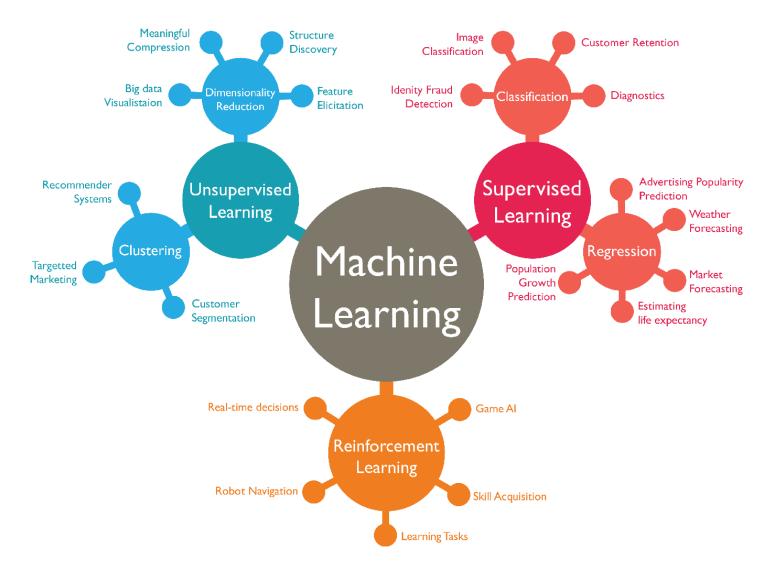
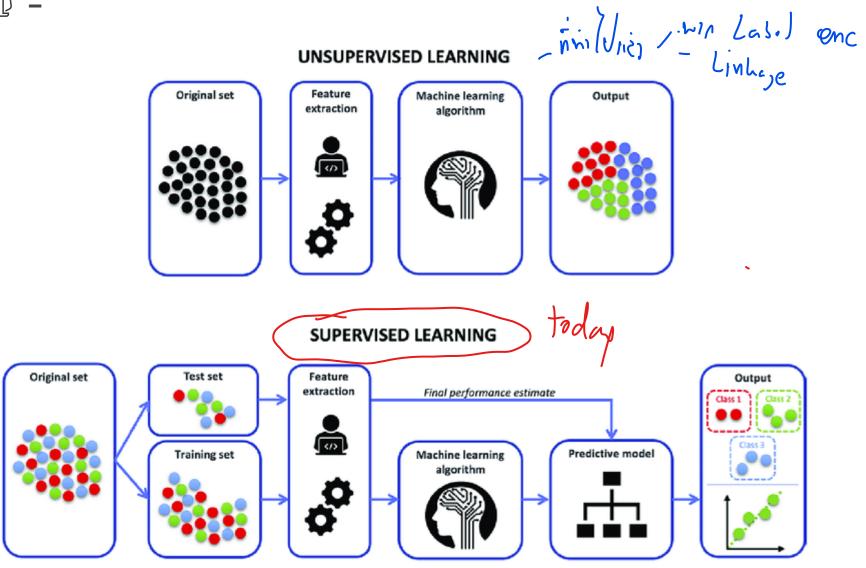
Today Focus



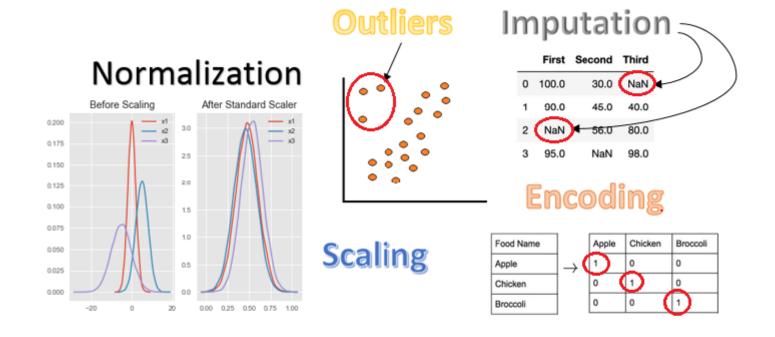








Today Focus

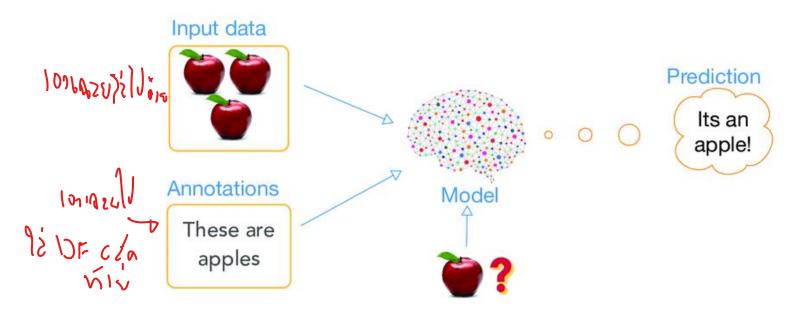


Data Preprocessing

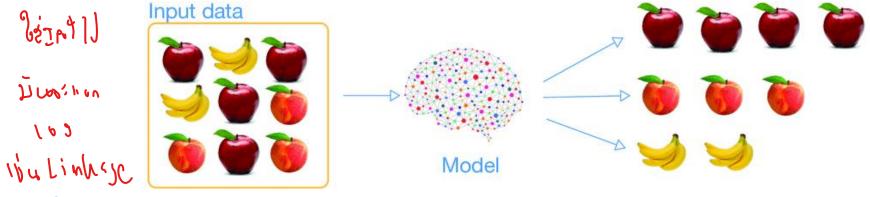


Classified by Type

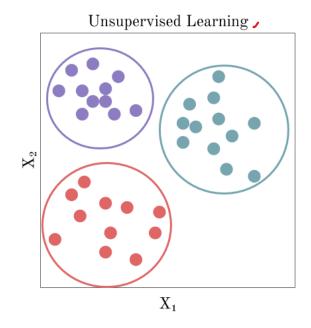
supervised learning

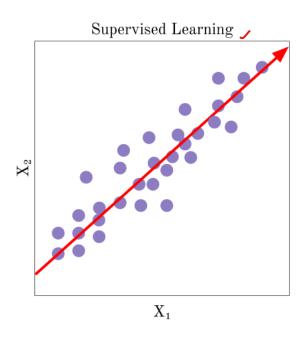


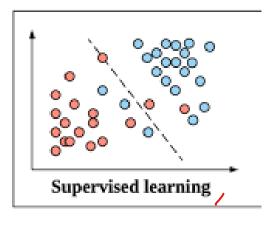
unsupervised learning



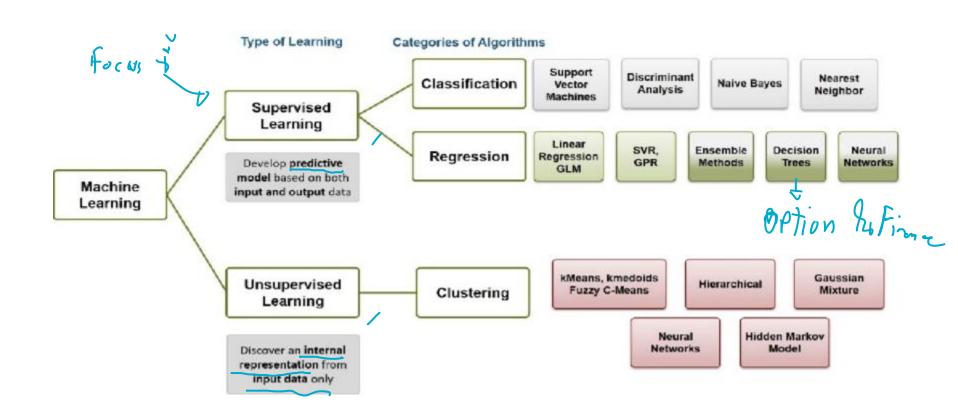








Regression & Classification



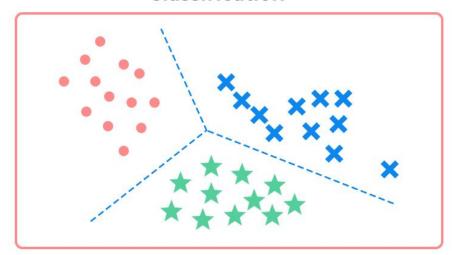






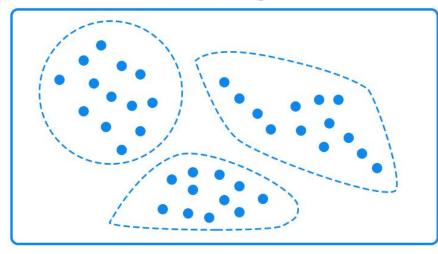
Supervised vs. Unsupervised Learning

Classification



Supervised learning

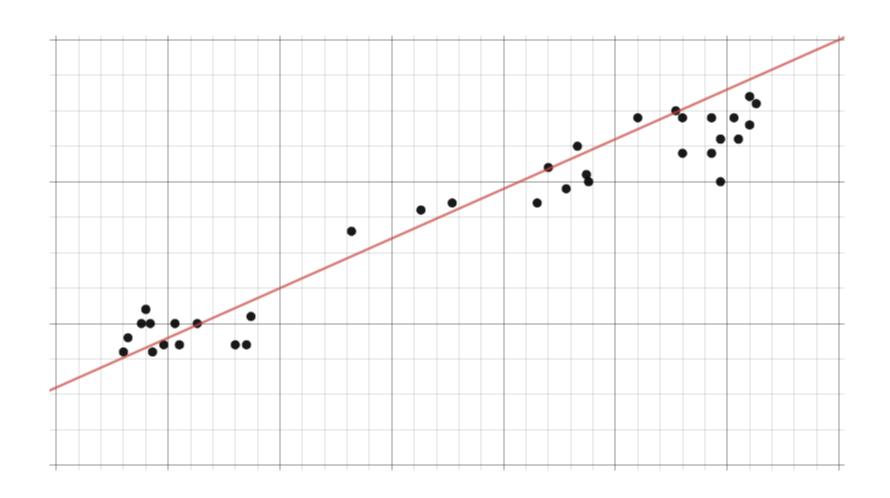
Clustering



Unsupervised learning



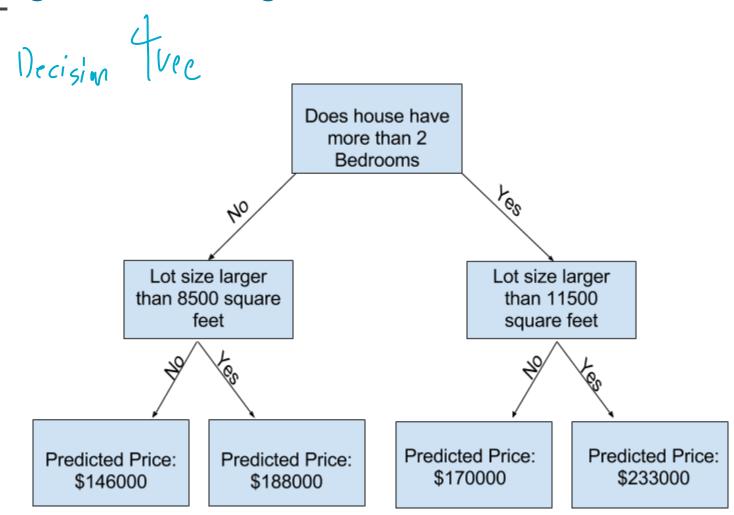
Regression Learning Model







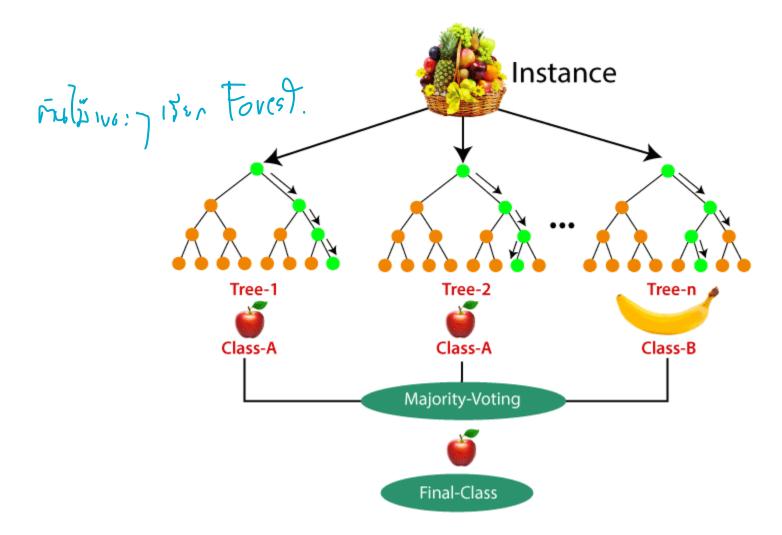
Regression Learning Model







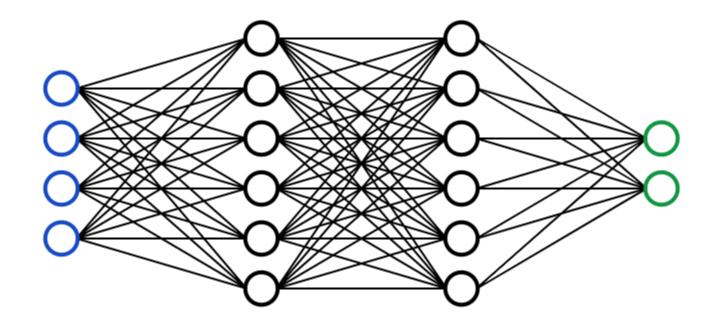
Regression Learning Model







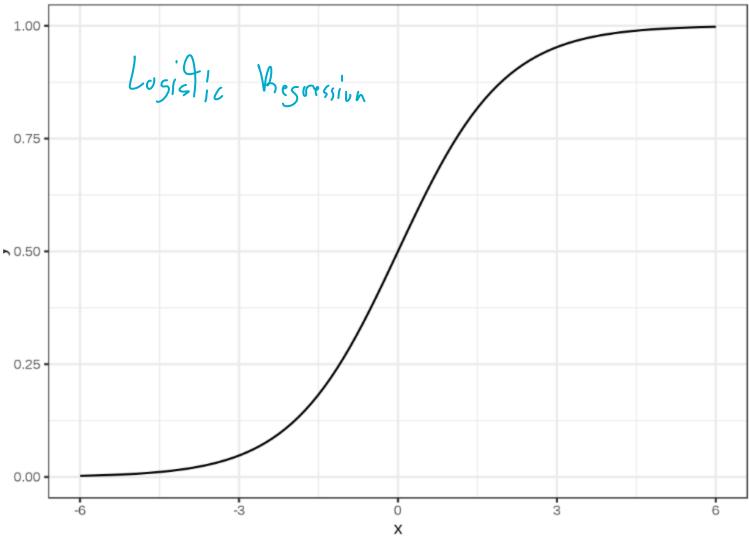
Neuval Wetorh





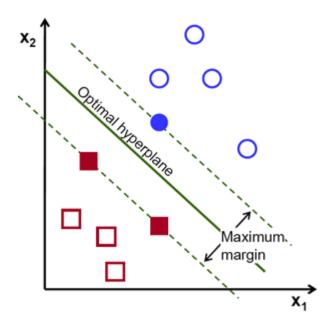








