Affective meaning

Drawing on literatures in

- affective computing (Picard 95)
- linguistic subjectivity (Wiebe and colleagues)
- social psychology (Pennebaker and colleagues)

Can we model the lexical semantics relevant to:

- sentiment
- emotion
- personality
- mood
- attitudes

Why compute affective meaning?

Detecting:

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

Could we generate:

- emotions or moods for literacy tutors in the children's storybook domain
- emotions or moods for computer games
- personalities for dialogue systems to match the user

Connotation in the lexicon

Words have connotation as well as sense

Can we build lexical resources that represent these connotations?

And use them in these computational tasks?

Scherer Typology of Affective States

Emotion: brief organically synchronized … evaluation of a major event

- *angry, sad, joyful, fearful, ashamed, proud, elated*

Mood: diffuse non-caused low-intensity long-duration change in subjective feeling

- *cheerful, gloomy, irritable, listless, depressed, buoyant*

Interpersonal stances: affective stance toward another person in a specific interaction

- *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*

Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons

- *liking, loving, hating, valuing, desiring*

Personality traits: stable personality dispositions and typical behavior tendencies

- *nervous, anxious, reckless, morose, hostile, jealous*

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What is a Lexicon?

A (usually hand-built) list of words that correspond to some meaning or class

Possibly with numeric values

Commonly used as simple classifiers, or as features to more complex classifiers

Scherer's typology of affective states

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

angry, sad, joyful, fearful, ashamed, proud, desperate

Mood: diffuse affect state …change in subjective feeling, of low intensity but relatively long duration, often without apparent cause

cheerful, gloomy, irritable, listless, depressed, buoyant

Interpersonal stance: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange

distant, cold, warm, supportive, contemptuous

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

liking, loving, hating, valuing, desiring

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

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

Two families of theories of emotion

Atomic basic emotions

- A finite list of 6 or 8, from which others are generated

Dimensions of emotion

- Valence (positive negative)
- Arousal (strong, weak)
- Control

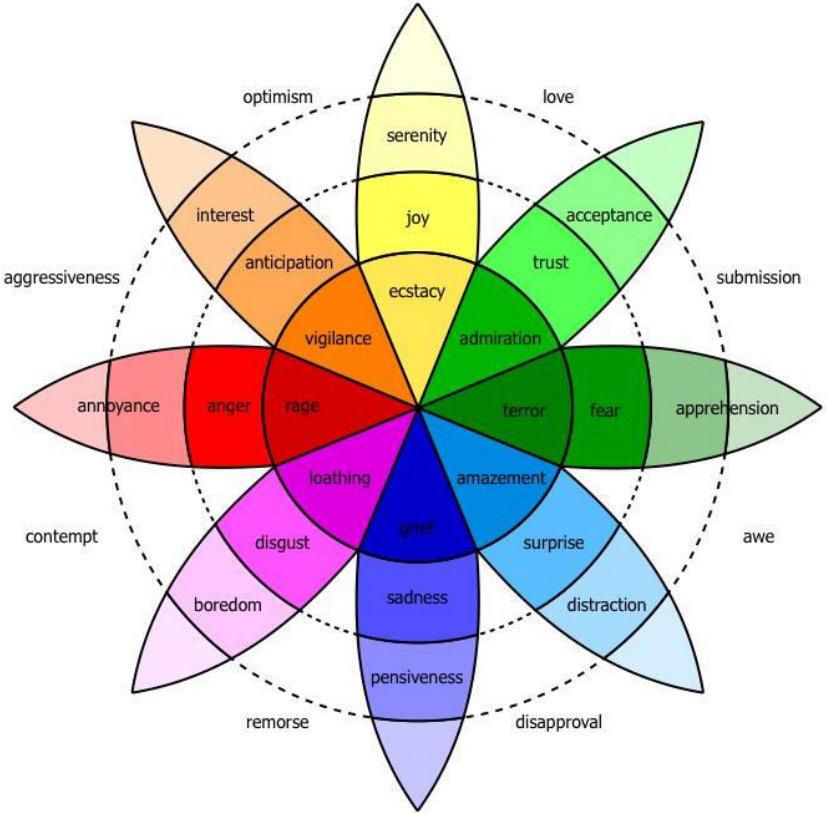
Ekman's 6 basic emotions:

Surprise, happiness, anger, fear, disgust, sadness

Ekman & Matsumoto 1989

Plutchick's wheel of emotion

- 8 basic emotions
- in four opposing pairs:
  - joy–sadness
  - anger–fear
  - trust–disgust
  - anticipation–surprise



