

Automated Fraud Detection

Using the Enron Email Corpus to Train Fraud Detection Models

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Problem Statement:

Create machine models to predict corruption in emails using text mining

Stakeholders:

- Auditors/Regulators
- Board of Directors



Background

ENRON SCANDAL (2001)

COMPANY

Houston-based commodities, energy and service corporation

WHAT HAPPENED

Shareholders lost \$74 billion, thousands of employees and investors lost their retirement accounts, and many employees lost their jobs.

MAIN PLAYERS

CEO Jeff Skilling and former CEO Ken Lay





HOW THEY DID IT

Kept huge debts off the balance sheets.



HOW THEY GOT CAUGHT

Turned in by internal whistleblower Sherron Watkins; high stock prices fueled suspicions.



FUN FACT

Fortune Magazine named Enron "America's Most Innovative Company" for six years in a row prior to the scandal.



Enron Email Dataset

- This data was originally made public by the Federal Energy Regulatory Commission during its investigation.
- Data has been downloaded from <u>www.Kaggle.com</u>
- Size: 1.3 GB
- The data contains more than 500,000 emails, retrieved from the user folders of 150 Enron employees
- These emails were sent by more than 20,000 unique email addresses.

```
file

0 allen-p/_sent_mail/1. Message-ID: <18782981.1075855378110.JavaMail.e...

1 allen-p/_sent_mail/10. Message-ID: <15464986.1075855378456.JavaMail.e...

2 allen-p/_sent_mail/100. Message-ID: <24216240.1075855687451.JavaMail.e...

3 allen-p/_sent_mail/1000. Message-ID: <13505866.1075863688222.JavaMail.e...

4 allen-p/_sent_mail/1001. Message-ID: <30922949.1075863688243.JavaMail.e...
```

Contents of a Sample Message

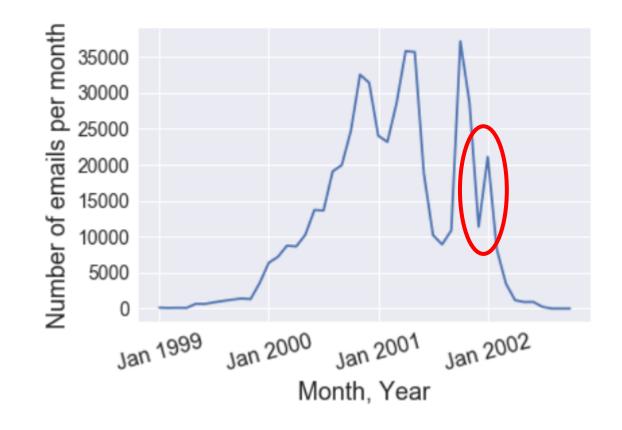
```
Message-ID: <13505866.1075863688222.JavaMail.evans@thyme>
Date: Mon, 23 Oct 2000 06:13:00 -0700 (PDT)
From: phillip.allen@enron.com
To: randall.gay@enron.com
Subject:
Mime-Version: 1.0
Content-Type: text/plain; charset=us-ascii
Content-Transfer-Encoding: 7bit
X-From: Phillip K Allen
X-To: Randall L Gay
X-cc:
X-bcc:
X-Folder: \Phillip Allen Dec2000\Notes Folders\'sent mail
X-Origin: Allen-P
X-FileName: pallen.nsf
Randy,
 Can you send me a schedule of the salary and level of everyone in the
scheduling group. Plus your thoughts on any changes that need to be made.
(Patti S for example)
Phillip
```

Final Data Frame

	user	Date	From	То	Subject	X- From	Х-То	X- X		X- Origin	X-FileName	content
Message-ID							_					
<18782981.1075855378110.JavaMail.evans@thyme>	allen- p	2001- 05-14 23:39:00	phillip.allen@enron.com	(tim.belden@enron.com)		Phillip K Allen	Tim Belden <tim Belden/Enron@EnronXGate></tim 		\Phillip_Allen_Jan2002_1\Allen, Phillip K.\'Se	Allen- P	pallen (Non- Privileged).pst	Here is our forecast\n\n
<15464986.1075855378456.JavaMail.evans@thyme>	allen- p	2001- 05-04 20:51:00	phillip.allen@enron.com	(john.lavorato@enron.com)	Re:	Phillip K Allen	John J Lavorato <john j<br="">Lavorato/ENRON@enronXg</john>		\Phillip_Allen_Jan2002_1\Allen, Phillip K.\'Se	Allen- P	pallen (Non- Privileged).pst	Traveling to have a business meeting takes the
<24216240.1075855687451.JavaMail.evans@thyme>	allen- p	2000- 10-18 10:00:00	phillip.allen@enron.com	(leah.arsdall@enron.com)	Re: test	Phillip K Allen	Leah Van Arsdall		\Phillip_Allen_Dec2000\Notes Folders\'sent mail	Allen- P	pallen.nsf	test successful. way to goll!
<13505866.1075863688222.JavaMail.evans@thyme>	allen- p	2000- 10-23 13:13:00	phillip.allen@enron.com	(randall.gay@enron.com)		Phillip K Allen	Randall L Gay		\Phillip_Allen_Dec2000\Notes Folders\'sent mail	Allen- P	pallen.nsf	Randy,\n\n Can you send me a schedule of the s
<30922949.1075863688243.JavaMail.evans@thyme>	allen- p	2000- 08-31 12:07:00	phillip.allen@enron.com	(greg.piper@enron.com)	Re: Hello	Phillip K Allen	Greg Piper		\Phillip_Allen_Dec2000\Notes Folders\'sent mail	Allen- P	pallen.nsf	Let's shoot for Tuesday at 11:45.

Exploratory Data Analysis (EDA)

- The use of emails at Enron picked up in 1999 and increased steadily during 2000s.
- In 2001, the year that Enron collapsed, there was a sudden drop in the volume of emails during summer months followed by a sharp peak in fall and a steady drop after the bankruptcy.



Exploratory Data Analysis (EDA)

Hourly and daily email volume





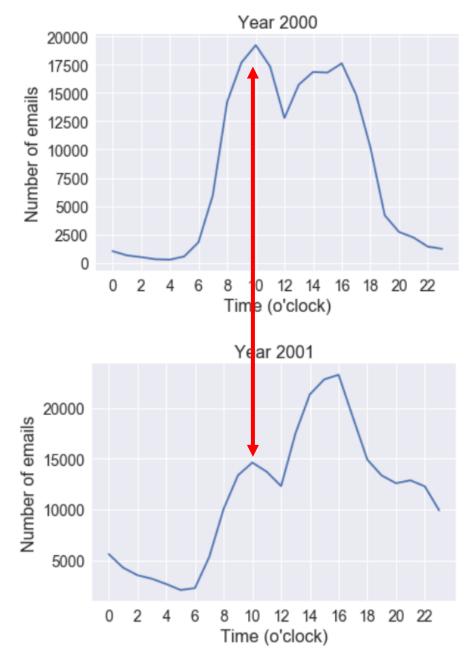
^{*} The y axis represent the total email count during the livelihood of Enron, not the average daily volume

Hypothesis Testing

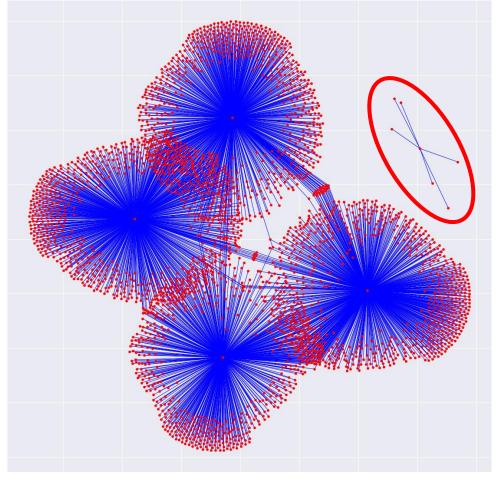
• Question: Is there any significant difference in the email volume between 8 to 10 am and 3 to 5 pm in 2001, excluding weekends?

 Motivation: By looking at the hourly email volume in 2000 and 2001 we can notice a difference between the volume of emails in the mornings and in the afternoons in 2001. 2001 is the year that Enron collapsed.

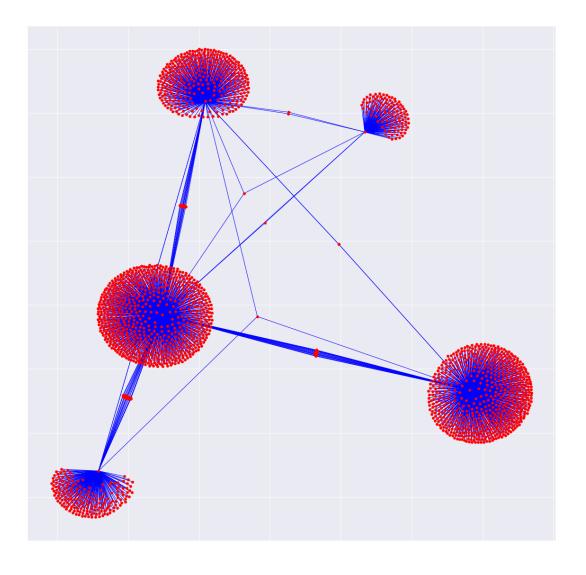
One may interpret a higher volume of emails in the afternoons vs. mornings as a *sign of procrastination* or *lack of interest by employees.*



Network Visualization



Network of top 5 email senders



Network of the next 5 email senders

Interesting observation - Outlier

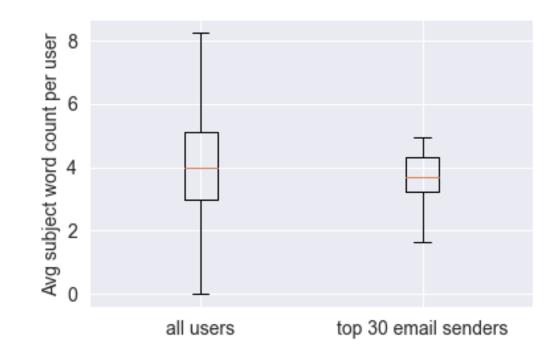
• Outlier - 80% of emails sent to oneself

Review of email content – as a lab notebook to keep a log of work.

```
from
frozenset({'jeff.dasovich@enron.com'}) 794
frozenset({'kay.mann@enron.com'}) 647
frozenset({'pete.davis@enron.com'}) 7
frozenset({'sara.shackleton@enron.com'}) 826
frozenset({'vince.kaminski@enron.com'}) 794
Name: Recipient_1, dtype: int64
```

Inferential Statistics - Question 1:

- Did people who send a lot of emails write shorter emails?
- Comparing top 30 email senders with all email senders in terms of subject and contents word count.
- From the boxplot it is clear that there is no significant difference in the subject and contents word count in these two groups.



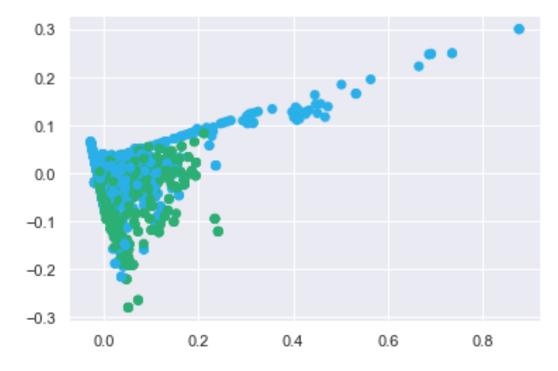
Word Cloud

- The figure was produced using the Word Cloud library
- Top words emails topics more around 'play' than work?



Modeling & Evaluation

- Unsupervised
 Learning K-Means
 Clustering
- 2 clusters
 - Batch size 500
 - 100 iterations
- Top Features
 - Non-work related



	features	score
0	meetings	0.396321
1	trip	0.303915
2	ski	0.279288
3	business	0.260357
4	takes	0.207651
5	presenter	0.174026
6	try	0.165728
7	stimulate	0.165694
8	speaks	0.150587
9	jet	0.146178
10	boat	0.144293
11	desired	0.139921
12	honest	0.139807
13	quiet	0.137759
14		
	productive	0.136461
15	productive rent	0.136461 0.133112
• • •		
15	rent	0.133112
15 16	rent flying	0.133112 0.130266
15 16 17	rent flying traveling	0.133112 0.130266 0.124373
15 16 17	rent flying traveling golf	0.133112 0.130266 0.124373 0.123238
15 16 17 18	rent flying traveling golf suggestion	0.133112 0.130266 0.124373 0.123238 0.121763
15 16 17 18 19 20	rent flying traveling golf suggestion formal	0.133112 0.130266 0.124373 0.123238 0.121763 0.116549
15 16 17 18 19 20 21	rent flying traveling golf suggestion formal opinions	0.133112 0.130266 0.124373 0.123238 0.121763 0.116549 0.115387

Modeling & Evaluation

- **Supervised Learning** *K-Nearest Neighbours*
- Test size 20%
- Words in emails separated into different clusters
 - Non-work related words vs common words
- Computation is deferred until classification – desired for large dataset

[[85815 1		-			
		precision	recall	f1-score	support
	0	0.98	0.99	0.98	86969
	1	0.90	0.88	0.89	12142
accura	асу			0.97	99111
macro a	avg	0.94	0.93	0.94	99111
weighted a	avg	0.97	0.97	0.97	99111

0.9734943649039965



Conclusion / Next Steps

- Application of trained model in Fraud and Risk Management
 - Utilize Machine Learning as first indicator of red flags
 - ✓ Highlight people at risk of committing fraud more efficient for auditors to do in-depth review
- Recommendations
 - Getting access to computing resources to run the algorithm on full dataset
 - Deeper review of language used in emails



Questions?

