P1 Assignment: Dimension Modelling

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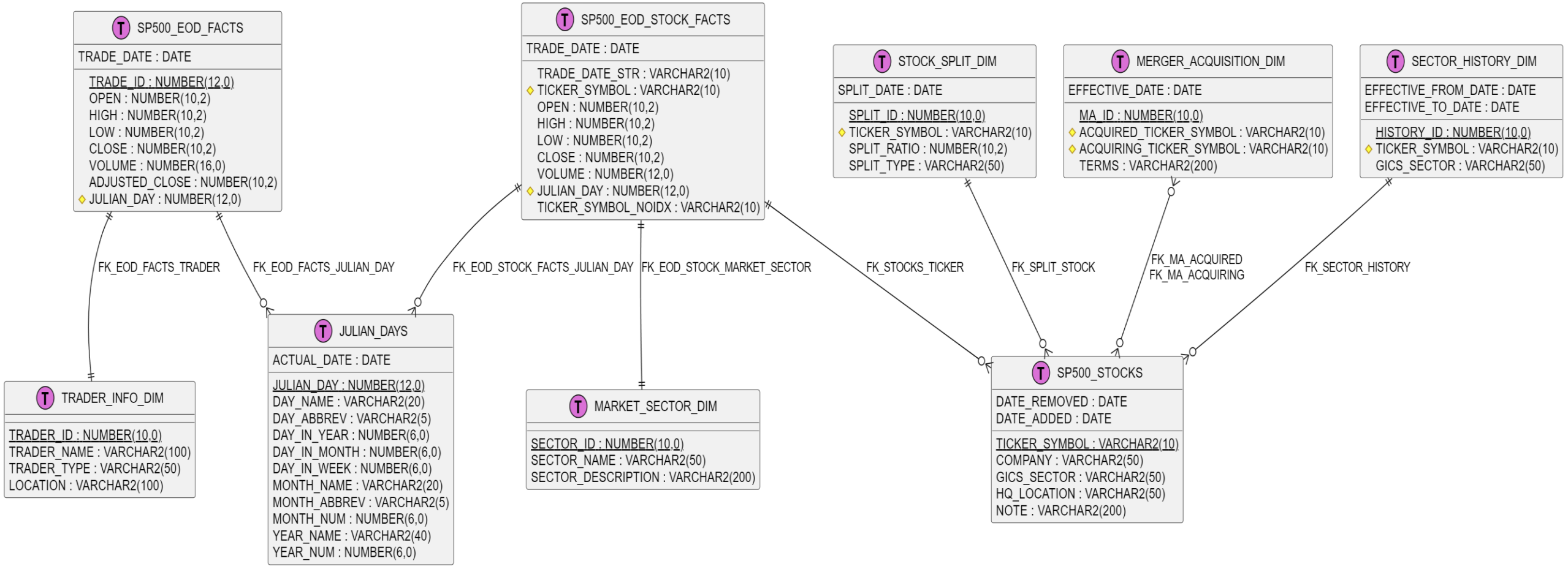
Part A: Design for Stock Market Data

Entity Relationship Diagram



Fact Tables

A fact table is a central table in a data warehouse that stores quantitative data, also known as facts, related to a business process. It is typically surrounded by dimension tables, which contain descriptive attributes that add context to the facts. Together, they form the basis for dimensional modeling, a popular approach to data warehousing and business intelligence (BI).

Fact tables in above ERD:

SP500_EOD_FACTS
SP500_EOD_STOCK_FACTS

Dimension Tables

Dimension tables are the companions to fact tables, storing descriptive attributes that add context and meaning to the quantitative data (facts) found in the fact table. Think of them as the labels on the data points in a chart or graph.

Dimension Tables in above ERD:

SP500_STOCKS
SP500_DATES
TRADER_INFO_DIM
JULIAN_DAYS
MARKET_SECTOR_DIM
STOCK_SPLIT_DIM
MERGER_ACQUSITION_DIM
SECTOR_HISTORY_DIM

Handling Stock Splits and Reverse Splits

Stock splits and reverse splits affect the stock price and volume, making historical comparisons challenging without adjustment. To handle this, we have created another dimension table.
STOCK_SPLIT_DIM table to record stock splits and reverse splits, including the date, split ratio, and type (split or reverse split). This table would have foreign keys linking back to the stock symbol.

Handling Mergers and Acquisitions

Mergers and acquisitions can result in the consolidation of companies, affecting historical data tracking.
For this we have created a MERGER_ACQUISITION_DIM table to log details about mergers and acquisitions, including the effective date, companies involved, and terms.

Handling Changes in Business Sectors

- Businesses evolve, and their sector classifications might change over time. To accommodate this:
- we have created another dimension history table,
- Sector History Table: Instead of updating the SP500_STOCKS table directly, maintain a SECTOR_HISTORY_DIM table that tracks the history of sector changes for each stock.

