CDS513 PREDICTIVE BUSINESS ANALYTICS

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Final Report

Implementing Predictive Business Analytics in Retail Business

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Group Contribution

Name	Matric No	Task
PHILIP TEU PUI LIK	P-COM0020/19	Problem Statement The Objective Motivation Scope & Limitations Methodology Experiments & Analysis Combining Poster
CHAN HUAN YANG	P-COM0068/19	Problem Statement Methodology Experiments & Analysis(Main)
CHENG XIYANG	P-COM0164/18	Abstract Problem Background Methodology Experiments & Analysis Conclusion & Future Work

Abstract

Usually, traditional retailers are just querying the data but they don’t make further analytics these data. While, modern retailer is using data science techniques especially business analytics to gain business insights from these data.

Business analytics is being used within the information technology industry to refer to the use of computing to gain insight from data. By using predictive business analytics, modern retailer seeks to leverage the digitized data from transaction systems and automated business processes to gain improved insight about their business operations. Also, it allows modern retailer to predict the trend of the marketplace.

In this study, we implement predictive business analytics in retail business. Market Basket Analysis is used to identify associated retail products. Also, recommender system is built to suggest customer items needed. In addition, ARIMA will be adopted to forecast number of customer while Random Forest is applied to forecast the demand. Based on experiments and results, an in-depth observation and analysis are performed. Marketing Strategies are proposed based on the findings. Finally, the study is concluded.

Problem Background

Retail is one of the most data-driven industries in the world. The retail industry is oriented towards individual consumers and groups in society, providing them with daily consumer goods and related services. The traditional retail sales terminal models include supermarkets, department stores, and convenience stores. The new retail sales terminal models of modern retail industry are chain supermarkets and chain stores.

Due to the rapid development of the market industry, the traditional retailers are facing increasingly fierce market competition. The traditional retailer once accounted for most of the shares, but later, the emergence of modern retailer broke this scenario, and expanded the scale of retail industry, so that the industry output value of retail industry increased. Compare with traditional retailer, the modern retailer adopted various business analytics methods especially predictive business analytics. Modern retailer uses predict business analytics to understand consumer behavior and to better predict the trend of the marketplace.

Business analytics is being used within the information technology industry to refer to the use of computing to gain insight from data. The data may be obtained from a company’s internal sources, third part data provider or public sources. One category of the business analytics methods, predictive analytics is using data to find out what could happen in the future. It predicts future probabilities and trends and finds relationships in data not clear with old-style analysis. In particular, predictive analytics uses data and mathematical techniques to uncover explanatory and predictive models of business performance representing the inherit relationship between data inputs and outputs. Predictive analytics is applied both in real time to affect the operational process and in batch. These predictions are made by examining data about the past, detecting patterns or relationships in this data and then extrapolating these relationships forward in time [1].

There are some existing cases of implementing predictive business analytics in retail business. By using Market Basket Analysis, Isti Surjandari and Annury Citra Seruni able to identify associated products, which then grouped in mix merchandise. This association between products then will be applied in the design layout of the product in the supermarket. The process of identifying the related products bought together in one transaction is done by using data mining technique. Apriori algorithm is chosen as a method in the data mining process. Using WEKA (Waikato Environment for Knowledge Analysis) software, the association rule between products is calculated. The results found five category association rules and fourteen sub-category association rules. These associations then will be interpreted as confidence and support to become consideration for the product layout [2].

Ayse Nur Sagın et al. conducted on a five-and-a-half year data of a large hardware company operating in the retail sector, and related product categories were identified by using Market Basket Analysis. In determining the association rules, both the Apriori and FP-Growth algorithms were run separately and their usefulness in such a set of data was compared. In addition, the data set was divided into Data Set-1 and Data Set-2 so that the consistency of the rules was discussed by comparing the correctness of rules extracted from the first data set with rules derived from the second data set containing consecutive timed data [3].

Marko Svetina and Jože Zupančič investigated a case of the company Merkur d.d., Slovenia, a trading company dealing in items for home improvement. The business intelligence system and market basket methodology used in Merkur are described. Use of market basket analyses in Merkur is explained and analyzed. In particular, the paper addresses issues such as sales promotion campaigns, placement of goods in retail stores, education of salespeople, offering system solutions and segmentation of customers. The discussed topics are explained using practical examples and guidelines for adequate business decisions. Their study demonstrated that market basket analyses are useful for Merkur, but a better direct marketing strategy must be defined and implemented [4].

Patrícia Ramos et al. compared the forecasting performance of state space models and ARIMA models. The forecasting performance is demonstrated through case study of retail sales of five different categories of women foot wear: Boots, Booties, Flats, Sandals and Shoes. On both methodologies the model with the minimum value of Akaike's Information Criteria for the in sample period was selected from all admissible models for further evaluation in the out-of-sample. Both one-step and multiple-step forecasts were produced. The results show that when an automatic algorithm the overall out-of-sample forecasting performance of state space and ARIMA models evaluated via RMSE, MAE and MAPE is quite similar on both one-step and multi-step forecasts. They also conclude that state space and ARIMA produce coverage probabilities that are close to the nominal rates for both one-step and multi-step forecasts [5].

Anastasia Griva et al. propose a business analytics approach that mines customer visit segments from basket sales data. They characterize a customer visit by the purchased product categories in the basket and identify the shopping intention or mission behind the visit e.g. a ‘breakfast’ visit to purchase cereal, milk, bread, cheese etc. They also suggest a semi-supervised feature selection approach that uses the product taxonomy as input and suggests customized categories as output. This approach is utilized to balance the product taxonomy tree that has a significant effect on the data mining results. They demonstrate the utility of our approach by applying it to a real case of a major European fast-moving consumer goods (FMCG) retailer. Apart from its theoretical contribution, the proposed approach extracts knowledge that may support several decisions ranging from marketing campaigns per customer segment, redesign of a store’s layout to product recommendations [6].

Problem Statement

The retail industry is usually a driving force in majority of countries economy, so it is part of the perception of the economy on how the retail industry is performing. However, the retail industry constantly changing and there are always new challenges faced by the players in this competitive industry.

One of the major challenges is how to understand customer behavior better. There are a lot of hidden customer purchasing patterns in transactional data. These patterns unable to be disclosed by traditional methods.

Another challenge is how to improving the chain operations efficiency and minimizing wastes. For example, improve staff planning and goods costing for a busines. Efficiency of chain operations is a key factor in creating brand loyalty and directly impact the turnover. One of the common mistakes made by retailers is ignoring the chain operation problem. If we keep this mindset, it is hard to sustain the business growth.

In this study, we propose to apply some predictive business analytics methods in retail business: Market Basket Analysis, Recommend System, Time Series Forecasting (ARIMA & Random Forest) to solve corresponding problems.

Objectives

The objectives of this project are as below:

- To gain business insight by implementing predictive business analytics in retail business.
- To identify associated products through market basket analysis
- To build recommender system for retailer
- To forecast number of customer and demand by time series forecasting.

Motivation

One of motivations of this project is to understand customer interest. Through this project, retailer can understand what consumers are likely to buy and not buy. In further, retailer can build more effective marketing program to encourage customer to spend more in further to increase retailer's revenue. Also, retailer would not promote uninterested products.

Another motivation is to increase customer retention. A good recommender system will narrow down the consumer's choice. consumer will save time and effort to choose items needed. So, it will improve customer shopping experience and increase customer satisfaction. With customer satisfaction, retailer will gain more customer trust and loyalty. In other words, it will increase customer retention rate. In further, it will increase customer purchasing activity and drive sales.

Final motivation is to gain insight about improving the chain operations efficiency and minimizing wastes. Sales forecasting provides retailer with future demand trends in order to prepare for logistics, scheduling, and procurement plans.

Scope & Limitations

This project focuses on the implementing predictive business analytics in retail business. This project will be conducted based on consumer's transaction history data. To reveal the pattern and insights, Market Basket Analysis, recommender systems, and Time Series (ARIMA and machine learning approaches) are adopted to perform predictive business analytics. Due to large dataset, Google Colab is used instead of Rapidminer. The programming language used is python.

In market basket analysis section, market basket analysis will be conducted with FP-Growth algorithm to mine frequent itemsets. Also, recommender system is built based on implicit feedback which is consumer's transaction history. Therefore, explicit feedback is not with the scope of this project. This project will not consider industrial, economic and political conditions of corresponding retailer's countries in sales forecasting section.

Methodology

Data Science has rendered Business Intelligence to incorporate a wide range of business operations. With the massive increase in the volume of data, businesses need data scientists to analyze and derive meaningful insights from the data.

The meaningful insights will help the data science companies to analyze information at a large scale and gain necessary decision-making strategies. The process of decision making involves the evaluation and assessment of various factors involved in it.

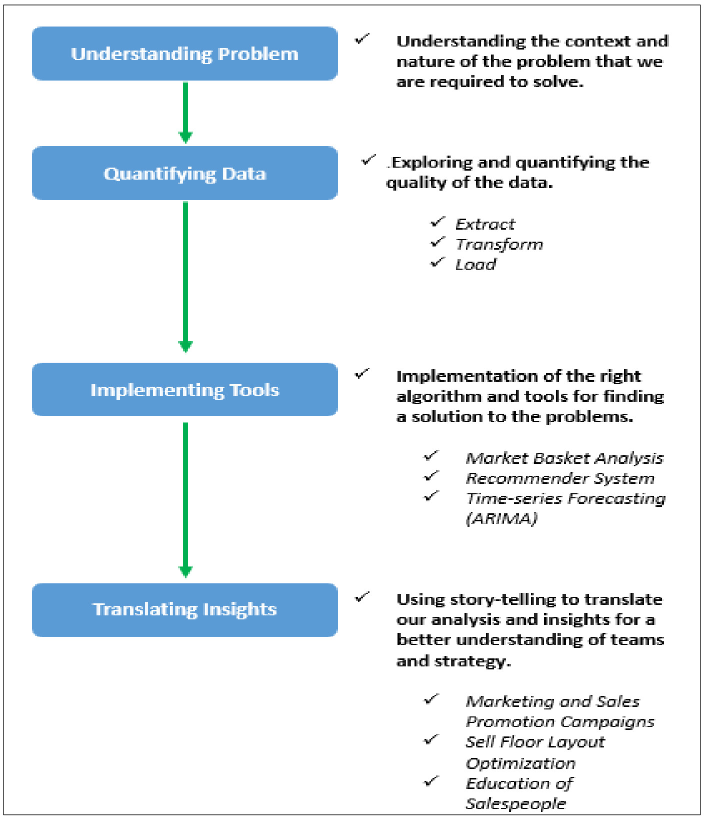


Figure 1: Project Framework

Phase 01 – Understanding Problem

Supermarket is a retail organization which contains large number of items, includes enormous customers and has more competitors. Company XXX is one of the leaders of the retail industry. The current scenario in the retail industry is characterized by its highly customer-centric nature. Retailers are leaving no stone unturned to discover new ways of getting to know their customers better.

Company XXX quickly realize that there is tough competition in the market and they need to make a more customer centric strategy to stand out in the market. Hence, we are appointed as their consultant to collect the most granular details of their customer behavior and build strategy accordingly to help Company XXX to increase their sales.

