Dillard’s Vendor Performance Analysis

Executive Summary

Dillard’s is a department store chain with approximately 282 stores headquartered in Little Rock, Arkansas [4]. With a large amount of data available regarding Dillard’s sales transactions, merchandise and vendor details, department information, and store descriptions, the project team aimed to identify the best-performing and worst-performing vendors upon defining best-performing as low cost, high purchase frequency, high recency, and high profit. After performing the initial Exploratory Data Analysis (EDA), the K-Means clustering algorithm was applied to separate the data into clusters and further investigate insights from each individual cluster. The clustering analysis result showed that beauty products and certain clothing brands dominated the best-performing vendors while categories such as shoes, luggage, and furniture tended to downgrade business performances. In addition, ROI analysis was conducted on the data. The analysis indicated that the best vendors make up 51% of Dillard’s revenue, 55% of costs, and 60% of profit, while the worst vendors contribute 2% of revenue, 2% of costs, and nearly 0% of the profit. As a result, Dillard’s is recommended to drop the vendors classified as worst-performing vendors and invest more in the best-performing vendors. This will cut total costs by $4.4 million (2% of total costs) and increase department stores' revenue by 6% in the next fiscal year. Although the K-Means algorithm was able to correctly distinguish the best-performing and worst-performing vendors, other clustering algorithms such as DBSCAN and Hierarchical Clustering could also be considered to increase the robustness and reliability of the clusters in the future.

Introduction

With 2351 distinct vendors selling a wide range of products, in the attempt of maximizing profit, how should Dillard’s define performance in order to identify the vendors with high and low performance and to allocate resources–such as advertising space–accordingly? Inspired by the recency, frequency, monetary value model used to segment customers, our group decided to define vendor performance for Dillard’s as a collection of four dimensions–cost, frequency of customers’ purchase, recency of customers’ purchase, and profit. Vendors with low cost, high frequency, high recency, and high profit are considered the best performing ones, while the worst vendors stand at the other end of the spectra. With a machine learning model that places vendors into clusters based on these four dimensions, not only can Dillard’s obtain lists of best and worst vendors, but also strategic decisions can be made by examining the common vendor characteristics within a cluster.

Preprocessing and EDA

Once we defined our business question, we decided on which datasets we would use. The most appropriate datasets for our business question were trnsact, skuinfo, and skstinfo. In terms of data cleaning, transact and skstinfo had no major issues, other than renaming the columns to the names based on the data set schema. Skuinfo required a lot of cleaning since all its columns were somehow merged into one, within which there were commas that were supposed to separate the independent 10 columns. After separating the columns of skuinfo, our datasets were prepared and we proceeded into exploratory data analysis on the relevant datasets.

After completing exploratory analysis on the trnsact data, we noticed that in most transactions only 1 or 2 items were sold and that the most frequent prices range between 6 and 39 dollars. In terms of the return rate of items, we found that the returns rates for each store lie around 7 and 9 percent. The state with the highest return rate was Illinois, and Wyoming had the lowest return rate. The city with the highest return rate was Chesterfield, and the lowest was Jackson.

For skstinfo, we noticed that, while the cost of the product ranges from 0 to 250 dollars, the retail price ranges from 0 to 500 dollars. The products being sold are mainly only in 20 stores. The 20 most popular and least popular products distribute unevenly, but the average prices for the most and least popular products are roughly the same. This leads our team to infer that retail price may not be influential in determining the popularity of a product.

For skuinfo, the most popular brand is *POLO FAS*, and there is a-159-way tie between the least popular brands who only appear once in the data. Most items are clothing, with the most popular sizes being large and medium. We found missing values in this dataset but decided that they would not affect our machine learning model since the null values would be dropped after merging the datasets.

Then we moved on to selecting the necessary data to investigate our machine learning problem. Since the data sets in hand are quite large–with trnsact having over 100 million rows–we decided to randomly select a 10% subset from each dataset of interest, and then inner join them based on the *SKU* number. The final merged dataset had a little over 15 million rows, which the team agreed was sufficient for our machine learning model. In the meantime, we selected the columns of interest to be *SKU, VENDOR, COST, RETAIL, TRANNUM, SALEDATE, STYPE, QUANTITY,* and *AMOUNT*. *STYPE* was then split into two columns–*PURCHASES* and *RETURNS*–based on whether the item was being purchased or returned. Following that we decided to group the rows by vendor based on the definitions detailed in the next section, and aggregate the remaining columns. The final resulting data has 891 rows and was used in our machine learning model to locate the best and worst performing vendors.

