Arvato Project Workbook

December 5, 2020

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

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

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

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

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

1.1 Part 0: Get to Know the Data

There are four data files associated with this project:

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

- `Udacity_MAILOUT_052018_TRAIN.csv`: Demographics data for individuals who were targets of a marketing campaign; 42 982 persons (rows) x 367 (columns).
- `Udacity_MAILOUT_052018_TEST.csv`: Demographics data for individuals who were targets of a marketing campaign; 42 833 persons (rows) x 366 (columns).

Each row of the demographics files represents a single person, but also includes information outside of individuals, including information about their household, building, and neighborhood. Use the information from the first two files to figure out how customers ("CUSTOMERS") are similar to or differ from the general population at large ("AZDIAS"), then use your analysis to make predictions on the other two files ("MAILOUT"), predicting which recipients are most likely to become a customer for the mail-order company.

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

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

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

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

1.2 Part 0.0 Load Data

```
In [2]: # load in the data
        azdias_chuch = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_AZDIAS_052018.
        customers_chuch = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_CUSTOMERS_0
```

```
In [3]: # Be sure to add in a lot more cells (both markdown and code) to document your
        # approach and findings!
        azdias_raw_data = pd.concat(azdias_chuch)
```

```
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2961: DtypeWarning: Colu
  exec(code_obj, self.user_global_ns, self.user_ns)
```

```
In [4]: customers_raw_data = pd.concat(customers_chuch)
```

1.3 Part 0.1 Load Support Data

```
In [5]: dias_attr_raw = pd.read_excel('./DIAS Attributes - Values 2017.xlsx').drop('Unnamed: 0',
        dias_information_levels_raw_data = pd.read_excel('./DIAS Information Levels - Attributes
```

1.4 Part 0.2 Analyse Data

```
In [6]: print("azdias : ", azdias_raw_data.shape)
        print("customers : ", customers_raw_data.shape)
        print("dias_attr_raw : ", dias_attr_raw.shape)
        print("dias_information_levels_raw_data : ", dias_information_levels_raw_data.shape)
```

```
azdias :  (891221, 366)
customers :  (191652, 369)
dias_attr_raw :  (2258, 4)
dias_information_levels_raw_data :  (313, 4)
```

```
In [7]: azdias_raw_data.head()
```

Out[7]:

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

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

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

	WOHNDAUER_2008	WOHNLAGE	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	NaN	NaN	3	1	2
1	9.0	4.0	5	2	1
2	9.0	2.0	5	2	3
3	9.0	7.0	3	2	4
4	9.0	3.0	4	1	3

[5 rows x 366 columns]

In [8]: customers_raw_data.head()

Out[8]:

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

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

	...	VK_ZG11	W_KEIT_KIND_HH	WOHNDAUER_2008	WOHNLAGE	\
0	...	2.0	6.0	9.0	7.0	
1	...	3.0	0.0	9.0	NaN	
2	...	11.0	6.0	9.0	2.0	
3	...	2.0	NaN	9.0	7.0	
4	...	4.0	2.0	9.0	3.0	

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

	ALTERSKATEGORIE_GROB
0	4
1	4
2	4
3	4
4	3

[5 rows x 369 columns]

In [9]: dias_attr_raw.head()

Out[9]:

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

In [10]: dias_information_levels_raw_data.head()

Out[10]:

	Information level	Attribute	Description	Additional notes
0	NaN	AGER_TYP	best-ager typology	in cooperation with Kantar TNS; the informatio...
1	Person	ALTERSKATEGORIE_GROB	age through prename analysis	modelled on millions of first name-age-referen...
2	NaN	ANREDE_KZ	gender	NaN
3	NaN	CJT_GESAMTTYP	Customer-Journey-Typology relating to the pref...	relating to the preferred information, marketi...
4	NaN	FINANZ_MINIMALIST	financial typology: low financial interest	Gfk-Typology based on a representative househo...

In [11]:
```
diff_column_information = ['CUSTOMER_GROUP', 'ONLINE_PURCHASE','PRODUCT_GROUP']
diff_column_information
```

Out[11]:
```
['CUSTOMER_GROUP', 'ONLINE_PURCHASE', 'PRODUCT_GROUP']
```

1.5 Part 0.3 Preprocess dias_attr_raw

In [12]:
```
dias_attr_raw["Attribute"] = dias_attr_raw["Attribute"].ffill()

dias_attr_raw.head(10)
```

Out[12]:

	Attribute	Description	Value	Meaning
0	AGER_TYP	best-ager typology	-1	unknown
1	AGER_TYP	NaN	0	no classification possible
2	AGER_TYP	NaN	1	passive elderly
3	AGER_TYP	NaN	2	cultural elderly
4	AGER_TYP	NaN	3	
5	ALTERSKATEGORIE_GROB	age classification through prename analysis	-1, 0	
6	ALTERSKATEGORIE_GROB	NaN	1	
7	ALTERSKATEGORIE_GROB	NaN	2	
8	ALTERSKATEGORIE_GROB	NaN	3	
9	ALTERSKATEGORIE_GROB	NaN	4	

```
4   experience-driven elderly
5                     unknown
6                  < 30 years
7               30 - 45 years
8               46 - 60 years
9                  > 60 years
```

1.6 Part 0.4 Get & Calculate List Unknown

```
In [13]: list_unknown = {}
         for index, row in dias_attr_raw.iterrows():
             if(row["Meaning"] == "unknown") :
                 # list_unknown[row['Attribute']] = str(row['Value']).split(",");
                 list_unknown[row['Attribute']] = [row['Value']];

In [14]: list_unknown

Out[14]: {'AGER_TYP': [-1],
          'ALTERSKATEGORIE_GROB': ['-1, 0'],
          'ANREDE_KZ': ['-1, 0'],
          'BALLRAUM': [-1],
          'BIP_FLAG': [-1],
          'CAMEO_DEUG_2015': [-1],
          'CAMEO_DEUINTL_2015': [-1],
          'CJT_GESAMTTYP': [0],
          'D19_KK_KUNDENTYP': [-1],
          'EWDICHTE': [-1],
          'FINANZTYP': [-1],
          'FINANZ_ANLEGER': [-1],
          'FINANZ_HAUSBAUER': [-1],
          'FINANZ_MINIMALIST': [-1],
          'FINANZ_SPARER': [-1],
          'FINANZ_UNAUFFAELLIGER': [-1],
          'FINANZ_VORSORGER': [-1],
          'GEBAEUDETYP': ['-1, 0'],
          'GEOSCORE_KLS7': ['-1, 0'],
          'HAUSHALTSSTRUKTUR': ['-1, 0'],
          'HEALTH_TYP': [-1],
          'HH_EINKOMMEN_SCORE': ['-1, 0'],
          'INNENSTADT': [-1],
          'KBA05_ALTER1': ['-1, 9'],
          'KBA05_ALTER2': ['-1, 9'],
          'KBA05_ALTER3': ['-1, 9'],
          'KBA05_ALTER4': ['-1, 9'],
          'KBA05_ANHANG': ['-1, 9'],
          'KBA05_ANTG1': [-1],
          'KBA05_ANTG2': [-1],
          'KBA05_ANTG3': [-1],
```

```
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'KBA05_CCM1': ['-1, 9'],
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'KBA05_CCM3': ['-1, 9'],
'KBA05_CCM4': ['-1, 9'],
'KBA05_DIESEL': ['-1, 9'],
'KBA05_FRAU': ['-1, 9'],
'KBA05_GBZ': ['-1, 0'],
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'KBA05_HERST3': ['-1, 9'],
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'KBA05_HERST5': ['-1, 9'],
'KBA05_HERSTTEMP': ['-1, 9'],
'KBA05_KRSAQUOT': ['-1, 9'],
'KBA05_KRSHERST1': ['-1, 9'],
'KBA05_KRSHERST2': ['-1, 9'],
'KBA05_KRSHERST3': ['-1, 9'],
'KBA05_KRSKLEIN': ['-1, 9'],
'KBA05_KRSOBER': ['-1, 9'],
'KBA05_KRSVAN': ['-1, 9'],
'KBA05_KRSZUL': ['-1, 9'],
'KBA05_KW1': ['-1, 9'],
'KBA05_KW2': ['-1, 9'],
'KBA05_KW3': ['-1, 9'],
'KBA05_MAXAH': ['-1, 9'],
'KBA05_MAXBJ': ['-1, 9'],
'KBA05_MAXHERST': ['-1, 9'],
'KBA05_MAXSEG': ['-1, 9'],
'KBA05_MAXVORB': ['-1, 9'],
'KBA05_MOD1': ['-1, 9'],
'KBA05_MOD2': ['-1, 9'],
'KBA05_MOD3': ['-1, 9'],
'KBA05_MOD4': ['-1, 9'],
'KBA05_MOD8': ['-1, 9'],
'KBA05_MODTEMP': ['-1, 9'],
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'KBA05_SEG3': ['-1, 9'],
'KBA05_SEG4': ['-1, 9'],
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'KBA05_SEG7': ['-1, 9'],
```

```
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'KBA13_BJ_2008': [-1],
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'KBA13_HALTER_60': [-1],
```

```
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'KBA13_HERST_AUDI_VW': [-1],
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'KBA13_KW_121': [-1],
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'KBA13_MERCEDES': [-1],
'KBA13_MOTOR': [-1],
'KBA13_NISSAN': [-1],
'KBA13_OPEL': [-1],
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'KBA13_RENAULT': [-1],
'KBA13_SEG_GELAENDEWAGEN': [-1],
'KBA13_SEG_GROSSRAUMVANS': [-1],
'KBA13_SEG_KLEINST': [-1],
'KBA13_SEG_KLEINWAGEN': [-1],
'KBA13_SEG_KOMPAKTKLASSE': [-1],
```

```
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'KBA13_SEG_MINIWAGEN': [-1],
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'KBA13_SEG_SPORTWAGEN': [-1],
'KBA13_SEG_UTILITIES': [-1],
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'KBA13_TOYOTA': [-1],
'KBA13_VORB_0': [-1],
'KBA13_VORB_1': [-1],
'KBA13_VORB_1_2': [-1],
'KBA13_VORB_2': [-1],
'KBA13_VORB_3': [-1],
'KBA13_VW': [-1],
'KKK': ['-1, 0'],
'NATIONALITAET_KZ': ['-1, 0'],
'ORTSGR_KLS9': ['-1'],
'OST_WEST_KZ': [-1],
'PLZ8_ANTG1': [-1],
'PLZ8_ANTG2': [-1],
'PLZ8_ANTG3': [-1],
'PLZ8_ANTG4': [-1],
'PLZ8_GBZ': [-1],
'PLZ8_HHZ': [-1],
'PRAEGENDE_JUGENDJAHRE': ['-1, 0'],
'REGIOTYP': ['-1, 0'],
'RELAT_AB': ['-1, 9'],
'RETOURTYP_BK_S': [0],
'SEMIO_DOM': ['-1, 9'],
'SEMIO_ERL': ['-1, 9'],
'SEMIO_FAM': ['-1, 9'],
'SEMIO_KAEM': ['-1, 9'],
'SEMIO_KRIT': ['-1, 9'],
'SEMIO_KULT': ['-1, 9'],
'SEMIO_LUST': ['-1, 9'],
'SEMIO_MAT': ['-1, 9'],
'SEMIO_PFLICHT': ['-1, 9'],
'SEMIO_RAT': ['-1, 9'],
'SEMIO_REL': ['-1, 9'],
'SEMIO_SOZ': ['-1, 9'],
'SEMIO_TRADV': ['-1, 9'],
'SEMIO_VERT': ['-1, 9'],
```

```
 'SHOPPER_TYP': [-1],
 'SOHO_FLAG': [-1],
 'TITEL_KZ': ['-1, 0'],
 'VERS_TYP': [-1],
 'WOHNDAUER_2008': ['-1, 0'],
 'WOHNLAGE': [-1],
 'WACHSTUMSGEBIET_NB': ['-1, 0'],
 'W_KEIT_KIND_HH': ['-1, 0'],
 'ZABEOTYP': ['-1, 9']}
```

1.7 Part 0.5 Helper Function

```
In [15]: def replace_unknown_data_with_nan(val, unkown):
             # print(val, " : ", unkown)
             full_unkown = str(unkown).split(",")
             if str(val) in full_unkown:
                 # print("return nan")
                 return np.nan
             else:
                 return val
```

```
In [16]: def preprocessing_data(target_df, list_unknown):
             for attrib_key,attrib_val in list_unknown.items():
                 if attrib_key in target_df.columns :
                     target_df[attrib_key] = target_df[attrib_key].apply(replace_unknown_data_wi

             return target_df
```

1.8 Part 0.6 Preprocessing Customers & Azdias Data

```
In [17]: customers = preprocessing_data(customers_raw_data,list_unknown)
```

```
In [18]: customers.head(10)
```

Out[18]:

	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	\
0	9626	2.0	1.0	10.0	NaN	NaN	
1	9628	NaN	9.0	11.0	NaN	NaN	
2	143872	NaN	1.0	6.0	NaN	NaN	
3	143873	1.0	1.0	8.0	NaN	NaN	
4	143874	NaN	1.0	20.0	NaN	NaN	
5	143888	1.0	1.0	11.0	NaN	NaN	
6	143904	2.0	1.0	10.0	NaN	NaN	
7	143910	1.0	1.0	10.0	NaN	NaN	
8	102160	2.0	3.0	5.0	NaN	NaN	
9	102173	1.0	1.0	20.0	NaN	NaN	

	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	ANZ_HAUSHALTE_AKTIV	\
0	NaN	NaN	10.0	1.0	
1	NaN	NaN	NaN	NaN	

```
2          NaN          NaN                  0.0                  1.0
3          NaN          NaN                  8.0                  0.0
4          NaN          NaN                 14.0                  7.0
5          NaN          NaN                 10.0                  1.0
6          NaN          NaN                 10.0                  1.0
7          NaN          NaN                  9.0                  1.0
8          NaN          NaN                  4.0                 74.0
9          NaN          NaN                 13.0                  1.0

          ...           VK_ZG11  W_KEIT_KIND_HH  WOHNDAUER_2008  WOHNLAGE  \
0         ...               2.0             6.0             9.0       7.0
1         ...               3.0             0.0             9.0       NaN
2         ...              11.0             6.0             9.0       2.0
3         ...               2.0             NaN             9.0       7.0
4         ...               4.0             2.0             9.0       3.0
5         ...               1.0             6.0             9.0       1.0
6         ...               2.0             6.0             9.0       7.0
7         ...               1.0             6.0             9.0       3.0
8         ...               9.0             6.0             3.0       4.0
9         ...               4.0             2.0             9.0       5.0

   ZABEOTYP      PRODUCT_GROUP  CUSTOMER_GROUP ONLINE_PURCHASE ANREDE_KZ  \
0         3  COSMETIC_AND_FOOD     MULTI_BUYER               0         1
1         3               FOOD    SINGLE_BUYER               0         1
2         3  COSMETIC_AND_FOOD     MULTI_BUYER               0         2
3         1           COSMETIC     MULTI_BUYER               0         1
4         1               FOOD     MULTI_BUYER               0         1
5         2  COSMETIC_AND_FOOD     MULTI_BUYER               0         1
6         1  COSMETIC_AND_FOOD     MULTI_BUYER               0         1
7         3               FOOD    SINGLE_BUYER               0         1
8         3           COSMETIC     MULTI_BUYER               0         2
9         1           COSMETIC     MULTI_BUYER               0         1

  ALTERSKATEGORIE_GROB
0                    4
1                    4
2                    4
3                    4
4                    3
5                    3
6                    4
7                    4
8                    4
9                    3

[10 rows x 369 columns]
```

In [19]:
```
azdiaz = preprocessing_data(azdias_raw_data,list_unknown)
```

```
In [20]: azdiaz.head(10)
```

Out[20]:

	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	\
0	910215	NaN	NaN	NaN	NaN	NaN	
1	910220	NaN	9.0	0.0	NaN	NaN	
2	910225	NaN	9.0	17.0	NaN	NaN	
3	910226	2.0	1.0	13.0	NaN	NaN	
4	910241	NaN	1.0	20.0	NaN	NaN	
5	910244	3.0	1.0	10.0	NaN	NaN	
6	910248	NaN	9.0	0.0	NaN	NaN	
7	910261	NaN	1.0	14.0	NaN	NaN	
8	645145	NaN	9.0	16.0	NaN	NaN	
9	645153	NaN	5.0	17.0	NaN	NaN	

	ALTER_KIND3	ALTER_KIND4	ALTERSKATEGORIE_FEIN	ANZ_HAUSHALTE_AKTIV	\
0	NaN	NaN	NaN	NaN	
1	NaN	NaN	21.0	11.0	
2	NaN	NaN	17.0	10.0	
3	NaN	NaN	13.0	1.0	
4	NaN	NaN	14.0	3.0	
5	NaN	NaN	10.0	5.0	
6	NaN	NaN	NaN	4.0	
7	NaN	NaN	14.0	6.0	
8	NaN	NaN	16.0	2.0	
9	NaN	NaN	17.0	9.0	

	...	VHN	VK_DHT4A	VK_DISTANZ	VK_ZG11	W_KEIT_KIND_HH	\
0	...	NaN	NaN	NaN	NaN	NaN	
1	...	4.0	8.0	11.0	10.0	3.0	
2	...	2.0	9.0	9.0	6.0	3.0	
3	...	0.0	7.0	10.0	11.0	NaN	
4	...	2.0	3.0	5.0	4.0	2.0	
5	...	2.0	10.0	7.0	4.0	6.0	
6	...	2.0	7.0	10.0	10.0	3.0	
7	...	2.0	10.0	12.0	9.0	5.0	
8	...	4.0	8.0	11.0	8.0	5.0	
9	...	4.0	1.0	1.0	1.0	4.0	

	WOHNDAUER_2008	WOHNLAGE	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	NaN	NaN	3	1	2
1	9.0	4.0	5	2	1
2	9.0	2.0	5	2	3
3	9.0	7.0	3	2	4
4	9.0	3.0	4	1	3
5	9.0	7.0	4	2	1
6	9.0	5.0	4	2	2
7	9.0	1.0	1	1	1
8	8.0	1.0	6	1	3

```
9             3.0       7.0        4         2                    3

[10 rows x 366 columns]
```

1.9 Part 0.7 Checkpoint 1 Preprocessing

```
In [21]: dias_attr_raw.to_csv('dias_attr_1.csv', index=False)
         customers.to_csv('customers_1.csv', index=False)
         azdiaz.to_csv('azdias_1.csv', index=False)
```

1.10 Part 0.8 Clean up Memory usage

```
In [22]: del dias_attr_raw
         del azdias_raw_data
         del customers_raw_data
         del azdiaz
         del customers
```

1.11 Part 0.9 Open Checkpoint 1 Preprocessing

```
In [23]: dias_attr = pd.read_csv('dias_attr_1.csv')
```

```
In [24]: # load in the data
         azdias_batch = pd.read_csv('azdias_1.csv', chunksize=50000)
         customers_batch = pd.read_csv('customers_1.csv', chunksize=10000)
```

```
In [25]: customers = pd.concat(customers_batch)
```

```
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2961: DtypeWarning: Colu
  exec(code_obj, self.user_global_ns, self.user_ns)
```

```
In [26]: azdias = pd.concat(azdias_batch)
```

```
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2961: DtypeWarning: Colu
  exec(code_obj, self.user_global_ns, self.user_ns)
```

```
In [27]: print("azdias : ", azdias.shape)
         print("customers : ", customers.shape)
         print("dias_attr : ", dias_attr.shape)

azdias :  (891221, 366)
customers :  (191652, 369)
dias_attr :  (2258, 4)
```

```
In [28]: azdias.head()
```

Out[28]:

	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	\
0	910215	NaN	NaN	NaN	NaN	NaN	
1	910220	NaN	9.0	0.0	NaN	NaN	
2	910225	NaN	9.0	17.0	NaN	NaN	
3	910226	2.0	1.0	13.0	NaN	NaN	
4	910241	NaN	1.0	20.0	NaN	NaN	

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

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

	WOHNDAUER_2008	WOHNLAGE	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	NaN	NaN	3	1	2
1	9.0	4.0	5	2	1
2	9.0	2.0	5	2	3
3	9.0	7.0	3	2	4
4	9.0	3.0	4	1	3

[5 rows x 366 columns]

In [29]:
```
customers.head()
```

Out[29]:

	LNR	AGER_TYP	AKT_DAT_KL	ALTER_HH	ALTER_KIND1	ALTER_KIND2	\
0	9626	2.0	1.0	10.0	NaN	NaN	
1	9628	NaN	9.0	11.0	NaN	NaN	
2	143872	NaN	1.0	6.0	NaN	NaN	
3	143873	1.0	1.0	8.0	NaN	NaN	
4	143874	NaN	1.0	20.0	NaN	NaN	

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

	...	VK_ZG11	W_KEIT_KIND_HH	WOHNDAUER_2008	WOHNLAGE	\
0	...	2.0	6.0	9.0	7.0	

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

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

  ALTERSKATEGORIE_GROB
0                    4
1                    4
2                    4
3                    4
4                    3

[5 rows x 369 columns]
```

```
In [30]: dias_attr.head()
```

```
Out[30]:   Attribute         Description Value                    Meaning
         0  AGER_TYP  best-ager typology    -1                    unknown
         1  AGER_TYP                 NaN     0  no classification possible
         2  AGER_TYP                 NaN     1             passive elderly
         3  AGER_TYP                 NaN     2            cultural elderly
         4  AGER_TYP                 NaN     3   experience-driven elderly
```

1.12 Part 0.11 calculate missing column

```
In [31]: def get_missing_report(df):
             percent_missing = df.isnull().sum() * 100 / len(df)
             missing_value_df = pd.DataFrame({'column_name': df.columns,
                                              'percent_missing': percent_missing}).reset_index(drop=
             return missing_value_df

