In [1]:
```
# Group 19. BUS 4023 - SPRING/SUMMER 2020. Final Assignment. Customer Segmentation. Aug. 14, 2020.

# In this cell we load the relevant modules required for this notebook.

from pathlib import Path

import pandas as pd
from sklearn import preprocessing
from sklearn.metrics import pairwise
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
from sklearn.cluster import KMeans
import matplotlib.pylab as plt
import seaborn as sns
from pandas.plotting import parallel_coordinates
```

In [2]:
```
# Load the data file.
BathSoapHousehold_df = pd.read_csv('BathSoapHousehold.csv')
```

In [3]:
```
# Visually inspect the data file.
#print(BathSoapHousehold_df)
BathSoapHousehold_df.head()
```

Out[3]:

	Member id	SEC	FEH	MT	SEX	AGE	EDU	HS	CHILD	CS	...	PropCat 6	PropCat 7	PropCat 8	PropCat 9	PropCat 10	PropCat 11	PropCat 12	PropCat 13
0	1010010	4	3	10	1	4	4	2	4	1	...	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.028037	0.0
1	1010020	3	2	10	2	2	4	4	2	1	...	0.347048	0.026834	0.016100	0.014311	0.0	0.059034	0.000000	0.0
2	1014020	2	3	10	2	4	5	6	4	1	...	0.121212	0.033550	0.010823	0.008658	0.0	0.000000	0.016234	0.0
3	1014030	4	0	0	0	4	0	0	5	0	...	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.0
4	1014190	4	1	10	2	3	4	4	3	1	...	0.000000	0.000000	0.048193	0.000000	0.0	0.000000	0.000000	0.0

5 rows × 46 columns

In [4]:
```
# Visually inspect the names of the variables
BathSoapHousehold_df.columns
```

Out[4]:
```
Index(['Member id', 'SEC', 'FEH', 'MT', 'SEX', 'AGE', 'EDU', 'HS', 'CHILD',
       'CS', 'Affluence Index', 'No. of Brands', 'Brand Runs', 'Total Volume',
       'No. of  Trans', 'Value', 'Trans / Brand Runs', 'Vol/Tran',
       'Avg. Price ', 'Pur Vol No Promo - %', 'Pur Vol Promo 6 %',
       'Pur Vol Other Promo %', 'Br. Cd. 57, 144', 'Br. Cd. 55', 'Br. Cd. 272',
       'Br. Cd. 286', 'Br. Cd. 24', 'Br. Cd. 481', 'Br. Cd. 352', 'Br. Cd. 5',
       'Others 999', 'Pr Cat 1', 'Pr Cat 2', 'Pr Cat 3', 'Pr Cat 4',
       'PropCat 5', 'PropCat 6', 'PropCat 7', 'PropCat 8', 'PropCat 9',
       'PropCat 10', 'PropCat 11', 'PropCat 12', 'PropCat 13', 'PropCat 14',
       'PropCat 15'],
      dtype='object')
```

In [5]:
```
# Remove special characters from the variable name.
# This is part of the data cleaning process, where the names of the variables are renamed to make them easier to referen

BathSoapHousehold_df.columns = [s.strip().replace(' / ', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace(' - ', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace('/', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace('. ', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace('  ', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace(' ', '_') for s in BathSoapHousehold_df.columns]
BathSoapHousehold_df.columns = [s.strip().replace('_%', '') for s in BathSoapHousehold_df.columns]
```

In [6]:
```
# We check the variable name after clearing the special characters from the variable name

BathSoapHousehold_df.columns
```

Out[6]:
```
Index(['Member_id', 'SEC', 'FEH', 'MT', 'SEX', 'AGE', 'EDU', 'HS', 'CHILD',
       'CS', 'Affluence_Index', 'No_of_Brands', 'Brand_Runs', 'Total_Volume',
       'No_of_Trans', 'Value', 'Trans_Brand_Runs', 'Vol_Tran', 'Avg_Price',
       'Pur_Vol_No_Promo', 'Pur_Vol_Promo_6', 'Pur_Vol_Other_Promo',
       'Br_Cd_57,_144', 'Br_Cd_55', 'Br_Cd_272', 'Br_Cd_286', 'Br_Cd_24',
       'Br_Cd_481', 'Br_Cd_352', 'Br_Cd_5', 'Others_999', 'Pr_Cat_1',
       'Pr_Cat_2', 'Pr_Cat_3', 'Pr_Cat_4', 'PropCat_5', 'PropCat_6',
       'PropCat_7', 'PropCat_8', 'PropCat_9', 'PropCat_10', 'PropCat_11',
       'PropCat_12', 'PropCat_13', 'PropCat_14', 'PropCat_15'],
      dtype='object')
```

In [7]:
```
# Data cleaning: Out of range value correction. We used the "filter" feature of Excel to see any out-of-bound
# or missing values for the various variables. Theose with out-of-bound or missing values will be corrected
# by replacing it with a median value.

# For gender, there are two possible values, (1 = male, 2 =female). We noticed that 0 is also present for several of
# of the records.
median_gender = BathSoapHousehold_df['SEX'].median()
BathSoapHousehold_df['SEX']=BathSoapHousehold_df['SEX'].replace(0, median_gender)

# For Education (EDU), the range of values are 1 to 9 (inclusive). The value of zero is replaced with the median value.
median_EDU = BathSoapHousehold_df['EDU'].median()
BathSoapHousehold_df['EDU']=BathSoapHousehold_df['EDU'].replace(0, median_EDU)

# Television availability (1 = available, 2 = unavailable). The zero value is replaced with the median value.
median_TV = BathSoapHousehold_df['CS'].median()
BathSoapHousehold_df['CS']=BathSoapHousehold_df['CS'].replace(0, median_TV)
```

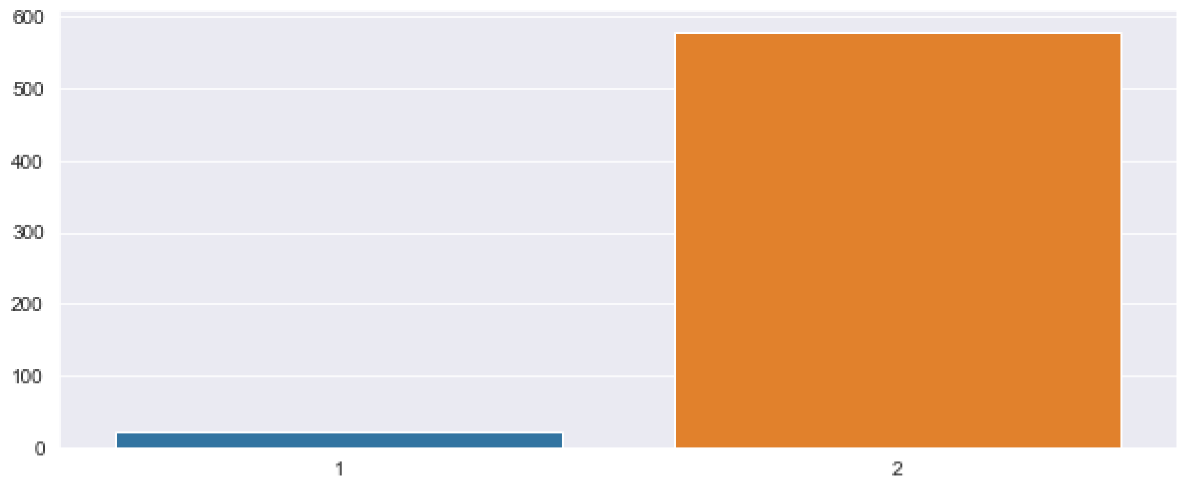
In [8]:
```
#https://stackoverflow.com/questions/15891038/change-data-type-of-columns-in-pandas

# In this cell we convert numeric varirables as float so that the numerical values are not treated as categorical
# data later when we apply dummy_variable creation function.

numeric_pred =['AGE', 'HS', 'Affluence_Index', 'No_of_Brands', 'Brand_Runs', 'Total_Volume',
       'No_of_Trans', 'Value', 'Trans_Brand_Runs', 'Vol_Tran', 'Avg_Price',
       'Pur_Vol_No_Promo', 'Pur_Vol_Promo_6', 'Pur_Vol_Other_Promo',
       'Br_Cd_57,_144', 'Br_Cd_55', 'Br_Cd_272', 'Br_Cd_286', 'Br_Cd_24',
       'Br_Cd_481', 'Br_Cd_352', 'Br_Cd_5', 'Others_999', 'Pr_Cat_1',
       'Pr_Cat_2', 'Pr_Cat_3', 'Pr_Cat_4', 'PropCat_5', 'PropCat_6',
       'PropCat_7', 'PropCat_8', 'PropCat_9', 'PropCat_10', 'PropCat_11',
       'PropCat_12', 'PropCat_13', 'PropCat_14', 'PropCat_15']

BathSoapHousehold_df[numeric_pred] = BathSoapHousehold_df[numeric_pred].apply(pd.to_numeric)

#ORDINAL categorical data:
ordinal_pred = ['SEC', 'EDU', 'CHILD']

BathSoapHousehold_df[ordinal_pred] = BathSoapHousehold_df[ordinal_pred].apply(pd.to_numeric)
```

