Affect Associations in Creative Language

Saif Mohammad
National Research Council Canada
Creative Language
Extraordinary, everyday
Creative Language

- Stories and poems
- Metaphors
- Hyperbole
- Sarcasm and irony
- Noun-noun compounds
  - soccer mom, mountain bike
- Opposing polarity phrases
  - happy accident, crazy cool, epic fail
- Hashtag words
  - #loveumom, #throwbackthursday
This talk

Will explore affect associations in creative language
Stories
STORIES
Tracking Emotions in Stories

- Can we automatically track the emotions of characters?
- Can we track the change in distribution of emotion words?
- Are there some canonical shapes common to most stories?
Word Associations

Beyond literal meaning, words have other associations that add to their meanings.

- Associations with sentiment
- Associations with emotions
- Associations with social overtones
- Associations with cultural implications
- Associations with colours

Connotations.
Word-Sentiment Associations

- Adjectives
  - *reliable* and *stunning* are typically associated with **positive** sentiment
  - *rude*, *and broken* are typically associated with **negative** sentiment

- Nouns and verbs
  - *holiday* and *smiling* are typically associated with **positive** sentiment
  - *death* and *crying* are typically associated with **negative** sentiment

**Goal:** Capture word-sentiment associations.
Word-Emotion Associations

Words have associations with emotions:

- **attack** and **public speaking** typically associated with **fear**
- **yummy** and **vacation** typically associated with **joy**
- **loss** and **crying** typically associated with **sadness**
- **result** and **wait** typically associated with **anticipation**

**Goal:** Capture word-emotion associations.
Which Emotions?
Charles Darwin

- published *The Expression of the Emotions in Man and Animals* in 1872
- seeks to trace the animal origins of human characteristics
  - pursing of the lips in concentration
  - tightening of the muscles around the eyes in anger
- claimed that certain facial expressions are universal
  - these facial expressions are associated with emotions

FIG. 20.—Terror, from a photograph by Dr. Duchenne.
**Debate: Universality of Perception of Emotions**

- **Circa 1950’s**, Margaret Mead and others believed facial expressions and their meanings were culturally determined
  - behavioural learning processes
- Paul Ekman provided the strongest evidence to date that Darwin, not Margaret Mead, was correct in claiming facial expressions are universal
- Found universality of six emotions

Margaret Mead
Cultural anthropologist

Paul Ekman
Psychologist and discoverer of micro expressions.
Paul Ekman, 1971: Six Basic Emotions

- Anger
- Disgust
- Fear
- Joy
- Sadness
- Surprise
Plutchik, 1980: Eight Basic Emotions

- Anger
- Anticipation
- Disgust
- Fear
- Joy
- Sadness
- Surprise
- Trust

Goal: We chose to capture word-emotion associations for the 8 Plutchik emotions.
Annotations by Crowdsourcing

- **Benefits**
  - Inexpensive
  - Convenient and time-saving
    - Especially for large-scale annotation

- **Challenges**
  - Quality control
    - Malicious annotations
    - Inadvertent errors
  - Words used in different senses are associated with different emotions.
Word-Choice Question

Q1. Which word is closest in meaning to *cry*?
   - *car*  
   - *tree*  
   - *tears*  
   - *olive*

- Generated automatically
  - Near-synonym taken from thesaurus
  - Distractors are randomly chosen

- Guides Turkers to desired sense

- Aids quality control
  - If Q1 is answered incorrectly:
    - Responses to the remaining questions for the word are discarded
Association Questions

Q2. How much is cry associated with the emotion sadness? (for example, death and gloomy are strongly associated with sadness)

- cry is not associated with sadness
- cry is weakly associated with sadness
- cry is moderately associated with sadness
- cry is strongly associated with sadness

- Eight such questions for the eight basic emotions.
- Two such questions for positive or negative sentiment.

