MA366: AI and Machine Learning Assignment

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1.0 - Introduction & Preliminary Analysis

1.1 - Importing Necessary Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report,confusion_matrix,f1_score,roc_auc_sco
from sklearn.model_selection import KFold,GridSearchCV,RandomizedSearchCV,train_test_sp
from sklearn.ensemble import RandomForestClassifier ,ExtraTreesClassifier, AdaBoostClas
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from sklearn.model_selection import KFold, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.inspection import permutation_importance
```

1.2 - Importing the Dataset

In [2]:

```
df = pd.read_csv('UCI_Credit_Card.csv')

df.head(5)
```

Out[2]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BI
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	0.0	
1	2	120000.0	2	2	2	26	-1	2	0	0	...	3272.0	
2	3	90000.0	2	2	2	34	0	0	0	0	...	14331.0	
3	4	50000.0	2	2	1	37	0	0	0	0	...	28314.0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	20940.0	

5 rows × 25 columns

1.3 - Exploratory Data Analysis

Understanding Basic Data Structure:

In [3]:
```
df.isnull().sum()
```

Out[3]:
```
ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default.payment.next.month    0
dtype: int64
```

In [4]:
```
df.info()

df[['AGE','LIMIT_BAL', 'PAY_0','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1'
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']].describe()

df[['SEX', 'EDUCATION', 'MARRIAGE']].describe()

df = df.rename(columns={'default.payment.next.month': 'default',
                        'PAY_0': 'PAY_1'})
```

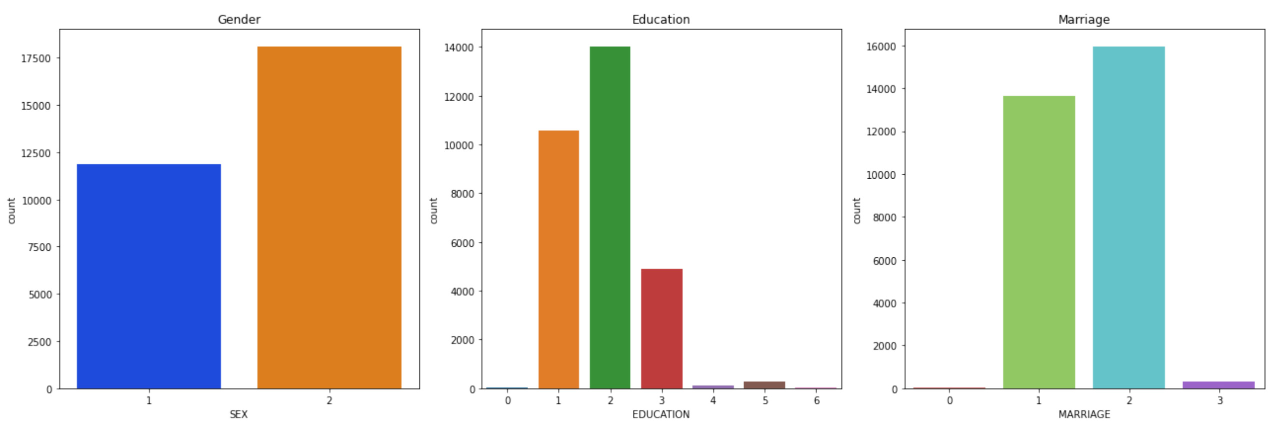
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   ID                          30000 non-null  int64
 1   LIMIT_BAL                   30000 non-null  float64
 2   SEX                         30000 non-null  int64
 3   EDUCATION                   30000 non-null  int64
 4   MARRIAGE                    30000 non-null  int64
 5   AGE                         30000 non-null  int64
 6   PAY_0                       30000 non-null  int64
 7   PAY_2                       30000 non-null  int64
 8   PAY_3                       30000 non-null  int64
 9   PAY_4                       30000 non-null  int64
 10  PAY_5                       30000 non-null  int64
 11  PAY_6                       30000 non-null  int64
 12  BILL_AMT1                   30000 non-null  float64
 13  BILL_AMT2                   30000 non-null  float64
 14  BILL_AMT3                   30000 non-null  float64
 15  BILL_AMT4                   30000 non-null  float64
```

```
 16  BILL_AMT5                   30000 non-null  float64
 17  BILL_AMT6                   30000 non-null  float64
 18  PAY_AMT1                    30000 non-null  float64
 19  PAY_AMT2                    30000 non-null  float64
 20  PAY_AMT3                    30000 non-null  float64
 21  PAY_AMT4                    30000 non-null  float64
 22  PAY_AMT5                    30000 non-null  float64
 23  PAY_AMT6                    30000 non-null  float64
 24  default.payment.next.month  30000 non-null  int64
dtypes: float64(13), int64(12)
memory usage: 5.7 MB
```

Plot For Gender, Age And Sex Against Frequency

In [5]:

```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(18, 6))
sns.countplot(x='SEX', data=df, palette='bright', ax=axes[0])
axes[0].set_title('Gender')
sns.countplot(x='EDUCATION', data=df, palette='tab10', ax=axes[1])
axes[1].set_title('Education')
sns.countplot(x='MARRIAGE', data=df, palette='hls', ax=axes[2])
axes[2].set_title('Marriage')
plt.tight_layout()
plt.show()
```

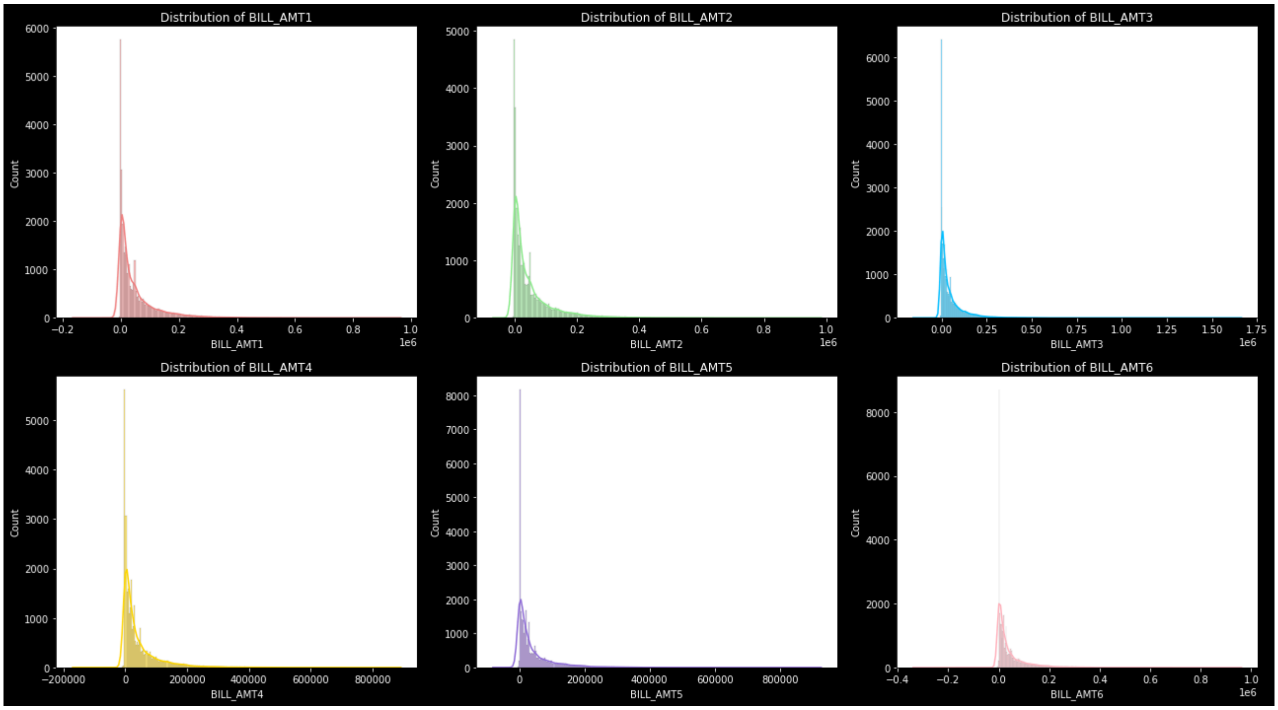


Distribution Of Bill Amounts

In [5]:

```
bills = df[['BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6

# Set up subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 10), facecolor='black')  # Set _

# Flatten the 2D array of subplots for easier indexing
axes = axes.flatten()

# Define bright colors for each bill
colors = ['lightcoral', 'lightgreen', 'deepskyblue', 'gold', 'mediumpurple', 'lightpink

# Loop through each bill amount column and plot with custom color
for i, (bill_col, color) in enumerate(zip(bills.columns, colors)):
    sns.histplot(bills[bill_col], ax=axes[i], kde=True, color=color)
    axes[i].set_title(f'Distribution of {bill_col}', color='white')  # Set title text c

    # Set axis label text color to white
    axes[i].xaxis.label.set_color('white')
    axes[i].yaxis.label.set_color('white')
```

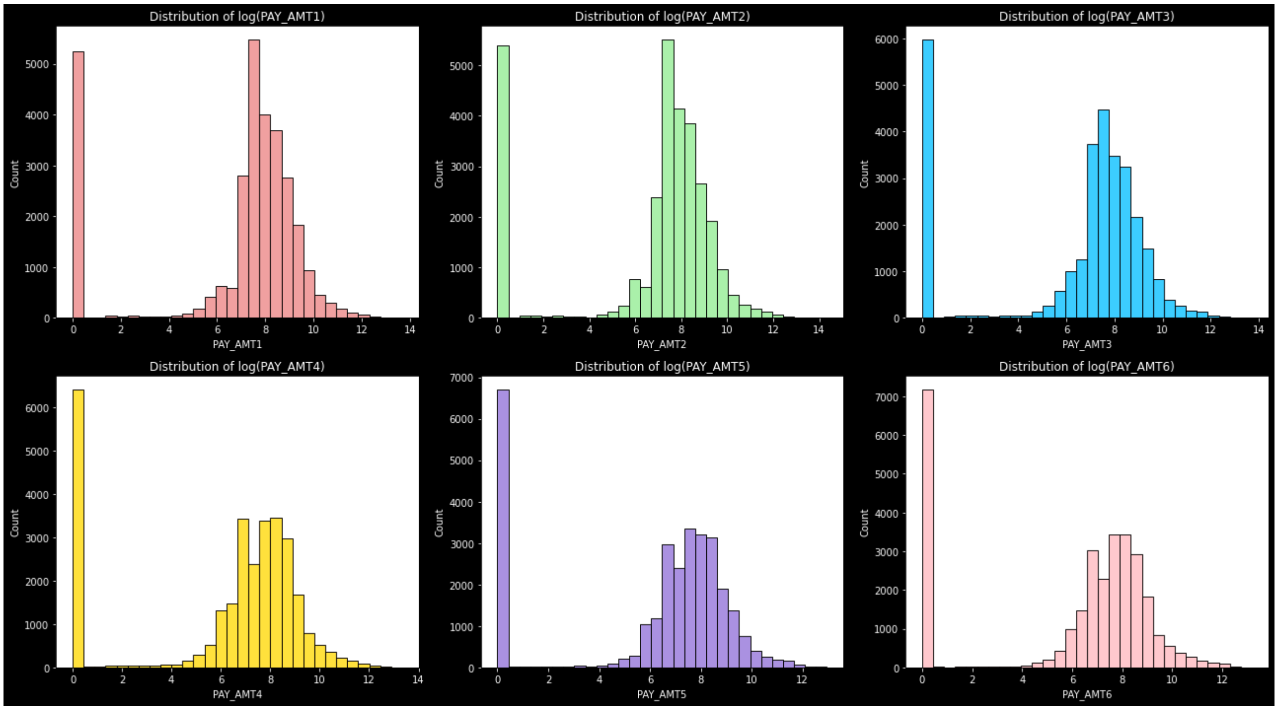
```
    # Set ticks color to white
    axes[i].tick_params(axis='both', colors='white')

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```



Distribution Of Repayment Amounts

In [6]:

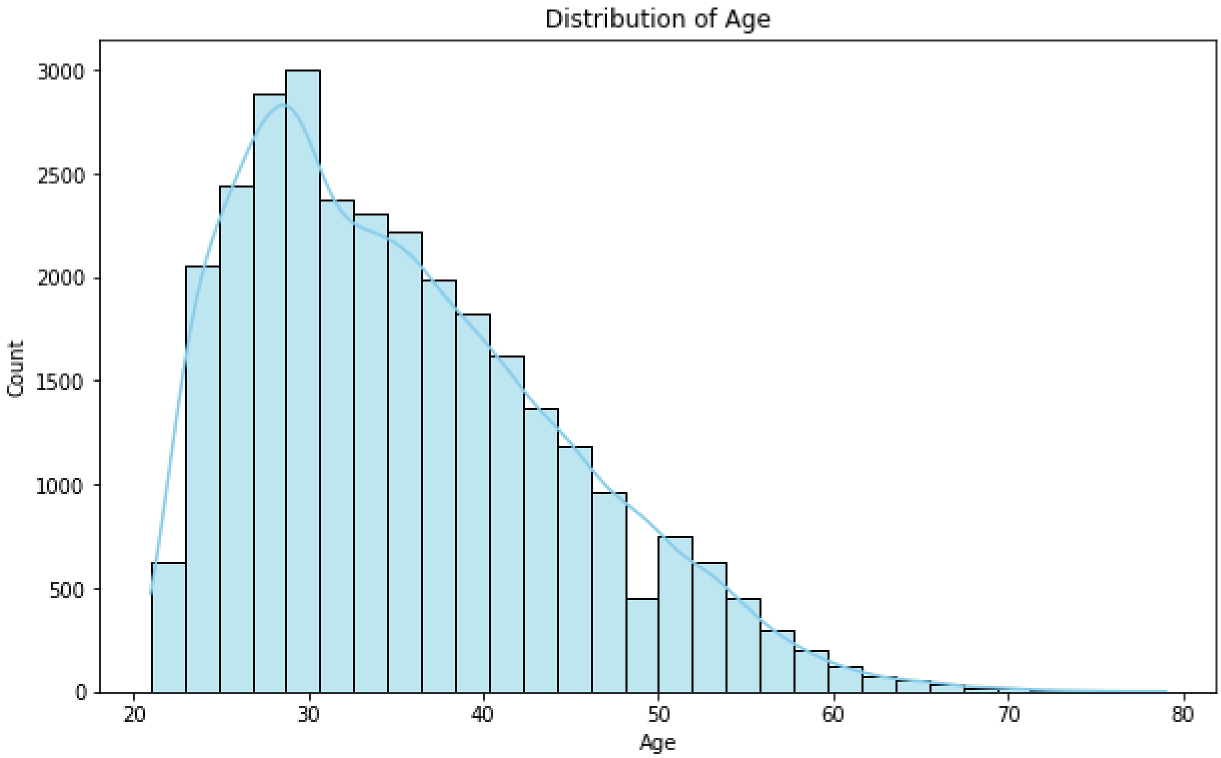
```
payments = df[['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']]
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 10), facecolor='black')  # Set
axes = axes.flatten()
colors = ['lightcoral', 'lightgreen', 'deepskyblue', 'gold', 'mediumpurple', 'lightpink
num_bins = 30
for i, (payment_col, color) in enumerate(zip(payments.columns, colors)):
    log_transformed = np.log1p(payments[payment_col])  # Apply log transformation
    sns.histplot(log_transformed, ax=axes[i], kde=False, color=color, bins=num_bins)  #

    axes[i].set_title(f'Distribution of log({payment_col})', color='white')  # Set titl

    # Set axis label text color to white
    axes[i].xaxis.label.set_color('white')
    axes[i].yaxis.label.set_color('white')

    # Set ticks color to white
    axes[i].tick_params(axis='both', colors='white')

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```

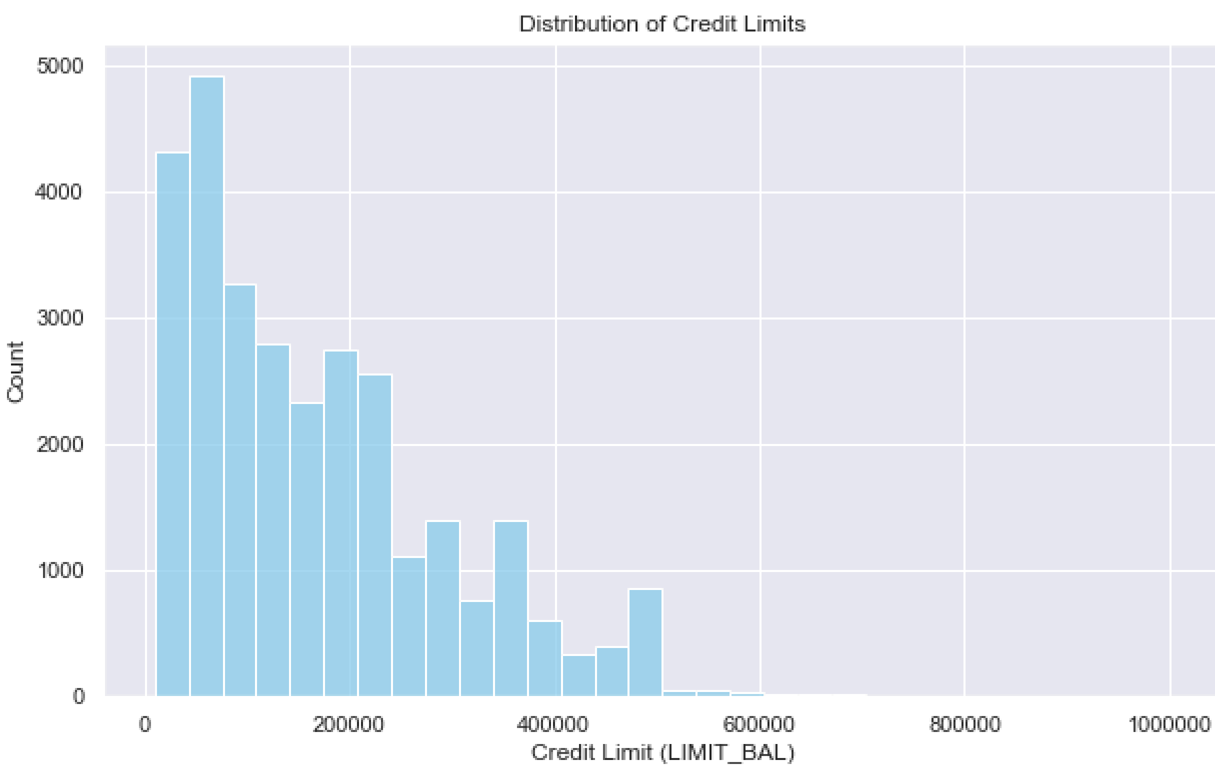


Age And Credit Limits

In [7]:

```
plt.figure(figsize=(10, 6))
sns.histplot(df['AGE'], bins=30, color='skyblue', kde=True)

# Adding labels and title
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Distribution of Age')

# Show the plot
plt.show()

sns.set(style="darkgrid")

# Create a histogram using Seaborn
plt.figure(figsize=(10, 6))
ax = sns.histplot(df['LIMIT_BAL'], bins=30, color='skyblue', kde=False)

# Adding labels and title
plt.xlabel('Credit Limit (LIMIT_BAL)')
plt.ylabel('Count')
plt.title('Distribution of Credit Limits')

# Format x-axis ticks as regular numbers
ax.ticklabel_format(style='plain', axis='x')

# Show the plot
plt.show()
```



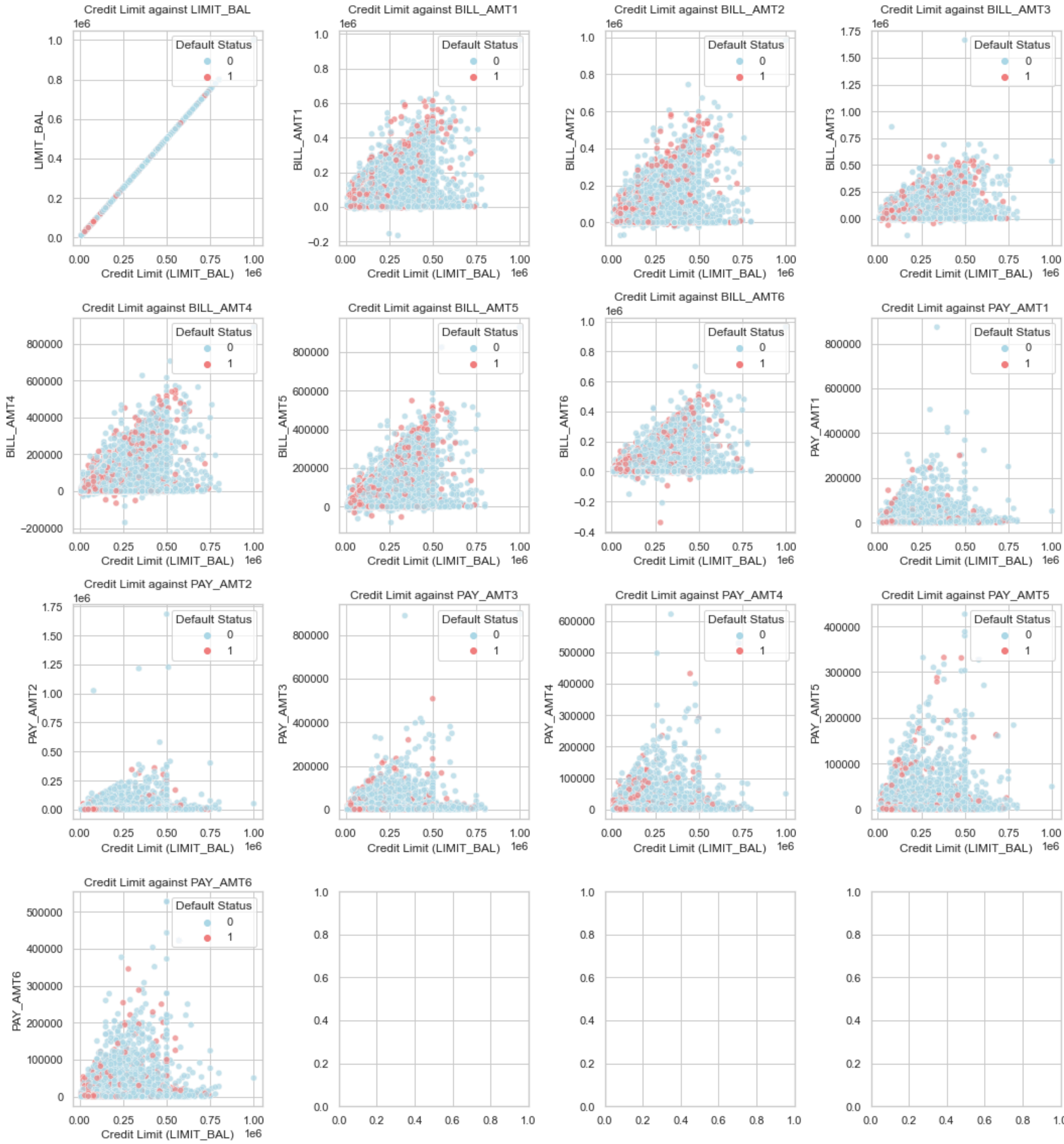


Bill Amounts Against Credit Limit

In [31]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import math

# Select relevant columns for the scatter plots
selected_columns = ['LIMIT_BAL', 'BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'B

# Subset the DataFrame with the selected columns
```

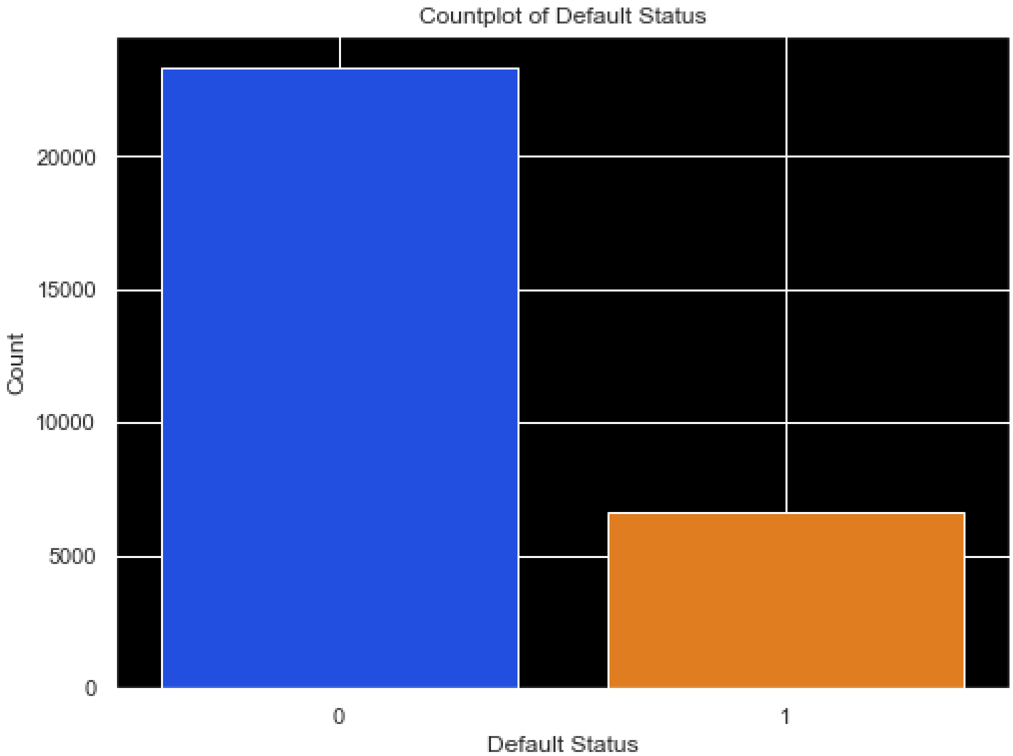
```python
scatter_data = df[selected_columns + ['default']]

# Calculate the number of rows and columns needed based on the number of variables
num_variables = len(selected_columns)
num_rows = math.ceil(num_variables / 4)  # Round up to the nearest integer
num_cols = min(4, num_variables)  # Maximum 4 columns for better layout

# Set the style for better aesthetics
sns.set(style="whitegrid")

# Create subplots
fig, axes = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(15, 4 * num_rows))

# Flatten the axes for easy indexing
axes = axes.flatten()

# Loop through each variable and create a scatter plot
for i, column in enumerate(selected_columns):
    if i < num_variables:  # Ensure not to exceed the number of variables
        sns.scatterplot(x='LIMIT_BAL', y=column, hue='default', data=scatter_data,
                        palette={0: 'lightblue', 1: 'lightcoral'}, alpha=0.7, ax=axes[i

        # Add labels and title
        axes[i].set_xlabel('Credit Limit (LIMIT_BAL)')
        axes[i].set_ylabel(column)
        axes[i].set_title(f'Credit Limit against {column}')

