Data Preparation

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [ ]:
```
## Reading in the dataframes. Train data and labels are stored in different CSV

train_data = pd.read_csv("data/train_data.csv", chunksize = 100000)
train_labels = pd.read_csv("data/train_labels.csv")
```

In [ ]:
```
## This is a very large dataset, and training models on it is computationally ex
## This cell reduces the size of the individual entries of the dataset to speed

df2 = pd.DataFrame()
for df in train_data:
    cols = ['customer_ID', 'S_2', 'B_30', 'B_38', 'D_63', 'D_64', 'D_66', 'D_68'
    df['customer_ID'] = df['customer_ID'].apply(lambda x: int(x[-16:],16) ).asty
    df['S_2'] = pd.to_datetime(df['S_2'])
    df['B_30'] = df['B_30'].fillna(-1).astype('int8')
    df['B_38'] = df['B_38'].fillna(-1).astype('int8')
    df['D_63'] = df['D_63'].astype('category').cat.codes.astype('int8')
    df['D_64'] = df['D_64'].astype('category').cat.codes.astype('int8')
    df['D_66'] = df['D_66'].astype('category').cat.codes.astype('int8')
    df['D_68'] = df['D_68'].astype('category').cat.codes.astype('int8')
    df['D_114'] = df['D_114'].fillna(-1).astype('int8')
    df['D_116'] = df['D_116'].fillna(-1).astype('int8')
    df['D_117'] = df['D_117'].fillna(-1).astype('int8')
    df['D_120'] = df['D_120'].fillna(-1).astype('int8')
    df['D_126'] = df['D_126'].fillna(-1).astype('int8')
    for c in df.columns:
        if c not in cols:
            df[c] = df[c].fillna(-1).astype('int16')
    df2 = pd.concat([df2, df])
```

In [ ]:
```
print("Total number of rows in train_data : ", len(df2))
print("Total number of unique customers in train_data : ", len(df2['customer_ID'
```

```
Total number of rows in train_data :  5531451
Total number of unique customers in train_data :  458884
```

In [ ]:
```
## This function removes all missing values from the dataframe
## This includes np.nan and -1 entries

def handle_nan_values(df, missing_values=[np.nan, -1]):
    df.replace(missing_values, np.nan, inplace=True)
    nan_percentage = (df.isna().sum() / len(df)) * 100
    columns_to_drop = nan_percentage[nan_percentage > 50].index
    df = df.drop(columns=columns_to_drop)
    df = df.apply(lambda col: col.fillna(col.mean()) if col.isna().any() else co
    return df
```

In [ ]:
```
df2 = handle_nan_values(df2)
```

In [ ]:
```
## Get lists of the categorical, time, and numerical columns in the dataframe
## This will be useful in data aggregation
```

```
cat_cols = ['B_30', 'B_38', 'D_114', 'D_116', 'D_117', 'D_120', 'D_126', 'D_63',
time_col = ['S_2']
id_col = ['customer_ID']
numeric_cols = []
for col in df2.columns:
    if col not in cat_cols and col not in time_col and col not in id_col:
        numeric_cols.append(col)

print(len(numeric_cols))
```

```
177
```

In [ ]:
```
## One of the aggregation steps involves finding the most recent value of each c

last_values_df = df2.sort_values(by=['customer_ID', 'S_2']).groupby('customer_ID

# Rename the columns to indicate they are the last values
last_values_df.columns = [f'{col}_last' for col in last_values_df.columns]
```

In [ ]:
```
columns_to_aggregate = numeric_cols

# Define aggregation functions for each numerical column
aggregation_functions = {
    col: ['mean', 'std', 'min', 'max'] for col in columns_to_aggregate
}

print(aggregation_functions)

# Aggregating the dataframe's numerical values
# Only numerical features appear in the resulting dataframe
aggregated_df = df2.groupby('customer_ID').agg(aggregation_functions).reset_inde
aggregated_df.columns = ['_'.join(col).strip() for col in aggregated_df.columns.

aggregated_df.rename(columns={'customer_ID_': 'customer_ID'}, inplace=True)
train_labels['customer_ID'] =train_labels['customer_ID'].apply(lambda x: int(x[-
```

```
{'P_2': ['mean', 'std', 'min', 'max'], 'D_39': ['mean', 'std', 'min', 'max'], 'B
_1': ['mean', 'std', 'min', 'max'], 'B_2': ['mean', 'std', 'min', 'max'], 'R_1':
['mean', 'std', 'min', 'max'], 'S_3': ['mean', 'std', 'min', 'max'], 'D_41': ['m
ean', 'std', 'min', 'max'], 'B_3': ['mean', 'std', 'min', 'max'], 'D_42': ['mea
n', 'std', 'min', 'max'], 'D_43': ['mean', 'std', 'min', 'max'], 'D_44': ['mea
n', 'std', 'min', 'max'], 'B_4': ['mean', 'std', 'min', 'max'], 'D_45': ['mean',
'std', 'min', 'max'], 'B_5': ['mean', 'std', 'min', 'max'], 'R_2': ['mean', 'st
d', 'min', 'max'], 'D_46': ['mean', 'std', 'min', 'max'], 'D_47': ['mean', 'st
d', 'min', 'max'], 'D_48': ['mean', 'std', 'min', 'max'], 'D_49': ['mean', 'st
d', 'min', 'max'], 'B_6': ['mean', 'std', 'min', 'max'], 'B_7': ['mean', 'std',
'min', 'max'], 'B_8': ['mean', 'std', 'min', 'max'], 'D_50': ['mean', 'std', 'mi
n', 'max'], 'D_51': ['mean', 'std', 'min', 'max'], 'B_9': ['mean', 'std', 'min',
'max'], 'R_3': ['mean', 'std', 'min', 'max'], 'D_52': ['mean', 'std', 'min', 'ma
x'], 'P_3': ['mean', 'std', 'min', 'max'], 'B_10': ['mean', 'std', 'min', 'ma
x'], 'D_53': ['mean', 'std', 'min', 'max'], 'S_5': ['mean', 'std', 'min', 'ma
x'], 'B_11': ['mean', 'std', 'min', 'max'], 'S_6': ['mean', 'std', 'min', 'ma
x'], 'D_54': ['mean', 'std', 'min', 'max'], 'R_4': ['mean', 'std', 'min', 'ma
x'], 'S_7': ['mean', 'std', 'min', 'max'], 'B_12': ['mean', 'std', 'min', 'ma
x'], 'S_8': ['mean', 'std', 'min', 'max'], 'D_55': ['mean', 'std', 'min', 'ma
x'], 'D_56': ['mean', 'std', 'min', 'max'], 'B_13': ['mean', 'std', 'min', 'ma
x'], 'R_5': ['mean', 'std', 'min', 'max'], 'D_58': ['mean', 'std', 'min', 'ma
x'], 'S_9': ['mean', 'std', 'min', 'max'], 'B_14': ['mean', 'std', 'min', 'ma
x'], 'D_59': ['mean', 'std', 'min', 'max'], 'D_60': ['mean', 'std', 'min', 'ma
x'], 'D_61': ['mean', 'std', 'min', 'max'], 'B_15': ['mean', 'std', 'min', 'ma
x'], 'S_11': ['mean', 'std', 'min', 'max'], 'D_62': ['mean', 'std', 'min', 'ma
```

```
x'], 'D_65': ['mean', 'std', 'min', 'max'], 'B_16': ['mean', 'std', 'min', 'ma
x'], 'B_17': ['mean', 'std', 'min', 'max'], 'B_18': ['mean', 'std', 'min', 'ma
x'], 'B_19': ['mean', 'std', 'min', 'max'], 'B_20': ['mean', 'std', 'min', 'ma
x'], 'S_12': ['mean', 'std', 'min', 'max'], 'R_6': ['mean', 'std', 'min', 'ma
x'], 'S_13': ['mean', 'std', 'min', 'max'], 'B_21': ['mean', 'std', 'min', 'ma
x'], 'D_69': ['mean', 'std', 'min', 'max'], 'B_22': ['mean', 'std', 'min', 'ma
x'], 'D_70': ['mean', 'std', 'min', 'max'], 'D_71': ['mean', 'std', 'min', 'ma
x'], 'D_72': ['mean', 'std', 'min', 'max'], 'S_15': ['mean', 'std', 'min', 'ma
x'], 'B_23': ['mean', 'std', 'min', 'max'], 'D_73': ['mean', 'std', 'min', 'ma
x'], 'P_4': ['mean', 'std', 'min', 'max'], 'D_74': ['mean', 'std', 'min', 'ma
x'], 'D_75': ['mean', 'std', 'min', 'max'], 'D_76': ['mean', 'std', 'min', 'ma
x'], 'B_24': ['mean', 'std', 'min', 'max'], 'R_7': ['mean', 'std', 'min', 'ma
x'], 'D_77': ['mean', 'std', 'min', 'max'], 'B_25': ['mean', 'std', 'min', 'ma
x'], 'B_26': ['mean', 'std', 'min', 'max'], 'D_78': ['mean', 'std', 'min', 'ma
x'], 'D_79': ['mean', 'std', 'min', 'max'], 'R_8': ['mean', 'std', 'min', 'ma
x'], 'R_9': ['mean', 'std', 'min', 'max'], 'S_16': ['mean', 'std', 'min', 'ma
x'], 'D_80': ['mean', 'std', 'min', 'max'], 'R_10': ['mean', 'std', 'min', 'ma
x'], 'R_11': ['mean', 'std', 'min', 'max'], 'B_27': ['mean', 'std', 'min', 'ma
x'], 'D_81': ['mean', 'std', 'min', 'max'], 'D_82': ['mean', 'std', 'min', 'ma
x'], 'S_17': ['mean', 'std', 'min', 'max'], 'R_12': ['mean', 'std', 'min', 'ma
x'], 'B_28': ['mean', 'std', 'min', 'max'], 'R_13': ['mean', 'std', 'min', 'ma
x'], 'D_83': ['mean', 'std', 'min', 'max'], 'R_14': ['mean', 'std', 'min', 'ma
x'], 'R_15': ['mean', 'std', 'min', 'max'], 'D_84': ['mean', 'std', 'min', 'ma
x'], 'R_16': ['mean', 'std', 'min', 'max'], 'B_29': ['mean', 'std', 'min', 'ma
x'], 'S_18': ['mean', 'std', 'min', 'max'], 'D_86': ['mean', 'std', 'min', 'ma
x'], 'D_87': ['mean', 'std', 'min', 'max'], 'R_17': ['mean', 'std', 'min', 'ma
x'], 'R_18': ['mean', 'std', 'min', 'max'], 'D_88': ['mean', 'std', 'min', 'ma
x'], 'B_31': ['mean', 'std', 'min', 'max'], 'S_19': ['mean', 'std', 'min', 'ma
x'], 'R_19': ['mean', 'std', 'min', 'max'], 'B_32': ['mean', 'std', 'min', 'ma
x'], 'S_20': ['mean', 'std', 'min', 'max'], 'R_20': ['mean', 'std', 'min', 'ma
x'], 'R_21': ['mean', 'std', 'min', 'max'], 'B_33': ['mean', 'std', 'min', 'ma
x'], 'D_89': ['mean', 'std', 'min', 'max'], 'R_22': ['mean', 'std', 'min', 'ma
x'], 'R_23': ['mean', 'std', 'min', 'max'], 'D_91': ['mean', 'std', 'min', 'ma
x'], 'D_92': ['mean', 'std', 'min', 'max'], 'D_93': ['mean', 'std', 'min', 'ma
x'], 'D_94': ['mean', 'std', 'min', 'max'], 'R_24': ['mean', 'std', 'min', 'ma
x'], 'R_25': ['mean', 'std', 'min', 'max'], 'D_96': ['mean', 'std', 'min', 'ma
x'], 'S_22': ['mean', 'std', 'min', 'max'], 'S_23': ['mean', 'std', 'min', 'ma
x'], 'S_24': ['mean', 'std', 'min', 'max'], 'S_25': ['mean', 'std', 'min', 'ma
x'], 'S_26': ['mean', 'std', 'min', 'max'], 'D_102': ['mean', 'std', 'min', 'ma
x'], 'D_103': ['mean', 'std', 'min', 'max'], 'D_104': ['mean', 'std', 'min', 'ma
x'], 'D_105': ['mean', 'std', 'min', 'max'], 'D_106': ['mean', 'std', 'min', 'ma
x'], 'D_107': ['mean', 'std', 'min', 'max'], 'B_36': ['mean', 'std', 'min', 'ma
x'], 'B_37': ['mean', 'std', 'min', 'max'], 'R_26': ['mean', 'std', 'min', 'ma
x'], 'R_27': ['mean', 'std', 'min', 'max'], 'D_108': ['mean', 'std', 'min', 'ma
x'], 'D_109': ['mean', 'std', 'min', 'max'], 'D_110': ['mean', 'std', 'min', 'ma
x'], 'D_111': ['mean', 'std', 'min', 'max'], 'B_39': ['mean', 'std', 'min', 'ma
x'], 'D_112': ['mean', 'std', 'min', 'max'], 'B_40': ['mean', 'std', 'min', 'ma
x'], 'S_27': ['mean', 'std', 'min', 'max'], 'D_113': ['mean', 'std', 'min', 'ma
x'], 'D_115': ['mean', 'std', 'min', 'max'], 'D_118': ['mean', 'std', 'min', 'ma
x'], 'D_119': ['mean', 'std', 'min', 'max'], 'D_121': ['mean', 'std', 'min', 'ma
x'], 'D_122': ['mean', 'std', 'min', 'max'], 'D_123': ['mean', 'std', 'min', 'ma
x'], 'D_124': ['mean', 'std', 'min', 'max'], 'D_125': ['mean', 'std', 'min', 'ma
x'], 'D_127': ['mean', 'std', 'min', 'max'], 'D_128': ['mean', 'std', 'min', 'ma
x'], 'D_129': ['mean', 'std', 'min', 'max'], 'B_41': ['mean', 'std', 'min', 'ma
x'], 'B_42': ['mean', 'std', 'min', 'max'], 'D_130': ['mean', 'std', 'min', 'ma
x'], 'D_131': ['mean', 'std', 'min', 'max'], 'D_132': ['mean', 'std', 'min', 'ma
x'], 'D_133': ['mean', 'std', 'min', 'max'], 'R_28': ['mean', 'std', 'min', 'ma
x'], 'D_134': ['mean', 'std', 'min', 'max'], 'D_135': ['mean', 'std', 'min', 'ma
x'], 'D_136': ['mean', 'std', 'min', 'max'], 'D_137': ['mean', 'std', 'min', 'ma
x'], 'D_138': ['mean', 'std', 'min', 'max'], 'D_139': ['mean', 'std', 'min', 'ma
x'], 'D_140': ['mean', 'std', 'min', 'max'], 'D_141': ['mean', 'std', 'min', 'ma
x'], 'D_142': ['mean', 'std', 'min', 'max'], 'D_143': ['mean', 'std', 'min', 'ma
x'], 'D_144': ['mean', 'std', 'min', 'max'], 'D_145': ['mean', 'std', 'min', 'ma
x']}
```

In [ ]:
```
## The variable name "final_df" is misleading; we are still missing the mode

final_df = pd.merge(aggregated_df, last_values_df, left_on='customer_ID', right_
final_df
```

Out[ ]:

	customer_ID	P_2_mean	P_2_std	P_2_min	P_2_max	D_39_mean	D_39_std	D_39_mi
0	-2147467588	0.000000	0.000000	0	0	0.000000	0.00000	
1	-2147461914	0.000000	0.000000	0	0	0.076923	0.27735	
2	-2147456568	0.000000	0.000000	0	0	0.000000	0.00000	
3	-2147448814	0.000000	0.000000	0	0	0.000000	0.00000	
4	-2147448315	0.000000	0.000000	0	0	0.000000	0.00000	
...	...	...	...	...	...	...	...	.
458879	2147393588	0.000000	0.000000	0	0	0.000000	0.00000	
458880	2147411856	0.000000	0.000000	0	0	0.000000	0.00000	
458881	2147464011	0.153846	0.375534	0	1	0.000000	0.00000	
458882	2147464257	0.000000	0.000000	0	0	0.000000	0.00000	
458883	2147482790	0.000000	0.000000	0	0	0.076923	0.27735	

458884 rows × 898 columns

In [ ]:
```
## Aggregating the mode for categorical columns

mode_aggregation = { col: [('mode', lambda x: x.mode().iat[0])] for col in cat_c
mode_df = df2.groupby('customer_ID').agg(mode_aggregation).reset_index()
mode_df.columns = [f'{col}_{agg}' for col, agg in mode_df.columns]
```

In [ ]:
```
# Fixing naming issue
mode_df=mode_df.rename(columns={"customer_ID_":"customer_ID"})
mode_df
```

Out[ ]:

	customer_ID	B_30_mode	B_38_mode	D_114_mode	D_116_mode	D_117_mode	D_120_r
0	-2147467588	0	1	-1	-1	-1	
1	-2147461914	1	3	0	0	-1	
2	-2147456568	0	7	0	0	-1	
3	-2147448814	0	5	0	0	-1	
4	-2147448315	0	4	0	0	3	
...	...	...	...	...	...	...	
458879	2147393588	0	1	0	0	-1	
458880	2147411856	1	6	1	0	2	
458881	2147464011	0	1	1	0	2	
458882	2147464257	0	3	0	0	4	
458883	2147482790	0	2	0	0	2	

458884 rows × 12 columns

In [ ]:
```
# Merging labels and values
merged_df = pd.merge(final_df, train_labels, on='customer_ID')
merged_df = merged_df.drop_duplicates(subset='customer_ID')
# Merging mode aggregation
merged_df = pd.merge(merged_df, mode_df, on='customer_ID')
```

In [ ]:
```
merged_df
```

Out[ ]:

	customer_ID	P_2_mean	P_2_std	P_2_min	P_2_max	D_39_mean	D_39_std	D_39_mi
0	-2147467588	0.000000	0.000000	0	0	0.000000	0.00000	
1	-2147461914	0.000000	0.000000	0	0	0.076923	0.27735	
2	-2147456568	0.000000	0.000000	0	0	0.000000	0.00000	
3	-2147448814	0.000000	0.000000	0	0	0.000000	0.00000	
4	-2147448315	0.000000	0.000000	0	0	0.000000	0.00000	
...	...	...	...	...	...	...	...	.
458879	2147393588	0.000000	0.000000	0	0	0.000000	0.00000	
458880	2147411856	0.000000	0.000000	0	0	0.000000	0.00000	
458881	2147464011	0.153846	0.375534	0	1	0.000000	0.00000	
458882	2147464257	0.000000	0.000000	0	0	0.000000	0.00000	
458883	2147482790	0.000000	0.000000	0	0	0.076923	0.27735	

458884 rows × 910 columns

In [ ]:
```
## Changing the type of S_2_last such that it may be interpreted by models

merged_df = merged_df.drop(columns=['Unnamed: 0'])
merged_df['S_2_last'] = pd.to_datetime(merged_df['S_2_last']).astype('int64')
```

In [ ]:
```
merged_df.to_csv("data/default.csv")
```

In [ ]:
```
default_df = pd.read_csv("data/default.csv")
```

Tree-based model training

In [ ]:
```
from sklearn.model_selection import train_test_split
```

In [ ]:
```
values = default_df.drop(columns=['Unnamed: 0', 'target'])
labels = default_df['target']
```

In [ ]:
```
train_X, test_X, train_Y, test_Y = train_test_split(values, labels, test_size=0.
```

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
```

In [ ]:
```
baseline_DT = DecisionTreeClassifier(random_state=42)
baseline_RF = RandomForestClassifier(random_state=42)
```

Baseline decision tree

In [ ]:
```
baseline_DT.fit(train_X, train_Y)
baseDT_preds = baseline_DT.predict(test_X)
base_DT_accuracy = accuracy_score(test_Y, baseDT_preds)
classification_report_str = classification_report(test_Y, baseDT_preds)

print(f"Baseline decision tree accuracy: {base_DT_accuracy}")
print(f"Baseline decision tree classification report:\n {classification_report_s
```

```
Baseline decision tree accuracy: 0.8210126058202499
Baseline decision tree classification report:
              precision    recall  f1-score   support

           0       0.88      0.88      0.88     68017
           1       0.66      0.65      0.65     23766

    accuracy                           0.82     91783
   macro avg       0.77      0.77      0.77     91783
weighted avg       0.82      0.82      0.82     91783
```

Baseline random forest

In [ ]:
```
baseline_RF.fit(train_X, train_Y)
baseRF_preds = baseline_RF.predict(test_X)
base_RF_accuracy = accuracy_score(test_Y, baseRF_preds)
base_RF_classRep = classification_report(test_Y, baseRF_preds)

print(f"Baseline random forest accuracy: {base_RF_accuracy}")
print(f"Baseline random forest classification report:\n {base_RF_classRep}")
```

```
Baseline decision tree accuracy: 0.8751838575771113
Baseline decision tree classification report:
              precision    recall  f1-score   support

           0       0.91      0.93      0.92     68017
           1       0.77      0.73      0.75     23766

    accuracy                           0.88     91783
   macro avg       0.84      0.83      0.83     91783
weighted avg       0.87      0.88      0.87     91783
```

Baseline Adaboost

In [ ]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [ ]:
```
baseline_ada = AdaBoostClassifier(random_state=42)
baseline_ada.fit(train_X, train_Y)
baseAda_preds = baseline_ada.predict(test_X)
base_Ada_accuracy = accuracy_score(test_Y, baseAda_preds)
```

```
base_Ada_classRep = classification_report(test_Y, baseAda_preds)

print(f"Baseline Adaboost model accuracy: {base_Ada_accuracy}")
print(f"Baseline Adaboost model classification report:\n {base_Ada_classRep}")
```

```
Baseline Adaboost model accuracy: 0.8684614797947332
Baseline Adaboost model classification report:
              precision    recall  f1-score   support

           0       0.90      0.93      0.91     68017
           1       0.77      0.70      0.73     23766

    accuracy                           0.87     91783
   macro avg       0.84      0.81      0.82     91783
weighted avg       0.87      0.87      0.87     91783
```

Baseline HistGradientBoosting

In [ ]:
```
from sklearn.ensemble import HistGradientBoostingClassifier
```

In [ ]:
```
baseline_HGB = HistGradientBoostingClassifier(random_state=42)
baseline_HGB.fit(train_X, train_Y)
baseHGB_preds = baseline_HGB.predict(test_X)
base_HGB_accuracy = accuracy_score(test_Y, baseHGB_preds)
base_HGB_classRep = classification_report(test_Y, baseHGB_preds)

print(f"Baseline HistGradientBoosting model accuracy: {base_HGB_accuracy}\n")
print(f"Baseline HistGradientBoosting model classification report:\n {base_HGB_c
```

```
Baseline HistGradientBoosting model accuracy: 0.8794983820533214

Baseline HistGradientBoosting model classification report:
              precision    recall  f1-score   support

           0       0.91      0.93      0.92     68017
           1       0.78      0.75      0.76     23766

    accuracy                           0.88     91783
   macro avg       0.85      0.84      0.84     91783
weighted avg       0.88      0.88      0.88     91783
```

Baseline XGBoost

In [ ]:
```
from xgboost import XGBClassifier
```

In [ ]:
```
baseline_XGB = XGBClassifier(random_state=42)
baseline_XGB.fit(train_X, train_Y)
baseXGB_preds = baseline_XGB.predict(test_X)
base_XGB_accuracy = accuracy_score(test_Y, baseXGB_preds)
base_XGB_classRep = classification_report(test_Y, baseXGB_preds)

print(f"Baseline XGBoost model accuracy: {base_XGB_accuracy}\n")
print(f"Baseline XGBoost model classification report:\n {base_XGB_classRep}")
```

```
Baseline XGBoost model accuracy: 0.8797271825937265

Baseline XGBoost model classification report:
              precision    recall  f1-score   support
```

```
           0       0.91      0.93      0.92     68017
           1       0.78      0.74      0.76     23766

    accuracy                           0.88     91783
   macro avg       0.85      0.84      0.84     91783
weighted avg       0.88      0.88      0.88     91783
```

Non-tree-based model training

Baseline logistic regression with l2 normalization

In [ ]:

```
from sklearn.linear_model import LogisticRegression
```

In [ ]:

```
baseline_LR = LogisticRegression(penalty='l2', random_state=42)
baseline_LR.fit(train_X, train_Y)
baseLR_preds = baseline_LR.predict(test_X)
base_LR_accuracy = accuracy_score(test_Y, baseLR_preds)
base_LR_classRep = classification_report(test_Y, baseLR_preds)

print(f"Baseline logistic regression (l2 normalization) accuracy: {base_LR_accur
print(f"Baseline logistic regression (l2 normalization) classification report:\r
```

```
Baseline logistic regression (l2 normalization) accuracy: 0.7410631598444156

Baseline logistic regression (l2 normalization) classification report:
              precision    recall  f1-score   support

           0       0.74      1.00      0.85     68017
           1       0.00      0.00      0.00     23766

    accuracy                           0.74     91783
   macro avg       0.37      0.50      0.43     91783
weighted avg       0.55      0.74      0.63     91783

/Users/fernandonotari/opt/anaconda3/envs/AML/lib/python3.8/site-packages/sklear
n/metrics/_classification.py:1469: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/fernandonotari/opt/anaconda3/envs/AML/lib/python3.8/site-packages/sklear
n/metrics/_classification.py:1469: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/fernandonotari/opt/anaconda3/envs/AML/lib/python3.8/site-packages/sklear
n/metrics/_classification.py:1469: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Baseline RBF Kernel SVM

In [ ]:

```
from sklearn.svm import SVC
```

In [ ]:

```
baseline_SVMrbf = SVC(kernel='rbf', random_state=42)
baseline_SVMrbf.fit(train_X, train_Y)
baseSVMrbf_preds = baseline_LR.predict(test_X)
base_SVMrbf_accuracy = accuracy_score(test_Y, baseSVMrbf_preds)
```

```
base_SVMrbf_classRep = classification_report(test_Y, baseSVMrbf_preds)

print(f"Baseline RBF kernel SVM accuracy: {base_SVMrbf_accuracy}\n")
print(f"Baseline RBF kernel SVM classification report:\n {base_SVMrbf_classRep}"
```

I trained this model for 200 minutes and my kernel timed out. I do not think pursuing this is efficient for the purposes of this project, especially because it is unlikely that it will perform better than the other models we tried.

BEST MODEL: XGBoost Classifier

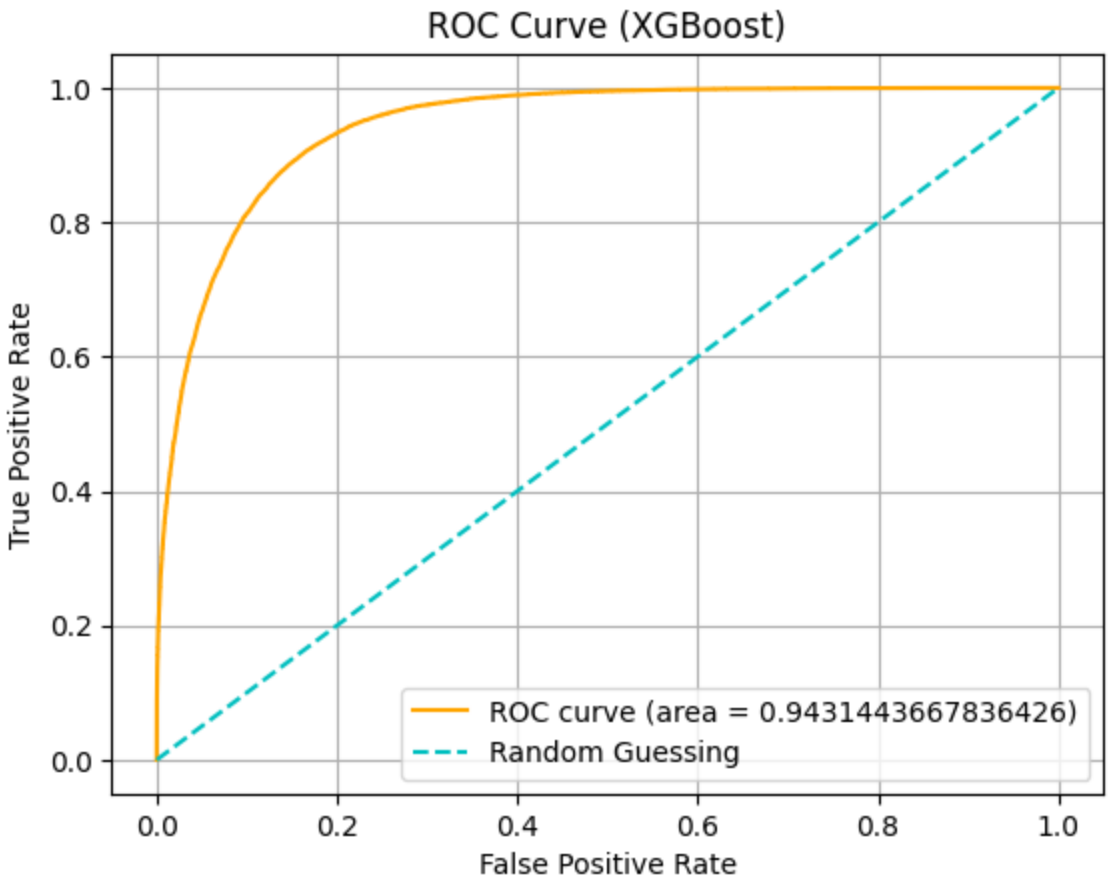
Model evaluation plots

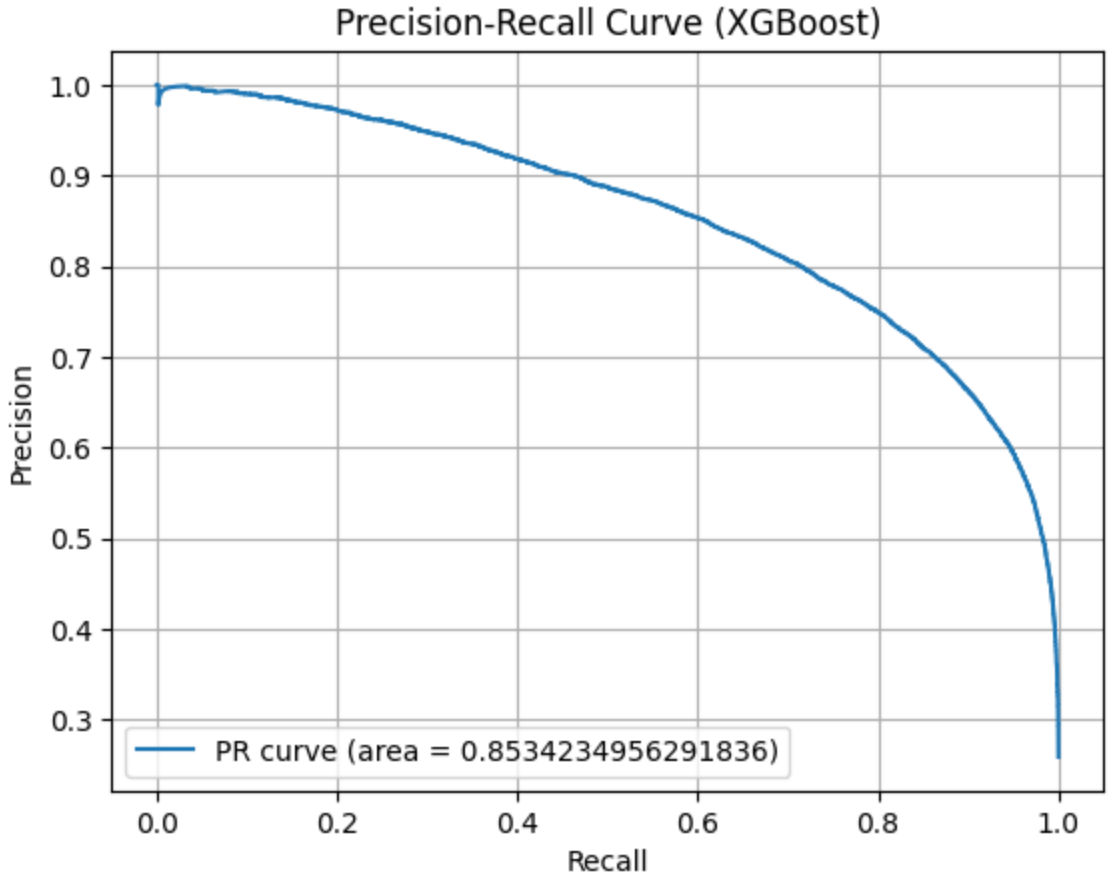
In [ ]:
```
from sklearn.metrics import roc_curve, precision_recall_curve, auc
```

In [ ]:
```
XGBlabel_probabilities = baseline_XGB.predict_proba(test_X)[:, 1]

fpr, tpr, _ = roc_curve(test_Y, XGBlabel_probabilities)
roc_auc = auc(fpr, tpr)
precision, recall, _ = precision_recall_curve(test_Y, XGBlabel_probabilities)
pr_auc = auc(recall, precision)
ROClabel = f"ROC curve (area = {roc_auc})"
PRlabel = f"PR curve (area = {pr_auc})"

plt.figure()
plt.plot(fpr, tpr, color='orange', label=ROClabel)
plt.plot([0, 1], [0, 1], color='c', linestyle='--', label='Random Guessing')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (XGBoost)')
plt.legend(loc='lower right')
plt.grid()
plt.show()
plt.figure()
plt.plot(recall,precision,label=PRlabel)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve (XGBoost)')
plt.legend(loc='lower left')
plt.grid()
plt.show()
```


ROC Curve (XGBoost)
True Positive Rate
False Positive Rate
ROC curve (area = 0.9431443667836426)
Random Guessing
0.0
0.2
0.4
0.6
0.8
1.0


Precision-Recall Curve (XGBoost)
Precision
Recall
PR curve (area = 0.8534234956291836)
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

In [ ]: