Customer Segmentation Report for Arvato Financial Solutions

1. Project overview

   Arvato Financial Solutions would like to use demographic information from individuals to decide whether or not it is worth it to include the individual in the campaign. The project is designed to address the challenge through unsupervised learning and supervised learning. The unsupervised learning techniques will be used to perform customer segmentation for a company for identifying the parts of the population that best describe the core customer base of the company, by exploring two dataset “Udacity_AZDIAS_052018.csv” and “Udacity_CUSTOMERS_052018.csv”. After that, supervised learning techniques will be used to make prediction on another two datasets “Udacity_MAILOUT_052018_TRAIN.csv” and “Udacity_MAILOUT_052018_TEST.csv”.

2. Data preprocessing

   1) 3 data files were loaded

Udacity_AZDIAS_052018

	Unnamed: 0	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	...	VHN	VK_DHT4A
0	0	910215	-1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN
1	1	910220	-1	9.0	0.0	NaN	NaN	NaN	NaN	21.0	...	4.0	8.0
2	2	910225	-1	9.0	17.0	NaN	NaN	NaN	NaN	17.0	...	2.0	9.0
3	3	910226	2	1.0	13.0	NaN	NaN	NaN	NaN	13.0	...	0.0	7.0
4	4	910241	-1	1.0	20.0	NaN	NaN	NaN	NaN	14.0	...	2.0	3.0

5 rows × 367 columns

Udacity_CUSTOMERS_052018

	Unnamed: 0	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	...	VK_ZG11
0	0	9626	2	1.0	10.0	NaN	NaN	NaN	NaN	10.0	...	2.0
1	1	9628	-1	9.0	11.0	NaN	NaN	NaN	NaN	NaN	...	3.0
2	2	143872	-1	1.0	6.0	NaN	NaN	NaN	NaN	0.0	...	11.0
3	3	143873	1	1.0	8.0	NaN	NaN	NaN	NaN	8.0	...	2.0
4	4	143874	-1	1.0	20.0	NaN	NaN	NaN	NaN	14.0	...	4.0

5 rows × 370 columns

DIAS Attributes - Values 2017

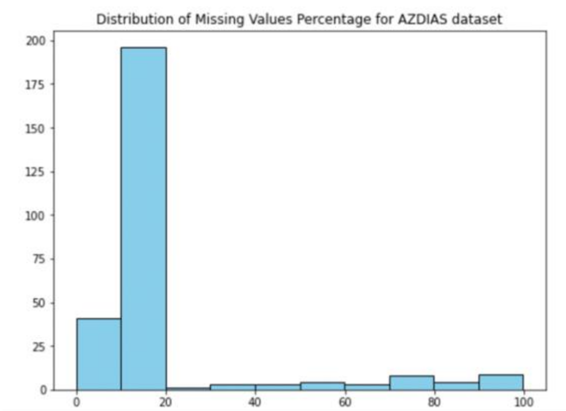
	Attribute	Description	Value	Meaning
0	AGER_TYP	best-ager typology	-1	unknown
1	NaN	NaN	0	no classification possible
2	NaN	NaN	1	passive elderly
3	NaN	NaN	2	cultural elderly
4	NaN	NaN	3	experience-driven elderly

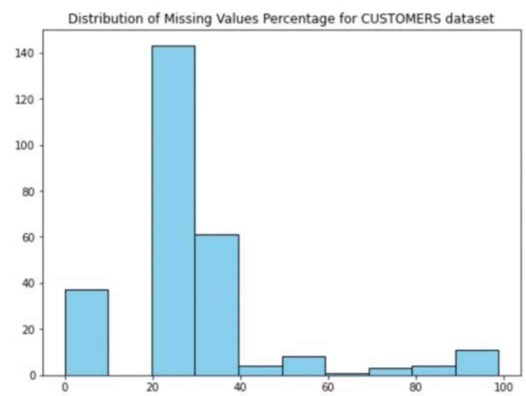
2) Identify missing value

The AZDIAS dataset has 367 columns and CUSTOMERS dataset has 370 columns, however, only 272 columns of both datasets can find description in Attributes dataset. So I decide to keep the 272 columns and remove the rest of columns from both datasets. According to the DIAS Attributes dataset, some attributes have meanings such as “unknown value” or “no classification possible”. These values are considered to be missing value and should be replaced with NA.

3) Remove columns with large portion of missing value

After above replace, percentage of missing value for each column for CUSTOMERS and AZDIAS datasets is calculated and plot into a histogram, as below. According to the charts, for AZDIAS dataset, most columns have missing value which are less than 20% while for CUSTOMERS dataset, most columns have missing value which are less than 40%. Then I decide to remove columns with more than 20% missing value for AZDIAS dataset and remove columns with more than 40% missing value for CUSTOMERS dataset.





4) Check columns with object data type

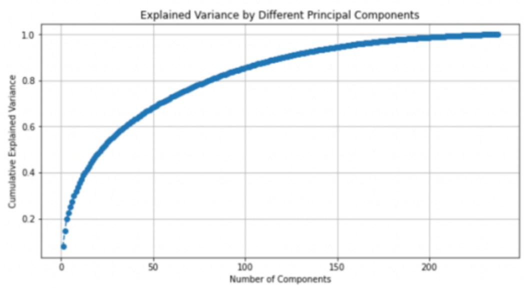
Columns with object data type can hold various types of data. 3 columns of CUSTOMERS dataset and AZDIAS dataset are found with mixed datatype, include: “CAMEO_DEUG_2015”, “CAMEO_DEU_2015”, “OST_WEST_KZ”. After checking the attribute dataset with all possible values under the 3 columns, I decide that all the 3 columns represent categorical variables, and their value should be string format. So all the 3 columns are transformed to string format. After that, all these 3 columns (categorical variable) are transformed into numeric format using label encoding.

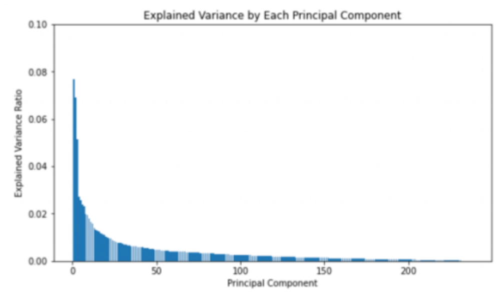
5) Impute missing value

Forward fill method is used to impute the missing value for all columns of CUSTOMERS dataset and AZDIAS dataset. However, if there is no previous value in the column, the missing value remains NA. In this case, all the rest of missing value is imputed with the most frequent value in the column.

3. Customer segmentation
   1) Principal component analysis

Principal component analysis is a great technique to reduce dimensionality of large dataset. Before perform clustering, I use principal component analysis to reduce the dimensionality. Below two chart shows “Explained Variance by Different Principal Components” and “Explained Variance by Each Principal Component” after performing PCA on the CUSTOMERS datasets. As shows in the chart, when the number of components increases to 100, more than 80% variance can be explained. I decide to use 100 components to perform clustering in the later part.





Before diving into clustering, I would like to look at the first three components individually, which explain the variance most.

1st component

As showed below, the characteristic of this group is related to the car owned by the person, such as share of luxury cars, share of cars with high max speed or share of small and very small cars (Ford Fiesta, Ford Ka etc.).

	Attribute	Description
203	KBA13_HERST_BMW_BENZ	share of BMW & Mercedes Benz within the PLZ8
212	KBA13_KMH_211	share of cars with a greater max speed than 210 km/h within the PLZ8
213	KBA13_KMH_250	share of cars with max speed between 210 and 250 km/h within the PLZ8
236	KBA13_MERCEDES	share of MERCEDES within the PLZ8
250	KBA13_SEG_OBEREMITTELKLASSE	share of upper middle class cars and upper class cars (BMW5er, BMW7er etc.)

	Attribute	Description
205	KBA13_HERST_FORD_OPEL	share of Ford & Opel/Vauxhall within the PLZ8
209	KBA13_KMH_180	share of cars with max speed between 110 km/h and 180km/h within the PLZ8
211	KBA13_KMH_140_210	share of cars with max speed between 140 and 210 km/h within the PLZ8
227	KBA13_KW_0_60	share of cars up to 60 KW engine power - PLZ8
245	KBA13_SEG_KLEINWAGEN	share of small and very small cars (Ford Fiesta, Ford Ka etc.) in the PLZ8

2nd component

The characteristic of this group appears to be related to socioeconomic profile such as financial typology, life stage, and social status.

	Attribute	Description
11	CAMEO_DEUG_2015	CAMEO classification 2015 - Uppergroup
12	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classification
81	FINANZ_SPARER	financial typology: money saver
295	SEMIO_KAEM	affinity indicating in what way the person is of a fightfull attitude
296	SEMIO_KRIT	affinity indicating in what way the person is critical minded

	Attribute	Description
80	FINANZ_MINIMALIST	financial typology: low financial interest
271	LP_LEBENSPHASE_FEIN	lifestage fine
272	LP_LEBENSPHASE_GROB	lifestage rough
273	LP_STATUS_FEIN	social status fine
274	LP_STATUS_GROB	social status rough

3rd component

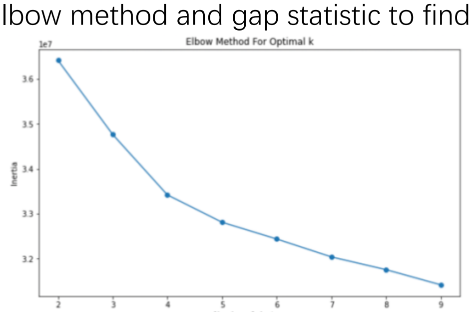
Like the characteristic of 2nd component, the characteristic of this group is also related to socioeconomic profile such as age, financial typology, and affinity of social minded.

	Attribute	Description
2	ALTERSKATEGORIE_GROB	age classification through prename analysis
83	FINANZ_VORSORGER	financial typology: be prepared
92	HH_EINKOMMEN_SCORE	estimated household net income
303	SEMIO_SOZ	affinity indicating in what way the person is social minded
305	SEMIO_VERT	affinity indicating in what way the person is dreamily

	Attribute	Description
78	FINANZ_ANLEGER	financial typology: investor
81	FINANZ_SPARER	financial typology: money saver
82	FINANZ_UNAUFFAELLIGER	financial typology: unremarkable
280	OST_WEST_KZ	flag indicating the former GDR/FRG
302	SEMIO_REL	affinity indicating in what way the person is religious

2) Clustering

The first 100 of PCA components were selected for performing clustering (K means). Then I use elbow method and gap statistic to find the optimal number of clusters, which is 9.



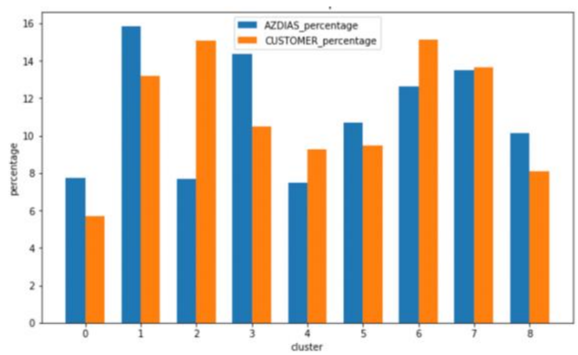

```
optimalK = OptimalK(parallel_backend='joblib')

# Calculating the optimal number of clusters
n_clusters = optimalK(CUSTOMER_pca, cluster_array=np.arange(2, 10))

print('Optimal number of clusters:', n_clusters)
```
```
Optimal number of clusters: 9
```

Once confirmed the number of clusters, I perform clustering for the AZDIAS dataset (demographics data for the population of Germany) and CUSTOMERS dataset (demographics data for customers of the mail order company. After that, the 9 clusters were mapped to the AZDIAS dataset and CUSTOMERS dataset and then we can see which cluster an individual is located in.

Below chart compare the population of Germany and customers of the mail order company by showing how much portion of individuals of the total population is in each of 9 clusters.



	cluster	AZDIAS_percentage	CUSTOMER_percentage
0	0	7.726927	5.710350
1	1	15.825480	13.168660
2	2	7.684850	15.046543
3	3	14.333931	10.508630
4	4	7.497691	9.238620
5	5	10.683658	9.451506
6	6	12.648378	15.122201
7	7	13.466132	13.641913
8	8	10.132952	8.111577

4. Supervised learning model

One of the primary limitations of unsupervised learning is the challenge in interpreting its results. This is because, in unsupervised learning, the algorithms are tasked with identifying patterns or structures in data without reference to known outcomes or labels. On the other hand, supervised learning, which operates on labeled data, provides clearer and more interpretable outcomes.

In this project, I employed supervised learning algorithms on the dataset“mailout_train.csv”. Prior to the training, I preprocessed the dataset to ensure optimal conditions for the models. The preprocessing is similar with the one used in the unsupervised learning part. After preprocessing, I trained 3 distinct machine learning models. To evaluate their performance, I used ROC-AUC score, which is a widely used metrics for measuring classification problems, especially for the highly imbalanced data. The 3 machine learning models used and corresponding results are as below:

1) Random Forest

   Random forest is made up of many decision trees. Each tree is trained on a random subset of data and make its own predictions. The Random Forest algorithm then aggregates these predictions to produce a more accurate and stable results. One of the benefits of Random Forest is that it reduces overfitting. Grid search is performed on parameter “n_estimators”(10, 50, 100) and “max_depth”(10, 20, 30), and the best ROC-AUC score for Random Forest is 0.66.

2) Logistic regression

   Logistic regression utilizes sigmoid function to output a probability of the targeted variable between 0 and 1. It is ideal for binary classification. Logistic regression works well for linearly separable classes. Grid search is performed on parameter “regularization strength” (0.001, 0.01, 0.1, 1, 10, 100) and the best ROC-AUC score for Logistic Regression is 0.67.

3) Gradient Boosting

   Gradient Boost combines multiple weak learner models to create a strong model using boosting techniques, which is a sequential process where each subsequent model attempts to correct the errors of the previous model. One of the benefits of Gradient Boost is that it provides predictive accuracy that is highly significantly better than other algorithms. Grid search is performed on parameter “n_estimators”(100, 200, 300), “learning_rate”(0.01, 0.1, 0.2), and “max_depth”(3, 4, 5). The best ROC-AUC score for Gradient Boost is 0.78.

	Model	ROC-AUC Score
0	Logistic regression	0.67
1	Random Forest	0.66
2	Gradient Boost	0.78

In summary, the Gradient Boost model has the best performance. The reason that why gradient boost has the best performance score might be due to 1) Regularization. Compared to Logistic Regression and Random Forest, Gradient Boost includes several forms of regularization, such as learning rate and depth of trees, which help to prevent overfitting 2) Feature Importance. Gradient Boost does a better job in feature selection, focusing on features that may be more informative for predictions, whereas Random Forest spread its focus evenly across features 3) Sequential Learning. Compared to Random Forest, where each of tree is built independent of others, Gradient Boost learns by adding one tree at a time, and each new tree is built to correct the errors made by previously trained trees. At the end, I choose gradient boost to make the final prediction on the test dataset “ mailout_test.csv”.

5. Conclusion

In this project, both unsupervised and supervised learning methodologies are explored to refine the understanding of Arvato Financial Services' customer base. They are also the most interesting parts since it enables me to apply my data science knowledge and skills into practice. To prepare for unsupervised and supervised model learning, I preprocess the raw dataset and conduct feature engineering to select and transform roughly 370 features. In the unsupervised learning part, I conduct customer segmentation analysis using Principal Component Analysis and K means clustering, identifying distinct groups within the population that align closely with the company's primary clientele. In the supervised learning part, utilizing machine learning techniques—specifically random forest, logistic regression, and gradient boosting—I develop predictive models to forecast customer behavior. The combined insights gained from our segmentation analysis and predictive modeling provide valuable intelligence that will inform and enhance Arvato's marketing strategies, ensuring they are targeted and efficient.

However, given the constraints of time and resources, there are opportunities to further enhance the project's outcomes in future iterations, include improving the interpretation for the PCA results as well as the clusters results, developing ensemble models experimenting with more parameters to make predictions and utilizing domain knowledge expert insights to understand which features may be more relevant.