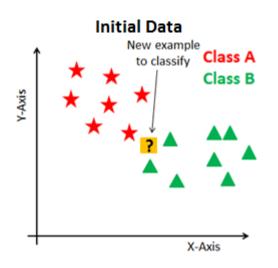


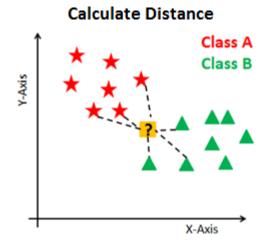




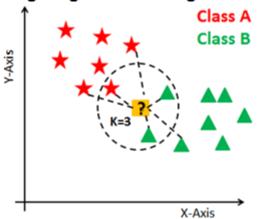


KNN
K-Neuret
Nelshors





Finding Neighbors & Voting for Labels







Naive Bayes



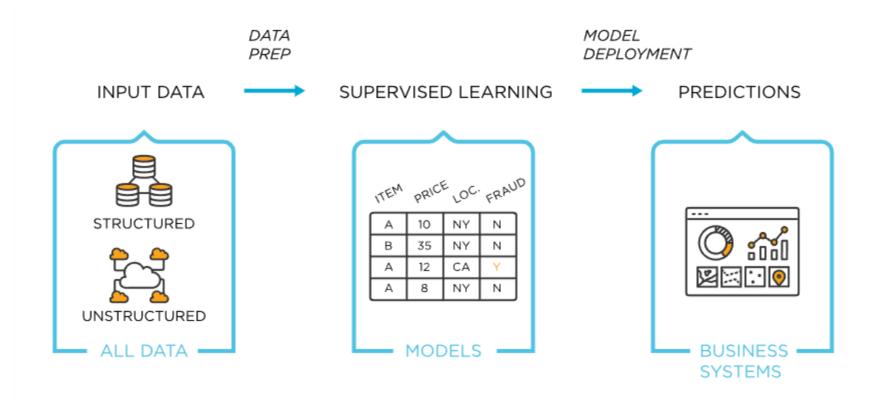
$$P(y|X) = \frac{P(X|y) * P(y)}{P(X)}$$

"What is the probability of y given X?"

$$P(y|X) \propto P(X|y) * P(y)$$

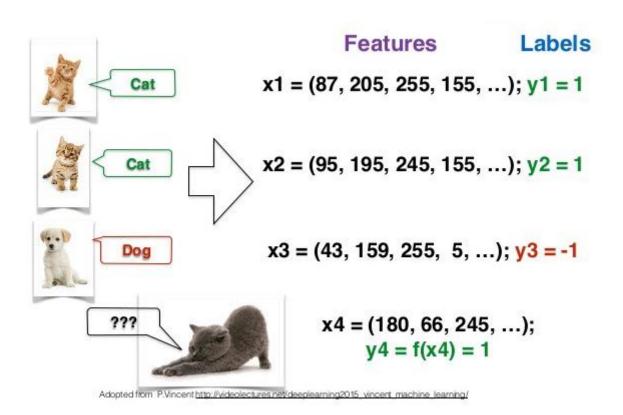
The goal is to find the class y with the maximum proportional probability.

Supervised Learning

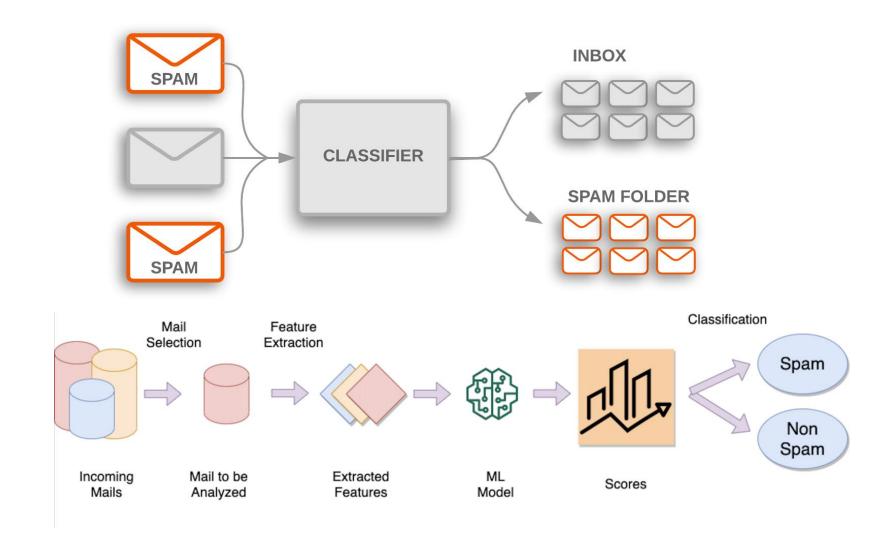




Supervised Learning



Complete picture







- 1. Prepare & Transform Data
 - 1. Normalizing/standardizing
 - 2. Label Encoding
- 2. Modeling
- 3. Evaluating





- 1. Prepare & Transform Data
 - 1. Outlier
 - 2. Feature Scaling
 - 1. Normalization
 - 2. Standardization
 - 3. Label encoding/ One hot encoding



ML Process Simple

- 1. Prepare & Transform Data
- 2. Model
- 3. Rumble!!
- 4. Backtest



Example





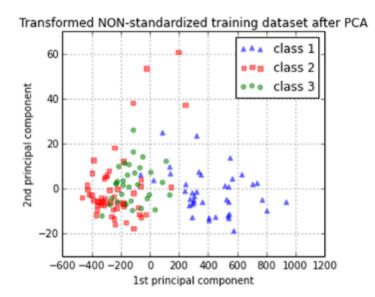
- 1. Prepare & Transform Data
 - 1. Outlier
 - 2. Feature Scaling
 - 1. Normalization
 - 2. Standardization
 - 3. Label encoding/ One hot encoding
- 2. Split Train/ Test Data

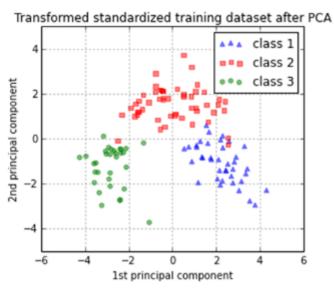




Is feature scaling that matter??

standandized in 1100 sin 8

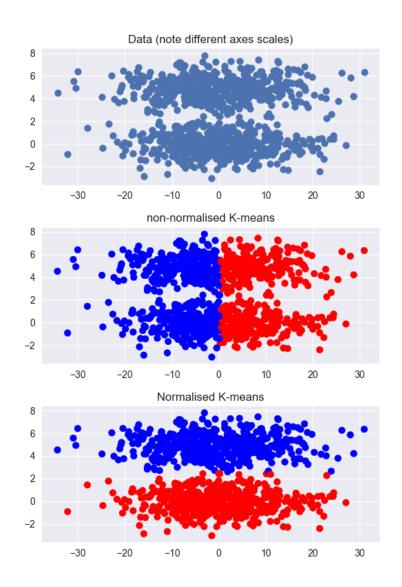








Is feature scaling that matter??



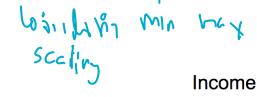


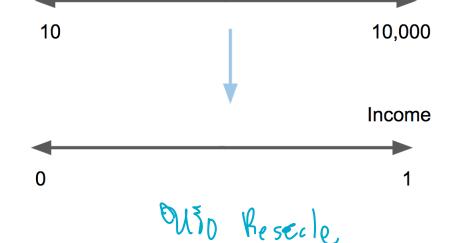


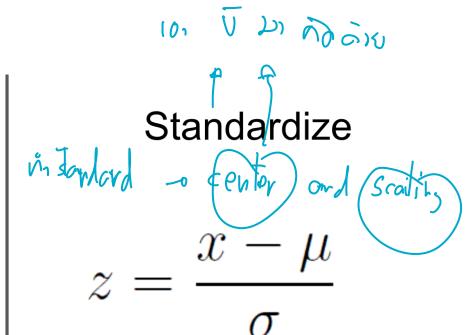
Feature Scaling



Normalize







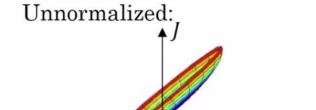
$$\mu=$$
 Mean $\sigma=$ Standard Deviation

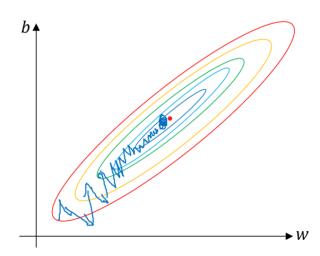


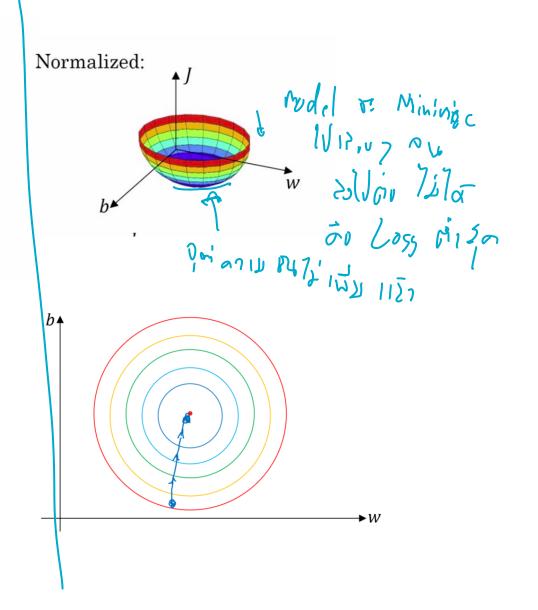




Why Normalized



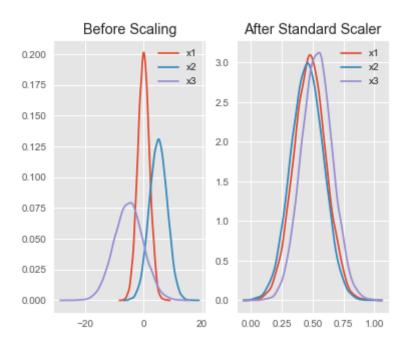








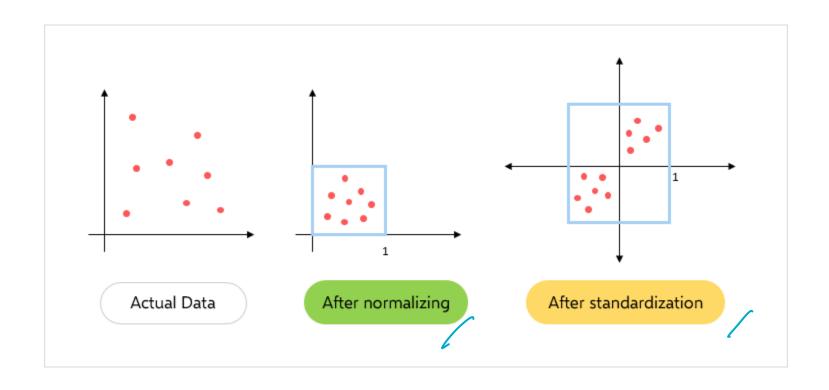
vilai standad (as) 24







Normalized vs Standardized







Normalized vs Standardized

· ma outienvivoir ex. ma -3, 3

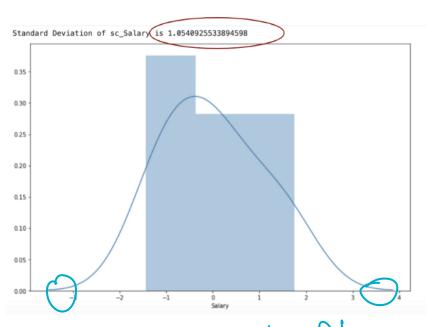
Column: Salary

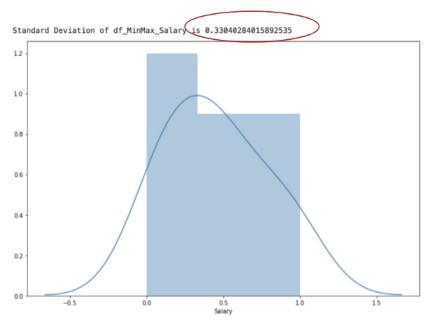
Standard Deviation (Salary):

Max-Min Normalization (0.33) < Standardisation (1.05)

Standardisation

Max-Min Normalisation





doise in Data follow Normal



Name	Sklearn_Class
StandardScaler	StandardScaler
MinMaxScaler	MinMaxScaler
MaxAbsScaler	MaxAbsScaler
RobustScaler	RobustScaler
QuantileTransformer-Normal	QuantileTransformer(output_distribution='normal')
QuantileTransformer-Uniform	QuantileTransformer(output_distribution='uniform')
PowerTransformer-Yeo-Johnson	PowerTransformer(method='yeo-johnson')
Normalizer	Normalizer





Normalized vs Standardized

Normalization is good to use when you know that the distribution of your data does not follow a Gaussian distribution

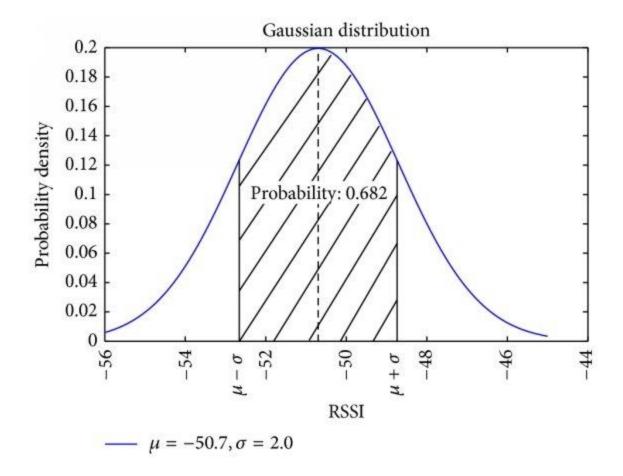
Lo no the Distribution N/ Standard 120

This can be useful in algorithms that do not assume any distribution of the data like K-Nearest Neighbors and Neural Networks.

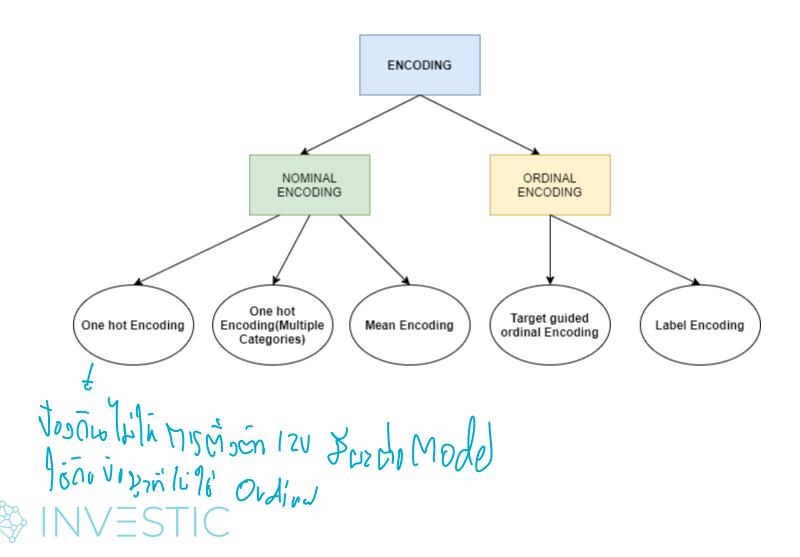




Gaussian = Normal Distribution







Encoding

Nominal categorical variables are those for which we do not have to worry about the arrangement of the categories.

Male and Female.

Different states like NY, FL, NV, TX

To One hot 10 hr

Ordinal categories are those in which we have to worry about the rank. These categories can be rearranged based on ranks.

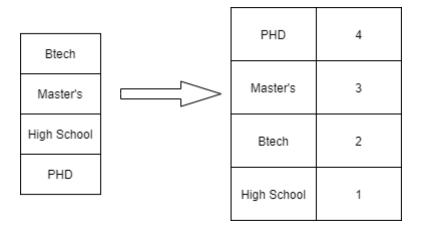
education level (PHD-1, masters-2, bachelors-3).

Drawn Po



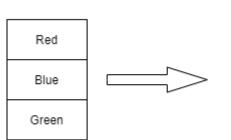
- 1. Prepare & Transform Data
 - 1. Outlier
 - 2. Feature Scaling
 - 1. Normalization
 - 2. Standardization
 - 3. Label encoding/ One hot encoding





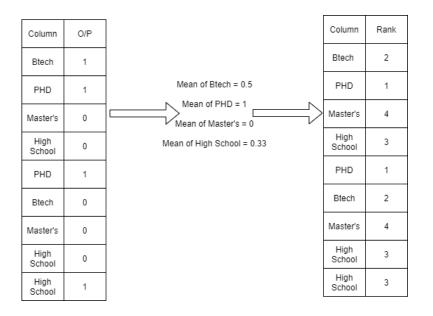


One Hot Encoding

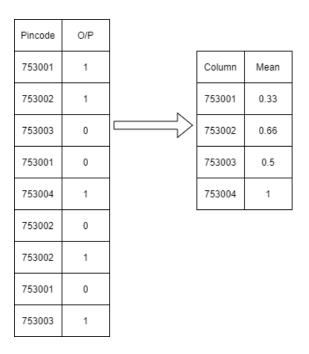


Red	Blue	Green
1	0	0
0	1	0
0	0	1

Target guided ordinal categories

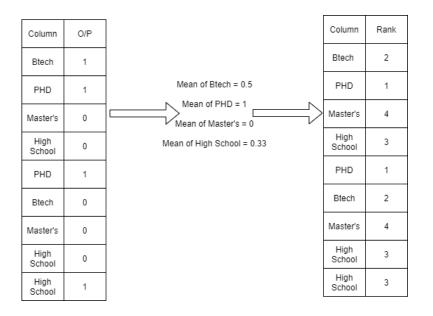


Mean Encoding

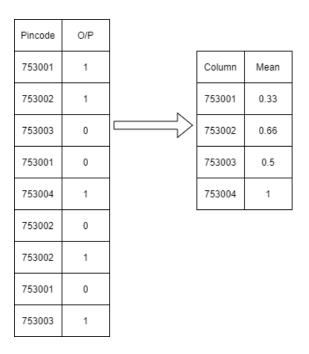




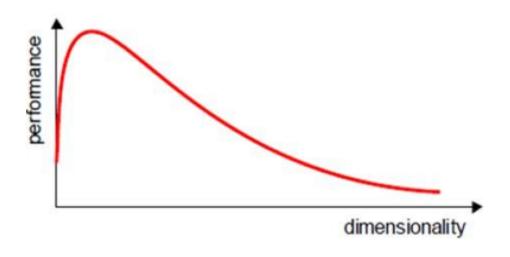
Target guided ordinal categories



Mean Encoding

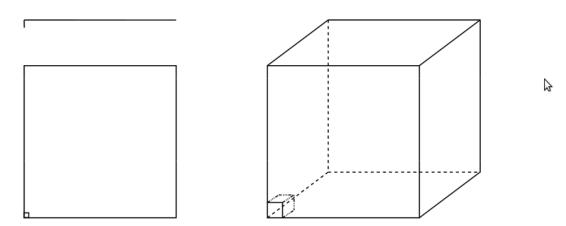








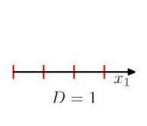
- kNN breaks down in high-dimensional space
 - "Neighborhood" becomes very large.
- Assume 5000 points uniformly distributed in the unit hypercube and we want to apply 5-nn. Suppose our query point is at the origin.
 - In 1-dimension, we must go a distance of 5/5000 = 0.001 on the average to capture 5 nearest neighbors
 - In 2 dimensions, we must go $\sqrt{0.001}$ to get a square that contains 0.001 of the volume.
 - In d dimensions, we must go (0.001)^{1/d}

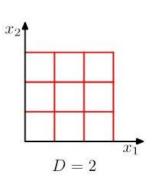


Source: mathematics stack exchange

Curse of Dimensionality

- Low dimension → good performance for nearest neighbor.
- · As dataset grows, the nearest neighbors are near and carry similar labels.
- Curse of dimensionality: in high dimensions, almost all points are far away from each other.





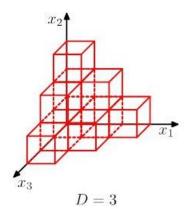


Figure Bishop 1.21

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