```
import pandas as pd
import numpy as np
import scipy
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.metrics import make_scorer, f1_score
from sklearn.inspection import permutation_importance
import shap
from mpl_toolkits.mplot3d import Axes3D
```

```
df = pd.read_csv("df_final.csv")
df.head()
```

	Intuition_Encoded	Age	Income	Employment_Status	High_Expectation	Industry_Experience	Highest_Degree_Ordinal	Hours_Learning_Weekly	Months_Prog
0	3.0	35.0	2.0	1.0	1.0	1.0	4.0	2.0	
1	3.0	27.0	2.0	1.0	1.0	1.0	4.0	10.0	
2	3.0	24.0	2.0	1.0	1.0	1.0	6.0	5.0	
3	3.0	44.0	2.0	1.0	1.0	1.0	3.0	8.0	
4	3.0	21.0	2.0	1.0	1.0	1.0	4.0	42.0	

5 rows × 29 columns

```
# Remove the top five outliers for Money_Spent

for i in range(0,5):
    df = df[df['Money_Spent'] != df['Money_Spent'].max()]
df['Money_Spent'].max()
```

```
60000.0
```

```
# Set our outcome variable
y = df['Job_Status_Income(Objective1)']

# Drop outcome variables, as well as any columns directly related to employment status
X = df.drop(columns=['Job_Status_Income(Objective1)','Job_Status_Expecation(Objective2)','Field_Working_Education','Field_Working_Others',
                    'Field_Working_Self-employed','Field_Working_Software development and IT','Field_Working_unemployed','Employment_Status',
                    'Laid_Off_Potential', 'Replacable_Job_Potential','Industry_Experience'])

# Check for correlated features
X.corr()
```

	Intuition_Encoded	Age	Income	High_Expectation	Highest_Degree_Ordinal	Hours_Learning_Weekly	Months_Programming
Intuition_Encoded	1.000000	0.090556	0.131706	0.173681	0.074111	0.088768	-0.007950
Age	0.090556	1.000000	0.472274	0.176099	-0.024744	-0.003074	0.071883
Income	0.131706	0.472274	1.000000	0.320787	-0.021986	-0.051267	0.037264
High_Expectation	0.173681	0.176099	0.320787	1.000000	0.054478	0.044058	0.002223
Highest_Degree_Ordinal	0.074111	-0.024744	-0.021986	0.054478	1.000000	0.035889	-0.015719
Hours_Learning_Weekly	0.088768	-0.003074	-0.051267	0.044058	0.035889	1.000000	0.003143
Months_Programming	-0.007950	0.071883	0.037264	0.002223	-0.015719	0.003143	1.000000
Money_Spent	0.038722	0.087551	0.093026	0.063645	-0.020973	0.057002	0.033600
Count_Learning_Methods	0.047709	0.044170	0.005411	0.048509	0.003364	0.168984	0.100183
Count_Online_Resources	0.087075	0.034187	0.004011	0.073308	0.014880	0.217995	0.080608
In-person Events	0.005363	0.027638	0.023173	0.018385	-0.014916	0.044667	0.064683
Listen_Podcasts	0.038103	0.067649	0.109020	0.059503	-0.012909	0.058738	0.041263
Youtube_Channels	0.058195	-0.051559	-0.079252	0.042241	0.046879	0.201024	0.031896
Months_Finding_New_Job	-0.065193	-0.185489	-0.308171	-0.151163	-0.044621	-0.002225	-0.010524
Study_Field_Computer-related	0.067286	-0.067325	-0.114075	-0.005273	0.112736	0.071346	0.062263
Study_Field_Not applicable	-0.133764	-0.264983	-0.204240	-0.090252	-0.034717	-0.027701	-0.036212
Study_Field_Other Science & Engineering	0.032216	0.128787	0.121403	0.027050	-0.051379	-0.008526	-0.005009
Study_Field_Others	0.039132	0.185229	0.174181	0.064555	-0.012498	-0.026069	-0.013582

Random Forest Classifier

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=0)

# Perform a grid search to identify the best parameters for the model

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [5, 10, 20, None],
    'min_samples_split': [2, 5, 10],
    'bootstrap': [True, False],
}
grid_search = GridSearchCV(RandomForestClassifier(random_state=0), param_grid, scoring='f1_weighted', cv=5)
grid_search.fit(X_train, y_train)

print("Best parameters found: ", grid_search.best_params_)
print("Best cross-validation score: {:.3f}".format(grid_search.best_score_))
```

```
Best parameters found:  {'bootstrap': False, 'max_depth': None, 'min_samples_split': 10, 'n_estimators': 100}
Best cross-validation score: 0.786
```

```
# Build the model with the recommended parameters, and score it on training and test sets
clf = RandomForestClassifier(random_state=0, **grid_search.best_params_).fit(X_train, y_train)

# Calculate the F1 score for the training set
y_train_pred = clf.predict(X_train)
f1_train = f1_score(y_train, y_train_pred, average='weighted')

# Calculate the F1 score for the test set
y_test_pred = clf.predict(X_test)
f1_test = f1_score(y_test, y_test_pred, average='weighted')

# Print the weighted F1 scores
print("F1 of RF classifier on training set: {:.3f}".format(f1_train))
print("F1 of RF classifier on test set: {:.3f}".format(f1_test))
```

```
F1 of RF classifier on training set: 0.985
F1 of RF classifier on test set: 0.797
```

```
# Print a confusion matrix and classification report for additional insight into model performance

print(confusion_matrix(y_test, y_test_pred))
print(classification_report(y_test, y_test_pred))
```

```
[[738   0  11   0]
 [  0 519 122   0]
 [141 237 171   0]
 [  0   0   0 840]]
              precision    recall  f1-score   support
```

```
           0       0.84      0.99      0.91       749
           1       0.69      0.81      0.74       641
           2       0.56      0.31      0.40       549
           3       1.00      1.00      1.00       840

    accuracy                           0.82      2779
   macro avg       0.77      0.78      0.76      2779
weighted avg       0.80      0.82      0.80      2779
```