Better agreement when asked ‘associated with’ rather than ‘evoke’.
Emotion Lexicon

- Each word-sense pair is annotated by 5 Turkers
- NRC Emotion Lexicon
  - sense-level lexicon
    - word sense pairs: 24,200
  - word-level lexicon
    - union of emotions associated with different senses
    - word types: 14,200

Available at: www.saifmohammad.com

Paper:
What if you want to capture fine-grained intensity of emotion/sentiment?
How to manually create sentiment lexicons with intensity values?

- Humans are not good at giving real-valued scores?
  - hard to be consistent across multiple annotations
  - difficult to maintain consistency across annotators
    - 0.8 for annotator may be 0.7 for another
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
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

Need a method that preserves the comparison aspect, without
greatly increasing the number of annotations needed.

Possible solution:

Best–Worst Scaling (Louviere & Woodworth, 1990):
(a.k.a. Maximum Difference Scaling or MaxDiff)
Best–Worst Scaling (BWS)  
aka Maximum Difference Scaling (MaxDiff)

- The annotator is presented with four words (say, A, B, C, and D) and asked:
  - which word is the most positive (least negative)
  - which is the least positive (most negative)

- By answering just these two questions, five out of the six inequalities are known
  - For e.g.:
    - If A is most positive
    - and D is least positive, then we know:
      \[ A > B, A > C, A > D, B > D, C > D \]
Example BWS 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

- Each of these BWS questions can be presented to multiple annotators.
- The responses to the BWS questions can then be easily translated into:
  - a real-valued score for all the terms (Orme, 2009)
    \[ \text{score}(w) = \frac{\text{#mostPositive}(w) - \text{#mostNegative}(w)}{\text{#annotations}(w)} \]
    - the scores range from:
      - -1 (least association with positive sentiment)
      - to 1 (most association with positive sentiment)
    - the scores can then be used to rank of all the terms
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)
# Best-Worst Scaling Lexicons

<table>
<thead>
<tr>
<th>Lexicon</th>
<th>Language</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. SemEval-2015 English Twitter Sentiment Lexicon</td>
<td>English</td>
<td>Twitter</td>
</tr>
<tr>
<td>2. SemEval-2016 Arabic Twitter Sentiment Lexicon</td>
<td>Arabic</td>
<td>Twitter</td>
</tr>
<tr>
<td>3. Sentiment Composition Lexicon for Negators, Modals, and Adverbs (SCL-NMA)</td>
<td>English</td>
<td>General</td>
</tr>
<tr>
<td>4. Sentiment Composition Lexicon for Opposing Polarity Phrases (SCL-OPP)</td>
<td>English</td>
<td>General</td>
</tr>
</tbody>
</table>

Lexicons and papers available at: [http://saifmohammad.com/WebPages/SCL.html](http://saifmohammad.com/WebPages/SCL.html)
## English Twitter Lexicon:
Examples sentiment scores obtained using BWS

<table>
<thead>
<tr>
<th>Term</th>
<th>Sentiment Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>awesomeness</td>
<td>0.827</td>
</tr>
<tr>
<td>#happygirl</td>
<td>0.625</td>
</tr>
<tr>
<td>cant waitttt</td>
<td>0.601</td>
</tr>
<tr>
<td>don't worry</td>
<td>0.152</td>
</tr>
<tr>
<td>not true</td>
<td>-0.226</td>
</tr>
<tr>
<td>cold</td>
<td>-0.450</td>
</tr>
<tr>
<td>#getagrip</td>
<td>-0.587</td>
</tr>
<tr>
<td>#sickening</td>
<td>-0.722</td>
</tr>
</tbody>
</table>
Robustness of the Annotations

BWS annotations

half of the BWS annotations

ranking of words by sentiment

half of the BWS annotations

ranking of words by sentiment
Robustness of the Annotations

The two rankings were very similar:

- average difference in scores was 0.04
- Spearman Rank Correlation coefficient between the two rankings was about 0.98 for all four lexicons
Two of the lexicons we created were sentiment composition lexicons.
Sentiment Composition Lexicon

