The Search for Emotions, Creativity, and Fairness in Language

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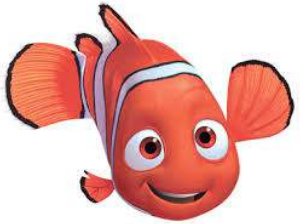
National Research Council Canada Conseil national de recherches Canada

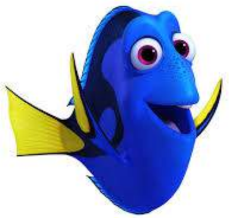
Canada

Emotions

- Determine human experience and behavior
- Condition our actions
- Central in organizing meaning
    - No cognition without emotion

The Search for Emotions in Language

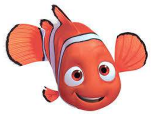




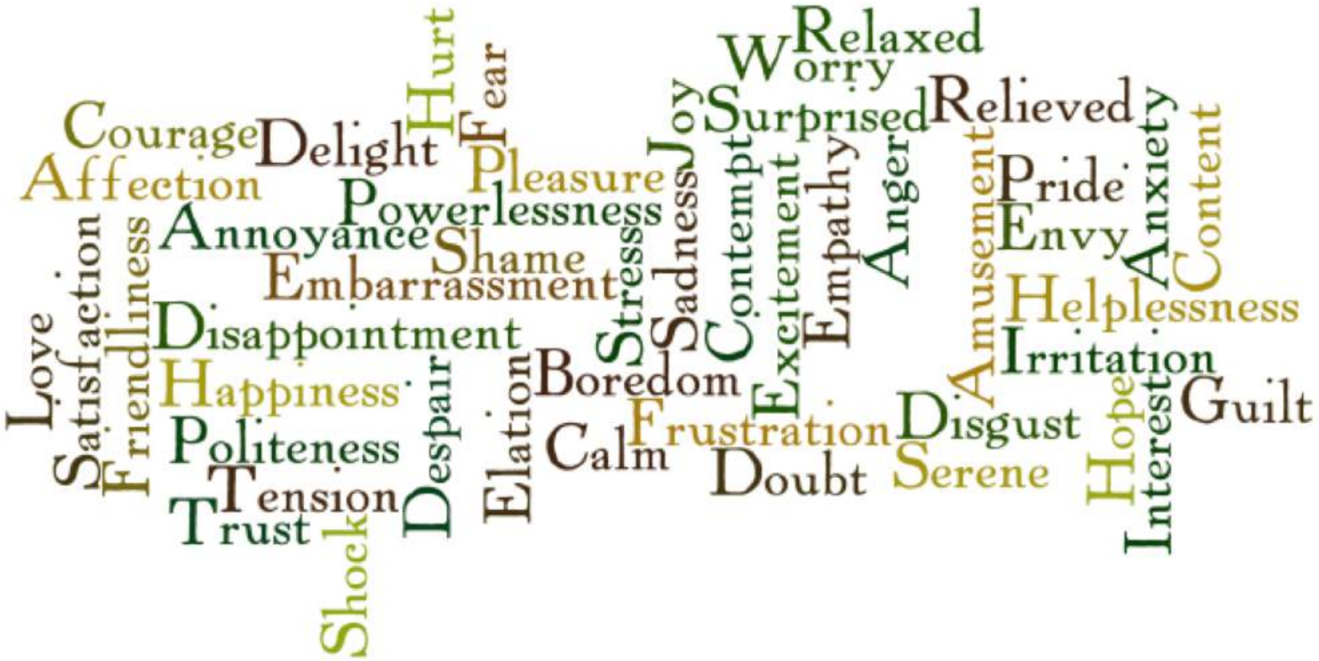
creativity

fairness

Emotions



How many emotions can we perceive?

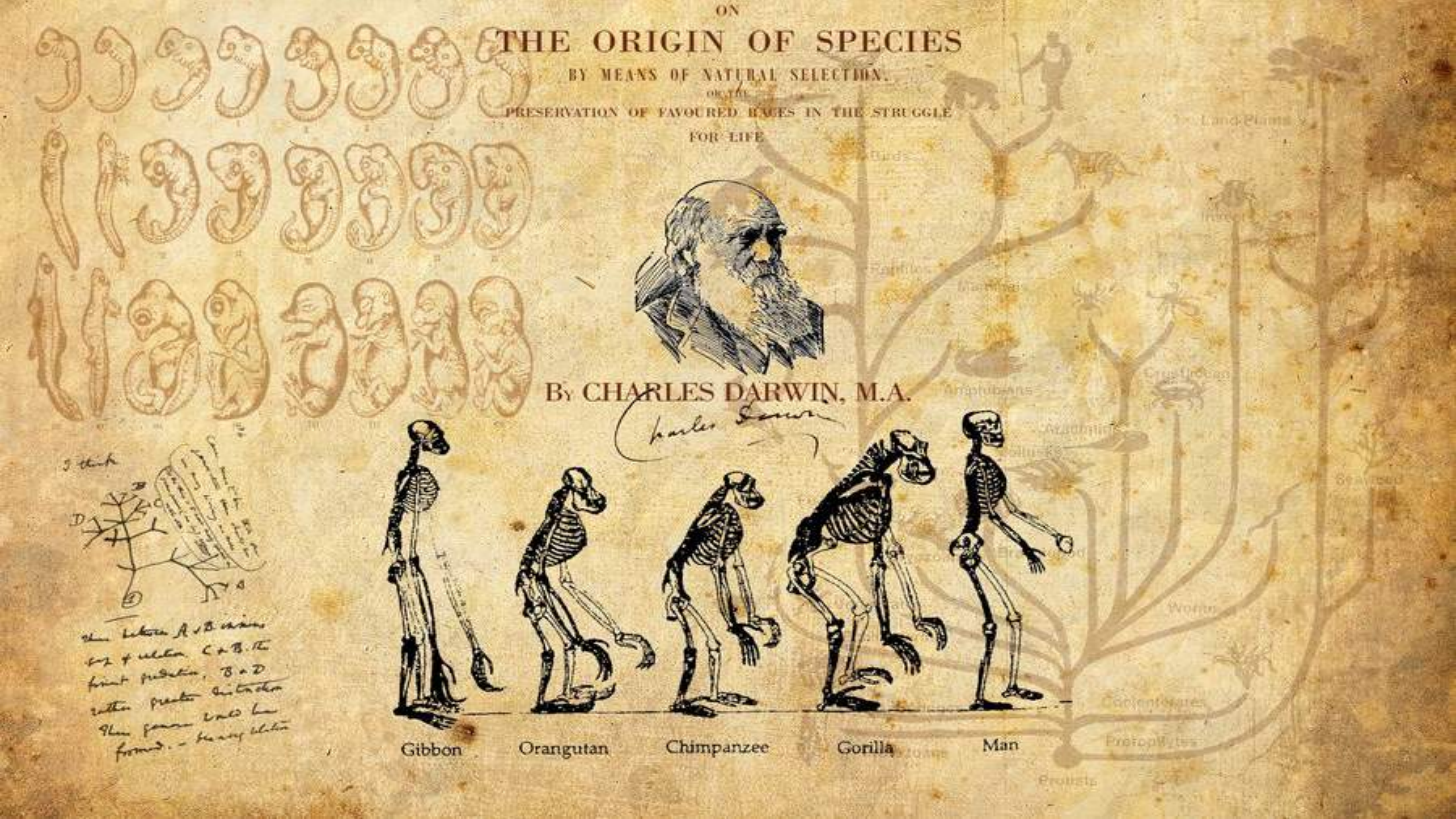


Difficult question:

- fuzzy emotion boundaries, overlapping meanings, socio-cultural influences, etc.

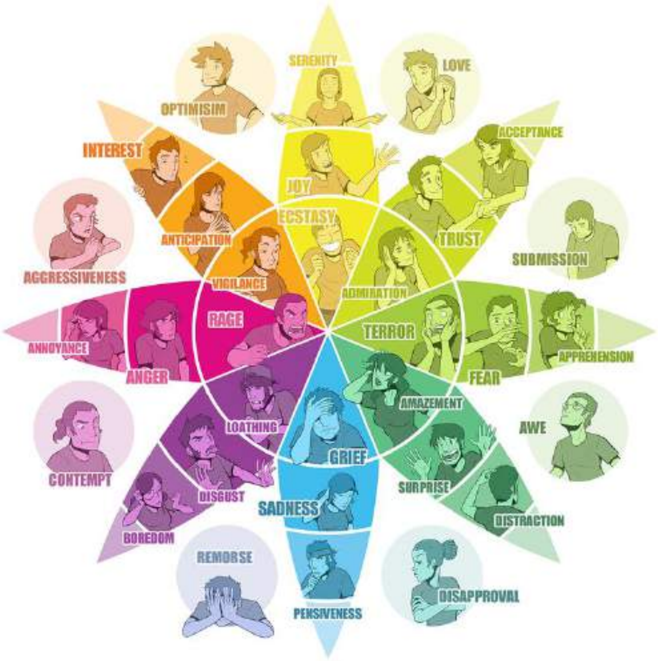
Some studies suggest 500 to 600 emotion categories!

