Machine Learning Engineer Nanodegree

Capstone Project Report

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Background and Introduction

In traditional markets, customer clustering / segmentation is one of the most significant methods used in studies of marketing. This study classifies existing customer cluster/segmentation methods into methodology-oriented and application-oriented approaches. Most methodology driven studies used mathematical methodologies; e.g. statistics, neural net, generic algorithm (GA) and Fuzzy set to identify the optimized segmented homogenous group.

In recent years, it has been recognized that the partitioned clustering technique is suited for clustering a large dataset due to their relatively low computational requirements. Behavioral clustering and segmentation help derive strategic marketing initiatives by using the variables that determine customer shareholder value. By conducting demographic clustering and segmentation within the behavioral segments, I can define tactical marketing campaigns and select the appropriate marketing channel and advertising for the tactical campaign. It is then possible to target those customers most likely to exhibit the desired behavior by creating predictive models.

A general literature review can be found in the paper *CUSTOMER DATA CLUSTERING USING DATA MINING TECHNIQUE* by Dr. Sankar Rajagopal from Tata Consultancy Services.

My main motivation to work on this project is to explore the possibility in applying ML in marketing areas. Besides, I have two internship experience in E-commerce companies, that make me wonder how to combine ML and business together and create true value instead of doing simple class projects.

Problem Statement

This competition is connected to one of Udacity's capstone project options for the Data Science Nanodegree program, in connection with Arvato Financial Solutions, a Bertelsmann subsidiary.

In the project, a mail-order sales company in Germany is interested in identifying segments of the general population to target with their marketing in order to grow. Demographics information has been provided for both the general population at large as Ill as for prior customers of the mail-order company in order to build a model of the customer base of the company. The target dataset contains demographics information for targets of a mailout marketing campaign. The objective is to identify which individuals are most likely to respond to the campaign and become customers of the mail-order company.

As part of the project, half of the mailout data has been provided with included response column. For the competition, the remaining half of the mailout data has had its response column withheld; the competition will be scored based on the predictions on that half of the data.

Datasets and Inputs

The data for this project is provided by Udacity partners at Bertelsmann Arvato Analytics, and represents a real-life data science task. It includes general population dataset, customer segment data set, dataset of mail-out campaign with response and test dataset that needs to make predictions.

There are four datasets, all of which have identical demographics features (only part of them are different)

Two dataset for customer segmentation analysis:

- *Udacity_AZDIAS_052018.csv*: Demographics data for the general population of Germany; 891,211 persons (rows) x 366 features (columns)
- *Udacity_CUSTOMERS_052018.csv*: Demographics data for customers of a mail-order company; 191,652 persons (rows) x 369 features (columns)

Because these two datasets are the demographics characteristics of general population and company's customers. It is worthy to explore and compare the clustering analysis between these two groups. And match the general population with our customers. Then, I are able to find out the targeted population that share similar behaviors as our current customers. After cleaning these two datasets in similar fashion, I would like to perform clustering analysis on both datasets with same number of clusters. And then these two cluster distributions Ire then compared to see where the strongest customer base for the company is.

Two dataset for customer conversion prediction:

- *Udacity_MAILOUT_052018_TRAIN.csv*: Demographics data for individuals who Ire targets of a marketing campaign; 42,982 persons (rows) x 367 (columns).
- *Udacity_MAILOUT_052018_TEST.csv*: Demographics data for individuals who Ire targets of a marketing campaign; 42,833 persons (rows) x 366 (columns). In addition to the above data, there are two additional meta-data:
- *DIAS Information Levels—Attributes 2017.xlsx*: a top-level list of attributes and descriptions, organized by informational category
- *DIAS Attributes—Values 2017.xlsx*: a detailed mapping of data values for each feature in alphabetical order

After customers segmentation, I also want to build a model that can predict whether a potential customer will convert or not in our mail-out list. However, only train set is retained. The test set is withheld for the purpose of Kaggle competition. In order to train and validate our classifier, I need to split the training set into training subset and validation subset. And because of the highly imbalanced nature of our dataset, I need to apply cross-validation(probably with 10 subsets) to train and validate our model.

After training and picking out the best kind of model, I may want to use the same train set to do parameters tuning to further improve our model performance. In the meantime, some classifying method may output the feature importance data that can allow us to communicate our result in business language easily.

In the last step, I prefer to use decision tree to repeat the process again for the sake of better understand and visualize classification results.

Solution Statement

There are 4 steps to finish the project:

- Data pre-processing: clean and re-encode data.

  Missing values by columns and rows will be analyzed, data will be divided by types followed by subsequent transformations.
- Segmentation: create clusters of customer and general population, and then identify the difference.

  Use principal component analysis (PCA) technique for dimensionality reduction. Then, elbow and other methods will be used to identify the best number of clusters for clustering algorithm. Finally, apply clustering to make segmentation of population and customers and determine description of target cluster for the company.
- Prediction: use the demographic features to predict whether or not a person became a customer after a mail-out campaign.

  Build machine learning model using response of marketing campaign and use model to predict which individuals are most likely to convert into becoming customers for the company.

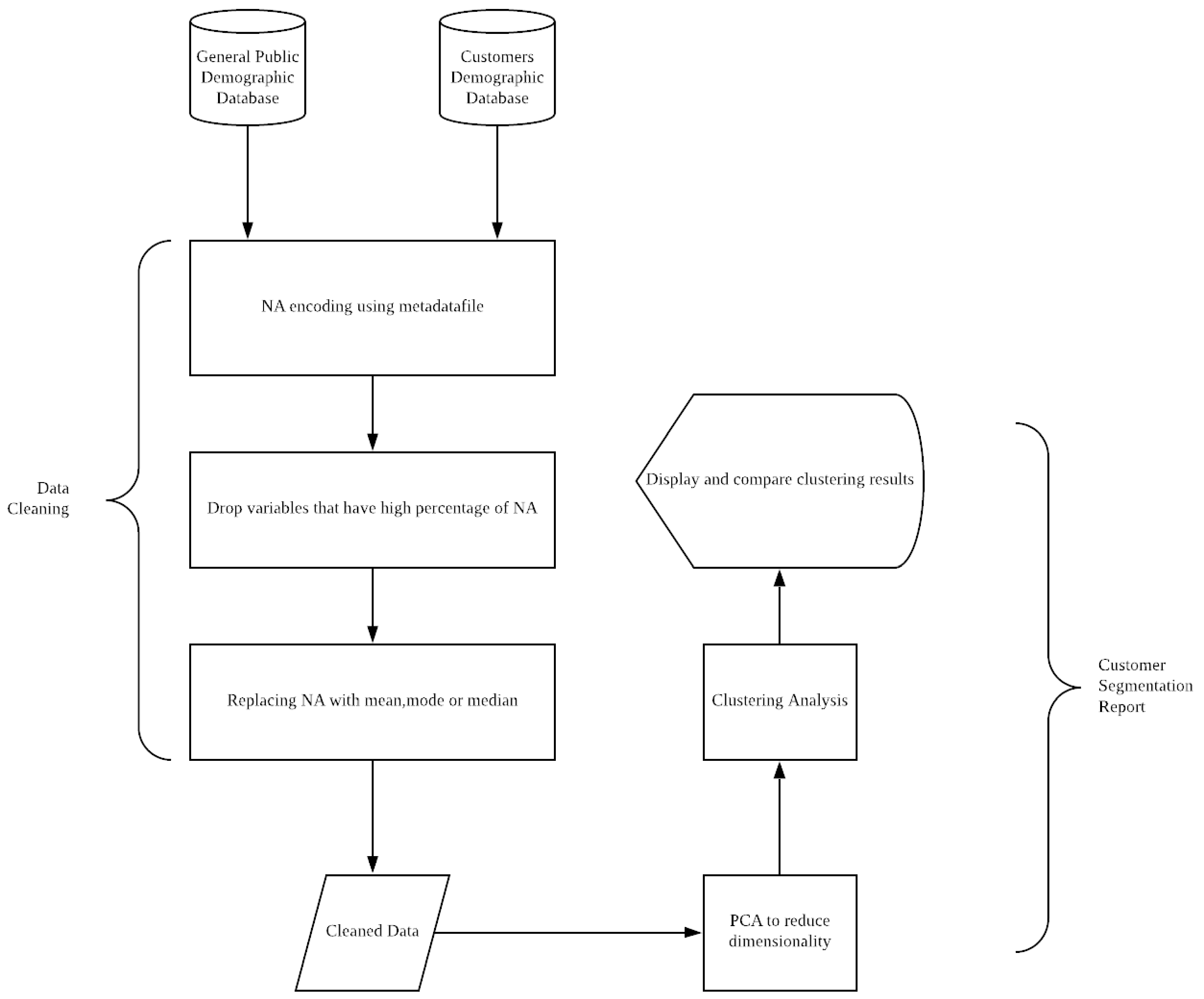
  I will use several machine learning classifiers and choose the best using analysis of learning curve(ROC-AUC). Then, I will parametrize the model and make predictions.
- Kaggle competition: The results of this part need to be submitted for Kaggle competition.

Evaluation Metrics

Because of the data imbalance, I cannot only use recall and accuracy as metrics to measure the model performance. I should consider TP and FP at the same time. Therefore, using ROC-AUC is much more suitable.

Analysis and Results

Customer Segmentation


General Public Demographic Database
Customers Demographic Database
NA encoding using metadatafile
Drop variables that have high percentage of NA
Replacing NA with mean,mode or median
Data Cleaning
Cleaned Data
PCA to reduce dimensionality
Clustering Analysis
Display and compare clustering results
Customer Segmentation Report

