```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\anaconda3\lib\site-packages (3.0.2)
Requirement already satisfied: numpy in c:\anaconda3\lib\site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\anaconda3\lib\site-packages (from xgboost) (1.13.1)
```

```
!pip install shap
```

```
Requirement already satisfied: shap in c:\anaconda3\lib\site-packages (0.48.0)
Requirement already satisfied: numpy in c:\anaconda3\lib\site-packages (from shap) (1.26.4)
Requirement already satisfied: scipy in c:\anaconda3\lib\site-packages (from shap) (1.13.1)
Requirement already satisfied: scikit-learn in c:\anaconda3\lib\site-packages (from shap) (1.5.1)
Requirement already satisfied: pandas in c:\anaconda3\lib\site-packages (from shap) (2.2.2)
Requirement already satisfied: tqdm>=4.27.0 in c:\anaconda3\lib\site-packages (from shap) (4.66.5)
Requirement already satisfied: packaging>20.9 in c:\anaconda3\lib\site-packages (from shap) (24.1)
Requirement already satisfied: slicer==0.0.8 in c:\anaconda3\lib\site-packages (from shap) (0.0.8)
Requirement already satisfied: numba>=0.54 in c:\anaconda3\lib\site-packages (from shap) (0.60.0)
Requirement already satisfied: cloudpickle in c:\anaconda3\lib\site-packages (from shap) (3.0.0)
Requirement already satisfied: typing-extensions in c:\anaconda3\lib\site-packages (from shap) (4.11.0)
Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in c:\anaconda3\lib\site-packages (from numba>=0.54->shap) (0.43.0)
Requirement already satisfied: colorama in c:\anaconda3\lib\site-packages (from tqdm>=4.27.0->shap) (0.4.6)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\anaconda3\lib\site-packages (from pandas->shap) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\anaconda3\lib\site-packages (from pandas->shap) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\anaconda3\lib\site-packages (from pandas->shap) (2023.3)
Requirement already satisfied: joblib>=1.2.0 in c:\anaconda3\lib\site-packages (from scikit-learn->shap) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\anaconda3\lib\site-packages (from scikit-learn->shap) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\anaconda3\lib\site-packages (from python-dateutil>=2.8.2->pandas->shap) (1.16.0)
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder,
StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score,
confusion_matrix, classification_report
import shap
import warnings
warnings.filterwarnings("ignore")

crx_data_path = r"C:\Users\aniru\OneDrive\Desktop\ML tutorial\Credit
adjuster\crx.data"
crx_names_path = r"C:\Users\aniru\OneDrive\Desktop\ML tutorial\Credit
adjuster\crx.names"
index_path = r"C:\Users\aniru\OneDrive\Desktop\ML tutorial\Credit
adjuster\Index"
credit_lisp_path = r"C:\Users\aniru\OneDrive\Desktop\ML tutorial\
Credit adjuster\credit.lisp"
credit_names_path = r"C:\Users\aniru\OneDrive\Desktop\ML tutorial\
Credit adjuster\credit.names"

column_names = [
    'A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8',
    'A9', 'A10', 'A11', 'A12', 'A13', 'A14', 'A15', 'Class'
]
df_credit = pd.read_csv(crx_data_path, names=column_names,
na_values='?')

with open(crx_names_path, 'r', encoding='latin-1') as f:
    crx_names = f.read()
with open(index_path, 'r', encoding='latin-1') as f:
    index_file = f.read()
with open(credit_lisp_path, 'r', encoding='latin-1') as f:
    credit_lisp = f.read()
with open(credit_names_path, 'r', encoding='latin-1') as f:
    credit_names = f.read()

print("Files loaded successfully.")
print("DataFrame shape:", df_credit.shape)
print("crx.names preview:\n", crx_names[:300])
```

```
Files loaded successfully.
DataFrame shape: (690, 16)
```

```
crx.names preview:

1. Title: Credit Approval

2. Sources:
    (confidential)
    Submitted by quinlan@cs.su.oz.au

3.  Past Usage:

    See Quinlan,
    * "Simplifying decision trees", Int J Man-Machine Studies 27,
      Dec 1987, pp. 221-234.
    * "C4.5: Programs for Machine Learning", Morgan Kaufmann, Oct 1992
```

```
df_clean = df_credit.copy()

categorical_cols =
df_clean.select_dtypes(include='object').columns.tolist()
categorical_cols.remove('Class')

numerical_cols = df_clean.columns.difference(categorical_cols +
['Class'])

cat_imputer = SimpleImputer(strategy='most_frequent')
num_imputer = SimpleImputer(strategy='mean')
df_clean[categorical_cols] =
cat_imputer.fit_transform(df_clean[categorical_cols])
df_clean[numerical_cols] =
num_imputer.fit_transform(df_clean[numerical_cols])

label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df_clean[col] = le.fit_transform(df_clean[col])
    label_encoders[col] = le

df_clean['Class'] = df_clean['Class'].map({'+': 1, '-': 0})

scaler = StandardScaler()
df_clean[numerical_cols] =
scaler.fit_transform(df_clean[numerical_cols])

print("Data cleaned and preprocessed.")
print("Feature matrix shape:", df_clean.shape)
df_clean.head()
```

