SGanguli_Assignment_4

June 3, 2024

1 Assignment 2.1: Home Credit Default Risk

The Kaggle dataset on Home Credit Default Risk provides information about the loan applicants' credit bureau data, previous loan records, and other attributes that could influence their ability to repay a loan. The goal is to use this information to predict whether or not an applicant will be able to repay a loan, which is a critical issue for financial services.

[40]:
```
# import libraries

import numpy as np
import pandas as pd
import missingno as msno
import seaborn as sns
import matplotlib.pyplot as plt


np.random.seed(42)
```

2 Read Dataset

[41]:
```
df = pd.read_csv('data/train_data.csv')

df.columns
```

[41]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY',
       …
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=122)
```

[42]:
```
# Identify categorical columns
categorical_columns = df.select_dtypes(include=['object', 'category']).columns
```

```python
# Drop categorical columns
df_numerical = df.drop(columns=categorical_columns)

df = df_numerical
```

3 Exploratory Data Analysis

[43]:
```python
df.shape
```

[43]:
```
(153755, 106)
```

[44]:
```python
df.head()
```

[44]:
```
   SK_ID_CURR  TARGET  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0      410704       0             1          157500.0    900000.0
1      381230       0             1           90000.0    733176.0
2      450177       0             0          189000.0   1795500.0
3      332445       0             0          175500.0    494550.0
4      357429       0             0          270000.0   1724688.0

   AMT_ANNUITY  AMT_GOODS_PRICE  REGION_POPULATION_RELATIVE  DAYS_BIRTH  \
0      26446.5         900000.0                    0.010006      -16180
1      21438.0         612000.0                    0.031329      -14969
2      62541.0        1795500.0                    0.028663      -22213
3      45490.5         450000.0                    0.004960      -19301
4      54283.5        1575000.0                    0.018850      -18409

   DAYS_EMPLOYED  …  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  \
0          -2037  …                 0                 0                 0
1           -162  …                 0                 0                 0
2         365243  …                 0                 0                 0
3         365243  …                 0                 0                 0
4           -886  …                 0                 0                 0

   FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                 0                         0.0                        0.0
1                 0                         0.0                        0.0
2                 0                         0.0                        0.0
3                 0                         0.0                        0.0
4                 0                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
```

```
3                        0.0                        0.0
4                        0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         0.0
1                        2.0                         1.0
2                        0.0                         0.0
3                        0.0                         1.0
4                        0.0                         0.0

[5 rows x 106 columns]
```

[45]:
```
df.describe()
```

[45]:
```
            SK_ID_CURR         TARGET   CNT_CHILDREN  AMT_INCOME_TOTAL  \
count  153755.000000  153755.000000  153755.000000      1.537550e+05
mean   277867.616930       0.080726       0.417398      1.692611e+05
std    102831.742645       0.272414       0.722523      3.180805e+05
min    100004.000000       0.000000       0.000000      2.565000e+04
25%    188542.000000       0.000000       0.000000      1.125000e+05
50%    277749.000000       0.000000       0.000000      1.462500e+05
75%    366718.000000       0.000000       1.000000      2.025000e+05
max    456255.000000       1.000000      19.000000      1.170000e+08

         AMT_CREDIT    AMT_ANNUITY  AMT_GOODS_PRICE  \
count  1.537550e+05  153750.000000     1.536060e+05
mean   5.988824e+05   27083.127015     5.383057e+05
std    4.023748e+05   14468.883776     3.693544e+05
min    4.500000e+04    1615.500000     4.500000e+04
25%    2.700000e+05   16506.000000     2.385000e+05
50%    5.135310e+05   24903.000000     4.500000e+05
75%    8.086500e+05   34587.000000     6.795000e+05
max    4.050000e+06  230161.500000     4.050000e+06

       REGION_POPULATION_RELATIVE     DAYS_BIRTH  DAYS_EMPLOYED  …   \
count               153755.000000  153755.000000  153755.000000  …
mean                     0.020813  -16025.981438   63742.602751  …
std                      0.013796    4363.552861  141204.275368  …
min                      0.000290  -25201.000000  -17583.000000  …
25%                      0.010006  -19662.000000   -2746.000000  …
50%                      0.018850  -15725.000000   -1211.000000  …
75%                      0.028663  -12399.000000    -290.000000  …
max                      0.072508   -7678.000000  365243.000000  …

       FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  \
count     153755.000000     153755.000000     153755.000000     153755.000000
mean           0.007909          0.000650          0.000501          0.000416
```

```
std          0.088579        0.025494        0.022373        0.020398
min          0.000000        0.000000        0.000000        0.000000
25%          0.000000        0.000000        0.000000        0.000000
50%          0.000000        0.000000        0.000000        0.000000
75%          0.000000        0.000000        0.000000        0.000000
max          1.000000        1.000000        1.000000        1.000000

       AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
count               132922.000000              132922.000000
mean                     0.006417                   0.006854
std                      0.084608                   0.110151
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      4.000000                   9.000000

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
count               132922.000000              132922.000000
mean                     0.034012                   0.265547
std                      0.201581                   0.907185
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      8.000000                  27.000000

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
count              132922.000000               132922.000000
mean                    0.267555                    1.901777
std                     0.941286                    1.873638
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    1.000000
75%                     0.000000                    3.000000
max                   261.000000                   25.000000

[8 rows x 106 columns]
```

3.1 Inspect dataset for missing data

Drop columns and rows with missing data

[46]:
```
msno.bar(df)
```

[46]:
```
<Axes: >
```

[48]:

```
# Calculate the percentage of missing values for each column
missing_percent = df.isnull().mean() * 100
```

```python
# Filter out columns with more than 50% missing values
columns_to_drop = missing_percent[missing_percent > 25].index
df.drop(columns=columns_to_drop, inplace=True)

df = df.dropna()

# Display the resulting DataFrame
msno.bar(df)

df.shape
```

```
/var/folders/d7/3y4pn1x55_583bts49jyqlxh0000gn/T/ipykernel_29196/3446558635.py:6
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.drop(columns=columns_to_drop, inplace=True)
```

[48]: (122498, 61)

4 Classification using K-means clustering

[57]:
```
from sklearn.preprocessing import StandardScaler # Import for feature
 ↪standardization
from sklearn.decomposition import PCA

# Remove TARGET
X = df.drop('TARGET', axis=1)

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA to reduce the dataset to the top 10 principal components
pca = PCA(n_components=10)
X_pca = pca.fit_transform(X_scaled)

X_pca.shape
```

[57]: (122498, 10)

[66]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score # For kmeans
 ↪evaluation

def kmeans_execution(df, num_clust, verbose=False):
    if verbose:
        print(f"Starting k-means clustering with k={num_clust}")

    # Create KMeans object
    kmn = KMeans(n_clusters=num_clust, n_init='auto', random_state=0)

    if verbose:
        print("Fitting the model to the data...")

    # Apply to the data
    kmn.fit(df)

    if verbose:
        print("Model fitting complete.")

    # Capture K-Means labels
    kmn_lbl = kmn.labels_

    if verbose:
        print(f"Labels assigned: {kmn_lbl[:10]}...")  # Show first 10 labels as
 ↪a sample
```

```python
    # Capture distortion (inertia)
    kmn_distortion = kmn.inertia_

    if verbose:
        print(f"Distortion (Inertia): {kmn_distortion}")

    return kmn, kmn_lbl, kmn_distortion

kmn_2_mod, kmn_2_labels, kmn_2_dist = kmeans_execution(X_pca, 2, verbose = True)
silhouette_2 = silhouette_score(X_pca, kmn_2_labels)
print(f'k=2 silhouette average score: {silhouette_2}')
kmn_3_mod, kmn_3_labels, kmn_3_dist = kmeans_execution(X_pca, 3, verbose = True)
silhouette_3 = silhouette_score(X_pca, kmn_3_labels)
print(f'k=3 silhouette average score: {silhouette_3}')
kmn_4_mod, kmn_4_labels, kmn_4_dist = kmeans_execution(X_pca, 4, verbose = True)
silhouette_4 = silhouette_score(X_pca, kmn_4_labels)
print(f'k=4 silhouette average score: {silhouette_4}')
kmn_5_mod, kmn_5_labels, kmn_5_dist = kmeans_execution(X_pca, 5, verbose = True)
silhouette_5 = silhouette_score(X_pca, kmn_5_labels)
print(f'k=5 silhouette average score: {silhouette_5}')
kmn_6_mod, kmn_6_labels, kmn_6_dist = kmeans_execution(X_pca, 6, verbose = True)
silhouette_6 = silhouette_score(X_pca, kmn_6_labels)
print(f'k=6 silhouette average score: {silhouette_6}')
```

