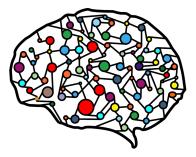
Lecture 14 – Taxonomy of Machine Learning & Clustering



DSC 40A, Fall 2022 @ UC San Diego Dr. Truong Son Hy, with help from many others

Agenda

- Review of feature transformation.
- Taxonomy of machine learning.
- Clustering.

How do we fit prediction rules that aren't linear in the parameters?

Suppose we want to fit the prediction rule

 $H(x) = w_0 e^{w_1 x}$

This is **not** linear in terms of w_0 and w_1 , so our results for linear regression don't apply.

Possible Solution: Try to apply a **transformation**.

Transformations

- Solution: Create a new prediction rule, T(x), with parameters b_0 and b_1 , where $T(x) = b_0 + b_1 x$.
 - ► This prediction rule is related to H(x) by the relationship $T(x) = \log H(x)$.
 - ▶ \vec{b} is related to \vec{w} by $b_0 = \log w_0$ and $b_1 = w_1$.

• Our new observation vector,
$$\vec{z}$$
, is $\begin{bmatrix} \log y_1 \\ \log y_2 \\ ... \\ \log y_n \end{bmatrix}$.

- T(x) = $b_0 + b_1 x$ is linear in its parameters, b_0 and b_1 .
- ▶ Use the solution to the normal equations to find \vec{b}^* , and the relationship between \vec{b} and \vec{w} to find \vec{w}^* .

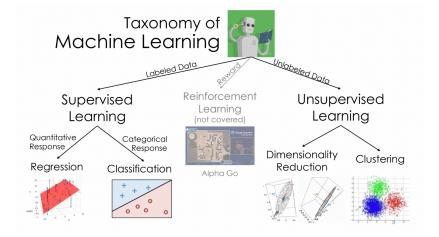
Non-linear prediction rules in general

- Sometimes, it's just not possible to transform a prediction rule to be linear in terms of some parameters.
- In those cases, you'd have to resort to other methods of finding the optimal parameters.
 - ► For example, with $H(x) = w_0 e^{w_1 x}$, we could use gradient descent or a similar method to minimize mean squared error, $R(w_0, w_1) = \frac{1}{n} \sum_{i=1}^{n} (y_i w_0 e^{w_1 x_i})^2$, and find w_0^*, w_1^* that way.
- Prediction rules that are linear in the parameters are much easier to work with.

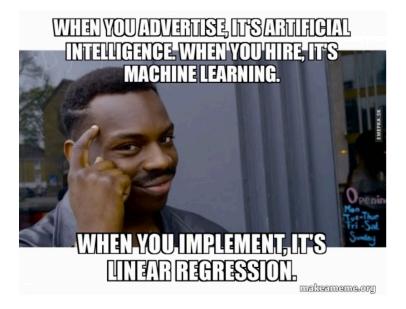
Taxonomy of machine learning

What is machine learning?

- One definition: Machine learning is about getting a computer to find patterns in data.
- Have we been doing machine learning in this class? Yes.
 Given a dataset containing salaries, predict what my future salary is going to be.
 - Given a dataset containing years of experience, GPAs, and salaries, predict what my future salary is going to be given my years of experience and GPA.

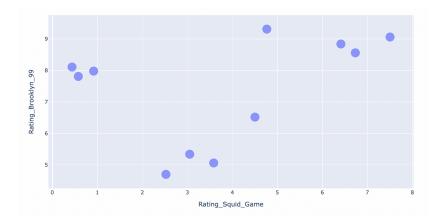


¹taken from Joseph Gonzalez @ UC Berkeley



Clustering

Question: how might we "cluster" these points into groups?



Problem statement: clustering

Goal: Given a list of *n* data points, stored as vectors in \mathbb{R}^d , $\vec{x}_1, \vec{x}_2, ..., \vec{x}_n$, and a positive integer *k*, **place the data points into** *k* **groups of nearby points**.

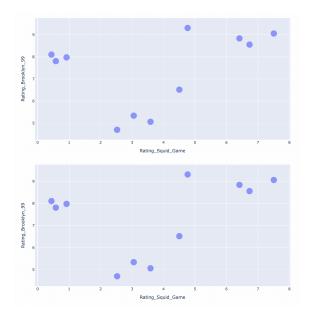
- These groups are called "clusters".
- ► Think about groups as **colors**.
 - i.e., the goal of clustering is to assign each point a color, such that points of the same color are close to one another.
- Note, unlike with regression, there is no "right answer" that we are trying to predict — there is no y!
 - Clustering is an unsupervised method.

How do we define a group?

One solution: pick k cluster centers, i.e. centroids:

 $\mu_1,\mu_2,...,\mu_k$

- ► These *k* centroids define the *k* groups.
- Each data point "belongs" to the group corresponding to the nearest centroid.
- This reduces our problem from being "find the best group for each data point" to being "find the best locations for the centroids".



How do we pick the centroids?

- Let's come up with an cost function, C, which describes how good a set of centroids is.
 - Cost functions are a generalization of empirical risk functions.
- One possible cost function:

 $C(\mu_1, \mu_2, ..., \mu_k)$ = total squared distance of each data point \vec{x}_i to its closest centroid μ_i

- This C has a special name, inertia.
- Lower values of C lead to "better" clusterings.
 - **Goal:** Find the centroids $\mu_1, \mu_2, ..., \mu_k$ that minimize C.

Discussion Question

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Suppose we have *n* data points, $\vec{x}_1, \vec{x}_2, ..., \vec{x}_n$, each of which are in \mathbb{R}^d .

Suppose we want to cluster our dataset into *k* clusters. How many ways can I assign points to clusters?

A)
$$d \cdot k$$

B) d^k
C) n^k
D) k^n
E) $n \cdot k$

Discussion Question

Suppose we have *n* data points, $\vec{x}_1, \vec{x}_2, ..., \vec{x}_n$, each of which are in \mathbb{R}^d .

Suppose we want to cluster our dataset into *k* clusters. How many ways can I assign points to clusters?

Answer: D

How do we minimize inertia?

- Problem: there are exponentially many possible clusterings. It would take too long to try them all.
- Another Problem: we can't use calculus or algebra to minimize C, since to calculate C we need to know which points are in which clusters.
- We need another solution.

k-Means Clustering, i.e. Lloyd's Algorithm

Here's an algorithm that attemps to minimize inertia:

- 1. Pick a value of *k* and randomly initialize *k* centroids.
- Keep the centroids fixed, and update the groups.
 Assign each point to the nearest centroid.
- 3. Keep the groups fixed, and update the centroids.
 Move each centroid to the center of its group.
- 4. Repeat steps 2 and 3 until the centroids stop changing.

Example

See the following site for an interactive visualization of k-Means Clustering: https://allisonhorst.com/k-means-clustering (shared by Suraj)

Summary, next time

Summary

- The process of creating new features is called feature engineering.
- As long as our prediction rule is linear in terms of its parameters $w_0, w_1, ..., w_d$, we can use the solution to the normal equations to find \vec{w}^* .
 - Sometimes it's possible to transform a prediction rule into one that is linear in its parameters.
- Linear regression is a form of supervised machine learning, while clustering is a form of unsupervised learning.
- Clustering aims to place data points into "groups" of points that are close to one another. k-means clustering is one method for finding clusters.

Next time

- How does k-means clustering attempt to minimize inertia?
- How do we choose good initial centroids?
- How do we choose the value of k, the number of clusters?