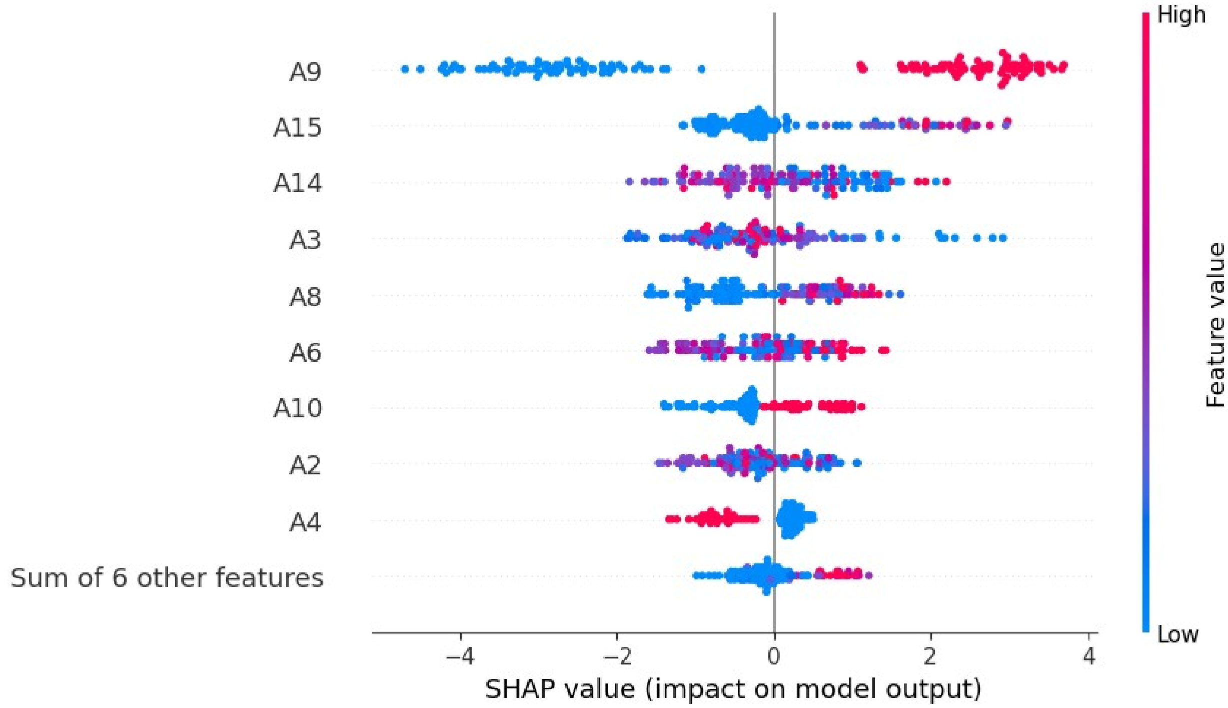
```
Data cleaned and preprocessed.
Feature matrix shape: (690, 16)
```

```
   A1         A2         A3  A4  A5  A6  A7         A8  A9  A10        A11  
A12  \
0   1 -0.062321 -0.956613   1   0  12   7 -0.291083   1    1 -0.288101   
0   
1   0  2.288101 -0.060051   1   0  10   3  0.244190   1    1  0.740830   
0   
2   0 -0.596738 -0.856102   1   0  10   3 -0.216324   1    0 -0.493887   
0   
3   1 -0.315599 -0.647038   1   0  12   7  0.456505   1    1  0.535044   
1   
4   1 -0.962303  0.174141   1   0  12   7 -0.153526   1    0 -0.493887   
0   

   A13       A14       A15  Class  
0    0  0.104544 -0.195413      1  
1    0 -0.819689 -0.087852      1  
2    0  0.557942 -0.037144      1  
3    0 -0.488360 -0.194837      1  
4    2 -0.372104 -0.195413      1  
```

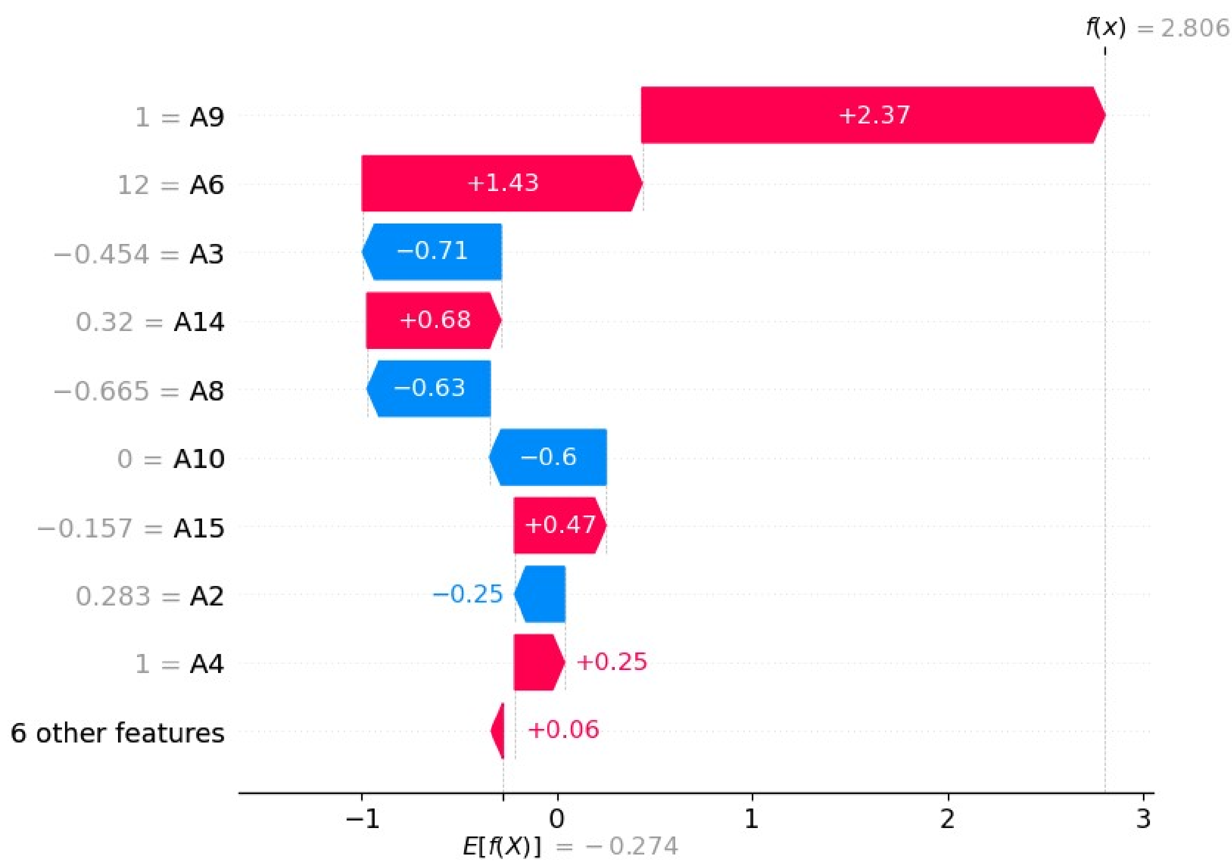
```
X = df_clean.drop('Class', axis=1)
y = df_clean['Class']

X_train, X_test, y_train, y_test = train_test_split(X, y, 
test_size=0.2, random_state=42, stratify=y)

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(n_estimators=100, 
random_state=42),
    "XGBoost": XGBClassifier(use_label_encoder=False, 
eval_metric='logloss', random_state=42)
}

for name, model in models.items():
    print(f"\nTraining: {name}")
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    probs = model.predict_proba(X_test)[:, 1]
    print("Accuracy:", round(accuracy_score(y_test, preds), 3))
    print("F1 Score:", round(f1_score(y_test, preds), 3))
    print("ROC AUC:", round(roc_auc_score(y_test, probs), 3))
    print("Classification Report:\n", classification_report(y_test, 
preds))
```

```
Training: Logistic Regression
Accuracy: 0.899
F1 Score: 0.889
ROC AUC: 0.958
Classification Report:
```

```
              precision    recall  f1-score   support

           0       0.93      0.88      0.91        77
           1       0.86      0.92      0.89        61

    accuracy                           0.90       138
   macro avg       0.90      0.90      0.90       138
weighted avg       0.90      0.90      0.90       138


Training: Random Forest
Accuracy: 0.891
F1 Score: 0.872
ROC AUC: 0.955
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.94      0.91        77
           1       0.91      0.84      0.87        61

    accuracy                           0.89       138
   macro avg       0.89      0.89      0.89       138
weighted avg       0.89      0.89      0.89       138


Training: XGBoost
Accuracy: 0.906
F1 Score: 0.891
ROC AUC: 0.946
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.94      0.92        77
           1       0.91      0.87      0.89        61

    accuracy                           0.91       138
   macro avg       0.91      0.90      0.90       138
weighted avg       0.91      0.91      0.91       138


explainer = shap.Explainer(models["XGBoost"])
shap_values = explainer(X_test)

shap.plots.beeswarm(shap_values)
```




```
shap.plots.waterfall(shap_values[0])
```



```python
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score,
classification_report

X = df_clean.drop('Class', axis=1)
y = df_clean['Class']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(n_estimators=100,
random_state=42),
    "XGBoost": XGBClassifier(use_label_encoder=False,
eval_metric='logloss', random_state=42)
}

for name, model in models.items():
    print(f"\nTraining: {name}")
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    probs = model.predict_proba(X_test)[:, 1]
    print("Accuracy:", round(accuracy_score(y_test, preds), 3))
    print("F1 Score:", round(f1_score(y_test, preds), 3))
    print("ROC AUC:", round(roc_auc_score(y_test, probs), 3))
    print("Classification Report:\n", classification_report(y_test,
preds))
```

```
Training: Logistic Regression
Accuracy: 0.899
F1 Score: 0.889
ROC AUC: 0.958
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.88      0.91        77
           1       0.86      0.92      0.89        61

    accuracy                           0.90       138
   macro avg       0.90      0.90      0.90       138
weighted avg       0.90      0.90      0.90       138


Training: Random Forest
Accuracy: 0.891
F1 Score: 0.872
ROC AUC: 0.955
Classification Report:
               precision    recall  f1-score   support
```

```
           0       0.88      0.94      0.91        77
           1       0.91      0.84      0.87        61

    accuracy                           0.89       138
   macro avg       0.89      0.89      0.89       138
weighted avg       0.89      0.89      0.89       138


Training: XGBoost
Accuracy: 0.906
F1 Score: 0.891
ROC AUC: 0.946
Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.94      0.92        77
           1       0.91      0.87      0.89        61

    accuracy                           0.91       138
   macro avg       0.91      0.90      0.90       138
weighted avg       0.91      0.91      0.91       138
```

```
xgb_model = XGBClassifier(use_label_encoder=False,
eval_metric='logloss', random_state=42)
xgb_model.fit(X_train, y_train)
```

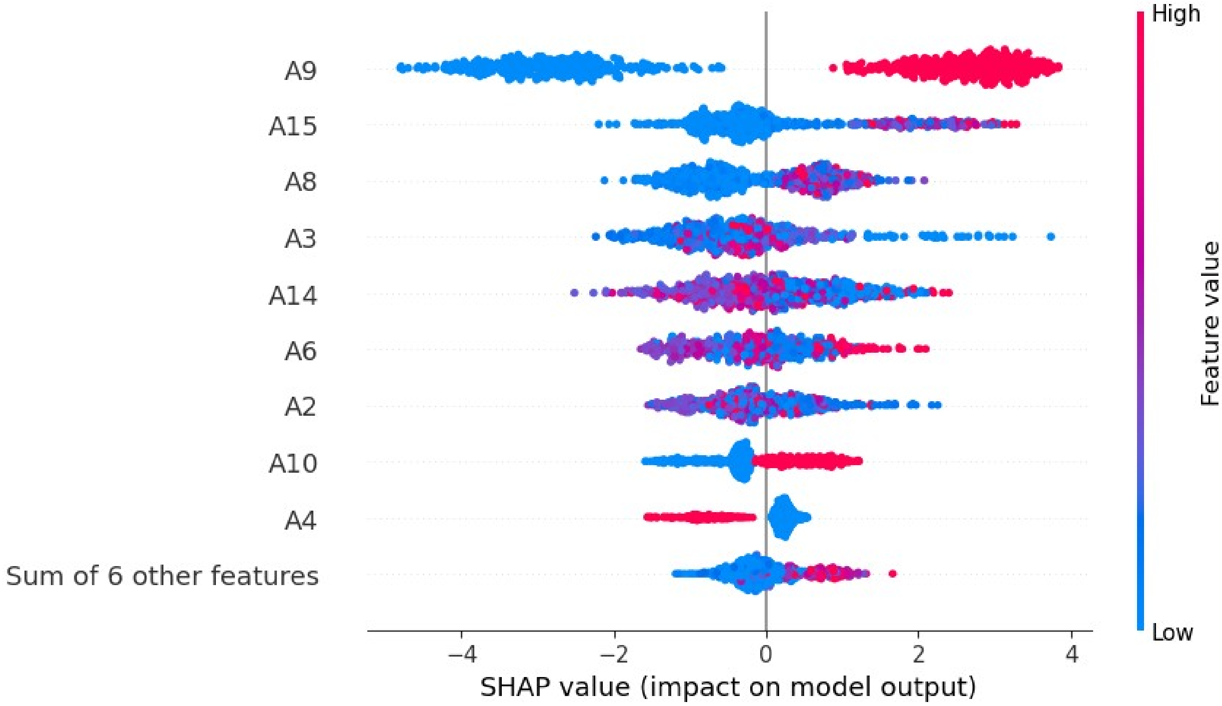
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None,
max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan,
monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, ...)
```

```
df_cross = df_clean.copy()

df_cross['approval_prob'] = xgb_model.predict_proba(X)[:, 1]

df_cross['decision'] = df_cross['approval_prob'].apply(
    lambda p: 'Approve' if p >= 0.6 else 'Manual Review'
)
```

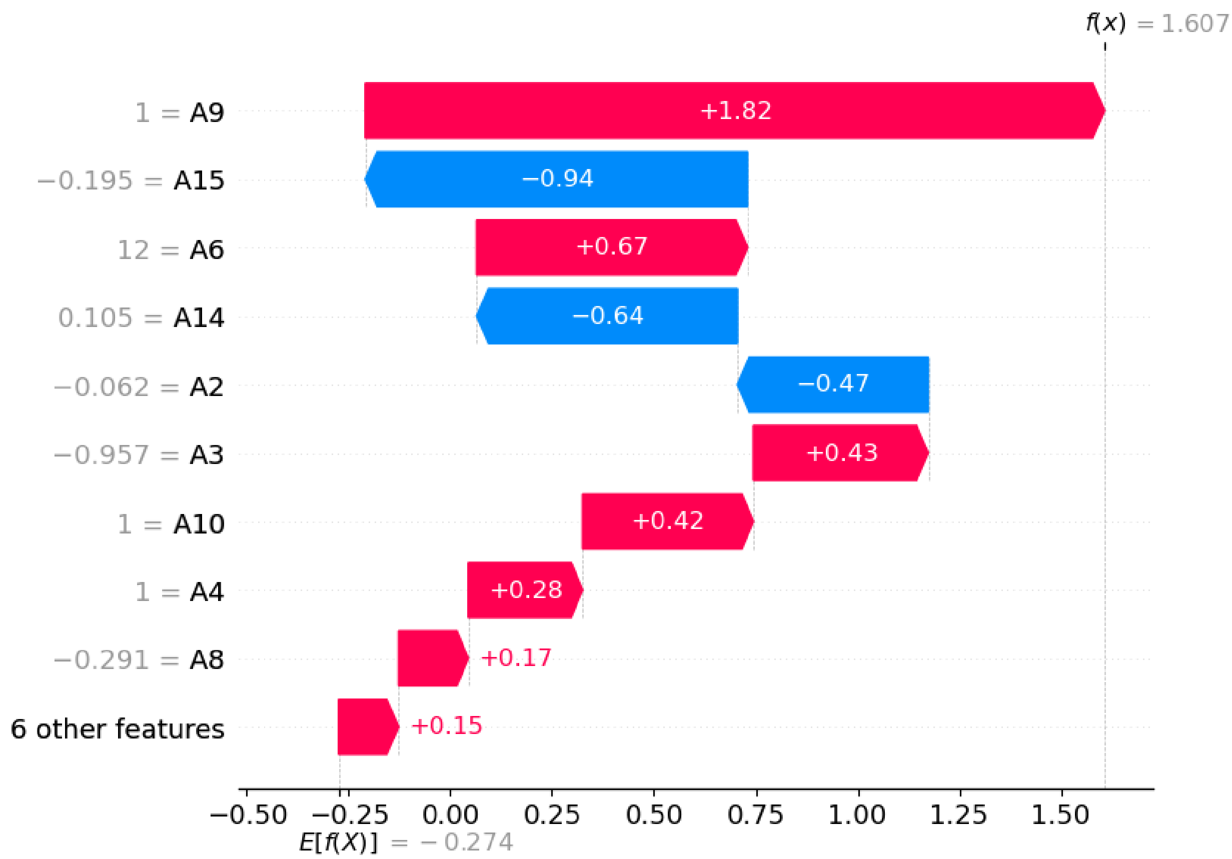
```python
def assign_risk(prob):
    if prob >= 0.8:
        return 'Low Risk'
    elif prob >= 0.6:
        return 'Moderate Risk'
    else:
        return 'High Risk'
df_cross['risk_bucket'] = df_cross['approval_prob'].apply(assign_risk)

df_cross['business_rule_flag'] = df_cross['risk_bucket'].apply(lambda
x: 1 if x == 'High Risk' else 0)

df_cross['final_decision'] = df_cross.apply(
    lambda row: 'Deny' if row['business_rule_flag'] == 1 else
row['decision'],
    axis=1
)

df_cross[['approval_prob', 'decision', 'risk_bucket',
'business_rule_flag', 'final_decision']].head()
```

```
   approval_prob decision risk_bucket  business_rule_flag
final_decision
0       0.833003  Approve    Low Risk                   0
Approve
1       0.999512  Approve    Low Risk                   0
Approve
2       0.998048  Approve    Low Risk                   0
Approve
3       0.988194  Approve    Low Risk                   0
Approve
4       0.982082  Approve    Low Risk                   0
Approve
```

```python
explainer = shap.Explainer(xgb_model)
shap_values = explainer(X)

shap.plots.beeswarm(shap_values)
```




```
sample_index = 0
shap.plots.waterfall(shap_values[sample_index])
```




```
group_approval_rates = df_cross.groupby('A1')
['final_decision'].value_counts(normalize=True).unstack()
print(group_approval_rates)
```

```
final_decision   Approve      Deny
A1
0               0.457143  0.542857
1               0.429167  0.570833
```

```
disparity = abs(group_approval_rates.loc[0, 'Approve'] -
group_approval_rates.loc[1, 'Approve'])
print(f"Disparate impact (A1): {round(disparity, 3)}")
```

```
Disparate impact (A1): 0.028
```

```
df_cross['needs_review'] = df_cross.apply(
    lambda row: 1 if (row['approval_prob'] < 0.6 or
row['business_rule_flag'] == 1) else 0,
    axis=1
)

df_cross[['approval_prob', 'final_decision', 'risk_bucket',
'business_rule_flag', 'needs_review']].head()
```

```
   approval_prob final_decision risk_bucket  business_rule_flag
needs_review
0       0.833003        Approve    Low Risk                   0
0
1       0.999512        Approve    Low Risk                   0
0
2       0.998048        Approve    Low Risk                   0
0
3       0.988194        Approve    Low Risk                   0
0
4       0.982082        Approve    Low Risk                   0
0
```

```
df_temporal = df_cross.copy()

df_temporal['application_time'] = pd.date_range(start='2022-01-01',
periods=len(df_temporal), freq='H')

df_temporal['application_day'] =
df_temporal['application_time'].dt.date
df_temporal['daily_applicant_count'] =
df_temporal.groupby('application_day')
['application_day'].transform('count')

high_risk_times = df_temporal[df_temporal['risk_bucket'] == 'High
Risk']['application_time']
df_temporal['time_since_last_high_risk'] =
df_temporal['application_time'].apply(
    lambda t: (t - high_risk_times[high_risk_times <
t].max()).total_seconds() / 3600
    if not high_risk_times[high_risk_times < t].empty else np.nan
)

df_temporal['rolling_approval_24h'] =
df_temporal['Class'].rolling(window=24, min_periods=1).mean()

df_temporal[['application_time', 'daily_applicant_count',
'time_since_last_high_risk', 'rolling_approval_24h']].head()
```

```
     application_time  daily_applicant_count
time_since_last_high_risk  \
0 2022-01-01 00:00:00                     24
NaN
1 2022-01-01 01:00:00                     24
NaN
2 2022-01-01 02:00:00                     24
NaN
3 2022-01-01 03:00:00                     24
NaN
4 2022-01-01 04:00:00                     24
NaN
```

```
   rolling_approval_24h
0                   1.0
1                   1.0
2                   1.0
3                   1.0
4                   1.0

df_anomaly = df_temporal.copy()

exclude_cols = ['application_time', 'application_day', 'risk_bucket',
'final_decision']

X_anomaly = df_anomaly.drop(columns=exclude_cols, errors='ignore')
X_anomaly = X_anomaly.select_dtypes(include=[np.number])

X_anomaly_clean = X_anomaly.dropna()

from sklearn.ensemble import IsolationForest

from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')
X_anomaly_clean = pd.DataFrame(imputer.fit_transform(X_anomaly),
columns=X_anomaly.columns)

iso_forest = IsolationForest(contamination=0.05, random_state=42)
df_anomaly.loc[X_anomaly_clean.index, 'anomaly_flag'] =
iso_forest.fit_predict(X_anomaly_clean)

df_anomaly['is_anomaly'] = df_anomaly['anomaly_flag'].map({-1: 1, 1:
0})

df_anomaly[['approval_prob', 'risk_bucket', 'is_anomaly']].head()

   approval_prob risk_bucket  is_anomaly
0       0.833003    Low Risk           0
1       0.999512    Low Risk           0
2       0.998048    Low Risk           0
3       0.988194    Low Risk           0
4       0.982082    Low Risk           0

X_cluster =
df_anomaly.select_dtypes(include=[np.number]).drop(columns=['anomaly_f
lag', 'is_anomaly'], errors='ignore')

X_cluster = X_cluster.fillna(X_cluster.mean())

df_cluster = df_anomaly.copy()

X_cluster = df_cluster.select_dtypes(include=[np.number])
```

```
X_cluster = X_cluster.dropna()
df_cluster = df_cluster.loc[X_cluster.index]

from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
df_cluster['cluster_id'] = kmeans.fit_predict(X_cluster)

cluster_risk_summary = df_cluster.groupby('cluster_id')
['risk_bucket'].value_counts(normalize=True).unstack()

print(cluster_risk_summary)
df_cluster[['cluster_id', 'risk_bucket', 'is_anomaly']].head()
```

```
risk_bucket  High Risk  Low Risk  Moderate Risk
cluster_id
0             0.831486  0.164080       0.004435
1             0.028571  0.952381       0.019048
2             0.118421  0.881579            NaN
```

```
    cluster_id risk_bucket  is_anomaly
58           0    Low Risk           1
59           0    Low Risk           0
60           0    Low Risk           0
61           0    Low Risk           0
62           1    Low Risk           0
```

```
X =
df_cluster.select_dtypes(include=[np.number]).drop(columns=['Class'],
errors='ignore').dropna()
y = df_cluster.loc[X.index, 'Class']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

xgb_cost_sensitive = XGBClassifier(
    use_label_encoder=False,
    eval_metric='logloss',
    random_state=42,
    scale_pos_weight=2.0  # Adjust based on business risk profile
)
xgb_cost_sensitive.fit(X_train, y_train)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
```

```
              interaction_constraints=None, learning_rate=None,
max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan,
monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, ...)
```

```
y_pred = xgb_cost_sensitive.predict(X_test)
y_prob = xgb_cost_sensitive.predict_proba(X_test)[:, 1]
print("Accuracy:", round(accuracy_score(y_test, y_pred), 3))
print("F1 Score:", round(f1_score(y_test, y_pred), 3))
print("ROC AUC:", round(roc_auc_score(y_test, y_prob), 3))
print("Classification Report:\n", classification_report(y_test,
y_pred))
```

```
Accuracy: 0.921
F1 Score: 0.909
ROC AUC: 0.995
Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.87      0.93        77
           1       0.83      1.00      0.91        50

    accuracy                           0.92       127
   macro avg       0.92      0.94      0.92       127
weighted avg       0.93      0.92      0.92       127
```

```
df_experimental = df_cluster.copy()

df_experimental['credit_utilization'] = df_experimental['A14'] /
(df_experimental['A15'] + 1)

df_experimental['is_new_customer'] = (df_experimental['A11'] ==
0).astype(int)

df_experimental['has_missed_payments'] = (df_experimental['A12'] ==
1).astype(int)

df_experimental[['A14', 'A15', 'credit_utilization', 'A11',
'is_new_customer', 'A12', 'has_missed_payments']].head()
```

```
         A14       A15  credit_utilization       A11  is_new_customer
A12  \
58  3.063254 -0.195413            3.807239 -0.493887                0
1
59 -0.604616 -0.195413           -0.751461  1.769760                0
0
```

```
60  0.092919 -0.195413           0.115486  0.329258                0
1
61  0.383558 -0.055199           0.405967  1.358188                0
0
62 -0.604616 -0.118584          -0.685959 -0.082314                0
1

    has_missed_payments
58                    1
59                    0
60                    1
61                    0
62                    1
```

```
df_experimental['A12'] = df_experimental['A12'].map({'t': 1, 'f': 0})
```

```
df = df_experimental.copy()
X = df.select_dtypes(include=[np.number]).drop(columns=['Class'],
errors='ignore').dropna()
y = df.loc[X.index, 'Class']
df = df.loc[X.index]
```

```
print(y.value_counts(dropna=False))
```

```
Series([], Name: count, dtype: int64)
```

```
df['Class'] = df['Class'].map({'+': 1, '-': 0})
```

```
df = df[df['Class'].notna()]
```

```
assert set(y.unique()).issubset({0, 1}), "Your target is not binary"
```

```
print("X shape:", X.shape)
print("df['Class'] shape:", df['Class'].shape)
print("Any NaNs in Class?", df['Class'].isna().sum())
print("Unique Class values:", df['Class'].unique())
```

```
X shape: (0, 27)
df['Class'] shape: (0,)
Any NaNs in Class? 0
Unique Class values: []
```

```
df['Class'] = df['Class'].map({'+': 1, '-': 0})
df = df[df['Class'].notna()]
```

```
X = df.select_dtypes(include=[np.number]).drop(columns=['Class'],
errors='ignore').dropna()
y = df.loc[X.index, 'Class']
```

```
print("Target Distribution:")
print(y.value_counts())
```

```
Target Distribution:
Series([], Name: count, dtype: int64)
```

```
print(df['Class'].value_counts(dropna=False))
print(df['Class'].unique())
print(df['Class'].head())
```

```
Series([], Name: count, dtype: int64)
[]
Series([], Name: Class, dtype: int64)
```

```
print(df_experimental.columns)
```

```
Index(['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9', 'A10',
'A11',
       'A12', 'A13', 'A14', 'A15', 'Class', 'approval_prob',
'decision',
       'risk_bucket', 'business_rule_flag', 'final_decision',
'needs_review',
       'application_time', 'application_day', 'daily_applicant_count',
       'time_since_last_high_risk', 'rolling_approval_24h',
'anomaly_flag',
       'is_anomaly', 'cluster_id', 'credit_utilization',
'is_new_customer',
       'has_missed_payments'],
      dtype='object')
```

```
print(df_experimental['Class'].value_counts(dropna=False))
print(df_experimental['Class'].unique())
print(df_experimental['Class'].dtype)
```

```
Class
0    383
1    249
Name: count, dtype: int64
[1 0]
int64
```

```
print("X shape:", X.shape)
print("Any NaNs in X?", X.isna().sum().sum())
print("X summary stats:\n", X.describe())
```

```
X shape: (0, 27)
Any NaNs in X? 0
X summary stats:
         A1   A2   A3   A4   A5   A6   A7   A8   A9  A10  ...
needs_review  \
count  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...
0.0
mean   NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
```

```
std     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
min     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
25%     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
50%     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
75%     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN
max     NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...
NaN

       daily_applicant_count  time_since_last_high_risk
rolling_approval_24h  \
count                    0.0                        0.0
0.0
mean                     NaN                        NaN
NaN
std                      NaN                        NaN
NaN
min                      NaN                        NaN
NaN
25%                      NaN                        NaN
NaN
50%                      NaN                        NaN
NaN
75%                      NaN                        NaN
NaN
max                      NaN                        NaN
NaN

       anomaly_flag  is_anomaly  cluster_id  credit_utilization  \
count           0.0         0.0         0.0                 0.0
mean            NaN         NaN         NaN                 NaN
std             NaN         NaN         NaN                 NaN
min             NaN         NaN         NaN                 NaN
25%             NaN         NaN         NaN                 NaN
50%             NaN         NaN         NaN                 NaN
75%             NaN         NaN         NaN                 NaN
max             NaN         NaN         NaN                 NaN

       is_new_customer  has_missed_payments
count              0.0                  0.0
mean               NaN                  NaN
std                NaN                  NaN
min                NaN                  NaN
25%                NaN                  NaN
50%                NaN                  NaN
75%                NaN                  NaN
```

```
max                    NaN                     NaN

[8 rows x 27 columns]
```

```
X =
df_experimental.select_dtypes(include=[np.number]).drop(columns=['Clas
s'], errors='ignore')
X = X.fillna(X.mean())

y = df_experimental['Class'].astype(int)

print(X.shape)
print(y.value_counts())
```

```
(632, 27)
Class
0    383
1    249
Name: count, dtype: int64
```

```
model = XGBClassifier(use_label_encoder=False, eval_metric='logloss',
random_state=42)
model.fit(X, y)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None,
max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan,
monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, ...)
```

```
df['approval_prob'] = model.predict_proba(X)[:, 1]
df['prediction'] = model.predict(X)
df['final_decision'] = df['approval_prob'].apply(lambda p: 'Approve'
if p >= 0.6 else 'Manual Review')
df['bias_flag'] = (df['A1'] == 0).astype(int)

explainer = shap.TreeExplainer(model)
shap_vals = explainer.shap_values(X)

top_shap_features = []
for row_vals in shap_vals:
```

```
    top_idx = np.argsort(np.abs(row_vals))[::-1][:3]
    top_feats = [X.columns[i] for i in top_idx]
    top_shap_features.append(', '.join(top_feats))
df['top_3_shap_features'] = top_shap_features

audit_trail = df[[
    'prediction', 'approval_prob', 'final_decision',
    'risk_bucket', 'bias_flag', 'top_3_shap_features'
]]

audit_trail.head()
```

```
   prediction  approval_prob final_decision risk_bucket  bias_flag  \
0           1       0.988367        Approve         NaN          0
1           1       0.998461        Approve         NaN          0
2           1       0.997990        Approve         NaN          0
3           1       0.999494        Approve         NaN          0
4           1       0.994939        Approve         NaN          0

                                 top_3_shap_features
0  approval_prob, rolling_approval_24h, time_sinc...
1  approval_prob, rolling_approval_24h, time_sinc...
2  approval_prob, rolling_approval_24h, time_sinc...
3  approval_prob, rolling_approval_24h, time_sinc...
4  approval_prob, rolling_approval_24h, time_sinc...
```