

CMSC 478

Intro. to Machine Learning

Fall 2023

KMA Solaiman

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Instructor: KMA Solaiman (Salvi)

ITE 201C/Remote

ksolaima@umbc.edu

Thu: 1-2 pm

Tuesday: 1-2pm (if needed)

by appointment

Multimodal Information
Retrieval

Vision & language processing

Learning with low-to-no
supervision

Novelties in Learning Models

TA

Surya Kiran, [LinkedIn](#)
ru17699@umbc.edu

Office hours:

Thu 3-5pm,

and by appointment

Location: TBD, discussion
board/ website

Administrivia

Text

- No specific text
- Hal Duame, CIML
- Tom Mitechell
- Lecture Notes
- Website

Course Website

WWW

Schedule, slides,
assignments, readings,
materials, syllabus here

<https://umbc-cmsc478.github.io/fall2023-public/>

<https://campuswire.com/c/G5403DC1B/feed>


This Week



- **Course announcements**, Q&A, discussion board here
- No public code, follow posted rules and etiquette

Pre-requisite

- Probability (CS109 or STAT 116)
 - distribution, random variable, expectation, conditional probability, variance, density
- Linear algebra (Math 104, Math 113, or CS205)
 - matrix multiplication
 - eigenvector
- Basic programming (in Python and NumPy)

This is a mathematically intense course. 
But that's why it's exciting and rewarding!

CMSC 478 — Introduction to Machine Learning

Fall 2023

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 - [Hate, Bias, Discrimination, and Harassment](#)
 - [Acknowledgements](#)

Course Project

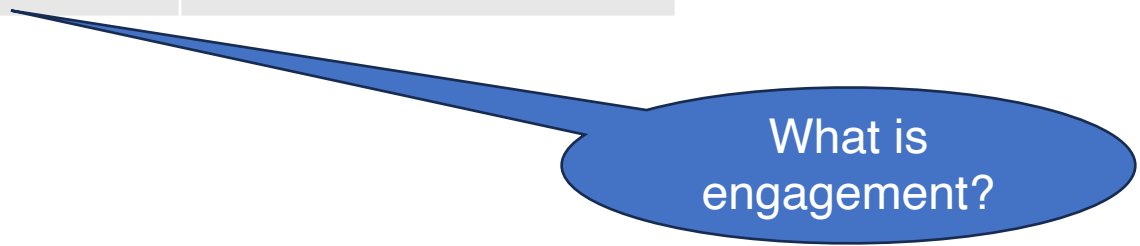
- We encourage you to form a group of 1-2 people
- More intense for bigger group, but suggested
- More information and previous course projects can be found on course website
- List of potential topics
 - Athletics & Sensing Devices
 - Audio & Music
 - Computer Vision
 - Finance & Commerce
 - General Machine Learning
 - Life Sciences
 - Natural Language
 - Physical Sciences
 - Theory
 - Reinforcement Learning

Academic Integrity

- Super important: I take it **very** seriously
- **You** are responsible for your (& your group's) own work: if in doubt, ask!
- Penalties could include 0 on the assignment, course failure, suspension, or expulsion (not exhaustive)

Course Evaluation

Components	Percentage
Project	20%
Assignments	50%
Exams (Midterm + Final)	30%
Course Engagement	--



What is engagement?

Final Grades

\geq	Letter
90	A
80	B
70	C
60	D
0	F

Programming Languages for **Assignments**

Python, though individual assignments could vary

Remember: programming languages are *tools*. Don't get too caught up in not "knowing" a language. This course will not be grading software engineering prowess.

Libraries: Assignment dependent. Generally OK, as long as you don't use their implementation of what you need to implement

If in doubt, ask first

Late Policy

Everyone has a budget of 10 *late days*, maximum 3 per assignment

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If you have them left: assignments turned in after the deadline will be graded and recorded, no questions asked

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If you don't have any left: still turn assignments in. They could count in your favor in borderline cases

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Use them as needed throughout the course

They're meant for personal reasons and **emergencies**

Do not procrastinate

Late Policy

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Contact me privately if an extended absence will occur

You must know how
many you've used

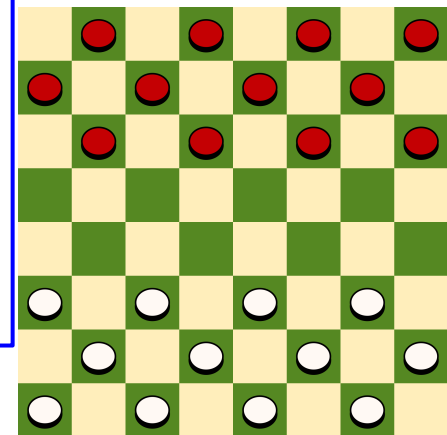
Definition of Machine Learning

Arthur Samuel (1959): Machine Learning is the field of study that gives the computer the ability to learn without being explicitly programmed.



A. L. Samuel*

**Some Studies in Machine Learning
Using the Game of Checkers. II—Recent Progress**



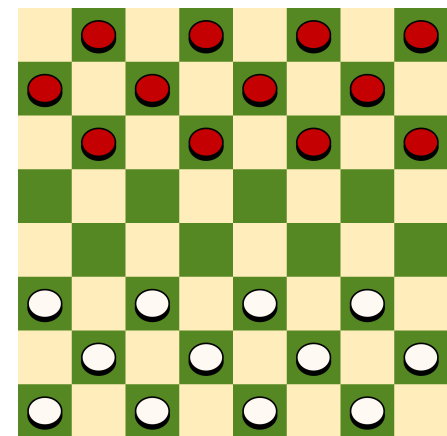
Definition of Machine Learning

Tom Mitchell (1998): a computer program 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 .



