Computational Analysis of Affect and Emotion in Language

Saif M. Mohammad
saif.mohammad@nrc-cnrc.gc.ca

Cecilia Ovesdotter Alm
coagla@rit.edu

Tutorial at EMNLP 2015, Lisboa, Portugal

EMNLP 2015
CONFERENCE ON EMPIRICAL METHODS IN NATURAL LANGUAGE PROCESSING
LISBON

(Mohammad and Alm, 2015)

Sentiment and emotions

Crowd annotations

Socia media posts

PhD in Computer Science, **Univ. of Toronto**

Postdoc, **Univ. of Maryland**

Senior Research Officer

NRC, Canada

Survey on Affect Analysis:
(Mohammad, 2015b)

Affect and subjectivity

Linguistic sensing

Health and wellness; education

PhD in Linguistics

AS in Lang & Speech Processing

GS in Comp. Science & Engineering

Assistant Professor

CLaSP Co-Director

UIUC

RIT, USA

(Mohammad and Alm, 2015)

Aims

- Convey why you should care about analysis of affect and affective conditions, experiences, and activities, and introduce prospects and challenges in this area

- Provide a broad background on terminology, conceptual frameworks, resources, and linguistic considerations (characteristics, data, annotation, etc.)

- Give an overview of affect processing which spans both the lexical level and the level of longer units, and discuss how visualizing outcomes may enhance analysis

- Exemplify the area's relevance in interesting application domains, followed by wrap-up on future directions

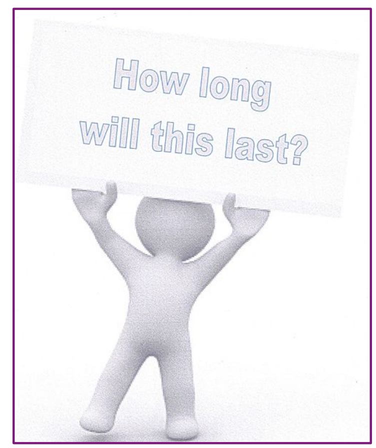
- Springboard a conversation as we head into EMNLP

(Mohammad and Alm, 2015)

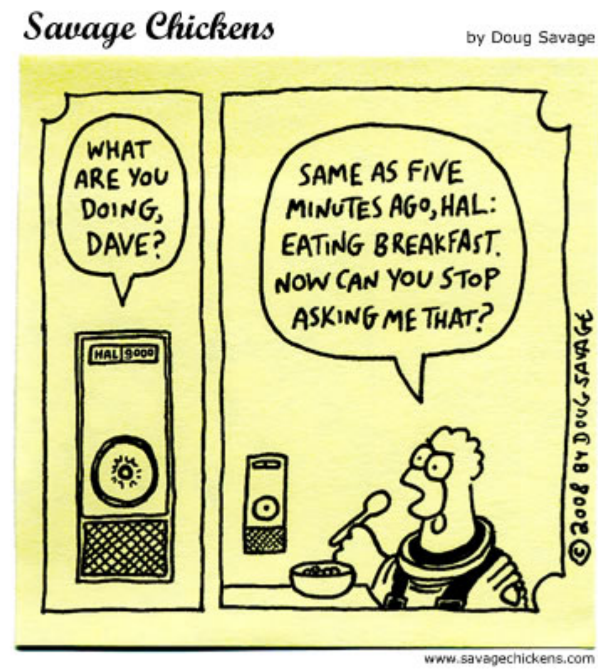
Tutorial roadmap

- Introduction
- Emotive Language Use
- Linguistic Data
- Computational Modeling (Part 1)
- Computational Modeling (Part 2)
- Visualizing Computational Outcomes
- Survey of Applications
- Future Directions and Wrap-up

BREAK
30 min



(Mohammad and Alm, 2015)



© Doug Savage.

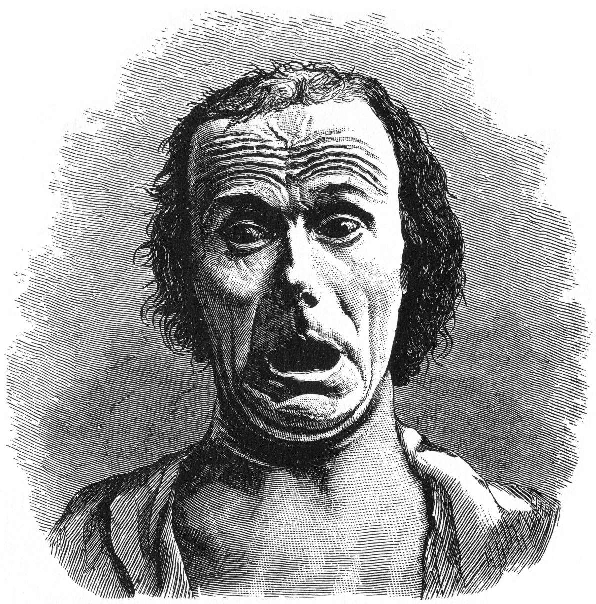
Introduction

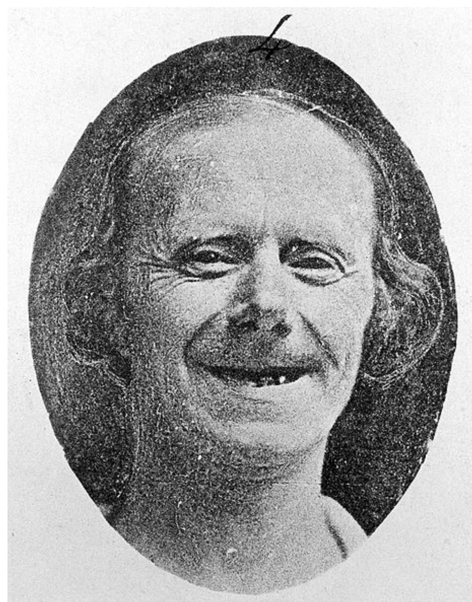
Topics:

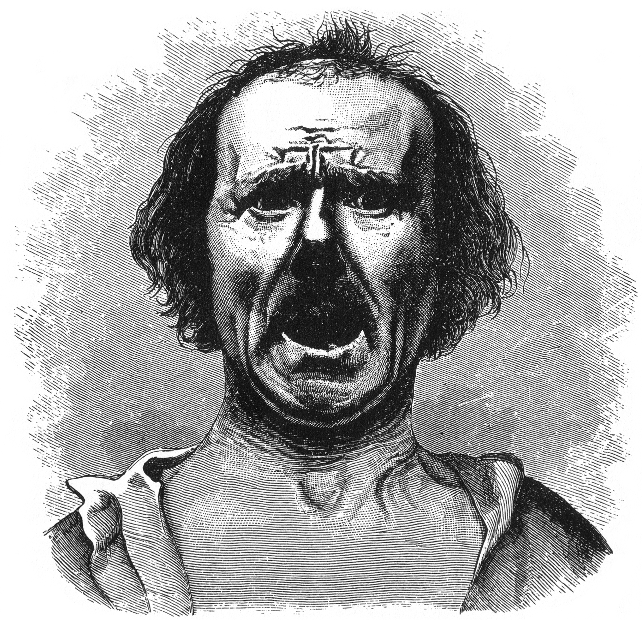
- Opportunities for language as a cognitive sensor of affect and emotion
- NLP tasks and applications involving affect and emotion
- Concepts and key terminology
- Challenges to automatic affect detection, characterization, and generation

(Mohammad and Alm, 2015)

Affect extends beyond thumbs up/down







(Mohammad and Alm, 2015)

(Darwin)

Your thoughts:

Which emotional tone is conveyed?

I now have my foot in the door of the custom cake decorating business. I start in customer service as a cashier/barista, work my way through frosting, and then either into wedding, birthday, or sculpted cakes! I have been unemployed for 3 months now and this is huge. It means I can start saving money again, paying my bills and loans, and all the while doing something I love!

I create these goals for myself, such as working out or finishing projects and until I finish the goals that I have set out for myself, I can't finish anything else. I can't go out, I can't do anything because all I'm thinking about are the unfinished goals.

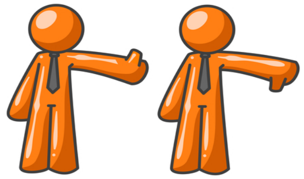
It seems like I invested too much in it to drop it and I get trapped in this mental prison. But when I try to work on my projects I just sit there lethargically doing nothing. […]

Relationships with people, such as a significant other, tend to be one of the most interesting things humans do. There is a lot of variability when dealing with people, so there's a lot more that tends to keep our interests. Perhaps finding a significant other isn't something that you should quit on just yet?

Unfortunately, it's an unrealistic expectation to believe that different milestones will automatically lead to a better life. You can only expect to get enjoyment from life when you make enjoyment a priority. You can't passively wander through life and hope things will pick up, you have to seek out what you want from life and strive for it.

(Mohammad and Alm, 2015)

Affect-related topics have evolved into a priority in CL

Language serves social and interpersonal functions. Affective meaning is key for human interaction and a prominent characteristic of language use.

This extends beyond opinions vs. factual or polarity distinctions into multiple phenomena: emotion, mood, personality, attitude, certainty, credibility, volition, veracity, friendliness, etc.

Besides recognition, characterization, or generation of affect states, this involves analysis of affect-related conditions, experiences, and activities. Consider for instance:

- Communication-oriented conditions (ASD)
- Job stress/satisfaction and attention
- Creative expression in literature and music
- Risk/protective factors in mental and cognitive health
- Reasoning dimensions such as decision style and confidence
- Emotive topics such as domestic violence

(Mohammad and Alm, 2015)

Affective meaning

- Early recognized as important (Bühler, Jakobson, Lyons, Halliday) yet quite neglected in language science and computational linguistics
- Affective computing field (Picard and beyond)
- Steadily growing interest in affective computational semantics

- Beyond 'propositional' meaning which tends to disregard emotive semantics (truth-conditional semantics: Katz, Fodor, Montague, Lyons, Russell, Frege)

(1) Bill Clinton was President of the United States.

(2) Bill Clinton never lies.

(3) Bill Clinton loves his wife.

(4) Hillary's husband is very intelligent/a fool.

(Mohammad and Alm, 2015)

Affect analysis for human-centered computing

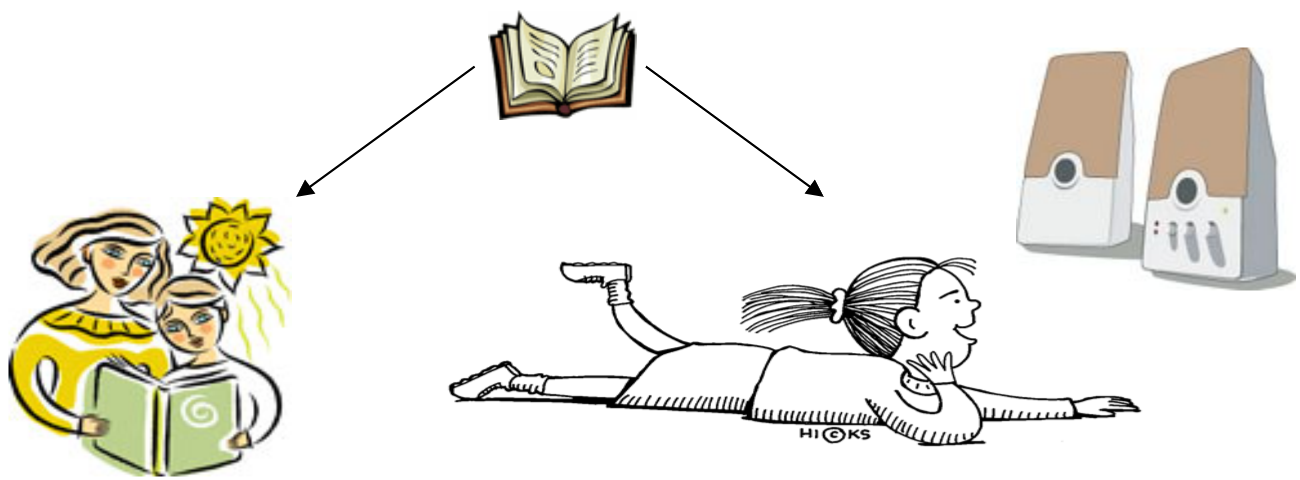
- **HCC as a theoretical/functional paradigm acknowledges…**
  - the central role of humans in computing
  - that humans and machines work better in tandem
  - and language is an essential component of the human condition

- **Linguistic sensing:**
  - Language as sensor of the body area network for personalized computing
  - Capture and measure the linguistic signal response of a language user
  - Language data analysis for non-linguistic aims
  - Linguistic data tend to…
    - link to a human individual and a group of individuals
    - be temporally unfolding (evolving states)
    - reflect language users' overt physical states and latent cognitive states

Linguistic sensing of affective states or affect-related behaviors and experiences can be used for exploring HCC problems – such as in healthcare, educational, political, or artistic domains.

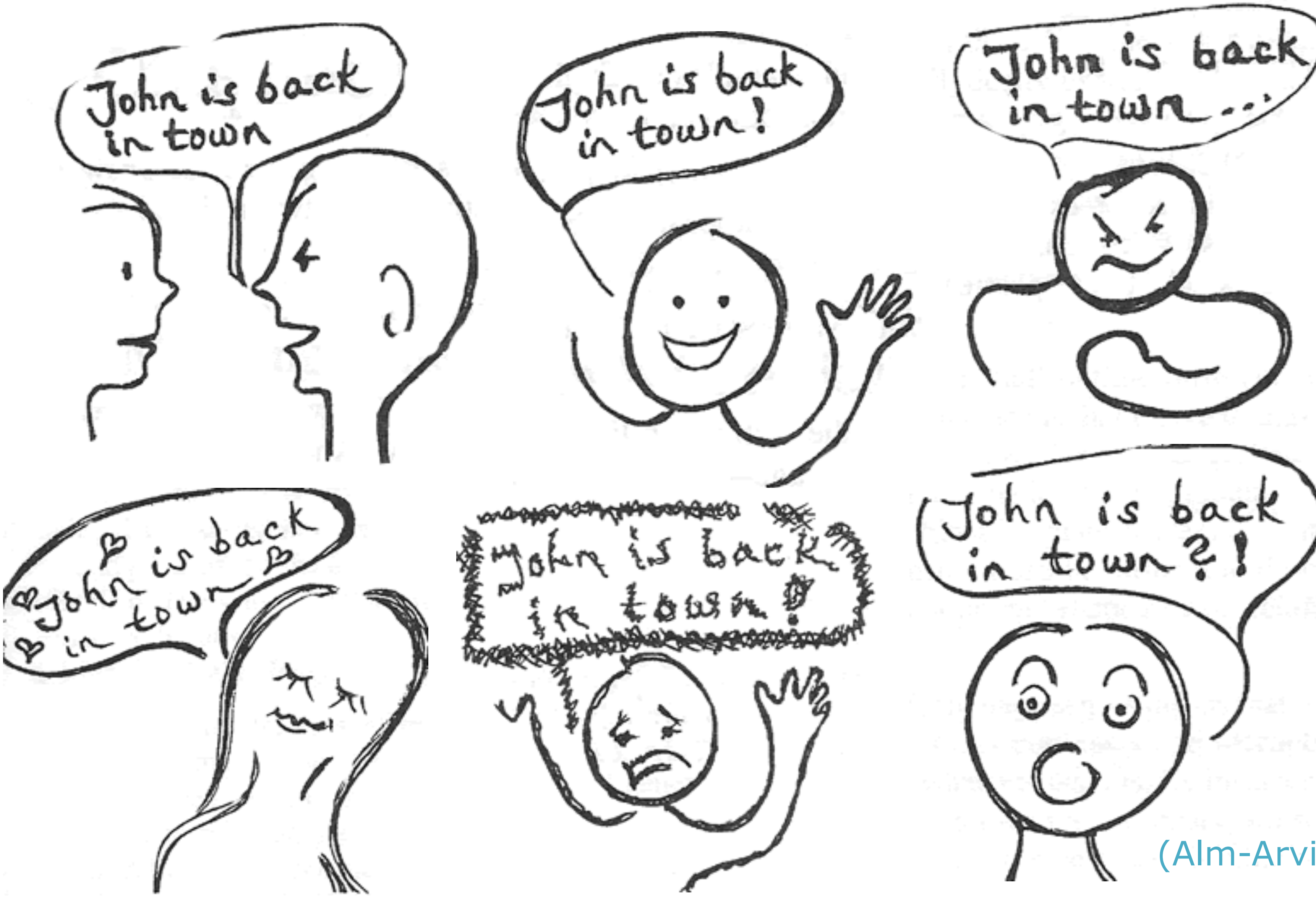
(Mohammad and Alm, 2015)

Take, for instance, expressive text-to-speech



Consider a person who reads stories. Storytelling is a complex performance act, and *emotional expressivity* is a critical part of good storytelling.

(Alm, 2009)



(Alm-Arvius, 1998)

Making sense of affective meaning for TTS is a hard problem, as any utterance could potentially be rendered with affective tone. Systems should understand when it is sensible to use a given affect and how to deal with affect ambiguity.

(Mohammad and Alm, 2015)

Long list of applied motivations

- Therapeutic education
- Customer service and branding
- Tutoring systems
- iCALL or edutainment
- Affective interfaces and dialog systems
- Medical support systems
- Public health exploration

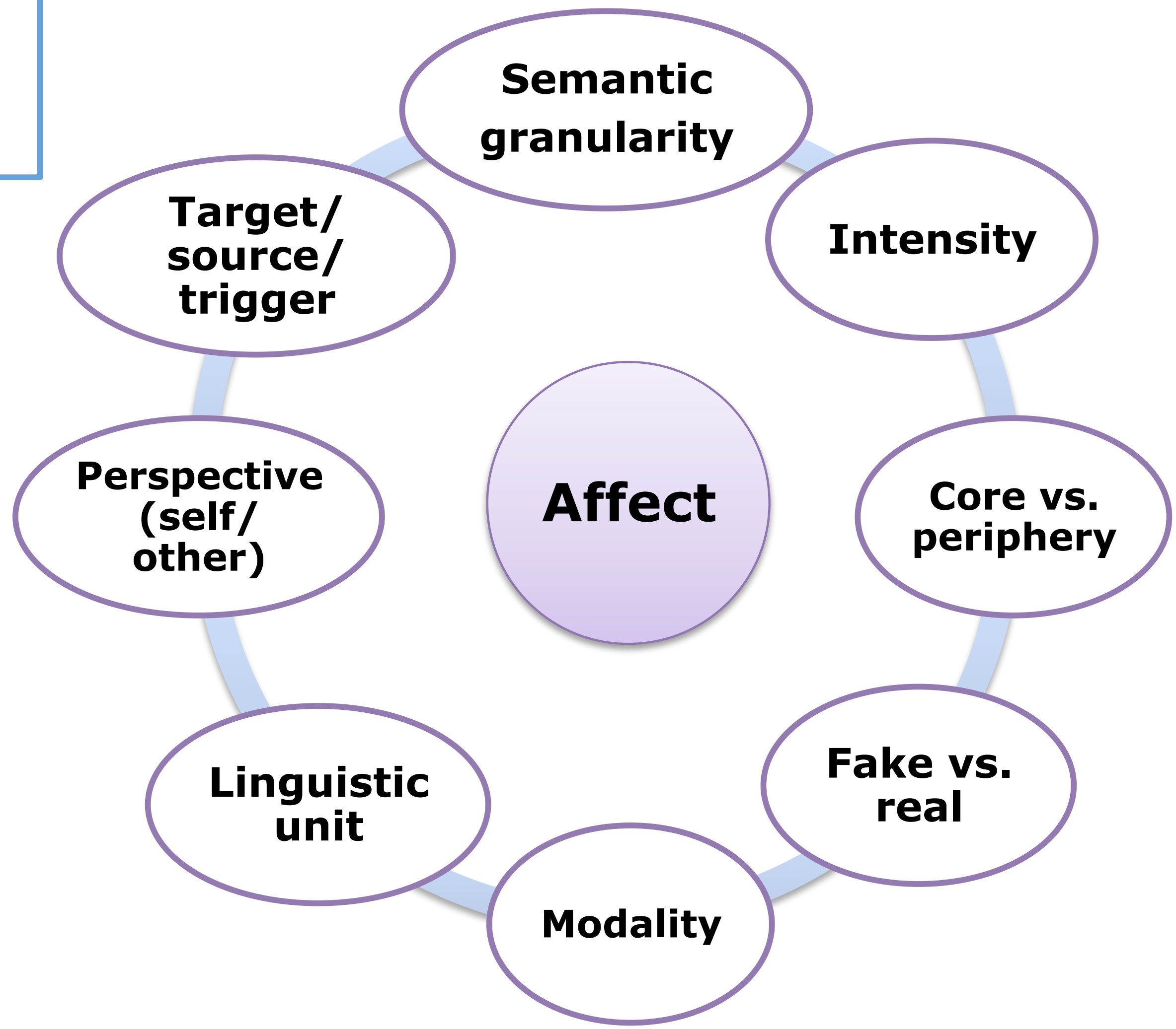
We will return to some of these application domains later on.

(Mohammad and Alm, 2015)

Concepts: affect states and affect attributes

- Emotion
- Mood
- Personality
- Attitude

Distinct temporal granularity
E < M < P



(Mohammad and Alm, 2015)

Challenges to automatic affect detection, characterization, and generation

- Emotional gist of an utterance is not simply the sum of emotional associations of its component words.

- Negation and modals impact affect of the text, without themselves having strong sentiment associations.

- Emotions are often not explicitly stated.

  Another Monday, and another week working my tail off.

  Conveys a sense of frustration without overt markers.

- Prosodic information often absent in text.

(Mohammad and Alm, 2015)

Challenges to automatic affect detection, characterization, and generation

- Different degrees of affect depending on sense and context.

Mary <u>hugged</u> her daughter before going to work.	emotional
The pipeline <u>hugged</u> the state border.	rather unemotional

- Difficult to interpret creative uses of language such as sarcasm, irony, humor, and metaphor/figurative language

- Some texts, such as social media or literary texts, can be rife in nonstandard language:
  - misspellings — parlament
  - creatively spelled words — happeee
  - hashtagged words or similar phenomena — #loveumom
  - abbreviations — lmao

(Mohammad and Alm, 2015)

Challenges to automatic affect detection, characterization, and generation

- Most machine learning algorithms for affect analysis require large amounts of training data
  - Numerous affect categories

- Texts/utterances may convey mixed, contrastive, or sequences of emotions
  - Multiple affect targets and stimuli

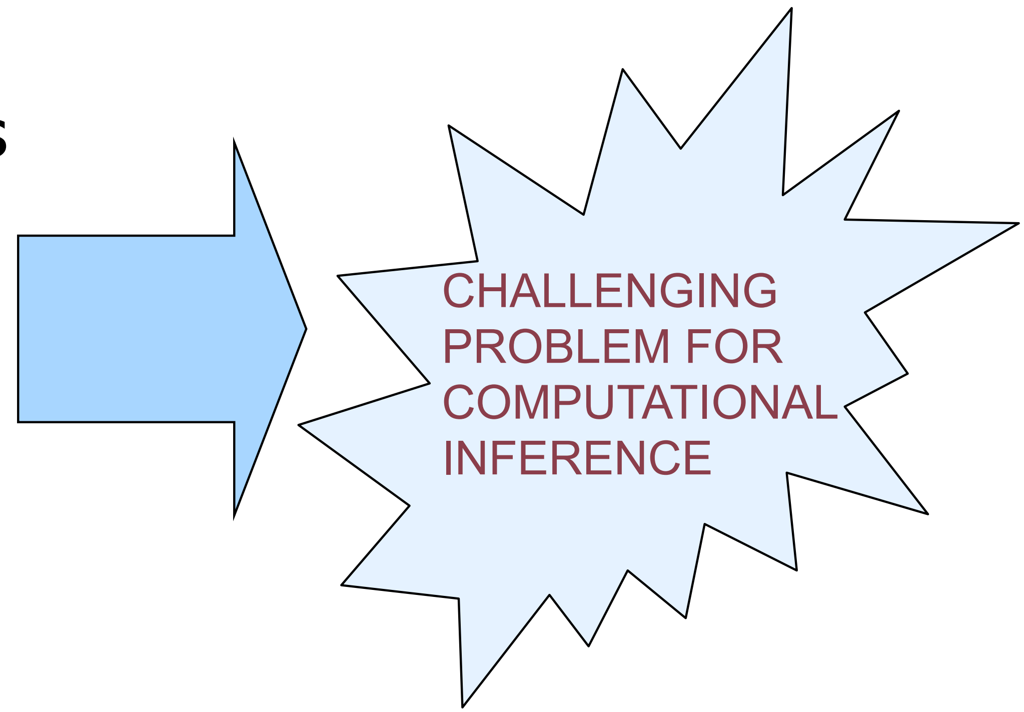
- Whose perspective?
  - May refer to emotional events without implicitly or explicitly expressing the message producer's view

(Mohammad and Alm, 2015)

Reference data – the elephant in the room

Human affect perception seems characterized by ...

- subjectivity & expectations
- contextual factors
- no real 'ground truth'



Yet – affect and related experiences are key to the human condition, and as such are critical to address in computational semantics.

(Mohammad and Alm, 2015)

A few summarizing observations

- Affective meaning goes beyond sentiment and polarity
- Affect is linked to naturalness, with implications for HCC
- Useful applications and several challenges makes this an interesting research area to engage with
- Distinctions among affect concepts and attributes
- Affect involves acceptable categories, not right vs. wrong
  - **Intersubjective agreement** tends to be relaxed
  - A **methodological challenge** to the ‘ground truth’ concept
    - What makes sense in a particular context?

Instructors: Affect-related tasks thus represent a pedagogical opportunity to explore tasks without right/wrong answers and clear solutions, and help emerging investigators develop skills to express and model such complex semantic problems.

(Mohammad and Alm, 2015)

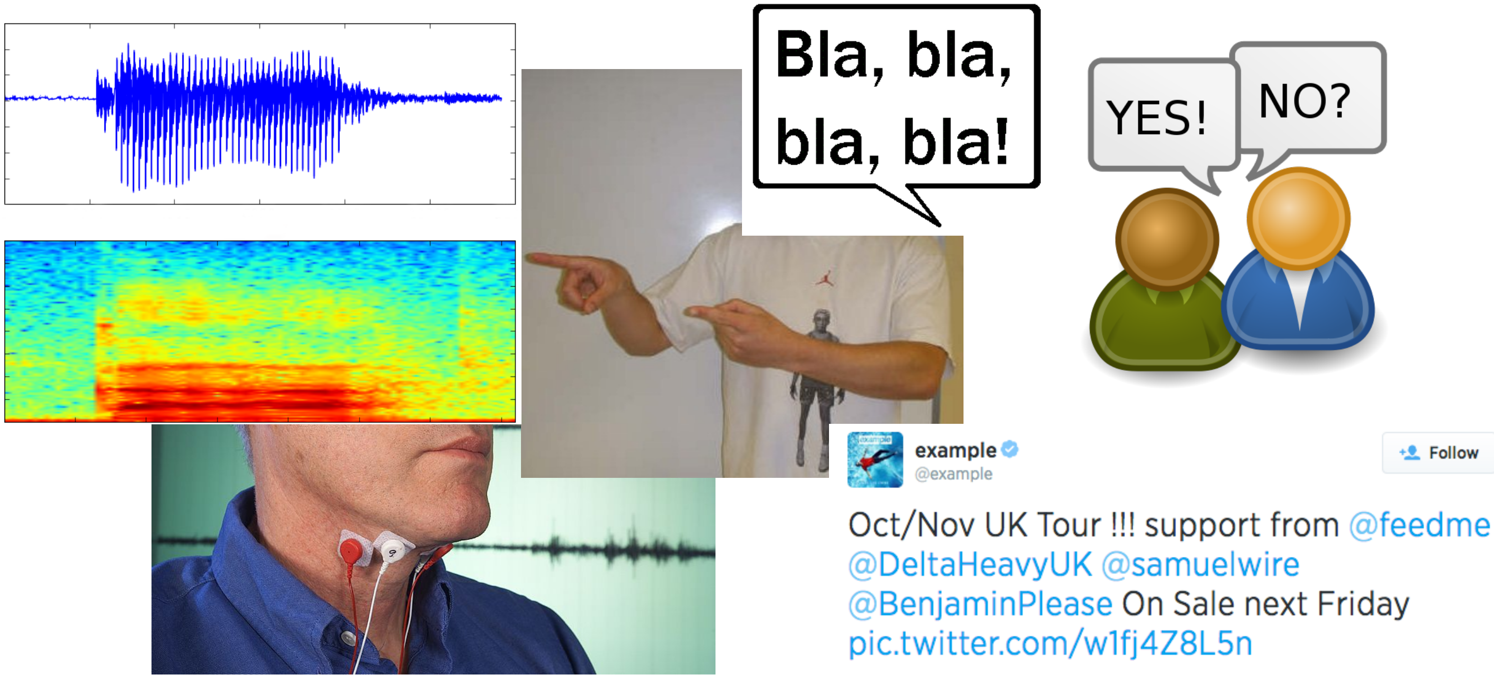
Emotive Language Use

Topics:

- How language users communicate affect and emotion across modalities in text, speech, signed, and multimodal data
- Links to sociolinguistic attributes of language users
- Implications for and translation into features for computational analysis

(Mohammad and Alm, 2015)

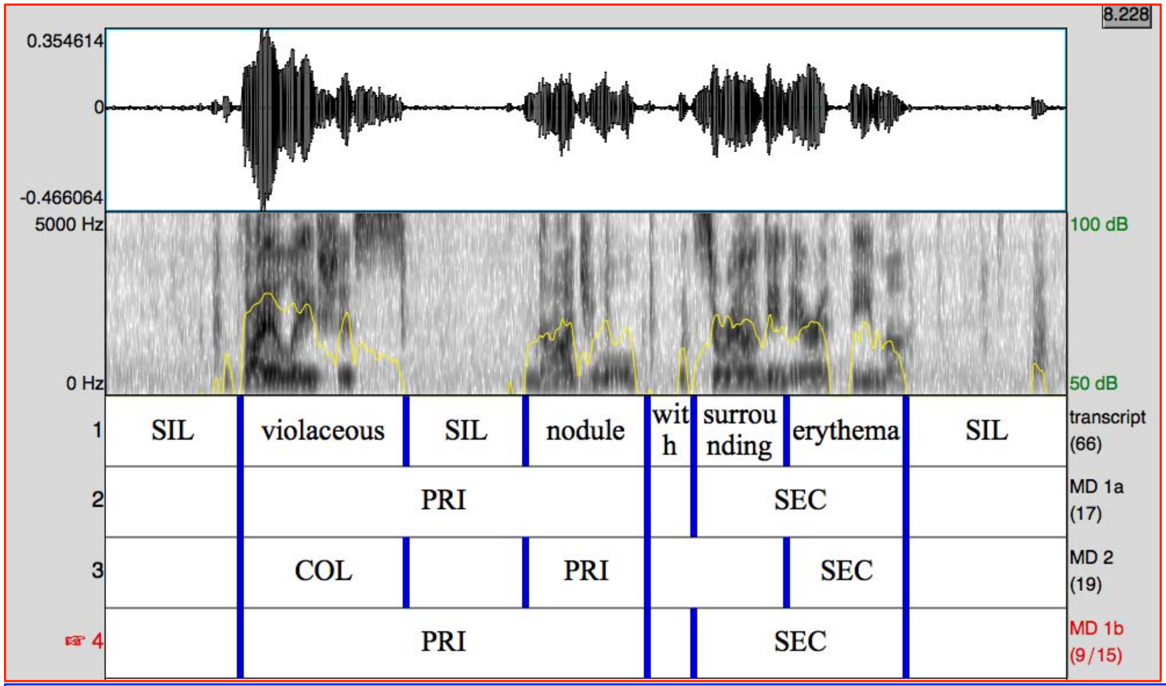
Language data for affect sensing have many guises

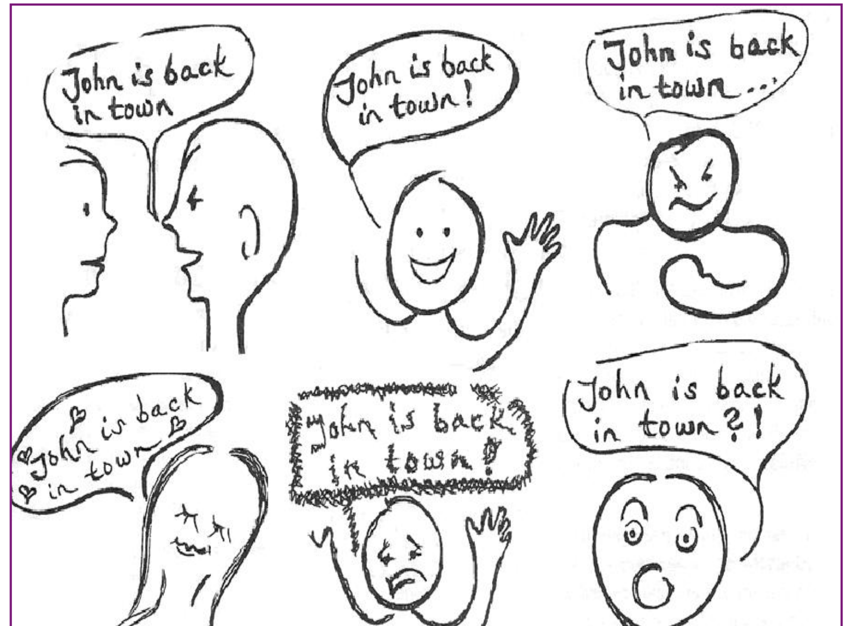


- Range of modes – standard/nonstandard, dialog/monolog/massive interaction, speech/signed/text, etc.
- On body or remotely (FB/Twitter) – temporally unfolding data
- Privacy consideration – voice recognition, conveying personal information, etc.
- Affect involves both **what** language users communicate and **how** they do it

(Mohammad and Alm, 2015)

Linguistic signals are rich and may involve meaningful layers that open doors to affective semantics





(Alm-Arvius)

... [um]$_3$ so given the distribution [my [SIL]$_1$ my]$_4$ differential would be [uh]$_2$ like [a a]$_4$ contact either [allergi-]$_5$ allergic contact dermatitis maybe ...

Language as window into cognition - how people think & conceptualize

(Mohammad and Alm, 2015)

Affect is subject to contextual variation

- Socio-cultural and interpersonal factors
  - Cultural conventions
  - Social expectations
  - Social stratification
  - Taboos and rituals

Moderated affect expressions/perceptions

- Individuals' social attributes as additional factors
- In general in affect perception, individuals' interpretation may vary by factors such as …
  - mood and personality
  - emotional intelligence
  - gender
  - boredom, fatigue

(Cowie et al., 2010 and studies cited therein; Alm, 2009)

(Mohammad and Alm, 2015)

Linguistic data are, by nature, comparatively natural, unobtrusive, and inexpensive to capture

FACE
POSTURE
GESTURE
HEART
SKIN
EYE GAZE
PUPILS
etc.

They are convenient to integrate in multimodal capture for affect sensing. Emotions tend to be conveyed across modalities, e.g., in facial expressions. (Ekman & Friesen, 1998)

(Mohammad and Alm, 2015)

Multimodal sensor capture is motivated by that multimodality characterizes affect expression; it can add vetting of linguistic signals

(Mohammad and Alm, 2015)

(Wang et al., 2014)

Examples of potential linguistic affect signals, per reports in the literature

- Lexical contents
- Orthographic forms and conventions
- Terms of address or kinship
- Diminutive or augmentative morphology, specific affixes
- Perspective markers, pronouns
- Length of discourses
- Politeness markers, honorifics, T/V pronouns
- Intensifiers, quantifiers and comparatives, evidentiality markers
- Mood, modals, hedges
- Exclamations, insults, interjections, curses, expletives, imprecations, case markings
- Syntactic constructions: left-dislocation, inversion, topicalization or focus, hedges, clefting, raising, and grammatical complexity
- Casuals, negatives (level/ratio)
- Affective or mental predicates
- Certain part-of-speech ratios
- Theme repetitions
- Speech acts: commands, warning, complimenting, thanking, apologizing, condolences, congratulating, flaming
- Laughing, weeping, disfluencies, stuttering, withdrawing, being inarticulate, speech errors
- Ideophones, sound symbolism, reduplications, onomatopoeia
- Voice/sign inflection: prosody (such as duration, pitch, intensity) and voice quality; silence and pausing; changes in tempo, signing form, etc.

The obvious complication is that linguistic signals are ambiguous and wear multiple hats – not just serving the expression of affect or affect-related behaviors.

(Mohammad and Alm, 2015)

(Besnier, 1990; Reilly & Seibert, 2003; inter alia)

Subtle stylistic shifts in syntax can contribute to affective meaning – as one function

Your canary frightened our cat this morning.

Unmarked construction

This morning your canary frightened our cat.

Fronting

It was your canary that frightened our cat this morning.

It-cleft

What your canary did was frighten our cat this morning.

Pseudo-cleft

Your canary – she frightened our cat this morning.

Left dislocation

(Mohammad and Alm, 2015)

Clear affect encoding in text may involve various clues

- **Lexicon** for affect states, contrastive states, affect-related words/expressions
- **Example sentence with affect-related lexical items:**
  They **laughed** and they **wept**; and Peter **embraced** the old Fire-drum. (HAPPY)
- Lexical examples from affect sentences judges agreed upon:

(Mohammad and Alm, 2015)

(Alm, 2010)

Clear affect encoding in text may involve various clues

- **Acquired knowledge and human experience, e.g. physical lack and need** (or addiction, incapability, appearance, sleep deprivation/allowance, etc.):
  He was **hungry and thirsty**, yet no one gave him anything; and when it became dark, and they were about to close the gardens, the porter **turned him out**. (SAD)

- **Speech acts**, e.g. cursing:
  Let her be expelled from the congregation and the Church. (ANGRY-DISGUSTED)

- **Forms of direct speech**, e.g. interjection:
  "**Mercy!**" cried Karen. (FEARFUL)

- **Mixed emotions** (affect sequencing):
  He now **felt glad** at having **suffered sorrow and trouble**, because it enabled him to **enjoy** so much better all the **pleasure and happiness** around him; for the great swans swam round the new-comer, and stroked his neck with their beaks, as a welcome. (HAPPY; mixed sad)

(Mohammad and Alm, 2015)

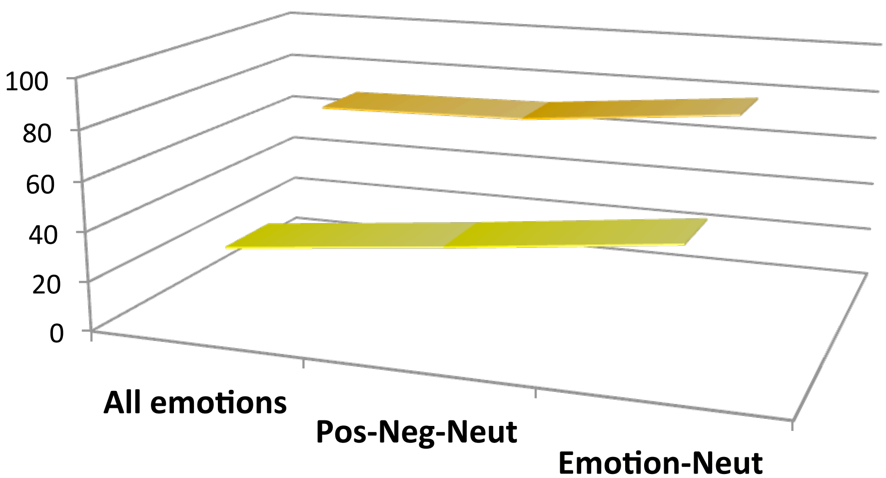
(Alm, 2010)

Classifying affect in sentences whose affect orientation annotators highly agreed on

Data: Fairytale texts
Linguistic unit of affect: Sentence

Can a model capture affect as a linguistic phenomenon? When dealing with sentences that human judges of affect had highly agreed upon, modeling identified emotion quite well in sentences based on linguistic features (substantially improving on random assignment considering size of affect classes)

Linguistic features toward classification: lexical, orthographic, story-related, syntactic, lexically derived scores, affect history, poetic structures, lexical sequences

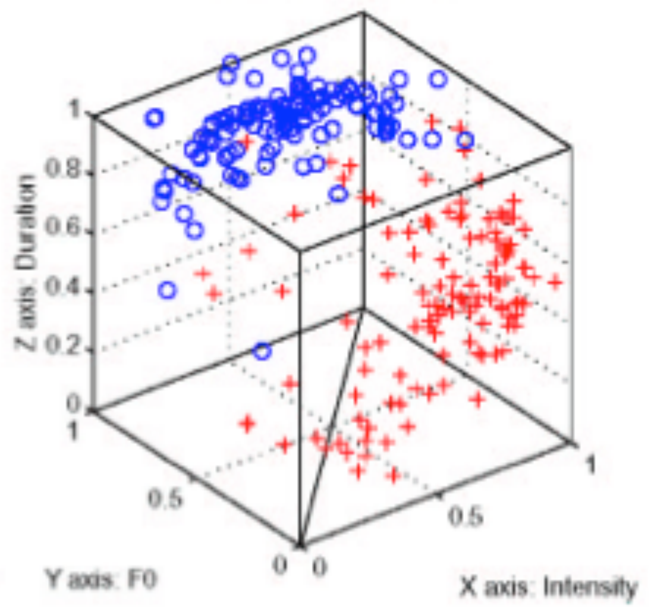


Related: Affect sequencing matters;
some degree of affect trajectory in stories

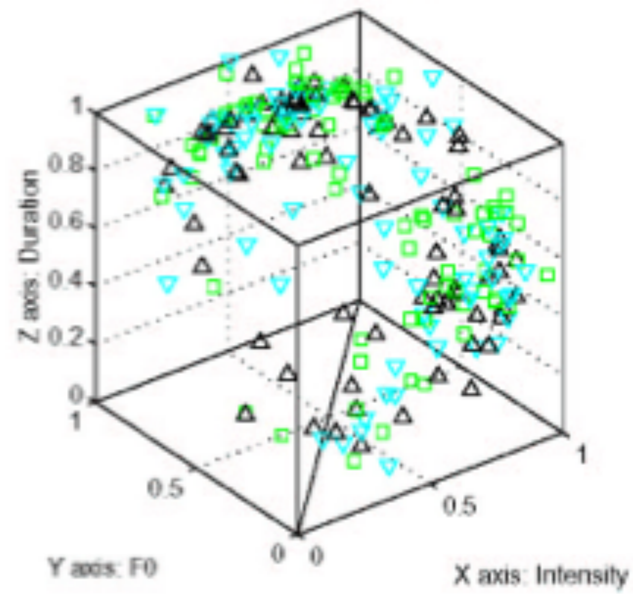
(Mohammad and Alm, 2015)

(Alm, 2009)

Characterizing affective voices



Solutions separate by emotion



But not by syllabic type (control)

Users listened to computationally modified utterances (such as SAD voices) and provided feedback based on their subjective preference

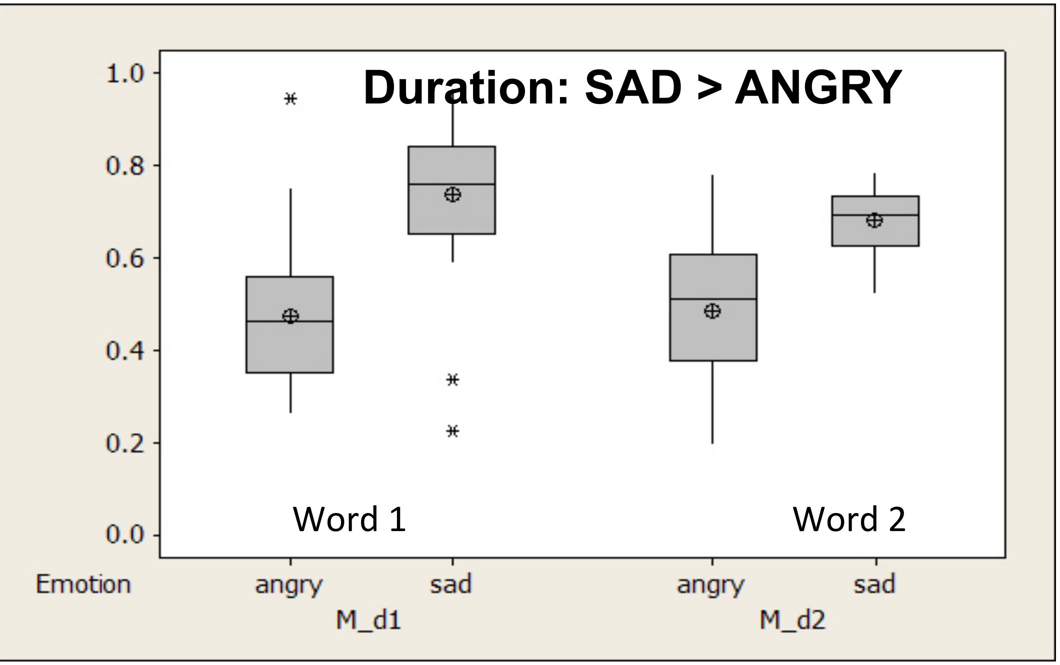
An interactive genetic algorithm evolved prosodic parameters

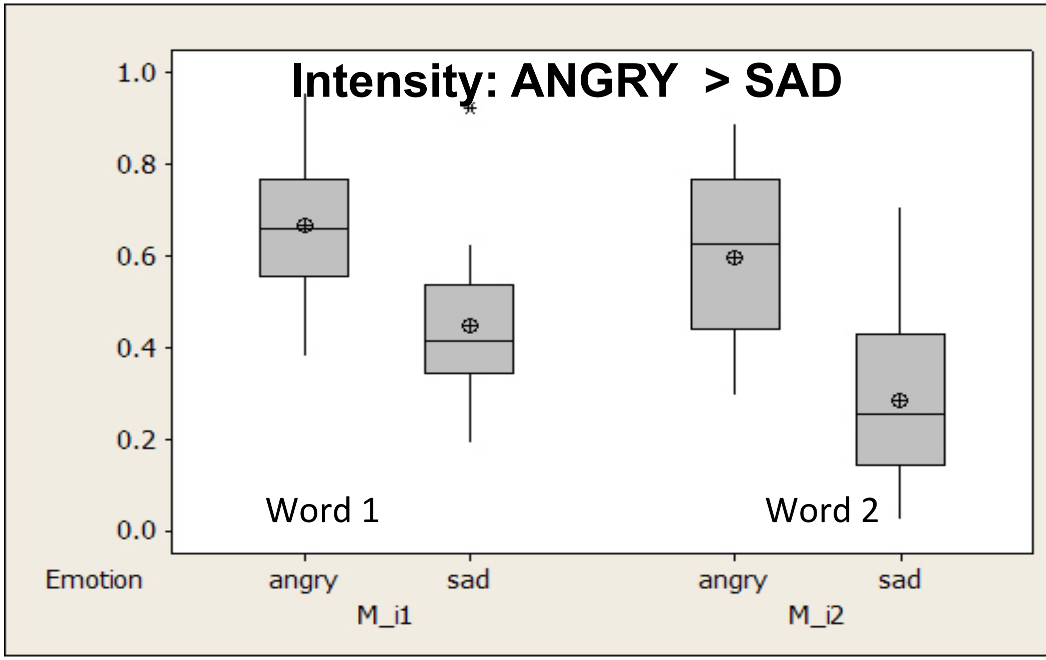
Evolving copy-synthesized utterances presented with constant verbal content

(Mohammad and Alm, 2015)

(Alm, 2009)

Angry vs. sad voices contrasted by basic voice inflection cues





Global trend with local variation (Alm, 2009)

Intensity seems to help convey moderate stress (Paul et al., 2015)

(Mohammad and Alm, 2015)

A few summarizing observations

- Linguistic affective signals are heterogeneous, pervasive, unobtrusive and inexpensive to capture. They are rich in meaning, can be layered, and offer a window into affect and human cognition. Both what and how may involve affect expression.

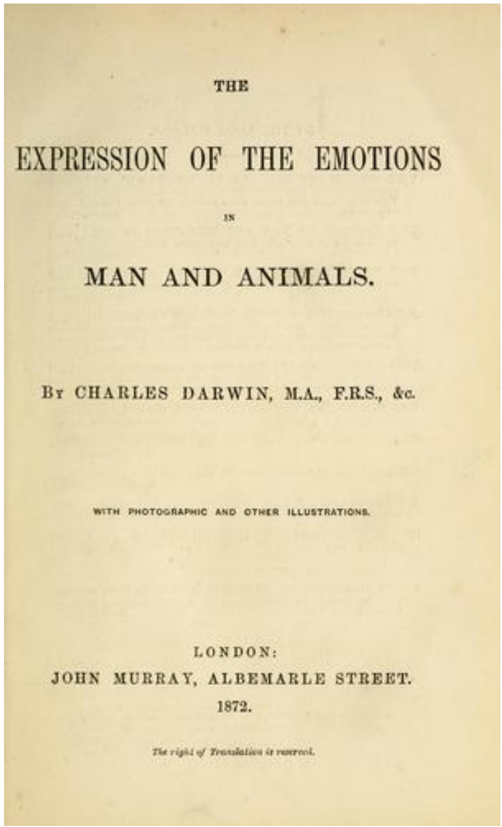
- Linguistic affect data are informative – either in isolation or in combination with other sensing modalities.

- Many linguistic cues potentially encode affect – but they tend to also wear other hats. Variation can be expected. Sequencing/trajectory may matter.

- Their prevalence is another factor to consider; while some features may aid useful analysis on data subsets where they are present, they may not be as useful for automated prediction/detection more broadly.

- Attributes of language users (sociolinguistic variables) may play a role. More work needed about production/perception.

(Mohammad and Alm, 2015)



Linguistic Data

Topics:

- Alternatives for conceptual computational modeling of affect in language, including lessons learned from theoretical frameworks in affective science
- Useful linguistic datasets and lexical resources for computational analysis—from social media to domain-specific corpora
- Issues and solutions for linguistic annotation of affect and emotion

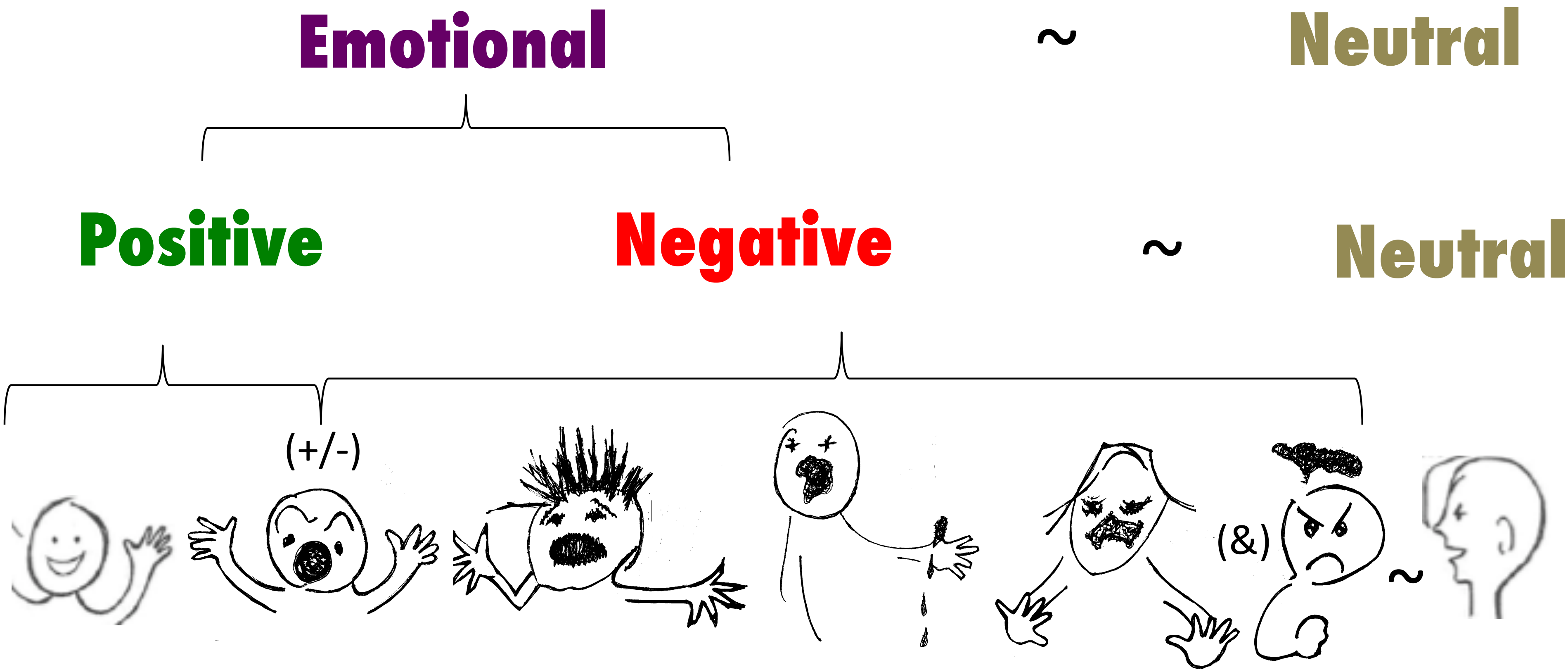
(Mohammad and Alm, 2015)

Four theoretical affect perspectives with a history

- **Darwinian**
  - evolved
  - survival-related
  - universal (basic)
- **Jamesian**
  - 1. physical response -> 2. emotion
  - pre-disposed reactions
- **Cognitive**
  - appraisal of events in context
  - appraisal -> action readiness
  - automated
- **Social constructivist**
  - cultural constructs (practices, values)
  - regulated
  - social functions
  - satisfy cultural norms

(Cornelius, 2000; and see Calvo & D'Mello, 2010 for an extended, comprehensive view of frameworks)

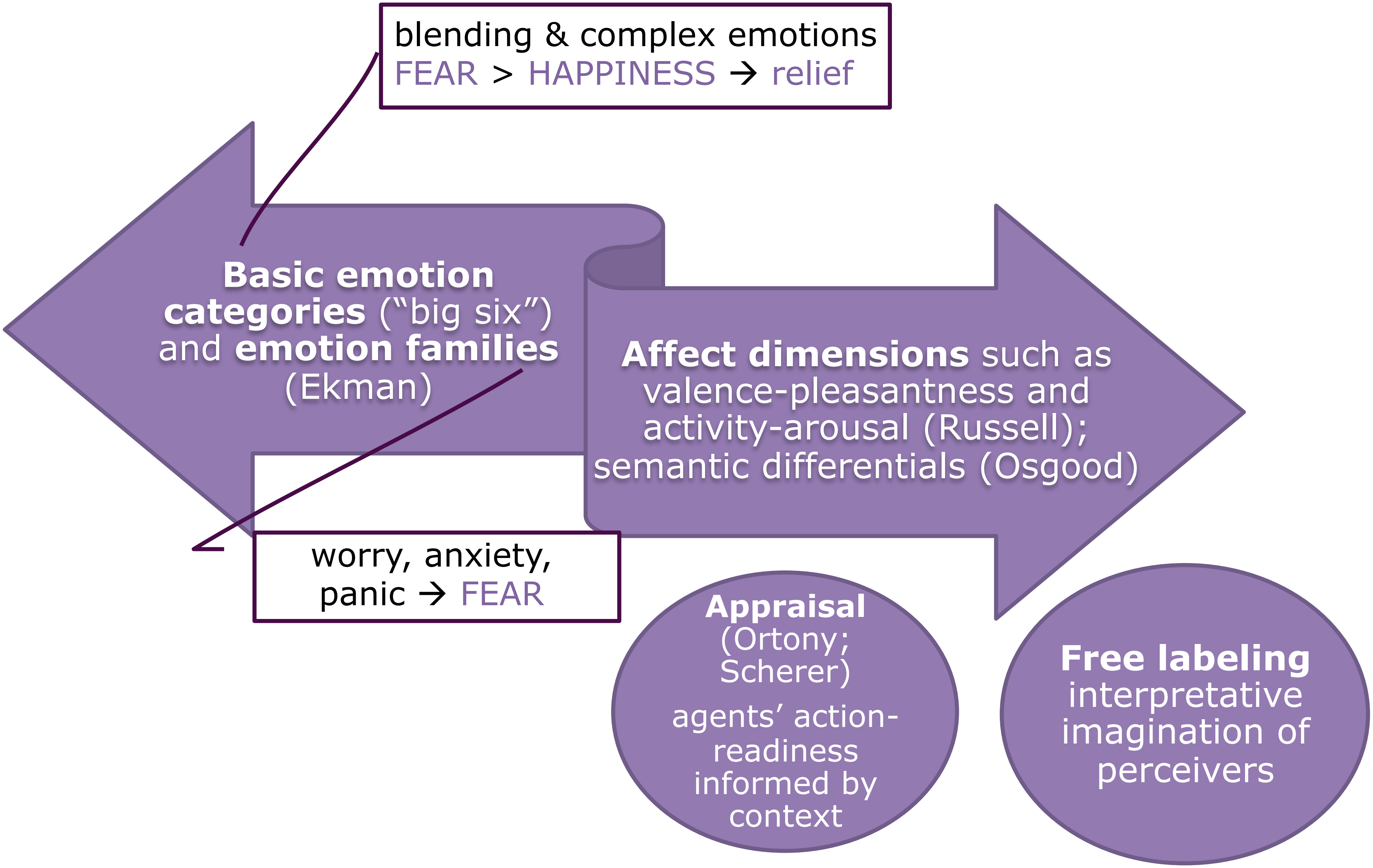
An example of one way to conceptualize affect as categories



A fuzzy ‘gray zone’ between affect and neutrality tends to characterize affect phenomena

(Mohammad and Alm, 2015)

Modeling and describing affect

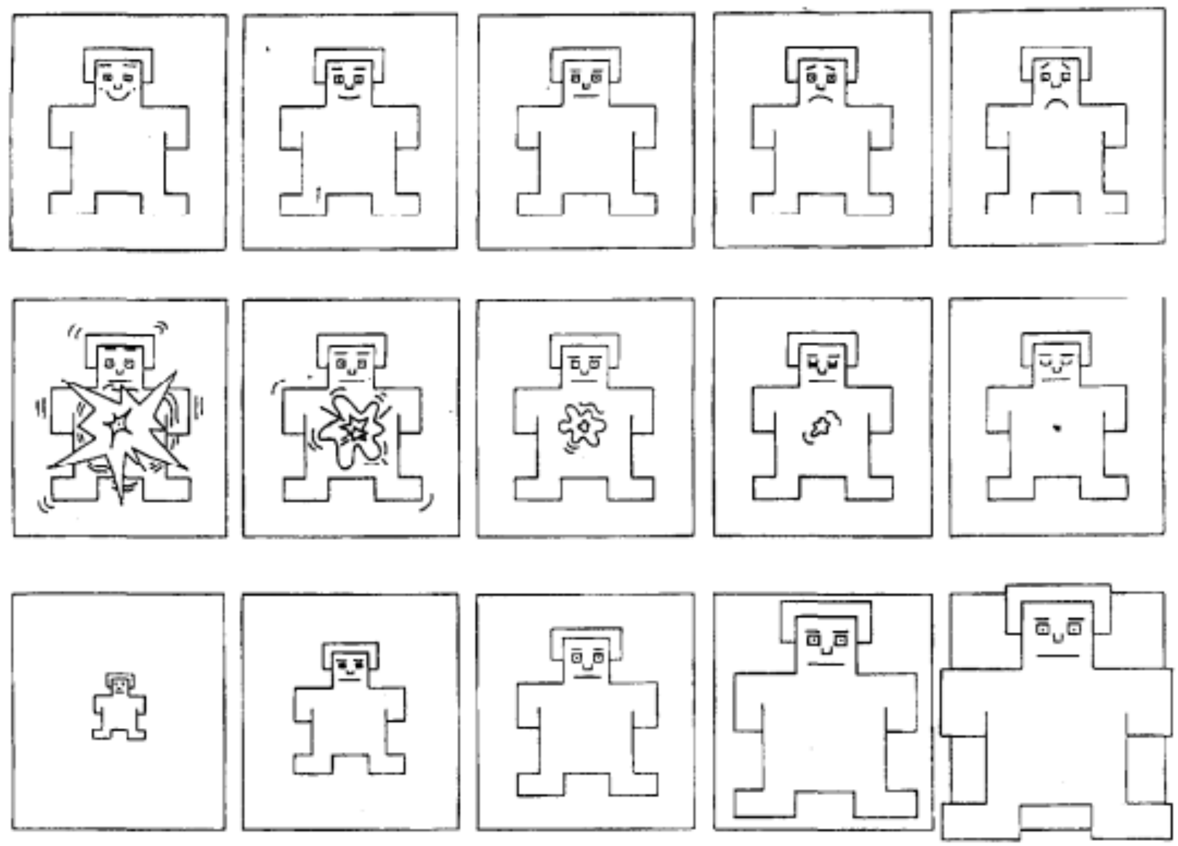


(Mohammad and Alm, 2015)

Affective categories vs. affective dimensions

"Big Six" (Cornelius, 2000)

SAM

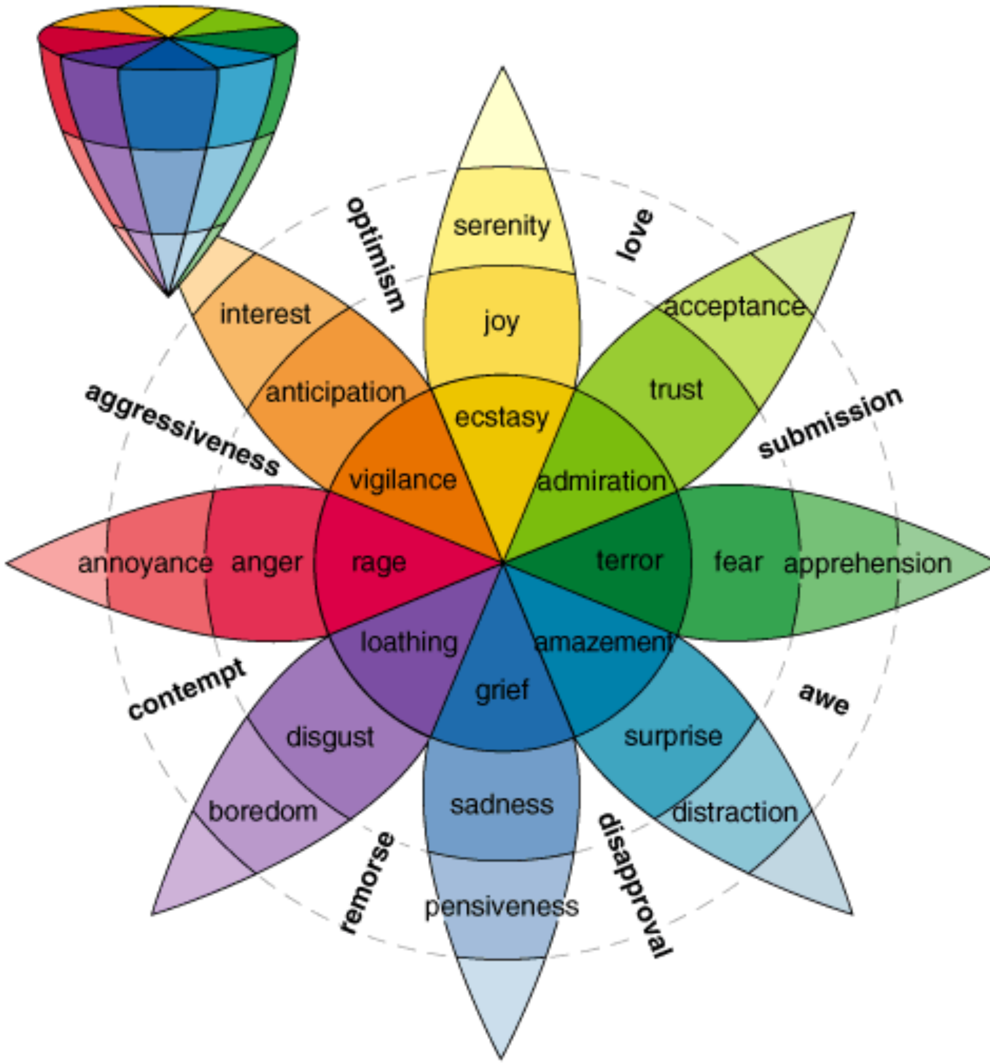


(Bradley & Lang, 1994)

(Mohammad and Alm, 2015)

Yet another Darwinian view – Plutchick

Anticipation
Trust
Anger
Disgust
Fear
Joy
Sadness
Surprise



Take home message:

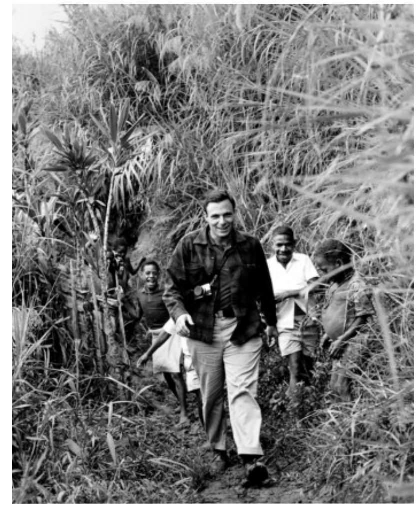
- No agreed upon model of affect and emotion
- Neutrality (non-emotion) is in the same limbo
- Preferences are quite strong in this area
- *Tip*! Important to reason comprehensively about design/application-related labeling choices, with adequate grounding in the affective sciences.

