ECS171 Final Report

Team 4

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1 Team Members

Leader: Kyle Ross
Group Members: Stephen Wong, Thalia Fay, Shawn Headley, Haley Chung, Yu Lai, Adarsh Pantula, Jie Shao, Bryce Naung, Fangjing Li, Yuhao Zhuang.

Project Repository Link: https://github.com/StephenW789/ECS-171-FinalProject

2 Introduction

Our team chose the project to be on customers segmentation and analysis. The dataset of our choice, the 2021 Customer Personality Analysis Dataset available on Kaggle, had a wide range of customer data and the consumption of products.

When large corporations market products aggressively towards specific customer groups, they seek to perform customer segmentation. Customer segmentation is a process in which customers are divided up into segments such that the customers in each segment are similar to one another in some category (i.e. spending habits, interests, gender, age, etc.).

In the context of sales marketing, customer segmentation allows businesses to make better data-driven inferences about their customers' needs/behaviors. Identifying why current customers chose a particular company's product over rival brands is critical. Once certain attributes are identified, they should be kept in mind for future releases, so current customers would remain loyal. Depending on a customer segment's characteristics, a business can modify their product to better suit the needs of their target customers.

Our group performed various unsupervised clustering techniques to compare and determine which technique would give us the best structure for the given dataset and allow us to segment the customer data into groups that are easily identified and profiled.

The goal of our project was to group similar customers and determine which attributes played a significant role in the customer segmentation. For instance, a question we had was what kind of customers purchased the highest amount of products in each product category.

3 Literature Review

Hung's and others' research focused on the usage of Agglomerative Clustering for customer segmentation using Credit Card datasets. Agglomerative Clustering was chosen over K-means because Agglomerative tends to provide better clusters. Agglomerative is more computationally expensive compared to K-means, but this difference will be negligable for smaller datasets (Hung et al. 2019).

Within Shihab's and others' research, comparative analysis between K-means, Agglomerative Clustering, and Advanced K-means was performed. Advanced K-means used additional data structures to avoid unnecessary distance computation between object and centroid. This new technique outperformed regular K-means and Agglomerative Clustering by far. However, there were also notable differences between the latter two methods (Shihab et al. 2019).

The reason why Agglomerative outperforms K-means was due to fact that the former does not force the data into exactly k clusters in the early stages of the clustering. Rather, each data point starts off as its own individual "cluster". As the algorithm progresses, similar data points are slowly placed into one small cluster. Towards the end of the algorithm, the many small clusters are agglomerated into exactly k-clusters (Shihab et al. 2019).

Ekhlassi's and others' research analyzed the relationship between customer personality and brand personality. A common marketing used by Big Tech, corporations build a certain "brand" of their product and market exclusively to customers whose personality, morals, and values align with that brand (Ekhlassi et al. 2012).

The research concluded a strong correlation between a conscientious customer valuing ethical corporations and the "social responsibility" of the brand image (Ekhlassi et al. 2012).

Our team's research will extend their research idea through analysis of individual attributes that affect customer purchases.

4 Dataset Description

Link: https://www.kaggle.com/imakash3011/customer-personality-analysis

The dataset contains 2240 rows of unlabeled data entries. The different columns in the dataset are split into 4 primary sections. The People section identifies each customer by education level, marital status, etc. The Products section lists the amount each customer has spent on different products such as meats, fruits, wines, etc. The Promotion section includes number of purchases made with discounts and which promotion deals were accepted by each customer. The Place section contains the number of purchases a customer has made from a specific medium, such as online versus in-store purchases.

At first glance, our group took note of some attributes listed under the People section that we believed would likely affect customer purchases. These included the customer's birth year, marital status, income, and education. However, we knew we needed to perform exploratory data analysis to determine which attributes were the most significant for customer segmentation. In addition, we decided to do some feature engineering after looking at the given attributes, such as calculating a customer's age based on their birth year.

We also noted that for the Promotions section, no information was given on what exactly the different deals offered to the customers were so we kept this in mind when performing our clustering (we removed some attributes from this section later on).

Lastly, we noticed that there were a few null values in the income column, which we made sure to remove in our data cleaning and pre-processing.

