Machine Learning Engineer Nanodegree Program - Project Capstone

I. Definition

Project Overview:

This project aims at building both supervised and unsupervised algorithms to segment the data of the general population into the customers of Arvato Financial services according to the various demographic information provided. Using this segmentation we can further predict the potential of a general person to be converted to a customer or not.

Why select this project:

Though I tried my initial analysis with an open dataset on Covid-19, I found many of the findings are repetitive and there was very less possibility for understanding clusters using unsupervised learnings.

Next I had to choose between the projects given by Udaciyt where I found the data of Arvato Financial services very interesting. It was also because I had a previous experience working with a company to understand customer segmentation.

Dataset

There following were the Datasets provided

1. DIAS Attributes - Values 2017.xlsx - The metadata
2. DIAS Information Levels - Attributes 2017.xlsx - Understanding the levels in the data
3. Udacity_AZDIAS_052018.csv: Demographics data for the general population of Germany; 891 211 persons (rows) x 366 features (columns).
4. Udacity_CUSTOMERS_052018.csv: Demographics data for customers of a mail-order company; 191 652 persons (rows) x 369 features (columns).
5. Udacity_MAILOUT_052018_TRAIN.csv: Demographics data for individuals who were targets of a marketing campaign; 42 982 persons (rows) x 367 (columns).
6. Udacity_MAILOUT_052018_TEST.csv: Demographics data for individuals who were targets of a marketing campaign; 42 833 persons (rows) x 366 (columns).

Problem Statement

From the massive amount of data of the general population of Germany we need to find the people or segment the population into a way that will help us easily identify the people who have high potential to be converted as a customer.

The problem will be approached in this manner. In this we are to perform Supervised learning using datasets 3 and 4 whereas with the same processing techniques apply unsupervised learning techniques using 5 and 6.

Metrics

As we are trying to use a classifier algorithm here and the evaluation metric to be used here should be one that can clearly evaluate the binary classifiers.

An important element of the supervised learning is the evaluation metrics.
Here I am choosing the Receiver operating characteristic (ROC).

To select the best classifier we are using ROC as ROC is used for understanding trade -offs in Binary Classifier. ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.

II. Analysis

Data Exploration

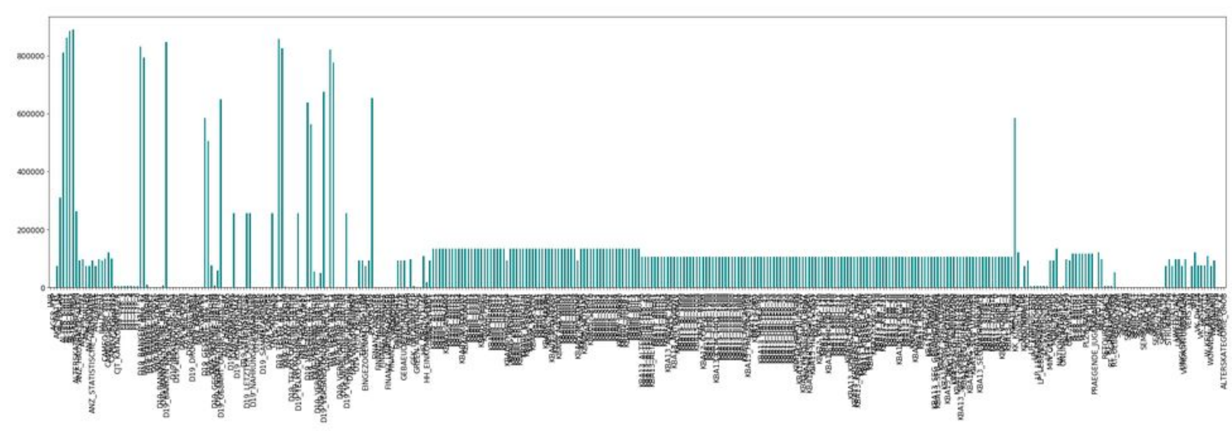
Upon loading the data for General data with demographics of people of Germany and the customer data of Arivato financial services we can understand the presence of NULL values in many of the columns.

Exploratory Visualization

	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	ANZ_HAUSHALTE_A
0	910215	-1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	910220	-1	9.0	0.0	NaN	NaN	NaN	NaN	21.0	
2	910225	-1	9.0	17.0	NaN	NaN	NaN	NaN	17.0	
3	910226	2	1.0	13.0	NaN	NaN	NaN	NaN	13.0	
4	910241	-1	1.0	20.0	NaN	NaN	NaN	NaN	14.0	

The image with head functions

Converting this into a visualization using Matplotlib library we get the following.



Plot showing the NULL/NaN values in the data

The NULL values can be classified into two categories.

- With columns more than 80% of NaN values that are irrelevant data
- With columns with lesser proportion of NaN values

Both these categories are to be considered separately in the pre-processing steps.

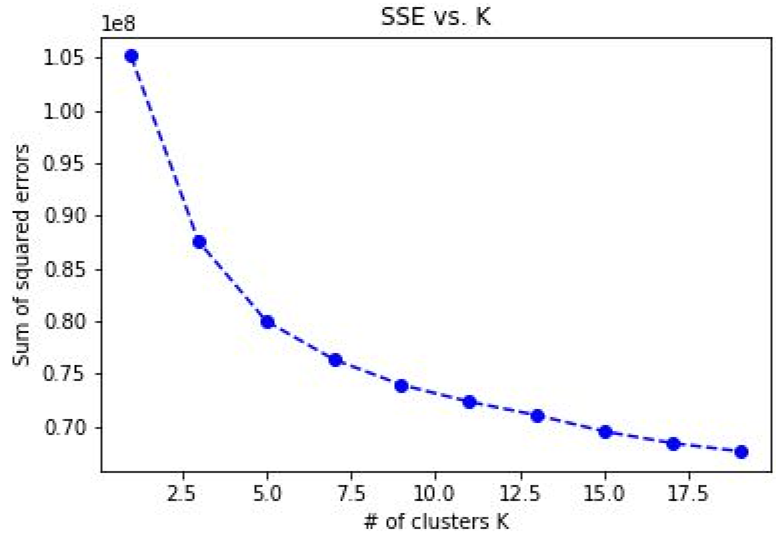
Another step is understanding the variable types in the category variables and re-encoding them. For this manual looking is done into the ‘DIAS Information Levels - Attributes 2017.xlsx’ file and conclusions are made on the datatype for each column.

Algorithms and Techniques

- Pre-process the data with a common function to clean the data for which a Python generic function was written called clean_data() passing arguments as the Dataframe that needs to be cleaned, along with a list of columns that needs to be dropped.
- Use Imputer, StandardScaler from sklearn.preprocessing to make uniformity in the data Both Imputer and StandardScaler are applied on the General data, Customer data, training data and test data. This helped in filling the missing values in columns with a lesser number of NaN values. Also in bringing uniformity to scaling.
- Principal Component Analysis was applied on datas prior to both supervised and unsupervised learning. This helped in identifying variables with greater variances and the unit vector in the direction of variance.
  With proper principal components it will be easier for the model to fit values.
- Use unsupervised learning techniques like K-Means to cluster the data
  To choose the right value for K-Value we used the Elbow method.
- Use supervised learning techniques like Logistic Regression, Random Forest algorithm, Gradient Boosting, AdaBoost classifier were used to classify each customer in the training set and evaluate using evaluation metrics
- Use evaluation metrics that focus on the accuracy and precision of the model to choose the model for evaluation
- Choose the best model and save it
- Used GridSearchCV method to input sample hyperparameter values in grid and search values from them.
- Use the saved model to predict on the test data
- Create CSV data for Kaggle submission

Benchmark:

For unsupervised learning we are using elbow method to choose the K-Value. The following is the diagram that helps in deciding the elbow point.



To benchmark the parameters to be passed for final model fitting GridSearchCV method has been used.

```
param_grid = {'learning_rate': [0.01, 0.1, 1.0],
               'max_depth' : [2,3,4],
              'n_estimators': [20, 50, 100]}
```

The parameter grid used for finding best parameters for the Gradient Boost Algorithm (best performer algorithm) in the supervised learning is as above.

```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.01, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)
```

The parameter values for the best algorithm chosen is as above.

