Modul 3

# ML Fundamental

Data Science Program

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## Agenda

**Session 1**: Basic Concept of Machine Learning

**Session 2**: Supervised ML & Use Cases

**Session 3**: Unsupervised ML & Use Cases

**Session 4**: Recap

**Assignment**

## Objective

Understand Machine Learning concept

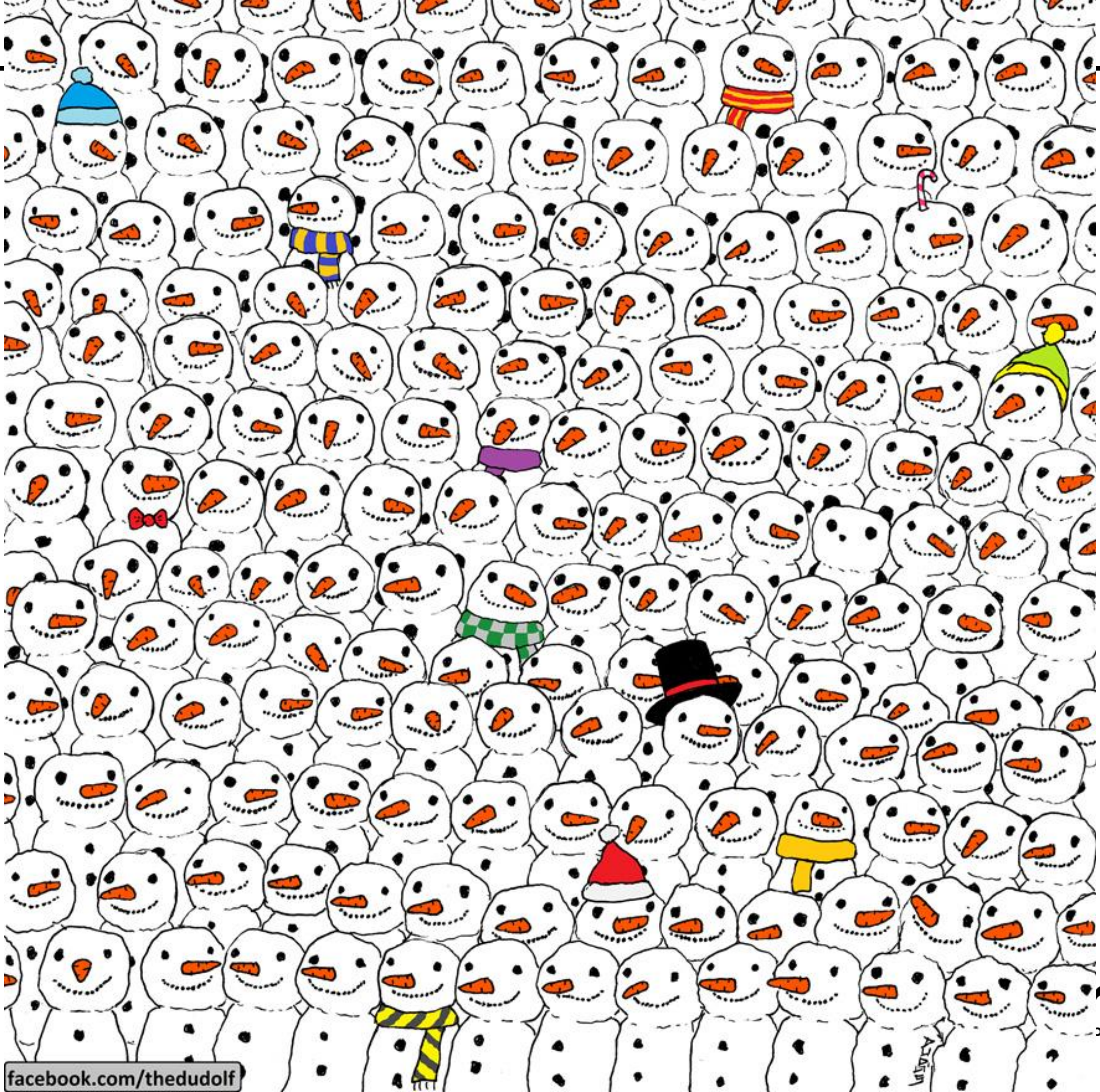
Understand concept of Supervised ML

Apply supervised ML to dataset

Understand concept of Unsupervised ML

Apply unsupervised ML to dataset

## Panda??



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## Cat??

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## Why?

- Human is really good at **detecting pattern**. However, we know the concept of **exhausting**.
- **Computer** is not born with our privileges. However, they can **work endlessly** 24/7, 7days a week, 30days per month, and 365 days to catch up with us.
- We can **leverage** this computer **advantages** to help us solve complex problems, which we might tired or unable to do.

## Which one is which??

## Which one is which??

## Which one is which??

- We don’t only want to **describe** data.
- We want to **PREDICT** new data.

## Machine Learning

- Able to incorporate **cumulative information,** in order to **learn** pattern form the data to predict new unseen data.
- It can **adapt** if exposed to **new data**, while human might have **subjective** bias on the decision.

## Idea

- Training Set: The available dataset, usually labeled. This dataset is used to train our model.

- Test Set: Dataset independent from training set and can not be used to train model. This dataset can be unlabeled. When the labels are available, we can use it to evaluate our model.

## Features

- To build our model, we need to **measure** the objects. Each of this measurement is what we call **feature**.
- Each object then is **described** by its features (collection of feature). This is what we called **features vector** approach.

Color

Weight

Age

Smell

$$\xrightarrow{\qquad\qquad} \quad \boldsymbol{X} = [\, x_1, x_2, x_3 \ldots\, x_n \,]$$

## Datasets

Feature

| Object | Color | Weight | Smell | Label |
|---|---|---|---|---|
| Apple 1 | 35 | 15 | 3 | 1 |
| Apple 2 | 37 | 13 | 2 | 1 |
| Pear 1 | 45 | 9 | 6 | 2 |
| Pear 2 | 46 | 10 | 5 | 2 |