Feature Definition

The four dimensions of vendor performance, which are also the features of our machine learning model, are calculated based on the columns of interest in the following way. Cost for each vendor is the average cost per unit of stocking item: sum(*COST* * *QUANTITY*)/count(*SKU*). Frequency of customers' purchase for each vendor only considers the records of purchase for each vendor: count(*SKU*) where *STYPE* = P. Recency for each vendor again takes only the purchase transactions into account and is the difference in seconds between the latest purchase record and the UNIX time: max(*SALEDATE*) - epoch. Profit for each vendor is defined as (*AMOUNT* * *QUANTITY* when *STYPE* = P) - (*AMOUNT* * *QUANTITY* when *STYPE* = R) - sum(*COST* * *QUANTITY*).

K-Means Algorithm

In order to identify the characteristics of best and worst performing vendors, we decided to utilize the unsupervised learning technique of k-means algorithm to separate the data into clusters. The objective of the k-means clustering algorithm is to divide *M* data points into *K* clusters to find an optimal inertia which minimizes the sum of squares within each cluster [2]. K-means clustering is also a fast algorithm that is computationally efficient and works well with large datasets, so we thought this algorithm would be a suitable case for our scenario.

We scaled the numerical attributes in each column by using StandardScaler() function followed by the .fit_transform() function in Python's sklearn.preprocessing package to ensure all the numerical data were on the same scale. To identify the clusterability and preview the clustering structure, we created t-SNE plots with perplexity values ranging from 10 to 50 and random states of 42 and 100, and chose the one with perplexity value of 50 and random state of 42 as the final representation plot (Figure 1). From the t-SNE plots, we observed that there were roughly 4 clusters and the clusters were well-separated. We also utilized the Elbow Plot (Figure 2) to help us determine the number of clusters to use in the k-mean algorithm. We collected the average inertia for 3 trials for the number of clusters ranging from 1 to 20, and the elbow plot suggested 4 clusters due to a dramatic elbow at k = 4. Finally, we implemented k-means clustering for the scaled numerical data with 4 clusters and created side-by-side boxplot visualizations to compare the clusters (Figure 3). We also obtained a silhouette score of 0.6593, which was an indication of great cohesion and separation between the clusters.

Cluster Analysis

To analyze K-Means clustering results, we first need to understand how cluster analysis could help decode our business question. A cluster analysis serves two purposes in general: to understand and to serve as a tool. As part of clustering for understanding, cluster analysis is used to automatically identify conceptually meaningful groups of objects that share common characteristics. By analyzing, describing and utilizing the valuable information hidden in groups, it also plays a vital role in helping people to effectively utilize them [5]. Specifically, with our business question in mind, we aim to understand the common traits of best performing vendors and worst performing vendors. We could then develop marketing strategies that will lead to even greater profits for the best-performing vendors, and how the worst-performing vendors can improve their capabilities in terms of features to increase their performance.

We analyzed the monetary features for the two clusters of interest. The cluster analysis result as in Table 1 shows that best performing vendors have a high frequency, a low average cost, a high profit, a high quantity, a high purchase, a high return ratio, and a low return ratio among the three types of vendor clusters. Vendors with low frequency, high average costs, medium profits, medium quantity, low purchase, low return and medium return ratio are the worst vendors in clusters. We could see that our best performing vendors also have the lowest return rate and lowest average cost, which are the features we did not use when doing K-Means clustering.

Then we analyzed the types of goods that were mainly sold by vendors in the two clusters respectively. From Table 2 and Table 3, we could see that vendors selling Clothes, Beauty, and Shoes dominate the best performing vendor cluster, and that Clothes vendors dominate the worst performing vendor cluster. Thus, we recommend conducting more market research on most and least popular clothes brands in order to further identify the vendors selling those popular clothing products. It would also be a good idea to target vendors who sell beauty and cosmetic products in trend to increase revenues. Before Dillard's decides to allocate more resources to vendors who provide bags, furniture, luggage, and shoes, more considerations would need to be made, as these categories are also likely to be poorly received by customers.