(Mohammad and Alm, 2015)

Ongoing debate:
Universality of perception of emotions

Margaret Mead
Cultural anthropologist

Paul Ekman
Psychologist



- Circa 1950's, Margaret Mead and others
  - Facial expressions, their meanings, culturally determined
- Paul Ekman
  - Most influential in providing evidence for Darwin, not Mead
  - Universality of six emotions

(Mohammad and Alm, 2015)

Ongoing debate: Universality of emotion perception

Margaret Mead
Cultural anthropologist

Paul Ekman
Psychologist

Lisa Barrett
Professor of Psychology

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

(Mohammad and Alm, 2015)

Manually created lexical resources

- **Dictionary of Affect** (Whissell)
  http://sail.usc.edu/dal_app.php
- **Affective Norms for English Words (Texts)** (Bradley & Lang)
  http://csea.phhp.ufl.edu/media.html
- **Harvard General Inquirer categories** (Stone etc.)
  http://www.wjh.harvard.edu/~inquirer/
- **NRC Emotion Lexicon** (Mohammad & Turney)
  http://saifmohammad.com/WebPages/lexicons.html
- **MaxDiff Sentiment Lexicon** (Kiritchenko, Zhu, & Mohammad)
  http://saifmohammad.com/WebPages/lexicons.html

(Mohammad and Alm, 2015)

Automatically generated lexical resources

- **SentiWordNet** (Esuli & Sebastiani)
  http://sentiwordnet.isti.cnr.it/
- **WordNet-Affect** (Strapparava & Valitutti)
  http://wndomains.fbk.eu/
- **NRC Twitter Lexicons** (Mohammad, Kiritchenko, & Zhu)
  – Hashtag Emotion Lexicon, Hashtag Sentiment Lexicon, Sentiment140 Emoticon Lexicon
    http://saifmohammad.com/WebPages/lexicons.html

(Mohammad and Alm, 2015)

Sample resources: Annotated corpora and other products

Annotated corpora (affect categories):

- **Affective Text Dataset** (Strapparava & Mihalcea) – news; headlines
  http://web.eecs.umich.edu/~mihalcea/downloads.html#affective
- **Affect Dataset** (Alm) – classic literary tales; sentences
  http://people.rc.rit.edu/~coagla/
- **2012 US Presidential Elections –** tweets (Mohammad et al.)
  http://saifmohammad.com/WebDocs/ElectoralTweetsData.zip
- **Emotional Prosody Speech and Transcripts –** actors/numbers (Liberman et al.) https://catalog.ldc.upenn.edu/LDC2002S28
- **HUMAINE** – multimodal (Douglas-Cowie et al.)
  http://emotion-research.net/download/pilot-db/

Other:

- **EmotionML** (Schröder et al.) http://www.w3.org/TR/emotionml/
- **ACII** (multiple data formats), **Interspeech** (spoken language)
- **IEEE Trans. on Affective Comp.** http://www.computer.org/web/tac
- **EMNLP 2014 Tutorial on Sentiment Analysis of Social Media Texts** (Mohammad & Zhu)
  Video & slides: https://www.youtube.com/watch?v=zv16Xyph7Ss
  http://www.saifmohammad.com/WebDocs/EMNLP2014-SentimentTutorial.pdf

Emotion datasets in Chinese

- News and blog posts with Ekman emotions (Wang, 2014)

- **Ren-CECps** blog emotion corpus (Quan & Ren, 2009)
  - The sentences are annotated with eight emotions: joy, expectation, love, surprise, anxiety, sorrow, anger, and hate.

- **2013 Chinese Microblog Sentiment Analysis Evaluation (CMSAE)** Dataset of posts from Sina Weibo annotated with seven emotions: anger, disgust, fear, happiness, like, sadness and surprise.
  - The train set: 4000 instances (13252 sentences)
  - The test set: 10000 instances (32185 sentences) http://tcci.ccf.org.cn/conference/2013/pages/page04_eva.html

Emotion datasets in Japanese

Japanese customer reviews corpus with the same eight emotions used in the Chinese Ren-CECps Corpus (Sun et al., 2014)

- The annotated corpus has ~3K sentences.
- Each adverb and sentence manually annotated for association with the eight emotions and the degree of emotion intensity (0.1 to 1.0)
- Also created an adverb emotion lexicon
  - 687 adverbs and their associations with the eight emotions.

(Mohammad and Alm, 2015)

Emotion datasets in Dutch

Dutch: Dutch sentences annotated into one of eight octants of Leary's Rose

- framework for interpersonal communication (Vaassen & Daelemans, 2011)
- evaluate the performance of several classification systems

(Mohammad and Alm, 2015)

More on the reference data problem

- Lower human intersubjective agreement; broadly impacts affect beyond NL&SP: "[o]btaining high inter-observer agreement is a challenge in affect data annotation" (Gunes & Schuller, 2013)
- Lack of a stable 'ground truth'
- Ratings may convey varying acceptability
- Methodological issues with 'training' annotators
- Immense implications for the development and evaluation of automated systems, yet the reference data problem remains quite understudied

(Mohammad and Alm, 2015)

Collecting data and annotation

Collecting data:
- Games with a Purpose, Master-Apprentice, Wizard of Oz
- Harvesting news, social media, literary texts, etc.
- Confederates/actors vs. naturalistic data
  - ‘Authenticity’ of naturalistic data
- Text external vs. text internal perspectives

Collecting reference labels:
- Independent annotations
  - Pairs/small groups, experts, crowds, GWOP
- Self-reports or self-annotation
  - Surveys, hashtags, post/forum labels
- Measurement-based
  - Vetting across modalities

(Mohammad and Alm, 2015)

Hashtag words as labels

- Hashtagged words may act as labels of valence or emotion categories:

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

- Hashtags labels are not always good labels:
  - Sarcasm

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

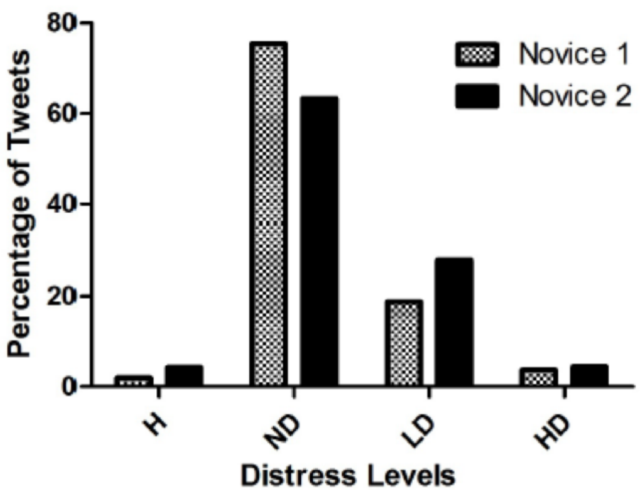
  - Unclear from rest of the message

    Mika used my photo on tumblr. **#anger**

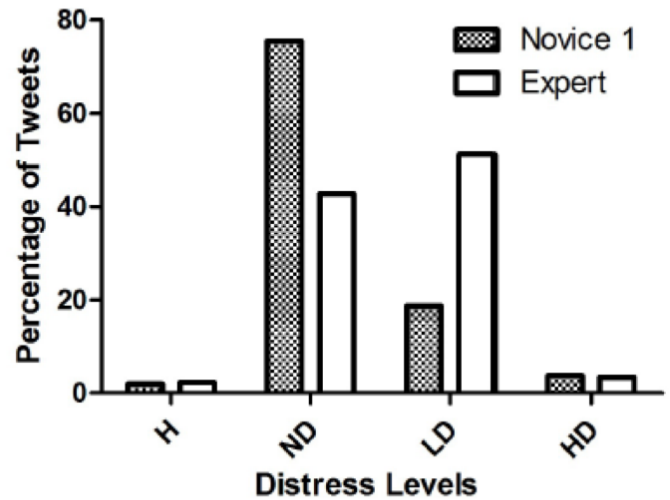
(Go, Bhayani, & Huang, 2009;
Mohammad, 2012a)

Affect ratings can be influenced by domain expertise

(a) Novices' perceptions are similar



(b) Expert is more sensitive to non-extreme distress

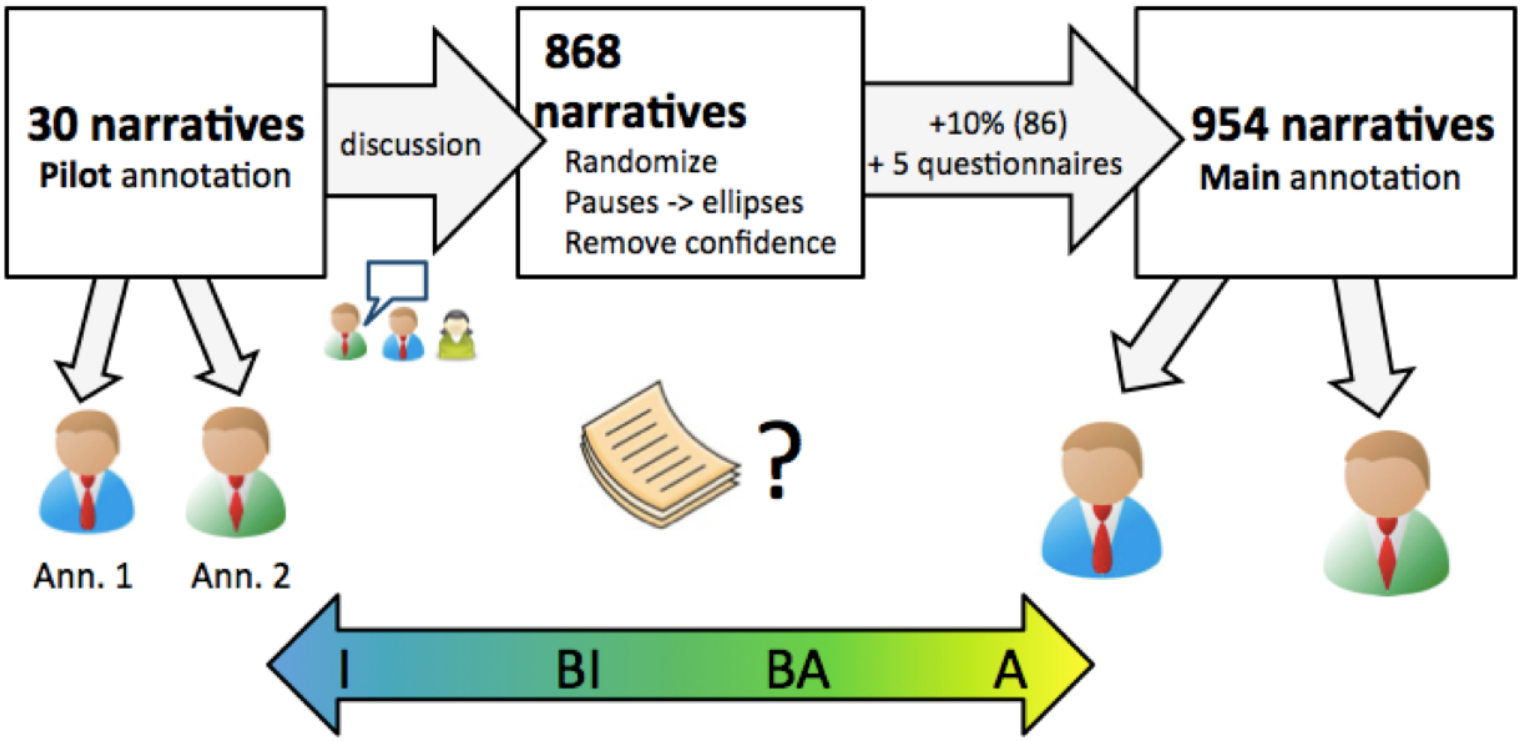


HD: High Distress   LD: Low Distress   ND: No Distress   H: Happy

(Mohammad and Alm, 2015)

(Homan et al., 2014)

Using annotation procedures to gain insights into affect-related meaning phenomena

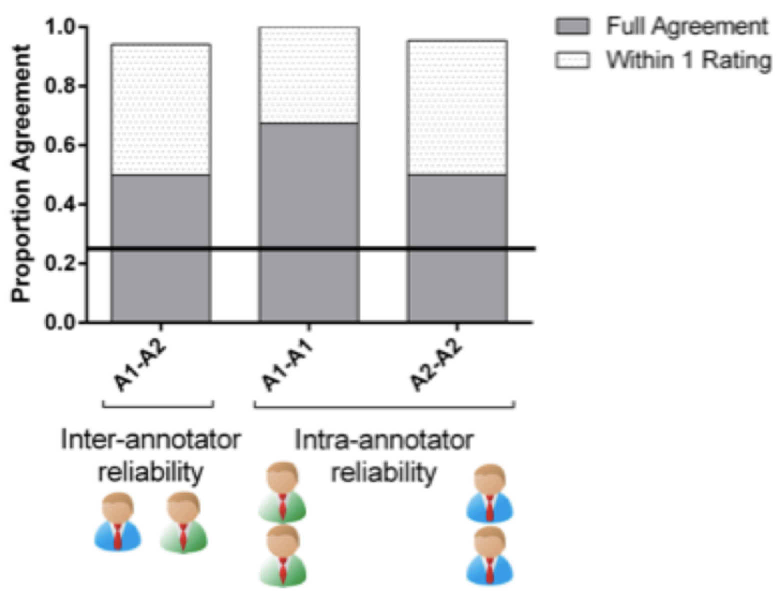


(Mohammad and Alm, 2015)

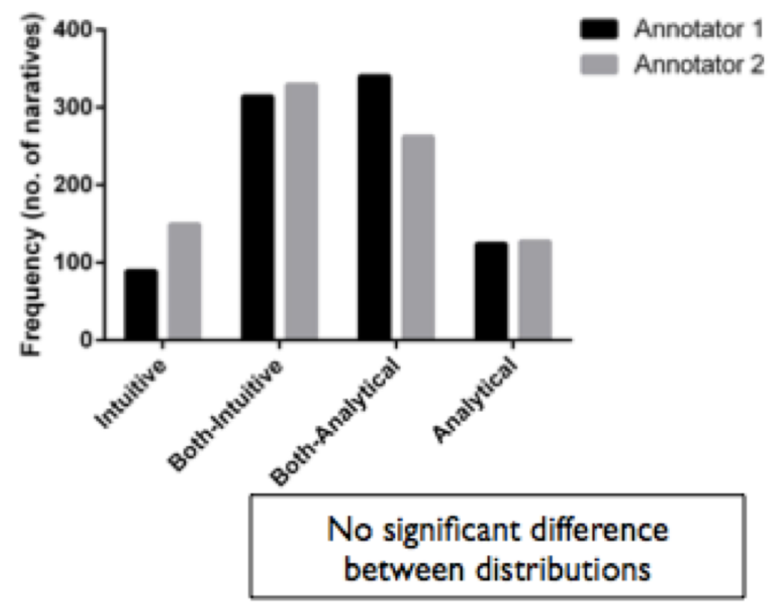
(Hochberg et al., 2014a)

Annotation analysis can help understanding fuzzy, yet systematic perception

a) Disagreements are minor and explicable



b) Perception centers on the fuzzier middle



Full agreement or within one rating on the continuum for over 90% on decision-style annotation

(Mohammad and Alm, 2015)

(Hochberg et al., 2014b)

Annotation surveys can show trends in factors' influence and how annotators' agree/diverge

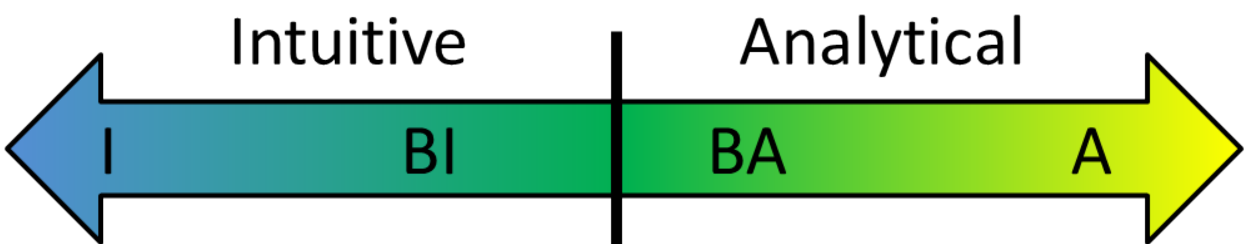
Factor	A1 (Avg)	A1 (SD)	A2 (Avg)	A2 (SD)
Switching between decision styles	1.0	0.0	3.6	0.9
Timing of switch between decision styles	1.6	0.5	4.2	0.4
Silent pauses (...)	2.0	0.0	3.6	0.5
Filled pauses (e.g. *uh, um*)	2.0	0.7	3.6	0.5
Rel. (similarity) of final & differential diagnosis	2.8	0.4	3.2	0.8
Use of logical rules and inference	3.2	0.8	2.2	0.4
False starts (in speech)	3.4	0.9	2.4	0.9
Automatic vs. controlled processing	3.4	0.5	4.0	0.0
Holistic vs. sequential processing	3.6	0.5	4.4	0.5
No. of diagnoses in differential diagnoses	4.0	0.0	1.6	0.5
Word choice	4.0	0.7	2.6	0.5
Rel. (similarity) of final & first-mentioned diagnosis	4.0	0.0	4.0	0.0
Perceived attitude	4.0	0.7	4.0	0.0
Rel. timing of differential diagnosis in the narrative	4.2	0.8	2.8	0.8
Degree of associative (vs. linear, ordered) processing	4.2	0.4	3.8	0.4
Use of justification (e.g. *X because Y*)	4.2	0.4	4.0	0.0
Perceived confidence	4.4	0.5	4.2	0.4

(Mohammad and Alm, 2015)

(Hochberg et al., 2014a)

One way of selecting ‘core’ reference data for modeling (if that is intended)

614 narratives Full agreement → center of gravity **+49** → **663 narratives** → secondary ratings **+9** → **672 narratives** Final dataset for modeling

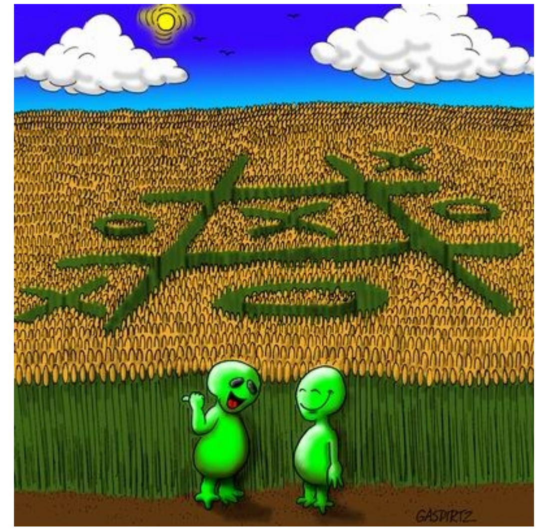


				Label
A1	**	A2		I
		A2	A1	
	A2	A1		
A1	A2			
	A2	**	A1	A
A2	A1			

(Mohammad and Alm, 2015)

(Hochberg et al., 2014b)

Example 1 of data elicitation:
Rich narration over images –
social-emotional vs. factual-material inference Qs



Why is there money on the table?

What is going on in this picture?

Who knows that the man has cards behind his back?

How rich is each person in this picture?

Where are they?

What is their relationship?

What kind of game are they playing?

How often do they play video games?

Why is this picture funny?

What does the crop “circle” look like?

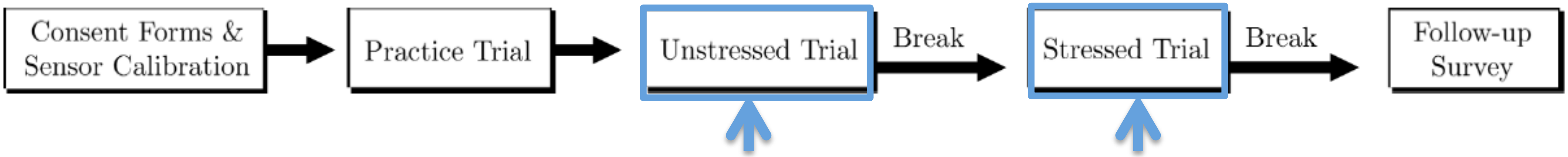
Where are the two green men from?

Why is the man on the left pointing and smiling?

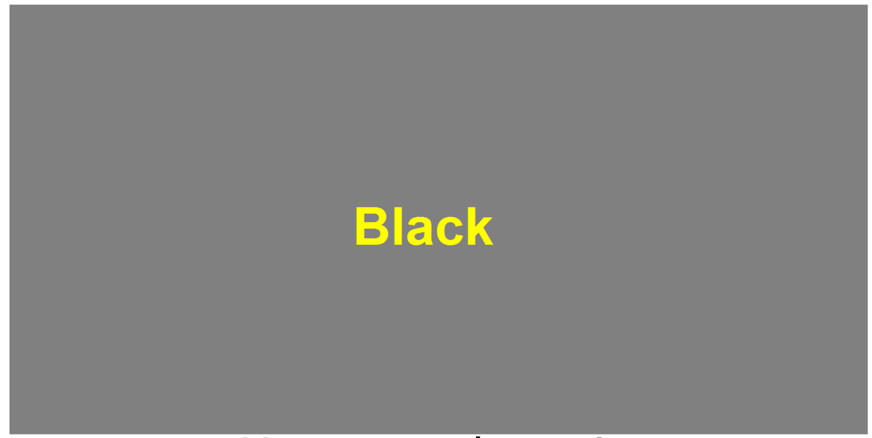
(Mohammad and Alm, 2015)

(Womack et al., 2014)

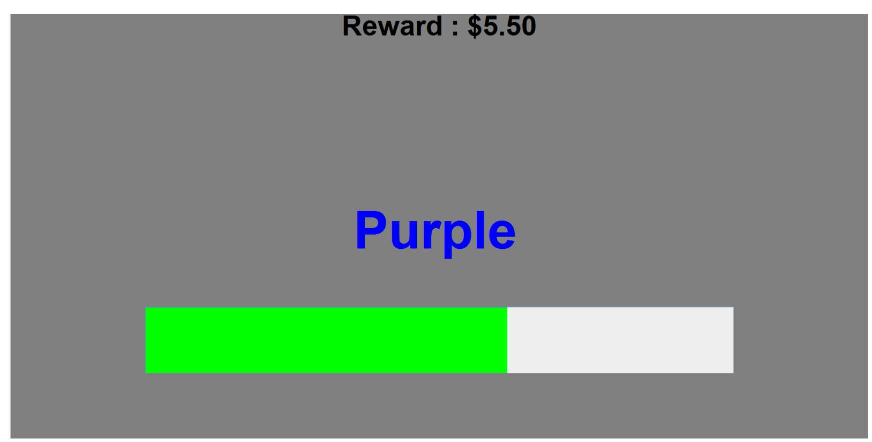
Example 2 of data elicitation: Controlled experimental set-up with moderate stress



- **Stroop Test** induces cognitive load
  - Color word is presented on screen. Task is to speak the font color, not the color word.
- **Induce stress** with time and penalty
  - Unstressed version has no time limit and no penalty for wrong answers
  - Stressed version adds a time limit, and a monetary penalty for each wrong answer
  - Rest period reduces effect of previous trial



Unstressed version



Stressed version

(Mohammad and Alm, 2015)

(Bethamcerla et al., 2015)

A few summarizing observations

- Options for affect modeling, with an ongoing debate
  - No one fit all solution
  - Alternatives may be constrained by the application
- Linguistic affect phenomena:
  - Capturable into lexical resources/datasets with reference labels
  - Multiple alternatives for their respective collection
  - Gradient semantics with narrow ‘core’ and wider ‘gray zone’
  - Contextual factors in interpretation (expertise)
- Annotations reveal insights into fuzzy phenomena involving language data, and can sort out ‘core’ vs. ‘periphery’ data subsets

(Mohammad and Alm, 2015)

Computational Modeling (Part 1): Word-level Affect Associations

Topics:

- Creating term-affect association lexicons: manually and automatically
- Real-valued associations
- Twitter-specific associations
- Negation

Affect in different textual chunks

- Words
- Sentences, tweets, SMS messages
- Paragraphs, documents, customer reviews, blog posts, essays, stories

(Mohammad and Alm, 2015)

Word associations

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

Associations with...

- sentiment
- emotions
- social overtones
- cultural implications
- colours
- music

Connotations.

(Mohammad and Alm, 2015)

Word-valence associations

- Adjectives
  - reliable and stunning typically positive
  - rude and broken typically negative

- Nouns and verbs
  - holiday and smiling typically positive
  - death and crying typically negative

Capture word-sentiment associations.

(Mohammad and Alm, 2015)

Word-emotion associations

Words have associations with emotions:

- attack and public speaking with fear
- yummy and vacation with joy
- loss and disease with sadness
- result and wait with anticipation

Goal: Capture word-emotion associations.

(Mohammad and Alm, 2015)

Manually Creating Valence and Emotion Association Lexicons

(Mohammad and Alm, 2015)

Crowdsourcing affect lexicons

- **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.

(Mohammad and Alm, 2015)

Word-choice question


Peter Turney, AI2

Q1. Which word is closest in meaning to *cry*?

- *car*
- *tree*
- *tears*
- *olive*

- Word sets generated automatically
  - Near-synonym taken from thesaurus
  - Distractors are randomly chosen
- Guides annotator to desired sense
- Aids quality control
  - If Q1 is answered incorrectly: Responses to the remaining questions for the word are discarded

(Mohammad & Turney, 2013)

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 Plutchik's eight basic emotions
- Two such questions for positive or negative valence
- Each instance annotated by five MTurk workers

Better agreement when asked '**associated with**' rather than '**evoke**'.

(Mohammad & Turney, 2013)

(Mohammad and Alm, 2015)

Resulting lexical resource

NRC Emotion Lexicon

- Sense-level lexicon
  - Has valence and emotion associations for 24,200 word-sense pairs
- Word-level lexicon
  - Union of emotions associated with different senses
  - Has valence and emotion associations for 14,200 word types

(Mohammad & Turney, 2013)

How to manually create sentiment lexicons with intensity values?

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

- Humans are much better at comparisons (Cohen, 2003)
  - Questions such as:
    Is one word more positive than another?
  - Large number of annotations needed.

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

(Mohammad and Alm, 2015)

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
  - which is the least positive

- By answering just these two questions, five out of the six inequalities are known, e.g.:
  - If A is most positive
  - and D is least positive, then we know:

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

(Mohammad and Alm, 2015)

MaxDiff

- Each MaxDiff question presented to multiple annotators.

- The responses translated into:
  - a ranking of all the terms
  - a real-valued score for all the terms (Orme, 2009)

- If two words have very different degrees of association, for example, if A >> D:
  - A will be chosen as most positive much more often than D
  - D will be chosen as least positive much more often than A

  Leading to a ranked list such that:
  - A and D are significantly farther apart
  - their real-valued association scores significantly different

(Mohammad and Alm, 2015)

Dataset of real-valued sentiment scores

- Selected ~1,500 terms from tweets
  - Regular English words

    peace, jumpy
  - Tweet-specific terms
    - Hashtags and conjoined words

      #inspiring, #happytweet, #needsleep
    - Creative spellings

      amazzing, goooood
  - Negated terms

    not nice, nothing better, not sad
- Obtained MaxDiff annotations

(Kiritchenko, Zhu, & Mohammad, 2014)

Examples of sentiment scores from the MaxDiff annotations

Term	Sentiment Score 0 (most negative) to 1 (most positive)
awesomeness	0.9133
#happygirl	0.8125
cant waitttt	0.8000
don't worry	0.5750
not true	0.3871
cold	0.2750
#getagrip	0.2063
#sickening	0.1389

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)

Robustness of the annotations

- Divided the MaxDiff responses into two equal halves
- Generated scores and ranking based on each set individually
- The two sets produced very similar results:
  - Average difference in scores was 0.04
  - Spearman's rank coefficient between the two rankings was 0.98

(Kiritchenko, Zhu, & Mohammad, 2014)

Real-valued valence associations created using MaxDiff

Dataset used in:

- SemEval-2015 Task 10 (Subtask E): Determining Prior Polarity
  - Dataset available: http://alt.qcri.org/semeval2015/task10/index.php?id=data-and-tools

New datasets to be used in:

- SemEval-2016 Task 7: Determining sentiment intensity of English and Arabic phrases.
  - Include phrases with modals and negators
  - Task website: http://alt.qcri.org/semeval2016/task7/

(Mohammad and Alm, 2015)

Automatically Generating Valence and Emotion Association Lexicons

(Mohammad and Alm, 2015)

Twitter-specific valence association lexicons

- Compiled a list of seed words by looking up synonyms of excellent, good, bad, and terrible:
  - 30 positive words
  - 46 negative words
- Used emoticons as seeds also like Go, Bhayani, & Huang (2009)
- Polled the Twitter API for tweets with seed-word hashtags
  - A set of 775,000 tweets was compiled from April to December 2012

(Mohammad, Kiritchenko, & Zhu, 2013)

Automatically generated new lexicons

- A tweet is considered:
  - positive if it has a positive hashtag
  - negative if it has a negative hashtag

- For every word w in the set of 775,000 tweets, an association score is generated:

$$\text{score}(\text{w}) = \text{PMI}(\text{w,positive}) - \text{PMI}(\text{w,negative})$$

PMI = pointwise mutual information

If $score(w) > 0$, then word w is positive

If $score(w) < 0$, then word w is negative

(Mohammad, Kiritchenko, & Zhu, 2013)

NRC Hashtag Sentiment Lexicon

- w can be:
  - any unigram in the tweets: ~54,000 entries
  - any bigram in the tweets: ~316,000 entries
  - non-contiguous pairs (any two words) from the same tweet: 308,000 entries
- Multi-word entries incorporate context:

  unpredictable story 0.4

  unpredictable steering -0.7

Available for download:

http://saifmohammad.com/WebPages/lexicons.html

(Mohammad, Kiritchenko, & Zhu, 2013)

Features of the Twitter lexicon

- Connotation and not necessarily denotation
  - tears, party, vacation
- Large vocabulary
  - covering wide variety of topics
  - covering words from informal language
  - including creative spellings, hashtags, conjoined words
- Seed hashtags have varying effectiveness
  - Study on sentiment predictability of different hashtags (Kunneman, Liebrecht, & van den Bosch, 2014)

(Mohammad and Alm, 2015)

Hashtag words as labels for emotions

- Hashtagged words may act as labels of valence or emotion categories

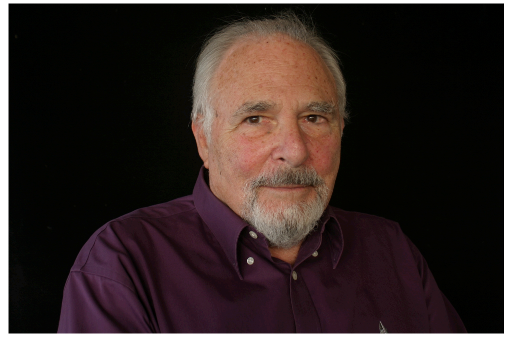
  Some jerk just stole my photo on #tumblr #grrr **#anger**

- Generated emotion association lexicons from this peudo-labeled data
  - Showed usefulness in automatic sentence-level emotion classification for the Ekman emotions

(Mohammad, 2012a)

Ongoing debate:
Universality of emotion perception

Margaret Mead
Cultural anthropologist



Paul Ekman
Psychologist

Lisa Barrett
Professor of Psychology

- Is there validity to the notion of a few basic emotions?
- Is it time to develop models for large numbers of emotions?

(Mohammad and Alm, 2015)

Generating emotion association lexicon for 500 emotions

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

(Mohammad, 2012a;
Mohammad & Kiritchenko, 2013a)

(Mohammad and Alm, 2015)

Negation

Jack was not thrilled at the prospect of working weekends ☹

negator

sentiment
label: negative

need to determine this word's
sentiment when negated

The bill is not garbage, but we need a more focused effort ☹

negator

sentiment
label: negative

need to determine this word's
sentiment when negated

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)

Handling negation

Jack was not thrilled at the prospect of working weekends ☹

in the list of negators

scope of negation

sentiment label: negative

The bill is not garbage, but we need a more focused effort ☹

in the list of negators

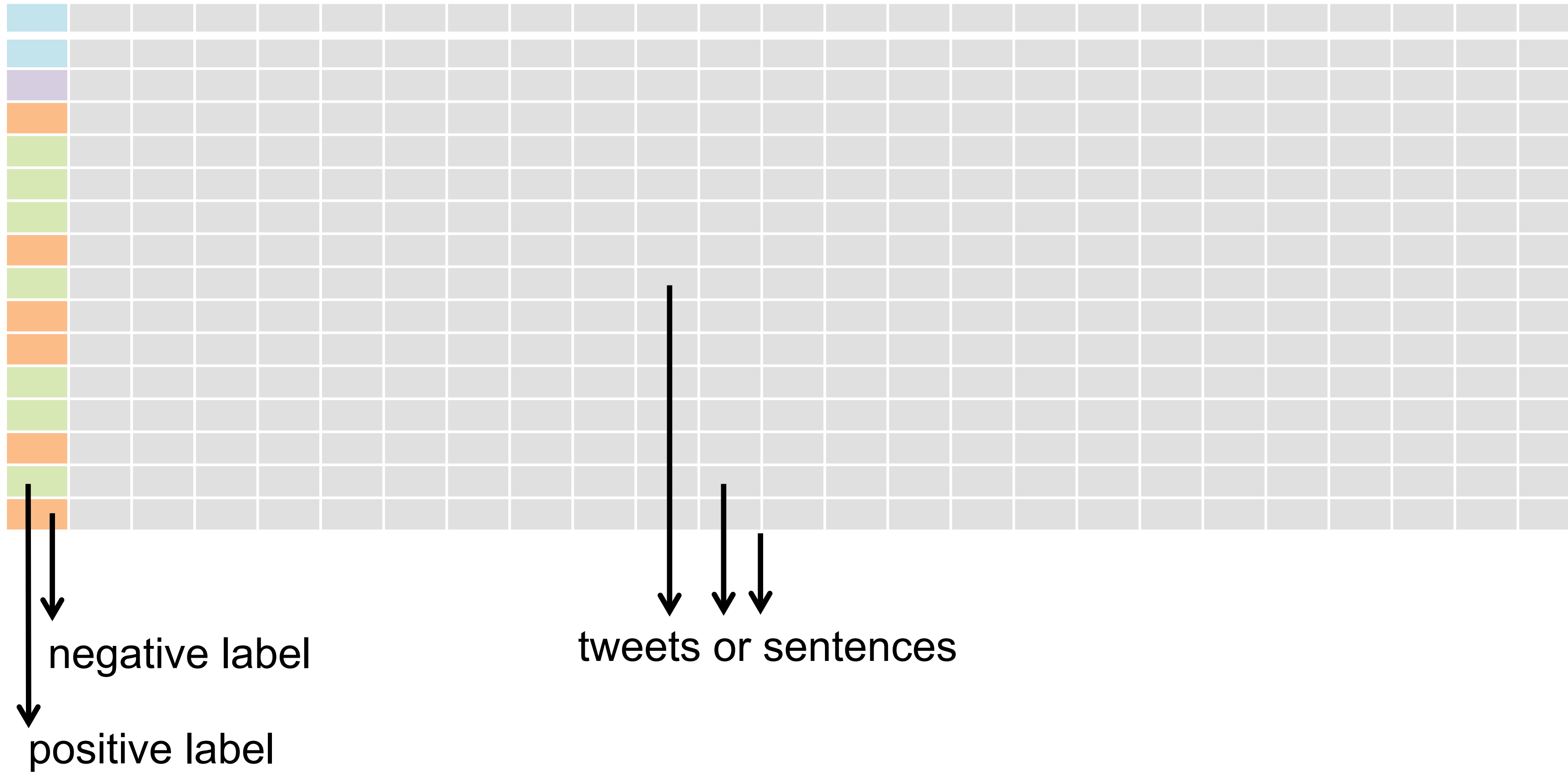
scope of negation

sentiment label: negative

Scope of negation: from negator until a punctuation (or end of sentence)

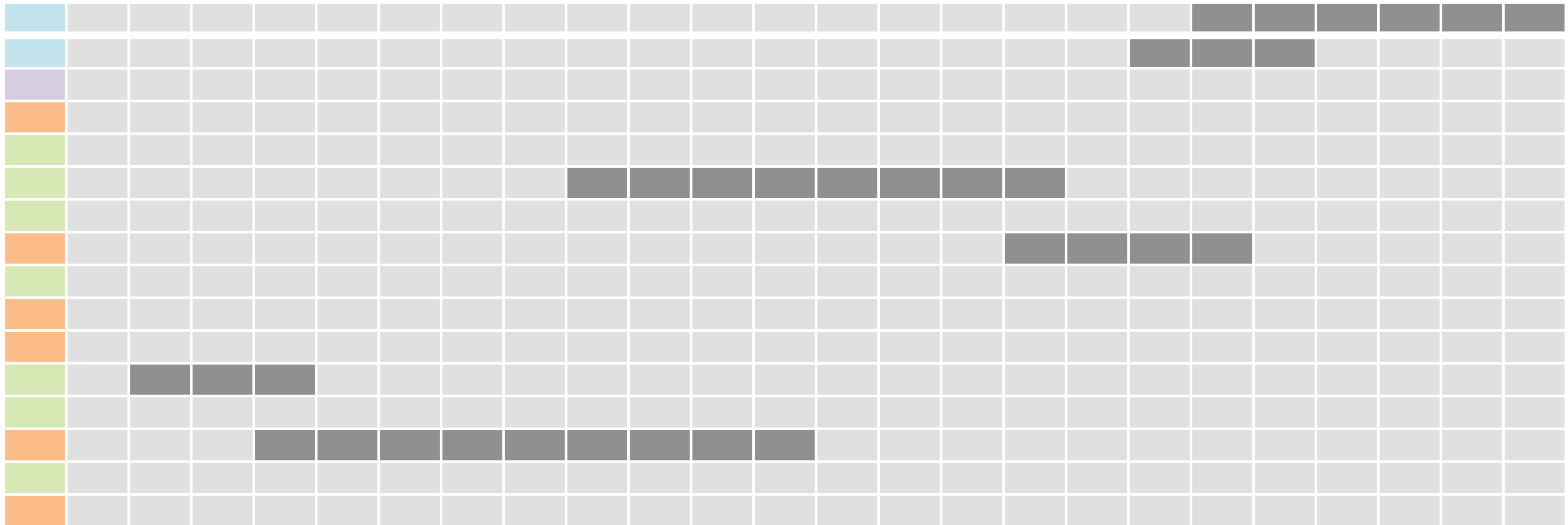
(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)



(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)



affirmative contexts
(in light grey)

negated contexts
(in dark grey)

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)

Other recent approaches to creating valence lexicons

- Using neural networks and deep learning techniques (Tang et al., 2014a)
- Constructing domain-specific lexicons (Chetviorkin & Loukachevitch, 2014)
- Other such works (Makki, Brooks, & Milios, 2014; Chen & Skiena, 2014)

Shared tasks at the word level

- SemEval-2013, 2014, 2015 Sentiment Analysis in Twitter (Subtask A): determine sentiment of term in context
  - Positive, negative, or neutral
  - unpredictable movie plot vs. unpredictable steering

  https://www.cs.york.ac.uk/semeval-2013/task2/
  http://alt.qcri.org/semeval2014/task9/, http://alt.qcri.org/semeval2015/task10/

- SemEval-2015 Sentiment Analysis in Twitter (Subtask): determine prior polarity of terms
  - Score between -1 (most negative) and 1 (most positive)

  http://alt.qcri.org/semeval2015/task10/index.php?id=subtaske-readme

- SemEval-2016 Determining Sentiment Intensity of English and Arabic Phrases
  - Score between -1 (most negative) and 1 (most positive)

  http://alt.qcri.org/semeval2016/task7/

(Mohammad and Alm, 2015)

A few summarizing observations

- Many lexical resources available for affect associations
  - Manually created, automatically generated
  - Word-level, sense-level
  - Binary, real-valued associations with a number of affect categories
- Annotation practices
  - How you phrase the question matters
  - Comparative aspect of task can lead to finer annotations
- Automatic methods
  - Naturally capture target data characteristics
  - Can generate large bigram, trigram,… lexicons (capture more context)
  - Help capture impact of negators and other affect modifiers

(Mohammad and Alm, 2015)

Computational Modeling (Part 2): Sentence-, Tweet-, Message-level Classification

Topics:

- Landscape of affect-related tasks
- Subjectivity, valence, and emotion classification: commonalities and differences
- Shared tasks

(Mohammad and Alm, 2015)

Analysis of affect

Subjectivity	Valence	Emotions
objective (factual) vs. subjective (opinions/ attitude)?	positive, negative, or neutral?	joy, sadness, fear, anger, guilt, pride, optimism, frustration,…

(Mohammad and Alm, 2015)

Subjectivity

- Early work on subjectivity (Wiebe et al., 2004; Wiebe & Riloff, 2005)
  - Subjective: having opinions and attitude
  - Objective: containing facts
- Applications
  - Question answering, information retreival, etc.

Query: Give details about the resolution of iPhone 5's screen?

Relevant: iPhone 5 has 326 pixels per inch

Not relevant: the iPhone has a beautiful touch screen

Query: How was the iPhone 5's screen received?

Relevant: the iPhone has a beautiful touch screen

Not relevant: iPhone 5 has 326 pixels per inch

(Mohammad and Alm, 2015)

Detecting subjectivity

- A number of techniques proposed (Hatzivassiloglou & Wiebe, 2000; Riloff & Wiebe, 2003; Wiebe et al., 2004; Su & Markert, 2008; Lin, He, & Everson, 2011; Wang & Fu, 2010)
  - Use patterns of word usage
  - Identifying certain kinds of adjectives
  - Detecting emotional terms
  - Occurrences of certain discourse connectives
- **Opinion Finder** is a popular freely available subjectivity system (Wilson et al., 2005)

Detecting valence

Cognitive structure of emotions (Ortony, Clore, & Collins, 1990)

valenced reaction to

consequences of events (pleased/displeased)	actions of agents (approving/disapproving)	aspects of objects (liking/disliking)

Thousands of papers on automatic valence classification (surveys by Pang & Lee, 2008; Liu & Zhang, 2012; Martinez-Camara et al., 2012)

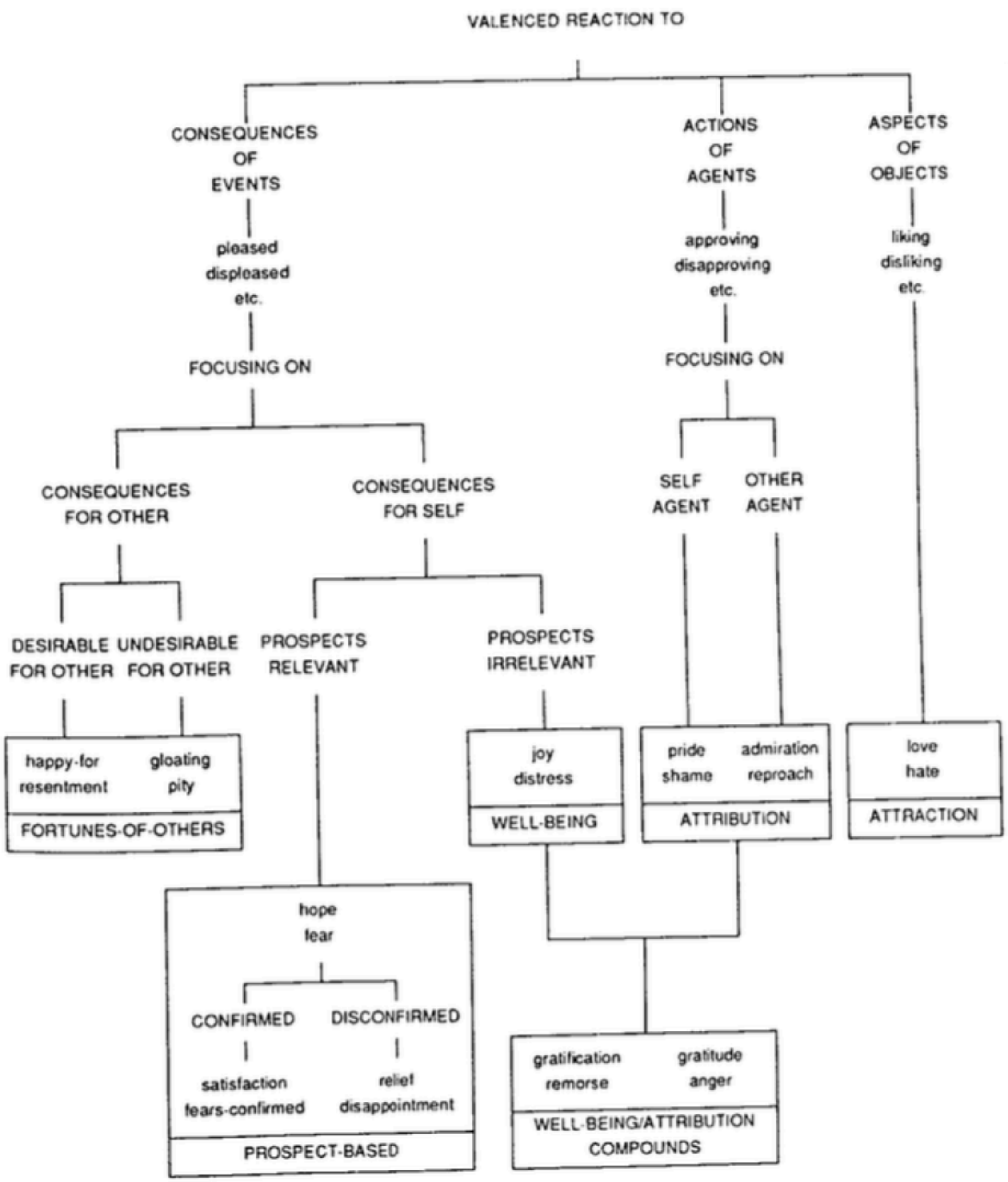


Figure 2.1. Global structure of emotion types.

(Ortony, Clore, & Collins, 1990)

(Mohammad and Alm, 2015)

Attitude of the writer, reader, and other entities

- Much of the work is focused on determining attitude of the writer.
- Is the speaker/writer explicitly expressing sentiment? Consider:

General Tapioca was killed in an explosion.

General Tapioca was ruthlessly executed today.

Mass-murdered General Tapioca finally found and killed in battle.

(Mohammad and Alm, 2015)

Detecting valence towards a target

Detecting aspects of products/service and sentiment towards these aspects (Popescu & Etzioni, 2005; Su et al., 2006; Qadir, 2009; Zhang et al., 2010)

The lasagna was delicious, but we had to wait 40 minutes before being seated.

food: positive

service: negative

SemEval-2014 and 2015 Shared Task: Aspect Based Sentiment Analysis in the laptop, restaurant domains

http://alt.qcri.org/semeval2014/task4/
http://alt.qcri.org/semeval2015/task12/

(Mohammad and Alm, 2015)

Detecting stance

Determining from text whether the author is in favor of, against, or neutral towards a proposition or target.

- Prior work on debates and discussions in online forums (Thomas et al., 2006; Somasundaran & Wiebe, 2009; Murakami & Raymond, 2010; Anand et al., 2011; Walker et al., 2012; Hasan & Ng, 2013; Sridhar, Getoor, & Walker, 2014)
- SemEval-2016 Shared Task: Detecting Stance in Tweets

Target: *Donald Trump*
Text: Jeb Bush is the only sane republican candidate for president.

Text expresses sentiment towards Jeb Bush.

Speaker is likely not in favor of Donald Trump.

Task website:

http://alt.qcri.org/semeval2016/task6/

(Mohammad and Alm, 2015)

SemEval-2013
Sentiment Analysis in Twitter

- International competition on sentiment analysis of tweets:
  - SemEval-2013 (co-located with NAACL-2013)
  - 44 teams
- Subtasks:
  - Is a given message positive, negative, or neutral?
    - tweet or SMS
  - Is a given term within a message positive, negative, or neutral?

Best performing submission:
NRC-Canada (Mohammad, Kiritchenko, & Zhu, 2013)

Setup

- Pre-processing:
  - URL -> http://someurl
  - UserID -> @someuser
  - Tokenization and part-of-speech (POS) tagging (CMU Twitter NLP tool)
- Classifier:
  - SVM with linear kernel
- Evaluation:
  - Macro-averaged F-pos and F-neg

(Mohammad, Kiritchenko, & Zhu, 2013)

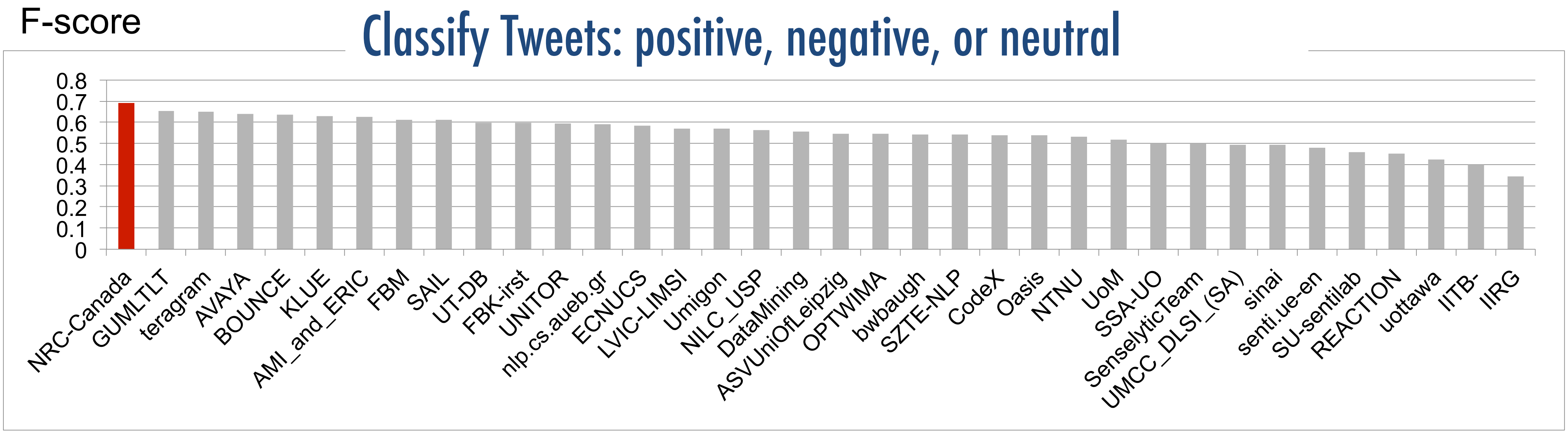
Features

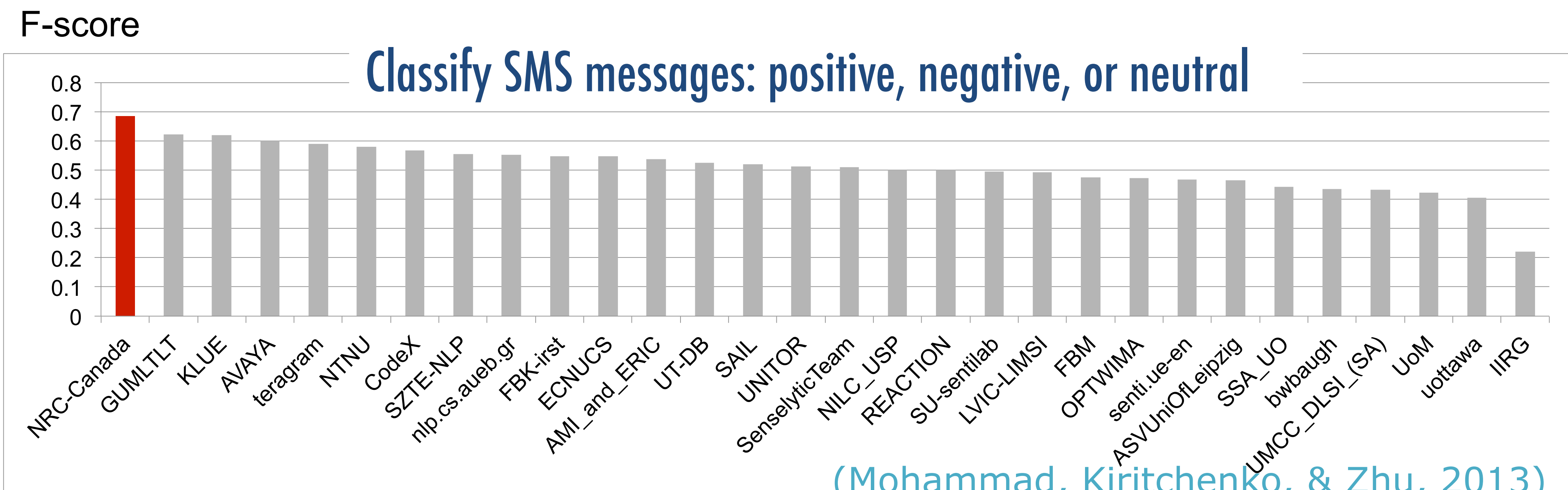
Features	Examples
sentiment lexicon	#positive: 3, scorePositive: 2.2; maxPositive: 1.3; last: 0.6, scoreNegative: 0.8, scorePositive_neg: 0.4
word n-grams	spectacular, like documentary
char n-grams	spect, docu, visua
part of speech	#N: 5, #V: 2, #A:1
negation	#Neg: 1; ngram:perfect → ngram:perfect_neg, polarity:positive → polarity:positive_neg
all-caps	YES, COOL
punctuation	#!+: 1, #?+: 0, #!?+: 0
word clusters	probably, definitely, probly
emoticons	:D, >:(
elongated words	soooo, yaayyy

(Mohammad, Kiritchenko, & Zhu, 2013)

(Mohammad and Alm, 2015)

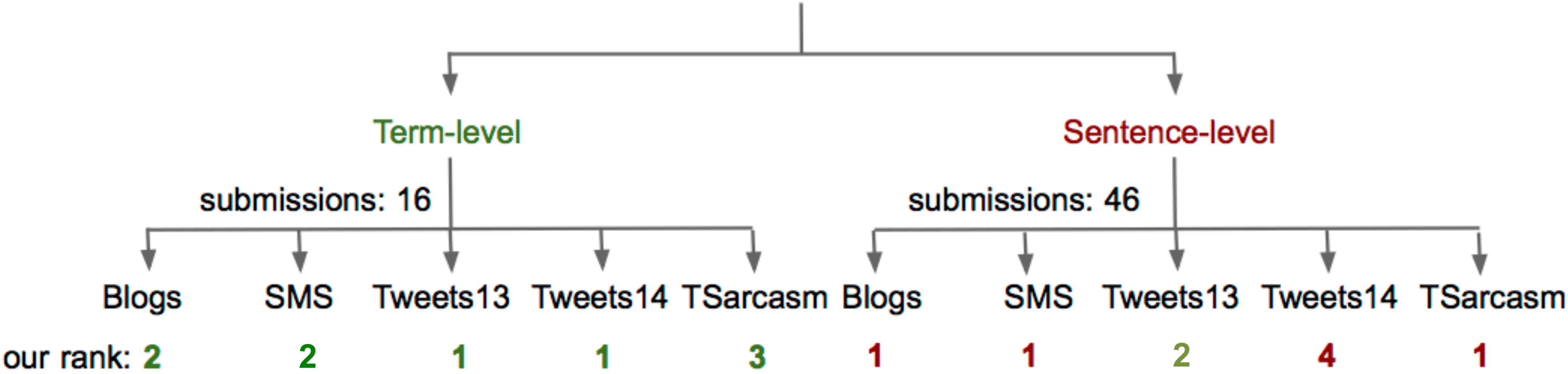
NRC-Canada's rankings in SemEval 2013 Shared Task
(Sentiment Analysis in Twitter)





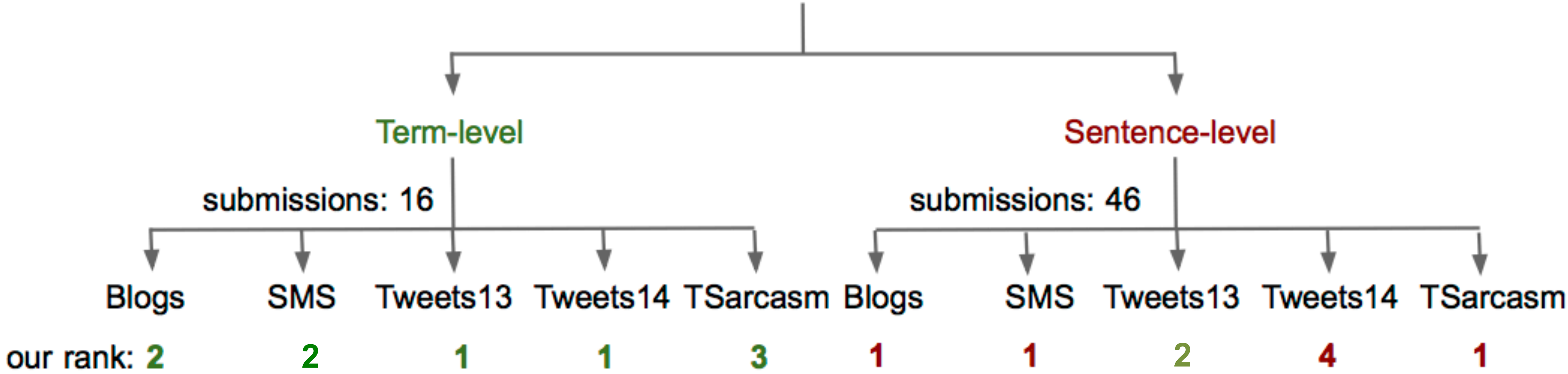
(Mohammad, Kiritchenko, & Zhu, 2013)

Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)



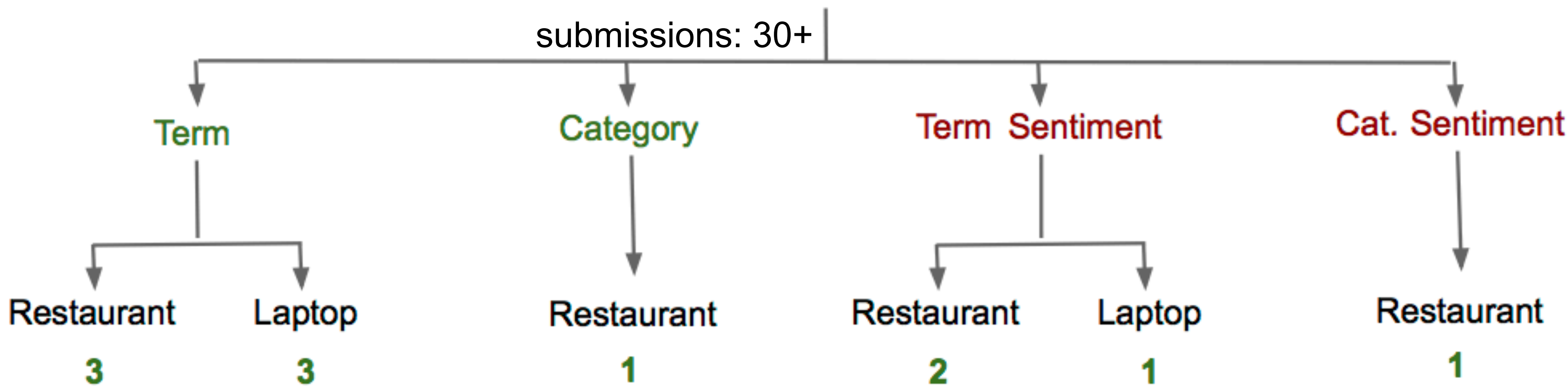
(Zhu, Kiritchenko, & Mohammad, 2014)

Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)



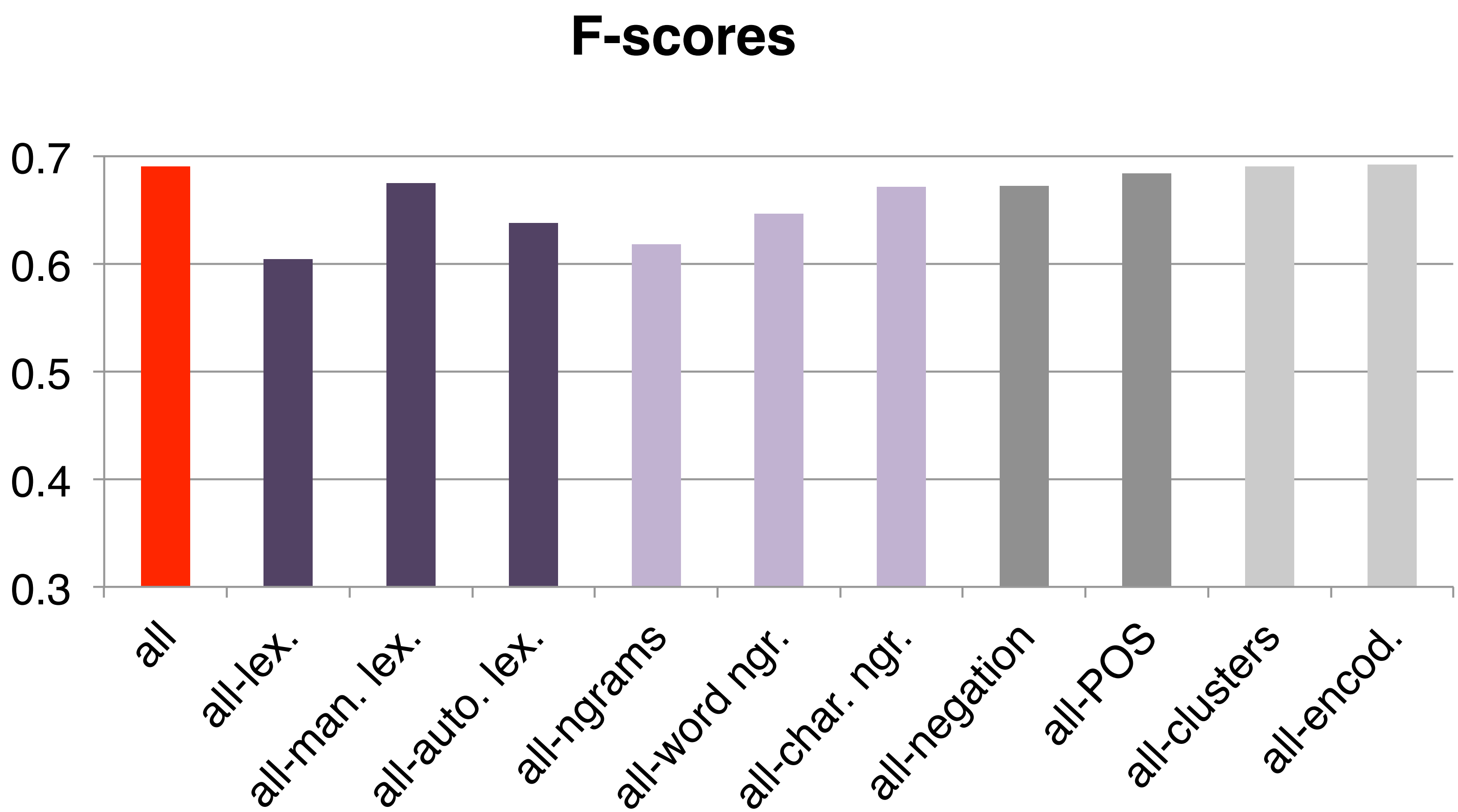
(Zhu, Kiritchenko, & Mohammad, 2014)

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



(Kiritchenko, Zhu, & Mohammad, 2014)

NRC system's feature contributions
(on Tweets)



(Mohammad, Kiritchenko, & Zhu, 2013)

On Movie Reviews Corpus

- Data from rottentomatoes.com (Pang & Lee, 2005)
- Train and test set up
- Two-way classification: positive or negative

	System	Accuracy
(a)	Majority baseline	50.1
(b)	SVM-unigrams	71.9
(c)	Previous best result (Socher et al., 2013)	85.4
(d)	Our system	**85.5**

(Kiritchenko, Zhu, & Mohammad, 2014)

Word embeddings

- Substantial improvements in vision, speech, and now NLP by representing units with low-dimensional continuous vectors
- In NLP, improvements shown in a number of areas including valence classification (Collobert et al., 2011; Mikolov et al., 2013; Le & Mikolov, 2014)
- Word embedding
  - A vector with a few hundred dimensions
  - Words closer in meaning are closer in this vector space
  - Vectors are learned from un-annotated data; can be combined with annotated data from target application

Expect improvements in affect detection using word embeddings and deep learning.

(Mohammad and Alm, 2015)

Emotions


Relaxed
Worry
Hurt
Fear
Courage
Delight
Joy
Surprised
Relieved
Affection
Pleasure
Powerlessness
Annoyance
Shame
Embarrassment
Pride
Envy
Anxiety
Content
Amusement
Anger
Empathy
Excitement
Contempt
Sadness
Stress
Helplessness
Love
Satisfaction
Friendliness
Disappointment
Irritation
Happiness
Boredom
Guilt
Elation
Despair
Frustration
Disgust
Hope
Interest
Politeness
Calm
Doubt
Serene
Tension
Trust
Shock

Six basic emotions
- generally associated with Ekman

- Anger
- Fear
- Disgust
- Joy
- Sadness
- Surprise

"Big Six" (Cornelius, 2000)

(Mohammad and Alm, 2015)

Work on fundamental affect categories

Writing style and vocabulary is different in different domains

- Chat messages (Holzman & Pottenger)
  - Annotated 1200 instances
- Classic literary tales (Alm)
  - Annotated at the sentence level: Affect Dataset
    http://people.rc.rit.edu/~coagla/
- News paper headlines (Strapparava & Mihalcea)
  - News paper headlines with intensity scores:
    Text Affect Dataset
    http://web.eecs.umich.edu/~mihalcea/downloads.html#affective
- Blog posts (Aman & Szpakowicz)
- Tweets (Mohammad et al.)
  – Tweets from the 2012 US presidential elections.
    http://saifmohammad.com/WebDocs/ElectoralTweetsData.zip

(Mohammad and Alm, 2015)

Supervised machine learning approaches

- Proposed by creators of different datasets and others (e.g., Chaffar & Inkpen, 2011; Mohammad, 2012c; Kirange & Deshmukh, 2013)
- Mostly binary classifiers for each affect category
  - Anger—NoAnger, Joy-NoJoy, etc.
- Features drawn from:
  - Character and word ngrams
  - Valence association lexicons
  - Emotion association lexicons
  - Part of speech
  - Word clusters
  - Negation

Accuracies for emotion categories usually lower than for valence classification.