Wikipedia

Alternative: spatial model

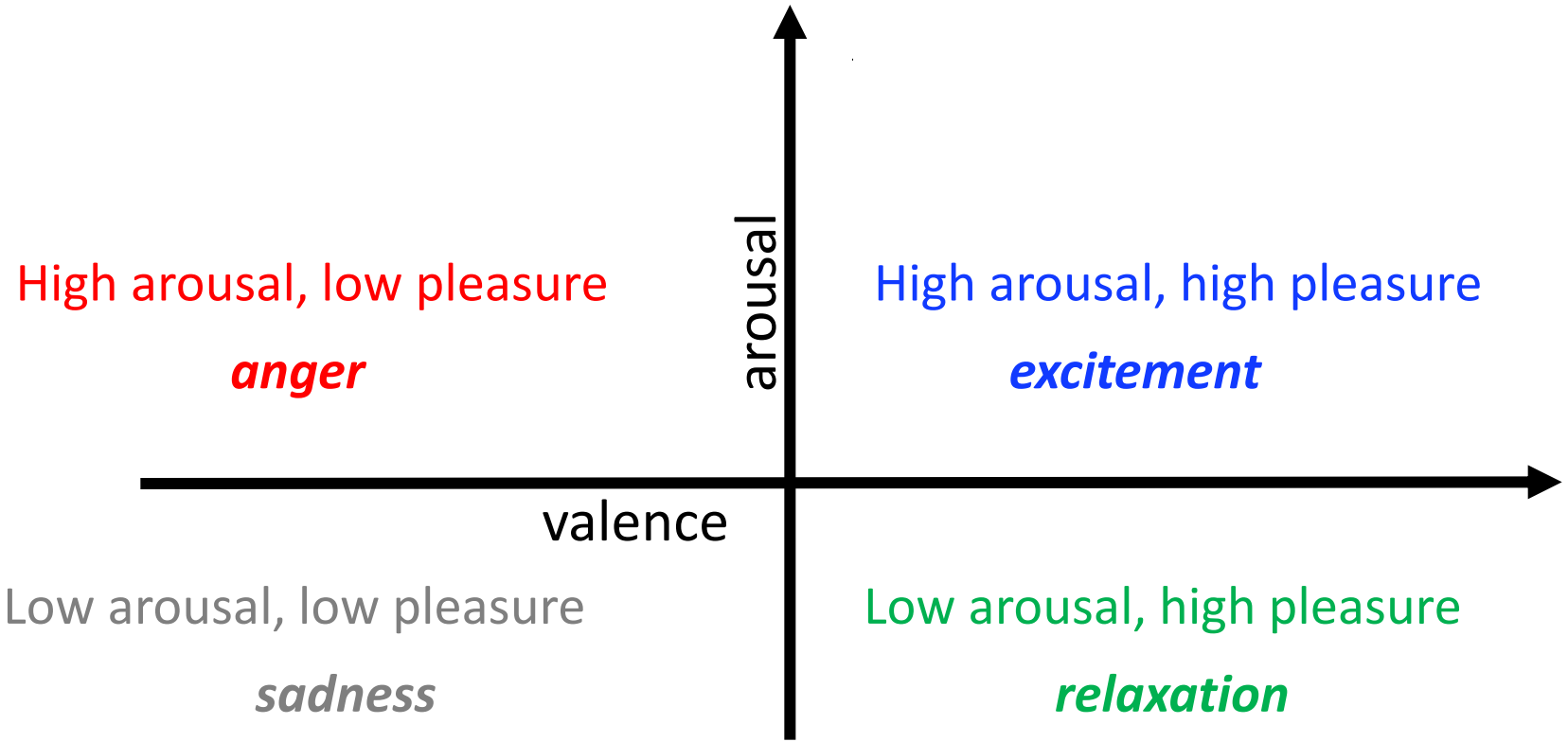
An emotion is a point in 2- or 3-dimensional space

valence: the pleasantness of the stimulus

arousal: the intensity of emotion provoked by the stimulus

(sometimes) **dominance**: the degree of control exerted by the stimulus

Valence/Arousal Dimensions



The General Inquirer

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

Positiv (1915 words)

Negativ (2291 words)

1	Entry	Source	Positiv	Negati
2586	DAKOTA	Lvd		
2587	DAMAGE#1	H4Lvd		Negati
2588	DAMAGE#2	H4Lvd		Negati
2589	DAMN	H4Lvd		Negati
2590	DAMNABLE	H4		Negati
2591	DAMNED	H4		Negati
2592	DAMP	H4Lvd		
2593	DANCE#1	H4Lvd	Positiv	
2594	DANCE#2	H4Lvd	Positiv	
2595	DANCE#3	H4Lvd	Positiv	
2596	DANCER	H4Lvd		
2597	DANGER	H4Lvd		Negati
2598	DANGEROUS	H4Lvd		Negati
2599	DANISH	Lvd		
2600	DARE	H4Lvd	Positiv	
2601	DARING	H4Lvd	Positiv	
2602	DARK	H4Lvd		Negati
2603	DARKEN	H4Lvd		Negati
2604	DARKNESS	H4Lvd		Negati
2605	DARLING	H4Lvd	Positiv	

MPQA Subjectivity Cues Lexicon

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

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

6885 words

Is a subjective word positive or negative?

- Strongly or weakly?

http://mpqa.cs.pitt.edu/lexicons/

GNU GPL

type=**weaksubj** len=1 word1=**abandoned** pos1=adj stemmed1=n priorpolarity=**negative**

type=weaksubj len=1 word1=**abandonment** pos1=noun stemmed1=n priorpolarity=negative

type=weaksubj len=1 word1=**abandon** pos1=verb stemmed1=y priorpolarity=negative

type=strongsubj len=1 word1=**abase** pos1=verb stemmed1=y priorpolarity=negative

type=**strongsub**j len=1 word1=**abasement** pos1=anypos stemmed1=y priorpolarity=negative

type=strongsubj len=1 word1=**abash** pos1=verb stemmed1=y priorpolarity=negative

type=weaksubj len=1 word1=**abate** pos1=verb stemmed1=y priorpolarity=negative

Words with consistent sentiment across lexicons

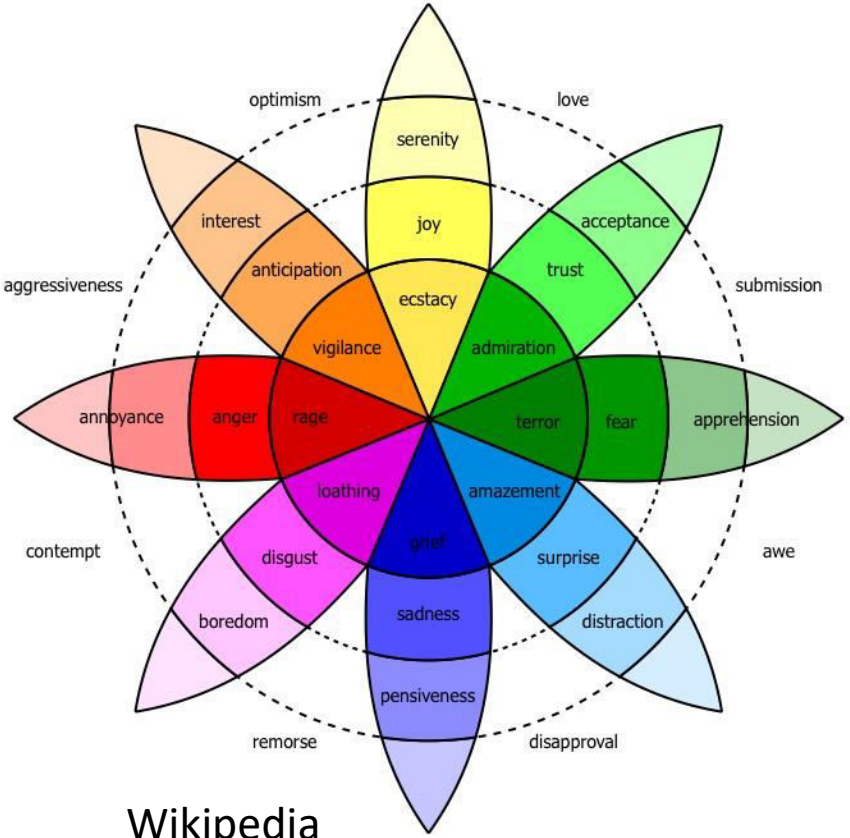
Positive	admire, amazing, assure, celebration, charm, eager, enthusiastic, excellent, fancy, fantastic, frolic, graceful, happy, joy, luck, majesty, mercy, nice, patience, perfect, proud, rejoice, relief, respect, satisfactorily, sensational, super, terrific, thank, vivid, wise, wonderful, zest
Negative	abominable, anger, anxious, bad, catastrophe, cheap, complaint, condescending, deceit, defective, disappointment, embarrass, fake, fear, filthy, fool, guilt, hate, idiot, inflict, lazy, miserable, mourn, nervous, objection, pest, plot, reject, scream, silly, terrible, unfriendly, vile, wicked

Let’s look at two emotion lexicons!

1. 8 basic emotions:
   - NRC Word-Emotion Association Lexicon (Mohammad and Turney 2011)
2. Dimensions of valence/arousal/dominance
   - NRC Valence-Arousal-Dominance Lexicon (Mohammad 2018)

Plutchick's wheel of emotion

- 8 basic emotions
- in four opposing pairs:
  - joy–sadness
  - anger–fear
  - trust–disgust
  - anticipation–surprise



Wikipedia

NRC Word-Emotion Association Lexicon

Mohammad and Turney 2011

```
amazingly   anger   0
amazingly   anticipation 0
amazingly   disgust 0
amazingly   fear    0
amazingly   joy      1
amazingly   sadness 0
amazingly   surprise    1
amazingly   trust     0
amazingly   negative    0
amazingly   positive    1
```

More examples

Word	anger	anticipation	disgust	fear	joy	sadness	surprise	trust	positive	negative
reward	0	1	0	0	1	0	1	1	1	0
worry	0	1	0	1	0	1	0	0	0	1
tenderness	0	0	0	0	1	0	0	0	1	0
sweetheart	0	1	0	0	1	1	0	1	1	0
suddenly	0	0	0	0	0	0	1	0	0	0
thirst	0	1	0	0	0	1	1	0	0	0
garbage	0	0	1	0	0	0	0	0	0	1

NRC Emotion/Affect Intensity Lexicon (Mohammad, 2018b); real values for 5814 words

Anger		Fear		Joy		Sadness	
outraged	0.964	horror	0.923	superb	0.864	sad	0.844
violence	0.742	anguish	0.703	cheered	0.773	guilt	0.750
coup	0.578	pestilence	0.625	rainbow	0.531	unkind	0.547
oust	0.484	stressed	0.531	gesture	0.387	difficulties	0.421
suspicious	0.484	failing	0.531	warms	0.391	beggar	0.422
nurture	0.059	confident	0.094	hardship	.031	sing	0.017

Other Useful Lexicons

LIWC: Linguistic Inquiry and Word Count

Positive Emotion	Negative Emotion	Insight	Inhibition	Family	Negate
appreciat*	anger*	aware*	avoid*	brother*	aren't
comfort*	bore*	believe	careful*	cousin*	cannot
great	cry	decid*	hesitat*	daughter*	didn't
happy	despair*	feel	limit*	family	neither
interest	fail*	figur*	oppos*	father*	never
joy*	fear	know	prevent*	grandf*	no
perfect*	griev*	knew	reluctan*	grandm*	nobod*
please*	hate*	means	safe*	husband	none
safe*	panic*	notice*	stop	mom	nor
terrific	suffers	recogni*	stubborn*	mother	nothing
value	terrify	sense	wait	niece*	nowhere
wow*	violent*	think	wary	wife	without

LIWC (Linguistic Inquiry and Word Count)

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

http://www.liwc.net/

2300 words

>70 classes

The General Inquirer

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

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls

Categories:

- Positiv (1915 words) and Negativ (2291 words)
- Strong vs Weak, Active vs Passive, Overstated versus Understated
- **Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc**

Free for Research Use

Concreteness versus abstractness

The degree to which the concept denoted by a word refers to a perceptible entity.

Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014) Concreteness ratings for 40 thousand generally known English word lemmas *Behavior Research Methods 46, 904-911.*

37,058 English words and 2,896 two-word expressions (“zebra crossing” and “zoom in”),

Rating from 1 (abstract) to 5 (concrete)

Concreteness versus abstractness

Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014) Concreteness ratings for 40 thousand generally known English word lemmas *Behavior Research Methods 46, 904-911.*

Some example ratings from the final dataset of 40,000 words and phrases

```
banana 5
bathrobe 5
bagel 5
brisk 2.5
badass 2.5
basically 1.32
belief 1.19
although 1.07
```

Building Lexicons using Human Labelers

Where do lexicons come from?

- One method: crowdsourcing!!!
- 10,000 words
  - Collected from earlier lexicons
- Labeled by workers on Amazon Mechanical Turk
  - “Turkers”
- 5 Turkers per hit

The AMT(Amazon Mechanical Turk) Hit(Human Intelligence Task)

Q4. How much is *startle* associated with the emotion joy? (For example, *happy* and *fun* are strongly associated with joy.)

- *startle* is not associated with joy
- *startle* is weakly associated with joy
- *startle* is moderately associated with joy
- *startle* is strongly associated with joy

Q5. How much is *startle* associated with the emotion sadness? (For example, *failure* and *heart-break* are strongly associated with sadness.)

- *startle* is not associated with sadness
- *startle* is weakly associated with sadness
- *startle* is moderately associated with sadness
- *startle* is strongly associated with sadness

Q6. How much is *startle* associated with the emotion fear? (For example, *horror* and *scary* are strongly associated with fear.)

...

NRC Valence, Arousal, Dominance (VAD) lexicon

Mohammad (2018)

20,000 words, 3 emotional dimensions:

- **valence** (the pleasantness of the stimulus)
- **arousal** (the intensity of emotion provoked by the stimulus)
- **dominance** (the degree of control exerted by the stimulus)

Best-worst scaling: valence

Q1. Which of the four words below is associated with the MOST happiness / pleasure / positiveness / satisfaction / contentedness / hopefulness OR LEAST unhappiness / annoyance / negativeness / dissatisfaction / melancholy / despair?

vacation, consolation, whistle, torture

Q2. Which of the four words below is associated with the LEAST happiness / pleasure / positiveness / satisfaction / contentedness / hopefulness OR MOST unhappiness / annoyance / negativeness / dissatisfaction / melancholy / despair?

Lexicon of valence, arousal, and dominance

Valence		Arousal		Dominance	
delightful	.918	enraged	.962	powerful	.991
vacation	.840	party	.840	authority	.935
whistle	.653	organized	.337	saxophone	.482
consolation	.408	effortless	.120	discouraged	.0090
torture	.115	napping	.046	weak	.045

Issues to keep in mind with crowdsourcing lexicons

Native (or very fluent) speakers

Making the task clear for non-linguists or non computer scientists

Paying minimum wage (fairwork.stanford.edu)

Building Lexicons using Human Labelers

Semi-supervised Induction of Affect Lexicons

Semantic Axis Methods

(An et al., 2018, Turney and Littman 2003)

Start with seed words like *good* or *bad* for the two poles

For each word to be added to lexicon

- Compute a word representation
- Use this to measure its distance from the poles
- Assign it to the pole it is closer to

Initial seeds for different domains

(1) Start with a single large seed lexicon and rely on the induction algorithm to fine-tune it to the domain

(2) Choose different seed words for different genres:

Domain	Positive seeds	Negative seeds
General	good, lovely, excellent, fortunate, pleasant, delightful, perfect, loved, love, happy	bad, horrible, poor, unfortunate, unpleasant, disgusting, evil, hated, hate, unhappy
Twitter	love, loved, loves, awesome, nice, amazing, best, fantastic, correct, happy	hate, hated, hates, terrible, nasty, awful, worst, horrible, wrong, sad
Finance	successful, excellent, profit, beneficial, improving, improved, success, gains, positive	negligent, loss, volatile, wrong, losses, damages, bad, litigation, failure, down, negative

Compute representation

Can just use off-the-shelf static embeddings

- word2vec, GloVe, etc.

Or compute on a corpus

Or fine-tune pre-trained embeddings to a corpus

Represent each pole

Start with embeddings for seed words:

$$S^+ = \{E(w_1^+), E(w_2^+), ..., E(w_n^+)\}$$

$$S^- = \{E(w_1^-), E(w_2^-), ..., E(w_m^-)\}$$

Pole centroids are:

$$\mathbf{V}^+ = \frac{1}{n}\sum_{1}^{n} E(w_i^+)$$

$$\mathbf{V}^- = \frac{1}{m}\sum_{1}^{m} E(w_i^-)$$

Semantic axis is:

$$\mathbf{V}_{axis} = \mathbf{V}^+ - \mathbf{V}^-$$

Word score is cosine with axis

$$\begin{aligned} \text{score}(w) &= \left(\cos(E(w), \mathbf{V}_{\text{axis}}\right) \\ &= \frac{E(w) \cdot \mathbf{V}_{\text{axis}}}{\|E(w)\| \|\mathbf{V}_{\text{axis}}\|} \end{aligned}$$

Label Propagation Methods

Alternative to axis methods: propagate sentiment labels on word graphs

First proposed by Hatzivassiloglou and McKeown (1997)

Let's see method of Hamilton et al. 2016

Label Propagation (Hamilton et al., 2016 version)

1. Define a graph: connecting each word with *k* nearest neighbor

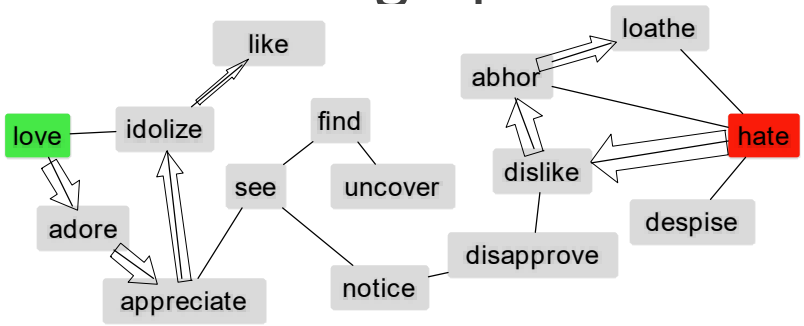
$$\mathbf{E}_{i,j} = \arccos\left(-\frac{\mathbf{w_i}^\top \mathbf{w_j}}{\|\mathbf{w_i}\|\|\mathbf{w_j}\|}\right)$$

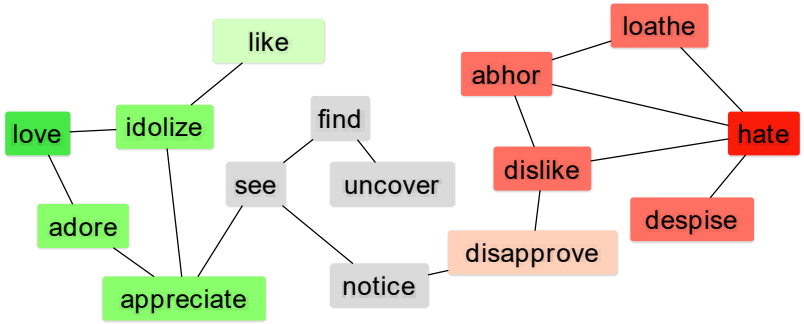
2. Define a seed set (pos and neg words)

love, hate, etc

Label Propagation (Hamilton et al., 2016 version)

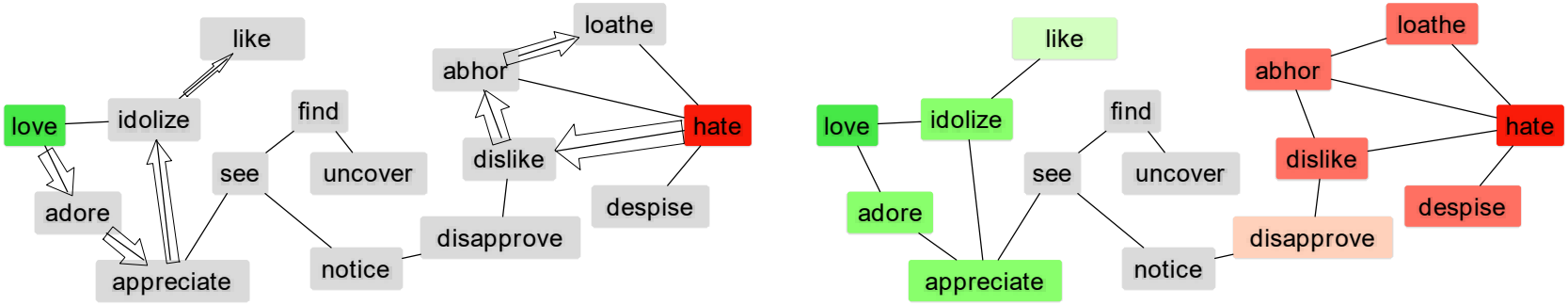
3. Propagate polarities from the seed set: randomly walk on the graph





Polarity score is proportional to probability of random walk landing on word

Label Propagation (Hamilton et al., 2016 version)

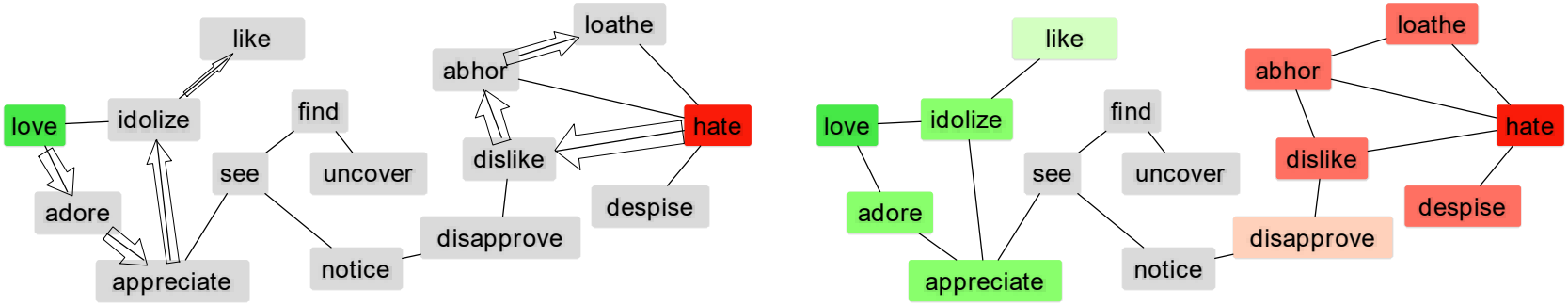


4. Create word scores:

- Walking from positive and negative seedsets
  - Gives $\text{rawscore}^{+}(w_i)$ and $\text{rawscore}^{-}(w_i)$
- Combine into one score:

$$\text{score}^{+}(w_i) = \frac{\text{rawscore}^{+}(w_i)}{\text{rawscore}^{+}(w_i) + \text{rawscore}^{-}(w_i)}$$

Label Propagation (Hamilton et al., 2016 version)



5. Assign confidence via bootstrap sampling:

- Compute the propagation *B* times over random subsets of the positive and negative seed sets
- The standard deviation of the bootstrap sampled polarity scores gives a confidence measure.

Other metrics besides cosine:

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

Adjectives conjoined by "*and*" have same polarity

- Fair **and** legitimate, corrupt **and** brutal
- *fair **and** brutal, *corrupt **and** legitimate

Adjectives conjoined by "*but*" do not

- fair **but** brutal

Supervised Learning of Word Sentiment

Learn word sentiment supervised by online review scores

Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.
Potts 2011 NSF Workshop talk.

Review datasets

- IMDB, Goodreads, Open Table, Amazon, Trip Advisor

Each review has a score (1-5, 1-10, etc)

Just count how many times each word occurs with each score

- (and normalize)

Online review data

	Movie review excerpts (IMDb)
10	A great movie. This film is just a wonderful experience. It's surreal, zany, witty and slapstick all at the same time. And terrific performances too.
1	This was probably the worst movie I have ever seen. The story went nowhere even though they could have done some interesting stuff with it.
	Restaurant review excerpts (Yelp)
5	The service was impeccable. The food was cooked and seasoned perfectly... The watermelon was perfectly square ... The grilled octopus was ... mouthwatering...
2	...it took a while to get our waters, we got our entree before our starter, and we never received silverware or napkins until we requested them...
	Book review excerpts (GoodReads)
1	I am going to try and stop being deceived by eye-catching titles. I so wanted to like this book and was so disappointed by it.
5	This book is hilarious. I would recommend it to anyone looking for a satirical read with a romantic twist and a narrator that keeps butting in
	Product review excerpts (Amazon)
5	The lid on this blender though is probably what I like the best about it... enables you to pour into something without even taking the lid off! ... the perfect pitcher! ... works fantastic.
1	I hate this blender... It is nearly impossible to get frozen fruit and ice to turn into a smoothie... You have to add a TON of liquid. I also wish it had a spout ...

Analyzing the polarity of each word in IMDB

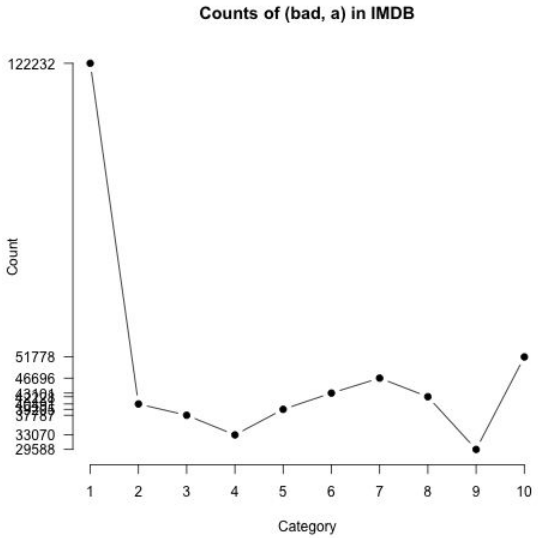
Potts, Christopher. 2011. On the negativity of negation. SALT 20, 636-659.

How likely is each word to appear in each sentiment class?

Count("bad") in 1-star, 2-star, 3-star, etc.

But can't use raw counts:

Instead, **likelihood:** $P(w|c) = \frac{f(w,c)}{\sum_{w} f(w,c)}$



Make them comparable between words

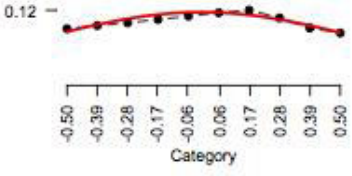
- **Scaled likelihood:** $\frac{P(w|c)}{P(w)}$

“Potts diagrams”

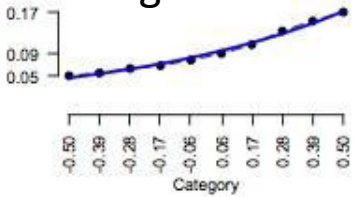
Potts, Christopher. 2011. NSF workshop on restructuring adjectives.

Positive scalars

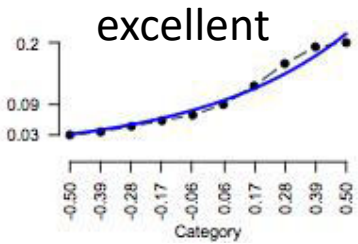
good



great

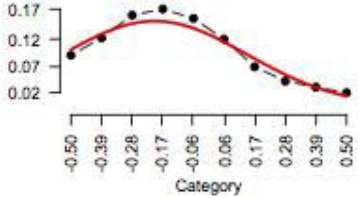


excellent

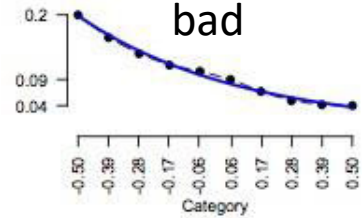


Negative scalars

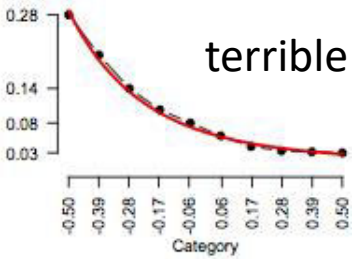
disappointing



bad

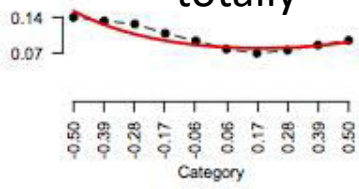


terrible

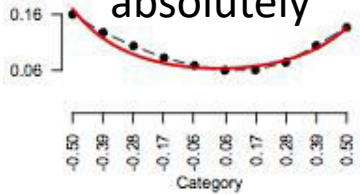


Emphatics

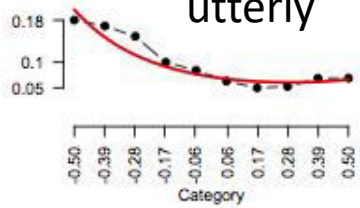
totally



absolutely

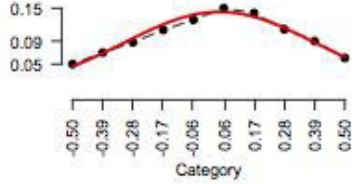


utterly

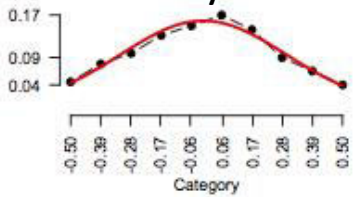


Attenuators

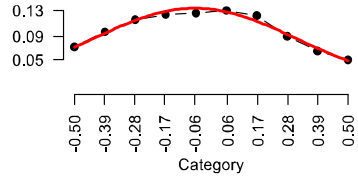
somewhat



fairly



pretty



Or use regression coefficients to weight words

Train a classifier based on supervised data

- Predict: human-labeled connotation of a document
- From: all the words and bigrams in it

Use the regression coefficients as the weights

Log odds ratio informative Dirichlet prior

Monroe, B. L., Colaresi, M. P., and Quinn, K. M. (2008). Fightin'words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis 16*(4), 372–403.

Log likelihood ratio: does "horrible" occur more % in corpus A or B?

$$\begin{aligned}
\text{llr}(horrible) &= \log \frac{P^i(horrible)}{P^j(horrible)} \\
&= \log P^i(horrible) - \log P^j(horrible) \\
&= \log \frac{\text{f}^i(horrible)}{n^i} - \log \frac{\text{f}^j(horrible)}{n^j}
\end{aligned}$$

Log odds ratio informative Dirichlet prior

Monroe, B. L., Colaresi, M. P., and Quinn, K. M. (2008). Fightin'words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis 16*(4), 372–403.

Log odds ratio: does "horrible" have higher odds in A or B?

$$\begin{aligned}
\text{lor}(horrible) &= \log\left(\frac{P^i(horrible)}{1-P^i(horrible)}\right) - \log\left(\frac{P^j(horrible)}{1-P^j(horrible)}\right) \\
&= \log\left(\frac{\frac{\text{f}^i(horrible)}{n^i}}{1-\frac{\text{f}^i(horrible)}{n^i}}\right) - \log\left(\frac{\frac{\text{f}^j(horrible)}{n^j}}{1-\frac{\text{f}^j(horrible)}{n^j}}\right) \\
&= \log\left(\frac{\text{f}^i(horrible)}{n^i-\text{f}^i(horrible)}\right) - \log\left(\frac{\text{f}^j(horrible)}{n^j-\text{f}^j(horrible)}\right)
\end{aligned}$$

Log odds ratio with a prior

Monroe, B. L., Colaresi, M. P., and Quinn, K. M. (2008). Fightin'words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis 16*(4), 372–403.

Log odds ratio from previous slide:

$$\log\left(\frac{\mathrm{f}^{i}(horrible)}{n^{i}-\mathrm{f}^{i}(horrible)}\right)-\log\left(\frac{\mathrm{f}^{j}(horrible)}{n^{j}-\mathrm{f}^{j}(horrible)}\right)$$

Now with a prior:

$$\delta_{w}^{(i-j)}=\log\left(\frac{f_{w}^{i}+\alpha_{w}}{n^{i}+\alpha_{0}-(f_{w}^{i}+\alpha_{w})}\right)-\log\left(\frac{f_{w}^{j}+\alpha_{w}}{n^{j}+\alpha_{0}-(f_{w}^{j}+\alpha_{w})}\right)$$

n^i = size of corpus *i*, n^j = size of corpus *j*, f_w^i = count of word *w* in corpus i, f_w^j = count of word *w* in corpus *j*, α_0 is the size of the background corpus, and α_w =count of word *w* in the background corpus.)

Log odds ratio informative Dirichlet prior

Monroe, B. L., Colaresi, M. P., and Quinn, K. M. (2008). Fightin'words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis 16*(4), 372–403.

$$\sigma^2\left(\hat{\delta}_w^{(i-j)}\right) \approx \frac{1}{y_w^i + \alpha_w} + \frac{1}{y_w^j + \alpha_w}$$

Final statistic for a word: z-score of its log-odds-ratio:

$$\frac{\hat{\delta}_w^{(i-j)}}{\sqrt{\sigma^2\left(\hat{\delta}_w^{(i-j)}\right)}}$$

Top 50 words associated with bad (= 1-star) reviews by Monroe, *et al.* (2008) method

Jurafsky et al., 2014

Class	Words in 1-star reviews	Class	Words in 5-star reviews
Negative	*worst, rude, terrible, horrible, bad, awful, disgusting, bland, tasteless, gross, mediocre, overpriced, worse, poor*	**Positive**	*great, best, love(d), delicious, amazing, favorite, perfect, excellent, awesome, friendly, fantastic, fresh, wonderful, incredible, sweet, yum(my)*
Negation	*no, not*	**Emphatics/ universals**	*very, highly, perfectly, definitely, absolutely, everything, every, always*
1Pl pro	*we, us, our*	**2 pro**	*you*
3 pro	*she, he, her, him*	**Articles**	*a, the*
Past verb	*was, were, asked, told, said, did, charged, waited, left, took*	**Advice**	*try, recommend*
Sequencers	*after, then*	**Conjunct**	*also, as, well, with, and*
Nouns	*manager, waitress, waiter, customer, customers, attitude, waste, poisoning, money, bill, minutes*	**Nouns**	*atmosphere, dessert, chocolate, wine, course, menu*
Irrealis modals	*would, should*	**Auxiliaries**	*is/'s, can, 've, are*
Comp	*to, that*	**Prep, other**	*in, of, die, city, mouth*

Using the lexicons to detect affect

Lexicons for detecting document affect: Simplest unsupervised method

Sentiment:

- Sum the weights of each positive word in the document
- Sum the weights of each negative word in the document
- Choose whichever value (positive or negative) has higher sum

Emotion:

- Do the same for each emotion lexicon

Lexicons for detecting document affect: Simplest unsupervised method

$$f^{+} = \sum_{w \text{ s.t. } w \in positivelexicon} \theta_w^{+} count(w)$$

$$f^{-} = \sum_{w \text{ s.t. } w \in negativelexicon} \theta_w^{-} count(w)$$

```
Sentiment = +    if    f+ > f-
```

Lexicons for detecting document affect: Slightly more complex unsupervised method

$$f^+ = \sum_{w \text{ s.t. } w \in positivelexicon} \theta_w^+ count(w)$$

$$f^- = \sum_{w \text{ s.t. } w \in negativelexicon} \theta_w^- count(w)$$

$$sentiment = \begin{cases} + & \text{if } \frac{f^+}{f^-} > \lambda \\ - & \text{if } \frac{f^-}{f^+} > \lambda \\ 0 & \text{otherwise.} \end{cases}$$

Lexicons for detecting document affect: Simplest supervised method

Use the lexicons as **features** for a classifier

Given a training set

- Each observation has a label (review X has sentiment Y)
- Assign features to each observation
- Use “counts of lexicon categories” as a features
  - NRC Emotion category “anticipation” had count of 2
    - 2 words in this document were in “anticipation” lexicon
  - LIWC category “cognition” had count of 7

Lexicons for detecting document affect: Simplest supervised method

Baseline

- Use counts of **all** the words and bigrams in the training set
  - Like the naïve bayes algorithm
- **This is hard to beat**
- But “using all the words” only works if the training and test sets are very similar
- In real life, sometimes the test set is very different
  - Lexicons are useful in that situation

Computing entity-centric affect

Suppose we want an affect score for an entity in a text (not the entire document)

Entity-centric method of Field and Tsvetkov (2019)

Entity-centric affect (Field and Tsvetkov 2019)

1: Train classifier to predict V/A/D from embeddings

1. For each word *w* in the training corpus:
   - Use off-the-shelf encoders (like BERT) to extract a contextual embedding *e* for each instance of the word.
   - Average over the *e* embeddings of each instance of *w* to obtain a single embedding vector for one training point *w*.
   - Use the NRC Lexicon to get V, A, and D scores for *w*.
2. Train (three) regression models on all words *w* to predict V, A, D scores from a word's average embedding.

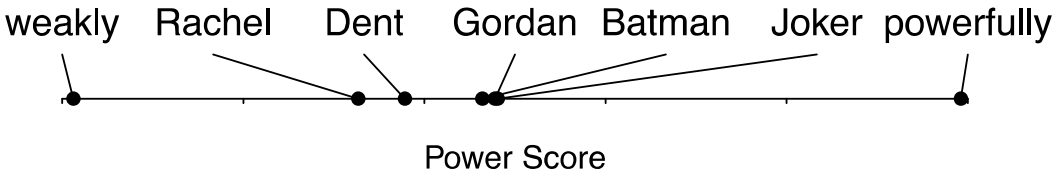
Entity-centric affect (Field and Tsvetkov 2019)

2: Assign scores to entity mentions

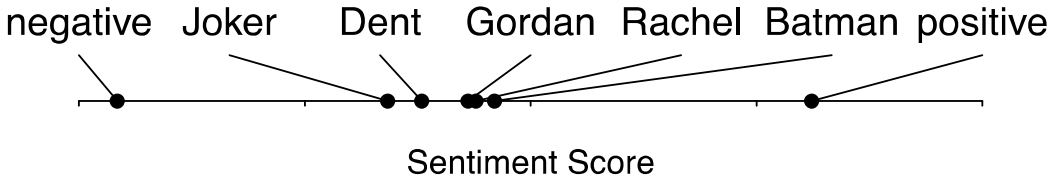
Given an entity mention *m* in a text, assign affect scores as follows:

- Use the same pretrained LM to get contextual embeddings for *m* in context.
- Feed this embedding through the 3 regression models to get V, A, D scores for the entity.

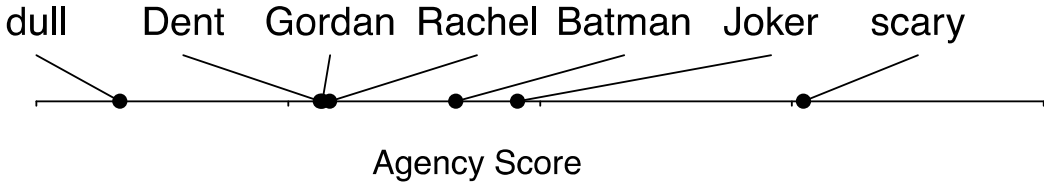
Entity-centric affect (Field and Tsvetkov 2019)



= dominance



= valence



= arousal

Connotation frames

Connotation Frames intuition

A predicate expresses connotations about its arguments (Rashkin et al. 2016, Rashkin et al. 2017).

By using *violate*, author is sympathizing with B, and expressing negative sentiment toward A:

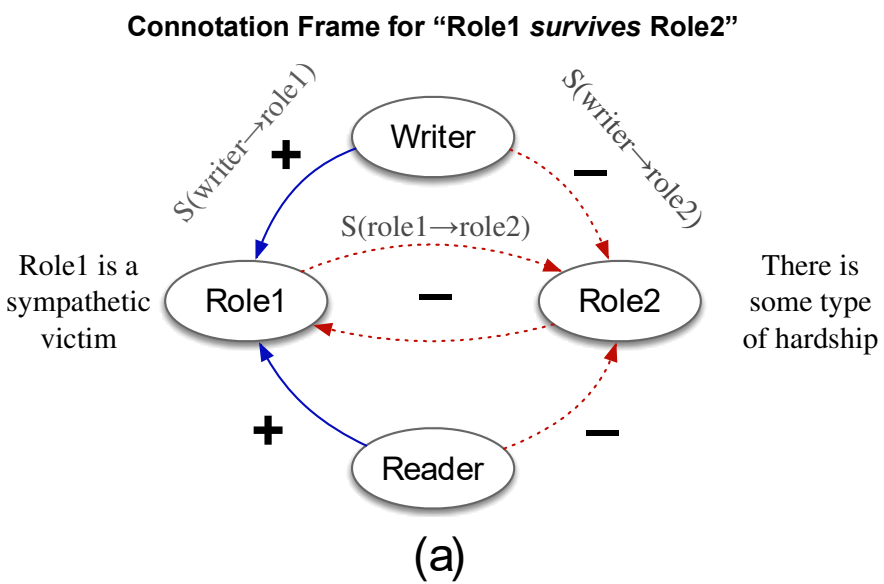
- Country A violated the sovereignty of Country B

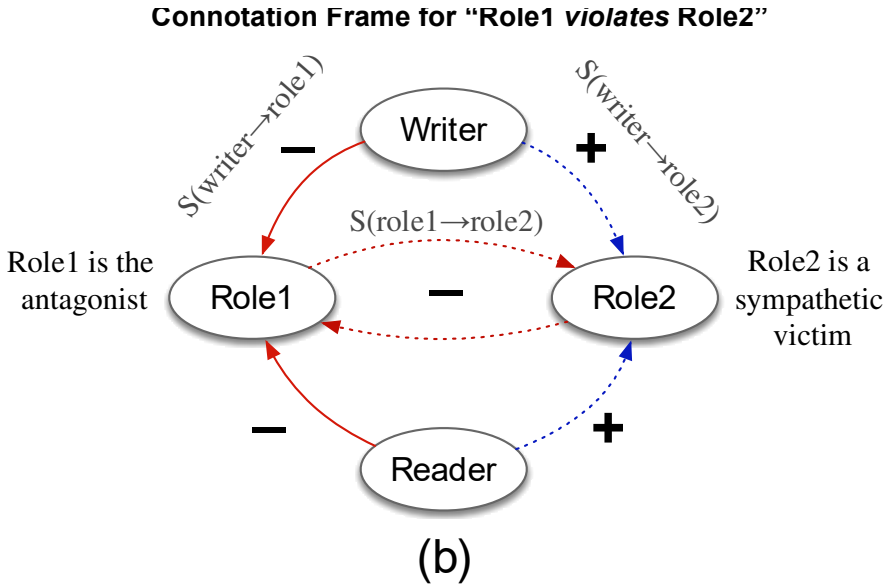
By using *survive*, author is saying that the bombing is negative, and sympathizing with teenager:

- the teenager ... survived the Boston Marathon bombing”

Connotation Frames

Rashkin et al., 2016, 2017





Connotation Frames can also mark power and agency

Sap et al. 2017