CS 441 - Final Project

You only need to complete and submit this once for the group. Be sure to add the other group members to the submission in Gradescope. List them here also.

Group Member Names	**NetIDs**
Hongxiao Chen	hc39

Complete the sections below. You do not need to fill out the checklist.

Total Points Available **[ ] / 150**

1. Problem description [ ] / 20
2. Model comparison
    a. Which models [ ] / 5
    b. Hyperparameter experiments [ ] / 35
    c. Best model/parameters result [ ] / 10
3. Analysis: Training Size or Features [ ] / 30
4. Stretch Goal: Innovation
    a. Approach description, experiments, innovation [ ] / 25
    b. Publishable with justification [ ] / 25
5. Attribution / Group Contributions [ ] -5 if incomplete (or page not selected)

1. Problem Description

Give an overview of the problem you are trying to solve.

During disaster, people may share the emergencies on their tweets before the government announce the formal alert. If we could discover whether a tweet is about a real disaster without human intervention, it may improve the speed of respond for such emergencies.

Explain what you are trying to predict, and what inputs (features) are available for prediction.

Predicting whether a tweet is about a real disaster or not by interpreting the context and language used in the tweets. Pure text tweets are available, with location, keyword, and main text for prediction.

Explain the experimental setup. How many examples for train, val, test? What are the metrics?

There are 10000 tweets, with format of id, keyword, location, text, target (1 for real disasters and 0 for not). I want to split it into train sets and validation sets with the ratio 8:2. The train.csv for training has 7613 tweets. There is another test dataset that has 3263 tweets.

What are some of the challenges in solving this problem?

The “keyword” column maybe crucial for deciding whether the “text” is indeed about disasters, but how to use “location” to help classification is not clear. I decide to try to ignore them first.

2. Model Comparison

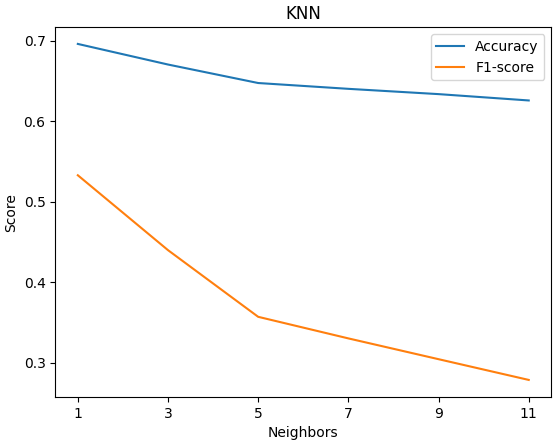
Which three models will you compare? Which hyperparameter(s) will you test?

K-Nearest Neighbors Param: K
Linear Regression Params: C, penalty
SVM Params: C, kernal

Use tables or plots to show the evaluated hyperparameter values for each model, and indicate which is best.
These experiments should use only the training and validation sets. Feel free to delete the boxes, as long as it's clear.

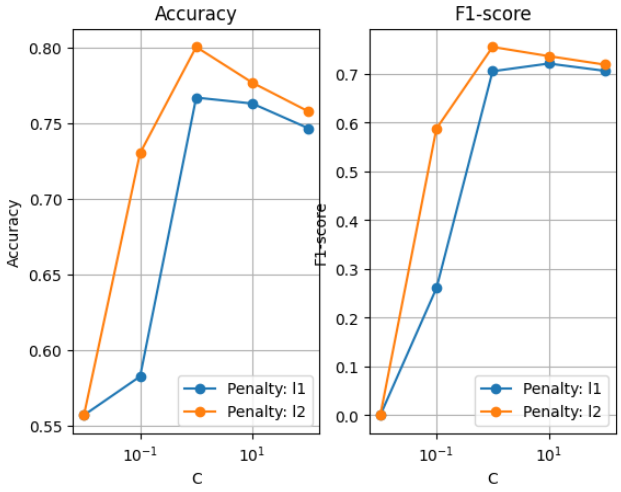
KNN:

K	Accuracy	F1-score
1	0.695995	0.532795
3	0.670387	0.439732
5	0.647406	0.356886
7	0.640184	0.330073
9	0.633618	0.304239
11	0.625739	0.278481



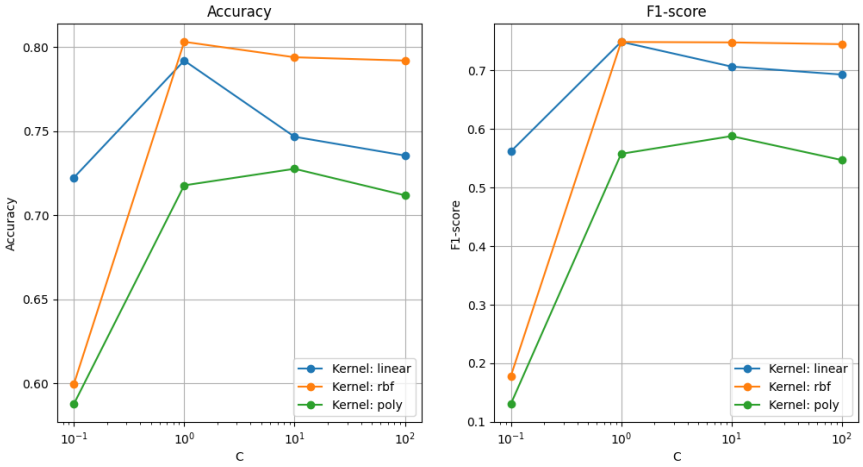
Linear Regression:

C	Penalty	Accuracy	F1-score
0.01	l1	0.556796	0.000000
0.01	l2	0.556796	0.000000
0.10	l1	0.582403	0.260465
0.10	l2	0.730138	0.587763
1.00	l1	0.766907	0.705394
1.00	l2	0.800394	0.755233
10.00	l1	0.762968	0.721236
10.00	l2	0.776756	0.736434
100.00	l1	0.746553	0.706240
100.00	l2	0.757715	0.718964



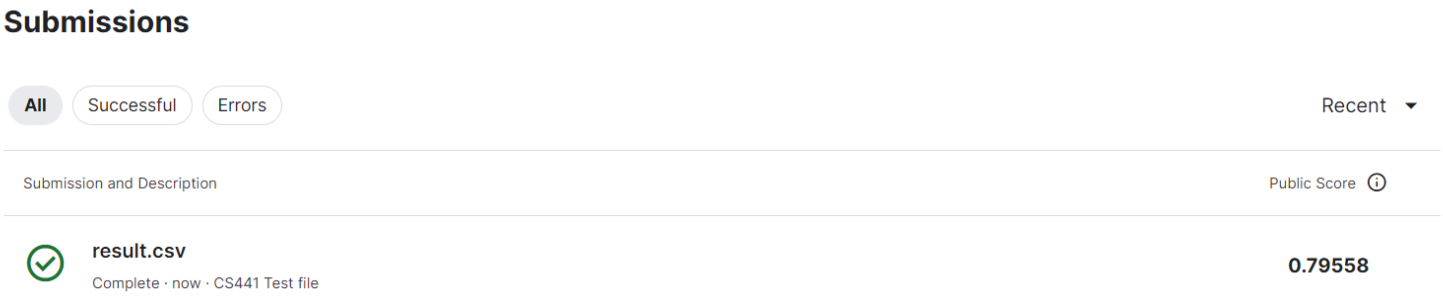
SVM:

C	Kernel	Accuracy	F1-score
0.1	linear	0.722259	0.561658
0.1	rbf	0.599475	0.177898
0.1	poly	0.587656	0.130194
1.0	linear	0.791858	0.749010
1.0	rbf	0.803020	0.748744
1.0	poly	0.717663	0.557613
10.0	linear	0.746553	0.706687
10.0	rbf	0.793828	0.747994
10.0	poly	0.727511	0.587885
100.0	linear	0.735391	0.693069
100.0	rbf	0.791858	0.744972
100.0	poly	0.711753	0.546956



Which model and hyperparameters are best overall? Train it using the combination of the train and validation sets and report test performance.

Best model: SVM with linear kernel and C = 1.0 has the highest F1-score.
Test F1-score: 0.79558



3. Additional Analysis: Either Effect of Training Data Size or Feature Analysis

Which type of analysis are you doing?

Training size

Present your experiments and conclusions. If evaluating features, include performance of your best model with different subsets of features and importance analysis using L1 regularization, mutual information, or similar. If evaluating training size, compare all three models using the selected hyperparameters.

4. Stretch Goal: Innovation

Describe your proposed approach

Provide and explain the experimental analysis of your proposed approach

What is innovative about your approach?

Is your approach potentially publishable? If not (the usual case), skip this part. If so, explain the research contributions and how it fits in with related work. What venue would you consider for publication?

5. Acknowledgments / Attribution

Link to your code (required!!)

https://github.com/Hongxiao-Chen/CS-441---Final-Project

Link to your data (if not pre-selected)

Disaster tweets: https://www.kaggle.com/competitions/nlp-getting-started/overview

External citations or resources

1. https://stackoverflow.com/questions/17390326/getting-rid-of-stop-words-and-document-tokenization-using-nltk

Group member contributions

Hongxiao Chen: everything

Did group members contribute roughly equally or unequally? If unequally, explain and specify whether one member went above and beyond, or someone contributed less than agreed or expected.
Equally

CS 441 - Final Project

April 25, 2024

1 CS 441 Final Project - Disaster Tweets

1.1 1. Import

[ ]:
```
import pandas as pd
import numpy as np
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, f1_score
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

[ ]:
```
train_df = pd.read_csv("train.csv")

# Split the dataset (80% train, 20% validation)
train_data, val_data = train_test_split(train_df, test_size = 0.2, random_state␣
 ↪= 441)

print("Training set:", train_data.shape)
print("Validation set:", val_data.shape)

print("Example:\n", train_df.iloc[32])
```

```
Training set: (6090, 5)
Validation set: (1523, 5)
Example:
 id                                                     49
keyword                                            ablaze
location                          Est. September 2012 - Bristol
text        We always try to bring the heavy. #metal #RT h…
target                                                  0
Name: 32, dtype: object
```

2 2. Preprocess

[ ]:
```
# Preprocess text, remove part of speech, stopwords, and http links
# https://stackoverflow.com/questions/17390326/
 ↪getting-rid-of-stop-words-and-document-tokenization-using-nltk
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words("english"))

def preprocess_text(text):
    tokens = nltk.word_tokenize(text.lower())
    tokens = [lemmatizer.lemmatize(token) for token in tokens if token.
 ↪isalpha() and token not in stop_words]
    return " ".join(tokens)

train_data["clean_text"] = train_data["text"].apply(preprocess_text)
val_data["clean_text"] = val_data["text"].apply(preprocess_text)

tfidf_vectorizer = TfidfVectorizer(max_features = 5000)

X_train = tfidf_vectorizer.fit_transform(train_data["clean_text"])
y_train = train_data["target"]

X_val = tfidf_vectorizer.transform(val_data["clean_text"])
y_val = val_data["target"]

print("Original:", train_data.iloc[1]["text"])
print("Processed:", train_data.iloc[1]["clean_text"])
```

```
Original: British diver Neil Anthony Fears found dead by the wreck of a
steamship - Daily Mail http://t.co/QP3GVvfoFq
Processed: british diver neil anthony fear found dead wreck steamship daily mail
http
```

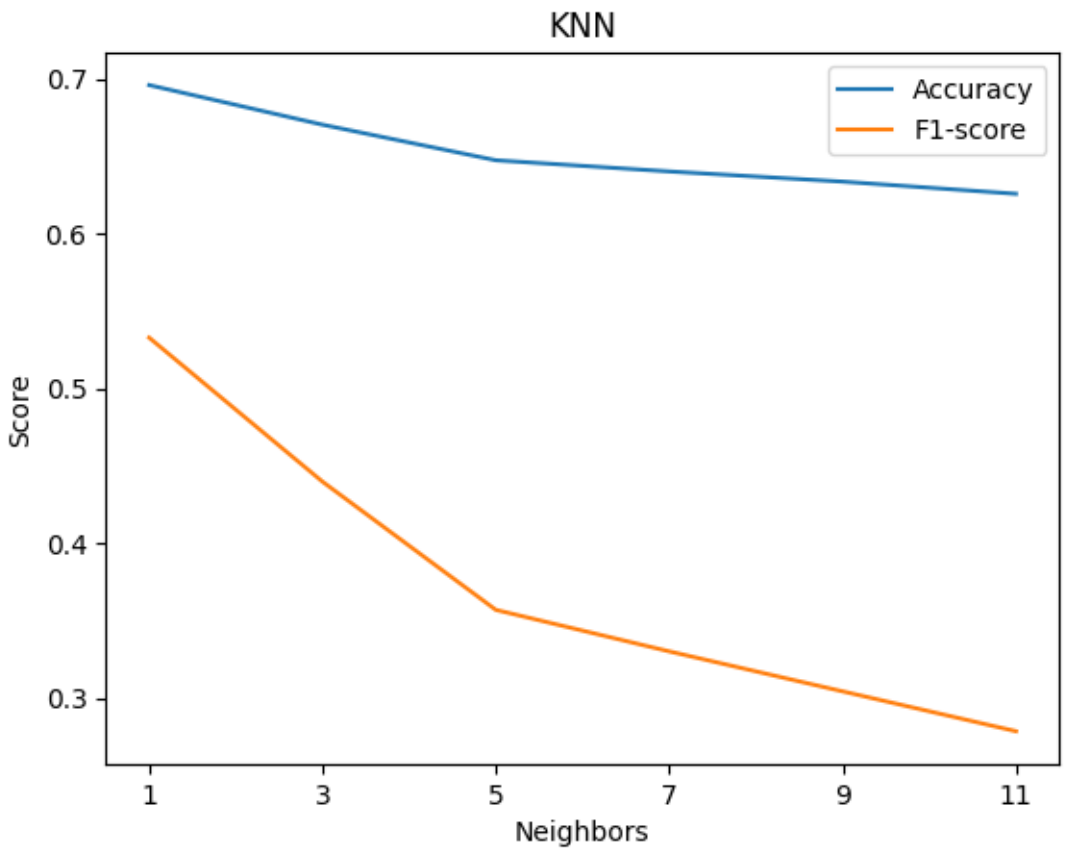
2.1 3. KNN

[ ]:
```
k_values = [1, 3, 5, 7, 9, 11]

accuracy_scores = []
f1_scores = []

for k in k_values:
    knn_model = KNeighborsClassifier(n_neighbors = k)
    knn_model.fit(X_train, y_train)

    y_pred = knn_model.predict(X_val)
    accuracy = accuracy_score(y_val, y_pred)
    f1 = f1_score(y_val, y_pred)
```

```
    accuracy_scores.append(accuracy)
    f1_scores.append(f1)

result_df = pd.DataFrame({
    'K': [K for K in k_values],
    'Accuracy': accuracy_scores,
    'F1-score': f1_scores
})
print(result_df)
```

```
    K  Accuracy  F1-score
0   1  0.695995  0.532795
1   3  0.670387  0.439732
2   5  0.647406  0.356886
3   7  0.640184  0.330073
4   9  0.633618  0.304239
5  11  0.625739  0.278481
```

[ ]:
```
plt.plot(k_values, accuracy_scores, label='Accuracy')
plt.plot(k_values, f1_scores, label='F1-score')
plt.xlabel('Neighbors')
plt.ylabel('Score')
plt.title('KNN')
plt.xticks(k_values)
plt.legend()
plt.show()
```



2.2 4. Logistic Regression

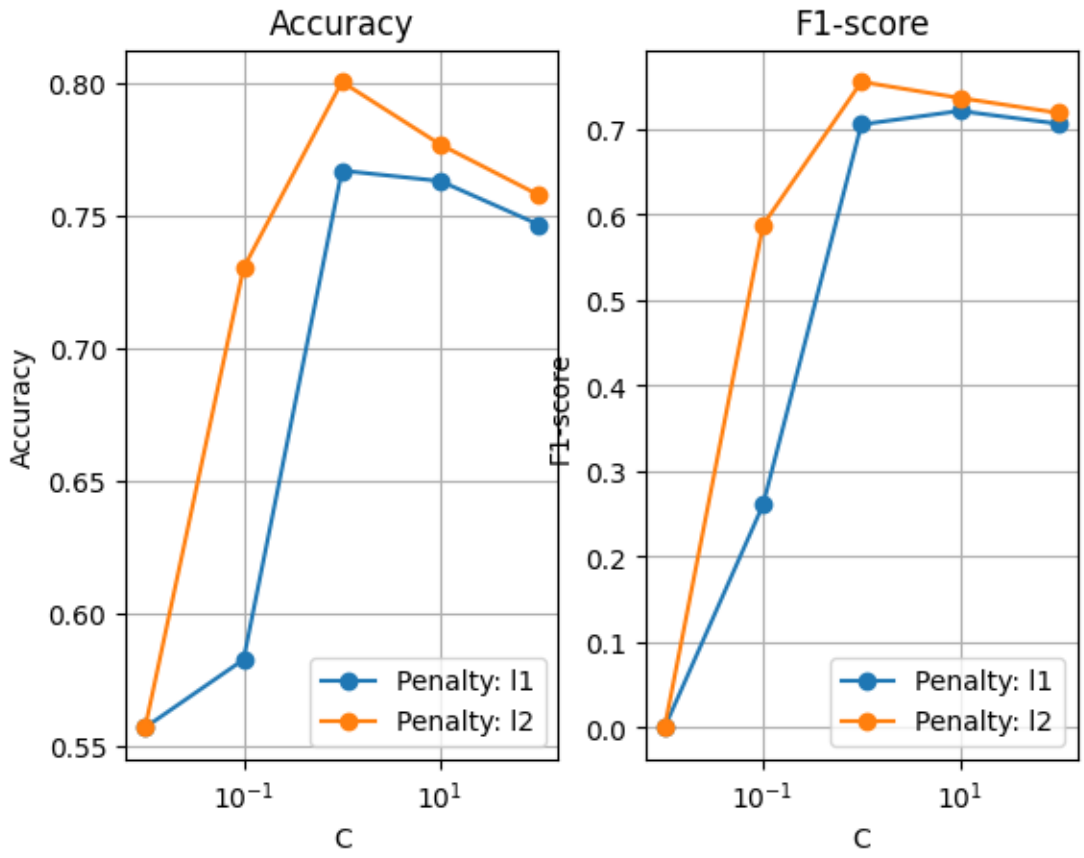
[ ]:
```
C_values = [0.01, 0.1, 1, 10, 100]
penalty_values = ['l1', 'l2']

hyperparam_values = []
accuracy_scores = []
f1_scores = []


for C in C_values:
    for penalty in penalty_values:
        lr_clf = LogisticRegression(C = C, penalty = penalty, solver =␣
 ↪'liblinear', random_state = 42)
        lr_clf.fit(X_train, y_train)

        y_pred = lr_clf.predict(X_val)
        accuracy = accuracy_score(y_val, y_pred)
        f1 = f1_score(y_val, y_pred)
```

```
        hyperparam_values.append((C, penalty))
        accuracy_scores.append(accuracy)
        f1_scores.append(f1)

results_df = pd.DataFrame({
    'C': [param[0] for param in hyperparam_values],
    'Penalty': [param[1] for param in hyperparam_values],
    'Accuracy': accuracy_scores,
    'F1-score': f1_scores
})

print(results_df)
```

```
        C Penalty  Accuracy  F1-score
0    0.01      l1  0.556796  0.000000
1    0.01      l2  0.556796  0.000000
2    0.10      l1  0.582403  0.260465
3    0.10      l2  0.730138  0.587763
4    1.00      l1  0.766907  0.705394
5    1.00      l2  0.800394  0.755233
6   10.00      l1  0.762968  0.721236
7   10.00      l2  0.776756  0.736434
8  100.00      l1  0.746553  0.706240
9  100.00      l2  0.757715  0.718964
```

[ ]:
```
plt.subplot(1, 2, 1)
for penalty in penalty_values:
    penalty_results = results_df[results_df['Penalty'] == penalty]
    plt.plot(penalty_results['C'], penalty_results['Accuracy'], marker='o',␣
 ↪label=f'Penalty: {penalty}')
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title('Accuracy')
plt.xscale('log')
plt.legend()
plt.grid(True)

plt.subplot(1, 2, 2)
for penalty in penalty_values:
    penalty_results = results_df[results_df['Penalty'] == penalty]
    plt.plot(penalty_results['C'], penalty_results['F1-score'], marker='o',␣
 ↪label = f'Penalty: {penalty}')
plt.xlabel('C')
plt.ylabel('F1-score')
plt.title('F1-score')
plt.xscale('log')
```

```
plt.legend()
plt.grid(True)

plt.show()
```



2.3 5. SVM

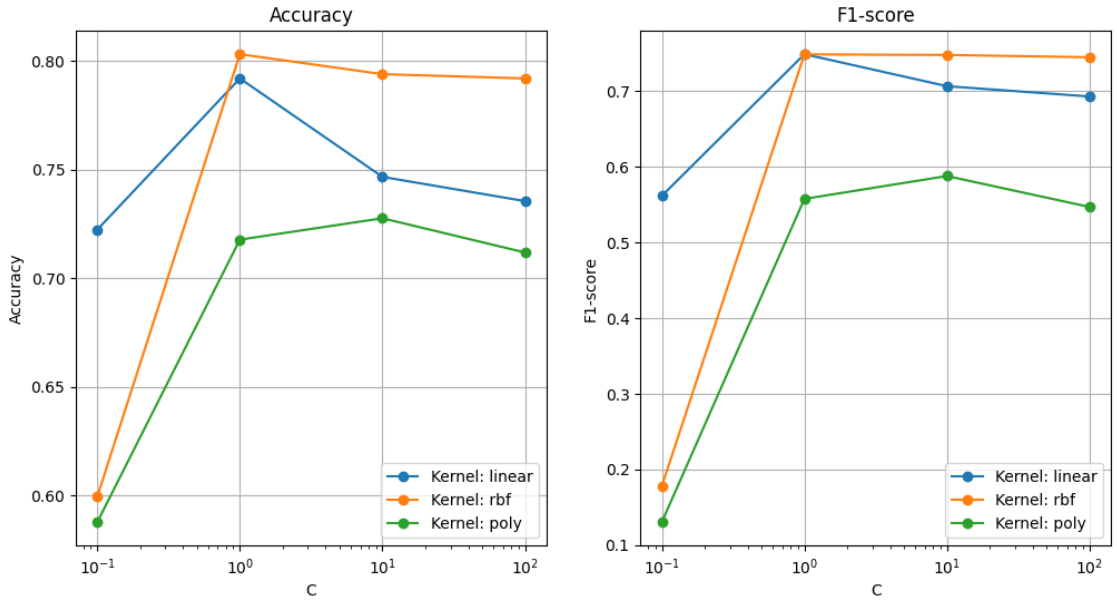
[ ]:
```
C_values = [0.1, 1, 10, 100]
kernel_values = ['linear', 'rbf', 'poly']

hyperparam_values = []
accuracy_scores = []
f1_scores = []

for C in C_values:
    for kernel in kernel_values:
        svm_model = SVC(C = C, kernel = kernel, random_state = 441)
        svm_model.fit(X_train, y_train)
```

```
        y_pred = svm_model.predict(X_val)
        accuracy = accuracy_score(y_val, y_pred)
        f1 = f1_score(y_val, y_pred)

        hyperparam_values.append((C, kernel))
        accuracy_scores.append(accuracy)
        f1_scores.append(f1)

results_df = pd.DataFrame({
    'C': [param[0] for param in hyperparam_values],
    'Kernel': [param[1] for param in hyperparam_values],
    'Accuracy': accuracy_scores,
    'F1-score': f1_scores
})

print(results_df)
```

```
        C  Kernel  Accuracy  F1-score
0     0.1  linear  0.722259  0.561658
1     0.1     rbf  0.599475  0.177898
2     0.1    poly  0.587656  0.130194
3     1.0  linear  0.791858  0.749010
4     1.0     rbf  0.803020  0.748744
5     1.0    poly  0.717663  0.557613
6    10.0  linear  0.746553  0.706687
7    10.0     rbf  0.793828  0.747994
8    10.0    poly  0.727511  0.587885
9   100.0  linear  0.735391  0.693069
10  100.0     rbf  0.791858  0.744972
11  100.0    poly  0.711753  0.546956
```

[ ]:
```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
for kernel in kernel_values:
    kernel_results = results_df[results_df['Kernel'] == kernel]
    plt.plot(kernel_results['C'], kernel_results['Accuracy'], marker='o',␣
  ↪label=f'Kernel: {kernel}')
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title('Accuracy')
plt.xscale('log')
plt.legend()
plt.grid(True)

plt.subplot(1, 2, 2)
for kernel in kernel_values:
    kernel_results = results_df[results_df['Kernel'] == kernel]
```

```
    plt.plot(kernel_results['C'], kernel_results['F1-score'], marker='o',␣
  ↪label=f'Kernel: {kernel}')
plt.xlabel('C')
plt.ylabel('F1-score')
plt.title('F1-score')
plt.xscale('log')
plt.legend()
plt.grid(True)

plt.show()
```



3 6. Test

[ ]:
```
train_df = pd.read_csv("train.csv")
train_df["clean_text"] = train_df["text"].apply(preprocess_text)
X_train = tfidf_vectorizer.transform(train_df["clean_text"])
y_train = train_df["target"]

test_df = pd.read_csv("test.csv")
test_df["clean_text"] = test_df["text"].apply(preprocess_text)
X_test = tfidf_vectorizer.transform(test_df["clean_text"])

svm_model = SVC(C = 1.0, kernel = 'linear', random_state = 441)
svm_model.fit(X_train, y_train)
y_test = svm_model.predict(X_test)
```

```
output = pd.DataFrame({'id': test_df['id']})
output['target'] = y_test
```

[ ]:
```
print(output)
output.to_csv("result.csv", index = False)
```

```
         id  target
0         0       1
1         2       1
2         3       1
3         9       1
4        11       1
…      …      …
3258  10861       1
3259  10865       1
3260  10868       1
3261  10874       1
3262  10875       0

[3263 rows x 2 columns]
```