EECS 545: Machine Learning
Lecture 1. Introduction

Honglak Lee & Michał Dereziński

1/5/2022

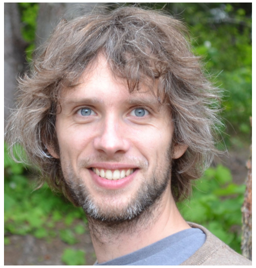
Outline

- Administrative
- What is machine learning?

Teaching staff

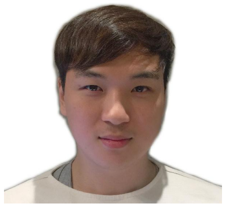
Instructors:

- Honglak Lee (honglak@umich.edu, Office: CSE 3773)
- Michał Dereziński (derezin@umich.edu, Office: CSE 2649)



Graduate Student Instructors:

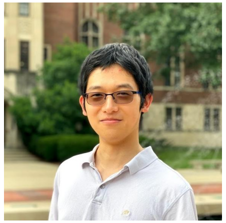
- Aabhaas Vaish (aabhaas@umich.edu)
- Junghwan Kim (kimjhj@umich.edu)
- Kevin Wang (musicer@umich.edu)
- Sudeep Katakol (sudeepk@umich.edu)



Junghwan

Sudeep

Aabhaas



Kevin

Please contact us via Piazza or eecs545.w22@gmail.com (please avoid sending to personal emails unless it's really necessary)

- For office hours, please see future announcements and calendar

About this course

- Graduate-level introduction of machine learning
- Foundations of machine learning
  - Mathematical derivation, Implementation of the algorithms, applications
- Topics
  - supervised learning
  - unsupervised learning
  - reinforcement learning
- Other topics
  - deep learning, learning theory, probabilistic models, sparsity and feature selection, Bayesian techniques, ensemble methods

About this course

- Cover practical applications of machine learning
  - computer vision, data mining, speech recognition, text processing, robot perception and control, etc.
- Our goal is to help you to
  - Understand fundamentals of machine learning
  - Learn technical details of ML algorithms
  - Learn how to implement some important algorithms
  - Use machine learning algorithms for your research and applications.

Textbooks

There will be no official textbook for the course. However, the following materials will be helpful (all of them are available online):

- Chris Bishop, "Pattern Recognition and Machine Learning". Springer, 2007.
- Kevin Murphy, "Machine Learning: A Probabilistic Perspective", 2012.
- David Barber, "Bayesian Reasoning and Machine Learning", 2017.
- Ian Goodfellow and Yoshua Bengio and Aaron Courville, "Deep Learning",
- Hastie, Tibshrani, Fiedman, "Elements of Statistical Learning". Springer, 2010.
- Sutton and Barto, "Reinforcement Learning: An Introduction," MIT Press, 2018.
- (optional) Boyd and Vandenberghe, "Convex Optimization," Cambridge University Press, 2004.
- (optional) Mackay, "Information Theory, Inference, and Learning Algorithms". Cambridge University Press. 2003.

Prerequisites

- Undergrad linear algebra (e.g., MATH 217, MATH 417) OR graduate matrix methods courses (EECS 505 / EECS 551) which have several relevant linear algebra concepts
- Multivariate calculus
- Undergrad probability and statistics (e.g., EECS 301)
- Programming skills (equivalent to EECS 280, EECS 281, and experience in Python)
  - Nontrivial level of programming is required.

- NOTE: If you **have not** taken **at least two** of linear algebra, multivariate calculus, and probability courses, it is **strongly recommended** that you finish them first before taking this course.

Grading policy

- Homework: 30%
- Midterm: 30% (tentative date: early April)
  - Honor code
- Project: 40%
  - progress report (10%)
  - final report (30%)

- Note: There will be no final exam.
- Extra credits: Up to 3% may be awarded for participation in class and piazza, as well as quizzes (details TBD).
  - Note: anonymous posts/comments are not counted

Language of Choice: **Python**

- **Python** is a great language overall for machine learning, with modern libraries and excellent online tutorials for various tasks
- We will use **Python 3** (3.6+) throughout the course.
  - We will be using popular libraries, such as **NumPy, Matplotlib,** and **PyTorch**.
- There will be a tutorial session (date: TBD)

Homework

- There will be 6 problem sets.
  - **The best 5 out of 6 scores will be used for final grading.**
- Goal: strengthen the understanding of the fundamental concepts, mathematical formulations, algorithms, detailed implementations, and the applications.
- The problem sets will also include programming assignments to implement algorithms covered in the class.
- Homework #1 will be out by next Tuesday (1/11) – due 1/25, 11:55 pm via Gradescope (linked to Canvas).

Late days

- 3 maximum late days per assignment (except homework #1)
  - No homework will be accepted 3 days after the due date.
  - Exception: due to Drop/Add deadline (Jan 25), homework #1 deadline will be Jan 25 with no late days (hard deadline; no late days will be allowed)
- Total 9 late days allowed.
- After using up all late days, your assignment will be penalized by 20% from your scores.

Study group

- Form your study group early on!
  - Up to <u>five</u> people are allowed.
- For homework, you may discuss between the study group members, but you should write your own solution <u>independently</u>.
- In the homework submissions, you must put:
  - the names of other people you collaborated.
  - submission time.
- Please start on homework early. (Warning: cramming will not work!)

Honor Code

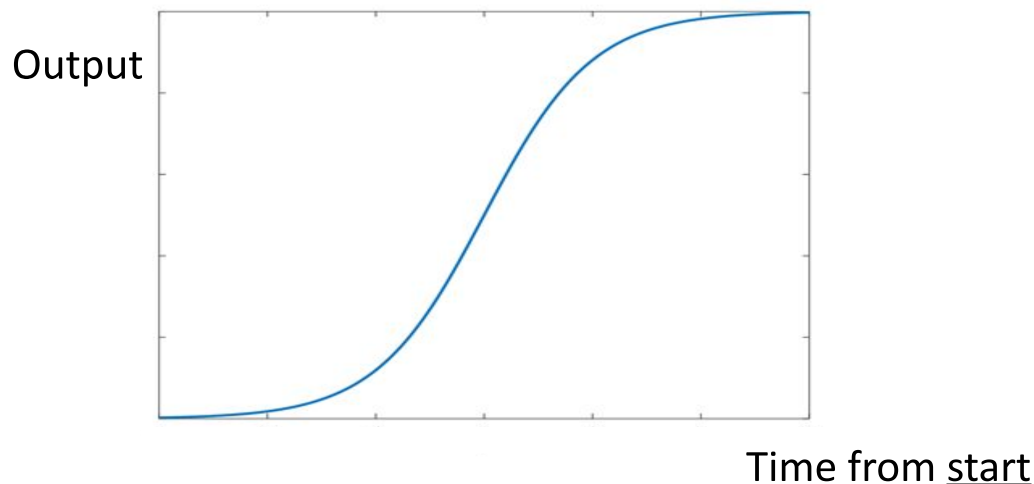
- No cheating of any kind shall be made.
- Previously, several incidents of violation of honor (plagiarism in homework submissions and cheatings in exams) were reported.
  - You will get into a **big trouble** if you violate the honor code. You may fail the course.
- Please review the UofM Honor Code.

Course Project

- Scope
  - develop new algorithms and theory in machine learning
  - apply existing algorithms to new problems
  - apply to your own problems of interest
- Milestones (tentative)
  - Project proposal due: February 1, 2022
  - Project milestone report due: March 8, 2022
  - Final project poster presentation: April 21, 2022
  - Final project report due: April 28, 2022 (No Late Days)
- Requirement
  - Write a 8-page paper
  - Submit the final code
  - Give a poster presentation
- Evaluation is based on:
  - novelty, technical quality, significance, and presentation quality of the project.
- More information available here (draft).

Course Project

- 4 or 5 people can form a project group.
- Talk to instructor if you want to get suggestions about project topics.
- Start early! (form your group and start working)



Expected Workload

- While EECS 545 is a 3 unit course, the expected workload is comparable to upper-level 4 unit courses.
- Previously, students who took EECS 545 reported the relative workload (Q891) as “lighter” (~15%), “typical” (~25%), “heavier” (~30%), or “much heavier” (~30%).
- You can expect to learn a lot of things but the workload could feel heavy or very heavy if you don’t have sufficient background in math (e.g., linear algebra, calculus, probabilities) and/or programming (e.g., nontrivial programming background).
- If you are concerned, please talk to us.

Other Information

- Review sessions
  - Will hold review sessions on background materials (linear algebra, probability, Python.) Dates TBD
- Midterm
  - Tentatively scheduled for April 7, 2022
- Beginning-of-course survey: https://forms.gle/rw2RCfY3GvCekZ646

Any questions?

Outline

- Administrative

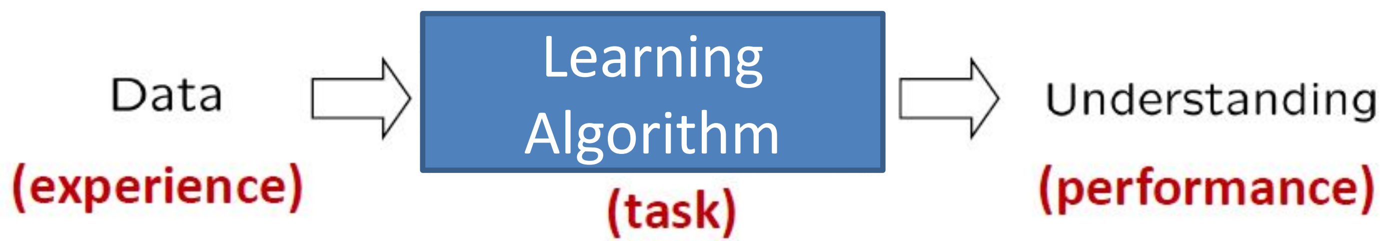
- What is machine learning?

Definition of Machine Learning

- Formal definition (Mitchell 1997): A computer program **A** is said to **learn** from experience **E** with respect to some class of tasks **T** and performance measure **P**, if its performance at tasks in **T**, as measured by **P**, improves with experience **E**.

Informal definition

- Algorithms that improve their prediction performance at some task with experience (or data).



Example: Spam email filtering

"A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."

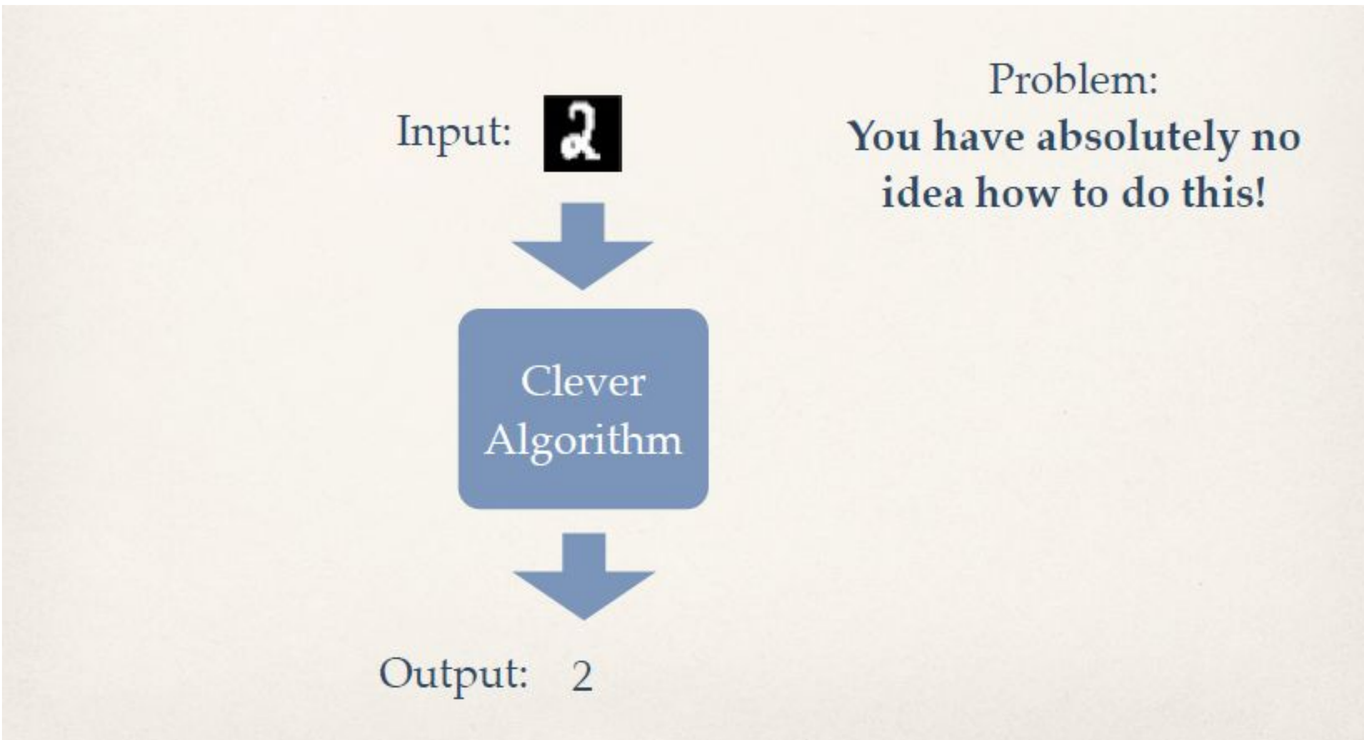
- Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam.

- Task:
  - Classifying emails as spam or not spam.
- Experience:
  - Watching you label emails as spam or not spam.
- Performance measure
  - The number (or fraction) of emails (disjoint from the training emails) correctly classified as spam/not spam.

Slide credit: Andrew Ng

Example

- Problem: Given an image of a handwritten digit, what digit is it?



Slide credit: Kilian Weinberger

Example

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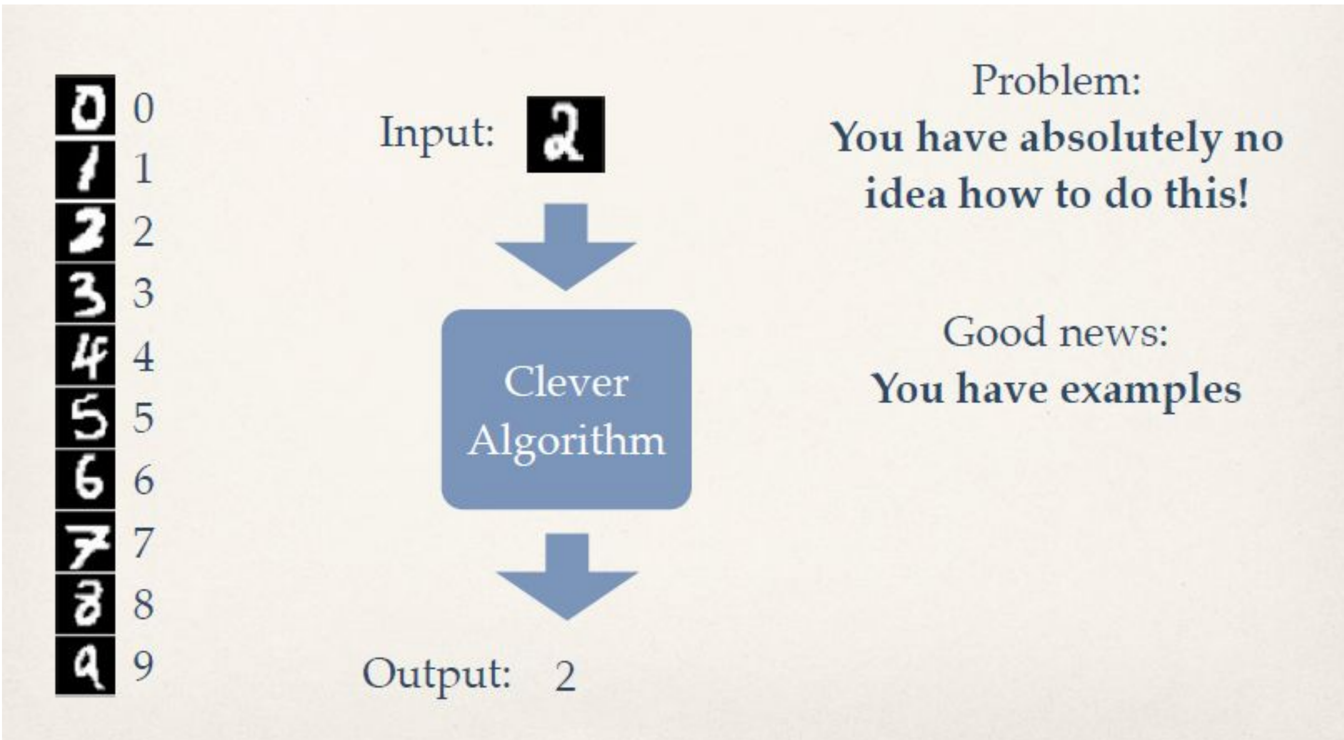

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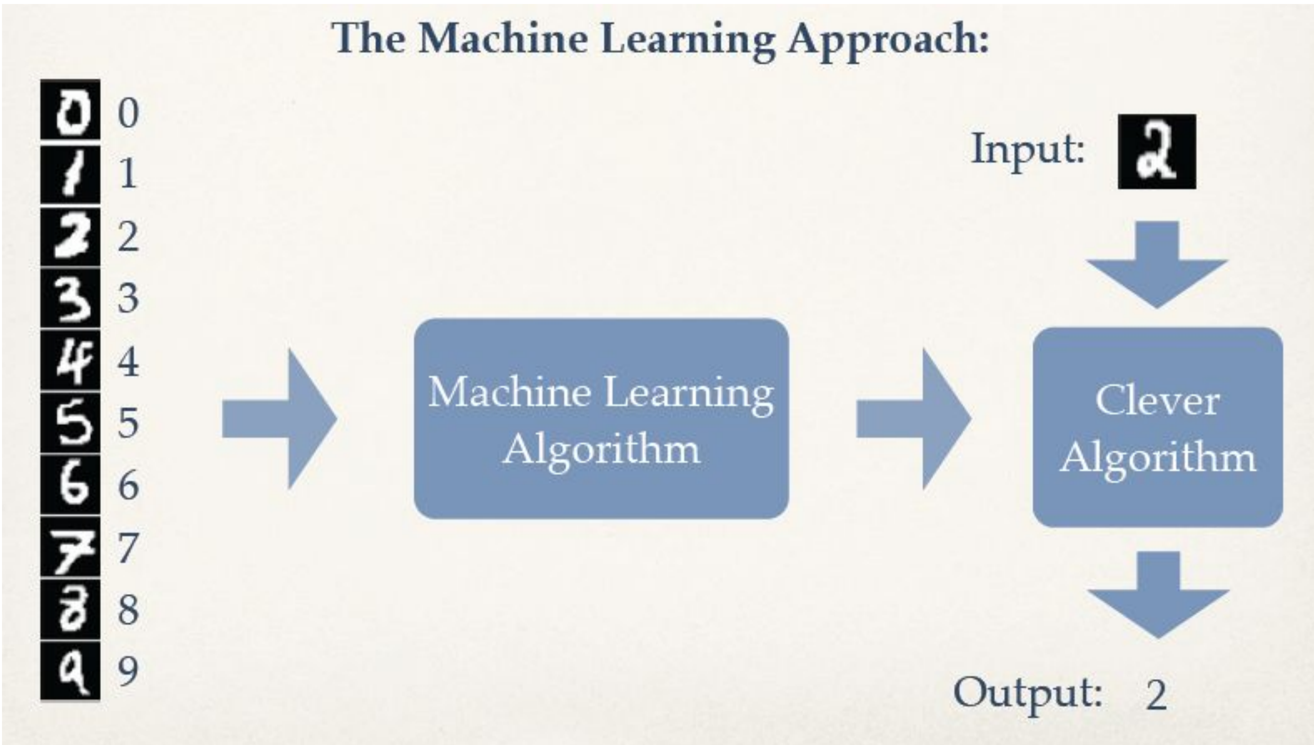

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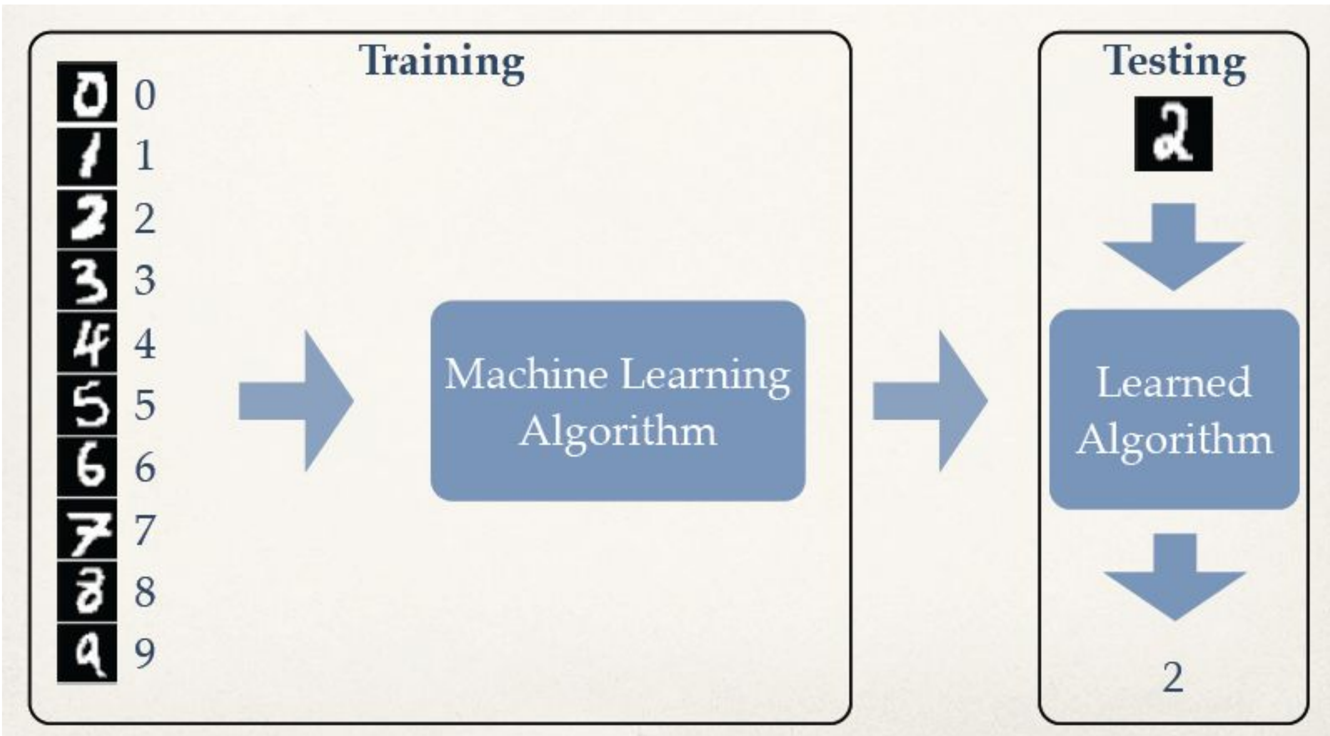


Slide credit: Kilian Weinberger

Machine Learning Tasks

- Supervised Learning
  - Classification
  - Regression
- Unsupervised Learning
  - Clustering
  - Density estimation
  - Embedding / Dimensionality reduction
- Reinforcement Learning
  - Learning to act (e.g., robot control, decision making, etc.)

Supervised Learning

Given a dataset $D = \{(x_1, y_1), \ldots, (x_n, y_n)\}$, where

- $x_i \in \mathcal{X}$: input (feature)
- $y_i \in \mathcal{Y}$: output (label)

a black box ML algorithm produces a prediction function $h : \mathcal{X} \to \mathcal{Y}$, such that $h(x)$ can predict the y values for all x (including training data $x_i \in D$ and unseen test data x^*).

Supervised Learning

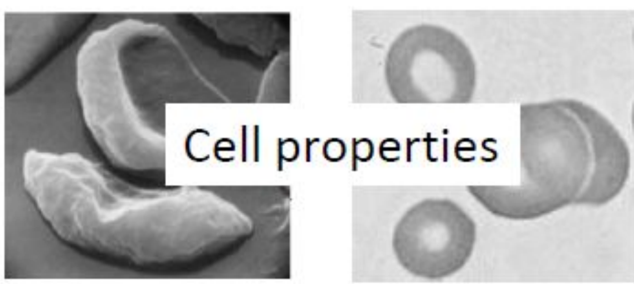
- Labels could be discrete or continuous
  - Discrete labels: **classification**
  - Continuous labels: **regression**

Supervised Learning - Classification

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

"Sports"
"News"
"Science"
...