         # source : https://stackoverflow.com/questions/51070985/find-out-the-percentage-of-miss
```

```
In [32]: calculate_missing_customers = get_missing_report(customers)
         calculate_missing_azdias = get_missing_report(azdias)
```

```
In [33]: calculate_missing_customers.sort_values('percent_missing', inplace=True, ascending=Fals
         calculate_missing_azdias.sort_values('percent_missing', inplace=True, ascending=False)
```

```
In [34]: calculate_missing_customers.head(30)
```

```
Out[34]:          column_name  percent_missing
         7        ALTER_KIND4        99.876860
```

```
6         ALTER_KIND3        99.334732
5         ALTER_KIND2        97.338927
4         ALTER_KIND1        93.860748
300     KK_KUNDENTYP        58.406382
1           AGER_TYP        48.059504
100       EXTSEL992        44.498883
149     KBA05_KRSVAN        29.209192
144  KBA05_KRSHERST1        29.209192
136        KBA05_GBZ        29.209192
137     KBA05_HERST1        29.209192
138     KBA05_HERST2        29.209192
139     KBA05_HERST3        29.209192
140     KBA05_HERST4        29.209192
141     KBA05_HERST5        29.209192
143   KBA05_KRSAQUOT        29.209192
148    KBA05_KRSOBER        29.209192
145  KBA05_KRSHERST2        29.209192
146  KBA05_KRSHERST3        29.209192
134     KBA05_DIESEL        29.209192
150     KBA05_KRSZUL        29.209192
151        KBA05_KW1        29.209192
152        KBA05_KW2        29.209192
153        KBA05_KW3        29.209192
135       KBA05_FRAU        29.209192
130       KBA05_CCM1        29.209192
133       KBA05_CCM4        29.209192
124      KBA05_ANTG1        29.209192
313       MOBI_REGIO        29.209192
119     KBA05_ALTER1        29.209192
```

In [35]:
```
calculate_missing_azdias.head(20)
```

Out[35]:
```
                     column_name  percent_missing
7                     ALTER_KIND4        99.864792
6                     ALTER_KIND3        99.307691
5                     ALTER_KIND2        96.690047
4                     ALTER_KIND1        90.904837
1                        AGER_TYP        76.019640
100                    EXTSEL992        73.399639
300                 KK_KUNDENTYP        65.596749
8            ALTERSKATEGORIE_FEIN        29.504130
61      D19_LETZTER_KAUF_BRANCHE        28.849522
53    D19_GESAMT_ONLINE_QUOTE_12        28.849522
69                  D19_SOZIALES        28.849522
62                     D19_LOTTO        28.849522
57                 D19_KONSUMTYP        28.849522
85   D19_VERSAND_ONLINE_QUOTE_12        28.849522
77     D19_TELKO_ONLINE_QUOTE_12        28.849522
```

```
92     D19_VERSI_ONLINE_QUOTE_12        28.849522
36    D19_BANKEN_ONLINE_QUOTE_12        28.849522
134                 KBA05_DIESEL        14.959701
136                    KBA05_GBZ        14.959701
135                   KBA05_FRAU        14.959701
```

1.13 Part 0.12 Analyse column missing that above threshold

```
In [36]: threshold_missing_rate = 25

In [37]: def calculate_missing_above_threshold(df) :
             return df[df["percent_missing"] > threshold_missing_rate]

In [38]: data_missing_customer_above = calculate_missing_above_threshold(calculate_missing_custo
         data_missing_azdias_above = calculate_missing_above_threshold(calculate_missing_azdias)

In [39]: print("data_missing_customer_above : " , data_missing_customer_above.shape)
         data_missing_customer_above.head()

data_missing_customer_above :  (232, 2)


Out[39]:       column_name  percent_missing
         7     ALTER_KIND4        99.876860
         6     ALTER_KIND3        99.334732
         5     ALTER_KIND2        97.338927
         4     ALTER_KIND1        93.860748
         300  KK_KUNDENTYP        58.406382

In [40]: print("data_missing_azdias_above : " , data_missing_azdias_above.shape)
         data_missing_azdias_above.head()

data_missing_azdias_above :  (17, 2)


Out[40]:    column_name  percent_missing
         7  ALTER_KIND4        99.864792
         6  ALTER_KIND3        99.307691
         5  ALTER_KIND2        96.690047
         4  ALTER_KIND1        90.904837
         1     AGER_TYP        76.019640

In [41]: list_data_missing_customers = data_missing_customer_above["column_name"].tolist()
         list_data_missing_azdias = data_missing_azdias_above["column_name"].tolist()

In [42]: print("count list_data_missing_customers : " ,len(list_data_missing_customers) )
         print("count list_data_missing_azdias : " ,len(list_data_missing_azdias) )

count list_data_missing_customers :  232
count list_data_missing_azdias :  17
```

1.14 Part 0.13 Compare both of data missing

```
In [43]: # compare two not match
         def returnNotMatches(a, b):
             return [[x for x in a if x not in b], [x for x in b if x not in a]]

         # source : https://stackoverflow.com/questions/35713093/how-can-i-compare-two-lists-in-

In [44]: not_match_customers, not_match_asdias = returnNotMatches(list_data_missing_customers,li

In [45]: print("count not_match_customers : " ,len(not_match_customers) )
         print("count not_match_asdias : " ,len(not_match_asdias) )

count not_match_customers :  224
count not_match_asdias :  9


In [46]: not_match_asdias

Out[46]: ['D19_LETZTER_KAUF_BRANCHE',
          'D19_GESAMT_ONLINE_QUOTE_12',
          'D19_SOZIALES',
          'D19_LOTTO',
          'D19_KONSUMTYP',
          'D19_VERSAND_ONLINE_QUOTE_12',
          'D19_TELKO_ONLINE_QUOTE_12',
          'D19_VERSI_ONLINE_QUOTE_12',
          'D19_BANKEN_ONLINE_QUOTE_12']

In [47]: calculate_missing_customers[calculate_missing_customers.column_name.isin(not_match_asdi

Out[47]:                     column_name  percent_missing
         57                D19_KONSUMTYP        24.887296
         36   D19_BANKEN_ONLINE_QUOTE_12        24.887296
         53   D19_GESAMT_ONLINE_QUOTE_12        24.887296
         61     D19_LETZTER_KAUF_BRANCHE        24.887296
         62                   D19_LOTTO        24.887296
         92    D19_VERSI_ONLINE_QUOTE_12        24.887296
         69                D19_SOZIALES        24.887296
         77    D19_TELKO_ONLINE_QUOTE_12        24.887296
         85  D19_VERSAND_ONLINE_QUOTE_12        24.887296
```

1.15 Part 0.14 Remove Selected missing Column

```
In [48]: def get_selected_missing_column() :
             if list_data_missing_customers >= list_data_missing_azdias :
                 return list_data_missing_customers
             else :
                 return list_data_missing_azdias
```

```
In [49]: selected_missing_column = get_selected_missing_column()
         print("selected_missing_column : ", len(selected_missing_column))
         for i in selected_missing_column:
             print(i, end=" ")

selected_missing_column :  232
ALTER_KIND4 ALTER_KIND3 ALTER_KIND2 ALTER_KIND1 KK_KUNDENTYP AGER_TYP EXTSEL992 KBA05_KRSVAN KBA

In [50]: def remove_columns(df):
             """
             Drops given list of columns from df.
             """
             return df.drop(selected_missing_column, axis = 1)

In [51]: customers = remove_columns(customers)

In [52]: azdias = remove_columns(azdias)

In [53]: customers.head()

Out[53]:       LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
         0    9626         1.0      10.0         0.0           2.0        0.0
         1    9628         9.0      11.0         0.0           3.0        0.0
         2  143872         1.0       6.0         0.0           1.0        0.0
         3  143873         1.0       8.0         0.0           0.0        0.0
         4  143874         1.0      20.0         0.0           4.0        0.0

            CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
         0            5.0                4.0        1.0        1.0
         1            NaN                NaN        NaN        NaN
         2            2.0                5.0        2.0        2.0
         3            2.0                5.0        1.0        1.0
         4            6.0                4.0        3.0        3.0

                    ...           VK_DHT4A  VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  \
         0          ...                5.0         3.0      2.0             9.0
         1          ...                6.0         6.0      3.0             9.0
         2          ...               10.0        13.0     11.0             9.0
         3          ...                6.0         4.0      2.0             9.0
         4          ...                3.0         5.0      4.0             9.0

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

            ALTERSKATEGORIE_GROB
```

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

[5 rows x 137 columns]
```

In [54]:
```
azdias.head()
```

Out[54]:
```
      LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
0  910215         NaN       NaN         NaN           NaN        NaN
1  910220         9.0       0.0         0.0           2.0        0.0
2  910225         9.0      17.0         0.0           1.0        0.0
3  910226         1.0      13.0         0.0           0.0        0.0
4  910241         1.0      20.0         0.0           4.0        0.0

   CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
0            2.0                5.0        1.0        1.0
1            5.0                1.0        5.0        5.0
2            3.0                2.0        4.0        4.0
3            2.0                3.0        2.0        2.0
4            5.0                3.0        3.0        3.0

            ...           TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  \
0           ...                NaN               NaN  NaN       NaN
1           ...                0.0               1.0  0.0       8.0
2           ...                0.0               0.0  0.0       9.0
3           ...                0.0               0.0  1.0       7.0
4           ...                0.0               0.0  0.0       3.0

   VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  \
0         NaN      NaN             NaN         3          1
1        11.0     10.0             9.0         5          2
2         9.0      6.0             9.0         5          2
3        10.0     11.0             9.0         3          2
4         5.0      4.0             9.0         4          1

   ALTERSKATEGORIE_GROB
0                     2
1                     1
2                     3
3                     4
4                     3

[5 rows x 134 columns]
```

1.16 Part 0.15 Checkpoint 2 Cleansing Column

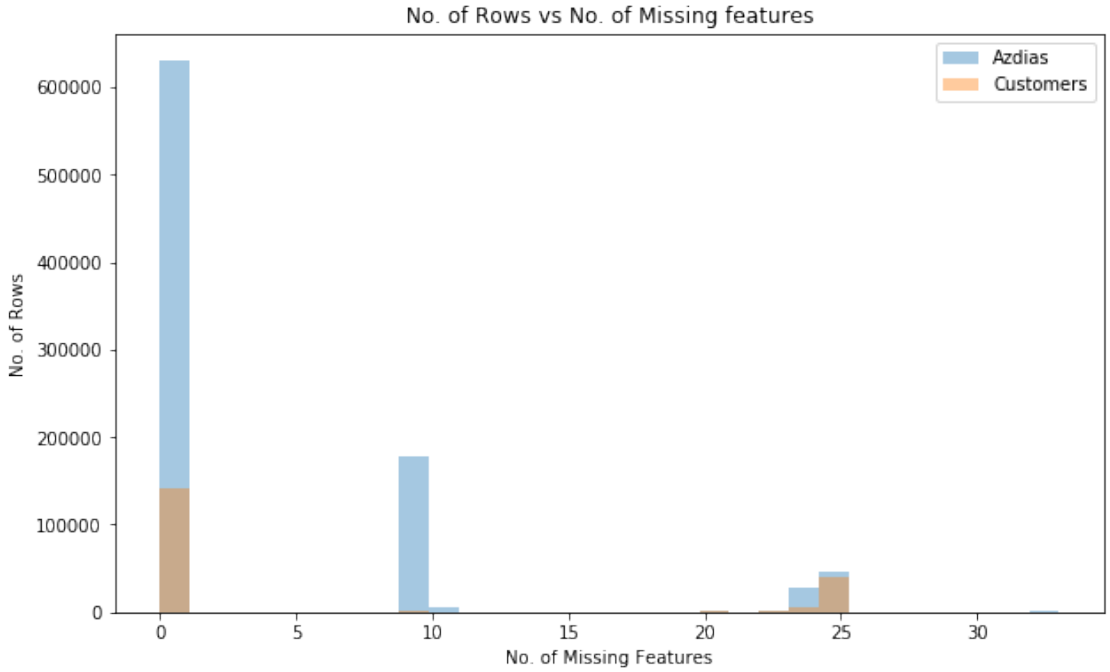
```
In [55]: dias_attr.to_csv('dias_attr_2.csv', index=False)
         customers.to_csv('customers_2.csv', index=False)
         azdias.to_csv('azdias_2.csv', index=False)

In [56]: del dias_attr
         del customers
         del azdias
```

