

The Role of Personality, Age and Gender in Tweeting about Mental Illnesses

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Problem

- Mental illnesses are massively underdiagnosed
- Goal is unobtrusive measurement via Social Media
- Focus on depression and PTSD

This presentation:

- Study the predictive power of multiple features
- Study the insights provided by each feature

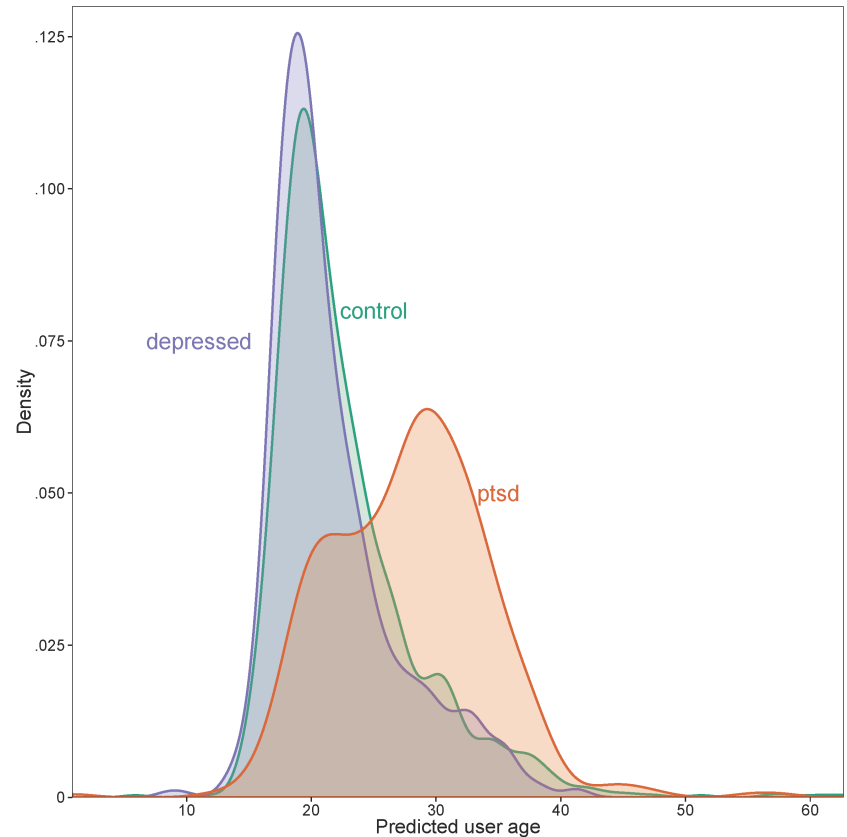
Data

- based on Twitter self-reports
 - ‘I have been diagnosed with depression’
 - 483 users with depression
 - 370 users with PTSD
 - 1104 control users
- each user has avg. 3400 messages

(Coppersmith et. al, CLPsych 2014)

Age, Gender

- automatically inferred from Twitter posts
(Sap et. al, EMNLP 2014)
- age predictive language use plays a massive role in separating PTSD users
- gender differences are smaller but still significant

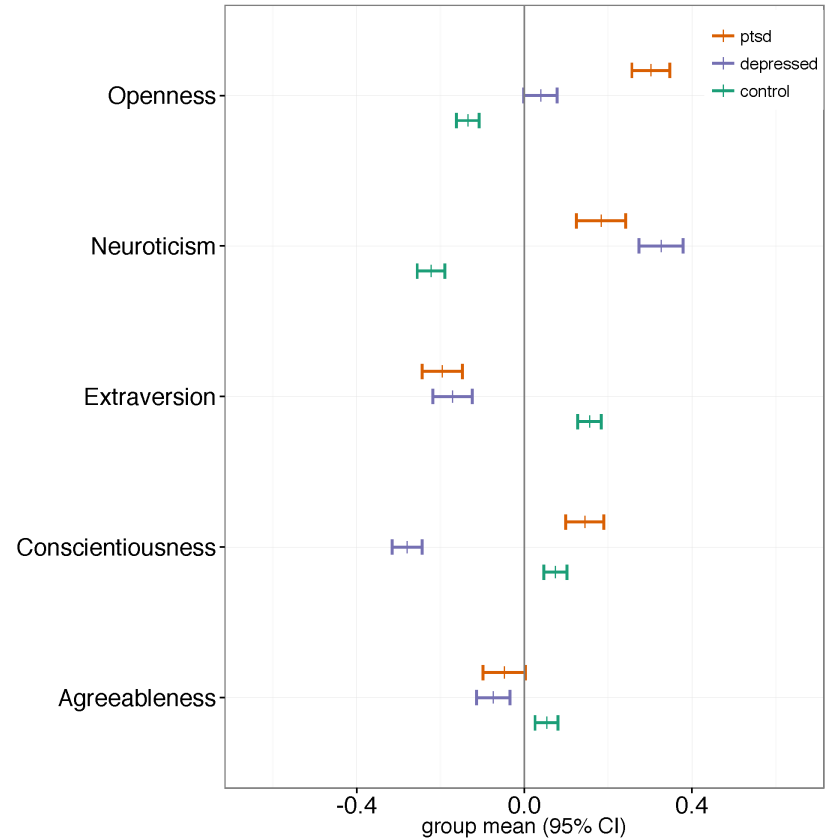


Age, Gender



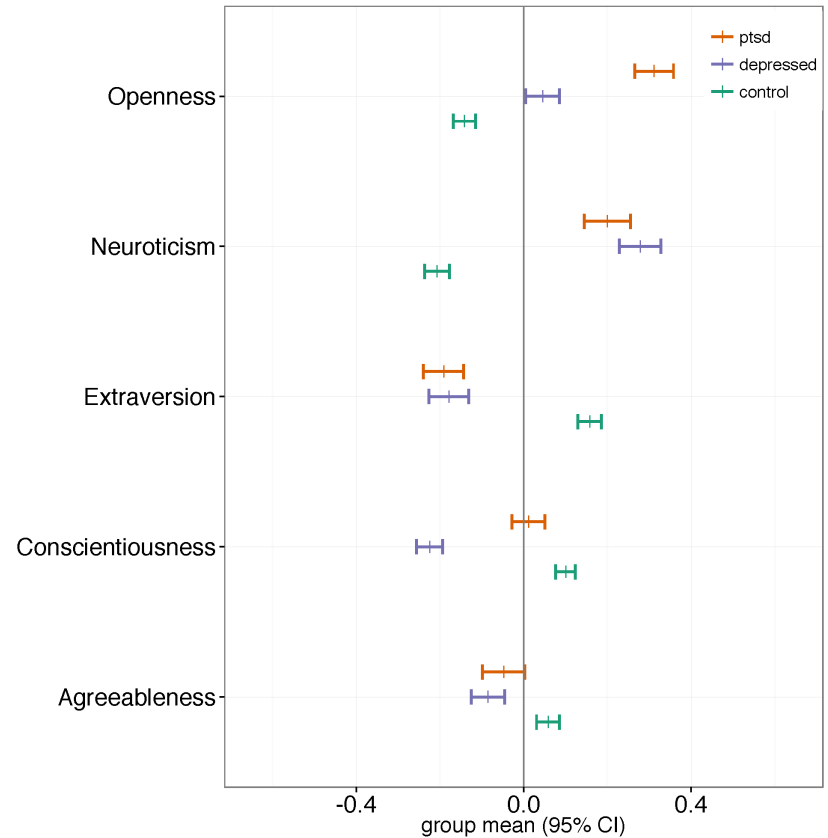
Personality

- automatically inferred from Twitter posts
(Park et. al 2014)
- Big Five model of personality
- showing group means of each trait

