Sentiment Analysis cont.

Overview

1. Sharper conceptualization of the problem
2. Applications, data, and resources
3. Sentiment lexicons (off-the-shelf and custom)
4. Basic feature extraction (tokenization, stemming, POS-tagging)
5. Sentiment and syntax (dependencies and sentiment rich phrases)
6. Probabilistic classifier models (with and without classification)
7. Sentiment
    - and compositional semantics
    - and context
    - and social networks

Applications

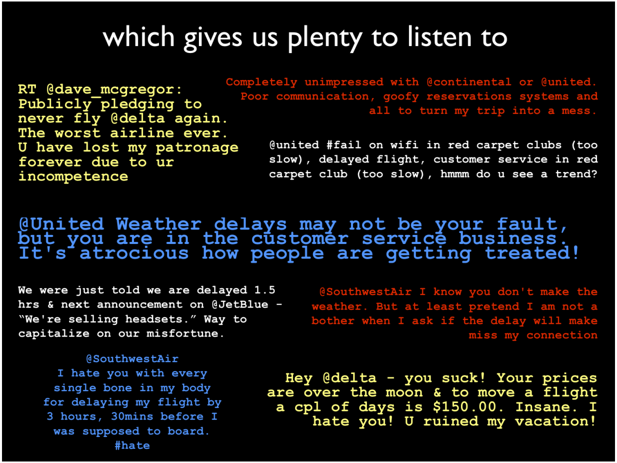


Figure: Understanding customer feedback. From Jeffrey Breen's 'R by example: mining Twitter for attitudes towards airlines': http://jeffreybreen.wordpress.com/2011/07/04/twitter-text-mining-r-slides/

Applications

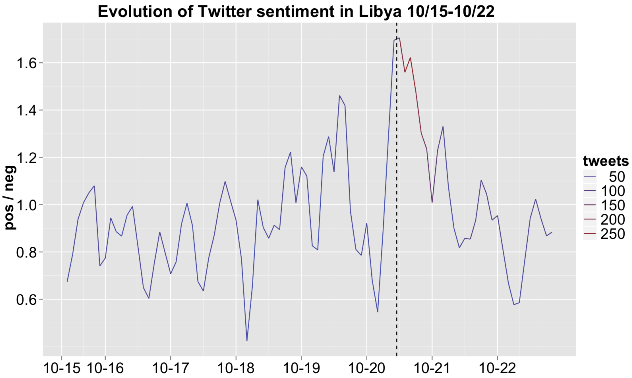
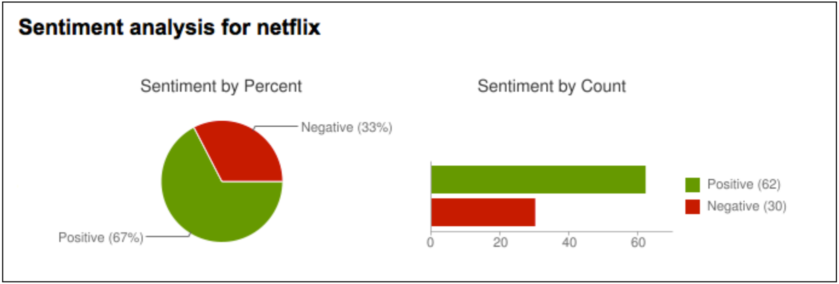


Figure: Twitter sentiment in tweets about Libya, from the project ‘Modeling Discourse and Social Dynamics in Authoritarian Regimes’. The vertical line marks the timing of the announcement that Gaddafi had been killed.

Applications

Many business leaders think they want this:



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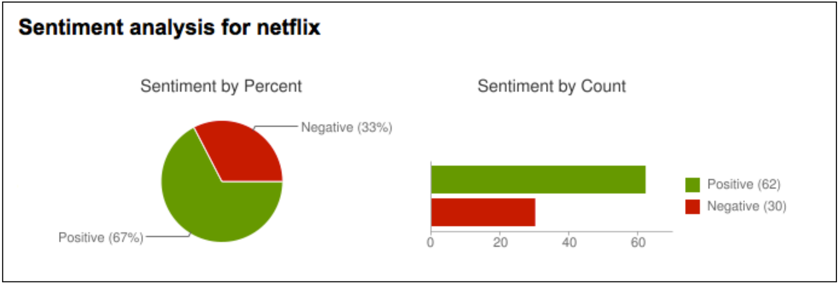

When they see it, they realize that it does not help them with decision-making. The distributions (assuming they reflect reality) are hiding the phenomena that are actually relevant.

Data

- Stanford sentiment treebank: http://nlp.stanford.edu/sentiment/
- Data from Lillian Lee's group: http://www.cs.cornell.edu/home/llee/data/
- Data from Bing Liu: http://www.cs.uic.edu/~liub/
- Large movie review dataset: http://ai.stanford.edu/~amaas/data/sentiment/
- Pranav Anand & co. (http://people.ucsc.edu/~panand/data.php):
  - Internet Argument Corpus
  - Annotated political TV ads
  - Focus of negation corpus
  - Persuasion corpus (blogs)
- Data on AFS:
  - `/afs/ir/data/linguistic-data/mnt/mnt4/PottsCorpora`
    `README.txt, Twitter.tgz, imdb-english-combined.tgz, opentable-english-processed.zip`
  - `/afs/ir/data/linguistic-data/mnt/mnt9/PottsCorpora`
    `opposingviews, product-reviews, weblogs`

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9. Here's to ya, ya bastard!
10. Of 2001, "Many consider the masterpiece bewildering, boring, slow-moving or annoying, . . . "

Affect and emotion

Type of affective state: brief definition (*examples*)	Intensity	Duration	Syn-chroni-zation	Event focus	Appraisal elicita-tion	Rapid-ity of change	Behav-ioral impact
Emotion: relatively brief episode of synchronized response of all or most organismic subsystems in 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 stances: affective stance taken toward another person in a specific interaction, colouring the interpersonal exchange in that situation (*distant, cold, warm, supportive, contemptuous*)	+–+ +	+–+ +	+	++	+	+ + +	++
Attitudes: relatively enduring, affectively coloured beliefs, preferences, and predispositions towards objects or persons (*liking, loving, hating, valueing, desiring*)	0–+ +	+ +–+ + +	0	0	+	0–+	+
Personality traits: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person (*nervous, anxious, reckless, morose, hostile, envious, jealous*)	0–+	+ + +	0	0	0	0	+

0: low, +: medium, ++: high, + + +: very high, –: indicates a range.

Figure: Scherer's (1984) typology of affective states provides a broad framework for understanding sentiment. In particular, it helps to reveal that emotions are likely to be just one kind of information that we want our computational systems to identify and characterize.

Sentiment is hard

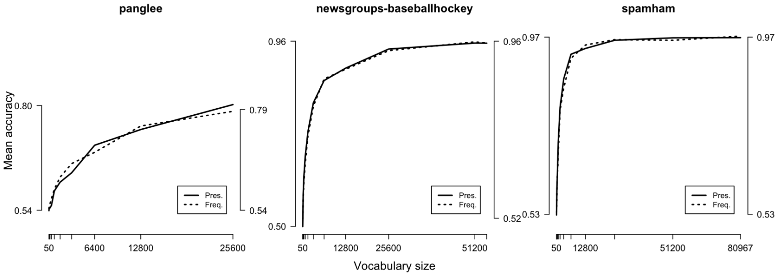

Figure: A single classifier model (MaxEnt) applied to three different domains at various vocabulary sizes. panglee is the widely used movie review corpus distributed by Lillian Lee's group. The 20 newsgroups corpus is a collection of newsgroup discussions on topics like sports, religion, and motorcycles, each with subtopics. spamham is a corpus of spam and ham email messages.

Sentiment lexicons

Understanding and deploying existing sentiment lexicons, or building your own from scratch using unsupervised methods.

Bing Liu's Opinion Lexicon

- http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html
- Positive words: 2006
- Negative words: 4783
- Useful properties: includes mis-spellings, morphological variants, slang, and social-media mark-up

MPQA subjectivity lexicon

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

1.	type=weaksubj	len=1	word1=abandoned	pos1=adj	stemmed1=n	priorpolarity=negative
2.	type=weaksubj	len=1	word1=abandonment	pos1=noun	stemmed1=n	priorpolarity=negative
3.	type=weaksubj	len=1	word1=abandon	pos1=verb	stemmed1=y	priorpolarity=negative
4.	type=strongsubj	len=1	word1=abase	pos1=verb	stemmed1=y	priorpolarity=negative
5.	type=strongsubj	len=1	word1=abasement	pos1=anypos	stemmed1=y	priorpolarity=negative
6.	type=strongsubj	len=1	word1=abash	pos1=verb	stemmed1=y	priorpolarity=negative
7.	type=weaksubj	len=1	word1=abate	pos1=verb	stemmed1=y	priorpolarity=negative
8.	type=weaksubj	len=1	word1=abdicate	pos1=verb	stemmed1=y	priorpolarity=negative
9.	type=strongsubj	len=1	word1=aberration	pos1=adj	stemmed1=n	priorpolarity=negative
10.	type=strongsubj	len=1	word1=aberration	pos1=noun	stemmed1=n	priorpolarity=negative
11.	type=strongsubj	len=1	word1=abhor	pos1=anypos	stemmed1=y	priorpolarity=negative
12.	type=strongsubj	len=1	word1=abhor	pos1=verb	stemmed1=y	priorpolarity=negative
13.	type=strongsubj	len=1	word1=abhorred	pos1=adj	stemmed1=n	priorpolarity=negative
14.	type=strongsubj	len=1	word1=abhorrence	pos1=noun	stemmed1=n	priorpolarity=negative
15.	type=strongsubj	len=1	word1=abhorrent	pos1=adj	stemmed1=n	priorpolarity=negative
16.	type=strongsubj	len=1	word1=abhorrently	pos1=anypos	stemmed1=n	priorpolarity=negative
17.	type=strongsubj	len=1	word1=abhors	pos1=adj	stemmed1=n	priorpolarity=negative
18.	type=strongsubj	len=1	word1=abhors	pos1=noun	stemmed1=n	priorpolarity=negative
19.	type=strongsubj	len=1	word1=abidance	pos1=adj	stemmed1=n	priorpolarity=positive
20.	type=strongsubj	len=1	word1=abidance	pos1=noun	stemmed1=n	priorpolarity=positive
⋮						
8221.	type=strongsubj	len=1	word1=zest	pos1=noun	stemmed1=n	priorpolarity=positive

SentiWordNet

POS	ID	PosScore	NegScore	SynsetTerms	Gloss
a	00001740	0.125	0	able#1	(usually followed by 'to') having the necessary means or [. . .]
a	00002098	0	0.75	unable#1	(usually followed by 'to') not having the necessary means or [. . .]
a	00002312	0	0	dorsal#2 abaxial#1	facing away from the axis of an organ or organism; [. . .]
a	00002527	0	0	ventral#2 adaxial#1	nearest to or facing toward the axis of an organ or organism; [. . .]
a	00002730	0	0	acroscopic#1	facing or on the side toward the apex
a	00002843	0	0	basiscopic#1	facing or on the side toward the base

- Project homepage: http://sentiwordnet.isti.cnr.it
- Python/NLTK interface: http://compprag.christopherpotts.net/wordnet.html

Harvard General Inquirer

	Entry	Positiv	Negativ	Hostile	… (184 classes)	Othtags	Defined
1	A					DET ART	…
2	ABANDON		Negativ			SUPV	
3	ABANDONMENT		Negativ			Noun	
4	ABATE		Negativ			SUPV	
5	ABATEMENT					Noun	
⋮							
35	ABSENT#1		Negativ			Modif	
36	ABSENT#2					SUPV	
⋮							
11788	ZONE					Noun	

Table: ‘#*n*’ differentiates senses. Binary category values: ‘Yes’ = category name; ‘No’ = blank. Heuristic mapping from Othtags into {a,n,r,v}.

- Download: `http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm`
- Documentation: `http://www.wjh.harvard.edu/~inquirer/homecat.htm`

Linguistic Inquiry and Word Counts (LIWC)

Linguistic Inquiry and Word Counts (LIWC) is a propriety database ($90) consisting of a lot of categorized regular expressions.

Category	Examples
Negate	aint, ain't, arent, aren't, cannot, cant, can't, couldnt, . . .
Swear	arse, arsehole*, arses, ass, asses, asshole*, bastard*, . . .
Social	acquainta*, admit, admits, admitted, admitting, adult, adults, advice, advis*
Affect	abandon*, abuse*, abusi*, accept, accepta*, accepted, accepting, accepts, ache*
Posemo	accept, accepta*, accepted, accepting, accepts, active*, admir*, ador*, advantag*
Negemo	abandon*, abuse*, abusi*, ache*, aching, advers*, afraid, aggravat*, aggress*,
Anx	afraid, alarm*, anguish*, anxi*, apprehens*, asham*, aversi*, avoid*, awkward*
Anger	jealous*, jerk, jerked, jerks, kill*, liar*, lied, lies, lous*, ludicrous*, lying, mad

Table: A fragment of LIWC.

Relationships

	MPQA	Opinion Lexicon	Inquirer	SentiWordNet	LIWC
MPQA	—	33/5402 (0.6%)	49/2867 (2%)	1127/4214 (27%)	12/363 (3%)
Opinion Lexicon		—	32/2411 (1%)	1004/3994 (25%)	9/403 (2%)
Inquirer			—	520/2306 (23%)	1/204 (0.5%)
SentiWordNet				—	174/694 (25%)
LIWC					—

Table: Disagreement levels for the sentiment lexicons.

- Where a lexicon had POS tags, I removed them and selected the most sentiment-rich sense available for the resulting string.
- For SentiWordNet, I counted a word as positive if its positive score was larger than its negative score; negative if its negative score was larger than its positive score; else neutral, which means that words with equal non-0 positive and negative scores are neutral.
- How to handle the disagreements?

Additional sentiment lexicon resources

- Happy/Sad lexicon (Data_Set_S1.txt) from Dodds et al. 2011
- My NASSLLI 2012 summer course: http://nasslli2012.christopherpotts.net
- UMass Amherst Multilingual Sentiment Corpora: http://semanticsarchive.net/Archive/jQ0ZGZiM/readme.html
- Developing adjective scales from user-supplied textual metadata: http://www.stanford.edu/~cgpotts/data/wordnetscales/

Bootstrapping domain-specific lexicons

Lexicons seem easy to use, but this can be deceptive. Their rigidity can lead to serious misdiagnosis tracing to how word senses vary by domain. Better to let the data speak for itself!

1. Turney and Littman's (2003) semantic orientation method (http://www.stanford.edu/class/cs224u/hw/hw1/)
2. Blair-Goldensohn et al.'s (2008) WordNet propagation algorithm (http://sentiment.christopherpotts.net)
3. Velikovich et al.'s (2010) unsupervised propagation algorithm (http://sentiment.christopherpotts.net)

Basic feature extraction

- Tokenizing (why this is important)
- Stemming (why you shouldn't)
- POS-tagging (in the service of other goals)
- Heuristic negation marking

Tokenizing

Raw text

@NLUers: can't wait for the Jun 2-4 #project talks! YAAAAAAY!!! >:-D http://stanford.edu/class/cs224u/.

Tokenizing

Isolate mark-up, and replace HTML entities.

@NLUers: can’t wait for the Jun 2-4 #project talks! YAAAAAAY!!! >:-D
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Whitespace tokenizer

@NLUers:
can’t
wait
for
the
Jun
2-4
#project
talks!
YAAAAAAY!!!
>:-D
http://stanford.edu/class/cs224u/.

Tokenizing

Isolate mark-up, and replace HTML entities.

@NLUers: can’t wait for the Jun 2-4 #project talks! YAAAAAAY!!! >:-D
http://stanford.edu/class/cs224u/.

Treebank tokenizer

@	!
NLUers	YAAAAAAY
:	!
ca	!
n’t	!
wait	>
for	:
the	-D
Jun	http
2-4	:
#	//stanford.edu/class/cs224u/
project	.
talks	

Tokenizing

Isolate mark-up, and replace HTML entities.

@NLUers: can't wait for the Jun 2-4 #project talks! YAAAAAAY!!! >:-D http://stanford.edu/class/cs224u/.

Elements of a sentiment-aware tokenizer

- Isolates emoticons
- Respects Twitter and other domain-specific markup
- Makes use of the underlying mark-up (e.g., <strong> tags)
- Captures those #$%ing masked curses!
- Preserves capitalization where it seems meaningful
- Regularizes lengthening (e.g., *YAAAAAAY*⇒*YAAAY*)
- Captures significant multiword expressions (e.g., *out of this world*)

For regexs and details:
`http://sentiment.christopherpotts.net/tokenizing.html`

Tokenizing

Isolate mark-up, and replace HTML entities.

@NLUers: can't wait for the Jun 2-4 #project talks! YAAAAAAY!!! >:-D
http://stanford.edu/class/cs224u/.

Sentiment-aware tokenizer

@nluers	!
:	YAAAY
can't	!
wait	!
for	!
the	>:-D
Jun_2-4	http://stanford.edu/class/cs224u/
#project	.
talks	

How much does sentiment-aware tokenizing help?

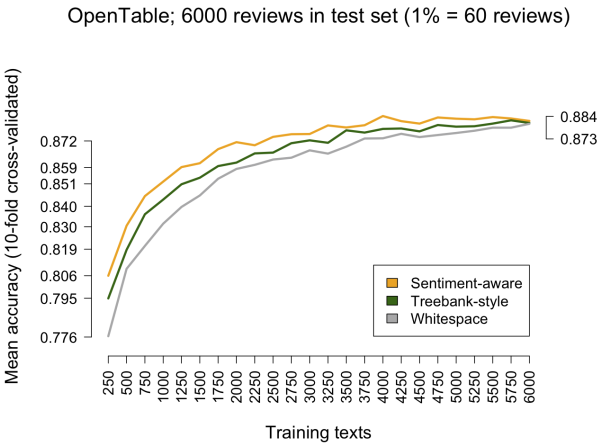

Figure: Training on 12,000 OpenTable reviews (6000 positive/4-5 stars; 6000 negative/1-2 stars). MaxEnt classifier.

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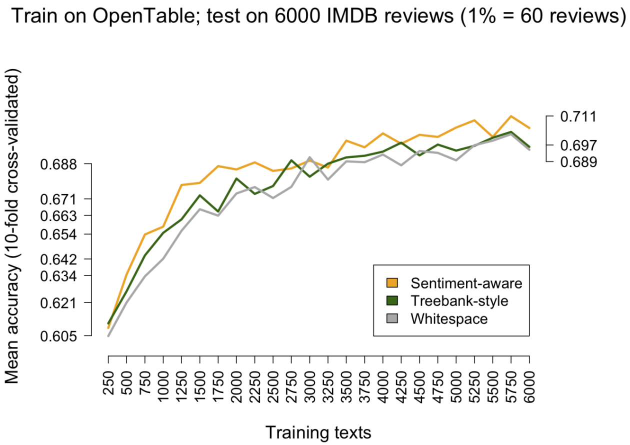

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Stemming

- Stemming collapses distinct word forms.
- Three common stemming algorithms in the context of sentiment:
  - the Porter stemmer
  - the Lancaster stemmer
  - the WordNet stemmer
- Porter and Lancaster destroy too many sentiment distinctions.
- The WordNet stemmer does not have this problem nearly so severely, but it generally doesn't do enough collapsing to be worth the resources necessary to run it.

Stemming

The Porter stemmer heuristically identifies word suffixes (endings) and strips them off, with some regularization of the endings.

Positiv	Negativ	Porter stemmed
defense	defensive	defens
extravagance	extravagant	extravag
affection	affectation	affect
competence	compete	compet
impetus	impetuous	impetu
objective	objection	object
temperance	temper	temper
tolerant	tolerable	toler

Table: Sample of instances in which the Porter stemmer destroys a Harvard Inquirer Positiv/Negativ distinction.

Stemming

The Lancaster stemmer uses the same strategy as the Porter stemmer.

Positiv	Negativ	Lancaster stemmed
call	callous	cal
compliment	complicate	comply
dependability	dependent	depend
famous	famished	fam
fill	filth	fil
flourish	floor	flo
notoriety	notorious	not
passionate	passe	pass
savings	savage	sav
truth	truant	tru

Table: Sample of instances in which the Lancaster stemmer destroys a Harvard Inquirer Positiv/Negativ distinction.

Stemming

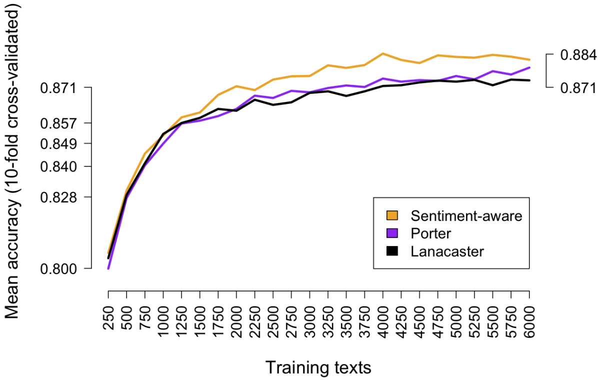
The WordNet stemmer (NLTK) is high-precision. It requires word–POS pairs. Its only general issue for sentiment is that it removes comparative morphology.

Positiv	WordNet stemmed
(exclaims, v)	exclaim
(exclaimed, v)	exclaim
(exclaiming, v)	exclaim
(exclamation, n)	exclamation
(proved, v)	prove
(proven, v)	prove
(proven, a)	proven
(happy, a)	happy
(happier, a)	happy
(happiest, a)	happy

Table: Representative examples of what WordNet stemming does and doesn't do.

How much does stemming help/hurt?

OpenTable; 6000 reviews in test set (1% = 60 reviews)



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Part-of-speech tagging

Word	Tag1	Val1	Tag2	Val2
arrest	jj	Positiv	vb	Negativ
even	jj	Positiv	vb	Negativ
even	rb	Positiv	vb	Negativ
fine	jj	Positiv	nn	Negativ
fine	jj	Positiv	vb	Negativ
fine	nn	Negativ	rb	Positiv
fine	rb	Positiv	vb	Negativ
help	jj	Positiv	vbn	Negativ
help	nn	Positiv	vbn	Negativ
help	vb	Positiv	vbn	Negativ
hit	jj	Negativ	vb	Positiv
mind	nn	Positiv	vb	Negativ
order	jj	Positiv	vb	Negativ
order	nn	Positiv	vb	Negativ
pass	nn	Negativ	vb	Positiv

Table: Harvard Inquirer POS contrasts.

How much does POS tagging help/hurt?

OpenTable; 6000 reviews in test set (1% = 60 reviews)

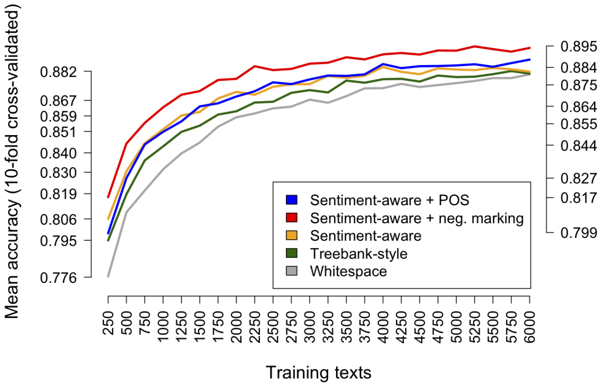
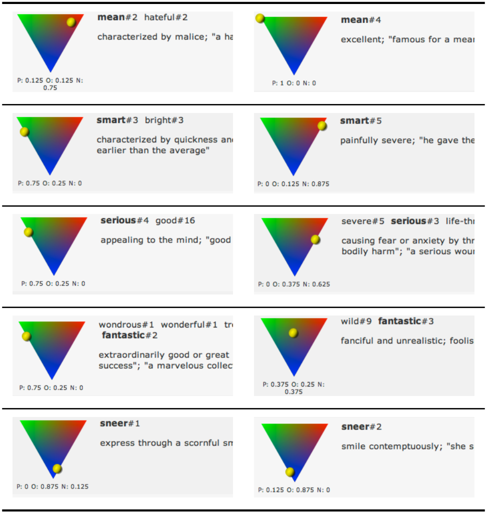


Figure: Training on 12,000 OpenTable reviews (6000 positive/4-5 stars; 6000 negative/1-2 stars). MaxEnt classifier.

SentiWordNet lemma contrasts

1,424 cases where a (word, tag) pair is consistent with pos. and neg. lemma-level sentiment



Word	Tag	ScoreDiff
mean	s	1.75
abject	s	1.625
benign	a	1.625
modest	s	1.625
positive	s	1.625
smart	s	1.625
solid	s	1.625
sweet	s	1.625
artful	a	1.5
clean	s	1.5
evil	n	1.5
firm	s	1.5
gross	s	1.5
iniquity	n	1.5
marvellous	s	1.5
marvelous	s	1.5
plain	s	1.5
rank	s	1.5
serious	s	1.5
sheer	s	1.5
sorry	s	1.5
stunning	s	1.5
wickedness	n	1.5
	[. . .]	
unexpectedly	r	0.25
velvet	s	0.25
vibration	n	0.25
weather-beaten	s	0.25
well-known	s	0.25
whine	v	0.25
wizard	n	0.25
wonderland	n	0.25
yawn	v	0.25

Negation

The phenomenon

1. I didn’t enjoy it.
2. I never enjoy it.
3. No one enjoys it.
4. I have yet to enjoy it.
5. I don’t think I will enjoy it.

Negation

The method (Das and Chen 2001; Pang et al. 2002)

- Append a _NEG suffix to every word appearing between a negation and a clause-level punctuation mark.
- For regex details: `http://sentiment.christopherpotts.net/lingstruc.html`

Negation

No one enjoys it.	no one_NEG enjoys_NEG it_NEG .
I don’t think I will enjoy it, but I might.	i don’t think_NEG i_NEG will_NEG enjoy_NEG it_NEG , but i might .

How much does negation-marking help?

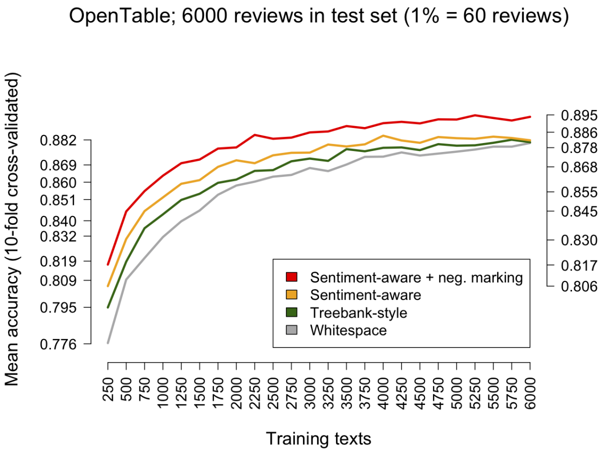


Figure: Training on 12,000 OpenTable reviews (6000 positive/4-5 stars; 6000 negative/1-2 stars). MaxEnt classifier.

How much does negation-marking help?

Train on OpenTable; test on 6000 IMDB reviews (1% = 60 reviews)

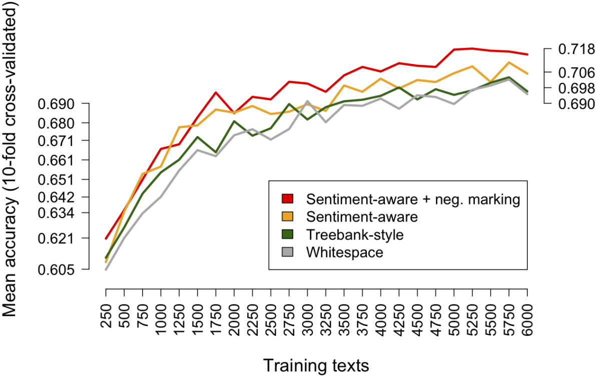


Figure: Training on 12,000 OpenTable reviews (6000 positive/4-5 stars; 6000 negative/1-2 stars). MaxEnt classifier.