



# Using text data to detect fraud

Charlotte Werger
Data Scientist



#### You will often encounter text data during fraud detection

#### Types of useful text data:

- 1. Emails from employees and/or clients
- 2. Transaction descriptions
- 3. Employee notes
- 4. Insurance claim form description box
- 5. Recorded telephone conversations
- 6. ...



#### Text mining techniques for fraud detection

- 1. Word search
- 2. Sentiment analysis
- 3. Word frequencies and topic analysis
- 4. Style



#### Word search for fraud detection

#### Flagging suspicious words:

- 1. Simple, straightforward and easy to explain
- Match results can be used as a filter on top of machine learning model
- 3. Match results can be used as a feature in a machine learning model





#### Word counts to flag fraud with pandas

```
# Using a string operator to find words
df['email_body'].str.contains('money laundering')

# Select data that matches
df.loc[df['email_body'].str.contains('money laundering', na=False)]

# Create a list of words to search for
list_of_words = ['police', 'money laundering']
df.loc[df['email_body'].str.contains('|'.join(list_of_words), na=False)]

# Create a fraud flag
df['flag'] = np.where((df['email_body'].str.contains('|'.join(list_of_words))) == True), 1, 0)
```





# Let's practice!





# Text mining techniques for fraud detection

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## Cleaning your text data

Must do's when working with textual data:

- 1. Tokenization
- 2. Remove all stopwords
- 3. Lemmatize your words
- 4. Stem your words



## Go from this...

	headline_text	index
0	aba decides against community broadcasting lic	0
1	act fire witnesses must be aware of defamation	1
2	a g calls for infrastructure protection summit	2
3	air nz staff in aust strike for pay rise	3
4	air nz strike to affect australian travellers	4

#### To this...

```
[decid, communiti, broadcast, licenc]
0
                                 [wit, awar, defam]
            [call, infrastructur, protect, summit]
3
                       [staff, aust, strike, rise]
              [strike, affect, australian, travel]
4
5
                [ambiti, olsson, win, tripl, jump]
            [antic, delight, record, break, barca]
6
     [aussi, qualifi, stosur, wast, memphi, match]
             [aust, address, secur, council, iraq]
8
9
                           [australia, lock, timet]
Name: headline_text, dtype: object
```

#### Data preprocessing part 1

```
# 1. Tokenization
from nltk import word_tokenize

text = df.apply(lambda row: word_tokenize(row["email_body"]), axis=1)
text = text.rstrip()
text = re.sub(r'[^a-zA-Z]', ' ', text)
```



#### Data preprocessing part 2

```
# Lemmatize words
from nltk.stem.wordnet import WordNetLemmatizer
lemma = WordNetLemmatizer()
normalized = " ".join(lemma.lemmatize(word) for word in punc free.split())
# Stem words
from nltk.stem.porter import PorterStemmer
porter= PorterStemmer()
cleaned text = " ".join(porter.stem(token) for token in normalized.split())
print (cleaned text)
['philip', 'going', 'street', 'curious', 'hear', 'perspective', 'may', 'wish',
'offer', 'trading', 'floor', 'enron', 'stock', 'lower', 'joined', 'company',
'business', 'school', 'imagine', 'quite', 'happy', 'people', 'day', 'relate',
'somewhat', 'stock', 'around', 'fact', 'broke', 'day', 'ago', 'knowing',
'imagine', 'letting', 'event', 'get', 'much', 'taken', 'similar',
'problem', 'hope', 'everything', 'else', 'going', 'well', 'family', 'knee',
'surgery', 'yet', 'give', 'call', 'chance', 'later']
```





# Let's practice!





## **Topic modelling**

Charlotte Werger
Data Scientist



#### Topic modelling: discover hidden patterns in text data

- 1. Discovering topics in text data
- 2. "What is the text about"
- 3. Conceptually similar to clustering data
- 4. Compare topics of fraud cases to non-fraud cases and use as a feature or flag
- 5. Or.. is there a particular topic in the data that seems to point to fraud?

### Latent Dirichlet Allocation (LDA)

#### With LDA you obtain:

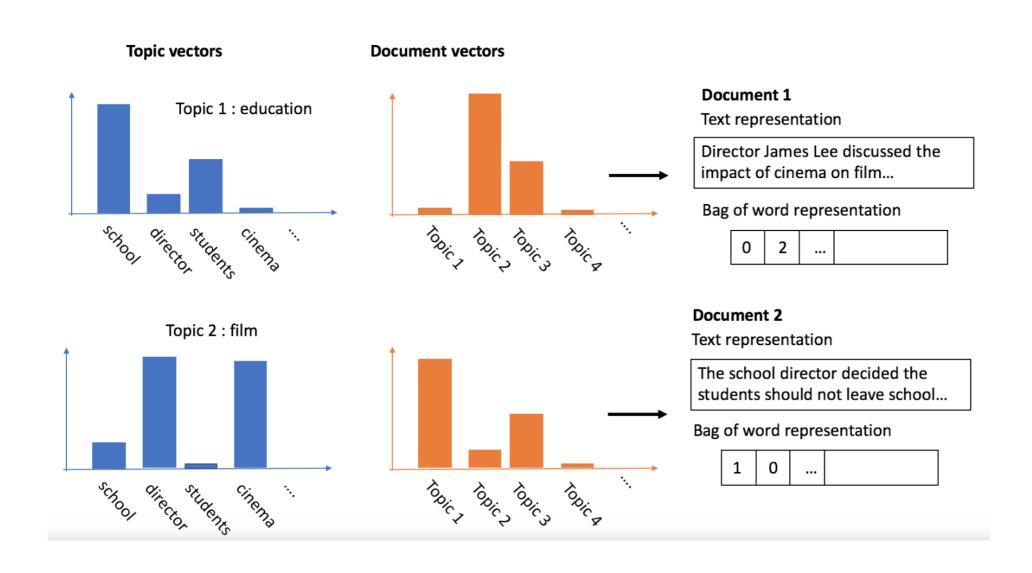
- 1. "topics per text item" model (i.e. probabilities)
- 2. "words per topic" model

#### Creating your own topic model:

- 1. Clean your data
- 2. Create a bag of words with dictionary and corpus
- 3. Feed dictionary and corpus into the LDA model



### Latent Dirichlet Allocation (LDA)





#### Bag of words: dictionary and corpus

```
from gensim import corpora

# Create dictionary number of times a word appears
dictionary = corpora.Dictionary(cleaned_emails)

# Filter out (non)frequent words
dictionary.filter_extremes(no_below=5, keep_n=50000)

# Create corpus
corpus = [dictionary.doc2bow(text) for text in cleaned_emails]
```



#### Latent Dirichlet Allocation (LDA) with gensim

```
import gensim

# Define the LDA model
ldamodel = gensim.models.ldamodel.LdaModel(corpus, num_topics = 3,
id2word=dictionary, passes=15)

# Print the three topics from the model with top words
topics = ldamodel.print_topics(num_words=4)
for topic in topics:
    print(topic)

(0, '0.029*"email" + 0.016*"send" + 0.016*"results" + 0.016*"invoice"')
(1, '0.026*"price" + 0.026*"work" + 0.026*"management" + 0.026*"sell"')
```

(2, '0.029\*"distribute" + 0.029\*"contact" + 0.016\*"supply" + 0.016\*"fast"')





# Let's practice!





# Flagging fraud based on topics

Charlotte Werger
Data Scientist



#### Using your LDA model results for fraud detection

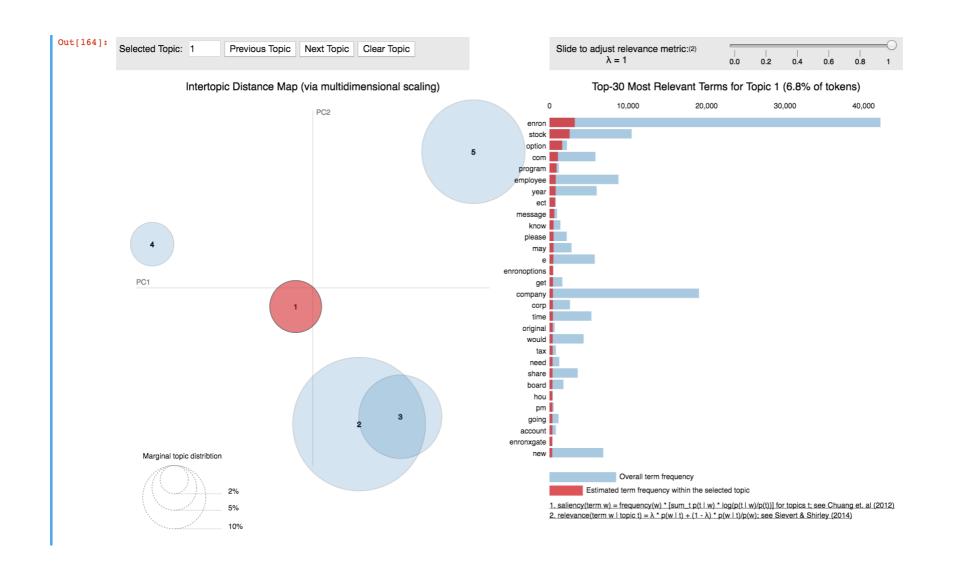
- 1. Are there any suspicious topics? (no labels)
- 2. Are the topics in fraud and non-fraud cases similar? (with labels)
- 3. Are fraud cases associated more with certain topics? (with labels)



### To understand topics, you need to visualize



## Inspecting how topics differ





#### Assign topics to your original data

```
def get topic details (ldamodel, corpus):
   topic details df = pd.DataFrame()
    for i, row in enumerate(ldamodel[corpus]):
       row = sorted(row, key=lambda x: (x[1]), reverse=True)
       for j, (topic num, prop topic) in enumerate (row):
            if j == 0: # => dominant topic
                wp = ldamodel.show topic(topic num)
                topic details df = topic details df.append(pd.Series([topic num,
   topic details df.columns = ['Dominant Topic', '% Score']
   return topic details df
contents = pd.DataFrame({'Original text':text clean})
topic details = pd.concat([get topic details(ldamodel,
                           corpus), contents], axis=1)
topic details.head()
    Dominant Topic
                      % Score
                                  Original text
                                  [investools, advisory, free, ...
    0.0
                      0.989108
    0.0
                      0.993513
                                  [forwarded, richard, b, ...
    1.0
                      0.964858
                                   [hey, wearing, target, purple, ...
    0.0
                      0.989241
                                   [leslie, milosevich, santa, clara, ...
```





# Let's practice!





# Fraud detection in Python Recap

Charlotte Werger
Data Scientist



## Working with imbalanced data

- Worked with highly imbalanced fraud data
- Learned how to resample your data
- Learned about different resampling methods



#### Fraud detection with labeled data

- Refreshed supervised learning techniques to detect fraud
- Learned how to get reliable performance metrics and worked with the precision recall trade-off
- Explored how to optimise your model parameters to handle fraud data
- Applied ensemble methods to fraud detection



#### Fraud detection without labels

- Learned about the importance of segmentation
- Refreshed your knowledge on clustering methods
- Learned how to detect fraud using outliers and small clusters with K-means clustering
- Applied a DB-scan clustering model for fraud detection



#### Text mining for fraud detection

- Know how to augment fraud detection analysis with text mining techniques
- Applied word searches to flag use of certain words, and learned how to apply topic modelling for fraud detection
- Learned how to effectively clean messy text data



#### Further learning for fraud detection

- Network analysis to detect fraud
- Different supervised and unsupervised learning techniques (e.g. Neural Networks)
- Working with very large data





## **End of this course**