Data Load and Preparation

In [1]:

```
import pandas as pd
pd.set_option('display.max_rows', 1000)
```

In [2]:

```
import seaborn as sns
```

In [3]:

```
#import sales csv
sales = pd.read_csv('cleaned_sales.csv')
census = pd.read_csv('cleaned_census.csv')
```

In [4]:

```
census = census.drop(['Unnamed: 0'], axis=1)
census_subset = census[['ZCTA','Average Household Size', 'Median Age',
'Percent Bachelors Deg' , 'Percent Graduate Deg', 'Median Mortgage', 'Mean
Income', 'Percent 65 and Over', 'Percent White']]
census_subset['ZCTA'] = census_subset['ZCTA'].astype(str)
```

```
C:\Users\julie\anaconda3\lib\site-packages\ipykernel_launcher.py:3:
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: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
```

In [5]:

```
sales['Practice Area'].value_counts()
```

Out[5]:

```
Estate Planning                 207
Estate Administration            42
Estate Admin - Package           24
Estate Admin - Hourly            19
Business                         14
Medicaid                         11
Business - Package                7
Estate Admin - Partial            6
Real Estate                       6
Business - LLC                    5
Guardianship                      4
Trust Administration              3
Estate Admin - SEP                3
Business - Hourly                 3
Non Profit                        2
Medicaid - Hourly                 2
```

```
Real Estate - Deed                 1
POA Agent Rep                      1
Estate Administration - Hourly     1
Medicaid - Package                 1
Name: Practice Area, dtype: int64
```

In [6]:

```
sales.loc[sales['Practice Area'].str.contains('Estate Admin'), 'Practice
Area'] = 'Estate Admin'
sales.loc[sales['Practice Area'].str.contains('Business'), 'Practice Area'] =
'Business'
sales.loc[sales['Practice Area'].str.contains('Medicaid'), 'Practice Area'] =
'Medicaid'
sales.loc[(sales['Practice Area'] != 'Estate Admin') &
           (sales['Practice Area'] !='Estate Planning')  &
          (sales['Practice Area'] !='Business')  &
           (sales['Practice Area']!='Medicaid'), 'Practice Area'] = 'Other'

sales['Practice Area'].value_counts()
```

Out[6]:

```
Estate Planning    207
Estate Admin        95
Business            29
Other               17
Medicaid            14
Name: Practice Area, dtype: int64
```

In [7]:

```
#join on zip
joined = sales.merge(census_subset, left_on='Zip', right_on='ZCTA')

#create column for bachelors and graduate degrees
joined['Degree'] = joined['Percent Bachelors Deg'].astype(float) +
joined['Percent Graduate Deg'].astype(float)

#one-hot encoding of practice area
dummies = pd.get_dummies(joined['Practice Area'])

#remove unneeded columns
joined = joined.drop(['Unnamed: 0', 'Percent Bachelors Deg',  'Percent
Graduate Deg',
                      'City', 'State', 'Zip', 'ZCTA', 'Contact Year',
'Practice Area', 'Referral'],axis=1)
joined['Median Mortgage'] = joined['Median
Mortgage'].str.replace('+','').str.replace(',','')

#concat all columns and remove rows with no fee
joined = pd.concat([joined,dummies],axis=1).dropna().reset_index(drop=True)
```

```
C:\Users\julie\anaconda3\lib\site-packages\ipykernel_launcher.py:13:
FutureWarning: The default value of regex will change from True to False in a
future version. In addition, single character regular expressions will*not*
be treated as literal strings when regex=True.
  del sys.path[0]
```

In [8]:

```
numeric = joined[['Fee', 'Average Household Size', 'Median Age',
       'Median Mortgage', 'Mean Income', 'Percent 65 and Over',
       'Percent White', 'Degree']].apply(pd.to_numeric)
categoric = joined[['Contact Month','Business', 'Estate Admin',
       'Estate Planning','Medicaid', 'Other']]

df = pd.concat([categoric, numeric], axis=1)
```

In [9]:

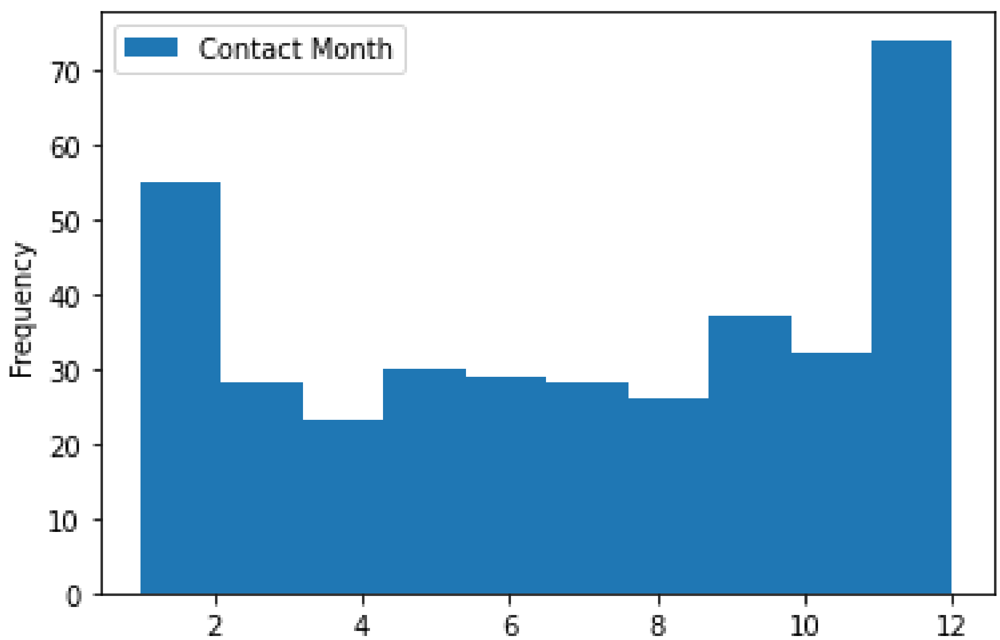
```
#df[['Fee', 'Average Household Size', 'Median Age',
#        'Median Mortgage', 'Mean Income', 'Percent 65 and Over',
#        'Percent White', 'Degree']].describe()
```

