# 電商技術 HW3 第三部分

# 1.載入 customer\_churn.csv,列出資料筆數、屬性數量以 及每個欄位的空值個數

customer\_churn.csv 原始資料共3083筆、屬性數20:

Current relation	
Relation: customer_churn	Attributes: 20
Instances: 3083	Sum of weights: 3083

#### 以下為每個欄位的空值個數:

#### 1. CustomerID 無空值

Distinct: 2079	Type: Numeric Unique: 3075 (100%)
Distinct: 5076	
	Value
5000	)1
5562	28
5280	7.294
1617	'. <mark>1</mark> 3
	5562 5280

#### 2. Churn 無空值

Selected attribute Name: Churn	Type: Numeric		
Missing: 0 (0%)	Distinct: 2	Unique: 0 (0%)	
Statistic		Value	
Minimum	0	0	
Maximum	1	1	
Mean	0.3	08	
StdDev	0.4	62	

### 3. Tenure 有153筆空值

Name: Tenure Missing: 153 (5%)	Distinct: 35	Type: Numeric Unique: 3 (0%)
Statisti	с	Value
Minimum	0	
Maximum	61	
Mean	9.109	
StdDev	8.549	

## 4. PreferredLoginDevice 無空值

	PreferredLoginDevic 0 (0%)	e Distinct: 3	Type: Nominal Unique: 0 (0%)
No.	Label	Cou	ınt Weight
1	Computer	928	928
2	Mobile Phone	1458	1458
3	Phone	697	697

## 5. CityTier 無空值

Missing: 0 (0%) Statistic	Distinct: 3 Unique: 0 (0%)  Value
Statistic	V-L
	value
Minimum	1
Maximum	3
Mean	1.682
StdDev	0.925

#### 6. WarehouseToHome 154筆空值

Name: WarehouseToHor Missing: 154 (5%)	me Distinct: 33	Type: Numeric Unique: 1 (0%)
Statistic		Value
Minimum	5	
Maximum	126	
Mean	15.771	
StdDev	8.557	

## 7. PreferredPaymentMode 無空值

	PreferredPaymentMo 0 (0%)	ode Distinct: 7	Type: Nominal Unique: 0 (0%)
No.	Label	Со	unt Weigh
1	Debit Card	1255	1255
2	Credit Card	789	789
3	E wallet	368	368
4	CC	147	147
5	COD	225	225
6	UPI	222	222
7	Cash on Delivery	77	77

## 8. Gender 無空值

	attribute Gender 0 (0%)	Distinct: 2	Type: Nominal Unique: 0 (0%)
No.	Labe	l Co	unt Weight
1	Male	1854	1854
2	Female	1229	1229

## 9. HourSpendOnApp 150筆空值

Distinct: 6	Type: Numeric Unique: 1 (0%)
	Value
0	
5	
2.946	
0.719	
	0 5 2.946

## 10. NumberOfDeviceRegistered 無空值

Statistic Value nimum 1 eximum 6	Name: NumberOfDev	Type: Numeric	
nimum 1 aximum 6	Missing: 0 (0%)	Distinct: 6	Unique: 0 (0%)
aximum 6	Statistic	=	Value
	Minimum	1	
an 3.75	Maximum	6	
	Mean	3.7	5
Dev 1.005	StdDev	1.0	05

#### 11. PreferredOrderCat 無空值

Name: lissing:	PreferedOrderCat 0 (0%) Di	stinct: 6		e: Nominal e: 0 (0%)
No.	Label	C	ount	Weight
1	Mobile Phone	772		772
2	Grocery	198		198
3	Laptop & Accessory	1066		1066
4	Mobile	463		463
5	Fashion	449		449
6	Others	135		135

#### 12. SatisfactionScore 無空值

Name: SatisfactionSc		Type: Numeric
Missing: 0 (0%)	Distinct: 5	Unique: 0 (0%)
Statisti	С	Value
Minimum	1	
Maximum	5	
Mean	3.	134
StdDev	1.	382

#### 13. MaritalStatus 無空值

•	Label	Cour	nt Weig
1 Sir	ngle	1102	1102
2 M	arried	1547	1547
3 Di	vorced	434	434

### 14. NumberOfAddress 無空值

Statistic	Value	
	value	•
Minimum	1	
Maximum	21	
Mean	4.335	
tdDev	2.663	

## 15. Complain 無空值

Name: Complain	D: .:	Type: Numeric
Missing: 0 (0%)	Distinct: 2	Unique: 0 (0%)
Statist	tic	Value
Minimum	0	
Maximum	1	
Mean	0.328	3
StdDev	0.47	

#### 16. OrderAmountHikeFromlastYear 131筆空值

	Name: OrderAmountHikeFromlastYear	
Missing: 131 (4%)	Distinct: 16	Unique: 0 (0%)
Statisti	с	Value
Minimum	11	
Maximum	26	
Mean	15.714	
StdDev	3.765	

## 17. CouponUsed 126筆空值

Name: CouponUsed Missing: 126 (4%)	Distinct: 17	Type: Numeric Unique: 3 (0%)
Statistic		Value
Minimum	0	
Maximum	16	
Mean	1.753	
StdDev	1.886	

#### 18. OrderCount 128筆空值

Name: OrderCount Missing: 128 (4%)	Distinct: 16	Type: Numeric Unique: 0 (0%)
Statistic		Value
Minimum	1	
Maximum	16	
Mean	2.994	
StdDev	2.948	

### 19. DaySinceLastOrder 166筆空值

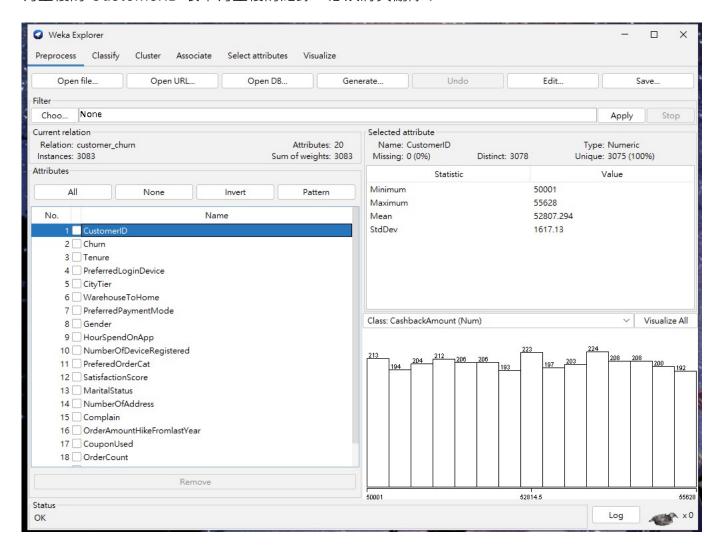
Name: DaySinceLastOrd Missing: 166 (5%)	der Distinct: 20	Type: Numeric Unique: 1 (0%)
Statistic		Value
Minimum	0	
Maximum	46	
Mean	4.349	
StdDev	3.609	

#### 20. CashbackAmount 無空值

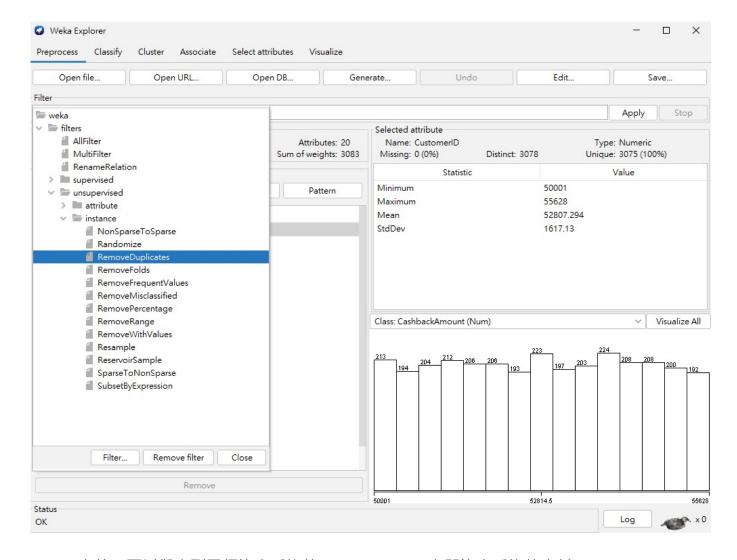
Value

# 2.請刪除重覆多餘的資料 (僅保留一筆),並列出剩餘的資料 筆數

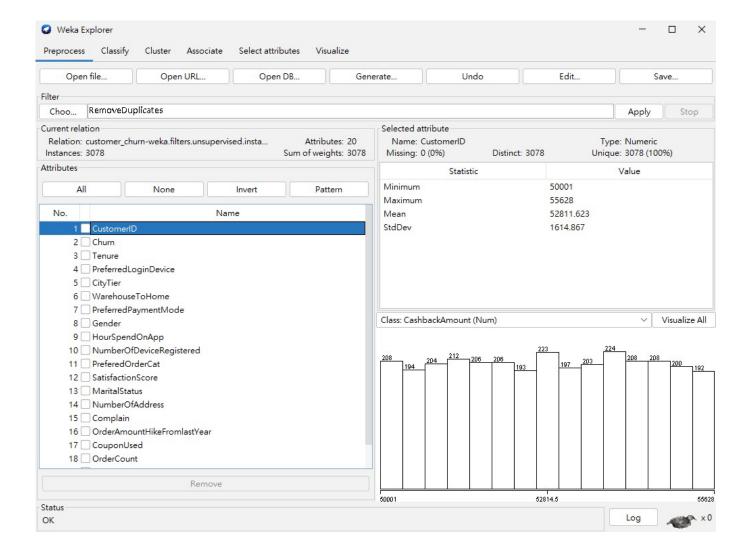
#### 有重複的 CustomerID 表示有重複的紀錄,必須將其刪除:



透過 fiter 找到 RemoveDuplicates 刪去重複資料:



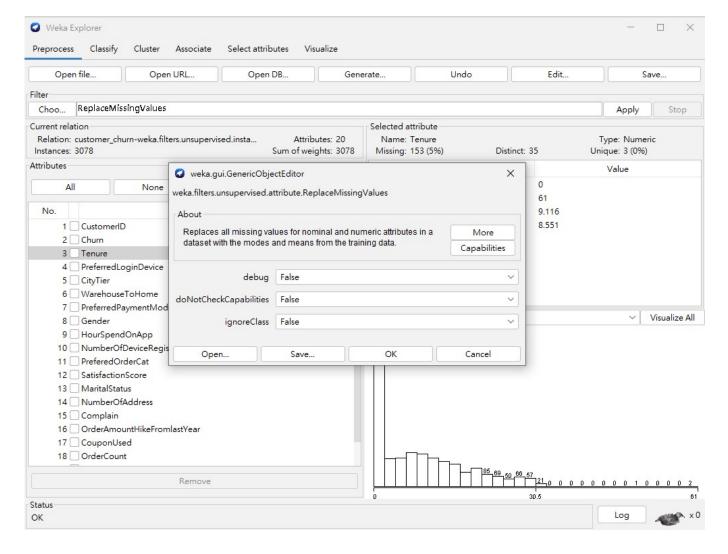
Apply 之後,可以觀察到已經沒有重複的 CustomerID,亦即沒有重複的資料:



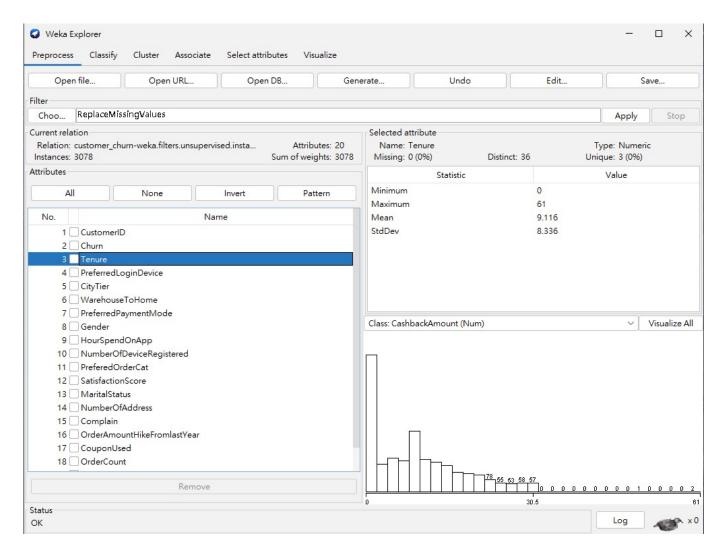
## 3.資料前處理

# 填補 Missing Value

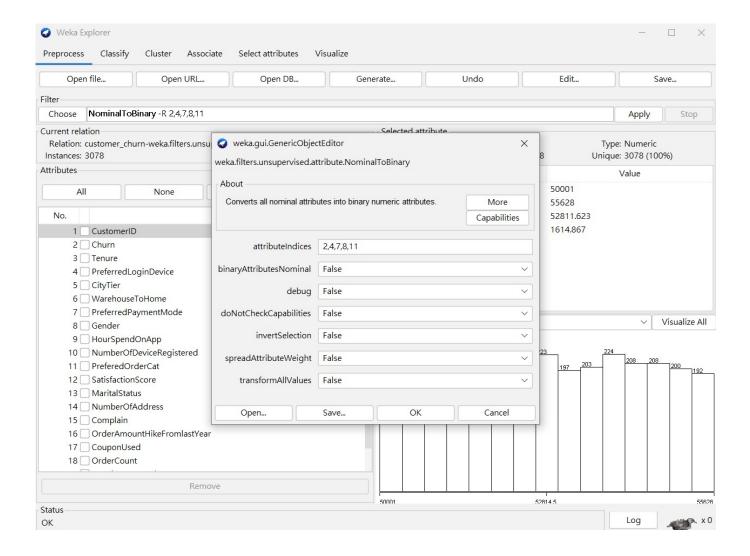
nominal 以 mode 填補 missing value numeric 以 mean 填補 missing value

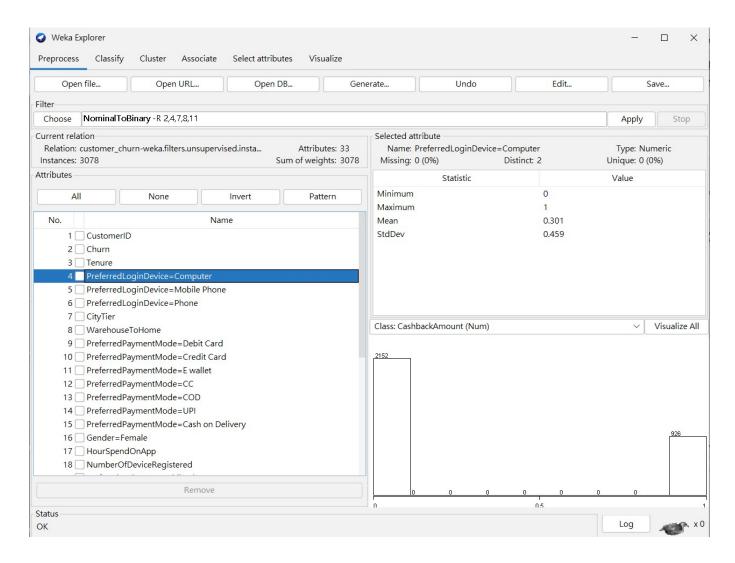


以 Tenure 為例·missing value 都不見了·其餘屬性也是如此

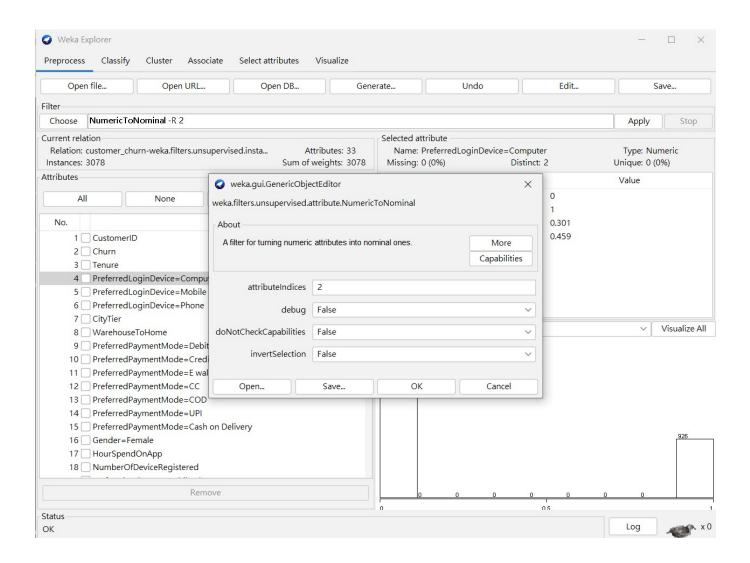


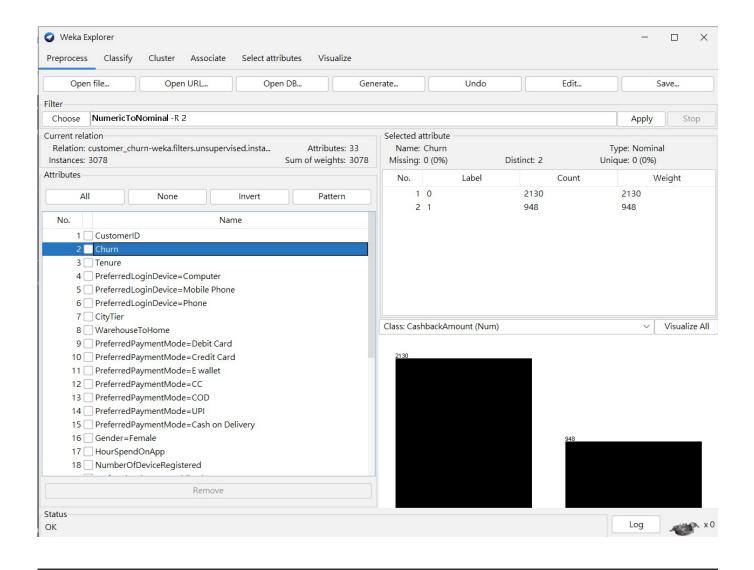
接下來將 categorical 屬性值都轉成 numeric value,我選擇的是 filter 中的 NominalToBinary,在屬性值不是二元可分的情況,其實就跟 Python 的 pandas.get\_dummies 很像,把屬性變得更多了。





最後,把 churn 用 filter 中的 NumericToNominal 就可以套用 SVM、Logistic Regression、Decision Tree 來預測 churn 了。



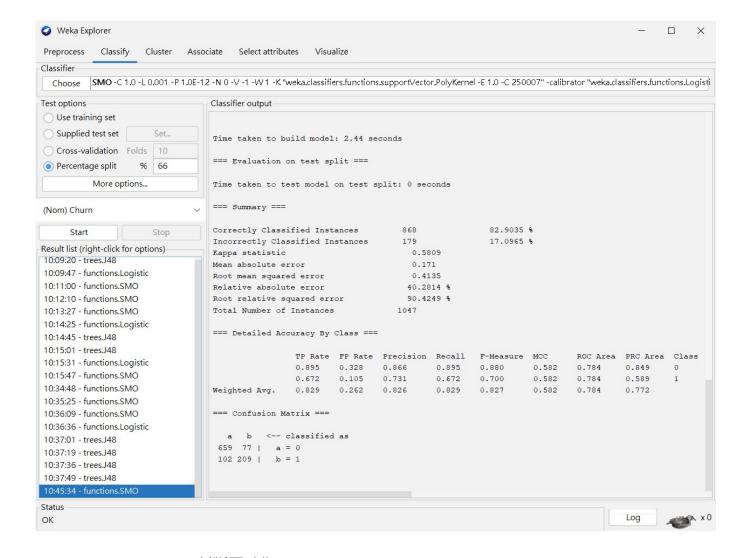


# 4.訓練、測試 SVM、Logistic Regression、Decision Tree 模型,請以 Accuracy 評估 模型表現

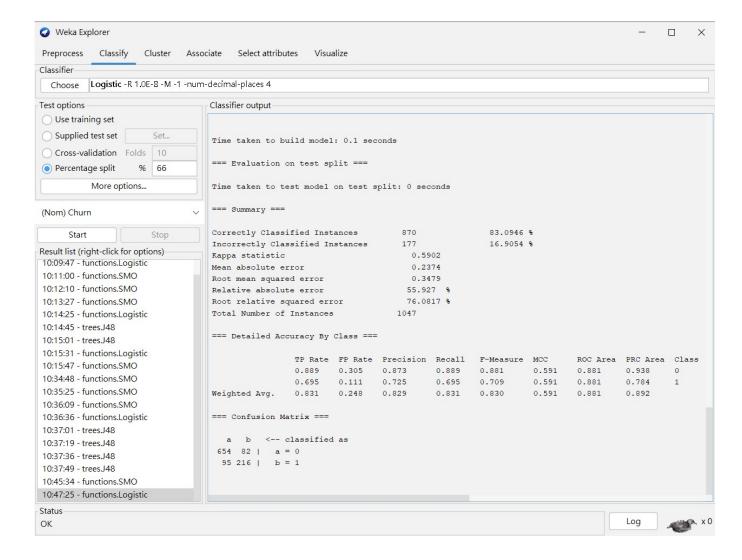
(模型皆為預設未調整, Training Data: 66%)

### 未用 NominalToBinary 前各模型準確率:

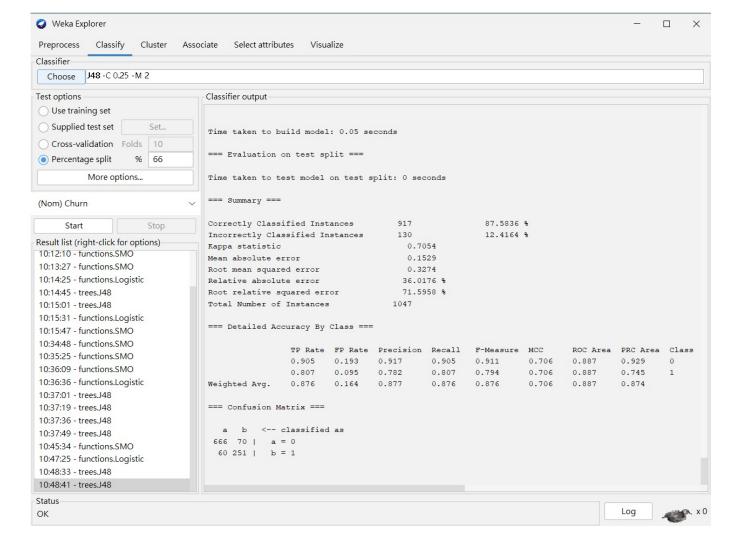
SVM: 判斷正確為 82.9035%



Logistic Regression: 判斷正確為 83.0946%

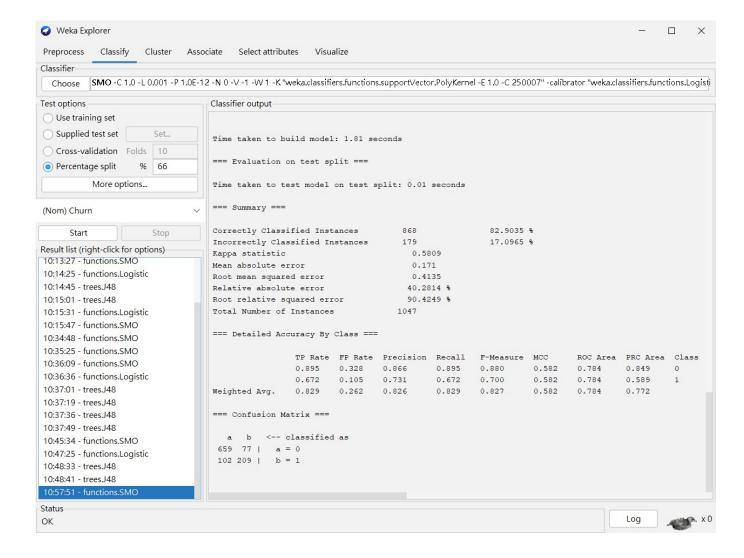


Decision Tree: 判斷正確為 87.5836%

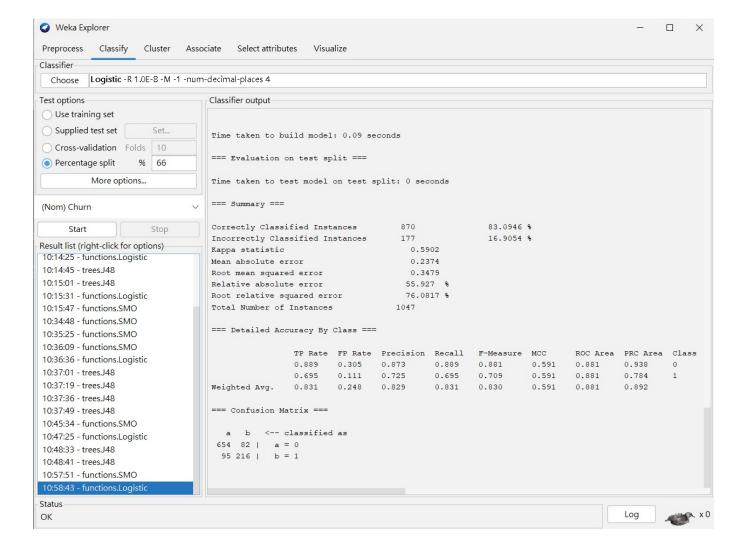


#### 用 NominalToBinary 後各模型準確率:

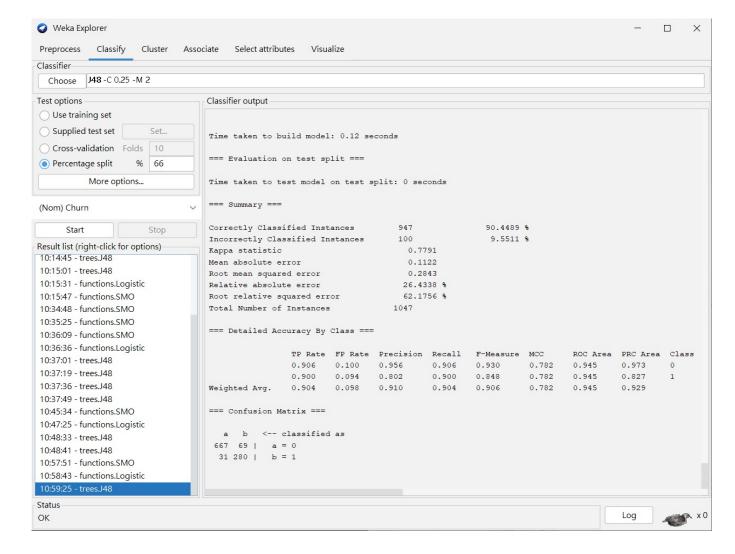
SVM: 判斷下確為 82.9035%



Logistic Regression: 判斷正確為 83.0946%



Decision Tree: 判斷正確為 90.4489%



結論:用 NominalToBinary 的前後·SVM 與 Logistic Regression 的準確率沒有影響·但 Decision Tree 的準確率有微幅上升。