MENTAL HEALTH
QUANTIFYING MENTAL HEALTH FROM SOCIAL MEDIA LANGUAGE

BIOMEDICAL NATURAL LANGUAGE PROCESSING

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MENTAL HEALTH IN SOCIAL MEDIA

"I would really like to be able to get through just one day without feeling anxious, tearful or exhausted"

"I once tried to kill myself. I still think about it once in a while. But I survived. I'm alive. So are my demons."

"If you're not trying to impress me then who are you trying to impress"

MENTAL HEALTH IN SOCIAL MEDIA

"I would really like to be able to get through just one day without feeling **anxious**, **tearful** or **exhausted**"

"**I** once tried to **kill myself**. **I** still think about it once in a while. But **I** survived. **I**'m alive. So are **my** demons."

"If you're not trying to impress me then who are you trying to impress"

OUTLINE

1. Introduction
2. Data
3. Feature Generation
   1. Lexicon-based approaches
   2. Open-vocabulary approaches
4. Conclusions
5. Sources

1. INTRODUCTION
„THERE IS NO HEALTH WITHOUT MENTAL HEALTH."

- Mental health impacts risk for chronic, non-communicable diseases
  - 14% of all diseases worldwide attributed to neuropsychiatric disorders
  - psychosomatic conditions
  - decreased life expectancy: 20 years for men, 15 years for women
- vice versa, physcial diseases can lead to mental disorders
- major risk factor of suicide
  - 2012: estimated 804,000 suicide deaths worldwide

1. INTRODUCTION
„THERE IS NO HEALTH WITHOUT MENTAL HEALTH."

- can affect everyone
  - 450 million people worldwide currently affected
    - → among the leading causes of ill-health and disability worldwide
  - throughout their lifetime, one in four people is affected
- huge costs
  - single largest health cost by 2030 with global costs of $6 Trillion/year
- difficult to diagnose
  - common for some mental diseases (as schizophrenia) is to not believe that you have it

→ **need for new and innovative methods for obtaining reliable information and evidence**

1. INTRODUCTION
MENTAL HEALTH ANALYSIS: CHALLENGES

- mental health research lacks the quantifiable data
  - due to the complexity of the underlying causes of mental illness
  - and to societal stigma making the topic a taboo subject

→ impedes mental health research in terms of developing reliable diagnoses and effective treatment for many disorders

- population-level analysis via traditional methods is time consuming, expensive, and comes with a significant delay

1. INTRODUCTION
MOTIVATION FOR USERS
… TO PUBLICLY SHARE THEIR PRIVATE HEALTH INFORMATION

- offer or seek support
  - *"If anybody suffers from OCD, I'd be happy to answer questions. I'm happy to share what I learned. CBT can be life-changing. "*
- fight the stigma of mental illness
  - *„Anorexia isn't an illness of a body, but it's an illness of a mind. Sometimes we want to stop, but we can't. We are too scared to do that. Anorexia is somehow a coping skill, for strong emotions or either events in your life"*
- offer an explanation for certain behaviors
  - *„Because the skinnier I become, the happier I'll feel."*

- … but: there is to consider that the disclosure of such sensitive information might further prevent individuals from self-reporting their conditions on social media!

1. INTRODUCTION
MENTAL HEALTH IN SOCIAL MEDIA

- What can we learn about mental health in social media?
  - Which linguistic features might indicate a given mental health condition?
  - Which methods do exist to extract these linguistic attributes?
  - How can we use these findings?

1. INTRODUCTION
MENTAL DISORDERS

- Mental health disorders we want to be able to identify:
  - **Depression**
  - **Schizophrenia**
  - **PTSD**: Post-Traumatic Stress Disorder
  - ADHD: Attention deficit hyperactivity disorder
  - Anxiety: Generalized Anxiety Disorder
  - Bipolar: disorder with periods of depression and elevated mood
  - Borderline: Personality Disorder
  - Eating disorders: includes anorexia, bulimia and not otherwise specified
  - OCD: Obsessive-compulsive Disorder
  - SAD: Seasonal Affective Disorder

2. DATA
DATA EXTRACTION

- mental health related **Twitter** and partly **Facebook** data (publicly available)
- using self-identification technique
  - statements such as „I have been diagnosed with CONDITION“
    - *„I was diagnosed with depression.“*
- schizophrenia: potential linguistic indicators
  - irrealis mood: „*think*“, „*believe*“
  - lack of emotions: potential signature of flat affect
- researchers cannot be sure that the individuals indeed suffer from these diseases
- selection bias

2. DATA
DATA

- self-reported diagnoses for one of ten conditions
- sometimes no obvious mapping
  - „*shell shock*“ = „*PTSD*“ vs. „*Anxiety*“ =? „*Generalized/Social Anxiety Disorder*“
- manually examined by one of the authors to exclude jokes, quotes, or disingenuous statements
  - *“I think I’m I’m diagnosed with SAD. Sexually active disorder”*

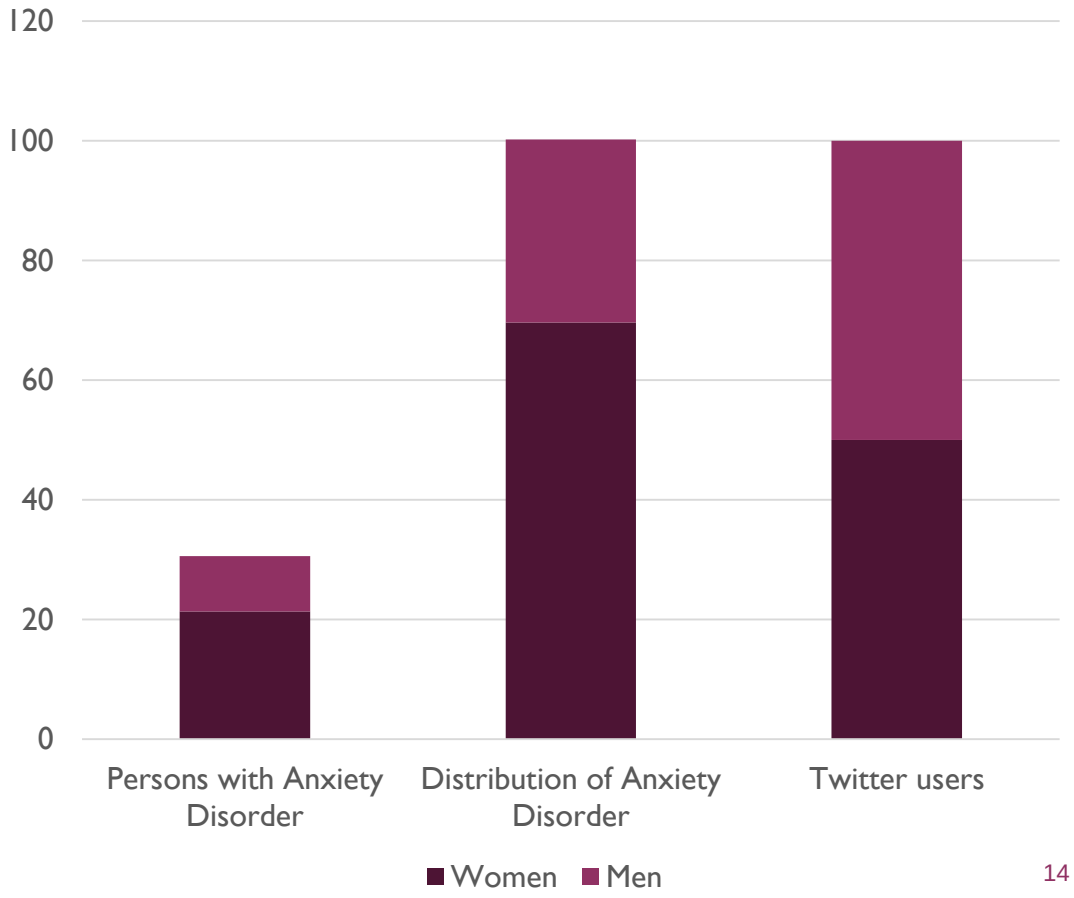
2. DATA
DATA

- set of public Twitter posts for each author of a genuine diagnosis tweet (at least 100/user)
- 6.684.000 tweets in total
- data publicly posted between 2008 and 2015
- schizophrenia study: 174 users with up to 3200 tweets per user

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
Seasonal Affective	100	3229	340k

2. DATA
IMPACT OF AGE AND GENDER

- In general: control groups via random selection
- But: physical and mental health conditions have different prevalence depending on age and gender
  - prevalence: proportion of a particular population found to be affected by a medical condition
  - ability to attribute any quantifiable signals to the presence or absence of a disorder rather than to a confounding age or gender divergence between the populations

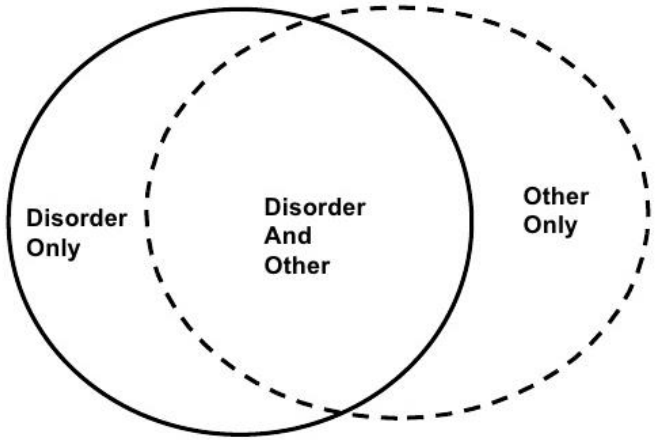


2. DATA
IMPACT OF AGE AND GENDER

- form approximate age- and gender-matched control groups to avoid skewed results
  - but: no demographic information provided by Twitter
  - → studies on influence of age and gender on language to infer this data
- Inferring gender and age information from social media
  - Tools by the World Well-Being Project
  - Publicly available lexica created using regression and classification models over language use in social media
- control group was formed from 1% Twitter sample from early 2014
  - for each user in the mental health collection, a user with the same gender label and closest in age, was selected

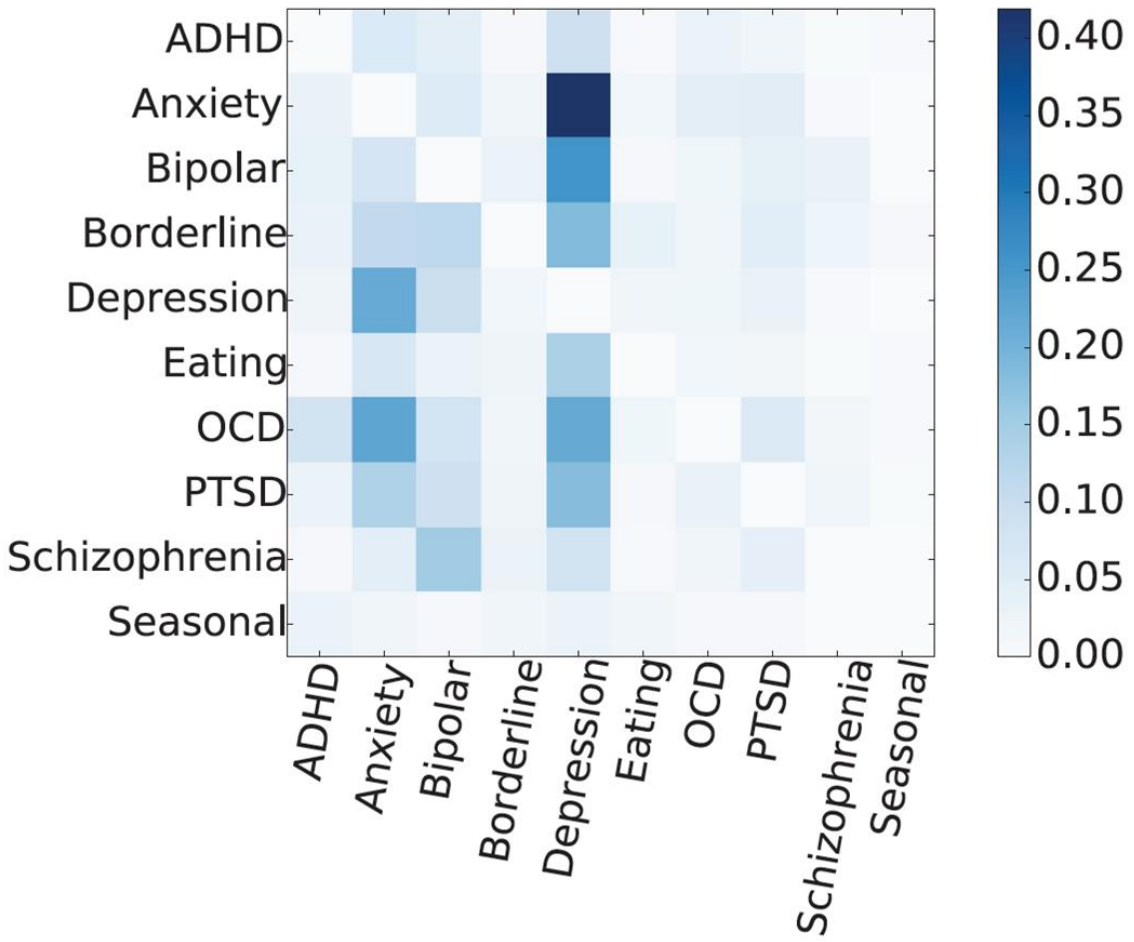
2. DATA
CONCOMITANCE AND COMORBIDITY

- **concomitance**: second illness occurring at the same time as a primary illness
- **comorbidity**: the presence of one or more disorders (or diseases) in addition to a primary disease or disorder
  - e.g. Borderline personality disorder shows high comorbidity with other mental diseases, so often it's accompanied by depressions or ADHD
- in cases where a user states a diagnosis for more than one condition, he is included in each condition



2. DATA
CONCOMITANCE AND COMORBIDITY

- up to 40% of users who have anxiety also have depression
- up to 30% of users who have schizophrenia are also bipolar



3. FEATURE GENERATION
DIFFERENT APPROACHES

Which methods can we use to extract linguistic features?

- lexicon-based approaches
  - LIWC
- open-vocabulary approaches
  - LDA
  - Brown Clustering
  - CLM
  - Perplexity

3. FEATURE GENERATION - LEXICON-BASED
LINGUISTIC INQUIRY AND WORD COUNT (LIWC)

- text analysis tool to allocate words to psychologically meaningful categories
- includes the main text analysis module along with a group of built-in dictionaries
  - each word is compared against a user-defined dictionary
  - dictionary maps each word to ist corresponding psychological category

- but: individual words may be misclassified, irony, sarcasm or metaphors aren‘t detected

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLES

- *„Sometimes I want to eat healthy, just like #normal people, but my ed says I can't.“*
- *„my problem I don't want to eat but I do and when I do I hate myself a little more“*
- *„Welcome to a world where being yourself isn't good enough.“*
- *„I feel extremely bloated, fat because I was forced fed by my parents today…“*
- *„Don't worry, I'm just "tired".“*
- *" I destroyed my body for a peace of mind. I never got“*
- *„When I realize that I have #eatingdisorder Try eating like a normal people but ending up by having 500 calories“*

- Total words: 96

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLE RESULTS

TRADITIONAL LIWC DIM	YOUR DATA	AVERAGE FOR SM
I-WORDS (I, ME, MY)	18.6	5,51
SOCIAL WORDS	6,2	9,71
POSITIVE EMOTIONS	4,1	4,57
NEGATIVE EMOTIONS	4,1	2,10
COGNITIVE PROCESSES	16,5	10,77
SUMMARY VARIABLES		
ANALYTIC	13,3	55,92
CLOUT	1,6	55,45
AUTHENCITY	97,7	55,66
EMOTIONAL TONE	25,8	63,35

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLES: I-WORDS

TRADITIONAL LIWC DIM	YOUR DATA	AVERAGE FOR SM
I-WORDS (I, ME, MY)	18.6	5,51

- *„Sometimes **I** want to eat healthy, just like #normal people, but **my** ed says I can't.“*
- *„**my** problem I don't want to eat but **I** do and when I do **I** hate **myself** a little more“*
- *„Welcome to a world where being yourself isn't good enough.“*
- *„**I** feel extremely bloated, fat because I was forced fed by **my** parents today...“*
- *„Don't worry, **I**'m just "tired".“*
- *" **I** destroyed my body for a peace of mind. **I** never got“*
- *„When **I** realize that **I** have #eatingdisorder Try eating like a normal people but ending up by having 500 calories“*

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLES: COGNITIVE PROCESSING

TRADITIONAL LIWC DIM	YOUR DATA	AVERAGE FOR SM
COGNITIVE PROCESSES	16,5	10,77

- *„**Sometimes** I **want** to eat healthy, just like #normal people, **but** my ed says I **can't**."*
- *„my problem I don't **want** to eat **but** I do **and** when I do I hate myself a little more"*
- *„Welcome to a world where being yourself isn't good enough."*
- *„I feel extremely bloated, fat **because** I was **forced** fed by my parents today..."*
- *„Don't worry, I'm just "tired"."*
- *" I destroyed my body for a peace of mind. I **never** got"*
- *„When I **realize** that I have #eatingdisorder **Try** eating like a normal people **but** ending up by having 500 calories"*

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLES: SOCIAL WORDS

TRADITIONAL LIWC DIM	YOUR DATA	AVERAGE FOR SM
SOCIAL WORDS	6,2	9,71

- *„Sometimes I want to eat healthy, just like #normal **people**, but my ed **says** I can't.“*
- *„my problem I don't want to eat but I do and when I do I hate myself a little more“*
- *„Welcome to a **world** where being yourself isn't good enough.“*
- *„I feel extremely bloated, fat because I was forced fed by my **parents** today...“*
- *„Don't worry, I'm just "tired".“*
- *" I destroyed my body for a peace of mind. I never got“*
- *„When I realize that I have #eatingdisorder Try eating like a normal **people** but ending up by having 500 calories“*

3. FEATURE GENERATION - LEXICON-BASED
TWEET EXAMPLES: EMOTIONS

TRADITIONAL LIWC DIM	YOUR DATA	AVERAGE FOR SM
POSITIVE EMOTIONS	4,1	4,57
NEGATIVE EMOTIONS	4,1	2,10

- *„Sometimes I want to eat **healthy**, just like #normal people, but my ed says I can't.“*
- *„my **problem** I don't want to eat but I do and when I do I **hate** myself a little more“*
- *„**Welcome** to a world where being yourself isn't **good** enough.“*
- *„I feel extremely bloated, fat because I was forced fed by my parents today…“*
- *„Don't **worry**, I'm just "tired".*
- *"I **destroyed** my body for a **peace** of mind. I never got. “*
- *„When I realize that I have #eatingdisorder Try eating like a normal people but ending up by having 500 calories“*

3. FEATURE GENERATION - LEXICON-BASED
LINGUISTIC INQUIRY AND WORD COUNT (LIWC)

- Analytical thinking
  - captures the degree to which people use words that suggest formal, logical and hierarchical thinking patterns
- Clout
  - relative social status, confidence, or leadership that people display through their writing or talking
- Authenticity
  - people, who reveal themselves in an authentic or honest way are more personal, humble and vulnerable
- Emotional tone
  - the higher the number, the more positive the tone

SUMMARY VARIABLES	YOUR DATA	AVERAGE FOR SM
ANALYTIC	13.3	55.92
CLOUT	1.6	55.45
AUTHENTICITY	97.7	55.66
EMOTIONAL TONE	25.8	63.35

3. FEATURE GENERATION - LEXICON-BASED
LINGUISTIC INQUIRY AND WORD COUNT (LIWC)

- lexicon-based approach step by step:
  - for each user: measure the proportion of tokens that falls into a given LIWC category
  - aggregate by condition
  - compare across conditions
  - for each user: calculate proportion of tokens that were part of a LIWC category
  - tested on all 10 MH conditions

→ **each category is a feature**

3. FEATURE GENERATION – OPEN-VOCABULARY CHARACTER N-GRAM LANGUAGE MODELS (CLM)

- idea:
  - examine sequence of charachters, incl. spaces, punctuations, emoticons etc.

    e.g. *"Just disown me... and get me a payee... I already disowned them before..."*
- realization:
  - 2 sets of classes: from a given MH condition and control
  - the model is trained to recognize which sequences of characters are likely to be generated by either class
  - higher score – user with MH condition, lower score – control user

→ **each character 5-gram is a feature**

3. FEATURE GENERATION - OPEN-VOCABULARY
LATENT DIRICHLET ALLOCATION (LDA)

- idea:
  - data is represented as "documents"
  - each document is a mixture of "topics"
  - each topic uses the words with different probabilities
  - topics are inferred automatically from the text
- realization:
  - each topic is a feature
  - feature value is the probability of that topic in the user's tweets
  - just used for schizophrenia

→ **each topic is a feature**
the feature value is the probability of that topic in the user's tweets

3. FEATURE GENERATION
BROWN CLUSTERING

- idea:
  - hierarchical algorithm that finds a clustering of words that maximizes the mutual information between adjacent clusters
  - each word is therefore associated to clusters of increasing granularity.
- realization:
  - leaf clusters as features
  - feature value – proportion of words from the user in that cluster
  - limit of 100 clusters

→ **each leaf cluster is a feature**

3. FEATURE GENERATION
PERPLEXITY

- idea:
  - measures the breadth of language used
  - the higher the conditional probability of the word sequence, the lower the perplexity
- realization:
  - trigram language model trained on 1 million tweets
  - measures how unexpected the user's language is
  - high perplexity score to recognize *word salad* effect observed in schizophrenic persons

→ **the perplexity score is one single feature value for each user**

3. FEATURE GENERATION - RESULTS

LIWC	ADHD	Anx	Bipol	Bord	Dep	Eating	OCD	PTSD	Schiz	Seaso
FUN	+++	+++	+++	+++	+++	+++	+++	+	+++	+++
I		+			+	+++	+++			
AUXV	+	+++	+++	+++	+++	+++	+++	+	+++	+
POSEMO							-	-		-
NEGEMO		+++	+	+++	+	+++				
ANX	+	+++	+	+++	+	+++	+++	+	+	+
COG MEC	+++	+++	+++	+++	+++	+++	+++	+	+++	
DEATH	+	+++	+	+++	+	+	+	+	+++	
HEALTH	+	+++	+++	+++	+	+++	+++	+	+	
PRO3	+							+		

+++ used significantly more frequently than by control users
+ used noticeably more frequently than by control users
- used less frequent than by control users

3. FEATURE GENERATION
RESULTS: LDA

Cond.	Topic	Top Words
Sch	2	don(’t) (I’)ve (I’)ll feel people doesn(’t) thing didn(’t) time twitter won(’t) make kind woman things isn(’t) bad cat makes
Sch	9	don(’t) love fuck fucking shit people life hell hate stop gonna god wanna die feel make kill time anymore
Sch	12	people don(’t) le world mental schizophrenia (I’)ve god jesus schizophrenic illness health care paranoid medical truth time life read
Sch	18	people work today good years time make call long find made point thought free twitter back thing days job
Con	6	lol shit nigga im tho fuck ass ain(’t) lmao don(’t) good niggas gotta bitch smh damn ya man back
Con	7	game rochester football girls basketball final boys billsmafia win rt valley team season sectional north play miami st soccer
Con	11	great love time hope today day rt support custserv big happy awesome amazing easy trip toronto forward orleans hear
Con	19	lol dd love don(’t) today day good happy time ddd miss hate work night back (I’)ll birthday tomorrow tonight

3. FEATURE GENERATION - RESULTS: BROWN CLUSTERING

Cond.	Topic	Top Words
Sch	01011111111	but because cause since maybe bc until cuz hopefully plus especially except
Sch	01011111110	if when sometimes unless whenever everytime someday
Sch	010000	i
Sch	010100111	know think thought care believe guess remember understand forget swear
Con	0001001	lol haha omg lmao idk hahaha wtf smh ugh o bruh lmfao ha #askemma tbh exactly k bye omfg hahahaha fr hahah btw jk
Con	01011011010	today
Con	0010111	! << >>
Con	01011010100	back home away checked forward asleep stuck button stream rewards closer messages anywhere apart swimming inspired dong tricks spree cv delivered tuned increased

3. FEATURE GENERATION
LDA VS. BROWN CLUSTERING

LDA	Brown Clustering
words for laughing asking for retweet ("rt") words like "today"	
-- positive sentiment words -- negated words -- words sepcific to MH	- first person pronoun 'I' - words marking irrealis mood - connectives - exclamation point

*controls
*schizophrenia sufferers

3. FEATURE GENERATION OVERVIEW

FEATURES CREATED USING	FEATURES CREATED
LIWC	each category
LDA	each topic
Brown cluster	each leaf cluster
Character language models	character 5-gram
Perplexity	perplexity score

- Machine Learning methods for Schizophrenia:
  - Support Vector Machines
  - Maximum Entropy Classifier

4. CONCLUSIONS
SCHIZOPHRENIA: RESULTS

FEATURES	SVM	MAXENT
Perplexity (ppl)	52.0	51.4
Brown-Cluster Dist (BDist)	53.3	72.3
LIWC	68.8	70.8
CLM	77.1	77.2
LIWC+CLM	78.2	77.2
LDA Topic Dist (TDist)	80.4	80.4
CLM+TDist+BDist+ppl	81.2	79.7
CLM+TDist	81.5	81.8
LIWC+TDist	82.3	81.9

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CLM+TDist	81.5	81.8
LIWC+TDist	82.3	81.9

4. CONCLUSIONS
GENERAL CONCLUSIONS

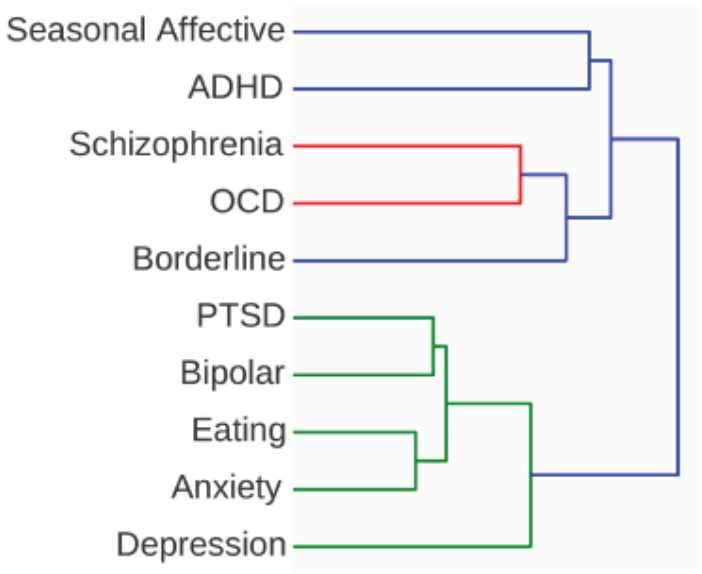
- **CLM** provides a reasonable score even for very short texts; robust to the creative spellings, lack of spaces and other "errors" made by users

- **LDA** and **Brown Clustering** can uncover meaningful and potentially useful latent structure for the automatic identification of important topics

- **Perplexity** may be useful in measuring how unexpected a user's language is („word salad" by schizophrenia sufferers)

4. CONCLUSIONS
GENERAL CONCLUSIONS

- relationship between the language use from different MH conditions – but just visible on the whole, not necessarily for a given pair
- finding some groupings of the conditions like they can be found in the literature
- already simple classifiers were able to distinguish users affected by MH problems from their age- and gender-matched controls



→ **it‘s possible to examine mental health by means of language processing and there are still many possibilities for improvement**

5. CONCLUSIONS
OPEN QUESTIONS

- How differ users who self-report their diagnosis from other diagnosed individuals?
- What linguistic signals can't be captured by these methods?
- What opportunities exist for interventions with identified users?
- Can we apply this methods to users who aren’t already aware of their MH state?

SOURCES

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