INTA 6450 Enron Course Project

Part 2: Report (Group 2)

Submitted By:

Hongru Liu (hliu467)
Min Zhang (mzhang469)
Wenyan Du (wdu63)
Zhuotong Liu (zliu775)

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1. Definition of Wrongdoing: Securities Fraud - Special-Purpose Entity (SPE)

Our definition of Enron's wrongdoing is securities fraud. By definition, securities fraud is an illegal practice that induces investors to make trading decisions based on false information[1]. After reading the book "The Smartest Guys in the Room"[2] and "Enron Fraud"[3], we believe Enron misconducted in multiple fields and met the definition of this wrongdoing. For example:

1) Enron abused special-purpose entities (SPE) to hide the company's debts from investors and creditors. They use SPEs such as Chewco to transfer and hide their troubled assets[4].
2) They partnered with banks such as Merrill Lynch and asked the bank to purchase Enron's assets which got sold back to Enron after Enron released their financial report. Those activities are shown as profits in Enron's financial report which was actually "loans".
3) They managed to get approval to use Market-to-Market accounting to reflect future earnings in their current financial statement. By abusing these accounting principles, they optimistically declared unrealized profits although their investment was not successful in many markets.

These misconducts are used to polish up Enron's financial statements to make Enron look profitable from the accounting perspective. By hiding their actual financial situation and only reporting stock-beneficial news to the public, investors were falsified to believe Enron was doing great at their business. They over evaluated Enron which reflected in the high stock price. We think these misconducts meet the definition of securities fraud.

Although these misconducts all belong to securities fraud, they are likely to involve different people and would require specific modeling for each misconduct. In this project, we decided to narrow down our scope to only focus on misconduct 1) abuse of special-purpose entities.

2. Strategy to Find Emails

Our strategy has four steps.

1) We start with using Python data manipulation techniques to prepare a cleaned dataset.
2) We then find People of Interests (POI) using network analysis methods.
3) After that, we select suspicious keywords by applying topic modeling algorithms to emails sent by POI we identify in step 2).
4) Finally, we find emails indicating securities fraud by filtering POI's emails based on the keywords we select in step 3).

We are going to explain each step in detail.

2.1 Step 1: Data Preparation - Data Manipulation

First of all, we need a clean dataset to start our analysis.

While the professor provided us with a power tool - ElasticSearch, we notice this tool has certain limitations such as it only returns up to 10,000 records each time. This tool lacks the flexibility we need, therefore, we decided to make use of Python to build a clean dataset from the raw data by ourselves. The raw data is in Json format, and each json file represents an email. After parsing those json files and conducting some data manipulation, we get a Pandas dataframe with 251,734 rows and 11 columns.

Each row represents an email and here is an explanation of the columns:

Column	**Explanation**
Index	The index of the email, starting from 0 to 251733.
Text	The email body
Subject	The email subject

Priority	The email priority
From	The sender of the email
To	The recipient of the email
Date	The data when the email is sent
CC	People cc'd in the email
BCC	People bcc'd in the email
Headers	The email header
MessageId	The email ID

Table 1: Cleaned Dataset Columns

We exported the cleaned data frame to a csv file so that it's accessible to all team members.

2.2 Step 2: People of Interests Recognition - Network Analysis

We notice there are 251,734 emails in the dataset. Since the majority of the emails would be legitimate emails, we believe this big number makes it almost impossible to generate useful insights by applying any Natural Language Processing (NLP) models directly. Therefore, we think it is necessary to narrow down the scope to a smaller subset of emails first.

We start our analysis with People of Interest (POI) recognition. Our definition of POI is Enron executives and people who are closely communicating with those executives. Our strategy is to find POI and focus only on emails among those POI.

Since we want to investigate securities fraud, we start with executives that might be familiar with the company's finance. After some literature review[5], we select 4 people - Kennth Lay, Jeffrey Skilling, Andrew Fastow, and Ben Glisan - to begin our research. Table 2 below explains why we select them and lists their emails addresses inside the dataset. We get the email addresses by filtering substrings of those people's first name and last name (e.g. ken and lay for Kennth Lay)

in the ‘from’, ‘to’, ‘cc’ and ‘bcc’ columns. We notice that everyone has multiple email addresses. After the initial search, we get a POI list containing 24 email addresses of 4 people.

Name	**Reasons to Select**	**Emails in the Dataset**
Kennth Lay	CEO	'kenneth.l.lay@enron.com', 'ssskenneth.lay@enron.com', 'kenneth_lay@enron.net', 'lay.kenneth@enron.com', 'kenlay@enron.com', 'ken.lay-.chairman.of.the.board@enron.com', 'kenneth_lay@enron.com', 'ken.lay@enron.com', 'ken_lay@enron.net', 'ken_lay@enron.com', 'kennethlay@enron.com', 'kenneth.lay@enron.com', 'ken.lay-@enron.com'
Jeffrey Skilling	COO	'jeff.skilling@enron.com', 'jeff_skilling@enron.com', 'jeffrey.skilling@enron.com', 'jeffreyskilling@yahoo.com', 'jeffrey.k.skilling@enron.com'
Andrew Fastow	CFO	'andy.fastow@enron.com', 'andrew.fastow@ljminvestments.com', 'andrew.s.fastow@enron.com', 'andrew.fastow@enron.com'
Ben Glisan	Manage Enron’s account in Anderson and then work in Enron as corporate treasurer	"ben'.'glisan@enron.com", 'ben.glisan@enron.com', 'ben_f_glisan@enron.com'

Table 2: Enron Executives

However, as explained earlier, our POI should contain not only these 4 people but also those that closely communicate with them. We believe this is necessary because if someone directly reports to the CEO of Enron quite often, they must be playing an important role inside the company as well. In order to find the remaining POI, we build a network model to show the relationship

between people inside the Enron. A network model consists of nodes and edges. Each node represents an email address. And an edge between two nodes represents an email has been sent from one node to the other.

For example, Table 3 shows the sender and recipients of email No. 111.

From	To	CC	BCC
asem.atta@enron.com	cara.semperger@enron.com corry.bentley@enron.com	duong.luu@enron.com	NaN

Table 3: Network Example

This record creates 4 nodes and 3 edges during network analysis:

1) Nodes: asem.atta/ cara.semperger/ corry.bentley/ duong.luu@enron.com.
2) Edge 1: from asem.atta@enron.com to cara.semperger@enron.com
3) Edge 2: from asem.atta@enron.com to corry.bentley@enron.com
4) Edge 3: from asem.atta@enron.com to duong.luu@enron.com

After looping through all the 251,734 emails, we get a network of 87,130 nodes and 1,616,855 edges. We have more edges than the total number of emails (251,734), this is because an email may have multiple recipients (emails in ‘to’, ‘cc’ and ‘bcc’) thus would lead to multiple edges. However, we are only interested in nodes that are closely connected to the 4 POI. The 4 POI has 24 different email addresses, that is 24 nodes in the network. We loop through neighbours of these 24 nodes and only keep neighbours that have at least 5 edges (means 5 emails) with one of the 24 nodes.

During the process, we notice most emails within the 24 nodes do not have any neighbour that has more than 5 emails. This indicates while those emails do belong to the initial 4 POI, they are barely used by that person. We excluded those emails from the POI list and these reduced our POI list from 24 to 4 emails (andrew.fastow@enron.com, ben.glisan@enron.com,

jeff.skilling@enron.com and kenneth.lay@enron.com). We think this makes sense as one person should be mostly using one email address inside the company rather than multiple aliases.

We also find 13 neighbours that have at least 5 emails with the 4 POI and we add them into the POI lists. Finally, we get a POI list of 17 emails: greg.whalley/ andrew.fastow/ k..allen/ don.miller/ sherri.sera/ kevin.hannon/ l..wells/ jeff.skilling/ david.delainey/ richard.shapiro/ ben.glisan/ kenneth.lay/ joannie.williamson/ christie.patrick/ louise.kitchen/ j..kean@enron.com and eharris@insightpartners.com.