III. Methodology

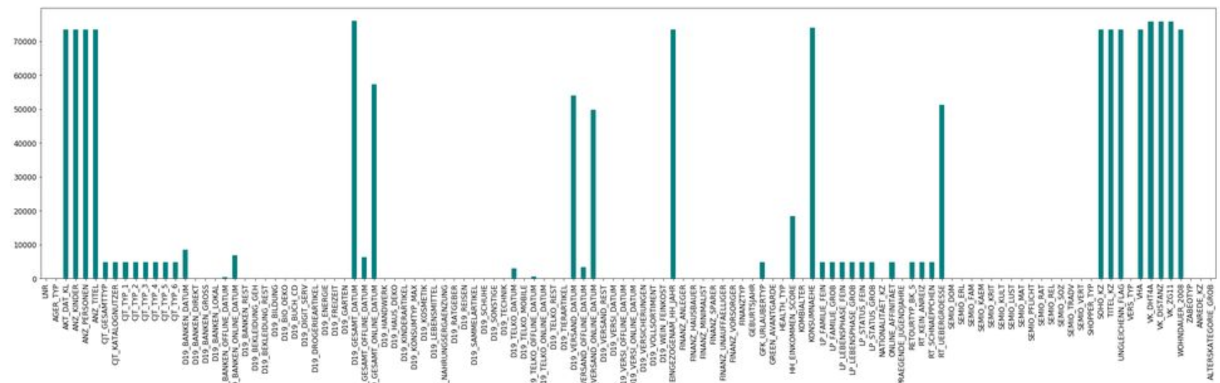
Data Preprocessing

- The pre-processing steps include removing columns with more than 80% of NaN values. This made me keep a threshold value for the number of NULL values in each column. Drop the columns that have NaNs values more than the threshold.

- Another step that calls for a pre-processing is understanding the variable types in the category variables and re-encoding them. For this manual looking is done into the ‘DIAS Information Levels - Attributes 2017.xlsx’ file and conclusions are made on the datatype for each column.

- The third pre-processing done on the data is to fill with dummy variables and forward filling methods for NaN values.

After the preprocessing the data plot looks like as below



Plot made using Matplotlib - The ratio of columns with NULL values has been reduced

The same steps are applied on the ‘Customer’ data too. However, we need to handle the three extra columns that are present in this data, which classify the customer’s activity from the ‘General’ data. For this purpose the three extra columns are stored in a different dataframe and dropped from the original dataframe.

Implementation

The following were the implementation steps:

1. **Utilizing the memory efficiently**

On reaching till this point we find that the preprocessed data takes up a lot of memory that can affect the performance of the code and over usage of the memory of the machine. Hence we can store the data as pickle files. The below are some examples of the pickle files generated.

These files can be further unloaded using pickle commands for later use.

2. Bringing uniformity to the data

Applying feature scaling will be the next step.

Here feature scaling was done using StandardScaler. As we know there are other scalars such Quantile transforms or normal feature scaling. As we have data here with considerable missing value and where I have used the mean method to impute values standard scaling can maintain the accuracy of the data very well.

The StandardScaler from the sklearn library will be the choice to implement. And below are the general data and customer data after applying feature scaling.

In [55]:
```
# View the first few lines of the azdias dataset after scaling
azdias_clean.head()
```

Out[55]:

	LNR	AGER_TYP	AKT_DAT_KL	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	CJT_GESAMTTYP	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	...
0	1.060942	-0.535207	-2.548188e-16	5.767669e-17	-6.016590e-16	1.315086e-17	-1.026509	1.117603	-1.735371	-1.570605	...
1	1.060961	-0.535207	1.313451e+00	-3.200530e-01	2.460008e-01	-6.309721e-02	0.859488	-1.567755	1.195893	1.291527	...
2	1.060981	-0.535207	1.313451e+00	-3.200530e-01	-6.572095e-01	-6.309721e-02	-0.397844	-0.896415	0.463077	0.575994	...
3	1.060984	1.967456	-9.817530e-01	-3.200530e-01	-1.560420e+00	-6.309721e-02	-1.026509	-0.225076	-1.002555	-0.855072	...
4	1.061043	-0.535207	-9.817530e-01	-3.200530e-01	2.052422e+00	-6.309721e-02	0.859488	-0.225076	-0.269739	-0.139539	...

