Language as a Measure of Mental Health

JSALT Summer Workshop Tutorial Lecture

Kristy Hollingshead Seitz, PhD 23 June 2016 hollingk@gmail.com





whois

- Research Scientist, 2014-present @ IHMC in Ocala FL
 - Assistive technologies
 - Hybrid systems combining human- and machine-learned features
- Co-organizer of CLPsych Workshop, 2015 & 2016
 - CLPsych: Computational Linguistics and Clinical Psychology from Linguistic Signal to Clinical Reality
 - Social media analysis
- Researcher, 2012-2014 @ DoD
- PostDoc, 2010-2012 @ University of Maryland
 - Machine translation
- PhD, 2010 @ Oregon Health & Science University
 - Parsing, language modeling, assistive technologies

Highlights & Take-Aways

- Language written or spoken provides a quantifiable signal that can be used to automatically assess mental health status
- There are various NLP techniques tools in the toolbox that could be applied to automated assessments
 - Automated assessments do not replace, but rather assist, diagnosticians
- Many POVs for applications: healthcare providers (clinicians, therapists, doctors), insurance providers, friends/family, self



Outline

- Motivation
- Related work
- Data collection: Twitter
- Data validation
- Linguistic & multi-modal features
- Data analysis

Modeling Language

- So far this week, you've been learning a myriad of ways to model language
 - Language modeling (spoken and written)
 - Language understanding (spoken and written)
 - Machine learning techniques
- ...but what does language, itself, model?
 Everyday language a signal of our cognitive state
 Used to measure our mental, neuro, physical health

Motivation: Language as a Signal

- Language is something we use every day a natural, stressfree, typically unforced activity
- Language is a sensitive signal showing signs of cognitive health/stress long before other symptoms manifest
 - For clinical psychologists, language plays a central role in diagnosis & many clinical instruments rely on manual coding of patient language
 - Linguistic memory tests are most effective for detecting Alzheimer's
- But isn't language a *qualitative* signal?

Motivation: Quantify Language

- Language really seems like a *qualitative* signal we all have a vague sense of when and how our language changes
- To *quantify* the signal, we end up counting
 e.g., Total story words recalled during narrative recall tests
- Natural language processing (NLP) quantifies language
 - Measures many things, from rapid changes in topic...
 - ...to an increased use of pronouns...
 - ...to slightly longer pauses between words, etc.
- Quantified language measured by NLP techniques allows us to measure language change over time, space, and situations

Motivation: Social Media Analysis

• Language as an everyday activity – "natural, stress-free, typically unforced"

- Social media provides unprecedented access to truly unforced, natural language
 - Provides an ecologically valid measure
- Big data, quick to gather
- Removes reporting & hindsight biases



Motivation: Mental Health

- Mental health is a global issue that affects us all
- Global cost of mental health conditions: \$2.5 trillion in \$\$
 2010, increasing to >\$6 trillion in 2030
- 1 in 4 worldwide will suffer from a mental health condition in their lifetime; 1 in 5 Americans experience a mental health problem in any given year
- Suicide is the 10th leading cause of death in America
- Mental, neurological, & substance use disorders are the leading cause of disability worldwide



Language on social media provides a natural signal of our cognitive state, with the potential to help assess mental health status.





Outline

- Motivation
- Background
- Data collection: Twitter
- Data validation
- Linguistic & multi-modal features
- Data analysis



Related Work in Social Media

• Research in political science & social science

[Boydstun et al., 2013] [Al Zamal et al., 2012]

- Tracking physical health conditions such as cancer or the flu [Paul and Dredze, 2011; Dredze, 2012; Aramaki et al., 2011; Hawn, 2009]
- Discovering latent characteristics and personality traits of people

[Sap et al., 2014; Beller et al.,

2014; Schwartz et al., 2013]

• Recent explosion of work detecting depression [DeChoudhury et al., 2013-2015; Coppersmith et al., 2014; many others]

Prior related work

- Detected mild cognitive impairment (MCI; earliest stage of Alzheimer's) based on spoken language samples
 - Roark et al., 2011. Spoken language derived measures for detecting Mild Cognitive Impairment. IEEE TASLP, 19(7):2081-2090.
 - Roark et al., 2007. Syntactic complexity measures for detecting Mild Cognitive Impairment. In Proceedings of BioNLP.
- Classified users with PTSD, depression, bipolar, anxiety, ADHD, OCD, and schizophrenia based on language of tweets ***
 - Coppersmith et al., 2015. CLPsych 2015 Shared Task: Depression and PTSD on Twitter. In Proceedings of CLPsych.
 - Coppersmith et al., 2015. From ADHD to SAD: Analyzing the Language of Mental Health on Twitter through Self-Reported Diagnoses. In Proceedings of CLPsych.
- Recent explosion of research on detecting depression in social media

For this talk

Results reported in this talk are largely from the following papers

- Glen Coppersmith, Mark Dredze, Craig Harman, and Kristy Hollingshead. 2015. From ADHD to SAD: Analyzing the Language of Mental Health on Twitter through Self-Reported Diagnoses. In *Proceedings of the 2nd ACL Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality (CLPsych)*.
- Margaret Mitchell, Kristy Hollingshead, and Glen Coppersmith. 2015. Quantifying the Language of Schizophrenia in Social Media. In *Proceedings of the 2nd CLPsych Workshop*.
- Glen Coppersmith, Mark Dredze, Craig Harman. Quantifying Mental Health Signals in Twitter. 2014. In *Proceedings of the 1st CLPsych Workshop*.
- Glen Coppersmith, Craig Harman, Mark Dredze. Measuring Post Traumatic Stress Disorder in Twitter. 2014. In *Proceedings of the International Conference on Weblogs and Social Media (ICWSM)*.

Outline

- Motivation
- Related Work
- Data collection: Twitter
 - Started with bipolar, depression, post-traumatic stress disorder (PTSD), seasonal affectiveness disorder
 - Added attention deficit hyperactivity disorder (ADHD), borderline, eating disorders (anorexia, bulimia), obsessive compulsive disorder (OCD), and schizophrenia
- Data validation
- Linguistic & multi-modal features
- Data analysis

Pulling Data from Twitter

- Requires API keys
- Streaming API
 - Samples public data posted to Twitter (<=1%)
 - Real-time only
- RESTAPIs: GET and POST
 - Search: keyword search historical tweets <1 week ago
 - Trends: trending topics
 - User: tweets, profile, followers of a username

Wei Xu's Twitter API tutorial: http://socialmedia-class.org/twittertutorial.html

'Found' Data

Originally collected for: Dredze (2012), Paul & Dredze (2011)

- Ongoing search for tweets with health-related keywords
 - [fever, cough, nausea, sickness, diagnosed ...]
 - 2011 to present
 - $\sim 8m$ tweets/day 8.7B tweets
 - ~1.5 Gb/day
- 'Diagnosed with X' tweets
 - ~ 100 tweets/day 1m tweets
 - ~30 k/day

☆ihmc

Example Diagnosis Tweets

started therapy today. got diagnosed with depression and anxiety disorder. this therapist wants me to ...

Just wanted to share some things helping me heal lately. I was diagnosed with severe complex PTSD several years ago and...



'Self-Stated Diagnoses'

- Why publicly state a mental health diagnosis on social media?
 - To seek support from social network
 - To fight the prejudice against mental illness
 - To explain some of their behavior
 - To identify as a member of a group
- Not self-diagnoses



Filter Users

• Assert genuine diagnosis

- At least 25 tweets
- At least 75% tweets in English
 - Using Google's Compact Language Detector, not Twitter's



Nitty Gritty and Black Magic

- Lowercase everything
 - [shouldn't lose THAT much information...]
- Strip unicode badness
- Exclude tweets with URLs
- Exclude retweets
- Replace all @mentions with single token: "@".

Mental Health Conditions

[Coppersmith et al. (CLPsych, 2015)]

Condition*	Users	Median	Total
ADHD	102	3273	384k
Anxiety	216	3619	1591k
Bipolar	188	3383	720k
Borderline	101	3330	321k
Depression	393	3306	546k
Eating	238	3229	724k
OCD	100	3331	314k
PTSD	403	3241	1251k
Schizophrenia	172	3236	493k
SAD	100	3229	340k

Matched Controls

- Will be building classifiers capable of separating users with each condition from "control" users.
- In some previous studies, control users were randomly pulled from Twitter
 - Resulted in demographic effects on the results



Comorbid Conditions



Outline

- Motivation
- Background
- Data collection: Twitter
- Data validation
- Linguistic & multi-modal features
- Data analysis



Data Validation

[Coppersmith et al. (ICWSM, 2014)]

Experiment: PTSD and Military Bases

- Tweets geo-located to 4 types of regions
 - Military: High-deploy, Low-deploy
 - Civilian: Urban, Rural
- Score all tweets with LM-based classifiers
- Proportions of PTSD-like tweets for each region
- Binomial test:
 - Military > Civilian
 - High-deploy > Low-deploy

Outline

- Motivation
- Background
- Data collection: Twitter
- Data validation
- Linguistic & multi-modal features
- Data analysis



Features

• Language models

- Unigram-based (ULM), character-based (CLM)

- Linguistic Inquiry Word Count (LIWC) [Chung & Pennebaker 2007]
 - Lexicons with associated psychological meaning
 - Pronouns, emotions, functional words
- Sentiment analysis
 - Lexicon-based

Unigram Language Model (ULM)

- Train language models (LMs) on a collection of tweets
- Score whether a tweet likely generated by Condition (e.g., PTSD) vs Control LM
- Tokenization/normalization: ~words
- One label per user
 - [remove 'diagnosed with x' tweets]
 - Discriminatively trained (e.g., PTSD vs Control)
- "Open Vocabulary" approach

Character n-gram Language Model (CLM)

- Sliding window of character n-grams (n=5)
- Why?
 - Compensates for some spelling errors
 - Captures some writing peculiarities
 - (which I've neeeeeeeeever seen happen in tweets)

• "Open Vocabulary" approach

Linguistic Inquiry Word Count

[Chung & Pennebaker (2007)]

- Lexicons with associated psychological meaning
 - Words associated with trauma
 - First, second, third person pronouns
- Traditionally used to analyze patient writing
 - "This person uses a lot of words related to death."
 - "Depressed patients use 'I' more than controls."
- Pro1, Pro2, Pro3, Swear, Anger, PosEmo, NegEmo, Anxiety, Functioning

Sentiment Analysis

Lexicon from: [Mitchell, Aguilar, Wilson & Van Durme (2013)]

- Lexicon of sentiment-bearing words
 - Happy, joyful, sweet, celebrate, ...
 - Sad, angry, bitter, irritated, ...
- Weighted by 'subjectivity score'
- Tweets scored by summing weights associated with words in lexicon

->0: positive, =0: none, <0: negative

- Proportion of positive tweets
- Proportion of negative tweets

☆ihmc

Outline

- Motivation
- Background
- Data collection: Twitter
- Data validation
- Linguistic & multi-modal features
- Data analysis



Exploratory Data Analysis

Legend -	Common Cloud -	Occurences filter -	Rarity filter -	Word Length Filter -	Size 🗸	Opacity -	Sort by -	

Left Dataset: control tweets

u rt today right has shit happy much follow off new well thanks haha work night 2 dd great last thank better man im always game come should let tonight here over hope best us first morning home where getting these hate our tomorrow gonna c wanna yes big ain't done girl birthday 4 ddd real every little keep ya week nice made bitch 5 play damn watch watching long yoo ready already looking win x wish gotta days another beautiful start show football baby smh Imao pretty rochester bed guys da phone hey school money team weekend coming boys talk house amazing white niggas looks call ur such soon funny ?? 10 6 stay xx basketball dat left vet went cause final bout dont talking hair season class hear awesome both car o half job seen crazy p glad xxx 7 music hit text early we're / making hahaha 0 b haven't wit friday blue ima perfect playing sounds needs run tired dey red finally gets bitches wow excited lost mad movie #billsmafia ill working far omg dddd dad change em cute send song << hot bbc aww hours 8 top 30 says cant y'all cuz vall seriously ??? boy gone kids as forward till

Right Dataset: schizophrenia_tweets ᅌ

3 ' am you're her then because life < only never i've did him even being fuck could say feel their i'll than its oh into were way take please fucking very down someone god thing something world yeah again didn't ever look many bad things any other sorry n try said next wait tho nigga after ass sure 1 miss year girls sleep though stop same trying tell everyone might years myself give help before does those also away maybe mean i'd twitter thought doing around most doesn't eyes find nothing friends lot old put actually anything which may mind person hell ok own everything live believe face anyone having care used hard they're through fun two makes name friend end guess use head read since won't must kill guy remember wrong told while bit true enough women isn't probably cool tweet men die stuff without few once le ai point else eat okay least book high mom understand wanted kind feeling times heart free fine woman black place thinking until #dmradionet hi ask family human yourself leave called saying idea saw > dead sometimes part reason hand mental against wouldn't whatever stupid tweets whole comic thats food tried wasn't anymore different sad side jesus problem found hurt almost taking ago



Bipolar LM	I'm uncomfortable being around your ex, little chica. Ok.
Depression LM	Pain doesn't change who you are, but it's like that person is now underneath and suppressed.
PTSD LM	I really need to get up and prepare for work, but I don't wanna get out of bed yet. ugh.
Sentiment(+)	@NAME is super awesome, she just gets better and better every I see her perform. Best in the world, no doubt!!
Sentiment(-)	It hurts so much to lose people in my life, I try not to let it happen
PosEmo	Woo crazy day Got done with more than I thought but super happy for bed. Grateful for my awesome kids & loving hubby
Functioning	if i had a dollar for all the grammatical errors ive ever typed, my college tuition, book cost, and dorm rent would be paid in full
NegEmo	Everything hurts. My head, my back, my stomachkill me now.
Anx	no need to stress over someone who isn't stressing over you
Anger	I hate arrogant and ugly people, no excuse for that shit ³⁵

Pattern of Life

- Social Engagement
 - Tweet rate

- [Greetham et al (2011), World Heath Organization (2001), Berkman et al (2000)]
- Number/proportion @mentions
- Number/proportion @self
- Unique users @mentioned (1x, 3x)
- Insomnia
- Exercise

[Weissman et al (1996)]

[Penedo and Dahn (2005), Callaghan (2004)]

Many also explored by: [De Choudhury, Gamon, Counts, Horvitz (2013)]

Experiment: Separating Users

- Leave-two-out crossfold validation
- ULM and CLM models trained on remaining users' text
- Log-linear model
 - ULM score, CLM score, Insomnia, Sentiment, LIWC categories, Social Engagement





Classifier Performance



Classifier Performance

[Coppersmith et al. (CLPsych, 2015)]



Condition	Prec
ADHD	52%
Anxiety	85%
Bipolar	63%
Borderline	58%
Depression	48%
Eating	76%
OCD	27%
PTSD	55%
Schizophrenia	67%
SAD	5%

Classifier precision at 10% false alarm rate.

Feature Performance

[Coppersmith et al. (CLPsych, 2014)]









Language Model Performance

- Why do language models perform so well?
- Topic models (e.g., Latent Dirichlet Allocation) [MALLET] [McCallum, 2002]
 - Discovers groups of words that often appear together in documents
 - Top-*n* words of highest probability represent the topic
 - Each document represented as a mixture of topics
 - Unsupervised: no annotations required
 - Study on schizophrenia in Twitter [Mitchell et al. (CLPsych, 2015)]

Population-Level Topics

[Mitchell et al. (CLPsych, 2015)]

tihmc



- 9 don('t) love f**k f**king s**t people life hell hate stop gonna god wanna die feel make kill time anymore
- 12 people don('t) le world mental schizophrenia (I')ve god jesus schizophrenic illness health care paranoid medical truth time life read
- 11 great love time hope today day rt support custserv big happy awesome amazing easy trip toronto forward orleans hear
- 19 lol dd love don('t) today day good happy time ddd miss hate work night back (I')ll birthday tomorrow tonight

46

Timeseries Analysis

[Mitchell et al. (CLPsych, 2015)]

- Health cognitive, neurological, and physiological changes over time
- Are these changes reflected in language?
- Empirical test:
 - For each user, sequentially order their tweets in time
 - For each tweet, score with schizophrenia-trained language model



Individuals' Timelines

Timeline of tweets from two individuals (schizophrenia: red, control: blue).



Population-Level Timelines

Timeline of tweets from schizophrenia group (red) and control (blue).



Timeseries Applications

- Once we had the timeseries analysis...what now?
 - Why do peaks begin? (Why the ramp up?)
 - Why do peaks drop off (instead of ramping up higher)?
- What does the timeline tell us about the individual, and about the population?
- Measure different conditions
 Stress, cognitive load?
- Going beyond language analysis
 - Pattern of life, diet, exercise
 - Network analysis

Highlights & Take-Aways

- Language written or spoken provides a quantifiable signal that can be used to automatically assess mental health status
- There are various NLP techniques tools in the toolbox that could be applied to automated assessments
 - Automated assessments do not replace, but rather assist, diagnosticians
- Many POVs for applications: healthcare providers (clinicians, therapists, doctors), insurance providers, friends/family, self





Thank You

Questions?

Kristy Hollingshead Seitz, PhD hollingk@gmail.com

Many many thanks to my co-authors: Glen Coppersmith (Qntfy), Meg Mitchell (Microsoft), Mark Dredze (JHU), Craig Harman (HLTCOE, Rochester)