In [9]:
```
#df = df.astype(str)

# In this cell we ensure that the NOMINAL categorical data are treated as string values so that only these are
# later converted as dummy variables.

# Member ID provides no useful information and would be later dropped from the list.

nominal_cat = ['FEH', 'MT', 'SEX', 'CS']
BathSoapHousehold_df[nominal_cat] = BathSoapHousehold_df[nominal_cat].astype(str)
```

In [10]:
```
# https://www.geeksforgeeks.org/adding-new-column-to-existing-dataframe-in-pandas/

# VARIABLE REDUCTION.
# The columns "Percent of volume purchased under promotion code 6" and "Percent of volume purchased under
# other promotions" provide the same information. We will merge these two variables in to a single variable (derived var
# and drop these original variable (source variable).

BathSoapHousehold_df['Pur_Vol_Promo'] = BathSoapHousehold_df['Pur_Vol_Promo_6'] + BathSoapHousehold_df['Pur_Vol_Other_Pr
```

In [11]:
```
# Variable REDUCTION
# Now based on our preliminary variable analysis, we can drop those variables from the pandas data frame.

d_col = ['Pur_Vol_Promo_6', 'Pur_Vol_Other_Promo', 'Member_id'] # d_col means columns which will be dropped.
BathSoapHousehold_df = BathSoapHousehold_df.drop(d_col, axis=1)
```

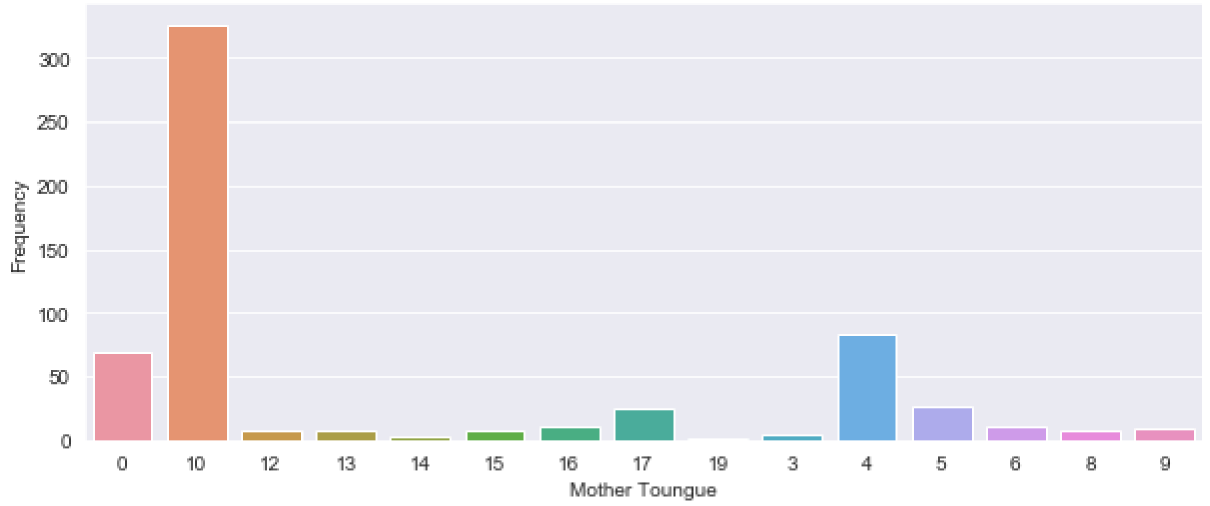
In [12]:
```
# DATA EXPLORATION - AND - DATA REDUCTION
# Now before converting the NOMINAL categorical data into dummy variable, we would like to see how much variance there
# in the variable data. If the variance is close to zero, then we will drop this variable.

genders = BathSoapHousehold_df.SEX.value_counts()
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x=genders.index, y=genders.values)
plt.show()
```



Data Reduction

It can be seen from the above bar chart of gender, that there is not significant variability in the data after data cleaning this variable. The bar chart is heavily skewed, hence we will drop this variable from further analysis.

In [13]:
```
# Purpose: Data Exploration and Data Reduction.
# We now evaluate the mother language variable MT.

mother_lang = BathSoapHousehold_df.MT.value_counts()
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x=mother_lang.index, y=mother_lang.values)
plt.xlabel('Mother Toungue')
plt.ylabel('Frequency')
plt.show()
```



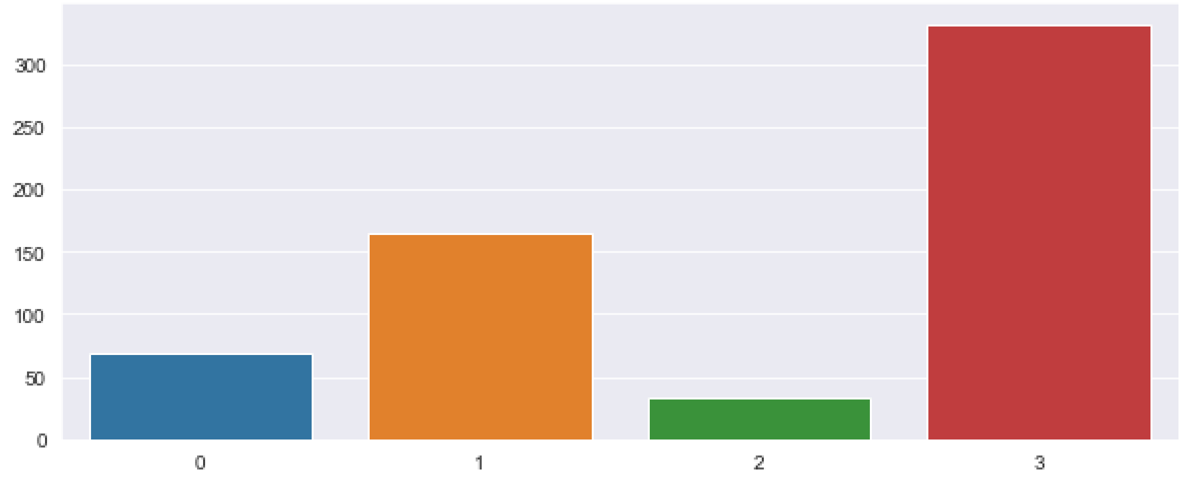
Data Binning

It can seen from the Mother Language bar chart that approx. 70% of mother language are represented by 2 languages (4 & 10). Given this, we will group all languages (except 4 and 10) into one single bin which we will call "Other", and label it as 1.

A major advantage of data binning is that it will minimize the number of variables after dummy variables are created.

