TUNIS BUSINESS SCHOOL
UNIVERSITY OF TUNIS

BitWise

IT300 : Business Intelligene
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Mini-project
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Content

Chapter 1

Introduction : Decoding Cryptocurrency Trends for Smart Investments

Welcome to our Cryptocurrency Investment Project, a strategic exploration aimed at providing you with a clear, data-driven understanding of the cryptocurrency market. In this Business Intelligence (BI) initiative, we focus on simplifying complex data to empower our client with valuable insights. Our journey begins with gathering data on cryptocurrency prices, moving averages, RSI analyses, and Blockchain Supply Metrics...... We then meticulously prepare and transform this data, ensuring its integrity and clarity.

The subsequent steps involve comprehensive cleaning, aggregation, and merging to create a robust dataset for enhanced visualization and analysis. As we load this refined data, we pave the way for constructing Fact-Dimension tables, setting the stage for impactful data analysis.

Our ultimate goal is to guide our client decisions in navigating the cryptocurrency investment landscape, providing actionable intelligence for a more informed and strategic approach.

Chapter 2

Project Description

2.1 Data Gathering

Four databases were gathered from different sources.

The types of data that were used are: csv files, and JSON files.

1- EUR.json

2- bitcoin.csv

3-ethereum classic.csv

4- litecoin.csv

The following section will detail the steps of data preparation.

2.2 Data Preparation and Transformation

Using Pandas, the files were cleaned and transformed. Here is the process of the data transformation:

2.2.1 Preparing the long-term and the short-term moving averages and the cross over between them :

- **Adding columns**

- added a column name to differentiate it in the further analysis :
- added 3 columns 'short_ma' and 'long_ma',cross_ma:The short-term moving average is calculated over a relatively short period, such as 20 days, to capture recent price trends. The long-term moving average is calculated over a more extended period, such as 50 days, to capture broader price trends.

The cross_ma column represents the crossover between short-term and long-term moving averages:A value of 1 in the Cross_MA column suggests a bullish signal. It indicates that the short-term moving average has crossed above the long-term moving average, potentially signaling the start of an uptrend.

	Date	Open	High	Low	Close	Volume	Currency
0	2010-07-18	0.0	0.1	0.1	0.1	75	USD
1	2010-07-19	0.1	0.1	0.1	0.1	574	USD
2	2010-07-20	0.1	0.1	0.1	0.1	262	USD
3	2010-07-21	0.1	0.1	0.1	0.1	575	USD
4	2010-07-22	0.1	0.1	0.1	0.1	2160	USD
...	...	...	...	...	...	...	...
4415	2022-08-19	23201.6	23202.3	20807.8	20831.3	339472	USD
4416	2022-08-20	20830.7	21357.4	20784.8	21138.9	206943	USD
4417	2022-08-21	21138.9	21692.4	21077.4	21517.2	177522	USD
4418	2022-08-22	21516.8	21517.4	20912.1	21416.3	251833	USD
4419	2022-08-23	21416.5	21458.2	21271.2	21309.0	251695	USD

Figure 2.1 : initial Bitcoin dataframe

A value of 0 in the Cross_MA column suggests a bearish signal. It indicates that the short-term moving average has crossed below the long-term moving average, potentially signaling the start of a downtrend.

	Date	Open	High	Low	Close	Volume	Currency	name	short_ma	long_ma	ma_cross
0	2010-07-18	0.0	0.1	0.1	0.1	75	USD	bitcoin	0.000	0.0000	0
1	2010-07-19	0.1	0.1	0.1	0.1	574	USD	bitcoin	0.000	0.0000	0
2	2010-07-20	0.1	0.1	0.1	0.1	262	USD	bitcoin	0.000	0.0000	0
3	2010-07-21	0.1	0.1	0.1	0.1	575	USD	bitcoin	0.000	0.0000	0
4	2010-07-22	0.1	0.1	0.1	0.1	2160	USD	bitcoin	0.000	0.0000	0
...	...	...	...	...	...	...	...	...	...	...	...
4415	2022-08-19	23201.6	23202.3	20807.8	20831.3	339472	USD	bitcoin	22239.556	32547.5970	0
4416	2022-08-20	20830.7	21357.4	20784.8	21138.9	206943	USD	bitcoin	22277.076	32459.7430	0
4417	2022-08-21	21138.9	21692.4	21077.4	21517.2	177522	USD	bitcoin	22322.556	32382.8780	0
4418	2022-08-22	21516.8	21517.4	20912.1	21416.3	251833	USD	bitcoin	22364.684	32303.5205	0
4419	2022-08-23	21416.5	21458.2	21271.2	21309.0	251695	USD	bitcoin	22386.548	32202.2275	0

Figure 2.2: Bitcoin dataframe after adding columns

BITCOIN	ETHEREUM CLASSIC	LITECOIN
THE ANALYSIS REVEALS THAT BITCOIN DEMONSTRATES A ROBUST BULLISH SIGNAL, WITH THE SHORT-TERM MOVING AVERAGE CROSSING ABOVE THE LONG-TERM MOVING AVERAGE APPROXIMATELY 65.54% OF THE TIME. THIS HIGHER FREQUENCY OF POSITIVE TRENDS SUGGESTS A RELATIVELY STRONGER MARKET PERFORMANCE COMPARED TO LITECOIN AND ETHEREUM CLASSIC.	LITECOIN EXHIBITS A SUBSTANTIAL PROPORTION OF BULLISH SIGNALS, AS THE SHORT-TERM MOVING AVERAGE CROSSES ABOVE THE LONG-TERM MOVING AVERAGE AROUND 51.80% OF THE TIME. WHILE SLIGHTLY LOWER THAN BITCOIN, THIS INDICATES AN ATTRACTIVE OPTION FOR INVESTORS CONSIDERING THE FREQUENCY OF POSITIVE TRENDS.	ETHEREUM CLASSIC SHOWS A LOWER PERCENTAGE OF BULLISH SIGNALS, WITH THE SHORT-TERM MOVING AVERAGE CROSSING ABOVE THE LONG-TERM MOVING AVERAGE APPROXIMATELY 48.69% OF THE TIME. THIS SUGGESTS A SLIGHTLY LOWER FREQUENCY OF POSITIVE TRENDS COMPARED TO BOTH BITCOIN AND LITECOIN.
1 65.542986 0 34.457014 Name: ma_cross, dtype: float64	0 51.307484 1 48.692516 Name: ma_cross, dtype: float64	1 51.80283 0 48.19717 Name: ma_cross, dtype: float64

In summary, Bitcoin stands out with a higher frequency of positive trends, followed by Litecoin, while Ethereum Classic exhibits a relatively lower occurrence of bullish signals. These are valuable insights to be considered when evaluating potential investment opportunities in these cryptocurrencies.

[link to full code]

2.2.2 Preparing the currency table :

- **Dropping columns**

dropped the column Currency: The 'Currency' column was dropped from the dataset as it contained identical values for all rows.All data points in the dataset belong to a single currency, making the 'Currency' column redundant.

- **Operating Upon "Date" column : converting column**

The 'Date' column was converted to a timestamp format to enhance temporal analysis capabilities.Timestamps provide a standardized numerical representation of time, facilitating chronological ordering and time-based calculations.

	Date	Open	High	Low	Close	Volume	name	short_ma	long_ma	ma_cross	Timestamp
0	2016-07-28	1.6000	2.1100	1.3600	1.6800	890279	ethereum classic	0.000000	0.000000	0	2016-07-28
1	2016-07-29	1.6800	1.7900	1.5200	1.6400	696558	ethereum classic	0.000000	0.000000	0	2016-07-29
2	2016-07-30	1.6400	1.7000	1.5500	1.5700	290616	ethereum classic	0.000000	0.000000	0	2016-07-30
3	2016-07-31	1.5700	1.9200	1.4100	1.7900	777390	ethereum classic	0.000000	0.000000	0	2016-07-31
4	2016-08-01	1.7900	2.2900	1.7000	2.2900	1407690	ethereum classic	0.000000	0.000000	0	2016-08-01
...	...	...	...	...	...	...	...	...	...	...	...
2213	2022-08-19	39.5602	39.6214	32.5182	32.9677	11223970	ethereum classic	28.187490	28.516263	0	2022-08-19
2214	2022-08-20	32.9677	34.5483	31.2604	32.7902	5196067	ethereum classic	28.550686	28.546265	1	2022-08-20
2215	2022-08-21	32.7868	34.1481	32.1598	33.6202	3227236	ethereum classic	28.927708	28.582871	1	2022-08-21
2216	2022-08-22	33.6202	34.1020	31.2995	34.0988	3320587	ethereum classic	29.313474	28.614102	1	2022-08-22
2217	2022-08-23	34.0988	34.6883	33.6913	33.8179	3663631	ethereum classic	29.681852	28.634738	1	2022-08-23

Figure 2.3: Ethereum classic dataframe after dropping currency column and performing timestamp

2.2.3 Preparing the RSI analysis :

- **Adding RSI column**

Adding the RSI column : RSI is particularly useful in signaling potential overbought or oversold market conditions. Traditionally, RSI values above 70 suggest overbought conditions, indicating a potential reversal or correction, while values below 30 suggest oversold conditions, indicating a potential buying opportunity.

Overbought Conditions (RSI > 70):

RSI values above 70 suggest that an asset may be overbought. This could imply that the price has risen too rapidly and may be due for a correction or a reversal.

RSI
32.500000
27.659574
20.000000
19.977802
24.697987
...
37.868073
38.447801
40.844479

Figure 2.4: RSI values

Oversold Conditions (RSI < 30):

RSI values below 30 suggest that an asset may be oversold. This could indicate a potential buying opportunity as the price may have declined too rapidly.

Adding the RSI (Relative Strength Index) column significantly improves our dataset by providing a strong number-based measure to gauge how fast prices are changing in the market. This enhancement is especially crucial for traders and analysts who want a precise tool to assess potential extreme market conditions and the strength of ongoing trends.

2.2.4 Preparing the MA20 and the MA50 analysis :

- **Adding MA20 and MA50 column**

MA20 Calculation:

The MA20 is calculated by taking the average of the closing prices over the last 20 days. This moving average is more sensitive to short-term price changes, providing a timely reflection of recent market dynamics.

MA50 Calculation: The MA50, on the other hand, is calculated by averaging the closing prices over the last 50 days. This moving average is smoother and less responsive to short-term fluctuations, offering a longer-term perspective on market trends.

The convergence or divergence of prices from MA20 and MA50 can confirm or challenge the strength of a trend. Traders often use these moving averages to validate trend directions before making significant trading decisions.

	Date	Open	High	Low	Close	Volume	name	short_ma	long_ma	ma_cross	Timestamp	rsi	MA20	MA50
49	2010-09-05	0.1	0.1	0.1	0.1	8459	bitcoin	0.100	0.0000	1	2010-09-05	0.000000	0.100	0.100
50	2010-09-06	0.1	0.1	0.1	0.1	910	bitcoin	0.100	0.0000	1	2010-09-06	0.000000	0.100	0.100
51	2010-09-07	0.1	0.1	0.1	0.1	3457	bitcoin	0.100	0.0000	1	2010-09-07	0.000000	0.100	0.100
52	2010-09-08	0.1	0.1	0.1	0.1	2345	bitcoin	0.100	0.0000	1	2010-09-08	0.000000	0.100	0.100
53	2010-09-09	0.1	0.1	0.1	0.1	1734	bitcoin	0.100	0.0000	1	2010-09-09	0.000000	0.100	0.100
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4415	2022-08-19	23201.6	23202.3	20807.8	20831.3	339472	bitcoin	22239.556	32547.5970	0	2022-08-19	31.967559	23388.020	22239.556
4416	2022-08-20	20830.7	21357.4	20784.8	21138.9	206943	bitcoin	22277.076	32459.7430	0	2022-08-20	36.748147	23279.795	22277.076
4417	2022-08-21	21138.9	21692.4	21077.4	21517.2	177522	bitcoin	22322.556	32382.8780	0	2022-08-21	38.086137	23192.095	22322.556
4418	2022-08-22	21516.8	21517.4	20912.1	21416.3	251833	bitcoin	22364.684	32303.5205	0	2022-08-22	31.304334	23113.480	22364.684
4419	2022-08-23	21416.5	21458.2	21271.2	21309.0	251695	bitcoin	22386.548	32202.2275	0	2022-08-23	34.310059	23037.890	22386.548

Figure 2.5: Updated version of Bitcoin dataframe after adding RSI and MA20 and MA50 columns

[link to full code]

- **Integrating ".dropna" Function for Robustness in Column Additions**

In conjunction with each column addition performed earlier, the data transformation process was fortified with the strategic inclusion of the ".dropna function". This step was implemented to meticulously remove any NaN values present in the dataset, ensuring a more resilient and complete transformation. By systematically dropping invalid or missing entries, the data underwent a comprehensive cleansing process, reinforcing the accuracy and reliability of the final dataset.

```
df1.dropna(subset=['supply'], inplace=True)
df2.dropna(subset=['supply'], inplace=True)
df3.dropna(subset=['supply'], inplace=True)
df1.dropna(subset=['MA20'],inplace=True)
df1.dropna(subset=['MA50'],inplace=True)
df2.dropna(subset=['MA20'],inplace=True)
df2.dropna(subset=['MA50'],inplace=True)
df3.dropna(subset=['MA20'],inplace=True)
df3.dropna(subset=['MA50'],inplace=True)
df1.dropna(subset=['RSI'],inplace=True)
df2.dropna(subset=['RSI'],inplace=True)
df3.dropna(subset=['RSI'],inplace=True)
```

Figure 2.6: Data Cleaning operations using the".dropna" function

2.2.5 Converting Blockchain Supply Metrics from JSON to CSV :

Blockchain Supply Metrics:

- **Transform the blockchain supply metrics json file into a csv file :**

Using the function ".to_csv" ,we convert the json file to a csv file called "Supply_And_Market_info.csv"

- **Delete rows that contained invalid JSON strings :**

Find the row containing the invalid JSON string , Delete the row from the DataFrame then save the DataFrame to a new CSV file called 'filtered_data.csv'

- **Converted JSON String to Dictionary :**

After loading the CSV file into a DataFrame ,convert the string representation of dictionaries to actual dictionaries.

- **Flattened the DataFrame**

- **Extracted the nested columns and transfomed the data to the final csv file :**

Extract the 'quote' column to separate columns and save the resulting DataFrame to a new CSV file called 'cryptoinfo.csv'

.

```
print(df10.columns)
```

```
Index(['level_0', 'index', 'id', 'name', 'symbol', 'slug', 'num_market_pairs',
       'date_added', 'tags', 'max_supply', 'circulating_supply',
       'total_supply', 'infinite_supply', 'platform', 'cmc_rank',
       'self_reported_circulating_supply', 'self_reported_market_cap',
       'tvl_ratio', 'last_updated', 'EUR'],
      dtype='object')
```

[link to full code]

2.2.6 Comprehensive Data Cleaning and Aggregation csv files for Cryptocurrency Analysis :

The primary goal of this part is to consolidate the data and prepare it for further analysis, potentially merging it with the cleaned json file for a more holistic view and only for analytical purposes. Below is a descriptive paragraph outlining the key steps in this process:

- **Group data by the “name” column :**

the cryptocurrency DataFrame is first grouped by the 'name' column, which represents different cryptocurrencies. This grouping ensures that subsequent operations are applied independently to each cryptocurrency, facilitating a more granular analysis

- **Define aggregation functions for each column :**

The aggregation functions are defined for various columns to condense the data and extract meaningful information.

For the 'Date' column, the minimum and maximum dates are computed to establish the temporal range of each cryptocurrency's data. Numeric columns such as 'Open,' 'High,' 'Low,' 'Close,' 'Volume,' 'short_ma,' 'long_ma,' 'MA20,' 'MA50,' and 'RSI' are aggregated using the mean function to obtain representative values. Additionally, for categorical columns like 'ma_cross' and 'Signal,' lambda functions are employed to extract the mode, representing the most frequent values.

- **Rename the columns to clarify the results**

The resulting aggregated DataFrame is presented with a clearer set of columns, each providing essential insights into the cryptocurrency data.

[link to full code]

```
              name   Min_Date   Max_Date         Open         High  \
0          bitcoin 2010-10-26 2022-08-23  8512.133055  8747.691464
1  ethereum classic 2016-09-28 2022-08-23    17.072683    17.987095
2         litecoin 2016-10-25 2022-08-23    90.174245    94.135184

          Low        Close        Volume     short_ma      long_ma  ma_cross  \
0  8246.842890  8517.000673  1.431046e+07  8387.443499  7882.093516         1
1    16.122733    17.086288  3.501846e+07    16.706876    15.808413         0
2    85.779730    90.190294  2.482154e+07    89.557619    86.881523         1

         MA20         MA50  Signal        RSI
0  8467.061913  8387.443499       1  54.477382
1    16.926984    16.706876      -1  49.727887
2    89.944763    89.557619       1  50.684057
```

Figure 2.7: final view of csv file after aggregation and cleaning

2.2.7 Merging of Detailed and Aggregated Cryptocurrency Data for Enhanced Visualization and Analysis

The merging step involves combining two cleaned and aggregated datasets, specifically the 'selected_df' containing three rows of cryptocurrency data and the 'aggregated_df' providing summarized statistics per cryptocurrency.

The merging is executed based on the 'name' column, creating a comprehensive dataset, 'result_df,' that incorporates both detailed and aggregated information for each cryptocurrency. While the resulting file, 'Combineddata.xlsx,' serves as an intermediate step for graph generation, it is not intended for data warehousing or loading. Due to its limited size, the file is more suitable for exploratory analysis and visualization purposes. The merging process strategically combines distinct datasets to leverage relevant columns from each, potentially revealing meaningful insights when generating graphs or pies that can aid in decision-making or trend identification. The 'Combineddata.xlsx' file serves as a bridge to efficiently synthesize diverse information for visualization without the need for extensive data management due to its relatively compact size.

[link to full code]

	name	Min_Date	Max_Date	Open	High	Low	Close	Volume	short_ma	long_ma	ma_cross	MA20	MA50	Signal	RSI
0	bitcoin	2010-10-26	2022-08-23	8512.133055	8747.691464	8246.842890	8517.000673	1.431046e+07	8387.443499	7882.093516	1	8467.061913	8387.443499	1	54.477382
1	ethereum classic	2016-09-28	2022-08-23	17.072683	17.987095	16.122733	17.086288	3.501846e+07	16.706876	15.808413	0	16.926984	16.706876	-1	49.727887
2	litecoin	2016-10-25	2022-08-23	90.174245	94.135184	85.779730	90.190294	2.482154e+07	89.557619	86.881523	1	89.944763	89.557619	1	50.684057

Figure 2.8 : Final Dataframe after merging

2.3 DataLoading

Using Talend , all relevant files were directed to the data warehouse ” Talend_db.sql”.

TMAP component was used to transform and map data from multiple input sources (all seven files present in the figure below) to an output source (Talend_db.sql) . It allows us to define multiple input and output flows, and then map the fields from the input flows to the output flow using drag-and-drop functionality.

This component was used to perform data transformation and mapping tasks such as:

-Joining data from multiple input sources.

-Filtering and selecting specific data fields(table columns present in the database)

-Renaming and changing data types of fields.

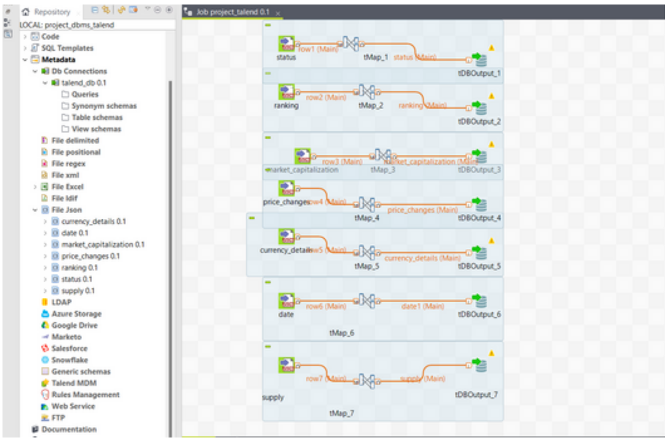

Figure 2.9: Talend Job Loading

The datawarehouse was created successfully

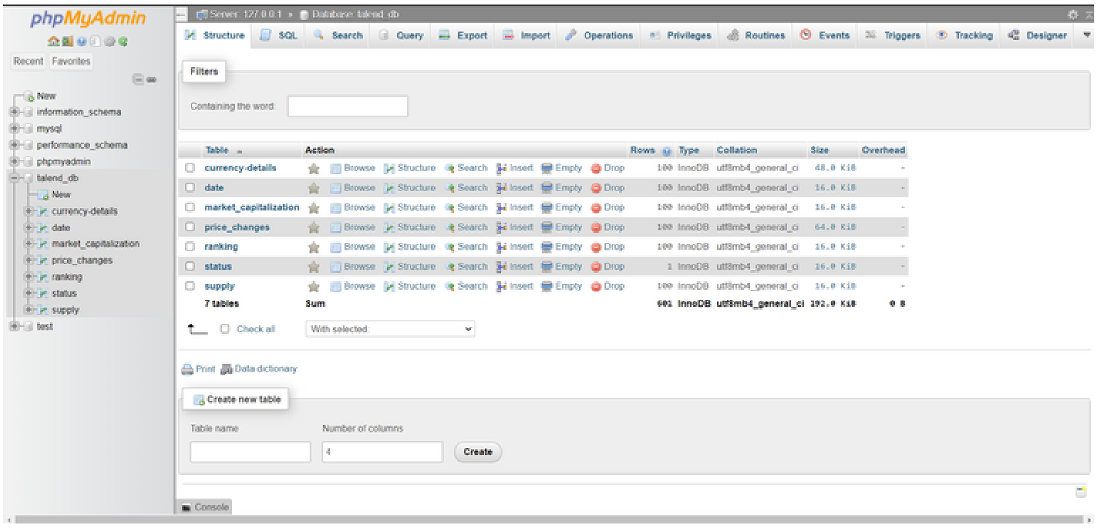

Figure 2.10 :The database view of data

2.3.1 Fact-Dimension tables

In this Galaxy Schema, a first fact table " Price change " is connected to one or more dimension tables " Currency_detail " , " Date" ,"Supply" through foreign key relationships.

A second fact table " Market Capitalization" is connected to one or more dimension tables " Status " and " Ranking " through foreign key relationships

The fact table contains the measures of the data("quote_eur_percent_change_1h" ,"quote_eur_percent_change_24h","quote_eur_percent_change_7d","quote_eur_percent_change_30d", "quote_eur_percent_change_60d","quote_eur_percent_change_90d) ("quote_eur_market_cap", "quote_eur_market_cap_dominance"......)

while the dimension tables contain the attributes or characteristics of the data, such as "Status", "time", "Currency" and "Ranking".....

The central fact tables and the dimension tables are connected through a primary key-foreign key relationship, forming a galaxy structure.

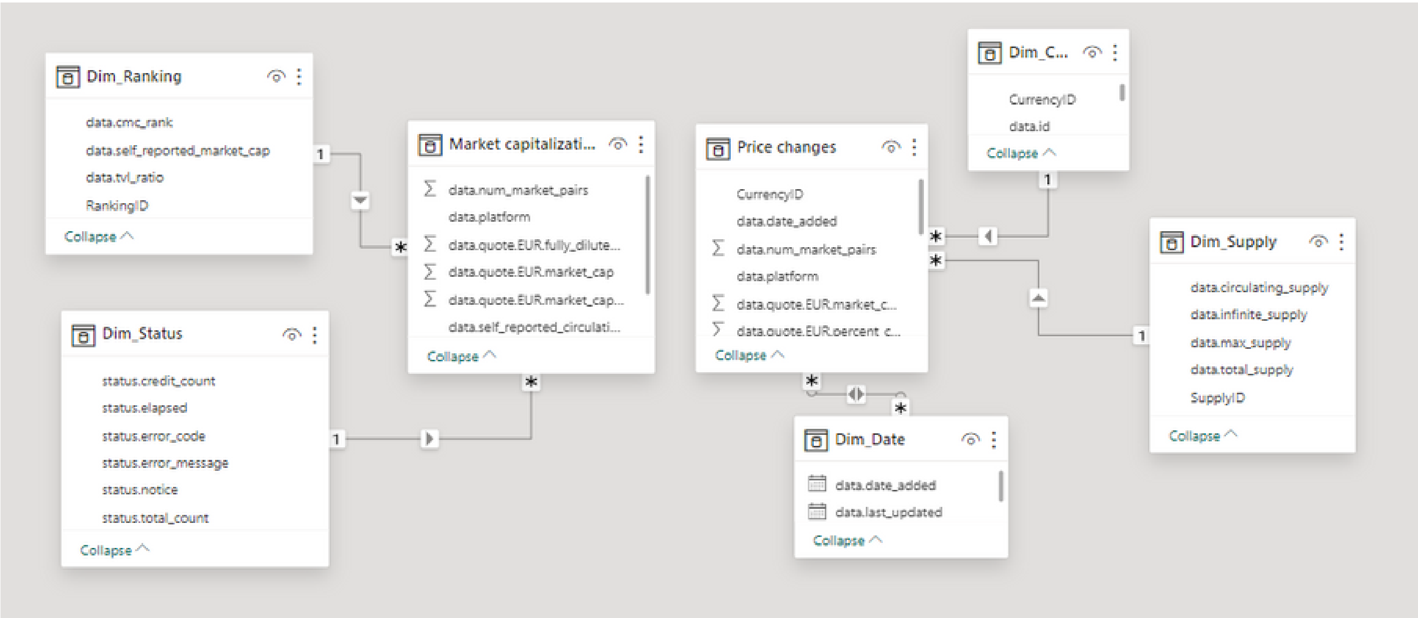

Figure 2.3.1: Galaxy schema

2.4 DataAnalysis

2.4.1 Decisions and possible enhancements

In this analysis, we examine the crossover signals generated by the comparison of the 20-day Moving Average (MA20) and the 50-day Moving Average (MA50) for three major cryptocurrencies: Bitcoin, Ethereum Classic, and Litecoin. Crossover signals, specifically Golden Crosses and Death Crosses, are widely used in technical analysis to identify potential trend reversals and make informed trading decisions.

Methodology: We calculated the crossover signals as follows:

A signal of 1 represents a Golden Cross, suggesting a potential bullish trend (Buy Signal). A signal of -1 represents a Death Cross, indicating a potential bearish trend (Sell Signal). A signal of 0 represents no crossover, meaning the MA20 and MA50 are not crossing each other significantly.

About Signal

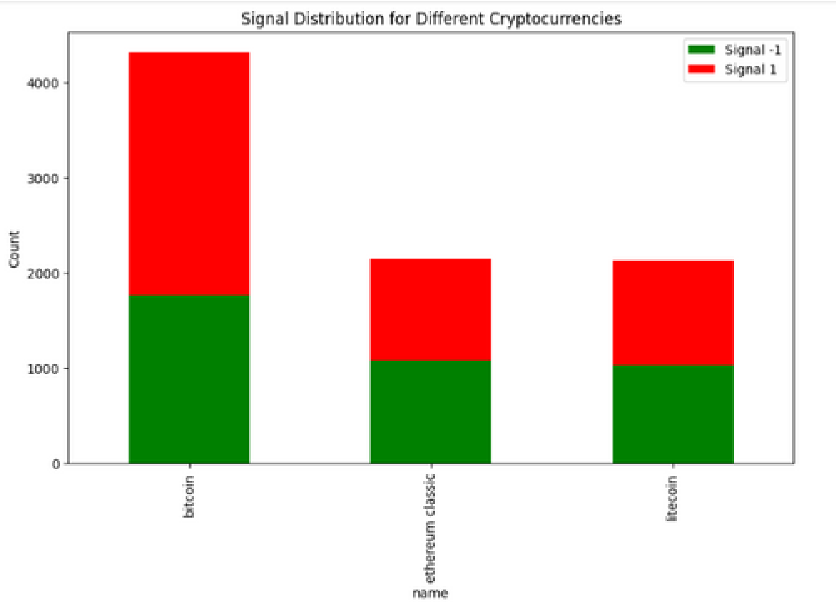

Figure 2.4.1: Signal distribution for different cryptocurrencies

Bitcoin
Buy Signals (Signal=1): 59.17%
Sell Signals (Signal=-1): 40.83%

Ethereum Classic:
Buy Signals (Signal=1): 49.51%
Sell Signals (Signal=-1): 50.49%

Litecoin:
Buy Signals (Signal=1): 51.71%
Sell Signals (Signal=-1): 48.29%

Decision:

Bitcoin: Based on the provided criteria, the distribution of signals for Bitcoin suggests a relatively bullish trend. For investors looking for potential opportunities, Bitcoin may be considered for both short-term and long-term investments.

