



消費者價值模型與預測

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CONTENTS

- 1 Introduction
- 2 Data Pre-processing
- 3 Model Structure
- 4 Conclusion



PART 01

INTRODUCTION



01 - SCENARIO

網路購物興起
電商時代來臨

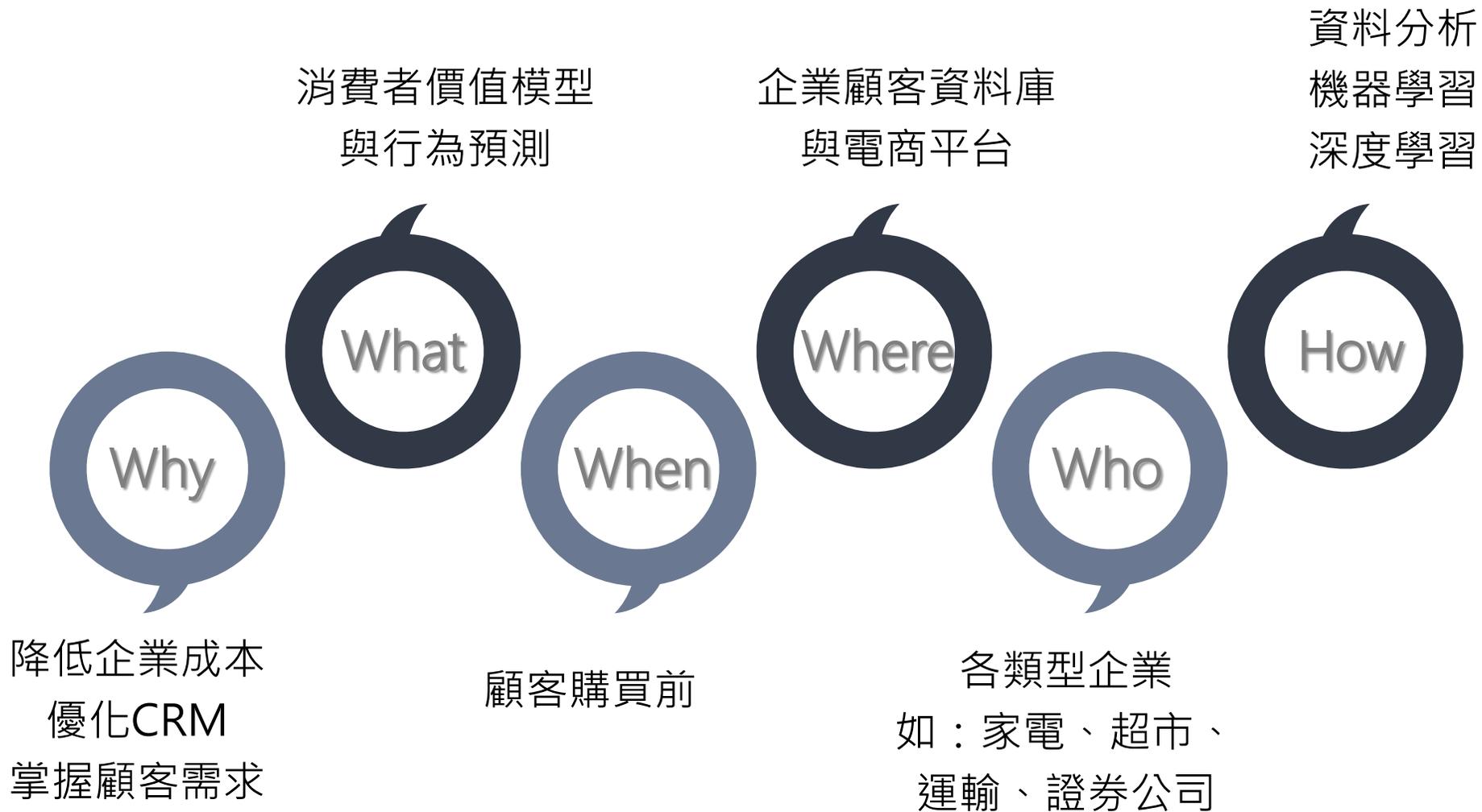


消費型態改變
網購市場擴大

大量交易紀錄
與消費者資料



01 – 5W1H





PART 02

DATA PREPROCESSING



02 – Data Source

- 資料來源：Kaggle
- 期間：2010年12月1日至2011年12月9日
- 企業：跨國禮品公司
- 資料筆數：共計541909筆

```
#import the database  
data = pd.read_csv('data.csv', encoding="ISO-8859-1", dtype={'CustomerID': str, 'InvoiceID': str})  
data.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850	United Kingdom



02 – Data Preprocessing

```
#check the data information  
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 541909 entries, 0 to 541908  
Data columns (total 8 columns):  
InvoiceNo      541909 non-null object  
StockCode      541909 non-null object  
Description    540455 non-null object  
Quantity       541909 non-null int64  
InvoiceDate    541909 non-null object  
UnitPrice      541909 non-null float64  
CustomerID     406829 non-null object  
Country        541909 non-null object  
dtypes: float64(1), int64(1), object(6)  
memory usage: 33.1+ MB
```

檢測是否存在遺漏值

```
#check the special code in stockcode
```

```
list_special_codes = df_cleaned[df_cleaned['StockCode'].str.contains('[a-zA-Z]+', regex=True)]['StockCode'].unique()  
list_special_codes
```

```
array(['POST', 'D', 'C2', 'M', 'BANK CHARGES', 'PADS', 'DOT'],  
      dtype=object)
```

刪去存在特殊編碼
之商品購買紀錄



02 – Data Preprocessing

轉換country欄位數值

```
l = [i for i in range(37)]  
dict(zip(list(le.classes_), l))
```

```
{'Australia': 0, 'Channel Islands': 6,  
'Austria': 1, 'Cyprus': 7,  
'Bahrain': 2, 'Czech Republic': 8,  
'Belgium': 3, 'Denmark': 9,  
'Brazil': 4, 'EIRE': 10,  
'Canada': 5, 'European Community': 11,
```

計算total price欄位

```
# Total price feature  
df_cleaned['TotalPrice'] = df_cleaned['UnitPrice'] * (df_cleaned['Quantity'] - df_cleaned['QuantityCanceled'])  
df_cleaned.head(5)
```

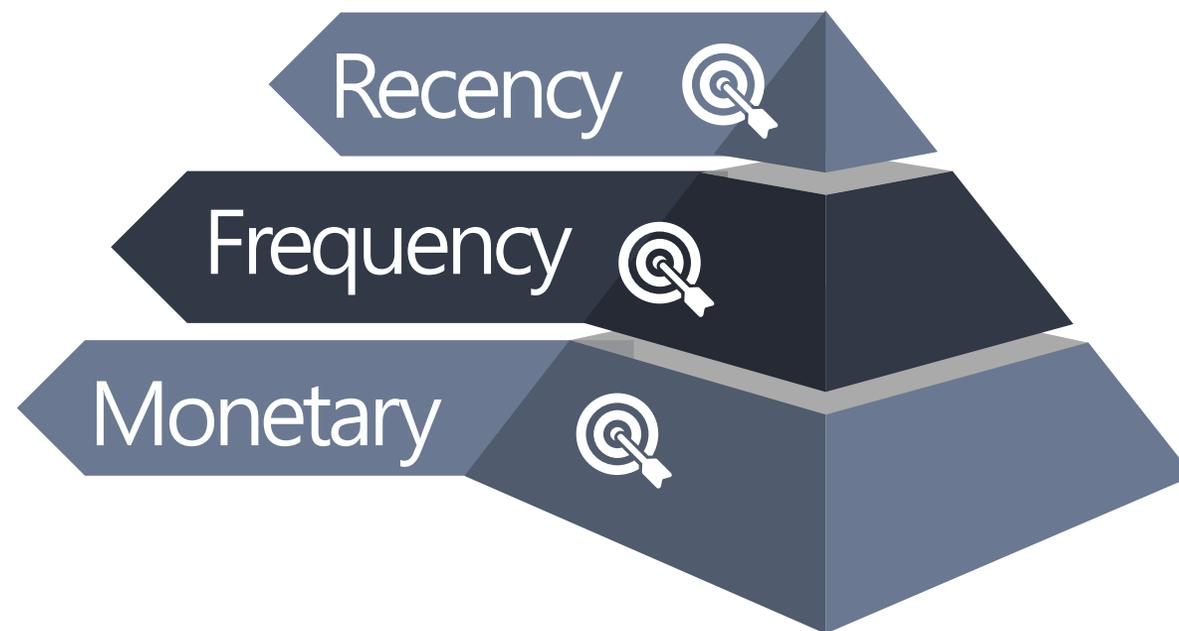
	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	QuantityCanceled	TotalPrice
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850	35	0	15.30
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850	35	0	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850	35	0	22.00
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850	35	0	20.34
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850	35	0	20.34

02 – RFM Model

- 「R:新客」(近期有消費的人)
- 「F:常客」(常常來消費的人)
- 「M:貴客」(消費金額大的人)

George Cullinan,1961

判斷顧客價值





02 – RFM Model

計算R欄位數值

```
#RFM model
df_cleaned['InvoiceDate'].min()

'1/10/2011 10:32'

df_cleaned['InvoiceDate'].max()

'9/9/2011 9:52'

NOW = dt.datetime(2011,12,10)
df_cleaned['InvoiceDate'] = pd.to_datetime(df_cleaned['InvoiceDate'])

custom_aggregation = {}
custom_aggregation["InvoiceDate"] = lambda x:x.iloc[0]
custom_aggregation["CustomerID"] = lambda x:x.iloc[0]
custom_aggregation["TotalPrice"] = "sum"

rfmTable = df_cleaned.groupby("InvoiceNo").agg(custom_aggregation)

rfmTable["Recency"] = NOW - rfmTable["InvoiceDate"]
rfmTable["Recency"] = pd.to_timedelta(rfmTable["Recency"]).astype("timedelta64[D]")
```



02 – RFM Model

計算F、M欄位數值

```
#construct the RFM feature
custom_aggregation = {}

custom_aggregation["Recency"] = ["min", "max"]
custom_aggregation["InvoiceDate"] = lambda x: len(x)
custom_aggregation["TotalPrice"] = "sum"

rfmTable_final = rfmTable.groupby("CustomerID").agg(custom_aggregation)

#show the result of RFM table
rfmTable_final.columns = ["min_recency", "max_recency", "frequency", "monetary_value"]
rfmTable_final.head(5)
```

CustomerID	min_recency	max_recency	frequency	monetary_value
12346	325.0	325.0	1	0.00
12347	2.0	367.0	7	4310.00
12348	75.0	358.0	4	1437.24
12349	18.0	18.0	1	1457.55
12350	310.0	310.0	1	294.40



02 – RFM Model

將RFM欄位轉換為分數
1為最佳值

```
#define the segmentation of each score, each score is divided to categories
def RScore(x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4

def FMScore(x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
```



02 – RFM Model

```
segmented_rfm['r_quartile'] = segmented_rfm['min_recency'].apply(RScore, args=('min_recency',quantiles,))  
segmented_rfm['f_quartile'] = segmented_rfm['frequency'].apply(FMScore, args=('frequency',quantiles,))  
segmented_rfm['m_quartile'] = segmented_rfm['monetary_value'].apply(FMScore, args=('monetary_value',quantiles,))  
segmented_rfm.head()
```

	min_recency	max_recency	frequency	monetary_value	r_quartile	f_quartile	m_quartile
CustomerID							
12346	325.0	325.0	1	0.00	4	4	4
12347	2.0	367.0	7	4310.00	1	1	1
12348	75.0	358.0	4	1437.24	3	2	2
12349	18.0	18.0	1	1457.55	2	4	2
12350	310.0	310.0	1	294.40	4	4	4

以此分數進行消費者分類，並根據不同類型的客群進行精準行銷



PART 03

MODEL STRUCTURE



03 – MLP

```
#MLP
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(64,64,64),
                    activation='logistic',
                    solver='adam',
                    batch_size='auto',
                    learning_rate='constant',
                    learning_rate_init=0.001,
                    max_iter=10,
                    random_state=0)

mlp.fit(X_train, y_train)
print("Train accuracy of MLP: {:.3f}".format(mlp.score(X_train, y_train)))
print("Test accuracy of MLP: {:.3f}".format(mlp.score(X_test, y_test)))
```

PARAMETERS	activation=logistic solver=SGD max iteration=auto	solver=adam	max iteration=100	activation=relu
ACCURACY	0.358	0.555	0.826	0.919

調整參數：activation、solver、max iteration
準確率：0.358 -> 0.555 -> 0.826 -> 0.919



03 – Linear SVC

```
#Linear SVC
from sklearn.svm import LinearSVC
lsvc = LinearSVC(
    random_state=None,
    max_iter=10
)
svc.fit(X_train, y_train)
print("Train accuracy of SVC: {:.3f}".format(svc.score(X_train, y_train)))
print("Test accuracy of SVC: {:.3f}".format(svc.score(X_test, y_test)))
```

具備良好的適配性
相較於kNN，僅需較少的樣本數即可用來建立分類模型
準確率：0.931



03 – Random Forest

```
#Random Forest
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(max_features=None, criterion='gini', max_depth=None,
                           random_state=0, n_estimators = 100)

param_grid = {
    'n_estimators' : [10, 50, 100],
    'max_features' : ['auto', 'sqrt', 'log2'],
    'max_depth' : [2, 4],
    'criterion' :['gini', 'entropy']
}
rfc=RandomForestClassifier(random_state=0, n_estimators = 100,
                           criterion='entropy', max_depth=3, max_features='auto')
rfc.fit(X_train, y_train)
print("Train accuracy of RFC: {:.3f}".format(rfc.score(X_train, y_train)))
print("Test accuracy of RFC: {:.3f}".format(rfc.score(X_test, y_test)))
```

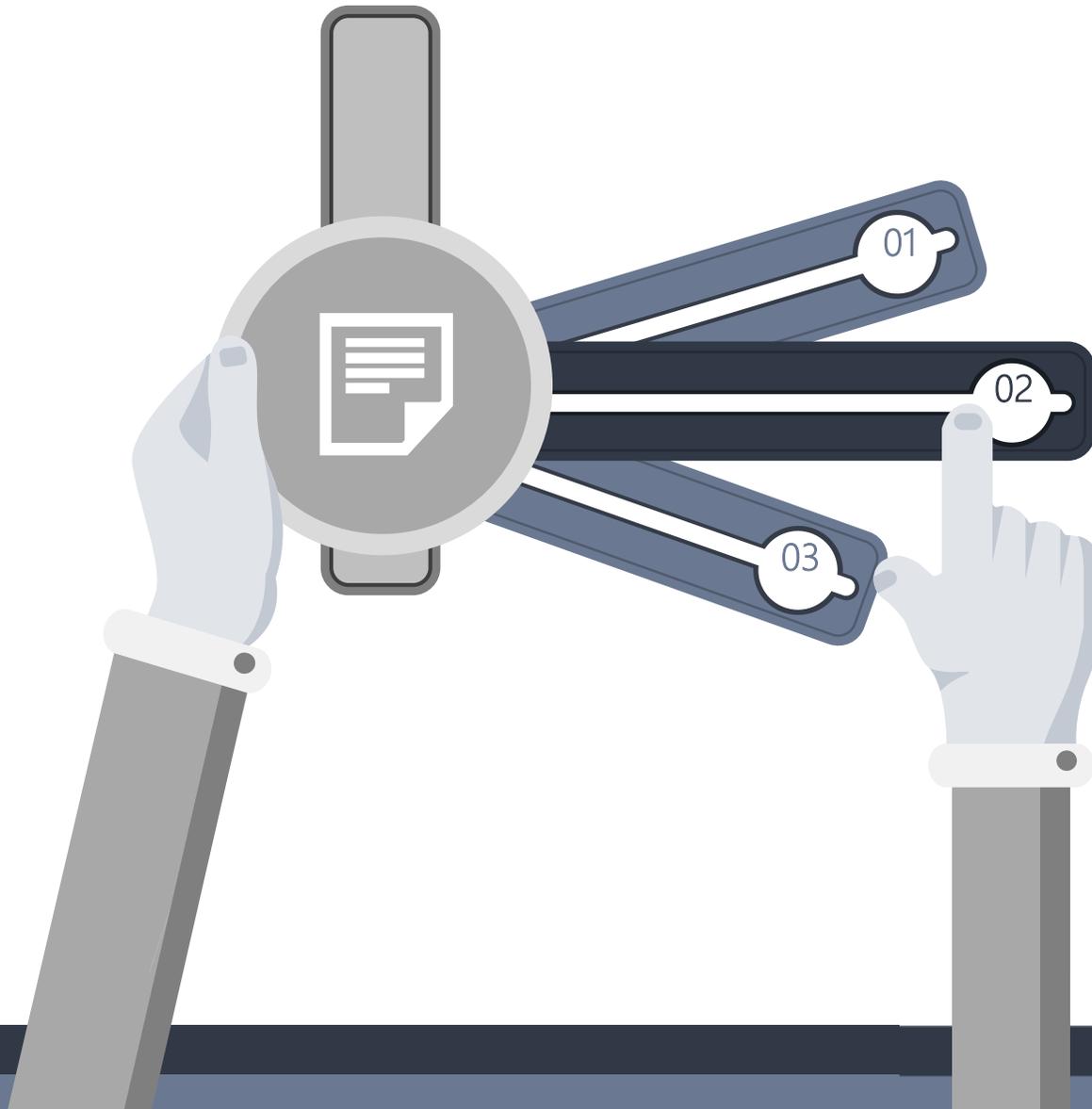
	10	50	100
gini	0.817	0.840	0.843
entropy	0.826	0.857	0.865

調整參數 : criterion、max_estimators
準確率 : 0.865



PART 04

CONCLUSION



資料前處理

刪除重複/缺失值
轉換數值
刪去不合理數值

01

RFM模型

資料分析
欄位建立
顧客分群

02

預測模型

MLP
SVC
Random Forest

03



04 – Future Work

多店交叉預測

連鎖店分析

競品購物
行為預測



Thanks for listening

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