**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 useful for studying sentiment composition.
**Sentiment Composition Lexicon**
for Negators, Modals, and Adverbs (SCL-NMA)

- SCL-NMA provides fine-grained sentiment associations for 3207 terms:
  - phrases involving negators (e.g., *did not harm*)
  - phrases involving modal verbs (e.g., *should be better*)
  - phrases involving degree adverbs (e.g., *certainly agree*)
  - phrases involving combinations (e.g., *would be very easy*)
  - their constituent content words (e.g., *harm, better, agree, easy*)

- Use SCL-NMA to help understand how modifiers (negators, modal verbs, degree adverbs) affect sentiment in phrases
Sentiment Composition Lexicon
for Negators, Modals, and Adverbs (SCL-NMA)

On combination with a negator:
- positive words become negative but sentiment intensity is reduced
- some negative words become positive, but many just become less negative

On combination with a modal:
- intensity of sentiment is reduced
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Start the presentation.
Sentiment Composition Lexicon for Opposing Polarity Phrases

a.k.a. SemEval-2016 English Twitter Mixed Polarity Lexicon

- Sentiment composition is easy when both terms have same polarity, or if one or both terms are neutral
  - we wanted to create a dataset particularly challenging for determining sentiment composition

- Opposing Polarity Phrase (OPP): includes at least one positive word and at least one negative word

- Lexicon includes 1,661 English terms:
  - 851 OPP bigrams and trigrams: happy accident, guilty pleasures, best winter break
  - 810 unigrams that are part of the selected ngrams: happy, accident, winter
LiveSlides web content

To view

Download the add-in.
liveslides.com/download

Start the presentation.
Papers:


- **The Effect of Negators, Modals, and Degree Adverbs on Sentiment Composition.** Svetlana Kiritchenko and Saif M. Mohammad, In Proceedings of the NAACL 2016 Workshop on Computational Approaches to Subjectivity, Sentiment, and Social Media (WASSA), June 2014, San Diego, California.

Visualizing Emotions in Text
Analysis of Emotion Words in Books

Percentage of fear words in close proximity to occurrences of America, China, Germany, and India in books.
Percentage of joy and anger words in close proximity to occurrences of man and woman in books.
Tracking Emotions in Stories

- Can we track the change in distribution of emotion words?
As You Like It

Hamlet

Frankenstein
Work on shapes of stories

- From Once Upon a Time to Happily Ever After: Tracking Emotions in Novels and Fairy Tales, Saif Mohammad, In Proceedings of the ACL 2011 Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities (LaTeCH), June 2011, Portland, OR.


Generating music from text

Paper:
A method to generate music from literature.
- music that captures the change in the distribution of emotion words.
Challenges

- Not changing existing music -- generating novel pieces
- Paralysis of choice
- Has to sound good
- No one way is the right way -- evaluation is tricky
Music-Emotion Associations

- Major and Minor Keys
  - major keys: happiness
  - minor keys: sadness

- Tempo
  - fast tempo: happiness or excitement

- Melody
  - a sequence of consonant notes: joy and calm
  - a sequence of dissonant notes: excitement, anger, or unpleasantness

TransProse

Automatically generates three simultaneous piano melodies pertaining to the dominant emotions in the text, using the NRC Emotion Lexicon.

Examples

TransProse: [www.musicfromtext.com](http://www.musicfromtext.com)
Music played 300,000 times since website launched in April 2014.
TransProse Music Played by an Orchestra, at the Louvre Museum, Paris

A symphony orchestra performs under the glass of the Louvre museum in Paris on Sept. 20. Accenture Strategy has created a symphonic experience enabled by human insight and artificial intelligence technology. (Michel Euler/AP)
Debate: Universality of Perception of Emotions

Grad school experiment on people’s ability to distinguish photos of depression from anxiety
- one is based on sadness, and the other on fear
- found agreement to be poor

Agreement also drops for Ekman emotions when participants are given:
- Just the pictures (no emotion word options)
- Or say, two scowling faces and asked if the two are feeling the same emotion

Margaret Mead
Cultural anthropologist

Paul Ekman
Psychologist and discoverer of micro expressions.

Lisa Barrett
University Distinguished Professor of Psychology, Northeastern University
Some Emotions more basic than others?
may be not…
Hashtagged Tweets

• Hashtagged words are good labels of sentiments and emotions

  Some jerk just stole my photo on #tumblr #grrr #anger

• Hashtags are not always good labels:
  ◦ hashtag used sarcastically

  The reviewers want me to re-annotate the data. #joy

Paper:

Generating lexicon for 500 emotions

NRC Hashtag Emotion Lexicon: About 20,000 words associated with about 500 emotions

Papers:
• Using Nuances of Emotion to Identify Personality. Saif M. Mohammad and Svetlana Kiritchenko, In Proceedings of the ICWSM Workshop on Computational Personality Recognition, July 2013, Boston, USA.
• Using Hashtags to Capture Fine Emotion Categories from Tweets. Saif M. Mohammad, Svetlana Kiritchenko, Computational Intelligence, in press.
Sentiment Lexicons

Created a sentiment lexicon using a Turney (2003) inspired method that uses PMI of a word with co-occurring positive and negative seed hashtags.

**Positive**
- spectacular 0.91
- okay 0.3

**Negative**
- lousy -0.84
- unpredictable -0.17
SemEval Shared task on the Sentiment Analysis of Tweets
and the role of word-sentiment associations

Papers:
- **Sentiment Analysis of Short Informal Texts.** Svetlana Kiritchenko, Xiaodan Zhu and Saif Mohammad. Journal of Artificial Intelligence Research, 50, August 2014.
**Sentiment Analysis Competition**

**SemEval-2013: Classify Tweets, 44 teams**

The diagram shows the F-score of various teams in the competition. The X-axis represents the teams, and the Y-axis represents the F-score. The teams are listed along the X-axis, and their corresponding F-scores are shown on the Y-axis. The teams include NRC-Canada, GUMLTLT, AVAYA, and others. The diagram visually represents the performance of each team in the competition.
Sentiment Analysis Competition
SemEval-2013: Classify SMS messages, 30 teams

F-score

- NRC-Canada
- GUMILTL
- KLUE
- AVA
- teragram
- NTNU
- CodeX
- nlp.cs.aueb.gr
- FBK-irst
- ECNUCS
- AML_andERIC
- UT-DB
- SAIL
- UNITOR
- SentifyicTeam
- NILC
- USP
- RÉACTION
- SU-sentilab
- LVIC-LIMSI
- FBM
- OPTWIMA
- senti.ue-en
- ASYU/nOL-Leipzig
- SSA-UO
- bvbaugh
- UMCC_DLSI(sA)
- UoM
- uottawa
- IIRG
Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)

Term-level
- Blogs
- SMS
- Tweets13
- Tweets14
- TSarcasm

Sentence-level
- Blogs
- SMS
- Tweets13
- Tweets14
- TSarcasm

submissions: 16

submissions: 46

our rank:
- Blogs: 2
- SMS: 2
- Tweets13: 1
- Tweets14: 1
- TSarcasm: 3
- Blogs: 1
- SMS: 1
- Tweets13: 2
- Tweets14: 4
- TSarcasm: 1
Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)

Term-level
- Blogs
- SMS
- Tweets13
- Tweets14
- TSarcasm
- Submissions: 16

Sentence-level
- Blogs
- SMS
- Tweets13
- Tweets14
- TSarcasm
- Submissions: 46

Our rank:
- 2
- 2
- 1
- 1
- 3

Aspect-Based Sentiment Analysis (SemEval-2014 Task 4)

Submissions: 30+

Term
- Restaurant
- Laptop
- 3
- 3

Category
- Restaurant
- 1

Term Sentiment
- Restaurant
- 2

Cat. Sentiment
- Restaurant
- 1

Saif M. Mohammad
Feature Contributions (on Tweets)

F-scores

- all
- all-lex.
- all-man. lex.
- all-auto. lex.
- all-ngrams
- all-word ngr.
- all-char. ngr.
- all-negation
- all-POS
- all-clusters
- all-encod.
Detecting Stance in Tweets

Given a tweet text and a target determine whether:

- the tweeter is in favor of the given target
- the tweeter is against the given target
- neither inference is likely

Example 1:

Target: Donald Trump
Tweet: Jeb Bush is the only sane candidate in this republican lineup.

Systems have to deduce that the tweeter is likely against the target.

Example 2:

Target: pro-life movement
Tweet: The pregnant are more than walking incubators, and have rights!

Systems have to deduce that the tweeter is likely against the target.
SemEval-2016 Task#6: Detecting Stance in Tweets

Task A: **Supervised Framework**

- provided training and test data for five targets
- atheism, climate change is a real concern, feminist movement, Hillary Clinton, legalization of abortion
Metaphor as a Medium for Emotion

Paper:
Metaphor

A figure of speech that refers to something as being the same as another thing for rhetorical effect.

- betrayal is stabbing someone in the back
- anger is a hot fluid (the boss boiled over)
- books are keys to one’s imagination
- arguments are planes (he shot down all of my arguments)
Metaphor: Knowledge Projection (Lakoff & Johnson, 1980)

**Source domain**
physical
closely experienced

**Target domain**
more abstract
more vague

Example: He shot down all of my arguments

Projects knowledge and inferences:
from the domain of battle (source domain)
on to the domain of arguments and debates (target domain).
Metaphor: Knowledge Projection (Lakoff & Johnson, 1980)

Source domain
- physical
- closely experienced

Target domain
- more abstract
- more vague

Example: He shot down all of my arguments

Projects knowledge and inferences:
from the domain of battle (source domain)
onto the domain of arguments and debates (target domain).

- preserves the core meaning of the sentence
- emphasizes certain aspects of the target domain, while downplaying others: framing
Research Questions

Q. Is a metaphorical statement likely to convey a stronger emotional content than its literal counterpart?
   ◦ to what extent?

Q. How does this emotional content arise in the metaphor:
   ◦ from the source domain,
   ◦ from the target domain, or
   ◦ compositionally through interaction of the source and the target?
Hypotheses

Hypothesis 1: metaphorical uses of words tend to convey more emotion than their literal paraphrases in the same context.

Example:

a. The spaceship blazed off into the space.  METAPHORIC
b. The spaceship departed into the space.  LITERAL

Hypothesis 2: the metaphorical sense of a word tends to carry more emotion than the literal sense of the same word.

Example:

a. Hillary brushed off the accusations.  METAPHORIC
b. He brushed off the snow.  LITERAL

Underline: verb
Green font: text that is common across a. and b.
Hypotheses

Hypothesis 1: metaphorical uses of words tend to convey more emotion than their literal paraphrases in the same context.

Example:

a. Hillary *brushed off* the accusations. **METAPHORIC**
b. Hillary *dismissed* the accusations. **LITERAL**

Hypothesis 2: the metaphorical sense of a word tends to carry more emotion than the literal sense of the same word.

Example:

a. Hillary *brushed off* the accusations. **METAPHORIC**
b. He *brushed off* the snow. **LITERAL**

**Underline:** verb  
**Green font:** text that is common across a. and b.
Data for Our Experiments

- Focus on metaphors expressed by a verb
  - most frequent type of metaphor (Cameron, 2003; Shutova and Teufel, 2010)

- Extract verbs, senses, and sentences from WordNet
  - WordNet organizes senses in synsets
  - each synset has a gloss and example sentence

- Manually annotated for:
  - metaphoric or literal
  - which is more metaphoric or both equally metaphoric
  - no emotion or some emotion
  - which is more emotional or both equally emotional
Results for Hypothesis 1 Pairs (same context, synonym verbs): Absolute Metaphoricity & Relative Emotionality

