Evaluating Email
Outreach Performance
with Advanced Machine
Learning Techniques

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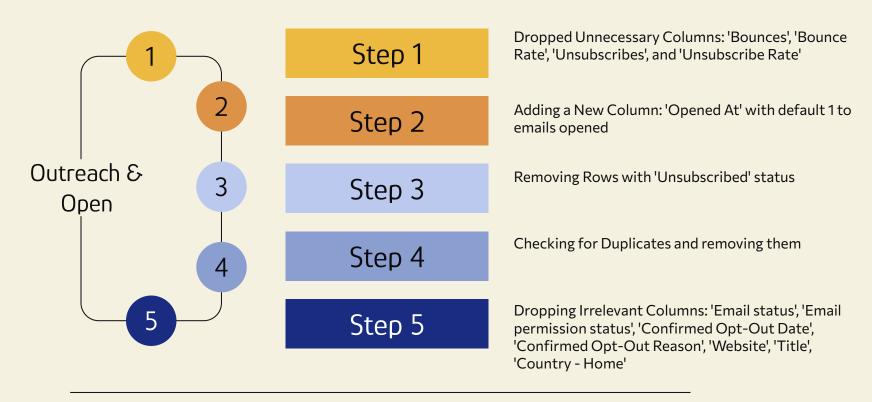
Project Description

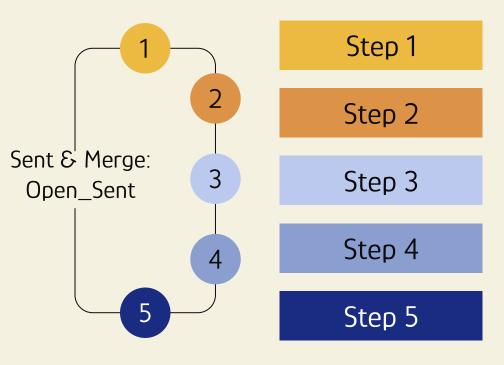
Background:

- This project analyzes email outreach data to improve campaign effectiveness by understanding effect of the time email sent, revenue of the company, the date, company type and number of employees, and location of the company.
- Problem Statement:
 - Identify factors influencing the likelihood of recipients engaging with the email (opens) and increase the outreach efficiency.
 - Dependent Variable (DV): Email open status (opened or not).
 - Independent Variables (IVs): City Home, Date Sent, Time Sent, State,
 Company type, Revenue, Headcount.









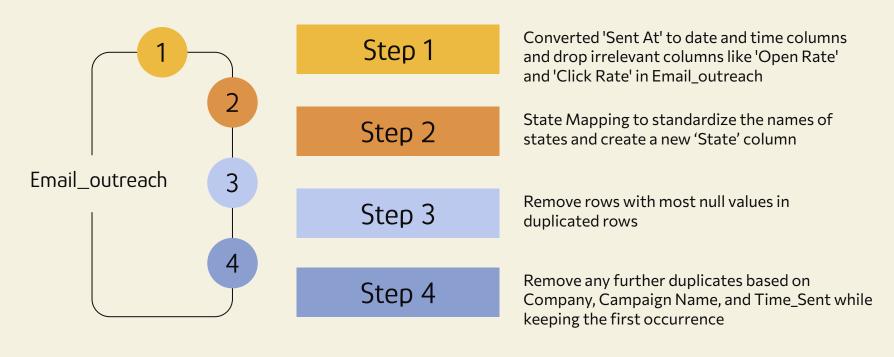
Removed Unsubscribed Records, Remove Duplicates: 'Campaign Name', 'Company', 'City -Home', and 'Created At'

Dropping Irrelevant Columns just like Open dataset

Left join Sent and Open datasets using 'Campaign Name' and 'Company' columns, Dropping Duplicate Columns with suffixes _x for 'sent' and _y for 'open'

Renaming columns like 'City - Home_x': 'City - Home', 'State/Province - Home_x': 'State/Province - Home', 'Created At_x': 'Created At', 'Updated At_x': 'Updated At'

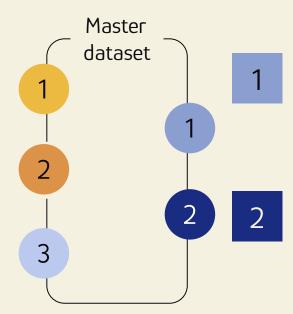
Filled missing values in 'Opened At' with 0 and ensure there are no duplicates in Open_Sent which is merged with Outreach summary dataset using 'Campaign Name'



Company names from various sources were normalized by converting them to lowercase and removing special characters to ensure consistency.

