

# 資料科學 期末報告

## 預測忠誠分數

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# dataset

- 五個table
  - 較舊的交易紀錄
  - 較新的交易紀錄
  - 商品種類
  - train (201917個卡號)
  - test (123623個卡號)



## train (201917個卡號)

train.csv	
Columns	Description
card_id	Unique card identifier
first_active_month	'YYYY-MM', month of first purchase
feature_1	Anonymized card categorical feature
feature_2	Anonymized card categorical feature
feature_3	Anonymized card categorical feature
target	Loyalty numerical score calculated 2 months after historical and evaluation period

含card id、target

## 較舊的交易紀錄

historical_transactions.csv	
Columns	Description
card_id	Card identifier
month_lag	month lag to reference date
purchase_date	Purchase date
authorized_flag	Y' if approved, 'N' if denied
category_3	anonymized category
installments	number of installments of purchase
category_1	anonymized category
merchant_category_id	Merchant category identifier (anonymized )
subsector_id	Merchant category group identifier (anonymized )
merchant_id	Merchant identifier (anonymized)
purchase_amount	Normalized purchase amount
city_id	City identifier (anonymized )
state_id	State identifier (anonymized )
category_2	anonymized category

- 29m筆交易紀錄
  - 325540張卡
  - 1Jan17-1Mar18
  - 共含326k種商品
  - card id
  - merchant id

## 較新的交易紀錄

new_merchant_period.csv	
Columns	Description
card_id	Card identifier
month_lag	month lag to reference date
purchase_date	Purchase date
authorized_flag	Y' if approved, 'N' if denied
category_3	anonymized category
installments	number of installments of purchase
category_1	anonymized category
merchant_category_id	Merchant category identifier (anonymized )
subsector_id	Merchant category group identifier (anonymized )
merchant_id	Merchant identifier (anonymized)
purchase_amount	Normalized purchase amount
city_id	City identifier (anonymized )
state_id	State identifier (anonymized )
category_2	anonymized category

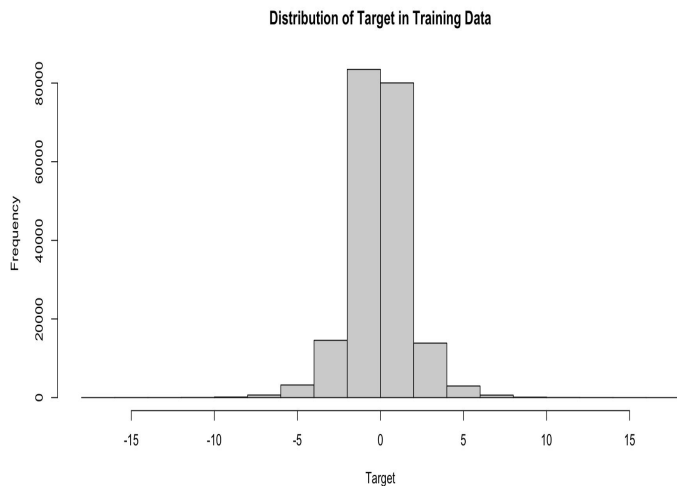
- 1.96m筆交易紀錄
  - 290001張卡
  - 1Mar17-1May18
  - 共含226k種商品
  - card id
  - merchant id

# 商品種類

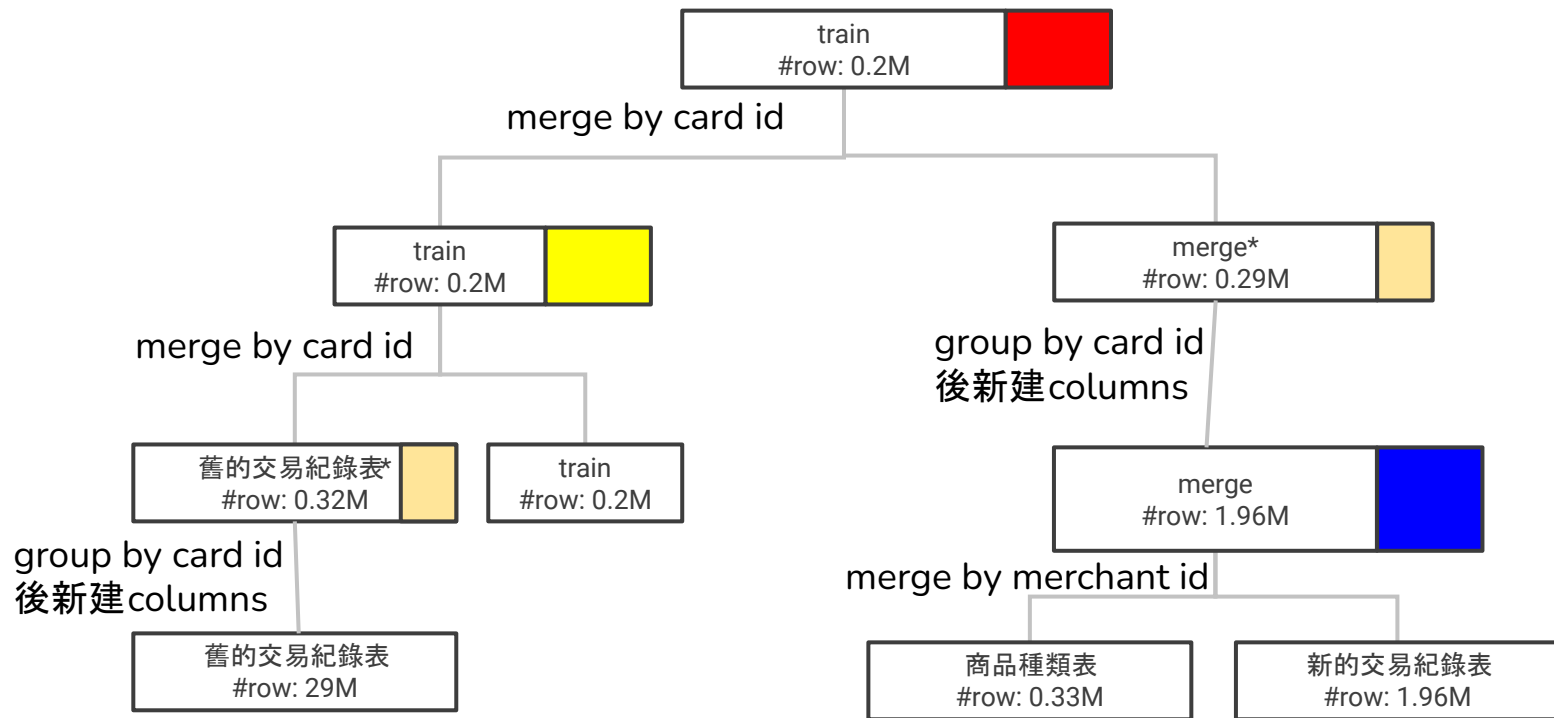
merchants.csv	
Columns	Description
merchant_id	Unique merchant identifier
merchant_group_id	Merchant group (anonymized )
merchant_category_id	Unique identifier for merchant category (anonymized )
subsector_id	Merchant category group (anonymized )
numerical_1	anonymized measure
numerical_2	anonymized measure
category_1	anonymized category
most_recent_sales_range	Range of revenue (monetary units) in last active month --> A > B > C > D > E
most_recent_purchases_range	Range of quantity of transactions in last active month --> A > B > C > D > E
avg_sales_lag3	Monthly average of revenue in last 3 months divided by revenue in last active month
avg_purchases_lag3	Monthly average of transactions in last 3 months divided by transactions in last active month
active_months_lag3	Quantity of active months within last 3 months
avg_sales_lag6	Monthly average of revenue in last 6 months divided by revenue in last active month
avg_purchases_lag6	Monthly average of transactions in last 6 months divided by transactions in last active month
active_months_lag6	Quantity of active months within last 6 months
avg_sales_lag12	Monthly average of revenue in last 12 months divided by revenue in last active month
avg_purchases_lag12	Monthly average of transactions in last 12 months divided by transactions in last active month
active_months_lag12	Quantity of active months within last 12 months
category_4	anonymized category
city_id	City identifier (anonymized )
state_id	State identifier (anonymized )
category_2	anonymized category

- 334633種商品  
merchant id

# 預測值(target)的分布



- 我們發現train資料集裡面的target column的分布大多介於0上下，因此取以e為底的指數後 $\exp\{\text{target}\}$ 其大多會呈現介於1上下，因此推斷其為某兩個數相除之比例，而那兩個數就由特徵工程創造出來的新特徵去發掘！







# 一些新建的columns

建了84個columns

舊的交易紀錄-日期相關

舊的交易紀錄-消費金額相關

舊的交易紀錄-其他

新的交易紀錄-日期相關

新的交易紀錄-消費金額相關

新的交易紀錄-其他

舊新相除算比例

基本款

hist\_purchase\_date\_month\_nunique

中階款

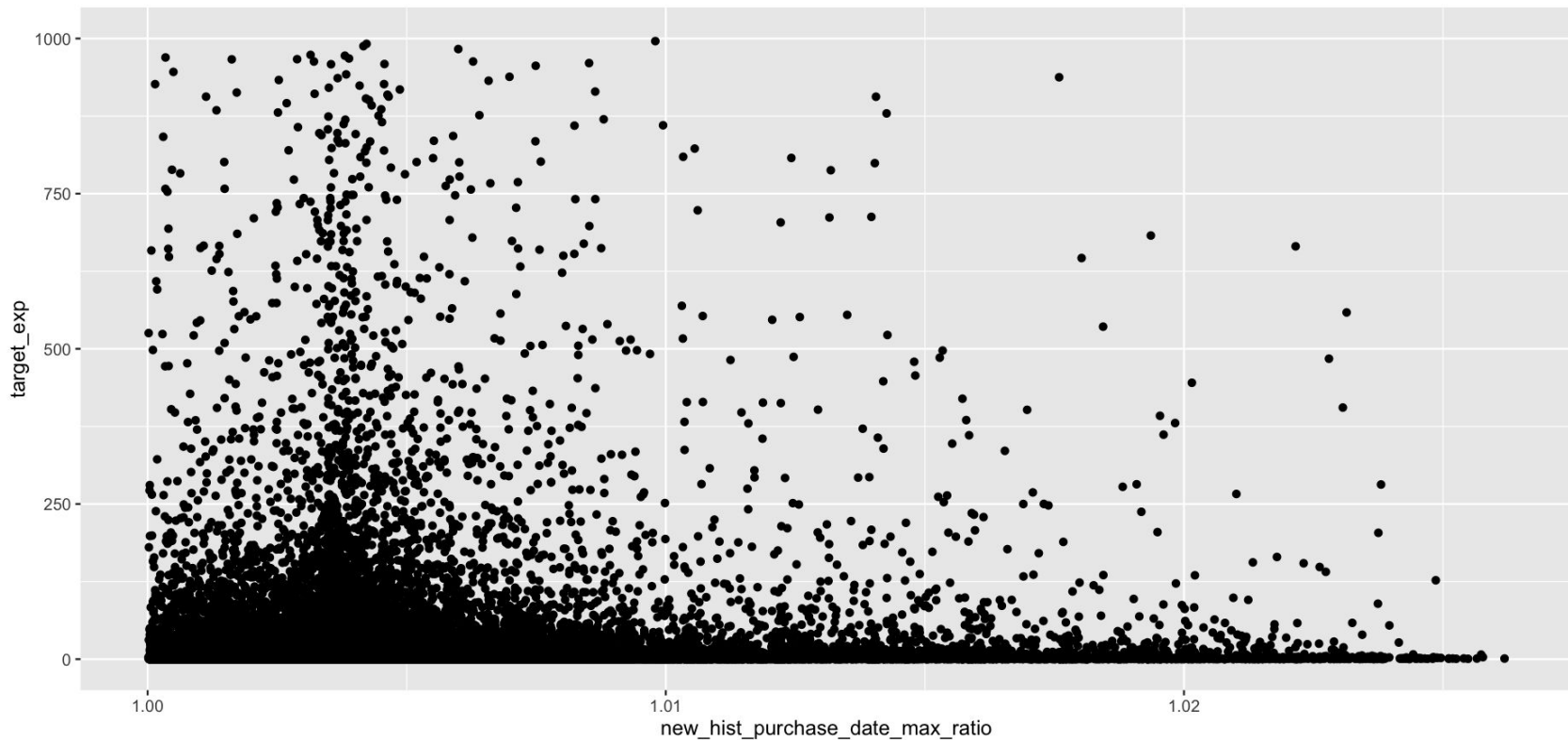
new\_merchant\_merchants\_most\_recent\_sal

es\_range\_mean\_max

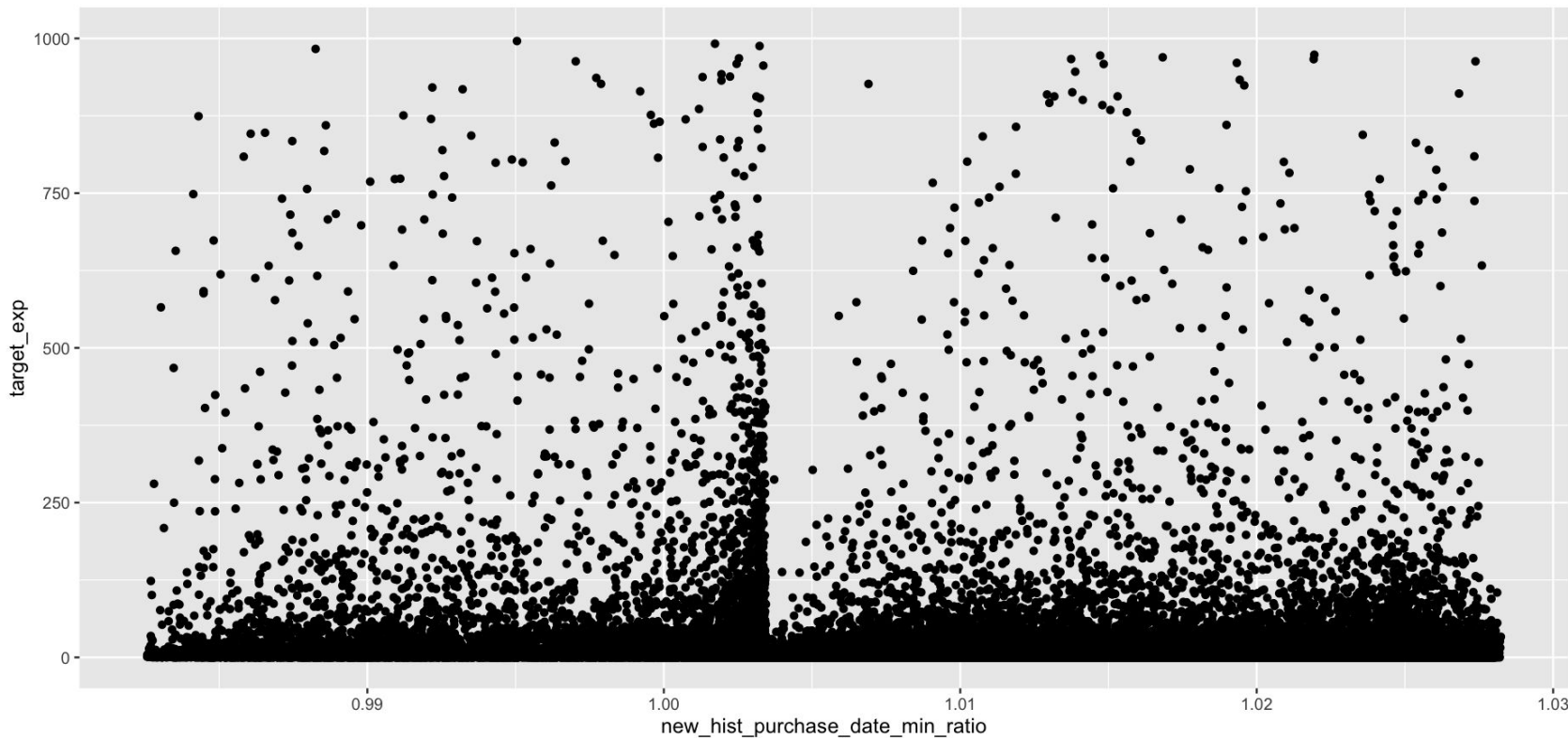
進階款

new\_hist\_card\_id\_size\_ratio

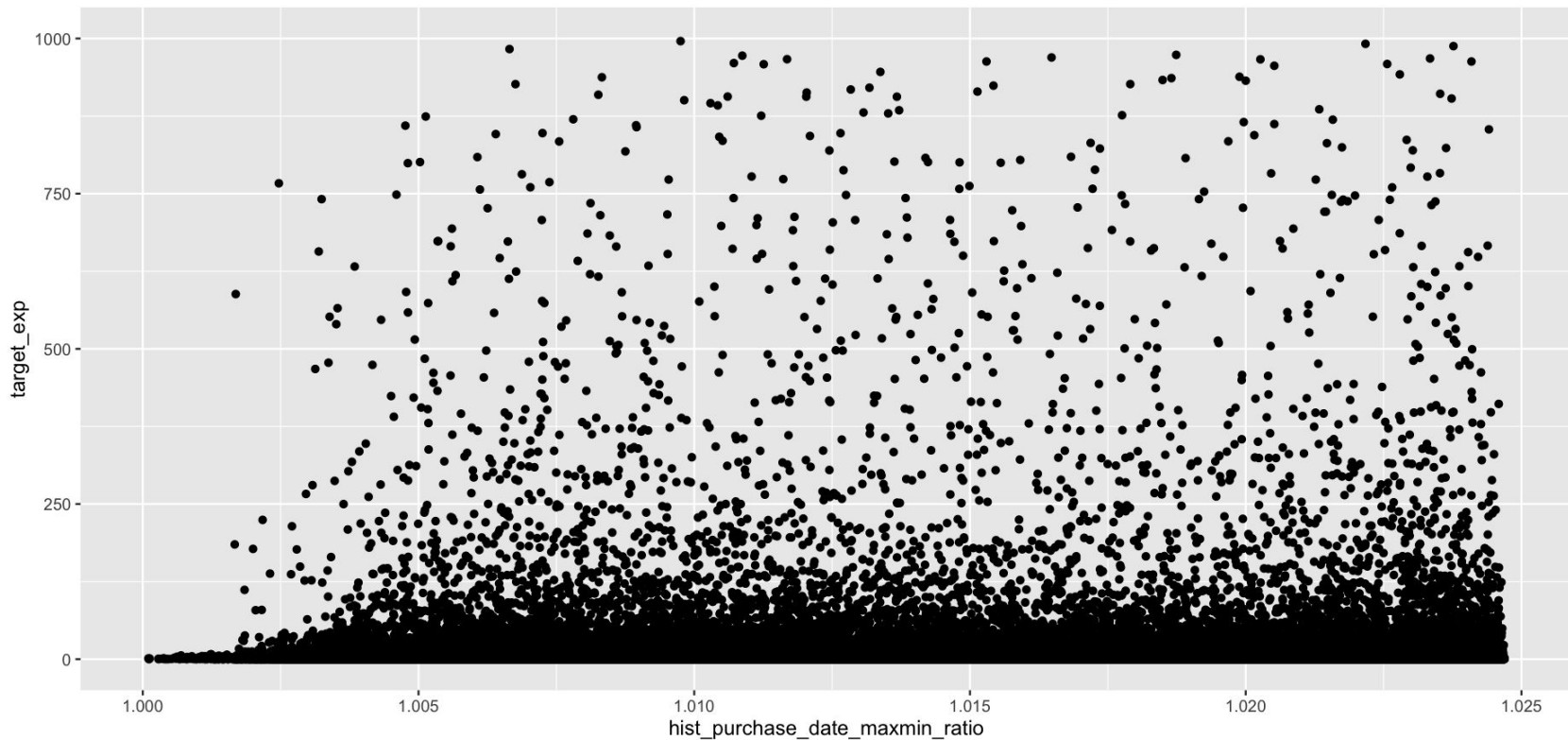
# 預測值(target)的分布



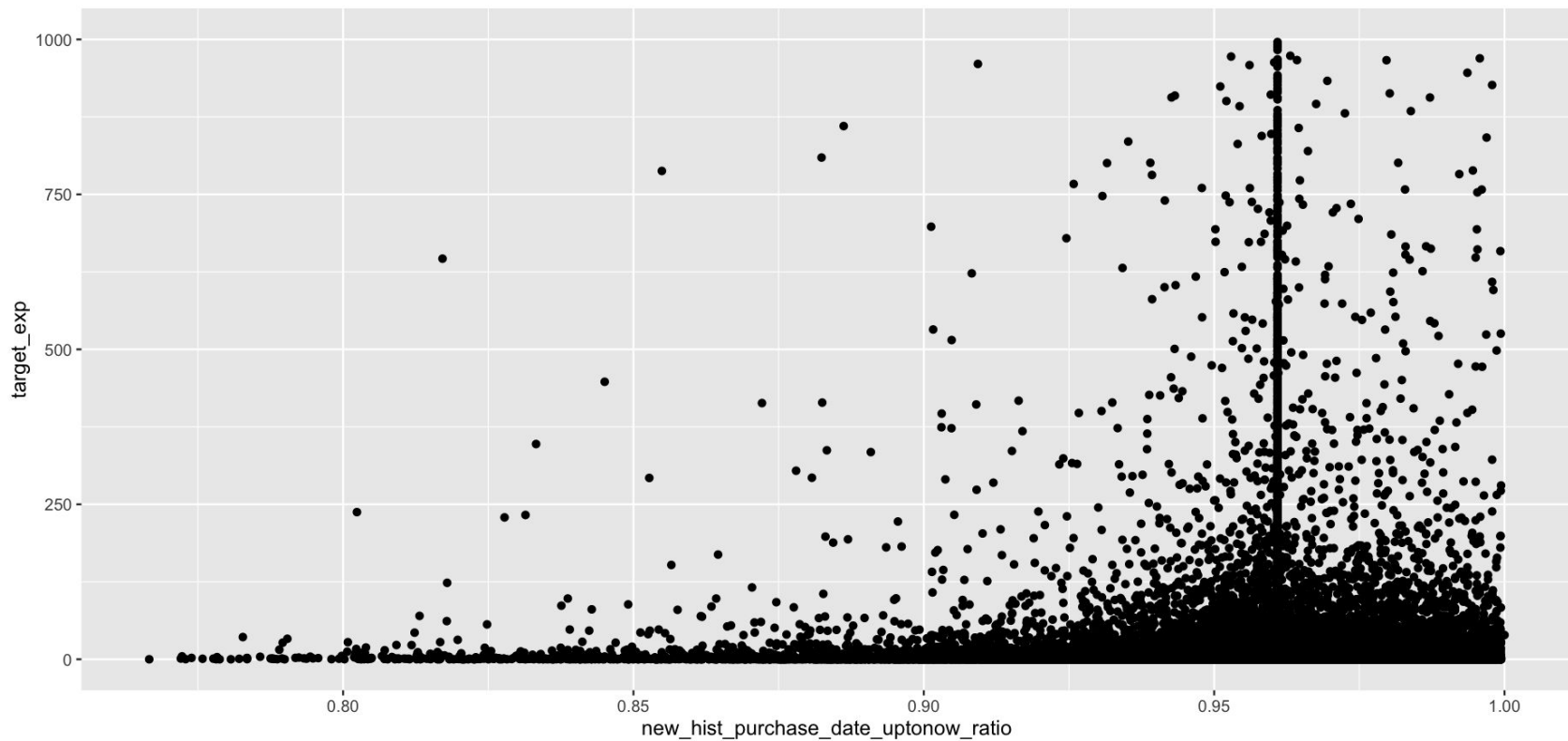
# 預測值(target)的分布



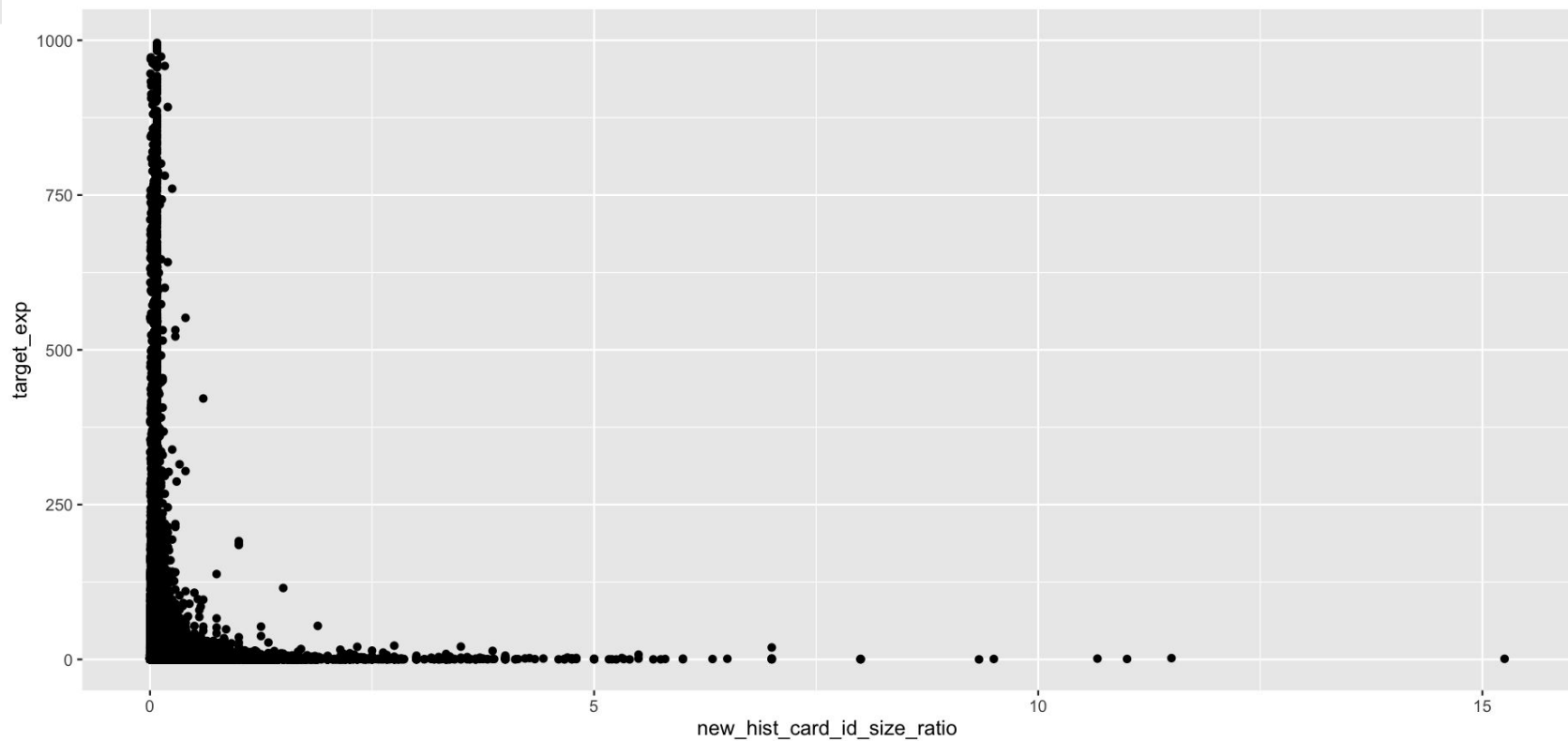
# 預測值(target)的分布



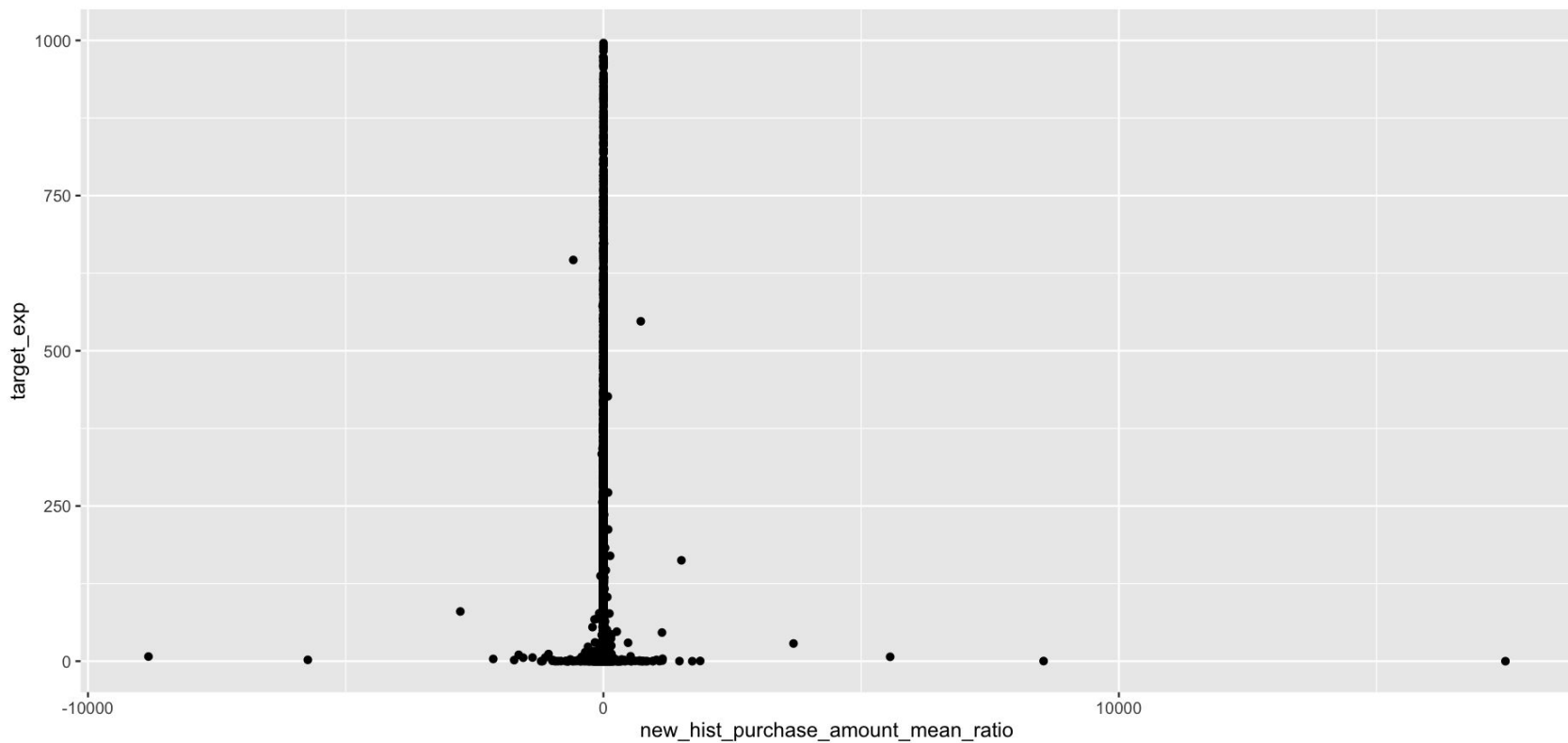
# 預測值(target)的分布



# 預測值(target)的分布



# 預測值(target)的分布





# Shiny APP-Data Analysis







# Modeling

- 最終使用資料集大小
  - Training Set:  $197710 * 85$  (83 features + 1 target + 1 exp(target))
  - Testing Set:  $123623 * 83$



# Modeling

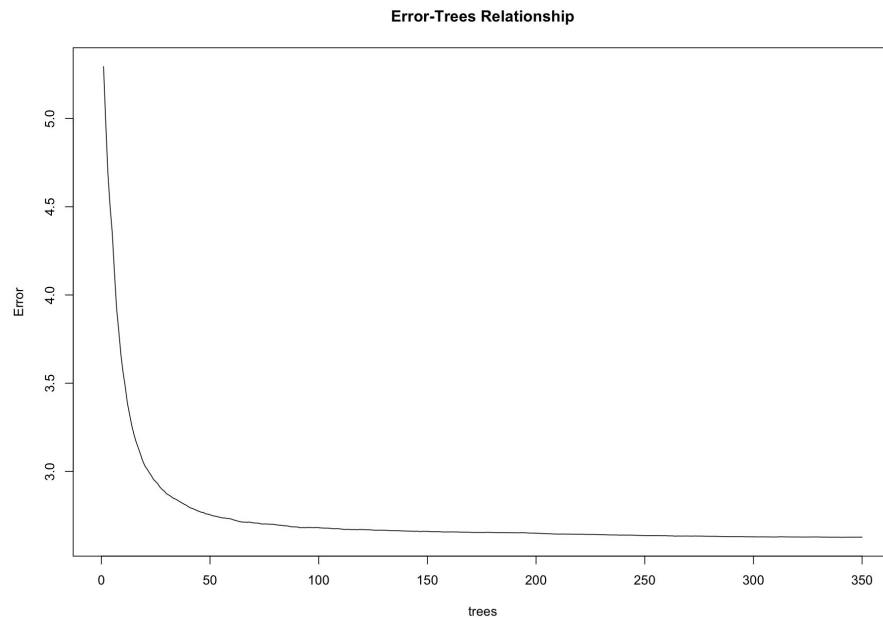
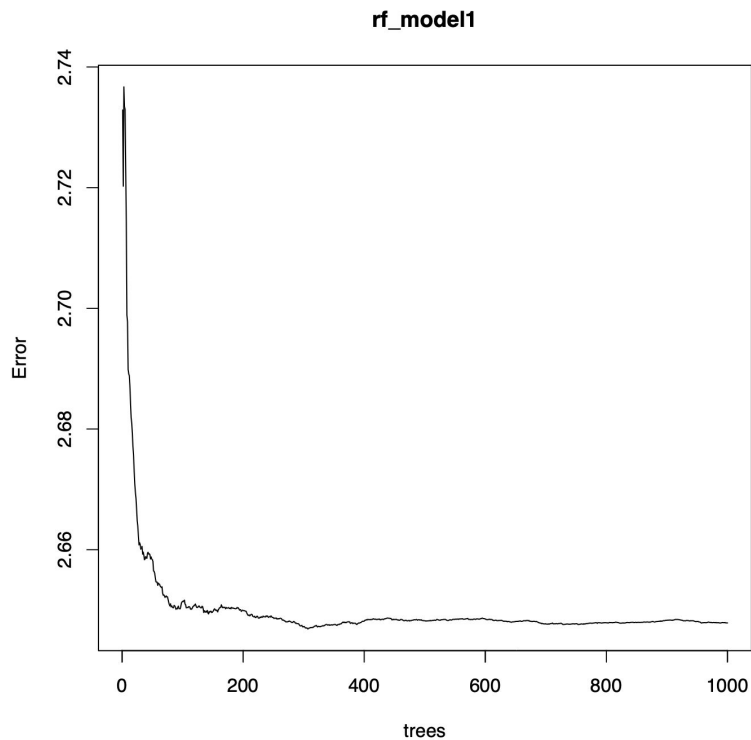
- 使用Random forest
  - 隨機選取50000筆資料, 隨機分8成為training data, 剩下為testing data
  - 套用RandomForest()
  - 建構五個model
    - 差別: 選擇不同seed
    - 去掉最大和最小的預測值, 以剩下三個預測數的平均, 作為最終的預測值



# Modeling

- 調整: ntree

■ plot(rfmodel)





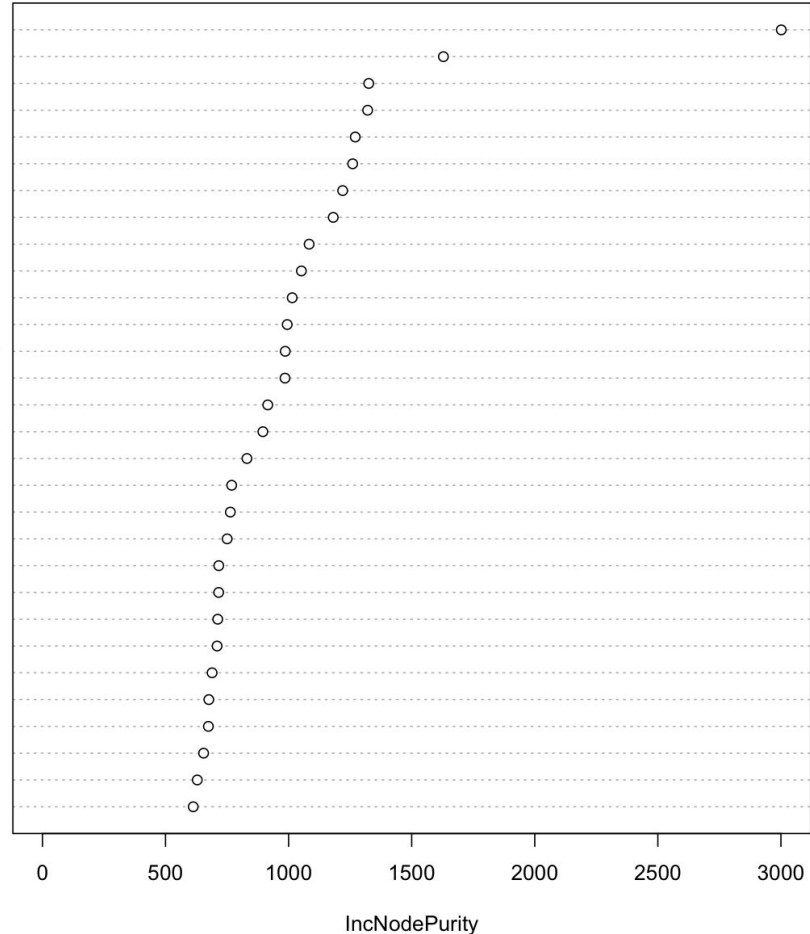
# Modeling

- 調整
  - mtry:
    - 每次在決定切割變數時，所隨機抽樣的潛在變數清單數量
    - tuneRF()
  - maxnodes
    - 內部節點最大個數值
    - ?

```
mtry = 28  OOB error = 3.630661
Searching left ...
mtry = 14          OOB error = 3.716262
-0.02357708 0.05
Searching right ...
mtry = 56          OOB error = 3.634553
-0.00107188 0.05
      mtry OOBError
14      14 3.716262
28      28 3.630661
56      56 3.634553
[1] 0.06454707
```

## Feature Importance

new\_merchant\_card\_sum\_purchase\_amount\_new  
 new\_hist\_purchase\_amount\_mean\_ratio  
 X  
 new\_merchant\_purchase\_amount\_std  
 new\_merchant\_card\_std\_purchase\_amount\_new  
 card\_id  
 hist\_card\_sum\_purchase\_amount\_new  
 hist\_purchase\_date\_weekend\_mean  
 new\_hist\_purchase\_date\_max\_ratio  
 new\_merchant\_purchase\_date\_uptonow  
 hist\_authozied\_flag\_mean  
 new\_merchant\_purchase\_amount\_sum  
 hist\_card\_sum\_authozied\_flag\_0\_purchase\_amount\_mean  
 hist\_month\_lag\_std  
 hist\_purchase\_date\_uptonow  
 hist\_card\_sum\_authozied\_flag\_1\_purchase\_amount\_mean  
 new\_hist\_purchase\_date\_min\_ratio  
 hist\_purchase\_amount\_std  
 hist\_card\_std\_purchase\_amount\_new  
 hist\_merchant\_id\_nunique  
 hist\_installments\_std  
 hist\_purchase\_amount\_mean  
 new\_hist\_purchase\_date\_uptonow\_ratio  
 hist\_category\_3\_mean  
 hist\_card\_mean\_purchase\_amount\_new  
 new\_purchase\_date\_maxmin\_ratio  
 hist\_category\_2\_mean  
 hist\_merchant\_category\_id\_nunique  
 hist\_purchase\_amount\_sum  
 hist\_purchase\_date\_weekofyear\_nunique





# Output

- Performance
  - 計算MSE、RMSE、R-squared

model	MSE	RMSE	R_squared
model1	2.50392833755562	1.58238059187909	0.145607831457867
model2	2.53340248087143	1.59166657339766	0.141162036549647
model3	2.53713669648272	1.59283919354175	0.142224570445541
model4	2.52434626642342	1.58881914213778	0.149136665173404
model5	2.54223940374232	1.59444015370359	0.140129245478388

# Output

- kaggle評測：
  - kaggle提供的null model: 3.87852
  - 若用未preprocessing的資料: 4.58
- 可改進處：
  - nodesize
  - 用所有資料

The screenshot shows the Kaggle competition page for "Elo Merchant Category Recommendation". The page has a dark header with the competition title, a prize money of \$50,000, and the Elo logo. Below the header is a navigation bar with links for Overview, Data, Code, Discussion, Leaderboard, Rules, Team, My Submissions, and a Late Submission button. The main content area shows the user's most recent submission, "predict.csv", which was submitted "just now" and has a score of 3.87717. The submission status is "Complete". Below the submission table is a link to "Jump to your position on the leaderboard". At the bottom, there is a terminal window showing the command to submit the file and a message box. The footer contains a link to make a submission for the competition ID 1101DS@NCCU\_108703005.

Featured Prediction Competition

## Elo Merchant Category Recommendation

Help understand customer loyalty

\$50,000  
Prize Money

Elo · 4,110 teams · 3 years ago

Overview Data Code Discussion Leaderboard Rules Team My Submissions **Late Submission** ...

Your most recent submission

Name	Submitted	Wait time	Execution time	Score
predict.csv	just now	1 seconds	1 seconds	3.87717

Complete

[Jump to your position on the leaderboard](#)

```
> kaggle competitions submit -c elo-merchant-category-recommendation -f submission.csv -m "Message"
```

Make a submission for [1101DS@NCCU\\_108703005](#)



# Shiny APP-Model Analysis







# 困難-Anonymized Feature

問題: 許多資料的數值和類別是匿名的, 因此無法用常理判斷處理方式及是否為合適特徵。

解決: 將許多特徵的分佈畫出, 以及將商品特徵與消費者特徵進行比較。例如: 在category\_3中, 值為A、B、C。根據分析我們發現在target的均值上,  $A > B > C$ , 因此將特徵轉換為A:2、B:1、C:0



# 困難-Feature Enigeering

問題: 資料龐大但資訊分散, 需要進行多層處理。主表上只有個特徵, 最後我們共造出84個特徵

解決: 先將商品的主表中重複和缺值的商品進行處理, 接著分別針對過去和近期資料groupby消費者進行整合, 最後將過去和近期資料進行比較



# 困難-Shiny APP & Preprocessing

問題: input 的檔案很大, 導致部署到ShinyIO時, 會因為out of memory無法正常運作。

Preprocessing處理資料時也會因為檔案太大在跑不動function

modeling也要跑很久

解決: 將 input 檔案處理過後再上傳, 只留下處理後的資料, 去除原始資料

把function拆開一行一行執行

降低資料量, 隨機選取



# QA時間



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