measurement

Feature Vector

Unlabeled object

Labeled object

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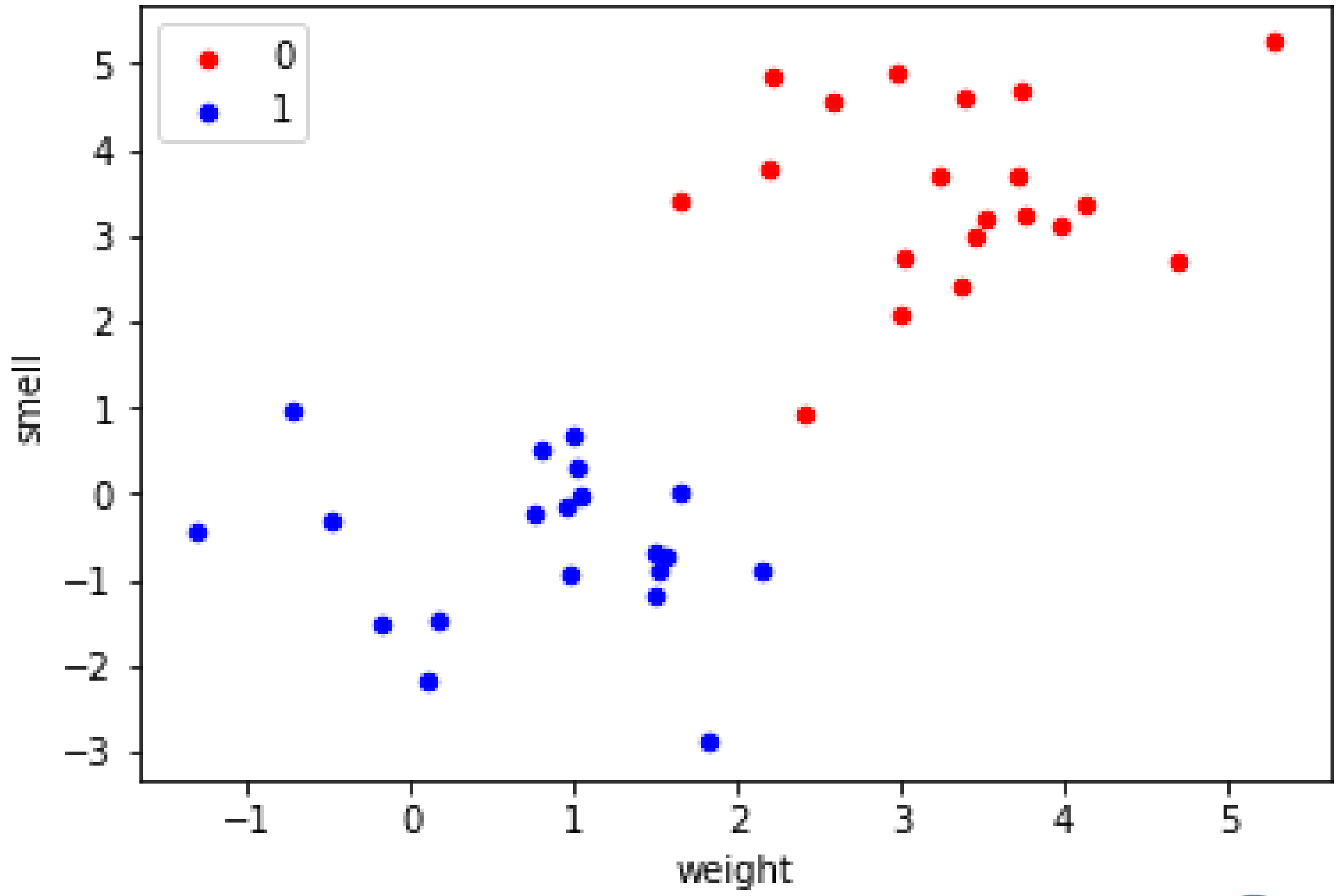
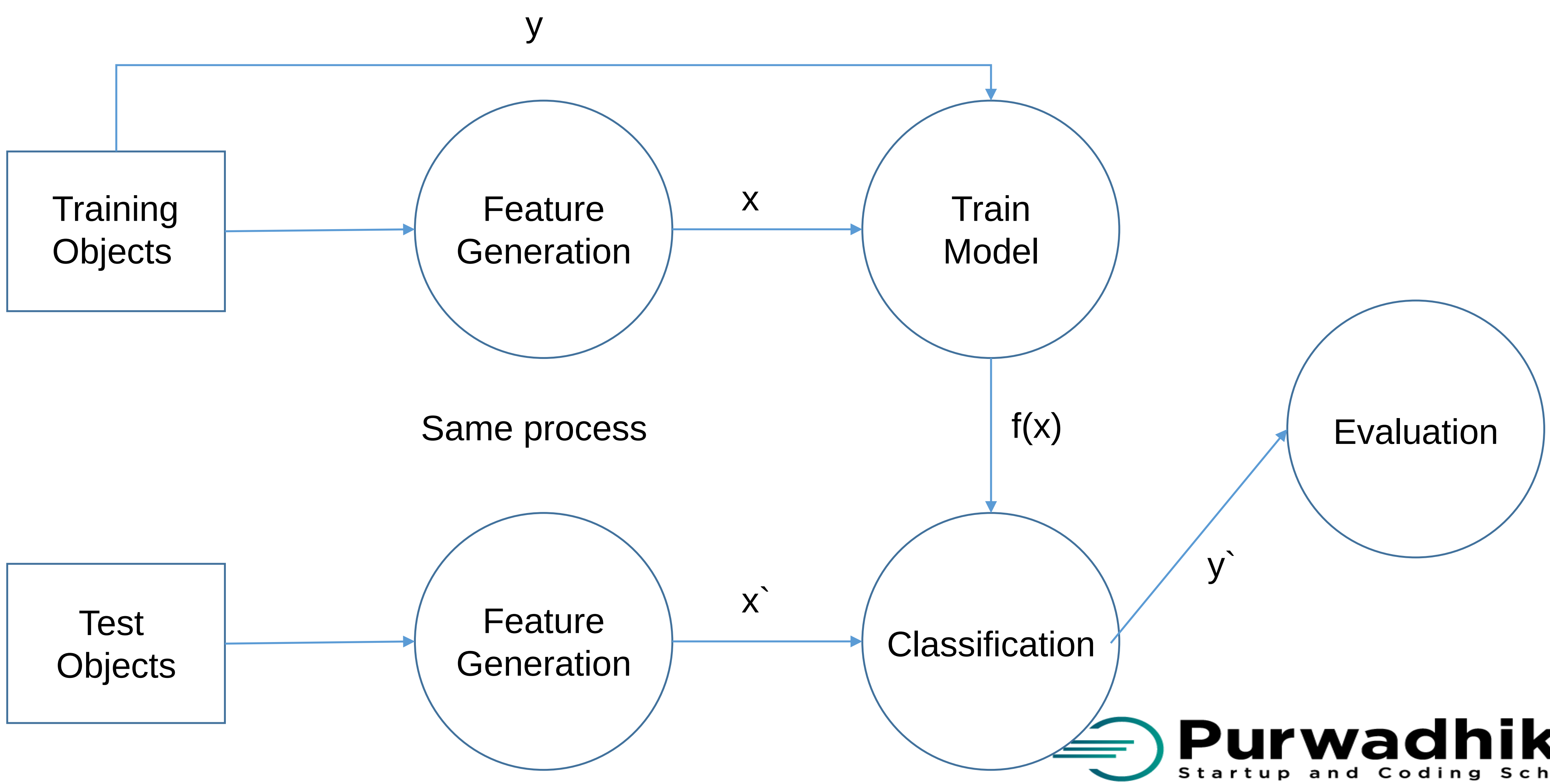
## Other Approaches

- Feature vectors approach is **not the only** approach. There are others such as Dissimilarity and Graph. However, we only discuss this approach because it is well developed.

