Arvato Project Workbook

May 2, 2023

1 Capstone Project: Create a Customer Segmentation Report for Arvato Financial Services

In this project, you will analyze demographics data for customers of a mail-order sales company in Germany, comparing it against demographics information for the general population. You'll use unsupervised learning techniques to perform customer segmentation, identifying the parts of the population that best describe the core customer base of the company. Then, you'll apply what you've learned on a third dataset with demographics information for targets of a marketing campaign for the company, and use a model to predict which individuals are most likely to convert into becoming customers for the company. The data that you will use has been provided by our partners at Bertelsmann Arvato Analytics, and represents a real-life data science task.

The versions of those two datasets used in this project will include many more features and has not been pre-cleaned. You are also free to choose whatever approach you'd like to analyzing the data rather than follow pre-determined steps. In your work on this project, make sure that you carefully document your steps and decisions, since your main deliverable for this project will be a blog post reporting your findings.

[ ]:
```
# import libraries here; add more as necessary
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from src.utils import *

# magic word for producing visualizations in notebook
%matplotlib inline
```

[ ]:
```
import types
import pickle
import dill
```

[ ]:
```
# from sklearn.preprocessing import Imputer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

```
[ ]: randomState = 42
```

1.1 Part 0: Get to Know the Data

There are four data files associated with this project:

- `Udacity_AZDIAS_052018.csv`: Demographics data for the general population of Germany; 891 211 persons (rows) x 366 features (columns).
- `Udacity_CUSTOMERS_052018.csv`: Demographics data for customers of a mail-order company; 191 652 persons (rows) x 369 features (columns).
- `Udacity_MAILOUT_052018_TRAIN.csv`: Demographics data for individuals who were targets of a marketing campaign; 42 982 persons (rows) x 367 (columns).
- `Udacity_MAILOUT_052018_TEST.csv`: Demographics data for individuals who were targets of a marketing campaign; 42 833 persons (rows) x 366 (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. Use the information from the first two files to figure out how customers ("CUSTOMERS") are similar to or differ from the general population at large ("AZDIAS"), then use your analysis to make predictions on the other two files ("MAILOUT"), predicting which recipients are most likely to become a customer for the mail-order company.

The "CUSTOMERS" file contains three extra columns ('CUSTOMER_GROUP', 'ONLINE_PURCHASE', and 'PRODUCT_GROUP'), which provide broad information about the customers depicted in the file. The original "MAILOUT" file included one additional column, "RESPONSE", which indicated whether or not each recipient became a customer of the company. For the "TRAIN" subset, this column has been retained, but in the "TEST" subset it has been removed; it is against that withheld column that your final predictions will be assessed in the Kaggle competition.

Otherwise, all of the remaining columns are the same between the three data files. For more information about the columns depicted in the files, you can refer to two Excel spreadsheets provided in the workspace. One of them is a top-level list of attributes and descriptions, organized by informational category. The other is a detailed mapping of data values for each feature in alphabetical order.

In the below cell, we've provided some initial code to load in the first two datasets. Note for all of the `.csv` data files in this project that they're semicolon (`;`) delimited, so an additional argument in the `read_csv()` call has been included to read in the data properly. Also, considering the size of the datasets, it may take some time for them to load completely.

You'll notice when the data is loaded in that a warning message will immediately pop up. Before you really start digging into the modeling and analysis, you're going to need to perform some cleaning. Take some time to browse the structure of the data and look over the informational spreadsheets to understand the data values. Make some decisions on which features to keep, which features to drop, and if any revisions need to be made on data formats. It'll be a good idea to create a function with pre-processing steps, since you'll need to clean all of the datasets before you work with them.

[ ]:
```
# load in the data
azdias = pd.read_csv('../../data/Term2/capstone/arvato_data/
↪Udacity_AZDIAS_052018.csv', sep=';')
customers = pd.read_csv('../../data/Term2/capstone/arvato_data/
↪Udacity_CUSTOMERS_052018.csv', sep=';')
```

```
C:\Users\Satya\AppData\Local\Temp\ipykernel_23664\2758223681.py:2: DtypeWarning:
Columns (18,19) have mixed types. Specify dtype option on import or set
low_memory=False.
  azdias =
pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_AZDIAS_052018.csv',
sep=';')
C:\Users\Satya\AppData\Local\Temp\ipykernel_23664\2758223681.py:3: DtypeWarning:
Columns (18,19) have mixed types. Specify dtype option on import or set
low_memory=False.
  customers = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_CUSTOME
RS_052018.csv', sep=';')
```

[ ]:
```
azdias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891221 entries, 0 to 891220
Columns: 366 entries, LNR to ALTERSKATEGORIE_GROB
dtypes: float64(267), int64(93), object(6)
memory usage: 2.4+ GB
```

[ ]:
```
customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 191652 entries, 0 to 191651
Columns: 369 entries, LNR to ALTERSKATEGORIE_GROB
dtypes: float64(267), int64(94), object(8)
memory usage: 539.5+ MB
```

Check the values in the Columns that threw a warning when we loaded the csv files.

[ ]:
```
attributes = load_info('data/DIAS Attributes - Values 2017.xlsx', skiprows=1)
```

[ ]:
```
attributes.head()
```

[ ]:

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

[ ]:
```
# Gettig the name of the columns that read_csv warned about having mixed data␣
↪types
```

```
azdias.columns[18:20]
```

[ ]: Index(['CAMEO_DEUG_2015', 'CAMEO_INTL_2015'], dtype='object')

[ ]:
```
find_columns('CAMEO', azdias)
```

[ ]: Index(['CAMEO_DEU_2015', 'CAMEO_DEUG_2015', 'CAMEO_INTL_2015'], dtype='object')

[ ]:
```
get_attributes('CAMEO', attributes)
```

[ ]: ['CAMEO_DEUG_2015', 'CAMEO_DEU_2015', 'CAMEO_DEUINTL_2015']

[ ]:
```
# The value 'CAMEO_DEUINTL_2015' in attributes excel corresponds to the column␣
↪'CAMEO_INTL_2015'
attributes.replace({'Attribute':{'CAMEO_DEUINTL_2015':'CAMEO_INTL_2015'}},␣
↪inplace=True)
```

[ ]:
```
cameo_cols = get_attributes('CAMEO', attributes)
cols_cameo = get_attributes('CAMEO', attributes)
```

Lets check the unqiue values in each of the above columns

[ ]:
```
for col in cameo_cols:
    get_unique_vals(azdias, col)
```

```
Unique Values in Column CAMEO_DEUG_2015:  [nan 8.0 4.0 2.0 6.0 1.0 9.0 5.0 7.0
3.0 '4' '3' '7' '2' '8' '9' '6' '5'
 '1' 'X']
Unique Values in Column CAMEO_DEU_2015:  [nan '8A' '4C' '2A' '6B' '8C' '4A' '2D'
'1A' '1E' '9D' '5C' '8B' '7A' '5D'
 '9E' '9B' '1B' '3D' '4E' '4B' '3C' '5A' '7B' '9A' '6D' '6E' '2C' '7C'
 '9C' '7D' '5E' '1D' '8D' '6C' '6A' '5B' '4D' '3A' '2B' '7E' '3B' '6F'
 '5F' '1C' 'XX']
Unique Values in Column CAMEO_INTL_2015:  [nan 51.0 24.0 12.0 43.0 54.0 22.0
14.0 13.0 15.0 33.0 41.0 34.0 55.0 25.0
 23.0 31.0 52.0 35.0 45.0 44.0 32.0 '22' '24' '41' '12' '54' '51' '44'
 '35' '23' '25' '14' '34' '52' '55' '31' '32' '15' '13' '43' '33' '45'
 'XX']
```

[ ]:
```
for col in cameo_cols:
    get_unique_vals(customers, col)
```

```
Unique Values in Column CAMEO_DEUG_2015:  [1.0 nan 5.0 4.0 7.0 3.0 9.0 2.0 6.0
8.0 '6' '3' '8' '9' '2' '4' '1' '7'
 '5' 'X']
Unique Values in Column CAMEO_DEU_2015:  ['1A' nan '5D' '4C' '7B' '3B' '1D' '9E'
'2D' '4A' '6B' '9D' '8B' '5C' '9C'
 '4E' '6C' '8C' '8A' '5B' '9B' '3D' '2A' '3C' '5F' '7A' '1E' '2C' '7C'
 '5A' '2B' '6D' '7E' '5E' '6E' '3A' '9A' '4B' '1C' '1B' '6A' '8D' '7D'
```

```
 '6F' '4D' 'XX']
Unique Values in Column CAMEO_INTL_2015:  [13.0 nan 34.0 24.0 41.0 23.0 15.0
55.0 14.0 22.0 43.0 51.0 33.0 25.0 44.0
 54.0 32.0 12.0 35.0 31.0 45.0 52.0 '45' '25' '55' '51' '14' '54' '43'
 '22' '15' '24' '35' '23' '12' '44' '41' '52' '31' '13' '34' '32' '33'
 'XX']
```

Create a column to indicate missing values info; taken from attributes CSVs that have been provided

[ ]:
```
attributes['Missing'].unique()
```

[ ]:
```
array([True, False, nan], dtype=object)
```

Categorical Features or columns can be identified using three approaches: - columns with dtype object in the dataframe - columns containing the string 'klasse' or 'typ' in their name - columns mentioned in the attribute file with the words classification or typology in their description

Out of all the potential categorical columns obtained using the above methods, some of them already might be in an encoded format, while some might need further transformation or contain information that could be made into a different columns altogether.

[ ]:
```
categorical_attributes_info = attributes.loc[attributes.Value.apply(lambda x:␣
 ↪(type(x)==str) & (x!='-1, 0') & (x!='-1, 9')), :]
categorical_attributes_info = categorical_attributes_info.reset_index(drop=True)
categorical_attributes_info
```

[ ]:
```
                Attribute                                         Description  \
0   ANZ_HAUSHALTE_AKTIV                number of households in the building
1           ANZ_HH_TITEL           number of academic title holder in building
2          ANZ_PERSONEN              number of adult persons in the household
3             ANZ_TITEL  number of professional title holder in household
4        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
5        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
6        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
7        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
8        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
9        CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
10       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
11       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
12       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
13       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
14       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
15       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
16       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
17       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
18       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
19       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
20       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
21       CAMEO_DEU_2015  CAMEO classification 2015 - detailled classifi…
```

22	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
23	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
24	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
25	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
26	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
27	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
28	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
29	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
30	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
31	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
32	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
33	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
34	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
35	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
36	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
37	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
38	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
39	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
40	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
41	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
42	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
43	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
44	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
45	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
46	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
47	CAMEO_DEU_2015	CAMEO classification 2015 - detailled classifi…
48	GEBURTSJAHR	year of birth
49	KBA13_ANZAHL_PKW	number of cars in the PLZ8
50	MIN_GEBAEUDEJAHR	year the building was first mentioned in our d…
51	ORTSGR_KLS9	size of the community
52	OST_WEST_KZ	flag indicating the former GDR/FRG
53	OST_WEST_KZ	flag indicating the former GDR/FRG

	Value	Meaning	Missing
0	…	numeric value (typically coded from 1-10)	False
1	…	numeric value (typically coded from 1-10)	False
2	…	numeric value (typically coded from 1-3)	False
3	…	numeric value (typically coded from 1-10)	False
4	1A	Work-Life-Balance	False
5	1B	Wealthy Best Ager	False
6	1C	Successful Songwriter	False
7	1D	Old Nobility	False
8	1E	City Nobility	False
9	2A	Cottage Chic	False
10	2B	Noble Jogger	False
11	2C	Established gourmet	False
12	2D	Fine Management	False

```
13     3A                  Career & Family   False
14     3B           Powershopping Families   False
15     3C              Rural Neighborhood   False
16     3D               Secure Retirement   False
17     4A                  Family Starter   False
18     4B                     Family Life   False
19     4C                  String Trimmer   False
20     4D                      Empty Nest   False
21     4E                     Golden Ager   False
22     5A               Younger Employees   False
23     5B                 Suddenly Family   False
24     5C                    Family First   False
25     5D             Stock Market Junkies   False
26     5E                    Coffee Rider   False
27     5F               Active Retirement   False
28     6A                      Jobstarter   False
29     6B                 Petty Bourgeois   False
30     6C                Long-established   False
31     6D                   Sportgardener   False
32     6E                   Urban Parents   False
33     6F                    Frugal Aging   False
34     7A                      Journeymen   False
35     7B                     Mantaplatte   False
36     7C                  Factory Worker   False
37     7D                     Rear Window   False
38     7E             Interested Retirees   False
39     8A                  Multi-culteral   False
40     8B                  Young & Mobile   False
41     8C                          Prefab   False
42     8D                    Town Seniors   False
43     9A          First Shared Apartment   False
44     9B               Temporary Workers   False
45     9C             Afternoon Talk Show   False
46     9D                     Mini-Jobber   False
47     9E                    Socking Away   False
48      …                   numeric value   False
49      …                   numeric value   False
50      …                   numeric value   False
51     -1                         unknown    True
52      O                      East (GDR)   False
53      W                      West (FRG)   False
```

[ ]:
```
categorical_attributes_info.loc[1, 'Value']
```

[ ]: '…'

[ ]:
```python
# slicing off all numeric value cols from the above
categorical_attributes_info =␣
 ↪categorical_attributes_info[categorical_attributes_info.Value!='…']
categorical_attributes = categorical_attributes_info.Attribute.unique()
categorical_attributes
```

[ ]:
```
array(['CAMEO_DEU_2015', 'ORTSGR_KLS9', 'OST_WEST_KZ'], dtype=object)
```

[ ]:
```python
binary_attrib = attributes.query("Missing == False").groupby('Attribute').size()
binary_attrib_index = binary_attrib[binary_attrib  == 2].index
binary_attributes_info = attributes.loc[attributes.Attribute.apply(lambda x: x␣
 ↪in binary_attrib_index), :].query("Missing == False")
binary_attributes_info.reset_index(inplace=True, drop=True)
binary_attributes_info
```

[ ]:
```
             Attribute                                        Description Value  \
0            ANREDE_KZ                                             gender     1
1            ANREDE_KZ                                             gender     2
2             BIP_FLAG  business-flag indicating companies in the buil…     0
3             BIP_FLAG  business-flag indicating companies in the buil…     1
4     GREEN_AVANTGARDE                                  Green avantgarde     0
5     GREEN_AVANTGARDE  the environmental sustainability is the domina…     1
6           KBA05_SEG6  share of upper class cars (BMW 7er etc.) in th…     0
7           KBA05_SEG6  share of upper class cars (BMW 7er etc.) in th…     1
8          OST_WEST_KZ                flag indicating the former GDR/FRG     O
9          OST_WEST_KZ                flag indicating the former GDR/FRG     W
10           SOHO_FLAG                     small office/home office flag     0
11           SOHO_FLAG                     small office/home office flag     1
12            VERS_TYP                               insurance typology     1
13            VERS_TYP                               insurance typology     2

                                  Meaning Missing
0                                    male   False
1                                  female   False
2                  no company in the building   False
3                     company in the building   False
4     doesn't belong to the green avantgarde   False
5            belongs to the green avantgarde   False
6                                    none   False
7                                    some   False
8                               East (GDR)   False
9                               West (FRG)   False
10                no small office/home office   False
11                   small office/home office   False
12                      social-safety driven   False
13          individualistic-accepting risks   False
```

```
[ ]: categorical_cols = set(list(categorical_attributes_info.Attribute.unique()) +
     ↪list(binary_attributes_info.Attribute.unique()))
```

```
[ ]: typ_attributes_slicer = attributes.Attribute.str.contains('TYP')
     klasse_attributes_slicer = attributes.Attribute.str.contains('KLASSE')
     typ_descr_slicer = attributes.Description.str.contains('typ')
     class_descr_slicer = attributes.Description.str.contains('class')
     klasse_type_slicer = (typ_attributes_slicer | klasse_attributes_slicer |
     ↪typ_descr_slicer | class_descr_slicer)

     klasse_type_attributes = attributes.loc[klasse_type_slicer, :]
```

```
[ ]: klasse_type_cols = klasse_type_attributes.Attribute.unique()
     klasse_type_cols = list(set(klasse_type_cols)&set(azdias.columns))
     klasse_type_cols
```