Business Queries

- Query using OVER for window function analysis:
- This query calculates the running total of trading volume and the average closing price over time within each GICS sector, using the SP500_EOD_STOCK_FACTS table, categorized by the GICS_SECTOR from SP500_STOCKS and ordered by trade date.

```
SELECT
    s.GICS_SECTOR,
    f.TRADE_DATE,
    f.VOLUME,
    SUM(f.VOLUME) OVER(PARTITION BY s.GICS_SECTOR ORDER BY f.TRADE_DATE) AS Running_Total_Volume,
    AVG(f.CLOSE) OVER(PARTITION BY s.GICS_SECTOR ORDER BY f.TRADE_DATE) AS Avg_Close_Price
FROM
    SP500_EOD_STOCK_FACTS f
JOIN SP500_STOCKS s ON
    f.TICKER_SYMBOL = s.TICKER_SYMBOL
ORDER BY
    s.GICS_SECTOR,
    f.TRADE_DATE;
```

Query Result | Query Result 1

SQL | Fetched 50 rows in 0.095 seconds

	GICS_SECTOR	TRADE_DATE	VOLUME	RUNNING_TOTAL_VOLUME	AVG_CLOSE_PRICE
1	Consumer Discretionary	21-08-09	15682	4317758	38.868630136986301369863013698630136986301369863
2	Consumer Discretionary	21-08-09	21641	4317758	38.868630136986301369863013698630136986301369863
3	Consumer Discretionary	21-08-09	61312	4317758	38.868630136986301369863013698630136986301369863
4	Consumer Discretionary	21-08-09	79639	4317758	38.868630136986301369863013698630136986301369863
5	Consumer Discretionary	21-08-09	43249	4317758	38.868630136986301369863013698630136986301369863
6	Consumer Discretionary	21-08-09	22686	4317758	38.868630136986301369863013698630136986301369863
7	Consumer Discretionary	21-08-09	5204	4317758	38.868630136986301369863013698630136986301369863
8	Consumer Discretionary	21-08-09	7309	4317758	38.868630136986301369863013698630136986301369863
9	Consumer Discretionary	21-08-09	62953	4317758	38.868630136986301369863013698630136986301369863

Query using ROLLUP for Sales Analysis by Date and Sector
This query aggregates total volumes and average closing prices for stocks, summarized by year and GICS sector, and then further aggregates these metrics at higher levels of the hierarchy (yearly, sector-wise, and overall).

```
SELECT
    EXTRACT(YEAR FROM d.ACTUAL_DATE) AS Year,
    s.GICS_SECTOR,
    SUM(f.VOLUME) AS Total_Volume,
    AVG(f.CLOSE) AS Average_Closing_Price
FROM
    SP500_EOD_STOCK_FACTS f
JOIN SP500_DATES d ON
    f.JULIAN_DAY = d.JULIAN_DAY
JOIN SP500_STOCKS s ON
    f.TICKER_SYMBOL = s.TICKER_SYMBOL
GROUP BY ROLLUP(EXTRACT(YEAR FROM d.ACTUAL_DATE), s.GICS_SECTOR)
ORDER BY
    Year,
    s.GICS_SECTOR;
```

Query Result

SQL | All Rows Fetched: 25 in 0.141 seconds

	YEAR	GICS_SECTOR	TOTAL_VOLUME	AVERAGE_CLOSING_PRICE
1	2009	Consumer Discretionary	370336150	40.859909566872917658257972394098048548 31
2	2009	Consumer Staples	161912263	39.674614930658011212747123045146060784 89
3	2009	Energy	168898593	46.282740863787375415282392026578073089 7
4	2009	Financials	1173000795	36.588705164458996874534901026938532519 72
5	2009	Health Care	219755334	47.743263752455795677799607072691552062 87
6	2009	Industrials	210442865	49.134740048740861088545897644191714053 61
7	2009	Information Technology	555673779	39.769280965710286913925822253324002799 16

Query using CUBE for Aggregated Trading Activity by Trader and Month:
This query provides a multi-dimensional aggregation of trading activity from the SP500_EOD_FACTS table, analyzed by trader name (from TRADER_INFO_DIM) and month. It calculates total trading volumes and the average adjusted close price, allowing for analysis across different combinations of trader and time.

```
SELECT
    ti.TRADER_NAME,
    TO_CHAR(d.ACTUAL_DATE, 'YYYY-MM') AS Trade_Month,
    SUM(ef.VOLUME) AS Total_Trading_Volume,
    AVG(ef.ADJUSTED_CLOSE) AS Average_Adjusted_Close
FROM
    SP500_EOD_FACTS ef
JOIN SP500_DATES d ON
    ef.JULIAN_DAY = d.JULIAN_DAY
JOIN TRADER_INFO_DIM ti ON
    ef.TRADER_ID = ti.TRADER_ID
GROUP BY CUBE(ti.TRADER_NAME, TO_CHAR(d.ACTUAL_DATE, 'YYYY-MM'))
ORDER BY
    ti.TRADER_NAME,
    Trade_Month;
```

Query Result

SQL | Fetched 50 rows in 0.054 seconds

	TRADER_NAME	TRADE_MONTH	TOTAL_TRADING_VOLUME	AVERAGE_ADJUSTED_CLOSE
1	Alpha Investments	2000-01	21494400000	1425.5855
2	Alpha Investments	2000-02	20912000000	1388.8745
3	Alpha Investments	2000-03	26156200000	1442.212608695652173913043478260869565217
4	Alpha Investments	2000-04	20106460000	1461.355263157894736842105263157894736842
5	Alpha Investments	2000-05	19898300000	1418.479545454545454545454545454545454545
6	Alpha Investments	2000-06	21738300000	1461.959090909090909090909090909090909091
7	Alpha Investments	2000-07	19089100000	1473.0025

PART B: Dimensional Data Model for Analyzing School Student Absences

Objectives

Understand the key factors contributing to student absenteeism (e.g., illness, academic struggles, family issues).

