BC COMS 2710: Computational Text Analysis

Lecture 8 – Dictionary Methods

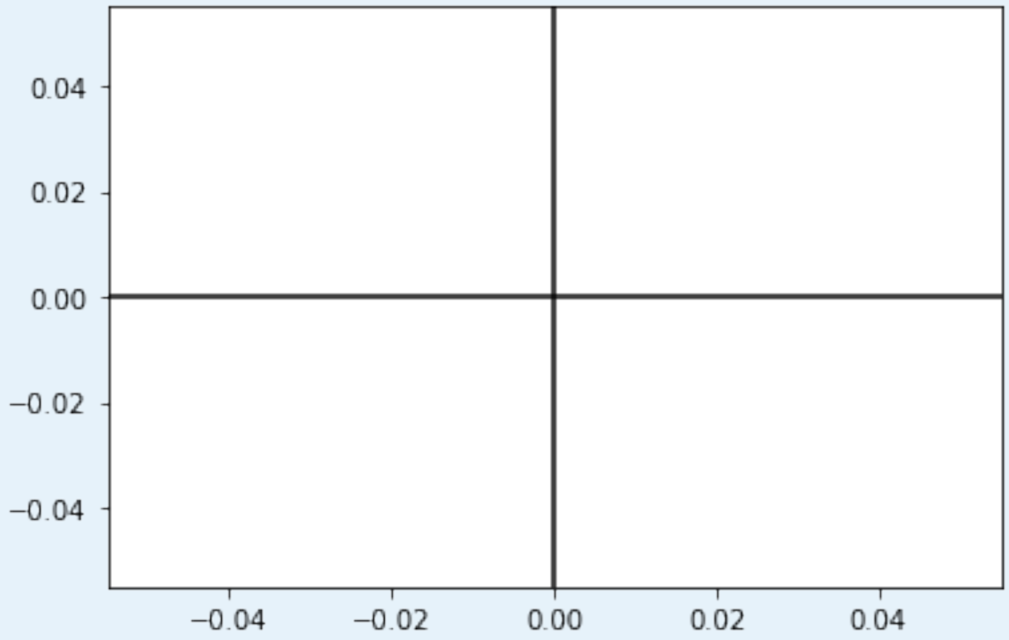
Outline

- Cosine similarity explained
- Motivating Dictionaries:
  - Graph from yesterday, but what about categories of words

Cosine Similarity

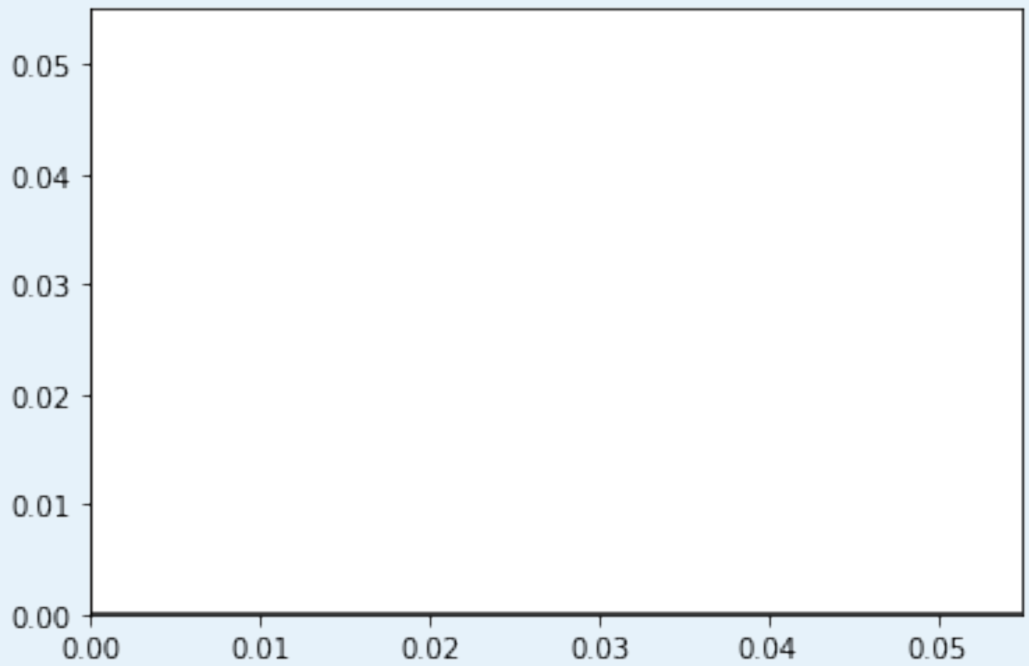
TF-IDF Matrix

- All values are positive
  - Which Quadrant on the graph will the vectors line on?



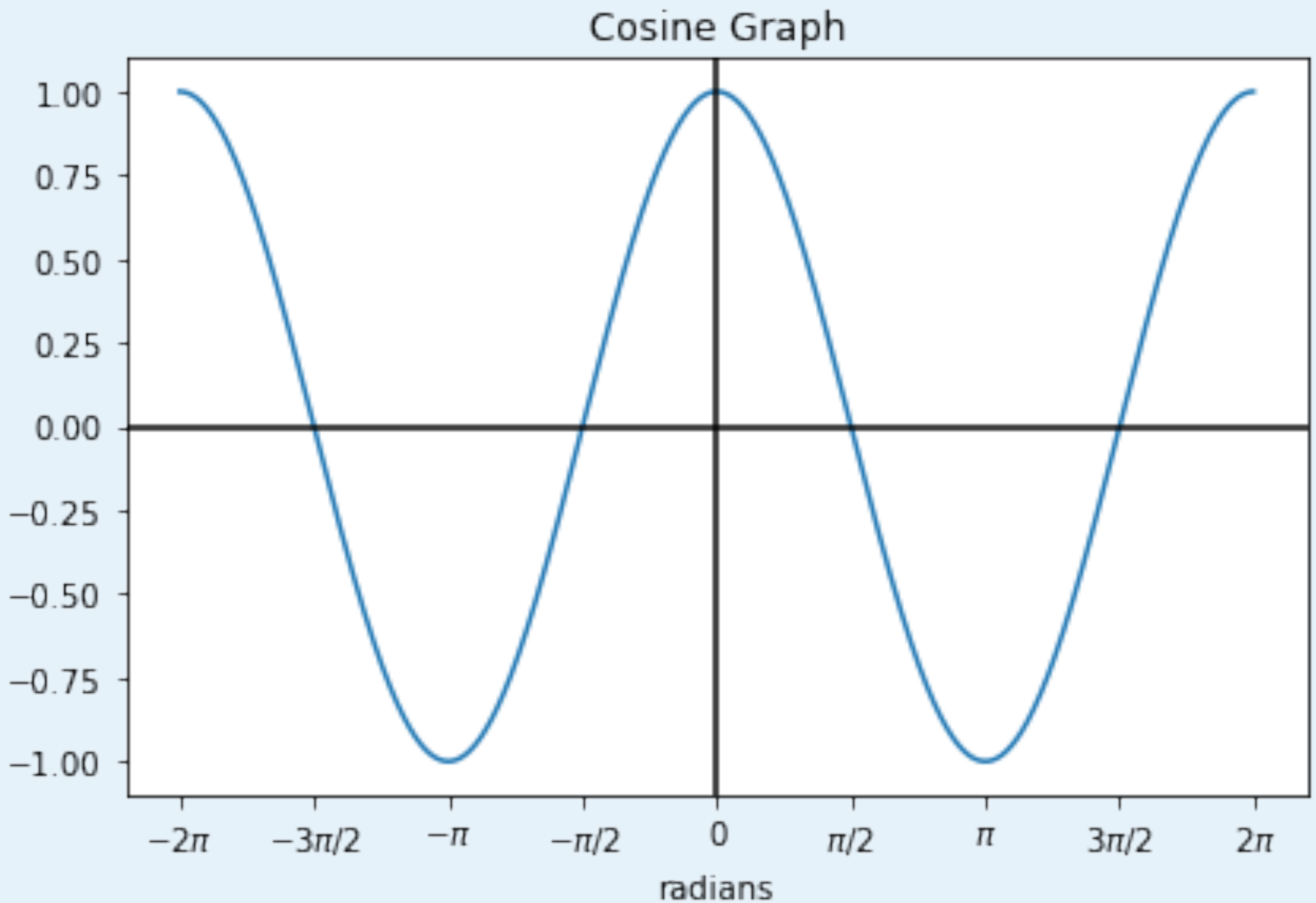
TF-IDF Matrix

- What is the maximum angle between 2 vectors?

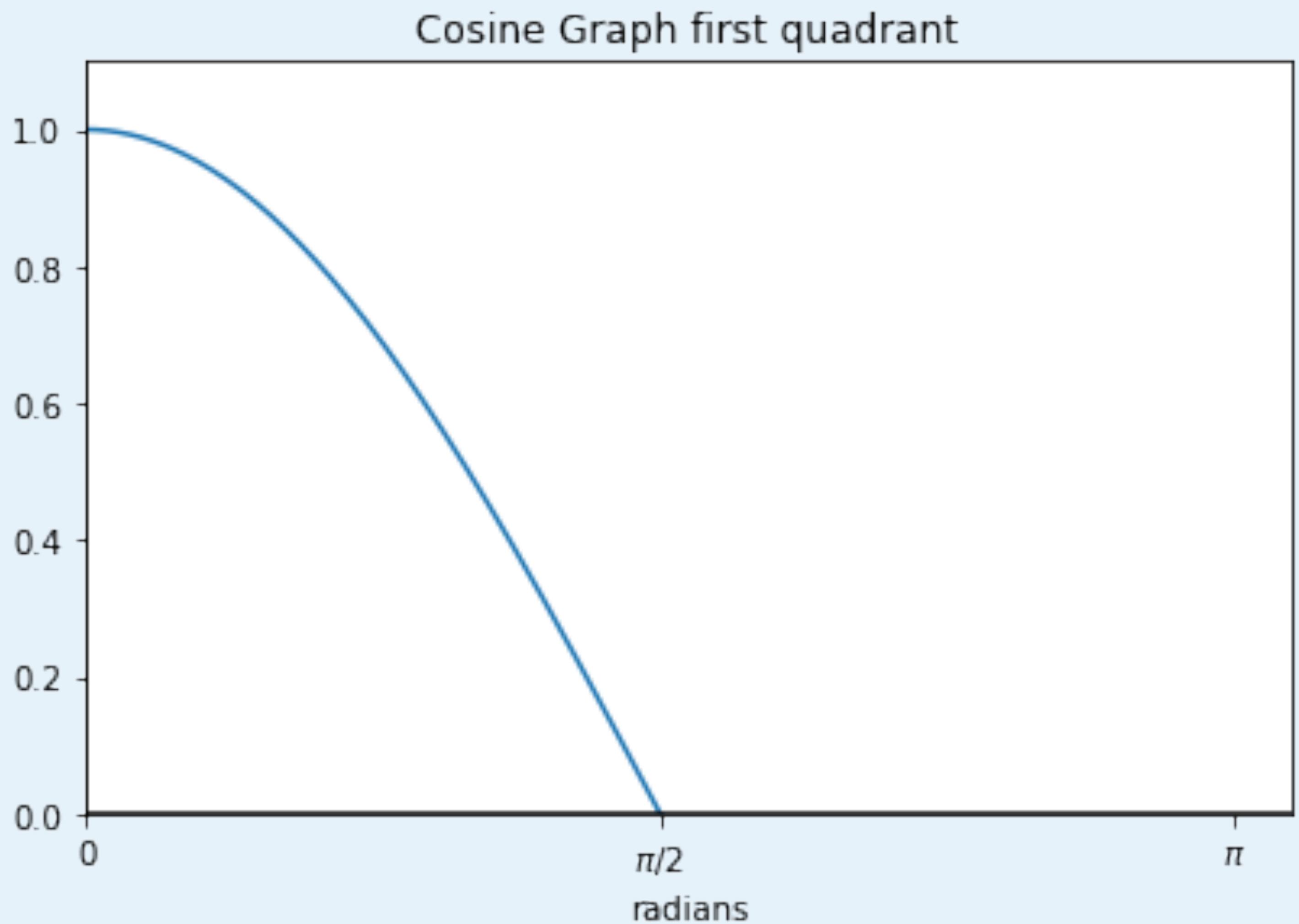


- 90 degrees or $\frac{\pi}{2}$ in radians

Cosine Graph

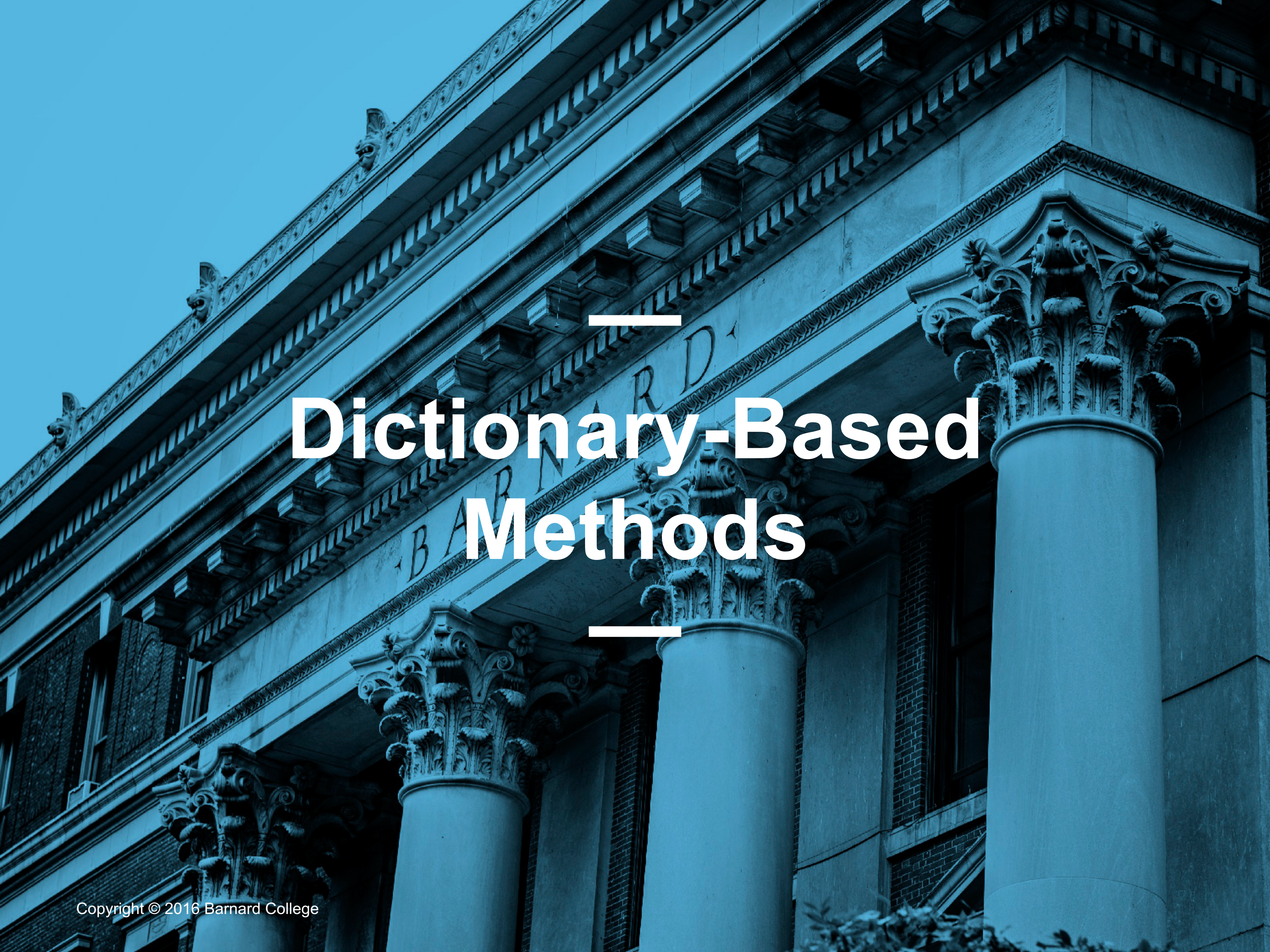


Zoomed in Cosine Graph



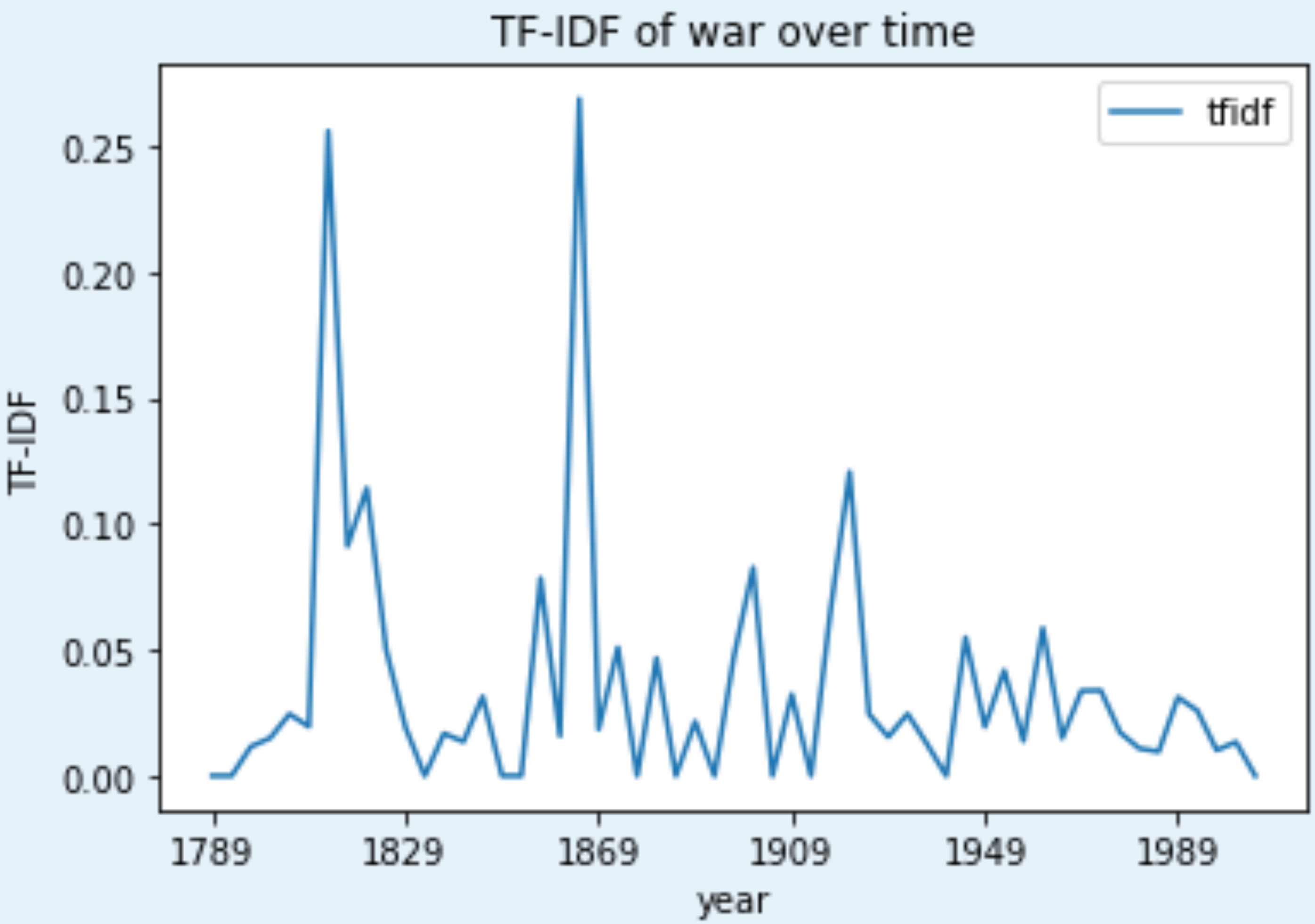
Computing cosine from vectors

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \text{ x } \|B\|} = \frac{\sum_{i=1}^{n} A_i \text{ x } B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \text{ x } \sqrt{\sum_{i=1}^{n} B_i^2}}$$