This network graph shows the connection between them. The arrow in edges from node A to node B indicates A is the sender and B is the recipient for the email that edge represents.

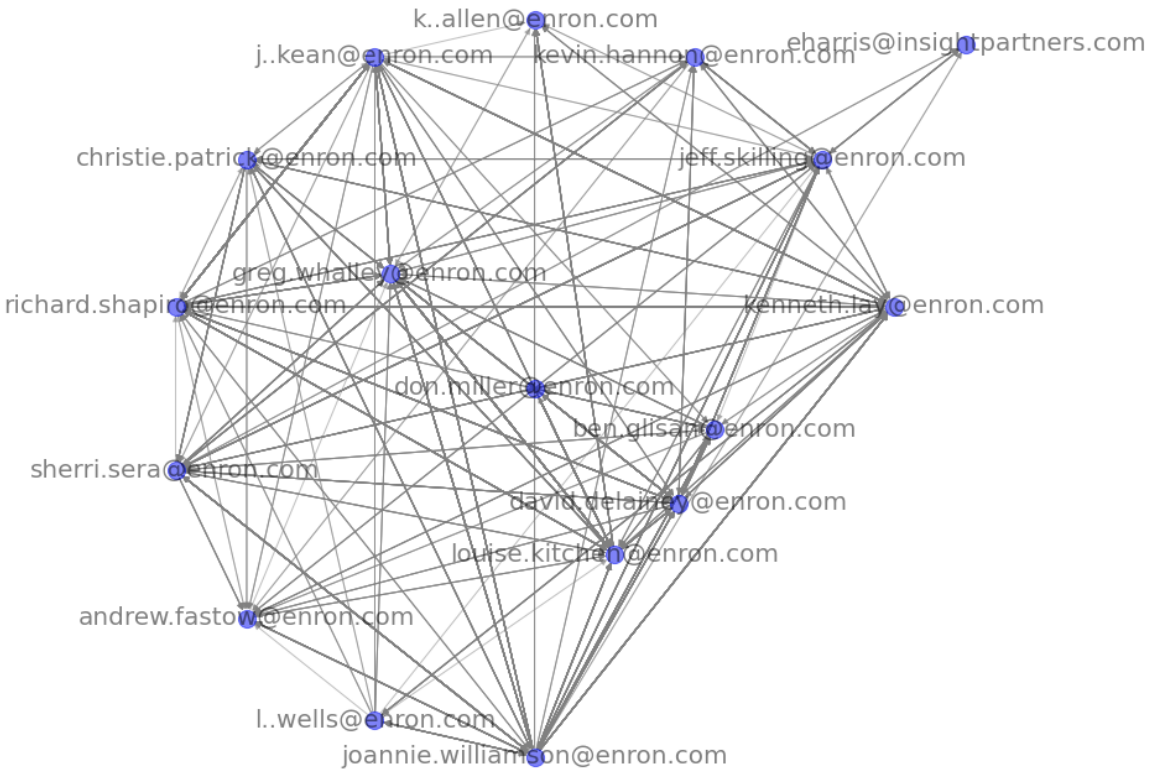

Figure 1: POI Network Graph

We filter the dataset by only keeping emails sent from those 17 POI email addresses and reduce the number of emails from 251,734 to 4,288.

2.3 Step 3: Keywords Selection - Topic Modeling

After identifying POIs, we narrow down the data from 251,731emails to 4,288. This expedites the process and reduces a lot of noise but this is still a very large number. Therefore, we create a large corpus that includes the 4,288 emails sent from the POI and try to understand what they are talking about through those emails. We want to identify suspicious topics from the corpus and find people and keywords that contribute most to those suspicious topics to reduce our scope further.

A topic modeling algorithm will help us understand what major topics are included and determine what emails may be relevant. There are many ways to explore the topics of these emails. Latent Dirichlet Allocation (LDA) is one way to do this. It is a bag-of-words algorithm that helps us to automatically discover topics that are contained within a set of documents. The underlying assumption is that any text is actually a bag of words that are generated by a distribution over distributions of a vocabulary, and our goal is to find the hidden underlying generative elements.

To begin with, we need to do some data preprocessing to clean those text data. First, we use regular expressions to remove email information such as message ID, filenames, subjects, and ccs. Besides, there are many punctuations and special characters that are not helpful in building the topic model, such as question marks, and extra spaces. We will also remove them to keep only texts of emails. The NLTK (Natural Language Toolkit) is a suite that contains libraries and programs for statistical language processing. The Python NLTK library contains various utilities that allow us to effectively manipulate and analyze linguistic data. We then tokenize the email texts by splitting up words. Stemming and lemmatization are also performed to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form.

Stopwords are also removed from those tokens to potentially help improve the performance as there are fewer and only meaningful tokens left. Tokens with a length less than 2 and appeared less than 4 times are also removed.

After the corpus is built, we choose the number of topics to be 20 and build the LDA model. A topic is a distribution over words, so what we see in each discovered topic is the recipe of words that cluster together. In the table below, we demonstrate the topics we observed.

Topics	**Keywords**
Topic 1	"plan" "phase" "first" "number" "customer" "unit" "process" "prc" "detail" "contact" "month" "list" "associate" "enw" "budget" "top" "start" "individual" "question" "analyst"
Topic 2	"plan" "phase" "first" "number" "customer" "unit" "process" "prc" "detail" "contact" "month" "list" "associate" "enw" "budget" "top" "start" "individual" "question" "analyst"
Topic 3	"inc" "message" "email" "system" "transmission" "confidential" "received" "intended" "copy" "individual" "named" "sender" "marketing" "paso" "notify" "attached" "trading" "free" "hard" "solicitation"
Topic 4	"california" "utility" "state" "ferc" "price" "said" "commission" "electricity" "staff" "rto" "rate" "iso" "transmission" "governor" "plant" "plan" "cost" "davis" "order" "proposal"
Topic 5	"program" "wharton" "university" "level" "research" "school" "presentation" "best" "forward" "professor" "vince" "director" "look" "project" "senior" "forum" "christie" "corporate" "harvard" "help"
Topic 6	"program" "wharton" "university" "level" "research" "school" "presentation" "best" "forward" "professor" "vince" "director" "look" "project" "senior" "forum" "christie" "corporate" "harvard" "help"
Topic 7	"program" "wharton" "university" "level" "research" "school" "presentation" "best" "forward" "professor" "vince" "director" "look" "project" "senior" "forum" "christie" "corporate" "harvard" "help"
Topic 8	"program" "wharton" "university" "level" "research" "school" "presentation" "best" "forward" "professor" "vince" "director" "look" "project" "senior" "forum" "christie" "corporate" "harvard" "help"
Topic 9	"committee" "conference" "date" "attend" "monday" "fastow" "october"

	"tuesday" "wednesday" "december" "august" "chief" "management" "analyst" "friday" "thursday" "member" "stock" "plan" "lay"
Topic 10	"message" "intended" "recipient" "use" "copy" "confidential" "attachment" "privileged" "sender" "error" "contain" "distribution" "contract" "strictly" "thank" "prohibited" "corp" "affiliate" "material" "immediately"
Topic 11	"million" "said" "transaction" "deal" "investment" "share" "financial" "value" "stock" "price" "asset" "partnership" "turbine" "investor" "sale" "last" "could" "right" "inc" "billion"
Topic 12	"deal" "cost" "project" "000" "contract" "value" "dave" "ena" "payment" "agreement" "development" "west" "regard" "back" "forward" "way" "look" "tax" "position" "million"
Topic 13	"report" "europe" "employee" "expense" "management" "conference" "name" "team" "following" "number" "deal" "outsourcing" "link" "click" "last" "friday" "forward" "review" "paul" "approval"
Topic 14	"chairman" "ceo" "option" "president" "executive" "list" "image" "louise" "pjm" "last" "judge" "order" "board" "date" "proposal" "chief" "john" "woman" "make" "vice"
Topic 15	"office" "louise" "regard" "thank" "assistant" "skilling" "contact" "send" "number" "last" "houston" "phone" "could" "look" "morning" "greg" "home" "forward" "make" "friday"
Topic 16	"price" "customer" "contract" "capacity" "site" "system" "password" "france" "agreement" "service" "term" "provide" "process" "response" "first" "question" "volume" "end" "read" "supply"
Topic 17	"ena" "team" "america" "commercial" "delainey" "dave" "support" "process" "report" "john" "trading" "mark" "management" "organization" "effort" "regulatory" "well" "risk" "unit" "service"
Topic 18	"file" "attached" "document" "list" "section" "ubs" "change" "version" "comment" "review" "people" "revised" "employee" "final" "date" "suggested" "see" "feedback" "support" "share"
Topic 19	"713" "853" "fax" "646" "officer" "tel" "operating" "chief" "3488" "netco" "plan" "list" "estate" "really" "possible" "2001" "room" "start" "agreement" "today"
Topic 20	"transaction" "enrononline" "trading" "credit" "system" "trade" "agreement" "product" "application" "data" "risk" "online" "counterparty" "commodity" "eol" "legal" "customer" "term" "contract" "question"

Table 4: Topic Modeling Results

After identifying those topics that appear often in the corpus, we can explore in more depth to find documents that are related to the wrongdoings. For example, Topic 4 seems to be related to the manipulation of the power supply in California as it includes keywords such as "california", "utility", "price", "electricity", "governor" and "plant". But since we are interested in securities fraud, Topic 20 that mentions keywords such as "transaction", "trading", "risk". "legal" and "contract" is a better point to start with.

2.4 Step 4: Fraud Emails Identification - Keywords Filtering

We rank people by their score of topic 20. Figure 2 shows that Ben Glisan has the highest score (0.13) for this topic. In another word, Ben is mostly related to this topic, which makes him a highly suspicious person to investigate.

```
for person, score in sorted_topic_person.items():
    print(person, score)
```

```
ben.glisan@enron.com 0.12899075386335307
andrew.fastow@enron.com 0.10517243872207027
sherri.sera@enron.com 0.06745847102884073
k..allen@enron.com 0.06729716299500763
greg.whalley@enron.com 0.06633520095045423
david.delainey@enron.com 0.06418101014706323
j..kean@enron.com 0.06418101014706323
richard.shapiro@enron.com 0.06347117808158895
louise.kitchen@enron.com 0.06225887558762464
joannie.williamson@enron.com 0.0621735928109611
jeff.skilling@enron.com 0.06020400839693778
don.miller@enron.com 0.05939826648276149
christie.patrick@enron.com 0.048590827096549216
kevin.hannon@enron.com 0.04144896350649671
kenneth.lay@enron.com 0.03883824018322769
```

Figure 2: People's Score Ranking of Topic 20

There are only 8 emails sent by Ben Glisan among the 4,288 emails. We decided to review them manually to find interesting keywords. After analysis, we figured that "Raptor" was the word being discussed repetitively among the 8 emails, which is also associated with SPE. Therefore, we applied "Raptor" as a filter word to our selected 4,288 emails from POI derived from step 2. It generated a list of 12 emails. Here is the index of these emails: 2694, 7188, 26474, 38702,

86200, 93255, 102229, 119164, 126920, 185833, 231041, 243594 (Figure 3). From these 12 emails, we reviewed and selected 5 emails that support our target wrongdoing. The content and analysis of these 5 emails would be described in the following sections.

	from	to	cc	bcc	subject	text
2694	david.delainey@enron.com	wes.colwell@enron.com richard.causey@enron.com	ben.glisan@enron.com joseph.deffner@enron.com ...	ben.glisan@enron.com joseph.deffner@enron.com ...	Raptor et al	Rick, we have re-examined the portfolio as a r...
7188	ben.glisan@enron.com	richard.causey@enron.com rick.buy@enron.com ro...	david.gorte@enron.com george.mckean@enron.com ...	david.gorte@enron.com george.mckean@enron.com ...	RE: Raptor Debris	George & Gordon\n\nPlease work with RAC (Dave ...
26474	david.delainey@enron.com	mike.jakubik@enron.com			Re: Raptor	How do we immunize ourselves from the workouts...
38702	david.delainey@enron.com	richard.lydecker@enron.com	jesse.neyman@enron.com brandi.morris@enron.com	jesse.neyman@enron.com brandi.morris@enron.com	Brigham	Great job guys - keep it coming!\n\nRegards\n...
86200	david.delainey@enron.com	david.oxley@enron.com			Re: ENA Comp suggestions for Project Raptor	David , if this is going to cause you politica...
93255	david.delainey@enron.com	mike.jakubik@enron.com	raymond.bowen@enron.com	raymond.bowen@enron.com	Re: Raptor	That may work - I don't want to end up with a...
102229	david.delainey@enron.com	wes.colwell@enron.com joseph.deffner@enron.com			Catalytica	Guys, I suggest that we write it down in order...
119164	andrew.fastow@enron.com	john.lavorato@enron.com	louise.kitchen@enron.com	louise.kitchen@enron.com	RE:	John:\n\nThanks for the e-mail. I wasn't tryi...
126920	j..kean@enron.com	.palmer@enron.com			FW: Erroneous press	\n\n -----Original Message-----\nFrom: \tKoeni...
185833	ben.glisan@enron.com	greg.whalley@enron.com			Raptor Position Reports for 11/20/00	Greg,\n\nAttached are the daily position repor...
231041	david.delainey@enron.com	wes.colwell@enron.com	mark.frevert@enron.com john.lavorato@enron.com...	mark.frevert@enron.com john.lavorato@enron.com...	ROCE and Cost Iniatives	Wes, as per our discussion, I wanted to detail...
243594	david.delainey@enron.com	joseph.deffner@enron.com david.gorte@enron.com...	andrew.fastow@enron.com rick.buy@enron.com lar...	andrew.fastow@enron.com rick.buy@enron.com lar...	AIG Fund	Guys, I would like to add the following commen...

Figure 3: Emails filtered with keyword "Raptor" sent by POI

3. Set of Emails Indicating Wrongdoing

By applying network analysis, topic modeling, and keywords filter, we were able to identify 5 emails on the abuse of SPE in Enron (see Appendix). The index numbers of 5 emails are 38702, 86200, 93255, 102229, 185833.

4. Emails Analysis

The emails we identified make it clear that Enron has utilized SPE to hide its assets and debts. This is a good set of emails because they all indicated our target wrongdoing -- abuse of SPE (security fraud). A brief summary of the email content is listed below:

- Email ID: 38702

  This email shows that Enron used raptor to hedge ENA and their specialists worked hard to balance severely distressed assets, which indicates that Enron exploited SPE in balancing their account. This is an example of the abuse of SPE, since SPE is not supposed to be used to balance mark-to-market losses.

- Email ID: 86200

  In this email, David suggested that they pay compensation/rewards to VPs and directors assigned to the project using money in Raptor, although they already realized the possible downside for this project could be $300 mm. Using SPE, Enron was permitted to increase leverage without reporting debts on its balance sheet. However, it is improper to not follow regulations in using SPE.

- Email ID: 93255

  As Delainey wrote in this email “raptor may be a good accounting hedge”, Enron employees exploited SPE as a hedge against their losses and SPE was abused to hedge their JEDI investment.

- Email ID: 102229

  Here, Richard mentioned the value of Enron’s Catalytica investment is affected by raptor capacity, not real earnings. This is clearly the abuse of SPE, since the value of investment should be evaluated based on real earnings. Enron’s use of SPE violated Generally Accepted Accounting Principles (GAAP) SPE requirements.

- Email ID: 185833

  Enron took the use of SPE to increase their credit capacity. This email indicates that the credit capacity of Raptor is $94 million.

5. Problems to Fix Next Time

5.1 POI

In this project, we started with a set of POI and did a network analysis to select people that interact with our initial set of POI. Then we used this as a primary filter to narrow down email from 251,734 to 4,288. The original dataset was shrunk around 60 times. This selection is so intense that if the filter was not selected properly, we may miss a lot of useful information or some useless information may be kept. The key to this selection is the initial four people of interest. The next time, we can try to change the initial POI or add a few more people in there. The results may or may not change dramatically.

5.2 Keyword selection

Another area that could influence the input is the key word selection. Through topic modeling, we identified topic 20 that is suspicious. Topic 20 pointed to Ben Glisan. We then inspected Ben's email and found the keyword "Raptor". What if the keyword we selected didn't generate fraud emails that satisfying our needs? We probably have to keep changing new key words in the search. What if with the keywords, it generates hundreds of emails? We can't read through everything to determine which ones are the ones we needed. In this case, we can add one or a few more keywords to filter and narrow down the list.

6. Problems Unfixable

Topic modeling is a type of unsupervised machine learning approach.

While we did find our desired emails in this study, there are a few drawbacks for topic modeling:

1. The topics could be uncorrelated. As shown in table 4, the topics are uncorrelated with each other. This is due to the algorithm we used, latent dirichlet allocation (LDA).
2. LDA does not model sentence structure as it assumes words are exchangeable.
3. Most critically, since it is an unsupervised method, we don't have ground truth to validate the results.

Because of these drawbacks, when we search through all the topics generated, we didn't get an expected topic group until topic 20.

Unless we implement supervised learning methods together with topic modeling, the problem probably won't be fixed.

References

[1]"Securities fraud", En.wikipedia.org, 2021. [Online]. Available: https://en.wikipedia.org/wiki/Securities_fraud. [Accessed: 03- Feb- 2021].

[2]B. McLean and P. Elkind, The smartest guys in the room.

[3]"Enron Fraud", Impactlaw.com, 2021. [Online]. Available: https://www.impactlaw.com/criminal-law/white-collar/securities-fraud/lawsuits/enron. [Accessed: 03- Feb- 2021].

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[5]"10 Enron Players: Where They Landed After the Fall (Published 2006)", Nytimes.com, 2021. [Online]. Available: https://www.nytimes.com/2006/01/29/business/businessspecial3/10-enron-players-where-they-landed-after-the-fall.html. [Accessed: 03- Apr- 2021].

Appendix

- ***Email ID: 38702***

Subject: Brigham
Text:
We have completed the sale of our Brigham investment for $20.0 million (JEDI/ENA). ENA's net share of the proceeds for $12.5 million. The transaction has been closed and funded and at the book/raptor value.
My metaphor for pulling together liquidation transactions of severely distressed assets like Brigham is trying to shield a pencil balanced on its point in the midst of a hurricane. In the case of the Brigham deal the hurricane was a Force Five.
Jempy Neyman, who led the transaction, and Brandi Morris, a senior specialist in Special Assets, did an outstanding job getting this tough deal done.
The next ""balanced pencil"" is closing the Basic Energy (Sierra Well Service) sale by mid-November. We're on track: so far, the hurricane has not blown the pencil away.
2000-11-02T14:19:00.000Z

- ***Email ID: 86200***

Subject:
Re: ENA Comp suggestions for Project Raptor,"David , if this is going to cause you political flack with Mary Joyce lets just kill it - we have revised the original plan and this is probably not needed.
Text:
I have been discussing with Dave Delainey how we might align the compensation/rewards for the group of 4 or 5 VP's and Directors we have assigned to disposing of our large portfolio ($650mm). The project is due to complete in June 01 and Dave and my concern is whether we can make sure they are motivated to close on time and get the best possible price for us. Dave believe the up side could be as much as $150mm and the downside as much as $300mm (the difference between best and worst prices/sales).

My suggestion is that we do the following and I would like your comments or concerns if any:

Enter into contracts or an agreement (the later would be one way - us to them and obviously easier) with each of them outlining the following:
Bonus targets based on financial targets and PRC performance for calendar 01 (ie if you rank in top 3 categories and you realise over $650 from this project we will pay you not less than $300k)
Equity award on closing, on the basis of successful closure and above line value (ie only in the event that this closes in June 01 and realises more than $650mm we will grant you $200k in options, if above $800m then $350k in options.)
Dave would like for me to get back to him on this asap.
David
2000-09-06T15:29:00.000Z

- ***Email ID: 93255***

Subject: Raptor
Text:

That may work - I don't want to end up with an equity position I just worked hard to eliminate. Further, raptor may be a good accounting hedge but if we took back JEDI's share at existing marks we would be destroying significant real value. Will the buy back price of the equity/debt we get back from JEDI incorporate the write downs we think should occur?
Regards
Delainey
---------- Forwarded by David W Delainey/HOU/ECT on 05/11/2000 02:29 PM ----------

Enron Global Finance
From: Mike Jakubik 05/11/2000 02:09 PM

To: David W Delainey/HOU/ECT@ECT
cc:
Subject: Re: Raptor
Dave, I assume you are asking how we hedge the portion of JEDI II investments that will come back to us after the restructuring. As any buyout price for CALPERS will reflect the state of the assets at closing, I think we are well hedged until the closing of the restructuring. We can see if we can reserve some Raptor capacity upfront to hege us moving forward from the restructuring closin. If this does not answer your question, let me know. Mike

David W Delainey
05/11/2000 01:37 PM
To: Mike Jakubik/HOU/ECT@ECT
cc:
Subject: Re: Raptor
How do we immunize ourselves from the workouts being shed into Raptor?
Regards
Delainey
2000-05-11T14:32:00.000Z

- ***Email ID: 102229***

Subject: Catalytica
Text:
Guys, I suggest that we write it down in order to ensure that we don't get it back as other groups use up the Raptor capacity. We have sufficient market data points to do this. Please advise.
Regards
Delainey
---------- Forwarded by David W Delainey/HOU/ECT on 12/12/2000 12:30 PM ----------

Richard Lydecker@ENRON
12/12/2000 10:50 AM
To: Thomas E White/HOU/EES@EES, David W Delainey/HOU/ECT@ECT, Brian Redmond/HOU/ECT@ECT

cc: Wes Colwell/HOU/ECT@ECT, Andrea V Reed/HOU/ECT@ECT, Barton Clark/HOU/ECT@ECT
Subject: Catalytica
Catalytica filed a prospectus supplement with the SEC yesterday, December 11th which disclosed that because of recent market conditions the Board had decided not to proceed with the planned stock split prior to the spin-off. The supplement indicates an expected initial trading range ""at a price between $20 and no less than $10 per share"". Based upon these new Catalytica's estimates, the value of the Enron investment would be $13.5 to $27.0 million. **Enron's Catalytica investment is part of the raptor structure so that the impact is on raptor capacity rather than earnings.** The investment has also been monetized in a FAS 125 structure for cash flow Purposes.
2000-12-12T12:31:00.000Z

- ***Email ID: 185833***

Subject: Raptor Position Reports for 11/20/00
Text:
The Raptor I credit capacity is at $94 million. The credit capacity will be impacted by fourth quarter revaluations on Catalytica, Heartland Steel and other assets. If the credit capacity is exceeded, Enron will need to reserve for the loss and any future losses.
The TNPC stock closed at $9.38 on November 20. The closing price on November 21 is $8.94 which results Raptor III exceeding its credit capacity by $12 million.
2000-11-22T06:59:00.000Z