

Data Analytics Capstone Topic Approval Form

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Capstone Project Name: Machine Learning [SPAM](#) Detection Powered by Enron/TREC Public Spam Corpus

Project Topic: This initiative aims to develop a proficient model capable of accurately classifying unlabeled content as either SPAM or HAM (Not Spam). To achieve this, the project will utilize the TREC Public Spam Corpus and Enron Emails dataset from 2007, available at <https://www.kaggle.com/datasets/purusinghvi/email-spam-classification-dataset>.

☒ **This project does not involve human subjects research and is exempt from [WGU](#) IRB review.**

Research Question:

Is it possible to develop a machine learning model that can accurately classify new content as SPAM or non-SPAM (HAM), using a dataset comprising known SPAM and regular content from the 2007 TREC Public Spam Corpus and Enron emails?

Hypothesis:

Null hypothesis (H_0)- The machine learning model developed using the 2007 TREC Public Spam Corpus and Enron emails dataset cannot accurately classify new content as SPAM or non-SPAM (HAM) with an accuracy score of 95% or higher. This implies that any observed accuracy in classification does not significantly exceed what would be expected by chance.

Alternate Hypothesis (H_a)- The machine learning model developed using the 2007 TREC Public Spam Corpus and Enron emails dataset can accurately classify new content as SPAM or non-SPAM (HAM) with an accuracy score of 95% or higher. This suggests that the model has learned effective patterns within the dataset, enabling it to differentiate between SPAM and non-SPAM content significantly better than chance.

Context: *Explain why the situation or question would benefit from a data analysis in less than 500 words.*

The proposed question, focusing on the development of a machine learning model for SPAM and HAM classification, is an excellent candidate for data analysis due to several reasons:

1. **Practical Relevance and Application:** Spam detection is a significant issue in digital communication, impacting both individuals and organizations. Effective spam filters can save time, protect against malware and phishing attacks, and improve overall user experience. By analyzing this data, we can create models that are not only academically interesting but also have practical applications.
2. **Complexity of SPAM and HAM differentiation:** The distinction between SPAM and HAM is not always clear-cut. Spam messages have evolved to be more sophisticated, often mimicking legitimate content. A data-driven approach can uncover subtle patterns and characteristics of spam and non-spam content that may not be immediately apparent to human observers.

3. **Model Evaluation and Improvement:** Data analysis allows for quantitative evaluation of the model's performance. Metrics such as accuracy, precision, recall, and F1-score provide insight into how well the model is performing and where it might be failing. This feedback loop is crucial for refining and improving the model.
4. **Machine Learning Model Selection and Optimization:** Data analysis is not just about processing data; it is also about choosing the right algorithm for the task. Different machine learning models have their strengths and weaknesses. Through analysis, we can determine which model (like Logistical Regression, Naïve Bayes, SVM, Neural Networks) best suits our data characteristics and requirements.
5. **Adaptability to New Spam Techniques:** Spam tactics evolve, and a model trained on historical data might become less effective over time. Regular analysis of new data sets can help in updating and tuning the model to adapt to new spamming techniques.

In summary, the application of data analysis to this problem is not only apt but necessary. It provides the tools and methodologies to extract insights from complex and large datasets, build and refine predictive models, and ultimately, contribute to solving a problem with significant real-world implications.

Data: *Identify data you will need to collect that is relevant to the situation or question.*

The data that will be needed to be collected is a collection of email contents which has been correctly labeled as SPAM or NOT (HAM).

*If an existing data set will be used, describe the data set. **(Dataset Exists):***

Feature	Datatype	Description
label	Qualitative	This is the feature that is the label of the dataset. It is a Boolean represented as 1 or 0. 1 represents the associated text is SPAM 0 represents the associated text is HAM (Not SPAM)
text	Qualitative	This is just text content (unstructured data). In the case of this dataset the contents are an Email. This is the data that will be used to train and is pre-labeled for the Machine Learning model.

Notes: *Within the code these will be renamed. label -> IsSpam and text -> EmailContent for readability.*

Explain who owns the data and why you are allowed to use this data for your capstone project.

Dataset Hosting: www.kaggle.com

Dataset Name: 'Spam Email Classification Dataset'.

Created by: Puru Singhvi

Dataset License: [MIT](https://creativecommons.org/licenses/by/4.0/)

Note: If you are using restricted information, please have the Third-Party Authorization Form signed by an authorized agent on behalf of the data owner. The data owner's legal name is required on the form.

Data Gathering: *Describe the data-gathering methodology you will use to collect data.*

The dataset required for this project is a pre-labeled set of training data, readily available for download. It can

be accessed as a **.csv** file from Kaggle at [\[https://www.kaggle.com/datasets/purusinghvi/email-spam-classification-dataset\]](https://www.kaggle.com/datasets/purusinghvi/email-spam-classification-dataset).

However, there are additional considerations regarding data management due to GitHub's file size constraints. Specifically, GitHub imposes a limit of 100MB per file, while the dataset in question is 133MB. To address this, the original dataset has been divided into two separate **.csv** files with index added in case we need to maintain order. These files are stored in a private repository associated with my academic coursework. In the Jupyter Notebook environment, these two files will be merged back into a single dataset for analysis and model training. This approach is a practical solution to the repository's file size limitations and does not reflect any inherent constraints of the data itself.

Data Analytics Tools and Techniques: *Identify the appropriate data-analysis technique you will use to analyze this data. (Justifications are in-line with the chosen items)*

Exploratory Data Analysis (EDA):

The Exploratory Data Analysis (EDA) will be conducted utilizing the [Polars](#) Python package. This approach will enable us to reassemble the dataset, taking into account the limitation that "GitHub blocks files larger than 100 MiB" (GitHub, n.d.). The process will involve meticulous checks for missing values, analysis of data distributions, identification of any unusual characters, and computation of summary statistics for both the original dataset and the character lengths relevant to the neural networks. Subsequently, the data will be systematically divided into training, validation, and test datasets, ensuring a comprehensive and robust preparation for further modeling stages.

Principal Statistical Method (Regression Analysis in form of Logistical Regression):

I will be using Logistical Regression as per Wikipedia it's a great option to test if our 'label' (IsSpam) has a good relationship with our dependent variable 'text' (EmailContent)

"In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome' or 'response' variable, or a 'label' in machine learning parlance) and one or more independent variables (often called 'predictors', 'covariates', 'explanatory variables' or 'features')." ("Regression Analysis", Last Update: 10/31/2023)

I will be using a Logistical Regression Model to generate a model for spam detection. This is important because SPAM, particularly in the form of PHISHING, is constantly evolving and can cost a business significantly if it compromises the company's network.

Reasons:

- Logistical Regression Models are efficient in binary classification, which is ideal for distinguishing between SPAM and non-SPAM emails.

- These models are straightforward and computationally less intensive, making them suitable for initial or simpler spam detection systems.
- Logistical Regression can provide clear probabilistic outcomes, which can be useful in assessing the likelihood of an email being SPAM.
 - Statistical analysis
 - Probability scoring
- These models are less sensitive to overfitting on smaller datasets, which can be beneficial when the available SPAM dataset is on the smaller side.
- Logistical Regression Models can handle a mix of continuous and categorical data, common in email formats.

Tools:

- [Jupyter](#) Notebook
 - Jupyter notebook is an experimentation and documentation platform. This lends itself well to providing out concepts and performance assessments.
- [Python](#) Programming Language
 - A bigger chunk of the data science and data analytics community build libraries around Python. So, I have chosen to use the simpler and more community supported language.
- **Python Packages:**
 - [Polars](#) (Was not taught during [WGU](#) courses)
 - [Polars](#) is a data manipulation library akin to [Pandas](#), renowned for its efficiency with small to medium-sized datasets. However, Polars distinguishes itself by being developed in [Rust](#), a language that combines Python's simplicity with the high performance of [C](#). This project will employ Polars not only as a practical example of its application but also to address the common occurrence of large datasets in real-life scenarios.
 - [Matplotlib](#)
 - This is a community standard visualization library and performed well for all other performance assessments. Although, it has heavy integration with [Pandas](#), it is not a requirement to use the visualization library.
 - [Emoji](#) (Was not taught during [WGU](#) courses)
 - During the pre-processing process before the model is created this library makes it easier to identify non-standard characters that come in the form of emojis and will aid in removing them before modeling.
 - [Unidecode](#) (Was not taught during [WGU](#) courses)
 - During the pre-processing process before the model is created, this helps remove Unicode ASCII type characters that may be introduced and cause issues. These will be removed.
 - [Scikit-Learn](#):
 - This package is a Python-based machine learning toolkit designed for predictive analysis. It is particularly suited for applications such as [SPAM](#) detection, which inherently involve predictive processes.

- [train test split](#)
 - Splits data set into training and testing data. Generally, an 80/20 split.
- [CountVectorizer](#)
 - Models work with numerical data. CountVectorizer is used to convert unstructured text into numerical data for predictive analytic modeling.
- [LogisticRegression](#)
 - This is the Machine Learning Model. Because the emails are labeled as 1 or 0 to indicated if it is SPAM or not logistical is the proper choice.
- [accuracy score](#)
 - Calculates the accuracy of the model's ability to match data appropriately.
- [confusion matrix](#)
 - This matrix is used to evaluate how accurate the classifications are.

Project Outcomes:

The primary goal of the project is to develop a machine learning model that specializes in identifying and classifying email content as SPAM or non-SPAM (HAM). This model, trained on the 2007 TREC Public Spam Corpus and Enron emails dataset, aims to achieve an accuracy rate of 95% or higher in its classification tasks, thereby significantly enhancing email security and efficiency within business contexts.

Projected Project End Date: 02/29/24 (End of Final Term)

Sources:

- PURU SINGHVI. (n.d.). Spam Email Classification Dataset Kaggle.
Retrieved from <https://www.kaggle.com/datasets/purusinghvi/email-spam-classification-dataset>
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- Wikipedia contributors. (n.d.). Regression analysis. In Wikipedia. Retrieved 11/16/2023, from https://en.wikipedia.org/wiki/Regression_analysis

Course Instructor Signature/Date:

- ☒ The research is exempt from an IRB Review.
- ☐ An IRB approval is in place (provide proof in appendix B).

Course Instructor's Approval Status: Approved

Date: 11/20/2023

Reviewed by:

Comments: [Click here to enter text.](#)