__Phase 02 – Quantifying Data__

The most important data that we need will be transactional data. Transactional data is by far the richest data throughout all industries. Transaction data is data describing an event (the change as a result of a transaction) and is usually described with verbs. Transaction data always has a time dimension, a numerical value and refers to one or more objects. The ETL process of data is described in figure below:

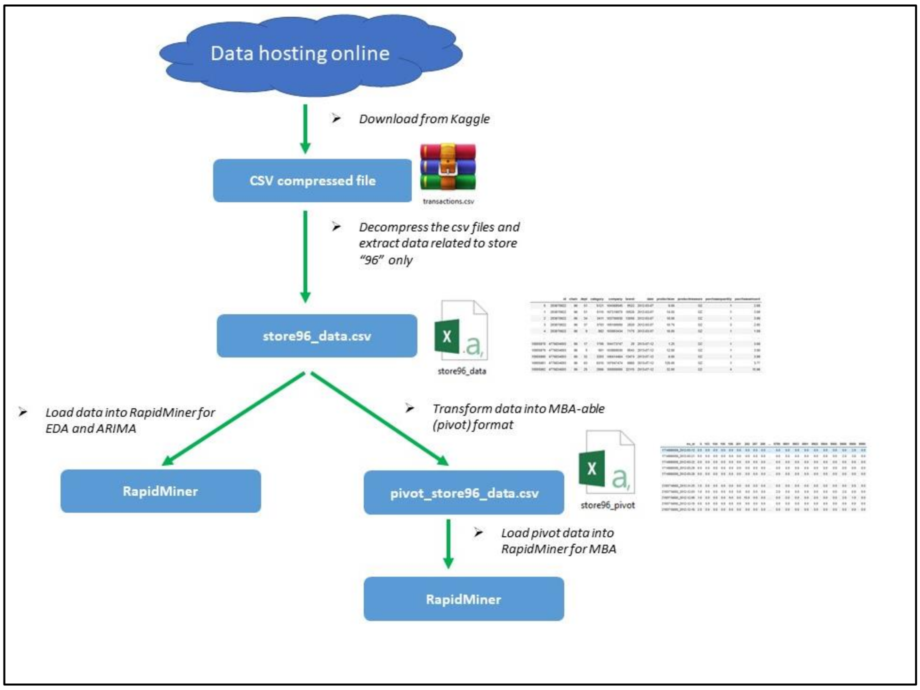


Figure 2: Extract, transform and load of data

Since our raw data is stored online, we need to download and save the data somewhere, then prepare it for visualization, analysis and decision-taking. The raw data we get is in a compressed csv format and it contains four relational csv files. We will only use the file ""transactions.csv" as it serves the objective of our project. However, to get the data down to a more manageable size, we extracted only records where the store chain equal to "96" by using Python. The table is then saved as "store96_data.csv".

In order to load data into Google Colab for Market Basket Analysis, we need to transform the table format type into pivot. This can be easily been done by using Python Pandas Dataframe pivot_table function. The pivot table is then saved as "store96_pivot.csv".

Phase 03 – Implementing Tools

To achieve the objectives of the project, we are going to perform three different approaches for the discovering of knowledge. They are:

- Market Basket Analysis
- Recommender Systems
- Time Series Forecasting (ARIMA)

Market Basket Analysis

Market basket analyses are an important component of analytical system in retail organizations. It is one of the key techniques used by large retailers to uncover associations between items. It works by looking for combinations of items that occur together frequently in transactions. To put it another way, it allows retailers to identify relationships between the items that people buy.

Recommender Systems

Recommender systems aim to predict users' interests and recommend product items that quite likely are interesting for them. They are among the most powerful machine learning systems that retailers implement in order to drive sales. Data required for recommender systems stems from explicit user ratings after watching a movie or listening to a song, from implicit search engine queries and purchase histories, or from other knowledge about the users/items themselves. Companies using recommender systems focus on increasing sales as a result of very personalized offers and an enhanced customer experience.

Time Series Forecasting (ARIMA)

A time series is a sequence where a metric is recorded over regular time intervals. Depending on the frequency, a time series can be of yearly (ex: annual budget), quarterly (ex: expenses), monthly (ex: air traffic), weekly (ex: sales qty), daily (ex: weather), hourly (ex: stocks price), minutes (ex: inbound calls in a call canter) and even seconds wise (ex: web traffic).

When explaining why demand forecasting is important, the answer spans across several areas of a retail business. One Retail Systems Research report found that nearly three-quarters of "winning" retailers rate demand forecasting technologies as "very important" to their business and their success. How does demand forecasting contribute to growing businesses? It mostly comes down to two things: becoming more cost-efficient and improving the customer experience.

The forecasting technique we are going to use is ARIMA. ARIMA, short for 'Auto Regressive Integrated Moving Average', is a forecasting algorithm based on the idea that the information in the past values of the time series can alone be used to predict the future values.

Phase 04 – Translating Insights

Strategy 1 - Marketing and Sales Promotion Campaigns

During a marketing and sales promotion campaign, by using recommender systems we could gain and retain customers by sending out emails with links to new offers that meet the recipients' interests. The user starts to feel known and understood and is more likely to buy additional products. By knowing what a user wants, the company gains competitive advantage and the threat of losing a customer to a competitor decreases.

Market basket analyses increase cross-selling and up-selling opportunities. We can do this since we know which products are top sellers and which ones drive the sales of extra items. We can market promotions around products that drive the sale of other products (especially high profit margin product) while at the same time avoid including both products on the same promotion since we know one will drive the sale of the other.

Time Series Forecasting (ARIMA) also playing an important role in marketing and sales promotion campaigns. An accurate demand forecasting is important in planning both advertising and marketing campaigns and budgets. It will also indirectly enhance the customer experience (avoid out-of-stocks, backorders, late shipments, etc. that may happen during campaigns).

Strategy 2 - Sell Floor Layout Optimization

Market basket analyses give retailer good information about related sales on group of goods basis. We could use this information to define a sell floor layout to induce clients to increase their in-store walking distance. We can assume that the increase of exposure of products due to longer in-store trips will indirectly increase unplanned purchases.

Strategy 3 - Education of Salespeople

The interesting results of both market basket analyses and recommender system must be presented to the salespeople in retail centers. The employees must be aware of them and they should use them in the process of selling and promoting the new product if necessary. Every salesperson has some knowledge about related items from his or her experience. With market basket analyses we can structure this knowledge and use it to teach less experienced personnel.

Data Description

The data used in this project belongs to an online source: https://www.kaggle.com/c/acquire-valued-shoppers-challenge/data.

The data contributor provides almost 350 million rows of completely anonymized transactional data from over 300,000 shoppers. This is a large data set and the “transactions.csv” file size is about 35GB without compression. To get the data down to a more manageable size, we extracted only transactions where the “chain” equal to “96”. This got the transactions down from about 20GB to about 1GB (15million records). All of the fields are anonymized and categorized to protect customer and sales information. The specific meanings of the fields are not provided. A negative value in productquantity and purchaseamount indicates a return.

Attribute	Description	Type
id	A unique id representing a customer	Categorical
chain	An integer representing a store chain	Categorical
dept	An aggregate grouping of the Category (e.g. water)	Categorical
category	The product category (e.g. sparkling water)	Categorical
company	An id of the company that sells the item	Categorical
brand	An id of the brand to which the item belongs	Categorical
date	The date of purchase	Ordinal
productsize	The amount of the product purchase (e.g. 16 oz of water)	Numerical
productmeasure	The units of the product purchase (e.g. ounces)	Categorical
purchasequantity	The number of units purchased	Numerical
purchaseamount	The dollar amount of the purchase	Numerical

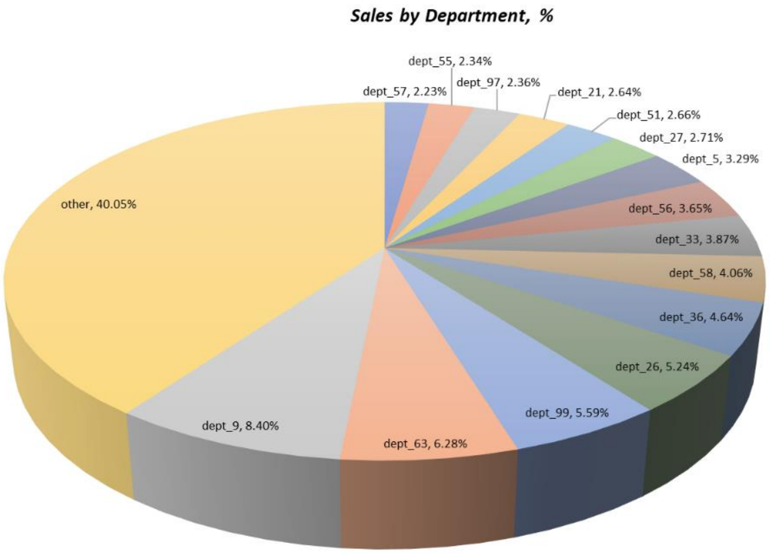
Table 1. Attributes and type of “transaction.csv”

EXPERIMENT AND ANALYSIS

Exploratory Data Analysis

In this section, we will explore the datasets provided, join information between some of them, and make relevant transformations. Let's start by exploring sales data by department, category, and item.

There is a total of 82 departments in the store. Department "dept_9" contributes the highest sales to the store with total sales of $4.2M (8.4% of total sales). Meanwhile department "dept_91" contributes the least with only a sales amount of $6.2k.



Row Labels	Sales, %	Sales, $
other	40.0%	20,282,266
dept_9	8.4%	4,253,573
dept_63	6.3%	3,181,814
dept_99	5.6%	2,829,390
dept_26	5.2%	2,654,417
dept_36	4.6%	2,349,645
dept_58	4.1%	2,056,356
dept_33	3.9%	1,960,157
dept_56	3.6%	1,846,758
dept_5	3.3%	1,667,359
dept_27	2.7%	1,373,222
dept_51	2.7%	1,344,836
dept_21	2.6%	1,338,034
dept_97	2.4%	1,194,412
dept_55	2.3%	1,186,552
dept_57	2.2%	1,128,123
Grand Total	**100.0%**	**50,646,913**

Figure 3: Sales by Department

There is a total of 778 product categories in the store. Product category "cat_907" contributes the highest sale to the store with total sales of $1.4M. If we plot all the product categories into the same chart, we can easily identify which product category is the high runner, which product category is low. By doing so, we can introduce a different price strategy based on a different type of runner. A high-runner product is another term for the top-performing products in store. A great example of a high runner product category in this store is "cat_907" and "cat_6305". These are the products that have the highest number of purchases, and which are eagerly sought after by the public. They are generally highly elastic and extremely sensitive to market price changes. With a high-runner strategy, we discount heavily on these high-visibility products to increase the number of customers into our store. This increases the amount of traffic in our store as well as the number of sales on that product. This is just the first step of the process though, and if we did this for every product in our assortment we'd end up losing money on margins. That's why the beauty of this strategy lies in what we do with the increased traffic. Once we have this traffic on our store, present consumers with upsells and cross-sells on inelastic products at full price.

Another way to use the high-runner strategy is to drive consumer perception about our store. If we consistently advertise ourselves as the lowest price on this high-visibility and high runner items, consumers will associate our store with low prices but high-quality products. As a result, we'll become their default store for any of their needs in our niche and increase their loyalty to our store.

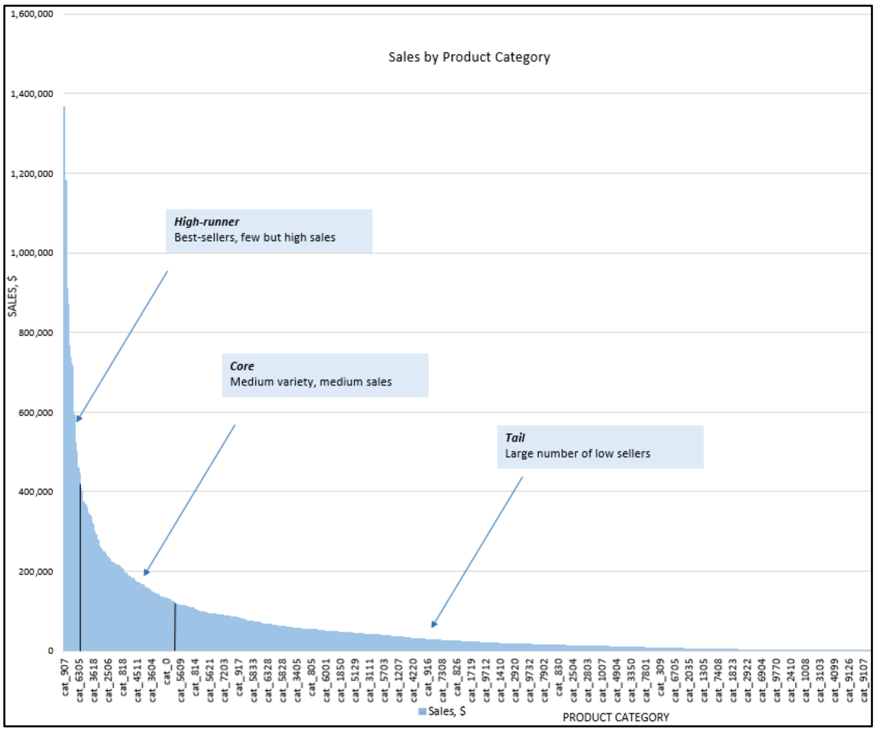


Figure 4: Sales by Product Category

We further drill down to sales by item level. There is a total of 13988 items in the store. Item "cat_9904_103338333_33170" is the best seller item with a sales amount of $0.55M.

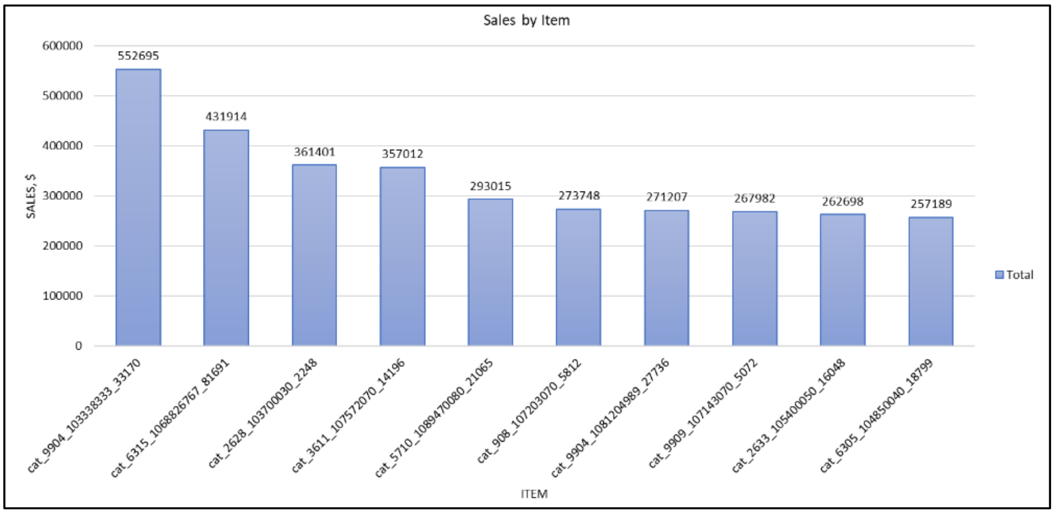


Figure 5: Top 10 Sales by Item

Let have a look at the spending habit. Seems like January, March, and December have a higher number of the customer. However, a higher number of customers will not necessarily convert into a higher amount of sales. We can see that although December is not having the highest number of customer however it has the highest sales. This leads us to further drill down to analyze the spending habit of the customer each month. From Figure 4, we can observe that customer generally has the lower spending power during Q2 and Q3. This could be due to several possible reasons such as lesser festive season, lesser promotion activity, or lesser public holiday during this period.

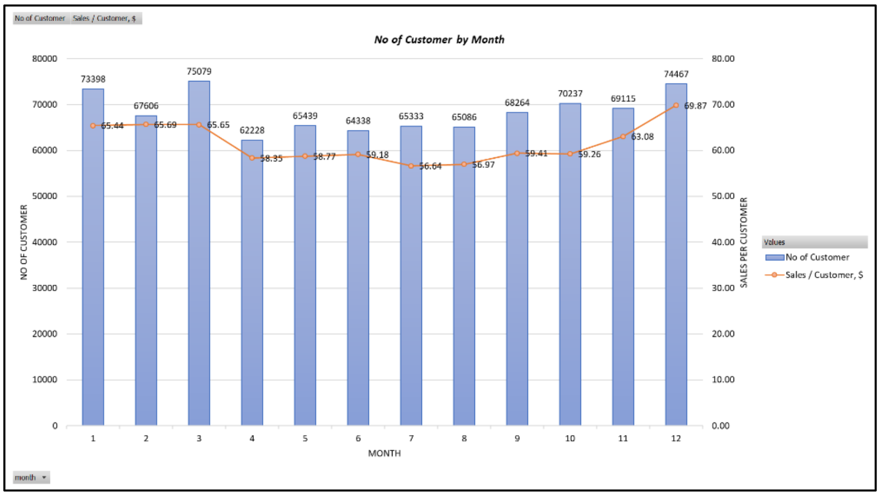


Figure 6: No of Customer by Month

Let have a look at the spending trend on the day of the week. There is a clear effect on the day of the week. Most of the sales happen on Friday, Saturday, and Sunday. This is quite understandable as during the weekend we have more free time to do shopping in the store. And also this is probably due to most of the promotion campaigns and events were only happened at the weekend.

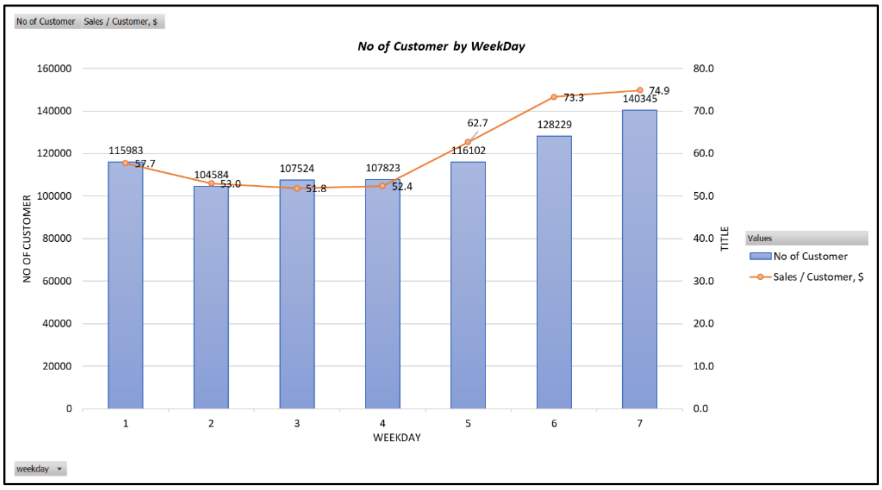


Figure 7: No of Customer by WeekDay

Market Basket Analysis

The Market Basket Analysis of the store is done using Python. At first, we have to get our pandas and MLxtend code imported and read the data. There is a little cleanup, we need to do. After the cleanup, we need to consolidate the items into 1 transaction per row with each product category 1 hot encoded. There are a lot of zeros in the data but we also need to make sure any positive values are converted to a 1 and anything less the 0 is set to 0. This step will complete the one-hot encoding of the data. Here's what the first few columns look like.

trx_id	cat_0	cat_1004	cat_1006	cat_1007	cat_1008	cat_1009	cat_1010	cat_1011	cat_1012
4427711419_2012-12-11	1	1	0	0	0	0	1	1	0
4427711419_2012-12-12	1	1	0	1	0	0	1	0	0
4427711419_2012-12-13	1	1	0	0	0	0	1	1	1
4427711419_2012-12-14	1	1	1	1	1	0	1	1	1
4427711419_2012-12-15	1	1	1	1	0	0	1	1	1
4427711419_2012-12-16	1	1	0	0	0	0	1	1	1
4427711419_2012-12-17	1	1	1	0	1	0	1	1	0
4427711419_2012-12-18	1	0	0	1	1	0	1	1	0
4427711419_2012-12-19	1	1	0	0	0	0	1	1	1
4427711419_2012-12-20	1	1	1	1	0	0	1	1	0

Table 2: Sample of the pivoted dataset for Market Basket Analysis

Now that the data is structured properly, we can generate frequent itemsets using apriori algorithm that have the support of at least 5%. Support is the percentage of transactions that contain all of the items in an itemset. The higher the support the more frequently the itemset occurs. Rules with high support are preferred since they are likely to apply to a large number of future transactions. There is a total of 73 frequent itemsets are generated. Here's what the first few rows of frequent itemset look like.

support	itemsets
0.324	cat_907
0.317	cat_6315
0.212	cat_9908
0.188	cat_9904
0.171	cat_9909
0.170	cat_6320
0.163	cat_501
0.153	cat_9753
0.152	cat_902
0.151	cat_6315, cat_907

Table 3: Sample of frequent itemsets

The final step is to generate the rules with their corresponding support, confidence, and lift. Confidence is the probability that a transaction that contains the items on the left-hand side of the rule (in our example, "cat_6315" and "cat_907") also contains the item on the right-hand side (a "cat_501"). The higher the confidence, the greater the likelihood that the item on the right-hand side will be purchased or, in other words, the greater the return rate we can expect for a given rule. Lift is the probability of all of the items in a rule occurring together (otherwise known as the support) divided by the product of the probabilities of the items on the left and right-hand side occurring as if there was no association between them. For example, if "cat_501", "cat_6315" and "cat_907" occurred together in 5.3% of all transactions, "cat_6315" and "cat_907" in 15.1% of transactions and "cat_501" in 16.3% of transactions, then the lift would be: 0.053/(0.151*0.163) = 2.148. A lift of more than 1 suggests that the presence of "cat_6315" and "cat_907" increases the probability that a cat_501 will also occur in the transaction. Overall, lift summarizes the strength of association between the products on the left and right-hand side of the rule; the larger the lift the greater the link between the two products. That's all there is to it! Build the frequent items using apriori then build the rules with association rules.

antecedents	consequents	antecedent support	consequnt support	support	confidence	lift
cat_501	cat_6315, cat_907	0.163	0.151	0.053	0.324	2.148
cat_6315, cat_907	cat_501	0.151	0.163	0.053	0.351	2.148
cat_6320	cat_6315, cat_907	0.170	0.151	0.055	0.321	2.122
cat_6315, cat_907	cat_6320	0.151	0.170	0.055	0.361	2.122
cat_6315	cat_501, cat_907	0.317	0.084	0.053	0.167	1.976
cat_501, cat_907	cat_6315	0.084	0.317	0.053	0.627	1.976
cat_6315	cat_6320, cat_907	0.317	0.087	0.055	0.172	1.972
cat_6320, cat_907	cat_6315	0.087	0.317	0.055	0.626	1.972
cat_9908	cat_9909	0.212	0.171	0.071	0.337	1.968
cat_9909	cat_9908	0.171	0.212	0.071	0.418	1.968
cat_9908	cat_9904	0.212	0.188	0.074	0.350	1.865
cat_9904	cat_9908	0.188	0.212	0.074	0.396	1.865
cat_9904	cat_9753	0.188	0.153	0.053	0.285	1.865
cat_9753	cat_9904	0.153	0.188	0.053	0.350	1.865
cat_907	cat_501, cat_6315	0.324	0.089	0.053	0.163	1.841
cat_501, cat_6315	cat_907	0.089	0.324	0.053	0.596	1.841
cat_9908	cat_9753	0.212	0.153	0.060	0.281	1.840
cat_9753	cat_9908	0.153	0.212	0.060	0.390	1.840
cat_9904	cat_9909	0.188	0.171	0.058	0.309	1.808
cat_9909	cat_9904	0.171	0.188	0.058	0.339	1.808
cat_907	cat_6315, cat_6320	0.324	0.094	0.055	0.169	1.801
cat_6315, cat_6320	cat_907	0.094	0.324	0.055	0.583	1.801

Table 4: Sample of rules generated by Market Basket Analysis

Now, the tricky part is figuring out what this tells us. For instance, we can see that there are quite a few rules with a high lift value which means that it occurs more frequently than would be expected given the number of transactions and product combinations. We can also see several where the confidence is high as well. This part of the analysis is where the domain knowledge will come in handy and creates actionable insights for:

- designing store layout
- building pricing strategies
- targeted marketing and cross-selling

We will just look for a couple of illustrative examples.

Designing store layout

Based on the insights from market basket analysis we can organize our store to increase revenues. Items that go along with each other (for example those rules with lift > 1) should be placed near each other to help consumers notice them. This will guide the way a store should be organized to shoot for the best revenues. With the help of this data, we can eliminate the guesswork while determining the optimal store layout.

Building pricing strategies

When we recognize a pattern in SKUs about frequent concurrent sales of two or more items, we can also determine the effect of markdowns or markups on the sales of these items and build a more profitable pricing strategy.

For instance, using our rule build with association rules, “cat_9908” and “cat_9909” have a high affinity of being bought together. Furthermore, currently, we give a discount on “cat_9909” every Monday. Now, by doing a market basket analysis we find out that irrespective of the day of the week, “cat_9909” is always bought alongside “cat_9908”, then it would mean that the Monday markdowns do not affect its sale in any way and therefore, we can stop giving the markdowns altogether.

Targeted marketing and cross-selling

We can leverage association rules applied to customer shopping baskets to pave way for targeted marketing aimed at increasing customer spend. At this point, we may want to look at how much opportunity there is to use the popularity of one product to drive sales of another. For instance, based on the table, we can see that we sell 280822 units of “cat_9908” but only 194571 units of “cat_9909” so maybe we can drive more “cat_9909” sales through target marketing, for example, email customers that purchased product ”cat_9908” with a discount coupon for product “cat_9909”.

antecedents	consequents	antecedent qty	consequent qty	ratio of qty	support	confidence	lift
cat_9908	cat_9909	280822	194571	1.44	0.071	0.337	1.968
cat_9909	cat_9908	194571	280822	1.44	0.071	0.418	1.968
cat_9908	cat_9904	280822	244175	1.15	0.074	0.350	1.865
cat_9904	cat_9908	244175	280822	1.15	0.074	0.396	1.865
cat_9904	cat_9753	244175	216200	1.13	0.053	0.285	1.865
cat_9753	cat_9904	216200	244175	1.13	0.053	0.350	1.865
cat_9908	cat_9753	280822	216200	1.30	0.060	0.281	1.840
cat_9753	cat_9908	216200	280822	1.30	0.060	0.390	1.840
cat_9904	cat_9909	244175	194571	1.25	0.058	0.309	1.808
cat_9909	cat_9904	194571	244175	1.25	0.058	0.339	1.808

Table 5: Antecendent and consequent qty

Whether it is email, phone, social media, or an offer by a direct promoter, market basket analysis can improve the efficiency of all of them. By using rules from MBA we can suggest the next best product which a customer is likely to buy. Hence we will help our customers with fruitful suggestions instead of annoying them with marketing blasts.

Cross-selling is another practice of increasing sales by promoting related products alongside the items a customer is looking at or buying. The key is offering products that are complementary to the primary one they're looking at. This makes the items being promoted more attractive because the customer will see how they enhance their original purchase.

Cross-selling allows us to bundle in less-expensive items the customer is more likely to buy on impulse. Using the example “cat_6315, cat_907”, retailers could show customers a “cat_501” as add-ons during the checkout process. Many consumers who are already spending $6.77 on a combo “cat_6315, cat_907” (cat_6315 = $3.47, cat_907 = $3.30), won't think too much about product “cat_501” (cat_501 = $3.83) or stop to compare our prices to the competition. Instead, they'll go ahead and add it to their cart and pay for the convenience of a packaged delivery. They're also paying for the assurance that the products work well together so they won't need to go through the hassle of returning a defunct product. By using this strategy we able to increase our sales by an extra $3.83!

Recommender Systems

An SVD recommender system of retail was created using the Surprise library in Python. The famous SVD algorithm, as popularized by Simon Funk during the Netflix Prize is a Matrix Factorization techniques While user-based or item-based collaborative filtering methods are simple and intuitive, Matrix Factorization techniques are usually more effective because they allow us to discover the latent features underlying the interactions between users and items. We don't know these latent features. It employs the use of gradient descent to minimize the squared error between predicted rating and actual rating, eventually getting the best model.

At first, we have read the data and do a little cleanup. After the cleanup, we need to provide an implicit rating for our dataset since our dataset doesn't have any customer explicit ratings for the product. The implicit rating can be derived using the purchase history of customers. For example, a customer that purchased the same item frequently probably likes that item. Hence, the more frequent a customer purchases an item, the higher the rating will be given. Figure 5 below illustrates how we provide the implicit ratings for our “Item B”

Step 1:
Aggregate the total purchase amount of Item B for each customer

Customer ID	Item B Total Purchase Amount
customer_01	1000
customer_02	345
customer_03	300
customer_04	200
customer_05	70
customer_06	57
customer_07	44
customer_08	31
customer_09	18
customer_10	5

Step 2:
Locate the percentile value of the total purchase amount of Item B

Percentile	Value
25%	34.3
50%	63.5
75%	275.0

Step 3:
Develop scale (1-4) rating system based on the range of each percentile boundary

Rating Given	Range of Total Purchase Amount
1	0.0 < x <= 34.3
2	34.3 < x <= 63.5
3	63.5 < x <= 275.0
4	275.0 < x

Step 4:
Assign a rating for each customer by checking on which rating category their purchase amount falls into

Customer ID	Item B Total Purchase Amount	Rating Given for Item B
customer_01	1000	4
customer_02	345	4
customer_03	300	4
customer_04	200	3
customer_05	70	3
customer_06	57	2
customer_07	44	2
customer_08	31	1
customer_09	18	1
customer_10	5	1

Figure 8: How to implement implicit rating using customer historical purchase record

Now we will split our dataset for 5-fold cross-validation, and compute the MAE of the SVD algorithm. Below is the output of the 5-fold cross-validation.

```
Evaluating MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
MAE (testset)     0.9406  0.9407  0.9403  0.9412  0.9415  0.9409  0.0004
Fit time          106.72  110.88  105.74  106.25  105.82  107.08  1.93
Test time         6.79    5.96    5.79    5.23    5.76    5.91    0.50
```

Figure 9: Performance of algorithm SVD on 5 splits

The MAE of our SVD model is around 0.94 which is not bad at all. The final step is to fit our data into the model and then predict the rating for all pairs (customer-item pair) that are not in the dataset. Now we’ve fitted the model. To recommend the best products to customers, we only generate customer-item pairs that have the predicted rating higher than three. In the end, a total of 432084 customer-item pairs are generated for 11057 different customers.

Customer ID	Item	Predicted Rating
4427711419	cat_7005	3.85
4427711419	cat_799	3.78
4427711419	cat_3103	3.30
4427711419	cat_9899	3.75
4427711419	cat_7109	4.00
4427711419	cat_9733	3.83
4440809528	cat_1102	3.23
4440809528	cat_1411	3.19
4440809528	cat_1415	3.04
4440809528	cat_1416	3.14
4440809528	cat_1604	3.01
4440809528	cat_1707	3.07
4440809528	cat_1841	3.17
4440809528	cat_1854	3.10
4440809528	cat_212	3.14
4440809528	cat_2210	3.18
4440809528	cat_2214	3.23
4440809528	cat_2501	3.11

Table 6: Sample outputs generated by the recommendation engine

Targeted marketing and cross-selling

Similar to Market Basket Analysis, results generated using a recommender engine could be used as a targeted marketing tool. Traditionally, retail stores and supermarkets offer their goods via outdoor advertising, radio advertising, and mobile applications. However, ads work even better when it is personal. A recommender system turns impersonal advertisement into customized and appealing offers. For example, we could send emails targeted at products that the customer has not yet purchase before. As a result, both customers and retailers benefit from the recommendations.

Business is successful when it is beneficial for clients and solves their problems. Recommendations simplify daily shopping and help to not overlook something. That's why customers are happy and willing to pay for what they really need.

How recommendations boost retail

- Help to understand what customers really need
- The personal approach increases customers' loyalty by saving their time
- Motivate people to buy more
- We can create demand for new products by adding them to suggestions

Customer Number Forecasting using ARIMA

The forecasting future customer inflow numbers of the store is done using Python. At first, we have to get our packages imported and read the data. There is a little cleanup, we need to do. After the cleanup, we need to aggregate the total number of customers by date. Here’s what the first few rows of dataset look like.

min date:2012-04-01 00:00:00, max date:2013-03-31 00:00:00

	date	id
0	2012-04-01	2439.0
1	2012-04-02	2098.0
2	2012-04-03	1895.0
3	2012-04-04	1916.0
4	2012-04-05	2109.0
...	...	...
360	2013-03-27	2094.0
361	2013-03-28	2184.0
362	2013-03-29	2705.0
363	2013-03-30	3262.0
364	2013-03-31	1514.0

365 rows × 2 columns

Figure 10: Time series data of customer by date

The data is also plotted as a time series with the date along the x-axis and customer figures on the y-axis.

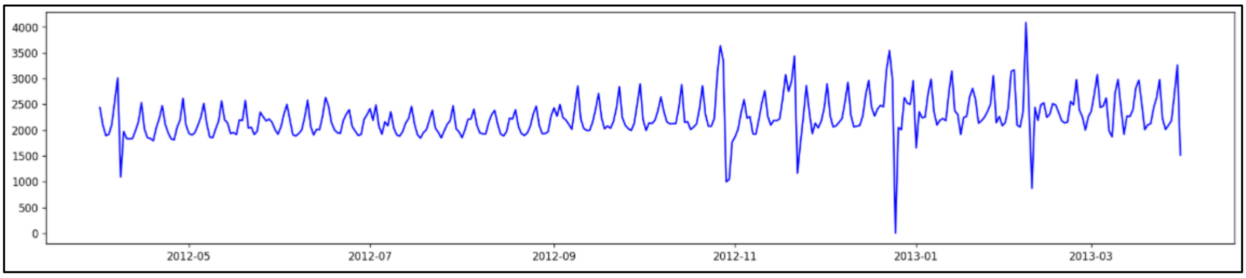


Figure 11: Time Series chart of customers

We must develop a test harness to investigate the data and evaluate candidate models. The dataset is not current. This means that we cannot easily collect updated data to validate the model. Therefore we will pretend that it is February 2013 and withhold the last two months of data from analysis and model selection. These final two months of data will be used to validate the final model. The specific contents of these training and validation sets are:

- training set: Observations from 2012-04-01 to 2013-01-31 (306 observations)
- validation set: Observations from 2013-02-01 to 2013-03-31 (59 observations)

The validation dataset is about 16% of the original dataset.

Trend & Seasonality are two reasons why a Time Series is not stationary & hence need to be corrected. Before applying any statistical model on a Time Series, the series has to be stationary, which means that, over different periods,

- It should have a constant mean.
- It should have a constant variance or standard deviation.
- Auto-covariance should not depend on time.

We've performed the Augmented Dickey-Fuller test to check for stationarity of a Time Series. Because we need differencing only if the series is non-stationary. Else, no differencing is needed, that is, d=0. The null hypothesis of the ADF test is that the time series is non-stationary. So, if the p-value of the test is less than the significance level (0.05) then we reject the null hypothesis and infer that the time series is indeed stationary. So, in our case, the p-value is 0.153 which means that we need to do the differencing.

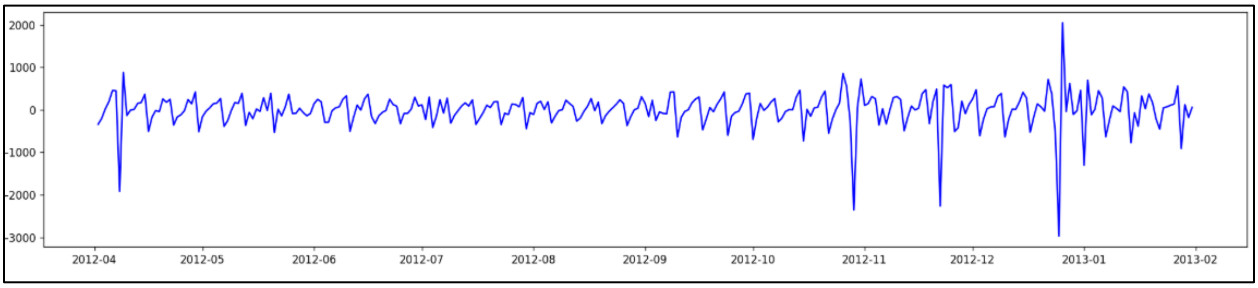


Figure 12: Time Series chart after differencing (order = 1)

The next first step is to select the lag values for Autoregression (AR) and Moving Average (MA) parameters, p, and q respectively. We can do this by reviewing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Note, we are now using the differenced data (order = 1) to plot the ACF and PACF charts.

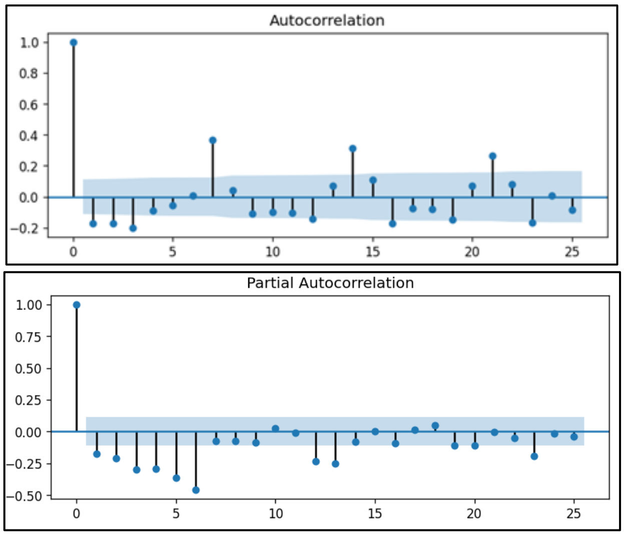


Figure 13: Partial autocorrelation (PACF) and Autocorrelation (ACF) chart

Below are some observations from the plots. The ACF shows a significant lag for 1,2,3,7,14,21. The PACF shows a significant lag for 1,2,3,4,5,6, with perhaps some significant lag at 12 and 13 days. Both the ACF and PACF show a drop-off at the same point, perhaps suggesting a mix of AR and MA. A good starting point for the p and q values is also 1. The ACF and PACF plots suggest that an ARIMA(1,1,1) or similar may be the best that we can do. To confirm this analysis, we grid search a suite of ARIMA hyperparameters and check that no models result in better out of sample MAE performance. We will search for all combinations of the following parameters:

- p: 1 to 3
- d: 0 and 1
- q: 1 to 3

Below are the model results and reports generated from those ARIMA models that converge without error:

p,d,q	aic	bic	mae
1,0,1	4449	4464	350.96
1,0,2	4451	4470	350.76
1,0,3	4440	4463	351.94
2,0,1	4436	4454	350.74
2,0,2	4391	4414	324.97
2,0,3	4377	4403	315.49
2,1,1	4413	4431	318.83
2,1,2	4385	4408	316.05
3,0,1	4433	4456	350.60
3,1,1	4389	4412	314.94
3,1,2	4381	4407	316.39
3,1,3	4358	4388	264.28

Figure 14: Performance of ARIMA models

The Akaike Information Criteria (AIC) is a widely used measure of a statistical model. It quantifies the goodness of fit, and the simplicity/parsimony, of the model into a single statistic. When comparing multiple models, the one with the lower AIC is generally “better”. By checking Figure 11, the ARIMA model with parameter (3,1,3) is the best fit ARIMA model as it showing the lowest AIC and BIC values.

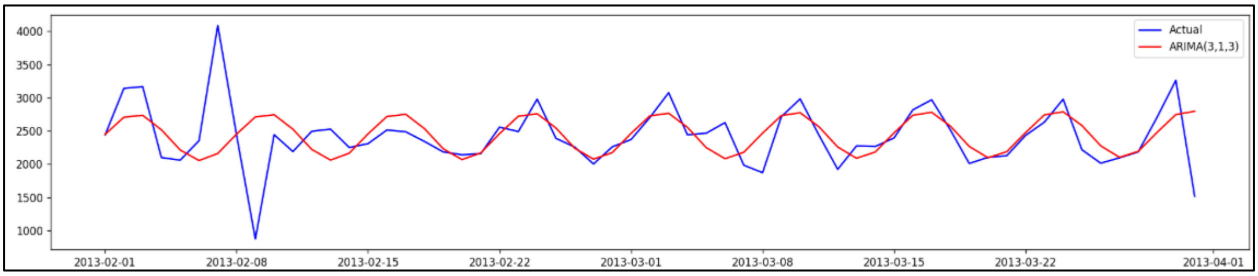
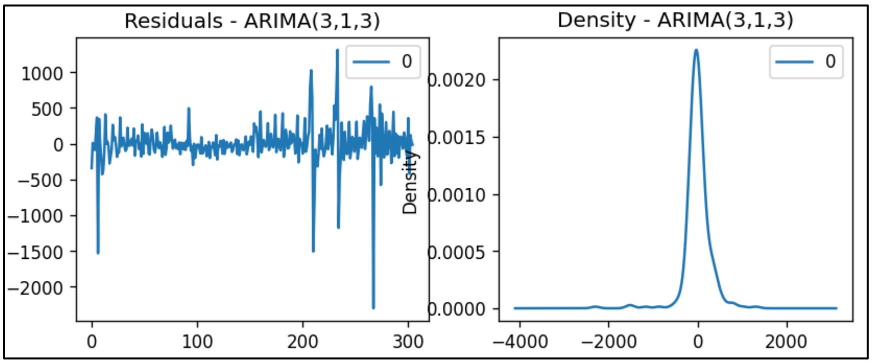


Figure 15: Actual customer no. vs predicted customer no. using ARIMA(3,1,3) model

A good final check of models is to review residual forecast errors. Ideally, the distribution of residual errors should be a Gaussian with a zero mean. The plots (Figure 16) of the residual errors show that the mean values of our ARIMA(3,1,3) model is very close to zero.



Residuals - ARIMA(3,1,3)

	0
count	305.000000
mean	1.509218
std	293.322927
min	-2299.508243
25%	-101.582198
50%	-12.764205
75%	91.939952
max	1310.381014

Figure 16: Residual errors of ARIMA(3,1,3) model

It is also a good idea to check the time series of the residual errors for any type of autocorrelation. If present, it would suggest that the model has more opportunity to model the temporal structure in the data. By checking Figure 14, The results suggest that very little autocorrelation is present in the time series has been captured by the models.

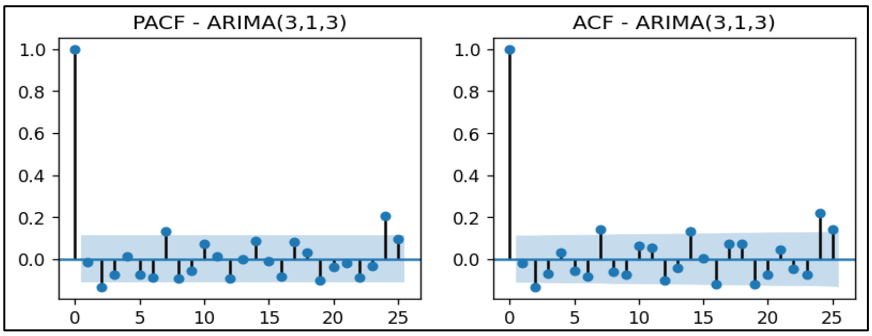


Figure 17: ACF and PACF of residuals of the ARIMA(3,1,3) model

The final step is to generate the forecast of the next 6 months (180 days) starting from 2013-04-01 by using ARIMA(3,1,3) model.

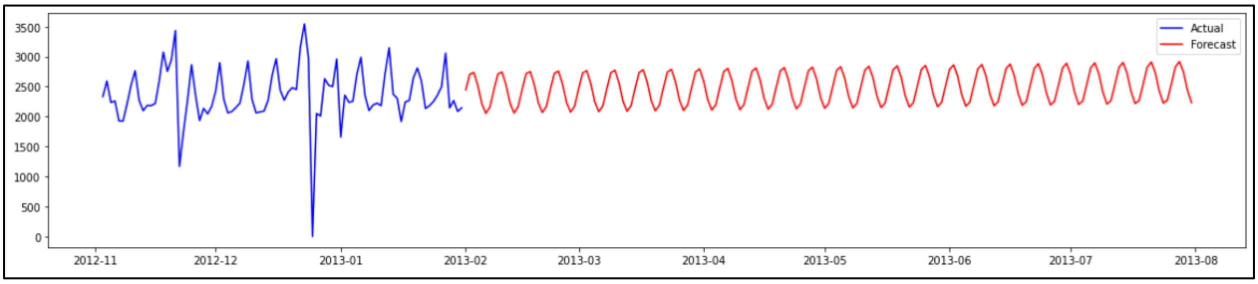


Figure 18: Forecast of the customer no. for the next 180days

Efficient staff planning using forecasting

Having accurate forecasting of the future customer number is very important for a retail store. We can use this information to make operational decisions. For instance, by looking at the peaks of the forecast chart, the high traffic in the number of customers is happening at the weekend. Hence, when we anticipate a bigger customer number, we can bring in additional staff to handle the increased traffic.

As a business owner, our primary goal is to increase profit. This requires a careful balance of resources, expenditures, pricing, and numerous other factors intended to ensure that we earn more than we spend. And when we own and operate a retail store, our staff plays a major role in our bottom line. Payroll can take a big chunk out of our budget if we don't manage it wisely. But our retail staff is also a crucial component of the customer experience. If we skimp on staffing, customers may not receive the help they need with product questions, they may have to wait in prohibitively long lines to make purchases, and their experience may cause them to walk away without making a purchase. On top of all that, they may refuse to return to our store, or even complain to other consumers, quashing potential future sales in the process. Hence, having an accurate forecasting

Demand Forecasting using Random Forest

The forecasting of future demand for a high runner product of the store is done using Python. At first, we have to get our packages imported and read the data. There is a little cleanup, we need to do. The store top seller item is 'cat_9904_103338333_33170'. After the cleanup, we need to aggregate the total purchase quantity of 'cat_9904_103338333_33170' by date. Same as ARIMA, the entire record (365 days) was divided into two parts as the training set (2012-04-01 to 2013-01-31) and validation set (2013-02-01 to 2013-03-31) periods. However extra steps have to be done to transform the time series to supervised machine learning by adding lags. Lags are the shift of the data one step or more backward in the time. A total of 10 different lag values have been chosen. They are 1, 2, 3, 4, 5, 6, 7, 14, 21, and 28. Lags 14, 21, and 28 were chosen to represent the weekly cyclic nature of data.

min date:2012-04-01 00:00:00, max date:2013-03-31 00:00:00

	Date	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	Lag_6	Lag_7	Lag_14	Lag_21	Lag_28	Qty
28	2012-04-29	502.0	383.0	234.0	225.0	271.0	375.0	598.0	448.0	188.0	720.0	608.0
29	2012-04-30	608.0	502.0	383.0	234.0	225.0	271.0	375.0	281.0	319.0	445.0	381.0
30	2012-05-01	381.0	608.0	502.0	383.0	234.0	225.0	271.0	208.0	340.0	294.0	373.0
31	2012-05-02	373.0	381.0	608.0	502.0	383.0	234.0	225.0	174.0	227.0	343.0	283.0
32	2012-05-03	283.0	373.0	381.0	608.0	502.0	383.0	234.0	156.0	230.0	334.0	252.0
...	...	...	...	...	...	...	...	...	...	...	...	...
360	2013-03-27	216.0	344.0	536.0	400.0	292.0	257.0	264.0	417.0	162.0	186.0	183.0
361	2013-03-28	183.0	216.0	344.0	536.0	400.0	292.0	257.0	363.0	112.0	222.0	258.0
362	2013-03-29	258.0	183.0	216.0	344.0	536.0	400.0	292.0	287.0	132.0	286.0	431.0
363	2013-03-30	431.0	258.0	183.0	216.0	344.0	536.0	400.0	351.0	340.0	251.0	490.0
364	2013-03-31	490.0	431.0	258.0	183.0	216.0	344.0	536.0	448.0	620.0	235.0	159.0

Figure 19: Dataset for Random Forest Regressor

Random Forest algorithm is created to make the forecasting. It is an ensemble machine learning technique capable of performing both regression and classification tasks using multiple decision trees and a statistical technique called bagging. The model's performance turns out to have a mean absolute error (MAE) of 72.10 and no further hyperparameter tuning is carried out.

