this part creates new features and prepares data for modeling

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, RobustScaler, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest, f_classif, mutual_info_cl
import pickle
import timeit
import datetime as dt
import warnings
warnings.filterwarnings('ignore')
# self-defined function
from func import get_FDR

plt.style.use('seaborn-v0_8-deep')
```

In [2]:
```
# Load the dataset
df = pd.read_csv('./data/cleaned.csv', index_col=0)
print(f"Dataset loaded: {df.shape}")

df['date'] = pd.to_datetime(df['date'])
df.zip5 = df.zip5.astype(str).str.zfill(5)
df.ssn = df.ssn.astype(str)
df.dob = df.dob.astype(str)
df.homephone = df.homephone.astype(str)

print(f"\nDataset info:")
df.info()
```

```
Dataset loaded: (981694, 9)

Dataset info:
<class 'pandas.core.frame.DataFrame'>
Index: 981694 entries, 0 to 981693
Data columns (total 9 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   date         981694 non-null  datetime64[ns]
 1   ssn          981694 non-null  object
 2   firstname    981694 non-null  object
 3   lastname     981694 non-null  object
 4   address      981694 non-null  object
 5   zip5         981694 non-null  object
 6   dob          981694 non-null  object
 7   homephone    981694 non-null  object
 8   fraud_label  981694 non-null  int64
dtypes: datetime64[ns](1), int64(1), object(7)
memory usage: 74.9+ MB
```

Dimension Expand

In [3]:
```
# Extract time features
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
#df['dow'] = df['date'].dt.dayofweek
df['dow'] = df['date'].dt.day_name()
```

Risk table for day of week

by sigmoid-based smoothing

In [4]:
```
train_test = df[df.date < '2016-11-01']
```

In [5]:
```
# do statistical smoothing
c = 4
nmid = 20
y_avg = train_test['fraud_label'].mean()
y_dow = train_test.groupby('dow')['fraud_label'].mean()
num = train_test.groupby('dow').size()
y_dow_smooth = y_avg + (y_dow - y_avg)/(1 + np.exp(-(num - nmid)/c))
df['dow_risk'] = df.dow.map(y_dow_smooth)
```

In [6]:
```
df[['year', 'month', 'day', 'dow', 'dow_risk', 'fraud_label']].sample(5)
```

Out[6]:

	year	month	day	dow	dow_risk	fraud_label
288476	2016	4	18	Monday	0.013641	0
841106	2016	11	9	Wednesday	0.015339	0
712851	2016	9	22	Thursday	0.015111	0
119414	2016	2	14	Sunday	0.013860	0
127610	2016	2	17	Wednesday	0.015339	0

Create entitties

In [7]:
```
df['name'] = df.firstname + df.lastname
df['fulladdress'] = df.address + df.zip5
df['name_dob'] = df.name + df.dob
df['name_fulladdress'] = df.name + df.fulladdress
df['name_homephone'] = df.name + df.homephone
df['fulladdress_dob'] = df.fulladdress + df.dob
df['fulladdress_homephone'] = df.fulladdress + df.homephone
df['dob_homephone'] = df.dob + df.homephone
df['homephone_name_dob'] = df.homephone + df.name_dob
```

In [8]:
```
for field in df.select_dtypes(include=['object', 'category']).columns:
    df['ssn_' + field] = df.ssn + df[field]
```

```
attributes = df.select_dtypes(include=['object', 'category']).columns
print(attributes)
```

```
Index(['ssn', 'firstname', 'lastname', 'address', 'zip5', 'dob', 'homephon
e',
       'dow', 'name', 'fulladdress', 'name_dob', 'name_fulladdress',
       'name_homephone', 'fulladdress_dob', 'fulladdress_homephone',
       'dob_homephone', 'homephone_name_dob', 'ssn_ssn', 'ssn_firstname',
       'ssn_lastname', 'ssn_address', 'ssn_zip5', 'ssn_dob', 'ssn_homephon
e',
       'ssn_dow', 'ssn_name', 'ssn_fulladdress', 'ssn_name_dob',
       'ssn_name_fulladdress', 'ssn_name_homephone', 'ssn_fulladdress_dob',
       'ssn_fulladdress_homephone', 'ssn_dob_homephone',
       'ssn_homephone_name_dob'],
      dtype='object')
```

Velocity + Day since

In [ ]:

```
# previous:
# start = timeit.default_timer()

# for entity in attributes:

#     try: print('Run time for the last entity ----------------- {}s'.format
#     except: print('\n')
#     st = timeit.default_timer()

#     df_l = df1[['record', 'date', entity]]
#     df_r = df1[['check_record', 'check_date', entity]]

#     temp = pd.merge(df_l, df_r, left_on = entity, right_on = entity)


#     temp1 = temp[temp.record > temp.check_record][['record','date','check_
#                                                   .groupby('record')[['date'
#     mapper = (temp1.date - temp1.check_date).dt.days
#     final[entity + '_day_since'] = final.record.map(mapper)
#     final[entity + '_day_since'].fillna((final.date - pd.to_datetime('2016

#     print('\n' + entity + '_day_since ---> Done')

#     for time in [0,1,3,7,14,30]:

#         temp_1 = temp[(temp.check_date >= (temp.date - dt.timedelta(time))
#                       (temp.record >= temp.check_record)]

#         col_name = entity + '_count_' + str(time)
#         mapper2 = temp_1.groupby('record')[entity].count()
#         final[col_name] = final.record.map(mapper2)

#         print(entity + '_count_' + str(time) + ' ---> Done')

# print('Total run time: {}mins'.format((timeit.default_timer() - start)/60)
```

```
Run time for the last entity ----------------- 17.981693499954417s

ssn_day_since ---> Done
ssn_count_0 ---> Done
ssn_count_1 ---> Done
ssn_count_3 ---> Done
ssn_count_7 ---> Done
ssn_count_14 ---> Done
ssn_count_30 ---> Done
Run time for the last entity ----------------- 1.1341381249949336s
```

In [9]:

```
df1 = df.copy()
df1['record'] = list(df1.index)
final = df.copy()
final['record'] = list(final.index)
df1['check_date'] = df1.date
df1['check_record'] = df1.record
```

In [12]:

```
import timeit
import datetime as dt
from typing import Dict, List
import gc
```

on a million-record dataset, the previous code is not efficient, to optimize, can apply:

1. Optimize Data Types

Reduce memory footprint before processing

In [ ]:

```
def optimize_dtypes(df: pd.DataFrame) -> pd.DataFrame:
    """Optimize DataFrame data types to reduce memory usage."""
    for col in df.columns:
        col_type = df[col].dtype

        if col_type != 'object':
            c_min = df[col].min()
            c_max = df[col].max()

            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.
                    df[col] = df[col].astype(np.int32)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.finfo(r
                    df[col] = df[col].astype(np.float32)

    return df
```

2. Process in Chunks

Instead of merging the entire dataset, process in smaller chunks/ pieces 3. Use Iterator-based Merge
For very large datasets, use chunksize parameter in merge operations 4. Garbage collection
Explicitly free memory after each step 5. Avoid duplicating data
Process and immediately aggregate

In [ ]:

```python
def process_entity_chunked(df1: pd.DataFrame, entity: str, final: pd.DataFra
                          chunk_size: int = 50000) -> pd.DataFrame:
    """Process entity with chunking to reduce memory usage."""

    print(f"\nProcessing {entity}...")
    st = timeit.default_timer()

    # Sort data once for efficiency
    df1_sorted = df1.sort_values('record')

    # Process day_since in chunks
    day_since_results = {}

    for start_idx in range(0, len(df1_sorted), chunk_size):
        end_idx = min(start_idx + chunk_size, len(df1_sorted))
        chunk_records = df1_sorted.iloc[start_idx:end_idx]['record'].unique(

        # Get relevant data for this chunk
        chunk_data = df1[df1['record'].isin(chunk_records) |
                         df1['check_record'].isin(chunk_records)]

        # Self-join on entity
        df_l = chunk_data[['record', 'date', entity]]
        df_r = chunk_data[['check_record', 'check_date', entity]]

        temp = pd.merge(df_l, df_r, on=entity, suffixes=('', '_r'))
        temp = temp[temp.record > temp.check_record]

        if len(temp) > 0:
            # Calculate days since
            temp1 = temp[['record', 'date', 'check_date']].groupby('record')
            days_diff = (temp1['date'] - temp1['check_date']).dt.days

            for record, days in days_diff.items():
                day_since_results[record] = days

        # Clean up
        del temp, df_l, df_r
        gc.collect()

    # Map results
    final[entity + '_day_since'] = final['record'].map(day_since_results)
    final[entity + '_day_since'].fillna(
        (final['date'] - pd.to_datetime('2016-01-01')).dt.days,
        inplace=True
    )
```

```python
    print(f'{entity}_day_since ---> Done')

    # Process counts for different time windows
    for time_window in [0, 1, 3, 7, 14, 30]:
        count_results = {}

        for start_idx in range(0, len(df1_sorted), chunk_size):
            end_idx = min(start_idx + chunk_size, len(df1_sorted))
            chunk_records = df1_sorted.iloc[start_idx:end_idx]['record'].uni

            # Get relevant data
            chunk_data = df1[df1['record'].isin(chunk_records) |
                                df1['check_record'].isin(chunk_records)]

            # Self-join
            df_l = chunk_data[['record', 'date', entity]]
            df_r = chunk_data[['check_record', 'check_date', entity]]

            temp = pd.merge(df_l, df_r, on=entity, suffixes=('', '_r'))

            # Filter by time window
            temp_filtered = temp[
                (temp['check_date'] >= (temp['date'] - pd.Timedelta(days=tim
                (temp['record'] >= temp['check_record'])
            ]

            if len(temp_filtered) > 0:
                counts = temp_filtered.groupby('record')[entity].count()
                for record, count in counts.items():
                    count_results[record] = count

            # Clean up
            del temp, temp_filtered, df_l, df_r
            gc.collect()

        # Map results
        col_name = f'{entity}_count_{time_window}'
        final[col_name] = final['record'].map(count_results).fillna(0).astyp

        print(f'{col_name} ---> Done')

    print(f'Entity {entity} completed in {(timeit.default_timer() - st):.2f}
    return final
```

In [ ]:

```python
def process_all_entities(df1: pd.DataFrame, attributes: List[str],
                         final: pd.DataFrame, chunk_size: int = 50000) -> pd.
    """Process all entities with memory optimization."""

    start = timeit.default_timer()

    # Optimize data types first
    print("Optimizing data types...")
    df1 = optimize_dtypes(df1)

    # Ensure date columns are datetime
```

```python
    df1['date'] = pd.to_datetime(df1['date'])
    df1['check_date'] = pd.to_datetime(df1['check_date'])

    # Process each entity
    for entity in attributes:
        final = process_entity_chunked(df1, entity, final, chunk_size)

        # Force garbage collection after each entity
        gc.collect()

    print(f'\nTotal run time: {(timeit.default_timer() - start)/60:.2f} mins
    return final
```

6. SQL-based Approach with DuckDB

For large self-joins, DuckDB is much more memory-efficient

In [ ]:

```python
def process_with_duckdb(df1: pd.DataFrame, attributes: List[str],
                        final: pd.DataFrame) -> pd.DataFrame:
    """Process using DuckDB for better memory efficiency."""

    import duckdb

    start = timeit.default_timer()
    conn = duckdb.connect(':memory:')

    # Register DataFrame
    conn.register('df1', df1)
    conn.register('final', final)

    for entity in attributes:
        st = timeit.default_timer()

        # Calculate day_since using SQL
        query_day_since = f"""
        WITH last_records AS (
            SELECT
                l.record,
                MAX(l.date - r.check_date) as days_diff
            FROM df1 l
            JOIN df1 r ON l.{entity} = r.{entity}
            WHERE l.record > r.check_record
            GROUP BY l.record
        )
        SELECT * FROM last_records
        """

        day_since_df = conn.execute(query_day_since).df()

        # Process each time window
        for time_window in [0, 1, 3, 7, 14, 30]:
            query_count = f"""
            SELECT
                l.record,
```

```
                COUNT(*) as count
            FROM df1 l
            JOIN df1 r ON l.{entity} = r.{entity}
            WHERE l.record >= r.check_record
                AND r.check_date >= l.date - INTERVAL '{time_window} days'
            GROUP BY l.record
            """

            count_df = conn.execute(query_count).df()
            col_name = f'{entity}_count_{time_window}'
            final = final.merge(count_df, on='record', how='left')
            final.rename(columns={'count': col_name}, inplace=True)
            final[col_name].fillna(0, inplace=True)

        print(f'Entity {entity} completed in {(timeit.default_timer() - st):

    conn.close()
    print(f'\nTotal run time: {(timeit.default_timer() - start)/60:.2f} mins
    return final
```

In [11]:

```
# final = process_all_entities(df1, attributes, final, chunk_size=25000)
# or for very large datasets:
final = process_with_duckdb(df1, attributes, final)
```

```
Entity ssn completed in 2.99s
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
Entity firstname completed in 20.43s
Entity lastname completed in 9.80s
Entity address completed in 3.10s
Entity zip5 completed in 5.73s
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
Entity dob completed in 90.28s
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
```

```
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
Entity homephone completed in 37.07s
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
Entity dow completed in 816.35s
Entity name completed in 4.04s
Entity fulladdress completed in 3.89s
Entity name_dob completed in 4.41s
Entity name_fulladdress completed in 4.70s
Entity name_homephone completed in 4.99s
Entity fulladdress_dob completed in 6.13s
Entity fulladdress_homephone completed in 5.93s
FloatProgress(value=0.0, layout=Layout(width='auto'), style=ProgressStyle(ba
r_color='black'))
```

```
Entity dob_homephone completed in 16.99s
Entity homephone_name_dob completed in 6.64s
Entity ssn_ssn completed in 8.29s
Entity ssn_firstname completed in 7.64s
Entity ssn_lastname completed in 8.50s
Entity ssn_address completed in 9.57s
Entity ssn_zip5 completed in 10.26s
Entity ssn_dob completed in 9.22s
Entity ssn_homephone completed in 10.83s
Entity ssn_dow completed in 11.14s
Entity ssn_name completed in 12.22s
Entity ssn_fulladdress completed in 13.70s
Entity ssn_name_dob completed in 14.42s
Entity ssn_name_fulladdress completed in 15.43s
Entity ssn_name_homephone completed in 15.14s
Entity ssn_fulladdress_dob completed in 15.07s
Entity ssn_fulladdress_homephone completed in 15.22s
Entity ssn_dob_homephone completed in 15.73s
Entity ssn_homephone_name_dob completed in 17.49s

Total run time: 20.89 mins
```

Relative Velocity

- calculate rate ratios or normalized counts for different time windows
- count_in_X_days / (count_in_Y_days / Y)
- which gives us: How many times higher is X's count compared to the average daily count over the last Y days
- is commonly used in Fraud detection where sudden spikes in activity (high ratio) happened

In [13]:
```
for att in attributes:
    for d in ['0', '1']:
        for dd in ['3', '7', '14', '30']:
            final[att + '_count_' + d + '_by_' + dd] =\
            final[att + '_count_' + d]/(final[att + '_count_' + dd]/float(dc
```

DOB and Age

In [18]:
```
final['dob'].sample(5)
```

Out[18]:
```
151358    19800629
132501    19841003
451252    20001101
241643    19410607
615067    19700418
Name: dob, dtype: object
```

In [19]:
```
final['birth_year'] = final['dob'].str[:4].astype(int)
final['birth_month'] = final['dob'].str[4:6].astype(int)
final['birth_day'] = final['dob'].str[6:8].astype(int)
```

```
# Calculate age at transaction
final['age'] = (final['date'].dt.year - final['birth_year']) + \
                                ((final['date'].dt.month - final['birth_month
```

Keep desired variables

In [22]:
```
# only keep the numerical variables
final_cut = final.copy()
for field in final_cut.select_dtypes(include=['object', 'category']).columns
    final_cut.drop(field, inplace=True, axis=1)
```

In [28]:
```
final_cut.drop(['date','record'], axis=1, inplace = True)
```

In [29]:
```
final_cut.columns.to_list()
```

```
Out[29]: ['fraud_label',
 'year',
 'month',
 'day',
 'dow_risk',
 'ssn_count_0',
 'ssn_count_1',
 'ssn_count_3',
 'ssn_count_7',
 'ssn_count_14',
 'ssn_count_30',
 'firstname_count_0',
 'firstname_count_1',
 'firstname_count_3',
 'firstname_count_7',
 'firstname_count_14',
 'firstname_count_30',
 'lastname_count_0',
 'lastname_count_1',
 'lastname_count_3',
 'lastname_count_7',
 'lastname_count_14',
 'lastname_count_30',
 'address_count_0',
 'address_count_1',
 'address_count_3',
 'address_count_7',
 'address_count_14',
 'address_count_30',
 'zip5_count_0',
 'zip5_count_1',
 'zip5_count_3',
 'zip5_count_7',
 'zip5_count_14',
 'zip5_count_30',
 'dob_count_0',
 'dob_count_1',
 'dob_count_3',
 'dob_count_7',
 'dob_count_14',
 'dob_count_30',
 'homephone_count_0',
 'homephone_count_1',
 'homephone_count_3',
 'homephone_count_7',
 'homephone_count_14',
 'homephone_count_30',
 'dow_count_0',
 'dow_count_1',
 'dow_count_3',
 'dow_count_7',
 'dow_count_14',
 'dow_count_30',
 'name_count_0',
 'name_count_1',
 'name_count_3',
```

```
'name_count_7',
'name_count_14',
'name_count_30',
'fulladdress_count_0',
'fulladdress_count_1',
'fulladdress_count_3',
'fulladdress_count_7',
'fulladdress_count_14',
'fulladdress_count_30',
'name_dob_count_0',
'name_dob_count_1',
'name_dob_count_3',
'name_dob_count_7',
'name_dob_count_14',
'name_dob_count_30',
'name_fulladdress_count_0',
'name_fulladdress_count_1',
'name_fulladdress_count_3',
'name_fulladdress_count_7',
'name_fulladdress_count_14',
'name_fulladdress_count_30',
'name_homephone_count_0',
'name_homephone_count_1',
'name_homephone_count_3',
'name_homephone_count_7',
'name_homephone_count_14',
'name_homephone_count_30',
'fulladdress_dob_count_0',
'fulladdress_dob_count_1',
'fulladdress_dob_count_3',
'fulladdress_dob_count_7',
'fulladdress_dob_count_14',
'fulladdress_dob_count_30',
'fulladdress_homephone_count_0',
'fulladdress_homephone_count_1',
'fulladdress_homephone_count_3',
'fulladdress_homephone_count_7',
'fulladdress_homephone_count_14',
'fulladdress_homephone_count_30',
'dob_homephone_count_0',
'dob_homephone_count_1',
'dob_homephone_count_3',
'dob_homephone_count_7',
'dob_homephone_count_14',
'dob_homephone_count_30',
'homephone_name_dob_count_0',
'homephone_name_dob_count_1',
'homephone_name_dob_count_3',
'homephone_name_dob_count_7',
'homephone_name_dob_count_14',
'homephone_name_dob_count_30',
'ssn_ssn_count_0',
'ssn_ssn_count_1',
'ssn_ssn_count_3',
'ssn_ssn_count_7',
'ssn_ssn_count_14',
```

```
'ssn_ssn_count_30',
'ssn_firstname_count_0',
'ssn_firstname_count_1',
'ssn_firstname_count_3',
'ssn_firstname_count_7',
'ssn_firstname_count_14',
'ssn_firstname_count_30',
'ssn_lastname_count_0',
'ssn_lastname_count_1',
'ssn_lastname_count_3',
'ssn_lastname_count_7',
'ssn_lastname_count_14',
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```

In [30]:
```
final_cut.shape
```

Out[30]:
```
(981694, 485)
```

In [32]:
```
final_cut.sample(5)
```

Out[32]:

	fraud_label	year	month	day	dow_risk	ssn_count_0	ssn_count_1	ssn_co
663247	0	2016	9	4	0.013860	1	1	
663901	0	2016	9	4	0.013860	1	1	
433918	0	2016	6	10	0.014702	1	1	
386577	0	2016	5	24	0.014220	1	1	
863720	0	2016	11	18	0.014702	1	1	

5 rows × 485 columns

In [33]:
```
final_cut.to_csv('./data/vars 485.csv')
```

Feature Selection

In [2]:
```
final_cut = pd.read_csv('./data/vars 485.csv', index_col=0)
data = final_cut.loc[(final_cut.index <= 790000)&(final_cut.index >= 35755)]
data['RANDOM'] = np.random.ranf(len(data))
del final_cut
```

Filter

In [3]:
```
from scipy.stats import ks_2samp
from sklearn.feature_selection import SelectKBest
```

The **ks_2samp()** function computes the Kolmogorov–Smirnov (KS) statistic, which measures the maximum distance between the cumulative distribution functions (CDFs) of two groups (fraud vs. non-fraud) for a given feature

- KS value ranges from 0 to 1.

Higher KS means better separation → the feature is more discriminatory

- To measure how well a feature distinguishes between frauds (fraud_label = 1) and non-frauds (fraud_label = 0)

In [4]:
```
num_vars = data.shape[1]
goods = data[data['fraud_label'] == 0]
bads = data[data['fraud_label'] == 1]
results = {}
for col in data.columns:
    if col != 'fraud_label':
        try:
            results[col] = ks_2samp(goods[col],bads[col])[0]
        except Exception as e:
            print(f"Could not process column {col}: {e}")
filter_df = pd.DataFrame([results]).T.reset_index()
```

```
filter_df.columns = ['feature', 'KS']
filter_df.sort_values(by=['KS'], ascending = False, inplace = True)
filter_df.head(10)
```

Out[4]:

	feature	KS
27	address_count_30	0.329452
63	fulladdress_count_30	0.328546
26	address_count_14	0.318845
62	fulladdress_count_14	0.318109
25	address_count_7	0.297637
61	fulladdress_count_7	0.297425
235	address_count_0_by_30	0.287879
283	fulladdress_count_0_by_30	0.287071
234	address_count_0_by_14	0.277491
282	fulladdress_count_0_by_14	0.276820

In [5]:
```
del goods, bads
```

Fraud Detection Rate (FDR): Take the top 3% and bottom 3% values of each feature. Compute the fraud rate (i.e., proportion of frauds) in both subsets. then keep the maximum FDR between the two tails.

- Higher FDR means fraud cases are concentrated in the extreme values of the feature. Indicates the feature is useful for detecting fraud in high- or low-end values.
- Measures how concentrated the frauds are at the extremes of each feature.

In [6]:
```
KSFDR = pd.merge(filter_df, get_FDR(data), on='feature')
```

In [7]:
```
KSFDR['rank_ks'] = KSFDR['KS'].rank(ascending = True)
KSFDR['rank_FDR'] = KSFDR['FDR'].rank(ascending = True)
KSFDR['avg_rank'] = (KSFDR['rank_ks']+KSFDR['rank_FDR'])/2
KSFDR.sort_values(by=['avg_rank'], ascending = False, inplace = True)
```

In [8]:
```
KSFDR.reset_index(drop=True)
num_keep = 70
cols_keep = list(KSFDR['feature'][1:num_keep])
cols_keep
```

```
Out[8]: ['fulladdress_count_30',
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```
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 'zip5_count_7']
```

Wrapper

In [9]:

```
newX = data.drop(['fraud_label'],axis=1).loc[:,cols_keep]
y = data.fraud_label
del data
```

In [10]:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFECV

# Create the pipeline to avoid data leakage
# first standardized, then build logistic regression model
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('logreg', LogisticRegression(max_iter=1000))
])

# Define a custom importance getter function
def get_coef(estimator):
    return abs(estimator.named_steps['logreg'].coef_[0])

# Use the custom importance getter in RFECV
rfecv = RFECV(
    estimator=pipeline,
    step=1,
    cv=3,
    scoring='roc_auc',
    verbose=3,
    n_jobs=-1,
    importance_getter=get_coef
)

rfecv.fit(newX, y)
```

```
Fitting estimator with 69 features.
Fitting estimator with 68 features.
Fitting estimator with 67 features.
Fitting estimator with 66 features.
Fitting estimator with 65 features.
Fitting estimator with 64 features.
Fitting estimator with 63 features.
Fitting estimator with 62 features.
Fitting estimator with 61 features.
Fitting estimator with 60 features.
Fitting estimator with 59 features.
Fitting estimator with 58 features.
Fitting estimator with 57 features.
Fitting estimator with 56 features.
Fitting estimator with 55 features.
Fitting estimator with 54 features.
Fitting estimator with 53 features.
Fitting estimator with 52 features.
Fitting estimator with 51 features.
Fitting estimator with 50 features.
Fitting estimator with 49 features.
Fitting estimator with 48 features.
Fitting estimator with 47 features.
Fitting estimator with 46 features.
Fitting estimator with 45 features.
Fitting estimator with 44 features.
Fitting estimator with 43 features.
Fitting estimator with 42 features.
Fitting estimator with 41 features.
Fitting estimator with 40 features.
Fitting estimator with 39 features.
```

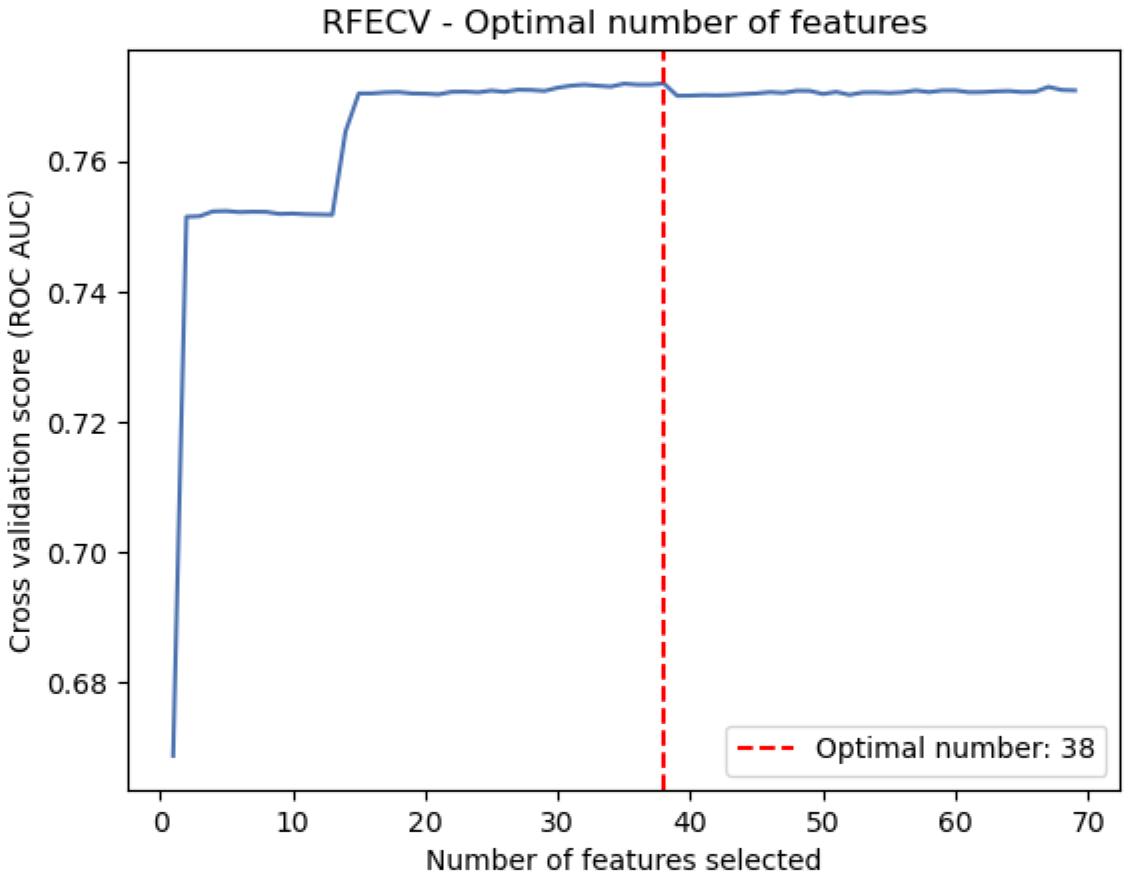
Out[10]:

```
▸ RFECV
▸ estimator: Pipeline
    ▸ StandardScaler
    ▸ LogisticRegression
```

In [11]:

```
plt.figure()
# Get the cross-validation scores
min_features_to_select = 1
n_scores = len(rfecv.cv_results_['mean_test_score'])
plt.plot(range(min_features_to_select, n_scores + min_features_to_select),
         rfecv.cv_results_['mean_test_score'])
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (ROC AUC)")
# add the optimal number of features line
plt.axvline(x=rfecv.n_features_, color='r', linestyle='--',
            label=f'Optimal number: {rfecv.n_features_}')
plt.legend()
plt.title("RFECV - Optimal number of features")
```

```
plt.savefig('./plots/RFECV.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [12]:
```
selected_feature_names = list(newX.columns[rfecv.support_])
print(f"{rfecv.n_features_} selected feature names: {selected_feature_names}

# Show all features with their rankings
feature_ranking_df = pd.DataFrame({
    'feature': newX.columns,
    'ranking': rfecv.ranking_
}).sort_values('ranking')
print("\nFeature rankings:")
with pd.option_context('display.max_rows', None):
    print(feature_ranking_df)
```

```
38 selected feature names: ['fulladdress_count_30', 'address_count_14', 'ful
laddress_count_14', 'address_count_7', 'fulladdress_count_7', 'fulladdress_c
ount_0_by_7', 'address_count_1', 'fulladdress_count_1', 'ssn_dob_count_30', 
'ssn_count_30', 'ssn_ssn_count_30', 'ssn_firstname_count_30', 'ssn_lastname_
count_30', 'fulladdress_homephone_count_30', 'ssn_name_dob_count_30', 'name_
dob_count_30', 'ssn_name_count_30', 'ssn_ssn_count_14', 'ssn_count_14', 'ssn
_dob_count_14', 'ssn_firstname_count_14', 'zip5_count_1', 'ssn_lastname_coun
t_14', 'zip5_count_3', 'name_dob_count_14', 'ssn_name_count_14', 'ssn_name_d
ob_count_14', 'ssn_name_dob_count_0_by_30', 'fulladdress_count_1_by_14', 'fu
lladdress_homephone_count_7', 'fulladdress_homephone_count_0_by_30', 'ssn_do
b_count_0_by_14', 'ssn_ssn_count_0_by_30', 'ssn_firstname_count_0_by_14', 's
sn_ssn_count_7', 'ssn_lastname_count_0_by_30', 'ssn_name_count_0_by_30', 'na
me_dob_count_0_by_30']

Feature rankings:
                                 feature  ranking
0                   fulladdress_count_30        1
28                          ssn_count_14        1
29                      ssn_dob_count_14        1
30                ssn_firstname_count_14        1
31                          zip5_count_1        1
33                 ssn_lastname_count_14        1
35                     name_dob_count_14        1
36                     ssn_name_count_14        1
37                 ssn_name_dob_count_14        1
39            ssn_name_dob_count_0_by_30        1
41             fulladdress_count_1_by_14        1
42         fulladdress_homephone_count_7        1
45    fulladdress_homephone_count_0_by_30        1
46                 ssn_dob_count_0_by_14        1
47                 ssn_ssn_count_0_by_30        1
51           ssn_firstname_count_0_by_14        1
53                       ssn_ssn_count_7        1
54            ssn_lastname_count_0_by_30        1
55                ssn_name_count_0_by_30        1
61                name_dob_count_0_by_30        1
27                      ssn_ssn_count_14        1
23                     ssn_name_count_30        1
34                          zip5_count_3        1
21                 ssn_name_dob_count_30        1
1                       address_count_14        1
2                   fulladdress_count_14        1
3                        address_count_7        1
20        fulladdress_homephone_count_30        1
19                 ssn_lastname_count_30        1
18                ssn_firstname_count_30        1
17                      ssn_ssn_count_30        1
16                          ssn_count_30        1
4                    fulladdress_count_7        1
15                      ssn_dob_count_30        1
22                     name_dob_count_30        1
14                   fulladdress_count_1        1
13                       address_count_1        1
12               fulladdress_count_0_by_7        1
68                          zip5_count_7        2
49                      ssn_count_0_by_30        3
```

43	ssn_count_0_by_14	4
10	address_count_0_by_30	5
50	ssn_firstname_count_0_by_30	6
26	fulladdress_homephone_count_14	7
44	ssn_ssn_count_0_by_14	8
40	address_count_1_by_14	9
59	ssn_lastname_count_0_by_14	10
5	address_count_0_by_14	11
6	fulladdress_count_0_by_14	12
24	fulladdress_count_0_by_3	13
7	address_count_3	14
48	name_count_14	15
32	name_count_30	16
52	ssn_count_7	17
58	ssn_dob_count_7	18
38	ssn_dob_count_0_by_30	19
64	ssn_name_count_0_by_14	20
8	fulladdress_count_3	21
11	address_count_0_by_7	22
25	address_count_0_by_3	23
9	fulladdress_count_0_by_30	24
56	name_dob_count_0_by_14	25
65	fulladdress_homephone_count_0_by_14	26
60	ssn_firstname_count_7	27
63	ssn_lastname_count_7	28
62	ssn_name_dob_count_0_by_14	29
57	name_dob_count_7	30
67	ssn_name_dob_count_7	31
66	ssn_name_count_7	32

In [13]:
```
del newX, y
```

In [14]:
```
final_cut = pd.read_csv('./data/vars 485.csv', index_col=0)
final_cut = final_cut[selected_feature_names + ['fraud_label']]
final_cut.to_csv('./data/selected.csv')
```

Standardization

In [2]:
```
#final_cut = pd.read_csv('./data/vars 485.csv', index_col=0)
```

In [15]:
```
label = final_cut.fraud_label
label.shape
```

Out[15]: (981694,)

In [16]:
```
only_feature = final_cut.drop(['fraud_label'], axis=1)
print('features shape: ', only_feature.shape)
std = only_feature.std()
mean = only_feature.mean()
z_scaled = (only_feature - mean)/std
del final_cut
# Prevent extreme values after z-scaled
```

```
z_scaled = z_scaled.clip(lower=-1000, upper=1000)
z_scaled.describe()
```

```
features shape:  (981694, 38)
```

Out[16]:

	fulladdress_count_30	address_count_14	fulladdress_count_14	address_count_
count	9.816940e+05	9.816940e+05	9.816940e+05	9.816940e+0
mean	-1.779950e-16	1.749262e-16	-1.817588e-16	4.771240e-1
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+0
min	-1.014801e-01	-8.811756e-02	-7.861317e-02	-7.224399e-0
25%	-1.014801e-01	-8.811756e-02	-7.861317e-02	-7.224399e-0
50%	-1.014801e-01	-8.811756e-02	-7.861317e-02	-7.224399e-0
75%	-1.014801e-01	-8.811756e-02	-7.861317e-02	-7.224399e-0
max	4.534025e+01	4.648183e+01	4.733666e+01	4.903885e+0

8 rows × 38 columns

In [17]:

```
z_scaled['fraud_label']=label
z_scaled.to_csv('./data/z_scaled.csv')
```

Feature Reduction

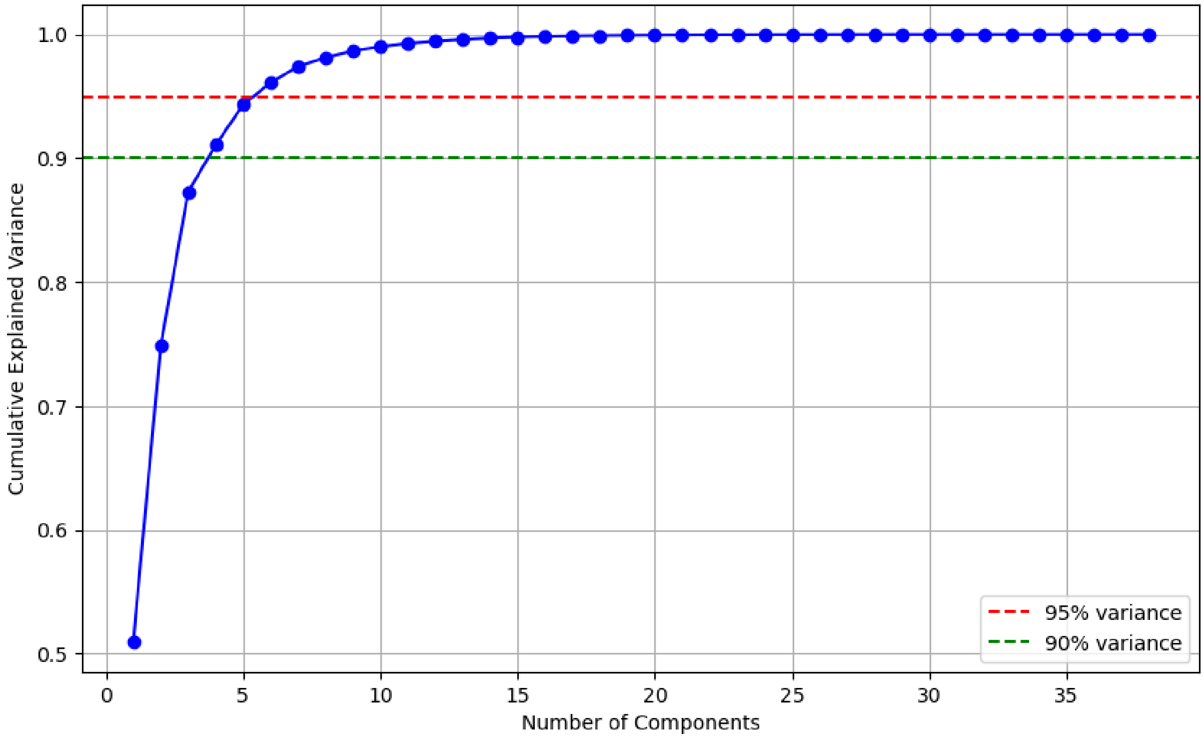
In [18]:

```
from sklearn.decomposition import PCA

X = z_scaled.drop(['fraud_label'], axis=1)
y = z_scaled.fraud_label
# Fit PCA with all components
pca = PCA()
pca.fit(X)
# Calculate cumulative variance explained
cumsum_var = np.cumsum(pca.explained_variance_ratio_)

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(range(1, len(cumsum_var) + 1), cumsum_var, 'bo-')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.axhline(y=0.95, color='r', linestyle='--', label='95% variance')
plt.axhline(y=0.90, color='g', linestyle='--', label='90% variance')
plt.legend()
plt.grid(True)
plt.show()
# Find number of components for desired variance
n_components_95 = round(np.argmax(cumsum_var >= 0.95))
```

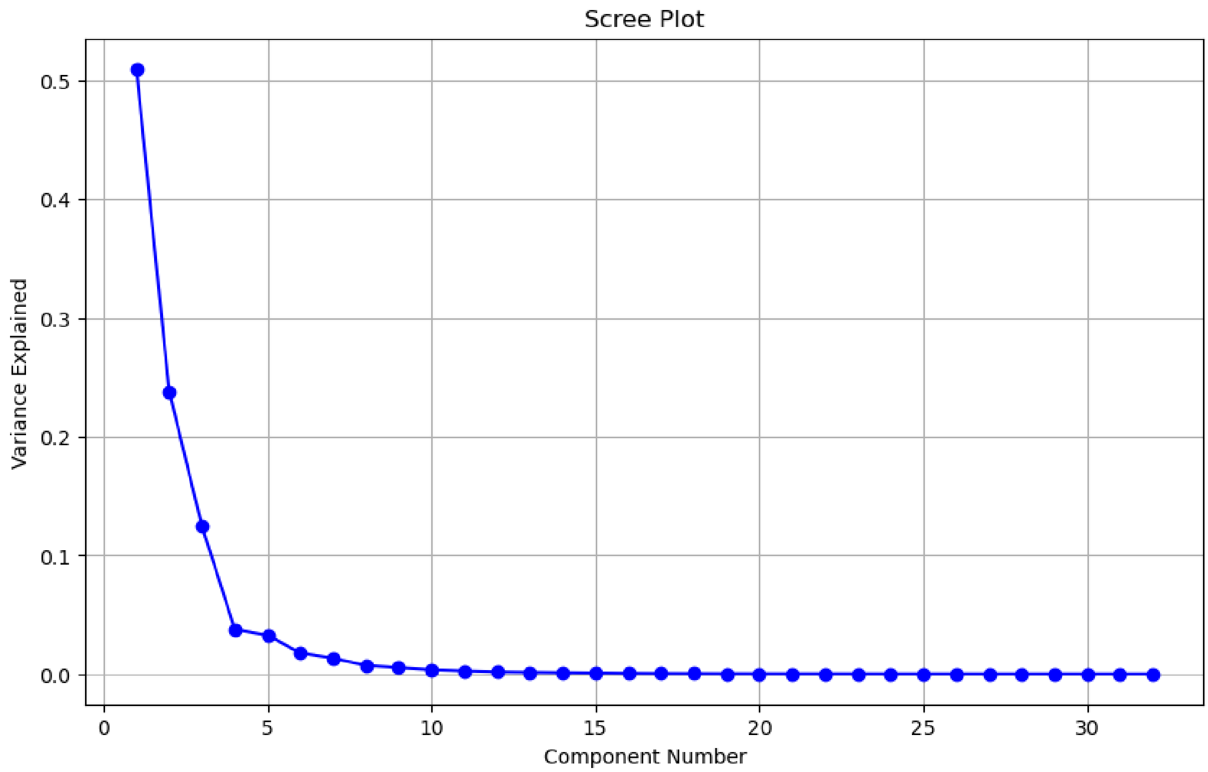
```
n_components_90 = round(np.argmax(cumsum_var >= 0.90))
print(f"Components for 95% variance: {n_components_95}")
print(f"Components for 90% variance: {n_components_90}")
```




```
Components for 95% variance: 5
Components for 90% variance: 3
```

In [19]:

```
# Plot individual variance explained
plt.figure(figsize=(10, 6))
plt.plot(range(1, 33), pca.explained_variance_ratio_[:32], 'bo-')
plt.xlabel('Component Number')
plt.ylabel('Variance Explained')
plt.title('Scree Plot')
plt.grid(True)
plt.show()
```



split statistics to about 80% train, test set (X, y will be divided by train_test_split function) and 20% Out Of Time (OOT)

In [20]:
```
total = X.shape[0]
X = X[0:round(total*0.8)]
y = y[0:round(total*0.8)]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [21]:
```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline

# Test different numbers of components
n_components_range = [3, 5, 7, 10]
cv_scores = []

for n in n_components_range:
    pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('pca', PCA(n_components=n)),
        ('classifier', RandomForestClassifier(n_estimators=100, random_state
    ])

    scores = cross_val_score(pipeline, X_train, y_train, cv=5, scoring='roc_
    cv_scores.append(scores.mean())
    print(f"n_components={n}, AUC={scores.mean():.4f} (+/- {scores.std():.4f

# Plot results
plt.figure(figsize=(10, 6))
plt.plot(n_components_range, cv_scores, 'bo-')
plt.xlabel('Number of PCA Components')
```

```
plt.ylabel('Cross-validated AUC Score')
plt.grid(True)
plt.show()
```

```
n_components=3, AUC=0.7651 (+/- 0.0043)
Fitting estimator with 69 features.
Fitting estimator with 68 features.
Fitting estimator with 67 features.
Fitting estimator with 66 features.
Fitting estimator with 65 features.
Fitting estimator with 64 features.
Fitting estimator with 63 features.
Fitting estimator with 62 features.
Fitting estimator with 61 features.
Fitting estimator with 60 features.
Fitting estimator with 59 features.
Fitting estimator with 58 features.
Fitting estimator with 57 features.
Fitting estimator with 56 features.
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Fitting estimator with 39 features.
Fitting estimator with 38 features.
Fitting estimator with 37 features.
Fitting estimator with 36 features.
Fitting estimator with 35 features.
Fitting estimator with 34 features.
Fitting estimator with 33 features.
Fitting estimator with 32 features.
Fitting estimator with 31 features.
Fitting estimator with 30 features.
Fitting estimator with 29 features.
Fitting estimator with 28 features.
Fitting estimator with 27 features.
Fitting estimator with 26 features.
Fitting estimator with 25 features.
Fitting estimator with 24 features.
Fitting estimator with 23 features.
Fitting estimator with 22 features.
Fitting estimator with 21 features.
Fitting estimator with 20 features.
Fitting estimator with 19 features.
Fitting estimator with 18 features.
Fitting estimator with 17 features.
Fitting estimator with 16 features.
Fitting estimator with 15 features.
```

```
Fitting estimator with 14 features.
Fitting estimator with 13 features.
Fitting estimator with 12 features.
Fitting estimator with 11 features.
Fitting estimator with 10 features.
Fitting estimator with 9 features.
Fitting estimator with 8 features.
Fitting estimator with 7 features.
Fitting estimator with 6 features.
Fitting estimator with 5 features.
Fitting estimator with 4 features.
Fitting estimator with 3 features.
Fitting estimator with 2 features.
Fitting estimator with 69 features.
Fitting estimator with 68 features.
Fitting estimator with 67 features.
Fitting estimator with 66 features.
Fitting estimator with 65 features.
Fitting estimator with 64 features.
Fitting estimator with 63 features.
Fitting estimator with 62 features.
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Fitting estimator with 34 features.
Fitting estimator with 33 features.
Fitting estimator with 32 features.
Fitting estimator with 31 features.
Fitting estimator with 30 features.
Fitting estimator with 29 features.
Fitting estimator with 28 features.
Fitting estimator with 27 features.
```

```
Fitting estimator with 26 features.
Fitting estimator with 25 features.
Fitting estimator with 24 features.
Fitting estimator with 23 features.
Fitting estimator with 22 features.
Fitting estimator with 21 features.
Fitting estimator with 20 features.
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Fitting estimator with 12 features.
Fitting estimator with 11 features.
Fitting estimator with 10 features.
Fitting estimator with 9 features.
Fitting estimator with 8 features.
Fitting estimator with 7 features.
Fitting estimator with 6 features.
Fitting estimator with 5 features.
Fitting estimator with 4 features.
Fitting estimator with 3 features.
Fitting estimator with 2 features.
Fitting estimator with 69 features.
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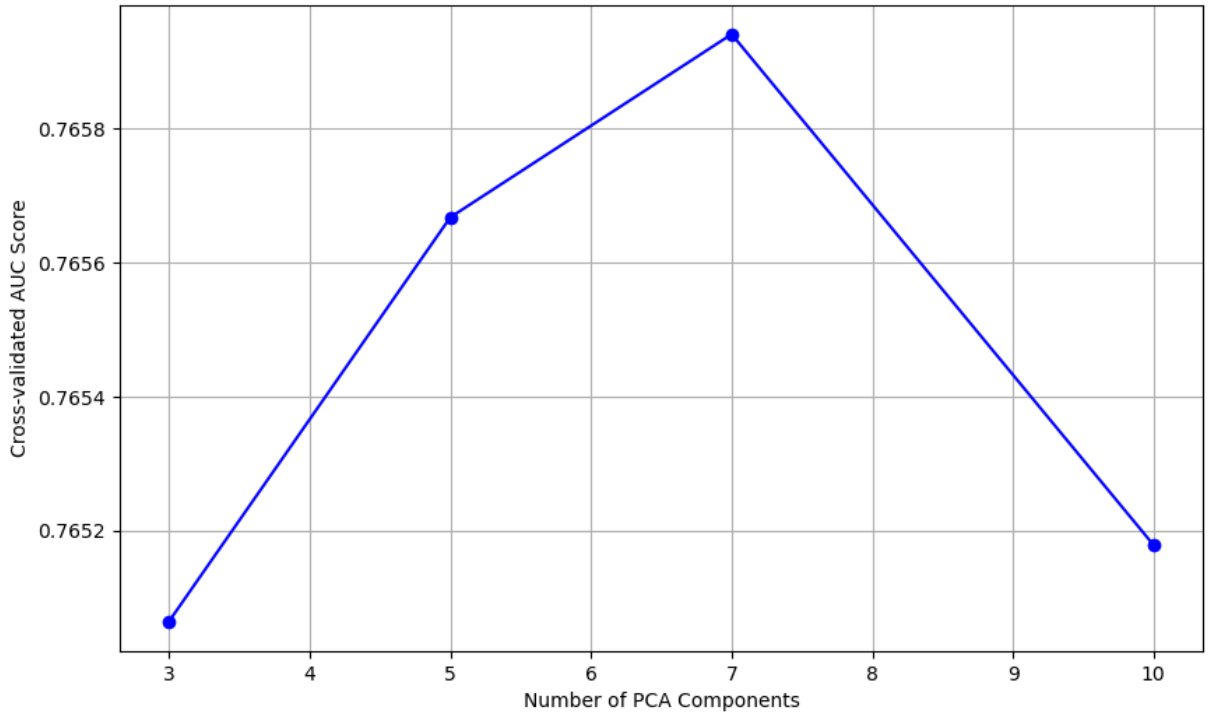
Fitting estimator with 45 features.
Fitting estimator with 44 features.
Fitting estimator with 43 features.
Fitting estimator with 42 features.
Fitting estimator with 41 features.
Fitting estimator with 40 features.
Fitting estimator with 39 features.
```

```
Fitting estimator with 38 features.
Fitting estimator with 37 features.
Fitting estimator with 36 features.
Fitting estimator with 35 features.
Fitting estimator with 34 features.
Fitting estimator with 33 features.
Fitting estimator with 32 features.
Fitting estimator with 31 features.
Fitting estimator with 30 features.
Fitting estimator with 29 features.
Fitting estimator with 28 features.
Fitting estimator with 27 features.
Fitting estimator with 26 features.
Fitting estimator with 25 features.
Fitting estimator with 24 features.
Fitting estimator with 23 features.
Fitting estimator with 22 features.
Fitting estimator with 21 features.
Fitting estimator with 20 features.
Fitting estimator with 19 features.
Fitting estimator with 18 features.
Fitting estimator with 17 features.
Fitting estimator with 16 features.
Fitting estimator with 15 features.
Fitting estimator with 14 features.
Fitting estimator with 13 features.
Fitting estimator with 12 features.
Fitting estimator with 11 features.
Fitting estimator with 10 features.
Fitting estimator with 9 features.
Fitting estimator with 8 features.
Fitting estimator with 7 features.
Fitting estimator with 6 features.
Fitting estimator with 5 features.
Fitting estimator with 4 features.
Fitting estimator with 3 features.
Fitting estimator with 2 features.
n_components=5, AUC=0.7657 (+/- 0.0035)
n_components=7, AUC=0.7659 (+/- 0.0042)
n_components=10, AUC=0.7652 (+/- 0.0044)
```



In [22]:
```
X = z_scaled.drop(['fraud_label'], axis=1)
y = z_scaled.fraud_label

# Apply PCA with 5 components
pca = PCA(n_components=5)
X_pca = pca.fit_transform(X)
pca_columns = [f'PC{i+1}' for i in range(5)]
df_pca = pd.DataFrame(X_pca, columns=pca_columns)
df_pca['fraud'] = y
df_pca.to_csv('./data/reduced_pca.csv')
```

In [ ]:
```
```