Data Preprocessing

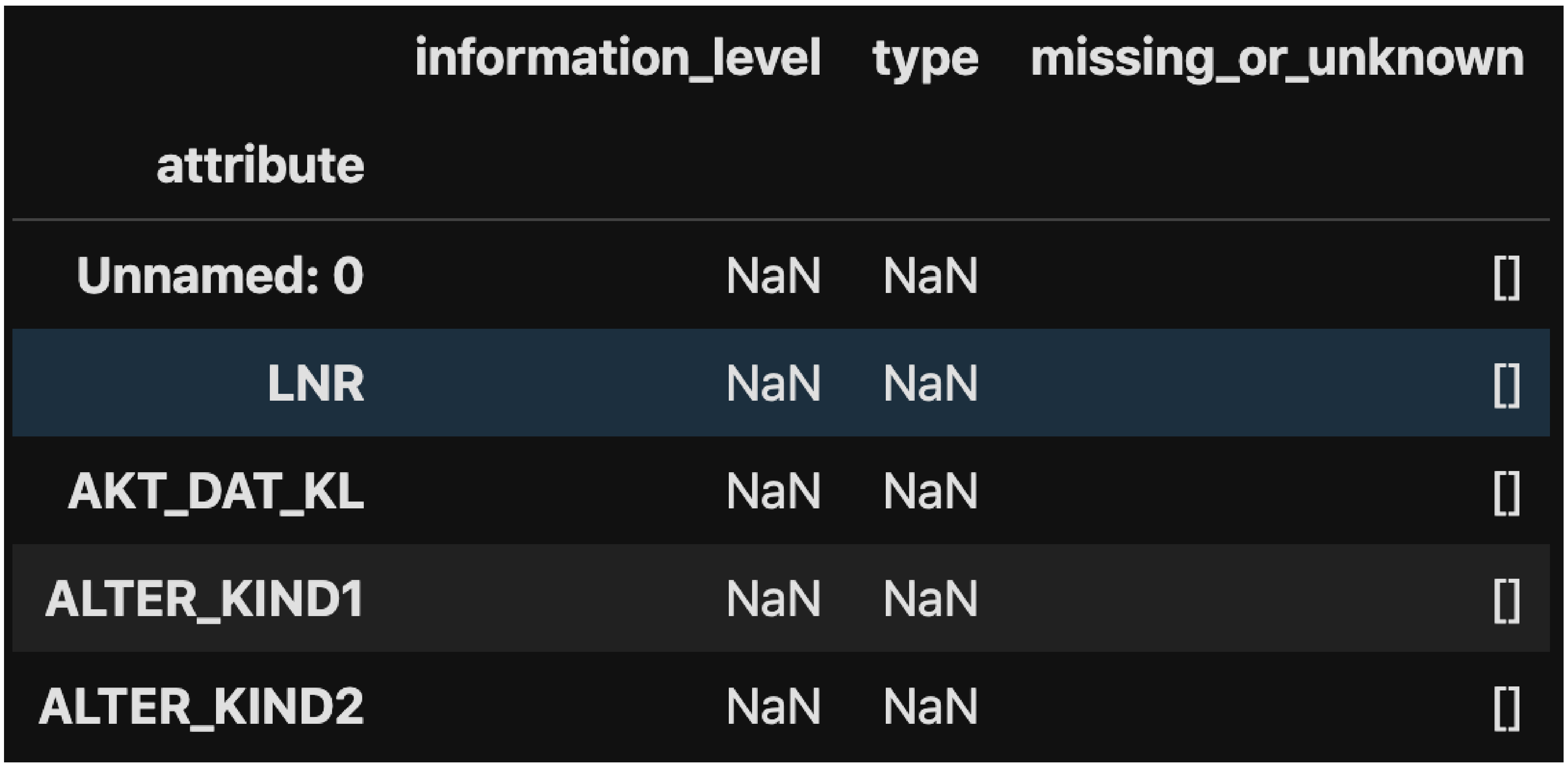
Missing Value Dictionary

After long hours of manual work, I general a csv file documented the missing value of every attributes mentions inside the meta-data file.

	attribute	information_level	type	missing_or_unknown	Comment
0	AGER_TYP	person	categorical	[-1,0]	NaN
1	ALTER_HH	household	interval	[0]	NaN
2	ALTERSKATEGORIE_GROB	person	ordinal	[-1,0,9]	NaN
3	ANREDE_KZ	person	categorical	[-1,0]	NaN
4	ANZ_HAUSHALTE_AKTIV	building	numeric	[0]	NaN

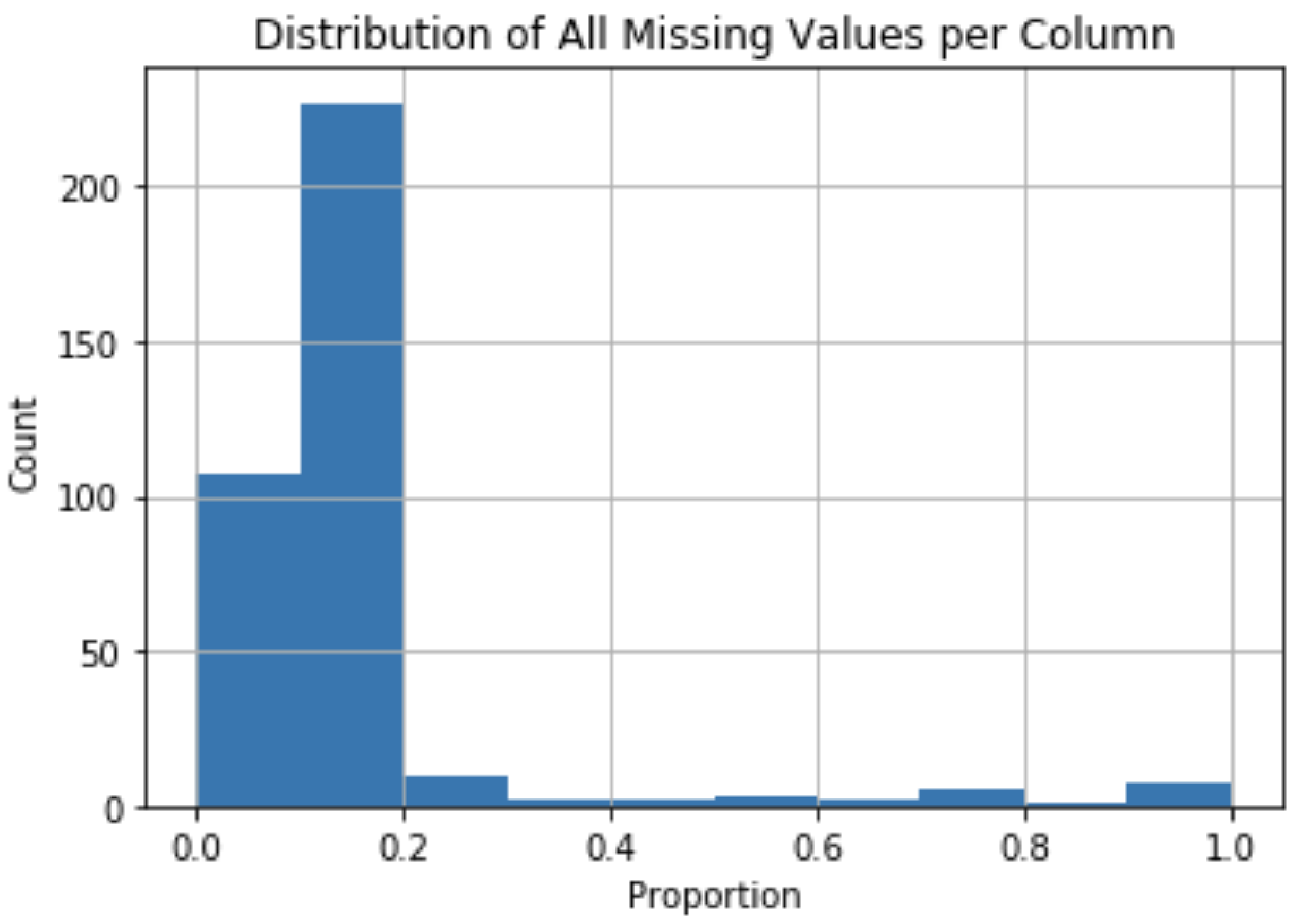
- Delete the variables found in the meta-data file but not found in the general population.
- For those variables that are found in the general population but missing in features I would like to take a closer look and try to maintain the information as much as possible.

First I append these variables inside the missing value manual file to enlarge our missing value documentation for further NA analysis. Then I replace those missing_or_unknown inside the dataset with NaN.

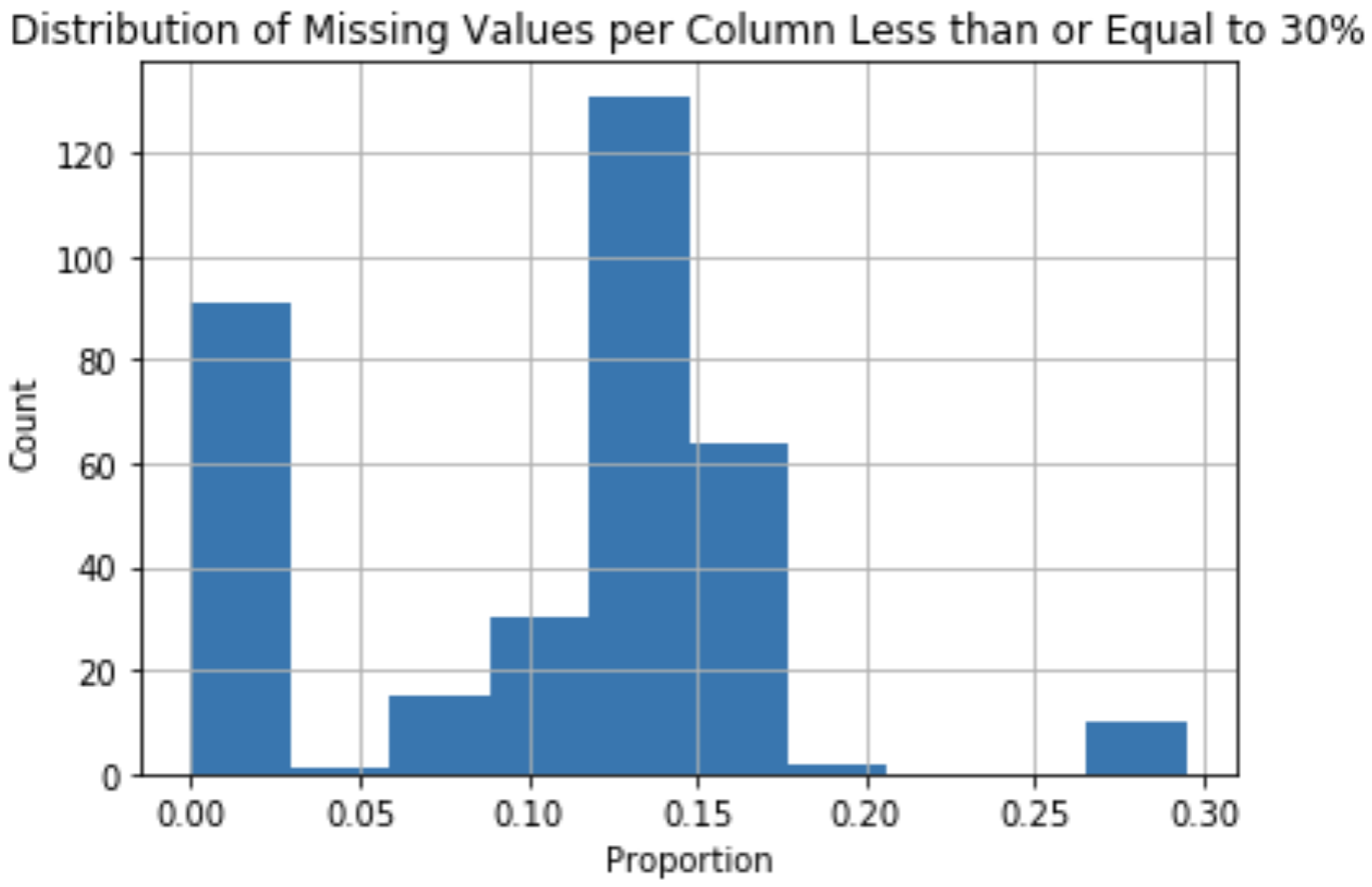


	information_level	type	missing_or_unknown
attribute			
Unnamed: 0	NaN	NaN	[]
LNR	NaN	NaN	[]
AKT_DAT_KL	NaN	NaN	[]
ALTER_KIND1	NaN	NaN	[]
ALTER_KIND2	NaN	NaN	[]

Assess Missing Data



By plotting the percentage of missing value in each variables, I am able to tell that most of the variables are missing less than 30% of data.

