4. Supervised Techniques I

DS-GA 3001, Text as Data
Arthur Spirling

February 20, 2018

Housekeeping

Housekeeping

1 Homework out now, coming back to Leslie on Feb 28, 5pm to her mailbox.

Housekeeping

1 Homework out now, coming back to Leslie on Feb 28, 5pm to her mailbox. Must be your own work, and must provide a code appendix!

Housekeeping

1. Homework out now, coming back to Leslie on Feb 28, 5pm to her mailbox. Must be your own work, and must provide a code appendix!

2. Speaker series not meeting this week.

Housekeeping

1 Homework out now, coming back to Leslie on Feb 28, 5pm to her mailbox. Must be your own work, and must provide a code appendix!

2 Speaker series not meeting this week.

3 Lecture again on Thursday during section

Follow up: Causal Relationships

Follow up: Causal Relationships

Gibson, 1998 "Linguistic complexity: locality of syntactic dependencies" ($\sim$ 2100 cites)

Follow up: Causal Relationships

Gibson, 1998 "Linguistic complexity: locality of syntactic dependencies" ($\sim$ 2100 cites)

$\rightarrow$ complexity is about "memory cost associated with keeping track of obligatory syntactic requirements":

Follow up: Causal Relationships

Gibson, 1998 "Linguistic complexity: locality of syntactic dependencies" ($\sim$ 2100 cites)

$\rightarrow$ complexity is about "memory cost associated with keeping track of obligatory syntactic requirements": so, longer reader has to keep idea/entity in mind before confirming its relationship to another, the harder the text.

Follow up: Causal Relationships

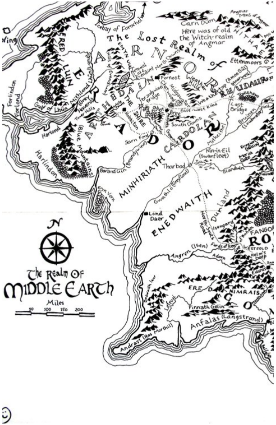
Gibson, 1998 "Linguistic complexity: locality of syntactic dependencies" ($\sim$ 2100 cites)

$\rightarrow$ complexity is about "memory cost associated with keeping track of obligatory syntactic requirements": so, longer reader has to keep idea/entity in mind before confirming its relationship to another, the harder the text.

"`The reporter who the senator attacked admitted the error`" is harder than "`The reporter who attacked the senator admitted the error`" because less obvious to whom 'who' refers.

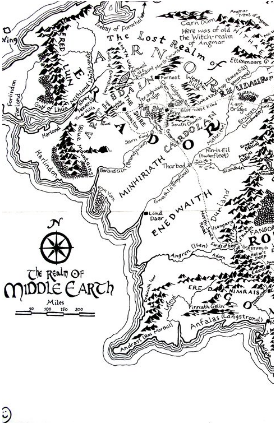
Where Are We?

Where Are We?



The Lost Realm of
ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
THE SHIRE
Hobbiton
Brandywine Bridge
Sarn Ford
Gulf of Lhûn
Forlindon
Forlond
Harlond
Harlindon
Blue Mountains
ERIADOR
CARDOLAN
MINHIRIATH
Tharbad
Nîn-in-Eilph (Swanfleet)
Gwathló (Greyflood)
ENEDWAITH
Dunland
Lond Daer
Isengard
Adorn
Angren
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Helm's Deep
Edoras
FANGORN
The Realm of Middle Earth
Miles
50
100
150
200

Where Are We?



We've covered the basics of document representation and characterization.

Where Are We?

We've covered the basics of document representation and characterization.

Now begin to think about documents as members of categories or classes

Where Are We?

We've covered the basics of document representation and characterization.

Now begin to think about documents as members of categories or classes

→ simple, fast dictionary based ways to classify/categorize

Where Are We?

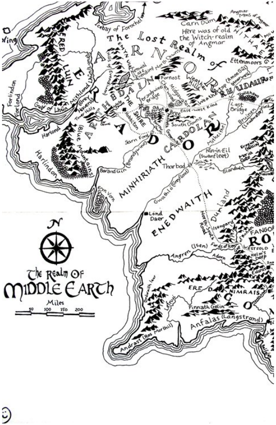
We've covered the basics of document representation and characterization.

Now begin to think about documents as members of categories or classes

→ simple, fast dictionary based ways to classify/categorize

cover some 'major' dictionaries in social science

Where Are We?



We've covered the basics of document representation and characterization.

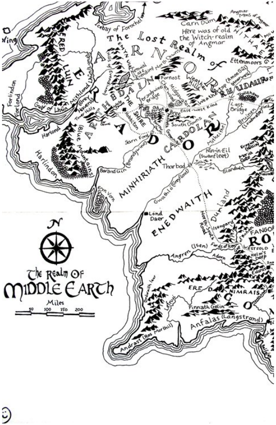
Now begin to think about documents as members of categories or classes

→ simple, fast dictionary based ways to classify/categorize

cover some 'major' dictionaries in social science

and demonstrate challenges that emerge in constructing and using dictionaries,

Where Are We?



We've covered the basics of document representation and characterization.

Now begin to think about documents as members of categories or classes

→ simple, fast dictionary based ways to classify/categorize

cover some 'major' dictionaries in social science

and demonstrate challenges that emerge in constructing and using dictionaries, especially for novel tasks.

Terminology

Terminology

Unsupervised techniques:

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes:

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—

Terminology

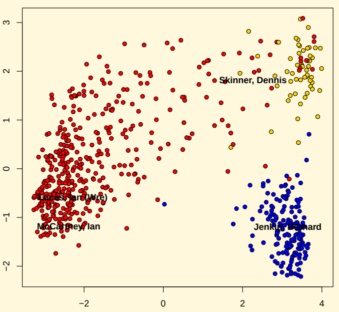
Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

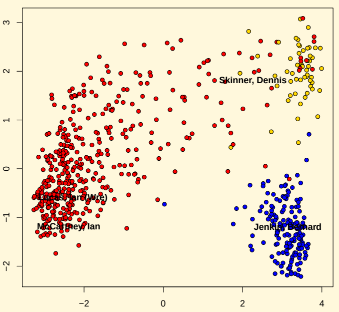
e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?



Terminology

<u>Unsupervised</u> techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?

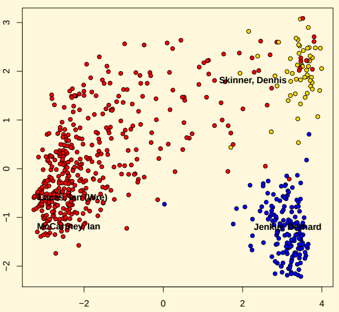


<u>Supervised</u> techniques:

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?

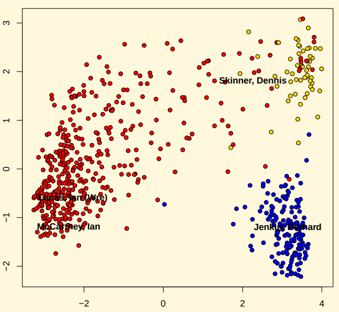


Supervised techniques: learning relationship between inputs and a labeled set of outputs.

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?



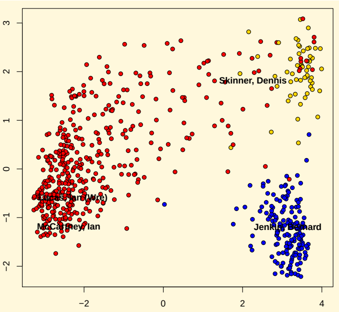
Supervised techniques: learning relationship between inputs and a labeled set of outputs.

e.g. opinion mining:

Terminology

Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?



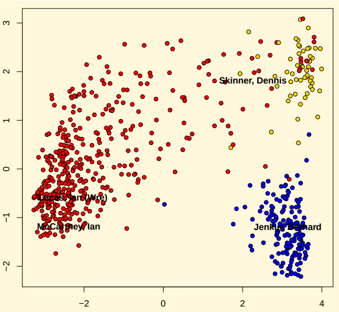
Supervised techniques: learning relationship between inputs and a labeled set of outputs.

e.g. opinion mining: what makes a critic like or dislike a movie ($y \in \{0, 1\}$)?

Terminology

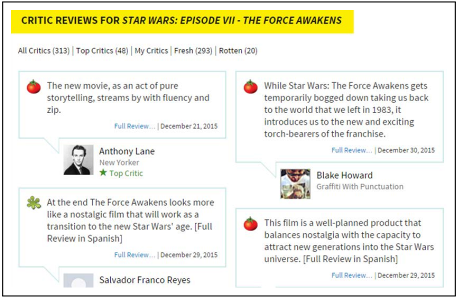
Unsupervised techniques: learning (hidden or latent) structure in unlabeled data.

e.g. PCA of legislators's votes: want to see how they are organized—by party? by ideology? by race?



Supervised techniques: learning relationship between inputs and a labeled set of outputs.

e.g. opinion mining: what makes a critic like or dislike a movie ($y \in \{0, 1\}$)?


CRITIC REVIEWS FOR *STAR WARS: EPISODE VII - THE FORCE AWAKENS*

All Critics (313) | Top Critics (48) | My Critics | Fresh (293) | Rotten (20)

The new movie, as an act of pure storytelling, streams by with fluency and zip.

Full Review... | December 21, 2015

Anthony Lane
New Yorker
★ Top Critic

While Star Wars: The Force Awakens gets temporarily bogged down taking us back to the world that we left in 1983, it introduces us to the new and exciting torch-bearers of the franchise.

Full Review... | December 30, 2015

Blake Howard
Graffiti With Punctuation

At the end The Force Awakens looks more like a nostalgic film that will work as a transition to the new Star Wars' age. [Full Review in Spanish]

Full Review... | December 29, 2015

Salvador Franco Reyes

This film is a well-planned product that balances nostalgia with the capacity to attract new generations into the Star Wars universe. [Full Review in Spanish]

Full Review... | December 29, 2015

Overview: Supervised Learning

Overview: Supervised Learning

label some examples of each category

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$)

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal,

Overview: Supervised Learning

label some examples of each category

- **e.g.** some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

train a 'machine' on these examples (e.g. logistic regression),

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

train a 'machine' on these examples (e.g. logistic regression), using the features (DTM, other stuff) as the 'independent' variables.

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

train a 'machine' on these examples (e.g. logistic regression), using the features (DTM, other stuff) as the 'independent' variables.

e.g. does the commentator use the word '`fetus`' or '`baby`' in discussing abortion law?

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

train a 'machine' on these examples (e.g. logistic regression), using the features (DTM, other stuff) as the 'independent' variables.

e.g. does the commentator use the word '`fetus`' or '`baby`' in discussing abortion law?

classify use the learned relationship—some $f(x)$—to predict the outcomes of documents ($y \in \{0, 1\}$, review sentiment)

Overview: Supervised Learning

label some examples of each category

e.g. some reviews that were positive ($y = 1$), some that were negative ($y = 0$); some statements that were liberal, some that were conservative.

train a 'machine' on these examples (e.g. logistic regression), using the features (DTM, other stuff) as the 'independent' variables.

e.g. does the commentator use the word '`fetus`' or '`baby`' in discussing abortion law?

classify use the learned relationship—some $f(x)$—to predict the outcomes of documents ($y \in \{0, 1\}$, review sentiment) not in the training set.

Overview: Dictionary

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis,

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis, and in coding events or manifestos.

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis, and in coding events or manifestos.

Often derived from supervised learning techniques

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis, and in coding events or manifestos.

Often derived from supervised learning techniques

and often used in supervised learning problems, as a starting point.

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis, and in coding events or manifestos.

Often derived from supervised learning techniques

and often used in supervised learning problems, as a starting point.

so we'll cover them here.

Overview: Dictionary

idea: set of pre-defined words with specific connotations that allow us to classify documents automatically, quickly and accurately.

$\rightarrow$ common in opinion mining/sentiment analysis, and in coding events or manifestos.

Often derived from supervised learning techniques

and often used in supervised learning problems, as a starting point.

so we'll cover them here.

Classification with Dictionary Methods

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1. Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1 Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is 'positive',

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1. Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is 'positive', this speech is 'liberal'

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1. Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is 'positive', this speech is 'liberal'

2. Measure extent to which document is associated with given category

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1. Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is 'positive', this speech is 'liberal'

2. Measure extent to which document is associated with given category

e.g. this review is generally 'positive', but has some negative elements.

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1 Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is 'positive', this speech is 'liberal'

2 Measure extent to which document is associated with given category

e.g. this review is generally 'positive', but has some negative elements.

We have a pre-determined list of words, the (weighted) presence of which helps us with (1) and (2).

Classification with Dictionary Methods

Aim Typically we are trying to do one of two closely related things:

1. Categorize documents as belonging to a certain class (mutually exclusive? jointly exhaustive?)

e.g. this review is ‘positive’, this speech is ‘liberal’

2. Measure extent to which document is associated with given category

e.g. this review is generally ‘positive’, but has some negative elements.

We have a pre-determined list of words, the (weighted) presence of which helps us with (1) and (2).

More Specifically

More Specifically

We have a set of key words, with attendant scores,

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: ‘`terrible`’ is scored as -1; ‘`fantastic`’ as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

$$\boxed{\text{tone of document } i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}}$$

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

$$\boxed{\text{tone of document } i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}}$$

where s_m is the score of word m

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

$$\boxed{\text{tone of document } i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}}$$

where s_m is the score of word m

and w_{im} is the number of occurrences of the mth dictionary word in the document i

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

$$\boxed{\text{tone of document } i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}}$$

where s_m is the score of word m

and w_{im} is the number of occurrences of the mth dictionary word in the document i

and N_i is the total number of all dictionary words in the document.

More Specifically

We have a set of key words, with attendant scores,

e.g. for movie reviews: '`terrible`' is scored as -1; '`fantastic`' as $+1$

$\rightarrow$ the relative rate of occurrence of these terms tells us about the overall tone or category that the document should be placed in.

i.e. for document i and words $m = 1, \ldots, M$ in the dictionary,

$$\boxed{\text{tone of document } i = \sum_{m=1}^{M} \frac{s_m w_{im}}{N_i}}$$

where s_m is the score of word m

and w_{im} is the number of occurrences of the mth dictionary word in the document i

and N_i is the total number of all dictionary words in the document.

$\rightarrow$ just add up the number of times the words appear and multiply by the score (normalizing by doc dictionary presence)

(Simple) Example: Barnes' review of *The Big Short*

(Simple) Example: Barnes' review of *The Big Short*

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.

Retain words in Hu & Liu Dictionary...

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.

Retain words in Hu & Liu Dictionary...

great *savage*
crisis *wasting*

tenuously
killing
superficially swelled

bad

complex
brutal

drunk
enough

Simple math. . .

Simple math...

negative 11

Simple math...

negative 11

positive 2

Simple math...

negative	11
positive	2
total	13

Simple math...

negative 11

positive 2

total 13

$$\text{tone} = \frac{2-11}{13} = \frac{-9}{13}$$

Simple math...

negative 11

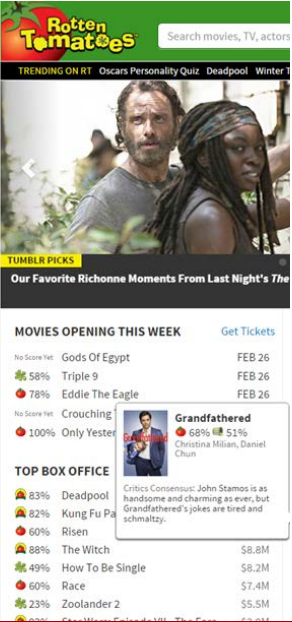
positive 2

total 13

tone $= \frac{2-11}{13} = \frac{-9}{13}$

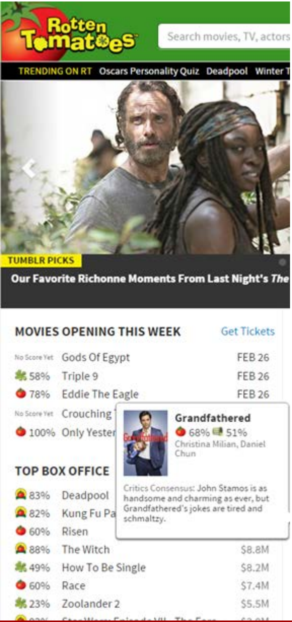
Partner Exercise

Partner Exercise



You are working for `rottentomatoes.com`, and want to automatically code (written) movie reviews as being between 1 and 5 stars.

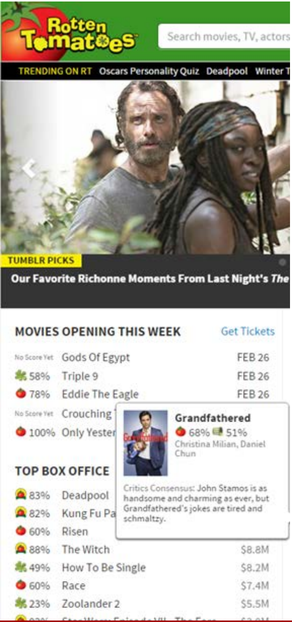
Partner Exercise



You are working for `rottentomatoes.com`, and want to automatically code (written) movie reviews as being between 1 and 5 stars.

1 Would the Hu & Liu approach work better for distinguishing a 1 star review from a 5 star review, or a 4 from a 5 star review? Why? How could you improve upon this?

Partner Exercise

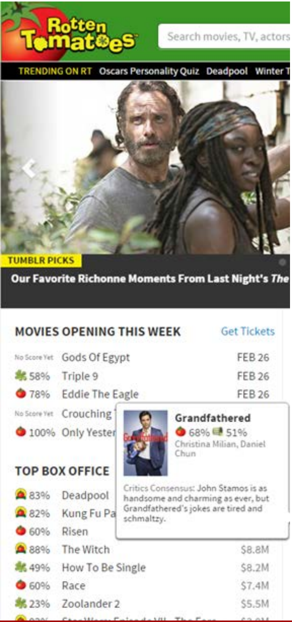


You are working for `rottentomatoes.com`, and want to automatically code (written) movie reviews as being between 1 and 5 stars.

1. Would the Hu & Liu approach work better for distinguishing a 1 star review from a 5 star review, or a 4 from a 5 star review? Why? How could you improve upon this?

2. Why does sarcasm cause problems, and what should we do about it?

Partner Exercise



You are working for `rottentomatoes.com`, and want to automatically code (written) movie reviews as being between 1 and 5 stars.

1. Would the Hu & Liu approach work better for distinguishing a 1 star review from a 5 star review, or a 4 from a 5 star review? Why? How could you improve upon this?
2. Why does sarcasm cause problems, and what should we do about it?
3. Why might be generally nervous about BOW approaches?

Notes

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka):

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued:

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate 'good' from 'great' from 'best'. Hard to come up with rules!

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate 'good' from 'great' from 'best'. Hard to come up with rules!

NB Tone of the document can be presented as a continuous value,

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate '`good`' from '`great`' from '`best`'. Hard to come up with rules!

NB Tone of the document can be presented as a continuous value, or used to put documents in categories via some cutoff rule.

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate 'good' from 'great' from 'best'. Hard to come up with rules!

NB Tone of the document can be presented as a continuous value, or used to put documents in categories via some cutoff rule.

e.g. all documents with tone>0 are deemed 'positive'

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate 'good' from 'great' from 'best'. Hard to come up with rules!

NB Tone of the document can be presented as a continuous value, or used to put documents in categories via some cutoff rule.

e.g. all documents with tone>0 are deemed 'positive'

NB Bag-of-words assn may be especially dubious for some dictionary tasks

Notes

Typically assume that "every word contributes isomorphically" (Young & Saroka): each word in dictionary has one of two values and sum totals matter.

But no requirement that s_m be dichotomous or integer valued: could be continuous.

e.g. might want to differentiate 'good' from 'great' from 'best'. Hard to come up with rules!

NB Tone of the document can be presented as a continuous value, or used to put documents in categories via some cutoff rule.

e.g. all documents with tone>0 are deemed 'positive'

NB Bag-of-words assn may be especially dubious for some dictionary tasks

e.g. context matters: "was `not` good" gets $+1$!

Sarcasm Detection

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic.

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic. Or prosody in spoken word (e.g. lower pitch).

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic. Or prosody in spoken word (e.g. lower pitch).

Davidov et al ('Semi-Supervised Recognition of Sarcastic Sentences in Twitter and Amazon') get good results by looking for particular pattern:

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic. Or prosody in spoken word (e.g. lower pitch).

Davidov et al ('Semi-Supervised Recognition of Sarcastic Sentences in Twitter and Amazon') get good results by looking for particular pattern: [high frequency word] [content word] [high frequency word] in reviews

Sarcasm Detection

Notoriously difficult problem (see Pang & Lee, 2008)

e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic. Or prosody in spoken word (e.g. lower pitch).

Davidov et al ('Semi-Supervised Recognition of Sarcastic Sentences in Twitter and Amazon') get good results by looking for particular pattern: [high frequency word] [content word] [high frequency word] in reviews

btw punctuation adds relatively little to accuracy.