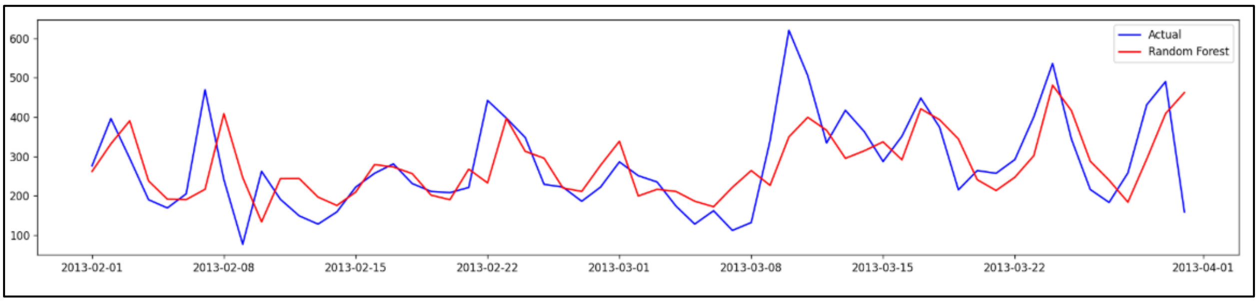
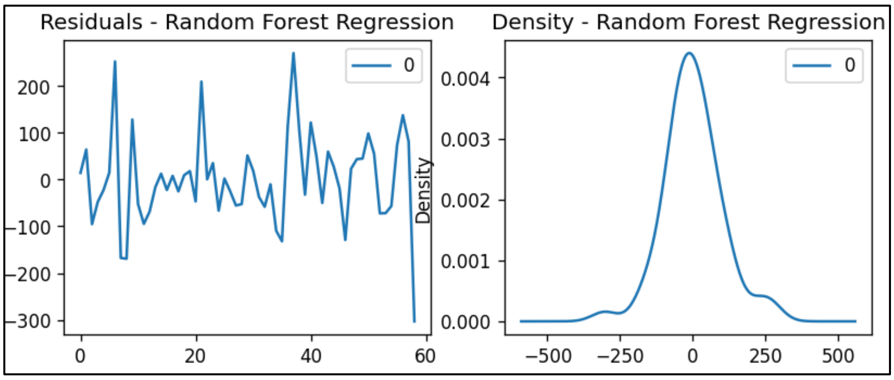


Figure 20: Actual quantity. vs predicted quantity using the Random Forest model

The plots of the residual errors also show that the mean value of the Random Forest model is very close to zero which is 0.631.




```
Random Forest

              0
count  59.000000
mean    0.631356
std    98.272280
min  -303.100000
25%   -53.975000
50%     0.650000
75%    50.200000
max   270.450000
```

Figure 21: Residual errors of the Random Forest model

The final step is to generate the forecast of the next 1 month (30 days) starting from 2013-04-01 by using the Random Forest model. Compare with ARIMA, using machine learning for time series is not suitable for long-range time forecasting as it will require more historical values to generate a training dataset. We will need more than 1-year data if we want to include a factor of yearly cyclic nature into the learning process.

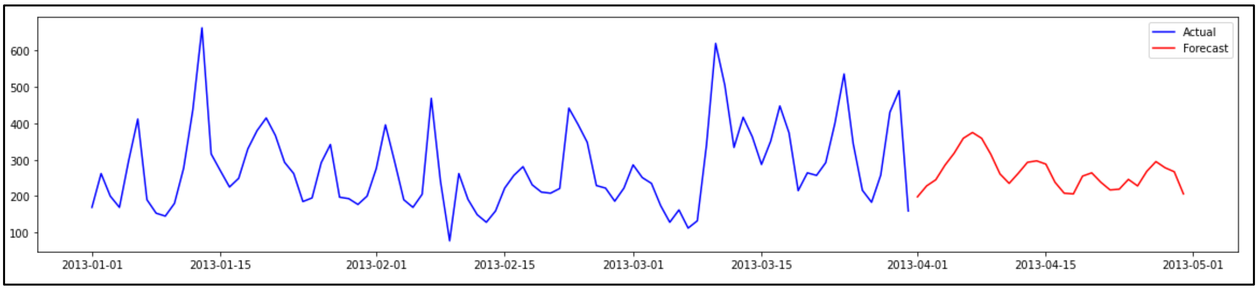


Figure 22: Forecast of the item 'cat_9904_103338333_33170' for the next 30days

<u>Demand forecasting makes our business more cost-efficient</u>

Now we have a proper demand forecasting process for our business, we can use it for cutting costs in a few ways.

Firstly, we're reducing the amount of capital we have tied up in unneeded inventory. And the less stock on hand we have, the lower our holding costs. Secondly, we're making sure we capitalize on every sale opportunity by not disappointing customers with out-of-stocks.

Those are the two most straightforward ways, but we can also use demand forecasting to operate a lean and agile business, only investing money in more stock when we need to. When we've forecasted demand, we can easily check-in before the period's over to see if we're on target to hit our predicted sales. If we're looking shy of our goal, we can ramp up marketing and advertising. If it looks like we've underestimated, we could reorder to cross-promote a related product.

Conclusion

In this project, we have implemented Market Basket Analysis, Recommender Systems and Time series for predicting business analytics in retail industry. These techniques help to design the store layout, build pricing strategies, perform targeted marketing and cross-selling. MBA allows retailers to identify the relationships between the items that people buy. By using Recommender Systems, companies focus on increasing sales as a result of very personalized offers and enhance customers experience. Such as we can create demand for new products by adding them to suggestions. ARIMA is helpful to predict the future values for the business.

According to the results and our understanding of the three techniques, each of the technique has their own advantages. MBA is very simple and intuitive to implement; Recommender Systems is able to personalize marketing strategies; ARIMA only need less data compare with random forest. In summary, all the three techniques MBA, RS, and ARIMA do help us to gain business insights. So, which technique to choose depends on the actual situation of the company.

Future research

The sales forecast research in this paper has achieved good forecast results on this dataset, due to time constraints, there are still some problems in the research process that need to be improved. In the future research work, the following deficiencies will be studied improve:

1. For Recommender Systems, we might try to do AB testing to prove our hypothesis. AB testing is very suitable to do online user evaluation, so we can create a recommender system with the help of AB testing.
2. For ARIMA models, all forecasting methods, are essentially backward looking. Such that, the long term forecast eventually goes to be straight line and poor at predicting series with turning points. So that we can maybe look for other techniques that at least can weaken the side effects.
3. The model parameters set in the experiments may not be optimal, the next step we can continue to optimize the parameter settings

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APPENDIX

Market Basket Analysis – Frequent Itemsets

support	itemsets
0.324	cat_907
0.317	cat_6315
0.212	cat_9908
0.188	cat_9904
0.171	cat_9909
0.170	cat_6320
0.163	cat_501
0.153	cat_9753
0.152	cat_902
0.151	cat_6315, cat_907
0.148	cat_901
0.133	cat_2301
0.113	cat_3611
0.111	cat_6305
0.108	cat_5710
0.105	cat_5307
0.099	cat_9908, cat_907
0.096	cat_9908, cat_6315
0.094	cat_6315, cat_6320
0.089	cat_501, cat_6315
0.088	cat_2628
0.088	cat_2119
0.087	cat_9904, cat_6315
0.087	cat_6320, cat_907
0.087	cat_3303
0.087	cat_9904, cat_907
0.084	cat_501, cat_907
0.084	cat_5902
0.083	cat_3635
0.080	cat_9909, cat_907
0.076	cat_902, cat_907
0.075	cat_6315, cat_9909
0.075	cat_901, cat_907
0.074	cat_9904, cat_9908
0.072	cat_6315, cat_902
0.071	cat_9908, cat_9909
0.071	cat_9753, cat_907
0.070	cat_901, cat_6315
0.069	cat_9753, cat_6315
0.068	cat_907, cat_2301
0.067	cat_5704
0.065	cat_2509
0.064	cat_4107
0.063	cat_5552
0.063	cat_3618
0.063	cat_6315, cat_2301
0.062	cat_6305, cat_6315
0.062	cat_2630
0.061	cat_516
0.061	cat_9908, cat_6320
0.060	cat_9908, cat_9753
0.060	cat_908
0.060	cat_3307
0.059	cat_3305
0.059	cat_2633
0.059	cat_2506
0.058	cat_5620
0.058	cat_9904, cat_9909
0.058	cat_6305, cat_907
0.057	cat_3318
0.056	cat_3101
0.056	cat_5607
0.055	cat_9908, cat_6315, cat_907
0.055	cat_9908, cat_501
0.055	cat_6315, cat_6320, cat_907
0.054	cat_5705

0.054	cat_5710, cat_6315
0.053	cat_9904, cat_9753
0.053	cat_3601
0.053	cat_9904, cat_6320
0.053	cat_2609
0.053	cat_501, cat_6315, cat_907
0.053	cat_9904, cat_501
0.052	cat_5307, cat_907
0.052	cat_3611, cat_907
0.052	cat_9908, cat_902
0.051	cat_5710, cat_907
0.051	cat_418

Market Basket Analysis – Rule Sets

antecedents	consequents	antecedent support	consequent support	support	confidenc e	lift
cat_501	cat_6315, cat_907	0.163	0.151	0.053	0.324	2.148
cat_6315, cat_907	cat_501	0.151	0.163	0.053	0.351	2.148
cat_6320	cat_6315, cat_907	0.170	0.151	0.055	0.321	2.122
cat_6315, cat_907	cat_6320	0.151	0.170	0.055	0.361	2.122
cat_6315	cat_501, cat_907	0.317	0.084	0.053	0.167	1.976
cat_501, cat_907	cat_6315	0.084	0.317	0.053	0.627	1.976
cat_6315	cat_6320, cat_907	0.317	0.087	0.055	0.172	1.972
cat_6320, cat_907	cat_6315	0.087	0.317	0.055	0.626	1.972
cat_9908	cat_9909	0.212	0.171	0.071	0.337	1.968
cat_9909	cat_9908	0.171	0.212	0.071	0.418	1.968
cat_9908	cat_9904	0.212	0.188	0.074	0.350	1.865
cat_9904	cat_9908	0.188	0.212	0.074	0.396	1.865
cat_9904	cat_9753	0.188	0.153	0.053	0.285	1.865
cat_9753	cat_9904	0.153	0.188	0.053	0.350	1.865
cat_907	cat_501, cat_6315	0.324	0.089	0.053	0.163	1.841
cat_501, cat_6315	cat_907	0.089	0.324	0.053	0.596	1.841
cat_9908	cat_9753	0.212	0.153	0.060	0.281	1.840
cat_9753	cat_9908	0.153	0.212	0.060	0.390	1.840
cat_9904	cat_9909	0.188	0.171	0.058	0.309	1.808
cat_9909	cat_9904	0.171	0.188	0.058	0.339	1.808
cat_907	cat_6315, cat_6320	0.324	0.094	0.055	0.169	1.801
cat_6315, cat_6320	cat_907	0.094	0.324	0.055	0.583	1.801
cat_907	cat_9908, cat_6315	0.324	0.096	0.055	0.171	1.788
cat_9908, cat_6315	cat_907	0.096	0.324	0.055	0.579	1.788
cat_6315	cat_6305	0.317	0.111	0.062	0.197	1.778
cat_6305	cat_6315	0.111	0.317	0.062	0.565	1.778
cat_6315	cat_9908, cat_907	0.317	0.099	0.055	0.175	1.759
cat_9908, cat_907	cat_6315	0.099	0.317	0.055	0.558	1.759
cat_9908	cat_6315, cat_907	0.212	0.151	0.055	0.262	1.732
cat_6315, cat_907	cat_9908	0.151	0.212	0.055	0.367	1.732
cat_6315	cat_6320	0.317	0.170	0.094	0.295	1.731
cat_6320	cat_6315	0.170	0.317	0.094	0.550	1.731
cat_9904	cat_501	0.188	0.163	0.053	0.281	1.719
cat_501	cat_9904	0.163	0.188	0.053	0.322	1.719
cat_6315	cat_501	0.317	0.163	0.089	0.280	1.713
cat_501	cat_6315	0.163	0.317	0.089	0.544	1.713
cat_9908	cat_6320	0.212	0.170	0.061	0.289	1.698
cat_6320	cat_9908	0.170	0.212	0.061	0.360	1.698
cat_9904	cat_6320	0.188	0.170	0.053	0.284	1.669
cat_6320	cat_9904	0.170	0.188	0.053	0.313	1.669
cat_907	cat_6305	0.324	0.111	0.058	0.178	1.607
cat_6305	cat_907	0.111	0.324	0.058	0.520	1.607
cat_9908	cat_902	0.212	0.152	0.052	0.244	1.599
cat_902	cat_9908	0.152	0.212	0.052	0.339	1.599
cat_907	cat_501	0.324	0.163	0.084	0.261	1.597
cat_501	cat_907	0.163	0.324	0.084	0.517	1.597
cat_9908	cat_501	0.212	0.163	0.055	0.258	1.583
cat_501	cat_9908	0.163	0.212	0.055	0.336	1.583
cat_907	cat_6320	0.324	0.170	0.087	0.269	1.581
cat_6320	cat_907	0.170	0.324	0.087	0.512	1.581
cat_907	cat_2301	0.324	0.133	0.068	0.210	1.570
cat_2301	cat_907	0.133	0.324	0.068	0.509	1.570

cat_6315	cat_5710	0.317	0.108	0.054	0.170	1.567
cat_5710	cat_6315	0.108	0.317	0.054	0.497	1.567
cat_907	cat_901	0.324	0.148	0.075	0.231	1.566
cat_901	cat_907	0.148	0.324	0.075	0.507	1.566
cat_907	cat_902	0.324	0.152	0.076	0.236	1.549
cat_902	cat_907	0.152	0.324	0.076	0.502	1.549
cat_907	cat_5307	0.324	0.105	0.052	0.160	1.527
cat_5307	cat_907	0.105	0.324	0.052	0.494	1.527
cat_6315	cat_901	0.317	0.148	0.070	0.222	1.501
cat_901	cat_6315	0.148	0.317	0.070	0.477	1.501
cat_6315	cat_2301	0.317	0.133	0.063	0.198	1.483
cat_2301	cat_6315	0.133	0.317	0.063	0.471	1.483
cat_6315	cat_902	0.317	0.152	0.072	0.225	1.480
cat_902	cat_6315	0.152	0.317	0.072	0.470	1.480
cat_907	cat_6315	0.324	0.317	0.151	0.466	1.469
cat_6315	cat_907	0.317	0.324	0.151	0.476	1.469
cat_6315	cat_9904	0.317	0.188	0.087	0.275	1.468
cat_9904	cat_6315	0.188	0.317	0.087	0.466	1.468
cat_907	cat_5710	0.324	0.108	0.051	0.158	1.459
cat_5710	cat_907	0.108	0.324	0.051	0.472	1.459
cat_907	cat_9908	0.324	0.212	0.099	0.307	1.446
cat_9908	cat_907	0.212	0.324	0.099	0.468	1.446
cat_907	cat_9909	0.324	0.171	0.080	0.246	1.441
cat_9909	cat_907	0.171	0.324	0.080	0.467	1.441
cat_907	cat_9753	0.324	0.153	0.071	0.219	1.434
cat_9753	cat_907	0.153	0.324	0.071	0.464	1.434
cat_907	cat_9904	0.324	0.188	0.087	0.267	1.424
cat_9904	cat_907	0.188	0.324	0.087	0.461	1.424
cat_6315	cat_9908	0.317	0.212	0.096	0.302	1.422
cat_9908	cat_6315	0.212	0.317	0.096	0.452	1.422
cat_6315	cat_9753	0.317	0.153	0.069	0.217	1.422
cat_9753	cat_6315	0.153	0.317	0.069	0.451	1.422
cat_907	cat_3611	0.324	0.113	0.052	0.160	1.417
cat_3611	cat_907	0.113	0.324	0.052	0.459	1.417
cat_6315	cat_9909	0.317	0.171	0.075	0.238	1.391
cat_9909	cat_6315	0.171	0.317	0.075	0.441	1.391

Recommender System – Predicted Rating (rating = 4.0)

Customer ID	Item	Predicted Rating
4427711419	cat_7109	4.00
4427711419	cat_6401	4.00
4427711419	cat_2722	4.00
4427711419	cat_6409	4.00
4427711419	cat_3404	4.00
4427711419	cat_6707	4.00
4427711419	cat_7099	4.00
4427711419	cat_9133	4.00
4427711419	cat_2724	4.00
4427711419	cat_9115	4.00
4427711419	cat_9120	4.00
4427711419	cat_9106	4.00
4427711419	cat_9110	4.00
4427711419	cat_9129	4.00
4427711419	cat_9108	4.00
4427711419	cat_2199	4.00
4440809692	cat_6330	4.00
4445492170	cat_4508	4.00
4445492170	cat_5124	4.00
4445492170	cat_5402	4.00
4445492170	cat_7106	4.00
4445492170	cat_7309	4.00
4445492170	cat_7515	4.00
4447987580	cat_4606	4.00
4454224475	cat_2609	4.00
4475388522	cat_6321	4.00
4486715723	cat_303	4.00
4510640725	cat_2406	4.00
4517078072	cat_3612	4.00

4528107384	cat_2920	4.00
4528107384	cat_835	4.00
4565164181	cat_6314	4.00
4615852218	cat_6308	4.00
4615896972	cat_2117	4.00
4615900917	cat_7303	4.00
4615909705	cat_2106	4.00
4615914304	cat_1504	4.00
4615914304	cat_2926	4.00
4615914304	cat_5706	4.00
4615919788	cat_2111	4.00
4615919788	cat_2606	4.00
4615919788	cat_2702	4.00
4615944205	cat_7307	4.00
4615949082	cat_1111	4.00
4615982109	cat_5559	4.00
4615997714	cat_7901	4.00
4616008896	cat_2923	4.00
4616023912	cat_4508	4.00
4616054884	cat_2118	4.00
4616054884	cat_3612	4.00
4616077890	cat_9731	4.00
4616106221	cat_821	4.00
4616143604	cat_5127	4.00
4616157142	cat_2633	4.00
4616157142	cat_2705	4.00
4616158054	cat_1850	4.00
4616158054	cat_2111	4.00
4616173813	cat_1841	4.00
4616173813	cat_407	4.00
4616199703	cat_415	4.00
4616203036	cat_3633	4.00
4616219457	cat_3010	4.00
4616267519	cat_8115	4.00
4616268873	cat_5611	4.00
4616289967	cat_5814	4.00
4616311917	cat_9631	4.00
4616341316	cat_6202	4.00
4616380030	cat_5831	4.00
4616460448	cat_9204	4.00
4616460448	cat_9210	4.00
4616471334	cat_2626	4.00
4616471334	cat_3603	4.00
4616471334	cat_5564	4.00
4616495635	cat_6410	4.00
4616503329	cat_7106	4.00
4616540851	cat_2704	4.00
4616540851	cat_3315	4.00
4616557718	cat_3709	4.00
4616572181	cat_1112	4.00
4616650831	cat_1707	4.00
4616650831	cat_3405	4.00
4616663573	cat_2908	4.00
4616675439	cat_2113	4.00
4616676768	cat_5560	4.00
4616676768	cat_5613	4.00
4616766992	cat_5826	4.00
4616768251	cat_3204	4.00
4616790749	cat_912	4.00
4616797073	cat_5703	4.00
4616823516	cat_1701	4.00
4616910542	cat_4606	4.00
4616938643	cat_4004	4.00
4616938643	cat_5618	4.00
4616939255	cat_3351	4.00
4616994927	cat_2109	4.00
4617010521	cat_3601	4.00
4617010521	cat_3604	4.00
4617015518	cat_3705	4.00
4617032930	cat_6502	4.00
4617112781	cat_1841	4.00

4617136439	cat_2704	4.00
4617148039	cat_2706	4.00
4617155890	cat_4402	4.00
4617155890	cat_5910	4.00
4617166842	cat_5899	4.00
4617198300	cat_1207	4.00
4617257153	cat_2706	4.00
4617314367	cat_1841	4.00
4617314367	cat_5611	4.00
4617325678	cat_916	4.00
4617327020	cat_9631	4.00
4617363839	cat_1206	4.00
4617386252	cat_4405	4.00
4617405229	cat_2504	4.00
4617405229	cat_2803	4.00
4617405229	cat_423	4.00
4617405229	cat_521	4.00
4617405229	cat_522	4.00
4617405229	cat_6011	4.00
4617405229	cat_6501	4.00
4617405229	cat_7902	4.00
4617405229	cat_837	4.00
4617419087	cat_211	4.00
4617523419	cat_2111	4.00
4617523419	cat_504	4.00
4617525966	cat_2610	4.00
4617525966	cat_2701	4.00
4617525966	cat_2710	4.00
4617534696	cat_213	4.00
4617562472	cat_2117	4.00
4617562472	cat_4109	4.00
4617566027	cat_1905	4.00
4617600774	cat_3509	4.00
4617630540	cat_2634	4.00
4617630540	cat_3405	4.00
4617669406	cat_5609	4.00
4617719426	cat_7902	4.00
4617720406	cat_1305	4.00
4617746105	cat_2608	4.00
4617746105	cat_2620	4.00
4617746105	cat_7515	4.00
4617746105	cat_9517	4.00
4617746105	cat_9732	4.00
4617784346	cat_212	4.00
4617843268	cat_2608	4.00
4617843268	cat_5199	4.00
4617850392	cat_5828	4.00
4617852282	cat_1006	4.00
4617852282	cat_6319	4.00
4617897332	cat_1013	4.00
4617979615	cat_3304	4.00
4617980852	cat_1004	4.00
4617980852	cat_2105	4.00
4617980852	cat_2903	4.00
4617980852	cat_5814	4.00
4617980852	cat_835	4.00
4618012145	cat_5907	4.00
4618019834	cat_912	4.00
4618069590	cat_5833	4.00
4618084835	cat_2122	4.00
4618093656	cat_7214	4.00
4618109048	cat_7102	4.00
4618118450	cat_3309	4.00
4618142738	cat_106	4.00
4618207145	cat_4705	4.00
4618237677	cat_5130	4.00
4618248324	cat_7106	4.00
4618296786	cat_2705	4.00
4618296786	cat_3002	4.00
4618296786	cat_3508	4.00
4618296786	cat_5703	4.00

4618296786	cat_5910	4.00
4618296786	cat_7405	4.00
4618306165	cat_9204	4.00
4618344264	cat_2920	4.00
4618344264	cat_3601	4.00
4618344264	cat_5814	4.00
4618366187	cat_4508	4.00
4618404390	cat_2710	4.00
4618423140	cat_4903	4.00
4618423140	cat_912	4.00
4618436723	cat_2505	4.00
4618436723	cat_5837	4.00
4618442606	cat_4516	4.00
4618474209	cat_5710	4.00
4618481222	cat_2908	4.00
4618519729	cat_1306	4.00
4618537955	cat_2103	4.00
4618537955	cat_2406	4.00
4618537955	cat_5910	4.00
4618548975	cat_5129	4.00
4618563768	cat_1112	4.00
4618596642	cat_610	4.00
4618606027	cat_5910	4.00
4618613569	cat_2702	4.00
4618624883	cat_2701	4.00
4618625312	cat_1837	4.00
4618641360	cat_2705	4.00
4618661967	cat_7212	4.00
4618682741	cat_3703	4.00
4618692758	cat_6399	4.00
4618766687	cat_4004	4.00
4618766687	cat_7356	4.00
4618809739	cat_2701	4.00
4618815468	cat_3633	4.00
4618827474	cat_2701	4.00
4618845470	cat_7357	4.00
4618855238	cat_5703	4.00
4618908147	cat_5127	4.00
4618908147	cat_9716	4.00
4618951979	cat_1007	4.00
4618974183	cat_5127	4.00
4618980559	cat_821	4.00
4618986985	cat_5124	4.00
4618989499	cat_607	4.00
4618989499	cat_708	4.00
4618998126	cat_2804	4.00
4619011784	cat_1505	4.00
4619011784	cat_916	4.00
4619042832	cat_3313	4.00
4619042832	cat_3351	4.00
4619042832	cat_5134	4.00
4619042832	cat_709	4.00
4619050437	cat_2926	4.00
4619164753	cat_9631	4.00
4619226404	cat_1306	4.00
4619236897	cat_2310	4.00
4619260226	cat_412	4.00
4619268657	cat_2505	4.00
4619309325	cat_9701	4.00
4619349430	cat_2035	4.00
4619349430	cat_4404	4.00
4619349430	cat_5825	4.00
4619412200	cat_2505	4.00
4619413911	cat_811	4.00
4619437545	cat_3313	4.00
4619455114	cat_5813	4.00
4619458194	cat_5116	4.00
4619458194	cat_5124	4.00
4619458194	cat_5823	4.00
4619458194	cat_6308	4.00
4619459592	cat_2508	4.00