1.17 Part 0.16 Open Checkpoint 2 Cleansing Column

```
In [57]: # load in the data
         azdias_batch = pd.read_csv('azdias_2.csv', chunksize=50000)
         customers_batch = pd.read_csv('customers_2.csv', chunksize=10000)

In [58]: dias_attr = pd.read_csv('dias_attr_2.csv')
         customers = pd.concat(customers_batch)
         azdias = pd.concat(azdias_batch)

In [59]: print("azdias : ", azdias.shape)
         print("customers : ", customers.shape)
         print("dias_attr : ", dias_attr.shape)

azdias :  (891221, 134)
customers :  (191652, 137)
dias_attr :  (2258, 4)
```

1.18 Part 0.17 Analyse Missing Rows

```
In [60]: def plot_missing_rowwise_histogram(df1, df2, bins=30, figsize=(10,6)):
             """
             Takes in two dataframes and plots a barchart comparing two dataframes
             rows and percentage of missing values based on a threshold percentage given
             """
             fig = plt.figure(figsize=figsize)

             ax = fig.add_subplot(111)
             ax.set_title("No. of Rows vs No. of Missing features")
             ax.set_xlabel("No. of Missing Features")
             ax.set_ylabel("No. of Rows")
             sns.distplot(df1.isnull().sum(axis=1), bins, kde=False, ax=ax, label="Azdias")
             sns.distplot(df2.isnull().sum(axis=1), bins, kde=False, ax=ax, label="Customers")
             ax.legend()

             plt.show()

In [61]: plot_missing_rowwise_histogram(azdias, customers)
```



1.19 Part 0.18 Remove Missing Rows

```
In [62]: threshold_remove_missing_rows = 20

In [63]: def remove_missing_rows(df):
             total_rows = df.shape[0]
             df = df.dropna(thresh=df.shape[1]-threshold_remove_missing_rows)
             return df

In [64]: customers = remove_missing_rows(customers)

In [65]: azdias = remove_missing_rows(azdias)

In [66]: print("azdias : ", azdias.shape)
         print("customers : ", customers.shape)
         print("dias_attr : ", dias_attr.shape)

azdias :  (815149, 134)
customers :  (143724, 137)
dias_attr :  (2258, 4)


In [67]: customers.head()

Out[67]:       LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
         0    9626         1.0      10.0         0.0           2.0        0.0
```

```
2  143872         1.0       6.0         0.0           1.0        0.0
3  143873         1.0       8.0         0.0           0.0        0.0
4  143874         1.0      20.0         0.0           4.0        0.0
5  143888         1.0      11.0         0.0           2.0        0.0

   CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
0            5.0                4.0        1.0        1.0
2            2.0                5.0        2.0        2.0
3            2.0                5.0        1.0        1.0
4            6.0                4.0        3.0        3.0
5            4.0                3.0        1.0        1.0

             ...           VK_DHT4A  VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  \
0            ...                5.0         3.0      2.0             9.0
2            ...               10.0        13.0     11.0             9.0
3            ...                6.0         4.0      2.0             9.0
4            ...                3.0         5.0      4.0             9.0
5            ...                1.0         2.0      1.0             9.0

   ZABEOTYP      PRODUCT_GROUP  CUSTOMER_GROUP  ONLINE_PURCHASE  ANREDE_KZ  \
0         3  COSMETIC_AND_FOOD     MULTI_BUYER                0          1
2         3  COSMETIC_AND_FOOD     MULTI_BUYER                0          2
3         1           COSMETIC     MULTI_BUYER                0          1
4         1               FOOD     MULTI_BUYER                0          1
5         2  COSMETIC_AND_FOOD     MULTI_BUYER                0          1

   ALTERSKATEGORIE_GROB
0                     4
2                     4
3                     4
4                     3
5                     3

[5 rows x 137 columns]
```

In [68]:
```
azdias.head()
```

Out[68]:
```
      LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
1  910220         9.0       0.0         0.0           2.0        0.0
2  910225         9.0      17.0         0.0           1.0        0.0
3  910226         1.0      13.0         0.0           0.0        0.0
4  910241         1.0      20.0         0.0           4.0        0.0
5  910244         1.0      10.0         0.0           1.0        0.0

   CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
1            5.0                1.0        5.0        5.0
2            3.0                2.0        4.0        4.0
3            2.0                3.0        2.0        2.0
```

```
4            5.0                3.0        3.0        3.0
5            2.0                5.0        2.0        1.0

             ...           TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  \
1            ...                0.0               1.0  0.0       8.0
2            ...                0.0               0.0  0.0       9.0
3            ...                0.0               0.0  1.0       7.0
4            ...                0.0               0.0  0.0       3.0
5            ...                0.0               0.0  0.0      10.0

   VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  \
1        11.0     10.0             9.0         5          2
2         9.0      6.0             9.0         5          2
3        10.0     11.0             9.0         3          2
4         5.0      4.0             9.0         4          1
5         7.0      4.0             9.0         4          2

   ALTERSKATEGORIE_GROB
1                     1
2                     3
3                     4
4                     3
5                     1

[5 rows x 134 columns]
```

In [69]:
```
diff_column_information = ['CUSTOMER_GROUP', 'ONLINE_PURCHASE','PRODUCT_GROUP']
```

```
def adjust_column_customers(df, list_diff_column_information) :
    return df.drop(list_diff_column_information, axis = 1)
```

In [70]:
```
customers = adjust_column_customers(customers,diff_column_information)
```

In [71]:
```
print("azdias : ", azdias.shape)
print("customers : ", customers.shape)
print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 134)
customers :  (143724, 134)
dias_attr :  (2258, 4)
```

In [72]:
```
customers.head()
```

Out[72]:

```
      LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
0    9626         1.0      10.0         0.0           2.0        0.0
2  143872         1.0       6.0         0.0           1.0        0.0
3  143873         1.0       8.0         0.0           0.0        0.0
```

```
4  143874         1.0      20.0         0.0           4.0        0.0
5  143888         1.0      11.0         0.0           2.0        0.0

   CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
0            5.0                4.0        1.0        1.0
2            2.0                5.0        2.0        2.0
3            2.0                5.0        1.0        1.0
4            6.0                4.0        3.0        3.0
5            4.0                3.0        1.0        1.0

             ...           TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  \
0            ...                0.0               0.0  0.0       5.0
2            ...                0.0               0.0  0.0      10.0
3            ...                0.0               0.0  0.0       6.0
4            ...                0.0               0.0  0.0       3.0
5            ...                0.0               0.0  5.0       1.0

   VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  \
0         3.0      2.0             9.0         3          1
2        13.0     11.0             9.0         3          2
3         4.0      2.0             9.0         1          1
4         5.0      4.0             9.0         1          1
5         2.0      1.0             9.0         2          1

   ALTERSKATEGORIE_GROB
0                     4
2                     4
3                     4
4                     3
5                     3

[5 rows x 134 columns]
```

In [73]:
```
azdias.head()
```

Out[73]:
```
      LNR  AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  \
1  910220         9.0       0.0         0.0           2.0        0.0
2  910225         9.0      17.0         0.0           1.0        0.0
3  910226         1.0      13.0         0.0           0.0        0.0
4  910241         1.0      20.0         0.0           4.0        0.0
5  910244         1.0      10.0         0.0           1.0        0.0

   CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  \
1            5.0                1.0        5.0        5.0
2            3.0                2.0        4.0        4.0
3            2.0                3.0        2.0        2.0
4            5.0                3.0        3.0        3.0
5            2.0                5.0        2.0        1.0
```

```
            ...           TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  \
1           ...                0.0               1.0  0.0       8.0
2           ...                0.0               0.0  0.0       9.0
3           ...                0.0               0.0  1.0       7.0
4           ...                0.0               0.0  0.0       3.0
5           ...                0.0               0.0  0.0      10.0

   VK_DISTANZ  VK_ZG11  WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  \
1        11.0     10.0             9.0         5          2
2         9.0      6.0             9.0         5          2
3        10.0     11.0             9.0         3          2
4         5.0      4.0             9.0         4          1
5         7.0      4.0             9.0         4          2

   ALTERSKATEGORIE_GROB
1                     1
2                     3
3                     4
4                     3
5                     1

[5 rows x 134 columns]
```

1.20 Part 0.19 Checkpoint 3 Remove Missing Rows

```
In [74]: dias_attr.to_csv('dias_attr_3.csv', index=False)
         customers.to_csv('customers_3.csv', index=False)
         azdias.to_csv('azdias_3.csv', index=False)
```

```
In [75]: import os

         del dias_attr
         del customers
         del azdias
         os.remove("dias_attr_1.csv")
         os.remove("customers_1.csv")
         os.remove("azdias_1.csv")
```

1.21 Part 0.20 Open Checkpoint 3 Remove Missing Rows

```
In [76]: # load in the data
         azdias_batch = pd.read_csv('azdias_3.csv', chunksize=50000)
         customers_batch = pd.read_csv('customers_3.csv', chunksize=10000)
```

```
In [77]: dias_attr = pd.read_csv('dias_attr_3.csv')
         customers = pd.concat(customers_batch)
         azdias = pd.concat(azdias_batch)
```

```
In [78]: print("azdias : ", azdias.shape)
         print("customers : ", customers.shape)
         print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 134)
customers :  (143724, 134)
dias_attr :  (2258, 4)
```