Ethereum Classic: The distribution of signals for Ethereum Classic indicates a higher percentage of Sell signals, suggesting caution. Investors may want to carefully assess the risk associated with a potential bearish trend.

Litecoin: The distribution of signals for Litecoin leans slightly towards Buy signals. Investors might consider Litecoin for potential opportunities, but it's essential to monitor the market closely.

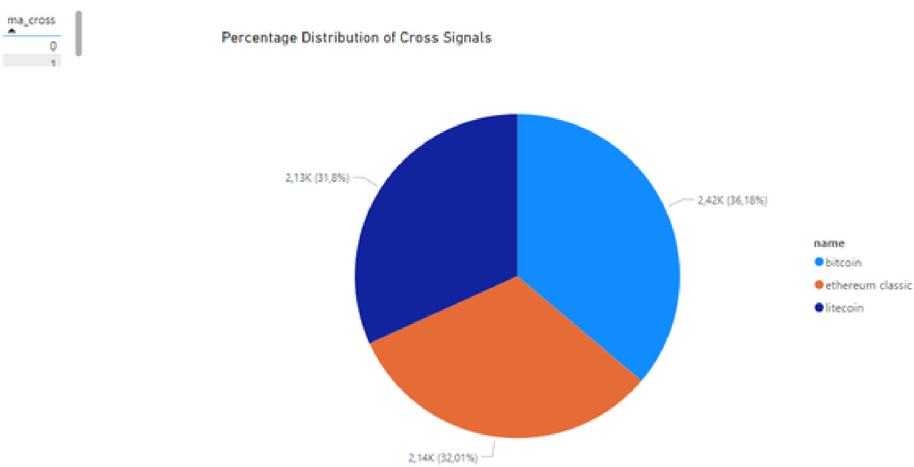

Figure 2.4.2: Pie chart showing the percentage distribution of cross signals

About trading volume

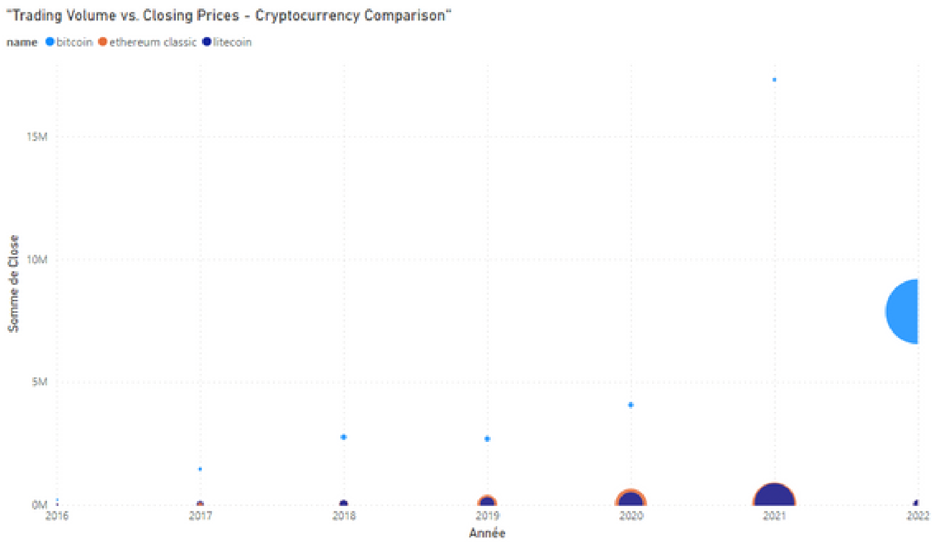

Figure 2.4.3: Scatter plot showing trading volume vs. Closing prices - Cryptocurrency Comparaison

The graph shows how the values of Bitcoin, Ethereum Classic, and Litecoin have changed over time, from 2016 to 2022. It gives us a picture of how much people are valuing these cryptocurrencies in the market. In 2022, Bitcoin's value has risen quite a bit, showing that more people are willing to pay a higher price for each Bitcoin compared to the other two. Ethereum Classic and Litecoin have been somewhat stable in value during the earlier years, with both having similar values. This stability suggests that people perceived them as having similar worth.

Toolip Information

```
Tooltip Information =
"Date: " & FORMAT(Sheet1[Date], "Short Date") &
UNICHAR(10) & -- Line break
"Closing Price: $" & FORMAT(Sheet1[Close], "0.00") &
UNICHAR(10) & -- Line break
"Trading Volume: " & FORMAT(Sheet1[Volume], "#,##0")
```

The DAX measure for tooltip information combines key data points, enhancing the scatter plot discussed above

Date: Displays the date in a user-friendly short format.

Closing Price: Presents the closing price with a dollar sign and two decimal places.

Trading Volume: Exhibits the trading volume formatted with commas for better readability.

This consolidated tooltip, with line breaks for clarity, provides detailed insights into each data point, promoting a more comprehensive understanding of the scatter plot.

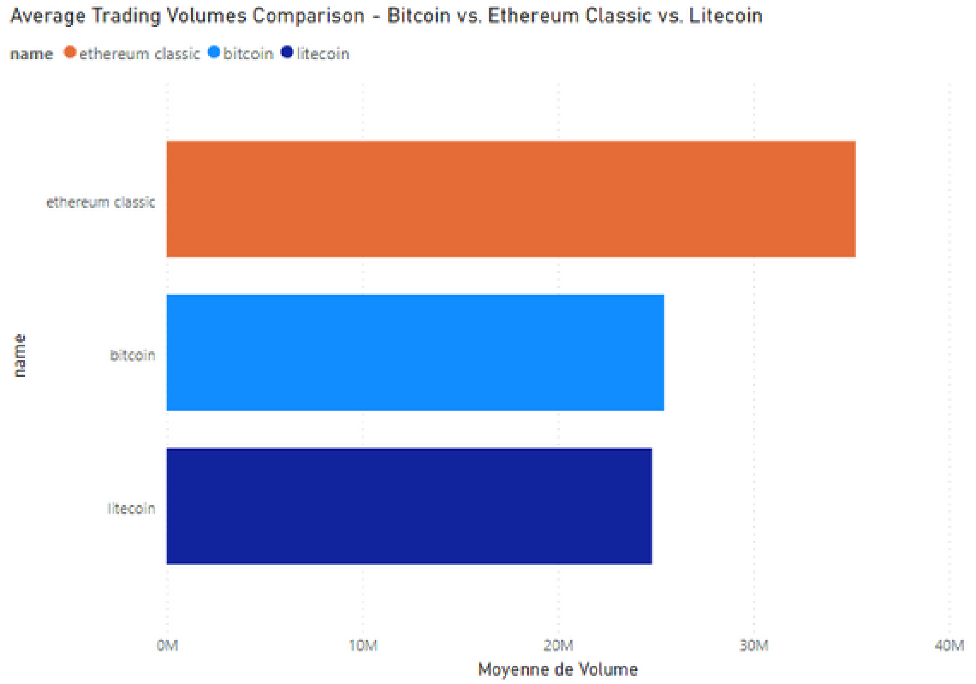

Figure 2.4.4: Histogram showing a comparison of average trading volume between bitcoin, Ethereum Classic and Litecoin

About Prices :

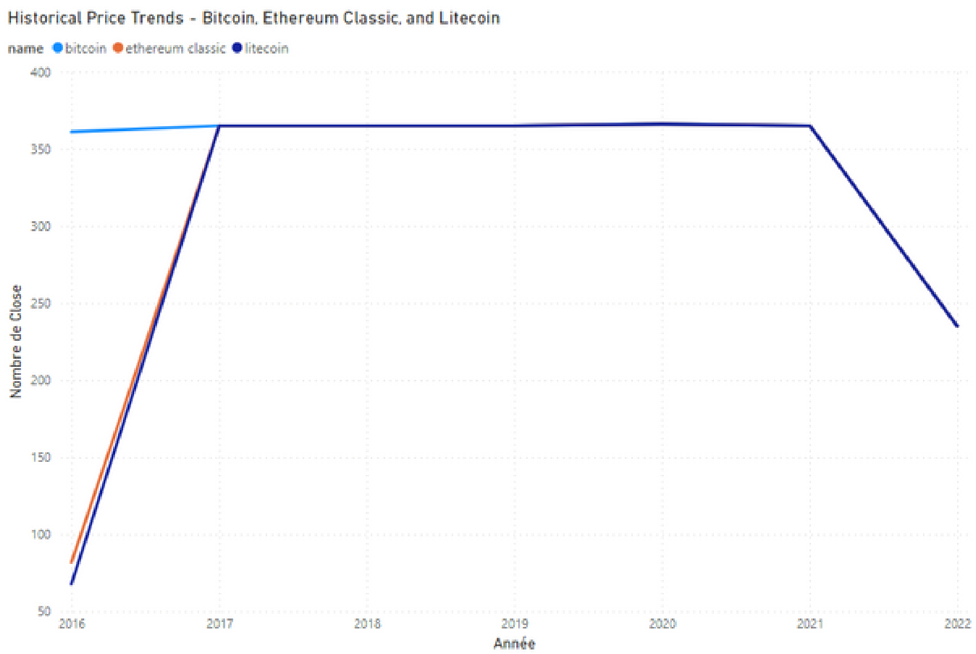

Figure 2.4.5 : Historical Price Trends

The scenario where the curve of Bitcoin is initially above that of Ethereum and Litecoin, and then they become identical suggests a dynamic relationship in the market. :

Initial Outperformance: In the beginning, Bitcoin may have experienced a period of outperformance compared to Ethereum and Litecoin. This could be due to various factors such as market sentiment, specific events impacting Bitcoin, or changes in investor preferences.

Convergence: The subsequent period where the curves become identical indicates a convergence or leveling of the performance between Bitcoin, Ethereum, and Litecoin. This suggests a more synchronize market movement where the three cryptocurrencies are influenced by common factors or trends.

About Supply :

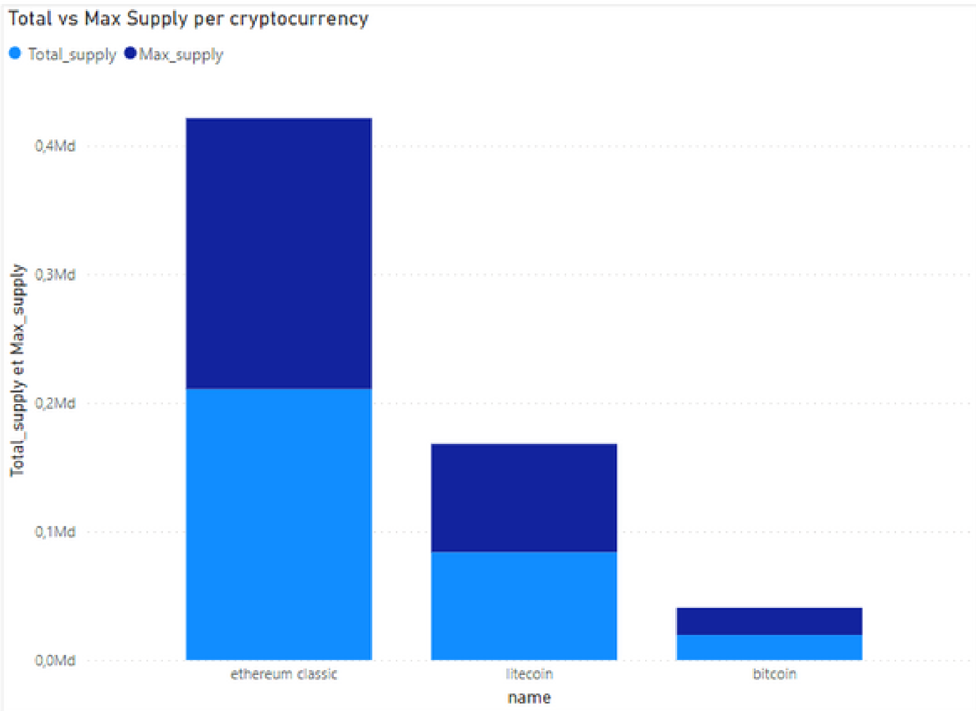

Figure 2.4.6: Bar chart showing the total vs max Supply per cryptocurrency

The height of each bar corresponds to the numerical value of the supply (either 'Total Supply' or 'Max Supply'). The taller the bar, the larger the corresponding supply value for that entity.

RSI analysis :

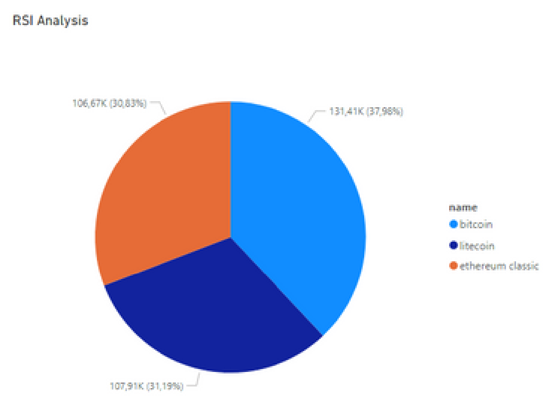

Figure 2.4.7: Pie chart showing RSI for diffferent cryptocurrencies

This analysis implies that, at the given time, Bitcoin exhibits a higher level of relative strength compared to Ethereum and Litecoin, making it potentially more resilient to market fluctuations. This information may be considered important when evaluating the momentum and potential investment attractiveness of each cryptocurrency.

Divergence analysis :

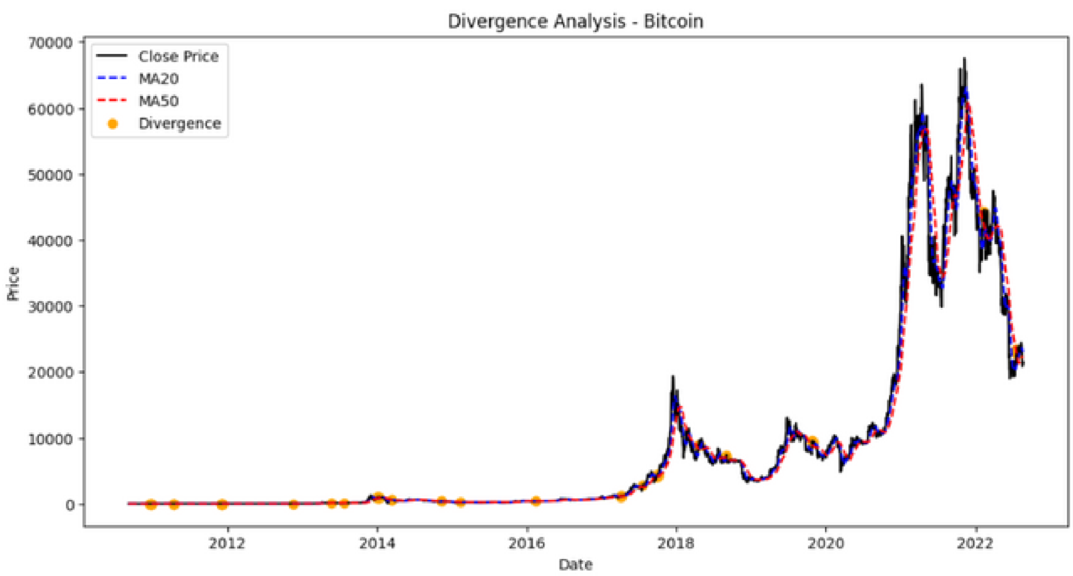

Figure 2.4.8 : Divergence analysis for bitcoin

The divergence analysis of the Bitcoin graph reveals a notable peak in the price trajectory during the period spanning from 2021 to 2022. Intriguingly, this distinctive price movement is mirrored in the divergence graphs of both Litecoin and Ethereum, indicating a similar peak period across these cryptocurrencies. The synchronous occurrence of these peaks suggests a shared market behavior or external factors influencing the broader cryptocurrency landscape during that specific timeframe.

Chapter 3

Conclusion : Navigating Cryptocurrency Trends for Informed Investment

In this comprehensive project, the journey from data gathering to visualization has illuminated key insights into the world of cryptocurrency investment. The meticulous cleaning of data paved the way for robust analysis, enabling us to delve into multiple dimensions. Noteworthy tools like RSI analysis, total vs max supply per cryptocurrency graphs, and cross-signal distribution graphs consistently pointed towards Bitcoin as a promising investment option.

However, a nuanced perspective emerges when examining additional metrics. The average trading volumes comparison graph highlights Ethereum Classic as having the most significant trade volume, presenting a compelling alternative. Divergence analysis and historical price trends indicate that Bitcoin, Ethereum Classic, and Litecoin yield comparable results, leaving investors with options to consider.

As we navigate through these analyses, a key takeaway surfaces—the importance of dynamic monitoring in the volatile cryptocurrency market. Trends can swiftly shift, and as evident from our findings, the market is ever-changing. This underscores the significance of adaptive strategies, emphasizing the need for continuous vigilance and a keen eye on evolving market dynamics. In conclusion, while Bitcoin shines prominently, the nuanced comparison allows for informed decision-making, recognizing that the cryptocurrency market is a dynamic landscape demanding ongoing observation and strategic adaptability.