Identify_Customer_Segments

July 9, 2022

1 Project: Identify Customer Segments

In this project, you will apply unsupervised learning techniques to identify segments of the population that form the core customer base for a mail-order sales company in Germany. These segments can then be used to direct marketing campaigns towards audiences that will have the highest expected rate of returns. The data that you will use has been provided by our partners at Bertelsmann Arvato Analytics, and represents a real-life data science task.

This notebook will help you complete this task by providing a framework within which you will perform your analysis steps. In each step of the project, you will see some text describing the subtask that you will perform, followed by one or more code cells for you to complete your work. **Feel free to add additional code and markdown cells as you go along so that you can explore everything in precise chunks.** The code cells provided in the base template will outline only the major tasks, and will usually not be enough to cover all of the minor tasks that comprise it.

It should be noted that while there will be precise guidelines on how you should handle certain tasks in the project, there will also be places where an exact specification is not provided. **There will be times in the project where you will need to make and justify your own decisions on how to treat the data.** These are places where there may not be only one way to handle the data. In real-life tasks, there may be many valid ways to approach an analysis task. One of the most important things you can do is clearly document your approach so that other scientists can understand the decisions you've made.

At the end of most sections, there will be a Markdown cell labeled **Discussion**. In these cells, you will report your findings for the completed section, as well as document the decisions that you made in your approach to each subtask. **Your project will be evaluated not just on the code used to complete the tasks outlined, but also your communication about your observations and conclusions at each stage.**

```
In [1]: # import libraries here; add more as necessary
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns

        import math
        from sklearn.preprocessing import Imputer, StandardScaler
        from sklearn.decomposition import PCA
        from sklearn.cluster import KMeans
        pd.options.mode.chained_assignment = None  # default='warn'
        #pd.options.display.max_columns = None

        # magic word for producing visualizations in notebook
        %matplotlib inline

        '''
        Import note: The classroom currently uses sklearn version 0.19.
        If you need to use an imputer, it is available in sklearn.preprocessing.Imputer,
        instead of sklearn.impute as in newer versions of sklearn.
        '''
```

```
Out[1]: '\nImport note: The classroom currently uses sklearn version 0.19.\nIf you need to use a
```

1.0.1 Step 0: Load the Data

There are four files associated with this project (not including this one):

- `Udacity_AZDIAS_Subset.csv`: Demographics data for the general population of Germany; 891211 persons (rows) x 85 features (columns).
- `Udacity_CUSTOMERS_Subset.csv`: Demographics data for customers of a mail-order company; 191652 persons (rows) x 85 features (columns).
- `Data_Dictionary.md`: Detailed information file about the features in the provided datasets.
- `AZDIAS_Feature_Summary.csv`: Summary of feature attributes for demographics data; 85 features (rows) x 4 columns

Each row of the demographics files represents a single person, but also includes information outside of individuals, including information about their household, building, and neighborhood. You will use this information to cluster the general population into groups with similar demographic properties. Then, you will see how the people in the customers dataset fit into those created clusters. The hope here is that certain clusters are over-represented in the customers data, as compared to the general population; those over-represented clusters will be assumed to be part of the core userbase. This information can then be used for further applications, such as targeting for a marketing campaign.

To start off with, load in the demographics data for the general population into a pandas DataFrame, and do the same for the feature attributes summary. Note for all of the `.csv` data files in this project: they're semicolon (`;`) delimited, so you'll need an additional argument in your `read_csv()` call to read in the data properly. Also, considering the size of the main dataset, it may take some time for it to load completely.

Once the dataset is loaded, it's recommended that you take a little bit of time just browsing the general structure of the dataset and feature summary file. You'll be getting deep into the innards of the cleaning in the first major step of the project, so gaining some general familiarity can help you get your bearings.

```
In [2]: # Load in the general demographics data.
        azdias = pd.read_csv('Udacity_AZDIAS_Subset.csv', delimiter=';')

        # Load in the feature summary file.
        feat_info = pd.read_csv('AZDIAS_Feature_Summary.csv', delimiter=';')
```

```
In [3]: # Check the structure of the data after it's loaded (e.g. print the number of
        # rows and columns, print the first few rows).

        print('Overview of the general demographics data:')
        print("-- Shape: ", azdias.shape)

        print("-- Data head:")
        display(azdias.head())
```

```
Overview of the general demographics data:
-- Shape:  (891221, 85)
-- Data head:
```

```
   AGER_TYP  ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  \
0        -1                     2          1            2.0
1        -1                     1          2            5.0
2        -1                     3          2            3.0
3         2                     4          2            2.0
4        -1                     3          1            5.0

   FINANZ_MINIMALIST  FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  \
0                  3              4                 3               5
1                  1              5                 2               5
2                  1              4                 1               2
3                  4              2                 5               2
4                  4              3                 4               1

   FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER    ...     PLZ8_ANTG1  PLZ8_ANTG2  \
0                      5                 3    ...            NaN         NaN
1                      4                 5    ...            2.0         3.0
2                      3                 5    ...            3.0         3.0
3                      1                 2    ...            2.0         2.0
4                      3                 2    ...            2.0         4.0

   PLZ8_ANTG3  PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  \
0         NaN         NaN          NaN       NaN       NaN     NaN
1         2.0         1.0          1.0       5.0       4.0     3.0
2         1.0         0.0          1.0       4.0       4.0     3.0
3         2.0         0.0          1.0       3.0       4.0     2.0
4         2.0         1.0          2.0       3.0       3.0     4.0

   ORTSGR_KLS9  RELAT_AB
0          NaN       NaN
1          5.0       4.0
2          5.0       2.0
3          3.0       3.0
4          6.0       5.0
```

```
[5 rows x 85 columns]
```

> **Tip**: Add additional cells to keep everything in reasonably-sized chunks! Keyboard shortcut `esc --> a` (press escape to enter command mode, then press the 'A' key) adds a new cell before the active cell, and `esc --> b` adds a new cell after the active cell. If you need to convert an active cell to a markdown cell, use `esc --> m` and to convert to a code cell, use `esc --> y`.

1.1 Step 1: Preprocessing

1.1.1 Step 1.1: Assess Missing Data

The feature summary file contains a summary of properties for each demographics data column. You will use this file to help you make cleaning decisions during this stage of the project. First of all, you should assess the demographics data in terms of missing data. Pay attention to the following points as you perform your analysis, and take notes on what you observe. Make sure that you fill in the **Discussion** cell with your findings and decisions at the end of each step that has one!

Step 1.1.1: Convert Missing Value Codes to NaNs The fourth column of the feature attributes summary (loaded in above as `feat_info`) documents the codes from the data dictionary that indicate missing or unknown data. While the file encodes this as a list (e.g. `[-1,0]`), this will get read in as a string object. You'll need to do a little bit of parsing to make use of it to identify and clean the data. Convert data that matches a 'missing' or 'unknown' value code into a numpy NaN value. You might want to see how much data takes on a 'missing' or 'unknown' code, and how much data is naturally missing, as a point of interest.

As one more reminder, you are encouraged to add additional cells to break up your analysis into manageable chunks.

```
In [4]: # Identify missing or unknown data values and convert them to NaNs.
        dict_replacements = {}
        for attribute, missing_or_unknown in zip(feat_info['attribute'], feat_info['missing_or_u
            missing_items = missing_or_unknown.strip('[]').split(',')
            if(len(missing_items)>0):
                dict_replacements[attribute] = len(azdias[azdias[attribute].isin(missing_items)]
                azdias.loc[azdias[attribute].isin(missing_items), attribute] = np.nan

        # insights
        print("number of entries updated with NaN:")
        display(dict_replacements)

        total_entries = azdias.shape[0]*azdias.shape[1]
        total_missing = sum(dict_replacements.values())
        percentage = total_missing/total_entries
        print('{:-9} total missing entries ({:2.2%})'.format(total_missing, percentage))
        print("updated data (head):")
        azdias.head(10)
```

```
number of entries updated with NaN:


{'AGER_TYP': 685843,
 'ALTERSKATEGORIE_GROB': 2881,
 'ANREDE_KZ': 0,
 'CJT_GESAMTTYP': 0,
 'FINANZ_MINIMALIST': 0,
 'FINANZ_SPARER': 0,
 'FINANZ_VORSORGER': 0,
 'FINANZ_ANLEGER': 0,
 'FINANZ_UNAUFFAELLIGER': 0,
 'FINANZ_HAUSBAUER': 0,
 'FINANZTYP': 0,
 'GEBURTSJAHR': 392318,
 'GFK_URLAUBERTYP': 0,
 'GREEN_AVANTGARDE': 0,
 'HEALTH_TYP': 111196,
 'LP_LEBENSPHASE_FEIN': 92778,
 'LP_LEBENSPHASE_GROB': 89718,
 'LP_FAMILIE_FEIN': 72938,
 'LP_FAMILIE_GROB': 72938,
 'LP_STATUS_FEIN': 0,
 'LP_STATUS_GROB': 0,
 'NATIONALITAET_KZ': 108315,
 'PRAEGENDE_JUGENDJAHRE': 108164,
 'RETOURTYP_BK_S': 0,
 'SEMIO_SOZ': 0,
 'SEMIO_FAM': 0,
 'SEMIO_REL': 0,
 'SEMIO_MAT': 0,
 'SEMIO_VERT': 0,
 'SEMIO_LUST': 0,
 'SEMIO_ERL': 0,
 'SEMIO_KULT': 0,
 'SEMIO_RAT': 0,
 'SEMIO_KRIT': 0,
 'SEMIO_DOM': 0,
 'SEMIO_KAEM': 0,
 'SEMIO_PFLICHT': 0,
 'SEMIO_TRADV': 0,
 'SHOPPER_TYP': 111196,
 'SOHO_KZ': 0,
 'TITEL_KZ': 815562,
 'VERS_TYP': 111196,
 'ZABEOTYP': 0,
 'ALTER_HH': 236768,
 'ANZ_PERSONEN': 0,
 'ANZ_TITEL': 0,
 'HH_EINKOMMEN_SCORE': 0,
 'KK_KUNDENTYP': 0,
 'W_KEIT_KIND_HH': 40386,
 'WOHNDAUER_2008': 0,
 'ANZ_HAUSHALTE_AKTIV': 6463,
 'ANZ_HH_TITEL': 0,
 'GEBAEUDETYP': 0,
 'KONSUMNAEHE': 0,
 'MIN_GEBAEUDEJAHR': 0,
 'OST_WEST_KZ': 0,
 'WOHNLAGE': 0,
 'CAMEO_DEUG_2015': 373,
 'CAMEO_DEU_2015': 373,
 'CAMEO_INTL_2015': 373,
 'KBA05_ANTG1': 0,
 'KBA05_ANTG2': 0,
 'KBA05_ANTG3': 0,
 'KBA05_ANTG4': 0,
 'KBA05_BAUMAX': 343200,
 'KBA05_GBZ': 0,
 'BALLRAUM': 0,
 'EWDICHTE': 0,
 'INNENSTADT': 0,
 'GEBAEUDETYP_RASTER': 0,
 'KKK': 36868,
 'MOBI_REGIO': 0,
 'ONLINE_AFFINITAET': 0,
 'REGIOTYP': 36868,
 'KBA13_ANZAHL_PKW': 0,
 'PLZ8_ANTG1': 0,
 'PLZ8_ANTG2': 0,
 'PLZ8_ANTG3': 0,
 'PLZ8_ANTG4': 0,
 'PLZ8_BAUMAX': 0,
 'PLZ8_HHZ': 0,
 'PLZ8_GBZ': 0,
 'ARBEIT': 159,
 'ORTSGR_KLS9': 58,
 'RELAT_AB': 159}


  3477091 total missing entries (4.59%)
updated data (head):
```

```
Out[4]:    AGER_TYP  ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  \
        0       NaN                   2.0        1.0            2.0   
        1       NaN                   1.0        2.0            5.0   
        2       NaN                   3.0        2.0            3.0   
        3       2.0                   4.0        2.0            2.0   
        4       NaN                   3.0        1.0            5.0   
        5       3.0                   1.0        2.0            2.0   
        6       NaN                   2.0        2.0            5.0   
        7       NaN                   1.0        1.0            3.0   
        8       NaN                   3.0        1.0            3.0   
        9       NaN                   3.0        2.0            4.0   

           FINANZ_MINIMALIST  FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  \
        0                3.0            4.0               3.0             5.0   
        1                1.0            5.0               2.0             5.0   
        2                1.0            4.0               1.0             2.0   
        3                4.0            2.0               5.0             2.0   
        4                4.0            3.0               4.0             1.0   
        5                3.0            1.0               5.0             2.0   
        6                1.0            5.0               1.0             5.0   
        7                3.0            3.0               4.0             1.0   
        8                4.0            4.0               2.0             4.0   
        9                2.0            4.0               2.0             3.0   

           FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER    ...     PLZ8_ANTG1  PLZ8_ANTG2  \
        0                    5.0               3.0    ...            NaN         NaN   
        1                    4.0               5.0    ...            2.0         3.0   
        2                    3.0               5.0    ...            3.0         3.0   
        3                    1.0               2.0    ...            2.0         2.0   
        4                    3.0               2.0    ...            2.0         4.0   
        5                    2.0               5.0    ...            2.0         3.0   
        6                    4.0               3.0    ...            3.0         3.0   
        7                    3.0               2.0    ...            3.0         3.0   
        8                    2.0               2.0    ...            2.0         3.0   
        9                    5.0               4.0    ...            2.0         3.0   

           PLZ8_ANTG3  PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  \
        0         NaN         NaN          NaN       NaN       NaN     NaN   
        1         2.0         1.0          1.0       5.0       4.0     3.0   
        2         1.0         0.0          1.0       4.0       4.0     3.0   
        3         2.0         0.0          1.0       3.0       4.0     2.0   
        4         2.0         1.0          2.0       3.0       3.0     4.0   
        5         1.0         1.0          1.0       5.0       5.0     2.0   
        6         1.0         0.0          1.0       5.0       5.0     4.0   
        7         1.0         0.0          1.0       4.0       4.0     2.0   
        8         2.0         1.0          1.0       3.0       3.0     2.0   
        9         2.0         1.0          1.0       3.0       3.0     2.0   
```

```
   ORTSGR_KLS9  RELAT_AB
0          NaN       NaN
1          5.0       4.0
2          5.0       2.0
3          3.0       3.0
4          6.0       5.0
5          3.0       3.0
6          6.0       3.0
7          5.0       2.0
8          4.0       3.0
9          3.0       1.0

[10 rows x 85 columns]
```

Step 1.1.2: Assess Missing Data in Each Column How much missing data is present in each column? There are a few columns that are outliers in terms of the proportion of values that are missing. You will want to use matplotlib's `hist()` function to visualize the distribution of missing value counts to find these columns. Identify and document these columns. While some of these columns might have justifications for keeping or re-encoding the data, for this project you should just remove them from the dataframe. (Feel free to make remarks about these outlier columns in the discussion, however!)

For the remaining features, are there any patterns in which columns have, or share, missing data?

```
In [5]: # Perform an assessment of how much missing data there is in each column of the
        # dataset.

        dict_nans = {}
        for attribute in feat_info['attribute']:
            dict_nans[attribute] = azdias[attribute].isnull().sum(axis=0)

        missing_data_stats_df = pd.DataFrame([dict_nans, dict_replacements]).T
        missing_data_stats_df.columns = ["total missing", "converted missing"]
        missing_data_stats_df["initial missing"] = missing_data_stats_df["total missing"]-missin
        missing_data_stats_df["percentage of total missing"] = np.floor(1000 * missing_data_stat

        print('a total of {:-2} out of {:-2} columns have missing entries.'.format(len(missing_d
        display(missing_data_stats_df)
```

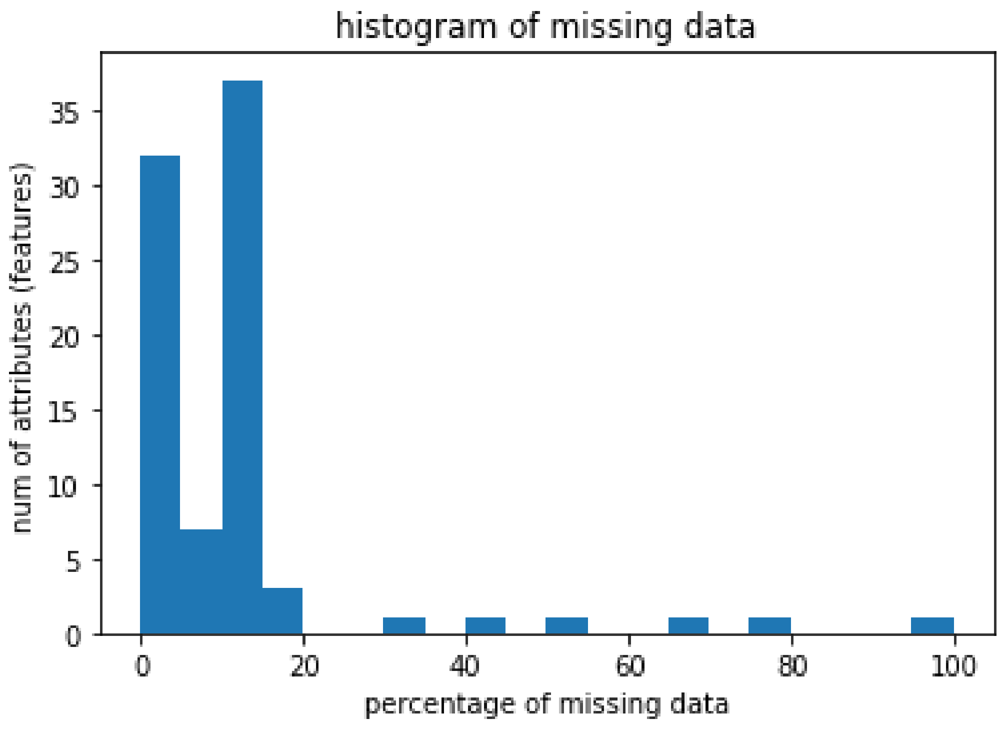
```
a total of 61 out of 85 columns have missing entries.


                       total missing  converted missing  initial missing  \
AGER_TYP                      685843             685843                0
ALTERSKATEGORIE_GROB            2881               2881                0
ALTER_HH                      310267             236768            73499
ANREDE_KZ                          0                  0                0
ANZ_HAUSHALTE_AKTIV            99611               6463            93148
```

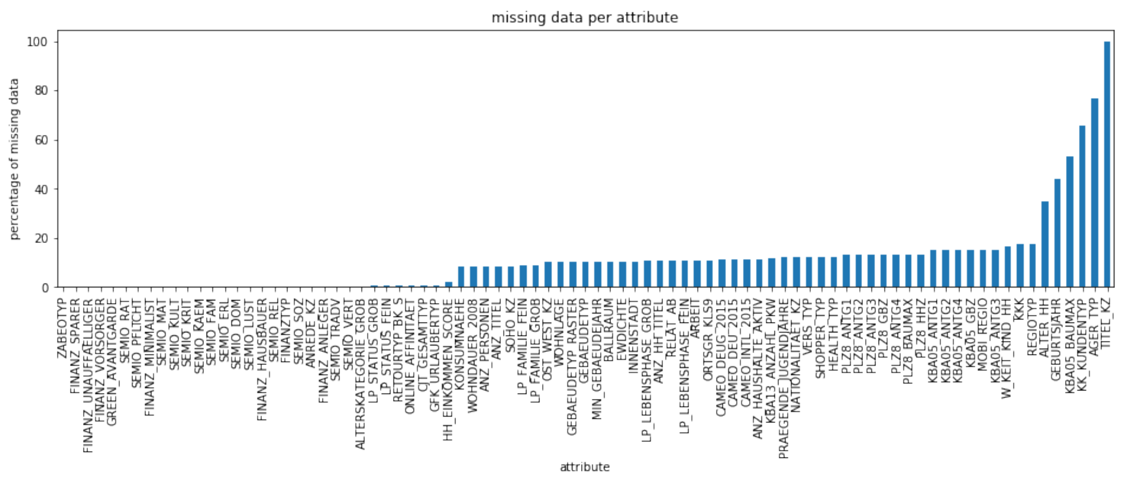
```
ANZ_HH_TITEL               97008          0      97008
ANZ_PERSONEN               73499          0      73499
ANZ_TITEL                  73499          0      73499
ARBEIT                     97375        159      97216
BALLRAUM                   93740          0      93740
CAMEO_DEUG_2015            99352        373      98979
CAMEO_DEU_2015             99352        373      98979
CAMEO_INTL_2015            99352        373      98979
CJT_GESAMTTYP               4854          0       4854
EWDICHTE                   93740          0      93740
FINANZTYP                      0          0          0
FINANZ_ANLEGER                 0          0          0
FINANZ_HAUSBAUER               0          0          0
FINANZ_MINIMALIST              0          0          0
FINANZ_SPARER                  0          0          0
FINANZ_UNAUFFAELLIGER          0          0          0
FINANZ_VORSORGER               0          0          0
GEBAEUDETYP                93148          0      93148
GEBAEUDETYP_RASTER         93155          0      93155
GEBURTSJAHR               392318     392318          0
GFK_URLAUBERTYP             4854          0       4854
GREEN_AVANTGARDE               0          0          0
HEALTH_TYP                111196     111196          0
HH_EINKOMMEN_SCORE         18348          0      18348
INNENSTADT                 93740          0      93740
...                          ...        ...        ...
PLZ8_ANTG4                116515          0     116515
PLZ8_BAUMAX               116515          0     116515
PLZ8_GBZ                  116515          0     116515
PLZ8_HHZ                  116515          0     116515
PRAEGENDE_JUGENDJAHRE     108164     108164          0
REGIOTYP                  158064      36868     121196
RELAT_AB                   97375        159      97216
RETOURTYP_BK_S              4854          0       4854
SEMIO_DOM                      0          0          0
SEMIO_ERL                      0          0          0
SEMIO_FAM                      0          0          0
SEMIO_KAEM                     0          0          0
SEMIO_KRIT                     0          0          0
SEMIO_KULT                     0          0          0
SEMIO_LUST                     0          0          0
SEMIO_MAT                      0          0          0
SEMIO_PFLICHT                  0          0          0
SEMIO_RAT                      0          0          0
SEMIO_REL                      0          0          0
SEMIO_SOZ                      0          0          0
SEMIO_TRADV                    0          0          0
SEMIO_VERT                     0          0          0
```

```
SHOPPER_TYP                 111196            111196                 0
SOHO_KZ                      73499                 0             73499
TITEL_KZ                    889061            815562             73499
VERS_TYP                    111196            111196                 0
WOHNDAUER_2008               73499                 0             73499
WOHNLAGE                     93148                 0             93148
W_KEIT_KIND_HH              147988             40386            107602
ZABEOTYP                         0                 0                 0

                       percentage of total missing
AGER_TYP                                      76.9
ALTERSKATEGORIE_GROB                           0.3
ALTER_HH                                      34.8
ANREDE_KZ                                      0.0
ANZ_HAUSHALTE_AKTIV                           11.1
ANZ_HH_TITEL                                  10.8
ANZ_PERSONEN                                   8.2
ANZ_TITEL                                      8.2
ARBEIT                                        10.9
BALLRAUM                                      10.5
CAMEO_DEUG_2015                               11.1
CAMEO_DEU_2015                                11.1
CAMEO_INTL_2015                               11.1
CJT_GESAMTTYP                                  0.5
EWDICHTE                                      10.5
FINANZTYP                                      0.0
FINANZ_ANLEGER                                 0.0
FINANZ_HAUSBAUER                               0.0
FINANZ_MINIMALIST                              0.0
FINANZ_SPARER                                  0.0
FINANZ_UNAUFFAELLIGER                          0.0
FINANZ_VORSORGER                               0.0
GEBAEUDETYP                                   10.4
GEBAEUDETYP_RASTER                            10.4
GEBURTSJAHR                                   44.0
GFK_URLAUBERTYP                                0.5
GREEN_AVANTGARDE                               0.0
HEALTH_TYP                                    12.4
HH_EINKOMMEN_SCORE                             2.0
INNENSTADT                                    10.5
...                                            ...
PLZ8_ANTG4                                    13.0
PLZ8_BAUMAX                                   13.0
PLZ8_GBZ                                      13.0
PLZ8_HHZ                                      13.0
PRAEGENDE_JUGENDJAHRE                         12.1
REGIOTYP                                      17.7
RELAT_AB                                      10.9
```

```
RETOURTYP_BK_S                                   0.5
SEMIO_DOM                                        0.0
SEMIO_ERL                                        0.0
SEMIO_FAM                                        0.0
SEMIO_KAEM                                       0.0
SEMIO_KRIT                                       0.0
SEMIO_KULT                                       0.0
SEMIO_LUST                                       0.0
SEMIO_MAT                                        0.0
SEMIO_PFLICHT                                    0.0
SEMIO_RAT                                        0.0
SEMIO_REL                                        0.0
SEMIO_SOZ                                        0.0
SEMIO_TRADV                                      0.0
SEMIO_VERT                                       0.0
SHOPPER_TYP                                     12.4
SOHO_KZ                                          8.2
TITEL_KZ                                        99.7
VERS_TYP                                        12.4
WOHNDAUER_2008                                   8.2
WOHNLAGE                                        10.4
W_KEIT_KIND_HH                                  16.6
ZABEOTYP                                         0.0

[85 rows x 4 columns]
```

```
In [6]: # Investigate patterns in the amount of missing data in each column.
        plt.hist(missing_data_stats_df["percentage of total missing"], bins=20)
        plt.ylabel('num of attributes (features)')
        plt.xlabel('percentage of missing data')
        plt.title('histogram of missing data')
        plt.show()

        missing_data_stats_df.sort_values("percentage of total missing").plot.bar(y="percentage
        plt.ylabel('percentage of missing data')
        plt.xlabel('attribute')
        plt.title('missing data per attribute')
        plt.show()
```





```
In [7]: # Remove the outlier columns from the dataset. (You'll perform other data
        # engineering tasks such as re-encoding and imputation later.)

        outlier_cols = missing_data_stats_df[missing_data_stats_df["percentage of total missing"

        print("outlier columns (attributes) to be dropped:")
        display(outlier_cols)

        # dropping the outlier attributes
        print("data after dropping the outlier attributes (head):")
        azdias.drop(outlier_cols.index, axis=1, inplace=True)
        display(azdias.head())
```

```
outlier columns (attributes) to be dropped:


              total missing  converted missing  initial missing  \
AGER_TYP             685843             685843                0
ALTER_HH             310267             236768            73499
GEBURTSJAHR          392318             392318                0
KBA05_BAUMAX         476524             343200           133324
KK_KUNDENTYP         584612                  0           584612
TITEL_KZ             889061             815562            73499

              percentage of total missing
AGER_TYP                             76.9
ALTER_HH                             34.8
GEBURTSJAHR                          44.0
KBA05_BAUMAX                         53.4
KK_KUNDENTYP                         65.5
TITEL_KZ                             99.7


data after dropping the outlier attributes (head):


   ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  FINANZ_MINIMALIST  \
0                   2.0        1.0            2.0                3.0
1                   1.0        2.0            5.0                1.0
2                   3.0        2.0            3.0                1.0
3                   4.0        2.0            2.0                4.0
4                   3.0        1.0            5.0                4.0

   FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  \
0            4.0               3.0             5.0                    5.0
1            5.0               2.0             5.0                    4.0
2            4.0               1.0             2.0                    3.0
3            2.0               5.0             2.0                    1.0
4            3.0               4.0             1.0                    3.0

   FINANZ_HAUSBAUER  FINANZTYP     ...     PLZ8_ANTG1  PLZ8_ANTG2  PLZ8_ANTG3  \
0               3.0        4.0     ...            NaN         NaN         NaN
1               5.0        1.0     ...            2.0         3.0         2.0
2               5.0        1.0     ...            3.0         3.0         1.0
3               2.0        6.0     ...            2.0         2.0         2.0
```

```
4             2.0         5.0    ...           2.0         4.0         2.0

   PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB
0         NaN          NaN       NaN       NaN     NaN          NaN       NaN
1         1.0          1.0       5.0       4.0     3.0          5.0       4.0
2         0.0          1.0       4.0       4.0     3.0          5.0       2.0
3         0.0          1.0       3.0       4.0     2.0          3.0       3.0
4         1.0          2.0       3.0       3.0     4.0          6.0       5.0

[5 rows x 79 columns]
```

Discussion 1.1.2: Assess Missing Data in Each Column (Double click this cell and replace this text with your own text, reporting your observations regarding the amount of missing data in each column. Are there any patterns in missing values? Which columns were removed from the dataset?)

61 of the 85 columns have missing data. The majority of these columns have around 20% missing data. However, 6 of these columns have over 34% missing data, and these columns would be considered the outliers. These columns are: AGER_TYP, ALTER_HH, GEBURTSJAHR, KBA05_BAUMAX, KK_KUNDENTYP, and TITEL_KZ. Since so much of their data is missing, including these columns in the analysis would influence the results, so they should be taken out. That leaves 79 columns with closer to 20% missing data.

Step 1.1.3: Assess Missing Data in Each Row Now, you'll perform a similar assessment for the rows of the dataset. How much data is missing in each row? As with the columns, you should see some groups of points that have a very different numbers of missing values. Divide the data into two subsets: one for data points that are above some threshold for missing values, and a second subset for points below that threshold.

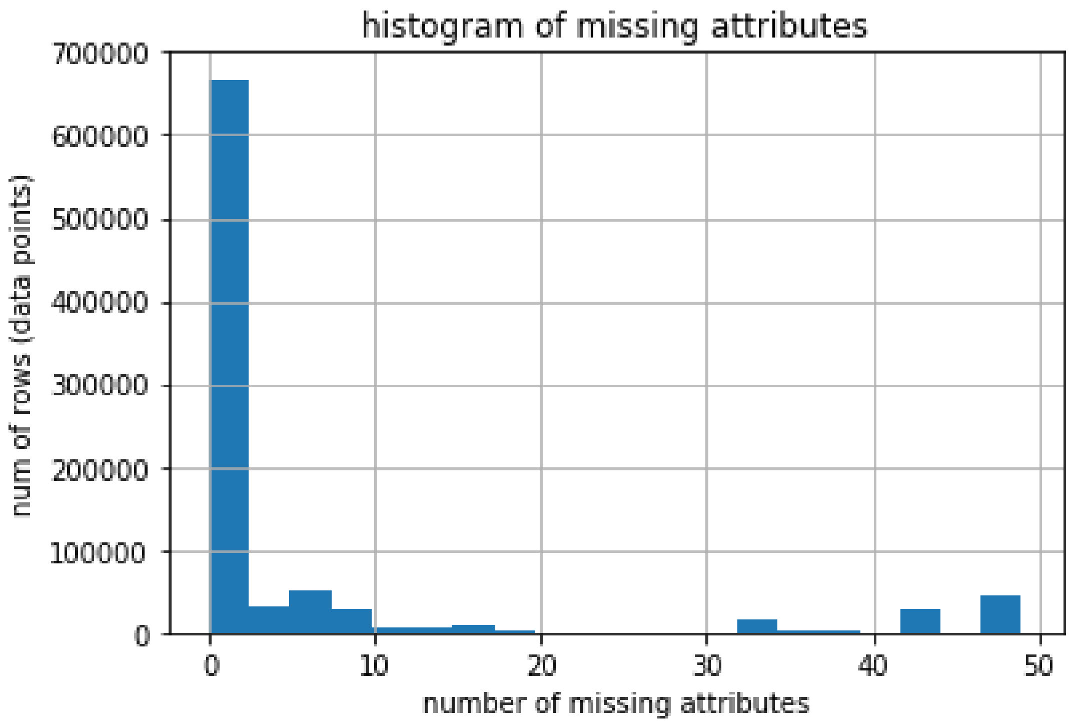
In order to know what to do with the outlier rows, we should see if the distribution of data values on columns that are not missing data (or are missing very little data) are similar or different between the two groups. Select at least five of these columns and compare the distribution of values. - You can use seaborn's `countplot()` function to create a bar chart of code frequencies and matplotlib's `subplot()` function to put bar charts for the two subplots side by side. - To reduce repeated code, you might want to write a function that can perform this comparison, taking as one of its arguments a column to be compared.

Depending on what you observe in your comparison, this will have implications on how you approach your conclusions later in the analysis. If the distributions of non-missing features look similar between the data with many missing values and the data with few or no missing values, then we could argue that simply dropping those points from the analysis won't present a major issue. On the other hand, if the data with many missing values looks very different from the data with few or no missing values, then we should make a note on those data as special. We'll revisit these data later on. **Either way, you should continue your analysis for now using just the subset of the data with few or no missing values.**

```
In [8]: # How much data is missing in each row of the dataset?

        num_data_with_missing_attr = sum(azdias.isnull().any(axis=1))
```

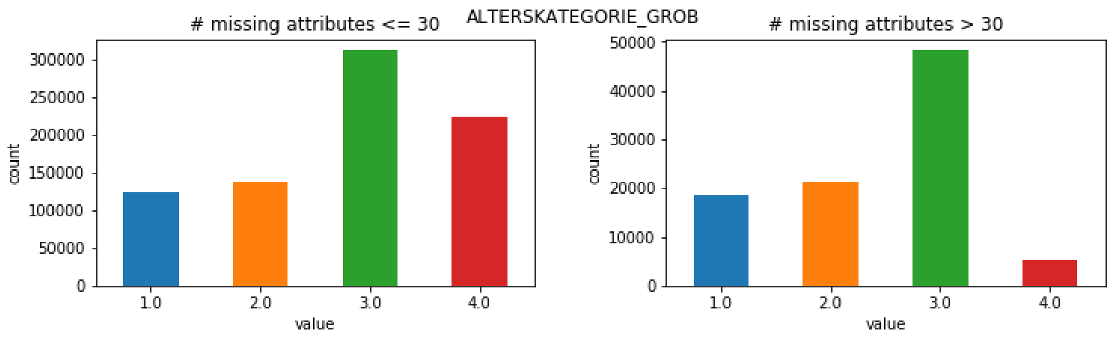
```
percentage = num_data_with_missing_attr/azdias.shape[0]
print('{:-2} out of {:-2} rows ({:2.2%}) have missing entries.'.format(num_data_with_mis

data_with_missing_attr = azdias.isnull().sum(axis=1)
data_with_missing_attr.hist(bins=20)
plt.ylabel('num of rows (data points)')
plt.xlabel('number of missing attributes')
plt.title('histogram of missing attributes')
plt.show()
```

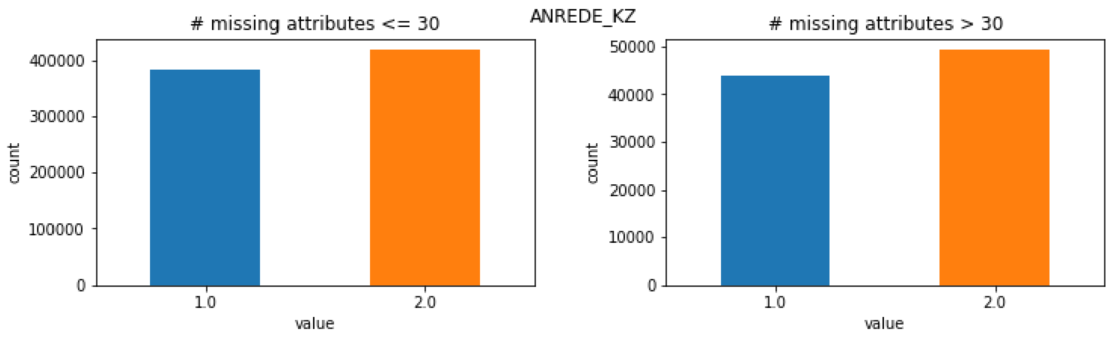
```
268012 out of 891221 rows (30.07%) have missing entries.
```

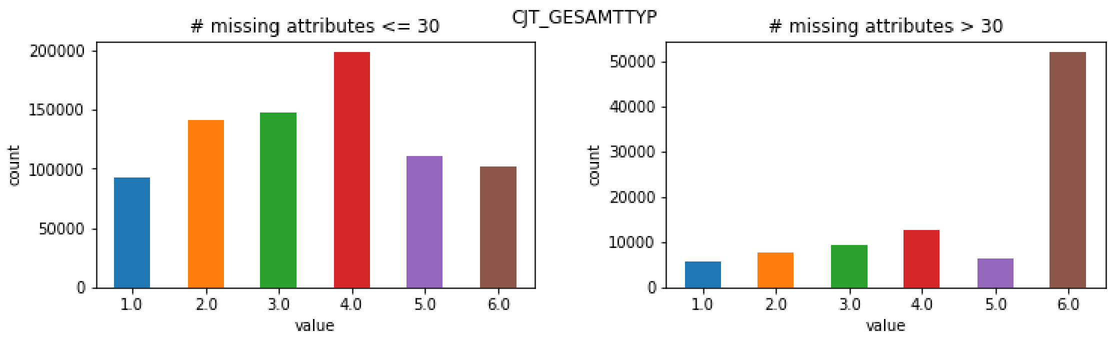


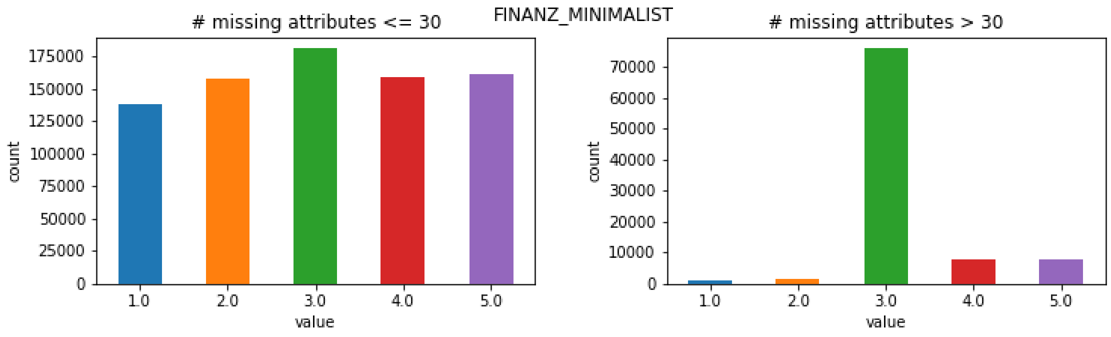
In [9]:
```
# Write code to divide the data into two subsets based on the number of missing
# values in each row.

split_threshold = 30
azdias_low_missing = azdias[azdias.isnull().sum(axis=1) <= 25]
azdias_high_missing = azdias[azdias.isnull().sum(axis=1) > 25]

print('result for a split threshold of ', split_threshold, ' missing attributes:')
print('-- subframe with low missing data has {:-2} data points ({:2.2%} of all)'.format(
print('-- subframe with high missing data has {:-2} data points ({:2.2%} of all)'.format
result for a split threshold of  30  missing attributes:
-- subframe with low missing data has 797961 data points (89.54% of all)
-- subframe with high missing data has 93260 data points (10.46% of all)
```

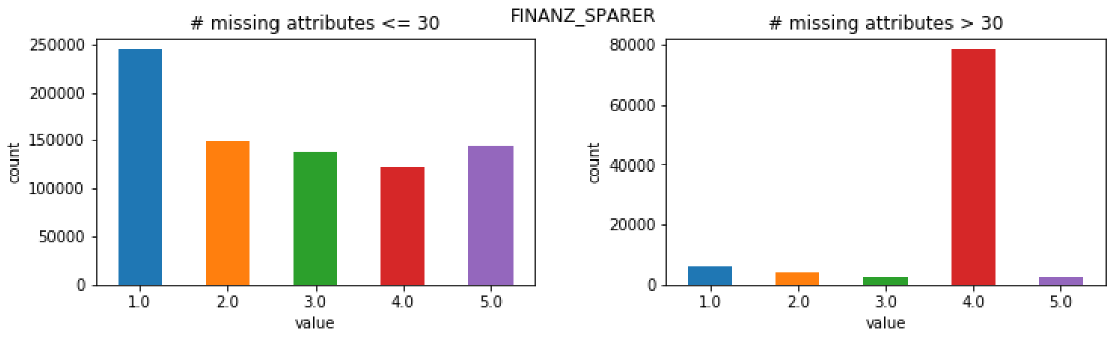
```
In [10]: # Compare the distribution of values for at least five columns where there are
         # no or few missing values, between the two subsets.
         def plot_distributions(df_low, df_high, column_name):
             fig, ax = plt.subplots(1, 2, figsize=(12,3))
             fig.subplots_adjust(wspace=0.3)
             fig.suptitle(column_name)
             df_low[column_name].value_counts().sort_index(axis=0).plot(kind='bar', ax=ax[0], ro
             ax[0].set(title="# missing attributes <= 30", xlabel="value", ylabel="count")

             df_high[column_name].value_counts().sort_index(axis=0).plot(kind='bar', ax=ax[1], r
             ax[1].set(title="# missing attributes > 30", xlabel="value", ylabel="count")

             plt.show()

         for column in azdias.columns[0:6]:
             plot_distributions(azdias_low_missing,azdias_high_missing,column)
```

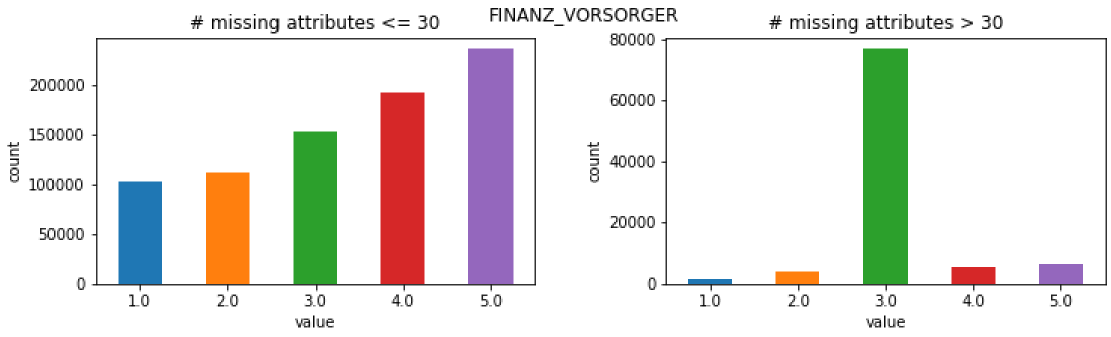





CJT_GESAMTTYP
# missing attributes <= 30
# missing attributes > 30
count
value
0
50000
100000
150000
200000
10000
20000
30000
40000
50000
1.0
2.0
3.0
4.0
5.0
6.0


FINANZ_MINIMALIST
# missing attributes <= 30
# missing attributes > 30
count
value
0
25000
50000
75000
100000
125000
150000
175000
10000
20000
30000
40000
50000
60000
70000
1.0
2.0
3.0
4.0
5.0


FINANZ_SPARER
# missing attributes <= 30
# missing attributes > 30
count
value
0
50000
100000
150000
200000
250000
20000
40000
60000
80000
1.0
2.0
3.0
4.0
5.0


FINANZ_VORSORGER
# missing attributes <= 30
# missing attributes > 30
count
value
0
50000
100000
150000
200000
20000
40000
60000
80000
1.0
2.0
3.0
4.0
5.0

Discussion 1.1.3: Assess Missing Data in Each Row (Double-click this cell and replace this text with your own text, reporting your observations regarding missing data in rows. Are the data with lots of missing values are qualitatively different from data with few or no missing values?)

As shown, 268012 out of 891221 rows of data have missing features, which is around 30% of the data. The histogram shows that most of the data either has 20 or less missing features or more than 30, so there is a split in the data. The majority of the data have 10 or less missing features, while a very small percentage have 30-50 missing features, with no rows having over 50.

If you consider 30 as the split threshold, the data can be split into two sets: one set with a high number of missing features, and the other with a low number of missing features. The set with the low number of missing features has around 90% of the data, while the set with the high number of missing features has around 10% of the data.

As shown from the bar graphs above, the data from the set of higher number of missing features is differently distributed than the set with the low number of missing features. Since this is only around 10% of the data, it should be taken out so as to no influence the results by affecting the distribution as a whole.

1.1.2 Step 1.2: Select and Re-Encode Features

Checking for missing data isn't the only way in which you can prepare a dataset for analysis. Since the unsupervised learning techniques to be used will only work on data that is encoded numerically, you need to make a few encoding changes or additional assumptions to be able to make progress. In addition, while almost all of the values in the dataset are encoded using numbers, not all of them represent numeric values. Check the third column of the feature summary (`feat_info`) for a summary of types of measurement. - For numeric and interval data, these features can be kept without changes. - Most of the variables in the dataset are ordinal in nature. While ordinal values may technically be non-linear in spacing, make the simplifying assumption that the ordinal variables can be treated as being interval in nature (that is, kept without any changes). - Special handling may be necessary for the remaining two variable types: categorical, and 'mixed'.

In the first two parts of this sub-step, you will perform an investigation of the categorical and mixed-type features and make a decision on each of them, whether you will keep, drop, or re-encode each. Then, in the last part, you will create a new data frame with only the selected and engineered columns.

