Text as Data

Justin Grimmer

Professor
Department of Political Science
Stanford University

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Text and Social Science

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    - Statistical methods/algorithms, computationally intensive

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- Foreign news sources, treaties, sermons, fatwas, ...

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Haystack metaphor:

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What automated text methods don't do:

- Develop a comprehensive statistical model of language
- Replace the need to read
- Develop a single tool + evaluation for all tasks

Texts are Deceptively Complex

```
We've got some difficult days ahead.  But it doesn't matter
with me now.  Because I've been to the mountaintop.  And I
don't mind.  Like anybody, I would like to live a long
life.  Longevity has its place.  But I'm not concerned
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Texts$\rightsquigarrow$ high dimensional, not self contained

Texts are Surprisingly Simple

(Lamar Alexander (R-TN) Feb 10, 2005)

Word	No. Times Used in Press Release
department	12
grant	9
program	7
firefight	7
secure	5
homeland	4
fund	3
award	2
safety	2
service	2
AFGP	2
support	2
equip	2
applaud	2
assist	2

Texts are Surprisingly Simple (?)

`US Senators Bill Frist (R-TN) and Lamar Alexander (R-TN) today applauded the U S Department of Homeland Security for awarding a $8,190 grant to the Tracy City Volunteer Fire Department under the 2004 Assistance to Firefighters Grant Program's (AFGP) Fire Prevention and Safety Program...`

Not just for "big data"

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Manually develop categorization scheme for partitioning small (100) set of documents

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Automated methods can help with even small problems

Goal for this morning: Document-Term Matrices

$$
\boldsymbol{X} = \begin{pmatrix} 1 & 0 & 0 & \ldots & 3 \\ 0 & 2 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 5 \end{pmatrix}
$$

$\boldsymbol{X} = N \times J$ matrix

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$\boldsymbol{X} = N \times J$ matrix

- N = Number of documents
- J = Number of features

Learning From Text

A plan for using texts

1) Acquiring text data
2) Regular expression search in text
3) Creating document-term matrices (term-document matrices)

Finding Text Data

Many places to find text

Finding Text Data

Many places to find text
Goal: plain text (.txt) file. (UTF-8, ASCII)

Finding Text Data

Many places to find text
Goal: plain text (.txt) file. (UTF-8, ASCII)
(May also want to create an `XML` or `JSON` file)

Plain Text

```
September 19, 2010 Sunday 10:46 AM EST
REP. FOXX VISITS LOCAL SCHOOLS, TALKS WITH STUDENTS ON
CONSTITUTION DAY
LENGTH: 320 words
CLEMMONS, N.C., Sept.  17 -- Rep.  Virginia Foxx, R-N.C.
(5th CD), issued the following press release:
Congresswoman Virginia Foxx is celebrating Constitution Day
today by visiting several schools in her district to talk
with students about the Constitution and the individuals
who helped create our charter document.  She will visit
Davie County High School, Forbush High School in Yadkin
County and Piney Creek School in Alleghany County.
```

XML

```
<DOC>
<DOCNO>101-levin-mi-1-19901027< /DOCNO>
<TEXT>
Mr.  LEVIN. Mr.  President, today the House passed and sent
to the President the Great Lakes Critical Programs Act.
...  Mr.  President, I commend and thank Ms.  Bean for her
exceptional efforts on the Great Lakes Critical Programs
Act
< /TEXT>
< /DOC>
```

JSON