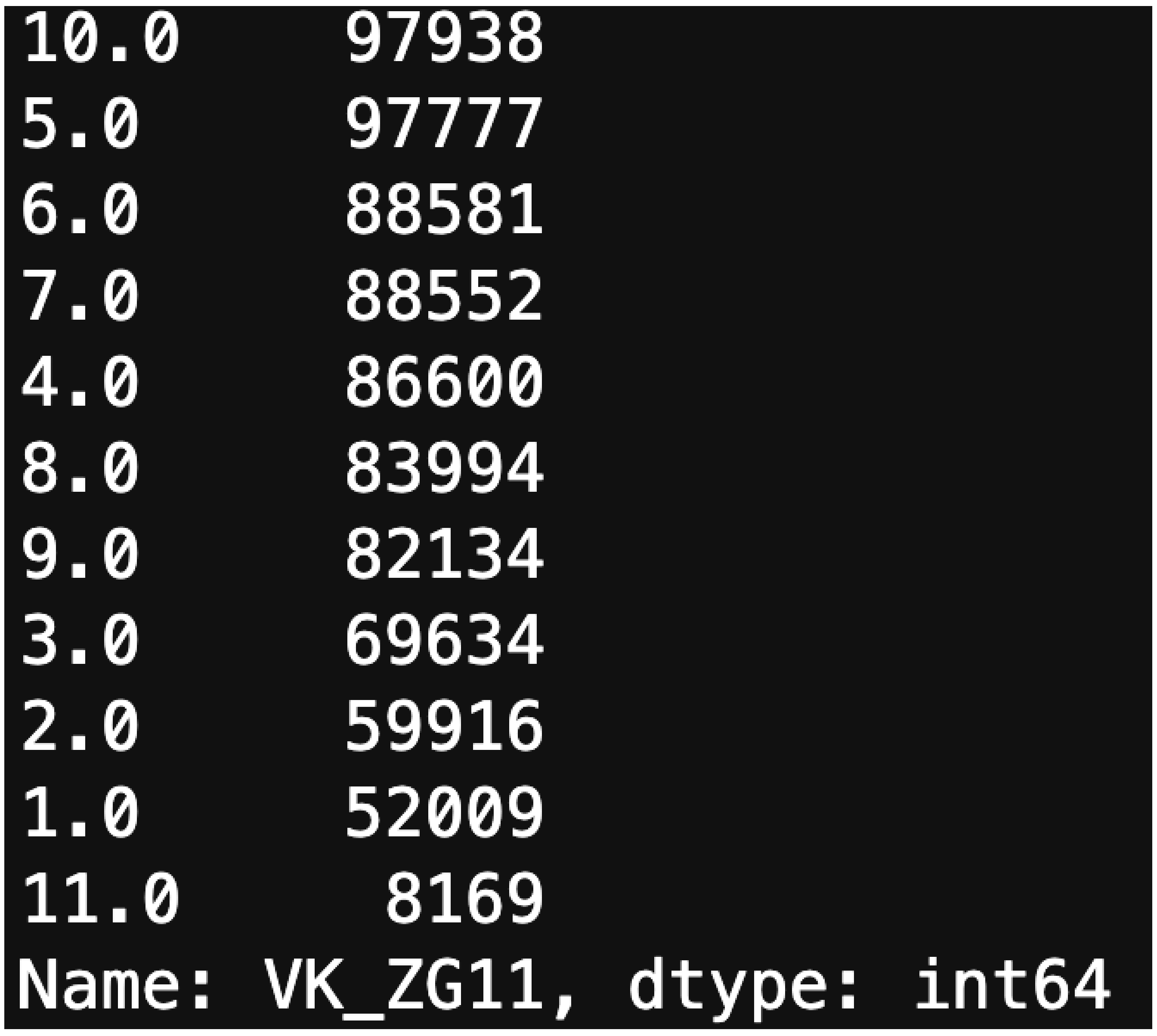


Therefore, it is reasonable to set 30% as a cutoff value to clean our data. I drop the variables that have over 30% missing values.

Re-encode features

Variables Type Identification

Inside the *new_feature.csv*, I already identified most of the data variable types. However, after including some new variables from the general population dataset, I need to further investigate the data distribution of these new variables and try to identify their data types.



```
10.0    97938
5.0     97777
6.0     88581
7.0     88552
4.0     86600
8.0     83994
9.0     82134
3.0     69634
2.0     59916
1.0     52009
11.0     8169
Name: VK_ZG11, dtype: int64
```

For example, the variable VK_ZG11 has 10 types of output, which means it could possibly be a categorical or ordinal variable. Combining with the data name and compared it with the existing variable names in our meta-data files, I can assume that this is an ordinal variable.

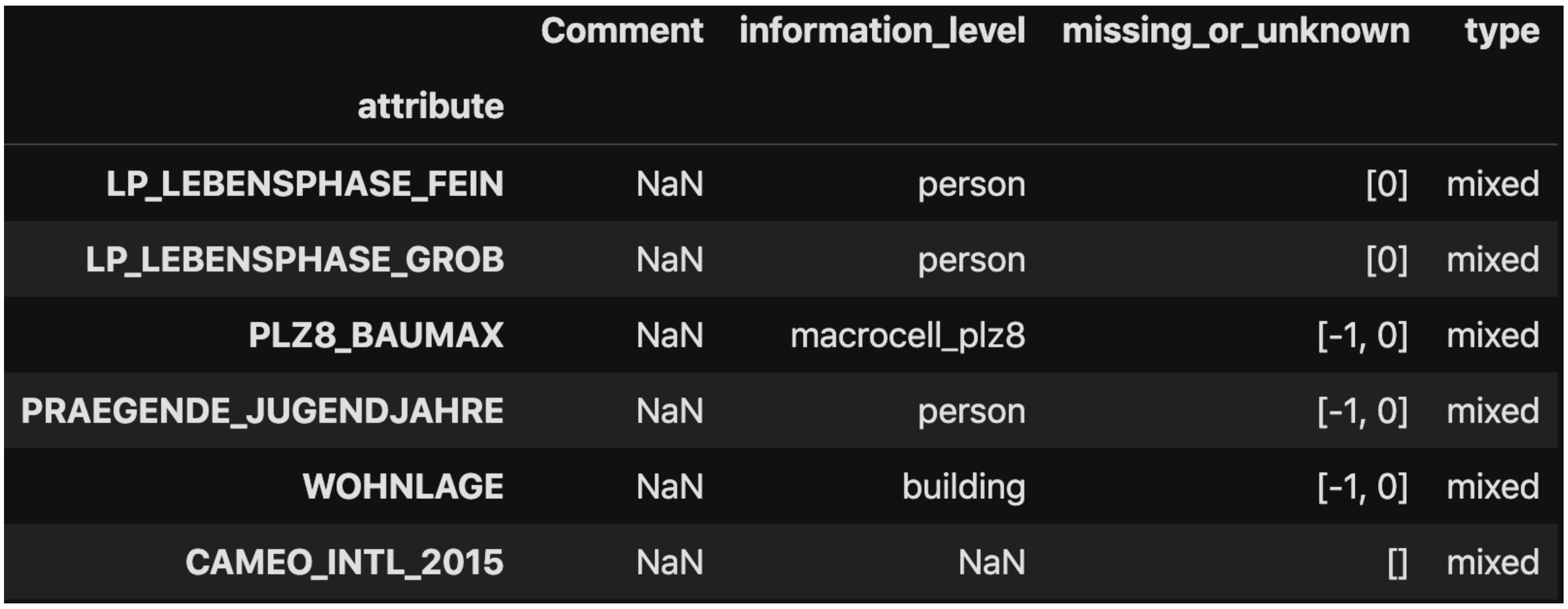
After tedious manual work, I can roughly classify our new variables into numerical, ordinal, categorical and mixed data types.

Categorical variables

For the categorical variable, I can go further and identify that whether they are binary or multilevel variables for the purpose of one-hot encoding.

Mixed-Type variables

After taking a look at several project reports online, I realize that this Mixed-Type variables engineering is the key point to boost your prediction result in Kaggle competition. There are totally 6 variables that are mixed types.



	Comment	information_level	missing_or_unknown	type
attribute				
LP_LEBENSPHASE_FEIN	NaN	person	[0]	mixed
LP_LEBENSPHASE_GROB	NaN	person	[0]	mixed
PLZ8_BAUMAX	NaN	macrocell_plz8	[-1, 0]	mixed
PRAEGENDE_JUGENDJAHRE	NaN	person	[-1, 0]	mixed
WOHNLAGE	NaN	building	[-1, 0]	mixed
CAMEO_INTL_2015	NaN	NaN	[]	mixed

By digging into the definition of every variables via meta-data files, I choose to reengineer the 'PRAEGENDE_JUGENDJAHRE' and 'CAMEO_INTL_2015'.

- *PRAEGENDE_JUGENDJAHRE* - combines information on three dimensions: generation by decade, movement (mainstream vs. avantgarde), and nation (east vs. west). Three new variables will be created to capture the other two dimensions: an interval-type variable for decade, and two binary variables for movement and nation.
- *CAMEO_INTL_2015* - combines information on two axes: wealth and life stage. The two-digit codes will be broken by their 'tens'-place and 'ones'-place digits into two new ordinal variables (which, for the purposes of this project, is equivalent to just treating them as their raw numeric values).

And for simplicity, I just drop the variable 'LP_LEBENSPHASE_FEIN' because it contains so many levels and not easy to further reengineer.