4619500249	cat_7405	4.00
4619574108	cat_2606	4.00
4619586132	cat_2002	4.00
4619589991	cat_702	4.00
4619601699	cat_5834	4.00
4619663776	cat_1837	4.00
4619680482	cat_6401	4.00
4619701532	cat_2108	4.00
4619701532	cat_3304	4.00
4619709533	cat_6308	4.00
4619763776	cat_2406	4.00
4619772732	cat_2122	4.00
4619785422	cat_1004	4.00
4619785422	cat_2606	4.00
4619785422	cat_2922	4.00
4619785422	cat_837	4.00
4619816553	cat_2930	4.00
4619816553	cat_3311	4.00
4619816553	cat_7902	4.00
4619819715	cat_917	4.00
4619847007	cat_5823	4.00
4619852814	cat_5402	4.00
4619889836	cat_3204	4.00
4619895415	cat_3008	4.00
4619908655	cat_4220	4.00
4619908655	cat_5307	4.00
4619944176	cat_4404	4.00
4619997417	cat_1721	4.00
4620026835	cat_9709	4.00
4620027442	cat_1707	4.00
4620027442	cat_3309	4.00
4620027442	cat_5822	4.00
4620042429	cat_1841	4.00
4620043306	cat_5837	4.00
4620047001	cat_1835	4.00
4620047001	cat_4121	4.00
4620052568	cat_2801	4.00
4620081934	cat_1841	4.00
4620127805	cat_1904	4.00
4620127805	cat_2103	4.00
4620135435	cat_5611	4.00
4620139187	cat_1709	4.00
4620139187	cat_5560	4.00
4620139187	cat_8101	4.00
4620159773	cat_2117	4.00
4620177549	cat_2110	4.00
4620177549	cat_2634	4.00
4620177549	cat_2705	4.00
4620177549	cat_5124	4.00
4620193967	cat_3319	4.00
4620198168	cat_1414	4.00
4620198168	cat_520	4.00
4620198168	cat_6319	4.00
4620202539	cat_5706	4.00
4620203595	cat_5618	4.00
4620250688	cat_2505	4.00
4620250688	cat_7203	4.00
4620256115	cat_3309	4.00
4620315533	cat_1111	4.00
4620315533	cat_1837	4.00
4620337598	cat_914	4.00
4620379622	cat_6401	4.00
4620386645	cat_6315	4.00
4620420409	cat_2635	4.00
4620424033	cat_3612	4.00
4620424033	cat_6308	4.00
4620424033	cat_7114	4.00
4620433198	cat_1904	4.00
4620473601	cat_4515	4.00
4620498636	cat_2709	4.00
4620498636	cat_4121	4.00

4620506697	cat_5837	4.00
4620506697	cat_6311	4.00
4620554257	cat_6332	4.00
4620592301	cat_1703	4.00
4620593512	cat_1842	4.00
4620618706	cat_5613	4.00
4620627135	cat_2926	4.00
4620661334	cat_6318	4.00
4620697753	cat_1410	4.00
4620734547	cat_3311	4.00
4620742047	cat_2706	4.00
4620805662	cat_835	4.00
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4640718429	cat_3636	4.00
4640718429	cat_5618	4.00
4640731961	cat_707	4.00
4640744686	cat_6399	4.00
4640769384	cat_3311	4.00
4640769915	cat_1410	4.00
4640780752	cat_106	4.00
4640780752	cat_601	4.00
4640780752	cat_958	4.00
4640782918	cat_1719	4.00
4640804589	cat_910	4.00
4640838570	cat_5826	4.00
4640849829	cat_5199	4.00
4640854612	cat_4402	4.00
4640932353	cat_211	4.00
4640955672	cat_6318	4.00
4640955672	cat_906	4.00
4640957868	cat_5131	4.00
4640964754	cat_1302	4.00
4640973626	cat_1416	4.00
4640987980	cat_212	4.00
4640987980	cat_703	4.00
4640996496	cat_3108	4.00
4640998928	cat_2504	4.00
4641043059	cat_5907	4.00
4641048273	cat_5826	4.00
4641086100	cat_2505	4.00
4641086100	cat_421	4.00
4641115866	cat_1822	4.00
4641153092	cat_3309	4.00
4641170658	cat_2119	4.00
4641170658	cat_4517	4.00
4641170658	cat_517	4.00
4641182691	cat_1721	4.00
4641196433	cat_2702	4.00
4641201677	cat_2508	4.00
4641223792	cat_2501	4.00
4641233858	cat_1404	4.00
4641233858	cat_6319	4.00
4641233858	cat_835	4.00
4641240707	cat_5906	4.00
4641255259	cat_2920	4.00
4641273776	cat_829	4.00
4641276403	cat_2508	4.00
4641276854	cat_202	4.00
4641305809	cat_3628	4.00
4641307559	cat_3636	4.00
4641308148	cat_1721	4.00

4641308148	cat_2706	4.00
4641308148	cat_3411	4.00
4641308148	cat_7345	4.00
4641323405	cat_3509	4.00
4641323405	cat_6328	4.00
4641357022	cat_5125	4.00
4641371548	cat_5562	4.00
4641404805	cat_3631	4.00
4641404805	cat_6202	4.00
4641439497	cat_9631	4.00
4641507299	cat_6323	4.00
4641528417	cat_1305	4.00
4641528417	cat_2214	4.00
4641528417	cat_5824	4.00
4641572325	cat_3638	4.00
4641586669	cat_2501	4.00
4641598868	cat_2103	4.00
4641706550	cat_9632	4.00
4641744443	cat_4001	4.00
4641744443	cat_5826	4.00
4641761775	cat_5609	4.00
4641826914	cat_2619	4.00
4641839221	cat_3007	4.00
4641839221	cat_4110	4.00
4641839221	cat_5910	4.00
4641839221	cat_6320	4.00
4641866779	cat_9632	4.00
4641869167	cat_1721	4.00
4641875528	cat_6332	4.00
4641892549	cat_912	4.00
4641903378	cat_811	4.00
4641903378	cat_837	4.00
4641913739	cat_5905	4.00
4641926571	cat_6328	4.00
4641978724	cat_2703	4.00
4641978724	cat_6502	4.00
4642030537	cat_829	4.00
4642044859	cat_213	4.00
4642057295	cat_3110	4.00
4642057295	cat_5131	4.00
4642057295	cat_6325	4.00
4642057295	cat_6326	4.00
4642057295	cat_7345	4.00
4642070513	cat_708	4.00
4642072699	cat_1007	4.00
4642088962	cat_818	4.00
4642115767	cat_419	4.00
4642115767	cat_9631	4.00
4642132090	cat_308	4.00
4642144494	cat_9631	4.00
4642179546	cat_1724	4.00
4642225257	cat_5128	4.00
4642227574	cat_4406	4.00
4642235773	cat_702	4.00
4642257732	cat_1205	4.00
4642257732	cat_3325	4.00
4642257732	cat_4509	4.00
4642340317	cat_2926	4.00
4642345304	cat_412	4.00
4642346134	cat_2103	4.00
4642346134	cat_7318	4.00
4642346134	cat_910	4.00
4642364871	cat_6319	4.00
4642372908	cat_2705	4.00
4642372908	cat_3508	4.00
4642410952	cat_2002	4.00
4642410952	cat_5124	4.00
4642440294	cat_2631	4.00
4642471984	cat_2508	4.00

Forecast of the next 6 months using ARIMA(3,1,3) model

Date	Forecast
2013-02-01	2447
2013-02-02	2706
2013-02-03	2736
2013-02-04	2516
2013-02-05	2212
2013-02-06	2053
2013-02-07	2159
2013-02-08	2452
2013-02-09	2711
2013-02-10	2743
2013-02-11	2525
2013-02-12	2221
2013-02-13	2060
2013-02-14	2164
2013-02-15	2455
2013-02-16	2716
2013-02-17	2751
2013-02-18	2534
2013-02-19	2230
2013-02-20	2067
2013-02-21	2169
2013-02-22	2459
2013-02-23	2721
2013-02-24	2758
2013-02-25	2544
2013-02-26	2239
2013-02-27	2074
2013-02-28	2173
2013-03-01	2463
2013-03-02	2726
2013-03-03	2766
2013-03-04	2553
2013-03-05	2248
2013-03-06	2081
2013-03-07	2178
2013-03-08	2466
2013-03-09	2731
2013-03-10	2773
2013-03-11	2562
2013-03-12	2257
2013-03-13	2088
2013-03-14	2182
2013-03-15	2470
2013-03-16	2736
2013-03-17	2781
2013-03-18	2571
2013-03-19	2266
2013-03-20	2095
2013-03-21	2187
2013-03-22	2474
2013-03-23	2741
2013-03-24	2788
2013-03-25	2580
2013-03-26	2275
2013-03-27	2102
2013-03-28	2191
2013-03-29	2478
2013-03-30	2746
2013-03-31	2795
2013-04-01	2590
2013-04-02	2284
2013-04-03	2109
2013-04-04	2196
2013-04-05	2481
2013-04-06	2751
2013-04-07	2803
2013-04-08	2599
2013-04-09	2293

2013-04-10	2116
2013-04-11	2201
2013-04-12	2485
2013-04-13	2756
2013-04-14	2810
2013-04-15	2608
2013-04-16	2302
2013-04-17	2123
2013-04-18	2205
2013-04-19	2489
2013-04-20	2761
2013-04-21	2817
2013-04-22	2617
2013-04-23	2311
2013-04-24	2130
2013-04-25	2210
2013-04-26	2492
2013-04-27	2765
2013-04-28	2825
2013-04-29	2626
2013-04-30	2320
2013-05-01	2137
2013-05-02	2215
2013-05-03	2496
2013-05-04	2770
2013-05-05	2832
2013-05-06	2636
2013-05-07	2329
2013-05-08	2144
2013-05-09	2219
2013-05-10	2500
2013-05-11	2775
2013-05-12	2839
2013-05-13	2645
2013-05-14	2338
2013-05-15	2151
2013-05-16	2224
2013-05-17	2503
2013-05-18	2780
2013-05-19	2846
2013-05-20	2654
2013-05-21	2347
2013-05-22	2158
2013-05-23	2229
2013-05-24	2507
2013-05-25	2785
2013-05-26	2854
2013-05-27	2663
2013-05-28	2357
2013-05-29	2165
2013-05-30	2234
2013-05-31	2511
2013-06-01	2789
2013-06-02	2861
2013-06-03	2672
2013-06-04	2366
2013-06-05	2173
2013-06-06	2238
2013-06-07	2515
2013-06-08	2794
2013-06-09	2868
2013-06-10	2681
2013-06-11	2375
2013-06-12	2180
2013-06-13	2243
2013-06-14	2518
2013-06-15	2799
2013-06-16	2875
2013-06-17	2690
2013-06-18	2384
2013-06-19	2187

2013-06-20	2248
2013-06-21	2522
2013-06-22	2804
2013-06-23	2882
2013-06-24	2699
2013-06-25	2393
2013-06-26	2194
2013-06-27	2253
2013-06-28	2526
2013-06-29	2808
2013-06-30	2889
2013-07-01	2708
2013-07-02	2402
2013-07-03	2202
2013-07-04	2258
2013-07-05	2529
2013-07-06	2813
2013-07-07	2896
2013-07-08	2717
2013-07-09	2412
2013-07-10	2209
2013-07-11	2263
2013-07-12	2533
2013-07-13	2818
2013-07-14	2903
2013-07-15	2727
2013-07-16	2421
2013-07-17	2216
2013-07-18	2268
2013-07-19	2537
2013-07-20	2822
2013-07-21	2910
2013-07-22	2736
2013-07-23	2430
2013-07-24	2224
2013-07-25	2272
2013-07-26	2540
2013-07-27	2827
2013-07-28	2917
2013-07-29	2745
2013-07-30	2439
2013-07-31	2231

Forecast of the next 1 month by using the Random Forest model

Date	Forecast
2013-04-01	198
2013-04-02	228
2013-04-03	245
2013-04-04	285
2013-04-05	318
2013-04-06	359
2013-04-07	375
2013-04-08	359
2013-04-09	315
2013-04-10	261
2013-04-11	235
2013-04-12	263
2013-04-13	293
2013-04-14	297
2013-04-15	288
2013-04-16	238
2013-04-17	208
2013-04-18	206
2013-04-19	255
2013-04-20	264
2013-04-21	238
2013-04-22	217
2013-04-23	219

2013-04-24	246
2013-04-25	228
2013-04-26	268
2013-04-27	295
2013-04-28	278
2013-04-29	267
2013-04-30	206