Identify_Customer_Segments (full)

January 29, 2026

0.0.1 Prerequsite - Upgrade Scikit Learn

The current workspace has scikit-learn v0.19.1 installed. However, you can upgrade scikit-learn to 0.24.x. and use this OneHotEncoder library.

[65]:
```
import sklearn
print('The scikit-learn version is {}.'.format(sklearn.__version__))
```

```
The scikit-learn version is 1.6.1.
```

[66]:
```
import os
os.environ['PATH'] = f"{os.environ['PATH']}:/root/.local/bin"
```

[67]:
```
# Restart the Kernel.
#from IPython.display import display, Javascript

#def restart_kernel():
#    display(Javascript('IPython.notebook.kernel.restart()'))

#restart_kernel()
```

[ ]:
```

```

[68]:
```
"""
!python -m pip install --upgrade scikit-learn
import sklearn
import os
print('The scikit-learn version is {}.'.format(sklearn.__version__))

!pip install --upgrade pandas
import pandas as pd
print(pd.__version__)

!pip install --upgrade numpy
import numpy as np
print(np.__version__)

# Update visualization libraries
!pip install --upgrade matplotlib
```

```
!pip install --upgrade seaborn
!pip install --upgrade plotly
!pip install --upgrade missingno

# Similarly, should you need any other package, they can install it as:
!python -m pip install 'tensorflow-tensorboard<0.2.0,>=0.1.0'
"""
```

[68]:

```
"\n!python -m pip install --upgrade scikit-learn\nimport sklearn\nimport
os\nprint('The scikit-learn version is {}.'.format(sklearn.__version__))\n\n!pip
install --upgrade pandas\nimport pandas as pd\nprint(pd.__version__)\n\n!pip
install --upgrade numpy\nimport numpy as np\nprint(np.__version__)\n\n# Update
visualization libraries\n!pip install --upgrade matplotlib\n!pip install
--upgrade seaborn\n!pip install --upgrade plotly\n!pip install --upgrade
missingno\n\n# Similarly, should you need any other package, they can install it
as:\n!python -m pip install 'tensorflow-tensorboard<0.2.0,>=0.1.0'\n"
```

[69]:

```
# Now you can import and use OneHotEncoder

# your code goes here
from sklearn.preprocessing import OneHotEncoder

#encoder = OneHotEncoder(sparse=False)
```

1 Project: Identify Customer Segments

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

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

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

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

[71]:
```
# import libraries here; add more as necessary
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# magic word for producing visualizations in notebook
%matplotlib inline

'''
Import note: The classroom currently uses sklearn version 0.19.
If you need to use an imputer, it is available in sklearn.preprocessing.Imputer,
instead of sklearn.impute as in newer versions of sklearn.
'''
#pd.options.display.max_rows = None
#pd.options.display.max_columns = None
```

[71]:
```
'\nImport note: The classroom currently uses sklearn version 0.19.\nIf you need
to use an imputer, it is available in sklearn.preprocessing.Imputer,\ninstead of
sklearn.impute as in newer versions of sklearn.\n'
```

1.0.1 Step 0: Load the Data

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

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

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

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

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

[73]:
```
# Load in the general demographics data.

all_data = pd.read_csv('Udacity_AZDIAS_Subset.csv', sep = ";")

# Load in the feature summary file.
summary_data = pd.read_csv('AZDIAS_Feature_Summary.csv', sep =";")
```

[74]:
```
display(summary_data.head())
display(all_data.head())
```

```
              attribute information_level         type missing_or_unknown
0              AGER_TYP            person  categorical             [-1,0]
1  ALTERSKATEGORIE_GROB            person      ordinal           [-1,0,9]
2             ANREDE_KZ            person  categorical             [-1,0]
3         CJT_GESAMTTYP            person  categorical                [0]
4     FINANZ_MINIMALIST            person      ordinal               [-1]

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

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

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

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

```
2         1.0          0.0          1.0        4.0        4.0       3.0
3         2.0          0.0          1.0        3.0        4.0       2.0
4         2.0          1.0          2.0        3.0        3.0       4.0

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

[5 rows x 85 columns]
```

[75]:

```python
# Check the structure of the data after it's loaded (e.g. print the number of
# rows and columns, print the first few rows).
print("All demographics data shape is:", all_data.shape)
print("Feature summary data shape is:", summary_data.shape)
print("\n")

all_data.info()
print("\n")
summary_data.info()
```

```
All demographics data shape is: (891221, 85)
Feature summary data shape is: (85, 4)


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891221 entries, 0 to 891220
Data columns (total 85 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   AGER_TYP               891221 non-null  int64
 1   ALTERSKATEGORIE_GROB   891221 non-null  int64
 2   ANREDE_KZ              891221 non-null  int64
 3   CJT_GESAMTTYP          886367 non-null  float64
 4   FINANZ_MINIMALIST      891221 non-null  int64
 5   FINANZ_SPARER          891221 non-null  int64
 6   FINANZ_VORSORGER       891221 non-null  int64
 7   FINANZ_ANLEGER         891221 non-null  int64
 8   FINANZ_UNAUFFAELLIGER  891221 non-null  int64
 9   FINANZ_HAUSBAUER       891221 non-null  int64
 10  FINANZTYP              891221 non-null  int64
 11  GEBURTSJAHR            891221 non-null  int64
 12  GFK_URLAUBERTYP        886367 non-null  float64
 13  GREEN_AVANTGARDE       891221 non-null  int64
 14  HEALTH_TYP             891221 non-null  int64
 15  LP_LEBENSPHASE_FEIN    886367 non-null  float64
```

```
16  LP_LEBENSPHASE_GROB    886367 non-null  float64
17  LP_FAMILIE_FEIN        886367 non-null  float64
18  LP_FAMILIE_GROB        886367 non-null  float64
19  LP_STATUS_FEIN         886367 non-null  float64
20  LP_STATUS_GROB         886367 non-null  float64
21  NATIONALITAET_KZ       891221 non-null  int64
22  PRAEGENDE_JUGENDJAHRE  891221 non-null  int64
23  RETOURTYP_BK_S         886367 non-null  float64
24  SEMIO_SOZ              891221 non-null  int64
25  SEMIO_FAM              891221 non-null  int64
26  SEMIO_REL              891221 non-null  int64
27  SEMIO_MAT              891221 non-null  int64
28  SEMIO_VERT             891221 non-null  int64
29  SEMIO_LUST             891221 non-null  int64
30  SEMIO_ERL              891221 non-null  int64
31  SEMIO_KULT             891221 non-null  int64
32  SEMIO_RAT              891221 non-null  int64
33  SEMIO_KRIT             891221 non-null  int64
34  SEMIO_DOM              891221 non-null  int64
35  SEMIO_KAEM             891221 non-null  int64
36  SEMIO_PFLICHT          891221 non-null  int64
37  SEMIO_TRADV            891221 non-null  int64
38  SHOPPER_TYP            891221 non-null  int64
39  SOHO_KZ                817722 non-null  float64
40  TITEL_KZ               817722 non-null  float64
41  VERS_TYP               891221 non-null  int64
42  ZABEOTYP               891221 non-null  int64
43  ALTER_HH               817722 non-null  float64
44  ANZ_PERSONEN           817722 non-null  float64
45  ANZ_TITEL              817722 non-null  float64
46  HH_EINKOMMEN_SCORE     872873 non-null  float64
47  KK_KUNDENTYP           306609 non-null  float64
48  W_KEIT_KIND_HH         783619 non-null  float64
49  WOHNDAUER_2008         817722 non-null  float64
50  ANZ_HAUSHALTE_AKTIV    798073 non-null  float64
51  ANZ_HH_TITEL           794213 non-null  float64
52  GEBAEUDETYP            798073 non-null  float64
53  KONSUMNAEHE            817252 non-null  float64
54  MIN_GEBAEUDEJAHR       798073 non-null  float64
55  OST_WEST_KZ            798073 non-null  object
56  WOHNLAGE               798073 non-null  float64
57  CAMEO_DEUG_2015        792242 non-null  object
58  CAMEO_DEU_2015         792242 non-null  object
59  CAMEO_INTL_2015        792242 non-null  object
60  KBA05_ANTG1            757897 non-null  float64
61  KBA05_ANTG2            757897 non-null  float64
62  KBA05_ANTG3            757897 non-null  float64
63  KBA05_ANTG4            757897 non-null  float64
```

```
 64  KBA05_BAUMAX          757897 non-null  float64
 65  KBA05_GBZ             757897 non-null  float64
 66  BALLRAUM              797481 non-null  float64
 67  EWDICHTE              797481 non-null  float64
 68  INNENSTADT            797481 non-null  float64
 69  GEBAEUDETYP_RASTER    798066 non-null  float64
 70  KKK                   770025 non-null  float64
 71  MOBI_REGIO            757897 non-null  float64
 72  ONLINE_AFFINITAET     886367 non-null  float64
 73  REGIOTYP              770025 non-null  float64
 74  KBA13_ANZAHL_PKW      785421 non-null  float64
 75  PLZ8_ANTG1            774706 non-null  float64
 76  PLZ8_ANTG2            774706 non-null  float64
 77  PLZ8_ANTG3            774706 non-null  float64
 78  PLZ8_ANTG4            774706 non-null  float64
 79  PLZ8_BAUMAX           774706 non-null  float64
 80  PLZ8_HHZ              774706 non-null  float64
 81  PLZ8_GBZ              774706 non-null  float64
 82  ARBEIT                794005 non-null  float64
 83  ORTSGR_KLS9           794005 non-null  float64
 84  RELAT_AB              794005 non-null  float64
dtypes: float64(49), int64(32), object(4)
memory usage: 578.0+ MB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85 entries, 0 to 84
Data columns (total 4 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   attribute           85 non-null     object
 1   information_level   85 non-null     object
 2   type                85 non-null     object
 3   missing_or_unknown  85 non-null     object
dtypes: object(4)
memory usage: 2.8+ KB
```

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

1.1 Step 1: Preprocessing

1.1.1 Step 1.1: Assess Missing Data

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

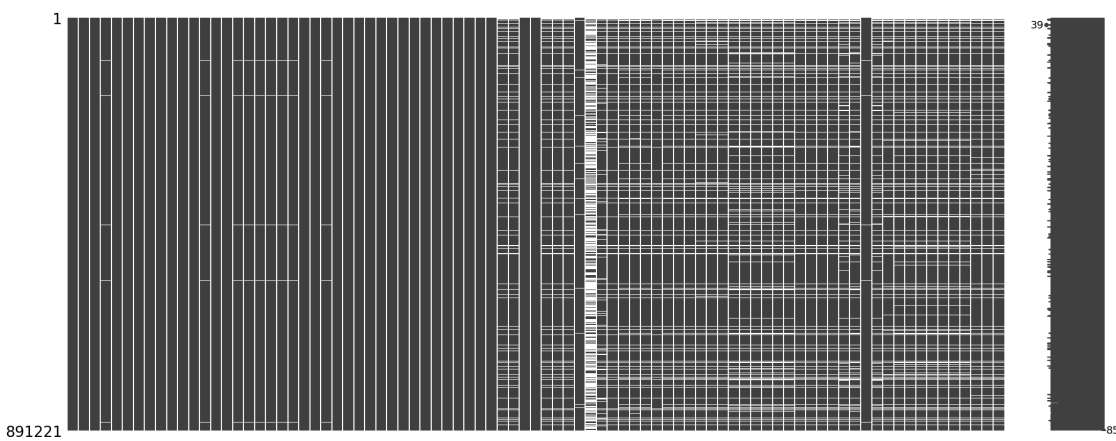
Step 1.1.1: Convert Missing Value Codes to NaNs The fourth column of the feature attributes summary (loaded in above as `feat_info`) documents the codes from the data dictionary that indicate missing or unknown data. While the file encodes this as a list (e.g. `[-1,0]`), this will get read in as a string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

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

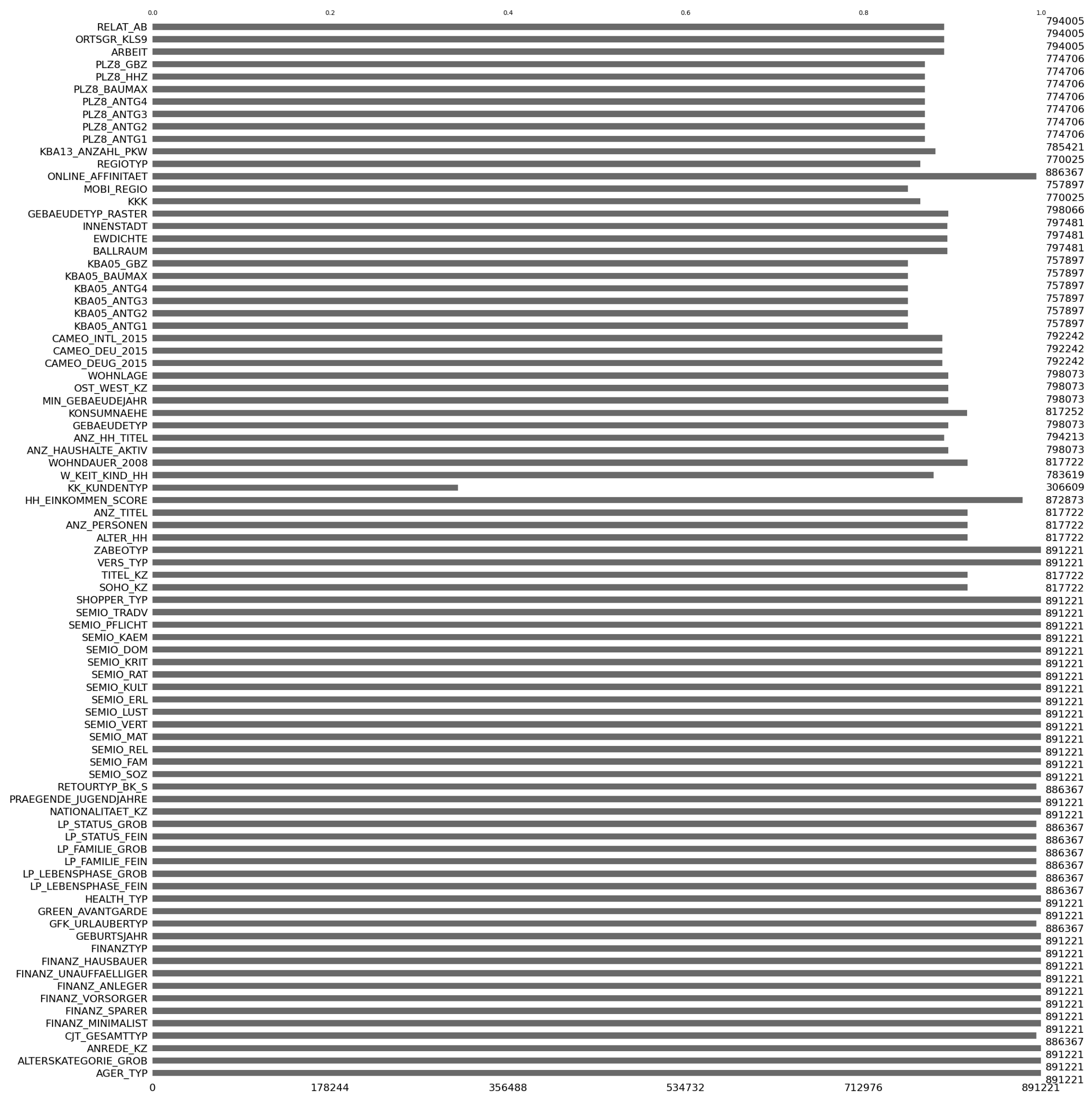
[77]:
```
import missingno as msno
import matplotlib.pyplot as plt
```

[78]:
```
# Visualize missing data

plt.figure(figsize=(10,20))
msno.matrix(all_data)
plt.show()

plt.figure(figsize=(10,200))
msno.bar(all_data)
```

<Figure size 1000x2000 with 0 Axes>



[78]: <Axes: >



[79]:
```
# Identify missing or unknown data values and convert them to NaNs.



print("Missing values report for all demographics file: \n")
miss_count = all_data.isnull().sum()
total_miss_count = all_data.isna().sum().sum()
print(f"Total missing values for demographics = {total_miss_count} =␣
 ↪{total_miss_count/(all_data.shape[0]*all_data.shape[1]):.2f}% of total␣
 ↪values")
print(miss_count)
```

```
Missing values report for all demographics file:
```

```
Total missing values for demographics = 4896838 = 0.06% of total values
AGER_TYP                    0
ALTERSKATEGORIE_GROB        0
ANREDE_KZ                   0
CJT_GESAMTTYP            4854
FINANZ_MINIMALIST           0
                        …
PLZ8_HHZ               116515
PLZ8_GBZ               116515
ARBEIT                  97216
ORTSGR_KLS9             97216
RELAT_AB                97216
Length: 85, dtype: int64
```

[80]:

```python
#Here we exctract the list of all the missing and uknown codes

import ast


def try_convert(value):
    """Convert string values to numbers if they represent a number."""
    try:
        return int(value) if '.' not in value else float(value)
    except ValueError:
        return value  # If it's not a number, return as string


def try_eval(value):
    try:
        return ast.literal_eval(value)
    except (ValueError, SyntaxError):
        # If it's not a valid literal, check if it looks like a list
        if isinstance(value, str) and value.startswith('[') and value.
 ↪endswith(']'):
            # Remove the brackets and split by comma, then return as a list
            cleaned_value = value[1:-1]  # Remove leading '[' and trailing ']'
            return [try_convert(item.strip()) for item in cleaned_value.
 ↪split(',')]  # Split by comma and strip spaces


last_column_as_list = summary_data['missing_or_unknown'].apply(try_eval)
print(last_column_as_list, "\n")

for index, element in enumerate(last_column_as_list):
    print(f"Element at index {index}: {element} - Type: {type(element)}")
```

