Project Results

What is in your data?

We decided to look at data from Kaggle, and discovered a dataset that included information from phishing emails, and around 15,000 messages. We decided to focus our energy on TREC_06, a recently updated but smaller size file of information. The variables included are “sender”, “receiver”, “subject”, “body”, “date”, “label”, and “urls”. Sender and receiver refer to metadata used to keep track of information sent, subject and body are the main email content, date refers to when the email was sent, label highlights whether the email was flagged as spam, and urls contains information if the email contained any.

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Emails Containing URLs:
 0    7246
1    4225
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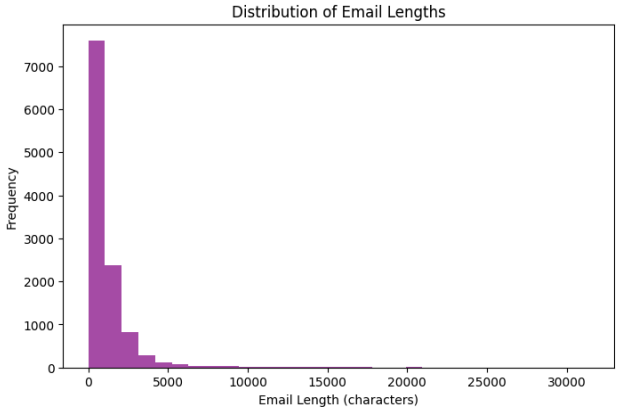
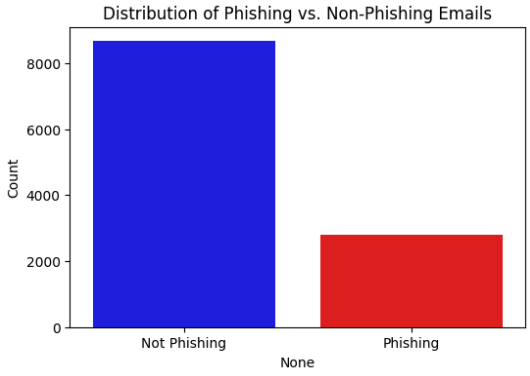


How will these data be useful for studying the phenomenon you're interested in?

Our main goal with this data is to eventually create a predictive model that can successfully categorize phishing emails. These Text Retrieval Conference (TREC) Spam Track datasets were actually developed for this exact purpose; to simulate incoming emails that required filters to determine if they were spam or not spam. Since we will have the label variable available for us, we will know whether an email was flagged or not, so the model can successfully train

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Phishing Email Counts:
 0    8668
1    2803
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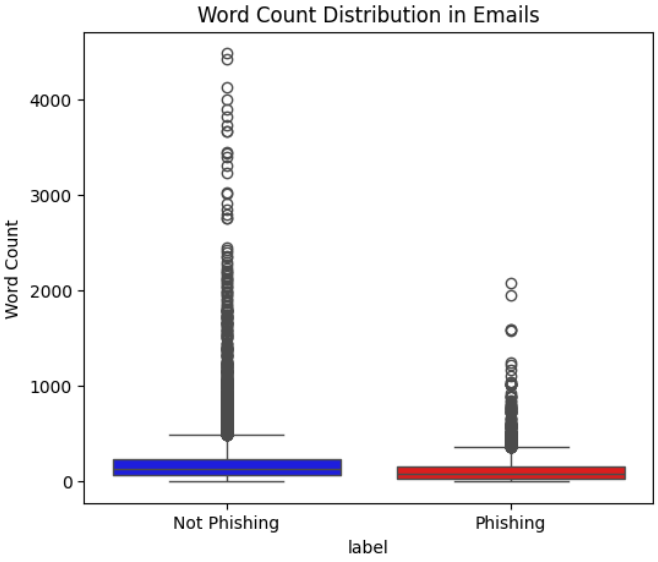
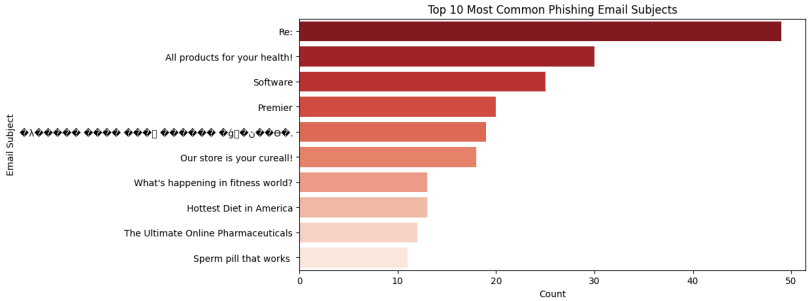
and be tested without this category. Based on initial statistical analyses, we know that there are 8,668 non-spam and 2,803 spam emails present.

There are a few different aspects of the data that we might predict the model will learn to use in its distinctions. Phishing emails seem to include less words, often include “A0” and demanding language such as “will”, “need”, “now”, “want”, and are likely to include “money” as well. The subject line might also be incredibly telling, with distinct lines including “Re:”, long strings of special characters, exclamation points and question marks, and other eye-catching titles.



What are the challenges you've resolved or expect to face in using them?

The main issue we expect to deal with is the sheer size of the dataset. At 15.5 MB, processing with python will be tedious, especially if we attempt to filter it for specific entries. Unfortunately, there is not much that can be done about the processing delays we will likely experience, writing the model code and testing it will take a lot of time, so we will need to carefully plan ahead. Furthermore, as of right now we are planning on splitting the data into training and non-training for model accuracy testing, however we are unsure of exactly how we will want to split it percentage wise to avoid overfitting or underfitting our model.



Research Question

What characteristics make an email most likely to be a phishing attempt?

Data and Observations

We use the TREC_06 dataset from Kaggle, which consists of approximately 15,000 emails, each labeled as either phishing (1) or not (0). In this study, each observation is a single email, represented as a row containing features such as body text, subject line, sender, presence of URLs, and timestamp. Since our target variable is binary, this study will use supervised learning for classification rather than regression.

Models and Algorithms

To classify phishing emails, we will experiment with models including Logistic Regression, Random Forest Classifier, and SVM with TF-IDF Vectorization--each of which serves a different purpose. Logistic Regression is a simple classification approach that will estable a baseline for prediction performance. Random Forest Classifier can handle structured features like presence of URLs, email length, and sender frequency while simultaneously reducing overfitting. SVM with TF-IDF Vectorization allows us to extract textural patterns from email bodies using Term Frequency-Inverse Document Frequency (TF-IDF) to convert text into numerical features, like the email body, subject line, and URLs, and then use SVM to analyze those textural features. This aids in capturing the importance of specific words within the context of the email while reducing the impact of more common words including "and", "in", and "the".

Feature Engineering

Given that phishing emails rely heavily on textual deception, Natural Language Processing (NLP) techniques will be employed to refine the dataset. Specifically, we will experiment with different NLP techniques such as stemming, lemmatization, and n-grams. Furthermore, the data may require additional cleaning to fix inconsistent timestamps, missing values, or encoding errors in emails.

Model Evaluation and Success Metrics

Success is defined by a model that achieves high predictive accuracy without significant overfitting. Success of the model was measured through accuracy (overall classification correctness), precision and recall (missed phishing email classifications), F1 score (balance between precision and recall), and ROC-AUC score (measure of overall classifier performance). Precision and recall is particularly important for phishing detection since false negatives are riskier than false positives, as these emails can contain potentially dangerous links that steal pertinent receiver information. Visualizations such as confusion matrices and feature importance plots will provide deeper insights into model performance.

Anticipated Challenges & Mitigation Strategies

Feature engineering may require multiple iterations. We will experiment with different NLP techniques to improve classification accuracy. Additionally, inconsistent timestamps, missing values, and encoding errors may arise. We will preprocess data to address these issues before model training. Finally, regularization techniques and cross-validation will be used to ensure models generalize well to unseen data. If our approach does not achieve the desired performance, we may gain insights into identifying additional phishing indicators. We may find ourselves exploring deep learning models like LSTMs or BERT, or understanding evolving tactics used in phishing campaigns. By iterating on these approaches, we aim to develop an interpretable model for phishing email detection.

Plan for Results

Once the models are trained and evaluated, we will present our findings through various visualizations and performance metrics. We will use confusion matrices to analyze misclassification patterns and evaluate false positives and false negatives, which are critical in phishing detection. Similarly, we will have a summary table comparing accuracy, precision, recall, F1-score, and ROC-AUC for each model to determine the best-performing classifier. Additionally, we will look into the importance of given features for the best performing classification algorithm. Through these results, we aim to answer which characteristics most

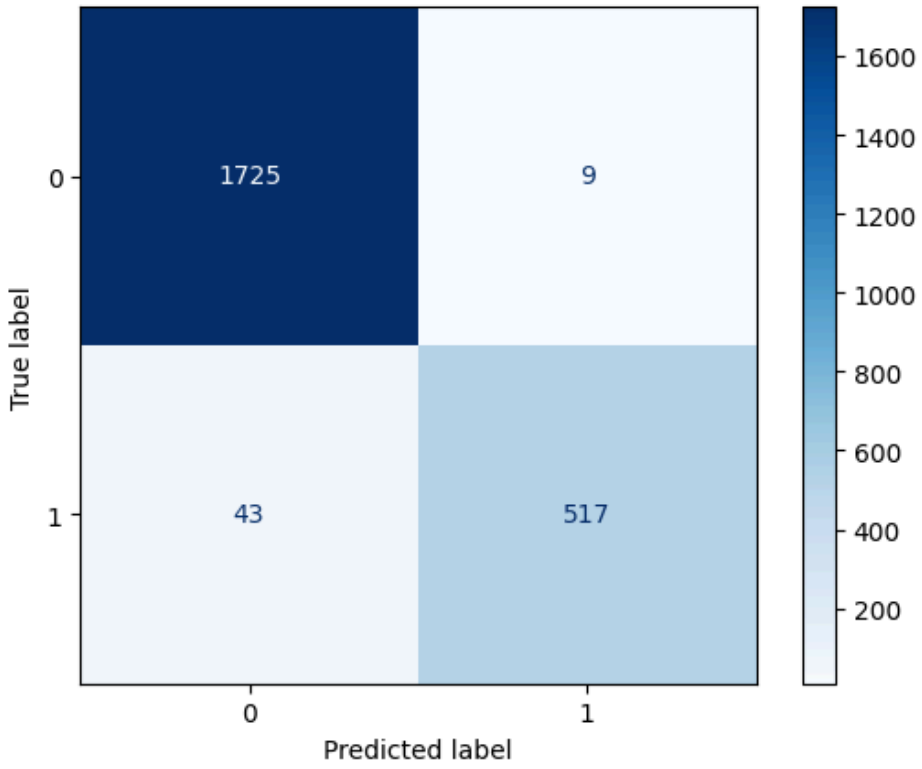
strongly indicate phishing emails and determine which model is best suited for practical phishing detection applications.

Final Results

Before delving into full analyses, we wanted to determine which of three models performed the best. These models included support vector machine (SVM) and TF-IDF vectorization, random forest, and linear regression, and of these the linear regression had the highest accuracy of 97.69% and the highest precision of 98.29%. Additionally, this model had a recall percentage of 0.9232, meaning it was able to successfully identify positive phishing emails 92.32% of the time. Finally, linear regression had the second highest F1 score of 0.9521 and highest ROC AUC score of 0.9982, meaning this model was incredibly successful in predicting what emails were and were not phishing.

	Linear Regression	**Random Forest**	**SVM/TF-IDF Vectorization**
Accuracy	0.9773	0.9769	0.9647
Precision	0.9829	0.9828	0.9650
Recall	0.9232	0.9210	0.9647
F1 Score	0.9521	0.9509	0.9648
ROC AUC Score	0.9982	0.9982	0.9871

To better visualize the accuracy of this linear regression model we settled on, we decided to create a confusion matrix to analyze the relationship between predicted and true labels, either phishing or not. We discovered that out of 1,734 not phishing emails, our model correctly labeled 1,725 of them with only 9 being misidentified. Similarly, out of 560 phishing emails, our model correctly labeled 517 and only incorrectly labeled 43. Though the accuracy was higher in determining non-phishing emails, we can still say that this linear regression model is very effective overall.



Knowing this, we decided to use linear regression to determine which characteristics are indicative of a phishing email. This is the most important factor in being able to determine, and predict, whether an email is phishing or not. We decided to look at feature importances, in which a positive importance value means an increased chance the email is phishing, and a negative importance value means an increased chance the email is not phishing. Interestingly, we found that characters like “thanks” and “edu” are two of the most important features present in non-phishing emails. This is likely due to the fact that legitimate correspondence have human touches like saying thanks or including any educational links. Furthermore, “http”, “com”,

“000”, and “company” were highly indicative of phishing emails. Many of these emails include links to external and insecure websites indicated by the “http” instead of “https” and likely less reputable domains such as “com” instead of “edu” or “gov”. The presence of triple zeros is likely due to the presence of large numbers with multiple zeros present at the end, used to grab the recipients attention, either malicious saying they owe money or trying to pull at their greed by stating they could be endowed with money if they respond. Finally, “company” is a very general term, and if a specific company were to be contacting someone they would be much more likely to utilize their actual name instead.

	feature	importance	abs_importance
4532	thanks	-5.324070	5.324070
2295	http	4.873127	4.873127
1640	edu	-4.822734	4.822734
3685	ra	4.269415	4.269415
4749	use	-3.732315	3.732315
776	board	-3.682443	3.682443
4973	wrote	-3.506038	3.506038
1547	does	-3.302036	3.302036
2717	list	-3.300271	3.300271
1087	com	3.201612	3.201612
2181	handyboard	-3.195584	3.195584
1	000	3.081886	3.081886
4756	using	-2.964023	2.964023
1111	company	2.876386	2.876386
3923	robot	-2.836361	2.836361
2202	hb	-2.817252	2.817252
4660	try	2.795099	2.795099
4715	university	-2.794609	2.794609
3562	problem	-2.633563	2.633563
2294	html	-2.592719	2.592719

We also determined the prevalence of different categories of special characters present in phishing and non-phishing emails. Overall, we really only found a higher occurrence of uppercase letters in phishing emails, which is likely a tactic used to better grab the recipient's attention and persuade them to think the email contains pertinent and time sensitive information.

Conclusion

Overall, we successfully created a prediction model utilizing linear regression to label emails as either phishing or non-phishing based on the prevalence of specific words and characters using 80% of the TREC_06 dataset to train this model and 20% for testing purposes. Models such as these could be used for preliminary elimination of phishing emails from recipient inboxes. However, we have several criticisms of our predictive model, mainly that it might not perform well outside of the organization that the emails within the dataset were taken from for training, as phishing emails are often tailored to the users they are sent to or the company they represent. Additionally, while accurate, it still will likely not catch all spam emails for this organization– especially as attackers are constantly evolving their tactics to evade detection. In the future, we could utilize UVA's database and logs of phishing emails it has received, as it could be useful to create a predictive model to filter phishing emails for students and staff before they receive them.

References

1. A. I. Champa, M. F. Rabbi, and M. F. Zibran, “Why phishing emails escape detection: A closer look at the failure points,” in *12th Interna- tional Symposium on Digital Forensics and Security (ISDFS)*, 2024, pp. 1–6.

2. A. I. Champa, M. F. Rabbi, and M. F. Zibran, “Curated datasets and feature analysis for phishing email detection with machine learning,” in 3rd IEEE International Conference on Computing and Machine Intelligence (ICMI), 2024, pp. 1–7.