## CASE 5

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# PART 1 What do we think



### **Definition:**

- One of the largest frustrations for Internet users.
- For businesses, this frustration adds up to dollars lost and spent trying to prevent it

### Spam /spam/ noun

Spam is an unsolicited email message, instant message, or text message – usually sent to the recipient for commercial purposes

### **Dangerous email**



#### WPI Mail Admin





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Final Notice, upgrade your WPI.EDU email to office 2017 server for better performance and more storage space, <u>CLICK HERE</u> and update. Failure to follow this instruction will lead to permanent deactivation of your mail box in the next 24 hours.

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### The Effects





- 1. Spam contributes to a loss of productivity and profit.
- 2. Spam poses legal risks
- 3. Spam contains various malware threats
- 4. Spam can also hurt the reputation of your business

### **Business Problem**



## To Filter Junk/Spam Emails more efficiently using Machine Learning.

We are going to use sklearn package to do email classification: ham (non-junk mail)and spam(junk mail)

### **Potential Clients**









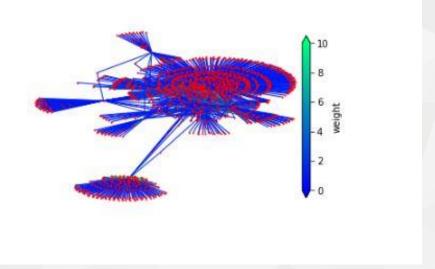
# PART 2 Data Collection

### **Data Exploration**

### **Exploring the Email Dataset**

#### **Plot Email Communication Graph/Network**

- Each node is an email account
- Take totally 10812 emails
- Color represents the weight of each edge
- The weight of an edge between two accounts depends on how many emails have been sent between them.



### **Data Collection**



- Loading raw email data into a workable format
- The Enron Email Dataset
- Used Inbox and Deleted folder of all the users

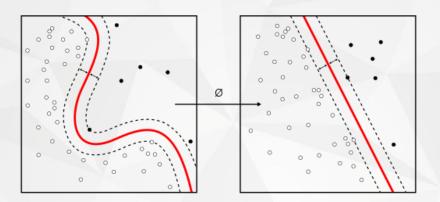
# PART 3 Methods

### **CountVectorizer**



- It learns the vocabulary of the corpus and extracts word count features.
- This method is an efficient way to do both steps, and for us it does the job.
- CountVectorizer provides fit and transform methods to do them separately.
- Additionally, you can provide a vocabulary in the constructor.

### **Naïve Bayes**



- We're going to use a naïve Bayes classifier to learn from the features.
- A naïve Bayes classifier applies the Bayes theorem with naïve independence assumptions.
- Each feature is independent from every other one and each one contributes to the probability that an example belongs to a particular class.

# PART 4 Data Processing

# of users we considered: 149
# of mails in ham set: 44542
# of mails in spam set: 50941

C:/Users/sun_f_000/Documents/maildir\steffes-j\deleted_items\40 spam \n\nDear Customer,\n\nThe electric utility i  C:/Users/sun_f_000/Documents/maildir\shackleton-s\deleted_items\299 spam \n\n[IMAGE] Forums Discuss these points in the  C:/Users/sun_f_000/Documents/maildir\heard-m\inbox\64 ham Sara,\n\nGSI Give up agreement. We would want  C:/Users/sun_f_000/Documents/maildir\kaminski-v\deleted_items\2122 spam \n\n From the Desk of George W. Pratt, III, Di
C:/Users/sun_f_000/Documents/maildir\heard-m\inbox\64 ham Sara,\n\nGSI Give up agreement. We would want
C:/Users/sun_f_000/Documents/maildir\kaminski-v\deleted_items\2122 spam \n\n From the Desk of George W. Pratt, III, Di
C:/Users/sun_f_000/Documents/maildir\nemec-g\inbox\64 ham Gerald,\n\n\n\nThis CA is to cover a proposed
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C:/Users/sun_f_000/Documents/maildir\benson-r\inbox\292 ham \n\n\n\nOriginal Message\n\nFrom: \
C:/Users/sun_f_000/Documents/maildir\heard-m\inbox\master_netting\109 ham Marie,\n\n\nThanks for your response. Pleas
C:/Users/sun_f_000/Documents/maildir\meyers-a\deleted_items\914 spam \n\n\n\start Date: 1/5/02; HourAhead hour: 18

class text

- Store the text data in a pandas data frame with class label "spam" or "ham"
- Shuffle the rows of the data frame so that the dataset become random
- 44542 ham emails and 50941 spam emails are selected under 149 users

- Reduce the mass of unstructured data into some uniform set of attributes that
  an algorithm can learn from by vectorizing all mail text to a sparse matrix with
  the same row number as the data frame and large column number
- (In numerical analysis, a sparse matrix is a matrix in which most of the elements are zero)
- In our sparse matrix, each element is an integer from 0 to 10, representing the feature of a word in the text
- The sparse matrix is our predictors matrix.

Train the dataset and try the following example

```
# here's one example of classification test after the training
examples = ['Free Viagra call today!', "Tomorrow's meeting canceled."]
example_counts = count_vectorizer.transform(examples)
predictions = classifier.predict(example_counts)
predictions

array(['spam', 'ham'],
    dtype='<U4')</pre>
```

 In this example, with our vectorizer classifier, the two sentences are accurately classified by computer

#### **Classification Results**

- Apply 6-flod cross validation
- The overall accuracy regarding to all users' mails is 0.633
- If we turn to the dataset of some single users, accuracies are larger, this will be explained in our data limitation slide

All users' classification result

```
Total emails classified: 95483
```

Score: 0.551185756035

Confusion matrix:

[[38868 5674]

[29399 21542]]

Accuracy: 0.632678068347

#### Single users' classification result

```
Total emails classified: 427
Score: 0.873316711025
Confusion matrix:
[[ 12 54]
[ 39 322]]
Accuracy: 0.782201405152
```

```
Total emails classified: 1253
Score: 0.319930746275
Confusion matrix:
[[1114 29]
[ 84 26]]
Accuracy: 0.909816440543
```

# PART 5 Limitation

### Limitation

#### 1. Highly personalized

- People have different habits, some people just delete the advertisement emails and people's attitude toward junk mails are different.
- People could delete some emails by mistake.
- Some people even don't delete junk mails.

#### 2. Overfitting

 After transferring the text into sparse matrix, the number of predictors is very large, even larger than the training size which will lead to overfitting.

# PART 6 Conclusion

### Conclusion

- We analyzed the email data and use machine learning to filter junk mails.
- Our analysis can help email users to have a cleaner and safer using environment.
- We can also use our methods to do more specific classification of all emails in the future to increase working efficiency.



## Thank you!