```
# Calculate the F1 score with 10-fold cross-validation
f1_scorer = make_scorer(f1_score, average='weighted')
f1_scores = cross_val_score(clf, X, y, cv=10, scoring=f1_scorer)

# Print the F1 scores for each fold and the average score
print("F1 Scores for each fold: ", f1_scores)
print("Average F1 Score: {:.3f} + {:.3f}".format(f1_scores.mean(),f1_scores.std()))
```

```
F1 Scores for each fold:  [0.78602757 0.79064562 0.7963856  0.77654197 0.77313895 0.78460738
 0.76859233 0.78190617 0.79498776 0.80308206]
Average F1 Score: 0.786 + 0.010
```

SVM Model

```
# Define numerical features
numerical_features = ['Age', 'Hours_Learning_Weekly', 'Months_Programming',
                      'Money_Spent', 'Count_Learning_Methods', 'Count_Online_Resources',
                      'Youtube_Channels', 'Months_Finding_New_Job']

# Create preprocessor with StandardScaler
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features)
    ],
    remainder='passthrough'  # Keep other columns unchanged
)

# Create the pipeline
pipe = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('svm', SVC(probability=True, random_state=0))  # Enable probability estimates
])

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# Define hyperparameter grid
param_grid = {
    'svm__C': [0.1, 1, 10, 100],
    'svm__kernel': ['rbf'],
    'svm__gamma': ['scale', 'auto', 0.1, 1, 10]
}

# Set up Grid Search
grid_search = GridSearchCV(pipe, param_grid, cv=5, scoring='f1_weighted', n_jobs=-1, verbose=2)
grid_search.fit(X_train, y_train)

# Retrieve and print the best parameters and score
best_params = grid_search.best_params_
print("Best parameters found: ", best_params)
print("Best cross-validation score: {:.3f}".format(grid_search.best_score_))

# Set the best parameters to the pipeline (not strictly necessary since fit already sets them)
pipe.set_params(**best_params)

# Now fit the pipeline to the training data
pipe.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
Best parameters found:  {'svm__C': 10, 'svm__gamma': 'auto', 'svm__kernel': 'rbf'}
Best cross-validation score: 0.771
```

```
Pipeline
  preprocessor: ColumnTransformer
    num                 remainder
    StandardScaler      passthrough
  SVC
```

```
# Calculate the weighted F1 score on training data using 10-fold CV
train_f1_scores = cross_val_score(pipe, X_train, y_train, cv=10, scoring='f1_weighted')
print("Weighted F1 score (10-fold CV) on training set: {:.3f} ± {:.3f}".format(train_f1_scores.mean(),train_f1_scores.std()))

# Calculate the weighted F1 score on the test data using 10-fold CV
```

```
test_f1_scores = cross_val_score(pipe, X_test, y_test, cv=10, scoring='f1_weighted')
print("Weighted F1 score (10-fold CV) on test set: {:.3f} ± {:.3f}".format(test_f1_scores.mean(),train_f1_scores.std()))
```

```
Weighted F1 score (10-fold CV) on training set: 0.772 ± 0.004
Weighted F1 score (10-fold CV) on test set: 0.787 ± 0.004
```

```
# Calculate the F1 score with 10-fold cross-validation
f1_scorer = make_scorer(f1_score, average='weighted')
f1_scores = cross_val_score(pipe, X, y, cv=10, scoring=f1_scorer)

