Spam SMS Detection Model

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Outline

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Business Problem

In our day-to-day lives, we are plagued by spam text messages. These messages are not only annoying, but also pose a security risk to our customers.

Solution: Build a spam detection model that will block potentially harmful messages from users' inboxes while minimizing the number of false positives

Data Overview

Using a dataset of 5,574 text messages from 2015, consisting of both spam and non-spam entries.

86% non-spam14% spam

Data Preprocessing

- 1. Lower case
- 2. Remove punctuation
- 3. Remove stopwords (very common words like "and", "the", "a", etc.)
- 4. Lemmatization (reducing every word to its root form; ex: "running" → "run")
- 5. Applied a TF-IDF Vectorizer, which generated a score for each word based on how frequently it occurred in each string and the whole dataset

nokia min go 150p message holiday reply gift box draw msg c orange video draw msg c orange video weeklys valid tone weeklys weeklys valid tone weeklys mob ringtone will be poly phone date of the poly phone date or the poly phone or date or the poly phone or date or the poly phone date or the poly phone or date or the phone or date or the poly phone or date or the phone or date or the poly phone or date or date

Spam

Not Spam



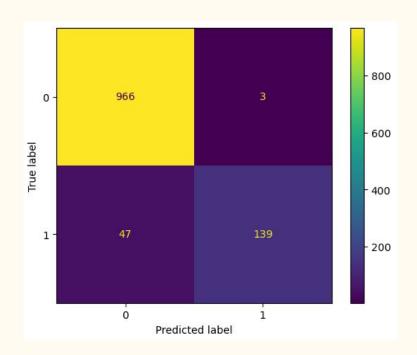
Baseline Model

Created a Logistic Regression model with no modification to the data

Precision Score = 0.98

Recall Score = 0.75

 $F1\ Score = 0.84$



Logistic Regression

Improvements from Baseline

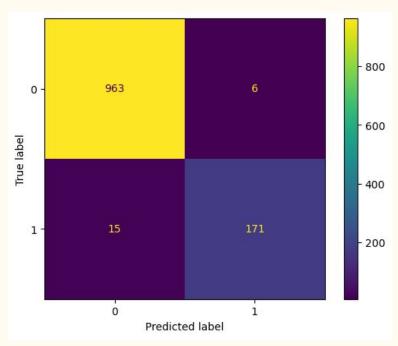
- Implementing oversampling using SMOTE
- Adjusting the C-value for the model
- Adjusting the parameters of the TFIDF Vectorizer

Results

Precision Score = 0.97

Recall Score = 0.92

 $F1\ Score = 0.94$



Multinominal Naive Bayes

Baseline

Precision (Spam):

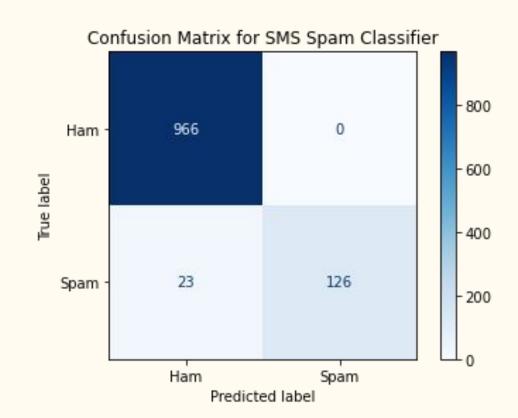
• 100%

Recall (Spam):

• 84.56%

F1 Score (Spam):

• 91.6%



Threshold Adjustment

Precision (Spam):

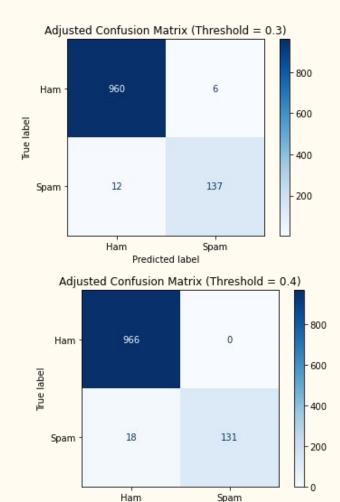
• 100%

Recall (Spam):

• 87.9%

F1 Score (Spam):

• 93.8%



Predicted label

Enhanced Naive Bayes Code with N-grams

Precision (Spam):

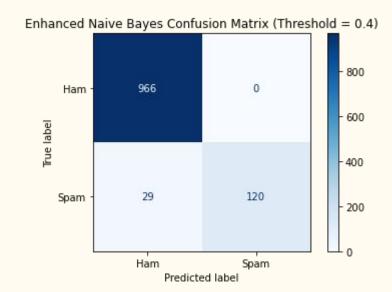
• 100%

Recall (Spam):

• 80.6%

F1 Score (Spam):

• 89.3%



Regex Features

Use Regex to detect phone numbers and URLS

Precision (Spam):

99.3%

Recall (Spam):

91.9%

F1 Score (Spam):

95.5%

Use Regex to detect pricing cues and short codes

Precision (Spam):

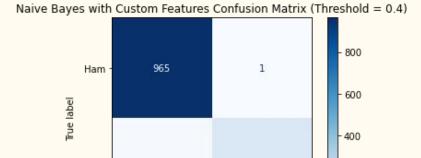
99.3%

Recall (Spam):

93.3%

F1 Score (Spam):

96.2%



137

Spam

200

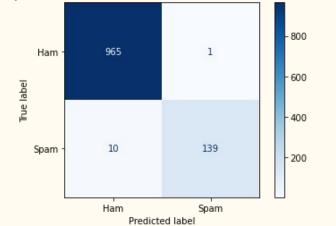
12

Ham

Spam



Predicted label



Business Recommendation

Use the tuned Multinominal Naive Bayes model to detect spam with an F1 Score of

96.2%

Next Steps

- Gather modern SMS data and retrain the model to keep the model accurate as spam patterns change
- Train the model for other messaging services, like email and IM