## To give you idea



# Simple Pipeline



## Feature Generation

- We already know that in order to make a model, we need measurements (features). Now our **goal** to make a model is to have a really good one, having a **good accuracy.**
- In the world that data is hard to obtained. Should we just do other measurements to **generate more features** to increase the accuracy?

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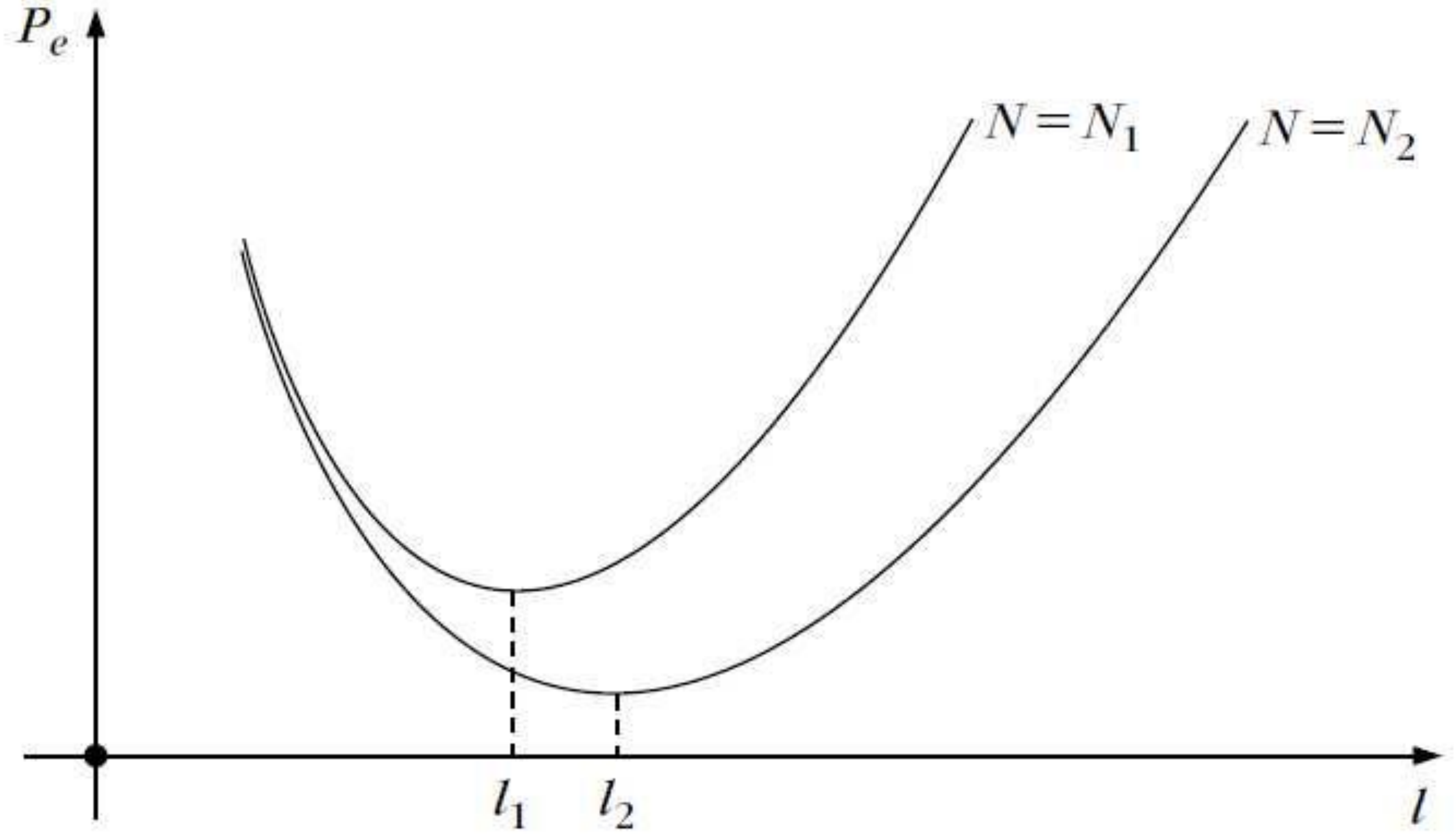
## Curse of Dimensionality



## Dimensionality Reduction

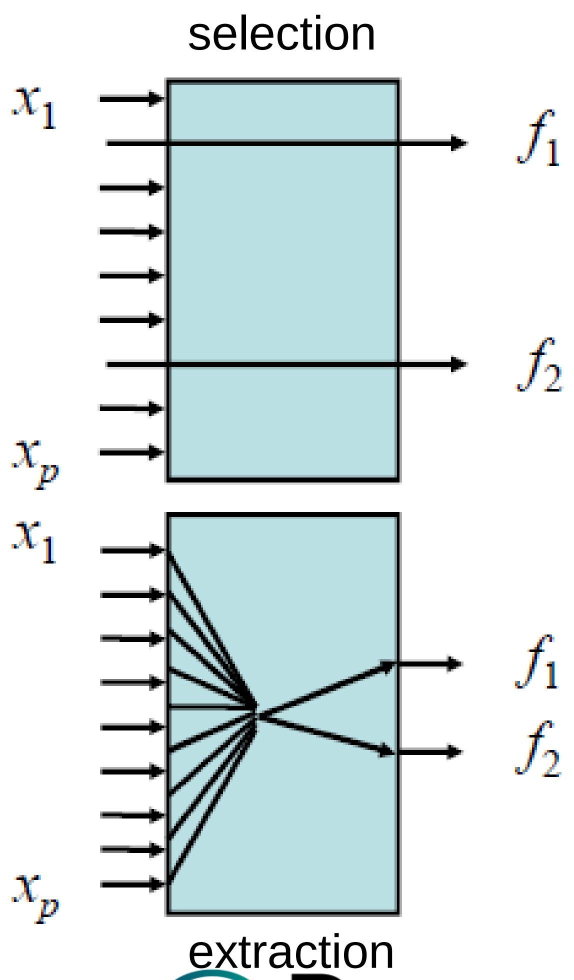
- Benefit:
  - Fewer features means **faster** to obtain result.
  - Get the **important** features
  - Avoid curse of dimensionality

- How:
  - Feature Selection
  - Feature Extraction

## Selection vs Extraction

- Feature Selection:
- Select *d* best features out of *p* features.