In [14]:
```
#In this cell we bin all the other languages into a single "Other" language.

# includes all the index of MT except 10 and 4.
lang_index=['0', '12', '13', '14', '15', '16', '17', '19', '3', '5', '6', '8', '9']

for i in lang_index:
    BathSoapHousehold_df['MT']=BathSoapHousehold_df['MT'].replace(i, '1')
```

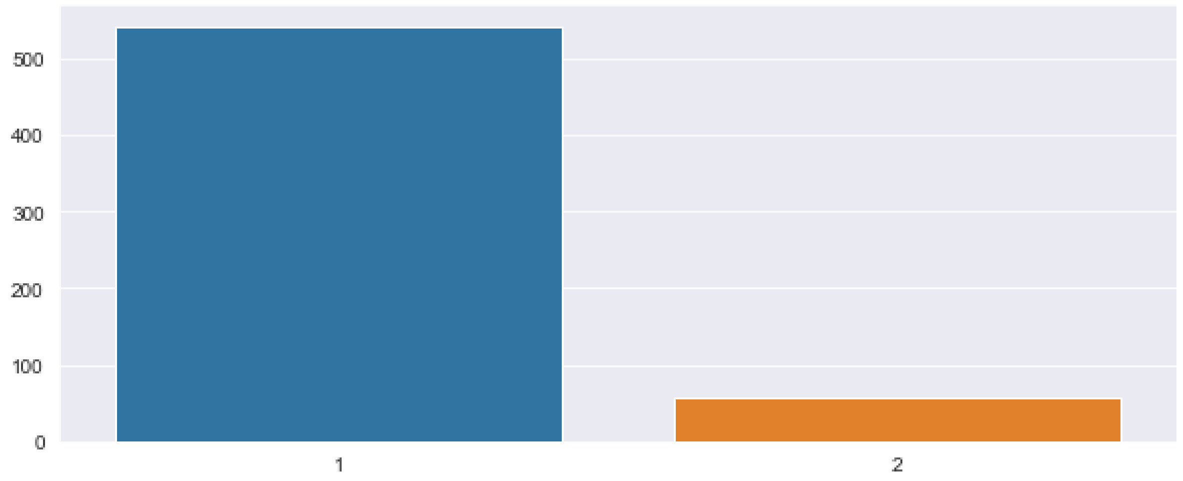
In [15]:
```
# Purpose: Data Exploration and Data Reduction.
# We now evaluate the Eating Habit variable MT.

eat_habit = BathSoapHousehold_df.FEH.value_counts()
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x=eat_habit.index, y=eat_habit.values)
plt.show()
```



Data Binning
As 1 and 2 both represents vegetarian, and considering that number of records in with FEH label equal to 2 is in very small number, we merge 2 with 1.
Note, both of these categrical classes are near-similar.

In [16]:
```
# Merging the two vegetarian classes.
BathSoapHousehold_df.FEH=BathSoapHousehold_df.FEH.replace("2", "1")
```

In [17]:
```
# Purpose: Data Exploration and Data Reduction.
# We now evaluate the Television availability variable CS.

tv_avl = BathSoapHousehold_df.CS.value_counts()
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x=tv_avl.index, y=tv_avl.values)
plt.show()
```



Data Reduction
It can be seen from the above bar chart of gender, that there is not significant variability in the data after data cleaning this variable. The bar chart is heavily skewed, hence we will drop this variable (CS) from further analysis.

In [18]:
```
# Variable REDUCTION
# Now based on our analysis of the bar chrt of the NOMINAL categorical data we drop CS, and SEX.

d_col = ['CS', 'SEX'] # d_col means columns which will be dropped.
BathSoapHousehold_df = BathSoapHousehold_df.drop(d_col, axis=1)
```

Variable Reduction (LINEAR DEPENDENCE)

We then go over the variable descriptors to remove any linearly dependent variable. A variable in the data-set is linearly dependent if it can be derived from some linear combination of other variable. The following two variables are linearly dependent on other variables and will be dropped.

- Trans/Brand Runs - Average transactions per brand run. It is given by dividing 'No. of Trans' with 'Brand Runs'
- Vol/Trans - Average volume per transaction. It is given by dividing 'Total Volume' with 'No. of Trans'.

Hence we will drop these two variables.

```
In [19]: d_col = ['Trans_Brand_Runs', 'Vol_Tran'] # d_col means columns which will be dropped.
         BathSoapHousehold_df = BathSoapHousehold_df.drop(d_col, axis=1)
```

In [20]:
```
# DATA INTEGRITY. We now verify whether there are any missing values for any of the source variable.

pd.DataFrame({
'missing value': BathSoapHousehold_df.isnull().sum(),
})
```

Out[20]:
```
                 missing value
SEC                          0
FEH                          0
MT                           0
AGE                          0
EDU                          0
HS                           0
CHILD                        0
Affluence_Index              0
No_of_Brands                 0
Brand_Runs                   0
Total_Volume                 0
No_of_Trans                  0
Value                        0
Avg_Price                    0
Pur_Vol_No_Promo             0
Br_Cd_57,_144                0
Br_Cd_55                     0
Br_Cd_272                    0
Br_Cd_286                    0
Br_Cd_24                     0
Br_Cd_481                    0
Br_Cd_352                    0
```

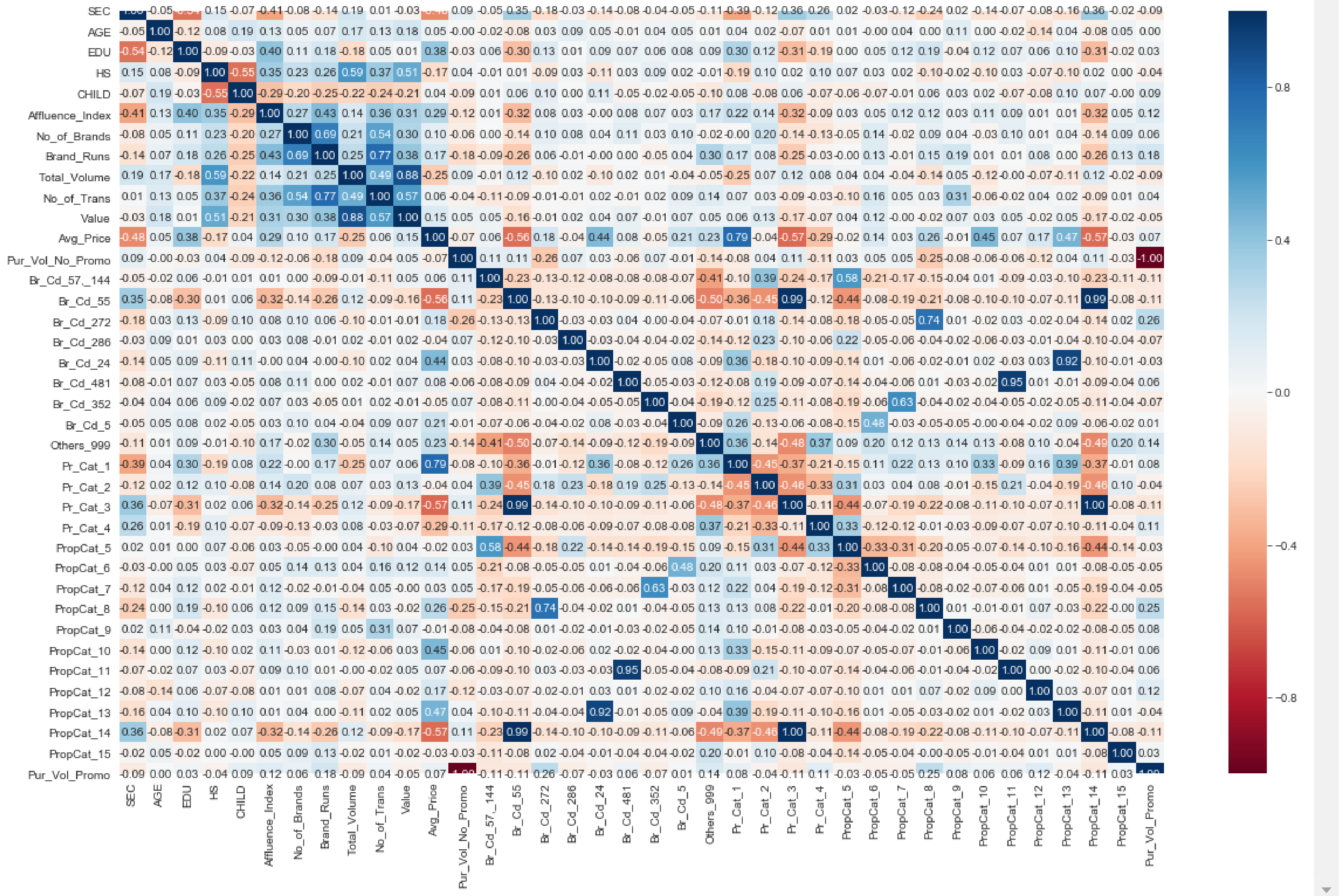
	missing value
Br_Cd_5	0
Others_999	0
Pr_Cat_1	0
Pr_Cat_2	0
Pr_Cat_3	0
Pr_Cat_4	0
PropCat_5	0
PropCat_6	0
PropCat_7	0
PropCat_8	0
PropCat_9	0
PropCat_10	0
PropCat_11	0
PropCat_12	0
PropCat_13	0
PropCat_14	0
PropCat_15	0
Pur_Vol_Promo	0

In [21]:
```
# Data Exploration of all the variables.
BathSoapHousehold_df.describe()
```

Out[21]:
```
              SEC         AGE         EDU          HS       CHILD  Affluence_Index  No_of_Brands  Brand_Runs  Total_Volume  No_of_Trans  ...  Pr
count  600.000000  600.000000  600.000000  600.000000  600.000000        600.00000    600.000000  600.000000    600.000000   600.000000  ...  60(
 mean    2.500000    3.213333    4.590833    4.191667    3.233333         17.02000      3.636667   15.751667  11914.770000    31.153333  ...   (
  std    1.118967    0.865489    1.590246    2.300090    1.217110         11.41008      1.579709   10.396481   7770.374508    17.427258  ...   (
  min    1.000000    1.000000    1.000000    0.000000    1.000000          0.00000      1.000000    1.000000    150.000000     1.000000  ...   (
  25%    1.750000    3.000000    4.000000    3.000000    2.000000         10.00000      2.000000    8.000000   6825.000000    22.000000  ...   (
  50%    2.500000    3.000000    4.750000    4.000000    4.000000         15.00000      3.000000   15.000000  10360.000000    28.000000  ...   (
  75%    3.250000    4.000000    5.000000    5.000000    4.000000         24.00000      5.000000   21.000000  15343.750000    40.000000  ...   (
  max    4.000000    4.000000    9.000000   15.000000    5.000000         53.00000      9.000000   74.000000  50895.000000   138.000000  ...

8 rows × 38 columns
```

In [22]:
```
# We look at correlation between various variables and drop those variables which are strongly correlated.
# Since for two varibles which are strongly correlated, one of the variable can be dropped, as the information contained
# in the dropped variable is contained in the correlated variable which is not dropped.
# Pge 148

## simple heatmap of correlations. Nominal Cat. variable is excluded by Python.
corr = BathSoapHousehold_df.corr()
fig, ax = plt.subplots()
fig.set_size_inches(20, 12)
sns.heatmap(corr, annot=True, fmt=".2f", cmap="RdBu", center=0, ax=ax)
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e2f2977e88>
```



Variable reduction based on Correlation

We Variation in one variable that is duplicated by similar variation in the other variable. We can use his fact to remove some of the variables. Based on the above heat map, the pairs with correlation |r|>=0.85 are:

- Value - Total_Volume: 0.88
- Pr_Cat_3 - Br_Cd_55: 0.99
- Pur_Vol_Promo - Pur_Vol_No_Promo: -1
- PropCat_11 - Br_Cd_481: 0.95
- PropCat_14 - Br_Cd_24: 0.92
- PropCat_14 - Br_Cd_55: 0.99
- PropCat_14 - Pr_Cat_3: 1.00

Based on this we will now drop "Value", "Br_Cd_55", "Pur_Vol_No_Promo", "Br_Cd_481", "Br_Cd_24", "Br_Cd_55", "Pr_Cat_3"

In [23]:
```
# VARIABLE REDUCTION.
# In this cell we now remove those variables which are already correlated.
# d_col means columns which will be dropped.

d_col = ["Value", "Br_Cd_55", "Pur_Vol_No_Promo", "Br_Cd_481", "Br_Cd_24", "Br_Cd_55", "Pr_Cat_3"]
BathSoapHousehold_df = BathSoapHousehold_df.drop(d_col, axis=1)
```

In [24]:
```
BathSoapHousehold_df.columns
```

Out[24]:
```
Index(['SEC', 'FEH', 'MT', 'AGE', 'EDU', 'HS', 'CHILD', 'Affluence_Index',
       'No_of_Brands', 'Brand_Runs', 'Total_Volume', 'No_of_Trans',
       'Avg_Price', 'Br_Cd_57,_144', 'Br_Cd_272', 'Br_Cd_286', 'Br_Cd_352',
       'Br_Cd_5', 'Others_999', 'Pr_Cat_1', 'Pr_Cat_2', 'Pr_Cat_4',
       'PropCat_5', 'PropCat_6', 'PropCat_7', 'PropCat_8', 'PropCat_9',
       'PropCat_10', 'PropCat_11', 'PropCat_12', 'PropCat_13', 'PropCat_14',
       'PropCat_15', 'Pur_Vol_Promo'],
      dtype='object')
```

In [25]:
```
# DATA NORMALIZATION. Nominal Categorical data will not be normalized.
# Now we will evaluate the performance of our variable selection using the PCA.
# It would be useful for this stage and later stages to normalize the data in the [0,1] interval.
# We now evaluate which variables are not in the [0,1], and then normalize that variables.

# PCA does not runs on nominal categrical data.

norm_pred = ['SEC', 'AGE', 'EDU', 'HS', 'CHILD', 'Affluence_Index',
             'No_of_Trans','No_of_Brands', 'Brand_Runs', 'Total_Volume', 'Avg_Price']

min_max_scaler = preprocessing.MinMaxScaler()
BathSoapHousehold_df[norm_pred] = min_max_scaler.fit_transform(BathSoapHousehold_df[norm_pred])
```

In [26]:
```
# Validating the data normaliation process
# we print the range of the data to ensure that the range of the data is in the [0,1] interval
# except nominal categorical data.

pd.DataFrame({'mean': BathSoapHousehold_df.mean(),
'min': BathSoapHousehold_df.min(),
'max': BathSoapHousehold_df.max(),

})
```

Out[26]:

	mean	min	max
SEC	0.500000	0.0	1.000000
FEH	inf	0.0	3.000000
MT	inf	1.0	4.000000
AGE	0.737778	0.0	1.000000
EDU	0.448854	0.0	1.000000
HS	0.279444	0.0	1.000000
CHILD	0.558333	0.0	1.000000
Affluence_Index	0.321132	0.0	1.000000
No_of_Brands	0.329583	0.0	1.000000
Brand_Runs	0.202078	0.0	1.000000
Total_Volume	0.231841	0.0	1.000000
No_of_Trans	0.220097	0.0	1.000000
Avg_Price	0.224277	0.0	1.000000
Br_Cd_57,_144	0.183822	0.0	1.000000
Br_Cd_272	0.033155	0.0	0.963636
Br_Cd_286	0.033948	0.0	1.000000
Br_Cd_352	0.034232	0.0	0.993197
Br_Cd_5	0.018186	0.0	0.971098
Others_999	0.521992	0.0	1.000000

	mean	min	max
Pr_Cat_1	0.279037	0.0	1.000000
Pr_Cat_2	0.493142	0.0	1.000000
Pr_Cat_4	0.088618	0.0	1.000000
PropCat_5	0.457164	0.0	1.000000
PropCat_6	0.092324	0.0	0.971098
PropCat_7	0.096909	0.0	1.000000
PropCat_8	0.080148	0.0	0.963636
PropCat_9	0.030806	0.0	0.407643
PropCat_10	0.020248	0.0	1.000000
PropCat_11	0.029367	0.0	0.897507
PropCat_12	0.006217	0.0	0.333333
PropCat_13	0.024938	0.0	1.000000
PropCat_14	0.136481	0.0	1.000000
PropCat_15	0.025398	0.0	0.840194
Pur_Vol_Promo	0.086992	0.0	1.000000

In [27]:
```
# We perform Principal Component Analysis (PCA) on the numerical data. (page 152)
nominal_pred = ['SEC', 'FEH', 'MT'] # to exclude the nominal cat. predictors.

from sklearn.decomposition import PCA

pcs = PCA()
pcs.fit(BathSoapHousehold_df.drop(nominal_pred, axis=1))
```

Out[27]:
```
PCA()
```

In [28]:
```
import numpy as np

pcsSummary_df = pd.DataFrame({'Standard deviation': np.sqrt(pcs.explained_variance_),
                           'Proportion of variance': pcs.explained_variance_ratio_,
                           'Cumulative proportion': np.cumsum(pcs.explained_variance_ratio_)})
pcsSummary_df = pcsSummary_df.transpose()
pcsSummary_df.columns = ['PC{}'.format(i) for i in range(1, len(pcsSummary_df.columns) + 1)]
pd.set_option('display.max_columns', None)
pcsSummary_df
```

Out[28]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	P
Standard deviation	0.440836	0.423728	0.353724	0.333619	0.303070	0.279624	0.227822	0.199980	0.194174	0.175063	0.153973	0.150928	0.143464	0.134
Proportion of variance	0.174895	0.161584	0.112604	0.100167	0.082663	0.070367	0.046711	0.035991	0.033932	0.027581	0.021336	0.020501	0.018523	0.016
Cumulative proportion	0.174895	0.336479	0.449083	0.549250	0.631913	0.702281	0.748991	0.784983	0.818914	0.846496	0.867831	0.888332	0.906855	0.923

PCA RESULT DISCUSSION

It can be seen from the table above that the use of PCA does not significantly reduces the number of variables. For instance to maintain >90% variance in the data, we need to use >=13 PCA. Hence as this does not lead to any significant reduction in the number of variables, we do not further use PCA for the simplicity of analysis.

In [29]:
```
# Dummy variables creation.
# Now we convert all the categorical data into dummy variable.
BathSoapHousehold_df = pd.get_dummies(BathSoapHousehold_df, prefix_sep='_', drop_first=False)
```

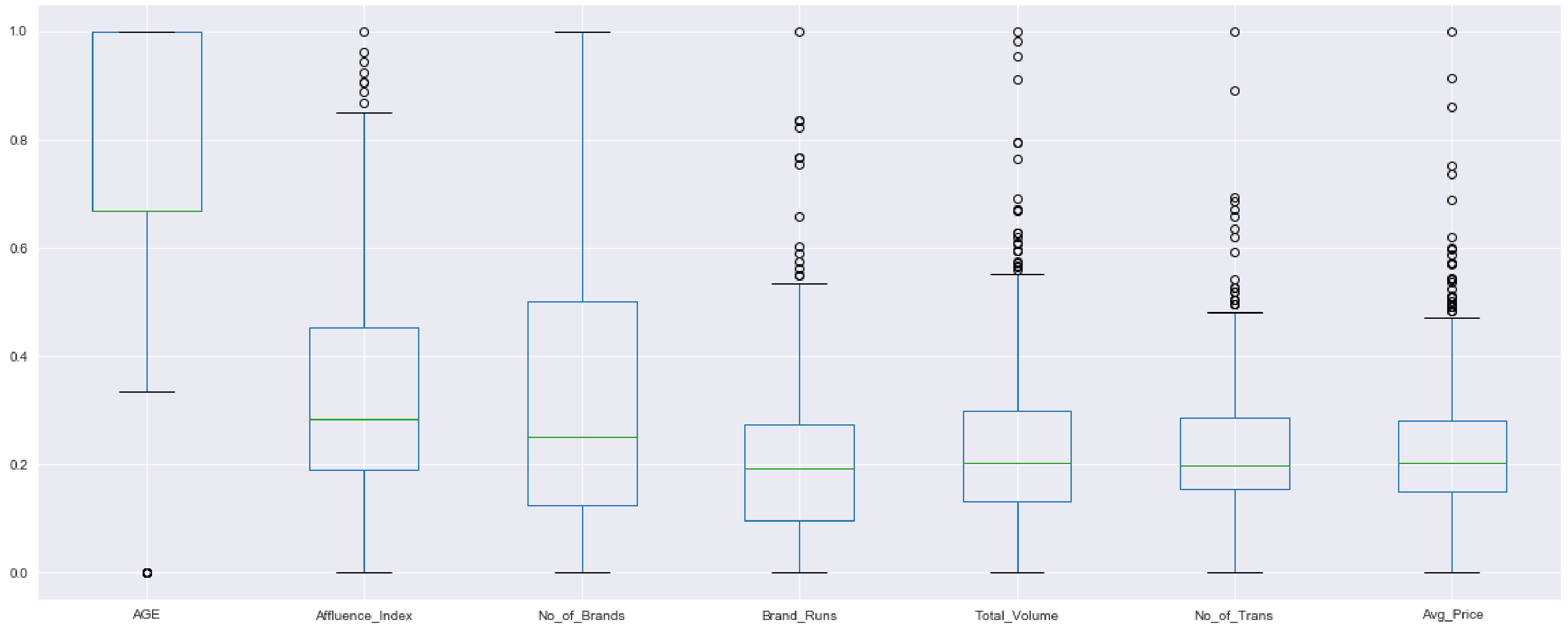
In [30]:
```
# Now we can visually inspect to see the new dummy variables.

# It is interesting to note that we have 6 binary dummy variables due to reduction applied earlier.

BathSoapHousehold_df.head()
```

Out[30]:

	SEC	AGE	EDU	HS	CHILD	Affluence_Index	No_of_Brands	Brand_Runs	Total_Volume	No_of_Trans	Avg_Price	Br_Cd_57,_144
0	1.000000	1.000000	0.3750	0.133333	0.75	0.037736	0.250	0.219178	0.155188	0.167883	0.164922	0.376947
1	0.666667	0.333333	0.3750	0.266667	0.25	0.358491	0.500	0.328767	0.272441	0.284672	0.231324	0.021467
2	0.333333	1.000000	0.5000	0.400000	0.75	0.433962	0.500	0.493151	0.452261	0.452555	0.101768	0.025974
3	1.000000	1.000000	0.4375	0.000000	1.00	0.000000	0.125	0.041096	0.026604	0.021898	0.071454	0.40000
4	1.000000	0.666667	0.3750	0.266667	0.50	0.188679	0.250	0.068493	0.160607	0.087591	0.054132	0.04819

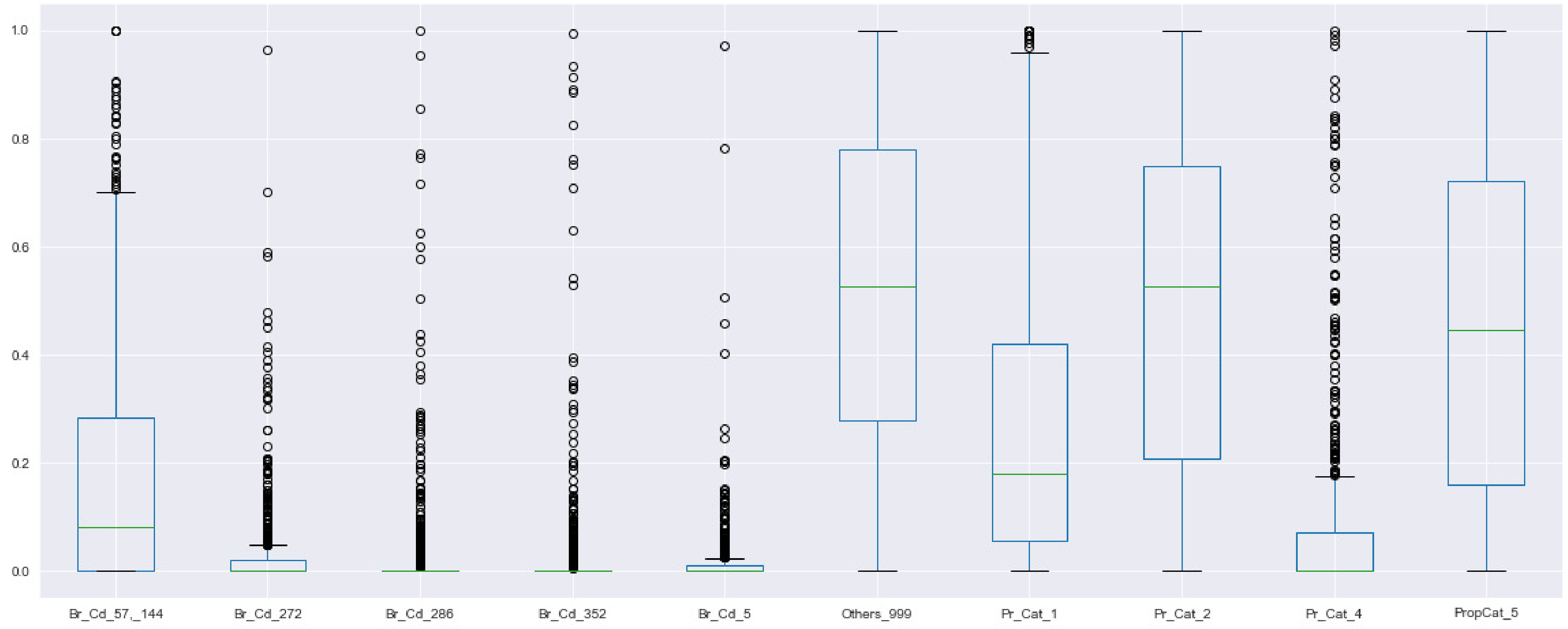
In [31]:
```
# DATA EXPLORATION of numerical value by using box plots. We can also see outliers in the data.

numeric_pred=['AGE', 'Affluence_Index', 'No_of_Brands',
       'Brand_Runs', 'Total_Volume', 'No_of_Trans', 'Avg_Price']

BathSoapHousehold_df[numeric_pred].plot(kind='box', figsize=(20, 8))
```

