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Data Mining
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Supermarket Analysis

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1 Data Understanding

The dataset contains *471910* entries, each of them represent a purchase related to a supermarket made by a customer over a period of two years.

1.1 Data Semantics

The dataset contains 8 attributes that correspond to:

- **BasketID** (*24627*): a 6 digit integer number uniquely assigned to each purchase; if it starts with a *C*, it indicates a cancellation (*3754*);
- **BasketDate**: the day (*from 2010/12/01 to 2011/12/09*) and time (*from 6am to 21pm*) when each purchase was placed;
- **Sale** (∼*4avg*): the unit product price, all in the same currency, probably in sterling;
- **CustomerID** (*4372 + 65073na*): a 5 digit integer number uniquely assigned to each customer;
- **CustomerCountry** (*37*): the name of the country where each customer resides;
- **ProdID** (*3953*): a 5 digit + 1 letter identifier uniquely assigned to each distinct product; identical codes with different letters identify the same products with different characteristics (*e.g.*, *84997D*: '*pink piece polkadot cutlery set* vs. *84997C*: '*blue piece polkadot cutlery set*);
- **ProdDescr** (*4097 + 753na*): the description of the product purchased;
- **Qta** (∼*11avg*): the purchased quantities of each product per order.

1.2 Assessing Data Quality

In order to assess the quality of data, we proceed by removing the *5232* duplicate entries which represents the 1.11% of the entire dataset, so we will work with the remaining *466678* rows.

Then, we proceed by removing the entries corresponding to the *65073* null *CustomerID* values, the 13.94% of the dataset, since our main goal is to outline the customer behavior and there is no way to integrate them to trace the customer's orders.

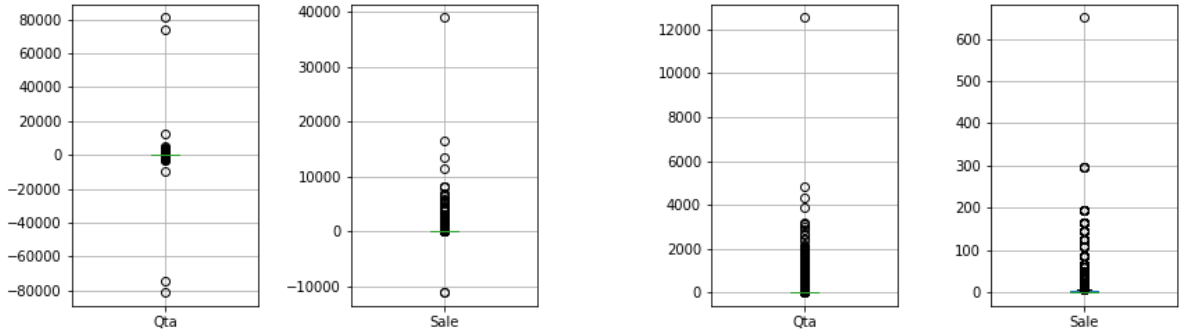
Afterwards, we removed the *ProdID* that does not respect the defined format and we found some that contains only letters, *e.g.*, '*POST*', '*D*', '*C2*', '*M*', '*BANK CHARGES*', etc. with the following respective *ProdDescr*: '*POSTAGE*', '*Discount*', '*CARRIAGE*', '*Manual*', '*Bank Charges*', etc.. As a result, we dropped *1273* entries.

1.3 Variables Transformations

In order to manage the presence of negative quantities as shown in the first boxplot in Figure 1a, we decide to keep track of the portion of each order that has been canceled. At this point we should face three different cases:

- a *cancelation exists with a counterpart*, i.e., exists an order with the same (but positive) quantity and a previous date, so both are canceled;
- a *cancelation exists without a counterpart*, this is probably due to the fact that the orders were performed before December 2010 (the entry point of the database), so we remove this;
- a *cancelation exists with multiple counterparts*, so we delete the most recent.

To also manage the presence of the remaining prices equal to zero, 34 entries to be exact, as shown in the second boxplot in Figure 1a, we filled these values with the average of the selling prices of the products with the same id.

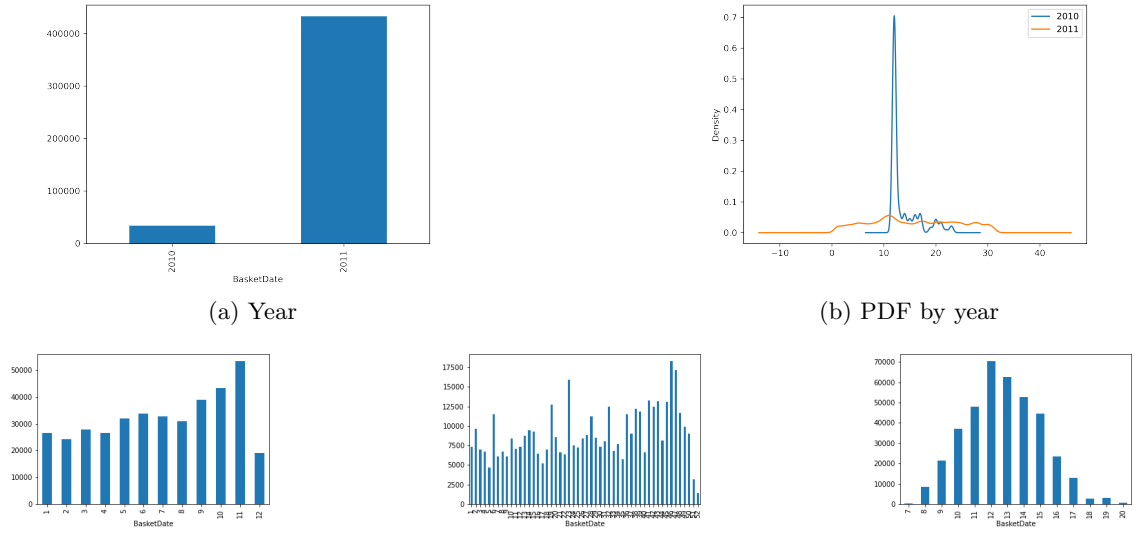


(a) (b)

Figure 1: *Qta* and *Sale* boxplots before and after data cleaning

We decided to create the attribute *TotSale*, i.e., the product between *Sale* and *Qta*, that represents the total amount spent by a customer for each type of product purchased. We made this choice mainly to have a clearer look to the dataset, emphasizing an important information that was not explicit in the original table, and also for the feature extraction later.

1.4 Variables Distribution



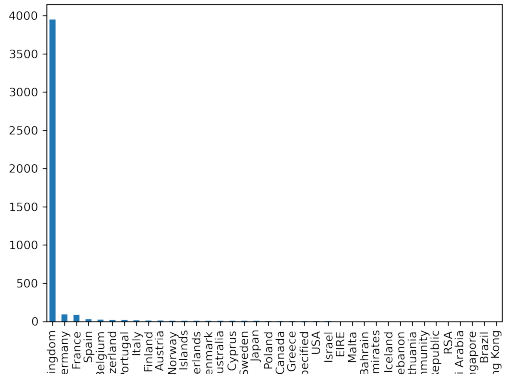
(a) Year (b) PDF by year

(c) PDF by month (d) PDF by week (e) PDF by hour

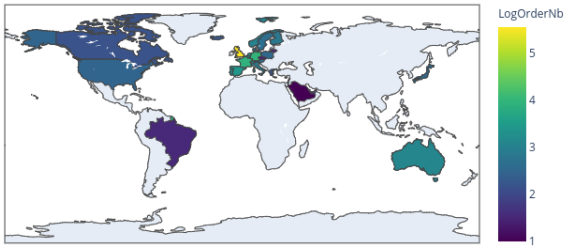
Figure 2: BasketDate distributions

From the Figure 2a, we can see that the attribute is highly unbalanced; in fact, we have that almost all the records are related to transaction of the 2011, while the objects from 2010 are very few. Indeed, the rows of 2011 represent about the 93% of the whole dataset.
Furthermore, from the Figure 2b, that represents an estimation of the probability density function of *BasketDate* divided by year, we can appreciate the two different distributions.
In fact, for the 2010, we have a very uneven plot, which indicates that the records are not uniformly distributed

with respect to the days in a month. This because, for the majority of the months in 2010, there were registered only transactions from a single day, the 12th; this is the value for which the plot shows the peak. On the other hand, the distribution for the 2011 is much more homogeneous, meaning that the transactions were registered for most days in the months of that year. For these reasons we decided to remove the entries of the 2010, since the data were not taken regularly, and so they could alter our next study. We will focus on the 2011 entries, which were present much more uniformly and for this reason they could be more representative.
Other interesting distributions are plotted in Figure 2c, 2d and 2e. In the first one, we can see that the last weeks of the year are the one with more purchases; that is consistent with our expectations, since those are the weeks closest to Christmas time, that typically represents a great period of shopping. This thesis is supported also from the second one, in which we can see that December is the month with the most purchases. The third one is focused instead on the hours in a day; we found that, unsurprisingly, the most popular hourly is lunchtime.



(a)



(b)

Figure 3: CustomerCountry distributions

In Figure 3a and 3b, we can see the distribution of the *CustomerID* with respect to the country; from the plot, it is clear that the most frequent country is the *United Kingdom*, that is present in about the 90% of the rows.

Finally, we see some informations about the correlation of the attributes, to see if some of them are redundant. From the Figure 6, we can see that almost all the attributes are uncorrelated, except for *TotSale*, that shows ah high correlation with *Qta*; that follows what we expected, since *TotSale* is, by construction, dependent on *Qta*. So, we conclude that all the original columns are independent, and so we don't need to perform any further manipulation.

Figure 4: Correlation Matrix

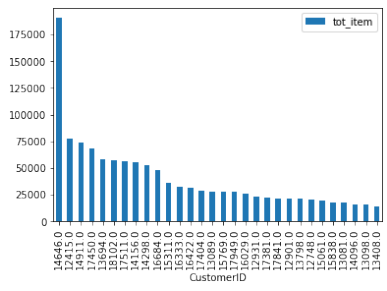
We ended up with a cleaned dataset, consisting of *363577* entries.

2 Data Preparation

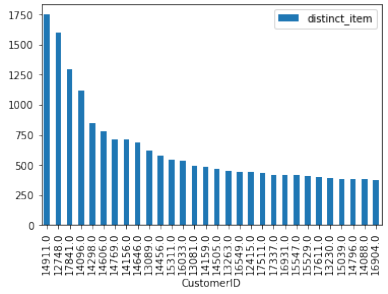
In order to describe the customers behavior, we extract the following new features from the dataset:

- the total number of items purchased by a customer;
- the number of distinct items bought by a customer;
- the maximum number of items purchased by a customer during a shopping session.

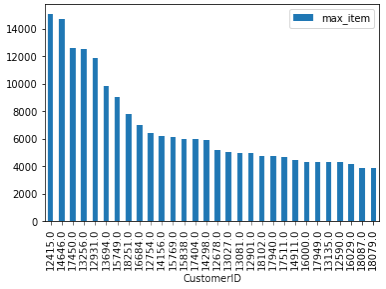
In Figure 5, we can see some visualization for these features; in particular, they represent the first 30 customers with the biggest values for each feature.
An interesting information is clear from the plot 5c, where we can see that the maximum quantities purchased in a single shopping session are very big; they are all above 3500, with the maximum equal to 15049. These are very high values, unlikely for a retail customer; this led us to think that the supermarket in question also sells wholesale.



(a) Total number of items per customer



(b) Number of distinct items per customer



(c) Maximum number of items per customer

Figure 5: Visualization for the extracted features

Now, with respect to the *TotSale* attribute we can take into account:

- the average price spent by a customer during a shopping session;
- the Shannon entropy on the purchasing behavior of the customer.

The entropy represents the variability of the customer's spending habits; i.e. a bigger value means that the customer did not have a regular behavior since he spent always a different amount of money, while lower values identify predictable spending behavior since the customer tends to spend always the same amount of money.
As shown in 8a, we have a small peak corresponding to 0, meaning that there are some customers with very specific habits, but the maximum is reached for ~ 4, which means that the majority of the clients have a quite unpredictable behavior.

At this point we decide to introduce a domain specific model, called *RFM*, to provide an intresting customer segmentation based on the purchasing behavior of the customers. In particular, the *RFM (Recency, Frequency, Monetary)* analysis refers to:

- *Frequency* is the number of orders for each customer;
- *Recency* is the number of days between present date and date of last purchase each customer;
- *Monetary* is the purchase price for each customer.

and it helps divide customers into various categories or clusters to identify customers who are more likely to respond to promotions and also for future personalization services as shown in 8a.

To calculate the individual RFM we will use the quartil statistical method, i.e. dividing score into four parts, by associating them a number from 1 to 4, so we will deal with the following:

Segment	RFM	Description	Marketing
Best Customers	111	Bought most recently and most often, and spend the most	No price incentives, new products, and loyalty programs
Loyal Customers	X1X	Buy most frequently	Use R and M to further segment
Big Spenders	XX1	Spend the most	Market your most expensive products
Almost Lost	311	Haven't purchased for some time, but purchased frequently and spend the most	Aggressive price incentives
Lost Customers	411	Haven't purchased for some time, but purchased frequently and spend the most	Aggressive price incentives
Lost Cheap Customers	444	Last purchased long ago, purchased few, and spent little	Don't spend too much trying to re-acquire

Figure 6: RFM Segmentation

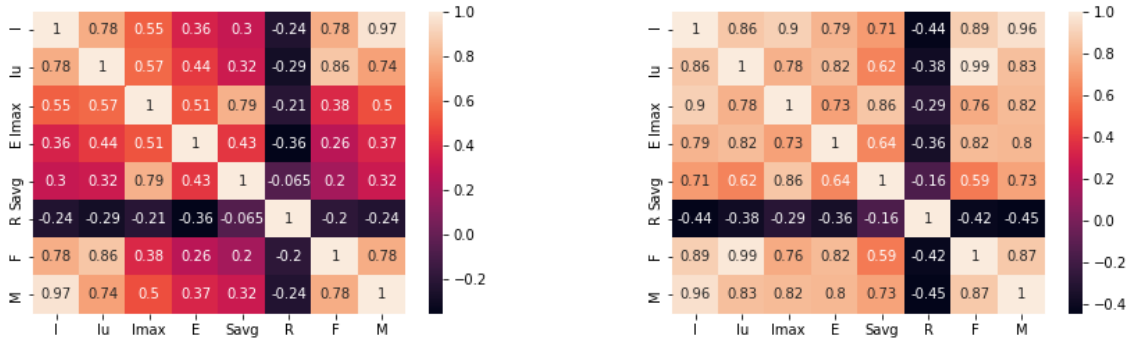
- best Recency score = 1: most recently purchase
- best Frequency score = 1: most quantity purchase
- best Monetary score = 1: spent the most

Wrt our dataset the customer segmentation result as following:

- the number of Best Customers is 394
- the number of Loyal Customers is 1041
- the number of Big Spenders is 1052
- the number of Almost Lost is 112
- the number of Lost Customers is 28
- the number of Lost Cheap Customers is 360

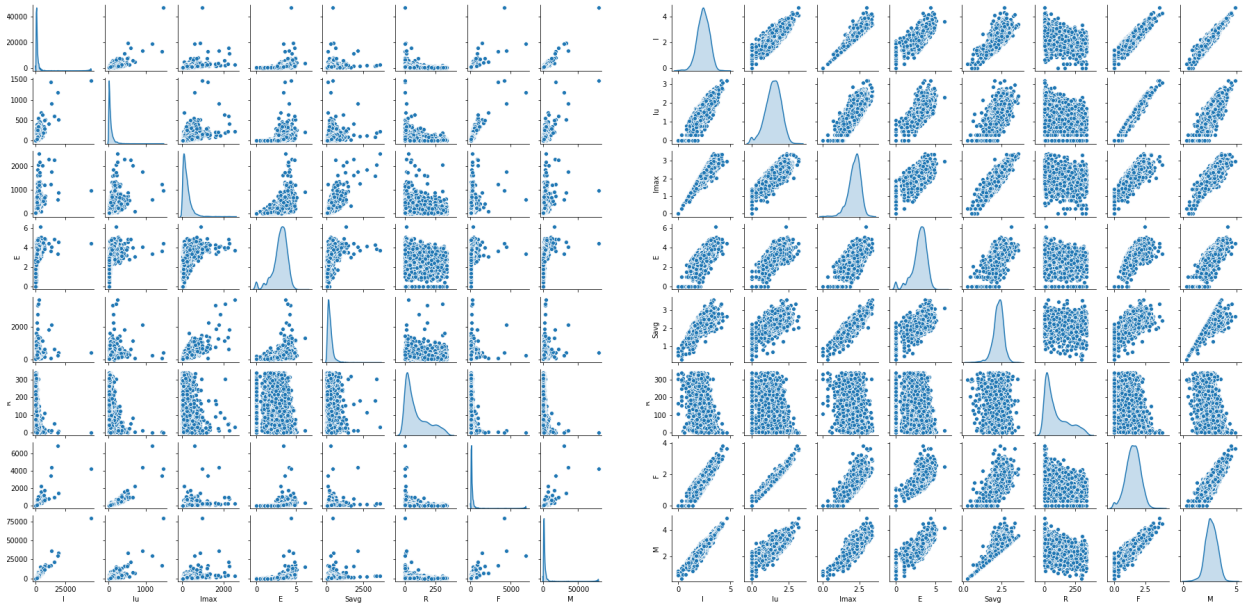
Now, we can visualize the correlation between the attributes. In Figure **??**, as expected, we find that the average basket value is highly correlated with the total quantity purchased and the amount of money spent. Furthermore, we can see that also the monthly frequency is correlated with the amount spent and the total quantity. In the end, of course, the quantity purchased is very highly correlated with the total amount spent.

In Figure 15, we can visualize the pairplot for the attributes we have.
On the diagonal, we have the density plots, where we can appreciate the distribution of the features. Instead, the other scatter plots show the relationship between two variables. By analyzing those, we can have a confirmation of what we already found thanks to the previous plot.



(a) (b)

Figure 7: Correlation Matrix before and after log-normalization



(a) (b)

Figure 8: Pairplots before and after log-normalization

3 Clustering

We now run and compare some clustering algorithm in order to find some structures among the data. First we start with a basic *K-Means* followed with some *Hierarchical clustering techniques* and *DBSCAN*.

3.1 Preprocessing

The data matrix was first standardized and then the two principal components were extracted. The choice was between two and tree principal component since they retain respectively ∼0.75 and ∼0.89 of the variance of the data.

We selected the two principal components, in this way, we could also have a visual inspection.

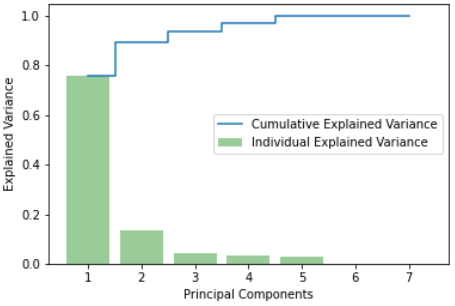
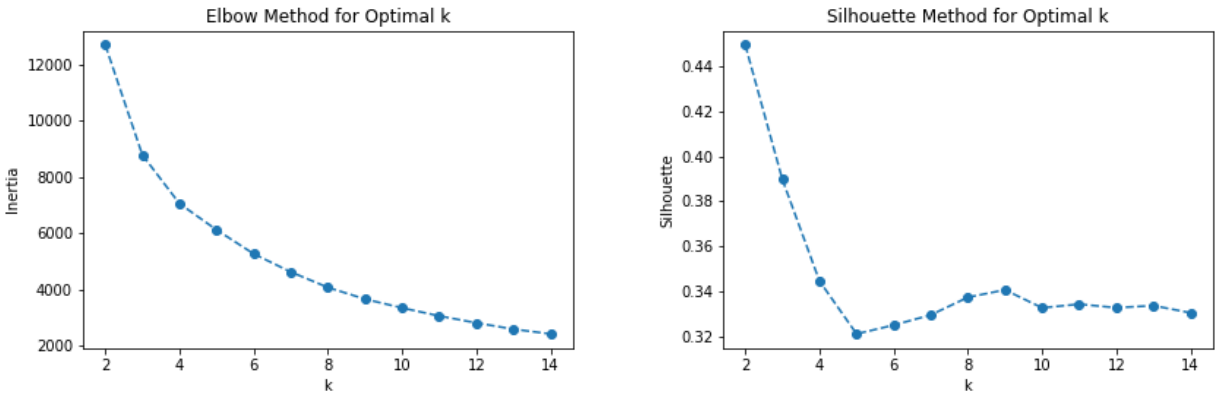


Figure 9: Explained variance ratio

3.2 K-Means

The algorithm run for K ranging from *2* to *15* clusters. For each iteration the SSE and the average silhouette value were computed.



(a) SSE

(b) Average silhouette

Figure 10: *K-Means* metrics

By looking at the plots in Figure 10, we can see that there isn't a prominent *elbow shape*, so we needed the analysis of more metrics to get the optimal number of clusters. By inspecting the silhouette score, it is possible to see that it has its maximum for $K = 2$, followed by $K = 3$. In conclusion, we opted for 3 clusters, to get a trade off between high silhouette and low SSE.

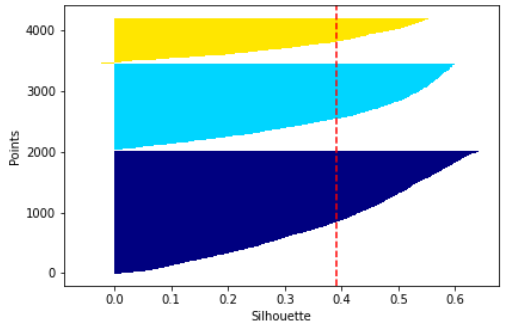
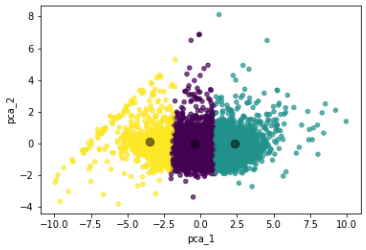


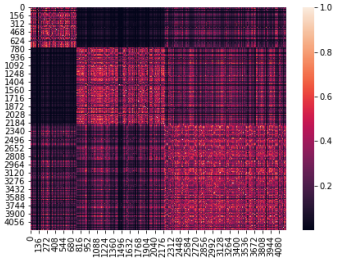
Figure 11: Silhouette score for each data point

The resulting clusters have a comparable number of points. In particular *Cluster 0* has **2006** points, *Cluster 1* **1440** and *Cluster 2* **760**.

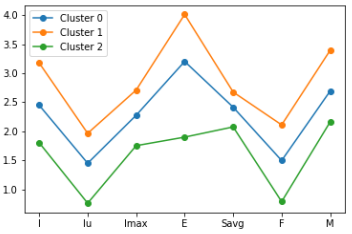
In Figure 11, we can see the plot of the Silhouette score, where each different color represents a different cluster, and the dotted red line is the average silhouette score. In particular we have that *Cluster 0* has a silhouette of *0.39*, *0.40* for *Cluster 1* and *0.35* for *Cluster 2*, with an overall average silhouette of *0.39*. We see that a small fraction of points in *Cluster 0* have a negative value but overall the Silhouette suggests a good clustering.



(a) Clustering result



(b) Similarity heatmap



(c) Average values per cluster

In Figure 12a, we can appreciate the results of the algorithm, where we can see that the clusters are well separated from one another.
The similarity matrix (Figure 12b) shows the affinity of elements inside a cluster; we can see that the results are pretty good.
The plot in Figure 12c shows the average values for each attribute divided by the clusters. In particular, it is possible to see that *Cluster 1* contains the most frequent and spending customers, followed by *Cluster 1* and *Cluster 2*.

3.3 Hierarchical clustering

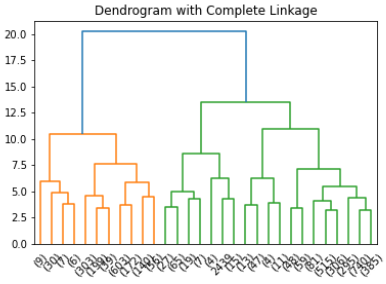
We used different kinds of algorithm: *Complete Link*, *Single Link*, *Ward* and *Average Link*. By looking at the dendograms in Figure 13, if we cut the tree by selecting two or three clusters, we can see that *Single Link* and *Average Link* generate an unbalanced clustering leaving the last merges between a large cluster and a small one, in some cases even a singleton. The most balanced are obtain with *Ward* and *Complete Link*.

3.4 DBSCAN

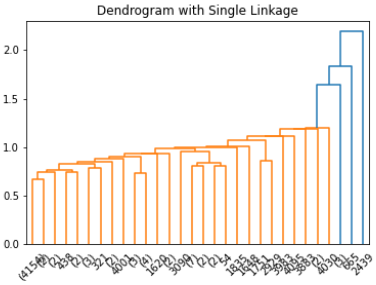
We explored different combination of *eps* for a given *MinPts*; to choose *eps* we checked the *KNN* distance, with K equal to *MinPts*.
If *MinPts* is 20, the optimal *eps* is around 0.25. In this case the algorithm found a large dense area surrounded by noise points, as is showed in Figure 14. By increasing *eps* to 0.3 the results are the same, if instead the value of 0.2 is used the algorithm finds more clusters of negligible dimension.

3.5 Clustering results

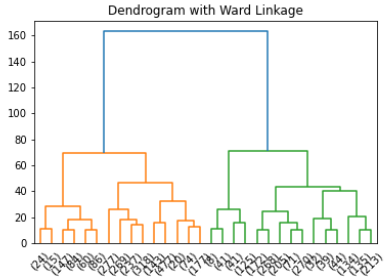
In conclusion we opted for the *K-Means* clustering to characterize the customers. In fact it is able to characterize the customer based on its purchasing behavior as in seen in Figure 15.



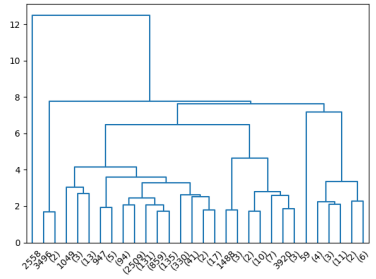
(a) *Complete Link*



(b) *Single Link*

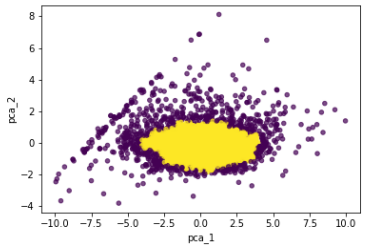


(c) *Ward*



(d) *Centroids*

Figure 13: Dendograms



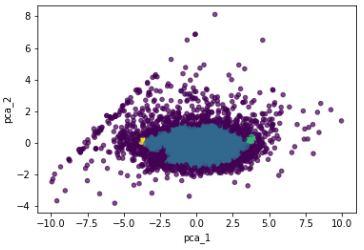


Figure 14: Results of DBSCAN

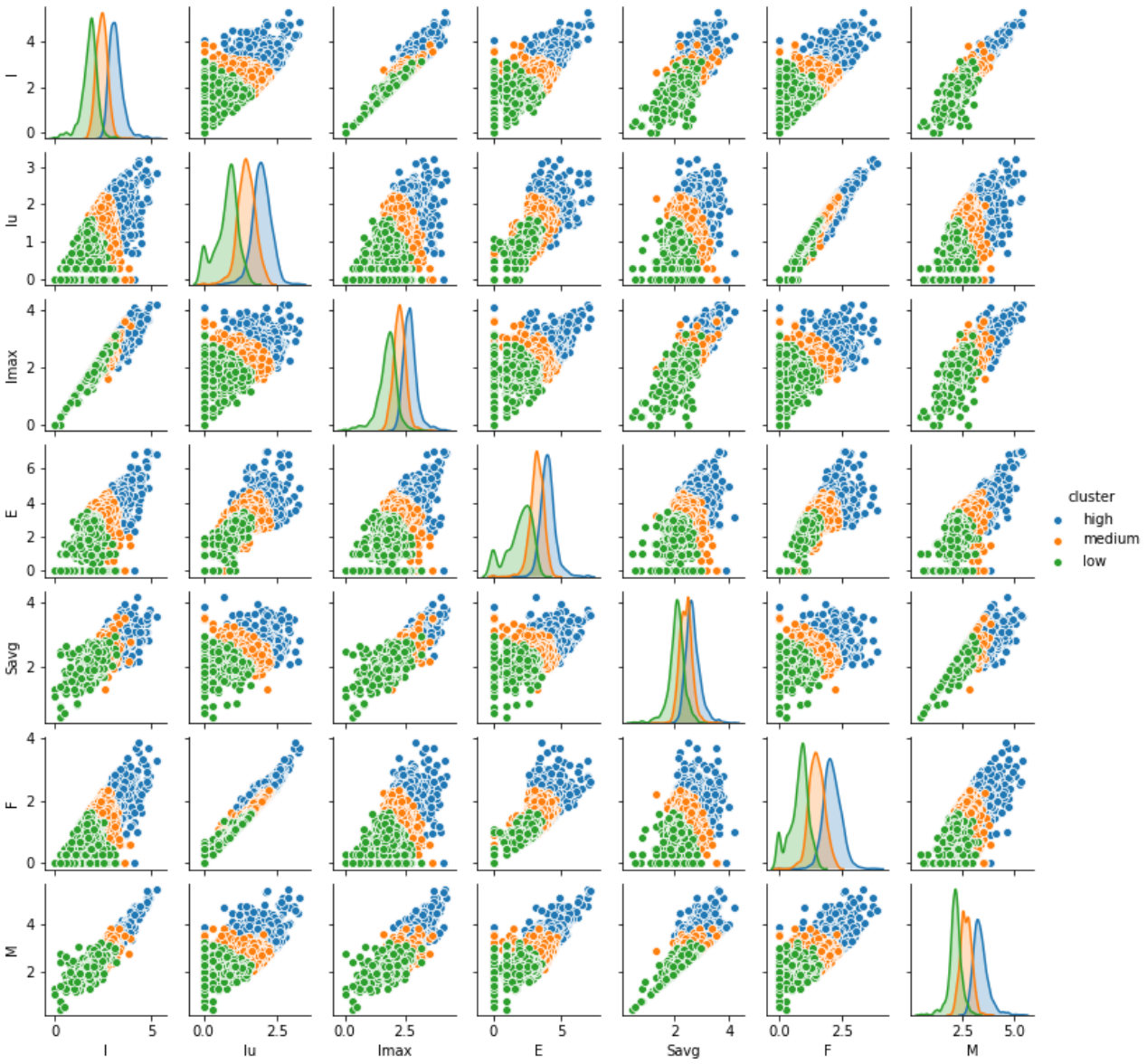


Figure 15: K-Means results

4 Predictive Analysis

In this section, we consider the problem of predicting the spending behavior of each customer.We will use the main classifier models and evaluate their performances.

First, we will use the customer profile deriving from the K-means clustering, from the previous section. From the Figure 12a, we recall that we partitioned the dataset in 3 clusters, that represent the **high-spending** customers, the **medium-spending** customers and the **low-spending** customers. We can see that the clusters are well separated from each other, and so we can use them as customer classification.

To perform the task, which is a *supervised* one, we split the dataset into training and test set, equal to the 75% and 25% of the dataset respectively. Plus, during the splitting, we specify that each partition must have approximately the same relative class frequencies; that is to manage the unbalance we have in the original dataset, in which the **medium-spending** customers are much more frequent than the other classes.
We also standardize the data with a standard scaler, achieving a distribution with 0 mean and unit variance.

For each model, we perform a grid search, to find the best values for some hyperparameters; for that, we used a *5-fold cross validation*.

4.1 Support Vector Classifier

The first model we analyze is the **SVM**, that is a classifier that searches for an hyperplane that can linearly separate the data points, possibly in a transformed space, in the non-separable case. We use a Linear Support Vector Classifier and, after the grid search, we found that the best value for the regularization parameter is $C = 1000$.
With this configuration, we achieved a training accuracy of 0.9906 and a test accuracy of 0.9962.
From the Figure 16, we can see the confusion matrix related to the results on the test set, and we notice that the model made only 4 mistakes on the whole dataset; for that, we have that also the precision and the recall for each class are all above 0.98.

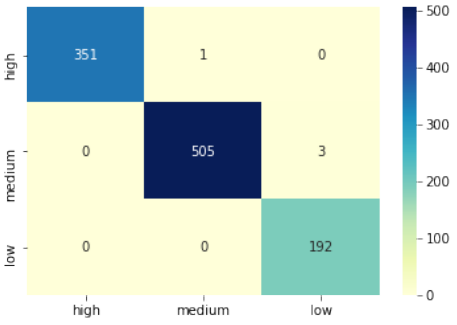


Figure 16: Confusion Matrix for SVM Classifier

4.2 Neural Network

Now, we use a Neural Network, in particular a **Multi Layer Perceptron**.
The best values for the hyperparameters that we found was:

- 1 hidden layer with 50 units
- Logistic activation function
- Learning rate equal to 0.001
- The *lbfgs* optimizer, that can converge faster and with better results on small datasets like ours

With this model, we got a training accuracy of 1 and a test accuracy of 0.999; the reason is clear in Figure 17, where we can see that just one data point was misclassified.

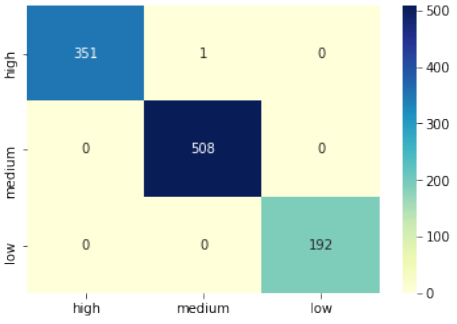


Figure 17: Confusion Matrix for Neural Network

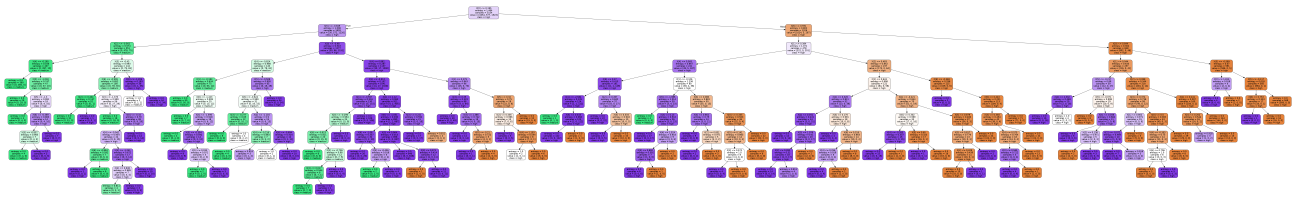


Figure 20: Decision Tree

4.3 Naive Bayes Classifier

The Naive Bayes Classifier tries to estimate the class conditional probability for each item, using the *Bayes* theorem, with the assumption that all the features are conditionally independent. In particular, we used a **GaussianNB**, where the likelihood of the features is assumed to be Gaussian.
In Figure 18, we can see that the performances of this model are slightly worse than the previous ones; in fact, we achieve a training accuracy of 0.9668 and a test accuracy of 0.9525.

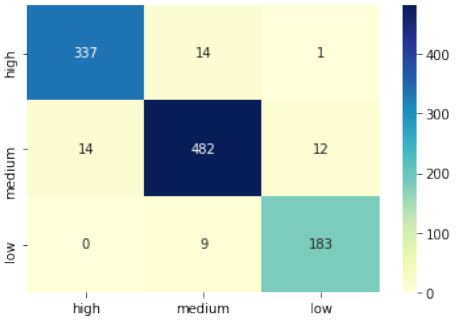


Figure 18: Confusion Matrix for Naive Bayes

4.4 K-Nearest Neighbors

The K-Nearest Neighbors model is an instance-based classifier, that, for each record, selects the class label based on the majority of its nearest neighbors.
The grid search showed that the best configuration is

- *n_neighbors* equal to 50
- *distance* as weight function; that makes the weight of a point to be inversely proportional to its distance

With these values, we have a training accuracy of 1 and a test accuracy of 0.9781. The Figure 19 shows that some points are misclassified, with some customers, belonging to the high and low profile, incorrectly labeled as medium.

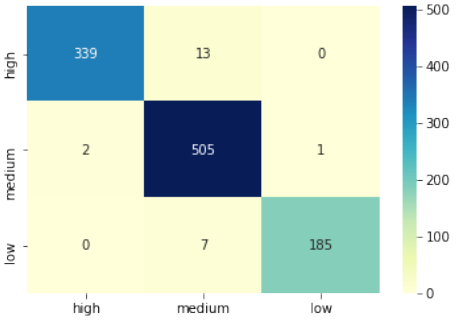


Figure 19: Confusion Matrix for K-Nearest Neighbors

4.5 Decision Tree

A Decision Tree model learns some decision rules from the training data, in order to grow a tree that is able to predict the class label for our test points. The best configuration found is:

- *criterion* equal to *gini*
- *max_depth* equal to 200
- *max_features* equal to 5
- *min_samples_leaf* equal to 1
- *min_samples_split* equal to 2
- *splitter* equal to *best*

The best result is a training accuracy of 1 and a test accuracy of 0.9392, but one of the advantages of this kind of model is that it is easy to interpret, since it can be visualized. In Figure 20, we can have a representation of the best estimator that we found.
The Figure 21 shows the model makes several mistakes, with respect to the other classifiers, given that the decision tree is a quite simple model.

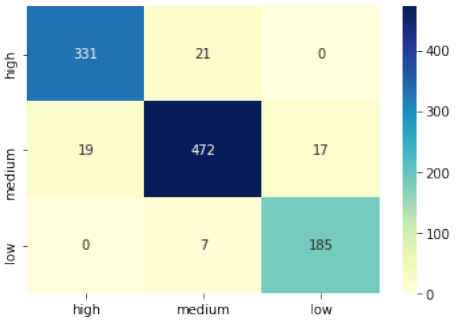


Figure 21: Confusion Matrix for Decision Tree

4.6 Random Forest

Lastly, we analyze the Random Forest. It is an *ensemble* model, composed by several decision trees, and the result is given by averaging the predictions of the single classifier. In this case, the best hyperparameters are:

- *max_depth* equal to 30
- *max_features* equal to 1
- *min_samples_leaf* equal to 1
- *min_samples_split* equal to 2
- *n_estimators* equal to 1500

As a results, we have a training accuracy of 1 and a test accuracy of 0.9952; these good results are confirmed by the Figure 22, that shows that the errors made by the model are very few.

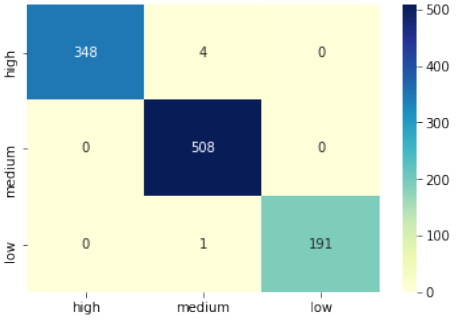


Figure 22: Confusion Matrix for Random Forest

4.7 Conclusion

In conclusion, the model that performs the best is the Neural Network, which is almost perfect both on training and test set; also the SVM and Random Forest have very good performances, having an accuracy of 99%.
Overall, even if the other models give slightly worse results, they all have an accuracy greater than 93%, which is pretty good. That is because the dataset is not very complex, since the clusters given by K-Means(Fig. 12a) are almost linearly separable.

5 Sequential Pattern Mining

In this section, we want extract some patterns from the dataset, in order to capture some frequent purchasing behavior of the customers.

5.1 Dataset Modeling

First of all, we need to model the dataset, to be able to apply the algorithm afterwards.
For each customer, we have to extract from our data the list of his baskets, containing all the products he purchased, with a temporal information. We decided to use as a timestamp the day of the year, since the dataset covers a period of about an year, and the vast majority of the customers purchased at most one basket per day; hence, we defined *BasketDayOfYear*, a numerical attribute that goes from 2 to 344.

We ended up having, for each customer, a list of tuple, composed by the day of the year and the list of products, identified by the *ProdDescr*, he purchased at that time.

Then, we checked for consecutive duplicate rows, that are those consecutive records with the same value for each attribute; we found **1103** sequences of this kind and we decided to drop them. That occurs because some products share the same description, while having different ids, and so they are distinguished in a basket; maybe, that is due to some minor differences which are not indicated in the descriptions, and so they cannot be considered in our analysis.

5.2 GSP Algorithm

We now apply the *Generalized Sequential Pattern*, an apriori-based Sequential Pattern Mining algorithm to discover the frequent patterns present in our dataset.
GSP algorithm starts by finding all the 1-sequences that are frequent, that are those patterns with a support greater than the *min_sup*. We set *min_sup* equal to 5%.
Then, at each step, it generates new longer candidates by merging pairs of the previous ones, and later it eliminates all the sequences with a low support. It stops when no more frequent sequences are found.

With this method, after filtering all those by one object, we found 42 frequent patterns, all of them made up by just two products; plus, the maximum support is 0.087, which is quite low. That means that, in the dataset, there are not very frequent patterns, and so we can say that the customers' behavior is quite different from each other.

Nevertheless, we can see some interesting characteristics of the patterns we found.
In particular, we notice the majority of them are constituted by the same item, with the only difference of the colour, design or some other minor detail. That is unsurprisingly, since it is common for wholesalers to buy several versions of the same product. Some examples are:

- {*WHITE HANGING HEART TLIGHT HOLDER*}, {*WHITE HANGING HEART TLIGHT HOLDER*}
- {*JUMBO BAG RED RETROSPOT*}, {*JUMBO BAG RED RETROSPOT*}
- {*REGENCY CAKESTAND TIER*}, {*REGENCY CAKESTAND TIER*}
- {*ASSORTED COLOUR BIRD ORNAMENT*}, {*ASSORTED COLOUR BIRD ORNAMENT*}
- {*PARTY BUNTING*}, {*PARTY BUNTING*}
- {*LUNCH BAG RED RETROSPOT*}, {*LUNCH BAG RED RETROSPOT*}
- {*LUNCH BAG BLACK SKULL*}, {*LUNCH BAG BLACK SKULL*}
- {*LUNCH BAG SUKI DESIGN*}, {*LUNCH BAG SUKI DESIGN*}
- {*SET OF CAKE TINS PANTRY DESIGN*}, {*SET OF CAKE TINS PANTRY DESIGN*}

In other cases, we found sequences of products related to each other, which is quite normal also for single customers; an example can be {*REGENCY CAKESTAND TIER*, *ROSES REGENCY TEACUP AND SAUCER*}.

- {*GREEN REGENCY TEACUP AND SAUCER*, *PINK REGENCY TEACUP AND SAUCER*, *ROSES REGENCY TEACUP AND SAUCER*}
- {*GARDENERS KNEELING PAD CUP OF TEA*, *GARDENERS KNEELING PAD KEEP CALM*}
- {*HEART OF WICKER LARGE*, *HEART OF WICKER SMALL*}
- {*WOODEN HEART CHRISTMAS SCANDINAVIAN*, *WOODEN STAR CHRISTMAS SCANDINAVIAN*}
- etc.

5.2.1 Including Temporal Constraints

We can extend our analysis by considering some temporal constraints in the pattern mining.
In fact, it is important to take into account the time elapsed between two purchases, as long as the total duration of the sequence.

This constraints can be add in the **GSP** algorithm, by introducing some new parameters:

- *max_span*, the maximum duration of the whole sequence;
- *min_gap*, the minimum time between two elements of the sequence;
- *max_gap*, the maximum gap between two elements of the sequence.

The algorithm proceeds as before, with the addiction that it prunes also all the candidates that violate these time constraints.

We imposed the distance between two elements to be at least of one day and at most of one week, and the overall duration of one month; hence, $max_span = 30$, $min_gap = 1$ and $max_gap = 7$. Also in this scenario, we kept the $min_sup = 0.05$.

We expect the sequences found in this case to be a subset of the ones we found before, and in fact the method returns **32** frequent patterns, all of them already present in the previous results; we do not consider the sequences made by one element in this case too.