Support Vector Machines

In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.svm import LinearSVC, SVC
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, f1_score, pre
from tqdm import tqdm
```

First, load in our dataset.

In [ ]:
```
df = pd.read_csv("./data/nan_removed_cleaned_data.csv")
df.columns
```

Out[ ]:
```
Index(['budget', 'genres', 'id', 'imdb_id', 'original_title', 'overview',
       'popularity', 'poster_path', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'tagline', 'title', 'vote_average', 'vote_count',
       'log_popularity', 'title_length', 'num_languages', 'num_genres',
       'imdb_rating', 'imdb_budget', 'imdb_revenue', 'budget_currency',
       'revenue_currency', 'converted_budget', 'converted_revenue',
       'combined_budget', 'combined_revenue'],
      dtype='object')
```

SVMs are a supervised learning process for binary classification. So let's classify our data on a binary variable.

Just as we did with Naive Bayes, we can attempt to classify whether our film will be a box-office flop or success.

But this time, we can use most the data available to us instead of just a classifier based on the text description of the movie.

Let's set up the data:

In [ ]:
```
print(df.shape[0])

# First, convert our datetime objects to Unix timestamps
df['release_unix'] = pd.to_datetime(df['release_date'])
df['release_unix'] = df.release_unix.values.astype(np.int64) // 10 ** 9

# Next, only pick out any relevant columns
df = df[['runtime', 'vote_count', 'log_popularity', 'title_length', 'num_languages'
         'combined_revenue', 'release_unix']]

# Next, remove any missing data
df.dropna(inplace=True)

df.shape[0]
```

```
16012
```

Out[ ]:
```
13894
```

As shown, we only lost 2118 rows after removing missing data. We're left with 13894 rows of data!

We can use the same method as in Naive Bayes to create a new column that holds whether a film is a box office success or flop (binary).

In [ ]:
```python
def box_office_success(row):
    if row['combined_budget'] < row['combined_revenue']:
        return 1
    else:
        return 0

df['labels'] = df.apply(box_office_success, axis=1)

display(df.head(10))

display(df['labels'].value_counts())
```

	runtime	vote_count	log_popularity	title_length	num_languages	num_genres	imdb_rating	co
0	80	21	1.209259	32	5	1	8.1	
1	100	17305	4.680380	12	1	2	8.2	
2	122	10783	3.274462	15	1	1	8.4	
3	141	1506	2.635121	18	1	2	7.9	
4	87	225	2.127994	8	2	3	5.3	
5	126	9451	3.880470	17	3	5	7.6	
6	106	398	2.471653	18	1	2	7.4	
7	91	88	2.077690	18	1	1	7.6	
8	143	18370	4.407950	54	1	3	8.1	
9	111	15437	3.506308	17	3	2	8.2	

```
0    11684
1     2210
Name: labels, dtype: int64
```

Cool! As we can see, there are 2210 box office successes, and 11684 flops. Although we have a data imbalance, we can still apply SVM to our problem.

We'll want to keep the same proportion of class values in our training and testing set. Let's split our data:

In [ ]:
```python
# First, separate class labels
df_success = df[df['labels'] == 1]
```

```
df_fail = df[df['labels'] == 0]

# Next, just separate into predictors and response
x_success = df_success.drop('labels', axis=1)
y_success = df_success['labels']
x_fail = df_fail.drop('labels', axis=1)
y_fail = df_fail['labels']

# Next, take out specific class labels
x_success_train, x_success_test, y_success_train, y_success_test = train_test_split
x_fail_train, x_fail_test, y_fail_train, y_fail_test = train_test_split(x_fail, y_f

# Concatenate everything
x_train = pd.concat([x_success_train, x_fail_train])
x_test = pd.concat([x_success_test, x_fail_test])
y_train = pd.concat([y_success_train, y_fail_train])
y_test = pd.concat([y_success_test, y_fail_test])