<table>
<thead>
<tr>
<th># instances that are:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>metaphorical and more emotional</td>
<td>143</td>
</tr>
<tr>
<td>literal and more emotional</td>
<td>17</td>
</tr>
<tr>
<td>similarly emotional</td>
<td>11</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>171</strong></td>
</tr>
<tr>
<td><strong>Total percentage</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
**Results** for Hypothesis 2 Cross Pairs *(same verb, different senses)*: Absolute Metaphoricity & Relative Emotionality

<table>
<thead>
<tr>
<th># instances that are:</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>metaphorical and more emotional</td>
<td>211 (59.4%)</td>
</tr>
<tr>
<td>literal and more emotional</td>
<td>31 (08.7%)</td>
</tr>
<tr>
<td>similarly emotional</td>
<td>113 (31.8%)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>355 (100%)</strong></td>
</tr>
</tbody>
</table>
Results for Hypothesis 2 All Pairs (same verb, different senses): Relative Metaphoricity & Relative Emotionality

<table>
<thead>
<tr>
<th>Category</th>
<th>Count</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td># instances that are more metaphorical and more emotional</td>
<td>227</td>
<td>36.1%</td>
</tr>
<tr>
<td># instances that are more metaphorical but less emotional</td>
<td>28</td>
<td>04.4%</td>
</tr>
<tr>
<td># instances that are more metaphorical but similarly emotional</td>
<td>119</td>
<td>18.9%</td>
</tr>
<tr>
<td># instances that are similarly metaphorical and similarly emotional</td>
<td>196</td>
<td>31.2%</td>
</tr>
<tr>
<td># instances that are similarly metaphorical but differ in emotionality</td>
<td>59</td>
<td>09.4%</td>
</tr>
<tr>
<td>Total</td>
<td>629</td>
<td>100%</td>
</tr>
</tbody>
</table>
Discussion: Metaphors are More Emotional

- Our results confirm both hypotheses:
  - metaphorical uses of words carry stronger emotions than
    - their literal uses,
    - as well as their literal paraphrases.

- This is inline with recent findings in neuroscience: Citron et al. (2016)
  - Examined metaphoric and literal sentences that had one word different
  - Metaphors (even conventional ones) in textual passages evoked stronger affective brain response

- Our annotations confirm: the metaphorical/literal distinction is a common pattern for polysemous verbs
  - ~38% of all verb senses we annotated were metaphorical
Discussion: Mechanism of Emotionality in Metaphors

Emotional content:
- not merely a property of the source or the target domain
- but rather, it arises through metaphorical composition.

The spaceship *blazed* out into space. MET some emot.  
The spaceship *departed* out into space. LIT no emotion  
The summer sun can cause a pine to *blaze*. LIT no emot.

This is the first such finding, and it highlights the importance of metaphor as a mechanism for expressing emotion.
Summary: Created Affect Association Lexicons

- **Manually**
  - Traditional ratings
    - NRC Emotion Lexicon: ~14,000 words, 8 emotions, 2 sentiments
  - Best Worst Scaling
    - Twitter lexicons for English and Arabic
    - sentiment composition lexicons
      - for phrases with negators, modals, and adverbs
      - for opposing polarity phrases

- **Automatically**
  - for hundreds of affect categories
  - using hashtag words and emoticons
Affect Associations in Creative Language

- Shapes of stories
  - tracked the distribution of emotion words
  - created a system to generate music from text

- Tweet-, message-level sentiment analysis
  - creative tweets are especially challenging
    - sarcasm, hyperbole, irony

- Metaphorical uses of words carry stronger emotions than
  - their literal uses,
  - as well as their literal paraphrases

- Showed that metaphoric usages are common
  - one more indicator that creativity in language is common
**Resources Available at:** [www.saifmohammad.com/ResearchAreas.html](http://www.saifmohammad.com/ResearchAreas.html)

- word-emotion and word-sentiment association lexicons
  - manually created
    - best-worst scaling, sentiment composition
  - automatically generated
    - from tweets and hashtags
- word-colour association lexicon
- metaphor-emotion data
- interactive visualizations
- tutorials and book chapters on sentiment analysis

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creative language has emotional impact
Detecting Stance in Tweets

Given a tweet text and a target determine whether:

- the tweeter is in favor of the given target
- the tweeter is against the given target
- neither inference is likely

Example 1:

Target: Jeb Bush
Tweet: Jeb Bush is the only sane candidate in this republican lineup.

