Spam Email Filter -Machine Learning Model



Agenda

- 01 Business Problem
- 02 Exploratory Data Analysis
- 03 Predictive Modeling
- 04 Conclusions
- 05 Recommendation
- 06 Next Steps

01

Business Problem

Our telecommunications company wants to break into the email market and needs to implement an effective SPAM filter.

We are charged with:

- Create a model that reliably detects SPAM in a way that will maximize customer satisfaction



Data
Analysis

Actual emails in the form of individual HTML files were used in the analysis

- 5825 HTML files in total
- Each email was previously labeled as HAM or SPAM and sorted into folders



Source: Index of /old/publiccorpus (apache.org)

Email Importing and Preprocessing

```
From rssfeeds@jmason.org Tue Oct 8 10:56:10 2002
Return-Path:
Delivered-To: yyyy@localhost.example.com
Received: from localhost (jalapeno [127.0.0.1])
       by jmason.org (Postfix) with ESMTP id EEE0616F03
       for; Tue, 8 Oct 2002 10:56:09 +0100 (IST)
Received: from jalapeno [127.0.0.1]
       by localhost with IMAP (fetchmail-5.9.0)
       for jm@localhost (single-drop); Tue, 08 Oct 2002 10:56:09 +0100 (IST)
Received: from dogma.slashnull.org (localhost [127.0.0.1]) by
    dogma.slashnull.org (8.11.6/8.11.6) with ESMTP id g9881LK06173 for
    ; Tue, 8 Oct 2002 09:01:21 +0100
Message-Id: <200210080801.g9881LK06173@dogma.slashnull.org>
To: yyyy@example.com
From: newscientist
Subject: Species at risk of extinction growing
Date: Tue, 08 Oct 2002 08:01:21 -0000
Content-Type: text/plain; encoding=utf-8
X-Spam-Status: No, hits=-1014.1 required=5.0
        tests=AWL,T NONSENSE FROM 40 50
        version=2.50-cvs
X-Spam-Level:
URL: http://www.newsisfree.com/click/-2,8653742,1440/
Date: Not supplied
The latest "Red List" adds 124 to the 11,000 endangered species around the
globe - but also includes a stick insect revival
```

Subject: Species at risk of extinction growing

The latest "Red List" adds 124 to the 11,000 endangered species around the globe - but also includes a stick insect revival

Subject Line vs Email Body

Subject Line:
- We expect 'dense' information about the nature of the email

Email Body:

- More information about the nature of the email, more verbose

Subject: Species at risk of extinction growing

The latest "Red List" adds 124 to the 11,000 endangered species around the globe - but also includes a stick insect revival

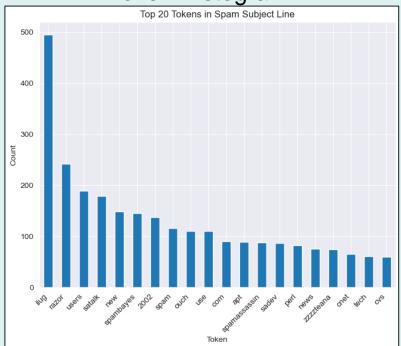
Modeling the Subject and Body separately...

Target Distribution Imbalance



Subject Line EDA – Ham Class

Token Histogram



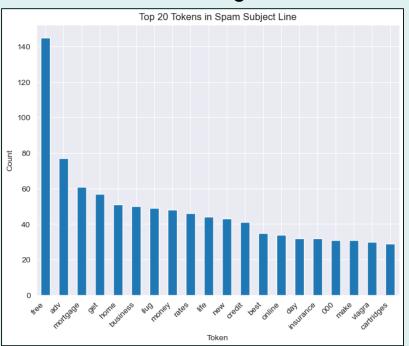
Word Cloud Top 100

```
false positive
    ilug slashdot selling wedded
    cvs spamassassin entrepreneurs window sequences window
                               gaeda fantasy
     gx260 redhatmoment silence
tech update high tech number six of united states
  slashdot dijkstra
 time policy review test sets
    almost made
```

Note: Models are built on company internal 'jargonized' email data, will need to adjust models trained on anonymized customer emails data after deployment

Subject Line EDA – Spam Class

Token Histogram



Word Cloud Top 100

```
herbal viagrahome
          pay approved Sale
          → increase
week
                               internet
  extended auto guaranteed
work<sub>cost</sub> cartridges less
                               long distance
```

03

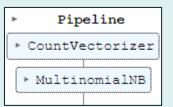
Predictive Modeling

BUSINESS REQUIREMENT:

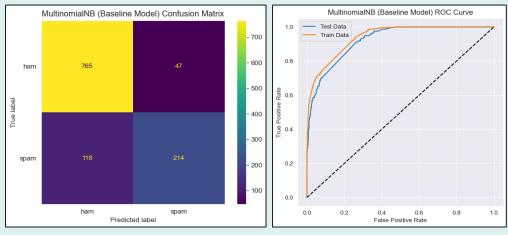
- Getting SPAM in the inbox irritates our customers, but missing an important message because we classified it as SPAM will really anger them!
- Optimizing models on **Precision (minimize False-Pos)**, then **Accuracy**
- Less than 1% of customers HAM emails are allowed to go to the SPAM classification

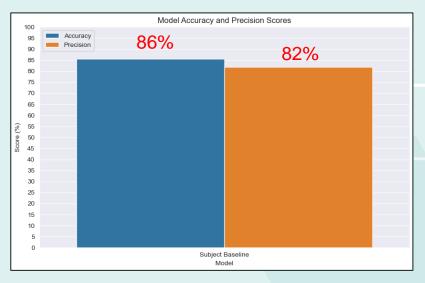


Subject Line Baseline Model

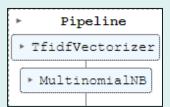


- Regex tokenizer of >2 characters
- Binary vectorizer
- Multinomial Bayes Classifier

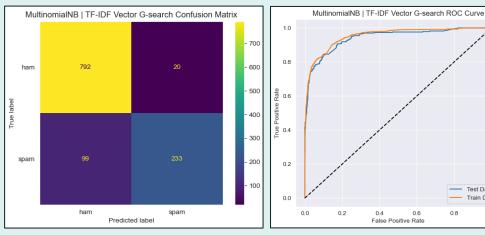


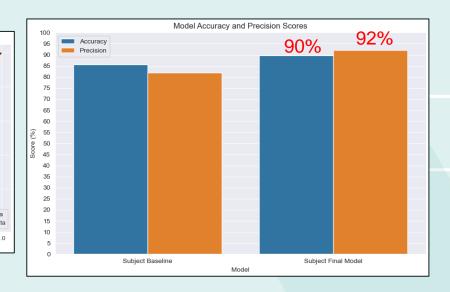


Subject Line Final Model

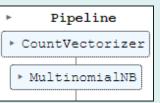


- Word_punct_tokenizer
- TFIDF vectorizer
- Multinomial Bayes Classifier

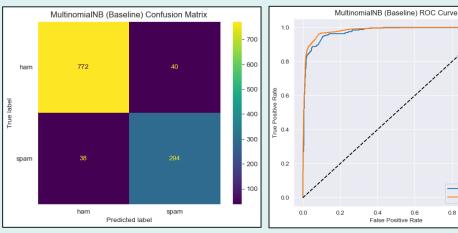


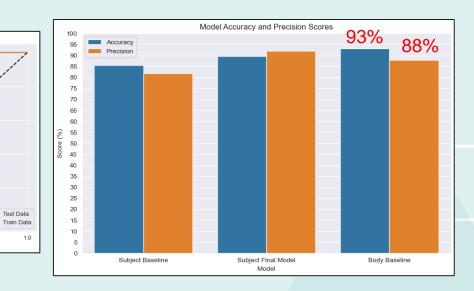


Email Body Baseline Model

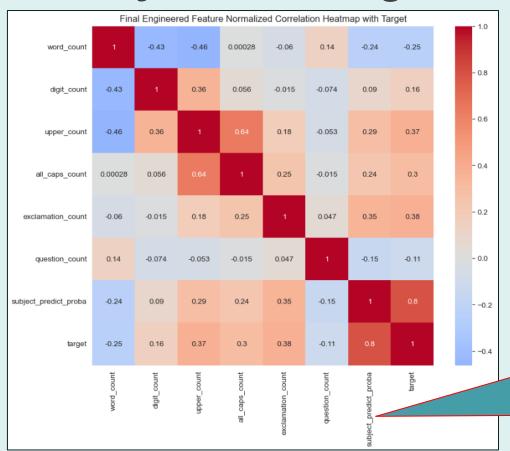


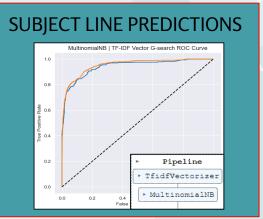
- Regex tokenizer of >2 characters
- Binary vectorizer
- Multinomial Bayes Classifier



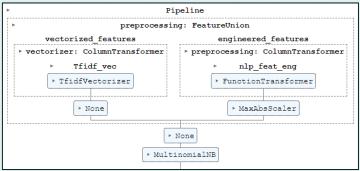


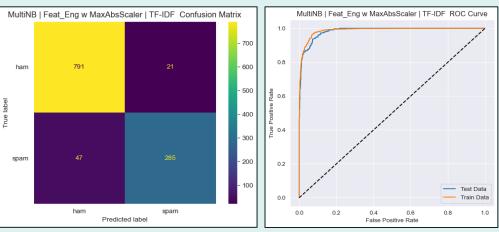
Email Body Feature Engineering



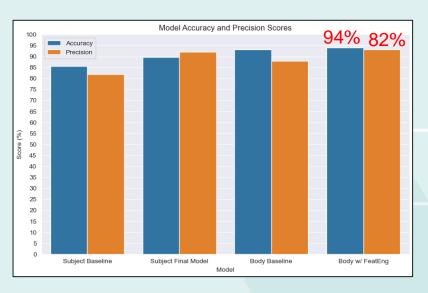


Email Body With Feature Engineering

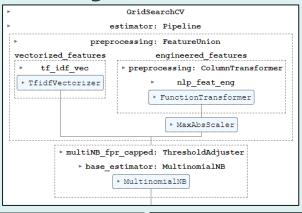




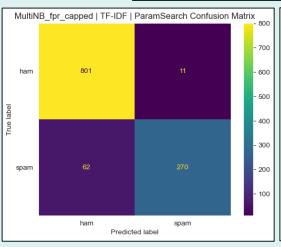
- Regex tokenizer of >2 characters
- TF-IDF vectorizer
- Multinomial Bayes Classifier

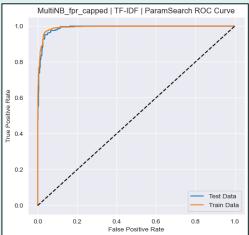


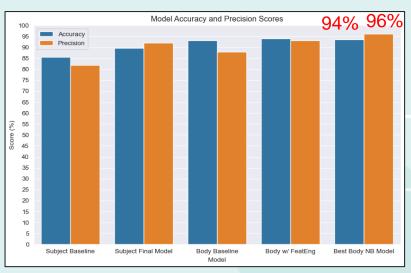
Email Body - Best Naive Bayes Model



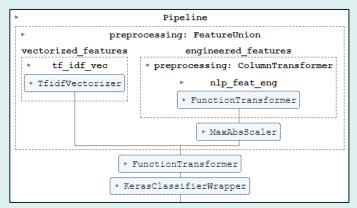
- Hyperparameter Gridsearch
- NB Model wrapped in Prob Threshold Adjuster (<1% FPR)

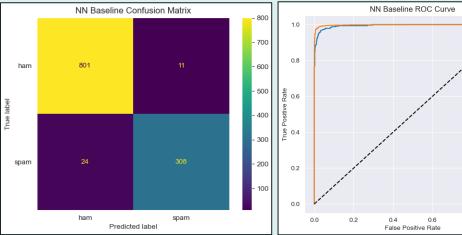






Email Body - Neural Network Baseline



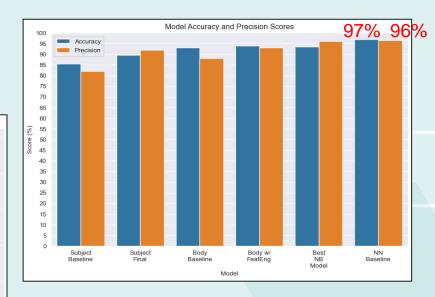


One hidden layer

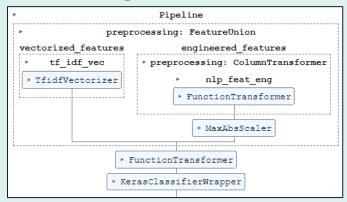
Train Data

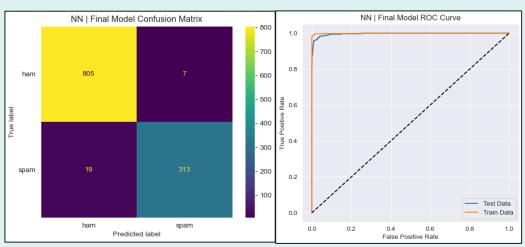
1.0

Threshold Adjusted (<1% FPR)

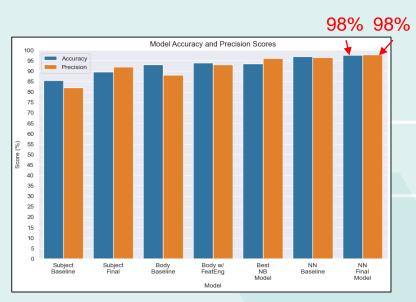


Email Body - Neural Network Final



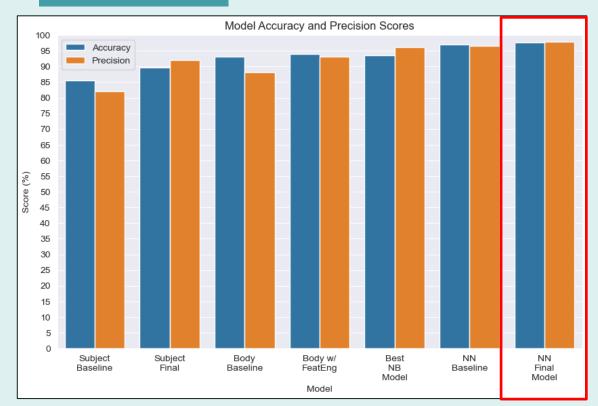


- 5 hidden layers
- 2 dropout layers
- Gridsearch using Hyperband()
- Threshold Adjusted (<1% FPR)



04

Conclusion



Final Model Test Metrics:

Precision: 97.7%Accuracy: 97.8%

Final Business Metrics:

False Pos Rate (HAM going to SPAM): 0.9%

False Neg Rate (SPAM going to HAM): 6%

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Recommendation

Implement the best Neural Network model during initial
 Email service rollout

2. Continue to retrain and retune the models on new anonymized customer data

Investigate other potential model improvements (see next steps)



06 Next Steps

- 1. Continue to improve the model
 - 1. Rerun and tune the models with the 'Cheat words' removed
 - 2. Investigate tokenizing based on wordcloud algorithm
 - 3. Check other model architectures (RandomForest, XGBoost)
 - 4. Tune NN for subject-line only, perhaps effective and more efficient
 - 5. Investigate verbiage and nature of SPAM, are there features we can capture
 - 6. Investigate the False cases; are there features we can capture
 - 7. Investigate keeping URLs instead of scrubbing them preprocess
- 2. Acquire larger data sets of up-to-date emails



Thanks!

Questions? Please contact me at:

Dale DeFord daledeford@gmail.com



