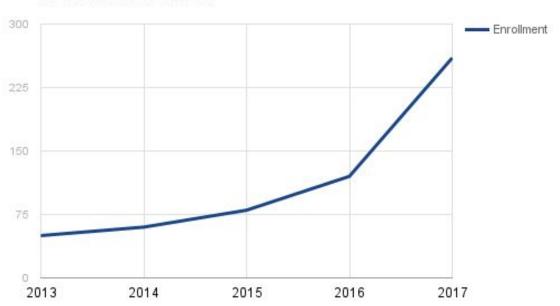
# ECE521 Lecture1

Introduction



### **ECE521 Enrollment**



## Outline

- History of machine learning
- Types of machine learning problems

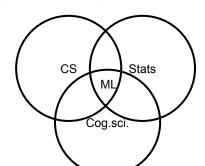
- A scientific field is best defined by the central question it studies. The intellectual endeavour underlying the field of machine learning is:
  - "How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?"
    - -- Tom Mitchell, Chair of the Machine Learning Department CMU, 2006

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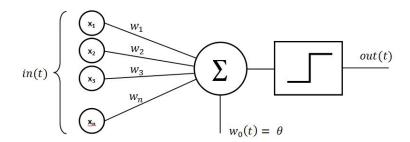
At the beginning there is the "shallow" learning...

- Alan Turing wrote a little known paper in 1948 "Intelligent Machinery" that highlighted:
  - An unorganized machine that consists of randomly connected networks of NAND logic gates.
  - A general search algorithm that is similar to a "genetic algorithm" to organize the unorganized machine.
  - The unorganized machine resembles the cortex structure in the brain.

# Lany unorganised machines have configurations such that if once that configuration is reached, and if the interference thereafter is appropriately restricted, the machine behaves as one organised for some definite purpose. For instance the 1-type anothine shown belowwas chosen at random

If the connections numbered 1, 3, 6, 4, are in condition ii) initially and connections

 Frank Rosenblatt in 1957 combined the ideas of the artificial neuron of McCulloch-Pitts and the Hebbian learning rule from Donald Hebb to develop the perceptron model:



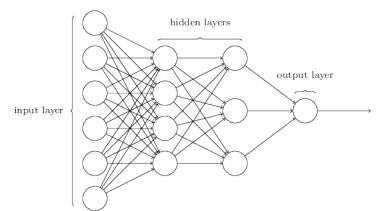
$$Out = f(\sum_{i=1}^{N} w_i x_i + \theta)$$

First implementation of

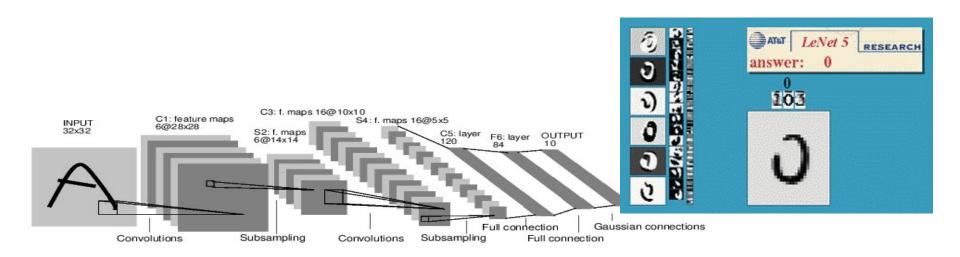
First implementation of perceptron <u>source</u>

- Then there was the first Al winter: 1970s
  - Machine translation did not make much progress from the breakthroughs of Chomsky's grammar
  - Perceptron was proven ineffective for non-linear classification problems

- The emergence of multi-layered perceptron and neural networks
  - Rumelhart, Hinton and Williams in 1986 highlighted a learning algorithm called
    "backpropagation" that can effectively train neural networks with multiple hidden layers.
  - Yann LeCun in 1989 proposed similar learning algorithm to train convolutional neural networks to recognize handwritten zip codes. Such a system has been used by USPS and bank ATMs saving hundreds of millions of dollars.



The improved convolutional neural network LeNet that was deployed in 1997

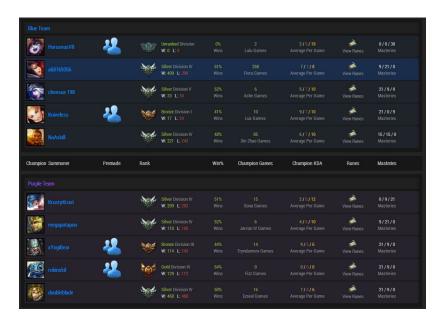


LeNet-5 (LeCun et al. 1998)

- Judea Pearl published Probabilistic Reasoning in Intelligent Systems in 1988 that changes the machine learning field to take statistical and probabilistic ideas seriously
  - Inspired statistical machine learning models for speech and language processing
  - It promotes the ideas of Hidden Markov Model, Kalman filter and particle filtering

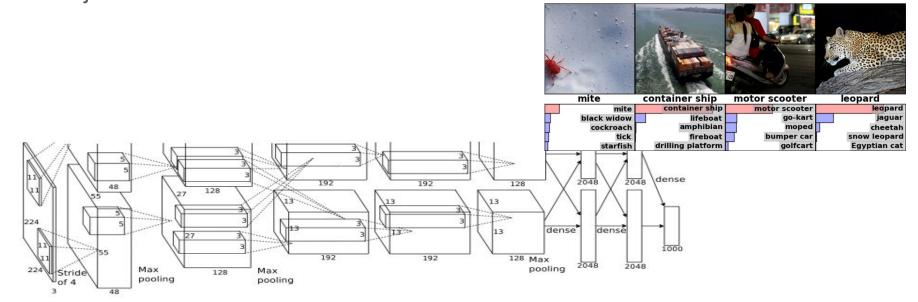
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One interesting application of Bayesian inference is in matchmaking systems:



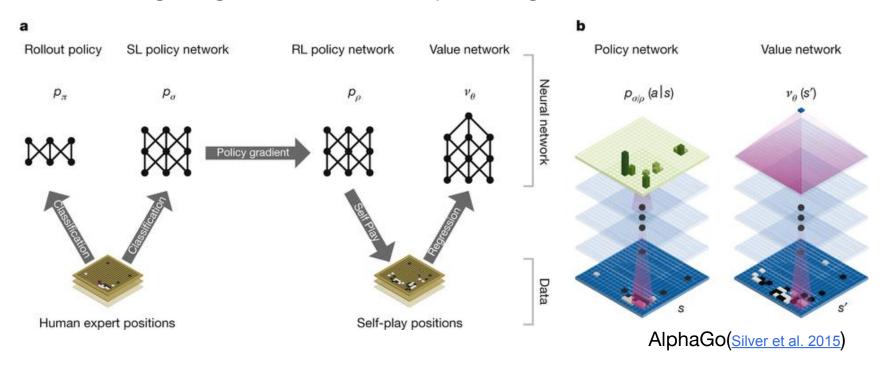
Then the computers were too slow so we did not make much progress till
 2012

 A large-scale convolutional neural network that can recognize 1000s of objects



AlexNet(Krizhevsky et al. 2012)

Mastering the game of Go with deep learning



Speech recognition









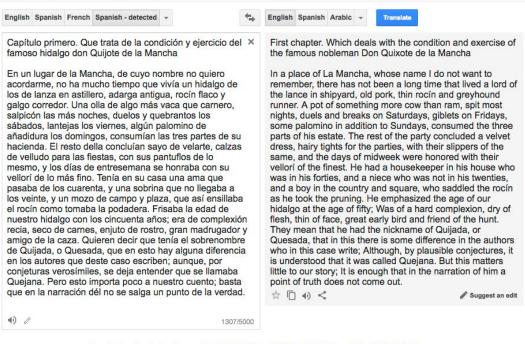
Computer vision

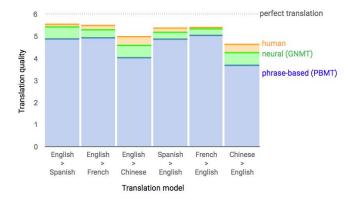






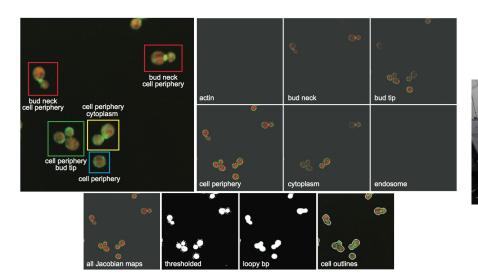
Natural language processing

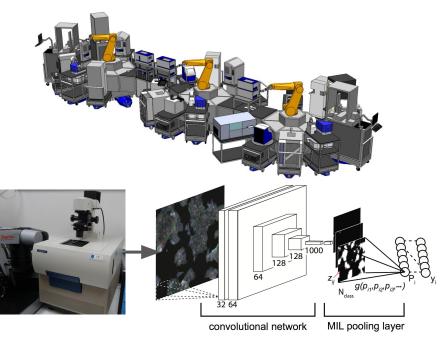




Google's Neural Machine Translation (Wu et al. 2016)

Computational biology





High-throughput microscopy of cellular data (Oren et al. 2016)

#### Robotics



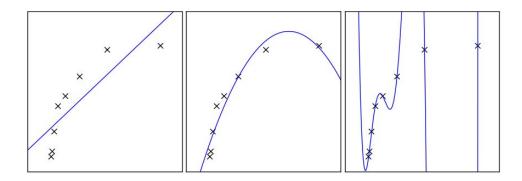


Berkeley's robot learnt using reinforcement learning(Levine et al. 2015)

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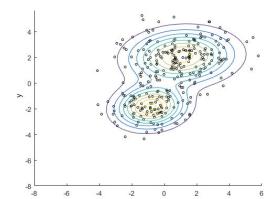
- Supervised learning:
  - $\circ$  Given a set of labeled training data points  $\,\{(x^i,y^i)\}\,$
  - $\circ$  Space of input data and labels:  $x \in \mathcal{X}, \quad y \in \mathcal{Y}$
  - $\circ$  The goal is to learn a function mapping f, that  $f:\mathcal{X} o\mathcal{Y}$



• "... Intelligence is not just about fitting some lines through bunch of points..."

- Unsupervised learning: There is not label in the dataset. We would like to discover interesting patterns and structures within the input data.
  - $\circ$  Given a set of unlabelled training data points:  $\{x^i\}$
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- Semi-supervised learning:
  - Given a dataset in terms of a mixture of labelled and unlabelled data



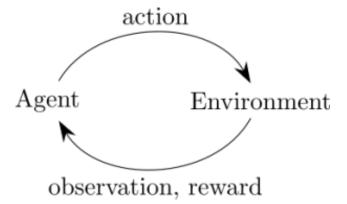
How to grow a mind (Tenenbaum, 2012)

What are the other "Tufa"?



How to grow a mind (Tenenbaum, 2012)

Reinforcement learning:



Concrete formulation of a learning problem in terms of a loss function

- Use gradient-based optimization algorithms to minimize the loss function
  - Learning: search for a set of parameters/weights that minimizes the loss function
  - o Inference: search for a set of latent causes to explain the observed data

- Learning algorithms
  - Back-propagation
  - Gradient descent
- Inference algorithms
  - Bayes rules
  - The sum-product algorithm

- Supervised learning models
  - > K-NN
  - Linear models: Linear regression, logistic regression
  - Neural networks
- Unsupervised learning models
  - o K-means, Mixtures-of-Gaussians
  - o PCA, Auto-encoder
  - Hidden Markov Models
  - Some acyclical graphs

- Mechanical questions (easy free marks)
  - Carry out an algorithm on particular models and data
- Brain teasers
  - What happens when we do this?
  - o Is it possible to have this scenario?

## Course topics:

