Assignment 4.1

September 30, 2024

[1]:
```python
import pandas as pd
import numpy as np
from IPython.display import display, HTML

# Load the data
df = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
↪Fundraising.csv"
)
dff = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
↪FutureFundraising.csv"
)

# Display both DataFrames side by side
display(HTML("<h3>Fundraising DataFrame</h3>"))
display(df.head())

display(HTML("<h3>Future Fundraising DataFrame</h3>"))
display(dff.head())
```

```
/var/folders/jw/4t4swxld5c5f_5xhv0_bzbr00000gn/T/ipykernel_26764/739611249.py:1:
DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of
pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better
interoperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

```
<IPython.core.display.HTML object>
```

```
   Row Id  Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  zipconvert_5  \
0       1       17             0             1             0             0
1       2       25             1             0             0             0
2       3       29             0             0             0             1
```

```
3       4      38              0              0              0              1
4       5      40              0              1              0              0

   homeowner dummy  NUMCHLD  INCOME  gender dummy  …  IC15  NUMPROM  \
0                1        1       5             1  …     1       74
1                1        1       1             0  …     4       46
2                0        2       5             1  …    13       32
3                1        1       3             0  …     4       94
4                1        1       4             0  …     7       20

   RAMNTALL  MAXRAMNT  LASTGIFT  totalmonths  TIMELAG   AVGGIFT  TARGET_B  \
0     102.0       6.0       5.0           29        3  4.857143         1
1      94.0      12.0      12.0           34        6  9.400000         1
2      30.0      10.0       5.0           29        7  4.285714         1
3     177.0      10.0       8.0           30        3  7.080000         0
4      23.0      11.0      11.0           30        6  7.666667         0

   TARGET_D
0       5.0
1      10.0
2       5.0
3       0.0
4       0.0

[5 rows x 24 columns]

<IPython.core.display.HTML object>

   Row Id  Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  zipconvert_5  \
0       1        3             0             1             0             0
1       2        4             0             0             1             0
2       3        5             0             0             0             1
3       4        1             0             0             0             0
4       5        4             0             0             1             0

   homeowner dummy  NUMCHLD  INCOME  gender dummy  …  IC15  NUMPROM  \
0                1        1       1             1  …     3       42
1                0        1       2             1  …     4       21
2                0        1       1             0  …    10       61
3                1        1       4             0  …    21       32
4                1        1       7             1  …     1       47

   RAMNTALL  MAXRAMNT  LASTGIFT  totalmonths  TIMELAG    AVGGIFT  TARGET_B  \
0      92.0      29.0      15.0           17        8  15.333333       NaN
1      30.0      20.0      20.0           33        9  15.000000       NaN
2     220.0      35.0      25.0           31        9  24.444444       NaN
3      41.0      19.0      19.0           31       13  13.666667       NaN
4      46.0      10.0      10.0           28        8   5.750000       NaN
```

```
   TARGET_D
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN

[5 rows x 24 columns]
```

[2]:

```python
import pandas as pd
import numpy as np
from IPython.display import display, HTML

# Load the data
df = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
 ↪Fundraising.csv"
)
dff = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
 ↪FutureFundraising.csv"
)

# 1. Understand the Data
display(HTML("<h3>First 5 rows of the Fundraising dataset:</h3>"))
display(df.head())

display(HTML("<h3>Data types and missing values in Fundraising dataset:</h3>"))
display(df.info())

display(HTML("<h3>Summary statistics of Fundraising dataset:</h3>"))
display(df.describe())

# 2. Handle Missing Values
display(HTML("<h3>Missing values per column in Fundraising dataset:</h3>"))
display(df.isnull().sum())

# Fill missing values with the mean
df.fillna(df.mean(), inplace=True)

# Handle the dff dataframe
display(HTML("<h3>First 5 rows of the Future Fundraising dataset:</h3>"))
display(dff.head())

display(HTML("<h3>Data types and missing values in Future Fundraising dataset:</
 ↪h3>"))
display(dff.info())
```

```python
display(HTML("<h3>Summary statistics of Future Fundraising dataset:</h3>"))
display(dff.describe())

display(HTML("<h3>Missing values per column in Future Fundraising dataset:</
    ↪h3>"))
display(dff.isnull().sum())

# Fill missing values in dff with the mean
dff.fillna(dff.mean(), inplace=True)
```

```
<IPython.core.display.HTML object>

   Row Id  Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  zipconvert_5  \
0       1       17             0             1             0             0
1       2       25             1             0             0             0
2       3       29             0             0             0             1
3       4       38             0             0             0             1
4       5       40             0             1             0             0

   homeowner dummy  NUMCHLD  INCOME  gender dummy  …  IC15  NUMPROM  \
0                1        1       5             1  …     1       74
1                1        1       1             0  …     4       46
2                0        2       5             1  …    13       32
3                1        1       3             0  …     4       94
4                1        1       4             0  …     7       20

   RAMNTALL  MAXRAMNT  LASTGIFT  totalmonths  TIMELAG   AVGGIFT  TARGET_B  \
0     102.0       6.0       5.0           29        3  4.857143         1
1      94.0      12.0      12.0           34        6  9.400000         1
2      30.0      10.0       5.0           29        7  4.285714         1
3     177.0      10.0       8.0           30        3  7.080000         0
4      23.0      11.0      11.0           30        6  7.666667         0

   TARGET_D
0       5.0
1      10.0
2       5.0
3       0.0
4       0.0

[5 rows x 24 columns]

<IPython.core.display.HTML object>

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3120 entries, 0 to 3119
Data columns (total 24 columns):
 #   Column           Non-Null Count  Dtype
```

```
---  ------           --------------  -----
 0   Row Id           3120 non-null   int64
 1   Row Id.          3120 non-null   int64
 2   zipconvert_2     3120 non-null   int64
 3   zipconvert_3     3120 non-null   int64
 4   zipconvert_4     3120 non-null   int64
 5   zipconvert_5     3120 non-null   int64
 6   homeowner dummy  3120 non-null   int64
 7   NUMCHLD          3120 non-null   int64
 8   INCOME           3120 non-null   int64
 9   gender dummy     3120 non-null   int64
 10  WEALTH           3120 non-null   int64
 11  HV               3120 non-null   int64
 12  Icmed            3120 non-null   int64
 13  Icavg            3120 non-null   int64
 14  IC15             3120 non-null   int64
 15  NUMPROM          3120 non-null   int64
 16  RAMNTALL         3120 non-null   float64
 17  MAXRAMNT         3120 non-null   float64
 18  LASTGIFT         3120 non-null   float64
 19  totalmonths      3120 non-null   int64
 20  TIMELAG          3120 non-null   int64
 21  AVGGIFT          3120 non-null   float64
 22  TARGET_B         3120 non-null   int64
 23  TARGET_D         3120 non-null   float64
dtypes: float64(5), int64(19)
memory usage: 585.1 KB
```

```
None
```

```
<IPython.core.display.HTML object>
```

```
            Row Id       Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  \
count  3120.000000   3120.000000   3120.000000   3120.000000   3120.000000
mean   1560.500000  11615.770833      0.214423      0.185256      0.214423
std     900.810746   6698.678131      0.410487      0.388568      0.410487
min       1.000000     17.000000      0.000000      0.000000      0.000000
25%     780.750000   5820.750000      0.000000      0.000000      0.000000
50%    1560.500000  11735.500000      0.000000      0.000000      0.000000
75%    2340.250000  17435.750000      0.000000      0.000000      0.000000
max    3120.000000  23293.000000      1.000000      1.000000      1.000000

       zipconvert_5  homeowner dummy      NUMCHLD       INCOME  gender dummy  \
count   3120.000000      3120.000000  3120.000000  3120.000000   3120.000000
mean       0.384615         0.770192     1.069231     3.893910      0.609295
std        0.486582         0.420777     0.347688     1.636186      0.487987
min        0.000000         0.000000     1.000000     1.000000      0.000000
25%        0.000000         1.000000     1.000000     3.000000      0.000000
50%        0.000000         1.000000     1.000000     4.000000      1.000000
```

```
75%        1.000000          1.000000     1.000000     5.000000      1.000000
max        1.000000          1.000000     5.000000     7.000000      1.000000

       …          IC15       NUMPROM     RAMNTALL     MAXRAMNT     LASTGIFT  \
count  …   3120.000000   3120.000000  3120.000000  3120.000000  3120.000000
mean   …     14.702885     49.089423   110.399875    16.651397    13.522917
std    …     12.079882     22.717130   147.299933    22.223521    10.581439
min    …      0.000000     11.000000    15.000000     5.000000     0.000000
25%    …      5.000000     29.000000    45.000000    10.000000     7.000000
50%    …     12.000000     48.000000    81.000000    15.000000    10.000000
75%    …     21.000000     65.000000   134.625000    20.000000    16.000000
max    …     90.000000    157.000000  5674.900000  1000.000000   219.000000

       totalmonths      TIMELAG      AVGGIFT    TARGET_B     TARGET_D
count  3120.000000  3120.000000  3120.000000  3120.00000  3120.000000
mean     31.136859     6.861859    10.690713     0.50000     6.499612
std       4.132952     5.561209     7.443980     0.50008    10.597849
min      17.000000     0.000000     2.138889     0.00000     0.000000
25%      29.000000     3.000000     6.356092     0.00000     0.000000
50%      31.000000     5.000000     9.000000     0.50000     0.500000
75%      34.000000     9.000000    12.811652     1.00000    10.000000
max      37.000000    77.000000   122.166667     1.00000   200.000000

[8 rows x 24 columns]

<IPython.core.display.HTML object>

Row Id             0
Row Id.            0
zipconvert_2       0
zipconvert_3       0
zipconvert_4       0
zipconvert_5       0
homeowner dummy    0
NUMCHLD            0
INCOME             0
gender dummy       0
WEALTH             0
HV                 0
Icmed              0
Icavg              0
IC15               0
NUMPROM            0
RAMNTALL           0
MAXRAMNT           0
LASTGIFT           0
totalmonths        0
TIMELAG            0
AVGGIFT            0
```

```
TARGET_B           0
TARGET_D           0
dtype: int64
```

```
<IPython.core.display.HTML object>
```

```
   Row Id  Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  zipconvert_5  \
0       1        3             0             1             0             0
1       2        4             0             0             1             0
2       3        5             0             0             0             1
3       4        1             0             0             0             0
4       5        4             0             0             1             0

   homeowner dummy  NUMCHLD  INCOME  gender dummy  …  IC15  NUMPROM  \
0                1        1       1             1  …     3       42
1                0        1       2             1  …     4       21
2                0        1       1             0  …    10       61
3                1        1       4             0  …    21       32
4                1        1       7             1  …     1       47

   RAMNTALL  MAXRAMNT  LASTGIFT  totalmonths  TIMELAG    AVGGIFT  TARGET_B  \
0      92.0      29.0      15.0           17        8  15.333333       NaN
1      30.0      20.0      20.0           33        9  15.000000       NaN
2     220.0      35.0      25.0           31        9  24.444444       NaN
3      41.0      19.0      19.0           31       13  13.666667       NaN
4      46.0      10.0      10.0           28        8   5.750000       NaN

   TARGET_D
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN

[5 rows x 24 columns]
```

```
<IPython.core.display.HTML object>
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 24 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Row Id           2000 non-null   int64
 1   Row Id.          2000 non-null   int64
 2   zipconvert_2     2000 non-null   int64
 3   zipconvert_3     2000 non-null   int64
 4   zipconvert_4     2000 non-null   int64
 5   zipconvert_5     2000 non-null   int64
 6   homeowner dummy  2000 non-null   int64
```

```
 7   NUMCHLD          2000 non-null   int64
 8   INCOME           2000 non-null   int64
 9   gender dummy     2000 non-null   int64
 10  WEALTH           2000 non-null   int64
 11  HV               2000 non-null   int64
 12  Icmed            2000 non-null   int64
 13  Icavg            2000 non-null   int64
 14  IC15             2000 non-null   int64
 15  NUMPROM          2000 non-null   int64
 16  RAMNTALL         2000 non-null   float64
 17  MAXRAMNT         2000 non-null   float64
 18  LASTGIFT         2000 non-null   float64
 19  totalmonths      2000 non-null   int64
 20  TIMELAG          2000 non-null   int64
 21  AVGGIFT          2000 non-null   float64
 22  TARGET_B         0 non-null      float64
 23  TARGET_D         0 non-null      float64
dtypes: float64(6), int64(18)
memory usage: 375.1 KB
```

```
None
```

```
<IPython.core.display.HTML object>
```

```
            Row Id      Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  \
count  2000.000000  2000.000000   2000.000000   2000.000000   2000.000000
mean   1000.500000     3.482500      0.237500      0.168500      0.230000
std     577.494589     1.300592      0.425658      0.374403      0.420938
min       1.000000     1.000000      0.000000      0.000000      0.000000
25%     500.750000     2.000000      0.000000      0.000000      0.000000
50%    1000.500000     4.000000      0.000000      0.000000      0.000000
75%    1500.250000     5.000000      0.000000      0.000000      0.000000
max    2000.000000     5.000000      1.000000      1.000000      1.000000

       zipconvert_5  homeowner dummy      NUMCHLD       INCOME  gender dummy  \
count    2000.00000       2000.00000  2000.000000  2000.000000   2000.000000
mean        0.30450          0.77850     1.052000     3.821500      0.595500
std         0.46031          0.41536     0.278091     1.638591      0.490918
min         0.00000          0.00000     1.000000     1.000000      0.000000
25%         0.00000          1.00000     1.000000     2.750000      0.000000
50%         0.00000          1.00000     1.000000     4.000000      1.000000
75%         1.00000          1.00000     1.000000     5.000000      1.000000
max         1.00000          1.00000     5.000000     7.000000      1.000000

       …         IC15      NUMPROM     RAMNTALL     MAXRAMNT     LASTGIFT  \
count  …  2000.000000  2000.000000  2000.000000  2000.000000  2000.000000
mean   …    15.177000    47.363000   103.005425    19.270305    16.478900
std    …    12.577988    22.963991    98.844943    11.752492     9.714386
min    …     0.000000     4.000000    15.000000     5.000000     0.000000
```

```
25%    ...     5.750000    27.000000    42.000000    14.000000    10.000000
50%    ...    12.000000    47.000000    80.000000    17.000000    15.000000
75%    ...    22.000000    64.000000   132.000000    22.000000    20.000000
max    ...    87.000000   148.000000  1526.000000   200.000000   105.000000

       totalmonths      TIMELAG      AVGGIFT  TARGET_B  TARGET_D
count   2000.00000  2000.000000  2000.000000       0.0       0.0
mean      31.29300     7.678000    13.051707       NaN       NaN
std        4.04244     5.652459     7.982889       NaN       NaN
min       17.00000     0.000000     1.636364       NaN       NaN
25%       29.00000     4.000000     8.408824       NaN       NaN
50%       31.00000     6.000000    11.600000       NaN       NaN
75%       33.00000    10.000000    15.211806       NaN       NaN
max       40.00000    45.000000   105.000000       NaN       NaN

[8 rows x 24 columns]

<IPython.core.display.HTML object>

Row Id                 0
Row Id.                0
zipconvert_2           0
zipconvert_3           0
zipconvert_4           0
zipconvert_5           0
homeowner dummy        0
NUMCHLD                0
INCOME                 0
gender dummy           0
WEALTH                 0
HV                     0
Icmed                  0
Icavg                  0
IC15                   0
NUMPROM                0
RAMNTALL               0
MAXRAMNT               0
LASTGIFT               0
totalmonths            0
TIMELAG                0
AVGGIFT                0
TARGET_B            2000
TARGET_D            2000
dtype: int64
```

[3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
from IPython.display import display, HTML

# Load the data
df = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
 ↪Fundraising.csv"
)
dff = pd.read_csv(
    "/Users/gabrielmancillas/Desktop/ADS 505-01/Mod 04/Assignment 4.1/
 ↪FutureFundraising.csv"
)

# 3. Data Types and Conversion
# Convert 'booking_created' to datetime if necessary
if "booking_created" in df.columns:
    df["booking_created"] = pd.to_datetime(df["booking_created"])

if "booking_created" in dff.columns:
    dff["booking_created"] = pd.to_datetime(dff["booking_created"])

# 4. Descriptive Statistics
display(
    HTML(
        "<h3>Updated summary statistics for Fundraising dataset after handling␣
 ↪missing values:</h3>"
    )
)
display(df.describe())

display(
    HTML(
        "<h3>Updated summary statistics for Future Fundraising dataset after␣
 ↪handling missing values:</h3>"
    )
)
display(dff.describe())

# 5. Data Visualization
# Distribution of numerical features
display(HTML("<h3>Distribution of numerical features in Fundraising dataset:</
 ↪h3>"))
df.hist(bins=30, figsize=(20, 15))
plt.show()

display(
```

```python
    HTML("<h3>Distribution of numerical features in Future Fundraising dataset:
  ↪</h3>")
)
dff.hist(bins=30, figsize=(20, 15))
plt.show()

# Correlation heatmap
display(HTML("<h3>Correlation Heatmap for Fundraising dataset:</h3>"))
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap - Fundraising")
plt.show()

display(HTML("<h3>Correlation Heatmap for Future Fundraising dataset:</h3>"))
plt.figure(figsize=(12, 8))
sns.heatmap(dff.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap - Future Fundraising")
plt.show()
```

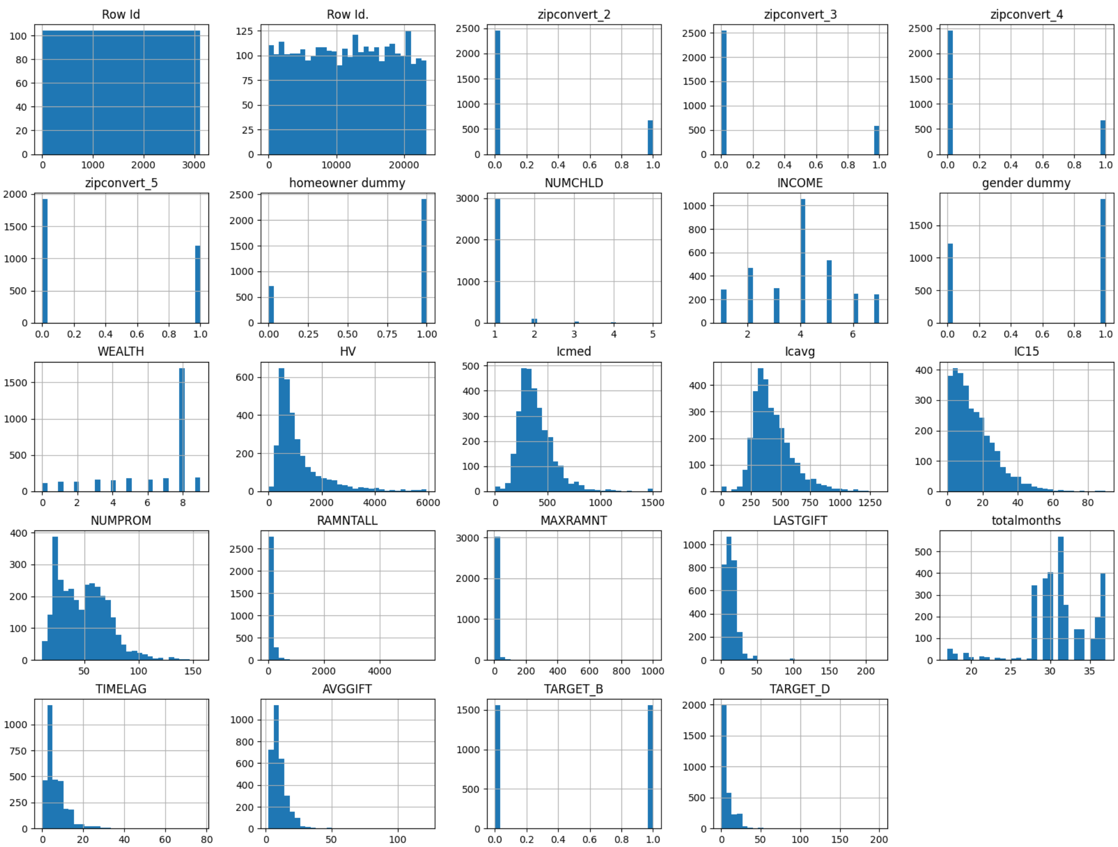
```
<IPython.core.display.HTML object>

            Row Id       Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  \
count  3120.000000   3120.000000   3120.000000   3120.000000   3120.000000
mean   1560.500000  11615.770833      0.214423      0.185256      0.214423
std     900.810746   6698.678131      0.410487      0.388568      0.410487
min       1.000000     17.000000      0.000000      0.000000      0.000000
25%     780.750000   5820.750000      0.000000      0.000000      0.000000
50%    1560.500000  11735.500000      0.000000      0.000000      0.000000
75%    2340.250000  17435.750000      0.000000      0.000000      0.000000
max    3120.000000  23293.000000      1.000000      1.000000      1.000000

       zipconvert_5  homeowner dummy      NUMCHLD       INCOME  gender dummy  \
count   3120.000000      3120.000000  3120.000000  3120.000000   3120.000000
mean       0.384615         0.770192     1.069231     3.893910      0.609295
std        0.486582         0.420777     0.347688     1.636186      0.487987
min        0.000000         0.000000     1.000000     1.000000      0.000000
25%        0.000000         1.000000     1.000000     3.000000      0.000000
50%        0.000000         1.000000     1.000000     4.000000      1.000000
75%        1.000000         1.000000     1.000000     5.000000      1.000000
max        1.000000         1.000000     5.000000     7.000000      1.000000

       …         IC15      NUMPROM     RAMNTALL     MAXRAMNT    LASTGIFT  \
count  …  3120.000000  3120.000000  3120.000000  3120.000000  3120.000000
mean   …    14.702885    49.089423   110.399875    16.651397    13.522917
std    …    12.079882    22.717130   147.299933    22.223521    10.581439
min    …     0.000000    11.000000    15.000000     5.000000     0.000000
25%    …     5.000000    29.000000    45.000000    10.000000     7.000000
50%    …    12.000000    48.000000    81.000000    15.000000    10.000000
```

```
75%    …    21.000000    65.000000   134.625000    20.000000    16.000000
max    …    90.000000   157.000000  5674.900000  1000.000000   219.000000

       totalmonths      TIMELAG      AVGGIFT    TARGET_B     TARGET_D
count  3120.000000  3120.000000  3120.000000  3120.00000  3120.000000
mean     31.136859     6.861859    10.690713     0.50000     6.499612
std       4.132952     5.561209     7.443980     0.50008    10.597849
min      17.000000     0.000000     2.138889     0.00000     0.000000
25%      29.000000     3.000000     6.356092     0.00000     0.000000
50%      31.000000     5.000000     9.000000     0.50000     0.500000
75%      34.000000     9.000000    12.811652     1.00000    10.000000
max      37.000000    77.000000   122.166667     1.00000   200.000000

[8 rows x 24 columns]

<IPython.core.display.HTML object>

            Row Id      Row Id.  zipconvert_2  zipconvert_3  zipconvert_4  \
count  2000.000000  2000.000000   2000.000000   2000.000000   2000.000000
mean   1000.500000     3.482500      0.237500      0.168500      0.230000
std     577.494589     1.300592      0.425658      0.374403      0.420938
min       1.000000     1.000000      0.000000      0.000000      0.000000
25%     500.750000     2.000000      0.000000      0.000000      0.000000
50%    1000.500000     4.000000      0.000000      0.000000      0.000000
75%    1500.250000     5.000000      0.000000      0.000000      0.000000
max    2000.000000     5.000000      1.000000      1.000000      1.000000

       zipconvert_5  homeowner dummy      NUMCHLD       INCOME  gender dummy  \
count    2000.00000       2000.00000  2000.000000  2000.000000   2000.000000
mean        0.30450          0.77850     1.052000     3.821500      0.595500
std         0.46031          0.41536     0.278091     1.638591      0.490918
min         0.00000          0.00000     1.000000     1.000000      0.000000
25%         0.00000          1.00000     1.000000     2.750000      0.000000
50%         0.00000          1.00000     1.000000     4.000000      1.000000
75%         1.00000          1.00000     1.000000     5.000000      1.000000
max         1.00000          1.00000     5.000000     7.000000      1.000000

       …         IC15      NUMPROM     RAMNTALL     MAXRAMNT     LASTGIFT  \
count  …  2000.000000  2000.000000  2000.000000  2000.000000  2000.000000
mean   …    15.177000    47.363000   103.005425    19.270305    16.478900
std    …    12.577988    22.963991    98.844943    11.752492     9.714386
min    …     0.000000     4.000000    15.000000     5.000000     0.000000
25%    …     5.750000    27.000000    42.000000    14.000000    10.000000
50%    …    12.000000    47.000000    80.000000    17.000000    15.000000
75%    …    22.000000    64.000000   132.000000    22.000000    20.000000
max    …    87.000000   148.000000  1526.000000   200.000000   105.000000

       totalmonths      TIMELAG      AVGGIFT  TARGET_B  TARGET_D
count   2000.00000  2000.000000  2000.000000       0.0       0.0
```

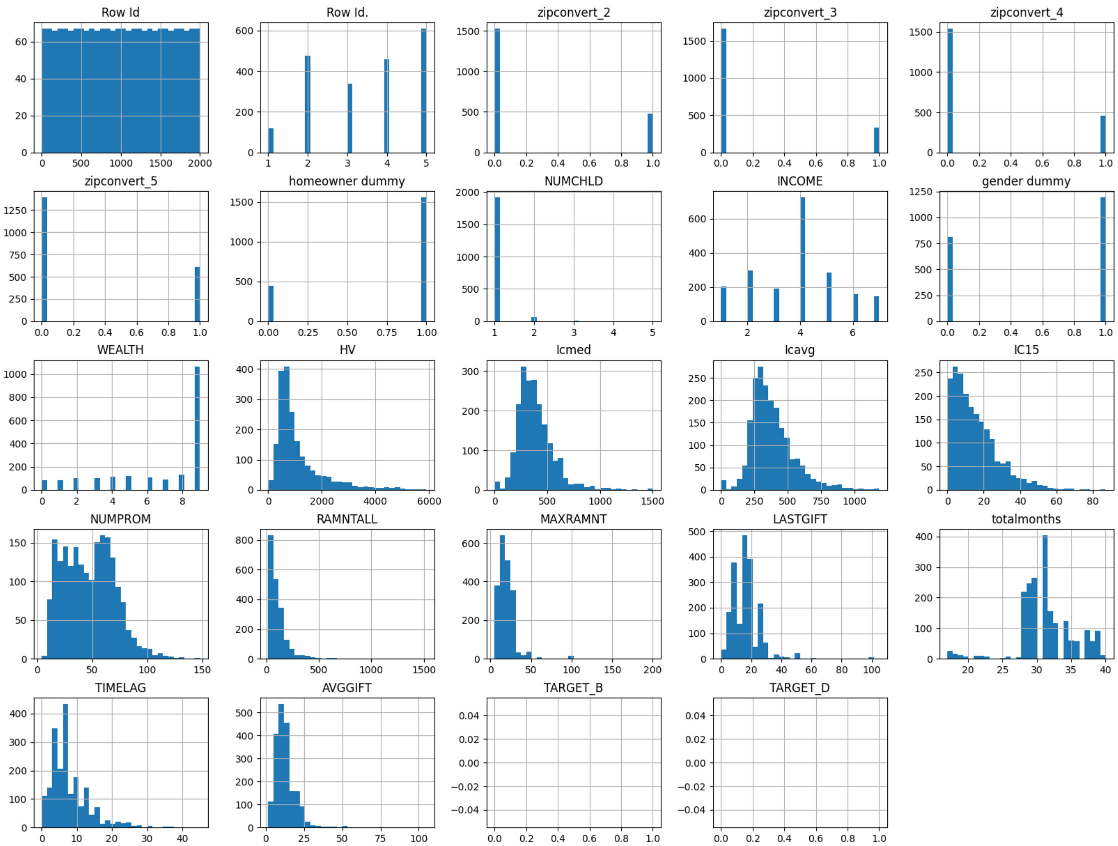
mean	31.29300	7.678000	13.051707	NaN	NaN
std	4.04244	5.652459	7.982889	NaN	NaN
min	17.00000	0.000000	1.636364	NaN	NaN
25%	29.00000	4.000000	8.408824	NaN	NaN
50%	31.00000	6.000000	11.600000	NaN	NaN
75%	33.00000	10.000000	15.211806	NaN	NaN
max	40.00000	45.000000	105.000000	NaN	NaN

[8 rows x 24 columns]

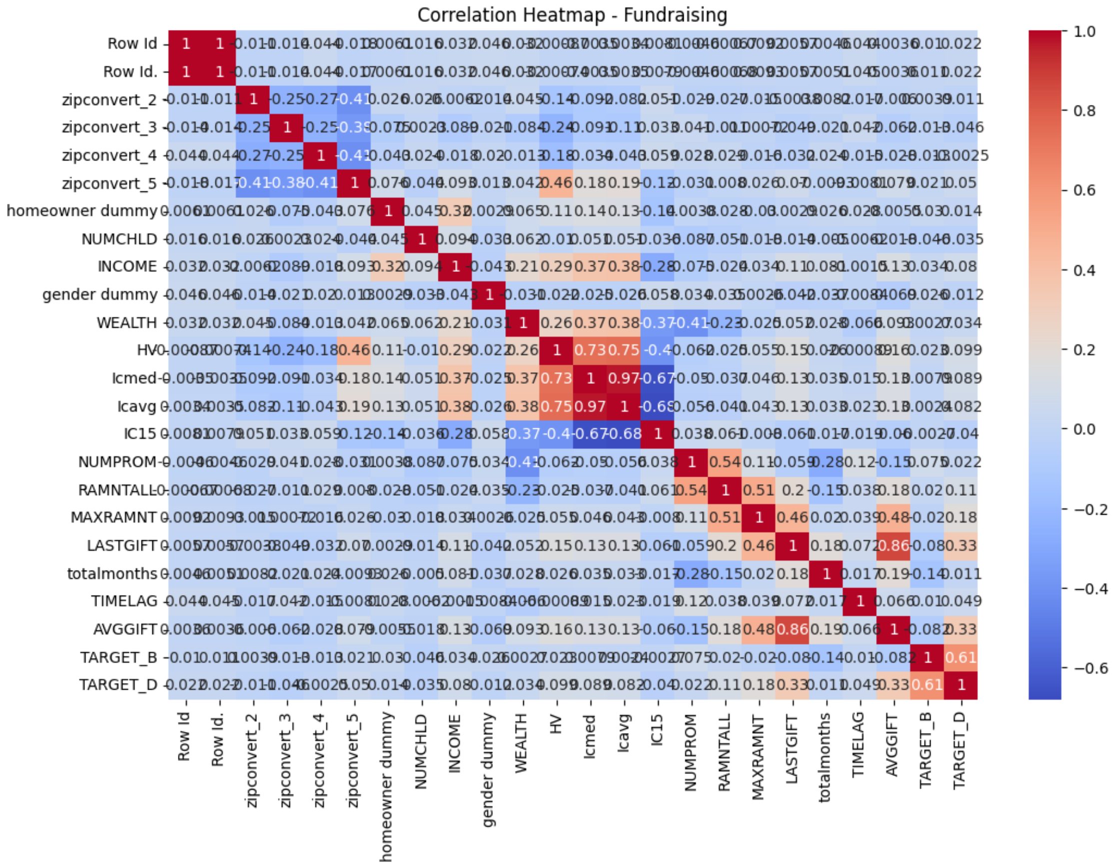
<IPython.core.display.HTML object>



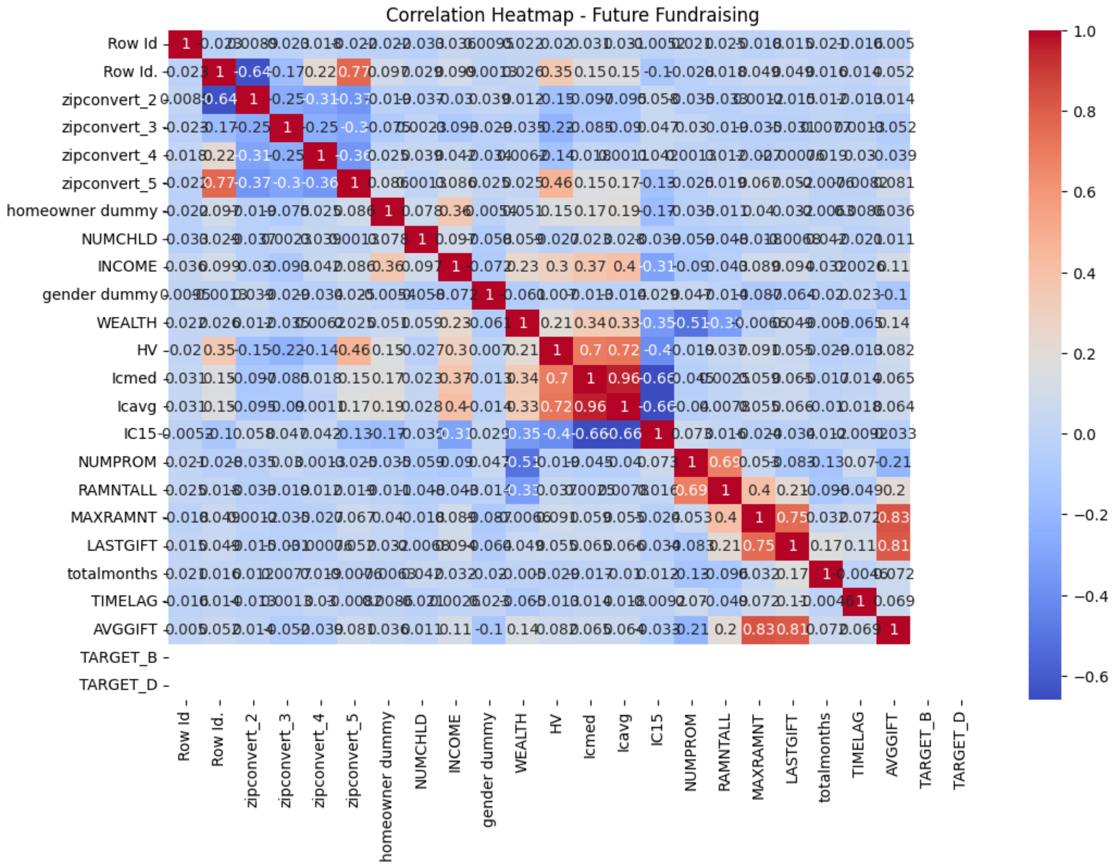
<IPython.core.display.HTML object>



<IPython.core.display.HTML object>




```
<IPython.core.display.HTML object>
```



Question 1

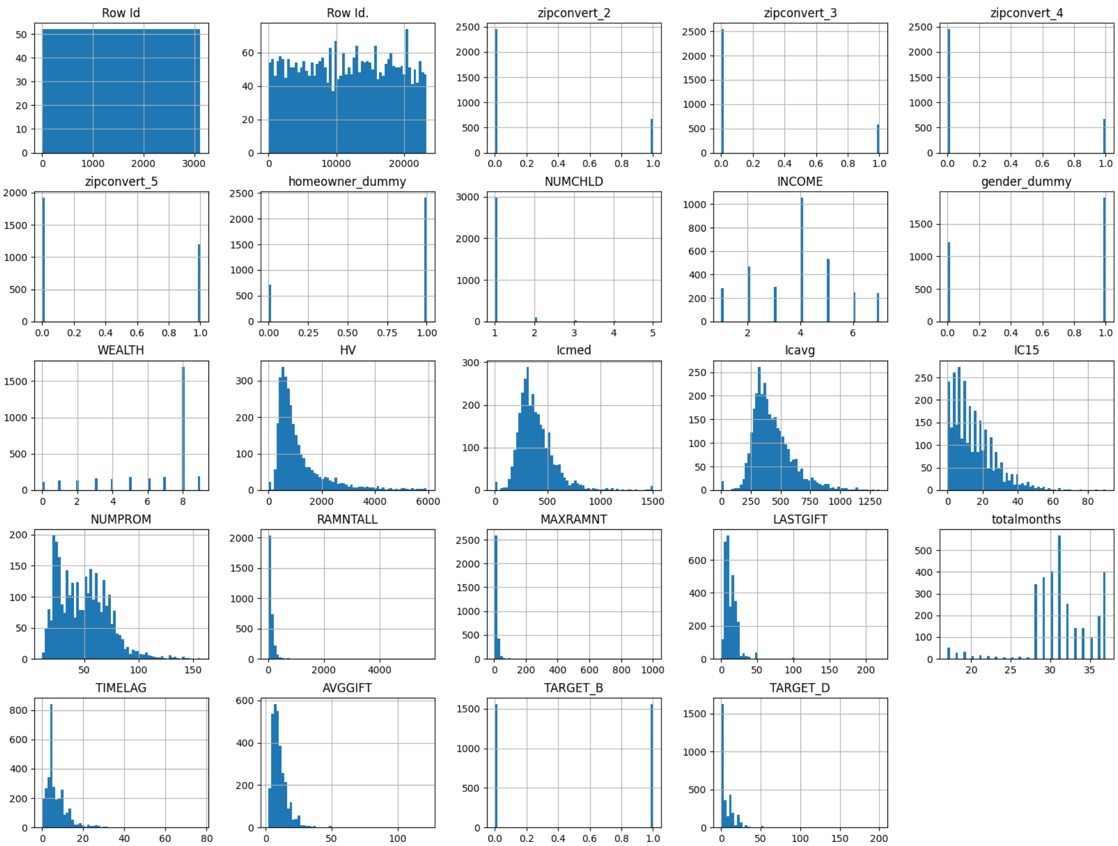
[4]:
```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix

X = df.drop("TARGET_B", axis=1)
y = df["TARGET_B"]

# 6. Data Preparation
train, val = train_test_split(df, test_size=0.4, random_state=12345)
```

[5]:
```python
df.duplicated().sum()
```

[5]: 0

[6]:
```
df.rename(columns={"gender dummy": "gender_dummy"}, inplace=True)
df.rename(columns={"homeowner dummy": "homeowner_dummy"}, inplace=True)
```

[7]:
```
df.hist(bins=60, figsize=(20, 15))
plt.show()
```



[8]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_num = df.copy()
l_cat = []

for col in df:
    if df[col].nunique() <= 21:
        df_num = df_num.drop(col, axis=1)
        l_cat.append(col)

# categorical
df_cat = df.filter(l_cat, axis=1)
```

```python
# Ratio
df_num_scaled = scaler.fit_transform(df_num)
df_num.head()
```

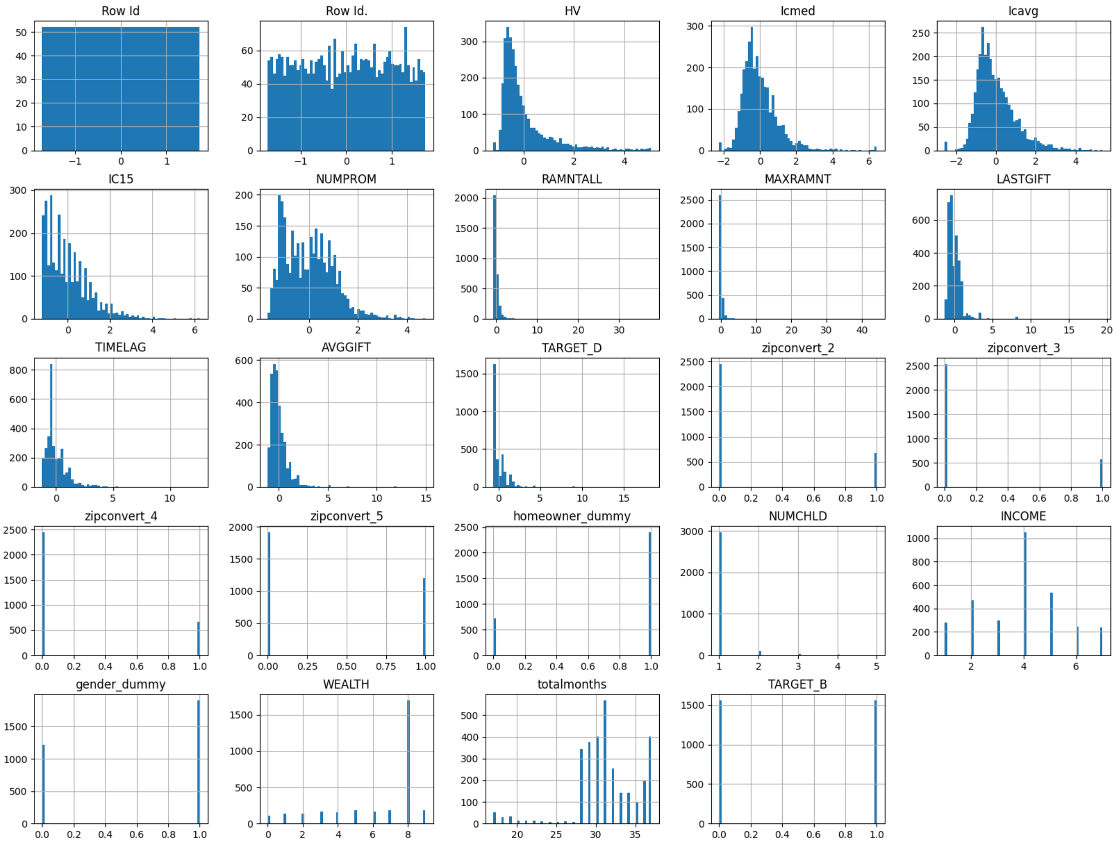
[8]:
```
   Row Id  Row Id.    HV  Icmed  Icavg  IC15  NUMPROM  RAMNTALL  MAXRAMNT  \
0       1       17  1399    637    703     1       74     102.0       6.0
1       2       25   698    422    463     4       46      94.0      12.0
2       3       29   828    358    376    13       32      30.0      10.0
3       4       38  1471    484    546     4       94     177.0      10.0
4       5       40   547    386    432     7       20      23.0      11.0

   LASTGIFT  TIMELAG   AVGGIFT  TARGET_D
0       5.0        3  4.857143       5.0
1      12.0        6  9.400000      10.0
2       5.0        7  4.285714       5.0
3       8.0        3  7.080000       0.0
4      11.0        6  7.666667       0.0
```

[9]:
```python
# concatenating datasets for visualization purposes

df_num_scaled = pd.DataFrame(df_num_scaled, columns=df_num.columns)
Scaled_df = pd.concat([df_num_scaled, df_cat], axis=1)
Scaled_df.head()
```

[9]:
```
     Row Id   Row Id.        HV     Icmed     Icavg      IC15   NUMPROM  \
0 -1.731496 -1.731779  0.272204  1.439813  1.610958 -1.134538  1.096731
1 -1.730385 -1.730585 -0.468427  0.195515  0.183815 -0.886151 -0.136017
2 -1.729275 -1.729987 -0.331078 -0.174881 -0.333524 -0.140991 -0.752391
3 -1.728165 -1.728644  0.348274  0.554336  0.677369 -0.886151  1.977265
4 -1.727055 -1.728345 -0.627964 -0.012833 -0.000524 -0.637764 -1.280711

   RAMNTALL  MAXRAMNT  LASTGIFT  …  zipconvert_3  zipconvert_4  \
0 -0.057035 -0.479362 -0.805588  …             1             0
1 -0.111354 -0.209334 -0.143946  …             0             0
2 -0.545912 -0.299343 -0.805588  …             0             0
3  0.452212 -0.299343 -0.522027  …             0             0
4 -0.593441 -0.254339 -0.238467  …             1             0

   zipconvert_5  homeowner_dummy  NUMCHLD  INCOME  gender_dummy  WEALTH  \
0             0                1        1       5             1       9
1             0                1        1       1             0       7
2             1                0        2       5             1       8
3             1                1        1       3             0       4
4             0                1        1       4             0       8

   totalmonths  TARGET_B
0           29         1
```

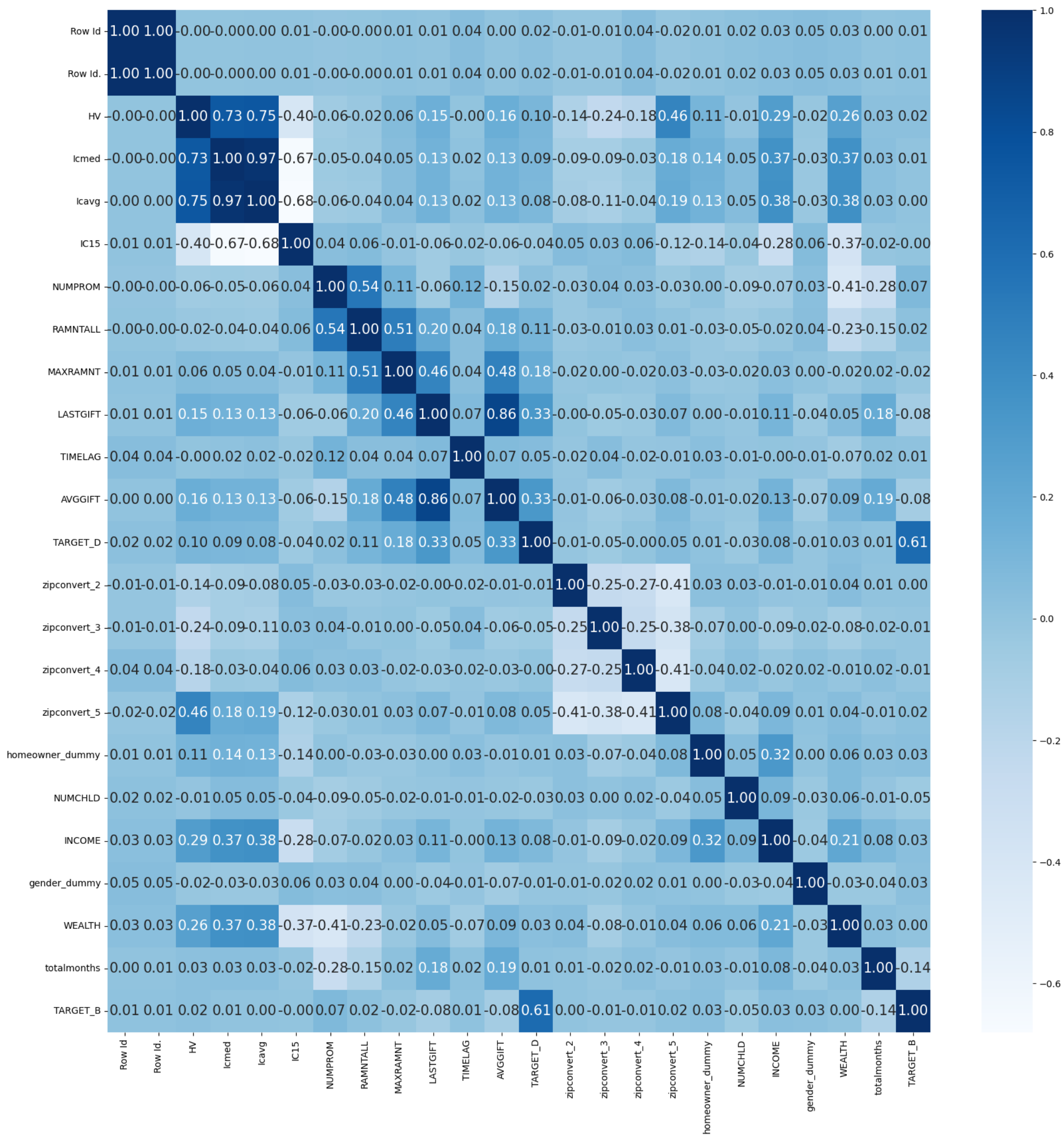
```
1            34          1
2            29          1
3            30          0
4            30          0

[5 rows x 24 columns]
```

[10]:
```python
Scaled_df.hist(bins=60, figsize=(20, 15))
plt.show()
```



[11]:
```python
corr = Scaled_df.corr()
plt.figure(figsize=(20, 20))
sns.heatmap(
    corr, cbar=True, fmt=".2f", annot=True, annot_kws={"size": 15}, cmap="Blues"
)
```

[11]: `<Axes: >`



[12]:
```python
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.compose import ColumnTransformer
```

[13]:
```python
Row_ix, RowId_ix, Target_d_ix = 0, 1, -1


class columnDropperTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, columns):
```

```
        self.columns = columns

    def transform(self, X):
        return X.drop(X.columns[self.columns], axis=1)

    def fit(self, X, y=None):
        return self


num_pipeline = Pipeline(
    [
        ("drop_data", columnDropperTransformer([Row_ix, RowId_ix,␣
↪Target_d_ix])),
        ("imputer", SimpleImputer(strategy="median")),
        ("std_scaler", StandardScaler()),
    ]
)

num_attribs = list(df.drop(df_cat.columns, axis=1))
cat_attribs = list(df_cat.drop(["TARGET_B"], axis=1).columns)

full_pipeline = ColumnTransformer(
    [
        ("num", num_pipeline, num_attribs),
    ],
    remainder="passthrough",
)

X_train, X_test, y_train, y_test = train_test_split(
    df.drop("TARGET_B", axis=1), df["TARGET_B"], test_size=0.2,␣
↪random_state=12345
)
X_prepared = full_pipeline.fit_transform(X_train)
```

[14]:
```
X_prepared = pd.DataFrame(X_prepared, columns=X_train.columns[2:-1])
```

[15]:
```
X_prepared.head()
```

[15]:
```
   zipconvert_2  zipconvert_3  zipconvert_4  zipconvert_5  homeowner_dummy  \
0     -0.162999     -0.140958     -0.153803     -0.643554        -1.069037
1     -0.793101     -0.625512     -0.587747      0.172578        -0.673346
2     -0.649169     -0.777299     -0.938470      0.825483        -1.244899
3     -0.042523      1.236807      1.231252     -1.214845         0.293897
4     -0.728065     -0.888221     -1.081136     -0.561940        -0.189725

    NUMCHLD    INCOME  gender_dummy    WEALTH        HV  Icmed  Icavg  IC15  \
0 -0.501734 -0.443354     -0.697739 -1.066196 -0.809061    0.0    0.0   0.0
```

```
1 -0.342814  0.339144      1.060521 -0.884070  0.095686    0.0    0.0   1.0
2 -0.482663  0.133224      0.135121 -0.519818  0.903901    1.0    0.0   0.0
3  0.477211  3.427954     -0.790279 -0.519818  1.049645    0.0    0.0   1.0
4 -0.387312 -0.072697      0.135121  6.765225 -0.089806    0.0    0.0   1.0

   NUMPROM  RAMNTALL  MAXRAMNT  LASTGIFT  totalmonths  TIMELAG  AVGGIFT
0      1.0       0.0       2.0       3.0          0.0      8.0     29.0
1      0.0       1.0       1.0       4.0          0.0      8.0     37.0
2      0.0       1.0       1.0       5.0          1.0      8.0     37.0
3      0.0       1.0       1.0       4.0          1.0      8.0     26.0
4      0.0       1.0       2.0       3.0          1.0      3.0     29.0
```

[16]:
```
def score(y_train, train_pred, y_test, test_pred):
    from sklearn import metrics

    print("Training precision: ", metrics.precision_score(y_train, train_pred))
    print("Validation precision: ", metrics.precision_score(y_test, test_pred))
    print("\n")
    print("Training accuracy: ", metrics.accuracy_score(y_train, train_pred))
    print("Validation accuracy: ", metrics.accuracy_score(y_test, test_pred))


def net(train, test):
    n_of_1s = np.unique(train, return_counts=True)
    n2_of_1s = np.unique(test, return_counts=True)
    n = n_of_1s[1][1]
    n2 = n2_of_1s[1][1]
    net = ((n * 13) - (0.68 * n)) / 9.8
    net2 = ((n2 * 13) - (0.68 * n2)) / 9.8
    return net, net2


def net_profit(
    train_pred_1, test_pred_1, train_pred_2, test_pred_2, train_pred_3,␣
 ↪test_pred_3
):
    import matplotlib.pyplot as plt

    net1, net2 = net(train_pred_1, test_pred_1)
    net3, net4 = net(train_pred_2, test_pred_2)
    net5, net6 = net(train_pred_3, test_pred_3)
    net_df = pd.DataFrame(
        [[net1, net3, net5], [net2, net4, net6]],
        columns=["LR", "XGB", "SVC"],
        index=["train", "test"],
    )
    plt.bar(["LR", "XGB", "SVC"], [net2, net4, net6])
```

```python
    return net_df
```

[17]:
```python
X_test_pre = full_pipeline.transform(X_test)
X_test_pre = pd.DataFrame(X_test_pre, columns=X_train.columns[2:-1])
```

[18]:
```python
# remove an error message

import warnings

warnings.filterwarnings("ignore")

from sklearn.linear_model import LogisticRegression

m = LogisticRegression().fit(X_prepared, y_train)

train_pred = m.predict(X_prepared)
test_pred = m.predict(X_test_pre)

score(y_train, train_pred, y_test, test_pred)
```

```
Training precision:  0.5737082066869301
Validation precision:  0.5391566265060241


Training accuracy:  0.5729166666666666
Validation accuracy:  0.5608974358974359
```

[19]:
```python
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import RandomizedSearchCV

xgb = XGBClassifier()
xgb.fit(X_prepared, y_train)

train_pred = xgb.predict(X_prepared)
test_pred = xgb.predict(X_test_pre)

score(y_train, train_pred, y_test, test_pred)

param_dist = {
    "n_estimators": [100, 200, 300],
    "learning_rate": [0.01, 0.1, 0.2],
    "max_depth": [3, 4, 5],
}

clf = RandomizedSearchCV(
    xgb,
```

```python
    param_distributions=param_dist,
    cv=5,
    n_iter=5,
    scoring="accuracy",
    n_jobs=-1,
    verbose=3,
    random_state=123,
)
clf.fit(X_prepared, y_train)
```

```
Training precision:  0.9992063492063492
Validation precision:  0.49693251533742333


Training accuracy:  0.999198717948718
Validation accuracy:  0.5160256410256411
Fitting 5 folds for each of 5 candidates, totalling 25 fits
[CV 1/5] END learning_rate=0.2, max_depth=4, n_estimators=300;, score=0.528
total time=   0.1s
[CV 3/5] END learning_rate=0.2, max_depth=4, n_estimators=300;, score=0.503
total time=   0.1s
[CV 2/5] END learning_rate=0.2, max_depth=4, n_estimators=300;, score=0.505
total time=   0.1s
[CV 4/5] END learning_rate=0.2, max_depth=4, n_estimators=300;, score=0.487
total time=   0.1s
[CV 5/5] END learning_rate=0.2, max_depth=4, n_estimators=300;, score=0.513
total time=   0.1s
[CV 1/5] END learning_rate=0.01, max_depth=4, n_estimators=300;, score=0.552
total time=   0.1s
[CV 2/5] END learning_rate=0.01, max_depth=4, n_estimators=300;, score=0.579
total time=   0.1s
[CV 3/5] END learning_rate=0.01, max_depth=4, n_estimators=300;, score=0.545
total time=   0.1s
[CV 1/5] END learning_rate=0.01, max_depth=5, n_estimators=200;, score=0.544
total time=   0.1s
[CV 5/5] END learning_rate=0.01, max_depth=4, n_estimators=300;, score=0.521
total time=   0.1s
[CV 2/5] END learning_rate=0.01, max_depth=5, n_estimators=200;, score=0.555
total time=   0.1s
[CV 4/5] END learning_rate=0.01, max_depth=4, n_estimators=300;, score=0.525
total time=   0.1s
[CV 3/5] END learning_rate=0.01, max_depth=5, n_estimators=200;, score=0.547
total time=   0.1s
[CV 4/5] END learning_rate=0.01, max_depth=5, n_estimators=200;, score=0.535
total time=   0.1s
[CV 1/5] END learning_rate=0.2, max_depth=5, n_estimators=100;, score=0.532
total time=   0.1s
[CV 5/5] END learning_rate=0.01, max_depth=5, n_estimators=200;, score=0.543
```

```
total time=   0.1s
[CV 3/5] END learning_rate=0.2, max_depth=5, n_estimators=100;, score=0.501
total time=   0.1s
[CV 2/5] END learning_rate=0.2, max_depth=5, n_estimators=100;, score=0.519
total time=   0.1s
[CV 4/5] END learning_rate=0.2, max_depth=5, n_estimators=100;, score=0.495
total time=   0.1s
[CV 5/5] END learning_rate=0.2, max_depth=5, n_estimators=100;, score=0.535
total time=   0.1s
[CV 1/5] END learning_rate=0.01, max_depth=5, n_estimators=300;, score=0.546
total time=   0.2s
[CV 3/5] END learning_rate=0.01, max_depth=5, n_estimators=300;, score=0.529
total time=   0.2s
[CV 2/5] END learning_rate=0.01, max_depth=5, n_estimators=300;, score=0.553
total time=   0.2s
[CV 4/5] END learning_rate=0.01, max_depth=5, n_estimators=300;, score=0.527
total time=   0.2s
[CV 5/5] END learning_rate=0.01, max_depth=5, n_estimators=300;, score=0.539
total time=   0.2s
```

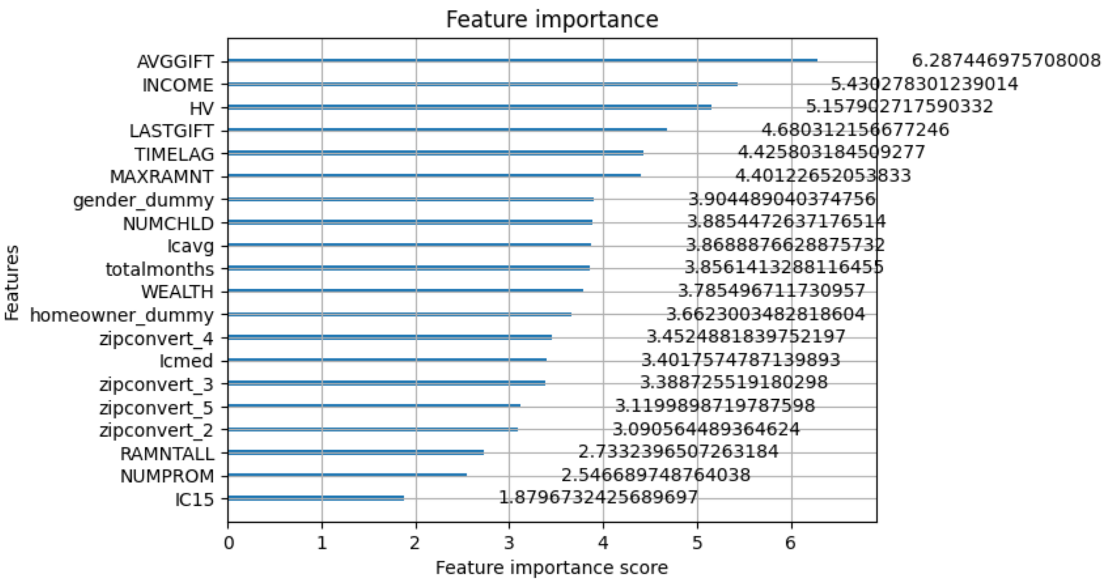
[19]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           callbacks=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, device=None,
                                           early_stopping_rounds=None,
                                           enable_categorical=False,
                                           eval_metric=None, feature_types=None,
                                           gamma=None, grow_policy=None,
                                           importance_type=None,
                                           interaction_constraints=None,
                                           learning_rate…
                                           max_delta_step=None, max_depth=None,
                                           max_leaves=None,
                                           min_child_weight=None, missing=nan,
                                           monotone_constraints=None,
                                           multi_strategy=None,
                                           n_estimators=None, n_jobs=None,
                                           num_parallel_tree=None,
                                           random_state=None, …),
                   n_iter=5, n_jobs=-1,
                   param_distributions={'learning_rate': [0.01, 0.1, 0.2],
                                        'max_depth': [3, 4, 5],
                                        'n_estimators': [100, 200, 300]},
                   random_state=123, scoring='accuracy', verbose=3)
```

[20]:
```python
# optimal hyperparameters
clf.best_params_
```

[20]: {'n_estimators': 200, 'max_depth': 5, 'learning_rate': 0.01}

[21]:
```python
train_pred2 = clf.predict(X_prepared)
test_pred2 = clf.predict(X_test_pre)
```

[22]:
```python
import xgboost as xgb

# Plot feature importance
xgb.plot_importance(
    clf.best_estimator_, importance_type="gain", xlabel="Feature importance␣
 ↪score"
)
plt.show()
```



[23]:
```python
score(y_train, train_pred2, y_test, test_pred2)
```

```
Training precision:  0.7288135593220338
Validation precision:  0.5533333333333333


Training accuracy:  0.7115384615384616
Validation accuracy:  0.5705128205128205
```

[24]:
```python
from sklearn.svm import SVC
```

```
clf = SVC(gamma="auto", probability=True).fit(X_prepared, y_train)

train_pred3 = clf.predict(X_prepared)
test_pred3 = clf.predict(X_test_pre)

score(y_train, train_pred3, y_test, test_pred3)
```

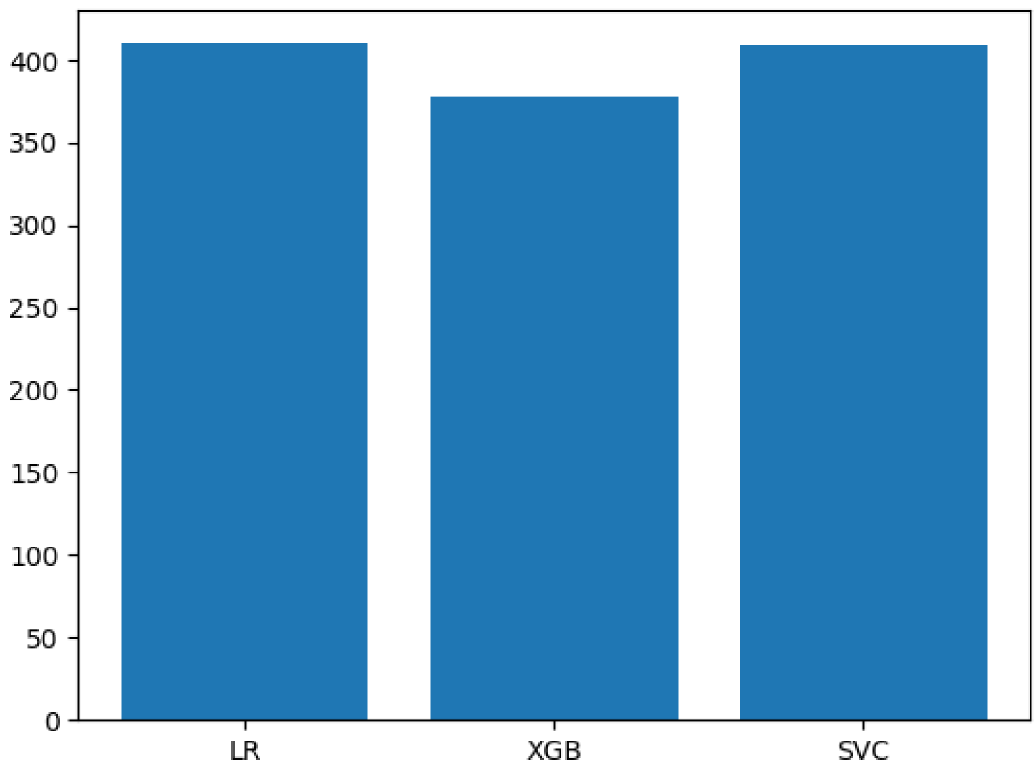
```
Training precision:  0.6549570647931303
Validation precision:  0.5292307692307693


Training accuracy:  0.6542467948717948
Validation accuracy:  0.5496794871794872
```

Question 2.3

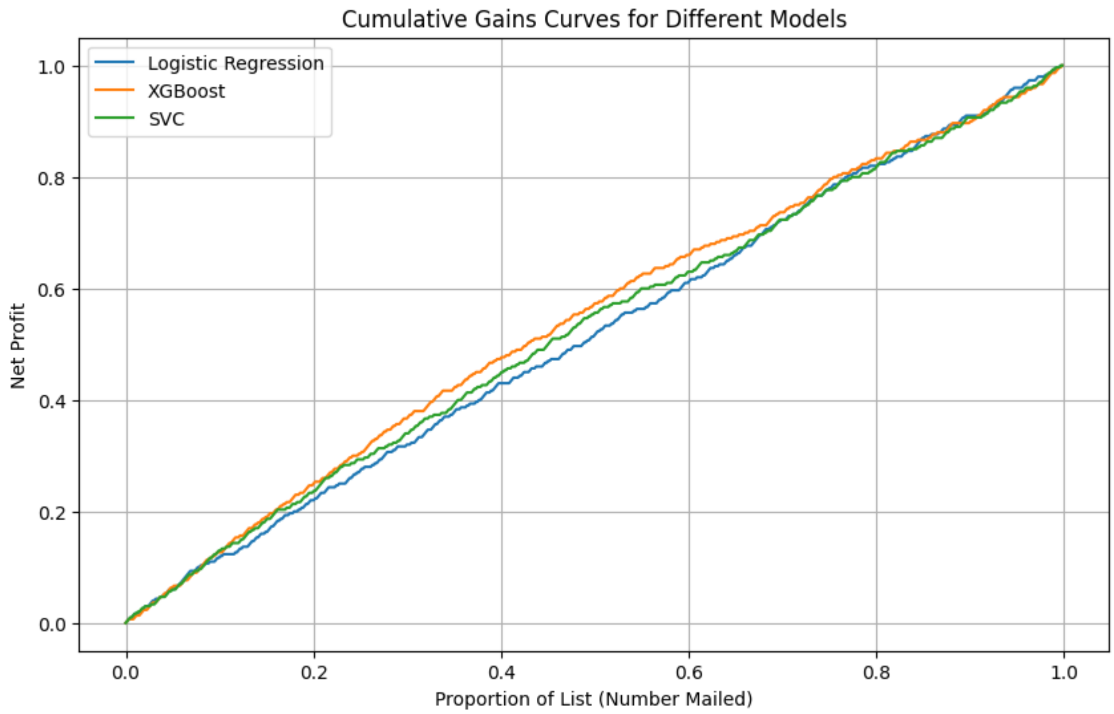
[25]:
```
net_profit(train_pred, test_pred, train_pred2, test_pred2, train_pred3,
    test_pred3)
```

[25]:

	LR	XGB	SVC
train	1584.000000	1483.428571	1610.400000
test	409.828571	377.142857	408.571429

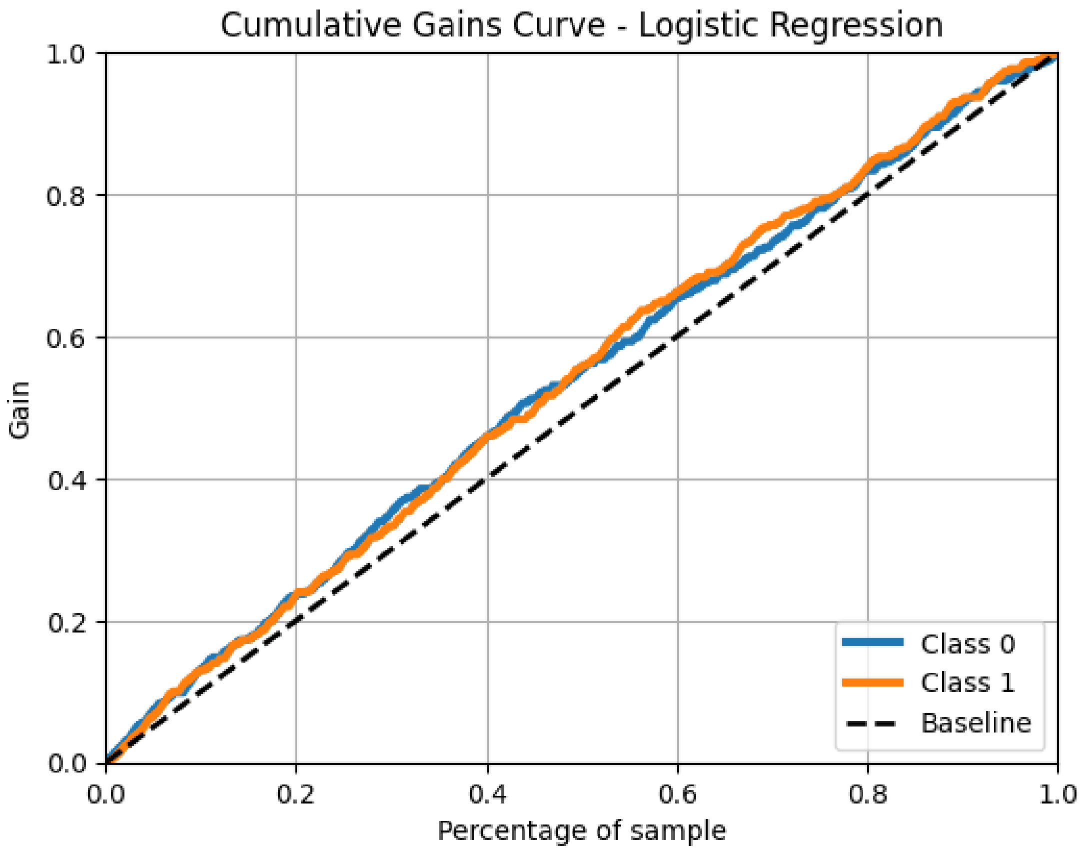


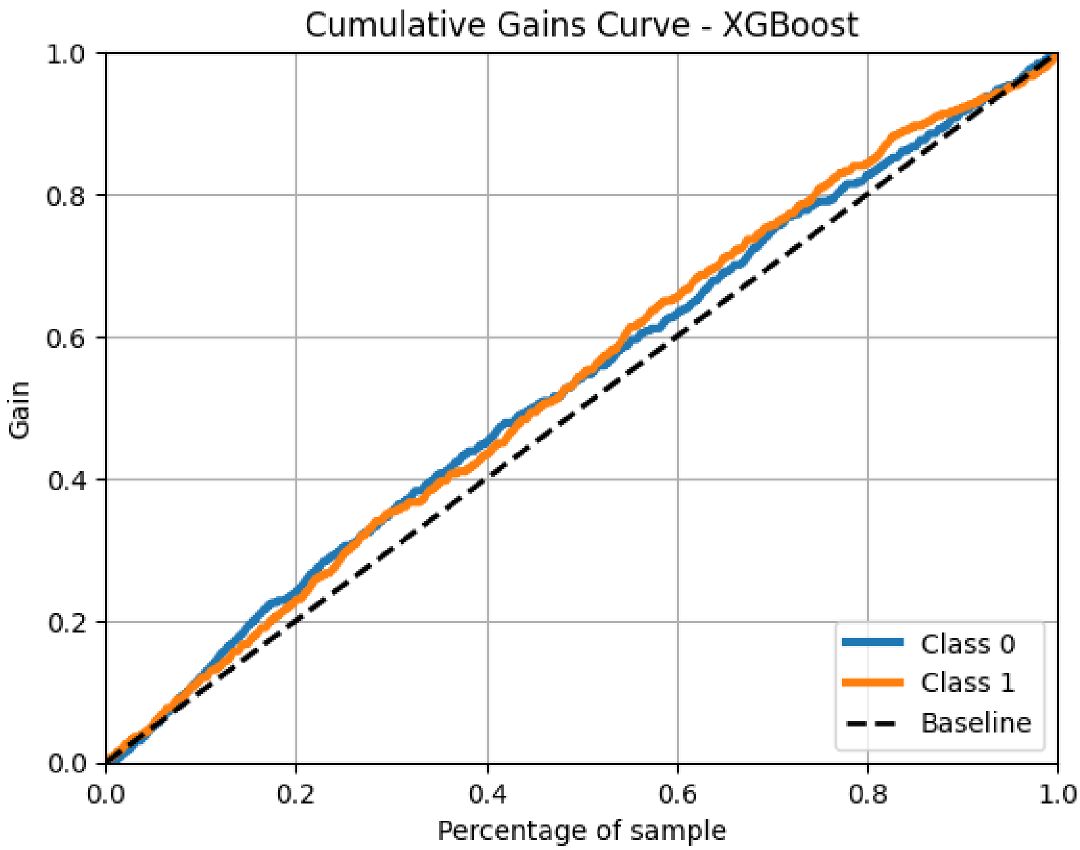
[26]:
```python
import numpy as np

import matplotlib.pyplot as plt


# Function to calculate cumulative gains
def cumulative_gains(y_true, y_pred):
    sorted_indices = np.argsort(y_pred)[::-1]
    y_true_sorted = y_true.iloc[sorted_indices]
    gains = np.cumsum(y_true_sorted) / np.sum(y_true_sorted)
    return gains


# Calculate cumulative gains for each model
gains_lr = cumulative_gains(y_test, test_pred)
gains_xgb = cumulative_gains(y_test, test_pred2)
gains_svc = cumulative_gains(y_test, test_pred3)

# Plot cumulative gains curves
plt.figure(figsize=(10, 6))
plt.plot(
    np.arange(len(gains_lr)) / len(gains_lr), gains_lr, label="Logistic␣
↪Regression"
)
plt.plot(np.arange(len(gains_xgb)) / len(gains_xgb), gains_xgb, label="XGBoost")
plt.plot(np.arange(len(gains_svc)) / len(gains_svc), gains_svc, label="SVC")
plt.xlabel("Proportion of List (Number Mailed)")
plt.ylabel("Net Profit")
plt.title("Cumulative Gains Curves for Different Models")
plt.legend()
plt.grid(True)
plt.show()
```

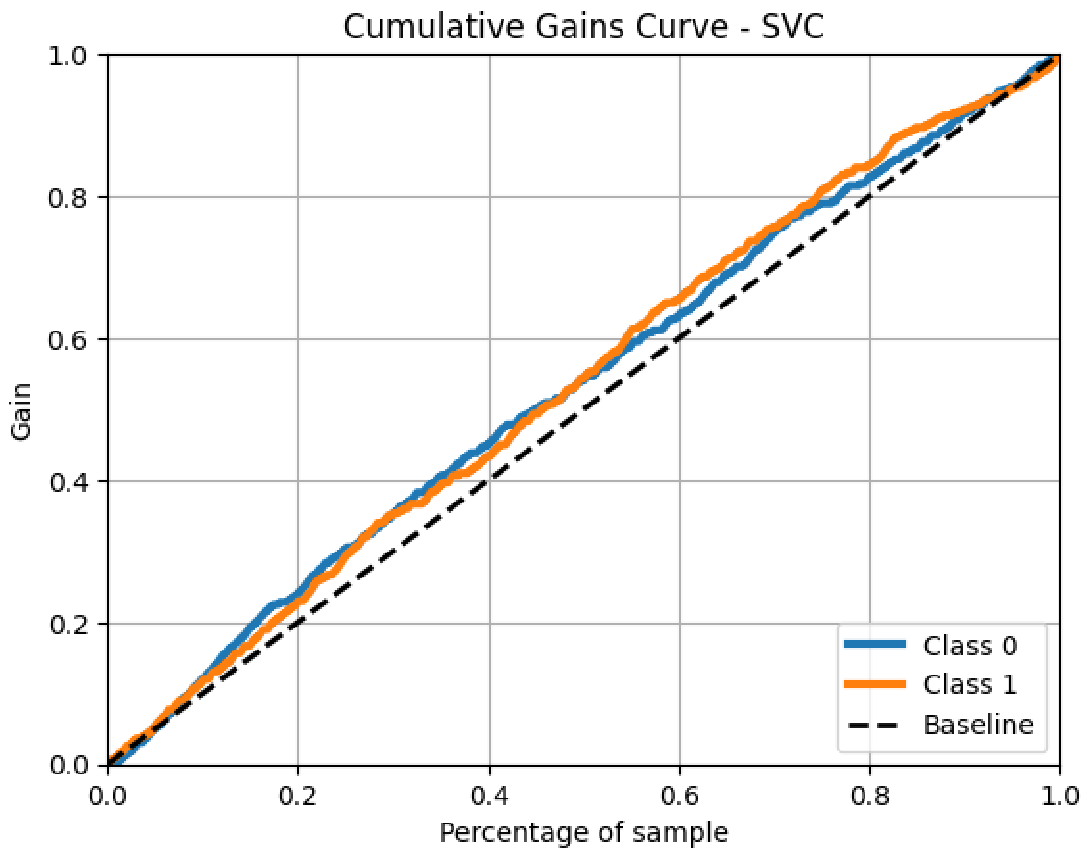


[27]:
```python
import scikitplot as skplt

# Deriving class probabilities for each model
predicted_probabilities_lr = m.predict_proba(X_test_pre)
predicted_probabilities_xgb = clf.predict_proba(X_test_pre)
predicted_probabilities_svc = clf.predict_proba(X_test_pre)

# Creating the plot
plt.figure(figsize=(10, 6))
skplt.metrics.plot_cumulative_gain(
    y_test,
    predicted_probabilities_lr,
    title="Cumulative Gains Curve - Logistic Regression",
)
skplt.metrics.plot_cumulative_gain(
    y_test, predicted_probabilities_xgb, title="Cumulative Gains Curve -␣
↪XGBoost"
)
skplt.metrics.plot_cumulative_gain(
    y_test, predicted_probabilities_svc, title="Cumulative Gains Curve - SVC"
)
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```


Cumulative Gains Curve - Logistic Regression
1.0
0.8
0.6
0.4
0.2
0.0
Gain
0.0
0.2
0.4
0.6
0.8
1.0
Percentage of sample
Class 0
Class 1
Baseline


Cumulative Gains Curve - XGBoost
Gain
Percentage of sample
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Class 0
Class 1
Baseline



[28]:
```
# use the future fundraising dataset to predict the target variable
dff.head()
```

[28]:

	Row Id	Row Id.	zipconvert_2	zipconvert_3	zipconvert_4	zipconvert_5	\
0	1	3	0	1	0	0	
1	2	4	0	0	1	0	
2	3	5	0	0	0	1	
3	4	1	0	0	0	0	
4	5	4	0	0	1	0	

	homeowner dummy	NUMCHLD	INCOME	gender dummy	…	IC15	NUMPROM	\
0	1	1	1	1	…	3	42	
1	0	1	2	1	…	4	21	
2	0	1	1	0	…	10	61	
3	1	1	4	0	…	21	32	
4	1	1	7	1	…	1	47	

	RAMNTALL	MAXRAMNT	LASTGIFT	totalmonths	TIMELAG	AVGGIFT	TARGET_B	\
0	92.0	29.0	15.0	17	8	15.333333	NaN	
1	30.0	20.0	20.0	33	9	15.000000	NaN	

```
2     220.0      35.0      25.0            31          9  24.444444        NaN
3      41.0      19.0      19.0            31         13  13.666667        NaN
4      46.0      10.0      10.0            28          8   5.750000        NaN

   TARGET_D
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN

[5 rows x 24 columns]
```

[29]:
```
# Split data
X = dff.drop("TARGET_B", axis=1)
y = dff["TARGET_B"]
```

[30]:
```
import pandas as pd

# Ensure X has all necessary columns
expected_columns = ["homeowner_dummy", "gender_dummy"]  # Add all expected␣
↪columns here
for col in expected_columns:
    if col not in X.columns:
        X[col] = 0  # or any default value that makes sense

# Process data using full pipeline
X_prepared = full_pipeline.transform(X)

# Predict target variable
from sklearn.svm import SVC

future_pred = clf.predict(X_prepared)

result_df = pd.DataFrame(future_pred, columns=["TARGET_B"])
```

[31]:
```
# predict probability
future_prob = clf.predict_proba(X_prepared)
future_prob = future_prob.reshape(2, 2000)

result_df["prop_0"] = future_prob[0]
result_df["prop_1"] = future_prob[1]
```

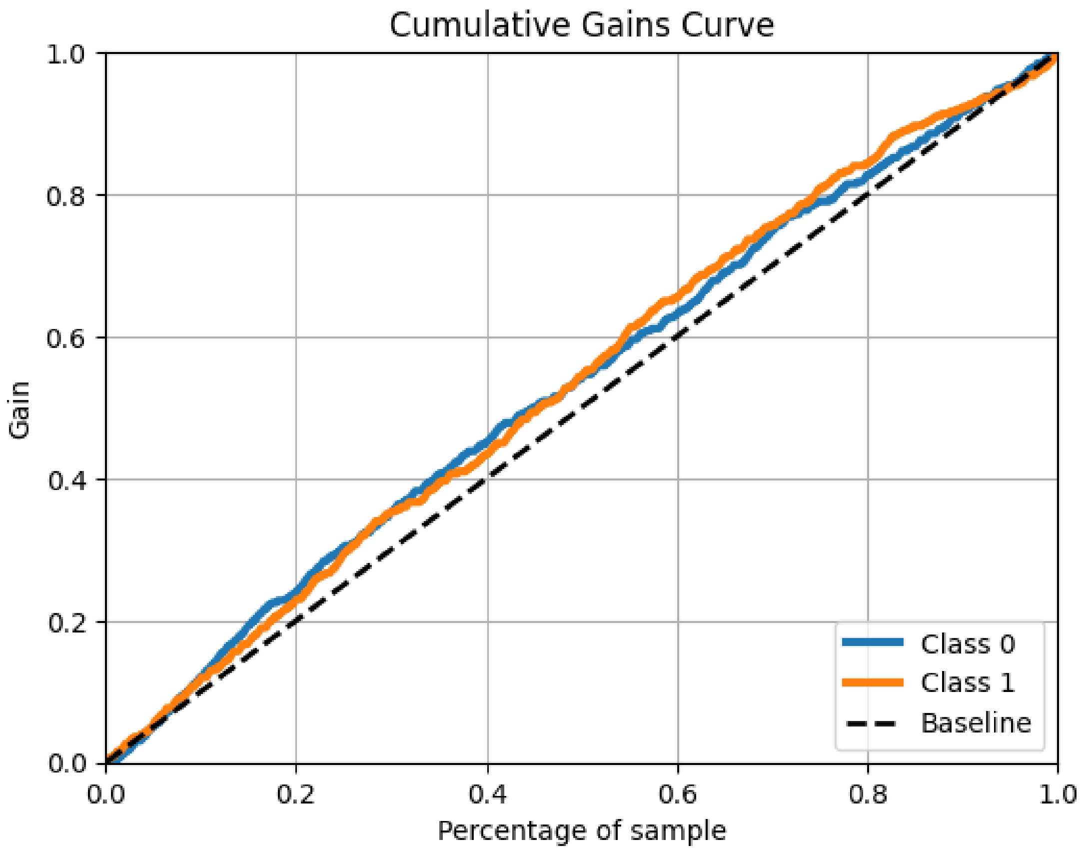
[32]:
```
result_df.sort_values(["prop_1", "prop_0"], ascending=[False, True],␣
↪ignore_index=True)
```

[32]:
```
      TARGET_B    prop_0    prop_1
0            0  0.397201  0.625518
1            0  0.413306  0.625504
2            1  0.494588  0.624108
3            1  0.559463  0.623918
4            0  0.512880  0.618290
…          …        …         …
1995         0  0.487120  0.381710
1996         1  0.440537  0.376082
1997         1  0.505412  0.375892
1998         0  0.586694  0.374496
1999         0  0.602799  0.374482

[2000 rows x 3 columns]
```

[33]:
```
len(result_df[result_df.prop_1 >= 0.53])
```

[33]:
```
613
```

[34]:
```
import scikitplot as skplt
import matplotlib.pyplot as plt

# Plot the cumulative gains curve for SVC
skplt.metrics.plot_cumulative_gain(y_test, clf.predict_proba(X_test_pre))
plt.show()

# Calculate the net profit from predictions
expected_donation = 13.00  # Average donation amount
mailing_cost = 0.68  # Mailing cost per mailing
response_rate = 0.051  # Overall response rate

# Calculate the number of targets you need to reach for $100,000 profit
desired_profit = 100000
number_targets_to_reach = desired_profit / (expected_donation - mailing_cost)

# Calculate the percentage of targets to reach in the total dataset
perc_targets_to_reach = number_targets_to_reach / len(df)

# Actual cumulative gains at 5.1% response rate
cumulative_gains = 0.051

# Calculate the number of donors to address
number_donors_to_reach = cumulative_gains * number_targets_to_reach

print(f"Number of targets to reach: {number_targets_to_reach}")
print(f"Percentage of targets to reach: {perc_targets_to_reach}")
print(f"Number of donors to address: {number_donors_to_reach}")
```




```
Number of targets to reach: 8116.883116883117
Percentage of targets to reach: 2.6015651015651016
Number of donors to address: 413.9610389610389
```