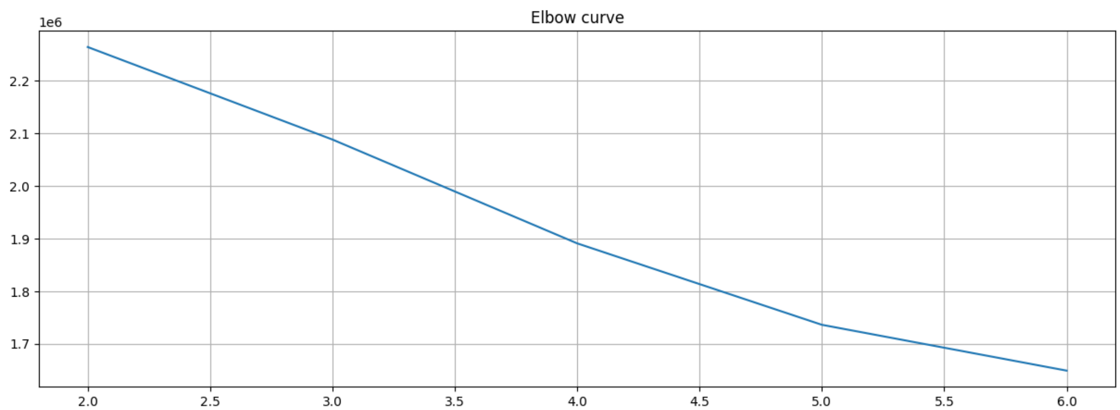
```
Starting k-means clustering with k=2
Fitting the model to the data…
Model fitting complete.
Labels assigned: [1 1 0 0 1 1 1 1 1 1]…
Distortion (Inertia): 2263806.860027661
k=2 silhouette average score: 0.2061311832094
Starting k-means clustering with k=3
Fitting the model to the data…
Model fitting complete.
Labels assigned: [1 2 0 0 1 1 1 1 1 1]…
Distortion (Inertia): 2088146.6609202027
k=3 silhouette average score: 0.19605461832338214
Starting k-means clustering with k=4
Fitting the model to the data…
Model fitting complete.
Labels assigned: [3 2 0 0 1 3 3 3 1 1]…
Distortion (Inertia): 1891036.5209039594
k=4 silhouette average score: 0.18845881766909128
Starting k-means clustering with k=5
Fitting the model to the data…
Model fitting complete.
Labels assigned: [3 4 1 0 1 3 3 3 4 4]…
Distortion (Inertia): 1736385.6861585043
```

```
k=5 silhouette average score: 0.16973303414303414
Starting k-means clustering with k=6
Fitting the model to the data…
Model fitting complete.
Labels assigned: [3 2 2 0 1 3 3 3 4 4]…
Distortion (Inertia): 1649360.5067255623
k=6 silhouette average score: 0.1736302363550738
```

[67]:
```
# Elbow Plot - seems like clear "elbow" at k=3

fig = plt.figure(figsize=(15, 5))
plt.plot(range(2, 7), [kmn_2_dist, kmn_3_dist, kmn_4_dist, kmn_5_dist,␣
 ↪kmn_6_dist])
plt.grid(True)
plt.title('Elbow curve')
```

[67]:
```
Text(0.5, 1.0, 'Elbow curve')
```



[68]:
```
# Get the PCA components
pca_components = pca.components_

# Get the explained variance ratio
explained_variance = pca.explained_variance_ratio_

# Create a DataFrame for the PCA components
pca_df = pd.DataFrame(pca_components, columns=X.columns)

# Display the first few rows of the PCA components
print("PCA Components (first few rows):")
print(pca_df.head())

# Display the contribution of original features to the first principal component
print("Contribution to the first principal component:")
```

```
print(pca_df.iloc[0].sort_values(ascending=False))

# Display the contribution of original features to the second principal␣
 ↪component
print("Contribution to the second principal component:")
print(pca_df.iloc[1].sort_values(ascending=False))
```

```
PCA Components (first few rows):
   SK_ID_CURR  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0   -0.003896      0.206265          0.046092    0.113762     0.132365
1    0.000500     -0.107404          0.087848    0.367074     0.343449
2    0.002940      0.096335          0.027585    0.270131     0.231016
3   -0.003330     -0.084701         -0.018569   -0.248157    -0.213305
4    0.001736     -0.163659          0.022881    0.231470     0.196545

   AMT_GOODS_PRICE  REGION_POPULATION_RELATIVE  DAYS_BIRTH  DAYS_EMPLOYED  \
0         0.113998                    0.039617    0.348883      -0.414838
1         0.369993                    0.289600   -0.150028       0.084812
2         0.267704                   -0.069792    0.000106      -0.034357
3        -0.246351                    0.191302    0.001431       0.043132
4         0.230276                   -0.222374   -0.118633       0.141179

   DAYS_REGISTRATION  …  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
0           0.162718  …          0.029460          0.007836
1          -0.100225  …          0.008018          0.007493
2           0.036744  …          0.009438          0.009671
3          -0.051775  …          0.003956         -0.007423
4          -0.013218  …          0.000133          0.008571

   FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
0          0.010734          0.005333                    0.000527
1          0.009487         -0.014312                   -0.005794
2          0.025579         -0.013455                    0.001838
3         -0.022154          0.009210                   -0.009161
4          0.012222         -0.013327                    0.005367

   AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
0                  -0.001453                   -0.001224
1                   0.001600                   -0.000867
2                  -0.000371                    0.000730
3                  -0.013539                   -0.009345
4                   0.003687                    0.004422

   AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
0                   0.022224                  -0.013548
1                   0.075213                   0.004788
2                   0.012222                   0.017617
3                   0.014787                  -0.013187
```

```
4                 -0.048403                   0.016680

   AMT_REQ_CREDIT_BUREAU_YEAR
0                   -0.040052
1                   -0.019797
2                    0.025348
3                    0.030584
4                    0.005877

[5 rows x 60 columns]
Contribution to the first principal component:
FLAG_EMP_PHONE                 4.156980e-01
DAYS_BIRTH                     3.488828e-01
REG_CITY_NOT_WORK_CITY         2.353738e-01
CNT_CHILDREN                   2.062649e-01
CNT_FAM_MEMBERS                2.059698e-01
LIVE_CITY_NOT_WORK_CITY        2.039350e-01
REG_REGION_NOT_WORK_REGION     1.647886e-01
DAYS_REGISTRATION              1.627182e-01
DAYS_ID_PUBLISH                1.475611e-01
LIVE_REGION_NOT_WORK_REGION    1.466456e-01
FLAG_DOCUMENT_3                1.444410e-01
FLAG_WORK_PHONE                1.403024e-01
AMT_ANNUITY                    1.323646e-01
AMT_GOODS_PRICE                1.139979e-01
AMT_CREDIT                     1.137622e-01
REG_CITY_NOT_LIVE_CITY         1.137052e-01
HOUR_APPR_PROCESS_START        8.332519e-02
REG_REGION_NOT_LIVE_REGION     8.244951e-02
FLAG_DOCUMENT_8                8.125100e-02
FLAG_EMAIL                     5.065378e-02
