

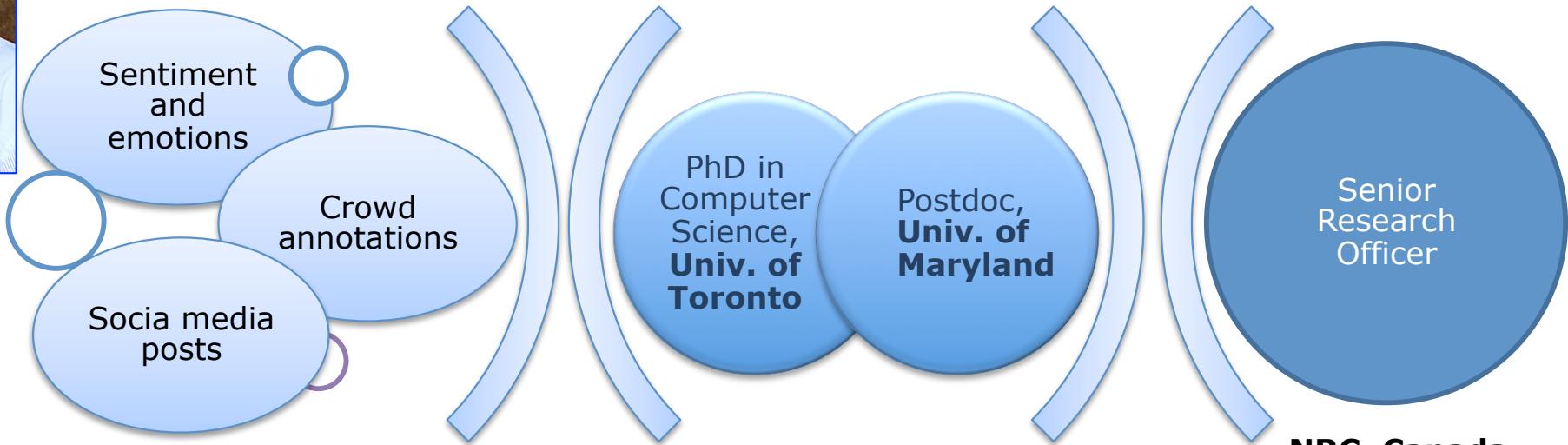


Computational Analysis of Affect and Emotion in Language

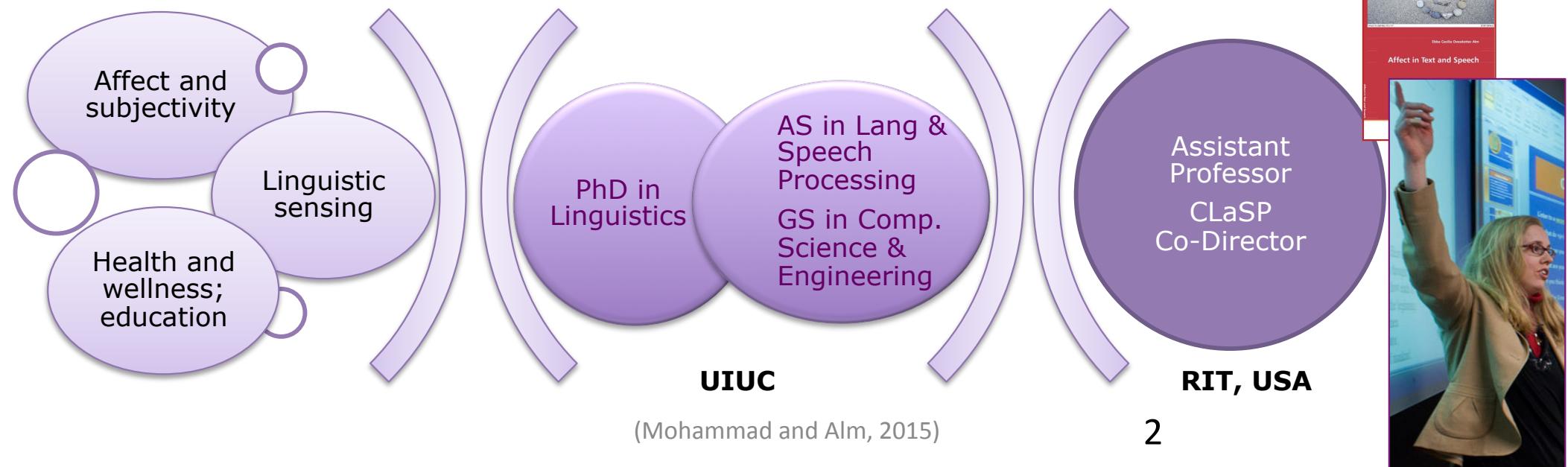
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Tutorial at EMNLP 2015, Lisboa, Portugal



Survey on Affect Analysis:
(Mohammad, 2015b)



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

Tutorial roadmap



Introduction



Emotive Language Use



Linguistic Data

BREAK
30 min



Computational Modeling (Part 1)



Computational Modeling (Part 2)



Visualizing Computational Outcomes

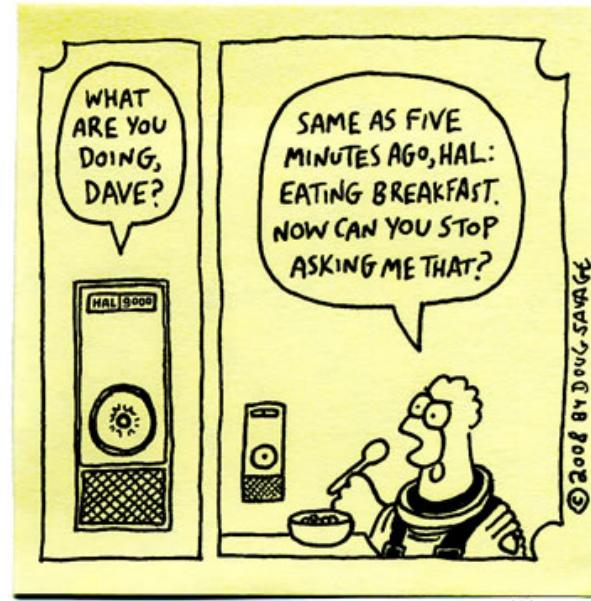


Survey of Applications



Future Directions and Wrap-up



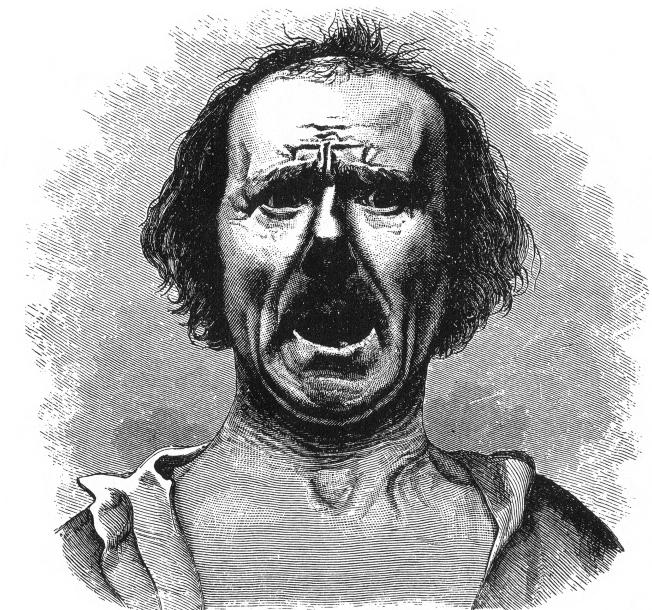
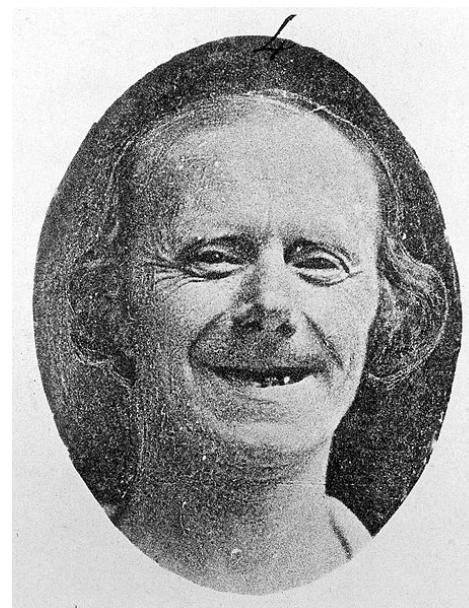
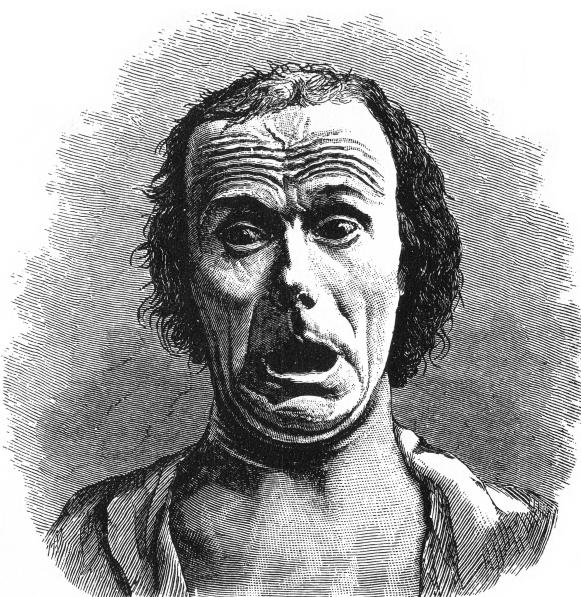


Introduction

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

Affect extends beyond thumbs up/down



(Mohammad and Alm, 2015)

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.

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

Affective meaning

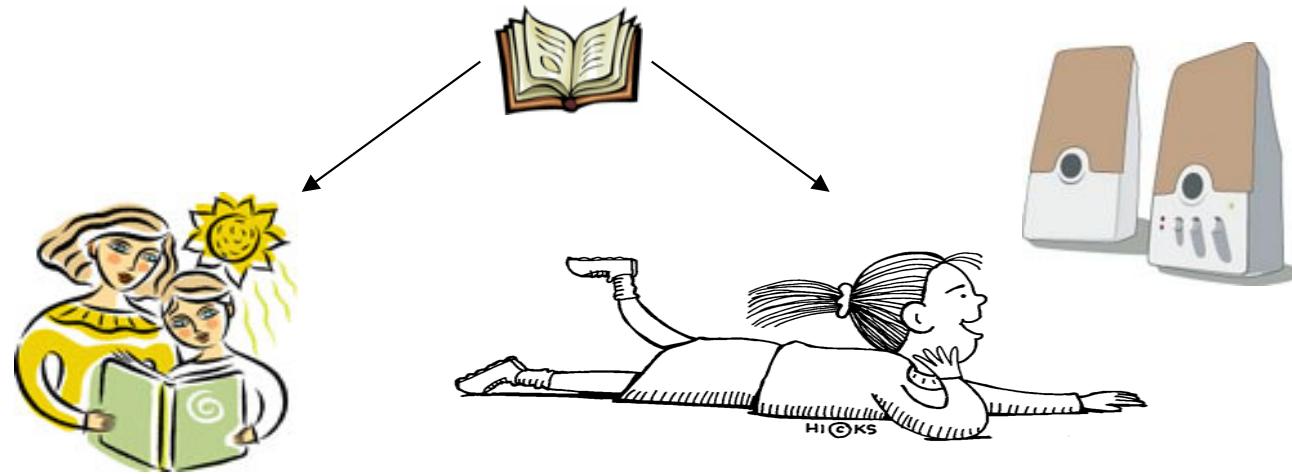
- Early recognized as important (Bühler, Jakobson, Lyons, Halliday) yet quite neglected in language science and computational linguistics
 - Affective computing field (Picard and beyond)
 - Steadily growing interest in affective computational semantics
-
- Beyond 'propositional' meaning which tends to 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.

Affect analysis for human-centered computing

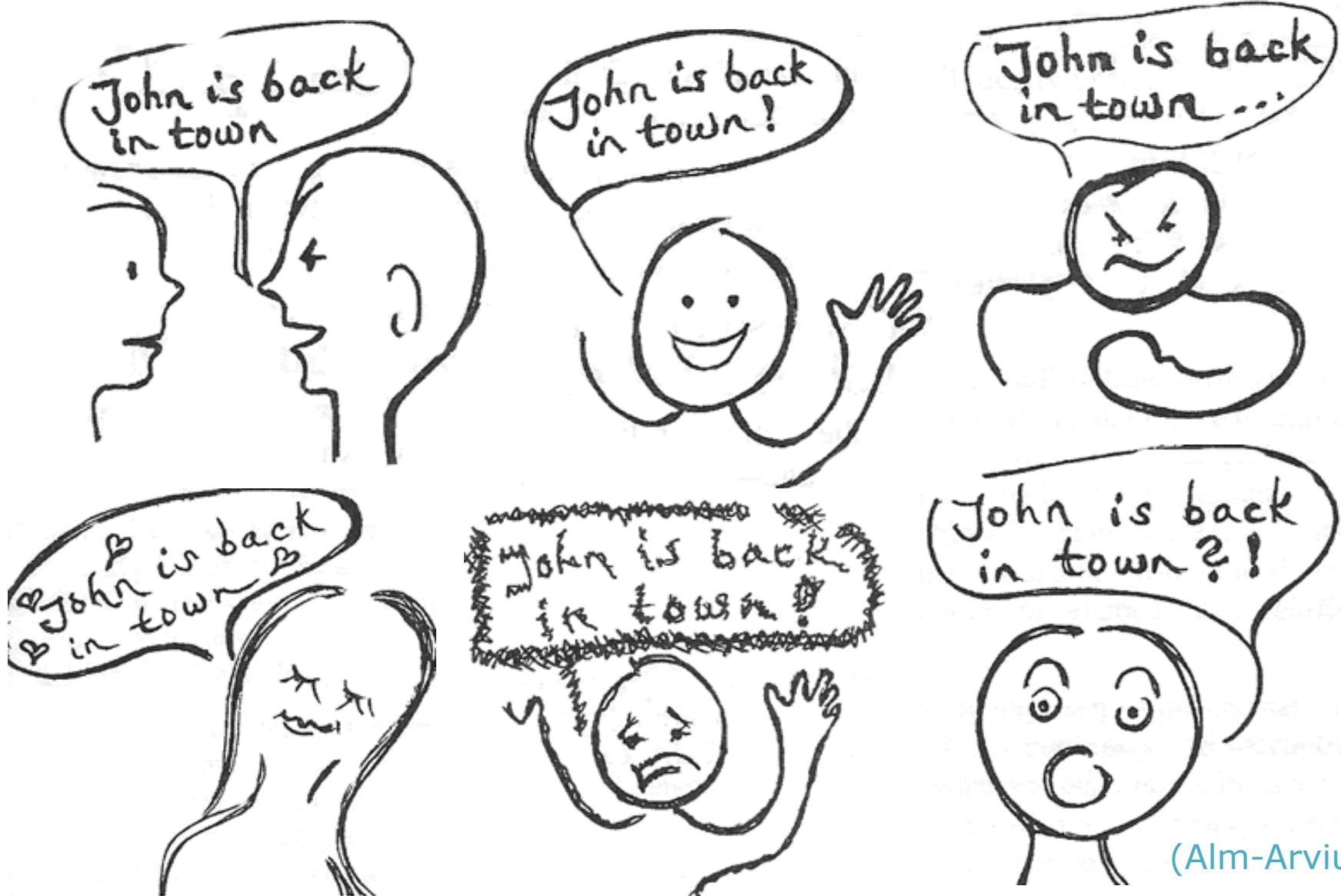
- **HCC as a theoretical/functional paradigm acknowledges...**
 - the central role of humans in computing
 - that humans and machines work better in tandem
 - and language is an essential component of the human condition
- **Linguistic sensing:**
 - Language as sensor of the body area network for personalized 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.

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-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.

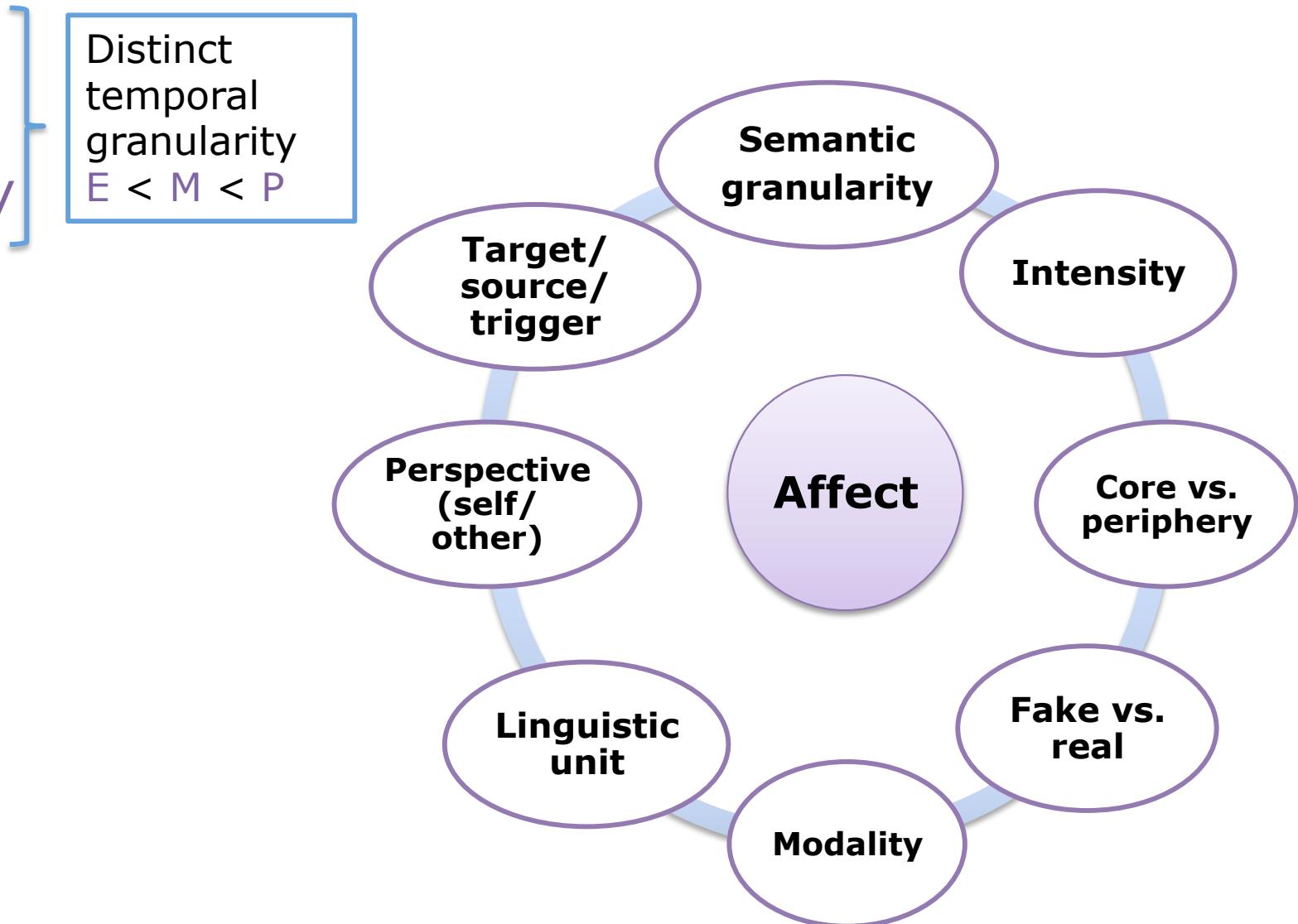
Long list of applied motivations

- 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.

Concepts: affect states and affect attributes

- Emotion
- Mood
- Personality
- Attitude



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.

Challenges to automatic affect detection, characterization, and generation

- Different degrees of affect depending on sense and context.

Mary hugged her daughter before going to work. emotional
The pipeline hugged 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

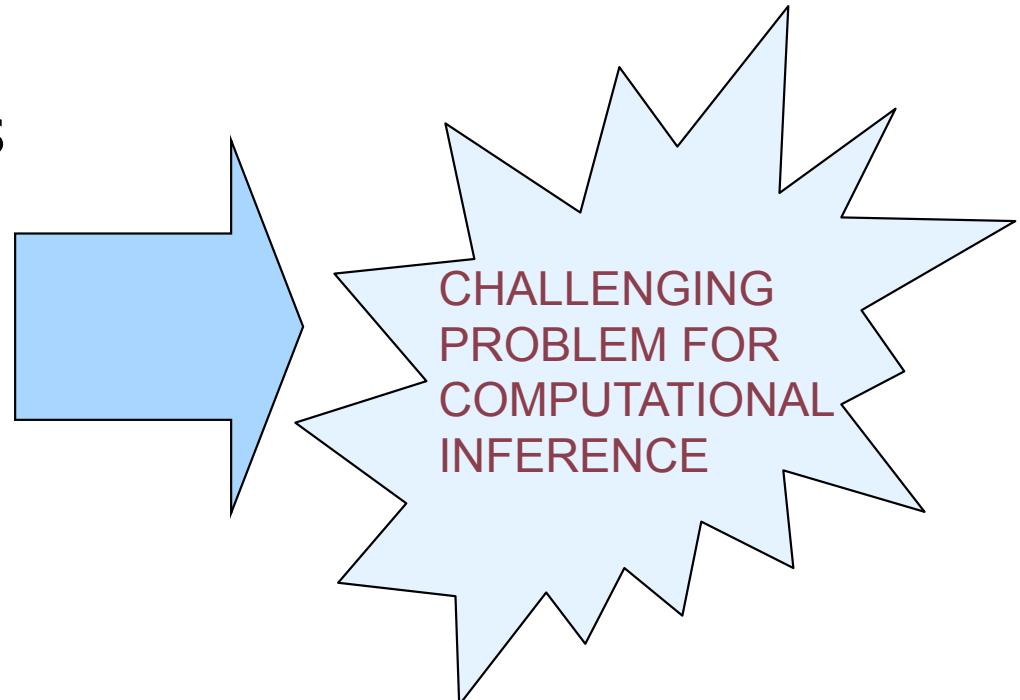
Challenges to automatic affect detection, characterization, and generation

- 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

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.

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.

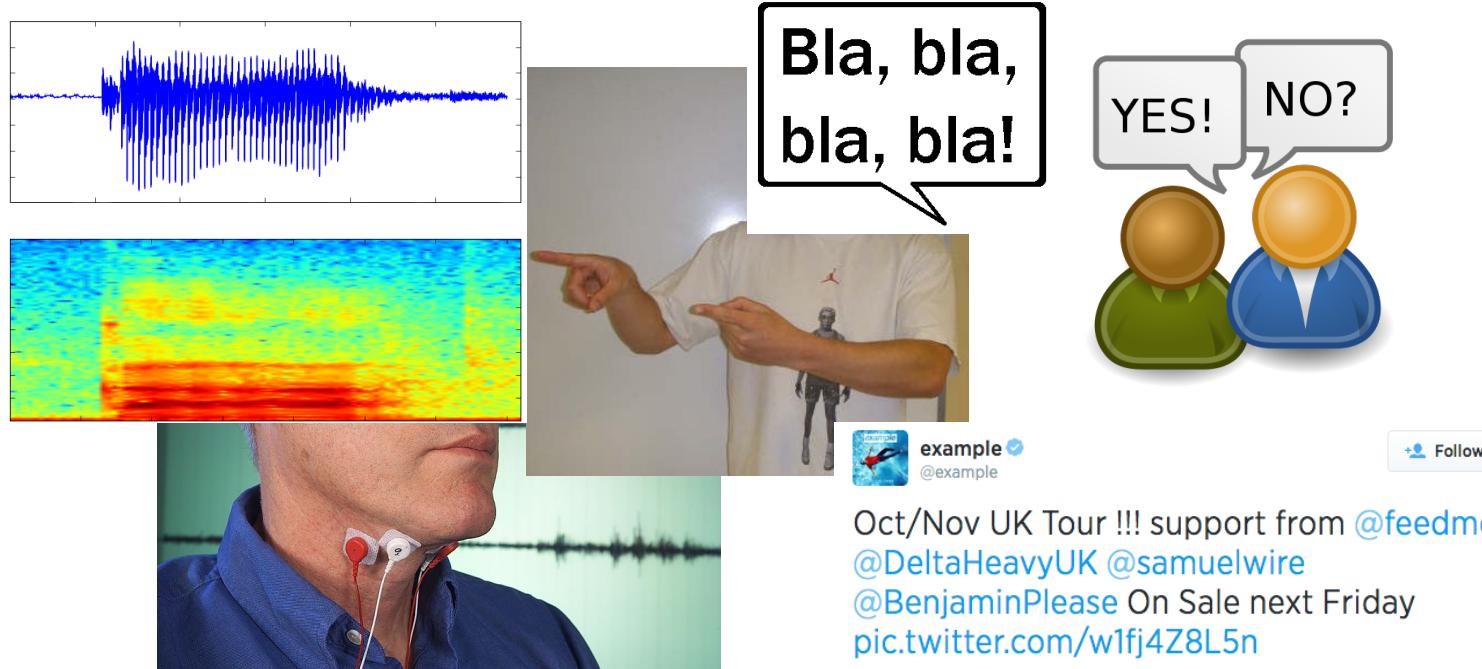


Emotive Language Use

Topics:

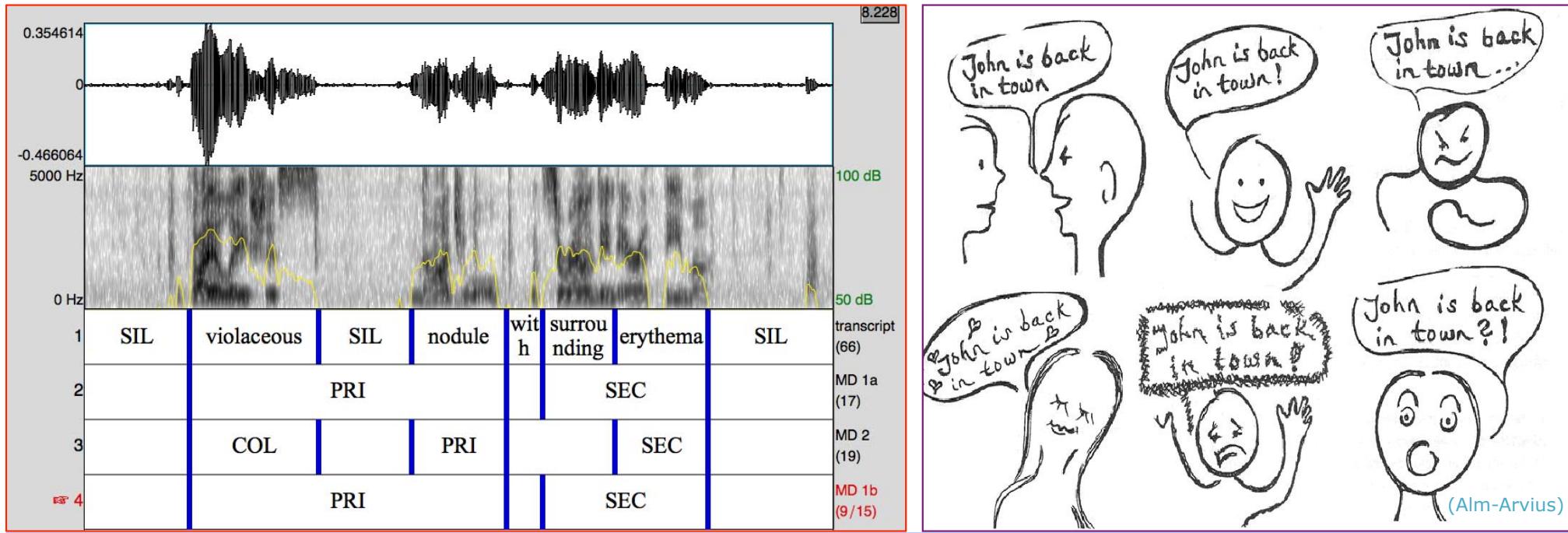
- How language users communicate affect and emotion across modalities in text, speech, signed, and multimodal data
- Links to sociolinguistic attributes of language users
- Implications for and translation into features for computational analysis

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

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



... [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

Affect is subject to contextual variation

- Socio-cultural and interpersonal factors
 - Cultural conventions
 - Social expectations
 - Social stratification
 - Taboos and rituals
 - 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
- Moderated affect
expressions/perceptions
- (Cowie et al., 2010 and
studies cited therein;
Alm, 2009)

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

FACE
POSTURE
GESTURE
HEART
SKIN
EYE GAZE
PUPILS
etc.

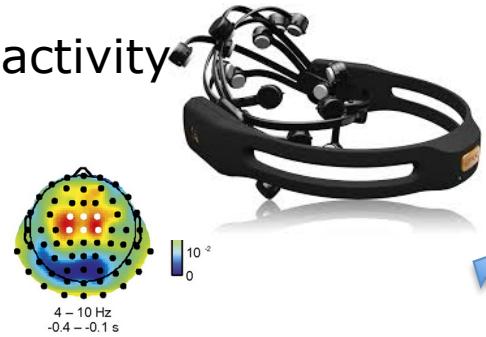


They are convenient to integrate in multimodal capture for affect sensing. Emotions tend to be conveyed across modalities, e.g., in facial expressions.

(Ekman & Friesen, 1998)

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

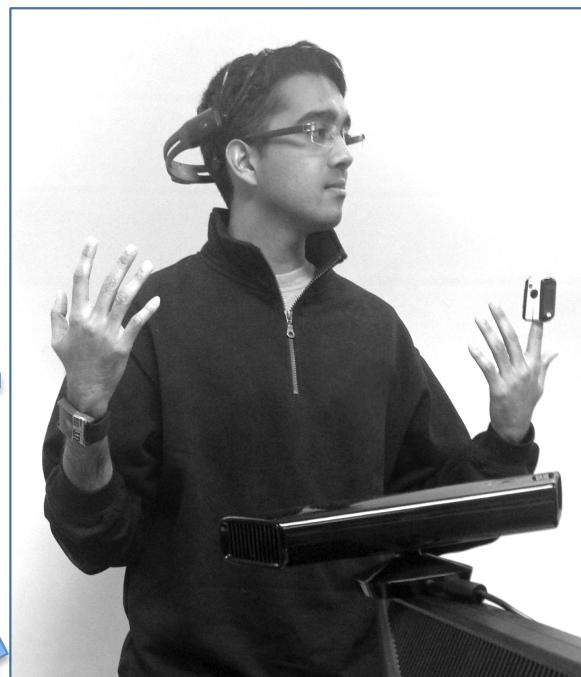
Brain activity
(EEG)



Skin conductance
(GSR)



Cardiac activity
(Oximeter)



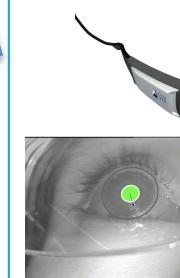
Speech/transcribed
(microphone)



Facial motion
(Kinect)



Gaze
(Eye-tracking)



(Mohammad and Alm, 2015)

25 (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.

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

Clear affect encoding in text may involve various clues

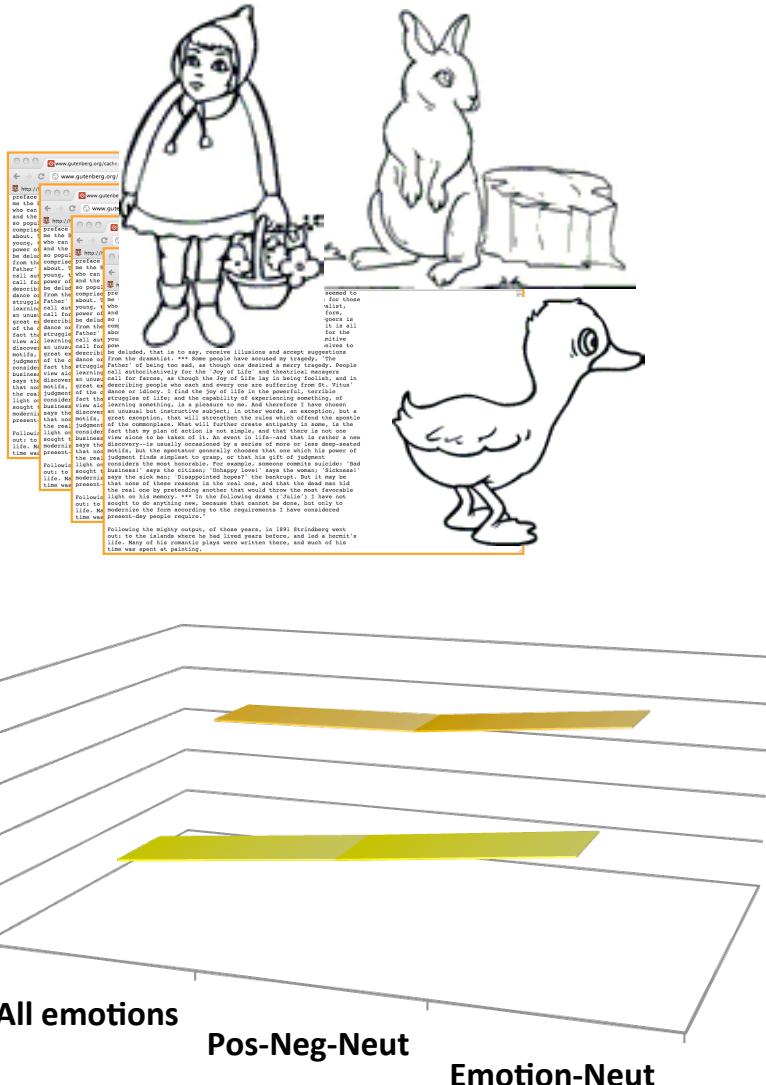
- **Lexicon** for affect states, contrastive states, affect-related words/expressions
 - **Example sentence with affect-related lexical items:**
They **laughed** and they **wept**; and Peter **embraced** the old Fire-drum. (HAPPY)
 - Lexical examples from affect sentences judges agreed upon:

A word cloud visualization showing various English adjectives in different colors. The words include: shudder, sneer, bewilder, tear, wretched, venture, tearful, dreadful, dare,粗鲁 (rude), pain, smiles, embrace, enjoy, enjoyment, groan, offend, offend, nod, wipe one's eyes, etremble, beg, droll, care, kiss, stare, laugh, lovingly, funny, whisper, faint, condescend, spit at, shake one's head, suddenly, grumble, jokes, banished, pleasure, excitement, amusement, fainting, whistle, insult, unexpected, laugh at, mock, hide, feel, brandish, growl, sting, despise, sooth, careess, troubled, lament, sigh, beat, cry, painful.

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)

Classifying affect in sentences whose affect orientation annotators highly agreed on



Data: Fairytale texts

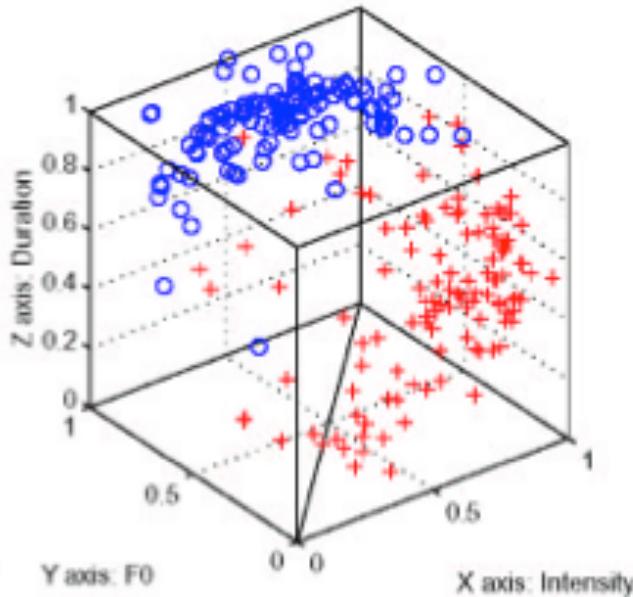
Linguistic unit of affect: Sentence

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)

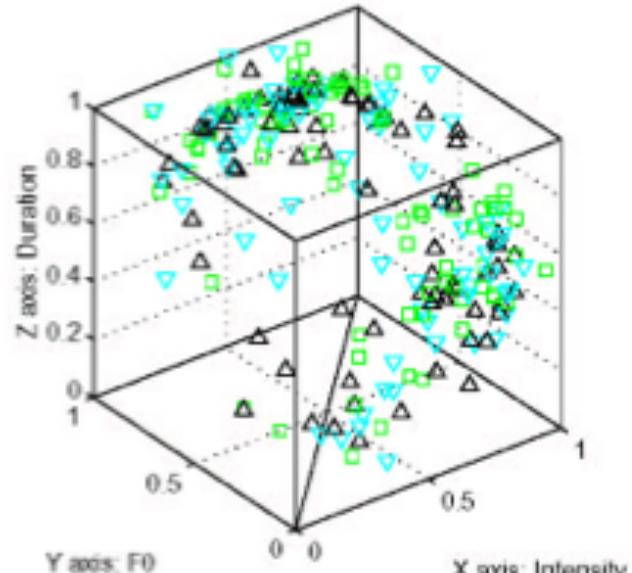
Linguistic features toward classification: lexical, orthographic, story-related, syntactic, lexically derived scores, affect history, poetic structures, lexical sequences

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

Characterizing affective voices



Solutions separate by emotion



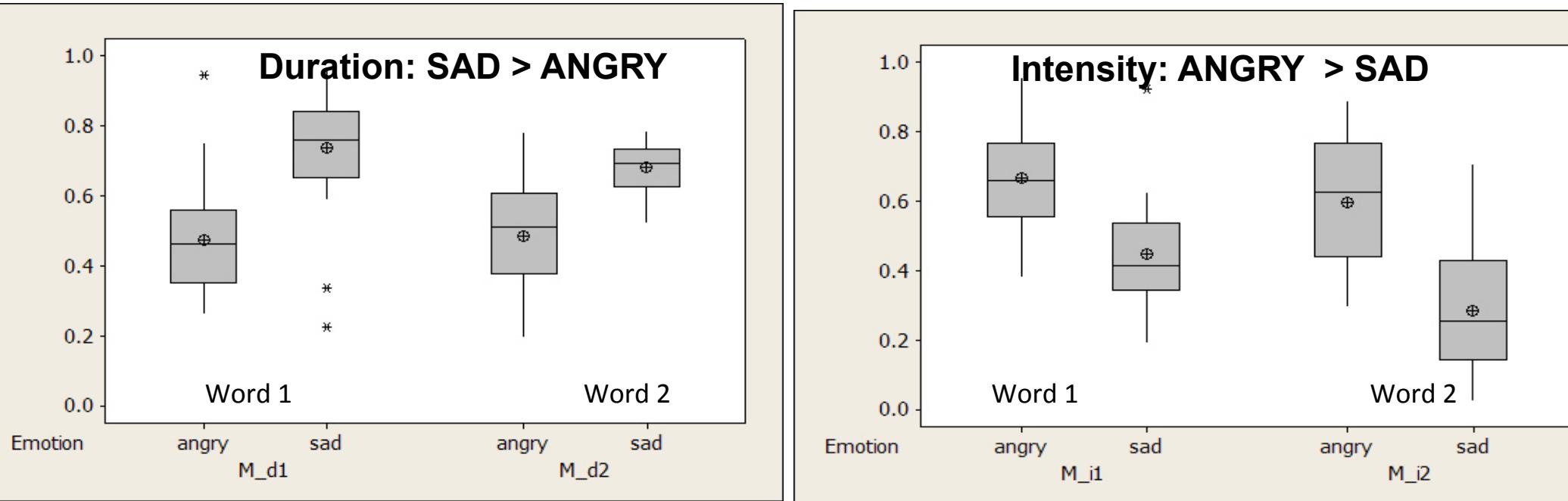
But not by syllabic type (control)

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



(Mohammad and Alm, 2015)

Angry vs. sad voices contrasted by basic voice inflection cues



Global trend with local variation

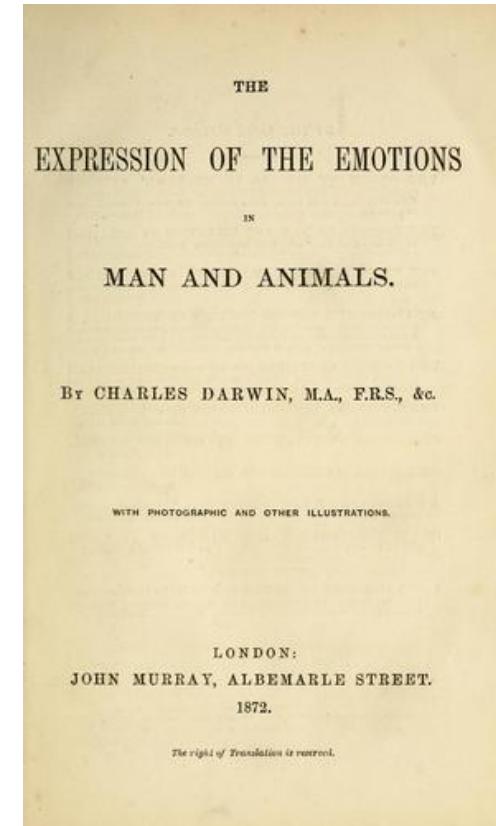
(Alm, 2009)

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

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.

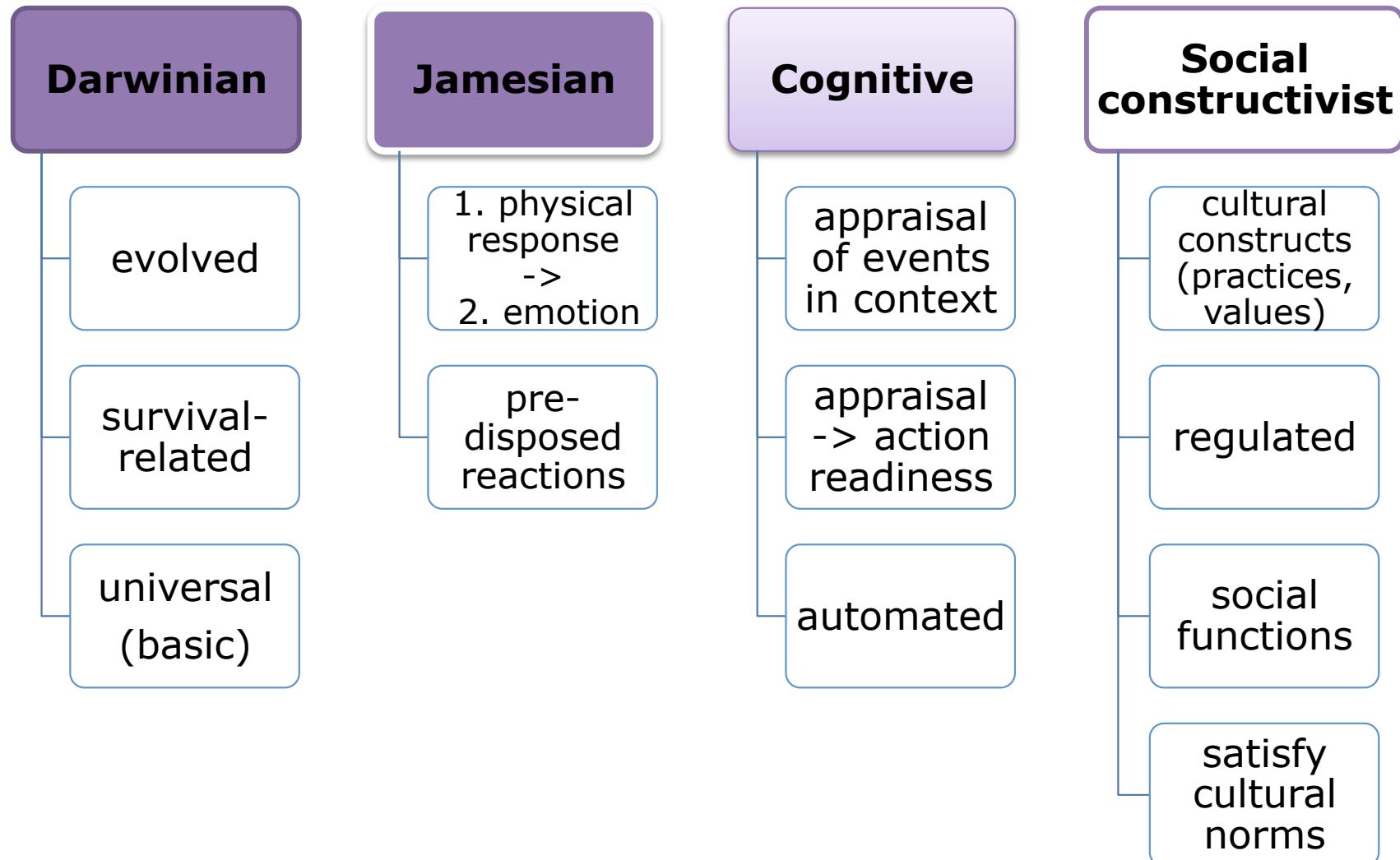
Linguistic Data



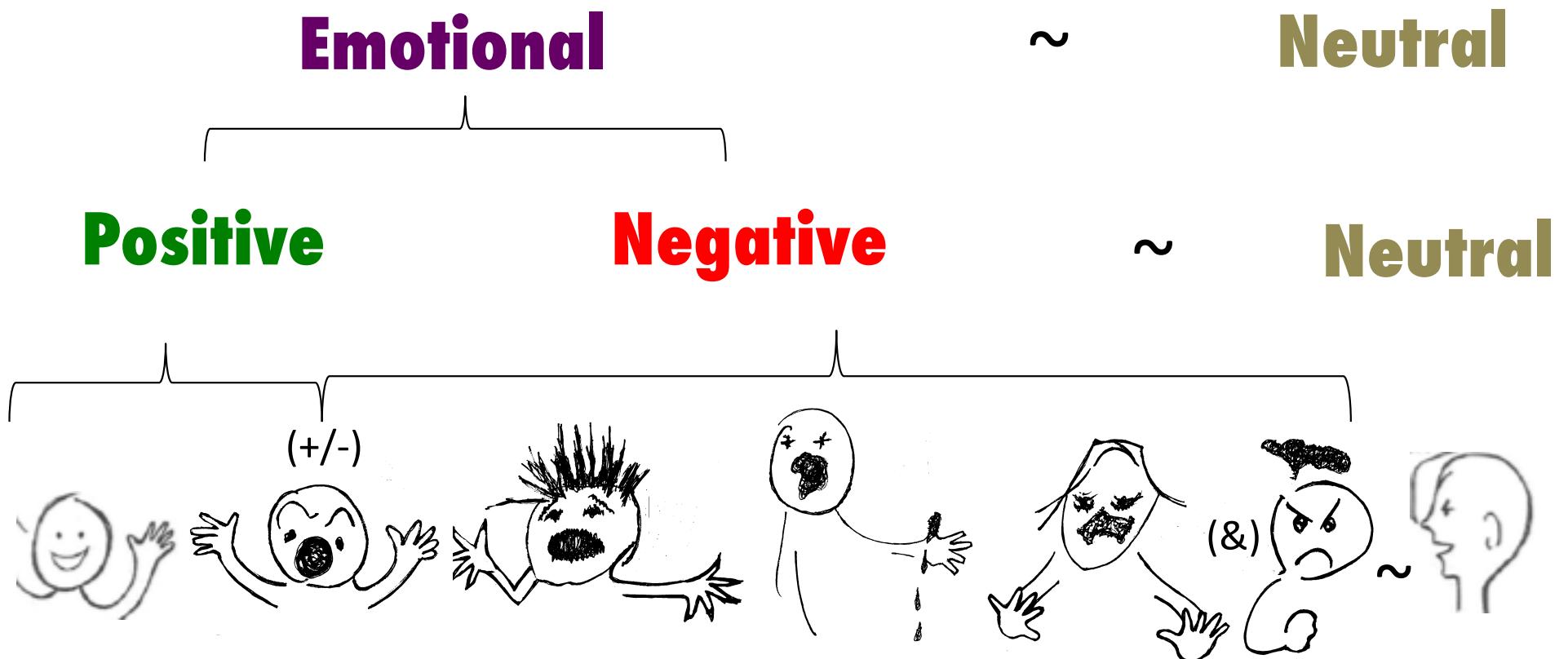
Topics:

- 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

Four theoretical affect perspectives with a history

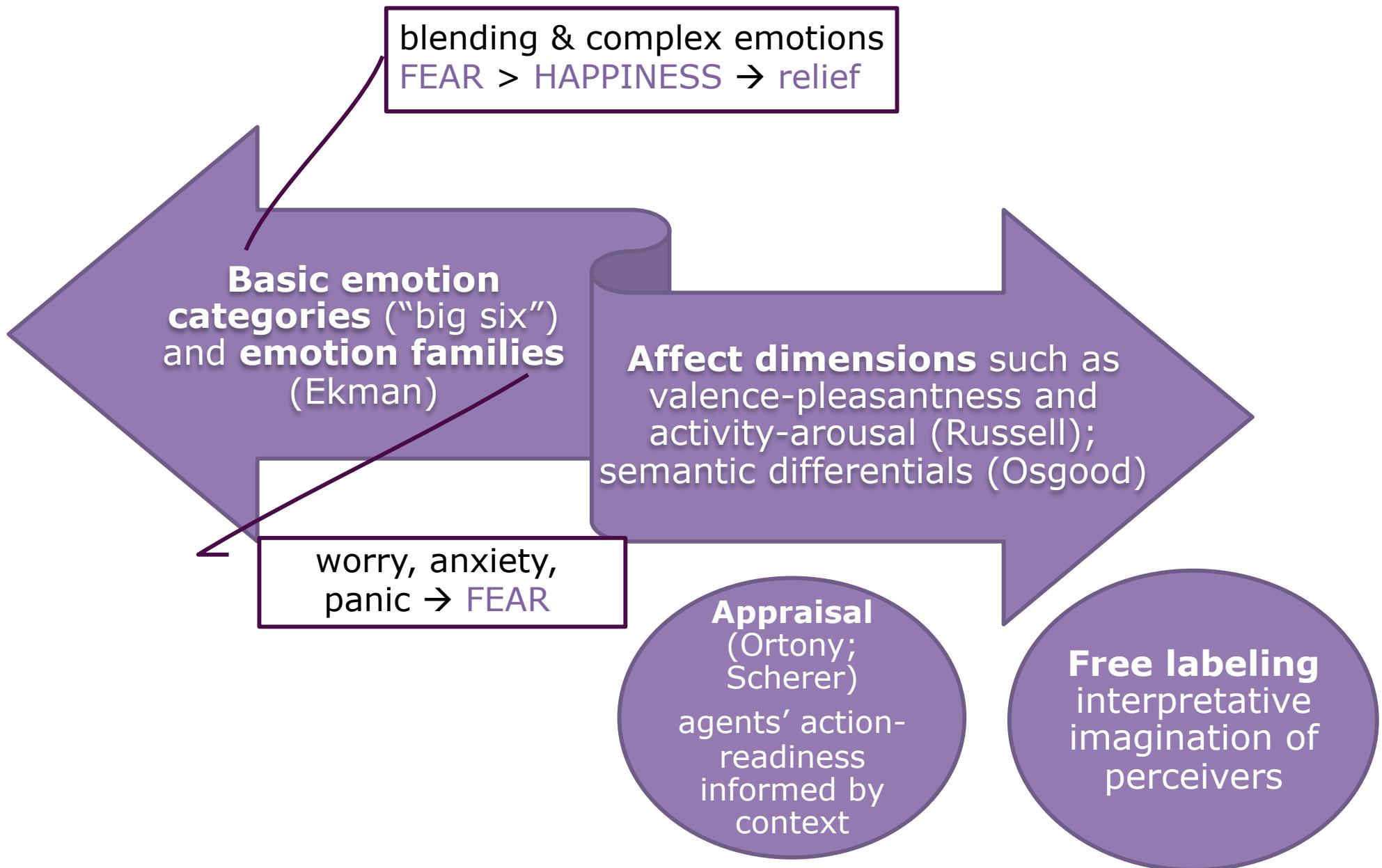


An example of one way to conceptualize affect as categories



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

Modeling and describing affect

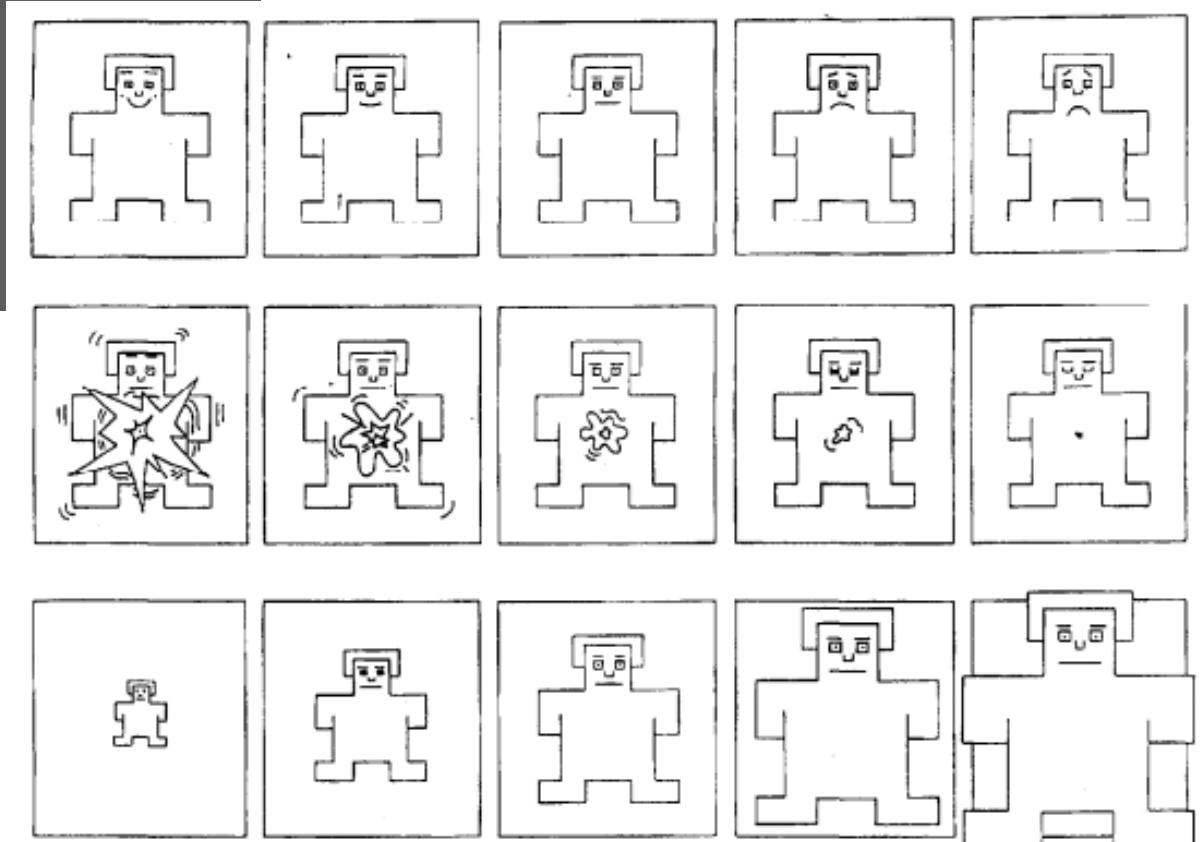


Affective categories vs. affective dimensions



SAM

"Big Six" (Cornelius, 2000)

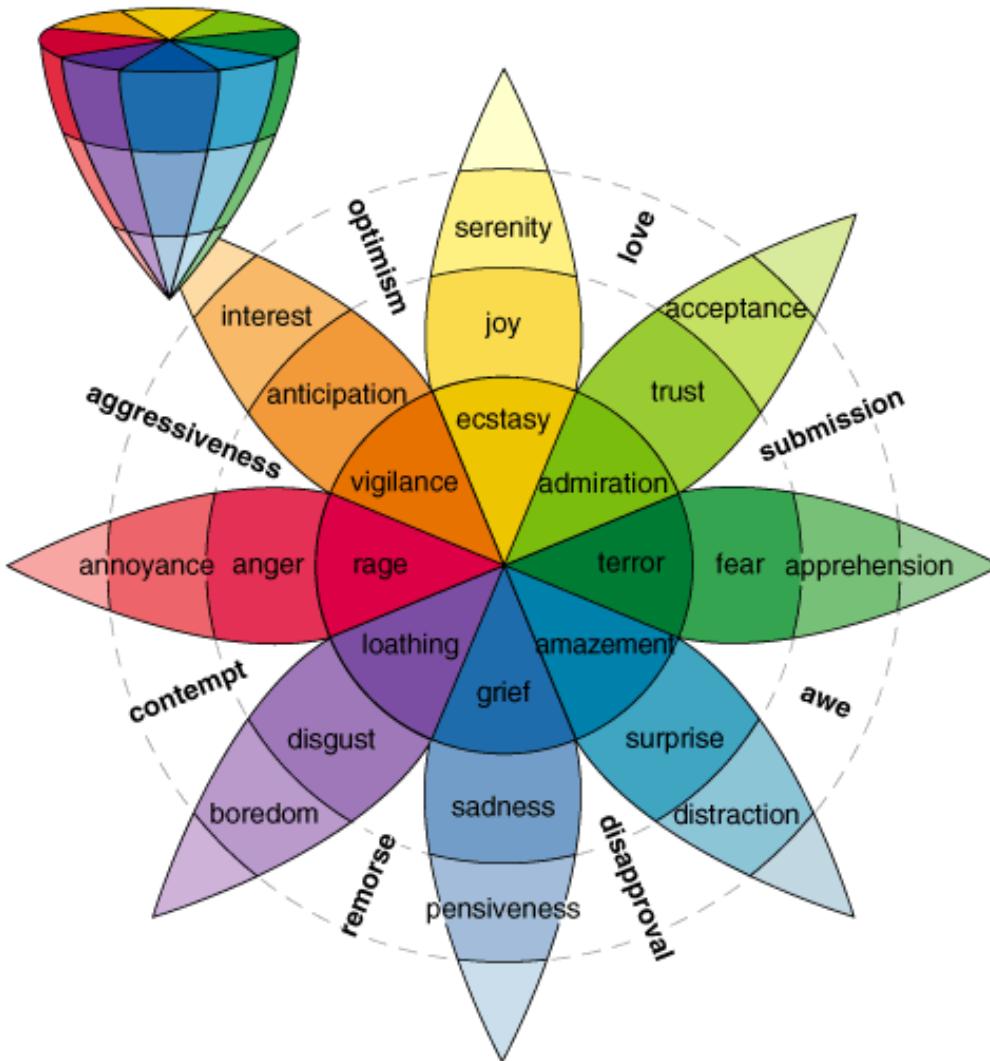


(Bradley & Lang, 1994)

(Mohammad and Alm, 2015)

Yet another Darwinian view – Plutchick

Anticipation
Trust
Anger
Disgust
Fear
Joy
Sadness
Surprise



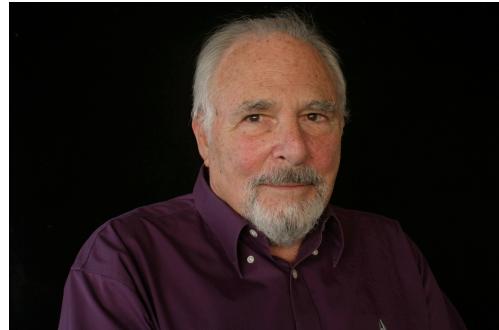
Take home message:

- 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.

Ongoing debate: Universality of perception of emotions



Margaret Mead
Cultural anthropologist



Paul Ekman
Psychologist

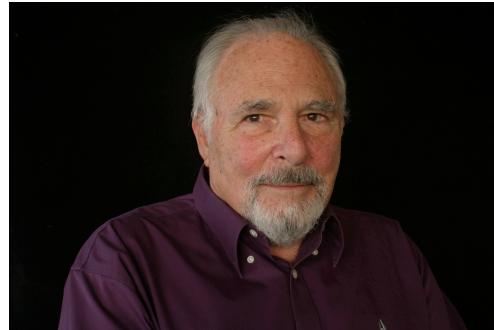


- Circa 1950's, Margaret Mead and others
 - Facial expressions, their meanings, culturally determined
- Paul Ekman
 - Most influential in providing evidence for Darwin, not Mead
 - Universality of six emotions

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

Manually created lexical resources

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

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>

Sample resources: Annotated corpora and other products

Annotated corpora (affect categories):

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

Other:

- **EmotionML** ([Schröder et al.](http://www.w3.org/TR/emotionml/)) <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](http://www.saifmohammad.com/WebDocs/EMNLP2014-SentimentTutorial.pdf))

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

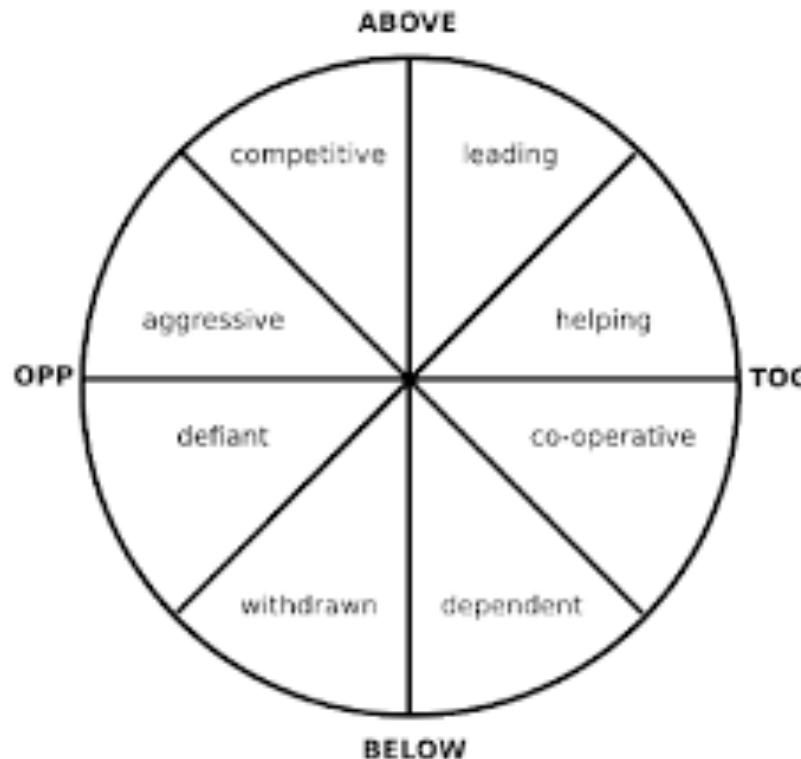
Japanese customer reviews corpus with the same eight emotions used in the Chinese Ren-CECps Corpus
(Sun et al., 2014)

- 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.

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

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

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**

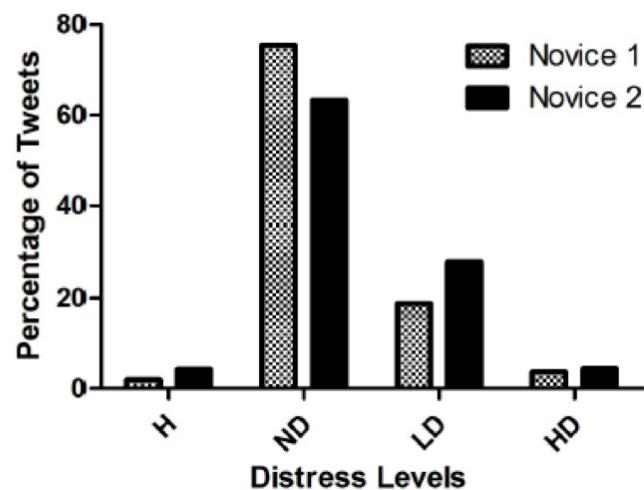
- Unclear from rest of the message

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

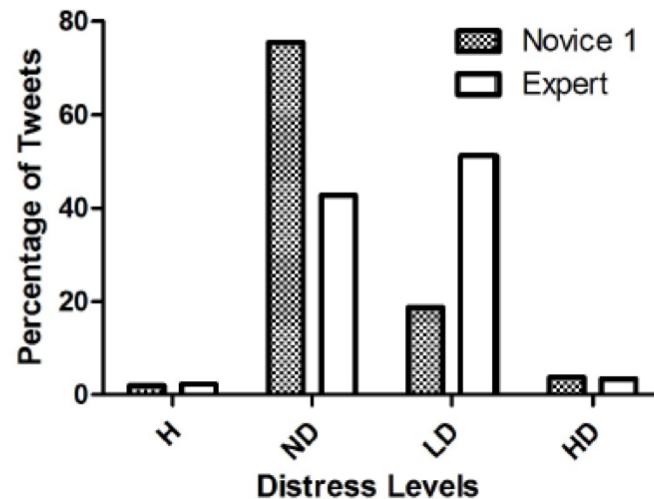
(Go, Bhayani, & Huang, 2009;
Mohammad, 2012a)

Affect ratings can be influenced by domain expertise

(a) Novices' perceptions are similar



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



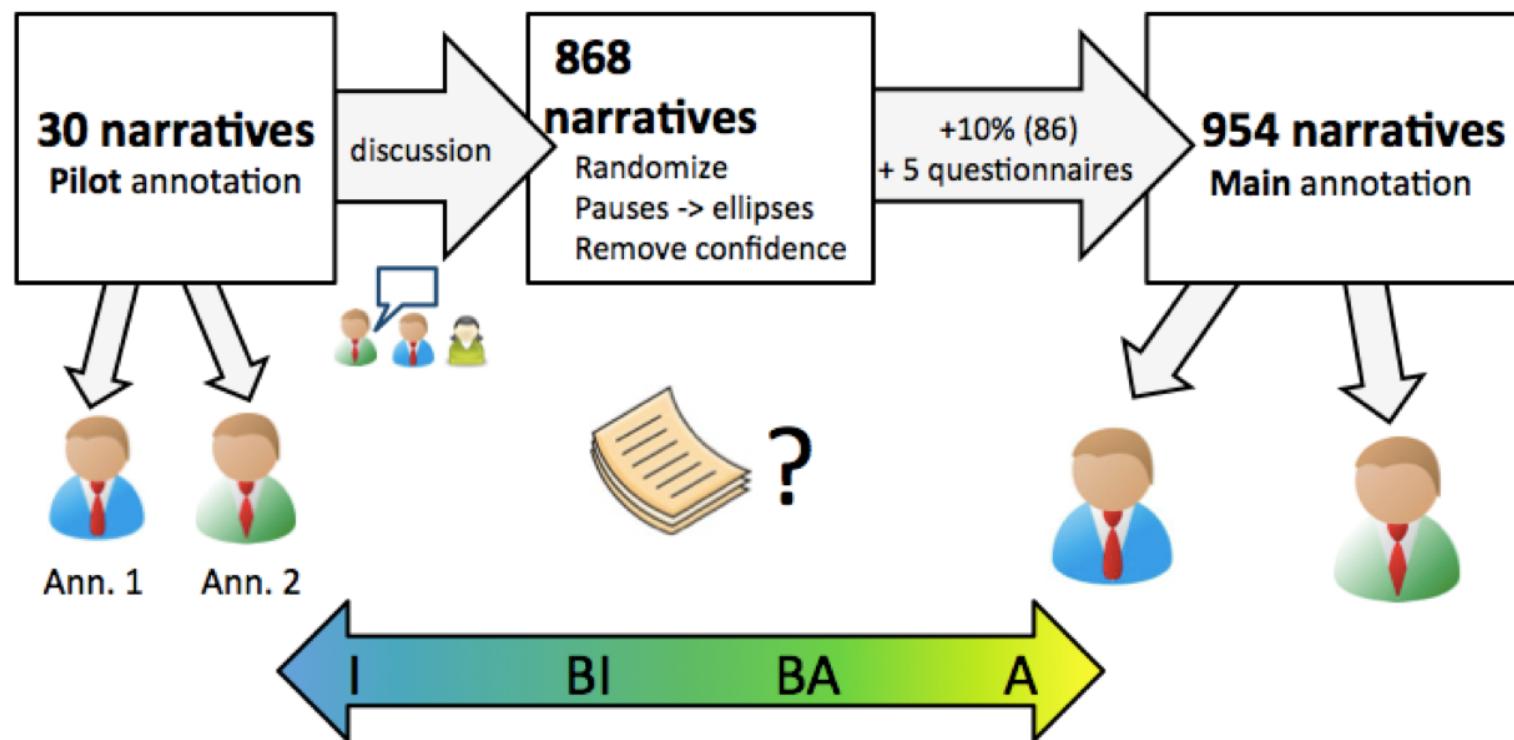
HD: High Distress

LD: Low Distress

ND: No Distress

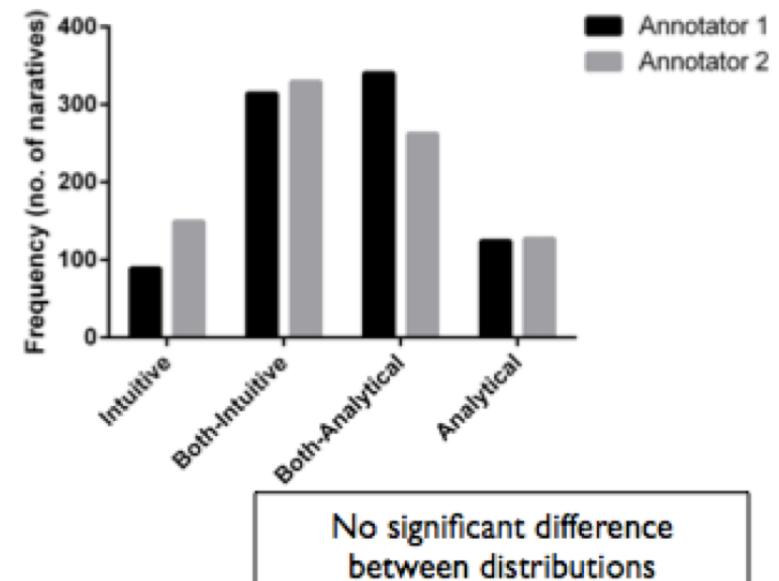
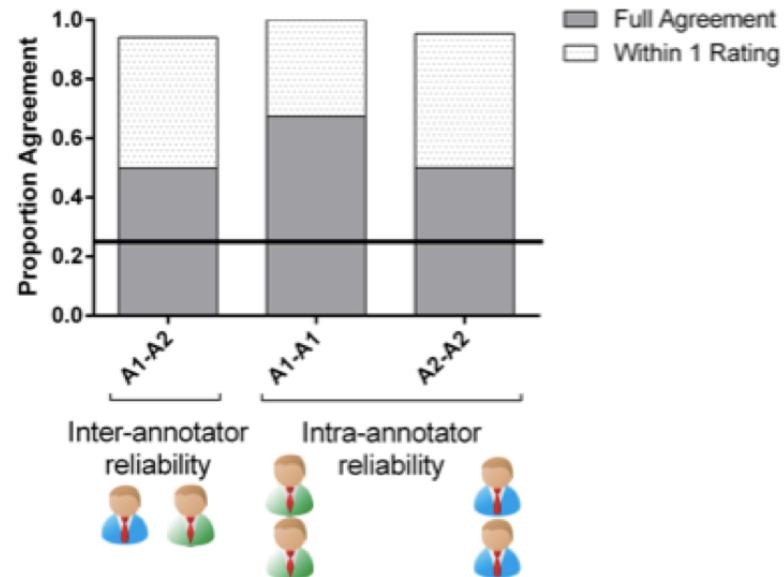
H: Happy

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



Annotation analysis can help understanding fuzzy, yet systematic perception

a) Disagreements are minor and explicable b) Perception centers on the fuzzier middle

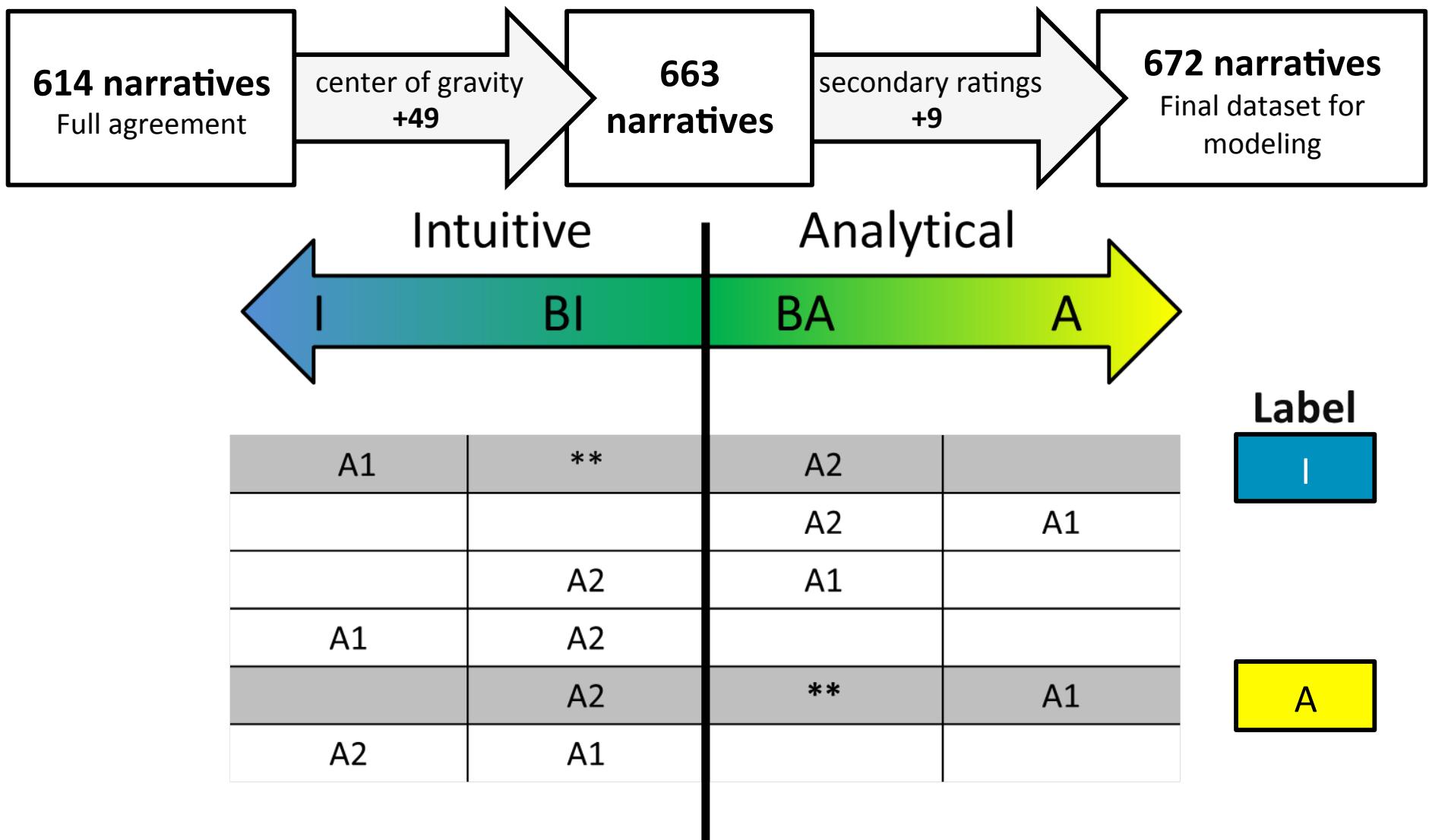


Full agreement or within one rating on the continuum for over 90% on decision-style annotation

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. <i>uh, um</i>)	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. <i>X because Y</i>)	4.2	0.4	4.0	0.0
Perceived confidence	4.4	0.5	4.2	0.4

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



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?



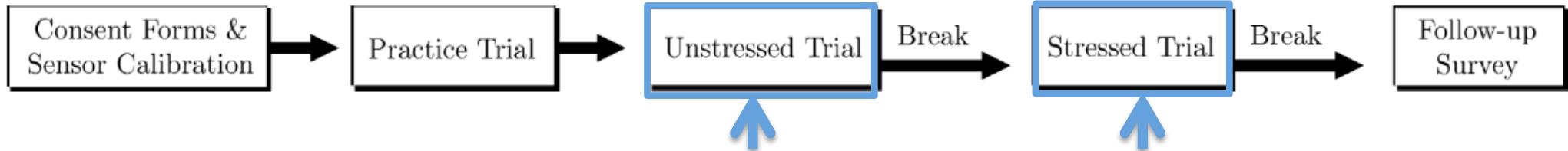
Why is this picture funny?

What does the crop “circle” look like?

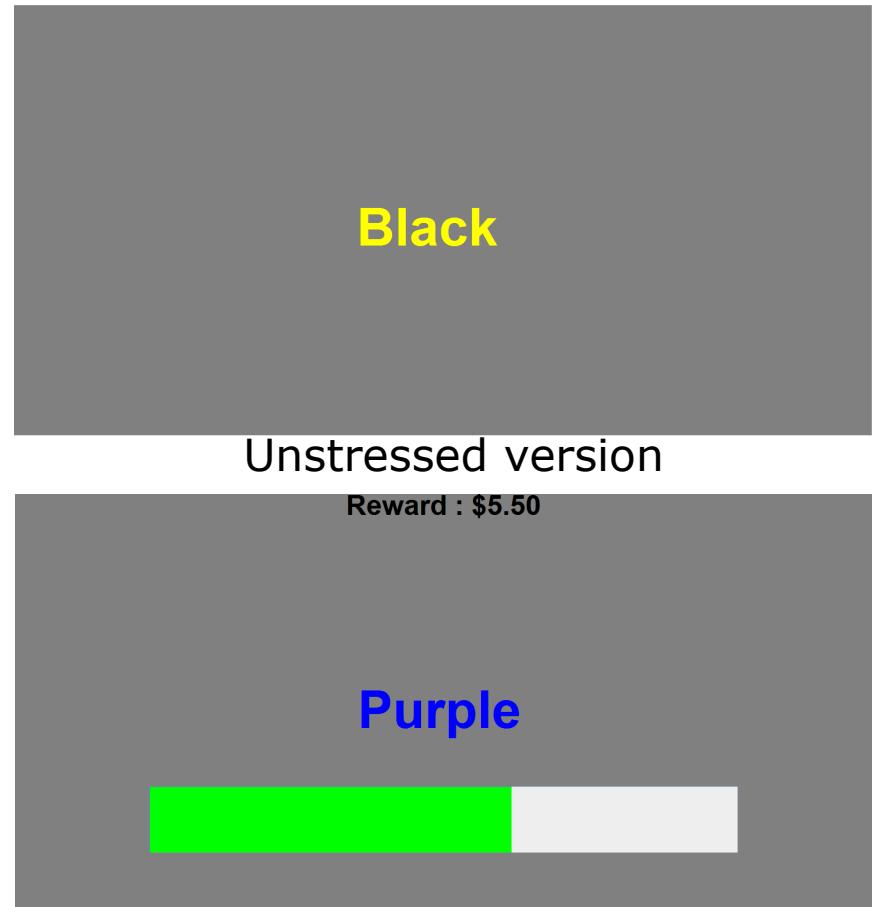
Where are the two green men from?

Why is the man on the left pointing and smiling?

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



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

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

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.

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.

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.

Manually Creating Valence and Emotion Association Lexicons

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.

Word-choice question

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

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



Peter Turney, AI2

- 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)

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.

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

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 $A \gg D$:
 - 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

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, gooooood
 - 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)

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/>

Automatically Generating Valence and Emotion Association Lexicons

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:

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

PMI = pointwise mutual information

If $\text{score}(w) > 0$, then word w is **positive**

If $\text{score}(w) < 0$, 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](#))

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**

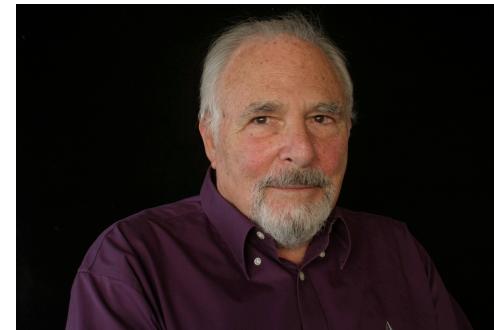
- Generated emotion association lexicons from this pseudo-labeled data
 - Showed usefulness in automatic sentence-level emotion classification for the Ekman emotions

(Mohammad, 2012a)

Ongoing debate: Universality of emotion perception



Margaret Mead
Cultural anthropologist



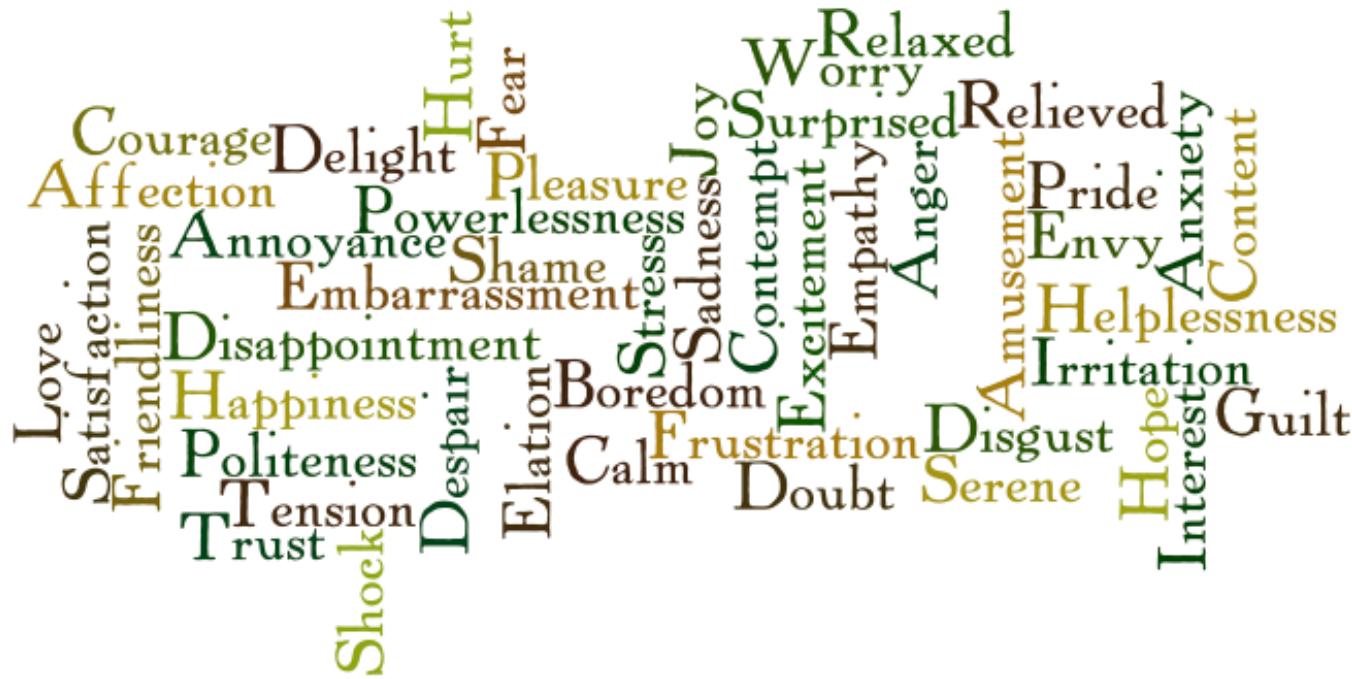
Paul Ekman
Psychologist



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?

Generating emotion association lexicon for 500 emotions

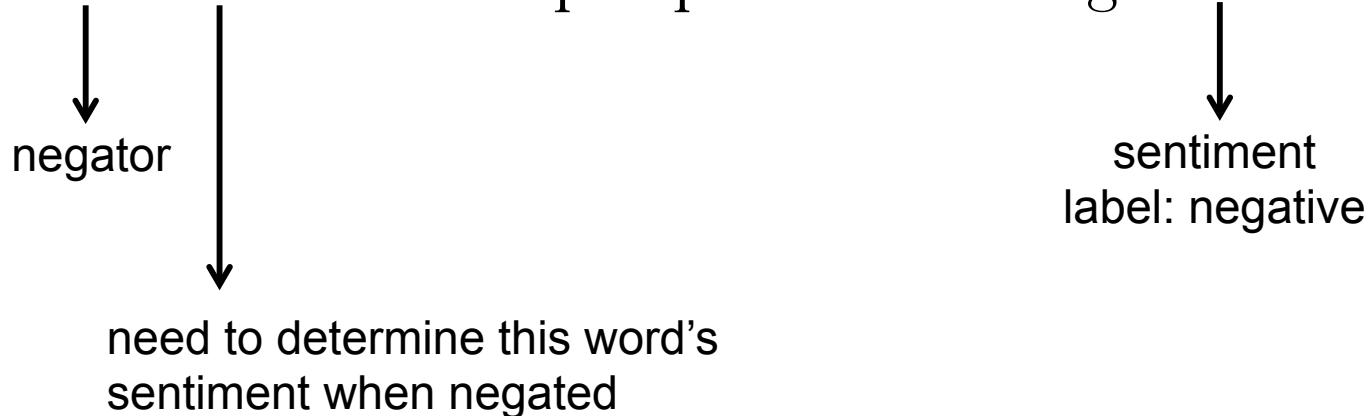


NRC Hashtag Emotion Lexicon: About 20,000 words associated with about 500 emotions

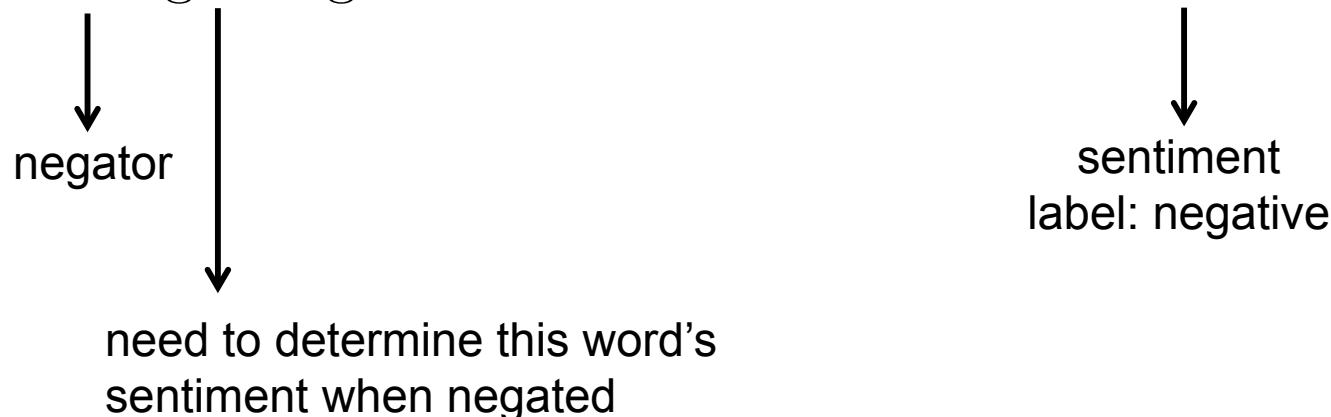
(Mohammad, 2012a;
Mohammad & Kiritchenko, 2013a)

Negation

Jack was not thrilled at the prospect of working weekends ☹



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



(Kiritchenko, Zhu, & Mohammad, 2014)

Handling negation

Jack was not thrilled at the prospect of working weekends ☹



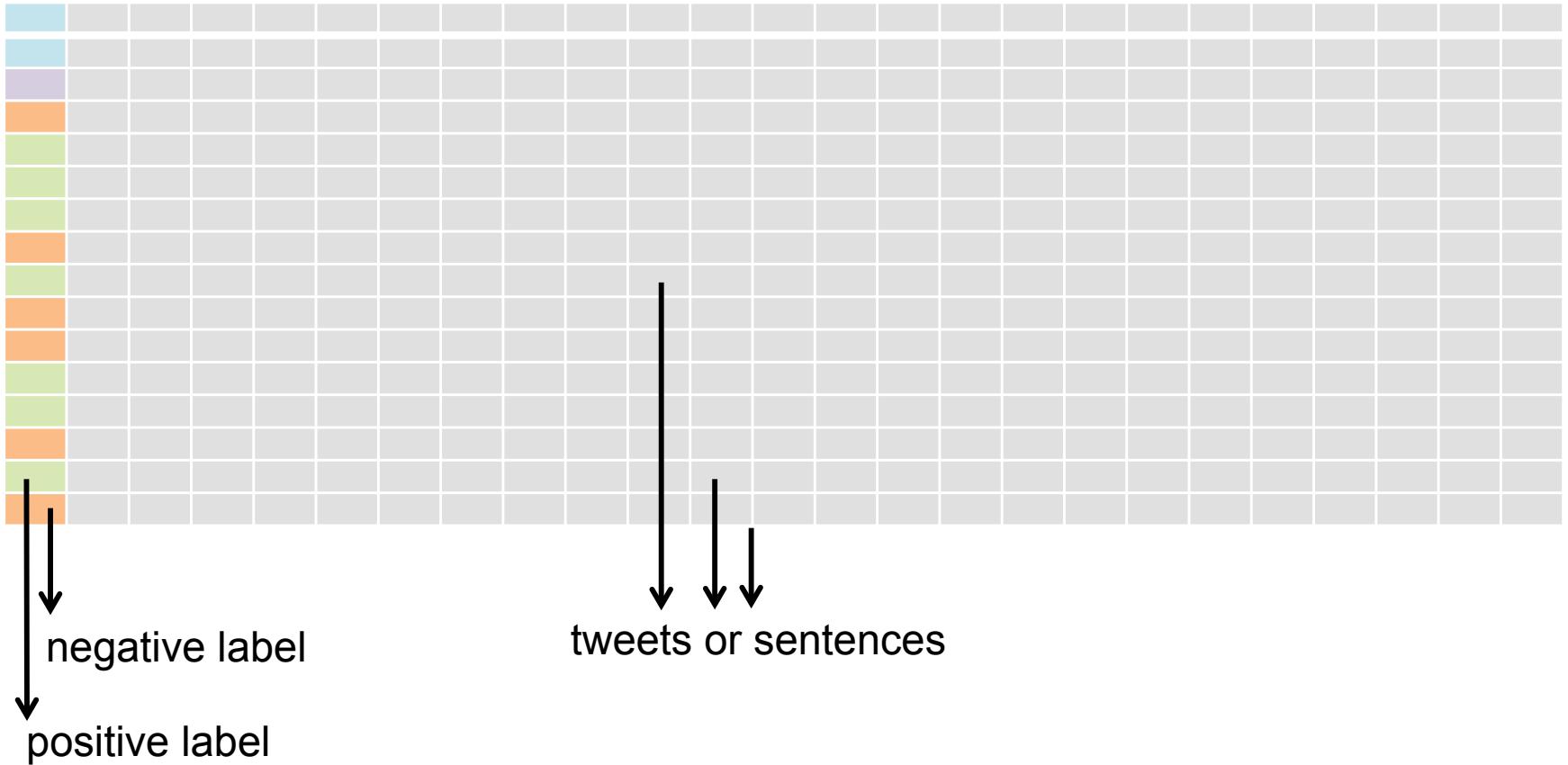
The bill is not garbage, but we need a more focused effort ☹

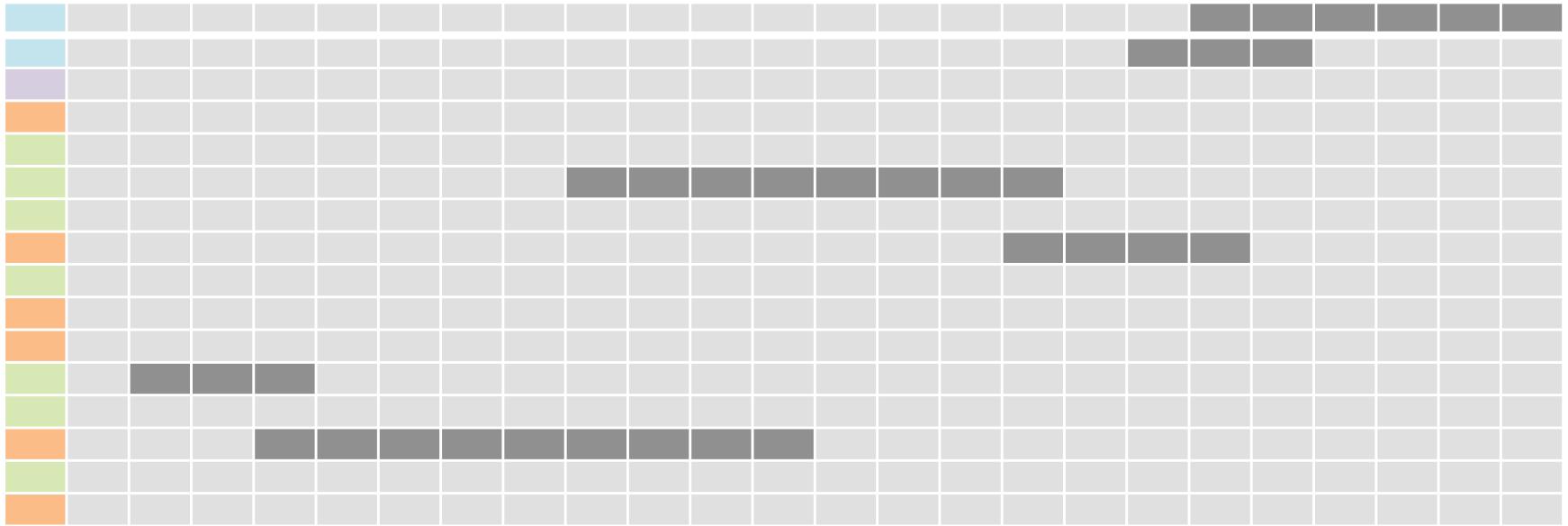


Scope of negation: from negator until a punctuation
(or end of sentence)

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)



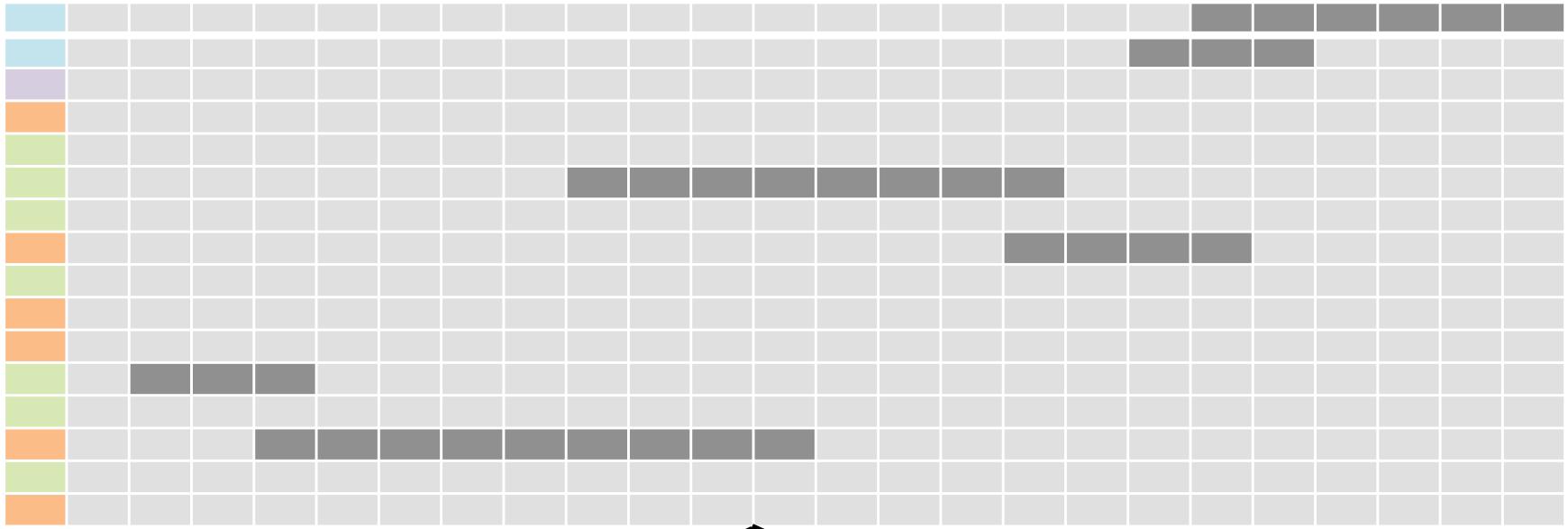


affirmative contexts
(in light grey)

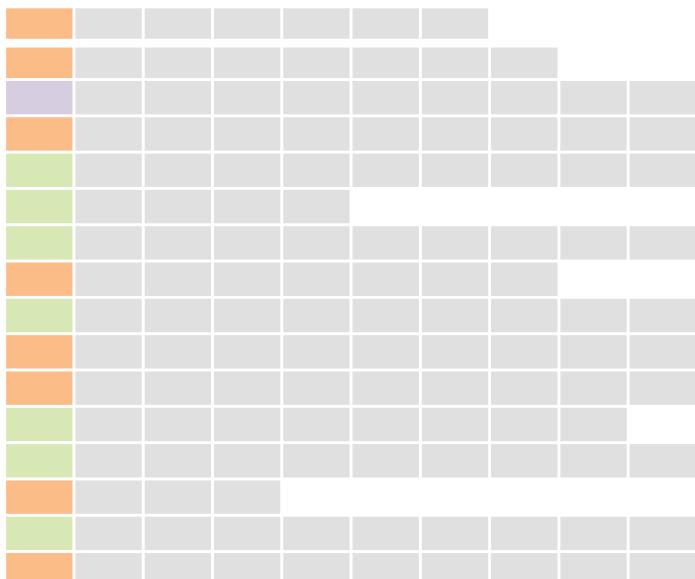
negated contexts
(in dark grey)

(Kiritchenko, Zhu, & Mohammad, 2014)

(Mohammad and Alm, 2015)



All the affirmative contexts



Generate sentiment lexicon for
words in affirmative context

All the negated contexts



Generate sentiment lexicon for
words in negated context

(Kiritchenko, Zhu, & Mohammad, 2014)

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=subtask-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/>

A few summarizing observations

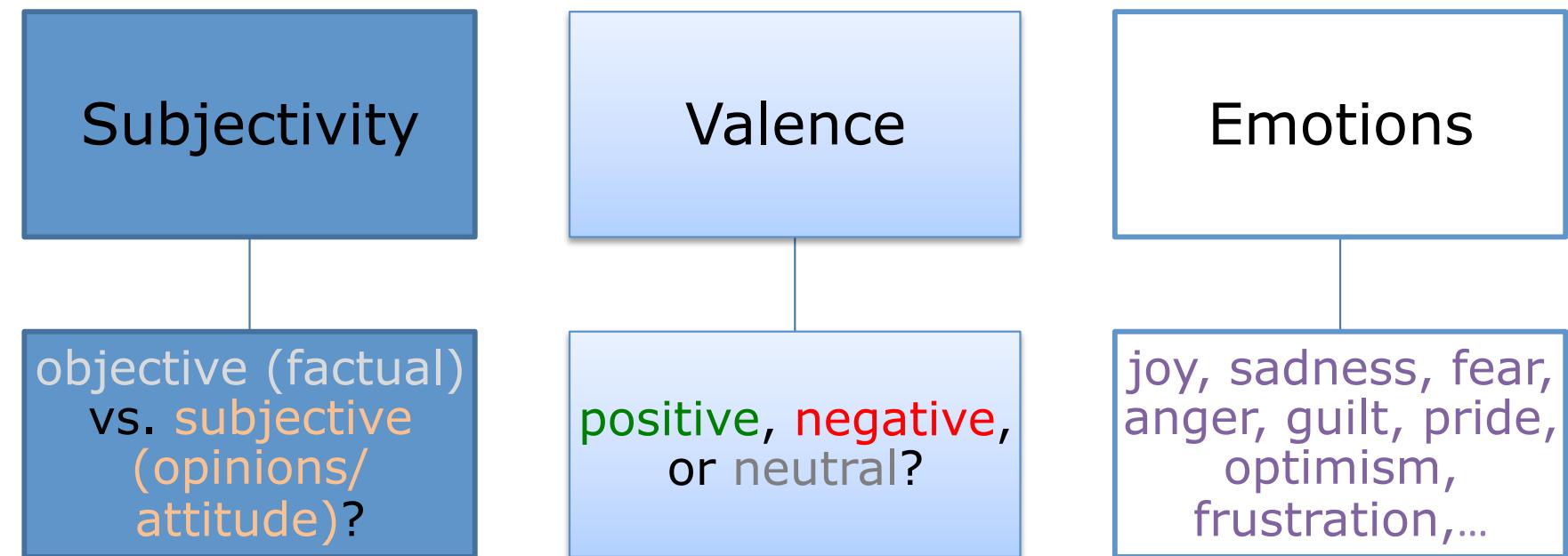
- Many lexical resources available for affect associations
 - Manually created, automatically generated
 - Word-level, sense-level
 - Binary, real-valued associations with a number of affect categories
- Annotation practices
 - How you phrase the question matters
 - Comparative aspect of task can lead 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

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

Analysis of affect



Subjectivity

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

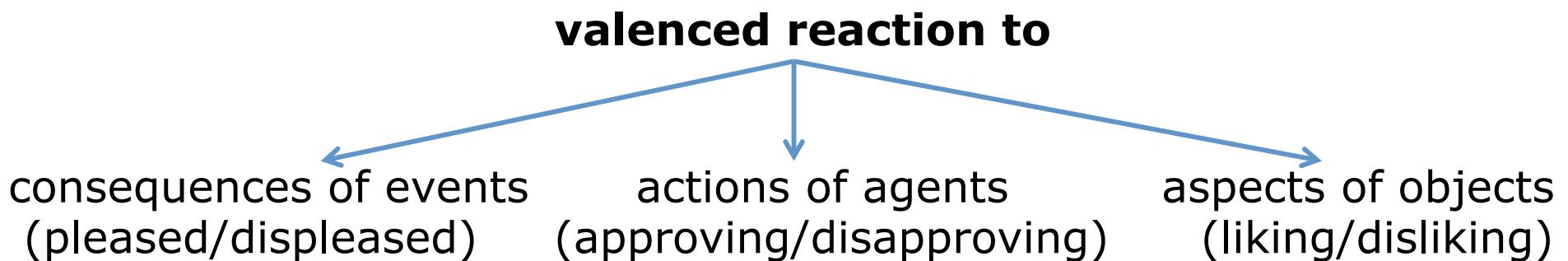
Not relevant: iPhone 5 has 326 pixels per inch

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)



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

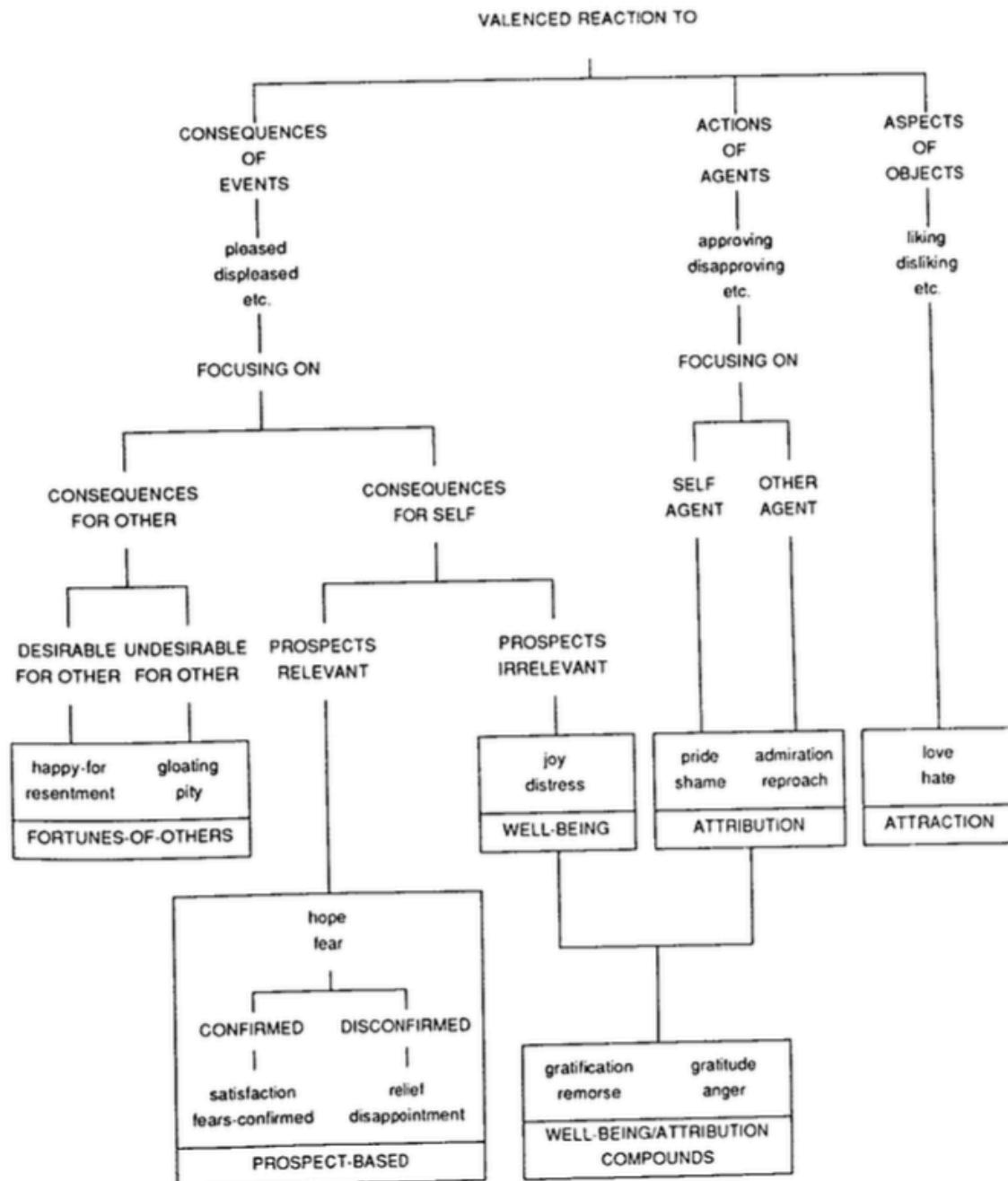


Figure 2.1. Global structure of emotion types.

(Ortony, Clore, & Collins, 1990)

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.

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/>

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/>

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

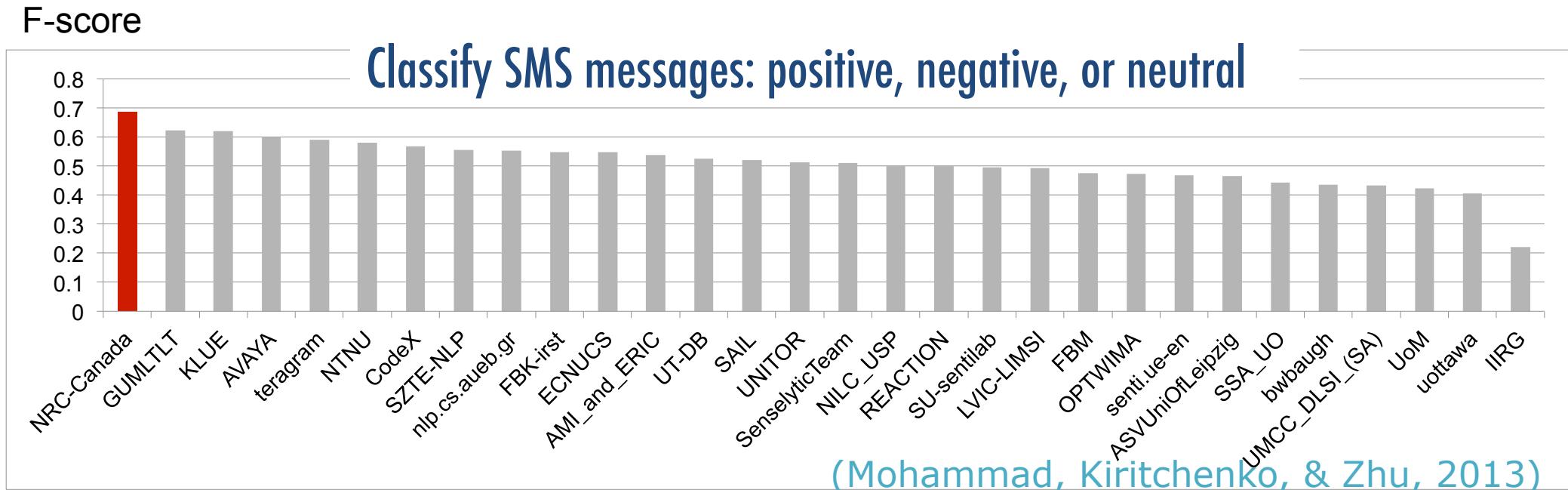
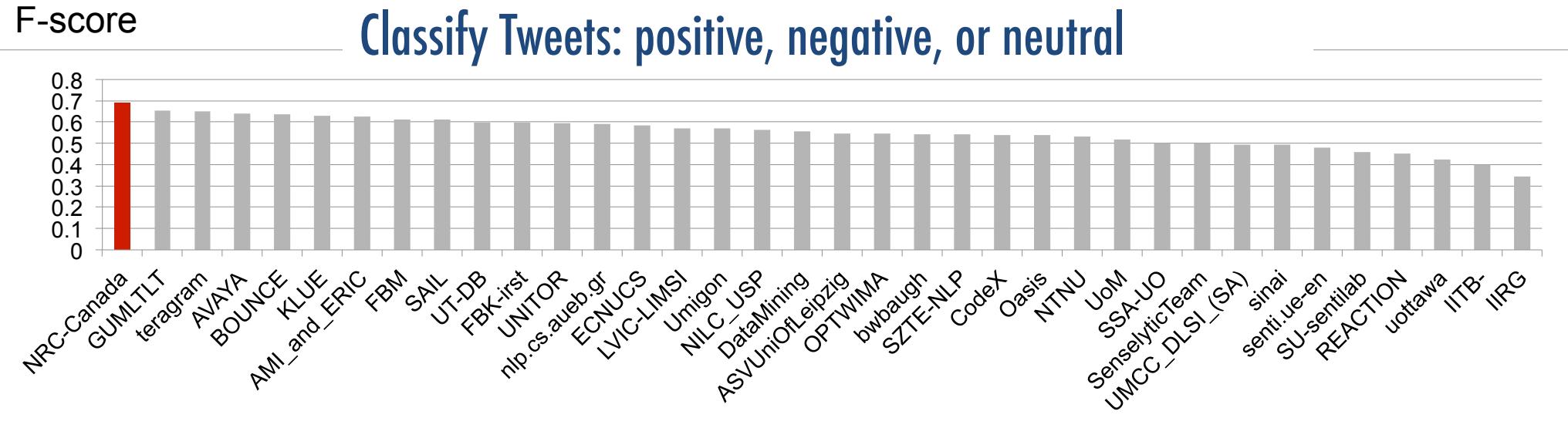
(Mohammad, Kiritchenko, & Zhu, 2013)

Features

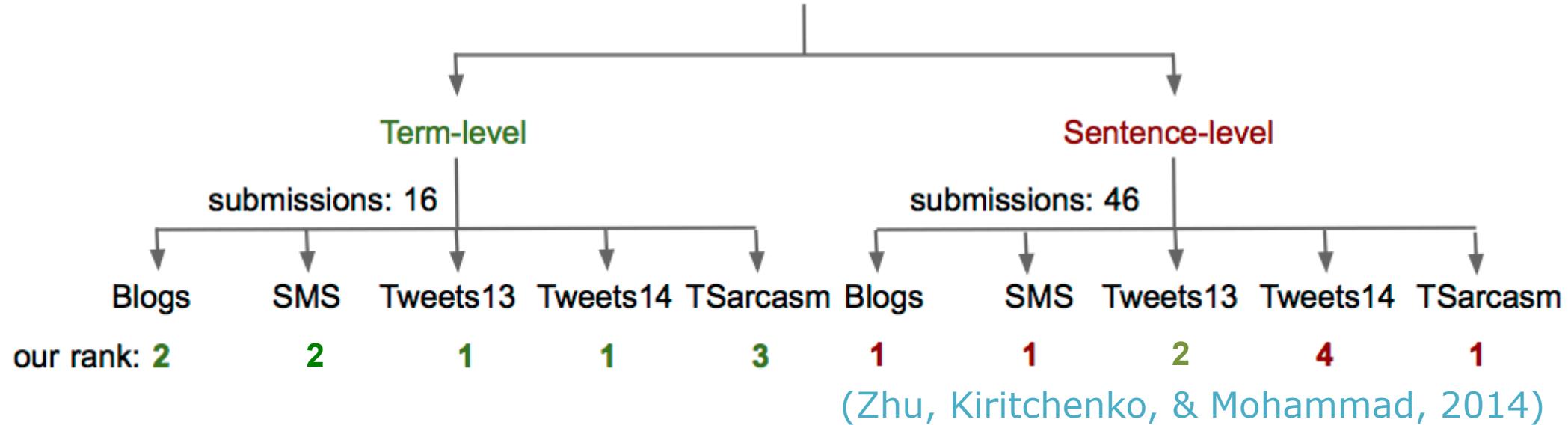
Features	Examples
sentiment lexicon	#positive: 3, scorePositive: 2.2; maxPositive: 1.3; last: 0.6, scoreNegative: 0.8, scorePositive_neg: 0.4
word n-grams	spectacular, like documentary
char n-grams	spect, docu, visua
part of speech	#N: 5, #V: 2, #A:1
negation	#Neg: 1; ngram:perfect → ngram:perfect_neg, 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)

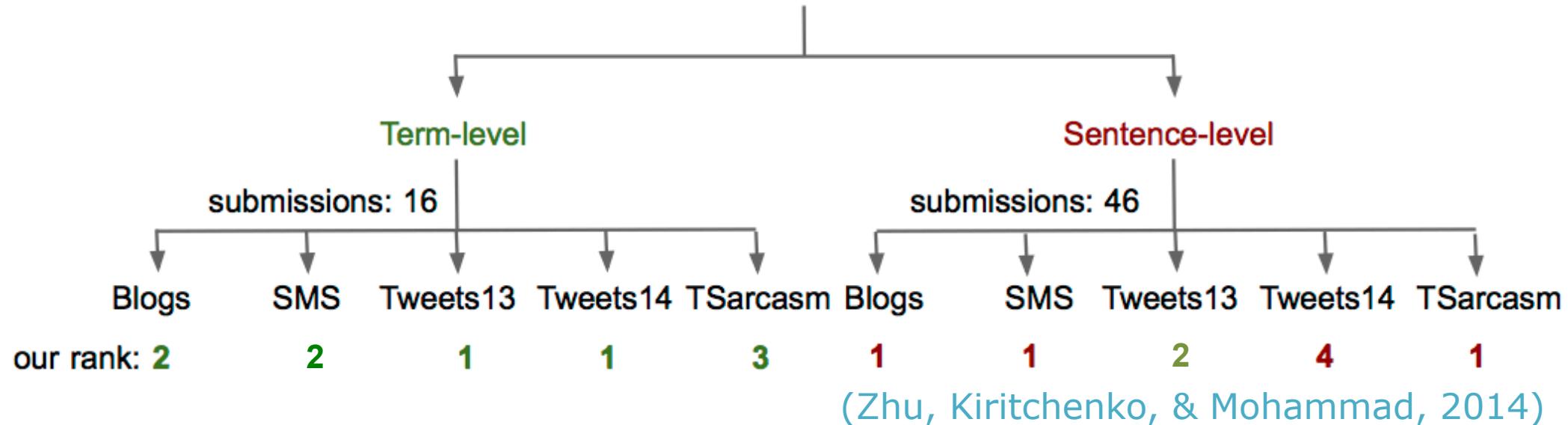
NRC-Canada's rankings in SemEval 2013 Shared Task (Sentiment Analysis in Twitter)



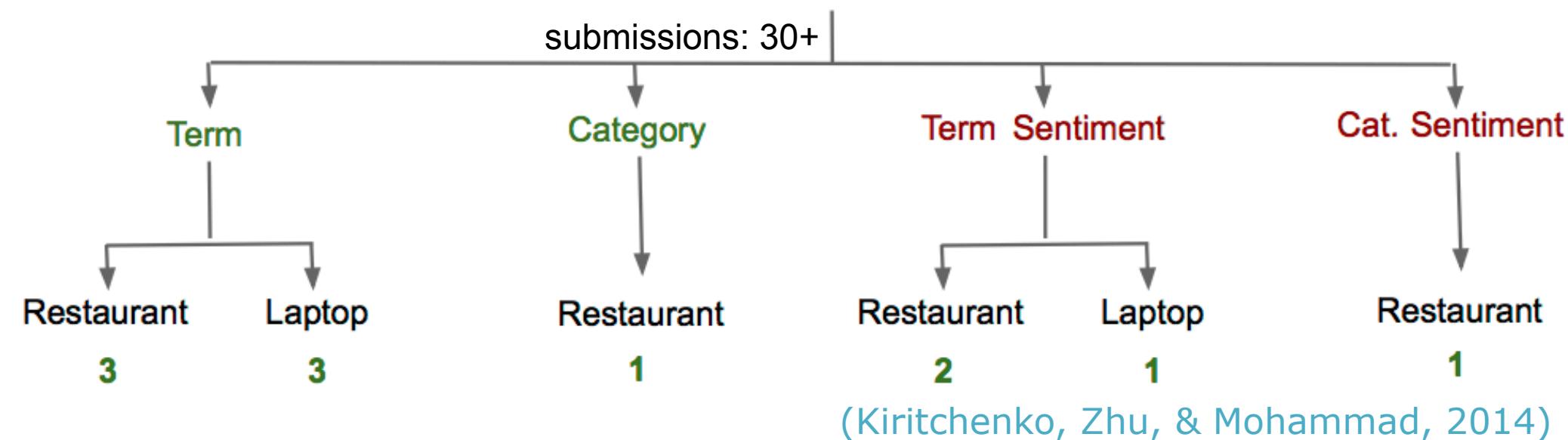
Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)



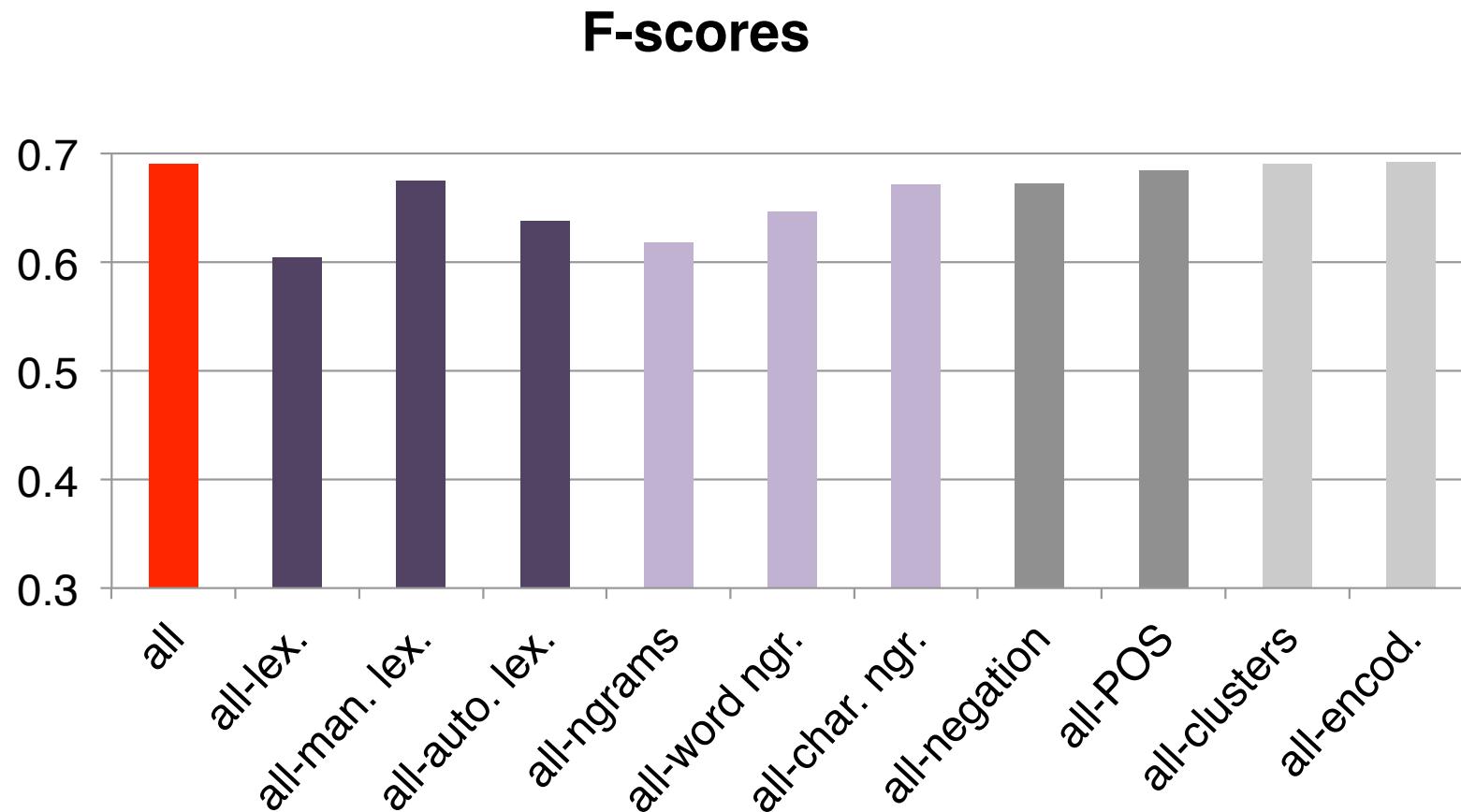
Sentiment Analysis of Social Media Texts (SemEval-2014 Task 9)



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



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.

Emotions

A word cloud representing a variety of emotions and sensations, including Love, Delight, Hurt, Fear, Pleasure, Powerlessness, Joy, Worry, Relaxed, Surprised, Relieved, Pride, Envy, Anger, Amusement, Helplessness, Irritation, Interest, Guilt, Contempt, Sadness, Embarrassment, Shame, Excitement, Empathy, Boredom, Stress, Disappointment, Happiness, Despair, Elation, Politeness, Calm, Frustration, Doubt, Serene, Shock, Tension, Trust, and Courage.

Six basic emotions

- generally associated with Ekman

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



"Big Six" ([Cornelius, 2000](#))

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>

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.

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.

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)

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.

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

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](#))

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

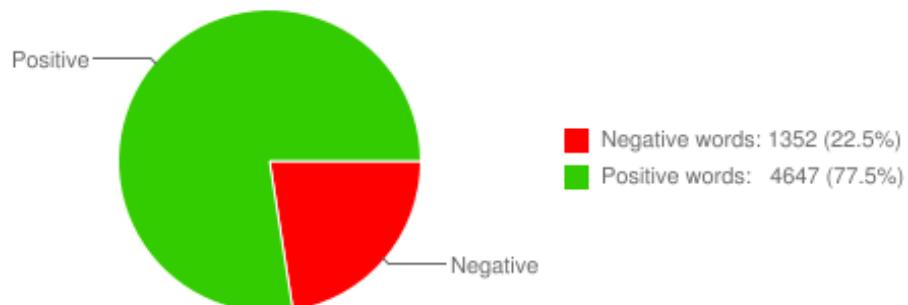
- Rich landscape of affect-related tasks
 - Subjectivity, valence, emotions
 - Reader or writer perspective
 - Attitude towards a target
- Many of the features and techniques used in valence classification are also helpful in emotion classification
- Additionally, for emotions:
 - Affect association 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

Visualizing Computational Outcomes

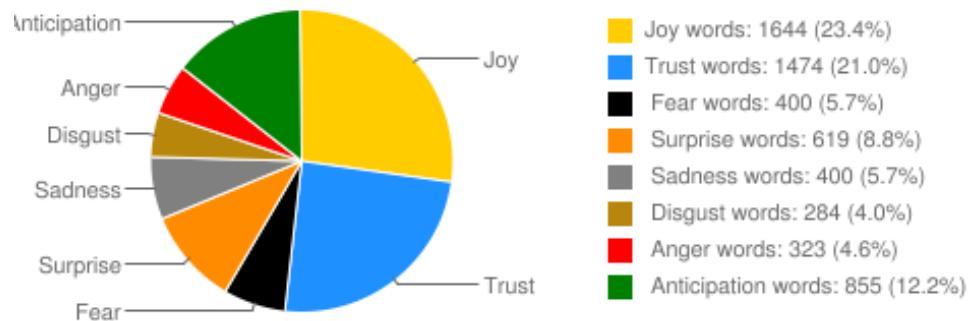
Topics:

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

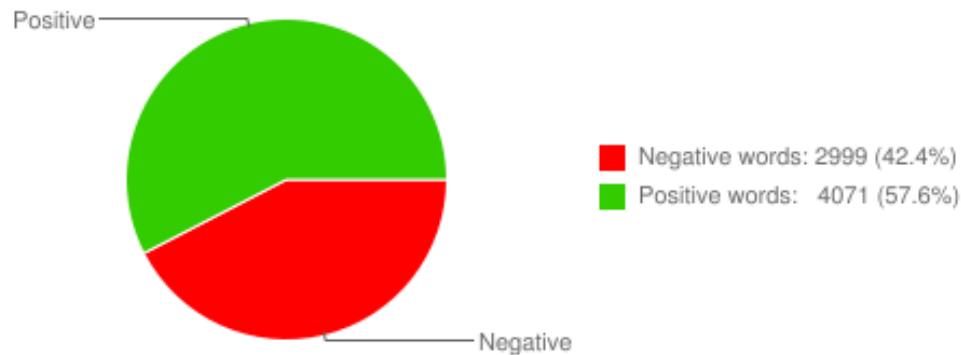
love letters



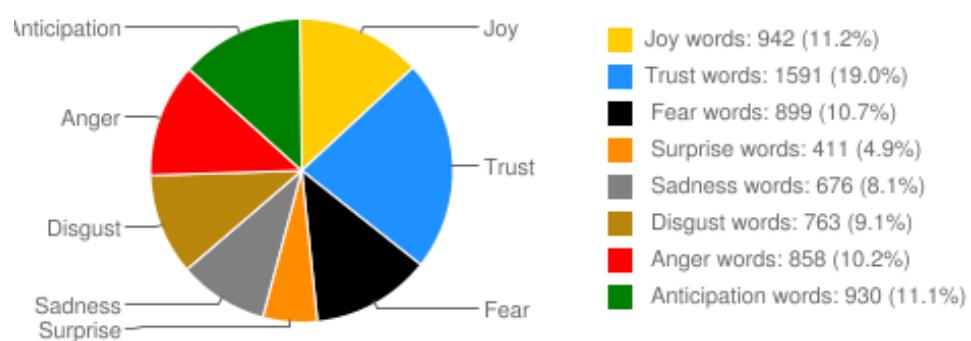
love letters



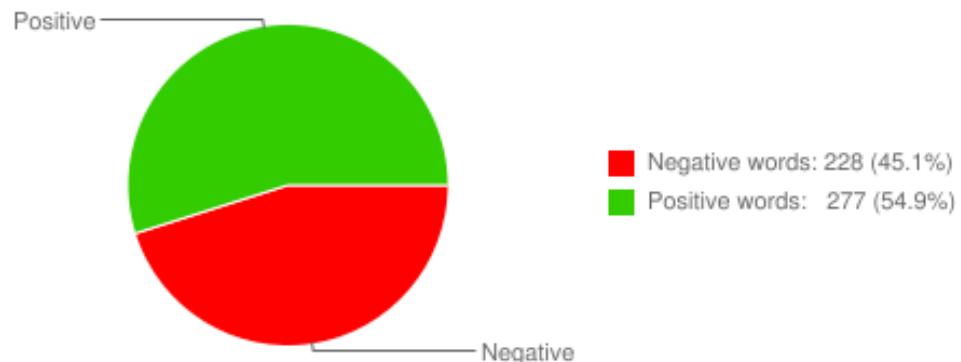
hate mail



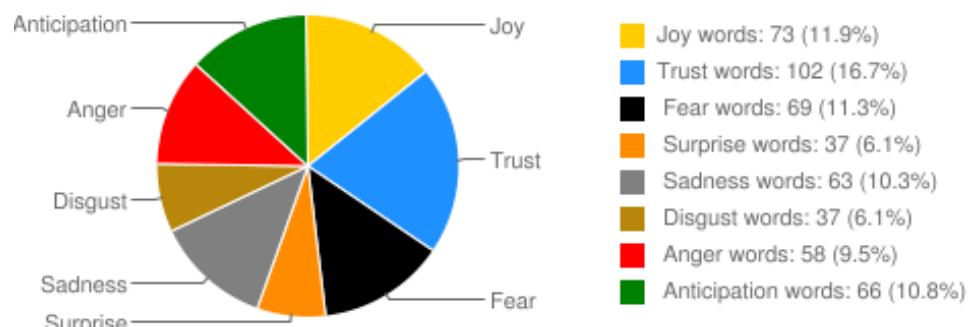
hate mail



suicide notes



suicide notes

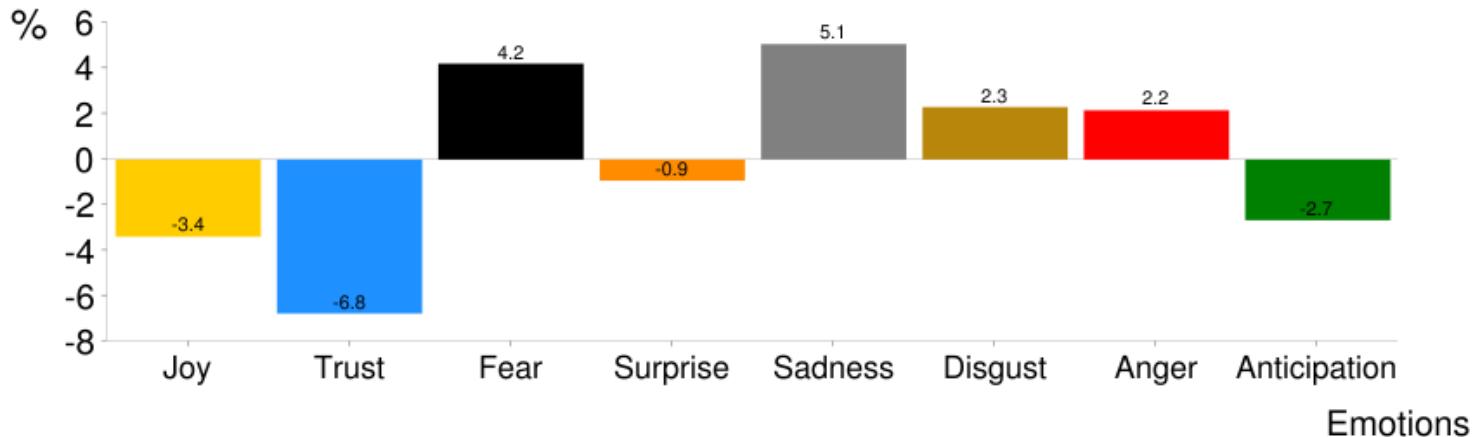


(Mohammad and Alm, 2015)

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(Mohammad & Yang, 2011)

Hamlet - As You Like It



servant esteem Sir **brother** marriage comfort
loving marry promise fortune virtuous smile
wonderful oath worthy money hope found remains faithful
tree honesty friendship **lover** sing synod respect
proud heavenly praise wear counsel perceive provide
wealth **pretty** church virgin perfect constant elder invite

relative salience of trust words

(Mohammad & Yang, 2011)

soldier sick beating buried forfeit doomsday

death malicious guilty confine **grief**

woe sorrow defeated **late** surrender scarcely

suppress **doubt** lose beg black mourning slaughter

frailty mourn dreadful **hell** loss shame perilous pious

hideous forbid prison **murder** fat witchcraft

shameful wretch cursed disappointed pernicious **mad**

shatter wreck jealousy sickness sadness wail sadly

slave confession sterile tragedy dismal gore hellish

unequal senseless crash prisoner bleeding wan **drown**

coward oppression drab **devil** affront affliction heartache

oppressor **plague** neglected tempest grieve barren suffering

guilt brute forgotten **poison** lament ashamed discomfort debt

murderer weeds dire retirement diseased lowest curse

sickly humble **feeling** nasty evil scourge disease offender

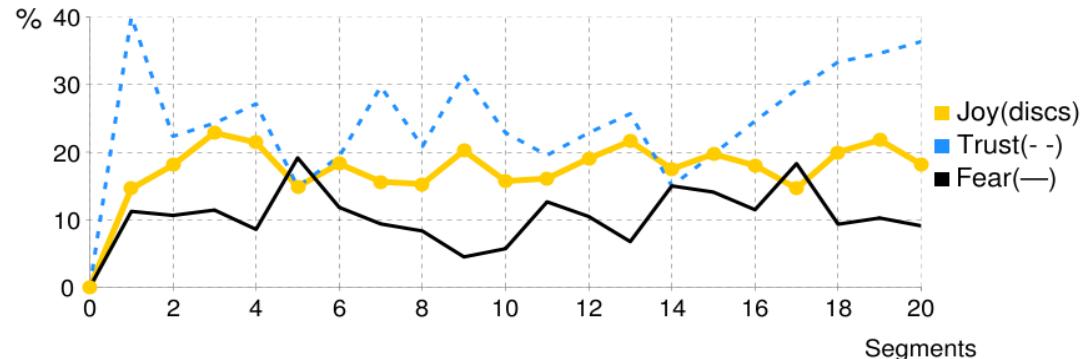
departed inter damnation bier **rue** wither **burial** ulcer remiss

gallows ache losing procession whine perdition shell defy
treachery murderous liquor dying

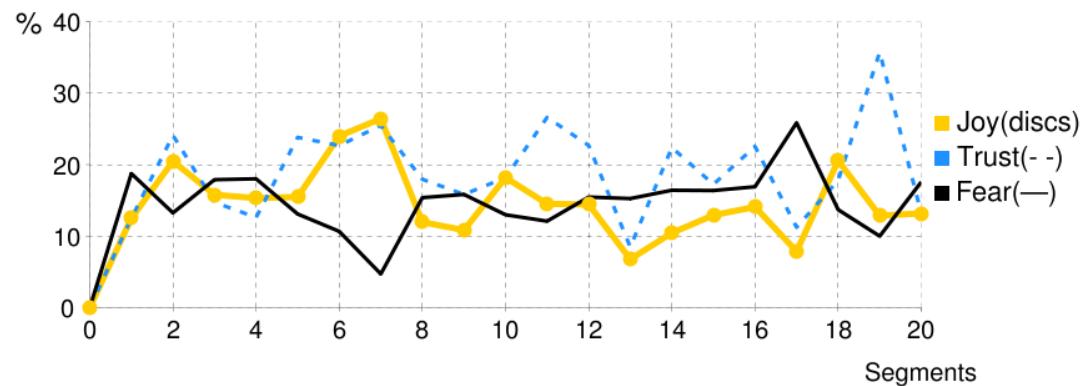
relative salience of sadness words

(Mohammad & Yang, 2011)

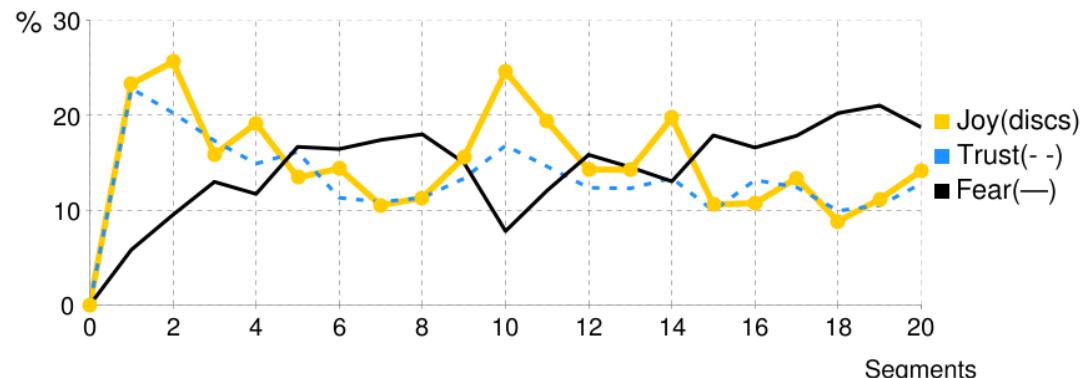
As You Like It



Hamlet



Frankenstein



(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)

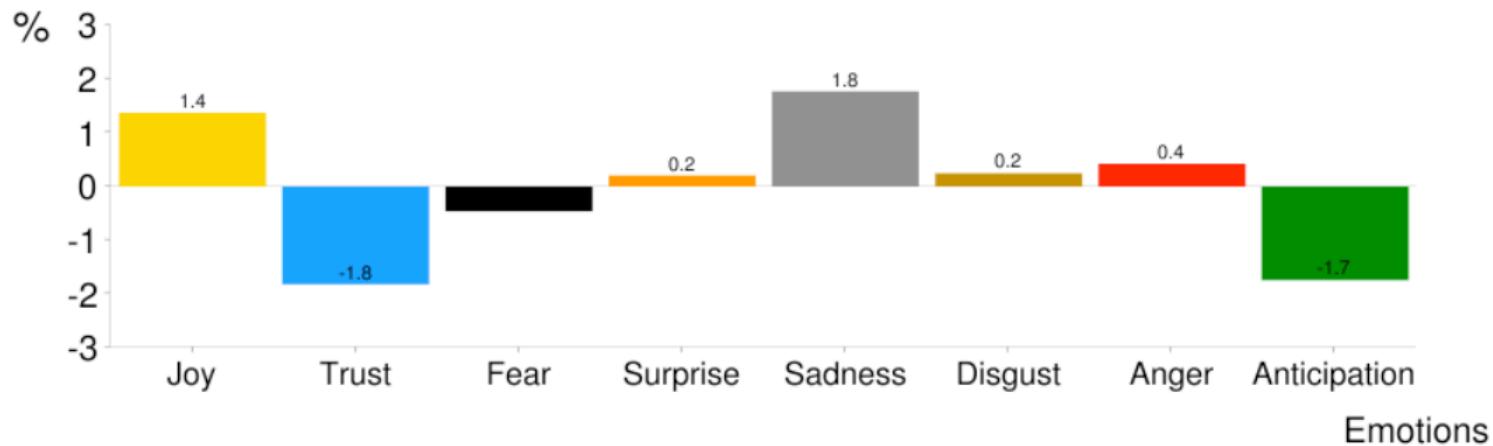
What are gender differences in
how writers use emotion words in work-place email?

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)

women to women - women to men

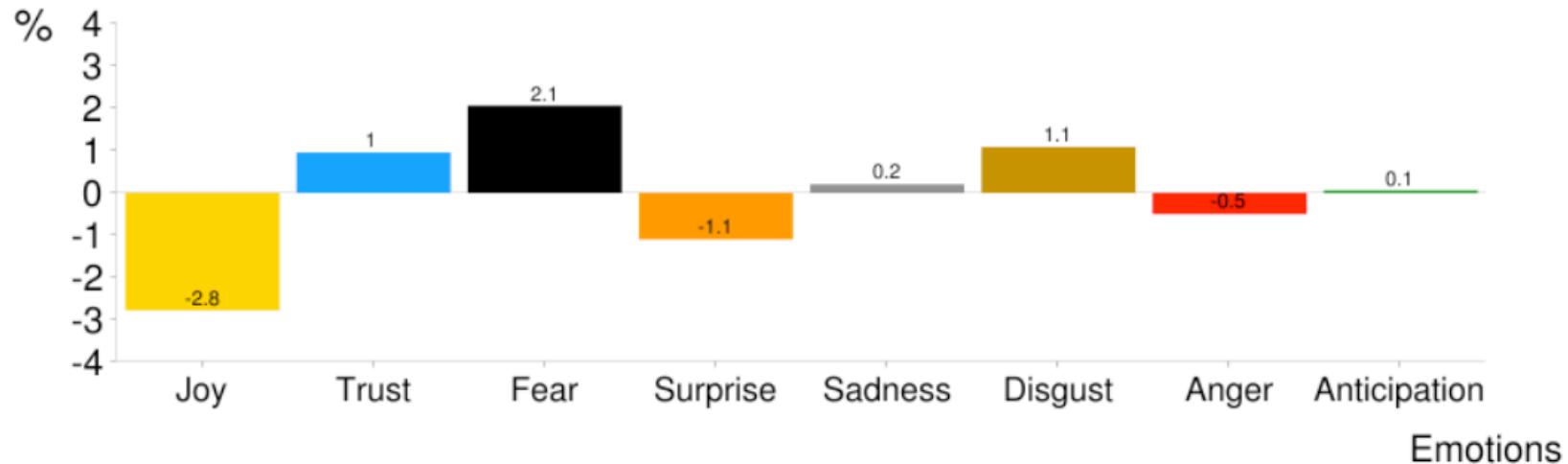


late **termination** missing sue sorrow tragedy
punished rob constraint art cancer regret bankruptcy
isolated cross bottom **problem** elimination
unsuccessful **feeling mistake** gore resign bankrupt
wanting sing sick exhausted broke adverse **error**
undesirable cumbersome violently kill wan struggle damage
margin ill hell crazy doubt resentment mourning
pointless misunderstanding woe **black** cancel bitch
condescension sin meaningless conflict hunter
lynch interrupted avalanche moody delay guilty

relative salience of sadness words

(Mohammad & Yang, 2011)

men to men - women to women



evil regulatory risk problem acrobat destination
prohibited nervous predicament shaky afraid

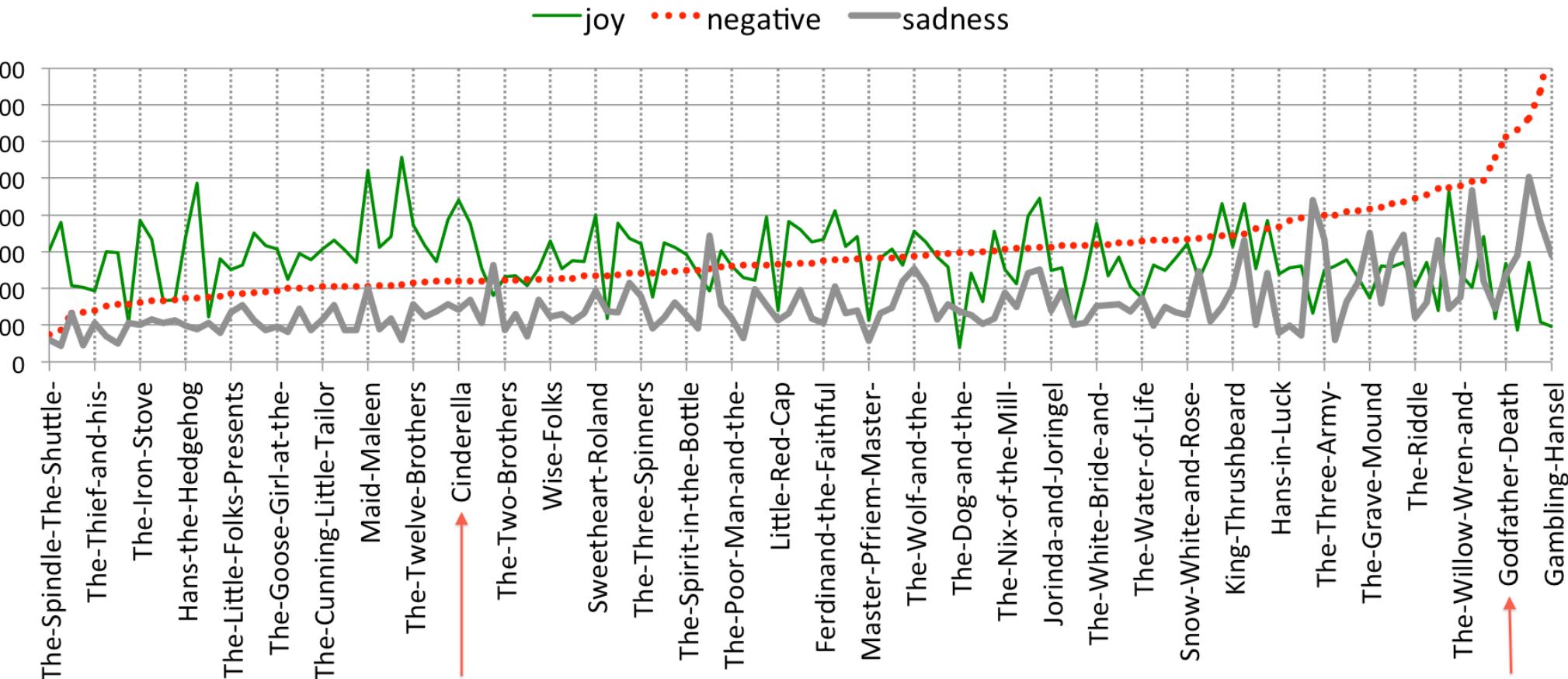
hearing forced attack lose lunacy avoid

missing worse attorney reluctant illegitimate horrible
bankruptcy government rob suspension suspect terminal
manipulation killing lawsuit hunting gun forgotten discourage
procedure confusion emergency **hunter** punitive
uncertain urgent threat opposed abomination police abandoned

relative salience of fear words

(Mohammad & Yang, 2011)

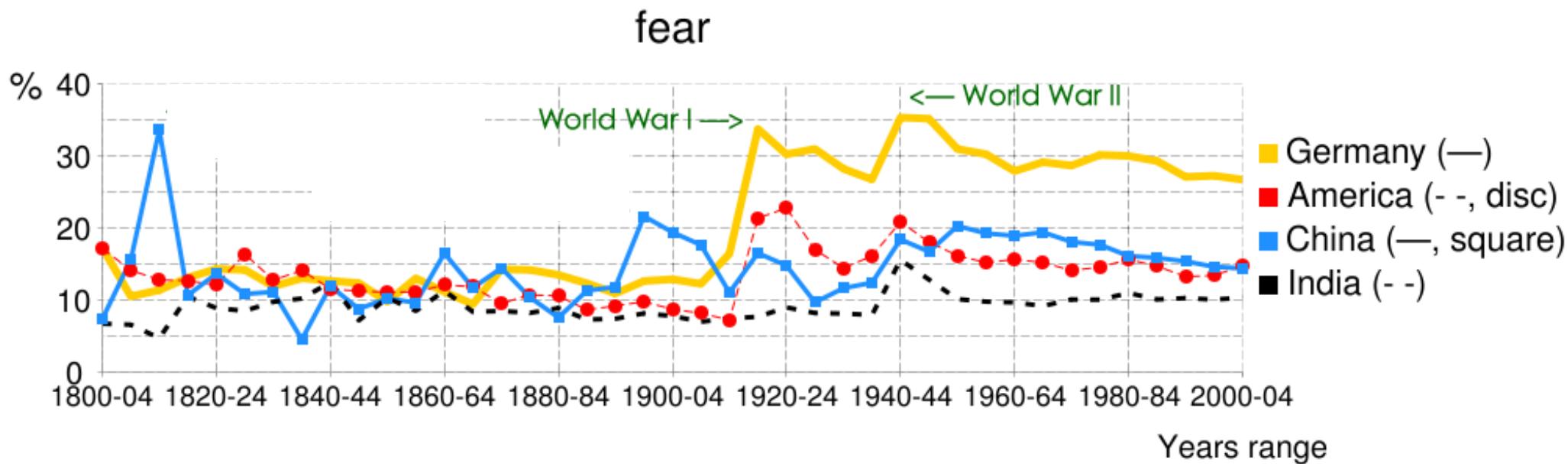
Emotion word density: Average number of emotion words in every X words



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

(Mohammad, 2011)

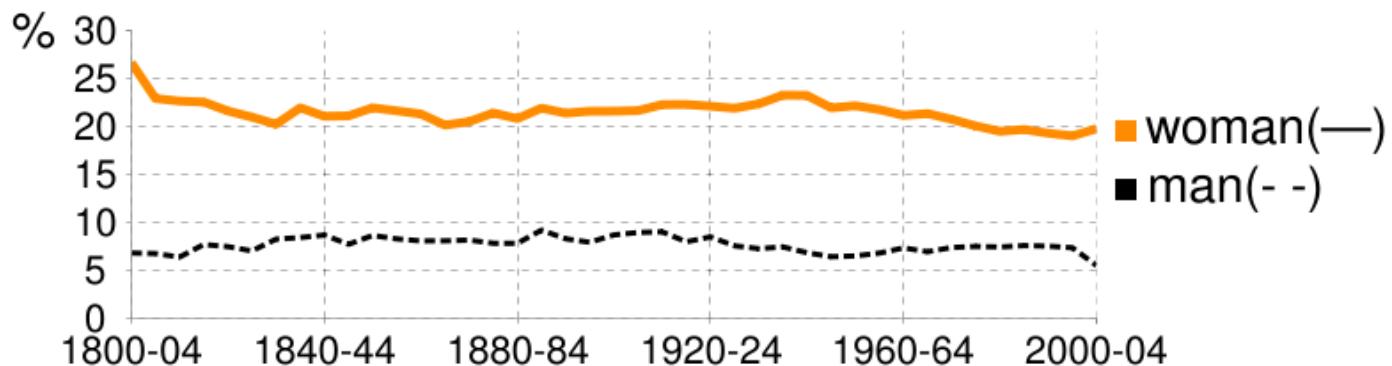
Analysis of emotion words in books



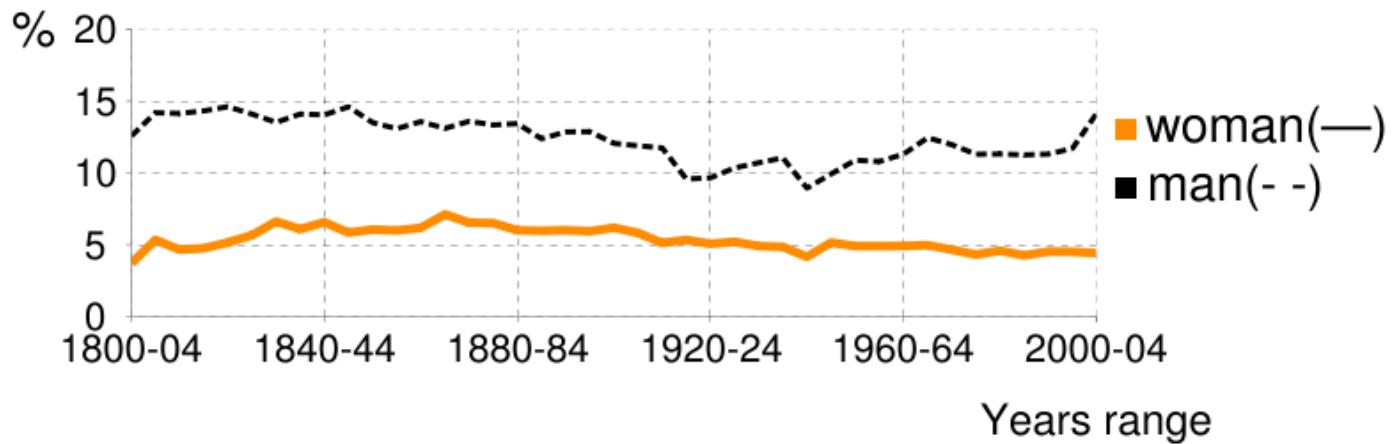
Percentage of fear words in close proximity to occurrences of America, China, Germany, and India in books.

(Mohammad, 2011)

joy



anger



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

(Mohammad, 2011)

(Mohammad and Alm, 2015)

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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>

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

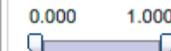
Term	Catnum	Secnum	Classnum
abacist	85	5	1
aback	235	10	2
abacus	85	5	1
abaft	235	10	2
abalienate	783	34	5
abalienation	783	34	5
abandon	293	12	2
	623	27	5
	624	27	5
	682	28	5
	703	28	5
	782	34	5
	859	36	6
	893	37	6
abandoned	460	17	4
	893	37	6
	945	38	6
abandonme..	624	27	5
	757	31	5
	782	34	5
	859	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

Classes



Category Affect Density

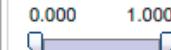
Negative



Positive



Anger



Anticipation



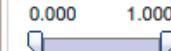
Disgust



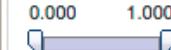
Fear



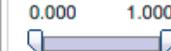
Joy



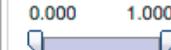
Sadness



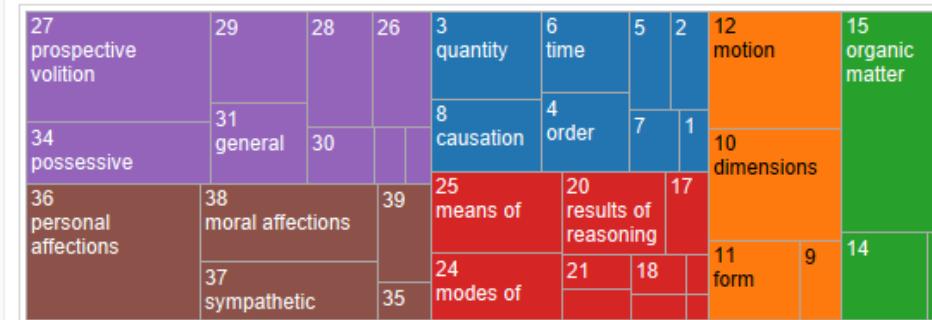
Surprise



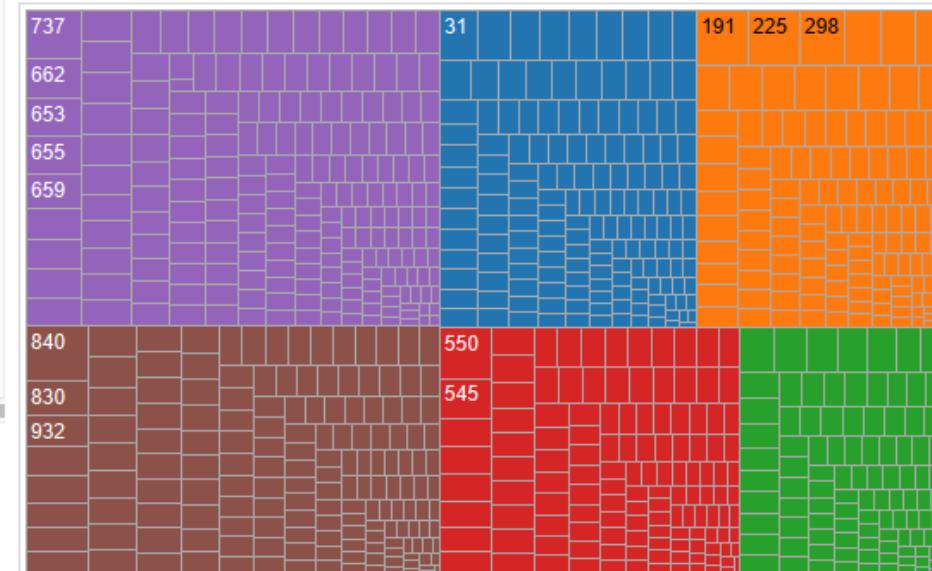
Trust



Sections



Categories



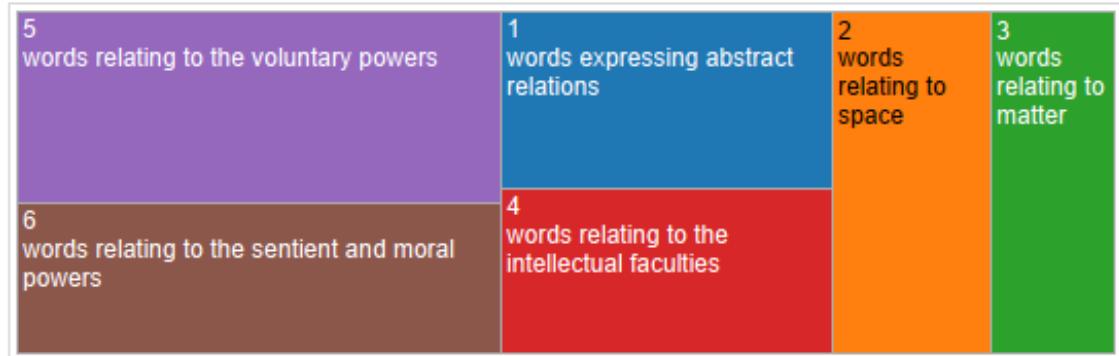
Note: Not all words in the thesaurus are listed in the emotion lexicon.

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

Classes



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

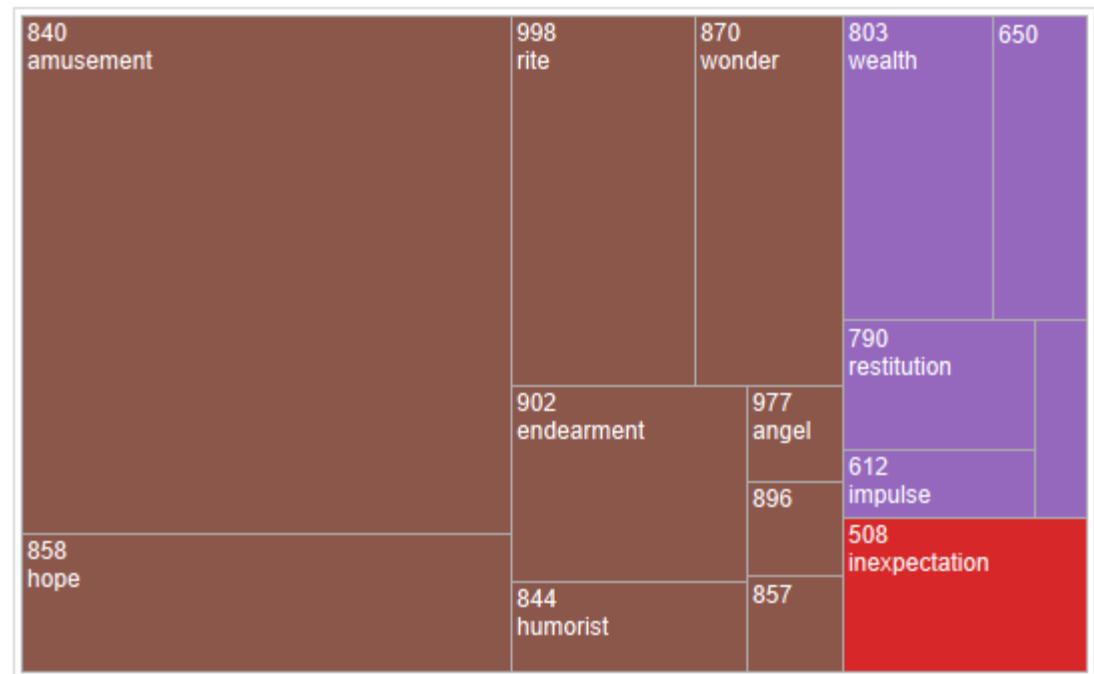
Categories

830 painfulness	972	895	851	867	938	886	934	988	545 deception	544	503	
	828	874 disrepute	893	879	863							
932	pain											
	940	929		880	975							
	945 vice											
837 dejection	839	898		962	866		848					
	860 fear				853		919					
900 resentment	907	954		930	950							
				964	947							
653 uncleanness	732 failure	791	645	674	756	792	804					
		699	640									
655 disease	649 badness	739	688	807	761							
				681	808							
	713 discord	735	752									
659 deterioration				719	617							
	716 attack	708	665	663	815							

(Mohammad, 2015a)

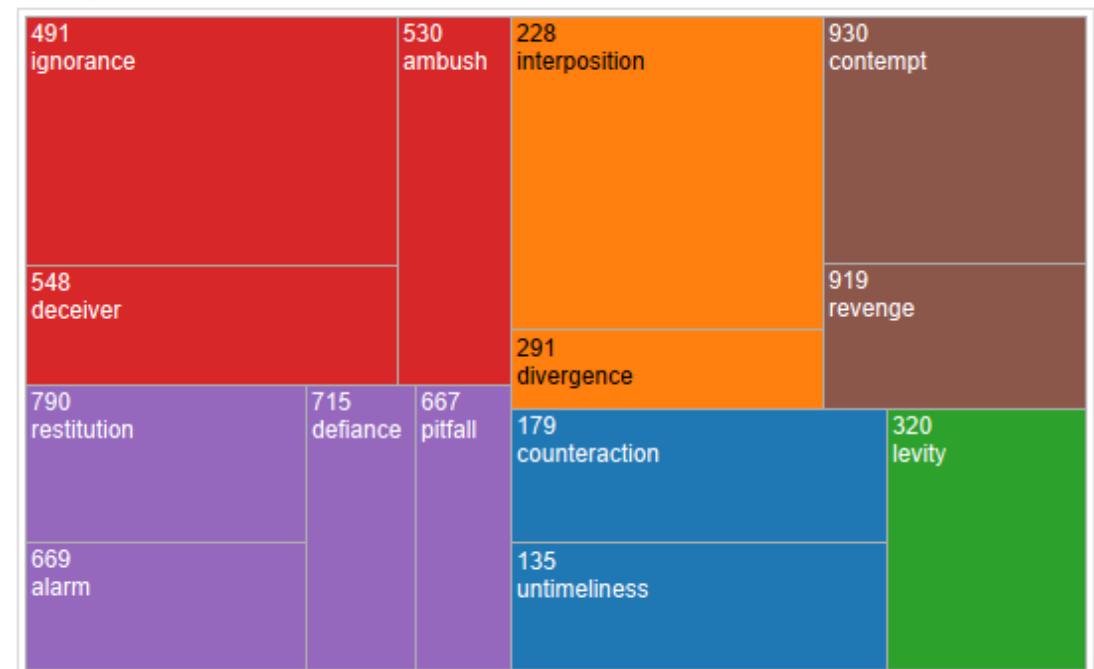
Surprise and Positive

Categories



Surprise and Negative

Categories



(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.

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

Political science

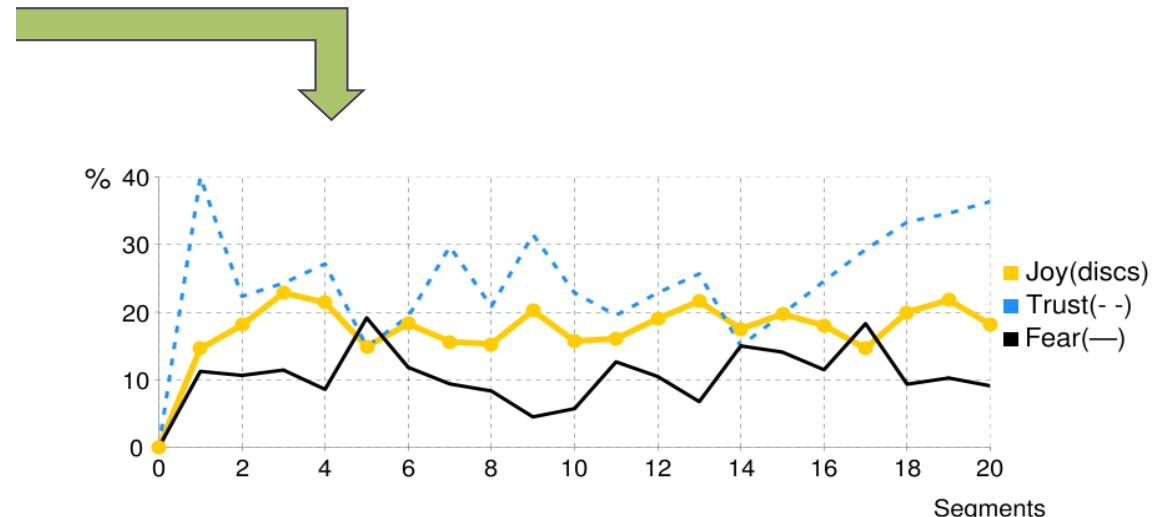
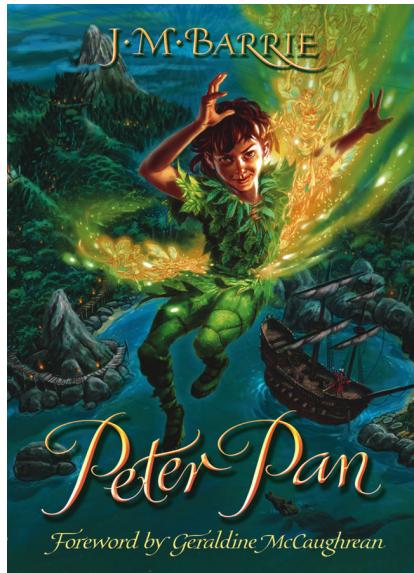
- Identify current public opinion towards the candidates in an election (nowcasting) (Golbeck & Hansen, 2011; Conover et al., 2011b; Mohammad et al., 2015)
- Identifying contentious issues (Maynard & Funk, 2011)
- Detecting voter polarization (Conover et al., 2011a)
- Predicting the number of votes a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

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)



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Pno.

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

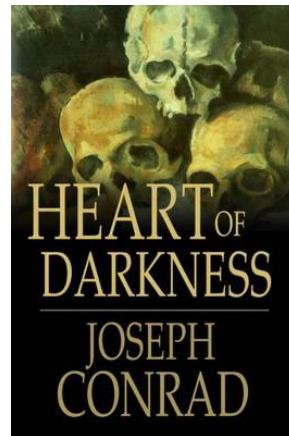
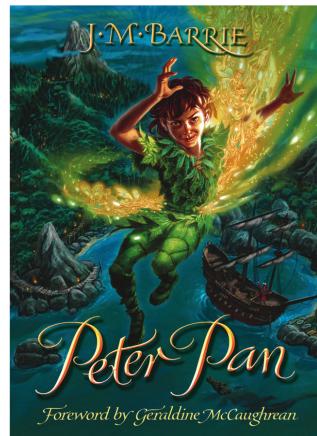
- Three simultaneous piano melodies pertaining to the dominant emotions.
- Overall positiveness (or, negativeness) determines:
 - whether C major or C minor
 - base octave
- Partition the novel into many small sections
- For each section, if emotion density is high:
 - play many short notes
 - more dissonant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

(Davis & Mohammad, 2014)

Pieces by TransProse

Three simultaneous piano melodies pertaining to the dominant emotions.

Examples

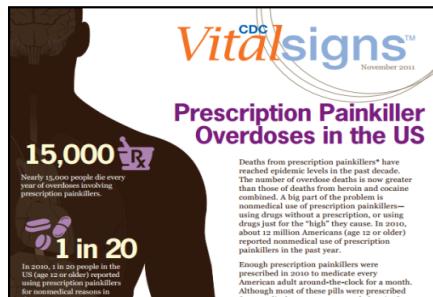


TransProse: www.musicfromtext.com

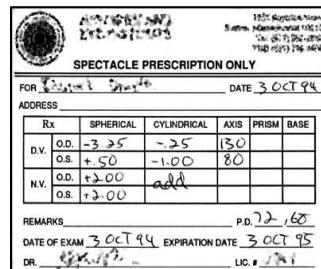
Music played 300,000 times since website launched in April 2014.

(Davis & Mohammad, 2014)

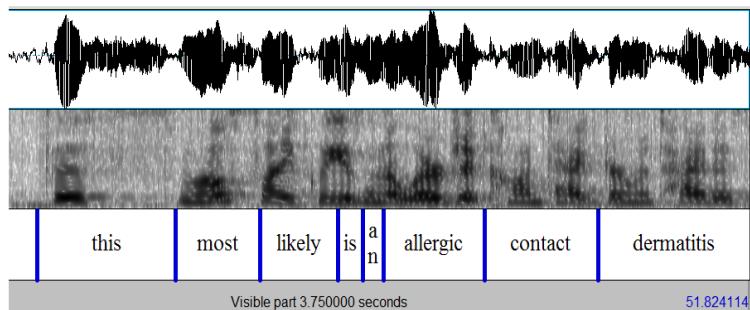
Pervasiveness of language data in the clinical domain



Medical ads



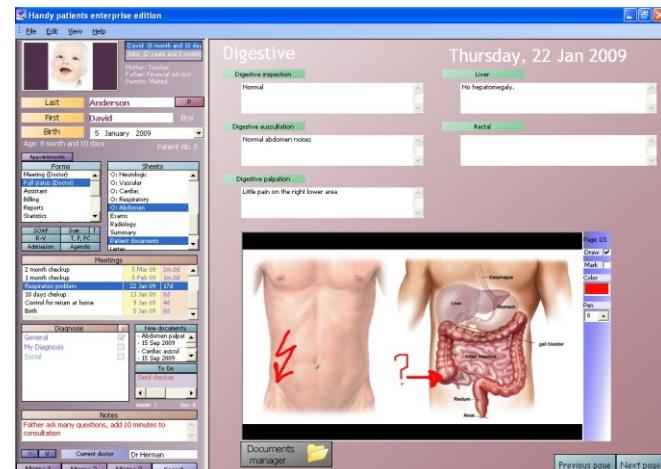
Prescriptions



Recordings of physicians/patients

A screenshot of a PubMed search results page. The URL is <https://pubmed.ncbi.nlm.nih.gov/20411480/>. The page title is 'Using Semantic Web technology to support ICD-11 textual definitions authoring'. It includes details about the study, authors (Jiang G, Solbrig HRS, Chute CG), and institutions (Department of Health Sciences Research, Mayo Clinic, Rochester, MN, USA). The text discusses the beta phase of the 11th revision of International Classification of Diseases (ICD-11) and how semantic web technology can be used to support its development.

Articles (PubMed)



Medical records



Patients
at home/on the go



Social media,
health forums
(Mohammad and Alm, 2015)



Patient-physician consultations
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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 physiotherapists for the elderly, disabled, and the sick

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)

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.

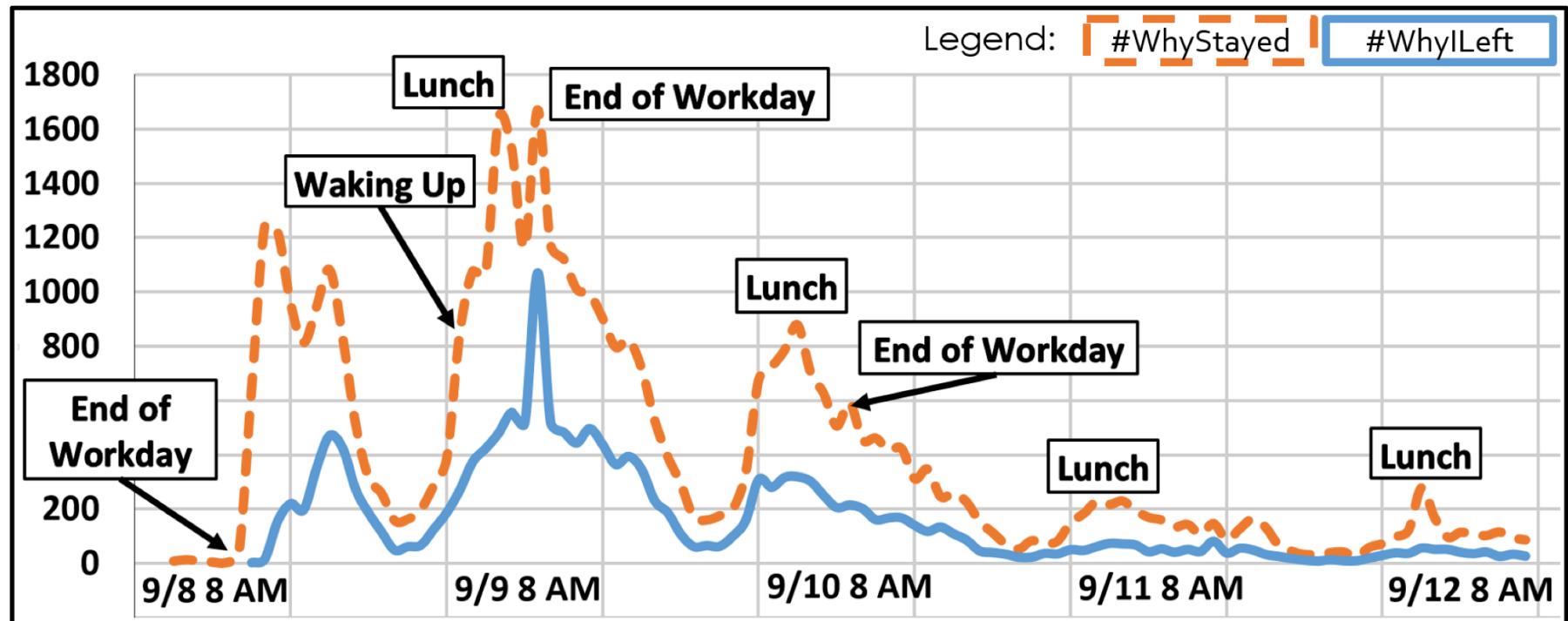
Twitter discussion about domestic abuse

#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

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

Diagnostic confidence as categories in prediction problems

		Correct	Incorrect
Confident	Correct	Appropriate Confidence	Overconfidence
	Incorrect	Underconfidence	Appropriate Confidence

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

Ideal vs. problematic

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.

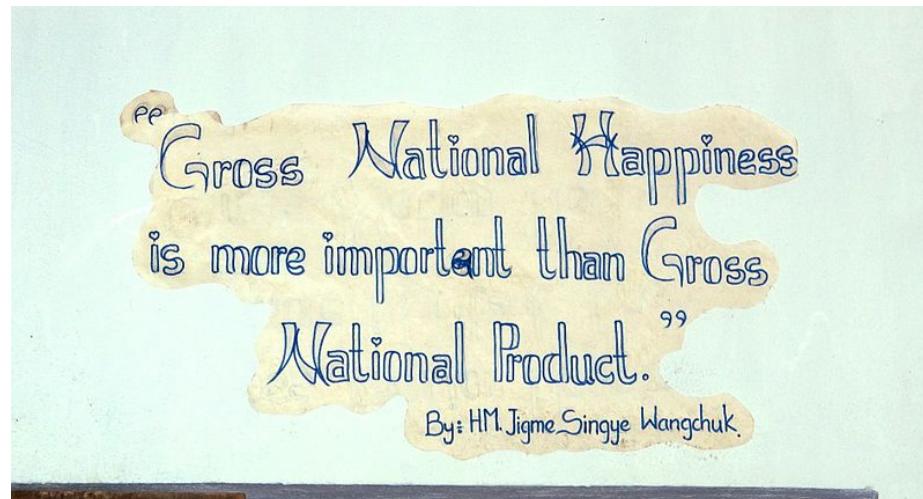
Education and affect analysis



- 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**.

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, & Fabrizio, 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

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!



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)

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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.

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