datascience

September 1, 2025

https://colab.research.google.com/drive/1mKuJXoANsyCy1Fs45GB3JN0Rlnn6kwLd?usp=sharing

Github Repository

[ ]:
```
%cd https://github.com/zoya4477/Data-Science.git
!git clone
!git config--global user.email "zoyahafeez785@gmail.com"
!git config--global user.name "zoya4477"
```

```
[Errno 2] No such file or directory: 'https://github.com/zoya4477/Data-
Science.git'
/content
fatal: You must specify a repository to clone.

usage: git clone [<options>] [--] <repo> [<dir>]

    -v, --verbose         be more verbose
    -q, --quiet           be more quiet
    --progress            force progress reporting
    --reject-shallow      don't clone shallow repository
    -n, --no-checkout     don't create a checkout
    --bare                create a bare repository
    --mirror              create a mirror repository (implies bare)
    -l, --local           to clone from a local repository
    --no-hardlinks        don't use local hardlinks, always copy
    -s, --shared          setup as shared repository
    --recurse-submodules[=<pathspec>]
                          initialize submodules in the clone
    --recursive …       alias of --recurse-submodules
    -j, --jobs <n>        number of submodules cloned in parallel
    --template <template-directory>
                          directory from which templates will be used
    --reference <repo>    reference repository
    --reference-if-able <repo>
                          reference repository
    --dissociate          use --reference only while cloning
    -o, --origin <name>   use <name> instead of 'origin' to track upstream
    -b, --branch <branch>
                          checkout <branch> instead of the remote's HEAD
```

```
    -u, --upload-pack <path>
                          path to git-upload-pack on the remote
    --depth <depth>       create a shallow clone of that depth
    --shallow-since <time>
                          create a shallow clone since a specific time
    --shallow-exclude <revision>
                          deepen history of shallow clone, excluding rev
    --single-branch       clone only one branch, HEAD or --branch
    --no-tags             don't clone any tags, and make later fetches not to
follow them
    --shallow-submodules  any cloned submodules will be shallow
    --separate-git-dir <gitdir>
                          separate git dir from working tree
    -c, --config <key=value>
                          set config inside the new repository
    --server-option <server-specific>
                          option to transmit
    -4, --ipv4            use IPv4 addresses only
    -6, --ipv6            use IPv6 addresses only
    --filter <args>       object filtering
    --remote-submodules   any cloned submodules will use their remote-tracking
branch
    --sparse              initialize sparse-checkout file to include only files
at root

git: 'config--global' is not a git command. See 'git --help'.
git: 'config--global' is not a git command. See 'git --help'.
```

Project :- 1

Exploratory Data Analysis (EDA)

Load and Inspect Data

[ ]:
```python
import pandas as pd

# Load dataset
df = pd.read_csv("/content/titanic.csv")

# First look at the data
print(df.head())
print(df.info())
print(df.describe())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
```

```
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
None
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
```

```
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[ ]:
```python
# Move 'Survived' column to the end
survived = df['Survived']
df = df.drop(columns=['Survived'])
df['Survived'] = survived

print(df.head())
```

```
   PassengerId  Pclass                                               Name  \
0            1       3                            Braund, Mr. Owen Harris
1            2       1  Cumings, Mrs. John Bradley (Florence Briggs Th…
2            3       3                             Heikkinen, Miss. Laina
3            4       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)
4            5       3                           Allen, Mr. William Henry

      Sex   Age  SibSp  Parch            Ticket     Fare Cabin Embarked  \
0    male  22.0      1      0         A/5 21171   7.2500   NaN        S
1  female  38.0      1      0          PC 17599  71.2833   C85        C
2  female  26.0      0      0  STON/O2. 3101282   7.9250   NaN        S
3  female  35.0      1      0            113803  53.1000  C123        S
4    male  35.0      0      0            373450   8.0500   NaN        S

   Survived
0         0
1         1
2         1
3         1
4         0
```

Data Cleaning

[ ]:
```python
# Check missing values
print(df.isnull().sum())

# Fill missing Age with mean
df['Age'].fillna(df['Age'].mean(), inplace=True)

# Fill missing Embarked with mode
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)

# Drop Cabin (too many missing values)
df.drop(columns=['Cabin'], inplace=True)
```

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
Survived         0
dtype: int64
```

```
/tmp/ipython-input-3258793014.py:5: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Age'].fillna(df['Age'].mean(), inplace=True)
/tmp/ipython-input-3258793014.py:8: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

Basic statistics analysis

[ ]:
```python
#Summary statistics
print(df.describe(include='all'))
```

```
        PassengerId      Pclass                 Name   Sex         Age  \
count    891.000000  891.000000                  891   891  891.000000
unique          NaN         NaN                  891     2         NaN
```

```
top              NaN         NaN  Dooley, Mr. Patrick  male         NaN
freq             NaN         NaN                    1   577         NaN
mean      446.000000    2.308642                  NaN   NaN   29.699118
std       257.353842    0.836071                  NaN   NaN   13.002015
min         1.000000    1.000000                  NaN   NaN    0.420000
25%       223.500000    2.000000                  NaN   NaN   22.000000
50%       446.000000    3.000000                  NaN   NaN   29.699118
75%       668.500000    3.000000                  NaN   NaN   35.000000
max       891.000000    3.000000                  NaN   NaN   80.000000