```
{"id":"tag:search.twitter.com,2005:287886850381713411",
"objectType":"activity"...displayName":"Linda Bowersox",
"postedTime":"2010-03-10T05:16:14.000Z"...
"body":"@JeffFlake thank you for standing firm and voting
NO on the #FiscalCliff (via #PJNET)","object"...
```

Regular Expressions (from Jurafsky Slides)

Systematic Searches

A language for searching texts:

- Count mentions of a person
- Calculate amount of money discussed
- Prepare texts for analysis: Identify where to "split" a document
- ...

Provide a quick introduction here, with some examples

Regular Expressions, Some Basics (from Jurafsky Slides)

- Disjunctions

RE	**Match**	**Example Patterns Matched**
`[mM]oney`	Money or money	"Money"
`[abc]`	'a', 'b', *or* 'c'	"Investing in Iran"
		"is dangerous business"
`[1234567890]`	any digit	"sitting on $7.5 billion dollars"
		"2005 and 2006, more than "
		"$150 million dollars"
`[\.]`	A period	" 'Run!', he screamed."

Regular Expressions, Some Basics (from Jurafsky Slides)

- Ranges

RE	Match	Example Patterns Matched
[A-Z]	an upper case letter	"Rep. Anthony Weiner (D-Brooklyn & Queens)"
[a-z]	a lower case letter	"ACORN's"
[0-9]	a single digit	"(9th CD) "

Regular Expressions, Some Basics (from Jurafsky Slides)

- Negations

RE	Match	Example Patterns Matched
`[^A-Z]`	not an upper case letter	"ACORN<u>'s</u>"
`[^Ss]`	neither 'S' nor 's'	"<u>ACORN'</u>s"
`[^\.]`	not a period	" '<u>Run!', he screamed</u>."

Regular Expressions, Some Basics (from Jurafsky Slides)

- Optional Characters: `?`, `*`, `+`

RE	**Match**	**Example Patterns Matched**
`colou?r`	Words with `u` 0 or 1 times	"color" or "colour "
`oo*h!`	Words with `o` 0 or more times	"oh!" or "ooh!" or "oooh!"
`o+h!`	Words with `o` 1 or more times	"oh!" or "ooh!" or "oooooh!" or

Regular Expressions, Some Basics (from Jurafsky Slides)

- Wild Cards .

RE	Match	Example Patterns Matched
`beg.n`	Any word with "beg" then "n"	"begin" or
		"began" or
		"begun" or
		"beggn" (Poor grammar!)

Regular Expressions, Some Basics (from Jurafsky Slides)

- Start of the line anchor ^, end of the line anchor $

RE	Match	Example Patterns Match
^[A-Z]	Upper case start of line	"Palo Alto"
		"the town of Palo Alto"
^[^A-Z]	Not upper case start of line	"the town of Palo Alto"
		"Palo Alto"
^.	Start of line	"Palo Alto"
		"the town of Palo Alto"
.$	Identify character that ends a line	"Wait!"
		"This is the end."

Regular Expressions, Some Basics (from Jurafsky Slides)

- "Or" | statements, Useful short hand

RE	**Match**	**Example Patterns Matched**
yours|mine	Matches "yours" or "mine"	"it's either yours or mine"
\d	Any digit	"1-Mississippi"
\D	Any non-digit	"1-Mississippi"
\s	Any whitespace character	"1, 2"
\S	Any non-whitespace character	"1, 2"
\w	Any alpha-numeric	"1-Mississippi "
\W	Any non-alpha numeric	"1-Mississippi"

Regular Expressions, Some Basics (from Jurafsky Slides)

Quick Example to Illuminate Differences:
A “simple” example: identify all instances of `the`.

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- `the`

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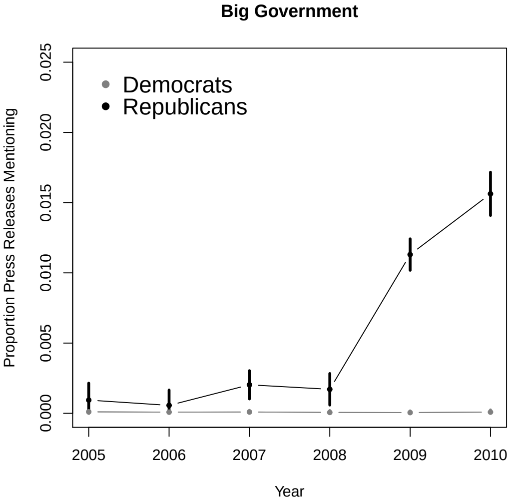

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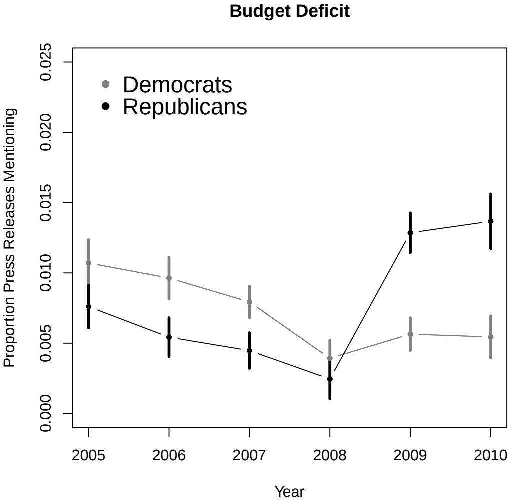

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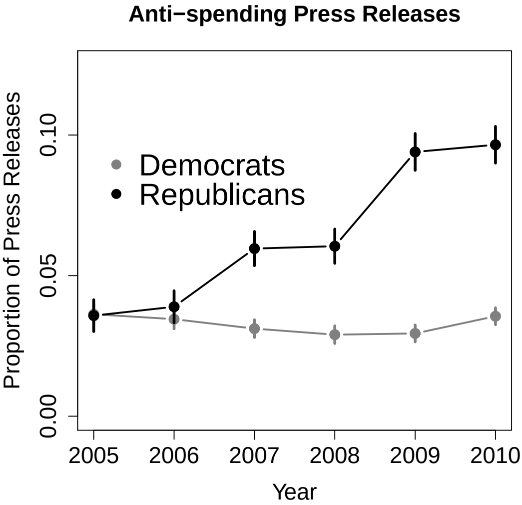

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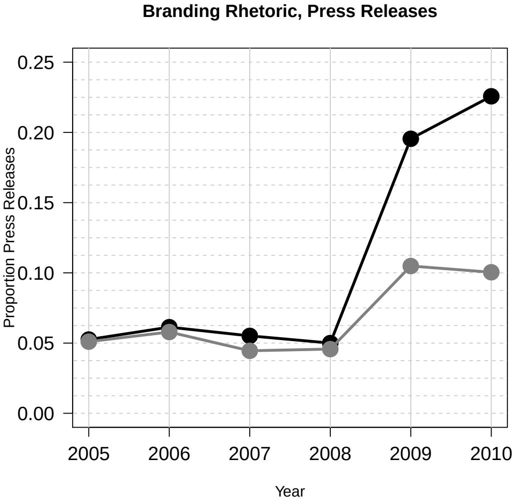

Regular Expressions on Steroids: Cheating Detection Software

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Document Term Matrices

Regular expressions and search are useful

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We want to use statistics/algorithms to characterize text

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We want to use statistics/algorithms to characterize text

We'll put it in a document-term matrix

Document Term Matrices

Preprocessing$\rightsquigarrow$Simplify text, make it useful

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Lower dimensionality

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Remember: characterize the Hay stack

- If you want to analyze a straw of hay, these methods are unlikely to work
- But even if you want to closely read texts, characterizing hay stack can be useful

Preprocessing for Quantitative Text Analysis

One (of many) recipe for preprocessing: retain useful information

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Output: Count vector, each element counts occurrence of stems

Provide tools to preprocess via this recipe

Preprocessing Texts

We're going to use the `Natural Language Toolkit (nltk)` to work with texts

- Built in functionality
- Ensures we can customize our feature spaces

Text Loaded into Python

Gettysburg Address

```
from BeautifulSoup import BeautifulSoup
from urllib import urlopen
import re, os
url =
urlopen('http://avalon.law.yale.edu/19th_century/gettyb.asp').read()
soup = BeautifulSoup(url)
text = soup.p.contents[0]
```

Preprocessing Texts

Removing capitalization:

- Python : `string.lower()`
- R : `tolower('string')`

Removing punctuation

- Python: `re.sub('\W', ' ', string)`
- R : `gsub('\\W', ' ', string)`

Preprocessing Texts

```
text_1 = text.lower()
text_2 = re.sub('\W', ' ', text_1)
```

The Bag of Words Assumption

Assumption: Discard Word Order

`Now we are engaged in a great civil war, testing whether that nation, or any nation`

The Bag of Words Assumption

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Unigrams

Unigram	Count
a	1
any	1
are	1
civil	1
engaged	1
great	1
in	1
nation	2
now	1
or	1
testing	1
that	1
war	1
we	1
whether	1

The Bag of Words Assumption

Assumption: Discard Word Order

Bigrams

Bigram	Count
now we	1
we are	1
are engaged	1
engaged in	1
in a	1
a great	1
great civil	1
civil war	1
war testing	1
testing whether	1
whether that	1
that nation	1
nation or	1
or any	1
any nation	1

The Bag of Words Assumption

Assumption: Discard Word Order

Trigrams

Trigram	Count
now we are	1
we are engaged	1
are engaged in	1
engaged in a	1
in a great	1
a great civil	1
great civil war	1
civil war testing	1
war testing whether	1
whether that nation	1
that nation or	1
nation or any	1
or any nation	1

How Could This Possibly Work?

Speech is:

- Ironic

  `A real strength of the Bears is their place kicking and I'm super glad they didn't give Robbie Gould a reasonable raise`

- Subtle Negation (Source: Janyce Wiebe) :

  `They have not succeeded, and will never succeed, in breaking the will of this valiant people`

- Order Dependent (Source: Arthur Spirling):

  `Peace, no more war`

  `War, no more peace`

How Could This Possibly Work?

Three answers

1) It might not: Validation is critical (task specific)
2) Central Tendency in Text: Words often imply what a text is about `war, civil, union` or tone `consecrate, dead, died, lives`.

   Likely to be used repeatedly: create a theme for an article
3) Human supervision: Inject human judgement (coders): helps methods identify subtle relationships between words and outcomes of interest

   Dictionaries

   Training Sets

Discarding Word Order in Python

```
from nltk import word_tokenize
from nltk import bigrams
from nltk import trigrams
from nltk import ngrams

text_3 = word_tokenize(text_2)
text_3_bi = bigrams(text_3)
text_3_tri = trigrams(text_3)
text_3_n = ngrams(text_3, 4)
```

Stop Words

- Stop Words: English Language place holding words

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  `the, it, if, a, able, at, be, because...`

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```
stop_words =
urlopen('http://www.ai.mit.edu/projects/jmlr/papers/volume5/lewis04a/a11-smart-stop-list/english.stop').read().
n')
```

```
text_4 = [x for x in text_3 if x not in stop_words]

text_rem = [x for x in text_3 if x not in text_4]
```

Creating an Equivalence Class of Words

Reduce dimensionality further

Creating an Equivalence Class of Words

Reduce dimensionality further $\rightsquigarrow$ create equivalence class between words

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- Stemming/Lemmatizing algorithms: Many-to-one mapping from words to stem/lemma

Comparing Stemming and Lemmatizing

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Key comparison: equivalence classes

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Lemmatizing algorithm:

- Condition on part of speech (noun, verb, etc)
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Key comparison: equivalence classes

```
from nltk.stem.lancaster import LancasterStemmer
st = LancasterStemmer()
from nltk.stem import PorterStemmer
pt = PorterStemmer()
from nltk.stem.snowball import EnglishStemmer
sb = EnglishStemmer()
from nltk.stem.wordnet import WordNetLemmatizer
wn = WordNetLemmatizer()
```

```
>>> st.stem('better')
'bet'
>>> pt.stem('better')
'better'
>>> sb.stem('better')
'better'
>>> wn.lemmatize('better', 'a')
'good'
>>> wn.lemmatize('families', 'n')
'family'
text_5 = map(pt.stem, text_4)
```

All together now...

```
Four score and seven years ago our fathers brought forth on
this continent a new nation, conceived in liberty, and
dedicated to the proposition that all men are created
equal.
```

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Step 1: Remove capitalization and punctuation:

:

:

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⋮

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Step 1: Remove capitalization and punctuation:

`four score and seven years ago our fathers brought forth on this continent a new nation conceived in liberty and dedicated to the proposition that all men are created equal`

Step 2: Discard word order:

All together now...

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`four score and seven years ago our fathers brought forth on this continent a new nation conceived in liberty and dedicated to the proposition that all men are created equal`

Step 2: Discard word order:

`four, score, and, seven, years, ago, our, fathers, brought, forth, on, this, continent, a, new, nation, conceived, in, liberty, and, dedicated, to, the, proposition, that, all, men, are, created, equal`

⋮

All together now...

Step 1: Remove capitalization and punctuation:
Step 2: Discard word order:
`four, score, and, seven, years, ago, our, fathers, brought, forth, on, this, continent, a, new, nation, conceived, in, liberty, and, dedicated, to, the, proposition, that, all, men, are, created, equal`
Step 3: Remove stop words :

All together now...

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Step 4: Applying Stemming Algorithm

All together now...

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Step 3: Remove stop words :
`four, score, seven, years, ago, fathers, brought, forth, continent, new, nation, conceived, liberty, dedicated, proposition, men, created, equal`
Step 4: Applying Stemming Algorithm
`four, score, seven, year, ago, father, brought, forth, contin, new, nation, conceiv, liberti, dedic, proposit, men, creat, equal`

All together now...

Step 1: Remove capitalization and punctuation:

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Step 4: Applying Stemming Algorithm

`four, score, seven, year, ago, father, brought, forth, contin, new, nation, conceiv, liberti, dedic, proposit, men, creat, equal`

Step 5: Create Count Vector

Stem	Count
ago	1
brought	1
seven	1
creat	1
conceiv	1
men	1
father	1
⋮	⋮

All together now...

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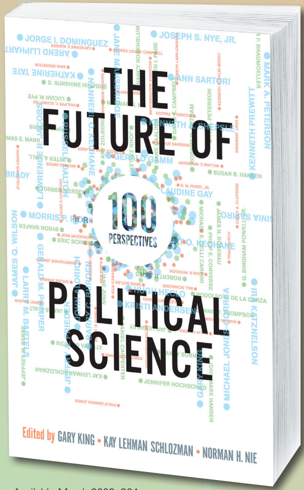
This Can Actually Work!



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Evaluators' Rate Machine Choices Better Than Their Own (Grimmer and King)

Generate pairs of similar documents: Humans vs Machines

- Scale: (1) unrelated, (2) loosely related, or (3) closely related
- Table reports: mean(scale)

Pairs from	Overall Mean	Evaluator 1	Evaluator 2

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Evaluators' Rate Machine Choices Better Than Their Own (Grimmer and King)

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- Scale: (1) unrelated, (2) loosely related, or (3) closely related
- Table reports: mean(scale)

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p.s. The hand-coders did the evaluation!

Pre-existing word weights $\rightsquigarrow$ Dictionaries

Pre-existing word weights⇝ Dictionaries

DICTION

DICTION is a computer-aided text analysis program for Windows® and Mac® that uses a series of dictionaries to search a passage for five semantic features—Activity, Optimism, Certainty, Realism and Commonality—as well as thirty-five sub-features. DICTION uses predefined dictionaries and can use up to thirty custom dictionaries built with words that the user has defined, such as topical or negative words, for particular research needs.

Pre-existing word weights$\rightsquigarrow$ Dictionaries

DICTION

DICTION 7, now with *Power Mode,* can read a variety of text formats and can accept a large number of files within a single project. Projects containing over 1000 files are analyzed using *power analysis* for enhanced speed and reporting efficiency, with results automatically exported to .csv-formatted spreadsheet file.

Pre-existing word weights⇝ Dictionaries

DICTION

On an average computer, DICTION can process over 20,000 passages in about five minutes. DICTION requires 4.9 MB of memory and 38.4 MB of hard disk space.

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> "provides both social scientific and humanistic understandings"
>
> —Don Waisanen, Baruch College

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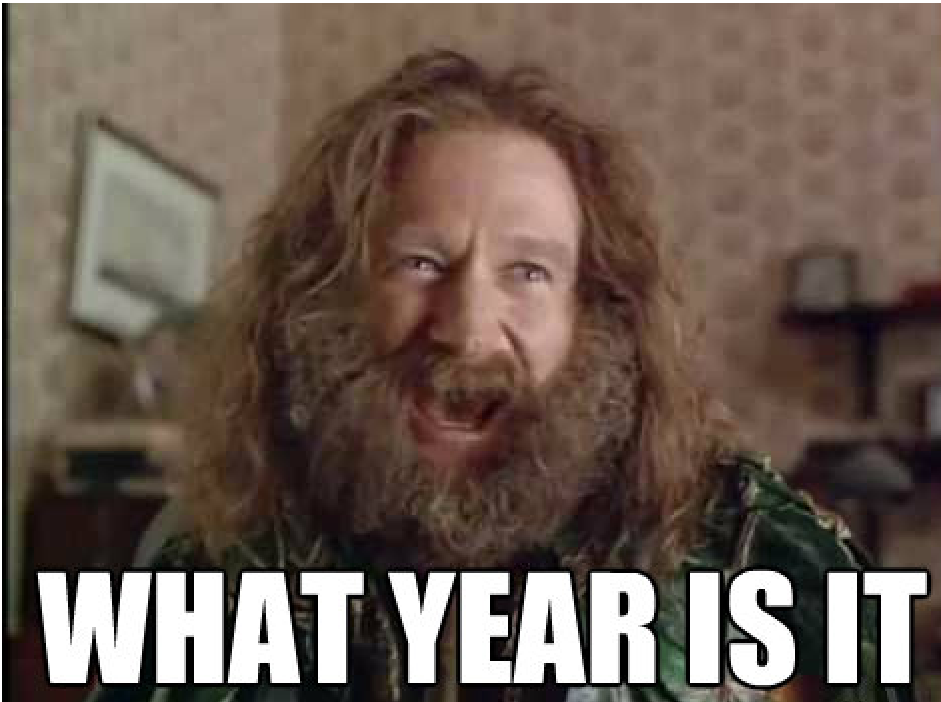
DICTION