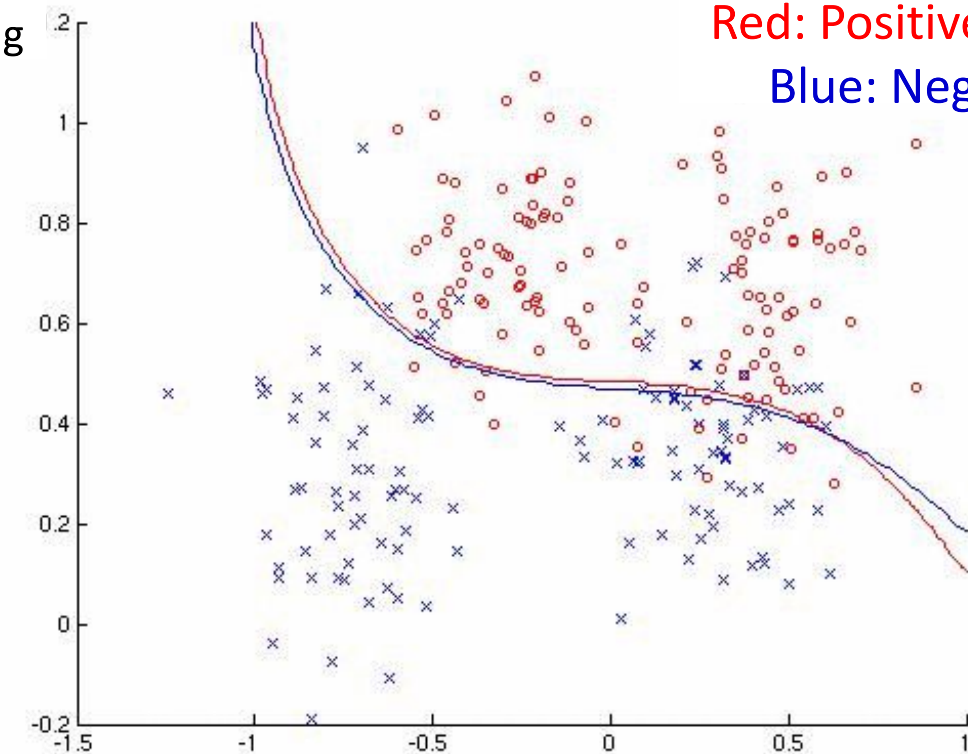
"Anemic cell"
"Healthy cell"

Discrete Labels

Slide credit: Aarti Singh

Supervised Learning - Classification

Smoking



Red: Positive label (e.g., lung cancer)
Blue: Negative label (e.g., normal)

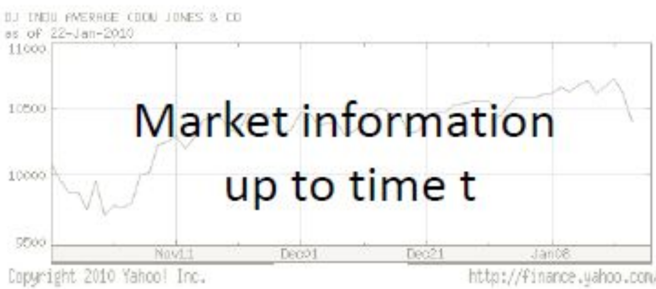
Age

"Learning decision boundaries"

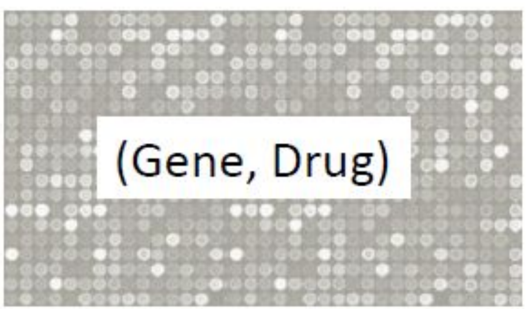
Supervised Learning - Regression

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$



Share Price
"$ 24.50"

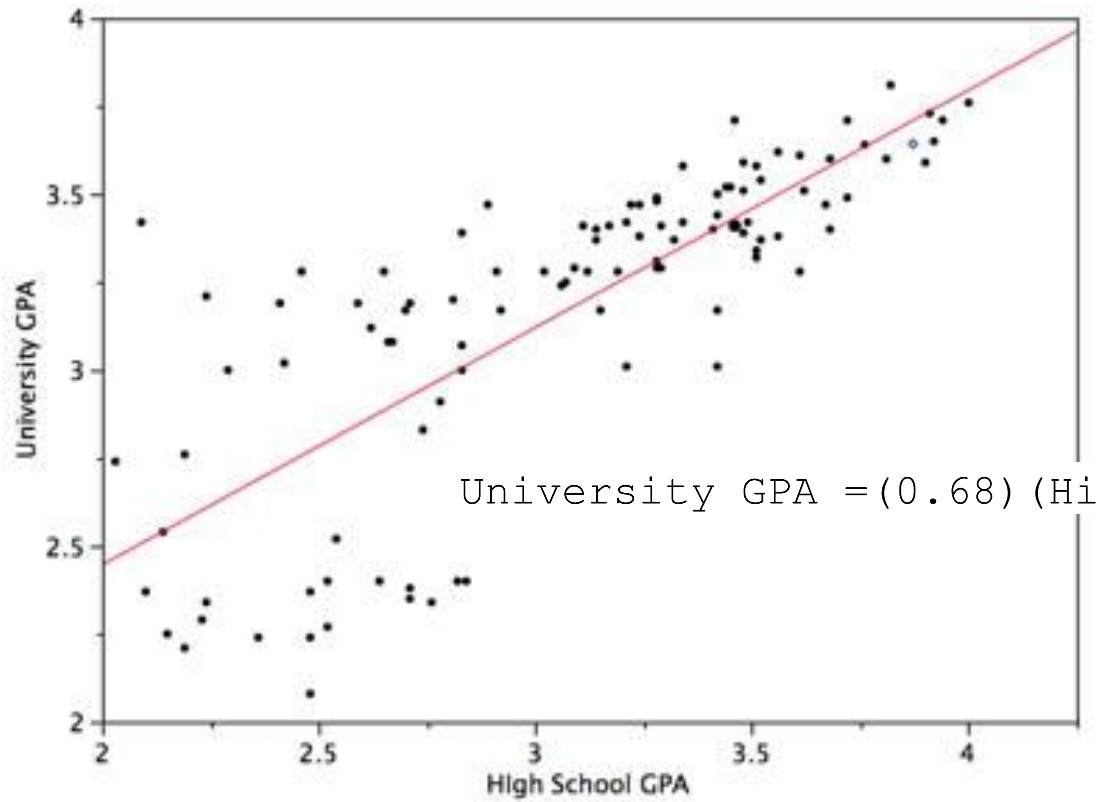


Expression level
"0.01"

Continuous Labels

Slide credit: Aarti Singh

Supervised Learning - Regression



University GPA =(0.68)(High School GPA)+ 1.1

"Learning regression function f(X)"

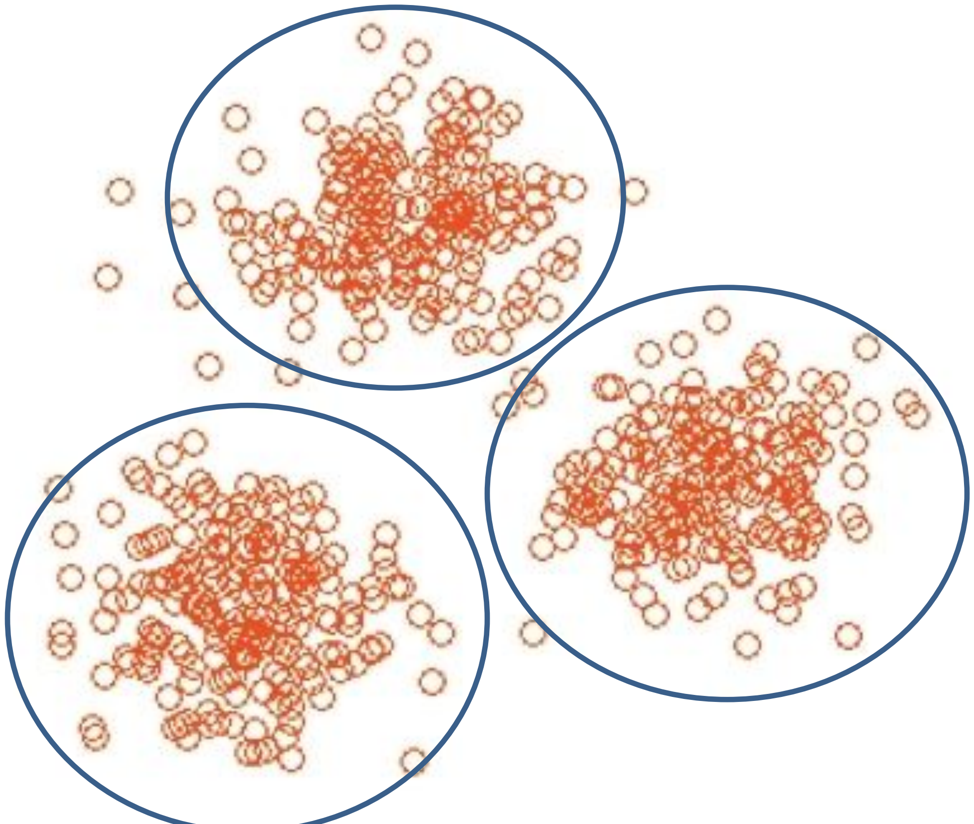
Slide credit: David M. Lane

Unsupervised Learning

- Goal:
  - Given data X <u>without any labels</u>
  - Learn the **structures** or **distribution** of the data
    - Clustering
    - Probability distribution (density)
    - Generating data
    - Embedding & neighborhood relations
- “Learning without teacher (supervision)”

Unsupervised Learning – Clustering

- “Grouping into similar examples”



Unsupervised Learning – Clustering

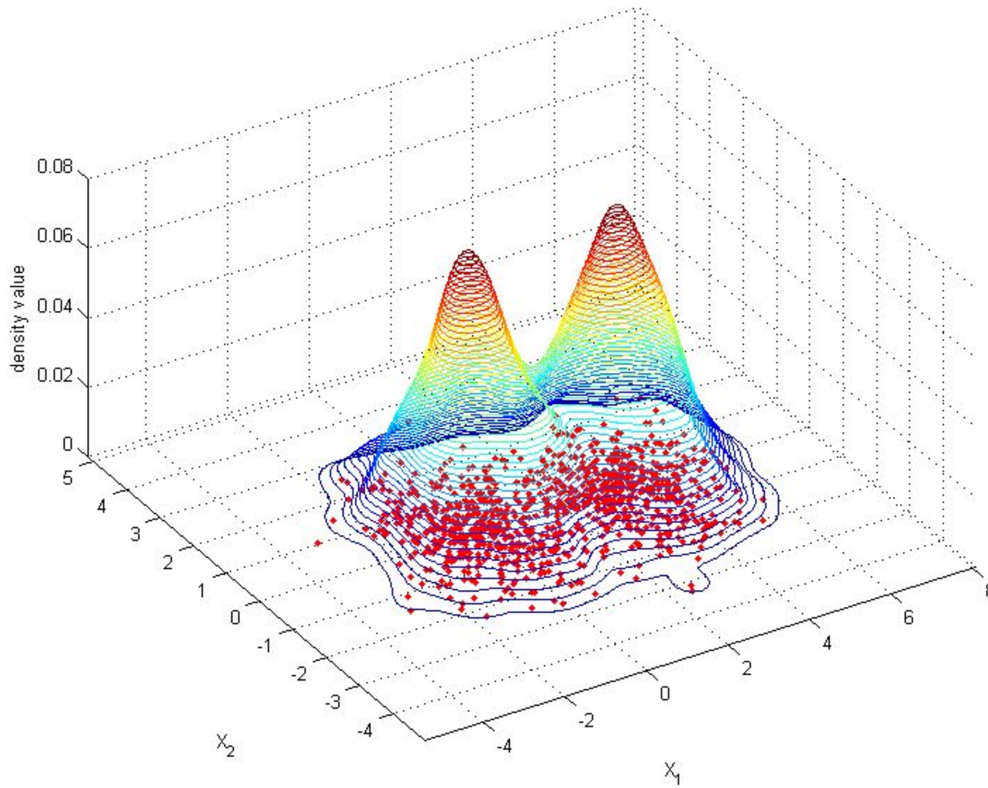
Group similar things e.g. images

[Goldberger et al.]