ROI Analysis

Dillards is a department store that carries a variety of products from a variety of vendors. According to *ibisworld* [3], the total revenue of all US department stores is $117 billion, of which our subset of data makes 0.25% or $292.38 million, with costs amounting to $198.91 million and profits totalling up to $93.46 million. According to our cluster analysis, the vendors we do recommend make 57% of that revenue, 55% of that cost, and 60% that profit. However, the vendors we do not recommend make up 2% of the total Dillards revenue, 2% of Dillard's cost, and roughly 0% of that profit. By dropping the vendors we do not recommend Dillards can cut costs by $4.4 million or 2% of the total costs. This will initially decrease revenue by 2%, however according to this *consumer report* [1], we can expect department stores revenue to increase by 6% in the next fiscal year, and in turn we can infer that Dillards will make up the lost revenue and profits. Based on our analysis, we would recommend to allocate the saved costs into investing more in the vendors we labeled as best in order to achieve higher growth in the next fiscal year.

Our group of four worked on it for 10 hours a week, at an hourly rate of $40/hr for the duration of 12 weeks. We spent 8760 hours using cloud computing at an hourly rate of $0.10/hr coming out to a total cost of $876. Adding this to our total consulting cost of $19200 we get the resulting total cost of our analysis and recommendation coming out $20000, which compared to the cost the vendors will save by dropping the worst vendors is an ROI of $4.25 million.

Conclusion

In this project, we aim to analyze how to define good vendors and bad vendors for Dillard's, and also how to use this information to boost ROI. We first defined vendor performance with four dimensions: cost, frequency of customers' purchase, recency of customers' purchase, and profit. We extracted relevant store information, order details, merchandise description from Dillard's database and then performed data preprocessing and

EDA to understand the basic statistics. We then feature engineered the four feature columns for further analysis of vendors for Dillard's. Using K-Means clustering and cluster analysis, we were able to successfully identify the best vendor characteristics and worst vendor characteristics. Based on our findings, we recommend Dillard's to target vendors who sell trending beauty and clothes products to increase revenues. It would be necessary for Dillard's to take additional considerations regarding vendors who provide bags, furniture, luggage, and shoes, since these categories are also likely to be poorly received by customers. We finally conducted ROI analysis to conclude our project. We found that by investing more in the vendors we labeled as best and cutting costs on vendors we do not recommend, Dillard's could expect department stores revenue to increase by 6% in the next fiscal year.

References

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Appendix

Table 1. Cluster Analysis result

	VENDOR_CATEGORY	FREQUENCY	AVG_COST	PROFIT	QUANTITY	PURCHASES	RETURNS	RETURN_RATIO
0	Average Performing Vendors	6533.10	19.03	34656.52	7154.65	6533.10	621.55	9.51
1	Best Performing Vendors	232230.03	16.71	1669030.81	246125.66	232230.03	13895.63	5.98
2	Worst Performing Vendors	1015.25	222.44	58732.59	1089.65	1015.25	74.40	7.33

Table 2. Best Vendors Merchandise Category

	CATEGORY	COUNT	CATEGORY_PERCENT
0	CLOTHES	20	52.63
1	BEAUTY	11	28.95
2	SHOES	5	13.16
3	ACCESSORIES	1	2.63
4	LUGGAGE	1	2.63