1.22 Part 0.21 Check all type data

```
In [79]: customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 143724 entries, 0 to 143723
Columns: 134 entries, LNR to ALTERSKATEGORIE_GROB
dtypes: float64(44), int64(89), object(1)
memory usage: 146.9+ MB
```

```
In [80]: azdias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 815149 entries, 0 to 815148
Columns: 134 entries, LNR to ALTERSKATEGORIE_GROB
dtypes: float64(44), int64(89), object(1)
memory usage: 833.4+ MB
```

```
In [81]: azdias_object_cols = azdias.columns[azdias.dtypes == "object"]
         customer_object_cols = customers.columns[customers.dtypes == "object"]
```

```
In [82]: print("azdias_object_cols : ",azdias_object_cols.values)
         print("customer_object_cols : ",customer_object_cols.values)
```

```
azdias_object_cols :  ['D19_LETZTER_KAUF_BRANCHE']
customer_object_cols :  ['D19_LETZTER_KAUF_BRANCHE']
```

```
In [83]: dias_information_levels_raw_data = pd.read_excel('./DIAS Information Levels - Attribute
```

```
In [84]: print("dias_information_levels_raw_data : ", dias_information_levels_raw_data.shape)
         dias_information_levels_raw_data.head()
```

```
dias_information_levels_raw_data :  (313, 4)
```

```
Out[84]:   Information level             Attribute  \
         0               NaN              AGER_TYP
         1            Person  ALTERSKATEGORIE_GROB
```

```
2               NaN             ANREDE_KZ
3               NaN         CJT_GESAMTTYP
4               NaN     FINANZ_MINIMALIST

                                        Description  \
0                                best-ager typology
1                      age through prename analysis
2                                            gender
3  Customer-Journey-Typology relating to the pref...
4         financial typology: low financial interest

                                     Additional notes
0  in cooperation with Kantar TNS; the informatio...
1  modelled on millions of first name-age-referen...
2                                                NaN
3  relating to the preferred information, marketi...
4  Gfk-Typology based on a representative househo...
```

In [85]:
```
dias_information_levels_raw_data[dias_information_levels_raw_data["Attribute"] == "D19_
```

Out[85]:
```
Empty DataFrame
Columns: [Information level, Attribute, Description, Additional notes]
Index: []
```

In [86]:
```
dias_attr[dias_attr["Attribute"] == "D19_LETZTER_KAUF_BRANCHE"]
```

Out[86]:
```
Empty DataFrame
Columns: [Attribute, Description, Value, Meaning]
Index: []
```

There is a Attribute that didn't have any information = D19_LETZTER_KAUF_BRANCHE

In [87]:
```
diff_column_information = ['D19_LETZTER_KAUF_BRANCHE']


def remove_undefined_column(df, list_diff_column_information) :
    return df.drop(list_diff_column_information, axis = 1)
```

In [88]:
```
customers = remove_undefined_column(customers,diff_column_information)
```

In [89]:
```
azdias = remove_undefined_column(azdias,diff_column_information)
```

In [90]:
```
print("azdias : ", azdias.shape)
print("customers : ", customers.shape)
print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 133)
customers :  (143724, 133)
dias_attr :  (2258, 4)
```

```
In [91]: customers.head()
```

Out[91]:

	LNR	AKT_DAT_KL	ALTER_HH	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	\
0	9626	1.0	10.0	0.0	2.0	0.0	
1	143872	1.0	6.0	0.0	1.0	0.0	
2	143873	1.0	8.0	0.0	0.0	0.0	
3	143874	1.0	20.0	0.0	4.0	0.0	
4	143888	1.0	11.0	0.0	2.0	0.0	

	CJT_GESAMTTYP	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	\
0	5.0	4.0	1.0	1.0	
1	2.0	5.0	2.0	2.0	
2	2.0	5.0	1.0	1.0	
3	6.0	4.0	3.0	3.0	
4	4.0	3.0	1.0	1.0	

	...	TITEL_KZ	UNGLEICHENN_FLAG	VHA	VK_DHT4A	\
0	...	0.0	0.0	0.0	5.0	
1	...	0.0	0.0	0.0	10.0	
2	...	0.0	0.0	0.0	6.0	
3	...	0.0	0.0	0.0	3.0	
4	...	0.0	0.0	5.0	1.0	

	VK_DISTANZ	VK_ZG11	WOHNDAUER_2008	ZABEOTYP	ANREDE_KZ	\
0	3.0	2.0	9.0	3	1	
1	13.0	11.0	9.0	3	2	
2	4.0	2.0	9.0	1	1	
3	5.0	4.0	9.0	1	1	
4	2.0	1.0	9.0	2	1	

	ALTERSKATEGORIE_GROB
0	4
1	4
2	4
3	3
4	3

[5 rows x 133 columns]

1.23 Part 0.22 Analyse data in each column

```
In [92]: def Get_Percentage_Of_Unique_Value_In_DF(name,df, threshold_unique_percentage) :
             total_data_df = len(df)
             for col in df:
                 each_total_unique = len(df[col].unique())
                 each_percentage = each_total_unique * 100 /total_data_df
                 if each_percentage > 10 :
                     print("df : ",name," col ",col, " : ", each_percentage)
```

```
                # print(customers[col].unique())

        ### source : https://stackoverflow.com/questions/27241253/print-the-unique-values-in-ev
```

In [93]:
```
threshold_unique_percentage = 10

percentage_each_column_unique_customers = Get_Percentage_Of_Unique_Value_In_DF("custome
percentage_each_column_unique_azdias = Get_Percentage_Of_Unique_Value_In_DF("azdias",az
```

```
df :  customers  col  LNR  :  100.0
df :  azdias  col  LNR  :  100.0
```

In [94]:
```
customers = remove_undefined_column(customers,["LNR"])
azdias = remove_undefined_column(azdias,["LNR"])
```

In [95]:
```
print("azdias : ", azdias.shape)
print("customers : ", customers.shape)
print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 132)
customers :  (143724, 132)
dias_attr :  (2258, 4)
```

1.24 Part 0.23 Checkpoint 4 Final Clean Data

In [96]:
```
dias_attr.to_csv('dias_attr_4.csv', index=False)
customers.to_csv('customers_4.csv', index=False)
azdias.to_csv('azdias_4.csv', index=False)
```

In [97]:
```
import os

del dias_attr
del customers
del azdias
os.remove("dias_attr_2.csv")
os.remove("customers_2.csv")
os.remove("azdias_2.csv")
```

In [98]:
```
# load in the data
azdias_batch = pd.read_csv('azdias_4.csv', chunksize=50000)
customers_batch = pd.read_csv('customers_4.csv', chunksize=10000)
```

In [99]:
```
dias_attr = pd.read_csv('dias_attr_4.csv')
customers = pd.concat(customers_batch)
azdias = pd.concat(azdias_batch)
```

In [100]:
```
print("azdias : ", azdias.shape)
print("customers : ", customers.shape)
print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 132)
customers :  (143724, 132)
dias_attr :  (2258, 4)
```

1.25 Part 0.24 Feature Inputter

```
In [101]: for key,val in customers.isna().sum().items() :
              if val > 0 :
                  print("key : ", key , " total : ", val)
```

```
key :  CJT_GESAMTTYP  total :  1881
key :  CJT_KATALOGNUTZER  total :  1881
key :  CJT_TYP_1  total :  1881
key :  CJT_TYP_2  total :  1881
key :  CJT_TYP_3  total :  1881
key :  CJT_TYP_4  total :  1881
key :  CJT_TYP_5  total :  1881
key :  CJT_TYP_6  total :  1881
key :  D19_BANKEN_ONLINE_QUOTE_12  total :  1022
key :  D19_GESAMT_ONLINE_QUOTE_12  total :  1022
key :  D19_KONSUMTYP  total :  1022
key :  D19_LOTTO  total :  1022
key :  D19_SOZIALES  total :  1022
key :  D19_TELKO_ONLINE_QUOTE_12  total :  1022
key :  D19_VERSAND_ONLINE_QUOTE_12  total :  1022
key :  D19_VERSI_ONLINE_QUOTE_12  total :  1022
key :  GFK_URLAUBERTYP  total :  1881
key :  HH_EINKOMMEN_SCORE  total :  2879
key :  KONSUMNAEHE  total :  54
key :  LP_FAMILIE_FEIN  total :  1881
key :  LP_FAMILIE_GROB  total :  1881
key :  LP_LEBENSPHASE_FEIN  total :  1881
key :  LP_LEBENSPHASE_GROB  total :  1881
key :  LP_STATUS_FEIN  total :  1881
key :  LP_STATUS_GROB  total :  1881
key :  ONLINE_AFFINITAET  total :  1881
key :  RETOURTYP_BK_S  total :  1881
key :  RT_KEIN_ANREIZ  total :  1881
key :  RT_SCHNAEPPCHEN  total :  1881
key :  RT_UEBERGROESSE  total :  1896
```

```
In [102]: for key,val in azdias.isna().sum().items() :
              if val > 0 :
                  print("key : ", key , " total : ", val)
```

```
key :  CJT_GESAMTTYP  total :  2281
key :  CJT_KATALOGNUTZER  total :  2281
```

```
key :  CJT_TYP_1  total :  2281
key :  CJT_TYP_2  total :  2281
key :  CJT_TYP_3  total :  2281
key :  CJT_TYP_4  total :  2281
key :  CJT_TYP_5  total :  2281
key :  CJT_TYP_6  total :  2281
key :  D19_BANKEN_ONLINE_QUOTE_12  total :  182845
key :  D19_GESAMT_ONLINE_QUOTE_12  total :  182845
key :  D19_KONSUMTYP  total :  182845
key :  D19_LOTTO  total :  182845
key :  D19_SOZIALES  total :  182845
key :  D19_TELKO_ONLINE_QUOTE_12  total :  182845
key :  D19_VERSAND_ONLINE_QUOTE_12  total :  182845
key :  D19_VERSI_ONLINE_QUOTE_12  total :  182845
key :  GFK_URLAUBERTYP  total :  2281
key :  HH_EINKOMMEN_SCORE  total :  18248
key :  KONSUMNAEHE  total :  468
key :  LP_FAMILIE_FEIN  total :  2281
key :  LP_FAMILIE_GROB  total :  2281
key :  LP_LEBENSPHASE_FEIN  total :  2281
key :  LP_LEBENSPHASE_GROB  total :  2281
key :  LP_STATUS_FEIN  total :  2281
key :  LP_STATUS_GROB  total :  2281
key :  ONLINE_AFFINITAET  total :  2281
key :  RETOURTYP_BK_S  total :  2281
key :  RT_KEIN_ANREIZ  total :  2281
key :  RT_SCHNAEPPCHEN  total :  2281
key :  RT_UEBERGROESSE  total :  3075
```

```
In [103]: from sklearn.preprocessing import Imputer

In [104]: imp = Imputer(missing_values=np.nan, strategy='mean')

In [105]: imputter_customer = imp.fit_transform(customers)
          imputter_azdias = imp.fit_transform(azdias)

In [106]: def df_add_inputter(target_df,imp) :
              imputter_value = imp.fit_transform(target_df)
              return pd.DataFrame(imputter_value, columns = target_df.columns)

In [107]: customers = df_add_inputter(customers,imp)
          azdias = df_add_inputter(azdias,imp)

In [108]: customers.head()

Out[108]:    AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  CJT_GESAMTTYP  \
          0         1.0      10.0         0.0           2.0        0.0            5.0
          1         1.0       6.0         0.0           1.0        0.0            2.0
```

```
2         1.0       8.0         0.0           0.0        0.0           2.0
3         1.0      20.0         0.0           4.0        0.0           6.0
4         1.0      11.0         0.0           2.0        0.0           4.0

   CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  CJT_TYP_3          ...           \
0                4.0        1.0        1.0        5.0          ...
1                5.0        2.0        2.0        5.0          ...
2                5.0        1.0        1.0        5.0          ...
3                4.0        3.0        3.0        3.0          ...
4                3.0        1.0        1.0        5.0          ...

   TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  VK_DISTANZ  VK_ZG11  \
0       0.0               0.0  0.0       5.0         3.0      2.0
1       0.0               0.0  0.0      10.0        13.0     11.0
2       0.0               0.0  0.0       6.0         4.0      2.0
3       0.0               0.0  0.0       3.0         5.0      4.0
4       0.0               0.0  5.0       1.0         2.0      1.0

   WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  ALTERSKATEGORIE_GROB
0             9.0       3.0        1.0                   4.0
1             9.0       3.0        2.0                   4.0
2             9.0       1.0        1.0                   4.0
3             9.0       1.0        1.0                   3.0
4             9.0       2.0        1.0                   3.0

[5 rows x 132 columns]
```

