國立臺北大學
National Taipei University

Group 1
Case Study-Titanic


Course: 資料探勘 Data mining
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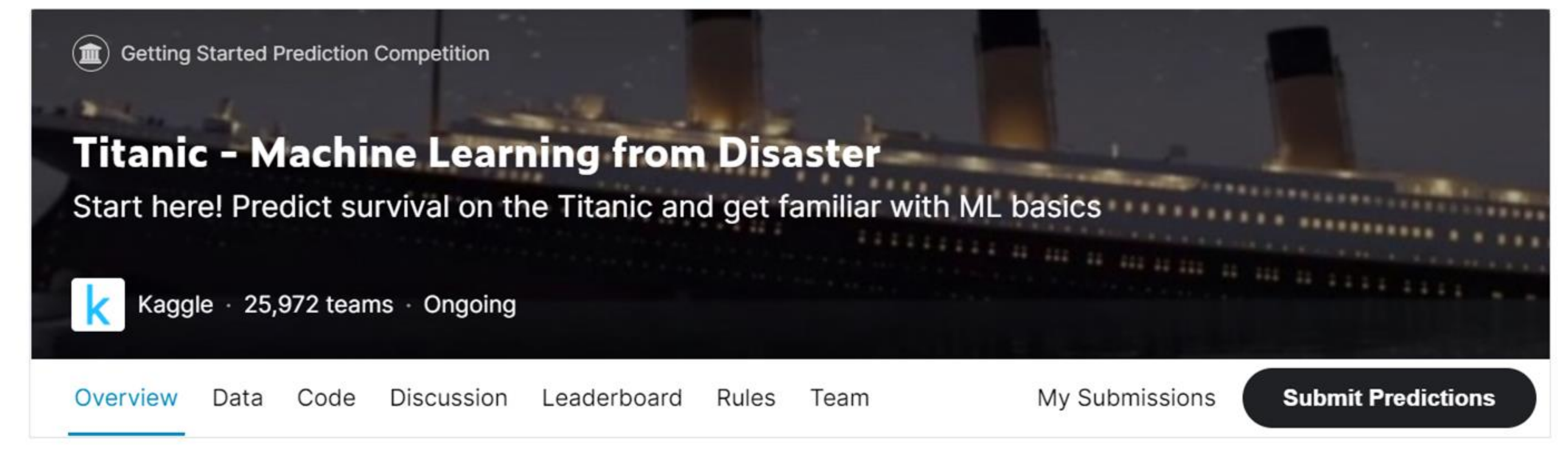
kaggle

Google



題目:

利用機器學習建立一個模型來預測在鐵達尼的乘客是否會存活

變數介紹

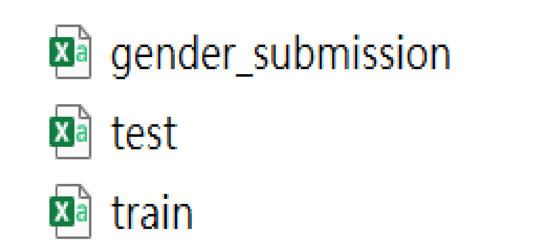
資料處理

模型使用

分析結果

變數介紹

- PassengerID
- Survived-survived(1),no survived(0)
- Pclass-upper(1),middle(2),lower(3)
- SibSp-兄弟姊妹與配偶數
- Parch-父母與小孩數
- Name
- Sex
- Age
- Ticket
- Fare
- Cabin-船艙
- Embarked-登船地點
(C = Cherbourg, Q = Queenstown, S = Southampton)



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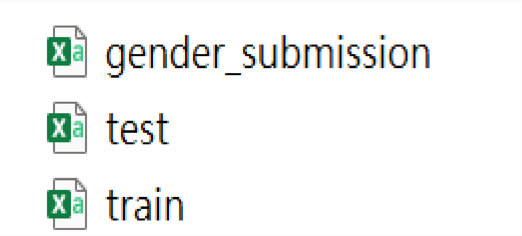

1. 了解資料集的組成
2. 算出變數空值數
3. 合併 train&test set
4. 補空值(age,embarked)
5. Encoding 及Standardization
6. 資料拆分
7. 查看相關係數(correlation coefficient)

資料處理

step 1- 了解資料集的組成

train set

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

test set

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Sex          418 non-null    object
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

step 2- 算出變數空值數

```
PassengerId : 0
Survived : 0
Pclass : 0
Name : 0
Sex : 0
Age : 177
SibSp : 0
Parch : 0
Ticket : 0
Fare : 0
Cabin : 687
Embarked : 2
```

step 3- 合併 train&test set

```
# 將train 、test set合併，一同進行Encoding及standardization
df_all = pd.concat([df_train_nosurvived,test],axis=0)
df_all = df_all.reset_index(drop=True)
df_all
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  1309 non-null   int64
 1   Pclass       1309 non-null   int64
 2   Name         1309 non-null   object
 3   Sex          1309 non-null   object
 4   Age          1046 non-null   float64
 5   SibSp        1309 non-null   int64
 6   Parch        1309 non-null   int64
 7   Ticket       1309 non-null   object
 8   Fare         1309 non-null   float64
 9   Cabin        295 non-null    object
 10  Embarked     1307 non-null   object
dtypes: float64(2), int64(4), object(5)
memory usage: 112.6+ KB
```

step 4- 補空值(Age,Embarked)

- Embarked-經過google 人名後發現兩人皆由southampton上船，因此填上"S"。
- Age- 查看與各變數的相關係數值，發現與Pclass有最高的相關係數，因此利用Pclass區分男女，取中位數來填補空值。

step 4- 補空值(Age,Embarked)

	Feature 1	Feature 2	Correlation Coefficient
3	Age	Age	1.000000
9	Age	Pclass	0.408106
12	Age	SibSp	0.243699
17	Age	Fare	0.178328
20	Age	Parch	0.150917
30	Age	PassengerId	0.028814

```
Median age of Pclass 1 females: 36.0
Median age of Pclass 1 males: 42.0
Median age of Pclass 2 females: 28.0
Median age of Pclass 2 males: 29.5
Median age of Pclass 3 females: 22.0
Median age of Pclass 3 males: 25.0
Median age of all passengers: 28.0
```

step 5 -Encoding & Standardization

1. 使用SKlearn中的 One Hot Encoding 將特徵轉為數字

Color
Red
Red
Yellow
Green

Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1

2. 標準化各變數，再把train & test set 分開

	Survived
Pclass	-0.338481
Age	-0.058635
SibSp	-0.035322
Parch	0.081629
Fare	0.257307
Sex_female	0.543351
Sex_male	-0.543351
Embarked_C	0.168240
Embarked_Q	0.003650
Embarked_S	-0.155660
PassengerId	-0.005007
Survived	1.000000

step 6- 資料拆分

-把 train set 資料集依照 8:2分為 訓練集(train set)及開發集(dev set)

step 7- 查看相關係數 (correlation coefficient)

-查看survived與其他變數的相關係數

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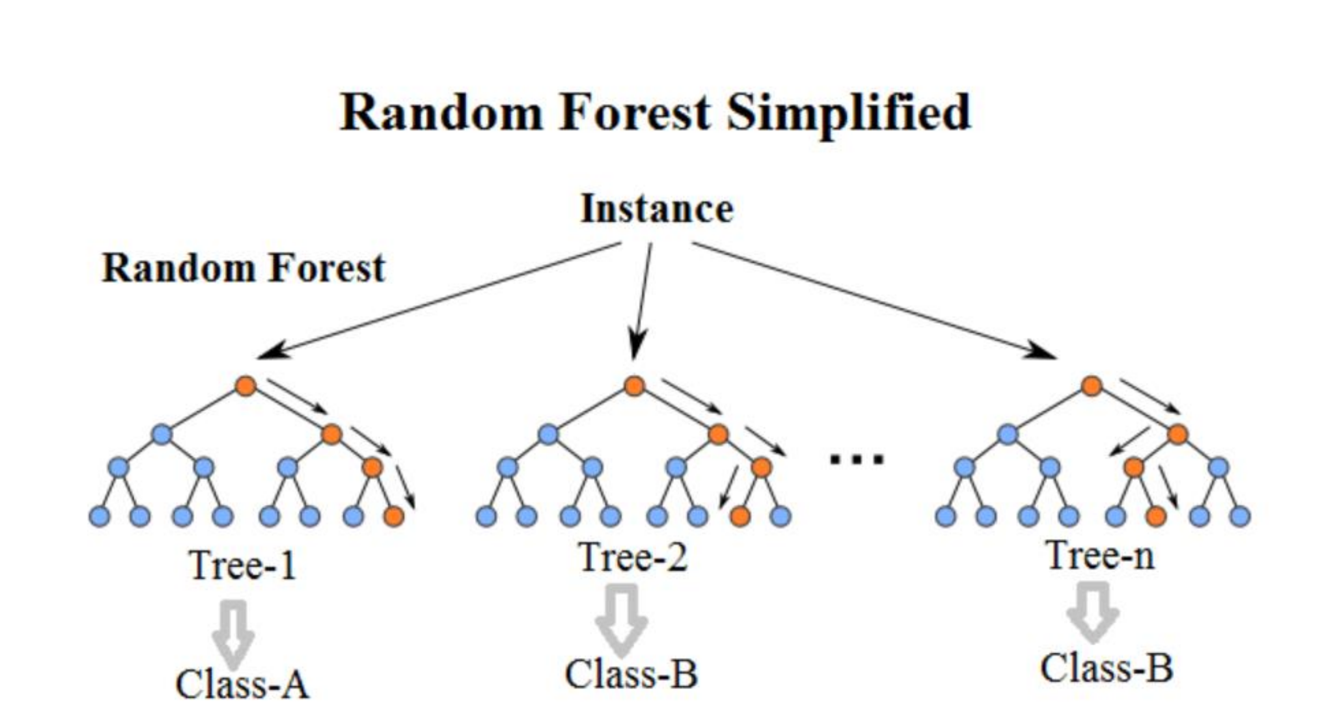
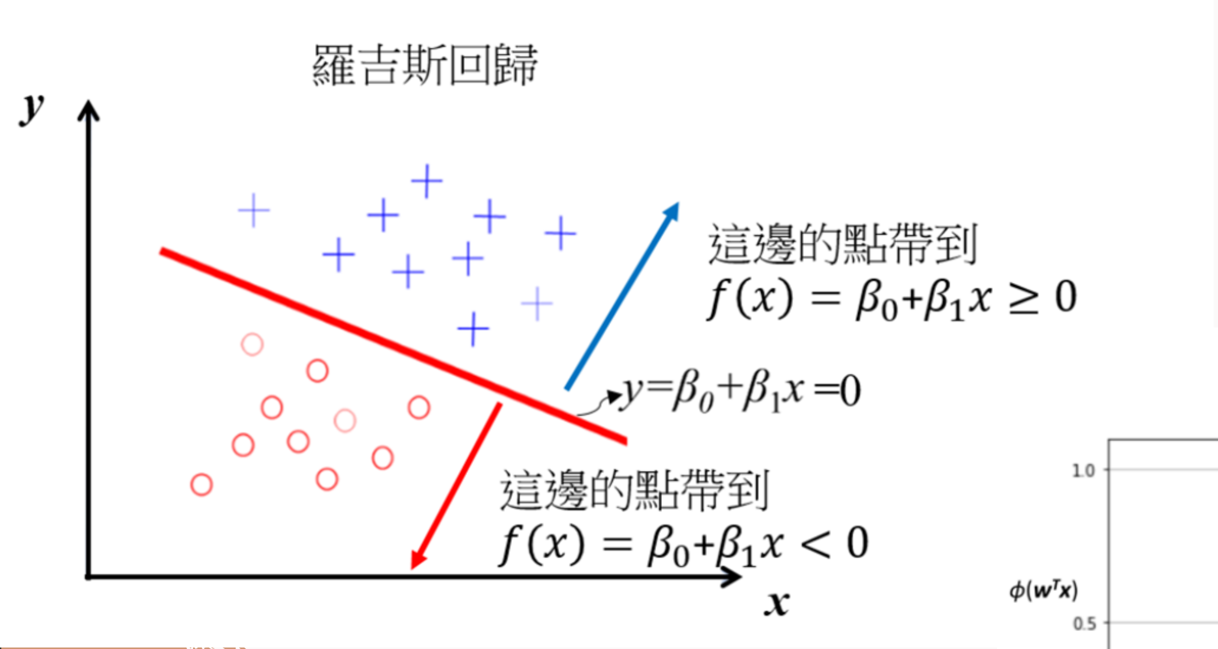
模型使用

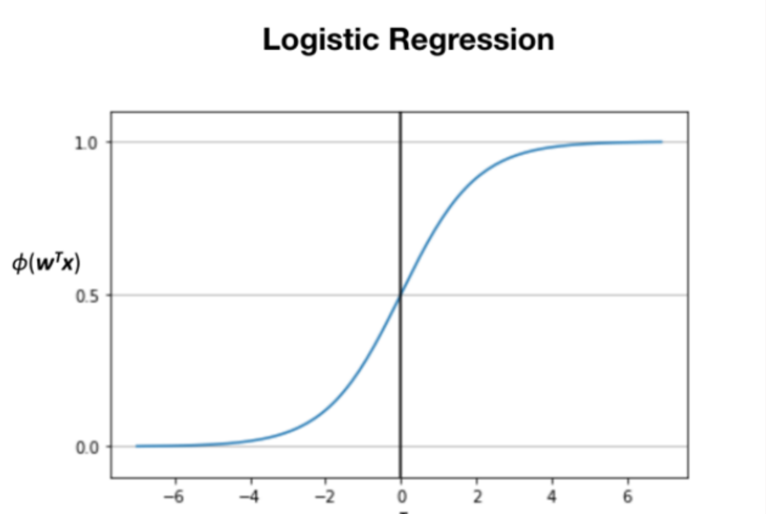
1. Random Forest
2. Logistic Regression
3. Support Vector Machine(SVM)

Random Forest

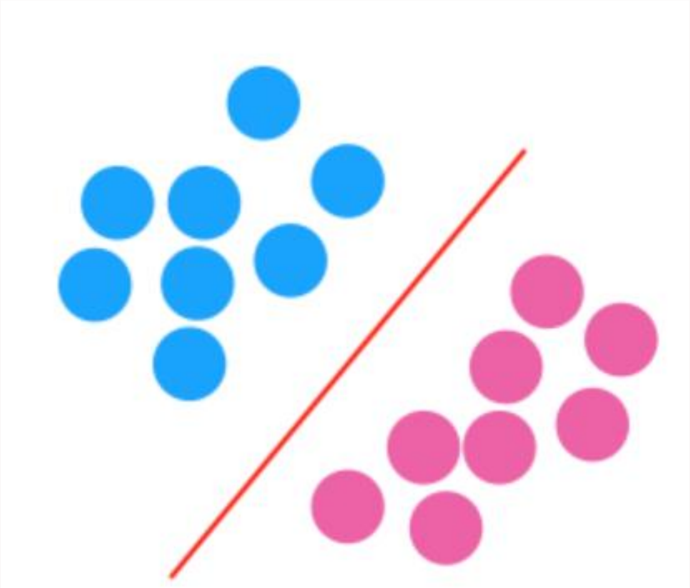


Logistic Regression

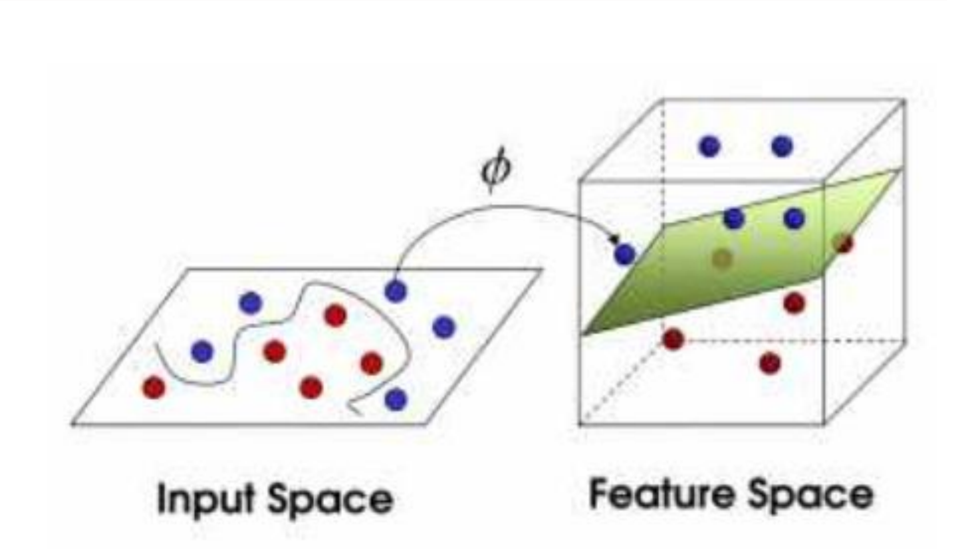


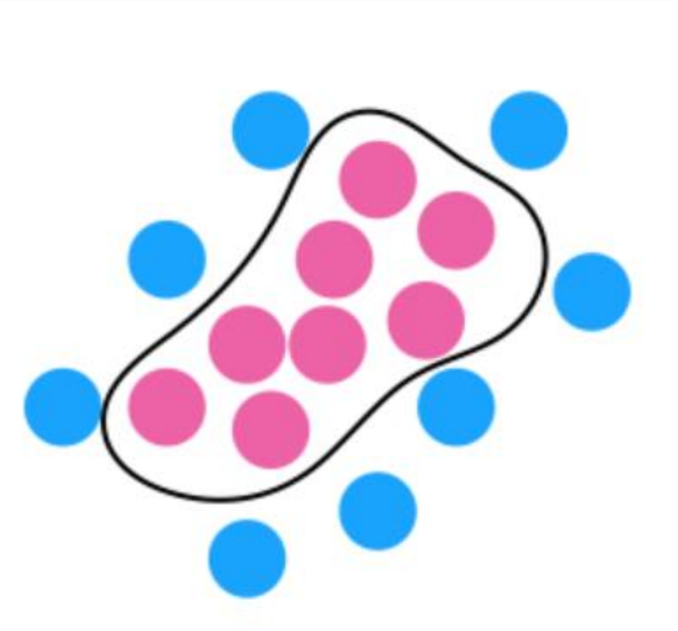


Support Vector Machine(SVM)



Support Vector Machine(SVM)





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		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

1. Random Forest→ 0.82

2. Logistic Regression→ 0.79

3. Support Vector Machine(SVM)→ 0.79

Dev Set

1. Random Forest→ 0.78

2. Logistic Regression→ 0.77

3. Support Vector Machine(SVM)→ 0.77

Test Set

8730/27740 (31%)

8563	NTPUIM-Day	0.77751	16	~10s

Your Best Entry ↑

Ranking

國立臺北大學
National Taipei University

Code：
https://colab.research.google.com/drive/1vJdNdwZoHOC8sLxAdOgnmIS4x6l3ALLY?usp=sharing

Data：
https://drive.google.com/drive/folders/1CEFNpF0Rdeai4e2UmwGraqmtNsblCvnX?usp=sharing


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心得


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QA

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Thank You