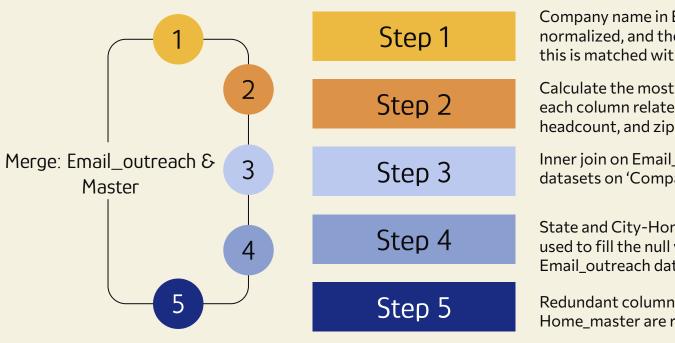
2 Missing city, state, revenue, headcount, and other key columns were populated using the mode into new columns.

Duplicate rows based on the Company column were removed and unnecessary columns were removed.



After normalization, stemming was applied to company names using the Porter Stemmer to reduce words to their root forms (e.g., "advanced" to "advanc").

The TF-IDF vectorizer was used to transform the stemmed company names into numerical vectors. Cosine similarity scores were calculated between Email_outreach and master datasets to identify the most likely matches based on the similarity of their company names.



Company name in Email_outreach is normalized, and the first word is extracted and this is matched with master dataset columns

Calculate the most frequent (mode) value for each column related to city, state, revenue, headcount, and zipcode in master

Inner join on Email_outreach and Master datasets on 'Company' column

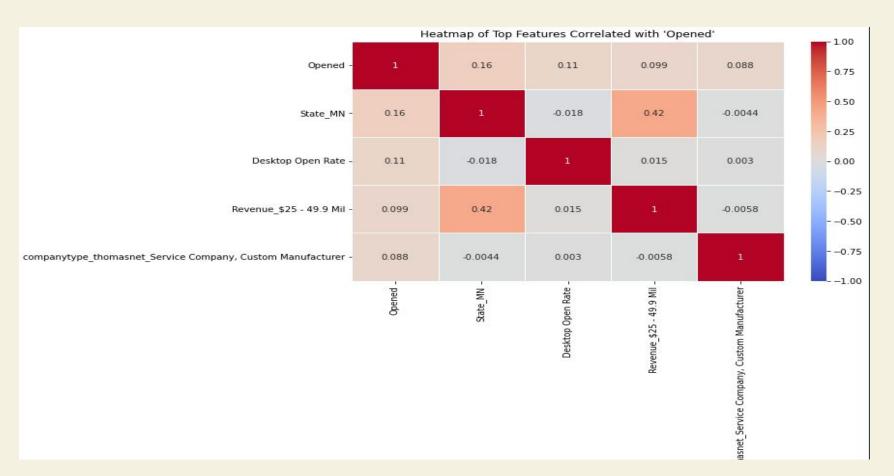
State and City-Home columns from Master are used to fill the null values in State and City of Email_outreach dataset

Redundant columns like State_master, City - Home_master are removed

Final dataset: Merged1

02 03 05 06 04 01 City - Home Company Date Sent State Revenue Campaign Name 10 11 12 80 09 07 Mobile Desktop Company type Headcount Time Sent Opened open rate open rate Binary Independent Variable

Correlation Matrix



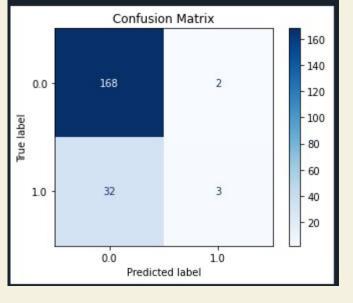
Data Analysis: Training the model

Random Forest Model: It is a learning method used for both classification and regression tasks. It operates by constructing a multitude of decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. Our Findings:

Accuracy: 0.8341463414634146

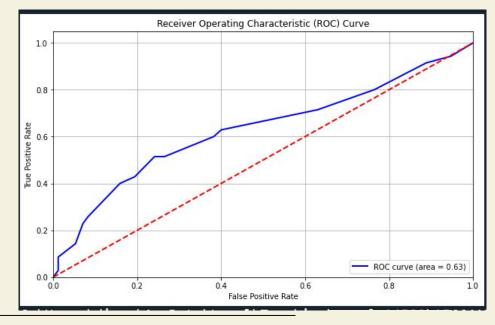
ROC-AUC Score: 0.6298319327731092

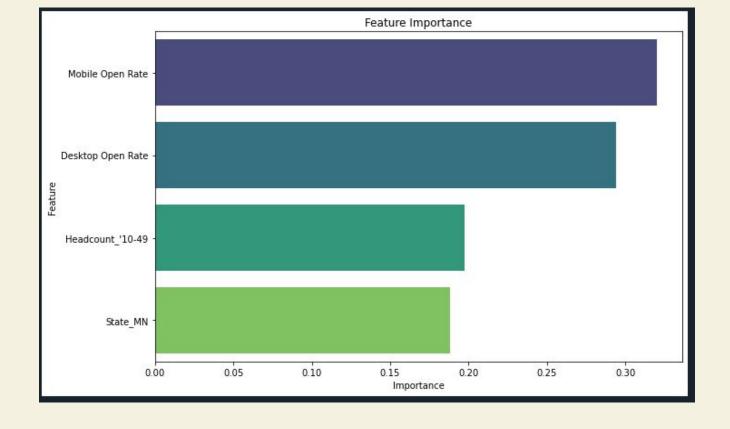
	precision	recall	f1-score	support
0.0	0.84	0.99	0.91	170
1.0	0.60	0.09	0.15	35
accuracy			0.83	205
macro avg	0.72	0.54	0.53	205
weighted avg	0.80	0.83	0.78	205



Confusion Matrix







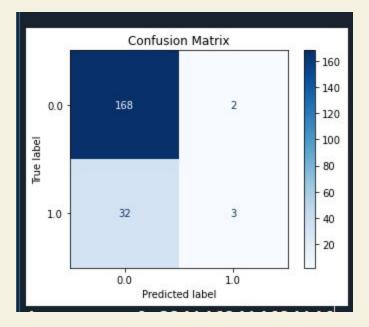
Feature Importance

Gradient Boosting Machine(GBM): It is an ensemble learning algorithm used for classification tasks. It builds a strong predictive model by combining the predictions of multiple weaker models, typically decision trees, in a sequential manner. Our Findings:

Accuracy: 0.8341463414634146

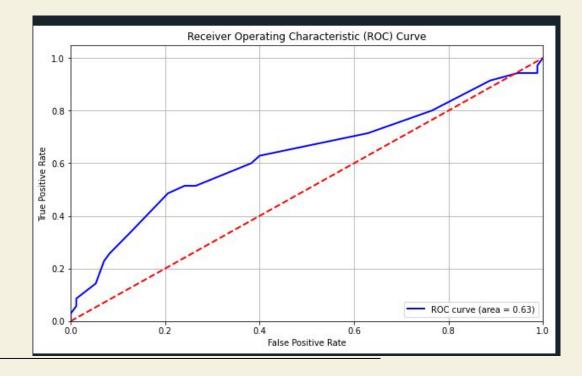
ROC-AUC Score: 0.6306722689075631

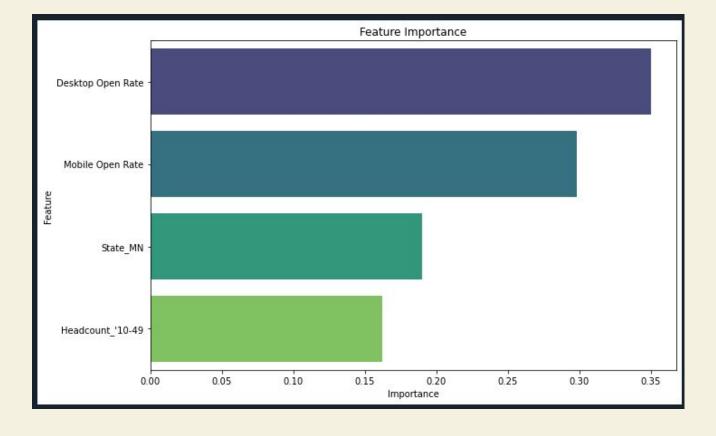
	precision	recall	f1-score	support
0.0	0.84	0.99	0.91	170
1.0	0.60	0.09	0.15	35
accuracy			0.83	205
macro avg	0.72	0.54	0.53	205
weighted avg	0.80	0.83	0.78	205



Receiver Operating Characteristic (ROC) curve

Confusion Matrix





Feature Importance

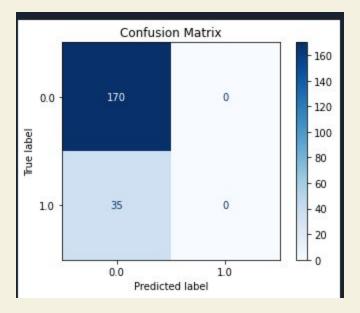
Support Vector Machine (SVM) a machine learning algorithm that classifies data and solves regression tasks. SVMs are particularly good at binary classification problems, where data is separated into two groups.

Our Findings:

Accuracy: 0.8292682926829268

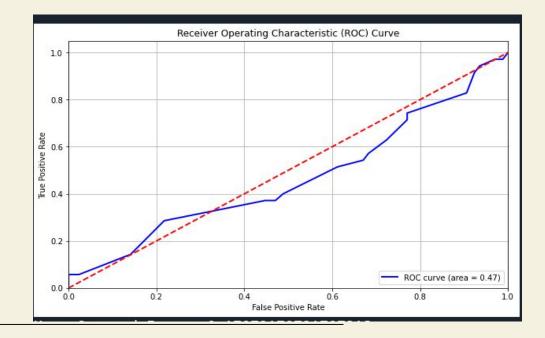
ROC-AUC Score: 0.4659663865546218

	precision	recall	f1-score	support
0.0	0.83	1	0.91	170
1.0	0.00	0.00	0.00	35
accuracy			0.83	205
macro avg	0.41	0.50	0.45	205
weighted avg	0.69	0.83	0.75	205



Receiver Operating Characteristic (ROC) Curve

Confusion Matrix



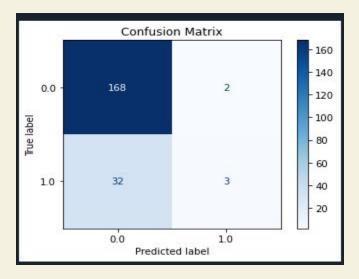
Decision Tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks.

Our Findings:

Accuracy: 0.8341463414634146

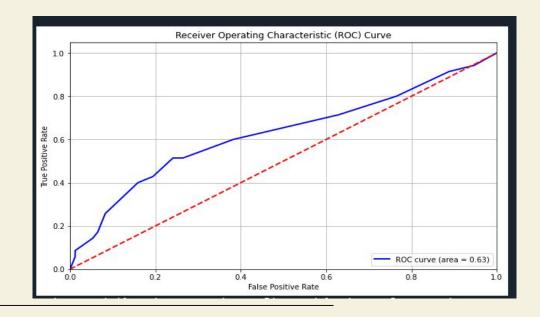
ROC-AUC Score: 0.6269747899159664

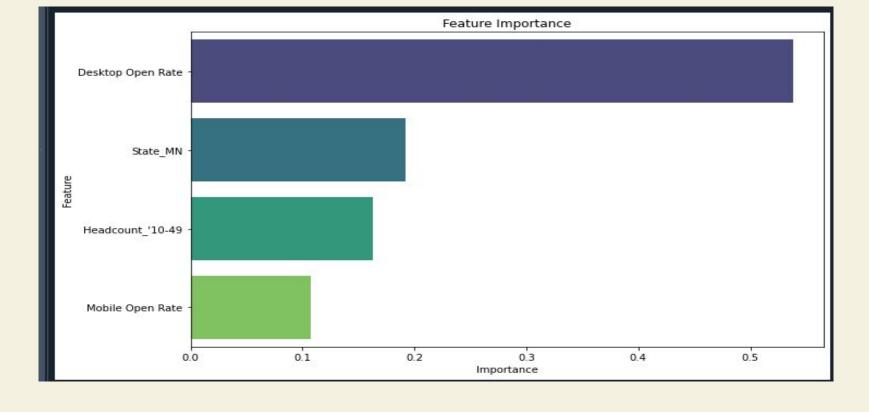
	precision	recall	f1-score	support
0.0	0.84	0.99	0.91	170
1.0	0.60	0.09	0.15	35
accuracy			0.83	205
macro avg	0.72	0.54	0.53	205
weighted avg	0.80	0.93	0.78	205



Receiver Operating Characteristic (ROC) Curve

Confusion Matrix





Feature Importance

Results

Random Forest	Gradient Boosting Machine	Support Vector Machine(SVM)	Decision Tree
Accuracy: 0.8341	Accuracy: 0.8341	Accuracy: 0.8293	Accuracy: 0.8341
ROC-AUC Score: 0.6298	ROC-AUC Score: 0.6307	ROC-AUC Score: 0.4660	ROC-AUC Score: 0.6270

- Since, correlation was strong between Desktop Open Rate, State_MN, Headcount '10-49 and Mobile Open Rate and Opened, we chose them for our independent variable.
- ☐ We found out that after comparing all the models, Training the company data with Gradient Boosting Machine (GBM) is the best fit as it has the more ROU AUC score in compare to other models.

Suggestions / Recommendations

- Final dataset can be increased by matching companies using other methods like Stemming, or other algorithms.
 - Stemming was tried which reduced number of rows to 706.
- Consistent way of recording data can make this analysis more focussed.
- ☐ Follow-up emails could be targeted more effectively to non-openers to increase interaction.
- Content of the email: Subject and going to spam can also impact the results of this analysis.



Summary of the Group Project



Biggest Challenge

Merging datasets especially master



Most Well-Done Aspect

Merging and modeling



Aspect Needing Improvement

The merging process could be further refined



Reference

- GeeksforGeeks: Provided guidance on data preprocessing, merging datasets, and applying specific Python functions.
 - Website: https://www.geeksforgeeks.org
- W3Schools: Helped with syntax, function usage, and understanding pandas, regex, and other Python-related concepts.
 - Website: https://www.w3schools.com
- For training the models like SVM, Decision tree and others:
 - Website: https://scikit-learn.org/stable/modules/svm.html
 - https://scikit-learn.org/stable/modules/tree.html
 - https://scikit-learn.org/stable/modules/ensemble.html







Questions

Task Division and Communication

Data Preprocessing: Outreach, Sent, and Open datasets	Handled by Riya and Vaishnavi.
Data Preprocessing: Master dataset	Handled by Sanika, Riya, Aswad and Vaishnavi.
Merging	Collaborative effort by Sanika, Riya, and Vaishnavi.
Modeling	Managed by Riya and Sanika.
<u>Presentation</u>	Created by Vaishnavi and Aswad.
<u>Communication</u>	Whatsapp, Google Colab, Google docs, Gmail
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