```
9. Uber Ride Price Prediction using PCA and EDA: Dataset can be
change(iris dataset)
● Perform Exploratory Data Analysis (EDA) on Uber ride data
● Use Principal Component Analysis (PCA) to reduce dimensionality
● Compare the performance of models with and without PCA
10. Uber Ride Price Prediction using PCA and EDA: Dataset can be
change(iris dataset)
● Perform Exploratory Data Analysis (EDA) on Uber ride data
● Use Principal Component Analysis (PCA) to reduce dimensionality
● Evaluate models using metrics like R², RMSE, MAE

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LinearRegression

data=pd.read_csv("uber - uber.csv",encoding='latin-1')
data.head()

   Unnamed: 0                  key  fare_amount
pickup_datetime  \
0    24238194  2015-05-07 19:52:06          7.5  2015-05-07 19:52:06
UTC
1    27835199  2009-07-17 20:04:56          7.7  2009-07-17 20:04:56
UTC
2    44984355  2009-08-24 21:45:00         12.9  2009-08-24 21:45:00
UTC
3    25894730   2009-06-26 8:22:21          5.3  2009-06-26 08:22:21
UTC
4    17610152  2014-08-28 17:47:00         16.0  2014-08-28 17:47:00
UTC

   pickup_longitude  pickup_latitude  dropoff_longitude
dropoff_latitude  \
0        -73.999817        40.738354         -73.999512
40.723217
1        -73.994355        40.728225         -73.994710
40.750325
2        -74.005043        40.740770         -73.962565
40.772647
3        -73.976124        40.790844         -73.965316
40.803349
4        -73.925023        40.744085         -73.973082
40.761247
```

```
   passenger_count
0                1
1                1
2                1
3                3
4                5
```

```
data.shape
```

```
(200000, 9)
```

```
data.columns
```

```
Index(['Unnamed: 0', 'key', 'fare_amount', 'pickup_datetime',
       'pickup_longitude', 'pickup_latitude', 'dropoff_longitude',
       'dropoff_latitude', 'passenger_count'],
      dtype='object')
```

```
data.info()
```

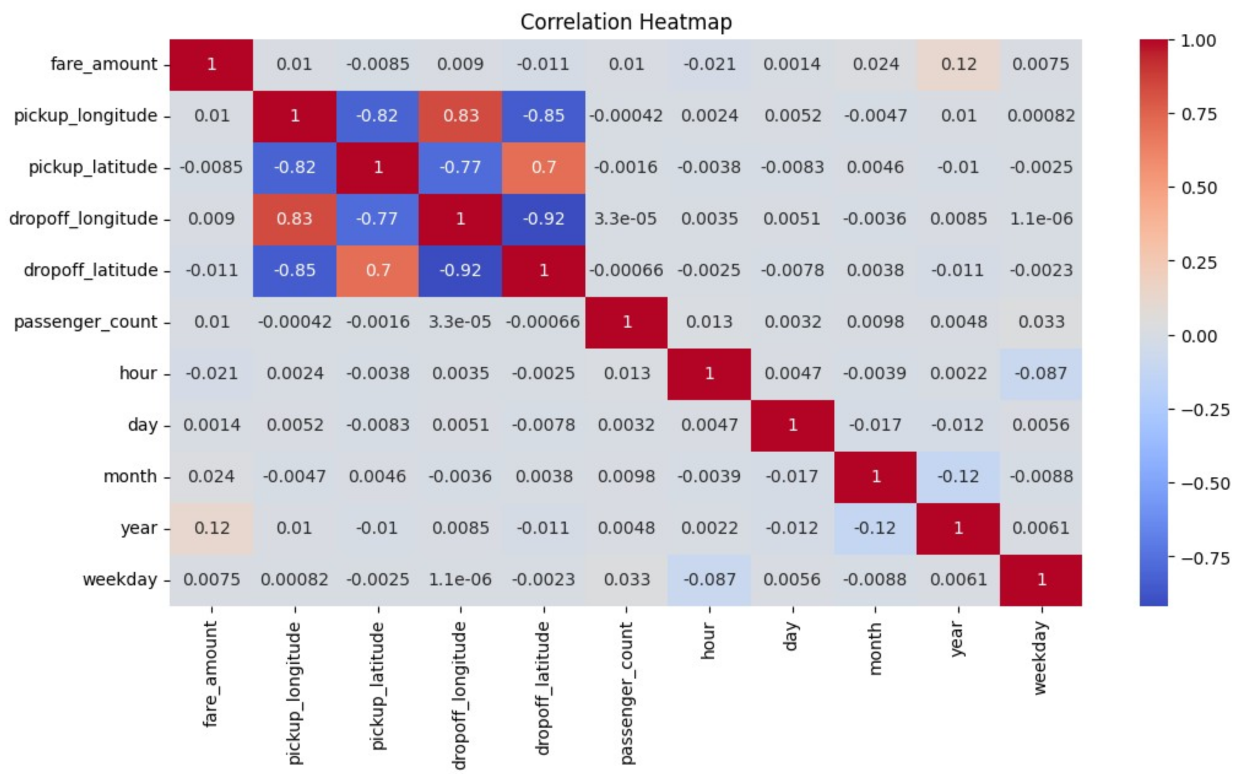
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         200000 non-null  int64
 1   key                200000 non-null  object
 2   fare_amount        200000 non-null  float64
 3   pickup_datetime    200000 non-null  object
 4   pickup_longitude   200000 non-null  float64
 5   pickup_latitude    200000 non-null  float64
 6   dropoff_longitude  199999 non-null  float64
 7   dropoff_latitude   199999 non-null  float64
 8   passenger_count    200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

```
data.isnull().sum()
```

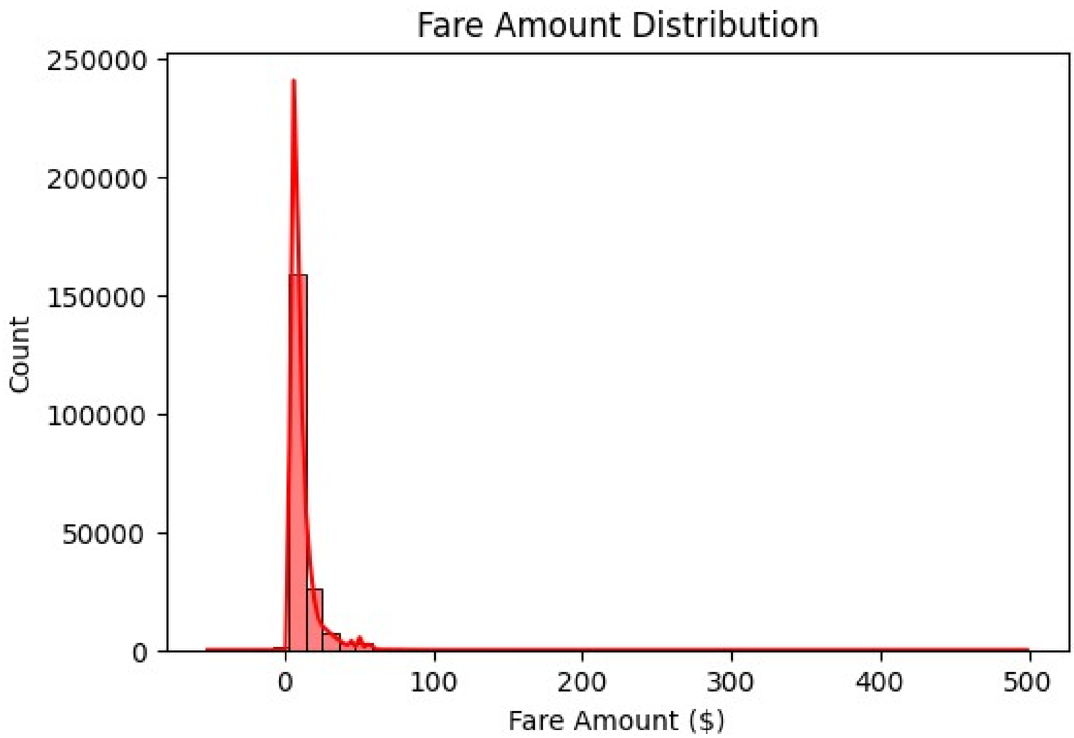
```
Unnamed: 0           0
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

```
data=data.drop(['Unnamed: 0','key'],axis=1)

data=data.dropna()

data.isnull().sum()


fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64

data['pickup_datetime']=pd.to_datetime(data['pickup_datetime'])

data['pickup_datetime'].head(10)

0   2015-05-07 19:52:06+00:00
1   2009-07-17 20:04:56+00:00
2   2009-08-24 21:45:00+00:00
3   2009-06-26 08:22:21+00:00
4   2014-08-28 17:47:00+00:00
5   2011-02-12 02:27:09+00:00
6   2014-10-12 07:04:00+00:00
7   2012-12-11 13:52:00+00:00
8   2012-02-17 09:32:00+00:00
9   2012-03-29 19:06:00+00:00
Name: pickup_datetime, dtype: datetime64[ns, UTC]

data['hour']=data["pickup_datetime"].dt.hour
data['day']=data["pickup_datetime"].dt.day
data['month']=data["pickup_datetime"].dt.month
data['year']=data["pickup_datetime"].dt.year
data['weekday']=data["pickup_datetime"].dt.weekday

data.describe()

         fare_amount  pickup_longitude  pickup_latitude
dropoff_longitude  \
count  199999.000000     199999.000000    199999.000000
199999.000000
mean       11.359892        -72.527631        39.935881          -
72.525292
std         9.901760         11.437815         7.720558
13.117408
min       -52.000000      -1340.648410       -74.015515        -
3356.666300
25%         6.000000        -73.992065        40.734796          -
```

```
73.991407
50%          8.500000         -73.981823         40.752592          -
73.980093
75%         12.500000         -73.967154         40.767158          -
73.963659
max        499.000000          57.418457       1644.421482
1153.572603

       dropoff_latitude  passenger_count           hour            day
\
count     199999.000000    199999.000000  199999.000000  199999.000000

mean          39.923890         1.684543      13.491387      15.704739

std            6.794829         1.385995       6.515505       8.687377

min         -881.985513         0.000000       0.000000       1.000000

25%           40.733823         1.000000       9.000000       8.000000

50%           40.753042         1.000000      14.000000      16.000000

75%           40.768001         2.000000      19.000000      23.000000

max          872.697628       208.000000      23.000000      31.000000


               month           year        weekday
count  199999.000000  199999.000000  199999.000000
mean        6.281791    2011.742434       3.048435
std         3.438933       1.856400       1.946946
min         1.000000    2009.000000       0.000000
25%         3.000000    2010.000000       1.000000
50%         6.000000    2012.000000       3.000000
75%         9.000000    2013.000000       5.000000
max        12.000000    2015.000000       6.000000

plt.figure(figsize=(12,6))
sns.heatmap(data.corr(numeric_only=True),annot=True,cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```

