

The Effect of Negators, Modals, and Degree Adverbs on Sentiment Composition

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Sentiment Lexicons

- **Sentiment lexicon:** a list of terms (usually single words) with association to positive (negative) sentiment

happy 0.9

awful -0.9

award 0.6

- Applications:
 - sentence-, tweet-, message-level sentiment classification
 - stance detection
 - literary analysis
 - detecting personality traits

Sentiment Composition

Sentiment composition: determining sentiment of a phrase (or a sentence) from its constituents.

Sentiment composition lexicon (SCL): a list of phrases and their constituent words with association to positive (negative) sentiment.

would not be happy -0.6

happy 0.9

These lexicons are especially useful for studying sentiment composition.

Our goal: through **manual annotation**, create a **fine-grained** sentiment composition lexicon for negators, modals, and degree adverbs to study their effect on sentiment.

Manually Created Sentiment Lexicons

- Features:
 - more accurate than automatically generated lexicons
 - less coverage than automatic lexicons
- Uses (that cannot be fulfilled by automatic lexicons):
 - to create automatic lexicons
 - to directly evaluate automatic lexicons
 - linguistic analysis
 - help understand how sentiment is conveyed by words and phrases
 - how sentiment is perceived by native speakers

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 - to create automatic lexicons
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 - **linguistic analysis**
 - help understand how modifiers (negators, modal verbs, degree adverbs) affect sentiment in phrases
 - how sentiment is perceived by native speakers

Existing Manually Created Lexicons

- most include only single words (lemmas)
- most have only coarse levels of sentiment (positive vs. negative)

Obtaining real-valued sentiment annotations is challenging:

- higher cognitive load than simply marking positive, negative, neutral
- hard to be consistent across multiple annotations
- difficult to maintain consistency across annotators
 - 0.8 for one annotator may be 0.7 for another

Method: Comparative Annotations

Paired Comparisons (Thurstone, 1927; David, 1963):

If X is the property of interest (positive, useful, etc.),
give two terms and ask which is more X

- less cognitive load
- helps with consistency issues
- requires a large number of annotations
 - order N^2 , where N is number of terms to be annotated



Method: Comparative Annotations

Paired Comparisons (Thurstone, 1927; David, 1963):

If X is the property of interest (positive, useful, etc.),
give two terms and ask which is more X

Best–Worst Scaling (Louviere & Woodworth, 1990):

(a.k.a. Maximum Difference Scaling or MaxDiff)

Give k terms and ask which is most X, and which is least X
(*k is usually 4 or 5*)

- preserves the **comparative nature**
- keeps the number of **annotations down to about 2N**
- leads to **more reliable annotations**
 - less biased and more discriminating (Cohen, 2003)

Our Contributions

- Create **Sentiment Composition Lexicon for Negators, Modals, and Degree Adverbs (SCL-NMA)**: a new fine-grained sentiment lexicon manually annotated through crowdsourcing and Best–Worst Scaling
 - **for phrases** and their constituent content words
 - phrases involving negators, modals, and degree adverbs
- Show that **the annotations are reliable**
- Analyze the lexicon to gain new understandings of human perception of sentiment
- Use the lexicon to study **how sentiment is composed** in phrases



Creating SCL–NMA

(Sentiment Composition Lexicon for Negators, Modals, and Degree Adverbs)

By Manual Annotation and Best–Worst Scaling



Term Selection

- 1,621 single words (Osgood's positive and negative lists)
- 1,586 multi-word phrases in the form 'modifier w', where w is an Osgood word and modifier is one of the following:
 - a negator (e.g., no, don't, never)
 - a modal verb (e.g., can, might, should)
 - a degree adverb (e.g., very, fairly)
 - a combination of the above (e.g., would be very)
- In total: 3,207 terms

Example Terms

Term	Sentiment Score
favor	
would be very easy	
certainly agree	
did not harm	
should be better	
unfavorable	
will not be interested	
was so difficult	
much trouble	
severe	

Annotation



Crowdsourcing:

- Manual annotation through crowdsourcing
- Each question was answered by ten respondents
- Quality control through a small set of gold answers

Annotation scheme: Best–Worst Scaling

- The annotator is presented with four terms (a 4-tuple) and asked:
 - which term is the most positive
 - which term is the most negative



Example Annotation Instance

Focus words:

1. worse 2. was not sufficient 3. more afraid 4. banish

Q1. Identify the word that is associated with the MOST amount of POSITIVE sentiment (or, least amount of negative sentiment) -- the most positive term.

- worse
- was not sufficient
- more afraid
- banish

❑

Q2. Identify the word that is associated with the MOST amount of NEGATIVE sentiment (or, least amount of positive sentiment) -- the most negative term.

- worse
- was not sufficient
- more afraid
- banish

❑

Best–Worst Scaling

- The annotator is presented with four terms (a 4-tuple) and asked:
 - which term is the most positive
 - which term is the most negative
- By answering just these two questions, five out of the six inequalities are known
 - For example, given the terms A, B, C, and D:
 - if A is most positive and D is most negative, then we know:

$$A > B, A > C, A > D, B > D, C > D$$

Best–Worst 4–tuples

We generate 4-tuples such that:

- no two 4-tuples have the same four terms;
- no two terms within a 4-tuple are identical;
- each term in the term list appears in about the same number of 4-tuples;
- each pair of terms appears in about the same number of 4-tuples.

This is to maximize the chance that each term is seen in a sufficient number, and a diverse set of 4-tuples.



Best–Worst Scaling:

Converting Responses to Real-Valued Scores

- Responses converted into real-valued scores for all the terms:
 - a simple counting procedure (Orme, 2009):

$$score(t) = \frac{\#most\ positive(t) - \#most\ negative(t)}{\#annotations(t)}$$

The scores range from:

-1 (least association with positive sentiment)

to 1 (most association with positive sentiment)

- terms can then be ranked by sentiment

Example Lexicon Entries

Term	Sentiment Score
favor	0.653
would be very easy	0.431
certainly agree	0.347
did not harm	0.194
should be better	0.069
unfavorable	-0.222
will not be interested	-0.319
was so difficult	-0.514
much trouble	-0.667
severe	-0.833

Quality of Annotations

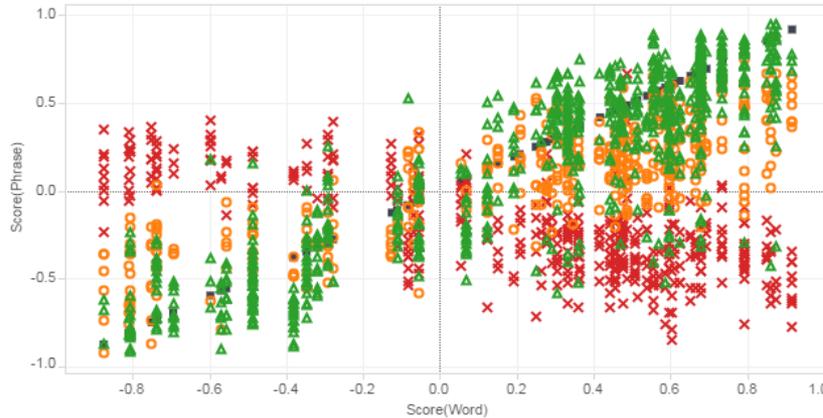
- Annotations are **reliable**
 - re-doing the annotations with different sets of annotators produces a very similar order of terms (an average Spearman rank correlation of 0.98)
- Such reliable rankings can be obtained with just two or three annotations per BWS question.

Svetlana Kiritchenko and Saif M. Mohammad. Capturing Reliable Fine-Grained Sentiment Associations by Crowdsourcing. *NAACL-2016*.

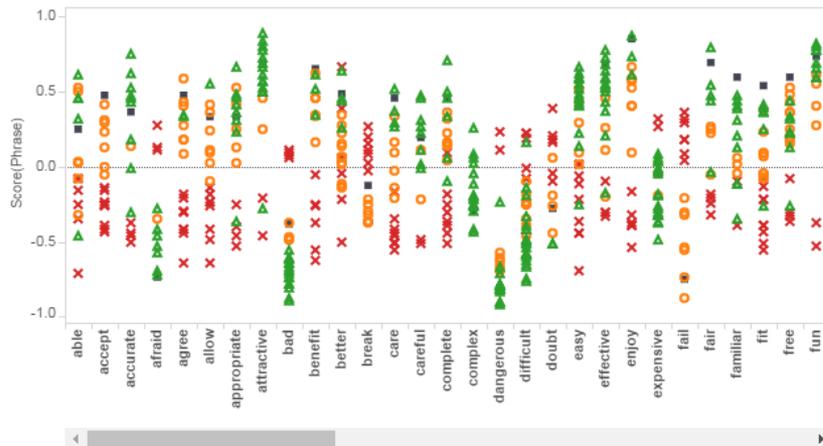
Interactive Visualization

Sentiment of a word vs. Sentiment of phrases consisting that word

Compressed x axis (sentiment of word)



Expanded x axis (sentiment of word)



Modifier Class

- ▲ adverb
- modal
- × negator
- word

Modifier Class

- ▲ adverb
- modal
- × negator
- word

Modifier Class

- (All)
- adverb
- modal
- negator
- word

Modifier Word/Phrase

- (All)
- Null
- can
- can be
- cannot
- certainly
- could
- could be
- could not
- did not
- does not
- especially
- extremely
- fairly
- had no
- have no
- highly
- increasingly
- less
- may
- may be

Score(Phrase)

-0.921

0.944

<http://www.saifmohammad.com/WebPages/SCL.html#NMA>





Analyzing Sentiment Composition

Impact of Sentiment Modifiers



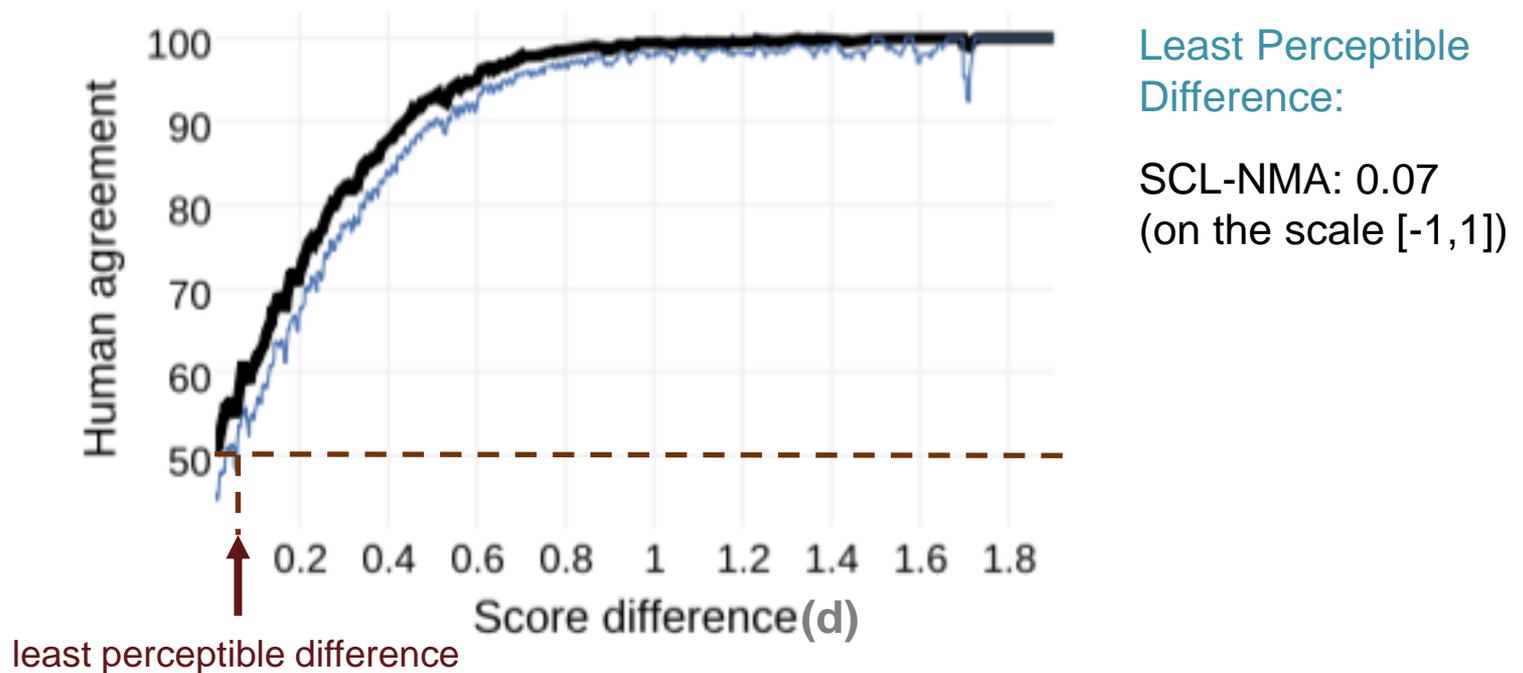
Least Perceptible Difference



- Least perceptible difference aka just-noticeable difference
 - a concept from psychophysics
 - the amount by which something that can be measured (e.g., weight or sound intensity) needs to be changed in order for the difference to be noticeable by a human (Fechner, 1966)
- With our fine-grained sentiment scores, we can measure the least perceptible difference in sentiment
 - useful in studying sentiment composition (e.g., to determine whether a modifier significantly impacts the sentiment of the word it modifies)

Measuring the Least Perceptible Difference

- Least perceptible difference in sentiment scores is a point d at which we can say with high confidence that the two terms do not have the same sentiment associations

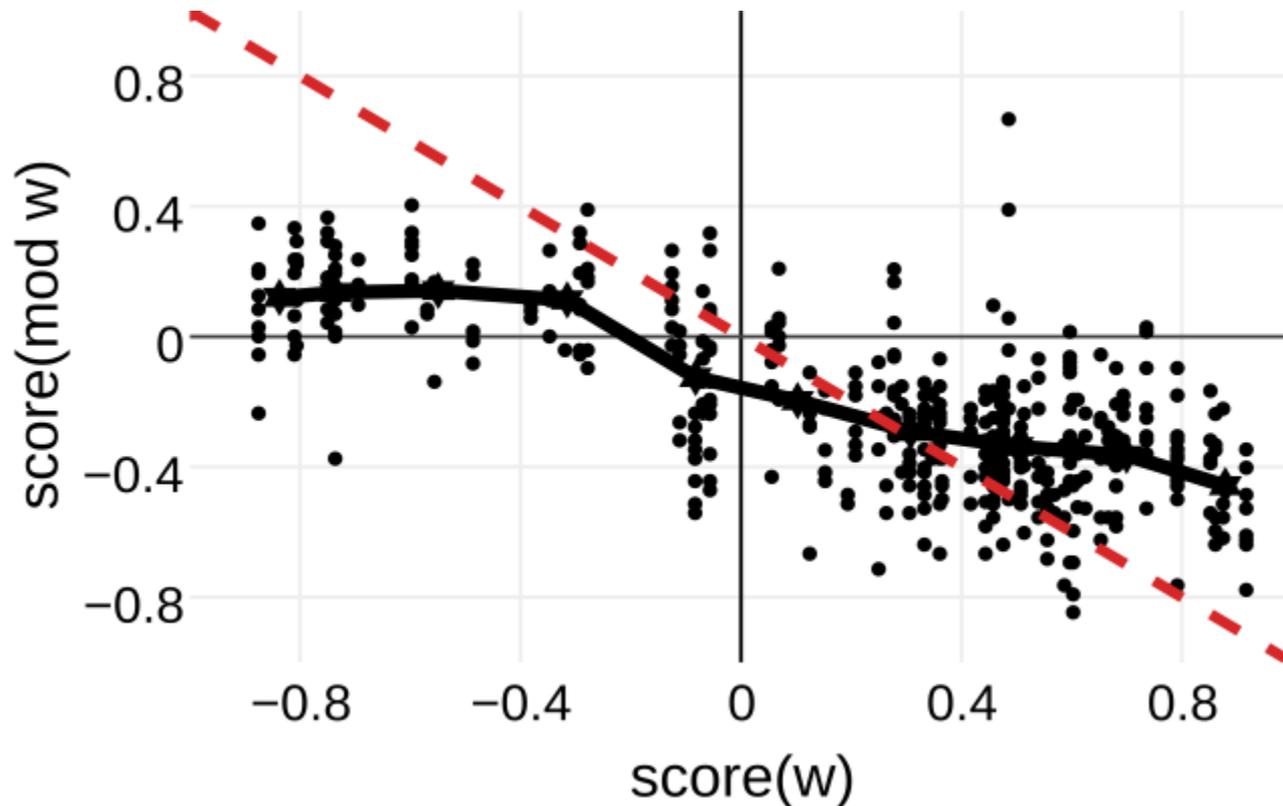


Overall Impact of Sentiment Modifiers

Modifier group	On positive words		On negative words	
	Avg. diff	# of pairs	Avg. diff.	# of pairs
negators	-0.93	265	0.79	71
modals	-0.32	258	0.24	72
degree adverbs	0.20	435	0.17	163



Impact of Negation on Sentiment

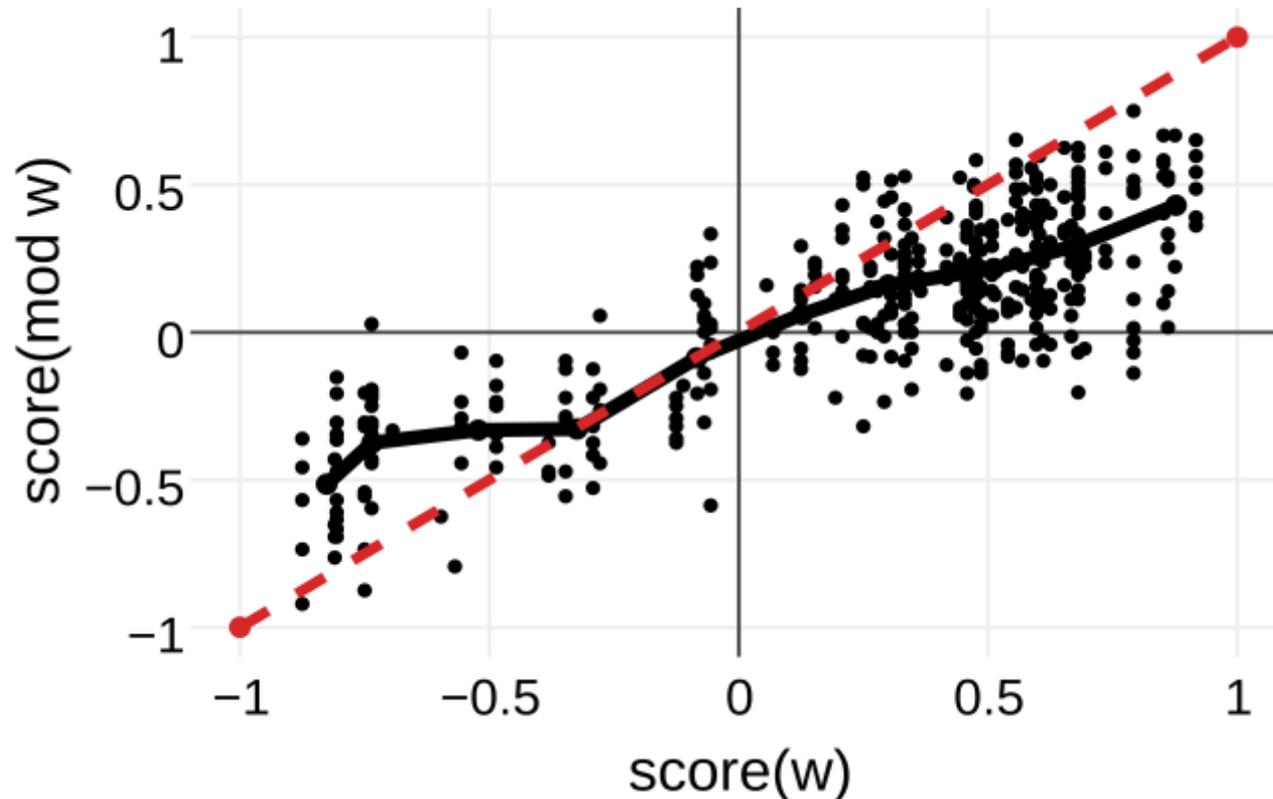


The black line shows an average effect of the negators group.
The red line shows the reversing hypothesis: $\text{score}(\text{mod } w) = -\text{score}(w)$.

Impact of Negation on Sentiment

- Most negators
 - decrease sentiment of positive words by 0.8-1.0 points
 - increase sentiment of negative words by 0.7-0.9 points
- The greatest shift is caused by **will not be** and **will not**
- The weakest effect is by **may not**, **nothing**, and **never**
- Verb tense seems not to affect the behavior of negators significantly
- Modals in combination with negators slightly influence the behavior of the modifier:
 - stronger negators: **will not**, **will not be**, and **cannot**
 - weaker negators: **could not**, **would not**, and **may not**

Impact of Modal Verbs on Sentiment



The black line shows an average effect of the modals group.
The red line shows the function: $\text{score}(\text{mod } w) = \text{score}(w)$.

Impact of Modal Verbs on Sentiment

- Most modal verbs
 - decrease sentiment of positive words by 0.2-0.4 points
 - increase sentiment of negative words by 0.2-0.3 points
- The greatest shift (about 0.4 points) is observed for words with high absolute sentiment values
- The most influential modal modifier is **would have been**
- Consistent and relatively strong modifiers are formed by modals **could** and **might**
- Smallest effect on sentiment is caused by **can**, **can be**, **would**, and **would be**

Impact of Degree Adverbs on Sentiment

- Many degree adverbs have a small and rather inconsistent effect on sentiment
- The only degree adverb that affects sentiment to a large extent (0.835 points) is **less**
 - acts as negator
- Modifiers that consistently reduce the intensity of positive words are **was too**, **too**, **probably**, **fairly**, and **relatively**
- One modifier, **highly**, consistently and significantly increases the sentiment of positive words
- The sentiment of negative words is noticeably lowered by modifiers **extremely** and **very very**

Conclusions

- Created a sentiment composition lexicon for English phrases involving common sentiment modifiers
 - manual annotation with Best-Worst Scaling
 - real-valued sentiment associations
- Showed that the annotations are reliable
- Analyzed the impact of negators, modals, and degree adverbs on sentiment:
 - these modifiers affect sentiment in complex ways so that their effect cannot be easily modeled with simple heuristics;
 - the effect of a modifier is often determined not only by the type of the modifier but also by the modifier word and the content word themselves.

Our Related Projects



- Sentiment Composition Lexicon for Opposing Polarity Phrases (SCL-OPP)

Svetlana Kiritchenko and Saif M. Mohammad. Sentiment Composition of Words with Opposing Polarities. *NAACL-2016*.

- Semeval-2016 Task #7 ‘Determining Sentiment Intensity of English and Arabic Phrases’
 - General English Sentiment Modifiers Set (SCL-NMA)
 - English Twitter Mixed Polarity Set (SCL-OPP)
 - Arabic Twitter Set

Lexicons Availability



All lexicons and their interactive visualizations are available at:
<http://www.saifmohammad.com/WebPages/SCL.html>

Code for Best–Worst Scaling will be available at:
<http://www.saifmohammad.com/WebPages/BestWorst.html>

SemEval-2016 Task 7: <http://alt.qcri.org/semEval2016/task7/>

