

Sectoral Dynamics and Market Forecasting - An Apriority-Based Study of NSE Nifty

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Abstract

Predicting stock market performance and identifying the factors that influence stock prices is both intellectually engaging and financially rewarding. Accurate market direction forecasting enhances the decision-making capabilities of individual investors, institutional participants, and regulatory bodies. As a result, financial managers continually seek sophisticated tools to improve predictive accuracy. This study applies a machine learning approach - specifically, the Apriori algorithm - to analyze the trend (bullish or bearish) of the widely followed Indian stock index, NSE NIFTY. It aims to uncover the relationship between various sectoral indices - each representing the performance of specific industrial sectors - and the broader market index, NSE NIFTY. By mining association rules, the research identifies patterns within sectoral movements that may signal the subsequent day's market direction, offering valuable insights for investors and financial decision-makers.

Keywords: Apriori Algorithm, Association Rule Mining, Predictive Analysis, Co-Movement of Market Index, Sectoral Indices.

1. Introduction

Stock markets evolve dynamically over time (Barsky & De Long, 1992; Hendershott & Moulton, 2011), making their prediction a longstanding and formidable challenge for financial researchers and practitioners (Hussein et al., 2015). With increasing data availability and technological advancements, High Performance Computing (HPC) techniques have been explored to enable near real-time predictions (Ahmad et al., 2004). Fu et al. proposed both rule-based and template-based approaches for detecting patterns in stock charts using Perceptually Important Points (PIPs). Globally, market participants increasingly rely on historical data to uncover hidden and potentially actionable insights for predicting future market behavior. Understanding the multifactorial dynamics that influence stock price movements is critical for enhancing investment strategies. Although traditional models have guided investors for decades, emerging technologies have rendered some of these models less effective, calling for more intelligent, adaptive approaches.

Association Rule Mining (ARM) is one such data mining technique that uncovers significant relationships among variables in large datasets. Applying ARM to financial data - particularly to uncover hidden patterns in stock movements - poses challenges due to the data's volatility and complexity. However, when successfully implemented, it offers powerful tools for visualizing and interpreting market behavior, enabling smarter investment decisions (Carea-Valente & Lopez-Chavarrias, 2000; Lerner et al., 2004). Financial forecasting is inherently complex, as markets are stochastic, nonlinear, time-varying, and influenced by both economic and political factors (Tan et al., 2007). Consequently, a major goal in modern finance is to identify efficient methods for summarizing and visualizing stock market data to support more informed decision-making (Boginski et al., 2005).

While numerous studies explore general market predictability, relatively few have focused on the co-movement between sectoral stock indices and a national benchmark index. In the context of India - where the economy is on a revival path supported by strong industrial policy initiatives - analyzing the co-movement between NSE NIFTY and its sectoral indices holds practical and strategic value. Understanding

sectoral contributions to the broader market index can aid investors in identifying which sectors significantly influence national market trends.

This study uses Association Rule Mining to examine the relationships between the NSE NIFTY 50 index and its constituent sectoral indices. By applying the Apriori algorithm to financial time series data, the study aims to extract statistically significant rules that reflect meaningful co-movement and directional patterns. These insights can enhance investor awareness and contribute to more nuanced financial decision-making. The rest of this paper is structured as follows: Section 2 reviews the existing literature, Section 3 details the data and its sources, Section 4 describes the methodology, Section 5 presents the results and analysis and Section 6 concludes the study with key insights and recommendations

2. Literature Review

Association Rule Mining (ARM) has been widely used in financial applications, particularly for discovering hidden patterns and relationships in large datasets. Initially conceptualized for market basket analysis, ARM has found relevance in diverse financial domains such as credit scoring, fraud detection, banking crises prediction, and insurance risk assessment (Baesens et al., 2003; Hand, 2007). In the context of stock market analysis, several studies have applied ARM to identify co-movement and predictive relationships among financial variables. Liao, Chu, and You (2001) examined the co-movement between foreign exchange rates and category-based stock indices in Taiwan, proposing portfolio strategies under varying market conditions. Liao, Ho, and Lin (2005) combined ARM with k-means clustering to detect investment opportunities and stock groupings in the Taiwanese market. Enke and Thawornwong (2005) employed machine learning techniques, including information gain, to assess the predictive power of economic and financial indicators. Jo Ting, Fu, and Chung (2006) introduced a pattern-based stock mining approach that transforms numerical stock data into symbolic sequences for intra-stock and inter-stock association analysis. Their work demonstrated how mined rules could be used to forecast future price movements. Similarly, Sung and So (2011) analyzed time-series data from multiple world indices using ARM to predict changes in the Korea Composite Stock Price Index (KOSPI).