Identify students at risk of chronic absenteeism.

Develop targeted interventions to improve student attendance.

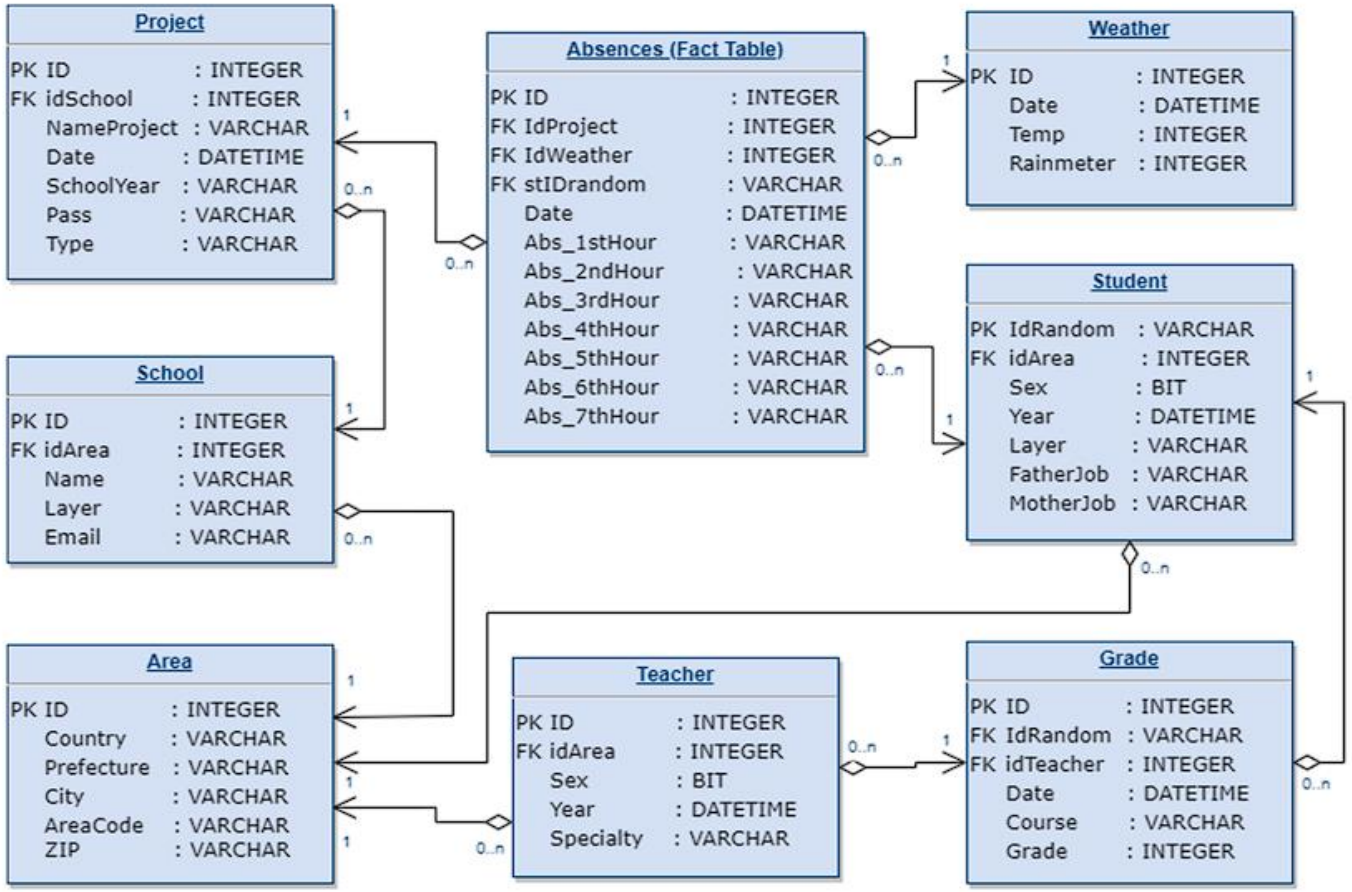
Conclusions

A dimensional database model can provide valuable insights into student absenteeism patterns and trends.

By analyzing data from multiple dimensions (e.g., time, student demographics, reason for absence), we can gain a deeper understanding of the root causes of absenteeism.

This information can be used to develop more effective strategies to improve student attendance and academic success.

Entity Relationship Diagram:



THANK YOU