Text Mining and Data Analysis

Definition

- Text mining foes by numerous names (not always with the same meaning
  - Text Data Mining
  - Natural Language Processing
  - Unstructured Data Analysis
  - Text analytics

- Text mining is the process of identifying novel information from a collection of texts (also known as a corpus).

More specifically text mining…

- Functions with respect to a corpus of text (i.e. documents, texts, tweets)
- Creates a dictionary or vocabulary to identify relevant terms.
- Accommodates a variety of metrics to quantify the corpus

Data Mining vs. Text Mining

- Data Mining
  - process directly
  - Structured numeric transaction data residing in rational data warehouse
- Text Mining
  - Linguistic processing or natural language processing (NLP)
  - Discover heretofore unknown information
  - Applications deal with much more diverse and eclectic collections of systems and formats

Confusion

- Is text mining the same as information extraction?
  - No, but often they are used in unison.
- Information Extraction (IE)
  - Extract facts about pre-specified entities, events or relationships from unrestricted text sources.
  - Used to identify entities such as names, places, dates, zip codes.

The idea of text mining ...

- ... is to go beyond frequency-counting
- ... is to go beyond the search-for-documents framework
- The goal is to find patterns (of meaning) *within* and especially *across* documents.
  - Sometimes, even within sentances.

The steps of text mining

1. Data generation and application understanding
2. Corpus generation
3. Data understanding
4. Text preprocessing
5. Search for patterns / modelling
    - Topical analysis
    - Sentiment analysis / opinion mining
6. Evaluation

Corpus Development

- A corpus is a structured vectorizer form of textual data.
  - Tweets
  - Grant proposals
  - Books
    - Chapters within books
    - Sentences within paragraphs

Example 1: Getting Twitter Data

- Most social media sites allow the public access to a random sample of postings for analysis.
  - This includes Twitter, Instagram, and many others.
  - Doesn't include facebook anymore.

- In order to access Twitter data you must first go to dev.twitter.com and register.
  - It is free and only takes a few minutes

‘twitteR’ Package in R

- Provides a easy application program interface (API) to interface with twitter data.
  - You must set search terms (can set multiple using Boolean logic)
  - Can set date restrictions
  - Can set geographic restrictions using geocoding
  - Also can restrict language (*kinda..*)

```
tweets <- searchTwitter("energy + sustainability" , n=500, lang="en", since="2017-03-20")
```

Caveat 1: Sampling

- Only a small random sample of tweets are available.
- This means that if you try to get information on a specific locality (e.g. Tallahassee), there may not be any in the database.

```
tally<-searchTwitter('fsu', geocode='30.4419,84.2985,50mi',  n=50, since="2017-03-20")
```

- This search returns nothing.

Caveat 2: Geocoding

- Locations for tweets are only recorded if the person posting has allowed GPS access on their device and to Twitter.
  - This was only around 1% back in 2012.
  - The percentage has grown steadily but is probably still under 5% of the total.
  - Many social media researchers impute locations.
    - This works very well at the regional level with over 80% accuracy.

Twitter Data and Metadata

- Text: The actual tweet
- Favorited, favoritedCount: How many followers favorited the tweet
- Created: Date of tweet
- Retweet, retweetCount: How many times was it share
- Longitude, latitude: If geocoded, these are provided
- There is some other columns, such as source.

Examining Twitter Data in R

- After inputting data, it is usually best to convert the object to a data frame in R.
- After converting, we can examine the data.

```
tweets.df <- twListToDF(tweets3) #converts to dataframe
summary(tweets.df) # summarizes metadata
tweets.df[1:5,1] #prints first 5 tweets
```

Cleaning and Converting

- In order to use the text data, we must turn it into a corpula (collection of documents) and clean it.
- Cleaning involves:
  - Removing special characters
  - Removing punctuation
  - Standardizing case
  - Removing stopwords
  - Stemming

Removing “Specials”

- In social media analysis, we must also worry about emojis and foreign language text that is placed into twitter.
  - These can be frustrating and there is no comprehensive list of emojis.
- There are numerous methods, but I am going to make all text into ASCII. Thus removing the problem text.
  - This may not always be the best method.

R code

- It is easiest to remove special characters prior to creating the Corpus in my opinion.

```
tweets.df$text <- sapply(tweets.df$text,function(row)
iconv(row, "latin1", "ASCII", sub="")) #removes
emojis and foreign words


# Create a Corpus (text data set)
tweet_corpus <- Corpus(VectorSource( tweets.df[,1]
))
tweet_corpus #displays info on Corpus
```

Removing Punctuation and Capitalization

- Pretty simple.
- Please note, each time I do a cleanse I overwrite the original dataset. This is dangerous.

```
tweet_corpus <- tm_map(tweet_corpus, removePunctuation) # removes punctuation


tweet_corpus <- tm_map(tweet_corpus, content_transformer(tolower)) #makes all lower case
```

Stopwords

- The removal of words that add little to no value in data analysis.
- Most programs come with a preset list of common stopwords.
  - A, the, very, that, which
- Also includes words defined by the user.
  - For instance, you need to exclude your search terms. They will obviously be in every tweet

Zipf’s Law

- Zipf's law states that given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the frequency table.
  - Thus the most frequent word will occur approximately twice as often as the second most frequent word, three times as often as the third most frequent word, etc.:
  - Doesn’t apply to all languages, but many

Stemming

- Stemming removes the ends of words so that that conjugated (e.g. “ing”) and pluralized words end up having the same core.
  - We usually want the computer to think that “sustainability” and “sustainable” are the same.
- This process can also lead to some mistakes.
  - Will make “Miner” and “Mine” the same sometimes.

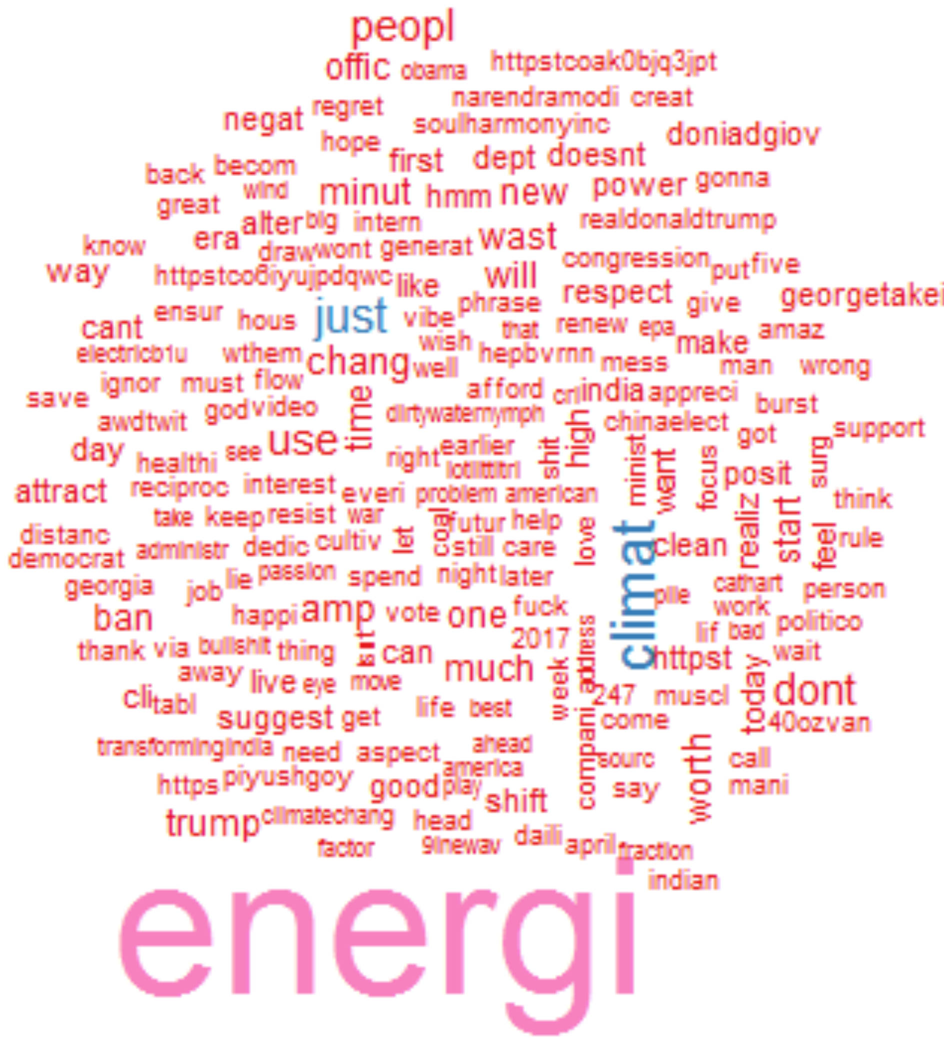
R Stemming and Stopword Code

```
tweet_corpus <- tm_map(tweet_corpus, function(x)removeWords(x,stopwords()))
#removes stop words

tweet_corpus <- tm_map(tweet_corpus, stemDocument)
```

Examining the Data in a Word Cloud

- Use a word cloud to examine the data after cleaning.
- It is usually best to exclude words that appear very few times (less than 2 at least)



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Removing Search Terms

- Search terms and words that appear too often make analysis difficult/impossible.
  - We want to remove the word “energy” because it is simply too frequently occurring.

```
tweet_corpus <- tm_map(tweet_corpus, function(x)removeWords(x,"energy"))  #removes additional term "energy"


wordcloud(tweet_corpus,min.freq=2, max.words=100, random.order=T, colors=pal2)
```


renew
develop
clean
amp
sourc
amplifi
siemensoilandga
via
global
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technolog
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world
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guardian
solar
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Other stuff you can do…

- You can define terms that stay together
  - climate change as one term
  - Make EPA = Environmental Protection Agency
- Remove URLs
- Remove white space
- Remove numbers
- Entity Identification – finding people, places,…
  - Lexica, heuristic rules, syntax parsing
  - Jigsaw is a great free tool for this

Preparing for Text Analytics

- Once the data is cleaned, we need to transform the data into a document term matrix (dtm) for analysis.
  - DTMs basically develops a numeric representation of the textual data and analyzes it with standard tools.
  - The standard approach treats documents as rows and terms (e.g. words) as columns.
  - This creates a very large, sparse matrix (lots of zeros)
- You can also use a term document matrix

Document Term Matrix Issues

- Since the DTM is very sparse, we usually can't simply analyze it "as is".

1. Reduce the dimensionality: eliminating any words that appear too frequently or too infrequently.
2. Weight terms: Calculate a numerical statistic that is intended to reflect how important a word is to a document in a corpus.

Reducing Dimensionality

- Text mining suffers from too much information, so we want to reduce it down to something manageable.
- Words that appear in all the texts are useless at discriminating between factors.
  - For example, the word energy appears in every tweet, so it adds no value to choosing between them.
    - Think of a regression variable that equals 1 for 98% of your cases and 0 otherwise. It would be unlikely to be predictive.
  - Text mining usually begins by removing these too frequently occurring words.
- Words that appear in too few texts add little value also.
  - Not frequent enough to compare between groups.
    - Think of a regression variable that equals 1 for 3% of your cases and 0 otherwise. It would be unlikely to be predictive.

Weighting Terms

- The default weight is based on term frequency (how many times a word appears).
- Term frequency-inverse document frequency (tf-idf) is the preferred option to emphasize words that discriminate between factors.
  - The tf-idf value increases proportionally to the number of times a word appears in the document, but is often offset by the frequency of the word in the corpus.

R code for TDM

```
tdm <- TermDocumentMatrix(tweet_corpus,
        control =     list(wordLengths = c(1, Inf),
        weighting = function(x)
        weightTfIdf(x, normalize =FALSE) ) )
```

- The control function determines the inputs. You can also do stemming and stopwords here, I just prefer to do them early

Descriptive Stats on Term Freq

- It is useful to look at the most frequent terms

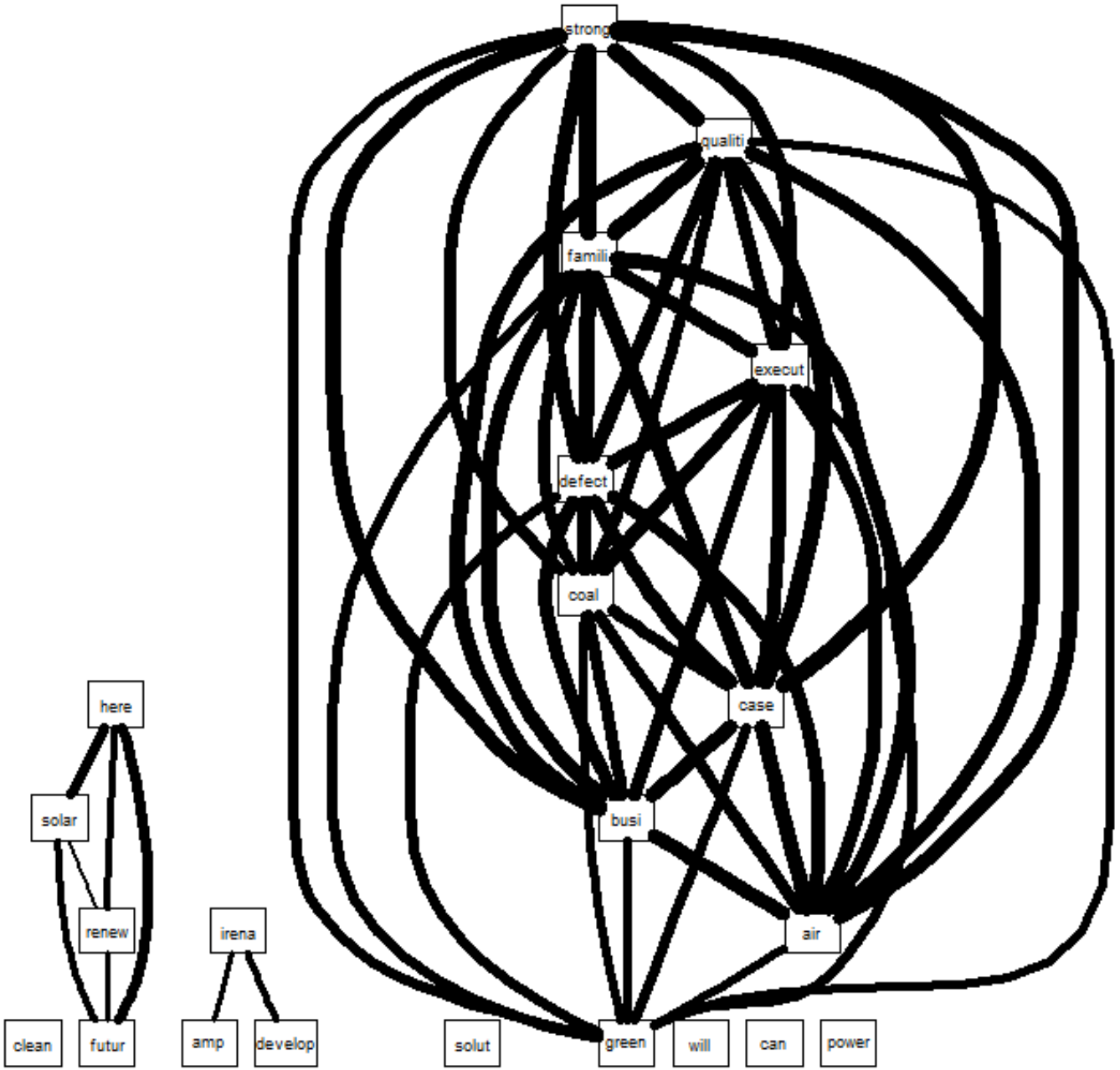
```
freq.terms <- findFreqTerms(tdm, lowfreq = 100)
term.freq <- rowSums(as.matrix(tdm))
term.freq <- subset(term.freq, term.freq >= 100)
df <- data.frame(term = names(term.freq), freq = term.freq)

ggplot(df, aes(x = term, y = freq)) + geom_bar(stat = "identity") + xlab("Terms") + ylab("Count") + coord_flip()
```

Examining Word Associations

- We may have a specific term we want to examine in relationship to others.
- I this case, I want terms that are over 20% correlated with “obama”

```
findAssocs(tdm, "obama", 0.2)
```

```
plot(tdm, term = freq.terms, corThreshold = 0.2,
weighting = T)
```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Removing Sparse Terms

- You have two basic options here:
  1. Submit a list of low frequency words to exclude in the stopwords list
  2. Choose to dump those under a frequency or correlation threshold

```
tdm2 <- removeSparseTerms(tdm, sparse = 0.95)
m2 <- as.matrix(tdm2)
```

Ex 2: Getting Documents into a Corpus with Energy Plans

- R does not have a good text extraction tool for .pdf and .doc files.
  - The read.pdf() in the tm package assumes you have another program added on (i.e. xpdf engine)
  - Strongly suggest using another tool such as SAS enterprise miner or Jigsaw

Clustering

- Clustering is a method of partitioning data into ‘k’ subsets or groups.
  - Each observation is assigned to the closest cluster based on the distance to the center of the cluster.
  - Clustering is a form of unsupervised learning.
- Clustering indicates the group assignment, but the researcher must make sense of the meaning.

Clustering Terms

- After the data is cleaned, cluster analysis runs basically the same as numeric data.
  - You can not cluster effectively if the matrix is still sparse. Your results will be nonsense.
  - Clustering is based on a distance measure (e.g. Euclidian) same as in numeric data
  - You can use k-means, hierarchical, or Bayesian clustering.

Hieratical Cluster code

```
distMatrix <- dist(scale(m2))
fit <- hclust(distMatrix, method = "ward")
plot(fit)
rect.hclust(fit, k = 3)
m3 <- t(m2) # transpose the matrix to cluster documents (tweets)
set.seed(1222) # set a fixed random seed
k <- 3 # number of clusters
kmeansResult <- kmeans(m3, k)
```

K- Means Clustering Code

- kmeans3<-kmeans(dtm,3)

- #Merge cluster assignment back to keywords
- # kw_with_cluster <- as.data.frame(cbind(dtm, kmeans3$cluster))
- # names(kw_with_cluster) <- c("keyword", "kmeans3")

- #accumulator for cost results
- cost_df <- data.frame()

Elbow Plot

```
#run kmeans for all clusters up to 20
for(i in 1:20){
  #Run kmeans for each level of i, allowing up to 100 iterations for convergence
  kmeans<- kmeans(x=dtm, centers=i, iter.max=100)

  #Combine cluster number and cost together, write to df
  cost_df<- rbind(cost_df, cbind(i, kmeans$tot.withinss))
}
names(cost_df) <- c("cluster", "cost")

ggplot(data=cost_df, aes(x=cluster, y=cost, group=1)) +
theme_bw(base_family="Garamond") +
geom_line(colour = "darkgreen")
```

Determining Themes from Clusters

- You can extract key words for each cluster to determine the theme.
- This is very useful to check face validity.

```
for (i in 1:k) {
cat(paste("cluster ", i, ": ", sep = ""))
s <- sort(kmeansResult$centers[i, ], decreasing = T)
cat(names(s)[1:5], "nn")
}
```

Methods Notes

- Most software uses singular value decomposition (SVD)
  - SVD is basically uncentered principal components analysis.
  - So is it the same Aaron???
- The weighting scheme will impact clustering!
  - term frequency–inverse document frequency is the most robust in most of what I have read.
    - a numerical statistic that is intended to reflect how important a word is to a document in a corpus

Topic Analysis

- Topic modeling automatically classifying sets of documents into themes.
- Topic modeling is more specific than cluster analysis.
  - Cluster analysis can be used to model topics, but clusters do not necessarily map to topics.

Latent Dirichlet Allocation

(Blei .et al. 2003)

- LDA determines the latent topic structure given the words and document.
- LDA does this by recreating the documents in the corpus by adjusting the relative importance of topics in documents and words in topics iteratively.
- I prefer a Bayesian LDA model (Gibbs sampling) when possible for many reasons not gone through here.

Caveat to LDA and Cluster

- Both LDA and clustering require the researcher to set the number of topics/groupings.
- While there are methods to optimize this, the decision is always subjective.
- The number of clusters does NOT need to agree with the number of topics.

How LDA works

- Iteratively for each word(W), topic (T) and document (D) :
  - Randomly assigns words to topics.
  - Calculates a conditional probability of membership using:
    - Computes the P(T | D) – the proportion of words in D that are assigned to T
    - Computes the P(W| T) – the proportion of topic T over all documents contain word W
  - Reassign W based on p(T | D) * p(W | T)
  - Repeat thousands of times

What LDA Provides

- LDA considers each document to be a mixture of all topics.
- We get a probability for each topic and assume association with the max.
  - So you can just use the max to get a single classification or employ all probabilities in a more sophisticated model.

Document Classification

- Classification is different from clustering.
- Classification is when we have “experts” build a training data set by which other documents are judged.

- Classification is significantly more powerful Statistically and theoretically) than the unsupervised techniques we are learning.

Document Classification Steps

- Have human judge themes in text and classify.
  - More then one judge whenever possible.
- Develop a score for each document.
- Choose a classification method:
  - Rule builder, Neural network, Tree, Regression, Hierarchical Bayes
- Run all the data, including the training set, through the algorithm.
  - Check for how many are classified correctly.

Anomaly Detection in Text

- We may want to detect anomalies between a known document and others or over time.
- Over time:
  - Usually we look ate the use of a term or theme over time.
  - AnomalyDetection (R) is a useful tool combined with twitter feeds or any other time based textual analysis.

Anomalies comparison to other documents

- Usually, the classification techniques discussed earlier are used here.
  - Often combined with semantic analysis to see if opinion/mood changes (Called semantic similarity).
  - Rare event models can be applied if the anomalies are expected to occur infrequently.
  - Local Outlier Factors (LOF) are also useful in these settings.

Using Text Modeling in Research

- Text mining by itself is not very "publishable"
  - I highly recommend combining text with other data, particularly surveys.
- Do a sensitivity analysis!!!
  - Cluster analysis in particular is sensitive to starting points and other specifications.
  - I usually check to see if I get the same clusters by removing the top and bottom 5% and 10% for instance.

Clustering Research using Text Modeling

- What if my clustering methods don't agree?
  - This is the norm, not the exception.
  - Many ostensibly similar techniques are not actually asking the same question.
- Don't just look at what words are included in a cluster, look at what terms are excluded.
  - This often tells you more.

Text Mining in Regression

- The most frequent use of text mining is to get clusters and place them in a regression model.
  - Be careful if actually adjusting standard errors on these clusters because there will be misclassified units.
    - Outliers can really cause problems in some panel models.
  - Consider interacting the clusters with other variables.
    - Interactions often lead to me finding more misclassifications from the text analysis

Multiple Documents per Unit

- What if I have multiple documents per observation in my regression?
  - No perfect answer.
  - I suggest LDA in these cases because you get a score for each theme and can judge numerically which is closes.
  - If using clustering, you can use the mode.
  - If you want to be real advanced, create a multilevel model and keep both.

In vino veritas

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