5 rows × 118 columns

The General data we see the data to have an uniform range

In [56]:
```
# View the first few lines of the customers dataset after scaling
customers_clean.head()
```

Out[56]:

	LNR	AGER_TYP	AKT_DAT_KL	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	CJT_GESAMTTYP	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	...
0	-2.439573	1.967456	-0.981753	-0.320053	0.246001	-0.063097	-2.283841	0.446263	-1.735371	-1.570605	...
1	-1.917770	-0.535207	-0.981753	-0.320053	-0.657210	-0.063097	-2.283841	1.117603	-1.002555	-0.855072	...
2	-1.917766	1.133235	-0.981753	-0.320053	-1.560420	-0.063097	-2.283841	1.117603	-1.735371	-1.570605	...
3	-1.917762	-0.535207	-0.981753	-0.320053	2.052422	-0.063097	-2.283841	0.446263	-0.269739	-0.139539	...
4	-1.917707	1.133235	-0.981753	-0.320053	0.246001	-0.063097	-2.283841	-0.225076	-1.735371	-1.570605	...

5 rows × 118 columns

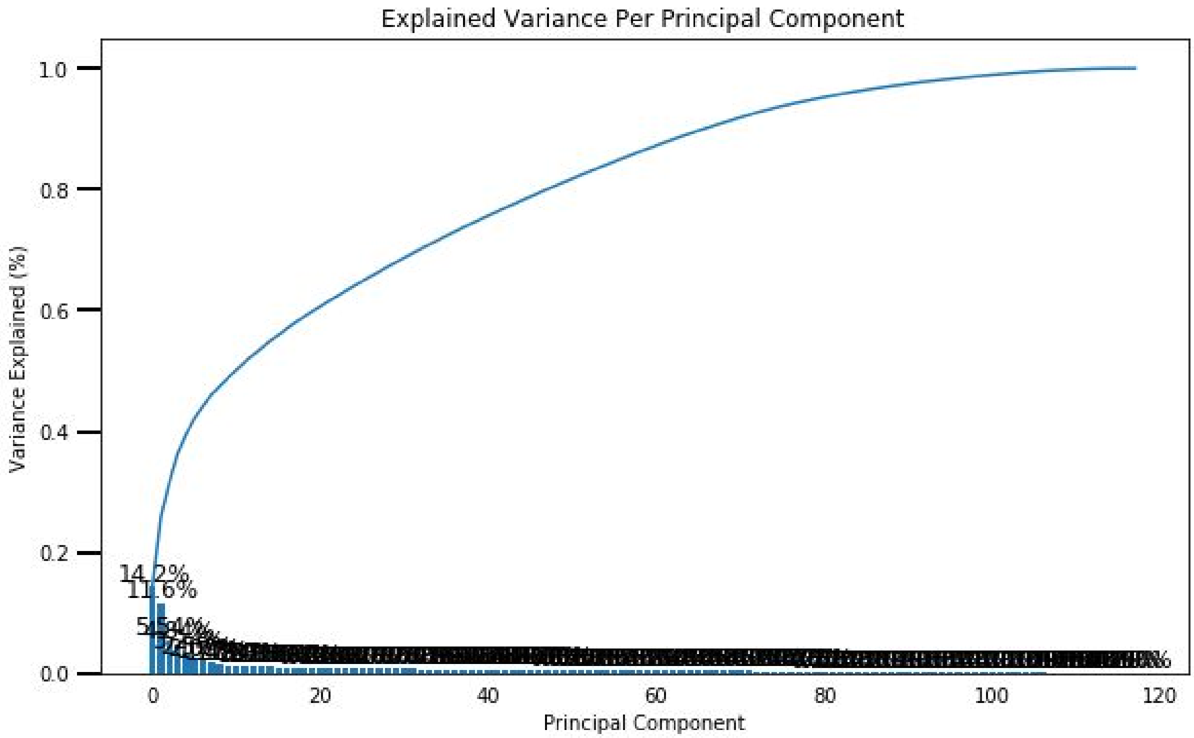
The Customer Data with uniformity brought to the values of various columns

3. Choosing the right variables using Principal Component Analysis

- Use sklearn's PCA class to apply Principle Component Analysis over the variables. We know we need to find variables that has maximum variance among themselves so that their impact is clearly seen over the predicted variables.

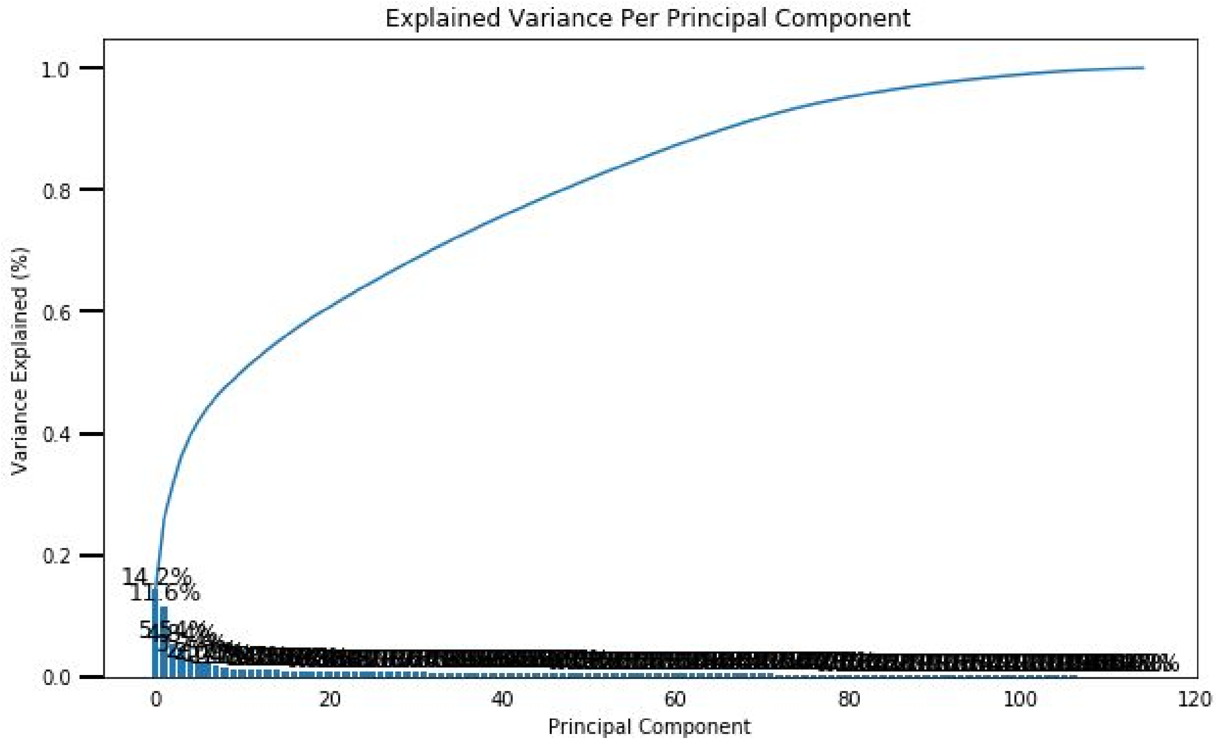
- We have to check out the ratio variance explained by each principle component as well as the cumulative variance explained.Try plotting the cumulative or sequential values using matplotlib's plot() function. Based on what you find, select a value for the number of transformed features you'll retain for the clustering part of the project.

- Once the choice for the number of components to keep is made, we can re-fit the transform to perform decide-on transformation.



Based on the graph we can choose either a value for PCA at the elbow or at 80% above variance. Hence I am choosing the value of 115.

Hence we can re-fit the data with 115 values for PCA.



The graph doesn’t show much of a difference as the previous value near 120 and 115 are slightly closer.

Each principal component is a unit vector that points in the direction of highest variance (after accounting for the variance captured by earlier principal components). The further a weight is from zero, the more the principal component is in the direction of the corresponding feature. If two features have large weights of the same sign (both positive or both negative), then increases in one tend to be associated with increases in the other. To contrast, features with different signs can be expected to show a negative correlation: increases in one variable should result in a decrease in the other.

To investigate the features, you should map each weight to their corresponding feature name, then sort the features according to weight. The most interesting features for each principal component, then, will be those at the beginning and end of the sorted list. Use the data dictionary document to help you understand these most prominent features, their relationships, and what a positive or negative value on the principal component might indicate. You should investigate and interpret feature associations from the first three principal components in this substep. To help facilitate this, you should write a function that you can call at any time to print the sorted list of feature weights, for the i-th principal component. This might come in handy in the next step of the project, when you interpret the tendencies of the discovered clusters.

Using the 115 value for PCA we can analyze each component.

4. **Apply Unsupervised learning**

For unsupervised learning I’m choosing K-Means clustering

- Use sklearn's KMeans class to perform k-means clustering on the PCA-transformed data.
- Then, compute the average difference from each point to its assigned cluster's center.
- Perform the above two steps for a number of different cluster counts. You can then see how the average distance decreases with an increasing number of clusters. However, each additional cluster provides a smaller net benefit. Use this fact to select a final number of clusters in which to group the data.
- Once you've selected a final number of clusters to use, re-fit a KMeans instance to perform the clustering operation

From the elbow method we can infer the K-value from the below diagram

With K-value as 8, we can fit the model and cluster the data, whose results are stored as an array.

```
array([[ -1.        ,  25.98929309],
       [  0.        ,   8.99599274],
       [  1.        ,   9.06330224],
       [  2.        ,   0.62404775],
       [  3.        ,  38.42067915],
       [  4.        ,   3.64045249],
       [  5.        ,  12.07657629],
       [  6.        ,   0.19097114],
       [  7.        ,   0.99868512]])
```

Using this array we can understand which of the clusters has maximum representation on customer data from the general data.

5. Supervised Learning Model

For this we use the Training dataset and Test dataset.

First step is to impute the values as part of the pre-processing and perform all same except dropping rows for the test data cleaning as we need all the data for the test dataset to be maintained.

Next perform standard scaling.

An important element of the supervised learning is the evaluation metrics.

Here I am choosing the Receiver operating characteristic (ROC).

To select the best classifier we are using ROC as ROC is used for understanding trade -offs in Binary Classifier. ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.

Since we aim for the best results we can try using different classifier algorithms and choose the best from them.

Refinement:
The results of each of the classifier algorithms are as in the below column.

Classifier	ROC Value	Time to run (s)
Logistic Regression	0.671	17
Random Forest Classifier	0.535	4.3
AdaBoost Classifier	0.692	27.02
Gradient Boost Classifier	0.704	71.9
Support Vector Machine	0.568	858.85

From the above table we understand the viable classifier is Gradient Boost Classifier even though it took 71.9 seconds to run on the training data, the accuracy is at highest.

Next we need to find the best hyperparameters selection for this model. From the parameters chosen by default for Gradient Boosting, I am providing a list of parameters for the following parameter grids.

```
param_grid = {'learning_rate': [0.01, 0.1, 1.0],
              'max_depth' : [2,3,4],
             'n_estimators': [20, 50, 100]}
```

GridSearch CV will choose between the best combination

For this we are using the GridSearch CV method from sklearn library.

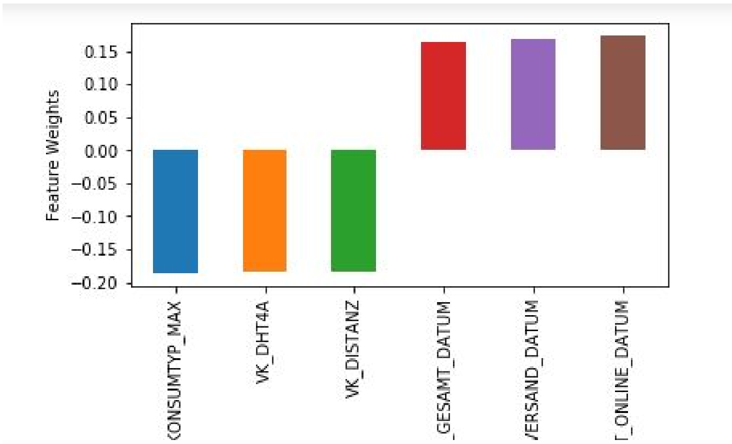
After optimizing the model, we can fit the training data with the optimized model and predict on the test data using the same model.

IV. Result

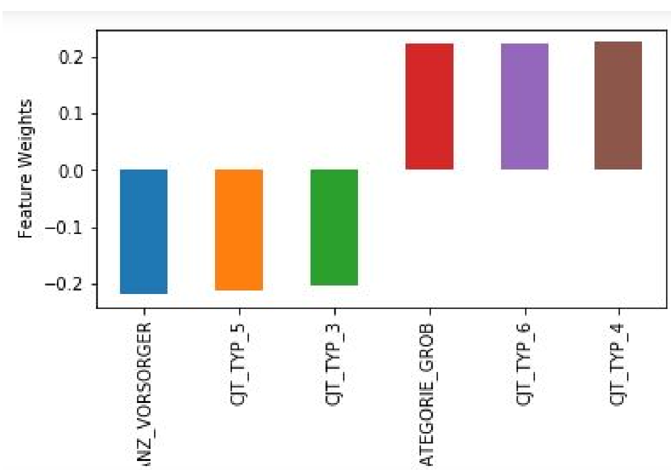
Model Evaluation and Validation:

Unsupervised Learning Results:
By choosing the PCA value to be 115. We analyse the 5 components as below:

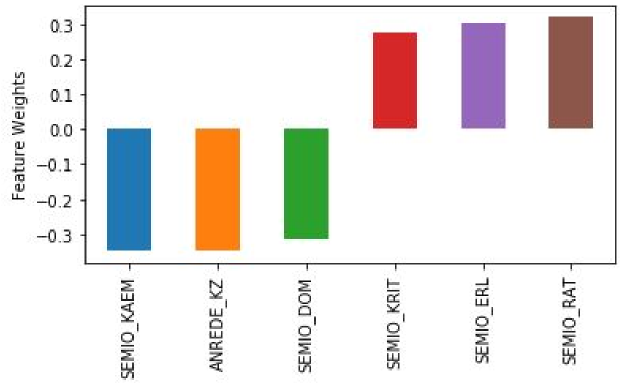
Component_Number = 1



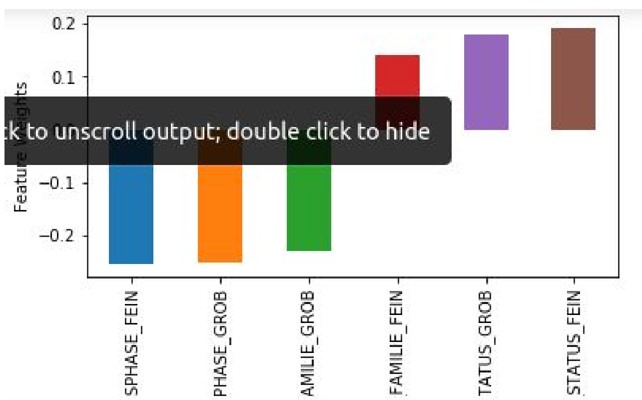
Component_Number = 2



Component_Number = 3



Component_Number = 5



For Component_Number = 1, this is the variables that constitute the cluster.

Weight Description	**Attribute**	**Variable Meaning**
#1negative	D19_KONSUMTYP_MAX	consumption type
#2negative	VK_DHT4A	Not known
#3negative	VK_DISTANZ	Not known
#1positive	D19_GESAMT_DATUM	actuality of the last transaction with the complete file TOTAL
#2positive	D19_VERSAND_DATUM	actuality of the last transaction for the segment mail-order TOTAL

#3positive	D19_GESAMT_ONLINE_DATUM	actuality of the last transaction with the complete file ONLINE

For Component_Number = 2 , this is the variable that constitutes the cluster.

Weight Description	**Attribute**	**Variable Meaning**
#1negative	FINANZ_VORSORGER	financial typology: be prepared
#2negative	CJT_TYP_5	Not known
#3negative	CJT_TYP_3	Not known
#1positive	ALTERSKATEGORIE_GROB	age through prename analysis
#2positive	CJT_TYP_6	Not known
#3positive	CJT_TYP_4	Not known

For Component_Number = 3 , this is the variable that constitutes the cluster.

Weight Description	**Attribute**	**Variable Meaning**
#1negative	SEMIO_KAEM	affinity indicating in what way the person is of a fightfull attitude
#2negative	ANREDE_KZ	Gender
#3negative	SEMIO_DOM	affinity indicating in what way the person is dominant minded

#1positive	SEMIO_KRIT	affinity indicating in what way the person is critical minded
#2positive	SEMIO_ERL	affinity indicating in what way the person is eventful orientated
#3positive	SEMIO_RAT	affinity indicating in what way the person is of a rational mind