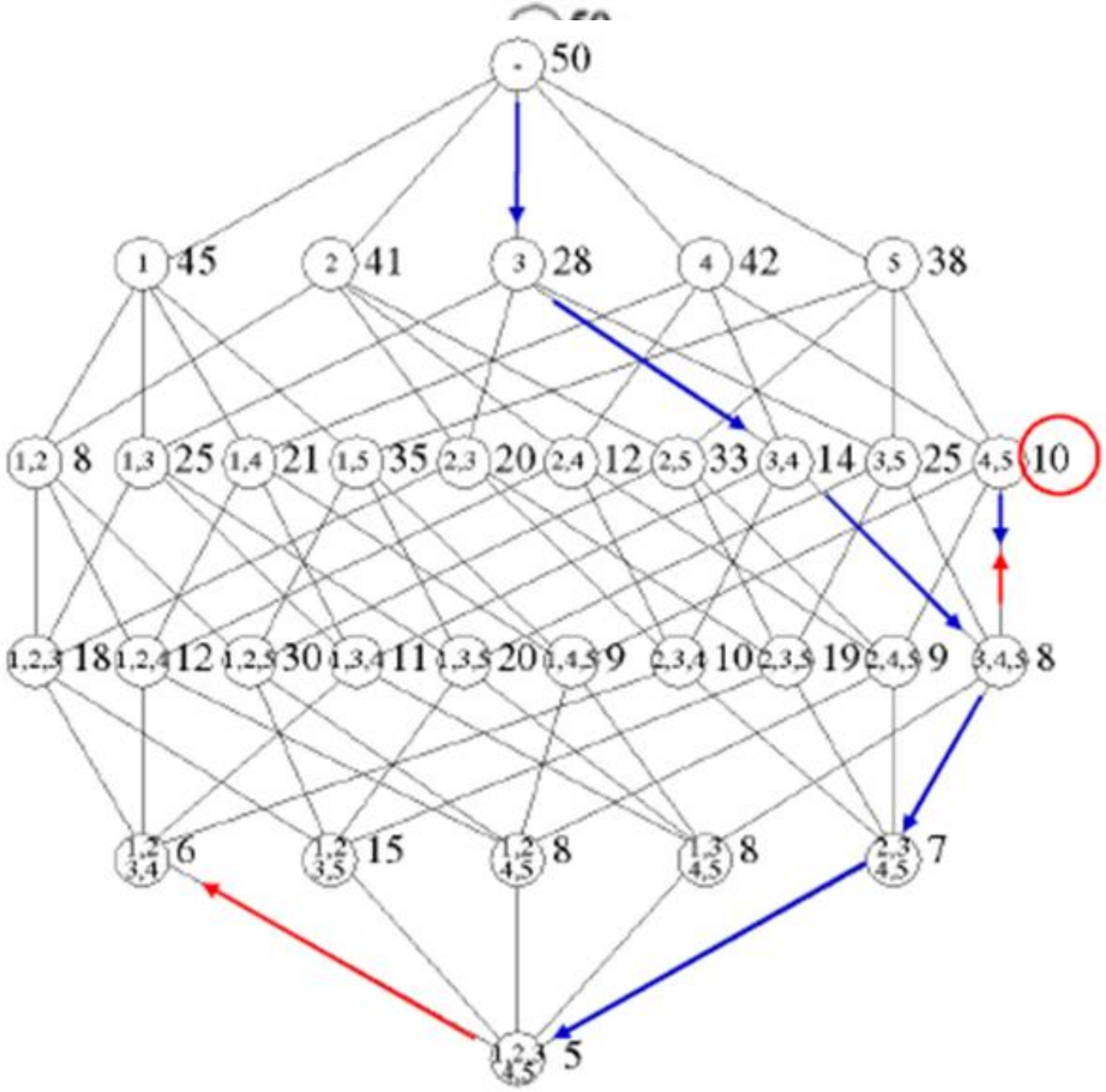
- Feature Extraction:
- Map *d* features from *p* features.



## Feature Selection

- What we need:
  - Criterion function: to measure between distributions.
  - Search algorithm: to pick features.
- Criterion example: Probabilistic, Scatter matrices, Mahalanobis distance.
- Search Algorithm example:
  - Forward Selection
  - Backward Selection
  - Floating Selection

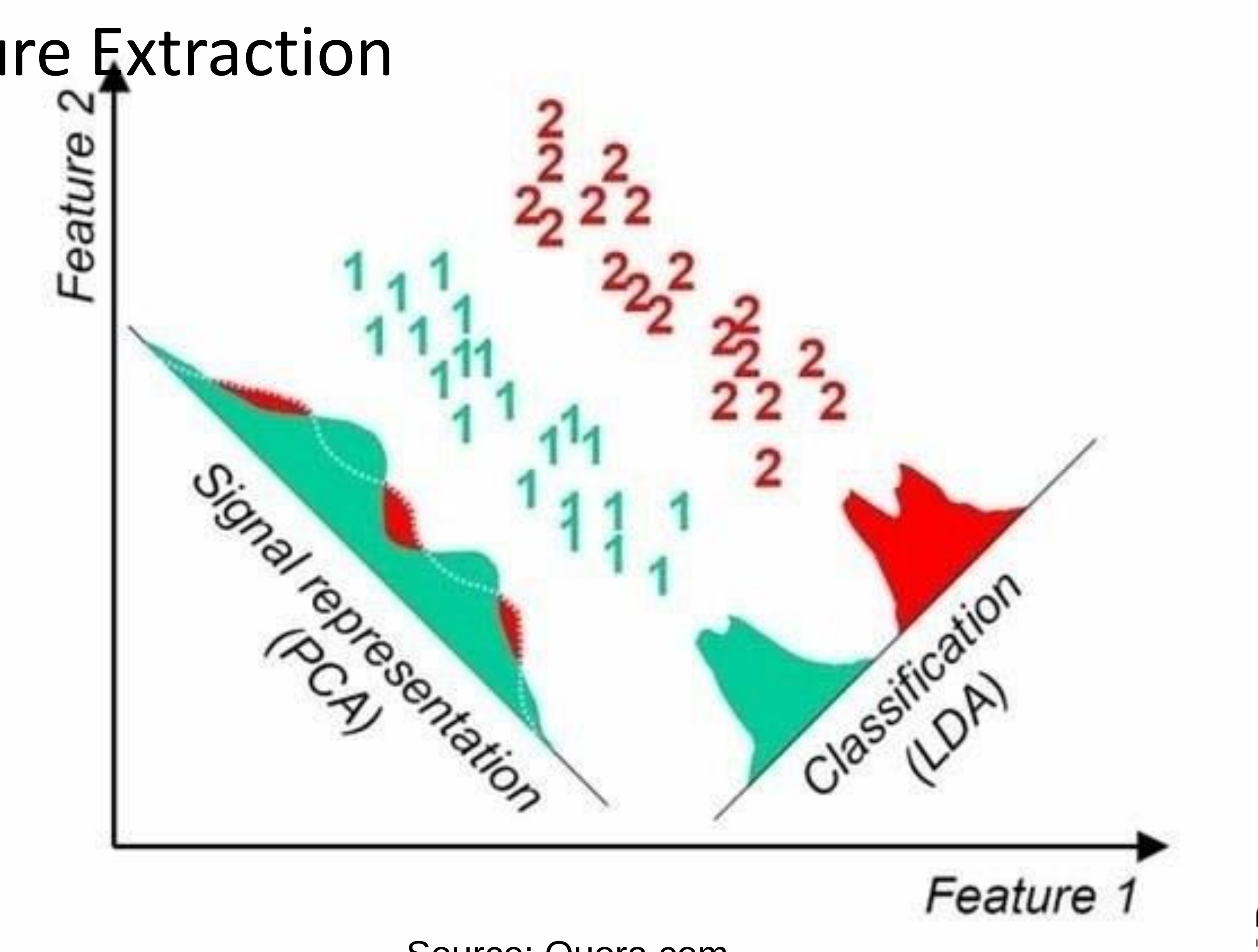
## Feature Selection



## Feature Extraction

- We will discuss two of the main feature extraction techniques commonly used: **PCA** and **LDA**.
- PCA (Principal Component Analysis) retains **as much variation as** possible for the data. It doesn’t necessarily retain class separation.
- LDA (Linear Discriminant Analysis) make sure that the **classes** are **maximally separated**.
- For the sake of our time, we only discuss PCA as it is the one that widely used.

## Feature Extraction



Source: Quora.com

## PCA

- Goals: Obtain **principal components** that explain variation of data as much as possible. Principal components are uncorrelated variables that is the result of mapping of the original (correlate) variables.

- How?
  - Obtain eigenvalues and eigenvectors.
  - Sort eigenvalues from the highest to lowest.
  - The highest eigenvalues determine the first principal component, and its eigenvector determine the direction.

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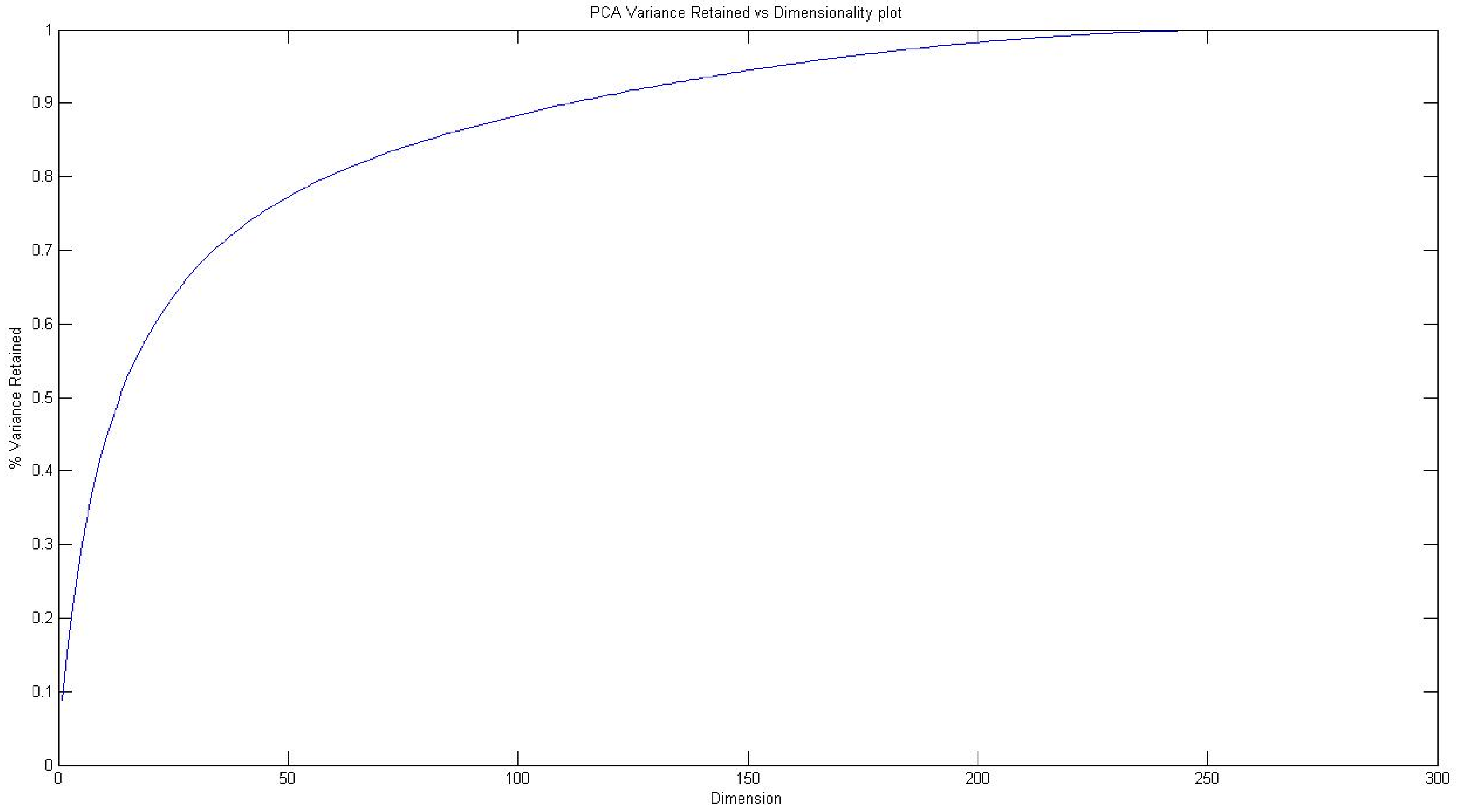
## PCA



PCA Variance Retained vs Dimensionality plot
% Variance Retained
Dimension
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
50
100
150
200
250
300

## Training Model

- Supervised Learning: When you have the data and also the labels to indicate classes.

- Unsupervised Learning: When you only have the data, but lack of labels and you can’t determine which one belong to which class.

