CS 124/LINGUIST 180
From Languages to Information

Dan Jurafsky
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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

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: 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)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

- Home page: http://www.liwc.net/
- 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

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: http://www.cs.pitt.edu/mpqa/subj_lexicon.html
- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

Bing Liu Opinion Lexicon

Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- 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

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- [estimable(J,3)] "may be computed or estimated"

```
Pos   0    Neg  0    Obj  1
```

- [estimable(J,1)] "deserving of respect or high regard"

```
Pos  .75   Neg  0    Obj  .25
```

Detecting Social and Affective Meaning

Sentiment Lexicons

Detecting Social and Affective Meaning

Emotion

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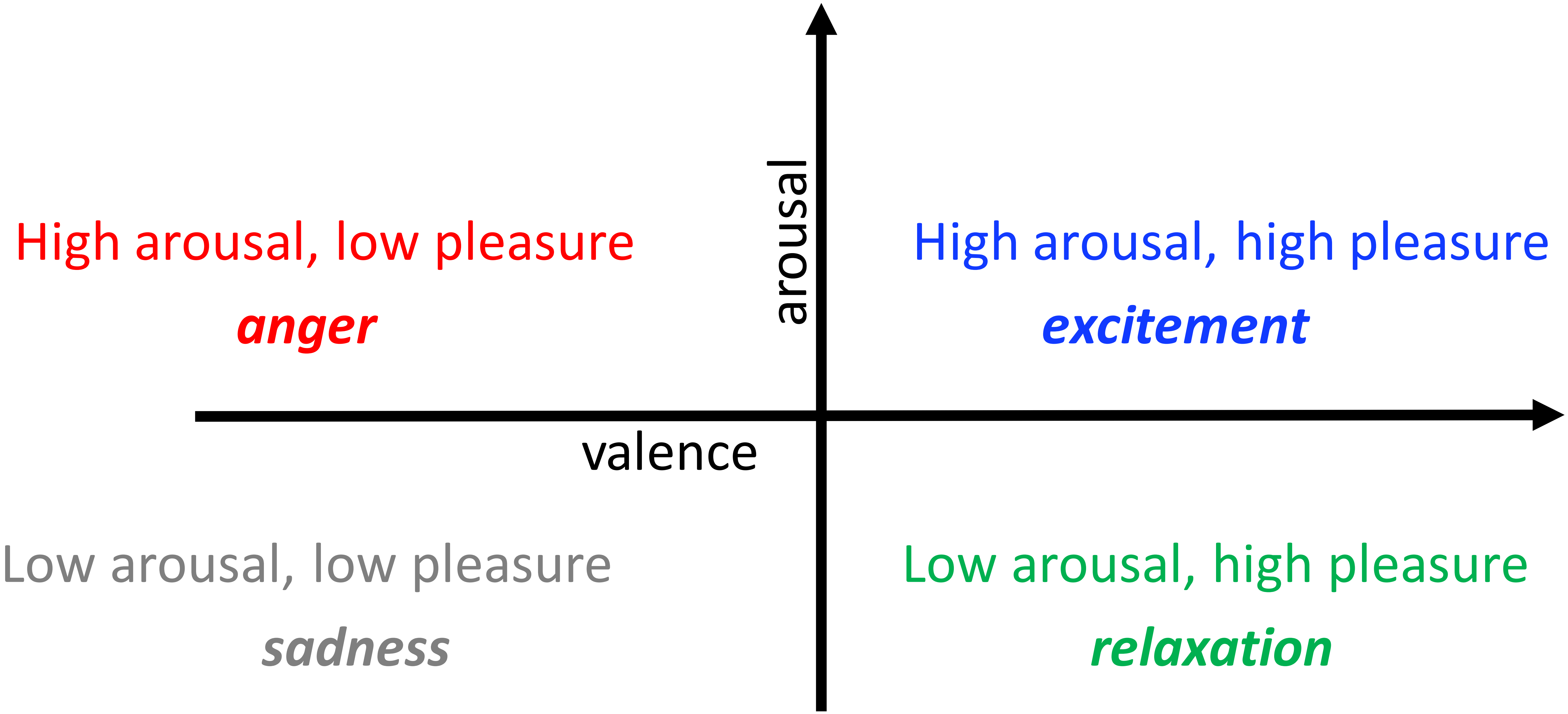
Two families of theories of emotion

- 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



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

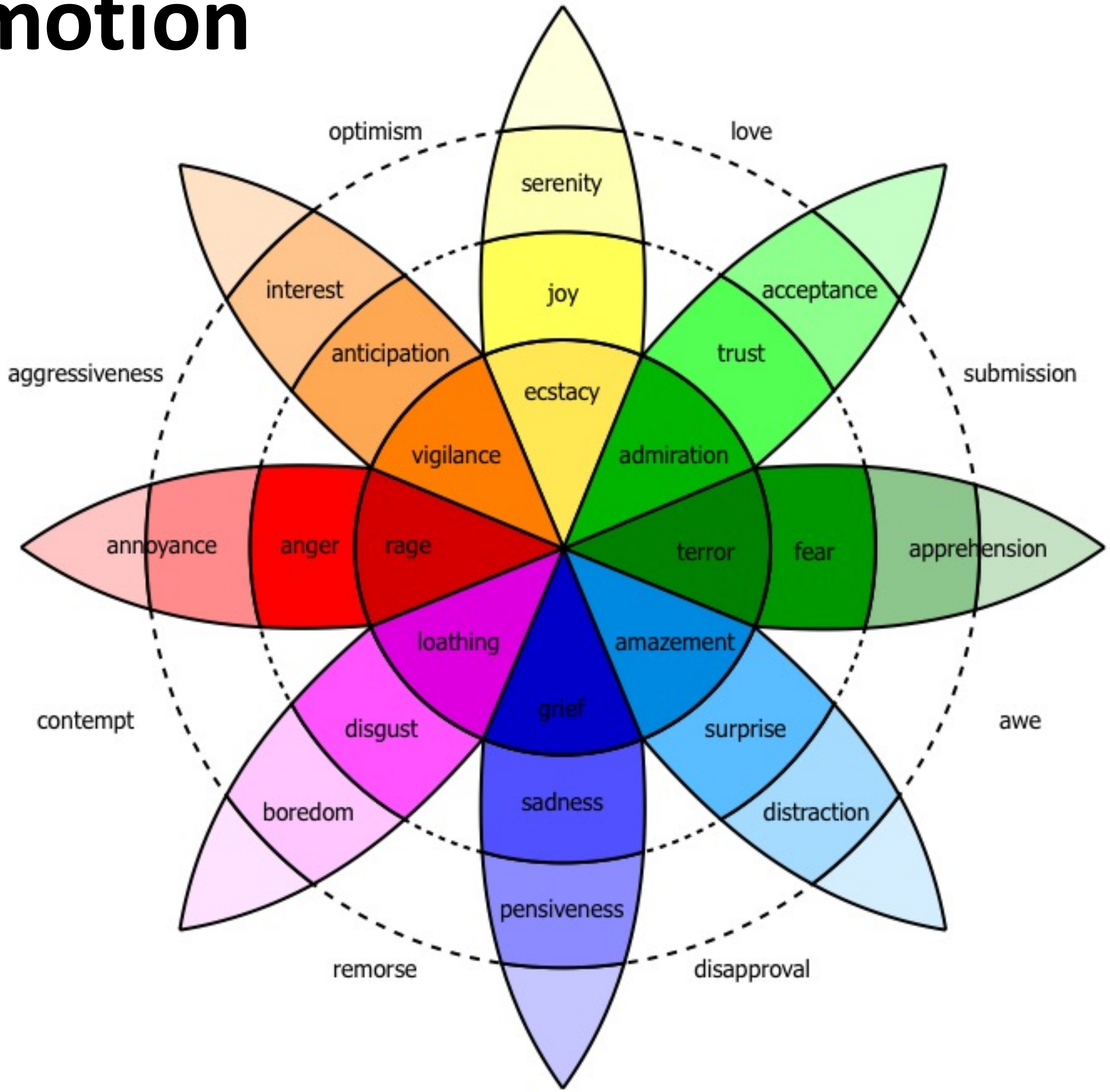
One emotion lexicon from each paradigm!

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	# of terms
EmoLex-Uni:	
Unigrams from Macquarie Thesaurus	
adjectives	200
adverbs	200
nouns	200
verbs	200
EmoLex-Bi:	
Bigrams from Macquarie Thesaurus	
adjectives	200
adverbs	187
nouns	200
verbs	200
EmoLex-GI:	
Terms from General Inquirer	
negative terms	2119
neutral terms	4226
positive terms	1787
EmoLex-WAL:	
Terms from WordNet Affect Lexicon	
anger terms	165
disgust terms	37
fear terms	100
joy terms	165
sadness terms	120
surprise terms	53
Union	**10170**

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 *heart-break* 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

- Warriner, A. B., **Kuperman**, V., and Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods 45, 1191-1207.*
- 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, or unaroused;
- **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

Valence		Arousal		Dominance	
vacation	8.53	rampage	7.56	self	7.74
happy	8.47	tornado	7.45	incredible	7.74
whistle	5.7	zucchini	4.18	skillet	5.33
conscious	5.53	dressy	4.15	concur	5.29
torture	1.4	dull	1.67	earthquake	2.14

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
- Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014) Concreteness ratings for 40 thousand generally known English word lemmas *Behavior Research Methods 46, 904-911.*
-
- 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

- Brysbaert, M., Warriner, A. B., and Kuperman, V. (2014) Concreteness ratings for 40 thousand generally known English word lemmas *Behavior Research Methods 46, 904-911.*
-
- 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

	Perceptual strength						
Word	Auditory	Gustatory	Haptic	Olfactory	Visual	Concreteness	Imageability
soap	0.35	1.29	4.12	4.00	4.06	589	600
noisy	4.95	0.05	0.29	0.05	1.67	293	138
atom	1.00	0.63	0.94	0.50	1.38	481	499
republic	0.53	0.67	0.27	0.07	1.79	376	356

Microsoft Excel
Worksheet

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

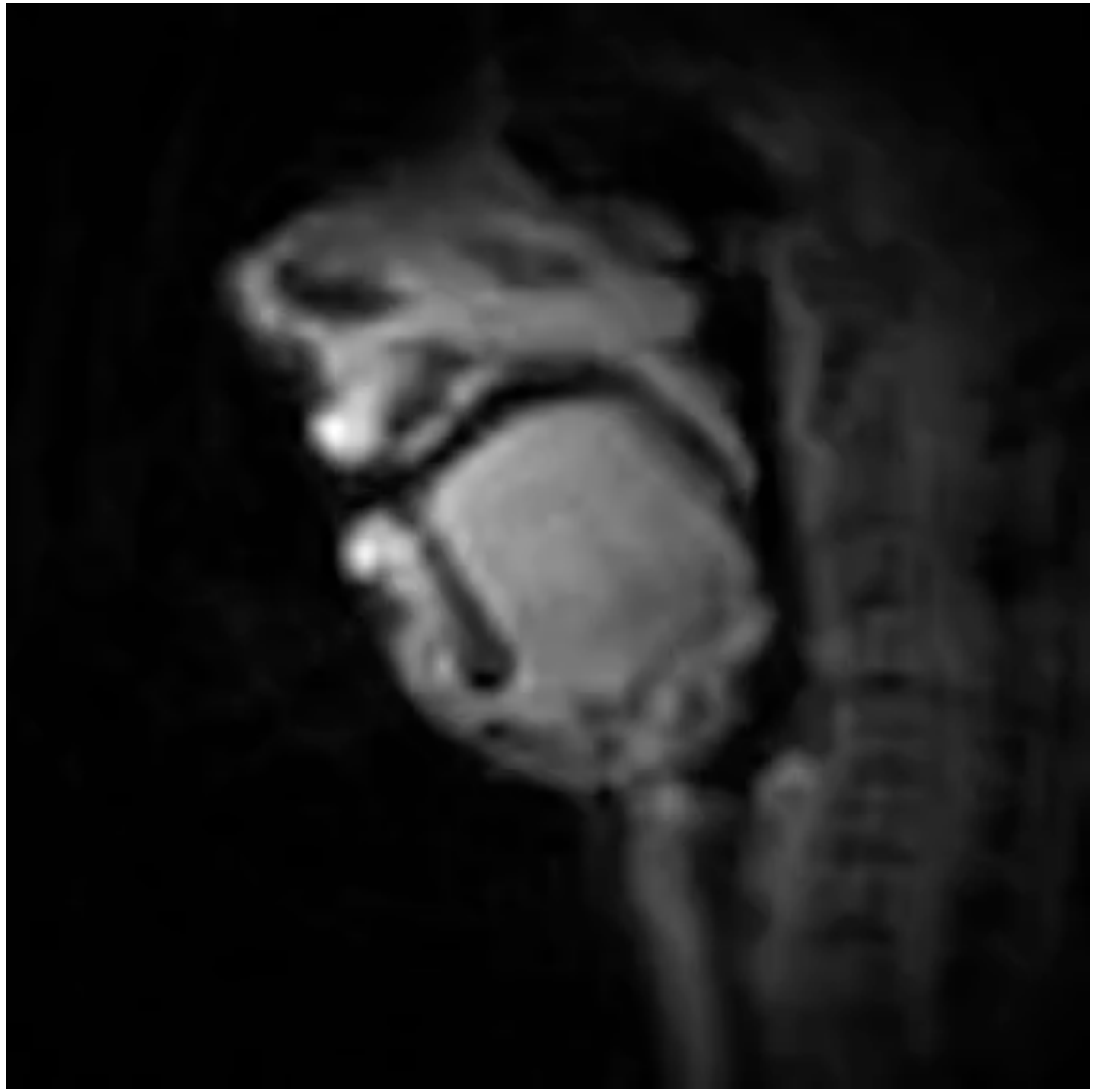
Prosody

Prosody

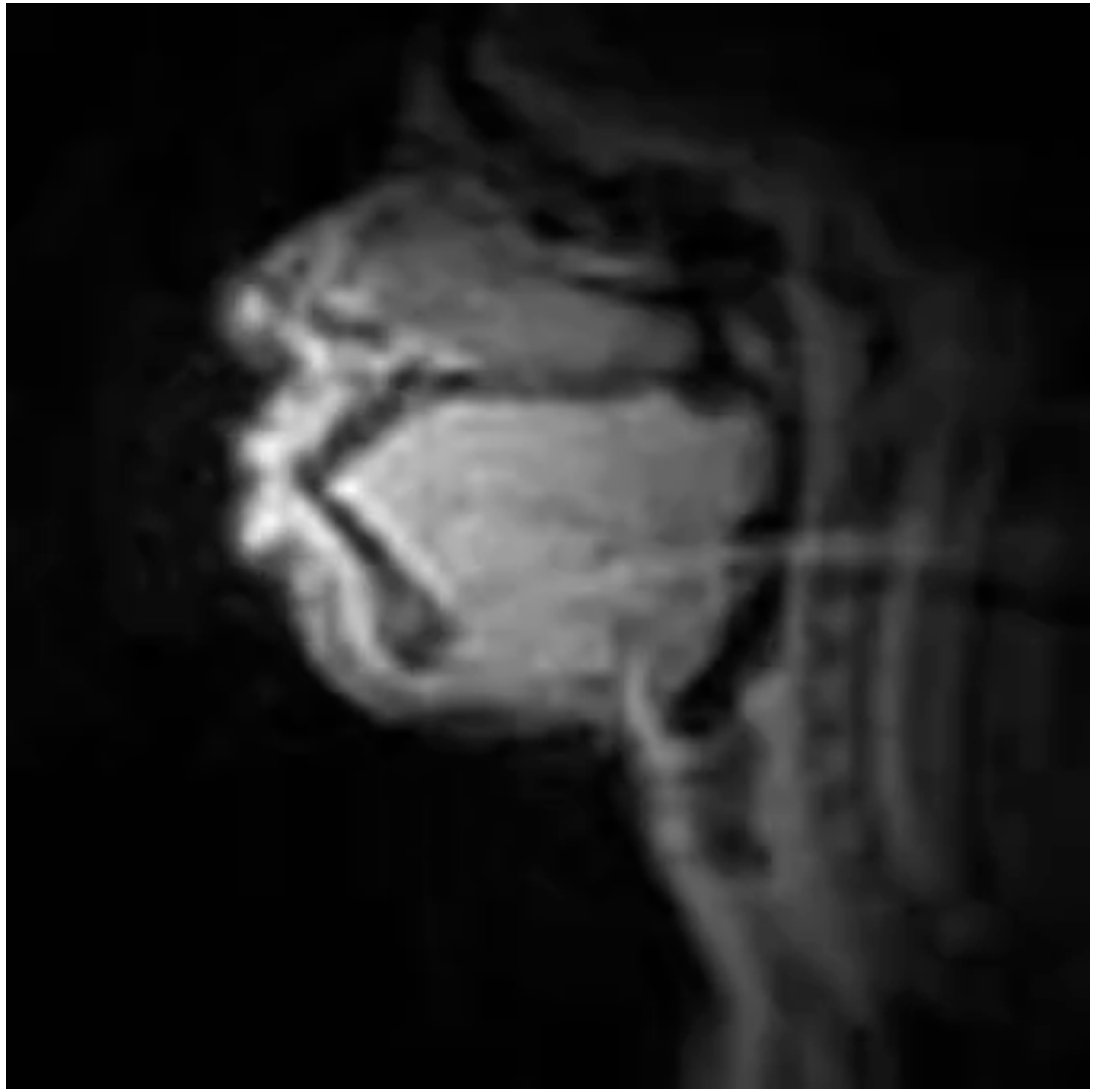
- Three characteristics of speech:
  - pitch
  - energy
  - duration/rate-of-speech
- That play a role in conveying meaning
- And especially social meaning

USC’s SAIL Lab

Shri Narayanan and Dani Byrd



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

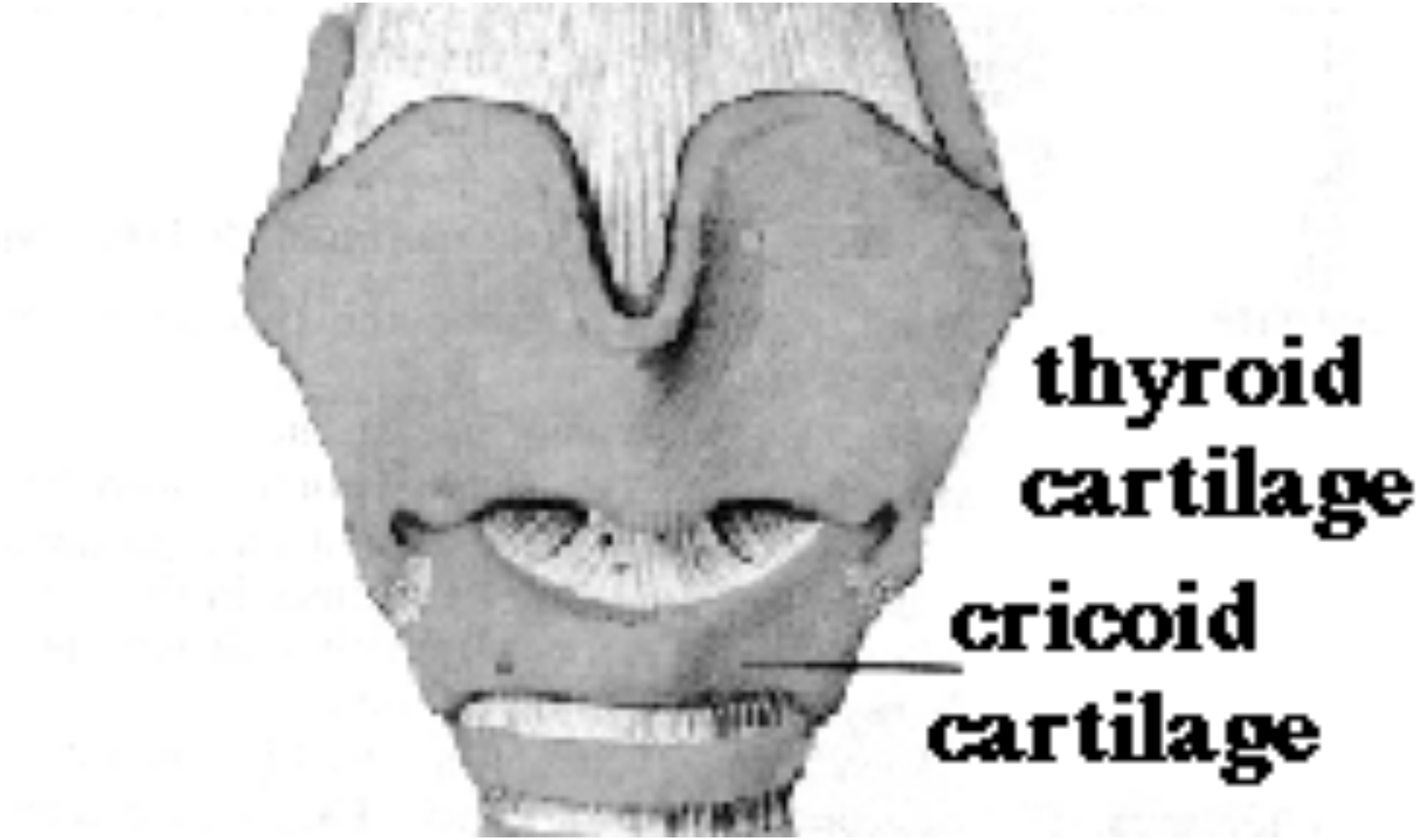


Figure thanks to John Coleman!!

Vertical slice through larynx, as seen from back

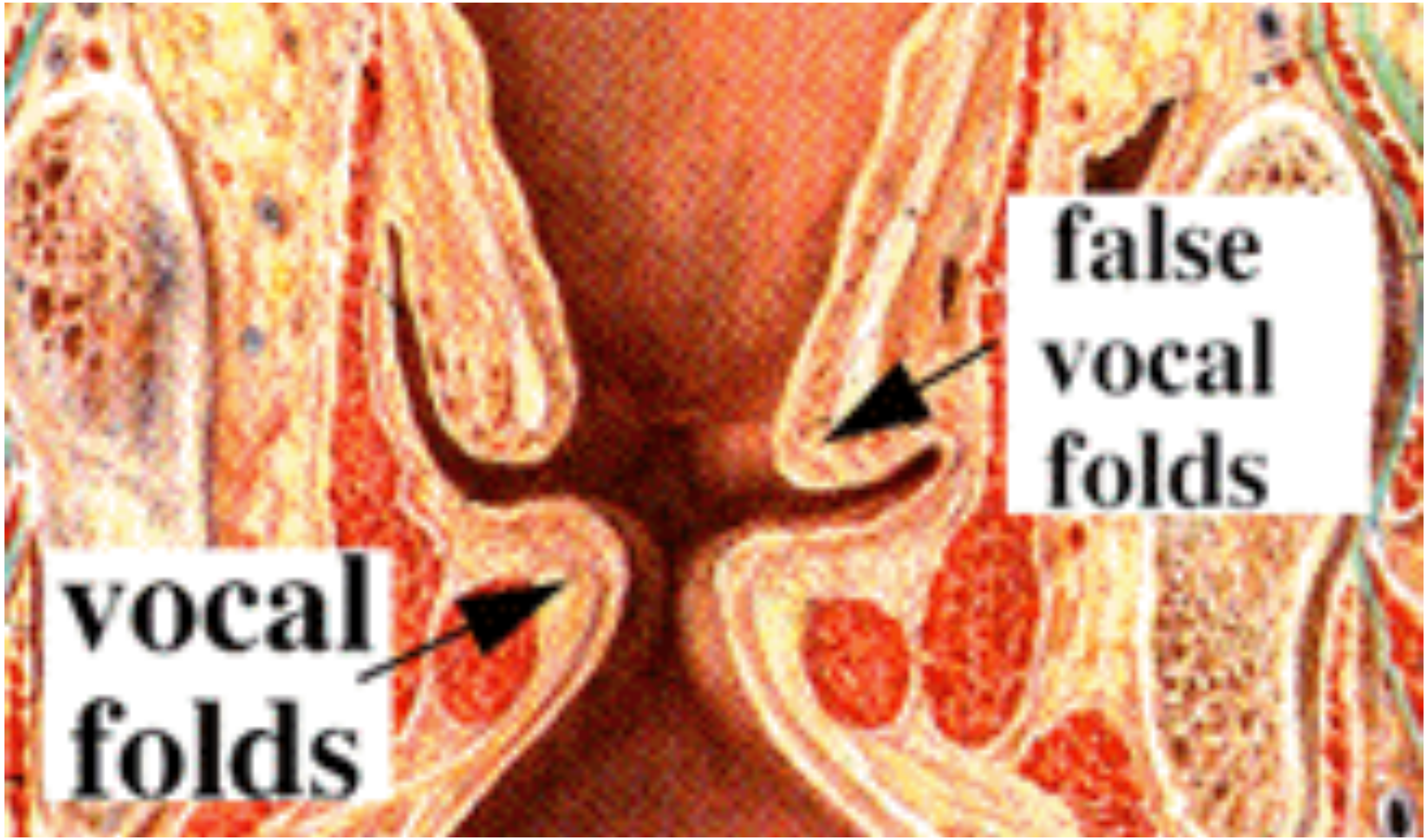
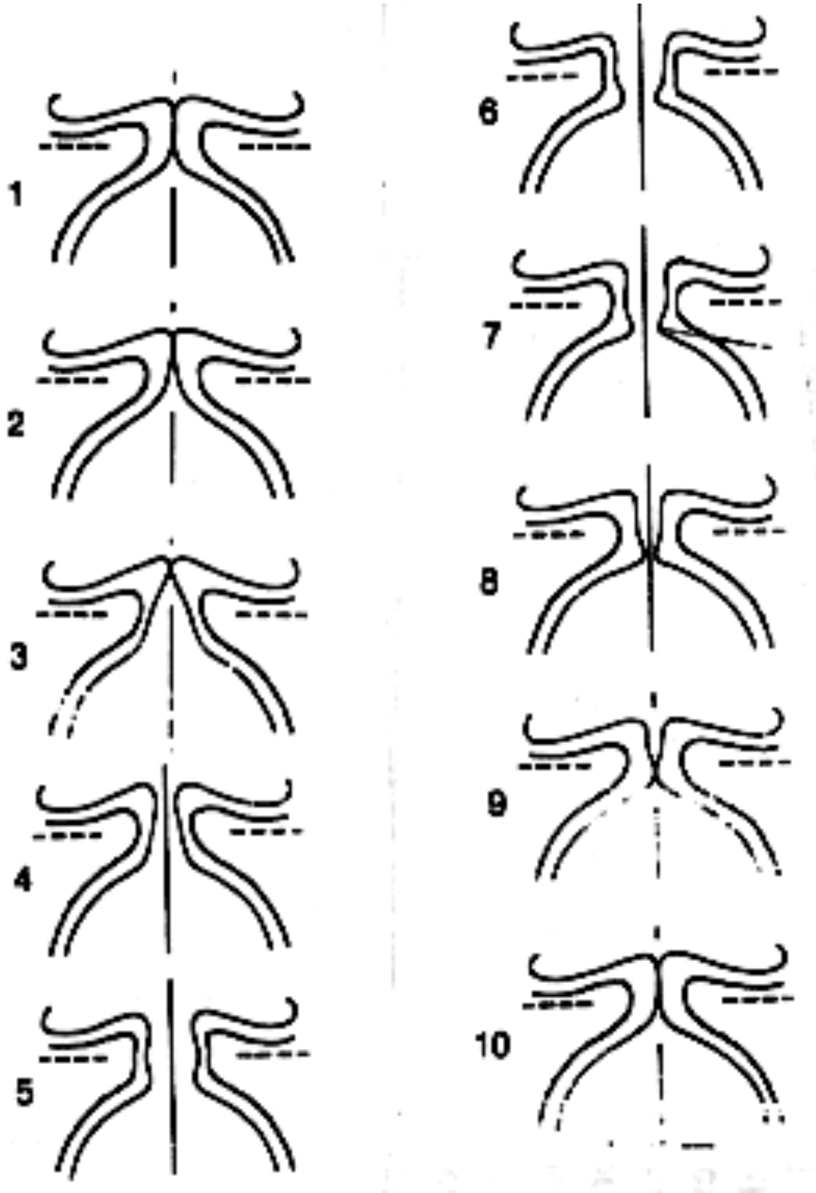


Figure thnx to John Coleman!!

Voicing:



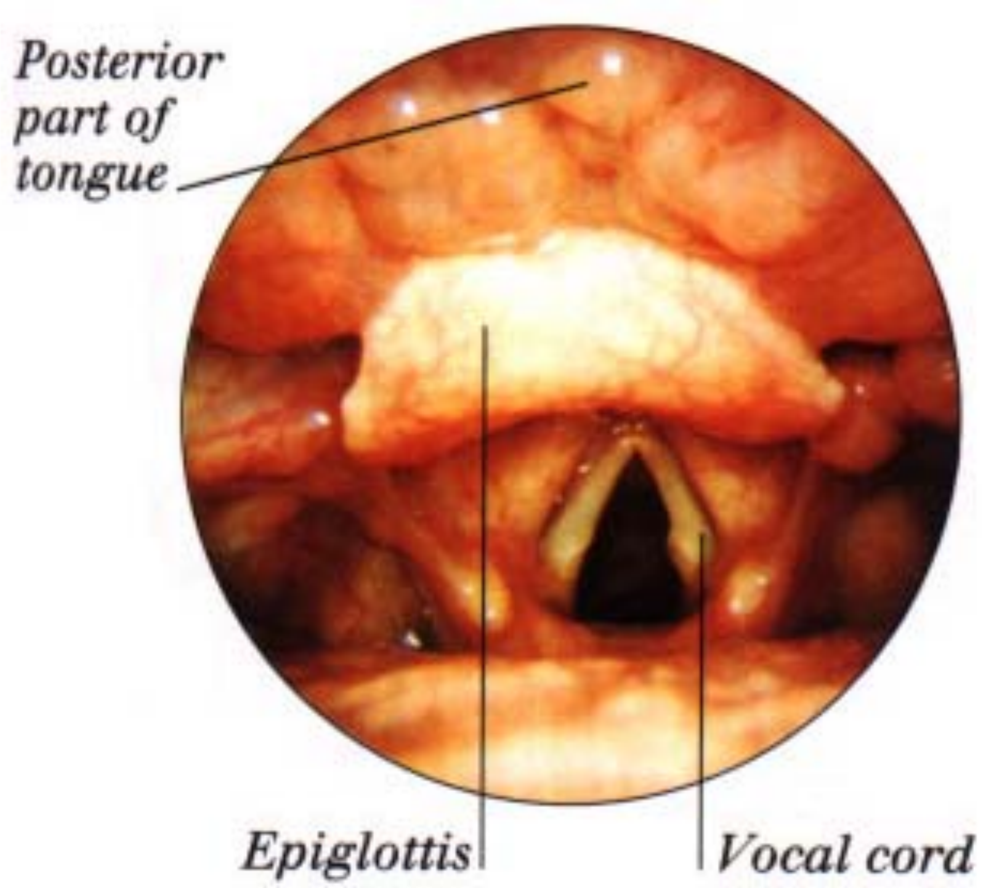
- Air comes up from lungs
- Forces its way through vocal cords, pushing open (2,3,4)
- This causes air pressure in glottis to fall, since:
  - when gas runs through constricted passage, its velocity increases (**Venturi tube effect**)
  - this increase in velocity results in a drop in pressure (**Bernoulli 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

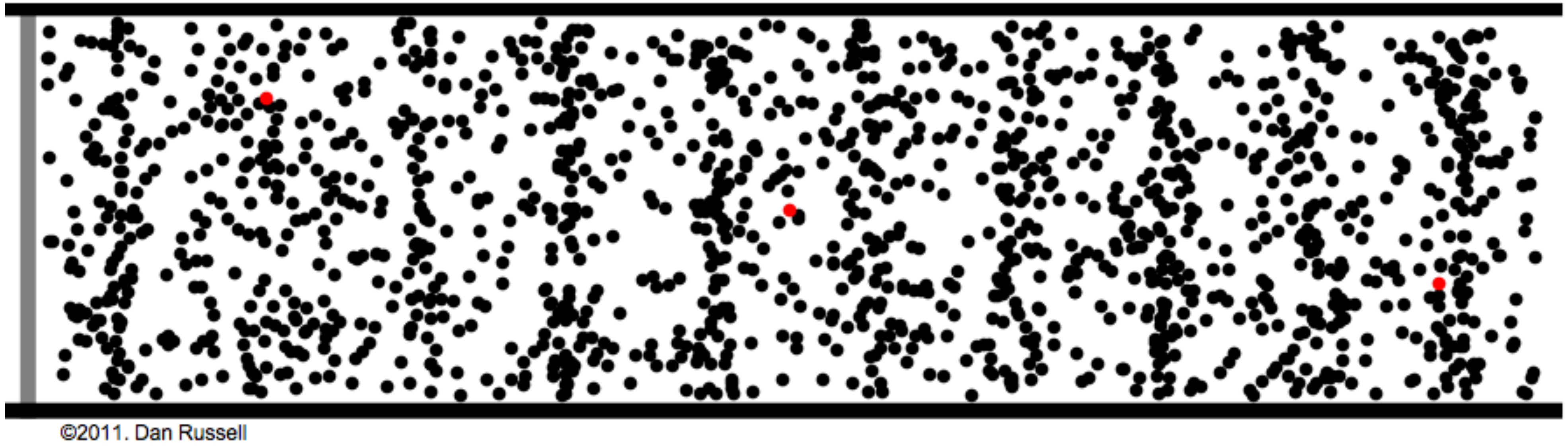


From Mark Liberman's web site, from Ultimate

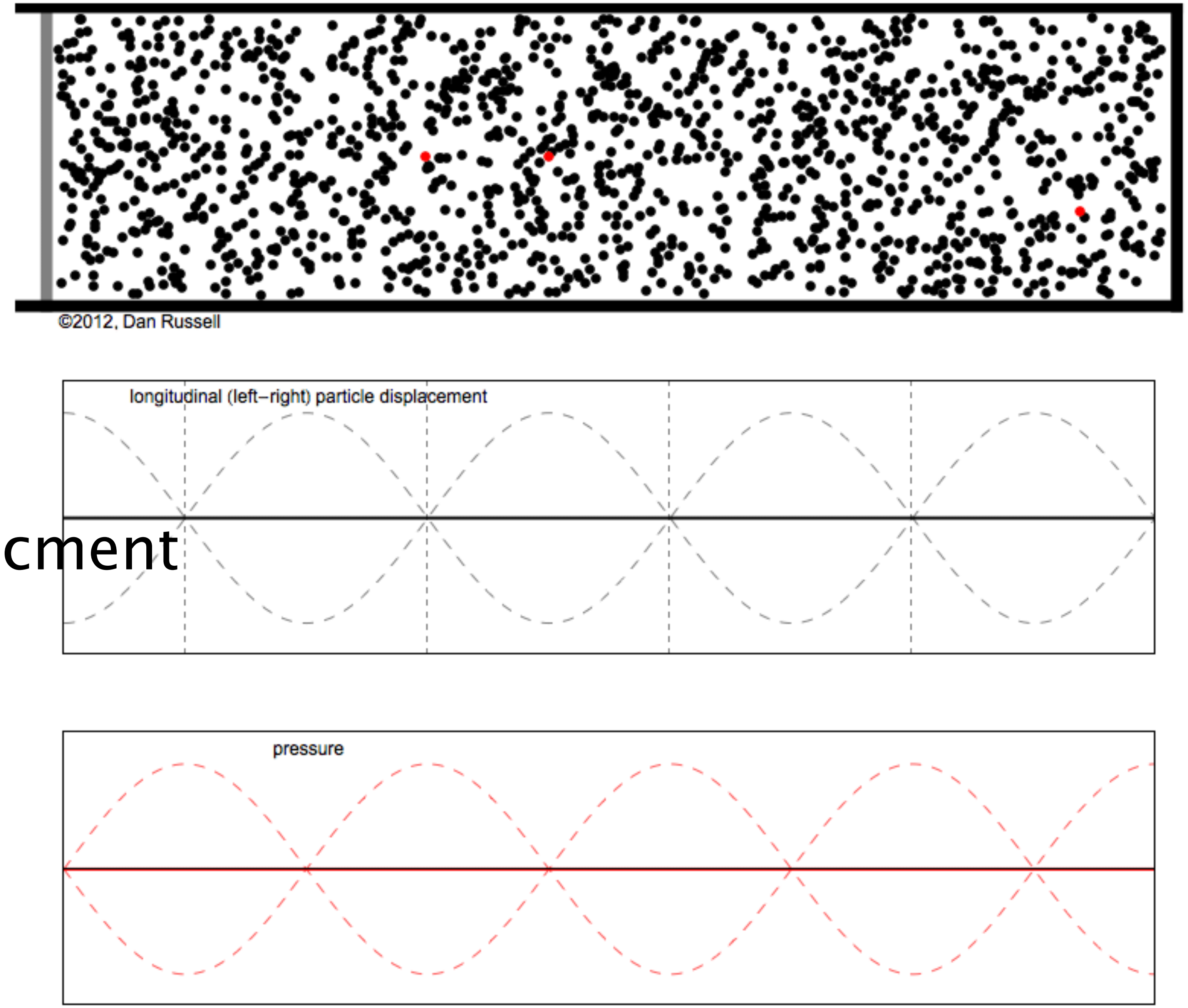
Vocal Fold Vibration

UCLA Phonetics Lab Demo

Sound waves are longitudinal waves



Dan Russell Figure



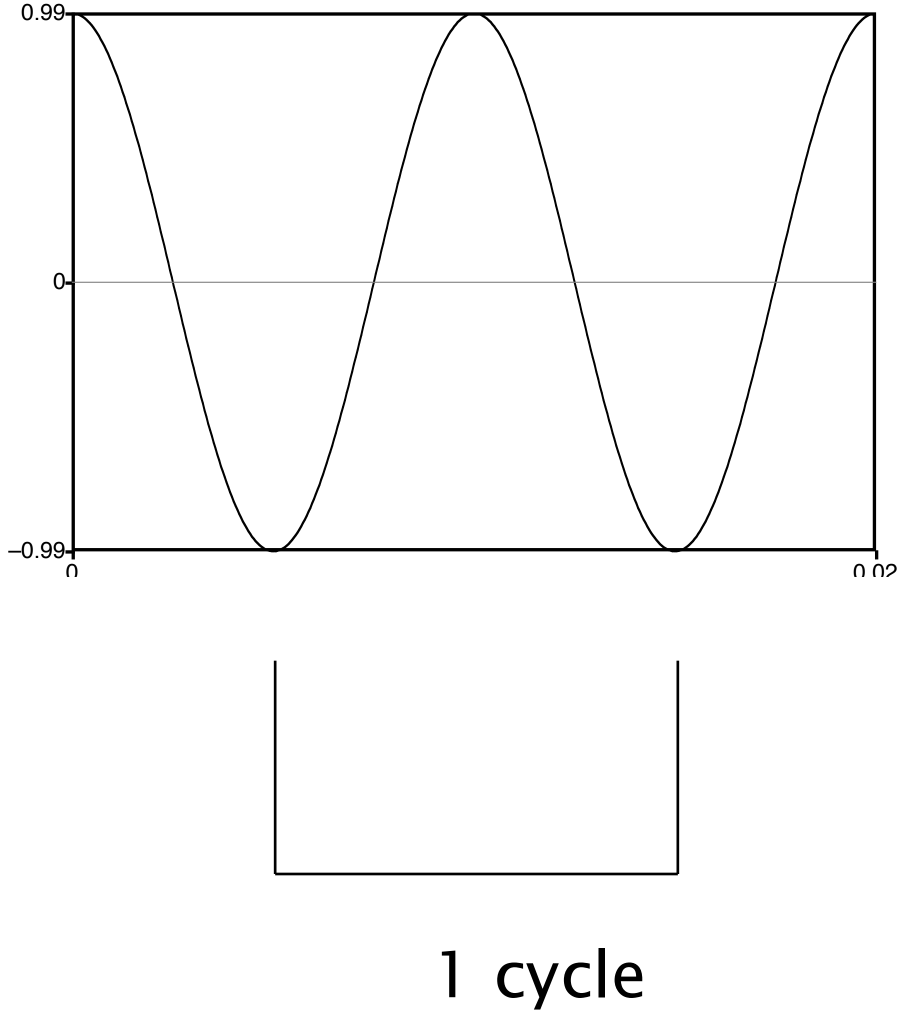
particle dispacment

pressure

Dan Russell Figure

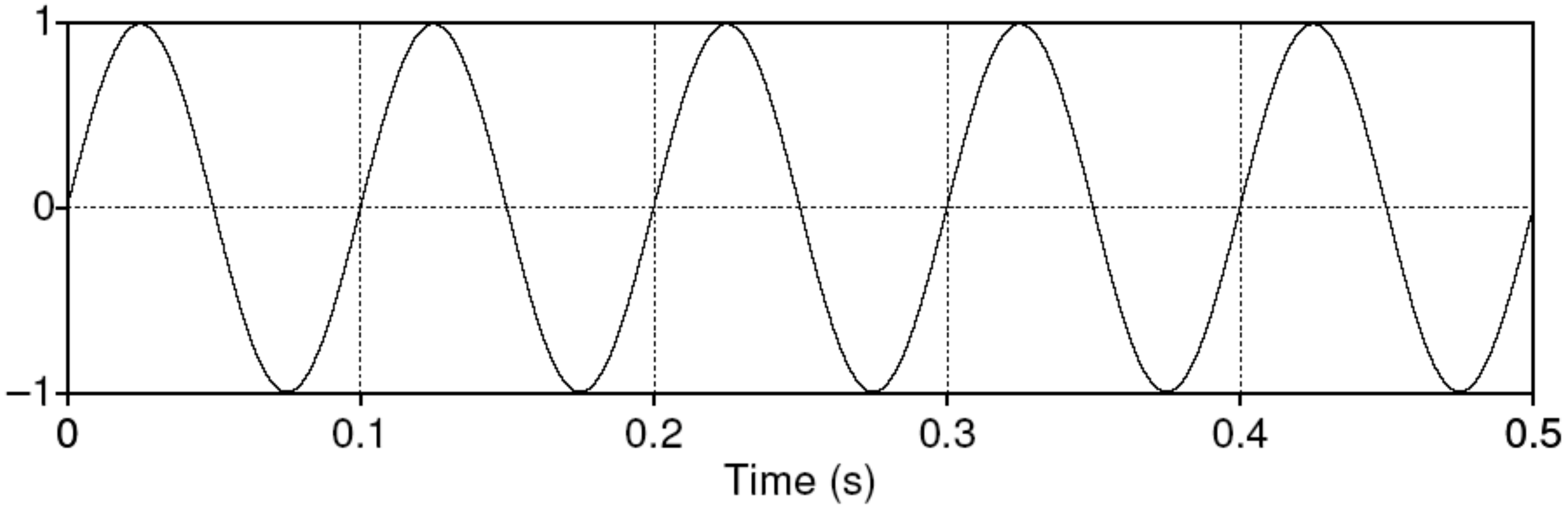
Remember High School Physics
Simple Period Waves (sine waves)

- Characterized by:
  - period: T
  - amplitude A
  - phase ϕ
- Fundamental frequency in cycles per second, or Hz
  - $F_0 = 1/T$

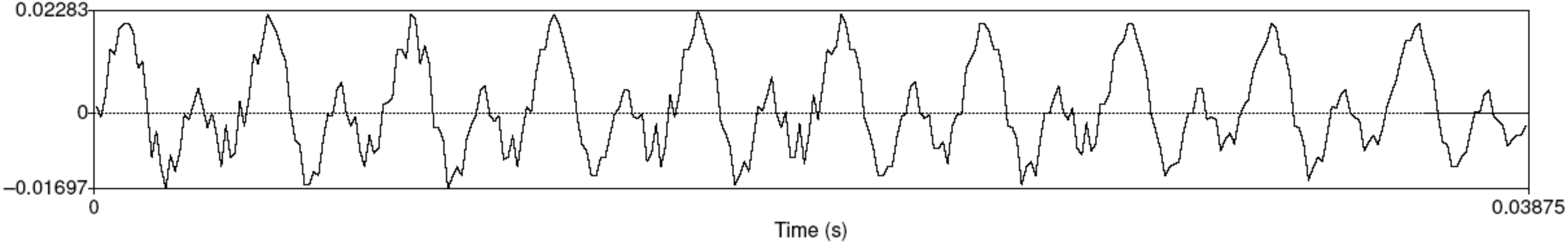


Simple periodic waves

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



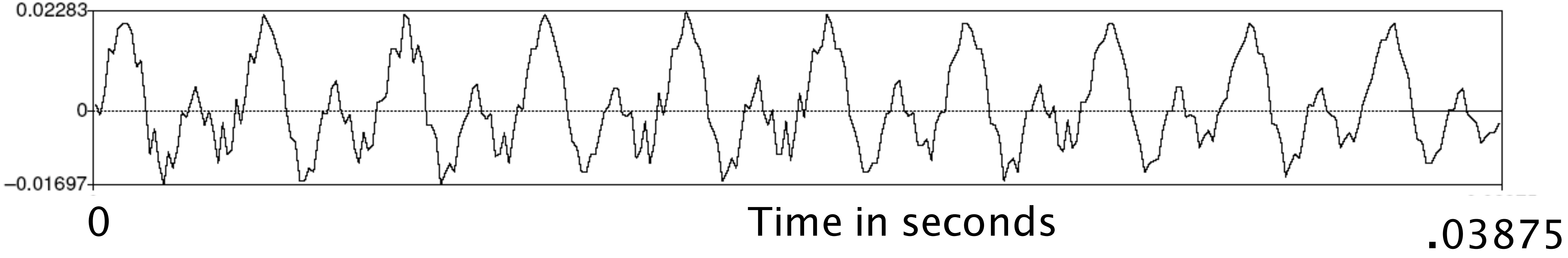
Speech sound waves



- 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

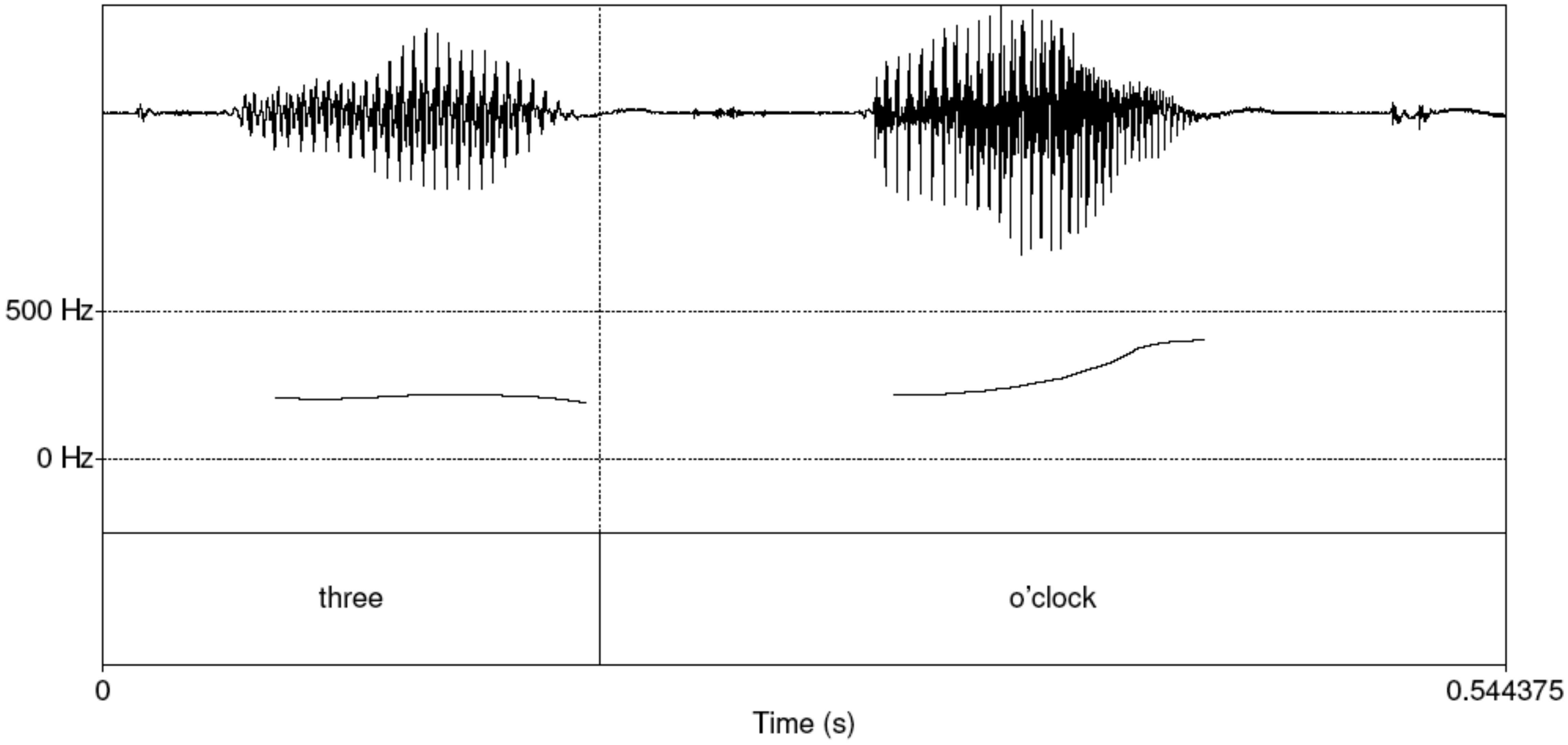
Back to waves: Fundamental frequency

- Waveform of the vowel [iy]



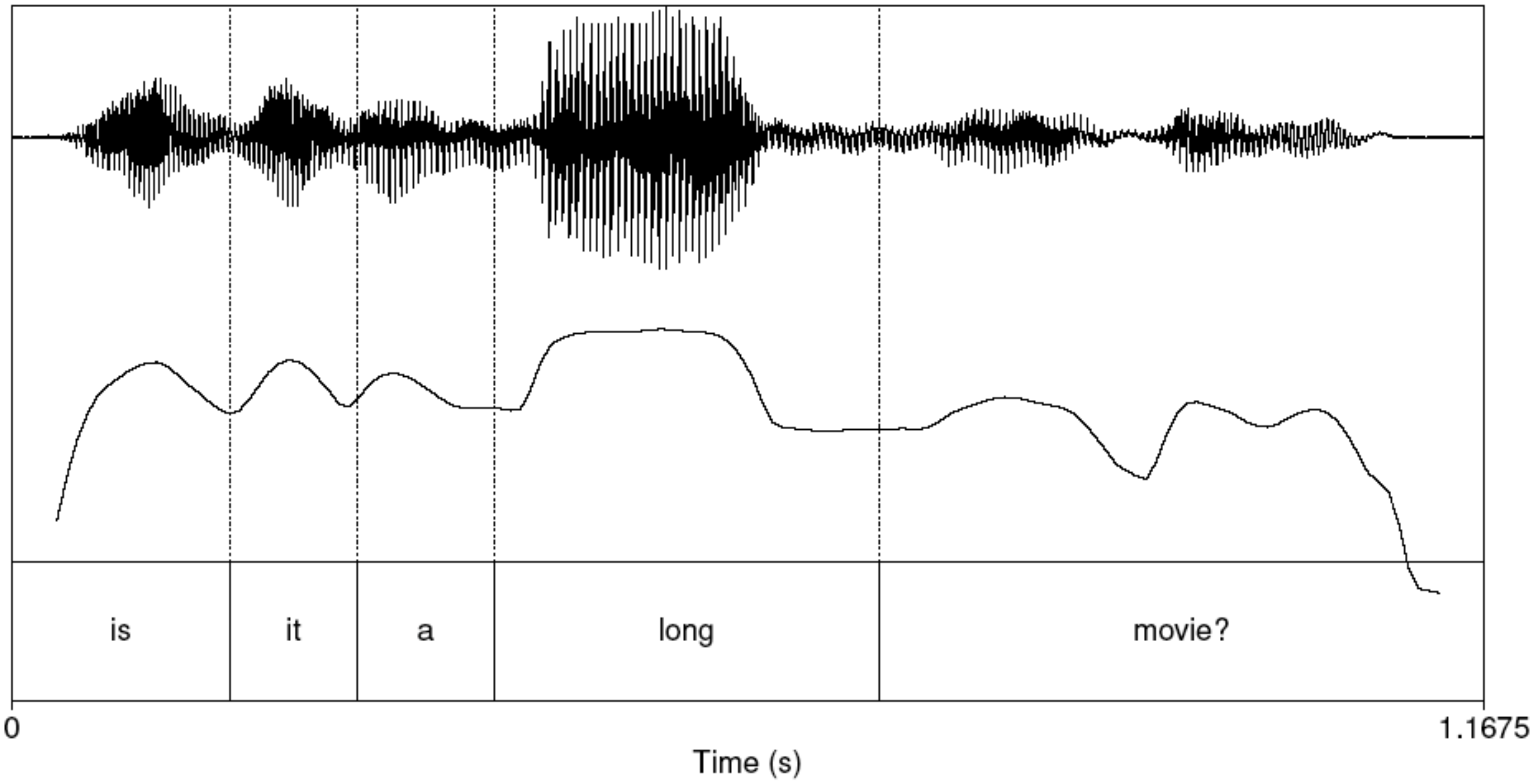
- Frequency: 10 repetitions / .03875 seconds = 258 Hz
- This is speed that vocal folds move, hence voicing
- Each peak corresponds to an opening of the vocal folds
- The low frequency of the complex wave is called the fundamental frequency of the wave or F0

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
  - http://www.ldc.upenn.edu/Catalog/LDC2002S28.html
- 8 actors read short dates and numbers in 15 emotional styles

Slide from Jackson Liscombe

EPSaT Examples

happy

sad

angry

confident

frustrated

friendly

interested

anxious

bored

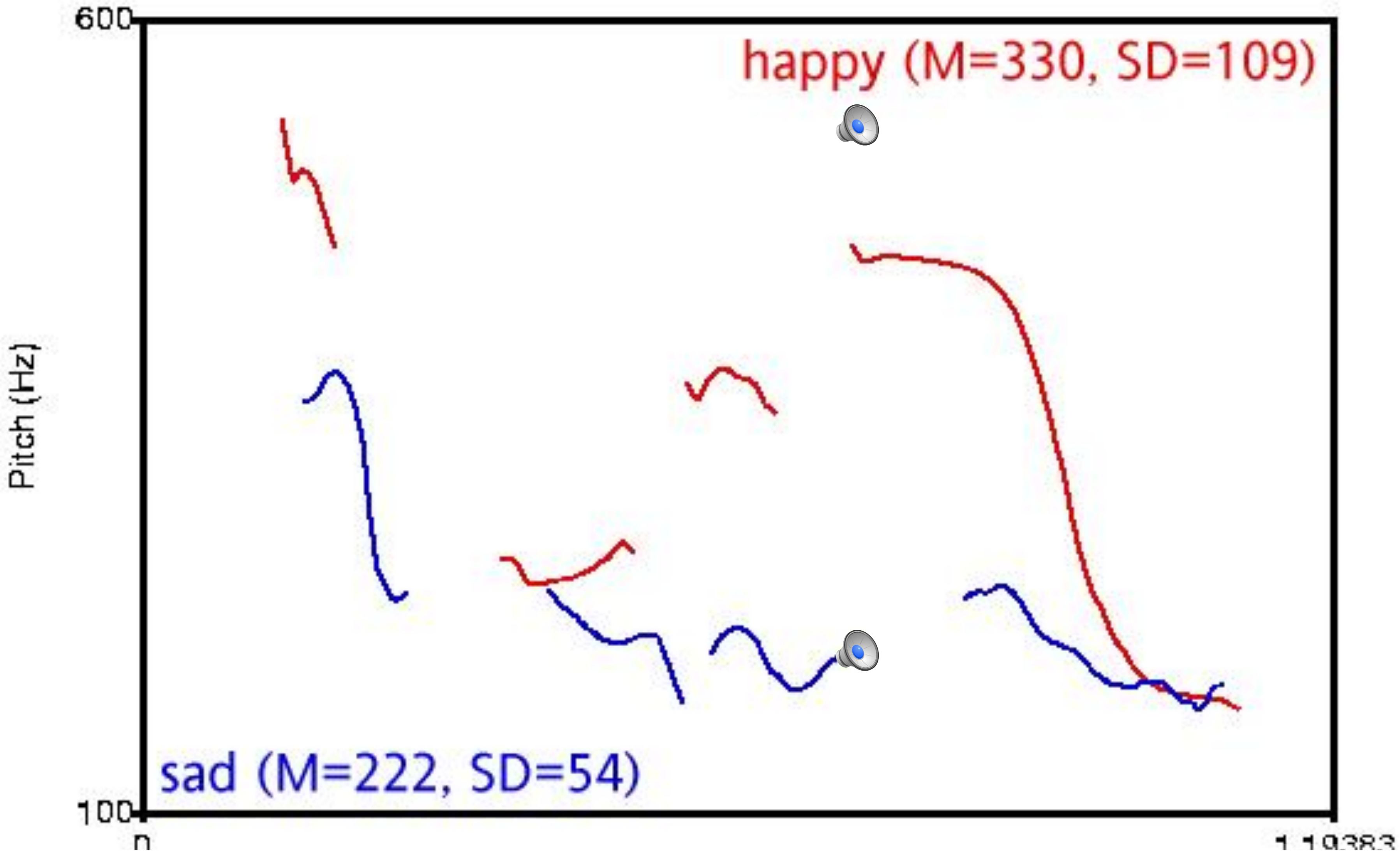
encouraging

Slide from Jackson Liscombe

Task 1

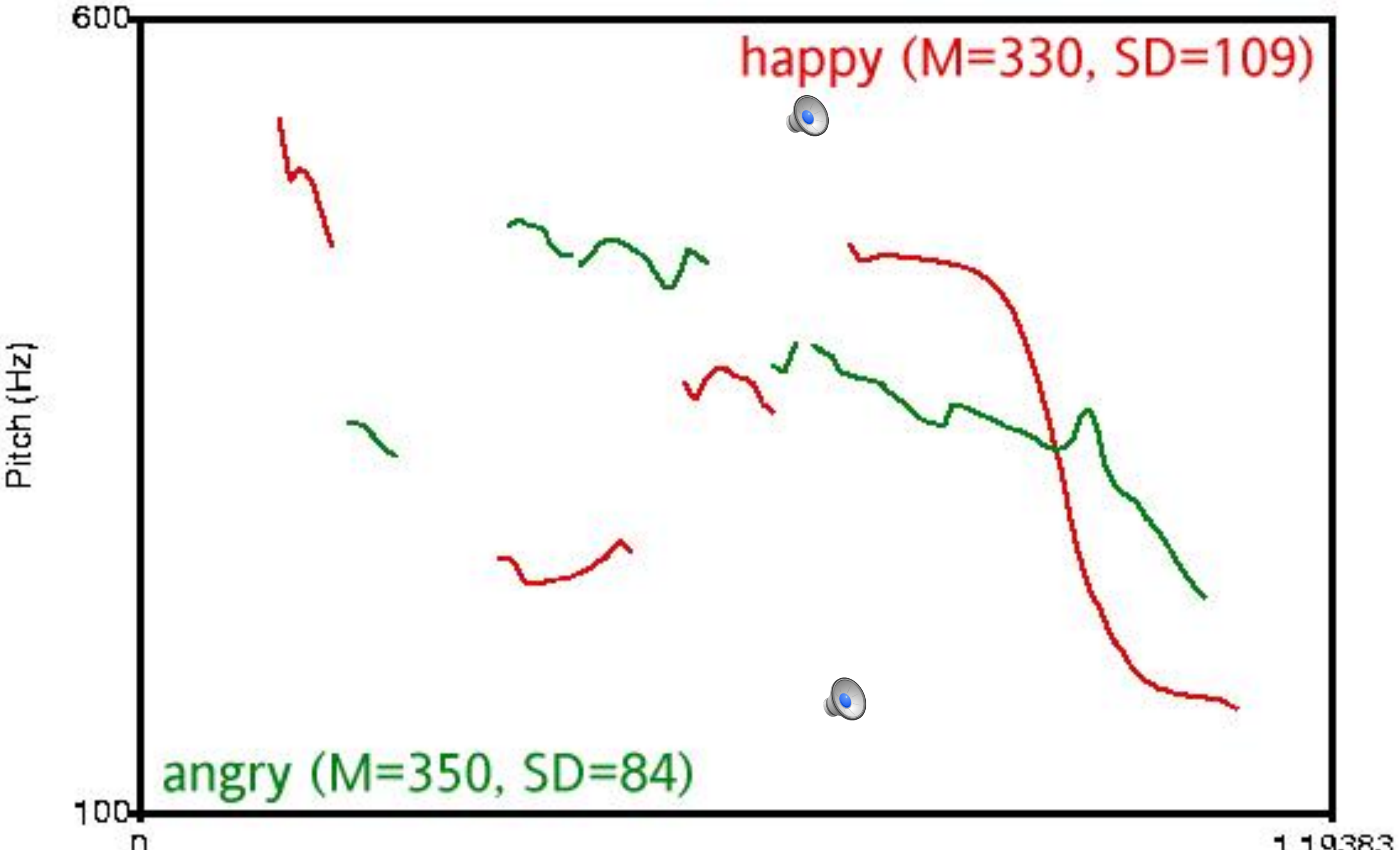
- Binary classification
- Detect the emotion the actor was instructed to use

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

  "Speech & Music Interpretation by Large-space Extraction"
- Praat

Scherer summary: Prosodic features for emotion

	Stress	Anger/rage	Fear/panic	Sadness	Joy/elation	Boredom
Intensity	↗	↗	↗	↘	↗	
F0 floor/mean	↗	↗	↗	↘	↗	
F0 variability		↗		↘	↗	↘
F0 range		↗	↗(↘)	↘	↗	↘
Sentence contours		↘		↘		
High frequency energy		↗	↗	↘	(↗)	
Speech and articulation rate		↗	↗	↘	(↗)	↘

Detecting Social and Affective Meaning

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, unimaginative

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

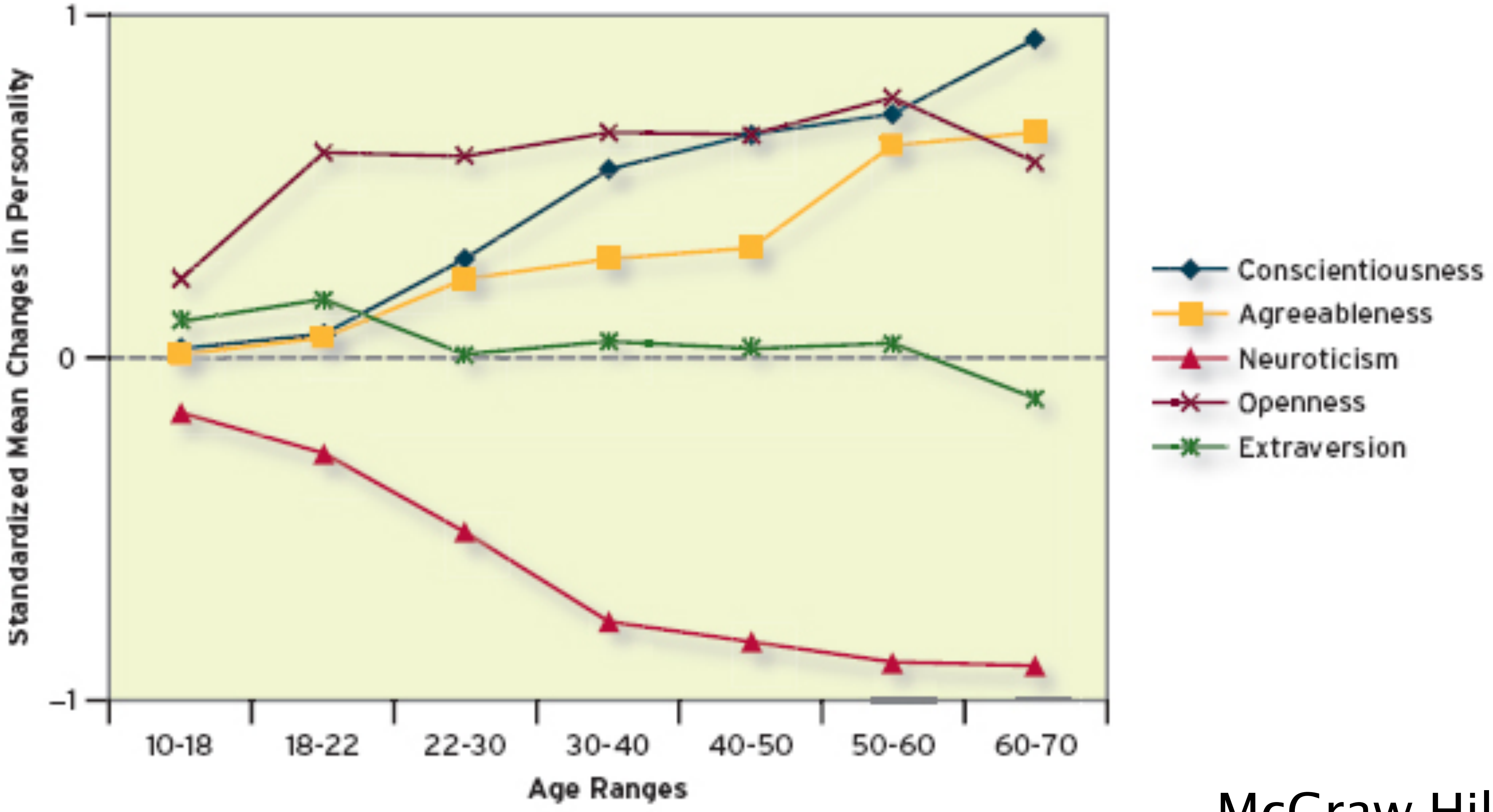
PEOPLE WITH AN EXTERNAL LOCUS OF CONTROL TEND TO BELIEVE:	PEOPLE WITH AN INTERNAL LOCUS OF CONTROL TEND TO BELIEVE:
Many of the unhappy things in people's lives are partly due to bad luck.	People's misfortunes result from the mistakes they make.
Getting a good job depends mainly on being in the right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

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



Aside: Do Animals Have Personalities?

- Gosling (1998) studied spotted hyenas.
- 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

Pennebaker, James W., and Laura A. King. 1999. "Linguistic styles: language use as an individual difference." *Journal of personality and social psychology* 77, no. 6.

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

Mehl, Matthias R, SD Gosling, JW Pennebaker. 2006. Personality in its natural habitat: manifestations and implicit folk theories of personality in daily life. Journal of personality and social psychology 90 (5), 862

- 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.)

Introvert	Extravert
- 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.
Unconscientious	**Conscientious**
- With the Chinese. Get it together. - I tried to yell at you through the window. Oh. xxxx'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 don't see [...]

Essays corpus (Pennebaker and King)

Introvert	Extravert
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 [...]	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.
Neurotic	**Emotionally stable**
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.	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.

Classifiers

- **Mairesse**, François, Marilyn A. Walker, Matthias R. Mehl, and Roger K. Moore. "Using linguistic cues for the automatic recognition of personality in conversation and text." *Journal of artificial intelligence research* (2007): 457-500.
  - Various classifiers, lexicon-based and prosodic features
- **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.
  - regression and SVM, lexicon-based and all-words

Sample LIWC Features

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

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

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:

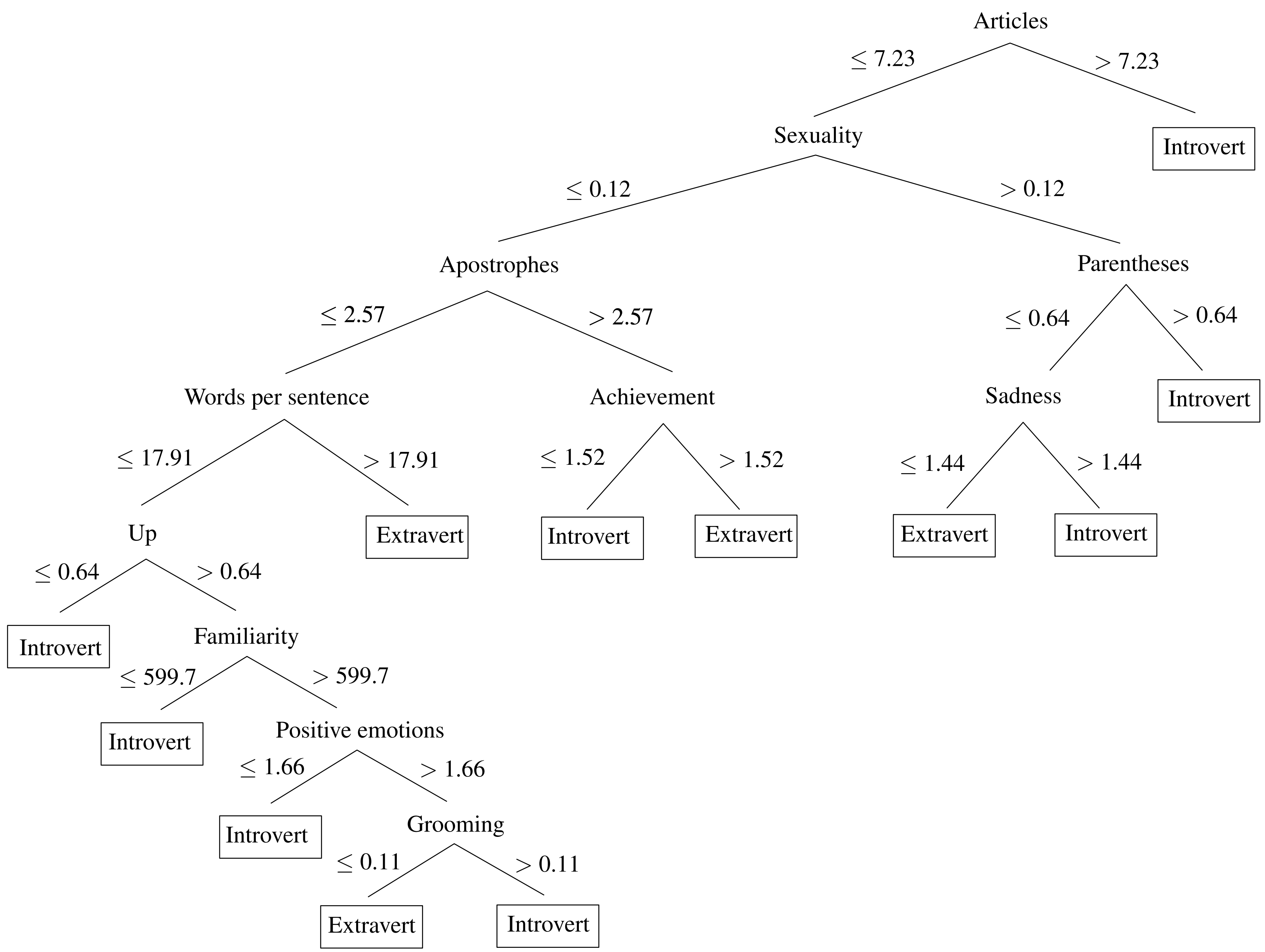
  Normalized per writer:

$$p\,(category \mid subject) = \frac{\sum_{word \in category} freq\,(word, subject)}{\sum_{word \in vocab\,(subject)} freq\,(word, subject)}$$

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)



Feature analysis: Observed Extraversion

more words

higher pitch

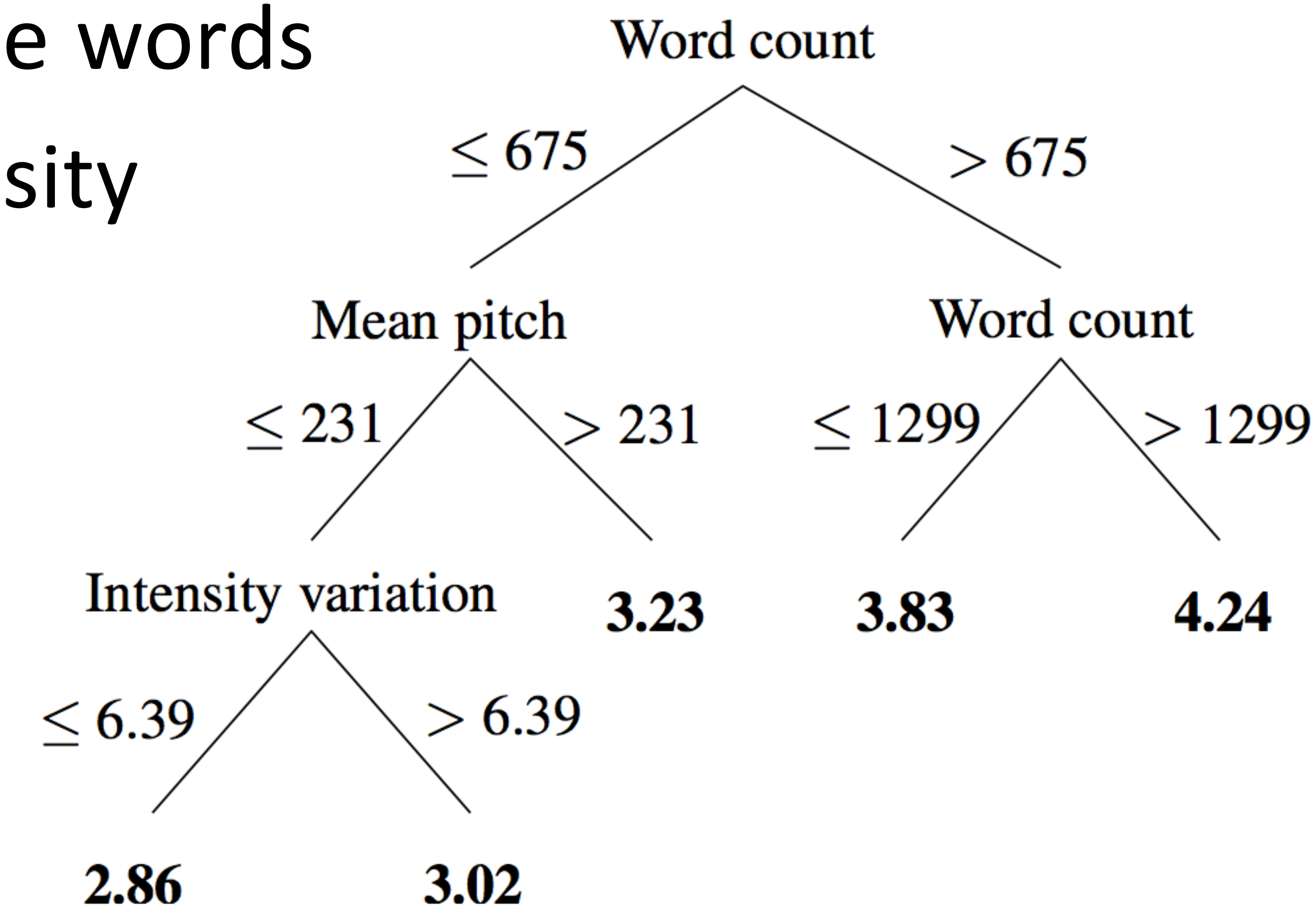
more concrete, imageable words

greater variation in intensity

greater mean intensity

more word repetitions

M5’ Regression Tree



Using all words instead of lexicons Facebook study

Schwartz et al. (2013)

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

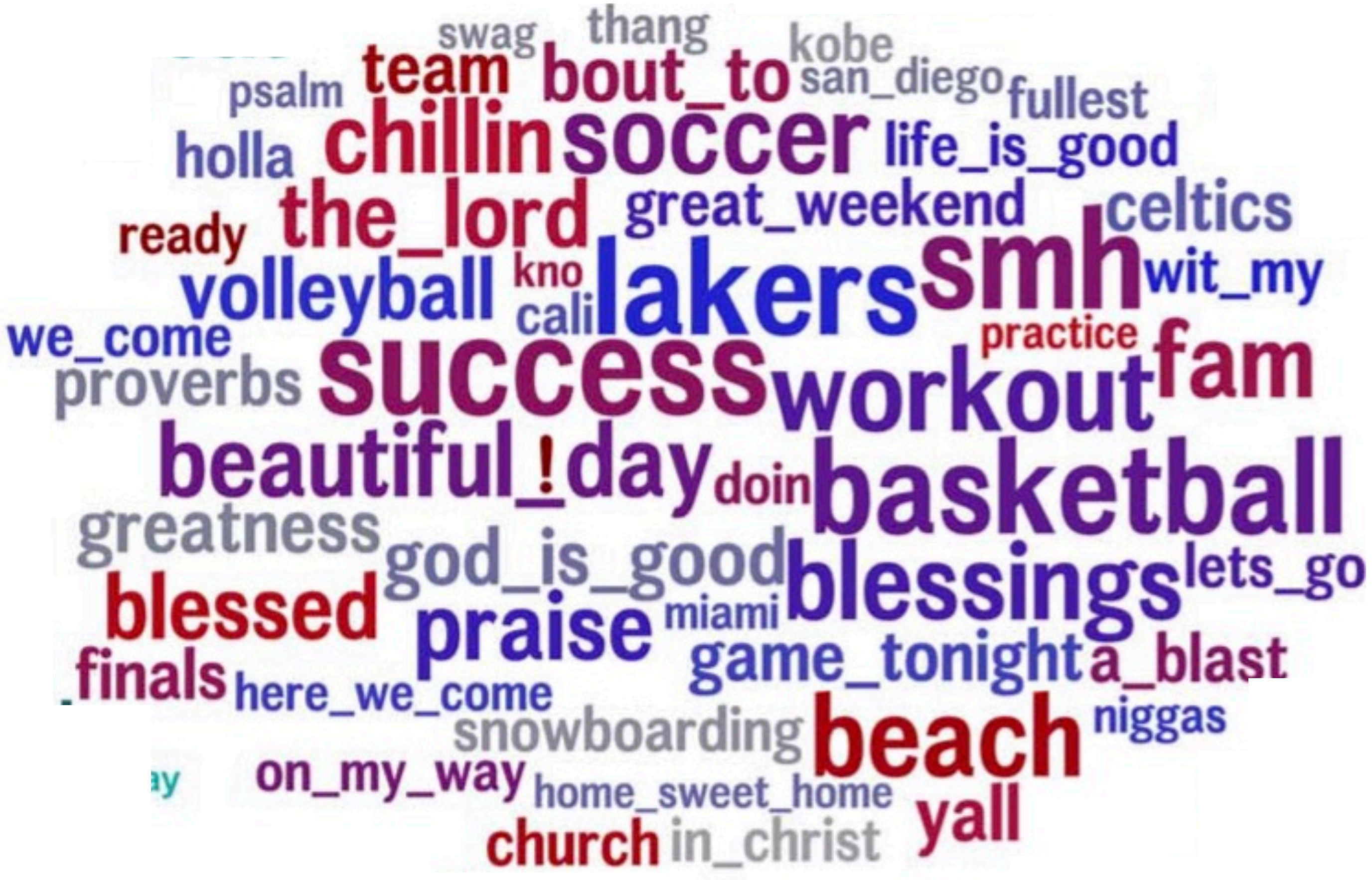
$$pmi\ (phrase) = \log \frac{p(phrase)}{\Pi_{w \in phrase}\, p(w)}$$

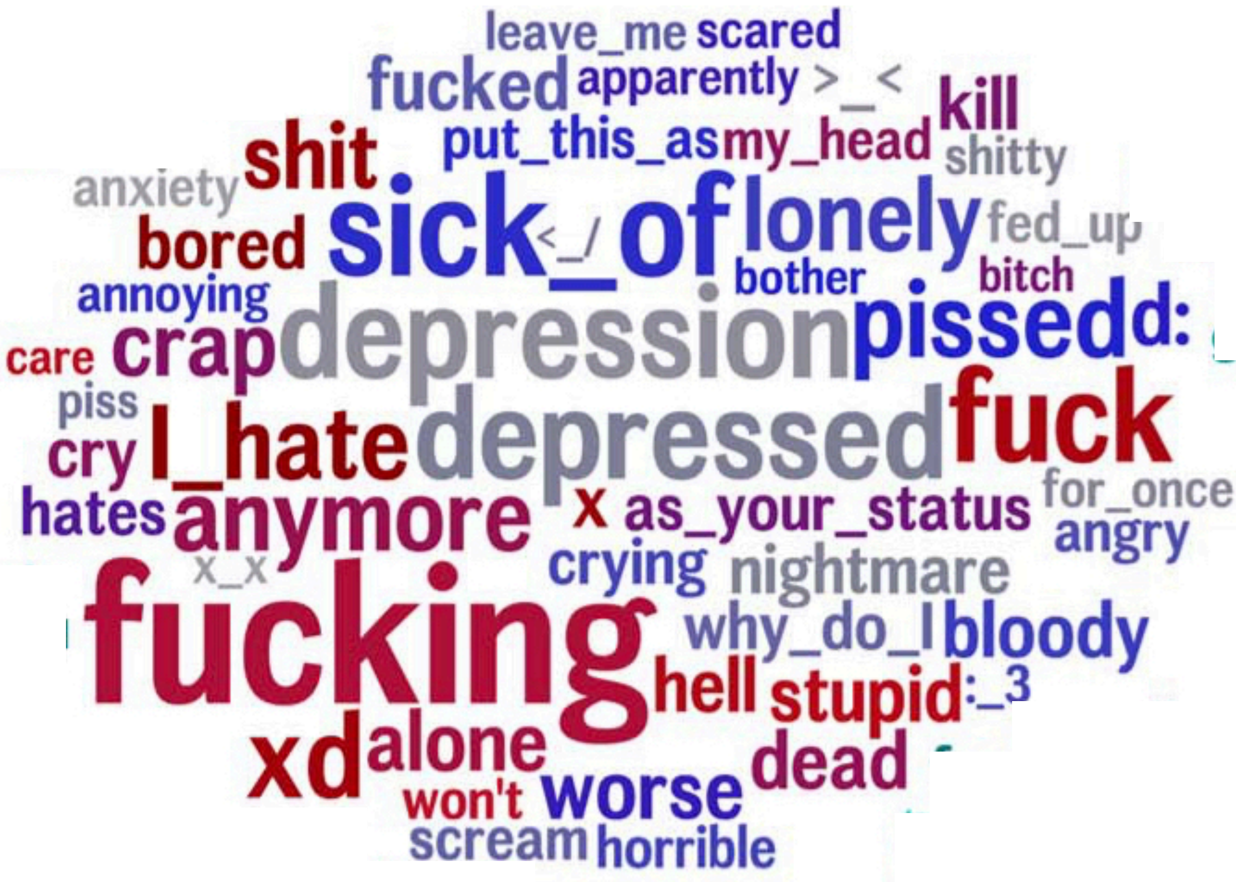
- Only use words/phrases used by at least 1% of writers
- Normalize counts of words and phrases by writer

$$p(phrase \mid subject) = \frac{freq\ (phrase, subject)}{\sum_{phrase' \in vocab(subject)} freq\ (phrase', subject)}$$

Facebook study, Learned words, Extraversion versus Introversion

Facebook study, Learned words
Neuroticism versus Emotional Stability





Evaluating Schwartz et al (2013) Facebook Classifier

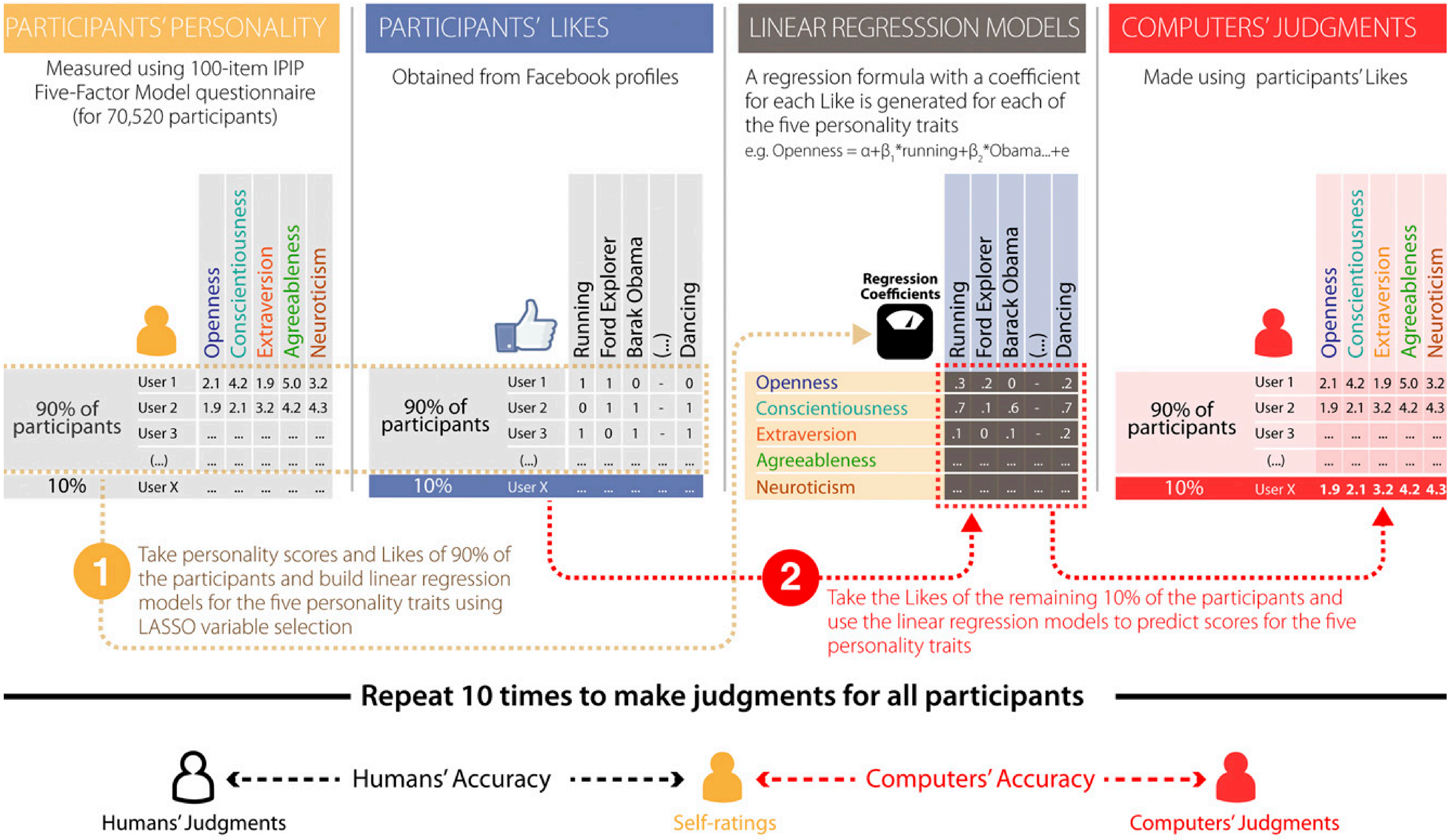
- Train on labeled training data
  - LIWC category counts
  - words and phrases (n-grams of size 1 to 3, passing a collocation filter
- Tested on a held-out set
- Correlations with human labels
  - LIWC .21-.29
  - All Words .29-.41

What about predicting personality from what someone likes?

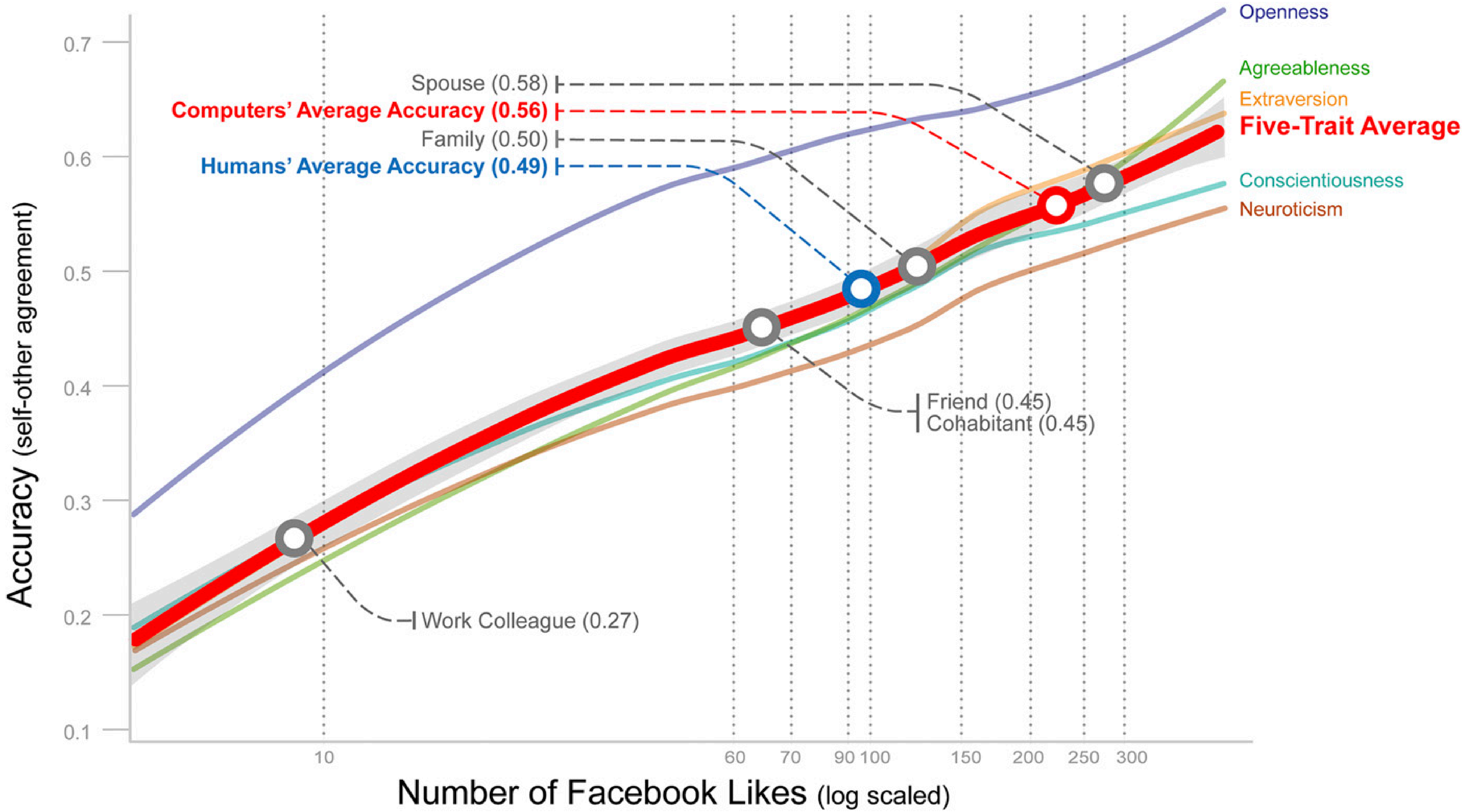
Youyou Wu, Michal Kosinski, and David Stillwell. "Computer-based personality judgments are more accurate than those made by humans." *Proceedings of the National Academy of Sciences* (2015)

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

Wu et al. Algorithm:



Results:



Openness
Agreeableness
Extraversion
Five-Trait Average
Conscientiousness
Neuroticism
Spouse (0.58)
Computers' Average Accuracy (0.56)
Family (0.50)
Humans' Average Accuracy (0.49)
Friend (0.45)
Cohabitant (0.45)
Work Colleague (0.27)
Accuracy (self-other agreement)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
10
60
70
90 100
150
200
250
300
Number of Facebook Likes (log scaled)

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 **T**utoring **Spoke**n Dialogue System

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

- Jackson Liscombe, Julia Hirschberg, Jennifer J. Venditti. 2005. Detecting Certainness in Spoken Tutorial Dialogues
- Forbes-Riley, Kate, and Diane Litman. "Benefits and challenges of real-time uncertainty detection and adaptation in a spoken dialogue computer tutor." Speech Communication 53, no. 9 (2011): 1115-1136.

Tutorial corpus: how **certain** is the student

Jackson Liscombe, Julia Hirschberg, Jennifer J. Venditti. 2005. Detecting Certainness in Spoken Tutorial Dialogues

- 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

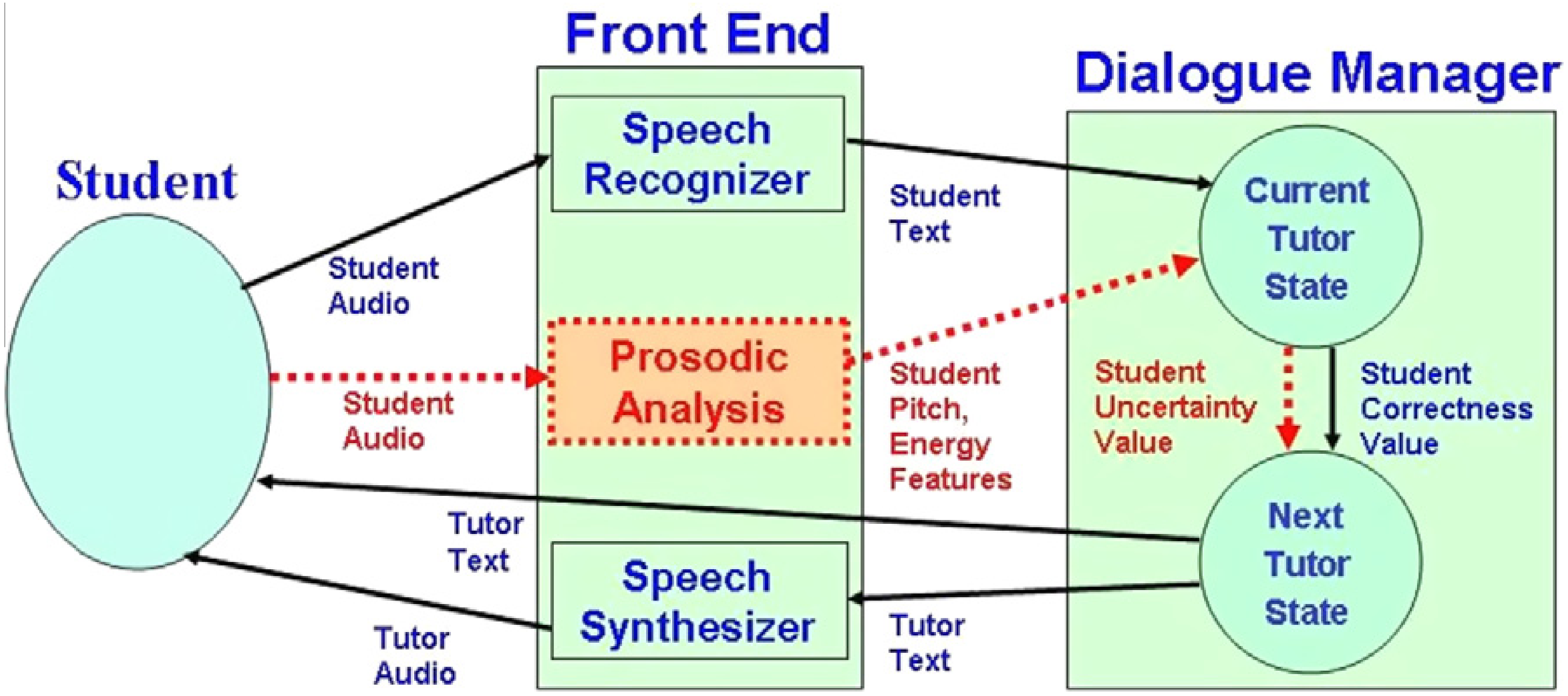
um <sigh> I don’t even think I have an idea here ...... now .. mass isn’t weight ...... mass is .... the .... space that an object takes up .... is that mass?

[71-67-1:92-113]

Slide from Jackson Liscombe

Does it help? A tutorial system that adapts to uncertainty

Forbes-Riley, Kate, and Diane Litman. "Benefits and challenges of real-time uncertainty detection and adaptation in a spoken dialogue computer tutor." Speech Communication 53, no. 9 (2011): 1115-1136.



Give more information if the student is uncertain

Forbes-Riley, Kate, and Diane Litman. "Benefits and challenges of real-time uncertainty detection and adaptation in a spoken dialogue computer tutor." Speech Communication 53, no. 9 (2011): 1115-1136.

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/s^2)?
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/s^2. 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 $9.8\text{m/s} + 9.8\text{m/s} = 19.6\text{m/s}$. 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/s^2. 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

ITSPOKE-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

Kate Forbes-Riley, Diane Litman, Heather Friedberg, Joanna Drummond. 2012. Intrinsic and Extrinsic Evaluation of an Automatic User Disengagement Detector for an Uncertainty-Adaptive Spoken Dialogue System. NAACL 2012.

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

  ITSPOKE-recognized lexical items in turn

  ITSPOKE-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?

Litman, Diane, and Kate Forbes-Riley. "Evaluating a Spoken Dialogue System that Detects and Adapts to User Affective States." In *15th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, p. 181. 2014

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

Rajesh Ranganath, Dan Jurafsky, and Daniel A. McFarland. 2013. Detecting friendly, flirtatious, awkward, and assertive speech in speed-dates. *Computer Speech and Language* 27:1, 89-115.

McFarland, Daniel, Dan Jurafsky, and Craig M. Rawlings. 2013. "Making the Connection: Social Bonding in Courtship Situations." *American Journal of Sociology.*

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:

	Male is flirting (1-10)
Male 101 says:	8
Female 127 says:	1

Why?

People assume their date is behaving like themselves:

	Male is flirting	Female is flirting
Male 101 says:	8	7
Female 127 says:	1	1

Correlations between my behavior and what I say about my date

	I label myself x I label date	I label date x date labels themselves
Flirting	.73	.15
Friendly	.77	.05
Awkward	.58	.07
Assertive	.58	.09

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)

construction (“collaborative completions”)

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

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

	Language	Traits	Language + Traits
Male flirt	66%	64	72
Female flirt	74	55	76

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