DICTION 7 for Mac (Educational) ($219.00)

This is the educational edition of DICTION Version 7 for Mac. You
purchase on the following page.


WHAT YEAR IS IT

Dictionary Methods

Many Dictionary Methods (like DICTION)

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1) Proprietary

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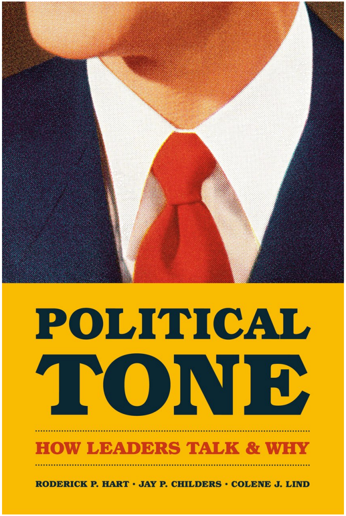
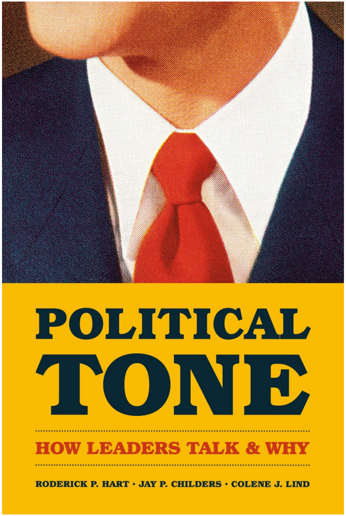

POLITICAL
TONE
HOW LEADERS TALK & WHY
RODERICK P. HART · JAY P. CHILDERS · COLENE J. LIND

DICTION



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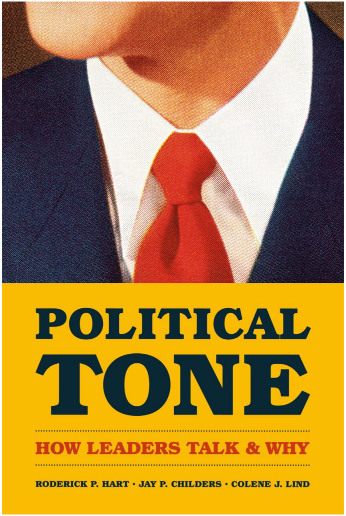

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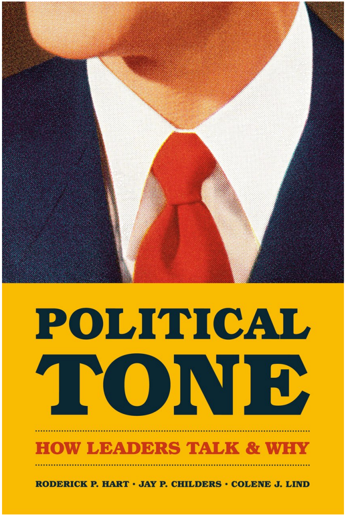

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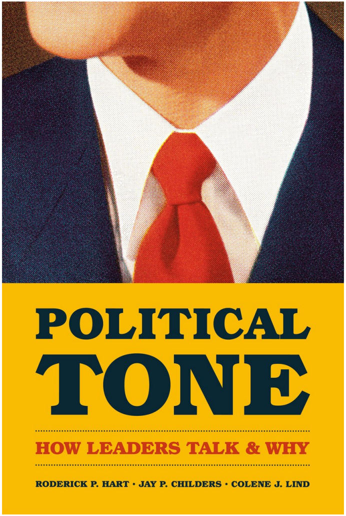

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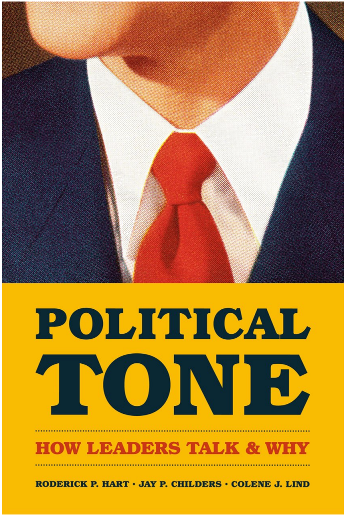

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Examining Positive and Negative Statements in Press Releases

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Least positive members of Congress:

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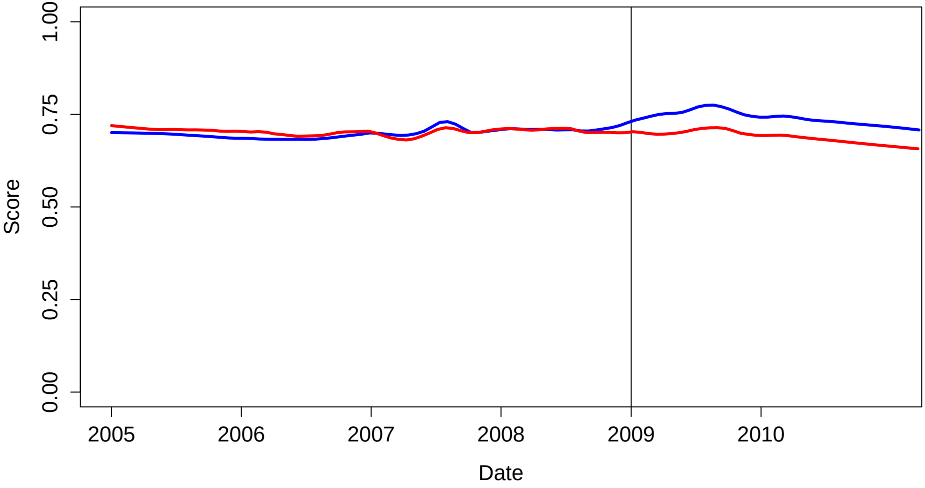
Legislators who are more extreme $\rightsquigarrow$ less positive in press releases

Examining Positive and Negative Statements in Press Releases



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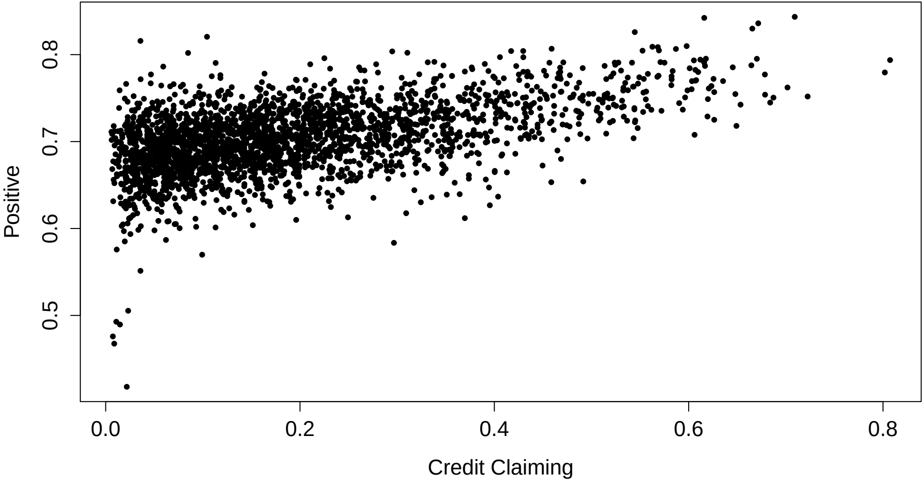

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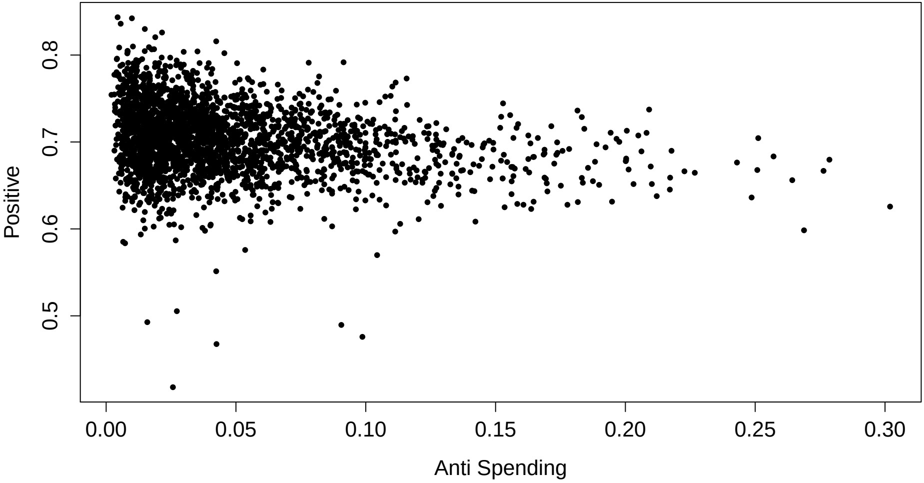

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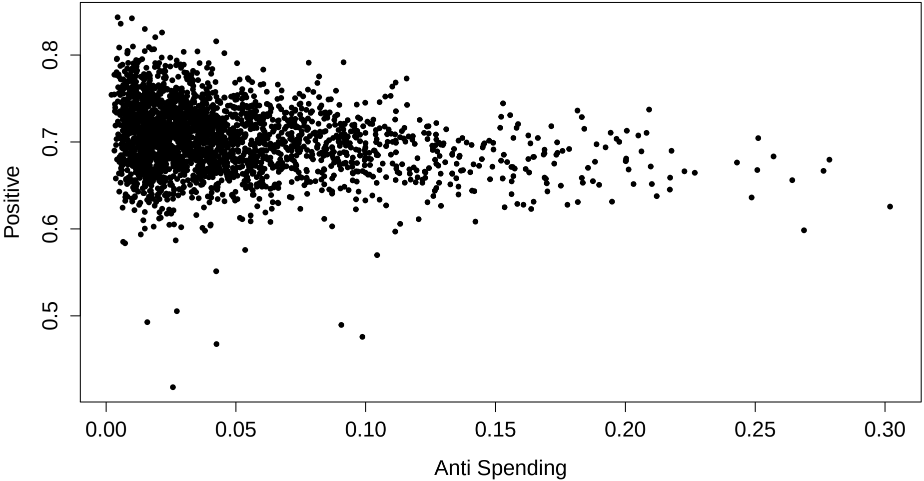

Methodological Issues/Problems with Dictionaries

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- A procedure for training coders:
  1) Coding rules
  2) Apply to new texts
  3) Assess coder agreement (we'll discuss more in a few weeks)
  4) Using information and discussion, revise coding rules

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Measures of classification performance

	Actual Label	
Guess	Liberal	Conservative
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Under reported for dictionary classification

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$\rightsquigarrow$

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Necessarily more complicated

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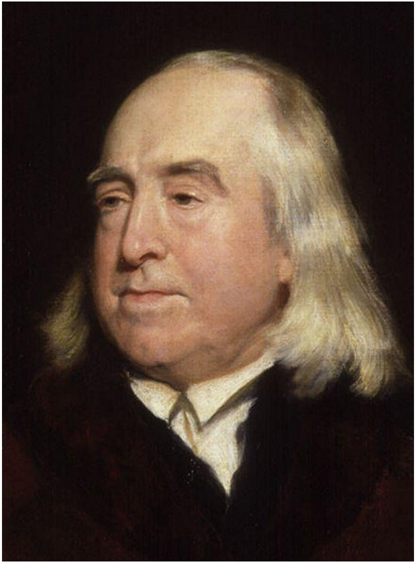
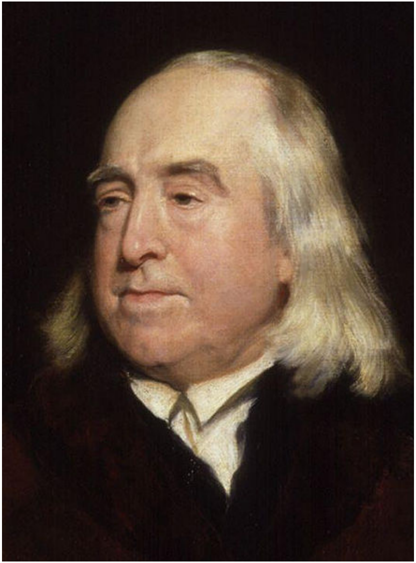


Measuring Happiness



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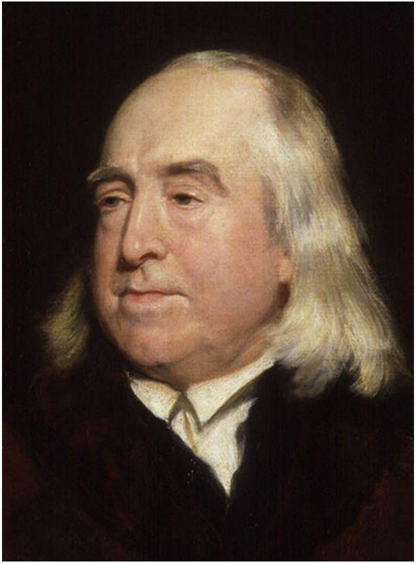

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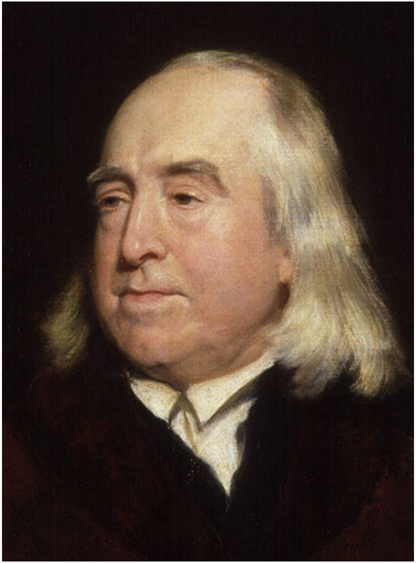

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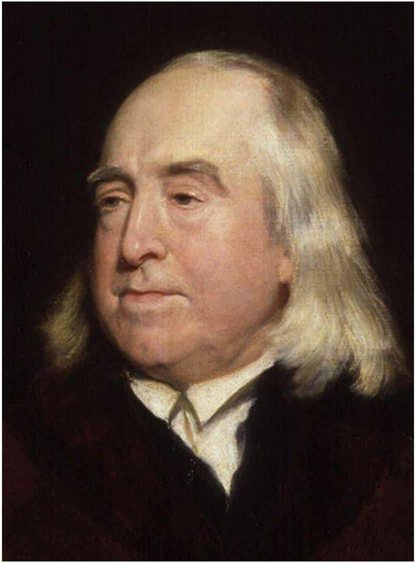

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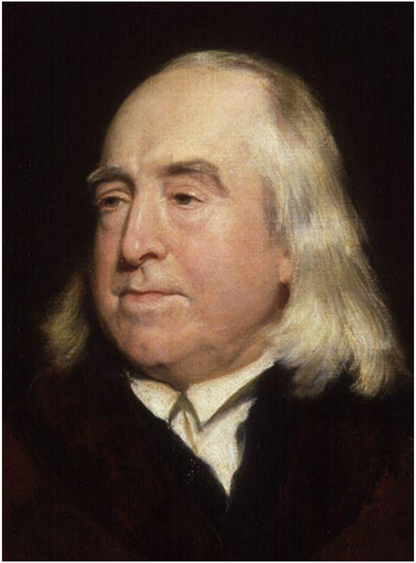

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$$\text{Happiness}_i = \frac{\sum_{k=1}^{K} \theta_k X_{ik}}{\sum_{k=1}^{K} X_{ik}}$$

Lyrics for
Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
⋮
And mother always told me,
be careful who you love.
And be careful of what you do
'cause the lie becomes the truth.