Dictionary-Based Methods

“War” in Presidential Addresses



Dictionary based methods

- Goal: Connect counts c_i to attributes v_i

- Dictionary-based methods:
  - Specify $\hat{v}_i = f(c_i)$ for some known function $f(\cdot)$
  - Define $f(\cdot)$ based on a prespecified dictionary of terms capturing particular categories of text
  - Common method in the social science literature using text
    - Appropriate in cases where prior information is strong

Text as Data, Gentzkow, Kelly, and Taddy
Journal of Economic Literature 2019

Sentiment Lexicons

Affective Meaning

- Affective: relating to moods, feelings, and attitudes
- Drawing on literatures in
  - affective computing (Picard 95)
  - linguistic subjectivity (Wiebe and colleagues)
  - social psychology (Pennebaker and colleagues)
- Can we identify:
  - sentiment
  - emotion
  - personality
  - mood
  - attitudes

Slide take from Dan Jurafsky

Affective Meaning

- Affective: relating to moods, feelings, and attitudes

- Drawing on literatures in
  - affective computing – Rosalind Picard
    - ***if we want computers to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even to have and express emotions.***

Affective Meaning

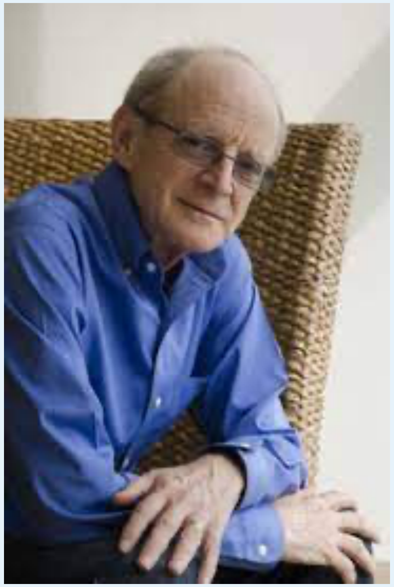
- Affective: relating to moods, feelings, and attitudes

- Drawing on literatures in
  - Linguistic subjectivity – Janyce Wiebe
    - ***Subjectivity in natural language refers to aspects of language used to express opinions, evaluations, and speculatins.***

Affective Meaning

- Affective: relating to moods, feelings, and attitudes

- Drawing on literatures in
  - Social Psychology – James Pennebaker
  - Developed LIWIC:
    - **a program that simply looked for and counted words in psychology-relevant categories across multiple text files.**



Affective Meaning

- Can we identify:
  - sentiment
  - emotion
  - personality
  - mood
  - attitudes

Slide take from Dan Jurafsky

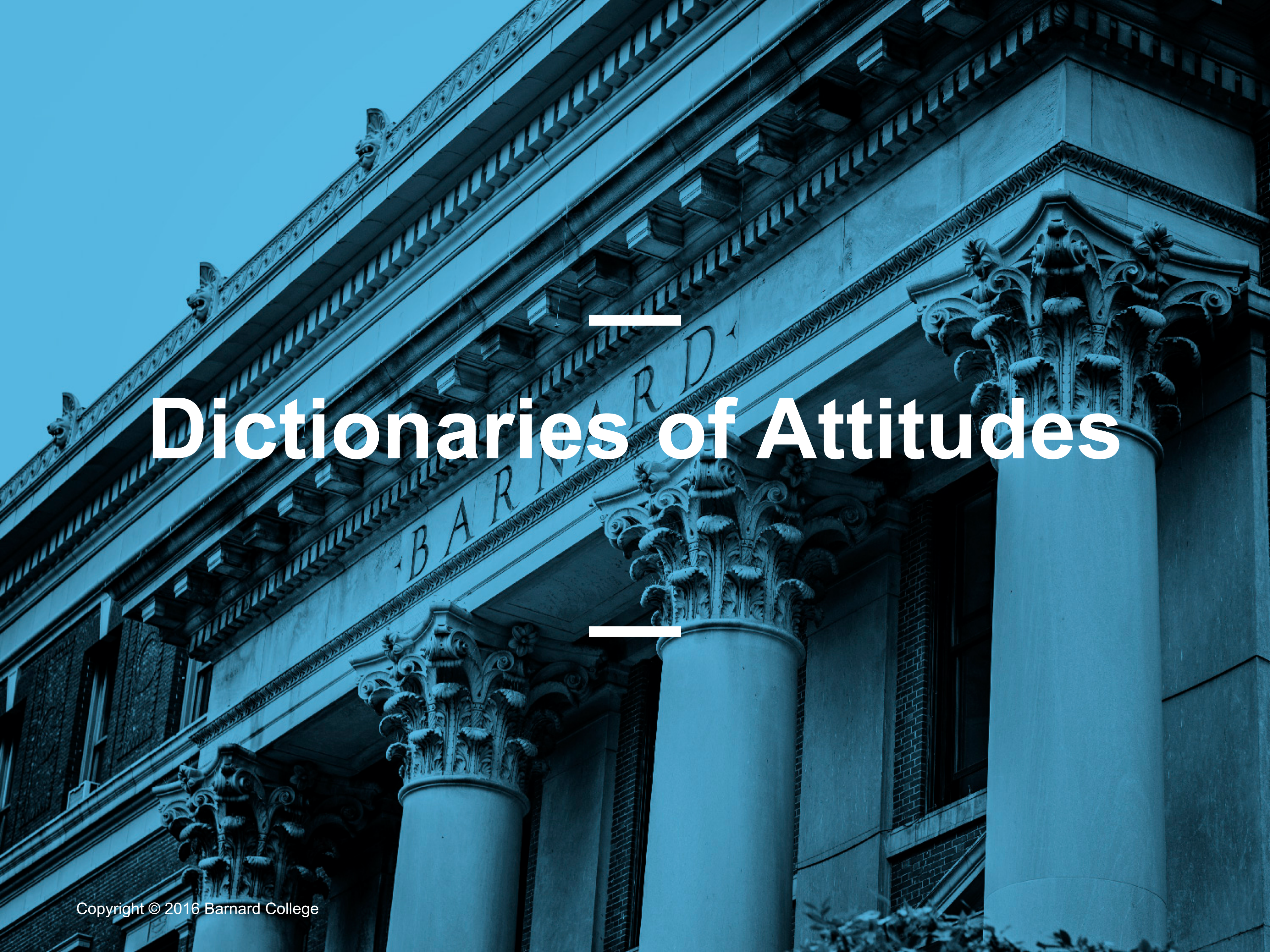
Why Compute Affective Meaning?

- Detection and Categorization
  - sentiment towards politicians, products, countries, ideas
  - frustration of callers to a help line
  - stress in drivers or pilots
  - depression and other medical conditions
  - confusion in students talking to e-tutors
  - emotions in novels (e.g., for studying groups that are feared over time)

Slide take from Dan Jurafsky

Connotations in the Vocabulary

- Words have connotations
- Goal of Dictionaries:
  - Build lexical recourses the represent word connotations
- Dictionary-based methods:
  - Deplore connotation-dictionaries to detect and categorize text



Dictionaries of Attitudes

Scherer's typology of affective states (1/2)

- **Emotion:** relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance

  angry, sad, joyful, fearful, ashamed, proud, desperate
- **Mood**: diffuse affect state …change in subjective feeling, of low intensity but relatively long duration, often without apparent cause

  cheerful, gloomy, irritable, listless, depressed, buoyant
- **Interpersonal stance**: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange

  distant, cold, warm, supportive, contemptuous

Scherer's typology of affective states (2/2)

- **Attitudes**: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons

  liking, loving, hating, valuing, desiring

- **Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person

  nervous, anxious, reckless, morose, hostile, envious, jealous

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The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
  - Positive (1915 words) and Negative (2291 words)
  - *Strong vs Weak, Active vs Passive, Overstated versus Understated*
  - *Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation,*
- Free for Research Use

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MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/
- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

- Home page: http://www.liwc.net/
- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- $30 or $90 fee

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LIWC Categories

LIWC			LIWC Cont.		
Category	**Example**	**T-statistics**	**Category**	**Example**	**T-statistics**
Linguistics Processes			Negative emotion	hurt, ugly, nasty	6.49***
Words > 6 letters		-3.41**	Anxiety	fearful, nervous	2.37
Dictionary words		9.60****	Anger	hate, kill, annoy	5.30***
Total function words		8.98****	Sadness	cry, grief, sad	3.54***
Personal pron.	I, them, her	7.07****	Cognitive process	cause, ought	6.09***
1st pers singular	I, me, mine	9.83****	Insight	think, know	0.11
1st pers plural	we, us, our	-2.38	Causation	effect, hence	0.93
2nd person	you, your, thou	-0.91	Discrepancy	should, would	5.53***
3rd pers singular	she, her, him	3.63**	Tentative	maybe, perhaps	5.95***
3rd pers plural	their, they'd	2.47	Certainty	always, never	4.02***
Impersonal pron.	it, it's, those	7.07****	Inhibition	block, constrain	0.32
Articles	a, an, the	4.13***	Inclusive	with, include	4.74 ***
Common verbs	walk, went, see	6.27***	Exclusive	but, without	7.53 ****
Auxiliary verbs	am, will, have	5.76***	Perceptual process		1.93
Past tense	went, ran, had	8.70****	See	view, saw, seen	1.68
Present tense	is, does, hear	4.00***	Hear	listen, hearing	-0.88
Future tense	will, gonna	5.84***	Feel	feels, touch	1.94
Adverbs	very, really	7.92****	Biological process		4.22***
Prepositions	to, with, above	7.62****	Body	cheek, spit	5.02***
Conjunctions	and, whereas	4.59***	Health	clinic, flu, pill	1.51
Negations	no, not, never	1.71	Sexual	horny, incest	-0.61
Quantifiers	few, many, much	2.98*	Ingestion	dish, eat, pizza	4.37***
Numbers	second, thousand	-3.68**	Relativity	area, bend, exit	9.52 ****
Swear words	damn, piss, fuck	5.53***	Motion	arrive, car	3.07*
Spoken Categories			Space	down, in, thin	8.87****
Assent	agree, OK, yes	7.05****	Time	end, until	5.87***
Nonfluency	er, hm, umm	1.41	**Personal Concerns**		
Filters	blah, imean		Work	job, majors	0.05
Psychological			Leisure	chat, movie	2.97*
Social process	mate, talk, child	0.10	Achievement	earn, win	-1.22
Family	son, mom, aunt	2.24	Home	family, kitchen	3.37**
Friends	buddy, neighbor	2.10	Money	audit, cash	0.23
Humans	adult, baby, boy	0.89	Religion	church, altar	-0.77
Affective process	happy, cry	3.55**	Death	bury, coffin	0.49
Positive emotion	love, nice, sweet	0.08			

Table 1. Two-sample T-test statistics of linguistic variables between geo-locator and non-locators. Significant differences of each LIWC attribute are indicated in the third column. (*p <0.01, **p<0.001, ***p<0.0001, ****p<1e-10)

Plenty of more examples

- See Chris Pott's Tutorial on Sentiment Lexicons
  - http://sentiment.christopherpotts.net/lexicons.html
  - Compares different dictionaries of sentiment

Discovering Connotations

Point-wise Mutual Information

- How much more do events ***x*** and ***y*** co-occur than if they were independent?

$$PMI(X,Y) \;=\; \log_2 \frac{P(X,Y)}{P(X)P(Y)}$$

Point-wise Mutual Information

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

- PMI between words and categories:

$$PMI\left(word_i, category_j\right) = \log_2 \frac{P(word_i, category_j)}{P(word_i)P(category_j)}$$

Discovering Gender Bias via PMI

First Women, Second Sex: Gender Bias in Wikipedia

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We approach the analysis of gender bias by defining a methodology for comparing the characterizations of men and women in biographies. In particular we refer to three dimensions of biographies: meta-data, language usage, and structure of the network built from links between articles. Our results show that, indeed, there are differences in characterization and structure.

PMI to measure gender bias

Associativity. To explore which words are more strongly associated with the different genders, we measure *Pointwise Mutual Information* (Church and Hanks, 1990) over the set of vocabulary in both genders. PMI is defined as:

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

where c is a class (*men* or *women*), and w is a word. The probabilities can be estimated from the proportions of biographies about men and women, and the corresponding proportions of words and bigrams. Since PMI overweights words with very small frequencies, we consider only words that appear in at least 1% of men or women biographies.

https://arxiv.org/abs/1502.02341