Table 3. Worst Vendors Merchandise Category

	CATEGORY	COUNT	CATEGORY_PERCENT
0	CLOTHES	19	82.61
1	BAGS	1	4.35
2	FURNITURE	1	4.35
3	LUGGAGE	1	4.35
4	SHOES	1	4.35

Figure 1. t-SNE Plot with Perplexity Value 50 and Random State 42

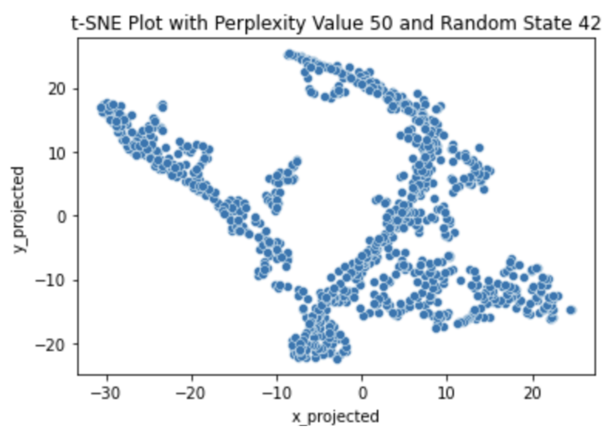


Figure 2. Elbow Plot

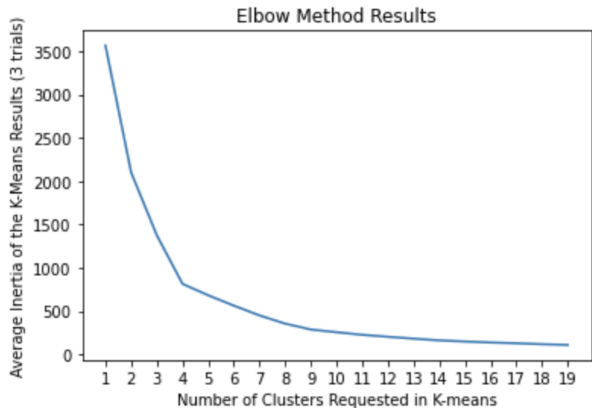
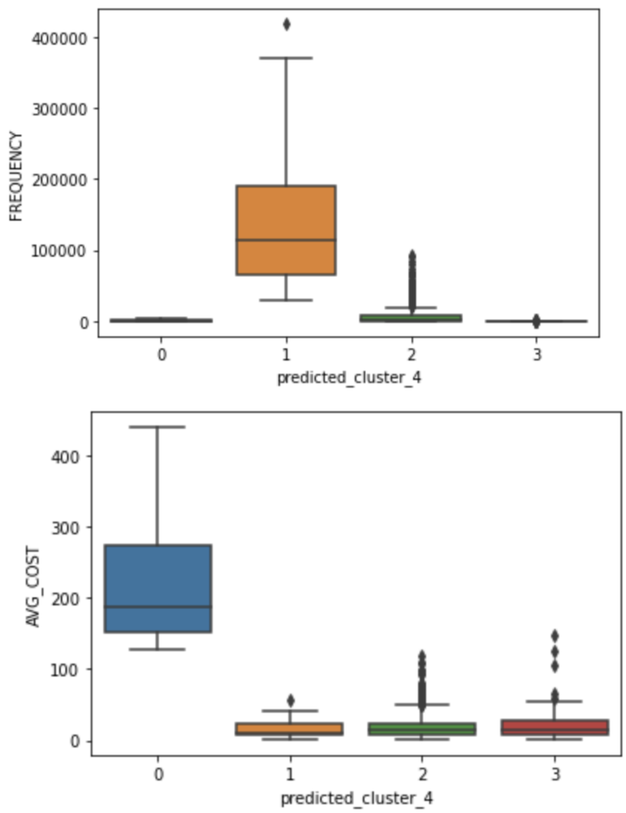
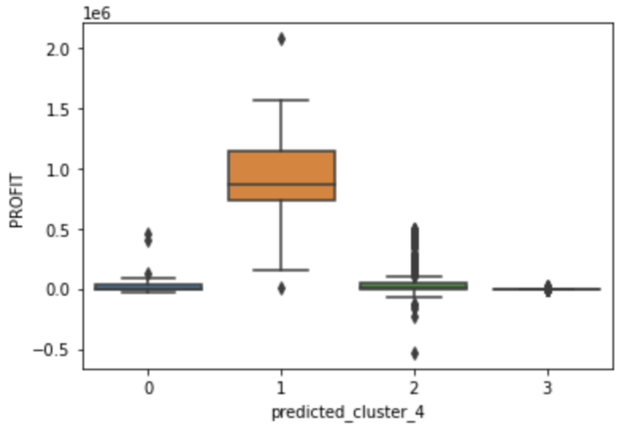


Figure 3. Side-By-Side Boxplots for Each Variable

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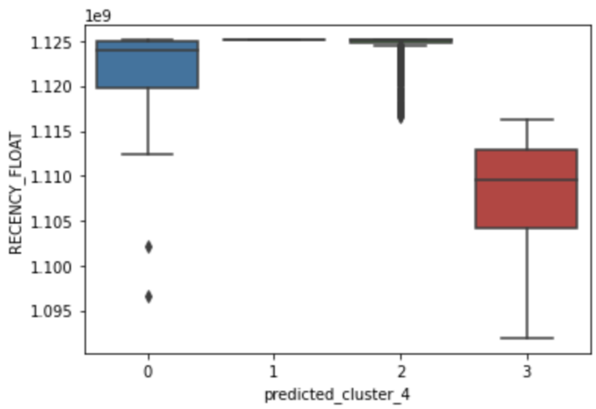
PROFIT
predicted_cluster_4


1e9
RECENCY_FLOAT
predicted_cluster_4