Communication

Using Knowledge Graphs for Enabling Collaborative Financial Market Data Analytical Processes

Bhushan Oza * and Ali Behnaz

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Using Knowledge Graphs for Enabling Collaborative Financial Market Data Analytical Processes

Bhushan Oza * and Ali Behnaz

University of New South Wales; ali.behnaz@unsw.edu.au
* Correspondence: b.oza@unsw.edu.au

Abstract: Financial market data analysts are increasingly turning towards machine learning techniques for data analysis and making decisions. This paper explores how knowledge graphs, essentially a network of real entities and their relationships, can be used to improve collaborative financial market data analysis and make it more efficient and user friendly. This paper reviews the current state of financial market data analysis, the challenges in deploying machine learning models in industrial environments, and the concepts such as ML-Ops and knowledge graphs. A software architecture comprising various roles, layers and services such as Data Engineers, Data Analysts, public users, APIs, workflows, analytics libraries, UX layer, Business Layer, etc. is introduced and described in detail. Then, it discusses how knowledge graphs can be used to enhance collaborative financial market data analysis. Finally, a case study is presented to demonstrate the usage of the whole system, within the context of financial market data analytics of equities.

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1. Introduction

Developing ML applications is becoming more popular and important, and with so many different types of ML algorithms available [11], building tools that can help choose appropriate machine learning techniques, help apply models to different datasets, and integrate it with operational systems is extremely significant. Many users or analysts working for the same organisation often have similar goals [8]. Hence, allowing them to contribute collaboratively at different stages of ML model lifecycle (i.e discovery, development, deployment, maintenance) becomes essential.

For example, analysts find it difficult to apply machine learning techniques to financial market data [8]. Most literature is only focused on building models and not implementation and integration with operational systems [10]. Hence, the provision of software tools for practitioners and researchers to implement, operate, and maintain models in a collaborative way is required.

To implement and maintain models, the users require methods and tools that can be customised to tailor to their needs specifically, for example, in financial markets as they are quite diverse when accurate analysis is required [9]. However, they lack expert computing skills [3]. Hence, software tools that provide easy customisation with minimal coding are required.

This paper identifies that existing tools and approaches have limitations, then contributes by proposing an architecture to overcome these limitations and shows a working example in the form of financial market data analysis.

2. Background

2.1. Related Work

The ML development cycle by an analyst within an organisation involves various steps. Firstly, they gather raw data and clean or prepare it. Then, they analyse the data by exploring it and choosing or creating relevant features, followed by training and testing the model. The final step is to deploy this ML application within the enterprise system. ML development is typically done by multiple people in an organisation, such as data analysts and data engineers.

There is a lot of interest in industrial ML applications, and to implement ML models. Obtaining data and preprocessing it appropriately for different ML models is a big task in itself. Many data scientists rely on features provided by vendors however in many cases they wish to create their own features [6]. Even then, there is a plethora of options to choose from, and each option requires a comprehensive understanding of how that ML algorithm works [8]. Operationalising models can also be challenging as fitting generic models to a specific business problem requires high proficiency [8]. Along with this, collaboration presents an additional challenge as it requires streamlining and synchronization across the team.

There are plenty of tools or libraries available for performing analytics using machine learning. Broadly, they can be classified into tools supporting programming languages, or part of a platform that offers Artificial Intelligence as a Service (AIaaS) [1]. There is also an increasing use of API/services to capture different stages of the analytics pipeline such as data acquisition, preprocessing, analysis and interpretation which necessitates a tool to integrate them properly.

On one hand, tools with programming languages require a high degree of understanding of those languages. AIaaS platforms, on the other hand, are focused more on how AI can be leveraged to accomplish your task. It is a type of AI outsourcing which seeks to enable users to experiment with AI without investing too much money or effort. There are quite a few AIaaS providers currently active in the market [1]. These tools are comprehensive as AI needs a detailed iterative approach to deal with quality data such as that of financial markets [2].

Due to a wide range of development tools and the increasing availability of services that can be used off-the shelf, this paper focuses on some innovative methods that allow teams to collaboratively assemble the entire solution from reading the data to presenting it.

2.2. ML Application Development Methods

Developing ML applications has become a collaborative effort as it is an appealing paradigm to build high-quality ML models [12]. Four types of methods that enable collaborative ML application development have been identified:

1. Community model sharing (e.g., OpenML): online platforms about sharing machine learning algorithms, models, experiments, and so on. It is meant to encourage open source development where people can freely collaborate and quickly build upon new advances in the field of machine learning [5].
2. Using a low code programming platform: an approach that requires some basic programming knowledge, in order to accomplish the required software development task. Instead of using complex coding tools, visual interfaces, combined with basic logic, can be used to perform any task, even those requiring multiple people to collaborate [3].
3. Composition and workflow platforms: enable the enactment of multiple services (typically developed by multiple people) to achieve a complex analytics goal, such as in MLFlow [15].
4. MLOps: a practice that unifies ML application development with ML system operations. It is about streamlining the process of deploying, maintaining and monitoring machine learning models efficiently with high reliability [4].

To make a useful comparison, ML analytics software development methods can be evaluated against the following features:

1. Maintaining domain knowledge- When analysts perform any task, they rely on shared understanding of domain knowledge, such as, in financial market data analysis within an organisation, they need to define and operate complex workflows that involve the entire analytics cycle where it is possible for multiple ML techniques to operate over a large number of measures to be included in one workflow [6].
2. ML pipeline composition- Analysts typically require customisable and collaborative solutions without the need for expert coding skills to define and maintain workflows. Many complex analysis problems require group effort but the majority of tools assume one analyst [7].

3. Quality control and testing- Quality control and software testing are essential components of any project to ensure successful deployment, and with many separate components such as in this case, it becomes critical to maintain quality and testing requirements collaboratively.

Table 1 below summarises how existing techniques address all required features.

Table 1. Comparison of existing techniques.

Methods	Collaboratively maintain domain knowledge	Collaborative composition	Collaborative quality control and testing
OpenML	✓	×	×
Low code platforms	×	✓	×
MLOps	✓	×	✓
Workflows	×	✓	×

While OpenML allows to maintain domain knowledge collaboratively, it lacks collaborative composition and quality control. Low code platforms and workflows allow collaborative composition but lack collaborative domain knowledge and quality control. MLOps performs the best out of the four methods by allowing collaborative domain knowledge maintenance and quality control but still lacks collaborative composition.

Hence, the purpose of this paper is to investigate a method that allows high customization, good user experience, and that can be used collaboratively. Basically, a solution fulfilling all three requirements mentioned in Table 1 is required.

3. Proposed Solution

3.1. Knowledge Graph

The proposed solution is based on using a knowledge graph, which makes collaboratively maintaining domain knowledge possible [13]. In practice, different roles such as data engineers, data scientists, software engineers, DevOps engineers, business analysts and researchers have different parts of knowledge who have to collaborate, and there are many services that perform different functions.

For example, consider a service that generates trading signals based on the stock price data. But, this price could be the daily open price, or it could also be the daily closing price. A knowledge graph would keep track of this information, making the whole service more convenient and not requiring to keep changing it based on which price we want to use. Also, a knowledge graph would be able to automatically suggest the most appropriate generating trading signal service if we present it with the price data, thus increasing usability and convenience. Hence, a knowledge graph shows how different data concepts relate to each other thus helping to perform composition, and it also identifies relevant services.

Competency questions are a set of queries that the artifact must be able to answer once it is built and implemented according to Design Science Research methodology [16,17]. They define the key requirements, problems, or use cases that the artifact should address. They help ensure the artifact meets the needs of its intended users and serves its purpose effectively. They act as a benchmark against which the quality and utility of the final artifact can be evaluated [16,17]. An example of this is shown below in Table 2 with the context being financial market data analysis.

Table 2. Competency Questions and Answers.

Questions	Answers
Which variable is linked to asset price?	Volatility
How is asset price determined?	Using mean as proxy
How is mean price determined?	Using daily price as proxy
How is daily price measured?	Using close price from the dataset

In normal programming, every analytic module is closely linked with data, or variables, whose information can be extracted from the knowledge graph. This is critical as almost all the measures are interdependent. For example, in financial market data analytics, trade count will have an effect on trading volume. It is important to figure out these dependencies, which can make the task more complicated. The amount of data is large, and there are plenty of ways or tools to interpret it. Choosing the correct combination and cleaning the data, such as removing outliers, is of paramount importance for accurate, reliable and precise prediction [14]. An illustration of such interdependencies is shown below in Figure 1.

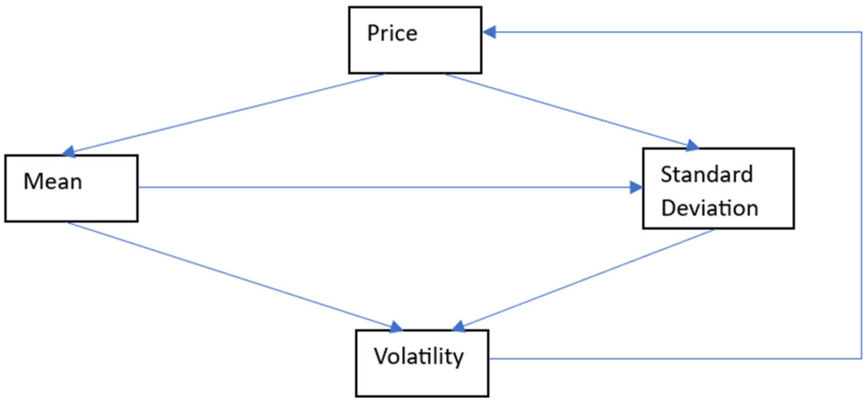


Figure 1. Interdependencies of Financial Measures.

Here, the mean and the standard deviation are calculated from the price, which are then used to determine the volatility. Volatility can affect the behaviour of market participants, thus influencing the price. In summary, a knowledge graph would answer various questions related to these measures. Figure 2 below shows an example of how would such a knowledge graph look like within the context of financial market data analysis. This knowledge graph is based on the Research Variable Ontology (RVO) [18].

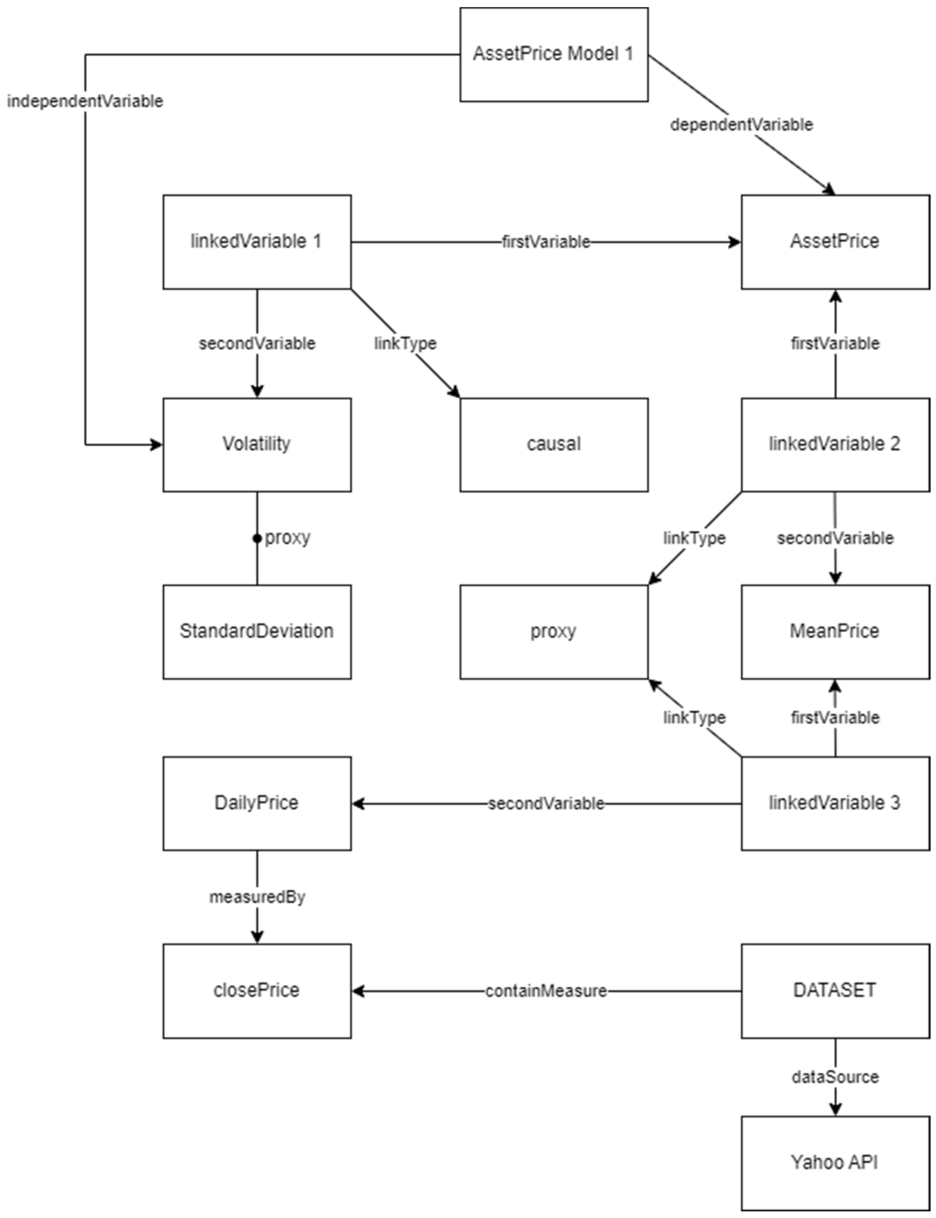


Figure 2. Knowledge Graph.

3.2. Architecture

As per the identified gap, a method to fully allow collaboration of ML analytics is required. Figure 3 shows the software architecture of the proposed solution.

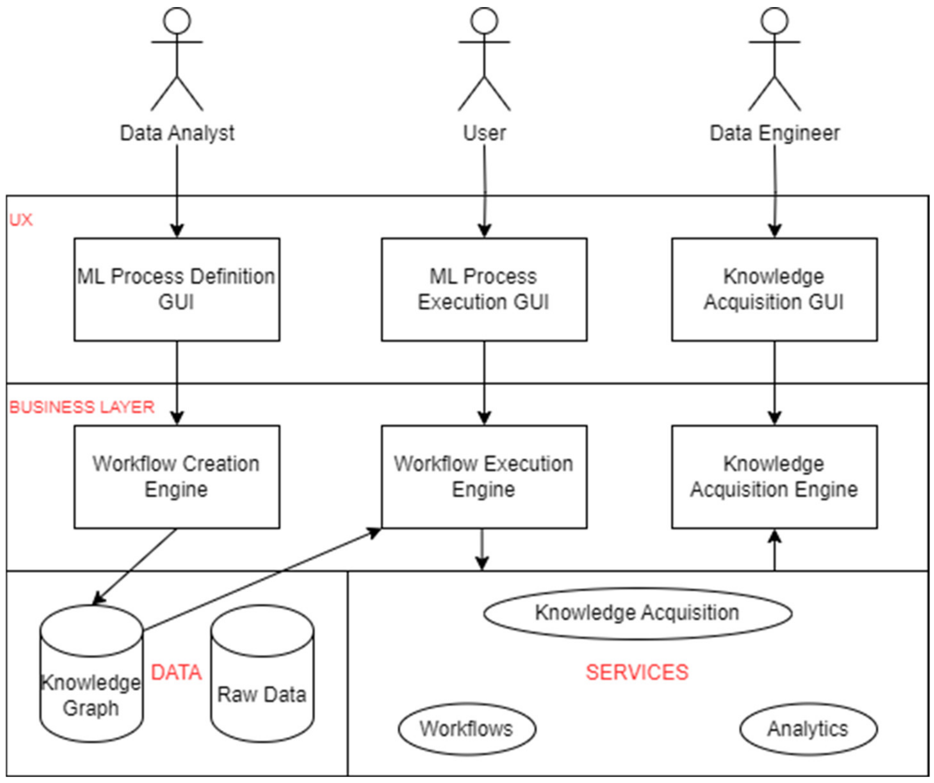


Figure 3. Software Architecture.

The architecture is organised in 4 layers. Under the Data Layer, we have raw data and the corresponding knowledge graph to ensure the ability to collaboratively maintain domain knowledge. Under the Services Layer, we have analytics along with knowledge acquisition and workflows to ensure collaborative quality control. On top of this, the business layer has engines which are connected to their respective GUIs at UX layer, to cater for collaborative composition. The knowledge graph takes input from the workflow creation engine and figures out what sort of data is required and then sends it to the workflow execution engine. This engine then feeds into the services layer which processes and feeds the information in the knowledge acquisition engine.

The three actors- data analyst, user, and data engineer are responsible for the defining, executing, and acquiring processes respectively. Data analysts are responsible for developing and fine-tuning ML models which includes collecting, preprocessing, analysing, training and testing models. Data engineers focus on building and maintaining data infrastructure that supports ML development and deployment which includes designing data pipelines, managing data storage and processing, and ensuring data quality and accessibility. Users are customers for which the solution is designed. Their feedback and usage enables evaluation of model performance and identification of improvements areas.

3.3. Development Processes

Performing development work collaboratively involves a few steps. Firstly, a workflow is agreed upon which includes the different component services and files that form the whole service. It also includes the order in which they will be executed. Then, these component services are allocated to different members of the development team. Once all of them are finished, they are executed as per the workflow, and the whole service is now functioning.

4. Demonstration and Evaluation

The example used here is a case study for conducting financial market data analysis. Basically, it is a workflow for intraday data analysis, shown below in Figure 4. It includes the required information, such as the component services, order, and files. Let’s assume that multiple people are collaborating to build this service. They can then collaborate by building smaller component services shown in blue in Figure 4, which are then integrated and executed into the overall service as shown.

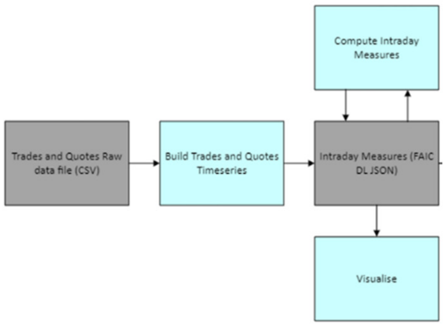
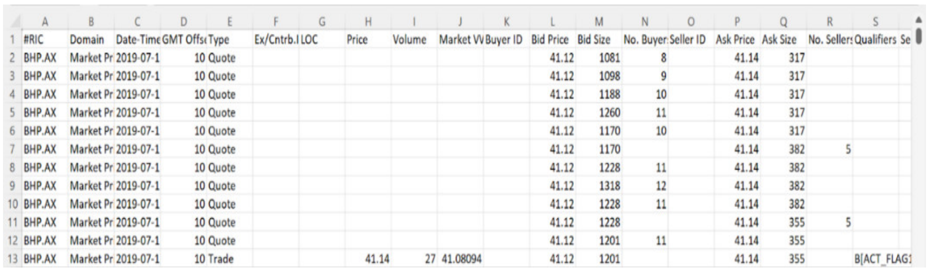

Compute Intraday Measures
Trades and Quotes Raw data file (CSV)
Build Trades and Quotes Timeseries
Intraday Measures (FAIC DL JSON)
Visualise

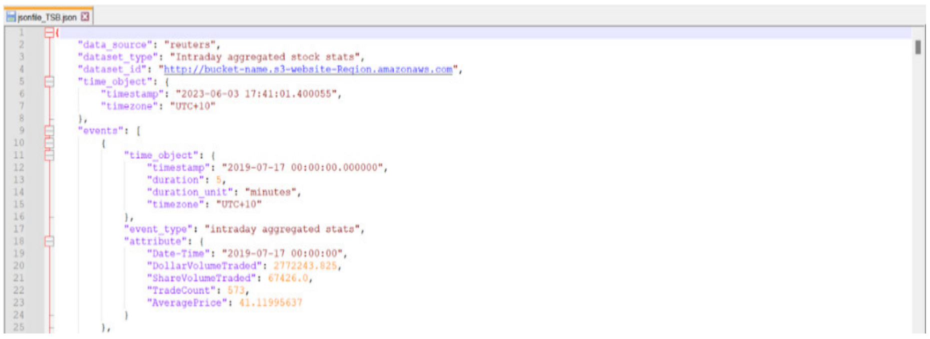
Figure 4. Workflow for intraday data analysis.

Here, we have the raw data in the form of a CSV file, from which a time series is built. This can be used to generate measures. Then, the results can be visualised or fed into models for generating trading signals. Once the signals are generated, orders can be placed for backtesting. A self-explanatory example concerning "timeseries" and "visualise" components is shown below in Figures 5 to 8. The "build trades and quotes timeseries" component is a python file that takes input from the CSV and creates the JSON file containing basic measures. The "visualise" component is a Jupyter Notebook file that takes in the JSON file and produces a HTML file containing the required visualisations.



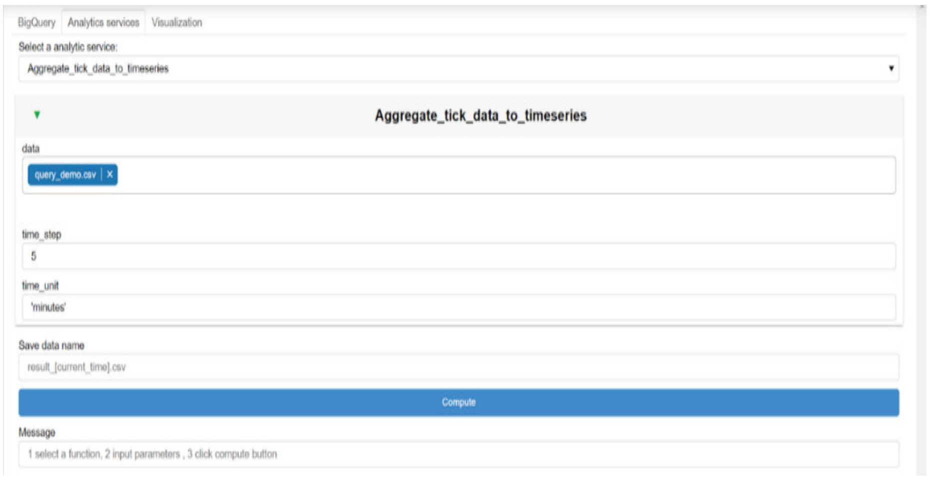
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
1	#RIC	Domain	Date-Time	GMT Offs	Type	Ex/Cntrb.I	LOC	Price	Volume	Market VV	Buyer ID	Bid Price	Bid Size	No. Buyer	Seller ID	Ask Price	Ask Size	No. Seller	Qualifiers	Se
2	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1081	8		41.14	317			
3	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1098	9		41.14	317			
4	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1188	10		41.14	317			
5	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1260	11		41.14	317			
6	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1170	10		41.14	317			
7	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1170			41.14	382	5		
8	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1228	11		41.14	382			
9	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1318	12		41.14	382			
10	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1228	11		41.14	382			
11	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1228			41.14	355	5		
12	BHP.AX	Market Pr	2019-07-1	10	Quote							41.12	1201	11		41.14	355			
13	BHP.AX	Market Pr	2019-07-1	10	Trade			41.14	27	41.08094		41.12	1201			41.14	355		B[ACT_FLAG1	

Figure 5. Raw intraday tick data (CSV file).



```
{
    "data_source": "reuters",
    "dataset_type": "Intraday aggregated stock stats",
    "dataset_id": "http://bucket-name.s3-website-Region.amazonaws.com",
    "time_object": {
        "timestamp": "2023-06-03 17:41:01.400055",
        "timezone": "UTC+10"
    },
    "events": [
        {
            "time_object": {
                "timestamp": "2019-07-17 00:00:00.000000",
                "duration": 5,
                "duration_unit": "minutes",
                "timezone": "UTC+10"
            },
            "event_type": "intraday aggregated stats",
            "attribute": {
                "Date-Time": "2019-07-17 00:00:00",
                "DollarVolumeTraded": 2772243.825,
                "ShareVolumeTraded": 67426.0,
                "TradeCount": 573,
                "AveragePrice": 41.11995637
            }
        },
```

Figure 6. JSON file with time series and intraday measures information from data in Figure 5.



Select a analytic service:
Aggregate_tick_data_to_timeseries

Aggregate_tick_data_to_timeseries

data
query_demo.csv

time_step
5

time_unit
'minutes'

Save data name
result_[current_time].csv

Message
1 select a function, 2 input parameters , 3 click compute button

Figure 7. Front-end (GUI) for modifying the JSON file of Figure 6 ad hoc.

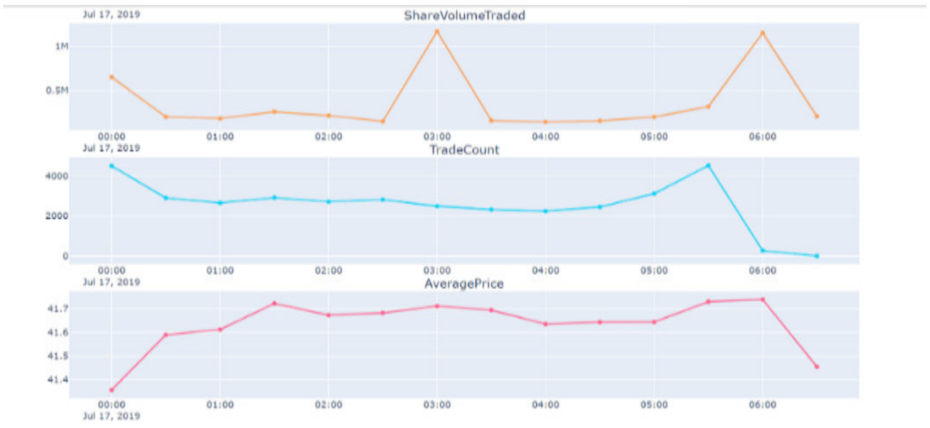


Figure 8. Visualisation of the generated time-series and intraday measures.

5. Conclusion

This paper has discussed how knowledge graphs can enable collaboration in the field of financial market data analysis. This is done by creating a software architecture that integrates workflows and knowledge graphs. This software architecture is described comprehensively and a case study demonstrating the usage within the context of equity markets has been shown at the end. This leads to an enhanced experience of collaborative financial market data analysis.

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