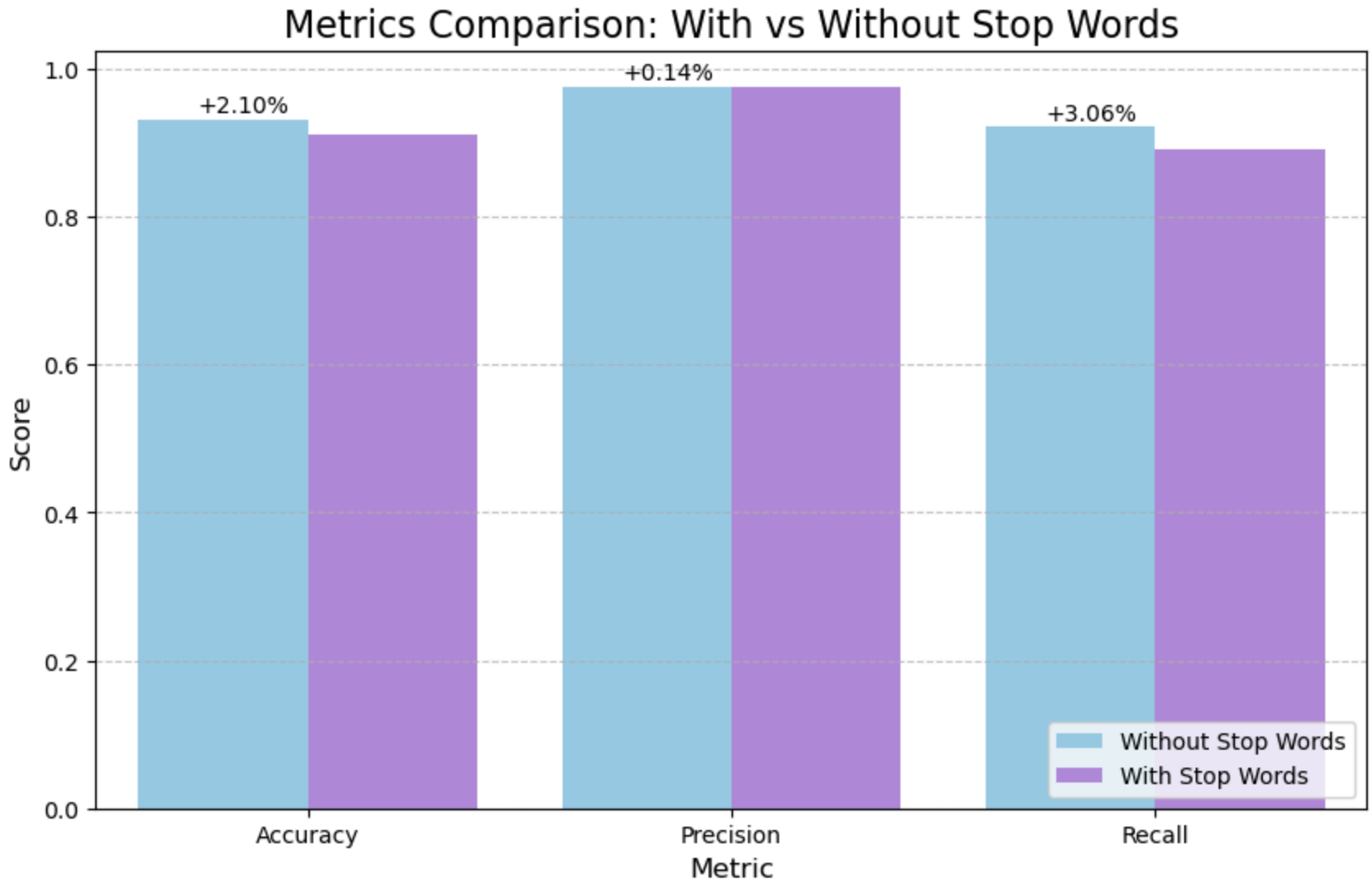
1. What is the effect of removing stop words in terms of precision, recall, and accuracy? Show a plot or a table of these results.

I created a **different notebook (with-stopwords.ipynb)** that contains the metric results for the model without removing the stop words in the dataset. So, I will just manually enter here the values that were already computed.

In [77]:
```
colors = ['#89CFF0', '#b47ee5']

# Create a df for the metrics
metrics_w_stopwords = {
    'Accuracy': 0.9106645684541823,
    'Precision': 0.9746437346437347,
    'Recall': 0.8906151773686574
}

metrics_wo_stopwords = {
    'Accuracy': 0.9316668684178671,
    'Precision': 0.976022835394862,
    'Recall': 0.921239335428828
}

metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall'],
    'Without Stop Words': [metrics_wo_stopwords['Accuracy'], metrics_wo_stopwords['Precision'], metrics_wo_stopwords[
    'With Stop Words': [metrics_w_stopwords['Accuracy'], metrics_w_stopwords['Precision'], metrics_w_stopwords['Recal
})

# Melt the df for easier plotting
metrics_melted = metrics_df.melt(id_vars='Metric', var_name='Condition', value_name='Value')

# Plot the bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='Metric', y='Value', hue='Condition', data=metrics_melted, palette=colors)

# Add titles and labels
plt.title('Metrics Comparison: With vs Without Stop Words', fontsize=16)
plt.ylabel('Score', fontsize=12)
plt.xlabel('Metric', fontsize=12)
plt.legend(loc='lower right')
```

```
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Show the difference between the two conditions
for index, row in metrics_df.iterrows():
    diff = row['Without Stop Words'] - row['With Stop Words']
    plt.text(index - 0.15, row['Without Stop Words'] + 0.01, f"+{diff:.2%}", color='black', ha="center", fontsize=10)

# Show plot
plt.show()
```



Removing stopwords resulted in a noticeable boost in accuracy (+2.10%) and recall (+3.06%), meaning the model became better at correctly identifying spam and ham messages. Although, the improvement in the precision (+0.14%) was minimal, it is still evident that removing stopwords improved the model's performance across the metrics. This is probably because eliminating non-informative words made it focus more on meaningful content which may lead to a better spam detection and fewer misclassifications.

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.

In [104…

```
# Filter the dictionary by word frequency for different k thresholds
filtered_dict_100 = {word: count for word, count in word_counter.items() if count > 100}
filtered_dict_50 = {word: count for word, count in word_counter.items() if count > 50}

# Get the top 1000 words from filtered_dict_100
top_1000_filtered_dict_100 = dict(sorted(filtered_dict_100.items(), key=lambda item: item[1], reverse=True)[:1000])

# For filtered_dict_50, exclude the words already present in top_1000_filtered_dict_100
filtered_dict_50_unique = {word: count for word, count in filtered_dict_50.items() if word not in top_1000_filtered_d

# Get the top 1000 words from this unique filtered_dict_50
top_1000_filtered_dict_50 = dict(sorted(filtered_dict_50_unique.items(), key=lambda item: item[1], reverse=True)[:100

# Create lists of the filtered words
filtered_list_100 = list(top_1000_filtered_dict_100.keys())
filtered_list_50 = list(top_1000_filtered_dict_50.keys())

# Output the number of words for each threshold
print(f"Words with frequency > 100 (Top 1000): {len(filtered_dict_100)}")
print(f"Words with frequency > 50 (Top 1000): {len(filtered_dict_50)}\n")

# Optionally print first and last 5 of each list for verification
print("Filtered list > 100 (Start/End):", filtered_list_100[:5], filtered_list_100[-5:])
print("Filtered list > 50 (Start/End):", filtered_list_50[:5], filtered_list_50[-5:])
```

```
Words with frequency > 100 (Top 1000): 2755
Words with frequency > 50 (Top 1000): 4833

Filtered list > 100 (Start/End): ['bb', 'will', 'board', 'company', 'price'] ['september', 'va', 'agent', 'kit', 'sui
te']
Filtered list > 50 (Start/End): ['require', 'direction', 'lowest', 'rework', 'trouble'] ['iwc', 'officine', 'exapml
e', 'signed', 'bob']
```

In [106…

```
# Redefine likelihood function to be used with filtered dictionary
def calculate_likelihoods_with_laplace_filtered(matrix, filtered_dict, lambda_smoothing):
```

```
    # Initialize likelihoods for the filtered dictionary size
    vocab_size = len(filtered_dict)
    likelihoods = np.zeros(vocab_size)

    # Calculate the total word count in the feature matrix (sum over all emails)
    word_counts = np.sum(matrix, axis=0)  # Sum across all rows (emails)
    total_word_count = np.sum(word_counts)  # Total number of words in the entire feature matrix

    # Calculate likelihoods with Laplace smoothing for each word in the filtered dictionary
    for i in range (vocab_size):
        likelihoods[i] = (word_counts[i] + lambda_smoothing) / (total_word_count + lambda_smoothing * vocab_size)

    return likelihoods
```

In [108…

```
# Redefine the classify function to be used with filtered dictionary
def classify(email, spam_word_probs, ham_word_probs, p_spam, p_ham, filtered_dict, filtered_list):
    # Initialize the log probability of spam and ham
    classify_spam = 0
    classify_ham = 0

    # Split the email into words
    words = str(email).split()

    # Compute the log probability of spam and ham
    for word in words:
        if word in filtered_dict:
            classify_spam += np.log(spam_word_probs[filtered_list.index(word)])
            classify_ham += np.log(ham_word_probs[filtered_list.index(word)])

    # Add the log probability of spam and ham
    classify_spam += np.log(p_spam)
    classify_ham += np.log(p_ham)

    # Return the class with the highest log probability
    return 1 if classify_spam > classify_ham else 0
```

In [110…

```
# Create feature matrices for spam and ham emails using filtered dictionaries
spam_train_matrix_100 = create_feature_matrix(train_spam_df, filtered_list_100)
ham_train_matrix_100 = create_feature_matrix(train_ham_df, filtered_list_100)
```

```
spam_train_matrix_50 = create_feature_matrix(train_spam_df, filtered_list_50)
ham_train_matrix_50 = create_feature_matrix(train_ham_df, filtered_list_50)
```

In [112…

```
# Calculate likelihoods using Laplace smoothing for each threshold
lambda_smoothing = 1  # Laplace smoothing parameter

# For k > 100
likelihood_spam_100 = calculate_likelihoods_with_laplace_filtered(spam_train_matrix_100, filtered_list_100, lambda_sr
likelihood_ham_100 = calculate_likelihoods_with_laplace_filtered(ham_train_matrix_100, filtered_list_100, lambda_smoo

# For k > 50
likelihood_spam_50 = calculate_likelihoods_with_laplace_filtered(spam_train_matrix_50, filtered_list_50, lambda_smoot
likelihood_ham_50 = calculate_likelihoods_with_laplace_filtered(ham_train_matrix_50, filtered_list_50, lambda_smoothi
```

In [122…

```
train_df_k = train_df.copy()
# Classify test emails for k > 100
train_df_k['predicted_k100'] = train_df_k['email_message'].apply(
    lambda x: classify(x, likelihood_spam_100, likelihood_ham_100, p_spam, p_ham, top_1000_filtered_dict_100, filtere
)

# Classify test emails for k > 50
train_df_k['predicted_k50'] = train_df_k['email_message'].apply(
    lambda x: classify(x, likelihood_spam_50, likelihood_ham_50, p_spam, p_ham, top_1000_filtered_dict_50, filtered_l
)
```

In [124…

```
train_df_k
```

Out[124...

	folder	file	email_message	category	predicted	predicted_k100	predicted_k50
0	0	0	mailing list queried weeks ago running set arc...	0	0	0	0
1	0	1	luxury watches buy rolex rolex cartier bvlgari...	1	1	1	1
2	0	2	academic qualifications prestigious nonacc red...	1	1	1	1
3	0	3	greetings verify subscription planfans list ch...	0	0	0	0
4	0	4	chauncey conferred luscious continued tonsillitis	1	0	1	1
...	...	...	...	...	...	...	...
21295	70	295	btijclnab binpqnejgmb httpgethighbizez bldb xi...	1	1	1	1
21296	70	296	special offer adobe video collection adobe pre...	1	1	1	1
21297	70	297	doctype html public wcdtd html transitionalen ...	1	1	1	1
21298	70	298	mounted isu infrared demodulator hb realised r...	0	0	0	0
21299	70	299	httptmqmctoverpacenet suffering pain depressio...	1	1	1	1

21300 rows × 7 columns

In [126...

```
test_df_k = test_df.copy()
# Classify test emails for k > 100
test_df_k['predicted_k100'] = test_df_k['email_message'].apply(
    lambda x: classify(x, likelihood_spam_100, likelihood_ham_100, p_spam, p_ham, top_1000_filtered_dict_100, filtere
)

# Classify test emails for k > 50
test_df_k['predicted_k50'] = test_df_k['email_message'].apply(
    lambda x: classify(x, likelihood_spam_50, likelihood_ham_50, p_spam, p_ham, top_1000_filtered_dict_50, filtered_
)
```

In [127...

```
test_df_k
```

Out[127...

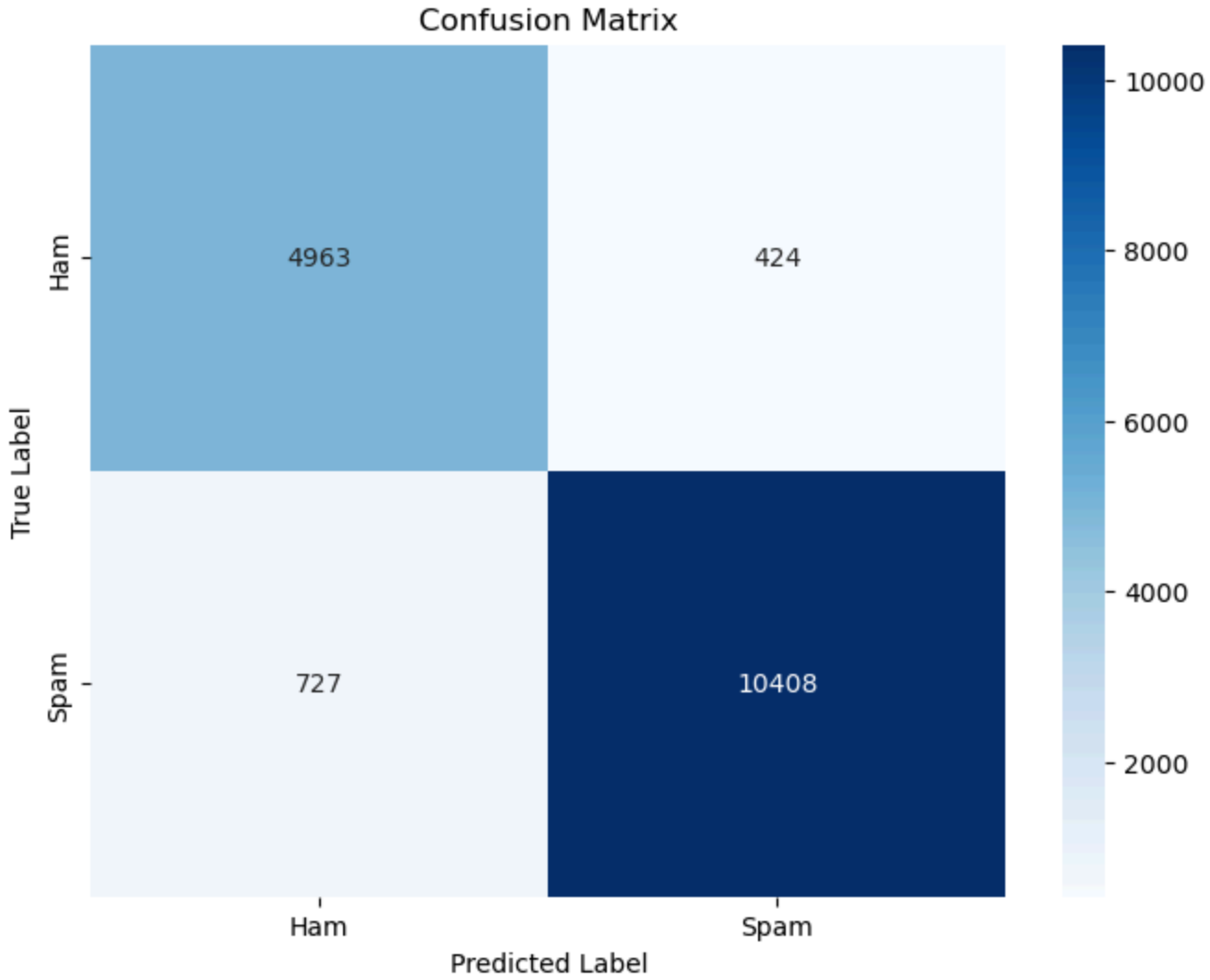
	folder	file	email_message	category	predicted	predicted_k100	predicted_k50
21300	71	0	hesitantly derive perverse satisfaction clodho...	1	1	0	1
21301	71	1	things perform experiment display will remain ...	0	0	0	0
21302	71	2	best offer month viggra ci ialis vaiium xa naa...	1	1	1	1
21303	71	3	de ar wne cr doesnt matter ow real st mmed ia ...	1	1	1	1
21304	71	4	special offer adobe video collection adobe pre...	1	1	1	1
...	...	...	...	...	...	...	...
37817	126	17	great news expec ted infinex ventures infx pri...	1	1	1	1
37818	126	18	oil sector going crazy weekly gift kkpt thing ...	1	1	1	1
37819	126	19	httpvdtobjdocscaninfo suffering pain depressio...	1	1	1	1
37820	126	20	prosperous future increased money earning powe...	1	1	1	1
37821	126	21	moat coverall cytochemistry planeload salk	1	1	1	1

16522 rows × 7 columns

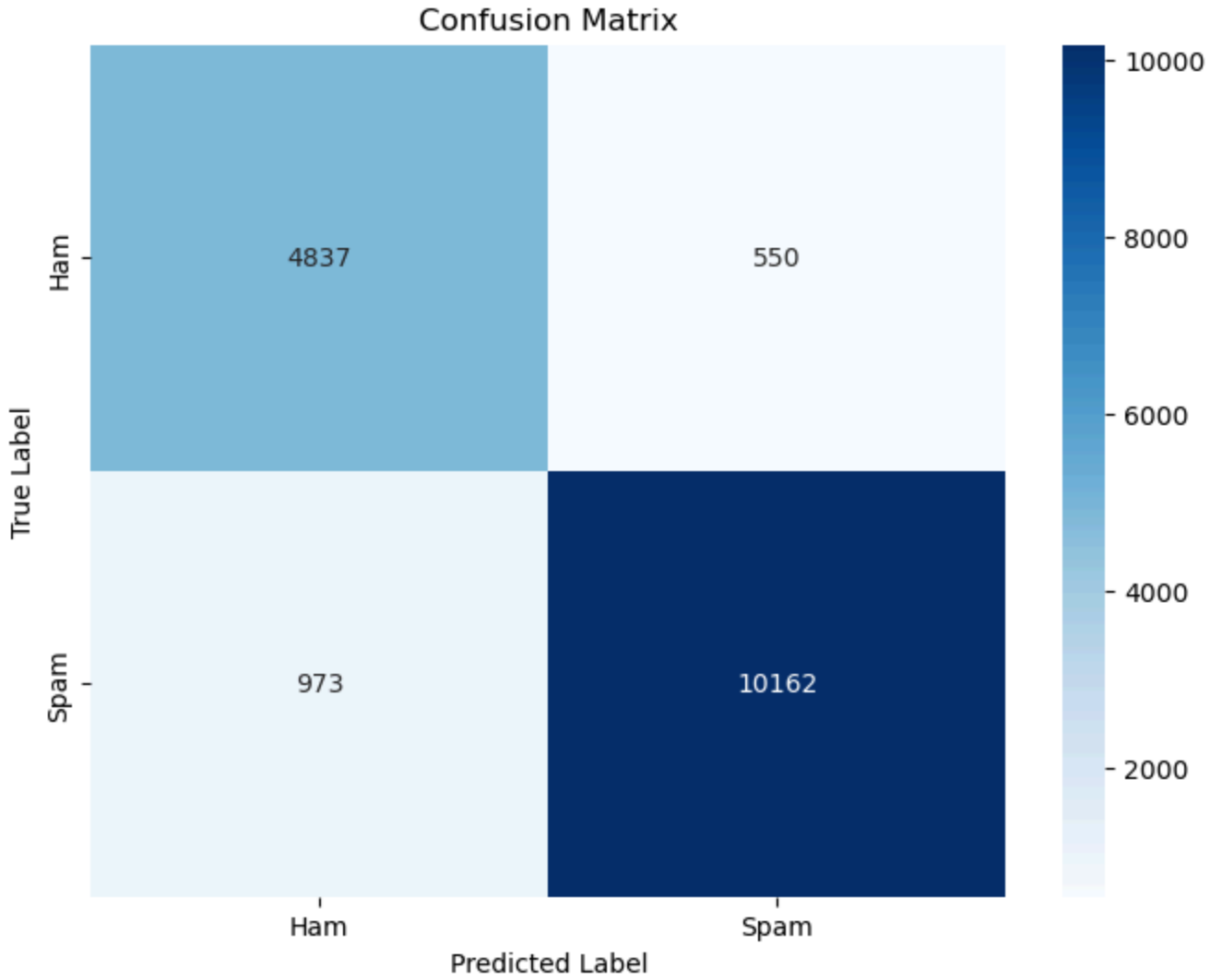
In [136...

```
# Evaluate the model for k > 100
print("Metrics for k > 100:")
metrics_k100 = evaluate_model(test_df_k, 'category', 'predicted_k100')

# Evaluate the model for k > 50
print("Metrics for k > 50:")
metrics_k50 = evaluate_model(test_df_k, 'category', 'predicted_k50')
```

```
Metrics for k > 100:
Accuracy: 0.9303353104950974 = 93.03%
Precision: 0.9608567208271788 = 96.09%
Recall: 0.9347103726986978 = 93.47%
```



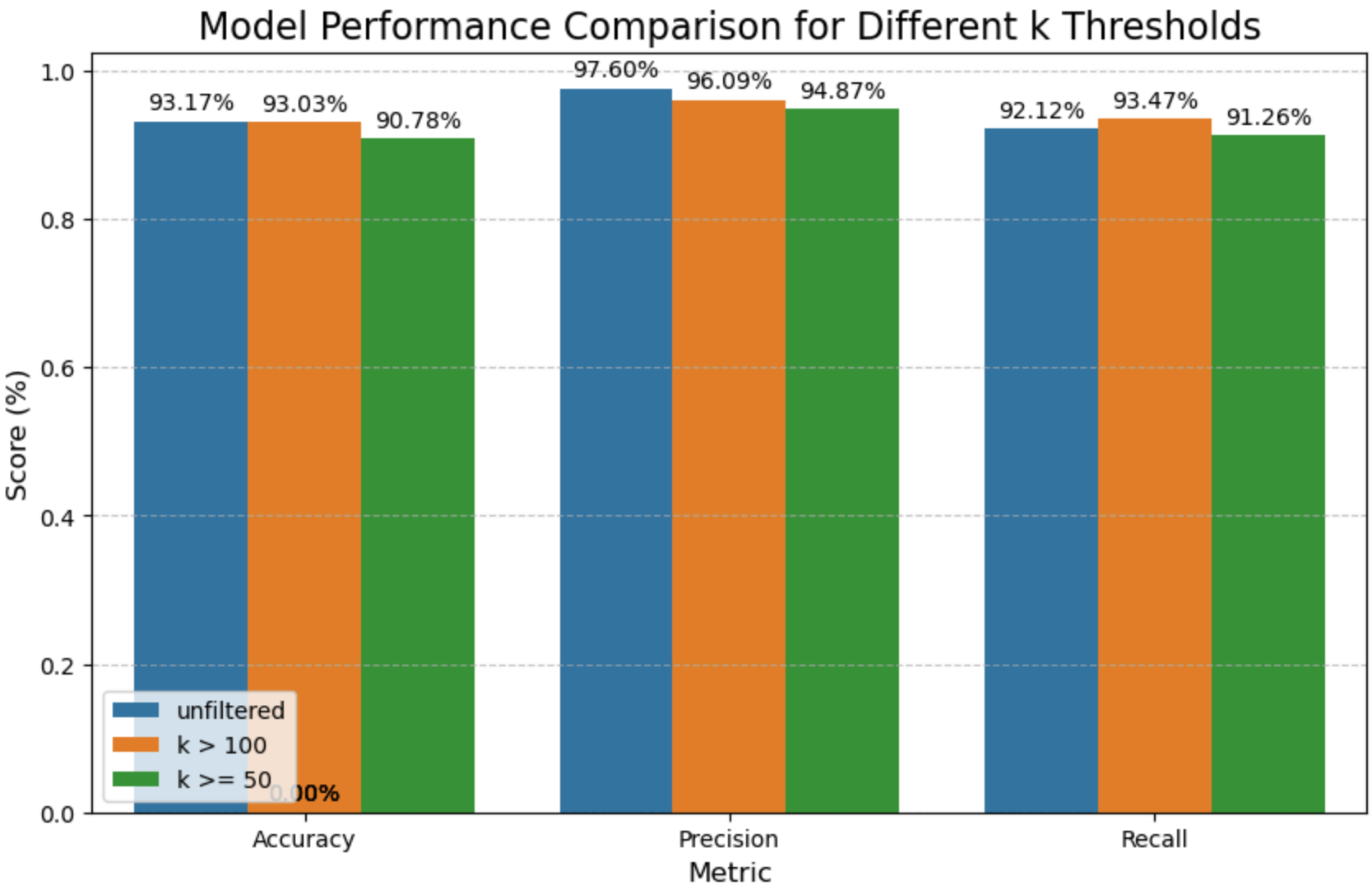
Metrics for k > 50:
Accuracy: 0.9078198765282653 = 90.78%
Precision: 0.94865571321882 = 94.87%
Recall: 0.9126178715761114 = 91.26%



In [148…

```
# Store the metrics in a dictionary for comparison
metrics_comparison = {
    'Metric': ['Accuracy', 'Precision', 'Recall'],
    'unfiltered': [metrics_no_stopwords['Accuracy'], metrics_no_stopwords['Precision'], metrics_no_stopwords['Recall
    'k > 100': [metrics_k100['Accuracy'], metrics_k100['Precision'], metrics_k100['Recall']],
    'k >= 50': [metrics_k50['Accuracy'], metrics_k50['Precision'], metrics_k50['Recall']]
}

# Convert the dictionary to a pandas df
```

```
metrics_df = pd.DataFrame(metrics_comparison)
metrics_melted = metrics_df.melt(id_vars='Metric', var_name='Condition', value_name='Value')

plt.figure(figsize=(10, 6))

# Create the bar plot
ax = sns.barplot(x='Metric', y='Value', hue='Condition', data=metrics_melted)

# Add titles and labels
plt.title('Model Performance Comparison for Different k Thresholds', fontsize=16)
plt.ylabel('Score (%)', fontsize=12)
plt.xlabel('Metric', fontsize=12)

# Add value labels on top of each bar
for p in ax.patches:
    ax.annotate(f"{p.get_height() * 100:.2f}%",
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline',
                fontsize=10, color='black', xytext=(0, 5),
                textcoords='offset points')

# Add grid lines
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Move the legend to the best position
plt.legend(loc='lower left')

# Display the plot
plt.show()
```



- **Accuracy** is highest for the unfiltered set (93.17%) and decreases as more lower-frequency words are included (90.78% for k > 50).
- **Precision** follows the same trend, with the unfiltered set at 97.60%, dropping to 94.87% for k > 50.
- **Recall** improves with lower thresholds, peaking at 93.47% for k > 100, but slightly drops when including k > 50.

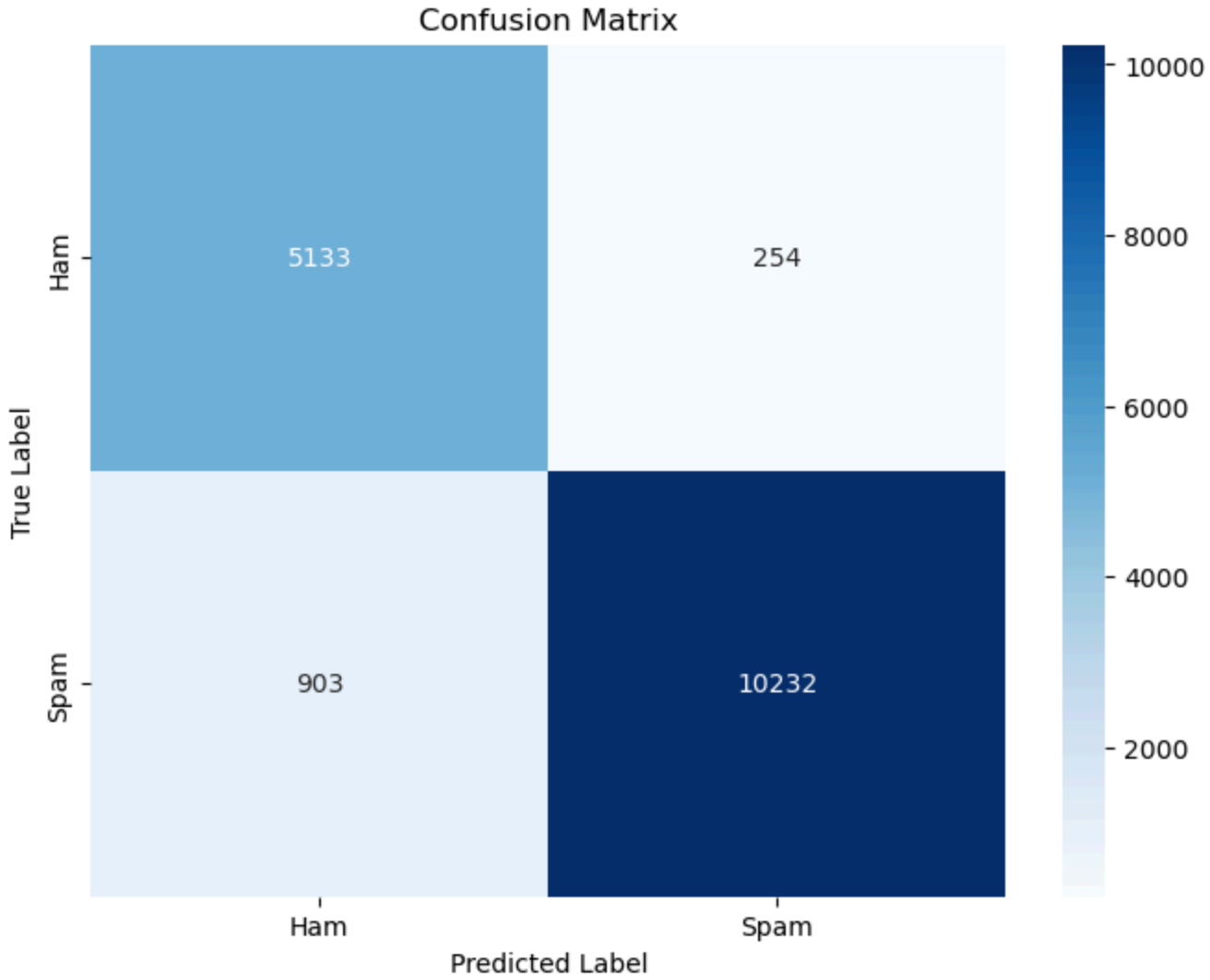
Using the unfiltered words delivers the best results, while adding more low-frequency words improves recall but in turn lowers precision and accuracy.

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

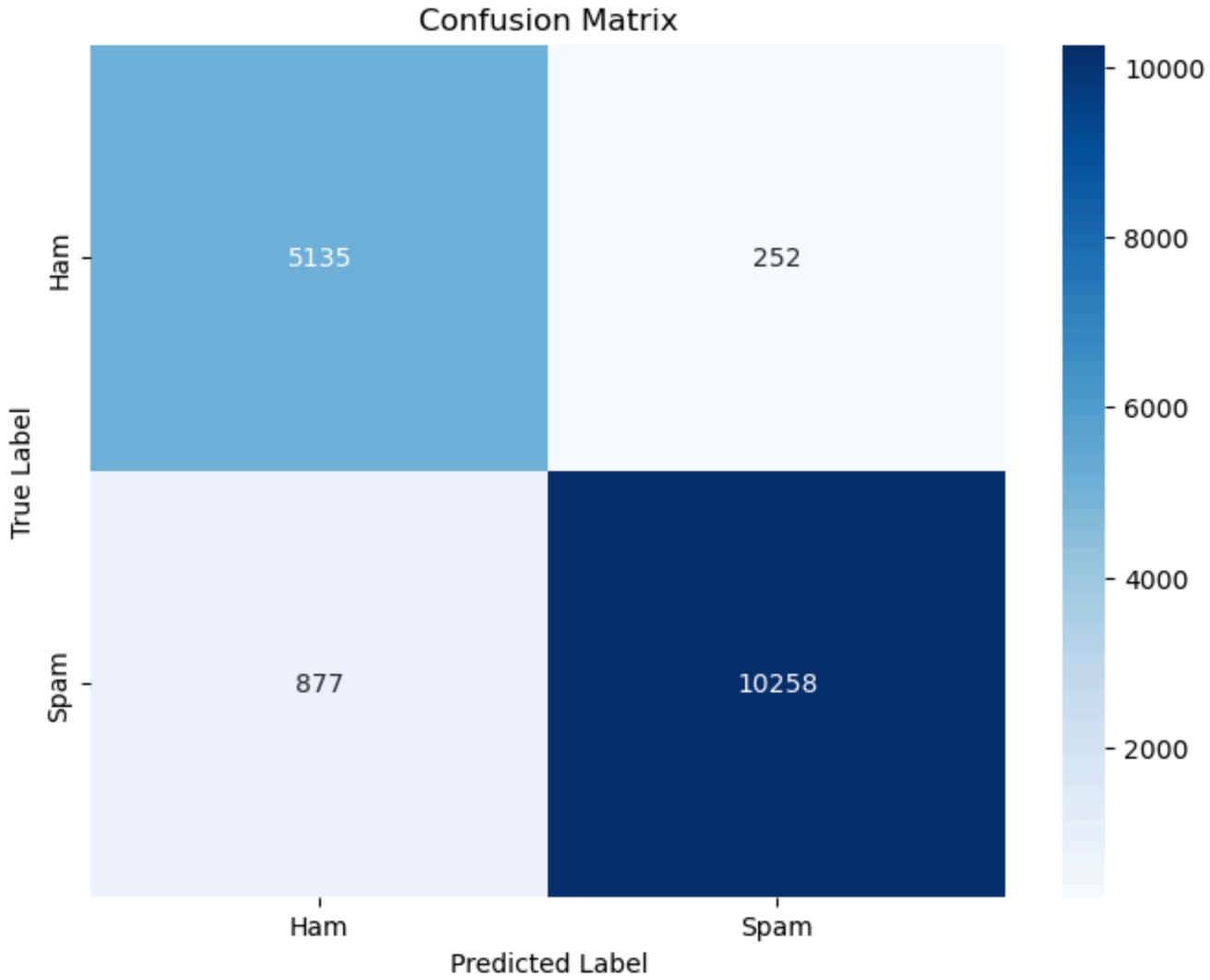
In [151…

```
# Define new lambda values to test
lambda_values_new = [2.0, 1.0, 0.5, 0.1, 0.005]

# Dictionary to store results
lambda_results_new = {}

for lambda_val in lambda_values_new:
    test_df_copy = test_df.copy()

    # Recalculate likelihoods
    likelihood_spam_lambda = calculate_likelihoods_with_laplace(spam_train_matrix, len(top_10000_words_list), lambda_
    likelihood_ham_lambda = calculate_likelihoods_with_laplace(ham_train_matrix, len(top_10000_words_list), lambda_va

    # Classify test emails
    test_df_copy[f'predicted_lambda_{lambda_val}'] = test_df_copy['email_message'].apply(
        lambda x: classify_email(x, likelihood_spam_lambda, likelihood_ham_lambda, p_spam, p_ham)
    )
    print(f"Results for Lambda = {lambda_val}:")
    # Evaluate performance metrics
    metrics_lambda = evaluate_model(test_df_copy, 'category', f'predicted_lambda_{lambda_val}')

    # Store the metrics
    lambda_results_new[lambda_val] = metrics_lambda
```

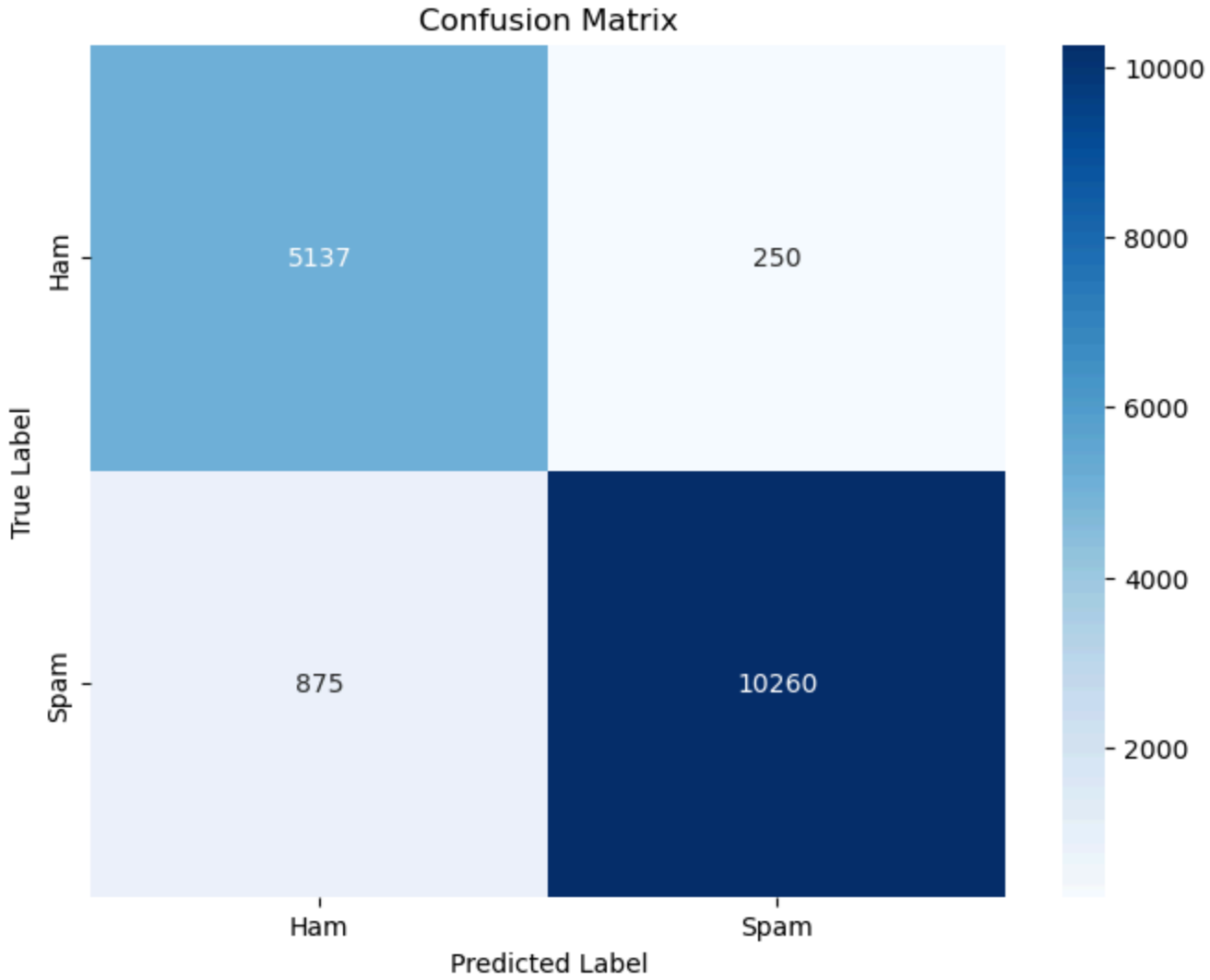
```
Results for Lambda = 2.0:
Accuracy: 0.9299721583343421 = 93.00%
Precision: 0.9757772267785619 = 97.58%
Recall: 0.918904355635384 = 91.89%
```



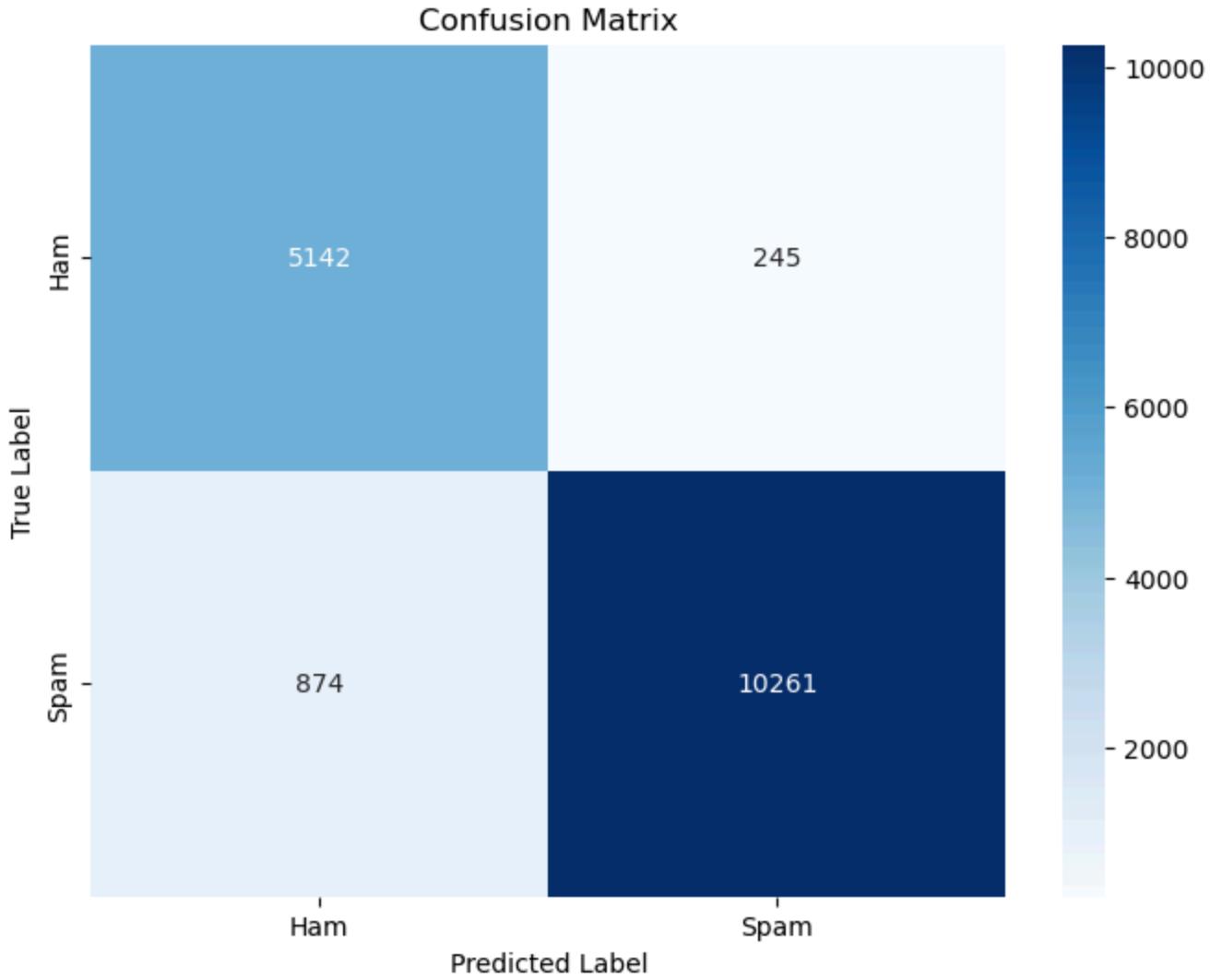

```
Results for Lambda = 1.0:
Accuracy: 0.9316668684178671 = 93.17%
Precision: 0.976022835394862 = 97.60%
Recall: 0.921239335428828 = 92.12%
```



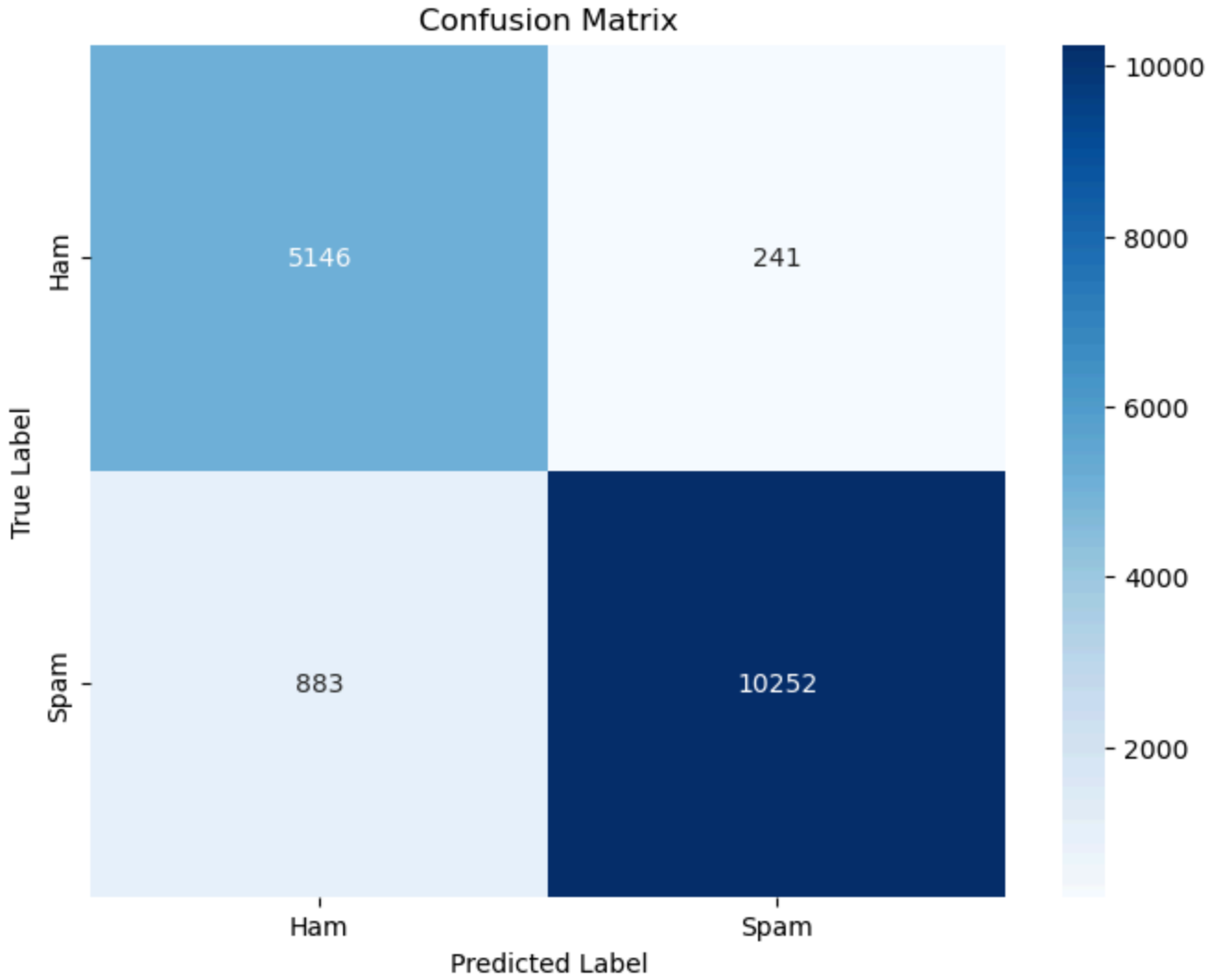
Results for Lambda = 0.5:
Accuracy: 0.9319089698583707 = 93.19%
Precision: 0.9762131303520457 = 97.62%
Recall: 0.921418949259093 = 92.14%



Results for Lambda = 0.1:
Accuracy: 0.932272122019126 = 93.23%
Precision: 0.9766799923853037 = 97.67%
Recall: 0.9215087561742255 = 92.15%



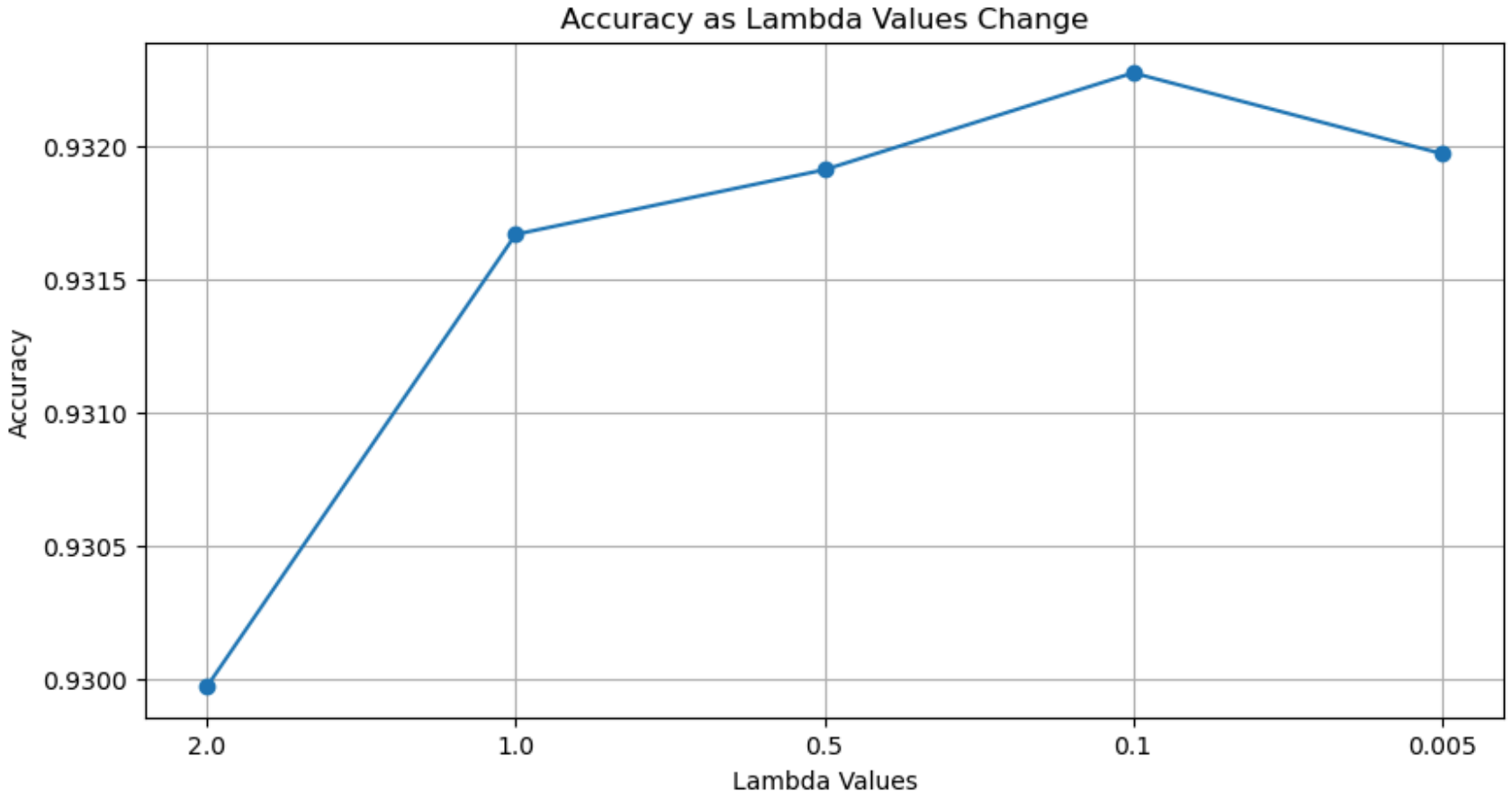

```
Results for Lambda = 0.005:
Accuracy: 0.9319694952184966 = 93.20%
Precision: 0.977032307252454 = 97.70%
Recall: 0.9207004939380332 = 92.07%
```

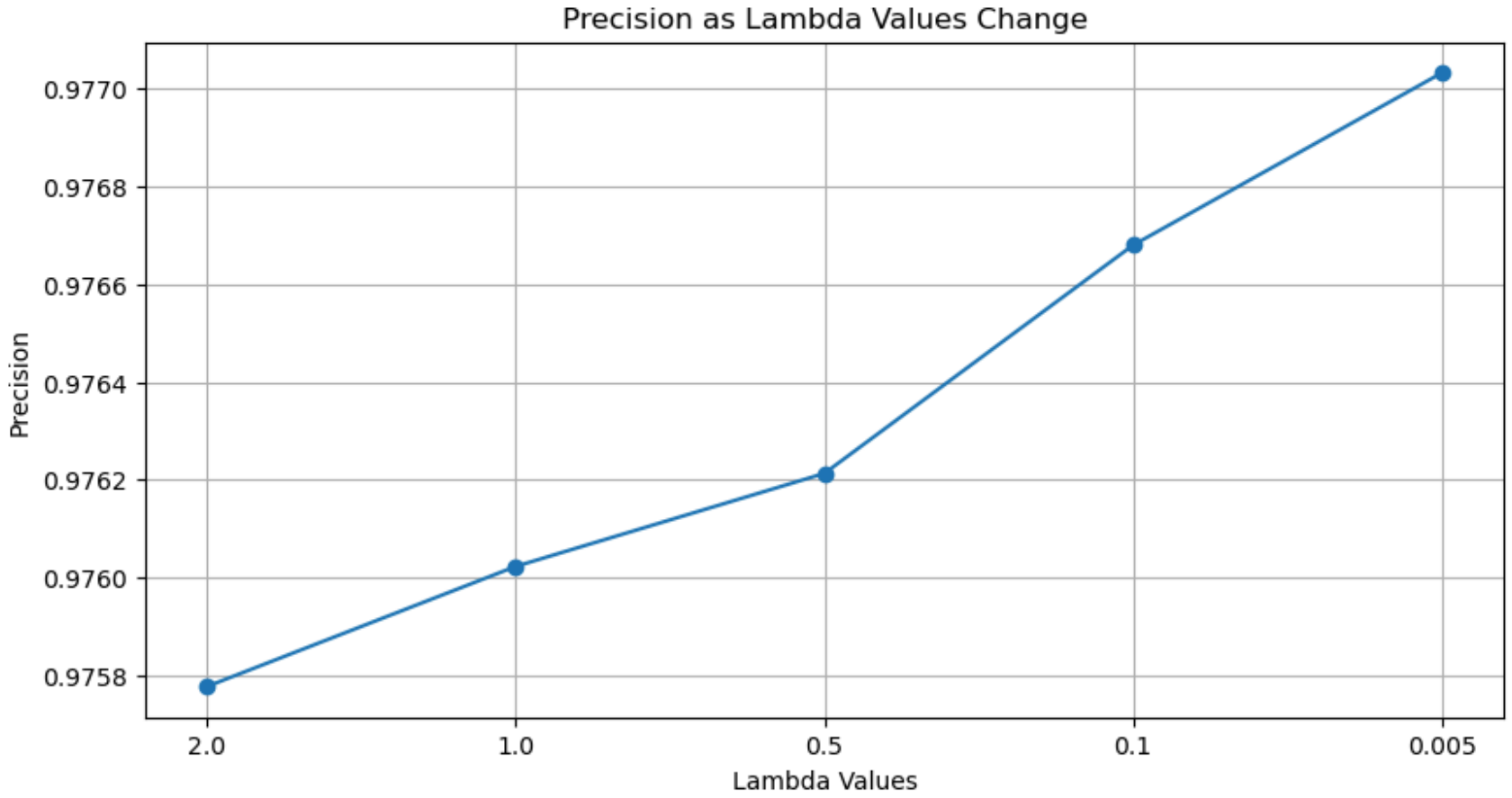


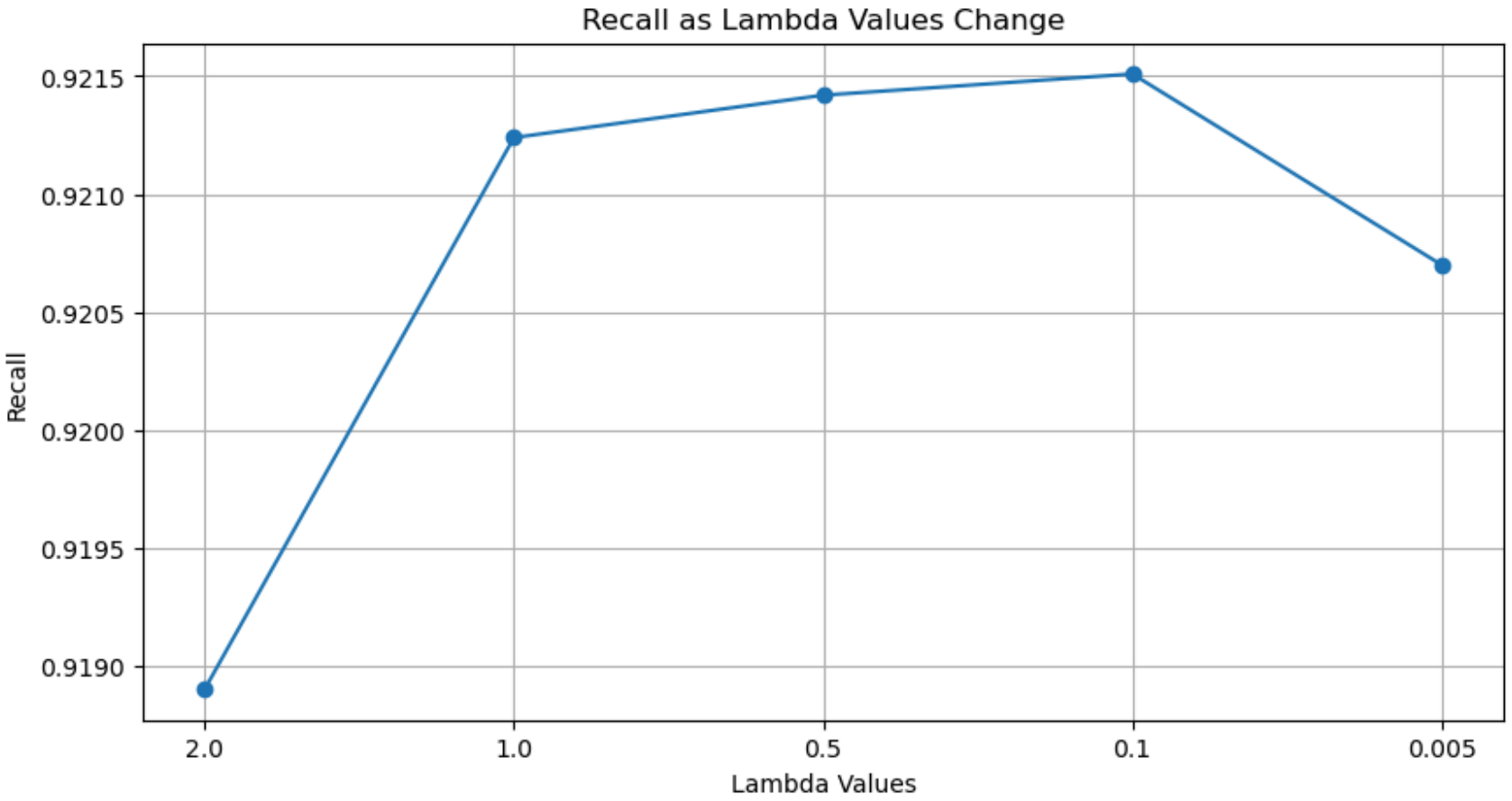
In [163…

```
# Lambda values and corresponding metrics from lambda_results_new
lambda_values_labels = ['2.0', '1.0', '0.5', '0.1', '0.005']
lambda_values = [2.0, 1.0, 0.5, 0.1, 0.005]

# Extract Accuracy, Precision, and Recall from lambda_results_new for each lambda
accuracy_lambda_metrics = [lambda_results_new[lambda_val]['Accuracy'] for lambda_val in lambda_values]
precision_lambda_metrics = [lambda_results_new[lambda_val]['Precision'] for lambda_val in lambda_values]
recall_lambda_metrics = [lambda_results_new[lambda_val]['Recall'] for lambda_val in lambda_values]
```

```
# Plot of Accuracy as lambda values change
fig, ax = plt.subplots(1, 1, figsize=(10, 5))
ax.plot(lambda_values_labels, accuracy_lambda_metrics, marker='o')
ax.set_title('Accuracy as Lambda Values Change', fontsize=12)
ax.set_ylabel('Accuracy')
ax.set_xlabel('Lambda Values')
plt.grid(True)
plt.show()

# Plot of Precision as lambda values change
fig, ax = plt.subplots(1, 1, figsize=(10, 5))
ax.plot(lambda_values_labels, precision_lambda_metrics, marker='o')
ax.set_title('Precision as Lambda Values Change', fontsize=12)
ax.set_ylabel('Precision')
ax.set_xlabel('Lambda Values')
plt.grid(True)
plt.show()

# Plot of Recall as lambda values change
fig, ax = plt.subplots(1, 1, figsize=(10, 5))
ax.plot(lambda_values_labels, recall_lambda_metrics, marker='o')
ax.set_title('Recall as Lambda Values Change', fontsize=12)
ax.set_ylabel('Recall')
ax.set_xlabel('Lambda Values')
plt.grid(True)
plt.show()
```


Accuracy as Lambda Values Change
0.9320
0.9315
0.9310
0.9305
0.9300
Accuracy
2.0
1.0
0.5
0.1
0.005
Lambda Values


Precision as Lambda Values Change
Precision
0.9770
0.9768
0.9766
0.9764
0.9762
0.9760
0.9758
2.0
1.0
0.5
0.1
0.005
Lambda Values



The three line graphs depict how different values of lambda (λ) affect Accuracy, Precision, and Recall:

- **Accuracy**: The model's accuracy peaks at λ = 0.1, indicating that this value of lambda balances the model's predictions best. Accuracy starts low at λ = 2.0 and slightly decreases again at λ = 0.005.
- **Precision**: Precision improves as lambda decreases, reaching its highest value at λ = 0.005. This suggests that smaller lambdas help the model focus more on identifying spam accurately, which reduces false positives.
- **Recall**: Recall peaks at λ = 0.5 but then declines as lambda gets smaller. This implies that while lower lambdas help with precision, the model becomes less sensitive to detecting all spam emails (i.e., missing some spam).

From the line graph, we can see that when lambda is around 1.0 or 0.5, the model performs best in terms of accuracy and recall. However, as lambda gets smaller (e.g., 0.005), precision continues to improve, but recall decreases. This indicates the **precision-recall tradeoff**: as the model becomes more focused on ensuring the emails it labels as spam are indeed spam (high precision), it becomes more conservative, missing some spam emails (lower recall). In contrast, at intermediate values (around 0.5 to 1.0), the model achieves a good balance between **identifying spam** (recall) and **not misclassifying legitimate emails** (precision), providing the best trade-offs for spam detection.

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

Based on my experience with this problem set, here are some recommendations to improve the model:

General suggestion (because this one was really a headache): Since the notebook took a long time and consumed a lot of resources, we could speed up the preprocessing stages by using stemming instead of lemmatization, or we could reduce the size of the feature set by limiting the number of top words. Furthermore, faster training and testing could be achieved without compromising too much accuracy by streamlining the handling of the data, like employing an efficient algorithm or batch processing.

Other suggestions:

- Experiment with how stop words are handled, or maybe only eliminate some of them to see if it improves outcome.
- Including bigrams or trigrams (two or three-word phrases) could capture more context from the emails.
- Make sure the dataset is balanced between spam and ham emails so the model doesn't favor one over the other.
- Try filtering out rare words or setting different frequency limits for words to improve feature selection.
- Fine-tune parameters like lambda and the number of top words to see if we can boost the model’s accuracy.