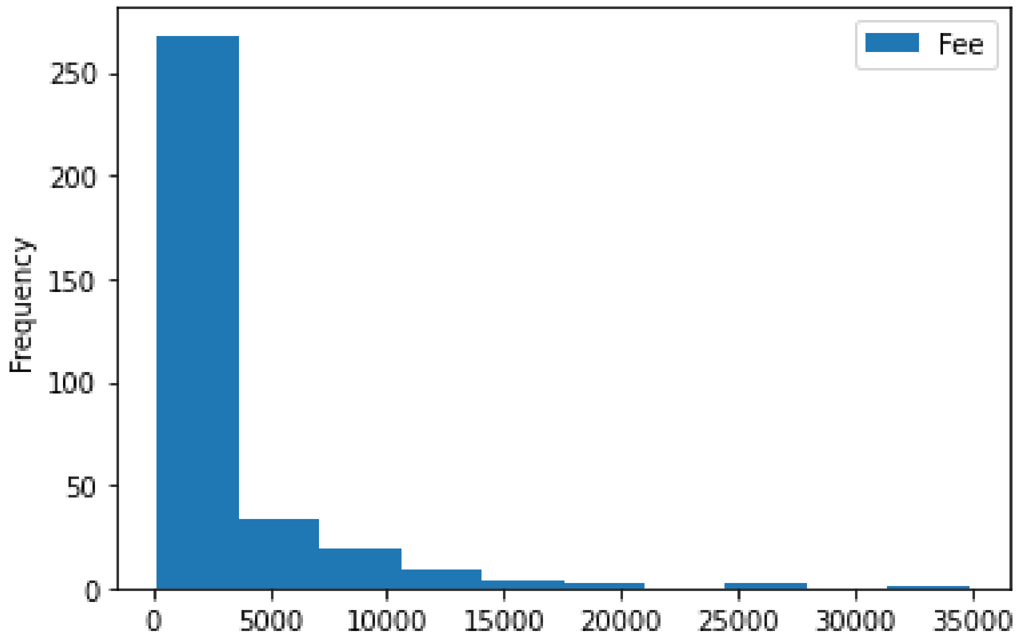
In [10]:

```
import matplotlib.pyplot as plt

ax = sales[['Contact Month']].plot.hist()
plt.show()

ax = sales[['Fee']].plot.hist()
plt.show()
```



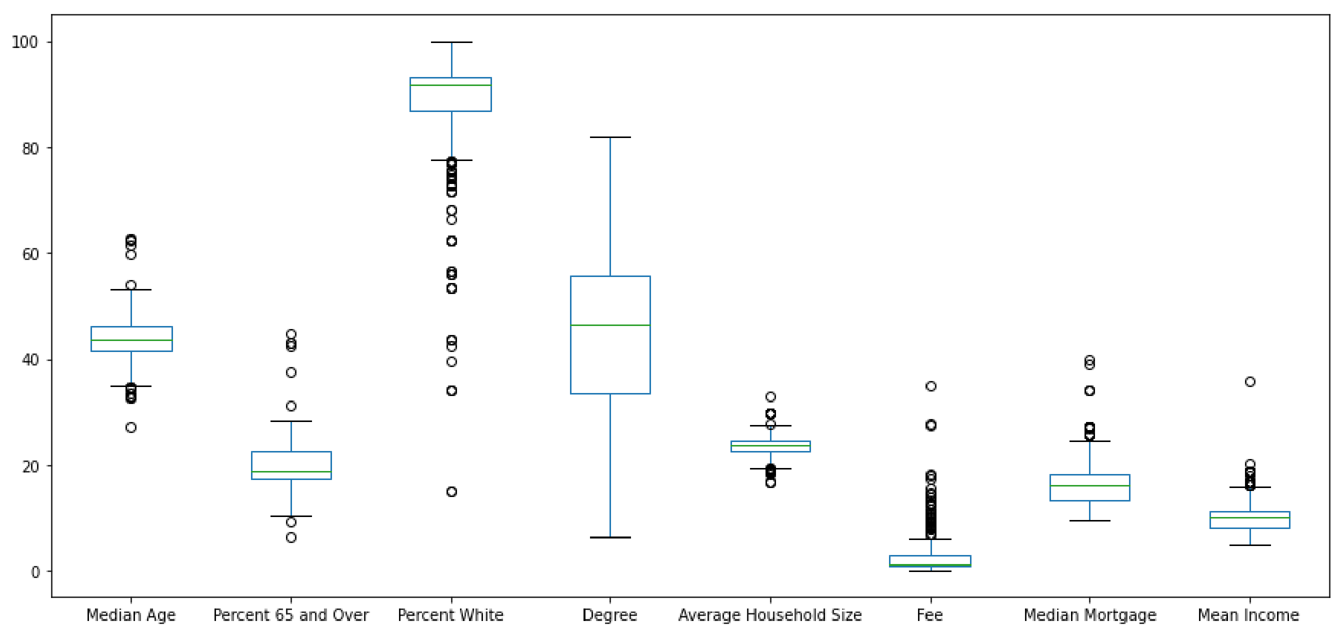


In [11]:

```
plotting_df = df.copy()
plotting_df['Mean Income'] = df['Mean Income']/10000
plotting_df['Fee'] = df['Fee']/1000
plotting_df['Median Mortgage'] = df['Median Mortgage']/100
plotting_df['Average Household Size'] = df['Average Household Size']*10
plotting_df[['Median Age','Percent 65 and Over',
       'Percent White', 'Degree','Average Household Size','Fee', 'Median
Mortgage', 'Mean Income']].plot.box(figsize=(15,7))
```

Out[11]:

```
<AxesSubplot:>
```



In [12]:

```
from sklearn.preprocessing import StandardScaler

# Instantiate scaler
scaler = StandardScaler()

numeric_scaled = pd.DataFrame(scaler.fit_transform(numeric),
columns=numeric.columns)

# Concatenate categoric and scaled numeric columns
scaled_DF = pd.concat([categoric, numeric_scaled], axis=1)
```

PCA

In [13]:

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
principalComponents = pca.fit_transform(scaled_DF)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
```

In [14]:

```
pca.explained_variance_ratio_
```

Out[14]:

```
array([0.59442492, 0.15070333])
```

In [15]:

```
print(scaled_DF.columns)
print(pca.components_)
```

```
Index(['Contact Month', 'Business', 'Estate Admin', 'Estate Planning',
       'Medicaid', 'Other', 'Fee', 'Average Household Size', 'Median Age',
       'Median Mortgage', 'Mean Income', 'Percent 65 and Over',
       'Percent White', 'Degree'],
      dtype='object')
[[-9.98965670e-01 -2.61358640e-03 -1.21751676e-03  2.61921441e-03
   5.85558065e-03 -4.64369189e-03  2.57409583e-03  3.43537820e-03
   2.97625745e-02 -2.88096399e-03 -1.04542425e-02  2.34024155e-02
   1.14688773e-02 -1.71909230e-02]
 [-2.95350112e-02  8.37680195e-03 -4.14276385e-03 -3.96034179e-04
   2.01727963e-03 -5.85528355e-03  9.93355754e-02  3.43991902e-01
  -2.43606623e-01  4.86551934e-01  4.89006048e-01 -3.54962082e-01
  -1.08665448e-01  4.44740046e-01]]
```

K-Means Clustering

In [16]:

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import numpy as np
```

In [17]:

```
# Import module
from sklearn.cluster import KMeans

# Instantiate
kmeans = KMeans(n_clusters=4, random_state=123)

# Fit
fit = kmeans.fit(scaled_DF)

# Print inertia
print("Sum of squared distances for 4 clusters is", kmeans.inertia_)
```

```
Sum of squared distances for 4 clusters is 2842.8272368509147
```

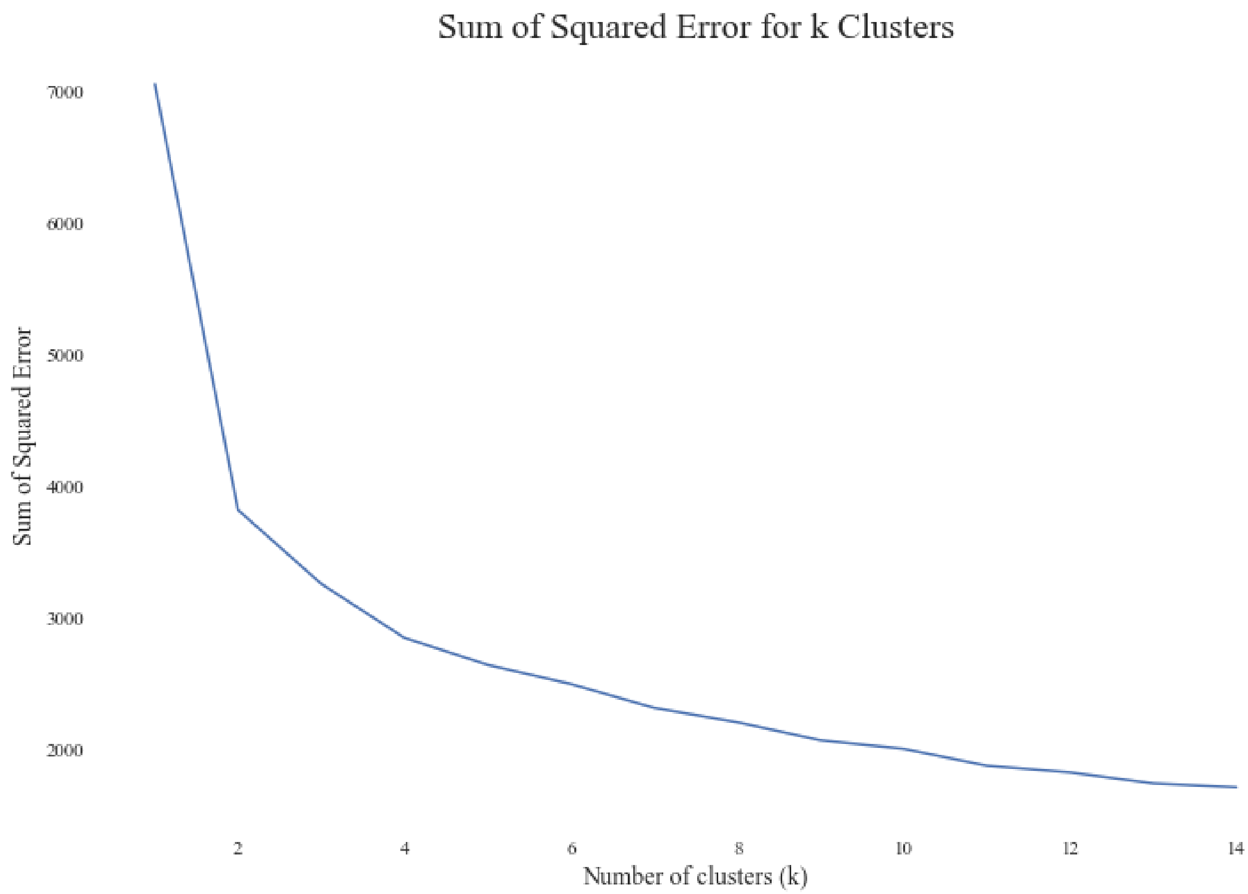
In [18]:

```
cluster_score = []
for k in range(1,15):
    k_means_model = KMeans(n_clusters=k)
    k_means_model.fit(scaled_DF)
    cluster_score.append(k_means_model.inertia_)
```

```
C:\Users\julie\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:882:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=2.
  f"KMeans is known to have a memory leak on Windows "
```

In [19]:

```
sns.set_theme(style="white")
sns.set_style({'axes.facecolor':'white', 'font.family':'Times New Roman'})
fig = plt.figure(figsize = (12,8))
ax = fig.add_subplot(1,1,1)
plt.xlabel('Number of clusters (k)', fontsize=14)
plt.ylabel('Sum of Squared Error', fontsize=14)
plt.title('Sum of Squared Error for k Clusters', fontsize=20)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['bottom'].set_visible(False)
ax.spines['left'].set_visible(False)
plt.plot(range(1,15), cluster_score, '-')
plt.show()
```



In [20]:

```
k_means_model = KMeans(n_clusters=4, random_state=1)
k_means_model.fit(scaled_DF)
scaled_DF['k_means_values']=k_means_model.predict(scaled_DF)
scaled_DF_x = scaled_DF.copy()
scaled_DF_x = scaled_DF_x.drop('k_means_values', axis=1)
```