AMT_INCOME_TOTAL               4.609248e-02
REGION_POPULATION_RELATIVE     3.961737e-02
FLAG_DOCUMENT_11               3.083201e-02
FLAG_DOCUMENT_18               2.946050e-02
FLAG_DOCUMENT_16               2.790587e-02
FLAG_DOCUMENT_13               2.489521e-02
FLAG_DOCUMENT_14               2.259067e-02
AMT_REQ_CREDIT_BUREAU_MON      2.222407e-02
EXT_SOURCE_2                   1.779079e-02
FLAG_DOCUMENT_9                1.492816e-02
FLAG_DOCUMENT_15               1.222525e-02
FLAG_DOCUMENT_20               1.073365e-02
FLAG_DOCUMENT_19               7.836203e-03
FLAG_DOCUMENT_17               6.615502e-03
FLAG_DOCUMENT_21               5.333186e-03
FLAG_DOCUMENT_5                5.196829e-03
DAYS_LAST_PHONE_CHANGE         2.170223e-03
```

```
FLAG_DOCUMENT_7                1.644867e-03
FLAG_PHONE                     8.631220e-04
AMT_REQ_CREDIT_BUREAU_HOUR     5.269700e-04
FLAG_MOBIL                     2.584939e-26
FLAG_DOCUMENT_12              -0.000000e+00
FLAG_DOCUMENT_2               -0.000000e+00
FLAG_DOCUMENT_4               -6.620260e-05
FLAG_DOCUMENT_10              -1.209871e-03
AMT_REQ_CREDIT_BUREAU_WEEK    -1.223842e-03
AMT_REQ_CREDIT_BUREAU_DAY     -1.452776e-03
SK_ID_CURR                    -3.896205e-03
FLAG_CONT_MOBILE              -5.873301e-03
AMT_REQ_CREDIT_BUREAU_QRT     -1.354769e-02
OBS_30_CNT_SOCIAL_CIRCLE      -1.567690e-02
OBS_60_CNT_SOCIAL_CIRCLE      -1.581662e-02
DEF_30_CNT_SOCIAL_CIRCLE      -1.947718e-02
DEF_60_CNT_SOCIAL_CIRCLE      -1.948266e-02
AMT_REQ_CREDIT_BUREAU_YEAR    -4.005242e-02
REGION_RATING_CLIENT_W_CITY   -7.458987e-02
REGION_RATING_CLIENT          -7.626349e-02
EXT_SOURCE_3                  -9.814668e-02
FLAG_DOCUMENT_6               -3.188620e-01
DAYS_EMPLOYED                 -4.148383e-01
Name: 0, dtype: float64
Contribution to the second principal component:
AMT_GOODS_PRICE                0.369993
AMT_CREDIT                     0.367074
AMT_ANNUITY                    0.343449
REGION_POPULATION_RELATIVE     0.289600
EXT_SOURCE_2                   0.231839
HOUR_APPR_PROCESS_START        0.148863
LIVE_REGION_NOT_WORK_REGION    0.111800
REG_REGION_NOT_WORK_REGION     0.106068
FLAG_DOCUMENT_8                0.090895
AMT_INCOME_TOTAL               0.087848
DAYS_EMPLOYED                  0.084812
FLAG_PHONE                     0.079272
EXT_SOURCE_3                   0.075668
AMT_REQ_CREDIT_BUREAU_MON      0.075213
FLAG_DOCUMENT_6                0.069387
FLAG_DOCUMENT_14               0.044999
FLAG_DOCUMENT_13               0.040163
FLAG_DOCUMENT_9                0.034615
REG_REGION_NOT_LIVE_REGION     0.033033
FLAG_EMAIL                     0.031996
FLAG_DOCUMENT_16               0.020378
FLAG_DOCUMENT_11               0.016721
FLAG_DOCUMENT_15               0.014821
```

```
FLAG_DOCUMENT_20               0.009487
FLAG_DOCUMENT_18               0.008018
FLAG_DOCUMENT_5                0.007834
FLAG_DOCUMENT_19               0.007493
FLAG_DOCUMENT_4                0.005518
AMT_REQ_CREDIT_BUREAU_QRT      0.004788
FLAG_DOCUMENT_17               0.002840
AMT_REQ_CREDIT_BUREAU_DAY      0.001600
FLAG_CONT_MOBILE               0.000905
SK_ID_CURR                     0.000500
FLAG_DOCUMENT_12              -0.000000
FLAG_DOCUMENT_2               -0.000000
FLAG_MOBIL                    -0.000000
AMT_REQ_CREDIT_BUREAU_WEEK    -0.000867
FLAG_DOCUMENT_10              -0.001468
FLAG_DOCUMENT_7               -0.002838
AMT_REQ_CREDIT_BUREAU_HOUR    -0.005794
FLAG_DOCUMENT_21              -0.014312
AMT_REQ_CREDIT_BUREAU_YEAR    -0.019797
FLAG_WORK_PHONE               -0.043880
DAYS_ID_PUBLISH               -0.053302
LIVE_CITY_NOT_WORK_CITY       -0.058058
OBS_60_CNT_SOCIAL_CIRCLE      -0.061872
OBS_30_CNT_SOCIAL_CIRCLE      -0.061986
DEF_60_CNT_SOCIAL_CIRCLE      -0.063186
DEF_30_CNT_SOCIAL_CIRCLE      -0.063617
FLAG_DOCUMENT_3               -0.065513
REG_CITY_NOT_LIVE_CITY        -0.068998
DAYS_LAST_PHONE_CHANGE        -0.073453
CNT_FAM_MEMBERS               -0.084072
FLAG_EMP_PHONE                -0.085644
REG_CITY_NOT_WORK_CITY        -0.091187
DAYS_REGISTRATION             -0.100225
CNT_CHILDREN                  -0.107404
DAYS_BIRTH                    -0.150028
REGION_RATING_CLIENT          -0.364481
REGION_RATING_CLIENT_W_CITY   -0.366647
Name: 1, dtype: float64
```