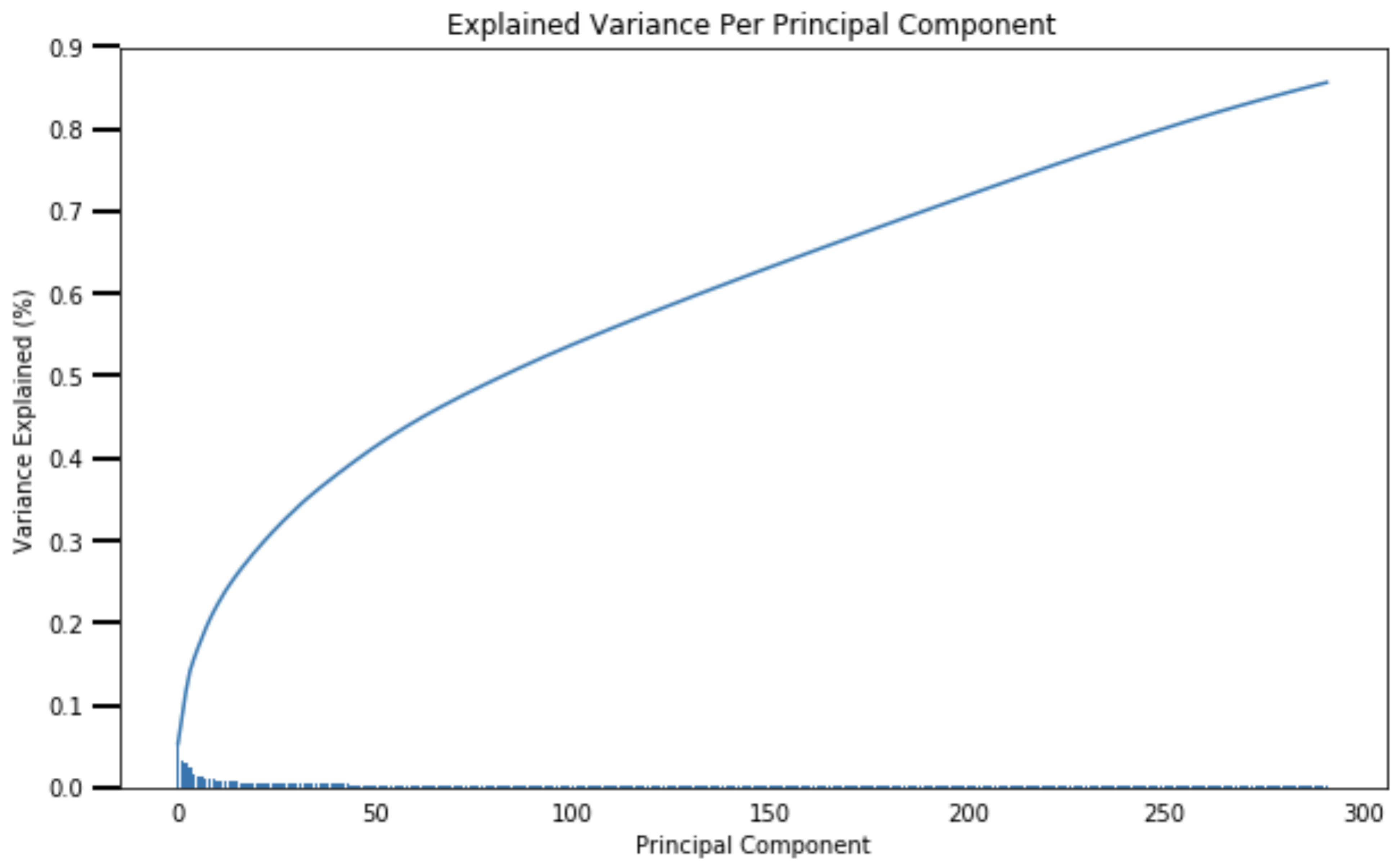
Other mixed types variables we be converted using one-hot encoding into several dummy variables.

Cleaning Pipeline

After formatting the strategy in cleaning data, I build a clean_data function in order to process the incoming new dataset in the same way.

Feature transformations

After replacing missing value with column' mean and scale our data, it is natural to perform dimension reduction for computational simplicity.



By reducing the dimensions to 300, the first 300 components can still explain 86% of our data.

Component analysis

For each principal component or dimension, the top 3 and bottom 3 weights with their corresponding feature names will be investigated for any associations.

Dimension 1:

- MOBI_REGIO-moving patterns
- PLZ8_ANTG1-number of 1-2 family houses in the PLZ8
- KBA13_ANTG1-unknown
- KBA13_ANTG4-unknown
- KBA13_ANTG3-unknown
- PLZ8_ANTG3-number of 6-10 family houses in the PLZ8

Interpretation:

The first principal component is strongly correlated with none to very low mobilities and high number of 1-2 family houses. KBA13 is not described in the attributes file but it can be related to car ownership. Higher car ownership and higher number of 6-10 family houses tend to negatively affect this principal component.

Dimension 2:

- KBA13_HERST_BMW_BENZ-share of BMW & Mercedes Benz within the PLZ8
- FINANZ_VORSORGER-financial typology: be prepared
- KBA13_MERCEDES-share of MERCEDES within the PLZ8
- KBA13_SITZE_5-number of cars with 5 seats in the PLZ8
- DECADE-dominating movement in the person's youth
- FINANZ_ANLEGER-financial typology: investor

Interpretation:

The principal component is primarily affected by car ownership and financial status. People who own a lot of luxury cars such as BWM and Mercedes increase this component. On the other hand, people who own budget cars decrease this component. People who don't have the need for financial preparation increase this component and who are less likely to invest decreases the component.

Dimension 3:

- DECADE-dominating movement in the person's youth
- CJT_TYP_2-unknown
- CJT_TYP_1-unknown
- ALTERSKATEGORIE_GROB-age classification through prename analysis
- CJT_TYP_5-unknown
- CJT_TYP_3-unknown

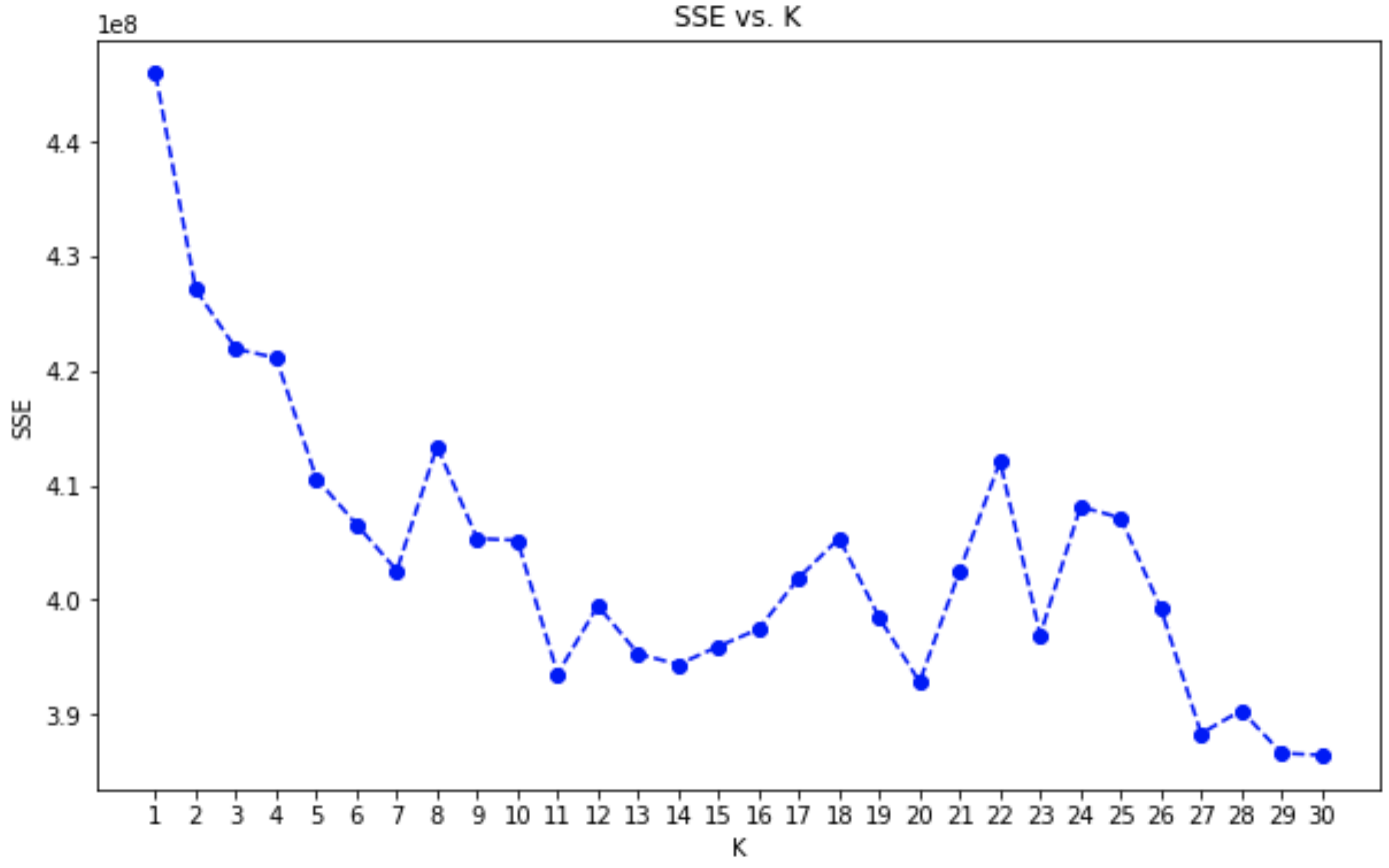
Interpretation:

The third principal component increases with more recent decade of the dominating movement. Likewise, CJT_TYP is also not described in the attributes file but it may be related to the customer journey typology. This principal component decreases with older people.

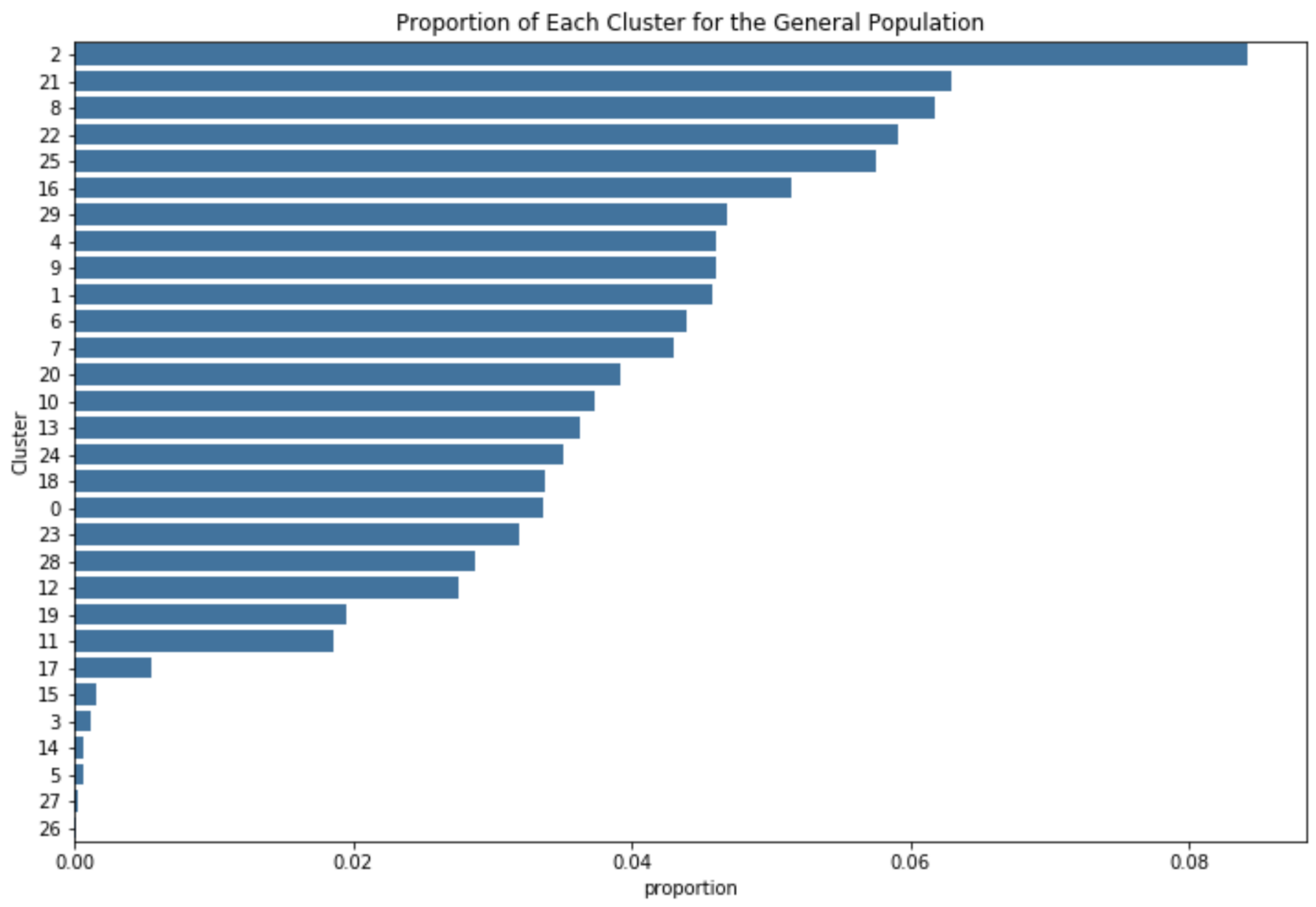
Clustering analysis

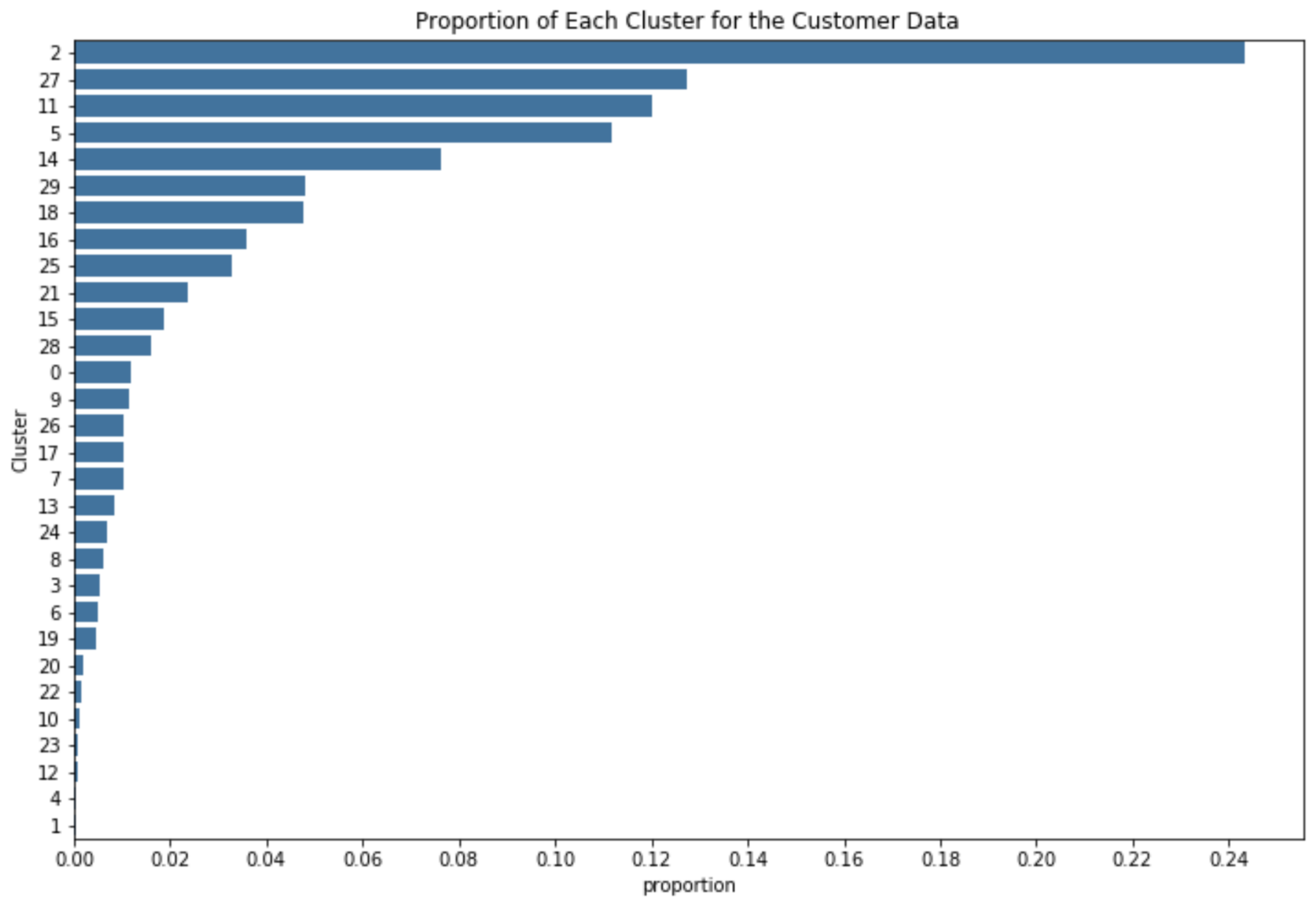
Pick number of clusters

The scree plot shows that the score or the sum of the squared errors (SSE) generally decreased as the number of clusters increased.

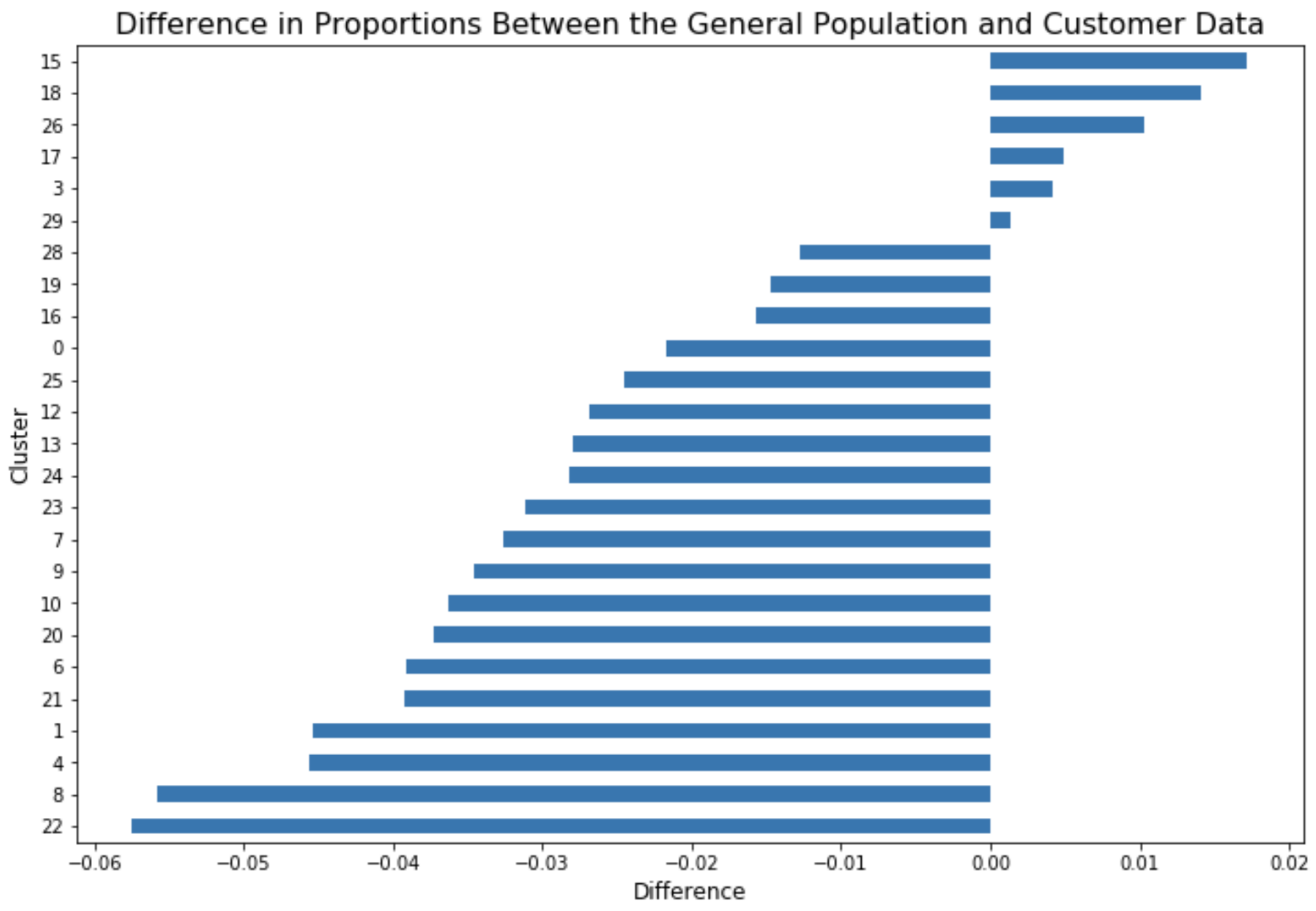


The 'elbow method' is not applicable in the plot because there is no visible leveling observed. Even though 30 clusters did not produce the lowest SSE, it was still used as the number of clusters for the full KMeans clustering operation.

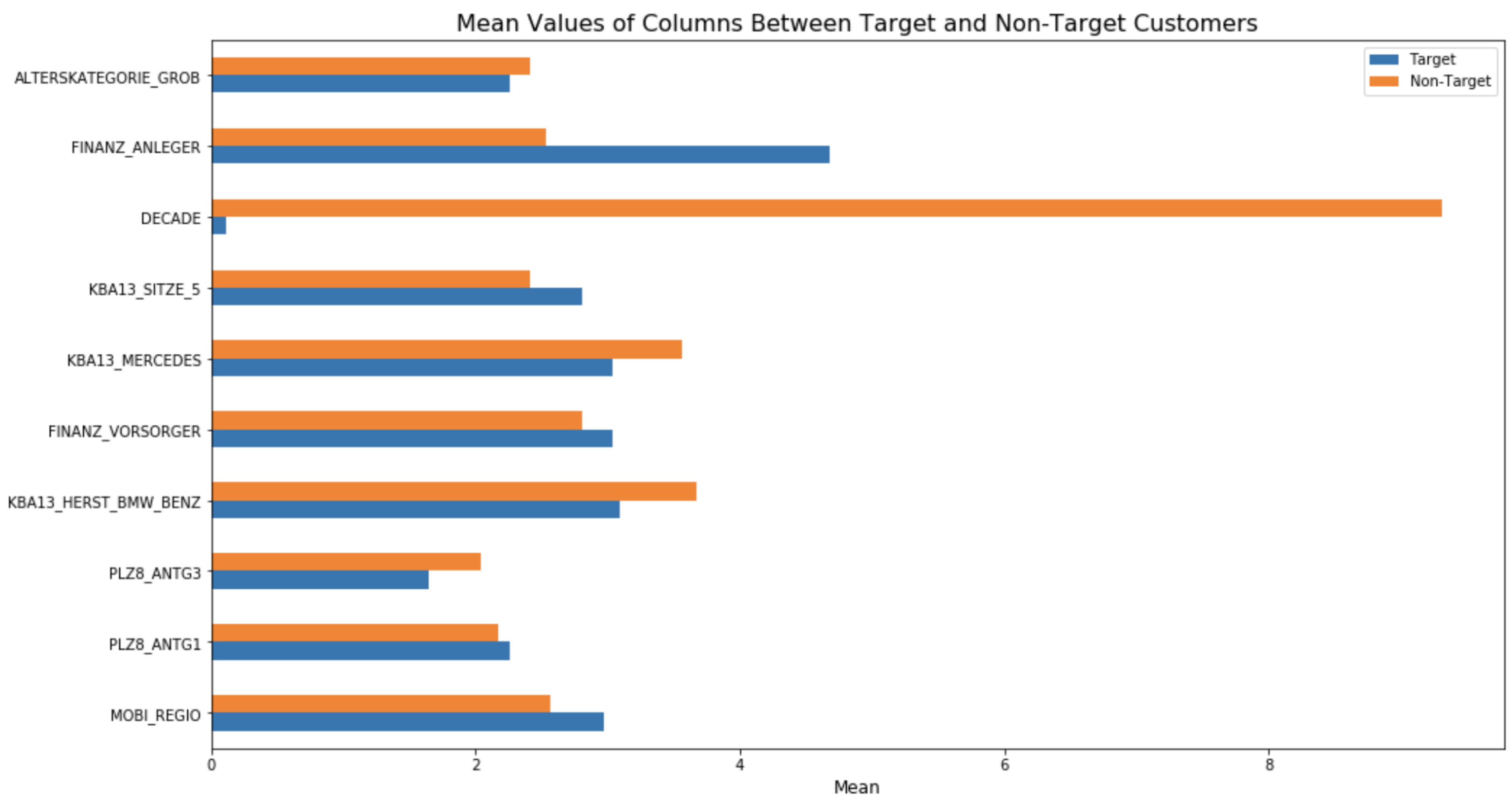




Compare Customers to general Population



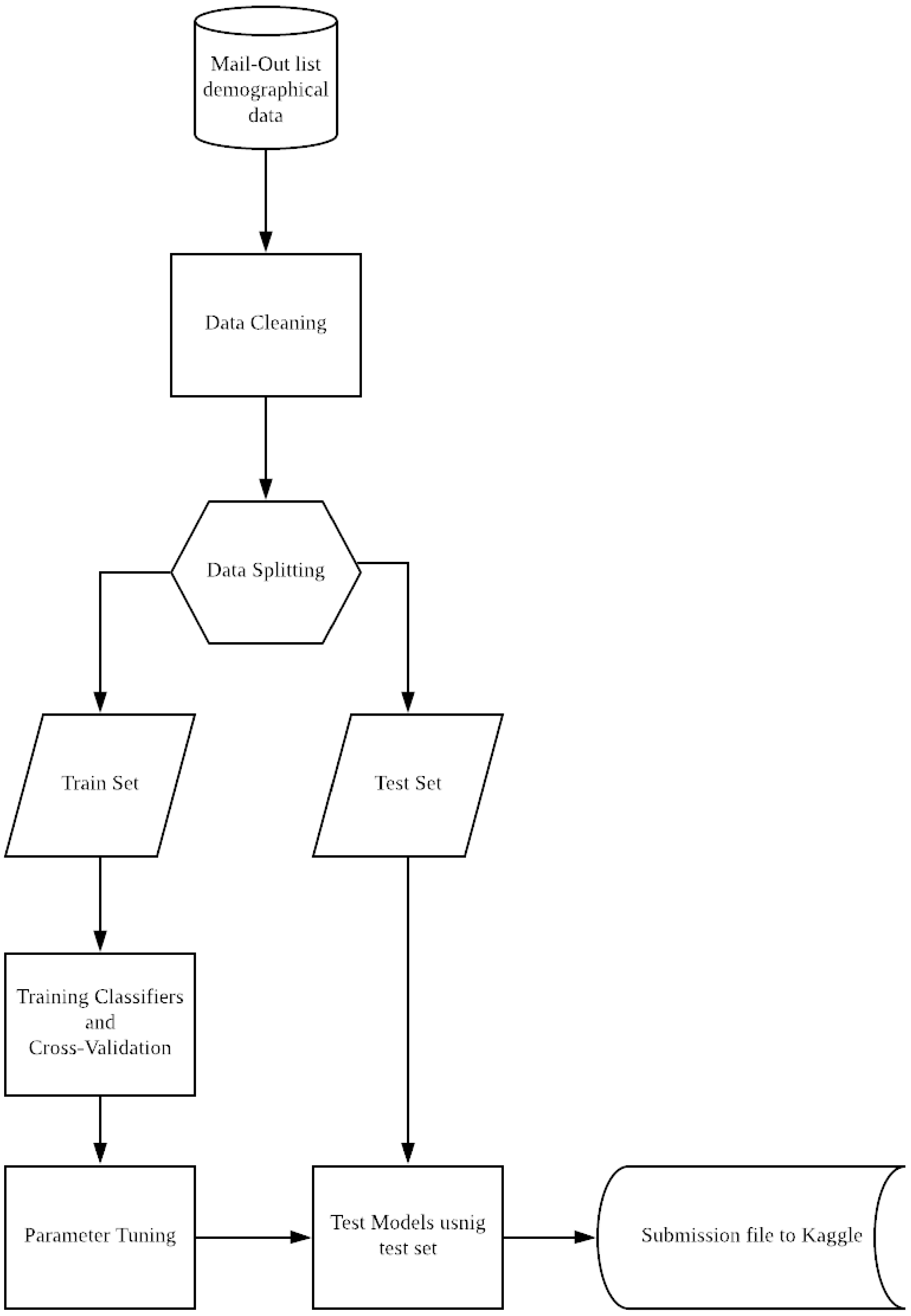
After calculating the proportion difference between 2 datasets' clusters, I can tell that cluster 2 is over-represented and cluster 22 is under-represented. For simplicity, I only compared the variables mentioned in the PCA sections.



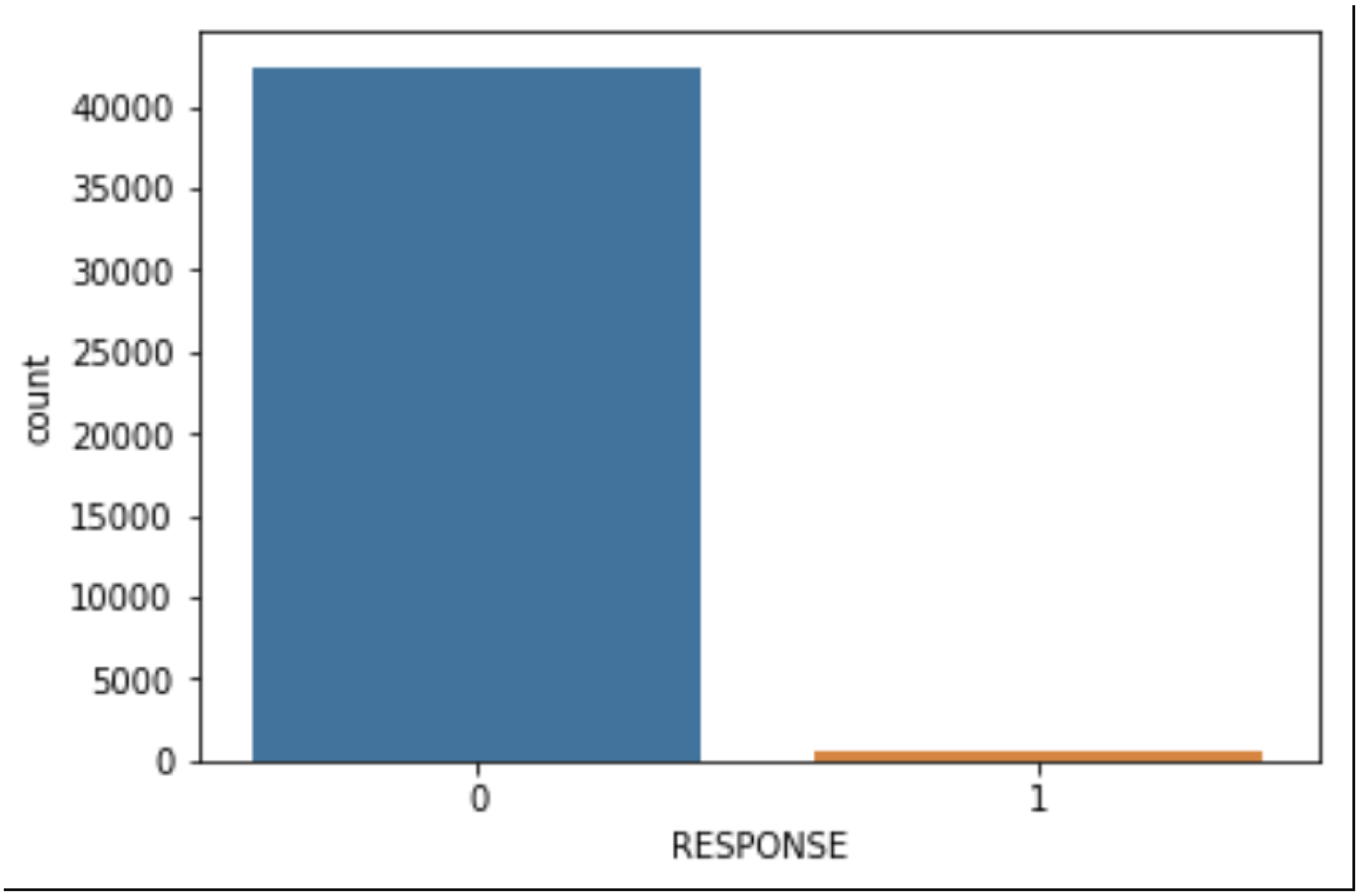
By comparing these two clusters, two out of the ten features above are clearly different. These are FINANZ_ANLEGER, DECADE. The target customers have less recent dominating movements in their youths which probably means they are older, and have less potential to invest.

Customer Conversion Prediction

Data Exploration


Mail-Out list demographical data
Data Cleaning
Data Splitting
Train Set
Test Set
Training Classifiers and Cross-Validation
Parameter Tuning
Test Models usnig test set
Submission file to Kaggle

The response of our data is highly imbalanced.



Algorithm Explanation

There are a number of approaches to deal with class imbalance which have been already explained by numerous blog posts from different experts. This particular article from Analytics Vidhya describes the following techniques:

- Random Over-sampling
- Random Under-sampling
- Cluster-Based Over-sampling
- Informed Over Sampling: Synthetic Minority Over-sampling Technique (SMOTE)
- Modified synthetic minority oversampling technique (MSMOTE)

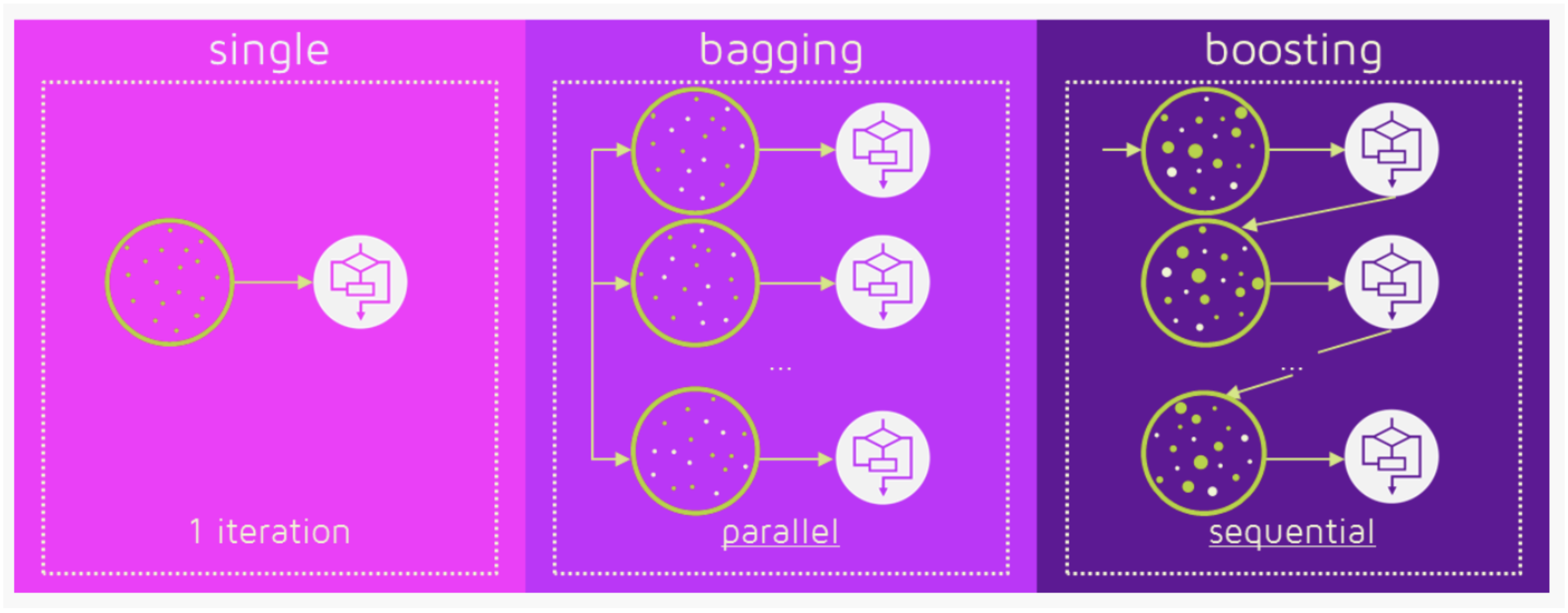
The above approaches deals with handling imbalanced data by resampling original data to provide balanced classes. The same article also provides an alternative approach of modifying existing classification algorithms to make them appropriate for imbalanced data sets.

- Bagging-Based
- Boosting-Based
- Adaptive Boosting
- Gradient Tree Boosting
- Extreme Gradient Boosting
- Light GBM
- CatBoost

The AdaBoost,XGBoost and Gradient Tree Boost algorithms will be investigated to determine which is best at modeling the data.

Boosting Method

The algorithms mentioned above are different kinds of gradient boosting method. Before jumping into the idea of boosting, it will be nice to clearify some basic concepts about ensemble learning.



Ensemble learning includes bagging and boosting.

- Bagging is a simple ensembling technique in which we build many independent predictors/models/learners and combine them using some model averaging techniques. (e.g. weighted average, majority vote or normal average)
- Boosting is an ensemble technique in which the predictors are not made independently, but sequentially.

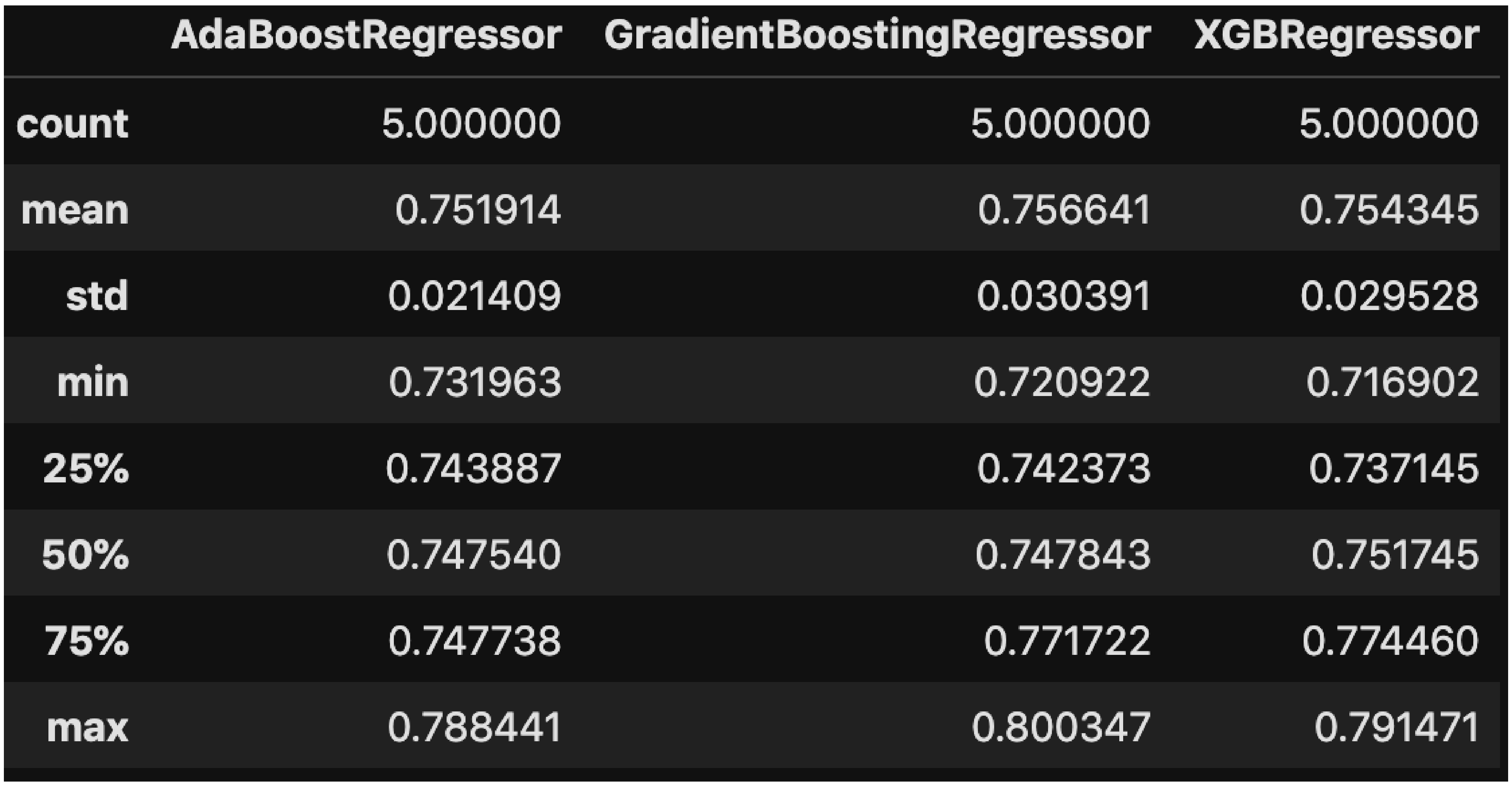
Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function. Here is some main differences among these 3 kinds of boosting algorithms:

- AdaBoost (Adaptive Boosting) uses decision stumps as the weak learners in boosting.
- Gradient Tree boosting uses decision trees as the weak learners in boosting.
- XGBoost(Extreme Gradient Boosting) is similar to Gradient Tree boosting. But it has several good features such as clever penalisation of trees, proportinal shrinking of leaf nodes and using newton boosting method(which makes it generally faster than gradient tree boosting method). Besides the extra randomisation parameter makes the weaker learners less likely to correlated hence increasing the performance.

Model Building

Benchmark Compare

In the model selection part, I will compare the performance of the above mentioned boosting algorithms and use Adaboost as the benchmark boosting algorithm.



	AdaBoostRegressor	GradientBoostingRegressor	XGBRegressor
count	5.000000	5.000000	5.000000
mean	0.751914	0.756641	0.754345
std	0.021409	0.030391	0.029528
min	0.731963	0.720922	0.716902
25%	0.743887	0.742373	0.737145
50%	0.747540	0.747843	0.751745
75%	0.747738	0.771722	0.774460
max	0.788441	0.800347	0.791471

After running cross validation by dividing the dataset into 5 subsets, the Gradient Tree Boosting method actually beats other two methods by a very small margin.

- Adaboost - the average AUC is 0.751914
- Gradient Tree Boosting - the average AUC is 0.756641
- XGBoosting - the average AUC is 0.754345

However, the difference of AUC is not that much between XGBoost and Gradient Tree Boosting. Considering the training time and tuning time, I will still choose XGBoost.

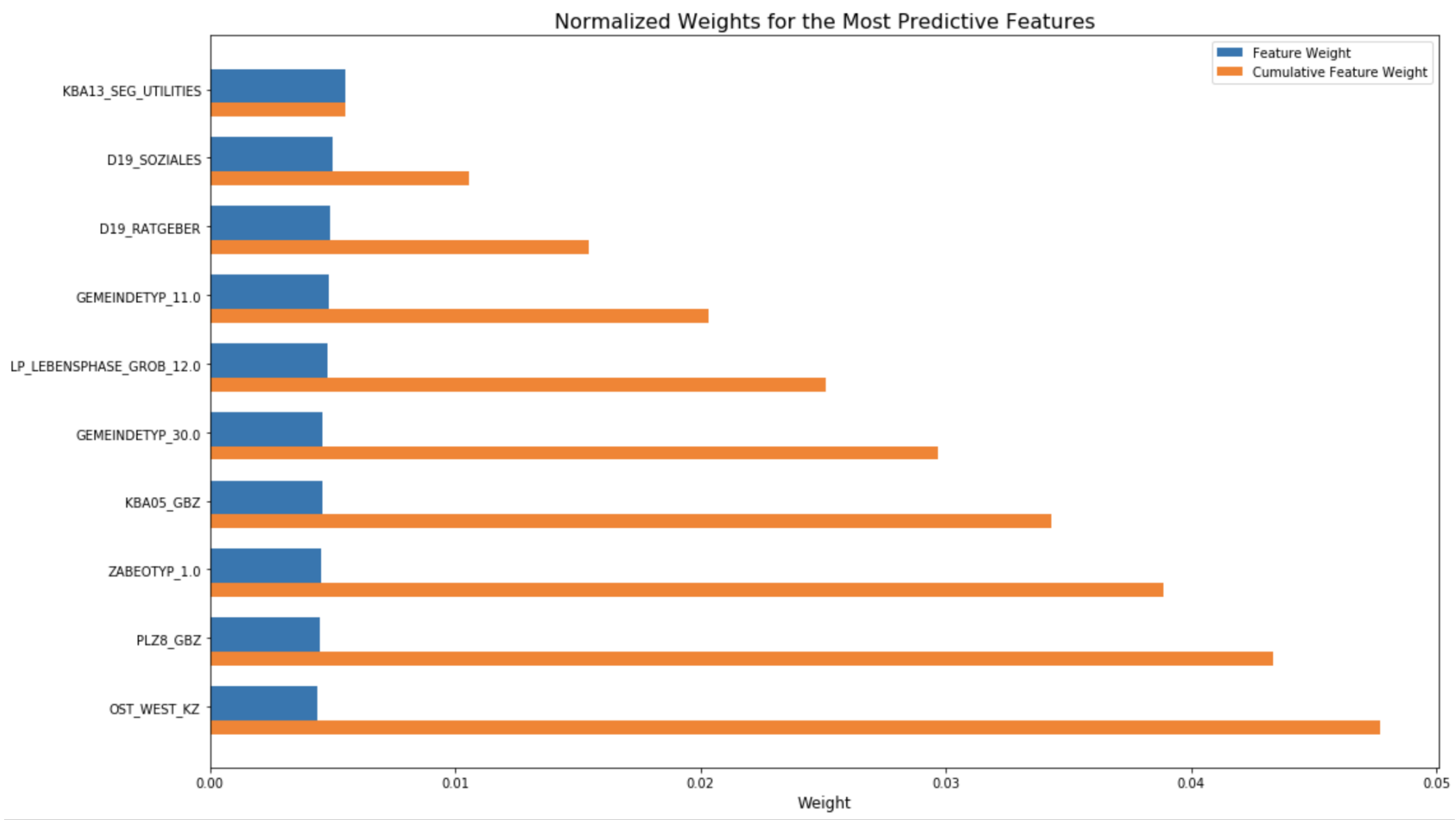
Final Model Evaluation

The final model of XGBoost has the following parameters:

- learning rate=0.01
- reg_alpha=0.05
- subsample=0.6
- colsample_bytree=0.7
- gamma=0.1
- max_depth =3
- min_child_weight =5
- objective ="binary:logistic"
- scale_pos_weight =1
- random_state=28 And the final score of 5-fold CV is 0.772124 which is much higher than the benchark model by 0.02. In order to test the robustness of our model is to test it using the dataset out of the training set. Therefore, I make use of the *Udacity_MAILOUT_052018_TEST.csv* to predict the response result and then submitted to the Kaggle competition for further analysis. Surprisingly, the model performs even better in testing set. I gets a 0.80657 average AUC.

Variable importance

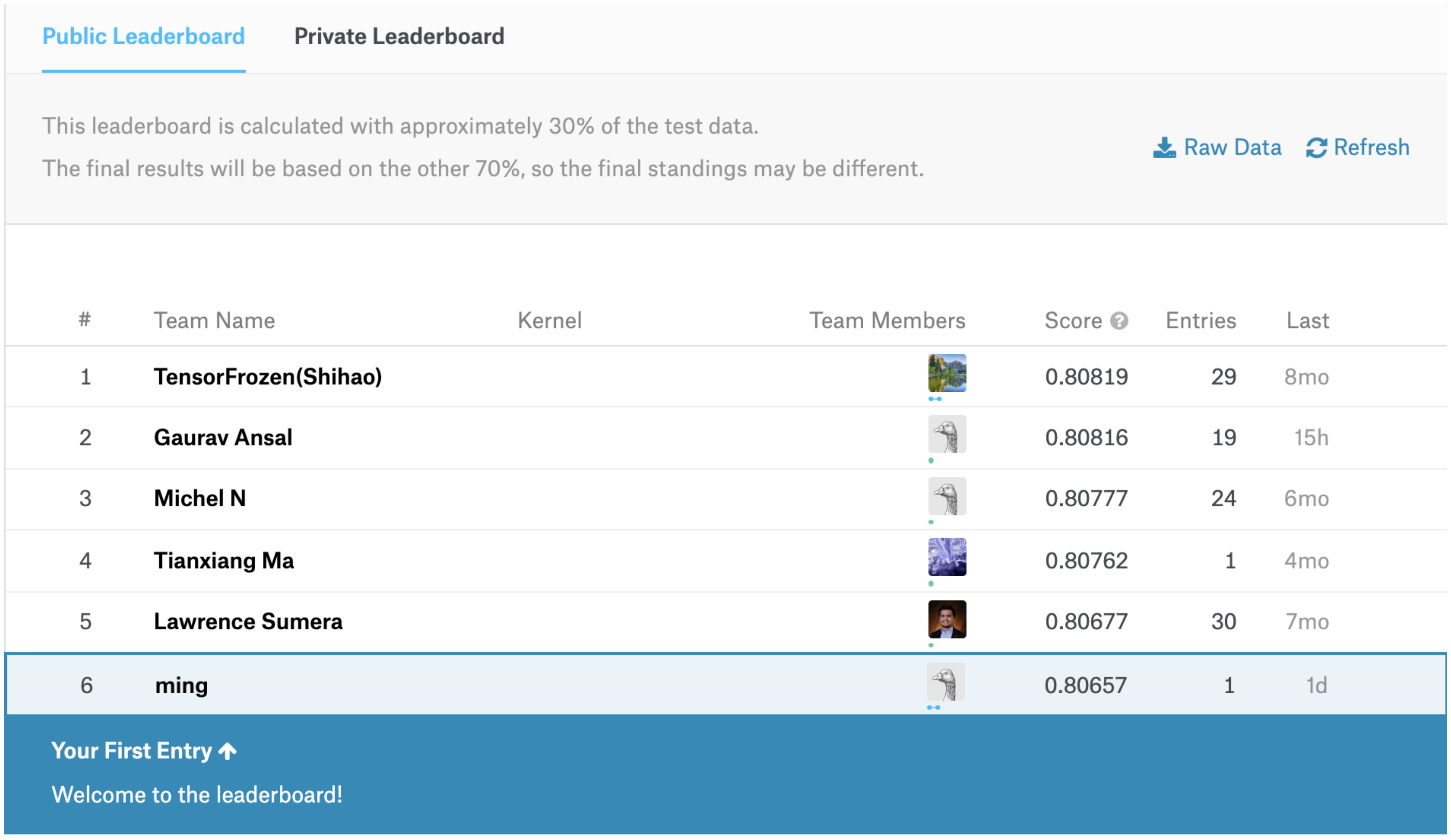
And here is the output of variable importance using the fine-tuned model. The top 10 variables are:



- KBA13_SEG_UTILITIES - share of MUVs/SUVs
- D19_RATGEBER_RZ - transactional activity based on the product group GUIDEBOOKS
- LP_LEBENSPHASE_GROB - life stage rough
- KBA05_GBZ - number of buildings in the microcell
- ZABEOTYP - typification of energy consumers
- PLZ8_GBZ - number of buildings within the PLZ8
- OST_WEST_KZ - flag indicating the former GDR/FRG

Kaggle competition

Using the model generated in the above section, I submitted my prediction result to the Kaggle competition portal.



This leaderboard is calculated with approximately 30% of the test data.
The final results will be based on the other 70%, so the final standings may be different.

#	Team Name	Kernel	Team Members	Score	Entries	Last
1	TensorFrozen(Shihao)			0.80819	29	8mo
2	Gaurav Ansal			0.80816	19	15h
3	Michel N			0.80777	24	6mo
4	Tianxiang Ma			0.80762	1	4mo
5	Lawrence Sumera			0.80677	30	7mo
6	ming			0.80657	1	1d

Your First Entry ↑
Welcome to the leaderboard!

And the final score is 0.80657 out of 1 using the metric of AUC-ROC.I ranked the 6th amount the whole population. Just slightly lower than the first place with score 0.80819.

Improvement

In order to save time and wrap up the project as fast as possible, I mainly follow the approach from other posts. If I have more time, I would also try LightGBM and CatBoost because these methods are also famous for fast training and high accuracy. Besides, I can also try other kinds of imputer and scaler when transforming data.

Challenges

There are several challenges I faced:

Data Cleaning:

I need to manually prepared the missing data dictionary first by looking through two meta-data files. By carefully documenting their data types and missing value format, I can apply data cleaning. I have uploaded the missing data file for people who want to reproduce my work.

Parameter Tuning:

I followed several githubs in applying parameter tuning. The girdsearch method is extremely useful. However, it is hard to select the initial parameter value and tuning so many parameters at the same time. One trick I used is to tune the parameter in terms of their importance.

1. max_depth and min_child_weight
2. gamma
3. subsample and colsample_bytree
4. reg_alpha

Pipeline

The last trick I use to make my code clean is building pipeline. There are two kinds of pipeline I built:

- Data Cleaning Pipeline: After setting the strategy of data cleaning, I wrap up a clean data function for further usage.
- Data transforming Pipeline: I built the pipeline starting from imputing data, scaling data to PCA. This pipeline can be further expanded in model tuning using the following code:

```
# Create initial model
clf_0 = XGBRegressor(
    objective = 'binary:logistic', #logistic regression for binary classification
    scale_pos_weight = 1, #because of high class imbalance
    random_state = 28)
pipeline = Pipeline([
        ('imp', imputer),
        ('scale', scaler),
        ('clf', clf_0)
])
parameters_1 = {
    'clf__max_depth': range(3,10,2),
    'clf__min_child_weight': range(1,6,2)
}
# Pass Pipeline into training
cv = GridSearchCV(estimator=pipeline, param_grid=parameters_1, scoring='roc_auc',n_jobs=-1, iid=False, cv=5)
cv.fit(features_raw, response_raw)
cv.grid_scores_, cv.best_params_, cv.best_score_
```