credit-risk-scoring-project

August 3, 2025

1 Credit Risk Scoring (Loan Approval Prediction)

Introduction & Problem Statement: In financial institutions, lending to unqualified applicants increases the risk of default and non-performing assets (NPAs). Traditional rule-based systems can be inefficient in identifying high-risk applicants.

Business Objective: To develop a credit risk model that predicts loan approval outcomes based on applicant profiles, improving lending decisions and minimizing risk exposure.

1.1 01- Import libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1.2 02- Load dataset

[2]:
```
df = pd.read_csv('train_data.csv')
df.head()
```

[2]:
```
    Loan_ID  Gender Married Dependents     Education Self_Employed  \
0  LP001722    Male     Yes          0      Graduate            No
1  LP002502  Female     Yes          2  Not Graduate           NaN
2  LP002949  Female      No         3+      Graduate           NaN
3  LP002603  Female      No          0      Graduate            No
4  LP001644     NaN     Yes          0      Graduate           Yes

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0              150             1800.0       135.0             360.0
1              210             2917.0        98.0             360.0
2              416            41667.0       350.0             180.0
3              645             3683.0       113.0             480.0
4              674             5296.0       168.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Rural           N
1             1.0     Semiurban           Y
```

```
2              NaN          Urban            N
3              1.0          Rural            Y
4              1.0          Rural            Y
```

2 03- EDA Steps

[3]:
```python
df.shape
```

[3]:
```
(614, 13)
```

[4]:
```python
df.describe()
```

[4]:
```
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[5]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
```

```
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

[6]:
```
df.isnull().sum()
```

[6]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

[7]:
```
df.duplicated().sum()
```

[7]:
```
np.int64(0)
```

[8]:
```
df.nunique()
```

[8]:
```
Loan_ID              614
Gender                 2
Married                2
Dependents             4
Education              2
Self_Employed          2
ApplicantIncome      505
CoapplicantIncome    287
LoanAmount           203
Loan_Amount_Term      10
Credit_History         2
Property_Area          3
Loan_Status            2
dtype: int64
```

[9]:
```python
df.columns
```

[9]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[10]:
```python
df.fillna(0, inplace=True)
print("NaNs has been replaced with 0")
```

```
NaNs has been replaced with 0
```

[11]:
```python
# Convert all column names to lowercase
df.columns = df.columns.str.lower()
```

[12]:
```python
df.columns
```

[12]:
```
Index(['loan_id', 'gender', 'married', 'dependents', 'education',
       'self_employed', 'applicantincome', 'coapplicantincome', 'loanamount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status'],
      dtype='object')
```

[13]:
```python
df.duplicated().sum()
```

[13]:
```
np.int64(0)
```

3 04- Data Wrangling

[14]:
```python
df["combined_income"]= df['applicantincome'] + df['coapplicantincome']
df["combined_income"].head()
```

[14]:
```
0     1950.0
1     3127.0
2    42083.0
3     4328.0
4     5970.0
Name: combined_income, dtype: float64
```

[15]:
```python
# Calculate mean values (excluding 0s to avoid skewing)
loan_amount_mean = df[df['loanamount'] != 0]['loanamount'].mean()
loan_term_mean = df[df['loan_amount_term'] != 0]['loan_amount_term'].mean()
```

[16]:
```python
# Replace 0 values with the calculated means
df['loanamount'] = np.where(df['loanamount'] == 0, loan_amount_mean,
 ↪df['loanamount'])
```

```
df['loan_amount_term'] = np.where(df['loan_amount_term'] == 0, loan_term_mean,␣
↪df['loan_amount_term'])
```

[17]:
```
df.head()
```

[17]:
```
    loan_id  gender married dependents     education self_employed  \
0  LP001722    Male     Yes          0      Graduate            No
1  LP002502  Female     Yes          2  Not Graduate             0
2  LP002949  Female      No         3+      Graduate             0
3  LP002603  Female      No          0      Graduate            No
4  LP001644       0     Yes          0      Graduate           Yes

   applicantincome  coapplicantincome  loanamount  loan_amount_term  \
0              150             1800.0       135.0             360.0
1              210             2917.0        98.0             360.0
2              416            41667.0       350.0             180.0
3              645             3683.0       113.0             480.0
4              674             5296.0       168.0             360.0

   credit_history property_area loan_status  combined_income
0             1.0         Rural           N           1950.0
1             1.0     Semiurban           Y           3127.0
2             0.0         Urban           N          42083.0
3             1.0         Rural           Y           4328.0
4             1.0         Rural           Y           5970.0
```

4 05- Feature Engineering & Preprocessing

[18]:
```
df['loan_id_extracted'] = df['loan_id'].str.replace('LP', '').astype(int)
```

[19]:
```
# Creates a numeric-encoded copy of the DataFrame with extracted loan IDs for␣
↪correlation analysis while preserving the original data.
from sklearn.preprocessing import LabelEncoder

# Create a copy to avoid modifying original dataframe
df_corr = df.copy()

# First ensure we've created the loan_id_extracted column if not already done
if 'loan_id_extracted' not in df_corr.columns:
    df_corr['loan_id_extracted'] = df_corr['loan_id'].str.extract('(\d+)').
↪astype(int)

# Encode categorical variables
for col in df_corr.select_dtypes(include=['object']).columns:
    if col != 'loan_id_extracted':  # Skip the original Loan_ID column
        le = LabelEncoder()
```

```
        df_corr[col] = le.fit_transform(df_corr[col].astype(str))
```

[20]:
```
from sklearn.preprocessing import StandardScaler

# Select numerical columns to scale (exclude categoricals and target)
num_cols = ['applicantincome', 'coapplicantincome', 'loanamount',␣
 ↪'loan_amount_term']
scaler = StandardScaler()

# Fit on training data ONLY, then transform both train/test
df[num_cols] = scaler.fit_transform(df[num_cols])
```

[21]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0, 1))  # Default is (0,1)
df[num_cols] = scaler.fit_transform(df[num_cols])
```

[22]:
```
df.head()
```

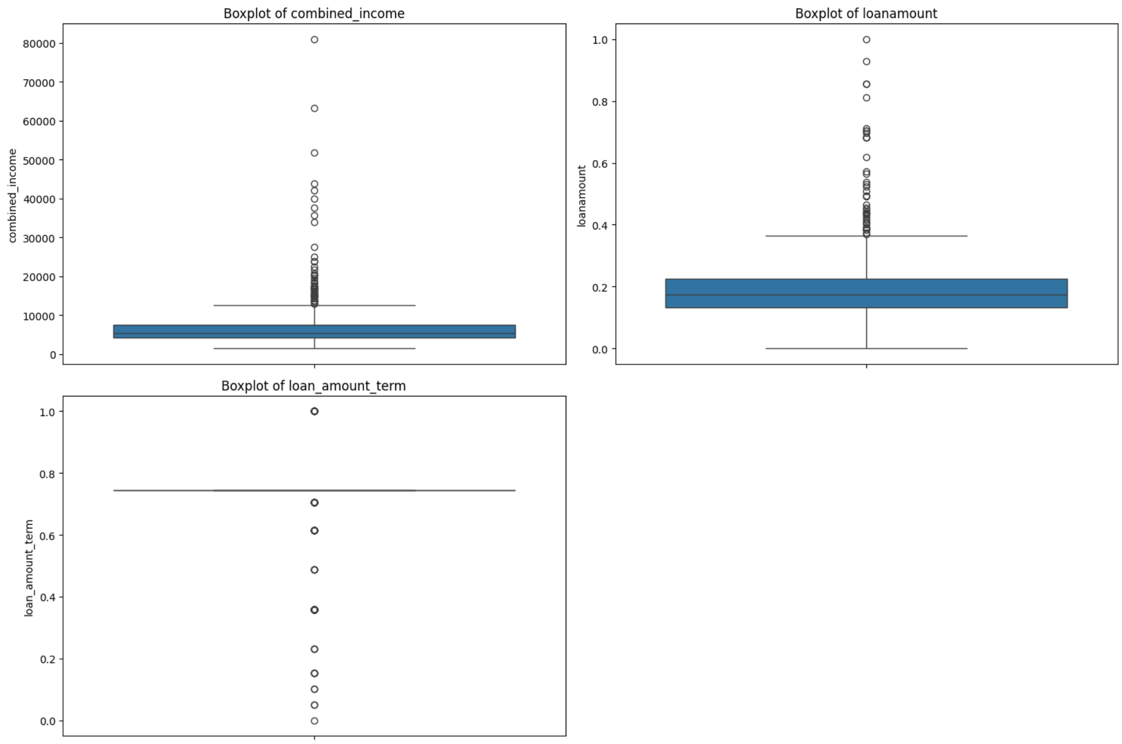
[22]:
```
    loan_id  gender married dependents     education self_employed  \
0  LP001722    Male     Yes          0      Graduate            No
1  LP002502  Female     Yes          2  Not Graduate             0
2  LP002949  Female      No         3+      Graduate             0
3  LP002603  Female      No          0      Graduate            No
4  LP001644       0     Yes          0      Graduate           Yes

   applicantincome  coapplicantincome  loanamount  loan_amount_term  \
0         0.000000           0.043200    0.182344          0.743590
1         0.000742           0.070007    0.128799          0.743590
2         0.003290           1.000000    0.493488          0.358974
3         0.006122           0.088391    0.150507          1.000000
4         0.006481           0.127103    0.230101          0.743590

   credit_history property_area loan_status  combined_income  \
0             1.0         Rural           N           1950.0
1             1.0     Semiurban           Y           3127.0
2             0.0         Urban           N          42083.0
3             1.0         Rural           Y           4328.0
4             1.0         Rural           Y           5970.0

   loan_id_extracted
0               1722
1               2502
2               2949
3               2603
4               1644
```

[23]:
```
# One-hot encode categoricals first
cat_cols = ['gender', 'married', 'education', 'self_employed']
df = pd.get_dummies(df, columns=cat_cols)
```

[24]:
```
# First get list of categorical columns before one-hot encoding
cat_cols = ['gender', 'married', 'education', 'self_employed', 'dependents',␣
↪'property_area']

# Create correlation dataframe BEFORE one-hot encoding
df_corr = df.copy()

# Convert categorical columns to numerical codes
for col in cat_cols:
    if col in df_corr.columns:  # Check if column exists
        df_corr[col] = pd.factorize(df_corr[col])[0]
```

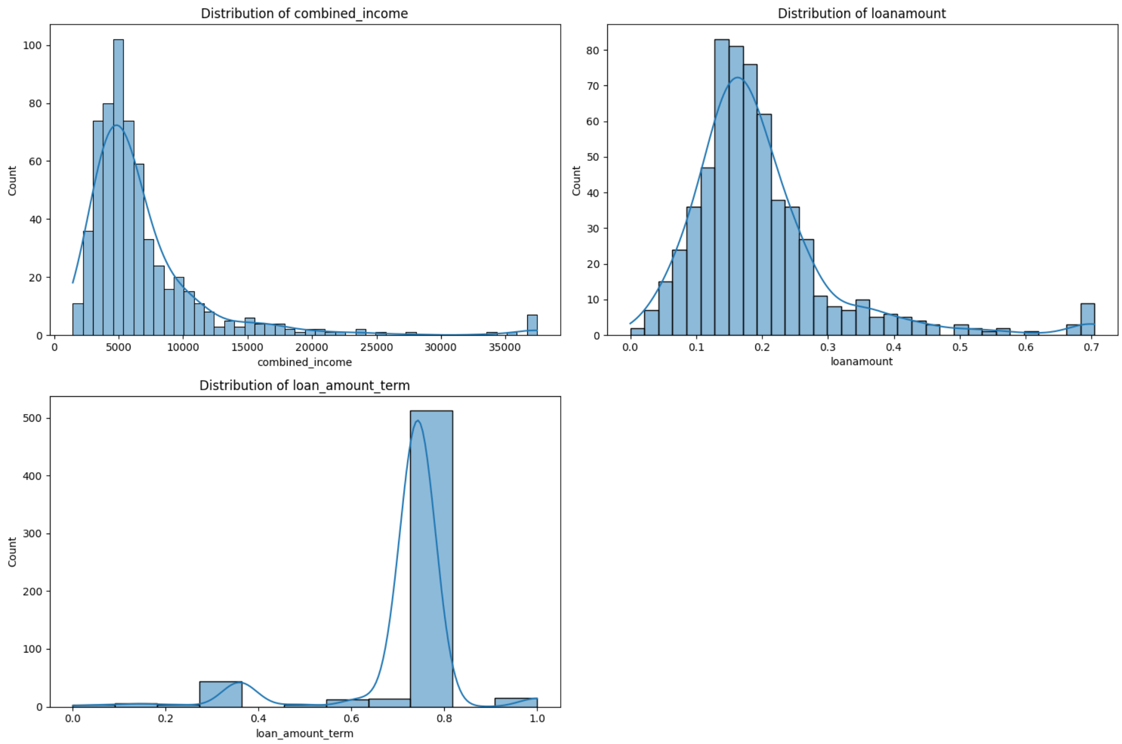
5 06- Data Visualization

[25]:
```
# Boxplots for numerical variables
num_cols = ['combined_income', 'loanamount', 'loan_amount_term']
plt.figure(figsize=(15,10))
for i, col in enumerate(num_cols, 1):
    plt.subplot(2,2,i)
    sns.boxplot(y=df[col])
    plt.title(f'Boxplot of {col}')
plt.tight_layout()
plt.show()
```



[26]:
```
# Treat outliers (cap at 99th percentile)
for col in ['combined_income', 'loanamount']:
    upper_limit = df[col].quantile(0.99)
    df[col] = np.where(df[col]>upper_limit, upper_limit, df[col])
```

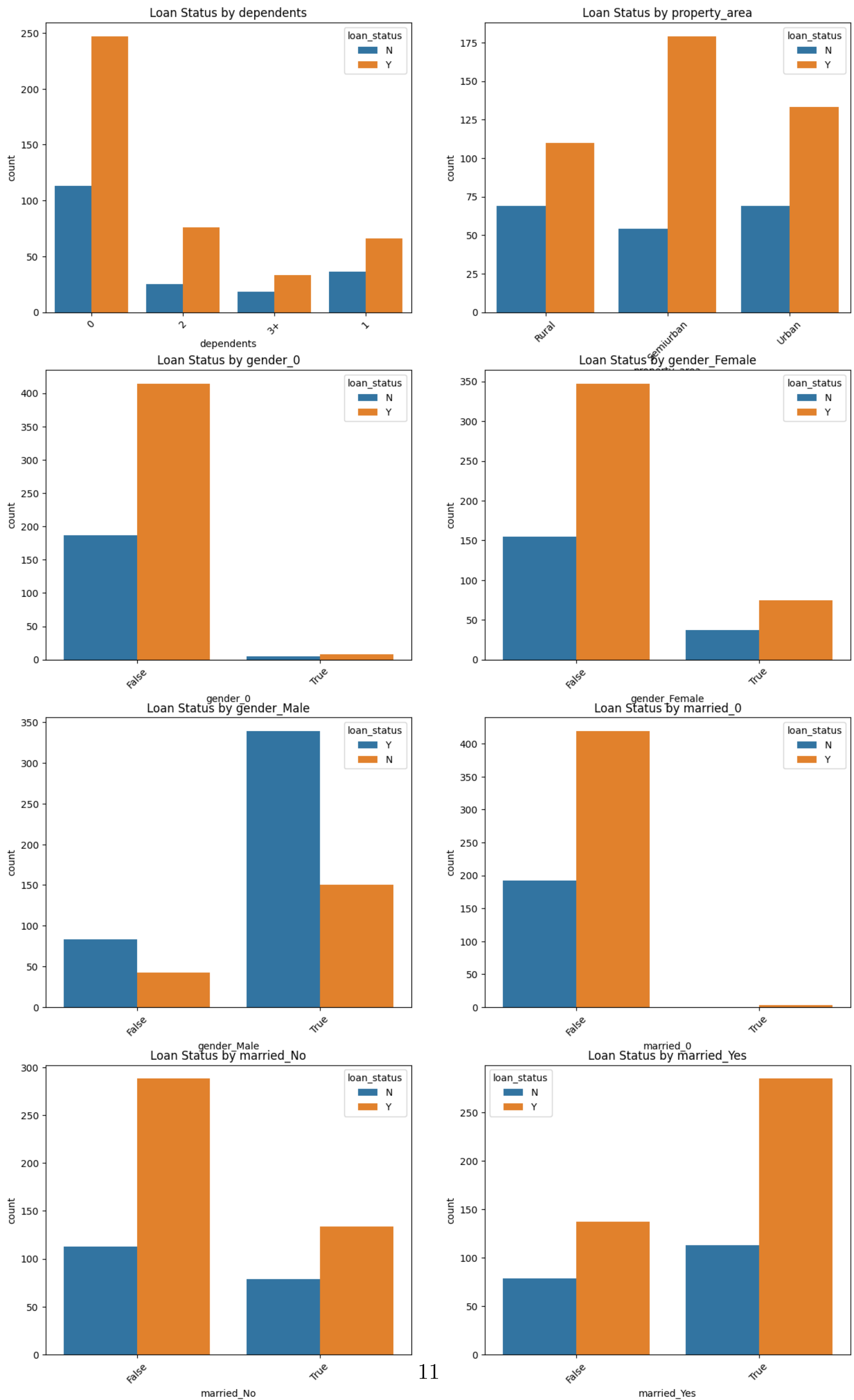
[27]:
```
# Numerical variables
plt.figure(figsize=(15,10))
for i, col in enumerate(num_cols, 1):
    plt.subplot(2,2,i)
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



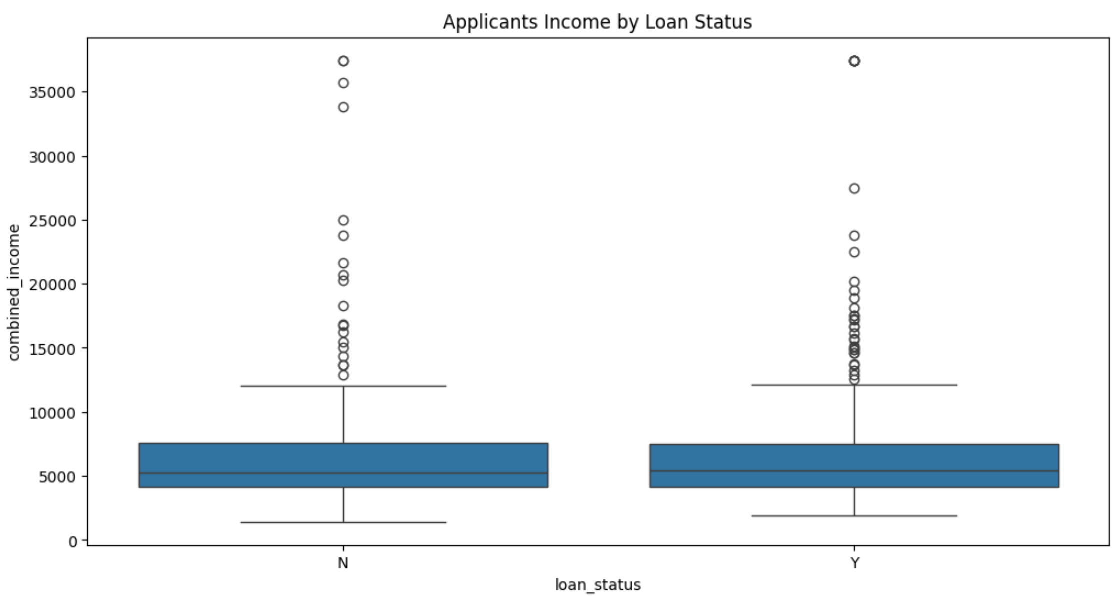
[28]:
```
# Loan Status vs other variables
# First get the dummy column names that were created from the original␣
↪categorical columns
dummy_cols = [col for col in df.columns if any(cat in col for cat in ['gender',␣
↪'married', 'education', 'self_employed', 'dependents', 'property_area'])]

plt.figure(figsize=(15,25))
for i, col in enumerate(dummy_cols, 1):
    plt.subplot(4,2,i)
    sns.countplot(data=df, x=col, hue='loan_status')
    plt.title(f'Loan Status by {col}')
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
/tmp/ipython-input-2040203495.py in <cell line: 0>()
      5 plt.figure(figsize=(15,25))
      6 for i, col in enumerate(dummy_cols, 1):
----> 7     plt.subplot(4,2,i)
      8     sns.countplot(data=df, x=col, hue='loan_status')
      9     plt.title(f'Loan Status by {col}')
```

```
/usr/local/lib/python3.11/dist-packages/matplotlib/pyplot.py in subplot(*args,␣
↪**kwargs)
   1548
   1549     # First, search for an existing subplot with a matching spec.
-> 1550     key = SubplotSpec._from_subplot_args(fig, args)
   1551
   1552     for ax in fig.axes:

/usr/local/lib/python3.11/dist-packages/matplotlib/gridspec.py in␣
↪_from_subplot_args(figure, args)
    587         else:
    588             if not isinstance(num, Integral) or num < 1 or num >␣
↪rows*cols:
--> 589                 raise ValueError(
    590                     f"num must be an integer with 1 <= num <=␣
↪{rows*cols}, "
    591                     f"not {num!r}"

ValueError: num must be an integer with 1 <= num <= 8, not 9
```

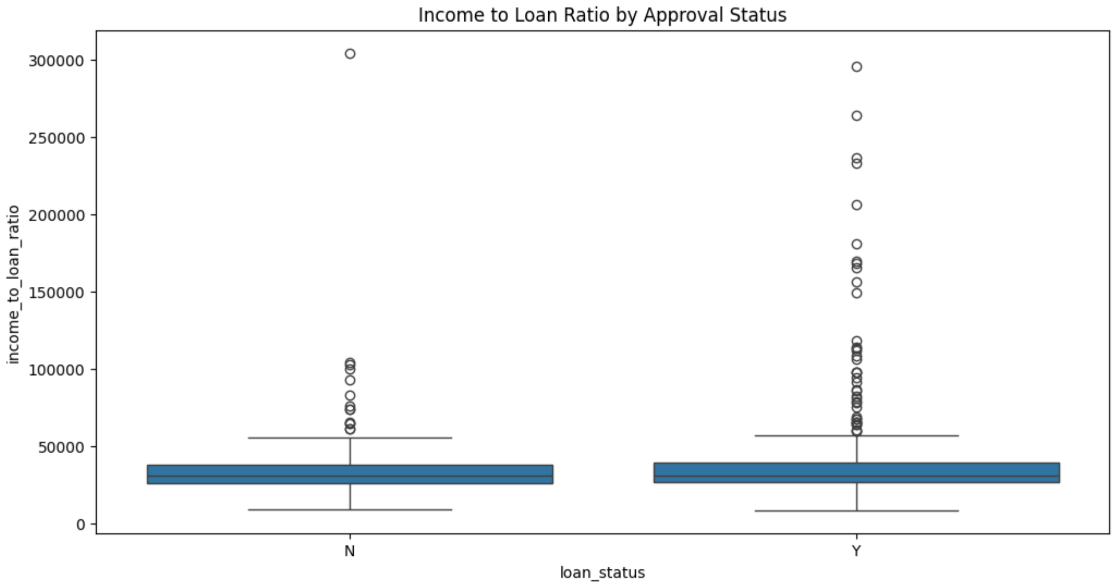

Loan Status by dependents
loan_status
N
Y
count
dependents
0
2
3+
1
Loan Status by property_area
Rural
Semiurban
Urban
Loan Status by gender_0
gender_0
False
True
Loan Status by gender_Female
gender_Female
Loan Status by gender_Male
gender_Male
Loan Status by married_0
married_0
Loan Status by married_No
married_No
Loan Status by married_Yes
married_Yes

[29]:
```python
# Income vs Loan Status
plt.figure(figsize=(12,6))
sns.boxplot(data=df, x='loan_status', y='combined_income')
plt.title('Applicants Income by Loan Status')
plt.show()
```



[30]:
```python
import plotly.express as px

# Interactive plot using existing columns
fig = px.scatter(df, x='applicantincome', y='loanamount', color='loan_status',
                 hover_data=['property_area', 'education_Graduate',␣
 ↪'education_Not Graduate'],
                 title='Income vs Loan Amount by Approval Status')
fig.show()
```

[31]:
```python
# Create Total Income feature
df['income_to_loan_ratio'] = df['combined_income'] / df['loanamount']

# Analyze new metrics
plt.figure(figsize=(12,6))
sns.boxplot(data=df, x='loan_status', y='income_to_loan_ratio')
plt.title('Income to Loan Ratio by Approval Status')
plt.show()
```



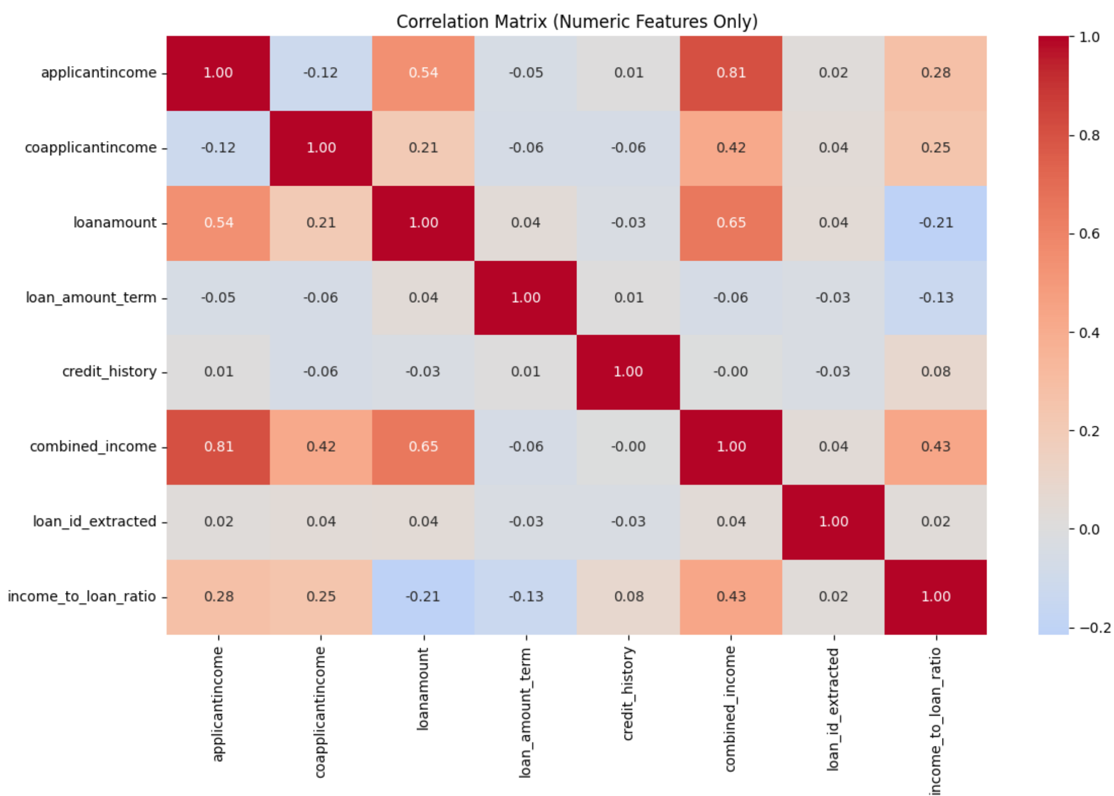
[32]:
```
df.head()
```

[32]:
```
     loan_id dependents  applicantincome  coapplicantincome  loanamount  \
0  LP001722          0         0.000000           0.043200    0.182344
1  LP002502          2         0.000742           0.070007    0.128799
2  LP002949         3+         0.003290           1.000000    0.493488
3  LP002603          0         0.006122           0.088391    0.150507
4  LP001644          0         0.006481           0.127103    0.230101

   loan_amount_term  credit_history property_area loan_status  \
0          0.743590             1.0         Rural           N
1          0.743590             1.0     Semiurban           Y
2          0.358974             0.0         Urban           N
3          1.000000             1.0         Rural           Y
4          0.743590             1.0         Rural           Y

   combined_income  …  gender_Male  married_0  married_No  married_Yes  \
0          1950.00  …         True      False       False         True
1          3127.00  …        False      False       False         True
2         37453.02  …        False      False        True        False
3          4328.00  …        False      False        True        False
4          5970.00  …        False      False       False         True

   education_Graduate  education_Not Graduate  self_employed_0  \
0                True                   False            False
1               False                    True             True
2                True                   False             True
```

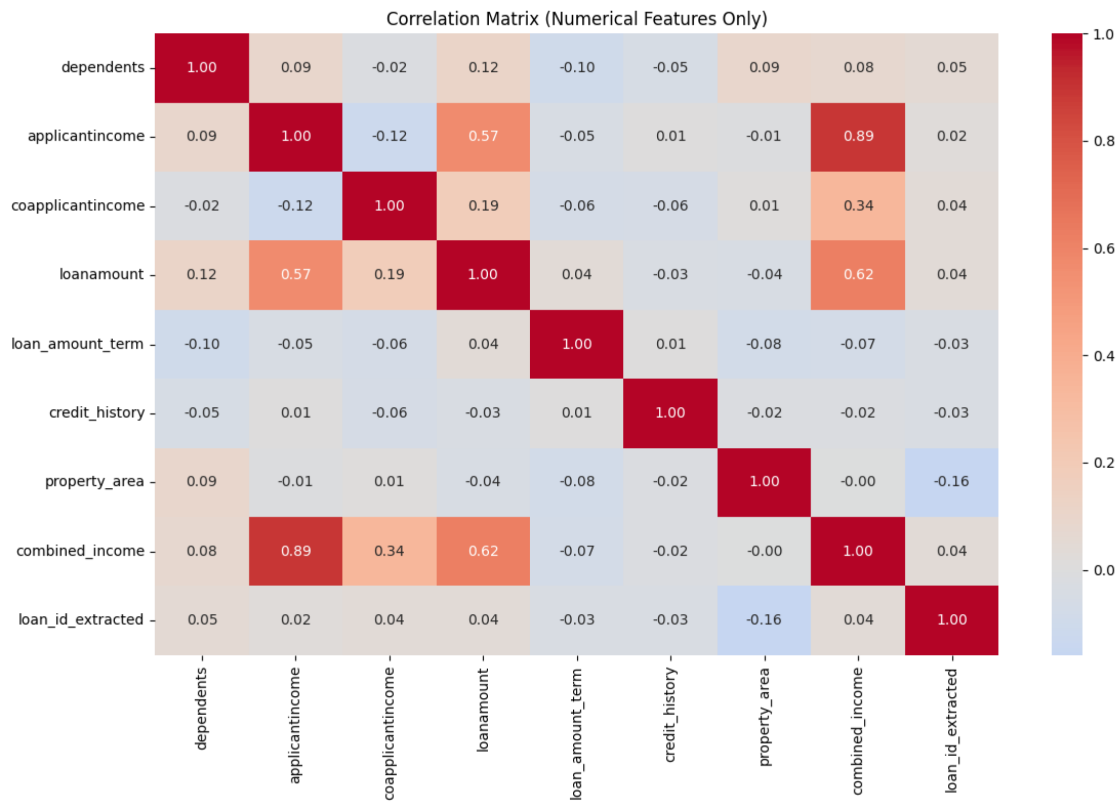
```
3                True                     False            False
4                True                     False            False

   self_employed_No  self_employed_Yes  income_to_loan_ratio
0              True              False          10694.047619
1             False              False          24278.168539
2             False              False          75894.536129
3              True              False          28756.230769
4             False               True          25945.094340

[5 rows x 23 columns]
```

[34]:

```python
# Create correlation matrix only with numeric columns
numeric_df = df.select_dtypes(include=['int64', 'float64'])

plt.figure(figsize=(12,8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', center=0, fmt='.2f')
plt.title('Correlation Matrix (Numeric Features Only)')
plt.tight_layout()
plt.show()
```



[35]:
```
# Now create correlation matrix
plt.figure(figsize=(12,8))
# Select only numerical columns for correlation
numerical_df = df_corr.select_dtypes(include=['number'])
sns.heatmap(numerical_df.corr(), annot=True, cmap='coolwarm', center=0, fmt='.
 ↪2f')
plt.title('Correlation Matrix (Numerical Features Only)')
plt.tight_layout()
plt.show()
```



6 07- Model Training

[36]:
```
# convert target to binary
df['loan_status'] = df['loan_status'].map({'Y': 1, 'N': 0}).astype(int)
```

[37]:
```
import pandas as pd
from sklearn.model_selection import train_test_split

# Create key features
df['income_gt_4000'] = (df['combined_income'] > 4000).astype(int)
```

```
# Select key features + target
features = ['income_gt_4000', 'credit_history', 'property_area']
X = pd.get_dummies(df[features], columns=['property_area'], drop_first=True)
y = df['loan_status']

# Split data (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC(random_state=42)
}

# Train and evaluate each model
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy
    print(f"{name} Accuracy: {accuracy:.4f}")
    print(classification_report(y_test, y_pred))
    print("-----------------------------------")

# Show results
print("\nModel Comparison:")
for name, acc in sorted(results.items(), key=lambda x: x[1], reverse=True):
    print(f"{name}: {acc:.4f}")
```

```
Logistic Regression Accuracy: 0.7480
              precision    recall  f1-score   support

           0       0.68      0.46      0.55        41
           1       0.77      0.89      0.82        82
```

```
    accuracy                           0.75       123
   macro avg       0.72      0.68      0.69       123
weighted avg       0.74      0.75      0.73       123

----------------------------------
Random Forest Accuracy: 0.6992
              precision    recall  f1-score   support

           0       0.60      0.29      0.39        41
           1       0.72      0.90      0.80        82

    accuracy                           0.70       123
   macro avg       0.66      0.60      0.60       123
weighted avg       0.68      0.70      0.66       123

----------------------------------
XGBoost Accuracy: 0.6992
              precision    recall  f1-score   support

           0       0.60      0.29      0.39        41
           1       0.72      0.90      0.80        82

    accuracy                           0.70       123
   macro avg       0.66      0.60      0.60       123
weighted avg       0.68      0.70      0.66       123

----------------------------------
KNN Accuracy: 0.7236
              precision    recall  f1-score   support

           0       0.64      0.39      0.48        41
           1       0.74      0.89      0.81        82

    accuracy                           0.72       123
   macro avg       0.69      0.64      0.65       123
weighted avg       0.71      0.72      0.70       123

----------------------------------
SVM Accuracy: 0.6992
              precision    recall  f1-score   support

           0       0.60      0.29      0.39        41
           1       0.72      0.90      0.80        82

    accuracy                           0.70       123
   macro avg       0.66      0.60      0.60       123
weighted avg       0.68      0.70      0.66       123
```

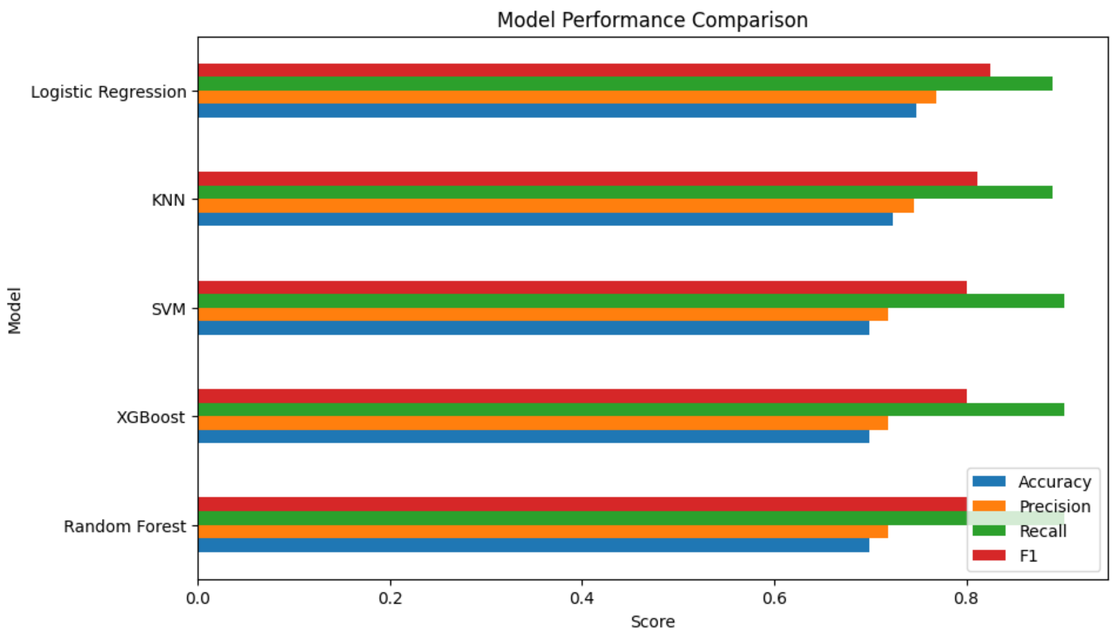
```
----------------------------------

Model Comparison:
Logistic Regression: 0.7480
KNN: 0.7236
Random Forest: 0.6992
XGBoost: 0.6992
SVM: 0.6992
```

7 08- Model Evaluation

[39]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
import pandas as pd

# Store results in a DataFrame
results = pd.DataFrame(columns=['Model', 'Accuracy', 'Precision', 'Recall',␣
 ↪'F1'])

for name, model in models.items():
    # Train and predict
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    # Store results
    results.loc[len(results)] = [name, accuracy, precision, recall, f1]

# Display all results
print("\n=== Model Performance Comparison ===")
print(results.sort_values('Accuracy', ascending=False))

# Identify best model
best_model = results.loc[results['Accuracy'].idxmax()]
print("\n=== Best Model ===")
print(f"Model: {best_model['Model']}")
print(f"Accuracy: {best_model['Accuracy']:.4f}")
print(f"F1-Score: {best_model['F1']:.4f}")

# Visual comparison
results.set_index('Model').sort_values('Accuracy').plot(kind='barh',␣
 ↪figsize=(10,6))
```

```
plt.title('Model Performance Comparison')
plt.xlabel('Score')
plt.show()
```

```
=== Model Performance Comparison ===
                 Model  Accuracy  Precision    Recall        F1
0  Logistic Regression  0.747967   0.768421  0.890244  0.824859
3                  KNN  0.723577   0.744898  0.890244  0.811111
1        Random Forest  0.699187   0.718447  0.902439  0.800000
2              XGBoost  0.699187   0.718447  0.902439  0.800000
4                  SVM  0.699187   0.718447  0.902439  0.800000

=== Best Model ===
Model: Logistic Regression
Accuracy: 0.7480
F1-Score: 0.8249
```



8 09- Hyperparameter Tuning

- Hyperparameter tuning is used to find the best model settings that improve accuracy and prevent overfitting.
- It optimizes model performance by testing different configurations.

[40]:
```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
```

```
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score
import numpy as np
```

Define Search Spaces for Each Model

[41]:
```
param_grids = {
    "Logistic Regression": {
        'C': np.logspace(-4, 4, 20),
        'penalty': ['l1', 'l2', 'elasticnet'],
        'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
    },
    "Random Forest": {
        'n_estimators': [50, 100, 200, 300],
        'max_depth': [None, 5, 10, 20],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4],
        'max_features': ['sqrt', 'log2']
    },
    "XGBoost": {
        'n_estimators': [50, 100, 200],
        'max_depth': [3, 6, 9],
        'learning_rate': [0.01, 0.1, 0.2],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0]
    },
    "KNN": {
        'n_neighbors': range(3, 21, 2),
        'weights': ['uniform', 'distance'],
        'metric': ['euclidean', 'manhattan', 'minkowski']
    },
    "SVM": {
        'C': [0.1, 1, 10, 100],
        'gamma': [1, 0.1, 0.01, 0.001],
        'kernel': ['rbf', 'poly', 'sigmoid']
    }
}
```

Tuning Implementation Using Randomized Search (Faster)

[42]:
```
def tune_models_randomized(models, param_grids, X_train, y_train, n_iter=50,␣
↪cv=5):
    best_models = {}

    for name, model in models.items():
        print(f"\n=== Tuning {name} ===")
```

```python
        # Use randomized search
        random_search = RandomizedSearchCV(
            estimator=model,
            param_distributions=param_grids[name],
            n_iter=n_iter,
            cv=cv,
            scoring='accuracy',
            n_jobs=-1,
            random_state=42
        )

        random_search.fit(X_train, y_train)
        best_models[name] = random_search.best_estimator_

        print(f"Best params: {random_search.best_params_}")
        print(f"Best score: {random_search.best_score_:.4f}")

    return best_models

best_models_random = tune_models_randomized(models, param_grids, X_train,␣
↪y_train)
```

```
=== Tuning Logistic Regression ===

/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py:528: FitFailedWarning:


145 fits failed out of a total of 250.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
```

```
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or None penalties, got elasticnet
penalty.

--------------------------------------------------------------------------------
30 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or None penalties, got l1 penalty.

--------------------------------------------------------------------------------
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^

  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver newton-cg supports only 'l2' or None penalties, got
elasticnet penalty.

--------------------------------------------------------------------------------
```

```
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 71, in _check_solver
    raise ValueError(
ValueError: Only 'saga' solver supports elasticnet penalty, got
solver=liblinear.

--------------------------------------------------------------------------------
20 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver newton-cg supports only 'l2' or None penalties, got l1
penalty.

--------------------------------------------------------------------------------
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
```

```
          ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver sag supports only 'l2' or None penalties, got elasticnet
penalty.

--------------------------------------------------------------------------------
20 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1193, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
             ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 63, in _check_solver
    raise ValueError(
ValueError: Solver sag supports only 'l2' or None penalties, got l1 penalty.

--------------------------------------------------------------------------------
15 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in
wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-
packages/sklearn/linear_model/_logistic.py", line 1203, in fit
    raise ValueError("l1_ratio must be specified when penalty is elasticnet.")
ValueError: l1_ratio must be specified when penalty is elasticnet.


/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_search.py:1108:
UserWarning:
```

```
One or more of the test scores are non-finite: [0.77600495        nan 0.77600495
0.69247578 0.77600495        nan
        nan 0.77600495 0.69247578        nan        nan        nan
 0.77600495        nan 0.77600495        nan 0.77600495        nan
        nan        nan        nan 0.75153577 0.77600495        nan
        nan        nan        nan        nan 0.77600495        nan
 0.30752422        nan        nan 0.69247578 0.77600495        nan
 0.69247578        nan        nan        nan        nan        nan
        nan        nan 0.77600495        nan 0.77600495 0.77600495
 0.75153577 0.77600495]


Best params: {'solver': 'sag', 'penalty': 'l2', 'C':
np.float64(29.763514416313132)}
Best score: 0.7760

=== Tuning Random Forest ===
Best params: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf':
2, 'max_features': 'sqrt', 'max_depth': 10}
Best score: 0.7740

=== Tuning XGBoost ===
Best params: {'subsample': 0.6, 'n_estimators': 50, 'max_depth': 9,
'learning_rate': 0.1, 'colsample_bytree': 0.6}
Best score: 0.7780

=== Tuning KNN ===
Best params: {'weights': 'uniform', 'n_neighbors': 13, 'metric': 'minkowski'}
Best score: 0.7780

=== Tuning SVM ===

/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_search.py:317:
UserWarning:

The total space of parameters 48 is smaller than n_iter=50. Running 48
iterations. For exhaustive searches, use GridSearchCV.


Best params: {'kernel': 'rbf', 'gamma': 0.1, 'C': 1}
Best score: 0.7760
```

Tuning Implementation Using Grid Search (More Thorough but Slower)

[43]:
```
def tune_models_grid(models, param_grids, X_train, y_train, cv=5):
    best_models = {}

    for name, model in models.items():
```

```
        print(f"\n=== Tuning {name} ===")

        # Use grid search
        grid_search = GridSearchCV(
            estimator=model,
            param_grid=param_grids[name],
            cv=cv,
            scoring='accuracy',
            n_jobs=-1
        )

        grid_search.fit(X_train, y_train)
        best_models[name] = grid_search.best_estimator_

        print(f"Best params: {grid_search.best_params_}")
        print(f"Best score: {grid_search.best_score_:.4f}")

    return best_models

# Use this only if your dataset is small or you have time
# best_models_grid = tune_models_grid(models, param_grids, X_train, y_train)
```

Evaluation of Tuned Models

[44]:
```
def evaluate_models(models, X_test, y_test):
    results = {}

    for name, model in models.items():
        y_pred = model.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)

        results[name] = {
            'accuracy': accuracy,
            'precision': precision,
            'recall': recall,
            'f1': f1
        }

        print(f"\n=== {name} ===")
        print(f"Accuracy: {accuracy:.4f}")
        print(f"Precision: {precision:.4f}")
        print(f"Recall: {recall:.4f}")
        print(f"F1 Score: {f1:.4f}")
        print(classification_report(y_test, y_pred))
```

```
    return results

# Evaluate the tuned models
tuned_results = evaluate_models(best_models_random, X_test, y_test)
```

```
=== Logistic Regression ===
Accuracy: 0.7480
Precision: 0.7684
Recall: 0.8902
F1 Score: 0.8249
              precision    recall  f1-score   support

           0       0.68      0.46      0.55        41
           1       0.77      0.89      0.82        82

    accuracy                           0.75       123
   macro avg       0.72      0.68      0.69       123
weighted avg       0.74      0.75      0.73       123


=== Random Forest ===
Accuracy: 0.6992
Precision: 0.7184
Recall: 0.9024
F1 Score: 0.8000
              precision    recall  f1-score   support

           0       0.60      0.29      0.39        41
           1       0.72      0.90      0.80        82

    accuracy                           0.70       123
   macro avg       0.66      0.60      0.60       123
weighted avg       0.68      0.70      0.66       123


=== XGBoost ===
Accuracy: 0.7236
Precision: 0.7449
Recall: 0.8902
F1 Score: 0.8111
              precision    recall  f1-score   support

           0       0.64      0.39      0.48        41
           1       0.74      0.89      0.81        82
```

```
    accuracy                           0.72       123
   macro avg       0.69      0.64      0.65       123
weighted avg       0.71      0.72      0.70       123


=== KNN ===
Accuracy: 0.6992
Precision: 0.7184
Recall: 0.9024
F1 Score: 0.8000
              precision    recall  f1-score   support

           0       0.60      0.29      0.39        41
           1       0.72      0.90      0.80        82

    accuracy                           0.70       123
   macro avg       0.66      0.60      0.60       123
weighted avg       0.68      0.70      0.66       123


=== SVM ===
Accuracy: 0.7480
Precision: 0.7684
Recall: 0.8902
F1 Score: 0.8249
              precision    recall  f1-score   support

           0       0.68      0.46      0.55        41
           1       0.77      0.89      0.82        82

    accuracy                           0.75       123
   macro avg       0.72      0.68      0.69       123
weighted avg       0.74      0.75      0.73       123
```

9 10- Saving Model

[51]:
```python
from joblib import dump

# Save all models with their exact names
for model_name, model in models.items():
    dump(model, f'{model_name.replace(" ", "_")}.joblib')
```

10 11- Conclusion & Business Insights

Loan Approval is Highly Influenced By: - Credit History (Most critical factor) - Applicant Income (Higher income → Higher approval chances) - Loan Amount vs. Income Ratio (Lower ratio → Better approval odds) - Co-applicant Income (Improves approval likelihood)

Best Model Choice:

- XGBoost (if highest accuracy is needed).
- Random Forest (if interpretability is important).
- Logistic Regression (if probability estimates are needed for risk scoring).