In [109]:
```
## validate
for key,val in customers.isna().sum().items() :
    if val > 0 :
        print("key : ", key , " total : ", val)
for key,val in azdias.isna().sum().items() :
    if val > 0 :
        print("key : ", key , " total : ", val)
```

1.26 Part 0.25 Checkpoint 5 DF Have Inputter

In [110]:
```
dias_attr.to_csv('dias_attr_5.csv', index=False)
customers.to_csv('customers_5.csv', index=False)
azdias.to_csv('azdias_5.csv', index=False)
```

In [111]:
```
import os

del dias_attr
del customers
del azdias

os.remove("dias_attr_3.csv")
```

```
os.remove("customers_3.csv")
os.remove("azdias_3.csv")
```

```
In [112]: # load in the data
          azdias_batch = pd.read_csv('azdias_5.csv', chunksize=50000)
          customers_batch = pd.read_csv('customers_5.csv', chunksize=10000)
```

```
In [113]: dias_attr = pd.read_csv('dias_attr_5.csv')
          customers = pd.concat(customers_batch)
          azdias = pd.concat(azdias_batch)
```

```
In [114]: print("azdias : ", azdias.shape)
          print("customers : ", customers.shape)
          print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 132)
customers :  (143724, 132)
dias_attr :  (2258, 4)
```

1.27 Part 0.27 Feature Scaling

```
In [115]: from sklearn.preprocessing import MinMaxScaler
```

```
In [116]: scaler = MinMaxScaler()
```

```
In [117]: scaler.fit(azdias)
```

```
Out[117]: MinMaxScaler(copy=True, feature_range=(0, 1))
```

```
In [118]: def MinMaxScalerHelper(df, scaler) :
              return pd.DataFrame(scaler.transform(df), columns = df.columns)
```

```
In [119]: azdias = MinMaxScalerHelper(azdias,scaler)
          customers = MinMaxScalerHelper(customers,scaler)
```

```
In [120]: print("azdias : ", azdias.shape)
          print("customers : ", customers.shape)
          print("dias_attr : ", dias_attr.shape)
```

```
azdias :  (815149, 132)
customers :  (143724, 132)
dias_attr :  (2258, 4)
```

```
In [121]: customers.head()
```

```
Out[121]:    AKT_DAT_KL  ALTER_HH  ANZ_KINDER  ANZ_PERSONEN  ANZ_TITEL  CJT_GESAMTTYP  \
          0         0.0  0.476190         0.0      0.044444        0.0            0.8
          1         0.0  0.285714         0.0      0.022222        0.0            0.2
```

```
2         0.0  0.380952         0.0      0.000000        0.0            0.2
3         0.0  0.952381         0.0      0.088889        0.0            1.0
4         0.0  0.523810         0.0      0.044444        0.0            0.6

   CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  CJT_TYP_3          ...           \
0               0.75       0.00       0.00        1.0          ...
1               1.00       0.25       0.25        1.0          ...
2               1.00       0.00       0.00        1.0          ...
3               0.75       0.50       0.50        0.5          ...
4               0.50       0.00       0.00        1.0          ...

   TITEL_KZ  UNGLEICHENN_FLAG  VHA  VK_DHT4A  VK_DISTANZ  VK_ZG11  \
0       0.0               0.0  0.0       0.4    0.166667      0.1
1       0.0               0.0  0.0       0.9    1.000000      1.0
2       0.0               0.0  0.0       0.5    0.250000      0.1
3       0.0               0.0  0.0       0.2    0.333333      0.3
4       0.0               0.0  1.0       0.0    0.083333      0.0

   WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  ALTERSKATEGORIE_GROB
0             1.0       0.4        0.0                 0.375
1             1.0       0.4        1.0                 0.375
2             1.0       0.0        0.0                 0.375
3             1.0       0.0        0.0                 0.250
4             1.0       0.2        0.0                 0.250

[5 rows x 132 columns]
```

1.27.1 Part 0.28 Final Data

```
In [122]: dias_attr.to_csv('dias_attr_6.csv', index=False)
          customers.to_csv('customers_6.csv', index=False)
          azdias.to_csv('azdias_6.csv', index=False)
```

1.28 Part 1: Customer Segmentation Report

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

1.29 Part 1.1 Load Data

```
In [123]: # load in the data
          azdias_batch = pd.read_csv('azdias_6.csv', chunksize=50000)
          customers_batch = pd.read_csv('customers_6.csv', chunksize=10000)

In [124]: dias_attr = pd.read_csv('dias_attr_6.csv')
```

```
customers = pd.concat(customers_batch)
azdias = pd.concat(azdias_batch)
```

In [125]:
```
customers.head()
```

Out[125]:

	AKT_DAT_KL	ALTER_HH	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	CJT_GESAMTTYP	\
0	0.0	0.476190	0.0	0.044444	0.0	0.8	
1	0.0	0.285714	0.0	0.022222	0.0	0.2	
2	0.0	0.380952	0.0	0.000000	0.0	0.2	
3	0.0	0.952381	0.0	0.088889	0.0	1.0	
4	0.0	0.523810	0.0	0.044444	0.0	0.6	

	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	CJT_TYP_3	...	\
0	0.75	0.00	0.00	1.0	...	
1	1.00	0.25	0.25	1.0	...	
2	1.00	0.00	0.00	1.0	...	
3	0.75	0.50	0.50	0.5	...	
4	0.50	0.00	0.00	1.0	...	

	TITEL_KZ	UNGLEICHENN_FLAG	VHA	VK_DHT4A	VK_DISTANZ	VK_ZG11	\
0	0.0	0.0	0.0	0.4	0.166667	0.1	
1	0.0	0.0	0.0	0.9	1.000000	1.0	
2	0.0	0.0	0.0	0.5	0.250000	0.1	
3	0.0	0.0	0.0	0.2	0.333333	0.3	
4	0.0	0.0	1.0	0.0	0.083333	0.0	

	WOHNDAUER_2008	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	1.0	0.4	0.0	0.375
1	1.0	0.4	1.0	0.375
2	1.0	0.0	0.0	0.375
3	1.0	0.0	0.0	0.250
4	1.0	0.2	0.0	0.250

[5 rows x 132 columns]

1.30 Part 1.2 Analyse PCA

In [126]:
```
from sklearn.decomposition import PCA
```

In [127]:
```
pca_azdias = PCA(n_components=10)
```

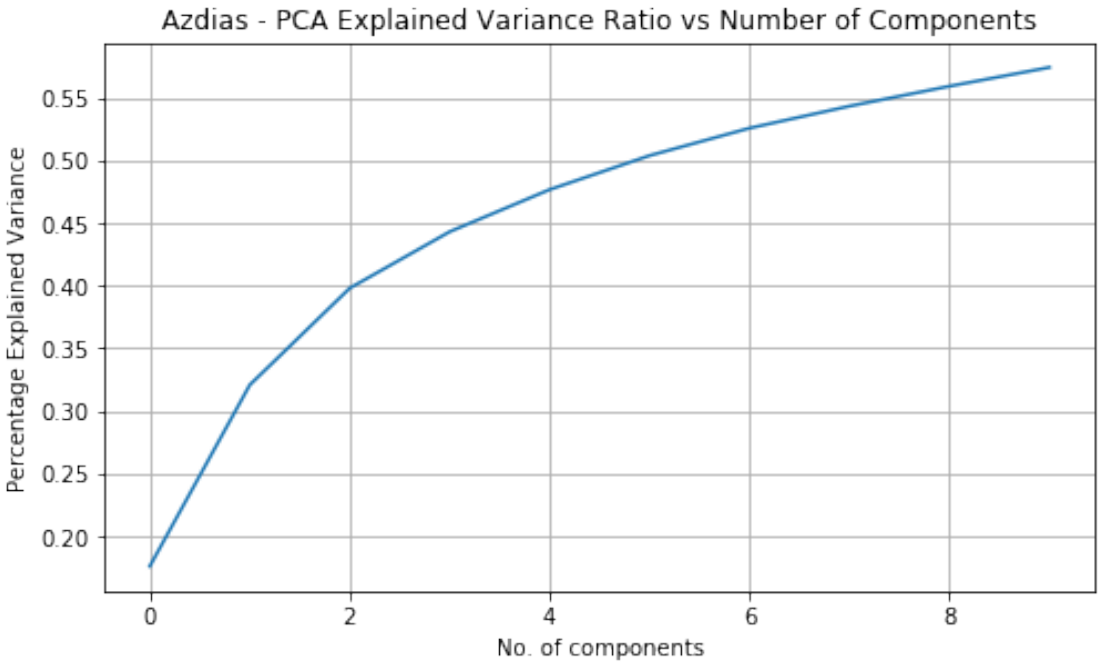
In [128]:
```
pca_azdias.fit(azdias)
```

Out[128]:
```
PCA(copy=True, iterated_power='auto', n_components=10, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)
```

In [129]:
```
def plot_pca_exp_variance(pca_azdias, cumulative=True, figsize=(8,10)):
    """
    Takes in two PCA models (which are fit on corresponding data) and plots
```

```
        their Explained Variance vs Number of components

        """

        if cumulative:
            azdias_variance = np.cumsum(pca_azdias.explained_variance_ratio_)
            y_label = "Percentage Explained Variance"
        else:
            azdias_variance = pca_azdias.explained_variance_ratio_
            y_label = "Explained Variance Ratio"

        fig = plt.figure(figsize=figsize)

        ax = fig.add_subplot(211)
        ax.plot(azdias_variance)
        ax.set_xlabel("No. of components")
        ax.set_ylabel(y_label)
        ax.set_title("Azdias - PCA Explained Variance Ratio vs Number of Components")
        ax.grid()
        plt.show()
```

In [130]:
```
plot_pca_exp_variance(pca_azdias)
```



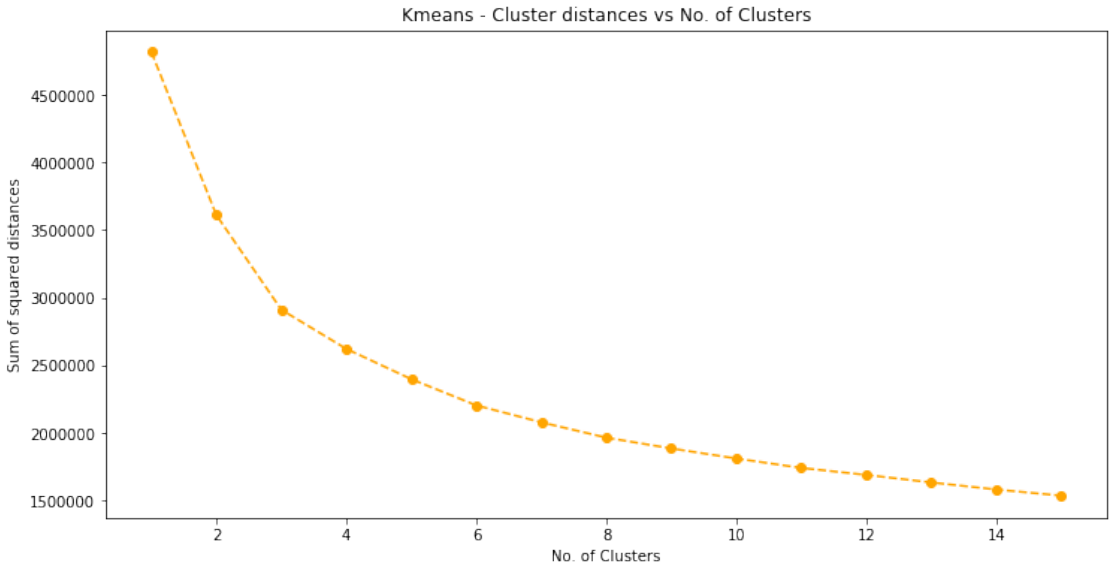
In [131]:
```
pca_8 = PCA(n_components=8)
pca_8.fit(azdias)
```

```
Out[131]: PCA(copy=True, iterated_power='auto', n_components=8, random_state=None,
            svd_solver='auto', tol=0.0, whiten=False)

In [132]: azdias_pca = pca_8.transform(azdias)
          customers_pca = pca_8.transform(customers)

In [133]: def get_Kmeans_scores(data, K_start, K_end, step=1):

              scores = []

              print("Performing K-Means clustering")
              print("Given range min:{}, max:{}, step:{}".format(K_start, K_end, step))

              for n in range(K_start, K_end+1, step):

                  print("Training Cluster Start : ", n)

                  kmeans = KMeans(n)
                  model = kmeans.fit(data)
                  scores.append(abs(model.score(data)))
                  print("Training Cluster Done : ", n, " with scores : ", scores[-1])

              return scores, range(K_start, K_end+1, step)

In [134]: from sklearn.cluster import KMeans

          scores, range_ = get_Kmeans_scores(azdias_pca, 1, 15, 1)

Performing K-Means clustering
Given range min:1, max:15, step:1
Training Cluster Start :  1
Training Cluster Done :  1  with scores :  4816934.79203
Training Cluster Start :  2
Training Cluster Done :  2  with scores :  3610318.2603
Training Cluster Start :  3
Training Cluster Done :  3  with scores :  2910250.81196
Training Cluster Start :  4
Training Cluster Done :  4  with scores :  2620671.51632
Training Cluster Start :  5
Training Cluster Done :  5  with scores :  2396546.4586
Training Cluster Start :  6
Training Cluster Done :  6  with scores :  2202653.74581
Training Cluster Start :  7
Training Cluster Done :  7  with scores :  2077336.80577
Training Cluster Start :  8
Training Cluster Done :  8  with scores :  1964039.67146
Training Cluster Start :  9
Training Cluster Done :  9  with scores :  1883948.16699
Training Cluster Start :  10
```

```
Training Cluster Done :  10  with scores :  1809691.09987
Training Cluster Start :  11
Training Cluster Done :  11  with scores :  1739966.78332
Training Cluster Start :  12
Training Cluster Done :  12  with scores :  1688203.7121
Training Cluster Start :  13
Training Cluster Done :  13  with scores :  1632533.67063
Training Cluster Start :  14
Training Cluster Done :  14  with scores :  1580191.82489
Training Cluster Start :  15
Training Cluster Done :  15  with scores :  1534696.10482
```

In [135]:
```
def plot_elbow(scores, range_):

    fig = plt.figure(figsize=(12,6))
    ax = fig.add_subplot(111)

    ax.plot(range_, scores, linestyle= "--",marker = "o", color="orange")
    ax.set_xlabel("No. of Clusters")
    ax.set_ylabel("Sum of squared distances")
    ax.set_title("Kmeans - Cluster distances vs No. of Clusters")

    plt.show()
```

In [136]:
```
plot_elbow(scores, range_)
```



1.30.1 Part 1.3 Customer Report

In [137]:
```
kmeans = KMeans(6)

kmeans.fit(azdias_pca)
```

Out[137]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=6, n_init=10, n_jobs=1, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

In [138]:
```
azdias_kmeans_result = kmeans.predict(azdias_pca)

azdias_kmeans_result
```

Out[138]:
```
array([1, 1, 4, ..., 2, 3, 0], dtype=int32)
```

In [139]:
```
customers_kmeans_result = kmeans.predict(customers_pca)
customers_kmeans_result
```

Out[139]:
```
array([0, 4, 0, ..., 0, 5, 5], dtype=int32)
```

In [140]:
```
customers_clusters = pd.Series(customers_kmeans_result)
azdias_clusters = pd.Series(azdias_kmeans_result)
```

In [141]:
```
cluster_info = pd.DataFrame([])

cluster_info["Population"] = azdias_clusters.value_counts().sort_index()
cluster_info["Customers"] = customers_clusters.value_counts().sort_index()
cluster_info.reset_index(inplace=True)
cluster_info.rename(columns={"index":"Cluster"}, inplace=True)
```

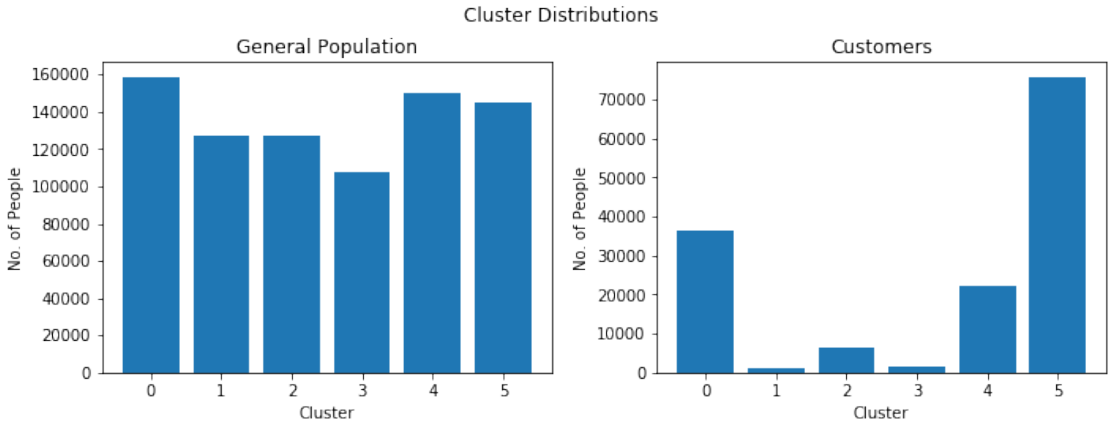
In [142]:
```
cluster_info
```

Out[142]:

	Cluster	Population	Customers
0	0	158702	36354
1	1	126940	1305
2	2	127131	6531
3	3	107334	1651
4	4	150104	22070
5	5	144938	75813

In [143]:
```
fig, (ax1, ax2) = plt.subplots(1,2, figsize=(10, 4))

ax1.bar(cluster_info["Cluster"], cluster_info["Population"])
ax1.set_xlabel("Cluster")
ax1.set_ylabel("No. of People")
ax1.set_title("General Population")

ax2.bar(cluster_info["Cluster"], cluster_info["Customers"])
ax2.set_xlabel("Cluster")
```

```
ax2.set_ylabel("No. of People")
ax2.set_title("Customers")

fig.suptitle("Cluster Distributions")
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



1.31 Part 2: Supervised Learning Model

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

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

```
In [144]: # load in the data
          azdias_batch = pd.read_csv('azdias_6.csv', chunksize=50000)
          customers_batch = pd.read_csv('customers_6.csv', chunksize=10000)

In [145]: dias_attr = pd.read_csv('dias_attr_6.csv')
          customers = pd.concat(customers_batch)
          azdias = pd.concat(azdias_batch)

In [146]: mailout_train_raw = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_MAILOUT

/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785: DtypeWarning: Colu
  interactivity=interactivity, compiler=compiler, result=result)
```

In [147]:
```
print("mailout_train_raw : ", mailout_train_raw.shape)
print("customers : ", customers.shape)
labels = mailout_train_raw["RESPONSE"]

customers.head()
```

```
mailout_train_raw :  (42962, 367)
customers :  (143724, 132)
```

Out[147]:

	AKT_DAT_KL	ALTER_HH	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	CJT_GESAMTTYP	\
0	0.0	0.476190	0.0	0.044444	0.0	0.8	
1	0.0	0.285714	0.0	0.022222	0.0	0.2	
2	0.0	0.380952	0.0	0.000000	0.0	0.2	
3	0.0	0.952381	0.0	0.088889	0.0	1.0	
4	0.0	0.523810	0.0	0.044444	0.0	0.6	

	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	CJT_TYP_3	...	\
0	0.75	0.00	0.00	1.0	...	
1	1.00	0.25	0.25	1.0	...	
2	1.00	0.00	0.00	1.0	...	
3	0.75	0.50	0.50	0.5	...	
4	0.50	0.00	0.00	1.0	...	

	TITEL_KZ	UNGLEICHENN_FLAG	VHA	VK_DHT4A	VK_DISTANZ	VK_ZG11	\
0	0.0	0.0	0.0	0.4	0.166667	0.1	
1	0.0	0.0	0.0	0.9	1.000000	1.0	
2	0.0	0.0	0.0	0.5	0.250000	0.1	
3	0.0	0.0	0.0	0.2	0.333333	0.3	
4	0.0	0.0	1.0	0.0	0.083333	0.0	

	WOHNDAUER_2008	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	1.0	0.4	0.0	0.375
1	1.0	0.4	1.0	0.375
2	1.0	0.0	0.0	0.375
3	1.0	0.0	0.0	0.250
4	1.0	0.2	0.0	0.250

[5 rows x 132 columns]

In [148]:
```
list_unknown = {}
for index, row in dias_attr.iterrows():
    if(row["Meaning"] == "unknown") :
        # list_unknown[row['Attribute']] = str(row['Value']).split(",");
        list_unknown[row['Attribute']] = [row['Value']];
```

In [149]:
```
def replace_unknown_data_with_nan(val, unkown):
    # print(val, " : ", unkown)
    full_unkown = str(unkown).split(",")
```

```
            if str(val) in full_unkown:
                # print("return nan")
                return np.nan
            else:
                return val


        def preprocessing_data(target_df, list_unknown):
            for attrib_key,attrib_val in list_unknown.items():
                if attrib_key in target_df.columns :
                    target_df[attrib_key] = target_df[attrib_key].apply(replace_unknown_data_w

            return target_df
```

In [150]:
```
from sklearn.preprocessing import Imputer

def df_add_inputter(target_df,imp) :
    imputter_value = imp.fit_transform(target_df)
    return pd.DataFrame(imputter_value, columns = target_df.columns)
```

In [151]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(azdias)



def MinMaxScalerHelper(df, scaler) :
    return pd.DataFrame(scaler.transform(df), columns = df.columns)
```

In [152]:
```
def cleansing_transform_data(df,df_target) :

    imp = Imputer(missing_values=np.nan, strategy='mean')


    df = df[list(df_target)]
    df = preprocessing_data(df,list_unknown)
    df =  df_add_inputter(df,imp)
    return MinMaxScalerHelper(df,scaler)
```

In [153]:
```
mailout_train = cleansing_transform_data(mailout_train_raw,customers)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

In [154]:
```
print("mailout_train : ", mailout_train.shape)

mailout_train.head()
```

```
mailout_train :  (42962, 132)
```

Out[154]:

	AKT_DAT_KL	ALTER_HH	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	CJT_GESAMTTYP	\
0	1.0	8.0	0.0	1.0	0.0	2.0	
1	4.0	13.0	0.0	2.0	0.0	2.0	
2	1.0	9.0	0.0	0.0	0.0	4.0	
3	1.0	6.0	0.0	2.0	0.0	2.0	
4	1.0	9.0	0.0	1.0	0.0	6.0	

	CJT_KATALOGNUTZER	CJT_TYP_1	CJT_TYP_2	CJT_TYP_3	...	\
0	5.0	2.0	2.0	5.0	...	
1	2.0	2.0	2.0	4.0	...	
2	5.0	1.0	1.0	5.0	...	
3	5.0	2.0	2.0	5.0	...	
4	5.0	1.0	2.0	5.0	...	

	TITEL_KZ	UNGLEICHENN_FLAG	VHA	VK_DHT4A	VK_DISTANZ	VK_ZG11	\
0	0.0	0.0	1.0	5.0	2.0	1.0	
1	0.0	0.0	1.0	1.0	2.0	1.0	
2	0.0	0.0	4.0	6.0	4.0	2.0	
3	0.0	0.0	1.0	8.0	11.0	11.0	
4	0.0	0.0	0.0	2.0	2.0	1.0	

	WOHNDAUER_2008	ZABEOTYP	ANREDE_KZ	ALTERSKATEGORIE_GROB
0	9.0	3.0	2.0	4.0
1	9.0	1.0	2.0	3.0
2	9.0	3.0	1.0	4.0
3	9.0	3.0	2.0	4.0
4	9.0	3.0	1.0	3.0

[5 rows x 132 columns]

1.32 Part 2.2 Model Selection

In [155]:
```
from sklearn.model_selection import train_test_split, cross_val_score
```

In [156]:
```
X_train_red, X_val_red, y_train_red, y_val_red = train_test_split(mailout_train, label
```

In [157]:
```
X_train_red.head()
```

Out[157]:

	AKT_DAT_KL	ALTER_HH	ANZ_KINDER	ANZ_PERSONEN	ANZ_TITEL	\
36696	1.000000	18.000000	0.00000	2.000000	0.000000	
25391	1.000000	10.000000	0.00000	3.000000	0.000000	
16089	1.525241	10.285556	0.08899	2.017087	0.009585	

```
7149     1.000000  21.000000     1.00000      3.000000   0.000000
33427    1.000000  21.000000     0.00000      6.000000   0.000000

       CJT_GESAMTTYP  CJT_KATALOGNUTZER  CJT_TYP_1  CJT_TYP_2  CJT_TYP_3  \
36696            6.0                2.0        4.0        2.0        4.0
25391            1.0                5.0        2.0        2.0        5.0
16089            2.0                4.0        2.0        1.0        5.0
7149             1.0                1.0        2.0        3.0        3.0
33427            3.0                4.0        3.0        1.0        4.0

                ...           TITEL_KZ  UNGLEICHENN_FLAG       VHA  VK_DHT4A  \
36696           ...           0.000000          0.000000  1.000000  1.000000
25391           ...           0.000000          1.000000  0.000000  6.000000
16089           ...           0.007918          0.071264  1.137443  4.318644
7149            ...           0.000000          0.000000  0.000000  3.000000
33427           ...           0.000000          0.000000  5.000000  2.000000

       VK_DISTANZ   VK_ZG11  WOHNDAUER_2008  ZABEOTYP  ANREDE_KZ  \
36696    2.000000  1.000000        9.000000       4.0        2.0
25391    3.000000  2.000000        9.000000       3.0        2.0
16089    4.505953  3.116963        8.729947       3.0        2.0
7149     6.000000  5.000000        6.000000       4.0        1.0
33427    3.000000  3.000000        9.000000       1.0        1.0

       ALTERSKATEGORIE_GROB
36696                   3.0
25391                   4.0
16089                   1.0
7149                    3.0
33427                   4.0

[5 rows x 132 columns]
```

In [158]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingRegressor, AdaBoostRegressor
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier


from sklearn.metrics import accuracy_score, roc_auc_score, confusion_matrix

import time
from sklearn.model_selection import GridSearchCV

SEED = 2
```

In [159]:
```
def train_and_predict(model, X_train, y_train, X_test, y_test):
    """
```

```
    Fit a model on X_train, y_train
    predicts on X_text, y_test
    Calculate AUROC on predictions made on test data

    Outputs - AUROC score, time elapse for training and prediction
    """
    start = time.time()
    model = model.fit(X_train, y_train)

    roc_score = roc_auc_score(y_test, model.predict_proba(X_test)[:,1])

    end = time.time()
    time_elapsed = end - start

    return roc_score, time_elapsed
```

In [160]:
```
models = [("LogisticRegression", LogisticRegression(random_state=SEED)),
          ("DecisionTreeClassifier", DecisionTreeClassifier(random_state=SEED)),
          ("RandomForestClassifier", RandomForestClassifier(random_state=SEED)),
          ("GradientBoostingClassifier", GradientBoostingClassifier(random_state=SEED)),
          ("AdaBoostClassifier", AdaBoostClassifier(random_state=SEED))]

results_reduced = {"Model":[],
                   "AUCROC_score":[],
                   "Time_in_sec":[]}

for name, model in models:
    roc, time_ = train_and_predict(model, X_train_red, y_train_red, X_val_red, y_val_r
    results_reduced["Model"].append(name)
    results_reduced["AUCROC_score"].append(roc)
    results_reduced["Time_in_sec"].append(time_)

results_reduced = pd.DataFrame.from_dict(results_reduced, orient='index').transpose()
results_reduced
```

Out[160]:

	Model	AUCROC_score	Time_in_sec
0	LogisticRegression	0.677756	4.32021
1	DecisionTreeClassifier	0.523673	1.20045
2	RandomForestClassifier	0.583718	0.797185
3	GradientBoostingClassifier	0.744328	17.9662
4	AdaBoostClassifier	0.727555	6.07132

1.33 Part 2.3 Train Model

In [161]:
```
param_grid = {"n_estimators": [50,100,150,200],
              "learning_rate": [0.01,0.1,0.5,0.9,1.],
              "algorithm":["SAMME.R"]
              }
```

```
adaboost_grid = GridSearchCV(estimator = AdaBoostClassifier(random_state=SEED),
                             param_grid = param_grid,
                             scoring = "roc_auc",
                             cv = 5, n_jobs = -1, verbose=2)
```

In [162]:
```
adaboost_grid.fit(X_train_red, y_train_red)

best_adaboost = adaboost_grid.best_estimator_

print("Best Score: ", adaboost_grid.best_score_)
print("Best Params: ", adaboost_grid.best_params_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[CV] algorithm=SAMME.R, learning_rate=0.01, n_estimators=50 ...
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[Parallel(n_jobs=-1)]: Done   1 out of   1 | elapsed:    5.0s remaining:    0.0s


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[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=100 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=100, total=   9.3s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=150 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=150, total=  14.0s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=150 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=150, total=  13.9s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=150 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=150, total=  14.2s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=150 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=150, total=  13.9s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=150 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=150, total=  14.0s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=200 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=200, total=  18.6s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=200 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=200, total=  18.9s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=200 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=200, total=  18.6s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=200 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=200, total=  18.6s
[CV] algorithm=SAMME.R, learning_rate=1.0, n_estimators=200 ...
[CV]  algorithm=SAMME.R, learning_rate=1.0, n_estimators=200, total=  18.6s


[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed: 20.5min finished


Best Score:  0.770352053847
Best Params:  {'algorithm': 'SAMME.R', 'learning_rate': 0.1, 'n_estimators': 50}
```

```
In [163]: preds_adaboost = best_adaboost.predict_proba(X_val_red)[:,1]

          print("ROC score on validation data: {:.4f}".format(roc_auc_score(y_val_red, preds_ada

ROC score on validation data: 0.7322
```

1.34 Part 3: Kaggle Competition

Now that you've created a model to predict which individuals are most likely to respond to a mailout campaign, it's time to test that model in competition through Kaggle. If you click on the link here, you'll be taken to the competition page where, if you have a Kaggle account, you can enter. If you're one of the top performers, you may have the chance to be contacted by a hiring manager from Arvato or Bertelsmann for an interview!

Your entry to the competition should be a CSV file with two columns. The first column should be a copy of "LNR", which acts as an ID number for each individual in the "TEST" partition. The second column, "RESPONSE", should be some measure of how likely each individual became a customer – this might not be a straightforward probability. As you should have found in Part 2, there is a large output class imbalance, where most individuals did not respond to the mailout. Thus, predicting individual classes and using accuracy does not seem to be an appropriate performance evaluation method. Instead, the competition will be using AUC to evaluate performance. The exact values of the "RESPONSE" column do not matter as much: only that the higher values try to capture as many of the actual customers as possible, early in the ROC curve sweep.

```
In [164]: mailout_test_raw = pd.read_csv('../../data/Term2/capstone/arvato_data/Udacity_MAILOUT_

/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785: DtypeWarning: Colu
  interactivity=interactivity, compiler=compiler, result=result)


In [165]: mailout_test_LNR = mailout_test_raw["LNR"]

          mailout_test = cleansing_transform_data(mailout_test_raw,customers)

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#



In [166]: preds_test_adaboost = best_adaboost.predict_proba(mailout_test)[:,1]

In [167]: kaggle_adaboost = pd.DataFrame(index=mailout_test_LNR, data=preds_test_adaboost)
          kaggle_adaboost.rename(columns={0: "RESPONSE"}, inplace=True)

In [168]: kaggle_adaboost.head()

Out[168]:       RESPONSE
          LNR
          1754  0.332197
          1770  0.332197
          1465  0.248535
          1470  0.247213
          1478  0.240376

In [169]: kaggle_adaboost.to_csv("kaggle_thomas_udacity.csv")

In [ ]:
```