Slide credit: Aarti Singh

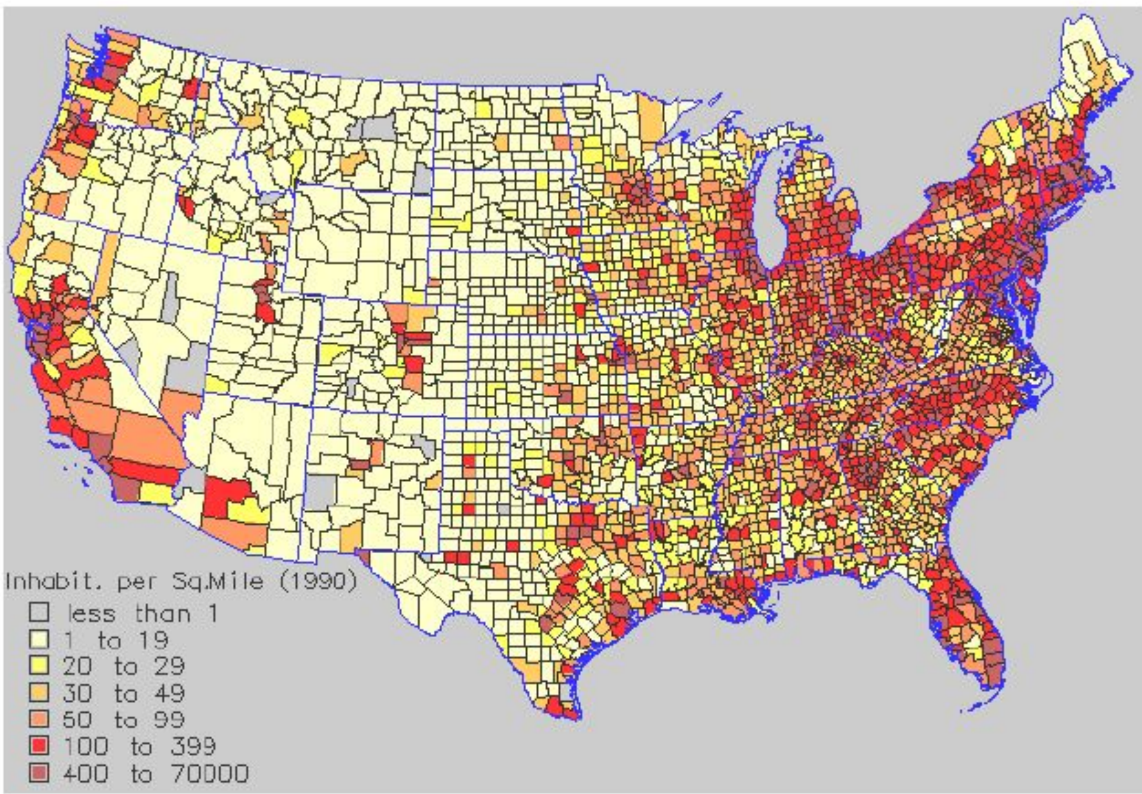
Unsupervised Learning – Density estimation

P(X1, X2)
"Probability"



Unsupervised Learning – Density estimation

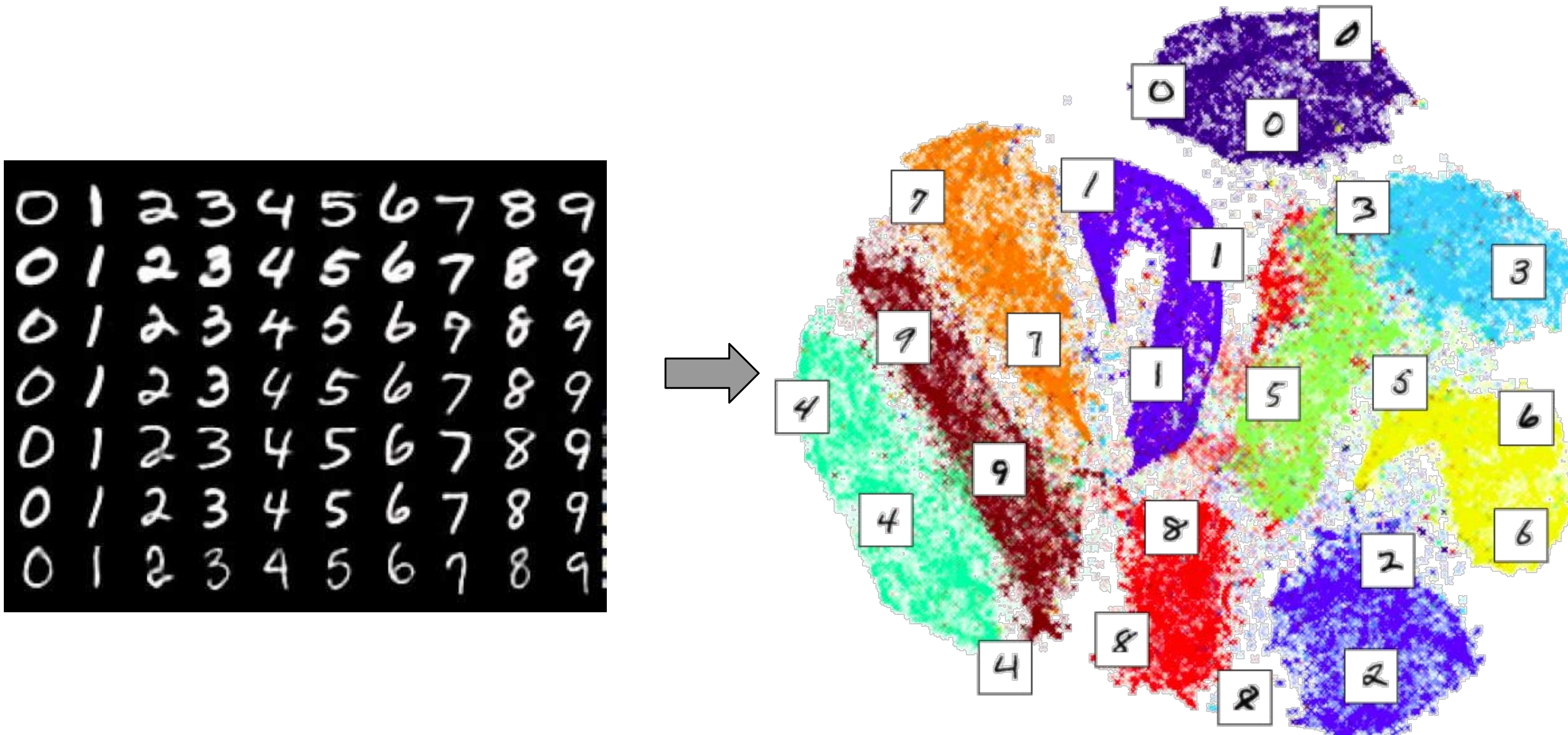
Population density



Slide credit: Aarti Singh

Unsupervised Learning-Embedding and Dimensionality reduction

- E.g., Reducing handwritten digits (784 dim) into low dimensional coordinates



[Maaten and Hinton, 08]

Reinforcement Learning

- Setting
  - Given sequence of states X and <u>“rewards” (e.g., delayed labels)</u>
  - Agent has to take actions A for each time step
- Goal:
  - How to “learn to act” or “make decisions” to maximize the sum of future rewards
- Example: Robot navigation task
  - Input: Dynamical environment + sensor input
  - Action: control signals
  - Rewards: time to reach goal without colliding with obstacles

Reinforcement Learning – learning to control

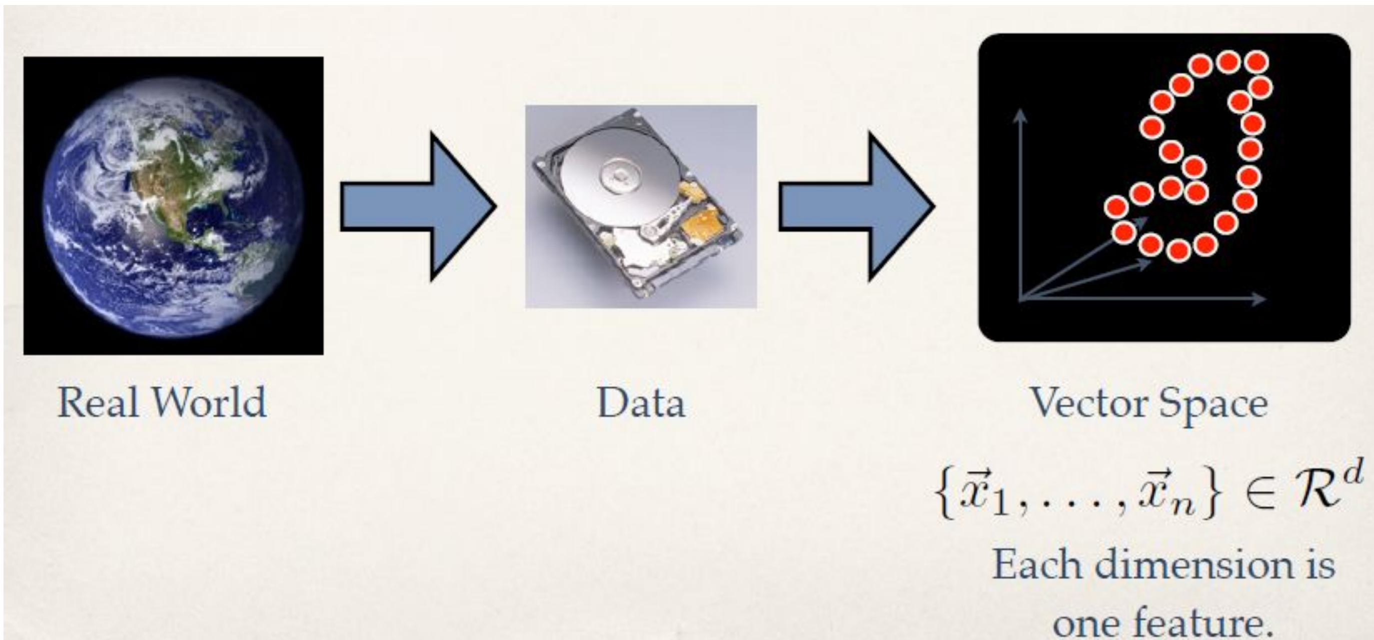
- Example: Robot walking
  - States: sensor inputs, joint angles
  - Action: servo commands for joints
  - Rewards:
    - 1 for reaching the goal
    - -1 for falling down
    - 0 otherwise

- Goal: How can we provide control inputs to maximize the expected future rewards?

Feature representations

Feature Extraction

- Represent data in terms of vectors.
  - Features are **statistics** or **attributes** that describe the data.



Slide credit: Kilian Weinberger

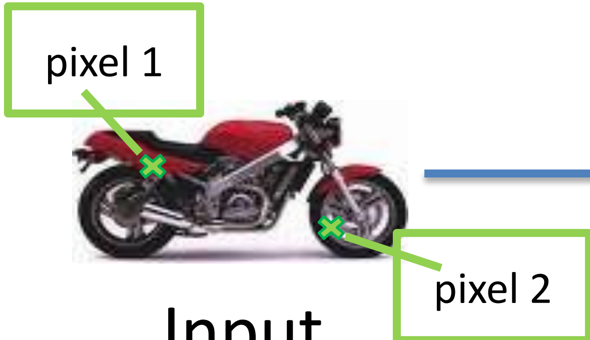
Examples of features: Housing data

- **Given statistics about houses in a local area, predict median value of homes.**
  - #ROOM: average number of rooms per dwelling
  - AREA: average area of house in square foot
  - AGE: proportion of owner-occupied units built prior to 1940
  - CRIME: per capita crime rate by town
  - RESZONE: proportion of residential land zoned for lots over 25,000 sq.ft.
  - INDUS: proportion of non-retail business acres per town
  - NOX: nitric oxides concentration (parts per 10 million)
  - …..
- **Label: Median value of owner-occupied homes**

Examples of features: Recognizing handwritten-digits

- Input: 28 x 28 pixel images
- Output: Class Labels $\in$ {0,1,2, …, 9}
- The following basic features can be used:
  - Pixel Values (784 dimensional vectors)
  - Aspect Ratio of the tight bounding boxes
  - Existence of long vertical strokes
  - Existence of long horizontal strokes

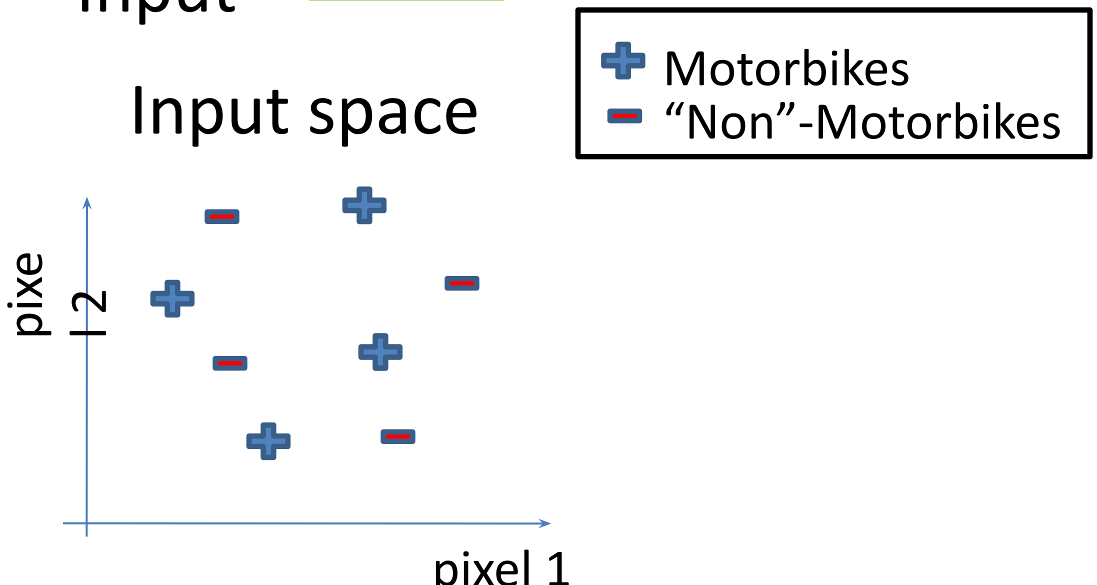
Learning pipeline



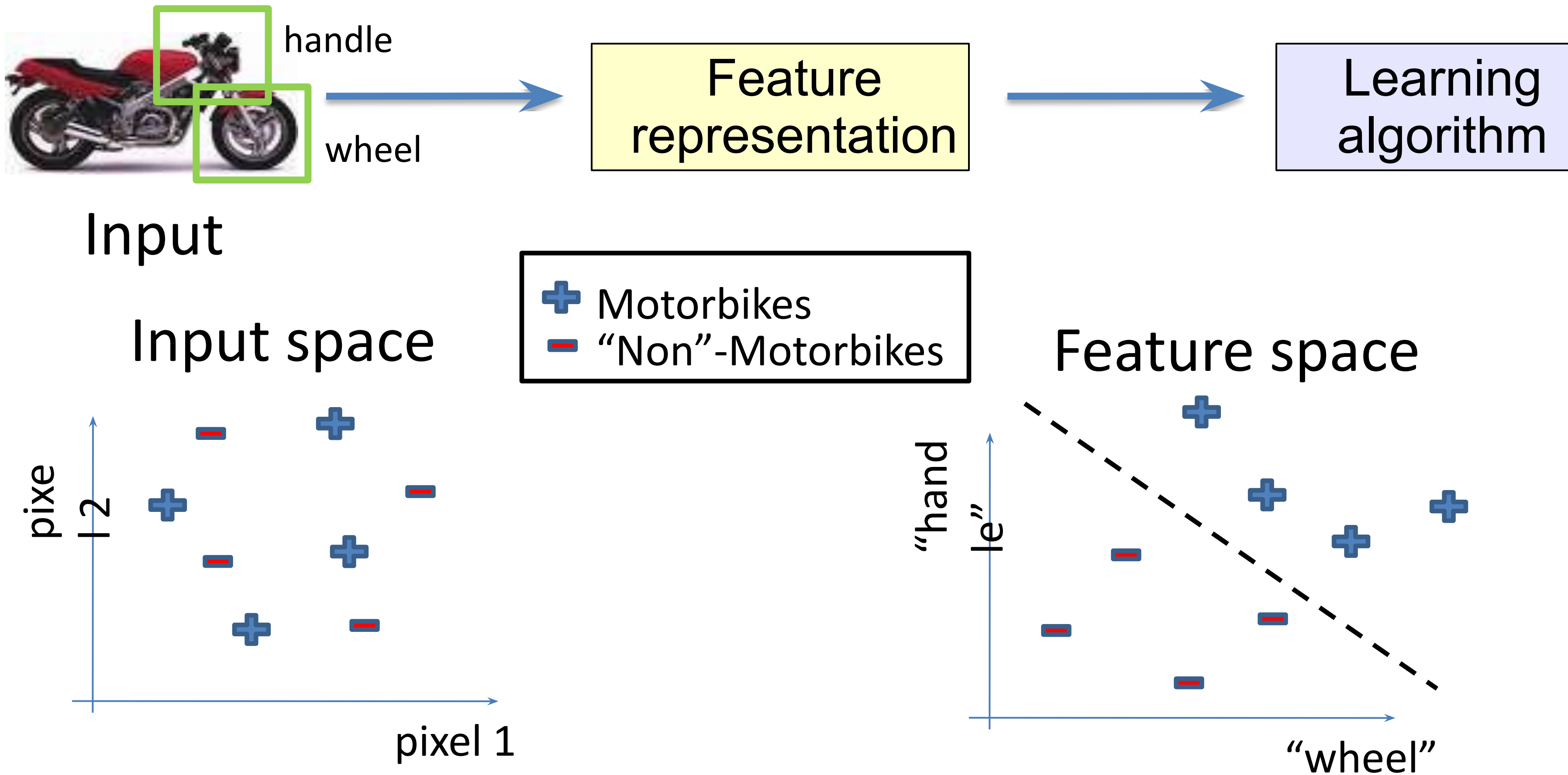
Input

Learning algorithm

Input space



Learning pipeline

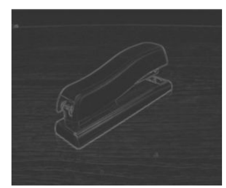


(Traditional) Computer Perception Pipeline

Input data → Feature representation → Learning algorithm

Object Detection

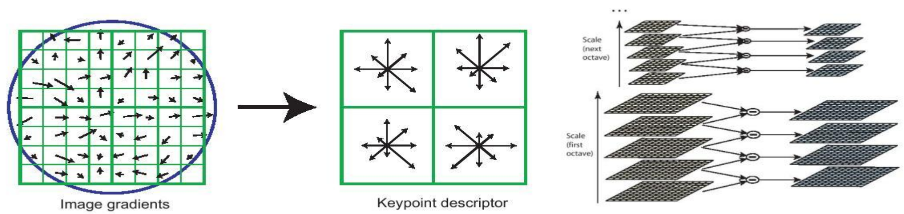
Image



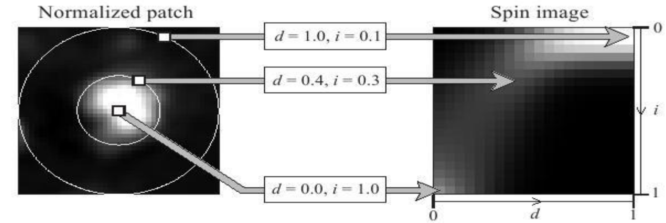
Low-level vision features

Recognition

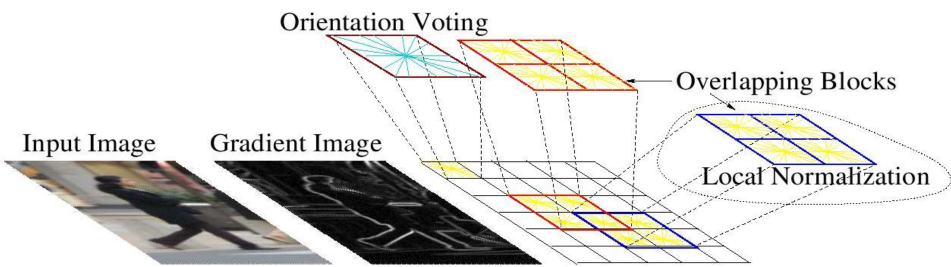
(Traditional) Computer vision features



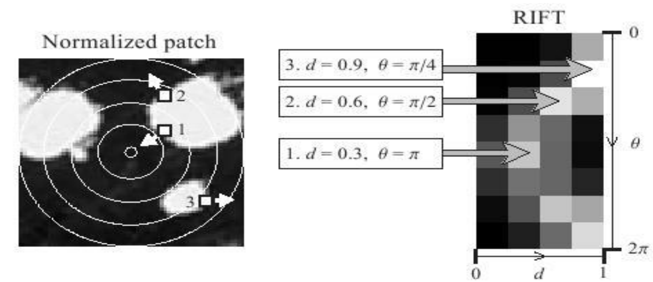
SIFT



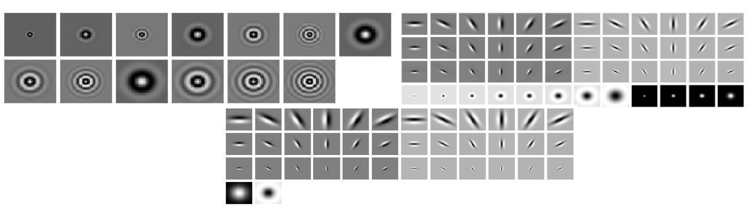
Spin image



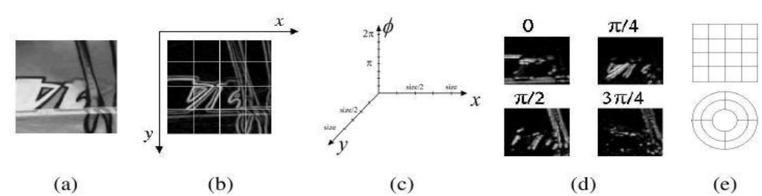
HoG



RIFT



Textons



GLOH

Learning feature hierarchies with Deep Learning

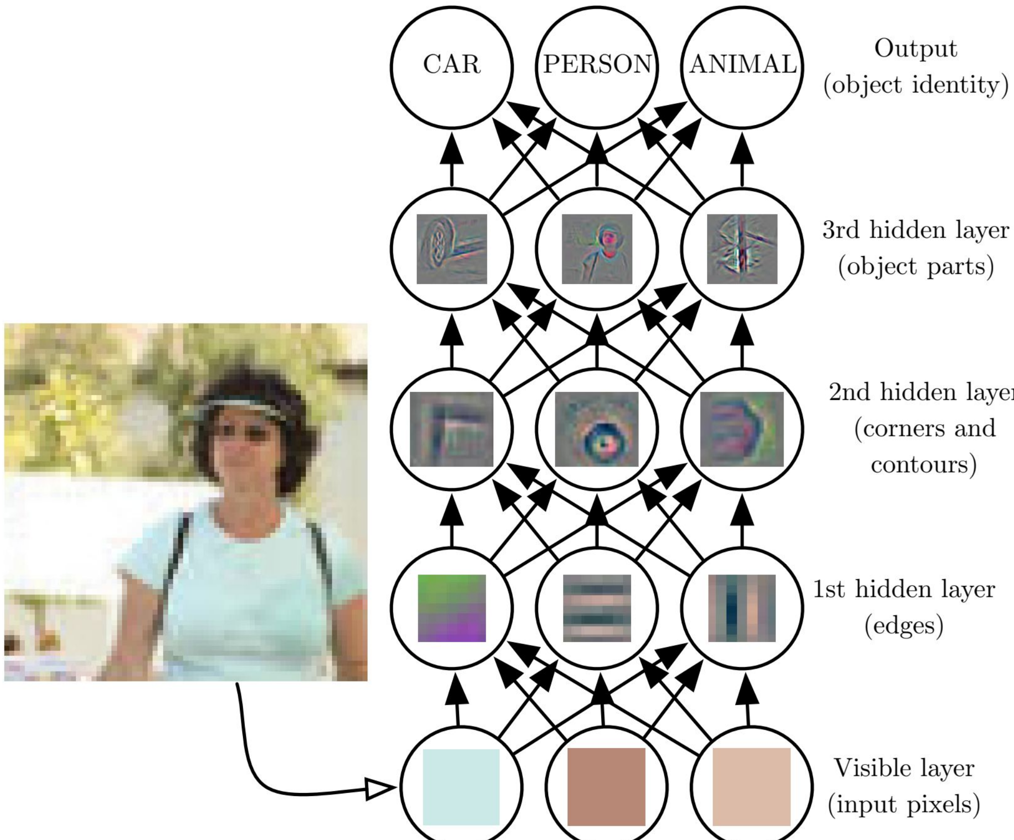
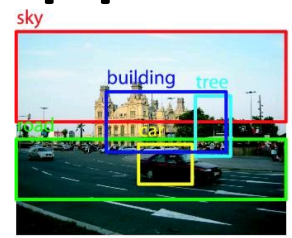


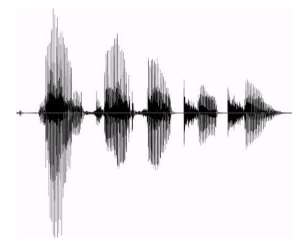
Figure source: Ian Goodfellow, Yoshua Bengio, Aaron Courville. Deep Learning, 2016

ML applications

Examples of ML applications

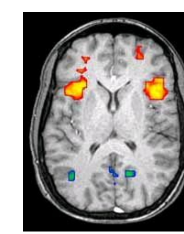
- Computer vision
- Speech recognition
- Robotics
- Text classification
- Medical image recognition
- Time series prediction/classification
- ….





WIKIPEDIA

REUTERS



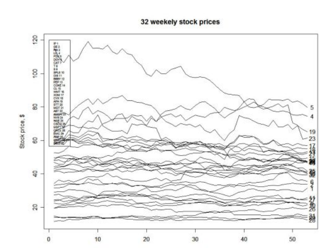


Image classification

- Goal: predict the class of input image

Training dataset
(image, label)

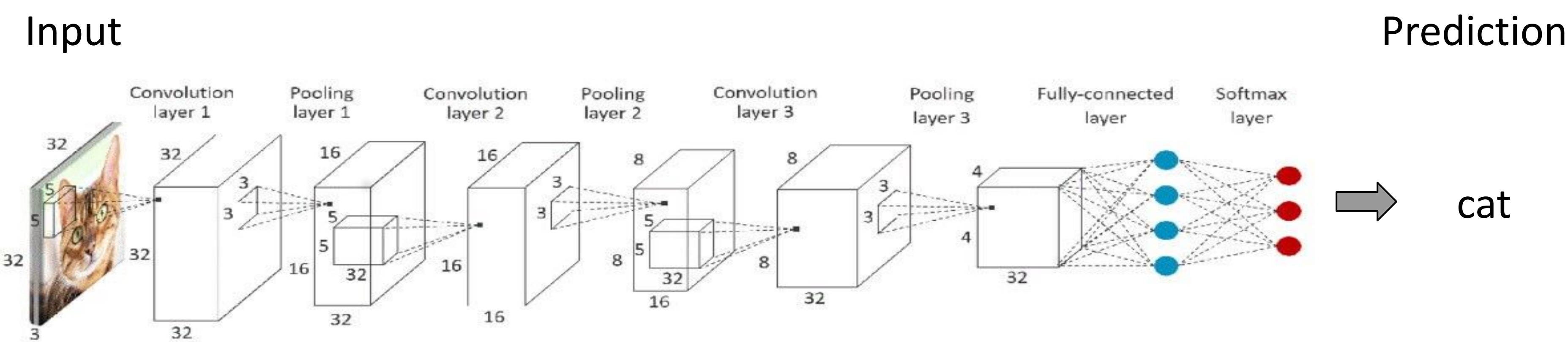
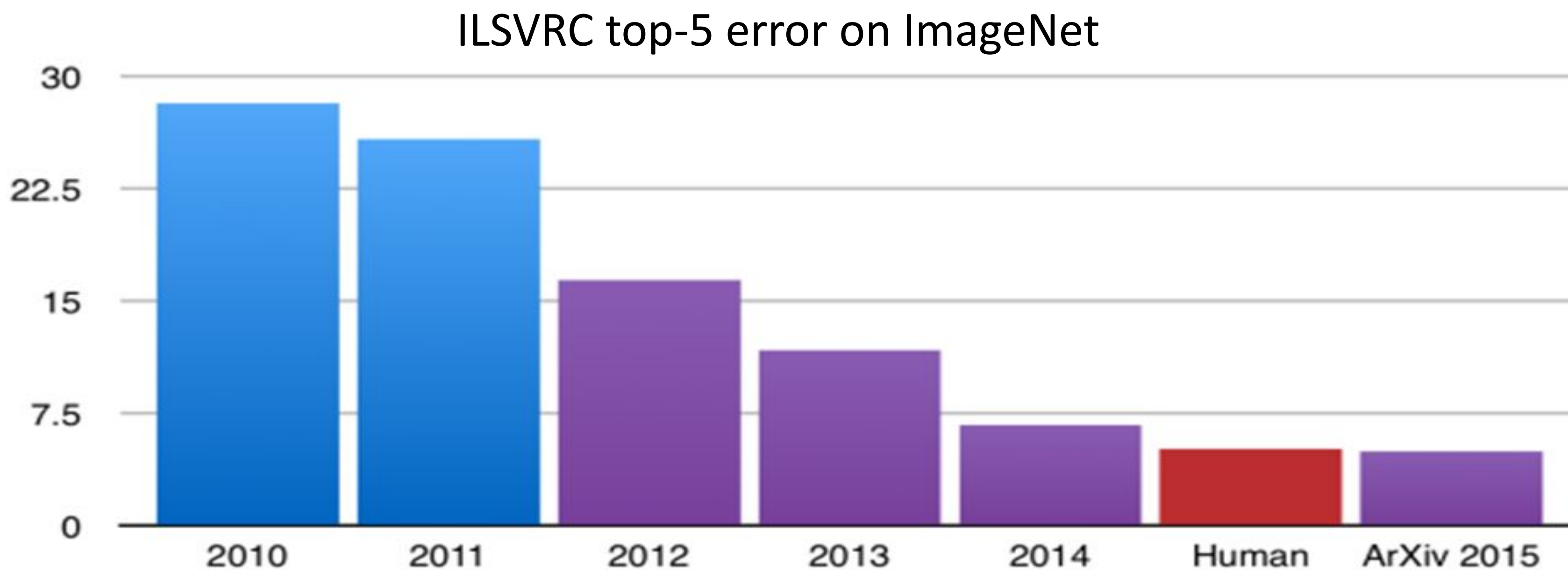
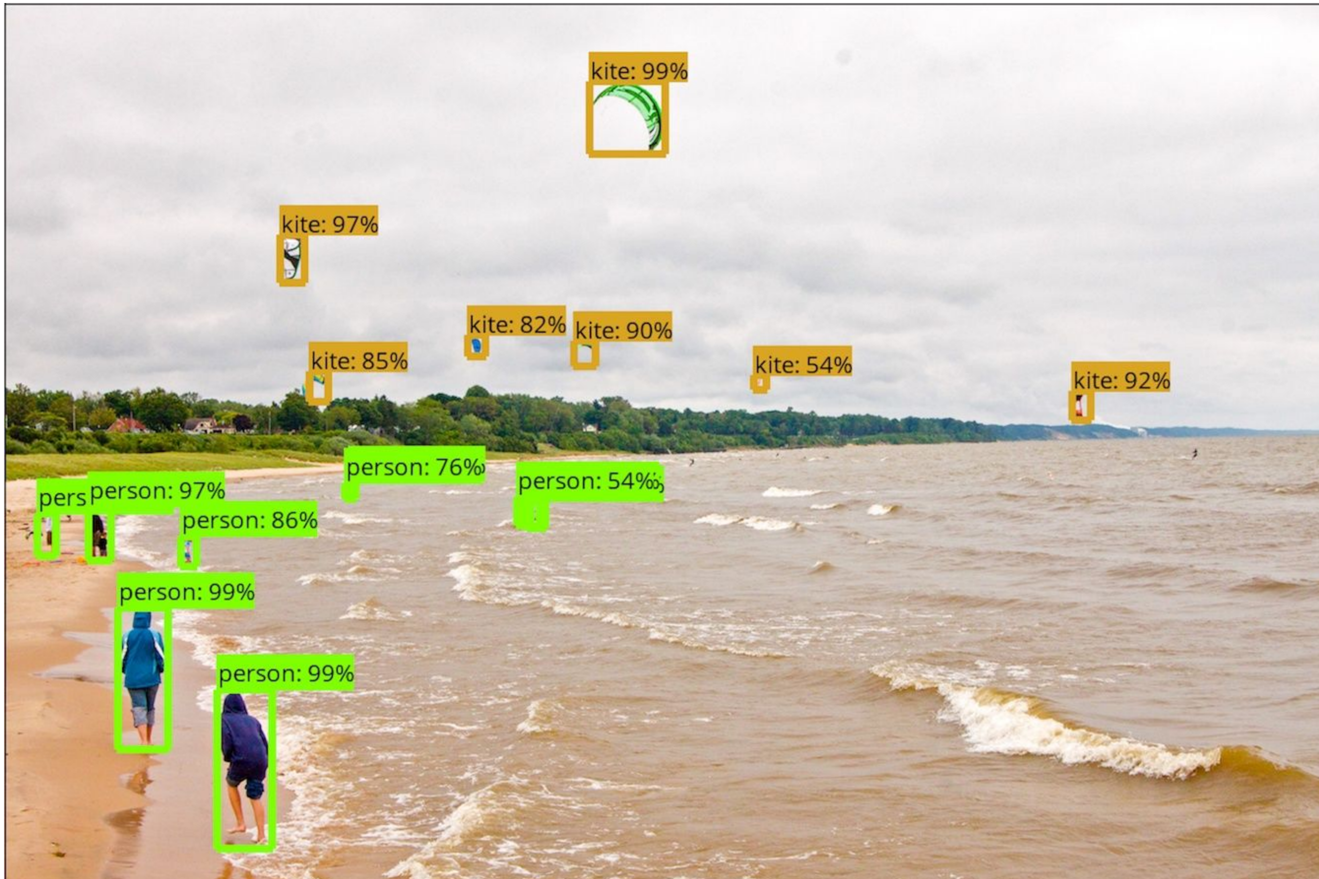


Image classification



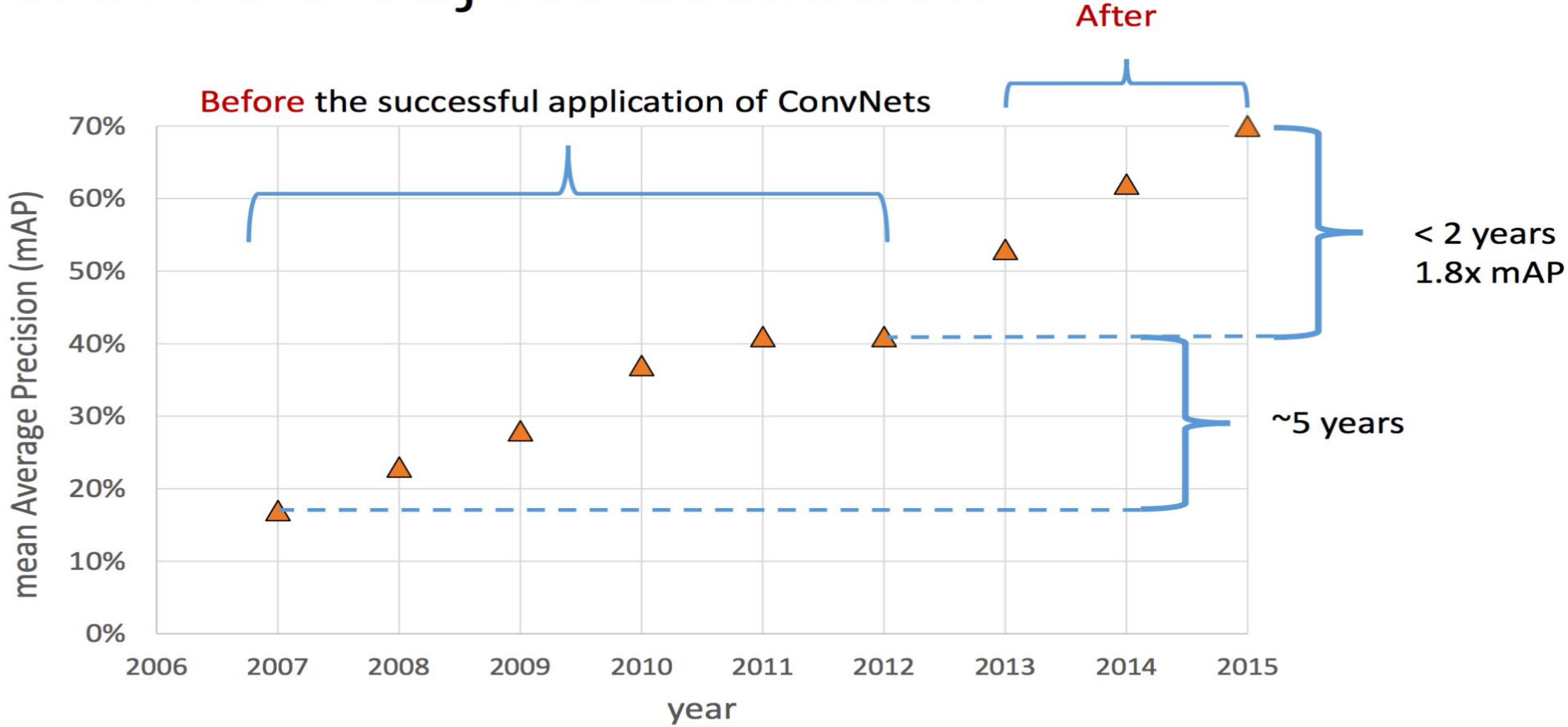
Slide credit: Rob Fergus

Object Detection



Huang et al., Speed/accuracy trade-offs for modern convolutional object detectors. CVPR 2017
figure/code at: https://github.com/tensorflow/models/tree/master/research/object_detection

PASCAL VOC object detection

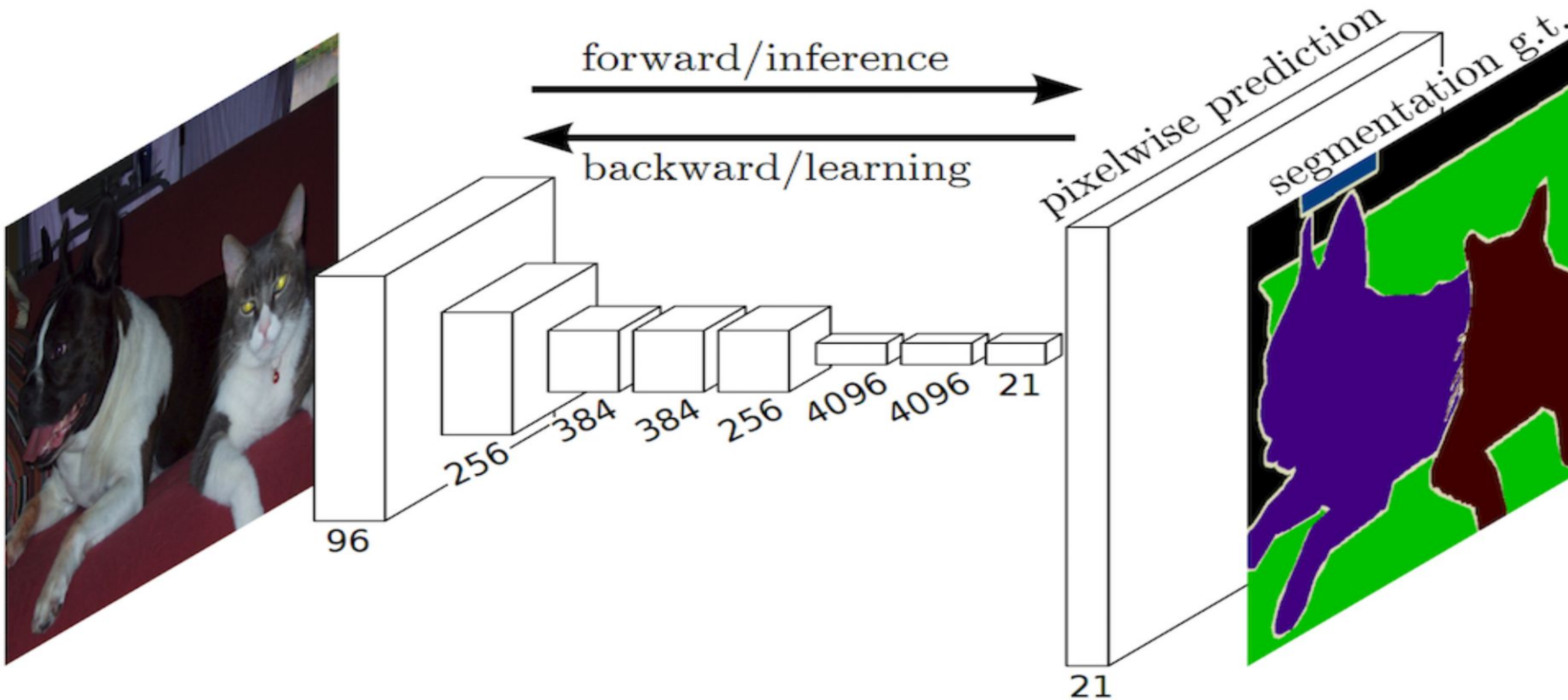


Precision: higher is better

(Figur from Ross Girshick)

Semantic Segmentation

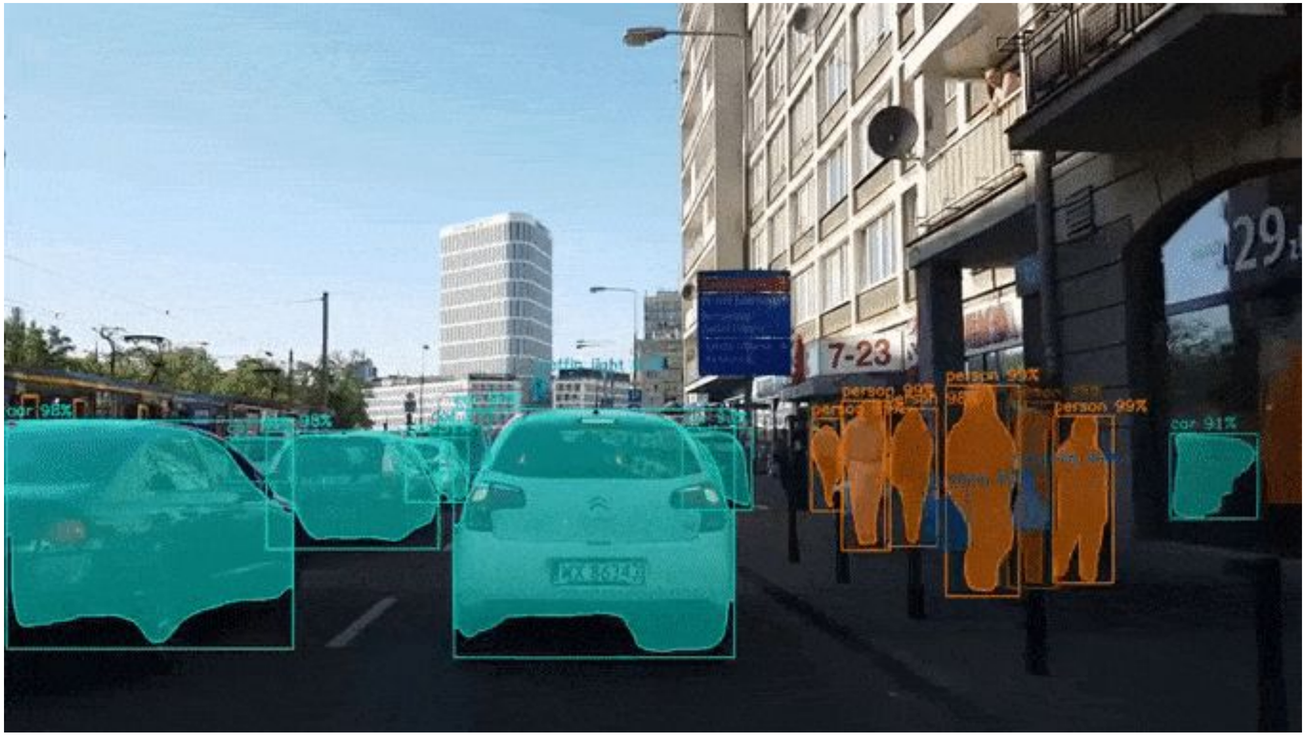
- Goal: Segment object regions and predict class labels for each region
- Can be formulated as pixel-wise classification



(Long et al, "Fully Convolutional Networks for Semantic Segmentation", CVPR, 2015.)

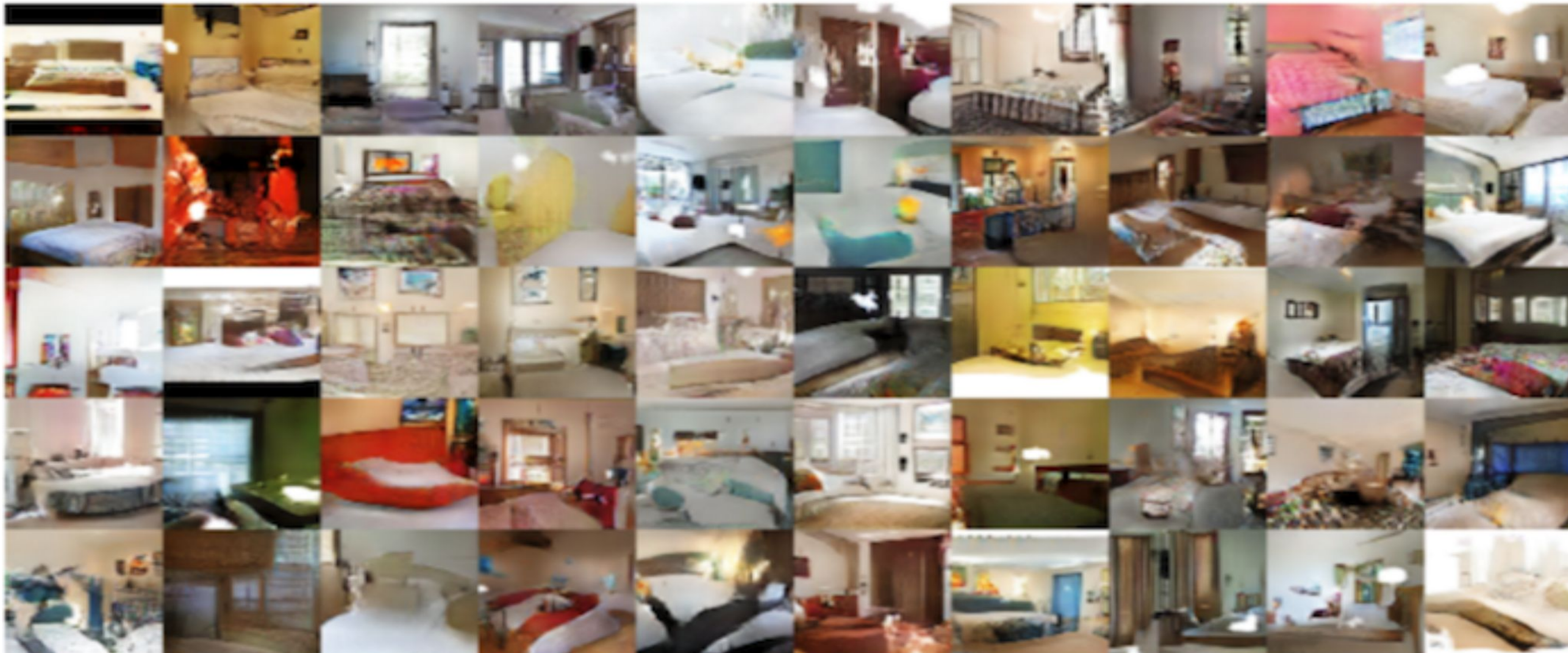
Instance Segmentation

Goal: Perform segmentation (pixel-level masking) for each individual object



Mask R-CNN (He et al., 2017)
Image from: https://github.com/matterport/Mask_RCNN

Image Generation: Generative Adversarial Networks

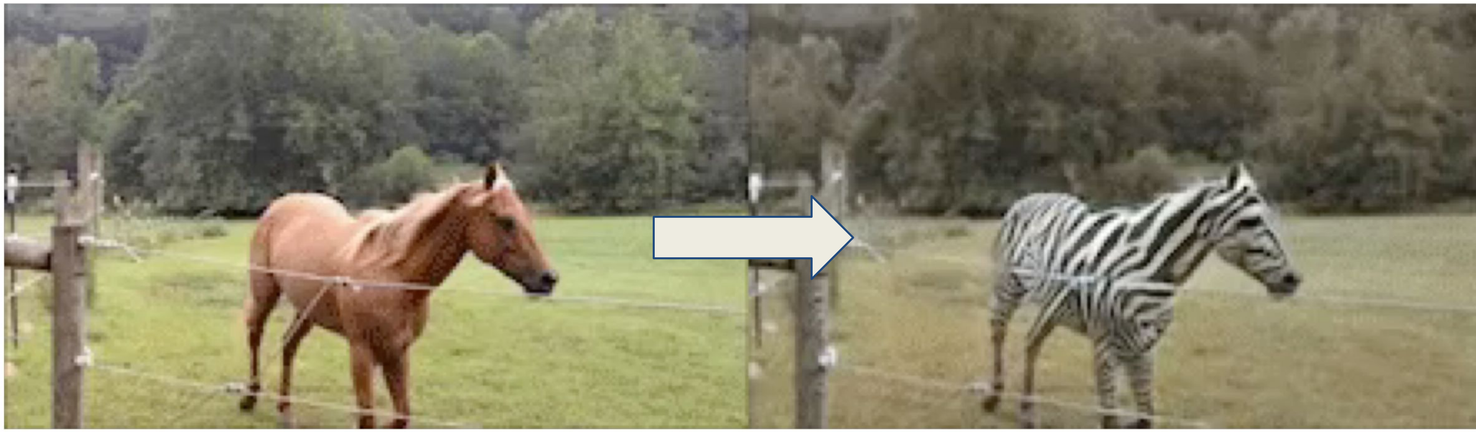


(Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR, 2016.)

