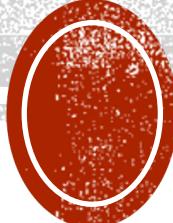




การพัฒนาระบบ อัจฉริยะแบบ AIoT (part 2)

ผศ.ดร. กัธรวิทย์ พลพินิจ

วิศวกรรมคอมพิวเตอร์ คณะวิศวกรรมศาสตร์ มหาวิทยาลัยขอนแก่น



Outline

➤ Introduction

- Introduction to AI / ML (This slide)

➤ Coding

- Coding in Python
- Choosing and Building Models
- Evaluate Model

➤ Assignment

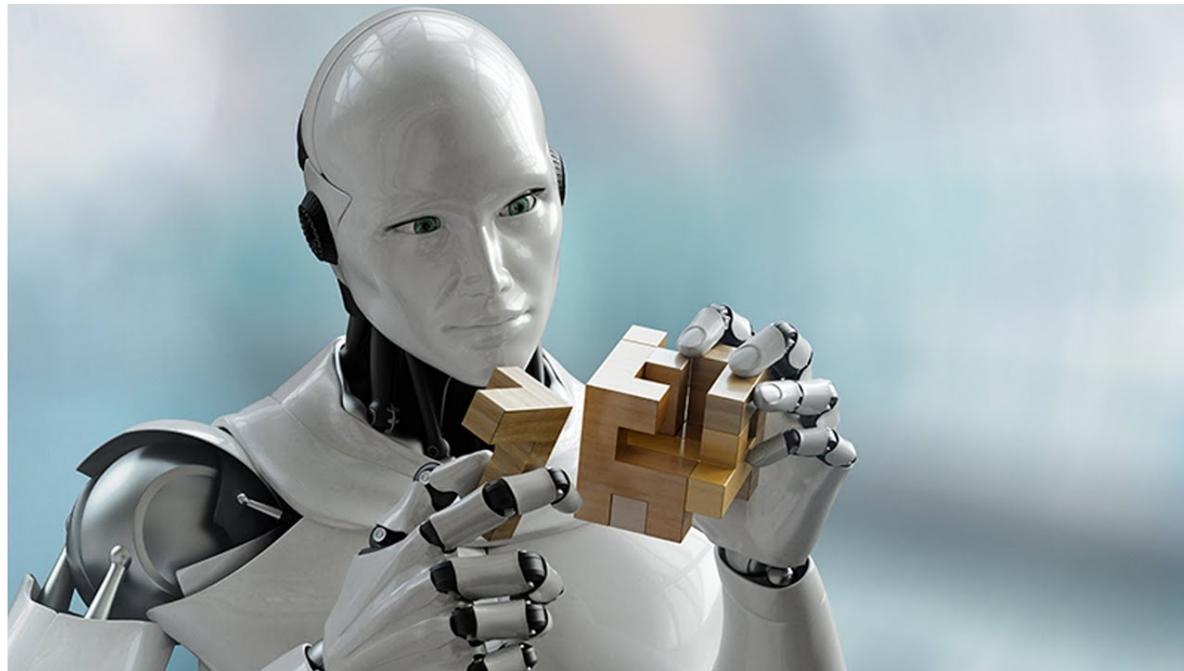
➤ Conclusion

Objective

- Have a fundamental understanding of AI and ML
- Learn how to use necessary tools to code ML in python
- Have experience building ML models(regression and classification)
- Can choose appropriate model for a real-world example

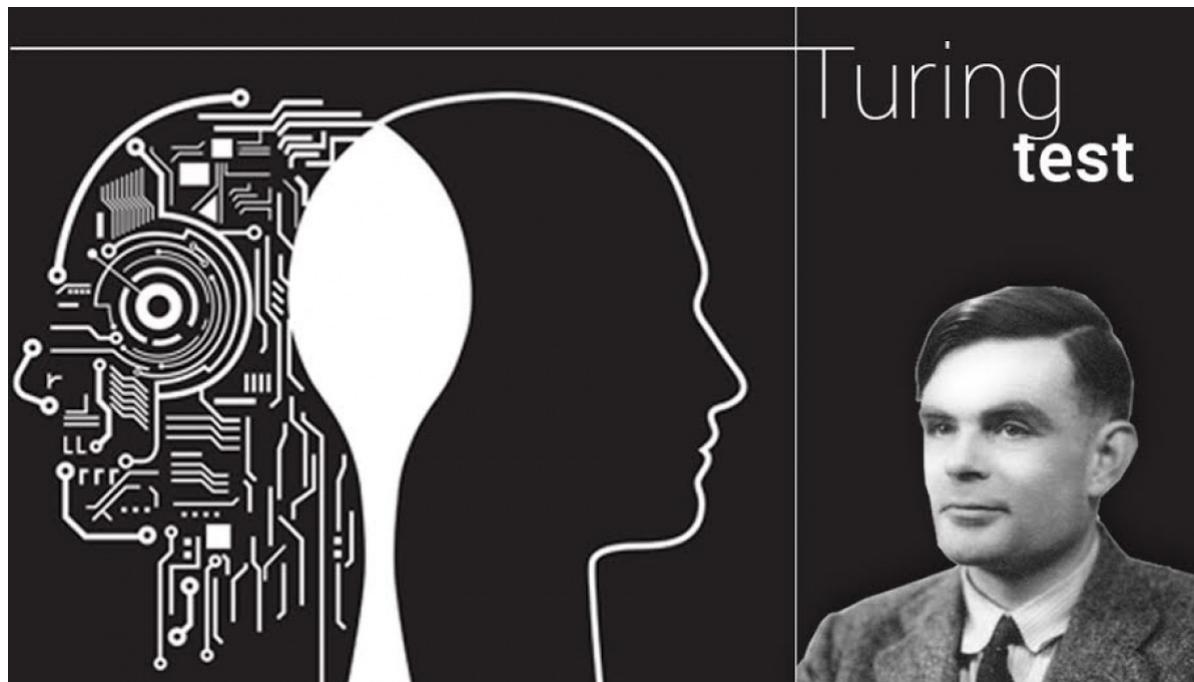
What is Artificial Intelligence?

- **Artificial Intelligence (AI)** is an area of computer science that emphasizes the creation of intelligent machines that work and react like humans.



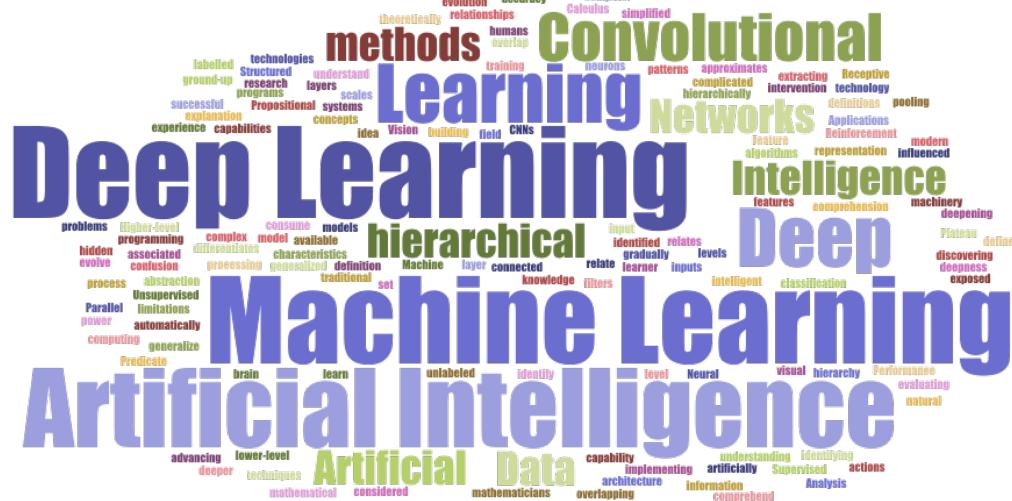
AI Early History

- In 1950 English mathematician **Alan Turing** write a landmark paper titled “Computing Machinery and Intelligence” that asked the question: “Can machine think?”



AI and Machine Learning and Deep Learning

- Deep learning and machine learning are sub-fields of artificial intelligence, and deep learning is a sub-field of machine learning.



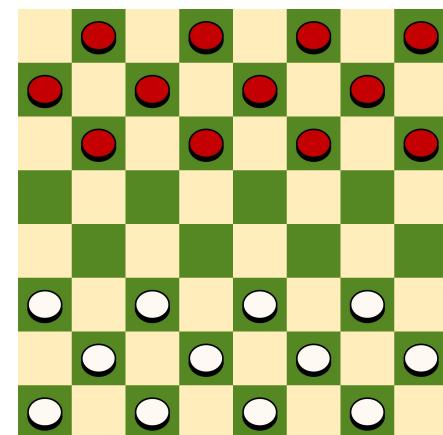
Definition of Machine Learning

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**

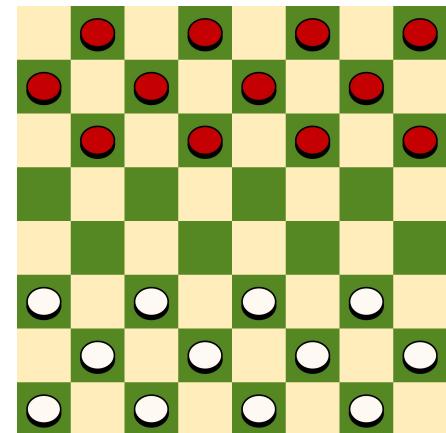


Definition of Machine Learning

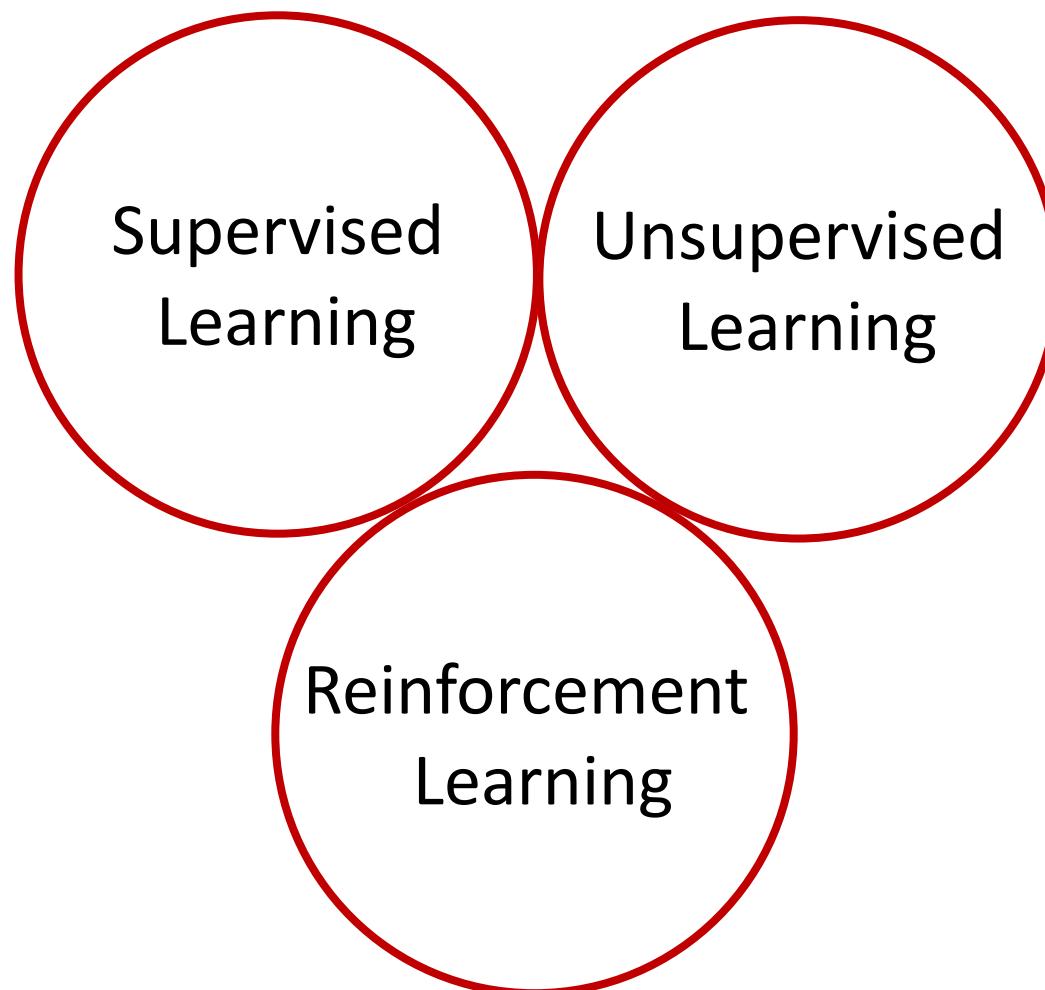
Tom Mitchell (1998): a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.



- Experience (data): games played by the program (with itself)
- Performance measure: winning rate
- A learning task is given by $\langle P, T, E \rangle$



Taxonomy of Machine Learning



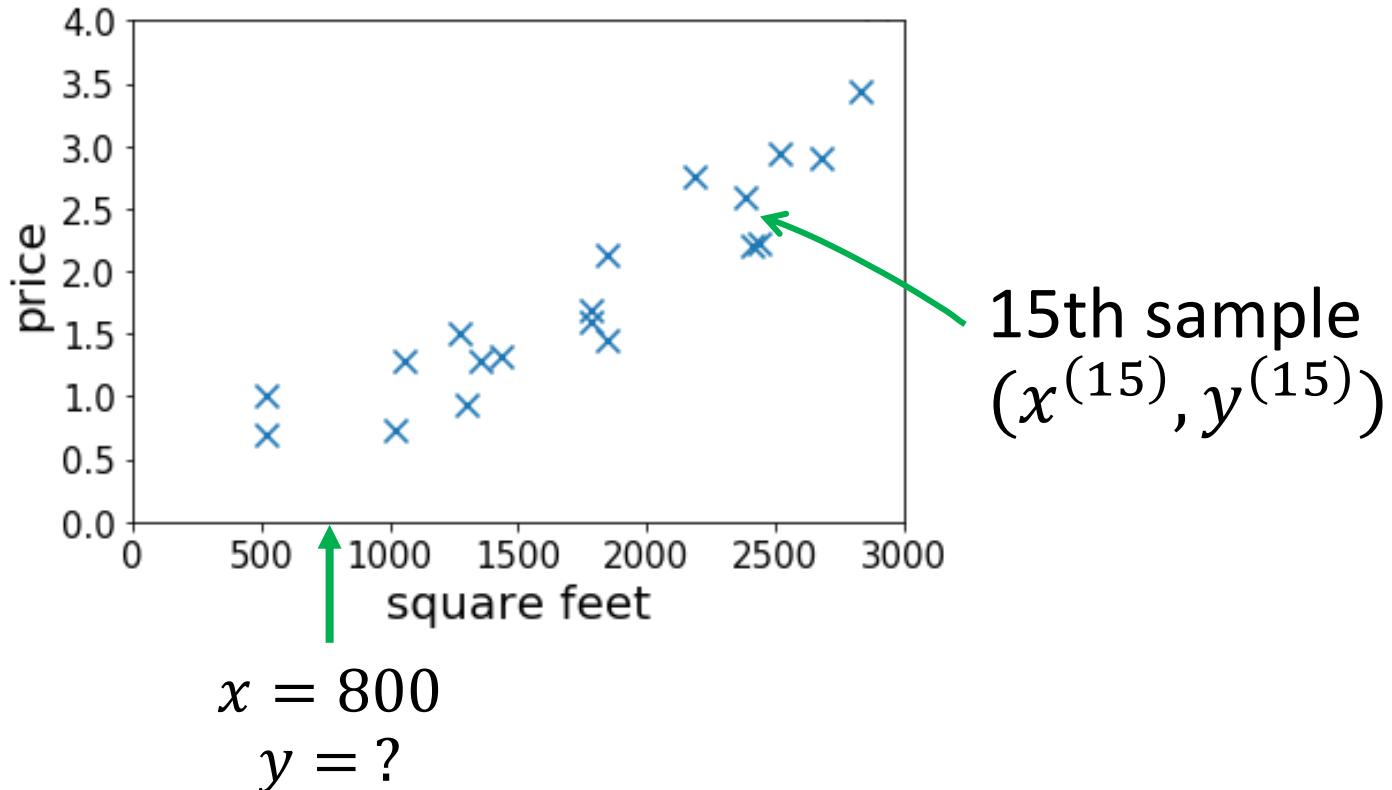
Supervised Learning

Housing Price Prediction (Regression)

- 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?

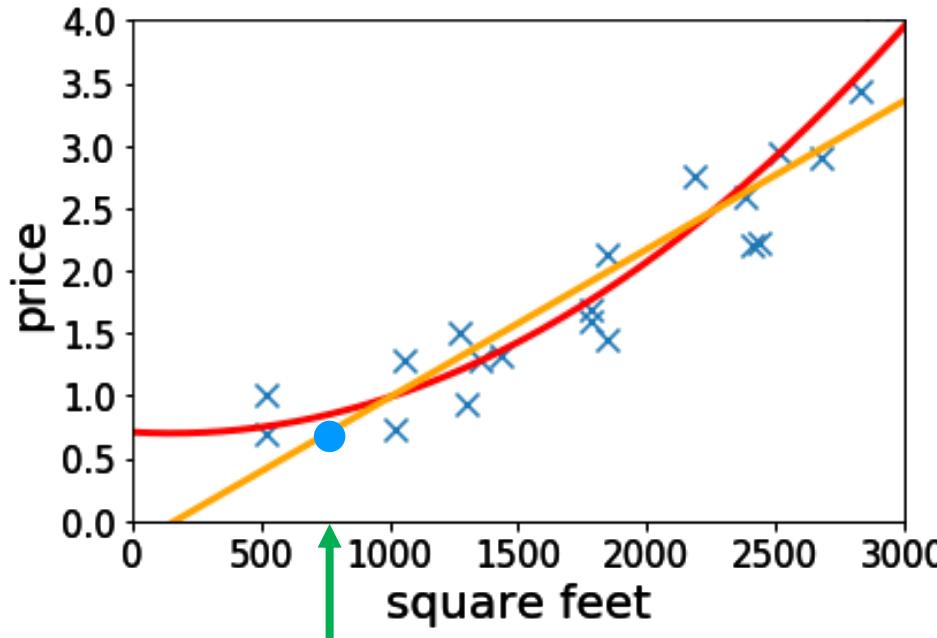


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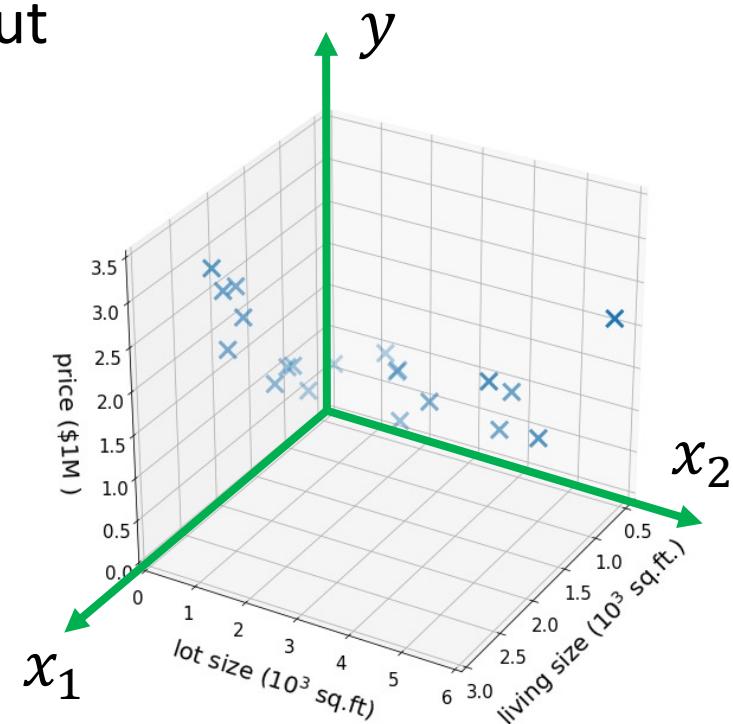
- Try fitting linear/quadratic functions to the dataset
 $y = ?$

More Features

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

The diagram illustrates a function mapping from a set of features (input) to a label (output). On the left, a green bracket groups the text "(size, lot size)" above it, with the label "features/input" below it and the mathematical expression $x \in \mathbb{R}^2$ at the bottom. An arrow points from this group to the word "price" on the right, which is also enclosed in a green bracket. Below "price" is the label "label/output" and the mathematical expression $y \in \mathbb{R}$.

- 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

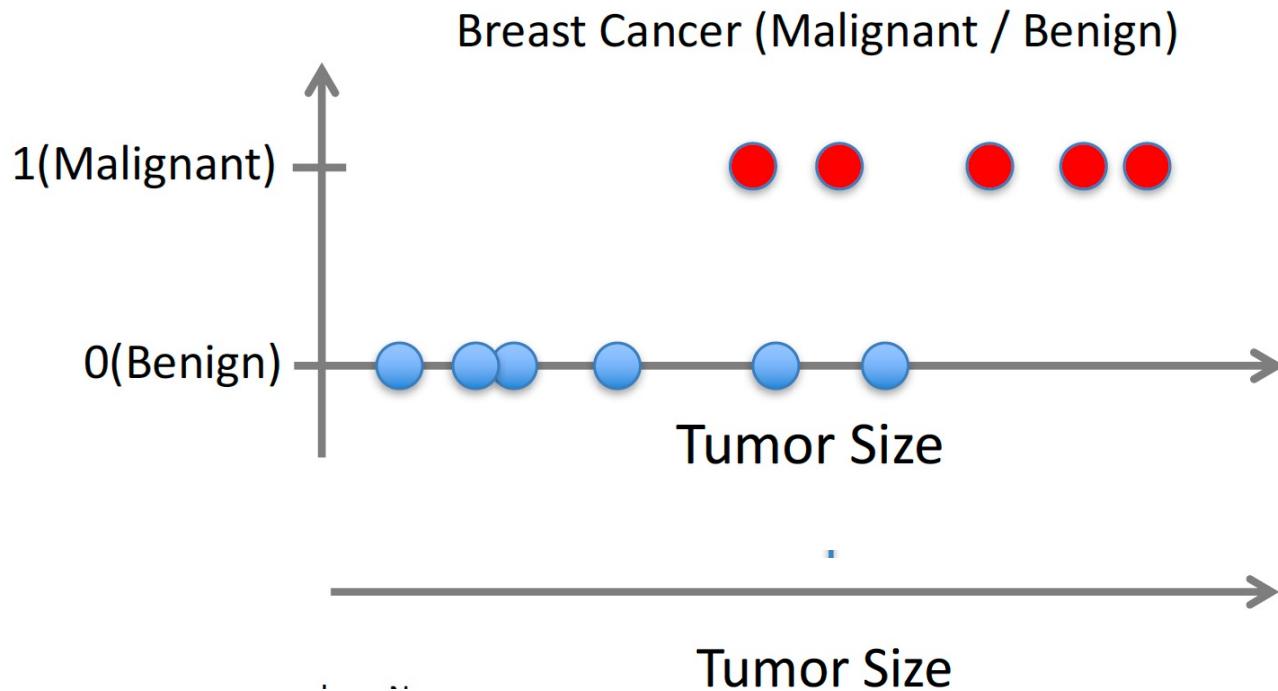
- E.g.,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ \vdots \\ x_d \end{bmatrix} \begin{array}{l} \text{--- living size} \\ \text{--- lot size} \\ \text{--- \# floors} \\ \text{--- condition} \\ \text{--- zip code} \\ \vdots \end{array} \xrightarrow{\hspace{1cm}} y \text{ --- price}$$