```
0        [-1, 0]
1     [-1, 0, 9]
```

```
2        [-1, 0]
3            [0]
4           [-1]
         …
80          [-1]
81          [-1]
82       [-1, 9]
83       [-1, 0]
84       [-1, 9]
Name: missing_or_unknown, Length: 85, dtype: object

Element at index 0: [-1, 0] - Type: <class 'list'>
Element at index 1: [-1, 0, 9] - Type: <class 'list'>
Element at index 2: [-1, 0] - Type: <class 'list'>
Element at index 3: [0] - Type: <class 'list'>
Element at index 4: [-1] - Type: <class 'list'>
Element at index 5: [-1] - Type: <class 'list'>
Element at index 6: [-1] - Type: <class 'list'>
Element at index 7: [-1] - Type: <class 'list'>
Element at index 8: [-1] - Type: <class 'list'>
Element at index 9: [-1] - Type: <class 'list'>
Element at index 10: [-1] - Type: <class 'list'>
Element at index 11: [0] - Type: <class 'list'>
Element at index 12: [] - Type: <class 'list'>
Element at index 13: [] - Type: <class 'list'>
Element at index 14: [-1, 0] - Type: <class 'list'>
Element at index 15: [0] - Type: <class 'list'>
Element at index 16: [0] - Type: <class 'list'>
Element at index 17: [0] - Type: <class 'list'>
Element at index 18: [0] - Type: <class 'list'>
Element at index 19: [0] - Type: <class 'list'>
Element at index 20: [0] - Type: <class 'list'>
Element at index 21: [-1, 0] - Type: <class 'list'>
Element at index 22: [-1, 0] - Type: <class 'list'>
Element at index 23: [0] - Type: <class 'list'>
Element at index 24: [-1, 9] - Type: <class 'list'>
Element at index 25: [-1, 9] - Type: <class 'list'>
Element at index 26: [-1, 9] - Type: <class 'list'>
Element at index 27: [-1, 9] - Type: <class 'list'>
Element at index 28: [-1, 9] - Type: <class 'list'>
Element at index 29: [-1, 9] - Type: <class 'list'>
Element at index 30: [-1, 9] - Type: <class 'list'>
Element at index 31: [-1, 9] - Type: <class 'list'>
Element at index 32: [-1, 9] - Type: <class 'list'>
Element at index 33: [-1, 9] - Type: <class 'list'>
Element at index 34: [-1, 9] - Type: <class 'list'>
Element at index 35: [-1, 9] - Type: <class 'list'>
Element at index 36: [-1, 9] - Type: <class 'list'>
```

```
Element at index 37: [-1, 9] - Type: <class 'list'>
Element at index 38: [-1] - Type: <class 'list'>
Element at index 39: [-1] - Type: <class 'list'>
Element at index 40: [-1, 0] - Type: <class 'list'>
Element at index 41: [-1] - Type: <class 'list'>
Element at index 42: [-1, 9] - Type: <class 'list'>
Element at index 43: [0] - Type: <class 'list'>
Element at index 44: [] - Type: <class 'list'>
Element at index 45: [] - Type: <class 'list'>
Element at index 46: [-1, 0] - Type: <class 'list'>
Element at index 47: [-1] - Type: <class 'list'>
Element at index 48: [-1, 0] - Type: <class 'list'>
Element at index 49: [-1, 0] - Type: <class 'list'>
Element at index 50: [0] - Type: <class 'list'>
Element at index 51: [] - Type: <class 'list'>
Element at index 52: [-1, 0] - Type: <class 'list'>
Element at index 53: [] - Type: <class 'list'>
Element at index 54: [0] - Type: <class 'list'>
Element at index 55: [-1] - Type: <class 'list'>
Element at index 56: [-1] - Type: <class 'list'>
Element at index 57: [-1, 'X'] - Type: <class 'list'>
Element at index 58: ['XX'] - Type: <class 'list'>
Element at index 59: [-1, 'XX'] - Type: <class 'list'>
Element at index 60: [-1] - Type: <class 'list'>
Element at index 61: [-1] - Type: <class 'list'>
Element at index 62: [-1] - Type: <class 'list'>
Element at index 63: [-1] - Type: <class 'list'>
Element at index 64: [-1, 0] - Type: <class 'list'>
Element at index 65: [-1, 0] - Type: <class 'list'>
Element at index 66: [-1] - Type: <class 'list'>
Element at index 67: [-1] - Type: <class 'list'>
Element at index 68: [-1] - Type: <class 'list'>
Element at index 69: [] - Type: <class 'list'>
Element at index 70: [-1, 0] - Type: <class 'list'>
Element at index 71: [] - Type: <class 'list'>
Element at index 72: [] - Type: <class 'list'>
Element at index 73: [-1, 0] - Type: <class 'list'>
Element at index 74: [] - Type: <class 'list'>
Element at index 75: [-1] - Type: <class 'list'>
Element at index 76: [-1] - Type: <class 'list'>
Element at index 77: [-1] - Type: <class 'list'>
Element at index 78: [-1] - Type: <class 'list'>
Element at index 79: [-1, 0] - Type: <class 'list'>
Element at index 80: [-1] - Type: <class 'list'>
Element at index 81: [-1] - Type: <class 'list'>
Element at index 82: [-1, 9] - Type: <class 'list'>
Element at index 83: [-1, 0] - Type: <class 'list'>
Element at index 84: [-1, 9] - Type: <class 'list'>
```

[81]:
```python
#Here we Replace the missing or unknown values with NANs.

keys = summary_data['attribute']  # First column (keys)
values = last_column_as_list         # List of values


# Create the dictionary using zip to pair the keys with values
feature_dict = dict(zip(keys, values))

# Check the dictionary
print(feature_dict,"\n")

all_data2 = all_data.replace(feature_dict, np.nan)
```

```
{'AGER_TYP': [-1, 0], 'ALTERSKATEGORIE_GROB': [-1, 0, 9], 'ANREDE_KZ': [-1, 0],
'CJT_GESAMTTYP': [0], 'FINANZ_MINIMALIST': [-1], 'FINANZ_SPARER': [-1],
'FINANZ_VORSORGER': [-1], 'FINANZ_ANLEGER': [-1], 'FINANZ_UNAUFFAELLIGER': [-1],
'FINANZ_HAUSBAUER': [-1], 'FINANZTYP': [-1], 'GEBURTSJAHR': [0],
'GFK_URLAUBERTYP': [], 'GREEN_AVANTGARDE': [], 'HEALTH_TYP': [-1, 0],
'LP_LEBENSPHASE_FEIN': [0], 'LP_LEBENSPHASE_GROB': [0], 'LP_FAMILIE_FEIN': [0],
'LP_FAMILIE_GROB': [0], 'LP_STATUS_FEIN': [0], 'LP_STATUS_GROB': [0],
'NATIONALITAET_KZ': [-1, 0], 'PRAEGENDE_JUGENDJAHRE': [-1, 0], 'RETOURTYP_BK_S':
[0], 'SEMIO_SOZ': [-1, 9], 'SEMIO_FAM': [-1, 9], 'SEMIO_REL': [-1, 9],
'SEMIO_MAT': [-1, 9], 'SEMIO_VERT': [-1, 9], 'SEMIO_LUST': [-1, 9], 'SEMIO_ERL':
[-1, 9], 'SEMIO_KULT': [-1, 9], 'SEMIO_RAT': [-1, 9], 'SEMIO_KRIT': [-1, 9],
'SEMIO_DOM': [-1, 9], 'SEMIO_KAEM': [-1, 9], 'SEMIO_PFLICHT': [-1, 9],
'SEMIO_TRADV': [-1, 9], 'SHOPPER_TYP': [-1], 'SOHO_KZ': [-1], 'TITEL_KZ': [-1,
0], 'VERS_TYP': [-1], 'ZABEOTYP': [-1, 9], 'ALTER_HH': [0], 'ANZ_PERSONEN': [],
'ANZ_TITEL': [], 'HH_EINKOMMEN_SCORE': [-1, 0], 'KK_KUNDENTYP': [-1],
'W_KEIT_KIND_HH': [-1, 0], 'WOHNDAUER_2008': [-1, 0], 'ANZ_HAUSHALTE_AKTIV':
[0], 'ANZ_HH_TITEL': [], 'GEBAEUDETYP': [-1, 0], 'KONSUMNAEHE': [],
'MIN_GEBAEUDEJAHR': [0], 'OST_WEST_KZ': [-1], 'WOHNLAGE': [-1],
'CAMEO_DEUG_2015': [-1, 'X'], 'CAMEO_DEU_2015': ['XX'], 'CAMEO_INTL_2015': [-1,
'XX'], 'KBA05_ANTG1': [-1], 'KBA05_ANTG2': [-1], 'KBA05_ANTG3': [-1],
'KBA05_ANTG4': [-1], 'KBA05_BAUMAX': [-1, 0], 'KBA05_GBZ': [-1, 0], 'BALLRAUM':
[-1], 'EWDICHTE': [-1], 'INNENSTADT': [-1], 'GEBAEUDETYP_RASTER': [], 'KKK':
[-1, 0], 'MOBI_REGIO': [], 'ONLINE_AFFINITAET': [], 'REGIOTYP': [-1, 0],
'KBA13_ANZAHL_PKW': [], 'PLZ8_ANTG1': [-1], 'PLZ8_ANTG2': [-1], 'PLZ8_ANTG3':
[-1], 'PLZ8_ANTG4': [-1], 'PLZ8_BAUMAX': [-1, 0], 'PLZ8_HHZ': [-1], 'PLZ8_GBZ':
[-1], 'ARBEIT': [-1, 9], 'ORTSGR_KLS9': [-1, 0], 'RELAT_AB': [-1, 9]}
```

[82]:
```python
# check how many X, XX, missing values we have on each column to check if we␣
↪replaced everything

counts = {}
```

```python
# Iterate over each column in the DataFrame
for column in all_data2.columns:
    x_count = all_data2[column].apply(lambda x: str(x).strip()).value_counts().
↪get('X', 0)
    xx_count = all_data2[column].apply(lambda x: str(x).strip()).value_counts().
↪get('XX', 0)
    zero_count = all_data2[column].apply(lambda x: str(x).strip()).
↪value_counts().get('0', 0)
    minus1_count = all_data2[column].apply(lambda x: str(x).strip()).
↪value_counts().get('-1', 0)
    nan_count = all_data2[column].isna().sum()

    counts[column] = {'X': x_count, 'XX': xx_count, '0': zero_count, '-1':␣
↪minus1_count, 'Nan': nan_count}


# Convert the counts to a DataFrame for easier inspection
counts_df = pd.DataFrame(counts).T  # Transpose to have columns as rows


# Display the counts
print(counts_df)
```

```
                     X  XX  0  -1     Nan
AGER_TYP             0   0  0   0  685843
ALTERSKATEGORIE_GROB 0   0  0   0    2881
ANREDE_KZ            0   0  0   0       0
CJT_GESAMTTYP        0   0  0   0    4854
FINANZ_MINIMALIST    0   0  0   0       0
…                   ..  .. ..  ..     …
PLZ8_HHZ             0   0  0   0  116515
PLZ8_GBZ             0   0  0   0  116515
ARBEIT               0   0  0   0   97375
ORTSGR_KLS9          0   0  0   0   97274
RELAT_AB             0   0  0   0   97375

[85 rows x 5 columns]
```

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

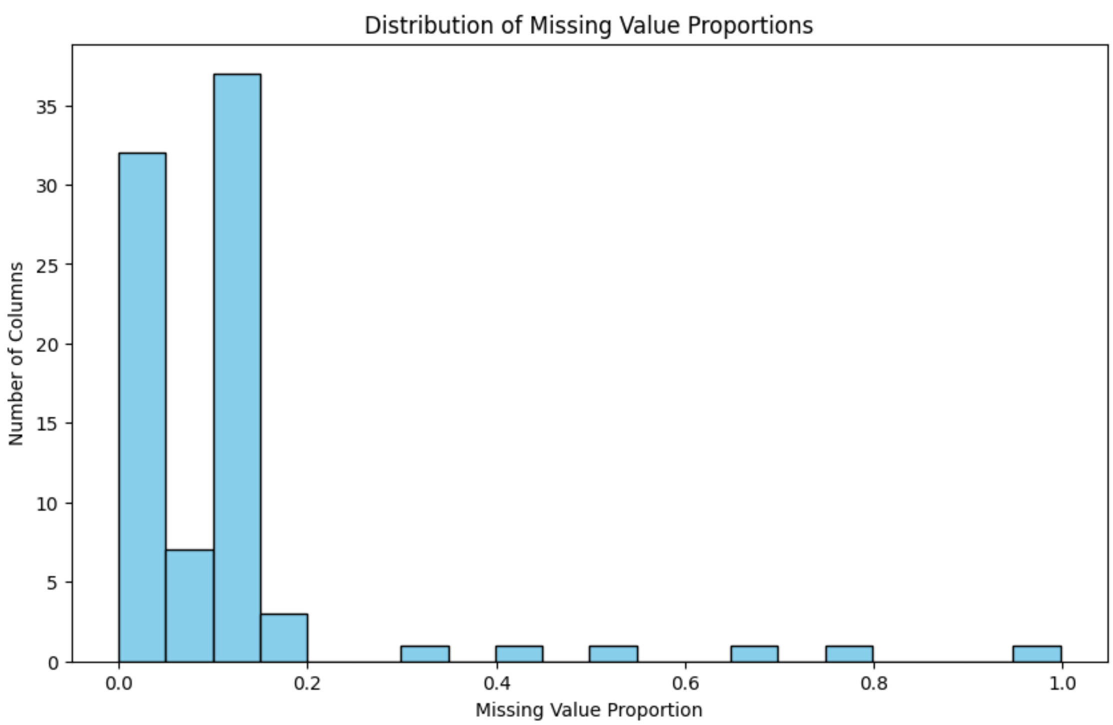
For the remaining features, are there any patterns in which columns have, or share, missing data?

[84]:
```
# Perform an assessment of how much missing data there is in each column of the
# dataset before replacements with Nans.

print("Missing values report for all demographics file: \n")
miss_count = all_data2.isnull().sum()
total_miss_count = all_data2.isna().sum().sum()
miss_proportion = all_data2.isna().mean()

print(f"Total missing values for demographics = {total_miss_count} =␣
↪{total_miss_count/(all_data2.shape[0]*all_data2.shape[1]):.2f}% of total␣
↪values \n")

missing_df = miss_proportion.reset_index()
missing_df.columns = ['attribute', 'Missing_Proportion']
missing_df = missing_df.sort_values(by='Missing_Proportion', ascending=False)

print(missing_df)
```

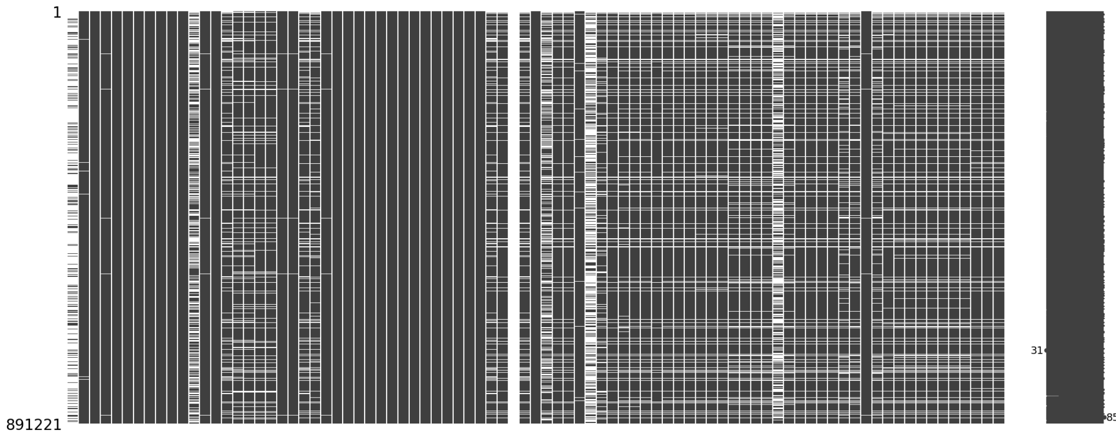
```
Missing values report for all demographics file:

Total missing values for demographics = 8373929 = 0.11% of total values

        attribute  Missing_Proportion
40        TITEL_KZ            0.997576
0         AGER_TYP            0.769554
47    KK_KUNDENTYP            0.655967
64    KBA05_BAUMAX            0.534687
11     GEBURTSJAHR            0.440203
..             …                  …
32       SEMIO_RAT            0.000000
33      SEMIO_KRIT            0.000000
34       SEMIO_DOM            0.000000
36   SEMIO_PFLICHT            0.000000
28      SEMIO_VERT            0.000000

[85 rows x 2 columns]
```

[85]:
```
# Investigate patterns in the amount of missing data in each column.