Within Indian financial markets, studies leveraging ARM remain relatively limited. Subha and Nambi (2013) examined co-movements between Indian indices and global economic cues such as exchange rates, commodity prices, and global stock indices. Their findings revealed significant associations that could inform investment strategies. More recently, Jain et al. (2018) applied ARM to sectoral indices of the Indian stock market to explore short-term predictive relationships, while Singh and Bhattacharya (2020) analyzed ARM's effectiveness in capturing sectoral interdependencies during volatile market phases. In another study, Patel and Shah (2021) demonstrated the use of ARM in combination with time series models to enhance the interpretability of stock trend forecasts.

Despite these developments, gaps persist in understanding the dynamic interactions between sector-specific indices and broader national benchmarks such as the NSE NIFTY. Most existing research either focuses on international markets or treats stock data purely as time series without exploring structural co-movement. This study addresses the gap by applying the Apriori algorithm to uncover statistically significant association rules that capture co-movement patterns and next-day predictive trends between NSE sectoral indices and the NIFTY 50 index. By contributing to the literature on pattern recognition and predictive analytics in financial markets, this work supports more nuanced investment decisions and offers practical value to financial analysts, traders, and policy-makers.

3. Data and Sources of Data

The NIFTY 50 is a well-diversified index comprising 50 large-cap stocks representing key sectors of the Indian economy. Introduced with a base date of November 3, 1995 - the date marking one year of operations of NSE's Capital Market Segment - the index had a base value of 1000 and base capital of ₹2.06 trillion. As of March 31, 2016, the NIFTY 50 represented approximately 65% of the free-float market capitalization of all NSE-listed

stocks. Computed using the free-float market capitalization method, the index is widely used for benchmarking portfolios, launching ETFs, index funds, and structured products.

To capture the sectoral dynamics within the Indian equity market, this study considers 14 sectoral indices, 4 thematic indices, and 2 broad-based indices, alongside the NIFTY 50. The 14 sectoral indices cover diverse market segments: NIFTY Auto (15 automobile-related companies including 2/3/4-wheelers and auto ancillaries), NIFTY Bank (12 highly liquid banking stocks), NIFTY Financial Services (15 companies including banks, housing finance, and NBFCs), NIFTY IT (10 leading IT firms), NIFTY FMCG (15 fast-moving consumer goods companies), NIFTY Media (15 media and entertainment firms), NIFTY Metal (15 metal and mining companies), NIFTY Pharma (10 pharmaceutical companies), NIFTY Private Bank (10 private-sector banks), NIFTY PSU Bank (11 public-sector banks), NIFTY Realty (10 real estate firms), NIFTY Consumer Durables (up to 15 companies), NIFTY Healthcare (up to 20 healthcare firms), and NIFTY Oil & Gas (15 companies in oil, gas, and petroleum).

The thematic indices include NIFTY Commodities (30 companies across sectors like oil, chemicals, power, cement, sugar, and mining), NIFTY CPSE (10 major central public sector enterprises earmarked for government disinvestment *via* ETFs), NIFTY Energy (10 petroleum, gas, and power companies), and NIFTY MNC (15 companies with majority foreign ownership or control).

The broad indices comprise NIFTY Midcap 50 and NIFTY Smallcap 50, representing 50 top midcap and smallcap companies by market capitalization from their respective NIFTY indices.

For analysis, daily closing prices of all 21 indices (14 sectoral, 4 thematic, 2 broad, and NIFTY 50) were collected for the whole calendar year 2024, approximately 250 trading days, sourced from the official NSE website. These indices provide a comprehensive representation of market segments, enabling detailed tracking of sectoral and thematic influences on the broader market trends.

4. Methodology

The Apriori algorithm, a foundational technique in association rule mining (ARM), was introduced by Agrawal and Srikant in 1994. It operates on the principle of using prior knowledge of frequent itemset properties to efficiently identify associations between variables in large datasets. The core objective is to discover itemsets that occur frequently in a dataset, followed by the generation of rules with high predictive value.

The Apriori algorithm follows a sequence of steps to find frequent itemsets and generate association rules. First, it identifies frequent single-item sets by counting their occurrences and filtering out those below a minimum support threshold. Then, it creates candidate itemsets of increasing size by combining previously identified frequent itemsets and recalculates their support values. Throughout this process, itemsets that do not meet the minimum support are pruned to reduce computation. These steps of candidate generation, support calculation, and pruning continue iteratively until no further frequent itemsets are found. Finally, the algorithm generates association rules from these frequent itemsets that satisfy the minimum confidence level, enabling the discovery of meaningful patterns and relationships in the data. This iterative and pruning-based approach ensures computational efficiency while uncovering strong item associations.

This iterative, bottom-up approach ensures that only the most relevant and frequent associations are considered, improving both efficiency and interpretability. The pseudo code for the apriori algorithm is illustrated as below.

```
Apriori (T, minSupport) { //T is the database and minSupport is the minimum support
L1= {frequent items};
for(k= 2; Lk-1 !=∅; k++) {
Ck= candidates generated from Lk -1
//that is Cartesian product Lk -1 x Lk -1 and eliminating any k -1 size //itemset that is not frequent
```

```

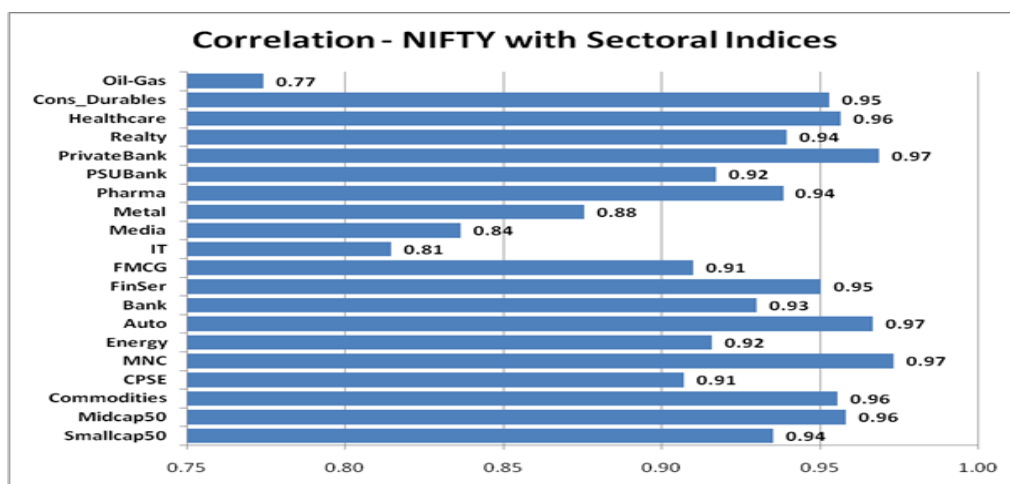
for each transaction tin database do{
#increment the count of all candidates in Ck that are contained in t
Lk = candidates in Ck with minSupport
} //end for each
} //end for
Return  $U_k L_k$ 
}
    
```

From the large itemsets identified by the Apriori algorithm, strong association rules can be generated and represented in the form 'A => B', which is read as "if A then B". Here, 'A' is the antecedent and 'B' is the consequent. This rule has a support value, which is the percentage of transactions in the dataset that contain both A and B representing the probability P(AUB). The confidence of the rule is the percentage of transactions containing A that also contain B, representing the conditional probability P(B|A). In other words, support measures how frequently the itemset occurs in the dataset, while confidence measures the strength of the association rule.

Typically, the Apriori algorithm starts with a minimum support threshold of 100% and gradually decreases it in steps of 5% until at least 10 rules meet the minimum confidence level of 0.9 or the support threshold reaches a lower limit of 10%, whichever occurs first. This flexibility allows association rule mining algorithms like Apriori to generate rules that satisfy desired support and confidence criteria, facilitating the discovery of meaningful and strong item associations for this study, the Apriori algorithm was implemented using the data mining tool WEKA. Co-movement patterns were extracted using a minimum support of 0.35 and confidence of 0.90. Predictive rules for next-day NIFTY movement were explored using a reduced support of 0.10 and minimum confidence of 0.80. This dual-threshold approach enabled the identification of both frequent co-movements and potentially predictive trends

5. Analysis and Inferences

To understand the strength of association between NSE NIFTY 50 and other sectoral indices, correlation coefficients were first computed.



It is evident from the above chart that the most correlated sectors with NIFTY are Private Bank, Auto and MNC with the correlation coefficient of 0.97. Surprisingly, the least correlated sectors are found to be Oil& Gas, IT and Media with the measure of 0.77, 0.81 and 0.84 respectively.