- This can go to infinite dimensional features

Breast Cancer Determination (Classification)

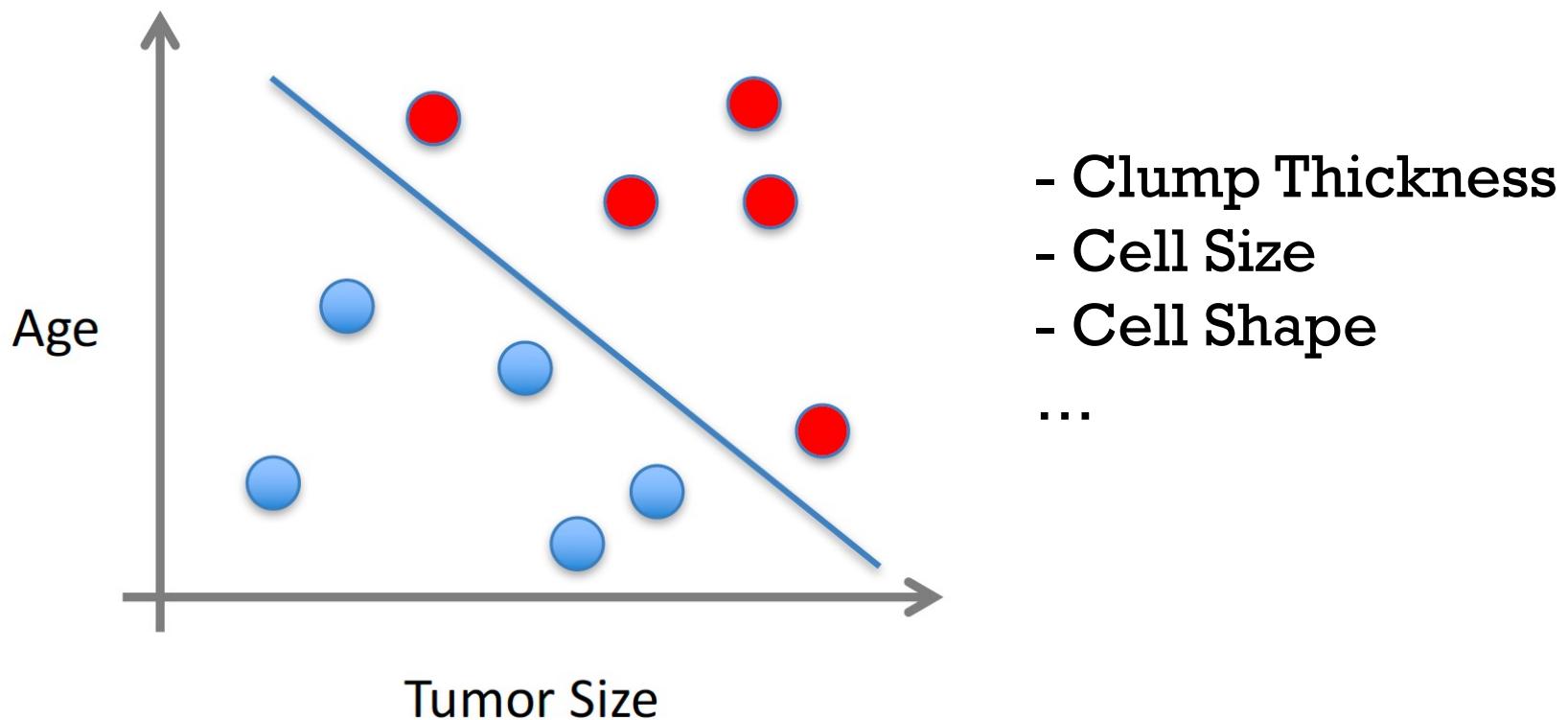
- Given $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$
- Learn a function $f(x)$ to predict y given x
 - y is categorical == classification



Breast Cancer Determination (Classification)

Higher Dimension Features

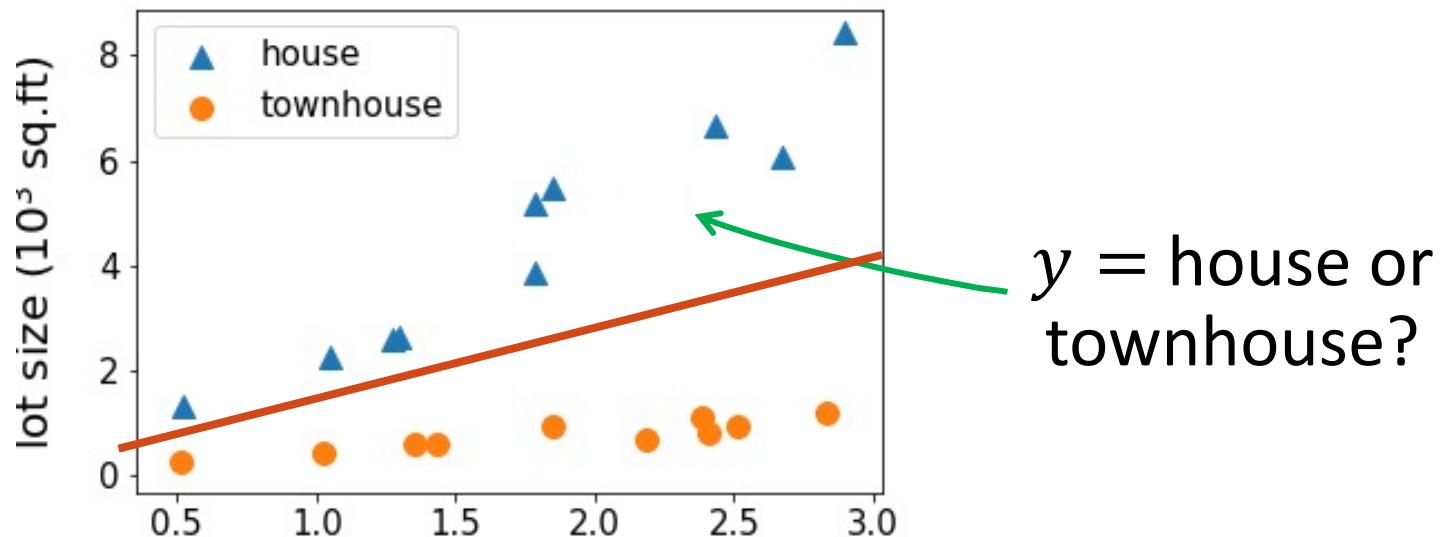
- x can be multi-dimensional
 - Each dimension corresponds to an attribute



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) \rightarrow house or townhouse?



Supervised Learning in Computer Vision

➤ Image Classification

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

ILSVRC



flamingo



cock



ruffed grouse



quail



partridge

...