- ✓ Supervised Learning
- ✓ Parametric vs Non-parametric
- ✓ Linear vs Nonlinear
- ✓ Use Cases

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## Supervised

| Object | Color | Weight | Smell | Label |
|---|---|---|---|---|
| Apple 1 | 35 | 15 | 3 | 1 |
| Apple 2 | 37 | 13 | 2 | 1 |
| Pear 1 | 45 | 9 | 6 | 2 |
| Pear 2 | 46 | 10 | 5 | 2 |

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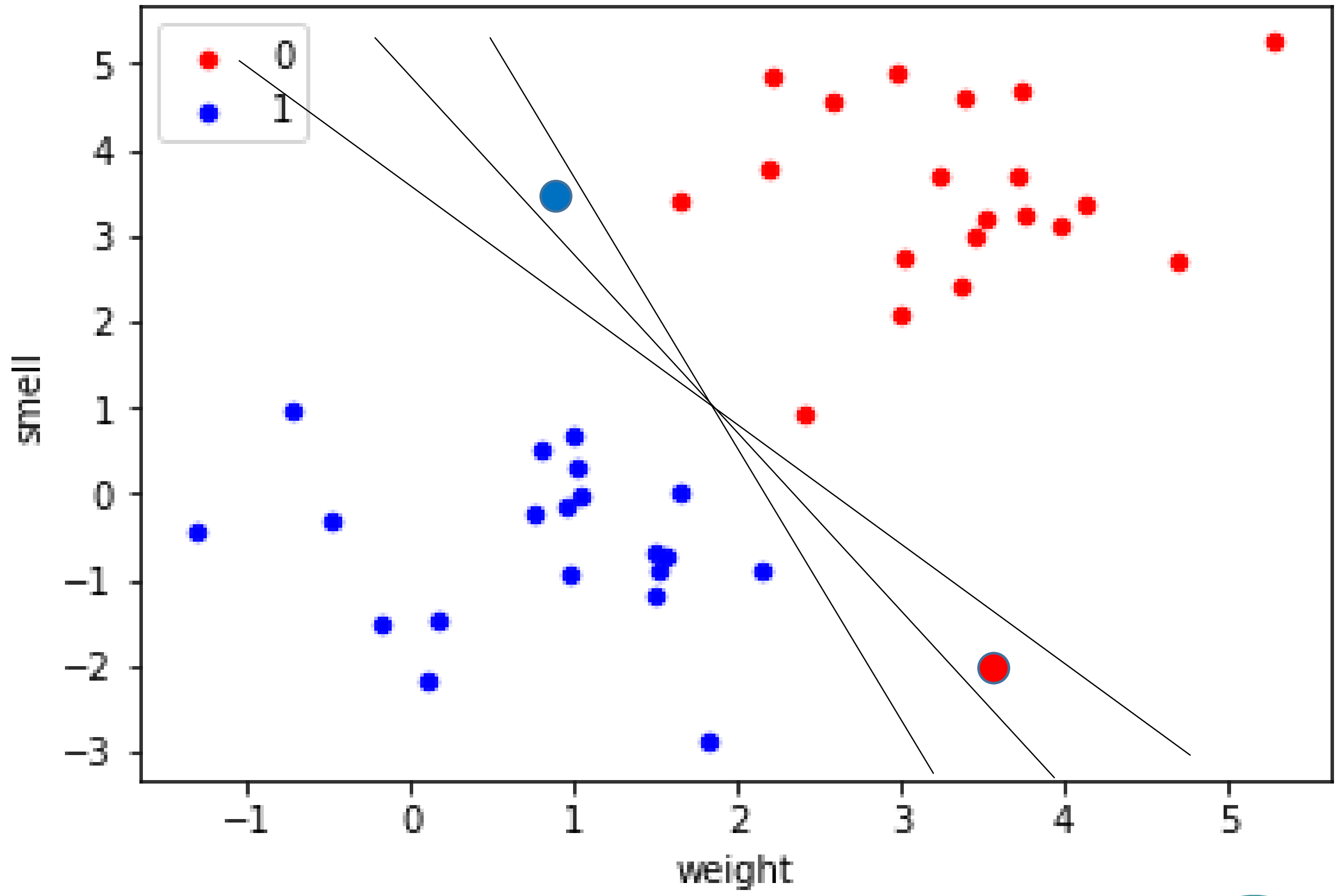
## Supervised

- We have the **privileges** of having data that is labeled. According to experiences, it is some effort to label data from real life case.

- **Assign** each object to a **class**, we splits feature space in to separate region for each class.

- Splitting feature space region means that we have to create **decision boundaries**.

## Supervised



## Supervised

- Parametric: known distribution and we can estimate parameter
- Example: Nearest Mean Classifier (NMC), etc.

- Non-parametric: unknown distribution
- Example: k-Nearest Neighbor, Parzen Density Estimation, etc.

## Nearest Mean Classifier

- Assume one knows the distribution (let say Gaussian) we can estimate the **mean** and **variance** of each classes.

- The decision boundary then can be inferred: (two class problem)

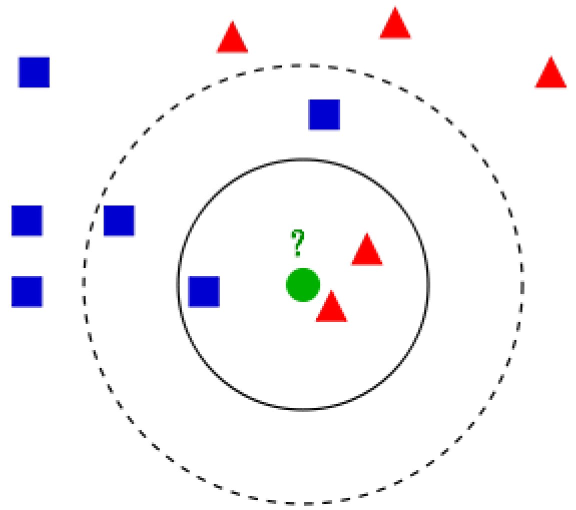
$$f(x) = w^T x + w_0$$

$$\boldsymbol{w} = \hat{\mu}_2 - \hat{\mu}_1$$

$$w_0 = \frac{1}{2}\hat{\mu}_2^T \hat{\mu}_2 - \frac{1}{2}\hat{\mu}_1^T \hat{\mu}_1 + \sigma^2 \log \frac{p(\omega_1)}{p(\omega_2)}$$

## k-Nearest Neighbor

- Estimation density is **hard**. Instead we can use the approach of picking *k*, user-defined constant, and label the object based on the **most frequent** class **member** among k nearest training object.
- On two class classification problem, the k-value should be **odd** to avoid tie. It can be optimized using several techniques that we won’t discuss here.



## Supervised

- Linear: decision boundary is linear
- Example: NMC, Perceptron, SVM, etc.

- Non-linear: decision boundary is non-linear
- Example: SVM polynomial kernel, Quadratic classifier, etc.

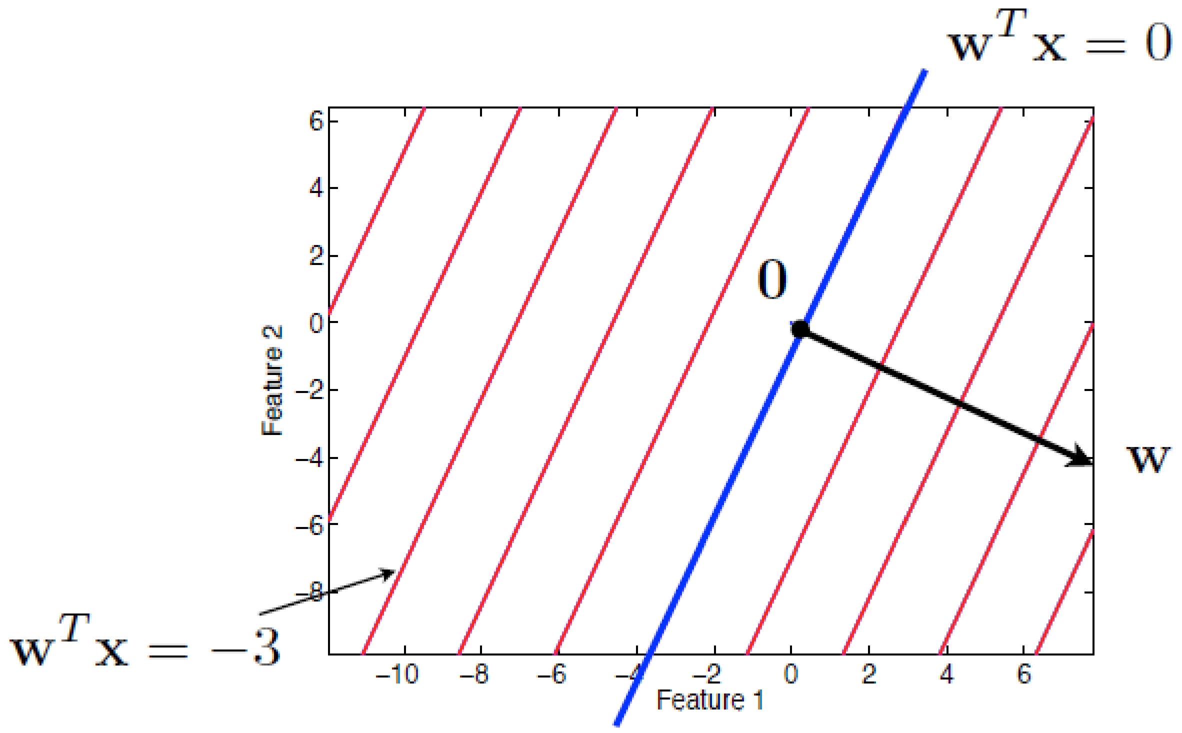
## Linear Classifier

- Assume our decision boundary is $g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0 = 0$

$$\text{classify } \mathbf{x} \text{ to } \begin{cases} \omega_1 & \text{if } \mathbf{w}^T\mathbf{x} + w_0 \geq 0 \\ \omega_2 & \text{if } \mathbf{w}^T\mathbf{x} + w_0 < 0 \end{cases}$$

What do we mean by $w^Tx$? What is $w_0$?

## Linear Classifier



How do we find **w** & $w_0$?

## Perceptron

$$\begin{aligned} \mathbf{w}^{*T}\mathbf{x} > 0 \quad \forall \mathbf{x} \in \omega_1 \quad (y = +1) \\ \mathbf{w}^{*T}\mathbf{x} < 0 \quad \forall \mathbf{x} \in \omega_2 \quad (y = -1) \end{aligned}$$

$$J(\mathbf{w}) = \sum_{\text{misclassified}\,\mathbf{x}_i} -y_i \mathbf{w}^T \mathbf{x}_i$$

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \rho_t \sum_{\text{misclassified}\,\mathbf{x}_i} y_i \mathbf{x}_i$$

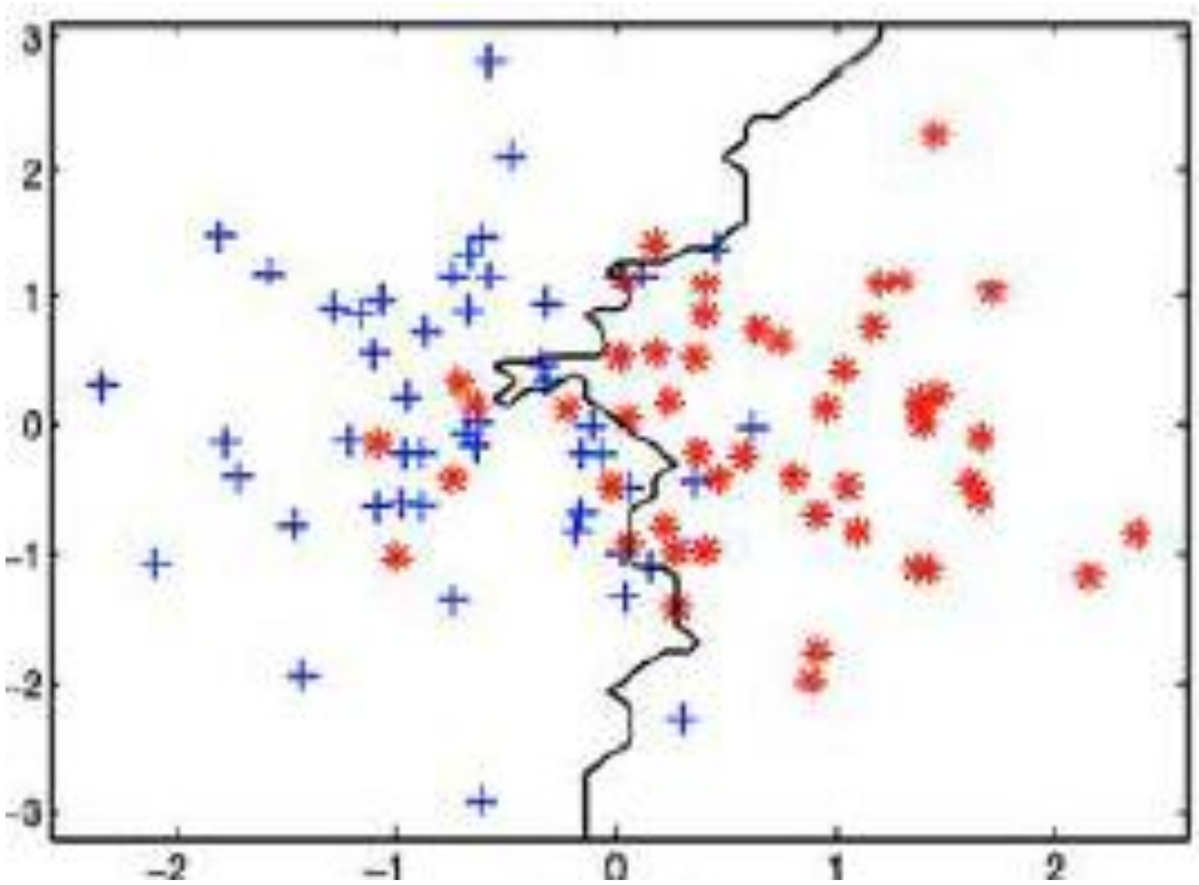
## Perceptron

- How perceptron algorithm works?
  - Define initial **w**
  - Define learning rate ρ for gradient descent.
  - Determine the **misclassified** objects
  - Calculate the next weight
  - Iterate until convergence

## Non-Linear Classifier

- Why non-linear? Many problems can’t be solved by a mere linear classifier. Non-linear classifier introduce flexibility but also complexity.
- I won’t discuss here the normal non-linear classifier such as quadratic classifier, 2-layer Perceptron (NN) and such. However, we can do some trick to make existing linear classifiers become non-linear.
- You can choose to incorporate **kernel** to many classifiers, for example SVM (Support Vector Machine). For example polynomial kernel or gaussian kernel.

## Non-Linear Classifier



## Supervised Use Case

- For its new fintech company, Astra want to have a model that can predict whether a person will be able to return the lending money on time or not. Astra can have the data source from previous motor industry credit.

- Astra wants to boost its car division sales by using targeted sales / advertisement based on profile. You can create a model to predict which model suitable for which user profile by using past sales.

- ✓ Unsupervised Learning
- ✓ K-Means Clustering

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## Unsupervised Classifier

| Object | Object | Color | Color | Weight | Weight | Smell | Smell | Label |
|---|---|---|---|---|---|---|---|---|
| Apple 1 | Object 1 | 35 | 35 | 15 | 15 | 3 | 3 | 1 |
| Apple 2 | Object 2 | 37 | 37 | 13 | 13 | 2 | 2 | 1 |
| Pear 1 | Object 3 | 45 | 45 | 9 | 9 | 6 | 6 | 2 |
| Pear 2 | Object 4 | 46 | 46 | 10 | 10 | 5 | 5 | 2 |

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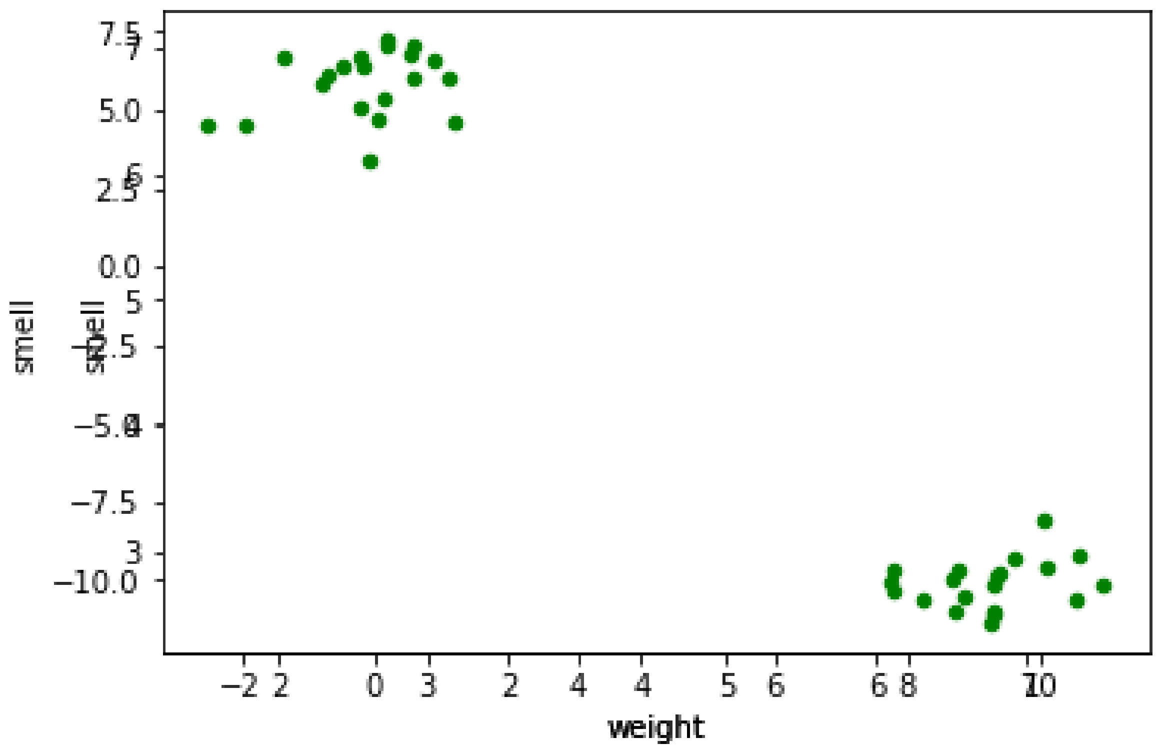
# Unsupervised Classifier



## Unsupervised

- We **don’t have** the **label** of data. Either we start labelling it now, or we should find other approaches.
- Sometimes, labeling the data itself **can be tricky**. It can introduce personal bias, takes a lot of time, etc.
- Or we can try **clustering**. Approach on grouping data that are closer together. But how we define **close together** or **far apart**?
- We can use (dis)similarity measure to define it.

## k-Means Clustering

- Goals: cluster data into **k** cluster.
- Each cluster is represented by **prototypes**.
- Use **dissimilarity** (squared Euclidean distance) of prototypes to group data.
- **Start with random** prototypes and **iteratively** choose others until convergence. (There are techniques to choose better prototypes)
- Produce **local maxima** depend on initial prototypes.

## k-Means Clustering

- How to do:

  1. Choose the desired number of cluster **k**
  2. Choose initial prototypes
  3. For each objects, compute distance to prototypes to label the data.
  4. Compute cluster means as the new prototypes.
  5. Repeat step 3 & 4 until there is no change in prototypes.

## Clustering

•Important Questions:

- How to determine the number of clusters? Is it arbitrary?
- How to evaluate the clustering result?

•Please take these questions as a consideration if you use clustering algorithm and do some homework on how to do it ☺

## Unsupervised Use Case

- For its new maintenance company, Astra want to have a model that can predict whether a car is on good condition or not based on images. Astra does not have this kind of data as they have only the images. So what they can do is cluster images that *similar* to determine group of condition.

- Astra wants to detect customer behavior but do not know what are differences between behavior so they can determine the labels. What you can do is group people that *similar* together and go from there.

✓ Recap

## Recap

- We now know about the basic of machine learning, on constructing dataset, the simple pipeline, and how to acquire the *best* features.
- We understand the differences between supervised and unsupervised learning.
- We have knowledge on the differences between parametric and non-parametric, as well as between linear and non-linear for supervised learning.
- We know how to cope with unlabeled data, especially on training clustering model using k-means clustering.

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