```
[ ]: ['KBA13_SEG_MITTELKLASSE',
      'ORTSGR_KLS9',
      'VERS_TYP',
      'ALTERSKATEGORIE_GROB',
      'GFK_URLAUBERTYP',
      'KBA13_SEG_OBERKLASSE',
      'KBA05_SEG4',
      'KBA13_SEG_KOMPAKTKLASSE',
      'KBA13_SEG_OBEREMITTELKLASSE',
      'REGIOTYP',
      'CAMEO_INTL_2015',
      'KBA05_BAUMAX',
      'SHOPPER_TYP',
      'PLZ8_BAUMAX',
      'ZABEOTYP',
      'CAMEO_DEU_2015',
      'LP_FAMILIE_GROB',
      'KBA05_SEG3',
      'KBA13_KRSSEG_OBER',
      'KBA05_SEG6',
      'LP_FAMILIE_FEIN',
      'CAMEO_DEUG_2015',
      'FINANZ_HAUSBAUER',
      'GEBAEUDETYP_RASTER',
      'KBA05_MOD2',
      'RETOURTYP_BK_S',
      'KBA05_KRSOBER',
      'FINANZ_UNAUFFAELLIGER',
      'FINANZ_VORSORGER',
      'CJT_GESAMTTYP',
      'AGER_TYP',
```

```
 'FINANZ_SPARER',
 'FINANZ_MINIMALIST',
 'KBA05_MOD3',
 'KBA05_MOD1',
 'GEBAEUDETYP',
 'FINANZ_ANLEGER',
 'HEALTH_TYP',
 'FINANZTYP',
 'KBA05_SEG5',
 'D19_KONSUMTYP']
```

[ ]:
```
high_cardinality_klasse_type_cols = [col for col in klasse_type_cols if␣
 ↪(azdias[col].nunique()>5)]
high_cardinality_klasse_type_cols
```

[ ]:
```
['ORTSGR_KLS9',
 'GFK_URLAUBERTYP',
 'KBA13_SEG_OBERKLASSE',
 'KBA05_SEG4',
 'REGIOTYP',
 'CAMEO_INTL_2015',
 'KBA05_BAUMAX',
 'ZABEOTYP',
 'CAMEO_DEU_2015',
 'LP_FAMILIE_GROB',
 'KBA05_SEG3',
 'LP_FAMILIE_FEIN',
 'CAMEO_DEUG_2015',
 'KBA05_MOD2',
 'CJT_GESAMTTYP',
 'KBA05_MOD3',
 'KBA05_MOD1',
 'GEBAEUDETYP',
 'FINANZTYP',
 'KBA05_SEG5',
 'D19_KONSUMTYP']
```

[ ]:
```
cols_cat = azdias.select_dtypes(exclude=np.number).columns
cols_cat
```

[ ]:
```
Index(['CAMEO_DEU_2015', 'CAMEO_DEUG_2015', 'CAMEO_INTL_2015',
       'D19_LETZTER_KAUF_BRANCHE', 'EINGEFUEGT_AM', 'OST_WEST_KZ'],
      dtype='object')
```

[ ]:
```
from src.pipelines import Clean
```

[ ]:
```
clean_data = Clean(azdias)
```

As mentioned in the warning by the read_csv call these columns seem to have mixed data types. Before wed deal with that problem we will replace the **'X'** or **'XX'** values with NaNsas these strings represent unknowns/missing values

[ ]:
```
# Replacing 'X' & 'XX' Values
clean_data.fit_transform('CAMEO_DEUG_2015', {'X': np.nan})
clean_data.fit_transform('CAMEO_INTL_2015', {'XX': np.nan})
clean_data.fit_transform('CAMEO_DEU_2015', {'XX': np.nan})

# Checking the col unique values after replacement
for col in cameo_cols:
    get_unique_vals(azdias, col)
```

```
Unique Values in Column CAMEO_DEUG_2015:  [nan 8.0 4.0 2.0 6.0 1.0 9.0 5.0 7.0
3.0 '4' '3' '7' '2' '8' '9' '6' '5'
 '1']
Unique Values in Column CAMEO_DEU_2015:  [nan '8A' '4C' '2A' '6B' '8C' '4A' '2D'
'1A' '1E' '9D' '5C' '8B' '7A' '5D'
 '9E' '9B' '1B' '3D' '4E' '4B' '3C' '5A' '7B' '9A' '6D' '6E' '2C' '7C'
 '9C' '7D' '5E' '1D' '8D' '6C' '6A' '5B' '4D' '3A' '2B' '7E' '3B' '6F'
 '5F' '1C']
Unique Values in Column CAMEO_INTL_2015:  [nan 51.0 24.0 12.0 43.0 54.0 22.0
14.0 13.0 15.0 33.0 41.0 34.0 55.0 25.0
 23.0 31.0 52.0 35.0 45.0 44.0 32.0 '22' '24' '41' '12' '54' '51' '44'
 '35' '23' '25' '14' '34' '52' '55' '31' '32' '15' '13' '43' '33' '45']
```

Convert string values to int so that the columns have right dtype

[ ]:
```
azdias.iloc[:, 18:20].dtypes
```

[ ]:
```
CAMEO_DEUG_2015    object
CAMEO_INTL_2015    object
dtype: object
```

[ ]:
```
clean_data.fit_transform('CAMEO_DEUG_2015', lambda x: eval(x) if type(x)==str␣
 ↪else x)
clean_data.fit_transform('CAMEO_INTL_2015', lambda x: eval(x) if type(x)==str␣
 ↪else x)
```

[ ]:
```
azdias.iloc[:, 18:20].dtypes
```

[ ]:
```
CAMEO_DEUG_2015    float64
CAMEO_INTL_2015    float64
dtype: object
```

Quick glance at the data we have (including metadata)

[ ]:
```
azdias.head()
```

```
[ ]:       LNR  AGER_TYP  AKT_DAT_KL  ALTER_HH  ALTER_KIND1  ALTER_KIND2  \
     0  910215        -1         NaN       NaN          NaN          NaN
     1  910220        -1         9.0       0.0          NaN          NaN
     2  910225        -1         9.0      17.0          NaN          NaN
     3  910226         2         1.0      13.0          NaN          NaN
     4  910241        -1         1.0      20.0          NaN          NaN

        ALTER_KIND3  ALTER_KIND4  ALTERSKATEGORIE_FEIN  ANZ_HAUSHALTE_AKTIV  …  \
     0          NaN          NaN                   NaN                  NaN  …
     1          NaN          NaN                  21.0                 11.0  …
     2          NaN          NaN                  17.0                 10.0  …
     3          NaN          NaN                  13.0                  1.0  …
     4          NaN          NaN                  14.0                  3.0  …

        VHN  VK_DHT4A  VK_DISTANZ  VK_ZG11  W_KEIT_KIND_HH  WOHNDAUER_2008  \
     0  NaN       NaN         NaN      NaN             NaN             NaN
     1  4.0       8.0        11.0     10.0             3.0             9.0
     2  2.0       9.0         9.0      6.0             3.0             9.0
     3  0.0       7.0        10.0     11.0             NaN             9.0
     4  2.0       3.0         5.0      4.0             2.0             9.0

        WOHNLAGE ZABEOTYP  ANREDE_KZ  ALTERSKATEGORIE_GROB
     0       NaN        3          1                     2
     1       4.0        5          2                     1
     2       2.0        5          2                     3
     3       7.0        3          2                     4
     4       3.0        4          1                     3

     [5 rows x 366 columns]
```

```
[ ]: customers.head()
```

```
[ ]:       LNR  AGER_TYP  AKT_DAT_KL  ALTER_HH  ALTER_KIND1  ALTER_KIND2  \
     0    9626         2         1.0      10.0          NaN          NaN
     1    9628        -1         9.0      11.0          NaN          NaN
     2  143872        -1         1.0       6.0          NaN          NaN
     3  143873         1         1.0       8.0          NaN          NaN
     4  143874        -1         1.0      20.0          NaN          NaN

        ALTER_KIND3  ALTER_KIND4  ALTERSKATEGORIE_FEIN  ANZ_HAUSHALTE_AKTIV  …  \
     0          NaN          NaN                  10.0                  1.0  …
     1          NaN          NaN                   NaN                  NaN  …
     2          NaN          NaN                   0.0                  1.0  …
     3          NaN          NaN                   8.0                  0.0  …
     4          NaN          NaN                  14.0                  7.0  …

        VK_ZG11  W_KEIT_KIND_HH  WOHNDAUER_2008  WOHNLAGE  ZABEOTYP  \
```

```
0      2.0             6.0             9.0        7.0           3
1      3.0             0.0             9.0        NaN           3
2     11.0             6.0             9.0        2.0           3
3      2.0             NaN             9.0        7.0           1
4      4.0             2.0             9.0        3.0           1

      PRODUCT_GROUP  CUSTOMER_GROUP ONLINE_PURCHASE ANREDE_KZ  \
0  COSMETIC_AND_FOOD     MULTI_BUYER               0         1
1               FOOD    SINGLE_BUYER               0         1
2  COSMETIC_AND_FOOD     MULTI_BUYER               0         2
3           COSMETIC     MULTI_BUYER               0         1
4               FOOD     MULTI_BUYER               0         1

  ALTERSKATEGORIE_GROB
0                    4
1                    4
2                    4
3                    4
4                    3

[5 rows x 369 columns]
```

[ ]:
```python
# Selecting attribute info for Values that mean unkown or missing info
unknowns = attributes[(attributes.Missing == True)|(attributes.Meaning ==
 ↪'unknown')].copy()
unknowns.reset_index(inplace=True, drop=True)

# Fix the values in the Value column so that they all have a uniform pattern
unknowns.loc[:, 'Val'] = unknowns.Value.apply(create_missing_val_list)
unknowns.head()
```

[ ]:
```
              Attribute                                 Description  Value  \
0               AGER_TYP                          best-ager typology     -1
1  ALTERSKATEGORIE_GROB  age classification through prename analysis  -1, 0
2                ALTER_HH                main age within the household      0
3               ANREDE_KZ                                       gender  -1, 0
4                BALLRAUM                distance to next urban centre     -1

                        Meaning Missing      Val
0                       unknown    True     [-1]
1                       unknown    True  [-1, 0]
2  unknown / no main age detectable    True      [0]
3                       unknown    True  [-1, 0]
4                       unknown    True     [-1]
```

[ ]:
```python
# Creating a dict mapping missing/unknown values to NaN for each column
```

```
unknowns_dict = {v.Attribute: {val: np.nan for val in v.Val} for _, v in␣
↪unknowns.iterrows()}

# Number of Columns to perform the replacement operation on
len(unknowns_dict.keys())
```

[ ]: 233

[ ]:
```
# Replacing all values that indicate missing values with NaNs
for col, map_dict in unknowns_dict.items():
    if col in azdias.columns:
        clean_data.fit_transform(col, map_dict)
    else:
        print(col)
```

```
BIP_FLAG
D19_KK_KUNDENTYP
GEOSCORE_KLS7
HAUSHALTSSTRUKTUR
KBA13_CCM_1400_2500
SOHO_FLAG
WACHSTUMSGEBIET_NB
```

[ ]:
```
# azdias.replace(unknowns_dict, inplace=True)
# customers.replace(unknowns_dict, inplace=True)
```

[ ]:
```
cols_with_extra_encoding = []
# Select columns that have been decribed in attributes excel
attributes_without_numeric_vals = set(attributes[~(attributes.Meaning.
↪apply(lambda x: 'numer' in str(x)))].Attribute)
described_cols = list(set(azdias.columns)&attributes_without_numeric_vals)
for col in described_cols:
    # Extracts all unique non-null values of the column and stores it in␣
↪data_col_unique_vals
    data_col_unique_vals = azdias[col].dropna().unique()
    # Fetch all unique values of the 'Value' column of the attribute info for␣
↪the given column and store it in attr_encodings
    attr_encodings = get_attribute_info(col, attributes)['Value'].unique()
    # Take the set difference between data_col_unique_vals and attr_encodings,␣
↪store it in diff_encodings
    diff_encodings = set(data_col_unique_vals) - (set(attr_encodings)-{'…'})
    # If there is at least one encoding difference, append the column name to␣
↪the cols_with_extra_encoding list
    if (len(diff_encodings)>=1):
        cols_with_extra_encoding.append(col)

# Remove columns that we have already processed
```

```
cols_with_extra_encoding = list(set(cols_with_extra_encoding) - ␣
 ↪(set(binary_attributes_info.Attribute)))
cols_with_extra_encoding
```

```
[ ]: ['ORTSGR_KLS9',
 'LP_LEBENSPHASE_FEIN',
 'LP_FAMILIE_GROB',
 'KBA05_MODTEMP',
 'LP_LEBENSPHASE_GROB',
 'LP_FAMILIE_FEIN']
```

Dealing with binary columns

```
[ ]: binary_attributes_info
```

```
[ ]:           Attribute                                         Description Value  \
0          ANREDE_KZ                                              gender     1
1          ANREDE_KZ                                              gender     2
2           BIP_FLAG  business-flag indicating companies in the buil…     0
3           BIP_FLAG  business-flag indicating companies in the buil…     1
4   GREEN_AVANTGARDE                                    Green avantgarde     0
5   GREEN_AVANTGARDE  the environmental sustainability is the domina…     1
6         KBA05_SEG6  share of upper class cars (BMW 7er etc.) in th…     0
7         KBA05_SEG6  share of upper class cars (BMW 7er etc.) in th…     1
8         OST_WEST_KZ                  flag indicating the former GDR/FRG     O
9         OST_WEST_KZ                  flag indicating the former GDR/FRG     W
10         SOHO_FLAG                        small office/home office flag     0
11         SOHO_FLAG                        small office/home office flag     1
12          VERS_TYP                               insurance typology     1
13          VERS_TYP                               insurance typology     2

                               Meaning Missing
0                                 male   False
1                               female   False
2             no company in the building   False
3                company in the building   False
4   doesn't belong to the green avantgarde   False
5        belongs to the green avantgarde   False
6                                 none   False
7                                 some   False
8                          East (GDR)   False
9                          West (FRG)   False
10            no small office/home office   False
11               small office/home office   False
12                  social-safety driven   False
13       individualistic-accepting risks   False
```

There are a few columns above with values other than 0,1 used to indicate a binary choice; We will re-encode these values even though a a pair like 1,2 equally serves the purpose in order to standardise interpretation

```
[ ]: clean_data.fit_transform('OST_WEST_KZ',{'O':0, 'W':1})
     clean_data.fit_transform('ANREDE_KZ', {1:0, 2:1})
     clean_data.fit_transform('VERS_TYP', {1:0, 2:1})
```

Lets deal with columns that have mismatched encodings; values whose meaning hasn't been described in the attributes excel files that have been provided

```
[ ]: azdias['LP_FAMILIE_GROB'].unique()
```

```
[ ]: array([ 2.,  3.,  1.,  0.,  5.,  4., nan])
```

```
[ ]: customers['LP_FAMILIE_GROB'].unique()
```

```
[ ]: array([ 2., nan,  1.,  0.,  5.,  4.,  3.])
```

```
[ ]: get_attribute_info('LP_FAMILIE_GROB', attributes)
```

```
[ ]:            Attribute      Description Value                Meaning Missing
     1903  LP_FAMILIE_GROB  familytyp rough     1                 single   False
     1904  LP_FAMILIE_GROB  familytyp rough     2                 couple   False
     1905  LP_FAMILIE_GROB  familytyp rough     3          single parent   False
     1906  LP_FAMILIE_GROB  familytyp rough     4                    NaN     NaN
     1907  LP_FAMILIE_GROB  familytyp rough     5                    NaN     NaN
     1908  LP_FAMILIE_GROB  familytyp rough     6                 family   False
     1909  LP_FAMILIE_GROB  familytyp rough     7                    NaN     NaN
     1910  LP_FAMILIE_GROB  familytyp rough     8                    NaN     NaN
     1911  LP_FAMILIE_GROB  familytyp rough     9  multiperson household   False
     1912  LP_FAMILIE_GROB  familytyp rough    10                    NaN     NaN
     1913  LP_FAMILIE_GROB  familytyp rough    11                    NaN     NaN
```

```
[ ]: clean_data.fit_transform('LP_FAMILIE_GROB', {0:np.nan})
```

```
[ ]: azdias['LP_FAMILIE_FEIN'].unique()
```

```
[ ]: array([ 2.,  5.,  1.,  0., 10.,  7., 11.,  3.,  8.,  4.,  6., nan,  9.])
```

```
[ ]: customers['LP_FAMILIE_FEIN'].unique()
```

```
[ ]: array([ 2., nan,  1.,  0., 10.,  8.,  6., 11.,  9.,  7.,  5.,  3.,  4.])
```

```
[ ]: clean_data.fit_transform('LP_FAMILIE_FEIN', {0:np.nan})
```

```
[ ]: azdias['LP_LEBENSPHASE_GROB'].unique()
```

```
[ ]: array([ 4.,  6.,  1.,  0., 10.,  2.,  3.,  5.,  7., 12., 11.,  9.,  8.,
            nan])
```

[ ]:
```
customers['LP_LEBENSPHASE_GROB'].unique()
```

[ ]:
```
array([ 5., nan,  3.,  0., 10.,  2.,  8., 12., 11.,  1.,  4.,  6.,  7.,
        9.])
```

[ ]:
```
get_attribute_info('LP_LEBENSPHASE_GROB', attributes)
```

[ ]:
```
                Attribute      Description Value  \
1954  LP_LEBENSPHASE_GROB  lifestage rough     1
1955  LP_LEBENSPHASE_GROB  lifestage rough     2
1956  LP_LEBENSPHASE_GROB  lifestage rough     3
1957  LP_LEBENSPHASE_GROB  lifestage rough     4
1958  LP_LEBENSPHASE_GROB  lifestage rough     5
1959  LP_LEBENSPHASE_GROB  lifestage rough     6
1960  LP_LEBENSPHASE_GROB  lifestage rough     7
1961  LP_LEBENSPHASE_GROB  lifestage rough     8
1962  LP_LEBENSPHASE_GROB  lifestage rough     9
1963  LP_LEBENSPHASE_GROB  lifestage rough    10
1964  LP_LEBENSPHASE_GROB  lifestage rough    11
1965  LP_LEBENSPHASE_GROB  lifestage rough    12

                                                Meaning Missing
1954  single low-income- and average earners of youn…   False
1955  single low-income- and average earners of high…   False
1956                           single high-income earners   False
1957     single low-income- and average earner-couples   False
1958                    single high-income earner-couples   False
1959                                     single parents   False
1960     single low-income- and average earner-families   False
1961                         high-income earner-families   False
1962  average earners of younger age from mulitperso…   False
1963  low-income- and average earners of higher age …   False
1964  high-income earners of younger age from multip…   False
1965  high-income earners of higher age from multipe…   False
```

[ ]:
```
clean_data.fit_transform('LP_LEBENSPHASE_GROB', {0:np.nan})
```

[ ]:
```
azdias['LP_LEBENSPHASE_FEIN'].unique()
```

[ ]:
```
array([15., 21.,  3.,  0., 32.,  8.,  2.,  5., 10.,  4.,  6., 23., 12.,
       20.,  1., 11., 25., 13.,  7., 18., 31., 19., 38., 35., 30., 22.,
       14., 33., 29., 24., 28., 37., 26., 39., 27., 36.,  9., 34., nan,
       40., 16., 17.])
```

[ ]:
```
customers['LP_LEBENSPHASE_FEIN'].unique()
```

```
[ ]: array([20., nan, 13.,  0., 31., 17.,  6., 28.,  5., 27., 40., 35.,  2.,
            19., 38., 36.,  8., 34., 10., 12., 26., 11.,  9., 37., 14., 39.,
            32.,  7., 15., 23., 21., 25., 33., 16., 24., 30., 18.,  4., 22.,
             1., 29.,  3.])
```

```
[ ]: get_attribute_info('LP_LEBENSPHASE_FEIN', attributes)
```

```
[ ]:                 Attribute      Description Value  \
     1914  LP_LEBENSPHASE_FEIN  lifestage fine     1
     1915  LP_LEBENSPHASE_FEIN  lifestage fine     2
     1916  LP_LEBENSPHASE_FEIN  lifestage fine     3
     1917  LP_LEBENSPHASE_FEIN  lifestage fine     4
     1918  LP_LEBENSPHASE_FEIN  lifestage fine     5
     1919  LP_LEBENSPHASE_FEIN  lifestage fine     6
     1920  LP_LEBENSPHASE_FEIN  lifestage fine     7
     1921  LP_LEBENSPHASE_FEIN  lifestage fine     8
     1922  LP_LEBENSPHASE_FEIN  lifestage fine     9
     1923  LP_LEBENSPHASE_FEIN  lifestage fine    10
     1924  LP_LEBENSPHASE_FEIN  lifestage fine    11
     1925  LP_LEBENSPHASE_FEIN  lifestage fine    12
     1926  LP_LEBENSPHASE_FEIN  lifestage fine    13
     1927  LP_LEBENSPHASE_FEIN  lifestage fine    14
     1928  LP_LEBENSPHASE_FEIN  lifestage fine    15
     1929  LP_LEBENSPHASE_FEIN  lifestage fine    16
     1930  LP_LEBENSPHASE_FEIN  lifestage fine    17
     1931  LP_LEBENSPHASE_FEIN  lifestage fine    18
     1932  LP_LEBENSPHASE_FEIN  lifestage fine    19
     1933  LP_LEBENSPHASE_FEIN  lifestage fine    20
     1934  LP_LEBENSPHASE_FEIN  lifestage fine    21
     1935  LP_LEBENSPHASE_FEIN  lifestage fine    22
     1936  LP_LEBENSPHASE_FEIN  lifestage fine    23
     1937  LP_LEBENSPHASE_FEIN  lifestage fine    24
     1938  LP_LEBENSPHASE_FEIN  lifestage fine    25
     1939  LP_LEBENSPHASE_FEIN  lifestage fine    26
     1940  LP_LEBENSPHASE_FEIN  lifestage fine    27
     1941  LP_LEBENSPHASE_FEIN  lifestage fine    28
     1942  LP_LEBENSPHASE_FEIN  lifestage fine    29
     1943  LP_LEBENSPHASE_FEIN  lifestage fine    30
     1944  LP_LEBENSPHASE_FEIN  lifestage fine    31
     1945  LP_LEBENSPHASE_FEIN  lifestage fine    32
     1946  LP_LEBENSPHASE_FEIN  lifestage fine    33
     1947  LP_LEBENSPHASE_FEIN  lifestage fine    34
     1948  LP_LEBENSPHASE_FEIN  lifestage fine    35
     1949  LP_LEBENSPHASE_FEIN  lifestage fine    36
     1950  LP_LEBENSPHASE_FEIN  lifestage fine    37
     1951  LP_LEBENSPHASE_FEIN  lifestage fine    38
     1952  LP_LEBENSPHASE_FEIN  lifestage fine    39
```

```
1953  LP_LEBENSPHASE_FEIN  lifestage fine     40

                                                  Meaning Missing
1914           single low-income earners of younger age   False
1915            single low-income earners of middle age   False
1916             single average earners of younger age    False
1917               single average earners of middle age   False
1918          single low-income earners of advanced age   False
1919       single low-income earners at retirement age    False
1920             single average earners of advanced age   False
1921           single average earners at retirement age   False
1922                         single independant persons   False
1923                          wealthy single homeowners   False
1924                 single homeowners of advanced age   False
1925               single homeowners at retirement age   False
1926                 single top earners of higher age    False
1927  low-income- and average earner-couples of youn…   False
1928            low-income earner-couples of higher age   False
1929              average earner-couples of higher age    False
1930                               independant couples   False
1931          wealthy homeowner-couples of younger age    False
1932                  homeowner-couples of higher age   False
1933                 top earner-couples of higher age   False
1934                 single parent low-income earners   False
1935                    single parent average earners   False
1936                single parent high-income earners   False
1937                         low-income earner-families   False
1938                           average earner-families    False
1939                              independant families   False
1940                                homeowner-families   False
1941                               top earner-families   False
1942  low-income earners of younger age from mulitpe…   False
1943  average earners of younger age from mulitperso…   False
1944  low-income earners of higher age from mulitper…   False
1945  average earners of higher age from mulitperson…   False
1946  independant persons of younger age from mulitp…   False
1947  homeowners of younger age from mulitperson hou…   False
1948  top earners of younger age from mulitperson ho…   False
1949  independant persons of higher age from mulitpe…   False
1950  homeowners of advanced age from mulitperson ho…   False
1951  homeowners at retirement age from mulitperson …   False
1952  top earners of middle age from mulitperson hou…   False
1953  top earners at retirement age from mulitperson…   False
```

[ ]:
```
clean_data.fit_transform('LP_LEBENSPHASE_FEIN', {0:np.nan})
```

[ ]:
```
get_attribute_info('ORTSGR_KLS9',attributes)
```

```
[ ]:         Attribute                            Description Value  \
     2003  ORTSGR_KLS9                  size of the community    -1
     2004  ORTSGR_KLS9  '- classified number of inhabitants     1
     2005  ORTSGR_KLS9  '- classified number of inhabitants     2
     2006  ORTSGR_KLS9  '- classified number of inhabitants     3
     2007  ORTSGR_KLS9  '- classified number of inhabitants     4
     2008  ORTSGR_KLS9  '- classified number of inhabitants     5
     2009  ORTSGR_KLS9  '- classified number of inhabitants     6
     2010  ORTSGR_KLS9  '- classified number of inhabitants     7
     2011  ORTSGR_KLS9  '- classified number of inhabitants     8
     2012  ORTSGR_KLS9  '- classified number of inhabitants     9

                              Meaning Missing
     2003                      unknown    True
     2004             <= 2.000 inhabitants   False
     2005       2.001 to 5.000 inhabitants   False
     2006      5.001 to 10.000 inhabitants   False
     2007     10.001 to 20.000 inhabitants   False
     2008     20.001 to 50.000 inhabitants   False
     2009    50.001 to 100.000 inhabitants   False
     2010   100.001 to 300.000 inhabitants   False
     2011   300.001 to 700.000 inhabitants   False
     2012          > 700.000  inhabitants   False
```

```
[ ]: get_attribute_info('KBA05_MODTEMP',attributes)
```

```
[ ]:          Attribute                                       Description  Value  \
     1025  KBA05_MODTEMP  development of the most common car segment in …  -1, 9
     1026  KBA05_MODTEMP  development of the most common car segment in …      1
     1027  KBA05_MODTEMP  development of the most common car segment in …      2
     1028  KBA05_MODTEMP  development of the most common car segment in …      3
     1029  KBA05_MODTEMP  development of the most common car segment in …      4
     1030  KBA05_MODTEMP  development of the most common car segment in …      5

                          Meaning Missing
     1025                  unknown    True
     1026                 promoted   False
     1027        stayed upper level   False
     1028  stayed lower/average level   False
     1029                  demoted   False
     1030             new building   False
```

Lets deal with attributes that have values with unexplained meaning

```
[ ]: attributes.query("Value == 0 & Missing == False").Meaning.unique()
```

```
[ ]: array(['no classification possible', 'no company in the building',
            'no transactions known', 'no transaction known',
```

```
       'no Online-transactions within the last 12 months',
       "doesn't belong to the green avantgarde",
       'classification not possible', 'none', 'no 1-2 family homes',
       'no 3-5 family homes', 'no 6-10 family homes',
       'no >10 family homes', 'external supplied hedonists ',
       'no small office/home office', 'no score calculated'], dtype=object)
```

[ ]:
```
attributes[attributes.Meaning.isin(['classification not possible', 'no score␣
↪calculated'])]
```

[ ]:
```
       Attribute        Description Value                      Meaning Missing
745   HEALTH_TYP    health typology     0  classification not possible   False
2230    WOHNLAGE   residential-area     0          no score calculated   False
```

[ ]:
```
get_attribute_info('WOHNLAGE', attributes)
```

[ ]:
```
     Attribute        Description Value                              Meaning  \
2229  WOHNLAGE  residential-area     -1                              unknown
2230  WOHNLAGE  residential-area      0                  no score calculated
2231  WOHNLAGE  residential-area      1               very good neighbourhood
2232  WOHNLAGE  residential-area      2                    good neighbourhood
2233  WOHNLAGE  residential-area      3                 average neighbourhood
2234  WOHNLAGE  residential-area      4                    poor neighbourhood
2235  WOHNLAGE  residential-area      5               very poor neighbourhood
2236  WOHNLAGE  residential-area      7                   rural neighbourhood
2237  WOHNLAGE  residential-area      8  new building in rural neighbourhood

     Missing
2229    True
2230   False
2231   False
2232   False
2233   False
2234   False
2235   False
2236   False
2237   False
```

[ ]:
```
clean_data.fit_transform('WOHNLAGE', {0:np.nan})
```

[ ]:
```
get_attribute_info('HEALTH_TYP', attributes)
```

[ ]:
```
      Attribute      Description Value                      Meaning Missing
744  HEALTH_TYP  health typology    -1                      unknown    True
745  HEALTH_TYP  health typology     0  classification not possible   False
746  HEALTH_TYP  health typology     1            critical reserved   False
747  HEALTH_TYP  health typology     2               sanitary affine   False
```

```
748  HEALTH_TYP  health typology     3           jaunty hedonists    False
```

[ ]:
```
# Apply all transformations to customers dataframe
clean_data.transform(customers)
```

Check columns that might be specific to a particular dataframe and refer the attributes file for more info

[ ]:
```
len(set(azdias.columns) & set(attributes.Attribute) & set(customers.columns))
```

[ ]:
```
273
```

[ ]:
```
len(set(attributes.Attribute))
```

[ ]:
```
314
```

[ ]:
```
# Getting columns exclusive to a dataframe
attributes_notin_df = set(attributes.Attribute) - set(customers.columns)
cols_not_in_attributes = set(customers.columns) - set(attributes.Attribute)
customers_only_cols = list(set(customers.columns) - set(azdias.columns))
```

[ ]:
```
# Printing Unique Values in customer only columns
for col in customers_only_cols:
    print(f'{col} unique values: ',customers[col].unique())
```

```
PRODUCT_GROUP unique values:  ['COSMETIC_AND_FOOD' 'FOOD' 'COSMETIC']
CUSTOMER_GROUP unique values:  ['MULTI_BUYER' 'SINGLE_BUYER']
ONLINE_PURCHASE unique values:  [0 1]
```

For now we will drop the customer specific columns. We can always perform a join post cleaning and add the required values back.

[ ]:
```
cols_to_drop = customers_only_cols
cols_to_drop
```

[ ]:
```
['PRODUCT_GROUP', 'CUSTOMER_GROUP', 'ONLINE_PURCHASE']
```

[ ]:
```
# Dropping Customer only cols
customers.drop(cols_to_drop, axis=1, inplace=True)
```

Figure out the optimum percentage of NaN threshold such that both dataframes end up with same number of columns being dropped

[ ]:
```
# calculates the number columns with NaNs greater than 0
customers_missing_val = customers.isnull().sum() / len(customers)
customers_missing_val = customers_missing_val[customers_missing_val>0]
azdias_missing_val = azdias.isnull().sum() / len(azdias)
azdias_missing_val = azdias_missing_val[azdias_missing_val>0]

# gets the columns with NaNs greater than 30 % of df len (num of rows)
```

```
customers_cols_to_drop = get_cols_to_drop(customers, 0.30)
azdias_cols_to_drop = get_cols_to_drop(azdias, 0.30)
set(customers_cols_to_drop) - set(azdias_cols_to_drop)
```

[ ]: {'KKK', 'REGIOTYP'}

[ ]:
```
customers_missing_val[['KKK', 'REGIOTYP']]
```

[ ]:
```
KKK         0.313401
REGIOTYP    0.313401
dtype: float64
```

[ ]:
```
azdias_missing_val[['KKK', 'REGIOTYP']]
```

[ ]:
```
KKK         0.177357
REGIOTYP    0.177357
dtype: float64
```

[ ]:
```
# Change the threshold such that equal number of cols are dropped
customers_cols_to_drop = get_cols_to_drop(customers, 0.33)
azdias_cols_to_drop = get_cols_to_drop(azdias, 0.33)
set(customers_cols_to_drop) - set(azdias_cols_to_drop)
```

[ ]: set()

[ ]:
```
# Drop columns based on above threshold
customers.dropna(thresh=int(0.66*len(customers)), axis=1, inplace=True)
azdias.dropna(thresh=int(0.66*len(azdias)), axis=1, inplace=True)
```

[ ]:
```
# Verify same num of columns are present
set(azdias.columns) == set(customers.columns)
```

[ ]: True

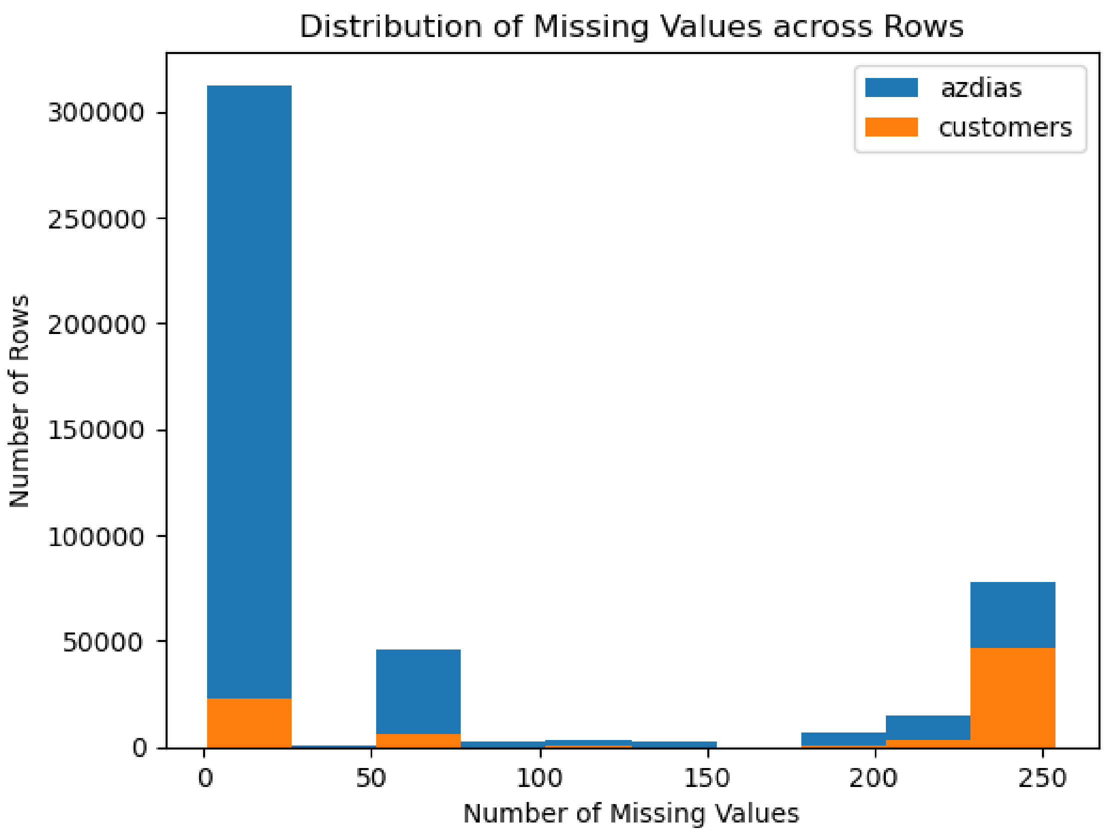
Let us look at the number of missing values per row and then construct a hist to check both dataframes

[ ]:
```
# calculates the number rows with NaNs greater than 0
azdias_missing_rows = azdias.isnull().sum(axis=1)
azdias_missing_rows = azdias_missing_rows[azdias_missing_rows>0]
customers_missing_rows = customers.isnull().sum(axis=1)
customers_missing_rows = customers_missing_rows[customers_missing_rows>0]
```

Visualizing the missing data

[ ]:
```
plt.hist(azdias_missing_rows.values, label='azdias')
plt.hist(customers_missing_rows.values, label='customers')
plt.xlabel('Number of Missing Values')
plt.ylabel('Number of Rows')
```

```
plt.legend()
plt.title('Distribution of Missing Values across Rows');
```



[ ]:
```
# get the % of row size
proportion_cols = {}
for percent in [20, 25, 50, 70, 75, 80]:
    proportion_cols[percent] = (percent/100)*azdias.shape[1]

proportion_cols
```

[ ]: {20: 71.2, 25: 89.0, 50: 178.0, 70: 249.2, 75: 267.0, 80: 284.8}

[ ]:
```
# Get proportion of rows that would be dropped given a particular threshold␣
↪(100) of missing values
get_missing_rows_percent(customers, 100), get_missing_rows_percent(azdias, 100)
```

[ ]: (26.75735186692547, 11.87225166372875)

[ ]:
```
# Get proportion of rows that would be dropped given a particular threshold (25␣
↪% of columns length) of missing values
```

```
get_missing_rows_percent(customers, proportion_cols[25]),␣
 ↪get_missing_rows_percent(azdias, proportion_cols[25])
```

[ ]: (26.768309227140858, 11.890316767670422)

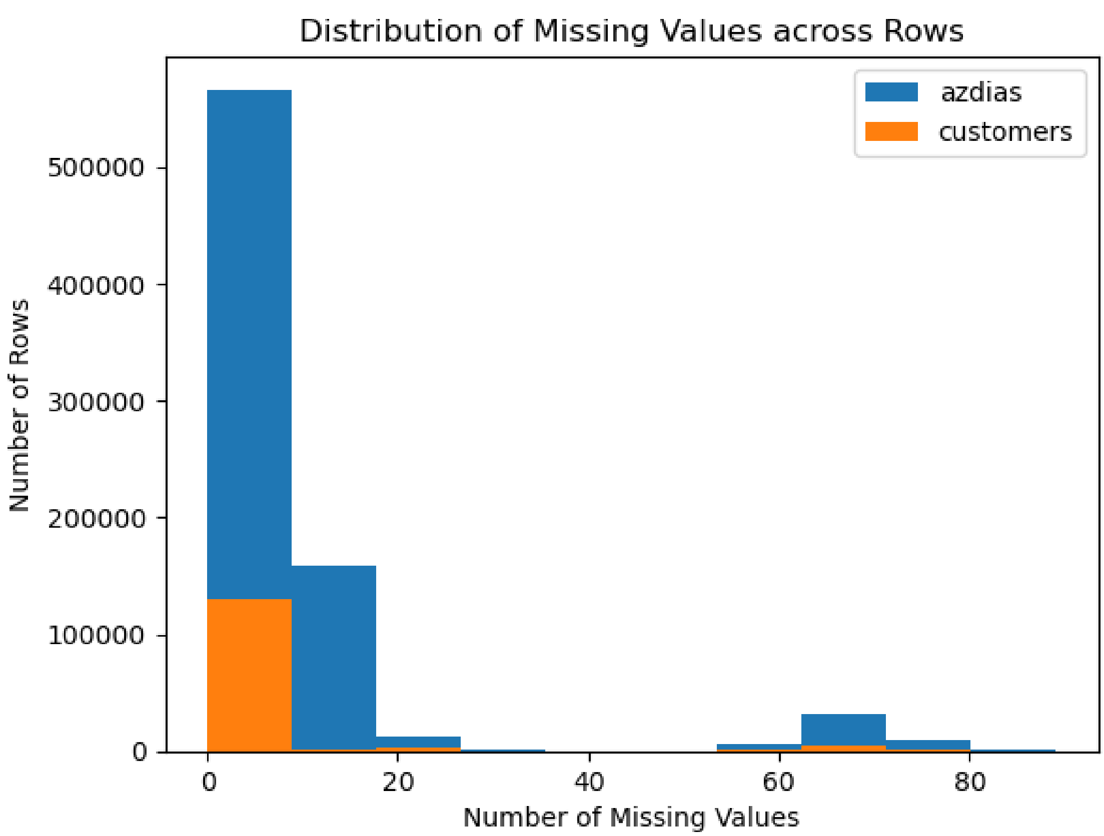
```
[ ]: na_threshold_rows = np.ceil(proportion_cols[75])
na_threshold_rows
```

[ ]: 267.0

```
[ ]: # value of thresh arg determines the minimum non-na values required beyond␣
 ↪which the row is considered for dropping
azdias.dropna(thresh=na_threshold_rows, axis=0, inplace=True)
customers.dropna(thresh=na_threshold_rows, axis=0, inplace=True)
```

Visualizing the missing data

```
[ ]: plt.hist(azdias.isnull().sum(axis=1).values, label='azdias')
plt.hist(customers.isnull().sum(axis=1).values, label='customers')
plt.xlabel('Number of Missing Values')
plt.ylabel('Number of Rows')
plt.legend()
plt.title('Distribution of Missing Values across Rows');
```



Checkpoint

```
[ ]: with open('models/clean_data.pkl', 'wb') as file:
         dill.dump(clean_data, file)
```

```
[ ]: azdias.to_pickle('data/azdias_cleaned.pkl')
     customers.to_pickle('data/customers_cleaned.pkl')
```

```
[ ]: azdias=pd.read_pickle('data/azdias_cleaned.pkl')
     customers=pd.read_pickle('data/customers_cleaned.pkl')
```

1.1.1 Feature Engineering by re-encoding certain columns

```
[ ]: from src.pipelines import FeatureEngineer
```

```
[ ]: feature_engine = FeatureEngineer(azdias)
```

Dealing with cameo Cols

```
[ ]: get_attribute_info(cols_cameo[2], attributes)
```

```
[ ]:            Attribute                                        Description Value  \
     105  CAMEO_INTL_2015  CAMEO classification 2015 - international typo…    -1
     106  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    11
     107  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    12
     108  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    13
     109  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    14
     110  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    15
     111  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    21
     112  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    22
     113  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    23
     114  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    24
     115  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    25
     116  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    31
     117  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    32
     118  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    33
     119  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    34
     120  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    35
     121  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    41
     122  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    42
     123  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    43
     124  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    44
     125  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    45
     126  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    51
     127  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    52
     128  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    53
```

```
129  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    54
130  CAMEO_INTL_2015  (each German CAMEO code belongs to one interna…    55

                                                    Meaning Missing
105                                                 unknown    True
106    Wealthy Households-Pre-Family Couples & Singles   False
107     Wealthy Households-Young Couples With Children   False
108  Wealthy Households-Families With School Age Ch…   False
109  Wealthy Households-Older Families &  Mature Co…   False
110            Wealthy Households-Elders In Retirement   False
111  Prosperous Households-Pre-Family Couples & Sin…   False
112  Prosperous Households-Young Couples With Children   False
113  Prosperous Households-Families With School Age…   False
114  Prosperous Households-Older Families & Mature …   False
115         Prosperous Households-Elders In Retirement   False
116  Comfortable Households-Pre-Family Couples & Si…   False
117  Comfortable Households-Young Couples With Chil…   False
118  Comfortable Households-Families With School Ag…   False
119  Comfortable Households-Older Families & Mature…   False
120        Comfortable Households-Elders In Retirement   False
121  Less Affluent Households-Pre-Family Couples & …   False
122  Less Affluent Households-Young Couples With Ch…   False
123  Less Affluent Households-Families With School …   False
124  Less Affluent Households-Older Families & Matu…   False
125      Less Affluent Households-Elders In Retirement   False
126     Poorer Households-Pre-Family Couples & Singles   False
127      Poorer Households-Young Couples With Children   False
128  Poorer Households-Families With School Age Chi…   False
129  Poorer Households-Older Families & Mature Couples   False
130             Poorer Households-Elders In Retirement   False
```

[ ]:
```
# Create new columns by applying function to cameo cols
feature_engine.apply_transform('CAMEO_INTL_HH_ECON', cols_cameo[2], lambda x: x/
 ↪/10)
feature_engine.apply_transform('CAMEO_INTL_FAM_INFO', cols_cameo[2], lambda x:␣
 ↪x%10)
```

[ ]:
```
# feature_engine.apply_transform('CAMEO_DEU_LEBENSSTIL', cols_cameo[1], lambda␣
 ↪x: x[1] if type(x)==str else x)
# azdias['CAMEO_DEU_LEBENSSTIL'].unique()
```

[ ]:
```
# print(azdias['CAMEO_DEU_LEBENSSTIL'].unique())
# feature_engine.apply_remap('CAMEO_DEU_LEBENSSTIL', 'CAMEO_DEU_LEBENSSTIL',␣
 ↪{'A':1, 'C':3, 'B':2, 'D':4, 'E':5, 'F':6})
# print(azdias['CAMEO_DEU_LEBENSSTIL'].unique())
```

Dealing with ther columns with extra encodings & other issues we noticed earlier

[ ]:
```
LP_FAMILIE_GROB_attribute_values = get_attribute_info('LP_FAMILIE_GROB',␣
↪attributes).copy()
LP_FAMILIE_GROB_attribute_values
```

[ ]:
```
            Attribute      Description Value                  Meaning Missing
1903  LP_FAMILIE_GROB  familytyp rough     1                   single   False
1904  LP_FAMILIE_GROB  familytyp rough     2                   couple   False
1905  LP_FAMILIE_GROB  familytyp rough     3            single parent   False
1906  LP_FAMILIE_GROB  familytyp rough     4                      NaN     NaN
1907  LP_FAMILIE_GROB  familytyp rough     5                      NaN     NaN
1908  LP_FAMILIE_GROB  familytyp rough     6                   family   False
1909  LP_FAMILIE_GROB  familytyp rough     7                      NaN     NaN
1910  LP_FAMILIE_GROB  familytyp rough     8                      NaN     NaN
1911  LP_FAMILIE_GROB  familytyp rough     9    multiperson household   False
1912  LP_FAMILIE_GROB  familytyp rough    10                      NaN     NaN
1913  LP_FAMILIE_GROB  familytyp rough    11                      NaN     NaN
```

[ ]:
```
azdias['LP_FAMILIE_GROB'].unique()
```

[ ]:
```
array([ 3.,  1., nan,  5.,  2.,  4.])
```

[ ]:
```
# Creates a dict using attributes df
LP_FAMILIE_GROB_attribute_values.Meaning = LP_FAMILIE_GROB_attribute_values.
↪Meaning.str.strip()
# https://stackoverflow.com/questions/18695605/
↪how-to-convert-a-dataframe-to-a-dictionary
LP_FAMILIE_GROB_attribute_values.ffill(inplace=True)
LP_FAMILIE_GROB_attribute_values['Meaning'].replace(
    {'single':1, 'couple':2, 'single parent':3, 'family':4, 'multiperson␣
↪household':5},
    inplace=True)
LP_FAMILIE_GROB_dict = LP_FAMILIE_GROB_attribute_values.
↪set_index('Value')['Meaning'].to_dict()

# Create new column from the applied encoding
feature_engine.apply_remap('LP_FAMILIE_GROB_HH', 'LP_FAMILIE_GROB',
                           LP_FAMILIE_GROB_dict
                           )
```

[ ]:
```
LP_FAMILIE_FEIN_attribute_values = get_attribute_info('LP_FAMILIE_FEIN',␣
↪attributes).copy()
LP_FAMILIE_FEIN_attribute_values
```

[ ]:
```
            Attribute     Description Value  \
1892  LP_FAMILIE_FEIN  familytyp fine     1
1893  LP_FAMILIE_FEIN  familytyp fine     2
1894  LP_FAMILIE_FEIN  familytyp fine     3
```

```
1895  LP_FAMILIE_FEIN  familytyp fine     4
1896  LP_FAMILIE_FEIN  familytyp fine     5
1897  LP_FAMILIE_FEIN  familytyp fine     6
1898  LP_FAMILIE_FEIN  familytyp fine     7
1899  LP_FAMILIE_FEIN  familytyp fine     8
1900  LP_FAMILIE_FEIN  familytyp fine     9
1901  LP_FAMILIE_FEIN  familytyp fine    10
1902  LP_FAMILIE_FEIN  familytyp fine    11

                                Meaning Missing
1892                             single   False
1893                             couple   False
1894               young single parent    False
1895           single parent with teenager   False
1896  single parent with child of full age   False
1897                       young family   False
1898                 family with teenager   False
1899         family with child of full age   False
1900                        shared flat   False
1901          two-generational household   False
1902        multi-generational household   False
```

[ ]:
```
azdias['LP_FAMILIE_FEIN'].unique()
```

[ ]:
```
array([ 5.,  1., nan, 10.,  2.,  7., 11.,  8.,  4.,  6.,  9.,  3.])
```

[ ]:
```
# Create new column from the applied encoding
# We will use the dict above as the values are similar
feature_engine.apply_remap('LP_FAMILIE_FEIN_HH', 'LP_FAMILIE_FEIN',
                           LP_FAMILIE_GROB_dict
                           )
```

[ ]:
```
# Check unique values in above columns after transformations/replacement
for col in ['LP_FAMILIE_GROB', 'LP_FAMILIE_FEIN']:
    get_unique_vals(azdias, col)
```

```
Unique Values in Column LP_FAMILIE_GROB:  [ 3.  1. nan  5.  2.  4.]
Unique Values in Column LP_FAMILIE_FEIN:  [ 5.  1. nan 10.  2.  7. 11.  8.  4.
6.  9.  3.]
```

[ ]:
```
LP_FAMILIE_FEIN_attribute_values
```

[ ]:
```
            Attribute     Description Value  \
1892  LP_FAMILIE_FEIN  familytyp fine     1
1893  LP_FAMILIE_FEIN  familytyp fine     2
1894  LP_FAMILIE_FEIN  familytyp fine     3
1895  LP_FAMILIE_FEIN  familytyp fine     4
1896  LP_FAMILIE_FEIN  familytyp fine     5
```

```
1897  LP_FAMILIE_FEIN  familytyp fine     6
1898  LP_FAMILIE_FEIN  familytyp fine     7
1899  LP_FAMILIE_FEIN  familytyp fine     8
1900  LP_FAMILIE_FEIN  familytyp fine     9
1901  LP_FAMILIE_FEIN  familytyp fine    10
1902  LP_FAMILIE_FEIN  familytyp fine    11

                                  Meaning Missing
1892                               single   False
1893                               couple   False
1894                  young single parent   False
1895          single parent with teenager   False
1896  single parent with child of full age  False
1897                         young family   False
1898                 family with teenager   False
1899        family with child of full age   False
1900                          shared flat   False
1901         two-generational household     False
1902       multi-generational household     False
```

[ ]:
```
# Creates a dict using attributes df
LP_FAMILIE_FEIN_attribute_values.Meaning = ['no_child', 'no_child', 'young',
                                            'with_teenager',␣
 ↪'with_full_age_child',
                                            'young', 'with_teenager',␣
 ↪'with_full_age_child',
                                            'shared', 'two_generational',␣
 ↪'multi_generational'
                                            ]
LP_FAMILIE_FEIN_attribute_values.Meaning.replace({'no_child':1, 'young':2,␣
 ↪'with_teenager':3, 'with_full_age_child':4,
                                                  'shared':5,␣
 ↪'two_generational':6, 'multi_generational':7},
                                                  inplace=True
                                                  )

LP_FAMILIE_FEIN_dict = LP_FAMILIE_FEIN_attribute_values.
 ↪set_index("Value")['Meaning'].to_dict()

# Create new column from the applied encoding
feature_engine.apply_remap('LP_FAMILIE_FEIN_INFO', 'LP_FAMILIE_FEIN',␣
 ↪LP_FAMILIE_FEIN_dict)
```

[ ]:
```
azdias['LP_FAMILIE_FEIN_INFO'].unique()
```

[ ]:
```
array([ 4.,  1., nan,  6.,  3.,  7.,  2.,  5.])
```

[ ]:
```
LP_STATUS_GROB_attribute_values = get_attribute_info('LP_STATUS_GROB',␣
↪attributes).copy()
LP_STATUS_GROB_attribute_values
```

[ ]:

	Attribute	Description	Value	Meaning	Missing
1976	LP_STATUS_GROB	social status rough	1	low-income earners	False
1977	LP_STATUS_GROB	social status rough	2	NaN	NaN
1978	LP_STATUS_GROB	social status rough	3	average earners	False
1979	LP_STATUS_GROB	social status rough	4	NaN	NaN
1980	LP_STATUS_GROB	social status rough	5	NaN	NaN
1981	LP_STATUS_GROB	social status rough	6	independants	False
1982	LP_STATUS_GROB	social status rough	7	NaN	NaN
1983	LP_STATUS_GROB	social status rough	8	houseowners	False
1984	LP_STATUS_GROB	social status rough	9	NaN	NaN
1985	LP_STATUS_GROB	social status rough	10	top earners	False

[ ]:
```
azdias['LP_STATUS_GROB'].unique()
```

[ ]: array([1., 2., 4., 5., 3., nan])

[ ]:
```
# Creates a dict using attributes df
LP_STATUS_GROB_attribute_values.Meaning.ffill(inplace=True)
LP_STATUS_GROB_attribute_values.Meaning.replace({'low-income earners':1,␣
↪'average earners':2,
                                                 'independants':3,␣
↪'houseowners':4, 'top earners ':5
                                                 },
                                                 inplace=True
                                                )
LP_STATUS_GROB_dict = LP_STATUS_GROB_attribute_values.
↪set_index('Value')['Meaning'].to_dict()

# Replace column values using the applied encoding
feature_engine.apply_remap('LP_STATUS_GROB', 'LP_STATUS_GROB',␣
↪LP_STATUS_GROB_dict)
```

[ ]:
```
azdias['LP_STATUS_GROB'].unique()
```

[ ]: array([1., 2., nan])

[ ]:
```
LP_LEBENSPHASE_FEIN_attribute_values =␣
↪get_attribute_info('LP_LEBENSPHASE_FEIN', attributes).copy()
LP_LEBENSPHASE_FEIN_attribute_values
```

[ ]:

	Attribute	Description	Value	\
1914	LP_LEBENSPHASE_FEIN	lifestage fine	1	
1915	LP_LEBENSPHASE_FEIN	lifestage fine	2	

1916	LP_LEBENSPHASE_FEIN	lifestage fine	3
1917	LP_LEBENSPHASE_FEIN	lifestage fine	4
1918	LP_LEBENSPHASE_FEIN	lifestage fine	5
1919	LP_LEBENSPHASE_FEIN	lifestage fine	6
1920	LP_LEBENSPHASE_FEIN	lifestage fine	7
1921	LP_LEBENSPHASE_FEIN	lifestage fine	8
1922	LP_LEBENSPHASE_FEIN	lifestage fine	9
1923	LP_LEBENSPHASE_FEIN	lifestage fine	10
1924	LP_LEBENSPHASE_FEIN	lifestage fine	11
1925	LP_LEBENSPHASE_FEIN	lifestage fine	12
1926	LP_LEBENSPHASE_FEIN	lifestage fine	13
1927	LP_LEBENSPHASE_FEIN	lifestage fine	14
1928	LP_LEBENSPHASE_FEIN	lifestage fine	15
1929	LP_LEBENSPHASE_FEIN	lifestage fine	16
1930	LP_LEBENSPHASE_FEIN	lifestage fine	17
1931	LP_LEBENSPHASE_FEIN	lifestage fine	18
1932	LP_LEBENSPHASE_FEIN	lifestage fine	19
1933	LP_LEBENSPHASE_FEIN	lifestage fine	20
1934	LP_LEBENSPHASE_FEIN	lifestage fine	21
1935	LP_LEBENSPHASE_FEIN	lifestage fine	22
1936	LP_LEBENSPHASE_FEIN	lifestage fine	23
1937	LP_LEBENSPHASE_FEIN	lifestage fine	24
1938	LP_LEBENSPHASE_FEIN	lifestage fine	25
1939	LP_LEBENSPHASE_FEIN	lifestage fine	26
1940	LP_LEBENSPHASE_FEIN	lifestage fine	27
1941	LP_LEBENSPHASE_FEIN	lifestage fine	28
1942	LP_LEBENSPHASE_FEIN	lifestage fine	29
1943	LP_LEBENSPHASE_FEIN	lifestage fine	30
1944	LP_LEBENSPHASE_FEIN	lifestage fine	31
1945	LP_LEBENSPHASE_FEIN	lifestage fine	32
1946	LP_LEBENSPHASE_FEIN	lifestage fine	33
1947	LP_LEBENSPHASE_FEIN	lifestage fine	34
1948	LP_LEBENSPHASE_FEIN	lifestage fine	35
1949	LP_LEBENSPHASE_FEIN	lifestage fine	36
1950	LP_LEBENSPHASE_FEIN	lifestage fine	37
1951	LP_LEBENSPHASE_FEIN	lifestage fine	38
1952	LP_LEBENSPHASE_FEIN	lifestage fine	39
1953	LP_LEBENSPHASE_FEIN	lifestage fine	40

	Meaning	Missing
1914	single low-income earners of younger age	False
1915	single low-income earners of middle age	False
1916	single average earners of younger age	False
1917	single average earners of middle age	False
1918	single low-income earners of advanced age	False
1919	single low-income earners at retirement age	False
1920	single average earners of advanced age	False

```
1921           single average earners at retirement age   False
1922                         single independant persons   False
1923                          wealthy single homeowners   False
1924                    single homeowners of advanced age   False
1925                  single homeowners at retirement age   False
1926                    single top earners of higher age    False
1927  low-income- and average earner-couples of youn…   False
1928            low-income earner-couples of higher age   False
1929              average earner-couples of higher age    False
1930                               independant couples   False
1931         wealthy homeowner-couples of younger age    False
1932                     homeowner-couples of higher age   False
1933                    top earner-couples of higher age   False
1934                    single parent low-income earners   False
1935                       single parent average earners   False
1936                    single parent high-income earners   False
1937                           low-income earner-families   False
1938                             average earner-families    False
1939                                independant families   False
1940                                  homeowner-families   False
1941                                 top earner-families   False
1942  low-income earners of younger age from mulitpe…   False
1943  average earners of younger age from mulitperso…   False
1944  low-income earners of higher age from mulitper…   False
1945  average earners of higher age from mulitperson…   False
1946  independant persons of younger age from mulitp…   False
1947  homeowners of younger age from mulitperson hou…   False
1948  top earners of younger age from mulitperson ho…   False
1949  independant persons of higher age from mulitpe…   False
1950  homeowners of advanced age from mulitperson ho…   False
1951  homeowners at retirement age from mulitperson …   False
1952  top earners of middle age from mulitperson hou…   False
1953  top earners at retirement age from mulitperson…   False
```

[ ]:

```
# Create a dict of encodings using attributes df
LP_LEBENSPHASE_FEIN_attribute_values.Meaning = ['younger', 'middle', 'younger',␣
 ↪'middle', 'advanced',
                                                'retirement', 'advanced',␣
 ↪'retirement', 'middle', 'middle',
                                                'advanced', 'retirement',␣
 ↪'higher', 'younger', 'higher',
                                                'higher', 'middle', 'younger',␣
 ↪'higher', 'higher',
                                                'middle', 'middle', 'middle',␣
 ↪'middle', 'middle',
                                                'middle', 'middle', 'middle',␣
 ↪'younger', 'younger',
```

```
                                                'higher', 'higher', 'younger',␣
 ↪'younger', 'younger',
                                                'higher', 'advanced',␣
 ↪'retirement', 'middle', 'retirement']
LP_LEBENSPHASE_FEIN_attribute_values.Meaning.replace({'younger':1, 'middle':2,␣
 ↪'higher':3, 'advanced':4, 'retirement':5},
                                                    inplace=True
                                                    )
LP_LEBENSPHASE_FEIN_dict = LP_LEBENSPHASE_FEIN_attribute_values.
 ↪set_index('Value')['Meaning'].to_dict()

# Create a new column using above dict
feature_engine.apply_remap('LP_LEBENSPHASE_FEIN_ALTER', 'LP_LEBENSPHASE_FEIN',␣
 ↪LP_LEBENSPHASE_FEIN_dict)
```

[ ]:
```
azdias['LP_LEBENSPHASE_FEIN_ALTER'].unique()
```

[ ]:
```
array([ 2.,  1., nan,  3.,  5.,  4.])
```

[ ]:
```
# Create a dict of encodings using attributes df
lebensphase_einkomnen = ['low', 'low', 'average', 'average', 'low',
                         'low', 'average', 'average', 'average', 'wealthy',
                         'average', 'average', 'top', 'average', 'low',
                         'average', 'average', 'wealthy', 'wealthy', 'top',
                         'low', 'average', 'wealthy', 'low', 'average',
                         'average', 'average', 'top', 'low', 'average',
                         'low', 'average', 'average', 'average', 'top',
                         'average', 'average', 'average', 'top', 'top']
LP_LEBENSPHASE_FEIN_attribute_values.Meaning = lebensphase_einkomnen
LP_LEBENSPHASE_FEIN_attribute_values.Meaning.replace({'low':1, 'average':2,␣
 ↪'wealthy':3, 'top':4}, inplace=True)
LP_LEBENSPHASE_FEIN_einkomnen_dict = LP_LEBENSPHASE_FEIN_attribute_values.
 ↪set_index('Value')['Meaning'].to_dict()

# Create a new column using above encoding dict
feature_engine.apply_remap('LP_LEBENSPHASE_FEIN_EINK', 'LP_LEBENSPHASE_FEIN',␣
 ↪LP_LEBENSPHASE_FEIN_einkomnen_dict)
```

[ ]:
```
azdias['LP_LEBENSPHASE_FEIN_EINK'].unique()
```

[ ]:
```
array([ 1.,  2., nan,  3.,  4.])
```

[ ]:
```
azdias['LP_STATUS_FEIN'].unique()
```

[ ]:
```
array([ 2.,  3.,  9.,  4.,  1., 10.,  5.,  8.,  6.,  7., nan])
```

[ ]:
```
get_attribute_info('WOHNLAGE', attributes)
```

```
[ ]:       Attribute        Description Value                              Meaning  \
     2229  WOHNLAGE  residential-area     -1                              unknown
     2230  WOHNLAGE  residential-area      0                   no score calculated
     2231  WOHNLAGE  residential-area      1               very good neighbourhood
     2232  WOHNLAGE  residential-area      2                    good neighbourhood
     2233  WOHNLAGE  residential-area      3                 average neighbourhood
     2234  WOHNLAGE  residential-area      4                    poor neighbourhood
     2235  WOHNLAGE  residential-area      5               very poor neighbourhood
     2236  WOHNLAGE  residential-area      7                   rural neighbourhood
     2237  WOHNLAGE  residential-area      8  new building in rural neighbourhood

          Missing
     2229    True
     2230   False
     2231   False
     2232   False
     2233   False
     2234   False
     2235   False
     2236   False
     2237   False
```

```
[ ]: azdias['WOHNLAGE'].unique()
```

```
[ ]: array([ 4.,  2.,  7.,  3.,  5.,  1.,  8., nan])
```

```
[ ]: # Create new column indicating rural neighbourhood
     feature_engine.apply_transform('WOHNLAGE_LANDLICH', 'WOHNLAGE', lambda x: 1 if
      ↪((x==7) or (x==8)) else 0)
```

```
[ ]: azdias['WOHNLAGE_LANDLICH'].unique()
```

```
[ ]: array([0, 1], dtype=int64)
```

```
[ ]: # Create new columns based on class of neighbourhood w.r.t. ordinal scale
     feature_engine.apply_remap('WOHNLAGE_KLASSE', 'WOHNLAGE', {5:1, 4:2, 3:3, 2:4,
      ↪1:5, 7:1, 8:2})
     # Create new columns based on type of neighbourhood w.r.t. ordinal scale
     feature_engine.apply_remap('WOHNLAGE_TYP', 'WOHNLAGE', {5:3, 4:4, 3:5, 2:6, 1:
      ↪7, 7:1, 8:2})
```

```
[ ]: azdias.dtypes[azdias.dtypes == object]
```

```
[ ]: CAMEO_DEU_2015              object
     D19_LETZTER_KAUF_BRANCHE    object
     EINGEFUEGT_AM               object
     dtype: object
```

```
[ ]: # Create numerical encodings for D19_LETZTER_KAUF_BRANCHE column
     # sklearn's column transformers and categorical encoder would have also worked
     LETZTER_KAUF_BRANCHE_dict = {v:k for k, v in enumerate([category for category␣
      ↪in list(azdias['D19_LETZTER_KAUF_BRANCHE'].unique()) if␣
      ↪type(category)==str])}

     # Apply encodings
     feature_engine.apply_remap('D19_LETZTER_KAUF_BRANCHE',␣
      ↪'D19_LETZTER_KAUF_BRANCHE', LETZTER_KAUF_BRANCHE_dict)
```

```
[ ]: azdias['D19_LETZTER_KAUF_BRANCHE'].unique()
```

```
[ ]: array([nan,  0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.,  8.,  9., 10., 11.,
            12., 13., 14., 15., 16., 17., 18., 19., 20., 21., 22., 23., 24.,
            25., 26., 27., 28., 29., 30., 31., 32., 33., 34.])
```

```
[ ]: # Create numerical encodings using values in attributes df
     cameo_deu_2015_map = {v:k+1 for k,v in enumerate(attributes[attributes.
      ↪Attribute=='CAMEO_DEU_2015'].Value)}

     # Apply encodings
     feature_engine.apply_remap('CAMEO_DEU_2015', cols_cameo[1], cameo_deu_2015_map)
```

```
[ ]: CAMEO_DEUG_attribute_values = get_attribute_info(cols_cameo[0], attributes).
      ↪copy()
     CAMEO_DEUG_attribute_values
```

```
[ ]:           Attribute                          Description Value  \
     51  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup    -1
     52  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     1
     53  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     2
     54  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     3
     55  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     4
     56  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     5
     57  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     6
     58  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     7
     59  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     8
     60  CAMEO_DEUG_2015  CAMEO classification 2015 - Uppergroup     9

                                Meaning Missing
     51                         unknown    True
     52                     upper class   False
     53               upper middleclass   False
     54        established middleclasse   False
     55  consumption-oriented middleclass    False
     56              active middleclass    False
     57        low-consumption middleclass   False
```

```
58                  lower middleclass   False
59                      working class   False
60                urban working class   False
```

[ ]:
```
azdias[cols_cameo[0]].unique()
```

[ ]:
```
array([ 8.,  4.,  2.,  6.,  1.,  9.,  5.,  7.,  3., nan])
```

[ ]:
```
# Create new columns based on income class w.r.t. ordinal scale
feature_engine.apply_remap(f'{cols_cameo[0]}_KLASSE', cols_cameo[0], {8:1,9:1,7:
 ↪2,6:2,5:2,4:2,3:2,2:2,1:3})
feature_engine.apply_remap(f'{cols_cameo[0]}_TYP', cols_cameo[0], {8:1,9:2,7:
 ↪3,6:4,5:5,4:6,3:7,2:8,1:9})
```

[ ]:
```
# Apply all transformations to customers dataframe
feature_engine.transform(customers)
```

[ ]:
```
# Checking if columns are same
assert(len(set(azdias.columns)-set(customers.columns)) == 0)
assert(len(set(customers.columns)-set(azdias.columns)) == 0)
```

[ ]:
```
# Clearing up memory usage
for i in [LP_FAMILIE_GROB_attribute_values, LP_FAMILIE_FEIN_attribute_values,␣
 ↪LP_STATUS_GROB_attribute_values, LP_LEBENSPHASE_FEIN_attribute_values]:
    i = None
```

[ ]:
```
# Dropping columns that have become redundant after above processing
# LNR represents unique code for each observation & 'EINGEFUEGT_AM' literally␣
 ↪translates to inserted on
azdias.drop(['LNR', 'EINGEFUEGT_AM', 'LP_FAMILIE_FEIN', 'LP_LEBENSPHASE_FEIN',␣
 ↪'CAMEO_INTL_2015'], axis=1, inplace=True)
customers.drop(['LNR', 'EINGEFUEGT_AM', 'LP_FAMILIE_FEIN',␣
 ↪'LP_LEBENSPHASE_FEIN', 'CAMEO_INTL_2015'], axis=1, inplace=True)
```

[ ]:
```
def reduce_mem_usage(df):
    '''Reduce Memory usage of df'''
    int_64_cols = df.select_dtypes(include='int64').columns
    df[int_64_cols] = df[int_64_cols].astype('int32')

    float_64_cols = df.select_dtypes(include='float64').columns
    df[float_64_cols] = df[float_64_cols].astype('float32')
```

[ ]:
```
azdias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 785252 entries, 1 to 891220
Columns: 363 entries, AKT_DAT_KL to CAMEO_DEUG_2015_TYP
```

```
dtypes: float64(276), int64(87)
memory usage: 2.1 GB
```

[ ]:
```
reduce_mem_usage(azdias)
```

[ ]:
```
azdias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 785252 entries, 1 to 891220
Columns: 363 entries, AKT_DAT_KL to CAMEO_DEUG_2015_TYP
dtypes: float32(276), int32(87)
memory usage: 1.1 GB
```

[ ]:
```
customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 140350 entries, 0 to 191651
Columns: 363 entries, AKT_DAT_KL to CAMEO_DEUG_2015_TYP
dtypes: float64(276), int64(87)
memory usage: 389.8 MB
```

[ ]:
```
reduce_mem_usage(customers)
```

[ ]:
```
customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 140350 entries, 0 to 191651
Columns: 363 entries, AKT_DAT_KL to CAMEO_DEUG_2015_TYP
dtypes: float32(276), int32(87)
memory usage: 195.4 MB
```

Checkpoint

[ ]:
```
with open('models/feat_eng.pkl', 'wb') as handle:
    dill.dump(feature_engine, handle)
```

[ ]:
```
azdias.to_pickle('data/azdias_feat_engineered.pkl')
customers.to_pickle('data/customers_feat_engineered.pkl')
```

[ ]:
```
azdias = pd.read_pickle('data/azdias_feat_engineered.pkl')
customers = pd.read_pickle('data/customers_feat_engineered.pkl')
```

1.2 Part 1: Customer Segmentation Report

The main bulk of your analysis will come in this part of the project. Here, you should use unsupervised learning techniques to describe the relationship between the demographics of the company's existing customers and the general population of Germany. By the end of this part, you should be able to describe parts of the general population that are more likely to be part of the mail-order company's main customer base, and which parts of the general population are less so.

Impute missing Values

[ ]:
```
# impute = Imputer(strategy='most_frequent')
imputer = SimpleImputer(strategy='median')
imputer.set_output(transform='pandas')

imputer.fit(azdias)
azdias = imputer.transform(azdias)
customers = imputer.transform(customers)
```

Checkpoint

[ ]:
```
azdias.to_pickle('data/azdias_imputed.pkl')
customers.to_pickle('data/customers_imputed.pkl')
```

[ ]:
```
azdias = pd.read_pickle('data/azdias_imputed.pkl')
customers = pd.read_pickle('data/customers_imputed.pkl')
```

Scale Values before performing dimensional reduction

[ ]:
```
scaler = StandardScaler()

scaler.fit(azdias)
scaler.set_output(transform='pandas')

azdias = pd.DataFrame(scaler.transform(azdias), columns=azdias.columns)

customers = pd.DataFrame(scaler.transform(customers), columns=customers.columns)
```

Checkpoint

[ ]:
```
azdias.to_pickle('data/azdias_scaled.pkl')
customers.to_pickle('data/customers_scaled.pkl')
```

[ ]:
```
azdias = pd.read_pickle('data/azdias_scaled.pkl')
customers = pd.read_pickle('data/customers_scaled.pkl')
```

1.2.1 Perform PCA

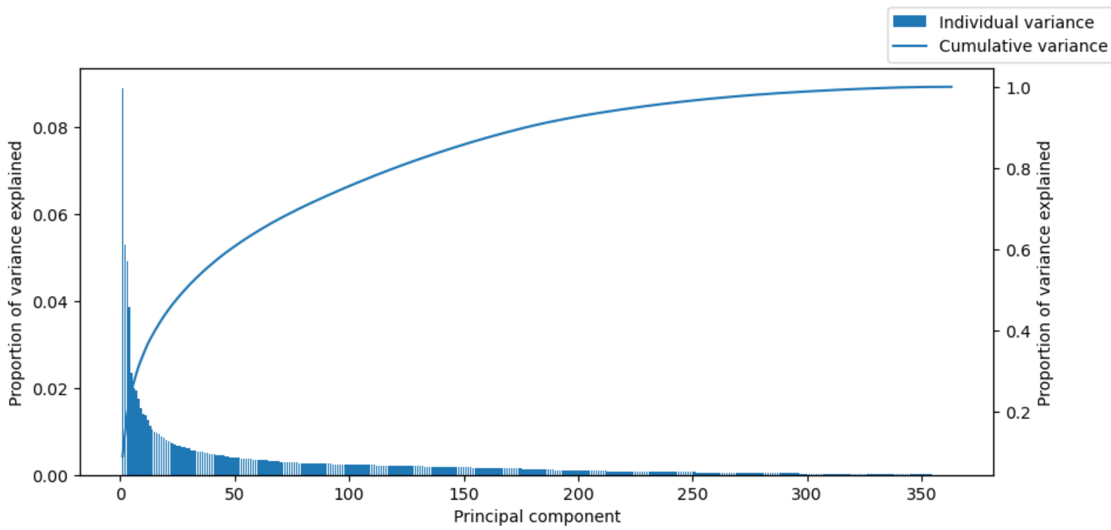
[ ]:
```
pca = PCA(random_state=randomState)
pca.fit(azdias)
```

[ ]:
```
PCA(random_state=42)
```

[ ]:
```
variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(variance)
```

[ ]:
```
# Plot Variance explained by Components
fig, ax1 = plt.subplots(figsize=(10, 5))
ax1.bar(range(1, len(variance)+1), variance, label='Individual variance')
ax1.set_xlabel('Principal component')
```

```
ax1.set_ylabel('Proportion of variance explained')
ax2 = ax1.twinx()
ax2.plot(range(1, len(variance)+1), cumulative_variance, label='Cumulative␣
↪variance')
ax2.set_ylabel('Proportion of variance explained')
fig.legend()
fig.tight_layout(pad=4)
plt.show();
```



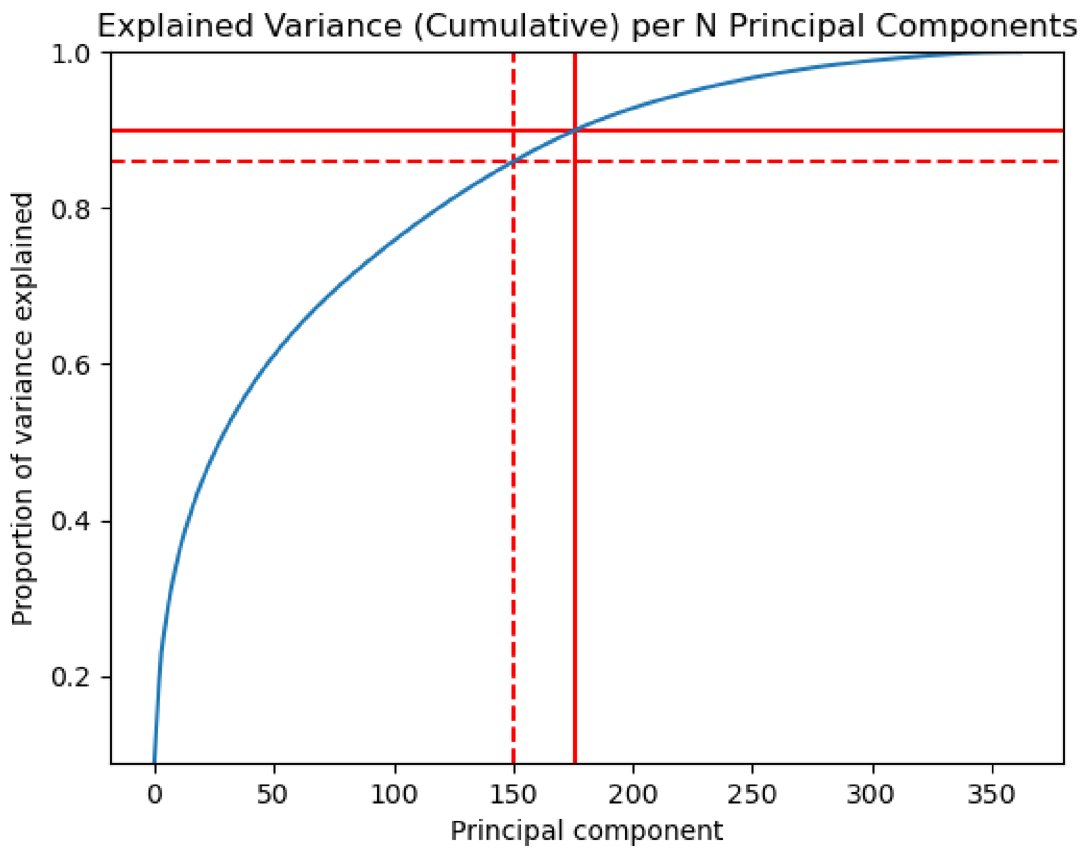
[ ]:
```
# Check thresholds
indices_evr_lt_90 = np.where(cumulative_variance<=0.90)
indices_evr_gt_90 = np.where(cumulative_variance>0.90)
indices_evr_lt_90[0][-1], indices_evr_gt_90[0][0]
```

[ ]: (176, 177)

[ ]:
```
# Plot lines indicating thresholds
plt.ylim(min(cumulative_variance))
plt.axhline(y=0.9, color='r')
plt.axvline(x=176, color='r')

plt.axhline(y=0.86, color='r', linestyle='--')
plt.axvline(x=150, color='r', linestyle='--')

plt.plot(cumulative_variance)
plt.xlabel('Principal component')
plt.ylabel('Proportion of variance explained')
plt.title("Explained Variance (Cumulative) per N Principal Components")
plt.show();
```

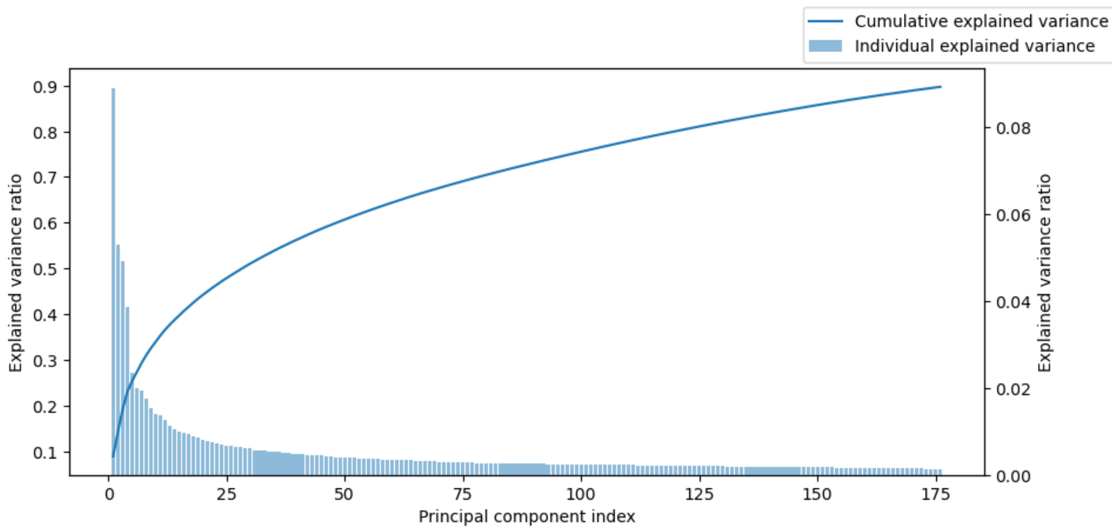


We will perform PCA considering both ~90% & ~85% of variance explained

```
[ ]: # PCA with 176 Components ~ 90% Variance
     pca_176 = PCA(random_state=randomState, n_components=176)
     pca_176.fit(azdias)
     azdias_pca_176 = pca_176.transform(azdias)
     customers_pca_176 = pca_176.transform(customers)
```

Plotting Explained Variance of Components

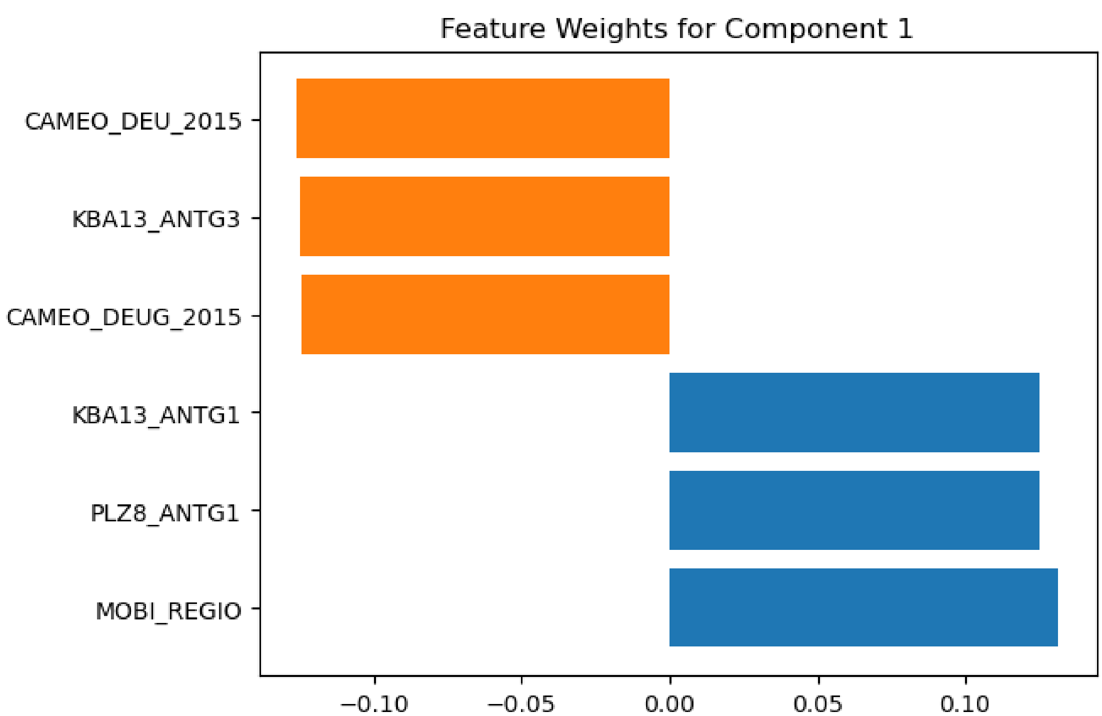
```
[ ]: plot_evr(pca_176)
```

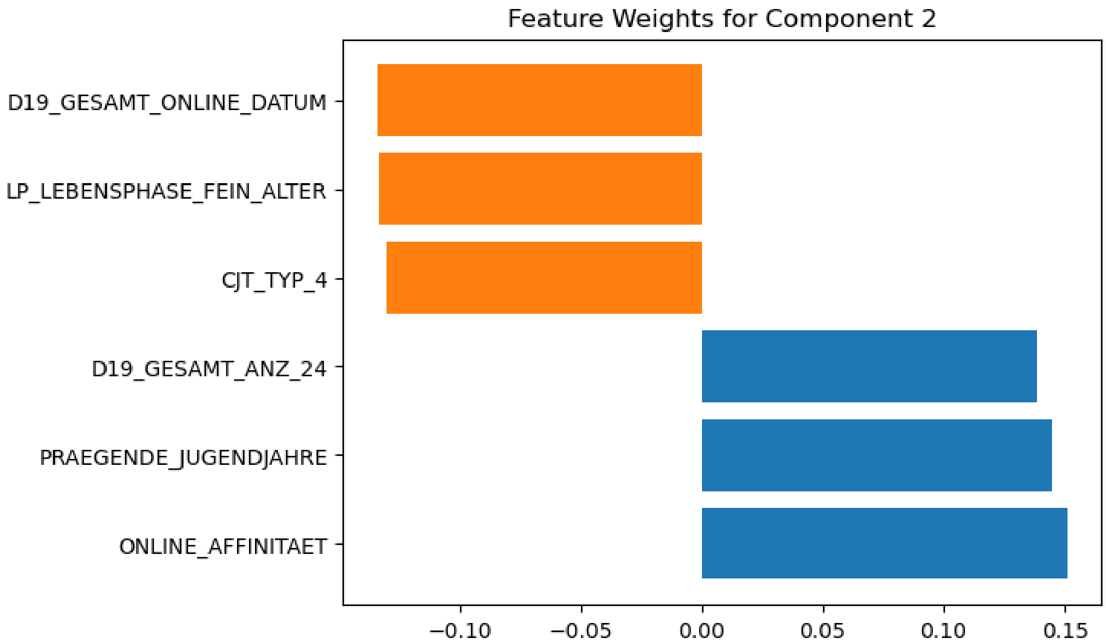


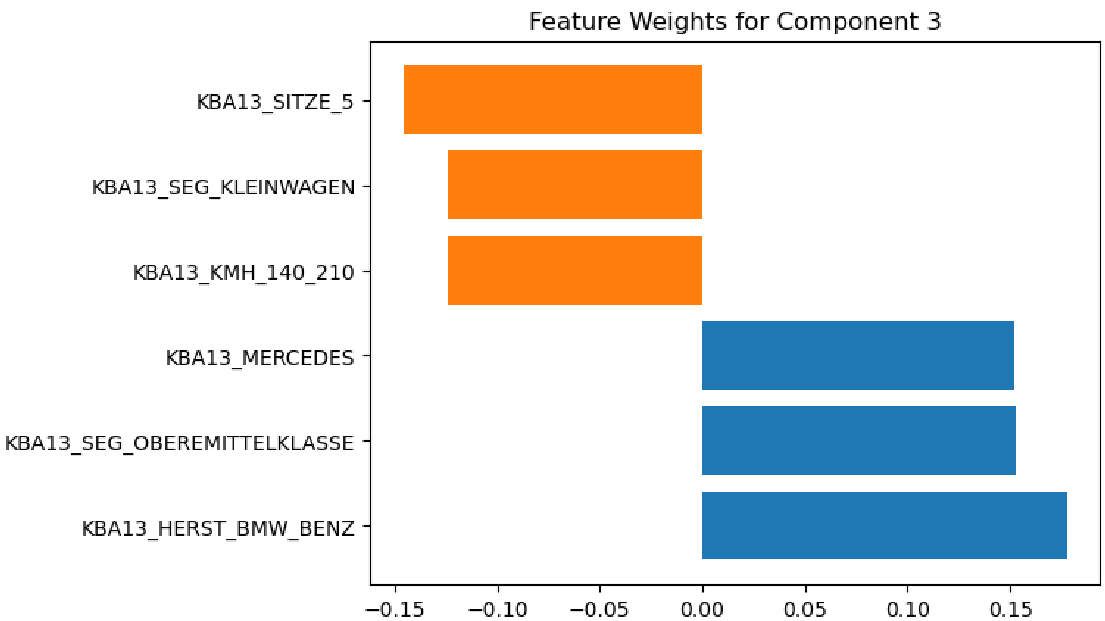
Check Feature Weights of top 4 components

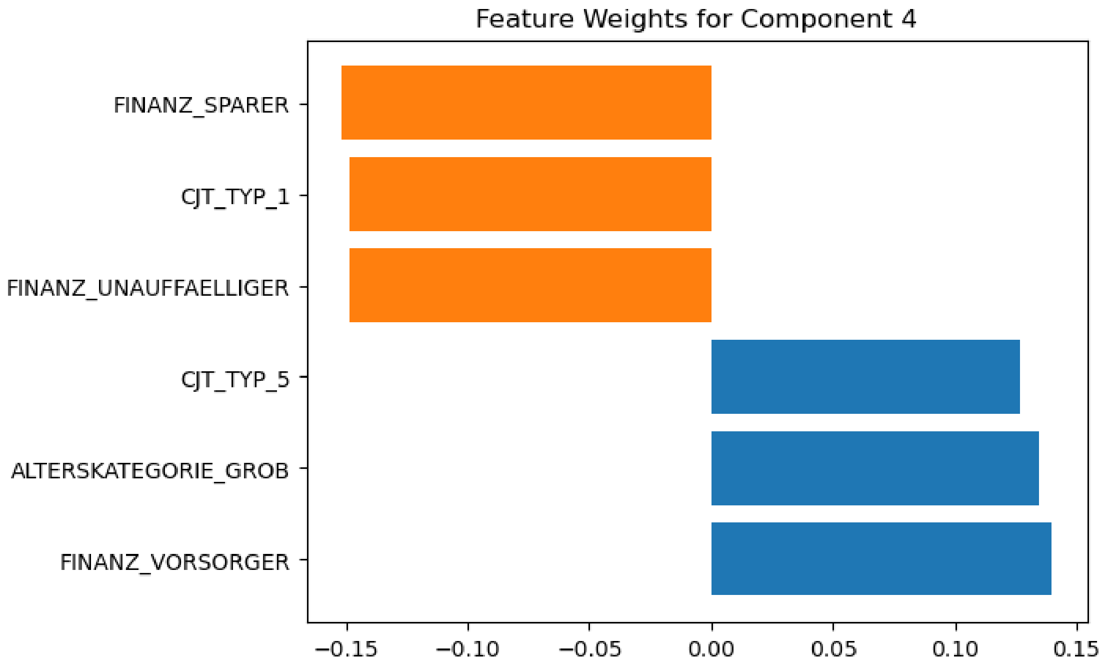
[ ]:
```
top_feature_weights_list = [get_feature_weights(pca_176, azdias, i) for i in␣
↪range(4)]
```

[ ]:
```
for i in range(4):
    feature_weights_i = top_feature_weights_list[i]
    plt.title(f'Feature Weights for Component {i+1}')
    plot_feature_weights(feature_weights_i)
```




Feature Weights for Component 2
D19_GESAMT_ONLINE_DATUM
LP_LEBENSPHASE_FEIN_ALTER
CJT_TYP_4
D19_GESAMT_ANZ_24
PRAEGENDE_JUGENDJAHRE
ONLINE_AFFINITAET
−0.10
−0.05
0.00
0.05
0.10
0.15


Feature Weights for Component 3
KBA13_SITZE_5
KBA13_SEG_KLEINWAGEN
KBA13_KMH_140_210
KBA13_MERCEDES
KBA13_SEG_OBEREMITTELKLASSE
KBA13_HERST_BMW_BENZ
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15

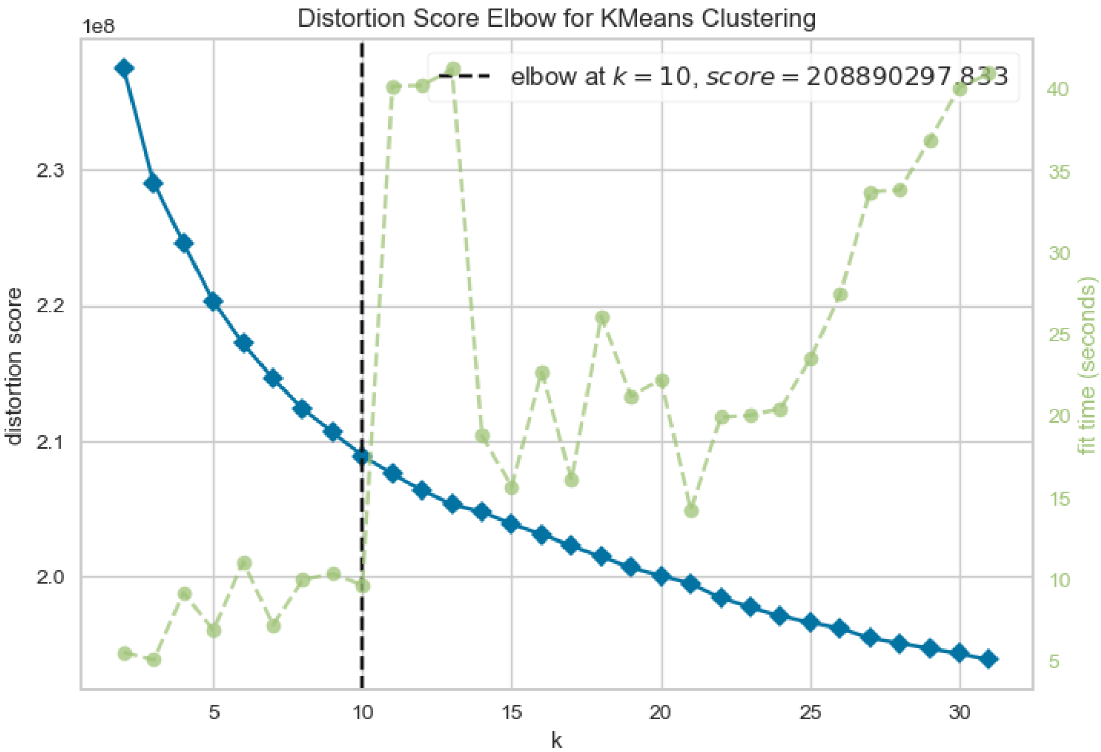


1.2.2 KMeans Clusering

Elbow method to choose optimum number of clusters We will use yellowbrick's KElbowVisualizer to visualize the optimum value

[ ]:
```
from src.modelling import plot_elbow
```

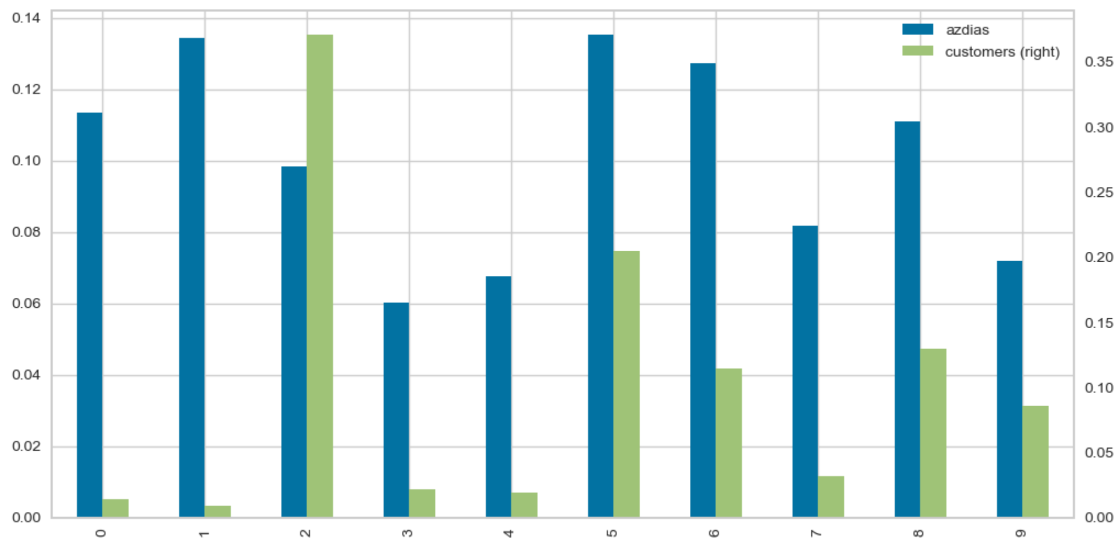
[ ]:
```
plot_elbow(azdias_pca_176)
```



[ ]:
```
# KMeans Clustering for data with 176 dims
kmeans = KMeans(n_clusters=10, random_state=randomState, n_init='auto')
kmeans.fit(azdias_pca_176)
azdias_clusters = kmeans.predict(azdias_pca_176)
customers_clusters = kmeans.predict(customers_pca_176)
```

[ ]:
```
from src.utils import plot_clusters
```

[ ]:
```
# Plot Num of Observations in each Cluster for data with 176 dims
plot_clusters(azdias_clusters, customers_clusters)
```



[ ]:
```
# with open('models/imputer.pkl', 'wb') as imputer_pkl:
#     pickle.dump(imputer, imputer_pkl)

# with open('models/scaler.pkl', 'wb') as scaler_pkl:
#     pickle.dump(scaler, scaler_pkl)

# with open('models/pca_176.pkl', 'wb') as pca_pkl:
#     pickle.dump(pca_176, pca_pkl)

# with open('models/kmeans.pkl', 'wb') as kmeans_pkl:
#     pickle.dump(kmeans, kmeans_pkl)

# with open('metadata/high_cardinality_klasse_type_cols.pkl', 'wb') as cols_pkl:
#     pickle.dump(high_cardinality_klasse_type_cols, cols_pkl)
```

1.3 Part 2: Supervised Learning Model

Now that you've found which parts of the population are more likely to be customers of the mail-order company, it's time to build a prediction model. Each of the rows in the "MAILOUT" data files represents an individual that was targeted for a mailout campaign. Ideally, we should be able to use the demographic information from each individual to decide whether or not it will be worth it to include that person in the campaign.

The "MAILOUT" data has been split into two approximately equal parts, each with almost 43 000 data rows. In this part, you can verify your model with the "TRAIN" partition, which includes a column, "RESPONSE", that states whether or not a person became a customer of the company following the campaign. In the next part, you'll need to create predictions on the "TEST" partition, where the "RESPONSE" column has been withheld.

[ ]:
```
# with open('models/imputer.pkl', 'rb') as imputer_pkl:
#     pickle.load(imputer, imputer_pkl)

# with open('models/scaler.pkl', 'rb') as scaler_pkl:
#     pickle.dump(scaler, scaler_pkl)

# with open('models/pca_176.pkl', 'rb') as pca_pkl:
#     pickle.dump(pca_176, pca_pkl)

# with open('models/kmeans.pkl', 'rb') as kmeans_pkl:
#     pickle.dump(kmeans, kmeans_pkl)

# with open('metadata/high_cardinality_klasse_type_cols.pkl', 'rb') as cols_pkl:
#     pickle.dump(high_cardinality_klasse_type_cols, cols_pkl)
```

[ ]:
```
# with open('models/clean_data.pkl', 'rb') as clean:
#     clean_data = dill.load(clean)
```

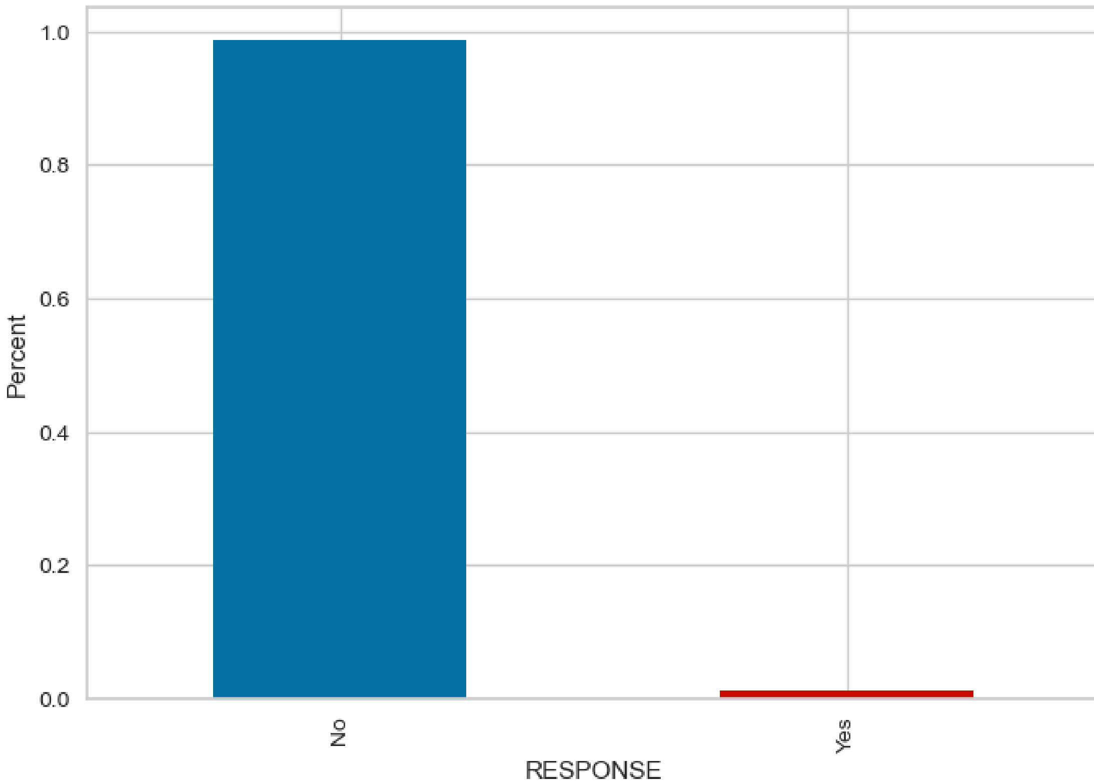
[ ]:
```
# with open('models/feat_eng.pkl', 'rb') as fe:
#     feature_engine = dill.load(fe)
```

1.3.1 Train

[ ]:
```
mailout_train = pd.read_csv('../../data/Term2/capstone/arvato_data/
 ↪Udacity_MAILOUT_052018_TRAIN.csv', sep=';')
```

```
C:\Users\Satya\AppData\Local\Temp\ipykernel_23664\2290286062.py:1: DtypeWarning:
Columns (18,19) have mixed types. Specify dtype option on import or set
low_memory=False.
  mailout_train = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_MAI
LOUT_052018_TRAIN.csv', sep=';')
```

[ ]:
```
response_counts = mailout_train['RESPONSE'].value_counts()/
 ↪len(mailout_train['RESPONSE'])
response_counts.plot.bar(color=['b', 'r'])
plt.xticks(ticks=[0,1], labels=['No', 'Yes'])
plt.xlabel('RESPONSE')
plt.ylabel('Percent')
plt.show();
```




```
[ ]: # Applying All Transformations\Processing applied to Gen Pop & Customers Data
     clean_data.transform(mailout_train)
     mailout_train_clean = mailout_train.copy()
     feature_engine.transform(mailout_train_clean)
```

```
[ ]: # Dropping Columns
     mailout_train_clean.drop(list(get_cols_to_drop(mailout_train_clean, 0.30)),␣
      ↪axis=1, inplace=True)
     mailout_train_clean.drop(['EINGEFUEGT_AM', 'LNR',
                               'CAMEO_INTL_2015', 'LP_FAMILIE_FEIN',␣
      ↪'LP_LEBENSPHASE_FEIN'
                               ], axis=1, inplace=True)
```

```
[ ]: # Creating X, y for modelling
     X_train, y_train = mailout_train_clean.drop('RESPONSE', axis=1),␣
      ↪mailout_train_clean['RESPONSE']

     # Verifying Integrity
     assert(X_train.shape[1] == azdias.shape[1])
```

Some more Feature Engineering

[ ]:
```
# Adding New Features to capture information learn during the Unsupervided␣
↪learning part i.e. Customer Segmentation
# We use the dimensional reduction and KMeans clustering performed on azdias␣
↪dataset to get two new features
X_train_imputed = imputer.transform(X_train)
X_train_imputed_scaled = scaler.transform(X_train_imputed)
X_train_pca_176 = pca_176.transform(X_train_imputed_scaled)
cluster_p176_c10 = kmeans.predict(X_train_pca_176)
X_train_imputed['cluster_p176_c10'] = cluster_p176_c10
```

[ ]:
```
# Creating One Hot Encoding for Certain Columns
ohe_cols =␣
↪list((set(klasse_type_cols)-set(high_cardinality_klasse_type_cols))&set(mailout_train_clean
↪columns))
X_train_ohe = pd.get_dummies(X_train_imputed, columns=ohe_cols)
```

[ ]:
```
# Imports for modelling
from sklearn.metrics import roc_auc_score
from src.modelling import GridSearch_ClassifierCV
```

Creating train dataset & labels that will taken as inputs by classification algorithms

[ ]:
```
# train = X_train_ohe
train = pd.concat([X_train_ohe, X_train_imputed[ohe_cols]], axis=1)

labels = y_train
```

Reduce mem usage

[ ]:
```
azdias = None
customers = None
```

[ ]:
```
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import RandomForestClassifier
```

[ ]:
```
# for hyper parameter for imbalanced dataset
scale_pos_weight = sum(y_train==0)/sum(y_train==1)
scale_pos_weight
```

[ ]:
```
79.75563909774436
```

[ ]:
```
xgb_clf = XGBClassifier(objective='binary:logistic',
                        random_state=randomState
                        )
xgb_param_grid = {
                  'scale_pos_weight': [None, 10, scale_pos_weight],
                  'learning_rate':[0.1,0.01],
```

```
                  'max_depth': [3,12,24]
                 }

xgb_grid = GridSearch_ClassifierCV(xgb_clf, train, labels,
                                   params=xgb_param_grid,
                                   cv=3
                                  )
xgb_grid.best_score_, xgb_grid.best_params_
```

[ ]: (0.764680952419457,
 {'learning_rate': 0.1, 'max_depth': 3, 'scale_pos_weight': None})

[ ]:
```
lgb_clf = LGBMClassifier(objective='binary',
                         random_state=randomState,
                         )

lgb_param_grid = {# 'feature_fraction':[1, 0.9],
                  'boosting_type' : ['gbdt', 'dart'],
                  'max_depth': [50, 100],
                  'is_unbalance' : [True, None]
                 # 'num_leaves':[100, 500]
                 }

lgb_grid = GridSearch_ClassifierCV(lgb_clf, train, labels,
                                   params=lgb_param_grid,
                                   cv=3
                                  )
lgb_grid.best_score_, lgb_grid.best_params_
```

[ ]: (0.7586573733567302,
 {'boosting_type': 'dart', 'is_unbalance': None, 'max_depth': 50})

[ ]:
```
rf_clf = RandomForestClassifier(random_state=randomState
                                )
rf_param_grid = {
                 'max_depth': [10, 50, 90],
                 'n_estimators':[100, 500, 900]
                 }

rf_grid = GridSearch_ClassifierCV(rf_clf, train, labels,
                                  params=rf_param_grid,
                                  cv=3
                                  )
rf_grid.best_score_, rf_grid.best_params_
```

[ ]: (0.6668600760932467, {'max_depth': 10, 'n_estimators': 900})

Algorithms/Techniques to deal with Imbalanced data

[ ]:
```
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
```

[ ]:
```
xgb_imb_clf = XGBClassifier(objective='binary:logistic',
                            random_state=randomState
                            )

xgb_imb_param_grid = {
                      'learning_rate':[0.1,0.01],
                      'max_depth': [3,12,24]
                      }

xgb_imb_clf_pipeline = Pipeline([('smote', SMOTE(random_state=randomState)),
                                 ('classifier', xgb_imb_clf)
                                 ])

xgb_imb_grid = GridSearch_ClassifierCV(xgb_imb_clf_pipeline, train, labels,
                                       params={'classifier__'+k:v for k,v in␣
 ↪xgb_imb_param_grid.items()},
                                       cv=3
                                       )

xgb_imb_grid.best_score_, xgb_imb_grid.best_params_
```

[ ]:
```
(0.7444815808662346,
 {'classifier__learning_rate': 0.01, 'classifier__max_depth': 3})
```

[ ]:
```
lgb_imb_clf = LGBMClassifier(objective='binary',
                        random_state=randomState,
                        )

lgb_imb_param_grid = {
                      'boosting_type' : ['gbdt', 'dart'],
                      'max_depth': [50, 100],
                      }

lgb_imb_clf_pipeline = Pipeline([('smote', SMOTE(random_state=randomState)),
                                 ('classifier', lgb_imb_clf)
                                 ])

lgb_imb_grid = GridSearch_ClassifierCV(lgb_imb_clf_pipeline, train, labels,
                                       params={'classifier__'+k:v for k,v in␣
 ↪lgb_imb_param_grid.items()},
                                       cv=3
                                      )

lgb_imb_grid.best_score_, lgb_imb_grid.best_params_
```

```
[ ]: (0.689834570512831,
      {'classifier__boosting_type': 'gbdt', 'classifier__max_depth': 50})
```

```
[ ]: rf_imb_clf = RandomForestClassifier(random_state=randomState
                                        )
     rf_imb_param_grid = {
                          'max_depth': [50, 90],
                          'n_estimators':[500, 900]
                          }

     rf_imb_clf_pipeline = Pipeline([('smote', SMOTE(random_state=randomState)),
                                     ('classifier', rf_imb_clf)
                                     ])

     rf_imb_grid = GridSearch_ClassifierCV(rf_imb_clf_pipeline, train, labels,
                                           params={'classifier__'+k:v for k,v in␣
      ↪rf_imb_param_grid.items()},
                                           cv=3
                                           )

     rf_imb_grid.best_score_, rf_imb_grid.best_params_
```

```
[ ]: (0.6371978247509427,
      {'classifier__max_depth': 90, 'classifier__n_estimators': 900})
```

Summarise Grid Search Results

```
[ ]: summary_df = pd.DataFrame({'model': ['xgboost', 'lightgbm', 'randomforest',
                                          'xgboost with smote', 'lightgbm with␣
      ↪smote',
                                          'randomforest with smote'
                                          ],
                                'best_params': [xgb_grid.best_params_, lgb_grid.
      ↪best_params_, rf_grid.best_params_,
                                                 xgb_imb_grid.best_params_,␣
      ↪lgb_imb_grid.best_params_,
                                                 rf_imb_grid.best_params_
                                                 ],
                                'score': [xgb_grid.best_score_, lgb_grid.
      ↪best_score_, rf_grid.best_score_,
                                          xgb_imb_grid.best_score_, lgb_imb_grid.
      ↪best_score_,
                                          rf_imb_grid.best_score_
                                          ]
                               })

     with pd.option_context('display.max_colwidth', None):
         display(summary_df)
```

```
                     model  \
0                  xgboost
1                 lightgbm
2             randomforest
3       xgboost with smote
4      lightgbm with smote
5  randomforest with smote

                                                    best_params  \
0    {'learning_rate': 0.1, 'max_depth': 3, 'scale_pos_weight': None}
1    {'boosting_type': 'dart', 'is_unbalance': None, 'max_depth': 50}
2                             {'max_depth': 10, 'n_estimators': 900}
3     {'classifier__learning_rate': 0.01, 'classifier__max_depth': 3}
4  {'classifier__boosting_type': 'gbdt', 'classifier__max_depth': 50}
5      {'classifier__max_depth': 90, 'classifier__n_estimators': 900}

      score
0  0.764681
1  0.758657
2  0.666860
3  0.744482
4  0.689835
5  0.637198
```

Retraining models using best params obtained above on entire dataset

[ ]:
```
model = XGBClassifier(objective='binary:logistic', random_state=randomState,
                      **xgb_grid.best_params_
                      )
model.fit(train, labels)

y_pred_probab = model.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_probab)
```

[ ]: 0.878149592694912

[ ]:
```
light_model = LGBMClassifier(random_state=randomState,
                             objective='binary',
                             **lgb_grid.best_params_
                             )
light_model.fit(train, labels)

y_pred_light_probab = light_model.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_light_probab)
```

[ ]: 0.9301486393334267

[ ]:
```
forest_model = RandomForestClassifier(random_state=randomState,
                                       **rf_grid.best_params_
                                       )
forest_model.fit(train, labels)

y_pred_forest_probab = forest_model.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_forest_probab)
```

[ ]: 0.955797009315653

[ ]:
```
# Synthetic Minority Oversampling Technique
sm = SMOTE(random_state=randomState)
train_resampled, labels_resampled = sm.fit_resample(train, labels)
```

[ ]:
```
model_imb = XGBClassifier(objective='binary:logistic',
                          random_state=randomState,
                         **{k.split('__')[1]:v for k,v in xgb_imb_grid.
 ↪best_params_.items()}
                       )
model_imb.fit(train_resampled, labels_resampled)

y_pred_imb_probab = model_imb.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_imb_probab)
```

[ ]: 0.7695094662770525

[ ]:
```
light_imb_model = LGBMClassifier(random_state=randomState,
                                 objective='binary',
                                 **{k.split('__')[1]: v for k, v in␣
 ↪lgb_imb_grid.best_params_.items()}
                                 )
light_imb_model.fit(train_resampled, labels_resampled)

y_pred_imb_light_probab = light_imb_model.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_imb_light_probab)
```

[ ]: 0.8973981249966774

[ ]:
```
forest_imb_model = RandomForestClassifier(random_state=randomState,
                                          **{k.split('__')[1]: v for k, v in␣
 ↪rf_imb_grid.best_params_.items()}
                                          )
forest_imb_model.fit(train_resampled, labels_resampled)

y_pred_imb_forest_probab = forest_imb_model.predict_proba(train)[:, 1]
roc_auc_score(y_train, y_pred_imb_forest_probab)
```

[ ]: 0.9919829697387472

Summarise Evaluation Scores on training data

[ ]:
```
results_df = pd.DataFrame({'model': ['xgboost', 'lightgbm', 'randomforest',
                                     'xgboost with smote', 'lightgbm with␣
 ↪smote',
                                     'randomforest with smote'
                                     ],
                           'training score': [roc_auc_score(y_train,␣
 ↪y_pred_probab),
                                              roc_auc_score(y_train,␣
 ↪y_pred_light_probab),
                                              roc_auc_score(y_train,␣
 ↪y_pred_forest_probab),
                                              roc_auc_score(y_train,␣
 ↪y_pred_imb_probab),
                                              roc_auc_score(y_train,␣
 ↪y_pred_imb_light_probab),
                                              roc_auc_score(y_train,␣
 ↪y_pred_imb_forest_probab)
                                              ]
                           })
results_df
```

[ ]:

	model	training score
0	xgboost	0.878150
1	lightgbm	0.930149
2	randomforest	0.955797
3	xgboost with smote	0.769509
4	lightgbm with smote	0.897398
5	randomforest with smote	0.991983

[ ]:
```
# save models
with open('models/xgb.pkl', 'wb') as model_file:
    pickle.dump(model, model_file)
with open('models/lgb.pkl', 'wb') as model_file:
    pickle.dump(light_model, model_file)
with open('models/rf.pkl', 'wb') as model_file:
    pickle.dump(forest_model, model_file)
with open('models/xgb_smote.pkl', 'wb') as model_file:
    pickle.dump(model_imb, model_file)
with open('models/lgb_smote.pkl', 'wb') as model_file:
    pickle.dump(light_imb_model, model_file)
with open('models/rf_smote.pkl', 'wb') as model_file:
    pickle.dump(forest_imb_model, model_file)
```

1.3.2 TEST

[ ]:
```
mailout_test = pd.read_csv('../../data/Term2/capstone/arvato_data/
↪Udacity_MAILOUT_052018_TEST.csv', sep=';')
```

```
C:\Users\Satya\AppData\Local\Temp\ipykernel_23664\440238055.py:1: DtypeWarning:
Columns (18,19) have mixed types. Specify dtype option on import or set
low_memory=False.
  mailout_test = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_MAIL
OUT_052018_TEST.csv', sep=';')
```

[ ]:
```
# Applying All Transformations\Processing applied to Gen Pop & Customers Data
clean_data.transform(mailout_test)
mailout_test_clean = mailout_test.copy()
feature_engine.transform(mailout_test_clean)
```

[ ]:
```
# Dropping Columns
mailout_test_clean.drop(get_cols_to_drop(mailout_test_clean, 0.3), axis=1,␣
↪inplace=True)
mailout_test_clean.drop(['EINGEFUEGT_AM',
                         'CAMEO_INTL_2015', 'LP_FAMILIE_FEIN',␣
↪'LP_LEBENSPHASE_FEIN'
                         ],
                         axis=1, inplace=True
                         )
```

[ ]:
```
# Dropping ID column
X_test = mailout_test_clean.drop('LNR', axis=1)
```

[ ]:
```
# Adding Features created from information extracted by KMeans model
X_test_imputed = imputer.transform(X_test)
X_test_imputed_scaled = scaler.transform(X_test_imputed)
X_test_pca_176 = pca_176.transform(X_test_imputed_scaled)
test_cluster_p176_c10 = kmeans.predict(X_test_pca_176)
X_test_imputed['cluster_p176_c10'] = test_cluster_p176_c10

# Creating OHE cols
X_test_ohe = pd.get_dummies(X_test_imputed, columns=ohe_cols)
```

[ ]:
```
# Creating test dataset for prediction

# test = X_test_ohe
test = pd.concat([X_test_ohe, X_test_imputed[ohe_cols]], axis=1)
```

Make Predictions

[ ]:
```
y_test = model.predict_proba(test)
y_test_light = light_model.predict_proba(test)
y_test_forest = forest_model.predict_proba(test)
```

```
y_test_imb = model_imb.predict_proba(test)
y_test_imb_light = light_imb_model.predict_proba(test)
y_test_imb_forest = forest_imb_model.predict_proba(test)
```

Submission

[ ]:
```
def create_submission(response_vals, submission_file='',␣
↪index_vals=mailout_test_clean.LNR):
    '''Creat Kaggle Submission CSV'''
    submission = pd.DataFrame({'LNR': index_vals, 'RESPONSE': response_vals})
    assert len(submission) == 42833
    submission.to_csv(f'results/arvato_kaggle_submission{submission_file}.csv',␣
↪index=False)
```

[ ]:
```
create_submission(y_test[:, 1], '_xgb')
create_submission(y_test_light[:, 1], '_light')
create_submission(y_test_forest[:, 1], '_forest')

create_submission(y_test_imb[:, 1], '_xgb_imb')
create_submission(y_test_imb_light[:, 1], '_light_imb')
create_submission(y_test_imb_forest[:, 1], '_forest_imb')
```

[ ]:
```

```