Introduction to Data Science



Last Update: 24 JAN 2020

Chapter 4 Predictive Analysis

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Outline

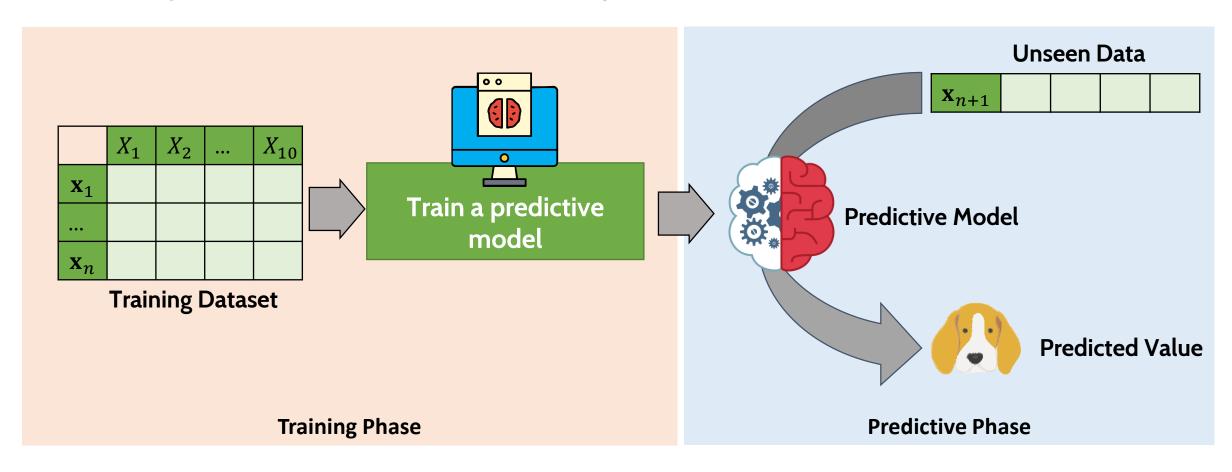
Predictive Analysis

- 1. Predictive Analysis
 - Preparing Datasets
- 2. Classification Analysis
 - K-Nearest Neighbor
 - Decision Tree
 - Naïve Bayes
 - Classification Assessment
- 3. Regression Analysis
 - Linear Regression
 - Polynomial Regression
 - Regression Assessment

- 4. Time Series Analysis
 - Moving Average
 - Autoregressive Integrated Moving
 - Curve Fitting

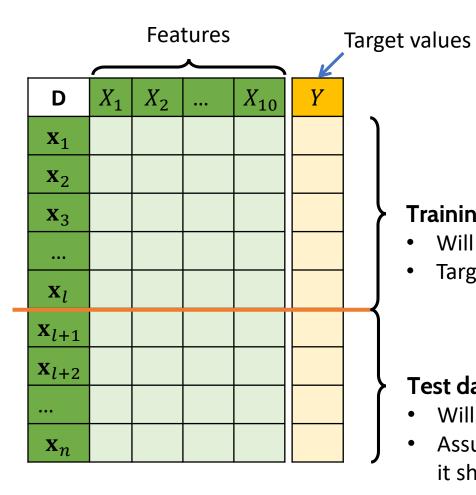
Predictive Analysis

Analyze current and historical data to make predictions about future or otherwise unknown events.



Preparing Dataset

Predictive Analysis



To perform a predictive analysis:

- We should have two dataset: training and test datasets.
- The target value of each datapoint must be available.

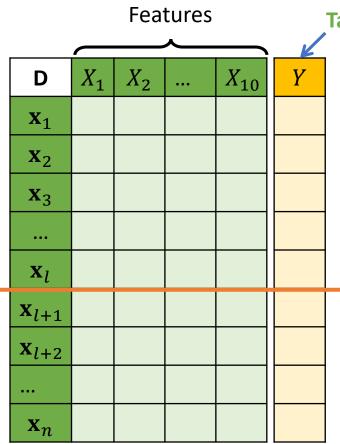
Training dataset

- Will be used to <u>train</u> a predictive model.
- Target value of each data point must be available.

Test dataset

- Will be used to <u>evaluate</u> the predictive model
- Assume that target value of each data point is not known, but it should be available.

Classification Analysis



Target class

For classification analysis

- The value we want to predict is categorical data.
- Known as class

Example

We know some characteristics of an animal, and we want to predict it is a cat or a dog.

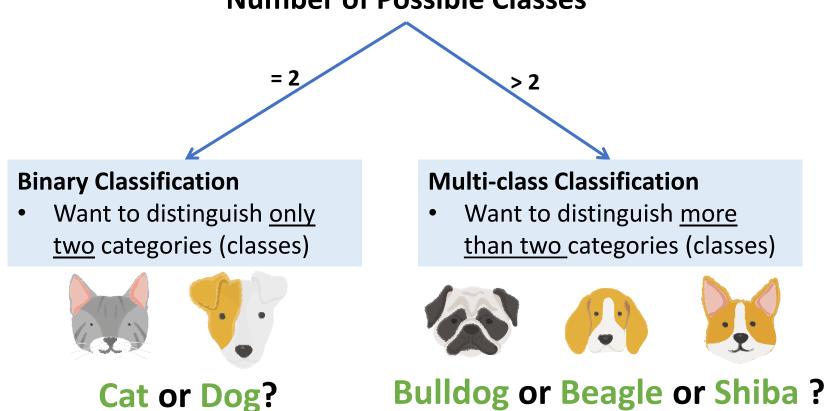


cat or dog?

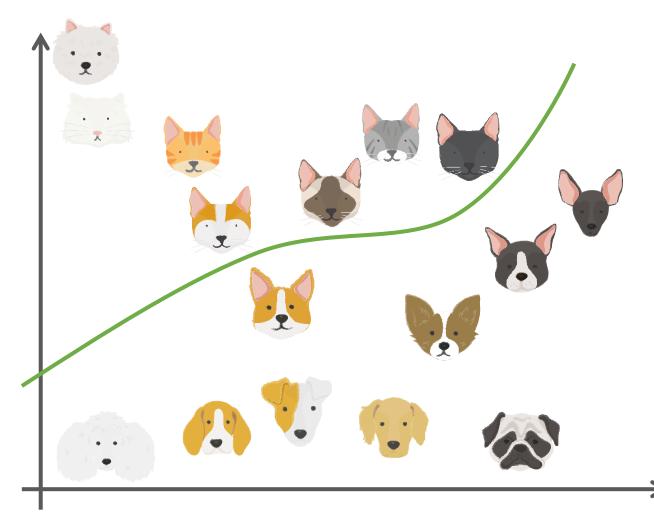
Classification Analysis

Types of Classification Problems

Number of Possible Classes



Classification Analysis



The task of classification is one of finding **separating lines** that separate classes of data from a training dataset as best as possible.

K-Nearest Neighbor

Classification Analysis

K-Nearest Neighbor classifier <u>assigns</u> the <u>class label of an unseen data with the</u> <u>majority class labels of k neighbor data</u> (in the training dataset)

How the k-nearest neighbor works

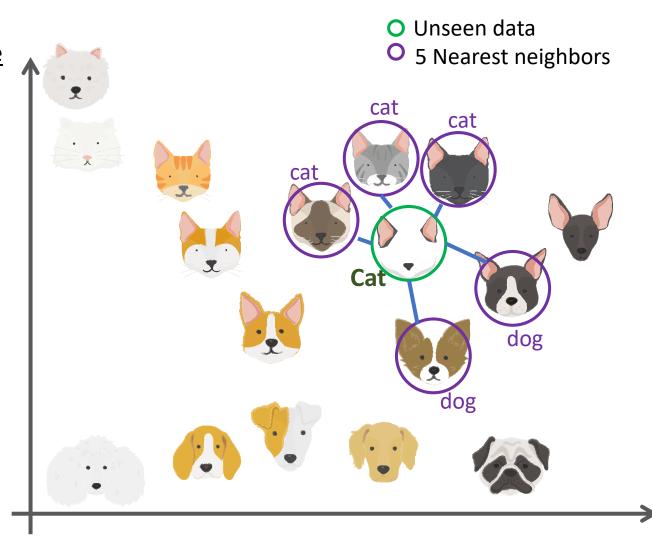
STEP 1: Calculate distances between an unseen data and training data

