Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

Finding new customers for a product is always a challenge. In an ideal world where you have a lot of funds available to acquire new customers, you can run promotions, discounts, online and offline campaigns to get new customers. However, when you have limited funds and staff hours available, you should narrow down your efforts to a target segment, which is more probable of buying your products.

"If I'm trying to expand sales, I have to find out who my existing customers are. What are their demographics? What do they look like?" Jerry Osteryoung, director of outreach for the Jim Moran Institute for Global Entrepreneurship at Florida State University. In this project, I will be creating a machine learning model to assist marketing team to target the right segment.

Problem Statement

In this project, I will be working on data provided by Arvato Bertelsmann. I will analyze demographics data for customers of a mail-order sales company in Germany, comparing it against demographics information for the general population.

1) I will be using a clustering algorithm to create a segment of customers and identifying a similar group of people in the global population dataset. Since the characteristics of these two groups are the same, we can expect them to more probable to become customers.
2) The learnings from the previous comparison will be used to create a model to predict which individuals are most likely to convert in the marketing campaign.

Metrics

It’s a classification problem, whether the person will respond to the mail or not. I am expecting the data to be unbalanced as very few people react to the mail campaigns; the best metrics to be used are AUC/ROC and f1 score metrics. I will be using AUC to evaluate the models.

II. Analysis

Data Exploration:

Six datasets included in this project:

1) AZDIAS: demographics data for the general population of Germany
2) CUSTOMERS: demographics data for customers of a mail-order company
3) DIAS Attributes: detailed mapping of data values for each feature in alphabetical order
4) DIAS Information Level: top-level list of attributes and descriptions, organized by informational category
5) Udacity_MAILOUT_052018_TRAIN: This dataset contains all the demographic information of the targeted population and the response whether they responded to the mail or not. This dataset is used to train the machine learning model
6) Udacity_MAILOUT_052018_TEST.csv: This is the dataset used to generate prediction, which is submitted to the Kaggle competition

Steps performed in the data exploration: Sample rows of the customer dataset:

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

From the snippet, this dataset looks very cryptic. I have to use Dias attributes and Dias Information level in order to understand what a particular value in a column means. Below is the snippet of the dias attributes dataset:

	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
5	ALTERSKATEGORIE_GROB	age classification through prename analysis	-1, 0	unknown
6	NaN	NaN	1	< 30 years
7	NaN	NaN	2	30 - 45 years
8	NaN	NaN	3	46 - 60 years
9	NaN	NaN	4	> 60 years

1) I calculated the shape of the dataset. Shape of the two main datasets is below:

	Rows	Columns
Azdias	891,221	366
Customers	191,652	369

The three extra columns in the customers dataset are: Product group, online group, customer group which basically represents which kind of customer they are.

2) I calculated mean, minimum, different percentiles of all the numerical columns of both the azdias and customer datasets. Most of the columns have similar values and not deviated a lot. Below is the snippet of the statistics in the customers dataset:

	count	mean	std	min	25%	50%	75%	max
LNR	191652.0	95826.500000	55325.311233	1.0	47913.75	95826.5	143739.25	191652.0
AGER_TYP	191652.0	0.344359	1.391672	-1.0	-1.00	0.0	2.00	3.0
AKT_DAT_KL	145056.0	1.747525	1.966334	1.0	1.00	1.0	1.00	9.0
ALTER_HH	145056.0	11.352009	6.275026	0.0	8.00	11.0	16.00	21.0
ALTER_KIND1	11766.0	12.337243	4.006050	2.0	9.00	13.0	16.00	18.0
ALTER_KIND2	5100.0	13.672353	3.243335	2.0	11.00	14.0	16.00	18.0
ALTER_KIND3	1275.0	14.647059	2.753787	5.0	13.00	15.0	17.00	18.0
ALTER_KIND4	236.0	15.377119	2.307653	8.0	14.00	16.0	17.00	18.0

3) After reading data, I realized the datatype in column 18 and 19 (i.e. 'CAMEO_DEUG_2015', 'CAMEO_INTL_2015') are of mixed type. From the DIAS Attributes dataset, I realized there are some garbage values in these two columns. Hence, I created a function to replace these garbage values with Nan.

4) Using DIAS Attributes dataset, I realized for most of the columns, some value represents null or unknown values. I identified those values for each column and then replaced those values with nan.
5) I visualized which columns have more than 27% of the rows as missing. I identified those columns and later deleted from further analysis. Below is the snippet displaying columns with the highest % of null values in the customer's dataset:

```
columns having  missing values >27% :  112
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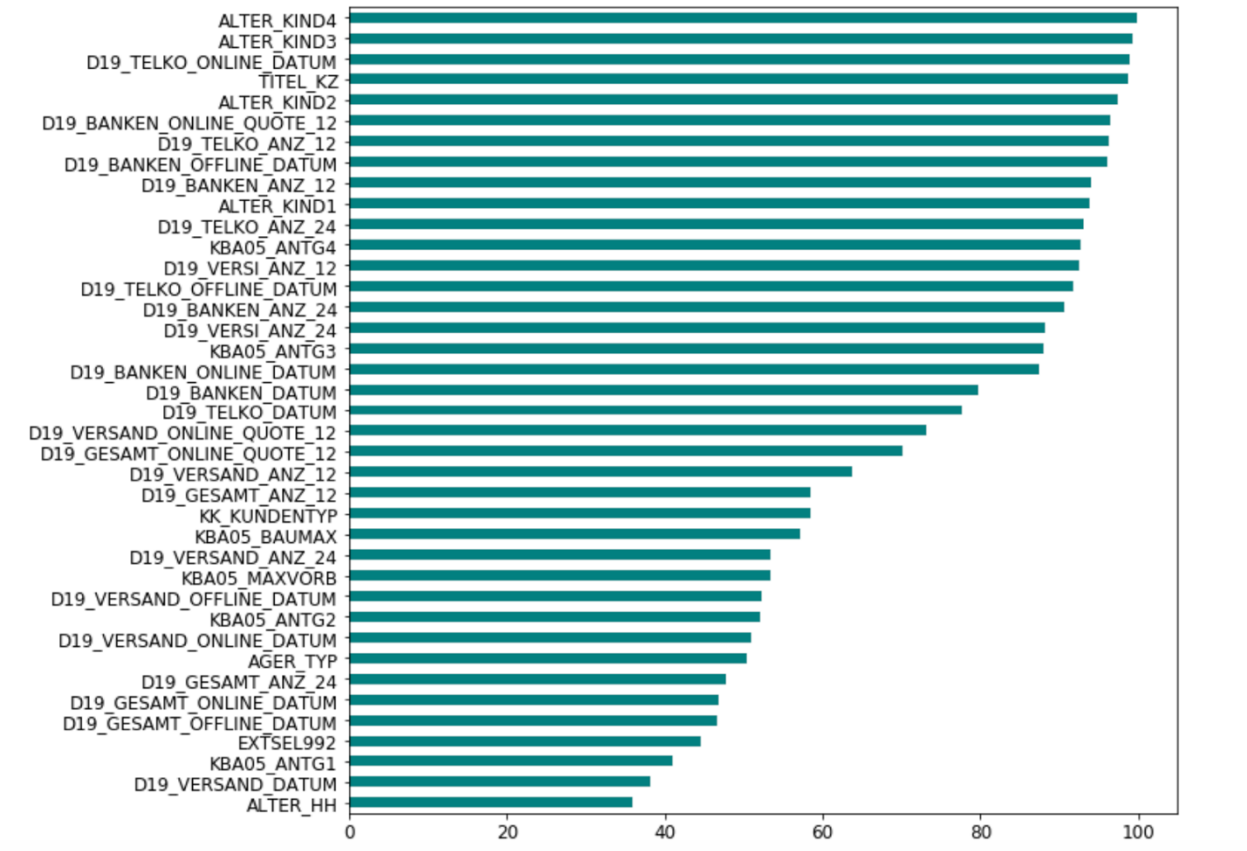
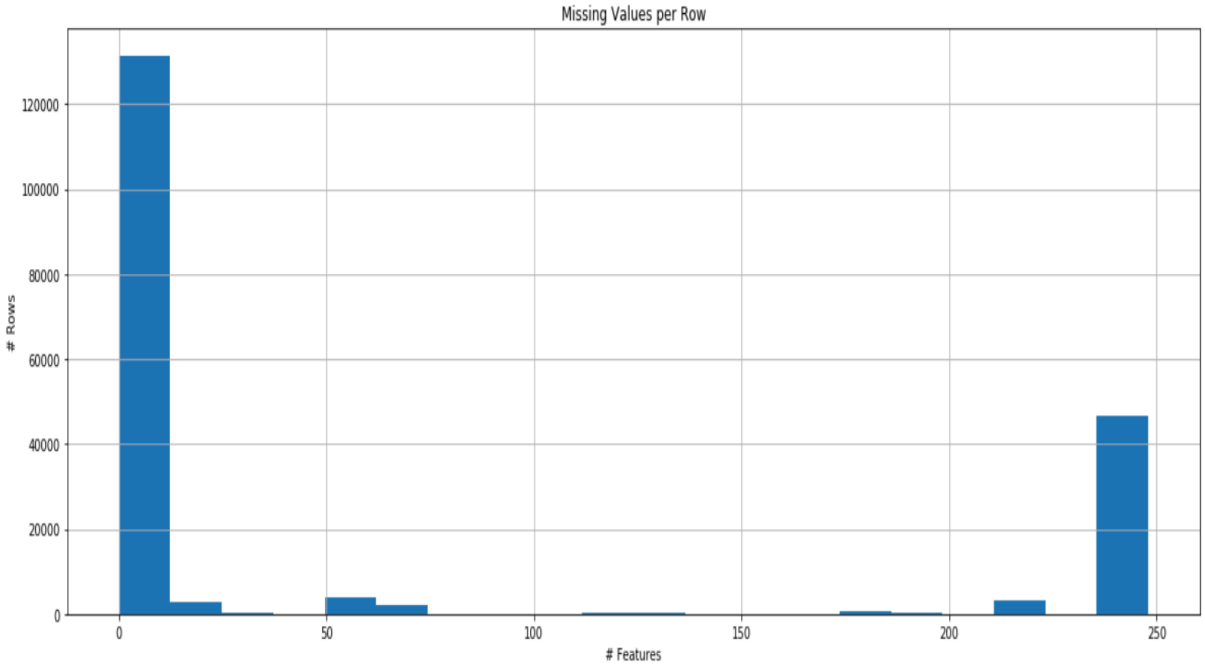


After deleteing columns, shape of the dataset becomes:

	Rows	Columns
Azdias	891,221	248
Customers	191,652	251

6) Next, I visualized the distribution of the rows with the number of null values in them. Lat er, I deleted rows with more than 150 null values. Below is the snippet of the distributio n of missing values per row in the customer's dataset:



After deleting rows, shape of the dataset becomes:

	Rows	Columns
Azdias	785,421	366
Customers	140,371	369

7) Also, by manual inspecting DIAS Attributes dataset, identified a few features which could be used to represent data in a better way. For example, reducing the number of categories in order to better represent the data.

III. Methodology

Data Preprocessing

Based on the learnings from the Data exploration:

1) Created a function to handle the mix datatype columns.
2) Deleted columns with more than 27% of the values missing.
3) Deleted rows with more than 150 null values.
4) Created some columns based on the learning from manually inspecting DIAS Attributes dataset.
5) All the columns present in the dataset are categorical. However, if I perform One Hot encoding (OHE) on every single column, then my dimensionality of the dataset will explode. Also, I noticed most of the variables have some ranking in their meanings (like – Very high, High, Low, Very low, etc.). To prevent the curse of dimensionality, I performed OHE only on those columns where categories don't have any ranking in them. The rest of the columns are treated as numerical columns.

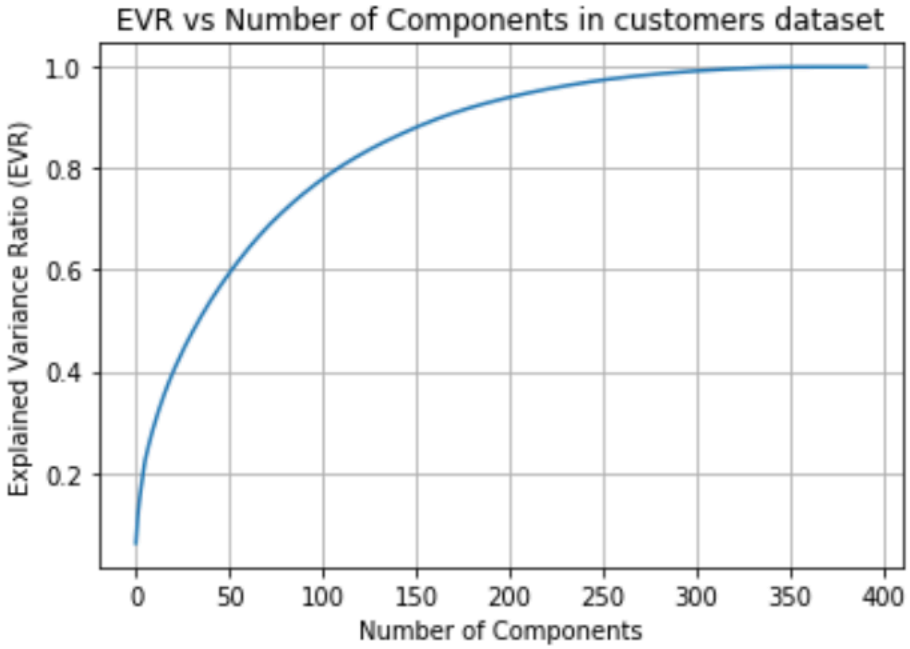
6) After OHE, I performed imputation replacing null values with the most common value in the column. For imputation, I tried Simple Imputer, but I received an error "could not convert a string into float". So, I created a function to replace null value with the most commonly occurring value in the column.

Implemented algorithms:

1) After imputation, the next step was to reduce dimensionality. By reducing the dimension of the data, we have a fewer relationship between variables to consider and are less likely to overfit the model and hence, accurate results.

   There are two ways to reduce dimensionality – features elimination and feature extraction. In feature elimination, we drop some variables and gain no information from those variables. However, in feature extraction techniques like Principal Component Analysis (PCA), we combine our input variables in a specific way, then we can drop the "least important" variables while still retaining the most valuable parts of all of the variables[1].

   Below is the snippet of percentage of variance explained by different principal components in customers dataset:



I decided to keep 100 principal components, as they are explaining approximately 80% of the data (which is big enough).

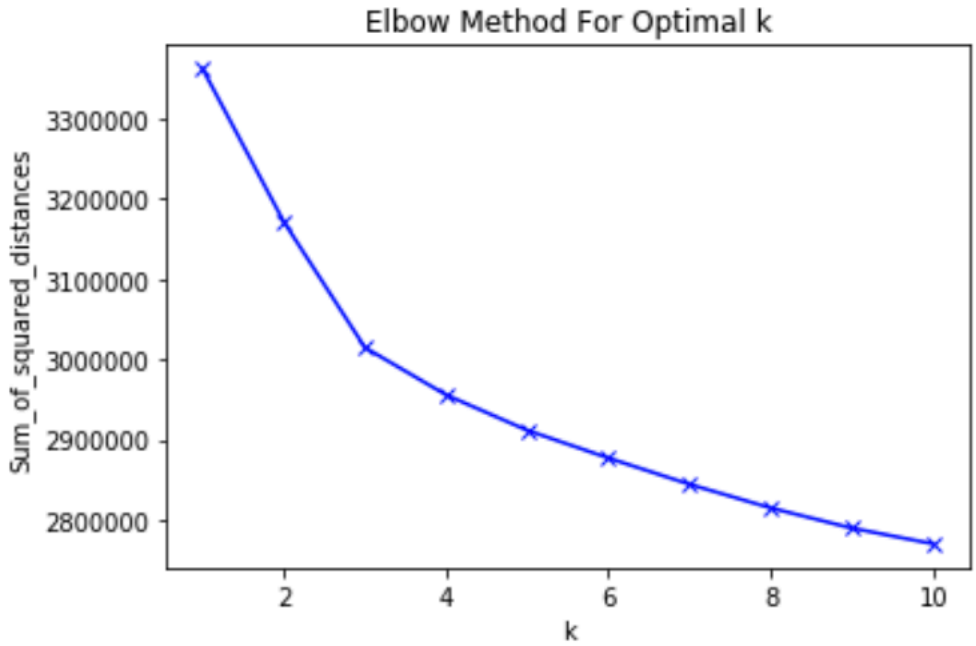
2) Identified columns which are contributing most to the First principal component (first principal component explained the highest variance in the dataset).

3) After applying PCA with 150 pc, the next step in the pipeline is clustering. We can use clustering to create segments of customers and then use that clustering algorithm to identify the similar segments in general population dataset. I used K-means algorithm to cluster the data. K-means algorithm is one of the simplest and popular unsupervised machine learning algorithms.

K-means algorithm starts with a first group of randomly selected centroids, which are used as the beginning points for every cluster, and then performs iterative (repetitive) calculations to optimize the positions of the centroids. The process stops when there is no change in the value of centroids or number of iterations has been achieved[2]. One of the inputs to the k-mean clustering is how many clusters you want to create. There are two ways (that I know of) to identify number of clusters – use subject matter expertise or use elbow method to identify the appropriate number of clusters.

The elbow method runs k-means clustering on the dataset for a range of values of k (say from 1-15) and then for each value of k computes an average score for all clusters. We can visualize this score by connecting score for each K. If the line chart resembles an arm, then the "elbow" is a good indication that the underlying model fits best at that point[3].

Below id the elbow graph for a range of clusters (K=1 to 10) for customers dataset:



As we can see from the elbow curve, we have an elbow at cluster number 3. I am taking 3 as the appropriate number of clusters.

4) Last part of the project is to create a supervise learning model on the mailout dataset. This dataset has output response from the targeted customer. I created a function which performs all the data cleaning steps explained in the previous section. After all the preprocessing I divided the dataset into train and test in a 75:25 ratio.

   Benchmark:
   I trained a simple logistic regression model using a 5-fold cross validation, as a benchmark model. I will be assessing more advanced machine learning models relative to the performance of the benchmark model. Cross validation split the dataset into k groups. For each group, take the group as test dataset and fit the model on the remaining of the groups. Cross validation is a resampling procedure used to evaluate machine learning models on a limited data sample[4].

5) Since the data is unbalanced, I also used Synthetic Minority Oversampling Technique (SMOTE). SMOTE oversample the examples in the minority class by generating new examples. Specifically, a random example from the minority class is first chosen. Then *k* of the nearest neighbors for that example are found (typically *k=5*). A randomly selected neighbor is chosen, and a synthetic example is created at a randomly selected point between the two examples in feature space[5].
   I applied SMOTE on the training dataset to generate more positive samples.

6) I used GridSearchCV approach to hyper tune the parameters of the model. In GridSearchCV, machine learning model is evaluated for a range of hyperparameters values. This approach is called GridSearchCV, because it searches for best set of hyperparameters from a grid of hyperparameter values[6].

IV. Results

There are two kinds of tasks performed in this project: unsupervised learning and supervised learning. In unsupervised learning, I used the k-means algorithm to identify the segments in the general population that looks similar to the customers. Below is the snippet of the clustering:

	cluster	population	customer
0	0	30.625614	29.035200
1	1	30.440745	31.459489
2	2	38.933642	39.505311

Cluster 2 represent the biggest chunk for the customer dataset. The mail order company can target people in the same cluster from the general population. As general population of cluster

3 is similar in characteristics with the customers, chances are more they will respond to the promotion.

For supervised learning, I created different machine learning models. As we are trying to predict that the customer will respond to the offer or not, classification algorithms are used. Below is the summary of the performance of various models:

		Best Cross Validation Score	Test set score
1	Logistic Regression (benchmark model)	0.63	0.50
2	Logistic Regression	0.86	0.54
3	Hyper tuned XG-Boost model	0.99	0.60
4	XG-Boost	-	0.53
5	Hyper tuned Light GBM	0.99	0.54
6	Light GBM	-	0.61

All models are trained using 5-fold cross validation. Model 2 onwards are using SMOTE. AUC is used as the score. Light GBM with 5-fold CV (model 5) is overfitting the dataset, as it is performing well in cross validation but failed poorly in test set.

The best model is hyper tuned xgboost model, this model achieved the best AUC 60% which is more than the AUC 50% of the benchmark simple logistic regression model. Our best model performed (60-50)/50 = 20% better than the benchmark model. The model gets an AUC of 80% on the test set for the Kaggle competition. A model with an AUC of 80% on the big test set is good enough to identify whether the person will become a customer or not.

V. Conclusion

K-means cluster algorithm could be used to identify the target population for the products. People who belong to cluster 2 could be targeted for products. Hyper tuned XG boost model could be used to make inference in real time or in batch to identify whether the person is going to buy or not and hence, assisting the team in making informed decisions.

Improvement:

1) We can create a few features based on the clustering result. For example, if a data point belongs to cluster to 2,3,7 or 8 then 1 or else 0.
2) An in-depth understanding of clusters might have helped in the generation of essential features.
3) A comparison of customers features and general population features might have helped in feature engineering (in generating more useful features).

Reference:

[1] – As One-Stop Shop for Pri**ncip**al Component Analysis, Matt Brems,
https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c

[2] – Understanding K-means Clustering in Machine Learning, Dr. Michael J. Garbade
https://towardsdatascience.com/understanding-k-means-clustering-in-machine-learning-6a6e67336aa1

[3] – scikit learn documentation
https://www.scikit-yb.org/en/latest/api/cluster/elbow.html

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https://machinelearningmastery.com/k-fold-cross-validation/

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https://www.geeksforgeeks.org/ml-hyperparameter-tuning/