# Plot histogram of missing proportions
plt.figure(figsize=(10, 6))
plt.hist(miss_proportion, bins=20, color='skyblue', edgecolor='black')
plt.title("Distribution of Missing Value Proportions")
plt.xlabel("Missing Value Proportion")
plt.ylabel("Number of Columns")
plt.show()
```

```python
# Visualize missing data

plt.figure(figsize=(10,20))
msno.matrix(all_data2, sparkline=True)
plt.show()

plt.figure(figsize=(10,200))
msno.bar(all_data2)

# Correlation of missing data across columns
missing_corr = all_data2.isnull().corr()

# Plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(missing_corr, cmap="coolwarm", annot=False)
plt.title("Correlation of Missing Data Across Columns")
plt.show()
```




```
<Figure size 1000x2000 with 0 Axes>
```


1
891221


0.0
0.2
0.4
0.6
0.8
1.0
RELAT_AB
ORTSGR_KLS9
ARBEIT
PLZ8_GBZ
PLZ8_HHZ
PLZ8_BAUMAX
PLZ8_ANTG4
PLZ8_ANTG3
PLZ8_ANTG2
PLZ8_ANTG1
KBA13_ANZAHL_PKW
REGIOTYP
ONLINE_AFFINITAET
MOBI_REGIO
KKK
GEBAEUDETYP_RASTER
INNENSTADT
EWDICHTE
BALLRAUM
KBA05_GBZ
KBA05_BAUMAX
KBA05_ANTG4
KBA05_ANTG3
KBA05_ANTG2
KBA05_ANTG1
CAMEO_INTL_2015
CAMEO_DEU_2015
CAMEO_DEUG_2015
WOHNLAGE
OST_WEST_KZ
MIN_GEBAEUDEJAHR
KONSUMNAEHE
GEBAEUDETYP
ANZ_HH_TITEL
ANZ_HAUSHALTE_AKTIV
WOHNDAUER_2008
W_KEIT_KIND_HH
KK_KUNDENTYP
HH_EINKOMMEN_SCORE
ANZ_TITEL
ANZ_PERSONEN
ALTER_HH
ZABEOTYP
VERS_TYP
TITEL_KZ
SOHO_KZ
SHOPPER_TYP
SEMIO_TRADV
SEMIO_PFLICHT
SEMIO_KAEM
SEMIO_DOM
SEMIO_KRIT
SEMIO_RAT
SEMIO_KULT
SEMIO_ERL
SEMIO_LUST
SEMIO_VERT
SEMIO_MAT
SEMIO_REL
SEMIO_FAM
SEMIO_SOZ
RETOURTYP_BK_S
PRAEGENDE_JUGENDJAHRE
NATIONALITAET_KZ
LP_STATUS_GROB
LP_STATUS_FEIN
LP_FAMILIE_GROB
LP_FAMILIE_FEIN
LP_LEBENSPHASE_GROB
LP_LEBENSPHASE_FEIN
HEALTH_TYP
GREEN_AVANTGARDE
GFK_URLAUBERTYP
GEBURTSJAHR
FINANZTYP
FINANZ_HAUSBAUER
FINANZ_UNAUFFAELLIGER
FINANZ_ANLEGER
FINANZ_VORSORGER
FINANZ_SPARER
FINANZ_MINIMALIST
CJT_GESAMTTYP
ANREDE_KZ
ALTERSKATEGORIE_GROB
AGER_TYP
793846
793947
793846
774706
774706
774706
774706
774706
774706
774706
785421
733157
886367
757897
733157
798066
797481
797481
797481
757897
414697
757897
757897
757897
757897
791869
791869
791869
798073
798073
798073
817252
798073
794213
791610
817722
743233
306609
872873
817722
817722
580954
891221
780025
2160
817722
780025
891221
891221
891221
891221
891221
891221
891221
891221
891221
891221
891221
891221
891221
891221
886367
783057
782906
886367
886367
813429
813429
796649
793589
780025
891221
886367
498903
891221
891221
891221
891221
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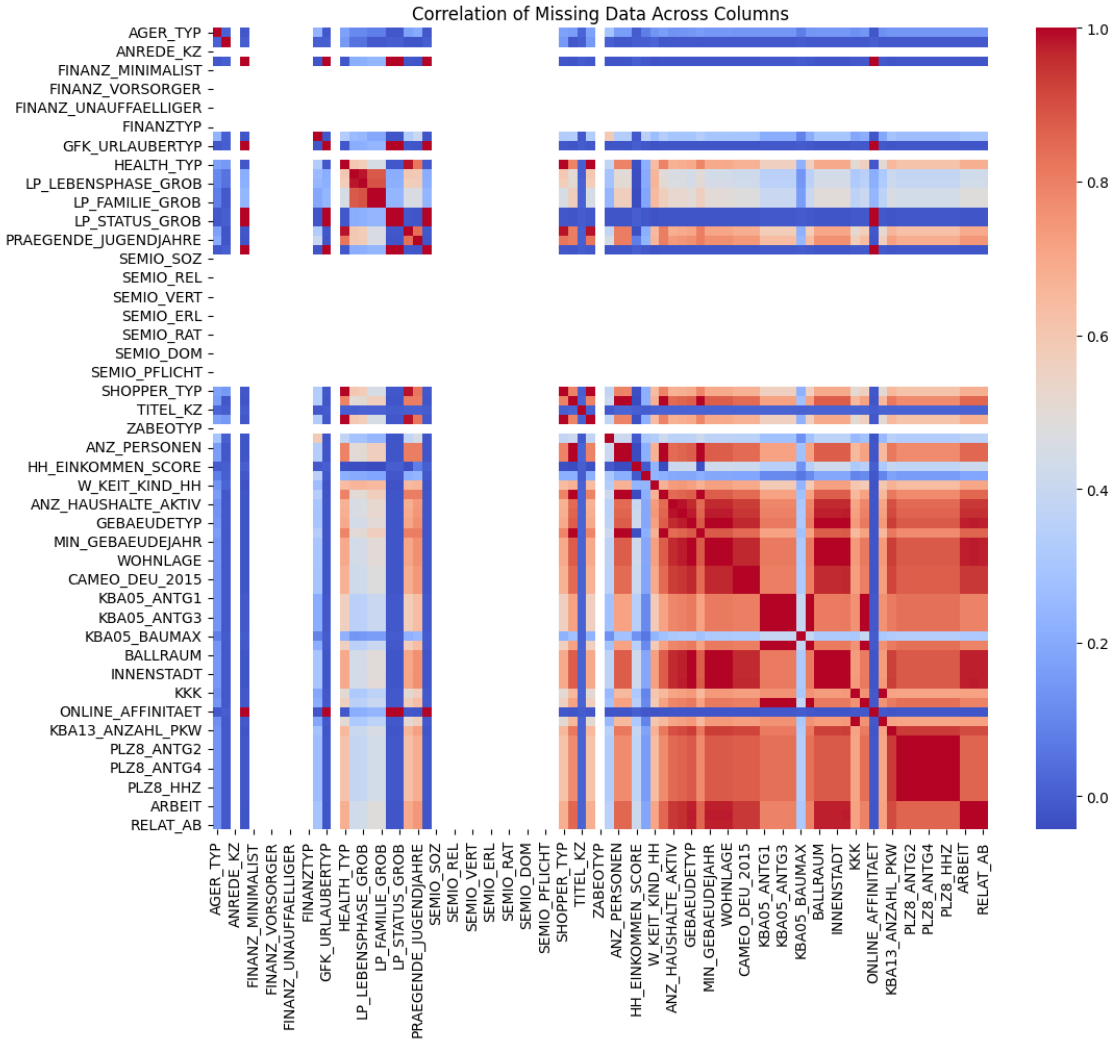
891221
886367
891221
888340
205378
0
178244
356488
534732
712976
891221




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

# Define the threshold for missing data proportion
threshold = 0.70

# Identify columns with missing proportion greater than the threshold
columns_to_remove = missing_df[missing_df['Missing_Proportion'] >␣
 ↪threshold]['attribute']

# Remove the identified columns from the dataset
all_data_cleaned = all_data2.drop(columns=columns_to_remove)
```

```python
# Print information about removed columns
print(f"Removed {len(columns_to_remove)} columns with missing proportion␣
↪greater than {threshold*100:.0f}%.\n")
print("Removed columns:")
print(columns_to_remove.tolist())
```

```
Removed 2 columns with missing proportion greater than 70%.

Removed columns:
['TITEL_KZ', 'AGER_TYP']
```

Discussion 1.1.2: Assess Missing Data in Each Column

1. Are there any patterns in missing values?
2. Which columns were removed from the dataset?

My Answer

1. **Total missing values for demographics = 4896838 = 0.06% of total values**

   ```
   attribute  Missing_Proportion
   ```

   40 TITEL_KZ 0.9972 0 AGER_TYP 0.7759 47 KK_KUNDENTYP 0.6596 64 KBA05_BAUMAX 0.5475

I do not know what patterns to see in the missing data, honestly…. I can see looking at the histogram of missing values distribtuion that the majority of columns are below 20% missing values so pretty good data I would say. In regards to correlations, I see some correlations between the missing values of one column to another but I see nothing usefull coming out of that observation.

2. All columns with missing values more than 70% were removed completely from the dataset. The result is stored in the all_data_cleaned dataframe You can see which columns were removed excactly above. They are unimportan columns in my opinion, I checked the descriptions.

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

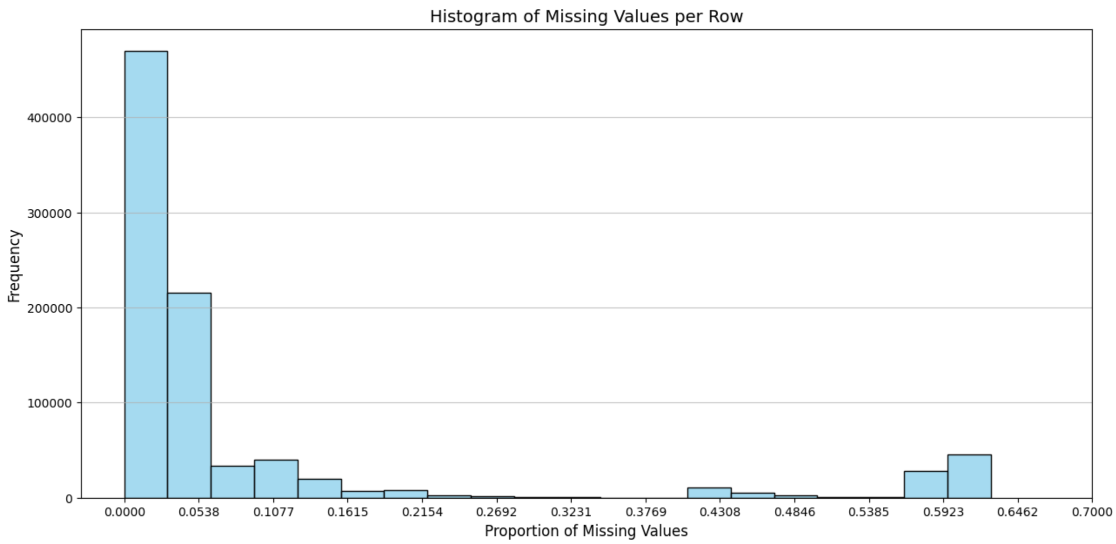
In order to know what to do with the outlier rows, we should see if the distribution of data values on columns that are not missing data (or are missing very little data) are similar or different between the two groups. Select at least five of these columns and compare the distribution of values. - You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

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

[89]:
```python
# How much data is missing in each row of the dataset?

print("Missing values report for all cleaned demographics file: \n")
miss_count_rows = all_data_cleaned.isnull().mean(axis=1)
print("Type = ", type(miss_count_rows), "\n")
print("miss count rows = ", miss_count_rows.head(10), "\n")


missing_rows_df = miss_count_rows.reset_index()
missing_rows_df.columns = ['Row_Index', 'Missing_Proportion']
missing_rows_df = missing_rows_df.sort_values(by='Missing_Proportion',␣
 ↪ascending=False)

print(missing_rows_df.head())


# ploted a histogram here to check for optimal threshold
plt.figure(figsize=(15, 7))
sns.histplot(miss_count_rows, bins=20, kde=False, color='skyblue',␣
 ↪edgecolor='black')

plt.title('Histogram of Missing Values per Row', fontsize=14)
plt.xlabel('Proportion of Missing Values', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.grid(axis='y', alpha=0.75)
xticks = np.linspace(0, 0.7, 14)
plt.xticks(xticks)
plt.show()
```

```
Missing values report for all cleaned demographics file:

Type =  <class 'pandas.core.series.Series'>

miss count rows =  0    0.566265
1    0.024096
2    0.024096
3    0.096386
4    0.012048
5    0.012048
6    0.036145
7    0.024096
```

```
8    0.024096
9    0.012048
dtype: float64

        Row_Index  Missing_Proportion
732775     732775            0.626506
113316     113316            0.614458
389329     389329            0.614458
389332     389332            0.614458
73550       73550            0.614458
```



[90]:

```
# Write code to divide the data into two subsets based on the number of missing
↪values in each row.

# Define the threshold for missing data proportion for rows
threshold2 = 0.15


# Identify rows with missing proportion greater than the threshold
good_rows = pd.Series(miss_count_rows[miss_count_rows <= threshold2].index)
bad_rows = pd.Series(miss_count_rows[miss_count_rows > threshold2].index)


# Here I want to split the all_data_cleaned into 2 subsets based on row
↪filtering
good_data = all_data_cleaned.loc[good_rows]
bad_data = all_data_cleaned.loc[bad_rows]

print('Good_Data shape = ', good_data.shape, "\n")
```

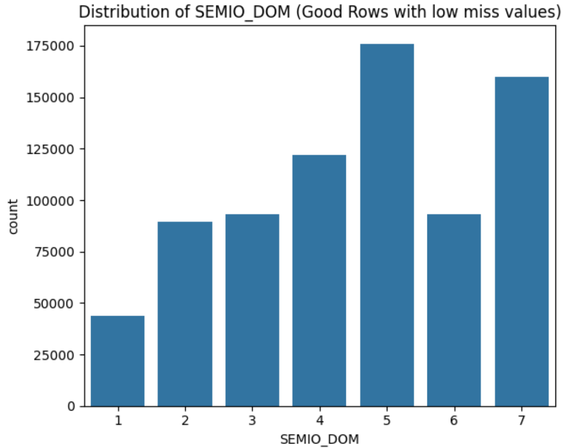
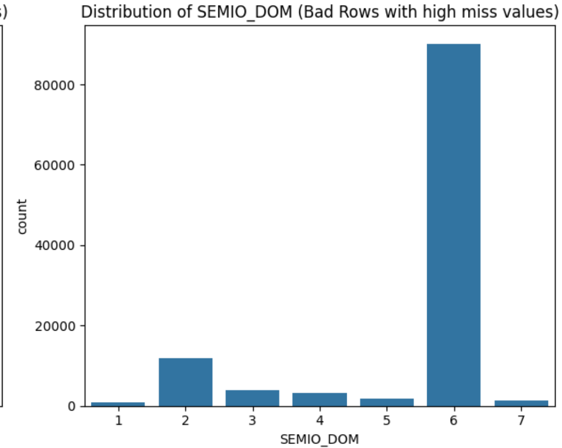
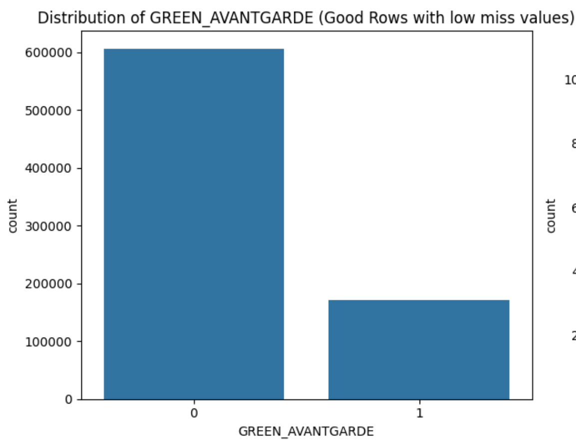
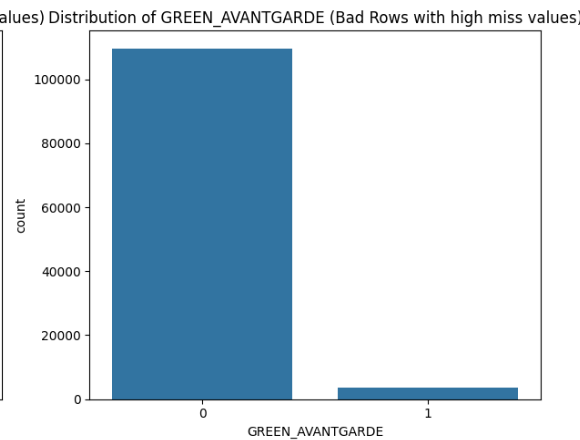
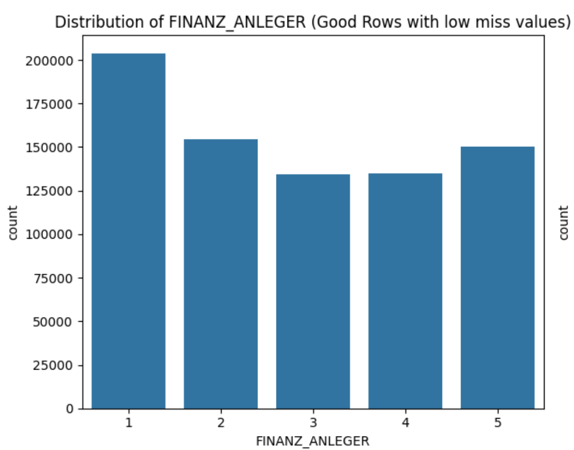
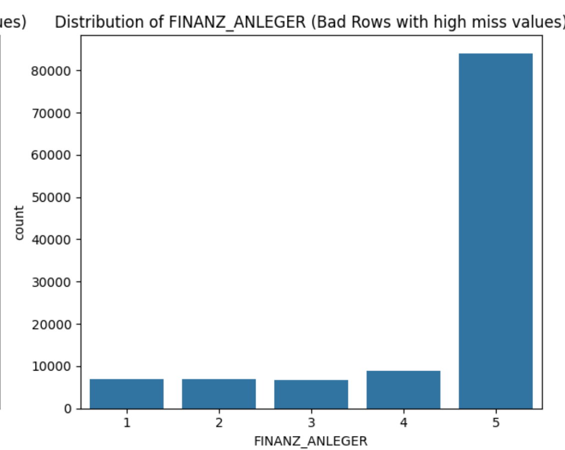
```
print('Bad_Data shape = ', bad_data.shape)
```