        # Show the legend
        axes[i].legend(title='Default Status', loc='upper right')

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```



Target Distribution

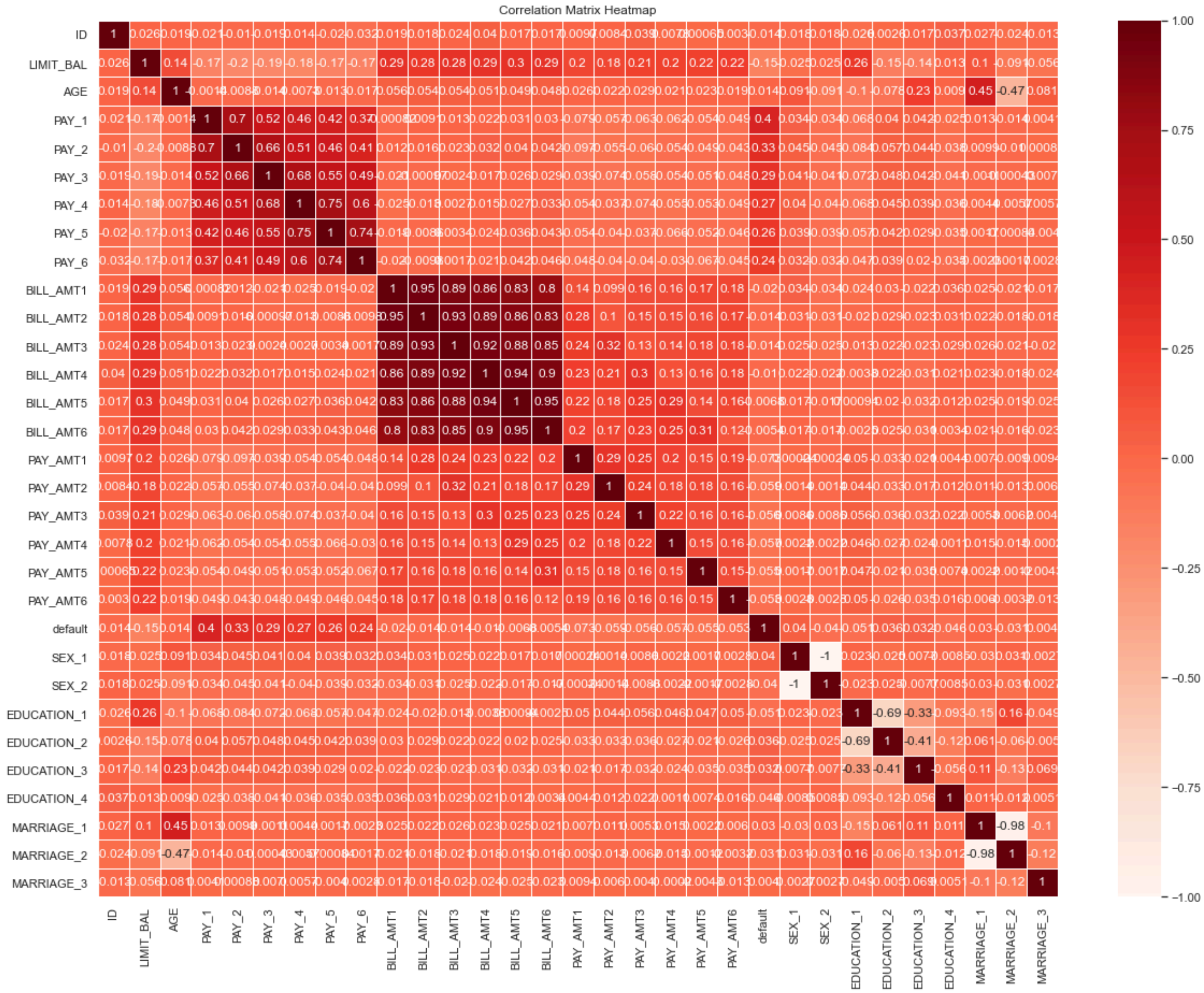
In [9]:

```
sns.set(style="darkgrid")
plt.figure(figsize=(8, 6))
sns.countplot(x='default', data=df, palette='bright')
plt.xlabel('Default Status')
plt.ylabel('Count')
plt.title('Countplot of Default Status')
plt.gca().set_facecolor('black')
plt.grid(color='white')
plt.show()
```



1.4 - Correlation Matrix

In [32]:
```
# Calculate the correlation matrix
correlation_matrix = df.corr()

# Set up the matplotlib figure
plt.figure(figsize=(20, 15))

# Set the style to darkgrid
sns.set(style="darkgrid")

# Create a heatmap of the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='Reds', linewidths=.5)

# Adding title
plt.title('Correlation Matrix Heatmap')

# Show the plot
plt.show()
```



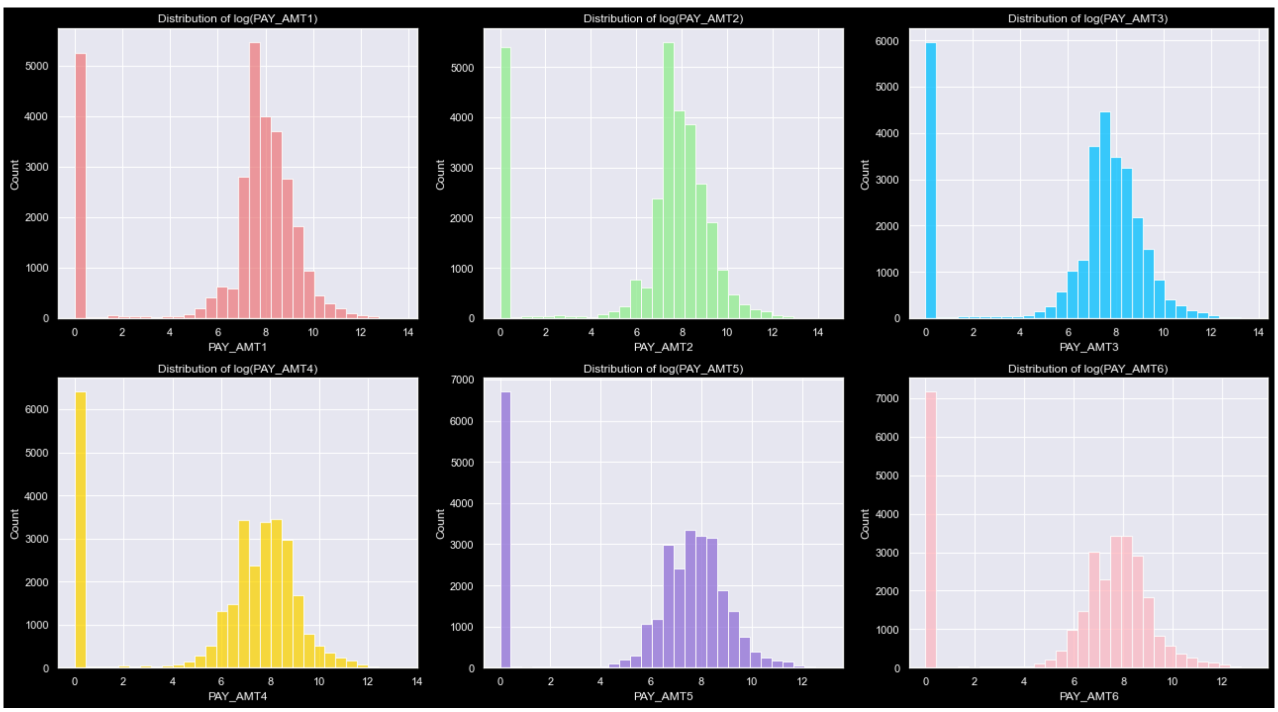
2.0 - Feature Engineering

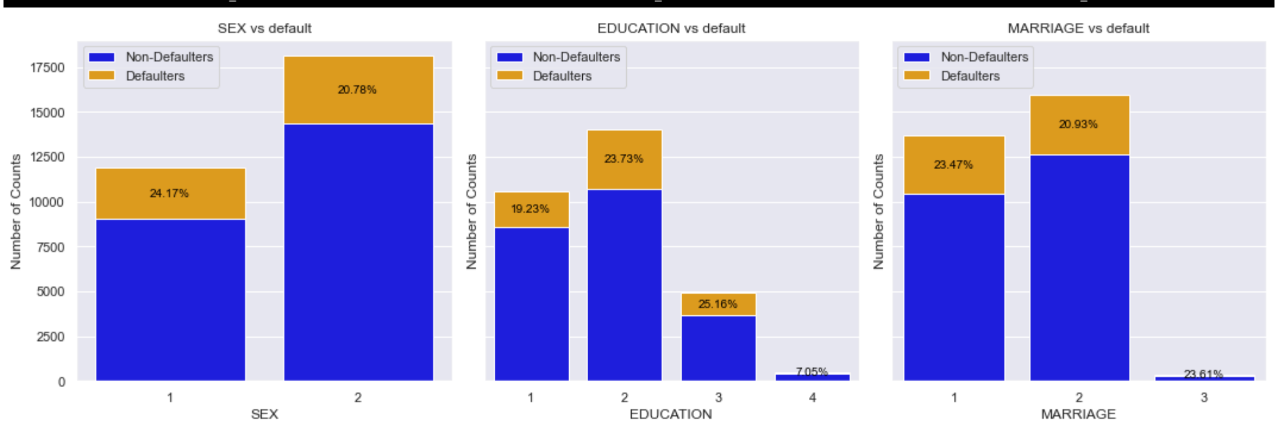
In [12]:

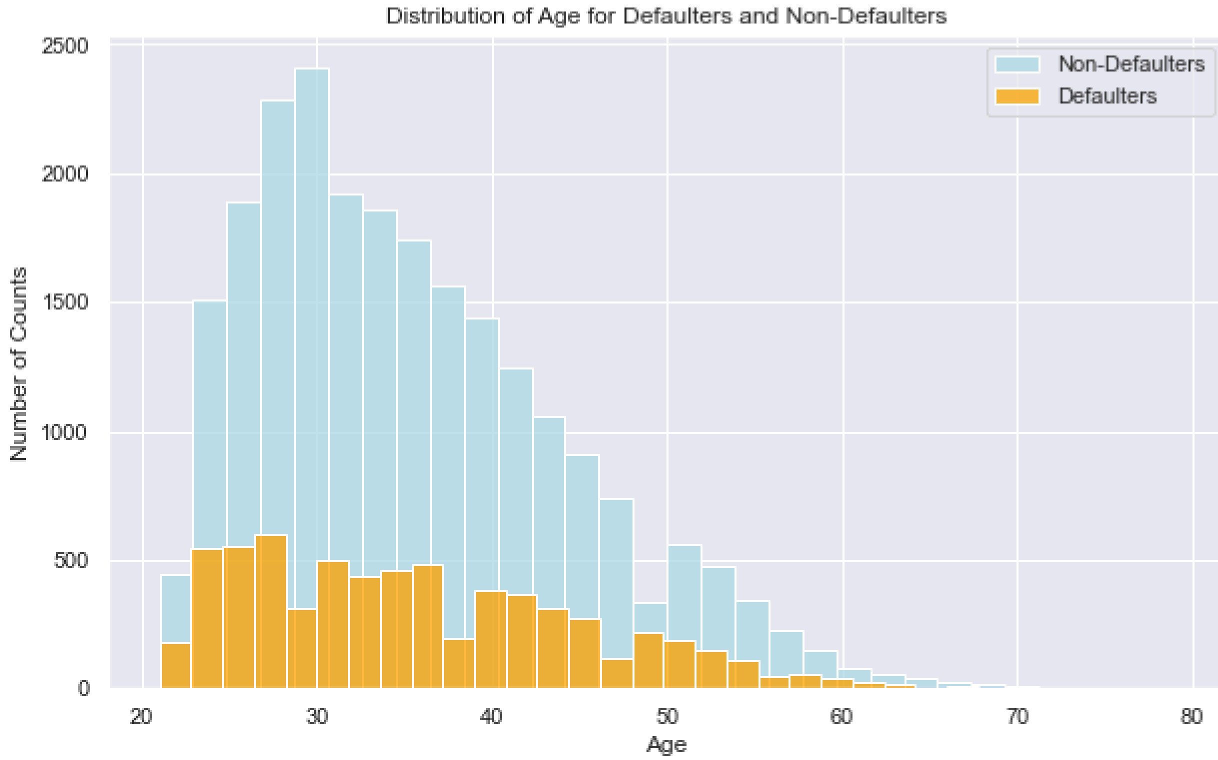
```
### Setting very small numbers of eductaion to 4
fil = (df.EDUCATION == 5) | (df.EDUCATION == 6) | (df.EDUCATION == 0)
df.loc[fil, 'EDUCATION'] = 4
df.EDUCATION.value_counts()

### Marriage to 'Other' (thus 3)
df.loc[df.MARRIAGE == 0, 'MARRIAGE'] = 3
df.MARRIAGE.value_counts()

### -1,-2 and 0 to 0

fil = (df.PAY_1 == -2) | (df.PAY_1 == -1) | (df.PAY_1 == 0)
df.loc[fil, 'PAY_1'] = 0
fil = (df.PAY_2 == -2) | (df.PAY_2 == -1) | (df.PAY_2 == 0)
df.loc[fil, 'PAY_2'] = 0
fil = (df.PAY_3 == -2) | (df.PAY_3 == -1) | (df.PAY_3 == 0)
df.loc[fil, 'PAY_3'] = 0
fil = (df.PAY_4 == -2) | (df.PAY_4 == -1) | (df.PAY_4 == 0)
df.loc[fil, 'PAY_4'] = 0
fil = (df.PAY_5 == -2) | (df.PAY_5 == -1) | (df.PAY_5 == 0)
df.loc[fil, 'PAY_5'] = 0
fil = (df.PAY_6 == -2) | (df.PAY_6 == -1) | (df.PAY_6 == 0)
df.loc[fil, 'PAY_6'] = 0
```

```python
payments = df[['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']]
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 10), facecolor='black')  # Set 
axes = axes.flatten()
colors = ['lightcoral', 'lightgreen', 'deepskyblue', 'gold', 'mediumpurple', 'lightpink
num_bins = 30
for i, (payment_col, color) in enumerate(zip(payments.columns, colors)):
    log_transformed = np.log1p(payments[payment_col])  # Apply log transformation
    sns.histplot(log_transformed, ax=axes[i], kde=False, color=color, bins=num_bins)  #

    axes[i].set_title(f'Distribution of log({payment_col})', color='white')  # Set titl

    # Set axis label text color to white
    axes[i].xaxis.label.set_color('white')
    axes[i].yaxis.label.set_color('white')

    # Set ticks color to white
    axes[i].tick_params(axis='both', colors='white')

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()

### Check Variables against defaulters
def cross_subplot(cols, target_col):
    num_cols = len(cols)
    fig, axes = plt.subplots(nrows=1, ncols=num_cols, figsize=(15, 5), sharey=True)

    for i, col in enumerate(cols):
        # Calculate the cross-tabulation
        res = pd.crosstab(df[col], df[target_col])
        res['Percentage'] = round((res[1] / (res[0] + res[1])) * 100, 2)

        # Plotting a stacked bar graph using Seaborn
        sns.barplot(x=res.index, y=res[0], color='blue', label='Non-Defaulters', ax=axe
        sns.barplot(x=res.index, y=res[1], color='orange', label='Defaulters', bottom=r

        # Adding percentage labels
        for j, value in enumerate(res['Percentage']):
            axes[i].text(j, res.iloc[j, 0] + res.iloc[j, 1] / 2, f"{value}%", ha='cente

        # Adding labels and title
        axes[i].set_xlabel(col)
        axes[i].set_ylabel('Number of Counts')
        axes[i].set_title(f'{col} vs {target_col}')

        # Show the legend with explicit location
        axes[i].legend(loc='upper left')

    # Adjust layout
    plt.tight_layout()

    # Show the plot
    plt.show()

# Example usage
cross_subplot(["SEX", "EDUCATION", "MARRIAGE"], "default")
```

```python
# Modified function for 'AGE'
def age_histogram():
    plt.figure(figsize=(10, 6))

    # Plotting histogram for age counts for defaulters and non-defaulters
    sns.histplot(df[df['default'] == 0]['AGE'], bins=30, color='lightblue', label='Non-
    sns.histplot(df[df['default'] == 1]['AGE'], bins=30, color='orange', label='Default

    # Adding labels and title
    plt.xlabel('Age')
    plt.ylabel('Number of Counts')
    plt.title('Distribution of Age for Defaulters and Non-Defaulters')

    # Show the legend
    plt.legend()

    # Show the plot
    plt.show()

# Example usage for 'AGE'
age_histogram()
```







In [13]:

```
df[['SEX','MARRIAGE','EDUCATION']] = df[['SEX','MARRIAGE','EDUCATION']].astype('object'
```

3.0 - Train - Test Split

In [14]:

```
# One Hot encoding
df = pd.get_dummies(df)
df.head()
```

Out[14]:

	ID	LIMIT_BAL	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	...	default	SEX_1	SE
0	1	20000.0	24	2	2	0	0	0	0	3913.0	...	1	0	
1	2	120000.0	26	0	2	0	0	0	2	2682.0	...	1	0	
2	3	90000.0	34	0	0	0	0	0	0	29239.0	...	0	0	
3	4	50000.0	37	0	0	0	0	0	0	46990.0	...	0	0	
4	5	50000.0	57	0	0	0	0	0	0	8617.0	...	0	1	

5 rows × 31 columns

In [15]:

```
X = df.drop(['default','ID'], axis=1)
y = df['default']
```

In [16]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, stratify=y, ran

# Create the training df by remerging X_train and y_train
```

```
df_train = X_train.join(y_train)

# Separate majority and minority classes
df_majority = df_train[df_train.default == 0]
df_minority = df_train[df_train.default == 1]
print(df_majority.default.count())
print("-----------")
print(df_minority.default.count())
print("-----------")
print(df_train.default.value_counts())
```

```
16355
-----------
4645
-----------
0    16355
1     4645
Name: default, dtype: int64
```

4.0 - SMOTE & Standardization

In [17]:

```
## !pip install -U threadpoolctl
```

```
Requirement already satisfied: threadpoolctl in c:\users\maisam\anaconda3\lib\site-packa
ges (3.4.0)
```

In [18]:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

sm = SMOTE(random_state=110)
X_SMOTE, y_SMOTE = sm.fit_resample(X_train_scaled, y_train)

print(len(y_SMOTE))
print(y_SMOTE.sum())
```

```
32710
16355
```

5.0 - Building Classification Models

5.1 - KNN Model

In [19]:

```
# Initialize KNN Classifier
knn_model = KNeighborsClassifier()

# Define hyperparameters grid for KNN
knn_param_grid = {
    'n_neighbors': [3, 5, 7],
    'weights': ['uniform', 'distance'],
    'p': [1, 2]  # Manhattan and Euclidean distance
}

# Train the KNN model on the entire SMOTE training dataset
knn_grid_search = GridSearchCV(knn_model, knn_param_grid, scoring='accuracy', n_jobs=-1
knn_grid_search.fit(X_SMOTE, y_SMOTE)
best_knn_model = knn_grid_search.best_estimator_
```

```python
# Make predictions on the validation set
y_pred_knn = best_knn_model.predict(X_test)

# Calculate classification report for KNN
knn_report_dict = classification_report(y_test, y_pred_knn, output_dict=True)
knn_report_df = pd.DataFrame(knn_report_dict, index=['precision', 'recall', 'f1-score',

# Display the classification report
print("Classification Report for KNN:")
print(knn_report_df)

# Get the confusion matrix
cm = confusion_matrix(y_test, y_pred_knn)
print("Confusion Matrix for KNN:")
print(cm)

# Get the best hyperparameters for KNN
print("Best Hyperparameters for KNN:")
print(best_knn_model.get_params())
```

```
C:\Users\Maisam\anaconda3\lib\site-packages\sklearn\base.py:458: UserWarning: X has feat
ure names, but KNeighborsClassifier was fitted without feature names
  warnings.warn(
Classification Report for KNN:
              precision    recall  f1-score      support
0              0.787107  0.961621  0.865656  7009.000000
1              0.384439  0.084380  0.138386  1991.000000
accuracy       0.767556  0.767556  0.767556     0.767556
macro avg      0.585773  0.523000  0.502021  9000.000000
weighted avg   0.698028  0.767556  0.704768  9000.000000
Confusion Matrix for KNN:
[[6740  269]
 [1823  168]]
Best Hyperparameters for KNN:
{'algorithm': 'auto', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params': None, 'n_
jobs': None, 'n_neighbors': 3, 'p': 1, 'weights': 'distance'}
```

5.2 - Logistic Regression Model

In [20]:

```python
# Initialize Logistic Regression Classifier
logistic_model = LogisticRegression()

# Define hyperparameters grid for Logistic Regression
logistic_param_grid = {
    'C': [0.1, 1, 10],  # Regularization parameter
    'solver': ['liblinear', 'lbfgs'],  # Optimization algorithm
    'max_iter': [100, 200, 300]  # Maximum number of iterations
}

# Train the Logistic Regression model on the entire SMOTE training dataset
logistic_grid_search = GridSearchCV(logistic_model, logistic_param_grid, scoring='accur
logistic_grid_search.fit(X_SMOTE, y_SMOTE)
best_logistic_model = logistic_grid_search.best_estimator_

# Make predictions on the validation set
y_pred_logistic = best_logistic_model.predict(X_test)

# Calculate classification report for Logistic Regression
logistic_report_dict = classification_report(y_test, y_pred_logistic, output_dict=True)
logistic_report_df = pd.DataFrame(logistic_report_dict, index=['precision', 'recall', '
```

```
# Display the classification report
print("Classification Report for Logistic Regression:")
print(logistic_report_df)

# Get the confusion matrix
cm = confusion_matrix(y_test, y_pred_logistic)
print("Confusion Matrix for Logistic Regression:")
print(cm)

# Get the best hyperparameters for Logistic Regression
print("Best Hyperparameters for Logistic Regression:")
print(best_logistic_model.get_params())
```

```
Classification Report for Logistic Regression:
              precision    recall  f1-score      support
0              0.778926  0.999857  0.875672  7009.000000
1              0.666667  0.001005  0.002006  1991.000000
accuracy       0.778889  0.778889  0.778889     0.778889
macro avg      0.722796  0.500431  0.438839  9000.000000
weighted avg   0.754092  0.778889  0.682397  9000.000000
Confusion Matrix for Logistic Regression:
[[7008    1]
 [1989    2]]
Best Hyperparameters for Logistic Regression:
{'C': 1, 'class_weight': None, 'dual': False, 'fit_intercept': True, 'intercept_scalin
g': 1, 'l1_ratio': None, 'max_iter': 100, 'multi_class': 'auto', 'n_jobs': None, 'penalt
y': 'l2', 'random_state': None, 'solver': 'liblinear', 'tol': 0.0001, 'verbose': 0, 'war
m_start': False}
```

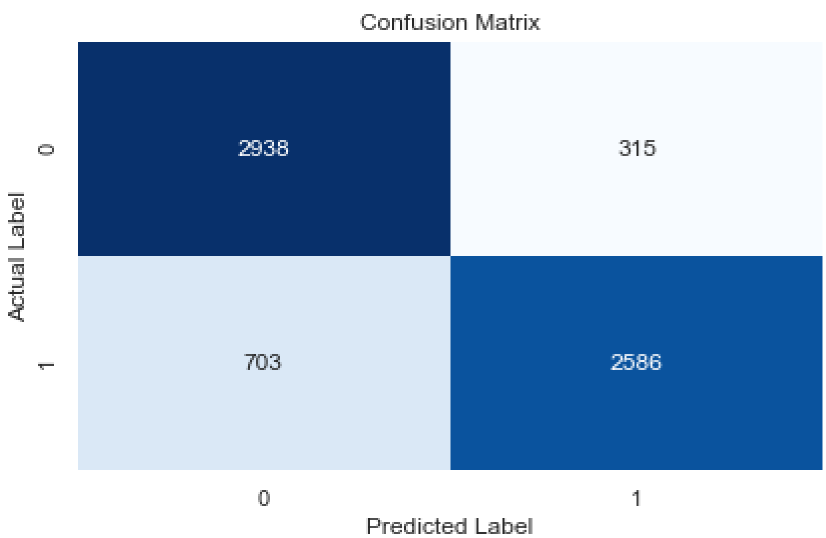
```
C:\Users\Maisam\anaconda3\lib\site-packages\sklearn\base.py:458: UserWarning: X has feat
ure names, but LogisticRegression was fitted without feature names
  warnings.warn(
```

5.3 - XGBoost

In [21]:

```
# Initialize XGBClassifier
model = XGBClassifier(random_state=110)
param_grid = {
    'learning_rate': [0.1, 0.01, 0.001],
    'max_depth': [3, 4, 5],
    'n_estimators': [100, 50, 200]
}

# Initialize KFold
kf = KFold(n_splits=5, shuffle=True, random_state=110)

# Create an empty DataFrame to store classification reports
classification_reports_df = pd.DataFrame()

# Create subplots for confusion matrices
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(6, 4))

# Iterate over each fold
for i, (train_index, test_index) in enumerate(kf.split(X_SMOTE)):
    X_train_fold, X_val_fold = X_SMOTE[train_index], X_SMOTE[test_index]
    y_train_fold, y_val_fold = y_SMOTE[train_index], y_SMOTE[test_index]

    # Initialize GridSearchCV
    grid_search = GridSearchCV(model, param_grid, cv=kf, scoring='accuracy', n_jobs=-1)
    grid_search.fit(X_train_fold, y_train_fold)
```

```
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_val_fold)

    # Calculate classification report
    report_dict = classification_report(y_val_fold, y_pred, output_dict=True)
    report_df = pd.DataFrame(report_dict).transpose()
    report_df["Fold"] = i + 1

    # Append to the main DataFrame
    classification_reports_df = pd.concat([classification_reports_df, report_df])

    # Plot confusion matrix with class labels for the last fold
    if i == kf.get_n_splits() - 1:
        cm = confusion_matrix(y_val_fold, y_pred)
        sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", ax=axes, cbar=False,
                    xticklabels=best_model.classes_, yticklabels=best_model.classes_)
        axes.set_title("Confusion Matrix")
        # Set x-axis and y-axis labels
        axes.set_xlabel("Predicted Label")
        axes.set_ylabel("Actual Label")

# Show the plot
plt.tight_layout()
plt.show()

# Display the table of classification reports
print("Table of Classification Reports:")
print(classification_reports_df)

# Calculate mean accuracy for each fold
mean_accuracy_by_fold = classification_reports_df.loc['accuracy'].groupby('Fold').mean(

# Find the fold with the highest mean accuracy
best_fold = mean_accuracy_by_fold.idxmax()

print("Best Fold:", best_fold)
print("Best Hyperparameters:")
print(best_model.get_params())
```




```
Table of Classification Reports:
              precision    recall  f1-score      support  Fold
0              0.813766  0.898835  0.854188  3262.000000     1
1              0.887717  0.795427  0.839042  3280.000000     1
```

```
accuracy       0.846989  0.846989  0.846989     0.846989     1
macro avg      0.850742  0.847131  0.846615  6542.000000     1
weighted avg   0.850843  0.846989  0.846594  6542.000000     1
0              0.813330  0.909146  0.858573  3302.000000     2
1              0.894774  0.787346  0.837629  3240.000000     2
accuracy       0.848823  0.848823  0.848823     0.848823     2
macro avg      0.854052  0.848246  0.848101  6542.000000     2
weighted avg   0.853666  0.848823  0.848200  6542.000000     2
0              0.811368  0.899876  0.853333  3236.000000     3
1              0.890281  0.795221  0.840070  3306.000000     3
accuracy       0.846989  0.846989  0.846989     0.846989     3
macro avg      0.850825  0.847549  0.846702  6542.000000     3
weighted avg   0.851247  0.846989  0.846631  6542.000000     3
0              0.820321  0.897335  0.857102  3302.000000     4
1              0.884300  0.799691  0.839870  3240.000000     4
accuracy       0.848976  0.848976  0.848976     0.848976     4
macro avg      0.852311  0.848513  0.848486  6542.000000     4
weighted avg   0.852008  0.848976  0.848568  6542.000000     4
0              0.806921  0.903166  0.852335  3253.000000     5
1              0.891417  0.786257  0.835541  3289.000000     5
accuracy       0.844390  0.844390  0.844390     0.844390     5
macro avg      0.849169  0.844712  0.843938  6542.000000     5
weighted avg   0.849401  0.844390  0.843892  6542.000000     5
Best Fold: precision    4
recall       4
f1-score     4
support      4
dtype: int64
Best Hyperparameters:
{'objective': 'binary:logistic', 'base_score': None, 'booster': None, 'callbacks': None,
'colsample_bylevel': None, 'colsample_bynode': None, 'colsample_bytree': None, 'device':
None, 'early_stopping_rounds': None, 'enable_categorical': False, 'eval_metric': None,
'feature_types': None, 'gamma': None, 'grow_policy': None, 'importance_type': None, 'int
eraction_constraints': None, 'learning_rate': 0.1, 'max_bin': None, 'max_cat_threshold':
None, 'max_cat_to_onehot': None, 'max_delta_step': None, 'max_depth': 5, 'max_leaves': N
one, 'min_child_weight': None, 'missing': nan, 'monotone_constraints': None, 'multi_stra
tegy': None, 'n_estimators': 200, 'n_jobs': None, 'num_parallel_tree': None, 'random_sta
te': 110, 'reg_alpha': None, 'reg_lambda': None, 'sampling_method': None, 'scale_pos_wei
ght': None, 'subsample': None, 'tree_method': None, 'validate_parameters': None, 'verbos
ity': None}
```

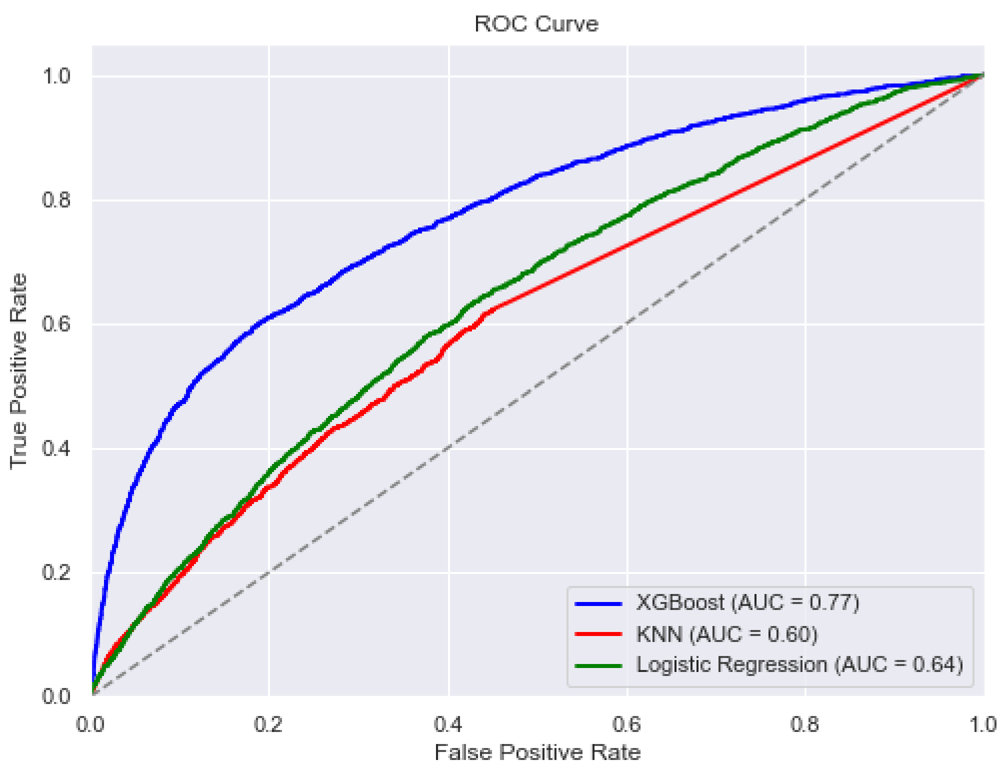
6.0 - Comparison of Models

6.1 - ROC Curve

In [22]:

```python
# Fit the XGBoost model
best_model.fit(X_train, y_train)

# Predict probabilities for XGBoost
y_pred_proba_xgb = best_model.predict_proba(X_test)[:, 1]

# Calculate ROC curve for XGBoost
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_pred_proba_xgb)
auc_xgb = roc_auc_score(y_test, y_pred_proba_xgb)

# Fit the KNN model
best_knn_model.fit(X_train, y_train)

# Predict probabilities for KNN
y_pred_proba_knn = best_knn_model.predict_proba(X_test)[:, 1]
```

```
# Calculate ROC curve for KNN
fpr_knn, tpr_knn, _ = roc_curve(y_test, y_pred_proba_knn)
auc_knn = roc_auc_score(y_test, y_pred_proba_knn)

# Fit the Logistic Regression model
best_logistic_model.fit(X_train, y_train)

# Predict probabilities for Logistic Regression
y_pred_proba_logistic = best_logistic_model.predict_proba(X_test)[:, 1]

# Calculate ROC curve for Logistic Regression
fpr_logistic, tpr_logistic, _ = roc_curve(y_test, y_pred_proba_logistic)
auc_logistic = roc_auc_score(y_test, y_pred_proba_logistic)

# Plot ROC curves
plt.figure(figsize=(8, 6))
plt.plot(fpr_xgb, tpr_xgb, color='blue', lw=2, label=f'XGBoost (AUC = {auc_xgb:.2f})')
plt.plot(fpr_knn, tpr_knn, color='red', lw=2, label=f'KNN (AUC = {auc_knn:.2f})')
plt.plot(fpr_logistic, tpr_logistic, color='green', lw=2, label=f'Logistic Regression (/
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



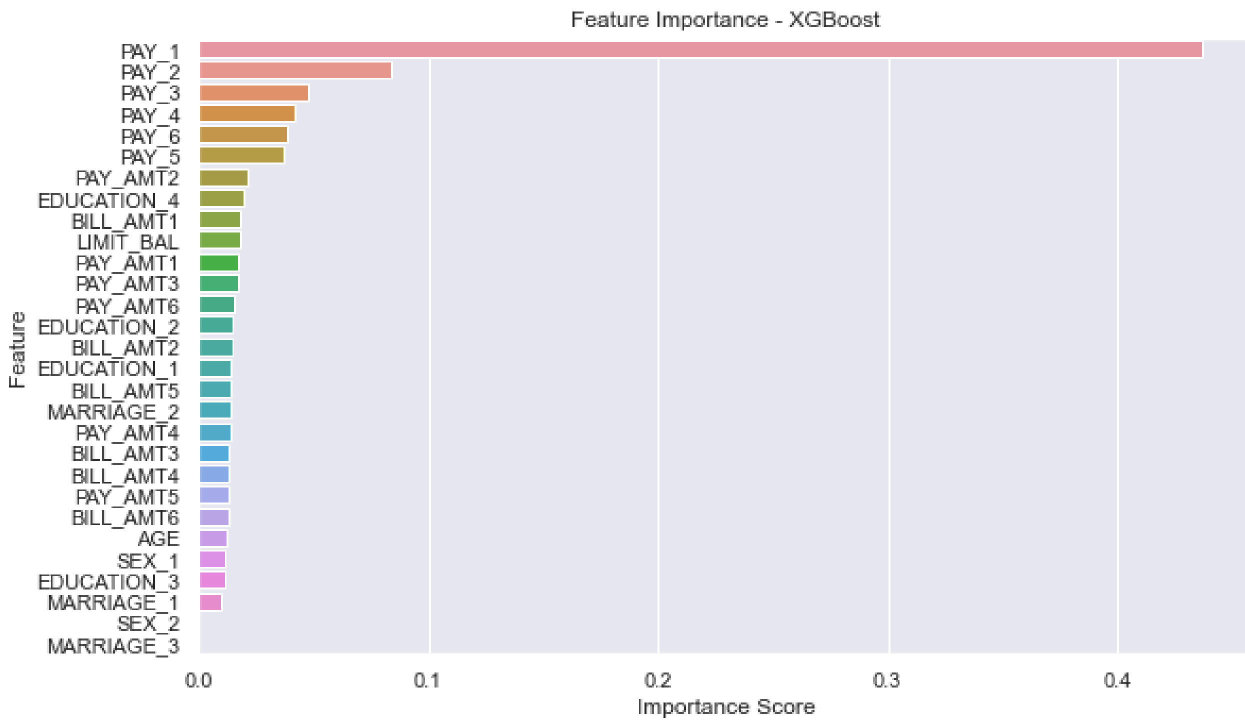
6.2 - Feature Importance Plots

XGBoost

In [23]:

```
# Extract feature importance from the XGBoost model
importance = best_model.feature_importances_
```

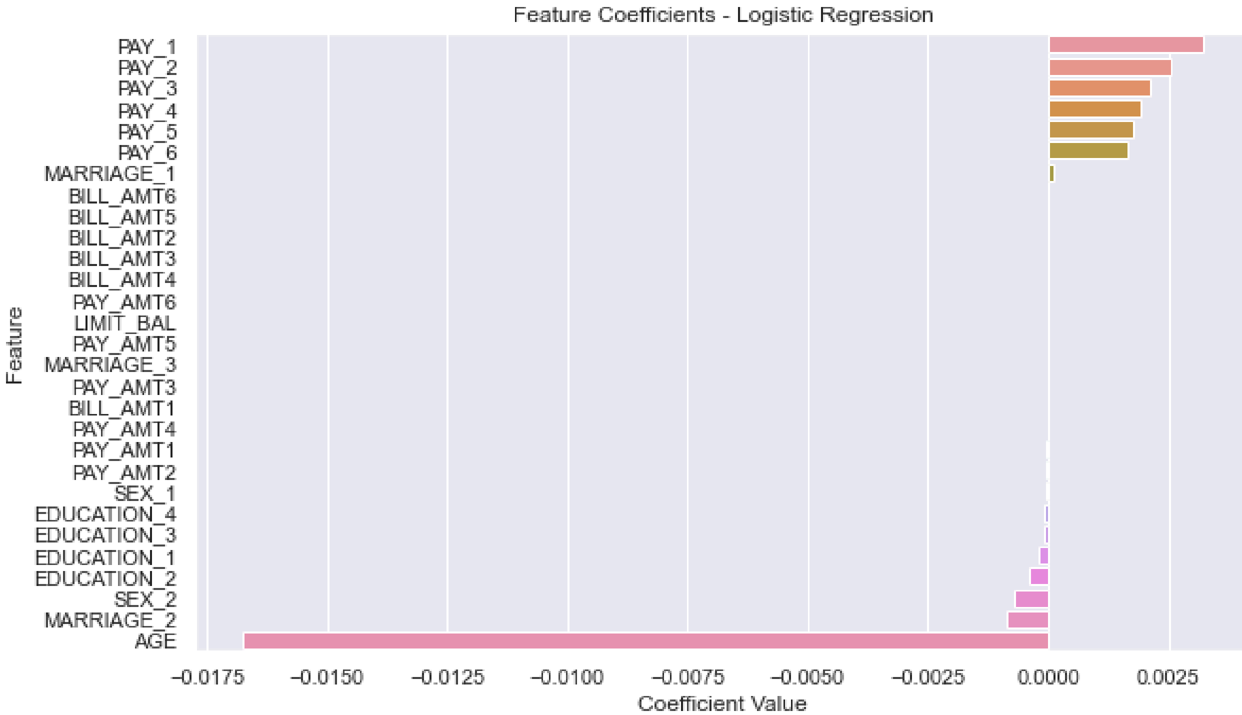
```python
# Create a DataFrame to hold feature names and importance scores
feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': importance})

# Sort features by importance score
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=Fa

# Plot the feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance - XGBoost')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.show()
```



Logistic Regression

In [24]:

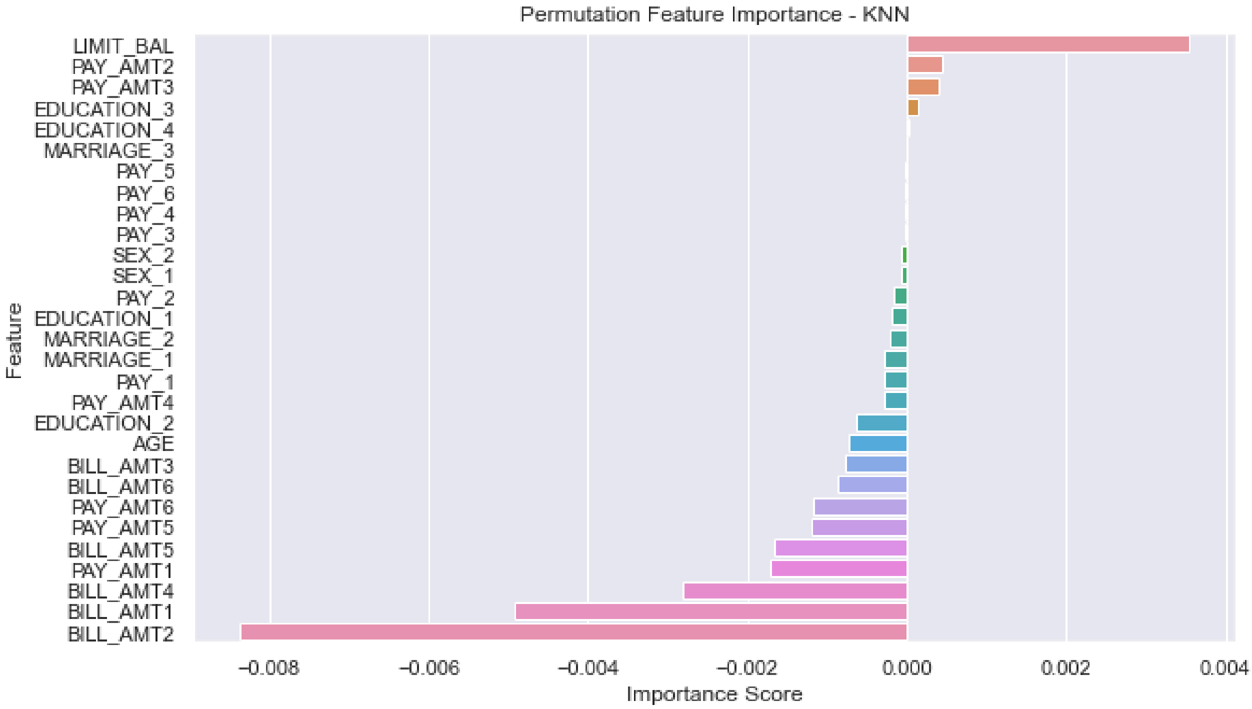
```python
# Extract feature coefficients from the logistic regression model
coefficients = best_logistic_model.coef_[0]

# Create a DataFrame to hold feature names and coefficient values
feature_coefficients_df = pd.DataFrame({'Feature': X.columns, 'Coefficient': coefficien

# Sort features by coefficient value
feature_coefficients_df = feature_coefficients_df.sort_values(by='Coefficient', ascendi

# Plot the feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Coefficient', y='Feature', data=feature_coefficients_df)
plt.title('Feature Coefficients - Logistic Regression')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()
```



KNN

In [25]:

```
# roc for knn
from sklearn.inspection import permutation_importance

# Compute permutation importances for KNN
result = permutation_importance(best_knn_model, X_test, y_test, n_repeats=4, random_sta

# Create a DataFrame to hold feature names and importance scores
feature_importance_df_knn = pd.DataFrame({'Feature': X.columns, 'Importance': result.im

# Sort features by importance score
feature_importance_df_knn = feature_importance_df_knn.sort_values(by='Importance', asce

# Plot the feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df_knn)
plt.title('Permutation Feature Importance - KNN')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.show()
```


Permutation Feature Importance - KNN
LIMIT_BAL
PAY_AMT2
PAY_AMT3
EDUCATION_3
EDUCATION_4
MARRIAGE_3
PAY_5
PAY_6
PAY_4
PAY_3
SEX_2
SEX_1
PAY_2
EDUCATION_1
MARRIAGE_2
MARRIAGE_1
PAY_1
PAY_AMT4
EDUCATION_2
AGE
BILL_AMT3
BILL_AMT6
PAY_AMT6
PAY_AMT5
BILL_AMT5
PAY_AMT1
BILL_AMT4
BILL_AMT1
BILL_AMT2
Feature
−0.008
−0.006
−0.004
−0.002
0.000
0.002
0.004
Importance Score