

# Module IV: Enron Email Classification

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# TABLE OF CONTENTS

- 01 **PROBLEM STATEMENT**
- 02 **BUSINESS VALUE**
- 03 **METHODOLOGY**
- 04 **FINDINGS**

# PROBLEM STATEMENT



Endless possibilities.™

**Email classification:** Classifying emails based on their content to automate manual processes and to increase the accuracy with which emails are labeled

**Tools:**

- Machine Learning
- Natural Language Processing
- Word Vectorizing
- Label Encoding
- TF-IDF Vectorization

# BUSINESS VALUE



1

AUTO-LABELING



2

PREDICTION

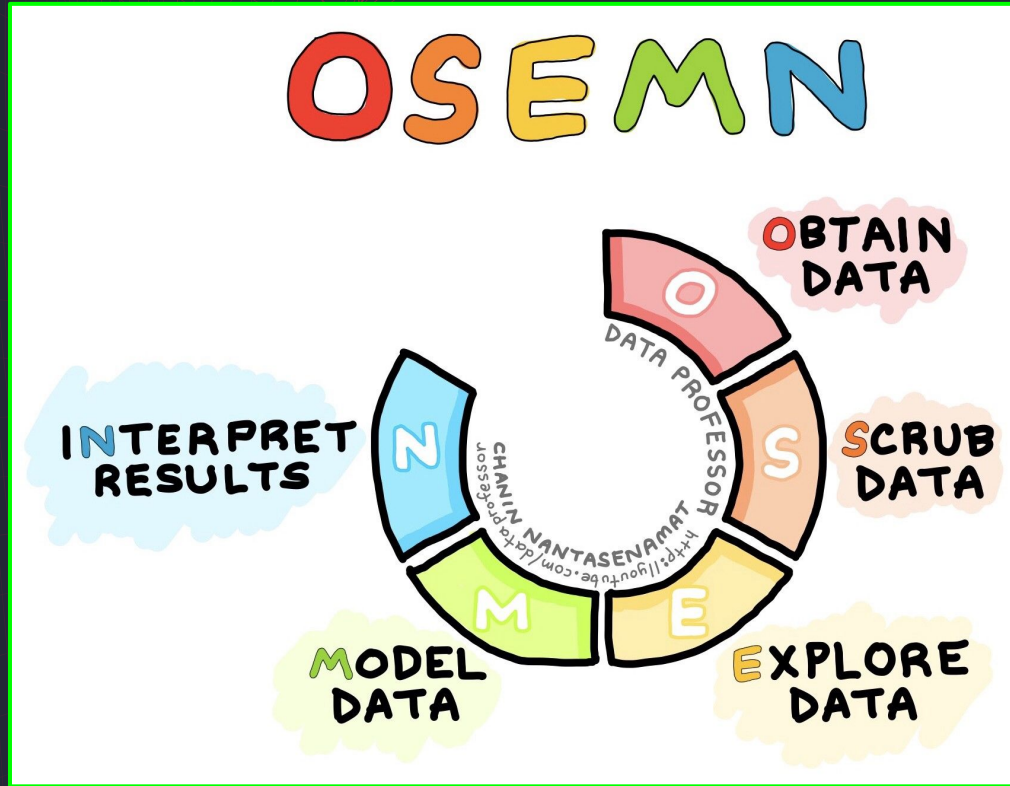


3

POSSIBILITIES

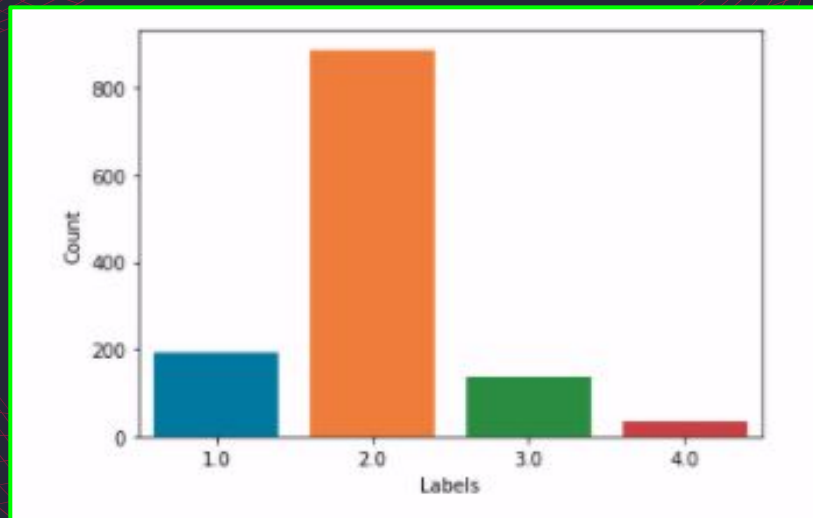


# METHODOLOGY



**OSEMN Framework**

# FINDINGS I



## Labels

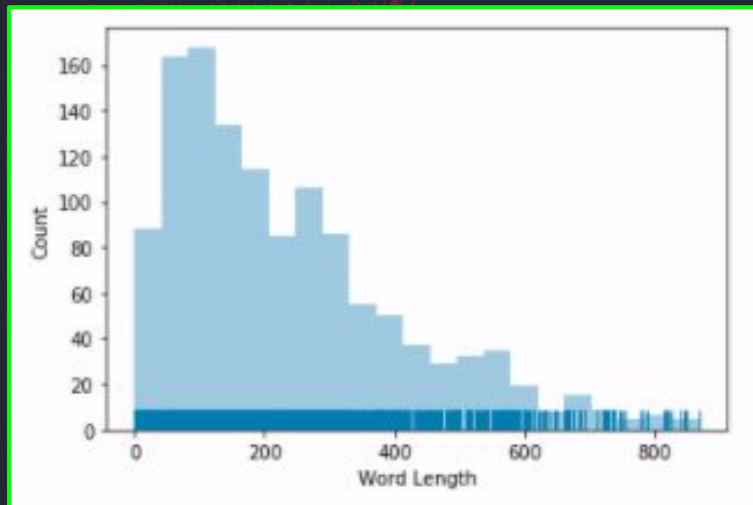
**1.0: Coarse genre (company strategy, logistic arrangements, etc) – 74%**

**2.0: Included/forwarded information (forwarded emails, press releases, etc) – 14%**

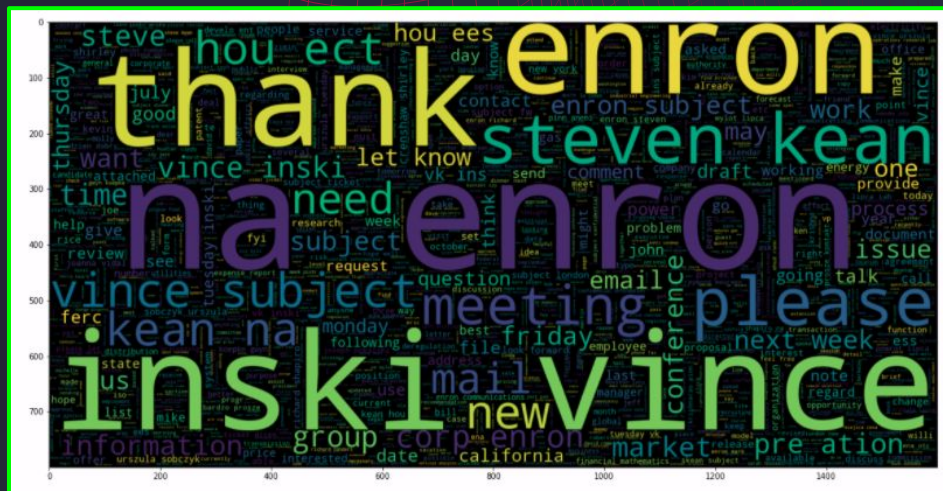
**3.0: Primary topics (meeting minutes, regulations, etc) – 10%**

**4.0: Emotional tone (jubilation, sarcasm, etc) – 2%**

# FINDINGS I



**Word length of emails is sizeable**

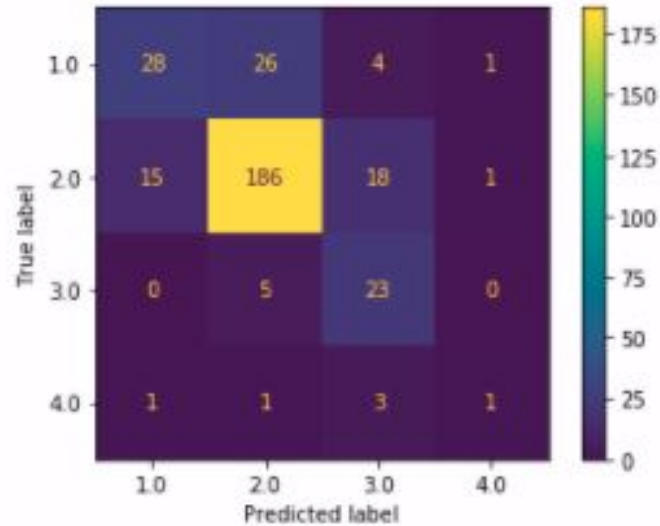


**Internal whistleblowers as topic of discussion for Category 1.0**

## FINDINGS 3

Train Accuracy: 0.9872754491017964  
Train Accuracy: 0.7603833865814696

Accuracy Score for model: 76.04%  
Precision Score for model: 76.89%  
Recall Score for model: 76.04%  
F1 Score for model: 75.79%



**MODEL #1: GRADIENT BOOSTING**

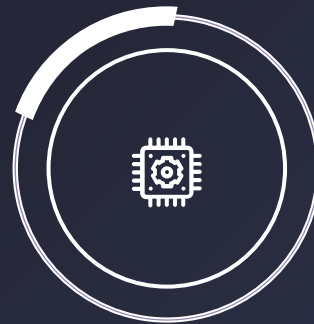


# FUTURE WORK



## LABELING

Use this model to label the 98K or so emails in our original dataset that are unlabeled



## AUTO-RESPONSES

Create an auto-response tool that responds to emails according the what label they receive