Text as Data

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    - Statistical methods/algorithms, computationally intensive

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

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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
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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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Automated methods can help with even small problems

Plan for the Course

Week 1:

1) 8/15: Acquiring, preprocessing, and comparing text
2) 8/16: **Discovery**: Vector Space Model of Text, Clustering Methods, Separating Words
3) 8/17: **Measurement**: Dictonary Methods, Hand Coding, Supervised Methods Part 1

Week 2:

4) 8/22: **Measurement**: Supervsed Methods Part 2
5) 8/23: **Measurement**: Topic Models
6) 8/24: **Causal Inference**: Train/Test Split, Analyst Induced SUTVA, Text as Dependent and Independent

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- Validation $\rightsquigarrow$ demonstrate methods perform task

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Principle 2: Quantitative Methods Augment Humans, Not Replace Them

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- Quantitative methods organize, direct, and suggest
- Humans: read and interpret

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Principle 3: There is no Globally Best Method for Automated Text Analysis

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- Debate $\rightsquigarrow$ acknowledge differences, resolved

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- Few theorems to guarantee performance
- Apply methods $\rightsquigarrow$ validate
- Avoid: blind application of methods

Goal for Today: Document-Term Matrices

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

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

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- $N =$ 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

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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

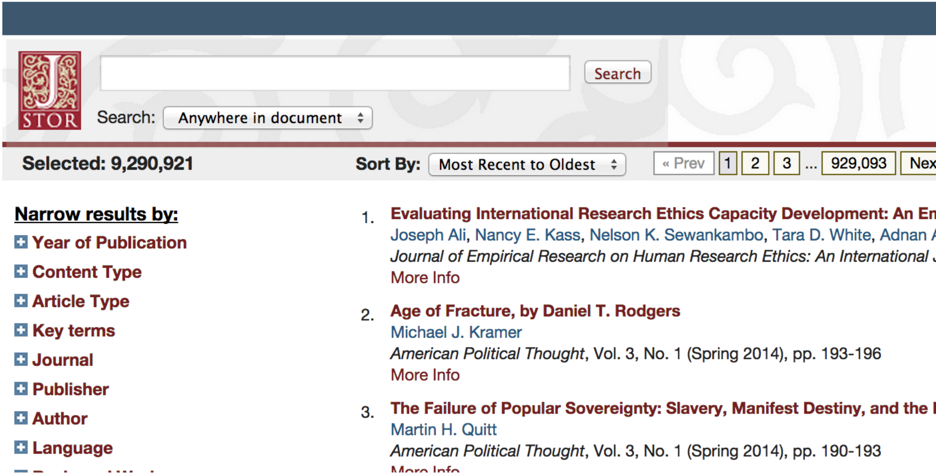
<DOC>
<DOCNO>101-levin-mi-1-19901027< /DOCNO>
<TEXT>
Mr. LEVIN. Mr. President, today the House passed and sent to the President the Great Lakes Critical Programs Act.
... Mr. President, I commend and thank Ms. Bean for her exceptional efforts on the Great Lakes Critical Programs Act
< /TEXT>
< /DOC>

JSON

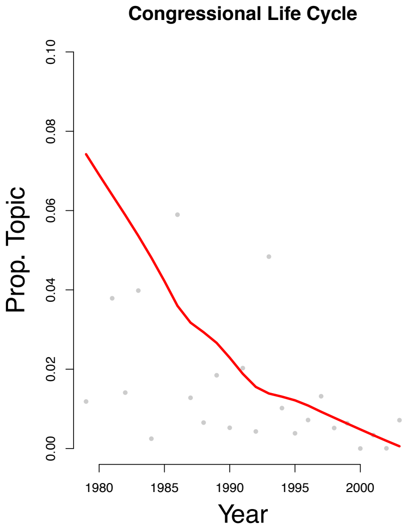
{"id":"tag:search.twitter.com,2005:287886850381713411",
"objectType":"activity"...displayName":"Linda Bowersox",
"postedTime":"2010-03-10T05:16:14.000Z"...
"body":"@JeffFlake thank you for standing firm and voting
NO on the #FiscalCliff (via #PJNET)","object"...

Prepackaged Data Sources

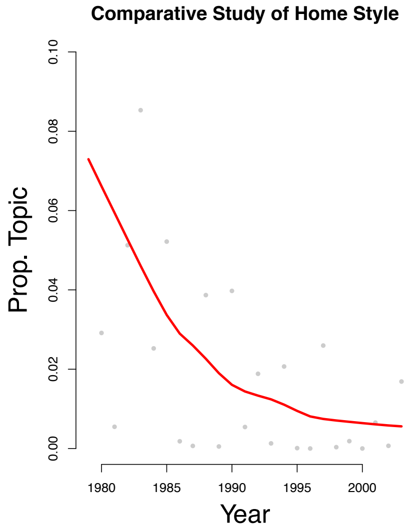
http://dfr.jstor.org



History of Home Style



History of Home Style



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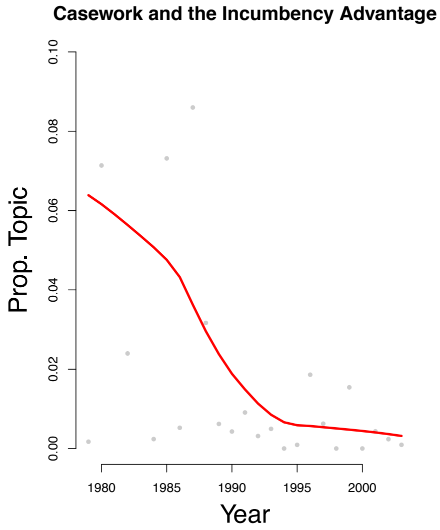

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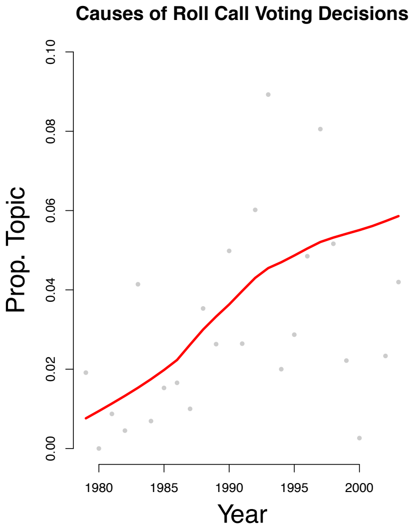

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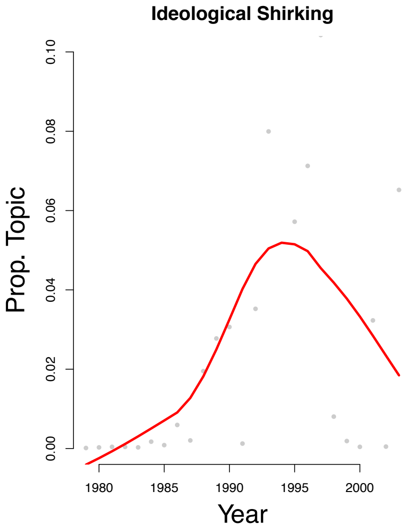

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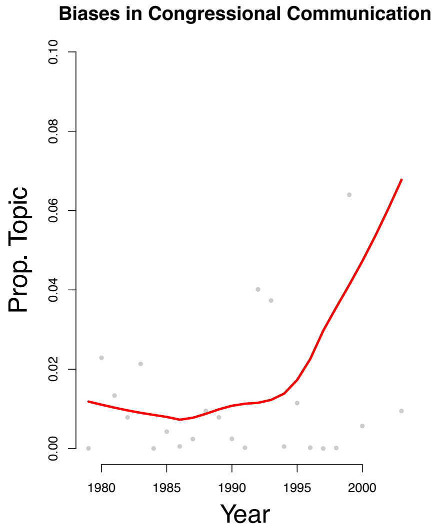

Prepackaged Data Sources

Lexis Nexis (and other data base sources)

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1) Batch search and download

Prepackaged Data Sources

Lexis Nexis (and other data base sources)

1) Batch search and download
2) Do not try to scrape Lexis Nexis(!!!!)

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Application Programming Interface (APIs)

Prepackaged Data Sources

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Application Programming Interface (APIs)

- Facilitate interaction with applications (like Twitter)

Prepackaged Data Sources

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1) Batch search and download
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Application Programming Interface (APIs)

- Facilitate interaction with applications (like Twitter)
- Download data (often in JSON format) $\rightsquigarrow$ Twitter, Data.gov, ...

Books, Archives, and Other Non-Digital Material

befit the servant towards the master; and he will not behave like many, who on meeting any great prince, with whom if only they have spoken but once, press forward with a certain smiling and friendly look, as if they" wished to caress an equal or show favour to an inferior.

"He will very rarely or almost never ask anything of his lord j for himself, lest his lord, being reluctant to deny it to him "directly, may sometimes grant it with an ill grace, which is much worse. Even in asking for others he will choose his time discreetly and ask proper and reasonable things; and he will so frame his request, by omitting what he knows may displease and by skilfully doing away with difficulties, that his lord shall always grant it, or shall not think him offended by refusal even if it be denied; for when lords have denied a favour to an importu nate suitor, they often reflect that he who asked it with such eagerness, must have desired it greatly, and so having failed to obtain it, must feel ill will towards him who denied it; and believing this, they begin to hate the man and can never more look upon him with favour., 19.–" He will not seek to intrude unasked into his masters chamber or private retreats, even though he be of great consequence; for when great lords are in private, they often like a little liberty to say and do what they please, and do not wish to be seen or heard by any who may criticise them; and it is very proper. Hence I think those men do ill who blame great lords for consorting privately with persons who are of little worth save in matters of personal service, for I do not see why lords should not have the same freedom to relax their minds that we fain would have to relax ours. But if a Courtier accustomed to deal with important matters, chances to find himself in private with his lord, he must put on another face, postpone grave concerns to another place and time, and give the conversation a cast that shall amuse and please his lord, so as not to

Books, Archives, and Other Non-Digital Material

1) Create images of texts

Books, Archives, and Other Non-Digital Material

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2) Optical Character Recognition

Books, Archives, and Other Non-Digital Material

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   - Built in Adobe Pro

Books, Archives, and Other Non-Digital Material

1) Create images of texts
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    - Abbyy FineReader (Batch processing)

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    - Tesseract (Google, command line tool)

Books, Archives, and Other Non-Digital Material

1) Create images of texts
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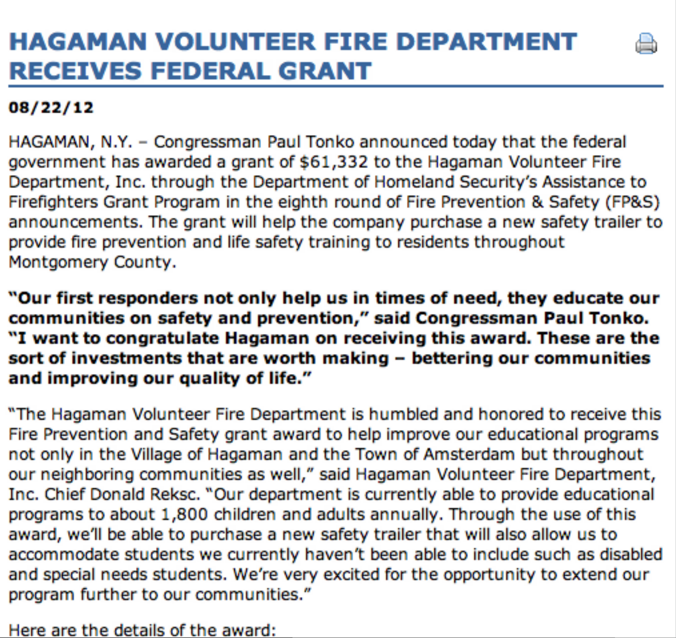
   - Tesseract (Google, command line tool)
3) Also use, e-book formats...

Acquiring Data from Web: Automated Web Collection


HAGAMAN VOLUNTEER FIRE DEPARTMENT RECEIVES FEDERAL GRANT

08/22/12

HAGAMAN, N.Y. – Congressman Paul Tonko announced today that the federal government has awarded a grant of $61,332 to the Hagaman Volunteer Fire Department, Inc. through the Department of Homeland Security's Assistance to Firefighters Grant Program in the eighth round of Fire Prevention & Safety (FP&S) announcements. The grant will help the company purchase a new safety trailer to provide fire prevention and life safety training to residents throughout Montgomery County.

"Our first responders not only help us in times of need, they educate our communities on safety and prevention," said Congressman Paul Tonko. "I want to congratulate Hagaman on receiving this award. These are the sort of investments that are worth making – bettering our communities and improving our quality of life."

"The Hagaman Volunteer Fire Department is humbled and honored to receive this Fire Prevention and Safety grant award to help improve our educational programs not only in the Village of Hagaman and the Town of Amsterdam but throughout our neighboring communities as well," said Hagaman Volunteer Fire Department, Inc. Chief Donald Reksc. "Our department is currently able to provide educational programs to about 1,800 children and adults annually. Through the use of this award, we'll be able to purchase a new safety trailer that will also allow us to accommodate students we currently haven't been able to include such as disabled and special needs students. We're very excited for the opportunity to extend our program further to our communities."

Here are the details of the award:

Acquiring Data from Web: Automated Web Collection

```
                <table border="0" cellpadding="0" cellspacing="0" align="right"><tr><td valign="top">

                <a href="#" onclick="return popup('/common/popup/popup.cfm?action=item.print&amp;itemID=715',600,500);"><img
src="/common/images/print3.gif" alt="Print" border="0" /></a>
                </td></tr></table>


                <h3><span>HAGAMAN VOLUNTEER FIRE DEPARTMENT RECEIVES FEDERAL GRANT </span></h3>

                <span class="contentdate">08/22/12</span>



                <div class="contentdata"><p>
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<p>
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said Congressman Paul Tonko. &ldquo;I want to congratulate Hagaman on receiving this award. These are the sort of investments that are worth
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We&rsquo;re very excited for the opportunity to extend our program further to our communities.&rdquo;</p>
<p>
        Here are the details of the award:</p>
<p>
        &middot;         Hagaman Volunteer Fire Department, Inc: $61,332 to purchase a new safety
trailer for fire prevention and training purposes.</p>
<p>
        On April 11, 2012 Congressman Tonko wrote a letter of support on behalf of the Hagaman Volunteer Fire Department for the grant to the
Assistant Administrator of Federal Emergency Management Agency (FEMA) Grant Programs.</p>
<p>
        The Fire Prevention and Safety Grants (FP&amp;S) are part of the Assistance to Firefighters Grants (AFG), and are under the purview of
the Grant Programs Directorate at FEMA. FP&amp;S Grants support projects that enhance the safety of the public and firefighters from fire and
related hazards. The primary goal is to target high-risk populations and reduce injury and prevent death. In 2005, Congress reauthorized
funding for FP&amp;S and expanded the eligible uses of funds to include Firefighter Safety Research and Development.</p>
<p>
        For more information on the FP&amp;S grants program, click <a href="http://www.fema.gov/fire-prevention-safety-grants">here.</a></p>
<p align="center">
        <strong><em># # #</em></strong></p>
```

Acquiring Data from Web: Automated Web Collection

```
base = 'http://tonko.house.gov'

for j in range(len(html)):#
    out = urlopen(html[j]).read()
    soup = BeautifulSoup(out)
    h3s = soup.findAllfindAll('h3')
    fr = []
    date = []
    for m in range(len(h3s)):
        dd = h3s[m].findNext('a')
        dd = dd['href']
        dd2 = base + dd.encode('UTF-8')
        fr.append(dd2)
        temp = h3s[m].findNext('span')
        temp2 = util.clean_html(str(temp)).split('/')
        mons = mon_key[temp2[0]]
        day =  temp2[1]
        year = '20' + temp2[2]
        temp3 = day + mons + year
        date.append(temp3)
    for num in range(len(fr)):
        out2 = urlopen(fr[num]).read()
        soup2 = BeautifulSoup(out2)
        divs = soup2.findAll('div')
        content = ''
        for m in range(len(divs)):
            if divs[m].has_key('class'):
                if divs[m]['class']=='contentdata':
                    stuff = util.clean_html(str(divs[m]))
                    content += stuff
        names = date[num] + 'Tonko' + str(num) +'.txt'
        files = open(names, 'w')
        files.write(content)
        files.close()
```

Acquiring Data from Web: Automated Web Collection

```
WASHINGTON, D.C. -- Rep. Paul Tonko (NY-21) released the following
statement on the passage of H.R. 3962, the Affordable Health Care for
America Act:
 &ldquo;Today the House of Representatives took a giant step towards fixing
our broken health care system by passing legislation that will provide
coverage for millions of uninsured Americans, strengthen Medicare for our
seniors, lower costs for businesses and individuals, and provide
protections for those who already have health care coverage. In the 21st
Congressional District alone, this bill will cover 22,000 of the uninsured
and close the Medicare Part &ldquo;D&rdquo; donut hole that currently has
7,300 of our seniors paying out of pocket for prescription drug costs.
 &ldquo;As I traveled throughout the district over the past 10 months, I
heard heartbreaking stories of families thrust into bankruptcy because they
had been denied coverage when they became ill, heard from people
who&rsquo;ve had to decide between buying food and prescription drugs, and
from small business owners who cannot provide coverage to their employees
because it&rsquo;s too expensive. The overwhelming number of voices have
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```

Exercise: Scraping a Presidential Speech

http://stanford.edu/∼jgrimmer/Text14/HW2.pdf :

- http://www.crummy.com/software/BeautifulSoup/
- Parse paragraphs, label speakers

Acquiring Data from Web: Distributed Human Computing

Amazon.com's Mechanical Turk

- Marketplace for Human Itensive Tasks
- Requester (you): create HITs, offer $ (about $0.05 per task)
- Workers (bored + broke people): complete task
- Requester: evaluate and pay

Odesk, elance, ...

You have text, now what?

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's"
`[^Ss]`	neither 'S' nor 's'	"ACORN's"
`[^\.]`	not a period	" 'Run!', he screamed."

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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  Misses capitalized examples

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  Returns words that are too long (`theocrat`, `theme`)

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- [^a-zA-Z][tT]he[^a-zA-Z]

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- [^a-zA-Z][tT]he[^a-zA-Z]

  Misses the first "the" in a sentence

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- `[tT]he`

  Returns words that are too long (`theocrat`, `theme`)

- [^a-zA-Z][tT]he[^a-zA-Z]

  Misses the first "the" in a sentence

- (^ | [^ a-zA-Z])[tT]he[^ a-zA-Z]

An Example: Searching for Tea Party Language

Grimmer, Westwood, and Messing (2014): Criticism and credit

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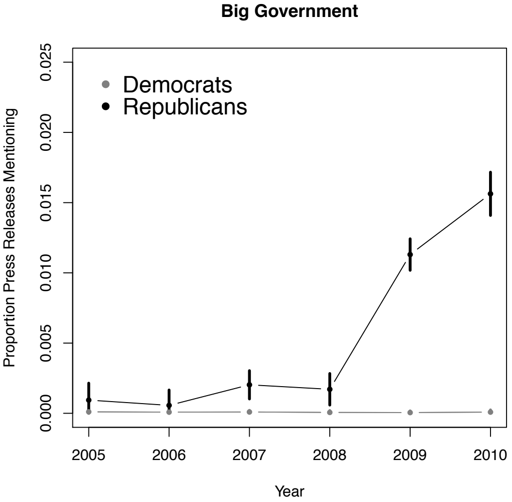

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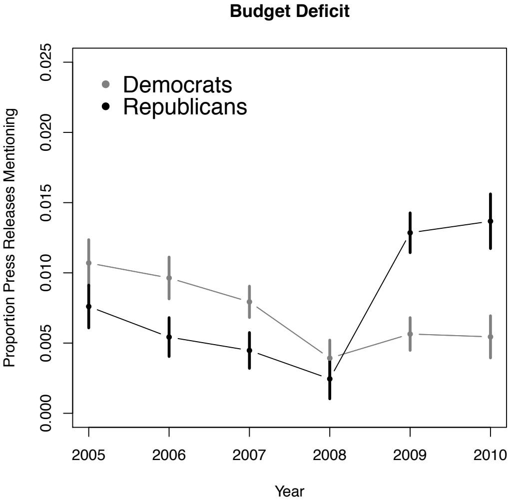

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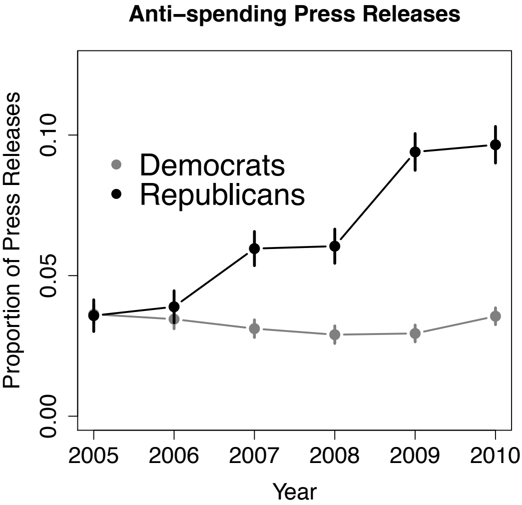
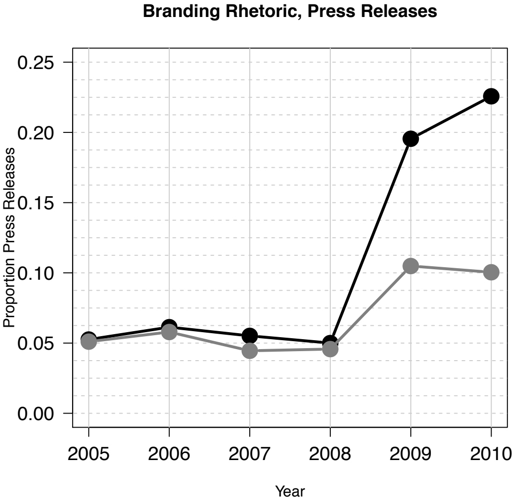


An Example: Searching for Tea Party Language

Goodman, Grimmer, Parker, Zlotnik (2015): Criticism



Regular Expressions on Steroids: Cheating Detection Software

- WCopyFind: `http://plagiarism.bloomfieldmedia.com/z-wordpress/software/wcopyfind/`

Regular Expressions on Steroids: Cheating Detection Software

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  - Number of matching strings to constitute match

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- Useful:
  - Media uptake

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  - Number of matching strings to constitute match
- Useful:
  - Media uptake
  - Joint Press Releases

Document Term Matrices

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We want to use statistics/algorithms to characterize text
We'll put it in a document-term matrix

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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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1) Remove capitalization, punctuation

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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

WUSTL_1.py
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`

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

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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

  `Cardinals fans are fun to have around, especially when the Cardinals are playing the Cubs`

- 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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`To the Python code!`

Creating an Equivalence Class of Words

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

Comparing Stemming and Lemmatizing

Stemming algorithm:

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Key comparison: equivalence classes

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

`Python Code!`

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.
```

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.`

Step 1: Remove capitalization and punctuation:

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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`

⋮

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Step 3: Remove stop words :

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Step 4: Applying Stemming Algorithm

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Step 4: Applying Stemming Algorithm
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`four, score, seven, year, ago, father, brought, forth, contin, new, nation, conceiv, liberti, dedic, proposit, men, creat, equal`

Step 5: Create Count Vector (`Python Code!`)

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

All together now...

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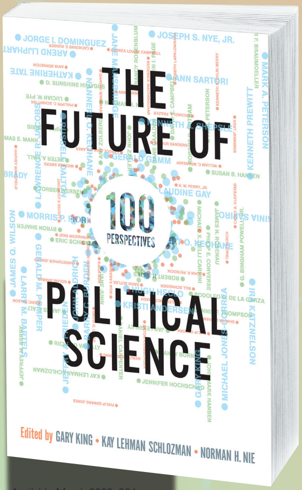
This Can Actually Work!



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