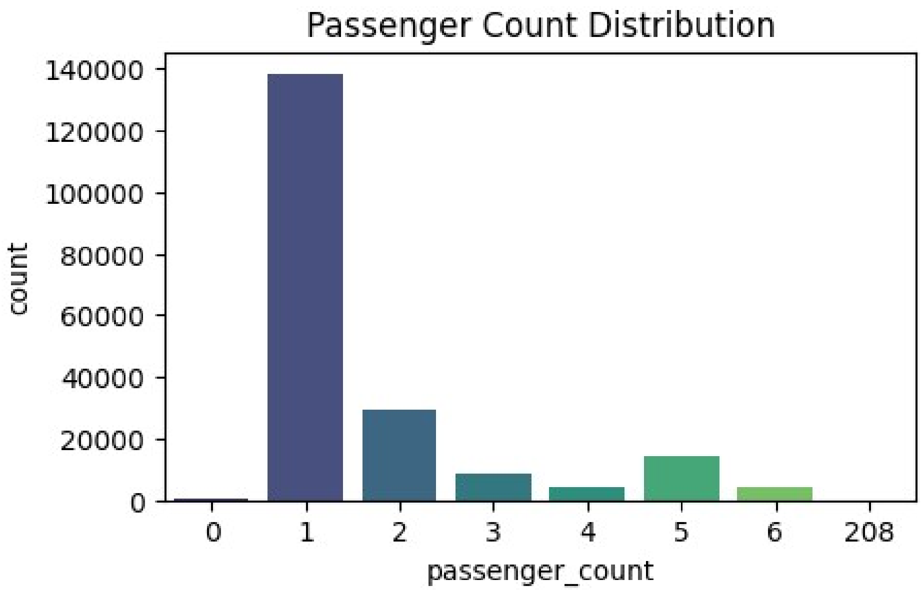



```
plt.figure(figsize=(6,4))
sns.histplot(data['fare_amount'],bins=50,kde=True,color="red")
plt.title("Fare Amount Distribution")
plt.xlabel("Fare Amount ($)")
plt.ylabel("Count")
plt.show()
```

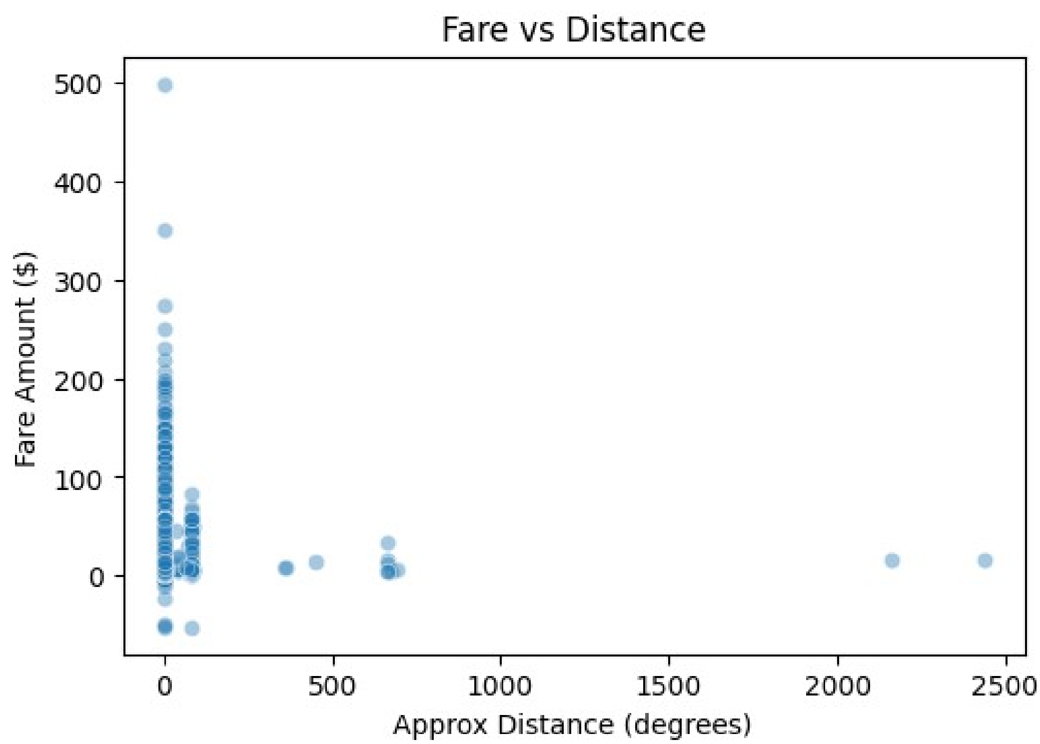



```
plt.figure(figsize=(5,3))
sns.countplot(x='passenger_count',data=data,palette='viridis')
plt.title("Passenger Count Distribution")
plt.show()
```

```
C:\Users\mehul\AppData\Local\Temp\ipykernel_28280\4220429717.py:2:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='passenger_count',data=data,palette='viridis')
```




```
data['distance']=np.sqrt(
    (data['dropoff_latitude']-data['pickup_latitude'])**2+
    (data['dropoff_longitude'] - data['pickup_longitude'])**2
)


plt.figure(figsize=(6,4))
sns.scatterplot(x='distance', y='fare_amount', data=data, alpha=0.4)
plt.title("Fare vs Distance")
plt.xlabel("Approx Distance (degrees)")
plt.ylabel("Fare Amount ($)")
plt.show()
```




```
data.columns
```

```
Index(['fare_amount', 'pickup_datetime', 'pickup_longitude',
'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
'hour',
       'day', 'month', 'year', 'weekday', 'distance'],
      dtype='object')
```

```
data=data[(data['fare_amount']>0) & (data['distance']<5)]
```

```
data.shape
```

```
(199540, 13)
```

```
X=data[['pickup_longitude', 'pickup_latitude',
       'dropoff_longitude', 'dropoff_latitude', 'passenger_count',
'hour',
       'day', 'month', 'year', 'weekday', 'distance']]
y=data['fare_amount']
```

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

```
X_train,X_test,y_train,y_test=train_test_split(X_Scaled,y,test_size=0.
2,random_state=42)
```

```
lr_nopca=LinearRegression()
```

```python
lr_nopca.fit(X_train,y_train)
y_pred=lr_nopca.predict(X_test)


mse_manual = np.mean((y_test - y_pred) ** 2)
rmse_pca = np.sqrt(mse_manual)

ss_res = np.sum((y_test - y_pred) ** 2)
ss_tot = np.sum((y_test - np.mean(y_test)) ** 2)
r2_pca = 1 - (ss_res / ss_tot)

print("Model Without PCA:")
print("RMSE:", round(rmse_pca, 4))
print("R² Score:", round(r2_pca, 4))
```

```
Model Without PCA:
RMSE: 5.9134
R² Score: 0.6299
```

```python
pca=PCA(n_components=8)
X_pca=pca.fit_transform(X_Scaled)


X_train_pca, X_test_pca, y_train_pca, y_test_pca =
train_test_split(X_pca, y, test_size=0.2, random_state=42)

lr_pca = LinearRegression()
lr_pca.fit(X_train_pca, y_train_pca)

y_pred_pca=lr_pca.predict(X_test_pca)




mse_manual = np.mean((y_test_pca - y_pred_pca) ** 2)
rmse_pca = np.sqrt(mse_manual)


ss_res = np.sum((y_test_pca - y_pred_pca) ** 2)           # residual
sum of squares
ss_tot = np.sum((y_test_pca - np.mean(y_test_pca)) ** 2)  # total sum
of squares
r2_pca = 1 - (ss_res / ss_tot)

print("Model With PCA:")
print("RMSE:", round(rmse_pca, 4))
print("R² Score:", round(r2_pca, 4))
```

```
Model With PCA:
RMSE: 5.9559
R² Score: 0.6245
```

```python
import numpy as np


mae_no_pca = np.mean(np.abs(y_test - y_pred))
mae_pca = np.mean(np.abs(y_test_pca - y_pred_pca))

print("MAE (Without PCA):", round(mae_no_pca, 4))
print("MAE (With PCA):", round(mae_pca, 4))
```

```
MAE (Without PCA): 2.8682
MAE (With PCA): 2.8638
```

```
11. Implement a Linear Regression model to predict house prices from
area, bedrooms, and location
features. Apply K-Fold Cross-Validation to validate the model.
```

```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder , StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

data=pd.read_csv("House.csv")
data.head()
```

|  | Area | Bedrooms | Location | Price |
|---|---|---|---|---|
| 0 | 1360 | 2 | Urban | 10998707 |
| 1 | 4272 | 3 | Urban | 34199426 |
| 2 | 3592 | 1 | Urban | 28695658 |
| 3 | 966 | 6 | Urban | 8444717 |
| 4 | 4926 | 1 | Suburban | 24865588 |

```python
data.shape
```

```
(1000, 4)
```

```python
data.isnull().sum()
```

```
Area        0
Bedrooms    0
Location    0
Price       0
dtype: int64
```

```python
le=LabelEncoder()
data['Location']=le.fit_transform(data['Location'])
```

```
data.head()
```

| | Area | Bedrooms | Location | Price |
|---|---|---|---|---|
| 0 | 1360 | 2 | 2 | 10998707 |
| 1 | 4272 | 3 | 2 | 34199426 |
| 2 | 3592 | 1 | 2 | 28695658 |
| 3 | 966 | 6 | 2 | 8444717 |
| 4 | 4926 | 1 | 1 | 24865588 |

```
X=data.drop(['Price'],axis=1)
y=data["Price"]

scaler=StandardScaler()
X_Scaled=scaler.fit_transform(X)

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


lr = LinearRegression()
lr.fit(X_train, y_train)


y_pred = lr.predict(X_test)




mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(" Linear Regression Evaluation on Test Data:")
print("Mean Squared Error (MSE):", round(mse, 2))
print("Root Mean Squared Error (RMSE):", round(rmse, 2))
print("R² Score:", round(r2, 2))
```

```
 Linear Regression Evaluation on Test Data:
Mean Squared Error (MSE): 6865816490864.58
Root Mean Squared Error (RMSE): 2620270.31
R² Score: 0.93
```

```
# ---------------------------------------------------------
# Step 6: Validate Model Accuracy using K-Fold (From Scratch)
# ---------------------------------------------------------

from sklearn.metrics import mean_squared_error, r2_score

k = 5  # Number of folds
n = len(X_Scaled)
fold_size = n // k
```

```python
r2_scores = []
mse_scores = []

print(f"\nManual K-Fold Cross-Validation (k={k}) Results:")

for i in range(k):
    # ---------------------------------------------
    # Step 6.1: Split data manually for fold i
    # ---------------------------------------------
    start = i * fold_size
    end = (i + 1) * fold_size

    X_test = X.iloc[start:end]
    y_test = y.iloc[start:end]

    X_train = pd.concat([X.iloc[:start], X.iloc[end:]])
    y_train = pd.concat([y.iloc[:start], y.iloc[end:]])

    # ---------------------------------------------
    # Step 6.2: Train Linear Regression model
    # ---------------------------------------------
    model = LinearRegression()
    model.fit(X_train, y_train)

    # Step 6.3: Predict and Evaluate using sklearn metrics
    # ---------------------------------------------
    y_pred = model.predict(X_test)

    #mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    #mse_scores.append(mse)
    r2_scores.append(r2)

    print(f"Fold {i+1}: MSE = {mse:.2f}, R² = {r2:.3f}")

# -----------------------------------------------------
# Step 6.4: Display average performance across folds
# -----------------------------------------------------
print("\nAverage Cross-Validation Results:")
#print(f"Mean MSE: {np.mean(mse_scores):.2f}")
print(f"Mean R² Score: {np.mean(r2_scores):.3f}")
    # ---------------------------------------------
    # Step 6.3: Predict and Evaluate using sklearn metrics
    # ---------------------------------------------
```

```
Manual K-Fold Cross-Validation (k=5) Results:
Fold 1: MSE = 6865816490864.58, R² = 0.933
Fold 2: MSE = 6865816490864.58, R² = 0.932
Fold 3: MSE = 6865816490864.58, R² = 0.928
```

```
Fold 4: MSE = 6865816490864.58, R² = 0.925
Fold 5: MSE = 6865816490864.58, R² = 0.931

Average Cross-Validation Results:
Mean R² Score: 0.930
```

```python
# 12. Build a Linear Regression model from scratch to predict
students' final exam scores based on
# their study hours. Implement all computations manually (without
using built-in regression
# libraries) — including parameter estimation, prediction, and model
evaluation using Mean
# Squared Error (MSE) and R² Score.


X = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

Y = [45,50,58,60,65,68,70,72,75,80]

print("Study Hours:", X)
print("Exam Scores:", Y)
```

```
Study Hours: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
Exam Scores: [45, 50, 58, 60, 65, 68, 70, 72, 75, 80]
```

```python
def mean(values):
    return sum(values)/len(values)

mean_x=mean(X)
mean_y=mean(Y)
print("Mean of Exam Hours: ",mean_x)
print("Mean of Exam Scores: ",mean_y)
```

```
Mean of Exam Hours:  5.5
Mean of Exam Scores:  64.3
```

```python
def calulate_coefficients(X,Y):
    mean_x=mean(X)
    mean_y=mean(Y)

    numerator=0
    denominator=0

    for i in range(len(X)):
        numerator+=((X[i]-mean_x)*(Y[i]-mean_y))
        denominator+=((X[i]-mean_x)**2)

    m=numerator/denominator
    c=mean_y-m*mean_x
    return m,c
```

```
m,c=calulate_coefficients(X,Y)

print(f"Slope of the line is (m): {m:.2f}")
print(f"Intercept (c): {c:.2f}")
print(f"Equation of the line is: Y = {m:.2f}X + {c:.2f}")

Slope of the line is (m): 3.59
Intercept (c): 44.53
Equation of the line is: Y = 3.59X + 44.53

def predict(x):
    return m*x+c

Y_pred=[predict(x) for x in X]

print("Predicted Exam Scores (Y_pred):")
for i in range(len(X)):
    print(f"Study Hours = {X[i]:2d}----> Predicted Score = 
{Y_pred[i]:.2f}")

Predicted Exam Scores (Y_pred):
Study Hours =  1----> Predicted Score = 48.13
Study Hours =  2----> Predicted Score = 51.72
Study Hours =  3----> Predicted Score = 55.32
Study Hours =  4----> Predicted Score = 58.91
Study Hours =  5----> Predicted Score = 62.50
Study Hours =  6----> Predicted Score = 66.10
Study Hours =  7----> Predicted Score = 69.69
Study Hours =  8----> Predicted Score = 73.28
Study Hours =  9----> Predicted Score = 76.88
Study Hours = 10----> Predicted Score = 80.47

from sklearn.metrics import mean_squared_error,r2_score

mse=mean_squared_error(Y,Y_pred)
r2=r2_score(Y,Y_pred)

print("Model Evaluation: ")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R2 Score: {r2:.3f}")

Model Evaluation: 
Mean Squared Error (MSE): 3.65
R2 Score: 0.967


def mean_squared_error(Y_true,Y_pred):
    mse=sum([(Y_true[i]-Y_pred[i])**2 for i in range
(len(Y_true))])/len(Y_true)
    return mse
def r2_score(Y_true,Y_pred):
```

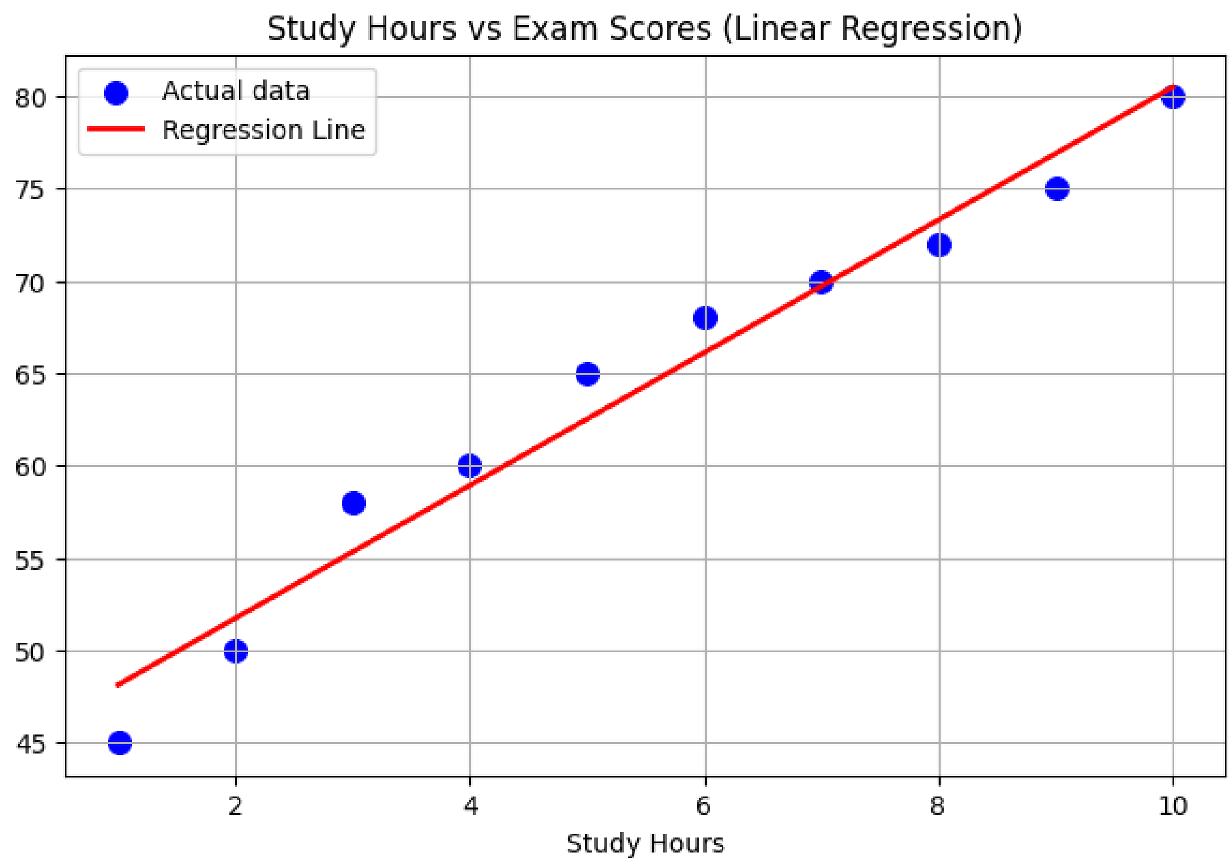
```python
    mean_y=mean(Y_true)
    ss_total=sum([(y-mean_y)**2 for y in Y_true])
    ss_residual=sum([(Y_true[i]-Y_pred[i])**2 for i in range
(len(Y_true))])
    r2=1-(ss_residual/ss_total)
    return r2

mse=mean_squared_error(Y,Y_pred)
r2=r2_score(Y,Y_pred)

print("Model Evaluation: ")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R2 Score: {r2:.3f}")
```

```
Model Evaluation:
Mean Squared Error (MSE): 3.65
R2 Score: 0.967
```

```python
# -------------------------------------------------------
# Step 6: Predict Scores for New Data
# -------------------------------------------------------

new_hours = [2.5, 5.5, 9.5]

print("Predictions for New Study Hours:")
for h in new_hours:
    predicted_score = predict(h)
    print(f"For {h} study hours → Predicted Score =
{predicted_score:.2f}")
```

```
Predictions for New Study Hours:
For 2.5 study hours → Predicted Score = 53.52
For 5.5 study hours → Predicted Score = 64.30
For 9.5 study hours → Predicted Score = 78.68
```

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(8,5))
plt.scatter(X,Y,color="blue" , label='Actual data',s=70)
plt.plot(X,Y_pred,color='red' , linewidth=2 , label="Regression Line")

plt.title("Study Hours vs Exam Scores (Linear Regression)")
plt.xlabel("Study Hours")
plt.legend()
plt.grid(True)
plt.show()
```




```
13. Build a Linear Regression model to predict students' exam scores
using study hours, attendance,
and internal marks. Validate model accuracy using K-Fold Cross-
Validation.

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

df=pd.read_csv("Student.csv")
print(df)
```

```
    student_id  hours_studied  sleep_hours  attendance_percent  \
0         S001            8.0          8.8                72.1
1         S002            1.3          8.6                60.7
2         S003            4.0          8.2                73.7
3         S004            3.5          4.8                95.1
4         S005            9.1          6.4                89.8
..         ...            ...          ...                 ...
195       S196           10.5          5.4                94.0
```

```
196       S197             7.1          6.1                  85.1
197       S198             1.6          6.9                  63.8
198       S199            12.0          7.3                  50.5
199       S200            10.2          6.3                  97.4

     Internal_marks  exam_score
0                45        30.2
1                55        25.0
2                86        35.8
3                66        34.0
4                71        40.3
..              ...         ...
195              87        42.7
196              92        40.4
197              76        28.2
198              58        42.0
199              68        37.8

[200 rows x 6 columns]
```

```
X=df[['hours_studied','attendance_percent','Internal_marks']]
y=df['exam_score']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
print("\nTrain shape:", X_train.shape, " Test shape:", X_test.shape)
```

```
Train shape: (160, 3)  Test shape: (40, 3)
```

```
model = LinearRegression()
model.fit(X_train, y_train)

print("\nIntercept (c):", model.intercept_)
print("Coefficients (m):", model.coef_)

# -------------------------------------------------------
# Step 5: Evaluate on Test Set
# -------------------------------------------------------
y_pred_test = model.predict(X_test)
r2 = r2_score(y_test, y_pred_test)
mse = mean_squared_error(y_test, y_pred_test)
print("\n--- Test Set Performance ---")
print(f"R² Score: {r2:.3f}")
print(f"Mean Squared Error: {mse:.3f}")
```

```
Intercept (c): 4.52343252168837
Coefficients (m): [1.58507318 0.11238446 0.16302299]
```

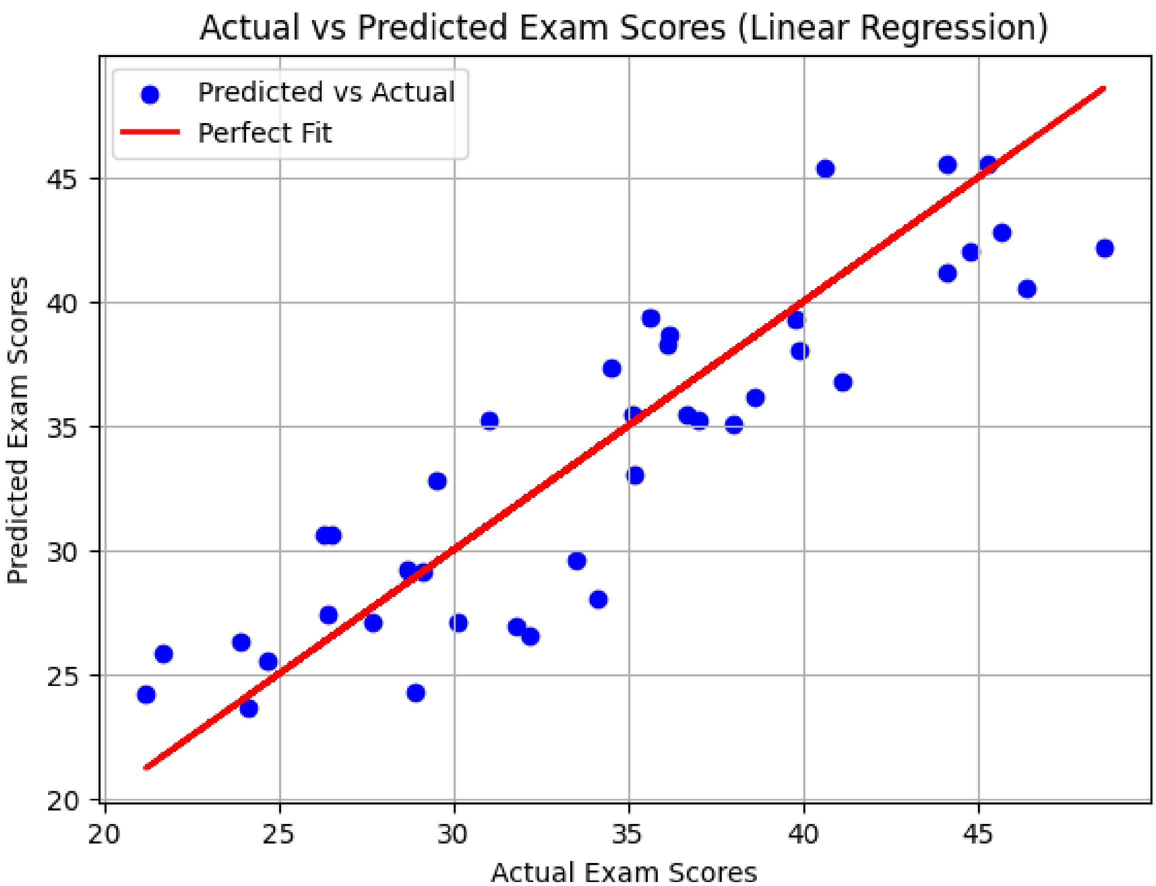
```
--- Test Set Performance ---
R² Score: 0.792
Mean Squared Error: 11.048
```

```
k = 5  # Number of folds
n = len(X)
fold_size = n // k
r2_scores = []

print(f"\nManual K-Fold Cross-Validation (k={k}) Results:")

for i in range(k):
    # Split data manually
    start = i * fold_size
    end = (i + 1) * fold_size

    X_test_fold = X.iloc[start:end]
    y_test_fold = y.iloc[start:end]
    X_train_fold = pd.concat([X.iloc[:start], X.iloc[end:]])
    y_train_fold = pd.concat([y.iloc[:start], y.iloc[end:]])

    # Train model on fold
    model = LinearRegression()
    model.fit(X_train_fold, y_train_fold)

    # Predict
    y_pred_fold = model.predict(X_test_fold)

    r2_fold=r2_score(y_test_fold,y_pred_fold)

    r2_scores.append(r2_fold)

    print(f"Fold {i+1}: R² = {r2_fold:.3f}")

print("\nAverage R² Score (K-Fold):", round(np.mean(r2_scores), 3))
```

```
Manual K-Fold Cross-Validation (k=5) Results:
Fold 1: R² = 0.718
Fold 2: R² = 0.790
Fold 3: R² = 0.842
Fold 4: R² = 0.769
Fold 5: R² = 0.821

Average R² Score (K-Fold): 0.788
```

```
plt.figure(figsize=(7,5))
plt.scatter(y_test, y_pred_test, color='blue', label='Predicted vs
Actual')
plt.plot(y_test,y_test ,
         color='red', linewidth=2, label='Perfect Fit')
```

```
plt.xlabel("Actual Exam Scores")
plt.ylabel("Predicted Exam Scores")
plt.title("Actual vs Predicted Exam Scores (Linear Regression)")
plt.legend()
plt.grid(True)
plt.show()
```




```
14. Develop a Linear Regression model to estimate IT professionals’
salaries based on experience,
education, and skills. Evaluate performance using 5-Fold Cross-
Validation.

import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder , StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split

data=pd.read_csv("Salary Data.csv")
data.head()
```

```
    Age  Gender Education Level          Job Title  Years of 
Experience  \
0  32.0    Male      Bachelor's  Software Engineer
5.0
1  28.0  Female        Master's       Data Analyst
3.0
2  45.0    Male             PhD     Senior Manager
15.0
3  36.0  Female      Bachelor's    Sales Associate
7.0
4  52.0    Male        Master's           Director
20.0

     Salary
0   90000.0
1   65000.0
2  150000.0
3   60000.0
4  200000.0
```

```
data.shape
```

```
(375, 6)
```

```
data.isnull().sum()
```

```
Age                    2
Gender                 2
Education Level        2
Job Title              2
Years of Experience    2
Salary                 2
dtype: int64
```

```
# Check for missing values
print("Missing values before handling:")
print(data.isnull().sum())


data = data.dropna()


print("\nMissing values after handling:")
print(data.isnull().sum())
```

```
Missing values before handling:
Age                    2
Gender                 2
Education Level        2
Job Title              2
Years of Experience    2
```

```
Salary                    2
dtype: int64

Missing values after handling:
Age                       0
Gender                    0
Education Level           0
Job Title                 0
Years of Experience       0
Salary                    0
dtype: int64
```

```
le1=LabelEncoder()
le2=LabelEncoder()

data["Education Level"]=le1.fit_transform(data["Education Level"])
data["Job Title"]=le2.fit_transform(data["Job Title"])

data.head()
```

```
    Age  Gender  Education Level  Job Title  Years of Experience
Salary
0  32.0    Male                0        159                  5.0
90000.0
1  28.0  Female                1         17                  3.0
65000.0
2  45.0    Male                2        130                 15.0
150000.0
3  36.0  Female                0        101                  7.0
60000.0
4  52.0    Male                1         22                 20.0
200000.0
```

```
X=data[["Education Level","Job Title","Years of Experience"]]
y=data["Salary"]

scaler=StandardScaler()
X_Scaled=scaler.fit_transform(X)

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


lr = LinearRegression()
lr.fit(X_train, y_train)


y_pred = lr.predict(X_test)
```

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(" Linear Regression Evaluation on Test Data:")
print("Mean Squared Error (MSE):", round(mse, 2))
print("Root Mean Squared Error (RMSE):", round(rmse, 2))
print("R² Score:", round(r2, 2))
```

```
 Linear Regression Evaluation on Test Data:
Mean Squared Error (MSE): 255188684.52
Root Mean Squared Error (RMSE): 15974.63
R² Score: 0.89
```

```
# -------------------------------------------------------
# Step 6: Validate Model Accuracy using K-Fold (From Scratch)
# -------------------------------------------------------

from sklearn.metrics import mean_squared_error, r2_score

k = 5  # Number of folds
n = len(X_Scaled)
fold_size = n // k
r2_scores = []
mse_scores = []

print(f"\nManual K-Fold Cross-Validation (k={k}) Results:")

for i in range(k):
    # ---------------------------------------------
    # Step 6.1: Split data manually for fold i
    # ---------------------------------------------
    start = i * fold_size
    end = (i + 1) * fold_size

    X_test = X.iloc[start:end]
    y_test = y.iloc[start:end]

    X_train = pd.concat([X.iloc[:start], X.iloc[end:]])
    y_train = pd.concat([y.iloc[:start], y.iloc[end:]])

    # ---------------------------------------------
    # Step 6.2: Train Linear Regression model
    # ---------------------------------------------
    model = LinearRegression()
    model.fit(X_train, y_train)

    # ---------------------------------------------
    # Step 6.3: Predict and Evaluate using sklearn metrics
    # ---------------------------------------------
```

```
    y_pred = model.predict(X_test)

    #mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    #mse_scores.append(mse)
    r2_scores.append(r2)

    print(f"Fold {i+1}: MSE = {mse:.2f}, R² = {r2:.3f}")

# ---------------------------------------------------------
# Step 6.4: Display average performance across folds
# ---------------------------------------------------------
print("\nAverage Cross-Validation Results:")
#print(f"Mean MSE: {np.mean(mse_scores):.2f}")
print(f"Mean R² Score: {np.mean(r2_scores):.3f}")
```

```
Manual K-Fold Cross-Validation (k=5) Results:

Average Cross-Validation Results:
Mean R² Score: 0.863
```

```
16. Apply the Naïve Bayes algorithm to a real-world classification
problem such as email spam
detection, sentiment analysis, or disease diagnosis. Train and test
the model, then evaluate its
performance using a Confusion Matrix and related metrics such as
accuracy, precision, recall, and
F1-score.
```

```
  Cell In[91], line 1
    16. Apply the Naïve Bayes algorithm to a real-world classification
problem such as email spam
        ^
SyntaxError: invalid syntax
```

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score , confusion_matrix ,
classification_report
import matplotlib.pyplot as plt
import seaborn as sns

data=pd.read_csv("emails.csv")
data.head()
```

```
  Email No.  the  to  ect  and  for  of    a  you  hou  ...  connevey
jay  \
```

```
0   Email 1    0    0     1     0     0    0     2     0     0  ...          0
0
1   Email 2    8   13    24     6     6    2   102     1    27  ...          0
0
2   Email 3    0    0     1     0     0    0     8     0     0  ...          0
0
3   Email 4    0    5    22     0     5    1    51     2    10  ...          0
0
4   Email 5    7    6    17     1     5    2    57     0     9  ...          0
0

   valued  lay  infrastructure  military  allowing  ff  dry
Prediction
0       0    0               0         0         0   0    0
0
1       0    0               0         0         0   1    0
0
2       0    0               0         0         0   0    0
0
3       0    0               0         0         0   0    0
0
4       0    0               0         0         0   1    0
0

[5 rows x 3002 columns]
```

```
data.shape
```

```
(5172, 3002)
```

```
data=data.drop(['Email No.'],axis=1)
```

```
data=data.sample(n=1500,random_state=42).reset_index(drop=True)
```

```
# Separate input features (X) and output label (y)
X = data.drop('Prediction', axis=1).astype(np.float32).values
y = data['Prediction'].astype(int).values

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

print("Training shape:", X_train.shape)
print("Testing shape:", X_test.shape)
```

```
Training shape: (1200, 3000)
Testing shape: (300, 3000)
```

```
import numpy as np
class naiveBayesFromScratch:
```

```python
    def fit(self,X,y,alpha=1.0):
        self.classes=np.unique(y)
        n_samples,n_features=X.shape


self.class_feature_count=np.zeros((len(self.classes)),n_features)
        self.class_count=np.zeros(len(self.classes))

        for idx,c in enumerate(self.classes):
            X_c=X[y==c]
            self.class_feature_count[idx,:]=X_c.sum(axis=0)
            self.class_count[idx]=X_c.shape[0]

        self.class_priors=self.class_count/n_samples

        #P(xi/c)


self.feature_log_prob=np.log((self.class_feature_count+alpha)/(self.cl
ass_feature_count.sum(axis=1).reshape(-1,1)+alpha*n_features))

    #log_prior+log_likelihood(xi*P(xi/c))
    def _predict_single(self,X):
        log_posteriors=[]
        for idx,c in enumerate(self.classes):
            log_prior=np.log(self.class_priors[idx])
            log_likelihood=np.sum(X*self.feature_log_prob[idx,:])
            log_posteriors.append(log_prior+log_likelihood)
        return self.classes[np.argmax(log_posteriors)]


    def predict(self,X):
        return np.array([self._predict_single(x) for x in X])



# Create and train model
nb = NaiveBayesFromScratch()
nb.fit(X_train, y_train)

print("□ Model training complete.")
```

```
□ Model training complete.
```

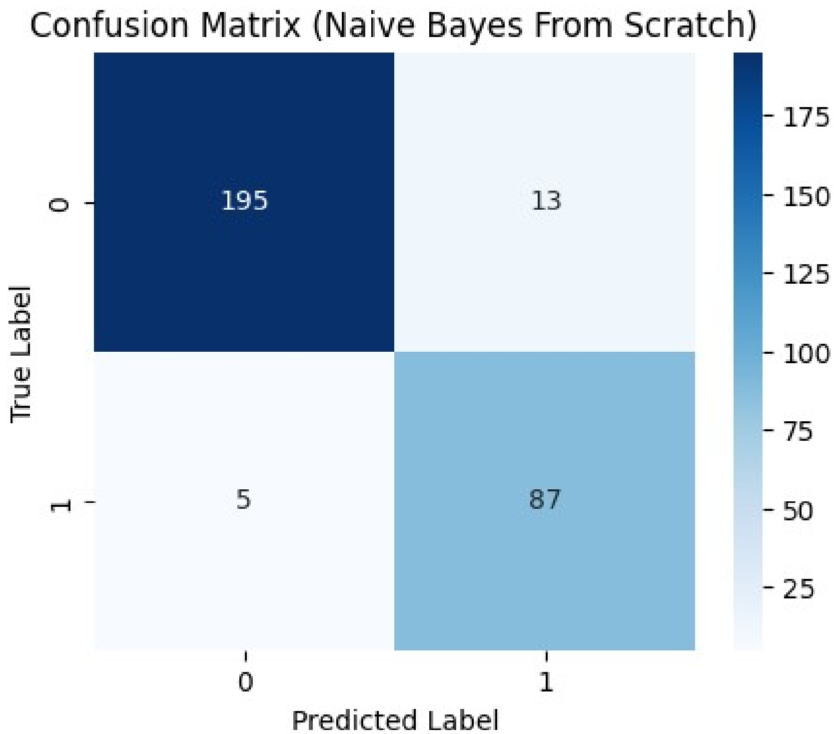
```python
# Predict on the test set
y_pred = nb.predict(X_test)

# Display few predictions
print("First 10 Predictions:", y_pred[:10])
print("First 10 Actual Labels:", y_test[:10])
```

```
First 10 Predictions: [0 0 0 0 0 1 0 0 1 0]
First 10 Actual Labels: [0 0 0 0 0 1 0 0 1 0]
```

```python
print("□ Naive Bayes From Scratch Results")
print("------------------------------------")
print("Accuracy:", round(accuracy_score(y_test, y_pred), 4))

print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
□ Naive Bayes From Scratch Results
------------------------------------
Accuracy: 0.94

Confusion Matrix:
 [[195  13]
 [  5  87]]

Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.94      0.96       208
           1       0.87      0.95      0.91        92

    accuracy                           0.94       300
   macro avg       0.92      0.94      0.93       300
weighted avg       0.94      0.94      0.94       300
```

```python
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix (Naive Bayes From Scratch)")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```




```
#Now for Sentiment dataset 16 and 17

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
from sklearn.feature_extraction.text import CountVectorizer

df=pd.read_csv("sentiment.csv")
df.head()

   Year  Month  Day Time of Tweet  \
0  2018      8   18       morning
1  2018      8   18          noon
2  2017      8   18         night
3  2022      6    8       morning
4  2022      6    8          noon

                                                text sentiment
Platform
0               What a great day!!! Looks like dream.  positive
Twitter
1     I feel sorry, I miss you here in the sea beach  positive
Facebook
2                                     Don't angry me  negative
Facebook
```

```
3  We attend in the class just for listening teac...  negative
Facebook
4                  Those who want to go, let them go  negative
Instagram

df=df[['text','sentiment']]

label_map = {'negative': 0, 'neutral': 1, 'positive': 2}
df['label'] = df['sentiment'].map(label_map)



# Extract features and labels
X = df['text'].values
y = df['label'].values.astype(int)

# Train-test split (with stratify to maintain class balance)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print(" Cleaned dataset size:", df.shape)
print("Samples per class:\n", df['label'].value_counts())

 Cleaned dataset size: (499, 3)
Samples per class:
 label
1    199
2    166
0    134
Name: count, dtype: int64

vectorizer=CountVectorizer()
X_train_vec=vectorizer.fit_transform(X_train).toarray()
X_test_vec=vectorizer.transform(X_test).toarray()

print("Vocabulary size:", len(vectorizer.vocabulary_))
print("Train shape:", X_train_vec.shape, " Test shape:",
X_test_vec.shape)



Vocabulary size: 1237
Train shape: (399, 1237)  Test shape: (100, 1237)

import numpy as np
class naiveBayesFromScratch:
    def fit(self,X,y,alpha=1.0):
        self.classes=np.unique(y)
        n_samples,n_features=X.shape
```

```
self.class_feature_count=np.zeros((len(self.classes),n_features))
        self.class_count=np.zeros(len(self.classes))

        for idx,c in enumerate(self.classes):
            X_c=X[y==c]
            self.class_feature_count[idx,:]=X_c.sum(axis=0)
            self.class_count[idx]=X_c.shape[0]

        #P(C)

        self.class_priors=self.class_count/n_samples

        #P(xi/c)


self.feature_log_prob=np.log((self.class_feature_count+alpha)/(self.cl
ass_feature_count.sum(axis=1).reshape(-1,1)+alpha*n_features))

    #log_prior+log_likelihood(xi*P(xi/c))
    def _predict_single(self,X):
        log_posteriors=[]
        for idx,c in enumerate(self.classes):
            log_prior=np.log(self.class_priors[idx])
            log_likelihood=np.sum(X*self.feature_log_prob[idx,:])
            log_posteriors.append(log_prior+log_likelihood)
        return int(self.classes[np.argmax(log_posteriors)])


    def predict(self,X):
        return np.array([self._predict_single(x) for x in X])



# Train model
nb = naiveBayesFromScratch()
nb.fit(X_train_vec, y_train, alpha=1.0)

# Predict
y_pred = nb.predict(X_test_vec)

# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(
    y_test,
    y_pred,
    target_names=['Negative', 'Neutral', 'Positive']
))
```

```
Accuracy: 0.65

Confusion Matrix:
 [[10 16  1]
 [ 0 34  6]
 [ 2 10 21]]

Classification Report:
               precision    recall  f1-score   support

    Negative       0.83      0.37      0.51        27
     Neutral       0.57      0.85      0.68        40
    Positive       0.75      0.64      0.69        33

    accuracy                           0.65       100
   macro avg       0.72      0.62      0.63       100
weighted avg       0.70      0.65      0.64       100


#Now For Disease Dataset

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

df = pd.read_csv('disease.csv')

df.head()

   Patient_ID  Age  Gender            Symptom_1    Symptom_2 Symptom_3
\
0           1   74    Male              Fatigue  Sore throat     Fever

1           2   66  Female          Sore throat      Fatigue     Cough

2           3   32    Male            Body ache  Sore throat   Fatigue

3           4   21  Female  Shortness of breath     Headache     Cough

4           5   53    Male           Runny nose  Sore throat   Fatigue


   Heart_Rate_bpm  Body_Temperature_C Blood_Pressure_mmHg  \
0              69                39.4              132/91
1              95                39.0              174/98
2              77                36.8              136/60
3              72                38.9              147/82
4             100                36.6             109/106
```

```
   Oxygen_Saturation_% Diagnosis  Severity       Treatment_Plan
0                   94       Flu  Moderate  Medication and rest
1                   98   Healthy      Mild      Rest and fluids
2                   96   Healthy      Mild      Rest and fluids
3                   99   Healthy      Mild      Rest and fluids
4                   92   Healthy      Mild      Rest and fluids
```

```
# Drop ID column (not a feature)
df = df.drop(['Patient_ID'], axis=1)

# Fill missing values
df = df.fillna('Unknown')

# Initialize LabelEncoder
le = LabelEncoder()

# Columns to encode
cat_cols = ['Gender', 'Symptom_1', 'Symptom_2', 'Symptom_3',
            'Severity', 'Treatment_Plan', 'Diagnosis']

for col in cat_cols:
    df[col] = le.fit_transform(df[col])

# Define features and target
X = df.drop(['Diagnosis','Blood_Pressure_mmHg'] ,axis=1).values
y = df['Diagnosis'].values

# 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
)

print("\n□ Data Encoded & Split Successfully!")
print("Train shape:", X_train.shape)
print("Test shape:", X_test.shape)
```

```
□ Data Encoded & Split Successfully!
Train shape: (1600, 10)
Test shape: (400, 10)
```

```
class MultinomialNaiveBayesScratch:
    def fit(self, X, y, alpha=1.0):
        self.classes = np.unique(y)
        n_samples, n_features = X.shape

        # Initialize class and feature counts
        self.class_feature_count = np.zeros((len(self.classes),
n_features))
        self.class_count = np.zeros(len(self.classes))
```