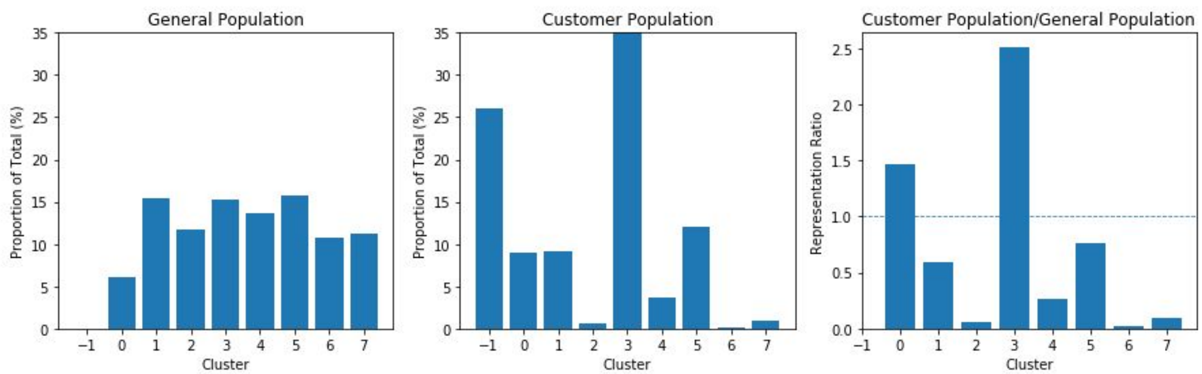
For Component_Number = 5 , this is the variable that constitutes the cluster.

Weight Description	**Attribute**	**Variable Meaning**
#1negative	SEMIO_KAEM	affinity indicating in what way the person is of a fightfull attitude
#2negative	ANREDE_KZ	Gender
#3negative	SEMIO_DOM	affinity indicating in what way the person is dominant minded
#1positive	SEMIO_KRIT	affinity indicating in what way the person is critical minded
#2positive	SEMIO_ERL	affinity indicating in what way the person is eventful orientated
#3positive	SEMIO_RAT	affinity indicating in what way the person is of a rational mind

From this we understand various clusters having distinction of people according to their ages or distance they travel to the shops. Then another with gender and critical thinking. That absolutely makes sense as age and travel go hand in hand as well as authority, gender and rational mind.

With that analysis and PCA being chosen as 115 with K value set to be 8, we get the results of probability for a cluster of people to respond or not.

This is represented as a chart showing the representation of the general customers in the customer's data.



From the Graph we can understand the clusters, 1, 3,4, 5 and 6 are underrepresented in the Customers data while 2 and 7 are over represented.

Supervised Learning Results:

From the table describing the performance of each classifier we understand the viable classifier is Gradient Boost Classifier even though it took 71.9 seconds to run on the training data, the accuracy is at highest.

After using the best classifier with the following parameters

```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.01, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)
```

We fit the training data with this model and parameters fit on the test data.

For Kaggle submission we can combine the ['LNR'] field and the response column to a CSV format as shown below.

	LNR	RESPONSE
0	1754	0.016196
1	1770	0.024638
2	1465	0.006509
3	1470	0.007304
4	1478	0.009218

Justification:

This algorithm used ROC evaluation to metric to evaluate the strength of each model. Compared to the Gradient Boost Algorithm that ran without hyper parameter tuning which gave 71% accuracy, the one ran after using GridSearchCV to find the best parameters gave a 1% increase in the accuracy to 72%.

Free-Form Visualization:

The above visualized results on the customer's proportion on the general data and classifying each record or individual into probabilities of their potential to be a customer absolutely solves our problem of finding the right customer or deciding whether or not to send a customer a promotion email or not. Or further invest in that customer.

The 72% accuracy in training data gives us a visualization that the model is trustworthy.

Reflection:

The project gave immense exposure in working with cleaning the raw data to be inputted to training and testing models. As discussed in the lesson, a DataScientist spends majority of the time cleaning the data and pre-processing it rather than training or prediction.
I understand the basics of understanding and communicating with the data very well now.

The difficult part is to find more accurate metrics to preserve more rows and columns in the data and perform wider training. As we know, more clean data the more results can be accurate.

As I expected I was able to classify each record in the testing data based on their probability to convert to a customer or not.

Improvement:

By using the availability of external cloud support like Amazon SageMaker we can improve the memory usage and speed of the algorithm. Thereby preserving more data. I haven’t run on the Amazon SageMaker platform as this is my first end to end machine learning pipeline building

Through this project we went from the basic raw data to building a pipeline to preprocess the data to be able to be input to both unsupervised and supervised models. Due to the generality of data unsupervised learning could give us an overview of clusters only and not perfect prediction. However, with the train and untrained data with the more curation of data the predictions were more accurate. The prediction accuracy can be further improved by maintaining more columns that possess NaNs and understanding correlation between the variables. The actual customer data appears to be a little sparse with many of the general population's data not being represented. If further improvement is made in the data collection strategy like one to one basis media campaigns via social media or surveys we can improve the accuracy of the customer behaviour better.