Psychological Models of Emotions

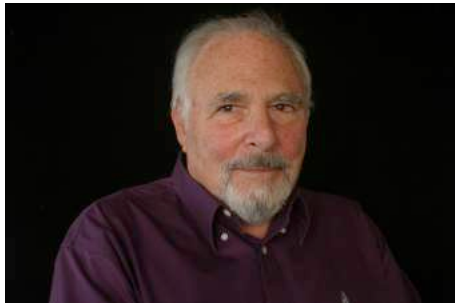

ON
THE ORIGIN OF SPECIES
BY MEANS OF NATURAL SELECTION,
OR THE
PRESERVATION OF FAVOURED RACES IN THE STRUGGLE
FOR LIFE
By CHARLES DARWIN, M.A.
I think
Gibbon
Orangutan
Chimpanzee
Gorilla
Man

Psychological Theories of Basic Emotions

- Paul Ekman, 1971: Six Basic Emotions
- Plutchik, 1980: Eight Basic Emotions
- And many others



Plutchik's Emotion Wheel
Image credit: Julia Belyanevych

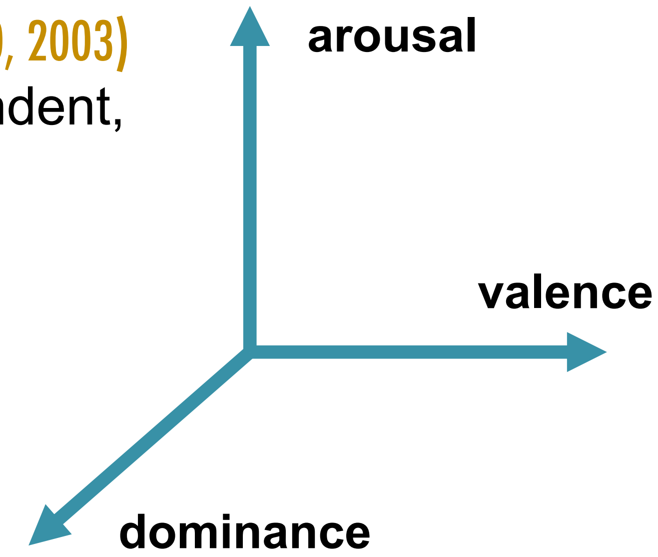


Paul Ekman, Psychologist

Core Dimensions of Connotative Meaning

Influential factor analysis studies (Osgood et al., 1957; Russell, 1980, 2003) have shown that the three most important, largely independent, dimensions of word meaning:

- valence (V): positive/pleasure – negative/displeasure
- arousal (A): active/stimulated – sluggish/bored
- dominance (D): powerful/strong – powerless/weak



Thus, when comparing the meanings of two words, we can compare their V, A, D scores. For example:

- *banquet* indicates more positiveness than *funeral*
- *nervous* indicates more arousal than *lazy*
- *queen* indicates more dominance than *delicate*

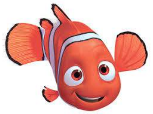
Psychological Models of Emotions

- the valence, arousal, and dominance model
- the basic emotions model

We work with both models

Two Parts To The Work

The Search for Emotions – by Humans

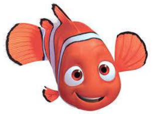


Human annotations of words, phrases, tweets, etc. for emotions

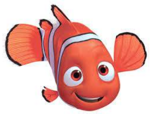
- Draw inferences about language and people:
  - understand how we (or different groups of people) use language to express meaning and emotions

The Search for Emotions – by Machines

Develop automatic emotion related systems



- predicting emotions of words, tweets, sentences, etc.
- detecting stance, personality traits, well-being, cyber-bullying, etc.



The Search for Emotions – by humans

NRC Emotion Lexicon


Peter Turney

- Entries for 14,200
- Associations (0 or 1) with 8 basic emotions

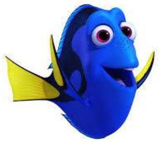
Available at: www.saifmohammad.com

Paper:

Crowdsourcing a Word-Emotion Association Lexicon, Saif M. Mohammad and Peter Turney, *Computational Intelligence*, 29 (3), pages 436-465, 2013. Lexicon Released in 2010.

Use of The NRC Emotion Lexicon

- For research by the scientific community
  - Computational linguistics, psychology, digital humanities, robotics, public health research, etc.
- To analyze text
  - Brexit tweets, Radiohead songs, Trump tweets, election debates,…
  - **Wishing Wall**, uses the NRC Emotion lexicon to visualize wishes. Displayed in:
    - **Barbican Centre**, London, England, 2014
    - **Tekniska Museet**, Stockholm, Sweden, 2014
    - **Onassis Cultural Centre**, Athens, Greece, 2015
    - **Zorlu Centre**, Istanbul, Turkey, 2016



creativity

- In commercial applications

fine-grained

Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance

for 20,000 English Words

National Research Council Canada
Conseil national de recherches Canada

@SaifMMohammad

Related Work: Existing VAD Lexicons

Affective Norms of English Words (ANEW) (Bradley and Lang, 1999)

- ~1,000 words
- 9-point rating scale

Warriner et al. Norms (Warriner et al. 2013)

- 14,000 words
- 9-point rating scale

Small number of VAD lexicons in non-English languages as well

- E.g.:
  - Moors et al. (2013) for Dutch
  - Vo et al. (2009) for German
  - Redondo et al. (2007) for Spanish
- rating scales

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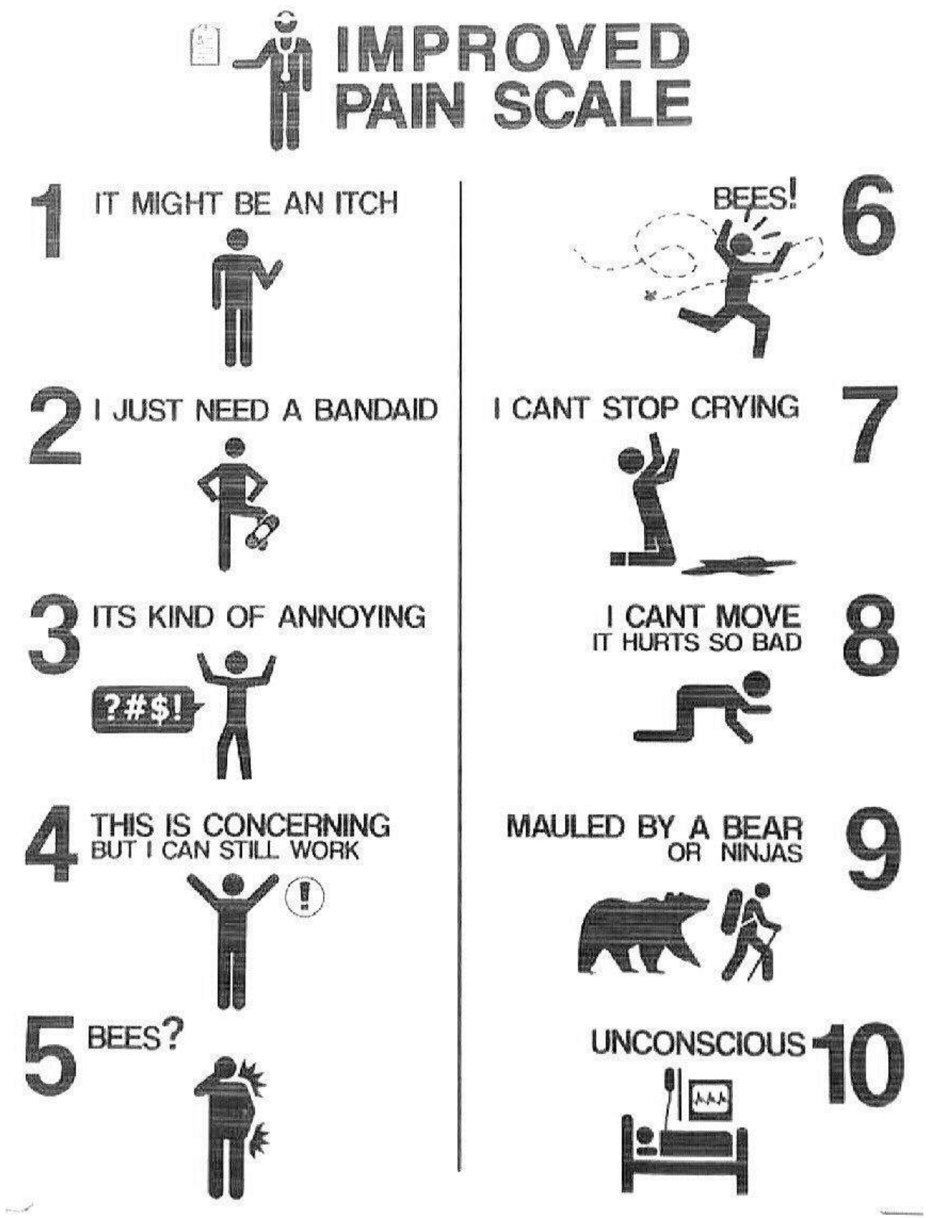
Rating scales:



source: imgur

Rating scales:

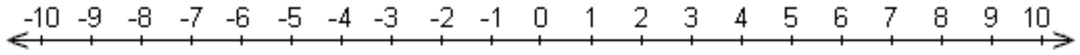
source: xkcd

Rating scales:

ACL-2018 Reviewing Scale

Overall Score (1-6)

- 6 = Transformative: This paper is likely to change our field. Give this score exceptionally for papers worth best paper consideration.
- 5 = Exciting: The work presented in this submission includes original, creative contributions, the methods are solid, and the paper is well written.
- 4 = Interesting: The work described in this submission is original and basically sound, but there are a few problems with the method or paper.
- 3 = Uninspiring: The work in this submission lacks creativity, originality, or insights. I'm ambivalent about this one.
- 2 = Borderline: This submission has some merits but there are significant issues with respect to originality, soundness, replicability or substance, readability, etc.
- 1 = Poor: I cannot find any reason for this submission to be accepted.



Problems with rating scales:

- fixed granularity
- difficult to maintain consistency across annotators
- difficult for an annotator to be self consistent
- scale region bias

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

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

- The annotator is presented with four words (say, A, B, C, and D) and asked:
  - which word is associated with the most/highest X (property of interest, say valence)
  - which word is associated with the least/lowest X
- By answering just these two questions, five out of the six inequalities are known
  - For e.g.:
    - If A: highest valence
    - and D: lowest valence, then we know:

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

Best–Worst Scaling (Louviere & Woodworth, 1990)

- Each of these BWS questions can be presented to multiple annotators.
- We can obtain real-valued scores for all the terms using a simple counting method (Orme, 2009)

  score(w) = (#best(w) - #worst(w)) / #annotations(w)

  the scores range from:
  -1 (least X)
  to 1 (most X)

  X = property of interest, say valence

  - the scores can then be used to rank all the terms

Best–Worst Scaling (Louviere & Woodworth, 1990)

- Uses comparative annotation—mitigates bias
- Keeps the number of annotations down to about 2N
- Leads to more reliable, less biased, more discriminating annotations (Kiritchenko and Mohammad, 2017, Cohen, 2003)

Best-Worst Questionnaire for Valence Annotations

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?

(Four words listed as options)

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?

(Four words listed as options)

Similar questions for arousal and dominance

This study was approved by the NRC Research Ethics Board (NRC-REB) under protocol number 2017-98.
REB review seeks to ensure that research projects involving humans as participants meet Canadian standards of ethics.

Crowdsourcing and Quality Control

About 2% of the data was annotated internally beforehand (by the author)

- These gold questions are interspersed with other questions
- If one gets a gold question wrong, they are immediately notified of it
  - feedback to improve task understanding
- If one's accuracy on the gold questions falls below 80%,
  - they are refused further annotation
  - all of their annotations are discarded

Mechanism to avoid malicious or random annotations

Valence, Arousal, and Dominance Annotations (with BWS)

Dataset	#words	Location of Annotators	Annotation Item	#Items	#Annotators	MAI	#Q/Item	#Best–Worst Annotations
valence	20,007	worldwide	4-tuple of words	40,014	1,020	6	2	243,295
arousal	20,007	worldwide	4-tuple of words	40,014	1,081	6	2	258,620
dominance	20,007	worldwide	4-tuple of words	40,014	965	6	2	276,170
Total								**778,085**

Includes:

- Terms from the NRC Emotion Lexicon
- Terms from the Warriner et al. (2013) VAD lexicon
- Terms common in tweets

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number of pairs of best—worst annotations

Best–Worst Scaling (Louviere & Woodworth, 1990)

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  score(w) = (#best(w) - #worst(w)) / #annotations(w)

  the scores range from:
  -1 (least X) X = property of interest, say valence
  to 1 (most X)

  - linearly transformed to scores between 0 and 1
  - the scores can then be used to rank all the terms

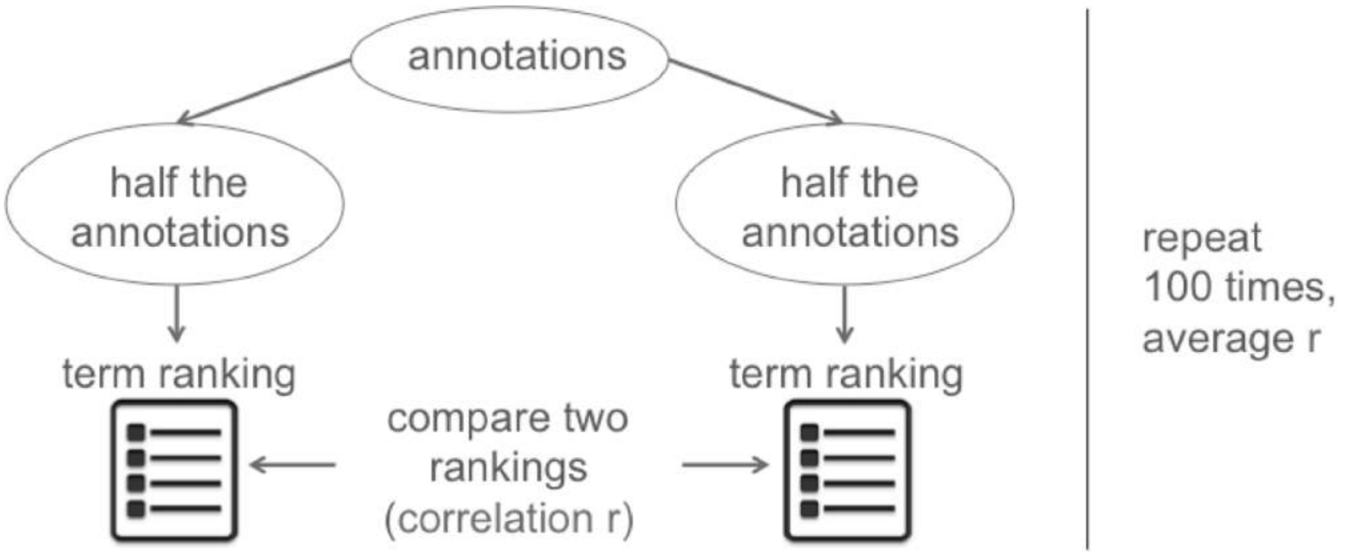
Entries with Highest and Lowest Scores in the VAD Lexicon

Dimension	Word	Score↑	Word	Score↓
valence	*love*	1.000	*toxic*	0.008
	happy	1.000	*nightmare*	0.005
	happily	1.000	*shit*	0.000
arousal	*abduction*	0.990	*mellow*	0.069
	exorcism	0.980	*siesta*	0.046
	homicide	0.973	*napping*	0.046
dominance	*powerful*	0.991	*empty*	0.081
	leadership	0.983	*frail*	0.069
	success	0.981	*weak*	0.045

Scores are in the range 0 (lowest V/A/D) to 1 (highest V/A/D).

Reliability (Reproducibility) of Annotations

Average split-half reliability (SHR): a commonly used approach to determine consistency (Kuder and Richardson, 1937; Cronbach, 1946)



Pearson correlation: -1(most inversely correlated) to 1(most correlated)
higher scores indicate higher reliability

Split-Half Reliability Scores for VAD Annotations

higher scores indicate higher reliability

Annotations	# Terms	# Annotations	V	A	D
Warriner et al. (2013)	13,915	20 per term	0.91	0.79	0.77

Markedly lower SHR for A and D.
The dominance ratings seem especially problematic since the Warriner V-D correlation is 0.71.

Split-Half Reliability Scores for VAD Annotations

higher scores indicate higher reliability

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Warriner et al. (2013)	13,915	20 per term	0.91	0.79	0.77
Ours (Warriner terms)	13,915	6 per tuple	0.95	0.91	0.91

Split-Half Reliability Scores for VAD Annotations

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Warriner et al. (2013)	13,915	20 per term	0.91	0.79	0.77
Ours (Warriner terms)	13,915	6 per tuple	0.95	0.91	0.91
Ours (all terms)	20,007	6 per tuple	0.95	0.90	0.90

These SHR scores show for the first time that highly reliable fine-grained ratings can be obtained for valence, arousal, and dominance. Also, our V-D correlation is 0.48.

NRC VAD Lexicon and the Warriner et al. Lexicon:

How Different are the Scores?

Pearson correlations r

Annotations	V	A	D
Ours-Warriner (for overlapping terms)	0.81	0.62	0.33

The especially low correlations for dominance and arousal indicate that our lexicon has substantially different scores and rankings of terms.

Gender Differences in Perception of the World (Core Dimensions)

fairness

- Men, women, and other genders are substantially more alike than different
- However, they have encountered different socio-cultural influences
- Often these disparities have been a means to exert unequal status and asymmetric power relations
- Gender studies examine
  - both the overt and subtle impacts of these socio-cultural influences
  - how different genders perceive and use language

Analysis of VAD Judgments by Different Demographic Groups

Showed that our demographic attributes impact how we view the world around us. E.g.:

- women have a higher shared understanding of arousal of terms
- men have a higher shared understanding of dominance and valence
- those above the age of 35 have a higher shared understanding of V and A
- extroverts and those that are open to experiences have a higher shared understanding of V, A, and D

Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words. Saif M. Mohammad. In *Proceedings of* the 56th Annual Meeting of the Association for Computational Linguistics (ACL), Melbourne, Australia, July 2018.

Best-Worst Scaling Lexicons

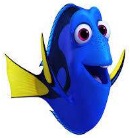
About 6000 Words from the NRC Emotion Lexicon Annotated for Intensity of Emotion

Lexicon	Affect Dimension	Language	Domain
1. Affect/Emotion Intensity Lexicon	Joy, Sadness, Fear, Anger	English	General
2. SemEval-2015 English Twitter Sentiment Lexicon	Valence	English	Twitter
3. SemEval-2016 Arabic Twitter Sentiment Lexicon	Valence	Arabic	Twitter
4. Sentiment Composition Lexicon for Negators, Modals, and Adverbs (SCL-NMA)	Valence	English	General
5. Sentiment Composition Lexicon for Opposing Polarity Phrases (SCL-OPP)	Valence	English	General

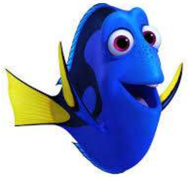
Lexicons and papers available at: http://saifmohammad.com/WebPages/lexicons.html

English Twitter Lexicon:
Examples sentiment scores obtained using BWS

Term	Sentiment Score -1 (most negative) to 1 (most positive)
awesomeness	0.827
#happygirl	0.625
cant waitttt	0.601
don't worry	0.152
not true	-0.226
cold	-0.450
#getagrip	-0.587
#sickening	-0.722



Art and Emotions



creativity

WikiArt Emotions: An Annotated Dataset of Emotions Evoked by Art. Saif M. Mohammad and Svetlana Kiritchenko. In *Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018)*, May 2018, Miyazaki, Japan.

WikiArt Emotions: An Annotated Dataset of Emotions Evoked by Art

- ~4K pieces of art (mostly paintings)
- From four styles:
  Renaissance Art, Post-Renaissance Art, Modern Art, and *Contemporary Art*
- 20 categories:
  Impressionism, Expressionism, Cubism, Figurative art, Realism, Baroque,…
- Annotated for emotions evoked, amount liked, does it depict a face.

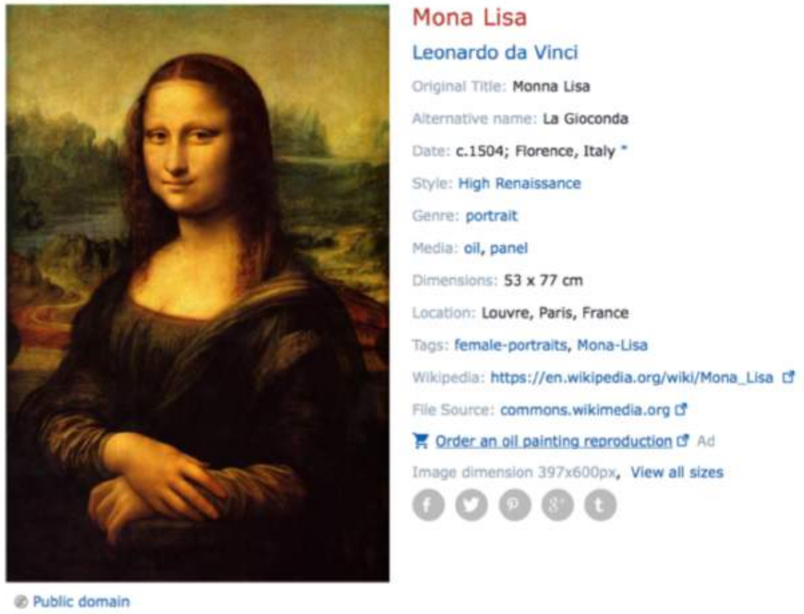


Figure 1: WikiArt.org's page for the *Mona Lisa*. In the WikiArt Emotions Dataset, the *Mona Lisa* is labeled as evoking happiness, love, and trust; its average rating is 2.1 (in the range of -3 to 3).

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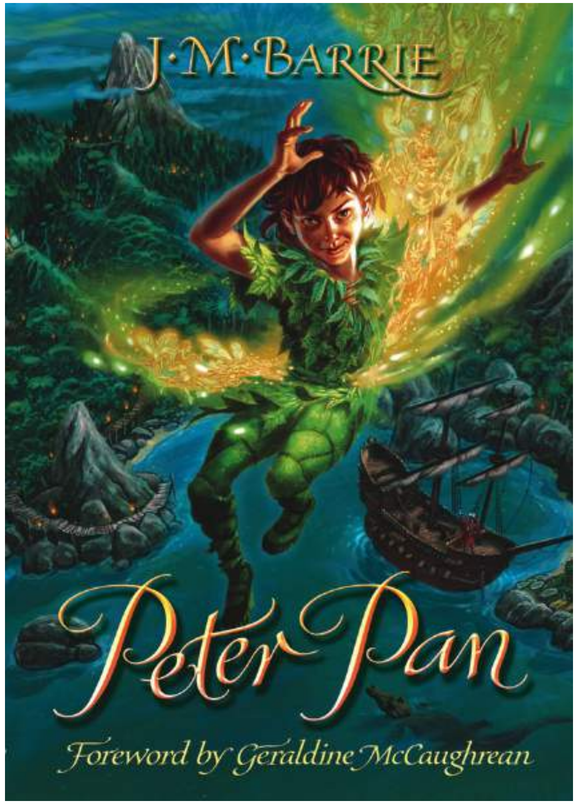
Papers:

- Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words. Saif M. Mohammad. In *Proceedings of* the 56th Annual Meeting of the Association for Computational Linguistics (ACL), Melbourne, Australia, July 2018.
- Capturing Reliable Fine-Grained Sentiment Associations by Crowdsourcing and Best-Worst Scaling. Svetlana Kiritchenko and Saif M. Mohammad. In Proceedings of the 15th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. June 2016. San Diego, CA.
- Word Affect Intensities. Saif M. Mohammad. In Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018), May 2018, Miyazaki, Japan.
- Sentiment Composition of Words with Opposing Polarities. Svetlana Kiritchenko and Saif M. Mohammad. In Proceedings of the 15th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. June 2016. San Diego, CA.
- 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.
- Semeval-2016 Task 7: Determining Sentiment Intensity of English and Arabic Phrases. Svetlana Kiritchenko, Saif M. Mohammad, and Mohammad Salameh. In Proceedings of the International Workshop on Semantic Evaluation (SemEval '16). June 2016. San Diego, California.

The Search for Emotions – by Machines

- automatic systems for detecting emotions in text, literary analysis, music generation, …

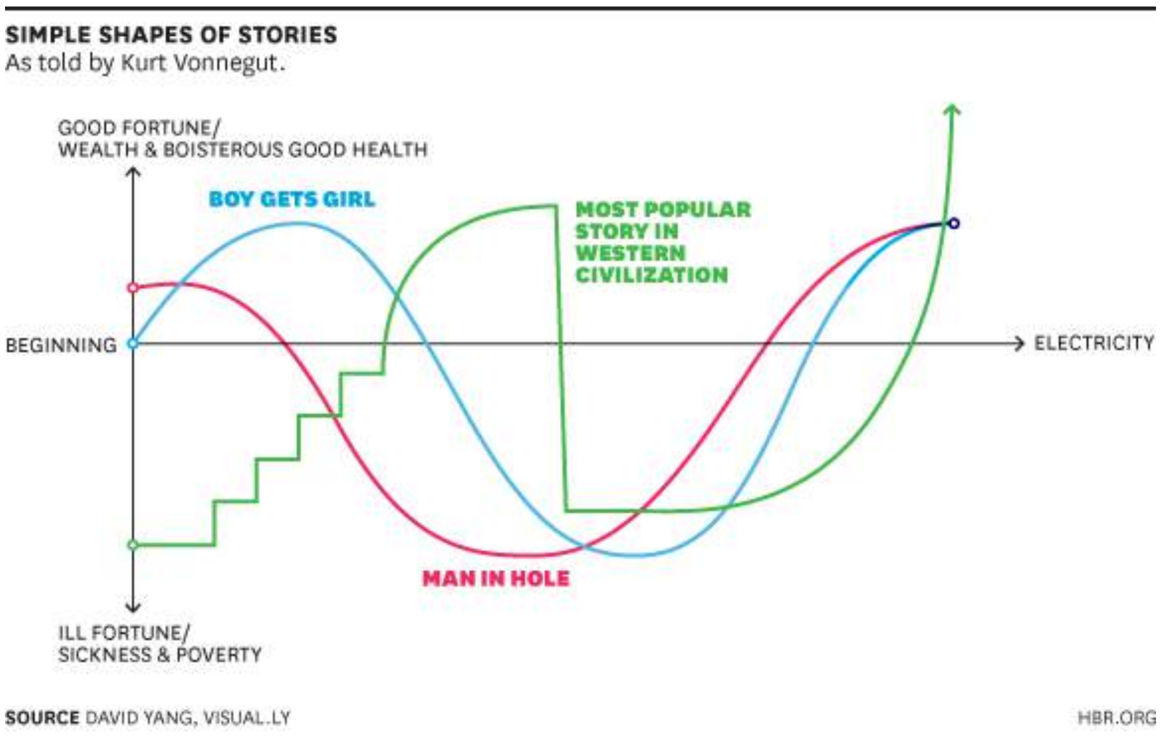


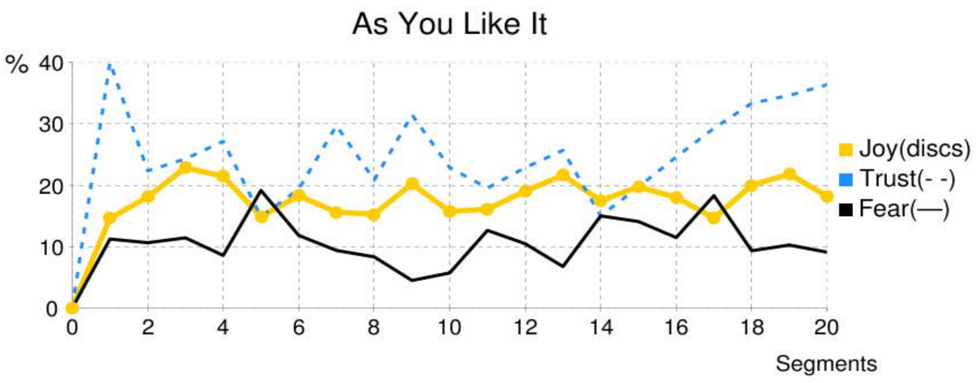
Detecting Emotions in Stories

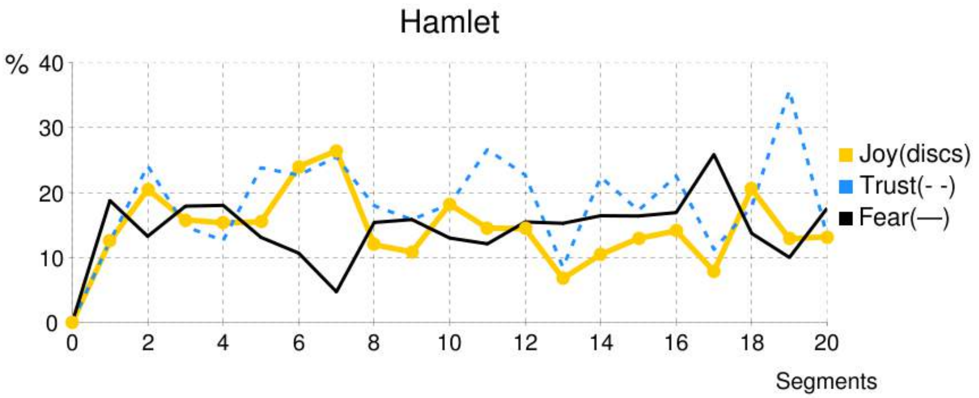
STORIES

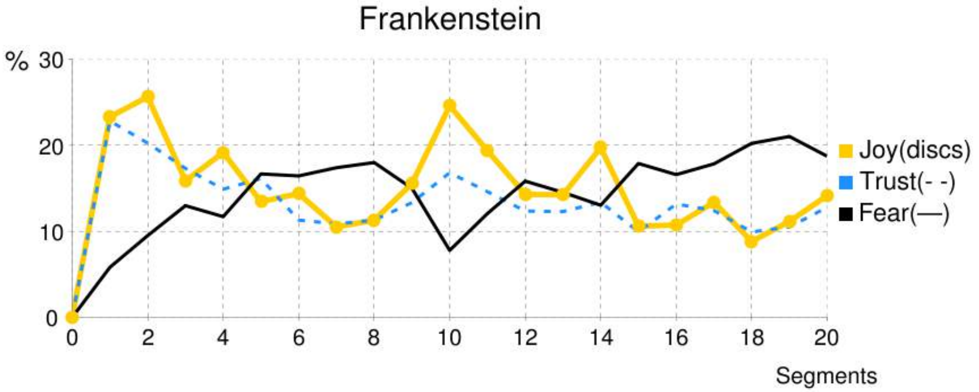
Tracking Emotions in Stories

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





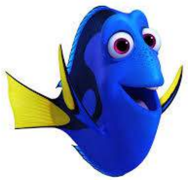




Tony Yang, Simon Fraser University

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.
- Character-based kernels for novelistic plot structure. Elsner, M., 2012, April. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics* (pp. 634-644). Association for Computational Linguistics.
- A novel method for detecting plot. M. Jockers http://www.matthewjockers.net/2014/06/05/a-novel-method-for-detecting-plot/, June 2014.
- The emotional arcs of stories are dominated by six basic shapes. Reagan, A.J., Mitchell, L., Kiley, D., Danforth, C.M. and Dodds, P.S., 2016. EPJ Data Science, 5(1), p.31.

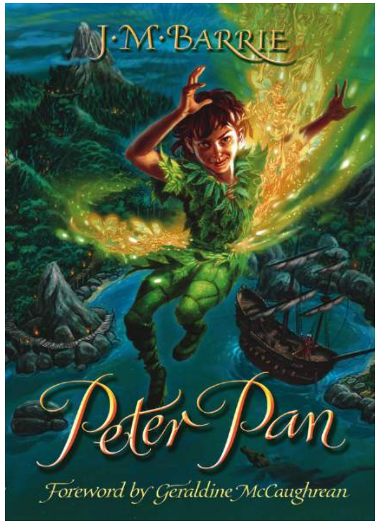


creativity

Generating music from text

Paper:

- Generating Music from Literature. Hannah Davis and Saif M. Mohammad, In Proceedings of the EACL Workshop on Computational Linguistics for Literature, April 2014, Gothenburg, Sweden.



A method to generate music from literature.

- music that captures the change in the distribution of emotion words.

Music-Emotion Associations

Hannah Davis
Artist/Programmer

- 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

Hunter et al., 2010, Hunter et al., 2008, Ali and Peynirciolu, 2010,
Gabrielsson and Lindstrom, 2001, Webster and Weir, 2005

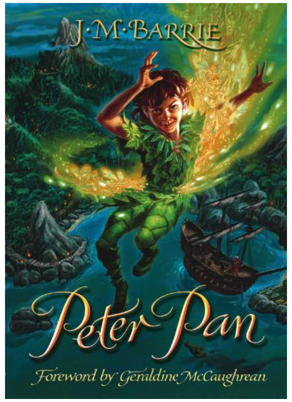
TransProse

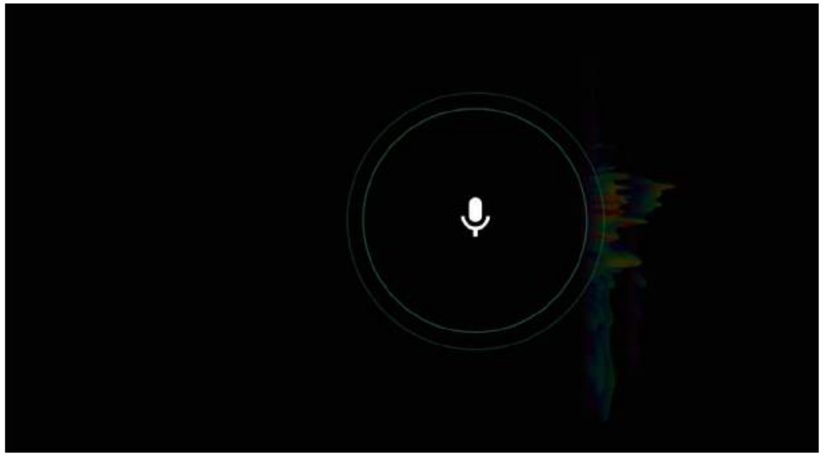
Automatically generates three simultaneous piano melodies pertaining to the dominant emotions in the text, using the NRC Emotion Lexicon.

TransProse

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

Examples





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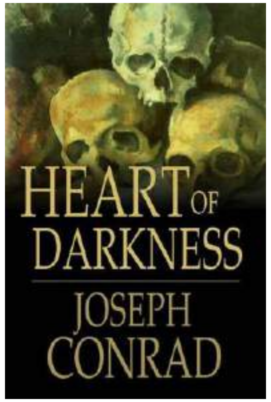

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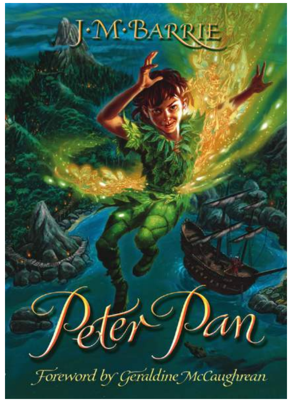
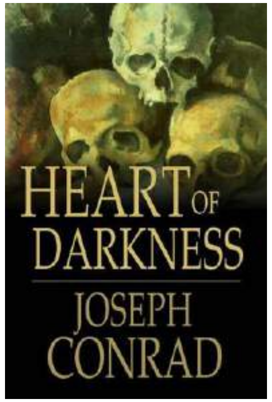




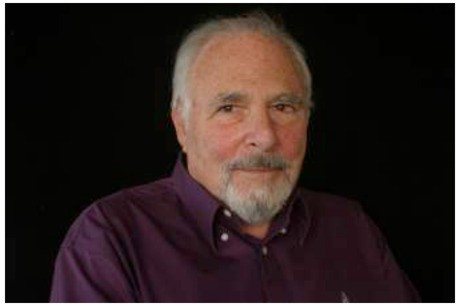
TransProse: www.musicfromtext.com
Music played 300,000 times since website launched in April 2014.

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

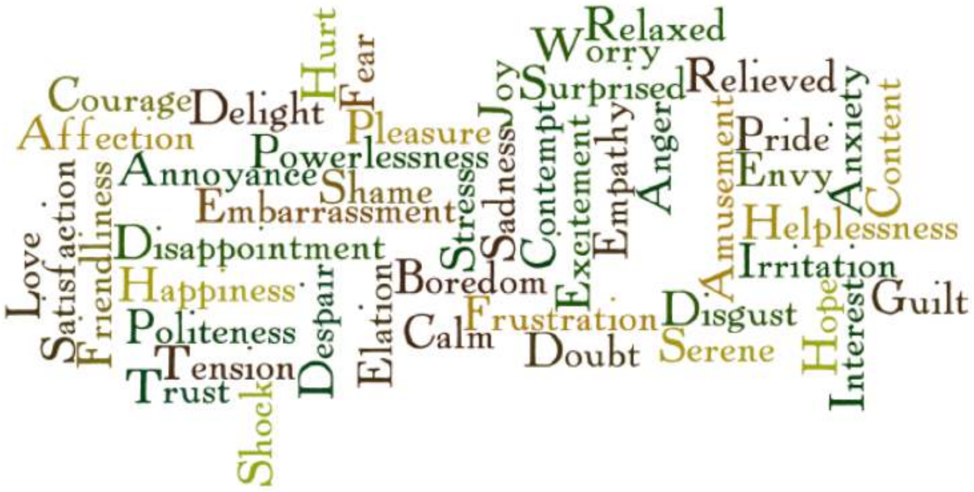
Margaret Mead
Cultural anthropologist



Paul Ekman
Psychologist and discoverer of micro expressions.

Lisa Barrett
University Distinguished Professor of Psychology, Northeastern University

- 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



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**

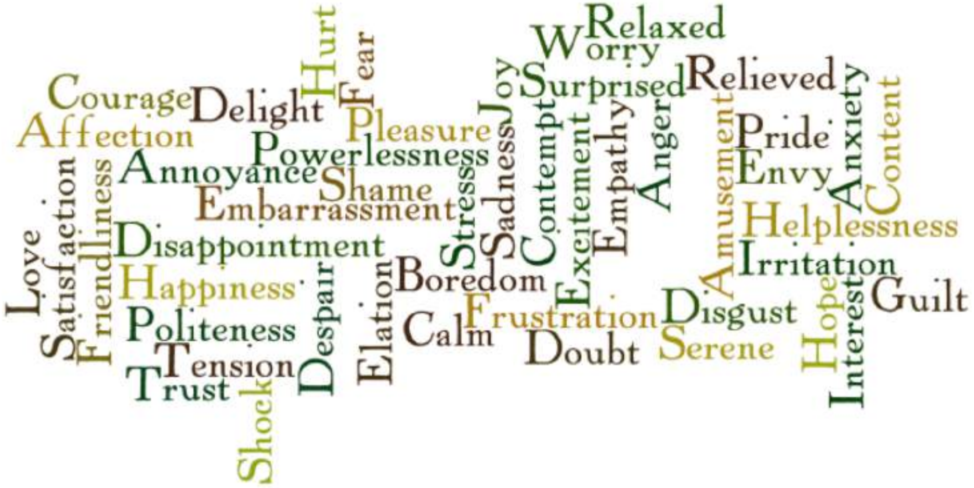
- Hashtags are not always good labels:
  - hashtag used sarcastically

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

Paper:

#Emotional Tweets, Saif Mohammad, In Proceedings of the First Joint Conference on Lexical and Computational Semantics (*Sem), June 2012, Montreal, Canada.

Data to Model Hundreds of 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, Volume 31, Issue 2, Pages 301-326, May 2015.

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 -0.74

murder -0.95

Svetlana Kiritchenko
NRC

Xiaodan Zhu
NRC

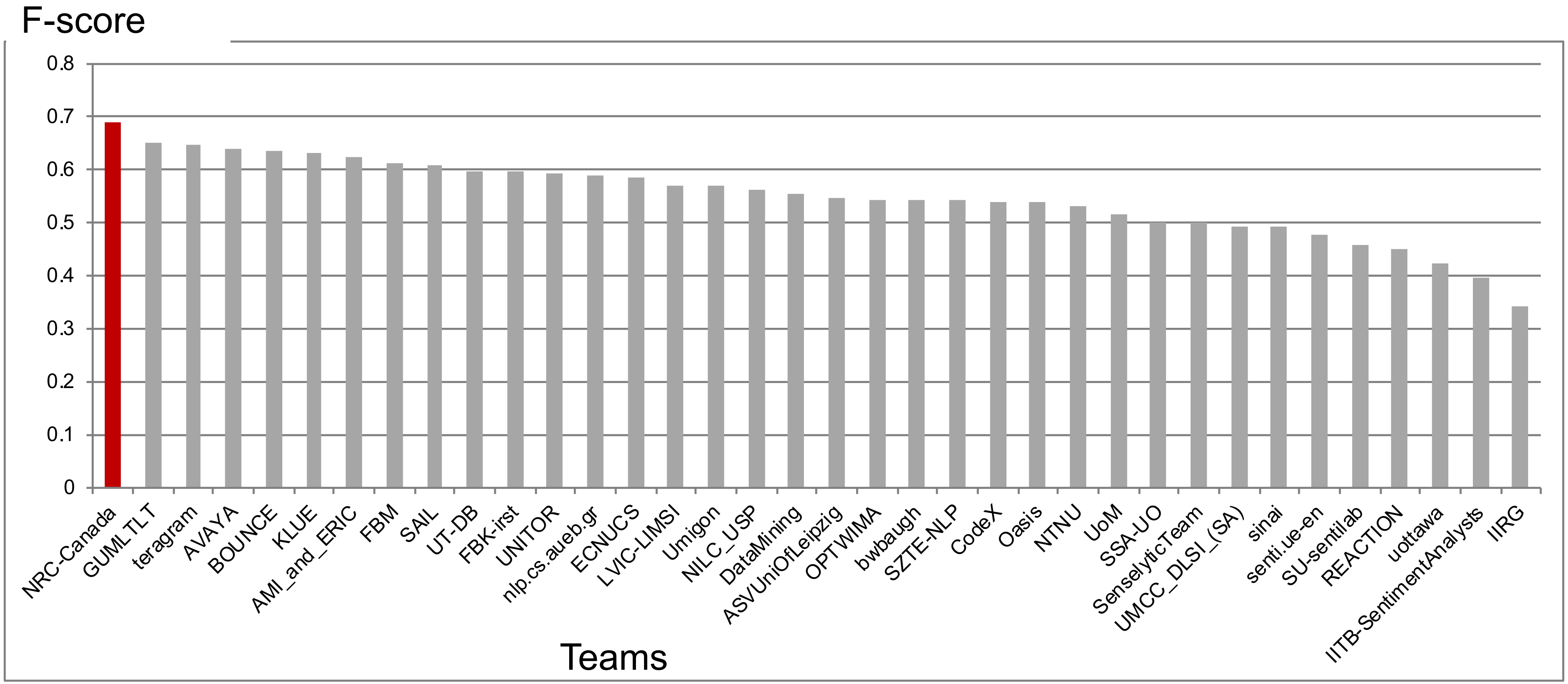
SemEval Shared task on the Sentiment Analysis of Tweets

Papers:

- Sentiment Analysis of Short Informal Texts. Svetlana Kiritchenko, Xiaodan Zhu and Saif Mohammad. *Journal of Artificial Intelligence Research*, 50, August 2014.
- NRC-Canada: Building the State-of-the-Art in Sentiment Analysis of Tweets, Saif M. Mohammad, Svetlana Kiritchenko, and Xiaodan Zhu, In *Proceedings of the seventh international workshop on Semantic Evaluation Exercises (SemEval-2013)*, June 2013, Atlanta, USA.

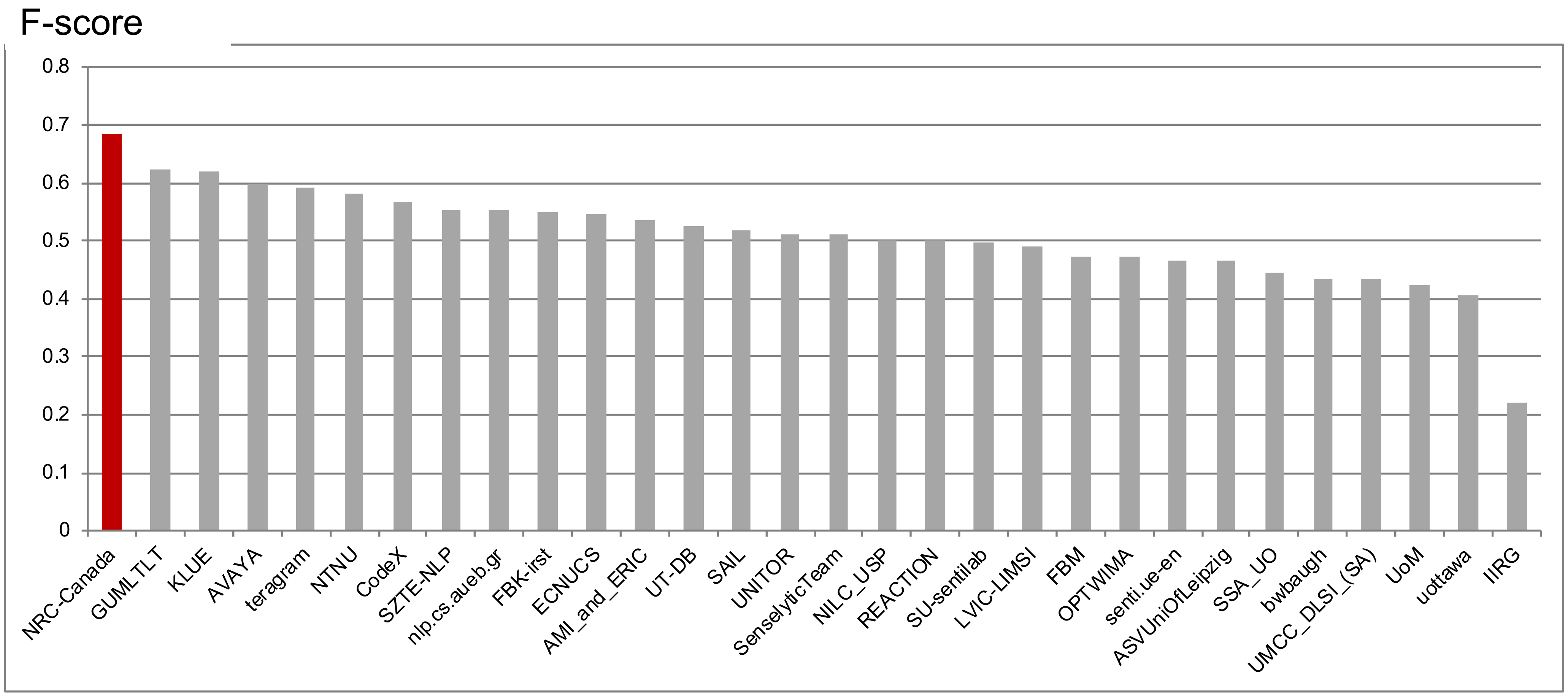
Sentiment Analysis Competition

SemEval-2013: Classify Tweets, 44 teams

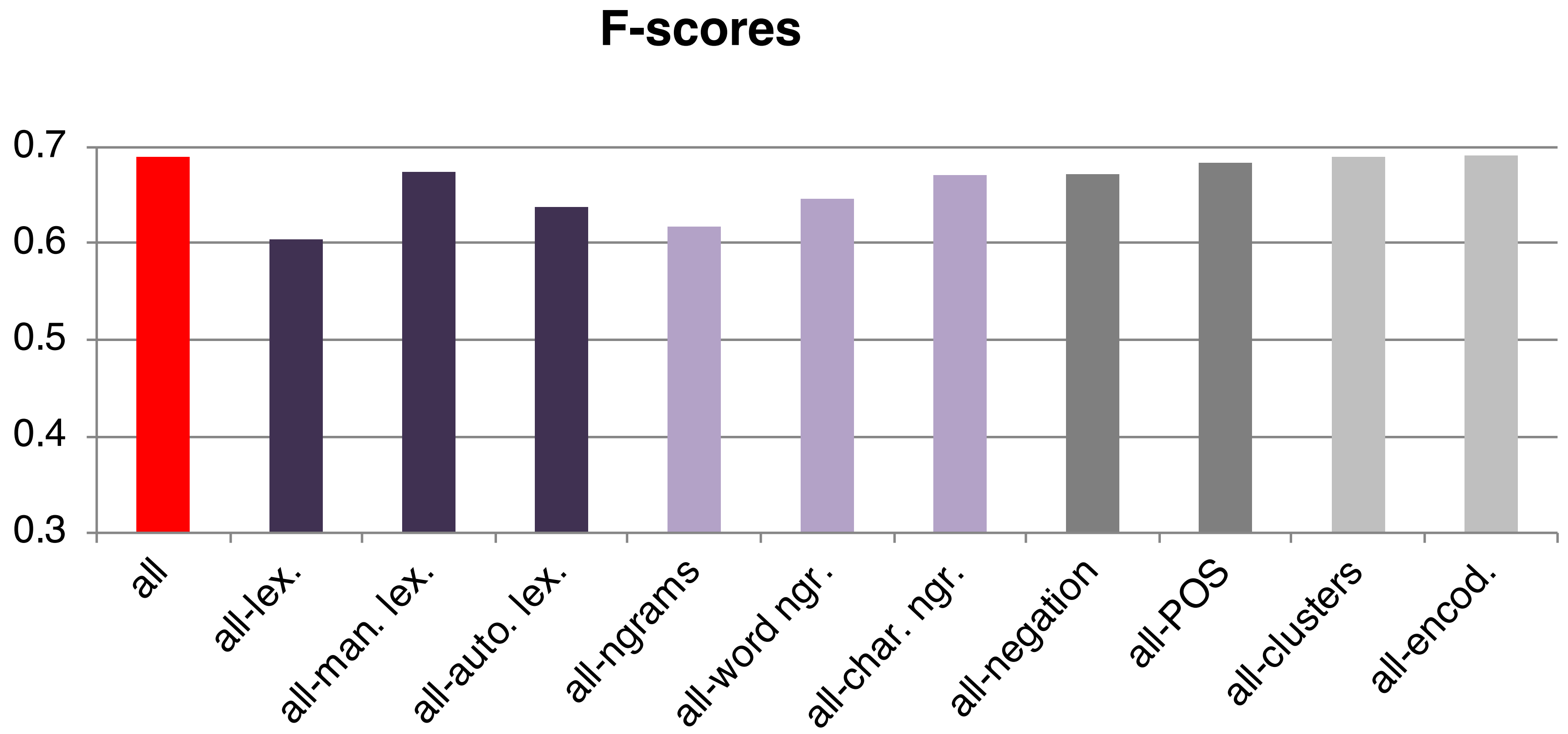


Sentiment Analysis Competition

SemEval-2013: Classify SMS messages, 30 teams



Feature Contributions (on Tweets)



The Sentiment Analysis that Companies Want!

Detecting Stance in Tweets

favor against neither


Parinaz Sobhani


Svetlana Kiritchenko


Xiaodan Zhu


Colin Cherry

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 viable candidate in this republican lineup.

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

Example 2:

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

Systems have to deduce that the tweeter is likely in favour the target.

SemEval-2018 Task 1: Affect in Tweets

https://competitions.codalab.org/competitions/17751

Tasks: Inferring likely affectual state of the tweeter

- emotion intensity regression (EI-reg)
- emotion intensity ordinal classification (EI-oc)
- sentiment intensity regression (V-reg)
- sentiment analysis, ordinal classification (V-oc)
- multi-label emotion classification task (E-c)

English, Arabic, and Spanish Tweets

75 Team (~200 participants)

Felipe José Bravo Márquez

Mohammad Salameh

Svetlana Kiritchenko

Semeval-2018 Task 1: Affect in tweets. Saif M. Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. In Proceedings of International Workshop on Semantic Evaluation (SemEval-2018), New Orleans, LA, USA, June 2018.

Participating Systems: ML algorithms

	#Teams				
ML algorithm	EI-reg	EI-oc	V-reg	V-oc	E-c
AdaBoost	1	1	3	1	0
Bi-LSTM	10	8	10	6	6
CNN	10	8	7	6	3
Gradient Boosting	8	3	5	4	1
Linear Regression	11	2	7	2	1
Logistic Regression	9	7	8	6	6
LSTM	13	9	10	5	4
Random Forest	8	7	5	6	6
RNN	0	0	0	0	1
SVM or SVR	15	9	8	6	6
Other	14	16	13	12	7

Participating Systems: features

Features/Resources	#Teams EI-reg	EI-oc	V-reg	V-oc	E-c
affect-specific word embeddings	10	8	9	9	5
affect/sentiment lexicons	24	16	16	15	12
character ngrams	6	4	3	4	2
dependency/parse features	2	3	3	3	2
distant-supervision corpora	10	8	7	5	4
manually labeled corpora (other)	6	4	4	5	3
AIT-2018 train-dev (other task)	6	5	5	5	3
sentence embeddings	10	8	7	8	6
unlabeled corpora	6	3	5	3	0
word embeddings	32	21	25	21	20
word ngrams	19	14	12	10	9
Other	5	5	5	5	5

SemEval-2018 Task 1: Affect in Tweets

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Tasks: Inferring likely affectual state of the tweeter

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- sentiment intensity regression
- sentiment analysis, ordinal classification
- emotion classification task

English, Arabic, and Spanish Tweets

75 Team (~200 participants)

fairness

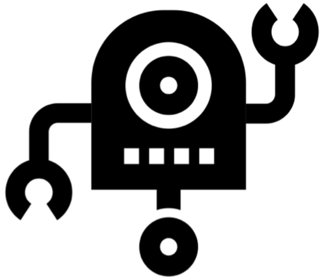
Includes a separate evaluation component for biases towards race and gender.

Do Machines Make Fair Decisions?

YES:

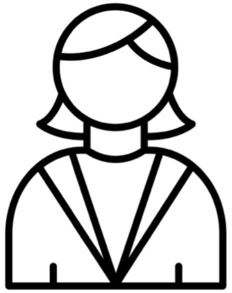
- they do not take bribes
- they can make decisions without being influenced by the user's gender, race, or sexual orientation

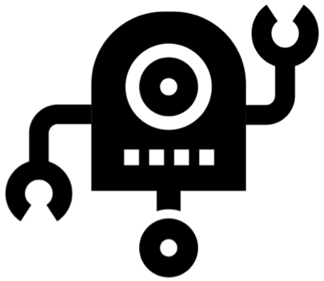
And NO—recent studies have demonstrated that as the models have become more sophisticated, they have inadvertently inherited inappropriate human biases



Examples of Biased AI

- Tay, Microsoft’s racist chat bot posting inflammatory and offensive tweets
- Amazon’s AI recruiting tool biased against women
    - penalized resumes that included the word “women’s,” as in “women’s chess club captain”
- Face recognition systems good for detecting faces of white men, but really bad for African American women
- Recidivism systems that are biased against people from African American neighborhoods





built on human data

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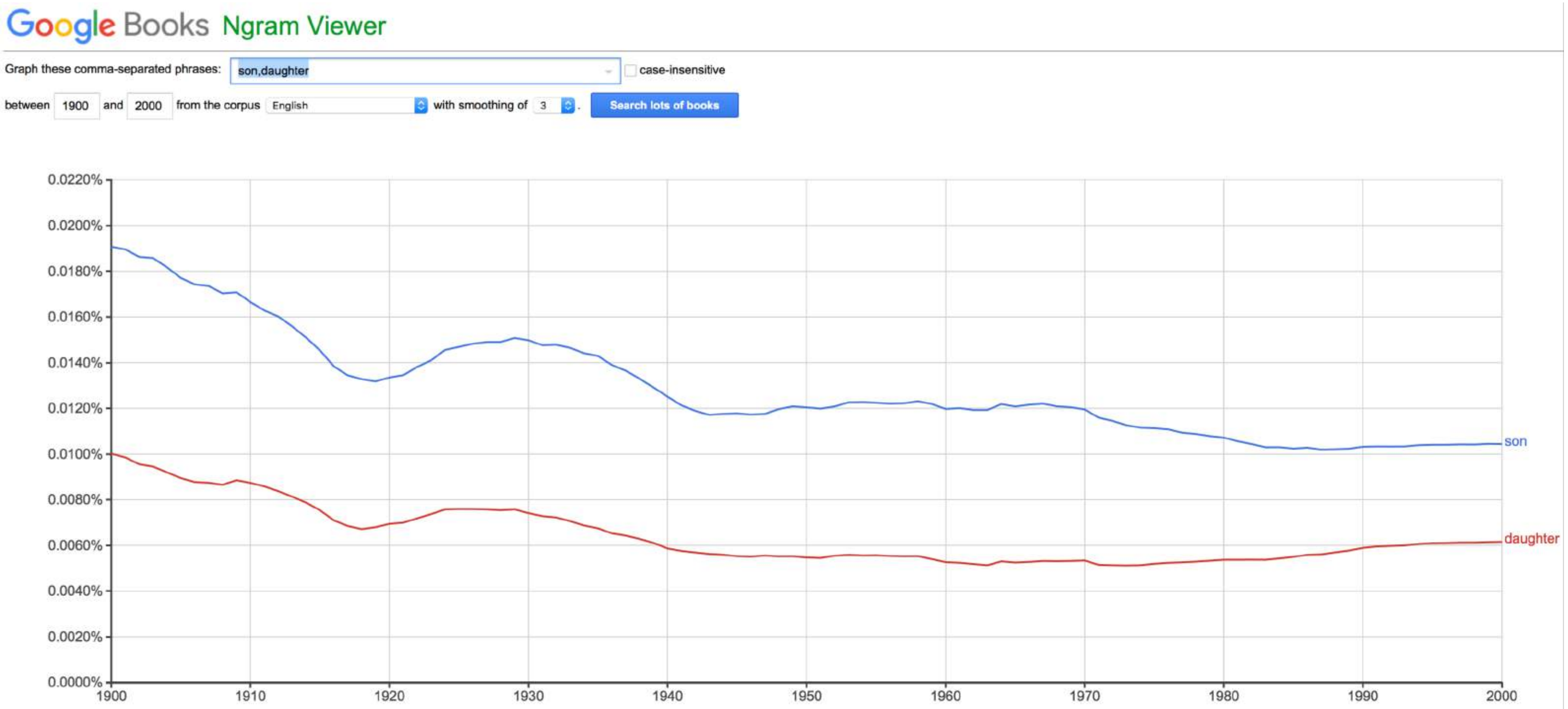
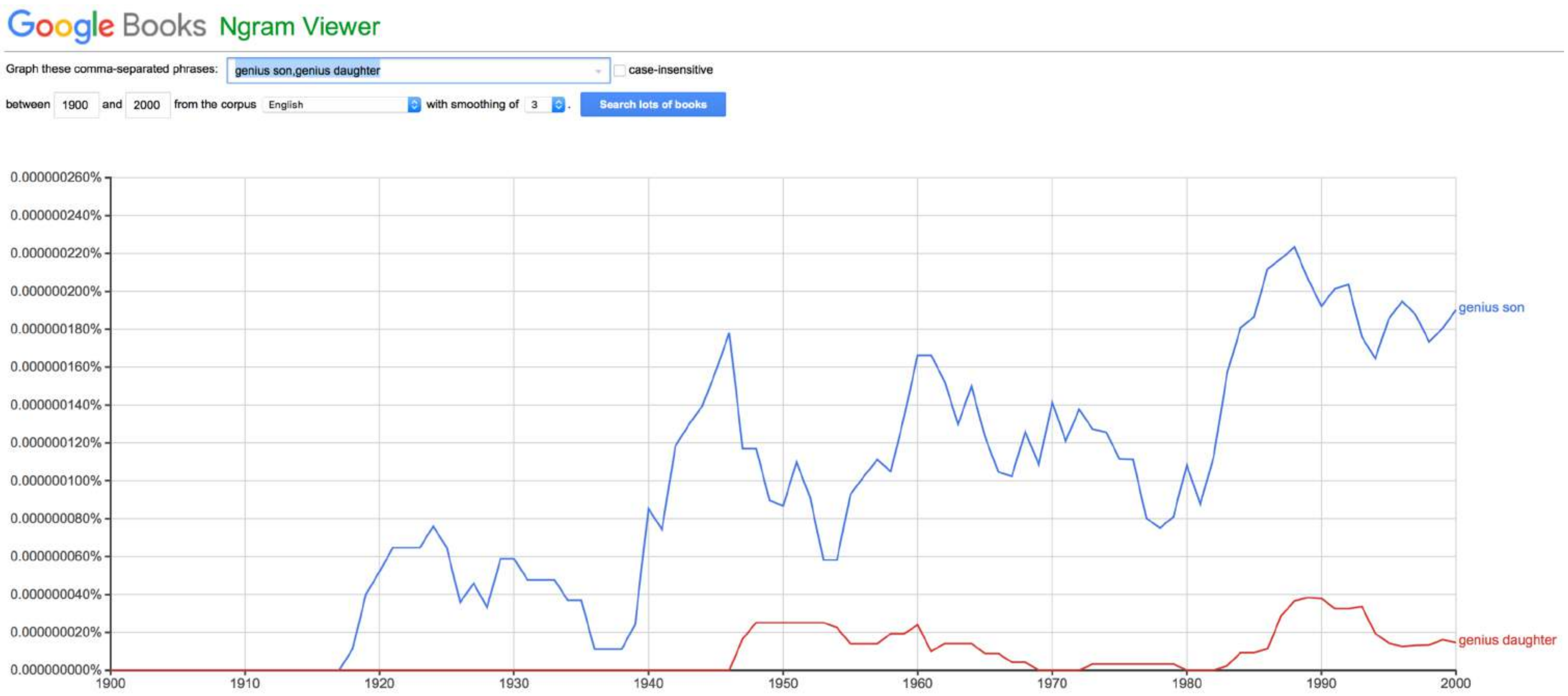
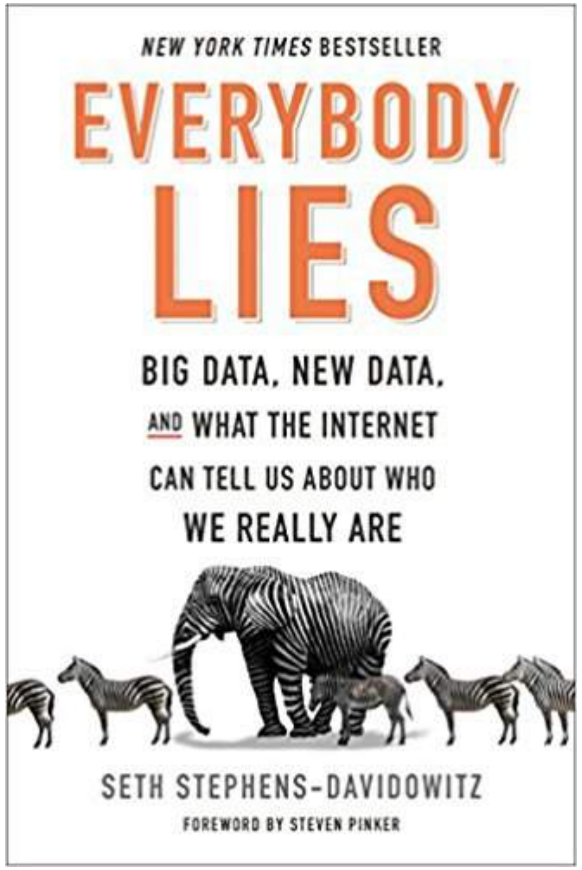
Occurrences of “son” and “daughter” in the Google Books Ngram corpus



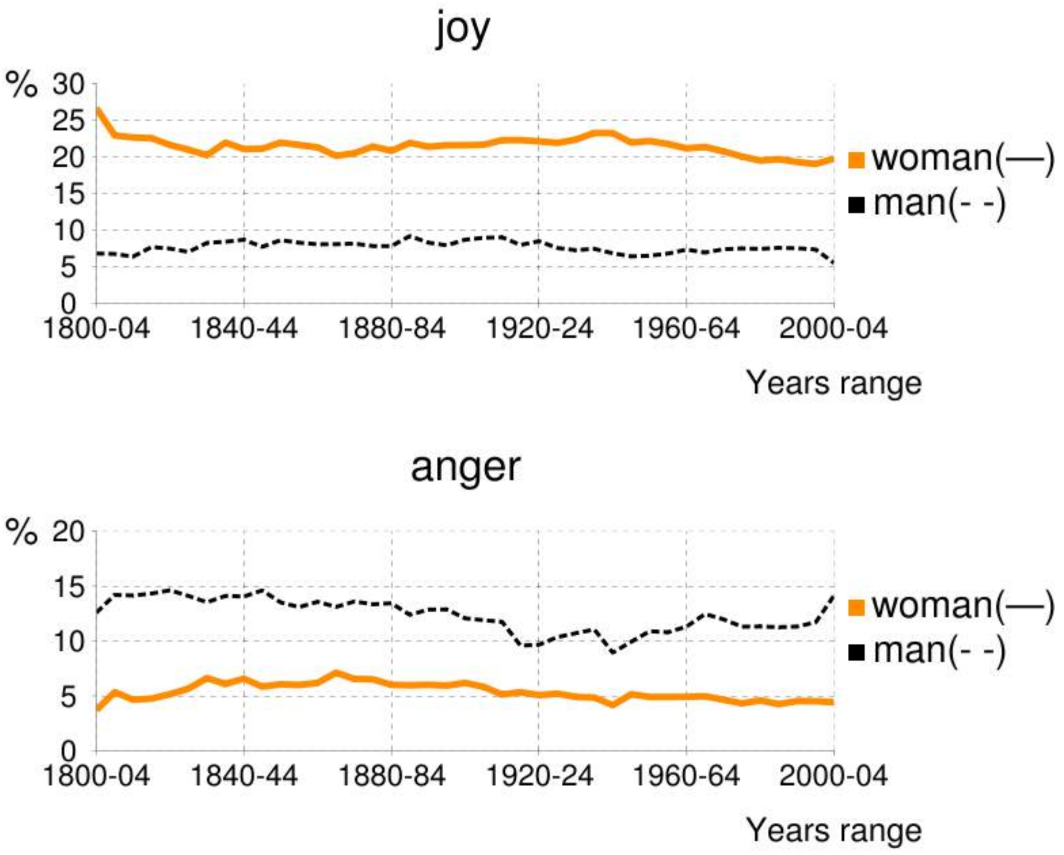
Occurrences of “genius son” and “genius daughter” in the Google Books Ngram corpus





Showed that parents search disproportionately more on Google for:

- is my son gifted? than is my daughter gifted?
- is my daughter overweight? than is my son overweight?



Percentage of joy and anger words in close proximity to occurrences of 'man' and 'woman' in books.

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

Svetlana Kiritchenko

Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems

- Found that most systems consistently give higher emotion intensity scores to sentences when they have mentions of one race/gender as opposed to another race/gender

Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems. Svetlana Kiritchenko and Saif M. Mohammad. In Proceedings of *Sem, New Orleans, LA, USA, June 2018.

We Need More Work On

- Measuring inappropriate biases in AI systems and **inappropriate biases in language**
- Mitigating inappropriate biases in automatic systems

Ongoing Work

- The Natural Selection of Words
  - How words compete to represent a meaning

  The Natural Selection of Words: Finding the Features of Fitness. Peter D. Turney and Saif M. Mohammad. PLoS One, 14 (1):e0211512. January 2019.

- Analyzing Developmental Trends via Poems written by Children

- Creating an Interactive Visualization to Study the ACL Anthology

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Checklist by Nick Bluth from the Noun Project
Generation by Creative Mahira from the Noun Project
Human by Adrien Coquet from the Noun Project
Search by Maxim Kulikov from the Noun Project

https://thenounproject.com

Resources Available at: www.saifmohammad.com

- Sentiment and emotion lexicons and corpora
- Links to shared tasks
- Interactive visualizations
- Tutorials and book chapters on sentiment and emotion analysis

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@SaifMMohammad