hw4-bulaong

October 9, 2024

Github Link: https://github.com/dreeew05/CMSC-197/tree/main/Assignment%203

[352]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Regex for removing unwanted characters
import re

# To read email
from email import policy
from email.parser import BytesParser

# To count common words
from collections import Counter
```

Define Constants

[353]:
```
FOLDER_PATH = "trec06p-cs280/"
```

Import the stop words and convert into array

[354]:
```
stop_words = open('stop_words.txt').read().splitlines()

# For visualization purposes
stop_words[:5]
```

[354]: ['a', 'able', 'about', 'above', 'abst']

Initial DataFrame

[355]:
```
data = {
    'file_path': [],
    'category': []
}
df = pd.DataFrame(data)
```

Preprocessing

[356]:
```
labels_path = f"{FOLDER_PATH}labels"
with open(labels_path) as f:
    # Remove ../to mitigate file access errors
    str_to_remove = "../"
    for line in f:
        category, path = line.split()
        clean_path = path.replace(str_to_remove, '')
        new_row = pd.DataFrame([[clean_path, category]], columns=["file_path",␣
↪"category"])
        df = pd.concat([df, new_row], ignore_index=True)

df
```

[356]:
```
          file_path category
0      data/000/000      ham
1      data/000/001     spam
2      data/000/002     spam
3      data/000/003      ham
4      data/000/004     spam
…               …       …
37817  data/126/017     spam
37818  data/126/018     spam
37819  data/126/019     spam
37820  data/126/020     spam
37821  data/126/021     spam

[37822 rows x 2 columns]
```

[413]:
```
category_counts = df["category"].value_counts()
category_counts
```

[413]:
```
category
spam    24912
ham     12910
Name: count, dtype: int64
```

Cleaning the email:

- Remove alphanumeric characters
- Remove punctuation marks
- Remove stop words

[357]:
```
def clean_email(email_body):
    # [^a-zA-Z\s]+ => For non-alphabetic and non-whitespace (punctuations, new␣
↪line, tab)
    # \s+ => For one or more whitespace characters
    pattern = r"[^a-zA-Z\s]+|\s+"  # Combine both patterns
    return re.sub(pattern, " ", email_body).strip().lower()
```

[358]:

```python
def remove_stop_words(clean_message):
    return [word for word in clean_message.split() if word not in stop_words]
```

Iterating to each mail: - Clean each mail - Tokenize the clean mail

[359]:

```python
def tokenize_mail(df, to_remove_stop_words = False):
    contents_arr = []

    for path in df["file_path"]:
        current_file_path = f"{FOLDER_PATH}{path}"
        with open(current_file_path, "rb") as f:
            raw_email = f.read()

        # Parse email content
        msg = BytesParser(policy=policy.default).parsebytes(raw_email)

        # Extract body (defaulting to empty string in case of issues)
        body = ""

        # Define a function to decode email parts safely
        def decode_payload(part):
            try:
                charset = part.get_content_charset() or "utf-8"
                return part.get_payload(decode=True).decode(charset)
            except (LookupError, UnicodeDecodeError):
                return part.get_payload(decode=True).decode("utf-8",␣
 ↪errors="replace")

        # Check for multipart or single-part message
        if msg.is_multipart():
            for part in msg.iter_parts():
                if part.get_content_type() == "text/plain":
                    body = decode_payload(part)
                    break
        else:
            body = decode_payload(msg)

        # Clean the email body and append the word list
        clean_email_body = clean_email(body)
        if to_remove_stop_words:
            word_list= remove_stop_words(clean_email_body)
        else:
            word_list = list(clean_email_body.split())
        contents_arr.append(word_list)
    return contents_arr
```

Adding another column to dataframe

[360]:
```
df['word_list'] = tokenize_mail(df, True)
```

Split the dataset into three groups:

- Training set for ham
- Training set for spam
- Testing set

[361]:
```
def split_dataset(df):
    train_df = df[df["file_path"] < "data/071"]
    train_ham_df = train_df[train_df["category"] == "ham"]
    train_spam_df = train_df[train_df["category"] == "spam"]

    test_df = df[df["file_path"] >= "data/071"]

    return train_df, train_ham_df, train_spam_df, test_df
```

[362]:
```
# For Visualization Purposes
train_df, train_ham_df, train_spam_df, test_df = split_dataset(df)
print("Training Set")
display(train_df)
print("Ham Training Set")
display(train_ham_df)
print("Spam Training Set")
display(train_spam_df)
print("Testing Set")
display(test_df)
```

```
Training Set

          file_path category  \
0      data/000/000      ham
1      data/000/001     spam
2      data/000/002     spam
3      data/000/003      ham
4      data/000/004     spam
…               …       …
21295  data/070/295     spam
21296  data/070/296     spam
21297  data/070/297     spam
21298  data/070/298      ham
21299  data/070/299     spam

                                               word_list
0      [mailing, list, queried, weeks, ago, running, …
1      [luxury, watches, buy, rolex, rolex, cartier, …
2      [academic, qualifications, prestigious, acc, r…
3      [greetings, verify, subscription, plan, fans, …
4      [chauncey, conferred, luscious, continued, ton…
```

```
…                                                    …
21295                  [http, high, biz, ez, xin, walla]
21296  [special, offer, adobe, video, collection, ado…
21297  [doctype, html, public, dtd, html, transitiona…
21298  [mounted, infrared, demodulator, hb, realised,…
21299  [http, tmqmct, overpace, net, suffering, pain,…

[21300 rows x 3 columns]
```

Ham Training Set

```
          file_path category  \
0      data/000/000      ham
3      data/000/003      ham
5      data/000/005      ham
6      data/000/006      ham
10     data/000/010      ham
…               …      …
21270  data/070/270      ham
21271  data/070/271      ham
21288  data/070/288      ham
21293  data/070/293      ham
21298  data/070/298      ham

                                               word_list
0      [mailing, list, queried, weeks, ago, running, …
3      [greetings, verify, subscription, plan, fans, …
5       [quiet, quiet, well, straw, poll, plan, running]
6      [working, departed, totally, bell, labs, recom…
10     [greetings, mass, acknowledgement, signed, pla…
…                                                    …
21270  [equation, generate, prime, numbers, equation,…
21271  [equation, generate, prime, numbers, equation,…
21288  [dear, dmdx, users, guidance, generating, dmdx…
21293  [built, handyboard, works, great, testmotor, p…
21298  [mounted, infrared, demodulator, hb, realised,…

[7523 rows x 3 columns]
```

Spam Training Set

```
          file_path category  \
1      data/000/001     spam
2      data/000/002     spam
4      data/000/004     spam
7      data/000/007     spam
8      data/000/008     spam
…               …      …
21294  data/070/294     spam
21295  data/070/295     spam
```

```
21296  data/070/296     spam
21297  data/070/297     spam
21299  data/070/299     spam

                                                word_list
1       [luxury, watches, buy, rolex, rolex, cartier, …
2       [academic, qualifications, prestigious, acc, r…
4       [chauncey, conferred, luscious, continued, ton…
7       [nbc, today, body, diet, beaches, magazines, h…
8       [oil, sector, going, crazy, weekly, gift, kkpt…
…                                                     …
21294                                        [txt, add]
21295                  [http, high, biz, ez, xin, walla]
21296  [special, offer, adobe, video, collection, ado…
21297  [doctype, html, public, dtd, html, transitiona…
21299  [http, tmqmct, overpace, net, suffering, pain,…

[13777 rows x 3 columns]
```

Testing Set

```
          file_path category  \
21300  data/071/000     spam
21301  data/071/001      ham
21302  data/071/002     spam
21303  data/071/003     spam
21304  data/071/004     spam
…               …        …
37817  data/126/017     spam
37818  data/126/018     spam
37819  data/126/019     spam
37820  data/126/020     spam
37821  data/126/021     spam

                                                word_list
21300  [hesitantly, derive, perverse, satisfaction, c…
21301  [things, perform, experiment, display, will, r…
21302  [best, offer, month, viggra, ci, ialis, vaiium…
21303  [de, ar, wne, cr, doesn, matter, ow, real, st,…
21304  [special, offer, adobe, video, collection, ado…
…                                                     …
37817  [great, news, expec, ted, infinex, ventures, i…
37818  [oil, sector, going, crazy, weekly, gift, kkpt…
37819  [http, vdtobj, docscan, info, suffering, pain,…
37820  [prosperous, future, increased, money, earning…
37821   [moat, coverall, cytochemistry, planeload, salk]

[16522 rows x 3 columns]
```

Get the 10000 most common words from the training set

[409]:
```python
def get_top_words(train_df, max_words = 10000):
    training_words = [word for sublist in train_df["word_list"] for word in␣
↪sublist]

    word_count = Counter(training_words)
    top_common_words_with_freq = word_count.most_common(max_words)
    common_words = [word for word, _ in top_common_words_with_freq]

    return top_common_words_with_freq, common_words
```

[364]:
```python
top_common_words_with_freq, common_words = get_top_words(train_df)

# For vizualization purposes
top_common_words_with_freq[:10]
```

[364]:
```
[('http', 27587),
 ('font', 27472),
 ('td', 27416),
 ('br', 24631),
 ('width', 13978),
 ('tr', 12527),
 ('will', 11484),
 ('size', 11289),
 ('color', 7526),
 ('html', 7319)]
```

Creating the feature matrices

[365]:
```python
def create_feature_matrix(emails, common_words):
    emails_num = len(emails)
    count = len(common_words)
    # Initialize with zeros
    feature_matrix = np.zeros((emails_num, count), dtype=int)

    for i, email in enumerate(emails):
        for word in email:
            if word in common_words:
                index = common_words.index(word)
                feature_matrix[i, index] += 1
    return feature_matrix
```

[366]:
```python
ham_fm = create_feature_matrix(train_ham_df['word_list'], common_words)
print(f'Ham Matrix: \n {ham_fm}\n')

spam_fm = create_feature_matrix(train_spam_df['word_list'], common_words)
print(f"Spam Matrix: \n {spam_fm}")
```

```
Ham Matrix:
 [[0 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]
 …
 [1 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]]

Spam Matrix:
 [[1 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]
 [0 0 0 … 0 0 0]
 …
 [0 0 0 … 0 0 0]
 [6 4 0 … 0 0 0]
 [2 0 0 … 0 0 0]]
```

Computing the priors

$$P(c = \text{ham}) = \frac{N_{\text{ham}}}{N_{\text{doc}}}$$

$$P(c = \text{spam}) = \frac{N_{\text{spam}}}{N_{\text{doc}}}$$

[367]:
```python
def compute_priors(train_df, train_ham_df, train_spam_df):
    n_ham = train_ham_df.shape[0]        # Number of ham emails in training set
    n_spam = train_spam_df.shape[0]      # Number of spam emails in training set
    n_doc = train_df.shape[0]            # Number of total emails in training set

    p_ham = n_ham / n_doc
    p_spam = n_spam / n_doc
    return p_ham, p_spam
```

[368]:
```python
p_ham, p_spam = compute_priors(train_df, train_ham_df, train_spam_df)
print(f"P_ham: {p_ham} | P_spam: {p_spam}")
```

```
P_ham: 0.3531924882629108 | P_spam: 0.6468075117370892
```

Computing the likelihood of each word

$$P(w_i|\text{spam}) = \frac{\text{count}(w_i, \text{spam}) + \lambda}{\left(\sum_{w \in V} \text{count}(w, \text{spam})\right) + \lambda|V|}$$

$$P(w_i|\text{ham}) = \frac{\text{count}(w_i, \text{ham}) + \lambda}{\left(\sum_{w \in V} \text{count}(w, \text{ham})\right) + \lambda|V|}$$

[369]:
```python
def compute_likelihood(ham_fm, spam_fm, common_words, lmbda=1):
    # Vectorized sum of word counts in ham and spam
    ham_word_count = np.sum(ham_fm, axis=0)
    spam_word_count = np.sum(spam_fm, axis=0)

    # Calculate total word counts for ham and spam
    ham_word_total = np.sum(ham_word_count)
    spam_word_total = np.sum(spam_word_count)

    # Initialize dictionaries for probabilities of each word in ham and spam␣
↪classes
    p_ham_count = {}
    p_spam_count = {}

    count = len(common_words)

    # Calculate probabilities with Laplace smoothing
    for i in range(count):
        curr_ham_word = (ham_word_count[i] + lmbda) / (ham_word_total + lmbda *␣
↪count)
        curr_spam_word = (spam_word_count[i] + lmbda) / (
            spam_word_total + lmbda * count
        )
        p_ham_count[common_words[i]] = curr_ham_word
        p_spam_count[common_words[i]] = curr_spam_word

    return p_ham_count, p_spam_count
```

[370]:
```python
p_ham_count, p_spam_count = compute_likelihood(ham_fm, spam_fm, common_words)
```

Classifying the emails

$$\log\left(P(c \mid w_d)\right) = \sum_{i=1}^{d} \log\left(w_i \mid c\right) + \log\left(P(c)\right)$$

- Returns the prediction (spam or ham)

[371]:
```python
def classify_emails(
    tokenized_email, p_ham, p_spam, p_ham_count, p_spam_count, common_words
):
    # Initialize log values of ham and spam with their prior probabilities
    log_p_ham = np.log(p_ham)
    log_p_spam = np.log(p_spam)

    # Iterate each tokenized words in the email's body and
    # only process words that are in the top 1000 words
    for w in tokenized_email:
        if w in common_words:
```

```
            log_p_ham += np.log(p_ham_count[w])
            log_p_spam += np.log(p_spam_count[w])

    return "ham" if log_p_ham > log_p_spam else "spam"
```

Testing the Classifier

[372]:
```
def test_classifier(
    test_df, p_ham, p_spam, p_ham_count, p_spam_count, common_words
):
    prediction = []
    # Loop through the emails in test_df
    for tokenized_email in test_df["word_list"]:
        category = classify_emails(
            tokenized_email, p_ham, p_spam, p_ham_count, p_spam_count,␣
 ↪common_words
        )
        prediction.append(category)
    return prediction
```

[373]:
```
test_df = test_df.copy()

test_df.loc[:, "prediction"] = test_classifier(
    test_df, p_ham, p_spam, p_ham_count, p_spam_count, common_words
)

test_df
```

[373]:
```
           file_path category  \
21300  data/071/000     spam
21301  data/071/001      ham
21302  data/071/002     spam
21303  data/071/003     spam
21304  data/071/004     spam
…               …        …
37817  data/126/017     spam
37818  data/126/018     spam
37819  data/126/019     spam
37820  data/126/020     spam
37821  data/126/021     spam

                                               word_list prediction
21300  [hesitantly, derive, perverse, satisfaction, c…       spam
21301  [things, perform, experiment, display, will, r…        ham
21302  [best, offer, month, viggra, ci, ialis, vaiium…       spam
21303  [de, ar, wne, cr, doesn, matter, ow, real, st,…       spam
21304  [special, offer, adobe, video, collection, ado…       spam
…                                                    …          …
```

```
37817  [great, news, expec, ted, infinex, ventures, i…       spam
37818  [oil, sector, going, crazy, weekly, gift, kkpt…       spam
37819  [http, vdtobj, docscan, info, suffering, pain,…       spam
37820  [prosperous, future, increased, money, earning…       spam
37821   [moat, coverall, cytochemistry, planeload, salk]       spam

[16522 rows x 4 columns]
```

Performance Evaluation

[374]:
```
def evaluate_performance(test_df):
    y_true = test_df["category"]
    y_pred = test_df["prediction"]

    tp = ((y_true == "spam") & (y_pred == "spam")).sum()
    tn = ((y_true == "ham") & (y_pred == "ham")).sum()
    fp = ((y_true == "ham") & (y_pred == "spam")).sum()
    fn = ((y_true == "spam") & (y_pred == "ham")).sum()

    accuracy = (tn + tp) / (tn + tp + fp + fn)
    recall = tp / (tp + fn)
    precision = tp / (tp + fp)

    return accuracy, recall, precision
```

[375]:
```
accuracy, recall, precision = evaluate_performance(test_df)
print(f"Accuracy: {accuracy}\nRecall: {recall}\nPrecision: {precision}")
```

```
Accuracy: 0.9196223217528144
Recall: 0.9163897620116749
Precision: 0.9625507027638902
```

Results and Discussions

1. What is the effect of removing stop words in terms of precision, recall, and accuracy? Show a plot or a table of these results.

- Call the functions again and run without stop words

[376]:
```
df_wo_stop = df.copy()
df_wo_stop['word_list'] = tokenize_mail(df_wo_stop, False)
train_df_wo_stop, train_ham_df_wo_stop, train_spam_df_wo_stop, test_df_wo_stop␣
 ↪= (
    split_dataset(df_wo_stop)
)
```

Top common words without removing stop words

[377]:
```
top_common_words_with_freq_wo_stop, common_words_wo_stop = get_top_words(
    train_df_wo_stop
```

```
)

# For vizualization purposes
top_common_words_with_freq_wo_stop[:10]
```

[377]:
```
[('the', 132456),
 ('a', 101655),
 ('to', 84414),
 ('and', 64342),
 ('i', 59997),
 ('of', 57634),
 ('in', 44268),
 ('is', 36561),
 ('b', 31967),
 ('you', 31784)]
```

[378]:
```
ham_fm_wo_stop = create_feature_matrix(train_ham_df_wo_stop["word_list"],␣
 ↪common_words_wo_stop)
spam_fm_wo_stop = create_feature_matrix(train_spam_df_wo_stop["word_list"],␣
 ↪common_words_wo_stop)

p_ham_wo_stop, p_spam_wo_stop = compute_priors(train_df_wo_stop,␣
 ↪train_ham_df_wo_stop, train_spam_df_wo_stop)
p_ham_count_wo_stop, p_spam_count_wo_stop = compute_likelihood(
    ham_fm_wo_stop, spam_fm_wo_stop, common_words_wo_stop
)
```

[414]:
```
test_df_wo_stop = test_df_wo_stop.copy()

test_df_wo_stop.loc[:, "prediction"] = test_classifier(
    test_df_wo_stop,
    p_ham_wo_stop,
    p_spam_wo_stop,
    p_ham_count_wo_stop,
    p_spam_count_wo_stop,
    common_words_wo_stop,
)
test_df_wo_stop
```

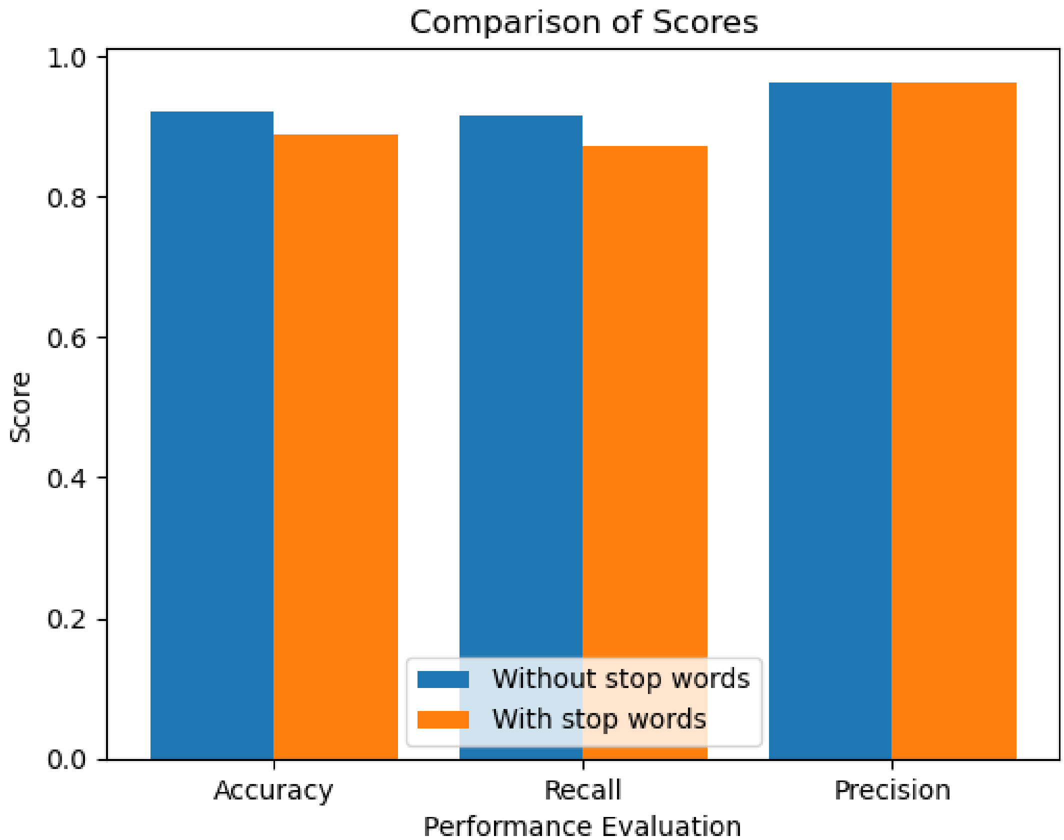
[414]:
```
          file_path category  \
21300  data/071/000     spam
21301  data/071/001      ham
21302  data/071/002     spam
21303  data/071/003     spam
21304  data/071/004     spam
…               …        …
37817  data/126/017     spam
```

```
37818  data/126/018     spam
37819  data/126/019     spam
37820  data/126/020     spam
37821  data/126/021     spam

                                                word_list prediction
21300  [where, we, can, hesitantly, derive, perverse,…       spam
21301  [there, are, several, things, you, can, use, t…        ham
21302  [best, offer, of, the, month, viggra, ci, iali…       spam
21303  [de, i, ar, home, o, h, wne, n, r, your, cr, v…       spam
21304  [special, offer, adobe, video, collection, ado…       spam
…                                                    …        …
37817  [great, news, expec, ted, infinex, ventures, i…       spam
37818  [the, oil, sector, is, going, crazy, this, is,…       spam
37819  [http, vdtobj, docscan, info, suffering, from,…       spam
37820  [u, n, i, v, e, r, s, i, t, y, d, i, p, l, o, …       spam
37821  [but, moat, coverall, be, cytochemistry, be, p…        ham

[16522 rows x 4 columns]
```

[380]:
```python
accuracy_wo_stop, recall_wo_stop, precision_wo_stop = evaluate_performance(
    test_df_wo_stop
)
```

Compare both scores using plot

[381]:
```python
titles = ['Accuracy', 'Recall', 'Precision']
score = [accuracy, recall, precision]
score_wo_stop = [accuracy_wo_stop, recall_wo_stop, precision_wo_stop]

X_axis = np.arange(len(titles))
plt.bar(X_axis - 0.2, score, 0.4, label="Without stop words")
plt.bar(X_axis + 0.2, score_wo_stop, 0.4, label="With stop words")

plt.xticks(X_axis, titles)
plt.xlabel("Performance Evaluation")
plt.ylabel("Score")
plt.title("Comparison of Scores")
plt.legend()
plt.show()

print("Without stop words:")
print(f"Accuracy: {accuracy}\nRecall: {recall}\nPrecision: {precision}\n")

print("With stop words:")
print(f"Accuracy: {accuracy_wo_stop}\nRecall: {recall_wo_stop}\nPrecision: 
 ↪{precision_wo_stop}\n")
```




```
Without stop words:
Accuracy: 0.9196223217528144
Recall: 0.9163897620116749
Precision: 0.9625507027638902

With stop words:
Accuracy: 0.8890570148892386
Recall: 0.8704984283789852
Precision: 0.9612257040856803
```

Conclusion:

Due to the removal of the stop words, all measures of performance evaluation is higher than without removing the said words. In this case, the difference does not exceed 5%, with recall (approx. 4.56%) being the most affected, followed by accuracy (approx. 3.06%), then precision (approx. 0.01%). Thus, removing these nuisance improves the model's performance.

2. Experiment on the number of words used for training. Filter the dictionary to include only words occurring more than k times (1000 words, then k > 100, and k = 50 times). For example, the word "offer" appears 150 times, that means that it will be included in the dictionary.

Search for words that appear only 50 times (k=50)

[382]:
```python
k_50_filtered_data = [entry for entry in top_common_words_with_freq if entry[1]␣
↪== 50]
k_50_words = [entry[0] for entry in k_50_filtered_data]
```

[402]:
```python
len(k_50_words)
```

[402]: 76

Copy the original splitted data

[383]:
```python
train_ham_df_k50 = train_ham_df.copy()
train_spam_df_k50 = train_spam_df.copy()
test_df_k50 = test_df.copy()
```

[386]:
```python
ham_fm_k50 = create_feature_matrix(train_ham_df_k50["word_list"], k_50_words)
spam_fm_k50 = create_feature_matrix(train_spam_df_k50["word_list"], k_50_words)

p_ham_k50, p_spam_k50 = compute_priors(train_df, train_ham_df, train_spam_df)
p_ham_count_k50, p_spam_count_k50 = compute_likelihood(
    ham_fm_k50, spam_fm_k50, k_50_words
)

test_df_k50 = test_df.copy()

test_df_k50.loc[:, "prediction"] = test_classifier(
    test_df,
    p_ham_k50,
    p_spam_k50,
    p_ham_count_k50,
    p_spam_count_k50,
    k_50_words,
)

accuracy_k_50, recall_k_50, precision_k_50 = evaluate_performance(test_df_k50)
print(
    f"Accuracy: {accuracy_k_50}\nRecall: {recall_k_50}\nPrecision:␣
↪{precision_k_50}\n"
)
```

```
Accuracy: 0.7154097566880523
Recall: 0.994611585092052
Precision: 0.704651014824712
```

Do the same for k > 100

```
[403]: k_100_filtered_data = [entry for entry in top_common_words_with_freq if␣
         ↪entry[1] > 100]
       k_100_words = [entry[0] for entry in k_100_filtered_data]
```

```
[404]: len(k_100_words)
```

```
[404]: 3134
```

Since there are more than 1000 words that have more than 100 occurences, limit only to 1000 (Get the first 1000 words)

```
[411]: k_100_words = k_100_words[:1000]
```

```
[412]: train_ham_df_k100 = train_ham_df.copy()
       train_spam_df_k100 = train_spam_df.copy()
       test_df_k100 = test_df.copy()

       ham_fm_k100 = create_feature_matrix(train_ham_df_k100["word_list"], k_100_words)
       spam_fm_k100 = create_feature_matrix(train_spam_df_k100["word_list"],␣
         ↪k_100_words)

       p_ham_k100, p_spam_k100 = compute_priors(train_df, train_ham_df, train_spam_df)
       p_ham_count_k100, p_spam_count_k100 = compute_likelihood(
           ham_fm_k100, spam_fm_k100, k_100_words
       )

       test_df_k100 = test_df.copy()

       test_df_k100.loc[:, "prediction"] = test_classifier(
           test_df,
           p_ham_k100,
           p_spam_k100,
           p_ham_count_k100,
           p_spam_count_k100,
           k_100_words,
       )

       accuracy_k_100, recall_k_100, precision_k_100 =␣
         ↪evaluate_performance(test_df_k100)
       print(
           f"Accuracy: {accuracy_k_100}\nRecall: {recall_k_100}\nPrecision:␣
         ↪{precision_k_100}\n"
       )
```

```
Accuracy: 0.9041883549207118
Recall: 0.9027391109115402
Precision: 0.9526156178923427
```

Conclusion:

The difference between the performance of k = 50 and k > 100 is somewhat mixed. Although in the latter, everything is greater than 90%, the recall of former is significantly higher with an astonishing value of 99%. However, for accuracy and precision, it can be observed that it lags behind with values of 71.5% and 70.4% respectively, compared to its counterpart which have a value of 90.1% and 95.2% respectively.

With this, even though k = 50 has a higher recall (highly sensitive to detecting spam), it sacrifices precision, which would lead to the increase of false postives that misclassifies legitimate emails as spam. On the other hand, k > 100 has a better balance with high accuracy and precision, with a little trade-off on recall. This means that the model becomes reliable in distingushing between ham and spam by focusing only on more frequent words that leads to a fewer false positives.

3. Discuss the results of the different parameters used for Lambda smoothing. Test it on 5 varying values of the (e.g. = 2.0, 1.0, 0.5, 0.1, 0.005), Evaluate performance metrics for each.

[390]:
```
lmbdas = [2.0, 1.0, 0.5, 0.1, 0.005]
results_list = []

for lmbda in lmbdas:
    p_ham_count_lmbda, p_spam_count_lmbda = compute_likelihood(
        ham_fm, spam_fm, common_words, lmbda=lmbda
    )

    test_df_lmbda = test_df.copy()
    test_df_lmbda.loc[:, "prediction"] = test_classifier(
        test_df_lmbda,
        p_ham,
        p_spam,
        p_ham_count_lmbda,
        p_spam_count_lmbda,
        common_words,
    )

    accuracy_lmbda, recall_lmbda, precision_lmbda =␣
↪evaluate_performance(test_df_lmbda)

    results_list.append(
        {
            "lambda": lmbda,
            "accuracy": accuracy_lmbda,
            "recall": recall_lmbda,
            "precision": precision_lmbda,
        }
    )

result_df = pd.DataFrame(results_list)
```

[391]:

```
result_df
```

[391]:

	lambda	accuracy	recall	precision
0	2.000	0.919501	0.916569	0.962195
1	1.000	0.919622	0.916390	0.962551
2	0.500	0.920167	0.916390	0.963369
3	0.100	0.921317	0.917198	0.964309
4	0.005	0.921135	0.915402	0.965795

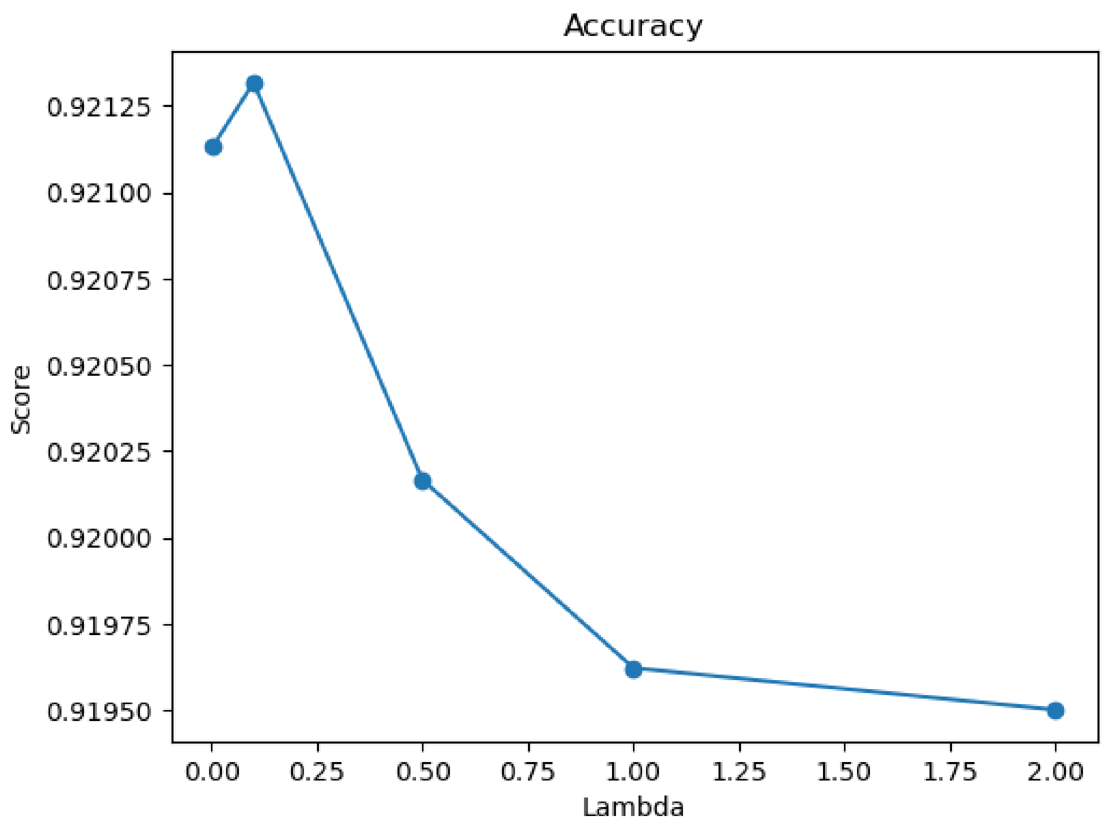
Plot each measurement

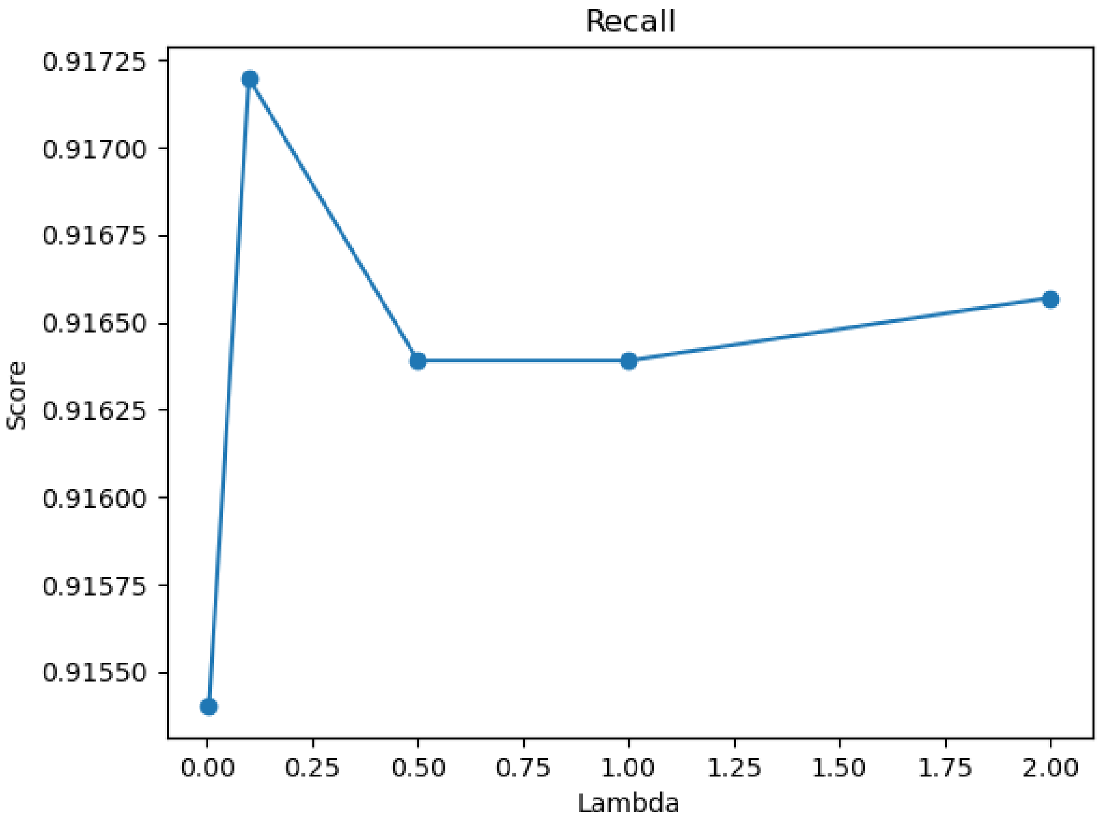
[400]:

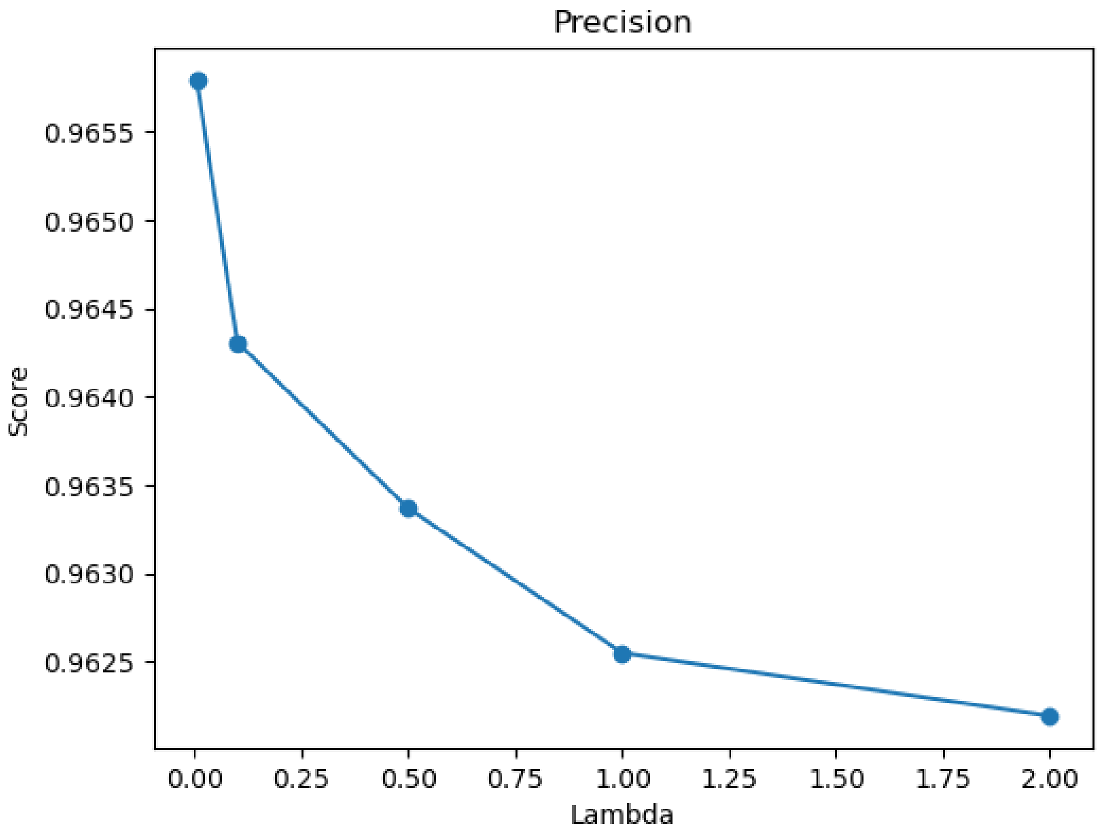
```
def plot_line(label):
    plt.plot(
        result_df["lambda"],
        result_df[label.lower()],
        label=label,
        marker="o",
    )

    plt.xlabel("Lambda")
    plt.ylabel("Score")
    plt.title(f"{label}")
    plt.show()
```

[401]:

```
plot_line('Accuracy')
plot_line('Recall')
plot_line('Precision')
```


Accuracy
Score
0.92125
0.92100
0.92075
0.92050
0.92025
0.92000
0.91975
0.91950
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Lambda


Recall
Score
Lambda
0.91725
0.91700
0.91675
0.91650
0.91625
0.91600
0.91575
0.91550
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00



Conclusion:

When observing the accuracy, it can be seen that it increases once and peaks at 0.1 before dropping as the value of lambda is getting higher. Thus, in this dataset, an increasing lambda higher than 0.1 introduces too much smoothing which reduces its ability to classify correctly. Moreover, in recall, there is a sharp increase of score from 0.005 to 0.1, which is its peak. After that, there is a stable increase as lambda increases. Lastly, in precision, as lambda increases, the score decreases.

With this, it can be said that the optimal value of lambda to use in this case is 0.1. It is because it provides the best balance between all measurements. It might have a lower precision than 0.005, but the precision score is still considered very good.

4. What are your recommendations to further improve the model?

- I tested the number of spams and hams from labels. I noticed that emails that are considered spam are about 67% of the dataset. Although not extremely balanced, it can still affect the accuracy score. Thus, I recommend to add samples of ham or decrease the samples of spam. There a lot methods that can be used to this such as SMOTE.
- When getting the top 10000 words, I noticed that there are nuisanced words such as td, br, which are indicative of HTML tags. I believe that these should be removed just like the stop words.