[69]:

```
# Create evaluation dataset

eval_df = df.copy()
eval_df['target'] = df['TARGET']
eval_df['kmn_3_label'] = kmn_3_labels
eval_df['kmn_4_label'] = kmn_4_labels
eval_df['kmn_5_label'] = kmn_5_labels
eval_df['kmn_6_label'] = kmn_6_labels
```

[72]:
```
# Create function to group by labels and look at output

def group_by_cluster(df, col_val):
    exclude_columns = ['target', 'kmn_3_label', 'kmn_4_label', 'kmn_5_label',␣
 ↪'kmn_6_label']
    cont_cols = [col for col in df.columns if col not in exclude_columns]
    # Get summary stats grouped by cluster
    df_group = df.groupby(col_val)[cont_cols].agg(['mean', 'median', 'std']).
 ↪reset_index()
    # See distribution of target variable grouped by cluster
    value_counts = df.groupby(col_val)['target'].agg(lambda x:x.value_counts().
 ↪to_dict())
    return df_group, value_counts

# Can execute across different values of k to determine differences in clusters
summary_stats, target_groups = group_by_cluster(eval_df, kmn_5_labels)
summary_stats
```

[72]:
```
  index      SK_ID_CURR                               TARGET                \
                   mean    median            std       mean median       std
0     0  278777.001844  278708.0  102746.504382  0.049503    0.0  0.216920
1     1  277537.512763  277455.5  102627.671374  0.046511    0.0  0.210593
2     2  280121.470946  280187.0  102628.980664  0.109853    0.0  0.312721
3     3  277468.335291  277009.0  102823.619953  0.082547    0.0  0.275199
4     4  276684.782885  276689.0  103010.805188  0.104105    0.0  0.305403

  CNT_CHILDREN                    … AMT_REQ_CREDIT_BUREAU_WEEK  \
          mean median       std   …                        std
0     0.032128    0.0  0.210703   …                   0.207917
1     0.408317    0.0  0.696846   …                   0.210897
2     0.489192    0.0  0.768709   …                   0.188791
3     0.539360    0.0  0.784548   …                   0.195225
4     0.528424    0.0  0.789873   …                   0.206492

  AMT_REQ_CREDIT_BUREAU_MON                     AMT_REQ_CREDIT_BUREAU_QRT         \
                       mean median       std                        mean median
0                  0.194176    0.0  0.702496                    0.295511    0.0
1                  0.501434    0.0  1.520954                    0.274283    0.0
2                  0.270609    0.0  0.918614                    0.263778    0.0
3                  0.232355    0.0  0.728486                    0.254811    0.0
4                  0.225213    0.0  0.710888                    0.252568    0.0

            AMT_REQ_CREDIT_BUREAU_YEAR
        std                       mean median       std
0  0.643940                   2.100364    2.0  2.036867
1  0.611417                   1.715201    1.0  1.750310
2  0.611314                   2.048844    2.0  1.920040
```