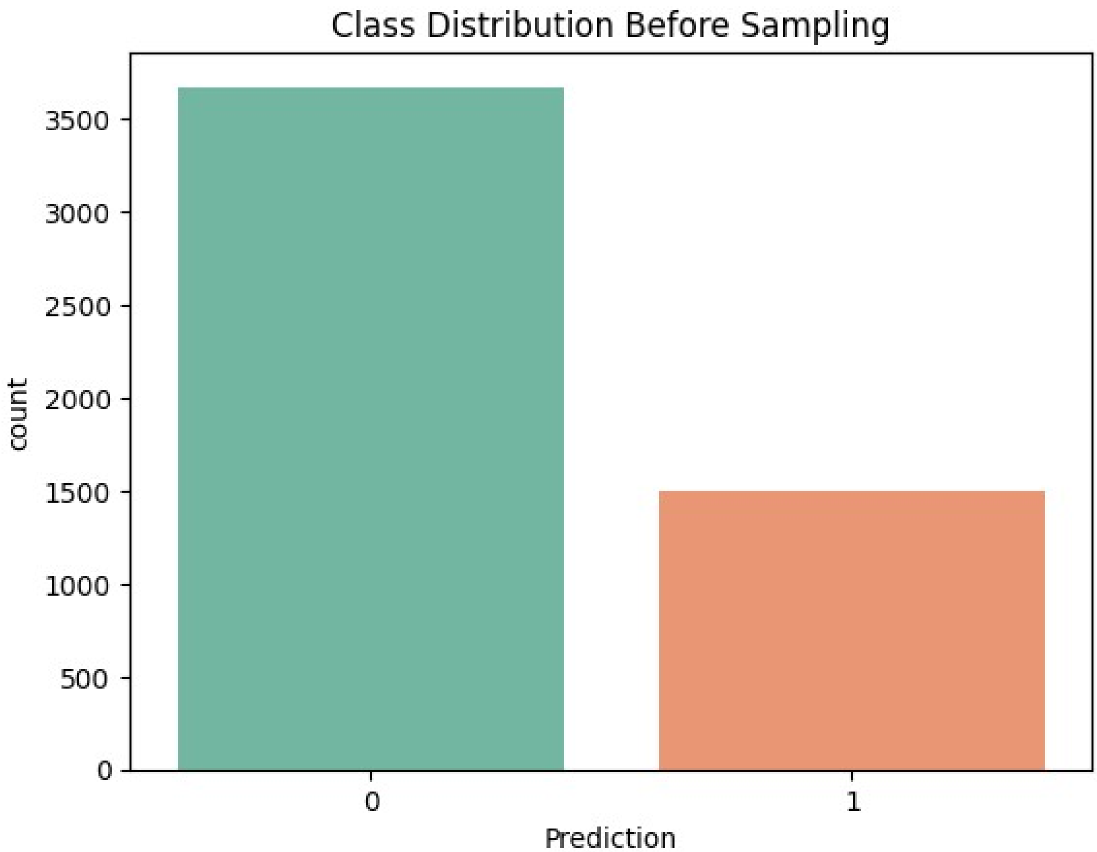
```
        # Count feature occurrences for each class
        for idx, c in enumerate(self.classes):
            X_c = X[y == c]
            self.class_feature_count[idx, :] = X_c.sum(axis=0)
            self.class_count[idx] = X_c.shape[0]

        # Prior probabilities P(C)
        self.class_priors = self.class_count / n_samples

        # Conditional probabilities with Laplace smoothing
        self.feature_log_prob = np.log(
            (self.class_feature_count + alpha) /
            (self.class_feature_count.sum(axis=1).reshape(-1, 1) +
alpha * n_features)
        )

    def _predict_single(self, x):
        log_posteriors = []
        for idx, c in enumerate(self.classes):
            log_prior = np.log(self.class_priors[idx])
            log_likelihood = np.sum(x * self.feature_log_prob[idx, :])
            log_posteriors.append(log_prior + log_likelihood)
        return int(self.classes[np.argmax(log_posteriors)])

    def predict(self, X):
        return np.array([self._predict_single(x) for x in X])

# Train model
nb = MultinomialNaiveBayesScratch()
nb.fit(X_train, y_train, alpha=1.0)

# Predict on test data
y_pred = nb.predict(X_test)

# Evaluate
print("□ Model Evaluation Results:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))
```

```
□ Model Evaluation Results:
Accuracy: 0.865

Confusion Matrix:
 [[ 52   0   4   0  11]
 [  0   0   0  33   0]
 [  0   0  57   0   1]
 [  0   0   1 232   0]
```

```
 [  4   0   0   0   5]]

Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.78      0.85        67
           1       0.00      0.00      0.00        33
           2       0.92      0.98      0.95        58
           3       0.88      1.00      0.93       233
           4       0.29      0.56      0.38         9

    accuracy                           0.86       400
   macro avg       0.60      0.66      0.62       400
weighted avg       0.81      0.86      0.83       400


D:\Anaconda Jupyter\Lib\site-packages\sklearn\metrics\
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
D:\Anaconda Jupyter\Lib\site-packages\sklearn\metrics\
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
D:\Anaconda Jupyter\Lib\site-packages\sklearn\metrics\
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))

#18. Implementation an Email Spam Detection model using a Support
Vector Machine (SVM) for
#binary classification, where emails are categorized as Normal (Not
Spam) or Abnormal (Spam).
#Apply oversampling or undersampling techniques to handle class
imbalance and analyze model
#performance using appropriate evaluation metrics.

# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
```

```python
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

# Step 2: Load dataset
data = pd.read_csv("emails.csv")

# Drop unnecessary columns
data = data.drop(['Email No.'], axis=1)

# Inspect dataset
print("Shape:", data.shape)
print("\nClass Distribution:\n", data['Prediction'].value_counts())

# Visualize initial class distribution
sns.countplot(x='Prediction', data=data, palette='Set2')
plt.title("Class Distribution Before Sampling")
plt.show()
```

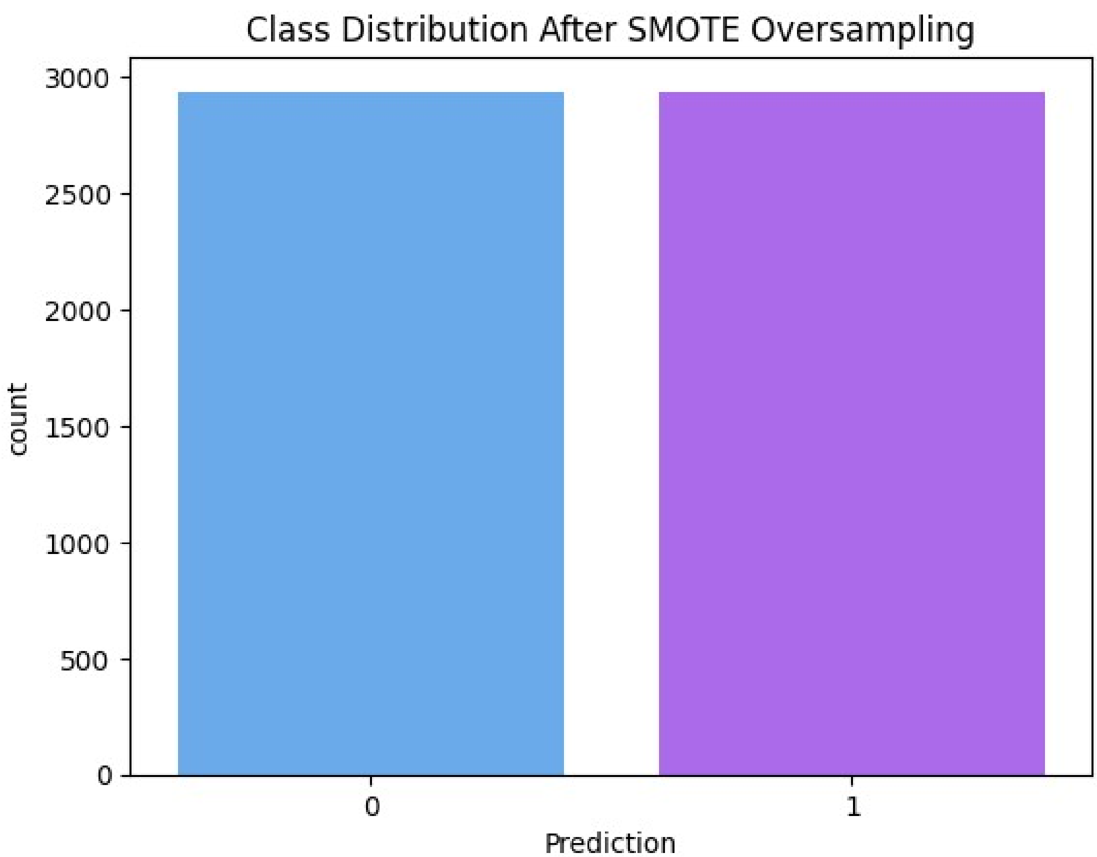
```
Shape: (5172, 3001)

Class Distribution:
 Prediction
0    3672
1    1500
Name: count, dtype: int64

C:\Users\mehul\AppData\Local\Temp\ipykernel_25824\974320911.py:12:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Prediction', data=data, palette='Set2')
```




```
# Step 3: Split data into features and target
X = data.drop('Prediction', axis=1)
y = data['Prediction']

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print("Before Sampling:")
print(y_train.value_counts())

Before Sampling:
Prediction
0    2937
1    1200
Name: count, dtype: int64

# Step 4: Apply SMOTE for oversampling minority class
smote = SMOTE(random_state=42)
X_train_bal, y_train_bal = smote.fit_resample(X_train, y_train)

print("After SMOTE Oversampling:")
```

```python
print(y_train_bal.value_counts())

# Visualize class distribution after SMOTE
sns.countplot(x=y_train_bal, palette='cool')
plt.title("Class Distribution After SMOTE Oversampling")
plt.show()
```

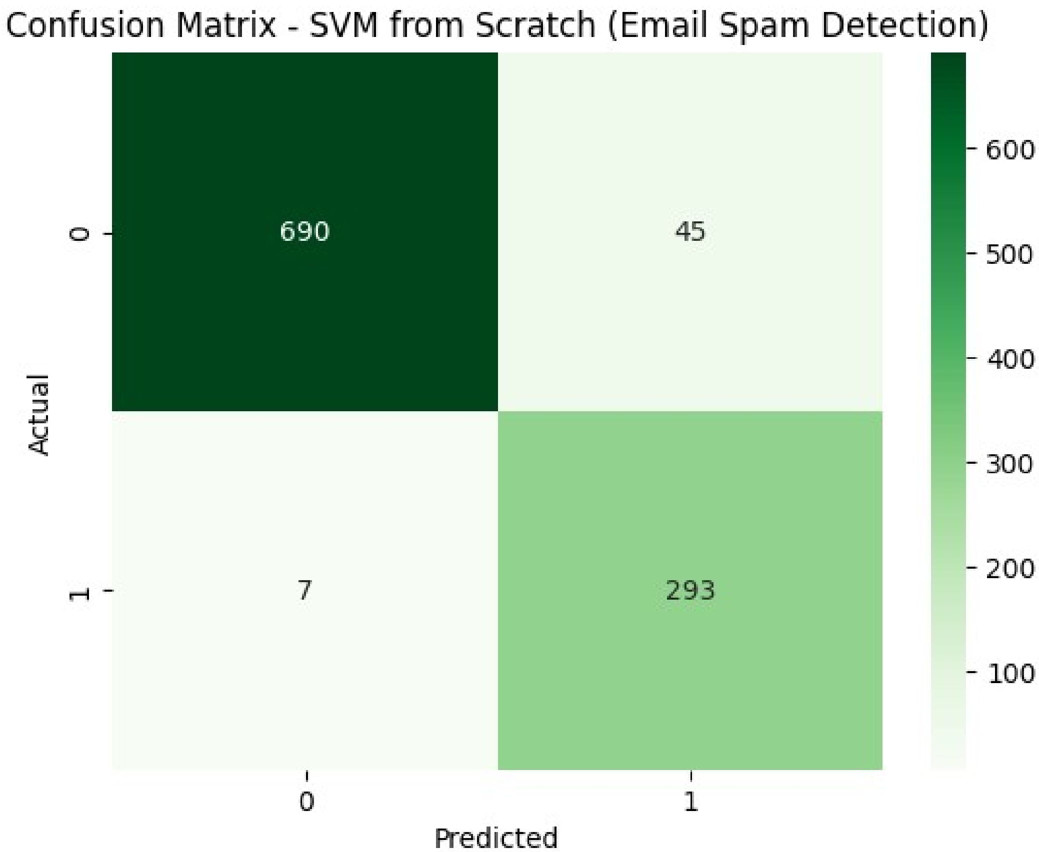
```
After SMOTE Oversampling:
Prediction
0    2937
1    2937
Name: count, dtype: int64

C:\Users\mehul\AppData\Local\Temp\ipykernel_25824\2794634887.py:9:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x=y_train_bal, palette='cool')
```



```
#undersampler=RandomUnderSampler(random_state=42)
#X_train_bal,y_train_bal=undersampler.fit_resample(X_train,y_train)

#y_train_bal.value_counts()

# Step 5: Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_bal)
X_test_scaled = scaler.transform(X_test)

# Step 6: Convert labels for hinge loss
y_train_bal_ = np.where(y_train_bal <= 0, -1, 1)
y_test_ = np.where(y_test <= 0, -1, 1)

# Step 7: Define SVM class (same structure and logic as Q19)

class SVMfromScratch:
    def __init__(self, learning_rate=0.0001, lambda_param=0.01,
n_iters=1000):
        self.lr = learning_rate        # learning rate
        self.lambda_param = lambda_param  # regularization (1/C)
        self.n_iters = n_iters
        self.w = None
        self.b = None

    def fit(self, X, y):
        n_samples, n_features = X.shape
        self.w = np.zeros(n_features)
        self.b = 0

        for _ in range(self.n_iters):
            for idx, x_i in enumerate(X):
                condition = y[idx] * (np.dot(x_i, self.w) - self.b) >=
1
                if condition:
                    # correctly classified → apply regularization only
                    self.w -= self.lr * (2 * self.lambda_param *
self.w)
                else:
                    # misclassified → apply hinge loss gradient
                    self.w -= self.lr * (2 * self.lambda_param *
self.w - np.dot(x_i, y[idx]))
                    self.b -= self.lr * y[idx]

    def predict(self, X):
        approx = np.dot(X, self.w) - self.b
        return np.sign(approx)

# Step 8: Train the model (same as 19)
svm_model = SVMfromScratch(learning_rate=0.0001, lambda_param=0.01,
```

```
n_iters=100)
svm_model.fit(X_train_scaled, y_train_bal_)

# Step 9: Prediction
y_pred = svm_model.predict(X_test_scaled)

# Convert {-1,1} back to {0,1}
y_pred_final = np.where(y_pred == -1, 0, 1)

# Step 10: Evaluation of performance
print("----- Custom SVM (from scratch) Performance -----")
print("Accuracy:", accuracy_score(y_test, y_pred_final)*100)
print("\nClassification Report:\n", classification_report(y_test,
y_pred_final))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred_final))

# Visualize Confusion Matrix
sns.heatmap(confusion_matrix(y_test, y_pred_final), annot=True,
fmt='d', cmap='Greens')
plt.title("Confusion Matrix - SVM from Scratch (Email Spam
Detection)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
----- Custom SVM (from scratch) Performance -----
Accuracy: 94.97584541062803

Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.94      0.96       735
           1       0.87      0.98      0.92       300

    accuracy                           0.95      1035
   macro avg       0.93      0.96      0.94      1035
weighted avg       0.95      0.95      0.95      1035


Confusion Matrix:
 [[690  45]
 [  7 293]]
```




```
#19. Implement an Email Spam Detection model from scratch using the
Support Vector Machine
#(SVM) algorithm for binary classification, where emails are labeled
as Normal (Not Spam) or
#Abnormal (Spam). Analyze model performance using appropriate
evaluation metrics.


import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
from sklearn.preprocessing import StandardScaler

data=pd.read_csv("emails.csv")

data.head()

  Email No.  the  to  ect  and  for  of    a  you  hou  ...  connevey
jay  \
0   Email 1    0   0    1    0    0   0    2    0    0  ...         0
0
1   Email 2    8  13   24    6    6   2  102    1   27  ...         0
```

```
0
2   Email 3    0   0    1    0    0   0    8    0    0  ...          0
0
3   Email 4    0   5   22    0    5   1   51    2   10  ...          0
0
4   Email 5    7   6   17    1    5   2   57    0    9  ...          0
0

   valued  lay  infrastructure  military  allowing  ff  dry
Prediction
0       0    0               0         0         0   0    0
0
1       0    0               0         0         0   1    0
0
2       0    0               0         0         0   0    0
0
3       0    0               0         0         0   0    0
0
4       0    0               0         0         0   1    0
0

[5 rows x 3002 columns]
```

```
data.shape
```

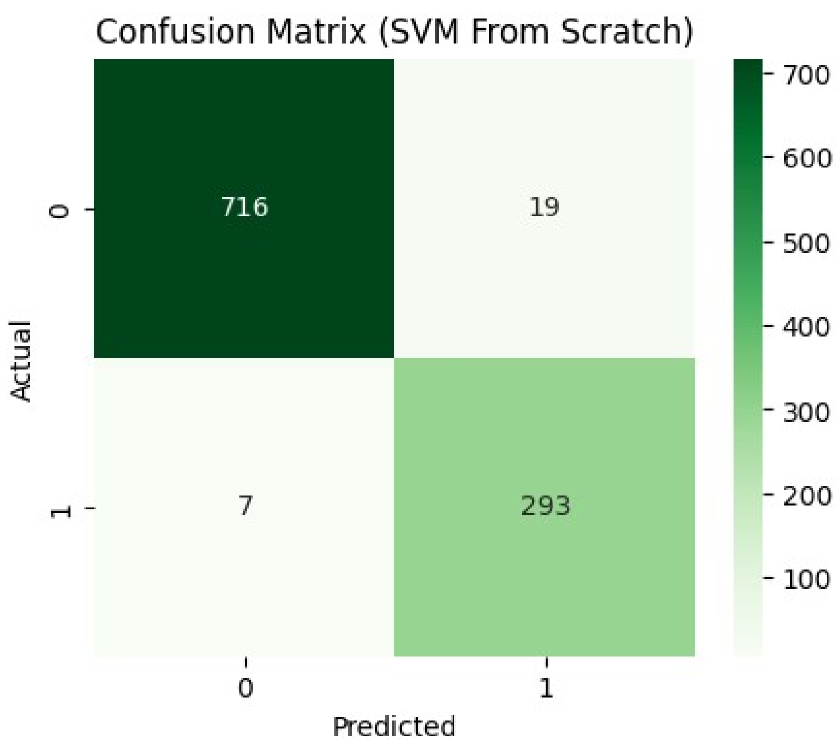
```
(5172, 3002)
```

```
data = data.drop(['Email No.'], axis=1)

X=data.drop('Prediction',axis=1).values
y=data['Prediction'].values

y=np.where(y==0,-1,1)

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

scaler=StandardScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)

class SVMfromScratch:
    def
__init__(self,learning_rate=0.001,lambda_param=0.01,n_iters=100):
        self.lr=learning_rate
        self.lambda_param=lambda_param
        self.n_iters=n_iters
        self.w=None
        self.b=None
```

```
    def fit(self,X,y):
        n_samples,n_features=X.shape
        self.w=np.zeros(n_features)
        self.b=0

        for _ in range(self.n_iters):
            for idx,x_i in enumerate(X):
                condition=y[idx]*(np.dot(x_i,self.w)-self.b)>=1


                if condition:
                    self.w-=self.lr*(2*self.lambda_param*self.w)
                else:
                    self.w=self.w-self.lr*(2*self.lambda_param*self.w-
np.dot(x_i,y[idx]))
                    self.b-=self.lr*y[idx]

    def predict(self,X):
        approx=np.dot(X,self.w)-self.b
        return np.sign(approx)


svm=SVMfromScratch()
svm.fit(X_train,y_train)

y_pred=svm.predict(X_test)

y_test_eval=np.where(y_test==-1,0,1)
y_pred_eval=np.where(y_pred==-1,0,1)




acc = accuracy_score(y_test_eval, y_pred_eval)
cm = confusion_matrix(y_test_eval, y_pred_eval)
cr = classification_report(y_test_eval, y_pred_eval)

print(f"Accuracy: {acc*100:.2f}%\n")
print("Confusion Matrix:\n", cm)
print("\nClassification Report:\n", cr)
```

```
Accuracy: 97.49%

Confusion Matrix:
 [[716  19]
 [  7 293]]

Classification Report:
               precision    recall  f1-score   support

           0       0.99      0.97      0.98       735
```

```
           1       0.94      0.98      0.96       300

    accuracy                           0.97      1035
   macro avg       0.96      0.98      0.97      1035
weighted avg       0.98      0.97      0.98      1035


import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(5,4))
sns.heatmap(cm,annot=True,fmt='d',cmap='Greens')
plt.title("Confusion Matrix (SVM From Scratch)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```




```
20. Implement an SVM model from scratch with a Polynomial Kernel to
predict student performance
(Pass/Fail) using the Student Performance Dataset based on features
like study time, absences,
and internal scores. Assess the model performance using precision,
recall, and F1-score.
```

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
data = pd.read_csv("student_performance.csv")

# Display first few rows
data.head()

  Student_ID  Gender  Study_Hours_per_Week  Attendance_Rate
Internal_Scores  \
0       S147    Male                    31        68.267841
86
1       S136    Male                    16        78.222927
73
2       S209  Female                    21        87.525096
74
3       S458  Female                    27        92.076483
99
4       S078  Female                    37        98.655517
63

  Parental_Education_Level Internet_Access_at_Home
Extracurricular_Activities  \
0              High School                     Yes
Yes
1                      PhD                      No
No
2                      PhD                     Yes
No
3                Bachelors                      No
No
4                  Masters                      No
Yes

   Final_Exam_Score Pass_Fail
0                63      Pass
1                50      Fail
2                55      Fail
3                65      Pass
4                70      Pass

data.shape
```

```
(708, 10)

# Keep only relevant features
data = data[[
    "Study_Hours_per_Week",
    "Attendance_Rate",
    "Internal_Scores",
    "Pass_Fail"
]]

# Encode target variable (Pass=1, Fail=0)
le_passfail = LabelEncoder()
data["Pass_Fail"] = le_passfail.fit_transform(data["Pass_Fail"])

# Check data
print("Dataset shape:", data.shape)
data.head()

Dataset shape: (708, 4)
```

| | Study_Hours_per_Week | Attendance_Rate | Internal_Scores | Pass_Fail |
|---|---|---|---|---|
| 0 | 31 | 68.267841 | 86 | 1 |
| 1 | 16 | 78.222927 | 73 | 0 |
| 2 | 21 | 87.525096 | 74 | 0 |
| 3 | 27 | 92.076483 | 99 | 1 |
| 4 | 37 | 98.655517 | 63 | 1 |

```
# Define X (features) and y (target)
X = data[["Study_Hours_per_Week", "Attendance_Rate",
"Internal_Scores"]].values
y = data["Pass_Fail"].values

# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split into train/test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

print("Train shape:", X_train.shape)
print("Test shape:", X_test.shape)

Train shape: (566, 3)
Test shape: (142, 3)

# ---------------------------------------------------------
# Step 3: Define Polynomial Kernel
# ---------------------------------------------------------
```

```
def polynomial_kernel(X1, X2, degree=3, c=1):
    return (np.dot(X1, X2.T) + c) ** degree

# --------------------------------------------------------
# Step 4: Define SVM Class with Polynomial Kernel (From Scratch)
# --------------------------------------------------------
class SVMPolynomial:
    def __init__(self, learning_rate=0.001, lambda_param=0.01,
n_iters=1000, degree=3, c=1):
        self.lr = learning_rate
        self.lambda_param = lambda_param
        self.n_iters = n_iters
        self.degree = degree
        self.c = c

    def fit(self, X, y):
        n_samples, n_features = X.shape
        y_ = np.where(y <= 0, -1, 1)  # convert 0 → -1
        self.alpha = np.zeros(n_samples)
        self.K = polynomial_kernel(X, X, self.degree, self.c)

        # Training loop
        for _ in range(self.n_iters):
            for i in range(n_samples):
                condition = y_[i] * (np.sum(self.alpha * y_ *
self.K[:, i])) >= 1
                if condition:
                    self.alpha[i] -= self.lr * (2 * self.lambda_param
* self.alpha[i])
                else:
                    self.alpha[i] += self.lr * (1 - y_[i] *
np.sum(self.alpha * y_ * self.K[:, i]))

        self.X_train = X
        self.y_train = y_

    def project(self, X):
        K = polynomial_kernel(X, self.X_train, self.degree, self.c)
        return np.dot(K, self.alpha * self.y_train)

    def predict(self, X):
        pred = self.project(X)
        return np.sign(pred)

# Initialize and train model (degree=3 polynomial)
svm_poly = SVMPolynomial(learning_rate=0.001, lambda_param=0.01,
n_iters=100, degree=2, c=1)
svm_poly.fit(X_train, y_train)
```

```
print("□ Training complete using Study Hours, Attendance Rate, and
Internal Scores.")

□ Training complete using Study Hours, Attendance Rate, and Internal
Scores.

# Predict test set
y_pred = svm_poly.predict(X_test)

# Convert {-1,1} → {0,1}
y_pred = np.where(y_pred == -1, 0, 1)

# Evaluate
print("□ SVM Polynomial Kernel Evaluation Results")
print("--------------------------------------------")
print("Accuracy:", round(accuracy_score(y_test, y_pred), 4))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test,
y_pred))

□ SVM Polynomial Kernel Evaluation Results
--------------------------------------------
Accuracy: 0.831

Confusion Matrix:
 [[57 14]
 [10 61]]

Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.80      0.83        71
           1       0.81      0.86      0.84        71

    accuracy                           0.83       142
   macro avg       0.83      0.83      0.83       142
weighted avg       0.83      0.83      0.83       142


21. Develop an SVM classifier from scratch using a Polynomial Kernel
on the Breast Cancer
Wisconsin Dataset to distinguish between benign and malignant tumors.
Evaluate the classifier using a confusion matrix and ROC curve to
analyze diagnostic accuracy.

import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix,roc_curve,auc
import matplotlib.pyplot as plt
```

```
data=pd.read_csv("brca.csv")

data.head()
```

```
   Unnamed: 0  x.radius_mean  x.texture_mean  x.perimeter_mean
x.area_mean  \
0           1         13.540           14.36             87.46
566.3
1           2         13.080           15.71             85.63
520.0
2           3          9.504           12.44             60.34
273.9
3           4         13.030           18.42             82.61
523.8
4           5          8.196           16.84             51.71
201.9

   x.smoothness_mean  x.compactness_mean  x.concavity_mean  \
0            0.09779             0.08129           0.06664
1            0.10750             0.12700           0.04568
2            0.10240             0.06492           0.02956
3            0.08983             0.03766           0.02562
4            0.08600             0.05943           0.01588

   x.concave_pts_mean  x.symmetry_mean  ...  x.texture_worst  \
0            0.047810           0.1885  ...            19.26
1            0.031100           0.1967  ...            20.49
2            0.020760           0.1815  ...            15.66
3            0.029230           0.1467  ...            22.81
4            0.005917           0.1769  ...            21.96

   x.perimeter_worst  x.area_worst  x.smoothness_worst
x.compactness_worst  \
0              99.70         711.2             0.14400
0.17730
1              96.09         630.5             0.13120
0.27760
2              65.13         314.9             0.13240
0.11480
3              84.46         545.9             0.09701
0.04619
4              57.26         242.2             0.12970
0.13570

   x.concavity_worst  x.concave_pts_worst  x.symmetry_worst  \
0            0.23900              0.12880            0.2977
1            0.18900              0.07283            0.3184
2            0.08867              0.06227            0.2450
3            0.04833              0.05013            0.1987
4            0.06880              0.02564            0.3105
```

```
   x.fractal_dim_worst  y
0              0.07259  B
1              0.08183  B
2              0.07773  B
3              0.06169  B
4              0.07409  B

[5 rows x 32 columns]
```

```
data.columns
```

```
Index(['Unnamed: 0', 'x.radius_mean', 'x.texture_mean',
'x.perimeter_mean',
       'x.area_mean', 'x.smoothness_mean', 'x.compactness_mean',
       'x.concavity_mean', 'x.concave_pts_mean', 'x.symmetry_mean',
       'x.fractal_dim_mean', 'x.radius_se', 'x.texture_se',
'x.perimeter_se',
       'x.area_se', 'x.smoothness_se', 'x.compactness_se',
'x.concavity_se',
       'x.concave_pts_se', 'x.symmetry_se', 'x.fractal_dim_se',
       'x.radius_worst', 'x.texture_worst', 'x.perimeter_worst',
       'x.area_worst', 'x.smoothness_worst', 'x.compactness_worst',
       'x.concavity_worst', 'x.concave_pts_worst', 'x.symmetry_worst',
       'x.fractal_dim_worst', 'y'],
      dtype='object')
```

```
data['y'].nunique()
```

```
2
```

```
data['y']=data['y'].map({'M':1,'B':0})

X=data.drop(columns=['y']).values
y=data['y'].values

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

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,rando
m_state=42)

print("Data Loaded Sucessfully!")
print("training Samples: ",X_train.shape[0])
print("Testing Samples: ",X_test.shape[0])
```

```
Data Loaded Sucessfully!
training Samples:  455
Testing Samples:  114
```

```
def polynomial_kernel(X1,X2,degrees=2,c=1):
    return (np.dot(X1,X2.T)+c)**degrees


# -------------------------------------------------------
# Step 4: Define SVM Class with Polynomial Kernel (From Scratch)
# -------------------------------------------------------
class SVMPolynomial:
    def __init__(self, learning_rate=0.001, lambda_param=0.01,
n_iters=1000, degree=2, c=1):
        self.lr = learning_rate
        self.lambda_param = lambda_param
        self.n_iters = n_iters
        self.degree = degree
        self.c = c

    def fit(self, X, y):
        n_samples, n_features = X.shape
        y_ = np.where(y <= 0, -1, 1)  # convert 0 → -1
        self.alpha = np.zeros(n_samples)
        self.K = polynomial_kernel(X, X, self.degree, self.c)

        for _ in range(self.n_iters):
            for i in range(n_samples):
                condition = y_[i] * (np.sum(self.alpha * y_ *
self.K[:, i])) >= 1
                if condition:
                    self.alpha[i] -= self.lr * (2 * self.lambda_param
* self.alpha[i])
                else:
                    self.alpha[i] += self.lr * (1 - y_[i] *
np.sum(self.alpha * y_ * self.K[:, i]))

        self.X_train = X
        self.y_train = y_

    def project(self, X):
        K = polynomial_kernel(X, self.X_train, self.degree, self.c)
        return np.dot(K, self.alpha * self.y_train)

    def predict(self, X):
        pred = self.project(X)
        return np.sign(pred)

# -------------------------------------------------------
# Step 5: Train SVM Model using Polynomial Kernel
# -------------------------------------------------------
svm_poly = SVMPolynomial(learning_rate=0.001, lambda_param=0.01,
n_iters=100, degree=2, c=1)
svm_poly.fit(X_train, y_train)
```

```
y_pred = svm_poly.predict(X_test)

# Convert {-1, 1} → {0, 1}
y_pred = np.where(y_pred == -1, 0, 1)

print("□ Model training completed successfully!")
```

```
□ Model training completed successfully!
```

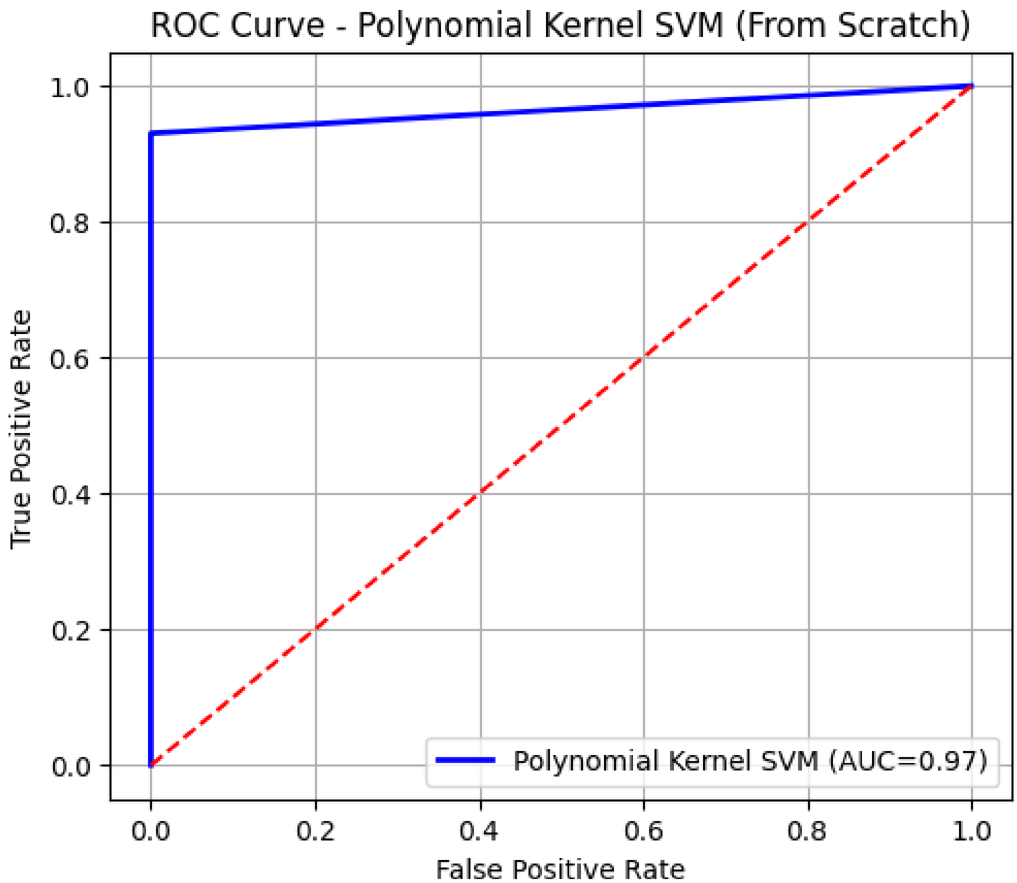
```
cm=confusion_matrix(y_test,y_pred)
print(cm)
```

```
[[71  0]
 [ 3 40]]
```

```
accuracy = np.mean(y_pred == y_test) * 100
print(f"Model Accuracy: {accuracy:.2f}%")
```

```
Model Accuracy: 97.37%
```

```
fpr,tpr,_=roc_curve(y_test,y_pred)
roc_auc=auc(fpr,tpr)

plt.figure(figsize=(6,5))
plt.plot(fpr,tpr,color='blue',lw=2,label=f"Polynomial Kernel SVM
(AUC={roc_auc:.2f})")
plt.plot([0,1],[0,1],color='red',linestyle='--')
plt.title('ROC Curve - Polynomial Kernel SVM (From Scratch)')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.grid(True)
plt.legend(loc='lower right')
plt.show()
```


ROC Curve - Polynomial Kernel SVM (From Scratch)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Polynomial Kernel SVM (AUC=0.97)