

Predicting Spam Emails

DS 4002 - 02/17/2025 Group 2: Ella Thomasson (Leader), Maggie Crowner, Emily McMahon

Motivation and Goals

Motivation: Spam emails have the intent to harm by encouraging users to download malicious software

Goal: Investigate the categorization of an email as spam or not spam. Be able to predict, with 80% accuracy, whether or not an unseen email is spam based on the contents of the email.

Hypothesis: We can detect spam emails with 80% accuracy

Research Question: How accurately can we predict whether or not an email is spam based on the contents of the email? How do the accuracy results vary across different classifiers?



Data Acquisition/Explanation

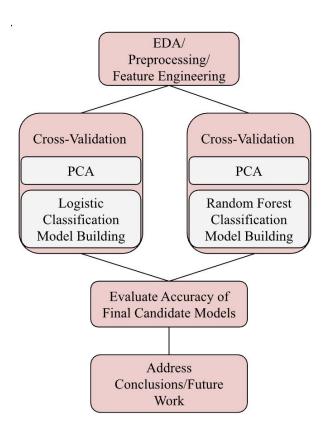
84 Rows(58 non-spam and 26 spam) and 3 Columns

| Title | str | A string containing the subject line of the email. | | |
|-------|-----|---|--|--|
| Text | str | A string containing the body text of the email. | | |
| Туре | str | Whether or not the email is spam - "spam" or "not spam" (response variable) | | |
| | | | | |



| 84 Rows(58 non-spam and 26 spam) and 104 columns | | | | | | |
|--|-------|--|--|--|--|--|
| Text Sentences str All instances of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of punctuation marks that indicate the content of the following structures of the follo | | All instances of punctuation marks that indicate the end of a sentence | | | | |
| Text Words | str | The number of words in each email's body | | | | |
| Company | dummy | Represents whether or not the email body has "company" in it | | | | |
| ••• | | | | | | |
| Type | str | Whether or not the email is spam | | | | |

Analysis Plan



Justification

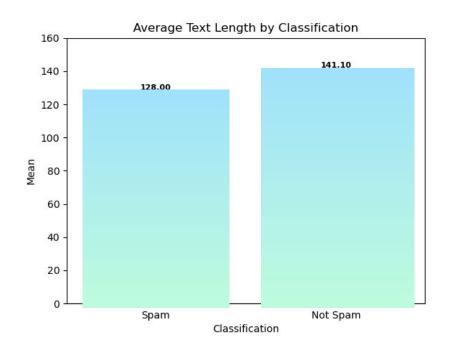
- Used 5-fold CV to obtain more accurate estimates on how the model will perform on unseen data
- Used PCA to decrease dimensionality before jumping into model building(bc #col>#rows)

Tricky Analysis Decisions

- Deciding which variables to include in the model
- Cut off values for dummy variables(10)- arbitrary
- Number of Components for PCA(0.8)- arbitrary

Bias and Uncertainty

- Small sample size
- Unequal number of spam and non-spam emails in the data





| Metric | LC Value | RF Value | Meaning |
|-----------|----------|----------|---|
| Accuracy | 0.7619 | 0.7143 | The probability of correctly predicting spam/not-spam emails |
| Precision | 0.6500 | 0.6667 | The probability of correctly predicting the positive class (a spam email) |
| Recall | 0.5000 | 0.1538 | Proportion of actual spam cases that the model correctly classifies as spam |
| F1-Score | 0.5652 | 0.2500 | The harmonic mean of precision and recall |
| ROC-AUC | 0.8345 | 0.6963 | The test's ability to distinguish between spam and non-spam individuals |

| LC Conf Matrix | Predicted Not Spam | Predicted Spam |
|-----------------|-----------------------|----------------|
| Actual Not Spam | 51 | 7 |
| Actual Spam | 13 | 13 |

| RF Conf Matrix | Predicted Not Spam | Predicted Spam |
|-----------------|-----------------------|----------------|
| Actual Not Spam | 56 | 2 |
| Actual Spam | 22 | 4 |

Conclusions

- Would choose the Logistic Regression Model based on the accuracy metrics
- We did not quite meet our 80% accuracy goal, but we got fairly close with a 76.2% accuracy
- The RF model seems to not detect "spam" emails well, based on recall/F1-score

Next Steps

- Tune parameters in the RF
- Add more variables(or use a larger threshold for words to include within the models)
- Obtain a dataset with a larger number of rows
- Try different classification models(Neural Networks, SVM, Naive Bayes, etc.)
- Would Lasso have been a better method than PCA?

References & Resources

Github: https://github.com/maggiecrowner/DS4002-Project1/tree/main

References:

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- [2] Ghazala Nasreen, Muhammad Murad Khan, M. Younus, B. Zafar, and Muhammad Kashif Hanif, "Email spam detection by deep learning models using novel feature selection technique and BERT," *Egyptian Informatics Journal/Egyptian Informatics Journal*, vol. 26, pp. 100473–100473, Jun. 2024, doi: https://doi.org/10.1016/j.eij.2024.100473.
- [3] A. Ajay, "What are the Advantages and Disadvantages of Random Forest?," *Pickl.AI*, Sep. 30, 2024. https://www.pickl.ai/blog/advantages-and-disadvantages-random-forest/.
- [4] A. Khan, "Email Spam Detection with Machine Learning: A Comprehensive Guide," Medium, Mar. 22, 2024.

 https://medium.com/@azimkhan8018/email-spam-detection-with-machine-learning-a-comprehensive-guide-b65c6936678b
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Thank You for Listening! Questions?



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