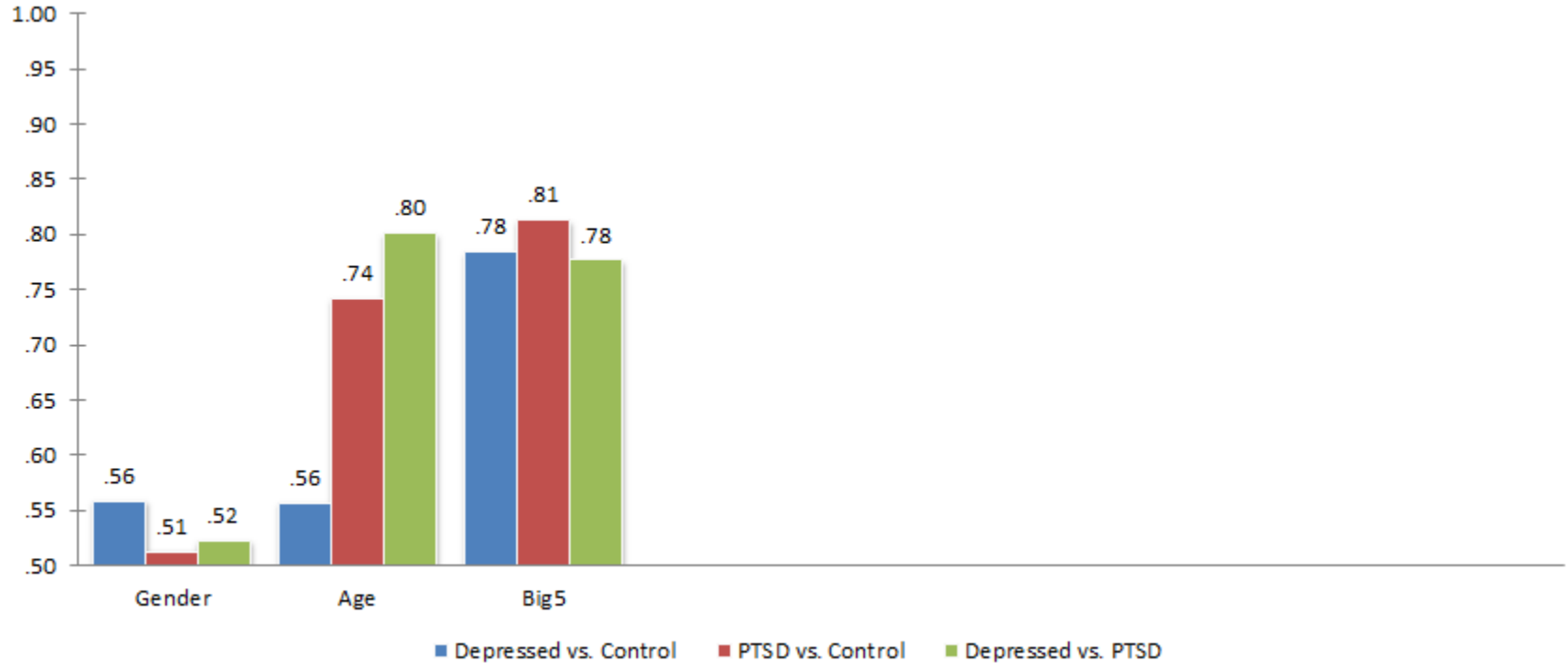


Personality

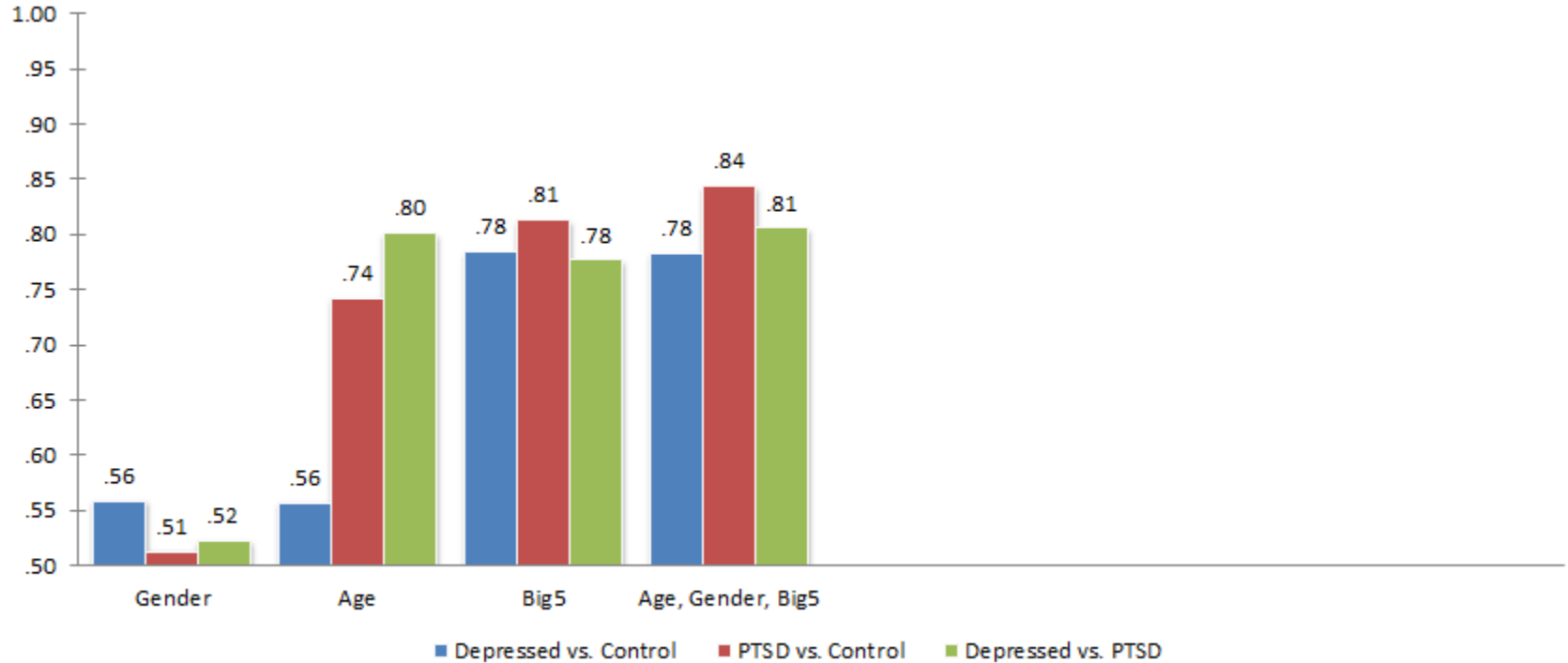
- controlling for age/gender
- mentally ill users:
 1. high on neuroticism
 2. more introverted
 3. less agreeable
- age removes some conscientiousness and neuroticism differences



Personality

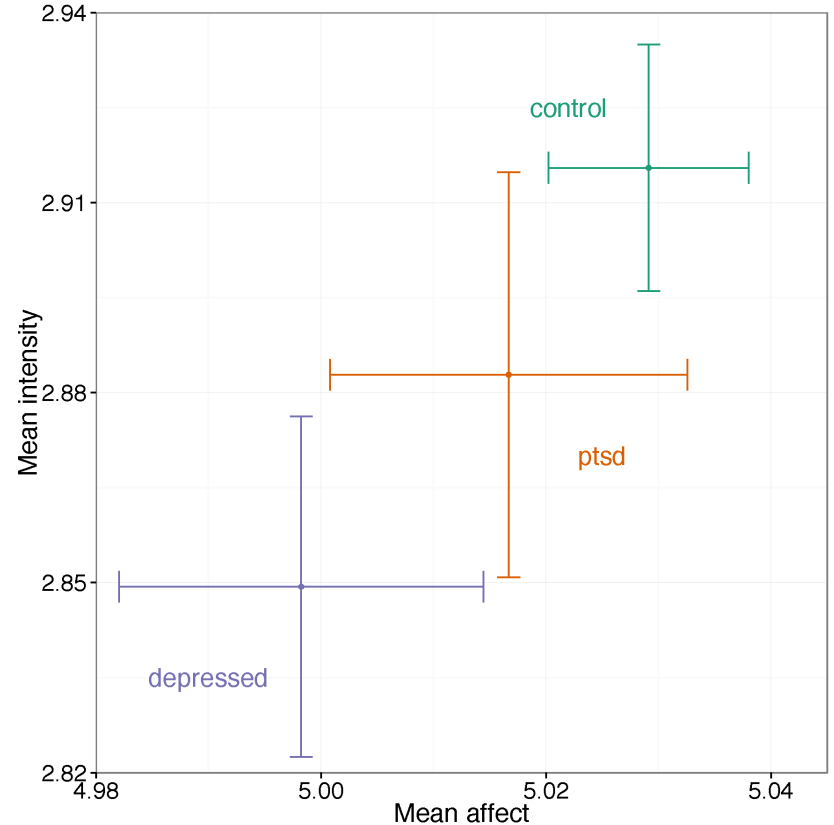


Age, Gender, Personality

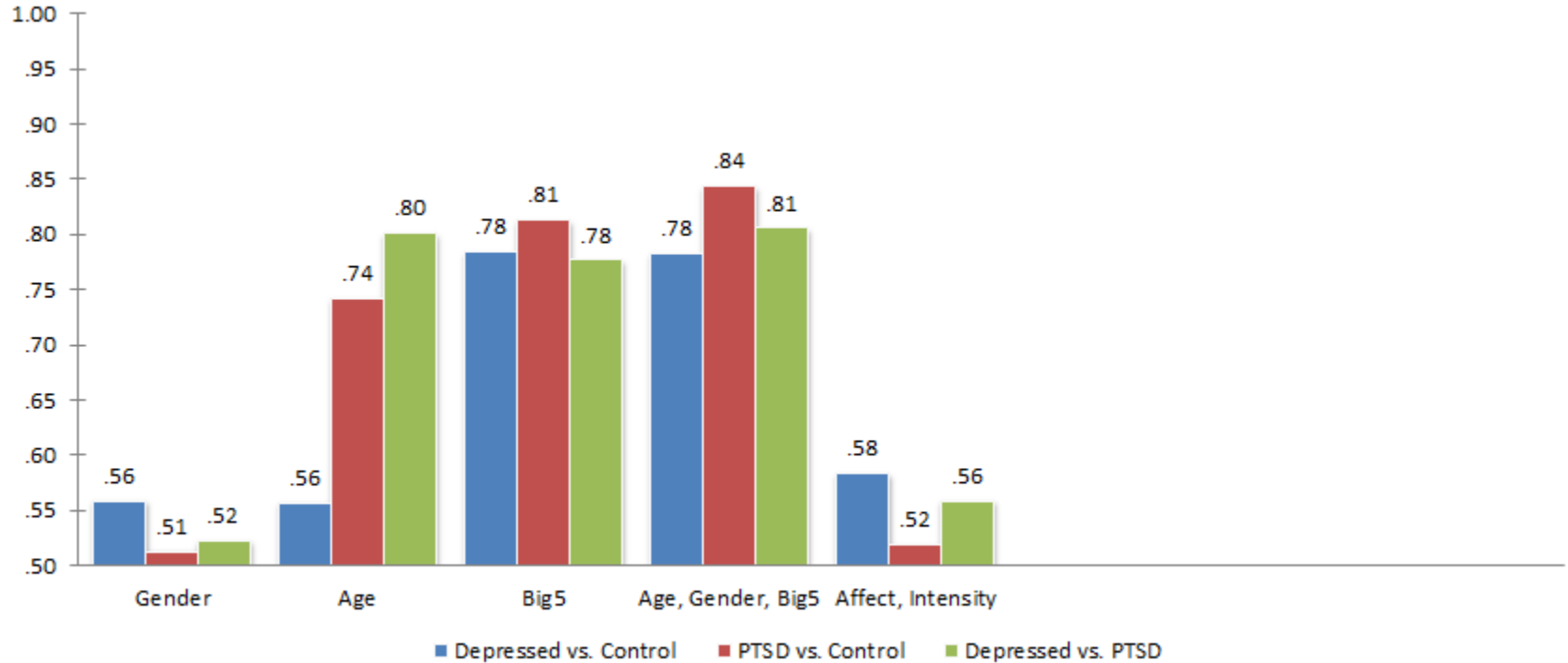


Affect and Intensity

- Model trained on 3000 annotated FB posts and applied to all user posts
- circumplex model similar to valence & arousal (ANEW)
- mentally ill users are less aroused and less positive



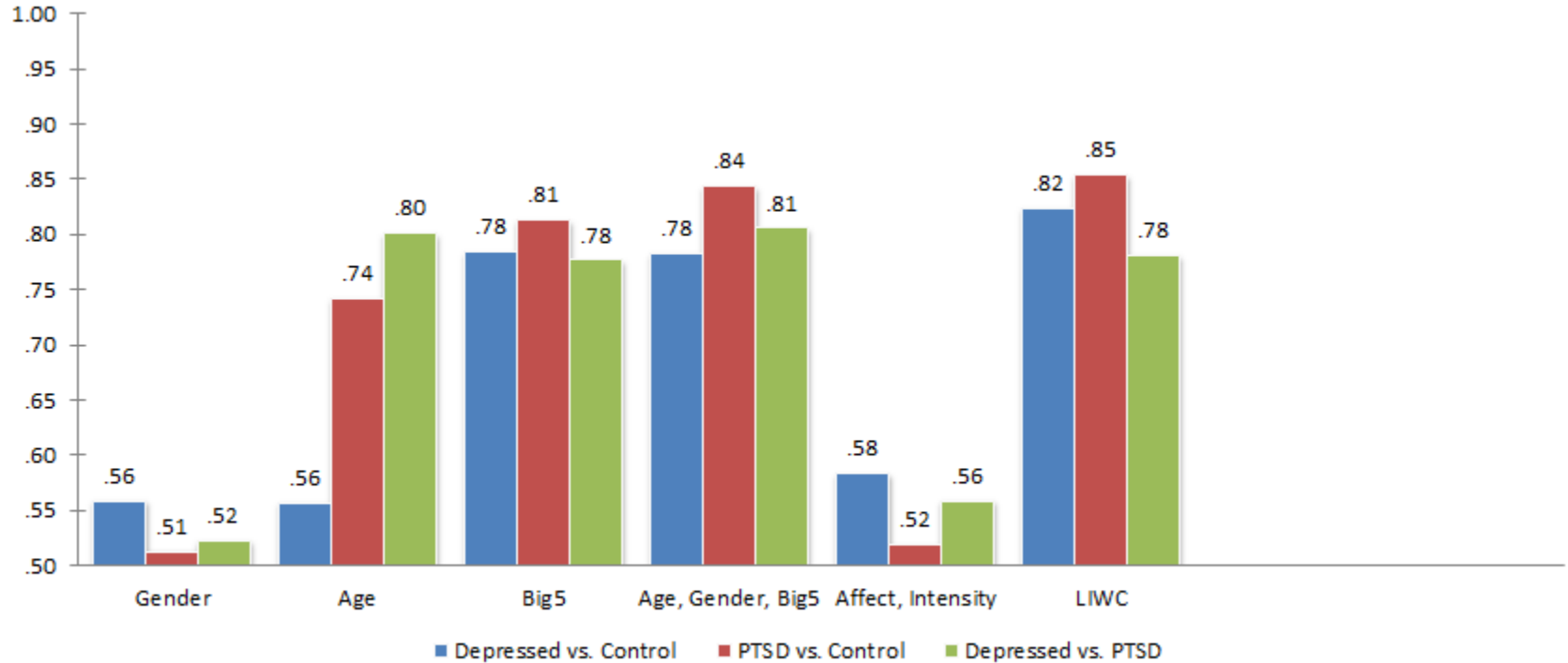
Affect and Intensity



LIWC

- standard psychologically inspired dictionaries
- 64 categories such as:
 - parts-of-speech
 - topical categories
 - emotions
- standard baseline for open vocabulary approaches

LIWC



Topics

- computed using Latent Dirichlet Allocation (LDA)
- underlying set of Facebook statuses
- 2000 topics in total
- soft clusters: a word can belong to multiple topics with a probability

Topics: Depression



(a) R=.282



(b) R=.271



(c) R=.244



(d) R=.239



(e) R=.239



(f) R=.238



(g) R=.237



(h) R=.235



(i) R=.230



(j) R=.229

Topics controlled for age and gender

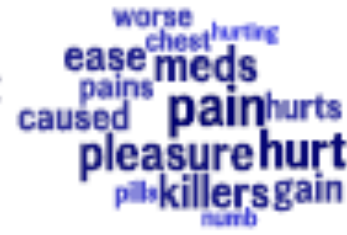
Topics: PTSD



(a) R=.280



(b) R=.280



(c) R=.277



(d) R=.266



(e) R=.255



(f) R=.254



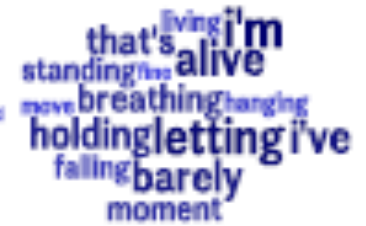
(g) R=.254



(h) R=.248



(i) R=.241

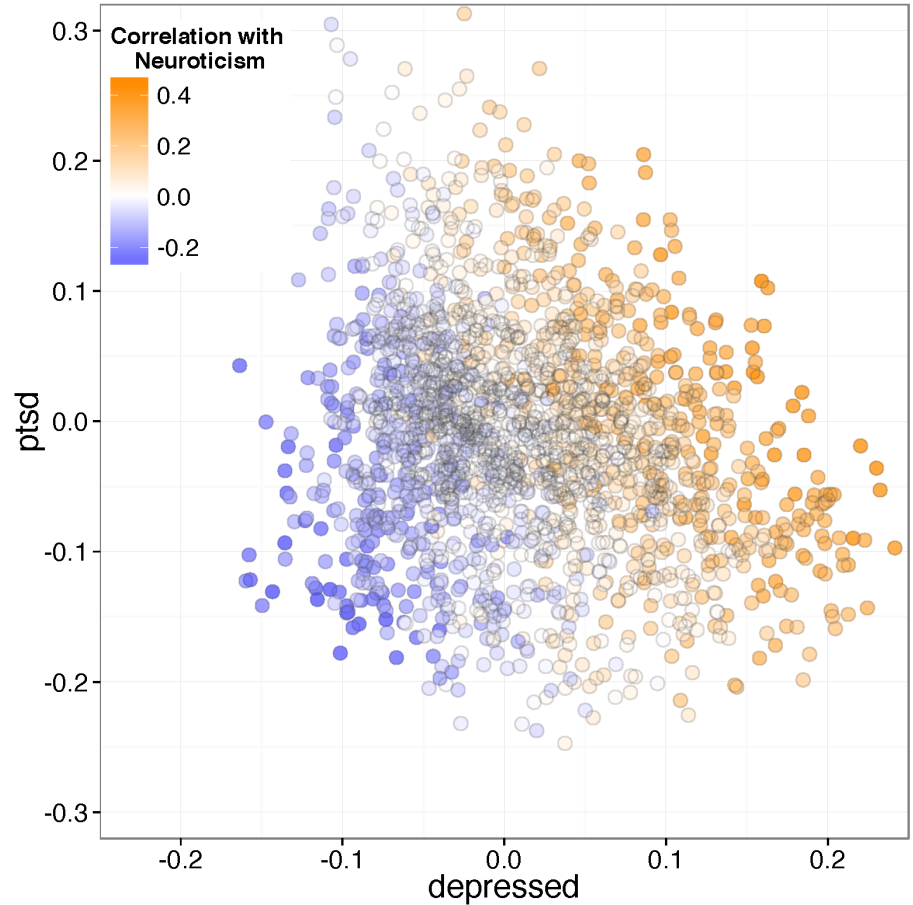


(j) R=.237

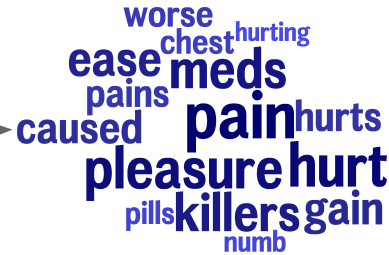
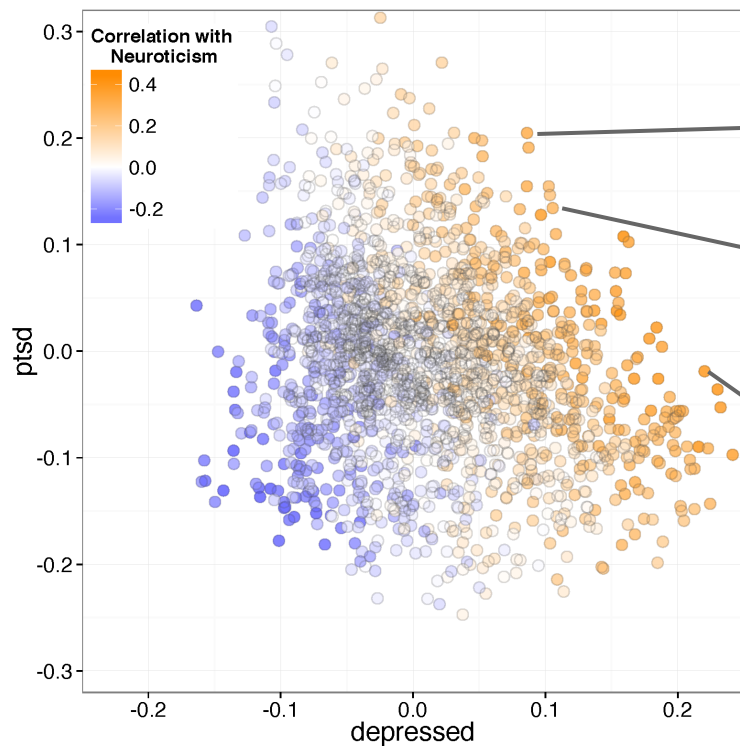
Topics controlled for age and gender

Topics: PTSD, Depression & Neuroticism

- Analysis of high neuroticism topics
- Neuroticism topics are high in both illnesses, but different ones are activated in each illness



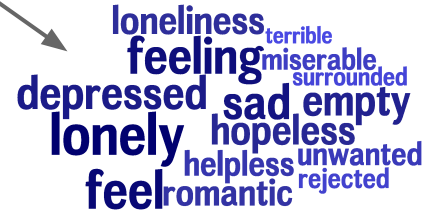
Topics: PTSD, Depression & Neuroticism



+ Dep, +++ PTSD

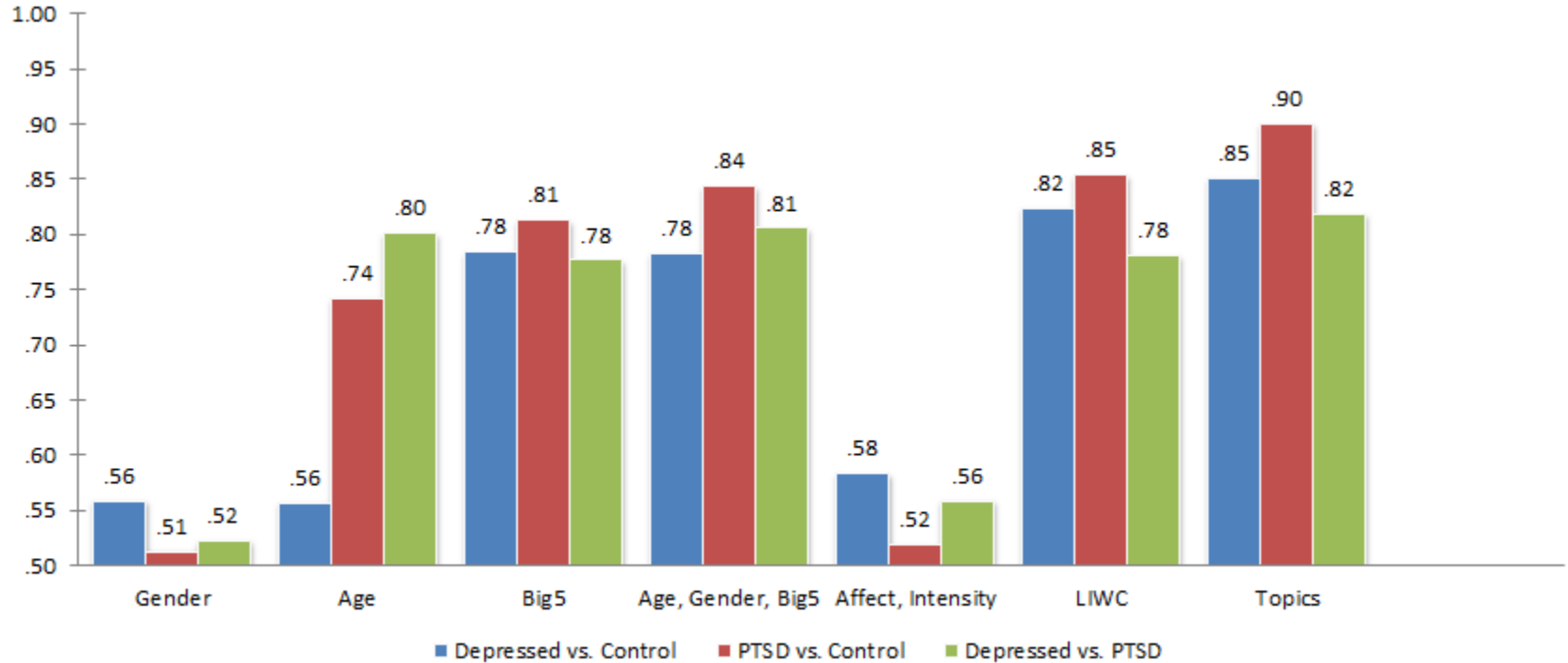


++ Dep, ++ PTSD



+++ Dep, 0 PTSD

Topics

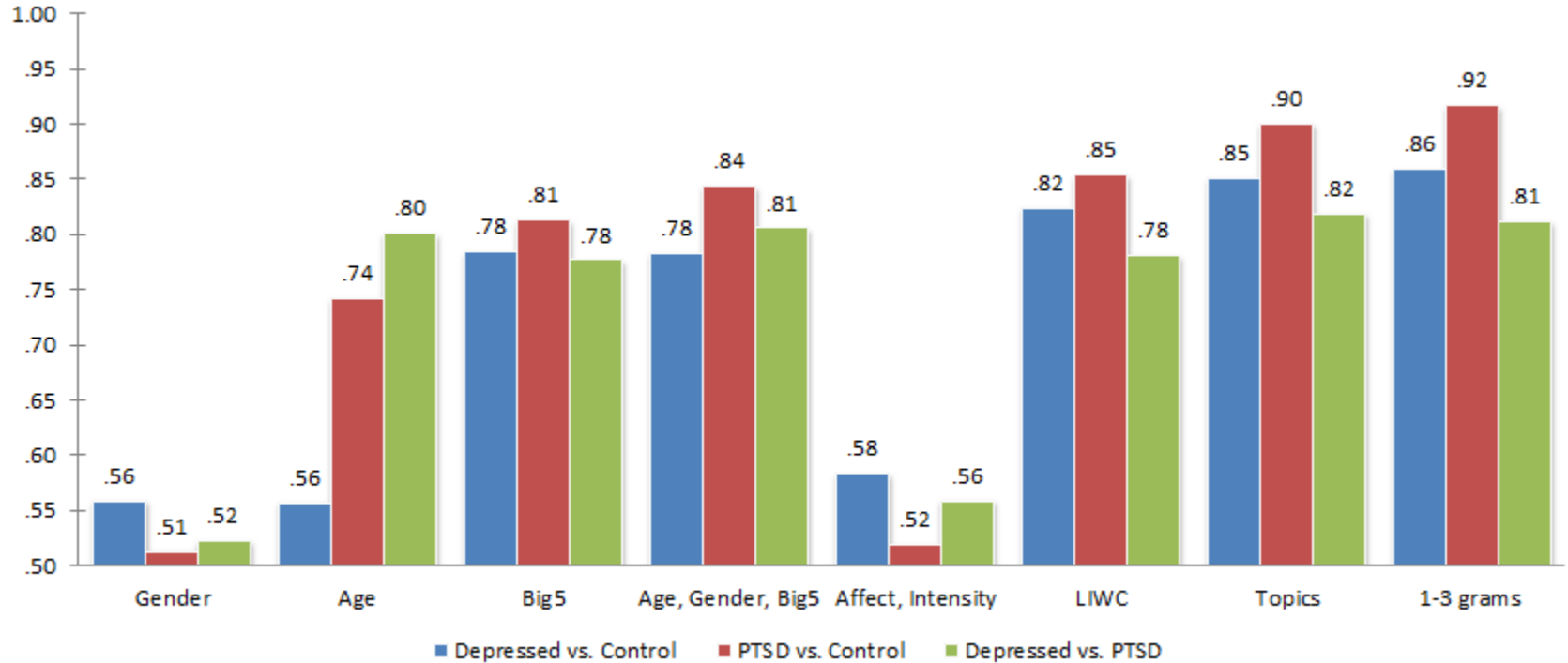


1-3 grams: Depressed vs. PTSD depression

way laundry
of somehow
kind_of maybe_when
out_of OWN realize
that right_? words
equal was_"

Almost nothing left when controlling for age and gender

1-3 grams



Better Predictions

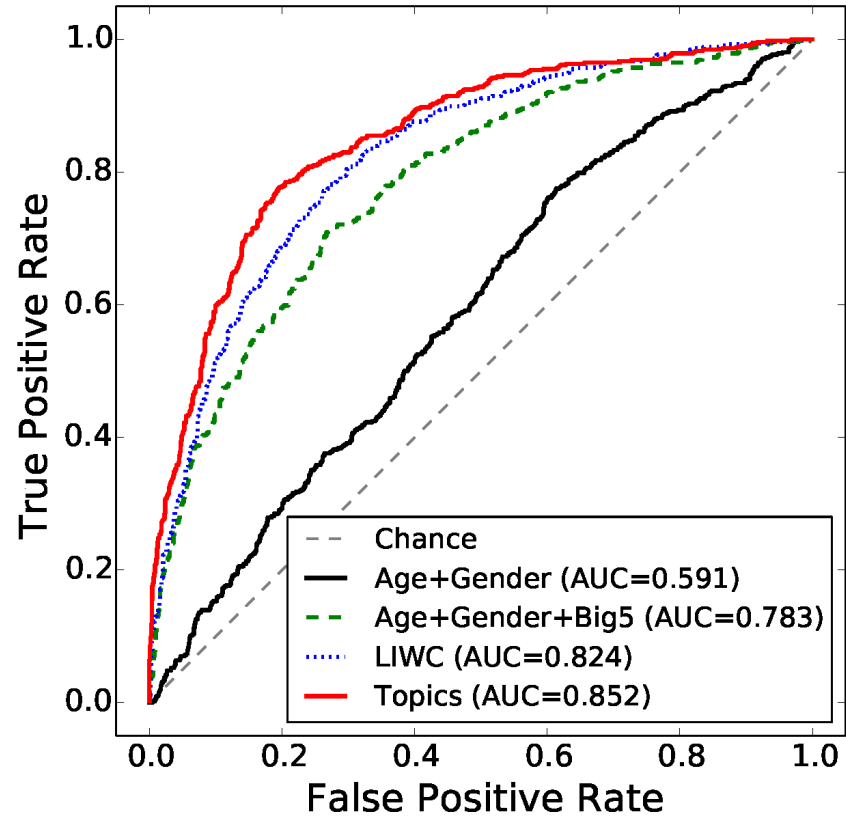
- use metadata features
friends, #statuses
- use different word clusters
Brown clustering, NPMI Spectral clustering, Word2Vec/GloVe embeddings
- linear ensemble of logistic regression classifiers

Mental Illness detection at the World Well-Being Project for the CLPsych 2015 Shared Task

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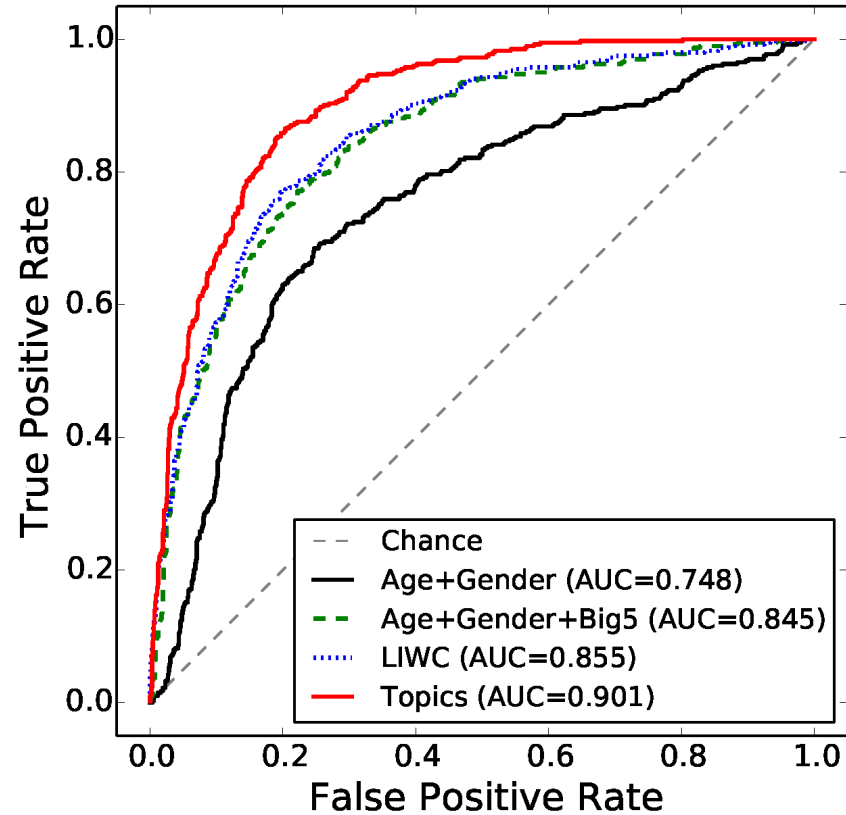
ROC Curve

Depressed
vs.
Controls



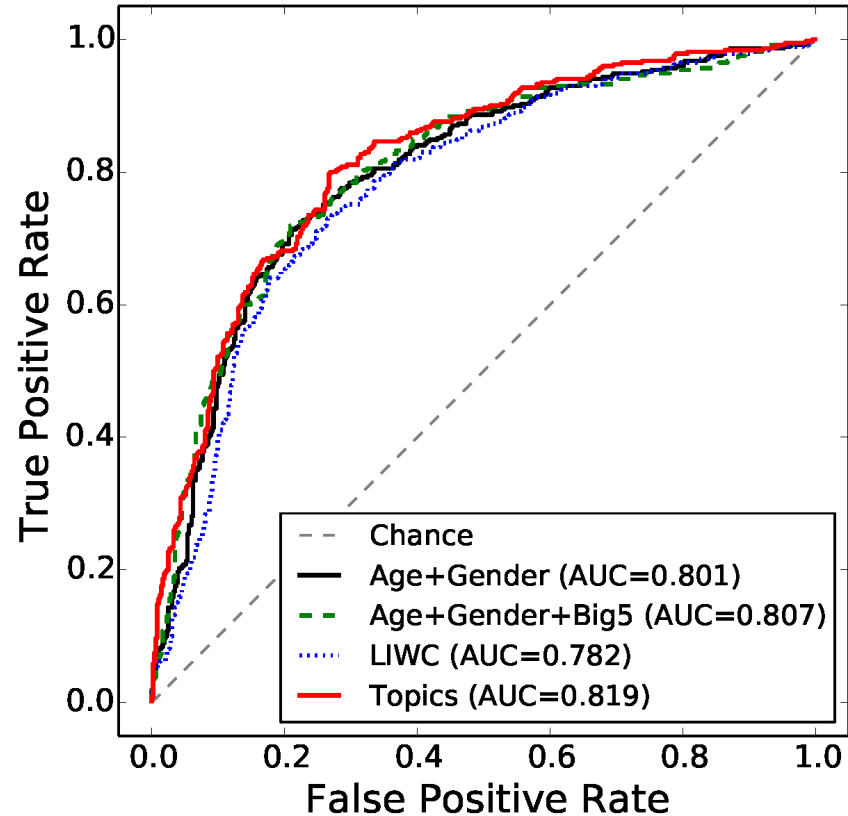
ROC Curve

PTSD
vs.
Controls



ROC Curve

Depressed
vs.
PTSD



Take Home

- Control the analysis for age & gender
- Personality plays an important role in mental illnesses
- Language use of depressed/PTSD users uncovers interesting patterns

Thank you!

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