5 Proposed Solution and Experimental Results

Because we have an unlabeled dataset, our team applied four different unsupervised learning techniques to perform custom segmentation: Agglomerative Clustering, Apriori Algorithm, K-Means, and Fuzzy C-Means.

Before performing all of our unsupervised learning methods, the first thing we made sure to do was data cleaning and pre-processing. We dropped all rows that contained null values in the Income column, reducing the number of data entries from 2240 to 2216 entries. Next, we performed feature engineering by modifying certain existing attributes and creating new features using the given attributes. We simplified attributes that had repetitive values and removed redundant attributes/columns. We created new features for the age of the customer, total spending across all the different products, total number of children, and family size. During our data cleaning process, we created pairplots with notable attributes such as Income and Age to identify potential outliers. A few outliers were visually identifiable, such as income that was 600,000k or above and age that was over 90 years, so we removed them from the our cleaned dataset. Additionally, we encoded all of our categorical attributes using the label encoder and standardized our data.

Along with the new features we created, there were over twenty different attributes in our cleaned dataset. We created a heatmap for our dataset to visualize which attributes have high correlations with each other. We noticed that certain attributes did have relatively high correlation with each other, such as income and the amount spent on wine purchases. When two attributes have high correlation, this means that one of them is redundant so we decided to perform dimensionality reduction using principal component analysis (PCA) to help us with feature selection. Using a Scree Plot and some trial and error, we found that the optimal number of principal components to include was three.

To determine the optimal number of clusters for our clustering methods, we used the Elbow Technique for K-Means clustering. Along with some trial and error, we found that having four clusters gave us the most evenly distributed clusters and least overlap between clusters; thus, we had four clusters for all three of our clustering methods.

After running the different models, we created bar charts for multiple attributes to help us find similarities between the customers in each cluster. Some of the bar charts used for the profiling of the four clusters from K-Means clustering are shown in figures 1 and 2. We also plotted the consumption of the different product categories for each cluster in figure 4. From our results, the profiling of each cluster is as follows:

- Cluster 0 are large families with middle aged parents often having multiple kids and teenagers. Having a large family leads to higher expenses.
- Cluster 1 are mostly high earning single individuals or childless couples.
- Cluster 2 are smaller families with lower earning young parents with mostly kids and very few teenagers.
- Cluster 3 are smaller families with high earning middle-aged parents and teenagers.