Image Generation: Generative Adversarial Networks

[Karras et al. 2017] Progressive Growing of GANs for Improved Quality, Stability, and Variation

Unsupervised Image-to-Image generation



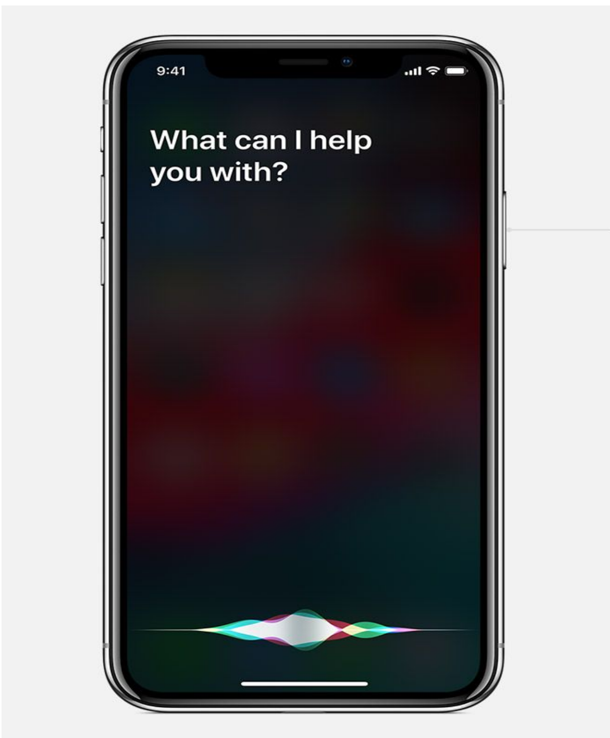
[CycleGAN: Zhu, Park, Isola & Efros, 2017]

Image Caption Generation

(Vinyals et al, "Show and Tell: A Neural Image Caption Generator", CVPR, 2015.)

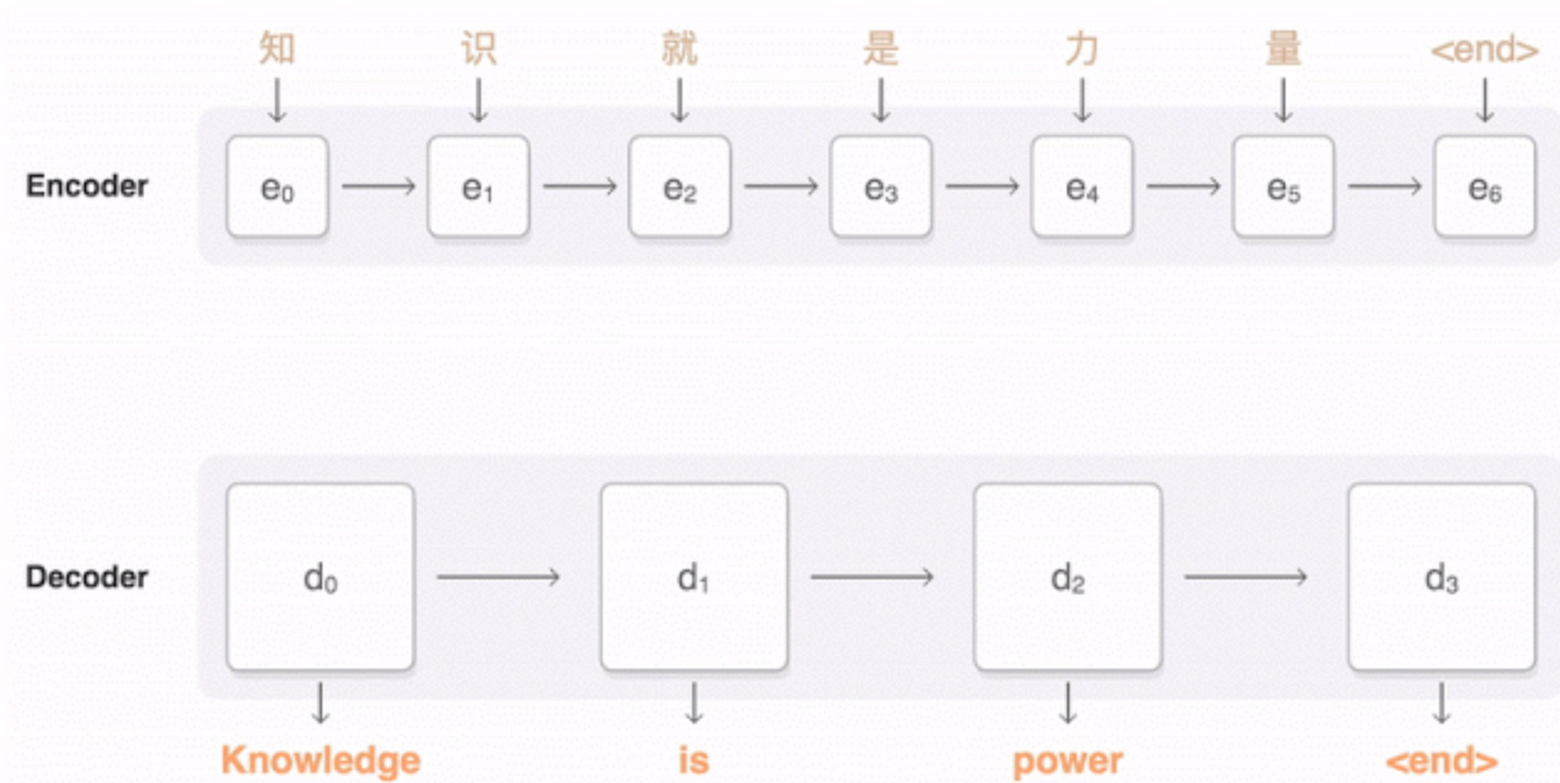
Speech recognition

Siri, Google home, and Google assistant achieves commercial-level performance



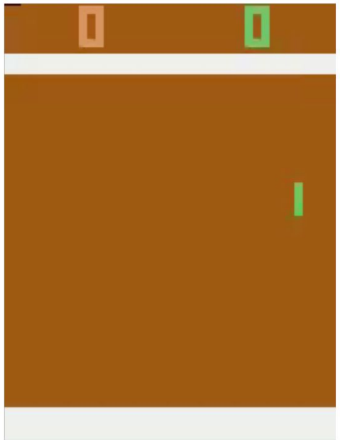
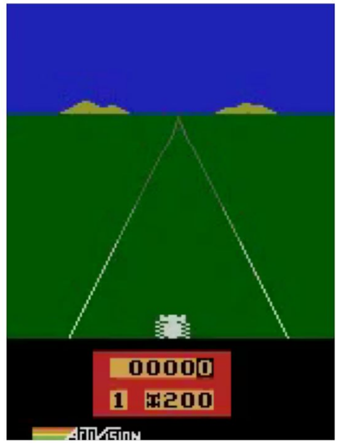
Machine Translation

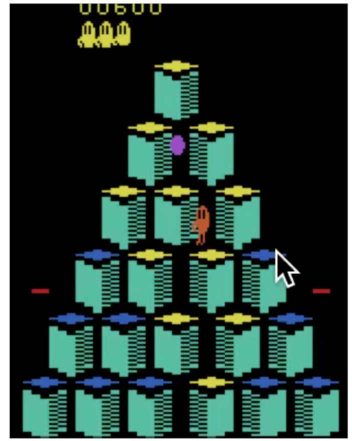
Google Neural Machine Translation (in production)



Slide credit: Pieter Abbeel

RL success stories: playing ATARI games




DQN Mnih et al, NIPS 2013 / Nature 2015;

MCTS Guo et al, NIPS 2014; **TRPO** Schulman, Levine, Moritz, Jordan, Abbeel, ICML 2015; **A3C** Mnih et al, ICML 2016; **Dueling DQN** Wang et al ICML 2016; **Double DQN** van Hasselt et al, AAAI 2016; **Prioritized Experience Replay** Schaul et al, ICLR 2016; **Bootstrapped DQN** Osband et al, 2016; **Q-Ensembles** Chen et al, 2017; **Rainbow** Hessel et al, 2017; ...

slide credit: Pieter Abbeel

AlphaGo

- Another breakthrough from Google DeepMind
- Combines Monte-Carlo Tree Search (MTCS) with deep neural networks

AlphaGo Silver et al, Nature 2015
AlphaGoZero Silver et al, Nature 2017
AlphaZero Silver et al, 2017
Tian et al, 2016; Maddison et al, 2014; Clark et al, 2015

slide credit: Pieter Abbeel

OpenAI's 1v1 Dota [2017] and 5v5 [2018]

Super-human agent on a competitive game, enabled by

- Reinforcement learning
- Self-play
- Enough computation

Cooperation emerges

slide credit: Pieter Abbeel

Robot learning

Levine et al., Learning Hand-Eye Coordination for Robotic Grasping. 2016
video: https://www.youtube.com/watch?v=cXaic_k80uM

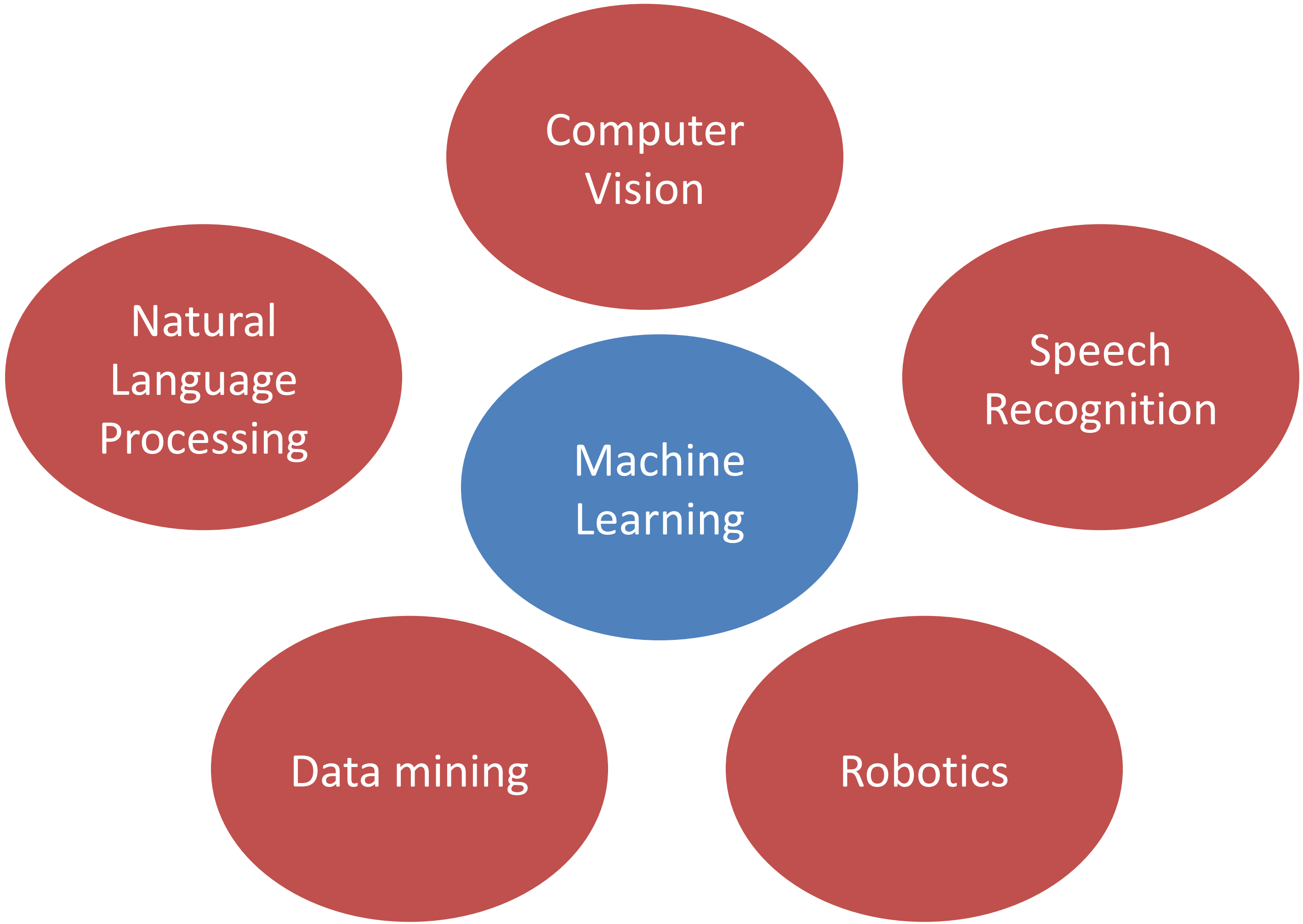
slide credit: Pieter Abbeel

Self-driving cars

https://youtu.be/O6DRfAC1JXA

See also: Chris Urmson: How a driverless car sees the road https://youtu.be/tiwVMrTLUWg

Machine Learning and other fields



Next class

- Supervised learning
  - Linear regression

Reminder

- Check syllabus at Canvas

- For all questions, please use Piazza (linked to Canvas)

Questions?