To study the co movement of NIFTY with sectoral indices, the daily close prices of Indian stock index NSE NIFTY, and the daily close prices of the above mentioned twenty sectoral indices are captured as a date-wise transactional database for the entire study period.

The values in the transactional database are converted either into 0 or 1 depending upon whether today’s price is lesser than yesterday’s price.

$$t_s = \begin{cases} 0, & p_t < p_{t-1} \\ 1, & p_t > p_{t-1} \end{cases}$$

Where t_s is today’s state; p_t is today’s price, p_{t-1} is yesterday’s price. Weka’s implementation of Apriori algorithm is used to generate association rules for the co-movement . The top twenty association rules based on the frequently occurring patterns for NSE NIFTY is listed below.

Table #1 Co-movement of Nifty 50 with Sectoral Indices @ min. support 0.35 and confidence 0.90

Rule	Antecedent	Consequent
1.	Commodities=1 FinSer =1 (99)	==> NIFTY50=1 (96) conf:(0.97)
2.	Commodities =1 Bank =1 FinSer =1 (95)	==> NIFTY50 =1(92) conf:(0.97)
3.	Commodities =1 FinSer =1 PrivateBank =1 (94)	==> NIFTY50 =1(91) conf:(0.97)
4.	Commodities =1 Bank =1 FinSer =1 PrivateBank =1 (93)	==> NIFTY50 =1 (90) conf:(0.97)
5.	Midcap50 =1 Commodities =1 FinSer =1 (92)	==> NIFTY50 =1 (89) conf:(0.97)
6.	Smallcap50 =1 Commodities =1 FinSer =1 (91)	==> NIFTY50 =1 (88) conf:(0.97)
7.	Commodities =1 MNC =1 FinSer =1 (90)	==> NIFTY50 =1 (87) conf:(0.97)
8.	Midcap50 =1 MNC =1 FinSer =1 (96)	==> NIFTY50 =1 (92) conf:(0.96)
9.	MNC =1 Bank =1 FinSer =1 96	==> NIFTY50 =1 (92) conf:(0.96)
10.	Commodities =1 Bank =1 PrivateBank =1(95)	==> NIFTY50 =1 (91) conf:(0.96)
11.	MNC =1 FinSer =1 PrivateBank =1 (94)	==> NIFTY50 =1 (90) conf:(0.96)
12.	MNC =1 Bank =1 FinSer =1 PrivateBank =1 (93)	==> NIFTY50 =1 (89) conf:(0.96)
13.	Smallcap50 =1 MNC =1 FinSer =1 (92)	==> NIFTY50 =1 (88) conf:(0.96)
14.	Midcap50 =1 Commodities =1 PrivateBank =1 (91)	==> NIFTY50 =1 (87) conf:(0.96)
15.	Midcap50 =1 MNC =1 Bank =1 FinSer =1 (91)	==> NIFTY50 =1 (87) conf:(0.96)
16.	Midcap50 =1 FinSer =1 PrivateBank =1 (101)	==> NIFTY50 =1 (96) conf:(0.95)
17.	Commodities =1 Bank =1 (100)	==> NIFTY50 =1 (95) conf:(0.95)

18.	Midcap50 =1 Bank =1 FinSer =1 PrivateBank =1 (100)	==>	NIFTY50 =1(95) conf:(0.95)
19.	Commodities =1 PrivateBank =1 (99)	==>	NIFTY50 =1 (94) conf:(0.95)
20.	Smallcap50 =1 Midcap50 =1 FinSer =1 PrivateBank =1 (96)	==>	NIFTY50 =1 (91) conf:(0.95)

The number within the bracket in the antecedent column represents the total number of instances the mentioned pattern is observed, and the number within the bracket in the consequent column represents the number of instances the specified trend of NIFTY is observed. Confidence is the ratio between these two numbers. Value ‘1’ represents the rise in today’s value compared to yesterday’s value (Bull) and ‘0’ represents the fall in today’s price compared to yesterday’s price (Bear).

Rule#1 identifies a frequently occurring antecedent pattern of rise in Commodities and Financial Services. The consequent is the rise in Nifty. As this is observed in 96 days out of 99 days, the rule has a confidence level of 97%.

Rule#2 identifies another frequently occurring antecedent pattern of rise in, Commodities, Bank and Financial Services. The consequent is the rise in Nifty. As this is observed in 92 days out of 85 days, the rule has a confidence of 97%.

