Text Mining, pt. I

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MACS 40800: Unsupervised Machine Learning

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Lecture Outline

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- Thursday: **unsupervised** (topic models)

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- And today? We are still interested in appying subjective judgement to explain and judge that which text is revealing
- Thus, our goal is *distant reading*, rather than *close reading*
- The “quantification” of text analysis is a monumental advance in this ancient field in that quantitative work is reliable, replicable, and can easily handle large volumes of material

A General Process

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4. Draw inferences

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  - *structured*: useful document information is known (e.g., beginning and end, authorship, etc.)
  - *unstructured*: desired quantity is unknown (e.g., sentiment)
- Further, a corpus may be annotated where metadata – *data not part of the document itself* – is available, e.g., date, linguistic tagging, etc.

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- But, *you still need to think about sampling error* $\rightsquigarrow$ there exists a *super*population of populations from which the universe you observed came from
- The point here? Be cautious as you approach text mining and think carefully about error, where texts came from, and so on, as the corpus *should be representative* in some sense for inferences to be meaningful

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- Though different in means, the end is the same in text mining: **reduce complexity for inferential clarity**

Quick Note on Terminology

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- a **term** is a **type** that the technique recognizes as a *type to be recorded*
    - e.g. stemmed words like 'motivat' or 'applica'

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- are, `wash`, `wash.`, `wash,`, `wash)` really different *words*?

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- And inversely, there might be unique cases where stopwords should actually be retained, such as studying linguistic complexity and/or readability

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- Ultimately, the choice of tokenizer depends on the needs of the specific project

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- e.g. lemmatization would return 'see' or 'saw' if it came across 'saw' (clearly this is subjective, and requires constant quality checking)

Stemming and Lemmatization

Original Word		Stemmed Word
abolish	$\mapsto$	`abolish`
abolished	$\mapsto$	`abolish`
abolishing	$\mapsto$	`abolish`
abolition	$\mapsto$	`abolit`
abortion	$\mapsto$	`abort`
abortions	$\mapsto$	`abort`
abortive	$\mapsto$	`abort`
treasure	$\mapsto$	`treasure`
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Emergency measures adopted for Beijing’s first ‘‘red alert" over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.

marked up

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- Here, **force** is a verb, not a noun
- Annotating in this way is called parts-of-speech tagging (e.g., the `RDRPOSTagger` library in R)

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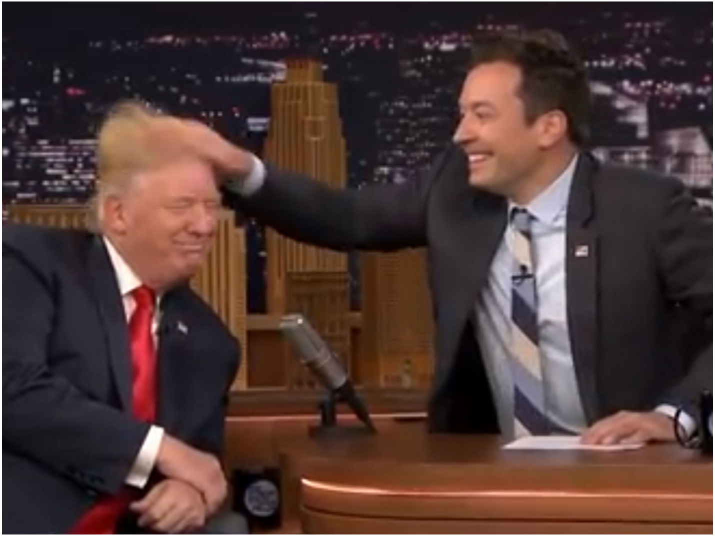

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- Thus, the vector space model represents a document vector in d-dimensional feature space

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- Stacking these vectors on top of each other gives the document term matrix (DTM) (sometimes called the document feature matrix (DFM))

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- Functionally, the tf-idf captures a decrease in the weight for commonly used words and, for more rarely used words, an increase in the weight for words use more rarely in some set of documents, D, that are not used very much in a collection of documents

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- This may provide increased clarity of the text, e.g., authors with limited vocabularies might have a low lexical diversity

Lecture Outline

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- This allows us to move on to supervised learning problems

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- The **goal**, then, is to classify by using the learned relationship between labels and features to predict the outcomes of *future* documents (e.g., $y \in \{0, 1\}$, sentiment) *not* in the training set

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- The tone, Y, based on document i and words $m = 1, \ldots, M$ in the **dictionary**,

$$Y_i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}$$

  where

  - s_m is the score of the word m
  - w_{im} is the number of occurences of the mth dictionary word in document i
  - N_i is the total number of all **dictionary** words in the document

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  - $Y \approx 0 \rightsquigarrow$ ambiguous

For example... The Big Short (newsreview.com)

Director and co-screenwriter Adam McKay (Step Brothers) bungles a great opportunity to savage the architects of the 2008 financial crisis in The Big Short, wasting an A-list ensemble cast in the process. Steve Carell, Brad Pitt, Christian Bale and Ryan Gosling play various tenuously related members of the finance industry, men who made made a killing by betting against the housing market, which at that point had superficially swelled to record highs. All of the elements are in place for a lacerating satire, but almost every aesthetic choice in the film is bad, from the U-Turn-era Oliver Stone visuals to Carell's sketch-comedy performance to the cheeky cutaways where Selena Gomez and Anthony Bourdain explain complex financial concepts. After a brutal opening half, it finally settles into a groove, and there's a queasy charge in watching a credit-drunk America walking towards that cliff's edge, but not enough to save the film.

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     - ⋆ Mechanical turkers, e.g., ask turkers: how happy is, `elevator`, `car`, `pretty`, `young`

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- Though there are a several ways, here are the three most widely used/recognized:

    1. Separating methods
    2. Manual generation $\rightsquigarrow$ careful thought about useful words
    3. Populations of people who are (*surprisingly*) willing to perform ill-defined tasks (i.e., crowd-sourcing)

        - Undergraduates: Pizza $\rightsquigarrow$ Research Output
        - Mechanical turkers, e.g., ask turkers: how happy is, `elevator`, `car`, `pretty`, `young` $\rightsquigarrow$ Output as dictionary

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  1. Exclusive/unique use: words used in a simgle document
  2. Difference in frequencies: *absolute* differences frequency of use
  3. Difference in rates/average usage: difference between proportions of same word use across documents (where high difference = good/distinct)

Separating Methods in R

- Quick demo of each in R

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- **Importantly**, just becuase we get a positive or negative score, does **NOT** mean that these are accurate measures in our text
- This points to the need for validation

Validation!

- Classification validity (requires hand coded documents):
  - *Training*: build dictionary on subset of documents with known labels
  - *Testing*: apply dictionary method to other documents with known labels
    - ★ Is the classification scheme well defined for your texts?
    - ★ Can humans accomplish the coding task with consistency (e.g., Cronbach's α)?
    - ★ Is the dictionary appropriate?
- Replicate classification exercise
  - How well does our method perform on *held out* documents?
  - Why "held out"? Over-fitting
  - (Cross)validation
  - Can also use off-the-shelf dictionaries to compare

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		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

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  - F1 score ("F-measure"): $\frac{2TP}{2TP+FP+FN}$

The Confusion Matrix

- Suppose our classification of fraudulent documents yielded the following results

	fraud (1)	*genuine* (0)
$\widehat{fraud}$ (1)	4	1
$\widehat{genuine}$ (0)	0	2

The Confusion Matrix

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- Now we can check our accuracy by simply plugging in the values
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  - F1 score ("F-measure"): $\frac{2TP}{2TP+FP+FN} \rightsquigarrow \frac{2(4)}{2(4)+1+0} = 0.89$
- In R: `table()`, e.g., `table(predicted_classes, actual_classes)`

Lecture Outline

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   - Positive Tone, Negative Tone

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- But how do we classify? many ways, but we will cover basic regression as an example

Regression models

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- J will likely be large (perhaps $J > N$)
- There many correlated variables
- Predictions will be *variable*

Ridge (Penalized) Regression

Penalty for model complexity

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$$f(\beta, \boldsymbol{X}, \boldsymbol{Y})$$

Ridge (Penalized) Regression

Penalty for model complexity

$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) \;=\; \sum_{i=1}^{N} \left(y_i - \; \beta_0 - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2$$

Ridge (Penalized) Regression

Penalty for model complexity

$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) \; = \; \sum_{i=1}^{N} \left(y_i - \; \beta_0 - \sum_{j=1}^{J} \beta_j x_{ij} \right)^2 + \underbrace{\lambda \sum_{j=1}^{J} \beta_j^2}_{\text{Penalty}}$$

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where:

- $\beta_0 \rightsquigarrow$ intercept
- $\lambda \rightsquigarrow$ penalty parameter
- Standardized $\boldsymbol{X}$ (coefficients on same scale)

Ridge Regression $\rightsquigarrow$ Optimization

$$\boldsymbol{\beta}^{\text{Ridge}} = \arg\min_{\boldsymbol{\beta}} \{f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y})\}$$

Ridge Regression ⇝ Optimization

$$
\begin{aligned}
\boldsymbol{\beta}^{\text{Ridge}} &= \text{arg min}_{\boldsymbol{\beta}} \{ f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) \} \\
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Other Penalized Objective Functions

Different Penalty for Model Complexity: LASSO

$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) \;=\; \sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{J}\underbrace{|\beta_j|}_{\text{Penalty}}$$

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And combining the two criteria $\rightsquigarrow$ Elastic-Net

$$f(\boldsymbol{\beta}, \boldsymbol{X}, \boldsymbol{Y}) \;=\; \frac{1}{2N}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{J}\beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{J}\left(\frac{1}{2}(1-\alpha)\beta_j^2 + \alpha|\beta_j|\right)$$

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Lecture Outline

- R
  - tm package (e.g., Corpus(), DocumentTermMatrix(), etc.)
  - tidytext package (e.g., get_sentiments(), etc.)
  - wordcloud package
  - (more for next class, but still for your problem set) topicmodels
  - stm package for structural topic models (may or may not get there)
- Python:
  - NLTK
  - spaCy
  - Scikit-Learn
  - For viz: Matplotlib and Seaborn