DECISION TREE

IKM LAB

OUTLINE

- What is Decision Tree?
- How can we use it?
- How can we know which attribute is important?
- Building my decision tree
- Ensemble method - Random forest
- Practice time!

WHAT IS DECISION TREE ?

- 藍色方形：決策點
- 紅色橢圓：結果

HOW CAN WE USE DECISION TREE ?

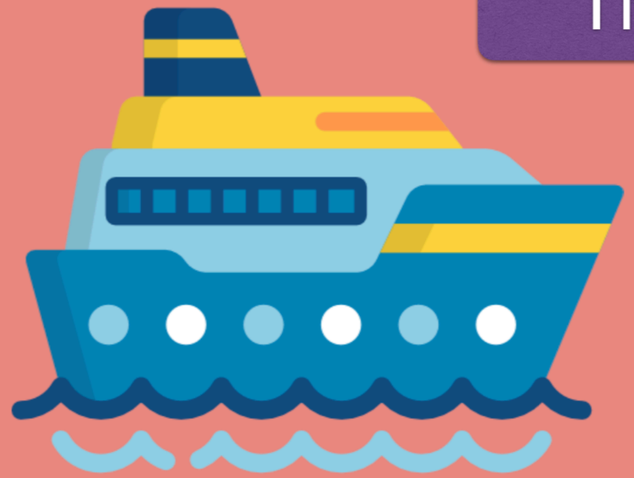
35-year-old
Ticket Class = 2nd
Parents. Wife

Passenger 1

7-month-old
Ticket Class = 3rd
Parents

Passenger 2

Titanic



62-year-old
Ticket Class = 1st
Husband. son

Passenger 3

TRAINING DATA

- PClass ：艙等（1~3）
- Sex：性別
- Age：年齡
- SibSp：兄弟姐妹、丈夫（妻子）人數
- Parch：父母、小孩人數
- Fare：票價
- Result：是否存活（1:存活，0:死亡）

result	Pclass	Sex	Age	SibSp	Parch	Fare
0	3	0	22	1	0	7.25
1	1	1	38	1	0	71.2833
1	3	1	26	0	0	7.925
1	1	1	35	1	0	53.1
0	3	0	35	0	0	8.05
0	1	0	54	0	0	51.8625
0	3	0	2	3	1	21.075
1	3	1	27	0	2	11.1333
1	2	1	14	1	0	30.0708
1	3	1	4	1	1	16.7
1	1	1	58	0	0	26.55
0	3	0	20	0	0	8.05

from : Kaggle

TESTING DATA

- 現在已知以下資訊：
  - PClass ：艙等（1~3）
  - Sex：性別
  - Age：年齡
  - SibSp：兄弟姐妹、丈夫（妻子）人數
  - Parch：父母、小孩人數
  - Fare：票價
- 希望猜出該乘客是否存活

result	Pclass	Sex	Age	SibSp	Parch	Fare
1	2	1	40	1	1	39
0	1	0	31	1	0	52
0	2	0	70	0	0	10.5
1	2	0	31	0	0	13
0	3	0	18	0	0	7.775
0	3	0	24.5	0	0	8.05
1	3	1	18	0	0	9.8417
0	3	1	43	1	6	46.9
1	1	0	36	0	1	512.3292
1	1	0	27	0	0	76.7292
0	3	0	20	0	0	9.225

FLOWCHART

Training Data → Build Decision Tree → Apply to Testing Data → Prediction

result	Pclass	Sex	Age	SibSp	Parch	Fare
0	3	0	22	1	0	7.25
1	1	1	38	1	0	71.2833
1	3	1	26	0	0	7.925
1	1	1	35	1	0	53.1
0	3	0	35	0	0	8.05
0	1	0	54	0	0	51.8625
0	3	0	2	3	1	21.075
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1	2	1	14	1	0	30.0708
1	3	1	4	1	1	16.7
1	1	1	58	0	0	26.55
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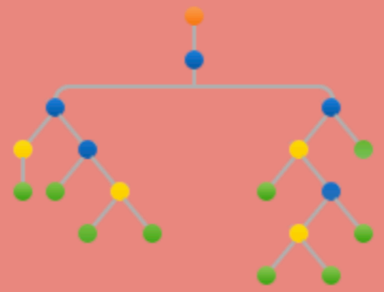

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1	1	0	36	0	1	512.3292
1	1	0	27	0	0	76.7292
0	3	0	20	0	0	9.225

HOW CAN WE KNOW WHICH ATTRIBUTE IS IMPORTANT?

資料集	人數
存活	100
死亡	200

Attribute 1

年齡 > 60

YES

NO

	人數
存活	50
死亡	50

	人數
存活	50
死亡	150

Attribute 2

艙等 = 1st

YES

NO

	人數
存活	99
死亡	1

	人數
存活	1
死亡	199

資料集	人數
存活	100
死亡	200

Attribute 1

年齡 > 60

YES

	人數
存活	50
死亡	50

NO

	人數
存活	50
死亡	150

Attribute 2

艙等 = 1st

YES

	人數
存活	99
死亡	1

NO

	人數
存活	1
死亡	199

GINI

- Gini impurity score is a measure of how the data would be incorrectly labeled.
- To compute Gini impurity for a set of items with J classes, suppose $i \in \{1,2,\ldots,J\}$, and pi be the fraction of items labeled with class i in the set.

$$1 - \sum_{i=1}^{J} {p_i}^2$$

- Gini = 0.0 -> best
  - when we use this attribute to classify the dataset, it can be clearly categorized.
- Gini = 0.5 -> worst
  - this attribute is not an important feature to make a decision.

J = # of classes = 2

Training Data	人數
存活	100
死亡	200

i=1 i=2

1-(100/300)^2-(200/300)^2
=0.44

年齡 > 60

YES NO

	人數
存活	50
死亡	50

1-(50/100)^2
-(50/100)^2
=0.5

	人數
存活	50
死亡	150

1-(50/200)^2
-(150/200)^2
=0.375

艙等 = 1st

YES NO

	人數
存活	99
死亡	1

1-(99/100)^2
-(1/100)^2
=0.02

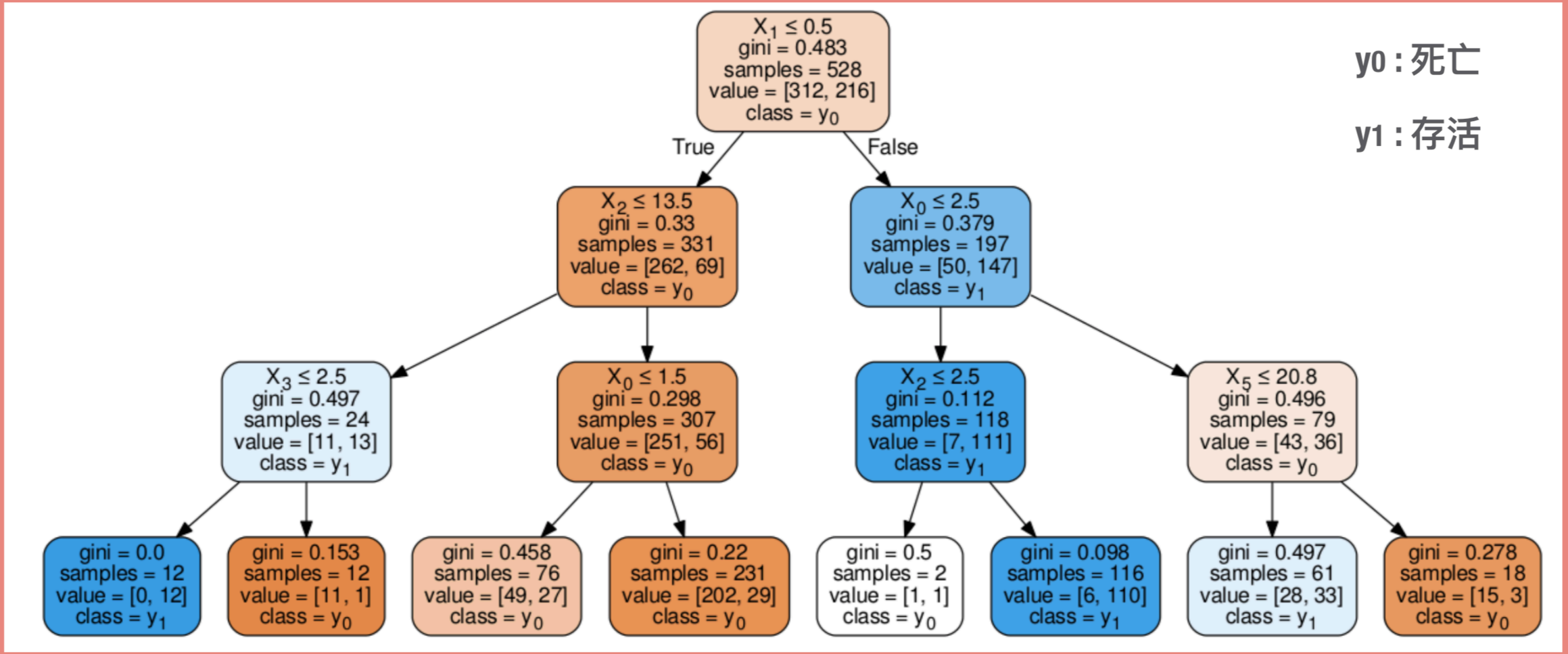
	人數
存活	1
死亡	199

1-(1/200)^2
-(199/200)^2
=0.01

TREE.PDF

X0 : PClass
X1 : Sex
X2 : Age
X3 : SibSp
X4 : Parch
X5 : Fare

y0 : 死亡
y1 : 存活



EVALUATION

result	Pclass	Sex	Age	SibSp	Parch	Fare
	2	1	40	1	1	39
	1	0	31	1	0	52
	2	0	70	0	0	10.5
	2	0	31	0	0	13
	3	0	18	0	0	7.775
	3	0	24.5	0	0	8.05
	3	1	18	0	0	9.8417
	3	1	43	1	6	46.9
	1	0	36	0	1	512.3292
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	3	0	20	0	0	9.225

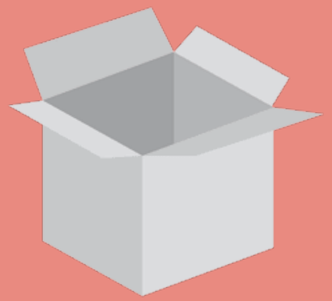
TESTING DATA

將答案遮住
使用剛剛的TREE
來預測每位乘客是否存活

```
accuracy :  0.853260869565217 4
```

PROS

- 白盒子

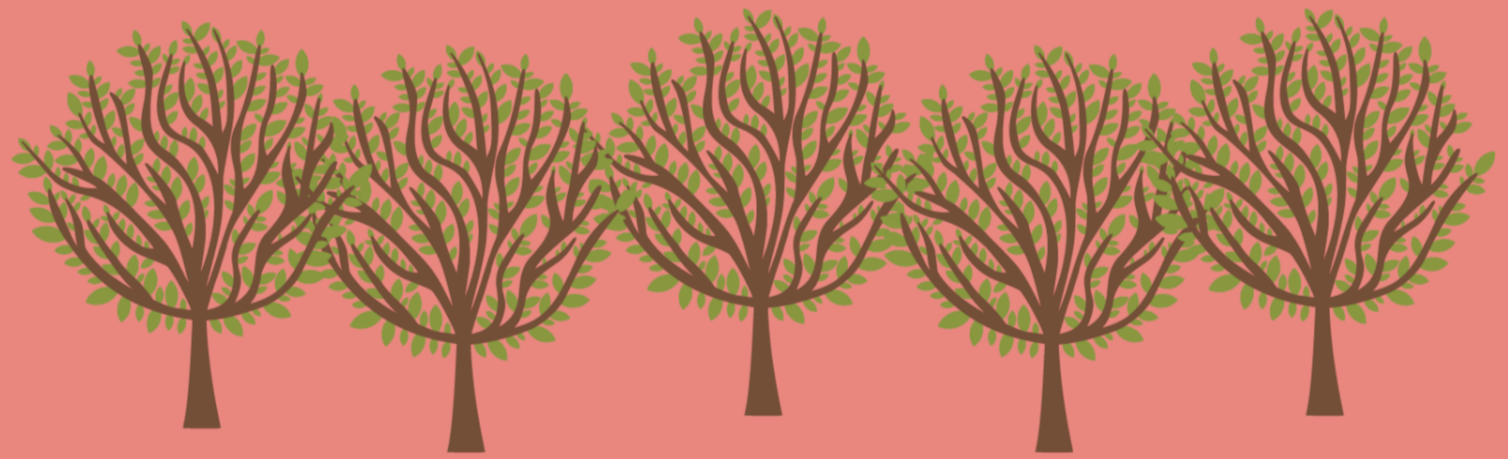


CONS

- Greedy
- 容易overfitting

三個臭皮匠
勝過一個諸葛亮

RANDOM FOREST

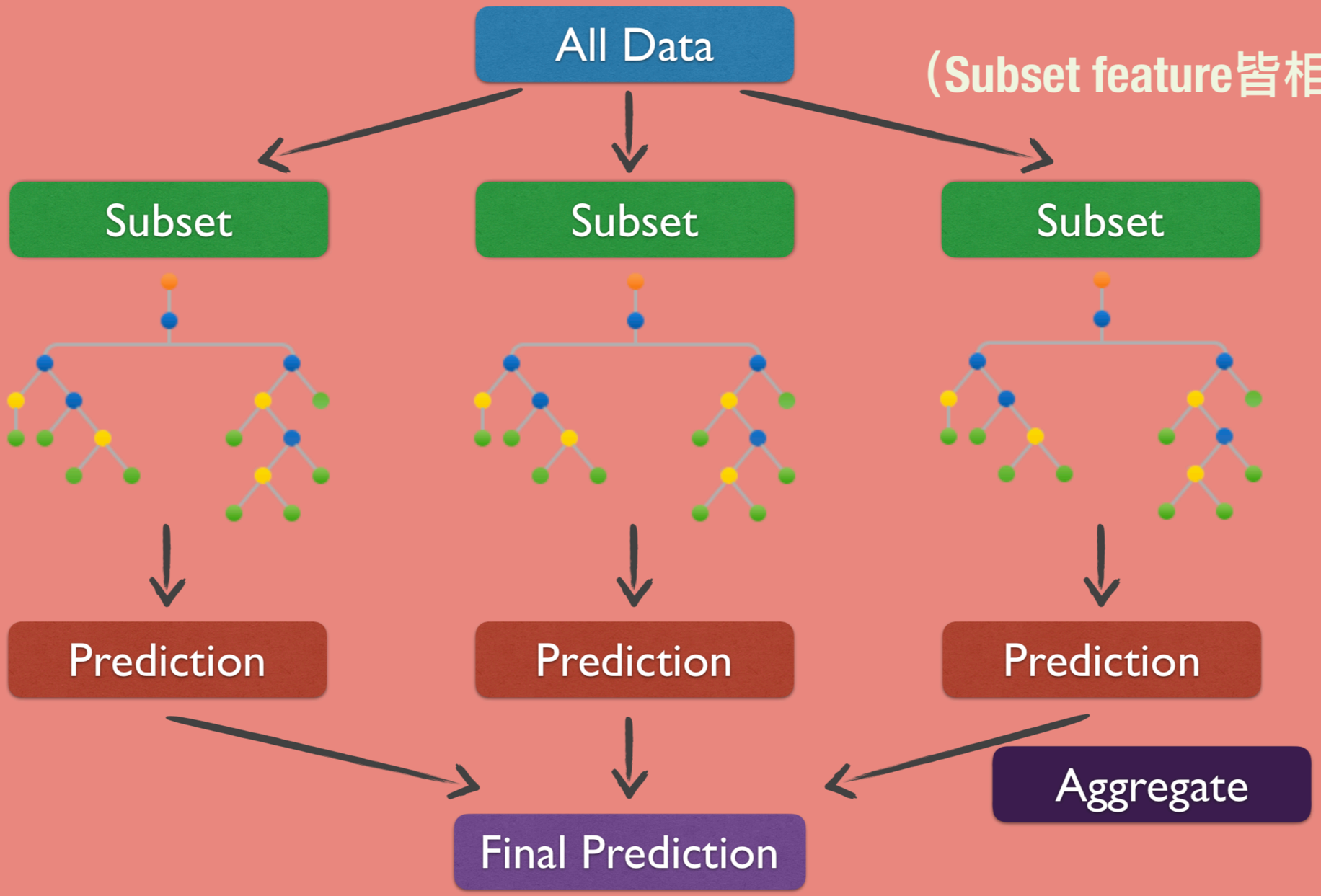


一個森林勝過一棵樹

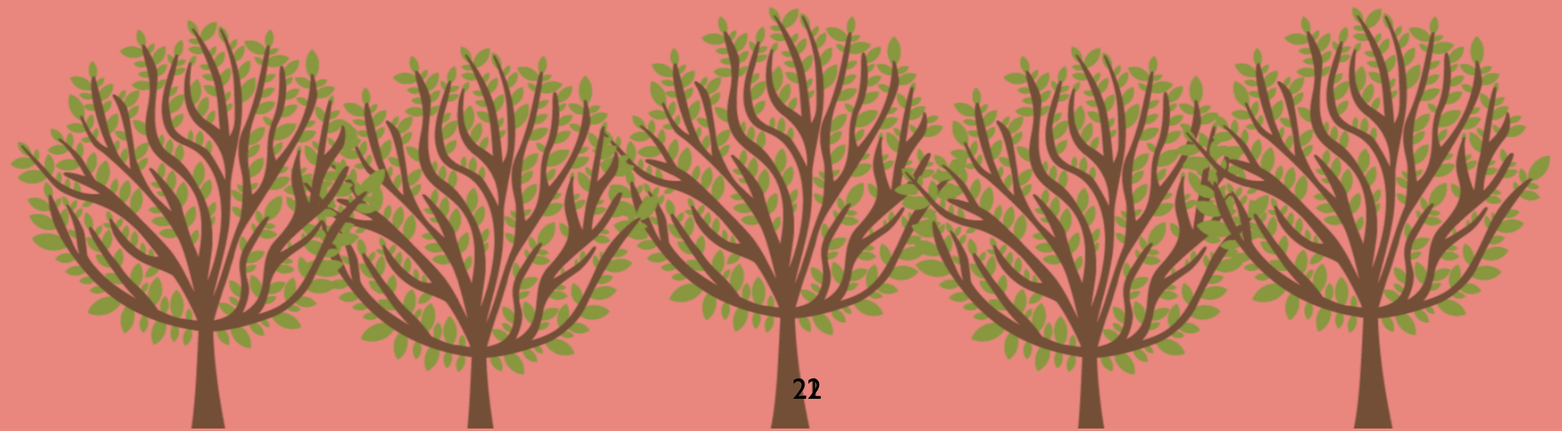
許多分類器合在一起預測就是

ENSEMBLE METHOD

讓所有樹一起投票


All Data
（Subset feature皆相同）
Subset
Subset
Subset
Prediction
Prediction
Prediction
Aggregate
Final Prediction

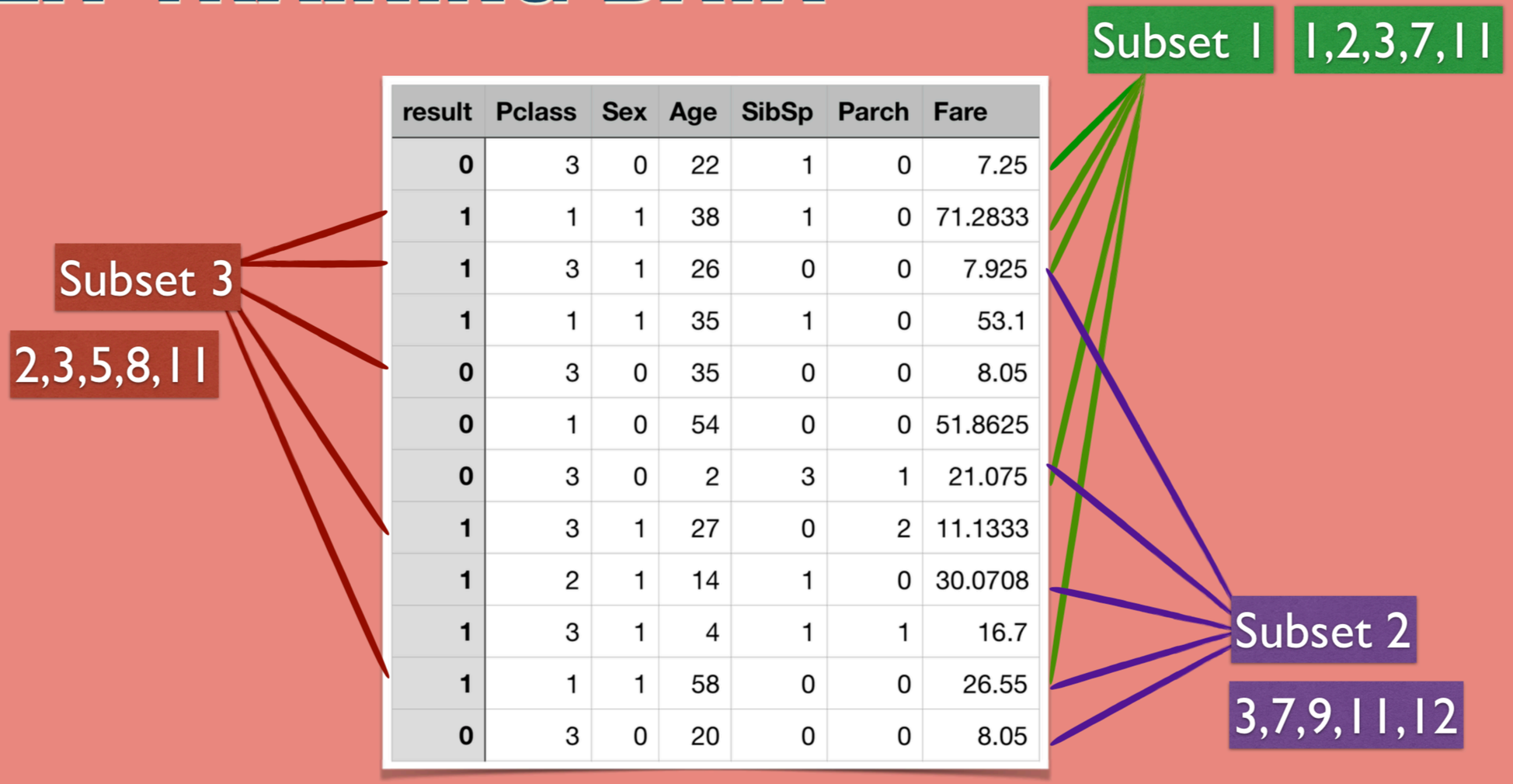
但如果森林裡每棵樹
都長得一樣也沒用
因為每棵樹預測的結果都一樣



如何讓樹長得不一樣？

ANS：讓每棵樹的 INPUT DATA 不同

SPLIT TRAINING DATA



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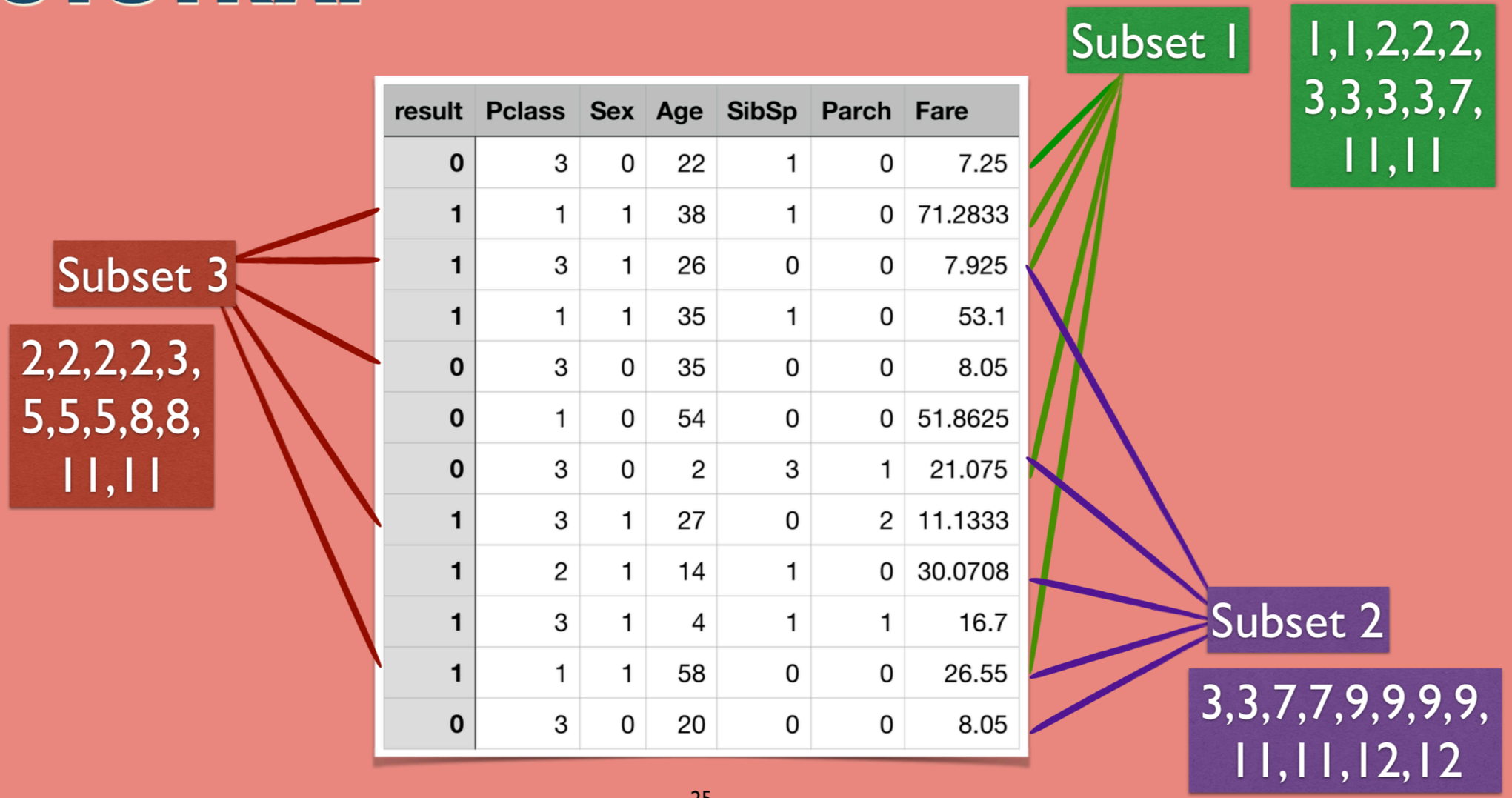
但這只是最一般的 SAMPLE 方式
有沒有更好的？

BOOTSTRAP

原本Data共有12筆，bootstrap 抽樣後
每個subset一樣也要12筆，但**允許**重複抽樣



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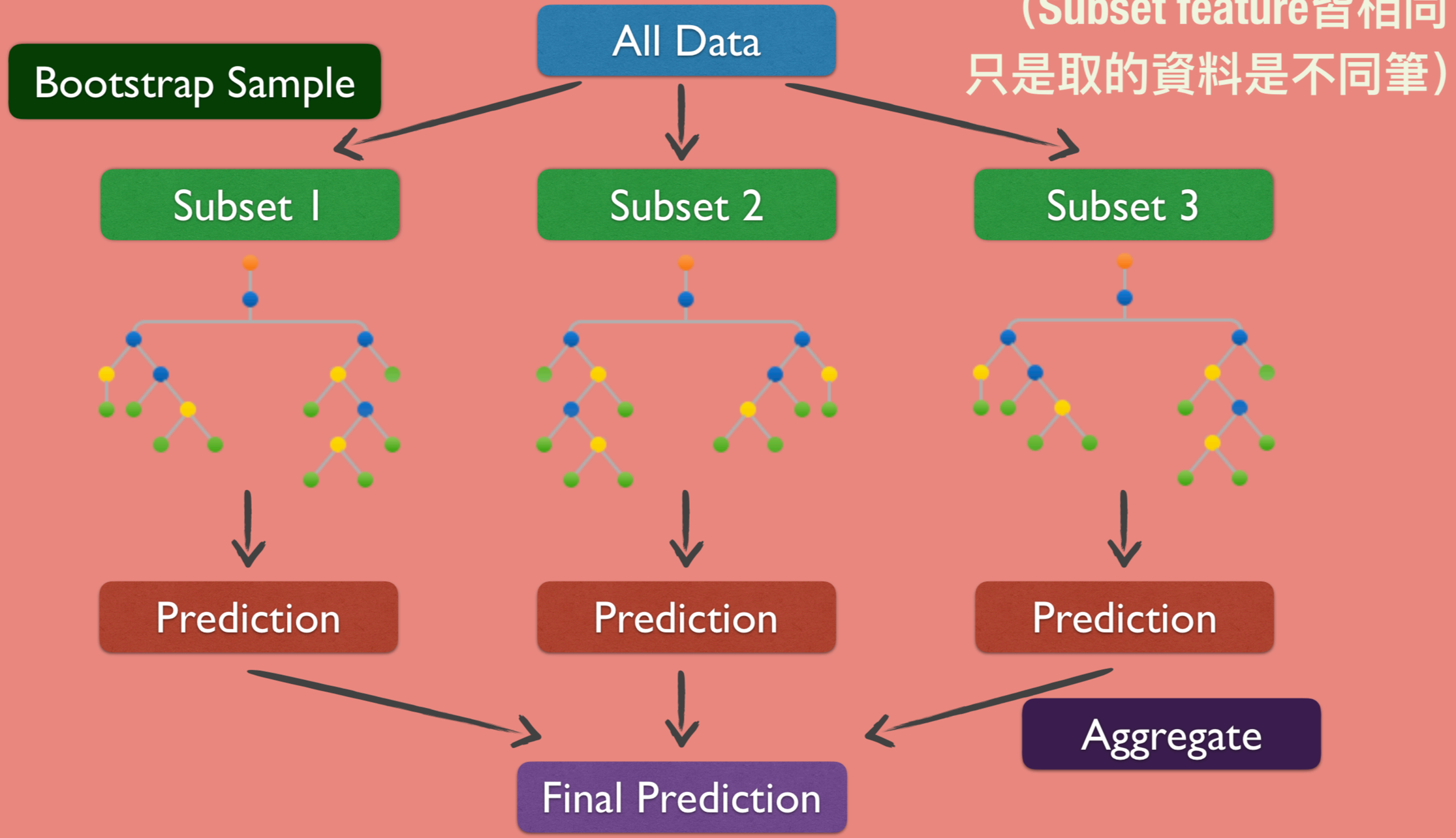

（Subset feature皆相同
只是取的資料是不同筆）


Bootstrap Sample
+
Aggregate
=
Bagging

DECISION TREE

accuracy : 0.8532608695652174

VS.

RANDOM FOREST

accuracy : 0.8641304347826086

PRACTICE TIME !

SCIKIT-LEARN

- Scikit-learn (sklearn) is a well-known machine learning library for Python.
- It features various classification, regression and clustering algorithms including decision tree, random forests, k-means and DBSCAN..., and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

IMPLEMENTATION

- Use DecisionTreeClassifier() to construct a tree.

```
from sklearn.tree import DecisionTreeClassifier
```

```
dtree=DecisionTreeClassifier()
dtree.fit(X,y)   ## X:attributes, y:labels
```

- After being fitted, the model can then be used to predict the class of samples.

```
y_predict = dtree.predict(X_test)
```

- Finally, evaluate your model.

```
from sklearn.metrics import accuracy_score

accuracy_score(y_test, y_predict)
```

IMPLEMENTATION

- Use RandomForestClassifier() to build a forest.

```
from sklearn.ensemble import RandomForestClassifier
```

```
clf = RandomForestClassifier()
clf.fit(X, y)
```

- After being fitted, the model can then be used to predict the class of samples.

```
y_predict = clf.predict(X_test)
```

- Finally, evaluate your model.

```
accuracy_score(y_test, y_predict)
```

PRACTICE TIME!

- Dataset link: https://www.kaggle.com/c/titanic
- Github link: https://github.com/IKMLab/PADS-Decision-tree-Random-forest

THANK YOU