Data wrangling is often the trickiest part of the data analysis process, and there's a lot of it to be done here. But stick with it: once you're done with this step, you'll be ready to get to the machine learning parts of the project!

```
In [11]: # How many features are there of each data type?

         feature_types = feat_info['type'].value_counts()
         display(feature_types)
```

```
ordinal        49
categorical    21
mixed           7
numeric         7
```

```
interval        1
Name: type, dtype: int64
```

Step 1.2.1: Re-Encode Categorical Features For categorical data, you would ordinarily need to encode the levels as dummy variables. Depending on the number of categories, perform one of the following: - For binary (two-level) categoricals that take numeric values, you can keep them without needing to do anything. - There is one binary variable that takes on non-numeric values. For this one, you need to re-encode the values as numbers or create a dummy variable. - For multi-level categoricals (three or more values), you can choose to encode the values using multiple dummy variables (e.g. via OneHotEncoder), or (to keep things straightforward) just drop them from the analysis. As always, document your choices in the Discussion section.

```
In [12]: # Assess categorical variables: which are binary, which are multi-level, and
         # which one needs to be re-encoded?
         binary_categories = {}
         multilevel_categories = {}
         for column in feat_info[feat_info['type']=='categorical'].attribute:
             if column in azdias_low_missing.columns:
                 if azdias[column].nunique() == 2:
                     binary_categories[column] = azdias_low_missing[column].unique()
                 if azdias[column].nunique() > 2:
                     multilevel_categories[column] = len(azdias_low_missing[column].unique())

         print('binary categories (name -> values):')
         display(binary_categories)

         print('multilevel categories (name -> numValues):')
         display(multilevel_categories)
```

```
binary categories (name -> values):


{'ANREDE_KZ': array([ 2.,  1.]),
 'GREEN_AVANTGARDE': array([ 0.,  1.]),
 'SOHO_KZ': array([ 1.,  0.]),
 'VERS_TYP': array([  2.,   1.,  nan]),
 'OST_WEST_KZ': array(['W', 'O'], dtype=object)}


multilevel categories (name -> numValues):


{'CJT_GESAMTTYP': 7,
 'FINANZTYP': 6,
 'GFK_URLAUBERTYP': 13,
 'LP_FAMILIE_FEIN': 12,
 'LP_FAMILIE_GROB': 6,
 'LP_STATUS_FEIN': 11,
 'LP_STATUS_GROB': 6,
 'NATIONALITAET_KZ': 4,
 'SHOPPER_TYP': 5,
 'ZABEOTYP': 6,
 'GEBAEUDETYP': 7,
 'CAMEO_DEUG_2015': 10,
 'CAMEO_DEU_2015': 45}
```

```
In [13]: # Re-encode categorical variable(s) to be kept in the analysis.

         dict_bin_enc = {'W': 0, 'O': 1}
         azdias_low_missing['OST_WEST_KZ'].replace(dict_bin_enc, inplace=True)
         print('updated encoding of the binary categorical variable: ', azdias_low_missing['OST_

         azdias_low_missing.drop(multilevel_categories.keys(), axis=1, inplace=True)

         print('num binary categorical variables: ', len(binary_categories.keys()))
         print('num dropped multilevel categorical variables: ', len(multilevel_categories.keys(
         display(azdias_low_missing.head())
```

```
updated encoding of the binary categorical variable:  [0 1]
num binary categorical variables:  5
num dropped multilevel categorical variables:  13
```

```
   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP     ...      PLZ8_ANTG1  PLZ8_ANTG2  PLZ8_ANTG3  \
1               0.0         3.0     ...             2.0         3.0         2.0
2               1.0         3.0     ...             3.0         3.0         1.0
3               0.0         2.0     ...             2.0         2.0         2.0
4               0.0         3.0     ...             2.0         4.0         2.0
5               0.0         3.0     ...             2.0         3.0         1.0
```

```
   PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB
1         1.0          1.0       5.0       4.0     3.0          5.0       4.0
2         0.0          1.0       4.0       4.0     3.0          5.0       2.0
3         0.0          1.0       3.0       4.0     2.0          3.0       3.0
4         1.0          2.0       3.0       3.0     4.0          6.0       5.0
5         1.0          1.0       5.0       5.0     2.0          3.0       3.0

[5 rows x 66 columns]
```

Discussion 1.2.1: Re-Encode Categorical Features (Double-click this cell and replace this text with your own text, reporting your findings and decisions regarding categorical features. Which ones did you keep, which did you drop, and what engineering steps did you perform?)

The dataset originally had 21 categorical columns. After dropping 6 columns earlier, the remaining dataset had 79 columns with 18 being categorical columns. There were 5 binary columns and 13 multilevel columns. The multilevel columns were dropped to leave the remaining 5 binary columns and the resulting dataset has 66 columns total. Column OST_WEST_KZ needed to be re-encoded to numerical binary values and it has values [0,1]

Step 1.2.2: Engineer Mixed-Type Features There are a handful of features that are marked as "mixed" in the feature summary that require special treatment in order to be included in the analysis. There are two in particular that deserve attention; the handling of the rest are up to your own choices: - "PRAEGENDE_JUGENDJAHRE" combines information on three dimensions: generation by decade, movement (mainstream vs. avantgarde), and nation (east vs. west). While there aren't enough levels to disentangle east from west, you should create two new variables to capture the other two dimensions: an interval-type variable for decade, and a binary variable for movement. - "CAMEO_INTL_2015" combines information on two axes: wealth and life stage. Break up the two-digit codes 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). - If you decide to keep or engineer new features around the other mixed-type features, make sure you note your steps in the Discussion section.

Be sure to check `Data_Dictionary.md` for the details needed to finish these tasks.

```
In [14]: # Investigate "PRAEGENDE_JUGENDJAHRE" and engineer two new variables.
         print('values of the PRAEGENDE_JUGENDJAHRE column in the dataset:\n', azdias_low_missin

         dict_decade = {1:40, 2:40, 3:50, 4:50, 5:60, 6:60, 7:60, 8:70, 9:70, 10:80, 11:80, 12:8
         azdias_low_missing['PRAEGENDE_JUGENDJAHRE_DECADE'] = azdias_low_missing['PRAEGENDE_JUGE

         avantgarde = 0
         mainstream = 1
         dict_movement= {1:mainstream, 2:avantgarde, 3:mainstream, 4:avantgarde, 5:mainstream, 6
         azdias_low_missing['PRAEGENDE_JUGENDJAHRE_MOVEMENT'] = azdias_low_missing['PRAEGENDE_JU

         print('dataset after engineering PRAEGENDE_JUGENDJAHRE:')
         display(azdias_low_missing.head())
```

```
values of the PRAEGENDE_JUGENDJAHRE column in the dataset:
 [ 14.  15.   8.   3.  10.  11.   5.   9.   6.   4.  nan   2.   1.  12.  13.
   7.]
dataset after engineering PRAEGENDE_JUGENDJAHRE:


   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP              ...                PLZ8_ANTG3  \
1               0.0         3.0              ...                       2.0
2               1.0         3.0              ...                       1.0
3               0.0         2.0              ...                       2.0
4               0.0         3.0              ...                       2.0
5               0.0         3.0              ...                       1.0

   PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
1         1.0          1.0       5.0       4.0     3.0          5.0       4.0
2         0.0          1.0       4.0       4.0     3.0          5.0       2.0
3         0.0          1.0       3.0       4.0     2.0          3.0       3.0
4         1.0          2.0       3.0       3.0     4.0          6.0       5.0
5         1.0          1.0       5.0       5.0     2.0          3.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT
1                          90.0                             1.0
2                          90.0                             0.0
3                          70.0                             1.0
4                          70.0                             1.0
5                          50.0                             1.0

[5 rows x 68 columns]
```

```
In [15]: # Investigate "CAMEO_INTL_2015" and engineer two new variables.


         print('values of the CAMEO_INTL_2015 column in the dataset:\n', azdias_low_missing['CAM
        azdias_low_missing['CAMEO_INTL_2015_WEALTH'] = azdias_low_missing['CAMEO_INTL_2015'].ap


        azdias_low_missing['CAMEO_INTL_2015_LIFE_STAGE'] = azdias_low_missing['CAMEO_INTL_2015'

        print('dataset after engineering CAMEO_INTL_2015:')
        display(azdias_low_missing.head())
```

```
values of the CAMEO_INTL_2015 column in the dataset:
 ['51' '24' '12' '43' '54' '22' '14' '13' '15' '33' '41' '34' '55' nan '25'
 '23' '31' '52' '35' '45' '44' '32']
dataset after engineering CAMEO_INTL_2015:


   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP             ...              PLZ8_BAUMAX  \
1               0.0         3.0             ...                      1.0
2               1.0         3.0             ...                      1.0
3               0.0         2.0             ...                      1.0
4               0.0         3.0             ...                      2.0
5               0.0         3.0             ...                      1.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
1       5.0       4.0     3.0          5.0       4.0
2       4.0       4.0     3.0          5.0       2.0
3       3.0       4.0     2.0          3.0       3.0
4       3.0       3.0     4.0          6.0       5.0
5       5.0       5.0     2.0          3.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
1                          90.0                             1.0
2                          90.0                             0.0
3                          70.0                             1.0
```

```
4                          70.0                              1.0
5                          50.0                              1.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
1                     5.0                         1.0
2                     2.0                         4.0
3                     1.0                         2.0
4                     4.0                         3.0
5                     5.0                         4.0

[5 rows x 70 columns]
```

Discussion 1.2.2: Engineer Mixed-Type Features (Double-click this cell and replace this text with your own text, reporting your findings and decisions regarding mixed-value features. Which ones did you keep, which did you drop, and what engineering steps did you perform?)

The main dataset has a total of 6 columns with mixed values. For each of the two columns 'PRAEGENDE_JUGENDJAHRE' and 'CAMEO_INTL_2015', I introduced two new columns that separate the aspects combined by each of these mixed columns as follows:

For 'PRAEGENDE_JUGENDJAHRE', two new columns are added which reflect 'decade' and 'movement' aspects. For 'CAMEO_INTL_2015', two new columns are added which reflect 'wealth' and 'life-stage' aspects. After introducing the above 4 new columns, the 6 mixed columns are dropped from the dataset, which would have contained data already made available in these new columns.

At the end, we have a dataset with 64 columns.

Step 1.2.3: Complete Feature Selection In order to finish this step up, you need to make sure that your data frame now only has the columns that you want to keep. To summarize, the dataframe should consist of the following: - All numeric, interval, and ordinal type columns from the original dataset. - Binary categorical features (all numerically-encoded). - Engineered features from other multi-level categorical features and mixed features.

Make sure that for any new columns that you have engineered, that you've excluded the original columns from the final dataset. Otherwise, their values will interfere with the analysis later on the project. For example, you should not keep "PRAEGENDE_JUGENDJAHRE", since its values won't be useful for the algorithm: only the values derived from it in the engineered features you created should be retained. As a reminder, your data should only be from **the subset with few or no missing values**.

```
In [16]: # If there are other re-engineering tasks you need to perform, make sure you
         # take care of them here. (Dealing with missing data will come in step 2.1.)

         mixed_categories = {}
         for column in feat_info[feat_info['type']=='mixed'].attribute:
             if column in azdias_low_missing.columns:
                 mixed_categories[column] = azdias_low_missing[column].unique()
                 print(column, ": ", len(mixed_categories[column]))
```

```
        print('dropping ', len(mixed_categories), ' mixed columns:\n', mixed_categories.keys())

        azdias_low_missing.drop(mixed_categories.keys(), axis=1, inplace=True)


        print('dataset after dropping mixed columns:')
        display(azdias_low_missing.head())
```

```
LP_LEBENSPHASE_FEIN :  41
LP_LEBENSPHASE_GROB :  13
PRAEGENDE_JUGENDJAHRE :  16
WOHNLAGE :  8
CAMEO_INTL_2015 :  22
PLZ8_BAUMAX :  6
dropping  6  mixed columns:
 dict_keys(['LP_LEBENSPHASE_FEIN', 'LP_LEBENSPHASE_GROB', 'PRAEGENDE_JUGENDJAHRE', 'WOHNLAGE', '
dataset after dropping mixed columns:


   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP              ...              PLZ8_ANTG4  \
1               0.0         3.0              ...                     1.0
2               1.0         3.0              ...                     0.0
3               0.0         2.0              ...                     0.0
4               0.0         3.0              ...                     1.0
5               0.0         3.0              ...                     1.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
1       5.0       4.0     3.0          5.0       4.0
2       4.0       4.0     3.0          5.0       2.0
3       3.0       4.0     2.0          3.0       3.0
4       3.0       3.0     4.0          6.0       5.0
5       5.0       5.0     2.0          3.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
1                         90.0                            1.0
2                         90.0                            0.0
3                         70.0                            1.0
4                         70.0                            1.0
5                         50.0                            1.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
1                     5.0                         1.0
2                     2.0                         4.0
3                     1.0                         2.0
4                     4.0                         3.0
5                     5.0                         4.0

[5 rows x 64 columns]
```

```
In [17]: # Do whatever you need to in order to ensure that the dataframe only contains
         # the columns that should be passed to the algorithm functions.

         display(azdias_low_missing.head())
```

```
   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP             ...              PLZ8_ANTG4  \
1               0.0         3.0             ...                     1.0
2               1.0         3.0             ...                     0.0
3               0.0         2.0             ...                     0.0
4               0.0         3.0             ...                     1.0
5               0.0         3.0             ...                     1.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
1       5.0       4.0     3.0          5.0       4.0
2       4.0       4.0     3.0          5.0       2.0
3       3.0       4.0     2.0          3.0       3.0
4       3.0       3.0     4.0          6.0       5.0
5       5.0       5.0     2.0          3.0       3.0
```

```
   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
1                          90.0                             1.0
2                          90.0                             0.0
3                          70.0                             1.0
4                          70.0                             1.0
5                          50.0                             1.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
1                     5.0                         1.0
2                     2.0                         4.0
3                     1.0                         2.0
4                     4.0                         3.0
5                     5.0                         4.0

[5 rows x 64 columns]
```

1.1.3 Step 1.3: Create a Cleaning Function

Even though you've finished cleaning up the general population demographics data, it's important to look ahead to the future and realize that you'll need to perform the same cleaning steps on the customer demographics data. In this substep, complete the function below to execute the main feature selection, encoding, and re-engineering steps you performed above. Then, when it comes to looking at the customer data in Step 3, you can just run this function on that DataFrame to get the trimmed dataset in a single step.

```
In [18]: def clean_data(df):
             """
             Perform feature trimming, re-encoding, and engineering for demographics
             data

             INPUT: Demographics DataFrame
             OUTPUT: Trimmed and cleaned demographics DataFrame
             """

             # code to execute all main cleaning steps:

             feat_info = pd.read_csv('AZDIAS_Feature_Summary.csv', delimiter=';')

             # convert missing value codes into NaNs
             dict_replacements = {}
             for attribute, missing_or_unknown in zip(feat_info['attribute'], feat_info['missing
                 missing_items = missing_or_unknown.strip('[]').split(',')
                 if(len(missing_items)>0):
                     dict_replacements[attribute] = len(df[df[attribute].isin(missing_items)])
                     df.loc[df[attribute].isin(missing_items), attribute] = np.nan
```

```
# remove selected columns and rows

## columns

outlier_cols = ['AGER_TYP', 'ALTER_HH', 'GEBURTSJAHR', 'KBA05_BAUMAX', 'KK_KUNDENTY
df.drop(outlier_cols, axis=1, inplace=True)

## rows
split_threshold = 25
df_low_missing = df[df.isnull().sum(axis=1) <= 25]
df_high_missing = df[df.isnull().sum(axis=1) > 25]

# select, re-encode, and engineer column values.

## binary variables
binary_categories = {}
multilevel_categories = {}
for column in feat_info[feat_info['type']=='categorical'].attribute:
    if column in df_low_missing.columns:
        if df[column].nunique() == 2:
            binary_categories[column] = df_low_missing[column].unique()
        if df[column].nunique() > 2:
            multilevel_categories[column] = df_low_missing[column].unique()
 ### 1) handling the binary categorical variable that must be re-encoded
dict_bin_enc = {'W': 0, 'O': 1}
df_low_missing.loc[:,'OST_WEST_KZ'].replace(dict_bin_enc, inplace=True)

### 2) dropping multilevel categorical variables
df_low_missing.drop(multilevel_categories.keys(), axis=1, inplace=True)

## mixed variables

### 1) engineering the decade and movement aspects of feature PRAEGENDE_JUGENDJAHRE
dict_decade = {1:40, 2:40, 3:50, 4:50, 5:60, 6:60, 7:60, 8:70, 9:70, 10:80, 11:80,
df_low_missing['PRAEGENDE_JUGENDJAHRE_DECADE'] = df_low_missing['PRAEGENDE_JUGENDJA

avantgarde = 0
mainstream = 1
dict_movement= {1:mainstream, 2:avantgarde, 3:mainstream, 4:avantgarde, 5:mainstrea
df_low_missing['PRAEGENDE_JUGENDJAHRE_MOVEMENT'] = df_low_missing['PRAEGENDE_JUGEND

### 2) engineering the wealth and life-stage aspects of feature CAMEO_INTL_2015
df_low_missing['CAMEO_INTL_2015_WEALTH'] = df_low_missing['CAMEO_INTL_2015'].apply(
df_low_missing['CAMEO_INTL_2015_LIFE_STAGE'] = df_low_missing['CAMEO_INTL_2015'].ap

### 3) dropping mixed variables
mixed_categories = {}
for column in feat_info[feat_info['type']=='mixed'].attribute:
```

```
            if column in df_low_missing.columns:
                mixed_categories[column] = df_low_missing[column].unique()
        df_low_missing.drop(mixed_categories.keys(), axis=1, inplace=True)

        # Return the cleaned dataframe.
        return df_low_missing
```

```
In [19]: azdias_dup = pd.read_csv('Udacity_AZDIAS_Subset.csv', delimiter=';')
         population_df = clean_data(azdias_dup)
         display(population_df.head())
```

```
   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
1                   1.0        2.0                1.0            5.0
2                   3.0        2.0                1.0            4.0
3                   4.0        2.0                4.0            2.0
4                   3.0        1.0                4.0            3.0
5                   1.0        2.0                3.0            1.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
1               2.0             5.0                    4.0               5.0
2               1.0             2.0                    3.0               5.0
3               5.0             2.0                    1.0               2.0
4               4.0             1.0                    3.0               2.0
5               5.0             2.0                    2.0               5.0

   GREEN_AVANTGARDE  HEALTH_TYP          ...            PLZ8_ANTG4  \
1               0.0         3.0          ...                   1.0
2               1.0         3.0          ...                   0.0
3               0.0         2.0          ...                   0.0
4               0.0         3.0          ...                   1.0
5               0.0         3.0          ...                   1.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
1       5.0       4.0     3.0          5.0       4.0
2       4.0       4.0     3.0          5.0       2.0
3       3.0       4.0     2.0          3.0       3.0
4       3.0       3.0     4.0          6.0       5.0
5       5.0       5.0     2.0          3.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
1                          90.0                             1.0
2                          90.0                             0.0
3                          70.0                             1.0
4                          70.0                             1.0
5                          50.0                             1.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
```

```
1                       5.0                            1.0
2                       2.0                            4.0
3                       1.0                            2.0
4                       4.0                            3.0
5                       5.0                            4.0

[5 rows x 64 columns]
```

1.2 Step 2: Feature Transformation

1.2.1 Step 2.1: Apply Feature Scaling

Before we apply dimensionality reduction techniques to the data, we need to perform feature scaling so that the principal component vectors are not influenced by the natural differences in scale for features. Starting from this part of the project, you'll want to keep an eye on the API reference page for sklearn to help you navigate to all of the classes and functions that you'll need. In this substep, you'll need to check the following:

- sklearn requires that data not have missing values in order for its estimators to work properly. So, before applying the scaler to your data, make sure that you've cleaned the DataFrame of the remaining missing values. This can be as simple as just removing all data points with missing data, or applying an Imputer to replace all missing values. You might also try a more complicated procedure where you temporarily remove missing values in order to compute the scaling parameters before re-introducing those missing values and applying imputation. Think about how much missing data you have and what possible effects each approach might have on your analysis, and justify your decision in the discussion section below.
- For the actual scaling function, a StandardScaler instance is suggested, scaling each feature to mean 0 and standard deviation 1.
- For these classes, you can make use of the `.fit_transform()` method to both fit a procedure to the data as well as apply the transformation to the data at the same time. Don't forget to keep the fit sklearn objects handy, since you'll be applying them to the customer demographics data towards the end of the project.

```
In [20]: # If you've not yet cleaned the dataset of all NaN values, then investigate and
         # do that now.

         imputer = Imputer(strategy="median")
         population_df = pd.DataFrame(imputer.fit_transform(population_df), columns = population
         print('num remaining NaN after imputation: ', population_df.isnull().sum(axis=0).sum())

num remaining NaN after imputation:  0
```

```
In [21]: # Apply feature scaling to the general population demographics data.
         stdScaler = StandardScaler()
         population_df = pd.DataFrame(stdScaler.fit_transform(population_df), columns = populati
         display(population_df.describe())
```

```
       ALTERSKATEGORIE_GROB     ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
count          7.979610e+05  7.979610e+05       7.979610e+05   7.979610e+05
mean           9.883972e-19 -6.482016e-17      -9.794927e-19   1.301657e-16
std            1.000001e+00  1.000001e+00       1.000001e+00   1.000001e+00
min           -1.766616e+00 -1.043914e+00      -1.494605e+00  -1.155482e+00
25%           -7.830433e-01 -1.043914e+00      -7.686846e-01  -1.155482e+00
50%            2.005292e-01  9.579333e-01      -4.276408e-02   1.912504e-01
75%            1.184102e+00  9.579333e-01       6.831564e-01   8.646166e-01
max            1.184102e+00  9.579333e-01       1.409077e+00   1.537983e+00

       FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  \
count      7.979610e+05    7.979610e+05           7.979610e+05
mean       1.510689e-16   -7.861320e-17           6.868025e-17
std        1.000001e+00    1.000001e+00           1.000001e+00
min       -1.766963e+00   -1.249960e+00          -1.184858e+00
25%       -1.040689e+00   -1.249960e+00          -1.184858e+00
50%        4.118594e-01    1.080440e-01          -4.702992e-01
75%        1.138133e+00    7.870460e-01           9.588178e-01
max        1.138133e+00    1.466048e+00           1.673376e+00

       FINANZ_HAUSBAUER  GREEN_AVANTGARDE    HEALTH_TYP  \
count      7.979610e+05      7.979610e+05  7.979610e+05
mean      -1.657836e-16      7.746007e-17  3.118349e-16
std        1.000001e+00      1.000001e+00  1.000001e+00
min       -1.501540e+00     -5.304422e-01 -1.610602e+00
25%       -7.913466e-01     -5.304422e-01 -2.570259e-01
50%       -8.115294e-02     -5.304422e-01 -2.570259e-01
75%        6.290407e-01     -5.304422e-01  1.096551e+00
max        1.339234e+00      1.885219e+00  1.096551e+00

                  ...              PLZ8_ANTG4      PLZ8_HHZ      PLZ8_GBZ  \
count             ...            7.979610e+05  7.979610e+05  7.979610e+05
mean              ...           -7.588397e-17 -1.300232e-16  2.708743e-17
std               ...            1.000001e+00  1.000001e+00  1.000001e+00
min               ...           -9.856398e-01 -2.728110e+00 -2.160117e+00
25%               ...           -9.856398e-01 -6.488407e-01 -3.372184e-01
50%               ...            4.066384e-01  3.907941e-01 -3.372184e-01
75%               ...            4.066384e-01  3.907941e-01  5.742308e-01
max               ...            1.798916e+00  1.430429e+00  1.485680e+00

             ARBEIT   ORTSGR_KLS9      RELAT_AB  PRAEGENDE_JUGENDJAHRE_DECADE  \
count  7.979610e+05  7.979610e+05  7.979610e+05                  7.979610e+05
mean   1.584997e-16  6.862237e-17 -4.692215e-17                  2.953082e-16
std    1.000001e+00  1.000001e+00  1.000001e+00                  1.000001e+00
min   -2.173492e+00 -1.868113e+00 -1.526014e+00                 -2.317978e+00
25%   -1.664319e-01 -5.623343e-01 -7.890585e-01                 -9.216222e-01
50%   -1.664319e-01 -1.270747e-01 -5.210290e-02                 -2.234444e-01
75%    8.370981e-01  7.434444e-01  6.848527e-01                  1.172911e+00
```

```
max    1.840628e+00  1.613964e+00  1.421808e+00                  1.172911e+00

       PRAEGENDE_JUGENDJAHRE_MOVEMENT  CAMEO_INTL_2015_WEALTH  \
count                    7.979610e+05            7.979610e+05
mean                    -7.746007e-17           -8.120885e-18
std                      1.000001e+00            1.000001e+00
min                     -1.885219e+00           -1.552980e+00
25%                      5.304422e-01           -8.681823e-01
50%                      5.304422e-01            5.014131e-01
75%                      5.304422e-01            1.186211e+00
max                      5.304422e-01            1.186211e+00

       CAMEO_INTL_2015_LIFE_STAGE
count                7.979610e+05
mean                 1.534776e-16
std                  1.000001e+00
min                 -1.266976e+00
25%                 -1.266976e+00
50%                  8.518887e-02
75%                  7.612714e-01
max                  1.437354e+00

[8 rows x 64 columns]
```

1.2.2 Discussion 2.1: Apply Feature Scaling

(Double-click this cell and replace this text with your own text, reporting your decisions regarding feature scaling.)

For missing values, I used Imputer to find the median of the column values and used that to fill the missing value.

I chose to use this median strategy because the median of the values provides a close estimate of the data's average values. Therefore, when filling the missing data, the new values would not deviate too far from the values that are present and not change further analysis.

For feature scaling, I applied StandardScaler. Feature scaling is applied to make sure that the algorithm is not biased to higher values. This helps the gradient descent flow smoother.

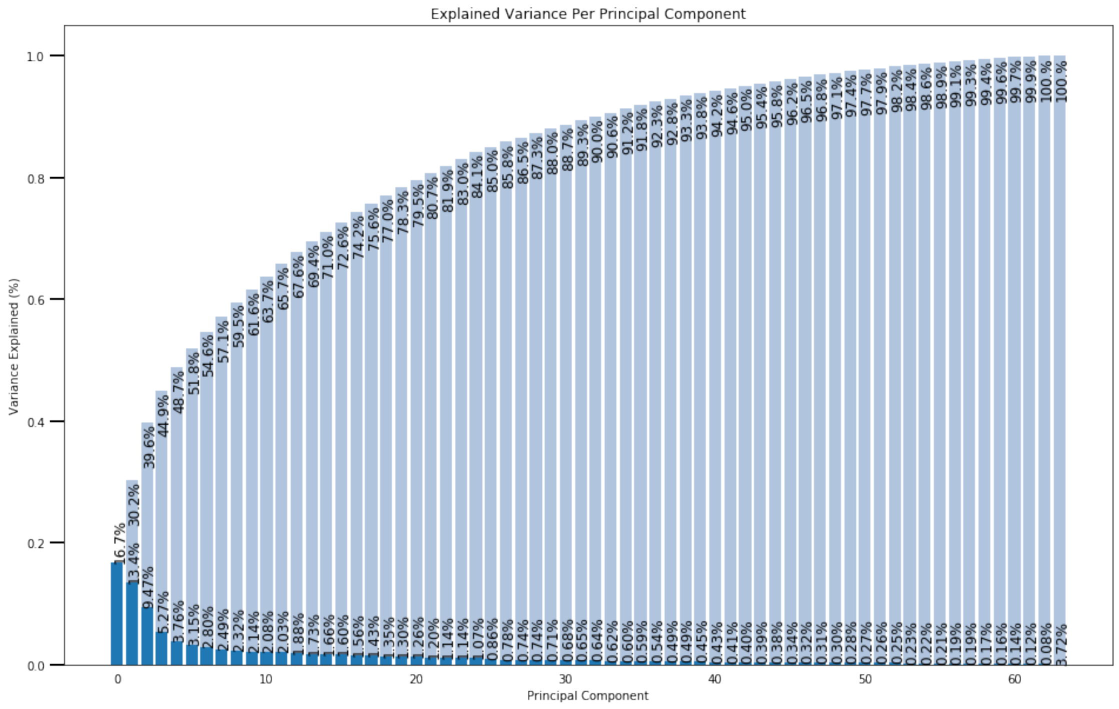
1.2.3 Step 2.2: Perform Dimensionality Reduction

On your scaled data, you are now ready to apply dimensionality reduction techniques.

- Use sklearn's PCA class to apply principal component analysis on the data, thus finding the vectors of maximal variance in the data. To start, you should not set any parameters (so all components are computed) or set a number of components that is at least half the number of features (so there's enough features to see the general trend in variability).
- Check out the ratio of variance explained by each principal 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 you've made a choice for the number of components to keep, make sure you re-fit a PCA instance to perform the decided-on transformation.

```
In [22]: # Apply PCA to the data.

         pca = PCA()
         pca_model = pca.fit_transform(population_df)

In [23]: # Investigate the variance accounted for by each principal component.

         def scree_plot(pca):
             '''
             Creates a scree plot associated with the principal components

             INPUT: pca - the result of instantian of PCA in scikit learn

             OUTPUT:
                     None
             '''
             num_components=len(pca.explained_variance_ratio_)
             ind = np.arange(num_components)
             vals = pca.explained_variance_ratio_

             plt.figure(figsize=(16, 10))
             ax = plt.subplot(111)
             cumvals = np.cumsum(vals)

             ax.bar(ind, cumvals, color='lightsteelblue')
             for i in range(1,num_components):
                 ax.annotate(r"%s%%" % ((str(cumvals[i]*100)[:4])), (ind[i]+0.2, cumvals[i]), ro

             ax.bar(ind, vals)
             for i in range(num_components):
                 ax.annotate(r"%s%%" % ((str(vals[i]*100)[:4])), (ind[i]+0.2, vals[i]), rotation


             ax.xaxis.set_tick_params(width=0)
             ax.yaxis.set_tick_params(width=2, length=12)

             ax.set_xlabel("Principal Component")
             ax.set_ylabel("Variance Explained (%)")
             plt.title('Explained Variance Per Principal Component')

         scree_plot(pca)
```



```
In [24]: # Re-apply PCA to the data while selecting for number of components to retain.
         n_pca_comp = 35
         pca = PCA(n_components=n_pca_comp)
         pca_population = pca.fit_transform(population_df)
         total_variance = pca.explained_variance_ratio_.sum()
         print("selected" ,  n_pca_comp, "components to achieve a total variance >=90\%. ", tota
```

```
selected 35 components to achieve a total variance >=90\%.  0.912425760892
```

1.2.4 Discussion 2.2: Perform Dimensionality Reduction

(Double-click this cell and replace this text with your own text, reporting your findings and decisions regarding dimensionality reduction. How many principal components / transformed features are you retaining for the next step of the analysis?)

I am retaining a variance of >=90% which is the first 35 components for the next step of the analysis..

1.2.5 Step 2.3: Interpret Principal Components

Now that we have our transformed principal components, it's a nice idea to check out the weight of each variable on the first few components to see if they can be interpreted in some fashion.

As a reminder, 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 expect 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.

```
In [25]: # Map weights for the first principal component to corresponding feature names
         # and then print the linked values, sorted by weight.
         # HINT: Try defining a function here or in a new cell that you can reuse in the
         # other cells.

         def get_weights(column_names, pca, component_index):
             # Dimension indexing
             dimensions = ['Dimension {}'.format(i) for i in range(1,len(pca.components_)+1)]

             # PCA components
             components = pd.DataFrame(np.round(pca.components_, 4), columns = column_names)
             components.index = dimensions
             # Weights
             weights = components.iloc[component_index].sort_values(ascending=False)

             return weights

         display(get_weights(population_df.columns, pca, 0))
```

```
PLZ8_ANTG3                        0.2271
PLZ8_ANTG4                        0.2203
CAMEO_INTL_2015_WEALTH            0.2075
HH_EINKOMMEN_SCORE                0.2040
ORTSGR_KLS9                       0.1983
EWDICHTE                          0.1966
FINANZ_HAUSBAUER                  0.1631
KBA05_ANTG4                       0.1562
PLZ8_ANTG2                        0.1548
ARBEIT                            0.1443
FINANZ_SPARER                     0.1435
KBA05_ANTG3                       0.1386
ANZ_HAUSHALTE_AKTIV               0.1373
```

```
RELAT_AB                          0.1362
SEMIO_PFLICHT                     0.1123
PRAEGENDE_JUGENDJAHRE_MOVEMENT    0.1095
SEMIO_REL                         0.1094
PRAEGENDE_JUGENDJAHRE_DECADE      0.0969
SEMIO_RAT                         0.0921
SEMIO_TRADV                       0.0857
SEMIO_MAT                         0.0763
SEMIO_FAM                         0.0756
FINANZ_UNAUFFAELLIGER             0.0711
SEMIO_KULT                        0.0697
REGIOTYP                          0.0686
FINANZ_ANLEGER                    0.0668
OST_WEST_KZ                       0.0542
SEMIO_SOZ                         0.0419
PLZ8_HHZ                          0.0417
SEMIO_KAEM                        0.0408
                                   ...
HEALTH_TYP                        0.0290
SEMIO_DOM                         0.0245
KBA05_ANTG2                       0.0102
ANREDE_KZ                         0.0084
SEMIO_KRIT                        0.0052
SOHO_KZ                          -0.0020
ANZ_TITEL                        -0.0040
RETOURTYP_BK_S                   -0.0163
SEMIO_VERT                       -0.0411
ONLINE_AFFINITAET                -0.0466
MIN_GEBAEUDEJAHR                 -0.0488
WOHNDAUER_2008                   -0.0582
SEMIO_LUST                       -0.0699
SEMIO_ERL                        -0.0732
KBA13_ANZAHL_PKW                 -0.0786
ANZ_PERSONEN                     -0.0790
GREEN_AVANTGARDE                 -0.1095
FINANZ_VORSORGER                 -0.1111
ALTERSKATEGORIE_GROB             -0.1161
GEBAEUDETYP_RASTER               -0.1179
CAMEO_INTL_2015_LIFE_STAGE       -0.1255
BALLRAUM                         -0.1282
INNENSTADT                       -0.1657
PLZ8_GBZ                         -0.1682
KONSUMNAEHE                      -0.1688
KBA05_GBZ                        -0.2173
FINANZ_MINIMALIST                -0.2188
KBA05_ANTG1                      -0.2238
PLZ8_ANTG1                       -0.2271
MOBI_REGIO                       -0.2434
```

```
Name: Dimension 1, Length: 64, dtype: float64
```

```
In [26]: # Map weights for the second principal component to corresponding feature names
         # and then print the linked values, sorted by weight.

         display(get_weights(population_df.columns, pca, 1))
```

```
ALTERSKATEGORIE_GROB              0.2611
FINANZ_VORSORGER                  0.2339
SEMIO_ERL                         0.2315
SEMIO_LUST                        0.1844
RETOURTYP_BK_S                    0.1640
W_KEIT_KIND_HH                    0.1194
FINANZ_HAUSBAUER                  0.1160
SEMIO_KRIT                        0.1155
SEMIO_KAEM                        0.1121
ANREDE_KZ                         0.0905
EWDICHTE                          0.0886
PLZ8_ANTG3                        0.0881
ORTSGR_KLS9                       0.0870
PLZ8_ANTG4                        0.0841
CAMEO_INTL_2015_WEALTH            0.0715
SEMIO_DOM                         0.0709
KBA05_ANTG4                       0.0695
FINANZ_MINIMALIST                 0.0681
ARBEIT                            0.0652
RELAT_AB                          0.0628
ANZ_HAUSHALTE_AKTIV               0.0612
WOHNDAUER_2008                    0.0612
PLZ8_ANTG2                        0.0610
HH_EINKOMMEN_SCORE                0.0541
KBA05_ANTG3                       0.0450
VERS_TYP                          0.0317
ANZ_HH_TITEL                      0.0306
OST_WEST_KZ                       0.0247
REGIOTYP                          0.0167
PRAEGENDE_JUGENDJAHRE_MOVEMENT    0.0148
                                   ...
SOHO_KZ                          -0.0019
KBA05_ANTG2                      -0.0080
GREEN_AVANTGARDE                 -0.0148
KBA13_ANZAHL_PKW                 -0.0344
GEBAEUDETYP_RASTER               -0.0421
MIN_GEBAEUDEJAHR                 -0.0481
HEALTH_TYP                       -0.0578
BALLRAUM                         -0.0583
ANZ_PERSONEN                     -0.0602
```

```
KONSUMNAEHE                     -0.0672
PLZ8_GBZ                        -0.0679
SEMIO_VERT                      -0.0698
INNENSTADT                      -0.0716
KBA05_ANTG1                     -0.0721
KBA05_GBZ                       -0.0834
MOBI_REGIO                      -0.0849
PLZ8_ANTG1                      -0.0860
SEMIO_SOZ                       -0.1033
SEMIO_MAT                       -0.1638
ONLINE_AFFINITAET               -0.1650
SEMIO_RAT                       -0.1712
SEMIO_FAM                       -0.1847
FINANZ_ANLEGER                  -0.2047
SEMIO_KULT                      -0.2201
FINANZ_UNAUFFAELLIGER           -0.2279
SEMIO_PFLICHT                   -0.2284
SEMIO_TRADV                     -0.2322
FINANZ_SPARER                   -0.2367
PRAEGENDE_JUGENDJAHRE_DECADE    -0.2529
SEMIO_REL                       -0.2551
Name: Dimension 2, Length: 64, dtype: float64
```

```
In [27]: # Map weights for the third principal component to corresponding feature names
         # and then print the linked values, sorted by weight.

         display(get_weights(population_df.columns, pca, 2))
```

```
SEMIO_VERT                       0.3451
SEMIO_SOZ                        0.2621
SEMIO_FAM                        0.2497
SEMIO_KULT                       0.2349
FINANZ_MINIMALIST                0.1559
RETOURTYP_BK_S                   0.1089
FINANZ_VORSORGER                 0.1014
W_KEIT_KIND_HH                   0.0913
ALTERSKATEGORIE_GROB             0.0794
SEMIO_REL                        0.0691
SEMIO_LUST                       0.0648
SEMIO_MAT                        0.0557
GREEN_AVANTGARDE                 0.0474
ORTSGR_KLS9                      0.0467
EWDICHTE                         0.0461
PLZ8_ANTG4                       0.0452
PLZ8_ANTG3                       0.0449
ARBEIT                           0.0350
WOHNDAUER_2008                   0.0329
```

```
RELAT_AB                          0.0319
PLZ8_ANTG2                        0.0301
KBA05_ANTG4                       0.0285
CAMEO_INTL_2015_WEALTH            0.0278
ANZ_HAUSHALTE_AKTIV               0.0254
OST_WEST_KZ                       0.0153
ANZ_HH_TITEL                      0.0134
KBA05_ANTG3                       0.0101
ANZ_TITEL                         0.0097
PLZ8_HHZ                          0.0039
VERS_TYP                          0.0024
                                   ...
KBA05_ANTG2                      -0.0100
KKK                              -0.0154
MIN_GEBAEUDEJAHR                 -0.0176
HH_EINKOMMEN_SCORE               -0.0185
HEALTH_TYP                       -0.0216
KBA05_ANTG1                      -0.0223
KBA13_ANZAHL_PKW                 -0.0234
KBA05_GBZ                        -0.0263
MOBI_REGIO                       -0.0297
GEBAEUDETYP_RASTER               -0.0305
BALLRAUM                         -0.0348
KONSUMNAEHE                      -0.0378
PLZ8_GBZ                         -0.0383
FINANZ_HAUSBAUER                 -0.0417
INNENSTADT                       -0.0428
PLZ8_ANTG1                       -0.0459
PRAEGENDE_JUGENDJAHRE_MOVEMENT   -0.0474
ONLINE_AFFINITAET                -0.0553
SEMIO_PFLICHT                    -0.0790
SEMIO_TRADV                      -0.0795
FINANZ_UNAUFFAELLIGER            -0.1001
FINANZ_SPARER                    -0.1067
PRAEGENDE_JUGENDJAHRE_DECADE     -0.1072
SEMIO_ERL                        -0.1759
FINANZ_ANLEGER                   -0.1896
SEMIO_RAT                        -0.2177
SEMIO_KRIT                       -0.2758
SEMIO_DOM                        -0.3140
SEMIO_KAEM                       -0.3367
ANREDE_KZ                        -0.3683
Name: Dimension 3, Length: 64, dtype: float64
```

1.2.6 Discussion 2.3: Interpret Principal Components

(Double-click this cell and replace this text with your own text, reporting your observations from detailed investigation of the first few principal components generated. Can we interpret positive and negative values from them in a meaningful way?)

Principal Component #0

The first principal components reflects a positive correlation between components like: PLZ8_ANTG3, PLZ8_ANTG4, CAMEO_INTL_2015_WEALTH, HH_EINKOMMEN_SCORE, ORTSGR_KLS9, and EWDICHTE. It is negatively correlated with components like: MOBI_REGIO, PLZ8_ANTG1, KBA05_ANTG1, FINANZ_MINIMALIST, and KBA05_GBZ. According to Data_Dictionary.md, these properties mostly correpsond to the population density and houshold size in the area as well as the wealth.

Principal Component #1

The first principal components reflects a positive correlation between components like: ALTERSKATEGORIE_GROB, FINANZ_VORSORGER, SEMIO_ERL, SEMIO_LUST, and RETOURTYP_BK_S. It is negatively correlated with components like: SEMIO_REL, PRAEGENDE_JUGENDJAHRE_DECADE, FINANZ_SPARER, SEMIO_TRADV, SEMIO_PFLICHT, and FINANZ_UNAUFFAELLIGER. According to Data_Dictionary.md, these properties mostly correpsond to the age, the personality and the shopping behavior of individuals.

Principal Component #2

The first principal components reflects a positive correlation between components like: SEMIO_VERT, SEMIO_SOZ, SEMIO_FAM, SEMIO_KULT, and FINANZ_MINIMALIST. It is negatively correlated with components like: ANREDE_KZ, SEMIO_KAEM, SEMIO_DOM, SEMIO_KRIT, SEMIO_RAT, FINANZ_ANLEGER, and SEMIO_ERL. According to Data_Dictionary.md, these properties correpsond to the personality of the individual , their shopping behavior, gender, and their attitude.

1.3 Step 3: Clustering

1.3.1 Step 3.1: Apply Clustering to General Population

You've assessed and cleaned the demographics data, then scaled and transformed them. Now, it's time to see how the data clusters in the principal components space. In this substep, you will apply k-means clustering to the dataset and use the average within-cluster distances from each point to their assigned cluster's centroid to decide on a number of clusters to keep.

- 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. **Hint**: The KMeans object's `.score()` method might be useful here, but note that in sklearn, scores tend to be defined so that larger is better. Try applying it to a small, toy dataset, or use an internet search to help your understanding.
- 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. **Warning**: because of the large size of the dataset, it can take a long time for the algorithm to resolve. The more clusters to fit, the longer the algorithm will take. You should test for cluster counts through at least 10 clusters to get the full picture, but you shouldn't need to test for a number of clusters above about 30.

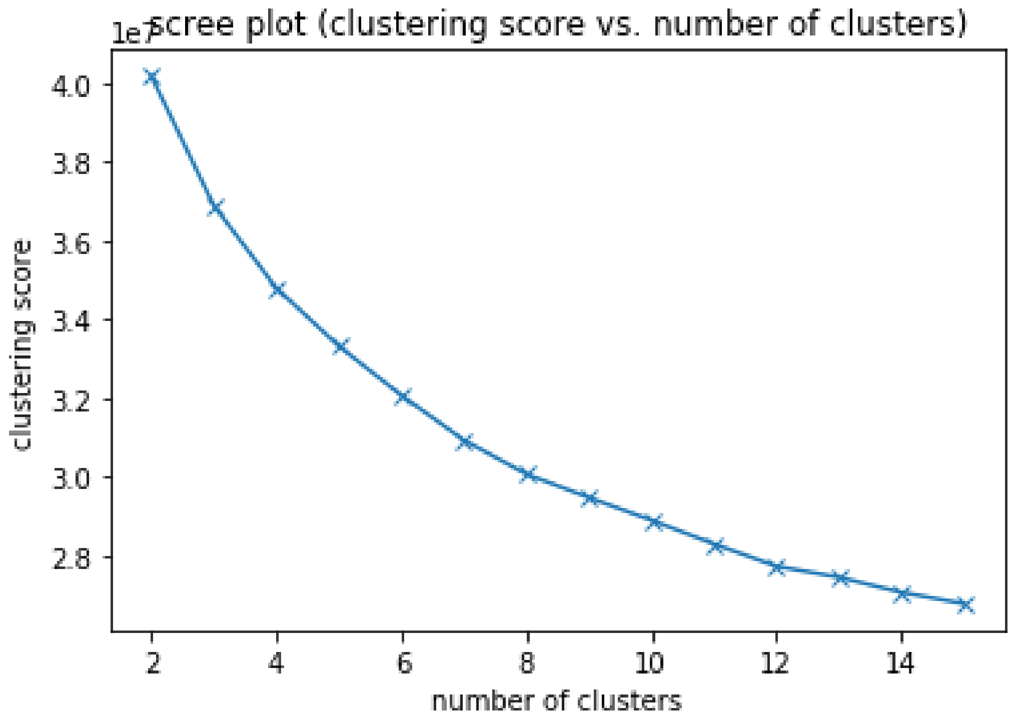
- Once you've selected a final number of clusters to use, re-fit a KMeans instance to perform the clustering operation. Make sure that you also obtain the cluster assignments for the general demographics data, since you'll be using them in the final Step 3.3.

```
In [28]: # Over a number of different cluster counts...


             # run k-means clustering on the data and...


             # compute the average within-cluster distances.


         def run_clustering(dataset, min_k, max_k):
             k_values = list(range(min_k, max_k+1))
             scores = []
             for k in k_values:
                 # run k-means clustering on the data and...
                 kmeans = KMeans(n_clusters=k)
                 model = kmeans.fit(dataset)

                 # compute the average within-cluster distances.
                 score = np.abs(model.score(dataset))
                 scores.append(score)
                 print('k=',k,': score=', score)
             return k_values, scores

         k_values, scores = run_clustering(pca_population, 2, 15)
```

```
k= 2 : score= 40164198.2517
k= 3 : score= 36880069.472
k= 4 : score= 34798348.3069
k= 5 : score= 33321989.3029
k= 6 : score= 32072552.8583
k= 7 : score= 30937210.9663
k= 8 : score= 30079172.4005
k= 9 : score= 29484289.4146
k= 10 : score= 28907996.3358
k= 11 : score= 28306460.5821
k= 12 : score= 27740888.0577
k= 13 : score= 27461441.7324
k= 14 : score= 27078892.4755
k= 15 : score= 26791069.8271
```

```
In [29]: # Investigate the change in within-cluster distance across number of clusters.
         # HINT: Use matplotlib's plot function to visualize this relationship.
```

```
plt.plot(k_values, scores, marker="x")
plt.ylabel('clustering score');
plt.xlabel('number of clusters');
plt.title('scree plot (clustering score vs. number of clusters)');
```



```
In [30]: # Re-fit the k-means model with the selected number of clusters and obtain
         # cluster predictions for the general population demographics data.

         kmeans = KMeans(n_clusters=9)
         kmeans_model = kmeans.fit(pca_population)
         prediction_population = kmeans_model.predict(pca_population)
         prediction_population

Out[30]: array([6, 5, 5, ..., 3, 4, 7], dtype=int32)
```

1.3.2 Discussion 3.1: Apply Clustering to General Population

(Double-click this cell and replace this text with your own text, reporting your findings and decisions regarding clustering. Into how many clusters have you decided to segment the population?)

I used a scree plot to visualize the clustering score as a function of the number of clusters. I choose k = 9 for the number of clusters to segment the population since there seems to be a steeper dip after k = 9.

1.3.3 Step 3.2: Apply All Steps to the Customer Data

Now that you have clusters and cluster centers for the general population, it's time to see how the customer data maps on to those clusters. Take care to not confuse this for re-fitting all of the models to the customer data. Instead, you're going to use the fits from the general population to clean, transform, and cluster the customer data. In the last step of the project, you will interpret how the general population fits apply to the customer data.

- Don't forget when loading in the customers data, that it is semicolon (`;`) delimited.
- Apply the same feature wrangling, selection, and engineering steps to the customer demographics using the `clean_data()` function you created earlier. (You can assume that the customer demographics data has similar meaning behind missing data patterns as the general demographics data.)
- Use the sklearn objects from the general demographics data, and apply their transformations to the customers data. That is, you should not be using a `.fit()` or `.fit_transform()` method to re-fit the old objects, nor should you be creating new sklearn objects! Carry the data through the feature scaling, PCA, and clustering steps, obtaining cluster assignments for all of the data in the customer demographics data.

```
In [31]: # Load in the customer demographics data.
         customers = pd.read_csv('Udacity_CUSTOMERS_Subset.csv', delimiter=";")
         customers.head()
```

```
Out[31]:    AGER_TYP  ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  \
         0         2                     4          1            5.0
         1        -1                     4          1            NaN
         2        -1                     4          2            2.0
         3         1                     4          1            2.0
         4        -1                     3          1            6.0

            FINANZ_MINIMALIST  FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  \
         0                  5              1                 5               1
         1                  5              1                 5               1
         2                  5              1                 5               1
         3                  5              1                 5               2
         4                  3              1                 4               4

            FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER    ...     PLZ8_ANTG1  PLZ8_ANTG2  \
         0                      2                 2    ...            3.0         3.0
         1                      3                 2    ...            NaN         NaN
         2                      4                 4    ...            2.0         3.0
         3                      1                 2    ...            3.0         2.0
         4                      5                 2    ...            2.0         4.0

            PLZ8_ANTG3  PLZ8_ANTG4  PLZ8_BAUMAX  PLZ8_HHZ  PLZ8_GBZ  ARBEIT  \
         0         1.0         0.0          1.0       5.0       5.0     1.0
         1         NaN         NaN          NaN       NaN       NaN     NaN
         2         3.0         1.0          3.0       3.0       2.0     3.0
         3         1.0         0.0          1.0       3.0       4.0     1.0
```

```
4         2.0         1.0          2.0       3.0       3.0     3.0

   ORTSGR_KLS9  RELAT_AB
0          2.0       1.0
1          NaN       NaN
2          5.0       3.0
3          3.0       1.0
4          5.0       1.0

[5 rows x 85 columns]
```

```
In [32]: # Apply preprocessing, feature transformation, and clustering from the general
         # demographics onto the customer data, obtaining cluster predictions for the
         # customer demographics data.

         preproc_customers_df = clean_data(customers)
         print('customer df shape:', preproc_customers_df.shape)
         preproc_customers_df = pd.DataFrame(imputer.transform(preproc_customers_df), columns =
         preproc_customers_df = pd.DataFrame(stdScaler.transform(preproc_customers_df), columns
         display(preproc_customers_df.head())

         # sanity check
         if len(list(set(population_df.columns) - set(preproc_customers_df))) > 0:
             print('sanity check failed.')

         # clustering
         print('clustering result:')
         preproc_customers_df_pca = pca.transform(preproc_customers_df)
         prediction_customers = kmeans_model.predict(preproc_customers_df_pca)
         prediction_customers
```

```
customer df shape: (141713, 64)


   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
0              1.184102  -1.043914           1.409077      -1.155482
1              1.184102   0.957933           1.409077      -1.155482
2              1.184102  -1.043914           1.409077      -1.155482
3              0.200529  -1.043914          -0.042764      -1.155482
4              0.200529  -1.043914           1.409077      -1.155482

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
0          1.138133       -1.249960              -0.470299         -0.791347
1          1.138133       -1.249960               0.958818          0.629041
2          1.138133       -0.570958              -1.184858         -0.791347
3          0.411859        0.787046               1.673376         -0.791347
4          1.138133       -1.249960              -0.470299         -0.081153
```

```
   GREEN_AVANTGARDE  HEALTH_TYP           ...            PLZ8_ANTG4  \
0          1.885219   -1.610602           ...             -0.985640
1          1.885219   -0.257026           ...              0.406638
2         -0.530442   -0.257026           ...             -0.985640
3         -0.530442    1.096551           ...              0.406638
4          1.885219    1.096551           ...              0.406638

   PLZ8_HHZ  PLZ8_GBZ    ARBEIT  ORTSGR_KLS9  RELAT_AB  \
0  1.430429  1.485680 -2.173492    -1.432853 -1.526014
1 -0.648841 -1.248668 -0.166432    -0.127075 -0.052103
2 -0.648841  0.574231 -2.173492    -0.997594 -1.526014
3 -0.648841 -0.337218 -0.166432    -0.127075 -1.526014
4  1.430429  1.485680 -0.166432     0.743444  1.421808

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
0                     -1.619800                       -1.885219
1                     -1.619800                       -1.885219
2                     -2.317978                        0.530442
3                     -0.223444                        0.530442
4                     -1.619800                       -1.885219

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
0               -1.552980                    0.085189
1               -0.183385                    0.761271
2               -0.868182                    0.761271
3                0.501413                   -1.266976
4               -0.183385                    0.761271

[5 rows x 64 columns]


clustering result:
```

```
Out[32]: array([0, 8, 7, ..., 0, 5, 7], dtype=int32)
```

1.3.4 Step 3.3: Compare Customer Data to Demographics Data

At this point, you have clustered data based on demographics of the general population of Germany, and seen how the customer data for a mail-order sales company maps onto those demographic clusters. In this final substep, you will compare the two cluster distributions to see where the strongest customer base for the company is.

Consider the proportion of persons in each cluster for the general population, and the proportions for the customers. If we think the company's customer base to be universal, then the cluster assignment proportions should be fairly similar between the two. If there are only particular segments of the population that are interested in the company's products, then we should see a mismatch from one to the other. If there is a higher proportion of persons in a cluster for the customer data compared to the general population (e.g. 5% of persons are assigned to a cluster for the general population, but 15% of the customer data is closest to that cluster's centroid) then that suggests the people in that cluster to be a target audience for the company. On the other hand, the proportion of the data in a cluster being larger in the general population than the customer data (e.g. only 2% of customers closest to a population centroid that captures 6% of the data) suggests that group of persons to be outside of the target demographics.

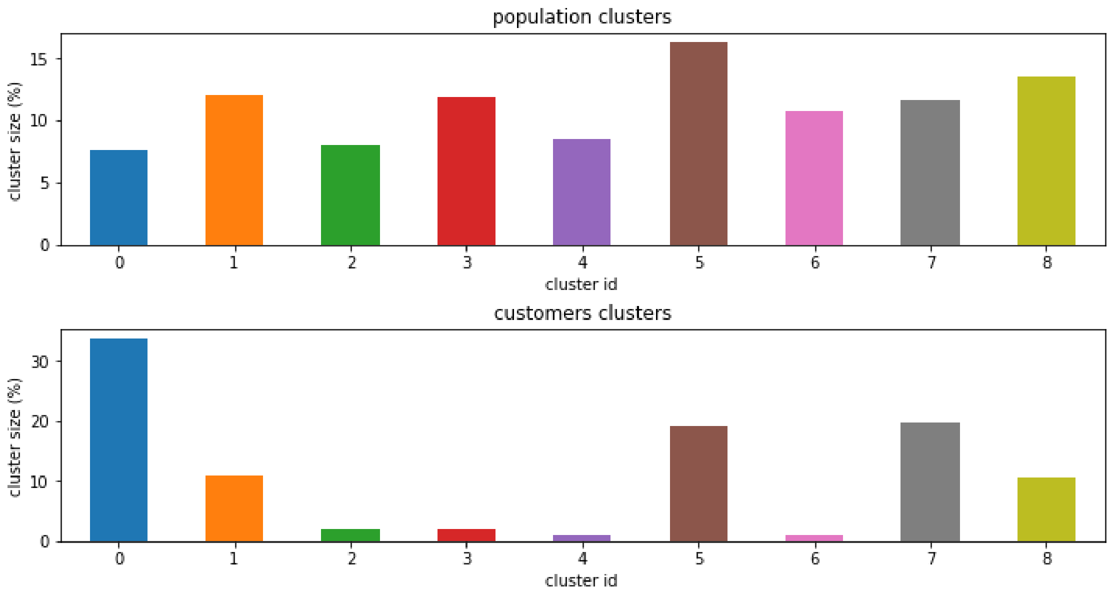
Take a look at the following points in this step:

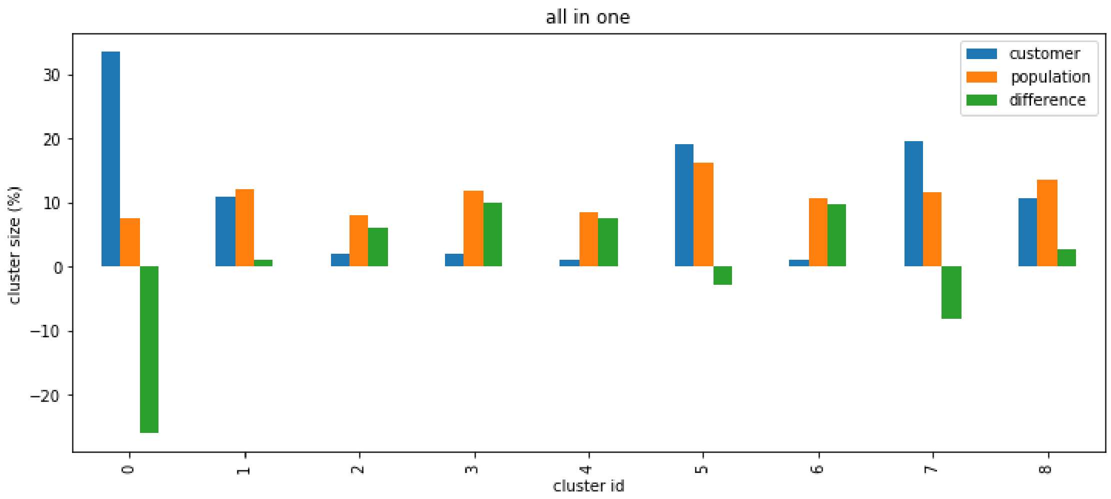
- Compute the proportion of data points in each cluster for the general population and the customer data. Visualizations will be useful here: both for the individual dataset proportions, but also to visualize the ratios in cluster representation between groups. Seaborn's `countplot()` or `barplot()` function could be handy.
- Recall the analysis you performed in step 1.1.3 of the project, where you separated out certain data points from the dataset if they had more than a specified threshold of missing values. If you found that this group was qualitatively different from the main bulk of the data, you should treat this as an additional data cluster in this analysis. Make sure that you account for the number of data points in this subset, for both the general population and customer datasets, when making your computations!
- Which cluster or clusters are overrepresented in the customer dataset compared to the general population? Select at least one such cluster and infer what kind of people might be represented by that cluster. Use the principal component interpretations from step 2.3 or look at additional components to help you make this inference. Alternatively, you can use the `.inverse_transform()` method of the PCA and StandardScaler objects to transform centroids back to the original data space and interpret the retrieved values directly.
- Perform a similar investigation for the underrepresented clusters. Which cluster or clusters are underrepresented in the customer dataset compared to the general population, and what kinds of people are typified by these clusters?

```
In [33]: # Compare the proportion of data in each cluster for the customer data to the
         # proportion of data in each cluster for the general population.

         df_cluster_sizes = pd.DataFrame(prediction_customers, columns=['clusters']).reset_index
         df_cluster_sizes.rename({'index':'customer'}, axis=1, inplace=True)
         df_cluster_sizes['population'] = pd.DataFrame(prediction_population, columns=['clusters
         df_cluster_sizes['difference'] = df_cluster_sizes['population']-df_cluster_sizes['custo

         print('distribution of of data points in different clusters (\%):')
         display(df_cluster_sizes)



         fig, ax = plt.subplots(2,1, figsize=(12,6))
         fig.subplots_adjust(hspace=0.4)
         df_cluster_sizes['population'].plot(kind='bar', ax=ax[0], rot=0)
         ax[0].set(title="population clusters", xlabel="cluster id", ylabel="cluster size (%)")


         df_cluster_sizes['customer'].plot(kind='bar', ax=ax[1], rot=0)
         ax[1].set(title="customers clusters", xlabel="cluster id", ylabel="cluster size (%)")
```

```
df_cluster_sizes.plot.bar(figsize=(12,5))
plt.ylabel('cluster size (%)')
plt.xlabel('cluster id')
plt.title('all in one')
plt.show()
```

```
distribution of of data points in different clusters (\%):


            customer  population  difference
clusters
0          33.565022    7.619796  -25.945226
1          10.905845   12.032292    1.126447
2           1.926429    7.912793    5.986364
3           1.963123   11.807720    9.844597
4           1.011199    8.514326    7.503127
5          19.170436   16.243150   -2.927286
6           1.107167   10.782482    9.675315
7          19.673566   11.592045   -8.081520
8          10.677214   13.495396    2.818183
```





```
In [34]: # What kinds of people are part of a cluster that is overrepresented in the
         # customer data compared to the general population?

         overrepresented_cluster_index = 4
         overrepresented_cluster_members = pd.DataFrame(stdScaler.inverse_transform(pca.inverse_
         display(overrepresented_cluster_members.head())
         display(overrepresented_cluster_members.describe())
```

```
   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
0                   2.0        1.0                3.0            4.0
1                   2.0        1.0                3.0            2.0
2                   2.0        1.0                2.0            5.0
3                   2.0        1.0                3.0            2.0
4                   2.0        1.0                4.0            2.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
0               3.0             3.0                    4.0               3.0
1               3.0             1.0                    2.0               3.0
2               1.0             4.0                    3.0               4.0
3               3.0             2.0                    1.0               3.0
4               3.0             2.0                    2.0               3.0

   GREEN_AVANTGARDE  HEALTH_TYP        ...          PLZ8_ANTG4  \
0              -0.0         1.0        ...                 2.0
1               1.0         2.0        ...                 0.0
2               0.0         3.0        ...                 2.0
3               0.0         3.0        ...                 2.0
4               0.0         1.0        ...                 1.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
0       3.0       1.0     3.0           8.0       4.0
1       3.0       3.0     4.0           8.0       4.0
2       4.0       2.0     4.0           9.0       3.0
3       3.0       1.0     3.0           6.0       2.0
4       4.0       3.0     4.0           7.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
0                          84.0                             1.0
1                          76.0                             0.0
2                          92.0                             1.0
3                          75.0                             1.0
4                          73.0                             1.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
0                     4.0                         1.0
1                     4.0                         5.0
2                     4.0                         1.0
3                     5.0                         4.0
4                     4.0                         5.0

[5 rows x 64 columns]


       ALTERSKATEGORIE_GROB    ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
count           1433.000000  1433.000000        1433.000000    1433.000000
mean               2.087230     1.000698           2.466853       3.796232
std                0.761365     0.026417           0.890936       0.978291
min                1.000000     1.000000           0.000000       1.000000
25%                2.000000     1.000000           2.000000       3.000000
50%                2.000000     1.000000           2.000000       4.000000
75%                3.000000     1.000000           3.000000       5.000000
max                4.000000     2.000000           5.000000       5.000000

       FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  \
count       1433.000000     1433.000000            1433.000000
mean           2.521284        2.879274               3.379623
std            0.980822        1.018719               1.173344
min            1.000000        0.000000              -1.000000
25%            2.000000        2.000000               3.000000
50%            2.000000        3.000000               4.000000
75%            3.000000        4.000000               4.000000
max            6.000000        5.000000               6.000000

       FINANZ_HAUSBAUER  GREEN_AVANTGARDE   HEALTH_TYP  \
count       1433.000000       1433.000000  1433.000000
mean           3.167481          0.247732     2.361479
std            1.051005          0.431846     0.712397
min            0.000000         -0.000000     1.000000
```

```
25%           2.000000          0.000000     2.000000
50%           3.000000         -0.000000     2.000000
75%           4.000000          0.000000     3.000000
max           6.000000          1.000000     3.000000

                  ...            PLZ8_ANTG4     PLZ8_HHZ     PLZ8_GBZ  \
count             ...           1433.000000  1433.000000  1433.000000
mean              ...              1.434054     3.767620     2.531054
std               ...              0.587354     0.828785     0.906551
min               ...              0.000000     1.000000     0.000000
25%               ...              1.000000     3.000000     2.000000
50%               ...              1.000000     4.000000     3.000000
75%               ...              2.000000     4.000000     3.000000
max               ...              3.000000     6.000000     5.000000

            ARBEIT  ORTSGR_KLS9     RELAT_AB  PRAEGENDE_JUGENDJAHRE_DECADE  \
count  1433.000000  1433.000000  1433.000000                   1433.000000
mean      3.535939     7.430565     3.718074                     83.390091
std       0.656084     1.459735     0.898518                      8.097906
min       1.000000     2.000000     0.000000                     57.000000
25%       3.000000     7.000000     3.000000                     77.000000
50%       4.000000     8.000000     4.000000                     86.000000
75%       4.000000     9.000000     4.000000                     89.000000
max       5.000000    10.000000     6.000000                    101.000000

       PRAEGENDE_JUGENDJAHRE_MOVEMENT  CAMEO_INTL_2015_WEALTH  \
count                     1433.000000             1433.000000
mean                         0.752268                4.138172
std                          0.431846                0.937518
min                          0.000000                1.000000
25%                          1.000000                4.000000
50%                          1.000000                4.000000
75%                          1.000000                5.000000
max                          1.000000                6.000000

       CAMEO_INTL_2015_LIFE_STAGE
count                 1433.000000
mean                     2.068388
std                      1.486743
min                      1.000000
25%                      1.000000
50%                      1.000000
75%                      4.000000
max                      5.000000

[8 rows x 64 columns]
```

```
In [35]: # What kinds of people are part of a cluster that is underrepresented in the
         # customer data compared to the general population?

         underrepresented_cluster_index = 0
         underrepresented_cluster_members = pd.DataFrame(stdScaler.inverse_transform(pca.inverse
         display(underrepresented_cluster_members.head())
         display(underrepresented_cluster_members.describe())


         mean_df = pd.DataFrame(overrepresented_cluster_members.mean(), columns=['cluster 4 (ove
         mean_df['cluster 0 (under)'] = pd.DataFrame(underrepresented_cluster_members.mean())
         mean_df['PC0 weight'] = pd.DataFrame(get_weights(population_df.columns, pca, 0))

         mean_df.sort_values(['PC0 weight'], ascending=False, inplace=True)
         mean_df
```

```
   ALTERSKATEGORIE_GROB  ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
0                   4.0        1.0                5.0            1.0
1                   3.0        1.0                5.0            1.0
2                   3.0        1.0                5.0            1.0
3                   4.0        1.0                5.0            1.0
4                   3.0        1.0                5.0            2.0

   FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  \
0               5.0             1.0                    2.0               2.0
1               5.0             1.0                    2.0               3.0
2               5.0             1.0                    1.0               2.0
3               5.0             1.0                    2.0               2.0
4               4.0             1.0                    3.0               1.0

   GREEN_AVANTGARDE  HEALTH_TYP          ...              PLZ8_ANTG4  \
0               1.0         1.0          ...                     0.0
1               1.0         3.0          ...                     1.0
2               1.0         2.0          ...                     0.0
3               1.0         1.0          ...                     1.0
4               1.0         3.0          ...                     0.0

   PLZ8_HHZ  PLZ8_GBZ  ARBEIT  ORTSGR_KLS9  RELAT_AB  \
0       5.0       5.0     1.0          3.0       0.0
1       5.0       5.0     4.0          5.0       5.0
2       5.0       5.0     2.0          3.0       2.0
3       3.0       3.0     3.0          4.0       3.0
4       5.0       5.0     3.0          7.0       3.0

   PRAEGENDE_JUGENDJAHRE_DECADE  PRAEGENDE_JUGENDJAHRE_MOVEMENT  \
0                          56.0                             0.0
1                          59.0                            -0.0
2                          57.0                             0.0
```

```
3                        56.0                              -0.0
4                        74.0                               0.0

   CAMEO_INTL_2015_WEALTH  CAMEO_INTL_2015_LIFE_STAGE
0                     1.0                         3.0
1                     2.0                         4.0
2                     2.0                         3.0
3                     1.0                         5.0
4                     1.0                         5.0

[5 rows x 64 columns]


       ALTERSKATEGORIE_GROB     ANREDE_KZ  FINANZ_MINIMALIST  FINANZ_SPARER  \
count          47566.000000  47566.000000       47566.000000   47566.000000
mean               3.521927      1.004604           4.933566       1.217445
std                0.580104      0.067698           0.468498       0.619389
min                1.000000      1.000000           1.000000       0.000000
25%                3.000000      1.000000           5.000000       1.000000
50%                4.000000      1.000000           5.000000       1.000000
75%                4.000000      1.000000           5.000000       1.000000
max                5.000000      2.000000           6.000000       5.000000

       FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  \
count      47566.000000    47566.000000           47566.000000
mean           4.734832        1.073729               1.867342
std            0.707076        0.792167               0.726269
min            1.000000       -1.000000               0.000000
25%            5.000000        1.000000               1.000000
50%            5.000000        1.000000               2.000000
75%            5.000000        1.000000               2.000000
max            6.000000        5.000000               6.000000

       FINANZ_HAUSBAUER  GREEN_AVANTGARDE    HEALTH_TYP  \
count      47566.000000      47566.000000  47566.000000
mean           2.124774          0.991885      1.843754
std            0.842656          0.089718      0.832898
min            0.000000          0.000000      1.000000
25%            2.000000          1.000000      1.000000
50%            2.000000          1.000000      2.000000
75%            2.000000          1.000000      3.000000
max            6.000000          1.000000      3.000000

                  ...              PLZ8_ANTG4     PLZ8_HHZ      PLZ8_GBZ  \
count             ...            47566.000000  47566.000000  47566.000000
mean              ...                0.430833      3.707985      3.843754
std               ...                0.519279      0.922247      0.873025
min               ...               -1.000000      1.000000      1.000000
```

```
25%                  ...                 0.000000       3.000000       3.000000
50%                  ...                 0.000000       4.000000       4.000000
75%                  ...                 1.000000       4.000000       4.000000
max                  ...                 2.000000       6.000000       6.000000

            ARBEIT   ORTSGR_KLS9      RELAT_AB  PRAEGENDE_JUGENDJAHRE_DECADE  \
count  47566.000000  47566.000000  47566.000000                  47566.000000
mean       2.881596      5.323004      2.942017                     61.044906
std        0.979246      1.633646      1.340270                      7.570812
min        1.000000      1.000000      0.000000                     47.000000
25%        2.000000      4.000000      2.000000                     56.000000
50%        3.000000      5.000000      3.000000                     59.000000
75%        4.000000      7.000000      4.000000                     63.000000
max        5.000000      9.000000      6.000000                     97.000000

       PRAEGENDE_JUGENDJAHRE_MOVEMENT  CAMEO_INTL_2015_WEALTH  \
count                    47566.000000            47566.000000
mean                         0.008115                1.951436
std                          0.089718                1.126833
min                          0.000000                0.000000
25%                         -0.000000                1.000000
50%                          0.000000                2.000000
75%                          0.000000                3.000000
max                          1.000000                6.000000

       CAMEO_INTL_2015_LIFE_STAGE
count                47566.000000
mean                     3.702056
std                      1.121294
min                      0.000000
25%                      3.000000
50%                      4.000000
75%                      4.000000
max                      6.000000

[8 rows x 64 columns]
```

```
Out[35]:                            cluster 4 (over)  cluster 0 (under)  \
         PLZ8_ANTG3                        2.526867           1.262120
         PLZ8_ANTG4                        1.434054           0.430833
         CAMEO_INTL_2015_WEALTH            4.138172           1.951436
         HH_EINKOMMEN_SCORE                4.975576           2.231993
         ORTSGR_KLS9                       7.430565           5.323004
         EWDICHTE                          5.572226           4.017870
         FINANZ_HAUSBAUER                  3.167481           2.124774
         KBA05_ANTG4                       0.630844           0.006770
         PLZ8_ANTG2                        3.329379           2.663751
```

```
ARBEIT                                 3.535939       2.881596
FINANZ_SPARER                          3.796232       1.217445
KBA05_ANTG3                            1.069086       0.056574
ANZ_HAUSHALTE_AKTIV                   15.146546       1.646659
RELAT_AB                               3.718074       2.942017
SEMIO_PFLICHT                          5.246336       2.895387
PRAEGENDE_JUGENDJAHRE_MOVEMENT         0.752268       0.008115
SEMIO_REL                              5.815073       3.558214
PRAEGENDE_JUGENDJAHRE_DECADE          83.390091      61.044906
SEMIO_RAT                              3.854850       2.509608
SEMIO_TRADV                            4.503838       2.938654
SEMIO_MAT                              4.967900       3.925514
SEMIO_FAM                              6.441731       4.769331
FINANZ_UNAUFFAELLIGER                  3.379623       1.867342
SEMIO_KULT                             6.571528       4.770971
REGIOTYP                               4.593859       3.391666
FINANZ_ANLEGER                         2.879274       1.073729
OST_WEST_KZ                            0.269365       0.039860
SEMIO_SOZ                              6.348918       4.844658
PLZ8_HHZ                               3.767620       3.707985
SEMIO_KAEM                             2.593859       2.518269
...                                         ...            ...
HEALTH_TYP                             2.361479       1.843754
SEMIO_DOM                              3.055827       3.096140
KBA05_ANTG2                            1.238660       1.144914
ANREDE_KZ                              1.000698       1.004604
SEMIO_KRIT                             3.043964       2.819220
SOHO_KZ                                0.003489       0.009902
ANZ_TITEL                              0.007676       0.038010
RETOURTYP_BK_S                         3.330077       4.120569
SEMIO_VERT                             6.097697       6.411660
ONLINE_AFFINITAET                      3.602931       3.200059
MIN_GEBAEUDEJAHR                    1992.884159    1992.654774
WOHNDAUER_2008                         7.347523       8.848652
SEMIO_LUST                             3.355897       5.770277
SEMIO_ERL                              2.471738       4.234853
KBA13_ANZAHL_PKW                     493.348221     690.441450
ANZ_PERSONEN                           1.704815       2.619960
GREEN_AVANTGARDE                       0.247732       0.991885
FINANZ_VORSORGER                       2.521284       4.734832
ALTERSKATEGORIE_GROB                   2.087230       3.521927
GEBAEUDETYP_RASTER                     3.114445       4.004100
CAMEO_INTL_2015_LIFE_STAGE             2.068388       3.702056
BALLRAUM                               2.697139       4.058025
INNENSTADT                             2.829728       4.654795
PLZ8_GBZ                               2.531054       3.843754
KONSUMNAEHE                            1.770412       3.270950
KBA05_GBZ                              2.123517       4.067716
```

```
FINANZ_MINIMALIST                          2.466853          4.933566
KBA05_ANTG1                                0.424983          2.753900
PLZ8_ANTG1                                 1.385904          2.727179
MOBI_REGIO                                 1.826936          4.195560

                              PC0 weight
PLZ8_ANTG3                        0.2271
PLZ8_ANTG4                        0.2203
CAMEO_INTL_2015_WEALTH            0.2075
HH_EINKOMMEN_SCORE                0.2040
ORTSGR_KLS9                       0.1983
EWDICHTE                          0.1966
FINANZ_HAUSBAUER                  0.1631
KBA05_ANTG4                       0.1562
PLZ8_ANTG2                        0.1548
ARBEIT                            0.1443
FINANZ_SPARER                     0.1435
KBA05_ANTG3                       0.1386
ANZ_HAUSHALTE_AKTIV               0.1373
RELAT_AB                          0.1362
SEMIO_PFLICHT                     0.1123
PRAEGENDE_JUGENDJAHRE_MOVEMENT    0.1095
SEMIO_REL                         0.1094
PRAEGENDE_JUGENDJAHRE_DECADE      0.0969
SEMIO_RAT                         0.0921
SEMIO_TRADV                       0.0857
SEMIO_MAT                         0.0763
SEMIO_FAM                         0.0756
FINANZ_UNAUFFAELLIGER             0.0711
SEMIO_KULT                        0.0697
REGIOTYP                          0.0686
FINANZ_ANLEGER                    0.0668
OST_WEST_KZ                       0.0542
SEMIO_SOZ                         0.0419
PLZ8_HHZ                          0.0417
SEMIO_KAEM                        0.0408
...                                  ...
HEALTH_TYP                        0.0290
SEMIO_DOM                         0.0245
KBA05_ANTG2                       0.0102
ANREDE_KZ                         0.0084
SEMIO_KRIT                        0.0052
SOHO_KZ                          -0.0020
ANZ_TITEL                        -0.0040
RETOURTYP_BK_S                   -0.0163
SEMIO_VERT                       -0.0411
ONLINE_AFFINITAET                -0.0466
MIN_GEBAEUDEJAHR                 -0.0488
```

```
WOHNDAUER_2008                       -0.0582
SEMIO_LUST                           -0.0699
SEMIO_ERL                            -0.0732
KBA13_ANZAHL_PKW                     -0.0786
ANZ_PERSONEN                         -0.0790
GREEN_AVANTGARDE                     -0.1095
FINANZ_VORSORGER                     -0.1111
ALTERSKATEGORIE_GROB                 -0.1161
GEBAEUDETYP_RASTER                   -0.1179
CAMEO_INTL_2015_LIFE_STAGE           -0.1255
BALLRAUM                             -0.1282
INNENSTADT                           -0.1657
PLZ8_GBZ                             -0.1682
KONSUMNAEHE                          -0.1688
KBA05_GBZ                            -0.2173
FINANZ_MINIMALIST                    -0.2188
KBA05_ANTG1                          -0.2238
PLZ8_ANTG1                           -0.2271
MOBI_REGIO                           -0.2434

[64 rows x 3 columns]
```

1.3.5 Discussion 3.3: Compare Customer Data to Demographics Data

(Double-click this cell and replace this text with your own text, reporting findings and conclusions from the clustering analysis. Can we describe segments of the population that are relatively popular with the mail-order company, or relatively unpopular with the company?)

The cluster sizes for the customer dataset suggest that the clusters 4 and 1 are overrepresented in the customers dataset. Thus, the individuals in these clusters are particularly good targets for the mail-oder company to focus on. Particularly, cluster 4 constitutes the most attractive customer segment.

On the other hand, the clusters 0, 8, 7, and 2 are underrepresented in the customers dataset. Thus, the individuals in these clusters are less likely to become mail-order customers and, therefore, are not attractive targets for the company to focus on.

The first principal component gives us the highest positive weights for the following features:

PLZ8_ANTG3 and PLZ8_ANTG4: the higher, the more populated homes CAMEO_INTL_2015_WEALTH: the lower, the wealthier HH_EINKOMMEN_SCORE: the lower, the higher household net income and, the highest negative weights for the following features:

MOBI_REGIO: the higher, the more movement PLZ8_ANTG1, KBA05_ANTG1: the higher, the more under-populated homes FINANZ_MINIMALIST: the higher, the lower financial interest KBA05_GBZ: the higher, the higher the density of buildings in the microcell (the description of the features is derived from the Data_Dictionary.md)

By comparing an overrepresented cluster (here, cluster 4) and an underpresented cluster (here, cluster 0) in the order of these weights, we see that the more attractive targets for the company (in cluster 4), generally have a smaller family size and a higher income level compared to the attractive segment (in cluster 0).

Congratulations on making it this far in the project! Before you finish, make sure to check through the entire notebook from top to bottom to make sure that your analysis follows a logical flow and all of your findings are documented in **Discussion** cells. Once you've checked over all of your work, you should export the notebook as an HTML document to submit for evaluation. You can do this from the menu, navigating to **File -> Download as -> HTML (.html)**. You will submit both that document and this notebook for your project submission.

```
In [ ]:
```