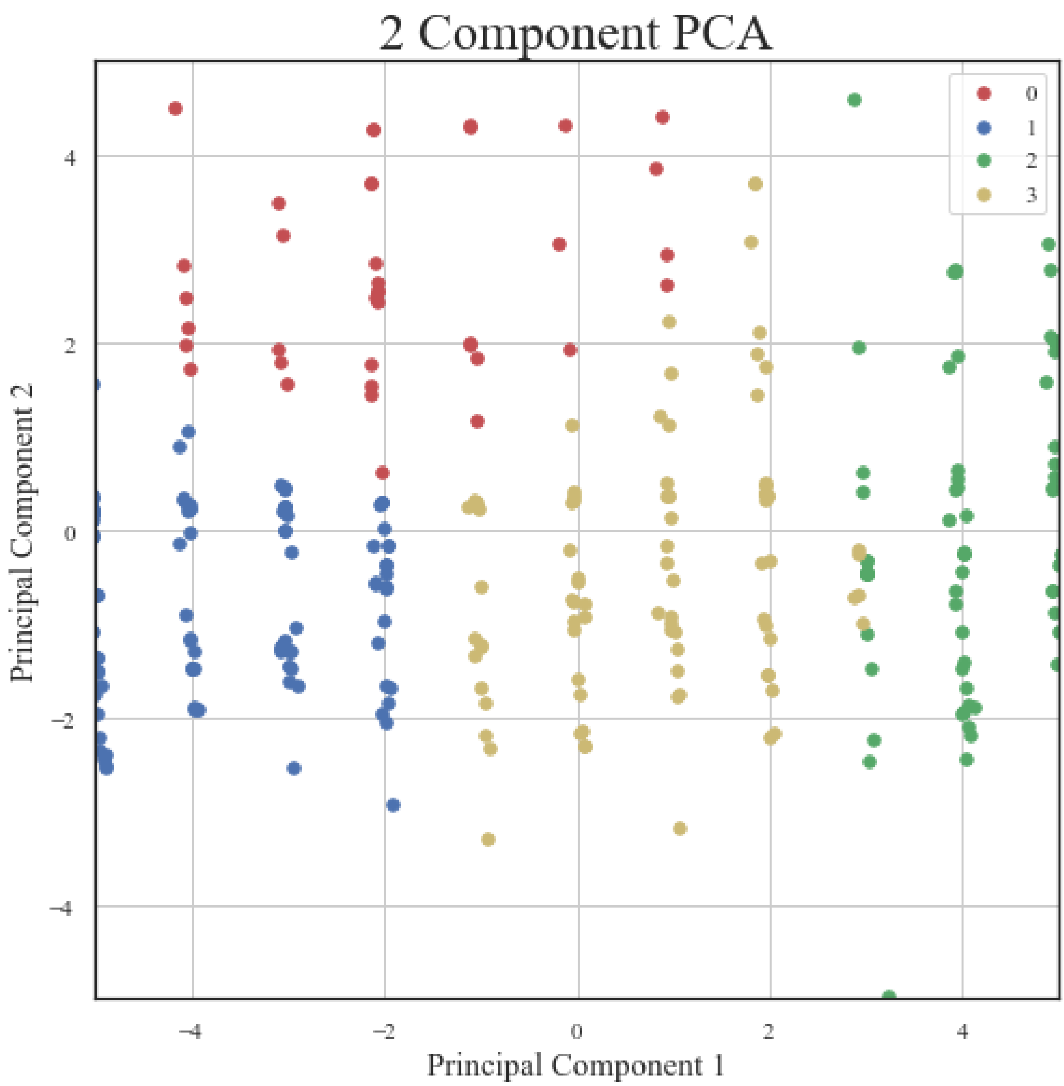
In [21]:

```
finalDf = pd.concat([principalDf, scaled_DF['k_means_values']], axis = 1)
```

In [22]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 Component PCA', fontsize = 24)
plt.xlim([-5, 5])
plt.ylim([-5, 5])
cluster = [0,1,2,3]
color = ['r', 'b', 'g','y']
for cluster, color in zip(cluster,color):
    clusInd = finalDf['k_means_values'] == cluster
    ax.scatter(finalDf.loc[clusInd, 'principal component 1']
               , finalDf.loc[clusInd, 'principal component 2']
```

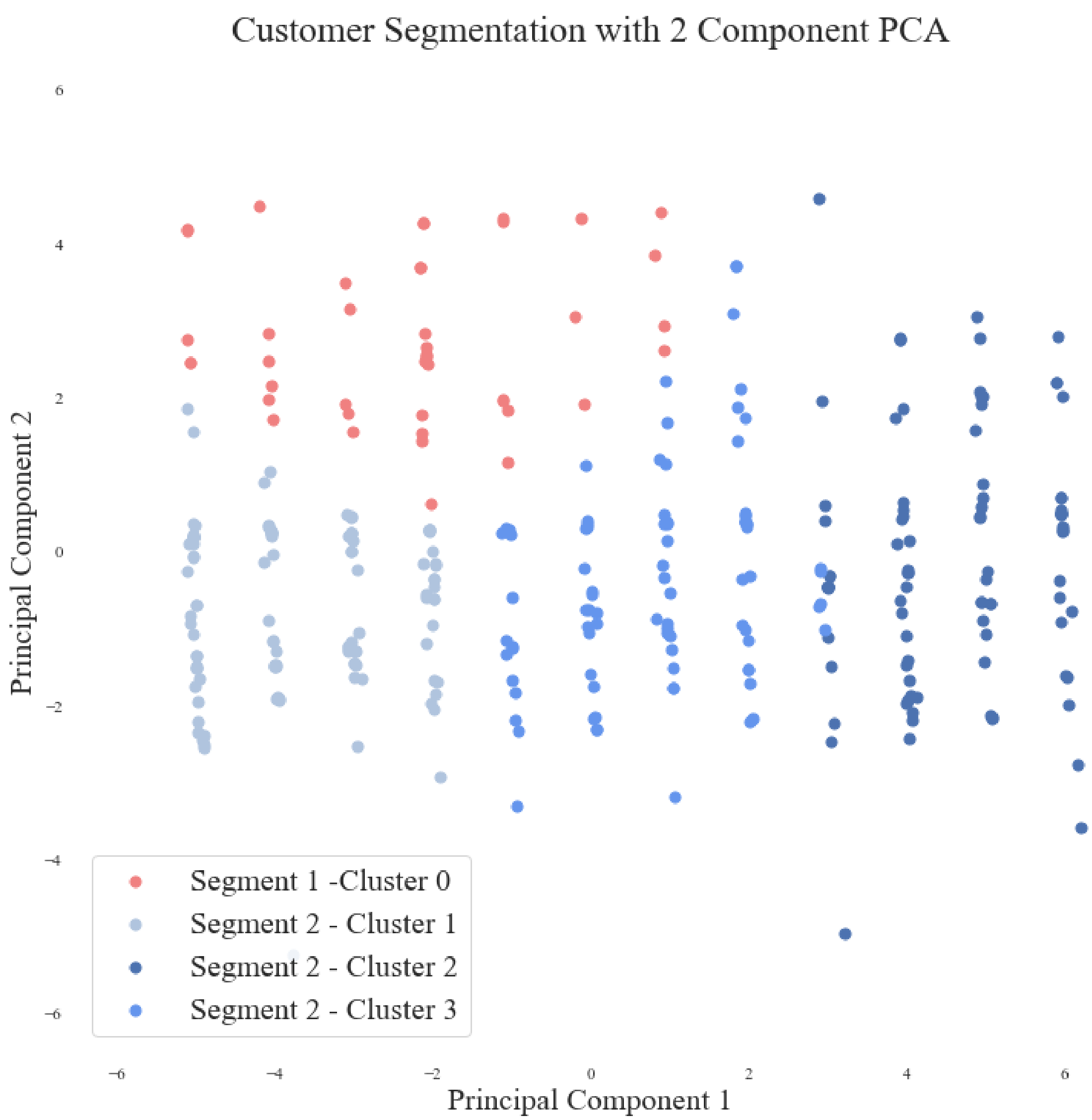
```
                  , c = color
                  , s = 30)
ax.legend([0,1,2,3])
ax.grid()
plt.show()
```



In [23]:

```
sns.set_theme(style="white")
sns.set_style({'axes.facecolor':'white', 'font.family':'Times New Roman'})
fig = plt.figure(figsize = (12,12))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 20)
ax.set_ylabel('Principal Component 2', fontsize = 20)
ax.set_title('Customer Segmentation with 2 Component PCA', fontsize = 24)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['bottom'].set_visible(False)
ax.spines['left'].set_visible(False)
```

```
plt.xlim([-6.5, 6.5])
plt.ylim([-6.5, 6.5])
plt.text(-8, -8, 'PC1 is primarily composed of \'Contact Month\'', ha='left',
fontsize = 16)
plt.text(-8, -8.5, 'PC2 is primarily composed of \'Mean Income\', \'Median
Mortgage\', \'Percent Degree\', \'Average Household Size, and \'Percent 65
and Over\'', ha='left', fontsize = 16)
cluster = [0,1,2,3]
color = ['lightcoral', 'lightsteelblue', 'b', 'cornflowerblue']
for cluster, color in zip(cluster,color):
    clusInd = finalDf['k_means_values'] == cluster
    ax.scatter(finalDf.loc[clusInd, 'principal component 1']
               , finalDf.loc[clusInd, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(['Segment 1 -Cluster 0','Segment 2 - Cluster 1', 'Segment 2 -
Cluster 2', 'Segment 2 - Cluster 3'], fontsize=20, loc = 'lower left')
plt.show()
```



PC1 is primarily composed of 'Contact Month'

PC2 is primarily composed of 'Mean Income', 'Median Mortgage', 'Percent Degree', 'Average Household Size, and 'Percent 65 and Over'

In [24]:

```
df_with_clusters = pd.concat([df, scaled_DF['k_means_values']], axis = 1)
```

In [25]:

```
df_with_clusters[df_with_clusters['k_means_values']==0].describe()
```

Out[25]:

	Contact Month	Business	Estate Admin	Estate Planning	Medicaid	Other	Fee	Average Household Size	Median Age	Median Mortgage	Mean Income	Percent 65 and Over	Percent White	Degree	k_means_values
count	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.000000	44.0
mean	9.159091	0.113636	0.340909	0.500000	0.022727	0.022727	5609.625000	2.592273	41.290909	2416.840909	159112.840909	15.697727	84.377273	63.729545	0.0
std	1.724558	0.321038	0.479495	0.505781	0.150756	0.150756	7888.049783	0.313538	3.850691	507.350892	40947.797211	3.932304	13.687048	9.346970	0.0
min	6.000000	0.000000	0.000000	0.000000	0.000000	0.000000	250.000000	1.690000	32.900000	1552.000000	85565.000000	6.300000	42.400000	33.300000	0.0
25%	8.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1000.000000	2.440000	40.100000	2083.000000	135569.750000	11.700000	80.150000	59.000000	0.0
50%	9.000000	0.000000	0.000000	0.500000	0.000000	0.000000	1800.000000	2.630000	41.900000	2271.000000	166720.000000	16.550000	89.800000	66.150000	0.0
75%	10.250000	0.000000	1.000000	1.000000	0.000000	0.000000	6500.000000	2.740000	43.700000	2706.000000	171881.500000	18.800000	93.100000	68.525000	0.0
max	12.000000	1.000000	1.000000	1.000000	1.000000	1.000000	34885.000000	3.290000	49.400000	4000.000000	358261.000000	24.900000	95.900000	82.000000	0.0

In [26]:

```
cluster1 =
df_with_clusters[df_with_clusters['k_means_values']==0].describe().loc['mean'
,:]
```

In [27]:

```
cluster2 =
df_with_clusters[df_with_clusters['k_means_values']==1].describe().loc['mean'
,:]
```

In [28]:

```
cluster3 =
df_with_clusters[df_with_clusters['k_means_values']==2].describe().loc['mean'
,:]
```

In [29]:

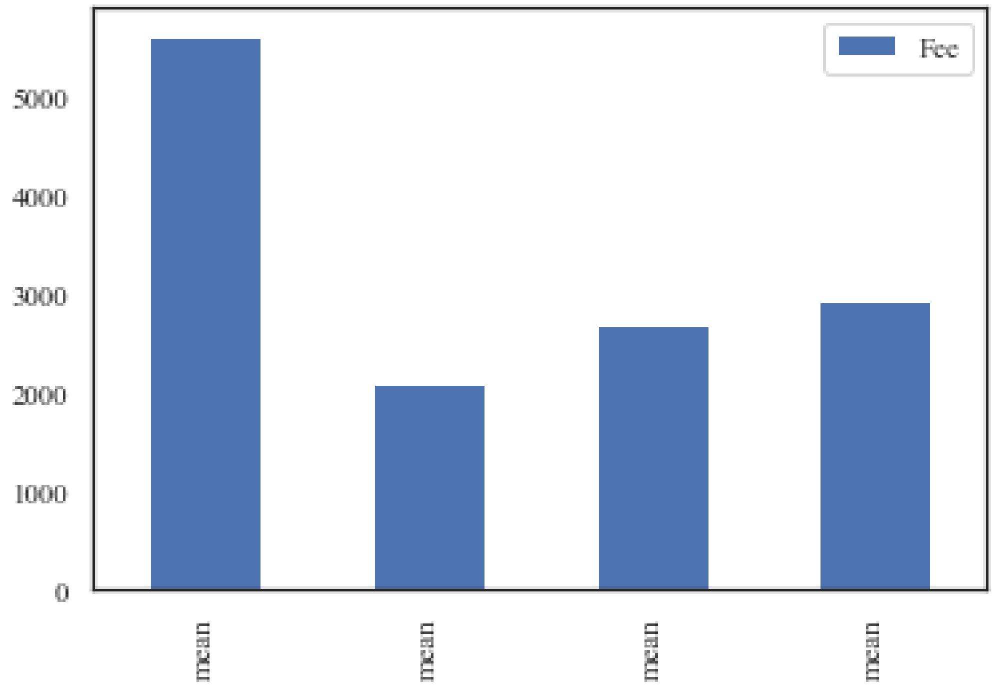
```
cluster4 =
df_with_clusters[df_with_clusters['k_means_values']==3].describe().loc['mean'
,:]
```

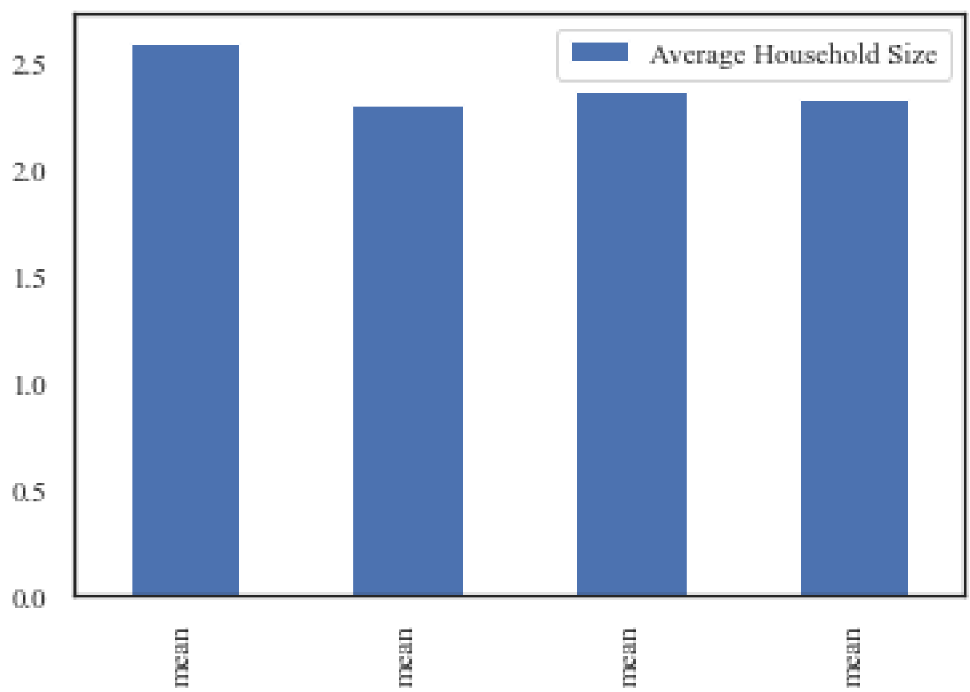
In [30]:

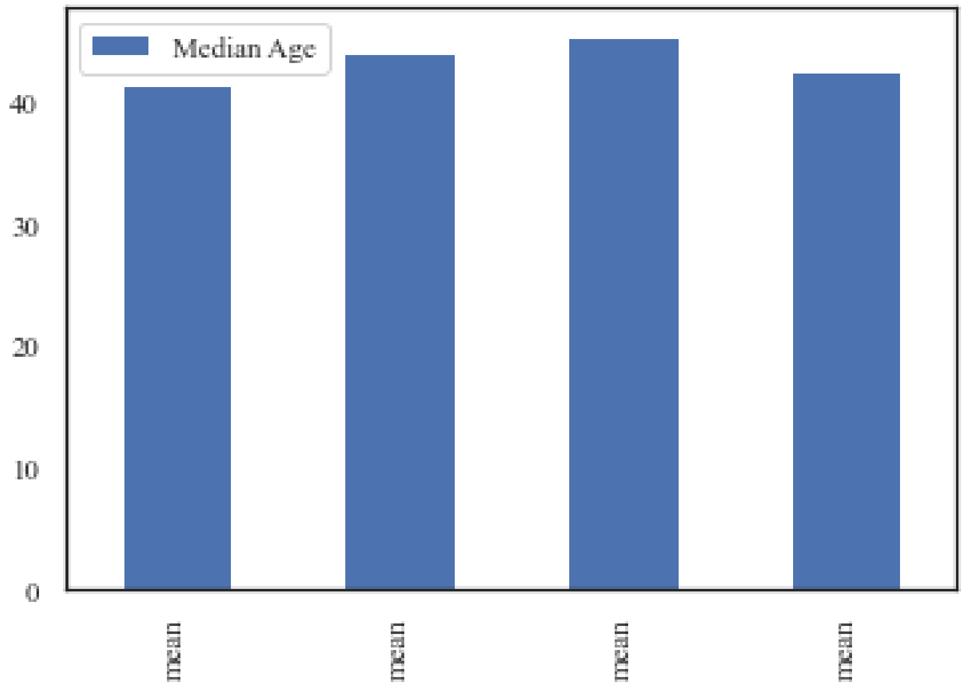
```
list_of_series = [cluster1,cluster2,cluster3,cluster4]
cluster_df = pd.DataFrame(list_of_series)
cluster_df[['Fee']].plot.bar()
cluster_df[['Average Household Size']].plot.bar()
cluster_df[['Median Age']].plot.bar()
cluster_df[['Median Mortgage']].plot.bar()
cluster_df[['Mean Income']].plot.bar()
cluster_df[['Percent 65 and Over']].plot.bar()
cluster_df[['Percent White']].plot.bar()
cluster_df[['Degree']].plot.bar()
cluster_df[['Contact Month']].plot.bar()
