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INFSCI 1540 Data Engineering

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Data Engineering Behind Stock Analysis

Overview

The project enables data-driven decision making and market analysis of stock trends for companies listed in the S&P 500. Utilizing data drawn from Wikipedia, Yahoo Finance, Stocktwits, and Statista, the repository combines trade information, quarterly revenues, and investor and analyst sentiments to provide a more comprehensive view of stocks within the index. From day to week to quarter, headquarters location to industry to sub-industry, the warehouse provides an aggregated view of the data along multiple dimensions, able to drill-down along a variety of paths for more granular data analysis. Using this data, the project seeks to answer the following questions:

- 1. Which city/state has the highest volume of stock trades in the S&P 500 per day/week/month/quarter/year?
- 2. What is the combined quarterly/yearly revenue for companies in the same sector/industry?
- 3. What are the market sentiments for different companies on the S&P 500?

The project can be found on GitHub at https://github.com/debdasghosh/Data-Engineering-Behind-Stock-Analysis.

Project Structure (Docker)

Utilizing the Docker platform to run components of the data pipeline in separate containers, the project is comprised of several key technologies. At the highest level, an Apache web server is used to support two instances of phpMyAdmin, each corresponding to a MySQL

database: an instance for the operational database (ODB) containing raw data and another for the aggregated data warehouse (DW). A Kafka broker container is utilized for streaming data from the ODB to the DW, while a ZooKeeper container manages storing the streaming data. The project's docker-compose file (contents listed below) can also be found at:

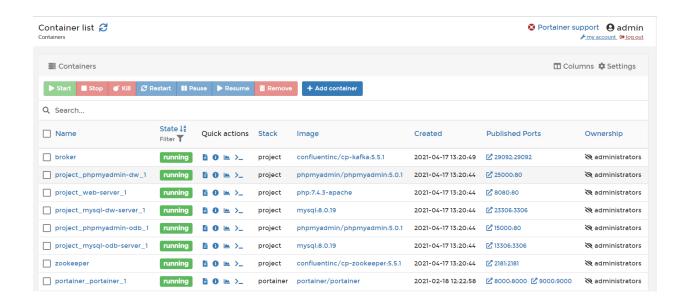
https://github.com/debdasghosh/Data-Engineering-Behind-Stock-Analysis/blob/main/docker-compose.yml.

docker-compose.yml

```
version: '2'
services:
web-server:
  image: php:7.4.3-apache
  volumes:
      - "./html/:/var/www/html/"
  ports:
      - "8080:80"
 mysql-odb-server:
  image: mysql:8.0.19
  environment:
    MYSQL ROOT PASSWORD: secret
  volumes:
    - mysql-data:/var/lib/mysql odb
  ports:
    - "13306:3306"
mysql-dw-server:
  image: mysql:8.0.19
  environment:
    MYSQL ROOT PASSWORD: secret
```

```
volumes:
   - mysql-data:/var/lib/mysql_dw
ports:
   - "23306:3306"
phpmyadmin-odb:
image: phpmyadmin/phpmyadmin:5.0.1
 environment:
   PMA_HOST: mysql-odb-server
   PMA_USER: root
   PMA_PASSWORD: secret
ports:
    - "15000:80"
phpmyadmin-dw:
image: phpmyadmin/phpmyadmin:5.0.1
environment:
   PMA_HOST: mysql-dw-server
   PMA_USER: root
   PMA PASSWORD: secret
ports:
    - "25000:80"
broker:
image: confluentinc/cp-kafka:5.5.1
hostname: broker
container_name: broker
depends_on:
  - zookeeper
ports:
  - "29092:29092"
environment:
```

```
KAFKA BROKER ID: 1
    KAFKA_ZOOKEEPER_CONNECT: 'zookeeper:2181'
    KAFKA LISTENER SECURITY PROTOCOL MAP:
PLAINTEXT: PLAINTEXT, PLAINTEXT HOST: PLAINTEXT
    KAFKA ADVERTISED LISTENERS:
PLAINTEXT://broker:9092,PLAINTEXT_HOST://192.168.1.227:29092
    KAFKA_OFFSETS_TOPIC_REPLICATION_FACTOR: 1
    KAFKA_GROUP_INITIAL_REBALANCE_DELAY_MS: 0
 zookeeper:
  image: confluentinc/cp-zookeeper:5.5.1
 hostname: zookeeper
  container_name: zookeeper
  ports:
    - "2181:2181"
  environment:
    ZOOKEEPER CLIENT PORT: 2181
    ZOOKEEPER TICK TIME: 2000
volumes:
  mysql-data:
```



Data ETL

Source	Type	Description
Wikipedia	Semi-Structured	Information about companies on the S&P 500 stock index
Yahoo Finance	Structured	Daily stock market data for S&P 500 companies, ranging from 1 January 2017 to 8 April 2021
StockTwits	Unstructured	Tweets about the stock market ("stock twits"), fetched from the website's API
Statista	Structured	Quarterly revenues of S&P 500 companies

Beginning with S&P 500 company information from Wikipedia, data for each company's stock symbol, security (company name), sector, sub-industry, and headquarters location is pulled from the page. While each company's name, associated stock symbol, sector, and sub-industry are used as-is, the headquarters location is separated into state and country, filtering out companies not headquartered in the United States. This information is then outputted to a CSV spreadsheet using a script written in R and later loaded into the ODB and DW by a Python script.

Next, the quarterly revenues for select companies are downloaded from the statistics website Statista based on available information. From the Microsoft Excel files provided by the website, the data for quarterly revenue (in billions of dollars) is extracted along with financial quarter, fiscal year, and stock symbol and outputted to a combined CSV file through another script written in R. In a similar manner to company information, the data is inserted into both databases using the aforementioned Python script, relegated to a separate table in the ODB and appearing in a derivative format in an aggregated FACT table in the DW.

Subsequently, daily stock information provided by Yahoo Finance is queried from the beginning of the 2017 fiscal year to April 2021 for each company included in the S&P 500 index (per Wikipedia), with information on the date, opening stock price, closing stock price, highest and lowest sale prices, and volume of stocks sold aggregated into a single, combined CSV

spreadsheet using an R script. In combination with the previous spreadsheets, this is the last data source loaded into each repository by the previous Python files.

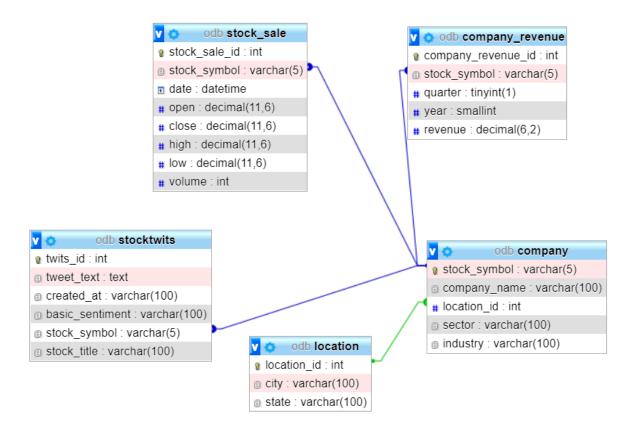
Finally, the Stocktwits API is used to collect information about the latest tweets and sentiments in relation to supported stocks (i.e., Apple), which are collected into a series of JSON files from an R script. (Due to limitations of the website's API, the data collected for the project includes 6000 "twits" each about Apple and Amazon.) The data in the JSON files is then streamed from an Apache Kafka producer into a consumer for inserting the raw data into the ODB, with updates subsequently streamed to another Kafka consumer used for aggregating this information and inserting it into the DW. Utilizing sentiment data from gathered "twits," a sentiment score considering the "bearishness," "bullishness," or "unemotionality" of each is aggregated for each company's stock.

Operational Database

The schema of the project's ODB includes the following five tables:

- company contains basic information on S&P 500 companies, including stock symbol (used as the primary key), company name, sector, industry, and location (a foreign key referencing the "location" table)
- location contains all unique city-state combinations for headquarters of S&P 500 companies included in the data set
- 3. company_revenue records quarterly revenues for S&P 500 companies (in billions of dollars), connecting to corresponding companies using stock symbols as foreign keys
- 4. stock_sale the main transaction table of the ODB, comprised of daily stock trade information for each company, including the opening and closing price, highest and

- lowest sale prices, and volume of stocks sold for a given day; connects stock trades to the corresponding company by the stock symbol foreign key
- 5. stocktwits records stock "twits" about companies, including the content of the twit, its date of creation, and basic sentiment; connects to the company table with the stock symbol foreign key, also including a company's name, mirroring the data retrieved from the Stocktwits API



The DDL statements for the ODB (listed below) can also be found at

https://github.com/debdasghosh/Data-Engineering-Behind-Stock-

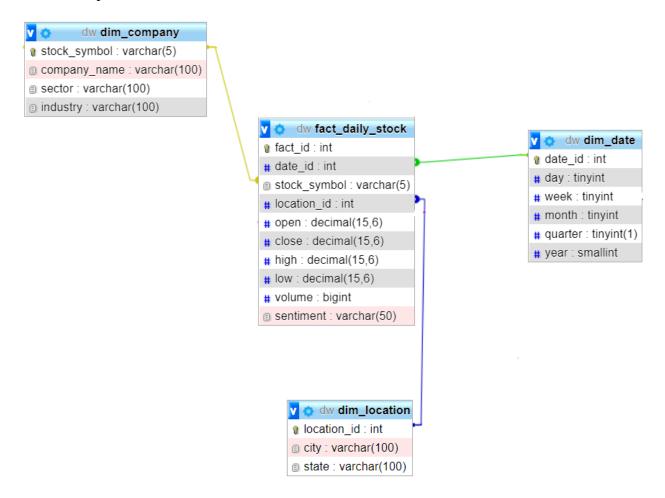
<u>Analysis/blob/main/create_odb.sql</u>. The combined SQL statements and programming logic for populating the ODB (sans stock twit data) can be found at https://github.com/debdasghosh/Data-Engineering-Behind-Stock-Analysis/blob/main/load_odb.py.

```
DROP SCHEMA IF EXISTS `odb`;
CREATE SCHEMA IF NOT EXISTS 'odb' DEFAULT CHARACTER SET utf8;
USE `odb`;
DROP TABLE IF EXISTS `odb`.`location` ;
CREATE TABLE IF NOT EXISTS `odb`.`location` ( `location_id` INT NOT NULL
AUTO_INCREMENT, `city` VARCHAR(100) NOT NULL, `state` VARCHAR(100) NOT NULL,
PRIMARY KEY (`location_id`))ENGINE = InnoDB;
DROP TABLE IF EXISTS `odb`.`company`;
CREATE TABLE IF NOT EXISTS `odb`.`company` ( `stock_symbol` VARCHAR(5) NOT NULL,
`company name` VARCHAR(100) NOT NULL, `location id` INT NOT NULL, `sector`
VARCHAR(100) NOT NULL, 'industry' VARCHAR(100) NOT NULL, PRIMARY KEY
(`stock_symbol`), INDEX `fk_location_id_idx` (`location_id` ASC) VISIBLE,
CONSTRAINT `fk location id` FOREIGN KEY (`location id`) REFERENCES
`odb`.`location` (`location id`) ON DELETE NO ACTION ON UPDATE NO
ACTION)ENGINE = InnoDB;
DROP TABLE IF EXISTS `odb`.`stock_sale` ;
CREATE TABLE IF NOT EXISTS `odb`.`stock sale` ( `stock sale id` INT NOT NULL
AUTO INCREMENT, 'stock symbol' VARCHAR(5) NOT NULL, 'date' DATETIME NOT NULL,
`open` DECIMAL(11,6) NOT NULL, `close` DECIMAL(11,6) NOT NULL, `high`
DECIMAL(11,6) NOT NULL, `low` DECIMAL(11,6) NOT NULL, `volume` INT NOT NULL,
PRIMARY KEY (`stock_sale_id`), INDEX `fk_s_stock_symbol_idx` (`stock_symbol`
ASC) VISIBLE, CONSTRAINT `fk_s_stock_symbol` FOREIGN KEY (`stock_symbol`)
REFERENCES `odb`.`company` (`stock symbol`) ON DELETE NO ACTION ON UPDATE
NO ACTION) ENGINE = InnoDB;
DROP TABLE IF EXISTS `odb`.`company_revenue` ;
CREATE TABLE IF NOT EXISTS `odb`.`company_revenue` ( `company_revenue_id` INT
NOT NULL AUTO_INCREMENT, `stock_symbol` VARCHAR(5) NOT NULL, `quarter`
TINYINT(1) NOT NULL, 'year' SMALLINT(4) NOT NULL, 'revenue' DECIMAL(6,2) NOT
NULL, PRIMARY KEY (`company_revenue_id`), INDEX `fk_r_stock_symbol_idx`
(`stock_symbol` ASC) VISIBLE, CONSTRAINT `fk_r_stock_symbol` FOREIGN KEY
(`stock_symbol`) REFERENCES `odb`.`company` (`stock_symbol`) ON DELETE
CASCADE ON UPDATE CASCADE)ENGINE = InnoDB;
DROP TABLE IF EXISTS `odb`.`stocktwits` ;
CREATE TABLE IF NOT EXISTS `odb` .`stocktwits` ( `twits id` INT NOT NULL
AUTO INCREMENT, `tweet text` text NOT NULL, `created at` varchar(100) NOT NULL,
`basic_sentiment` varchar(100) NOT NULL, `stock_symbol` VARCHAR(5) NOT NULL,
`stock title` varchar(100) NOT NULL, PRIMARY KEY (`twits id`), INDEX
`fk_t_stock_symbol_idx` (`stock_symbol` ASC) VISIBLE, CONSTRAINT
```

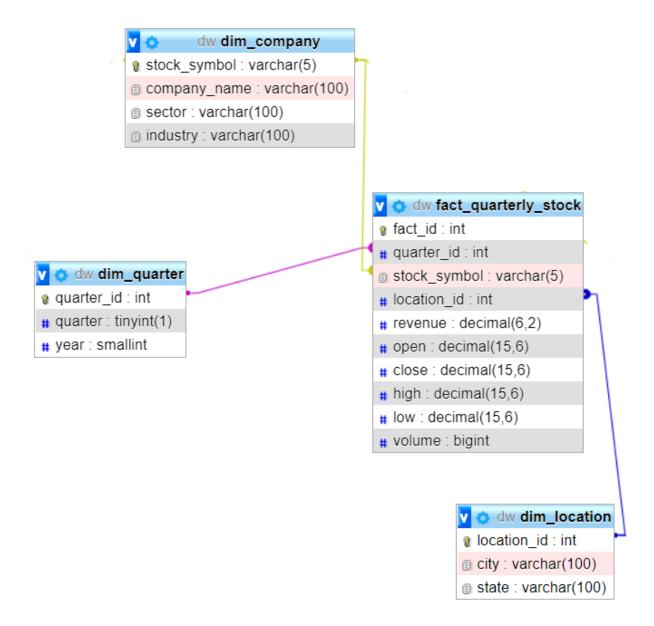
```
`fk_t_stock_symbol` FOREIGN KEY (`stock_symbol`) REFERENCES `odb`.`company`
(`stock_symbol`) ON DELETE CASCADE ON UPDATE CASCADE)ENGINE = InnoDB;
```

STAR Schema

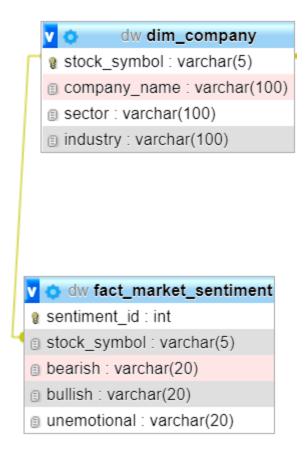
The STAR schema of the DW centers around three FACT tables. The first, the "fact_daily_stock," table includes three dimensions: date, company (stock), and (headquarters) location, describing several measures: the opening and closing prices of a stock, its highest and lowest sale prices, and the volume of trades.



The second FACT table, "fact_quarterly_stock," similarly describes these same measures with the addition of the corresponding quarterly revenue of the stock's company along three similar dimensions: fiscal quarter, company (stock), and (headquarters) location.



Finally, the third "fact_market_sentiment" table describes the "bearishness," "bullishness," and "unemotionality" of sentiments expressed about a stock along the single dimension of (stock) company.



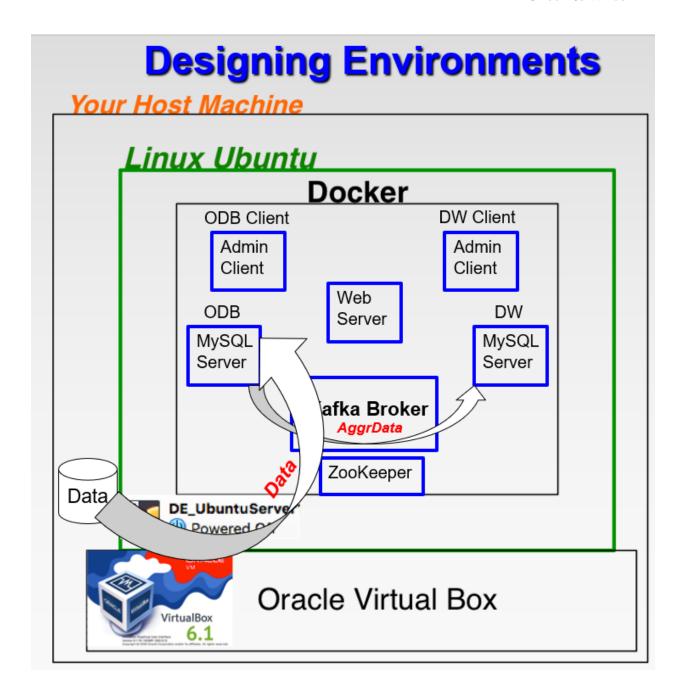
In total, the schema includes four unique dimension tables. The table "dim_quarter" represents the unique fiscal quarters for data contained in the warehouse. The "dim_date" table describes all unique dates of stock trade data stored in the warehouse, split into component days, weeks, months, fiscal quarters, and years. The "dim_location" table describes the city and state of various company's headquarters, and "dim_company" records information about S&P 500 companies, including their name, stock symbol, sector, and industry (sub-sector).

The DDL statements for the DW (listed below) can also be found at https://github.com/debdasghosh/Data-Engineering-Behind-Stock-

<u>Analysis/blob/main/create_dw.sql</u>. The combined SQL statements and programming logic for populating the DW can be found at https://github.com/debdasghosh/Data-Engineering-Behind-Btock-Analysis/blob/main/load_dw.py.

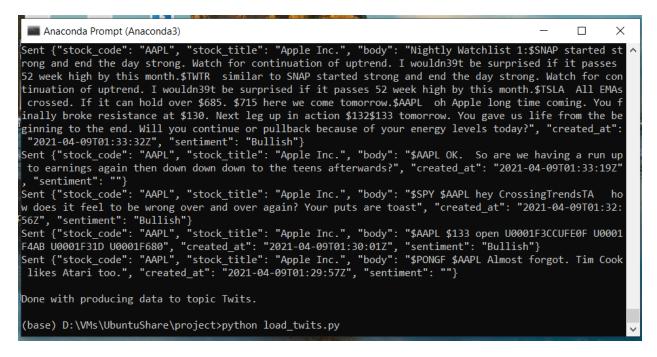
```
DROP SCHEMA IF EXISTS `dw`;
CREATE SCHEMA IF NOT EXISTS 'dw';
USE `dw`;
DROP TABLE IF EXISTS `dw`.`dim_date` ;
CREATE TABLE IF NOT EXISTS `dw`.`dim_date` ( `date_id` INT NOT NULL
AUTO_INCREMENT, `day` TINYINT(2) NOT NULL, `week` TINYINT(2) NOT NULL, `month`
TINYINT(2) NOT NULL, 'quarter' TINYINT(1) NOT NULL, 'year' SMALLINT(4) NOT
NULL, PRIMARY KEY (`date_id`))ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`dim location` ;
CREATE TABLE IF NOT EXISTS `dw`.`dim location` ( `location id` INT NOT NULL,
`city` VARCHAR(100) NOT NULL, `state` VARCHAR(100) NOT NULL, PRIMARY KEY
(`location_id`))ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`dim_company`;
CREATE TABLE IF NOT EXISTS `dw`.`dim company` ( `stock symbol` VARCHAR(5) NOT
NULL, `company_name` VARCHAR(100) NOT NULL, `sector` VARCHAR(100) NOT NULL,
`industry` VARCHAR(100) NOT NULL, PRIMARY KEY (`stock_symbol`))ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`fact daily stock` ;
CREATE TABLE IF NOT EXISTS `dw`.`fact_daily_stock` ( `fact_id` INT NOT NULL
AUTO_INCREMENT, `date_id` INT NOT NULL, `stock_symbol` VARCHAR(5) NOT NULL,
`location_id` INT NOT NULL, `open` DECIMAL(15,6) NOT NULL, `close`
DECIMAL(15,6) NOT NULL, 'high' DECIMAL(15,6) NOT NULL, 'low' DECIMAL(15,6) NOT
NULL, `volume` BIGINT NOT NULL, `sentiment` VARCHAR(50) NULL, PRIMARY KEY
(`fact_id`), INDEX `fk_date_id_idx` (`date_id` ASC) VISIBLE, INDEX
`fk location id idx` (`location id` ASC) VISIBLE, INDEX `fk stock symbol idx`
(`stock_symbol` ASC) VISIBLE, CONSTRAINT `fk_d_date_id` FOREIGN KEY
(`date_id`) REFERENCES `dw`.`dim_date` (`date_id`) ON DELETE CASCADE
UPDATE CASCADE, CONSTRAINT `fk_d_location_id` FOREIGN KEY (`location_id`)
REFERENCES `dw`.`dim_location` (`location_id`) ON DELETE CASCADE
                                                                     ON UPDATE
CASCADE, CONSTRAINT `fk_d_stock_symbol` FOREIGN KEY (`stock_symbol`)
REFERENCES `dw`.`dim company` (`stock symbol`) ON DELETE NO ACTION ON
UPDATE NO ACTION)ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`dim_quarter` ;
CREATE TABLE IF NOT EXISTS `dw`.`dim_quarter` ( `quarter_id` INT NOT NULL
AUTO_INCREMENT, 'quarter' TINYINT(1) NOT NULL, 'year' SMALLINT(4) NOT NULL,
PRIMARY KEY (`quarter id`))ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`fact quarterly stock`;
```

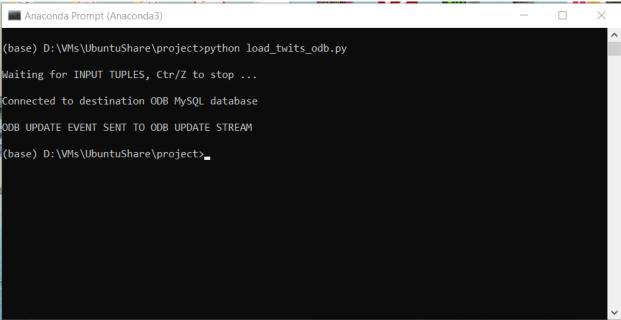
```
CREATE TABLE IF NOT EXISTS `dw`.`fact_quarterly_stock` ( `fact_id` INT NOT NULL
AUTO_INCREMENT, `quarter_id` INT NOT NULL, `stock symbol` VARCHAR(5) NOT NULL,
`location_id` INT NOT NULL, `revenue` DECIMAL(6,2) NOT NULL, `open`
DECIMAL(15,6) NOT NULL, `close` DECIMAL(15,6) NOT NULL, `high` DECIMAL(15,6)
NOT NULL, `low` DECIMAL(15,6) NOT NULL, `volume` BIGINT NOT NULL, PRIMARY KEY
(`fact id`), INDEX `fk quarter id idx` (`quarter id` ASC) VISIBLE, INDEX
`fk_location_id_idx` (`location_id` ASC) VISIBLE, INDEX `fk_stock_symbol_idx`
(`stock_symbol` ASC) VISIBLE, CONSTRAINT `fk_q_quarter_id` FOREIGN KEY
(`quarter id`) REFERENCES `dw`.`dim quarter` (`quarter id`) ON DELETE
CASCADE ON UPDATE CASCADE, CONSTRAINT `fk q location id`
                                                             FOREIGN KEY
(`location_id`) REFERENCES `dw`.`dim_location` (`location_id`) ON DELETE
CASCADE ON UPDATE CASCADE, CONSTRAINT `fk_q_stock_symbol` FOREIGN KEY
(`stock symbol`) REFERENCES `dw`.`dim company` (`stock symbol`) ON DELETE
NO ACTION ON UPDATE NO ACTION) ENGINE = InnoDB;
DROP TABLE IF EXISTS `dw`.`fact_market_sentiment` ;
CREATE TABLE IF NOT EXISTS `dw`.`fact market sentiment` ( `sentiment id` INT NOT
NULL AUTO INCREMENT, `stock symbol` VARCHAR(5) NOT NULL, `bearish` varchar(20)
NOT NULL, `bullish` varchar(20) NOT NULL, `unemotional` varchar(20) NOT NULL,
PRIMARY KEY (`sentiment_id`), INDEX `fk_tw_stock_symbol_idx` (`stock_symbol`
ASC) VISIBLE, CONSTRAINT `fk qtw stock symbol` FOREIGN KEY (`stock symbol`)
REFERENCES `dw`.`dim company` (`stock symbol`) ON DELETE NO ACTION ON
UPDATE NO ACTION)ENGINE = InnoDB;
```

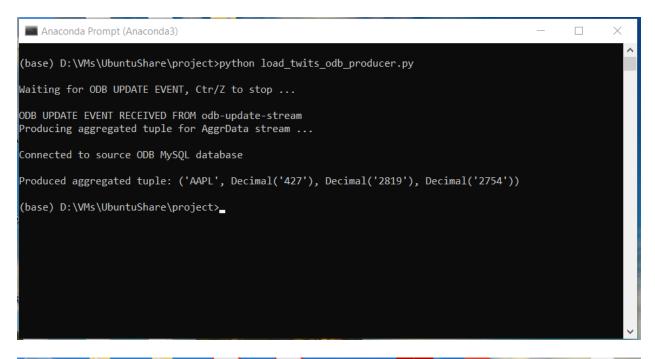


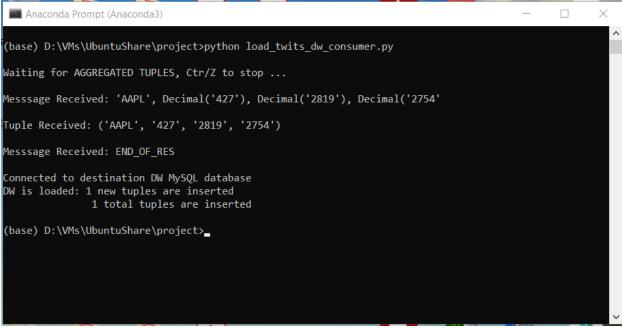
Data Streaming

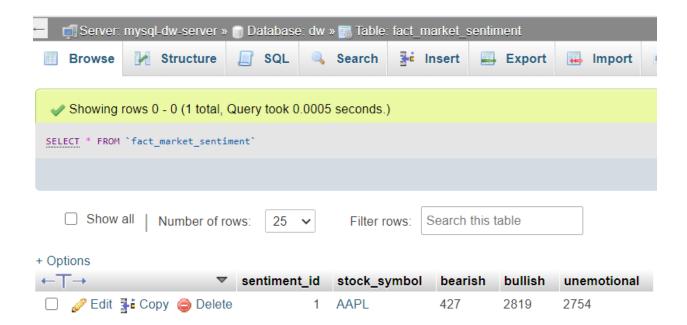
Data streaming using Apache Kafka was utilized for loading data from Stocktwits into the ODB and DW. The corresponding Python scripts include: load_twits.py, load_twits_odb.py, load_twits_odb_producer.py, and load_twits_dw_consumer.py, available on the provided GitHub repository.

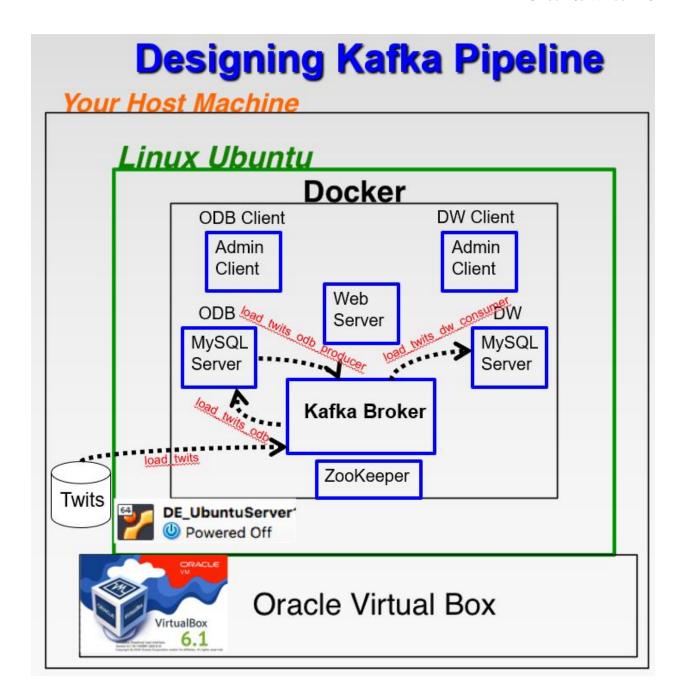












Summary Tables

In addition to the specified FACT and dimension tables, the DW also includes the following preaggregated tables:

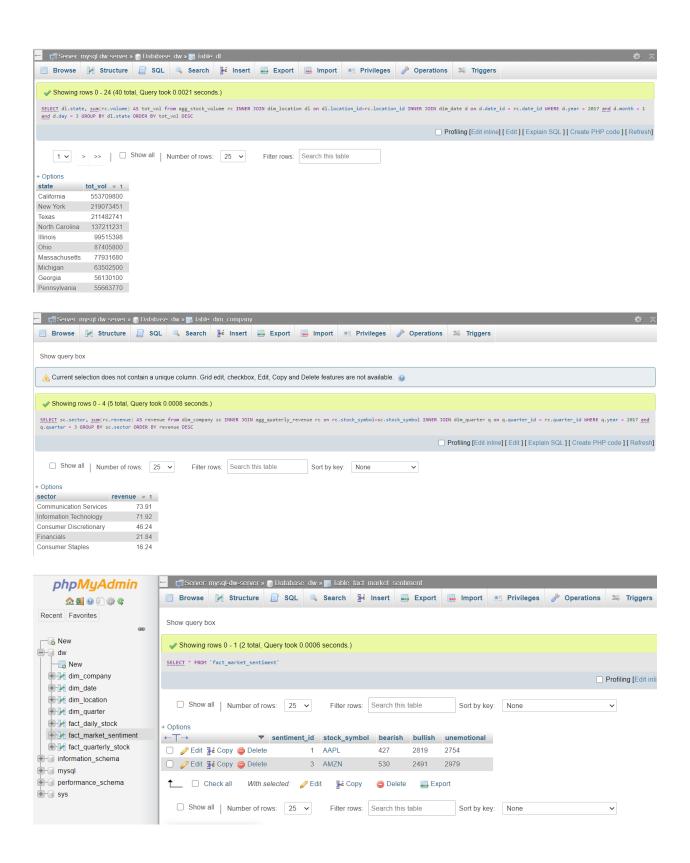
- agg_stock_volume aggregates the volume of stocks sold for date and (headquarters)
 location in the DW; supports queries of the type "Which city/state has the highest volume of stock trades in the S&P 500 per day/week/month/quarter/year?"
- 2. agg_quarterly_revenue aggregates company quarterly revenues by company; supports queries of the type "What is the combined quarterly/yearly revenue for companies in the same sector/industry?"

The following DDL queries create the aforementioned summary tables:

```
DROP TABLE IF EXISTS `dw`.`agg_stock_volume` ;
CREATE TABLE `dw`.`agg_stock_volume` (`agg_id` int NOT NULL
AUTO INCREMENT, `date id` int NOT NULL, `location id` int NOT NULL, `volume` bigint
NOT NULL, PRIMARY KEY (`agg id`), INDEX `fk agg date id idx` (`date id` ASC)
VISIBLE, INDEX `fk_agg_location_id_idx` (`location_id` ASC) VISIBLE, CONSTRAINT
`fk agg d date id` FOREIGN KEY (`date id`) REFERENCES `dw`.`dim date`
(`date id`) ON DELETE CASCADE
                                  ON UPDATE CASCADE, CONSTRAINT
`fk agg d location id` FOREIGN KEY (`location id`) REFERENCES
`dw`.`dim location` (`location id`) ON DELETE CASCADE ON UPDATE CASCADE )
DROP TABLE IF EXISTS `dw`.`agg quarterly revenue`;
CREATE TABLE `dw`.`agg quarterly revenue` (`agg id` int NOT NULL
AUTO INCREMENT, `quarter id` int NOT NULL, `stock symbol` varchar(5) NOT
NULL, revenue decimal(6,2) NOT NULL, PRIMARY KEY ('agg id'), INDEX
`fk agg quarter id idx` (`quarter id` ASC) VISIBLE, INDEX
`fk agg stock symbol idx` (`stock symbol` ASC) VISIBLE, CONSTRAINT
`fk agg q quarter id` FOREIGN KEY (`quarter id`) REFERENCES
`dw`.`dim_quarter` (`quarter_id`) ON DELETE CASCADE
                                                        ON UPDATE CASCADE,
CONSTRAINT `fk_agg_q_stock_symbol` FOREIGN KEY (`stock_symbol`) REFERENCES
`dw`.`dim_company` (`stock_symbol`) ON DELETE NO ACTION ON UPDATE NO
ACTION) ENGINE=InnoDB;
```

The following queries populate the previous summary tables with data:

```
INSERT INTO `agg_stock_volume` SELECT NULL, `date_id`, `location_id`,
SUM(`volume`) FROM `fact_daily_stock` GROUP BY `location_id`, `date_id`;
INSERT INTO `agg_quaterly_revenue` SELECT NULL, `quarter_id`, `stock_symbol`,
SUM(`revenue`) FROM `fact_quarterly_stock` GROUP BY `stock_symbol`, `quarter_id`;
Supported Queries
-- Which city/state has the highest volume of stock trades in the S&P 500 per
day/week/month/quarter/year?
-- Example: Which state has the highest volume of stock trades on a particular
day?
SELECT dl.state, sum(rc.volume) AS tot vol
from agg stock volume rc
INNER JOIN dim location dl on dl.location id=rc.location id
INNER JOIN dim date d on d.date id = rc.date id
WHERE d.year = 2017 and d.month = 1 and d.day = 3
GROUP BY dl.state ORDER BY tot vol DESC;
-- What is the combined quarterly/yearly revenue for companies in the same
sector/industry?
-- Example: Revenues per sector in a particular quarter
SELECT sc.sector, sum(rc.revenue) AS revenue
from dim company sc
INNER JOIN agg quaterly revenue rc on rc.stock symbol=sc.stock symbol
INNER JOIN dim_quarter q on q.quarter_id = rc.quarter_id
WHERE q.year = 2017 and q.quarter = 3
GROUP BY sc.sector ORDER BY revenue DESC;
-- Latest sentiments about an S&P 500 company
SELECT * FROM `fact_market_sentiment`;
```



Conclusions and Future Scope

This project's final data warehouse was developed to support business queries to analyze trends within the stock market, focused on American companies included in the S&P 500 index. While the supported queries enable the analysis of trends in stock trades by date (or fiscal quarter), company location, and sector/industry, the scope could further be expanded to incorporate additional companies and new dimensions. Most critically, the basic sentiment analysis utilized in the project could be further revised and expanded to help correlate market sentiments found on social media with actual trends seen in stock trades.