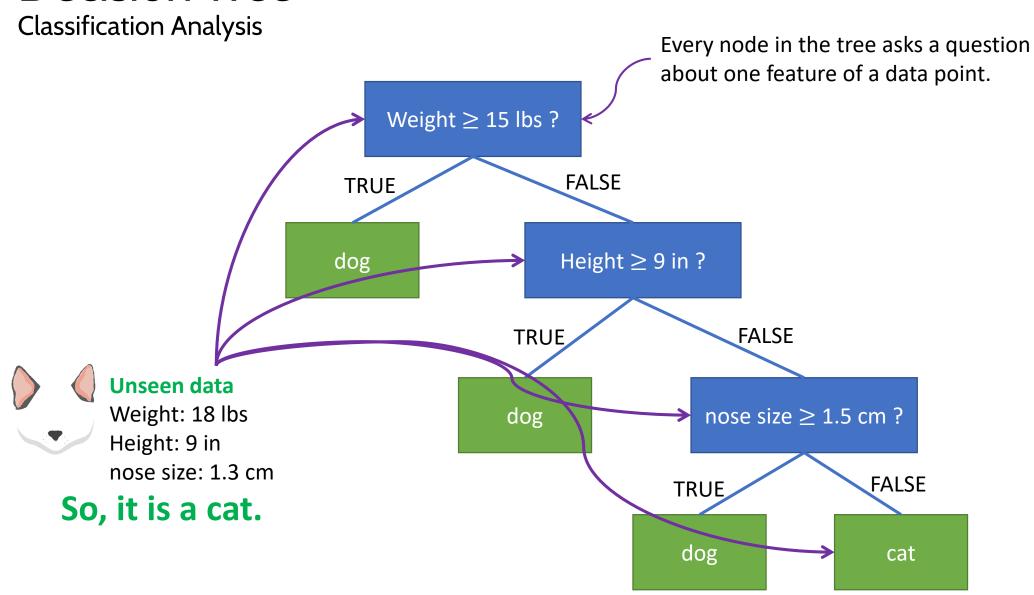
STEP 2: Find *k* nearest neighbor

STEP 3: Find majority class label

STEP 4: Assign the majority class label to

the class label of the unseen data





Classification Analysis

Construct a decision tree

STEP 1: Given a training data D, find the single feature (and cutoff for that feature, if it's numerical) that <u>best partitions your data into classes</u>.

STEP 2: This single best feature/cutoff becomes the root of your decision tree.

STEP 3: Partition *D* up according to the root node.

STEP 4: Recursively train each of the child nodes on its partition of the data until all of the data points in the partition have the same label.

D	Weight	Height	Nose size	Label
\mathbf{x}_1	8	8	1.6	Dog
\mathbf{x}_2	50	40	3	Dog
\mathbf{x}_3	8	9	1.3	Cat
\mathbf{x}_4	15	12	2.5	Dog
X ₅	9	9.8	1.4	Cat

FALSE

Weight \geq 15 lbs ?

TRUE

DWeightHeightNose sizeLabel \mathbf{x}_2 50403Dog \mathbf{x}_4 15122.5Dog

D	Weight	Height	Nose size	Label
\mathbf{x}_1	8	8	1.6	Dog
\mathbf{x}_3	8	9	1.3	Cat
x ₅	9	9.8	1.4	Cat

Classification Analysis

Weight \geq 15 lbs?

Construct a decision tree

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FALSE

D	Weight	Height	Nose size	Label
\mathbf{x}_1	8	8	1.6	Dog
\mathbf{x}_3	8	9	1.3	Cat
x ₅	9	8.5	1.4	Cat

Height \geq 9 in ?

TRUE

FALSE

D	Weight	Height	Nose size	Label
x ₃	8	9	1.3	Cat

D	Weight	Height	Nose size	Label
\mathbf{x}_1	8	8	1.6	Dog
\mathbf{x}_5	9	8.5	1.4	Cat

Classification Analysis

Height \geq 9 in ?

Construct a decision tree

STEP 1: Given a training data D, find the single feature (and cutoff for that feature, if it's numerical) that <u>best partitions your data into classes</u>.

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FA	LSE

D	Weight	Height	Nose size	Label
\mathbf{x}_1	8	8	1.6	Dog
x ₅	9	8.5	1.4	Cat

nose size \geq 1.5 cm ?

TRUE

D	Weight	Height	Nose size	Label
x ₁	8	8	1.6	Dog

FALSE

D	Weight	Height	Nose size	Label
X ₅	9	8.5	1.4	Cat

Classification Analysis

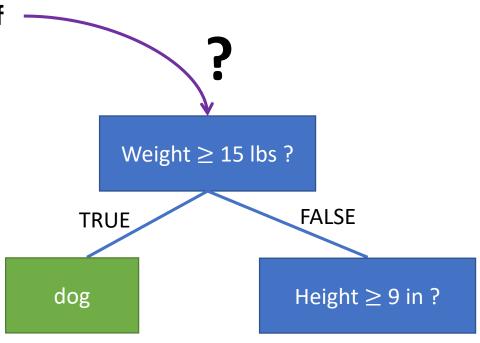
How to determine the best feature and cutoff

The most common ones are:

- Information gain
- Gini impurity.

You can find more details in:

- Zaki, M., & Meira, W. (2014). Data mining and analysis: Fundamental concepts and algorithms. New York: Cambridge University Press.
- https://en.wikipedia.org/wiki/Decision_tree_ learning



Naïve Bayes Classification Analysis

Bayes Theorem:

The *prior*, the initial degree of belief in *A*.

 $P(A|B) = \frac{P(A)P(B|A)}{P(B)}$

Probability of *A* happening, given that *B* has occurred

The likelihood of event **B** occurring given that **A** is true.



Thomas Bayes 1701-1761

Source:

https://en.wikipedia.org/wiki/Thomas B ayes#/media/File:Thomas Bayes.gif

Classification Analysis

<u>Classify</u> whether the day is suitable for <u>playing golf</u>, given the <u>features</u> <u>of the day</u>.

Bayes theorem can be rewritten as:

$$P(y|\mathbf{x}) = \frac{P(y)P(\mathbf{x}|y)}{P(\mathbf{x})}$$

We want to classify

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
\mathbf{x}_4	Sunny	Mild	High	False	Yes
X ₅	Sunny	Cool	Normal	False	Yes
x ₆	Sunny	Cool	Normal	True	No
X ₇	Overcast	Cool	Normal	True	Yes
x ₈	Rainy	Mild	High	False	No
X ₉	Rainy	Cool	Normal	False	Yes
x ₁₀	Sunny	Mild	Normal	False	Yes
X ₁₁	Rainy	Mild	Normal	True	Yes
x ₁₂	Overcast	Mild	High	Ture	Yes
x ₁₃	Overcast	Hot	Normal	False	Yes
X ₁₄	Sunny	Mild	High	True	No

Classification Analysis

How the Naïve Bayes works

STEP 1: Calculate P(y) for all possible value of y from the training dataset.

STEP 2: Calculate $P(\mathbf{x}|y) = \prod_{i=1}^{p} P(x_i|y)$ for all possible value of y from the training dataset.

STEP 3: Calculate $P(y|\mathbf{x}) = P(y) \prod_{i=1}^{p} P(x_i|y)$

STEP 4: Assign y that reach the highest $P(y|\mathbf{x})$ to the class label of \mathbf{x}

We want to classify

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
x ₄	Sunny	Mild	High	False	Yes
X ₅	Sunny	Cool	Normal	False	Yes
x ₆	Sunny	Cool	Normal	True	No
X ₇	Overcast	Cool	Normal	True	Yes
x ₈	Rainy	Mild	High	False	No
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X ₁₁	Rainy	Mild	Normal	True	Yes
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$$P(\text{Play golf} = \text{No}) = \frac{5}{14}$$

 $P(\text{Play golf} = \text{Yes}) = \frac{9}{14}$

We want to classify

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
\mathbf{x}_4	Sunny	Mild	High	False	Yes
X ₅	Sunny	Cool	Normal	False	Yes
x ₆	Sunny	Cool	Normal	True	No
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X ₁₄	Sunny	Mild	High	True	No

Naïve Bayes Classification Analysis

How the Naïve Bayes works

- STEP 1: Calculate P(y) for all possible value of y from the training dataset.
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- STEP 4: Assign y that reach the highest $P(y|\mathbf{x})$ to the class label of \mathbf{x}

$$P(\text{Outlook} = \text{Sunny}|\text{Play golf} = \text{No}) = \frac{2}{5}$$

 $P(\text{Outlook} = \text{Sunny}|\text{Play golf} = \text{Yes}) = \frac{3}{9}$

We want to classify

D	Outlook	Temperature	Humidity	Humidity Windy	
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
\mathbf{x}_4	Sunny	Mild	High	False	Yes
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x ₈	Rainy	Mild	High False		No
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Naïve Bayes Classification Analysis

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$$P(\text{Temperature} = \text{Hot}|\text{Play golf} = \text{No}) = \frac{2}{5}$$

 $P(\text{Temperature} = \text{Hot}|\text{Play golf} = \text{Yes}) = \frac{2}{9}$

We want to classify

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
X ₃	Overcast	Hot	High	False	Yes
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X ₁₃	Overcast	Hot	Normal False		Yes
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- STEP 1: Calculate P(y) for all possible value of y from the training dataset.
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- STEP 4: Assign y that reach the highest $P(y|\mathbf{x})$ to the class label of \mathbf{x}

$$P(\text{Humidity} = \text{Normal}|\text{Play golf} = \text{No}) = \frac{1}{5}$$

 $P(\text{Humidity} = \text{Normal}|\text{Play golf} = \text{Yes}) = \frac{6}{9}$

We want to classify

D	Outlook	ok Temperature Humidity Windy		Play golf	
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
\mathbf{x}_4	Sunny	Mild	High	False	Yes
X ₅	Sunny	Cool	Normal	False	Yes
x ₆	Sunny	Cool	Normal	True	No
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x ₈	Rainy	Mild	ld High False		No
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X ₁₄	Sunny	Mild	High	True	No

Classification Analysis

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- STEP 4: Assign y that reach the highest $P(y|\mathbf{x})$ to the class label of \mathbf{x}

$$P(\text{Windy} = \text{True}|\text{Play golf} = \text{No}) = \frac{3}{5}$$

 $P(\text{Windy} = \text{True}|\text{Play golf} = \text{Yes}) = \frac{3}{9}$

We want to classify

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
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X ₁₁	Rainy	Mild	Normal	True	Yes
X ₁₂	Overcast	Mild	High	Ture	Yes
X ₁₃	Overcast	Hot	Normal	Normal False	
X ₁₄	Sunny	Mild	High	True	No

Classification Analysis

How the Naïve Bayes works

STEP 1: Calculate P(y) for all possible value of y from the training dataset.

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STEP 4: Assign y that reach the highest $P(y|\mathbf{x})$ to the class label of x

$$P(\text{Play golf} = \text{No}|\text{Sunny, Hot, Normal, True})$$
$$= \frac{5}{14} \times \frac{2}{5} \times \frac{2}{5} \times \frac{1}{5} \times \frac{3}{5} = 0.0069$$

$$P(\text{Play golf} = \text{Yes}|\text{Sunny, Hot, Normal, True})$$
$$= \frac{9}{14} \times \frac{3}{9} \times \frac{2}{9} \times \frac{6}{9} \times \frac{3}{9} = \mathbf{0.0106}$$

So, it is suitable to **play golf** given the conditions (Outlook = Sunny, Temperature = Hot, Humidity = Normal and Windy = True).

We want to classify

 $\mathbf{x} = (Sunny, Hot, Normal, True)$ $P(\text{Play golf} = \text{No}) = \frac{5}{14}$ $P(\text{Play golf} = \text{Yes}) = \frac{9}{14}$ $P(\text{Outlook} = \text{Sunny}|\text{Play golf} = \text{No}) = \frac{2}{5}$ $P(\text{Outlook} = \text{Sunny}|\text{Play golf} = \text{Yes}) = \frac{3}{9}$ $P(\text{Temperature} = \text{Hot}|\text{Play golf} = \text{No}) = \frac{2}{5}$ $P(\text{Temperature} = \text{Hot}|\text{Play golf} = \text{Yes}) = \frac{2}{9}$ $P(\text{Humidity} = \text{Normal}|\text{Play golf} = \text{No}) = \frac{1}{5}$ $P(\text{Humidity} = \text{Normal}|\text{Play golf} = \text{Yes}) = \frac{6}{9}$ $P(\text{Windy} = \text{True}|\text{Play golf} = \text{No}) = \frac{3}{5}$ $P(\text{Windy} = \text{True}|\text{Play golf} = \text{Yes}) = \frac{3}{9}$

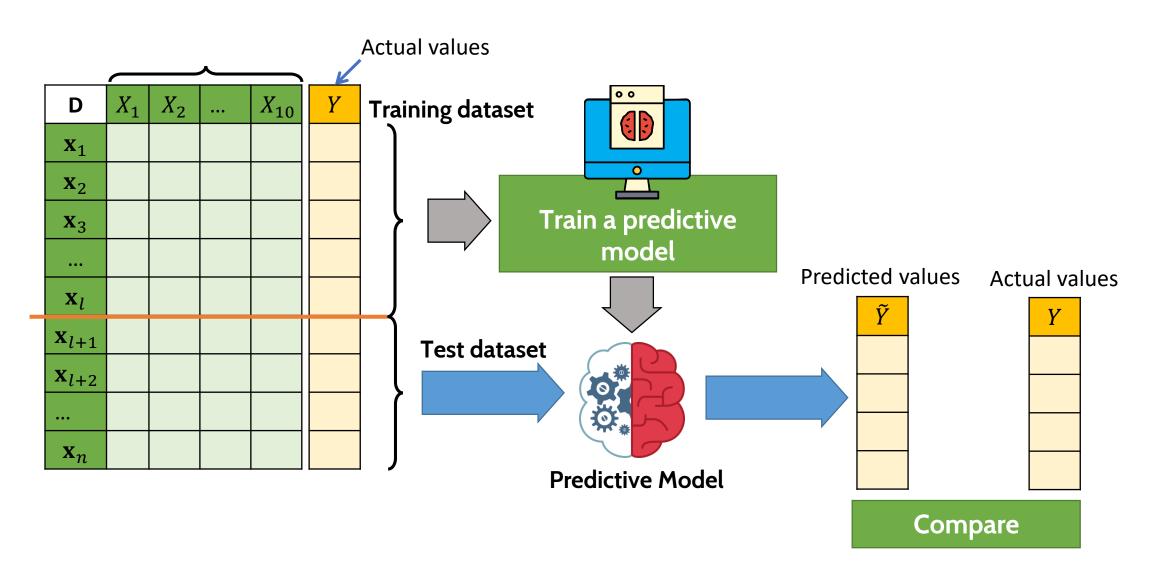
Classification Analysis

Quiz:

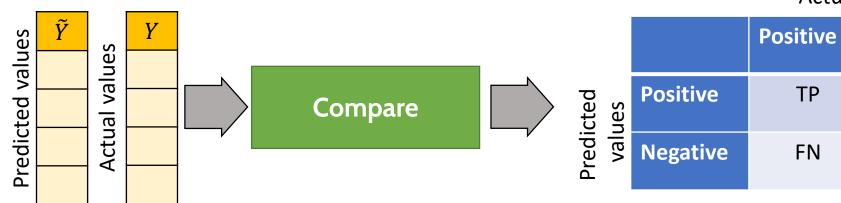
It is suitable to play golf or not given the conditions (Outlook = Rainy, Temperature = Mild, Humidity = Normal and Windy = False).

D	Outlook	Temperature	Humidity	Windy	Play golf
\mathbf{x}_1	Rainy	Hot	High	False	No
\mathbf{x}_2	Rainy	Hot	High	True	No
\mathbf{x}_3	Overcast	Hot	High	False	Yes
\mathbf{x}_4	Sunny	Mild	High	False	Yes
X ₅	Sunny	Cool	Normal	False	Yes
x ₆	Sunny	Cool	Normal	True	No
X ₇	Overcast	Cool	Normal	True	Yes
x ₈	Rainy	Mild	High	False	No
X 9	Rainy	Cool	Normal	False	Yes
x ₁₀	Sunny	Mild	Normal	False	Yes
X ₁₁	Rainy	Mild	Normal	True	Yes
X ₁₂	Overcast	Mild	High	Ture	Yes
X ₁₃	Overcast	Hot	Normal	False	Yes
X ₁₄	Sunny	Mild	High	True	No

Classification Analysis



Classification Analysis



Actual values

Negative

FP

TN

true positives (TP) true negatives (TN) false positives (FP) false negatives (FN)

Confusion matrix

$$Accuracy = \frac{(TP + TN)}{Total}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Misclassification Rate = \frac{(FP + FN)}{Total} = 1 - Accuracy$$

$$Precision = \frac{TP}{TP + FP}$$

Classification Analysis

Example

Predicted values

Actual values

	setosa	versicolor	virginica
setosa	10	2	4
versicolor	1	16	1
virginica	0	2	9

 $Recall_{virginica} = ?$

 $Precision_{virginica} = ?$

Accuracy =
$$\frac{(10+16+9)}{45} = \frac{35}{45} = 0.78$$

Misclassification Rate = 1 - 0.78 = 0.22

$$Recall_{setosa} = \frac{10}{10+1+0} = \frac{10}{11} = 0.91$$

$$Precision_{setosa} = \frac{10}{10 + 2 + 4} = \frac{10}{16} = 0.625$$

Recall_{versicolor} =
$$\frac{16}{2+16+2} = \frac{16}{20} = 0.8$$

Precision_{versicolor} =
$$\frac{16}{1+16+1} = \frac{16}{18} = 0.89$$

Classification Analysis

Example

Actual values

		Cat	Dog
cted Jes	Cat	5	2
Predicted values	Dog	3	3

Accuracy
$$=$$
 $\frac{(5+3)}{13} = \frac{8}{13} = 0.62$

Misclassification Rate
$$=$$
 $\frac{(2+3)}{13} = \frac{5}{13} = 0.38$

Recall =
$$\frac{5}{5+3} = \frac{5}{8} = 0.625$$

Precision =
$$\frac{5}{5+2} = \frac{5}{7} = 0.714$$

Regression analysis

Independent variable

Dependent variable

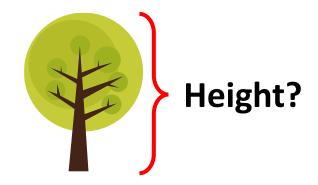
D	X_1	X_2		X ₁₀	Y
\mathbf{x}_1					
\mathbf{x}_2					
\mathbf{x}_3					
:					
\mathbf{x}_l					
\mathbf{x}_{l+1}					
\mathbf{x}_{l+2}					
\mathbf{x}_n					

For regression analysis

- The value we want to predict is numeric data.
- Known as **Dependent variable**

Example

- We know <u>quantities of water</u> and <u>fertilizer</u> providing to a tree for a month
- We want to predict the growth rate (height) of the tree.



Further Study

Book:

- Zaki, M., & Meira, W. (2014). Data mining and analysis: Fundamental concepts and algorithms. New York: Cambridge University Press.
- Enders, C. (2010), Applied Missing Data Analysis. New York: Guilford Press.
- Online lesson: วิทยาการข้อมูลเบื้องต้น (Introduction to Data Science) CMU MOOC

https://thaimooc.org/courses/course-v1:CMU-MOOC+cmu034+2019 T1/about