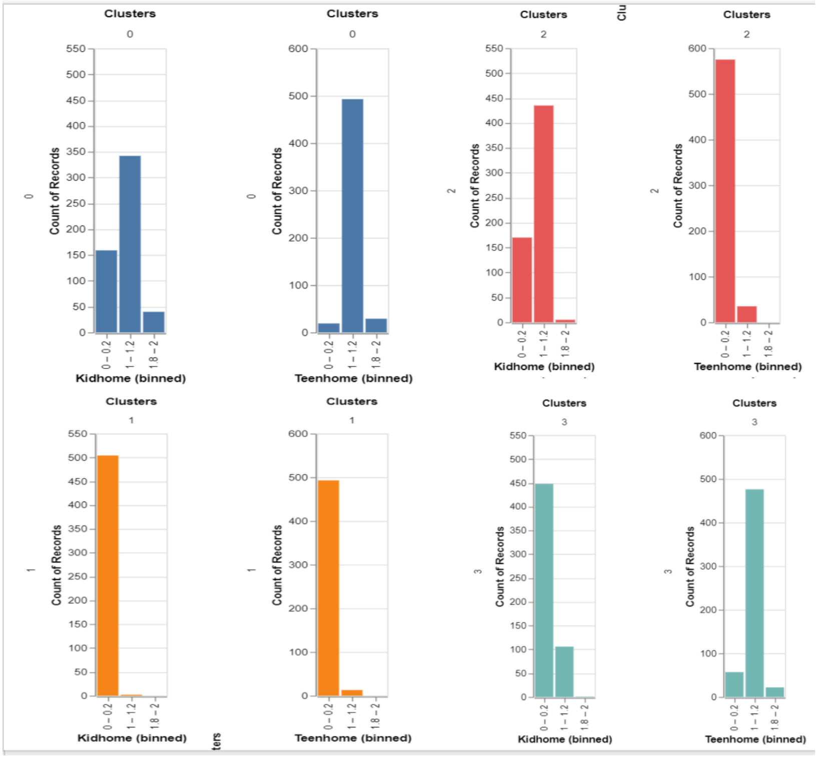


Figure 1: Clusters 0 - 4 statistics

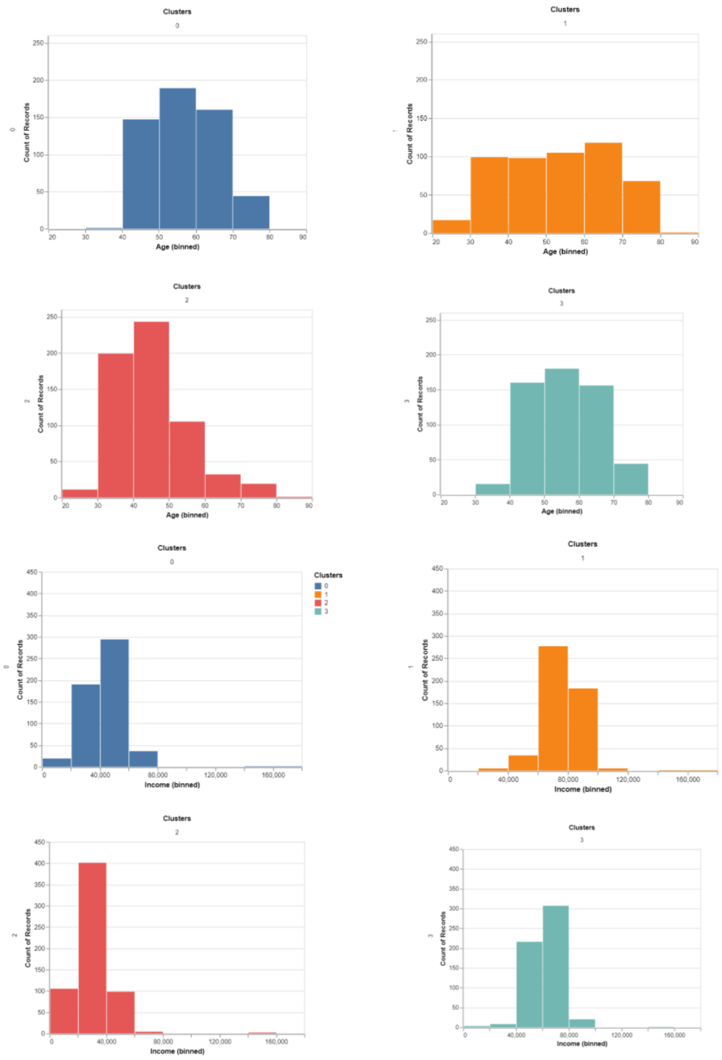


Figure 2: Clusters 0 - 4 statistics

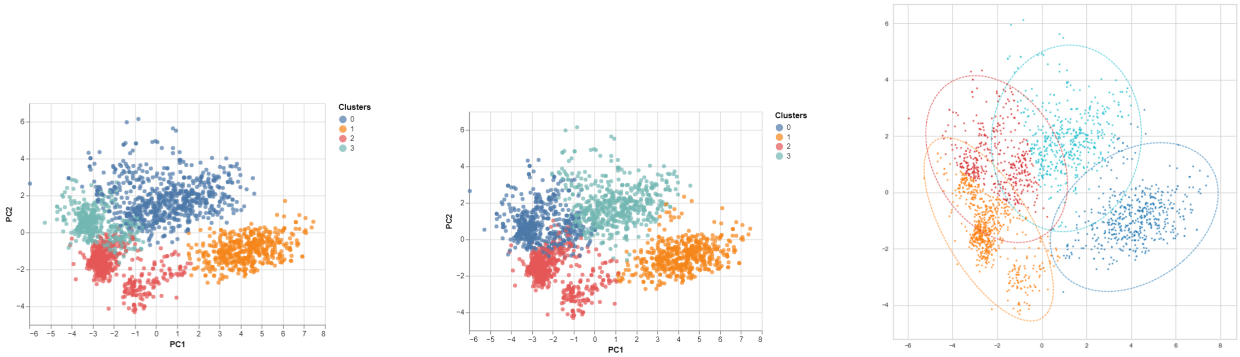


Figure 3: Left to Right - Agglomerative, K-Means, Fuzzy C-Means

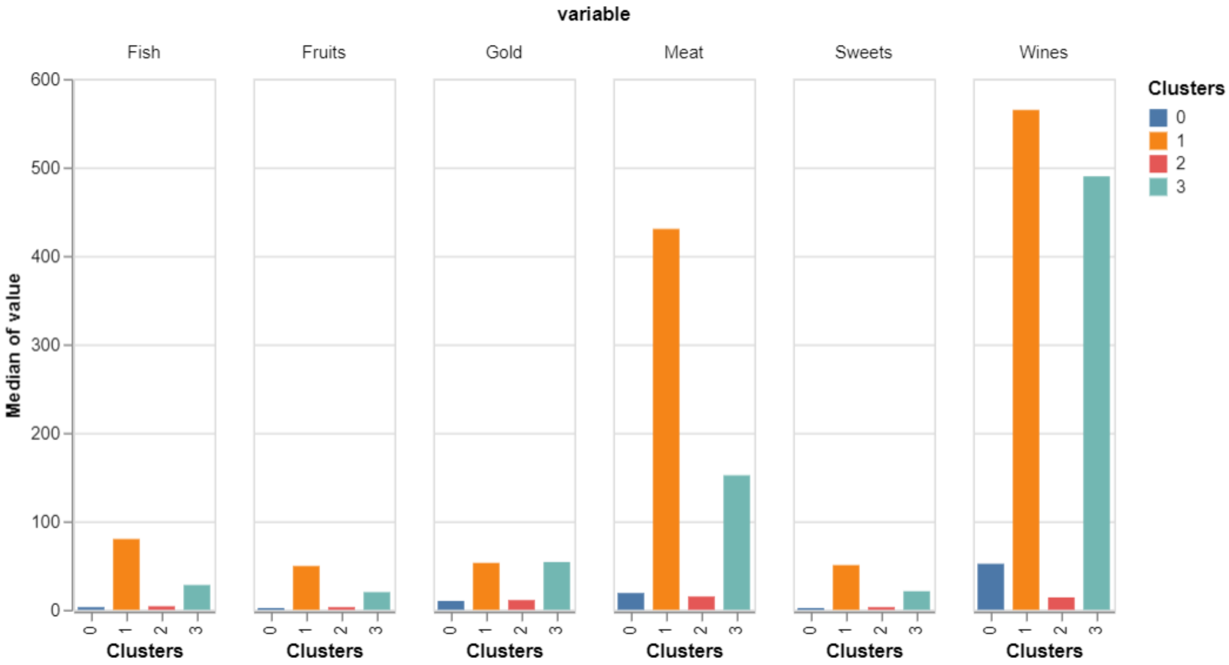
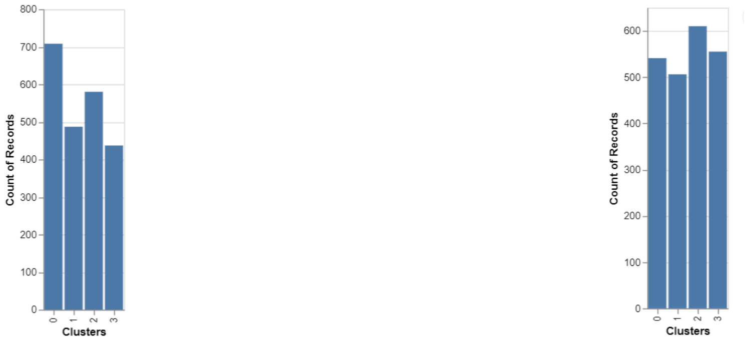


Figure 4: Consumption of Products

Both Agglomerative and Apriori methods identified Cluster 1 and Cluster 3 as the biggest consumers. The difference was much larger in the Meat and Wines department.

The Agglomerative, K-means, and Fuzzy C-means clustering methods all separated the data into very similar clusters. The three clustering methods yielded similar results due to the dataset's small size and uniformity. Nevertheless, we were able to pinpoint clear differences between the three methods.

The clusters yielded from Fuzzy C-means overlapped more so it's more difficult to profile compared to Agglomerative and K Means. Because customer segmentation relies on clear results, Fuzzy C-means would not be the best to use.



(a) Agglomerative distribution

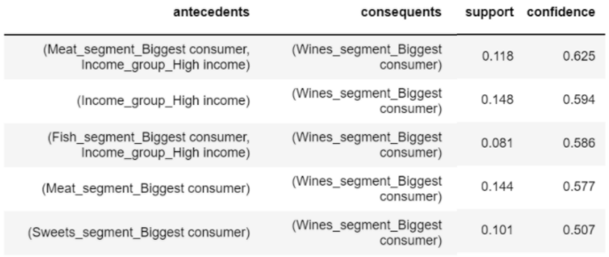
(b) K-Means distribution

Figure 5

Surprisingly, K-means yielded a more even distribution of cluster members than Agglomerative. For the former, Clusters 0, 2, and 3 were similar in size, with a larger difference between Cluster 1 and 2 of approximately 100 data points. The latter had differing cluster sizes, with a very large difference between Cluster 0 and 3 of over 250 data points. From figure 5, the difference in distribution for Agglomerative was larger than the difference for K-means. Thus, K-means is concluded to be the 'best' ML technique here.

These results go against the literature reviews. We postulate that our results are due to the nature of Agglomerative Clustering. Because it builds multiple minuscule clusters early on, the possibility remains that some undetected outliers may have interfered with the clustering formation. Given the small size of the dataset at around 2200 points, likely much smaller than the literature reviews' data, even a few outliers would influence the outcome.

Had our dataset been a larger size of 10000 points, the outcomes would be more consistent with the literature reviews. Agglomerative would likely out-perform K-means.



antecedents	consequents	support	confidence
(Meat_segment_Biggest consumer, Income_group_High income)	(Wines_segment_Biggest consumer)	0.118	0.625
(Income_group_High income)	(Wines_segment_Biggest consumer)	0.148	0.594
(Fish_segment_Biggest consumer, Income_group_High income)	(Wines_segment_Biggest consumer)	0.081	0.586
(Meat_segment_Biggest consumer)	(Wines_segment_Biggest consumer)	0.144	0.577
(Sweets_segment_Biggest consumer)	(Wines_segment_Biggest consumer)	0.101	0.507

Figure 6: Apriori Table

The Apriori Algorithm's table could be difficult to understand, since the support and confidence values were hard to understand/compare on their own. Due to this, Apriori was not the best ML method for this clustering application.

6 Conclusion and Discussion

The demand for product advertisement oriented towards specific customer markets was the inspirational basis for this project. Big Tech such as Amazon and Apple heavily rely on Machine Learning to focus their marketing on key customers.

Our main objective was determining which customers consumed the highest amounts of food products, in this case Wines and Meats.

The project pipeline entailed cleaning the dataset and removing invalid data, identifying general associations and trends within the dataset, then applying Agglomerative Clustering, Apriori Algorithm, K-Means, and Fuzzy C-Means to determine the clusters.

Our results indicated that Agglomerative clustering and K-means clustering yielded the most distinct clustering, and the most impactful attribute was Income. The latter yielded a more even distribution, so K-means is the winner.

Several interesting correlations were discovered. Education level did not meaningfully impact income amongst all clusters. Higher ages generally meant higher income (excluding highest earners [cluster 1]). In addition, more than 95% of the customers in the highest-earning cluster [cluster 1] did not have children, despite ages ranging fairly equally from 20 - 80 years old.

When running the code, differing results may occur. Our team attempted to use seed arguments to force same results every time, but the Agglomerative results still vary. The K-means is consistent, although the ordering of the clusters will switch. We suspect the random results may be due to the nature of hierarchical clustering algorithms.

7 References

Ekhlassi, A., Nezhad, M., Far, S. et al. The relationship between brand personality and customer personality, gender and income: A case study of the cell phone market in Iran. J Target Meas Anal Mark 20, 158–171 (2012). https://doi.org/10.1057/jt.2012.12

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