Dictionaries I: General Inquirer

Dictionaries I: General Inquirer

Stone (1965) begins efforts to automatically analyze psychological states of authors

Dictionaries I: General Inquirer

Stone (1965) begins efforts to automatically analyze psychological states of authors

'General Inquirer' combines several dictionaries to make total of 182 categories:

Dictionaries I: General Inquirer

Stone (1965) begins efforts to automatically analyze psychological states of authors

'General Inquirer' combines several dictionaries to make total of 182 categories:

- Harvard IV-4 dictionary: psychology, themes, topics

Dictionaries I: General Inquirer

Stone (1965) begins efforts to automatically analyze psychological states of authors

'General Inquirer' combines several dictionaries to make total of 182 categories:

- Harvard IV-4 dictionary: psychology, themes, topics
- Lasswell dictionary: "commonsense categories of meaning", 8 basic value categories

Dictionaries I: General Inquirer

Stone (1965) begins efforts to automatically analyze psychological states of authors

'General Inquirer' combines several dictionaries to make total of 182 categories:

- Harvard IV-4 dictionary: psychology, themes, topics
- Lasswell dictionary: "commonsense categories of meaning", 8 basic value categories
- Semin and Fielder categories: interpersonal/pyschological properties of words

General Inquirer (selected)

General Inquirer (selected)

Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
ABSOLUTE#2	H4Lvd							Strong	

General Inquirer (selected)

Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
ABSOLUTE#2	H4Lvd							Strong	

provides dictionaries and software,

General Inquirer (selected)

Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
ABSOLUTE#2	H4Lvd							Strong	

provides dictionaries and software, which performs some stemming and disambiguation in terms of context

General Inquirer (selected)

Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
ABSOLUTE#2	H4Lvd							Strong	

provides dictionaries and software, which performs some stemming and disambiguation in terms of context

e.g. ADULT has two meanings: one is a 'virtue', one is a 'role'

Bainbridge, “Personality Capture” (2014)

Bainbridge, "Personality Capture" (2014)

	Declaration of Independence	'Plymouth Rock and the Pilgrims'
	Jefferson et al	Mark Twain

Bainbridge, “Personality Capture” (2014)

	Declaration of Independence	‘Plymouth Rock and the Pilgrims’
	Jefferson et al	Mark Twain
Affiliation	4.7%	2.1%
Hostile	3.6%	1.1%
Power	8.5%	1.8%
Submission	2.1%	1.0%

Bainbridge, “Personality Capture” (2014)

	Declaration of Independence	‘Plymouth Rock and the Pilgrims’
	Jefferson et al	**Mark Twain**
Affiliation	4.7%	2.1%
Hostile	3.6%	1.1%
Power	8.5%	1.8%
Submission	2.1%	1.0%
Virtue	3.9%	2.7%
Vice	1.7%	1.1%
Overstated	5.6%	3.9%
Understated	0.6%	2.5%

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al,

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, http://liwc.wpengine.com/

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories,

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories, organized hierarchically into 4 larger groups.

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories, organized hierarchically into 4 larger groups.

e.g. all anger words (e.g. `hate`) $\subset$ negative emotion $\subset$ affective processes $\subset$ psychological processes

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories, organized hierarchically into 4 larger groups.

e.g. all anger words (e.g. `hate`) $\subset$ negative emotion $\subset$ affective processes $\subset$ psychological processes

NB words can be in multiple categories,

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories, organized hierarchically into 4 larger groups.

e.g. all anger words (e.g. `hate`) $\subset$ negative emotion $\subset$ affective processes $\subset$ psychological processes

NB words can be in multiple categories, and each subdictionary score is incremented as such words appear.

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

Pennebaker et al, `http://liwc.wpengine.com/`

LIWC2007 dictionary contains 2290 words and word stems (see also LIWC2015)

80 categories, organized hierarchically into 4 larger groups.

e.g. all anger words (e.g. `hate`) $\subset$ negative emotion $\subset$ affective processes $\subset$ psychological processes

NB words can be in multiple categories, and each subdictionary score is incremented as such words appear.

Based on somewhat involved human coding/judgement and proprietary.

Pennebaker & Chung, 2007: Computerized Analysis of Al-Qaeda Transcripts

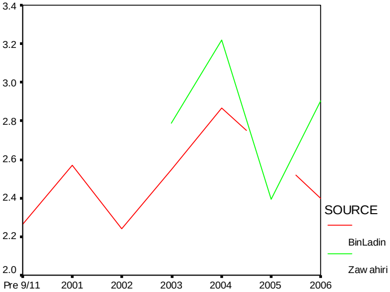
Pennebaker & Chung, 2007: Computerized Analysis of Al-Qaeda Transcripts

"The LIWC analyses suggest that Bin Ladin has been increasing in his cognitively complexity and emotionality since 9/11, as reflected by his increased use of exclusive, positive emotion, and negative emotion word use. "

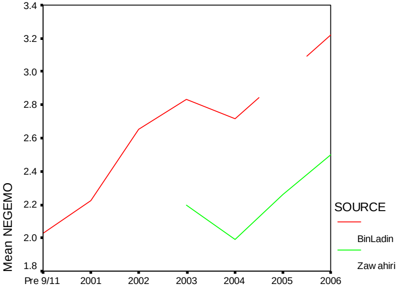
Pennebaker & Chung, 2007: Computerized Analysis of Al-Qaeda Transcripts

“The LIWC analyses suggest that Bin Ladin has been increasing in his cognitively complexity and emotionality since 9/11, as reflected by his increased use of exclusive, positive emotion, and negative emotion word use. ”

C. Positive emotion (happy, love)



D. Negative emotion (hate, sad)



Application: Ramey, Klingler & Hollibaugh

Application: Ramey, Klingler & Hollibaugh

Mairesse et al. (2007) provide estimates of 'big 5' personality traits from LIWC categories

Application: Ramey, Klingler & Hollibaugh

Mairesse et al. (2007) provide estimates of ‘big 5’ personality traits from LIWC categories

Application: Ramey, Klingler & Hollibaugh

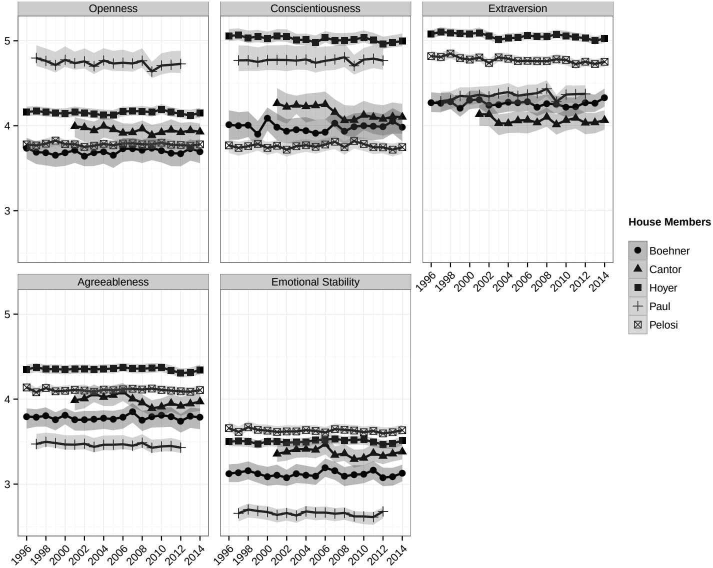
Mairesse et al. (2007) provide estimates of 'big 5' personality traits from LIWC categories

Ramey et al apply to Congressional speech.

Application: Ramey, Klingler & Hollibaugh

Mairesse et al. (2007) provide estimates of 'big 5' personality traits from LIWC categories

Ramey et al apply to Congressional speech.



Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

So combine GI and Roget's Thesaurus with...

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

So combine GI and Roget's Thesaurus with...

RID Regressive Imagery Dictionary which "was designed to distinguish between primordial and conceptual thinking"

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

So combine GI and Roget's Thesaurus with...

RID Regressive Imagery Dictionary which "was designed to distinguish between primordial and conceptual thinking"

plus much hand coding and validation using KWIC (from 10k newspapers), plus some special negation handling.