Egyptian cat



Persian cat



Siamese cat



tabby



lynx

...



dalmatian



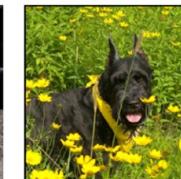
keeshond



miniature schnauzer



standard schnauzer

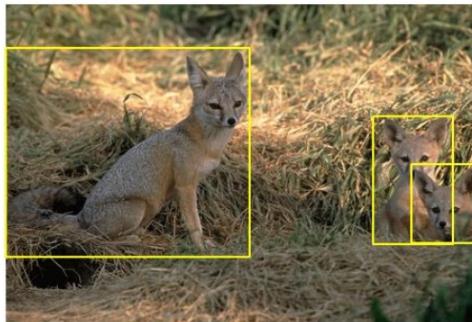


giant schnauzer

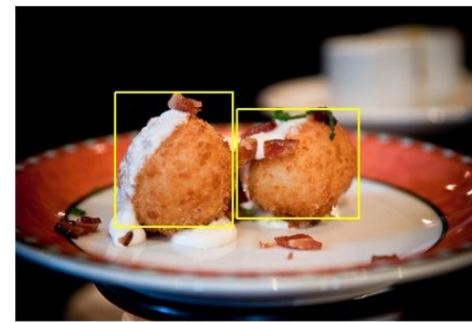
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Supervised Learning in Computer Vision

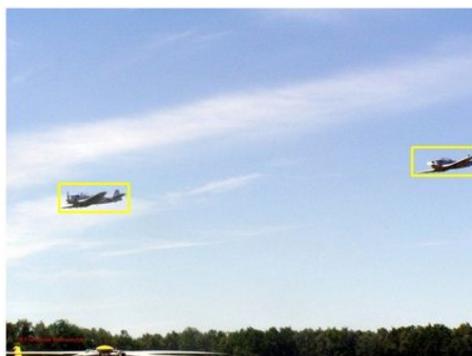
- Object localization and detection
- x = raw pixels of the image, y = the bounding boxes



kit fox



croquette



airplane

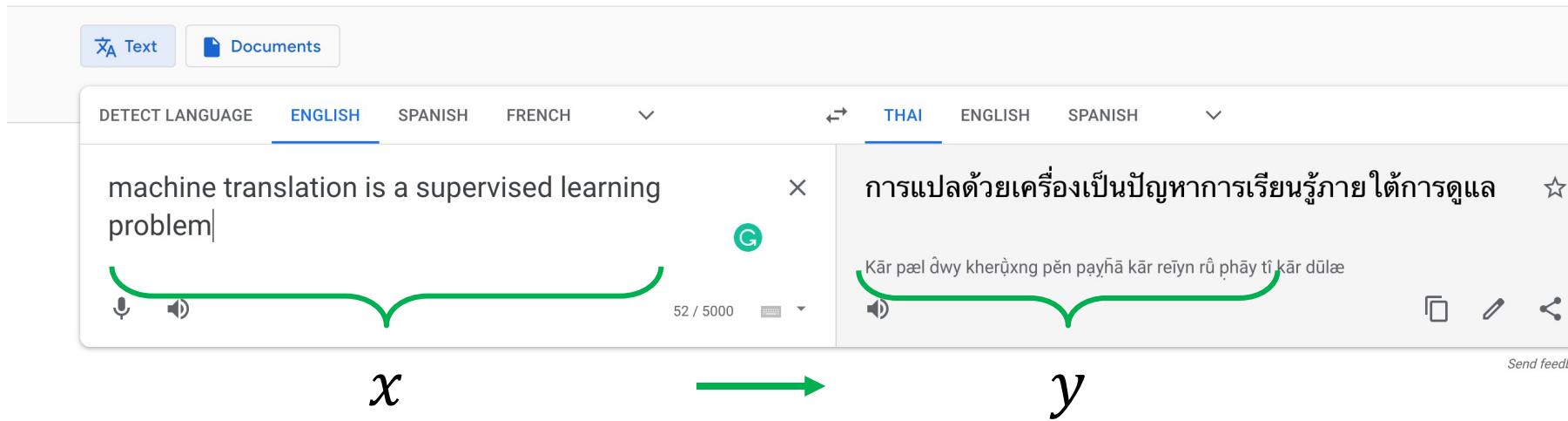


frog

Supervised Learning in Natural Language Processing

➤ Machine translation

≡ Google Translate

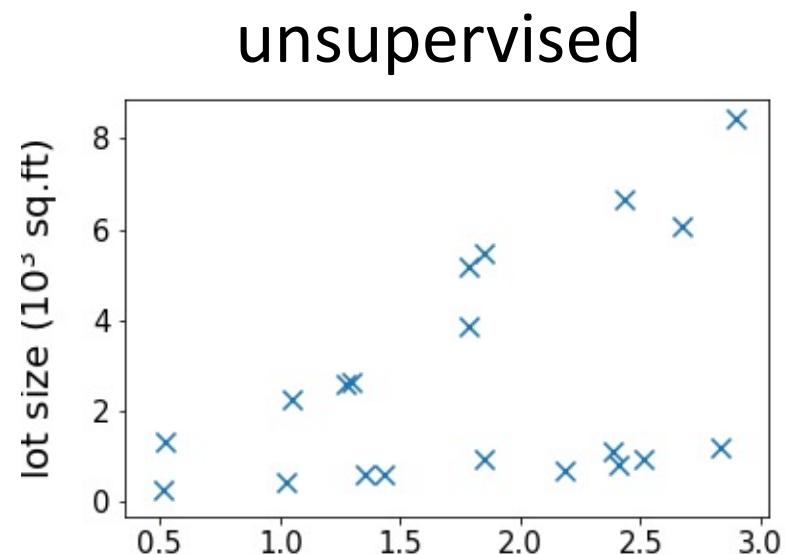
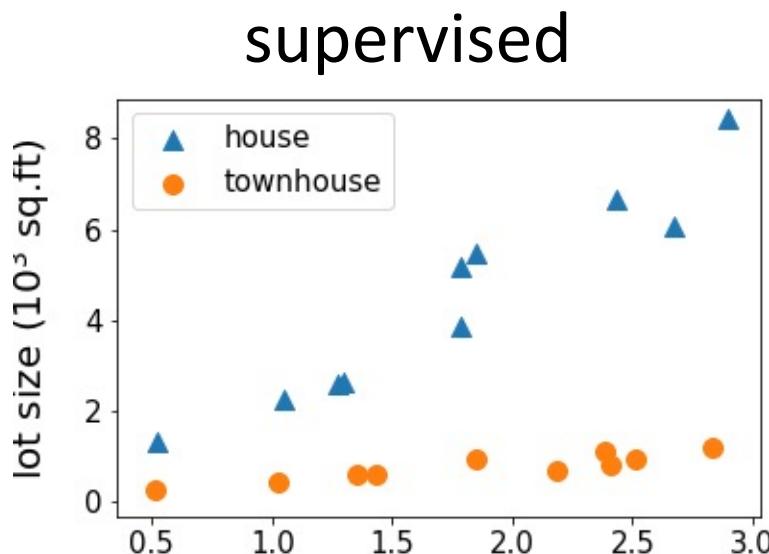


➤ Note: this will not be covered here. However, you should explore the topic more on your own as this is a very useful and important field.

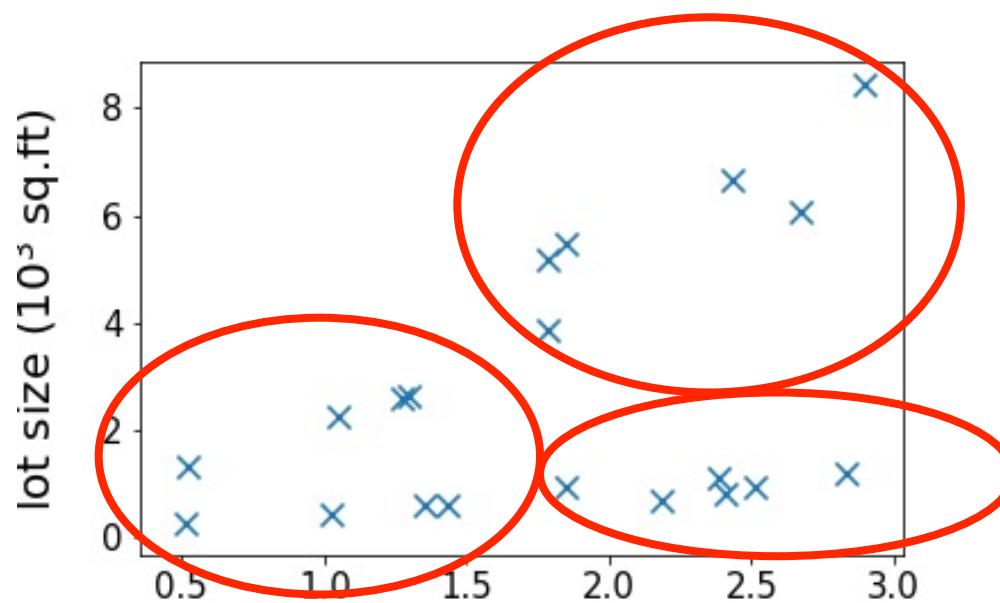
Unsupervised Learning

Unsupervised Learning

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

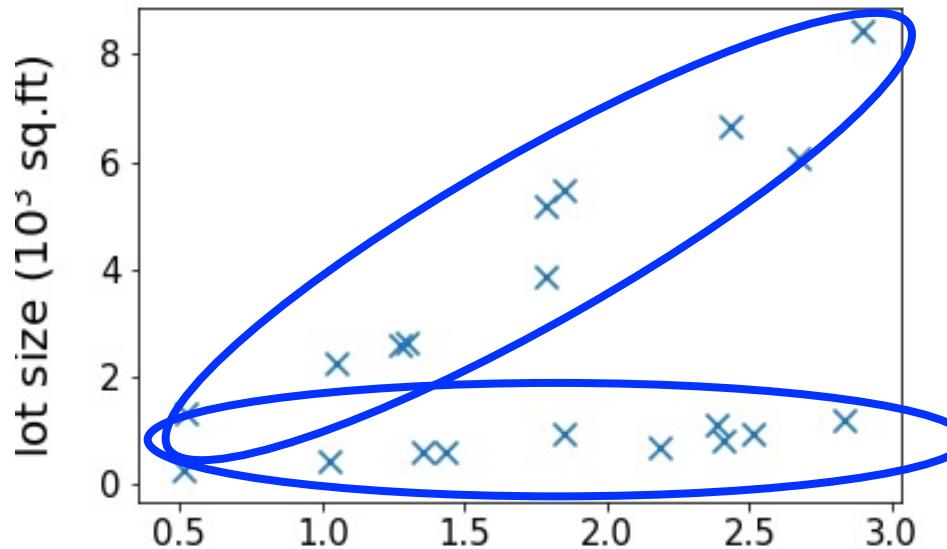


Clustering

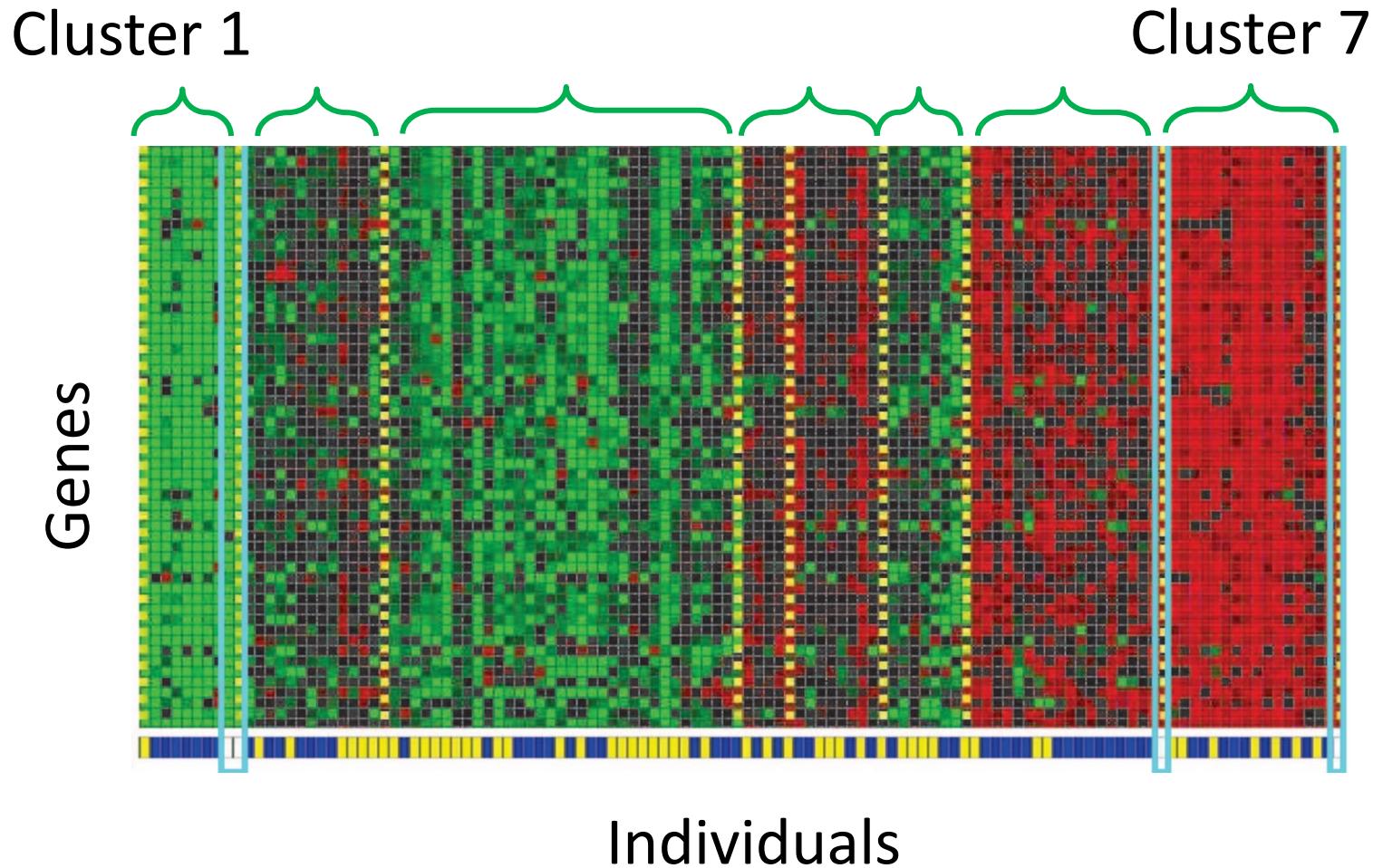


Clustering

➤ Example : k-mean clustering, mixture of Gaussians

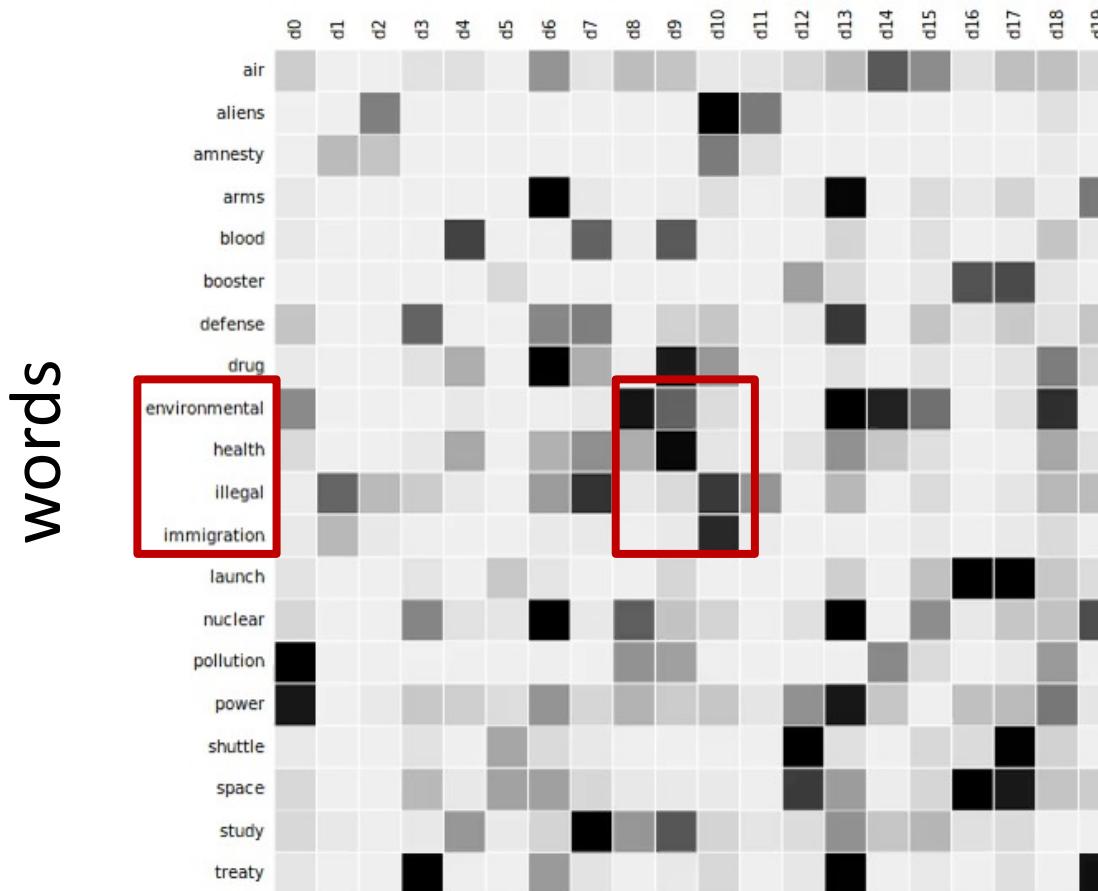


Clustering Genes

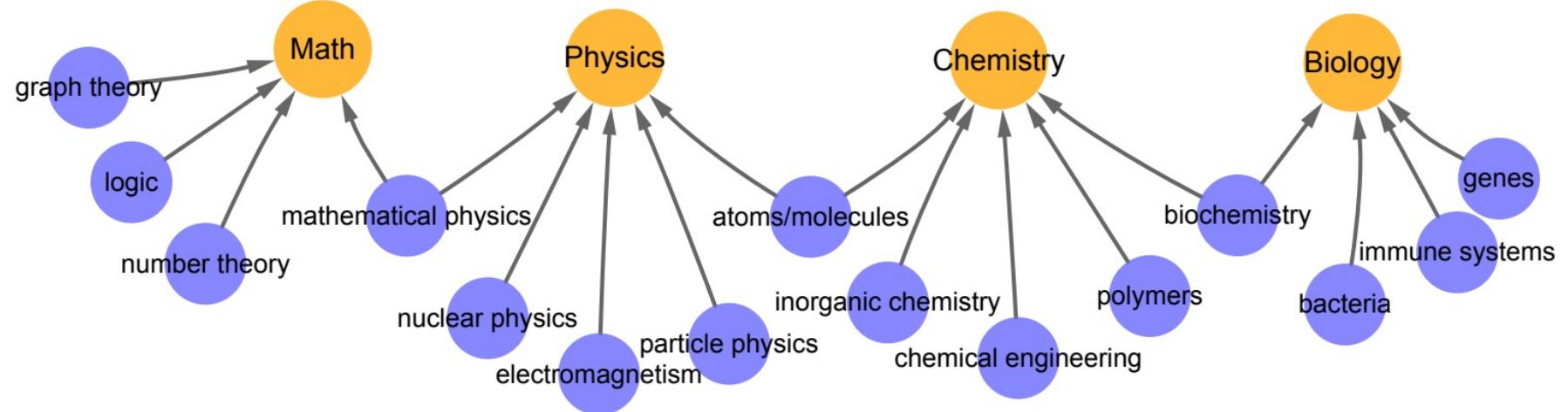


Latent Semantic Analysis (LSA)

documents



Clustering Words with Similar Meanings (Hierarchically)



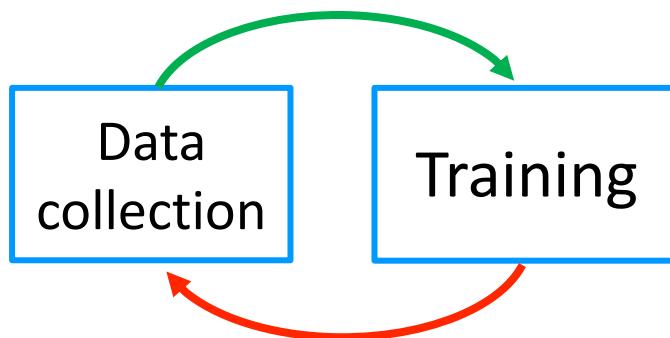
| | | | | | |
|-----|--|--|--|---|---|
| | logic deductive propositional semantics | graph subgraph bipartite vertex | boson massless particle higgs | polyester polypropylene resins epoxy | acids amino biosynthesis peptide |
| tag | <i>logic</i> | <i>graph theory</i> | <i>particle physics</i> | <i>polymer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

Reinforcement Learning

Reinforcement Learning

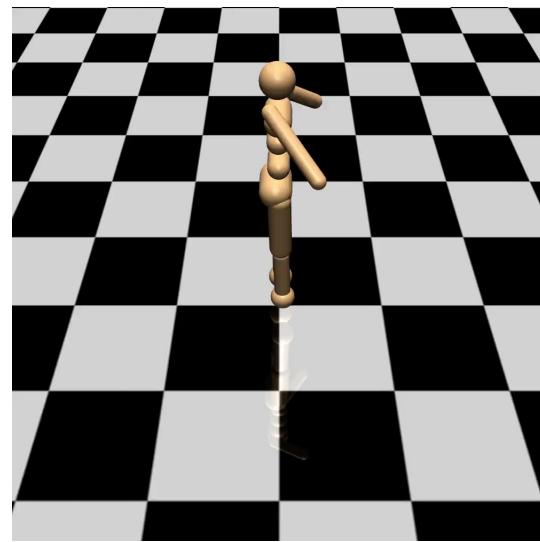
- The algorithm can collect data interactively

Try the strategy and collect feedbacks



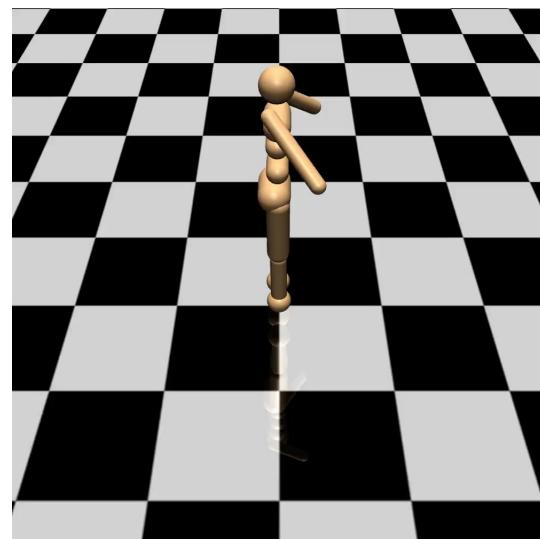
Improve the strategy based on the feedbacks

learning to walk to the right



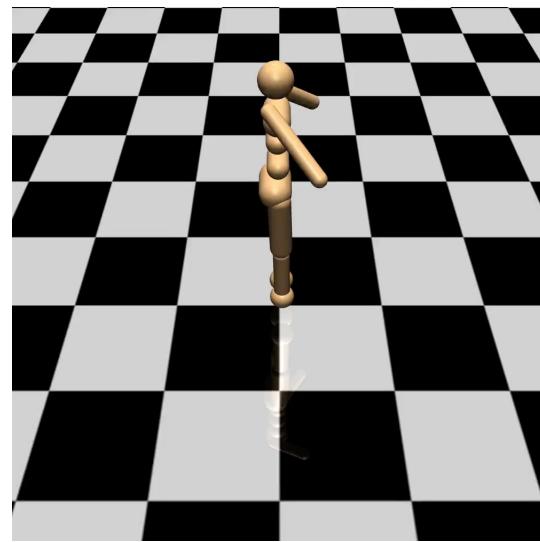
Iteration 10

learning to walk to the right



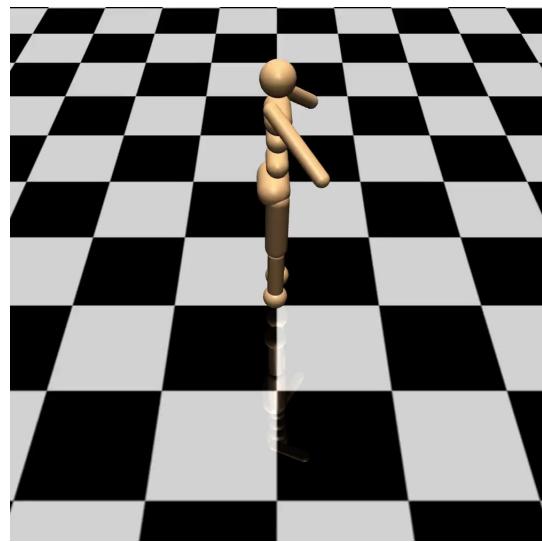
Iteration 20

learning to walk to the right



Iteration 80

learning to walk to the right

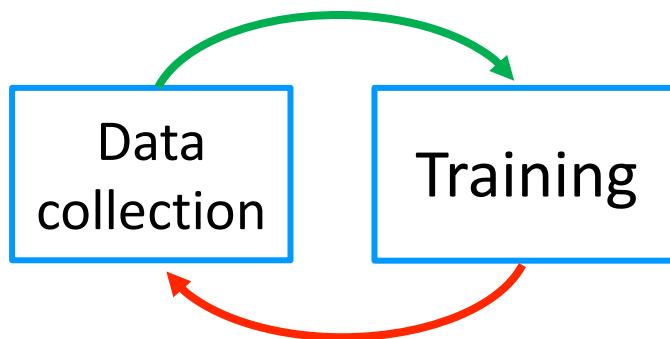


Iteration 210

Reinforcement Learning

- The algorithm can collect data interactively

Try the strategy and collect feedbacks

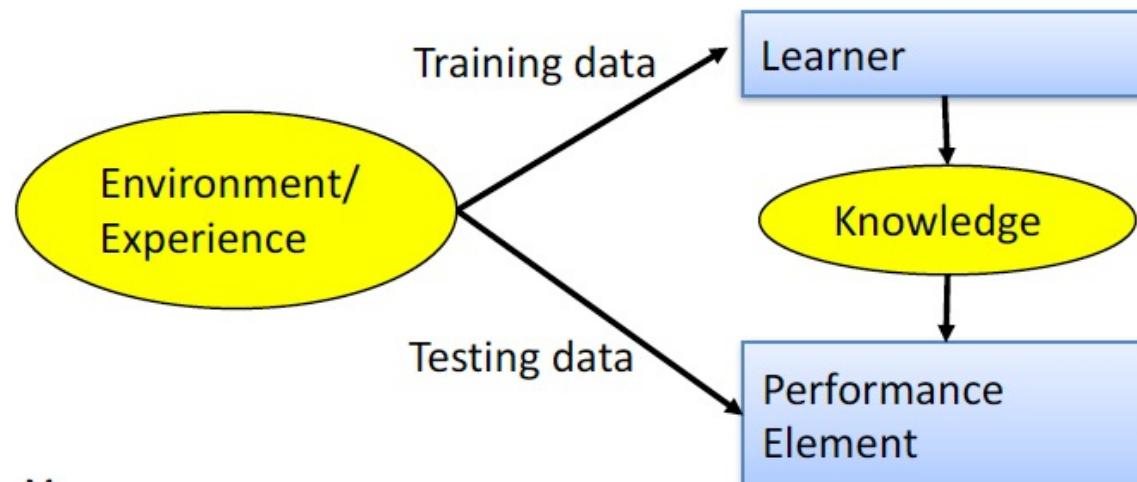


Improve the strategy based on the feedbacks

Framing a Learning Problem

Designing a Learning System

- Choose the training experience
- Choose exactly what is to be learned
 - i.e. the target function
- Choose how to represent the target function
- Choose a learning algorithm to infer the target function from the experience



Training vs. Test Distribution

- We generally assume that the training and test examples are **independently** drawn from the same overall distribution of data
- If examples are not independent, requires **collective classification**
- If test distribution is different, requires **transfer learning**

Machine Learning in a Nutshell

- Tens of thousands of machine learning algorithms
 - Hundreds new every year
- Every ML algorithm has three components:
 1. Representation
 2. Optimization
 3. Evaluation

Various Function Representations

- Numerical functions
 - Linear regression
 - Neural networks
 - Support vector machines
- Symbolic functions
 - Decision trees
 - Rules in propositional logic
 - Rules in first-order predicate logic
- Instance-based functions
 - Nearest-neighbor
 - Case-based
- Probabilistic Graphical Models
 - Naïve Bayes
 - Bayesian networks
 - Hidden-Markov Models (HMMs)
 - Probabilistic Context Free Grammars (PCFGs)
 - Markov networks

Search/Optimization Algorithms

➤ Gradient descent

- Perceptron
- Backpropagation

➤ Dynamic Programming

- MM Learning
- PCFGs Learning

➤ Divide and Conquer

- Decision tree induction
- Rule learning

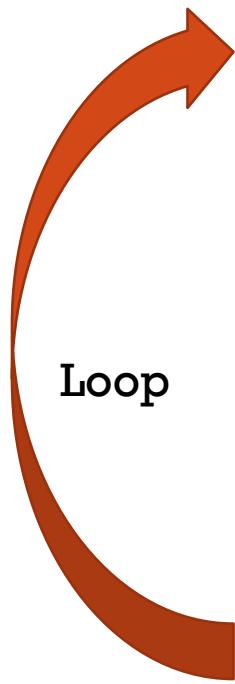
➤ Evolutionary Computation

- Genetic Algorithms (GAs)
- Genetic Programming (GP)
- Neuro-evolution

Evaluation

- Accuracy
- Precision and recall
- Squared error
- Likelihood
- Posterior probability
- Cost / Utility
- Margin
- Entropy
- K-L divergence
- etc.

Machine Learning in Practice



- Understand domain, prior knowledge, and goals
- Data integration, selection, cleaning, pre-processing, etc.
- Learn models
- Interpret results
- Consolidate and deploy discovered knowledge

Lessons Learned about Learning

- Learning can be viewed as using direct or indirect experience to approximate a chosen target function.
- Function approximation can be viewed as a search through a space of hypotheses (representations of functions) for one that best fits a set of training data.
- Different learning methods assume different hypothesis spaces (representation languages) and/or employ different search techniques.

Questions?

Thank you!