             SibSp       Parch  Ticket        Fare Embarked    Survived
count   891.000000  891.000000     891  891.000000      891  891.000000
unique         NaN         NaN     681         NaN        3         NaN
top            NaN         NaN  347082         NaN        S         NaN
freq           NaN         NaN       7         NaN      646         NaN
mean      0.523008    0.381594     NaN   32.204208      NaN    0.383838
std       1.102743    0.806057     NaN   49.693429      NaN    0.486592
min       0.000000    0.000000     NaN    0.000000      NaN    0.000000
25%       0.000000    0.000000     NaN    7.910400      NaN    0.000000
50%       0.000000    0.000000     NaN   14.454200      NaN    0.000000
75%       1.000000    0.000000     NaN   31.000000      NaN    1.000000
max       8.000000    6.000000     NaN  512.329200      NaN    1.000000
```

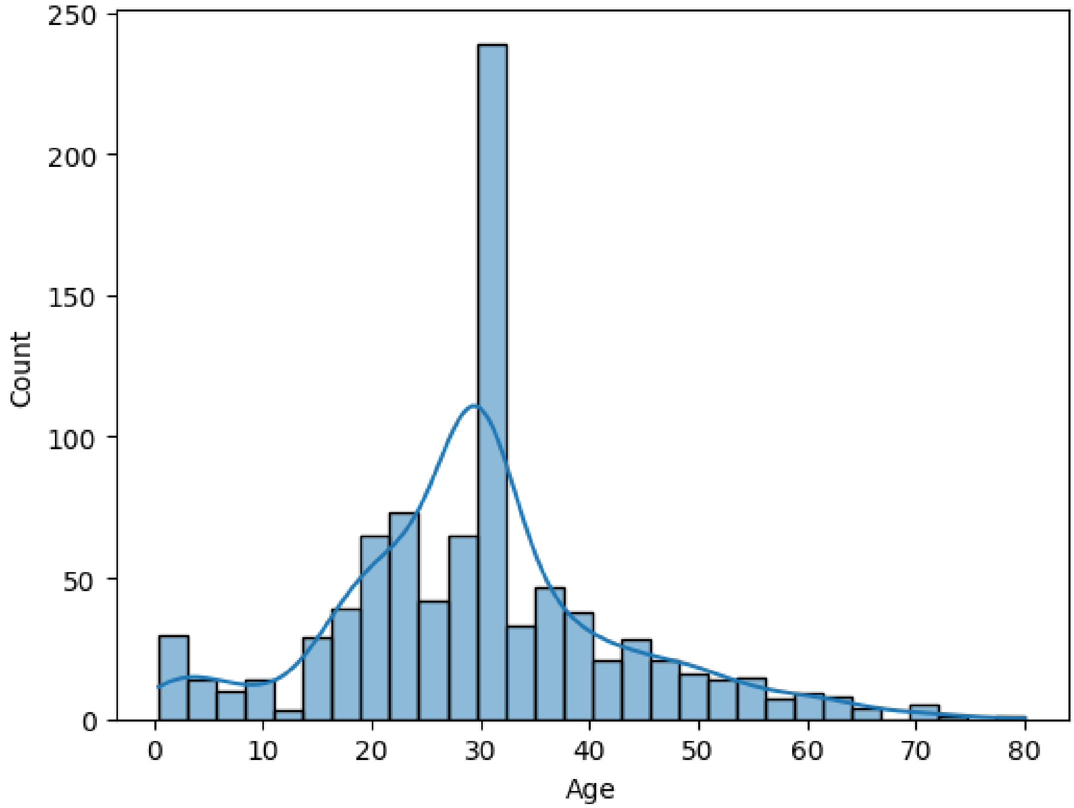
[ ]:
```
#Grouping
print(df.groupby('Survived')['Age'].mean())
print(df.groupby('Pclass')['Fare'].mean())
```

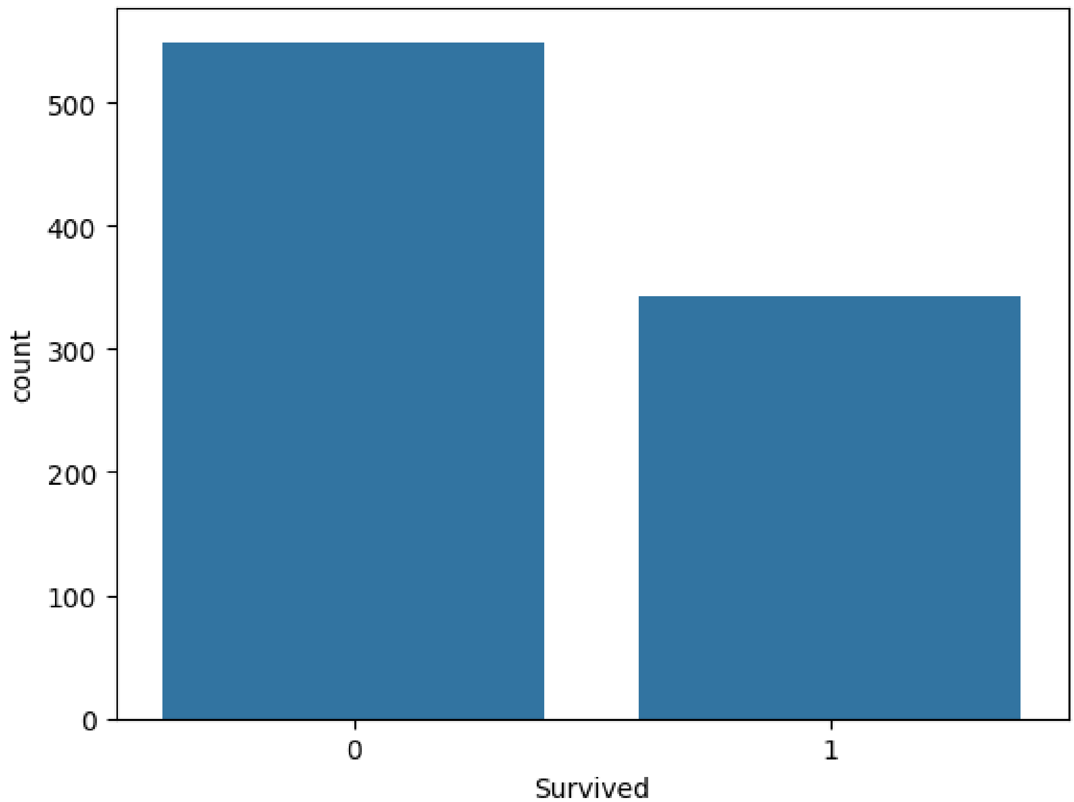
```
Survived
0    30.415100
1    28.549778
Name: Age, dtype: float64
Pclass
1    84.154687
2    20.662183
3    13.675550
Name: Fare, dtype: float64
```

Data Visualization

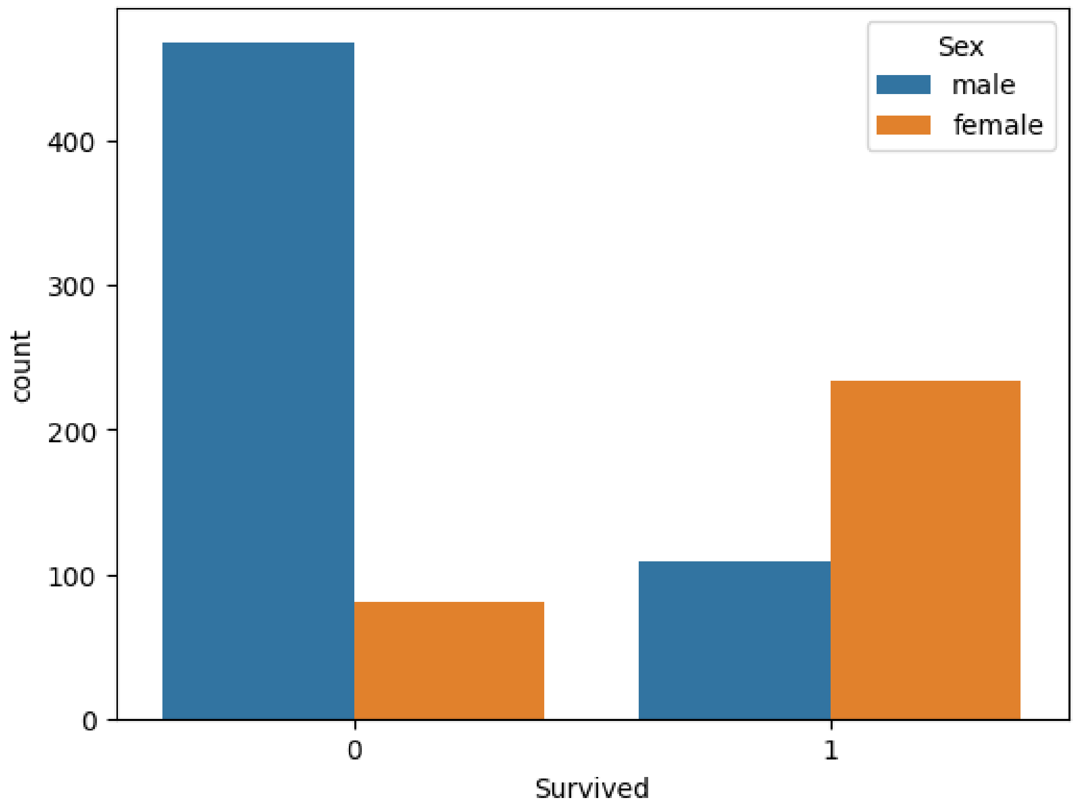
[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution of Age
sns.histplot(df['Age'], bins=30, kde=True)
plt.show()

# Count of Survivors
sns.countplot(x='Survived', data=df)
```

```
plt.show()
```

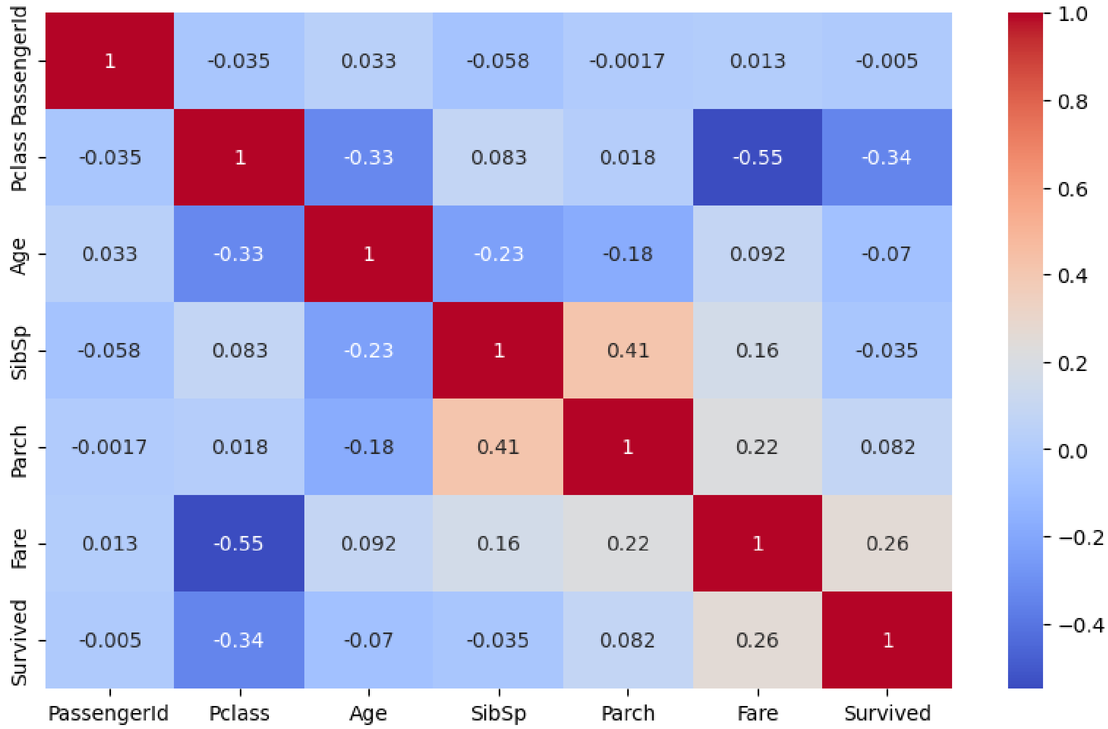




[ ]:
```python
# Survival by Gender
sns.countplot(x='Survived', hue='Sex', data=df)
plt.show()
```



[ ]:
```
# Correlation heatmap
plt.figure(figsize=(10,6))
sns.heatmap(df.select_dtypes(include=['number']).corr(), annot=True,␣
 ↪cmap="coolwarm")
plt.show()
```



[ ]:

Project :- 2

Simple Linear Regression on Housing Prices

Load Data

[4]:
```python
from sklearn.datasets import fetch_openml
import pandas as pd

# Load Boston Housing dataset from OpenML
boston = fetch_openml(name="boston", version=1, as_frame=True)

# DataFrame
df = boston.frame
print(df.head())
print(df.info())
```

```
      CRIM    ZN  INDUS CHAS    NOX     RM   AGE     DIS RAD    TAX  PTRATIO  \
0  0.00632  18.0   2.31    0  0.538  6.575  65.2  4.0900   1  296.0     15.3
1  0.02731   0.0   7.07    0  0.469  6.421  78.9  4.9671   2  242.0     17.8
2  0.02729   0.0   7.07    0  0.469  7.185  61.1  4.9671   2  242.0     17.8
3  0.03237   0.0   2.18    0  0.458  6.998  45.8  6.0622   3  222.0     18.7
4  0.06905   0.0   2.18    0  0.458  7.147  54.2  6.0622   3  222.0     18.7
```

```
        B  LSTAT  MEDV
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    category
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    category
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: category(2), float64(12)
memory usage: 49.0 KB
None
```

Data Preprocessing

[5]:
```
#null values
print(df.isnull().sum())
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
```

```
MEDV       0
dtype: int64
```

Feature Selection

```
[ ]: X = df[['RM']]    # independent variable (avg number of rooms)
     y = df['MEDV']    # dependent variable (house price)
```

Normalization

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

     scaler = StandardScaler()
     X_scaled = scaler.fit_transform(X)
```

Train Test Split

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

     X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
      ↪random_state=42)
```

Linear Regression Model

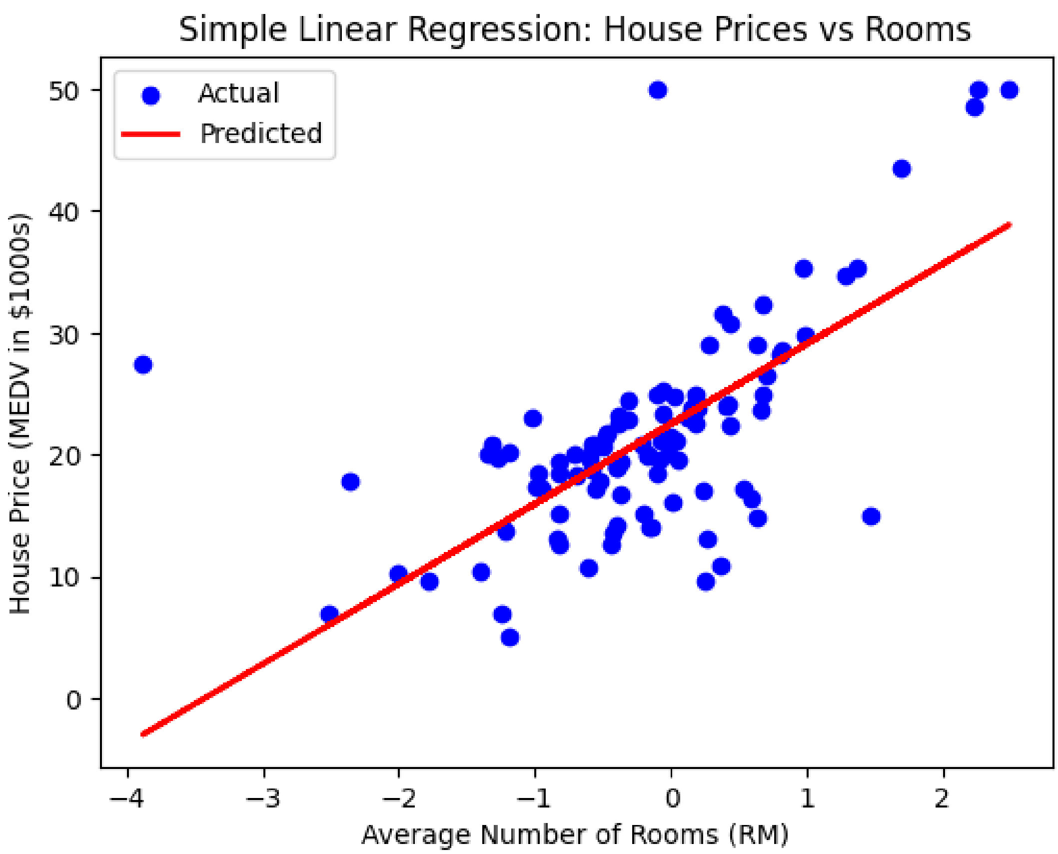
```
[ ]: from sklearn.linear_model import LinearRegression
     from sklearn.metrics import mean_squared_error, r2_score
     import numpy as np

     # Train the model
     model = LinearRegression()
     model.fit(X_train, y_train)

     # Predict
     y_pred = model.predict(X_test)

     # Evaluate
     print("Coefficient (Slope):", model.coef_[0])
     print("Intercept:", model.intercept_)
     print("R² Score:", r2_score(y_test, y_pred))
     print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
Coefficient (Slope): 6.561783228006269
Intercept: 22.504337584466665
R² Score: 0.3707569232254778
RMSE: 6.792994578778734
```

Visualization

```
[ ]: import matplotlib.pyplot as plt
```

```
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.plot(X_test, y_pred, color='red', linewidth=2, label='Predicted')
plt.xlabel("Average Number of Rooms (RM)")
plt.ylabel("House Price (MEDV in $1000s)")
plt.title("Simple Linear Regression: House Prices vs Rooms")
plt.legend()
plt.show()
```



Project :- 3

Loan Eligibility Prediction

[ ]:
```
#Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile
import os
```

```
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
↪cross_val_score, GridSearchCV
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score, confusion_matrix, classification_report,␣
↪RocCurveDisplay
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Load Data

[ ]:
```
zip_file_path = '/content/Loan eligible.zip'
extract_dir = '/content/'

with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
    zip_ref.extractall(extract_dir)

# Now load the desired CSV file
df = pd.read_csv(os.path.join(extract_dir, 'loan-train.csv'))
display(df.head())
```

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

Explore Structure & Target

```
[ ]: print("Shape:", df.shape)
     print("\nDTypes:\n", df.dtypes)
     print("\nTarget distribution:\n", df['Loan_Status'].value_counts(dropna=False))

     # Basic summaries
     display(df.describe(include='number').T)
     display(df.describe(include='object').T)

     # Missing values
     df.isnull().sum().sort_values(ascending=False)
```

```
Shape: (614, 13)

DTypes:
 Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object

Target distribution:
 Loan_Status
Y    422
N    192
Name: count, dtype: int64
```

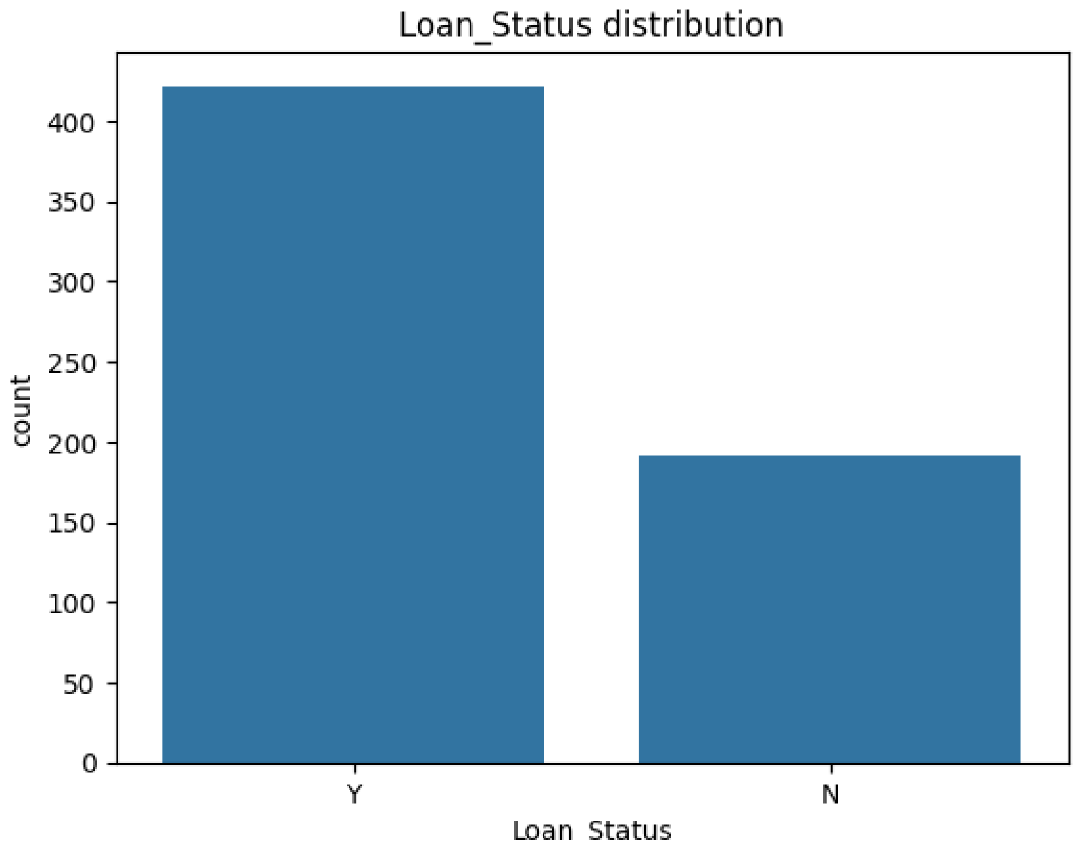
```
                   count         mean          std    min     25%     50%  \
ApplicantIncome    614.0  5403.459283  6109.041673  150.0  2877.5  3812.5
CoapplicantIncome  614.0  1621.245798  2926.248369    0.0     0.0  1188.5
LoanAmount         592.0   146.412162    85.587325    9.0   100.0   128.0
Loan_Amount_Term   600.0   342.000000    65.120410   12.0   360.0   360.0
Credit_History     564.0     0.842199     0.364878    0.0     1.0     1.0

                       75%      max
ApplicantIncome    5795.00  81000.0
CoapplicantIncome  2297.25  41667.0
LoanAmount          168.00    700.0
Loan_Amount_Term    360.00    480.0
Credit_History        1.00      1.0
```

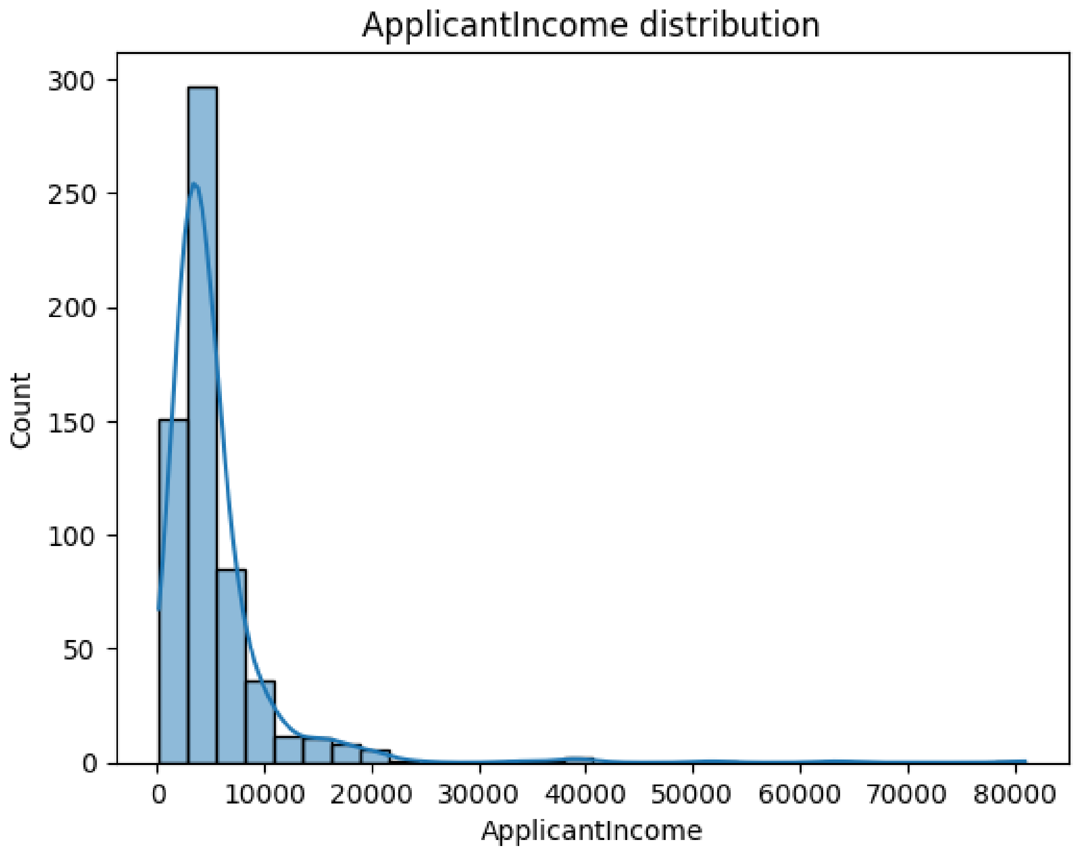
```
               count unique        top freq
Loan_ID          614    614   LP002990    1
Gender           601      2       Male  489
Married          611      2        Yes  398
Dependents       599      4          0  345
Education        614      2   Graduate  480
Self_Employed    582      2         No  500
Property_Area    614      3  Semiurban  233
Loan_Status      614      2          Y  422
```

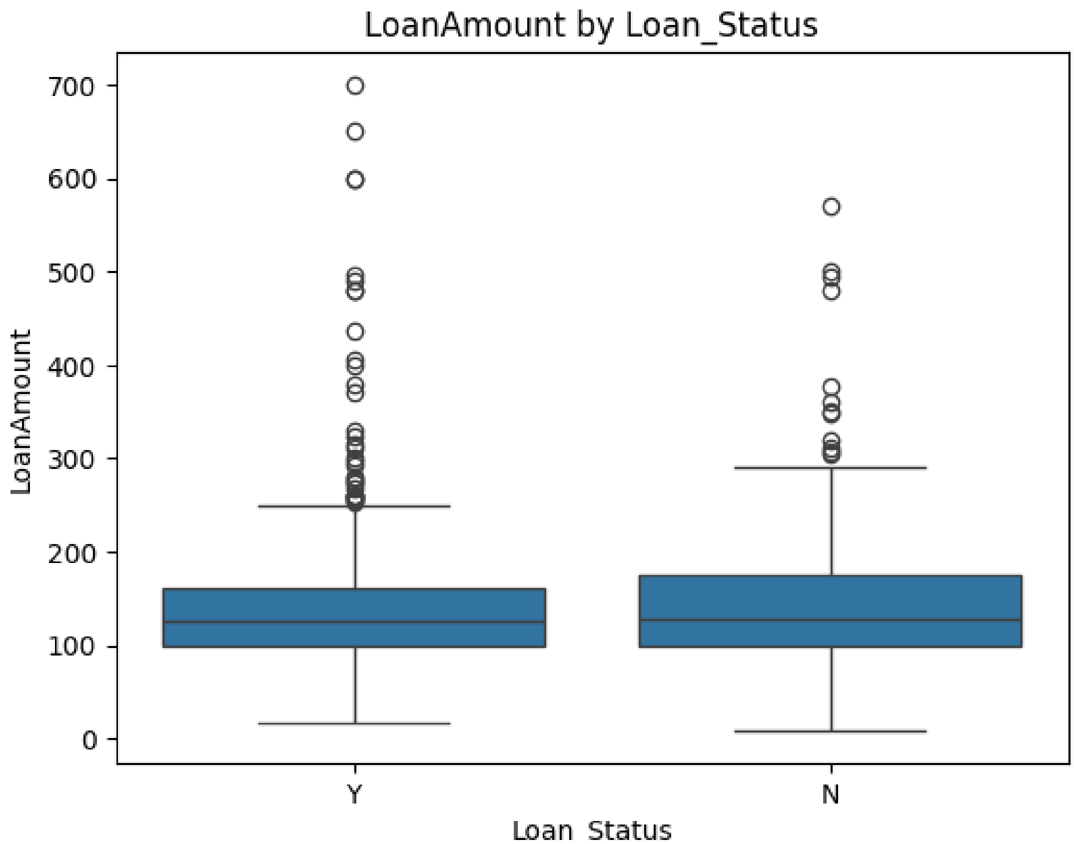
[ ]:
```
Credit_History       50
Self_Employed        32
LoanAmount           22
Dependents           15
Loan_Amount_Term     14
Gender               13
Married               3
Education             0
Loan_ID               0
CoapplicantIncome     0
ApplicantIncome       0
Property_Area         0
Loan_Status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

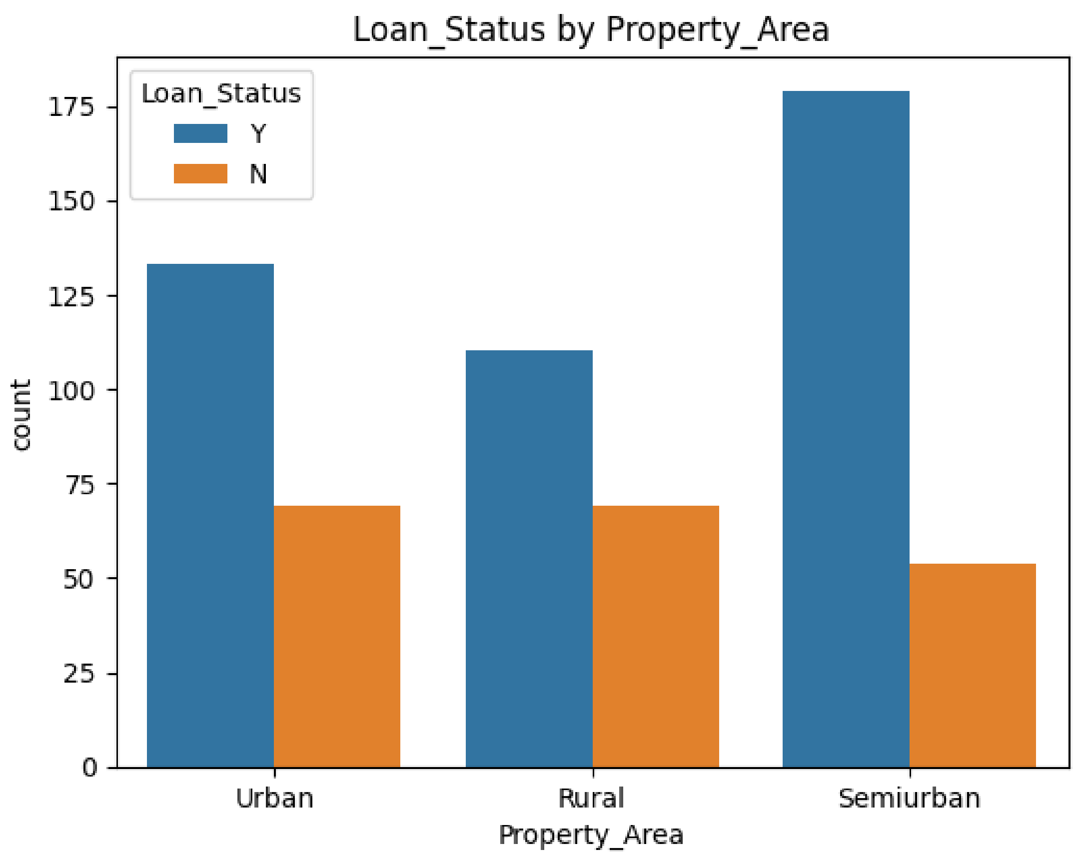
Visual check

[ ]:
```
# Class balance
sns.countplot(x='Loan_Status', data=df)
plt.title("Loan_Status distribution")
plt.show()

# Income distributions
fig, ax = plt.subplots()
sns.histplot(df['ApplicantIncome'], bins=30, kde=True, ax=ax)
ax.set_title("ApplicantIncome distribution")
plt.show()

# LoanAmount vs Status
sns.boxplot(x='Loan_Status', y='LoanAmount', data=df)
plt.title("LoanAmount by Loan_Status")
plt.show()

# Categorical relationship example
sns.countplot(x='Property_Area', hue='Loan_Status', data=df)
plt.title("Loan_Status by Property_Area")
plt.show()
```


Loan_Status distribution
count
400
350
300
250
200
150
100
50
0
Y
N
Loan_Status


ApplicantIncome distribution
Count
300
250
200
150
100
50
0
0
10000
20000
30000
40000
50000
60000
70000
80000
ApplicantIncome


LoanAmount by Loan_Status
700
600
500
400
300
200
100
0
LoanAmount
Y
N
Loan_Status



Target Encoding & Feature/Target Split

[ ]:
```
df = df.copy()
df['Loan_Status'] = df['Loan_Status'].map({'Y':1, 'N':0})

X = df.drop(columns=['Loan_ID','Loan_Status'])
y = df['Loan_Status']
```

[ ]:
```
#define column types
cat_cols = X.select_dtypes(include=['object']).columns.tolist()
num_cols = X.select_dtypes(exclude=['object']).columns.tolist()

cat_cols, num_cols
```

[ ]:
```
(['Gender',
  'Married',
  'Dependents',
  'Education',
  'Self_Employed',
  'Property_Area'],
```

```
['ApplicantIncome',
 'CoapplicantIncome',
 'LoanAmount',
 'Loan_Amount_Term',
 'Credit_History'])
```

Preprocessing Pipelines (Impute + Encode/Scale)

```
[ ]: # Categorical: impute most_frequent, then OneHot
cat_pre = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('ohe', OneHotEncoder(handle_unknown='ignore'))
])

# Numeric: impute median, then scale
num_pre = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

preprocessor = ColumnTransformer(
    transformers=[
        ('cat', cat_pre, cat_cols),
        ('num', num_pre, num_cols)
    ]
)
```

Train/Test split

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

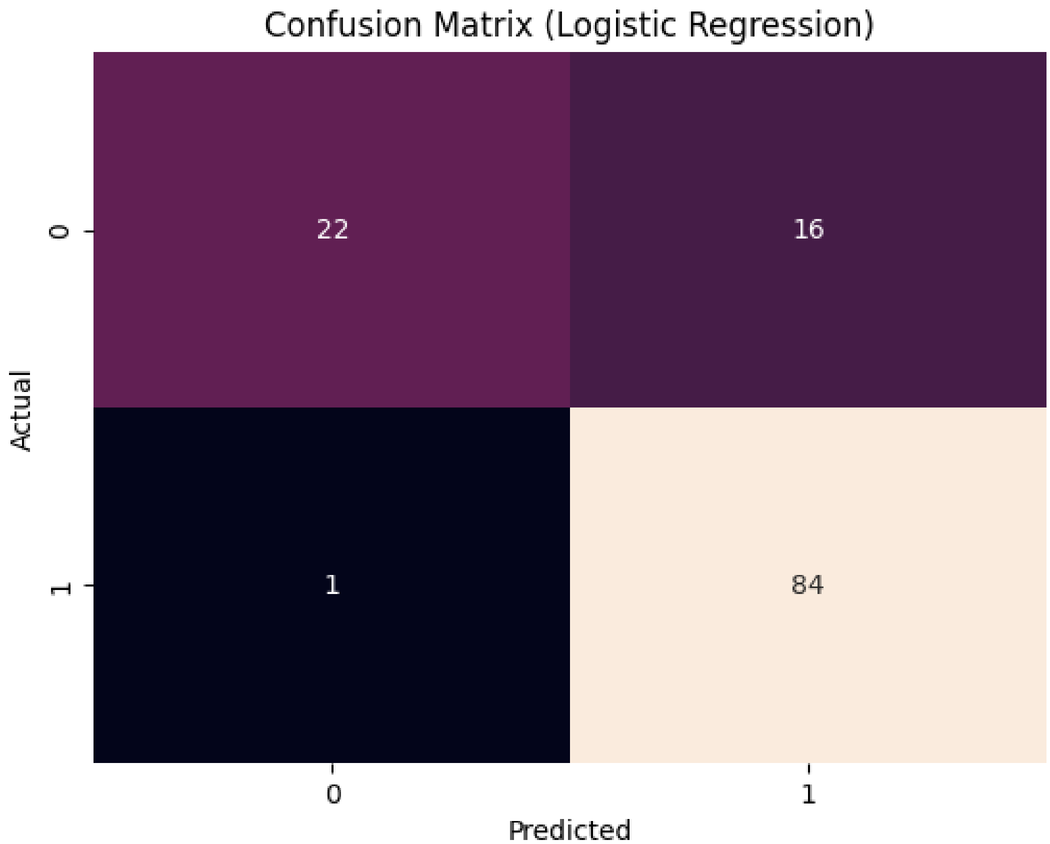
Logistic Regresssion

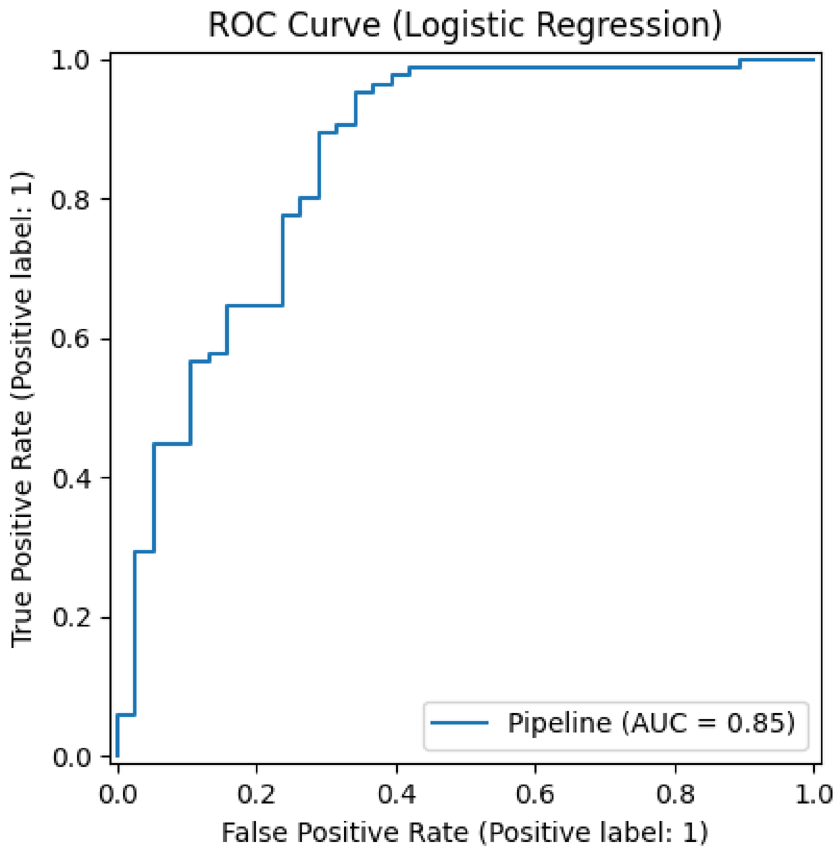
```
[ ]: logreg_clf = Pipeline(steps=[
    ('prep', preprocessor),
    ('model', LogisticRegression(max_iter=2000))
])

logreg_clf.fit(X_train, y_train)
y_pred = logreg_clf.predict(X_test)
y_proba = logreg_clf.predict_proba(X_test)[:,1]

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1:", f1_score(y_test, y_pred))
```

```
print("ROC-AUC:", roc_auc_score(y_test, y_proba))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8617886178861789
Precision: 0.84
Recall: 0.9882352941176471
F1: 0.9081081081081082
ROC-AUC: 0.8523219814241486

Classification Report:
               precision    recall  f1-score   support

           0       0.96      0.58      0.72        38
           1       0.84      0.99      0.91        85

    accuracy                           0.86       123
   macro avg       0.90      0.78      0.81       123
weighted avg       0.88      0.86      0.85       123
```

[ ]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='g', cbar=False)
plt.title("Confusion Matrix (Logistic Regression)")
plt.xlabel("Predicted"); plt.ylabel("Actual")
plt.show()

RocCurveDisplay.from_estimator(logreg_clf, X_test, y_test)
plt.title("ROC Curve (Logistic Regression)")
plt.show()
```


Confusion Matrix (Logistic Regression)
22
16
1
84
0
1
Actual
0
1
Predicted



Try Multiple Algorithms

[ ]:
```python
models = {
    "LogReg": LogisticRegression(max_iter=2000),
    "DecisionTree": DecisionTreeClassifier(random_state=42),
    "RandomForest": RandomForestClassifier(n_estimators=300, random_state=42)
}

for name, base in models.items():
    pipe = Pipeline([('prep', preprocessor), ('model', base)])
    cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    scores = cross_val_score(pipe, X, y, scoring='accuracy', cv=cv)
    print(f"{name}: CV Accuracy = {scores.mean():.3f} ± {scores.std():.3f}")
```

```
LogReg: CV Accuracy = 0.803 ± 0.025
DecisionTree: CV Accuracy = 0.704 ± 0.027
RandomForest: CV Accuracy = 0.767 ± 0.022
```

[ ]:
```python

```