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

So combine GI and Roget's Thesaurus with...

RID Regressive Imagery Dictionary which "was designed to distinguish between primordial and conceptual thinking"

plus much hand coding and validation using KWIC (from 10k newspapers), plus some special negation handling.

NB high (0.75) correlation with LIWC,

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

Create dictionary specifically for political communication

So combine GI and Roget's Thesaurus with...

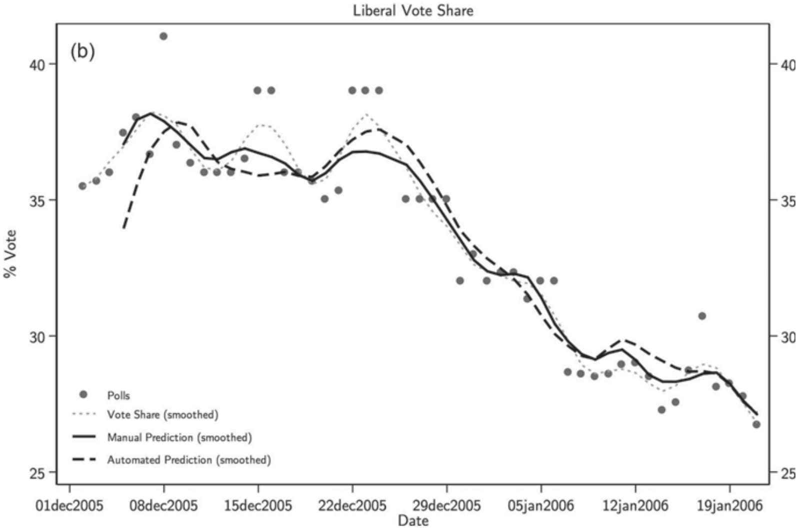
RID Regressive Imagery Dictionary which "was designed to distinguish between primordial and conceptual thinking"

plus much hand coding and validation using KWIC (from 10k newspapers), plus some special negation handling.

NB high (0.75) correlation with LIWC, though outperforms it when compared to manual coding of NYT.

Predicting Liberal Poll Vote (2006) as function of media tone

Predicting Liberal Poll Vote (2006) as function of media tone



Dictionaries IV: Laver & Garry

Dictionaries IV: Laver & Garry

2000 Laver and Garry create dictionary for manifestos where basic unit is strings of ~ 10 words in length.

Dictionaries IV: Laver & Garry

2000 Laver and Garry create dictionary for manifestos where basic unit is strings of ~ 10 words in length.

$\rightarrow$ hierarchical, with topmost level pertaining to five policy domains: economy, political system, social system, external relations, 'other' (waffle)

Dictionaries IV: Laver & Garry

2000 Laver and Garry create dictionary for manifestos where basic unit is strings of $\sim$ 10 words in length.

$\rightarrow$ hierarchical, with topmost level pertaining to five policy domains: economy, political system, social system, external relations, 'other' (waffle)

get good/valid results and high correlation with expert surveys.

Dictionaries IV: Laver & Garry

2000 Laver and Garry create dictionary for manifestos where basic unit is strings of ∼ 10 words in length.

→ hierarchical, with topmost level pertaining to five policy domains: economy, political system, social system, external relations, 'other' (waffle)

get good/valid results and high correlation with expert surveys.

1 1 1	ECONOMY/+State+/Budget Budget		
	1 1 1 1	ECONOMY/+State+/Budget/Spending Increase public spending	
		1 1 1 1 1	ECONOMY/+State+/Budget/Spending/Health
		1 1 1 1 2	ECONOMY/+State+/Budget/Spending/Educ. and training

Dictionaries V: Hu & Liu

Dictionaries V: Hu & Liu

2004 Hu and Liu ("Mining and Summarizing Customer Reviews")

Dictionaries V: Hu & Liu

2004 Hu and Liu ("Mining and Summarizing Customer Reviews") provide 6800 words which are positive and negative derived from `amazon.com` and others.

Dictionaries V: Hu & Liu

2004 Hu and Liu ("Mining and Summarizing Customer Reviews") provide 6800 words which are positive and negative derived from `amazon.com` and others.

Dictionaries V: Hu & Liu

2004 Hu and Liu ("Mining and Summarizing Customer Reviews") provide 6800 words which are positive and negative derived from `amazon.com` and others.

Being Careful. . .

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

$\rightarrow$ matter of adding extra words in the various categories.

Being Careful…

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

e.g. Loughran & MacDonald, 2011: common dictionaries fail badly when applied to financial texts

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

e.g. Loughran & MacDonald, 2011: common dictionaries fail badly when applied to financial texts—e.g. `cost` is a neutral term in reports, but negative in Harvard IV

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

e.g. Loughran & MacDonald, 2011: common dictionaries fail badly when applied to financial texts—e.g. `cost` is a neutral term in reports, but negative in Harvard IV

plus virtually impossible to validate dictionaries: very expensive,

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

e.g. Loughran & MacDonald, 2011: common dictionaries fail badly when applied to financial texts—e.g. `cost` is a neutral term in reports, but negative in Harvard IV

plus virtually impossible to validate dictionaries: very expensive, at least.

Being Careful...

In principle, it is straightforward to extend dictionary from one domain to another

→ matter of adding extra words in the various categories.

But much care is needed when a dictionary designed for one context is applied to another.

e.g. Loughran & MacDonald, 2011: common dictionaries fail badly when applied to financial texts—e.g. `cost` is a neutral term in reports, but negative in Harvard IV

plus virtually impossible to validate dictionaries: very expensive, at least.

btw humans *not* very good at producing discriminating terms for e.g. opinion mining (Pang et al, 2002)

Events, dear boy...

Events, dear boy...

Scholars of International Relations need access to events

Events, dear boy...

Scholars of International Relations need access to events

Real time media reports are obvious source...

Events, dear boy...

Scholars of International Relations need access to events

Real time media reports are obvious source...

ASIA PACIFIC

Leaders of South Korea and Japan Meet in Effort to Mend Ties

点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015

Events, dear boy. . .

Scholars of International Relations need access to events

Real time media reports are obvious source. . .


ASIA PACIFIC

Leaders of South Korea and Japan Meet in Effort to Mend Ties

点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015

Yet need to be coded automatically to be helpful.

Events, dear boy. . .

Scholars of International Relations need access to events

Real time media reports are obvious source. . .


ASIA PACIFIC

Leaders of South Korea and Japan Meet in Effort to Mend Ties

点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015

Yet need to be coded automatically to be helpful.

Partner Exercise

Partner Exercise

Consider compiling an events data set (by hand or by machine) from press reports.

Partner Exercise

Consider compiling an events data set (by hand or by machine) from press reports.

1 Would you prefer to have the universe of press reports from the United States, or the United Kingdom or North Korea? Why, and what does that tell you about journalistic agendas?

Partner Exercise

Consider compiling an events data set (by hand or by machine) from press reports.

1. Would you prefer to have the universe of press reports from the United States, or the United Kingdom or North Korea? Why, and what does that tell you about journalistic agendas?

2. Sports reports cause problems for automatic event extraction. Why?

Partner Exercise

Consider compiling an events data set (by hand or by machine) from press reports.

1. Would you prefer to have the universe of press reports from the United States, or the United Kingdom or North Korea? Why, and what does that tell you about journalistic agendas?

2. Sports reports cause problems for automatic event extraction. Why?

Premise and Resources

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 TABARI —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains. . .

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 TABARI —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed (‘lead’) contains...

source of event,

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 TABARI —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains...

source of event, subject of sentence

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 TABARI —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains...

source of event, subject of sentence

target of event,

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains...

source of event, subject of sentence

target of event, object of sentence (direct or indirect)

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains. . .

source of event, subject of sentence

target of event, object of sentence (direct or indirect)

type of event,

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains...

source of event, subject of sentence

target of event, object of sentence (direct or indirect)

type of event, transitive verb of sentence

Premise and Resources

1994 Philip Schrodt develops Kansas Event Data System

2000 `TABARI` —Textual Analysis by Augmeted Replacement Instructions—open source.

also many related products, including CAMEO dealing specifically with mediation

while Virtual Research Associates Reader VRA is proprietary version.

idea first sentence of Reuters news feed ('lead') contains...

source of event, subject of sentence

target of event, object of sentence (direct or indirect)

type of event, transitive verb of sentence

BTW...

BTW. . .

The Weather

Today—Showers, thunderstorms, high in 80s. Tuesday—Fair, less humid. Chance of rain, 20% tonight. Winds variable, 10-15 m.p.h. Temperature range: Today, 72-88; Yesterday, 78-88. Details, Page D3.

The Washington Post

Times Herald

FINAL

Amusements B 6 · Calendar B 4 · City Life D 1 · Classified D 4 · Comics C 8 · Crossword B 4 · Editorials A14 · Fed. Diary C 5 · Financial C 6 · Movie Guide B 7 · Obituaries D 2 · Sports C 1 · Style B 1 · TV-Radio B 5

92d Year ···· No. 228 · MONDAY, JULY 21, 1969 · Phone 223-6000 · 10c

'The Eagle Has Landed'— Two Men Walk on the Moon

BTW...

The Weather

Today—Showers, thunderstorms, high in 80s. Tuesday—Fair, less humid. Chance of rain, 20% tonight. Winds variable, 10-15 m.p.h. Temperature range: Today, 72-88; Yesterday, 78-88. Details, Page D3.

The Washington Post

Times Herald

FINAL

92d Year No. 228 MONDAY, JULY 21, 1969 Phone 223-6000 10c

'The Eagle Has Landed'—Two Men Walk on the Moon

intransitive

The Weather

Today—Showers, thunderstorms, high in 80s. Tuesday—Fair, less humid. Chance of rain, 20% tonight. Winds variable, 10-15 m.p.h. Temperature range: Today, 72-88; Yesterday, 76-88. Details, Page D3.

The Washington Post

Times Herald

FINAL

92d Year No. 228 — MONDAY, JULY 21, 1969 — Phone 223-6000 — 10c

'The Eagle Has Landed'—Two Men Walk on the Moon

intransitive

transitive

Use and Example (Lowe & King, 2003)

Use and Example (Lowe & King, 2003)

Russian artillery^{S} south of the Chechen capital Grozny blasted^{223} Chechen positions^{T} overnight before falling silent at dawn, witnesses said on Tuesday

Use and Example (Lowe & King, 2003)

Russian artillery^{S} south of the Chechen capital Grozny blasted^{223} Chechen positions^{T} overnight before falling silent at dawn, witnesses said on Tuesday

Use and Example (Lowe & King, 2003)

Russian artillery^{S} south of the Chechen capital Grozny blasted^{223} Chechen positions^{T} overnight before falling silent at dawn, witnesses said on Tuesday

S is the source

Use and Example (Lowe & King, 2003)

```
Russian artillery^S south of the Chechen capital
Grozny blasted^223 Chechen positions^T overnight
before falling silent at dawn, witnesses said on
Tuesday
```

S is the source

T is the target

Use and Example (Lowe & King, 2003)

> `Russian artillery`^{S} `south of the Chechen capital Grozny` `blasted`^{223} `Chechen positions`^{T} `overnight before falling silent at dawn, witnesses said on Tuesday`

S is the source

T is the target

223 is the code of the event between them

Hierarchical Coding Scheme (CAMEO)/Dictionary

Hierarchical Coding Scheme (CAMEO)/Dictionary

12: REJECT

120: Reject, not specified below

121: Reject material cooperation

- 1211: Reject economic cooperation
- 1212: Reject military cooperation

122: Reject request or demand for material aid, not specified below

- 1221: Reject request for economic aid
- 1222: Reject request for military aid
- 1223: Reject request for humanitarian aid
- 1224: Reject request for military protection or peacekeeping

12: REJECT

120: Reject, not specified below

121: Reject material cooperation

- 1211: Reject economic cooperation
- 1212: Reject military cooperation

122: Reject request or demand for material aid, not specified below

- 1221: Reject request for economic aid
- 1222: Reject request for military aid
- 1223: Reject request for humanitarian aid
- 1224: Reject request for military protection or peacekeeping

CAMEO	**1222**
Name	**Reject request for military aid**
Description	Refuse to extend military assistance.
Example	The Turkish government has refused to commit to any direct assistance to the US-led war against Iraq, citing domestic opposition.

Actors (CAMEO)/Dictionary

Actors (CAMEO)/Dictionary

UGAREBLRA	Lord's Resistance Army
UIG	Uighur (Chinese ethnic minority)
UIS	Unidentified state actors
UKR	Ukraine
URY	Uruguay
USA	United States
USR	Union of Soviet Socialist Republics (USSR)
UZB	Uzbekistan
VAT	Holy See (Vatican City)
VCT	Saint Vincent and the Grenadines
VEN	Venezuela
VGB	British Virgin Islands

Actors (CAMEO)/Dictionary

UGAREBLRA	Lord's Resistance Army
UIG	Uighur (Chinese ethnic minority)
UIS	Unidentified state actors
UKR	Ukraine
URY	Uruguay
USA	United States
USR	Union of Soviet Socialist Republics (USSR)
UZB	Uzbekistan
VAT	Holy See (Vatican City)
VCT	Saint Vincent and the Grenadines
VEN	Venezuela
VGB	British Virgin Islands

Delving More Deeply

Delving More Deeply

- Begins with basic parsing:

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.
- Much effort to disambiguate:

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. '`US`', '`American`'

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. `'US', 'American' ( 'US', 'Washington')`

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. `'US'`, `'American'` (`'US'`, `'Washington'`)

  Care over verb/noun problems.

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. `'US'`, `'American'` (`'US'`, `'Washington'`)

  Care over verb/noun problems.

  e.g. '`attack`' as noun and verb

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. `'US'`, `'American'` (`'US'`, `'Washington'`)

  Care over verb/noun problems.

  e.g. '`attack`' as noun and verb

- Excellent performance relative to human coders (Lowe & King, 2003):

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

  Use of pronouns causes problems.

  e.g. President is referred to as '`he`' in subsequent sentences

  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

  e.g. '`US`', '`American`' ('`US`', '`Washington`')

  Care over verb/noun problems.

  e.g. '`attack`' as noun and verb

- Excellent performance relative to human coders (Lowe & King, 2003): both in terms of reliability and validity.

Example: Dayton Peace Accords

Example: Dayton Peace Accords

Yugoslavia breaking up; Bosnian War

Example: Dayton Peace Accords

Yugoslavia breaking up; Bosnian War

$\rightarrow$ multiple peace attempts failed,

Example: Dayton Peace Accords

Yugoslavia breaking up; Bosnian War

→ multiple peace attempts failed,

Until US put intense pressure on parties.

Example: Dayton Peace Accords

Yugoslavia breaking up; Bosnian War

$\rightarrow$ multiple peace attempts failed,

Until US put intense pressure on parties.

$\rightarrow$ can we see this in automatic mediation estimates?

Example: Dayton Peace Accords

Yugoslavia breaking up; Bosnian War

→ multiple peace attempts failed,

Until US put intense pressure on parties.

→ can we see this in automatic mediation estimates?

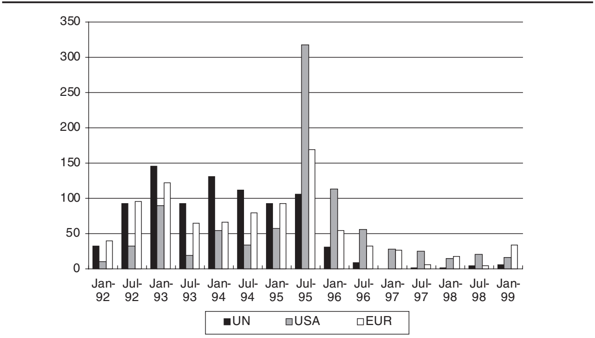


Figure 3: Six-Month Totals of Mediation Events in the Balkans by Mediator

NOTE: UN = United Nations; USA = United States; EUR = major European states, plus the European Union.

Making Dictionaries from Scratch

Making Dictionaries from Scratch

Not trivial,

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally,

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally, need to ensure that we get all relevant content (no false negatives) and only that content (no false positives)

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally, need to ensure that we get all relevant content (no false negatives) and only that content (no false positives)

Works best when the contrasts are binary/obvious

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally, need to ensure that we get all relevant content (no false negatives) and only that content (no false positives)

Works best when the contrasts are binary/obvious

e.g. obviously 'for' vs 'against'

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally, need to ensure that we get all relevant content (no false negatives) and only that content (no false positives)

Works best when the contrasts are binary/obvious

e.g. obviously ‘for’ vs ‘against’

NB Typically start with distinct types of documents (classified by hand),

Making Dictionaries from Scratch

Not trivial, extending pre-existing is the norm.

Generally, need to ensure that we get all relevant content (no false negatives) and only that content (no false positives)

Works best when the contrasts are binary/obvious

e.g. obviously ‘for’ vs ‘against’

NB Typically start with distinct types of documents (classified by hand), and learn which words are important for discriminating between them.

Word embeddings may offer automatic way forward here (Hamilton et al, “Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora”)

Discrimination

Discrimination

So Once researcher has *extreme* examples of text,

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them. . .

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them...

$\rightarrow$ these words then become scored as part of the dictionary/thesaurus.

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them...

$\rightarrow$ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them. . .

→ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

2013 Taddy provides *Multinomial Inverse Regression* to dimension reduce text, and make outcomes a product of that (reduced) set of Xs

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them. . .

$\rightarrow$ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

2013 Taddy provides *Multinomial Inverse Regression* to dimension reduce text, and make outcomes a product of that (reduced) set of Xs

$\rightarrow$ can be used to produce key predictors/keywords that discriminate in terms of categories.

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them...

→ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

2013 Taddy provides *Multinomial Inverse Regression* to dimension reduce text, and make outcomes a product of that (reduced) set of Xs

→ can be used to produce key predictors/keywords that discriminate in terms of categories.

2009 Monroe, Colaresi & Quinn consider ways to capture partisan differences in speech,

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them...

→ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

2013 Taddy provides *Multinomial Inverse Regression* to dimension reduce text, and make outcomes a product of that (reduced) set of Xs

→ can be used to produce key predictors/keywords that discriminate in terms of categories.

2009 Monroe, Colaresi & Quinn consider ways to capture partisan differences in speech, and suggest Bayesian shrinkage estimator approach.

Discrimination

So Once researcher has *extreme* examples of text, various methods to identify the words that discriminate between them...

→ these words then become scored as part of the dictionary/thesaurus. Can use `WordNet` to find synonyms.

2013 Taddy provides *Multinomial Inverse Regression* to dimension reduce text, and make outcomes a product of that (reduced) set of Xs

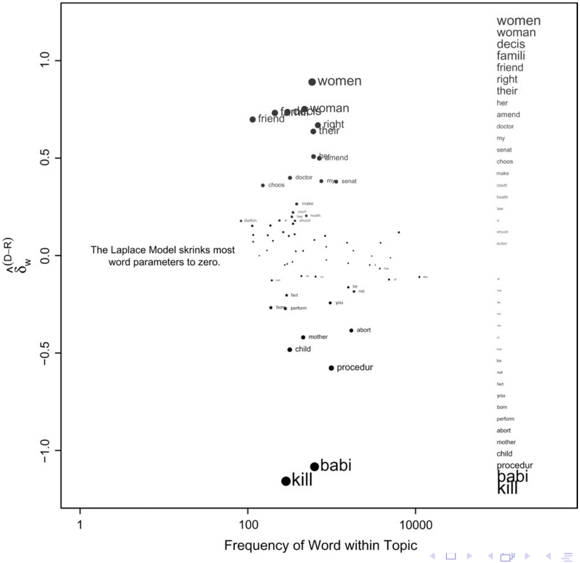
→ can be used to produce key predictors/keywords that discriminate in terms of categories.

2009 Monroe, Colaresi & Quinn consider ways to capture partisan differences in speech, and suggest Bayesian shrinkage estimator approach.

→ previous approaches tend to overfit to obscure words or groups that don't have much validity in context.

Most Democratic and Republican Words on Abortion (106th, Laplace prior)

Most Democratic and Republican Words on Abortion (106th, Laplace prior)



Goldman-Sachs Case Study

Goldman-Sachs Case Study

Goldman-Sachs Case Study

GS world's largest investment bank,

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Jari Stehn, GS Managing Director, senior economist in US Economics Group,

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Jari Stehn, GS Managing Director, senior economist in US Economics Group, Econ PhD from Oxford (macro focus),

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Jari Stehn, GS Managing Director, senior economist in US Economics Group, Econ PhD from Oxford (macro focus), previously employed at IMF.

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Jari Stehn, GS Managing Director, senior economist in US Economics Group, Econ PhD from Oxford (macro focus), previously employed at IMF.

Works alone or in pair to produce weekly report on investment topic of interest to clients, public, academics and policy makers.

Goldman-Sachs Case Study

GS world's largest investment bank, $\sim \$90B$ revenue.

Jari Stehn, GS Managing Director, senior economist in US Economics Group, Econ PhD from Oxford (macro focus), previously employed at IMF.

Works alone or in pair to produce weekly report on investment topic of interest to clients, public, academics and policy makers. Not peer-reviewed, but not 'journalism'.

Background

Background

Background

Federal Reserve Board oversees federal reserve system,

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Meet at least four times a year,

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Meet at least four times a year, and release statement after meeting (followed by minutes, also release 'Beige book' of economic indicators 8 times a year)

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Meet at least four times a year, and release statement after meeting (followed by minutes, also release ‘Beige book’ of economic indicators 8 times a year)

FOMC perception of economic situation has extremely influential effects on financial markets,

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Meet at least four times a year, and release statement after meeting (followed by minutes, also release 'Beige book' of economic indicators 8 times a year)

FOMC perception of economic situation has extremely influential effects on financial markets, so are made with great care via 'Fedspeak'—

Background

Federal Reserve Board oversees federal reserve system, and sets monetary policy via Federal Open Market Committee decisions on interest rates.

Meet at least four times a year, and release statement after meeting (followed by minutes, also release 'Beige book' of economic indicators 8 times a year)

FOMC perception of economic situation has extremely influential effects on financial markets, so are made with great care via 'Fedspeak'—which is ambiguous in tone.

Example from Sept 2015

Example from Sept 2015

Information received since the Federal Open Market Committee met in July suggests that economic activity is expanding at a moderate pace. Household spending and business fixed investment have been increasing moderately, and the housing sector has improved further; however, net exports have been soft.

Example from Sept 2015

Information received since the Federal Open Market Committee met in July suggests that economic activity is expanding at a moderate pace. Household spending and business fixed investment have been increasing moderately, and the housing sector has improved further; however, net exports have been soft.

The Committee continues to see the risks to the outlook for economic activity and the labor market as nearly balanced but is monitoring developments abroad. Inflation is anticipated to remain near its recent low level in the near term but the Committee expects inflation to rise gradually toward 2 percent over the medium term as the labor market improves further and the transitory effects of declines in energy and import prices dissipate.

Partner Exercise

Partner Exercise

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting?

Partner Exercise

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

Partner Exercise

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Partner Exercise

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Problem and Approach

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting?

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Use 'hawkish' and 'dovish' dictionary,

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Use ‘hawkish’ and ‘dovish’ dictionary, with key measure being ratio of those terms.

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Use 'hawkish' and 'dovish' dictionary, with key measure being ratio of those terms.

$\rightarrow$ nouns (`strength` vs `recession`) and adjectives (`healthy`, vs `weak`)

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Use 'hawkish' and 'dovish' dictionary, with key measure being ratio of those terms.

$\rightarrow$ nouns (`strength` vs `recession`) and adjectives (`healthy`, vs `weak`)

NB statements generally most marginally informative (as expected, since they come first),

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

$\rightarrow$ How?

Use 'hawkish' and 'dovish' dictionary, with key measure being ratio of those terms.

$\rightarrow$ nouns (`strength` vs `recession`) and adjectives (`healthy`, vs `weak`)

NB statements generally most marginally informative (as expected, since they come first), with pseudo-R^2 (from ordered logit/probit?) ~ 0.15

Problem and Approach

Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting? (range is 1994–2013)

→ How?

Use 'hawkish' and 'dovish' dictionary, with key measure being ratio of those terms.

→ nouns ('`strength`' vs '`recession`') and adjectives ('`healthy`', vs '`weak`')

NB statements generally most marginally informative (as expected, since they come first), with pseudo-R^2 (from ordered logit/probit?) ~ 0.15

→ rising to ~ 0.25 when all sources included (NB: speeches generally uninformative)

More Results

More Results

Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

More Results

Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

+ count terms pertaining to (un)certainty

More Results

Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

\+ count terms pertaining to (un)certainty

Themes about growth are most important for monetary policy

More Results

Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

+ count terms pertaining to (un)certainty

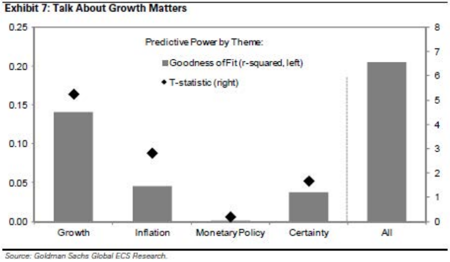
Themes about growth are most important for monetary policy

Show predictions from this model do a good job of tracking actual policy over time.

More Results

Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

+ count terms pertaining to (un)certainty



Themes about growth are most important for monetary policy

Show predictions from this model do a good job of tracking actual policy over time.

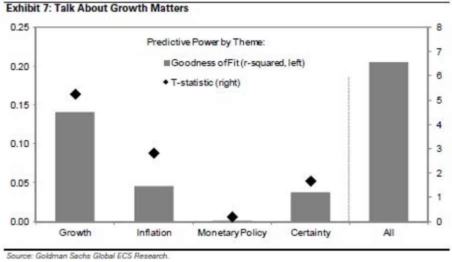
More Results

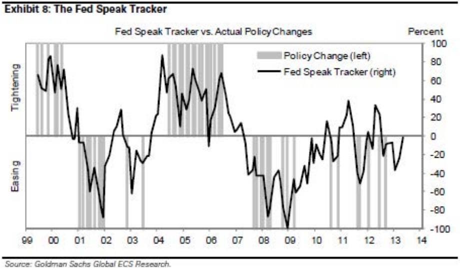
Next, study themes of documents: pairs of hawkish/dovish adjectives that pertain to nouns of various topics—growth, inflation, monetary policy.

+ count terms pertaining to (un)certainty

Themes about growth are most important for monetary policy

Show predictions from this model do a good job of tracking actual policy over time.





Lie Detection

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication—email.

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication—email.

So Recruit undergrad students,

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication—email.

So Recruit undergrad students, and have them play roles in Desert Survival Problem where they need to agree on 12 items to take from crashed jeep.

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication—email.

So Recruit undergrad students, and have them play roles in Desert Survival Problem where they need to agree on 12 items to take from crashed jeep.

+ one person in dyad told to deceive other and not represent true preferences about rank order.

Lie Detection

Zhou et al (2004) investigate whether deception can be detected in Text-based Asynchronous Computer-Mediated Communication—email.

So Recruit undergrad students, and have them play roles in Desert Survival Problem where they need to agree on 12 items to take from crashed jeep.

+ one person in dyad told to deceive other and not represent true preferences about rank order.

Item	Your Rank	Actual Rank	Team Rank	Team Difference	Your Difference
A ball of steel wool					
A small ax					
A loaded .45-caliber pistol					
Can of Crisco shortening					
Newspapers (one per person)					
Cigarette lighter (without fluid)					
Extra shirt and pants for each survivor					
20 x 20 ft. piece of heavy-duty canvas					
A sectional air map made of plastic					
One quart of 100-proof whiskey					
A compass					
Family-size chocolate bars (one per person)					
Score					

Partner Exercise

Partner Exercise

Partner Exercise

Q how would you expect deceiver's messages differ from truth tellers?

Partner Exercise

Q how would you expect deceiver's messages differ from truth tellers?

$\rightarrow$ in terms of e.g. number of words, informality, uncertainty, complexity, pausality etc.

Results

Results

Q how do deceiver's messages differ from truth tellers?

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality:

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

less complex and less diverse ($\sim$TTR)

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

less complex and less diverse ($\sim$TTR)

less pausality (more punctuation), more group references (`we`)

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

less complex and less diverse ($\sim$TTR)

less pausality (more punctuation), more group references ('we')

btw, passive voice means subject and object of sentence are switched:

Results

Q how do deceiver's messages differ from truth tellers?

A used more words, verbs, noun phrases, sentences

more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

less complex and less diverse ($\sim$TTR)

less pausality (more punctuation), more group references ('`we`')

btw, passive voice means subject and object of sentence are switched: "`I am packing my bag`" $\rightarrow$ "`My bag is being packed by me.`"

I will **definitely** see you next time, when I intend to forego persiflage and conduct a profound lucubration, skirring over new topics in a way that could never be described as prolix.