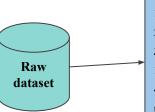
IA Go competition

Raw dataset first impressions



First impressions:

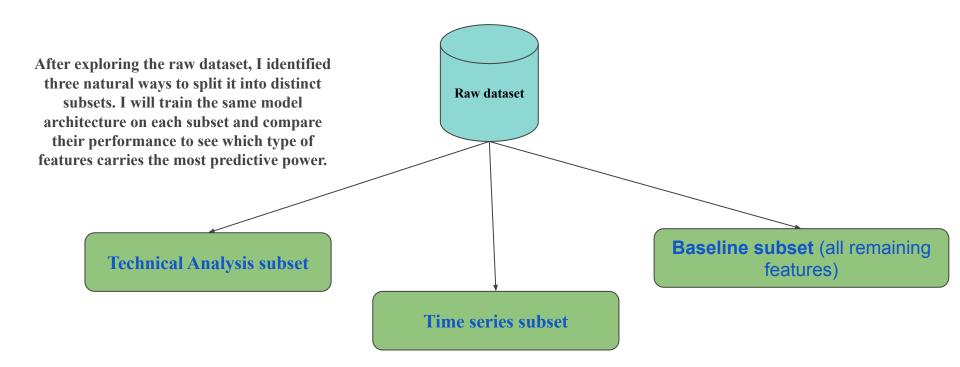
- 1) Big dataset (> 12GB).
- 2) Empty/ blanks/ null data.
- 3) Target feature('飆股') imbalanced 0: 199394 and 1: 1470 samples.
- 4) 3 kind of features: Time series or sequential data, technical analysis and common used data for stocks.

Phase 1

1) Big dataset (> 12GB): Since is a big dataset we used techniques to read some information inside, without open it, otherwise the PC crashes. (we used with open in python instead pandas for reading) 2) Target feature('飆政') imbalanced: we tried to create a balanced dataset by extracting the same among of 0 samples with respect to 1 samples, in other words the new dataset should have 2940 rows, since this dataset has a lot of null data points, we extracted those rows from 0 samples with less quantity of nulls

3 kind of features: i split the new balanced dataset into 3 new subsets depending on the king of of feature, so we can train different models specialized in those kind of data (sequential data, tabular data etc.) 2) Empty/ blanks/ null data: Since we can still perform other kind of data preprocessing such as dataset dimensionality reduction, consequently the number of null data points will be reduced, then we performed techniques to deal with null data later.

Subsets



Subsets description

Technical Analysis subset: this dataset has a total of 2940 rows and 30 columns.

```
---> The dataset has 2940 rows & 30 columns.
---> Analyzing target column: '飆股'
---> Number of unique classes: 2
---> Samples per class:
    Class 0: 1470 samples
    Class 1: 1470 samples
```

Since this dataset only has two columns with null values, I could delete them, because there is a column called 技術指標_乖離率(20日) with no null values that represents the same metric over 20 periods, then i could try dimensionality-reduction or redundancy-reduction techniques (these techniques cannot be applied when a column has missing values).

=== DA	TASET DESCRIPTION	\ ===							
1	技術指標_乖離率((60日) 技術指標	乖離率(250日)	技術指標_乖	離率(2	20日) 個股1天朝	强酬率 上市	加權指數5天成交	量波動度 上市加權指
數 10天	成交量波動度 上市	市加權指數20天成	交量波動度	飆股					7/10/10/10
count	2934.000000	2900.000000	2940.000000	2940.000000		2940.000000	2940.000000	2940.000000	2940.000000
mean	2.145741	2.225756	2.107961	1.612497		1.280190	1.238852	1.243960	0.500000
std	1.592988	1.611365	1.560352	1.525553		1.055891	1.032863	0.978809	0.500085
min	-2.291800	-2.203200	-3.581200	-3.426300		-0.515700	-0.379800	-0.154600	0.000000
25%	1.091775	1.098025	1.086675	0.835900		0.585800	0.564000	0.644175	0.000000
50%	1.792800	1.877250	1.735300	1.292900		1.164200	0.972450	0.992100	0.500000
75%	2.951975	3.066425	2.819525	2.088600		1.624100	1.670500	1.646000	1.000000
max	13.985400	17.010600	10.805500	5.818500		8.060900	7.334400	5.862500	1.000000

Columns with null values: 技術指標_乖離率(60日) 6 技術指標_乖離率(250日) 40 dtype: int64 a total of 2 null columns.

=== NULL PERCENTAGES === 技術指標_乖離率(60日) 0.20 技術指標_乖離率(250日) 1.36 dtype: float64 **Time series subset:** this dataset has a total of 2940 rows and 465 columns. (since this is a classification task and the target column has only binary values, we can not apply a time series transformation to train sequential models like CNN, Transformers etc..., however i can use this data to try Traditional ML models or Deep learning non sequential models.

```
---> The dataset has 2940 rows & 465 columns.
---> Analyzing target column: '飆股'
---> Number of unique classes: 2
---> Samples per class:
    Class 0: 1470 samples
    Class 1: 1470 samples
```

This subset has 458 columns with null values, which is a lot, so I need to delete some columns or impute missing data before reducing the dataset's dimensionality and redundancy.

=== DA	TASET DESCRIPTI								
	外資券商_前1天	分點進出 外資券	商_前1天分點買賣力	外資券商_前1天	分點原	戊交力(%) 外資	[券商_前1天分點	吃貨比(%)	. 個股前1天成交量
上市加	權指數前1天收盤	價 上市加權指數	前1天成交量	飆 股					
count	2940.000000	2233.000000	2929.000000	2929.000000		2940.000000	2940.000000	2940.000000	2940.000000
mean	1.276847	1.361642	1.225693	1.267450		1.621064	1.345265	1.353743	0.500000
std	1.781628	2.540052	0.735338	0.984561		2.287573	1.098313	1.082883	0.500085
min	-52.954800	-7.073600	-37.842800	0.522800		1.012000	-0.752100	-0.548000	0.000000
25%	1.215600	1.131200	1.211100	0.522800		1.030375	0.279100	0.593600	0.000000
50%	1.225800	1.214700	1.223800	0.911400		1.101850	1.539800	1.111200	0.500000
75%	1.258000	1.345700	1.253100	1.642000		1.436100	2.217000	1.931000	1.000000
max	42.949800	101.303100	4.421000	6.791200		73.647300	4.715500	7.677600	1.000000

Columns with null values:	
外資券商_前1天分點買賣力	707
外資券商_前1天分點成交力(%)	11
外資券商_前1天分點吃貨比(%)	11
外資券商_前1天分點出貨比(%)	11
主力券商_前1天分點買賣力	404
賣超第15名分點前1天賣均張	485
賣超第15名分點前1天買均價	485
賣超第15名分點前1天賣均價	485
賣超第15名分點前1天買均值(千)	485
賣超第15名分點前1天賣均值(千)	485
Length: 458, dtype: int64	
a total of 458 columns with nu	ill values.

=== NULL PERCENTAGES ===	
外資券商 前1天分點買賣力	24.05
外資券商_前1天分點成交力(%)	0.37
外資券商_前1天分點吃貨比(%)	0.37
外資券商_前1天分點出貨比(%)	0.37
主力券商_前1天分點買賣力	13.74
***	440 · 10
賣超第15名分點前1天賣均張	16.50
賣超第15名分點前1天買均價	16.50
賣超第15名分點前1天賣均價	16.50
賣超第15名分點前1天買均值(千)	16.50
賣超第15名分點前1天賣均值(千)	16.50
Length: 458, dtype: float64	

In theory, columns with more than 30 % missing values could be discarded if they do not contribute valuable information to the model. In our dataset, using a 10 % threshold would remove 452 columns; at 20 %, only 1 column; and at 30 %, none. Therefore, instead of dropping columns, we should impute the missing data.

Columns with more than 10.0% of 外資券商_前1天分點買賣力主力券商_前1天分點買賣力買超第1名分點前1天券商代號買超第1名分點前1天張增減買超第1名分點前1天金額增減(千)	null values: 707 404 399 399
貝尼第1石刀和削1大並銀塔/(十)	233
* * *	
賣超第15名分點前1天賣均張	485
賣超第15名分點前1天買均價	485
賣超第15名分點前1天賣均價	485
賣超第15名分點前1天買均值(千)	485
賣超第15名分點前1天賣均值(千)	485
Length: 452, dtype: int64	
A total of 452 discardable colu	mns.

```
Columns with more than 20.0% of null values:
外資券商_前1天分點買賣力 707
dtype: int64
A total of 1 discardable columns.
```

```
Columns with more than 30.0% of null values: Series([], dtype: int64)
A total of 0 discardable columns.
```

Baseline subset (all remaining features): this dataset has a total of 2940 rows and 905 columns

```
---> The dataset has 2940 rows & 905 columns.
---> Analyzing target column: '飆股'
---> Number of unique classes: 2
---> Samples per class:
    Class 0: 1470 samples
    Class 1: 1470 samples
```

this seems to be the most problematic dataset to handle with, it has more than 700 columns with null data.

=== DAT	ASET DES	CRIPTION ===									
	ID	外資券商_5	計進出 外資	券商_分點買賣力	外資券商_分黑	占成交	力(%) 外資券	商_分點吃貨比	(%)	個股收盤價	個股
成交量 上市加權指數收盤價 上市加權指數成交量			飆股								
count	2940	2940.000000	2225.000000	2930.000000	2930.000000		2940.000000	2940.000000	2940.000000	2940.000000	2940.000000
unique	2940	NaN	NaN	NaN	NaN		NaN	NaN	NaN	NaN	NaN_
top	TR-191	NaN	NaN	NaN	NaN		NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN		NaN	NaN	NaN	NaN	NaN
mean	NaN	1.282861	1.319383	1.314343	1.277476		1.365666	1.669728	1.345130	1.350145	0.500000
std	NaN	2.080165	0.918218	0.910556	1.021353		1.320179	2.411023	1.100097	1.074946	0.500085
min	NaN	-77.953400	-0.336300	-4.407300	0.531300		0.792700	1.007800	-0.765300	-0.688200	0.000000
25%	NaN	1.213400	0.689400	1.073325	0.531300		0.933800	1.026875	0.287400	0.558300	0.000000
50%	NaN	1.221900	1.368800	1.241300	0.899500		1.055650	1.102750	1.523400	1.151600	0.500000
75%	NaN	1.256800	2.018700	1.581650	1.593300		1.334225	1.482875	2.200400	1.983350	1.000000
max	NaN	35.986200	2.830300	5.813400	7.541600		26.921900	82.051900	4.830500	7.746000	1.000000

Columns with null values:	
外資券商_分點買賣力	715
外資券商_分點成交力(%)	10
外資券商_分點吃貨比(%)	10
外資券商 分點出貨比(%)	10
主力券商 分點買賣力	408
	v 870
賣超第15名分點賣均張	475
賣超第15名分點買均價	475
賣超第15名分點賣均價	475
賣超第15名分點買均值(千)	475
賣超第15名分點賣均值(千)	475
Length: 700, dtype: int64	
a total of 700 columns wit	h null values.

=== NULL PERCENTAGES ===	
外資券商 分點買賣力	24.32
外資券商_分點成交力(%)	0.34
外資券商_分點吃貨比(%)	0.34
外資券商_分點出貨比(%)	0.34
主力券商_分點買賣力	13.88
賣超第15名分點賣均張	16.16
賣超第15名分點買均價	16.16
賣超第15名分點賣均價	16.16
賣超第15名分點買均值(千)	16.16
賣超第15名分點賣均值(千)	16.16
Length: 700, dtype: floate	

For this dataset, deleting columns with more than 10% missing values would discard over 54% of the features; at a 20% threshold about 4.09% would be removed; and at 30% only 2.21%. Therefore, we should drop only the columns that exceed 30% missing data and impute the remaining missing values.

主力券商_分點買賣力 4 日外資_外資及陸資(不含外資自營商)買 日外資_外資及陸資(不含外資自營商)賣	715 408 !張 492 !張 492
日外資_外資及陸資(不含外資自營商)買	賣超 492
1444	
賣超第15名分點賣均張 4	475
賣超第15名分點買均價 4	475
賣超第15名分點賣均價 4	475
賣超第15名分點買均值(千)	475
賣超第15名分點賣均值(千)	475
Length: 497, dtype: int64	
A total of 497 discardable columns.	
If you discard all these columns yo	ou might delete 54.92% of the data in the dataset.

```
Columns with more than 20.0% of null values:
外資券商_分點買賣力 715
日外資_外資自營商買張 2940
```

A total of 37 discardable columns.

If you discard all these columns you might delete 4.09% of the data in the dataset.

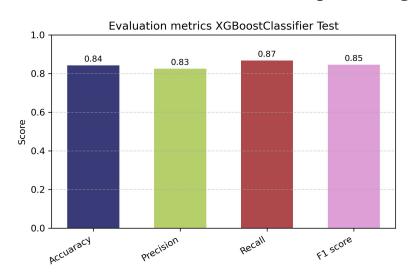
```
Columns with more than 30.0% of null values:
日外資 外資自營商買張
                              2940
日外資 外資自營商賣張
                              2940
                               2940
日外資 與前日異動原因
                              2916
日自營 自營商買均價
                             1524
                             1504
日自營 自營商賣均價
日投信 投信買均價
                            2432
                            2590
                             1140
                             2940
月營收 預估年營收(千)
                              2940
                                    2940
                                    2940
                                 1142
                                1142
                                 919
                               898
                             2493
季IFRS財報 稅額扣抵比率(%)
季 IFRS財報 預計稅額扣抵比率(%)
                               2498
季 IFRS財報 財務信評
                           2940
dtype: int64
A total of 20 discardable columns.
If you discard all these columns you might delete 2.21% of the data in the dataset.
```

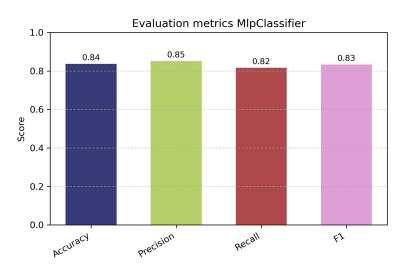
Data Cleanup & Modeling Strategy

Modeling Roadmap

- 1. **Start with non-linear traditional models**—Decision Tree, Random Forest, XGBoost, etc.—because they:
 - Naturally capture complex, nonlinear interactions
 - Provide built-in measures of feature importance to help me identify the most predictive inputs
- 2. **Apply the same workflow to the other subsets**, even those with many nulls (after appropriate cleaning), to compare how different feature groups perform.
- 3. **Refine feature selection**: once I know which variables matter most in each subset, I will:
 - Build a reduced "meta-dataset" that merges only the top features across subsets
 - Retrain and compare models on that distilled dataset
- 4. **Explore Deep Learning**: finally, with a lean set of highly relevant inputs, I'll experiment with feed-forward neural networks or other non-sequential deep models to see if they can further improve performance.

Deep learning vs Machine learning





Progress on MLPClassifier Optimization (Technical Analysis Subset)

An optimized **MLPClassifier** was implemented and trained on the *Technical Analysis* subset. The model achieved solid results: **Accuracy = 0.84**, **Precision = 0.85**, **Recall = 0.82**, and **F1-score = 0.83**, as shown in the figure. These scores are comparable to the **XGBoostClassifier**, which reached **Accuracy = 0.84**, **Precision = 0.83**, **Recall = 0.87**, and **F1-score = 0.85**.

While MLP didn't outperform in every metric, it shows competitive performance. The next step is to create an improved dataset using the **top features selected by XGBoost**, then retrain the MLP to evaluate potential improvements. Additionally, **cross-validation** will be applied to further optimize the model and assess its generalization.

