1.1 Dataset – Definition of ML Task







Predicting whether a newly IPO'd company will be delisted within the next five quarters.

Initial Public Offering (IPO): Process in which a privately owned company lists its shares on a stock exchange to raise capitals from investors

Binary Classification

1.2 Dataset – Use of Different File

File Name	Source	Number of Rows	Number of Columns	File Size (MB)	Main Entities	Usage
DS1-IPODataFull.csv	Kaggle	3673	1669	28.8MB	Name, LastSale, Market Cap, Sector, Industry, Summary Quote	Not Used
DS2- CompaniesRanked.csv	Companies MarketCap	8091	6	474KB	Rank, Name, Symbol, Employees Count, Price (USD), Country	Not Used
DS3-company_ipo.csv	Kaggle	1766	7	109KB	ID, IPO Date, Symbol, Company Name, IPO Price, Current Return	Not Used
DS4- final_merged_ipos.csv	StockAnalysis	2307	19	185KB	Company Name, Country, Current Deal Size, Employees, Exchange, Founded, IPO Date, IPO Price, Industry, Is SPAC, Market Cap, Open Price, Return, Return(Open), Sector, Shares Offered, Symbol, Volume	Used
DS5- delisted_companies.csv	AlphaVantage	7854	7	637KB	Symbol Name, Exchange, Asset Type, IPO Date, Delisting Date, Status	Used

1.2 Dataset – Data sources

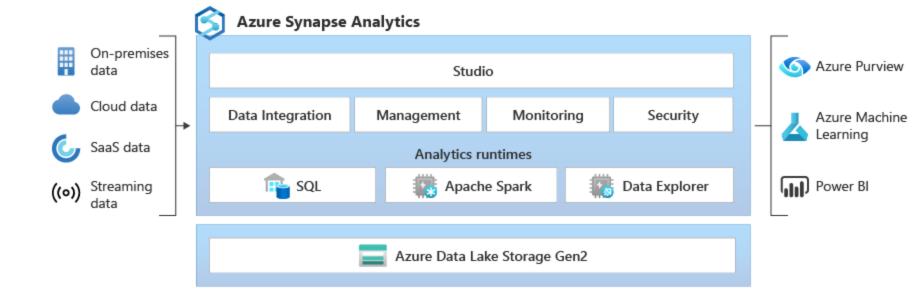
	Data source for listed companies	Data source for delisted companies
Company names & stock symbols	STOCK ANALYSIS	ALPHA VANTAGE
Financial Data	ALPHA VANTAGE	barchart

1.3 Dataset – Use of Storage Systems

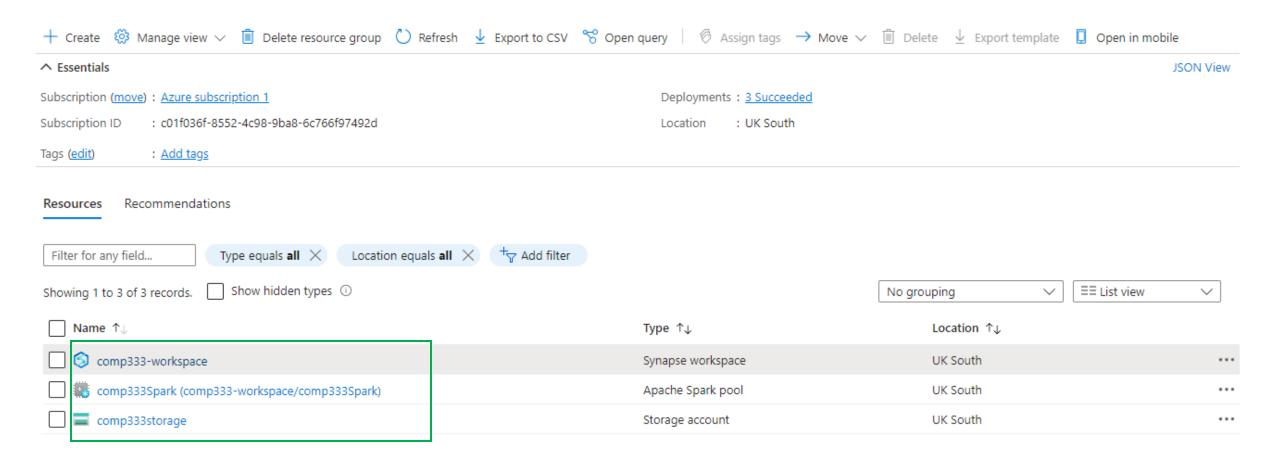
A mix of everything



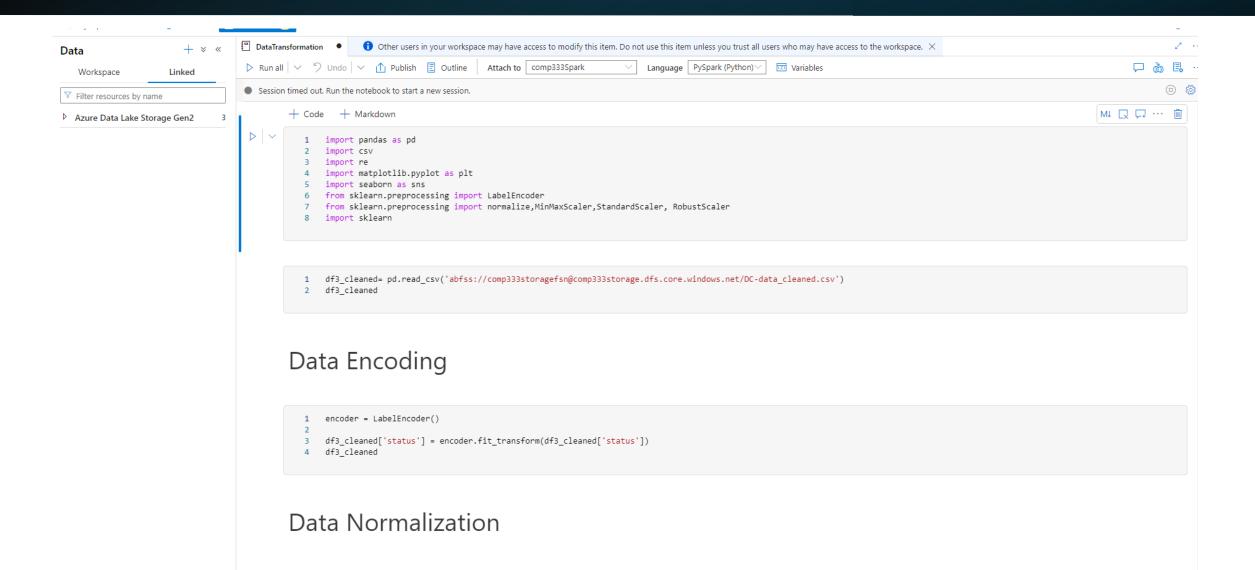




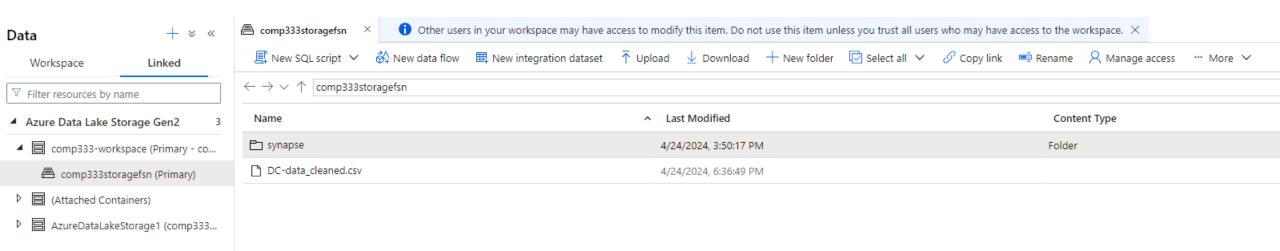
1.3 Dataset – Use of Storage Systems



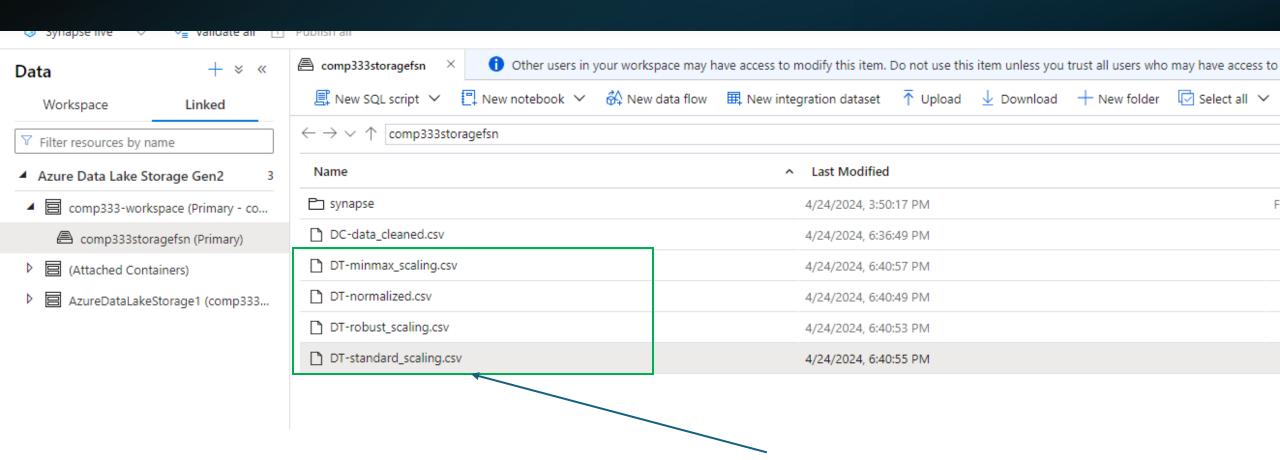
1.3 Dataset – Example with Data Transformation



1.3 Dataset – Data Lake Storage (Before)

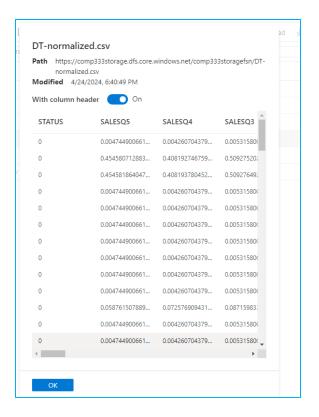


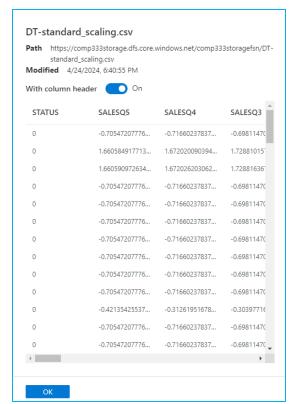
1.3 Dataset – Data Lake Storage (After)

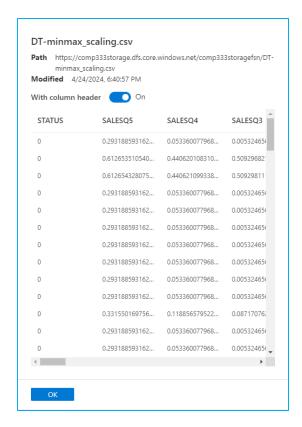


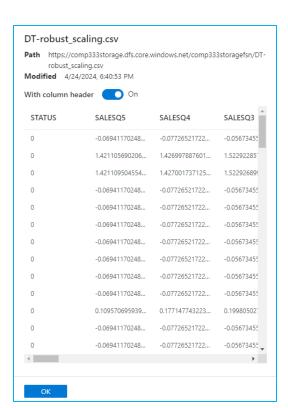
Outputted files from our DataTransformation code file can be seen directly in the data lake

1.3 Dataset – Quick Preview



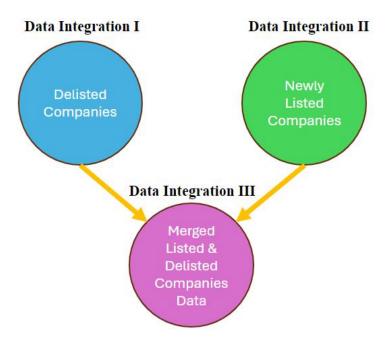






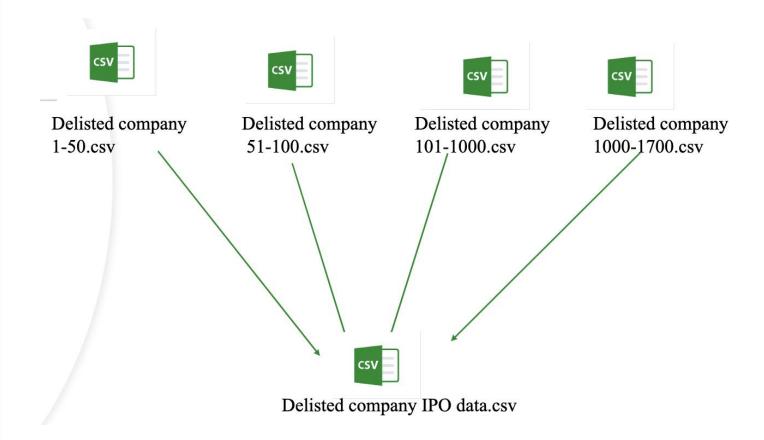
2. 1 Schema Integration- Overview

• Three main groups of Integration:



Schema Integration 1 and Mapping: Delisted IPO Data

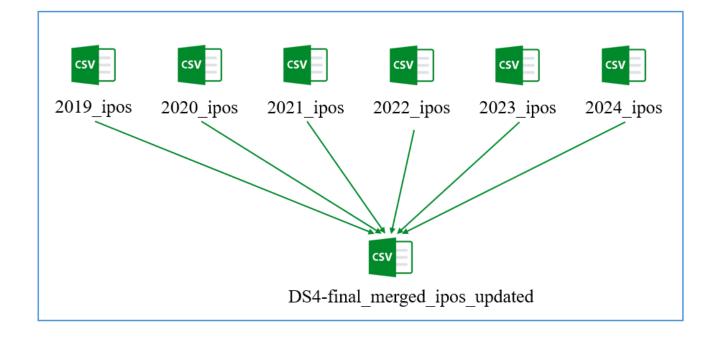
- Key: 'symbol'
- Initial Aggregation: Add monthly financial data from the first two files—'salesJan', 'salesFeb', 'salesMar' to calculate 'salesQ1'.
- Subsequent Mapping: Correspond 'salesQ1' from initial files with 'salesQ1' in subsequent datasets, where quarterly data already exists.
- Uniform Naming Convention: Consolidate figures under a standardized label 'XXQN' across all files for clarity and consistency in financial analysis.



Schema Integration and Mapping 2: Listed IPO Data

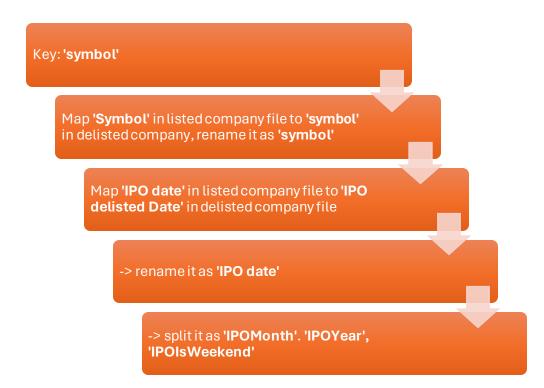
-Key: 'Symbol'

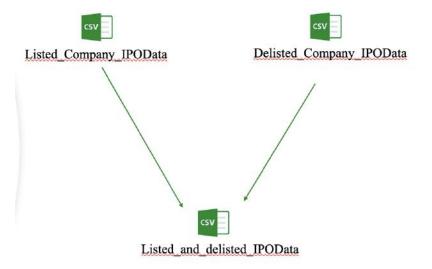
- -Date Harmonization: Align 'IPO Date' from 2019 and 2020 files with 'ipo date' in subsequent datasets.
- -Renaming for Consistency: Standardize field names by renaming all instances to 'IPO Date'.
- -Format Unification: Ensure date structure adheres to a consistent 'Year-Month-Date' format across all records.



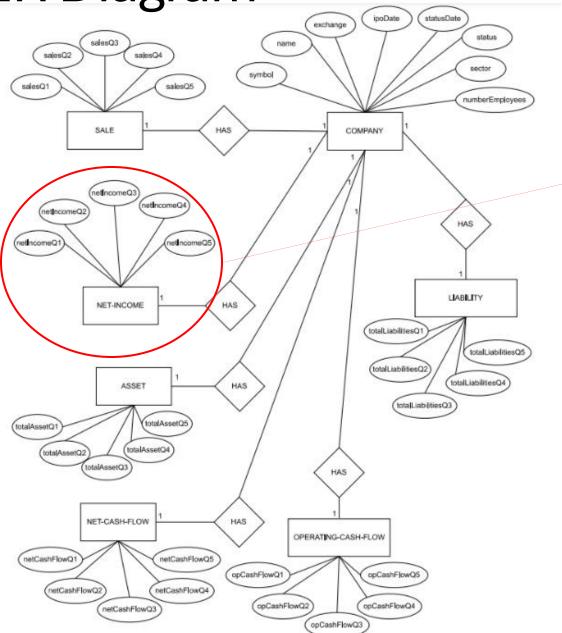
Schema Integration 3 and Mapping:

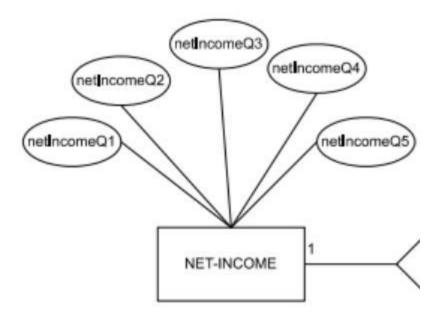
Listed and Delisted IPO Data



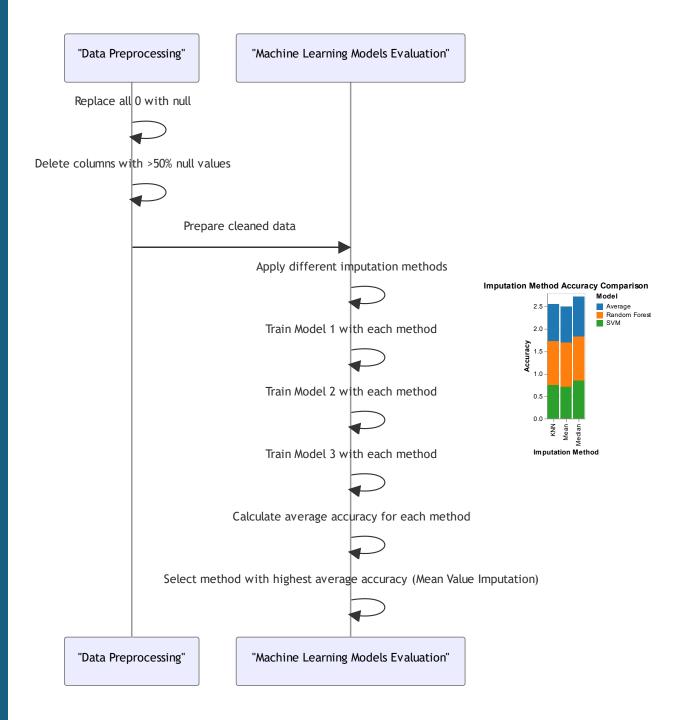


ER Diagram

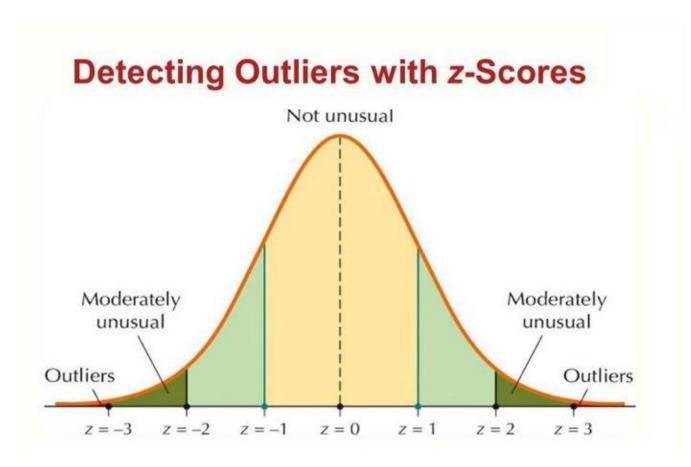




3. Data Cleaning: Support DC on Null values



3. Data Cleaning: Support DC for outliers



 After visualize our data, we notice it follows a Gaussian normal distribution.

-data points with a Z-Score greater than athreshold=3 are considered outliers

Model	Description	Accuracy Score
SVM	Before Data Cleaning	0.5969
SVM	After Data Cleaning	0.7286

3. Data
Cleaning: ML
model
Improvement



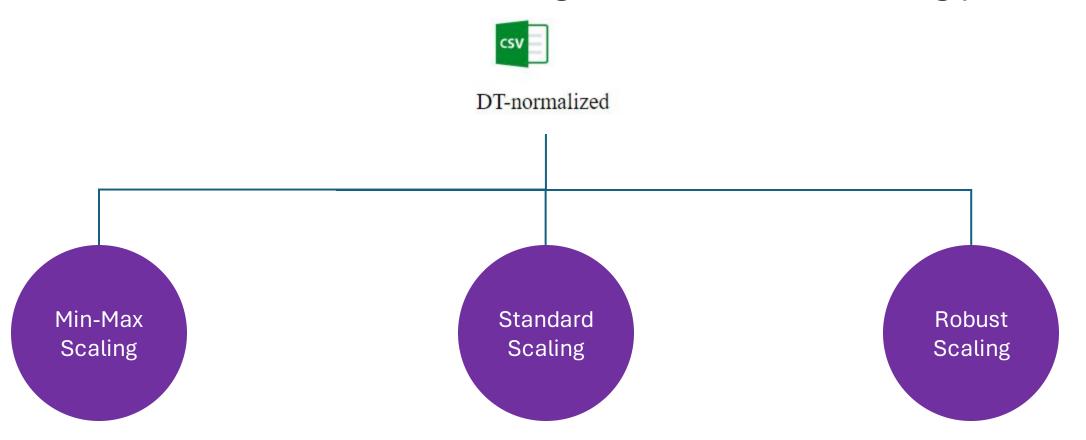
Data Processing – Normalization

- API: sklearn.preprocessing.Normalizer
- This API preserves unit norm, since our ML model is SVM, it relies on the distance between support vectors and boundary that maximizes the margin

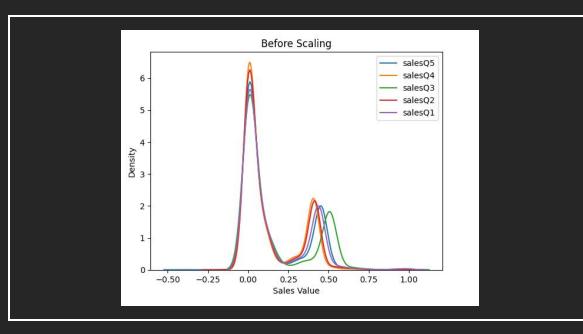
	df_scaled	head()									. •
	salesQ5	salesQ4	salesQ3	salesQ2	salesQ1	netIncomeQ5	netIncomeQ4	netIncomeQ3	netIncomeQ2	netIncomeQ1	
D	0.004745	0.004261	0.005316	0.004351	0.004593	-0.000097	-8.839976e-05	-5.628035e-05	-1.165012e-04	-1.133295e-03	
1	0.454581	0.408193	0.509275	0.416830	0.440023	0.000005	9.235170e-06	1.633772e-05	3.597637e-06	1.088563e-05	
2	0.454582	0.408194	0.509276	0.416832	0.440024	0.000001	-1.854457e-07	-5.563370e-07	-2.781685e-07	-4.079804e-07	
3	0.004745	0.004261	0.005316	0.004351	0.004593	-0.000097	-8.839976e-05	-5.628035e-05	-1.165012e-04	-1.133295e-03	
4	0.004745	0.004261	0.005316	0.004351	0.004593	-0.000097	-8.839976e-05	-5.628035e-05	-1.165012e-04	-1.133295e-03	
r	ows × 31 col	umns									

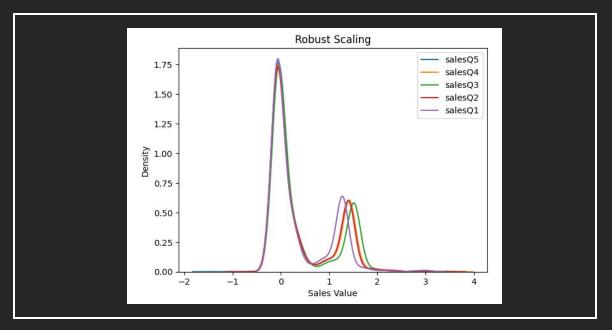
4. Data Transformation – Applying different scaling functions after normalization

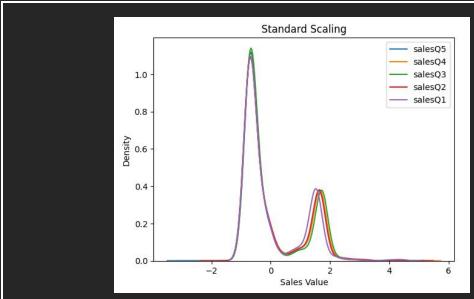
We considered different scaling functions in our scaling process

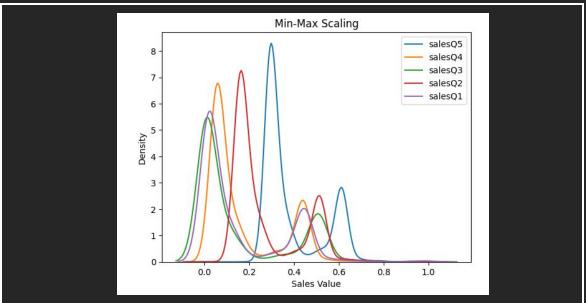


Sales

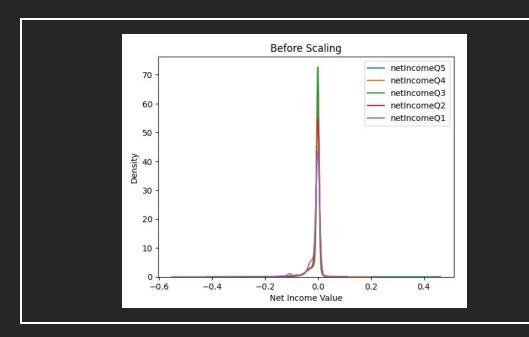


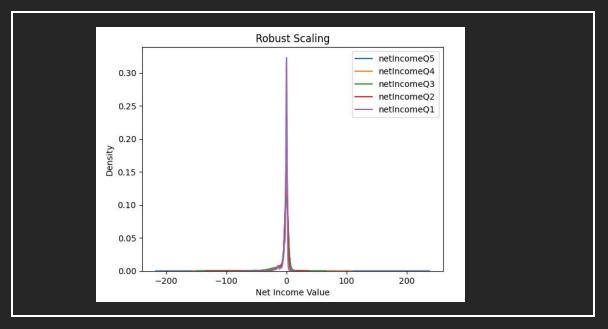


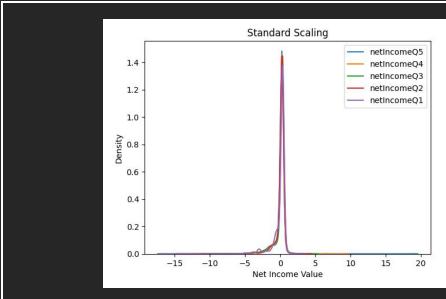


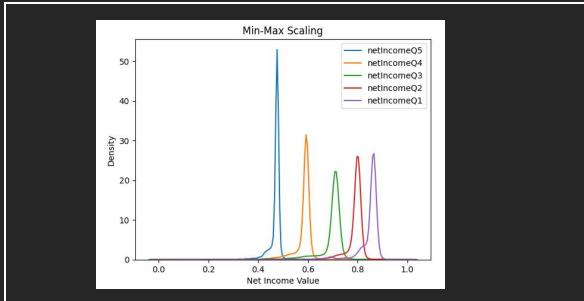


Net Income

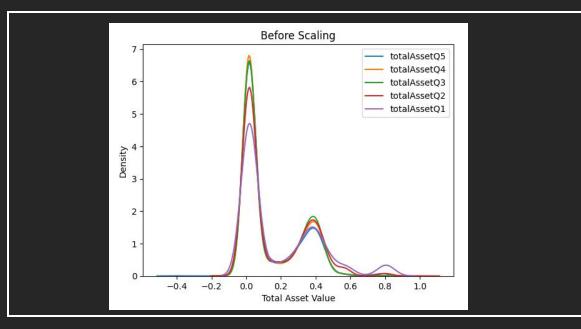


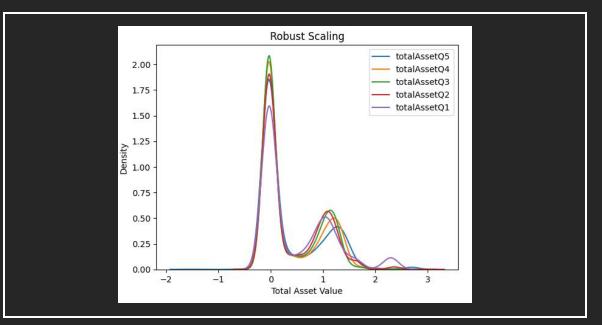


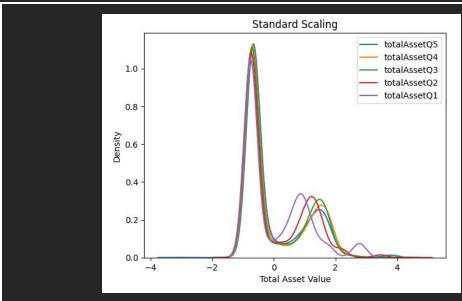


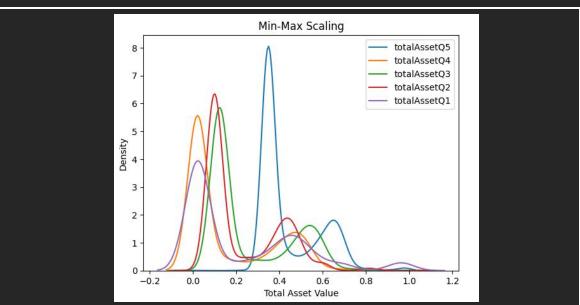


Total Asset

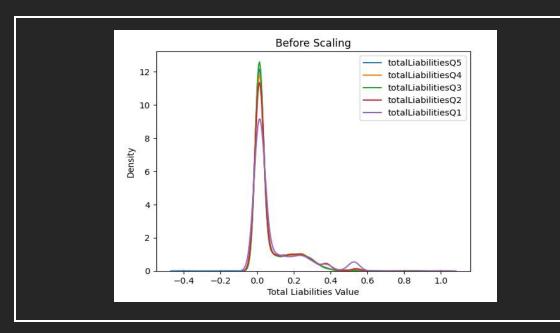


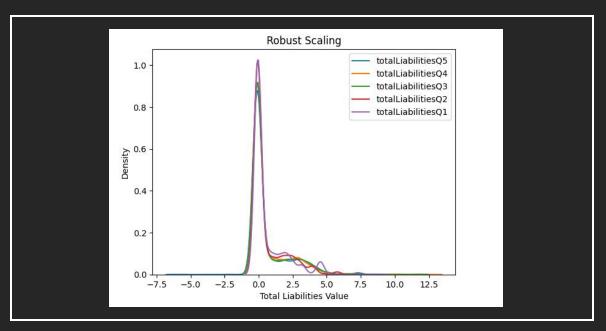


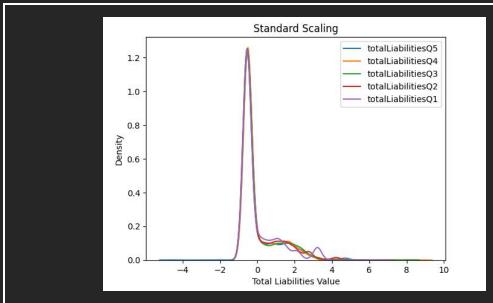


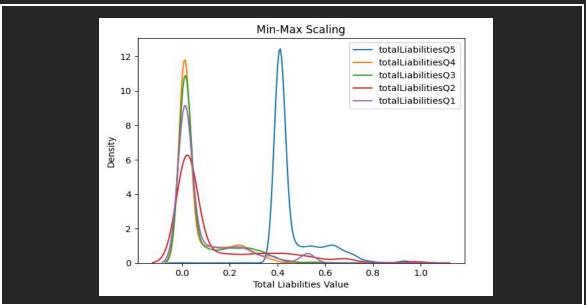


Total Liabilities

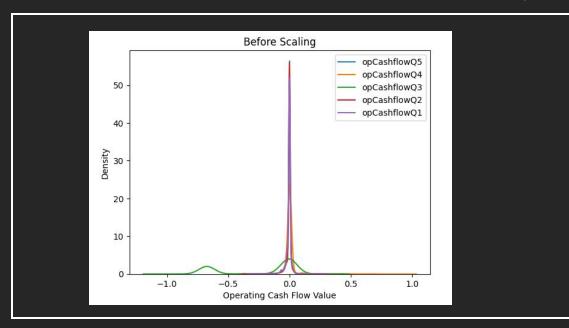


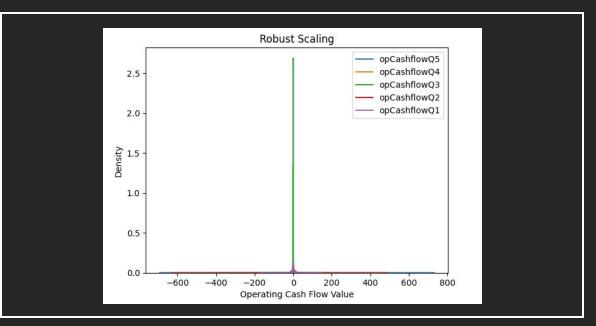


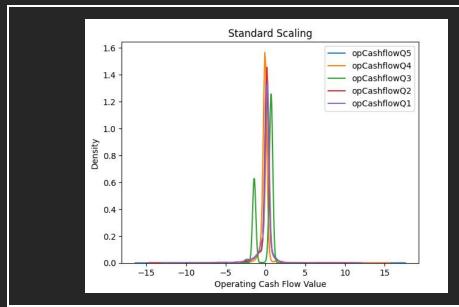


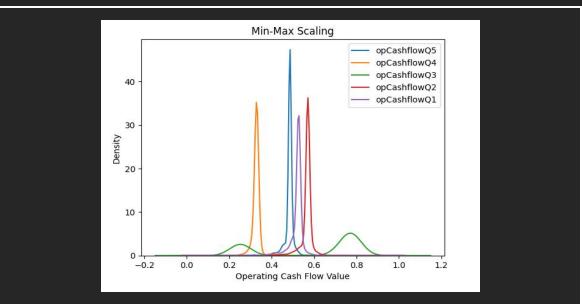


Operating Cash Flow

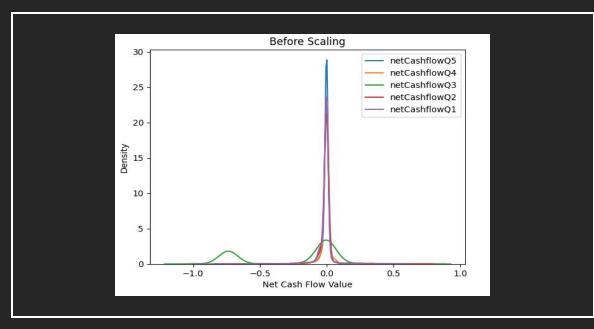


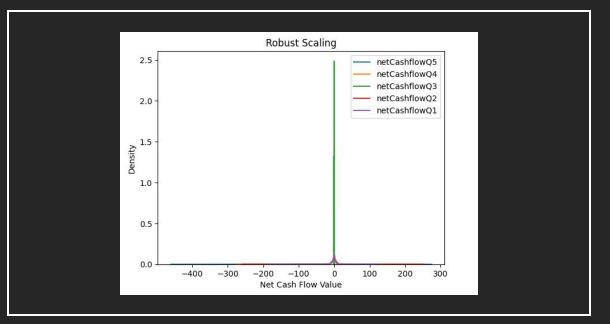


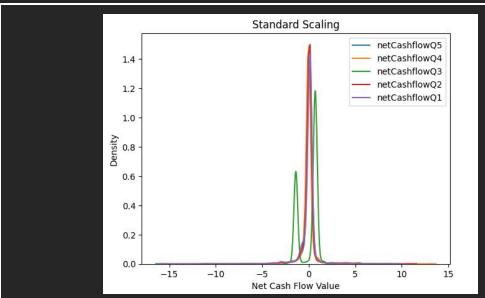


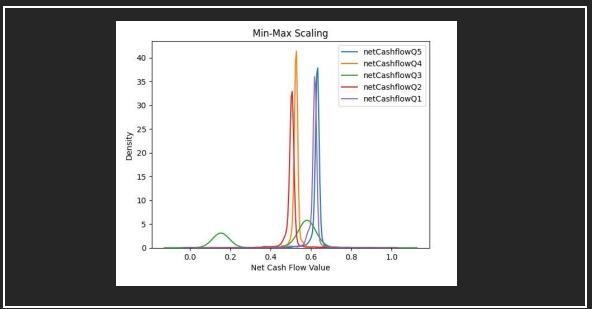


Net Cash Flow

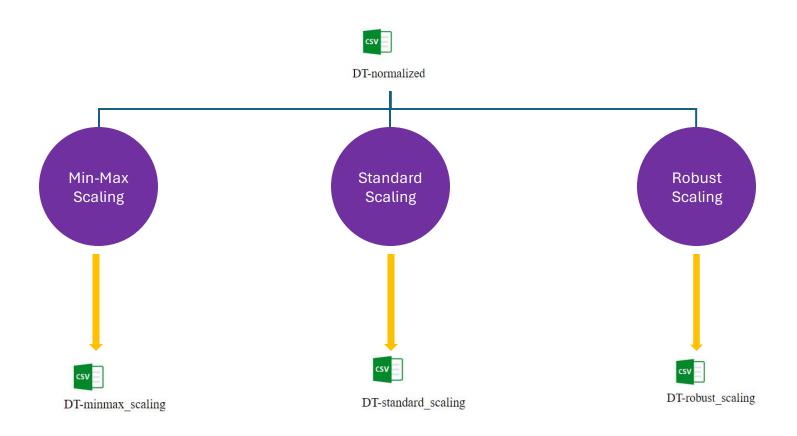








4. Data Transformation – Resulting output data



4. Data Transformation – Data Encoding

- We used the following to do our data encoding API: sklearn.preprocessing.LabelEncoder
- We transform status columns from "listed", "delisted" to 0 and 1

Data Encoding

```
encoder = LabelEncoder()

df3_cleaned['status'] = encoder.fit_transform(df3_cleaned['status'])
df3_cleaned
```

	status	sales05	sales04	sales03	sales02	sales01	netIncomeQ5	netIncomeQ4	netIncomeQ3	netIncomeQ2	
0	0		4.260704e- 03			0.004593		-8.839976e- 05			
1	0	4.545807e- 01	4.081927e- 01	5.092752e- 01	0.416830	0.440023	0.000005	9.235170e- 06	1.633772e- 05	3.597637e- 06	
2	0	4.545819e- 01	4.081938e- 01	5.092765e- 01	0.416832	0.440024	0.000001	-1.854457e- 07	-5.563370e- 07	-2.781685e- 07	
3	0	4.744901e- 03	4.260704e- 03	5.315800e- 03	0.004351	0.004593	-0.000097	-8.839976e- 05	-5.628035e- 05	-1.165012e- 04	
4	0	4.744901e- 03	4.260704e- 03	5.315800e- 03	0.004351	0.004593	-0.000097	-8.839976e- 05	-5.628035e- 05	-1.165012e- 04	
2795	1	5.586174e- 01	5.016129e- 01	1.473739e- 03	0.001158	0.540728	-0.001010	3.249664e- 04	6.626467e- 04	5.744568e- 05	
2796	1	1.895937e- 05	1.004333e- 06	7.850978e- 08	0.332960	0.351486	0.004391	3.952301e- 03	3.445666e- 03	2.209753e- 03	
2797	1	2.108767e- 03	2.479783e- 03	1.443247e- 03	0.000999	0.911613	0.000973	1.195231e- 03	5.832293e- 04	6.583507e- 04	
2798	1	7.998089e- 09	2.132824e- 08	9.331104e- 08	0.599251	0.632594	-0.000194	3.176116e- 03	1.404976e- 03	-7.768811e- 06	
2799	1	1.532547e- 03	2.321270e- 03	2.031616e- 03	0.001533	0.888784	-0.000010	7.094075e- 04	-8.396840e- 04	5.323506e- 04	

4. Data Transformation – ML Result

Condition	SVM Accuracy
Before Data Transformation	0.7976
After Data Transformation:	
MinMaxScaler	0.8619
StandardScaler	0.8810
RobustScaler	0.7976

5. Data Visualization and ETL-Use of Different Tools

- Python (Pandas, SQLite, BeautifulSoup, csv, requests, selenium), API, Google Collab.
- AWS Lambda, AWS SQS for creating multi-threading web scrapping tool.
- Delta Lake From Databricks
 (https://docs.databricks.com/en/delta/index.html).
- AWS Glue for ETL pipeline.

5.ETL to find Features-Feature Selection

Removing irrelevant Features

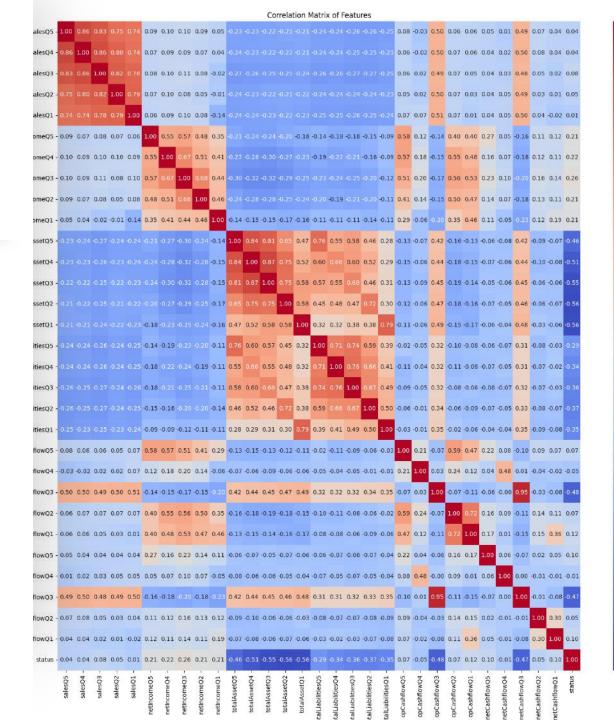
We only keep Times Series data

- Stock Symbol
- Company Name
- Exchange Center
- IPO Delisted Date (data leakage, in a real world, you won't know when your company is delisted)

5.ETL to find Features-Feature Selection

- Set correlation threshold=0.85
- Drop columns:

'salesQ3', 'totalAssetQ1', 'totalLiabilitiesQ4', 'opCashflowQ3', 'salesQ5', 'totalAssetQ5', 'totalAssetQ4', 'salesQ4', 'salesQ2'



5.ETL to find Features - Feature Selection ML accuracy

Description	SVM Accuracy
Before Feature Selection	0.8821
After Feature Selection	0.8833



5.ETL to find Features-Features Transformation

We perform PCA for features Transformation

Why?

-It maximize the variance of the dataset.

-filter out noise and less significant details

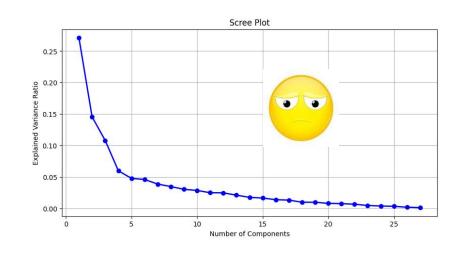
-decrease the feature correlation

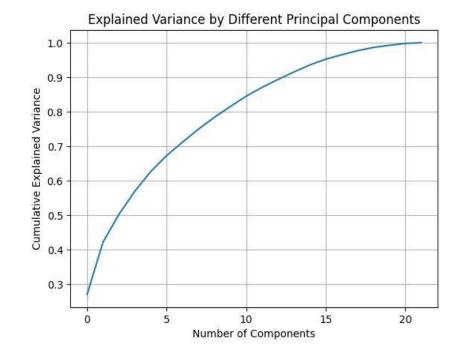
-easy for visualize as less columns remains

5.ETL to find Features-Hyperparameter Tuning

Objective: Let N = n of components, Select N to cover 95% of variance, 1<=N<=31

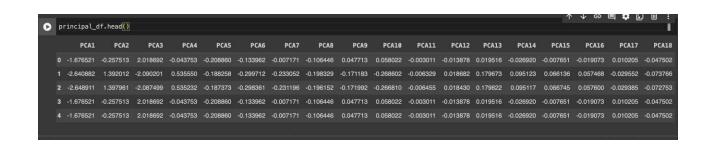
Plot the variance for each values:





Best hyperparameter N = 18

5.ETL to find Features-ML Accuracy



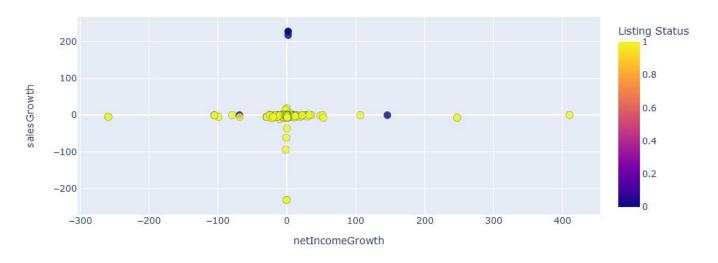
Description	SVM Accuracy
Before Feature Selection and Transformation	0.8821
After Feature Selection and Transformation	0.9000



- Used Python Dash + Plotly for visualization
- Some problems:
 Timing across time-series data only has 5 points(Q1-Q5).
- Making a few types of plots less reliable.

Net Income Growth vs. Sales Growth vs. Status

Net Income Growth vs. Sales Growth

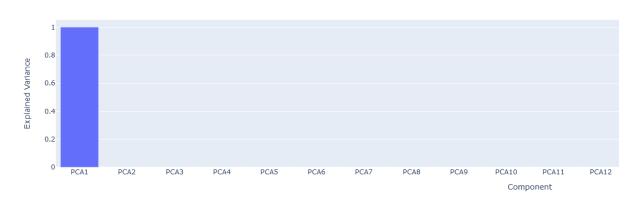


Scatter plot be looking like this

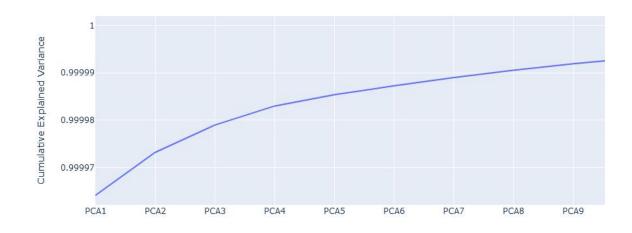
 Principal component analysis is used to help with this problem.

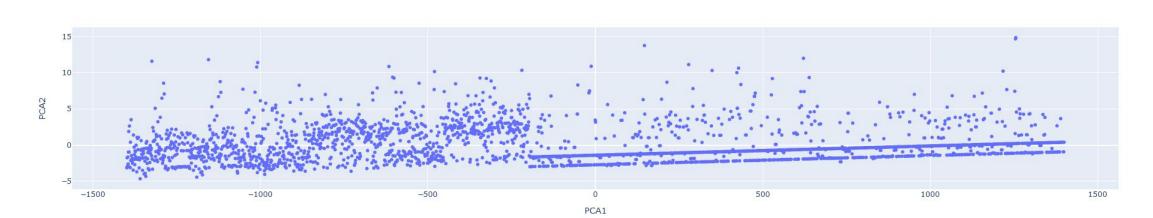
PCA Visualization Dashboard

PCA Variance Distribition



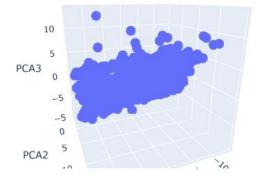
Cumulative Variance Plot





3D PCA Biplot (PCA1 vs PCA2 vs PCA3)

PCA Biplot (PCA1 vs PCA2)

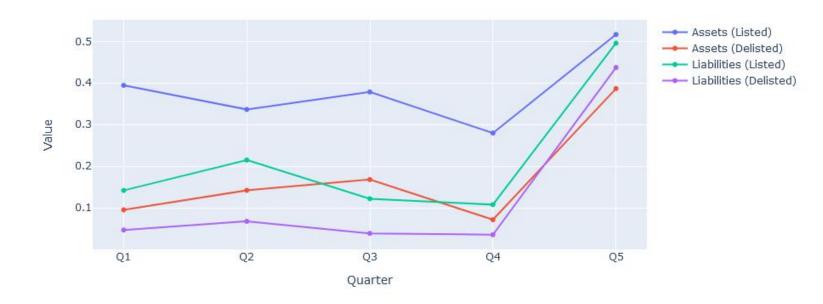


Correlation Matrix netCashflowQ1 0.07-0.08-0.06-0.07-0.06-0.03-0.02-0.03-0.07-0.080 netCashflowQ2 netCashflowQ3 0.16-0.18-0.2-0.18-0.2 netCashflowQ4 netCashflowQ5 opCashflowQ1 opCashflowQ2 opCashflowQ3 opCashflowQ4 opCashflow 05 0.6 totalLiabilitiesO1 totalLiabilitiesO2 0.08-0.0 totalLiabilitiesO3 .26-0.25-0.27-0.24-0.26-0.18-0.21-0.25-0.21-0.1 740.76 1.0 0.0 .080.060.080.0 totalLiabilitiesO4 71 1.0 0.76 0.11-0.0 0.07-0.0 0.4 1.0 0.71 0.74 totalLiabilitiesQ5 0.08-0.0 totalAssetQ1 0.15-0.17-0.06-0.0 totalAssetO2 0.18-0.16-0.07-0.0 totalAssetQ3 0.13-0.09 totalAssetQ4 0.18-0.15-0.07-0.0 0.2 totalAssetO5 0.090.0 netIncomeQ1 netIncomeQ2 netIncomeO3 netIncomeQ4 netIncomeQ5 salesQ2 080.830.86 1.0 0.820.7 salesQ3 -0.2 salesQ4 salesQ5

Select Metric for Time Series Analysis:



Assets/Liabilities Over Quarters for Listed vs Delisted Companies



Minmax-scaled Dataset

Select Metric for Time Series Analysis:

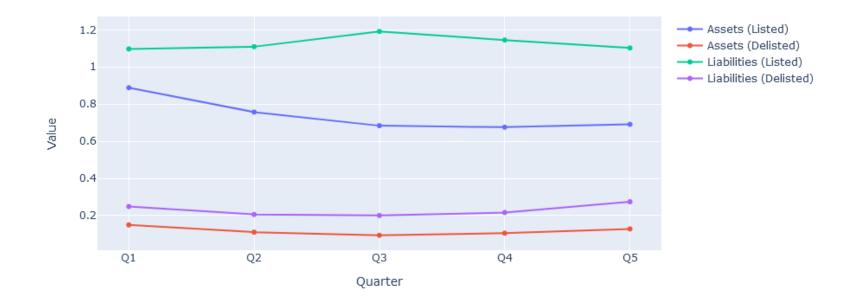


Standard-scaled Dataset

Select Metric for Time Series Analysis:



Assets/Liabilities Over Quarters for Listed vs Delisted Companies



Robust-scaled Dataset