svm

November 6, 2023

[ ]:
```
!pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.3-py3-none-any.whl (7.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.3
```

[ ]:
```
import pandas as pd
from ucimlrepo import fetch_ucirepo
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
from sklearn.preprocessing import StandardScaler
```

[ ]:
```
def calculate_metrics(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred, average='weighted')
    recall = recall_score(y_true, y_pred, average='weighted')
    f1 = f1_score(y_true, y_pred, average='weighted')
    return accuracy, precision, recall, f1
```

[ ]:
```
# fetch dataset
spambase = fetch_ucirepo(id=94)
# data (as pandas dataframes)
X = spambase.data.features.to_numpy()
y = spambase.data.targets.to_numpy()
scaler = StandardScaler()
X = scaler.fit_transform(X)
y=y.ravel()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)
# Get predictions
```

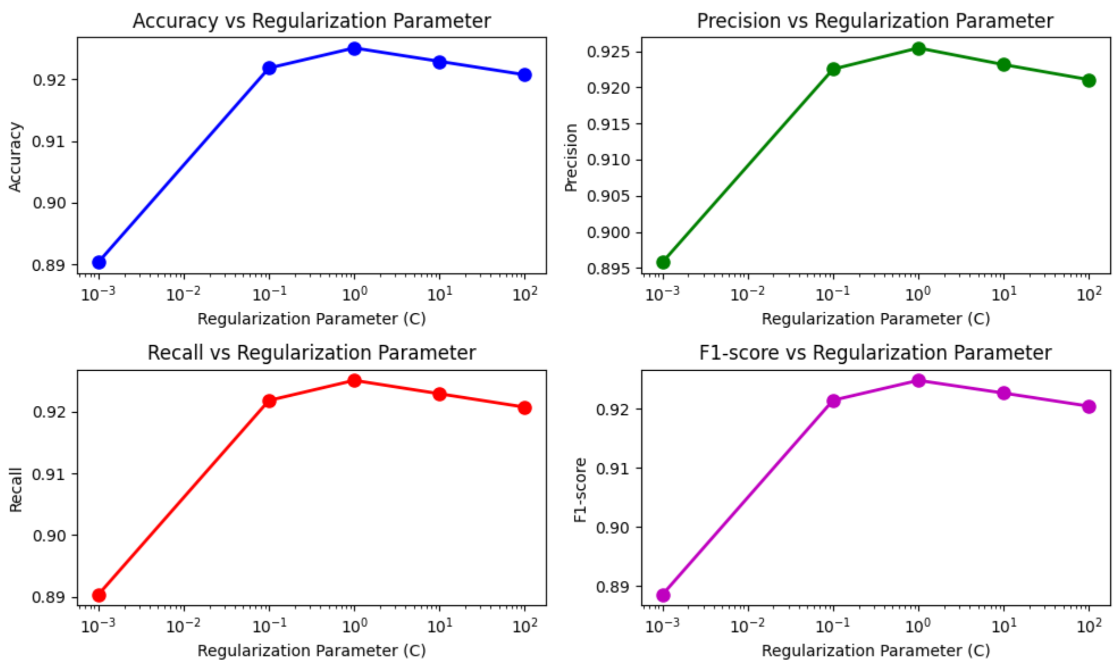
```
y_pred = svm_model.predict(X_test)

accuracy, precision, recall, f1 = calculate_metrics(y_test, y_pred)

# Print the metrics
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-score:", f1)
```

```
Accuracy: 0.9250814332247557
Precision: 0.9254572235213926
Recall: 0.9250814332247557
F1-score: 0.9247713676598335
```

[ ]:
```
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
import numpy as np
import matplotlib.pyplot as plt


X = spambase.data.features.to_numpy()
y = spambase.data.targets.to_numpy()
scaler = StandardScaler()
X = scaler.fit_transform(X)
y=y.ravel()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
# Regularization parameter values to test
C_values = [0.001, 0.1, 1, 10, 100]

# Lists to store evaluation metrics for different C values
accuracy_values = []
precision_values = []
recall_values = []
f1_values = []

# Train SVM models with different regularization parameters and calculate␣
↪metrics
for C in C_values:
    # Initialize SVM classifier with the current C value
    svm_model = SVC(kernel='linear', C=C, random_state=42)

    # Train the model
```

```
    svm_model.fit(X_train, y_train)

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

    # Calculate evaluation metrics and store them
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    accuracy_values.append(accuracy)
    precision_values.append(precision)
    recall_values.append(recall)
    f1_values.append(f1)

# Plotting the evaluation metrics
plt.figure(figsize=(10, 6))

# Plot accuracy
plt.subplot(2, 2, 1)
plt.plot(C_values, accuracy_values, marker='o', color='b', linestyle='-',␣
 ↪linewidth=2, markersize=8)
plt.xscale('log')
plt.xlabel('Regularization Parameter (C)')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Regularization Parameter')

# Plot precision
plt.subplot(2, 2, 2)
plt.plot(C_values, precision_values, marker='o', color='g', linestyle='-',␣
 ↪linewidth=2, markersize=8)
plt.xscale('log')
plt.xlabel('Regularization Parameter (C)')
plt.ylabel('Precision')
plt.title('Precision vs Regularization Parameter')

# Plot recall
plt.subplot(2, 2, 3)
plt.plot(C_values, recall_values, marker='o', color='r', linestyle='-',␣
 ↪linewidth=2, markersize=8)
plt.xscale('log')
plt.xlabel('Regularization Parameter (C)')
plt.ylabel('Recall')
plt.title('Recall vs Regularization Parameter')

# Plot F1-score
```

```
plt.subplot(2, 2, 4)
plt.plot(C_values, f1_values, marker='o', color='m', linestyle='-',␣
↪linewidth=2, markersize=8)
plt.xscale('log')
plt.xlabel('Regularization Parameter (C)')
plt.ylabel('F1-score')
plt.title('F1-score vs Regularization Parameter')

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

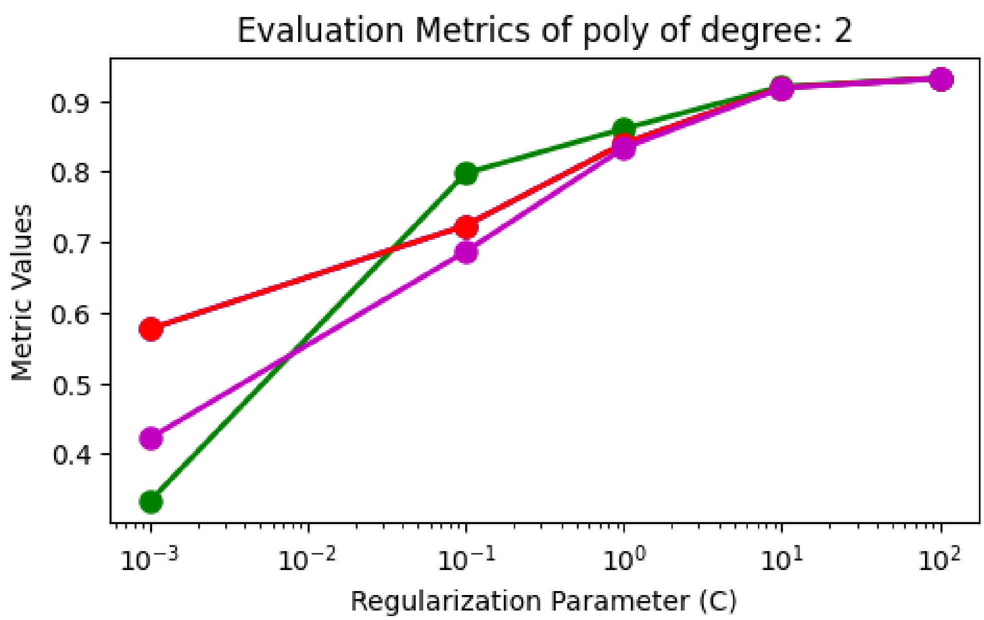


[ ]:
```
import warnings

warnings.simplefilter("ignore")

def plot_evaluation_metrics(evaluation_metrics,title):
  print(evaluation_metrics)
  colors=['b','g','r','m']
  plt.figure(figsize=(10, 6))
  j=0
  for metric_name, metric_values in evaluation_metrics.items():
    plt.subplot(2, 2, 2)
    plt.plot(C_values,metric_values, marker='o', color=colors[j],␣
↪linestyle='-', linewidth=2, markersize=8)
    plt.xscale('log')
```

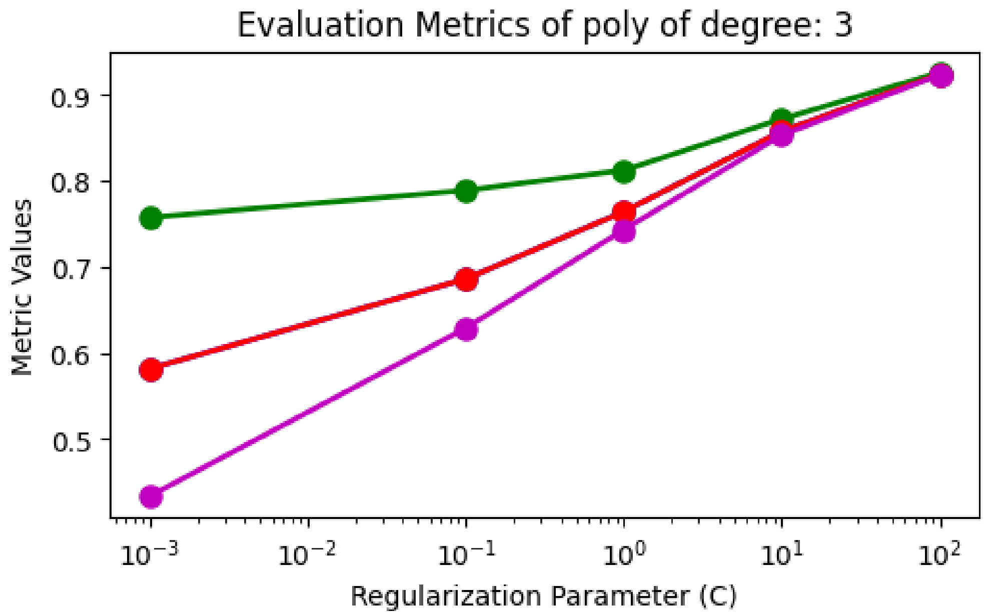
```python
    plt.xlabel('Regularization Parameter (C)')
    plt.ylabel('Metric Values')
    plt.title(f'Evaluation Metrics of {title}')
    j=j+1
  plt.tight_layout()
  plt.show()

for kernel_type in ['poly', 'rbf', 'sigmoid']:
  if(kernel_type=='poly'):
    degree_values = [2, 3]
  else:
    degree_values = [1]
  for kernel_degree in degree_values:
    accuracy_values = []
    precision_values = []
    recall_values = []
    f1_values = []
    for C in C_values:
        # Initialize SVM classifier with the current C value, kernel, and degree
        svm_model = SVC(kernel=kernel_type, degree=kernel_degree, C=C,␣
 ↪random_state=42)

        # Train the model
        svm_model.fit(X_train, y_train)

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

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

        # Store the evaluation metrics
        accuracy_values.append(accuracy)
        precision_values.append(precision)
        recall_values.append(recall)
        f1_values.append(f1)

    # Example usage:

    evaluation_metrics = {
        'accuracy': accuracy_values,#in blue color
        'precision': precision_values, # in green color
        'recall': recall_values, # in red color
        'f1_score': f1_values # in magenta color
```

```
    }
    title=kernel_type
    if(kernel_type=='poly'):
      title=title+" of degree: "+str(kernel_degree)
    plot_evaluation_metrics(evaluation_metrics,title)
```

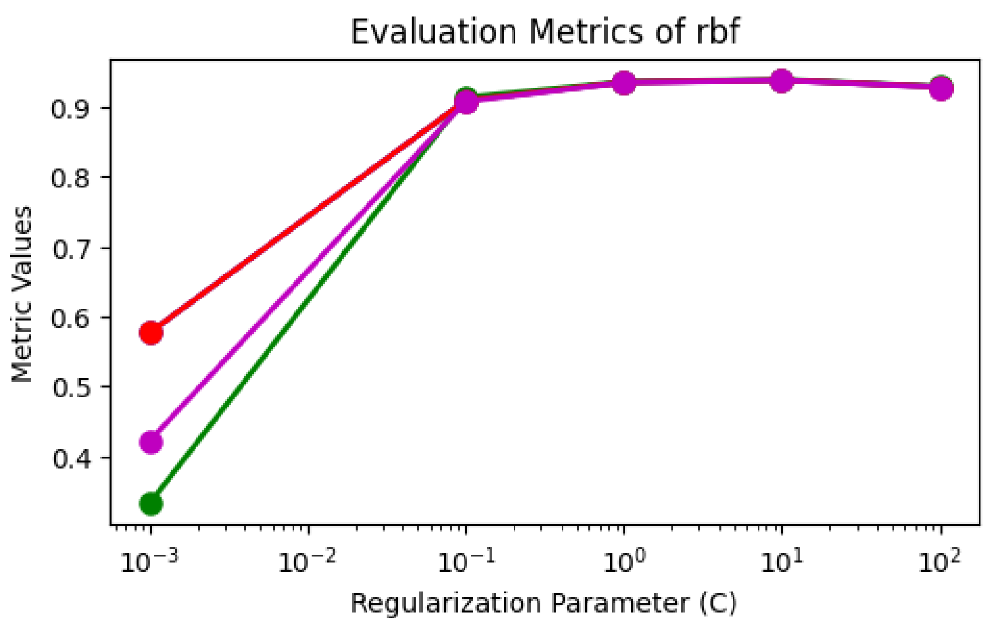
```
{'accuracy': [0.5765472312703583, 0.7231270358306189, 0.8393051031487514,
0.9185667752442996, 0.9315960912052117], 'precision': [0.33240670988551607,
0.7972378406706976, 0.86026508319177, 0.9198896829505937, 0.9320333378238186],
'recall': [0.5765472312703583, 0.7231270358306189, 0.8393051031487514,
0.9185667752442996, 0.9315960912052117], 'f1_score': [0.42168950386303067,
0.6862604219154048, 0.8326869003890973, 0.9179951253857518, 0.9313129878633263]}
```



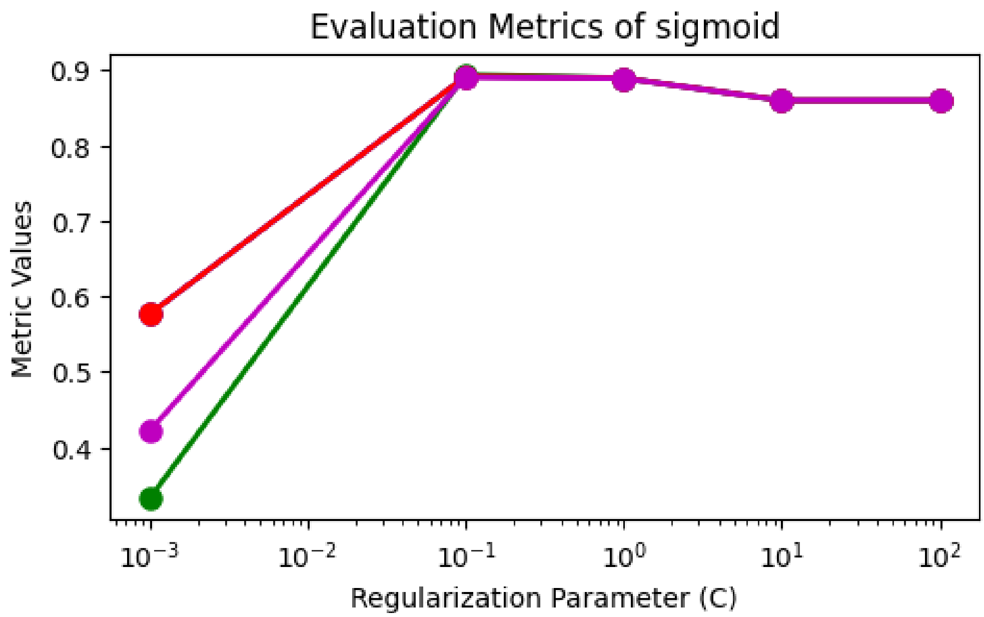

```
{'accuracy': [0.5819761129207384, 0.6862106406080347, 0.7643865363735071,
0.8577633007600435, 0.9239956568946797], 'precision': [0.7576739257215197,
0.7891535278606556, 0.8125196292208433, 0.8721995224220112, 0.9260358894267173],
'recall': [0.5819761129207384, 0.6862106406080347, 0.7643865363735071,
0.8577633007600435, 0.9239956568946797], 'f1_score': [0.4338669435831805,
0.6290733191772782, 0.7433931330909556, 0.8533608053057969, 0.923362256328884]}
```




```
{'accuracy': [0.5765472312703583, 0.9087947882736156, 0.9348534201954397,
0.9381107491856677, 0.9283387622149837], 'precision': [0.33240670988551607,
0.9134969798706446, 0.9355438527115785, 0.9387570626754904, 0.9288113297375262],
'recall': [0.5765472312703583, 0.9087947882736156, 0.9348534201954397,
0.9381107491856677, 0.9283387622149837], 'f1_score': [0.42168950386303067,
0.9075517241301602, 0.9345391992106767, 0.9378265248291895, 0.9280260130903975]}
```



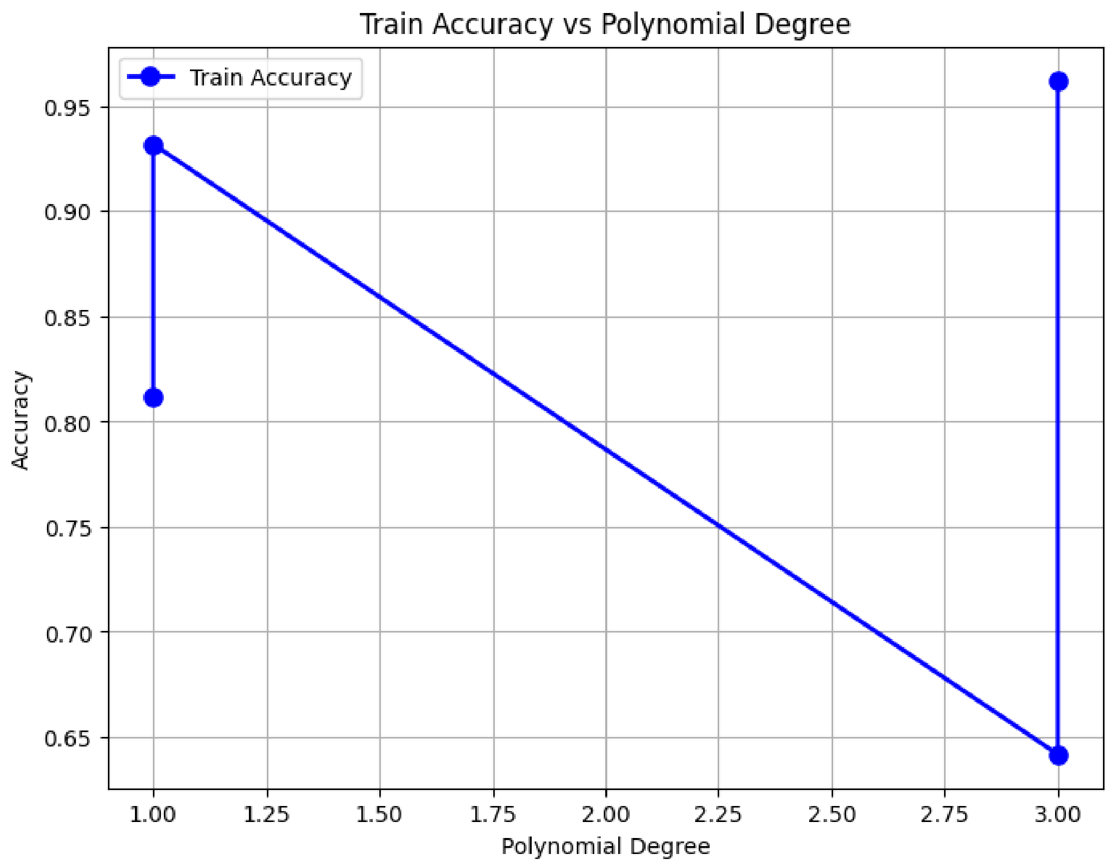
```
{'accuracy': [0.5765472312703583, 0.8914223669923995, 0.8892508143322475,
0.8599348534201955, 0.8599348534201955], 'precision': [0.33240670988551607,
0.8938211642230245, 0.8891272581680256, 0.8596180924551933, 0.859605527878904],
'recall': [0.5765472312703583, 0.8914223669923995, 0.8892508143322475,
0.8599348534201955, 0.8599348534201955], 'f1_score': [0.42168950386303067,
0.8902739384234444, 0.8889130233454514, 0.859651035187488, 0.8595947661900293]}
```

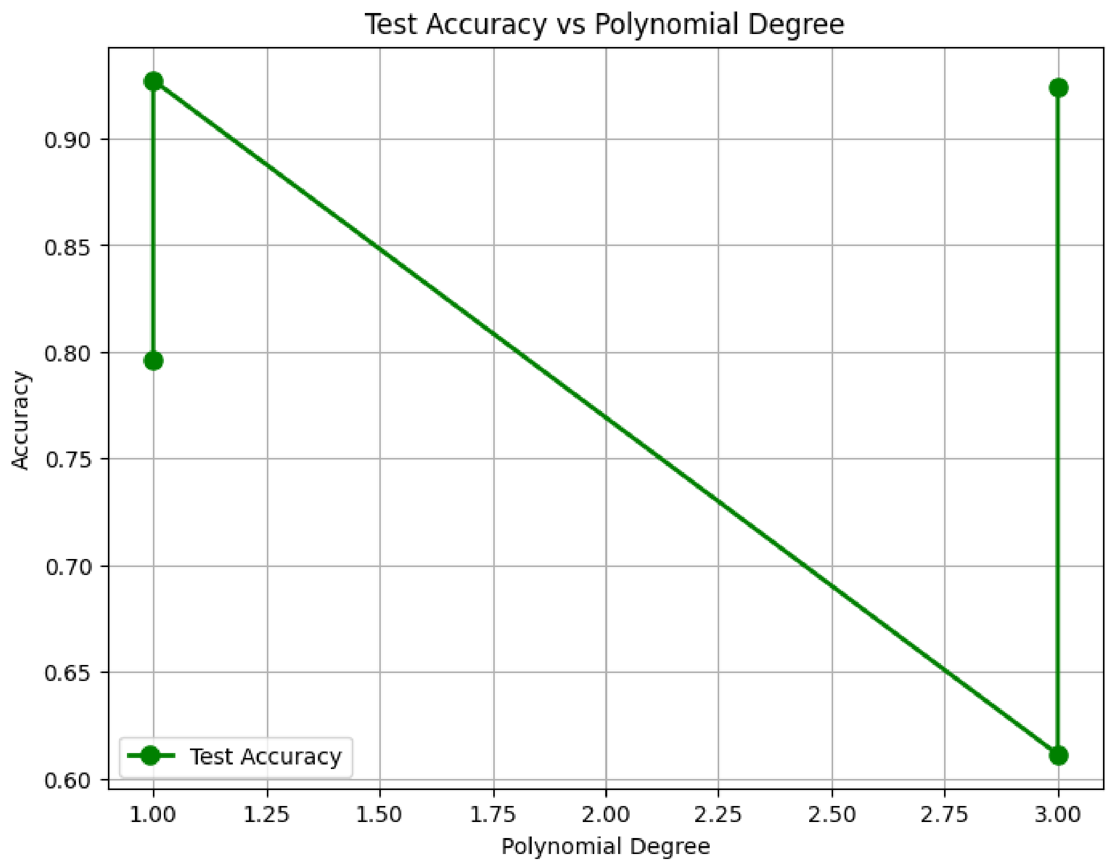


[ ]:
```python
degrees = [1, 1, 3, 3]
C_values = [0.01, 100, 0.01, 100]

train_accuracy_values = []
test_accuracy_values = []

for idx, degree in enumerate(degrees):

    C = C_values[idx]

    # Initialize SVM classifier with the current degree and C value
    svm_model = SVC(kernel='poly', degree=degree, C=C, random_state=42)

    # Train the model
    svm_model.fit(X_train, y_train)

    # Predict on training data
    y_train_pred = svm_model.predict(X_train)

    # Predict on test data
```

```
    y_test_pred = svm_model.predict(X_test)

    # Calculate accuracy for training and test sets
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)

    # Store accuracy values
    train_accuracy_values.append(train_accuracy)
    test_accuracy_values.append(test_accuracy)

# Tabulate and print the accuracy values
print("Polynomial Degree\tTrain Accuracy\tTest Accuracy")
for idx, degree in enumerate(degrees):
    print(f"{degree}\t\t\t{train_accuracy_values[idx]:.
 ↪4f}\t\t{test_accuracy_values[idx]:.4f}")

# Plotting the results
plt.figure(figsize=(8, 6))

# Plot train accuracy
plt.plot(degrees, train_accuracy_values, marker='o', color='b', linestyle='-',␣
 ↪linewidth=2, markersize=8, label='Train Accuracy')
plt.xlabel('Polynomial Degree')
plt.ylabel('Accuracy')
plt.title('Train Accuracy vs Polynomial Degree')
plt.grid(True)
plt.legend()
plt.show()

# Plot test accuracy
plt.figure(figsize=(8, 6))
plt.plot(degrees, test_accuracy_values, marker='o', color='g', linestyle='-',␣
 ↪linewidth=2, markersize=8, label='Test Accuracy')
plt.xlabel('Polynomial Degree')
plt.ylabel('Accuracy')
plt.title('Test Accuracy vs Polynomial Degree')
plt.grid(True)
plt.legend()
plt.show()
```

```
Polynomial Degree       Train Accuracy  Test Accuracy
1                       0.8117          0.7959
1                       0.9318          0.9273
3                       0.6418          0.6113
3                       0.9622          0.9240
```


Train Accuracy vs Polynomial Degree
Train Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
0.65
Accuracy
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Polynomial Degree


Test Accuracy vs Polynomial Degree
Accuracy
0.90
0.85
0.80
0.75
0.70
0.65
0.60
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Polynomial Degree
Test Accuracy

[ ]: