Analysis of subjectivity.[1]

Victor Kitov

v.v.kitov@yandex.ru

[1] With materials used from "Speech and Language Processing", D. Jurafsky and J. H. Martin.

Subjectivity types

Emotion: Relatively brief episode of response to the evaluation of an external or internal event as being of major significance.
(*angry, sad, joyful, fearful, ashamed, proud, elated, desperate*)

Mood: Diffuse affect state, most pronounced as 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, colouring the interpersonal exchange in that situation.
(*distant, cold, warm, supportive, contemptuous, friendly*)

Attitude: Relatively enduring, affectively colored beliefs, preferences, and 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, jealous*)

Applications

- Sentiment analysis - extraction of attitudes
- Detecting moods examples:
  - detecting whether a student is confused, engaged, or certain when interacting with a tutorial system
  - whether a caller to a help line is frustrated
  - whether someone's blog posts or tweets indicated depression
- Detecting interpersonal stances examples:
  - friendliness or awkwardness in interviews
  - friendliness/hostility during meetings
  - finding parts of a conversation where people are especially excited or engaged
    - for efficient summarization
- Detecting the personality of a user - match communication style of conversational agents

Lexicons

- Simplest lexicons match words to 1-D sentiment.
- General Inquirer: 1915 positive words and 2291 negative words
- MPQA Subjectivity lexicon: 2718 positive and 4912 negative words
  - also labeled for reliability (strongly subjective or weakly subjective)
- Example:

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

Table of Contents

General semi-supervised algorithm

- Lexicon can vary from domain to domain
- Building lexicon purely from human effort is expensive
- General semi-supervised algorithm

function BUILDSENTIMENTLEXICON(*posseeds*,*negseeds*) **returns** *poslex*,*neglex*

$\quad poslex \leftarrow posseeds$
$\quad neglex \leftarrow negseeds$
$\quad$ **Until done**
$\quad\quad poslex \leftarrow poslex + \text{FINDSIMILARWORDS}(poslex)$
$\quad\quad neglex \leftarrow neglex + \text{FINDSIMILARWORDS}(neglex)$
$\quad poslex, neglex \leftarrow \text{POSTPROCESS}(poslex, neglex)$

3 semi-supervised approaches

- 3 semisupervised approaches.
    - Using seed words and adjective coordination
    - Using mutual information
    - Using WordNet synonyms and antonyms

1. Semi-supervised algorithms for word labelling
   - Using seed words and adjective coordination
   - Using mutual information
   - Using WordNet synonyms and antonyms

Using seed words and adjective coordination[2]

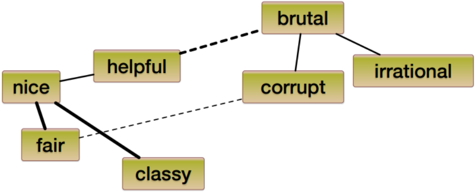
1. Create seed lexicon of positive (+) and negative (-) adjectives
2. Expand list of +,- adjectives with new adjectives:
    - adjectives cojoined by AND have similar polarity
        - e.g. fair and legitimate, corrupt and brutal
    - adjectives cojoined by BUT have opposite polarity
        - e.g. fair but brutal
    - morphological negation: un-<adjective>, im-<adjective>, <adjective>-less change polarity of adjective
        - e.g. adequate/inadequate, thoughtful/thoughtless

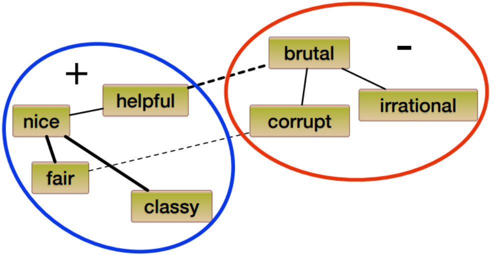
[2] Hatzivassiloglou and McKeown (1997)

Using seed words and adjective coordination

1. Build graph: adjectives - nodes, connections - polarity connection, weight - same or opposite polarity
    1. approach 1:
        - connect with weight 1 words used with AND
        - connect with weight -1 words used with BUT
    2. approach 2
    - train 2 classifiers, predicting for pair of words probability they have same polarity or opposite polarity.
    - features: words, how they were used together, morphological features (affixes)
    - using classifiers predict weight of polarity connection on the graph
2. Cluster graph nodes into 2 clusters: + and -.

Example


brutal
helpful
nice
corrupt
irrational
fair
classy


+
-
brutal
helpful
nice
corrupt
irrational
fair
classy

1. Semi-supervised algorithms for word labelling
   - Using seed words and adjective coordination
   - Using mutual information
   - Using WordNet synonyms and antonyms

Using mutual information[3]

1. Extract words or 2 words phrases for their polarity prediction
    - phrases extracted with POS pattern: adj+noun, adv+adj, etc.
2. Init seed words, e.g. +: excellent. -: poor
3. + words closely co-occur with 'excellent', - words closely co-occur with 'poor'
    - co-occurence context: within k words of each other
    - measure of co-occurence - PMI

$$PMI(w,s)=\ln\frac{p(w,s)}{p(w)p(s)}$$

[3] Turney (2002)

Using mutual information

- Web-search to find probabilities:

$$p(w) = \frac{hits(w)}{N} \quad p(w,s) = \frac{hits(w \text{ NEAR s})}{kN}$$

  - N: words in the web
  - k: co-occurence context length
  - each word pair can be near to each other in k different ways.

- PMI estimation:

$$PMI(w,s) = \ln\left(\frac{N}{k}\frac{hits(w \text{ NEAR } s)}{p(w)p(s)}\right)$$

Polarity estimation

$$
\begin{aligned}
polarity(w) = PMI(w,'excellent') - PMI(w,'poor') = \\
= \ln\left(\frac{N}{k}\frac{hits(w \text{ NEAR } 'excellent')}{p(w)p('excellent')}\right) - \ln\left(\frac{N}{k}\frac{hits(w \text{ NEAR } 'poor')}{p(w)p('poor')}\right) \\
= \ln\left(\frac{hits(w \text{ NEAR } 'excellent')p(w)p('poor')}{hits(w \text{ NEAR } 'poor')p(w)p('excellent')}\right) \\
= \ln\left(\frac{hits(w \text{ NEAR } 'excellent')p('poor')}{hits(w \text{ NEAR } 'poor')p('excellent')}\right)
\end{aligned}
$$

- Examples learned from bank reviews:

Extracted Phrase	Polarity
online experience	2.3
very handy	1.4
low fees	0.3
inconveniently located	-1.5
other problems	-2.8
unethical practices	-8.5

1. Semi-supervised algorithms for word labelling
    - Using seed words and adjective coordination
    - Using mutual information
    - Using WordNet synonyms and antonyms

Using WordNet synonyms and antonyms

1. init pos-words, neg-words
2. repeat:
   1. extent pos-words with
      - synonims of pos-words
      - antonyms of neg-words
   2. extent neg-words with
      - synonims of neg-words
      - antonyms of pos-words

SentiWordNet

- Extension of this algorithm was used to assign polarity to WordNet synsets
    1. 7 pos and 7 negseed words were selected
    2. pos and neg words were extended using synonymy, antonymy, see-also relationships
    3. on extended training set a classifier was trained, matching synset gloss to its polarity
    4. classifier was applied to all synsets of WordNet
    5. final classification is based on predicted polarity of synset and connected synsets on the WordNet graph
        - using connectivity measures, involving random walk algorithm

SentiWordNet

- WordNet with extended polarity was called SentiWordNet[4]
- Example:

Synset	Pos	Neg	Obj
good#6 ‘agreeable or pleasing’	1	0	0
respectable#2 honorable#4 good#4 estimable#2 ‘deserving of esteem’	0.75	0	0.25
estimable#3 computable#1 ‘may be computed or estimated’	0	0	1
sting#1 burn#4 bite#2 ‘cause a sharp or stinging pain’	0	0.875	.125
acute#6 ‘of critical importance and consequence’	0.625	0.125	.250
acute#4 ‘of an angle; less than 90 degrees’	0	0	1
acute#1 ‘having or experiencing a rapid onset and short but severe course’	0	0.5	0.5

[4] Baccianella et al., (2010).

Table of Contents

Supervised learning of words polarity

- Use online reviews datasets, having text and rating of items
  - e.g. reviews for restaurants, movies, books, or other products
- Example

	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 ...

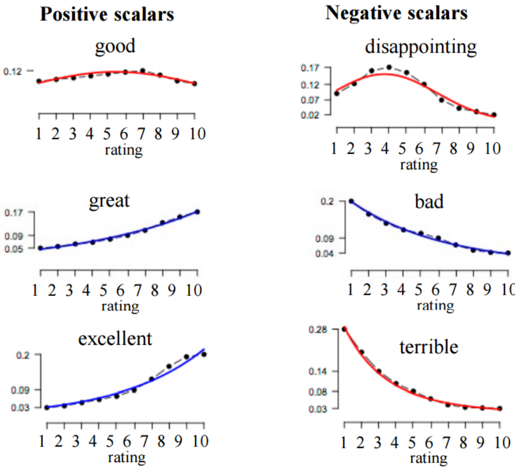
Words

- Let c denote rating of the review
- pos-words appear more in 5-star reviews
- neg-words appear more in 5-star reviews
- More informative measure - distribution of word over stars: $p(c|w)$
    - can extract wekly positive or weakly negative words
- Alternative: Potts score[5]

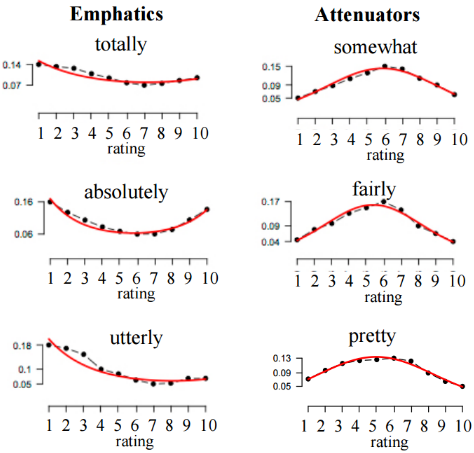
$$PottsScore(w) = \frac{p(w|c)}{\sum_c p(w|c)}$$

[5] Potts (2011).

Potts scores or different words



Potts scores for adverbs



Log odds ratio informative Dirichlet prior[6]

- Suppose we have texts from 2 categories:
  - pos/neg reviews
  - speeches from Democratic/Republican party
  - etc.
- Task - distinguish characteristic words frequent in 1 category and infrequent in another.
- Log odds ratio informative Dirichlet prior:

$$\delta_w^{(i-j)} = \ln\left(\frac{y_w^i + \alpha_w}{n^i + \alpha_0 - (y_w^i + \alpha_w)}\right) - \ln\left(\frac{y_w^j + \alpha_w}{n^j + \alpha_0 - (y_w^j + \alpha_w)}\right)$$

  - n^i: size of corpus i, y_w^i: count of word w in corpus i
  - α_0: size of background corpus, α_w: count of word w in background corpus
- This measure estimates the difference in frequencies of word w in cropora i and j.

[6] Monroe et al. (2008)

Log odds ratio informative Dirichlet prior

$$Var[\widehat{\delta}_w^{(i-j)}] \approx \frac{1}{y_w^i + \alpha_w} + \frac{1}{y_w^j + \alpha_w}$$

- We can order words by $\delta_w^{(i-j)} / \sqrt{Var[\widehat{\delta}_w^{(i-j)}]}$
- Key ideas of this approach:
  - smoothing using background corpus
  - accounting for word variance.

Example

Application of this approach to words in 1-star and 5-star reviews on restaurants:

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*

Baseline sentiment analysis

- Simple sentiment analysis algorithm:

1. calculate

$$f^+ = \sum_{w \in pos.words} \theta_w^+ count(w)$$
$$f^- = \sum_{w \in neg.words} \theta_w^- count(w)$$

2. rule-based prediction (for some threshold $\lambda > 0$)

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

- We can use f^+, f^- as features in supervised classification.

Emotions

- Emotion theories:
    1. all emotions consist of basic emotions: surprise, happiness, anger, fear, disgust, sadness.
    2. emotions are points in 3-D coordinates:
        - **valence**: the pleasantness of the stimulus
        - **arousal**: the intensity of emotion provoked by the stimulus
        - **dominance**: the degree of control exerted by the stimulus

Examples

- Datasets for emotions are crowdsourced.
- Sample datset of 1st emotions categorization: words:

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

Examples

- Sample datset of 2nd emotions categorization:

Valence		Arousal		Dominance	
vacation	8.53	rampage	7.56	self	7.74
happy	8.47	tornado	7.45	incredible	7.74
whistle	5.7	zucchini	4.18	skillet	5.33
conscious	5.53	dressy	4.15	concur	5.29
torture	1.4	dull	1.67	earthquake	2.14

- Other perceptions: strong vs. weak, active vs. passive, overstated vs. understated
- Other categories: virtue-vice, motivation, concrete-abstract (banana, bath vs. belief, although)

Personality

- Extroversion vs. Introversion: sociable, assertive, playful vs. aloof, reserved, shy
- Emotional stability vs. Neuroticism: calm, unemotional vs. insecure, anxious
- Agreeableness vs. Disagreeableness: friendly, cooperative vs. antagonistic, fault- finding
- Conscientiousness vs. Unconscientiousness: self-disciplined, organized vs. inefficient, careless Openness to experience: intellectual, insightful vs. shallow, unimaginative
- Openness to experience: intellectual, insightful vs. shallow, unimaginative

Personality datasets

- Dataset - text written by authors, who have also completed a psycological test.
- The essay corpus of Pennebaker and King (1999) consists of 2,479 essays (1.9 million words) from psychology students who were asked to “write whatever comes into your mind”.
- Example:
  - **neurotic:** One of my friends just barged in, and I jumped in my seat. This is crazy. I should tell him not to do that again. I’m not that fastidious actually. But certain things annoy me. The things that would annoy me would actually annoy any normal human being, so I know I’m not a freak.
  - **emotionally stable**: I should excel in this sport because I know how to push my body harder than anyone I know, no matter what the test I always push my body harder than everyone else. I want to be the best no matter what the sport or event. I should also be good at this because I love to ride my bike.