Systems have to deduce that the tweeter is likely in favor of the target.
Detecting Stance in Tweets

Given a tweet text and a target determine whether:
- the tweeter is in favor of the given target
- the tweeter is against the given target
- neither inference is likely

Example 2:
Target: Donald Trump
Tweet: Jeb Bush is the only sane candidate in this republican lineup.
Systems have to deduce that the tweeter is likely against the target.

Example 3:
Target: pro-life movement
Tweet: The pregnant are more than walking incubators, and have rights!
Systems have to deduce that the tweeter is likely against the target.
Stance vs. Sentiment

- positive language $\searrow$ favor; negative language $\nearrow$ against
- the target can be expressed in different ways
  - impacts whether the instance is labeled favor or against
- the target of interest may not be mentioned in the text
  - especially for issue targets: legalization of abortion
- the target of interest may not be the target of opinion in the text

Example 3:

Target: **Donald Trump**
Tweet: Jeb Bush is the only sane candidate in this republican lineup.

Applications of automatic stance detection:
information retrieval, text summarization, textual entailment, social media analytics.
SemEval-2016 Task#6: Detecting Stance in Tweets

Task A: **Supervised Framework**

- provided training and test data for five targets
- atheism, climate change is a real concern, feminist movement, Hillary Clinton, legalization of abortion
Word-Colour Associations

Papers:


Word-Colour Associations

Concrete concepts

- **iceberg** → white
- **vegetation** → green

Abstract concepts

- **danger** → red
- **honesty** → white

Saif M. Mohammad 86
Key Questions

- How much do we agree on word-colour associations?
- How many terms have strong colour associations?
- Do concrete concepts have a higher tendency to have colour association?
- Can we create a lexicon of such word-colour associations?

- Applications: advertising and marketing, information visualization, teaching aid for kids with learning disabilities
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- If a language has only two colours: white and black.
- If a language has three: white, black, red.
- And so on till eleven colours.

Berlin and Kay order:
1. white, 2. black, 3. red, 4. green, 5. yellow, 6. blue,
7. brown, 8. pink, 9. purple, 10. orange, 11. grey

Q. Which colour is associated with sleep?
- black  •  green  •  purple… (11 colour options in random order)

NRC Word-Colour Association Lexicon
- Color associations for ~14,000 words
Associations with Colours

% of terms

Berlin and Kay order

voted

white, black, red, green, yellow, blue, brown, pink, purple, orange, grey
Some Findings

- Colours in decreasing order of association frequency is highly correlated with the Berlin and Kay order.
  - Implications to the Sapir–Whorf hypothesis

- About 30% of the terms have strong colour associations.

- Terms for abstract concepts just as likely to have color associations as concrete concepts

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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.

Least Perceptible Differences in lexicons:

- General English: 0.069
- English Twitter: 0.080
- Arabic Twitter: 0.087

(~4% in range -1..1)
The Interplay of Metaphor and Emotion

Studied in:
- computational linguistics
  - sentiment polarity classification of metaphorical language
    (Veale and Li, 2012; Kozareva, 2013; Strzalkowski et al., 2014)
- linguistics (Blanchette et al., 2001; Kovecses, 2003)
- political science (Lakoff, 1980; Lakoff and Wehling, 2012)
- cognitive psychology (Crawford, 2009; Thibodeau and Boroditsky, 2011)
- neuroscience (Aziz-Zadeh and Damasio, 2008; Jabbi et al., 2008)

However, no quantitative study establishing:
- the extent to which metaphorical language is used to express emotion
- the mechanisms by which this happens.
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