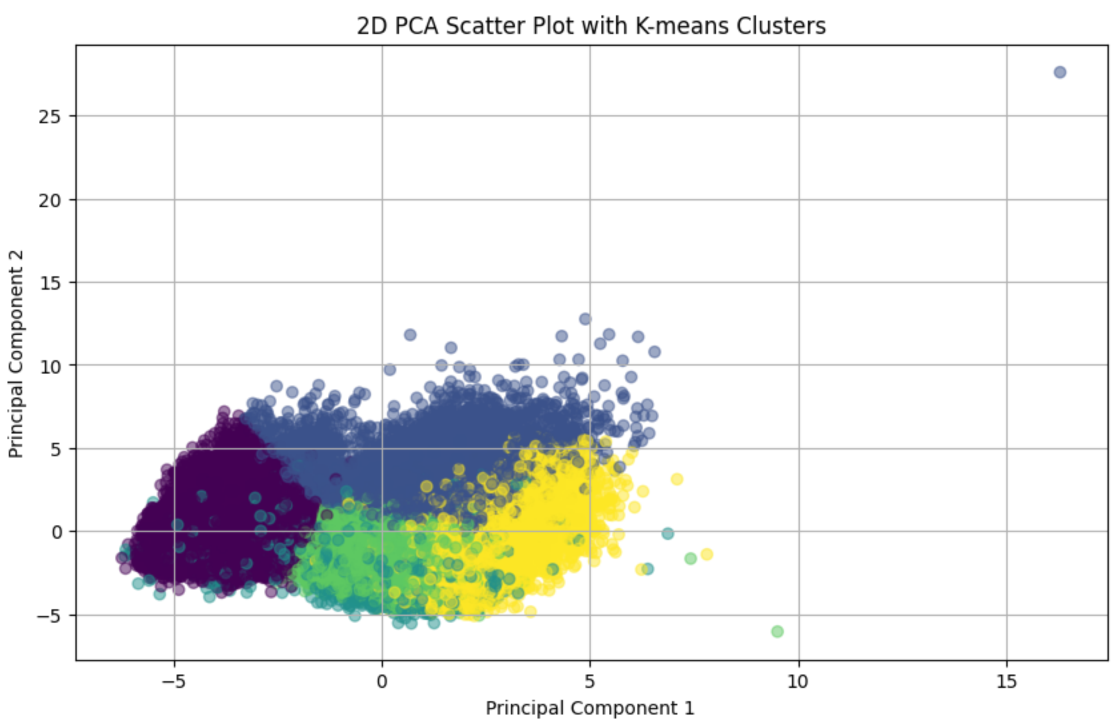
```
3  0.600659                        1.867392    1.0  1.824554
4  0.596581                        1.884856    1.0  1.827259

[5 rows x 184 columns]
```

The following plot shows all the 5 clusters based on first and second PCA components

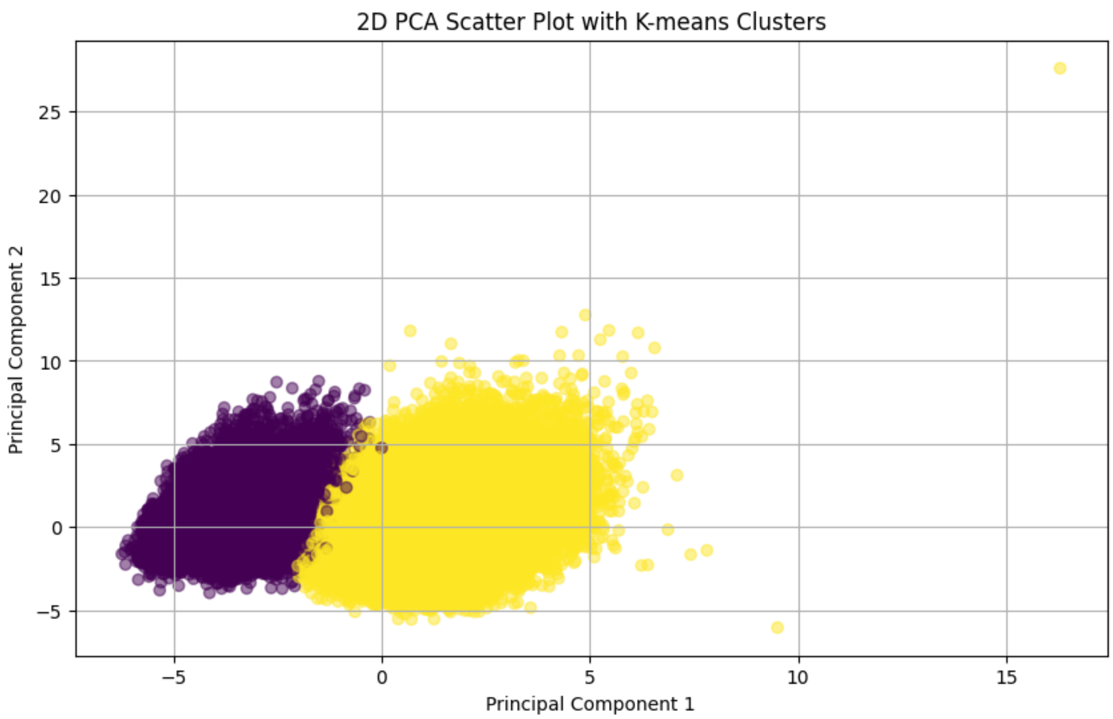
4.1 Scatter plot based on optimum value of k from elbow curve

[80]:
```python
# Create a scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=kmn_5_labels, cmap='viridis',␣
 ↪marker='o', alpha=0.5)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('2D PCA Scatter Plot with K-means Clusters')
plt.grid(True)
plt.show()
```



4.2 Scatter plot based on optimum value of k from silhouette score

[81]:
```
# Create a scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=kmn_2_labels, cmap='viridis',␣
    ↪marker='o', alpha=0.5)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('2D PCA Scatter Plot with K-means Clusters')
plt.grid(True)
plt.show()
```



4.3 Summary of Results and Business Interpretation

- What transformations did you apply to the raw dataset?

Here, we have: (a) removed the rows of data which have missing data (b) applied PCA to get the key components which can be used for clustering. We used PCA because using the features directly was giving low silhouette scores.

- What were different k's chosen? What were the differences in the output with those different k's? Why did you choose this k and distance metric?

We choose 5 k's - 2, 3, 4, 5, 6. The differences in the outputs can be interpreted from the silhouette scores: k = 2, silhouette score = 0.20 k = 3, silhouette score = 0.19 k = 4, silhouette score = 0.18 k = 5, silhouette score = 0.17 k = 6, silhouette score = 0.17

Note that based on the elbow curve, the best k value is 5, which does not match with the highest silhouette score of 0.20 for k = 2. This is because the elbow curve and silhouette scores use different optimization goals. The elbow Method focuses on minimizing within-cluster variance. The silhouette Score focuses on maximizing cluster separation and cohesion.

Based on the silhouette score, we select the best value for k = 2. The fact that the two clusters are distinct can be clearly seen from the scatter plots drawn above.

- What are the influential features? Are there any inferences you can draw that would be relevant from a business context about the different groups?

The influencing factor can be interpreted from the table 'summary_stats' as printed above. For example, the features AMT_REQ_CREDIT_BUREAU_MON, AMT_REQ_CREDIT_BUREAU_QRT and AMT_REQ_CREDIT_BUREAU_YEAR are important since they have relatively high mean values. Hence, these features can be considered important from the business point of view.

[ ]:

```

```