# Print the F1 scores for each fold and the average score
print("F1 Scores for each fold: ", f1_scores)
print("Average F1 Score: {:.3f} ± {:.3f}".format(f1_scores.mean(),f1_scores.std()))
```

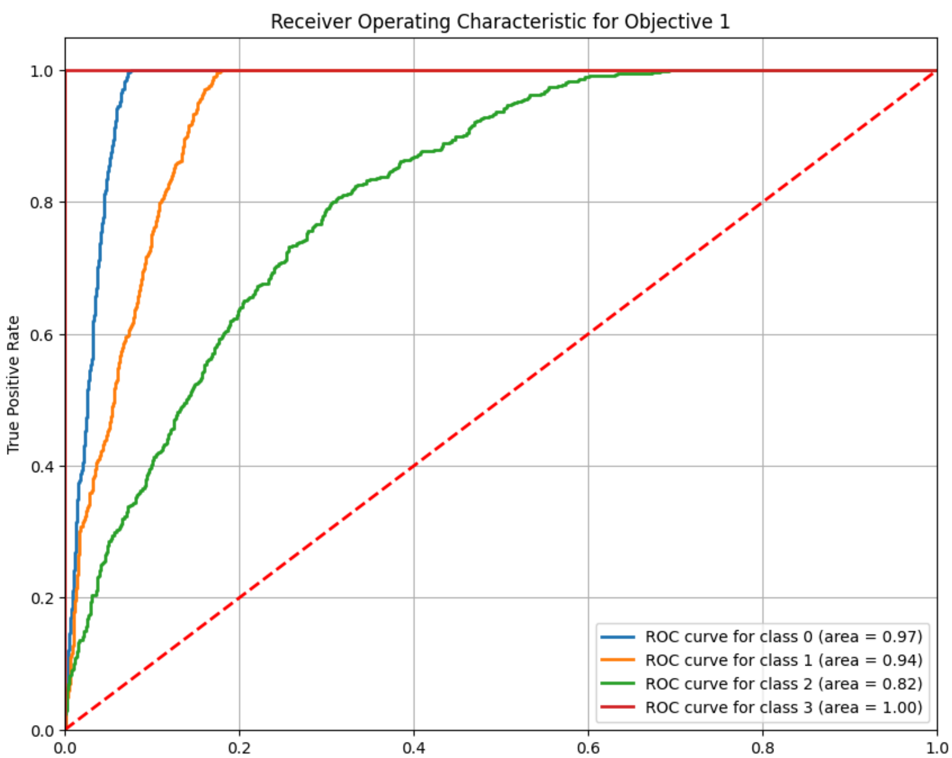
```
[CV] END .......svm__C=0.1, svm__gamma=auto, svm__kernel=rbf; total time=  40.7s
[CV] END ..........svm__C=0.1, svm__gamma=1, svm__kernel=rbf; total time= 1.4min
[CV] END .......svm__C=10, svm__gamma=scale, svm__kernel=rbf; total time=  21.5s
[CV] END ........svm__C=10, svm__gamma=auto, svm__kernel=rbf; total time=  26.9s
[CV] END .........svm__C=10, svm__gamma=0.1, svm__kernel=rbf; total time=  31.9s
[CV] END ..........svm__C=10, svm__gamma=10, svm__kernel=rbf; total time= 1.8min
[CV] END .......svm__C=0.1, svm__gamma=auto, svm__kernel=rbf; total time=  40.4s
[CV] END ..........svm__C=0.1, svm__gamma=1, svm__kernel=rbf; total time= 1.4min
[CV] END ...........svm__C=1, svm__gamma=10, svm__kernel=rbf; total time= 1.8min
[CV] END .......svm__C=100, svm__gamma=auto, svm__kernel=rbf; total time=  40.0s
[CV] END ........svm__C=100, svm__gamma=0.1, svm__kernel=rbf; total time=  46.8s
[CV] END ........svm__C=0.1, svm__gamma=0.1, svm__kernel=rbf; total time=  42.4s
[CV] END ........svm__C=1, svm__gamma=scale, svm__kernel=rbf; total time=  21.0s
[CV] END .........svm__C=1, svm__gamma=auto, svm__kernel=rbf; total time=  26.5s
[CV] END ............svm__C=1, svm__gamma=1, svm__kernel=rbf; total time= 1.5min
[CV] END .........svm__C=10, svm__gamma=0.1, svm__kernel=rbf; total time=  30.3s
[CV] END ..........svm__C=10, svm__gamma=10, svm__kernel=rbf; total time= 1.8min
[CV] END ......svm__C=0.1, svm__gamma=scale, svm__kernel=rbf; total time=  42.3s
[CV] END ........svm__C=1, svm__gamma=scale, svm__kernel=rbf; total time=  21.1s
[CV] END ..........svm__C=1, svm__gamma=0.1, svm__kernel=rbf; total time=  29.9s
[CV] END ............svm__C=1, svm__gamma=1, svm__kernel=rbf; total time= 1.5min
[CV] END ...........svm__C=10, svm__gamma=1, svm__kernel=rbf; total time= 1.6min
[CV] END ........svm__C=100, svm__gamma=0.1, svm__kernel=rbf; total time=  45.5s
[CV] END .......svm__C=0.1, svm__gamma=auto, svm__kernel=rbf; total time=  40.8s
[CV] END .........svm__C=0.1, svm__gamma=10, svm__kernel=rbf; total time= 1.6min
[CV] END .......svm__C=10, svm__gamma=scale, svm__kernel=rbf; total time=  21.8s
[CV] END ........svm__C=10, svm__gamma=auto, svm__kernel=rbf; total time=  27.2s
[CV] END ...........svm__C=10, svm__gamma=1, svm__kernel=rbf; total time= 1.6min
[CV] END ........svm__C=100, svm__gamma=0.1, svm__kernel=rbf; total time=  45.7s
[CV] END ......svm__C=0.1, svm__gamma=scale, svm__kernel=rbf; total time=  42.8s
[CV] END .........svm__C=1, svm__gamma=auto, svm__kernel=rbf; total time=  21.9s
[CV] END ..........svm__C=1, svm__gamma=0.1, svm__kernel=rbf; total time=  30.5s
[CV] END ............svm__C=1, svm__gamma=1, svm__kernel=rbf; total time= 1.5min
[CV] END ...........svm__C=10, svm__gamma=1, svm__kernel=rbf; total time= 1.6min
[CV] END ........svm__C=100, svm__gamma=0.1, svm__kernel=rbf; total time=  46.0s
[CV] END ........svm__C=0.1, svm__gamma=0.1, svm__kernel=rbf; total time=  41.6s
[CV] END .........svm__C=0.1, svm__gamma=10, svm__kernel=rbf; total time= 1.6min
[CV] END .......svm__C=10, svm__gamma=scale, svm__kernel=rbf; total time=  22.2s
[CV] END ........svm__C=10, svm__gamma=auto, svm__kernel=rbf; total time=  26.9s
[CV] END ...........svm__C=10, svm__gamma=1, svm__kernel=rbf; total time= 1.6min
[CV] END ..........svm__C=100, svm__gamma=1, svm__kernel=rbf; total time= 1.3min
[CV] END ........svm__C=0.1, svm__gamma=0.1, svm__kernel=rbf; total time=  41.6s
[CV] END .........svm__C=0.1, svm__gamma=10, svm__kernel=rbf; total time= 1.6min
[CV] END .......svm__C=10, svm__gamma=scale, svm__kernel=rbf; total time=  22.0s
[CV] END ........svm__C=10, svm__gamma=auto, svm__kernel=rbf; total time=  27.1s
[CV] END ...........svm__C=10, svm__gamma=1, svm__kernel=rbf; total time= 1.6min
[CV] END ..........svm__C=100, svm__gamma=1, svm__kernel=rbf; total time= 1.3min
[CV] END ........svm__C=0.1, svm__gamma=0.1, svm__kernel=rbf; total time=  42.5s
[CV] END ........svm__C=1, svm__gamma=scale, svm__kernel=rbf; total time=  20.9s
[CV] END .........svm__C=1, svm__gamma=auto, svm__kernel=rbf; total time=  26.8s
[CV] END ............svm__C=1, svm__gamma=1, svm__kernel=rbf; total time= 1.5min
[CV] END .........svm__C=10, svm__gamma=0.1, svm__kernel=rbf; total time=  31.0s
[CV] END ......svm__C=100, svm__gamma=scale, svm__kernel=rbf; total time=  35.0s
[CV] END .......svm__C=100, svm__gamma=auto, svm__kernel=rbf; total time=  41.9s
[CV] END ..........svm__C=100, svm__gamma=1, svm__kernel=rbf; total time= 1.3min
[CV] END ......svm__C=0.1, svm__gamma=scale, svm__kernel=rbf; total time=  42.3s
[CV] END ........svm__C=1, svm__gamma=scale, svm__kernel=rbf; total time=  20.2s
[CV] END .........svm__C=1, svm__gamma=auto, svm__kernel=rbf; total time=  26.2s
```

```
# Make predictions on the test set
y_pred = pipe.predict(X_test)

# Evaluate performance using a confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

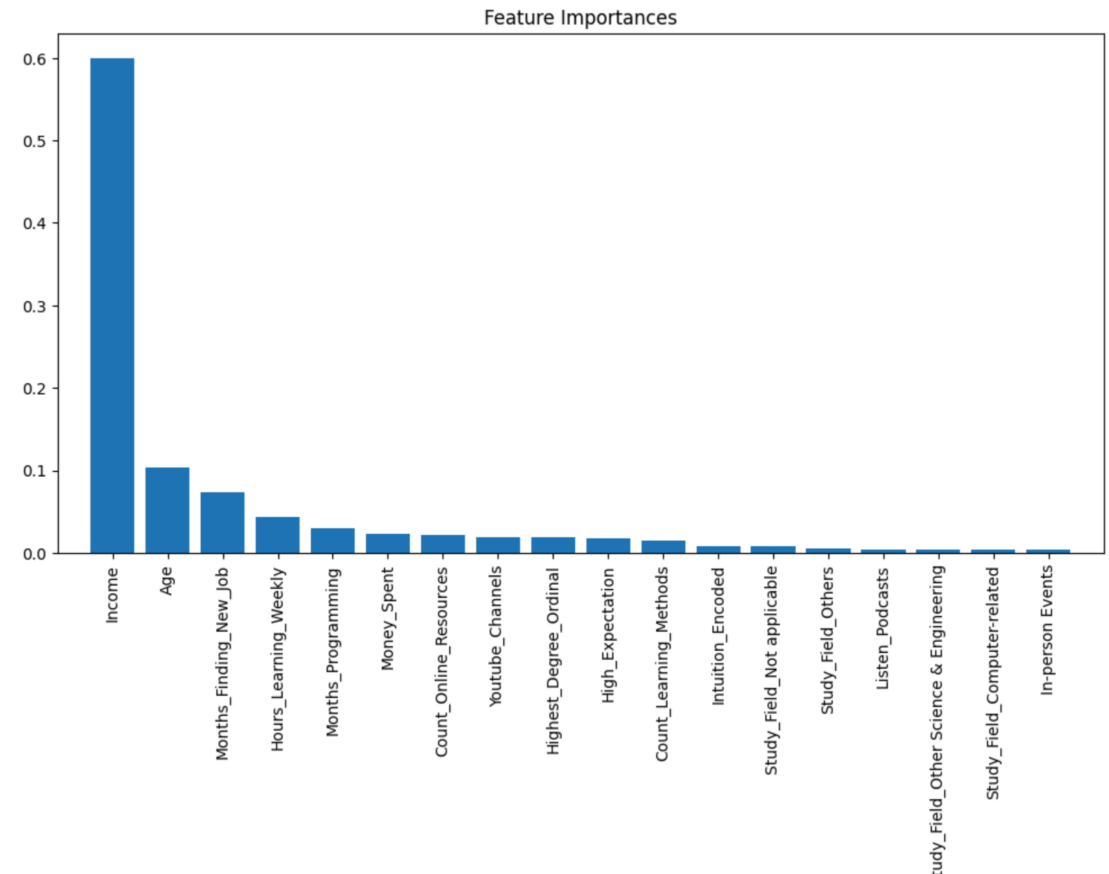
```
[[738   0  11   0]
 [  2 544  93   2]
 [149 278 121   1]
 [  0   0   1 839]]
              precision    recall  f1-score   support

           0       0.83      0.99      0.90       749
           1       0.66      0.85      0.74       641
           2       0.54      0.22      0.31       549
           3       1.00      1.00      1.00       840

    accuracy                           0.81      2779
   macro avg       0.76      0.76      0.74      2779
weighted avg       0.78      0.81      0.78      2779
```

Random Forest Model Evaluation

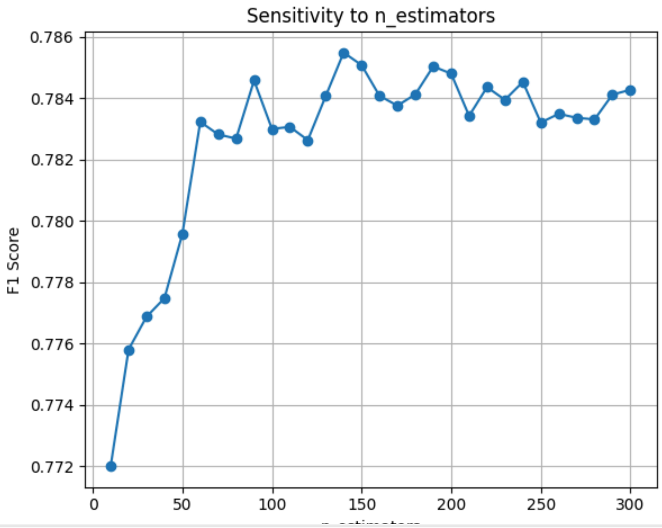
```
# Calculate predicted probabilities
y_prob = clf.predict_proba(X_test)

# Compute ROC curve and AUC for each class
n_classes = len(np.unique(y))  # Number of classes
fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    # Compute ROC curve
    fpr[i], tpr[i], _ = roc_curve((y_test == np.unique(y)[i]).astype(int), y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curves
plt.figure(figsize = (10, 8))

for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], lw = 2, label = "ROC curve for class {0} (area = {1:0.2f})".format(np.unique(y)[i], roc_auc[i]))

plt.plot([0, 1], [0, 1], color = "red", lw = 2, linestyle = "--")  # Diagonal line
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristic for Objective 1")
plt.legend(loc = "lower right")
plt.grid()
plt.show()
```

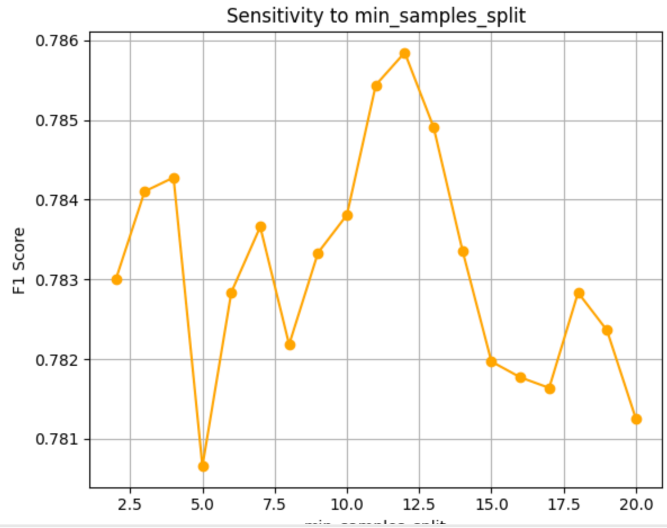



```
# Feature Importance
importances = clf.feature_importances_
indices = np.argsort(importances)[::-1]

# Plot feature importances
plt.figure(figsize = (12, 6))
plt.title("Feature Importances")
plt.bar(range(X.shape[1]), importances[indices], align = "center")
plt.xticks(range(X.shape[1]), X.columns[indices], rotation = 90)
plt.xlim([-1, X.shape[1]])
plt.show()
```




```python
# Define a range for n_estimators and min_samples_split to test
n_estimators_range = np.arange(10, 301, 10)  # 10 to 300 with a step of 10
min_samples_split_range = np.arange(2, 21, 1)  # 2 to 20 with a step of 1

# Store results
n_estimators_scores = []
min_samples_split_scores = []

# OAT Sensitivity for 'n_estimators' (vary n_estimators, keep min_samples_split fixed)
for n in n_estimators_range:
    clf = RandomForestClassifier(n_estimators=n, min_samples_split=2, random_state=0)  # min_samples_split fixed at 2
    scores = cross_val_score(clf, X_train, y_train, cv=3, scoring='f1_weighted')
    n_estimators_scores.append(scores.mean())

# OAT Sensitivity for 'min_samples_split' (vary min_samples_split, keep n_estimators fixed)
for min_samples_split in min_samples_split_range:
    clf = RandomForestClassifier(n_estimators=100, min_samples_split=min_samples_split, random_state=0)  # n_estimators fixed at 100
    scores = cross_val_score(clf, X_train, y_train, cv=3, scoring='f1_weighted')
    min_samples_split_scores.append(scores.mean())

# Plot the results
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Plot for n_estimators
axes[0].plot(n_estimators_range, n_estimators_scores, marker='o')
axes[0].set_title("Sensitivity to n_estimators")
axes[0].set_xlabel("n_estimators")
axes[0].set_ylabel("F1 Score")
axes[0].grid()

# Plot for min_samples_split
axes[1].plot(min_samples_split_range, min_samples_split_scores, marker='o', color='orange')
axes[1].set_title("Sensitivity to min_samples_split")
axes[1].set_xlabel("min_samples_split")
axes[1].set_ylabel("F1 Score")
axes[1].grid()

plt.tight_layout()
plt.show()
```





Failure analysis

```
# Create a DataFrame for misclassified instances
misclassified_mask = y_test != y_test_pred  # Create a boolean mask for misclassifications
misclassified_instances = X_test[misclassified_mask]  # Use the mask to filter X_test

# Add true and predicted labels to the misclassified DataFrame
misclassified_instances_df = pd.DataFrame(misclassified_instances)
misclassified_instances_df['True_Label'] = y_test[misclassified_mask]  # Get true labels using the mask
misclassified_instances_df['Predicted_Label'] = y_test_pred[misclassified_mask]  # Get predicted labels using the mask


# Analyze misclassified instances for each class
for class_label in np.unique(y_test):
    print(f"\n--- Analysis of Misclassifications for Class: {class_label} ---")

    # Instances where the true label is the class label but predicted incorrectly
    class_misclassifications = misclassified_instances_df[misclassified_instances_df['True_Label'] == class_label]

    # Number of misclassifications
    num_misclassified = len(class_misclassifications)

    if num_misclassified > 0:
        print("Number of misclassifications:", num_misclassified)
        print("Example Misclassifications:\n", class_misclassifications.head())
        print("\nFeature Distributions of Misclassifications:\n", class_misclassifications.describe())
    else:
        print("No misclassifications for this class.")
```

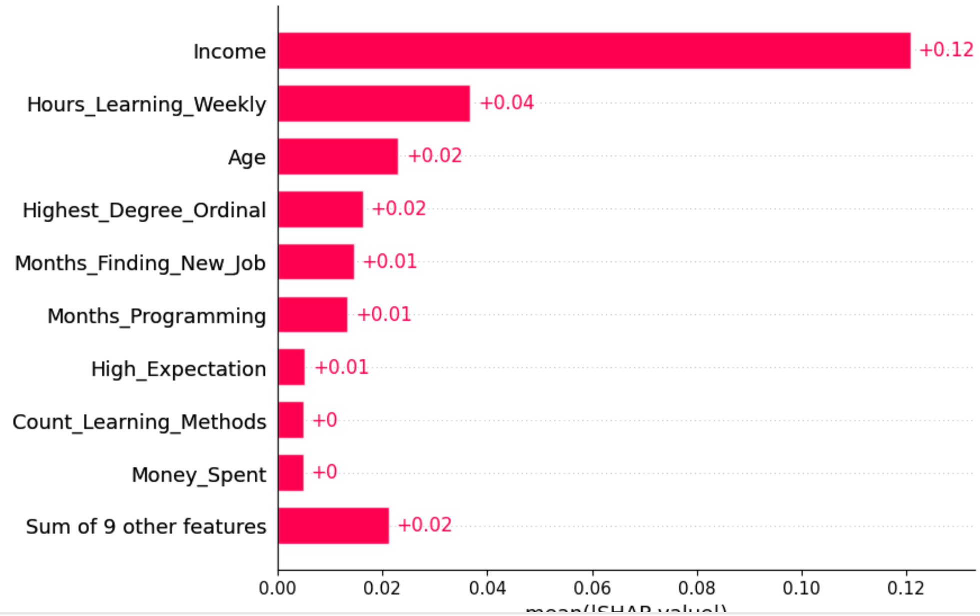
```
--- Analysis of Misclassifications for Class: 0 ---
Number of misclassifications: 11
Example Misclassifications:
       Intuition_Encoded   Age  Income  High_Expectation  \
1251                1.0  30.0     2.0               1.0
575                 3.0  27.0     2.0               1.0
44                  3.0  44.0     2.0               1.0
712                 3.0  24.0     2.0               1.0
2085                3.0  23.0     2.0               1.0

      Highest_Degree_Ordinal  Hours_Learning_Weekly  Months_Programming  \
1251                     6.0                   10.0                 1.0
575                      4.0                   30.0                 6.0
44                       3.0                   60.0                 3.0
712                      4.0                   30.0                 6.0
2085                     4.0                   50.0                 0.5

      Money_Spent  Count_Learning_Methods  Count_Online_Resources  \
1251          0.0                     1.0                     1.0
575           0.0                     1.0                     9.0
44           15.0                     2.0                     8.0
712           0.0                     3.0                     6.0
2085          0.0                     3.0                     4.0

      In-person Events  Listen_Podcasts  Youtube_Channels  \
1251               0.0              0.0               0.0
575                0.0              0.0               3.0
44                 0.0              0.0               4.0
712                0.0              1.0               2.0
2085               0.0              0.0               2.0

      Months_Finding_New_Job  Study_Field_Computer-related  \
1251                    24.0                           0.0
575                      1.0                           0.0
44                      24.0                           0.0
```

```
712                    1.0                            0.0
2085                   0.0                            0.0

      Study_Field_Not applicable  Study_Field_Other Science & Engineering  \
1251                         1.0                                      0.0
575                          0.0                                      0.0
44                           0.0                                      1.0
712                          0.0                                      0.0
2085                         0.0                                      1.0

      Study_Field_Others  True_Label  Predicted_Label
1251                 0.0           0                2
575                  1.0           0                2
44                   0.0           0                2
712                  1.0           0                2
2085                 0.0           0                2

Feature Distributions of Misclassifications:
        Intuition_Encoded        Age  Income  High_Expectation  \
count          11.000000  11.000000    11.0              11.0
mean            2.818182  31.909091     2.0               1.0
std             0.603023   9.148274     0.0               0.0
```

```
misclassified_instances_df.head(10)
```

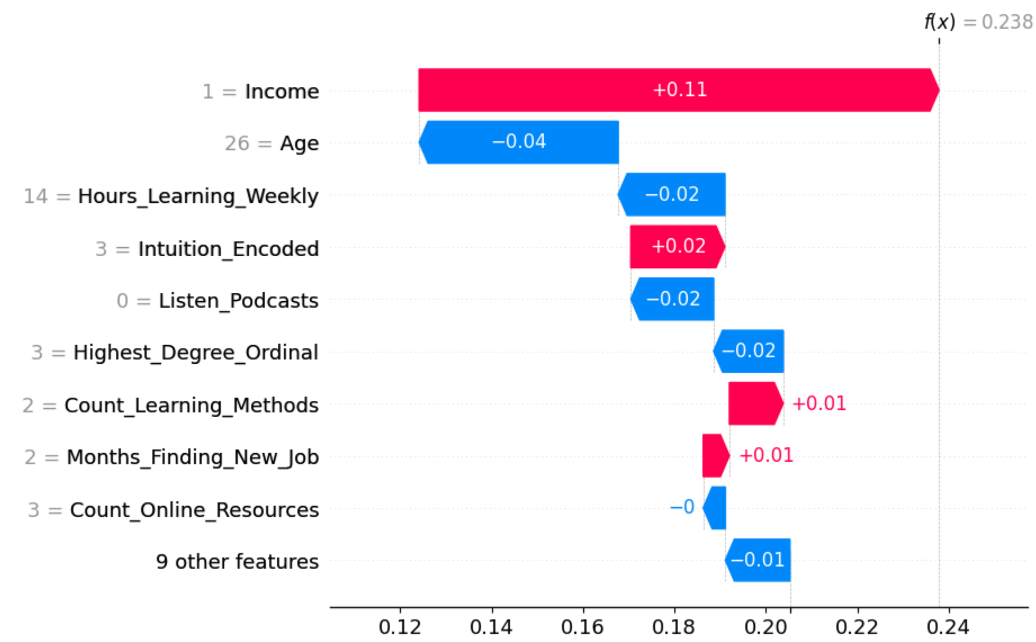
	Intuition_Encoded	Age	Income	High_Expectation	Highest_Degree_Ordinal	Hours_Learning_Weekly	Months_Programming	Money_Spent	Count_Learning_
7890	3.0	35.0	2.0	1.0	4.0	30.0	2.0	100.0	
6035	3.0	30.0	1.0	1.0	6.0	26.0	5.0	0.0	
7922	3.0	26.0	1.0	1.0	3.0	14.0	2.0	0.0	
9787	0.0	26.0	1.0	1.0	6.0	20.0	1.0	0.0	
7173	3.0	22.0	1.0	0.0	4.0	20.0	48.0	100.0	
8667	3.0	21.0	2.0	1.0	6.0	6.0	0.0	0.0	
9609	3.0	20.0	1.0	1.0	6.0	5.0	0.0	0.0	
9619	3.0	46.0	2.0	1.0	6.0	15.0	1.0	0.0	
6945	3.0	0.0	1.0	1.0	4.0	4.0	0.0	0.0	
7170	3.0	33.0	2.0	1.0	4.0	30.0	7.0	2000.0	

```
# Use SHAP TreeExplainer for Random Forest
clf.fit(X_train, y_train)
explainer = shap.TreeExplainer(clf)
shap_values = explainer.shap_values(X_test)

# Select a specific misclassified instance (you can choose the first one or any other)
misclassified_instance_index = 2  # Change this index to select another instance
misclassified_instance = misclassified_instances_df.iloc[misclassified_instance_index]

# Get the SHAP values for the misclassified instance
true_label_index = int(misclassified_instance['True_Label'])
shap_values_instance = shap_values[true_label_index][misclassified_instance_index]

# Create an Explanation object for the SHAP values
explanation = shap.Explanation(values=shap_values[true_label_index],
                                feature_names=X_test.columns,
                                base_values=explainer.expected_value[true_label_index],
                                data=X_test[misclassified_indices].values)
```




```
# Create the SHAP bar plot
shap.plots.bar(explanation)
```

```
shap.plots.waterfall(explanation[misclassified_instance_index])
```

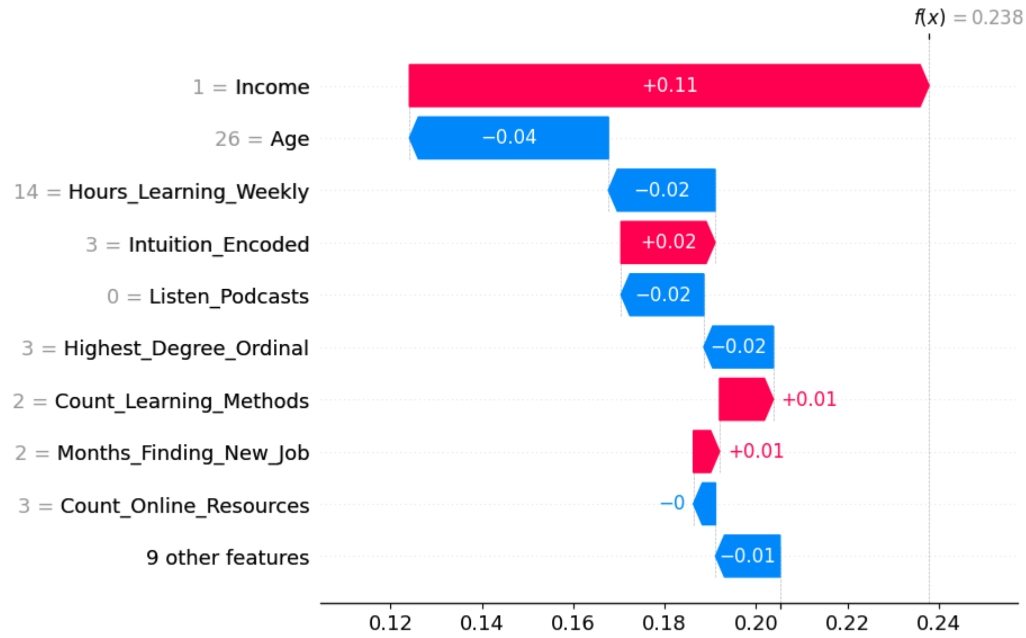



```
misclassified_instance
```

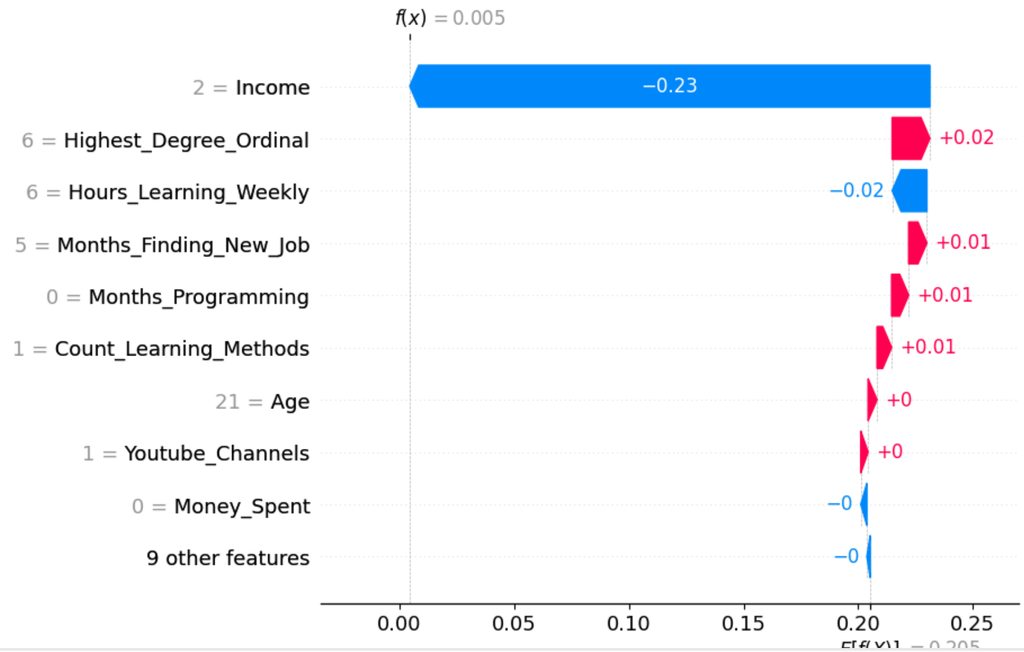
```
Intuition_Encoded                        3.0
Age                                     26.0
Income                                   1.0
High_Expectation                         1.0
Highest_Degree_Ordinal                   3.0
Hours_Learning_Weekly                   14.0
Months_Programming                       2.0
Money_Spent                              0.0
Count_Learning_Methods                   2.0
Count_Online_Resources                   3.0
In-person Events                         1.0
Listen_Podcasts                          0.0
Youtube_Channels                         1.0
Months_Finding_New_Job                   2.0
Study_Field_Computer-related             0.0
Study_Field_Not applicable               0.0
Study_Field_Other Science & Engineering  0.0
Study_Field_Others                       1.0
True_Label                               2.0
```

```
    Predicted_Label                           1.0
    Name: 7922, dtype: float64
```

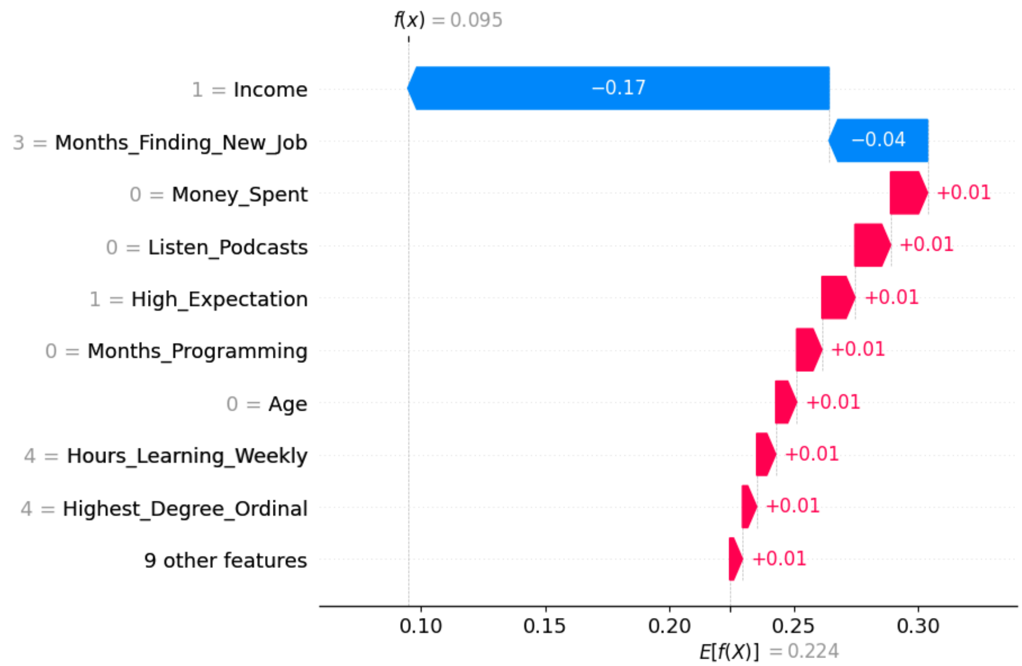
```
# Select a specific misclassified instance (you can choose the first one or any other)
misclassified_instance_index = 2  # Change this index to select another instance
misclassified_instance = misclassified_instances_df.iloc[misclassified_instance_index]

# Get the true label and the predicted label
true_label = int(misclassified_instance['True_Label'])
predicted_label = int(misclassified_instance['Predicted_Label'])

# Get the SHAP values for the misclassified instance for the true label
shap_values_instance = shap_values[true_label][misclassified_instance_index]

# Create an Explanation object for the SHAP values
explanation = shap.Explanation(
    values=shap_values[true_label][misclassified_instance_index],
    feature_names=X_test.columns,
    base_values=explainer.expected_value[true_label],
    data=misclassified_instance[:-2]  # Exclude True_Label and Predicted_Label
)

# Create a SHAP waterfall plot
shap.plots.waterfall(explanation)
```




```
# Select a specific misclassified instance (you can choose the first one or any other)
misclassified_instance_index = 5  # Change this index to select another instance
misclassified_instance = misclassified_instances_df.iloc[misclassified_instance_index]

# Get the true label and the predicted label
true_label = int(misclassified_instance['True_Label'])
predicted_label = int(misclassified_instance['Predicted_Label'])

# Get the SHAP values for the misclassified instance for the true label
shap_values_instance = shap_values[true_label][misclassified_instance_index]

# Create an Explanation object for the SHAP values
explanation = shap.Explanation(
    values=shap_values[true_label][misclassified_instance_index],
    feature_names=X_test.columns,
    base_values=explainer.expected_value[true_label],
    data=misclassified_instance[:-2]  # Exclude True_Label and Predicted_Label
)

# Create a SHAP waterfall plot
shap.plots.waterfall(explanation)
```




```
# Select a specific misclassified instance (you can choose the first one or any other)
misclassified_instance_index = 8  # Change this index to select another instance
misclassified_instance = misclassified_instances_df.iloc[misclassified_instance_index]

# Get the true label and the predicted label
true_label = int(misclassified_instance['True_Label'])
predicted_label = int(misclassified_instance['Predicted_Label'])

# Get the SHAP values for the misclassified instance for the true label
shap_values_instance = shap_values[true_label][misclassified_instance_index]

# Create an Explanation object for the SHAP values
explanation = shap.Explanation(
    values=shap_values[true_label][misclassified_instance_index],
    feature_names=X_test.columns,
    base_values=explainer.expected_value[true_label],
    data=misclassified_instance[:-2]  # Exclude True_Label and Predicted_Label
)

# Create a SHAP waterfall plot
shap.plots.waterfall(explanation)
```




```
# Select three different misclassified instances (adjust indices as needed)
indices = [2, 5, 8]  # Example indices of misclassified instances
```

```
# Create a figure with subplots (1 row, 3 columns)
fig, axes = plt.subplots(3, 1, figsize=(12, 18))  # Adjust the size as needed
```