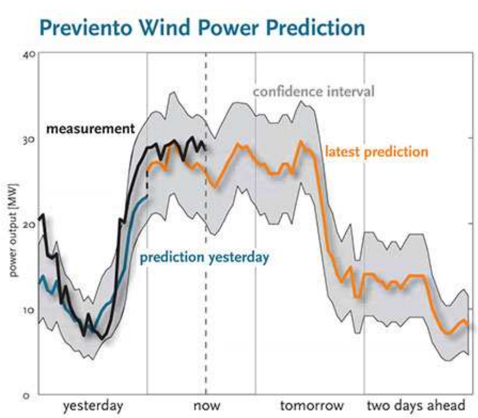
Can you pick out the tufas?

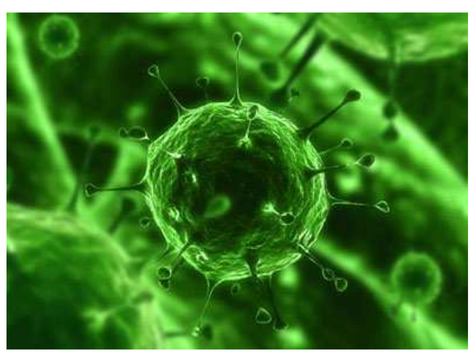
Josh Tenenbaum

Machine learning

Machine learning deals with the problem of extracting ***features*** from data so as to solve many different ***predictive*** tasks:

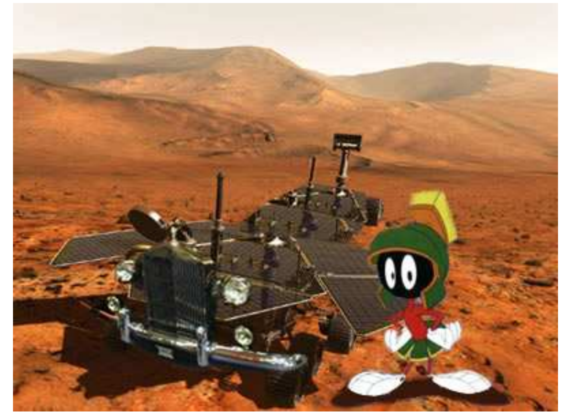
- ❑Forecasting (*e.g. Energy demand prediction, sales*)
- ❑Imputing missing data (*e.g. Netflix recommendations*)
- ❑Detecting anomalies (*e.g. Intruders, virus mutations*)
- ❑Classifying (*e.g. Credit risk assessment, cancer diagnosis*)
- ❑Ranking (*e.g. Google search, personalization*)
- ❑Summarizing (*e.g. News zeitgeist, social media sentiment*)
- ❑Decision making (*e.g. AI, robotics, compiler tuning, trading*)

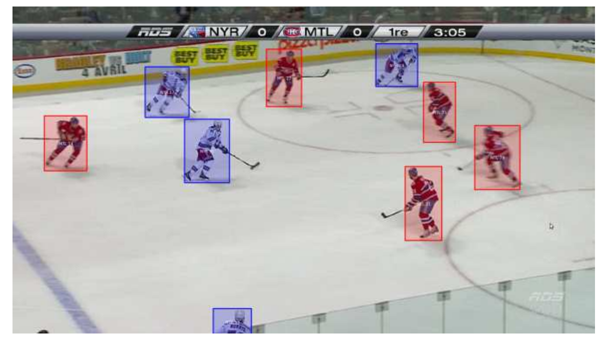




When to apply machine learning

- Human expertise is absent (*e.g. Navigating on Mars*)
- Humans are unable to explain their expertise (*e.g. Speech recognition, vision, language*)
- Solution changes with time (*e.g. Tracking, temperature control, preferences*)
- Solution needs to be adapted to particular cases (*e.g. Biometrics, personalization*)
- The problem size is to vast for our limited reasoning capabilities (*e.g. Calculating webpage ranks, matching ads to facebook pages*)





Machine learning in language

“Large” text dataset:

- **1,000,000 words in 1967**
- **1,000,000,000,000 words in 2006**

Success stories:

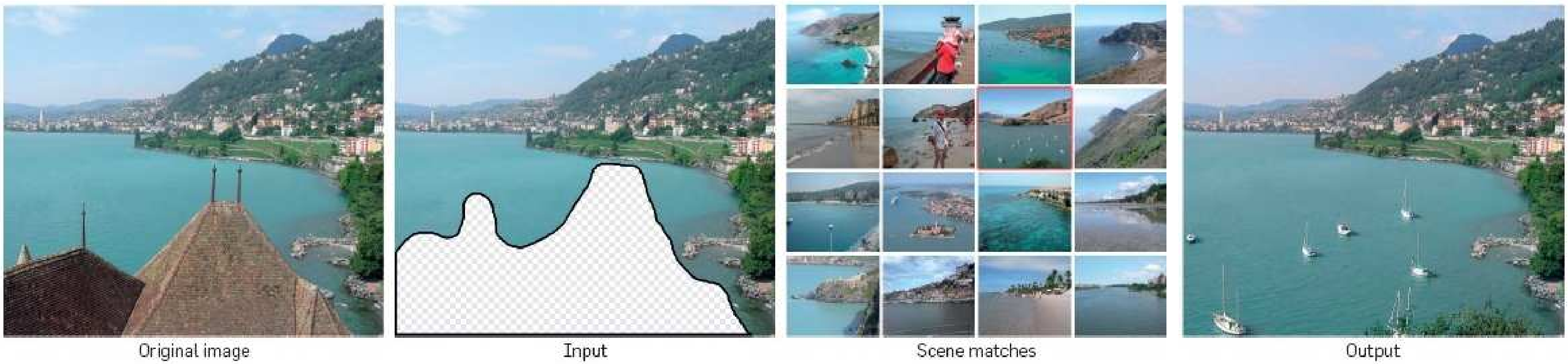
- **Speech recognition**
- **Machine translation**

What is a common thing that makes both of these work well?

- **Lots of labeled data**

[Halevy, Norvig & Pereira, 2009]

Scene completion: More data is better



Given an input image with a missing region, Efros uses matching scenes from a large collection of photographs to complete the image

[Efros, 2008]

The semantic challenge

- “We’ve already solved the sociological problem of building a network infrastructure that has encouraged hundreds of millions of authors to share a trillion pages of content.

- We’ve solved the technological problem of aggregating and indexing all this content.

