CS 1671/2071
Human Language Technologies

Session 8: Project match day, tf-idf, PPMI

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School of Computing and Information

Course logistics: quiz and homework

- Quiz on Canvas due **this Thu Feb 6**
  - What readings it covers is specified in the description on Canvas
- Homework 2 is due **Feb 20**
  - Build a text classification system to predict deception in a game (Diplomacy)
- Next project milestone: project proposal due Feb 28
  - Stay tuned for more details on that
  - If your data or task is a bit unspecified, book a meeting with Michael next week or later to discuss data

Overview: Project match day, tf-idf, PPMI

- Project match process
- Bag-of-word weighting: tf-idf and PPMI
- Coding activity

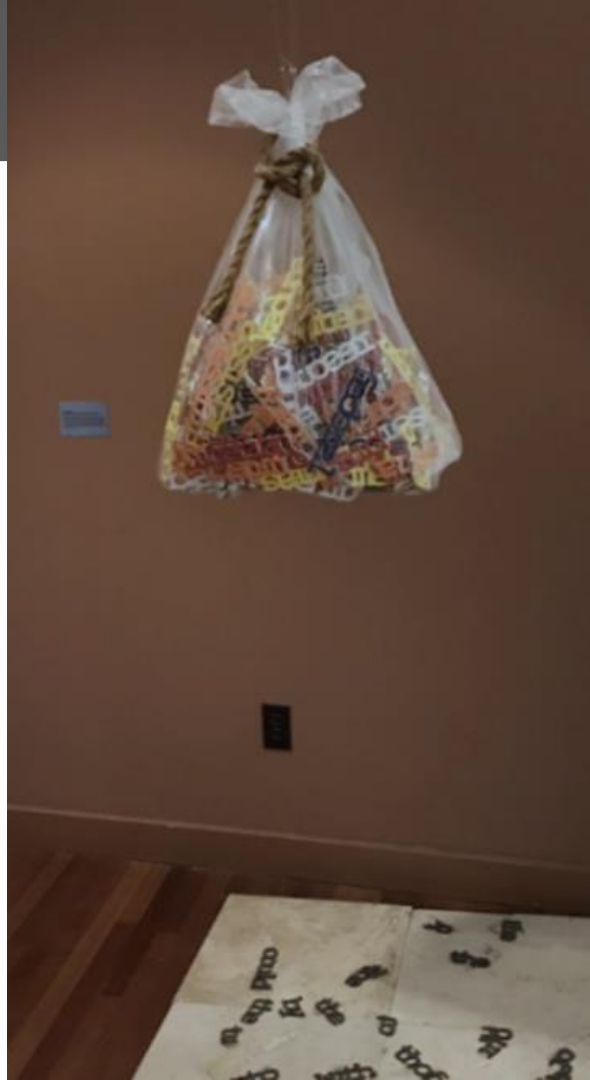
Project match

- Go to the spot in the room that corresponds to the project you are most interested in working on
  - We will likely do this for several rounds
- Goal: groups of 2-4 on projects
  - Groups of 3 or 4 students are ideal

Review activity

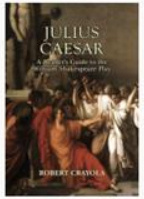
For term-document and term-term matrices:

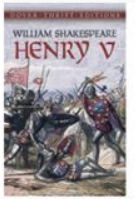
1. What do the dimensions (numbers of rows and columns) correspond to?
2. What does the value in each cell mean?



Term-document matrix

- Each cell is the count of term t in a document d ($tf_{t,d}$).
- Each document is a count vector in $\mathbb{N}^V$, a column below.





	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

Slide credit: David Mortensen

Sample Contexts of ±7 Words

sugar, a sliced lemon, a tablespoonful of **apricot** preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first **pineapple** and another fruit whose taste she likened
well suited to programming on the digital **computer**. In finding the optimal R-stage policy from
for the purpose of gathering data and **information** necessary for the study authorized in the

	aardvark	digital	data	pinch	result	sugar ...
⋮						
apricot	0	0	0	1	0	1
pineapple	0	0	0	1	0	1
computer	0	2	1	0	1	0
information	0	1	6	0	4	0
⋮						

Slide credit: David Mortensen

Tf-idf weighting

Raw frequency is a bad representation

- The co-occurrence matrices we have seen represent each cell by word frequencies
  - Whether in term-document or term-term matrices
- Frequency is clearly useful; if *sugar* appears a lot near *apricot*, that's useful information.
- But overly frequent words like *the*, *it*, or *they* are not very informative about the context
  - 2 documents that use a lot of *the* are not necessarily similar
- It's a paradox! How can we balance these two conflicting constraints?

Slide adapted from Jurafsky & Martin

Weighting words in term-document and term-term matrices

- **tf-idf** (term frequency-inverse document frequency)
  - For representing documents with their most unique words (for text classification, information retrieval)
  - Term-document matrix
- **PPMI** (positive pointwise mutual information)
  - For finding associations between words (which appear more often together than chance?)
  - Term-term matrix

Slide adapted from Jurafsky & Martin

Term frequency (tf)

$tf_{t,d} = count(t,d)$

Instead of using raw count, we squash a bit:

$tf_{t,d} = \log_{10}(count(t,d)+1)$

Slide adapted from Jurafsky & Martin

Document frequency (df)

df_t is the number of documents term *t* occurs in.

(note this is not collection frequency, which is the total count across all documents)

"Romeo" is very distinctive for one Shakespeare play:

	Collection Frequency	Document Frequency
Romeo	113	1
action	113	31

Slide adapted from Jurafsky & Martin

Inverse document frequency (idf)

$$\text{idf}_t = \log_{10}\left(\frac{N}{\text{df}_t}\right)$$

- N is the total number of documents in the collection
- Documents can be whatever you want! (Full documents, paragraphs, etc)

Word	df	idf
Romeo	1	1.57
salad	2	1.27
Falstaff	4	0.967
forest	12	0.489
battle	21	0.246
wit	34	0.037
fool	36	0.012
good	37	0
sweet	37	0

Slide adapted from Jurafsky & Martin

tf-idf Controls for Frequent but Uninformative Words

Some words are very common in a given document because they are common across all documents (e.g., *the*). They are not discriminative. `tf-idf` (product of term frequency and inverse document frequency) addresses this:

$$\text{tf}_{t,d} = \log_{10}(\text{count}(t,d) + 1)$$

$$\text{idf}_f = \log_{10} \frac{N}{\text{df}_t}$$

$$\text{tf-idf}(t,d) = \text{tf}_{t,d} \cdot \text{idf}_t$$

Slide adapted from Jurafsky & Martin, David Mortensen

Final tf-idf weighted values

Raw counts

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

tf-idf:

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

Positive pointwise mutual information (PPMI)

The Problem with Raw Counts

The **to** in **to walk** doesn't tell us as much about **walk** as the **slowly** in **walk slowly**.

Slide credit: David Mortensen

Problem with Raw Counts

- Raw word frequency is not a great measure of association between words.
- It is very skewed: “the” and “of” are very frequent, but maybe not the most discriminative.
- We would rather have a measure that asks whether a context word is **particularly informative** about the target word.

Positive Pointwise Mutual Information (PPMI)

Slide credit: David Mortensen

Pointwise mutual information

- Do events *x* and *y* co-occur more than if they were independent?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

- PMI between 2 words [Church+Hanks 1989]
  - Do words *x* and *y* co-occur more than if they were independent?

$$PMI(word_1, word_2) = \log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}$$

Slide adapted from Jurafsky & Martin

- In computational linguistics, PMI has been used for finding collocations and associations between words.

word 1	*word 2*	*count word 1*	*count word 2*	count of co-occurrences	PMI
puerto	rico	1938	1311	1159	10.0349081703
hong	kong	2438	2694	2205	9.72831972408
los	angeles	3501	2808	2791	9.56067615065
carbon	dioxide	4265	1353	1032	9.09852946116
prize	laureate	5131	1676	1210	8.85870710982
san	francisco	5237	2477	1779	8.83305176711
nobel	prize	4098	5131	2498	8.68948811416
ice	hockey	5607	3002	1933	8.6555759741
star	trek	8264	1594	1489	8.63974676575
car	driver	5578	2749	1384	8.41470768304
it	the	283891	3293296	3347	-1.72037278119
are	of	234458	1761436	1019	-2.09254205335
this	the	199882	3293296	1211	-2.38612756961
is	of	565679	1761436	1562	-2.54614706831
and	of	1375396	1761436	2949	-2.79911817902
a	and	984442	1375396	1457	-2.92239510038
in	and	1187652	1375396	1537	-3.05660070757
to	and	1025659	1375396	1286	-3.08825363041
to	in	1025659	1187652	1066	-3.12911348956
of	and	1761436	1375396	1190	-3.70663100173

Slide credit: David Mortensen

Positive Pointwise Mutual Information

- PMI ranges from $-\infty$ to $+\infty$
- But the negative values are problematic:
  - Things are co-occurring less than we expect by chance
  - Unreliable without enormous corpora
    - Imagine w_1 and w_2 whose probability is each 10^{-6}.
    - Hard to be sure $p(w_1, w_2)$ is significantly different than 10^{-12}.
  - Furthermore it's not clear people are good at "unrelatedness".
- So we just replace negative PMI values by 0.

$$\text{PPMI}(w, c) = max\left(\log_2 \frac{p(w, c)}{p(w)p(c)}, 0\right)$$

Slide credit: David Mortensen

Computing PPMI on a Term-Context Matrix

- We have matrix F with V rows (words) and C columns (contexts) (in general $C = V$)
- Each cell contains the co-occurrence count of words w and c, f_{wc}
- Let S be the total sum of all word-context word counts

					C	
	0	0	1	0	1	2
	0	0	1	0	1	
	2	1	0	1	0	
V	1	6	0	4	0	
	3					19

$$PMI(w,c) = \frac{p(w,c)}{p(w)p(c)}$$

$$p(w,c) = \frac{f_{wc}}{S}$$

$$p(w) = \frac{\sum_{c \in C} f_w}{S}$$

$$p(c) = \frac{\sum_{w \in W} f_c}{S}$$

$$PPMI(w,c) = \max(PMI(w,c), 0)$$

Slide adapted from David Mortensen

Worked Example: Computing PPMI from Term-Context Matrix (Part I)

	computer	data	pinch	result	sugar	
apricot	0	0	1	0	1	2
pineapple	0	0	1	0	1	2
digital	2	1	0	1	0	4
information	1	6	0	4	0	11
	3	7	2	5	2	19

$$p(w = information, c = data) = \frac{6}{19} = 0.32$$

$$p(w = information) = \frac{11}{19} = 0.58 \quad p(c = data) = \frac{7}{19} = 0.37$$

$$pmi(information, data) = \log_2 \frac{0.32}{0.37 \cdot 0.58} \approx 0.58$$

Slide credit: David Mortensen

Worked Example: Computing PPMI from Term-Context Matrix (Part II)

$PPMI(w, c)$

	computer	data	pinch	result	sugar
apricot	-	-	2.25	-	2.25
pineapple	-	-	2.25	-	2.25
digital	1.66	0.00	-	0.00	-
information	0.00	0.32	-	0.47	-

Slide credit: David Mortensen

Issues with PPMI

- PMI is biased toward infrequent events.
- Very rare words have very high PMI values.
- Two solutions:
  - Give rare words slightly higher probabilities
  - Use add-one smoothing (which has a similar effect)

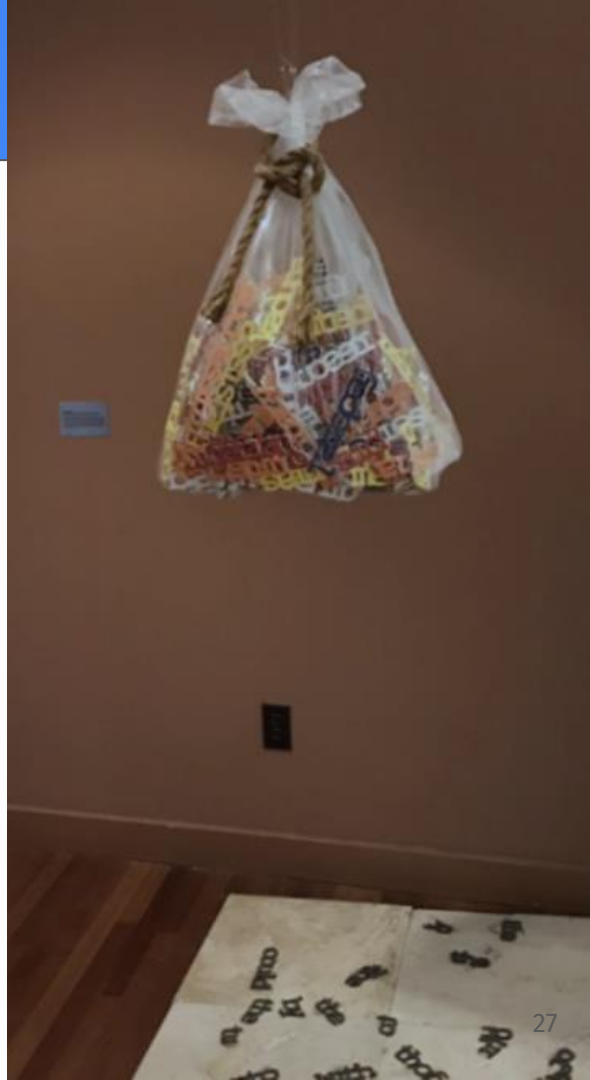
Slide credit: David Mortensen

View tf-idf document representations on JupyterHub

- Click on this nbgitpuller link
  - Or find the link on the course website
- Open **session8_clickbait_tfidf.ipynb**

Conclusion

- Downweighting words that appear frequently in term-document and term-term matrices
  - **tf-idf** for document representations
    - Downweight terms that appear across many documents
  - **PPMI** for word associations
    - Downweight words that appear with many other words



Questions?