Rule#3 identifies a frequently occurring antecedent pattern of rise in Commodities, Financial Services and Private bank. The consequent is the rise in Nifty. As this is observed in 91 days out of 94 days, the rule has a confidence of 97%.

The other rules can also be interpreted similarly. The generated association rules can be used identify the co-movement of NIFTY 50 with the sectoral indices and help to understand the market dynamics.

The study is extended further to identify the relationship between frequently occurring patterns (antecedent) today with the trend of next day’s close price of NIFTY 50 as consequent. This is with the aim of predicting tomorrow’s market trend from the observed patterns today. The result obtained is enumerated below.

Table 2. Association rules for Predicting NSE NIFTY @ support 0.1 and confidence 0.80

Rule	Antecedent	Consequent
1	CPSE =1 FMCG =1 Media =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (31)	NIFTY50-Nxt =1 (26) conf:(0.84)
2	MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (31)	NIFTY50-Nxt =1 (26) conf:(0.84)
3.	Smallcap50 =1 MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (31)	NIFTY50-Nxt =1 (26) conf:(0.84)
4.	Commodities =1 MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (31)	NIFTY50-Nxt =1 (26) conf:(0.84)
5.	Smallcap50 =1 Commodities =1 MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (31)	NIFTY50-Nxt =1 (26) conf:(0.84)
6.	FMCG =1 IT =1 Metal =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	NIFTY50-Nxt =1 (25) conf:(0.83)
7.	IT =1 Media =1 Metal =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	NIFTY50-Nxt =1 (25) conf:(0.83)

8.	Smallcap50 =1 CPSE =1 FMCG =1 Media =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
9.	Smallcap50 =1 FMCG =1 IT =1 Metal =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
10.	Midcap50 =1 CPSE =1 FMCG =1 Media =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
11.	Midcap50 =1 MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
12.	Commodities =1 FMCG =1 IT =1 Metal =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
13.	Commodities =1 IT =1 Media =1 Metal =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
14.	CPSE =1 MNC =1 FMCG =1 Media =1 Realty =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)
15.	Smallcap50 =1 Midcap50 =1 MNC =1 FMCG =1 IT =1 Metal =1 Cons_Durables =1 Oil-Gas =1 (30)	==>	NIFTY50-Nxt =1 (25) conf:(0.83)

- Rule#1 identifies a frequently occurring antecedent pattern of rise in CPSE,FMCG, Media, Realty, Consumer durable and Oil Gas. The consequent is the rise in Nifty. As this is observed in 26 days out of 31 days, the rule has a confidence of 84%.
 - Rule#2 identifies another antecedent pattern of rise in MNC, FMCG, IT, Metal, Cons_Durables, and Oil-Gas. The consequent is the rise in Nifty. As this is observed in 26 days out of 31 days, the rule has a confidence of 84%.
 - Rule#3 identifies a frequently occurring antecedent pattern of rise in smallcap50, MNC, FMCG, IT, Metal, Consumer durables and Oil Gas. The consequent is the rise in Nifty. This rule too has a confidence of 84%.
- Thus the other rules can be interpreted similarly. These predictive rules offer early signals for market movement based on current sectoral behavior. In summary, the generated association rules help to identify sectors most aligned with market movement (co-movement) and to forecast NIFTY's short-term direction with statistically significant confidence. This dual approach enhances market understanding for analysts, investors, and policymakers.

Conclusion

In today's globally integrated economic landscape, stock markets are continuously influenced by a wide array of factors - including domestic and global developments, political shifts, natural calamities, unforeseen events, and investor sentiment. This dynamic nature generates a massive trail of data, posing both challenges and opportunities. In this context, data analytics serves as a crucial tool, transforming raw data into actionable insights and preventing information overload. This study applied the renowned Apriori algorithm - traditionally used for market basket analysis - to identify association rules in the Indian stock market. Using daily closing prices of 20 sectoral and thematic indices along with the NSE NIFTY 50 for the calendar year 2024, the data was transformed into a transactional format for analysis.

The Apriori algorithm successfully generated high-confidence association rules that revealed significant co-movement patterns and next-day predictive trends. All generated rules pointed to bullish outcomes, with no strong rules identified for bearish movements. This asymmetry suggests that predicting a market uptrend is computationally more feasible than forecasting a downturn - an insight that aligns with prior research in behavioral finance and market complexity. The findings demonstrate the practical value of association rule mining in financial analytics. The derived rules can aid investors, financial analysts, and regulators in understanding the interrelationships among different sectors and their influence on overall market trends.

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