- But we’re left with a scientific problem of interpreting the content”

[Halevy, Norvig & Pereira, 2009]

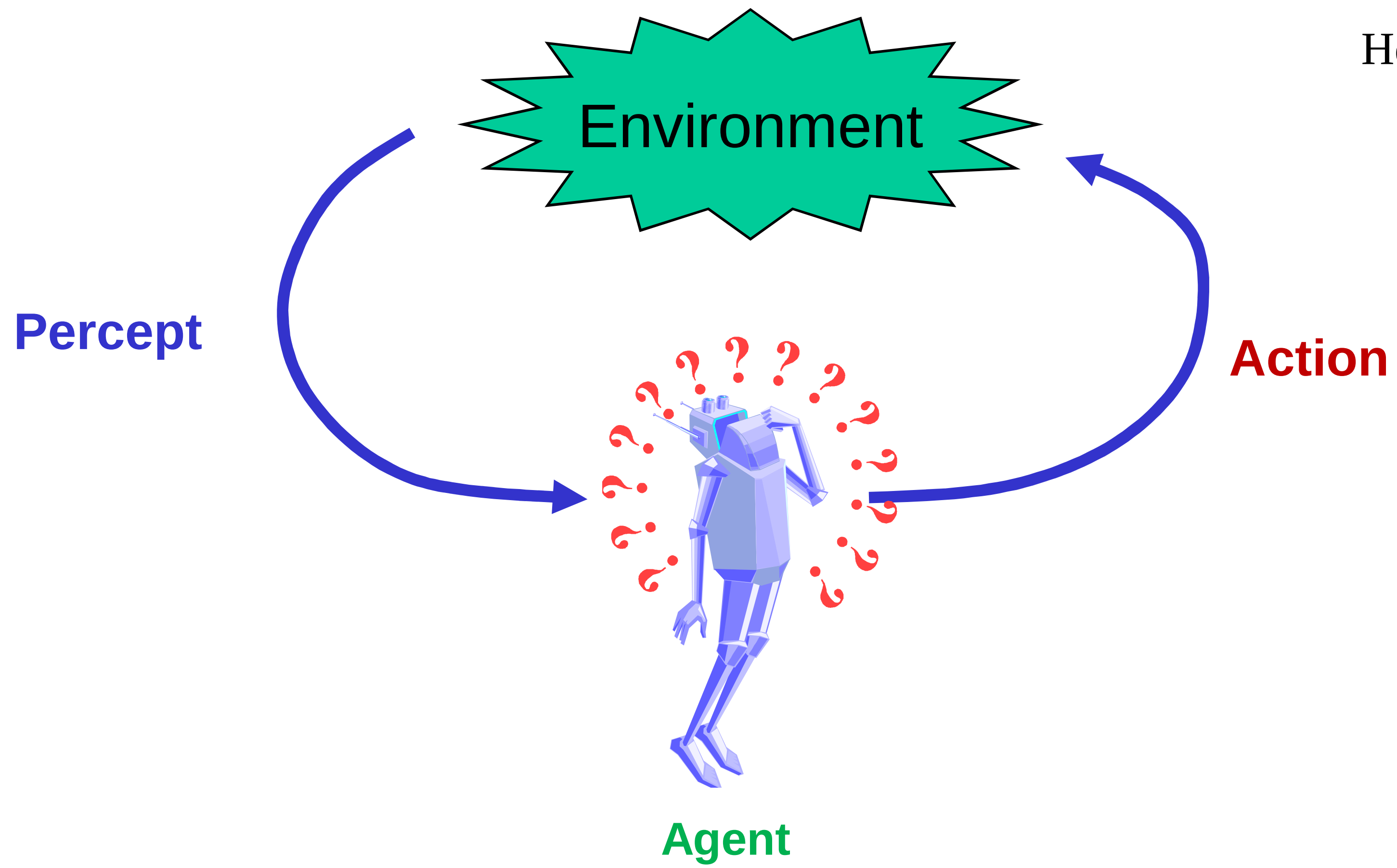
- **It’s not only about how big your data is. It is about understanding it and using this understanding to derive reasonable inferences. Think of citation matching.**

- **http://openie.cs.washington.edu/**

Learning, understanding and causality

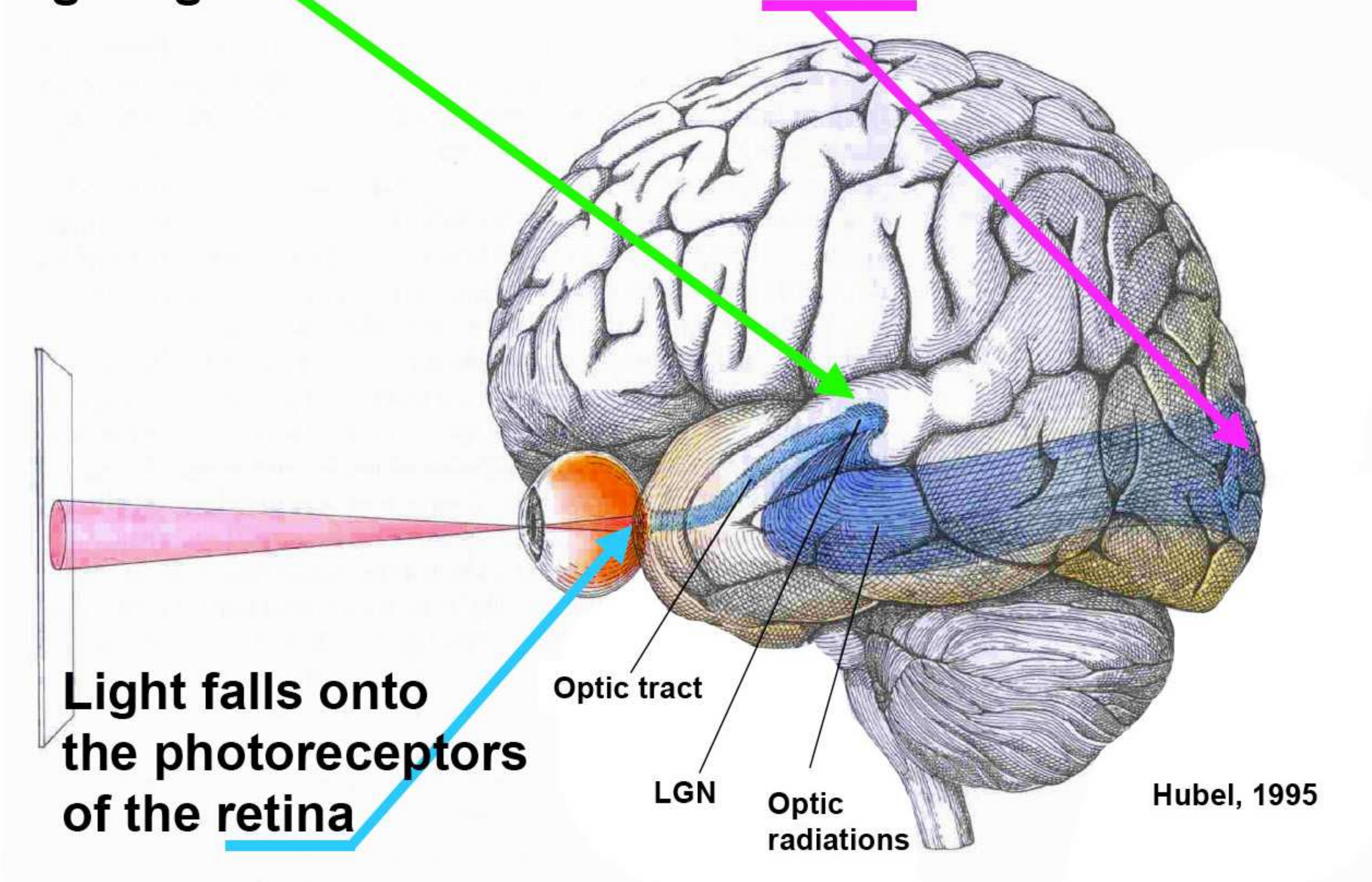
``Learning denotes changes in the system that are ***adaptive*** *in the sense that they enable the system to do the task or tasks drawn from the same population more efficiently and more effectively the next time.''*

Herbert Simon

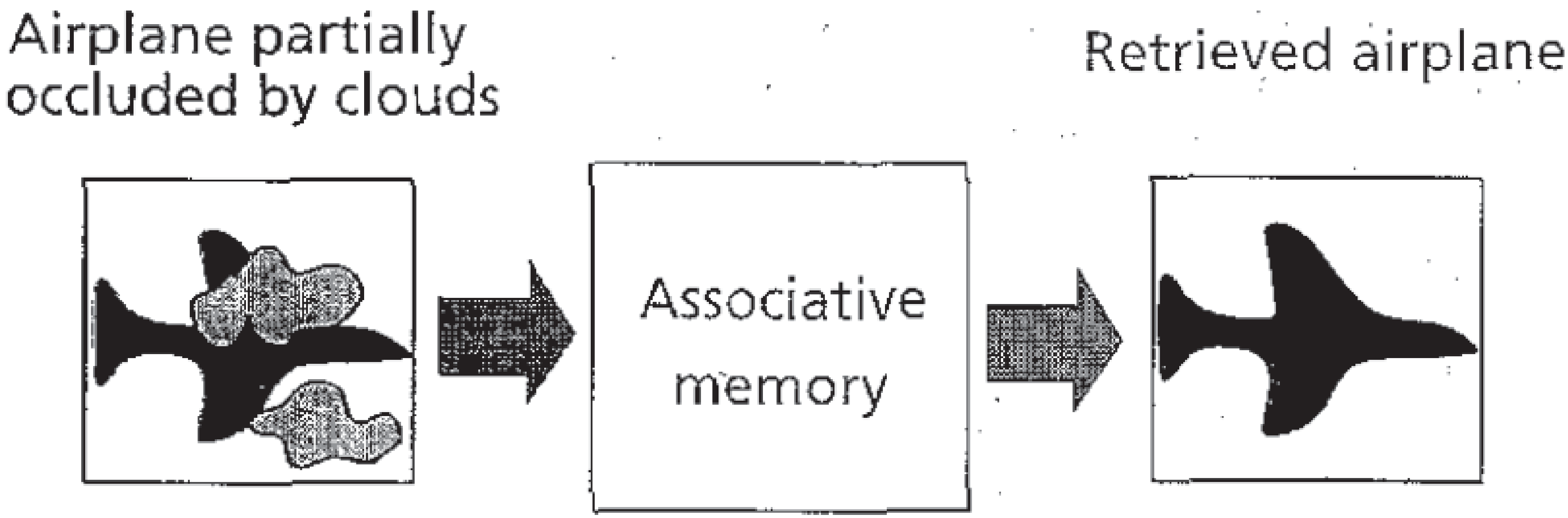


A source of inspiration

Thalamus (LGN) serves strategic role in gating of information flow to cortex

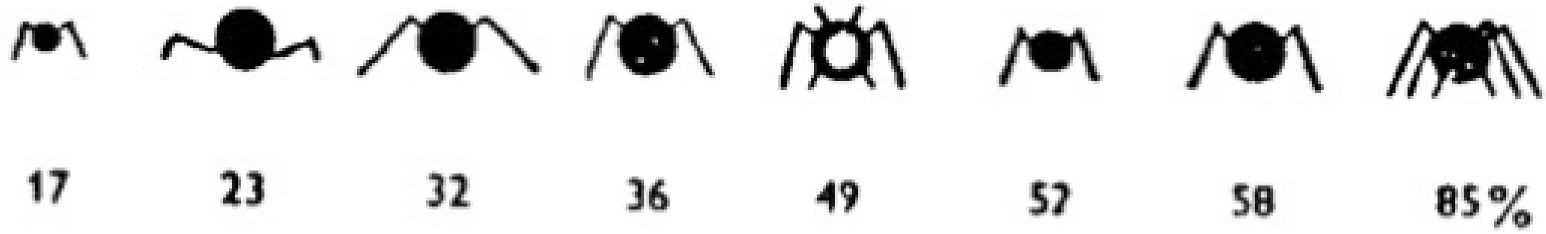


Associative memory

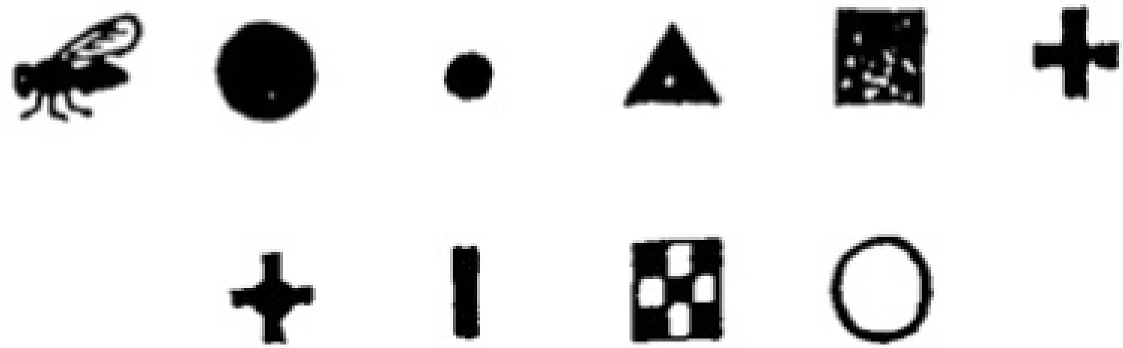


Example 2: Say the alphabet, …. backward

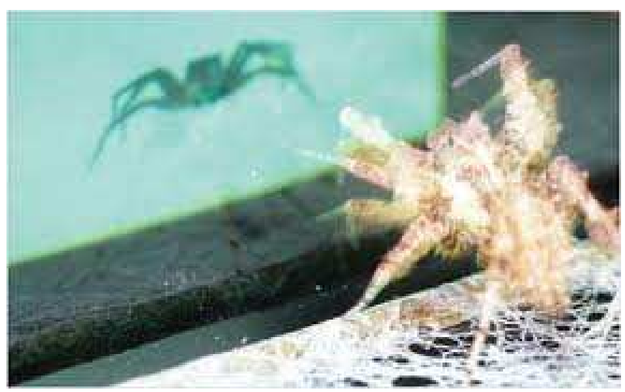
[Jain, Mao & Mohiuddin, 1996]

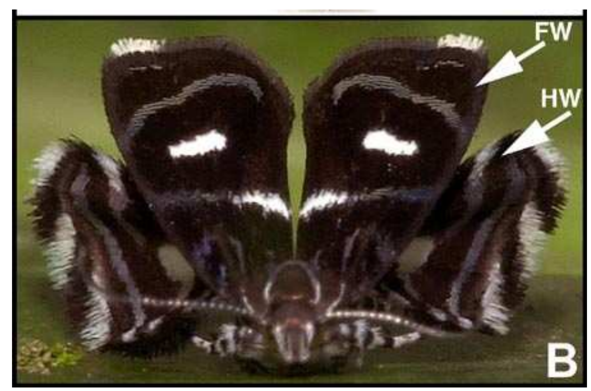


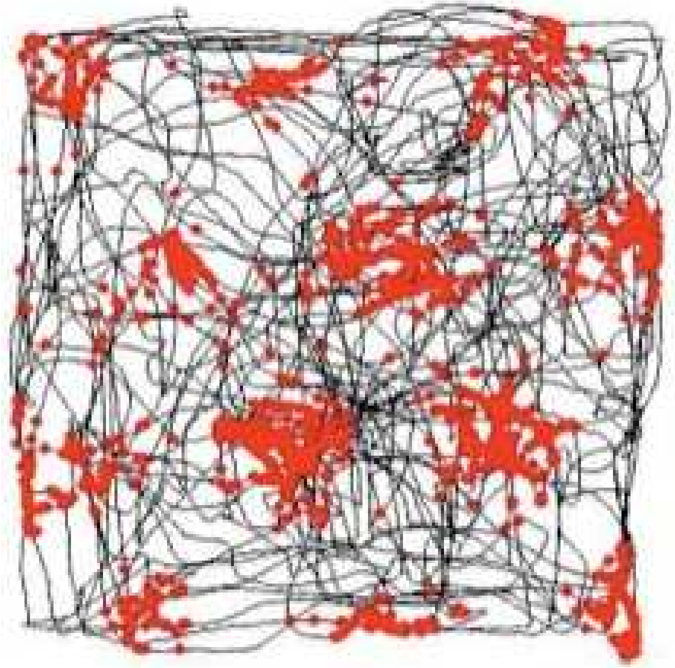
(b)

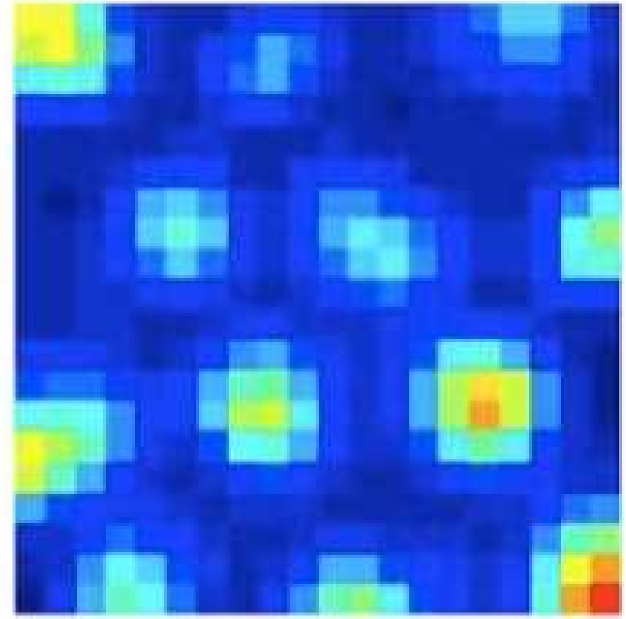


Text-fig. 12. Stimuli found by Drees to evoke courtship (*a*) and prey capture (*b*) in male jumping spiders (*Epiblemum scenicum*). The numbers beneath each figure in (*a*) are the percentage of trials on which courtship was evoked. After Drees (1952).







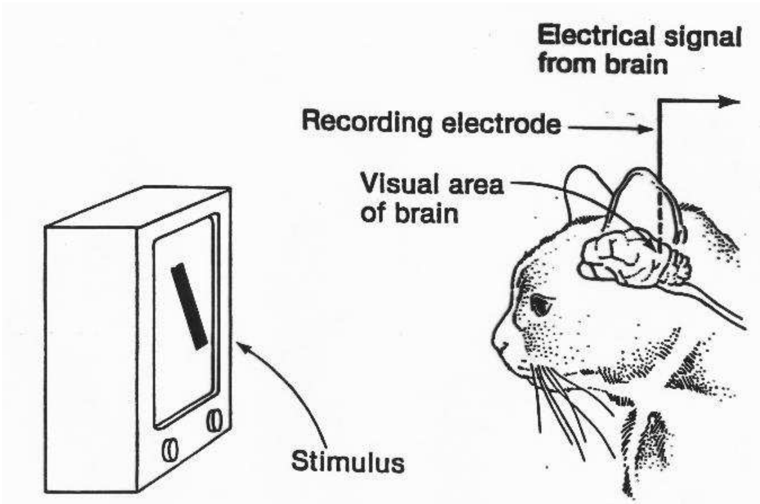


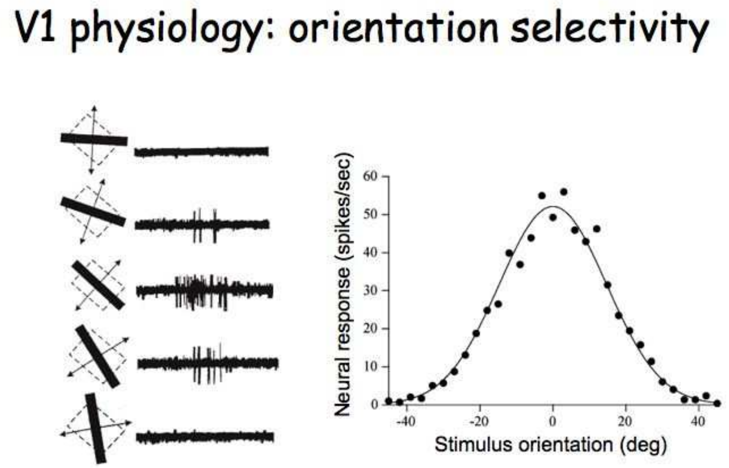
The x and y coordinates correspond to the spatial location of a rat.

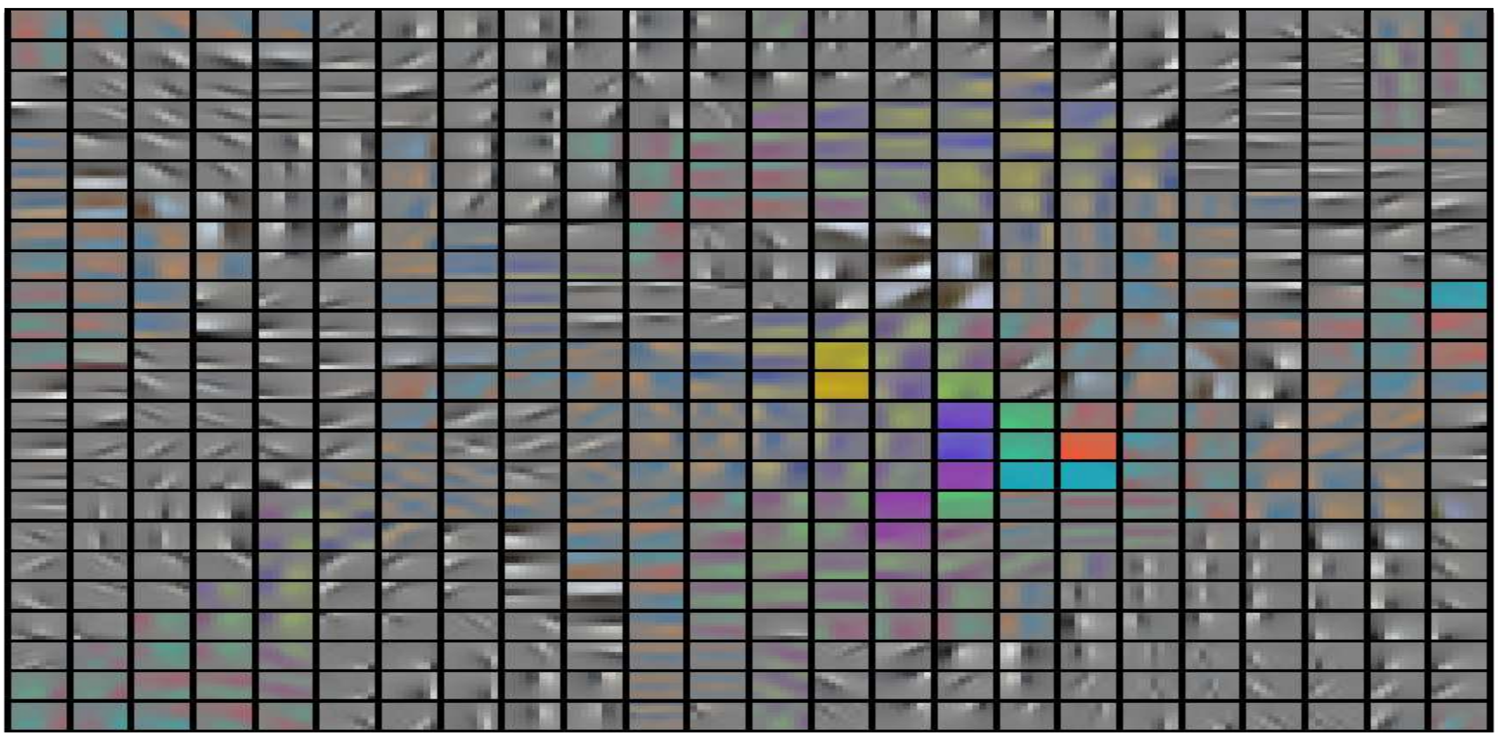
The red dots indicate the place where a particular neuron fires.