Billie Jean is not my lover,
She's just a girl who claims
that I am the one.
⋮

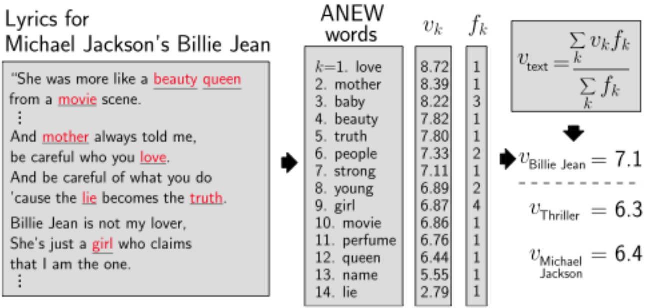
ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

$$v_{\text{Billie Jean}} = 7.1$$

$$v_{\text{Thriller}} = 6.3$$

$$v_{\text{Michael Jackson}} = 6.4$$



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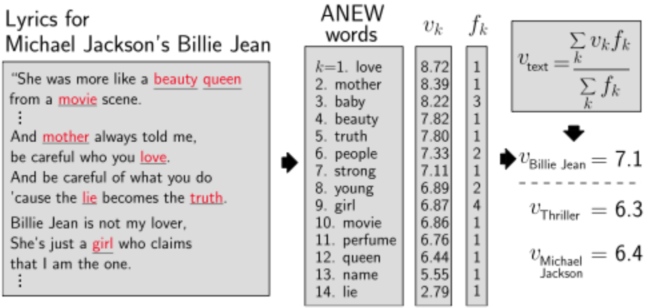

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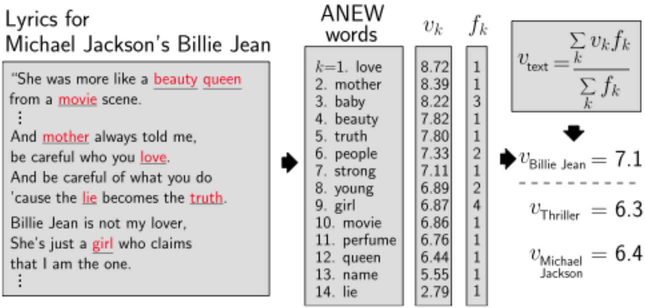

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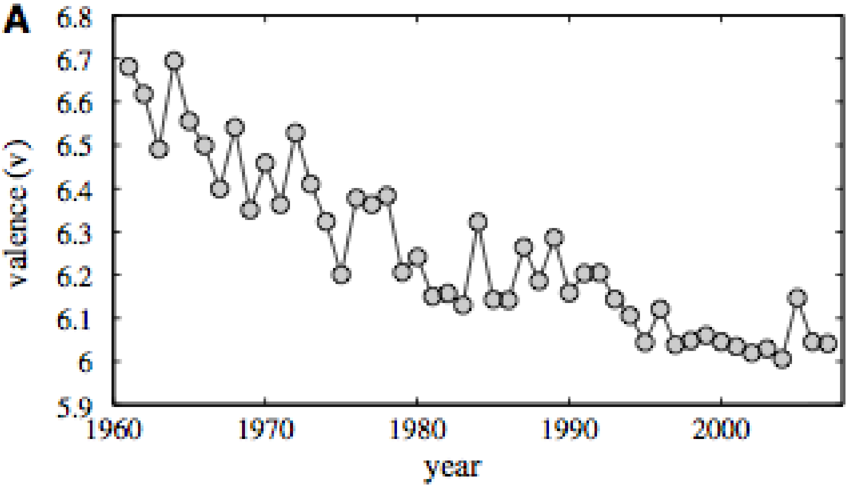
P.Y.T. (Pretty Young Thing) (This is the right answer!)

Happiness in Society



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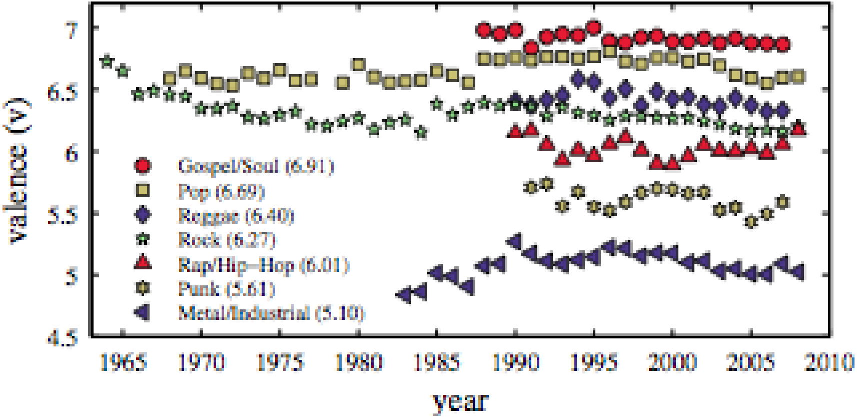

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