Experience (data): games played by the program (with itself)

Performance measure: winning rate



Taxonomy of Machine Learning

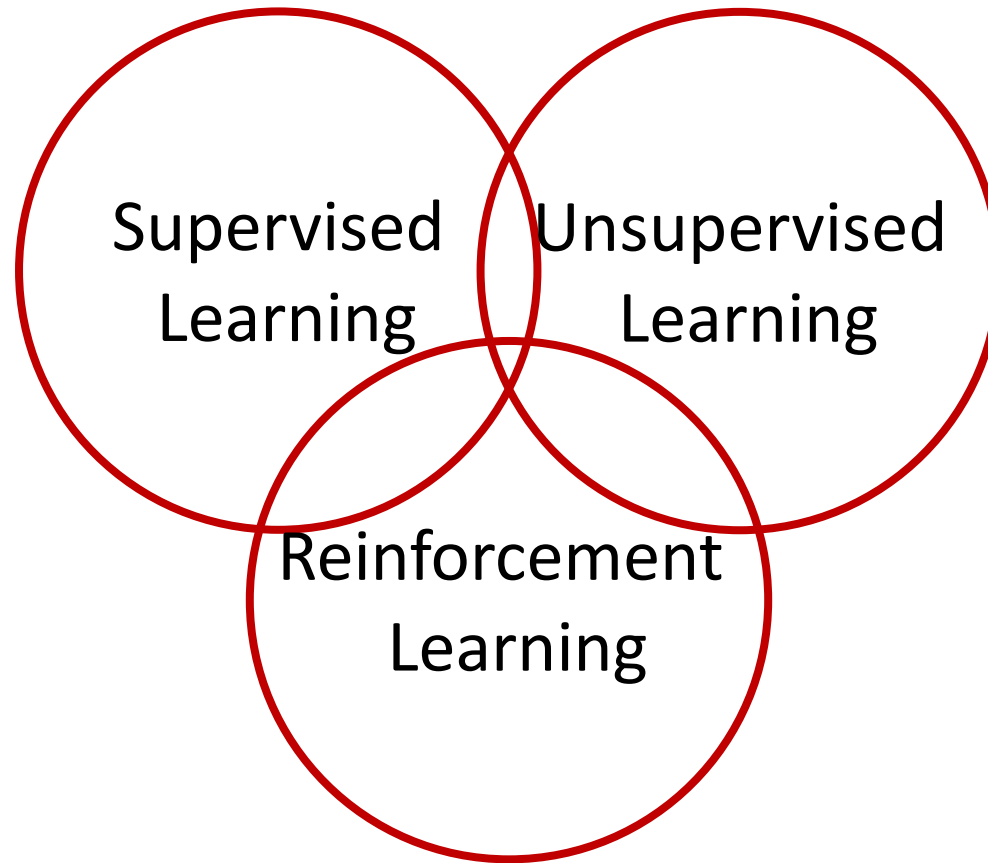
(A Simplistic View Based on Tasks)

Supervised
Learning

Unsupervised
Learning

Reinforcement
Learning

Taxonomy of Machine Learning (A Simplistic View Based on Tasks)



can also be viewed as tools/methods

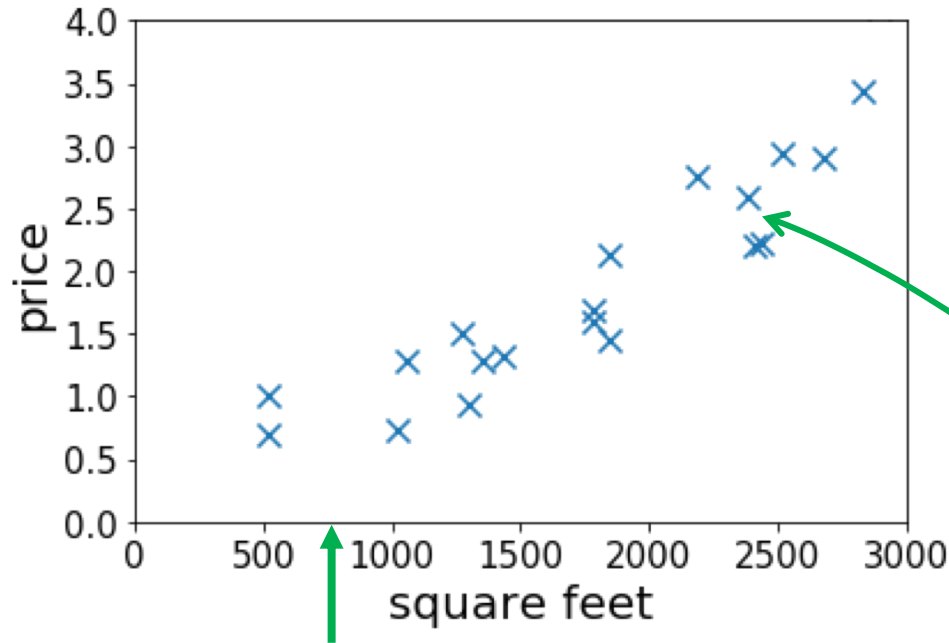
Supervised Learning

Housing Price Prediction

- Given: a dataset that contains n samples

$$(x^{(1)}, y^{(1)}), \dots (x^{(n)}, y^{(n)})$$

- **Task:** if a residence has x square feet, predict its price?



15th sample
 $(x^{(15)}, y^{(15)})$

$$x = 800$$

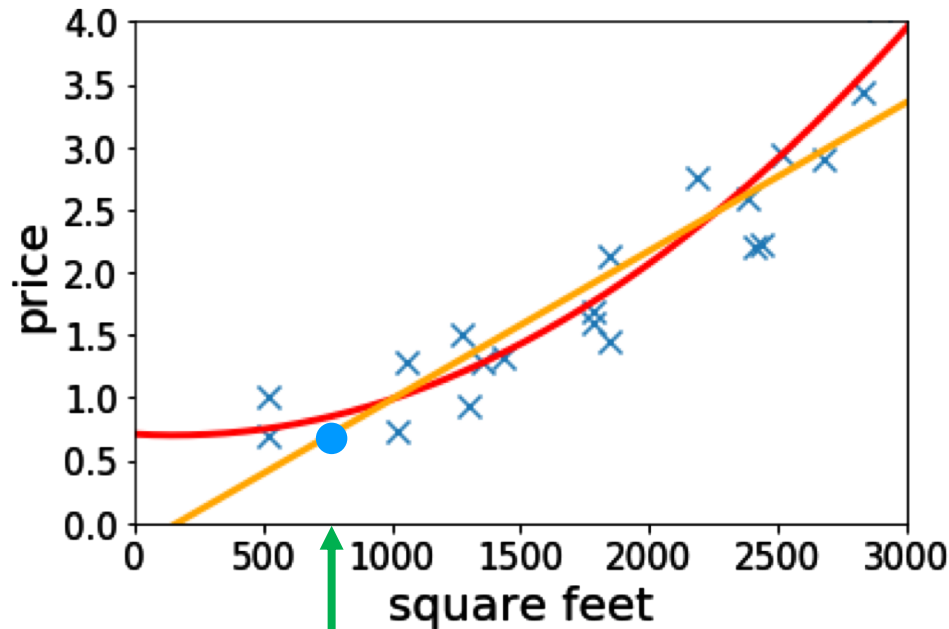
$$y = ?$$

Housing Price Prediction

- Given: a dataset that contains n samples

$$(x^{(1)}, y^{(1)}), \dots (x^{(n)}, y^{(n)})$$

- **Task:** if a residence has x square feet, predict its price?