```

Out[30]:

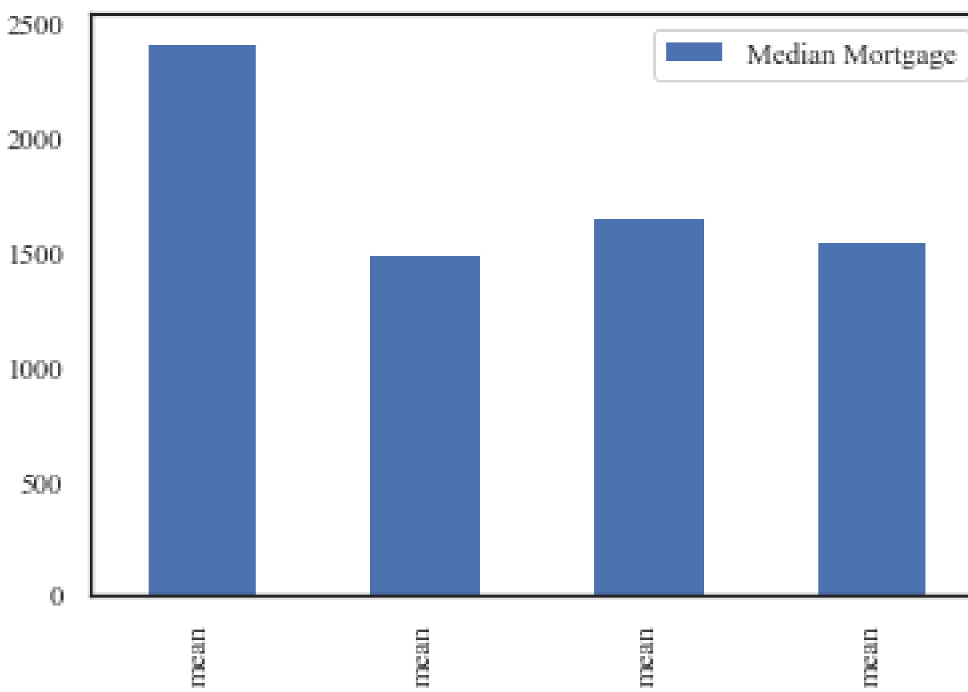
```
<AxesSubplot:>
```


Fee
5000
4000
3000
2000
1000
0
mean
mean
mean
mean

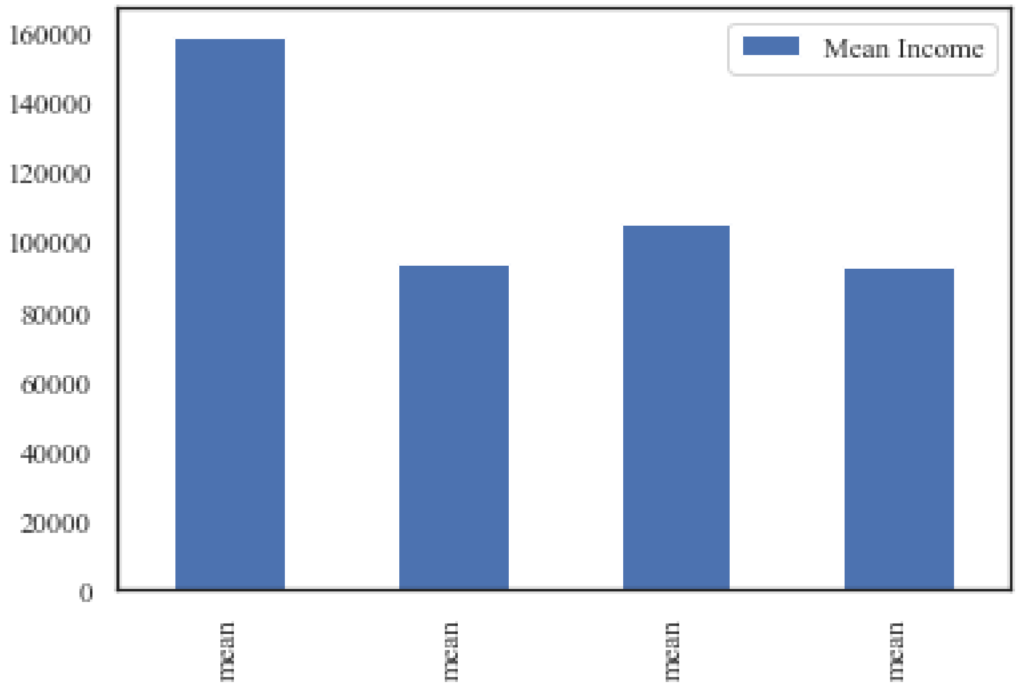

Average Household Size
2.5
2.0
1.5
1.0
0.5
0.0
mean
mean
mean
mean



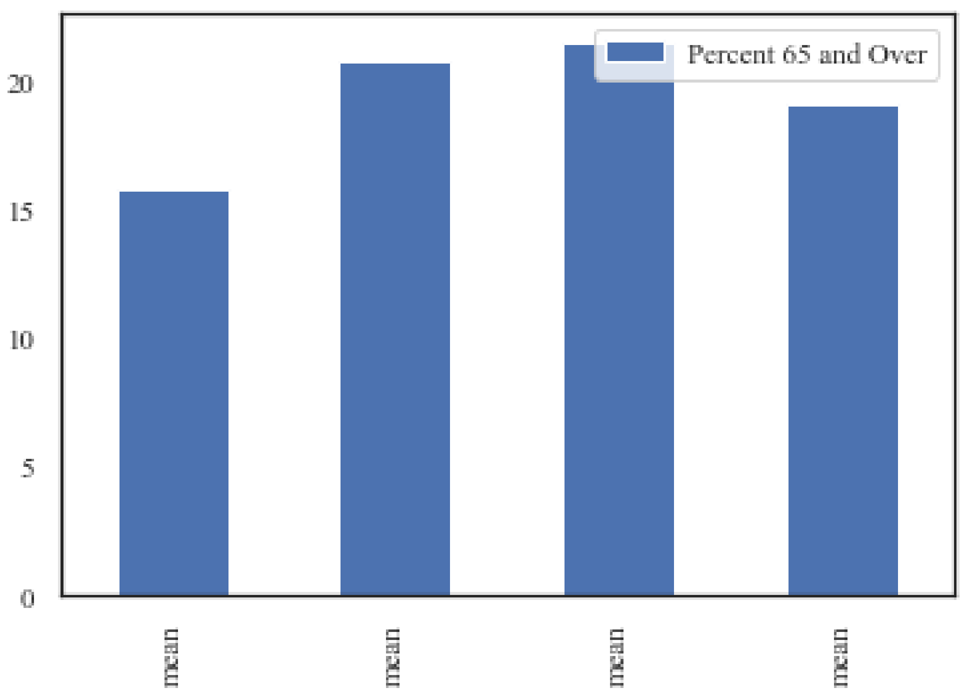
Median Age
0
10
20
30
40
mean
mean
mean
mean



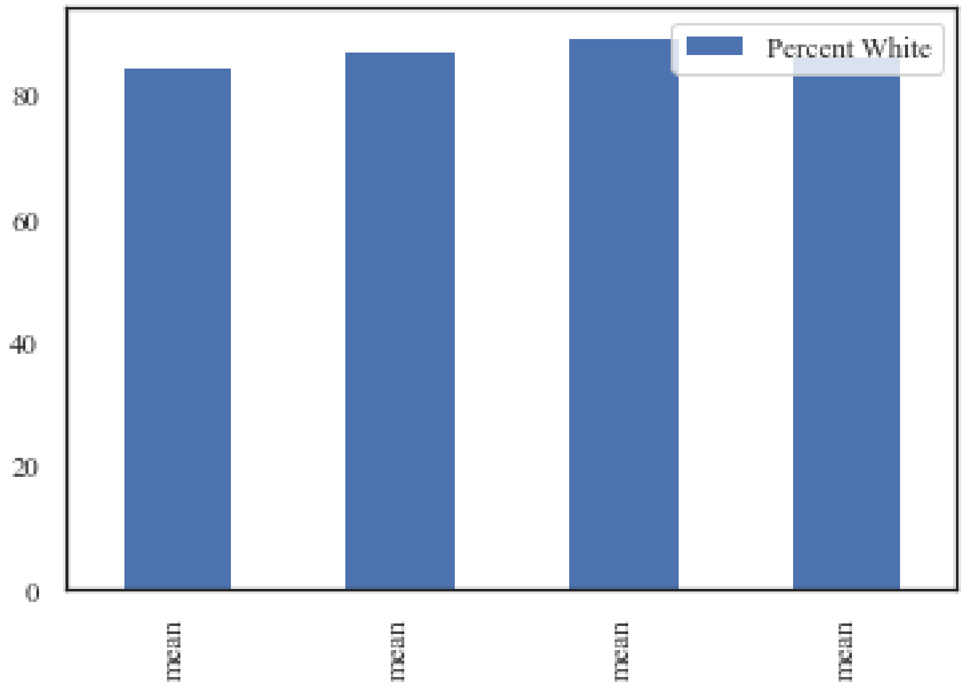
Median Mortgage
0
500
1000
1500
2000
2500
mean
mean
mean
mean

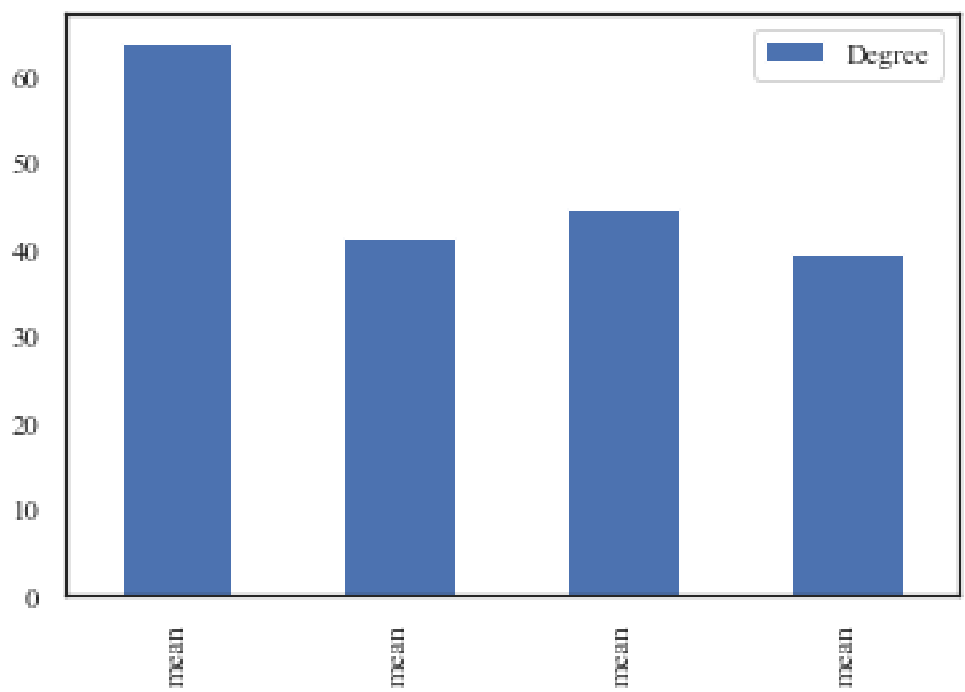


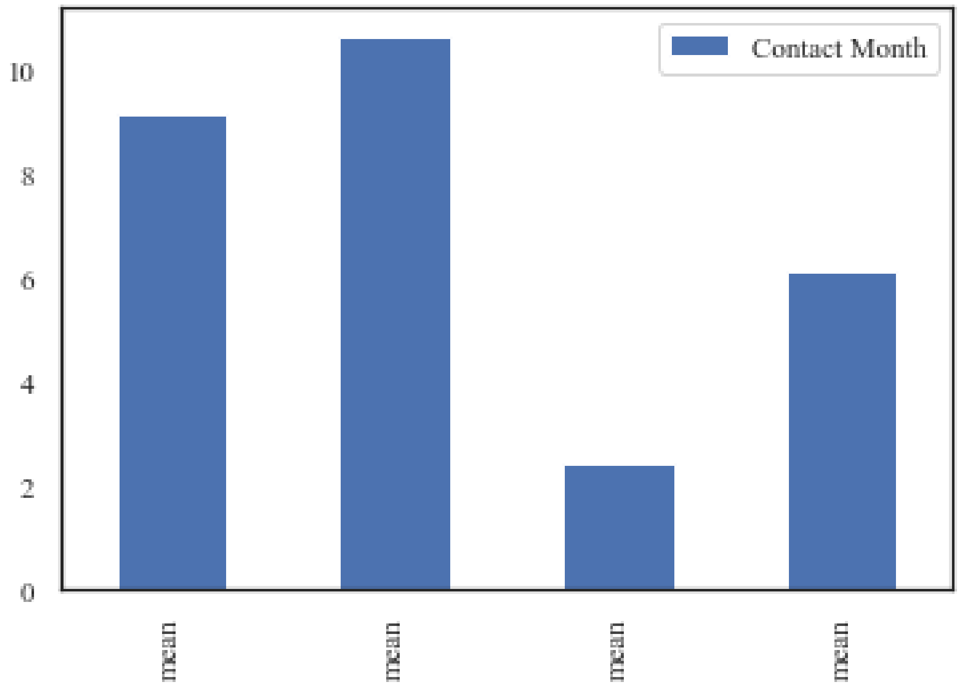
Mean Income
160000
140000
120000
100000
80000
60000
40000
20000
0
mean
mean
mean
mean



Percent 65 and Over
20
15
10
5
0
mean
mean
mean
mean


Percent White
80
60
40
20
0
mean
mean
mean
mean


Degree
60
50
40
30
20
10
0
mean
mean
mean
mean



In [31]:

```
cluster_df
```

Out[31]:

	Contact Month	Business	Estate Admin	Estate Planning	Medicaid	Other	Fee	Average Household Size	Median Age	Median Mortgage	Mean Income	Percent 65 and Over	Percent White	Degree	k_means_values
mean	9.159091	0.113636	0.340909	0.500000	0.022727	0.022727	5609.625000	2.592273	41.290909	2416.840909	159112.840909	15.697727	84.377273	63.729545	0.0
mean	10.660550	0.082569	0.211009	0.623853	0.009174	0.073394	2073.577982	2.295138	43.905505	1490.532110	93246.724771	20.657798	87.100917	41.125688	1.0
mean	2.408602	0.075269	0.215054	0.634409	0.043011	0.032258	2681.236559	2.356344	45.386022	1659.139785	105114.688172	21.476344	89.393548	44.556989	2.0
mean	6.125000	0.034091	0.340909	0.488636	0.079545	0.056818	2910.971591	2.324659	42.460227	1544.215909	92775.931818	19.002273	86.215909	39.238636	3.0

In [32]:

```
cluster1_areas =
df_with_clusters[df_with_clusters['k_means_values']==0][['Estate Planning',
'Estate Admin', 'Medicaid',
'Business','Other']].sum()/df_with_clusters[df_with_clusters['k_means_values'
]==0].shape[0]
cluster1_areas
```

Out[32]:

```
Estate Planning    0.500000
Estate Admin       0.340909
Medicaid           0.022727
Business           0.113636
Other              0.022727
dtype: float64
```

In [33]:

```
cluster2_areas =
df_with_clusters[df_with_clusters['k_means_values']==1][['Estate Planning',
'Estate Admin', 'Medicaid',
'Business','Other']].sum()/df_with_clusters[df_with_clusters['k_means_values'
]==1].shape[0]
```

```
cluster2_areas
```

Out[33]:

```
Estate Planning    0.623853
Estate Admin       0.211009
Medicaid           0.009174
Business           0.082569
Other              0.073394
dtype: float64
```

In [34]:

```
cluster3_areas =
df_with_clusters[df_with_clusters['k_means_values']==2][['Estate Planning',
'Estate Admin', 'Medicaid',
'Business','Other']].sum()/df_with_clusters[df_with_clusters['k_means_values'
]==2].shape[0]
cluster3_areas
```

Out[34]:

```
Estate Planning    0.634409
Estate Admin       0.215054
Medicaid           0.043011
Business           0.075269
Other              0.032258
dtype: float64
```

In [35]:

```
cluster4_areas =
df_with_clusters[df_with_clusters['k_means_values']==3][['Estate Planning',
'Estate Admin', 'Medicaid',
'Business','Other']].sum()/df_with_clusters[df_with_clusters['k_means_values'
]==3].shape[0]
cluster4_areas
```

Out[35]:

```
Estate Planning    0.488636
Estate Admin       0.340909
Medicaid           0.079545
Business           0.034091
Other              0.056818
dtype: float64
```

In [ ]: