Bank Clients Anomaly Prediction Project with Data Engineering

The aim of this project was to:

- ingest raw, real-world data from several tables stored in Google Cloud
- build unsupervised anomaly detection model

Data ingestion from Google Cloud Bucket:

- one excel file "Banking Clients' with three data sheets: 'Clients - Banking', 'Nationality', 'Clients';
- two .txt files: 'Banking Contact', 'Investment Advisor'

In [1]:
```
# Import nesseccary libriaries for data handling
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
warnings.filterwarnings("ignore", category=UserWarning)


# Feature Processing and Model (Scikit-learn processing, etc. )
from sklearn.preprocessing import StandardScaler, OrdinalEncoder
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.decomposition import PCA
from sklearn.neighbors import NearestNeighbors
from kneed import KneeLocator
from sklearn.inspection import DecisionBoundaryDisplay

# Model registering
import os
import joblib

# API / Cloud
import requests
import io
from google.cloud import storage
from typing import Dict, Optional, Sequence, Tuple
from google.cloud import aiplatform
from google.cloud.aiplatform import explain
```

In [2]:
```
# Use the default credentials to authenticate to Google Cloud
# Create and download Service account key under IAM & Admin Service Accounts (it's a json file
# download it and set the environment variable:
# set GOOGLE_APPLICATION_CREDENTIALS="path/to/your/service-account-file.json"

import io
import requests
from google.cloud import storage
from datetime import timedelta

# Resources needed to download data from
```

```python
bucket_name = 'bank_clients_raw_data'
excel_blob_name = 'Banking Clients.xlsx'
txt1_blob_name = 'Banking Contact.txt'
txt2_blob_name = 'Investment Advisor.txt'

# Connect to Google Cloud with a handler
def initialize_gcs_client():
    try:
        # Path to your service account key file
        key_path = r"C:\Users\user\PYTHON_Data Science\continual-air-441820-k0-40260413fce7.j

        # Set the environment variable
        os.environ["GOOGLE_APPLICATION_CREDENTIALS"] = key_path

        # Initialize the Google Cloud Storage client
        gcs_client = storage.Client()
        return gcs_client

    except Exception as e:
         print(f"Error connecting to Google Cloud: {e}")

# Initialize the handler itself - global var, needed later for uploading on gcs
gcs_client = initialize_gcs_client()

def get_blob_url(bucket_name, blob_name):
    bucket = gcs_client.bucket(bucket_name)
    blob = bucket.blob(blob_name)
    # Set URL to be valid for 30 days
    expiration_time = timedelta(days=30)
    return blob.generate_signed_url(expiration=expiration_time)

def load_data_from_gcs(bucket_name, txt1_blob_name, txt2_blob_name, excel_blob_name):
    try:
        # Get URLs for the blobs
        excel_url = get_blob_url(bucket_name, excel_blob_name)
        txt1_url = get_blob_url(bucket_name, txt1_blob_name)
        txt2_url = get_blob_url(bucket_name, txt2_blob_name)

        # Download the files using requests
        excel_response = requests.get(excel_url)
        txt1_response = requests.get(txt1_url)
        txt2_response = requests.get(txt2_url)

        # Check for successful response status
        if excel_response.status_code == 200:
            excel_content = excel_response.content
        else:
            raise Exception(f"Failed to download Excel file from {excel_url}")

        if txt1_response.status_code == 200:
            txt1_content = txt1_response.content
        else:
            raise Exception(f"Failed to download text file from {txt1_url}")

        if txt2_response.status_code == 200:
            txt2_content = txt2_response.content
        else:
            raise Exception(f"Failed to download text file from {txt2_url}")

        print("Downloading files...")

        # Read the files into pandas DataFrames directly from response contents
        with pd.ExcelFile(io.BytesIO(excel_content)) as excel_file:
            fact_table = pd.read_excel(excel_file, "Clients - Banking")
            dim_nationality = pd.read_excel(excel_file, "Nationality")
            dim_client_name = pd.read_excel(excel_file, "Clients")
```

```python
        dim_banking_contact = pd.read_csv(io.BytesIO(txt1_content), delimiter=';')
        dim_investment_advisor = pd.read_csv(io.BytesIO(txt2_content), delimiter=',')

        print(f'Successfully downloaded tables: \n \n {fact_table}, {dim_nationality}, {dim_c

        return fact_table, dim_nationality, dim_client_name, dim_banking_contact, dim_investm
        print('Successfully downloaded tables')

    except Exception as e:
        print(f"Error loading data: {e}")
        return None, None, None, None, None  # Return a tuple with None values

# Load data
fact_table, dim_nationality, dim_client_name, dim_banking_contact, dim_investment_advisor = l
```

```
Downloading files...
Successfully downloaded tables:

      Client ID  Age Sex  Joined Bank Banking Contact ID NationalityID  \
0       NZ81288   24   M        42391               BC_4             I
1       NZ65833   23   M        36035              BC_26             M
2       NZ47499   27   F        39003               BC_2             E
3       NZ72498   40   M        32856              BC_46             I
4       NZ60181   46   F        39910              BC_43             I
...         ...  ...  ..          ...                ...           ...
2995    NZ66827   82   F        40721              BC_27             I
2996    NZ40556   44   F        38649              BC_12             E
2997    NZ72414   70   F        38976              BC_29             I
2998    NZ46652   56   F        37561              BC_32             E
2999    NZ40216   79   F        37494              BC_24             I

                         Occupation AdvisorID  Last Contact  Last Meeting  \
0             Safety Technician IV      IA20         42305         42281
1              Software Consultant       IA9         42310         42388
2               Help Desk Operator       IA4         42276         42161
3                     Geologist II       IA3         42198         42227
4              Assistant Professor      IA12         42415         42519
...                             ...       ...           ...           ...
2995       Accounting Assistant III       IA2         42498         42423
2996                      Paralegal      IA16         42174         42380
2997                Statistician IV      IA19         42236         42130
2998  Human Resources Assistant III      IA11         42300         42377
2999              Biostatistician III      IA16         42399         42232

      ... Amount of Credit Cards Credit Card Balance    Bank Loans  \
0     ...                      1            484.5440  7.762429e+05
1     ...                      1           2256.8777  1.270615e+06
2     ...                      2           4568.7438  1.052716e+06
3     ...                      2           4205.0010  1.211951e+05
4     ...                      1           3779.4880  1.048302e+06
...   ...                    ...                 ...           ...
2995  ...                      1            649.8540  2.239351e+05
2996  ...                      1           1639.0350  5.959020e+05
2997  ...                      1           2352.8448  8.804930e+05
2998  ...                      2           3578.6088  2.686250e+05
2999  ...                      1           1494.6876  2.856407e+05

      Bank Deposits  Checking Accounts  Saving Accounts  \
0      1.485829e+06       6.036179e+05    607332.455240
1      6.414828e+05       2.295214e+05    344635.157402
2      1.033402e+06       6.526747e+05    203054.348179
3      1.048157e+06       1.048157e+06    234685.019326
4      4.877825e+05       4.466442e+05    128351.452320
...             ...                ...              ...
2995   1.089957e+06       5.328679e+05    657849.619325
2996   1.368913e+05       5.658174e+04     93195.608103
2997   2.148609e+05       1.587261e+05     35539.152952
2998   7.426302e+05       4.046383e+05     56411.334112
2999   6.561766e+04       7.776908e+04     32371.380536

      Foreign Currency Account  Business Lending  Properties Owned  \
0                   12249.9584      1.134475e+06                 1
1                   61162.3089      2.000526e+06                 1
2                   79071.7794      5.481376e+05                 1
3                   57513.6520      1.148402e+06                 0
4                   30012.1360      1.674412e+06                 0
...                        ...               ...               ...
2995                12947.3100      1.238860e+06                 1
2996                23205.6900      2.771711e+05                 1
2997                30291.8112      5.029472e+05                 2
2998                 6413.1444      1.538369e+06                 3
```

```
2999                 8992.3608      3.294125e+05                1

      Risk Weighting
0                  2
1                  3
2                  3
3                  4
4                  3
...              ...
2995               3
2996               2
2997               2
2998               1
2999               1

[3000 rows x 25 columns],         Nationality NationalityID
0             Asian             A
1          European             E
2            Indian             I
3             Maori             M
4  Pacific Islander            PI,      Client ID             Name
0      NZ63534     Aaron Bryant
1      NZ71163      Aaron Burke
2      NZ79052       Aaron Cook
3      NZ56539        Aaron Day
4      NZ88814    Aaron Edwards
...        ...              ...
2995   NZ24672  Willie Stephens
2996   NZ55262  Willie Sullivan
2997   NZ75766    Willie Wagner
2998   NZ77494    Willie Walker
2999   NZ89151   Willie Wheeler

[3000 rows x 2 columns],         Banking Contact Banking Contact ID
0        Adam Hernandez               BC_1
1         Anthony Berry               BC_2
2       Anthony Simpson               BC_3
3        Anthony Torres               BC_4
4          Benjamin Kim               BC_5
5          Bobby Burton               BC_6
6          Bruce Butler               BC_7
7          Bruce Porter               BC_8
8           Carl Nguyen               BC_9
9       Chris Armstrong              BC_10
10        Dennis Morris              BC_11
11          Dennis Ruiz              BC_12
12      Donald Reynolds              BC_13
13       Douglas Tucker              BC_14
14        Ernest Rivera              BC_15
15          Frank Brown              BC_16
16         George Lewis              BC_17
17      Gregory Simmons              BC_18
18       James Castillo              BC_19
19         Jason Duncan              BC_20
20       Jeremy Vasquez              BC_21
21          Jerry Green              BC_22
22          Jesse Evans              BC_23
23           Joe Hanson              BC_24
24            Joe Price              BC_25
25     Jonathan Hawkins              BC_26
26       Joshua Bennett              BC_27
27        Joshua Little              BC_28
28          Joshua Ryan              BC_29
29        Keith Griffin              BC_30
30       Mark Montgomery             BC_31
31  Nicholas Cunningham              BC_32
```

```
32      Nicholas Simmons            BC_33
33        Patrick Graham            BC_34
34           Paul Holmes            BC_35
35           Paul Larson            BC_36
36        Phillip Peters            BC_37
37     Raymond Alexander            BC_38
38      Roger Alexander             BC_39
39              Roy Rice            BC_40
40        Samuel Fowler             BC_41
41            Shawn Cook            BC_42
42            Shawn Long            BC_43
43         Shawn Wallace            BC_44
44         Stephen Payne            BC_45
45            Steve Diaz            BC_46
46          Todd Roberts            BC_47
47       Victor Martinez            BC_48
48          Victor Ramos            BC_49,     Investment Advisor     ID
0       Carl Anderson    IA1
1      Daniel Carroll    IA2
2           Eric Shaw    IA3
3       Ernest Knight    IA4
4   Eugene Cunningham    IA5
5         Fred Bryant    IA6
6        Gregory Boyd    IA7
7       Jack Phillips    IA8
8       Jeremy Porter    IA9
9         Joe Carroll   IA10
10       Juan Ramirez   IA11
11           Kevin Kim  IA12
12   Lawrence Sanchez   IA13
13  Nicholas Morrison   IA14
14      Nicholas Ward   IA15
15     Peter Castillo   IA16
16        Ryan Taylor   IA17
17      Sean Vasquez    IA18
18     Steve Sanchez    IA19
19        Victor Dean   IA20
20   Victor Gutierrez   IA21
21      Victor Rogers   IA22
```

In [3]:
```
# Overview of fact table
fact_table.head()
```

Out[3]:

	Client ID	Age	Sex	Joined Bank	Banking Contact ID	NationalityID	Occupation	AdvisorID	Last Contact	Last Meeting	...
0	NZ81288	24	M	42391	BC_4	I	Safety Technician IV	IA20	42305	42281	...
1	NZ65833	23	M	36035	BC_26	M	Software Consultant	IA9	42310	42388	...
2	NZ47499	27	F	39003	BC_2	E	Help Desk Operator	IA4	42276	42161	...
3	NZ72498	40	M	32856	BC_46	I	Geologist II	IA3	42198	42227	...
4	NZ60181	46	F	39910	BC_43	I	Assistant Professor	IA12	42415	42519	...

5 rows × 25 columns

In [ ]:

```

```

In [4]:

```
# Info for shape, column names and data types
# Notice that dates are stored as int64, need to ceonvert them into datetime format
fact_table.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 25 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Client ID                 3000 non-null   object 
 1   Age                       3000 non-null   int64  
 2   Sex                       3000 non-null   object 
 3   Joined Bank               3000 non-null   int64  
 4   Banking Contact ID        3000 non-null   object 
 5   NationalityID             3000 non-null   object 
 6   Occupation                3000 non-null   object 
 7   AdvisorID                 3000 non-null   object 
 8   Last Contact              3000 non-null   int64  
 9   Last Meeting              3000 non-null   int64  
 10  Fee Structure ID          3000 non-null   object 
 11  Loyalty Classification    3000 non-null   object 
 12  Banking Relationship      3000 non-null   object 
 13  Estimated Income          3000 non-null   float64
 14  Superannuation Savings    3000 non-null   float64
 15  Amount of Credit Cards    3000 non-null   int64  
 16  Credit Card Balance       3000 non-null   float64
 17  Bank Loans                3000 non-null   float64
 18  Bank Deposits             3000 non-null   float64
 19  Checking Accounts         3000 non-null   float64
 20  Saving Accounts           3000 non-null   float64
 21  Foreign Currency Account  3000 non-null   float64
 22  Business Lending          3000 non-null   float64
 23  Properties Owned          3000 non-null   int64  
 24  Risk Weighting            3000 non-null   int64  
dtypes: float64(9), int64(7), object(9)
memory usage: 586.1+ KB
```

In [5]:

```
# Convert excel dates into datetime format
def convert_dates(table):
    date_columns = ['Joined Bank','Last Contact', 'Last Meeting']
    table[date_columns] = table[date_columns].apply(pd.to_datetime, unit='D', origin='1899-12
    return table

dates_converted_table = convert_dates(fact_table)
dates_converted_table[['Joined Bank','Last Contact', 'Last Meeting']]
```

Out[5]:

	Joined Bank	Last Contact	Last Meeting
0	2016-01-22	2015-10-28	2015-10-04
1	1998-08-28	2015-11-02	2016-01-19
2	2006-10-13	2015-09-29	2015-06-06
3	1989-12-14	2015-07-13	2015-08-11
4	2009-04-07	2016-02-15	2016-05-29
...	...	...	...
2995	2011-06-27	2016-05-08	2016-02-23
2996	2005-10-24	2015-06-19	2016-01-11
2997	2006-09-16	2015-08-20	2015-05-06
2998	2002-11-01	2015-10-23	2016-01-08
2999	2002-08-26	2016-01-30	2015-08-16

3000 rows × 3 columns

In [6]:

```
# Creating new features that might be useful for detection of anomalies in differences
# between the last contacts made and the time client joined the bank.
# Calculating the difference between Last Contact and Last Meeting.
# Smaller value signals pottential anomaly

def diffrences_in_dates(data):
    # Calculate the days passed between the last meating and the last contact
    data['Contact_to_Meeting_Days'] = (data['Last Meeting'] - data['Last Contact']).dt.days

    # Calculate the days since client joined the bank
    data['Bank_Joined_Days'] = (pd.to_datetime('today') - data['Joined Bank']).dt.days
    return data

fact_df = diffrences_in_dates(dates_converted_table)
fact_df[['Contact_to_Meeting_Days', 'Bank_Joined_Days']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 2 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Contact_to_Meeting_Days  3000 non-null   int64
 1   Bank_Joined_Days         3000 non-null   int64
dtypes: int64(2)
memory usage: 47.0 KB
```

In [ ]:

In [7]:

```
# Missing this step would have cost me 87 clients while joining tables, having clients with sc
# or 2.96% of data, which is a significant portion considering the size of the data.
# Notice the 2940 unique ClientIDs in 3000 non-duplicate rows
fact_df.describe(include='all')
```

Out[7]:

	Client ID	Age	Sex	Joined Bank	Banking Contact ID	NationalityID	Occupation	AdvisorI
count	3000	3000.000000	3000	3000	3000	3000	3000	300
unique	2940	NaN	2	NaN	49	5	195	2
top	NZ48103	NaN	F	NaN	BC_15	E	Structural Analysis Engineer	IA
freq	3	NaN	1512	NaN	77	1309	28	15
mean	NaN	51.039667	NaN	2002-10-15 22:29:45.600000128	NaN	NaN	NaN	Na
min	NaN	17.000000	NaN	1989-02-08 00:00:00	NaN	NaN	NaN	Na
25%	NaN	34.000000	NaN	1995-09-17 18:00:00	NaN	NaN	NaN	Na
50%	NaN	51.000000	NaN	2002-10-30 00:00:00	NaN	NaN	NaN	Na
75%	NaN	69.000000	NaN	2009-11-22 00:00:00	NaN	NaN	NaN	Na
max	NaN	85.000000	NaN	2016-05-30 00:00:00	NaN	NaN	NaN	Na
std	NaN	19.854760	NaN	NaN	NaN	NaN	NaN	Na

11 rows × 27 columns

In [8]:

```
# Identify duplicates in the fact table
duplicates = fact_df[fact_df.duplicated()]
duplicates
```

Out[8]:

Client ID	Age	Sex	Joined Bank	Banking Contact ID	NationalityID	Occupation	AdvisorID	Last Contact	Last Meeting	...	Ba Lo

0 rows × 27 columns

In [ ]:

In [9]:

```
# No nulls in this data
fact_df.isnull().sum()
```

Out[9]:
```
Client ID                    0
Age                          0
Sex                          0
Joined Bank                  0
Banking Contact ID           0
NationalityID                0
Occupation                   0
AdvisorID                    0
Last Contact                 0
Last Meeting                 0
Fee Structure ID             0
Loyalty Classification       0
Banking Relationship         0
Estimated Income             0
Superannuation Savings       0
Amount of Credit Cards       0
Credit Card Balance          0
Bank Loans                   0
Bank Deposits                0
Checking Accounts            0
Saving Accounts              0
Foreign Currency Account     0
Business Lending             0
Properties Owned             0
Risk Weighting               0
Contact_to_Meeting_Days      0
Bank_Joined_Days             0
dtype: int64
```

In [10]:
```
# Preview of data in dim table nationality
dim_nationality
```

Out[10]:

	Nationality	NationalityID
0	Asian	A
1	European	E
2	Indian	I
3	Maori	M
4	Pacific Islander	PI

In [11]:
```
# General information about dataframe, number of features and their datatypes
dim_nationality.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Nationality    5 non-null      object
 1   NationalityID  5 non-null      object
dtypes: object(2)
memory usage: 212.0+ bytes
```

In [12]:
```
# Preview of data in dim table client_name
dim_client_name.head()
```

Out[12]:

	Client ID	Name
0	NZ63534	Aaron Bryant
1	NZ71163	Aaron Burke
2	NZ79052	Aaron Cook
3	NZ56539	Aaron Day
4	NZ88814	Aaron Edwards

In [13]:
```
dim_client_name.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Client ID  3000 non-null   object
 1   Name       3000 non-null   object
dtypes: object(2)
memory usage: 47.0+ KB
```

In [14]:
```
# This step was the most important step in cleaning and joining all five  into tables into one
# Realizing that there were mistyped (duplicated) ClientIDs in this dim table, which would hav
# the size of the already small data in fact table
dim_client_name['Client ID'].nunique()
```

Out[14]: 2940

In [15]:
```
# Identifying mistyped IDs
dim_client_name[dim_client_name['Client ID'].duplicated()]
```

Out[15]:

	Client ID	Name
908	NZ70122	Eugene Johnson
952	NZ19673	Frank Harper
1012	NZ48103	George Jones
1032	NZ52909	Gerald Frazier
1059	NZ43081	Gregory Meyer
1076	NZ40048	Harold Hunt
1085	NZ89040	Harold Williams
1121	NZ66416	Helen Brooks
1205	NZ76462	James Collins
1261	NZ37323	Jeffrey Adams
1345	NZ71209	Jesse Henderson
1435	NZ97314	John Davis
1468	NZ80089	Johnny Ryan
1483	NZ81182	Jonathan Larson
1509	NZ89708	Jose Romero
1512	NZ85232	Jose Stewart
1618	NZ35589	Judy Lawrence
1641	NZ87901	Justin Alvarez
1728	NZ17019	Keith Fuller
1740	NZ49489	Keith Weaver
1746	NZ85958	Kelly Grant
1750	NZ94062	Kelly Richards
1772	NZ93058	Kenneth Ramos
1783	NZ54314	Kevin Gomez
1787	NZ57483	Kevin Knight
1801	NZ31887	Kevin Weaver
1923	NZ96193	Lori Hawkins
1956	NZ15088	Margaret Coleman
1970	NZ26283	Maria Phillips
2052	NZ71679	Matthew Carroll
2133	NZ35485	Nancy Rogers
2159	NZ45303	Nicole Hall
2171	NZ69834	Norma Murphy
2174	NZ36167	Norma Sanchez
2186	NZ48103	Pamela Simmons
2259	NZ46502	Peter Simmons

	Client ID	Name
2289	NZ31656	Phillip Hansen
2299	NZ50658	Phillip Ryan
2326	NZ32752	Ralph Greene
2349	NZ46155	Randy Kim
2453	NZ88769	Roger Rose
2465	NZ74305	Ronald Larson
2484	NZ27091	Rose Myers
2494	NZ65968	Roy Hughes
2522	NZ74203	Russell Day
2531	NZ67912	Russell Lawson
2550	NZ35051	Ruth Kennedy
2556	NZ62022	Ruth Weaver
2573	NZ94055	Ryan Weaver
2575	NZ58197	Samuel Alvarez
2602	NZ18812	Samuel Wright
2709	NZ73287	Stephanie Grant
2779	NZ86610	Tammy Pierce
2805	NZ50738	Terry Shaw
2832	NZ87256	Thomas Reid
2913	NZ15955	Victor Williams
2962	NZ28199	Wayne Lane
2966	NZ54095	William Alvarez
2975	NZ84825	William Holmes
2988	NZ66163	Willie Lopez

In [16]:
```
# Getting the number of mistyped IDs
len(dim_client_name[dim_client_name['Client ID'].duplicated()])
```

Out[16]: 60

In [17]:
```
# Which IDs occure more then once?
mystyped_IDs = dim_client_name['Client ID'].value_counts()
mystyped_IDs[mystyped_IDs > 1]
```

Out[17]:
```
Client ID
NZ48103    3
NZ50738    2
NZ93058    2
NZ15088    2
NZ18812    2
NZ94055    2
NZ65968    2
NZ86610    2
NZ69834    2
NZ52909    2
NZ66163    2
NZ76462    2
NZ71679    2
NZ40048    2
NZ87901    2
NZ89708    2
NZ36167    2
NZ73287    2
NZ54314    2
NZ54095    2
NZ19673    2
NZ89040    2
NZ35589    2
NZ49489    2
NZ46502    2
NZ97314    2
NZ46155    2
NZ84825    2
NZ81182    2
NZ15955    2
NZ87256    2
NZ17019    2
NZ74305    2
NZ35485    2
NZ35051    2
NZ45303    2
NZ31656    2
NZ85958    2
NZ80089    2
NZ85232    2
NZ58197    2
NZ31887    2
NZ28199    2
NZ67912    2
NZ43081    2
NZ71209    2
NZ94062    2
NZ26283    2
NZ32752    2
NZ37323    2
NZ57483    2
NZ70122    2
NZ27091    2
NZ96193    2
NZ88769    2
NZ66416    2
NZ62022    2
NZ50658    2
NZ74203    2
Name: count, dtype: int64
```

In [18]:
```
# One ID has three occurences
dim_client_name[dim_client_name['Client ID'] == 'NZ48103']
```

Out[18]:

	Client ID	Name
792	NZ48103	Douglas Cole
1012	NZ48103	George Jones
2186	NZ48103	Pamela Simmons

In [19]:

```
# Overview of Banking Contact dim table

dim_banking_contact.head()
```

Out[19]:

	Banking Contact	Banking Contact ID
0	Adam Hernandez	BC_1
1	Anthony Berry	BC_2
2	Anthony Simpson	BC_3
3	Anthony Torres	BC_4
4	Benjamin Kim	BC_5

In [20]:

```
# Getting info
dim_banking_contact.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49 entries, 0 to 48
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Banking Contact     49 non-null     object
 1   Banking Contact ID  49 non-null     object
dtypes: object(2)
memory usage: 916.0+ bytes
```

In [21]:

```
# Identify duplicates in IDs
dim_banking_contact['Banking Contact ID'].nunique()
```

Out[21]: 49

In [22]:

```
# Overview of Investment Advisor dim table
dim_investment_advisor.tail()
```

Out[22]:

	Investment Advisor	ID
17	Sean Vasquez	IA18
18	Steve Sanchez	IA19
19	Victor Dean	IA20
20	Victor Gutierrez	IA21
21	Victor Rogers	IA22

In [23]:

```
# Getting info - no nulls
dim_investment_advisor.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22 entries, 0 to 21
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Investment Advisor  22 non-null     object
 1    ID                 22 non-null     object
dtypes: object(2)
memory usage: 484.0+ bytes
```

In [24]:
```
# Trying to get if any duplicate IDs
# dim_investment_advisor['ID'].nunique()
```

--- KeyError: 'ID'

In [25]:
```
# Since my intention was to flatten the data by joining all of the tables, I encountered the j
# a very unclean data, having leading and trailing whitespaces across all tables
# Notice the leading whitespace in ID column
dim_investment_advisor.columns
```

Out[25]:
```
Index(['Investment Advisor', ' ID'], dtype='object')
```

In [26]:
```
# Define a function to clean the column names and string values in all five tables
def clean_tables(df):
    # Strip whitespace from column names
    df.columns = df.columns.str.strip()
    # Strip whitespace from string values in all columns
    for col in df.select_dtypes(include=['object']).columns:
        df[col] = df[col].str.strip()
    return df

tables_to_be_cleaned = [fact_df, dim_client_name, dim_banking_contact, dim_nationality, dim_i
# Clean all tables in the list
tables_cleaned = [clean_tables(table) for table in tables_to_be_cleaned]

# Clean all tables in the list
dim_investment_advisor.columns
```

Out[26]:
```
Index(['Investment Advisor', 'ID'], dtype='object')
```

Merging tables

In [27]:
```
# Add an occurrence count column to both dataframes
fact_data = fact_df.copy()

def merge_fact_dim_tables(df, dim_client, dim_nat, dim_b_contact, dim_inv_adv):
    # In oder to preserve all the observations in th fact table I had to count all the occurer
    # of an ClientID in both tables
    df['Occurrence'] = df.groupby('Client ID').cumcount() + 1
    dim_client['Occurrence'] = dim_client.groupby('Client ID').cumcount() + 1

    # and then add the names to IDs by the order of occurence
    fact_data = df.merge(dim_client, how ='left', on=['Client ID', 'Occurrence']) \
    .merge(dim_nat, on='NationalityID', how ='left') \
    .merge(dim_b_contact, on='Banking Contact ID', how ='left') \
    .merge(dim_inv_adv, left_on='AdvisorID', right_on ='ID', how ='left')

    # Drop the occurrence column if it's no longer needed
    fact_data = fact_data.drop(columns=['Occurrence', 'ID'], axis =1)
    fact_data.reset_index(drop = True)
    return fact_data

flatten_table = merge_fact_dim_tables(fact_data, dim_client_name, dim_nationality, dim_bankin
flatten_table
```

Out[27]:

	Client ID	Age	Sex	Joined Bank	Banking Contact ID	NationalityID	Occupation	AdvisorID	Last Contact	Last Meeting
0	NZ81288	24	M	2016-01-22	BC_4	I	Safety Technician IV	IA20	2015-10-28	2015-10-04
1	NZ65833	23	M	1998-08-28	BC_26	M	Software Consultant	IA9	2015-11-02	2016-01-19
2	NZ47499	27	F	2006-10-13	BC_2	E	Help Desk Operator	IA4	2015-09-29	2015-06-06
3	NZ72498	40	M	1989-12-14	BC_46	I	Geologist II	IA3	2015-07-13	2015-08-11
4	NZ60181	46	F	2009-04-07	BC_43	I	Assistant Professor	IA12	2016-02-15	2016-05-29
...	...	...	...	...	...	...	...	...	...	...
2995	NZ66827	82	F	2011-06-27	BC_27	I	Accounting Assistant III	IA2	2016-05-08	2016-02-23
2996	NZ40556	44	F	2005-10-24	BC_12	E	Paralegal	IA16	2015-06-19	2016-01-11
2997	NZ72414	70	F	2006-09-16	BC_29	I	Statistician IV	IA19	2015-08-20	2015-05-06
2998	NZ46652	56	F	2002-11-01	BC_32	E	Human Resources Assistant III	IA11	2015-10-23	2016-01-08
2999	NZ40216	79	F	2002-08-26	BC_24	I	Biostatistician III	IA16	2016-01-30	2015-08-16

3000 rows × 31 columns

In [28]:

```python
import requests
from datetime import datetime

# Get today's date
today = datetime.today().strftime('%d.%m.%Y')

# Display the result
# print(f"Today's date is: {today}")

# NBRM API (Macedonian National bank)
nbrm_url = f'https://www.nbrm.mk/KLServiceNOV/GetExchangeRates?StartDate={today}&EndDate={tod

def get_rate_from_api(url):

    # Send the GET request
    response = requests.get(url)
    # print(response.status_code) # check if successful

    # Parse the JSON response
    if response.status_code == 200:
        kursna_lista = response.json()

        eur_to_mkd_rate = None
        for rate in kursna_lista:
            if rate['oznaka'] == 'EUR':
                eur_to_mkd_rate = rate['sreden']
```

```
                break
        return eur_to_mkd_rate
        if eur_to_mkd_rate is None:
            print("EUR to MKD rate not found in the response.")

    else:
        print("Failed to fetch data from the API.")

eur_to_mkd_rate = get_rate_from_api(nbrm_url)
eur_to_mkd_rate
```

Out[28]: 61.495

In [29]:

```
# Convert all features in MKD to EUR
flatten_data = flatten_table.copy()

def convert_mkd_to_eur(table, eur_to_mkd_rate):
    # Select all features in MKD
    currency_values_in_MKD = ['Estimated Income', 'Superannuation Savings','Credit Card Balan
                              'Bank Deposits','Checking Accounts','Saving Accounts','Business Lendi

    # Fetch the today's rate
    rate = eur_to_mkd_rate

    # Divide all numerical columns by the rate
    table = table.apply(lambda x: x / rate if x.name in currency_values_in_MKD else x)
    return table

convert_mkd_to_eur(flatten_data, eur_to_mkd_rate)

flatten_data[['Estimated Income', 'Superannuation Savings','Amount of Credit Cards', 'Credit 
                'Bank Deposits','Checking Accounts','Saving Accounts','Business Lending']]
```

Out[29]:

	Estimated Income	Superannuation Savings	Amount of Credit Cards	Credit Card Balance	Bank Loans	Bank Deposits	Checking Accounts	
0	75384.7686	17677.95	1	484.5440	7.762429e+05	1.485829e+06	6.036179e+05	6
1	289834.3140	17398.92	1	2256.8777	1.270615e+06	6.414828e+05	2.295214e+05	3
2	169935.2252	42825.90	2	4568.7438	1.052716e+06	1.033402e+06	6.526747e+05	2
3	356808.1125	5473.15	2	4205.0010	1.211951e+05	1.048157e+06	1.048157e+06	2
4	130711.6800	48077.60	1	3779.4880	1.048302e+06	4.877825e+05	4.466442e+05	1
...	...	...	...	...	...	...	...	
2995	297617.1424	61177.60	1	649.8540	2.239351e+05	1.089957e+06	5.328679e+05	6
2996	42397.4628	33356.88	1	1639.0350	5.959020e+05	1.368913e+05	5.658174e+04	
2997	48339.8784	18889.92	1	2352.8448	8.804930e+05	2.148609e+05	1.587261e+05	
2998	107265.8691	11283.09	2	3578.6088	2.686250e+05	7.426302e+05	4.046383e+05	
2999	56826.5324	8855.30	1	1494.6876	2.856407e+05	6.561766e+04	7.776908e+04	

3000 rows × 9 columns

In [30]:

```
# Checking if everything is in place
flatten_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 31 columns):
 #   Column                   Non-Null Count  Dtype         
---  ------                   --------------  -----         
 0   Client ID                3000 non-null   object        
 1   Age                      3000 non-null   int64         
 2   Sex                      3000 non-null   object        
 3   Joined Bank              3000 non-null   datetime64[ns]
 4   Banking Contact ID       3000 non-null   object        
 5   NationalityID            3000 non-null   object        
 6   Occupation               3000 non-null   object        
 7   AdvisorID                3000 non-null   object        
 8   Last Contact             3000 non-null   datetime64[ns]
 9   Last Meeting             3000 non-null   datetime64[ns]
 10  Fee Structure ID         3000 non-null   object        
 11  Loyalty Classification   3000 non-null   object        
 12  Banking Relationship     3000 non-null   object        
 13  Estimated Income         3000 non-null   float64       
 14  Superannuation Savings   3000 non-null   float64       
 15  Amount of Credit Cards   3000 non-null   int64         
 16  Credit Card Balance      3000 non-null   float64       
 17  Bank Loans               3000 non-null   float64       
 18  Bank Deposits            3000 non-null   float64       
 19  Checking Accounts        3000 non-null   float64       
 20  Saving Accounts          3000 non-null   float64       
 21  Foreign Currency Account 3000 non-null   float64       
 22  Business Lending         3000 non-null   float64       
 23  Properties Owned         3000 non-null   int64         
 24  Risk Weighting           3000 non-null   int64         
 25  Contact_to_Meeting_Days  3000 non-null   int64         
 26  Bank_Joined_Days         3000 non-null   int64         
 27  Name                     3000 non-null   object        
 28  Nationality              3000 non-null   object        
 29  Banking Contact          3000 non-null   object        
 30  Investment Advisor       3000 non-null   object        
dtypes: datetime64[ns](3), float64(9), int64(6), object(13)
memory usage: 726.7+ KB
```

In [31]:
```python
# Get the right names of features
flatten_data.columns
```

Out[31]:
```
Index(['Client ID', 'Age', 'Sex', 'Joined Bank', 'Banking Contact ID',
       'NationalityID', 'Occupation', 'AdvisorID', 'Last Contact',
       'Last Meeting', 'Fee Structure ID', 'Loyalty Classification',
       'Banking Relationship', 'Estimated Income', 'Superannuation Savings',
       'Amount of Credit Cards', 'Credit Card Balance', 'Bank Loans',
       'Bank Deposits', 'Checking Accounts', 'Saving Accounts',
       'Foreign Currency Account', 'Business Lending', 'Properties Owned',
       'Risk Weighting', 'Contact_to_Meeting_Days', 'Bank_Joined_Days', 'Name',
       'Nationality', 'Banking Contact', 'Investment Advisor'],
      dtype='object')
```

In [32]:
```python
# Remove all neccessary features with high cardinality and the Risk Weighting feature
data_uncleaned = flatten_data.copy()

def drop_data(data):
    columns=['Client ID', 'Joined Bank', 'Banking Contact ID', 'NationalityID', 'AdvisorID',
             'Last Contact', 'Last Meeting', 'Risk Weighting']
    data.drop(columns = columns, axis=1, inplace=True)
    data.reset_index(drop=True)

    return data

# Get the cleaned data
data_cleaned = drop_data(data_uncleaned)
```

```
# Create dataset for local ml modeling and for BI analysis on Cloud
data_cleaned = data_cleaned[['Name', 'Age', 'Sex', 'Occupation', 'Nationality', 'Banking Cont
       'Investment Advisor','Fee Structure ID', 'Loyalty Classification',
       'Banking Relationship','Properties Owned','Estimated Income', 'Superannuation Savings'
       'Amount of Credit Cards', 'Credit Card Balance', 'Bank Loans',
       'Bank Deposits', 'Checking Accounts', 'Saving Accounts',
       'Foreign Currency Account', 'Business Lending','Contact_to_Meeting_Days', 'Bank_Joined

data_cleaned.head(3)
```

Out[32]:

	Name	Age	Sex	Occupation	Nationality	Banking Contact	Investment Advisor	Fee Structure ID	Loyalty Classification	B Relati
0	Raymond Mills	24	M	Safety Technician IV	Indian	Anthony Torres	Victor Dean	H	Jade	
1	Julia Spencer	23	M	Software Consultant	Maori	Jonathan Hawkins	Jeremy Porter	H	Jade	
2	Stephen Murray	27	F	Help Desk Operator	European	Anthony Berry	Ernest Knight	H	Gold	Insti

3 rows × 23 columns

In [33]:

```
# Create dataset for ml on Cloud
data_cleaned_for_ml_gcs = data_cleaned.copy()

data_cleaned_for_ml_gcs.drop(columns = ['Name', 'Banking Contact', 'Investment Advisor'], axi
data_cleaned_for_ml_gcs.reset_index(drop=True)
```

Out[33]:

	Age	Sex	Occupation	Nationality	Fee Structure ID	Loyalty Classification	Banking Relationship	Properties Owned	Estima Inco
0	24	M	Safety Technician IV	Indian	H	Jade	Retail	1	75384.7
1	23	M	Software Consultant	Maori	H	Jade	Retail	1	289834.3
2	27	F	Help Desk Operator	European	H	Gold	Institutional	1	169935.2
3	40	M	Geologist II	Indian	MR	Silver	Investments Only	0	356808.1
4	46	F	Assistant Professor	Indian	MR	Platinum	Private Bank	0	130711.6
...	...	...	...	...	...	...	...	...	
2995	82	F	Accounting Assistant III	Indian	H	Gold	Retail	1	297617.1
2996	44	F	Paralegal	European	MR	Gold	Private Bank	1	42397.4
2997	70	F	Statistician IV	Indian	L	Jade	Retail	2	48339.8
2998	56	F	Human Resources Assistant III	European	MR	Jade	Commercial	3	107265.8
2999	79	F	Biostatistician III	Indian	H	Jade	Retail	1	56826.5

3000 rows × 20 columns

Uploading clean data to Cloud

In [34]:

```
# Save and export cleam data to Google Cloud, previously authenticated. Project Bank client ar
# added as default project

import os
from google.cloud import storage
import pyarrow as pa
import pyarrow.parquet as pq
import io

# Google Cloud client already initialized, still ghecking connection....

# Function to create bucket and upload Parquet file
def create_bucket_and_upload_parquet(bucket_name, destination_blob_name, data):
    try:
        client = initialize_gcs_client()

        print('Checking connection to Google Cloud...')

        # Check if bucket exists
        bucket = client.lookup_bucket(bucket_name)
        if bucket:
            print(f"Bucket {bucket_name} already exists. Using the existing bucket....")
        else:
            # Create a new bucket with the specified location
```

```python
            bucket = client.bucket(bucket_name)
            client.create_bucket(bucket)
            print(f"Bucket {bucket_name} created...")

        # Convert DataFrame to CSV file-like object
        csv_buffer = io.StringIO()
        data.to_csv(csv_buffer, index=False)
        csv_buffer.seek(0)

        # Initialize blob in the bucket
        blob = bucket.blob(destination_blob_name)

        try:
            # Check if the blob already exists
            if blob.exists():
                print(f"Blob {destination_blob_name} already exists in bucket {bucket_name}. 
                blob.delete()

            # Upload the file-like object to GCS
            blob.upload_from_file(csv_buffer, content_type='application/octet-stream')
            print(f"DataFrame uploaded to {destination_blob_name} in bucket {bucket_name} as 

        except Exception as e:
            print(f"Error uploading parquet data: {e}")

    except Exception as e:
        print(f"Error connecting to Google Cloud: {e}")

# Define bucket names and blob names
bucket_name_bi = 'bank_clients_bi_data'
destination_blob_bi_name = 'bank_clients_bi_data.csv'

# Copy data
data_cleaned_for_bi_gcs = data_cleaned.copy()

# Upload datasets to respective buckets
create_bucket_and_upload_parquet(bucket_name_bi, destination_blob_bi_name, data_cleaned_for_b
```

```
Checking connection to Google Cloud...
Bucket bank_clients_bi_data already exists. Using the existing bucket....
Blob bank_clients_bi_data.csv already exists in bucket bank_clients_bi_data. Replacing it...
DataFrame uploaded to bank_clients_bi_data.csv in bucket bank_clients_bi_data as CSV file.
```

In [35]:

```python
data_cleaned_for_bi_gcs
```

Out[35]:

	Name	Age	Sex	Occupation	Nationality	Banking Contact	Investment Advisor	Fee Structure ID	Loya Classificati
0	Raymond Mills	24	M	Safety Technician IV	Indian	Anthony Torres	Victor Dean	H	Ja
1	Julia Spencer	23	M	Software Consultant	Maori	Jonathan Hawkins	Jeremy Porter	H	Ja
2	Stephen Murray	27	F	Help Desk Operator	European	Anthony Berry	Ernest Knight	H	Go
3	Virginia Garza	40	M	Geologist II	Indian	Steve Diaz	Eric Shaw	MR	Silv
4	Melissa Sanders	46	F	Assistant Professor	Indian	Shawn Long	Kevin Kim	MR	Platinu
...	...	...	...	...	...	...	...	...	
2995	Earl Hall	82	F	Accounting Assistant III	Indian	Joshua Bennett	Daniel Carroll	H	Go
2996	Billy Williamson	44	F	Paralegal	European	Dennis Ruiz	Peter Castillo	MR	Go
2997	Victor Black	70	F	Statistician IV	Indian	Joshua Ryan	Steve Sanchez	L	Ja
2998	Andrew Ford	56	F	Human Resources Assistant III	European	Nicholas Cunningham	Juan Ramirez	MR	Ja
2999	Amy Nguyen	79	F	Biostatistician III	Indian	Joe Hanson	Peter Castillo	H	Ja

3000 rows × 23 columns

In [36]:

```
data_cleaned_for_ml_gcs
```

Out[36]:

	Age	Sex	Occupation	Nationality	Fee Structure ID	Loyalty Classification	Banking Relationship	Properties Owned	Estima Inco
0	24	M	Safety Technician IV	Indian	H	Jade	Retail	1	75384.7
1	23	M	Software Consultant	Maori	H	Jade	Retail	1	289834.3
2	27	F	Help Desk Operator	European	H	Gold	Institutional	1	169935.2
3	40	M	Geologist II	Indian	MR	Silver	Investments Only	0	356808.1
4	46	F	Assistant Professor	Indian	MR	Platinum	Private Bank	0	130711.6
...	...	...	...	...	...	...	...	...	
2995	82	F	Accounting Assistant III	Indian	H	Gold	Retail	1	297617.1
2996	44	F	Paralegal	European	MR	Gold	Private Bank	1	42397.4
2997	70	F	Statistician IV	Indian	L	Jade	Retail	2	48339.8
2998	56	F	Human Resources Assistant III	European	MR	Jade	Commercial	3	107265.8
2999	79	F	Biostatistician III	Indian	H	Jade	Retail	1	56826.5

3000 rows × 20 columns

ANOMALY DETECTION MODEL CREATION

Now that the data is cleaned, let's go into the depth of EDA and visualisation

Exploratory Data Analysis

In [37]:

```
# Understand more about the data
# The dimensionality of the dataset is high (30 features), having categorical and numerical da
data_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Name                     3000 non-null   object 
 1   Age                      3000 non-null   int64  
 2   Sex                      3000 non-null   object 
 3   Occupation               3000 non-null   object 
 4   Nationality              3000 non-null   object 
 5   Banking Contact          3000 non-null   object 
 6   Investment Advisor       3000 non-null   object 
 7   Fee Structure ID         3000 non-null   object 
 8   Loyalty Classification   3000 non-null   object 
 9   Banking Relationship     3000 non-null   object 
 10  Properties Owned         3000 non-null   int64  
 11  Estimated Income         3000 non-null   float64
 12  Superannuation Savings   3000 non-null   float64
 13  Amount of Credit Cards   3000 non-null   int64  
 14  Credit Card Balance      3000 non-null   float64
 15  Bank Loans               3000 non-null   float64
 16  Bank Deposits            3000 non-null   float64
 17  Checking Accounts        3000 non-null   float64
 18  Saving Accounts          3000 non-null   float64
 19  Foreign Currency Account 3000 non-null   float64
 20  Business Lending         3000 non-null   float64
 21  Contact_to_Meeting_Days  3000 non-null   int64  
 22  Bank_Joined_Days         3000 non-null   int64  
dtypes: float64(9), int64(5), object(9)
memory usage: 539.2+ KB
```

Descriptive Statistical Analysis

In [38]:

```
# Statistical analysis of the data within the categorical features by their datatype
# There are 195 unique occupations in a dataset of 3000 observations, indicating high cardina
# Nevertheless, it might be an important feature having calculated income, balance and loans
# The rest of the categorical features have low cardinality and they will be encoded accordin
data_cleaned.describe(include = 'object')
```

Out[38]:

	Name	Sex	Occupation	Nationality	Banking Contact	Investment Advisor	Fee Structure ID	Loyalty Classification	Rela
count	3000	3000	3000	3000	3000	3000	3000	3000	
unique	2913	2	195	5	49	22	3	4	
top	Raymond Mills	F	Structural Analysis Engineer	European	Ernest Rivera	Eugene Cunningham	H	Jade	
freq	2	1512	28	1309	77	155	1476	1331	

In [39]:

```
# Statistical analysis of the data within the numerical features
# All of them having different standard deviation
# Discrete values in Properties Owned, Amount of Credit Cards and Age
# Continuous values in the rest of the data
data_cleaned.describe(exclude = 'object')
```

Out[39]:

	Age	Properties Owned	Estimated Income	Superannuation Savings	Amount of Credit Cards	Credit Card Balance	Bank Lo
count	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3000.000000	3.000000e
mean	51.039667	1.518667	171305.034094	25531.599673	1.463667	3176.206780	5.913862e
std	19.854760	1.102145	111935.808260	16259.950770	0.676387	2497.094724	4.575570e
min	17.000000	0.000000	15919.475400	1482.030000	1.000000	1.174800	0.000000e
25%	34.000000	1.000000	82906.594300	12513.775000	1.000000	1236.633525	2.396281e
50%	51.000000	2.000000	142313.479600	22357.355000	1.000000	2560.800750	4.797934e
75%	69.000000	2.000000	242290.306650	35464.740000	2.000000	4522.633050	8.258130e
max	85.000000	3.000000	522330.259200	75963.900000	3.000000	13991.994000	2.667557e

Removing irrelevant feature for the model

In [40]:
```
# Removing high cardinality
data = data_cleaned.copy()
data.drop(columns = ['Name', 'Banking Contact', 'Investment Advisor'], axis=1, inplace =True)
data.reset_index(drop=True)
data.columns
```

Out[40]:
```
Index(['Age', 'Sex', 'Occupation', 'Nationality', 'Fee Structure ID',
       'Loyalty Classification', 'Banking Relationship', 'Properties Owned',
       'Estimated Income', 'Superannuation Savings', 'Amount of Credit Cards',
       'Credit Card Balance', 'Bank Loans', 'Bank Deposits',
       'Checking Accounts', 'Saving Accounts', 'Foreign Currency Account',
       'Business Lending', 'Contact_to_Meeting_Days', 'Bank_Joined_Days'],
      dtype='object')
```

In [41]:
```
# Get a list of categorical columns in our dataset
categorical_cols = [col for col in data.columns if data[col].dtype in ['object']]
for col in categorical_cols:
    print(col, ": unique values:" ,data_cleaned[col].nunique())
```

```
Sex : unique values: 2
Occupation : unique values: 195
Nationality : unique values: 5
Fee Structure ID : unique values: 3
Loyalty Classification : unique values: 4
Banking Relationship : unique values: 5
```

In [42]:
```
# Numeric features
numeric_cols = [col for col in data.columns if data[col].dtype in ['int64', 'float64']]
discrete_cols = ['Amount of Credit Cards', 'Properties Owned']
continuous_cols = [col for col in numeric_cols if col not in discrete_cols]
continuous_cols
```

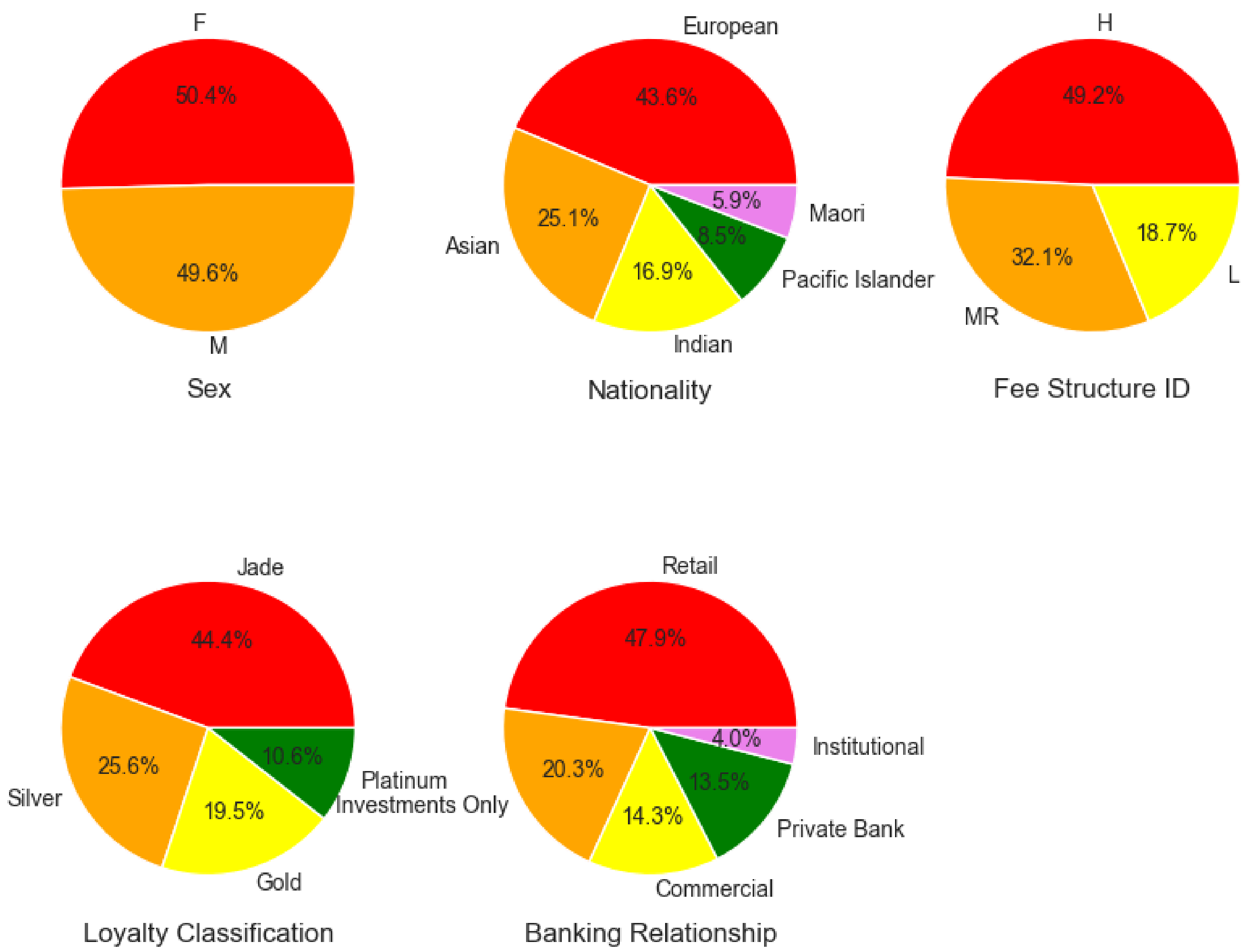
```
Out[42]: ['Age',
 'Estimated Income',
 'Superannuation Savings',
 'Credit Card Balance',
 'Bank Loans',
 'Bank Deposits',
 'Checking Accounts',
 'Saving Accounts',
 'Foreign Currency Account',
 'Business Lending',
 'Contact_to_Meeting_Days',
 'Bank_Joined_Days']
```

```
In [43]: len(continuous_cols)
```

```
Out[43]: 12
```

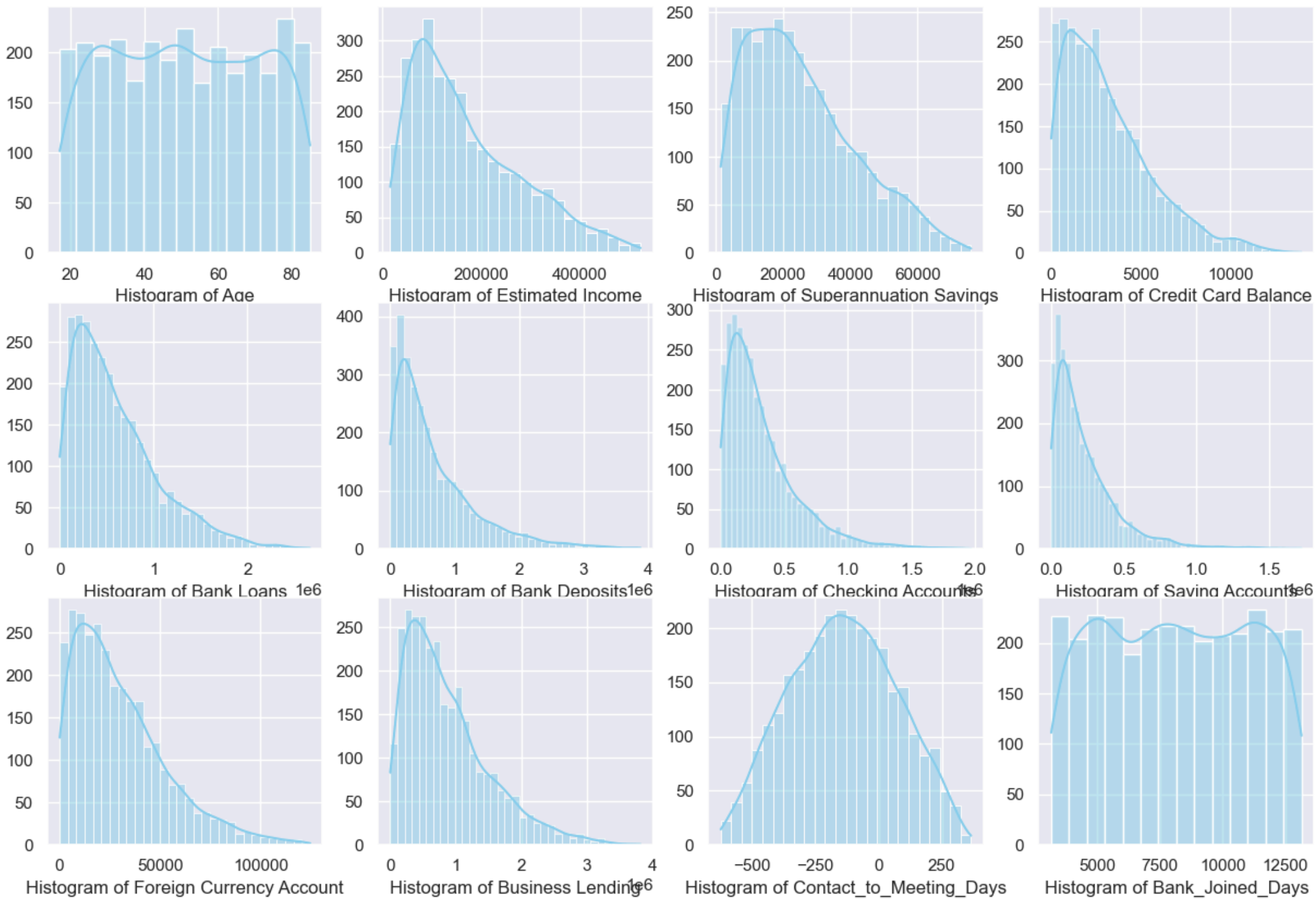
Data visualisation

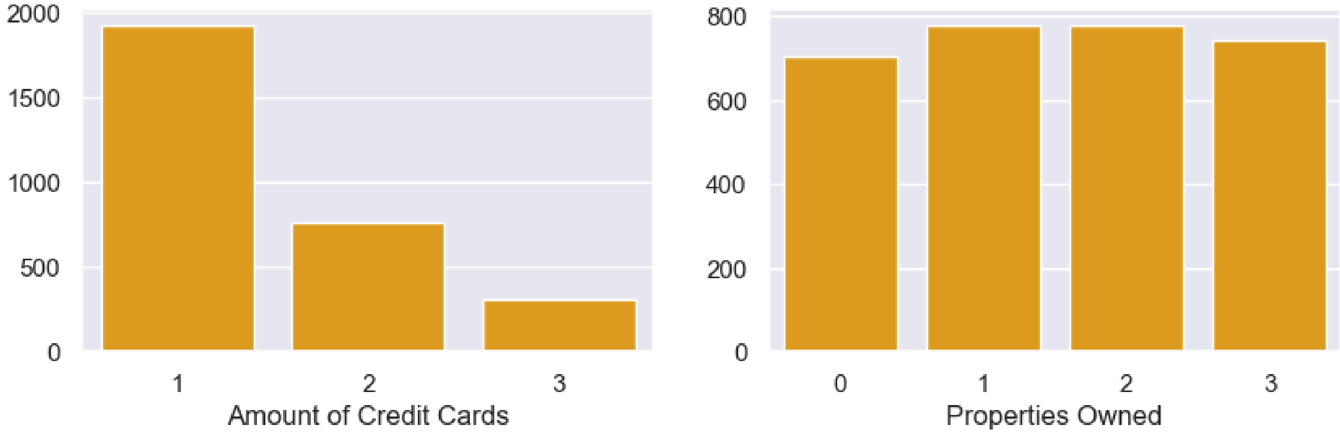
```
In [44]: # Categorical features
categorical_cols.remove('Occupation') # 195 values are not needed to be visualizied
def plot_categorical(data,categorical_cols):
    plt.figure(figsize=(10, 8))
    colors = ['red', 'orange', 'yellow', 'green', 'violet']
    for i, col in enumerate(categorical_cols,1):
        plt.subplot(2,3,i)
        data[col].value_counts().plot.pie(autopct='%1.1f%%', textprops={'fontsize':10},
                                          colors=colors[:len(data[col].value_counts())])
        plt.ylabel('')  # Remove y-axis label to avoid clutter
        plt.xlabel(col)
    plt.show()
plot_categorical(data,categorical_cols)
```



Fee Structure ID mapping: H = High; L = Low; MR = Mid Range (for clarification only, it is ordinal) Nearly 50% of clients are Europian, have Jade (lowest cardinality) cards with High Fee and come from the Retail industry.

In [45]:
```python
# Plot histogram for continuous columns
def plot_numerical(data, continuous_cols, discrete_cols):
    plt.figure(figsize=(15, 10))
    for i, col in enumerate(continuous_cols,1):
        plt.subplot(3,4,i)
        sns.histplot(data[col], kde=True, color='skyblue')
        plt.xlabel(f'Histogram of {col}')
        plt.ylabel('')
    plt.show()

    plt.figure(figsize=(10,6))
    for i, col in enumerate(discrete_cols,1):
        plt.subplot(2,2,i)
        sns.countplot(x=data[col],data=data,color='orange')
        plt.xlabel(col)
        plt.ylabel('')
    plt.show()
plot_numerical(data, continuous_cols, discrete_cols)
```





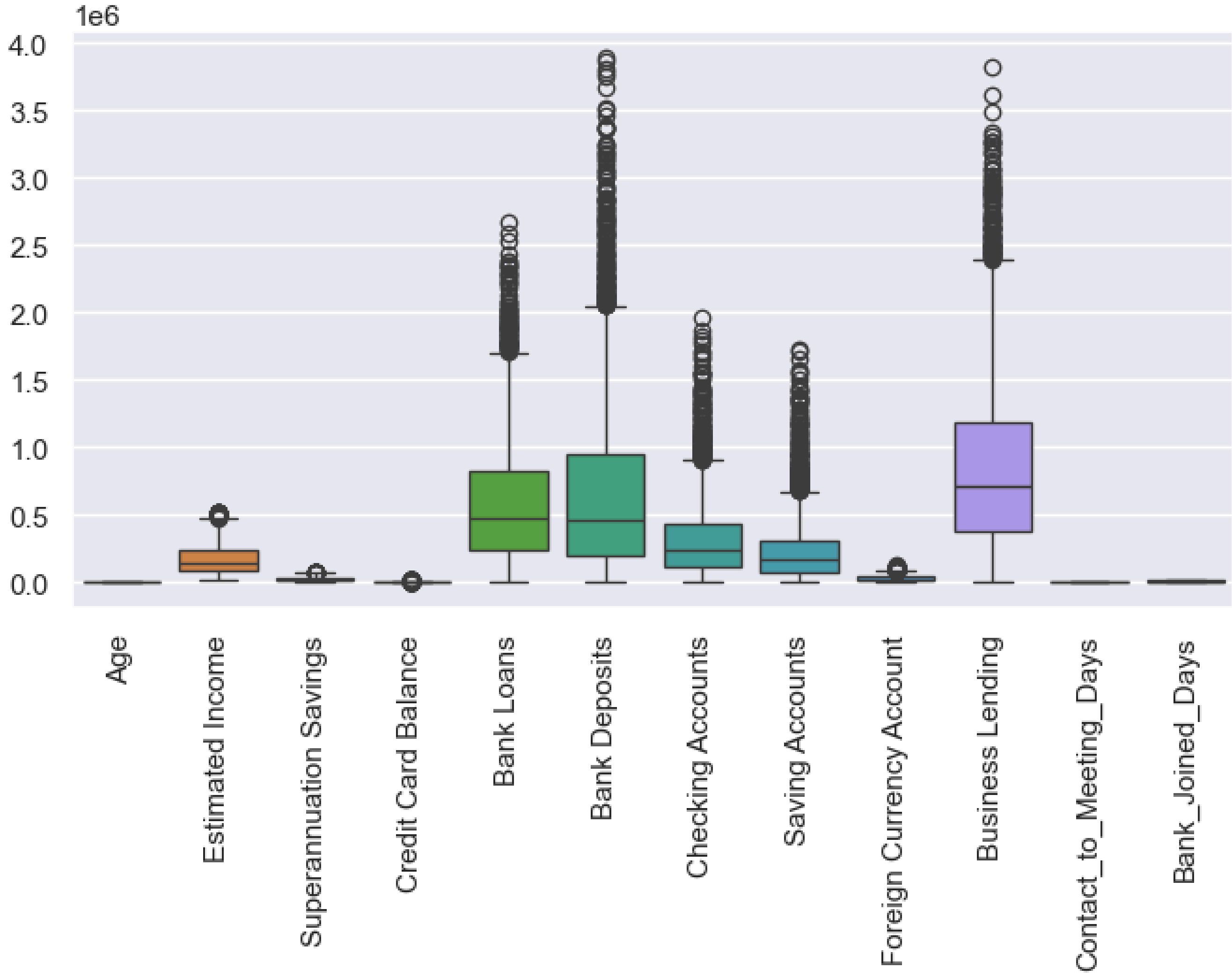
There are clients from all ages in range 17 to 85 (uniform distribution), same number of clients joined the bank in all periods, are the days between the last contact and last meeting held (normaly distributed), while all other continuous features have right skewed distributed values, mostly having lower values The majority of the clients has one credit card, the more cards implies potential fraud The range of properties owned is uniformly distributed among clients

Detecting outliers

In [46]:
```
# Let's check for outliers by applying the IQR method and plot them with box
def detect_outliers(data, continuous_cols):
    Q1 = data[continuous_cols].quantile(0.25)
    Q3 = data[continuous_cols].quantile(0.75)
    IQR = Q3-Q1
    outliers = ((data[continuous_cols] < (Q1-1.5 * IQR)) | (data[continuous_cols] > (Q3 + 1.5
    return outliers
outliers = detect_outliers(data, continuous_cols)
outliers.sum()
```

Out[46]:
```
Age                         0
Estimated Income           26
Superannuation Savings     19
Credit Card Balance        85
Bank Loans                 85
Bank Deposits             149
Checking Accounts         138
Saving Accounts           155
Foreign Currency Account   79
Business Lending           93
Contact_to_Meeting_Days     0
Bank_Joined_Days            0
dtype: int64
```

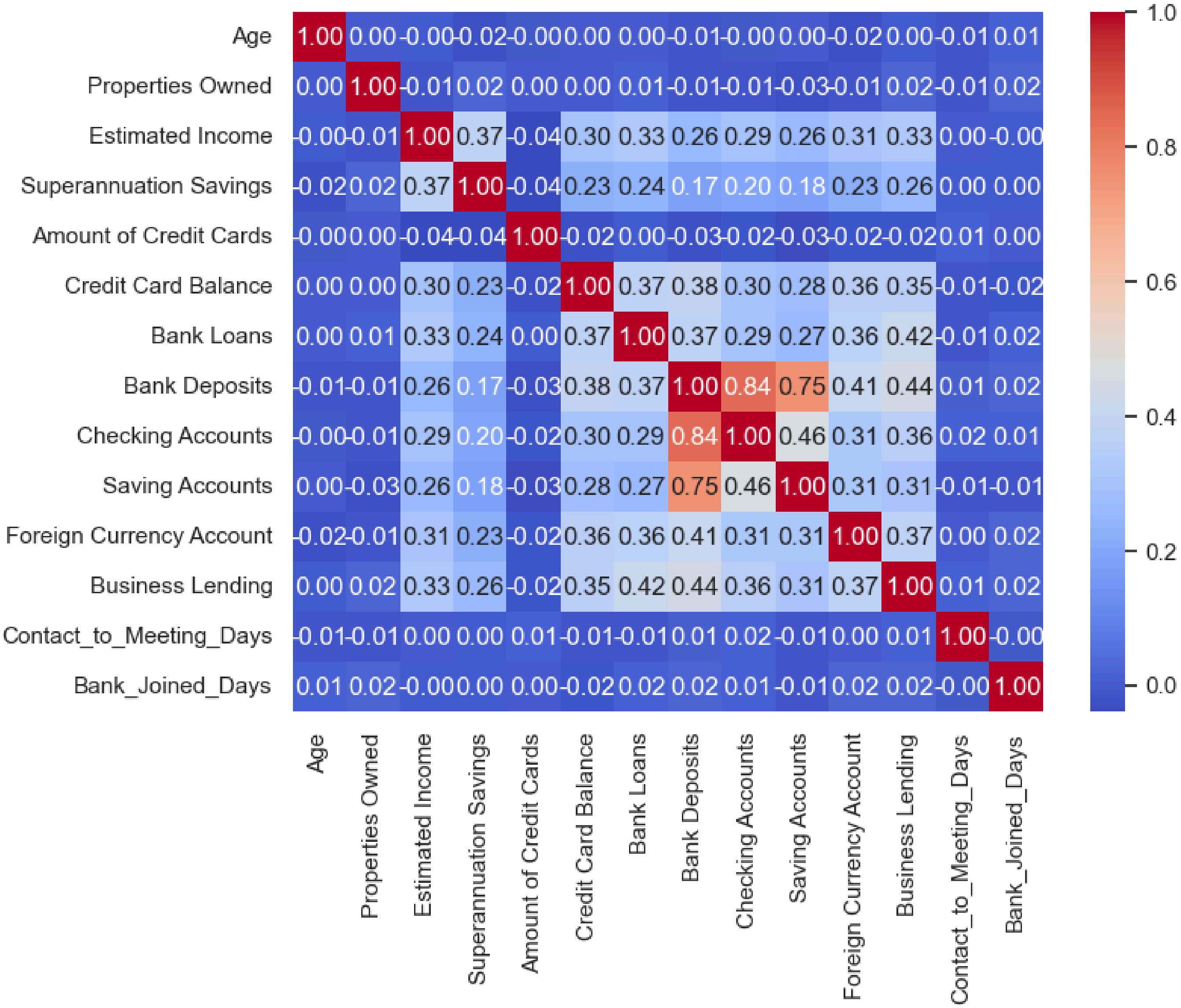
In [47]:
```
# Plot the outliers
def plot_density(data,cols):
    plt.figure(figsize=(8, 4))
    # Plot the boxplot
    # data[continuous_cols].boxplot()
    sns.boxplot(data=data[cols])
    # Rotate x-axis labels by 45 degrees
    plt.xticks(rotation=90)
    # Display the plot
    plt.show()
plot_density(data,continuous_cols)
```



The most of outliers are found with .quantile() in Bank deposits, Checking and Saving Accounts feature. Outlier Removal Tradeoff: Careful with the threshold for removing outliers The higher this threshold is, the less outliers will detect The Tradeoff: I want to focus more on "extreme outliers" rather than just outliers, avoiding the risk of information loss which will cause our models to have a lower performance. That's why I decided to keep the outliers

Correlation

In [48]:
```
# What's the correlation between features? Numerical

correlation = data[numeric_cols].corr()
plt.figure(figsize = (8,6))
sns.heatmap(correlation, annot=True, fmt='.2f', cmap = 'coolwarm')
plt.show()
```



In [49]:
```python
# correlation heatmap df
correlation = data[numeric_cols].corr()

# Get column pairs with correlation > 0.5
high_corr_pairs = []
for i in range(len(correlation.columns)):
    for j in range(i+1, len(correlation.columns)):
        if abs(correlation.iloc[i, j]) > 0.5:
            high_corr_pairs.append((correlation.columns[i], correlation.columns[j], correlati

# Check if there are high correlation pairs
if high_corr_pairs:
    # Print column pairs with correlation > 0.5 and their correlation values
    for pair in high_corr_pairs:
        print(pair[0], "-", pair[1], "Correlation:", pair[2])
else:
    print("No high correlation columns")
```

```
Bank Deposits - Checking Accounts Correlation: 0.8442778631339778
Bank Deposits - Saving Accounts Correlation: 0.7547444162737089
```

In [50]:
```python
# These pairs of variables have a very high correlation, so it common practice to remove the r
uncorrelated_data = data.copy()
uncorrelated_data.drop(columns=['Bank Deposits'], axis=1, inplace=True)
uncorrelated_data.reset_index(drop=True)
uncorrelated_data.columns
```

Out[50]:
```
Index(['Age', 'Sex', 'Occupation', 'Nationality', 'Fee Structure ID',
       'Loyalty Classification', 'Banking Relationship', 'Properties Owned',
       'Estimated Income', 'Superannuation Savings', 'Amount of Credit Cards',
       'Credit Card Balance', 'Bank Loans', 'Checking Accounts',
       'Saving Accounts', 'Foreign Currency Account', 'Business Lending',
       'Contact_to_Meeting_Days', 'Bank_Joined_Days'],
      dtype='object')
```

In [51]:
```
uncorrelated_data
```

Out[51]:

	Age	Sex	Occupation	Nationality	Fee Structure ID	Loyalty Classification	Banking Relationship	Properties Owned	Estima Inco
0	24	M	Safety Technician IV	Indian	H	Jade	Retail	1	75384.7
1	23	M	Software Consultant	Maori	H	Jade	Retail	1	289834.3
2	27	F	Help Desk Operator	European	H	Gold	Institutional	1	169935.2
3	40	M	Geologist II	Indian	MR	Silver	Investments Only	0	356808.1
4	46	F	Assistant Professor	Indian	MR	Platinum	Private Bank	0	130711.6
...	...	...	...	...	...	...	...	...	
2995	82	F	Accounting Assistant III	Indian	H	Gold	Retail	1	297617.1
2996	44	F	Paralegal	European	MR	Gold	Private Bank	1	42397.4
2997	70	F	Statistician IV	Indian	L	Jade	Retail	2	48339.8
2998	56	F	Human Resources Assistant III	European	MR	Jade	Commercial	3	107265.8
2999	79	F	Biostatistician III	Indian	H	Jade	Retail	1	56826.5

3000 rows × 19 columns

Encoding categorical features

In [52]:
```
# Check for the values to be encoded

ordinal_categorical = uncorrelated_data[['Fee Structure ID', 'Loyalty Classification']]
for col in ordinal_categorical:
    print(ordinal_categorical[col].unique())
```

```
['H' 'MR' 'L']
['Jade' 'Gold' 'Silver' 'Platinum']
```

In [53]:
```
# Convert categorical features into numerical using OrdinalEncoder
data_to_encode = uncorrelated_data.copy()
def ordinal_encoding(df):
    # Set order of values in each column by their rank
    # for [H' ,'MR','L' meaning 'High','Mid Range','Low' respectively ]
```

```
    fee_order = ['H','MR','L']
    loyalty_order = ['Jade', 'Silver', 'Gold', 'Platinum']

    # Initialize the OrdinalEncoder with the custom order ordinal_encoder
    ordinal_encoder = OrdinalEncoder(categories=[fee_order, loyalty_order])
    df[['Fee_Rank','Loyalty_Rank']] = ordinal_encoder.fit_transform(df[['Fee Structure ID','L
    df[['Fee_Rank','Loyalty_Rank']] = df[['Fee_Rank','Loyalty_Rank']].astype(int)
    return df

ord_data_encoded = ordinal_encoding(data_to_encode)
ord_data_encoded.drop(['Fee Structure ID','Loyalty Classification'], axis=1, inplace=True)
ord_data_encoded.reset_index(drop=True)
```

Out[53]:

	Age	Sex	Occupation	Nationality	Banking Relationship	Properties Owned	Estimated Income	Superannuation Savings	An
0	24	M	Safety Technician IV	Indian	Retail	1	75384.7686	17677.95	
1	23	M	Software Consultant	Maori	Retail	1	289834.3140	17398.92	
2	27	F	Help Desk Operator	European	Institutional	1	169935.2252	42825.90	
3	40	M	Geologist II	Indian	Investments Only	0	356808.1125	5473.15	
4	46	F	Assistant Professor	Indian	Private Bank	0	130711.6800	48077.60	
...	...	...	...	...	...	...	...	...	
2995	82	F	Accounting Assistant III	Indian	Retail	1	297617.1424	61177.60	
2996	44	F	Paralegal	European	Private Bank	1	42397.4628	33356.88	
2997	70	F	Statistician IV	Indian	Retail	2	48339.8784	18889.92	
2998	56	F	Human Resources Assistant III	European	Commercial	3	107265.8691	11283.09	
2999	79	F	Biostatistician III	Indian	Retail	1	56826.5324	8855.30	

3000 rows × 19 columns

In [54]:

```
# Convert categorical features into numerical using OneHotEncoder and e
def dummy_target_encoding(df,categorical_col,target_col):
    # Create dummies (True - False) columns for features with low cardinality
    df = pd.get_dummies(df, columns = ['Sex', 'Nationality', 'Properties Owned', 'Banking Rel

    # Assuming that Income is mostly infuenced by Occupation, the values of Occupation feature
    # with medium cardinality are mapped with Income mean
    target_mean = df.groupby(categorical_col)[target_col].mean()
    df_encoded = df.copy()
    df[categorical_col + '_encoded'] = df[categorical_col].map(target_mean)
    return df

encoded_data = dummy_target_encoding(ord_data_encoded,'Occupation', 'Estimated Income')
# Remove the categorical feature
encoded_data.drop(['Occupation'], axis=1, inplace=True)
```

```
encoded_data.reset_index(drop=True)
encoded_data
```

Out[54]:

	Age	Estimated Income	Superannuation Savings	Amount of Credit Cards	Credit Card Balance	Bank Loans	Checking Accounts	Sav Accou
0	24	75384.7686	17677.95	1	484.5440	7.762429e+05	6.036179e+05	607332.455
1	23	289834.3140	17398.92	1	2256.8777	1.270615e+06	2.295214e+05	344635.157
2	27	169935.2252	42825.90	2	4568.7438	1.052716e+06	6.526747e+05	203054.348
3	40	356808.1125	5473.15	2	4205.0010	1.211951e+05	1.048157e+06	234685.019
4	46	130711.6800	48077.60	1	3779.4880	1.048302e+06	4.466442e+05	128351.452
...	...	...	...	...	...	...	...	
2995	82	297617.1424	61177.60	1	649.8540	2.239351e+05	5.328679e+05	657849.619
2996	44	42397.4628	33356.88	1	1639.0350	5.959020e+05	5.658174e+04	93195.608
2997	70	48339.8784	18889.92	1	2352.8448	8.804930e+05	1.587261e+05	35539.152
2998	56	107265.8691	11283.09	2	3578.6088	2.686250e+05	4.046383e+05	56411.334
2999	79	56826.5324	8855.30	1	1494.6876	2.856407e+05	7.776908e+04	32371.380

3000 rows × 31 columns

In [55]:
```
encoded_data.shape
```

Out[55]:
```
(3000, 31)
```

Scaling data

In [56]:
```
encoded_data.columns
```

Out[56]:
```
Index(['Age', 'Estimated Income', 'Superannuation Savings',
       'Amount of Credit Cards', 'Credit Card Balance', 'Bank Loans',
       'Checking Accounts', 'Saving Accounts', 'Foreign Currency Account',
       'Business Lending', 'Contact_to_Meeting_Days', 'Bank_Joined_Days',
       'Fee_Rank', 'Loyalty_Rank', 'Sex_F', 'Sex_M', 'Nationality_Asian',
       'Nationality_European', 'Nationality_Indian', 'Nationality_Maori',
       'Nationality_Pacific Islander', 'Properties Owned_0',
       'Properties Owned_1', 'Properties Owned_2', 'Properties Owned_3',
       'Banking Relationship_Commercial', 'Banking Relationship_Institutional',
       'Banking Relationship_Investments Only',
       'Banking Relationship_Private Bank', 'Banking Relationship_Retail',
       'Occupation_encoded'],
      dtype='object')
```

In [57]:
```
# Apply StandardScaler to all values for not to weigh some features (especially) ordinal ones
# Dummy created columns are left behind
scaler = StandardScaler()
values_to_be_scaled = ['Age', 'Estimated Income', 'Superannuation Savings',
       'Amount of Credit Cards', 'Credit Card Balance', 'Bank Loans',
       'Checking Accounts', 'Saving Accounts', 'Foreign Currency Account',
       'Business Lending', 'Contact_to_Meeting_Days', 'Bank_Joined_Days',
       'Fee_Rank', 'Loyalty_Rank', 'Occupation_encoded']
```

```
# Scale just the features with continuous_data
scaled_data = encoded_data.copy()
scaled_data[values_to_be_scaled] = scaler.fit_transform(scaled_data[values_to_be_scaled])
scaled_data[values_to_be_scaled]
```

Out[57]:

	Age	Estimated Income	Superannuation Savings	Amount of Credit Cards	Credit Card Balance	Bank Loans	Checking Accounts	Saving Accounts	F Cu Ac
0	-1.362100	-0.857065	-0.483086	-0.685620	-1.078097	0.404075	1.001746	1.628147	-0.7
1	-1.412474	1.059081	-0.500250	-0.685620	-0.368221	1.484717	-0.324684	0.485833	1.3
2	-1.210978	-0.012239	1.063791	0.793071	0.557756	1.008413	1.175686	-0.129817	2.1
3	-0.556114	1.657504	-1.233816	0.793071	0.412065	-1.027783	2.577946	0.007726	1.1
4	-0.253869	-0.362709	1.386828	-0.685620	0.241634	0.998765	0.445166	-0.454656	0.0
...	...	...	...	...	...	...	...	...	
2995	1.559601	1.128622	2.192623	-0.685620	-1.011886	-0.803205	0.750888	1.847816	-0.7
2996	-0.354617	-1.151812	0.481341	-0.685620	-0.615687	0.009871	-0.937875	-0.607527	-0.2
2997	0.955111	-1.098716	-0.408537	-0.685620	-0.329783	0.631954	-0.575703	-0.858241	0.0
2998	0.249873	-0.572202	-0.876441	0.793071	0.161175	-0.705518	0.296226	-0.767480	-1.0
2999	1.408478	-1.022886	-1.025777	-0.685620	-0.673502	-0.668324	-0.862751	-0.872016	-0.9

3000 rows × 15 columns

In [58]:

```
scaled_data.describe()
```

Out[58]:

	Age	Estimated Income	Superannuation Savings	Amount of Credit Cards	Credit Card Balance	Bank Loans	
count	3.000000e+03	3.000000e+03	3.000000e+03	3.000000e+03	3.000000e+03	3.000000e+03	3.
mean	-1.231607e-16	-1.699381e-16	1.859253e-16	-1.065814e-17	-8.526513e-17	1.456613e-16	2
std	1.000167e+00	1.000167e+00	1.000167e+00	1.000167e+00	1.000167e+00	1.000167e+00	1.
min	-1.714719e+00	-1.388398e+00	-1.479314e+00	-6.856195e-01	-1.271702e+00	-1.292702e+00	-1.
25%	-8.583588e-01	-7.898561e-01	-8.007401e-01	-6.856195e-01	-7.768614e-01	-7.689023e-01	-7
50%	-1.998175e-03	-2.590448e-01	-1.952511e-01	-6.856195e-01	-2.464899e-01	-2.439288e-01	-2
75%	9.047366e-01	6.342663e-01	6.109979e-01	7.930710e-01	5.392870e-01	5.124300e-01	4
max	1.710723e+00	3.136474e+00	3.102144e+00	2.271762e+00	4.332070e+00	4.538268e+00	5.

In [ ]:

MODEL CREATION

Anomaly detection with Isolation Forest algorithm

State-of-the-art anomaly detection algorithm particularly effective for high-dimensional datasets which does not require labeled data and elatively insensitive to noise and outliers within the data, reliable for real-world datasets.

It works by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of that feature. It builds an ensemble of trees (forest) where anomalies are isolated quickly, resulting in shorter paths in the trees. Normal data points, on the other hand, require more splits to be isolated, leading to longer paths. The idea is that anomalies are few and different, making them easier to isolate

In [59]:
```
from sklearn.ensemble import IsolationForest
'''Parameters:
        n_estimators (int): The number of base estimators in the ensemble. Default is 100
        max_samples (int): The number of samples to draw from X to train each base estimator.
        max_features (float): The number of features to draw from X to train each base estima
        contamination (float): The proportion of outliers in the data set. Default is 0.01 or
        bootstrap (bool): If True, individual trees are fit on random subsets of the training
        n_jobs (int) : The number of jobs to run in parallel for fit
        random_state (int): Controls the randomness of the estimator '''

params = {
    'n_estimators': 100,
    'max_samples' : 256,
    'max_features' : 1.0,
    'contamination': 0.01,
    'bootstrap': True,
    'n_jobs' : -1,
    'random_state': 42
}

model = IsolationForest(**params).fit(scaled_data)

# Predict anomalies on entire set, setting anomaly value -1 to a value 1 (or, yes, it is an a
anomaly_predictions = model.predict(scaled_data)

normal_points = anomaly_predictions[anomaly_predictions == 1]
anomaly_points = anomaly_predictions[anomaly_predictions == -1]


# Evaluate the performance
anomalies = anomaly_predictions[anomaly_predictions == 1]
print(f"Anomalies detected in entire set: {len(anomaly_points)}")
```

```
Anomalies detected in entire set: 30
```

In [60]:
```
# Set the predictions in the original dataset
anomaly_predicted_data = data_cleaned.copy()
anomaly_predicted_data['Anomaly'] = anomaly_predictions
anomaly_predicted_data['Anomaly'] = anomaly_predicted_data['Anomaly'].map({1:0, -1:1})
anomaly_predicted_data[anomaly_predicted_data['Anomaly'] == 1].head()
```

Out[60]:

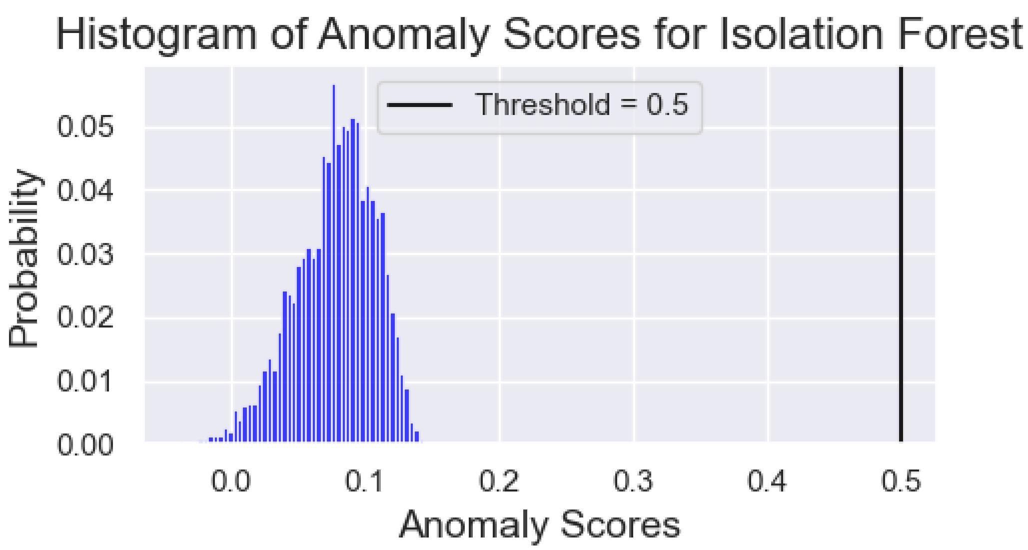
	Name	Age	Sex	Occupation	Nationality	Banking Contact	Investment Advisor	Fee Structure ID	Loyalty Classification
26	Maria Clark	34	M	Help Desk Operator	Asian	Joe Hanson	Carl Anderson	H	Silver
136	John Hart	31	F	Systems Administrator IV	Maori	Raymond Alexander	Jeremy Porter	H	Jade
368	Christopher Harper	28	M	Software Engineer II	Pacific Islander	Adam Hernandez	Victor Dean	L	Jade
376	Wayne Hart	17	F	Help Desk Technician	Asian	Adam Hernandez	Victor Dean	H	Jade
522	Phyllis Reed	26	F	Web Developer III	European	Benjamin Kim	Eric Shaw	L	Silver

5 rows × 24 columns

In [61]:

```
# Create the histogram plot
plt.figure(figsize=(10, 6))
score_threshold = 0.5  # Any datapoint with score above 0.5 is considered anomaly
anomaly_scores = model.decision_function(scaled_data)

# Create the histogram plot
plt.figure(figsize=(5, 3))
sns.histplot(anomaly_scores, kde=False, stat="probability", bins=50, color='blue')

# Add the vertical line for the threshold
plt.axvline(score_threshold, color='k', linestyle='-', label=f"Threshold = {score_threshold}"

# Add the title and labels
plt.title("Histogram of Anomaly Scores for Isolation Forest", fontsize=16)
plt.xlabel("Anomaly Scores", fontsize=14)
plt.ylabel("Probability", fontsize=14)
plt.legend()
plt.tight_layout()
plt.show()
```

<Figure size 1000x600 with 0 Axes>



In [62]:

```
print(len(anomaly_scores[anomaly_scores < 0]))
```

30

Anomaly detection with PCA reduced data dimesionality

In [63]:

```
# Apply PCA for visualization
pca = PCA(n_components=2)
reduced_data = pca.fit_transform(scaled_data)
pca_data = pd.DataFrame({'PCA Component 1':reduced_data[:, 0],'PCA Component 2':reduced_data[

''' Which features are the most important when reducing data to two components? '''

# Extract the loadings (principal component weights)
loadings = pca.components_.T

# Create a DataFrame to store the loadings
loadings_df = pd.DataFrame(loadings, columns=['PCA Component 1', 'PCA Component 2'])

# Adding feature names for better interpretation, assuming features are the columns in scaled_
loadings_df.index = pd.DataFrame(scaled_data).columns

print("Feature Importances for PCA Components:")
loadings_df
```

```
Feature Importances for PCA Components:
```

Out[63]:

	PCA Component 1	PCA Component 2
Age	-0.005565	0.022515
Estimated Income	0.358164	0.316062
Superannuation Savings	0.283268	0.239147
Amount of Credit Cards	-0.029277	-0.091489
Credit Card Balance	0.352692	-0.048068
Bank Loans	0.365895	-0.071955
Checking Accounts	0.355001	-0.201796
Saving Accounts	0.335028	-0.203749
Foreign Currency Account	0.361813	-0.092704
Business Lending	0.380165	-0.099781
Contact_to_Meeting_Days	-0.000528	-0.089386
Bank_Joined_Days	0.006074	-0.390860
Fee_Rank	-0.009253	0.237047
Loyalty_Rank	-0.023953	0.335598
Sex_F	-0.005225	-0.006319
Sex_M	0.005225	0.006319
Nationality_Asian	-0.000230	-0.001929
Nationality_European	0.007276	0.028011
Nationality_Indian	-0.005182	-0.013505
Nationality_Maori	0.000347	-0.006002
Nationality_Pacific Islander	-0.002210	-0.006576
Properties Owned_0	-0.000329	0.014688
Properties Owned_1	-0.001875	-0.016228
Properties Owned_2	0.003770	-0.010707
Properties Owned_3	-0.001567	0.012247
Banking Relationship_Commercial	-0.000051	-0.003158
Banking Relationship_Institutional	-0.001219	-0.001874
Banking Relationship_Investments Only	0.001564	0.005535
Banking Relationship_Private Bank	-0.005452	0.011069
Banking Relationship_Retail	0.005157	-0.011571
Occupation_encoded	0.133035	0.627702

In [64]:

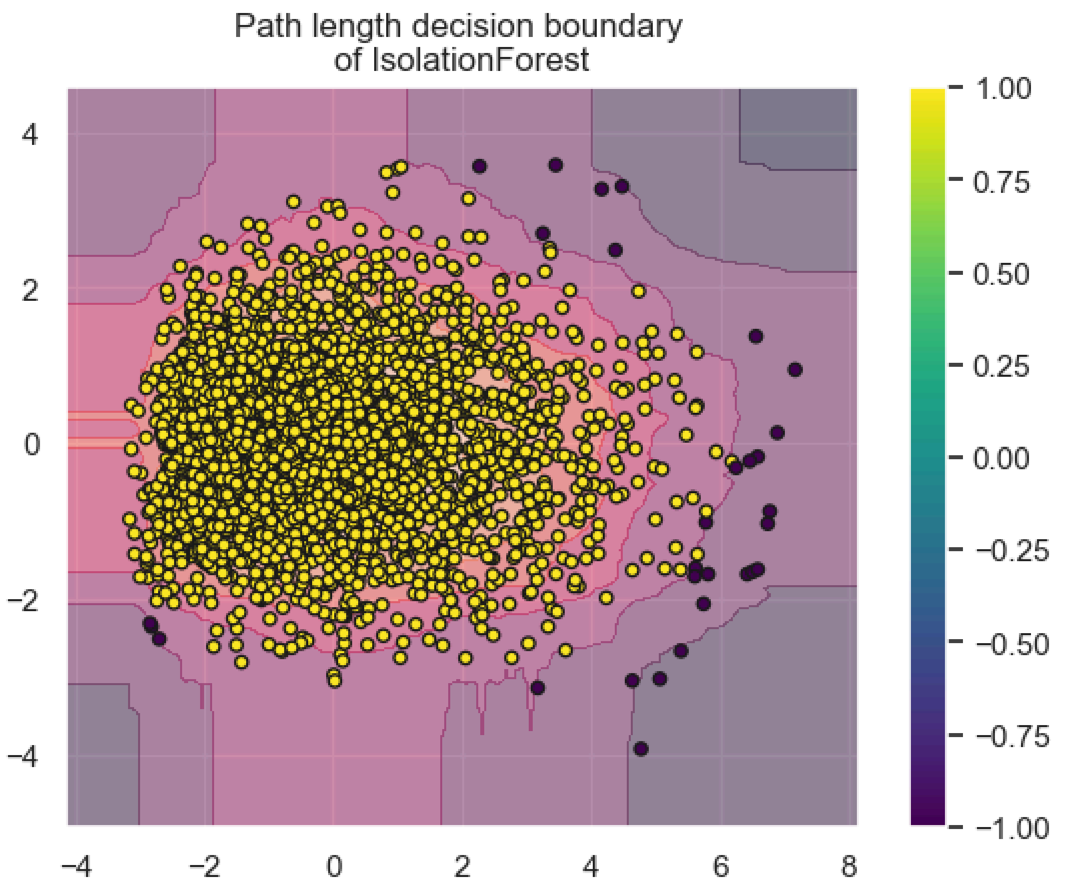
```
print(f"Biggest influenser on PCA_1: {loadings_df.loc[loadings_df['PCA Component 1'].idxmax()
print(f"Biggest influenser on PCA_2: {loadings_df.loc[loadings_df['PCA Component 2'].idxmax()
```

```
Biggest influenser on PCA_1: PCA Component 1    0.380165
Name: Business Lending, dtype: float64
Biggest influenser on PCA_2: PCA Component 2    0.627702
Name: Occupation_encoded, dtype: float64
```

In [ ]:

In [65]:

```
# When a forest of random trees collectively produce short path lengths for isolating
# some particular samples, they are highly likely to be anomalies and the measure of
# normality is close to 0. Similarly, large paths correspond to values close to 1 and are more
pca_model = IsolationForest(**params).fit(reduced_data)

disp = DecisionBoundaryDisplay.from_estimator(
    pca_model,
    reduced_data,
    response_method="decision_function",
    alpha=0.5,
)
pca_anomalies = pca_model.predict(reduced_data)

# Set axis
plt.figure(figsize=(5, 3))
disp.ax_.scatter(reduced_data[:, 0], reduced_data[:, 1], cmap='viridis', c = pca_anomalies, s
disp.ax_.set_title("Path length decision boundary \nof IsolationForest")
plt.colorbar(disp.ax_.collections[1])
plt.show()
```




```
<Figure size 500x300 with 0 Axes>
```

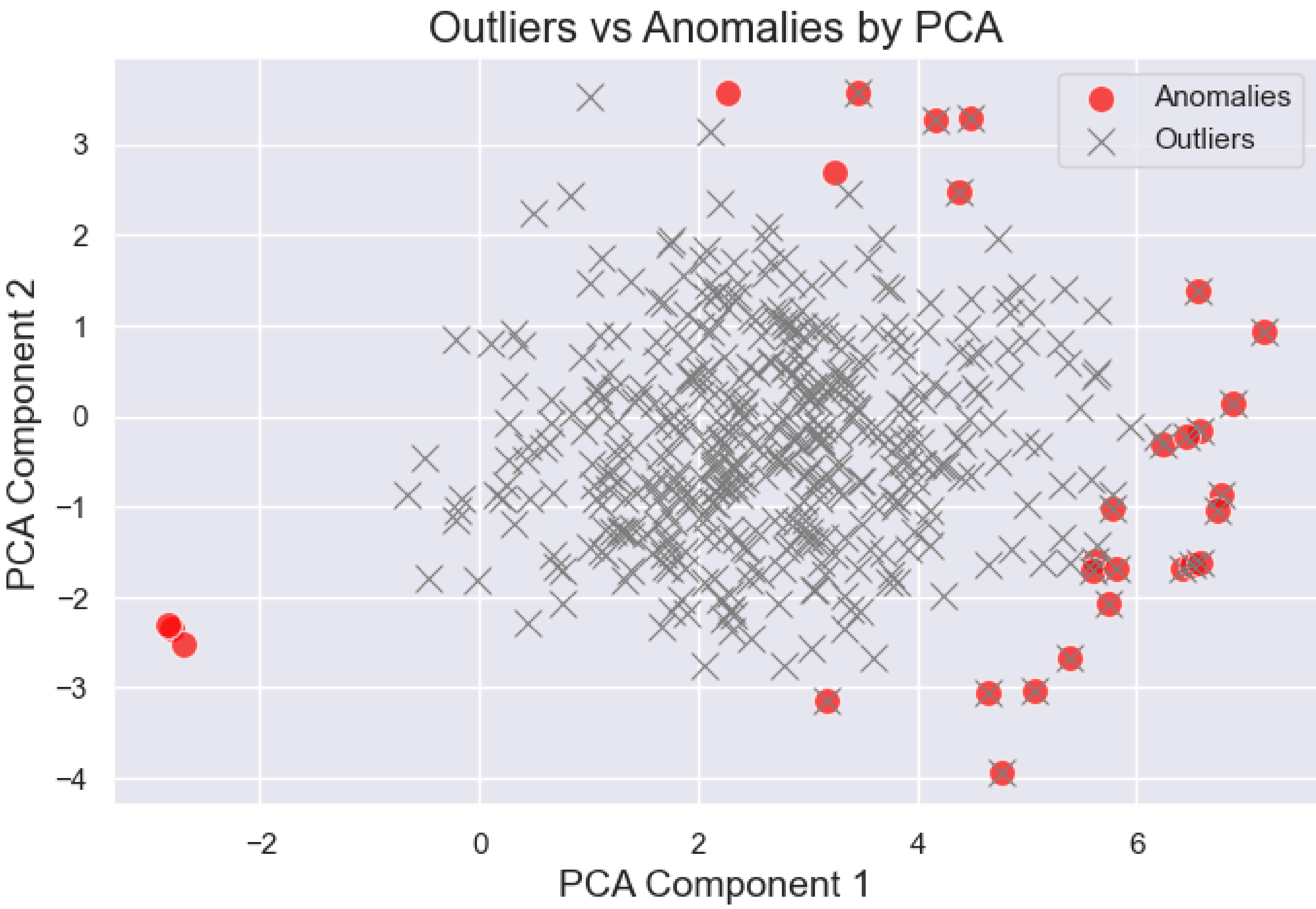
In [ ]:

Are model anomalies same as point anomalies (outliers)?

In [66]:

```
# Add found outliers in any axis to the comparision data
compare_data = pca_data.copy()
compare_data['Anomaly'] = pca_anomalies
compare_data['Outliers'] = outliers.any(axis=1).astype(int)

# Create the scatter plot
fig, ax = plt.subplots(figsize=(8, 5))

# Highlight the anomalies
```

```
sns.scatterplot(x='PCA Component 1', y='PCA Component 2', data=compare_data[compare_data['Anom
                color='red', ax=ax, s=100, edgecolor='w', alpha=0.7, label='Anomalies')

# Highlight the outliers
sns.scatterplot(x='PCA Component 1', y='PCA Component 2', data=compare_data[compare_data['Out
                color='grey', marker='x', s=100, ax=ax, label='Outliers')

# Set the title and labels
ax.set_title('Outliers vs Anomalies by PCA', fontsize=16)
ax.set_xlabel('PCA Component 1', fontsize=14)
ax.set_ylabel('PCA Component 2', fontsize=14)
plt.legend()
plt.show()
```



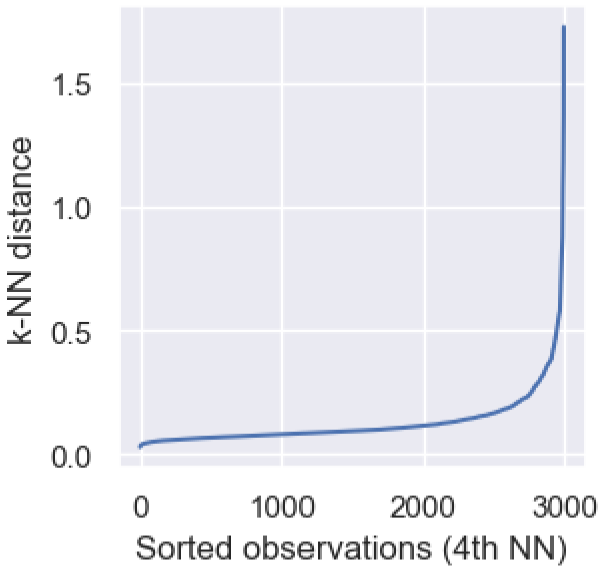
Not really, most outliers found with quantile aren't labeled as anomalies, proving the reason not to remove them from the data

Are there any clusters that the anomalies belong to? Can clustering be used for anomaly detection?

Density Based Spatial Clustering of Applications with Noise (abbreviated as DBSCAN) is a density-based unsupervised clustering algorithm. In DBSCAN, clusters are formed from dense regions and separated by regions of no or low densities. Not ideal for high-dimensional data and very sensitive to ε (eps) and minPts (min_samples) parameters. The ε should be as small as possible and sometimes, domain expertise is also required to be set. For this case, KNN will help finding the optimal value. The minPts parameter is easy to set (2 * number of dimensions)

In [67]:
```
from sklearn.neighbors import NearestNeighbors
plt.figure(figsize=(3, 3))
# n_neighbors = 5 as kneighbors function returns distance of point to itself
nbrs = NearestNeighbors(n_neighbors = 5).fit(reduced_data)
# Find the k-neighbors of a point
neigh_dist, neigh_ind = nbrs.kneighbors(reduced_data)
# sort the neighbor distances (lengths to points) in ascending order
# axis = 0 represents sort along first axis i.e. sort along row
sort_neigh_dist = np.sort(neigh_dist, axis = 0)
k_dist = sort_neigh_dist[:, 4]
plt.plot(k_dist)
```

```
plt.ylabel("k-NN distance")
plt.xlabel("Sorted observations (4th NN)")
plt.show()
```



In [68]:
```
# Finds the knee point in the distance curve using the KneeLocator
# Parameters:
    # neigh_dist (list): List of neighbor distances.
    # k_dist (list): List of k-distances.
kneedle = KneeLocator(x = range(1, len(neigh_dist)+1), y = k_dist, S = 1.0,
                      curve = "concave", direction = "increasing", online=True)
# Returns: float: The y-value of the knee point in the curve
eps = kneedle.knee_y
print(f'Use {eps} as optimum value of minimim distance between the datapoints for DBSCAN clus
```

```
Use 0.8737555626215568 as optimum value of minimim distance between the datapoints for DBSCAN
clustering
```

In [69]:
```
# Apply DBSCAN to cluster Bank clients with reduced dimesionalities
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=eps, min_samples=5)
dbscan.fit(reduced_data)

# Get cluster labels
cluster_labels = dbscan.labels_

# Add cluster labels and predictions to the pca dataframe
pca_data['Cluster'] = cluster_labels

print(f'DBSCAN found that the dataset can be divided to {pca_data['Cluster'].nunique()} clust
```

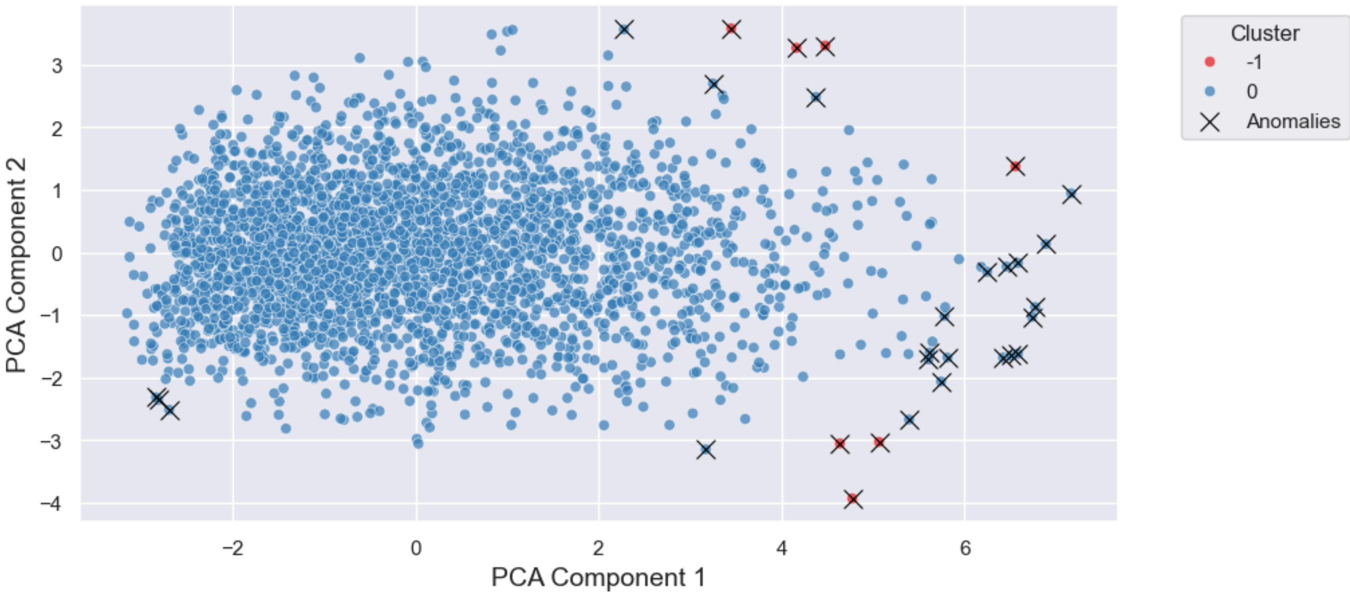
```
DBSCAN found that the dataset can be divided to 2 clusters
```

In [70]:
```
# Count the number of occurrences of each value in the 'Cluster' column
cluster_counts = pca_data['Cluster'].value_counts()

# Get the count of points with value -1 in the 'Cluster' column
count_of_minus_one = cluster_counts.get(-1, 0)

print(f"Number of noisy points or potential anomalies found: {count_of_minus_one}")
```

```
Number of noisy points or potential anomalies found: 7
```

In [71]:
```
# Plot the clusters and anomalies belonging to a cluster
fig, ax = plt.subplots(figsize=(10, 5))
sns.scatterplot(x='PCA Component 1', y='PCA Component 2', hue='Cluster', data=pca_data, palet
# Highlight the outliers
sns.scatterplot(x='PCA Component 1', y='PCA Component 2', data=compare_data[compare_data['Ano
                color='black', marker='x', s=100, ax=ax, label='Anomalies')
```

```
plt.legend(title='Cluster', bbox_to_anchor=(1.05, 1), loc='upper left')
ax.set_xlabel('PCA Component 1', fontsize=14)
ax.set_ylabel('PCA Component 2', fontsize=14)
plt.show()
```



Blue color represents normal points, whereas red respresents (-1 cluster) or noisy points which could not be assigned to any cluster. Probably anomalies acording to DBSCAN

Let's see where do anomalies really belong

In [72]:
```
final_data = anomaly_predicted_data.copy()
final_data
```

Out[72]:

	Name	Age	Sex	Occupation	Nationality	Banking Contact	Investment Advisor	Fee Structure ID	Loya Classificati
0	Raymond Mills	24	M	Safety Technician IV	Indian	Anthony Torres	Victor Dean	H	Ja
1	Julia Spencer	23	M	Software Consultant	Maori	Jonathan Hawkins	Jeremy Porter	H	Ja
2	Stephen Murray	27	F	Help Desk Operator	European	Anthony Berry	Ernest Knight	H	Go
3	Virginia Garza	40	M	Geologist II	Indian	Steve Diaz	Eric Shaw	MR	Sil
4	Melissa Sanders	46	F	Assistant Professor	Indian	Shawn Long	Kevin Kim	MR	Platinu
...	...	...	...	...	...	...	...	...	
2995	Earl Hall	82	F	Accounting Assistant III	Indian	Joshua Bennett	Daniel Carroll	H	Go
2996	Billy Williamson	44	F	Paralegal	European	Dennis Ruiz	Peter Castillo	MR	Go
2997	Victor Black	70	F	Statistician IV	Indian	Joshua Ryan	Steve Sanchez	L	Ja
2998	Andrew Ford	56	F	Human Resources Assistant III	European	Nicholas Cunningham	Juan Ramirez	MR	Ja
2999	Amy Nguyen	79	F	Biostatistician III	Indian	Joe Hanson	Peter Castillo	H	Ja

3000 rows × 24 columns

In [73]:

```
# Add cluster feature to the original dataset
final_data['Cluster'] = cluster_labels
# In which cluster do anomalies belong?
clustering_anomalies = pd.crosstab(final_data['Cluster'], final_data['Anomaly'])
clustering_anomalies
```

Out[73]:

Anomaly	0	1
Cluster		
-1	4	3
0	2966	27

3 noisy points (from DBSCAN) are anomalies (from Isolation forest model)

In [74]:

```
relation_anomaly = pd.crosstab(final_data['Banking Relationship'], final_data['Anomaly'])
# Calculate the percentage of anomalies
relation_anomaly['Pct'] = relation_anomaly[1] / (relation_anomaly[0] + relation_anomaly[1]) *

# Display the result
relation_anomaly.sort_values(by='Pct', ascending = False)
```

Out[74]:

Anomaly Banking Relationship	0	1	Pct
Commercial	420	10	2.325581
Institutional	117	2	1.680672
Private Bank	400	5	1.234568
Investments Only	603	7	1.147541
Retail	1430	6	0.417827

Most anomalies come from Retail related clients, least - from Institutional, but the highest percentage of anomalies is detected among Commercial related clients

In [75]:

```
occupation_anomaly = pd.crosstab(final_data['Occupation'], final_data['Anomaly'])
# Calculate the percentage of anomalies
occupation_anomaly['Pct'] = occupation_anomaly[1] / (occupation_anomaly[0] + occupation_anoma

# Display the result
occupation_anomaly[occupation_anomaly[1] > 0].sort_values(by='Pct', ascending = False).head(5
```

Out[75]:

Anomaly Occupation	0	1	Pct
Automation Specialist IV	19	3	13.636364
Software Engineer IV	13	2	13.333333
General Manager	14	2	12.500000
Desktop Support Technician	10	1	9.090909
Web Developer II	12	1	7.692308

And... in Automation Specialists IV occupation group - highest number and highest ratio of anomalies

Should the bank be more careful with Commercial related Automation Specialists' bank accounts?

GET PREDICTIONS

In [76]:

```
# Some sample data to imitate the real data values on which model should decide whether they 
# Sample data
inputs = [
    {
    'Age': 42,
    'Estimated Income': 137256.32,
    'Superannuation Savings': 49416.00,
    'Amount of Credit Cards': 2,
    'Credit Card Balance': 2866.23,
    'Bank Loans': 856.56,
    'Checking Accounts': 1001.27,
    'Saving Accounts': 25648.23,
    'Foreign Currency Account': 79562.46,
    'Business Lending': 564.89,
    'Contact_to_Meeting_Days': 76,
    'Bank_Joined_Days': 6524,
    'Fee_Rank': 0,
    'Loyalty_Rank': 1,
```

```
    'Sex_F': 1,
    'Sex_M': 0,
    'Nationality_Asian': 0,
    'Nationality_European': 1,
    'Nationality_Indian': 0,
    'Nationality_Maori': 0,
    'Nationality_Pacific Islander': 0,
    'Properties Owned_0': 0,
    'Properties Owned_1': 1,
    'Properties Owned_2': 0,
    'Properties Owned_3': 0,
    'Banking Relationship_Commercial': 1,
    'Banking Relationship_Institutional': 0,
    'Banking Relationship_Investments Only':0,
    'Banking Relationship_Private Bank': 0,
    'Banking Relationship_Retail': 0,
    'Occupation_encoded': 166458.62
   }
]
# Convert inputs to DataFrame for easier manipulation
df_inputs = pd.DataFrame(inputs)

# Extract features for scaling
values_to_be_scaled = ['Age', 'Estimated Income', 'Superannuation Savings',
       'Amount of Credit Cards', 'Credit Card Balance', 'Bank Loans',
       'Checking Accounts', 'Saving Accounts', 'Foreign Currency Account',
       'Business Lending', 'Contact_to_Meeting_Days', 'Bank_Joined_Days',
       'Fee_Rank', 'Loyalty_Rank', 'Occupation_encoded']

# Initialize the scaler
scaler = StandardScaler()

# Fit and transform the continuous columns
df_inputs[values_to_be_scaled] = scaler.fit_transform(df_inputs[values_to_be_scaled])

# Get new prediction
is_anomaly = model.predict(df_inputs)
print(f'Prediction: Is this an anomaly: {"no" if is_anomaly == 1 else "yes"}')
```

```
Prediction: Is this an anomaly: no
```

OK, that wasn't an anomaly.

Conclusion: This notebook is used as a test for script creation.

In [ ]: