CS 124/LINGUIST 180
From Languages to Information

Dan Jurafsky
Stanford University

Detecting Social and Affective Meaning
Affective meaning

• Drawing on literatures in
  • affective computing (Picard 95)
  • linguistic subjectivity (Wiebe and colleagues)
  • social psychology (Pennebaker and colleagues)

• Can we model the lexical semantics relevant to:
  • sentiment
  • emotion
  • personality
  • mood
  • attitudes
Why compute affective meaning?

- Detecting:
  - sentiment towards politicians, products, countries, ideas
  - frustration of callers to a help line
  - stress in drivers or pilots
  - depression and other medical conditions
  - confusion in students talking to e-tutors
  - emotions in novels (e.g., for studying groups that are feared over time)

- Could we generate:
  - emotions or moods for literacy tutors in the children’s storybook domain
  - emotions or moods for computer games
  - personalities for dialogue systems to match the user
Scherer’s typology of affective states

**Emotion:** relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance
  - angry, sad, joyful, fearful, ashamed, proud, desperate

**Mood:** diffuse affect state ... change in subjective feeling, of low intensity but relatively long duration, often without apparent cause
  - cheerful, gloomy, irritable, listless, depressed, buoyant

**Interpersonal stance:** affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange
  - distant, cold, warm, supportive, contemptuous

**Attitudes:** relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons
  - liking, loving, hating, valuing, desiring

**Personality traits:** emotionally laden, stable personality dispositions and behavior tendencies, typical for a person
  - nervous, anxious, reckless, morose, hostile, envious, jealous
Detecting Social and Affective Meaning

Reminder: Sentiment Lexicons
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The General Inquirer


- Home page: [http://www.wjh.harvard.edu/~inquirer](http://www.wjh.harvard.edu/~inquirer)
- List of Categories: [http://www.wjh.harvard.edu/~inquirer/homecat.htm](http://www.wjh.harvard.edu/~inquirer/homecat.htm)
- Spreadsheet: [http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls](http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls)
- Categories:
  - Positiv (1915 words) and Negativ (2291 words)
  - Strong vs Weak, Active vs Passive, Overstated versus Understated
  - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use
LIWC (Linguistic Inquiry and Word Count)


- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- $30 or $90 fee
MPQA Subjectivity Cues Lexicon


- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL
Bing Liu Opinion Lexicon


- Bing Liu's Page on Opinion Mining
- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar

- 6786 words
  - 2006 positive
  - 4783 negative
SentiWordNet


- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- \[ \text{estimable}(J,3) \] “may be computed or estimated”
  \[ \text{Pos} \ 0 \quad \text{Neg} \ 0 \quad \text{Obj} \ 1 \]
- \[ \text{estimable}(J,1) \] “deserving of respect or high regard”
  \[ \text{Pos} \ .75 \quad \text{Neg} \ 0 \quad \text{Obj} \ .25 \]
Detecting Social and Affective Meaning

Sentiment Lexicons
Detecting Social and Affective Meaning

Emotion
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Two families of theories of emotion

• Atomic basic emotions
  • A finite list of 6 or 8, from which others are generated

• Dimensions of emotion
  • Valence (positive negative)
  • Arousal (strong, weak)
  • Control
Ekman’s 6 basic emotions:
Surprise, happiness, anger, fear, disgust, sadness
Valence/Arousal Dimensions

High arousal, low pleasure
- anger

High arousal, high pleasure
- excitement

Low arousal, low pleasure
- sadness

Low arousal, high pleasure
- relaxation
Atomic units vs. Dimensions

Distinctive
- Emotions are units.
- Limited number of basic emotions.
- Basic emotions are innate and universal

Dimensional
- Emotions are dimensions.
- Limited # of labels but unlimited number of emotions.
- Emotions are culturally learned.

Adapted from Julia Braverman
One emotion lexicon from each paradigm!

1. 8 basic emotions:
   • NRC Word-Emotion Association Lexicon (Mohammad and Turney 2011)

2. Dimensions of valence/arousal/dominance
   • Warriner, A. B., Kuperman, V., and Brysbaert, M. (2013)
   • Both built using Amazon Mechanical Turk
Plutchick’s wheel of emotion

- 8 basic emotions
- in four opposing pairs:
  - joy–sadness
  - anger–fear
  - trust–disgust
  - anticipation–surprise
NRC Word-Emotion Association Lexicon

Mohammad and Turney 2011

- 10,000 words chosen mainly from earlier lexicons
- Labeled by Amazon Mechanical Turk
- 5 Turkers per hit
- Give Turkers an idea of the relevant sense of the word

Result:

- amazingly anger 0
- amazingly anticipation 0
- amazingly disgust 0
- amazingly fear 0
- amazingly joy 1
- amazingly sadness 0
- amazingly surprise 1
- amazingly trust 0
- amazingly negative 0
- amazingly positive 1

**EmoLex**

<table>
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<th># of terms</th>
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<td>Adjectives</td>
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<td>Adverbs</td>
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<td>Nouns</td>
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<td>Verbs</td>
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<td>Negative</td>
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<td>4226</td>
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<tr>
<td>Anger terms</td>
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<tr>
<td>Disgust terms</td>
<td>37</td>
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<tr>
<td>Fear terms</td>
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<tr>
<td>Joy terms</td>
<td>165</td>
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<tr>
<td>Sadness terms</td>
<td>120</td>
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<tr>
<td>Surprise terms</td>
<td>53</td>
</tr>
<tr>
<td>Union</td>
<td>10170</td>
</tr>
</tbody>
</table>
The AMT Hit

Prompt word: startle

Q1. Which word is closest in meaning (most related) to startle?
- automobile
- shake
- honesty
- entertain

Q2. How positive (good, praising) is the word startle?
- startle is not positive
- startle is weakly positive
- startle is moderately positive
- startle is strongly positive

Q3. How negative (bad, criticizing) is the word startle?
- startle is not negative
- startle is weakly negative
- startle is moderately negative
- startle is strongly negative

Q4. How much is startle associated with the emotion joy? (For example, happy and fun are strongly associated with joy.)
- startle is not associated with joy
- startle is weakly associated with joy
- startle is moderately associated with joy
- startle is strongly associated with joy

Q5. How much is startle associated with the emotion sadness? (For example, failure and heartbreak are strongly associated with sadness.)
- startle is not associated with sadness
- startle is weakly associated with sadness
- startle is moderately associated with sadness
- startle is strongly associated with sadness

Q6. How much is startle associated with the emotion fear? (For example, horror and scary are strongly associated with fear.)
- Similar choices as in 4 and 5 above

Q7. How much is startle associated with the emotion anger? (For example, rage and shouting are strongly associated with anger.)
- Similar choices as in 4 and 5 above

Q8. How much is startle associated with the emotion trust? (For example, faith and integrity are strongly associated with trust.)
- Similar choices as in 4 and 5 above

Q9. How much is startle associated with the emotion disgust? (For example, gross and cruelty are strongly associated with disgust.)
- Similar choices as in 4 and 5 above
Lexicon of valence, arousal, and dominance

- Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.

- Ratings for 14,000 words for emotional dimensions:
  - valence (the pleasantness of the stimulus)
  - arousal (the intensity of emotion provoked by the stimulus)
  - dominance (the degree of control exerted by the stimulus)
Lexicon of valence, arousal, and dominance

- **valence** (the pleasantness of the stimulus)
  - 9: happy, pleased, satisfied, contented, hopeful
  - 1: unhappy, annoyed, unsatisfied, melancholic, despaired, or bored
- **arousal** (the intensity of emotion provoked by the stimulus)
  - 9: stimulated, excited, frenzied, jittery, wide-awake, or aroused
  - 1: relaxed, calm, sluggish, dull, sleepy, orunaroused;
- **dominance** (the degree of control exerted by the stimulus)
  - 9: in control, influential, important, dominant, autonomous, or controlling
  - 1: controlled, influenced, cared-for, awed, submissive, or guided
- Again produced by AMT
Lexicon of valence, arousal, and dominance: Examples

<table>
<thead>
<tr>
<th></th>
<th>Valence</th>
<th>Arousal</th>
<th>Dominance</th>
</tr>
</thead>
<tbody>
<tr>
<td>vacation</td>
<td>8.53</td>
<td>rampage</td>
<td>7.56</td>
</tr>
<tr>
<td>happy</td>
<td>8.47</td>
<td>tornado</td>
<td>7.45</td>
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<tr>
<td>whistle</td>
<td>5.7</td>
<td>zucchini</td>
<td>4.18</td>
</tr>
<tr>
<td>conscious</td>
<td>5.53</td>
<td>dressy</td>
<td>4.15</td>
</tr>
<tr>
<td>torture</td>
<td>1.4</td>
<td>dull</td>
<td>1.67</td>
</tr>
</tbody>
</table>
Detecting Social and Affective Meaning

Other Useful Lexicons
Concreteness versus abstractness

- The degree to which the concept denoted by a word refers to a perceptible entity.
  - Do concrete and abstract words differ in connotation?
  - Storage and retrieval?
  - Bilingual processing?
  - Relevant for embodied view of cognition (Barsalou 1999 inter alia)
    - Do concrete words activate brain regions involved in relevant perception
- Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.
- 37,058 English words and 2,896 two-word expressions ("zebra crossing" and "zoom in"),
- Rating from 1 (abstract) to 5 (concrete)
- Calibrator words:
  - shirt, infinity, gas, grasshopper, marriage, kick, polite, whistle, theory, and sugar
Concreteness versus abstractness

- Supplementary data: This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License.
- Some example ratings from the final dataset of 40,000 words and phrases
  
  banana  5
  bathrobe  5
  bagel  5
  brisk  2.5
  badass  2.5
  basically  1.32
  belief  1.19
  although  1.07
Perceptual Strength Norms

Connell and Lynott norms

<table>
<thead>
<tr>
<th>Word</th>
<th>Auditory</th>
<th>Gustatory</th>
<th>Haptic</th>
<th>Olfactory</th>
<th>Visual</th>
<th>Concreteness</th>
<th>Imageability</th>
</tr>
</thead>
<tbody>
<tr>
<td>soap</td>
<td>0.35</td>
<td>1.29</td>
<td>4.12</td>
<td>4.00</td>
<td>4.06</td>
<td>589</td>
<td>600</td>
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<tr>
<td>noisy</td>
<td>4.95</td>
<td>0.05</td>
<td>0.29</td>
<td>0.05</td>
<td>1.67</td>
<td>293</td>
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<tr>
<td>atom</td>
<td>1.00</td>
<td>0.63</td>
<td>0.94</td>
<td>0.50</td>
<td>1.38</td>
<td>481</td>
<td>499</td>
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<td>republic</td>
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<td>0.67</td>
<td>0.27</td>
<td>0.07</td>
<td>1.79</td>
<td>376</td>
<td>356</td>
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</table>
Detecting Social and Affective Meaning

Using the lexicons to detect affect
Lexicons for detecting document affect:
Simplest unsupervised method

- **Sentiment:**
  - Sum the weights of each positive word in the document
  - Sum the weights of each negative word in the document
  - Choose whichever value (positive or negative) has higher sum

- **Emotion:**
  - Do the same for each emotion lexicon
Lexicons for detecting document affect: Simplest supervised method

• Build a classifier
  • Predict sentiment (or emotion, or personality) given features
  • Use “counts of lexicon categories” as a features
  • Sample features:
    • LIWC category “cognition” had count of 7
    • NRC Emotion category “anticipation” had count of 2

• Baseline
  • Instead use counts of all the words and bigrams in the training set
  • This is hard to beat
  • But only works if the training and test sets are very similar
Detecting Social and Affective Meaning

Prosody
Prosody

• Three characteristics of speech:
  • pitch
  • energy
  • duration/rate-of-speech
• That play a role in conveying meaning
• And especially social meaning
Happy
Sad
Larynx and Vocal Folds

- The Larynx (voice box)
  - A structure made of cartilage and muscle
  - Located above the trachea (windpipe) and below the pharynx (throat)
  - Contains the vocal folds
  - (adjective for larynx: laryngeal)

- Vocal Folds (older term: vocal cords)
  - Two bands of muscle and tissue in the larynx
  - Can be set in motion to produce sound (voicing)

Text from slides by Sharon Rose
The larynx, external structure, from front

Figure thanks to John Coleman!!
Vertical slice through larynx, as seen from back

Figure thnx to John Coleman!!
Voicing:

- Air comes up from lungs
- Forces its way through vocal cords, pushing open (2,3,4)
- This causes air pressure in glottis to fall, since:
  - when gas runs through constricted passage, its velocity increases (Venturi tube effect)
  - this increase in velocity results in a drop in pressure (Bernoulli principle)
- Because of drop in pressure, vocal cords snap together again (6-10)
- Single cycle: \(~1/100\) of a second.

Figure & text from John Coleman’s web site
Voicelessness

• When vocal cords are open, air passes through unobstructed
• Voiceless sounds: p/t/k/s/f/sh/th/ch
• If the air moves very quickly, the turbulence causes a different kind of phonation: whisper
Vocal folds open during breathing

From Mark Liberman’s web site, from Ultimate

Posterior part of tongue

Epiglottis

Vocal cord
Vocal Fold Vibration
Sound waves are longitudinal waves
particle displacement

pressure

Dan Russell Figure
Remember High School Physics
Simple Period Waves (sine waves)

- Characterized by:
  - period: $T$
  - amplitude $A$
  - phase $\phi$
- Fundamental frequency in cycles per second, or Hz
  - $F_0 = \frac{1}{T}$
Simple periodic waves

- Computing the frequency of a wave:
  - 5 cycles in .5 seconds = 10 cycles/second = 10 Hz
- Amplitude:
  - 1
- Equation:
  - $Y = A \sin(2\pi ft)$
Speech sound waves

- A little piece from the waveform of the vowel [iy]
- X axis: time.
- Y axis:
  - Amplitude = air pressure at that time
    - +: compression
    - 0: normal air pressure,
    - -: rarefaction
Back to waves:
Fundamental frequency

• Waveform of the vowel [iy]

![Waveform Graph]

• Frequency: 10 repetitions / .03875 seconds = 258 Hz
• This is speed that vocal folds move, hence voicing
• Each peak corresponds to an opening of the vocal folds
• The low frequency of the complex wave is called the fundamental frequency of the wave or F0
F0 (informally: pitch)

We can compute F0 mean, max, min for each turn
And the standard deviation across turns
Intensity

We can compute intensity mean, max, min for each turn
And the standard deviation across turns
Detecting Social and Affective Meaning

Prosody
Detecting Social and Affective Meaning

Prosody for Emotion Detection
Acted speech: Emotional Prosody Speech and Transcripts Corpus (EPSaT)

- Recordings from LDC
- 8 actors read short dates and numbers in 15 emotional styles
EPSaT Examples

happy
sad
angry
confident
frustrated
friendly
interested
anxious
bored
encouraging

Slide from Jackson Liscombe
Task 1

- Binary classification
- Detect the emotion the actor was instructed to use
Major Problems for Classification: Different Valence/Different Activation

slide from Julia Hirschberg
But....
Different Valence/ Same Activation

slide from Julia Hirschberg
Extracting audio features

• OpenSmile

• [http://www.audeering.com/research/opensmile](http://www.audeering.com/research/opensmile)  
  “Speech & Music Interpretation by Large-space Extraction”

• Praat
Scherer summary:
Prosodic features for emotion

<table>
<thead>
<tr>
<th></th>
<th>Stress</th>
<th>Anger/rage</th>
<th>Fear/panic</th>
<th>Sadness</th>
<th>Joy/elation</th>
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<td>🔄(?)</td>
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Prosody for Emotion
Detecting Social and Affective Meaning

Personality detection
Sample affective task: personality detection
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Personality

- The internal structures and propensities that explain a person’s characteristic patterns of thought, emotion, and behavior.
- Personality captures what people are like.
The Big Five Dimensions of Personality

Extraversion vs. Introversion
  sociable, assertive, playful vs. aloof, reserved, shy

Emotional stability vs. Neuroticism
  calm, unemotional vs. insecure, anxious

Agreeableness vs. Disagreeable
  friendly, cooperative vs. antagonistic, faultfinding

Conscientiousness vs. Unconscientious
  self-disciplined, organised vs. inefficient, careless

Openness to experience
  intellectual, insightful vs. shallow, unimagininative
Big Five Personality: Agreeableness

- warm, kind, cooperative, sympathetic, helpful, and courteous.
  - Strong desire to obtain acceptance in personal relationships as a means of expressing personality.
  - Agreeable people focus on “getting along,” not necessarily “getting ahead.”
Big Five Personality: Extraversion

talkative, sociable, passionate, assertive, bold, and dominant

- Easiest to judge immediately on first meeting
- Prioritize desire to obtain power and influence within a social structure as a means of expressing personality.
- High in positive affectivity — a tendency to experience pleasant, engaging moods such as enthusiasm, excitement, and elation.
Big Five Personality: Neuroticism

- experience unpleasant moods: hostility, nervousness, and annoyance.
- more likely to appraise day-to-day situations as stressful.
- less likely to believe they can cope with the stressors that they experience.
- related to locus of control (attribute causes of events to themselves or to the external environment)
  - Neurotics: external locus of control: believe that the events that occur around them are driven by luck, chance, or fate.
  - less neurotic people hold internal locus of control: believe that their own behavior dictates events.
## External and Internal Locus of Control

<table>
<thead>
<tr>
<th>PEOPLE WITH AN EXTERNAL LOCUS OF CONTROL TEND TO BELIEVE:</th>
<th>PEOPLE WITH AN INTERNAL LOCUS OF CONTROL TEND TO BELIEVE:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Many of the unhappy things in people's lives are partly due to bad luck.</td>
<td>People's misfortunes result from the mistakes they make.</td>
</tr>
<tr>
<td>Getting a good job depends mainly on being in the right place at the right time.</td>
<td>Becoming a success is a matter of hard work; luck has little or nothing to do with it.</td>
</tr>
<tr>
<td>Many times exam questions tend to be so unrelated to course work that studying is really useless.</td>
<td>In the case of the well-prepared student, there is rarely if ever such a thing as an unfair test.</td>
</tr>
<tr>
<td>This world is run by the few people in power, and there is not much the little guy can do about it.</td>
<td>The average citizen can have an influence in government decisions.</td>
</tr>
<tr>
<td>There's not much use in trying too hard to please people; if they like you, they like you.</td>
<td>People are lonely because they don't try to be friendly.</td>
</tr>
</tbody>
</table>
Big Five Personality: Openness to Experience

curious, imaginative, creative, complex, sophisticated

• Also called “Inquisitiveness” or “Intellectualness”
• high levels of creativity, the capacity to generate novel and useful ideas and solutions.
• Highly open individuals are more likely to migrate into artistic and scientific fields.
Changes in Big Five Dimensions Over the Life Span

- Conscientiousness
- Agreeableness
- Neuroticism
- Openness
- Extraversion

McGraw-Hill/Irwin Chapter 9
Aside: Do Animals Have Personalities?

- 4 human observers rated 44 personality traits of hyenas.
- Ran PCA on the ratings.
- Five dimensions: Assertiveness, Excitability, Human-Directed Agreeableness, Sociability, and Curiosity.
- Related to 3 human dimensions: neuroticism (excitability), openness (curiosity), agreeableness (sociability+agree).
Take the Big Five Inventory

http://www.outofservice.com/bigfive/
Various text corpora labeled for personality of author


- 2,479 essays from psychology students (1.9 million words), “write whatever comes into your mind” for 20 minutes


- Speech from Electronically Activated Recorder (EAR)
- Random snippets of conversation recorded, transcribed
- 96 participants, total of 97,468 words and 15,269 utterances

Schwartz, H. Andrew, Johannes C. Eichstaedt, Margaret L. Kern, Lukasz Dziurzynski, Stephanie M. Ramones, Megha Agrawal, Achal Shah et al. 2013. "Personality, gender, and age in the language of social media: The open-vocabulary approach." PloS one 8, no. 9

- Facebook
- 75,000 volunteers
- 309 million words
- All took a personality test
# Ears (speech) corpus (Mehl et al.)

<table>
<thead>
<tr>
<th>Introvert</th>
<th>Extravert</th>
</tr>
</thead>
</table>
| - Yeah you would do kilograms. Yeah I see what you’re saying.  
- On Tuesday I have class. I don’t know.  
- I don’t know. A16. Yeah, that is kind of cool.  
- I don’t know. I just can’t wait to be with you and not have to do this every night, you know?  
- Yeah. You don’t know. Is there a bed in there? Well ok just... | - That’s my first yogurt experience here. Really watery. Why?  
- Damn. New game.  
- Oh.  
- That’s so rude. That.  
- Yeah, but he, they like each other. He likes her.  
- They are going to end up breaking up and he’s going to be like. |

<table>
<thead>
<tr>
<th>Unconscientious</th>
<th>Conscientious</th>
</tr>
</thead>
</table>
| - With the Chinese. Get it together.  
- I tried to yell at you through the window.  
 Oh. xxx’s fucking a dumb ass. Look at him. Look at him, dude. Look at him. I wish we had a camera. He’s fucking brushing his t-shirt with a tooth brush. Get a kick of it. Don’t steal nothing. | - I don’t, I don’t know for a fact but I would imagine that historically women who have entered prostitution have done so, not everyone, but for the majority out of extreme desperation and I think. I don’t know, i think people understand that desperation and they don’t see [...]|
<table>
<thead>
<tr>
<th>Introvert</th>
<th>Extravert</th>
</tr>
</thead>
<tbody>
<tr>
<td>I’ve been waking up on time so far. What has it been, 5 days? Dear me, I’ll never keep it up, being such not a morning person and all. But maybe I’ll adjust, or not. I want internet access in my room, I don’t have it yet, but I will on Wed?? I think. But that ain’t soon enough, cause I got calculus homework [...]</td>
<td>I have some really random thoughts. I want the best things out of life. But I fear that I want too much! What if I fall flat on my face and don’t amount to anything. But I feel like I was born to do BIG things on this earth. But who knows... There is this Persian party today.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neurotic</th>
<th>Emotionally stable</th>
</tr>
</thead>
<tbody>
<tr>
<td>One of my friends just barged in, and I jumped in my seat. This is crazy. I should tell him not to do that again. I’m not that fastidious actually. But certain things annoy me. The things that would annoy me would actually annoy any normal human being, so I know I’m not a freak.</td>
<td>I should excel in this sport because I know how to push my body harder than anyone I know, no matter what the test I always push my body harder than everyone else. I want to be the best no matter what the sport or event. I should also be good at this because I love to ride my bike.</td>
</tr>
</tbody>
</table>
Classifiers

  - Various classifiers, lexicon-based and prosodic features
  - regression and SVM, lexicon-based and all-words
## Sample LIWC Features

LIWC (Linguistic Inquiry and Word Count)


<table>
<thead>
<tr>
<th>Feature</th>
<th>Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anger words</td>
<td>LIWC</td>
<td>hate, kill, pissed</td>
</tr>
<tr>
<td>Metaphysical issues</td>
<td>LIWC</td>
<td>God, heaven, coffin</td>
</tr>
<tr>
<td>Physical state/function</td>
<td>LIWC</td>
<td>ache, breast, sleep</td>
</tr>
<tr>
<td>Inclusive words</td>
<td>LIWC</td>
<td>with, and, include</td>
</tr>
<tr>
<td>Social processes</td>
<td>LIWC</td>
<td>talk, us, friend</td>
</tr>
<tr>
<td>Family members</td>
<td>LIWC</td>
<td>mom, brother, cousin</td>
</tr>
<tr>
<td>Past tense verbs</td>
<td>LIWC</td>
<td>walked, were, had</td>
</tr>
<tr>
<td>References to friends</td>
<td>LIWC</td>
<td>pal, buddy, coworker</td>
</tr>
<tr>
<td>Imagery of words</td>
<td>MRC</td>
<td>Low: future, peace - High: table, car</td>
</tr>
<tr>
<td>Syllables per word</td>
<td>MRC</td>
<td>Low: a - High: uncompromisingly</td>
</tr>
<tr>
<td>Concreteness</td>
<td>MRC</td>
<td>Low: patience, candor - High: ship</td>
</tr>
<tr>
<td>Frequency of use</td>
<td>MRC</td>
<td>Low: duly, nudity - High: he, the</td>
</tr>
</tbody>
</table>
Dialog act of utterance

Labeled by parsing each utterance and then using heuristic rules based on parse tree:

**Commands**: imperatives, “can you”, etc.

**Backchannels**: yeah, ok, uh-huh, huh

**Questions**

** Assertions** (anything else)
Prosodic features

*Computed via Praat*

- pitch (mean, min, max, sd):
- intensity (mean, min, max, sd)
- voiced time
- rate of speech (words/second)
Normalizing LIWC category features
(Schwartz et al 2013, Facebook study)

- **Mairesse:**
  Raw LIWC counts
- **Schwartz et al:**
  Normalized per writer:

\[
p (\text{category} | \text{subject}) = \frac{\sum_{\text{word} \in \text{category}} \text{freq} (\text{word}, \text{subject})}{\sum_{\text{word} \in \text{vocab} (\text{subject})} \text{freq} (\text{word}, \text{subject})}\]
Sample results

• Agreeable:
  • +Family, +Home, -Anger, -Swear

• Extravert
  • +Friend, +Religion, +Self

• Conscientiousness:
  • -Swear, -Anger, -NegEmotion,

• Emotional Stability:
  • -NegEmotion, +Sports,

• Openness
  • -Cause, -Space
Decision tree for predicting extraversion in essay corpus (Mairesse et al)

Figure 1: J48 decision tree for binary classification of extraversion, based on the essays corpus and self-reports.

Remarkably, we can see that the LIWC features outperform the MRC features for every trait, and the LIWC features on their own always perform slightly better than the full feature set. This clearly suggests that MRC features aren't as helpful as the LIWC features for classifying personality from written text, however Table 13 shows that they can still outperform the baseline for four traits out of five.

Concerning the algorithms, we find that AdaboostM1 performs the best for extraversion (56.3% correct classifications), while SMO produces the best models for all other traits. It suggests that support vector machines are promising for modelling personality in general. The easiest trait to model is still openness to experience, with 62.5% accuracy using LIWC features only.

4.2 EAR Corpus

Classification accuracies for the EAR corpus are in Table 14. We find that extraversion is the easiest trait to model using observer reports, with both Naive Bayes and AdaboostM1...
Feature analysis: Observed Extraversion

more words
higher pitch
more concrete, imageable words
greater variation in intensity
greater mean intensity
more word repetitions

M5’ Regression Tree

Word count
\[
\begin{align*}
&\text{Word count} \\
&\begin{cases}
\leq 675 \\
> 675
\end{cases}
\end{align*}
\]

Mean pitch
\[
\begin{align*}
&\begin{cases}
\leq 231 \\
> 231
\end{cases}
\end{align*}
\]

Intensity variation
\[
\begin{align*}
&\begin{cases}
\leq 6.39 \\
> 6.39
\end{cases}
\end{align*}
\]

Values:
- Word count: 3.23, 3.83, 4.24
- Mean pitch: 2.86, 3.02
Using all words instead of lexicons

Facebook study

Schwartz et al. (2013)

- Choosing phrases with pmi > 2*length [in words]

\[ pmi(phrase) = \log \frac{p(phrase)}{\prod_{w \in phrase} p(w)} \]

- Only use words/phrases used by at least 1% of writers
- Normalize counts of words and phrases by writer

\[ p(phrase \mid subject) = \frac{freq(phrase, subject)}{\sum_{phrase' \in vocab(subject)} freq(phrase', subject)} \]
Facebook study, Learned words, Extraversion versus Introversion
Facebook study, Learned words
Neuroticism versus Emotional Stability
Evaluating Schwartz et al (2013) Facebook Classifier

• Train on labeled training data
  • LIWC category counts
  • words and phrases (n-grams of size 1 to 3, passing a collocation filter
• Tested on a held-out set
• Correlations with human labels
  • LIWC .21-.29
  • All Words .29-.41
What about predicting personality from what someone likes?

Youyou Wu, Michal Kosinski, and David Stillwell. "Computer-based personality judgments are more accurate than those made by humans." Proceedings of the National Academy of Sciences (2015)

1. 86,220 volunteers filled in a 100-item questionnaire
   • International Personality Item Pool (IPIP) Five-Factor Model of personality
2. They then used Facebook likes to predict personality for 70,520 people
3. And asked their friends to answer a 10-item questionnaire for 17,622 people
Human judge in the present sample (Computer models need only 100 Likes to outperform an average Cronbach other agreement estimates were disattenuated using scales the number of Likes available on the participant accuracy across the Big Five traits (red line) steadily grows with Connely and Ones (20), which followed the same procedure. Comparisons of human self-other agreement with those reported by based judgments. Also, disattenuation allowed for direct com-(conservative) estimates of self-other agreement for computer-the computer model was assumed to be 0, resulting in the lower friends, spouses, family members, cohabitants, and work colleagues. Including estimates for different categories of human judges: previously published in a meta-analysis by Connely and Ones (20), relationship (18, 19), we further compared our results with those agreement varies greatly with the length and context of the re-

**Results**

Presented in Fig. 1. Judged by two friends. A diagram illustrating the methods is

**Wu et al. Algorithm:**

**Participants’ Personality**
- Measured using 100-item IPQ Five-Factor Model questionnaire (for 70,520 participants)

<table>
<thead>
<tr>
<th>Participants’ Likes</th>
<th>Linear Regression Models</th>
<th>Computers’ Judgments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obtained from Facebook profiles</td>
<td>A regression formula with a coefficient for each Like is generated for each of the five personality traits e.g. Openness = α + β1 * Like + β2 * Obama + e</td>
<td>Made using participants’ Likes</td>
</tr>
</tbody>
</table>

**1.** Take personality scores and Likes of 90% of the participants and build linear regression models for the five personality traits using LASSO variable selection

**2.** Take the Likes of the remaining 10% of the participants and use the linear regression models to predict scores for the five personality traits

Repeat 10 times to make judgments for all participants

Humans’ Accuracy ← Human’s Judgments

Self-ratings

Computers’ Accuracy ← Computers’ Judgments
Results:

- **Computers' Average Accuracy (0.56)**
- **Humans' Average Accuracy (0.49)**
- **Five-Trait Average**
- **Openness**
- **Agreeableness**
- **Extraversion**
- **Conscientiousness**
- **Neuroticism**

Accuracy vs. Number of Facebook Likes (log scaled)

- Spouse (0.58)
- Family (0.50)
- Friend (0.45)
- Cohabitant (0.45)
- "I Work Colleague (0.27)"

Accuracy (self-other agreement)
Summary on Personality Detection

• **From text and speech**
  • Not a solved task
  • Text and prosodic features both somewhat useful
  • Especially hard to extract self-labeled personality
  • Especially hard to detect openness

• **From likes:**
  • Seems to be an easier task
  • Computer-based judgment of personality ($r = 0.56$) correlates more strongly with self-ratings than average human judgments do ($r = 0.49$)
Detecting Social and Affective Meaning

Detecting Personality
Detecting Social and Affective Meaning

Other tasks: Detecting student uncertainty and disinterest for online education
Detecting student confusion in a tutoring system

**ITSpoke: Intelligent Tutoring Spoken Dialogue System**

Diane Litman, Katherine Forbes-Riley, Scott Silliman, Mihai Rotaru

Tutorial corpus: how certain is the student


- 151 dialogues from 17 subjects
- student first writes an essay, then discusses with tutor
- both are recorded with microphones
- manually transcribed and segmented into turns
- 6778 student utterances (average 2.3 seconds)
- each utterance hand-labeled for certainty
Uncertainty in ITSpoke

um <sigh> I don’t even think I have an idea here ...... now .. mass isn’t weight ...... mass is ............... the ........ space that an object takes up ........ is that mass?
Does it help? A tutorial system that adapts to uncertainty

Give more information if the student is uncertain


**tutor1:** What will the velocity of the object be a second after that (where the initial velocity is 9.8m/s and the acceleration is 9.8m/s²)?

**student1:** Is it 19.6 m/s? [Correct+Uncertain]

**nonadaptive-tutor2:** Good. Now back to the man and his keys. We’ve shown that they both have an acceleration of 9.8m/s². So, how do their velocities compare with each other, at every second during the fall?

**adaptive-tutor2:** Good. A second later, its velocity will be 9.8m/s + 9.8m/s = 19.6m/s. This is because its acceleration tells us that every second, its velocity increases by 9.8m/s. So, what’ll its velocity be, a second after that?

**adaptive-student2:** Um. I’m thinking. 29.4 m/s. [Correct+Certain]

**adaptive-tutor3:** Right. Now back to the man and his keys. We’ve shown that they both have an acceleration of 9.8m/s². So, how do their velocities compare with each other, at every second during the fall?
Features for uncertainty

Acoustic-Prosodic Features
4 fundamental frequency (f0) features: maximum, minimum, mean, standard deviation
4 energy (RMS) features: maximum, minimum, mean, standard deviation
3 temporal features: turn duration, prior pause duration, internal silence

Lexical and Dialogue Features
ITSPKOE-recognized lexical items in turn
tutor goal name
problem name
turn number
per-dialogue running totals and averages for 11 acoustic-prosodic features

Identifier Feature:
subject gender
Conclusions

• Uncertainty is very hard to detect
  • F-score of .27

• Even so, using the uncertainty detector improved learner outcomes a bit over not using it.

• But need better detection of uncertainty, and also better detection of correct answers.
Detecting **disengagement**


---

**T_1**: What is the definition of Newton’s Second Law?

**U_1**: I have no idea *<sigh>*. (**DISE**, incorrect, **UNC**)

... 

**T_2**: What’s the numerical value of the man’s acceleration? Please specify the units too.

**U_2**: The speed of the elevator. Meters per second. (**DISE**, incorrect, **UNC**)

...

**T_3**: What are the forces acting on the keys after the man releases them?

**U_3**: graaa-vi-tyyyyy *<sings the answer>* (**DISE**, correct, **CER**)

---

**Figure 1**: Corpus Example Illustrating the User Turn Labels ((Dis)Engagement, (In)Correctness, (Un)Certainty)
Disengagement Features

- **Acoustic-Prosodic Features**
  - temporal features: turn duration, prior pause duration, turn-internal silence
  - fundamental frequency (f0) and energy (RMS) features: maximum, minimum, mean, std. deviation
  - running totals and averages for all features

- **Lexical and Dialogue Features**
  - dialogue name and turn number
  - question name and question depth
  - ITSPROKEN-recognized lexical items in turn
  - ITSPROKEN-labeled turn (in)correctness
  - incorrect runs

- **User Identifier Features**:
  - gender and pretest score

Most important feature: Pause prior to start of turn

<250ms means disengagement
Does disengagement detection help the system?


Yes

But not for all students

Only for male students (improved their performance significantly)
Detecting Social and Affective Meaning Interpersonal Stance Detection
Scherer’s typology of affective states

**Emotion**: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance
  - angry, sad, joyful, fearful, ashamed, proud, desperate

**Mood**: diffuse affect state … change in subjective feeling, of low intensity but relatively long duration, often without apparent cause
  - cheerful, gloomy, irritable, listless, depressed, buoyant

**Interpersonal stance**: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange
  - distant, cold, warm, supportive, contemptuous

**Attitudes**: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons
  - liking, loving, hating, valuing, desiring

**Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person
  - nervous, anxious, reckless, morose, hostile, envious, jealous
Automatically Extracting Social Meaning from Speed Dates


Detecting stance

1000 4-minute speed dates
Subjects labeled selves and each other for
• friendly (each on a scale of 1-10)
• awkward
• flirtatious
• assertive
Linguistic features we examined

- **Words:**
  - **HEDGES:** kind of, sort of, a little, I don’t know, I guess
  - **NEGEMOTION:** bad, weird, crazy, problem, tough, awkward, boring
  - **LOVE:** love, loved, loving, passion, passions, passionate
  - **WORK:** research, advisor, lab, work, finish, PhD, department
  - **I:** I, me, mine, my, myself, you, your, yours, etc.

- **Prosody**
  - pitch ceiling, pitch floor, energy, rate of speech
Dialog act features

- Clarification questions
  - What?
  - Excuse me?

- Laughter
  - [Beginning of turn] [End of turn]

- Appreciations
  - Awesome!
  - That’s amazing!
  - Oh, great

- Sympathy
  - That sounds terrible!
  - That’s awful!
  - That sucks!
Positive and negative assessments

(Goodwin, 1996; Goodwin and Goodwin, 1987; Jurafsky et al., 1998)

**Sympathy**

(that’s|that is|that seems|it is|that sounds)
(very|really|a little|sort of)?
(terrible|awful|weird|sucks|a problem|tough|too bad)

**Appreciations (“Positive feedback”)**

(Oh)? (Awesome|Great|All right|Man|No kidding|wow|my god)

That
(‘s|is|sounds|would be)  (so|really)?
(great|funny|good|interesting|neat|amazing|nice|not bad|fun)
Interruptions

A: Not necessarily. I mean it happens to not necessarily be my thing, but there are plenty of--

B: No, no, I understand your point.
Model

• Multinomial logistic regression classifier
• Predict whether a conversation side is labeled flirt/friendly/assertive/awkward
  • Given linguistic features
• Then look at the feature weights
Linguistic signs of awkwardness

- Awkward men and women use more hedges
  - *kind of, sort of, a little*

- People who are so uncomfortable in the date
  - So in need of distancing themselves

- That they can’t even commit to their sentence.
What makes someone seem friendly? “Collaborative conversational style”

- Friendly people:
  - laugh at themselves
  - don’t use negative emotions
- Friendly men
  - are sympathetic and agree more often
  - don’t interrupt
  - don’t use hedges
- Friendly women:
  - higher max pitch
  - laugh at their date
What do flirters do?

Women:
- raise pitch ceiling
- laugh turn-finally
- (at themselves?)
- say “I”
- use negation (*don’t*, *no*, *not*)

Men:
- raise pitch floor
- laugh turn-initially (at their date, teasing?)
- say “you”
- don’t use words related to academics
Unlikely words for male flirting

- academia
- interview
- teacher
- phd
- advisor
- lab
- research
- management
- finish
How consistently do people read each others linguistic cues?

Each dater labeled themselves

• I flirted (from 1-10)
• I was friendly (from 1-10)
• I was awkward (from 1-10)
• I was assertive (from 1-10)

And labeled their partner

• My date flirted (from 1-10)
• ...

How much do these labels agree?

• If I thought I was friendly, does my date agree?
Not at all
Not at all!

People disagree with their date about stance:

<table>
<thead>
<tr>
<th></th>
<th>Male is flirting (1-10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male 101 says:</td>
<td>8</td>
</tr>
<tr>
<td>Female 127 says:</td>
<td>1</td>
</tr>
</tbody>
</table>
Why?

People assume their date is behaving like themselves:

<table>
<thead>
<tr>
<th></th>
<th>Male is flirting</th>
<th>Female is flirting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male 101 says:</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>Female 127 says:</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Correlations between my behavior and what I say about my date

<table>
<thead>
<tr>
<th></th>
<th>I label myself</th>
<th>x</th>
<th>I label date</th>
<th>x</th>
<th>I label date labels themselves</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flirting</td>
<td>.73</td>
<td></td>
<td>.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Friendly</td>
<td>.77</td>
<td></td>
<td>.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Awkward</td>
<td>.58</td>
<td></td>
<td>.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assertive</td>
<td>.58</td>
<td></td>
<td>.09</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
We are not very good at modeling each other’s intentions

- At least not in 4 minutes
- Speakers instead base their judgments on their own behavior or intentions
How does clicking happen?

- Sociology literature:
  - bonding or “sense of connection” is caused by
    - homophily: select mate who shares your attributes and attitudes
    - motives and skills
    - mutual coordination and excitement
      - (Durkheim: religious rituals, unison singing, military)
- But what is the role of language?
  - Background: speed dating has power asymmetry
    - women are pickier
      - Lot of other asymmetric role relationships (teacher-student, doctor-patient, boss-employee, etc.)
Our hypothesis: targeting of the empowered party

• The conversational target is the woman
  • both parties should talk about her more
• The woman’s face is important
  • the man should align to the woman and show understanding
• The woman’s engagement is key
  • in a successful bonding, she should be engaged
Results: Clicking associated with:

Hierarchical regression dyad model, net of actor, partner, dyad features

- both parties talk about the woman
  - women use *I,*
  - men use *you*
- man supports woman’s face
  - men use *appreciations* and *sympathy,*
  - men *accommodate* women’s laughter
  - men interrupt with *collaborative completions*
- woman is engaged
  - women raise their pitch, vary loudness and pitch
  - women avoid hedges
Function of Interruptions?

Theory 1: Control: Used by men to take the floor (Zimmerman and West 1975; West 1985)

Theory 2: Shared meaning, alignment, engagement: (Tannen 1994; Coates 1996, 1997), collaborative floor (Edelsky 1981)
We found: interruptions are joint construction ("collaborative completions")

- a turn where a speaker completes the utterance begun by the alter (Lerner, 1991; Lerner, 1996).

So are you almost--

On my way out, yeah.
Or showing shared understanding

**Female:** I didn’t used to like it but now I’m—

**Male:** Oh same for me....
Other factors that might matter

- Height
- BMI (Body mass index)
- Foreign-born
- Dating experience
- Looking for relationship?
- Order of date in evening
- Met before
- Age difference
- Hobby similarities
These factors do influence stance

• More likely to flirt:
  • high-BMI men or women
  • taller men and shorter women
  • men later in the evening
• More likely to be flirted with
  • low-BMI women
  • high-BMI men
• Bigger (taller, heavier) men say they are more assertive
But language still matters

<table>
<thead>
<tr>
<th></th>
<th>Language</th>
<th>Traits</th>
<th>Language + Traits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>66%</td>
<td>64</td>
<td>72</td>
</tr>
<tr>
<td>flirt</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>74</td>
<td>55</td>
<td>76</td>
</tr>
<tr>
<td>flirt</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

accuracy (baseline is 50%)
Conclusions from Dating

• We are not very good at reading intentions

• **How friendly people sound**
  • be sympathetic, ask clarification questions, agree, accommodate

• **How to date:**
  • Don’t talk about your advisor
  • **Daters focus on the empowered party**
  • We can detect this with relatively simple linguistic features
Detecting Social and Affective Meaning

Interpersonal Stance Detection
Detecting Social and Affective Meaning

Summary
Scherer’s typology of affective states

**Emotion**: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance

- angry, sad, joyful, fearful, ashamed, proud, desperate

**Mood**: diffuse affect state ... change in subjective feeling, of low intensity but relatively long duration, often without apparent cause

- cheerful, gloomy, irritable, listless, depressed, buoyant

**Interpersonal stance**: affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange

- distant, cold, warm, supportive, contemptuous

**Attitudes**: relatively enduring, affectively colored beliefs, preferences predispositions towards objects or persons

- liking, loving, hating, valuing, desiring

**Personality traits**: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person

- nervous, anxious, reckless, morose, hostile, envious, jealous