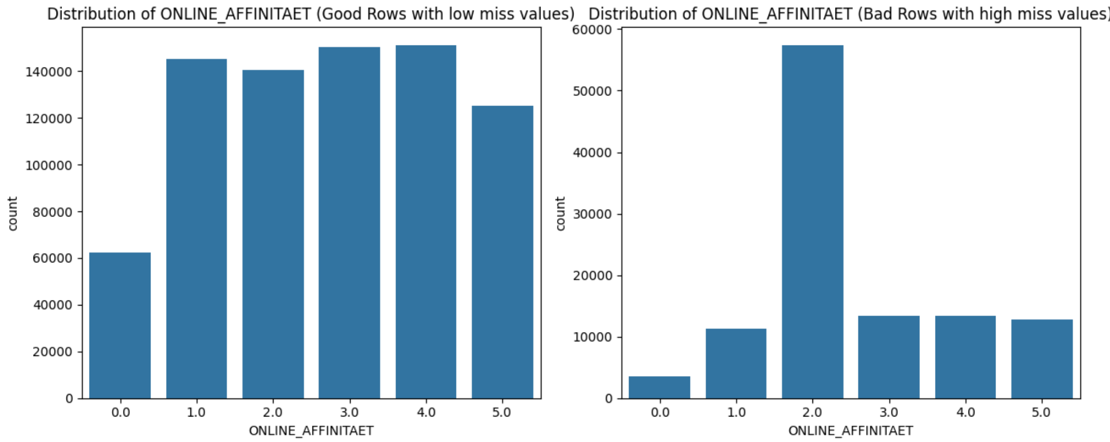
```
Good_Data shape =  (777909, 83)

Bad_Data shape =  (113312, 83)
```

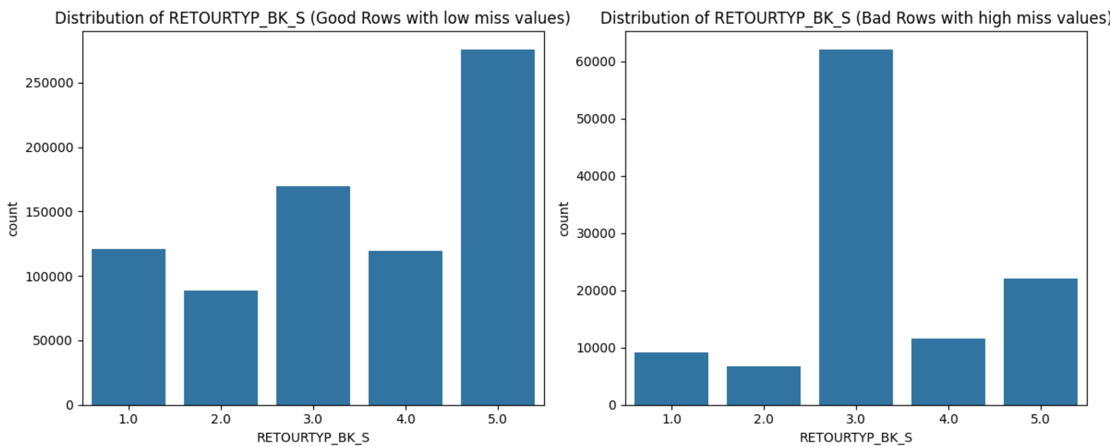
[91]:

```
# Compare the distribution of values for at least five columns where there are
# no or few missing values, between the two subsets.

# I selected here 5 Good Columns with low missing values
# and another 5 Bad Columns with High missing values
# just to see if the distribution of values is different
good_columns_to_compare = ['SEMIO_DOM', 'GREEN_AVANTGARDE', 'FINANZ_ANLEGER',␣
 ↪'ONLINE_AFFINITAET', 'RETOURTYP_BK_S']
bad_columns_to_compare = ['KK_KUNDENTYP', 'KBA05_BAUMAX', 'ALTER_HH',␣
 ↪'REGIOTYP', 'KKK']

def compare_columns(col):
    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    sns.countplot(data=good_data, x=col)
    plt.title(f'Distribution of {col} (Good Rows with low miss values)')

    plt.subplot(1, 2, 2)
    sns.countplot(data=bad_data, x=col)
    plt.title(f'Distribution of {col} (Bad Rows with high miss values)')

    plt.tight_layout()
    plt.show()


print("Distribution of Good Columns with low missing values \n")
for (col) in good_columns_to_compare:
    compare_columns(col)

print("Distribution of Bad Columns with high missing values \n")
for (col) in good_columns_to_compare:
    compare_columns(col)
```

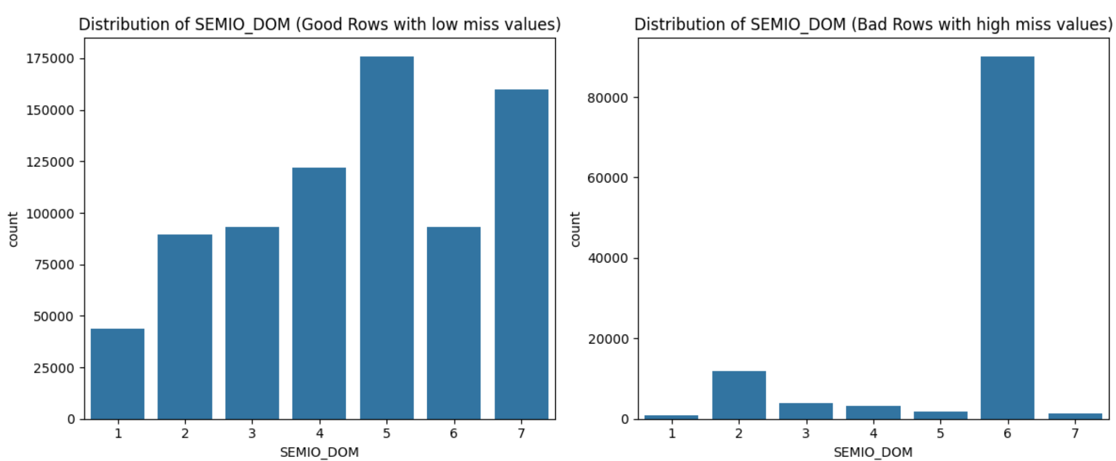
```
Distribution of Good Columns with low missing values
```

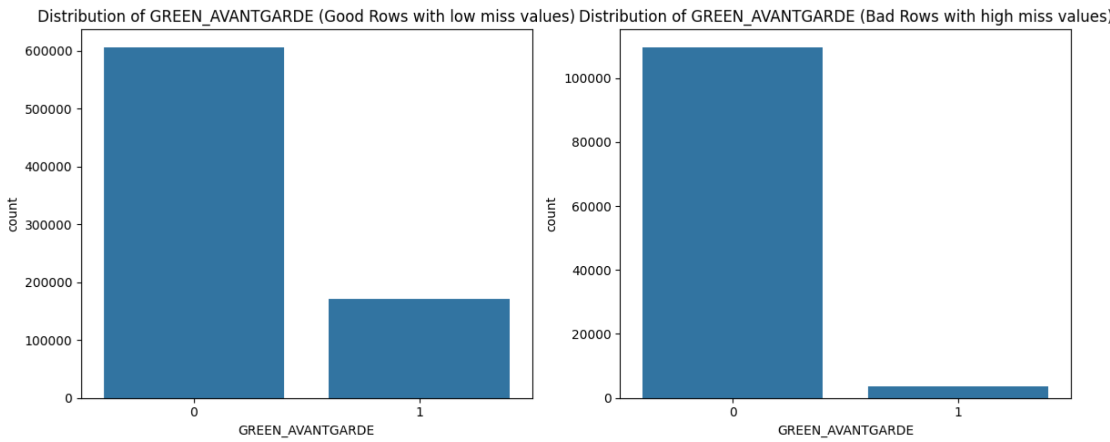

Distribution of SEMIO_DOM (Good Rows with low miss values)
count
SEMIO_DOM

Distribution of SEMIO_DOM (Bad Rows with high miss values)
count
SEMIO_DOM

Distribution of GREEN_AVANTGARDE (Good Rows with low miss values)
count
GREEN_AVANTGARDE

Distribution of GREEN_AVANTGARDE (Bad Rows with high miss values)
count
GREEN_AVANTGARDE

Distribution of FINANZ_ANLEGER (Good Rows with low miss values)
count
FINANZ_ANLEGER

Distribution of FINANZ_ANLEGER (Bad Rows with high miss values)
count
FINANZ_ANLEGER

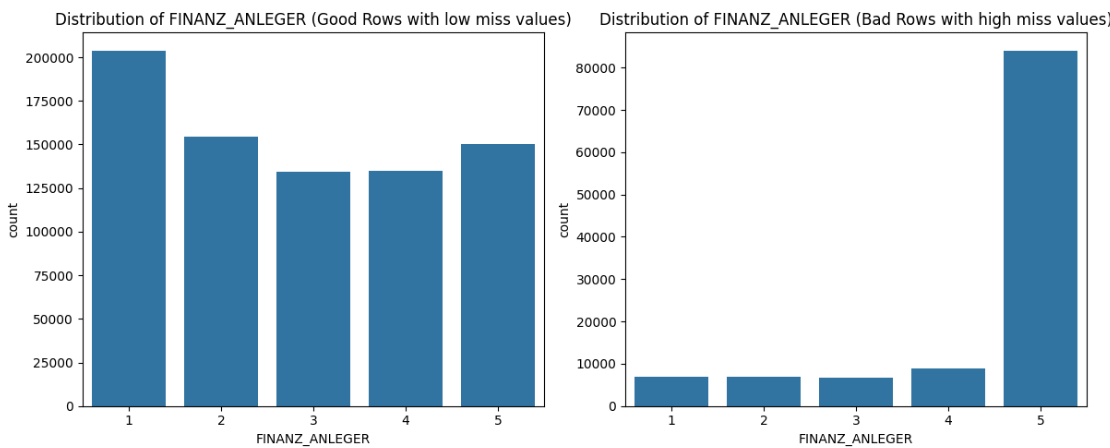


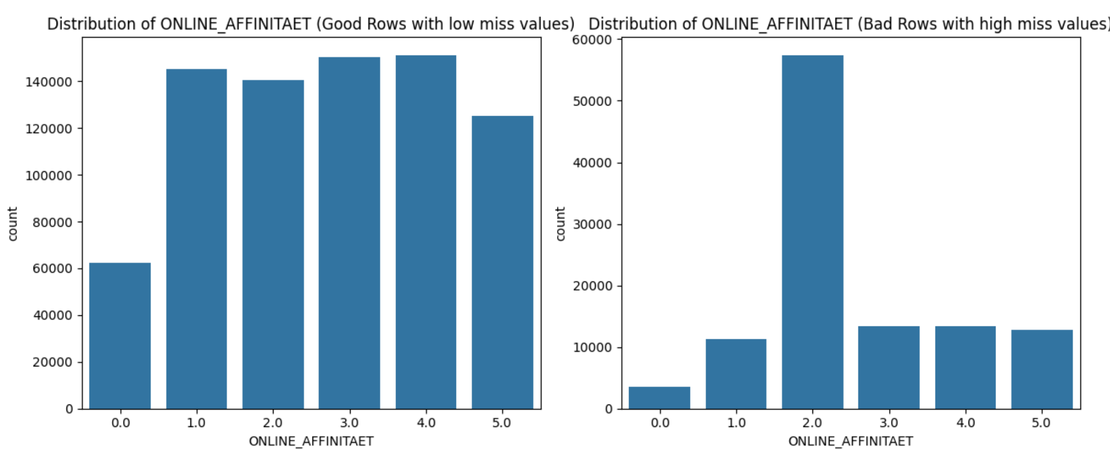


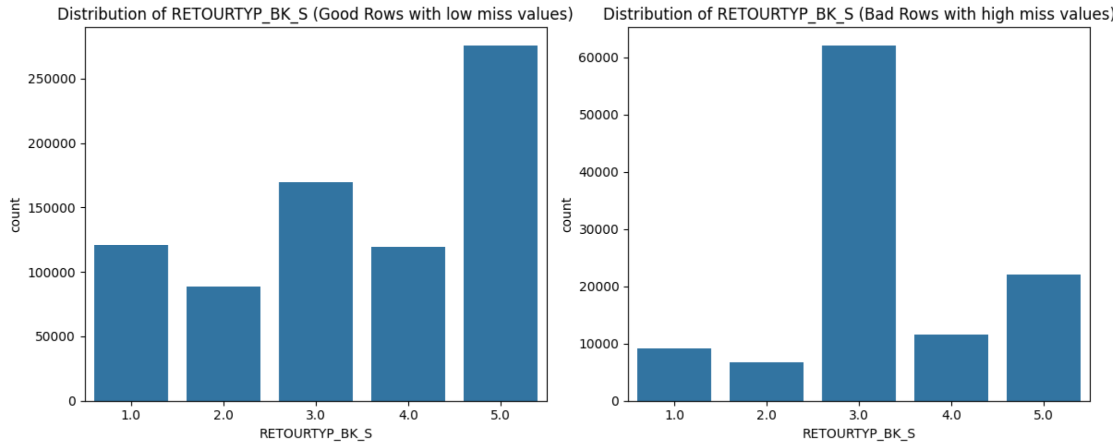
Distribution of Bad Columns with high missing values




Distribution of GREEN_AVANTGARDE (Good Rows with low miss values)
Distribution of GREEN_AVANTGARDE (Bad Rows with high miss values)
count
GREEN_AVANTGARDE
0
1
600000
500000
400000
300000
200000
100000
100000
80000
60000
40000
20000


Distribution of FINANZ_ANLEGER (Good Rows with low miss values)
Distribution of FINANZ_ANLEGER (Bad Rows with high miss values)
count
FINANZ_ANLEGER
1
2
3
4
5
200000
175000
150000
125000
100000
75000
50000
25000
80000
70000
60000
50000
40000
30000
20000
10000
0


Distribution of ONLINE_AFFINITAET (Good Rows with low miss values)
Distribution of ONLINE_AFFINITAET (Bad Rows with high miss values)
count
ONLINE_AFFINITAET
0.0
1.0
2.0
3.0
4.0
5.0
140000
120000
100000
80000
60000
40000
20000
60000
50000
40000
30000
20000
10000
0



Discussion 1.1.3: Assess Missing Data in Each Row Are the data with lots of missing values are qualitatively different from data with few or no missing values?

My Answer

1. I did a histogram of all the rows missing values. Looking at it I selected 15% of being the optimum threshold which would separate the dataset in 2 subsets.
2. I did a 2 histograms side by side to check the same column distribution in the good rows dataset vs the bad rows dataset As a bonus I selected here 5 Good Columns with low missing values and another 5 Bad Columns with High missing values just to see if the distribution of values is different.

Conclusion

It seems there is a big difference between the distributions. So if we remove the bad rows dataset my opinion is that we are losing important information.

1.1.2 Step 1.2: Select and Re-Encode Features

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

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

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

[94]:
```python
# How many features are there of each data type?


print("OST_WEST_KZ values: ", good_data['OST_WEST_KZ'].unique())
print('CAMEO_DEUG_2015 values: ', good_data['CAMEO_DEUG_2015'].unique())
print('CAMEO_DEU_2015 values: ', good_data['CAMEO_DEU_2015'].unique())
print('CAMEO_INTL_2015 values: ', good_data['CAMEO_INTL_2015'].unique())
print('\n')

good_data.info()
```

```
OST_WEST_KZ values:  ['W' 'O']
CAMEO_DEUG_2015 values:  ['8' '4' '2' '6' '1' '9' '5' '7' '3' nan]
CAMEO_DEU_2015 values:  ['8A' '4C' '2A' '6B' '8C' '4A' '2D' '1A' '1E' '9D' '5C'
'8B' '7A' '5D'
 '9E' '9B' '1B' '3D' nan '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']
CAMEO_INTL_2015 values:  ['51' '24' '12' '43' '54' '22' '14' '13' '15' '33' '41'
'34' '55' '25' nan
 '23' '31' '52' '35' '45' '44' '32']


<class 'pandas.core.frame.DataFrame'>
Index: 777909 entries, 1 to 891220
Data columns (total 83 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   ALTERSKATEGORIE_GROB   775316 non-null  float64
 1   ANREDE_KZ              777909 non-null  int64
 2   CJT_GESAMTTYP          774601 non-null  float64
 3   FINANZ_MINIMALIST      777909 non-null  int64
 4   FINANZ_SPARER          777909 non-null  int64
 5   FINANZ_VORSORGER       777909 non-null  int64
 6   FINANZ_ANLEGER         777909 non-null  int64
 7   FINANZ_UNAUFFAELLIGER  777909 non-null  int64
 8   FINANZ_HAUSBAUER       777909 non-null  int64
 9   FINANZTYP              777909 non-null  int64
 10  GEBURTSJAHR            475741 non-null  float64
 11  GFK_URLAUBERTYP        774601 non-null  float64
 12  GREEN_AVANTGARDE       777909 non-null  int64
 13  HEALTH_TYP             744293 non-null  float64
```

```
14  LP_LEBENSPHASE_FEIN    732812 non-null  float64
15  LP_LEBENSPHASE_GROB    735459 non-null  float64
16  LP_FAMILIE_FEIN        750053 non-null  float64
17  LP_FAMILIE_GROB        750053 non-null  float64
18  LP_STATUS_FEIN         774601 non-null  float64
19  LP_STATUS_GROB         774601 non-null  float64
20  NATIONALITAET_KZ       746886 non-null  float64
21  PRAEGENDE_JUGENDJAHRE  752939 non-null  float64
22  RETOURTYP_BK_S         774601 non-null  float64
23  SEMIO_SOZ              777909 non-null  int64
24  SEMIO_FAM              777909 non-null  int64
25  SEMIO_REL              777909 non-null  int64
26  SEMIO_MAT              777909 non-null  int64
27  SEMIO_VERT             777909 non-null  int64
28  SEMIO_LUST             777909 non-null  int64
29  SEMIO_ERL              777909 non-null  int64
30  SEMIO_KULT             777909 non-null  int64
31  SEMIO_RAT              777909 non-null  int64
32  SEMIO_KRIT             777909 non-null  int64
33  SEMIO_DOM              777909 non-null  int64
34  SEMIO_KAEM             777909 non-null  int64
35  SEMIO_PFLICHT          777909 non-null  int64
36  SEMIO_TRADV            777909 non-null  int64
37  SHOPPER_TYP            744293 non-null  float64
38  SOHO_KZ                777909 non-null  float64
39  VERS_TYP               744293 non-null  float64
40  ZABEOTYP               777909 non-null  int64
41  ALTER_HH               555062 non-null  float64
42  ANZ_PERSONEN           777909 non-null  float64
43  ANZ_TITEL              777909 non-null  float64
44  HH_EINKOMMEN_SCORE     777909 non-null  float64
45  KK_KUNDENTYP           290689 non-null  float64
46  W_KEIT_KIND_HH         722576 non-null  float64
47  WOHNDAUER_2008         777909 non-null  float64
48  ANZ_HAUSHALTE_AKTIV    772267 non-null  float64
49  ANZ_HH_TITEL           774709 non-null  float64
50  GEBAEUDETYP            777909 non-null  float64
51  KONSUMNAEHE            777859 non-null  float64
52  MIN_GEBAEUDEJAHR       777909 non-null  float64
53  OST_WEST_KZ            777909 non-null  object
54  WOHNLAGE               777909 non-null  float64
55  CAMEO_DEUG_2015        774323 non-null  object
56  CAMEO_DEU_2015         774323 non-null  object
57  CAMEO_INTL_2015        774323 non-null  object
58  KBA05_ANTG1            753908 non-null  float64
59  KBA05_ANTG2            753908 non-null  float64
60  KBA05_ANTG3            753908 non-null  float64
61  KBA05_ANTG4            753908 non-null  float64
```

```
 62  KBA05_BAUMAX           413309 non-null  float64
 63  KBA05_GBZ              753908 non-null  float64
 64  BALLRAUM               777376 non-null  float64
 65  EWDICHTE               777376 non-null  float64
 66  INNENSTADT             777376 non-null  float64
 67  GEBAEUDETYP_RASTER     777904 non-null  float64
 68  KKK                    724050 non-null  float64
 69  MOBI_REGIO             753908 non-null  float64
 70  ONLINE_AFFINITAET      774601 non-null  float64
 71  REGIOTYP               724050 non-null  float64
 72  KBA13_ANZAHL_PKW       772458 non-null  float64
 73  PLZ8_ANTG1             770061 non-null  float64
 74  PLZ8_ANTG2             770061 non-null  float64
 75  PLZ8_ANTG3             770061 non-null  float64
 76  PLZ8_ANTG4             770061 non-null  float64
 77  PLZ8_BAUMAX            770061 non-null  float64
 78  PLZ8_HHZ               770061 non-null  float64
 79  PLZ8_GBZ               770061 non-null  float64
 80  ARBEIT                 773947 non-null  float64
 81  ORTSGR_KLS9            774038 non-null  float64
 82  RELAT_AB               773947 non-null  float64
dtypes: float64(55), int64(24), object(4)
memory usage: 498.5+ MB
```

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

[96]:
```
# Assess categorical variables: which are binary, which are multi-level, and
# which one needs to be re-encoded?

good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
print("OST_WEST_KZ values: ", good_data['OST_WEST_KZ'].unique())


for col in good_data.columns:
    if len(good_data[col].unique()) == 2 or len(good_data[col].unique()) == 3:
        print("Column :", col, "is binary")
```

```
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\348089224.py:4:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
```

```
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\348089224.py:4:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)

OST_WEST_KZ values:  [1 2]
Column : ANREDE_KZ is binary
Column : GREEN_AVANTGARDE is binary
Column : SOHO_KZ is binary
Column : VERS_TYP is binary
Column : OST_WEST_KZ is binary
```

[97]:

```python
# Re-encode categorical variable(s) to be kept in the analysis.

# We remove one column from encoding because we will treat it manually later .
columns_for_encoding = ['CAMEO_DEUG_2015', 'CAMEO_DEU_2015']
all_data_one_hot = pd.get_dummies(good_data, columns = columns_for_encoding,␣
 ↪drop_first=False)


print("DataFrame after One-Hot Encoding:")
print ('Shape: ', all_data_one_hot.shape)
print(all_data_one_hot.head(10))
```

```
DataFrame after One-Hot Encoding:
Shape:  (777909, 134)
    ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  FINANZ_MINIMALIST  \
1                    1.0          2            5.0                  1
2                    3.0          2            3.0                  1
3                    4.0          2            2.0                  4
4                    3.0          1            5.0                  4
5                    1.0          2            2.0                  3
6                    2.0          2            5.0                  1
7                    1.0          1            3.0                  3
8                    3.0          1            3.0                  4
9                    3.0          2            4.0                  2
```

```
10                 3.0          2            1.0                     2

    FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  FINANZ_UNAUFFAELLIGER  \
1               5                 2               5                      4
2               4                 1               2                      3
3               2                 5               2                      1
4               3                 4               1                      3
5               1                 5               2                      2
6               5                 1               5                      4
7               3                 4               1                      3
8               4                 2               4                      2
9               4                 2               3                      5
10              2                 5               3                      1

    FINANZ_HAUSBAUER  FINANZTYP  …  CAMEO_DEU_2015_7E  CAMEO_DEU_2015_8A  \
1                  5          1  …              False               True
2                  5          1  …              False              False
3                  2          6  …              False              False
4                  2          5  …              False              False
5                  5          2  …              False              False
6                  3          4  …              False              False
7                  2          5  …              False              False
8                  2          6  …              False              False
9                  4          1  …              False              False
10                 5          6  …              False              False

    CAMEO_DEU_2015_8B  CAMEO_DEU_2015_8C  CAMEO_DEU_2015_8D  \
1               False              False              False
2               False              False              False
3               False              False              False
4               False              False              False
5               False               True              False
6               False              False              False
7               False              False              False
8               False              False              False
9               False              False              False
10              False              False              False

    CAMEO_DEU_2015_9A  CAMEO_DEU_2015_9B  CAMEO_DEU_2015_9C  \
1               False              False              False
2               False              False              False
3               False              False              False
4               False              False              False
5               False              False              False
6               False              False              False
7               False              False              False
8               False              False              False
9               False              False              False
```

```
10              False              False              False

    CAMEO_DEU_2015_9D  CAMEO_DEU_2015_9E
1               False              False
2               False              False
3               False              False
4               False              False
5               False              False
6               False              False
7               False              False
8               False              False
9               False              False
10               True              False

[10 rows x 134 columns]
```

Discussion 1.2.1: Re-Encode Categorical Features (. Which ones did you keep, which did you drop, and what engineering steps did you perform?)

My Answer 1. I checked for binary columns containing 2 or 3 unique values because NaN can be one value as well. I found one column OST_WEST_KZ which I encoded manually to 1 and 2 The rest of them are numeric and can remain unchanged. I checked the data-dictionary_md to understand the columns.

2. I searched for nominal categorical columns and I found 3: **CAMEO_DEUG_2015, CAMEO_DEU_2015, CAMEO_INTL_2015** I encoded them using pd.get_dummies() with 0 and 1s I tried the onehotencoder library, but I droped it, since it was encoding all columns not just the 3 I wanted.
3. The encoded data frame is now called all_data_one_hot
4. Then I came back and reomved **CAMEO_INTL_2015** because it was treated manually on a later step below

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

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

[100]:

```
# Investigate "PRAEGENDE_JUGENDJAHRE" and engineer two new variables.

print(all_data_one_hot['PRAEGENDE_JUGENDJAHRE'].unique())
print("\n")
all_data_one_hot['PRAEGENDE_JUGENDJAHRE'].dtype

# Step 1: Define the mapping dictionary
decade_mapping = {
    -1: 'unknown',
    0: 'unknown',
    1: '40s',
    2: '40s',
    3: '50s',
    4: '50s',
    5: '60s',
    6: '60s',
    7: '60s',
    8: '70s',
    9: '70s',
    10: '80s',
    11: '80s',
    12: '80s',
    13: '80s',
    14: '90s',
    15: '90s'
}

all_data_one_hot['PJ_Decade'] = all_data_one_hot['PRAEGENDE_JUGENDJAHRE'].
 ↪map(decade_mapping)

print(all_data_one_hot[['PJ_Decade','PRAEGENDE_JUGENDJAHRE']].head(10))

# Step 2: Define the mapping dictionary
generation_mapping = {
    -1: 'unknown',
    0: 'unknown',
    1: 'war years',
    2: 'reconstruction years',
    3: 'economic miracle',
    4: 'milk bar / Individualisation',
    5: 'economic miracle (',
    6: 'generation 68 / student protestors',
    7: 'opponents to the building of the Wall',
    8: 'family orientation',
    9: 'peace movement',
    10: 'Generation Golf',
    11: 'ecological awareness',
```

```
    12: 'FDJ / communist party youth organisation',
    13: 'Swords into ploughshares',
    14: 'digital media kids',
    15: 'ecological awareness'
}

all_data_one_hot['PJ_Generation'] = all_data_one_hot['PRAEGENDE_JUGENDJAHRE'].
 ↪map(generation_mapping)
print(all_data_one_hot[['PJ_Decade','PRAEGENDE_JUGENDJAHRE', 'PJ_Generation']].
 ↪head(10))
```

```
[14. 15.  8.  3. 10. 11.  5.  9.  6.  4. nan  2.  1. 12. 13.  7.]


   PJ_Decade  PRAEGENDE_JUGENDJAHRE
1        90s                   14.0
2        90s                   15.0
3        70s                    8.0
4        70s                    8.0
5        50s                    3.0
6        80s                   10.0
7        70s                    8.0
8        80s                   11.0
9        90s                   15.0
10       50s                    3.0
   PJ_Decade  PRAEGENDE_JUGENDJAHRE         PJ_Generation
1        90s                   14.0    digital media kids
2        90s                   15.0  ecological awareness
3        70s                    8.0    family orientation
4        70s                    8.0    family orientation
5        50s                    3.0      economic miracle
6        80s                   10.0       Generation Golf
7        70s                    8.0    family orientation
8        80s                   11.0  ecological awareness
9        90s                   15.0  ecological awareness
10       50s                    3.0      economic miracle
```

[101]:
```
# Investigate "CAMEO_INTL_2015" and engineer two new variables.

print(all_data_one_hot['CAMEO_INTL_2015'].unique())
print("\n")

all_data_one_hot['CI_Wealth'] = all_data_one_hot['CAMEO_INTL_2015'].str[0].
 ↪astype(float)  # First digit
all_data_one_hot['CI_Life_stage'] = all_data_one_hot['CAMEO_INTL_2015'].str[1].
 ↪astype(float)  # Second digit
```

```
print (all_data_one_hot[['CAMEO_INTL_2015','CI_Wealth', 'CI_Life_stage']].
 ↪head(15))
```

```
['51' '24' '12' '43' '54' '22' '14' '13' '15' '33' '41' '34' '55' '25' nan
 '23' '31' '52' '35' '45' '44' '32']
```

```
   CAMEO_INTL_2015  CI_Wealth  CI_Life_stage
1               51        5.0            1.0
2               24        2.0            4.0
3               12        1.0            2.0
4               43        4.0            3.0
5               54        5.0            4.0
6               22        2.0            2.0
7               14        1.0            4.0
8               13        1.0            3.0
9               15        1.0            5.0
10              51        5.0            1.0
12              43        4.0            3.0
13              33        3.0            3.0
15              41        4.0            1.0
16              41        4.0            1.0
18              24        2.0            4.0
```

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

My Answer

1. On "PRAEGENDE_JUGENDJAHRE" I made 2 new columns containing decade and generation
2. On "CAMEO_INTL_2015" I made 2 new columns with Wealth and Stage of Life. I kept the values as float
3. Now I need to re-encode ['PJ_Decade','PRAEGENDE_JUGENDJAHRE', 'PJ_Generation'] No need to re-e-ncode ['CAMEO_INTL_2015','CI_Wealth', 'CI_Life_stage since the numbers make sense here.

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

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

[104]:
```
# If there are other re-engineering tasks you need to perform, make sure you
# take care of them here. (Dealing with missing data will come in step 2.1.)


all_data_3 = all_data_one_hot.drop(columns=['PRAEGENDE_JUGENDJAHRE',␣
↪'CAMEO_INTL_2015'])
print ('Shape of all_data_3 before encoding: ', all_data_3)
columns_for_encoding2 = ['PJ_Decade', 'PJ_Generation']
all_data_3 = pd.get_dummies(all_data_3, columns = columns_for_encoding2,␣
↪drop_first=False)
print ('Shape of all_data_3 after encoding: ', all_data_3)
```

```
Shape of all_data_3 before encoding:          ALTERSKATEGORIE_GROB  ANREDE_KZ
CJT_GESAMTTYP  FINANZ_MINIMALIST  \
1                        1.0          2          5.0                 1
2                        3.0          2          3.0                 1
3                        4.0          2          2.0                 4
4                        3.0          1          5.0                 4
5                        1.0          2          2.0                 3
…                         …         …            …                 …
891216                   3.0          2          5.0                 1
891217                   2.0          1          4.0                 3
891218                   2.0          2          4.0                 2
891219                   1.0          1          3.0                 1
891220                   4.0          1          1.0                 4

        FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  \
1                   5                 2               5
2                   4                 1               2
3                   2                 5               2
4                   3                 4               1
5                   1                 5               2
…                 …               …             …
891216              4                 2               5
891217              3                 3               2
891218              4                 2               5
891219              5                 3               5
891220              2                 5               2

        FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  FINANZTYP  …  \
1                           4                 5          1  …
2                           3                 5          1  …
3                           1                 2          6  …
4                           3                 2          5  …
```

```
5                           2                 5          2  …
…                       …               …        …   …
891216                      4                 4          1  …
891217                      2                 3          6  …
891218                      4                 3          1  …
891219                      5                 5          1  …
891220                      1                 5          6  …

        CAMEO_DEU_2015_8D  CAMEO_DEU_2015_9A  CAMEO_DEU_2015_9B  \
1                   False              False              False
2                   False              False              False
3                   False              False              False
4                   False              False              False
5                   False              False              False
…                   …                …                …
891216              False              False              False
891217              False              False              False
891218              False              False              False
891219              False              False              False
891220              False              False              False

        CAMEO_DEU_2015_9C  CAMEO_DEU_2015_9D  CAMEO_DEU_2015_9E  PJ_Decade  \
1                   False              False              False        90s
2                   False              False              False        90s
3                   False              False              False        70s
4                   False              False              False        70s
5                   False              False              False        50s
…                   …                …                …        …
891216              False              False              False        90s
891217              False               True              False        80s
891218              False              False              False        90s
891219              False               True              False        90s
891220              False              False              False        50s

               PJ_Generation  CI_Wealth  CI_Life_stage
1          digital media kids        5.0            1.0
2        ecological awareness        2.0            4.0
3          family orientation        1.0            2.0
4          family orientation        4.0            3.0
5            economic miracle        5.0            4.0
…                      …         …             …
891216     digital media kids        4.0            1.0
891217        Generation Golf        5.0            1.0
891218     digital media kids        2.0            4.0
891219     digital media kids        5.0            1.0
891220       economic miracle        4.0            3.0

[777909 rows x 136 columns]
```

```
Shape of all_data_3 after encoding:         ALTERSKATEGORIE_GROB  ANREDE_KZ
CJT_GESAMTTYP  FINANZ_MINIMALIST  \
1                         1.0          2          5.0                 1
2                         3.0          2          3.0                 1
3                         4.0          2          2.0                 4
4                         3.0          1          5.0                 4
5                         1.0          2          2.0                 3
…                       …        …           …                 …
891216                    3.0          2          5.0                 1
891217                    2.0          1          4.0                 3
891218                    2.0          2          4.0                 2
891219                    1.0          1          3.0                 1
891220                    4.0          1          1.0                 4

        FINANZ_SPARER  FINANZ_VORSORGER  FINANZ_ANLEGER  \
1                   5                 2               5
2                   4                 1               2
3                   2                 5               2
4                   3                 4               1
5                   1                 5               2
…                …                …              …
891216              4                 2               5
891217              3                 3               2
891218              4                 2               5
891219              5                 3               5
891220              2                 5               2

        FINANZ_UNAUFFAELLIGER  FINANZ_HAUSBAUER  FINANZTYP  …  \
1                           4                 5          1  …
2                           3                 5          1  …
3                           1                 2          6  …
4                           3                 2          5  …
5                           2                 5          2  …
…                         …                …          …  …
891216                      4                 4          1  …
891217                      2                 3          6  …
891218                      4                 3          1  …
891219                      5                 5          1  …
891220                      1                 5          6  …

        PJ_Generation_ecological awareness  PJ_Generation_economic miracle  \
1                                    False                           False
2                                     True                           False
3                                    False                           False
4                                    False                           False
5                                    False                            True
…                                    …                             …
891216                               False                           False
```

```
891217                              False                          False
891218                              False                          False
891219                              False                          False
891220                              False                           True

        PJ_Generation_economic miracle (  PJ_Generation_family orientation  \
1                                 False                            False
2                                 False                            False
3                                 False                             True
4                                 False                             True
5                                 False                            False
…                                  …                             …
891216                            False                            False
891217                            False                            False
891218                            False                            False
891219                            False                            False
891220                            False                            False

        PJ_Generation_generation 68 / student protestors  \
1                                                 False
2                                                 False
3                                                 False
4                                                 False
5                                                 False
…                                                 …
891216                                            False
891217                                            False
891218                                            False
891219                                            False
891220                                            False

        PJ_Generation_milk bar / Individualisation  \
1                                           False
2                                           False
3                                           False
4                                           False
5                                           False
…                                           …
891216                                      False
891217                                      False
891218                                      False
891219                                      False
891220                                      False

        PJ_Generation_opponents to the building of the Wall  \
1                                                  False
2                                                  False
3                                                  False
```

```
4                                                       False
5                                                       False
…                                                       …
891216                                                  False
891217                                                  False
891218                                                  False
891219                                                  False
891220                                                  False

        PJ_Generation_peace movement  PJ_Generation_reconstruction years  \
1                                False                                False
2                                False                                False
3                                False                                False
4                                False                                False
5                                False                                False
…                                  …                                 …
891216                           False                                False
891217                           False                                False
891218                           False                                False
891219                           False                                False
891220                           False                                False

        PJ_Generation_war years
1                         False
2                         False
3                         False
4                         False
5                         False
…                         …
891216                    False
891217                    False
891218                    False
891219                    False
891220                    False

[777909 rows x 154 columns]
```

[105]:

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

1.1.3 Step 1.3: Create a Cleaning Function

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

[107]:
```python
customer_data = pd.read_csv('Udacity_CUSTOMERS_Subset.csv', sep = ";")
```

[108]:
```python
display(customer_data.shape)
display(customer_data.head())
```

```
(191652, 85)

   AGER_TYP  ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  \
0         2                     4          1            5.0
1        -1                     4          1            NaN
2        -1                     4          2            2.0
3         1                     4          1            2.0
4        -1                     3          1            6.0

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

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

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

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

[5 rows x 85 columns]
```

[109]:
```python
def clean_data(df):
    """
    Perform feature trimming, re-encoding, and engineering for demographics
    data
```

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

    # Put in code here to execute all main cleaning steps:
    # convert missing value codes into NaNs, ...
    df.replace(feature_dict, np.nan, inplace = True)

    # remove selected columns, ...
    df.drop(columns=columns_to_remove, inplace = True, errors='ignore')

    print(f"Removed {len(columns_to_remove)} columns with missing proportion greater than {threshold*100:.0f}%.\n")
    print("Removed columns:")
    print(columns_to_remove.tolist())

    # remove selected rows, ...
    threshold2 = 0.15
    miss_count_rows = df.isnull().mean(axis=1)
    good_rows = pd.Series(miss_count_rows[miss_count_rows <= threshold2].index)
    bad_rows = pd.Series(miss_count_rows[miss_count_rows > threshold2].index)
    good_data = df.loc[good_rows] #.reset_index(drop = True)
    bad_data = df.loc[bad_rows]

    print('Good_Data shape = ', good_data.shape, "\n")
    print('Bad_Data shape = ', bad_data.shape)


    # select, re-encode, and engineer column values.
    good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
    print("OST_WEST_KZ values: ", good_data['OST_WEST_KZ'].unique())
    good_data['PJ_Decade'] = good_data['PRAEGENDE_JUGENDJAHRE'].map(decade_mapping)
    good_data['PJ_Generation'] = good_data['PRAEGENDE_JUGENDJAHRE'].map(generation_mapping)
    good_data['CI_Wealth'] = good_data['CAMEO_INTL_2015'].str[0].astype(float) # First digit
    good_data['CI_Life_stage'] = good_data['CAMEO_INTL_2015'].str[1].astype(float)  # Second digit

    columns_for_encoding = ['CAMEO_DEUG_2015', 'CAMEO_DEU_2015', 'PJ_Decade', 'PJ_Generation']
    customer_clean_data = pd.get_dummies(good_data, columns = columns_for_encoding, drop_first=False)
```

```
    customer_clean_data.drop(columns=['PRAEGENDE_JUGENDJAHRE',␣
↪'CAMEO_INTL_2015'], inplace = True)


    # Return the cleaned dataframe.
    return customer_clean_data


customer_clean_data = clean_data(customer_data)
print("Clean Data shape after function: ",customer_clean_data.shape)
```

```
Removed 2 columns with missing proportion greater than 70%.

Removed columns:
['TITEL_KZ', 'AGER_TYP']
Good_Data shape =  (138523, 83)

Bad_Data shape =  (53129, 83)
OST_WEST_KZ values:  [1 2]
```

```
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\3287232146.py:34:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\3287232146.py:34:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
```

```
Clean Data shape after function:  (138523, 154)
```

1.2 Step 2: Feature Transformation

1.2.1 Step 2.1: Apply Feature Scaling

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

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

[111]:
```
# If you've not yet cleaned the dataset of all NaN values, then investigate and
# do that now.

from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent', copy = False)
all_data_4 = pd.DataFrame(imputer.fit_transform(all_data_3), columns=all_data_3.
 ↪columns)

print("all_data_4 shape: ", all_data_4.shape)
print(all_data_4.head())
```

```
all_data_4 shape:  (777909, 154)
   ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  FINANZ_MINIMALIST  \
0                   1.0        2.0            5.0                1.0
1                   3.0        2.0            3.0                1.0
2                   4.0        2.0            2.0                4.0
3                   3.0        1.0            5.0                4.0
4                   1.0        2.0            2.0                3.0

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

   FINANZ_HAUSBAUER  FINANZTYP  …  PJ_Generation_ecological awareness  \
0               5.0        1.0  …                                 0.0
1               5.0        1.0  …                                 1.0
2               2.0        6.0  …                                 0.0
```

```
3              2.0        5.0  …                                 0.0
4              5.0        2.0  …                                 0.0

   PJ_Generation_economic miracle  PJ_Generation_economic miracle (  \
0                             0.0                               0.0
1                             0.0                               0.0
2                             0.0                               0.0
3                             0.0                               0.0
4                             1.0                               0.0

   PJ_Generation_family orientation  \
0                               0.0
1                               0.0
2                               1.0
3                               1.0
4                               0.0

   PJ_Generation_generation 68 / student protestors  \
0                                               0.0
1                                               0.0
2                                               0.0
3                                               0.0
4                                               0.0

   PJ_Generation_milk bar / Individualisation  \
0                                         0.0
1                                         0.0
2                                         0.0
3                                         0.0
4                                         0.0

   PJ_Generation_opponents to the building of the Wall  \
0                                                0.0
1                                                0.0
2                                                0.0
3                                                0.0
4                                                0.0

   PJ_Generation_peace movement  PJ_Generation_reconstruction years  \
0                           0.0                                 0.0
1                           0.0                                 0.0
2                           0.0                                 0.0
3                           0.0                                 0.0
4                           0.0                                 0.0

   PJ_Generation_war years
0                      0.0
1                      0.0
```

```
2                       0.0
3                       0.0
4                       0.0

[5 rows x 154 columns]
```

[112]:
```
# Apply feature scaling to the general population demographics data.
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_list = scaler.fit_transform(all_data_4)
scaled_data = pd.DataFrame(scaled_list, columns=all_data_4.columns)

print("all_data_4 shape: ", all_data_4.shape)
print("scaled_data_4 shape:" , scaled_data.shape)

#print(scaled_data.head())
```

```
all_data_4 shape:  (777909, 154)
scaled_data_4 shape: (777909, 154)
```

1.2.2 Discussion 2.1: Apply Feature Scaling

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

My Answer

I did not want to drop any more columns or lines. I made the threshold decisions and removed already anything necessary. That is why I think imputation is the best mettod to replace NaNs. I chose the most frequent value to be placed in all NaNs. In my opinion this corrupts data the least because it does not generate any value which is not already present.

1.2.3 Step 2.2: Perform Dimensionality Reduction

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

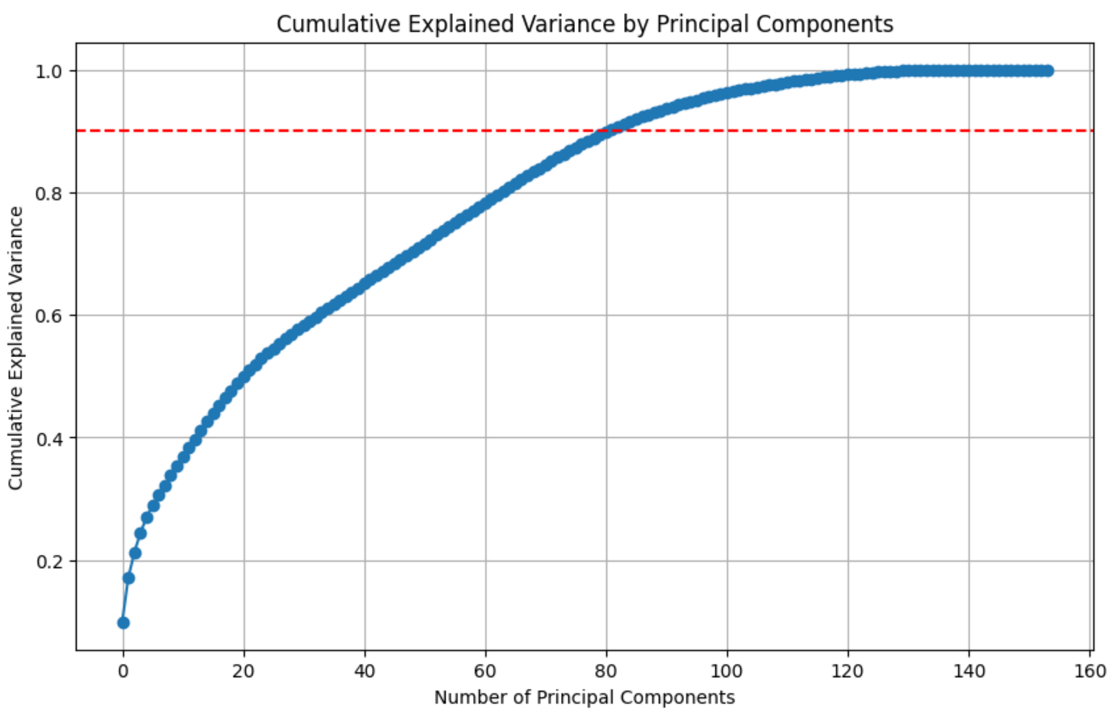
- Use sklearn's PCA class to apply principal component analysis on the data, thus finding the vectors of maximal variance in the data. To start, you should not set any parameters (so all components are computed) or set a number of components that is at least half the number of features (so there's enough features to see the general trend in variability).
- Check out the ratio of variance explained by each principal component as well as the cumulative variance explained. Try plotting the cumulative or sequential values using matplotlib's `plot()` function. Based on what you find, select a value for the number of transformed features you'll retain for the clustering part of the project.
- Once you've made a choice for the number of components to keep, make sure you re-fit a PCA instance to perform the decided-on transformation.

[115]:
```
# Apply PCA to the data.
```

```
from sklearn.decomposition import PCA

pca = PCA()  # Initialize PCA without parameters
pca.fit(scaled_data)
```

[115]: PCA()

[116]:
```
# Investigate the variance accounted for by each principal component.

# Step 2: Explained variance ratio
explained_variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance)


# Step 3: Plot cumulative variance
plt.figure(figsize=(10, 6))
plt.plot(cumulative_variance, marker='o')
plt.title('Cumulative Explained Variance by Principal Components')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.grid()
plt.axhline(y=0.90, color='r', linestyle='--')  # Example threshold line at 90%
plt.show()
```



[117]:
```
# Re-apply PCA to the data while selecting for number of components to retain.

# Step 4: Select number of components to keep
# For example, if you decide to keep components that explain at least 90%␣
↪variance
n_components = np.argmax(cumulative_variance >= 0.90) + 1  # +1 because of zero␣
↪indexing
print(f"Number of components to retain: {n_components}")

# Step 5: Refit PCA with the selected number of components
pca_final = PCA(n_components=n_components)
scaled_data_reduced = pca_final.fit_transform(scaled_data)

columns = [f'Princip_Comp {val +1}' for val in range (n_components)]
final_data = pd.DataFrame(scaled_data_reduced, columns=columns)

# Display the transformed data
print("Transformed data shape:", scaled_data_reduced.shape, "Type :",␣
↪type(scaled_data_reduced))
print("\n")
print("Transformed data:\n", scaled_data_reduced)
print("\n")
print("Final dataframe (final_data): \n", final_data.head())
```

```
Number of components to retain: 82
Transformed data shape: (777909, 82) Type : <class 'numpy.ndarray'>


Transformed data:
 [[-4.82655577 -3.85622188  2.825335   …  0.1081526  -1.20241822
  -1.35788558]
 [ 0.37512391 -0.87375036  3.61601851 … -1.01022612 -0.84752665
   0.42156618]
 [ 4.45299148  2.01233182  0.75714302 … -0.42465021 -0.49834229
  -0.38042071]
 …
 [ 0.36495569 -3.91708777  2.83127896 … -0.34699508  0.70657039
   0.27876565]
 [-6.01161982 -4.38987854 -2.9004895  … -0.7351623   0.42545673
  -0.29293924]
 [-0.01956811  2.27015856 -2.7141808  … -0.8833717  -0.99535461
  -0.32712776]]


Final dataframe (final_data):
    Princip_Comp 1  Princip_Comp 2  Princip_Comp 3  Princip_Comp 4  \
0       -4.826556       -3.856222        2.825335        0.536135
```

```
1       0.375124       -0.873750        3.616019       -0.818889
2       4.452991        2.012332        0.757143       -2.440777
3       0.403274        0.124109       -2.879216        3.423339
4       0.303587        0.241148        0.386541       -4.063606

   Princip_Comp 5  Princip_Comp 6  Princip_Comp 7  Princip_Comp 8  \
0       -0.844113       -1.630499       -2.077002        0.003691
1        3.105433       -0.550969       -1.048451        0.349835
2        0.616919        2.826983       -0.767724       -2.484463
3       -2.927090        1.068408       -2.073650        2.716670
4       -0.144470       -1.613547        0.466453        2.551468

   Princip_Comp 9  Princip_Comp 10  …  Princip_Comp 73  Princip_Comp 74  \
0       -1.155176        -1.467596  …        -0.965614        -0.335555
1        0.156050         0.518738  …         0.458374        -1.053305
2        0.371898         1.009738  …        -0.669123         0.366394
3        3.927174        -0.668310  …        -1.071446        -0.176989
4       -0.056083        -1.562936  …        -0.691509         0.702218

   Princip_Comp 75  Princip_Comp 76  Princip_Comp 77  Princip_Comp 78  \
0        -0.302333         1.705286        -0.876292        -0.047112
1        -0.110992         1.273416        -0.179752         0.384315
2         1.092375        -0.770124        -1.209100         0.686849
3         0.396424         0.603744        -0.162044        -0.892989
4        -0.630804        -1.148678        -0.282926        -0.944177

   Princip_Comp 79  Princip_Comp 80  Princip_Comp 81  Princip_Comp 82
0        -0.627054         0.108153        -1.202418        -1.357886
1        -0.113349        -1.010226        -0.847527         0.421566
2        -0.657710        -0.424650        -0.498342        -0.380421
3         0.292234        -0.837048        -0.208059         0.125354
4        -0.942516        -0.952912        -0.167242         0.010311

[5 rows x 82 columns]
```

1.2.4 Discussion 2.2: Perform Dimensionality Reduction

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

My Answer

I retained 82 components out of 155 coresponding to 90% of explained variance. So roughly 50% of the components.

1.2.5 Step 2.3: Interpret Principal Components

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

As a reminder, each principal component is a unit vector that points in the direction of highest variance (after accounting for the variance captured by earlier principal components). The further a weight is from zero, the more the principal component is in the direction of the corresponding feature. If two features have large weights of the same sign (both positive or both negative), then increases in one tend expect to be associated with increases in the other. To contrast, features with different signs can be expected to show a negative correlation: increases in one variable should result in a decrease in the other.

- To investigate the features, you should map each weight to their corresponding feature name, then sort the features according to weight. The most interesting features for each principal component, then, will be those at the beginning and end of the sorted list. Use the data dictionary document to help you understand these most prominent features, their relationships, and what a positive or negative value on the principal component might indicate.
- You should investigate and interpret feature associations from the first three principal components in this substep. To help facilitate this, you should write a function that you can call at any time to print the sorted list of feature weights, for the i-th principal component. This might come in handy in the next step of the project, when you interpret the tendencies of the discovered clusters.

[120]:
```
# Map weights for the first principal component to corresponding feature names
# and then print the linked values, sorted by weight.
# HINT: Try defining a function here or in a new cell that you can reuse in the
# other cells.

# Step 3: Create a function to print sorted feature weights
def print_feature_weights(pca, component_index):
    weights = pca.components_[component_index]
    feature_names = scaled_data.columns
    feature_weights = pd.DataFrame(weights, index=feature_names,␣
 ↪columns=['Weight'])
    sorted_weights = feature_weights.sort_values(by='Weight', ascending=False)
    print(f"Principal Component {component_index + 1} Feature Weights:")
    print(sorted_weights)
    print("\n")

print_feature_weights(pca_final, 0)
```

```
Principal Component 1 Feature Weights:
                      Weight
LP_STATUS_FEIN      0.202823
LP_STATUS_GROB      0.201907
MOBI_REGIO          0.193675
FINANZ_MINIMALIST   0.189106
PLZ8_ANTG1          0.186248
```

```
…                            …
PLZ8_BAUMAX         -0.176144
PLZ8_ANTG4          -0.179219
HH_EINKOMMEN_SCORE  -0.182009
CI_Wealth           -0.183876
PLZ8_ANTG3          -0.184987

[154 rows x 1 columns]
```

[121]:
```python
# Map weights for the second principal component to corresponding feature names
# and then print the linked values, sorted by weight.

print_feature_weights(pca_final, 1)
```

```
Principal Component 2 Feature Weights:
                         Weight
ALTERSKATEGORIE_GROB   0.232939
FINANZ_VORSORGER       0.222454
SEMIO_ERL              0.179211
SEMIO_LUST             0.162440
RETOURTYP_BK_S         0.159311
…                           …
SEMIO_PFLICHT         -0.203955
PJ_Decade_90s         -0.208877
SEMIO_REL             -0.210866
FINANZ_UNAUFFAELLIGER -0.219164
FINANZ_SPARER         -0.229606

[154 rows x 1 columns]
```

[122]:
```python
# Map weights for the third principal component to corresponding feature names
# and then print the linked values, sorted by weight.

print_feature_weights(pca_final, 2)
```

```
Principal Component 3 Feature Weights:
                     Weight
ANREDE_KZ          0.366284
SEMIO_KAEM         0.339026
SEMIO_DOM          0.308830
SEMIO_KRIT         0.281387
SEMIO_ERL          0.215264
…                       …
FINANZ_MINIMALIST -0.136061
SEMIO_KULT        -0.268440
```

```
SEMIO_SOZ          -0.269534
SEMIO_FAM          -0.276801
SEMIO_VERT         -0.338237

[154 rows x 1 columns]
```

1.2.6 Discussion 2.3: Interpret Principal Components

Can we interpret positive and negative values from them in a meaningful way?)

My Answer

Principal Component 1: Top 3 pozitive features: Weight FINANZ_HAUSBAUER 0.194440 PLZ8_BAUMAX 0.177768 HH_EINKOMMEN_SCORE 0.176405

Top 3 negative features: FINANZ_MINIMALIST -0.197853 LP_STATUS_FEIN -0.204278 MOBI_REGIO -0.211694

Interpretation: PC1 is correlated with Home ownership - very low, lives in PLZ8 region, income - very low and inverse correlated with: low financial interest , social status - low income , movement patterns - very high
So I would say PC1 high means a low income, not a home owner, high movement person

Principal Component 2: Top 3 pozitive features: Weight FINANZ_SPARER 0.282250 GEBURTSJAHR 0.266851 FINANZ_ANLEGER 0.247457

Top 3 negative features: SEMIO_LUST -0.188442 ALTERSKATEGORIE_GROB -0.231467 FINANZ_VORSORGER -0.277025

Interpretation: High score in PC2 means the person is a Money saver, young person, investor, very sensual-minded, probably under 30-40 years, financially prepared. So I would say a young investor.

Principal Component 3: Top 3 pozitive features: Weight SEMIO_KULT 0.282150 SEMIO_VERT 0.270438 SEMIO_FAM 0.255784

Top 3 negative features: SEMIO_ERL -0.264816 SEMIO_KAEM -0.287723 ANREDE_KZ -0.301370

Interpretation: High score in PC3 means the person is low cultural, less dreamful, less familiy oriented, event oriented, combative atitude, and a male. So we are talking about a practical, no culture fighter male.

1.3 Step 3: Clustering

1.3.1 Step 3.1: Apply Clustering to General Population

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

- Use sklearn's KMeans class to perform k-means clustering on the PCA-transformed data.
- Then, compute the average difference from each point to its assigned cluster's center. **Hint**: The KMeans object's `.score()` method might be useful here, but note that in sklearn, scores tend to be defined so that larger is better. Try applying it to a small, toy dataset, or use an internet search to help your understanding.
- Perform the above two steps for a number of different cluster counts. You can then see how the average distance decreases with an increasing number of clusters. However, each additional cluster provides a smaller net benefit. Use this fact to select a final number of clusters in which to group the data. **Warning**: because of the large size of the dataset, it can take a long time for the algorithm to resolve. The more clusters to fit, the longer the algorithm will take. You should test for cluster counts through at least 10 clusters to get the full picture, but you shouldn't need to test for a number of clusters above about 30.
- Once you've selected a final number of clusters to use, re-fit a KMeans instance to perform the clustering operation. Make sure that you also obtain the cluster assignments for the general demographics data, since you'll be using them in the final Step 3.3.

[125]:
```
# Over a number of different cluster counts...
from sklearn.cluster import KMeans

# i am testing on less cluster numbers since it takes a very long time
# but i tested on 30 clusters and observed 28 as the best fit.
inertia = []  # To store the inertia values
cluster_counts = range(2, 11)  # Testing cluster counts from 2 to 30



    # run k-means clustering on the data and...
for n_clusters in cluster_counts:
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    kmeans.fit(scaled_data_reduced)
    inertia.append(kmeans.inertia_)  # Store the inertia value
    print("I finished Cluster =", n_clusters, "...\n")
```

```
I finished Cluster = 2 …

I finished Cluster = 3 …

I finished Cluster = 4 …

I finished Cluster = 5 …

I finished Cluster = 6 …

I finished Cluster = 7 …

I finished Cluster = 8 …

I finished Cluster = 9 …
```

I finished Cluster = 10 …

[126]:
```
  # compute the average within-cluster distances.

labels = kmeans.labels_
centroids = kmeans.cluster_centers_
average_distances = []

for i in range(kmeans.n_clusters):
    # Get points in the current cluster
    cluster_points = scaled_data_reduced[labels == i]
    # Calculate distances from the centroid
    distances = np.linalg.norm(cluster_points - centroids[i], axis=1)
    # Compute the average distance for the current cluster
    average_distance = np.mean(distances)
    average_distances.append(average_distance)


# Display the average within-cluster distances
for i, avg_dist in enumerate(average_distances):
    print(f"Average distance for cluster {i}: {avg_dist:.4f}")


    # Display the cluster centers
print("Cluster centers:")
print(kmeans.cluster_centers_)
```

```
Average distance for cluster 0: 8.3123
Average distance for cluster 1: 8.9073
Average distance for cluster 2: 9.5670
Average distance for cluster 3: 10.0804
Average distance for cluster 4: 11.0009
Average distance for cluster 5: 9.6902
Average distance for cluster 6: 10.8177
Average distance for cluster 7: 9.8735
Average distance for cluster 8: 10.3932
Average distance for cluster 9: 11.2421
Cluster centers:
[[ 3.47894662e+00 -1.87249091e+00  3.71804605e-01  1.34698162e-01
  -2.61658567e-01  7.03792999e-01  8.65191582e-01 -4.68603525e-01
  -5.98300572e-01 -1.35509549e+00  1.41386571e+00 -5.41944222e-01
   7.40610055e-01 -1.38988881e+00  2.57509507e+00 -4.38270568e-02
   1.34375901e+00 -5.28070907e-01 -1.65286374e+00  3.37789810e-01
   3.31010553e-01 -1.71944348e+00  2.32621072e+00 -9.46694739e-01
  -2.33044791e+00  8.10449626e-01  2.74173390e+00 -4.48440106e-01
```

```
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  8.64616398e-01 -2.76006736e-01 -2.84468582e-02  1.13813565e-01
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```

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```

```
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```

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  2.25313091e-01  1.53794847e-01 -1.77679413e-01 -1.20933003e-01
 -6.63345013e-02 -1.70862237e-01 -2.33434393e-01 -3.62890093e-01
  5.08555926e-02  4.30952013e-02 -9.29018636e-02 -1.07034524e-01
 -1.13533369e-02  8.64741855e-02 -5.57512762e-02  1.25691345e-02
  8.61150381e-03  8.41650650e-02  5.29104821e-02  7.46418517e-03
 -1.10463226e-02 -2.66271892e-02  6.73079513e-02  6.30629136e-02
  6.52346853e-03 -4.84480804e-02  2.10285066e-02 -2.42482585e-02
  5.71863350e-03  5.01967535e-02 -1.15526782e-02 -1.86437825e-02
 -1.26363322e-02 -2.81910856e-02 -1.85353031e-02  3.20849188e-02
 -1.03100875e-01  4.47957382e-02 -7.20557170e-02  1.17160347e-02
  1.78179933e-01  6.26089872e-02 -9.44813165e-02 -2.17685705e-02
 -3.63280286e-03  6.07465430e-03 -1.22541788e-01  2.86358688e-02
 -5.78848949e-02 -2.19661423e-02  2.13454798e-02 -1.31268252e-01
 -8.03911562e-02  6.42053902e-02  5.16385776e-03 -6.40454470e-03
 -1.25925089e-02 -1.67794426e-01]
[-2.83831744e+00  3.80188967e+00 -2.57329443e-01  3.13215460e-01
 -5.51884223e-01  2.68457853e-01 -3.17357460e-01 -9.57194976e-02
  2.85480497e-02 -1.01361407e-01  1.08584350e-01  2.11200527e-01
  1.21819486e-02 -7.31465185e-02 -1.04987126e-02  1.99608564e-01
  8.08888151e-03  7.78420288e-02  7.95829573e-02  8.29154073e-02
 -6.44700266e-03  7.45528361e-02  2.78020677e-02 -1.63831735e-01
 -3.18856209e-02 -8.81450041e-02  1.34653609e-01  1.93255352e-01
 -1.60864528e-01  9.90752838e-02 -2.98470134e-02 -9.48811744e-02
  2.14041846e-02  1.84674490e-02 -8.86066390e-03 -1.39960345e-02
 -5.75738269e-02 -1.35201320e-02 -1.44071942e-02  3.36179521e-02
 -8.71449594e-03 -3.38781977e-03 -1.12786744e-02  9.48113239e-02
 -2.97616034e-02  7.22967095e-02  9.80737263e-02  3.73937742e-02
 -3.86734086e-02 -1.41115445e-02 -3.30759407e-03  2.38036756e-02
 -3.68208366e-03  6.75062322e-02  6.77652243e-03  3.22587227e-03
 -8.36210102e-02 -5.36976944e-02  2.23672134e-02  3.20718943e-02
  1.00304207e-01  1.60610051e-02  6.03771334e-02 -5.72692584e-02
  3.36532999e-03  5.07796247e-03 -4.22682772e-02  4.11032476e-02
  5.90852473e-03  1.62019673e-02 -5.46006724e-02 -6.45737383e-02
 -6.79034907e-02 -2.57715749e-02  5.38774696e-02  2.28309483e-02
 -3.64683117e-02  3.79702217e-02  4.03304270e-02  5.08406487e-02
 -3.31806821e-02  1.03380645e-02]
[ 3.82227833e+00  3.00979048e+00 -8.42735210e-01 -3.69368626e-01
  1.00127745e+00 -1.56295245e+00  7.14665069e-01  1.89465348e-01
 -5.84363436e-02 -8.06412788e-01 -1.55971213e+00  1.66931520e+00
  3.66726204e-01 -3.22063499e-02  3.63947447e-01 -1.75110802e+00
  2.36806422e-01  2.99614797e-01  2.02789490e-01 -4.51663620e-01
 -4.33137547e-01 -3.11796509e-01 -6.81641325e-02  4.43024260e-01
 -2.57534082e-01  1.52947332e-01 -2.34565254e-01 -3.51484582e-01
  4.12812577e-01 -2.58019517e-01 -3.52674234e-01 -1.54779134e-01
  2.11218051e-01 -6.55517988e-01  1.21415371e-01  1.70638798e-01
  8.29375328e-02  2.87582555e-01  3.72123998e-03 -1.16394092e-01
```
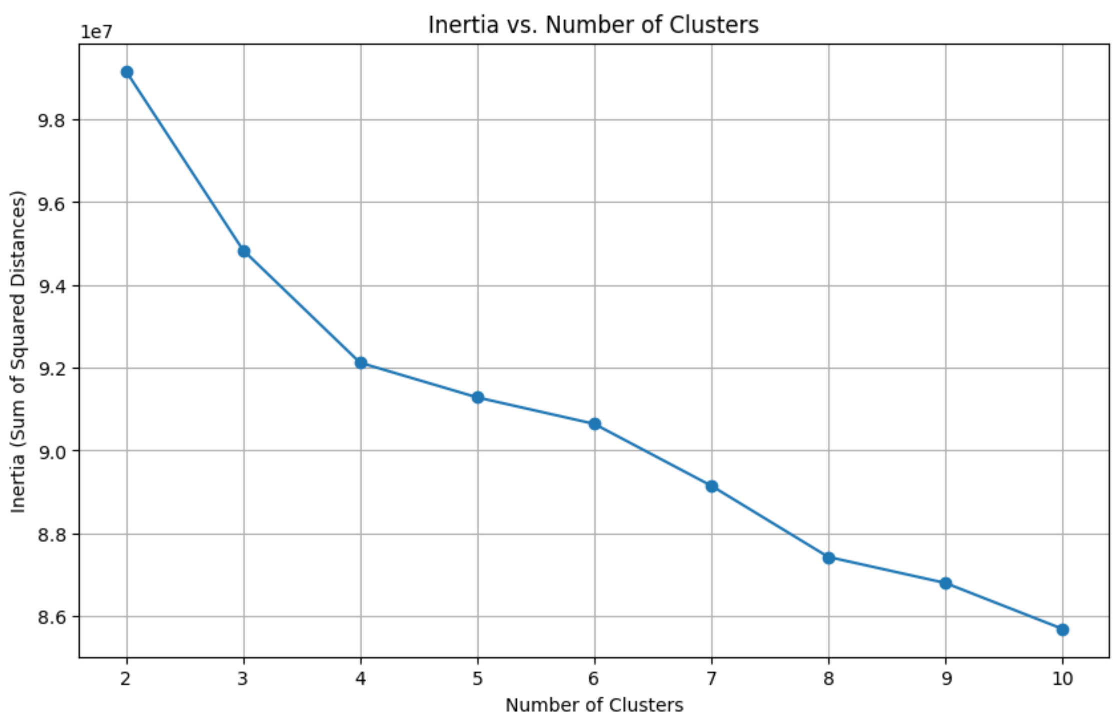

```
 2.42438007e-01  1.61631768e-01  9.02905083e-02  8.73543891e-02
 7.69774524e-02  9.65948221e-02  3.18744298e-02  9.03848137e-02
 2.18730858e-02  1.54844405e-01  3.32345604e-02 -3.92950057e-02
-6.45993440e-02  1.15089251e-01 -1.00630308e-01 -5.95637740e-02
-2.10567699e-01 -2.95099855e-01  6.10496334e-03 -3.46874980e-02
-1.52518468e-01 -5.39317087e-02  8.07024302e-02  2.74617066e-01
 1.28920628e-01 -1.56475266e-01 -2.43437961e-01 -3.15260464e-01
 2.10615765e-01 -2.47101039e-01  1.25066380e-01  1.65088036e-01
-8.57244953e-02  3.97042595e-02 -1.40796088e-02 -2.16921934e-02
-4.79965046e-02 -5.44971973e-02 -7.40093504e-02 -6.16269621e-02
-4.07328821e-02 -2.10298293e-02]]
```

[127]:
```python
# Investigate the change in within-cluster distance across number of clusters.
# HINT: Use matplotlib's plot function to visualize this relationship.

plt.figure(figsize=(10, 6))
plt.plot(cluster_counts, inertia, marker='o')
plt.title('Inertia vs. Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia (Sum of Squared Distances)')
plt.xticks(cluster_counts)
plt.grid()
plt.show()
```



[128]:

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

# I got this number with the elbow method on 30 clusters which took a huge␣
↪amount of time....
optimal_clusters = 28

final_kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
final_kmeans.fit(scaled_data_reduced)

final_data['Cluster'] = final_kmeans.labels_
original_pop_data_with_clusters = all_data_4
original_pop_data_with_clusters['Cluster'] = final_kmeans.labels_

# Display the DataFrame with cluster assignments
print(final_data.head())
```

```
   Princip_Comp 1  Princip_Comp 2  Princip_Comp 3  Princip_Comp 4  \
0       -4.826556       -3.856222        2.825335        0.536135
1        0.375124       -0.873750        3.616019       -0.818889
2        4.452991        2.012332        0.757143       -2.440777
3        0.403274        0.124109       -2.879216        3.423339
4        0.303587        0.241148        0.386541       -4.063606

   Princip_Comp 5  Princip_Comp 6  Princip_Comp 7  Princip_Comp 8  \
0       -0.844113       -1.630499       -2.077002        0.003691
1        3.105433       -0.550969       -1.048451        0.349835
2        0.616919        2.826983       -0.767724       -2.484463
3       -2.927090        1.068408       -2.073650        2.716670
4       -0.144470       -1.613547        0.466453        2.551468

   Princip_Comp 9  Princip_Comp 10  …  Princip_Comp 74  Princip_Comp 75  \
0       -1.155176        -1.467596  …        -0.335555        -0.302333
1        0.156050         0.518738  …        -1.053305        -0.110992
2        0.371898         1.009738  …         0.366394         1.092375
3        3.927174        -0.668310  …        -0.176989         0.396424
4       -0.056083        -1.562936  …         0.702218        -0.630804

   Princip_Comp 76  Princip_Comp 77  Princip_Comp 78  Princip_Comp 79  \
0         1.705286        -0.876292        -0.047112        -0.627054
1         1.273416        -0.179752         0.384315        -0.113349
2        -0.770124        -1.209100         0.686849        -0.657710
3         0.603744        -0.162044        -0.892989         0.292234
4        -1.148678        -0.282926        -0.944177        -0.942516

   Princip_Comp 80  Princip_Comp 81  Princip_Comp 82  Cluster
0         0.108153        -1.202418        -1.357886        4
1        -1.010226        -0.847527         0.421566        8
```

```
2        -0.424650        -0.498342        -0.380421       14
3        -0.837048        -0.208059         0.125354        2
4        -0.952912        -0.167242         0.010311        3

[5 rows x 83 columns]
```

[129]:
```python
original_pop_data_with_clusters = all_data_4
original_pop_data_with_clusters['Cluster'] = final_kmeans.labels_
print(original_pop_data_with_clusters.shape)
print(original_pop_data_with_clusters.head())
```

```
(777909, 155)
   ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  FINANZ_MINIMALIST  \
0                   1.0        2.0            5.0                1.0
1                   3.0        2.0            3.0                1.0
2                   4.0        2.0            2.0                4.0
3                   3.0        1.0            5.0                4.0
4                   1.0        2.0            2.0                3.0

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

   FINANZ_HAUSBAUER  FINANZTYP  …  PJ_Generation_economic miracle  \
0               5.0        1.0  …                             0.0
1               5.0        1.0  …                             0.0
2               2.0        6.0  …                             0.0
3               2.0        5.0  …                             0.0
4               5.0        2.0  …                             1.0

   PJ_Generation_economic miracle (  PJ_Generation_family orientation  \
0                               0.0                               0.0
1                               0.0                               0.0
2                               0.0                               1.0
3                               0.0                               1.0
4                               0.0                               0.0

   PJ_Generation_generation 68 / student protestors  \
0                                               0.0
1                                               0.0
2                                               0.0
3                                               0.0
4                                               0.0

   PJ_Generation_milk bar / Individualisation  \
```

```
0                                          0.0
1                                          0.0
2                                          0.0
3                                          0.0
4                                          0.0

   PJ_Generation_opponents to the building of the Wall  \
0                                                 0.0
1                                                 0.0
2                                                 0.0
3                                                 0.0
4                                                 0.0

   PJ_Generation_peace movement  PJ_Generation_reconstruction years  \
0                           0.0                                 0.0
1                           0.0                                 0.0
2                           0.0                                 0.0
3                           0.0                                 0.0
4                           0.0                                 0.0

   PJ_Generation_war years  Cluster
0                      0.0        4
1                      0.0        8
2                      0.0       14
3                      0.0        2
4                      0.0        3

[5 rows x 155 columns]
```

1.3.2 Discussion 3.1: Apply Clustering to General Population

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

My Answer:

After doing the elbow method we can see that the minimum optimal inertia (the sum of squares from all the points to the cluster centers) is 28. So optimum cluste numner = 28

I think if we go higher than 30 we might get a better cluster number.

1.3.3 Step 3.2: Apply All Steps to the Customer Data

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

- Don't forget when loading in the customers data, that it is semicolon (`;`) delimited.

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

[134]:
```python
# Load in the customer demographics data.

customer_data = pd.read_csv('Udacity_CUSTOMERS_Subset.csv', sep = ";")

display(customer_data.shape)
display(customer_data.head())
```

```
(191652, 85)

   AGER_TYP  ALTERSKATEGORIE_GROB  ANREDE_KZ  CJT_GESAMTTYP  \
0         2                     4          1            5.0
1        -1                     4          1            NaN
2        -1                     4          2            2.0
3         1                     4          1            2.0
4        -1                     3          1            6.0

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

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

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

   ORTSGR_KLS9  RELAT_AB
0          2.0       1.0
```

```
1           NaN       NaN
2           5.0       3.0
3           3.0       1.0
4           5.0       1.0

[5 rows x 85 columns]
```

[155]:
```
# Apply preprocessing, feature transformation, and clustering from the general
# demographics onto the customer data, obtaining cluster predictions for the
# customer demographics data.

customer_clean_data = clean_data(customer_data)


#imputer = SimpleImputer(strategy='most_frequent', copy = False)
customer_clean_data_2 = imputer.transform(customer_clean_data)
scaled_customer_list = scaler.transform(customer_clean_data_2)
pca_customer_data = pca_final.transform(scaled_customer_list)
cluster_assignments = final_kmeans.predict(pca_customer_data)

customer_clean_data['Cluster'] = cluster_assignments

#print("Customer Data with Cluster Assignments:")
#print(customer_clean_data_2.head())
```

```
Removed 2 columns with missing proportion greater than 70%.

Removed columns:
['TITEL_KZ', 'AGER_TYP']
Good_Data shape =  (138523, 83)

Bad_Data shape =  (53129, 83)
OST_WEST_KZ values:  [1 2]
```

```
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\3287232146.py:34:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
C:\Users\Cristi\AppData\Local\Temp\ipykernel_17276\3287232146.py:34:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
```

```
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  good_data['OST_WEST_KZ'].replace({'W': 1, 'O': 2}, inplace = True)
C:\Users\Cristi\AppData\Roaming\Python\Python311\site-
packages\sklearn\utils\validation.py:2739: UserWarning: X does not have valid
feature names, but StandardScaler was fitted with feature names
  warnings.warn(
C:\Users\Cristi\AppData\Roaming\Python\Python311\site-
packages\sklearn\utils\validation.py:2739: UserWarning: X does not have valid
feature names, but PCA was fitted with feature names
  warnings.warn(
```

1.3.4 Step 3.3: Compare Customer Data to Demographics Data

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

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

Take a look at the following points in this step:

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

centroids back to the original data space and interpret the retrieved values directly.

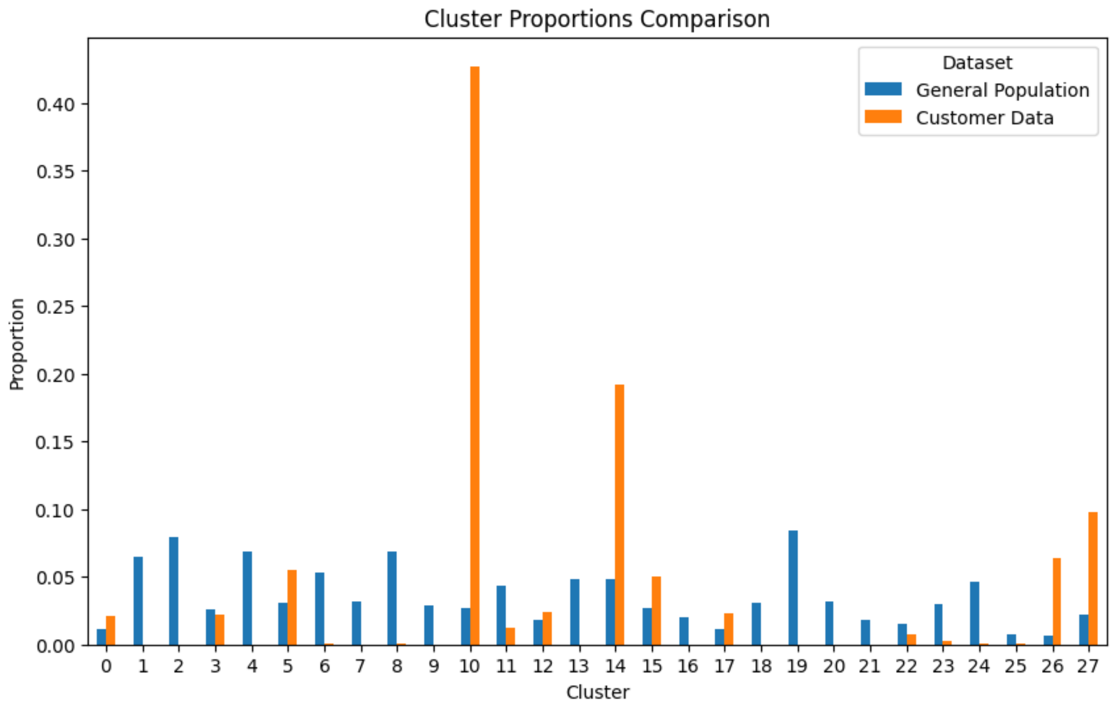
- Perform a similar investigation for the underrepresented clusters. Which cluster or clusters are underrepresented in the customer dataset compared to the general population, and what kinds of people are typified by these clusters?

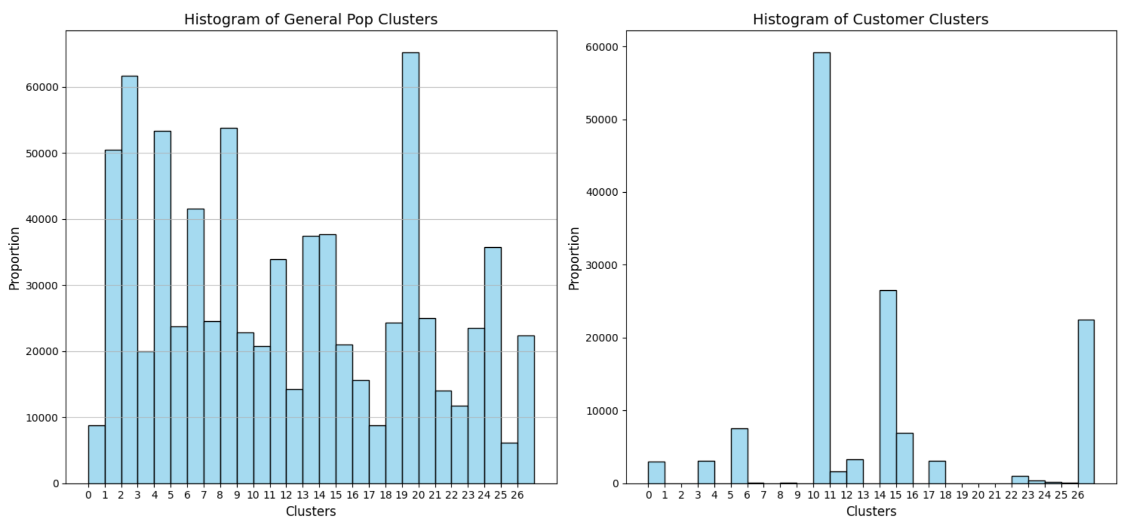
[166]:
```python
# Compute proportions for the general population
general_population_proportions = final_data['Cluster'].
 ↪value_counts(normalize=True).reset_index()
general_population_proportions.columns = ['Cluster', 'Proportion']

# Compute proportions for the customer data
customer_proportions = customer_clean_data['Cluster'].
 ↪value_counts(normalize=True).reset_index()
customer_proportions.columns = ['Cluster', 'Proportion']

# Merge the two DataFrames for comparison
comparison = pd.merge(general_population_proportions, customer_proportions,␣
 ↪on='Cluster', how='outer', suffixes=('_General', '_Customer'))
print(comparison)
```

```
    Cluster  Proportion_General  Proportion_Customer
0         0            0.011199             0.021274
1         1            0.064884             0.000072
2         2            0.079286             0.000116
3         3            0.025624             0.021931
4         4            0.068476             0.000051
5         5            0.030483             0.054706
6         6            0.053414             0.000722
7         7            0.031562                  NaN
8         8            0.069125             0.000339
9         9            0.029268                  NaN
10       10            0.026647             0.427294
11       11            0.043630             0.011955
12       12            0.018281             0.023714
13       13            0.048189                  NaN
14       14            0.048449             0.191571
15       15            0.027015             0.049941
16       16            0.020118                  NaN
17       17            0.011256             0.022588
18       18            0.031207                  NaN
19       19            0.083840             0.000123
20       20            0.032126                  NaN
21       21            0.017983                  NaN
22       22            0.015092             0.007363
23       23            0.030189             0.002909
24       24            0.046003             0.000975
25       25            0.007862             0.000383
26       26            0.006696             0.064170
```

```
27     27          0.022098          0.097803
```

[172]:
```
# Compare the proportion of data in each cluster for the customer data to the
# proportion of data in each cluster for the general population.


# Plotting the proportions
comparison.set_index('Cluster').plot(kind='bar', figsize=(10, 6))
plt.title('Cluster Proportions Comparison')
plt.ylabel('Proportion')
plt.xlabel('Cluster')
plt.xticks(rotation=0)
plt.legend(title='Dataset', labels=['General Population', 'Customer Data'])
plt.show()


# ploted a histogram here to see the clusters distribution
plt.figure(figsize=(15, 7))

plt.subplot(1, 2, 1)
sns.histplot(final_data['Cluster'], bins=27, kde=False, color='skyblue',␣
 ↪edgecolor='black')
plt.title('Histogram of General Pop Clusters', fontsize=14)
plt.xlabel('Clusters', fontsize=12)
plt.ylabel('Proportion', fontsize=12)
plt.grid(axis='y', alpha=0.75)
plt.xticks(np.arange(0,27,1))


plt.subplot(1, 2, 2)
sns.histplot(customer_clean_data['Cluster'], bins=27, kde=False,␣
 ↪color='skyblue', edgecolor='black')
plt.title('Histogram of Customer Clusters', fontsize=14)
plt.xlabel('Clusters', fontsize=12)
plt.ylabel('Proportion', fontsize=12)
plt.xticks(np.arange(0,27,1))


plt.tight_layout()
plt.show()
```





[198]:
```
# What kinds of people are part of a cluster that is overrepresented in the
# customer data compared to the general population?

# Identify overrepresented clusters
comparison['Difference'] = comparison['Proportion_Customer'] - comparison['Proportion_General']
```

```
overrepresented = comparison[comparison['Difference'] > 0]
underrepresented = comparison[comparison['Difference'] < 0]

over_sorted = overrepresented.sort_values(by='Difference', ascending=False)
print("Overrepresented Clusters:")
print(a)
```

```
Overrepresented Clusters:
    Cluster  Proportion_General  Proportion_Customer  Difference
10       10            0.026647             0.427294    0.400647
14       14            0.048449             0.191571    0.143122
27       27            0.022098             0.097803    0.075706
26       26            0.006696             0.064170    0.057474
5         5            0.030483             0.054706    0.024223
15       15            0.027015             0.049941    0.022926
17       17            0.011256             0.022588    0.011332
0         0            0.011199             0.021274    0.010075
12       12            0.018281             0.023714    0.005433
```

[200]:
```
cluster_selected = int(over_sorted.iloc[0]['Cluster'])
#centroid12 = final_kmeans.cluster_centers_[cluster_selected]
print("THe cluster selected for analysis is: ", over_sorted.iloc[0]['Cluster'])


filtered_data =␣
 ↪original_pop_data_with_clusters[original_pop_data_with_clusters['Cluster']␣
 ↪== cluster_selected]
most_frequent_values = filtered_data.mode().iloc[0]

print(f"Most frequent values for Cluster {cluster_selected}:")
print(most_frequent_values.sort_values(ascending=False))
```

```
THe cluster selected for analysis is:  10.0
Most frequent values for Cluster 10:
MIN_GEBAEUDEJAHR                                      1992.0
GEBURTSJAHR                                           1967.0
KBA13_ANZAHL_PKW                                      1400.0
ALTER_HH                                                18.0
Cluster                                                 10.0
                                                         …
PJ_Generation_generation 68 / student protestors         0.0
PJ_Generation_opponents to the building of the Wall      0.0
PJ_Generation_peace movement                             0.0
PJ_Generation_reconstruction years                       0.0
PJ_Generation_war years                                  0.0
Name: 0, Length: 155, dtype: float64
```

[202]:
```
# What kinds of people are part of a cluster that is underrepresented in the
# customer data compared to the general population?

print("\nUnderrepresented Clusters:")
print(underrepresented.sort_values(by='Difference', ascending=True))
```

```
Underrepresented Clusters:
    Cluster  Proportion_General  Proportion_Customer  Difference
19       19            0.083840             0.000123   -0.083717
2         2            0.079286             0.000116   -0.079170
8         8            0.069125             0.000339   -0.068786
4         4            0.068476             0.000051   -0.068425
1         1            0.064884             0.000072   -0.064812
6         6            0.053414             0.000722   -0.052692
24       24            0.046003             0.000975   -0.045028
11       11            0.043630             0.011955   -0.031675
23       23            0.030189             0.002909   -0.027279
22       22            0.015092             0.007363   -0.007728
25       25            0.007862             0.000383   -0.007479
3         3            0.025624             0.021931   -0.003692
```

1.3.5 Discussion 3.3: Compare Customer Data to Demographics Data

Can we describe segments of the population that are relatively popular with the mail-order company, or relatively unpopular with the company?

My Answer:

1. Based on the overrepresented columns from the charts we should focus on Cluster 10 as being the most important for us. Next in line, the clusters 14, 27 are also important.

Trying to describe Cluster 10 based on the orginial data before standardization and PCA. I extracted a mode = most frequent value of cluster 10 on each attribute. THis should give us an idea of who these customers are.

- they live in a house from 1992
- born in 1962
- live in PKW area
- the house owner is born between 1980 - 1984
- single top earners of higher age
- Connoisseurs
- top earners
- live in the same house for more than 9 years

Also it seems that Cluster 19 is the fartest away from our target audience. So we should never waste money on that cluster.

> Congratulations on making it this far in the project! Before you finish, make sure to check through the entire notebook from top to bottom to make sure that your analysis follows a logical flow and all of your findings are documented in **Discussion** cells. Once

you've checked over all of your work, you should export the notebook as an HTML document to submit for evaluation. You can do this from the menu, navigating to **File -> Download as -> HTML (.html)**. You will submit both that document and this notebook for your project submission.

[ ]:

```

```