Out[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e2f244a508>
```



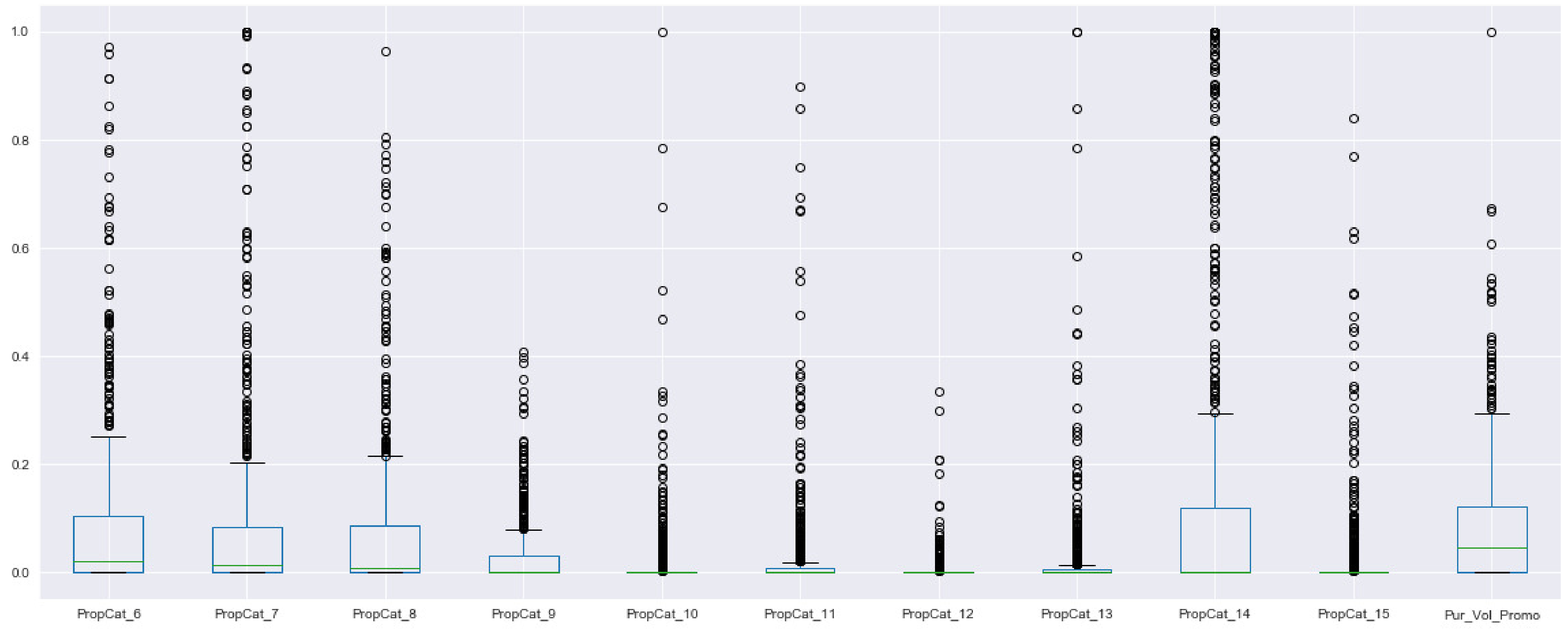
```
In [32]: # DATA EXPLORATION of numerical value by using box plots

         numeric_pred=['Br_Cd_57,_144', 'Br_Cd_272', 'Br_Cd_286', 'Br_Cd_352', 'Br_Cd_5',
                'Others_999', 'Pr_Cat_1', 'Pr_Cat_2', 'Pr_Cat_4', 'PropCat_5']
         BathSoapHousehold_df[numeric_pred].plot(kind='box', figsize=(20, 8))
```

```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1e2f06adec8>
```

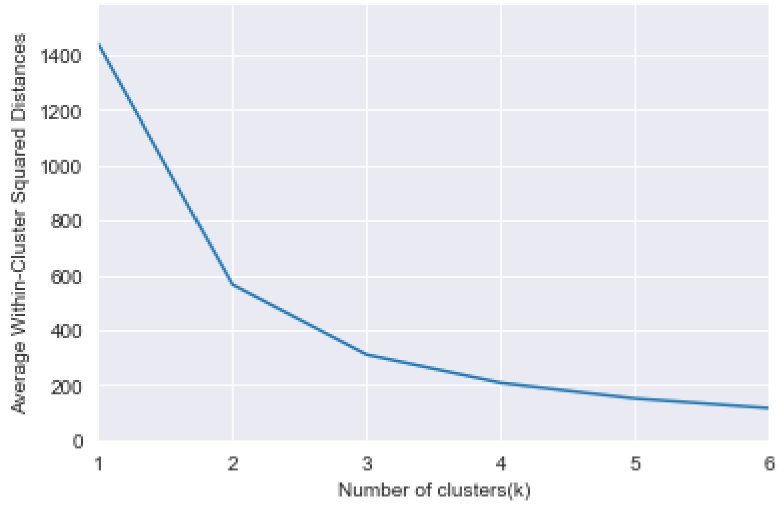


In [33]:
```
# DATA EXPLORATION of numerical value by using box plots

numeric_pred=['PropCat_6', 'PropCat_7', 'PropCat_8', 'PropCat_9', 'PropCat_10',
       'PropCat_11', 'PropCat_12', 'PropCat_13', 'PropCat_14', 'PropCat_15', 'Pur_Vol_Promo']
BathSoapHousehold_df[numeric_pred].plot(kind='box', figsize=(20, 8))
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e2f47c97c8>
```



In [34]:
```
# After the relevant data cleaning, and data reduction, we can now start applying our clustering scheme.
# There are various clustering algorithm, for our analysis we choose the KNN algorithm.

# NUMBER OF CLUSTER: ELBOW GRAPH. An important aspect of the clustering algorithm to decide what would be the suitable
# value of k, i.e. the number of cluster. This information is obtained from the elbow diagram.
# The value of k=3 is selected to be the one where the curve starts bending.

# Analyzing the suitable number of clusters.


inertia = []
for n_clusters in range(1, 7):
    kmeans = KMeans(n_clusters=n_clusters, random_state=0).fit(BathSoapHousehold_df)
    inertia.append(kmeans.inertia_ / n_clusters)
inertias = pd.DataFrame({'n_clusters': range(1, 7), 'inertia': inertia})
#plot.figure(figsize=(20, 6))
ax = inertias.plot(x='n_clusters', y='inertia')
plt.xlabel('Number of clusters(k)')
plt.ylabel('Average Within-Cluster Squared Distances')
plt.ylim((0, 1.1 * inertias.inertia.max()))
ax.legend().set_visible(False)
plt.show()
```



In [35]:
```
# Based on the elbow graph result, the number of cluster which we use is 3.
kmeans = KMeans(n_clusters=3, random_state=0).fit(BathSoapHousehold_df)
```

In [36]:
```
#DELETE THIS LATER

#centroids = pd.DataFrame(kmeans.cluster_centers_, columns=BathSoapHousehold_df.columns)
#pd.set_option('precision', 3)
#print(centroids)
#pd.set_option('precision', 3)
```

In [37]:
```
# calculate the distances of each data point to the cluster centers
distances = kmeans.transform(BathSoapHousehold_df)

# reduce to the minimum squared distance of each data point to the cluster centers
minSquaredDistances = distances.min(axis=1) ** 2

# combine with cluster labels into a data frame
df = pd.DataFrame({'squaredDistance': minSquaredDistances, 'cluster': kmeans.labels_},
    index=BathSoapHousehold_df.index)

# Group by cluster and print information
for cluster, data in df.groupby('cluster'):
    count = len(data)
    withinClustSS = data.squaredDistance.sum()
    print(f'Cluster {cluster} ({count} members): {withinClustSS:.2f} within cluster ')
```

```
Cluster 0 (148 members): 286.33 within cluster
Cluster 1 (196 members): 346.25 within cluster
Cluster 2 (256 members): 296.80 within cluster
```

In [38]:
```
df
```

Out[38]:

	squaredDistance	cluster
0	0.603460	2
1	1.215220	1
2	0.721016	2
3	1.844391	0
4	2.420861	1
...	...	...
595	1.701317	2
596	0.629572	2
597	1.092053	0
598	1.022630	1
599	1.176239	2

600 rows × 2 columns

In [39]:
```
# outputs the centroids corrdinates for the three clusters.
centroids = pd.DataFrame(kmeans.cluster_centers_, columns=BathSoapHousehold_df.columns)

centroids
```

Out[39]:

	SEC	AGE	EDU	HS	CHILD	Affluence_Index	No_of_Brands	Brand_Runs	Total_Volume	No_of_Trans	Avg_Price	Br_Cd_57
0	0.479730	0.650901	0.431166	0.179279	0.722973	0.193014	0.260135	0.152999	0.202322	0.168870	0.228798	0.1
1	0.346939	0.789116	0.510204	0.309184	0.516582	0.413458	0.350128	0.221764	0.222319	0.225235	0.252410	0.2
2	0.628906	0.748698	0.412109	0.314583	0.495117	0.324514	0.354004	0.215379	0.256197	0.245780	0.200124	0.1

In [42]:
```
# The variables for which there is high variance
var_variance =['SEC', 'EDU', 'Affluence_Index', 'Br_Cd_57,_144', 'Br_Cd_272', 'Br_Cd_286', 'Pr_Cat_2',
              'Pr_Cat_4', 'PropCat_7',  'PropCat_14', 'PropCat_15', 'FEH_1', 'FEH_3']
```

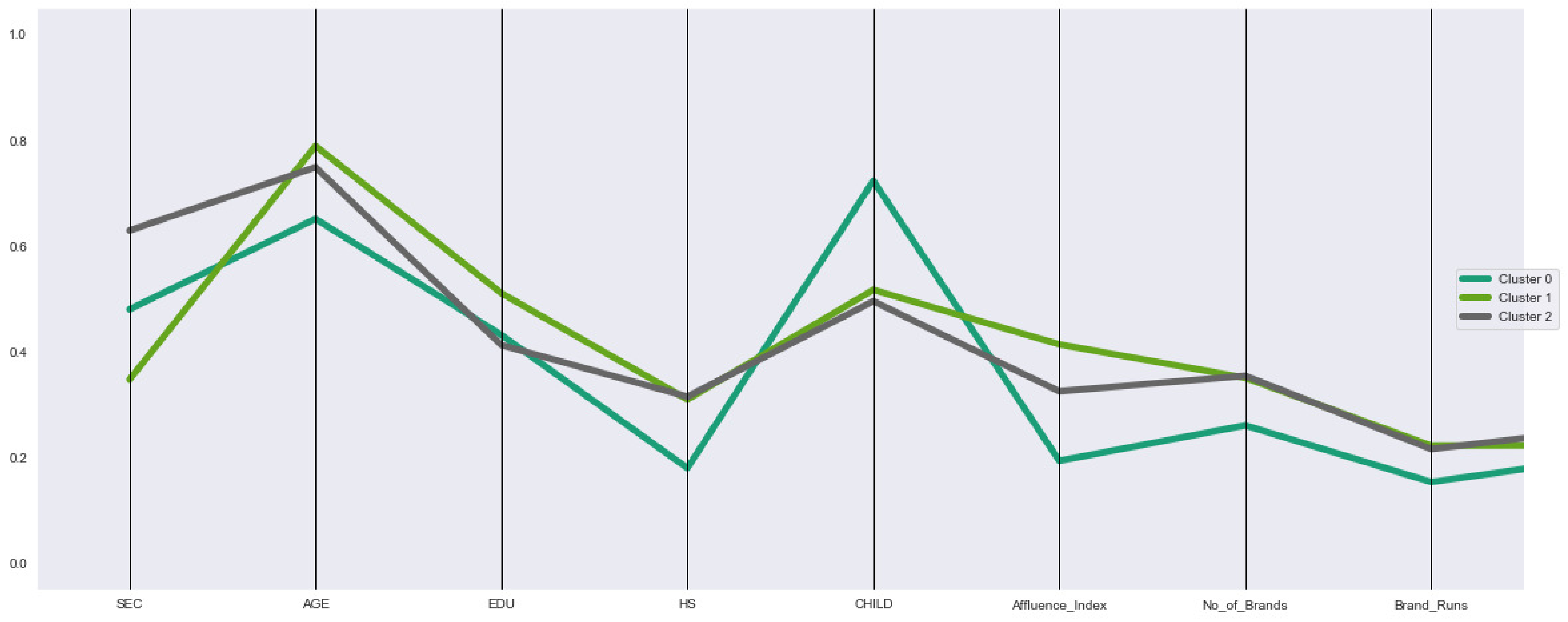
In [43]:
```
centroids[var_variance]
```

Out[43]:

	SEC	EDU	Affluence_Index	Br_Cd_57,_144	Br_Cd_272	Br_Cd_286	Pr_Cat_2	Pr_Cat_4	PropCat_7	PropCat_14	PropCat_15	FEH
0	0.479730	0.431166	0.193014	0.183179	0.033284	0.025384	0.427213	0.094454	0.087616	0.166643	0.013030	2.027027e
1	0.346939	0.510204	0.413458	0.206749	0.043866	0.041224	0.554624	0.067386	0.119221	0.066321	0.037031	1.000000e-
2	0.628906	0.412109	0.324514	0.166640	0.024881	0.033329	0.484185	0.101498	0.085199	0.172759	0.023642	3.330669e

In [47]:
```
centroids['cluster'] = ['Cluster {}'.format(i) for i in centroids.index]
plt.figure(figsize=(20,8))
fig.subplots_adjust(right=3)
ax = parallel_coordinates(centroids, class_column='cluster', colormap='Dark2', linewidth=5)
plt.legend(loc='center left', bbox_to_anchor=(0.95, 0.5))
plt.xlim(-0.5,7.5)
```

Out[47]:
```
(-0.5, 7.5)
```



In [48]:
```
BathSoapHousehold_df.groupby(kmeans.labels_).mean()
```

Out[48]:

	SEC	AGE	EDU	HS	CHILD	Affluence_Index	No_of_Brands	Brand_Runs	Total_Volume	No_of_Trans	Avg_Price	Br_Cd_57
0	0.479730	0.650901	0.431166	0.179279	0.722973	0.193014	0.260135	0.152999	0.202322	0.168870	0.228798	0.18
1	0.346939	0.789116	0.510204	0.309184	0.516582	0.413458	0.350128	0.221764	0.222319	0.225235	0.252410	0.20
2	0.628906	0.748698	0.412109	0.314583	0.495117	0.324514	0.354004	0.215379	0.256197	0.245780	0.200124	0.16

In [49]:
```
print(pd.DataFrame(pairwise.pairwise_distances(kmeans.cluster_centers_, metric='euclidean')))
```

```
          0         1         2
0  0.000000  1.599480  1.605611
1  1.599480  0.000000  1.643974
2  1.605611  1.643974  0.000000
```

Q # 2 DEVELOP A PREDICTIVE MODEL TO CLASSIFY CLIENTS AS VALUE CONSCIOUS OR NOT. BINARY LOGISTIC MODEL.

SOLUTION: Value consciousness means that consumers pay more attention to deals and special offers and are prepared to buy in bulk to secure discounts.

This information an be gauged from "Purchase within promotion" variable type. It can be seen from cluster analysis that cluster number 0 and 2 have low value for "Pur_Vol_Promo", i.e. consumers in these two clusters tend to buy less under promotion. Whereas customers in cluster 1 tend to buy more under promotion, hence cluster 1 would be assigned a class of "1", and cluster 0 & 2 will be assigned class of "0".

In [50]:
```
# We create a new variable in the data frame for the class, and assign the class value 0/1 based on which cluster it bel
BathSoapHousehold_df['class']=df.cluster.replace(2, 0)

BathSoapHousehold_df['class']
```

Out[50]:
```
0      0
1      1
2      0
3      0
4      1
      ..
595    0
596    0
597    0
598    1
599    0
Name: class, Length: 600, dtype: int32
```

In [51]:
```
# Import relevant modules to perform classification using logistic regression.

from sklearn.model_selection import train_test_split
from dmba import classificationSummary
from sklearn.model_selection import cross_val_score

from sklearn.linear_model import LogisticRegression #Logistic Regression
```

```
no display found. Using non-interactive Agg backend
```

In [52]:
```
# Partition the data columns into predictors and outcome.
X=BathSoapHousehold_df.drop('class', axis=1)
y=BathSoapHousehold_df['class']
```

In [53]:
```
# Partition the data into training and validation data.
train_X, valid_X, train_y, valid_y = train_test_split(X, y, test_size=0.4, random_state=1)
```

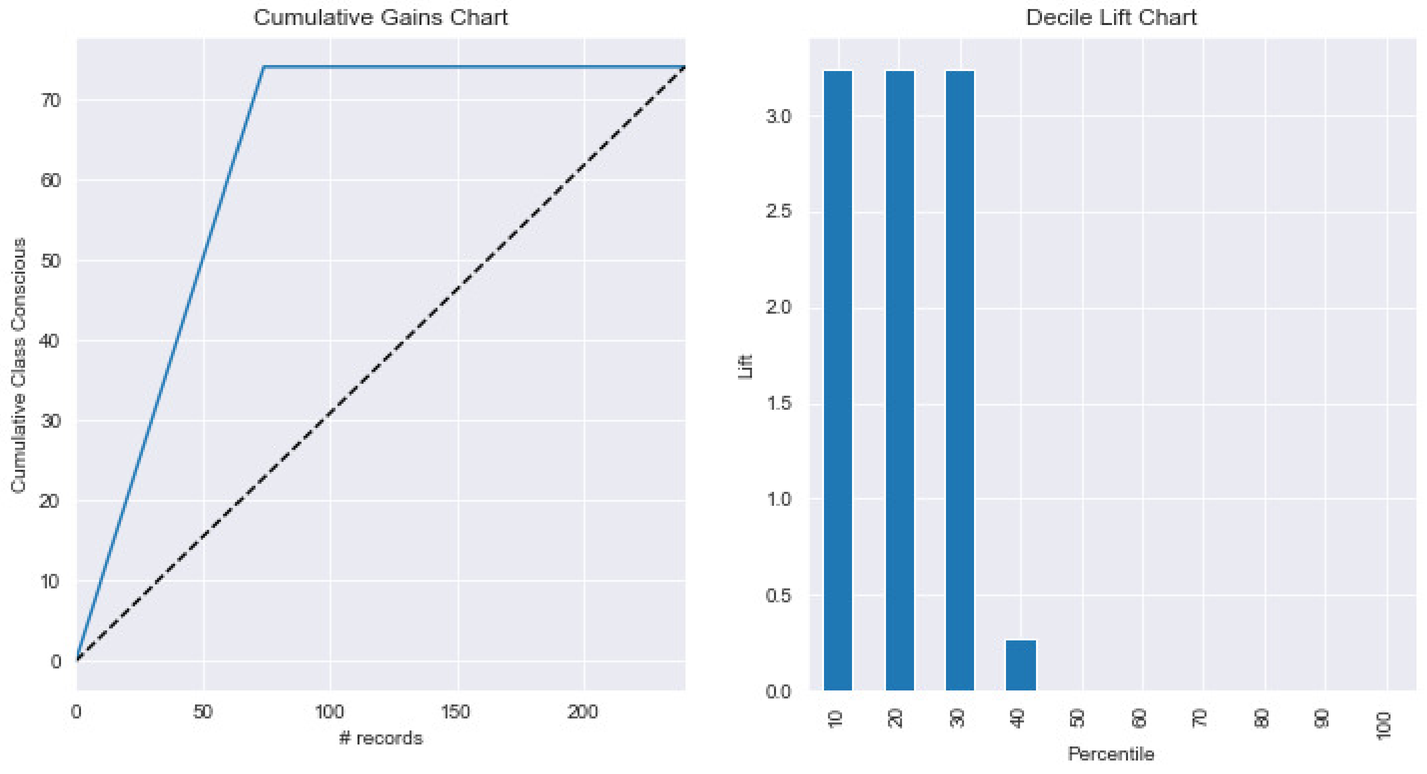
In [54]:
```
# This cell trains Logistic Regression and outputs the accuracy.
# No changes need to be made in this cell.

logit_reg = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
logit_reg.fit(train_X, train_y)
predict = logit_reg.predict(valid_X)
print('Class 0 represents NOT class-consciousness, whereas 1 means they are class-conscious')
classificationSummary(valid_y, logit_reg.predict(valid_X))
```

```
Class 0 represents NOT class-consciousness, whereas 1 means they are class-conscious
Confusion Matrix (Accuracy 0.9958)

       Prediction
Actual   0   1
     0 165   0
     1   1  74
```

In [55]:
```
pred_v = pd.Series(logit_reg.predict(valid_X))
pred_v = pred_v.sort_values(ascending=False)
```

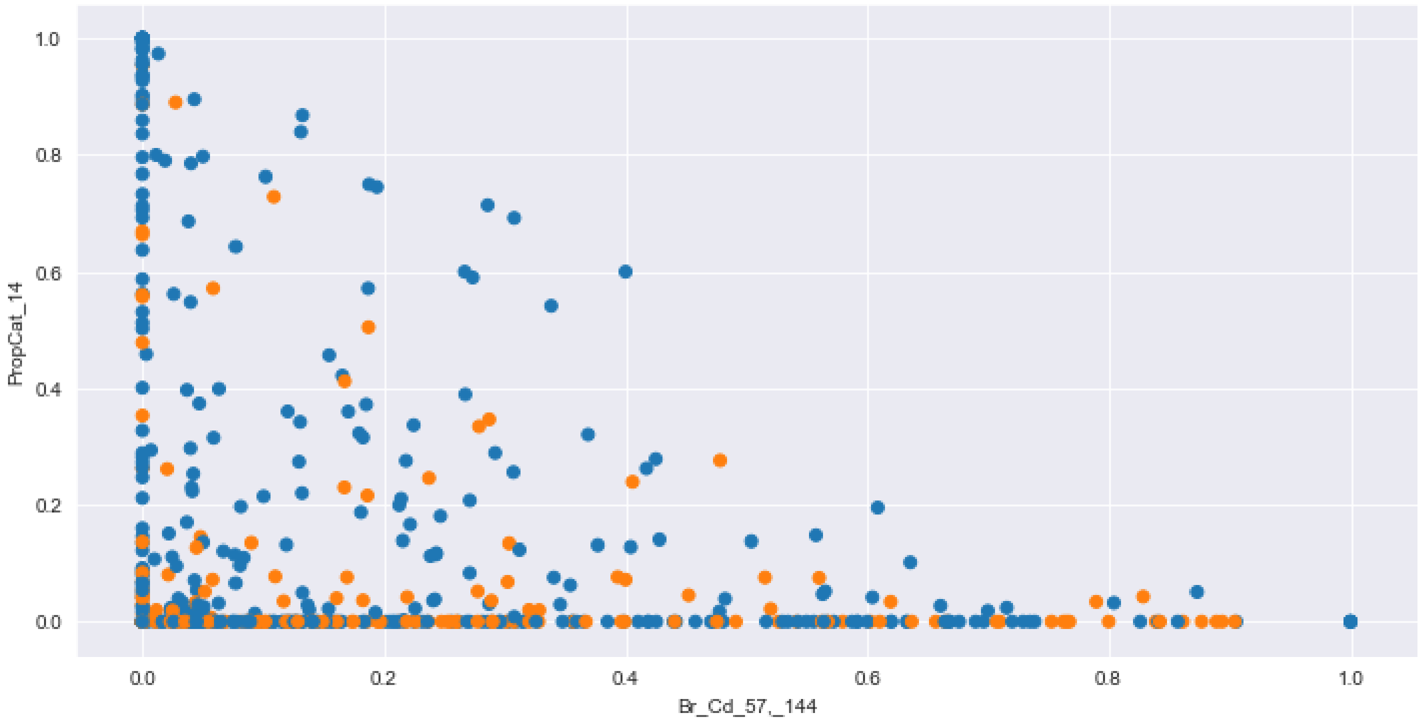
In [56]:
```
# We plot the cumulative and decile lift chart for analysis of the profit

from dmba import liftChart, gainsChart

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12,6))
ax = gainsChart(pred_v, ax=axes[0])
ax.set_ylabel('Cumulative Class Conscious')
ax.set_title('Cumulative Gains Chart')
ax = liftChart(pred_v, ax=axes[1], labelBars=False)
ax.set_ylabel('Lift')
```

Out[56]:
```
Text(0, 0.5, 'Lift')
```



In [57]:
```
# This plot is an example of how a scatter plot can be plotted for two different variables, with the markers marked
# differently.

plt.figure(figsize=(12, 6))
xaxis=BathSoapHousehold_df['Br_Cd_57,_144']
yaxis=BathSoapHousehold_df['PropCat_14']
plt.scatter(x=xaxis, y=yaxis,
            color=['C0' if p==0 else 'C1' for p in BathSoapHousehold_df['class']], label='Class Conscious')
plt.xlabel('Br_Cd_57,_144')
plt.ylabel('PropCat_14')
```

Out[57]:
```
Text(0, 0.5, 'PropCat_14')
```



The End !