

Makeni Metrics: Real-time Stock Application

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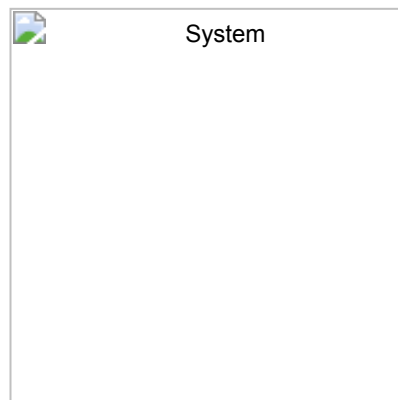
Main Repo: [Link \(https://github.com/longbui23/Maneki-Metrics\)](https://github.com/longbui23/Maneki-Metrics)

Summary: Real-time Stock Application provides investors with up-to-date stock data. Designed for the fast-paced nature of financial markets, it delivers live updates on prices, trends, and key metrics to support informed decision-making. Key features include real-time data streaming, intuitive analytics, customizable alerts, and seamless BigQuery & AWS Cloud integration with Airflow Pipelines and ending Streamlit dashboard.

- Want to use a free platform to analyze S&P500 stock? Click [here \(https://sp500py-hjwkdwbbaam5as3qd4ptz.streamlit.app/\)](https://sp500py-hjwkdwbbaam5as3qd4ptz.streamlit.app/) to view Makeni Metrics Interactive Dashboard.
- Link to Overview Report can be found [here \(https://colab.research.google.com/drive/19TelBMBNAJJhMQisA-Pz2DYSPeU5q0Lz?authuser=1#scrollTo=JAuHFHJqAj7Q\)](https://colab.research.google.com/drive/19TelBMBNAJJhMQisA-Pz2DYSPeU5q0Lz?authuser=1#scrollTo=JAuHFHJqAj7Q).

Data Collection

System Architecture:



- **Yahoo Finance API:** API to extract key finance data
- **PostgreSQL:** Relational DB that stores model prediction
- **IAM Role:** Security Layer to control permission before accessing AWS Cloud
- **Apache Airflow:** Workflow Management to create and schedule pipelines
- **Docker:** Wrap up project's microservices
- **EC2:** Cloud Computing Service to auto-run Airflow pipelines
- **S3:** Cloud Object Storage acted as Staging layer
- **MongoDB:** NoSQL Database
- **BigQuery:** Cloud Relational DataWarehouse

- **Streamlit**: Open-source Cloud Dashboard Infrastructure
- **Power BI**: Microsoft visualization platform
- **Quicksight**: Amazon Visualization Platform
- **FBProphet**: Time Series Deep Learning Model
- **LSTM**: Long-short Term Memory Deep Learning Model
- **OpenAI**: Large Language Model for Chatbot

Relational Database

BigQuery Warehouse:



- **Companies**: Information about companies in the S&P500, including attributes like sector, industry, and market capitalization.
- **Stock**: Historical stock performance for individual S&P500 companies, including open, close, high, low prices, and trading volume. **(2+ Million Records)**
- **Cash-flow**: Details on cash flow activities for S&P500 companies, segmented into operating, investing, and financing activities.
- **Balance Sheet**: Snapshot of S&P500 companies' financial health, with data on assets, liabilities, and equity.
- **Income Statement**: Financial performance data for S&P500 companies, including revenue, expenses, and net income.
- **Stock_sp500_market**: Overview of the S&P500 market's aggregated stock statistics, providing market-level insights and trends.

Atlas MongoDB:

- **News**: Store News

System Operations

The data collecting process involves the following steps:

1. **Extracting Data**: Data being extracted from web scrapping and yahoo finance APIs.
2. **User Authentication**: Passed passkey to AWS APIs to access role authentication
3. **Load data**: Data being extracted (temporarily in json format) is being stored in S3 bucket and MongoDB

4. **Data Processing:** Optimized Airflow to auto-process data to create new metrics and standardized formats
5. **Data Storage:** Storing data into BigQuery Warehouse
6. **Task Scheduler:** Used Airflow and pushed Airflow files into EC2 for automatic scheduling
7. **Visualization:** Utilize Streamlit and PowerBI for creating dashboards to serve non-technical users' needs

Predictive Modelling

The project utilizes Long-short Term Memory (LSTM) models to predict future stock price (~ 1 month head).

1. **Tokenization:** The job descriptions are tokenized using NLTK.
2. **Word Cloud:** A word cloud is generated for the job descriptions of a selected job title (e.g., 'data analyst') to understand the commonly used words and skills required.
3. **Skill Filtering:** A list of relevant skills is defined, and the tokenized job descriptions are filtered to keep only the relevant skills.
4. **TF-IDF Vectorization:** The filtered job descriptions are vectorized using TF-IDF to calculate the importance of each skill.
5. **Top Skills:** The top 10 most important skills are identified based on their TF-IDF scores and visualized using a bar chart.

Recommendation System

A recommendation system is implemented to match job postings with a candidate's profile. The steps involved are:

1. **Data Preparation:** The job postings data is loaded from the 'postings.csv' file.
2. **TF-IDF Matrix:** A TF-IDF matrix is created from the job descriptions.
3. **Cosine Similarity:** The cosine similarity between a given user profile and the job descriptions is calculated using the TF-IDF matrix.
4. **Top Recommendations:** The top N most similar job postings are recommended based on the cosine similarity scores, ensuring that only one job from each unique company is included.

Predictive Modeling

The project builds a predictive model to estimate the probability of landing a data job based on a candidate's profile. The steps involved are:

1. **Data Preprocessing:** Load historical stock data, normalize using Min-Max scaling, and create time series sequences as input features.
2. **Data Splitting:** Split data into training, validation, and testing sets, maintaining chronological order to avoid data leakage.
3. **Model Design:** Build the LSTM model architecture using TensorFlow or PyTorch with LSTM, Dropout, and Dense layers.
4. **Model Training:** Train the model using MSE loss function and Adam optimizer, validating on the validation set to tune hyperparameters.

5. **Prediction:** Use the trained model to predict stock prices for the test set and compare predictions with actual prices. .
6. **Visualization:** Plot actual vs. predicted stock prices and forecast trends for ~1 month ahead.
7. **Hyperparameter Tuning:** Optimize performance by experimenting with parameters like sequence length, LSTM units, learning rate, and batch size.

Large Language Modeling (LLM)

Incorporated OpenAI LLM to make a Makeni Chatbot where users can interact with the app by typing questions and comments in to receive response.

1. **Import Model:** Import LLM after-trained model providing by OpenAI
2. **Front-end Design:** Design a front-end user interface to interact with the back-end model

4. Implications

4.1. Implications for Stakeholders:

Investors:

- Tie to Revenue Growth and Profitability, Operational Efficiency and Management, Long-Term Value Creation
- Understanding a company's performance helps mitigate risks and ensures they're placing funds in financially sound and well-managed businesses.
- Market dynamics influence stock prices through broader trends and conditions that go beyond an individual company's control: Economic Climate, Industry Trends
- Relying solely on company performance without understanding market conditions can lead to poor timing, such as buying at peaks or selling during panic-driven declines.

4.2. Ethical, Legal, and Societal Implications:

Wealth Disparities:

- Promoting stocks that primarily benefit large corporations or wealthy investors could contribute to increasing societal inequality.
- Mitigation: Highlight opportunities for ethical and sustainable investments that support small or emerging companies.

Investment Advice Regulations:

- Providing financial recommendations can be considered investment advice and may require specific qualifications, licenses, or disclosures under regulations like the SEC (Securities and Exchange Commission) rules.
- Mitigation: Consider my suggestions as data-driven insights rather than definitive financial advice, and add disclaimers.

Market Influence and Herd Behavior:

- Recommending certain stocks could lead to concentrated investment, artificially inflating prices and creating volatility.
- Mitigation: Encourage diversification and educate audiences about the importance of balanced investment strategies.