# # And shuffle
# x_train = x_train.sample(frac=1, random_state=1)
# x_test = x_test.sample(frac=1, random_state=1)
# y_train = y_train.sample(frac=1, random_state=1612)
# y_test = y_test.sample(frac=1, random_state=1612)
```

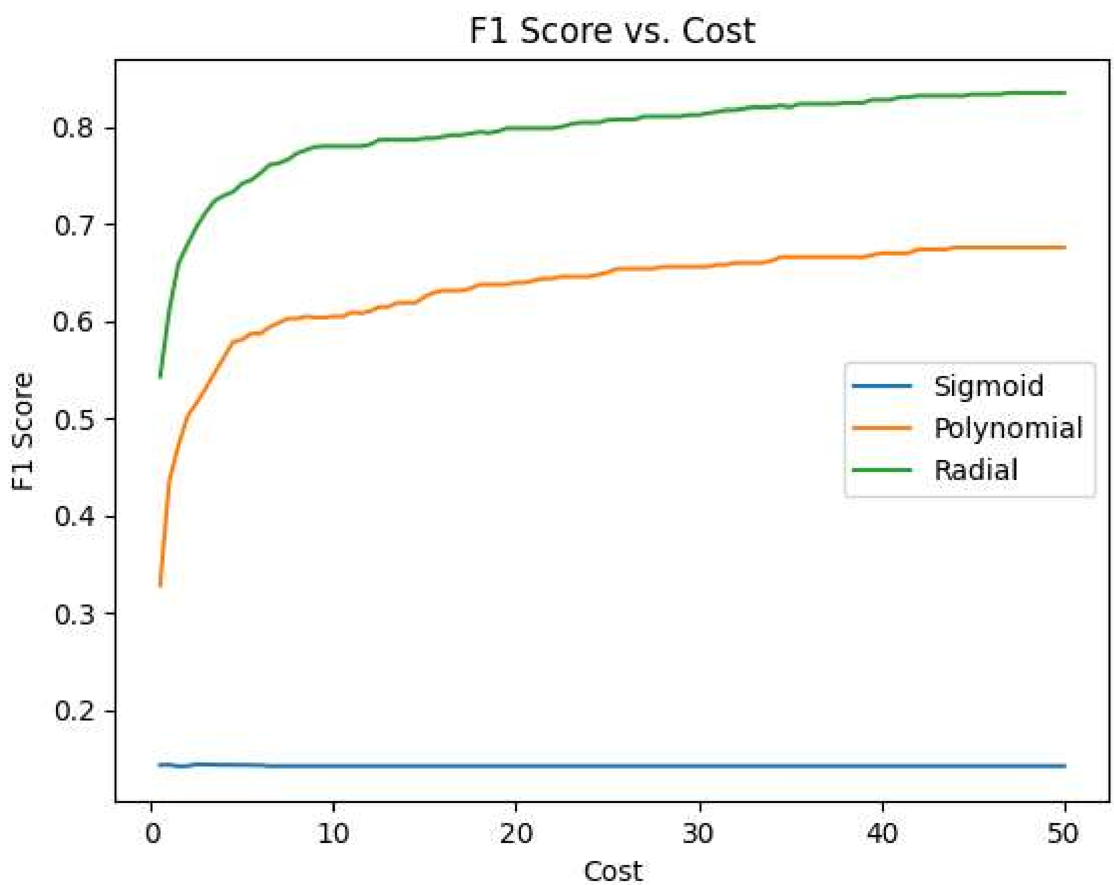
Great, now we have our separated data!

Let's run SVM on this:

In [ ]:
```
# Best costs for each kernel type
sigmoid_best_c = -1
sigmoid_best_f1 = -1
poly_best_c = -1
poly_best_f1 = -1
radial_best_c = -1
radial_best_f1 = -1

# Lists of f1 scores
sigmoid_f1s = []
poly_f1s = []
radial_f1s = []

# Range of costs to iterate over
costs = np.arange(0.5, 50.5, 0.5)

# Loop through a bunch of costs to determine the best one for each kernel
for cost in tqdm(costs):
    # Set up the SVMs
    SVM_sigmoid = SVC(C=cost, kernel='sigmoid')
    SVM_poly = SVC(C=cost, kernel='poly')
    SVM_radial = SVC(C=cost, kernel='rbf')

    # Fit each to the train data
    SVM_sigmoid.fit(x_train, y_train)
    SVM_poly.fit(x_train, y_train)
    SVM_radial.fit(x_train, y_train)
```

```python
    # Predict each on the test data
    pred_sigmoid = SVM_sigmoid.predict(x_test)
    pred_poly = SVM_poly.predict(x_test)
    pred_radial = SVM_radial.predict(x_test)

    # Calculate the best F1 for sigmoid
    sigmoid_f1 = f1_score(y_test, pred_sigmoid)
    if sigmoid_f1 > sigmoid_best_f1:
        sigmoid_best_c = cost
        sigmoid_best_f1 = sigmoid_f1

    # Calculate the best F1 for poly
    poly_f1 = f1_score(y_test, pred_poly)
    if poly_f1 > poly_best_f1:
        poly_best_c = cost
        poly_best_f1 = poly_f1

    # Calculate the best F1 for radial
    radial_f1 = f1_score(y_test, pred_radial)
    if radial_f1 > radial_best_f1:
        radial_best_c = cost
        radial_best_f1 = radial_f1

    # Append to arrays
    sigmoid_f1s.append(sigmoid_f1)
    poly_f1s.append(poly_f1)
    radial_f1s.append(radial_f1)

plt.figure()
plt.plot(costs, sigmoid_f1s, label='Sigmoid')
plt.plot(costs, poly_f1s, label='Polynomial')
plt.plot(costs, radial_f1s, label='Radial')
plt.legend()
plt.xlabel('Cost')
plt.ylabel('F1 Score')
plt.title('F1 Score vs. Cost')
plt.savefig('./imgs/svm_ims/cost_comparison.png')
plt.show()


print(f"Best cost for sigmoid kernel: {sigmoid_best_c}, F1 = {sigmoid_best_f1}")
print(f"Best cost for polynomial kernel: {poly_best_c}, F1 = {poly_best_f1}")
print(f"Best cost for radial kernel: {radial_best_c}, F1 = {radial_best_f1}")
```

```
100%|██████████| 100/100 [21:14<00:00, 12.74s/it]
```



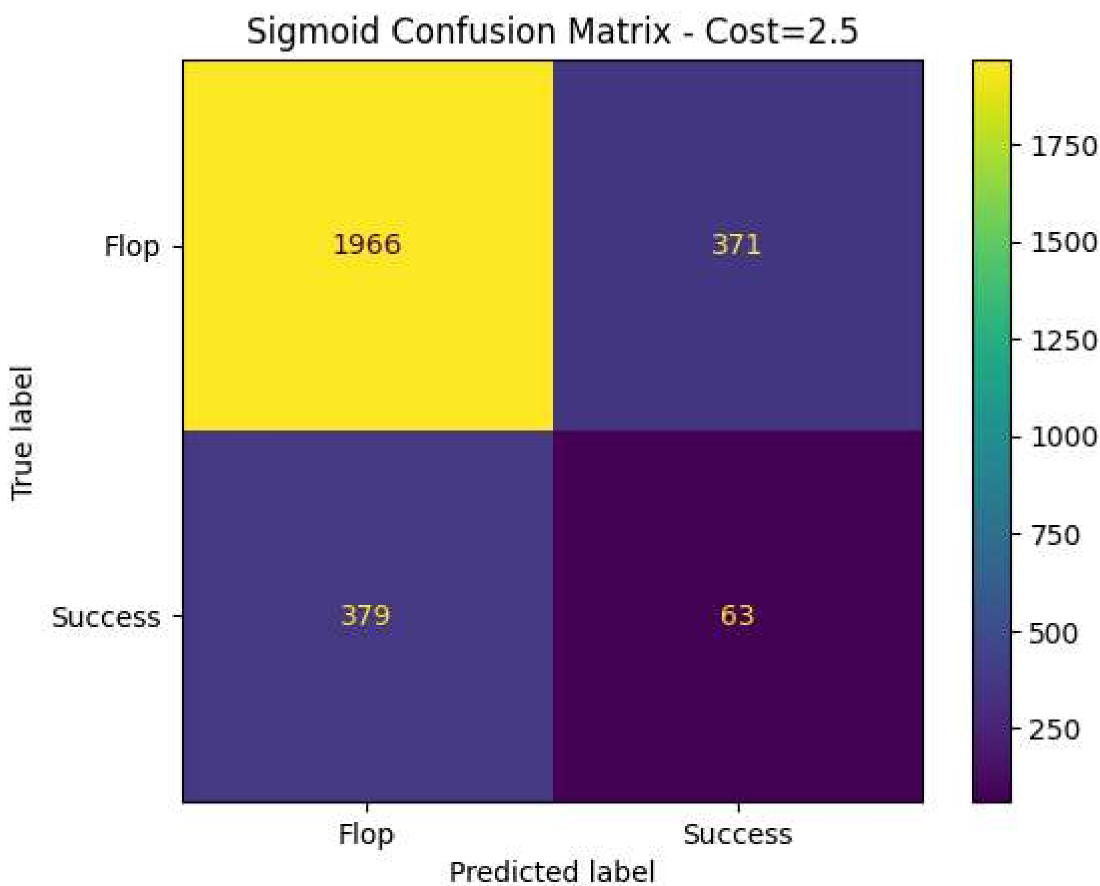

```
Best cost for sigmoid kernel: 2.5, F1 = 0.14383561643835616
Best cost for polynomial kernel: 44.0, F1 = 0.6755162241887906
Best cost for radial kernel: 47.0, F1 = 0.834419817470665
```

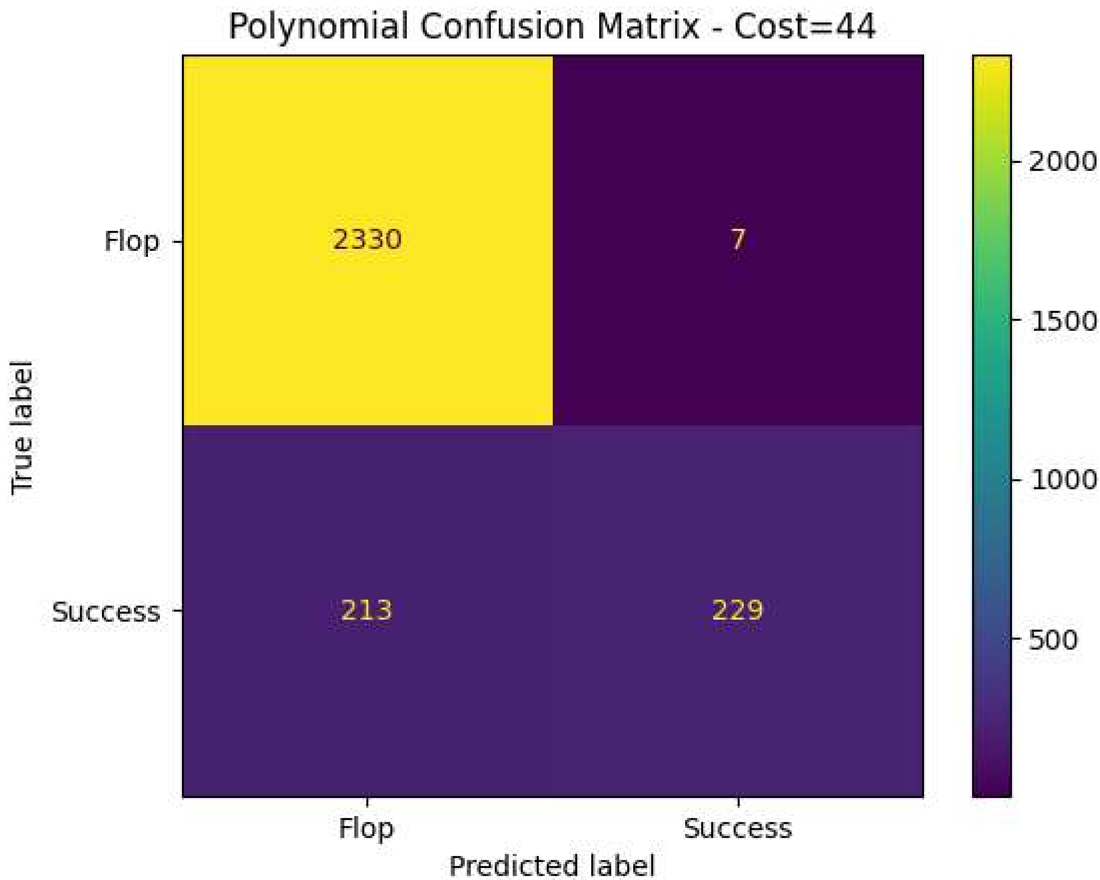
Great! Now we have (roughly) the best cost for each kernel. We can run the SVM on these specific models to evaluate our performance.

In [ ]:
```
# Set up the SVMs
SVM_sigmoid = SVC(C=2.5, kernel='sigmoid')
SVM_poly = SVC(C=44, kernel='poly')
SVM_radial = SVC(C=47, kernel='rbf')

# Fit each to the train data
SVM_sigmoid.fit(x_train, y_train)
SVM_poly.fit(x_train, y_train)
SVM_radial.fit(x_train, y_train)

# Predict each on the test data
pred_sigmoid = SVM_sigmoid.predict(x_test)
pred_poly = SVM_poly.predict(x_test)
pred_radial = SVM_radial.predict(x_test)

# Create confusion matrices
matrix_sigmoid = confusion_matrix(y_test, pred_sigmoid)
matrix_poly = confusion_matrix(y_test, pred_poly)
matrix_radial = confusion_matrix(y_test, pred_radial)

# Display conf. matrices
```

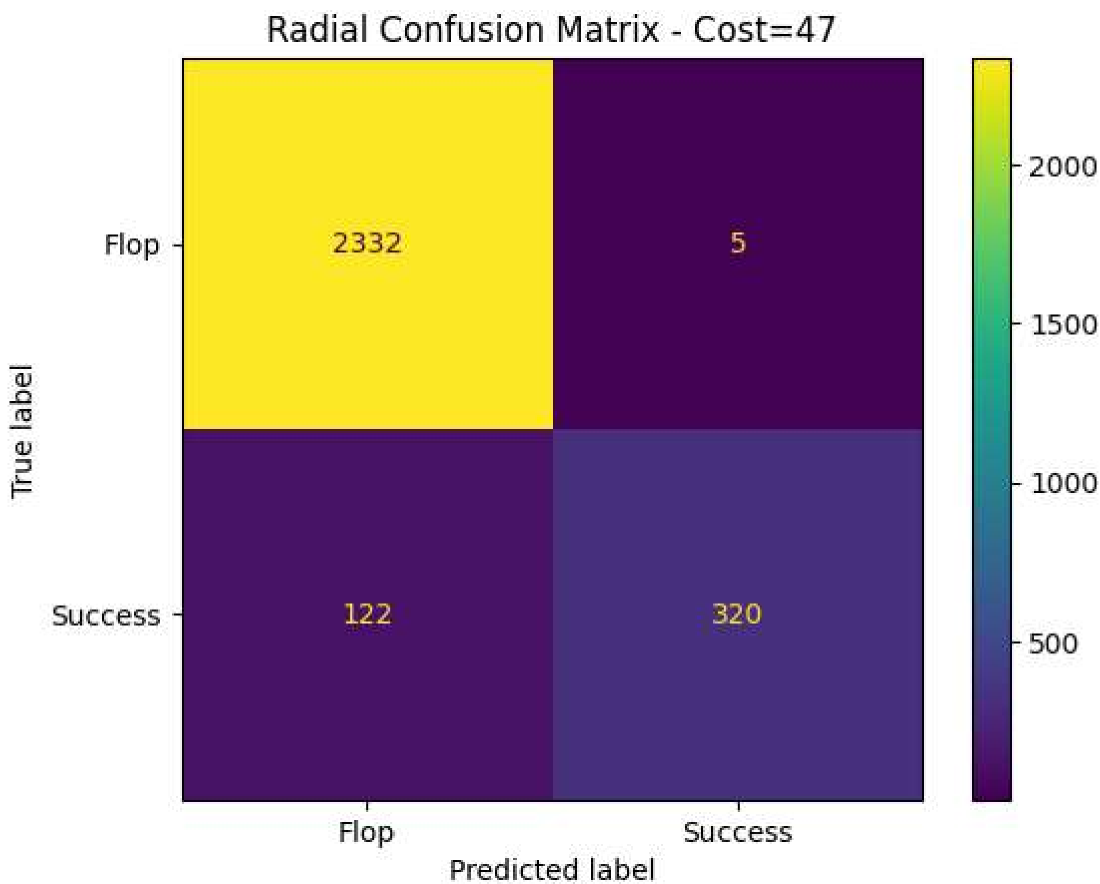
```python
# Also print info statistics about model performance
disp = ConfusionMatrixDisplay(matrix_sigmoid, display_labels=['Flop', 'Success'])
disp.plot()
plt.title('Sigmoid Confusion Matrix - Cost=2.5')
plt.savefig('./imgs/svm_ims/confusion_sigmoid.png')

print("Sigmoid Stats:")
sigmoid_prec, sigmoid_recall, sigmoid_f1, sigmoid_support = precision_recall_fscore
sigmoid_acc = accuracy_score(y_test, pred_sigmoid)
print(f"Accuracy = {sigmoid_acc:.4f}")
print(f"Average Precision = {np.mean(sigmoid_prec):.4f}")
print(f"Average Recall = {np.mean(sigmoid_recall):.4f}")
print(f"Averagge F1 Score = {np.mean(sigmoid_f1):.4f}")
print(f"Support = {sigmoid_support}\n")

disp = ConfusionMatrixDisplay(matrix_poly, display_labels=['Flop', 'Success'])
disp.plot()
plt.title('Polynomial Confusion Matrix - Cost=44')
plt.savefig(f'./imgs/svm_ims/confusion_poly.png')

print("Polynomial Stats:")
poly_prec, poly_recall, poly_f1, poly_support = precision_recall_fscore_support(y_t
poly_acc = accuracy_score(y_test, pred_poly)
print(f"Accuracy = {poly_acc:.4f}")
print(f"Average Precision = {np.mean(poly_prec):.4f}")
print(f"Average Recall = {np.mean(poly_recall):.4f}")
print(f"Average F1 Score = {np.mean(poly_f1):.4f}")
print(f"Support = {poly_support}\n")

disp = ConfusionMatrixDisplay(matrix_radial, display_labels=['Flop', 'Success'])
disp.plot()
plt.title('Radial Confusion Matrix - Cost=47')
plt.savefig(f'./imgs/svm_ims/confusion_radial.png')

print("Radial Stats:")
radial_prec, radial_recall, radial_f1, radial_support = precision_recall_fscore_sup
radial_acc = accuracy_score(y_test, pred_radial)
print(f"Accuracy = {radial_acc:.4f}")
print(f"Average Precision = {np.mean(radial_prec):.4f}")
print(f"Average Recall = {np.mean(radial_recall):.4f}")
print(f"Average F1 Score = {np.mean(radial_f1):.4f}")
print(f"Support = {radial_support}")
```

```
Sigmoid Stats:
Accuracy = 0.7301
Average Precision = 0.4918
Average Recall = 0.4919
Averagge F1 Score = 0.4918
Support = [2337  442]

Polynomial Stats:
Accuracy = 0.9208
Average Precision = 0.9433
Average Recall = 0.7576
Average F1 Score = 0.8152
Support = [2337  442]

Radial Stats:
Accuracy = 0.9543
Average Precision = 0.9675
Average Recall = 0.8609
Average F1 Score = 0.9040
Support = [2337  442]
```





Polynomial Confusion Matrix - Cost=44
True label
Flop
Success
2330
7
213
229
Predicted label
Flop
Success
2000
1500
1000
500



Radial Confusion Matrix - Cost=47
True label
Flop
Success
2332
5
122
320
Predicted label
Flop
Success
2000
1500
1000
500

As shown above, our Radial kernel is the most effective across **all of the** statistics, as also visible in the confusion matrix when compared to the others.

Going back to our Naive Bayes model from earlier, both the polynomial **and** radial kernel SVM models perform significantly better. This is not very surprising, since they are fed more data and are not restricted only to a text description of the film.