(Mohammad and Alm, 2015)

Work on Plutchik's model

- **Chat messages**:
  - Brooks, et al. (2013) annotated ~27,000 chat messages
    - between thirty astrophysics collaborators
    - with 40 affect categories inspired by Plutchik's taxonomy
- **Tweets:**
  - Mohammad (2012a) collected tweets that have hashtag emotion words such as #anger and #sadness
    - showed that these hashtag words act as good emotion labels for the rest of the tweets: distant supervision
  - Suttles and Ide (2013) collected tweets with emoticons, emoji, and hashtag words
    - developed an algorithm for binary classification of tweets along the four opposing Plutchik dimensions.

(Mohammad and Alm, 2015)

Work on other small emotion sets

- **ISEAR Project**: 3000 student respondents asked to report situations in which they had experienced joy, fear, anger, sadness, disgust, shame, or guilt.
  http://emotion-research.net/toolbox/toolboxdatabase2006-10-13.2581092615
  - Thomas et al. (2014)
    - supervised machine learning
    - 7-way emotion classification.
- Pearl and Steyvers (2010)
  - Online GWAP
  - Politeness, rudeness, embarrassment, formality, persuasion, deception, confidence, and disbelief
- **Experience Project**: Portal where users share life experiences
  www.experienceproject.com
  - Neviarouskaya, Prendinger, & Ishizuka (2009)
    - 1000 sentences from the Experience Project
    - manually annotated for fourteen affect categories

Rule-based system

- Affect of sentence determined by composing meaning of component pieces
- Developed rules such as:
  - Negation words (never, nothing) reverse polarity
  - Adverbs of doubt (scarcely, hardly) reverse polarity
  - Adverbs of falseness (wrongly) reverse the polarity
  - Prepositions (without, despite) neutralize attitude
  - Condition operators (if, even though) neutralize attitude
- Developed lexicons for attitude, affect modifiers, and modals (degree of confidence)

(Neviarouskaya, Prendinger, & Ishizuka, 2010)

(Mohammad and Alm, 2015)

Verb classes from VerbNet selected for affect detection

1 Psychological state or emotional reaction
1.1 Object-centered (oriented) emotional state (*adore*)
1.2 Subject-driven change in emotional state (trans.) (*charm*)
1.3 Subject-driven change in emotional state (intrans.) (*appeal to*)
2 Judgment
2.1 Positive judgment (*bless*, *honor*)
2.2 Negative judgment (*blame*, *punish*)
…

- For each verb class, developed set of rules that are applied to detect affect.

This work can be a source of ideas for current statistical models of compositionality, for capturing affect appropriately.

(Neviarouskaya, Prendinger, & Ishizuka, 2010)

Work on other small emotion sets

- Bollen, Pepe, & Mao (2011) analyzed ~9million tweets posted in the second half of 2008
  - Profile of Mood States (POMS) (McNair, Lorr, & Droppleman, 1989)
  - POMS is a psychometric instrument that measures the mood states of tension, depression, anger, vigor, fatigue, and confusion.
- Wang et al. (2012) compiled a set of 2.5 million tweets with emotion-related.
  - Hashtags correspond to seven emotion categories: joy, sadness, anger, love, fear, thankfulness, and surprise.
  - Machine learning algorithm to classify tweets into these seven emotion categories
  - Most useful features included unigrams, bigrams, sentiment and emotion lexicons (LIWC, MPQA, WordNet Affect), and part of speech.

(Mohammad and Alm, 2015)

Personality traits

The Big Five personality traits or dimensions of personality

- extroversion vs. introversion
  - sociable, assertive vs. aloof, shy
- openness to experience vs. conventionality
  - intellectual, insightful vs. shallow, unimaginative
- conscientiousness vs. spontaneous
  - self-disciplined, organized vs. inefficient, careless
- emotional stability vs. neuroticism
  - calm, unemotional vs. insecure, anxious
- agreeability vs. disagreeability
  - friendly, co-operative vs. antagonistic, fault-finding

(Mohammad and Alm, 2015)

Automatic detection of personality traits

From:

- Stream of consciousness essays
- Facebook posts, Twitter messages
- Blog or forum posts
- Literature

Features:

- Ngrams not that useful
- LIWC features for pronouns etc. useful
- Sentiment and emotion features useful
  - Fine emotion categories more helpful than coarse sentiment (Mohammad & Kiritchenko)

(Grijalva et al., 2014; Minamikawa & Yokoyama, 2011a, 2011b; Schwartz et al., 2013b; Malti & Krettenauer, 2013; Mohammad & Kiritchenko, 2013a, 2013b)

(Mohammad and Alm, 2015)

Shared tasks at the sentence level

- SemEval-2007: Affective Text
  http://nlp.cs.swarthmore.edu/semeval/tasks/task14/summary.shtml

- SemEval-2013, 2014, 2015: Sentiment Analysis in Twitter
  https://www.cs.york.ac.uk/semeval-2013/task2/
  http://alt.qcri.org/semeval2014/task9/
  http://alt.qcri.org/semeval2015/task10/

- SemEval-2014, 2015: Aspect Based Sentiment Analysis
  http://alt.qcri.org/semeval2014/task4/

- SemEval-2015: Sentiment Analysis of Figurative Language in Twitter
  http://alt.qcri.org/semeval2015/task11/

- Kaggle Competition: Sentiment Analysis on Movie reviews
  https://www.kaggle.com/c/sentiment-analysis-on-movie-reviews

A few summarizing observations

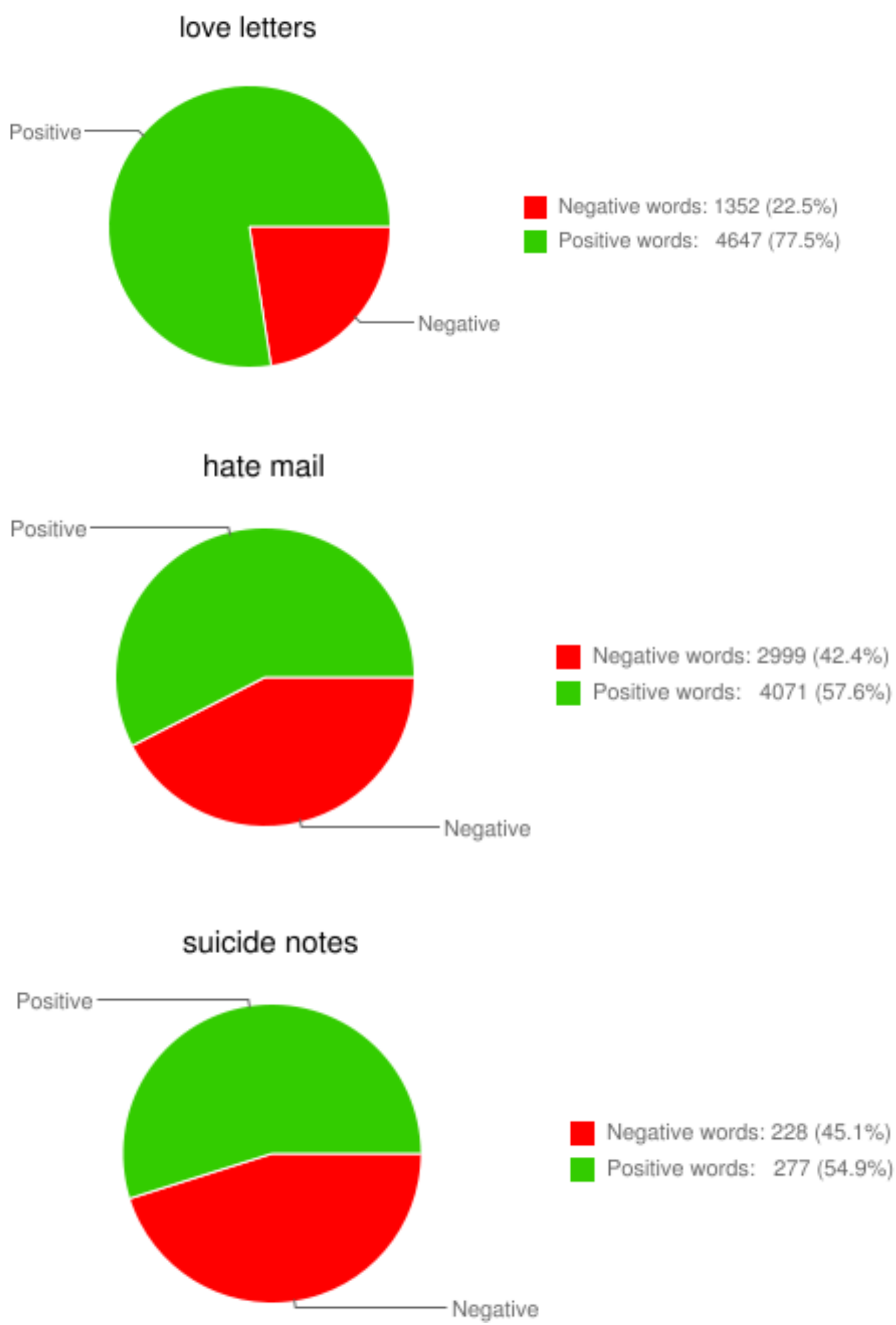
- Rich landscape of affect-related tasks
  - Subjectivity, valence, emotions
  - Reader or writer perspective
  - Attitude towards a target
- Many of the features and techniques used in valence classification are also helpful in emotion classification
- Additionally, for emotions:
  - Affect association lexicons
  - What else?
- Need emotion classification shared tasks
- Applications where emotion detection is shown to be useful
  - Application can guide the choice of affect labels to use

(Mohammad and Alm, 2015)

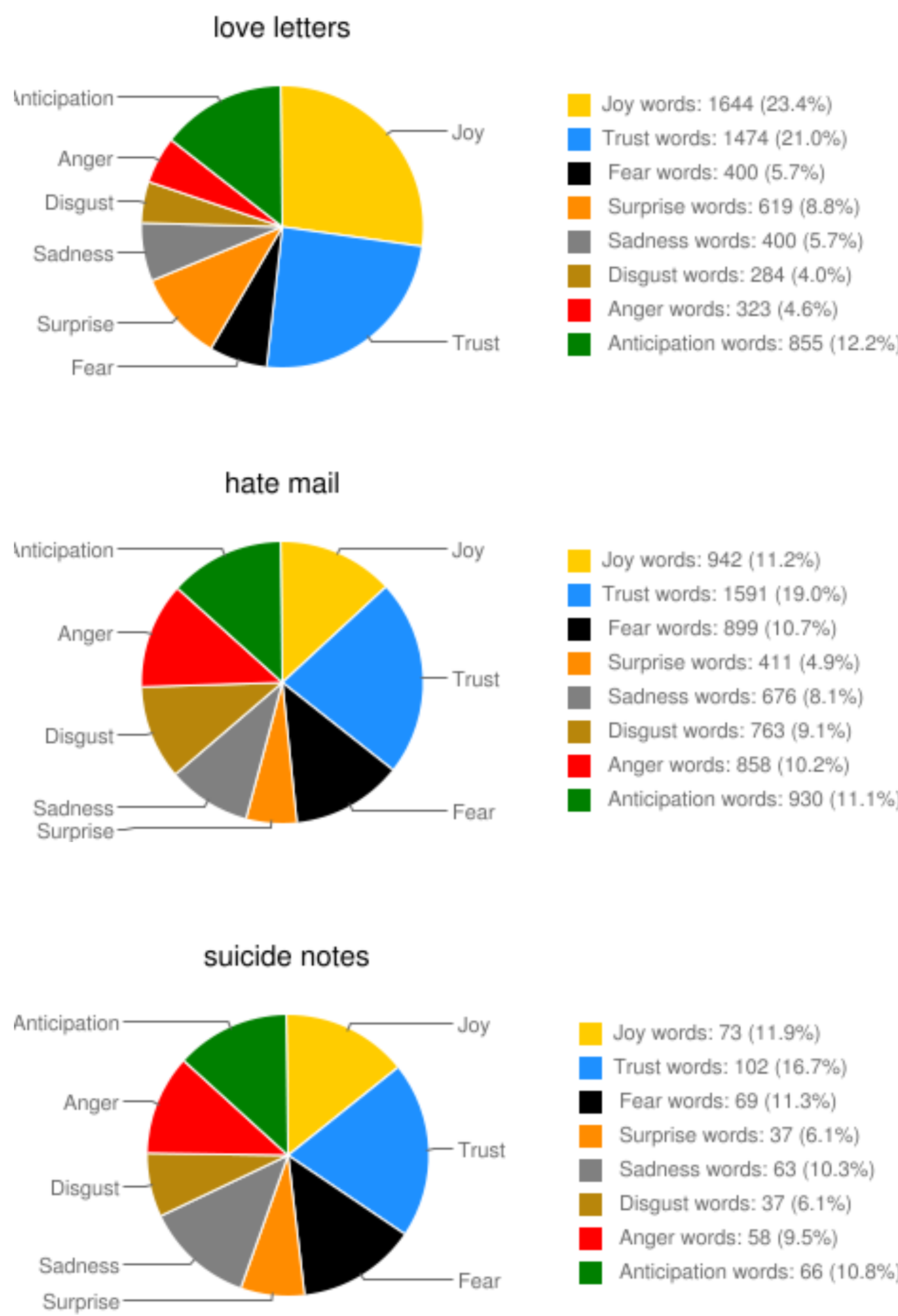
Visualizing Computational Outcomes

Topics:

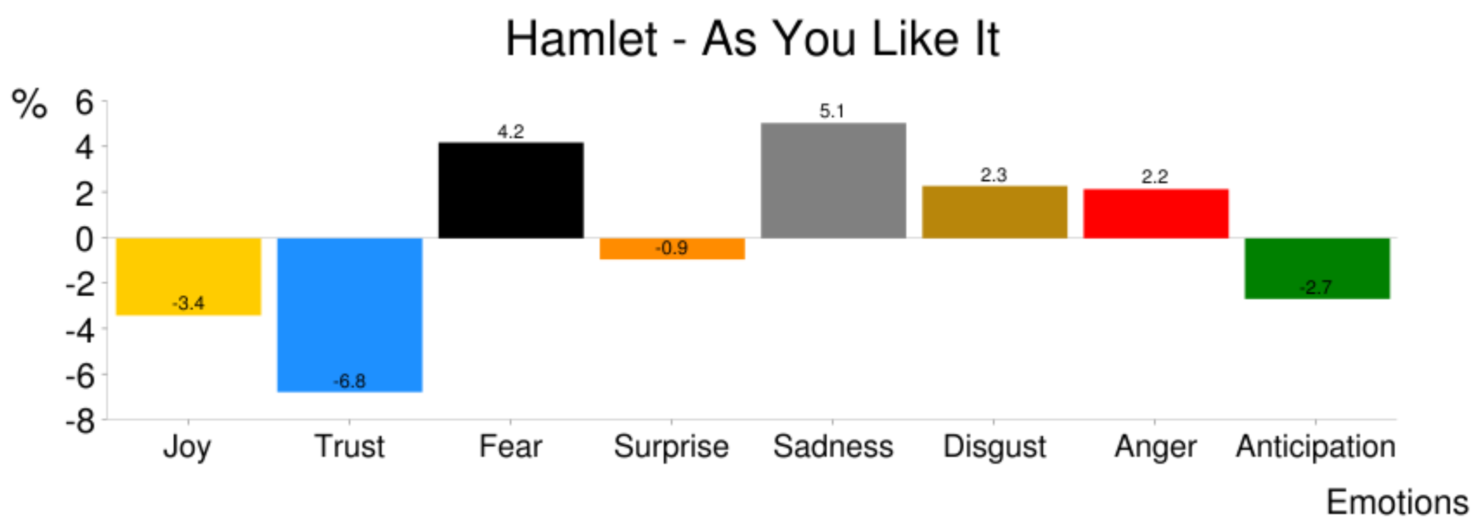
- Common visualization techniques
- Tracking emotions in large text corpora
- Interactive Visualizations



(Mohammad and Alm, 2015)



(Mohammad & Yang, 2011)



relative salience of trust words

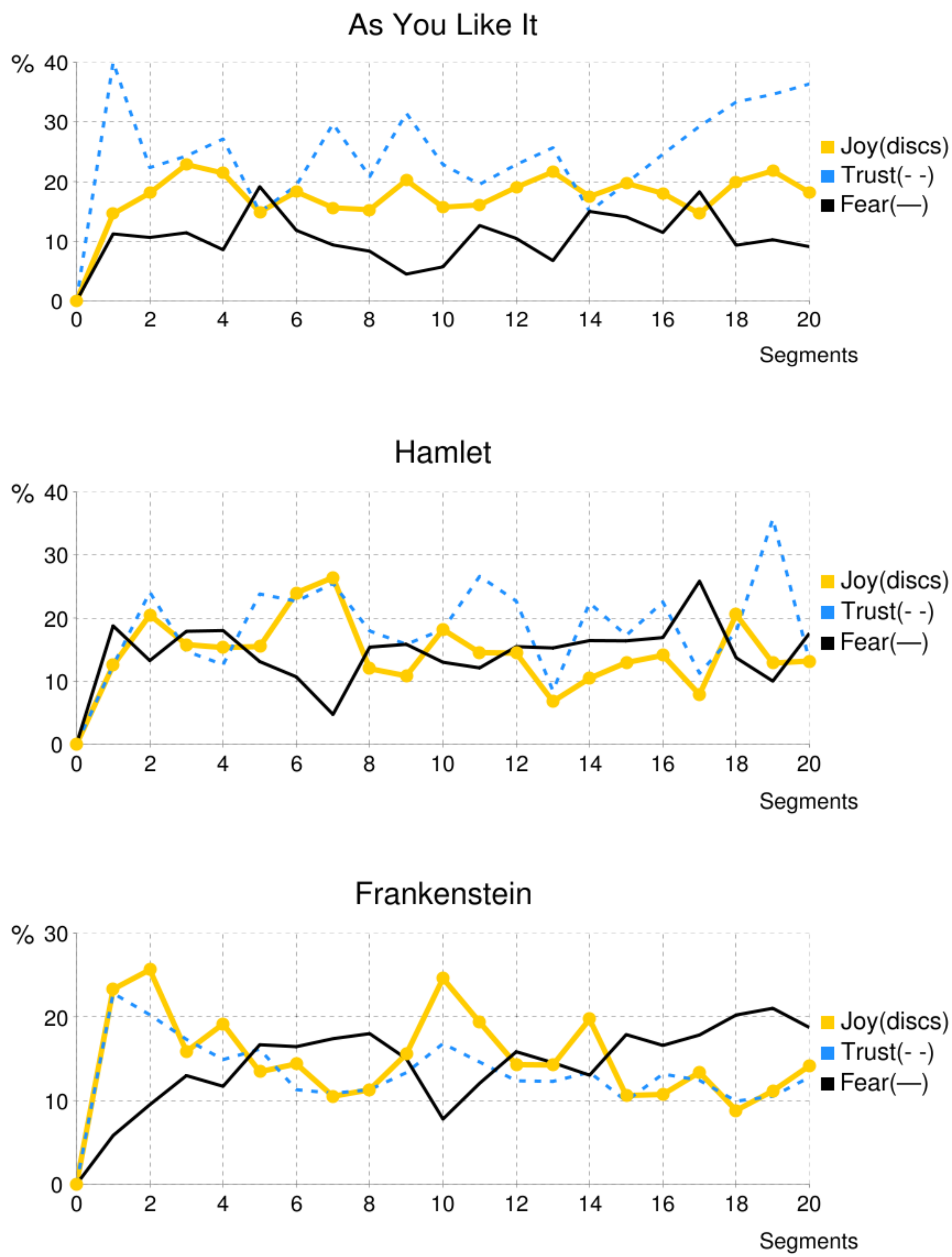
(Mohammad & Yang, 2011)

(Mohammad and Alm, 2015)

relative salience of sadness words

(Mohammad & Yang, 2011)

(Mohammad and Alm, 2015)



(Mohammad and Alm, 2015)

(Mohammad, 2011)

Gender differences in use of emotion words

Some of the claims made in the literature:

- Women:
  - foster personal relations (Deaux & Major, 1987; Eagly & Steffen, 1984)
  - share concerns and support others (Boneva et al., 2001)
- Men:
  - communicate for social position
  - prefer to talk about activities (Caldwell & Peplau, 1982; Davidson & Duberman, 1982)

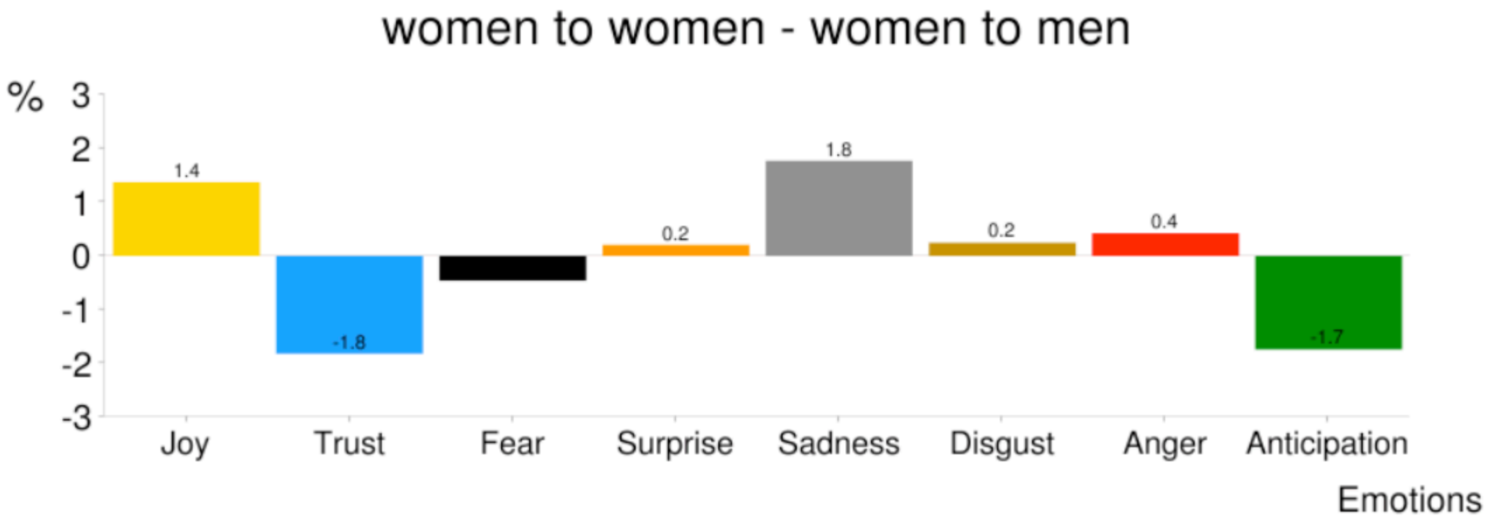
What are gender differences in
how writers use emotion words in work-place email?

(Mohammad and Alm, 2015)

Study of the Enron Email Corpus

- Discarded mails with less than 50 and more than 200 words
- Identified gender of senders by name:
  - 41 women, 89 men, 20 untagged
  - Mails from gender-unknown employees discarded
- Over 30K mails remaining:
  - More sent by men than by women
- Analyzed emotions words used
  - List of emotion associated words taken from NRC Emotion Lexicon

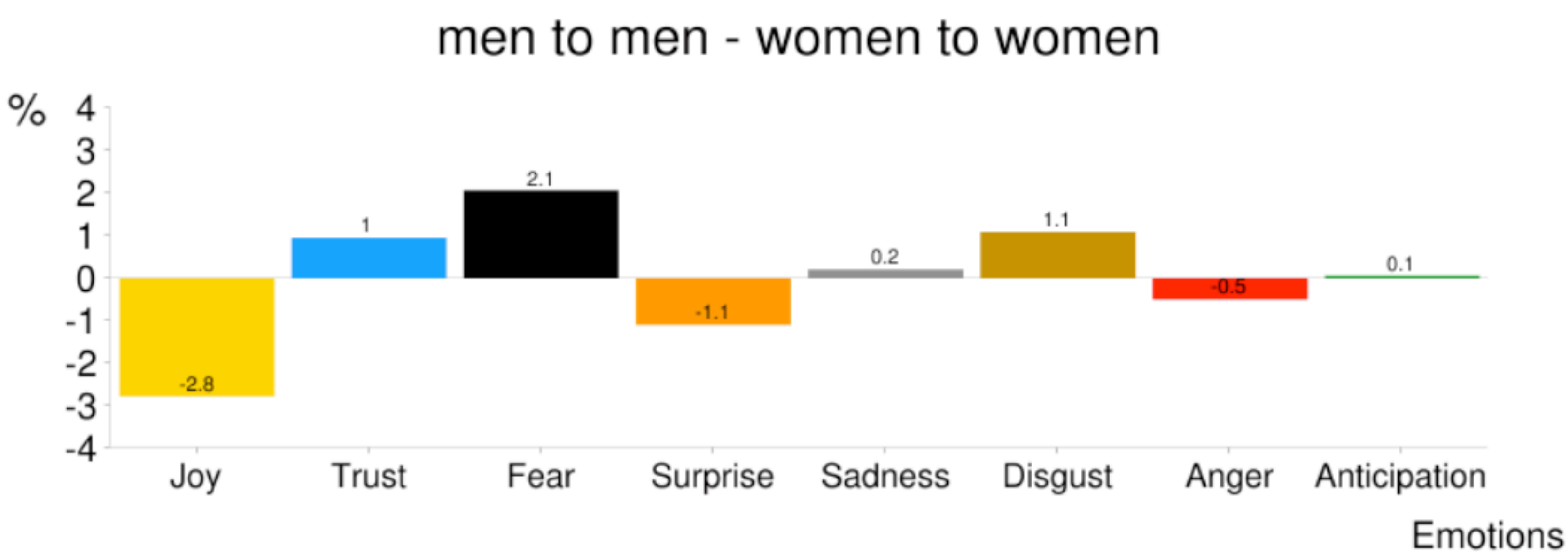
(Mohammad & Yang, 2011)



relative salience of sadness words

(Mohammad & Yang, 2011)

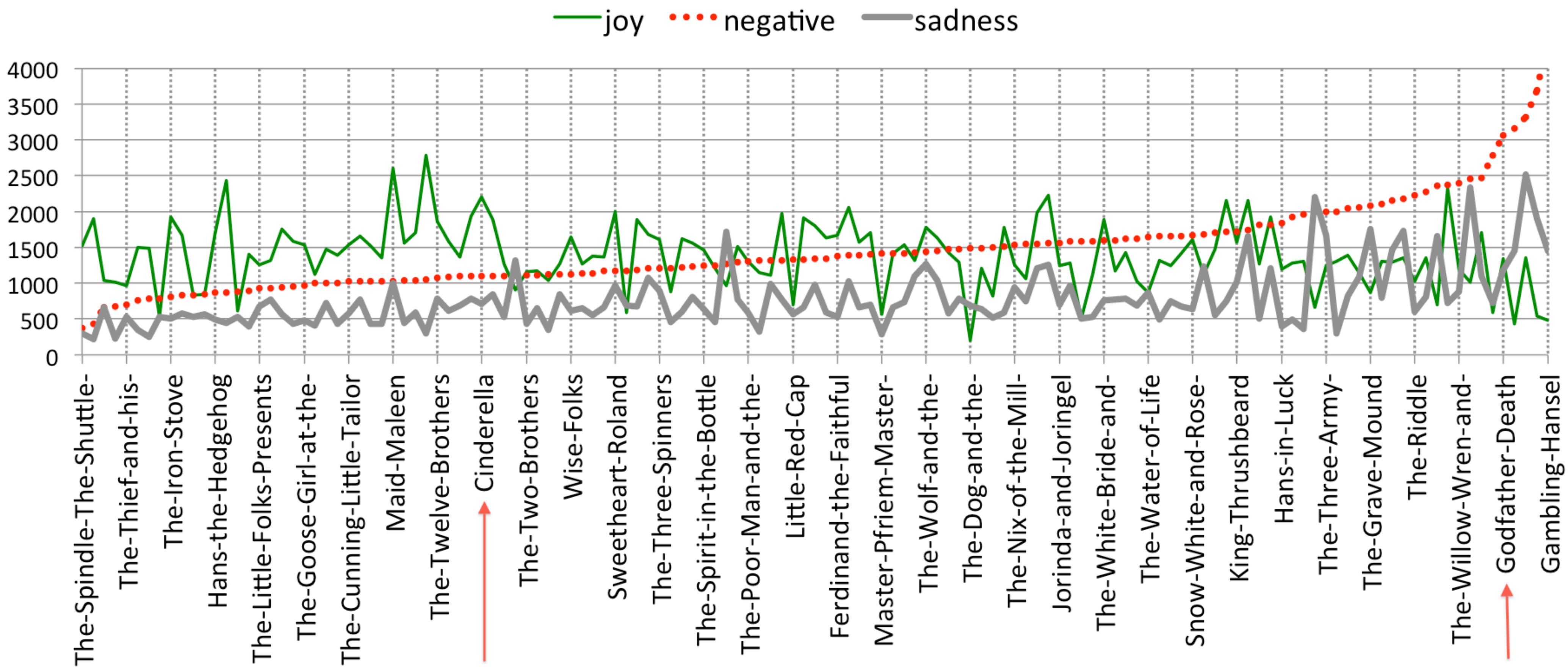
(Mohammad and Alm, 2015)



(Mohammad & Yang, 2011)

(Mohammad and Alm, 2015)

Emotion word density: Average number of emotion words in every X words

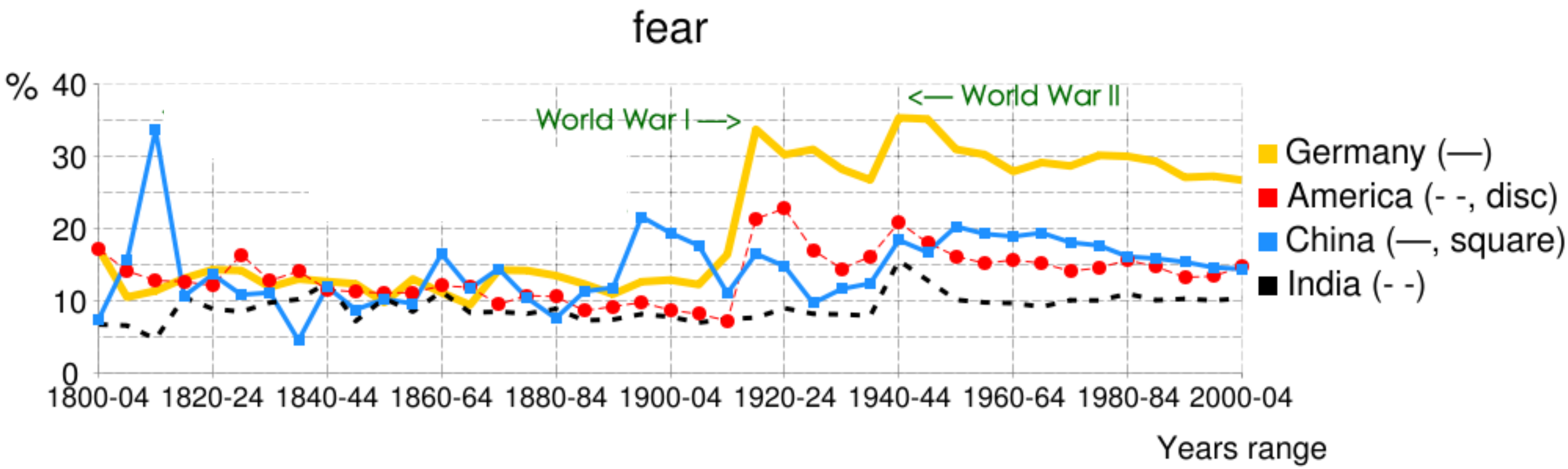


Brothers Grimm fairy tales ordered as per increasing negative word density. X = 10,000.

(Mohammad, 2011)

(Mohammad and Alm, 2015)

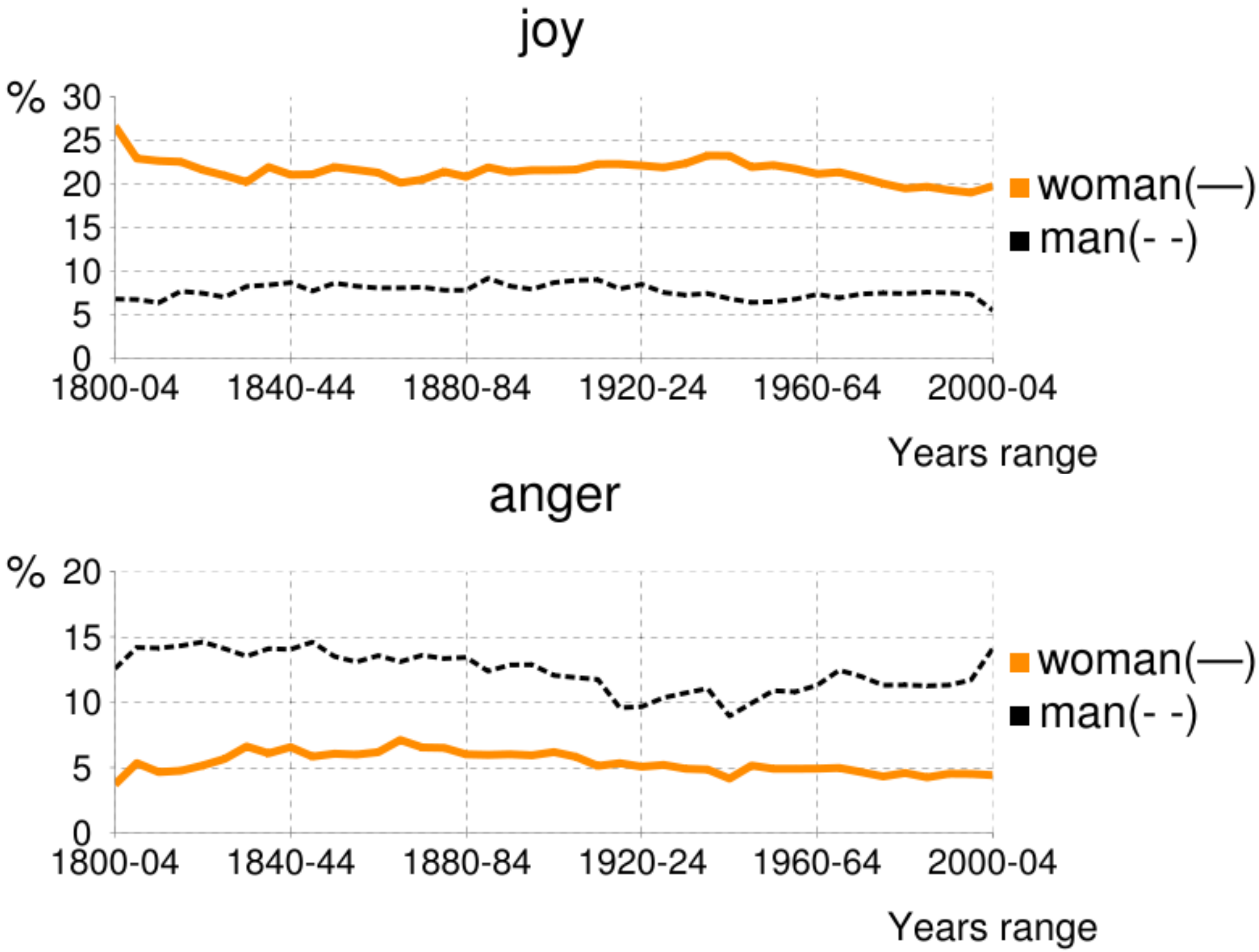
Analysis of emotion words in books



Percentage of fear words in close proximity to occurrences of America, China, Germany, and India in books.

(Mohammad, 2011)

(Mohammad and Alm, 2015)



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

(Mohammad, 2011)

(Mohammad and Alm, 2015)

Visualizing a thesaurus

- Thesauri such as **Roget's Thesaurus**
  - group words by meaning
  - have a taxonomy: classes, sections, categories,…
  - are used widely to help find the right word to use in a particular context

- Traditional means of accessing a thesaurus are limited

- Imagisaurus (Mohammad, 2015a)
  - interactive visualizer for **Roget's Thesaurus**
  - connects thesaurus with the NRC Emotion Lexicon

  http://www.purl.com/net/imagisaurus

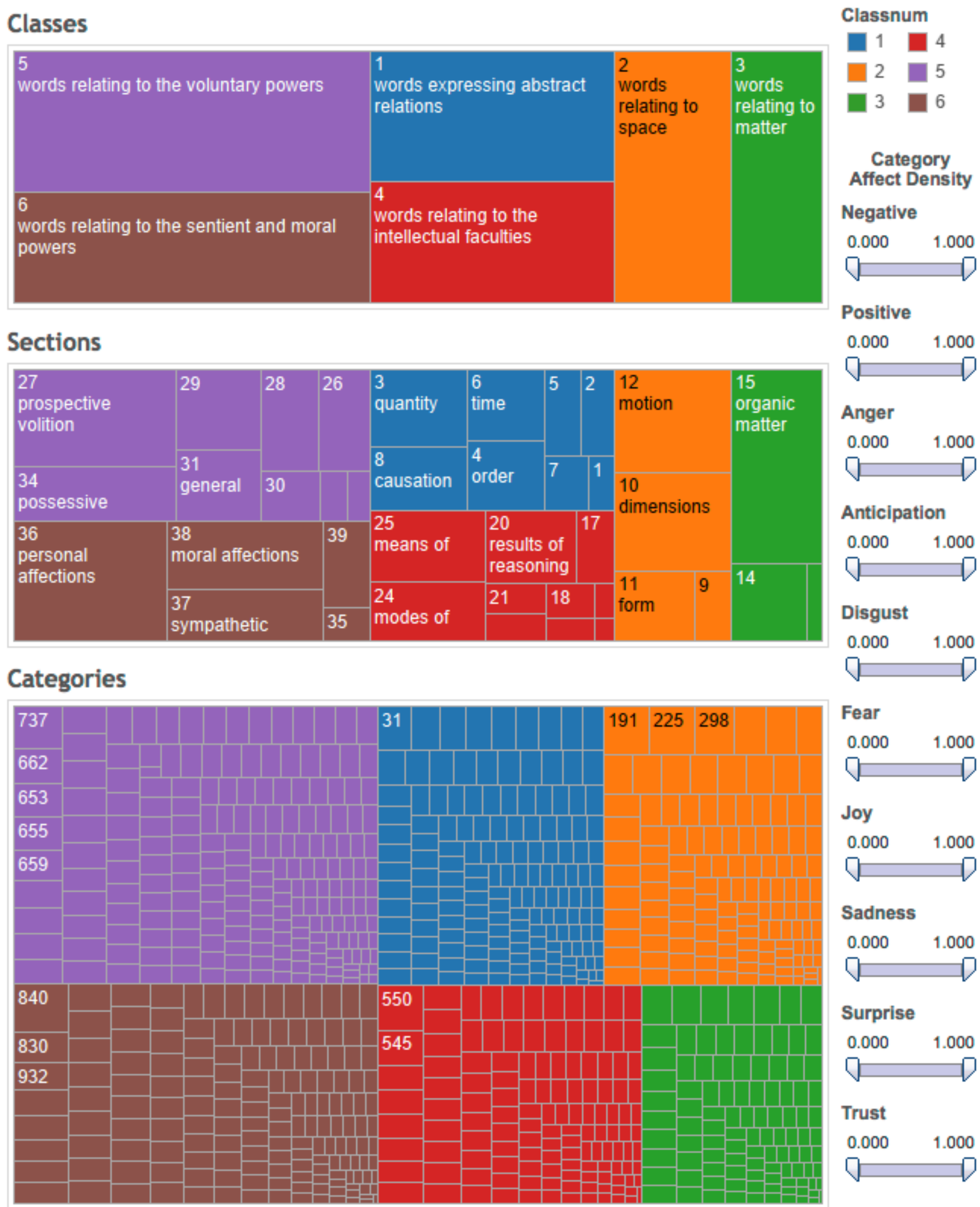
(Mohammad and Alm, 2015)

Imagisaurus: An Interactive Visualizer for the Roget's Thesaurus

Affect-associated categories can be viewed by adjusting sliders on the right. Affect words are taken from the NRC Emotion Lexicon.
(Click on a word or treemap tile to select. Click again to deselect. Undo, Redo, and Reset buttons are at the bottom left.)

Index

Term	Catnum	Secnum	Classnum
abacist	85	5	1
aback	235	10	2
abacus	85	5	1
abaft	235	10	2
abalienate	783	34	5
abalienation	783	34	5
abandon	293	12	2
	623	27	5
	624	27	5
	682	28	5
	703	28	5
	782	34	5
	859	36	6
	893	37	6
abandoned	460	17	4
	893	37	6
	945	38	6
abandonme..	624	27	5
	757	31	5
	782	34	5
	859	36	6
abase	308	12	2
	879	36	6
abased	886	36	6
abasement	308	12	2
	874	36	6
	879	36	6
	886	36	6
abash	860	36	6
	879	36	6
abashed	879	36	6
abate	36	3	1

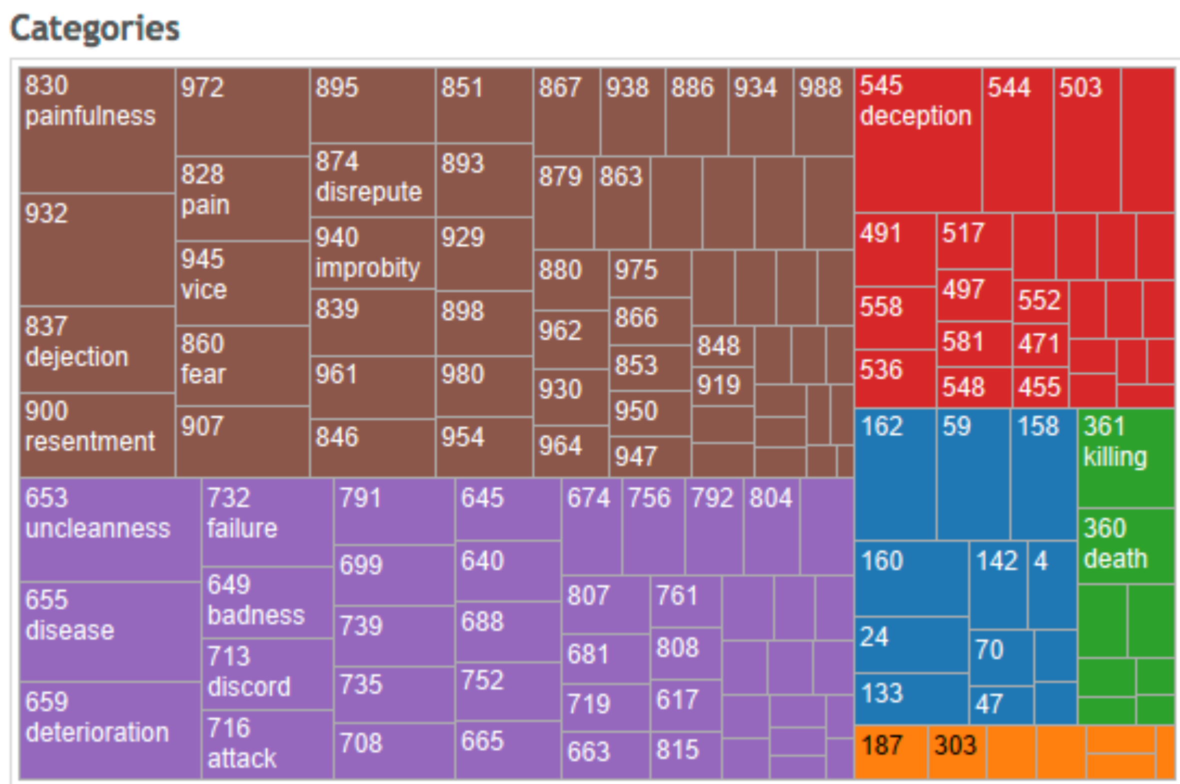


Note: Not all words in the thesaurus are listed in the emotion lexicon.
Category Affect Density = # words in the category that, as per the emotion lexicon, are associated with the particular affect / # words in the category that are in the emotion lexicon

(Mohammad, 2015a)

Default view of Roget's thesaurus Classes

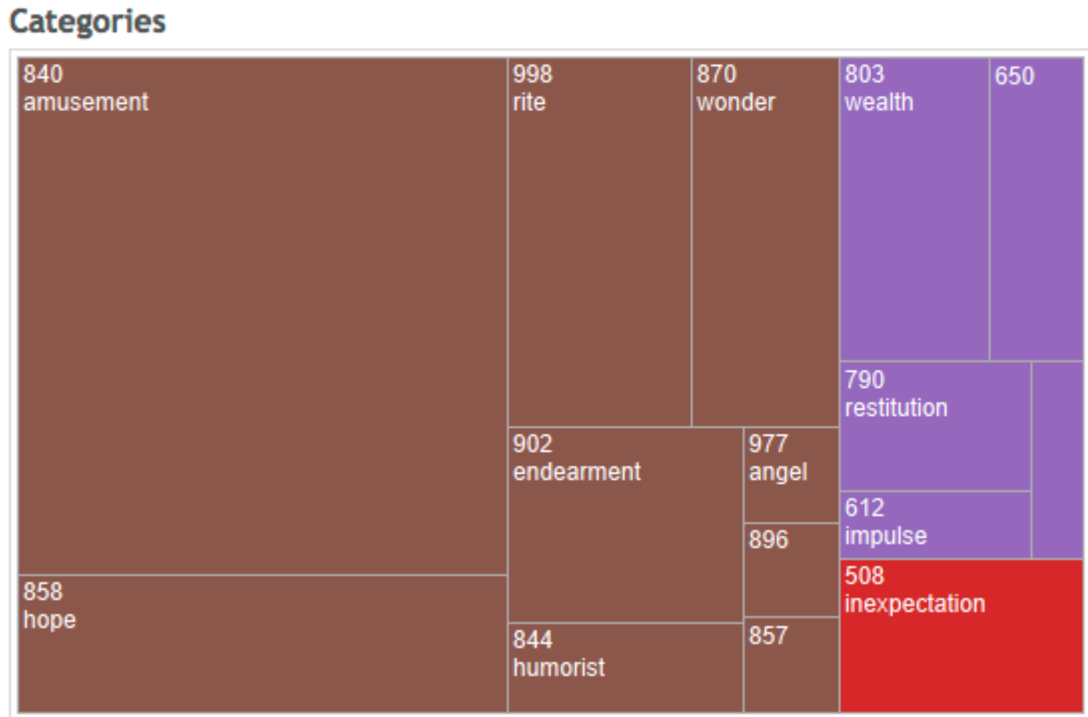
Category view after the slider for negativity is moved to show only the strongly negative categories



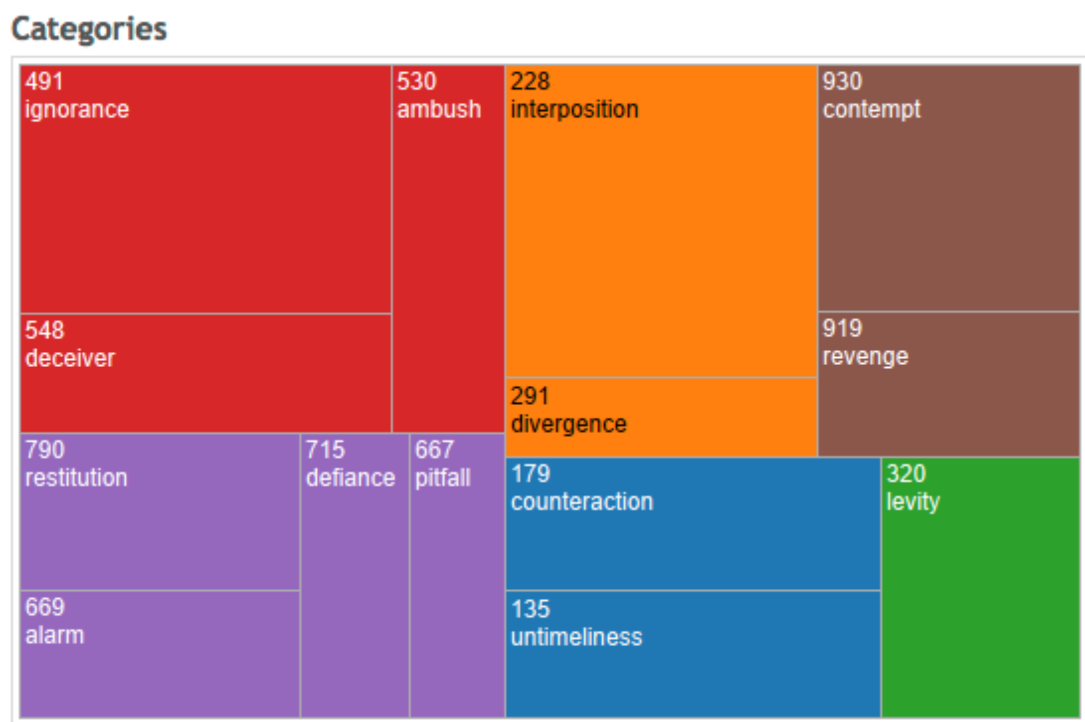
(Mohammad and Alm, 2015)

(Mohammad, 2015a)

Surprise and Positive



Surprise and Negative



(Mohammad, 2015a)

(Mohammad and Alm, 2015)

A few summarizing observations

- Visualizations…
  - allow new intuitive ways to access data
  - quickly convey the structure of data
  - help obtain new insights
- Interactivity…
  - allows abstraction of details while still allowing access when needed
  - shows only that information which is relevant to user needs

Good visualizations help us understand data, and they can act as demos to convey information effectively.

(Mohammad and Alm, 2015)

Survey of Applications

Topics:

- Political science: Social media analysis in electoral processes
- Creative and fine arts: Literary analysis and music generation
- Clinical: Mental health, cognitive health, and medical decision-making
- Business and education: Leveraging personalized/macro-level affect sensing

(Mohammad and Alm, 2015)

Political science

- Identify current public opinion towards the candidates in an election (nowcasting) (Golbeck & Hansen, 2011; Conover et al., 2011b; Mohammad et al., 2015)
- Identifying contentious issues (Maynard & Funk, 2011)
- Detecting voter polarization (Conover et al., 2011a)
- Predicting the number of votes a candidate will get (forecasting) (Tumasjan et al., 2010; Bermingham & Smeaton, 2011; Lampos, Preotiuc-Pietro, & Cohn, 2013)
- Skepticism at the extent to which this is possible possible (Avello, 2012)

(Mohammad and Alm, 2015)

Creative and fine arts: Literature

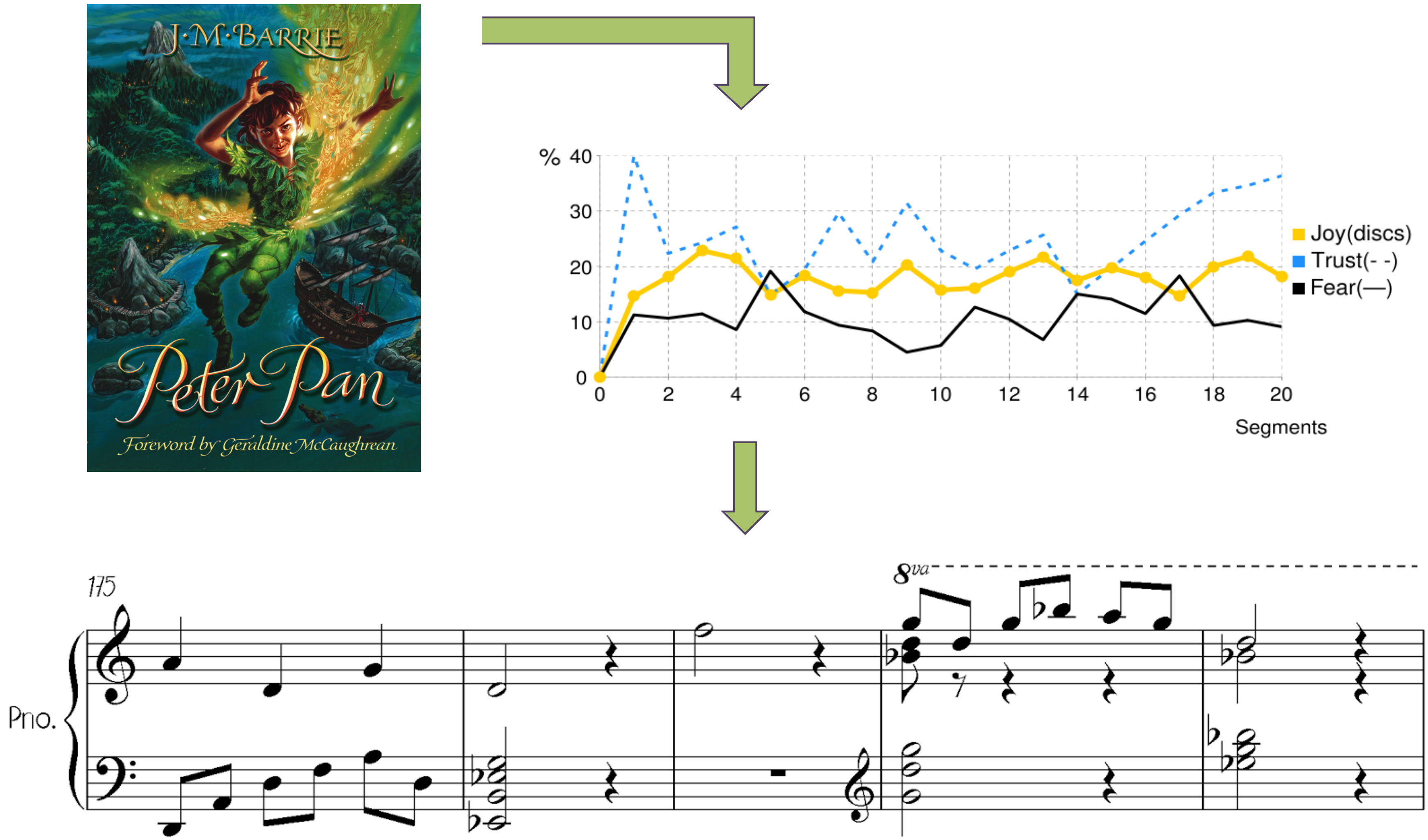
Analyzing (collections of) literary texts w.r.t. affect:

- Tracking the flow of emotions in novels, plays, and movie scripts
- Detecting patterns of sentiment common to large collections of texts
  - Kurt Vonnegut on the `Shapes of Stories'

    https://www.youtube.com/watch?v=oP3c1h8v2ZQ
  - Syuzhet package by Matthew Jockers:

    https://cran.r-project.org/web/packages/syuzhet/
- Tracking emotions of particular characters or entities over time

(Hartner, 2013; Kleres, 2011; Mohammad, 2011, 2012b; Alm & Sproat, 2005)



Generating music from literature:
Music that captures the change in the distribution of emotion words.

(Davis & Mohammad, 2014)

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

(Mohammad and Alm, 2015)

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

(Hunter et al., 2010; Hunter et al., 2008; Ali & Peynirciolu, 2010; Webster & Weir, 2005)

TransProse

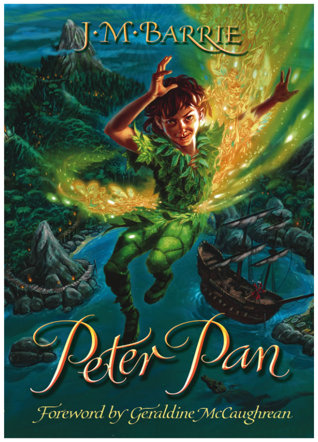
- Three simultaneous piano melodies pertaining to the dominant emotions.
- Overall positiveness (or, negativeness) determines:
  - whether C major or C minor
  - base octave
- Partition the novel into many small sections
- For each section, if emotion density is high:
  - play many short notes
  - more dissonant notes

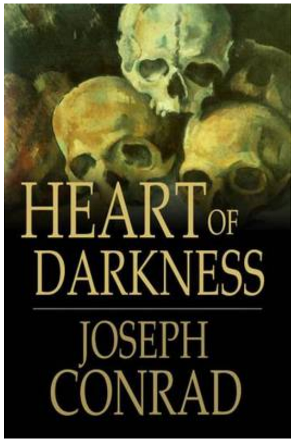
(Davis & Mohammad, 2014)

Pieces by TransProse

Three simultaneous piano melodies pertaining to the dominant emotions.

Examples

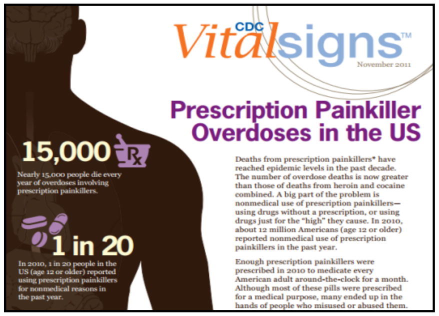




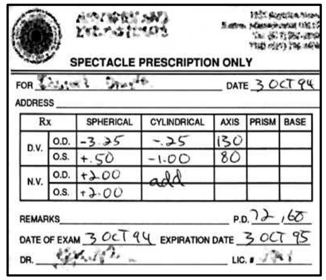
TransProse: www.musicfromtext.com
Music played 300,000 times since website launched in April 2014.

(Davis & Mohammad, 2014)

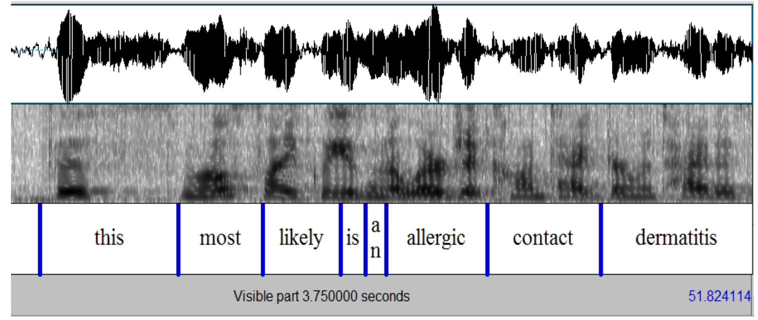
Pervasiveness of language data in the clinical domain



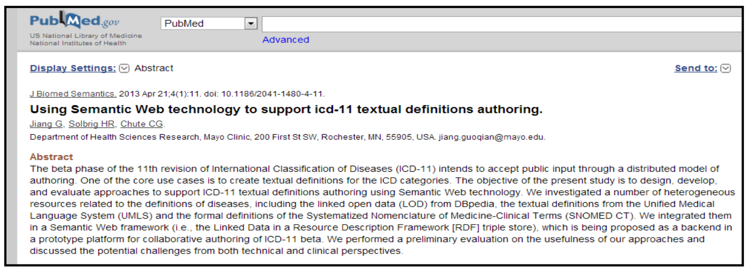
Medical ads



Prescriptions

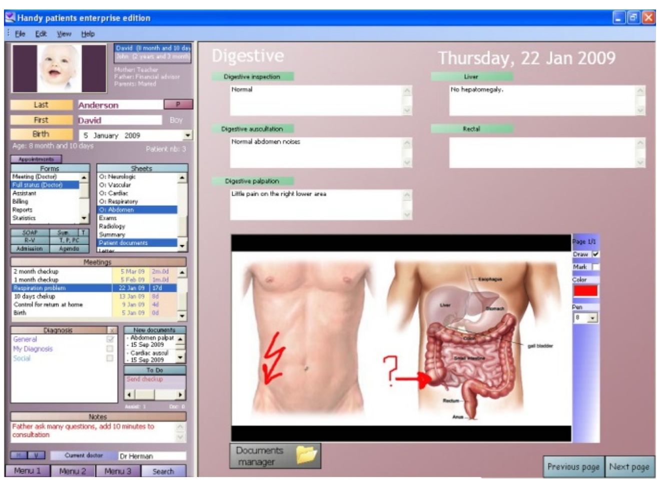


Recordings of physicians/patients



Articles (PubMed)

Patients
at home/on the go



Medical records

QUITNET
DON'T QUIT ALONE

Social media,
health forums

(Mohammad and Alm, 2015)

Patient-physician consultations

Public and mental health

- Cyber-bullying (Chen et al., 2012; Dadvar et al., 2013)
- Health attributes at a community level (Johnsen, et al., 2014; Eichstaedt et al., 2015)
- Tracking well-being (Schwartz et al., 2013a; Paul & Dredze, 2011)
- Developing robotic assistants and physio-therapists for the elderly, disabled, and the sick

(Mohammad and Alm, 2015)

Public and mental health

- Distress (Homan et al., 2014; Lehrman, Alm, & Proaño, 2012)
- Suicide and risk factors (Jashinsky et al., 2014; Matykiewicz, Duch, & Pestian, 2009; Pestian, Matykiewicz, Grupp-Phelan, 2008; Poulin et al., 2014)
- Depression and its severity (Schwartz et al., 2014; Coppersmith, Drezde, & Harman, 2014; Howes, Purver, & McCabe, 2014; Lamers et al., 2014; Pennebaker, Mehl, & Niederhoffer, 2003; Rude, Gortner, & Pennebaker, 2004; Cherry, Mohammad, & De Bruijn, 2012)

(Mohammad and Alm, 2015)

Dynamics of domestic abuse

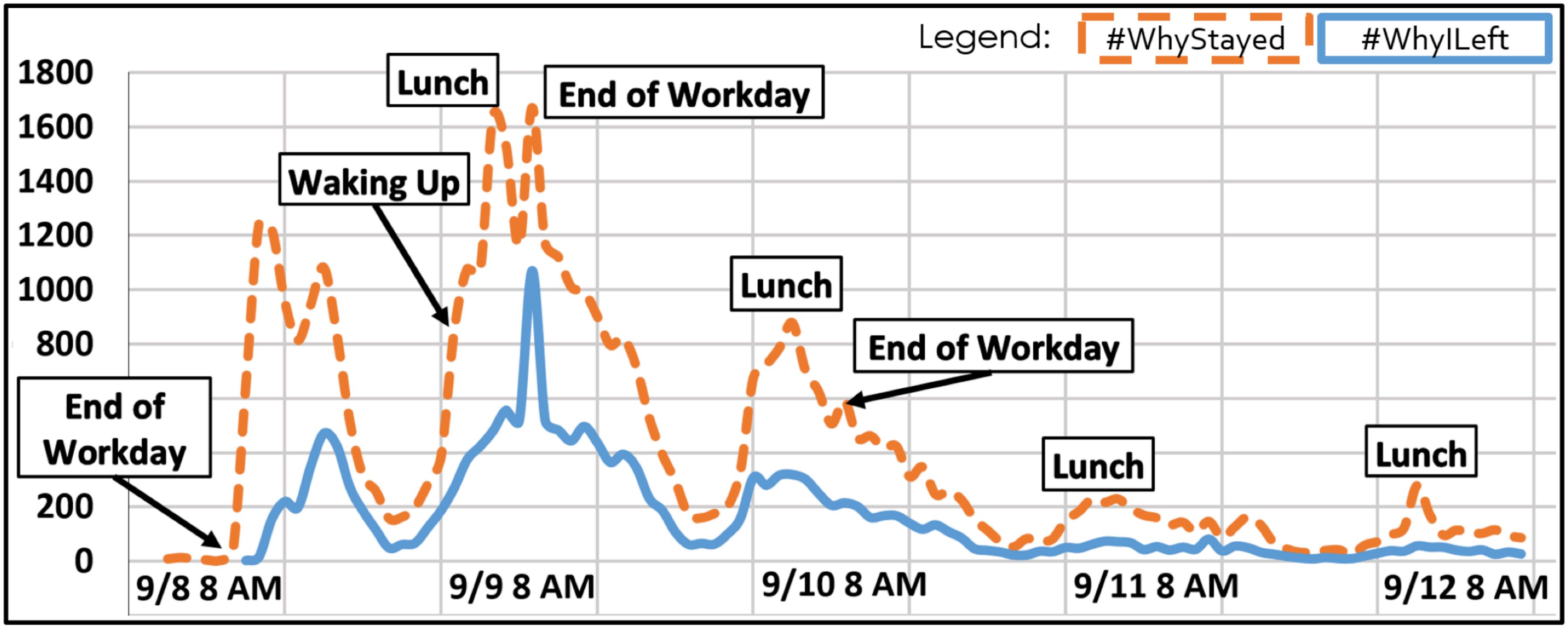
- Domestic abuse is a problem of pandemic proportions
- Taboo – domestic abuse discussions rare
- Issues with survey methods
- Use social media texts for analyzing reasons for staying in or leaving abusive relationships, and actions involving abusers and victims.

(Mohammad and Alm, 2015)

 (Schrading et al., 2015)

Twitter discussion about domestic abuse

#WhyIStayed -- why victims **stayed** in abusive relationships.
#WhyILeft -- why victims **escaped** them



From NLP analyses, micronarratives of staying and leaving emerge. Victims report:

- staying due to, e.g., cognitive manipulation, dire financial straits, keeping the nuclear family united, or experiencing shame.
- leaving, e.g. when threats are made towards loved ones, gaining agency, realizing their situation or self worth, or getting support from family/friends

(Mohammad and Alm, 2015)

 (Schrading et al., 2015)

Interplay between confidence and correctness in diagnostic contexts

- Medical misdiagnosis
  - Consequences for patients and unnecessary medical costs
- Causes of errors
  - Lack of expertise, technical errors, and many more
  - Cognitive errors may be the most challenging to reduce
- Studying the confidence-correctness interplay can yield insights into relative importance of language vs. multimodal markers

(Mohammad and Alm, 2015)

 (Bullard et al., 2014)

Diagnostic confidence as categories in prediction problems

	Correct	Incorrect
Confident	Appropriate Confidence	Overconfidence
Not confident	Underconfidence	Appropriate Confidence

- Correctness is reality
- Confidence is belief about correctness (self-estimated)

Ideal vs. problematic

(Mohammad and Alm, 2015)

 (Bullard et al., 2014)

Comparing modalities

Verbal

- Duration of narrative
- Silences (#, duration)
- Duration of init. silence
- Filled pauses
- Word type-token ratio
- Rate of speech
- Skin conditions mentioned
- Pronouns
- Modals
- Amplifiers
- Speculatives
- Negations
- Pitch
- Intensity

Eye Movements

- # fixations
- Duration of fixations
- Area of image fixated
- Saccade amplitude

Personal

- Years of experience
- Attending vs. Resident
- Past confidence
- Past correctness

Multimodal

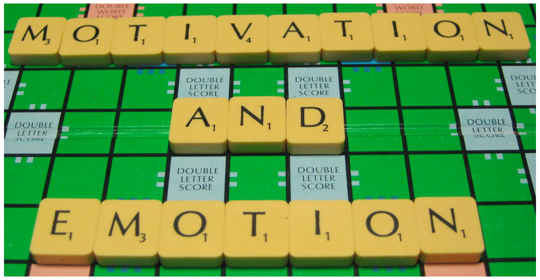
- % of initial silence in fixation
- % silent time in fixation
- % fixation time in silent
- Rate of speech during fixation
- Pitch during fixations
- Intensity during fixations
- Pitch of filled pauses
- Intensity of filled pauses

- Language-based features appeared most informative—tap into physicians' rich and tacit conceptual knowledge and understanding of a case.
- Performance gains possible with added modalities.
- Combined MM features → inappropriate representation. Need semantic alignment without time overlap assumption.

(Mohammad and Alm, 2015)

 (Bullard et al., 2014)

Education and affect analysis



- States such as attention and anxiety may impact learning. Automated tutoring systems may monitor student users' relevant states, e.g., to **personalize** their learning experiences or as a mechanism to deal with **attrition** in e-learning contexts.

- A computer tutoring system that adjusted its response based on the perceived confidence of the user resulted in more efficient learning by the student. (Forbes-Riley & Litman, 2011)

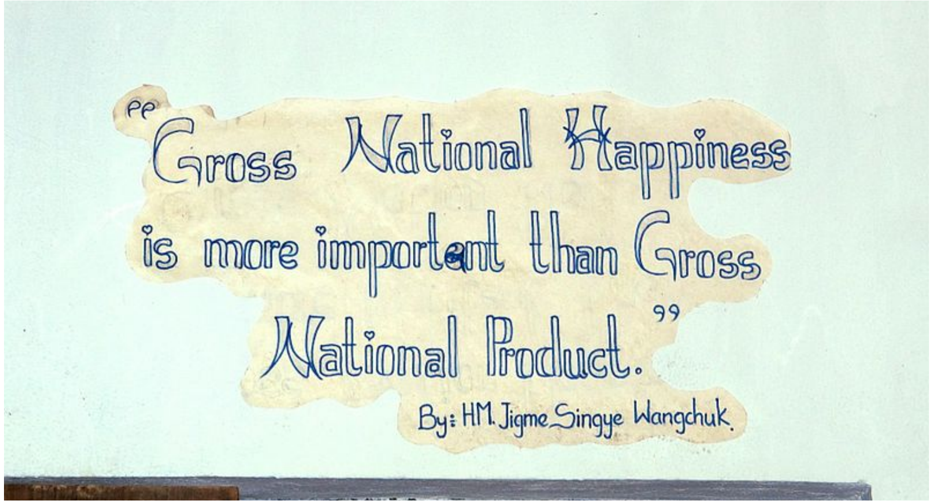
- Automated tutoring and student evaluation systems detect affect based on user responses both to determine correctness of responses and the user's emotional state (Dogan, 2012; Li et al., 2014). An intuitive finding is that learning improves when the student is in a happy and calm state as opposed to anxious or frustrated.

(Mohammad and Alm, 2015)

Business and affect analysis

- Analysis of social media has been applied towards shaping brand image, tracking customer response, and developing automated dialogue systems for customer queries and complaints (Ren & Quan, 2012; Gupta, Gilbert, & Fabbrizio, 2013; Bock et al., 2012).

- This domain is expected to snowball in the coming years.



Future Directions and Wrap-up

Topics:

- Emotions analysis for processing figurative language and metaphor
- Understanding relationships between emotions
- Enhancing evaluation procedures
- Effective integration of NLP into multimodal affect analysis
- Present and future tasks: What can emotion analysis do for your task?

Future directions

- Affect and creative use of language (metaphors, sarcasm)
  - Detecting affect, detecting figurative language
  - What makes figurative language more emotional?
- How is affect impacted by negators and other affect modifiers?
- Working on hundreds of affect categories
  - What is their relationship?
  - Is there a taxonomy?
  - Where can they be applied?
- Deep neural networks and low-dimensional word embeddings

(Mohammad and Alm, 2015)

Future directions

- Rethinking evaluation procedures (Alm, 2011)
  - Extrinsic evaluation, usability and user satisfaction (Liu, Lieberman, & Selker, 2003a), quality of life/safety improvements
  - Increase importance of visualization in evaluation

- Effective integration of linguistic data into multimodal affect analysis
  - Multimodal data fusion approaches (Castellano, Kessous, & Caridakis, 2008; Calvo & D'Mello, 2010; Gunes & Schuller, 2013)
  - Continue to address meaningful data synchronization (cf. language and vision) and the multimodal fusion challenges
  - Study strengths vs. weaknesses across modalities
  - Explore commonalities and differences between language and other sensors by context

MOST IMPORTANTLY

- What can analysis of affective states, or affect-related conditions, activities, or experiences do for you and your task? Please share your thoughts, comments, and questions!

(Mohammad and Alm, 2015)

Thank you!

- We look forward to continuing the discussion during the rest of the conference or in future interactions. Please stay in touch!

(Mohammad and Alm, 2015)

Tutorial resources

A note on references:

Citations to select relevant works are provided in two formats:

- An appended standard reference list of works cited
- An annotated bibliography with selected key sources

Please feel free to contact us about suggestions or refinements to these lists, or to associated aspects of these materials, for future versions.

A note on images:

Images in these materials tend to be from open repositories or personal/own collaborative sources. We have attempted to seek permission otherwise. Nonetheless, if you notice that image has slipped through the cracks and ought not to be included, please contact us so we can remove it in later versions of the materials.

Annotated Bibliography

1. Alm, C. O. (2012). The role of affect in the computational modeling of *natural* language. *Language and Linguistics Compass (Computational and Mathematical)*, 6(7), 416-430. SURVEY (GENERAL).
Written for interdisciplinary readers across career-levels, this succinct survey article provides literature review and discussion about theoretical background and applied topics of interest for analyzing affect in linguistic corpora and for incorporating mechanisms for processing affect into language technology.

2. Cahn, J. (1990). The generation of affect in synthesized speech. *Journal of the American Voice I/O Society*, 8, 1-19. SEMINAL/CLASSICAL.
This classical reading represents an early example of work on synthesizing emotional speech. It describes the Affect Editor, a tool for generating expressive speech, including a diverse set of speech parameters used for modeling, and it discusses the implementation and results of human-based evaluation. The work suggested that recognizable emotions could be synthesized. Some of the findings included that sad stimuli were particularly well identified, that lexical contents of sentences might influence perception, and that category mix-up might occur between more affectively similar concepts such as angry and disgusted. The paper also briefly reported on observing individual preferences. Affective expressiveness continues to be a research topic in speech science and technology communities.

3. Calvo, R. A., and D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, 1(1), 18-37. SURVEY (GENERAL).
This is a comprehensive survey article useful for readers who wish to deepen their understanding of the interdisciplinary landscape of work involved with detecting affect, the affective sciences, and affective computing. Given theoretical background and frameworks for modeling affect, the article dives into an overview of studied human modalities that contribute affect signals (with particular sections dedicated to spoken and written language), including methods, resources, and multimodal integration. Discussion synthesizes important topics and current/future research directions. The article presents an opportunity to become familiar with IEEE Transactions on Affective Computing.

4. Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12, 2493–2537. EMPIRICAL (SYSTEM).
This paper presents a neural network framework that was applied to part-of-speech tagging, chunking, named entity recognition, semantic role labeling, and some other NLP tasks. It is one of the more recent papers on deep learning in NLP that eschews task-specific engineering in favour of learning common internal representations from data. Even though affect-related tasks are not directly addressed in this paper, several deep learning papers on valence classification draw inspiration from this work.

5. Coppersmith, G., Dredze, M., and Harman, C. (2014). Quantifying mental health signals in Twitter. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA*, 51-60. APPLICATION (HEALTH).
This study from a recent workshop exemplifies the interest in textual data and social media for exploring affect-related phenomena in the domain of public health. Presenting an approach for gathering and studying microblog data for conditions such as depression and PTSD, the paper also discusses the opportunity for complementary use of natural language processing techniques in relation to a tradition of survey analysis in health contexts. The paper conveys some of the challenges (generational uses of social media, less mention of uncommon conditions, etc.) as well as the usefulness of interdisciplinary collaboration in this area.

6. Cornelius, R. R. (2000). Theoretical approaches to emotion. *Proceedings of the ISCA ITRW on Speech and Emotion (SpeechEmotion-2000)*, Newcastle, Northern Ireland, UK, 3-10. SURVEY (THEORY).
Cornelius advocates for the need to take theoretical accounts into consideration in emotion scholarship. He straightforwardly introduces four “perspectives” from the discipline of psychology: Darwinian, Jamesian, cognitive, and social constructivist, and also discusses how these views relate to each other. While positioning the discussion within emotional speech research, the author explicates some of the benefits of understanding where one’s work fits theoretically and how theoretical views are merging, including how that may aid the appreciation of assumptions involved or influence investigatory questions and insights to evolve.

7. Cowie, R., Douglas-Cowie, E., Martin, J.-C., and Devillers, L. (2010). The essential role of human databases for learning in and validation of affectively competent agents. In Scherer, K. R., Bänziger, T., and Roesch, E. B. (Eds.) *Blueprint for Affective Computing: A Sourcebook*. Oxford: Oxford University Press, 151-165. SURVEY (RESOURCE).
This book chapter about data resources touches upon many of the issues and topics under discussion with respect to affect data development, from the perspective of the affect sciences and affective computing. Database examples are covered for distinct modalities (albeit sparsely for text-oriented work). The chapter includes summarizing projections about next developments in this area.

8. Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., Merchant, R. M., Jha, S., Agrawal, M., Dziurzynski, L. A., Sap, M., Weeg, C., Larson, E. E., Ungar, L. H., and Seligman, M. E. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychological Science,* 26(2), 159-169. APPLICATION (HEALTH).
Traditional approaches for determining psychological states of people involve in-person or phone conversations. Such approaches are time intensive and expensive. This paper aims at determining psychological state, at the

community level, from tweets posted by the community. Specifically, it analyzes language in tweets and finds correlations of certain features with heart disease rates at the level of counties. Lexicons for anger, anxiety, positive and negative emotions, positive and negative social relationships, and engagement and disengagement were found to be useful. This is an interesting example of bridging the analysis of language (in this case tweets) with non-linguistic information (in this case heart disease data).

9. Kiritchenko, S., Zhu, X., and Mohammad, S. M. (2014). Sentiment analysis of short informal texts. *Journal of Artificial Intelligence Research*, 50, 723–762. EMPIRICAL (SYSTEM).
This paper gives details about the NRC-Canada system that came first in various sentiment-related shared tasks in Sem-Eval-2013 and 2014. A number of different kinds of features were used. Ablation experiments showed that the Twitter-specific valence-association lexicons were the most useful. These automatically generated lexicons capture non-standard language, such as creative spellings and word elongations. Methods to capture impact of negation on sentiment are also described. The paper additionally describes a maximum difference scaling approach to obtain reliable fine-grained annotations of sentiment.

10. Liu, H., Lieberman, H., and Selker, T. (2003). A model of textual affect sensing using real-world knowledge. *Proceedings of the International Conference on Intelligent User Interfaces, Miami, FL, USA,* 125-132. SEMINAL/CLASSICAL.
In this early paper on affect processing with text, the main application of interest was an affective email interface (EmpathyBuddy). The work involved interpreting affect in terms of fundamental emotion categories, using a textual resource of commonsense knowledge (Open Mind Commonsense). A user study evaluated the email client. Users interacted with three client versions, including the sensing-based version. They assessed the system for "entertainment, interactivity, intelligence, and adoption". The results suggested that the authors' main approach was perceived as more intelligent, adoptable, and interactive.

11. Mohammad, S. M., and Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational Intelligence*, 29 (3), 436-465. EMPIRICAL (RESOURCE).
This paper describes the creation of a large word—affect association lexicon by crowdsourcing. Several techniques are employed for quality control, most notably with the use of a separate word-choice question that ascertains whether the annotator knows the meaning of the target word. The question also guides the annotator to the desired sense of the word for which annotations are needed. The resulting lexicon, the NRC Emotion Lexicon, has entries for over 14,000 words and about 25,000 word senses. Each instance is marked for associations with eight emotions, as well as positive and negative sentiment. The lexicon is widely used by researchers and system builders for various affect-related tasks.

12. Mohammad, S. M., and Kiritchenko, S. (2013). Using nuances of emotion to identify personality. *Proceedings of the International Conference on Weblogs and Social Media (ICWSM-13)*, *Boston, MA*, 27-30. EMPIRICAL (SYSTEM).
This paper describes the collection and use of tweets with emotion word hashtags for automatic emotion detection. Experiments show that the emotion word hashtags act as good labels of emotions in the rest of the tweet. Thus the data can be used for training machine learning systems for emotion classification. The success of this approach also means that one can now quickly compile training data for any emotion which is used as a hashtag in tweets. Experiments are performed in an extrinsic task for personality trait classification, where it is shown that emotion-based features from hundreds of emotion categories are more useful than using features from a handful of affect categories (such as positive and negative sentiment, or the Big Six emotion categories).

13. Neviarouskaya, A., Prendinger, H., and Ishizuka, M. (2010). Recognition of affect, judgment, and appreciation in text. *Proceedings of the 23rd International Conference on Computational Linguistics, Beijing, China*, 806-814. EMPIRICAL (SYSTEM).
Even though a majority of current approaches in NLP are statistical, rule-based systems are more interpretable, for example, for understanding why a sentence was classified as having a certain emotion by the system. This paper presents a rule-based system for detecting emotions at sentence level. It employs a number of manually created lexicons for attitude, affect modifiers, and even a lexicon that captures the confidence signified by modal verbs. At the heart of the system is a method to combine affect-related information from different pieces of the text using rules. Developing compositional models statistically is a major area of research these days, and this work can be a source of ideas in developing composition models that capture affect appropriately.

14. Ortony, A., Clore, G. L., and Collins, A. (1990). *The Cognitive Structure of Emotions*. Cambridge: Cambridge University Press. SEMINAL/CLASSICAL.
Several authors have proposed mutually conflicting theories about emotions, and till date many key aspects of emotions are hotly debated. This book by Ortony, Clore, and Collins presents one such theoretical framework that argues that emotions are valence reactions. The valence reaction is broken down into several sub-categories and these subcategories are broken down into further sub-categories, based on whether the valence reaction was to the consequences of events, aspects of objects, whether the person approves or disapproves it, etc. Ideas on the theoretical underpinnings of emotions and different kinds of valence reaction can be helpful for developing instructions for affect annotations, as well as for developing features that can be useful in automatic affect classification.

15. Osgood, C. E., Suci, G. J., and Tannenbaum, P. (1957). *The Measurement of Meaning*. Urbana, USA: University of Illinois Press. SEMINAL/CLASSICAL.
This work studies the nature of meaning. One of its most influential experiments involves asking people to rate the meanings of concepts along several dimensions such as fair—unfair, strong—weak, safe—dangerous, etc. Factor analysis of the responses is used to show that the three dimensions conveying most of the variance in meaning across concepts are that of evaluativeness (good—bad), potency (strong—weak), and activity (active—passive). This work has influenced scholars in a number of fields including linguistics, psychology, mass communications, and natural language processing.

16-17. Brief mention of two book manuscripts. SURVEY (GENERAL).
Scherer, K. R., Bänziger, T., and Roesch, E. B. (Eds.) (2010). *Blueprint for Affective Computing: A Sourcebook*. Oxford: Oxford University Press.
In this collection, the editors gather nineteen chapters into seven sections on a range of topics pertinent for exploring affect in human- and machine-oriented research. Chapters range from topics such as "Emotions in interpersonal interactions" (Parkinson) to "Emotion in artificial neural networks" (Roesch, Korsten, Fragopanagos, and Taylor), with five chapters specifically devoted to "Approaches to an implementation of affectively competent agents".
Schuller, B., and Batliner, A. (2014). *Computational Paralinguistics: Emotion, Affect and Personality in Speech and Language Processing*. Chichester: Wiley.
This recent book is divided into "Foundations" and "Modelling", each comprising various chapters, such as "Taxonomies", "Functional aspects", and "Corpus engineering" in the first part, and "Linguistic features", "Machine-based modelling", and "'Hands-on': Existing toolkits and practical tutorial" in the second part. In the preface, the authors explain that a goal is "to provide the reader with a sort of map presenting an overview of the field, and useful for finding one's way through. The scale of this map is medium-sized, and we can only display a few of the houses in this virtual paralinguistic 'city' with their interiors, on an exemplary basis."

18. Strapparava, C., and Mihalcea, R. (2007). SemEval-2007 Task 14: Affective text. *Proceedings of SemEval-2007*, *Prague, Czech Republic,* 70–74. EMPIRICAL (RESOURCE).
This is a task-description paper of an early shared task competition on automatically detecting valence and emotions in text. The dataset chosen was a collection of newspaper headlines. Annotators were asked to give scores between 0 and 100 for each of the Big Six emotions and positive and negative valence. No training data was provided, and so only unsupervised systems were able to participate. Nonetheless, the testset created as part of this shared task has subsequently been used by supervised systems by splitting it into new train—test partitions. One of the key distinctions of this work compared to the shared tasks proposed in the last few years is that this is one of the few datasets that has fine-grained annotation for the degree of

affect. Several applications would benefit from a system that can predict the degree of affect in text.

19. Turney, P.D. (2002). Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, Philadelphia, PA*, 417-424. EMPIRICAL (SYSTEM).
This paper presents a way to classify customer reviews as positive (recommended) or negative (not recommended). At the heart of the method is a way to determine the degree of positiveness (or negativeness) of a word by calculating the mutual information score between it and sets of positive and negative seed terms. This fundamental approach is still used (possibly with minor modification) for creating sentiment and emotion association lexicons.

20. Wiebe, J., Wilson, T., Bruce, R., Bell, M., and Martin, M. (2004). Learning subjective language. *Computational Linguistics*, 30(3), 277–308. SEMINAL/CLASSICAL.
This article presents early, comprehensive efforts to automatically detect subjective language. Supervised classification is performed on a number of datasets using various features, including low-frequency words, collocations, and words that are distributionally similar to pre-chosen seed words. The paper is also an excellent resource for understanding the principles underpinning subjective language.

(Mohammad and Alm, 2015)

References

- Ali, O., and Peynirciolu, Z. (2010). Intensity of emotions conveyed and elicited by familiar and unfamiliar music. *Music Perception: An Interdisciplinary Journal*, 27(3), 177–182.
- Alm, C. O. (2009). *Affect in Text and Speech*. Saarbrücken: VDM Verlag.
- Alm, C. O. (2010). Characteristics of high agreement affect annotation in text. *Proceedings of the 4th Linguistic Annotation Workshop at the 48th Annual Meeting of the Association for Computational Linguistics, Uppsala, Sweden*, 118-122.
- Alm, C. O. (2011). Subjective natural language problems: Motivations, applications, characterizations, and implications. *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics, Portland, OR*, 107-112.
- Alm, C. O. (2012). The role of affect in the computational modeling of *natural* language. *Language and Linguistics Compass (Computational and Mathematical)*, 6(7), 416-430.
- Alm, C. O., and Sproat, R. (2005). Emotional sequencing and development in fairy tales. In Tao, J., Tan, T., and Picard, R. W. (Eds.) *First International Conference on Affective Computing and Intelligent Interaction, Beijing, China*. LNCS 3784. Berlin Heidelberg: Springer-Verlag, 668-674.
- Alm-Arvius, C. (1998). *Introduction to Semantics*. Lund: Studentlitteratur.
- Aman, S., and Szpakowicz, S. (2007). Identifying expressions of emotion in text. In Matoušek, V., and Mautner, P. (Eds.) *Text, Speech and Dialogue.* LNCS 4629. Berlin Heidelberg: Springer-Verlag, 196–205.
- Anagnostopoulos, C.N., Iliou, T., and Giannoukos, I. (2015). Features and classifiers for emotion recognition from speech: A survey from 2000 to 2011. *Artificial Intelligence Review*, 43(2), 155–177.
- Anand, P., Walker, M., Abbott, R., Tree, J. E. F., Bowmani, R., and Minor, M. (2011). Cats rule and dogs drool!: Classifying stance in online debate. *Proceedings of the 2nd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis*, *Portland, OR,* 1–9.
- Andreasen, N. G., and Pfohl, B. (1976). Linguistic analysis of speech in affective disorders. *Archives of General Psychiatry*, 33(11), 1361–1367.
- Avello, D. G. (2012). ”I wanted to predict elections with Twitter and all I got was this lousy paper” – A balanced survey on election prediction using Twitter data. *arXiv*, 1204.6441.
- Baker, C. F., Fillmore, C. J., and Lowe, J. B. (1998). The Berkeley FrameNet project. *Proceedings of the Annual Meeting of the Association for Computational Linguistics, Stroudsburg, PA*, 86–90.
- Barrett, L. F. (2006). Are emotions natural kinds? *Perspectives on Psychological Science*, 1(1), 28–58.
- Bellegarda, J. (2010). Emotion analysis using latent affective folding and embedding. *Proceedings of the NAACL-HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, *Los Angeles, CA*.
- Bermingham, A., and Smeaton, A. F. (2011). On using Twitter to monitor political sentiment and predict election results. *Proceedings of the IJCNLP Workshop on Sentiment Analysis where AI meets Psychology*, *Chiang Mai, Thailand,* 2–10.
- Besnier, N. (1990). Language and affect. *Annual Review of Anthropology*, 19, 419-451.

- Bethamcherla, V. P., Paul, W., Alm, C. O., Bailey, R., Geigel, J., and Wang, L. (2015). Face-speech sensor fusion for non-invasive stress detection. *Proceedings of 1st Joint Conference on Facial Analysis, Animation and Audio-Visual Speech Processing, Vienna, Austria.* Forthcoming.
- Bock, R., Gluge, S., Wendemuth, A., Limbrecht, K., Walter, S., Hrabal, D., and Traue, H. C. (2012). Intraindividual and interindividual multimodal emotion analyses in human-machine-interaction. *IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), New Orleans, LA*, 59–64.
- Bogdanova, D., Rosso, P., and Solorio, T. (2012). On the impact of sentiment and emotion based features in detecting online sexual predators. *Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis*, *Jeju, Korea,* 110–118.
- Bollen, J., Pepe, A., and Mao, H. (2011). Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. *Proceedings of the 5th International AAAI Conference on Weblogs and Social Media, Barcelona, Spain,* 450-453.
- Boneva, B., Kraut, R., and Frohlich, D. (2001). Using e-mail for personal relationships. *American Behavioral Scientist*, 45(3), 530–549.
- Bradley, M. M., and Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavioral Therapy and Experimental Psychiatry*, 25(1), 49-59.
- Bradley, M. M., and Lang, P. J. (1999). Affective norms for English words (ANEW): Stimuli, instruction manual and affective ratings. Technical report C-1, Gainesville, FL. The Center for Research in Psychophysiology, University of Florida.
- Bradley, M. M., and Lang, P. J. (2007). Affective norms for English text (ANET): Affective ratings of text and instruction manual. Tech. Rep. No. D-1. University of Florida, Gainesville, FL.
- Brody, S., and Diakopoulos, N. (2011). Cooooooooooooooollllllllllllll!!!!!!!!!!!!!!: Using word lengthening to detect sentiment in microblogs. *Proceedings of the Conference on Empirical Methods in Natural Language Processing, Edinburgh, Scotland*, 562–570.
- Brooks, M., Kuksenok, K., Torkildson, M. K., Perry, D., Robinson, J. J., Scott, T. J., Anicello, O., Zukowski, A., Harris, P., and Aragon, C. R. (2013). Statistical affect detection in collaborative chat. *Proceedings of the 2013 Conference on Computer Supported Cooperative Work, San Antonio, TX*, 317–328.
- Bullard, J., Alm, C. O., Yu, Q., Shi, P., and Haake, A. (2014). Towards multimodal modeling of physicians' diagnostic confidence and self-awareness using medical narratives. *Proceedings of 25th International Conference on Computational Linguistics, Dublin, Ireland,* 1718–1727.
- Bühler, K. (1934). *Sprachtheorie: Die Darstellungsfunktion der Sprache.* Stuttgart: Gustav Fischer Verlag.
- Cahn, J. (1990). The generation of affect in synthesized speech. *Journal of the American Voice I/O Society*, 8, 1-19.
- Caldwell, M. and Peplau, L. (1982). Sex differences in same-sex friendships. *Sex Roles*, 8, 721-732.

- Calvo, R. A., and D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, 1(1), 18-37.
- Carvalho, P., Sarmento, L., Silva, M. J., and De Oliveira, E. (2009). Clues for detecting irony in user-generated contents: Oh...!! It's "so easy";-). *Proceedings of the 1st International CIKM Workshop on Topic-sentiment Analysis for Mass Opinion*, *Hong-Kong, China,* 53–56.
- Castellano, G., Kessous, L., and Caridakis, G. (2008). Emotion recognition through multiple modalities: Face, body gesture, speech. In Peter, C., and Beale, R. (Eds.) *Affect and Emotion in Human-Computer Interaction: From Theory to Applications.* LNCS 4868. Berlin Heidelberg: Springer-Verlag, 92-103.
- Chaffar, S., and Inkpen, D. (2011). Using a heterogeneous dataset for emotion analysis in text. In Butz, C., and Lindgras, P. (Eds.) *Advances in Artificial Intelligence*. LNCS 6657. Berlin Heidelberg: Spring-Verlag, 62-67.
- Chen, Y., and Skiena, S. (2014). Building sentiment lexicons for all major languages. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD,* 383–389.
- Chen, Y., Zhou, Y., Zhu, S., and Xu, H. (2012). Detecting offensive language in social media to protect adolescent online safety. *IEEE International Conference on Privacy, Security, Risk and Trust (PASSAT) and 2012 International Conference on Social Computing (SocialCom)*, *Amsterdam*, 71–80.
- Cherry, C., Mohammad, S. M., and De Bruijn, B. (2012). Binary classifiers and latent sequence models for emotion detection in suicide notes. *Biomedical Informatics Insights*, 5(Suppl 1), 147.
- Chetviorkin, I., Moscow, L. G., and Loukachevitch, N. (2014). Two-step model for sentiment lexicon extraction from Twitter streams. *Proceedings of the Workshop on Computational Approaches to Subjectivity and Sentiment Analysis*, *Baltimore, MD*, 67–72.
- Cohen, S. H. (2003). Maximum difference scaling: Improved measures of importance and preference for segmentation. Technical report, Sawtooth Software, Inc., 1–17
- Collier, G. (1985). *Emotional Expression*. Hillsdale, N. J.: Lawrence Erlbaum Associates.
- Collobert, R., Weston, J., Bottou, L., Karlen, M., Kavukcuoglu, K., and Kuksa, P. (2011). Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12, 2493–2537.
- Conover, M. D., Ratkiewicz, J., Francisco, M., Gonc, B., Flammini, A., and Menczer, F. (2011a). Political polarization on Twitter. *Networks*, 133(26), 89–96.
- Conover, M. D., Goncalves, B., Ratkiewicz, J., Flammini, A., and Menczer, F. (2011b). Predicting the political alignment of Twitter users. *IEEE 3rd International Conference on Privacy Security Risk and Trust and IEEE 3rd International Conference on Social Computing*, 192–199.
- Coppersmith, G., Dredze, M., and Harman, C. (2014). Quantifying mental health signals in Twitter. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA*, 51-60.
- Cornelius, R. R. (2000). Theoretical approaches to emotion. *Proceedings of the*

ISCA ITRW on Speech and Emotion (SpeechEmotion-2000), Newcastle, Northern Ireland, UK, 3-10.

- Cowie, R., Douglas-Cowie, E., Martin, J.-C., and Devillers, L. (2010). The essential role of human databases for learning in and validation of affectively competent agents. In Scherer, K. R., Bänziger, T., and Roesch, E. B. (Eds.) *Blueprint for Affective Computing: A Sourcebook*. Oxford: Oxford University Press, 151-165.
- Dadvar, M., Trieschnigg, D., Ordelman, R., and de Jong, F. (2013). Improving cyberbullying detection with user context. In Serdyukov et al. (Eds.) *Advances in Information Retrieval*. LNCS 7814. Berlin Heidelberg: Springer-Verlag, 693–696.
- Darwin, C. (1998 [1890]). The expression of the emotions in man and animals [selected excerpts]. In Jenkins, J. M., Oatley, K., and Stein, N. L. (Eds.) *Human Emotions: A Reader.* Oxford: Blackwell, 13-20.
- Davidson, L. and Duberman, L. (1982). Friendship: Communication and interactional patterns in same-sex dyads. *Sex Roles*, 8, 809–822.
- Davis, H., and Mohammad, S. (2014). Generating music from literature. *Proceedings of the 3rd Workshop on Computational Linguistics for Literature (CLFL), Gothenburg, Sweden*, 1–10.
- Deaux, K. and Major, B. (1987). Putting gender into context: An interactive model of gender-related behavior. *Psychological Review*, 94(3), 369–389.
- Dogan, H. (2012). Emotion, confidence, perception and expectation case of mathematics. *International Journal of Science and Mathematics Education*, 10(1), 49–69.
- Douglas-Cowie, E., Cowie, R., Sneddon, I., Cox, C., Lowry, O., McRorie, M., Martin, J.-C., Devillers, L., Abrilian, S., Batliner, A., Amir, N., Karpousiz, K., and Martin, J.-C. (2007). The HUMAINE database: Addressing the collection and annotation of naturalistic and induced emotional data. In Paiva, A., Prada, R., and Picard, R. W. (Eds.) *Second International Conference on Affective Computing and Intelligent Interaction, Lisbon, Portugal*. LNCS 4738. Berlin Heidelberg: Springer-Verlag, 488-500.
- Eagly, A. and Steffen, V. (1984). Gender stereotypes stem from the distribution of women and men into social roles. *Journal of Personality and Social Psychology*, 46(4), 735–754.
- Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., Merchant, R. M., Jha, S., Agrawal, M., Dziurzynski, L. A., Sap, M., Weeg, C., Larson, E. E., Ungar, L. H., and Seligman, M. E. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychological Science,* 26(2), 159-169.
- Ekman, P. (1992). An argument for basic emotions. *Cognition and Emotion*, 6(3), 169–200.
- Ekman, P. (1994). All emotions are basic. In Ekman, P., and Davidson, R. J. (Eds.) *The Nature of Emotion: Fundamental Questions*. New York: Oxford University Press, 15-19.
- Ekman, P., and Friesen, W. V. (1998 [1971]). Constants across culture in the face and emotion. In Jenkins, J. M., Oatley, K., and Stein, N. L. (Eds.) *Human Emotions: A Reader.* Oxford: Blackwell, 63-72.
- Esuli, A., and Sebastiani, F. (2006). SentiWordNet: A publicly available lexical resource for opinion mining. *Proceedings of 5th Conference on Language Resources and Evaluation, Genova, IT*, 417–422.

- Foolen, A. (1997). The expressive function of language: Towards a cognitive semantic approach. In Niemeier, S., and Dirven, R. (Eds.) *The Language of Emotions: Conceptualization, Expression, and Theoretical Foundation*, Amsterdam: John Benjamins, 15–31.
- Forbes-Riley, K., and Litman, D. (2011). Designing and evaluating a wizarded uncertainty-adaptive spoken dialogue tutoring system. *Computer Speech and Language*, 25(1), 105-126.
- Francisco, V., and Gervás, P. (2006). Automated mark up of affective information in English texts. In Sojka, P., Kopeček, I., and Pala, K. (Eds.) *Text, Speech and Dialogue.* LNCS 4188. Berlin Heidelberg: Springer-Verlag, 375–382.
- Frege, G. (1952 [1892]). On sense and reference. In Geach, P., and Black, M. (Eds.) *Translations from the Philosophical Writings of Gottlob Frege*. Oxford: Blackwell, 56–78.
- Frijda, N. H. (1988). The laws of emotion. *American Psychologist*, 43(5), 349.
- Genereux, M., and Evans, R. P. (2006). Distinguishing affective states in weblogs. Proceedings of *AAAI-2006 Spring Symposium on Computational Approaches to Analysing Weblogs, Stanford, CA*, 27– 29.
- Go, A., Bhayani, R., and Huang, L. (2009). Twitter sentiment classification using distant supervision. Technical report, Stanford University. 1–6.
- Gobron, S., Ahn, J., Paltoglou, G., Thelwall, M., and Thalmann, D. (2010). From sentence to emotion: A real-time three-dimensional graphics metaphor of emotions extracted from text. *The Visual Computer*, 26(6-8), 505–519.
- Golbeck, J., and Hansen, D. (2011). Computing political preference among Twitter followers. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, New York, NY,* 1105–1108.
  González-Ibáñez, R., Muresan, S., and Wacholder, N. (2011). Identifying sarcasm in Twitter: A closer look. *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics, Portland, OR*, 581–586.
- Grijalva, E., and Harms, P. D. (2014). Narcissism: An integrative synthesis and dominance complementarity model. *The Academy of Management Perspectives*, 28(2), 108–127.
- Gunes, H., and Schuller, B. (2013). Categorical and dimensional affect analysis in continuous input: Current trends and future directions. *Journal of Image and Vision Computing*, 31(2), 120-136.
- Gupta, N., Gilbert, M., and Fabbrizio, G. D. (2013). Emotion detection in email customer care. *Computational Intelligence*, 29(3), 489–505.
- Halliday, M. A. K. (1996). Linguistic function and literary style: An inquiry into the language of William Golding's *The Inheritors*. In Weber, J. J. (Ed.) *The Stylistics Reader: From Roman Jakobson to the Present*. London: Arnold, 56–86.
- Hartner, M. (2013). The lingering after-effects in the readers mind – An investigation into the affective dimension of literary reading. *Journal of Literary Theory Online.* [Review of Burke, M. (2011). *Literary Reading, Cognition and Emotion. An Exploration of the Oceanic Mind*. New York/London: Routledge.]
- Hasan, K. S., and Ng, V. (2013). Stance classification of ideological debates: Data, models, features, and constraints. *Proceedings of the 6th International Joint Conference on Natural Language Processing, Nagoya, Japan,* 1348–1356.
- Hatzivassiloglou, V., and McKeown, K. R. (1997). Predicting the semantic orientation of adjectives. *Proceedings of the 8th Conference of European Chapter of*

the Association for Computational Linguistics, *Madrid, Spain,* 174–181.

- Hatzivassiloglou, V., and Wiebe, J. M. (2000). Effects of adjective orientation and gradability on sentence subjectivity. *Proceedings of the 18th Conference on Computational Linguistics*, *Saarbrucken, Germany,* 299–305.
- Hochberg, L., Alm, C. O., Rantanen, E. M., DeLong, C. M., and Haake, A. (2014a). Decision style in a clinical reasoning corpus. *Proceedings of the 2014 Workshop on Biomedical Natural Language Processing, Baltimore, MD, USA,* 83-87.
- Hochberg, L., Alm, C. O., Rantanen, E. M., Yu, Q., DeLong, C. M., and Haake, A. (2014b). Towards automatic annotation of clinical decision-making style. *Proceedings of LAW VIII - The 8th Linguistic Annotation Workshop at the 25th International Conference on Computational Linguistics, Dublin, Ireland,* 129-138.
- Holzman, L. E., and Pottenger, W. M. (2003). Classification of emotions in internet chat: An application of machine learning using speech phonemes. Technical report, Leigh University.
- Homan, C. M., Johar, R., Liu, T., Lytle, M., Silenzio, V., and Alm, C. O. (2014). Toward macro-insights for suicide prevention: Analyzing fine-grained distress at scale. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA,* 107-117.
- Howes, C., Purver, M., and McCabe, R. (2014). Linguistic indicators of severity and progress in online text-based therapy for depression. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA*, 7-16.
- Hu, M., and Liu, B. (2004). Mining and summarizing customer reviews. *Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, New York, NY, USA,* 168–177.
- Hunter, P.G., Schellenberg, G., and Schimmack, U. (2008). Mixed affective responses to music with conflicting cues. *Cognition & Emotion*, 22(2):327–352.
- Hunter, P.G., Schellenberg, G., and Schimmack, U. (2010). Feelings and perceptions of happiness and sadness induced by music: Similarities, differences, and mixed emotions. *Psychology of Aesthetics, Creativity, and the Arts*, 4(1):47.
- Irsoy, O., and Cardie, C. (2014). Deep recursive neural networks for compositionality in language. *Proceedings of Advances in Neural Information Processing Systems, Montreal, Quebec,* 2096–2104.
- Jakobson, R. (1996). Closing statement: Linguistics and poetics. In Weber, J. J. (Ed.) *The Stylistics Reader: From Roman Jakobson to the Present*. London: Arnold, 10-35.
- Jashinsky, J., Burton, S. H., Hanson, C. L., West, J., Giraud-Carrier, C., Barnes, M. D., and Argyle, T. (2014). Tracking suicide risk factors through Twitter in the US. *Crisis*, 35(1), 51-59.
- Jia, L., Yu, C., and Meng, W. (2009). The effect of negation on sentiment analysis and retrieval effectiveness. *Proceedings of the 18th ACM Conference on Information and Knowledge Management, New York, NY, USA,* 1827–1830.
- John, D., Boucouvalas, A. C., and Xu, Z. (2006). Representing emotional momentum within expressive internet communication. *Proceedings of the 24th IASTED International Conference on Internet and Multimedia Systems and Applications, Anaheim, CA,* 183–188.

- Johnsen, J.A. K., Vambheim, S. M., Wynn, R., and Wangberg, S. C. (2014). Language of motivation and emotion in an internet support group for smoking cessation: explorative use of automated content analysis to measure regulatory focus. *Psychology Research and Behavior Management*, 7, 19–29.
- Jurgens, D., Mohammad, S. M., Turney, P., and Holyoak, K. (2012). Semeval-2012 Task 2: Measuring degrees of relational similarity. *Proceedings of the 6th International Workshop on Semantic Evaluation, SemEval'12*, *Montreal, Canada*, 356–364.
- Karpathy, A., Joulin, A., and Li, F.-F. (2014). Deep fragment embeddings for bidirectional image sentence mapping. *Proceedings of Advances in Neural Information Processing Systems, Montreal, Quebec,* 1889–1897.
- Katz, J. J., and Fodor, J. A. (1963). The structure of a semantic theory. *Language,* 39(2), 170–210.
- Kilgarriff, A. (1997). "I don't believe in word senses". *Computers and the Humanities,* 31(2), 91–113.
- Kirange, D. K., and Deshmukh, R. R.. (2013). Emotion classification of news headlines using SVM. *Asian Journal of Computer Science and Information Technology*, 2(5), 104-106.
- Kiritchenko, S., Zhu, X., and Mohammad, S. M. (2014). Sentiment analysis of short informal texts. *Journal of Artificial Intelligence Research*, 50, 723–762.
- Kleres, J. (2011). Emotions and narrative analysis: A methodological approach. *Journal for the Theory of Social Behaviour*, 41(2), 182–202.
- Kramer, A. D. (2012). The spread of emotion via Facebook. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 767–770.
- Ku, L.W., Liang, Y.T., and Chen, H.-H. (2006). Opinion extraction, summarization and tracking in news and blog corpora. Proceedings of the *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs, Vol. 100107.*
- Kunneman, F., Liebrecht, C., and van den Bosch, A. (2014). The (un)predictability of emotional hashtags in Twitter. *Proceedings of the 5th Workshop on Language Analysis for Social Media*, *Gothenburg, Sweden,* 26–34.
- Lamers, S. M. A., Truong, K. P., Steunenberg, B., de Jong, F. and Westerhof, G. J. (2014). Applying prosodic speech features in mental health care: An exploratory study in a life-review intervention for depression. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA,* 61-68.
- Lampos, V., Preotiuc-Pietro, D., and Cohn, T. (2013). A user-centric model of voting intention from social media. *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, Sofia, Bulgaria*, 993–1003.
- Lassen, D. S., and Brown, A. R. (2011). Twitter: The electoral connection? *Social Science Computer Review*, 29(4), 419–436.
- Lazaridou, A., Bruni, E., and Baroni, M. (2014). Is this a wampimuk? Cross-modal mapping between distributional semantics and the visual world. *Proceedings of the 52ndAnnual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA*, 1403–1414.
- Le, Q. V., and Mikolov, T. (2014). Distributed representations of sentences and documents. *arXiv preprint* arXiv:1405.4053.

- Lehrman, M. T., Alm, C. O., and Proaño, R. A. (2012). Detecting distressed vs. non-distressed affect states in short forum texts. *Proceedings of the Workshop on Language in Social Media at the Conference of the North American Chapter of the Association for Computational Linguistics-Human Language Technologies, Montreal, Canada*, 9-18.
- Li, J., Zhou, G., Wang, H., and Zhu, Q. (2010). Learning the scope of negation via shallow semantic parsing. *Proceedings of the 23rd International Conference on Computational Linguistics, Beijing, China,* 671–679.
- Li, X. G., Li, S. M., Jiang, L. R., and Zhang, S. B. (2013). Study of English pronunciation quality evaluation system with tone and emotion analysis capabilities. *Applied Mechanics and Materials*, 475-476, 318–323.
- Liberman, M., Davis, K., Grossman, M., Martey, N., and Bell, J. (2002). *Emotional Prosody Speech and Transcripts LDC2002S28*. Web Download. Philadelphia: Linguistic Data Consortium.
- Lin, C., He, Y., and Everson, R. (2011). Sentence subjectivity detection with weakly-supervised learning. *Proceedings of the 5th International Joint Conference on Natural Language Processing,* 1153–1161.
- Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., and Barrett, L. F. (2012). The brain basis of emotion: A meta-analytic review. *Behavioral and Brain Sciences*, 35(3), 121–143.
- Liu, B., and Zhang, L. (2012). A survey of opinion mining and sentiment analysis. In Aggarwal, C. C., and Zhai, C. (Eds.) *Mining Text Data*. New York, NY: Springer Science+Business Media, 415–463.
- Liu, H., Lieberman, H., and Selker, T. (2003a). A model of textual affect sensing using real-world knowledge. *Proceedings of the International Conference on Intelligent User Interfaces, Miami, FL, USA,* 125-132.
- Liu, H., Selker, T., and Lieberman, H. (2003b). Visualizing the affective structure of a text document. Proceedings of *Conference on Human Factors in Computing Systems, Ft. Lauderdale, FL, USA,* 740–741.
- Lu, B., and Tsou, B. K. (2010). CityU-DAC: Disambiguating sentiment-ambiguous adjectives within context. *Proceedings of the 5th International Workshop on Semantic Evaluation*, 292–295.
- Lyons, J. (1995). *Linguistic Semantics: An Introduction.* Cambridge: Cambridge University Press.
- Makki, R., Brooks, S., and Milios, E. E. (2014). Context-specific sentiment lexicon expansion via minimal user interaction. *Proceedings of the International Conference on Information Visualization Theory and Applications, Rome, Italy,* 178–186.
- Malti, T., and Krettenauer, T. (2013). The relation of moral emotion attributions to prosocial and antisocial behavior: A meta-analysis. *Child Development*, 84(2), 397–412.
- Martinez-Camara, E., Martın-Valdivia, M. T., Urenalopez, L. A., and Montejoraez, A. R. (2012). Sentiment analysis in Twitter. *Natural Language Engineering*, 20(1), 1–28.
- Matykiewicz, P., Duch, W., and Pestian, J. P. (2009). Clustering semantic spaces of suicide notes and newsgroup articles. *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing, Boulder, CO*, 179-184.

- Maynard, D., and Funk, A. (2011 [2012]). Automatic detection of political opinions in tweets. In Garcia-Castro, R. et al. (Eds.) *The Semantic Web: ESWC 2011 Workshops, Heraklion, Greece.* LNCS 7117, 88–99.
- Mihalcea, R., Banea, C., and Wiebe, J. (2007). Learning multilingual subjective language via cross-lingual projections. *Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics, Prague, Czech Republic*, 976-983.
- Mihalcea, R., and Liu, H. (2006). A corpus-based approach to finding happiness. *Proceedings of AAAI-2006 Spring Symposium on Computational Approaches to Analysing Weblogs*, 139–144.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Proceedings of Advances in Neural Information Processing Systems*, 3111–3119.
- Minamikawa, A., and Yokoyama, H. (2011a). Blog tells what kind of personality you have: egogram estimation from Japanese weblog. *Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work*, 217–220, Hangzhou, China.
- Minamikawa, A., and Yokoyama, H. (2011b). Personality estimation based on weblog text classification. In Mehtrota, K. G. et al. (Eds.) *Modern Approaches in Applied Intelligence*. LNCS 6704. Berlin Heidelberg: Springer-Verlag, 89–97.
- Mohammad, S. M. (2011). From once upon a time to happily ever after: Tracking emotions in novels and fairy tales. *Proceedings of the 5th ACL-HLT Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities, Portland, OR, USA*, 105–114.
- Mohammad, S. M. (2012a). #Emotional tweets. *Proceedings of the 1st Conference on Lexical and Computational Semantics*, *Montreal, Canada,* 246–255.
- Mohammad, S. M. (2012b). From once upon a time to happily ever after: Tracking emotions in mail and books. *Decision Support Systems*, 53(4), 730–741.
- Mohammad, S. M. (2012c). Portable features for classifying emotional text. *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics-Human Language Technologies, Montreal, Canada,* 587–591.
- Mohammad, S. M. (2015a). Imagisaurus: An interactive visualizer of valence and emotion in the Roget's Thesaurus. *Proceedings of the ACL Workshop on Computational Approaches to Subjectivity and Sentiment Analysis*, *Lisbon, Portugal*. Forthcoming.
- Mohammad, S. M. (2015b) Sentiment analysis: Detecting valence, emotions, and other affectual states from text. *Emotion Measurement*. Forthcoming.
- Mohammad, S. M., Dunne, C., and Dorr, B. (2009). Generating high-coverage semantic orientation lexicons from overtly marked words and a thesaurus. *Proceedings of the Conference on Empirical Methods in Natural Language Processing, Waikiki, Hawaii,* 599–608.
- Mohammad, S. M., and Kiritchenko, S. (2013a). Using hashtags to capture fine emotion categories from tweets. *Computational Intelligence*, 31(2), 301–326.
- Mohammad, S. M., and Kiritchenko, S. (2013b). Using nuances of emotion to identify personality. *Proceedings of the International Conference on Weblogs and Social Media (ICWSM-13)*, *Boston, MA*, 27-30.
- Mohammad, S. M., Kiritchenko, S., and Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. *Proceedings of the 7th International Workshop on Semantic Evaluation Exercises (SemEval-2013)*, *Atlanta,*

GA, USA, 321-327.

- Mohammad, S. M., and Turney, P. D. (2010). Emotions evoked by common words and phrases: Using Mechanical Turk to create an emotion lexicon. *Proceedings of the NAACL-HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, *Los Angeles, CA,* 26-34.
- Mohammad, S. M., and Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational Intelligence*, 29 (3), 436-465.
- Mohammad, S. M., and Yang, T. (2011). Tracking sentiment in mail: How genders differ on emotional axes. *Proceedings of the 2nd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis (WASSA 2.011)*, *Portland, OR*, 70–79.
- Mohammad, S. M., Zhu, X., Kiritchenko, S., and Martin, J. (2015). Sentiment, emotion, purpose, and style in electoral tweets. *Information Processing and Management*, 51(4), 480–499.
- Montague, R. (1974). *Formal Philosophy: Selected Papers of Richard Montague*. Thomason, R. (Ed.) New Haven, CT: Yale University Press.
- Montero, C. S., Munezero, M., and Kakkonen, T. (2014). Investigating the role of emotion-based features in author gender classification of text. In Gelbukh, A. (Ed.) *Computational Linguistics and Intelligent Text Processing: 15th International Conference, CICLing 2014, Kathmandu, Nepal.* LNCS 8404. Berlin Heidelberg: Springer-Verlag, 98-114.
- Murakami, A., and Raymond, R. (2010). Support or oppose? Classifying positions in online debates from reply activities and opinion expressions. *Proceedings of the International Conference on Computational Linguistics*, *Beijing, China,* 869–875.
- Nalisnick, E. T., and Baird, H. S. (2013b). Extracting sentiment networks from Shakespeare's plays. *IEEE 12th International Conference on Document Analysis and Recognition (ICDAR),* 758–762.
- Neviarouskaya, A., Prendinger, H., and Ishizuka, M. (2009). Compositionality principle in recognition of fine-grained emotions from text. *Proceedings of the 3rd*
- *International Conference on Weblogs and Social Media (ICWSM-09)*, San Jose, CA, 278–281.
- Neviarouskaya, A., Prendinger, H., and Ishizuka, M. (2010). Recognition of affect, judgment, and appreciation in text. *Proceedings of the 23rd International Conference on Computational Linguistics, Beijing, China*, 806-814
- Orme, B. (2009). Maxdiff analysis: Simple counting, individual-level logit, and HB. Sawtooth Software, Inc.
- Ortony, A., Clore, G. L., and Collins, A. (1990). *The Cognitive Structure of Emotions*. Cambridge: Cambridge University Press.
- Osgood, C. E. (1969). On the whys and wherefores of E, P, and A. *Journal of Personality and Social Psychology*, 12 (3), 194–199.
- Osgood, C. E., Suci, G. J., and Tannenbaum, P. (1957). *The Measurement of Meaning*. Urbana, USA: University of Illinois Press.
- Pak, A., and Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. *Proceedings of the 7th Conference on International Language Resources and Evaluation, Valletta, Malta,* 1320-1326.
- Pang, B., and Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1–2), 1–135.
- Parrot, W. G. (Ed.) (2001). *Emotions in Social Psychology*. Philadelphia: Psychology

Press.
- Paul, M. J., and Dredze, M. (2011). You are what you tweet: Analyzing Twitter for public health. *Proceedings of the 5th International AAAI Conference on Weblogs and Social Media*, 265–272.
- Paul, W., Alm, C. O., Bailey, R., Geigel, J., and Wang, L. (2015). Stressed out: What speech tells us about stress. *Proceedings of Interspeech, Dresden, Germany*. Forthcoming.
- Pearl, L., and Steyvers, M. (2010). Identifying emotions, intentions, and attitudes in text using a game with a purpose. *Proceedings of the NAACL-HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text*, *Los Angeles, CA,* 71-79*.*
- Pennebaker, J. W., Mehl, M. R., and Niederhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology*, 54(1), 547–577.
- Pestian, J. P., Matykiewicz, P., and Grupp-Phelan, J. (2008). Using natural language processing to classify suicide notes. *Proceedings of the Workshop on Current Trends in Biomedical Natural Language Processing, Columbus, OH*, 96-97.
- Picard, R. (1997). *Affective Computing*. Cambridge: MIT Press.
- Plutchik, R. (1962). *The Emotions*. New York: Random House.
- Plutchik, R. (1980). A general psychoevolutionary theory of emotion. *Emotion: Theory, Research, and Experience*, 1(3), 3–33.
- Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, 89(4), 344–350.
- Polanyi, L., and Zaenen, A. (2004). Contextual valence shifters. *Exploring Attitude and Affect in Text: Theories and Applications (AAAI Spring Symposium Series).*
- Pontiki, M., Galanis, D., Pavlopoulos, J., Papageorgiou, H., Androutsopoulos, I., and Manandhar, S. (2014). SemEval-2014 Task 4: Aspect based sentiment analysis. *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014) at the 25th International Conference on Computational Linguistics, Dublin, Ireland,* 27-35.
- Popescu, A.-M., and Etzioni, O. (2005). Extracting product features and opinions from reviews. *Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing*, *Vancouver, Canada,* 339–346.
- Poulin, C., Shiner, B., Thompson, P., Vepstas, L., Young-Xu, Y., Goertzel, B., Watts, B., Flashman, L., and McAllister, T. (2014). Predicting the risk of suicide by analyzing the text of clinical notes. *PLOS ONE* 9(1).e85733.
- Purver, M., and Battersby, S. (2012). Experimenting with distant supervision for emotion classification. *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics, Avignon, France,* 482–491.
- Qadir, A. (2009). Detecting opinion sentences specific to product features in customer reviews using typed dependency relations. *Proceedings of the Workshop on Events in Emerging Text Types (eETTs ’09)*, *Borovets, Bulgaria,* 38–43.
- Quan, C., and Ren, F. (2009). Construction of a blog emotion corpus for Chinese emotional expression analysis. *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, Singapore,* 1446-1454.
- Quan, C., and Ren, F. (2014). Visualizing emotions from chinese blogs by textual emotion analysis and recognition techniques. *International Journal of Information*

Technology and Decision Making, 1–20.
- Ragin, A. B., and Oltmanns, T. F. (1983). Predictability as an index of impaired verbal communication in schizophrenic and affective disorders. *British Journal of Psychiatry*, 143(6), 578–583.
- Reilly, J., and Seibert, L. (2003). Language and emotion. In Davidson, R. J., Scherer, K. R., and Goldsmith, H. H. (Eds.) *Handbook of Affective Sciences*. Oxford: Oxford University Press, 535-559.
- Ren, F., and Quan, C. (2012). Linguistic-based emotion analysis and recognition for measuring consumer satisfaction: An application of affective computing. *Information Technology and Management*, 13(4), 321–332.
- Reyes, A., Rosso, P., and Veale, T. (2013). A multidimensional approach for detecting irony in Twitter. *Language Resources and Evaluation*, 47(1), 239–268.
- Riloff, E., and Wiebe, J. (2003). Learning extraction patterns for subjective expressions. *Proceedings of the 2003 Conference on Empirical Methods in Natural Language Processing*, *Sapporo, Japan,* 105–112.
- Rosenthal, S., Nakov, P., Kiritchenko, S., Mohammad, S. M., Ritter, A., and Stoyanov, V. (2015). SemEval-2015 Task 10: Sentiment analysis in Twitter. *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval-2015) Denver, CO,* 451-463.
- Rosenthal, S., Nakov, P., Ritter, A., and Stoyanov, V. (2014). SemEval-2014 Task 9: Sentiment Analysis in Twitter. *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval-2014) at the 25th International Conference on Computational Linguistics, Dublin, Ireland,* 73-80.
- Rude, S., Gortner, E.-M., and Pennebaker, J. (2004). Language use of depressed and depression-vulnerable college students. *Cognition and Emotion*, 18(8), 1121–1133.
- Russell, B. (1912). *The Problems of Philosophy*. Oxford: Oxford University Press.
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social psychology*, 39(6), 1161.
- Russell, J. A., and Fernández-Dols, J. M. (1998 [1997]). What does a facial expression mean? [selection]. In Jenkins, J. M., Oatley, K., and Stein, N. L. (Eds.) *Human Emotions: A Reader.* Oxford: Blackwell, 73–77.
- Salameh, M., Mohammad, S. M., and Kiritchenko, S. (2015). Sentiment after translation: A case-study on Arabic social media posts. *Proceedings of the North American Chapter of Association of Computational Linguistics*, *Denver, CO*, 767-777.
- Scherer, K. R. (2003). Vocal communication of emotion: A review of research paradigms. *Speech Communication*, *40*(1-2), 227-256.
- Scherer, K. R., Bänziger, T., and Roesch, E. B. (Eds.) (2010). *Blueprint for Affective Computing: A Sourcebook*. Oxford: Oxford University Press.
- Schrading, N., Alm, C. O., Ptucha, R., and Homan, C. M. (2015). #WhyIStayed, #WhyILeft: Microblogging to make sense of domestic abuse. *Proceedings of Human Language Technologies: The Annual Conference of the North American Chapter of the Association for Computational Linguistics, Denver, CO, USA,* 1281-1286.
- Schröder, M., Baggia, P., Burkhardt, F., Pelachaud, C., Peter, C., and Zovato, E. (2011). EmotionML - An upcoming standard for representing emotions and related states. *Proceedings of the 4th International Conference on Affective Computing and Intelligent Interaction, Memphis, TN,* 316-325.

- Schuller, B., and Batliner, A. (2014). *Computational Paralinguistics: Emotion, Affect and Personality in Speech and Language Processing*. Chichester: Wiley.
- Schwartz, H., Eichstaedt, J., Kern, M., Dziurzynski, L., Agrawal, M., Park, G., Lakshmikanth, S. K., Jha, S., Seligman, M. E. P., Ungar, L. H., and Lucas, R. E. (2013a). Characterizing geographic variation in well-being using tweets. *Proceedings of the 7th International AAAI Conference on Weblogs and Social Media, Ann Arbor, MI,* 583-591.
- Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., Shah, A., Kosinski, M., Stillwell, D., Seligman, M. E., and Ungar, L. H. (2013b). Personality, gender, and age in the language of social media: The open-vocabulary approach. *PloS One*, 8(9), 1–16.
- Schwartz, H. A, Eichstaedt, J. C., Kern, M. L., Park, G., Sap, M., Stillwell, D., Kosinski, M., and Ungar, L. H. (2014). Towards assessing changes in degree of depression through Facebook. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality at the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, MD, USA,* 118-125.
- Socher, R., Perelygin, A., Wu, J. Y., Chuang, J., Manning, C. D., Ng, A. Y., and Potts, C. (2013). Recursive deep models for semantic compositionality over a sentiment treebank. *Proceedings of the Conference on Empirical Methods in Natural Language Processing, Seattle, WA*, 1631-1642.
- Somasundaran, S. and Wiebe, J. (2009). Recognizing stances in online debates. *Proceedings of the Joint conference of the 47th Annual Meeting of the Association for Computational Linguistics and the 4th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing, Singapore,* 226–234.
- Sridhar, Dhanya, Getoor, Lise, and Walker, Marilyn. (2014). Collective stance classification of posts in online debate forums. *Proceedings of the Joint Workshop on Social Dynamics and Personal Attributes in Social Media, Baltimore, MD,* 109–117.
- Stone, P., Dunphy, D. C., Smith, M. S., Ogilvie, D. M. (1966). *The General Inquirer: A Computer Approach to Content Analysis*. Cambridge: MIT Press.
- Strapparava, C., and Mihalcea, R. (2007). SemEval-2007 Task 14: Affective text. *Proceedings of SemEval-2007*, *Prague, Czech Republic,* 70–74.
- Strapparava, C., and Mihalcea, R. (2010). Annotating and identifying emotions in text. In Armano, G., et al. (Eds.) *Intelligent Information Access*, SCI 301. Berlin Heidelberg: Springer-Verlag, 21–38.
- Strapparava, C., and Valitutti, A. (2004). WordNet-Affect: An affective extension of WordNet. *Proceedings of the 4th International Conference on Language Resources and Evaluation, Lisbon, Portugal,* 1083–1086.
- Su, F., and Markert, K. (2008). From words to senses: a case study of subjectivity recognition. *Proceedings of the 22nd International Conference on Computational Linguistics, Manchester, UK,* 825–832.
- Su, Q., Xiang, K., Wang, H., Sun, B., and Yu, S. (2006). Using pointwise mutual information to identify implicit features in customer reviews. *Proceedings of the 21st International Conference on Computer Processing of Oriental Languages, Singapore,* 22–30.
- Suero Montero, C., and Suhonen, J. (2014). Emotion analysis meets learning

analytics: On-line learner profiling beyond numerical data. *Proceedings of the 14th Koli Calling International Conference on Computing Education Research*, 165–169.

- Sun, Y., Quan, C., Kang, X., Zhang, Z., and Ren, F. (2014). Customer emotion detection by emotion expression analysis on adverbs*. Information Technology and Management*, 1–9.
- Suttles, J., and Ide, N. (2013). Distant supervision for emotion classification with discrete binary values. *Computational Linguistics and Intelligent Text Processing*, *Samos, Greece.* Berlin Heidelberg: Springer-Verlag, 121– 136.
- Taboada, M., Brooke, J., Tofiloski, M., Voll, K., and Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics*, 37(2), 267–307.
- Tang, D., Wei, F., Qin, B., Liu, T., and Zhou, M. (2014a). Coooolll: A deep learning system for twitter sentiment classification. *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), Dublin, Ireland,* 208–212.
- Tang, D., Wei, F., Qin, B., Zhou, M., and Liu, T. (2014b). Building large-scale Twitter-specific sentiment lexicon: A representation learning approach. *Proceedings of the International Conference on Computational Linguistics*, *Dublin, Ireland,* 172–182.
- Thelwall, M., Buckley, K., and Paltoglou, G. (2011). Sentiment in Twitter events. *Journal of the American Society for Information Science and Technology*, 62(2), 406–418.
- Thomas, B., Dhanya, K. A., and Vinod, P. (2014). Synthesized feature space for multiclass emotion classification. *IEEE 1st International Conference on Networks and Soft Computing (ICNSC), Guntur,* 188–192.
- Thomas, M., Pang, B., and Lee, L. (2006). Get out the vote: Determining support or opposition from congressional floor-debate transcripts. *Proceedings of the Conference on Empirical Methods in Natural Language Processing, Sydney, Australia,* 327–335.
- Tumasjan, A., Sprenger, T. O., Sandner, P. G., and Welpe, I. M. (2010). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social Science Computer Review*, 29(4), 402–418.
- Turney, P. D. (2002). Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, Philadelphia, PA*, 417-424.
- Turney, P., and Littman, M. L. (2003). Measuring praise and criticism: Inference of semantic orientation from association. *ACM Transactions on Information Systems*, 21(4), 315-346.
- Vaassen, F., and Daelemans, W. (2011). Automatic emotion classification for interpersonal communication. *Proceedings of the ACL Workshop on Computational Approaches to Subjectivity and Sentiment Analysis*, *Portland, OR,* 104–110.
- Vaidyanathan, P., Prud'hommeaux, E., Alm, C. O., Pelz, J. B., and Haake, A. (2015). Alignment of eye movements and spoken language for semantic image understanding. *Proceedings of the 11th International Conference on Computational Semantics, London, UK*, 76-81.
- Wang, C., and Wang, F. (2012). A bootstrapping method for extracting sentiment words using degree adverb patterns. *IEEE International Conference on Computer Science and Service System (CSSS),* 2173–2176.

(Mohammad and Alm, 2015)

- Wang, L., Bailey, R., Geigel, J., Alm, C. O., Bethamcherla, V., Krithika, S., John, B., and Kilroy, T. (2014). Sensor fusion for cognitive load and stress monitoring and detection. *RIT-VA, Canandaigua, NY.* Poster.
- Wang, W., Chen, L., Thirunarayan, K., and Sheth, A. P. (2012). Harnessing Twitter "big data" for automatic emotion identification. *Proceedings of the 2012 ASE/IEEE International Conference on Social Computing and 2012 ASE/IEEE International Conference on Privacy, Security, Risk and Trust, Washington, DC,* 587–592.
- Wang, X., and Fu, G.-H. (2010). Chinese subjectivity detection using a sentiment density-based naive Bayesian classifier. *IEEE International Conference on Machine Learning and Cybernetics (ICMLC), Vol. 6,* 3299–3304.
- Wang, Z. (2014). Segment-based fine-grained emotion detection for chinese text. *Proceedings of the 3rd CIPS-SIGHAN Joint Conference on Chinese Language Processing, Wuhan, China*. 52–60.
- Walker, M. A., Anand, P., Abbott, R., and Grant, R. (2012). Stance classification using dialogic properties of persuasion. *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics-Human Language Technologies, Montreal, Canada,* 592–596.
- Warriner, A. B., Kuperman, V., and Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, 45(4), 1191–1207.
- Webster, G. and Weir, C. (2005). Emotional responses to music: Interactive effects of mode, texture, and tempo. *Motivation and Emotion*, 29(1), 19–39.
- Whissell, C. (2000). Phonoemotional profiling: A description of the emotional flavour of English texts on the basis of the phonemes employed in them. *Perceptual and Motor Skills*, *91*(2), 617-648.
- Wiebe, J., and Riloff, E. (2005). Creating subjective and objective sentence classifiers from unannotated texts. *Proceedings of the 6th International Conference on Computational Linguistics and Intelligent Text Processing*, *Mexico City, Mexico,* 486–497.
- Wiebe, J., and Riloff, E. (2011). Finding mutual benefit between subjectivity analysis and information extraction. *IEEE Transactions on Affective Computing,* 2(4), 175–191.
- Wiebe, J., Wilson, T., Bruce, R., Bell, M., and Martin, M. (2004). Learning subjective language. *Computational Linguistics*, 30(3), 277–308.
- Wilson, T., Hoffmann, P., Somasundaran, S., Kessler, J., Wiebe, J., Choi, Y., Cardie, C., Riloff, E., and Patwardhan, S. (2005). Opinionfinder: A system for subjectivity analysis. *Proceedings of the Conference on Empirical Methods in Natural Language Processing, Interactive Demonstrations*, *Vancouver, Canada,* 34–35.
- Wilson, T., Kozareva, Z., Nakov, P., Rosenthal, S., Stoyanov, V., and Ritter, A. (2013). SemEval-2013 Task 2: Sentiment analysis in Twitter. *Proceedings of the 7th International Workshop on Semantic Evaluation (SemEval-2013)*, *Atlanta, GA, 312-320.*
- Womack, K., McGowen, V., Alm, C. O., Pelz, J., Haake, A., and Shi, P. (2014). Analyzing multimodal behaviors of students with autism spectrum disorders. *Effective Access Technology Conference, Rochester, NY*. Poster.
- Zhang, L., Liu, B., Lim, S. H., and O'Brien-Strain, E. (2010). Extracting and ranking product features in opinion documents. *Proceedings of the 23rd International Conference on Computational Linguistics, Beijing, China,* 1462–1470.

(Mohammad and Alm, 2015)

- Zhu, X., Guo, H., Mohammad, S., and Kiritchenko, S. (2014). An empirical study on the effect of negation words on sentiment. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, *Baltimore, Maryland,* 304–313.
- Zhu, X., Sobhani, P., and Guo, H. (2015). Long short-term memory over recursive structures. *International Conference on Machine Learning*, *Lile, France.*