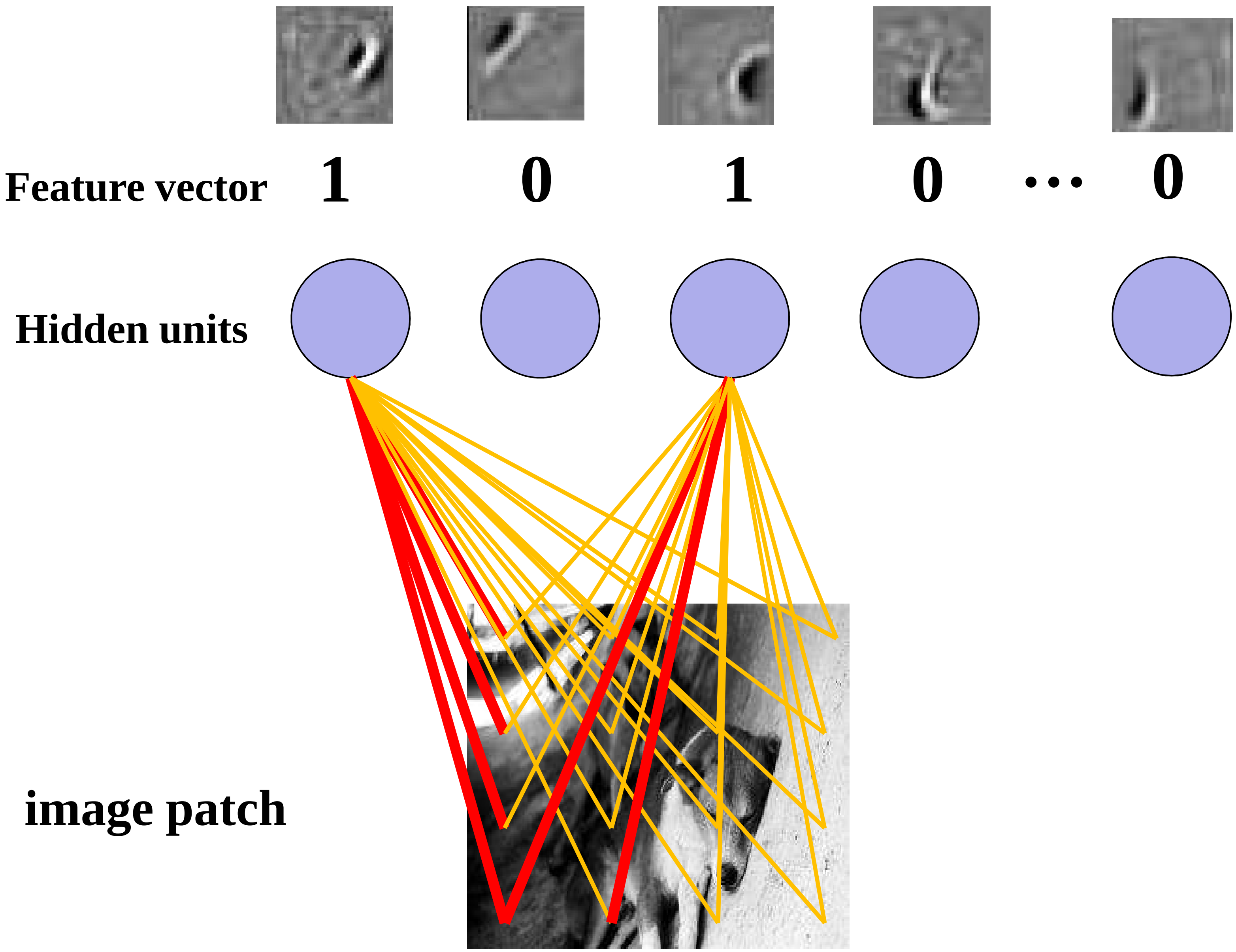
[Hafting et al 2005]

Selectivity and Topographic maps in V1

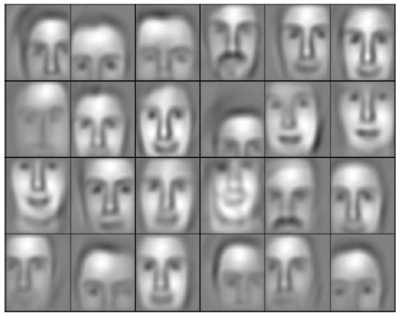


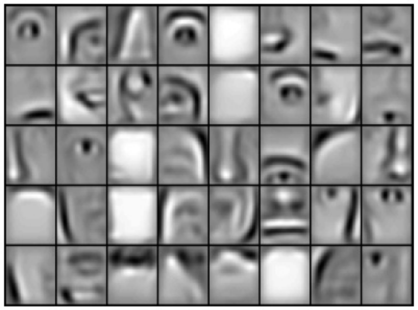


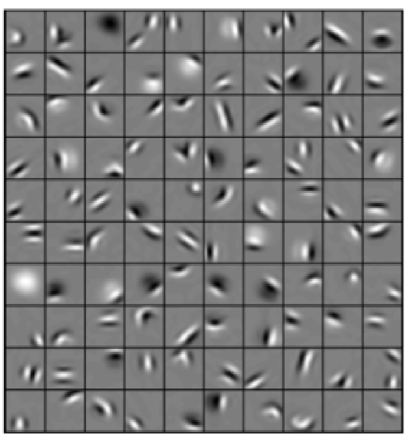


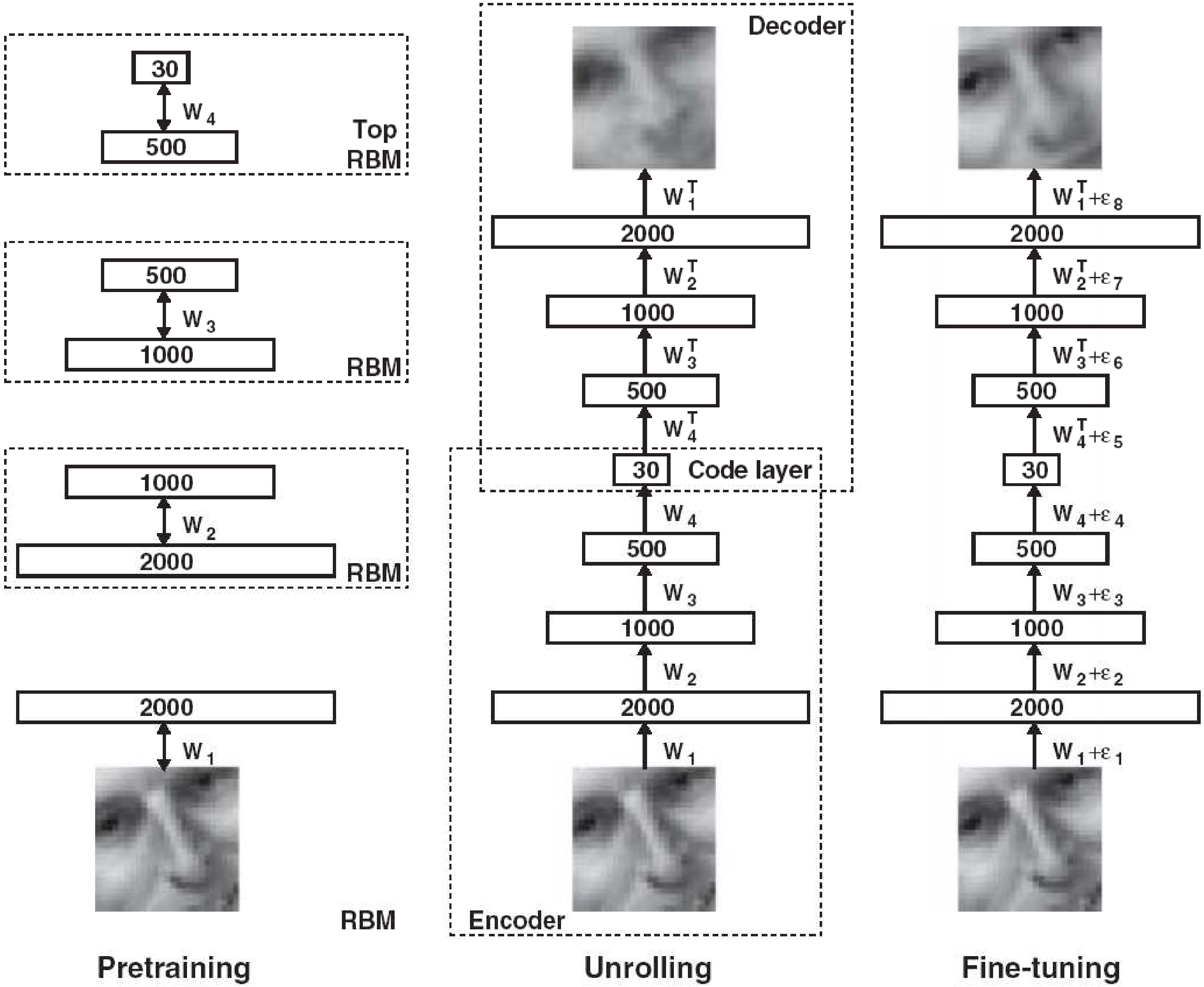

Feature vector
1
0
1
0
…
0
Hidden units
image patch

Deep learning with autoencoders



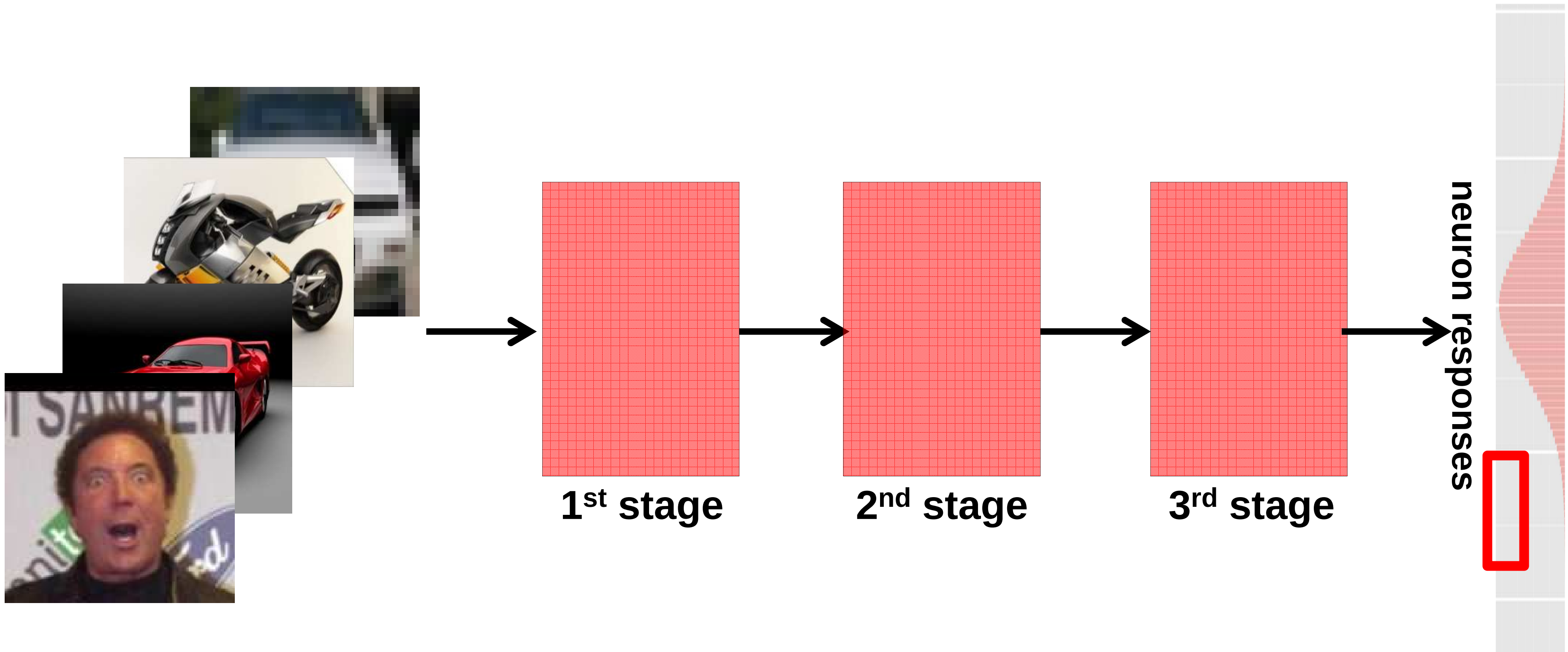






[Russ Salakhutdinov, Geoff Hinton, Yann Lecun, Yoshua Bengio, Andrew Ng, …]

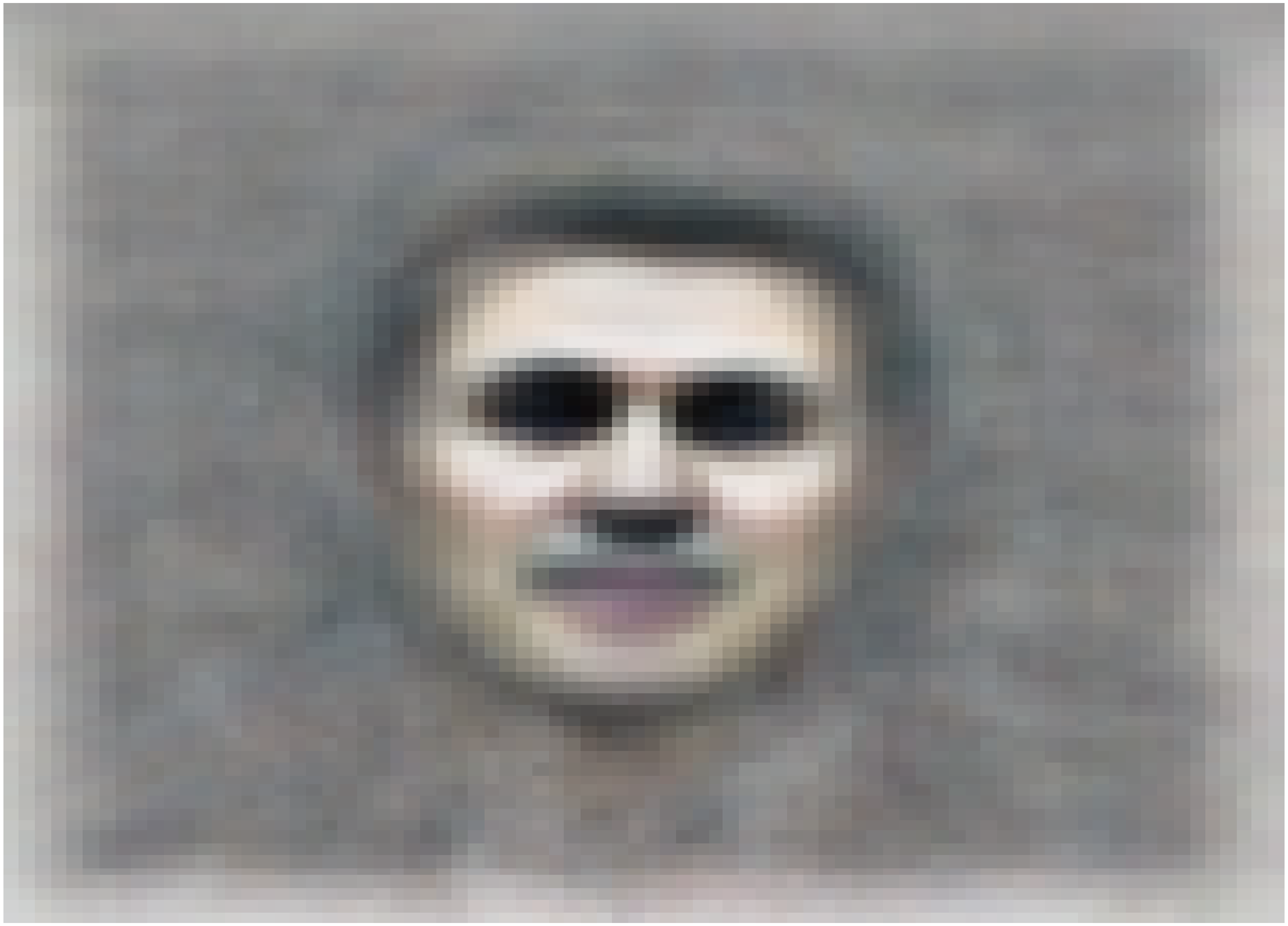
Validating Unsupervised Learning



Top Images For Best Face Neuron

Ranzato

Best Input For Face Neuron



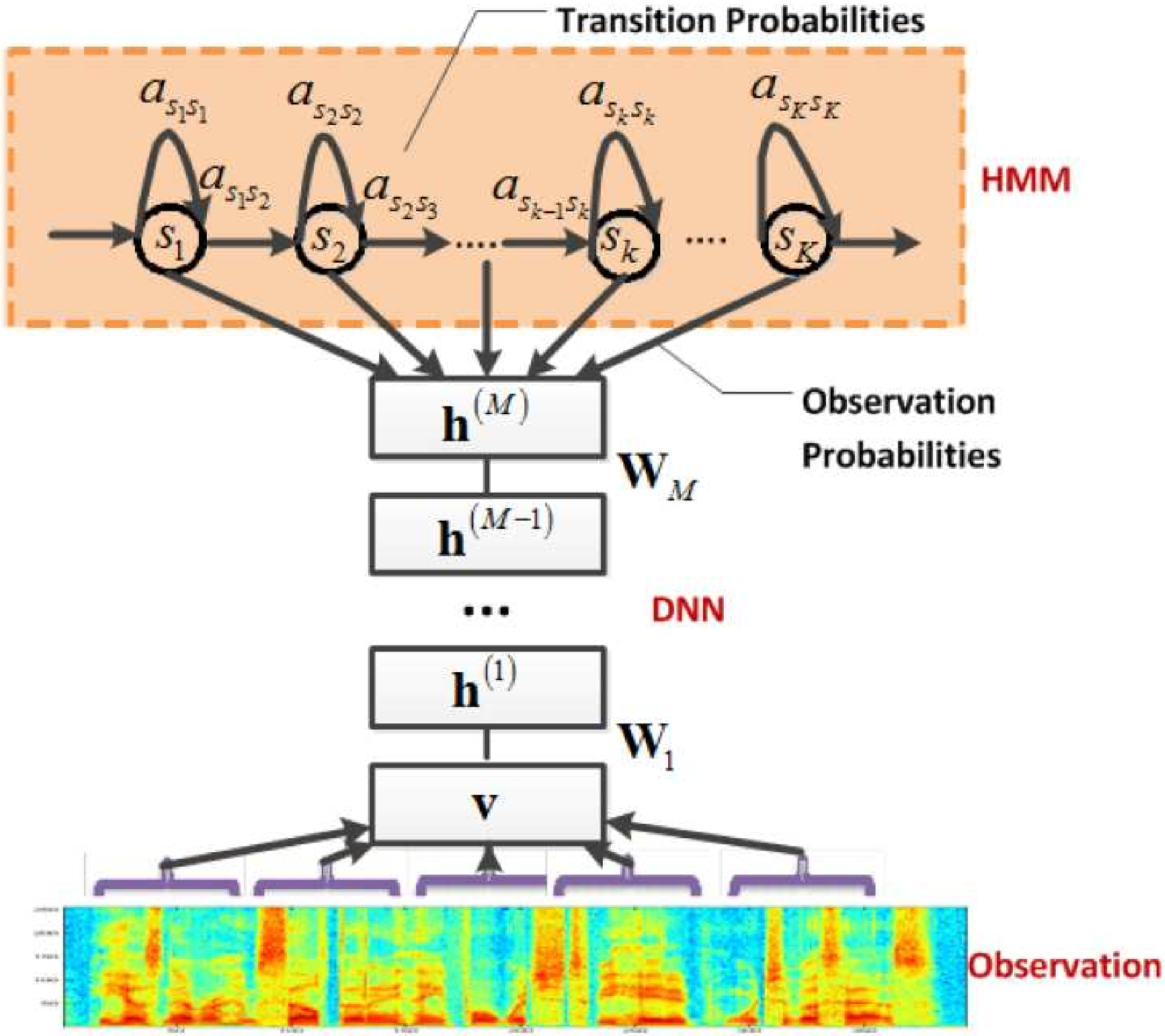
Hierarchical spatial-temporal feature learning

Observed gaze sequence

Model predictions

[Bo Chen et al 2010]

Application: Speech recognition



[George Dahl et al 2011]

Next lecture

In the following lecture we will revise least squares predictions.