$$x = 800$$

$$y = ?$$

- Lecture 2&3: fitting linear/ quadratic functions to the dataset

More Features

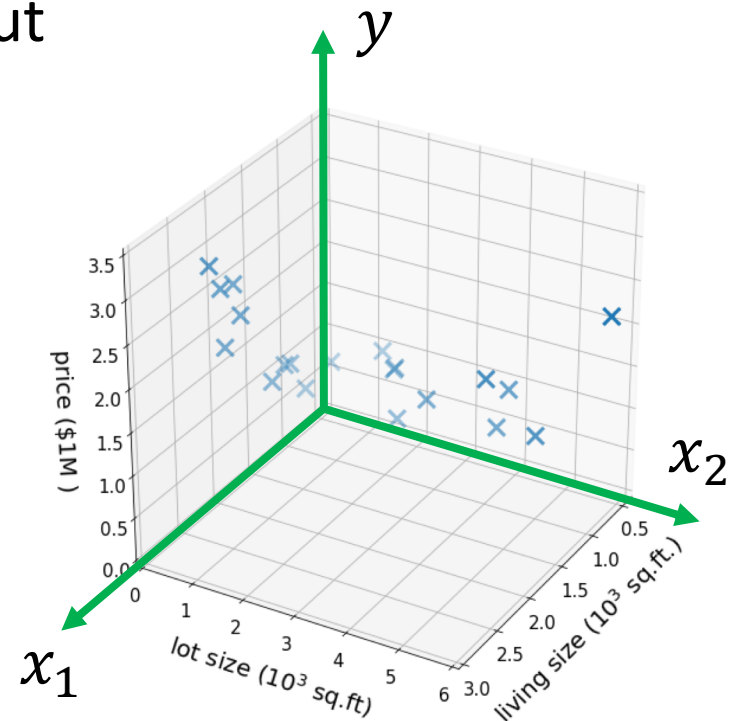
- Suppose we also know the lot size
- Task: find a function that maps

$$\underbrace{(\text{size, lot size})}_{\text{features/input } x \in \mathbb{R}^2} \rightarrow \underbrace{\text{price}}_{\text{label/output } y \in \mathbb{R}}$$

- Dataset: $(x^{(1)}, y^{(1)}), \dots, (x^{(n)}, y^{(n)})$

where $x^{(i)} = (x_1^{(i)}, x_2^{(i)})$

- “Supervision” refers to $y^{(1)}, \dots, y^{(n)}$



High-dimensional Features

➤ $x \in \mathbb{R}^d$ for large d

➤ E.g.,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ \vdots \\ \vdots \\ x_d \end{bmatrix} \begin{array}{l} \text{--- living size} \\ \text{--- lot size} \\ \text{--- \# floors} \\ \text{--- condition} \\ \text{--- zip code} \\ \quad \quad \quad \vdots \end{array} \longrightarrow y \text{ --- price}$$

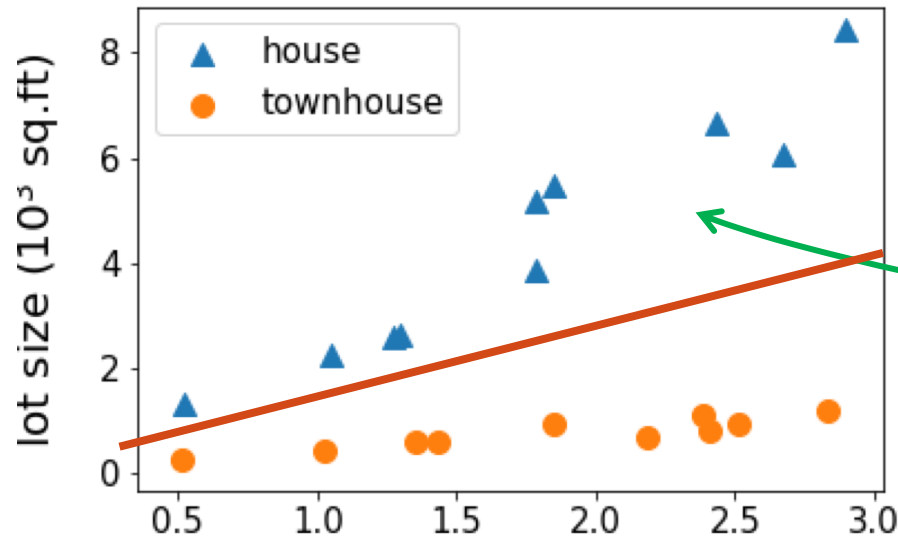
➤ Lecture 6-7: infinite dimensional features

➤ Lecture 10: select features based on the data

Regression vs Classification

- regression: if $y \in \mathbb{R}$ is a continuous variable
 - e.g., price prediction
- classification: the label is a discrete variable
 - e.g., the task of predicting the types of residence

(size, lot size) → house or townhouse?



$y = \text{house or townhouse?}$

Lecture 3&4:
classification

Supervised Learning in Computer Vision

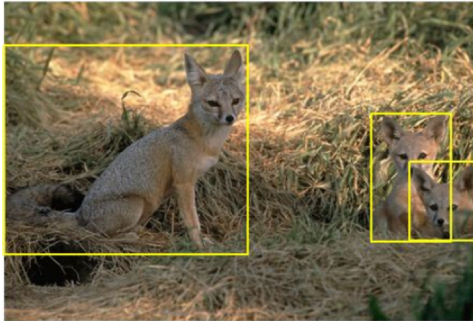
➤ Image Classification

➤ x = raw pixels of the image, y = the main object

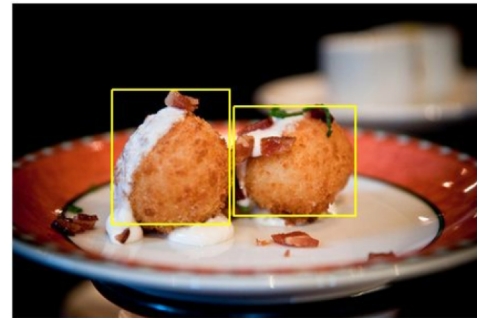


Supervised Learning in Computer Vision

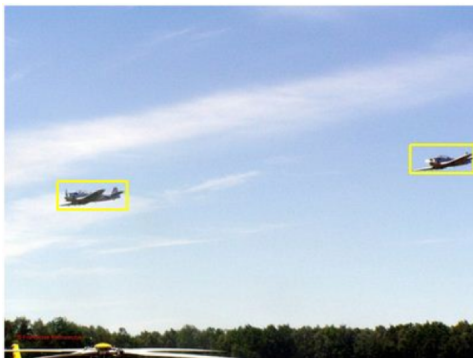
- Object localization and detection
 - x = raw pixels of the image, y = the bounding boxes



kit fox



croquette



airplane



frog

Supervised Learning in Natural Language Processing

➤ Machine translation

Google Translate



x



y

- **Note:** this course only covers the basic and fundamental techniques of supervised learning

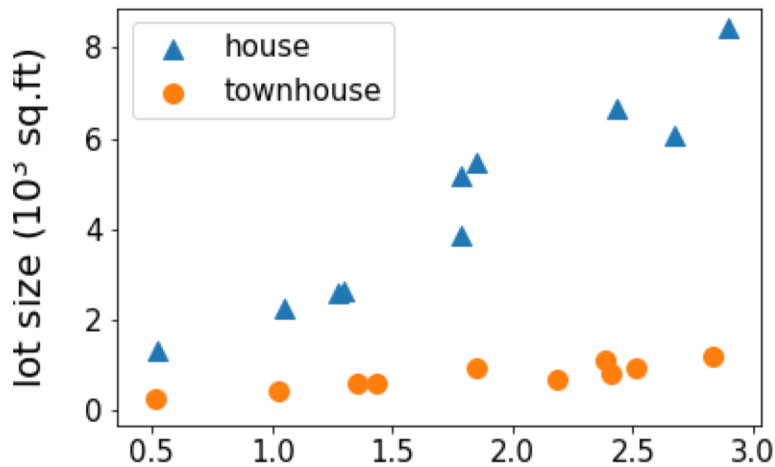


Unsupervised Learning

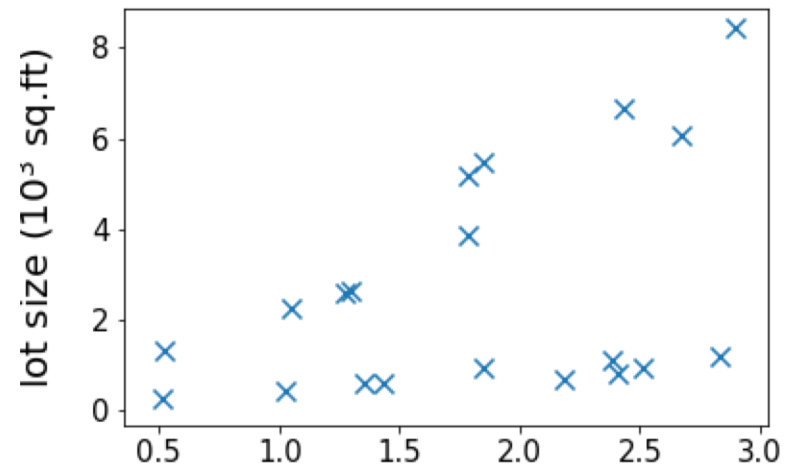
Unsupervised Learning

- Dataset contains **no labels**: $x^{(1)}, \dots, x^{(n)}$
- **Goal** (vaguely-posed): to find interesting structures in the data

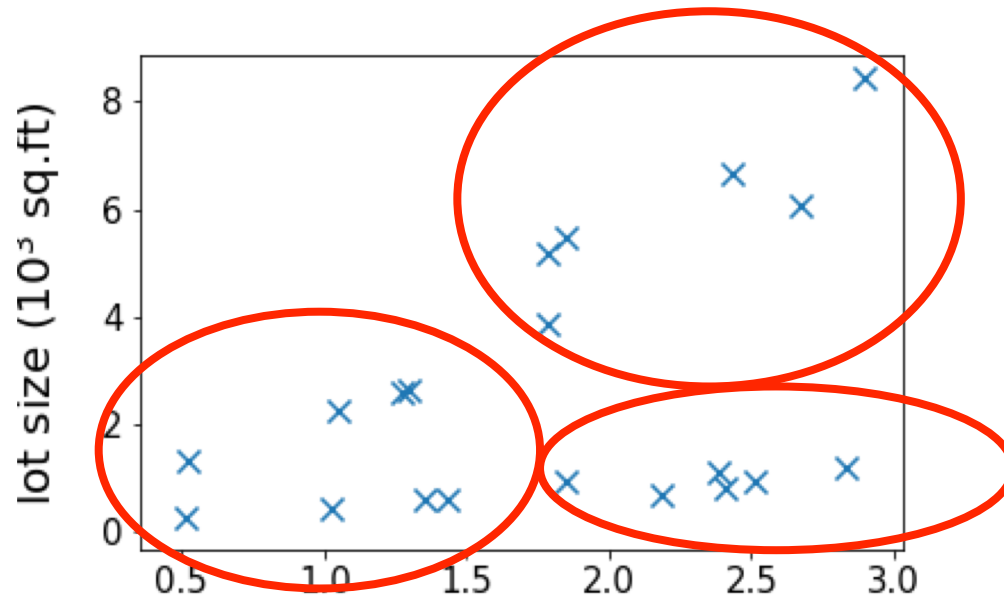
supervised



unsupervised

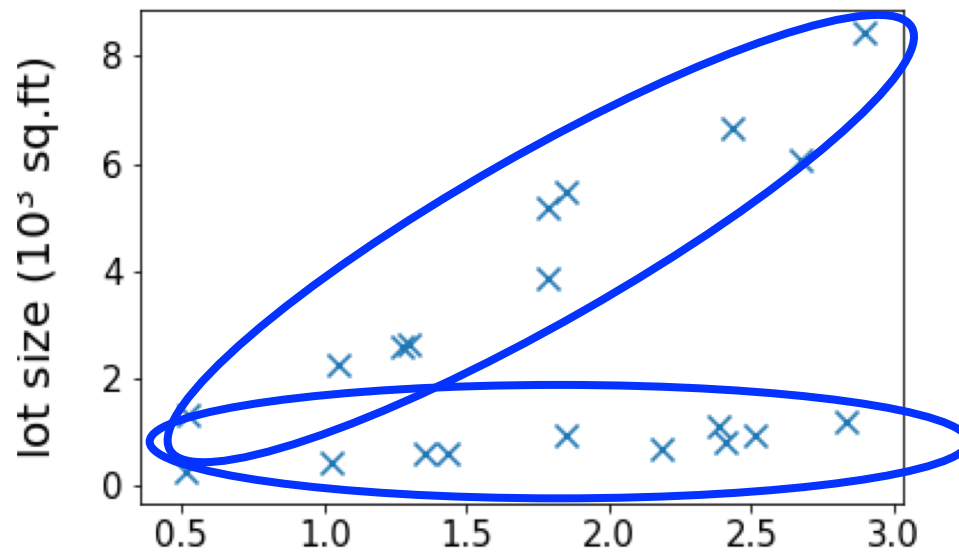


Clustering



Clustering

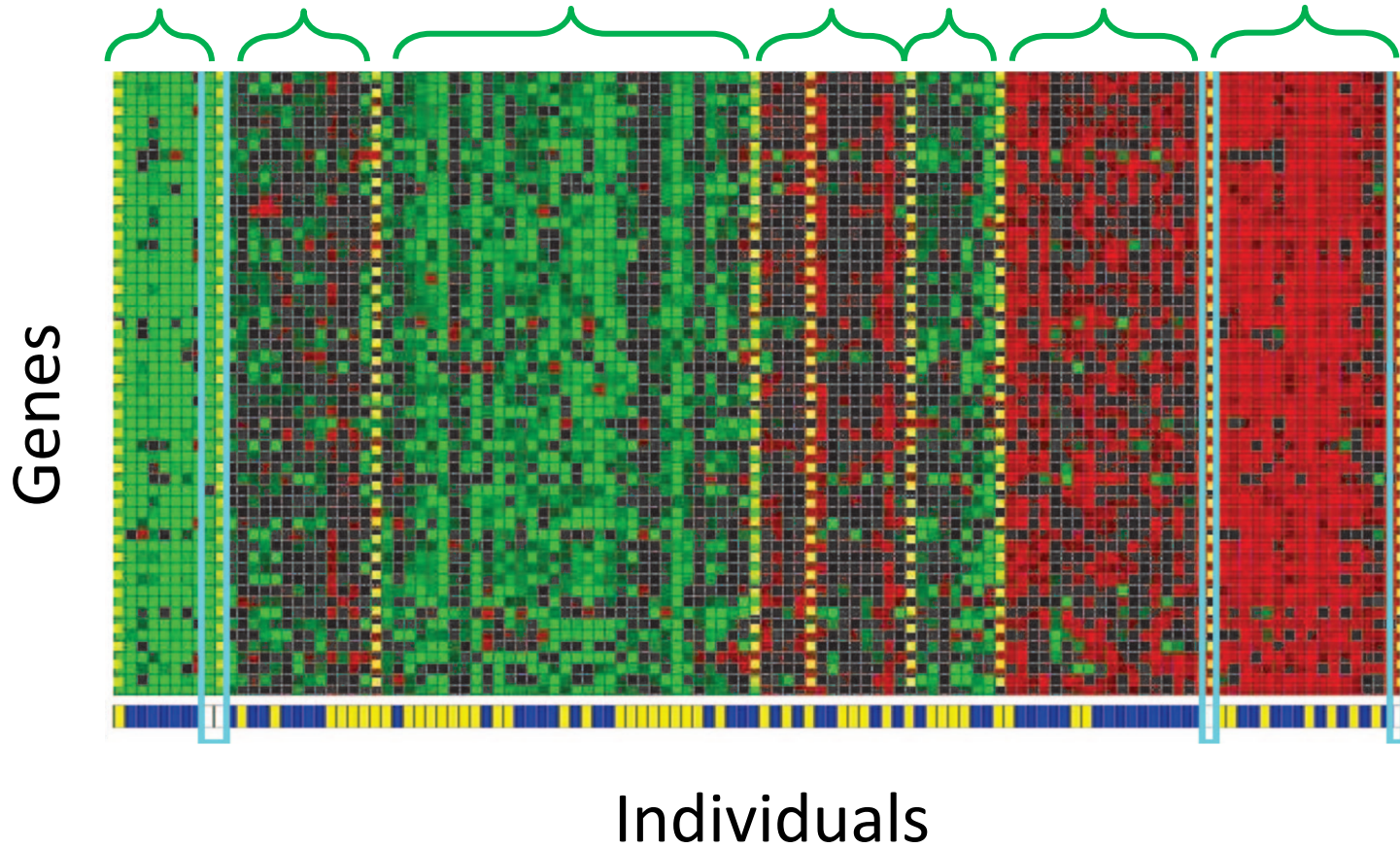
- Lecture 12&13: k-mean clustering, mixture of Gaussians



Clustering Genes

Cluster 1

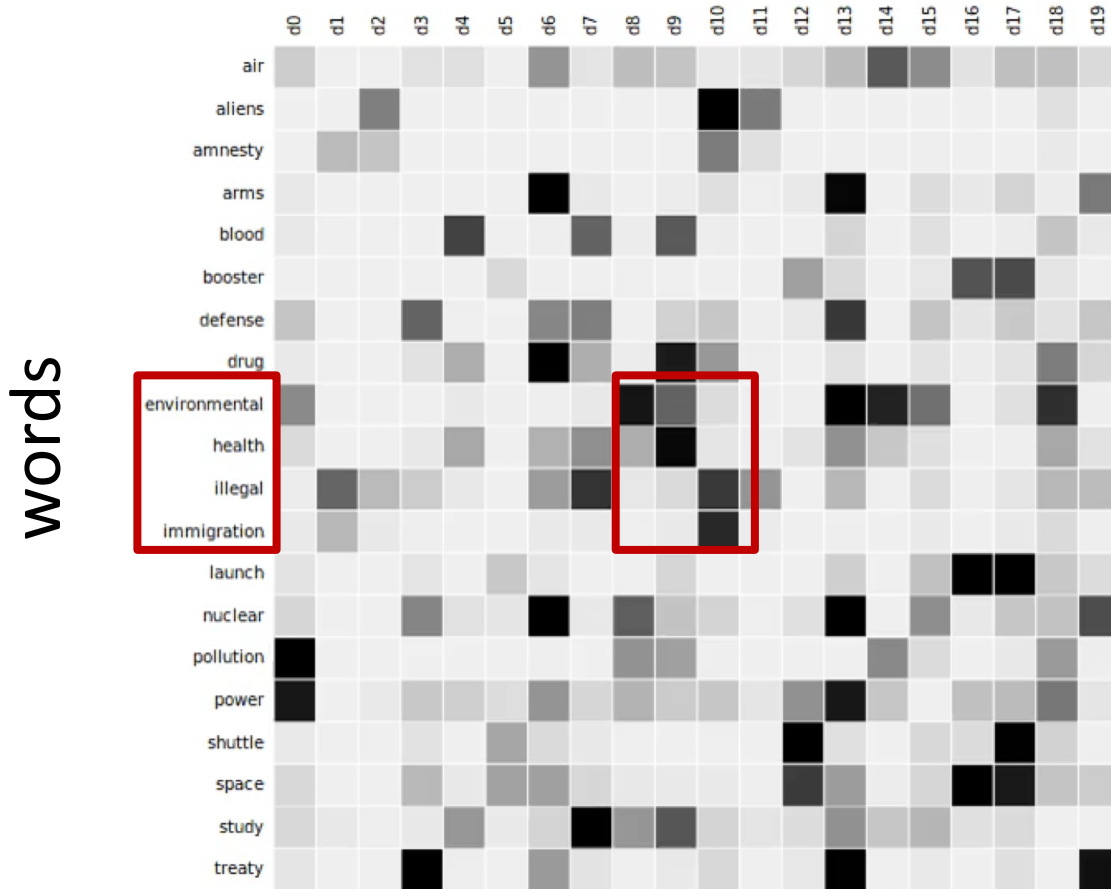
Cluster 7



Identifying Regulatory Mechanisms using Individual Variation Reveals Key Role for Chromatin Modification. [Su-In Lee, Dana Pe'er, Aimee M. Dudley, George M. Church and Daphne Koller. '06]

Latent Semantic Analysis (LSA)

documents



- Lecture 14: principal component analysis (tools used in LSA)

Image credit: https://commons.wikimedia.org/wiki/File:Topic_detection_in_a_document-word_matrix.gif

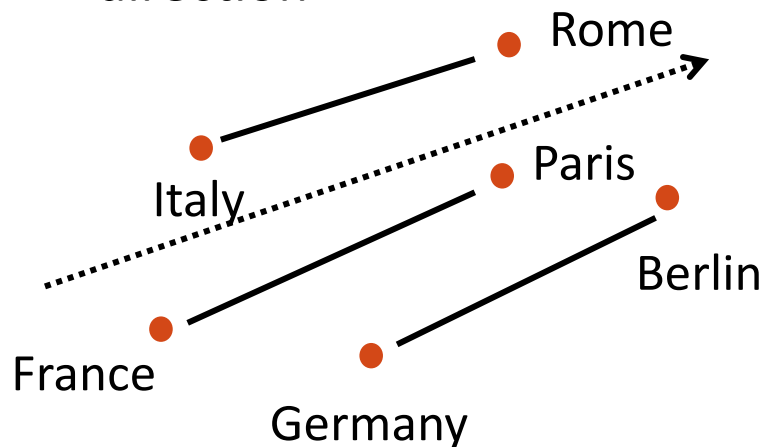
Word Embeddings



Unlabeled dataset

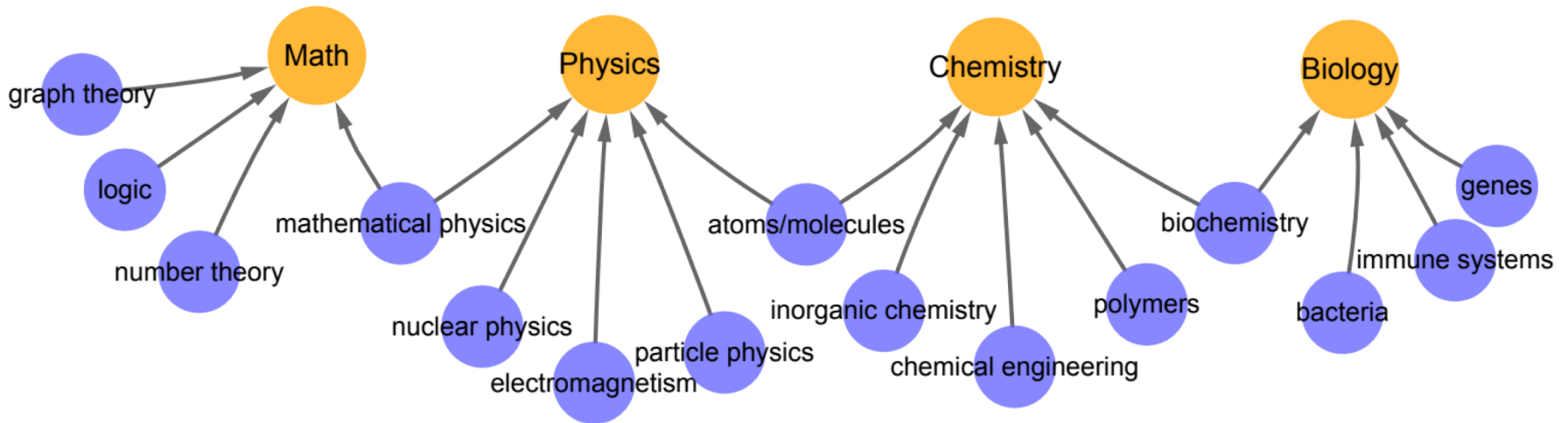
Represent words by vectors

- word $\xrightarrow{\text{encode}}$ vector
- relation $\xrightarrow{\text{encode}}$ direction



Word2vec [Mikolov et al'13]
GloVe [Pennington et al'14]

Clustering Words with Similar Meanings (Hierarchically)



	logic deductive propositional semantics	graph subgraph bipartite vertex	boson massless particle higgs	polyester polypropylene resins epoxy	acids amino biosynthesis peptide
tag	<i>logic</i>	<i>graph theory</i>	<i>particle physics</i>	<i>polymer</i>	<i>biochemistry</i>

Large Language Models (Lecture 16)

- machine learning models for language learnt on large-scale language datasets
- can be used for many purposes

SYSTEM PROMPT
(HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION
(MACHINE-WRITTEN,
10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

Context → Helsinki is the capital and largest city of Finland. It is in the region of Uusimaa, in southern Finland, on the shore of the Gulf of Finland. Helsinki has a population of , an urban population of , and a metropolitan population of over 1.4 million, making it the most populous municipality and urban area in Finland. Helsinki is some north of Tallinn, Estonia, east of Stockholm, Sweden, and west of Saint Petersburg, Russia. Helsinki has close historical connections with these three cities.

The Helsinki metropolitan area includes the urban core of Helsinki, Espoo, Vantaa, Kauniainen, and surrounding commuter towns. It is the world's northernmost metro area of over one million people, and the city is the northernmost capital of an EU member state. The Helsinki metropolitan area is the third largest metropolitan area in the Nordic countries after Stockholm and Copenhagen, and the City of Helsinki is the third largest after Stockholm and Oslo. Helsinki is Finland's major political, educational, financial, cultural, and research center as well as one of northern Europe's major cities. Approximately 75% of foreign companies that operate in Finland have settled in the Helsinki region. The nearby municipality of Vantaa is the location of Helsinki Airport, with frequent service to various destinations in Europe and Asia.

Q: what is the most populous municipality in Finland?

A: Helsinki

Q: how many people live there?

A: 1.4 million in the metropolitan area

Q: what percent of the foreign companies that operate in Finland are in Helsinki?

A: 75%

Q: what towns are a part of the metropolitan area?

A:

Target Completion → Helsinki, Espoo, Vantaa, Kauniainen, and surrounding commuter towns

Context → Please unscramble the letters into a word, and write that word:
taefed =

Target Completion → defeat

Context → L'analyse de la distribution de fréquence des stades larvaires d'I. verticalis dans une série d'étangs a également démontré que les larves mâles étaient à des stades plus avancés que les larves femelles. =

Target Completion → Analysis of instar distributions of larval I. verticalis collected from a series of ponds also indicated that males were in more advanced instars than females.

Context → Q: What is 95 times 45?
A:

Target Completion → 4275

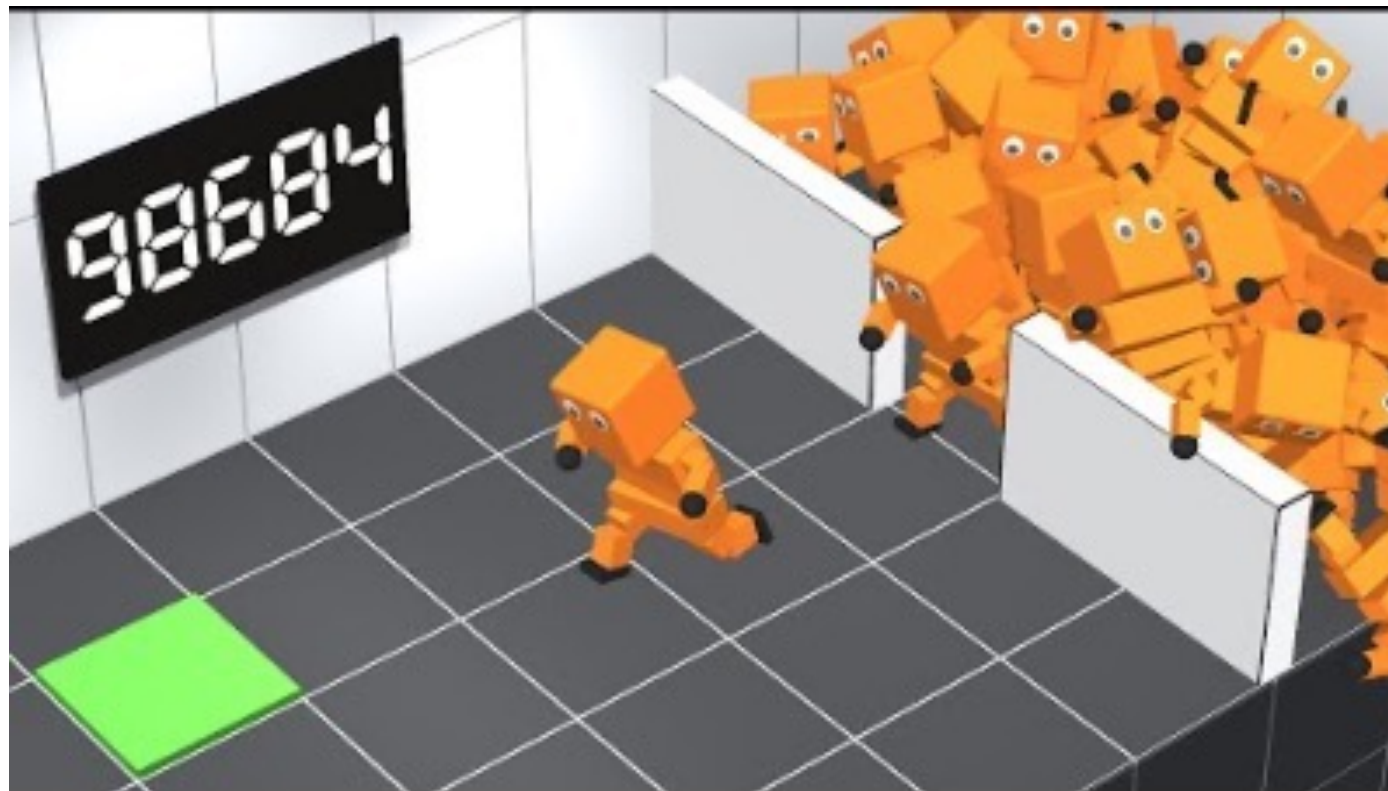
Reinforcement Learning

- Learning to make sequential **decisions**



ALPHAGO

Albert learns to walk



[Youtube Video Link](#)

Albert learns to walk



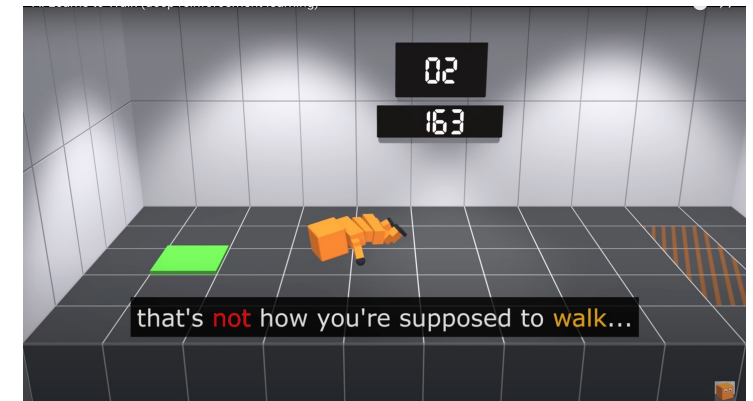
Iteration 1



Iteration 62



Iteration 163



Iteration 163

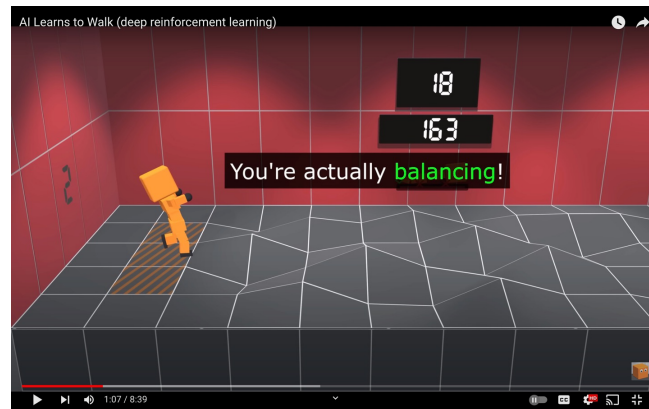
Albert learns to walk



Iteration 17
With new objective



Iteration 17



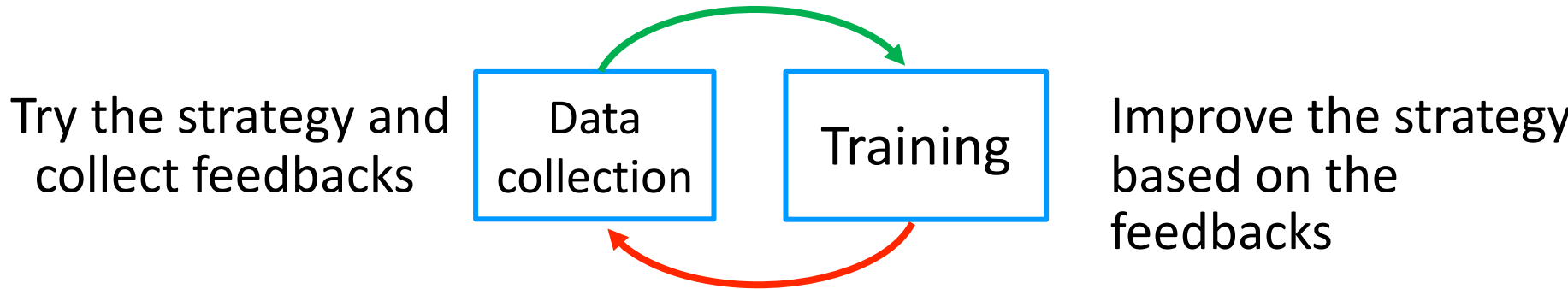
Iteration 163



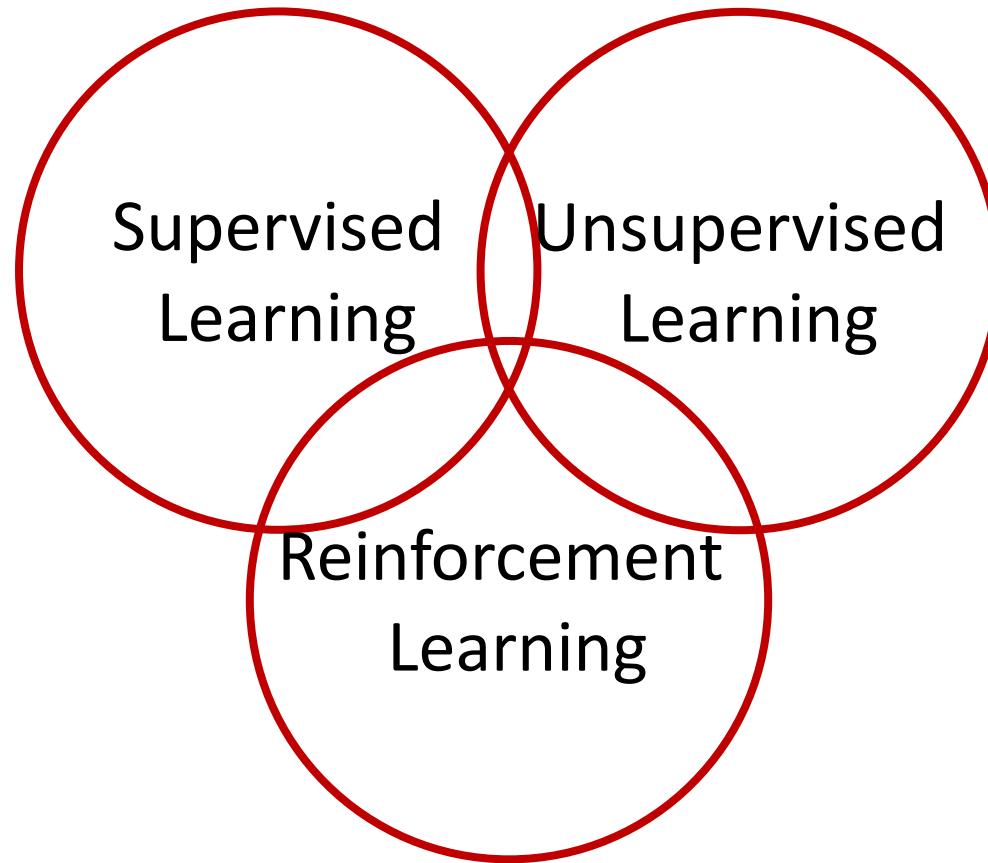
Iteration 932

Reinforcement Learning

- The algorithm can collect data interactively



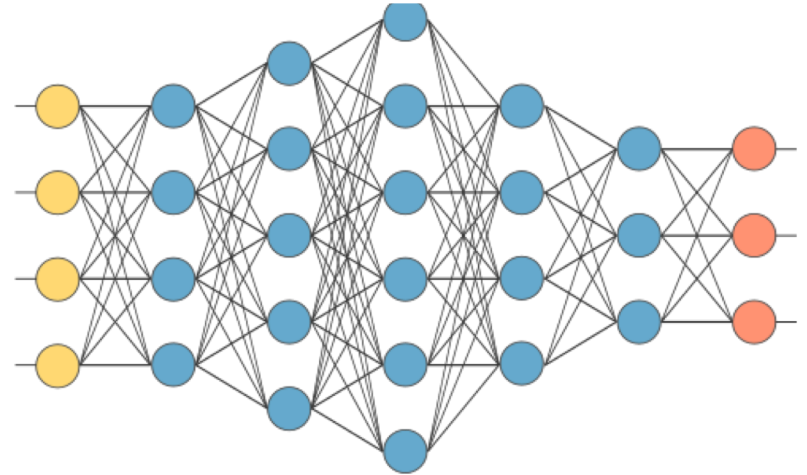
Taxonomy of Machine Learning (A Simplistic View Based on Tasks)



can also be viewed as tools/methods

Other Tools/Topics In This Course

- Deep learning basics
- Introduction to learning theory
 - Bias variance tradeoff
 - Feature selection
 - ML advice
- Broader aspects of ML
 - Robustness/fairness



Questions?

Thank you!