

Stock Trading & Investment Performance Analytics System

Project Overview:

This project implements an end-to-end Stock Trading and Investment Performance Analytics system. The objective is to transform raw historical stock market data and portfolio transaction records into actionable insights related to returns, risk, and investment performance.

The system automates data ingestion, cleaning, analytical processing, and visualization using Python, Pandas, Databricks (PySpark), Apache Airflow, and Power BI.

A. Data Ingestion

- Load historical stock price datasets using Python
- Validate date formats and numeric values

Data Description:

The project uses historical daily stock price data in OHLCV format (Open, High, Low, Close, Volume) for multiple stocks along with simulated portfolio transaction data representing buy and sell activities.

The raw datasets contain data quality issues such as missing values, unordered records, and missing trading days to simulate real-world financial data challenges and justify the data cleaning and transformation steps.

Date	A	B	C	D	E	F	G	I
	Open	High	Low	Close	Volume			
23-01-2012	1035.955	1038.871	1034.973	1038.162	2012902			
07-07-2006	1170.348	1171.994	1170.186	1171.898	5292016			
15-08-2019								
21-04-2020	1154.34	1157.246	1153.814	1156.568	2752003			
22-12-2015	1012.662	1012.798	1010.089	1011.559	4165172			
02-09-2016	1045.415	1046.786	1041.207	1042.634	2277960			
20-07-2010	1102.604	1103.3	1101.249	1102.531	4550179			
06-02-2007	1176.399	1180.81	1175.301	1179.946	5599280			
04-03-2013	966.2237	966.4113	965.7619	966.3081	5267848			
01-12-2020	1080.085	1080.743	1076.761	1076.937	4757033			
18-08-2008	1178.179	1179.423	1173.468	1174.505	2639181			
01-10-2015	1003.444	1004.876	1002.25	1004.123	2340094			
12-06-2007	1144.971	1147.704	1144.776	1147.26	3262855			
17-01-2011	1104.885	1110.173	1103.451	1109.385	1662748			
16-12-2004	1233.868	1235.167	1232.407	1234.534	3057033			
23-11-2001	1216.462	1217.465	1216.356	1216.615	3883753			
24-08-2015	995.2014	1000.742	995.1303	999.9887	4719757			

A	B	C	D	E	F	G
Date	Open	High	Low	Close	Volume	
08-11-2022	486.2539	487.5743	485.8805	486.4471	2156062	
26-05-2000	139.7902	141.7309	139.7135	140.2086	3516983	
03-10-2022	507.244	508.0785	506.8876	507.9686	1578140	
09-11-2018	491.4604	494.4543	487.6126	489.1601	2370674	
04-02-2011	311.066	315.0845	310.5077	314.0568	3806528	
01-08-2013	312.0177	313.7942	310.8067	312.9531	4159428	
31-03-2015	421.2834	422.1721	418.5445	419.2125	2733024	
13-09-2001	188.4608	190.3098	188.4543	189.8258	2236442	
31-03-2023	465.1751	467.5133	464.9753	467.2091	2145343	
24-07-2023	450.1489	453.6073	448.0042	452.5319	2820314	
04-10-2005	329.393	330.2362	328.3878	329.9402	801251	
19-09-2001	189.6271	189.7726	187.5088	188.6746	3360259	
11-06-2008	275.9419	277.8734	275.0724	277.0578	5743347	
07-09-2012	342.337	343.7987	340.6461	341.5628	1827243	
19-12-2003	275.3495	276.2588	275.066	276.0404	1238319	
29-11-2022	472.805	474.2465	470.8587	471.482	4098297	

	A	B	C	D	E	F
1	Date	Open	High	Low	Close	Volume
2	28-02-2011	149.0241	149.1813	148.6329	148.8039	1321558
3	21-04-2005	97.31234	97.46203	94.52312	95.89192	5739634
4	23-10-2000	218.5424	220.0114	216.999	217.9198	4172932
5	06-08-2019	-104.11	-103.309	-106.265	-104.445	1425239
6	09-12-2013					
7	12-08-2013	74.36169	74.59938	74.07258	74.53128	1542651
8	21-02-2008	292.5478	292.6984	290.2394	290.4283	1626252
9	12-09-2000	228.8005	230.2377	228.2775	229.5481	2820835
10	12-02-2003	130.3672	134.9892	130.1209	134.3998	4660273
11	08-01-2018	-123.429	-123.064	-124.701	-123.968	4263657
12	03-08-2011	147.5678	148.2183	145.6076	146.3	3371529
13	09-01-2004	102.7485	102.8381	100.1053	101.3938	5523693
14	31-10-2007	268.5144	274.8531	268.1264	274.4458	1484659
15	09-03-2007	238.6405	242.2199	237.1184	241.4888	5165259
16	15-06-2000	239.7259	240.2943	232.1315	232.1426	2265299
17	21-01-2002	110.0617	111.1727	109.9737	110.1763	4204448
18	25-12-2019	-101.455	-99.7684	-102.021	-100.201	2087789

	A	B	C	D	E
1	Trade_Date	Stock	Quantity	Price	Trade_Type
2	07-06-2005	GOOGL	25	296.1332	SELL
3	10-03-2008	GOOGL	50	1287.615	SELL
4	17-11-2020	AAPL	10	237.3399	
5	22-04-2024	AAPL	-10	143.0639	SELL
6	25-08-2021	AAPL	10	1291.845	BUY
7	31-07-2024	AAPL	-10	300.1235	BUY
8	13-03-2013	MSFT	10	847.8862	BUY
9	02-08-2007	MSFT	100	469.4901	
10	07-11-2008	AAPL	10	422.9987	BUY
11	09-09-2003	GOOGL	10	144.9857	SELL
12	09-05-2006	MSFT	50	1287.615	SELL
13	17-04-2014	MSFT		722.6341	SELL
14	12-07-2023	GOOGL	-10	333.9618	BUY
15	22-08-2017	MSFT	25	974.2747	
16	11-11-2013	GOOGL	50	1370.505	BUY
17	23-01-2001	GOOGL	25	881.6425	SELL

The above images show the raw historical stock price data for AAPL (Apple), MSFT (Microsoft), and GOOGL (Alphabet), along with portfolio transaction data capturing buy and sell activities used for investment performance analysis.

	Date	Open	High	Low	Close	Volume	Stock
0	2022-11-08	486.253934	487.574326	485.880527	486.447077	2156062.0	AAPL
1	2000-05-26	139.790236	141.730940	139.713502	140.208642	3516983.0	AAPL
2	2022-10-03	507.243992	508.078515	506.887568	507.968607	1578140.0	AAPL
3	2018-11-09	491.460368	494.454274	487.612624	489.160088	2370674.0	AAPL
4	2011-02-04	311.066012	315.084473	310.507703	314.056820	3806528.0	AAPL

The above is the file created by combining all the stocks data.

B. Data Cleaning & Transformation

- Handle missing trading days and null values
- Normalize price and volume data
- Create derived metrics such as daily returns and moving averages

This shows a sample of the raw historical stock price data for AAPL (Apple Inc.), containing Date, Open, High, Low, Close, and Volume values. The data is initially unordered and includes inconsistencies, representing real-world market data before cleaning and preprocessing.

```
# Checking missing values before cleaning
stocks_df.isnull().sum()

✓ 0.0s

Date      0
Open     442
High     442
Low      442
Close    442
Volume   442
Stock     0
dtype: int64
```

This view highlights the presence of missing values in the stock dataset before applying any cleaning operations. Columns such as Open, High, Low, Close, and Volume contain null values, which need to be addressed to ensure data quality.

```
# Verifying missing values after cleaning
stocks_df.isnull().sum()

✓ 0.0s

Date      0
Open      0
High      0
Low       0
Close     0
Volume    0
Stock     0
dtype: int64
```

This view confirms that the missing values have been successfully handled using data cleaning techniques such as removing invalid records and forward-filling values. All critical columns now contain zero missing values, making the dataset suitable for analysis.

	Date	Open	High	Low	Close	Volume	Stock	Daily_Return	MA_20	MA_50
0	2000-01-03	150.924766	151.687436	148.058832	148.873622	2227434.0	AAPL	NaN	NaN	NaN
1	2000-01-04	150.868034	151.828736	149.468681	150.037390	5362751.0	AAPL	0.007817	NaN	NaN
2	2000-01-05	150.082163	150.729431	146.974248	148.832975	2253115.0	AAPL	-0.008027	NaN	NaN
3	2000-01-06	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	2000-01-07	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

This view presents the cleaned stock dataset after handling missing trading days and null values. The dataset includes derived financial metrics such as Daily Return, Cumulative Return, 20-day Moving Average (MA_20), and 50-day Moving Average (MA_50), which are used to analyze stock price trends, overall performance, and return behavior over time. Initial NaN values in the moving average columns are expected due to insufficient historical data at the beginning of the time series and are handled appropriately during analysis.

	Trade_Date	Stock	Quantity	Price	Trade_Type
0	2005-06-07	GOOGL	25.0	296.133223	SELL
1	2008-03-10	GOOGL	50.0	1287.615079	SELL
4	2021-08-25	AAPL	10.0	1291.844776	BUY
6	2013-03-13	MSFT	10.0	847.886193	BUY
8	2008-11-07	AAPL	10.0	422.998729	BUY

The portfolio transactions dataset was cleaned separately by validating trade dates, removing invalid or incomplete records, and retaining only meaningful buy and sell transactions to ensure accurate portfolio performance evaluation.

C. Trading & Investment Analytics

- Stock price trend and volatility analysis
- Return and risk calculation
- Portfolio performance evaluation
- Sector-wise market comparison

Databricks was used to perform scalable stock, sub-sector, and portfolio analytics using PySpark, enabling efficient computation of returns, risk metrics, and investment performance.

Table ▼ +									
	Date	1.2_Open	1.2_High	1.2_Low	1.2_Close	1.2_Volume	A _C Stock	1.2_Daily_Return	1.2
1	2000-01-03	150.924766414740...	151.6874359651787	148.058832180880...	148.873621790851	2227434	AAPL	null	
2	2000-01-04	150.868034266377...	151.828736407096...	149.468680888618...	150.037389904654...	5362751	AAPL	0.007817154575832097	
3	2000-01-05	150.082163314248...	150.729430800689...	146.974247630785...	148.8329750018787	2253115	AAPL	-0.008027431719125011	
4	2000-01-06	null	null	null	null	null	null	null	
5	2000-01-07	null	null	null	null	null	null	null	
6	2000-01-10	null	null	null	null	null	null	null	
7	2000-01-11	150.0623737405173	150.317807585089...	147.630522877223...	149.347064765409...	5265559	AAPL	0.0034541388662339134	
8	2000-01-12	149.485782361886...	149.779520448444...	145.406564805028...	146.6947704120113	1119410	AAPL	-0.017759266695765108	

The cleaned and analytics-ready stock dataset was loaded into Databricks as a managed table to enable scalable processing using PySpark.

	Date	1.2 Open	1.2 High	1.2 Low	1.2 Close	1.2 Volume	A ^B _C Stock	1.2 Daily_Return	1.2
1	2000-01-04	150.868034266377...	151.828736407096...	149.468680888618...	150.037389904654...	5362751	AAPL	0.007817154575832097	
2	2000-01-05	150.082163314248...	150.729430800689...	146.974247630785...	148.8329750018787	2253115	AAPL	-0.008027431719125011	
3	2000-01-11	150.0623737405173	150.317807585089...	147.630522877223...	149.347064765409...	5265559	AAPL	0.0034541388662339134	
4	2000-01-12	149.485782361886...	149.779520448444...	145.406564805028...	146.6947704120113	1119410	AAPL	-0.017759266695765108	
5	2000-01-13	147.157974389963...	147.770603509650...	146.239544576902...	147.0339824849012	3592614	AAPL	0.0023123665004360916	
6	2000-01-17	148.3848138641215	149.368607781812...	144.3961726898986	145.386970778250...	2496667	AAPL	-0.011201571764673512	
7	2000-01-18	147.438764601543...	147.621758023349...	145.914649681808...	147.016959156050...	3310826	AAPL	0.011211378633683378	
8	2000-01-19	147.02803087023...	150.228762108146...	146.785093522597...	150.1752393102471	3419283	AAPL	0.02148242061546579	
9	2000-01-20	149.768943333360...	155.3608178182639	149.015319048088...	153.718793603218...	1810222	AAPL	0.0235961288242148	

Non-trading days introduced during time-series alignment were excluded from return-based analytics to ensure financial accuracy.

Table		+			
	A ^B _C Stock	1.2 Avg_Daily_Return	1.2 Avg_Cumulative_Return	1.2 Volatility	1.2 Max_Return
1	AAPL	0.00026334704123639574	0.979968542184206	0.009152502682774196	1.451182815599023
2	GOOGL	-0.000017853499902534566	-0.07409692322339781	0.00251191921452317...	0.03727151292483177
3	MSFT	0.0009651671161920782	1.3344817755502014	0.2909542345600647	8.099432925196023

Stock-wise performance metrics such as average returns, max returns and volatility were computed using PySpark aggregations to analyze return and risk characteristics of each stock.

	A ^B _C Stock	1.2 Year	1.2 Avg_Yearly_Return
1	AAPL	2000	0.000051187526449643823
2	AAPL	2001	0.00176753222720865
3	AAPL	2002	0.0009554404093127856
4	AAPL	2003	0.0008239329962123793
5	AAPL	2004	0.0008525451209928396
6	AAPL	2005	0.00010918099927055787
7	AAPL	2006	-0.00009515525857061141
8	AAPL	2007	-0.0012501301802746452
9	AAPL	2008	0.001514448997064515

Year-wise trend analysis was performed to study long-term stock performance patterns across multiple years.

Table		+					
	1.2 Volume	A ^B _C Stock	1.2 Daily_Return	1.2 MA_20	1.2 MA_50	1.2 Cumulative_Return	A ^B _C Sub_Sector
1	5362751	AAPL	0.007817154575832097	null	null	0.007817154575832097	Consumer Hardware & Ecosyste...
2	2253115	AAPL	-0.008027431719125011	null	null	-0.0021027714329291403	Consumer Hardware & Ecosyste...
3	5265559	AAPL	0.0034541388662339134	null	null	0.0032438617229409994	Consumer Hardware & Ecosyste...
4	1119410	AAPL	-0.017759266695765108	null	null	-0.014515404972824109	Consumer Hardware & Ecosyste...
5	3592614	AAPL	0.0023123665004360916	null	null	-0.012203038472388017	Consumer Hardware & Ecosyste...
6	2496667	AAPL	-0.011201571764673512	null	null	-0.02340461023706153	Consumer Hardware & Ecosyste...
7	3310826	AAPL	0.011211378633683378	null	null	-0.012193231603378152	Consumer Hardware & Ecosyste...
8	3419283	AAPL	0.02148242061546579	null	null	0.00928918901208764	Consumer Hardware & Ecosyste...
9	1810222	AAPL	0.0235961288242148	null	null	0.03288531783630244	Consumer Hardware & Ecosyste...

Since all selected stocks belong to the Technology sector, a sub-sector classification was introduced based on business models to enable meaningful comparative analysis.

Table +

	A ^B C Sub_Sector	1.2 Avg_Daily_Return	1.2 Avg_Cumulative_Return	1.2 Volatility
1	Consumer Hardware & Ecosyste...	0.00026334704123639574	0.9799685421842066	0.009152502682774196
2	Internet Services & Advertising	-0.000017853499902534566	-0.07409692322339781	0.00251191921452317...
3	Enterprise Software & Cloud	0.0013721228708131927	-0.20813946622626717	0.08468238393642662

Sub-sector-wise performance analysis was carried out to compare returns and risk profiles across different technology business models.

	A ^B C Trade_Date	A ^B C Stock	1.2 Quantity	1.2 Price	A ^B C Trade_Type
1	2005-06-07	GOOGL	25	296.1332229764703	SELL
2	2008-03-10	GOOGL	50	1287.615078660282	SELL
3	2021-08-25	AAPL	10	1291.844776074836	BUY
4	2013-03-13	MSFT	10	847.886192667285	BUY
5	2008-11-07	AAPL	10	422.9987292968231	BUY
6	2003-09-09	GOOGL	10	144.985690507770...	SELL
7	2006-05-09	MSFT	50	1287.615078660282	SELL
8	2013-11-11	GOOGL	50	1370.50499120983...	BUY
9	2001-01-23	GOOGL	25	881.6425318973613	SELL

Cleaned portfolio transaction data was loaded into Databricks to evaluate investment performance using actual trade information.

Table +

	A ^B C Trade_Date	A ^B C Stock	1.2 Quantity	1.2 Price	A ^B C Trade_Type	A ^B C Date	1.2 Open	1.2 High	1.2 Low
1	2005-06-07	GOOGL	25	296.1332229764703	SELL	2005-06-07	1183.20492435415...	1185.0798786739938	1182.
2	2008-03-10	GOOGL	50	1287.615078660282	SELL	2008-03-10	1144.590040622124	1144.9203097168072	1139.
3	2021-08-25	AAPL	10	1291.844776074836	BUY	2021-08-25	515.3752769957002	516.4283683636775	510.
4	2013-03-13	MSFT	10	847.886192667285	BUY	2013-03-13	125.2495209345943	125.60223649341916	123.6
5	2008-11-07	AAPL	10	422.9987292968231	BUY	2008-11-07	328.7665601729655	328.9484505633338	325.
6	2003-09-09	GOOGL	10	144.985690507770...	SELL	2003-09-09	1203.38294906265...	1204.315887536941	1199.
7	2006-05-09	MSFT	50	1287.615078660282	SELL	2006-05-09	213.49222400280...	214.649514637245	212.8
8	2013-11-11	GOOGL	50	1370.50499120983...	BUY	2013-11-11	968.3971457713174	969.5247494873204	967.
9	2001-01-23	GOOGL	25	881.6425318973613	SELL	2001-01-23	1199.46631467075...	1199.9334840652343	1198.

Portfolio transactions were enriched with corresponding stock market prices by joining transaction data with stock price data.

Table +

	Stock	Trade Date	1.2 Quantity	1.2 Price	1.2 Close	1.2 Invested_Value	1.2 Market_Value	1.2 Profit_Loss
1	GOOG	2005-06-07	25	296.1332229764703	1184.0743700003147	7403.330574411757	29601.859250007867	22198.52867559611
2	GOOG	2008-03-10	50	1287.615078660282	1141.825736930617	64380.7539330141	57091.28684653085	-7289.46708648325...
3		2021-08-25	10	1291.844776074836	512.9592021930509	12918.44776074836	5129.59202193051	-7788.855738817851
4		2013-03-13	10	847.886192667285	125.11538064069036	8478.86192667285	1251.1538064069036	-7227.708120265946
5		2008-11-07	10	422.9987292968231	325.25094241151174	4229.9872929682315	3252.5094241151173	-977.4778688531142
6	GOOG	2003-09-09	10	144.985690507770...	1200.8337360748285	1449.8569050777005	12008.337360748284	10558.480455670584
7		2006-05-09	50	1287.615078660282	214.52550052640595	64380.7539330141	10726.275026320298	-53654.4789066938
8	GOOG	2013-11-11	50	1370.50499120983...	967.6942240848136	68525.24956049198	48384.71120424068	-20140.5303562513
9	GOOG	2001-01-23	25	881.6425318973613	1197.066784224559	22041.063297434033	29926.669605613974	7885.60630817994
10		2002-05-22	50	469.4900503871553	220.58515704630088	23474.502519357764	11029.257852315044	-12445.24466704272
..		2020-10-17

Invested value, current market value, and profit or loss were calculated for each transaction to assess portfolio performance.

Table +

	A Stock	1.2 Total_Invested	1.2 Current_Value	1.2 Net_Profit_Loss
1	MSFT	5319196.756981235	653478.1645561601	-2355525.6458114088
2	GOOGL	5583440.380982089	8237440.1597901005	2686503.3702789964
3	AAPL	4883903.452573299	2513400.725116889	-2274958.330806825

Asset-wise portfolio performance was summarized to understand each stock's contribution to the overall portfolio.

Table +

	1.2 Portfolio_Invested	1.2 Portfolio_Value	1.2 Total_Profit_Loss
1	15786540.590536624	11404319.049463155	-1943980.6063392381

An overall portfolio performance summary was generated to provide a consolidated view of investment returns.

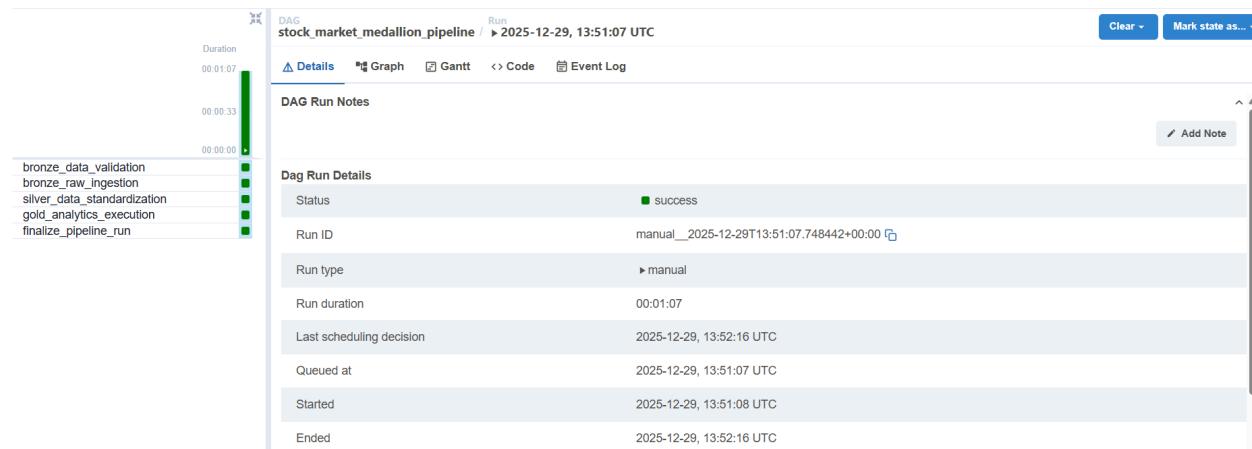
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	cleaned_stock_data	22071a12c2@vnrvjet.in	Dec 29, 2025, 11:31 AM	
	cleaned_transactions	22071a12c2@vnrvjet.in	Dec 29, 2025, 11:50 AM	
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	subsector_performance	22071a12c2@vnrvjet.in	Dec 29, 2025, 12:13 PM	

Final analytics outputs were stored as managed Databricks tables to enable reuse, governance, and downstream reporting.

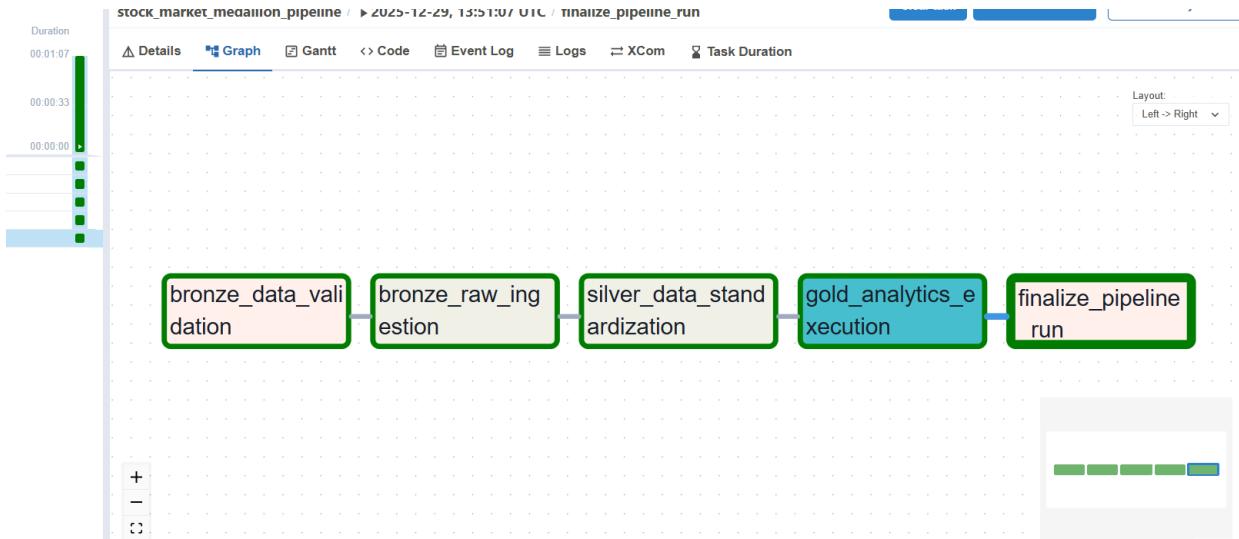
The pipeline follows an automated ETL architecture where Apache Airflow orchestrates execution, Databricks Spark performs scalable data processing, and Delta tables store analytics-ready results. This design ensures reliability, scalability, and production-grade data analytics.

D. Workflow Automation

- Design scheduled ETL pipelines using Airflow DAGs
- Implement retries, monitoring, and logging



This screenshot shows the Apache Airflow DAG used to orchestrate the stock analytics ETL pipeline. The DAG is responsible for scheduling, triggering, and monitoring the Databricks analytics job, enabling automated execution with retry and failure handling.



The screenshots illustrate the successful execution of the stock market medallion ETL pipeline using Apache Airflow. The Airflow DAG run view shows that all tasks completed successfully in a single pipeline run.

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1fb9d1b94371
▶ Log message source details
[2025-12-29, 13:52:14 UTC] {local_task_job_runner.py:123} * Pre task execution logs
[2025-12-29, 13:52:14 UTC] {taskinstance.py:2631} INFO - Dependencies all met for dep_context=non-requireable deps ti=<TaskInstance: stock_market_medallion_pipeline.finalize_pipeline_run manual_2025-12-29>
[2025-12-29, 13:52:14 UTC] {taskinstance.py:2631} INFO - Dependencies all met for dep_context=requireable deps ti=<TaskInstance: stock_market_medallion_pipeline.finalize_pipeline_run manual_2025-12-29>
[2025-12-29, 13:52:14 UTC] {taskinstance.py:2884} INFO - Starting attempt 1 of 2
[2025-12-29, 13:52:14 UTC] {taskinstance.py:1907} INFO - Executing <Task(PythonOperator): finalize_pipeline_run> on 2025-12-29 13:51:07.748442+00:00
[2025-12-29, 13:52:14 UTC] {warnings.py:112} WARNING - /home/***/.local/lib/python3.12/site-packages/***/task_runner/stdandard_task_runner.py:70: DeprecationWarning: This process (pid=221) is a pid = os.fork()
[2025-12-29, 13:52:14 UTC] {standard_task_runner.py:104} INFO - Running: ['***', 'tasks', 'run', 'stock_market_medallion_pipeline', 'finalize_pipeline_run', 'manual_2025-12-29T13:51:07.748442+00:00']
[2025-12-29, 13:52:14 UTC] {standard_task_runner.py:104} INFO - Started process 223 to run task
[2025-12-29, 13:52:14 UTC] {standard_task_runner.py:105} INFO - Job 118: Subtask finalize_pipeline_run
[2025-12-29, 13:52:15 UTC] {task_command.py:467} INFO - Running <TaskInstance: stock_market_medallion_pipeline.finalize_pipeline_run manual_2025-12-29T13:51:07.748442+00:00 [running]> on host 1fb9d1b94371
[2025-12-29, 13:52:15 UTC] {taskinstance.py:317} INFO - Exporting env vars: AIRFLOW_CTX_DAG_OWNER='***_user' AIRFLOW_CTX_DAG_ID='stock_market_medallion_pipeline' AIRFLOW_CTX_TASK_ID='finalize_pipeline_run'
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Task instance is in running state
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Previous state of the Task instance: queued
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Current task name:finalize_pipeline_run state:running start_date:2025-12-29 13:52:14.824250+00:00
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Dag name:stock_market_medallion_pipeline and current dag run status:running
[2025-12-29, 13:52:15 UTC] {taskinstance.py:740} *** Log group end
[2025-12-29, 13:52:15 UTC] {crypto.py:82} WARNING - empty cryptography key - values will not be stored encrypted.
[2025-12-29, 13:52:15 UTC] {phon.py:248} INFO - Done. Returned value was: None
[2025-12-29, 13:52:15 UTC] {taskinstance.py:349} * Post task execution logs
[2025-12-29, 13:52:15 UTC] {taskinstance.py:361} INFO - Marking task as SUCCESS. dag_id=stock_market_medallion_pipeline, task_id=finalize_pipeline_run, run_id=manual_2025-12-29T13:51:07.748442+00:00
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Task instance in success state
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Previous state of the Task instance: running
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Dag name:stock_market_medallion_pipeline queued_at:2025-12-29 13:51:07.785613+00:00
[2025-12-29, 13:52:15 UTC] {logging_mixin.py:190} INFO - Task hostname:1fb9d1b94371 operator:PythonOperator

```

This view displays the Airflow task execution logs, confirming successful submission and completion of the Databricks job. Logging and monitoring enable traceability, debugging, and operational reliability of the pipeline.

Start time	Job	Run as	Launched	Duration	Status	Error code	Run parameters
Dec 29, 2025, 07:22 PM	gold_analytics_execution	Harshanka Tirum... (API)	By runs submit API	7s	Success		
Dec 29, 2025, 07:21 PM	gold_analytics_execution	Harshanka Tirum... (API)	By runs submit API	7s	Success		
Dec 29, 2025, 07:21 PM	gold_analytics_execution	Harshanka Tirum... (API)	By runs submit API	9s	Success		

This image shows the Databricks gold analytics job runs triggered programmatically by Apache Airflow using the Databricks Submit Run API. It confirms the successful integration between Airflow and Databricks for automated pipeline execution.

The screenshot displays the Databricks job run details. Key information includes:

- Started: Dec 29, 2025, 07:22 PM
- Ended: Dec 29, 2025, 07:22 PM
- Duration: 7s
- Status: Succeeded
- Lineage: No lineage information for this job. [Learn more](#)
- Buttons: View run events, View run libraries

Below this, sections for Notebook and Compute are shown:

- Notebook:** /Users/22071a12c2@vnrvjet.in/stock_analytics_job
- Compute:** Rithika's Cluster (Single node: Standard_D4ds_v4 · Release: 17.3.3)
View details, Spark UI, Logs, Metrics

The job run details display the execution of the Spark-based analytics notebook on a Databricks cluster. The notebook performs large-scale transformations, aggregations, and analytical computations on the cleaned stock and portfolio data.

The screenshot shows the Databricks Catalog Explorer interface for the table `airflow_triggered_stock_summary`. The table has the following columns:

- Overview**
- Sample Data** (selected)
- Details**
- Permissions**
- Policies**
- History**
- Lineage**
- Insights**
- Quality**

Below the table header, there is a text input field: "Ask your question about the sample data..." and two AI-generated questions:

- What are the top 5 stocks by Avg_Daily_Return?
- Are there any stocks with Avg_Daily_Return < 0?

The **Sample** section displays the following data:

	Stock	Avg_Daily_Return
1	AAPL	2.6334704123639574E-4
2	GOOGL	-1.7853499902534566E-5
3	MSFT	0.0013721228708131927

This screenshot shows the final output of the ETL pipeline stored as a managed Delta table in Databricks. The table contains analytics-ready stock performance metrics generated after transformation and is used for downstream reporting and visualization.

E. Visualization & Reporting

- Stock trend dashboards
- Portfolio performance and return analysis
- Risk indicators and market summaries



Dashboard 1: Stock Market Performance Overview

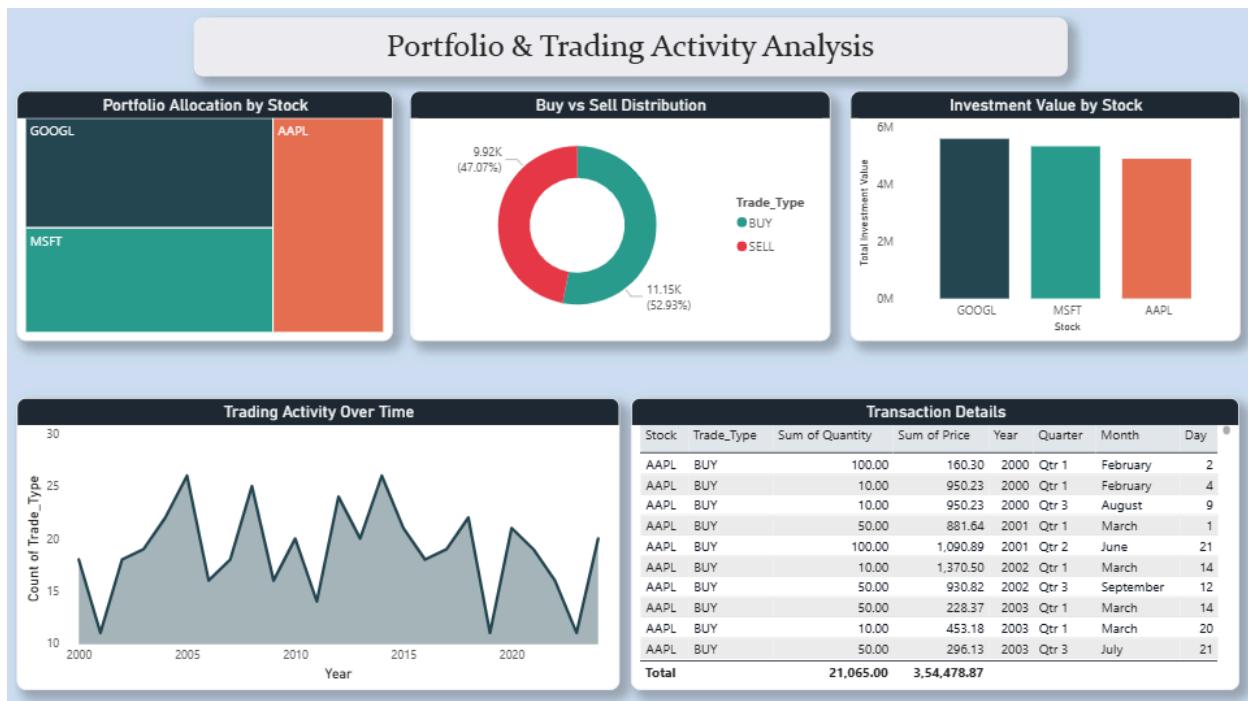
Purpose:

This dashboard provides a consolidated view of long-term stock price movements, return behavior, and trading intensity across selected stocks.

Visual explanations:

- **Normalized Stock Price Trend (Line Chart)**
Compares the relative price movement of AAPL, GOOGL, and MSFT over time by normalizing prices. This helps analyze long-term trends without price-scale bias.
- **Filter by Stock (Slicer)**
Allows interactive selection of individual stocks to focus analysis across all visuals.
- **Cumulative Return Growth Over Time (Line Chart)**
Shows how returns accumulate over time for each stock, highlighting growth consistency and major performance shifts.
- **Monthly Opening Price Intensity (Treemap)**
Displays the distribution of total opening prices across months, identifying periods of higher trading intensity.

- **Average Daily Return by Stock (Column Chart)**
Compares average daily returns to evaluate which stock delivers higher short-term profitability.
- **Stock-wise Distribution of Closing Prices (Donut Chart)**
Shows each stock's contribution to the total closing price volume.
- **Cards (Last Closing Price, YTD Cumulative Return, 50-Day Moving Average, Avg Trading Volume)**
Provide quick snapshot metrics for recent price levels, trend strength, and liquidity.



Dashboard 2: Portfolio & Trading Activity Analysis

Purpose:

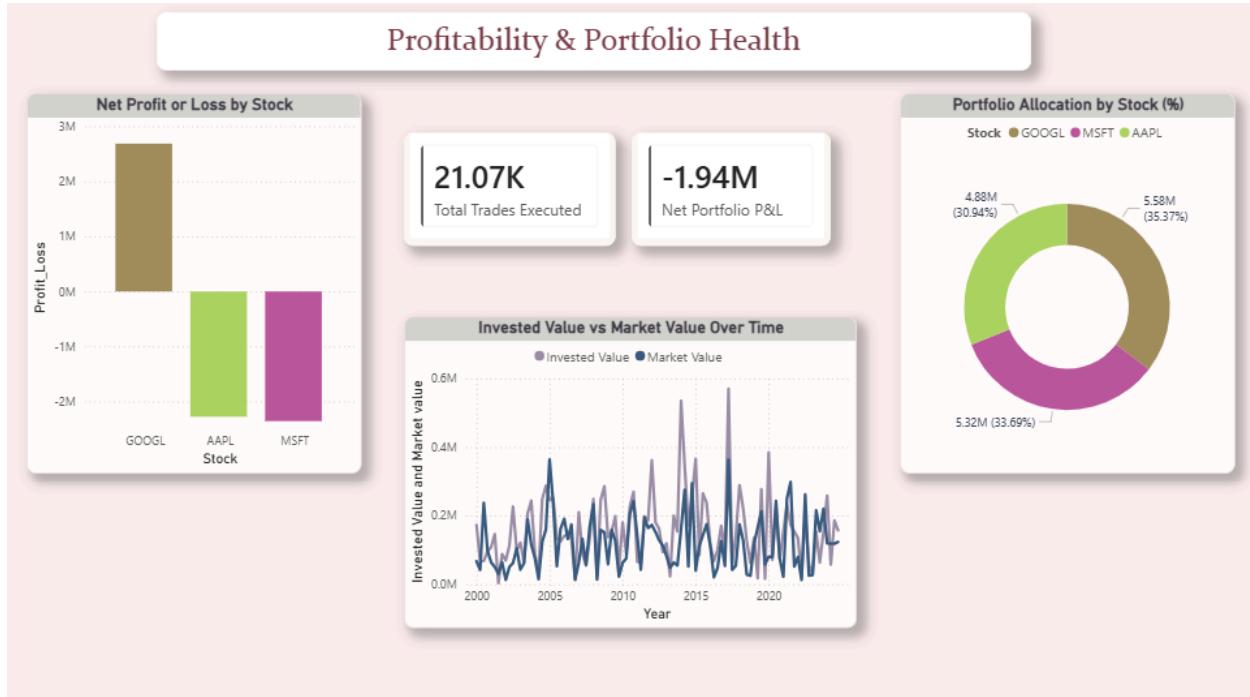
This dashboard focuses on trading behavior, portfolio allocation, and investment exposure derived from transaction data.

Visual explanations:

- **Portfolio Allocation by Stock (Treemap)**
Shows how total invested quantity is distributed across stocks, indicating portfolio diversification.
- **Buy vs Sell Distribution (Donut Chart)**
Compares buy and sell quantities to assess trading bias and activity balance.
- **Investment Value by Stock (Column Chart)**
Highlights total investment value per stock, showing where capital is most concentrated.
- **Trading Activity Over Time (Area Chart)**
Tracks the number of trades over time, identifying active and dormant trading periods.

- **Transaction Details (Table)**

Provides granular visibility into stock-wise trades, quantities, prices, and trade dates for validation and auditability.



Dashboard 3: Profitability & Portfolio Health

Purpose:

This dashboard evaluates portfolio performance in terms of profit/loss, capital deployment, and value evolution over time.

Visual explanations:

- **Net Profit or Loss by Stock (Column Chart)**
Shows realized profitability per stock, clearly distinguishing gainers and loss-makers.
- **Total Trades Executed (Card)**
Indicates overall trading activity volume.
- **Net Portfolio P&L (Card)**
Summarizes the overall financial outcome of the portfolio.
- **Invested Value vs Market Value Over Time (Line Chart)**
Compares capital invested against current market value to assess portfolio appreciation or erosion.
- **Portfolio Allocation by Stock (%) (Donut Chart)**
Displays proportional capital allocation across stocks, highlighting concentration risk



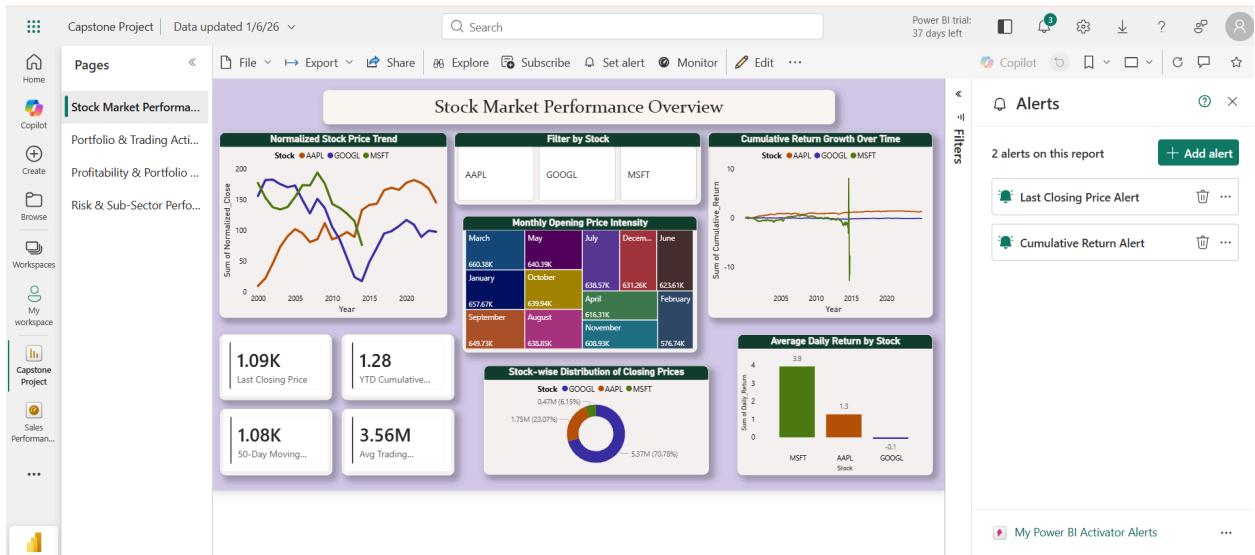
Dashboard 4: Risk & Sub-Sector Performance Insights

Purpose:

This dashboard analyzes risk-return characteristics and performance differences across sub-sectors.

Visual explanations:

- **Risk vs Return by Sub-Sector (Scatter Plot)**
Plots volatility against average daily return to identify high-risk–high-return and stable sub-sectors.
- **Average Cumulative Return by Sub-Sector (Bar Chart)**
Compares long-term return performance across sub-sectors.
- **Last ETL Snapshot (Card)**
Displays the timestamp of the most recent successful ETL run, ensuring data freshness and pipeline reliability.



After publishing the Power BI report to the Power BI Service, I configured data-driven alerts on key KPI cards to monitor important changes in stock performance.