Depression Screening with Text Messages

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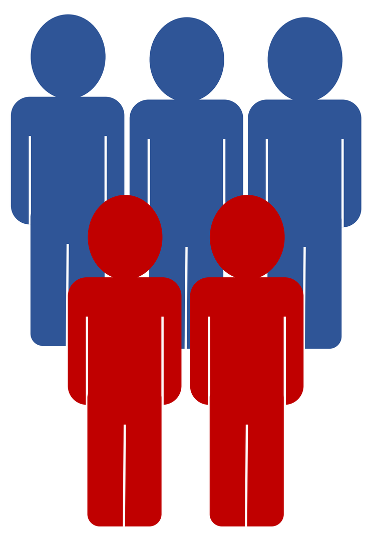
Motivation



2 in 5 graduate students suffer from **depression**[1].

Despite being the most treatable mental health disorder[2], it takes **11 years** on average to get treated[3].

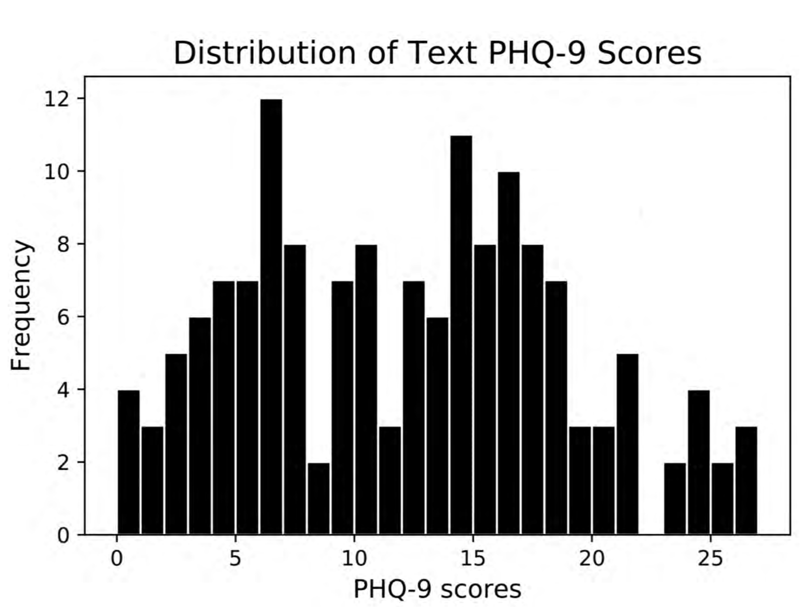
Suicide is the 2nd leading cause of death for US adults under 30. Globally depression is the leading cause of **disability**, costing $1 trillion[3].

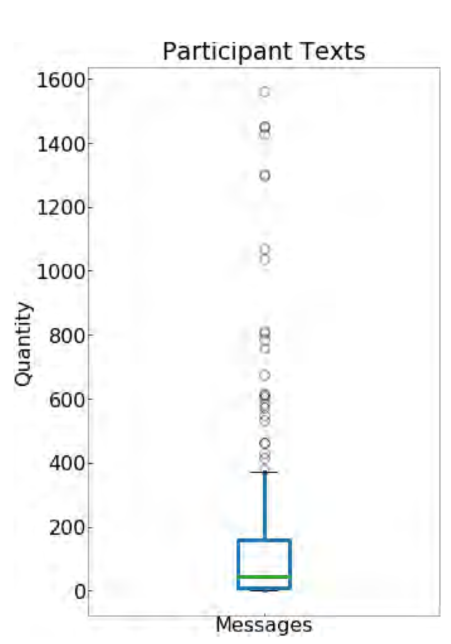
Given texting popularity, **text messages** could be used to passively screen for depression but only a **third** of people are willing to share this modality[4].

Data

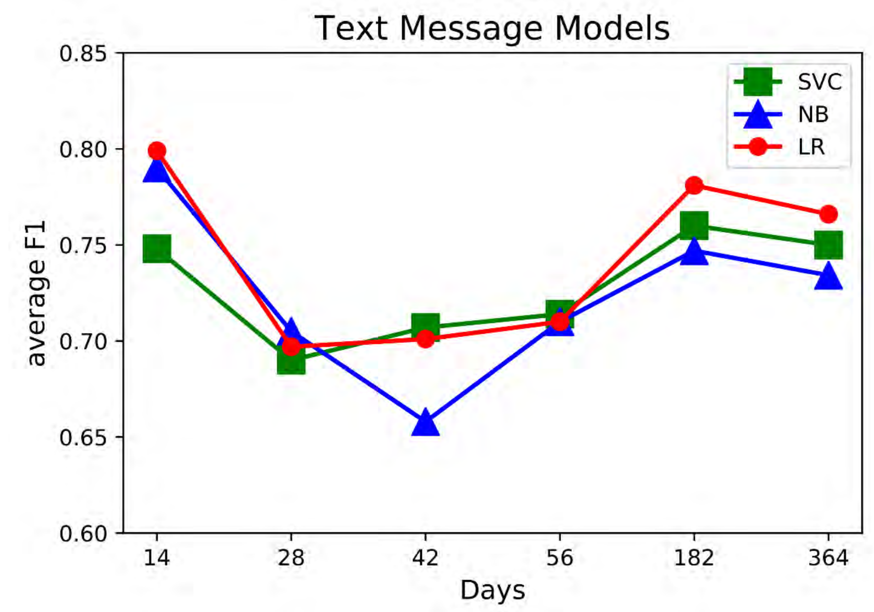
PHQ-9 score	Interpretation[2]	Treatment
0-4	Not Depressed	NA
5-9	Mildly Symptomatic	Monitor
10-14	Mild Depression	Support
15-19	Moderate Depression	Treatment
20+	Severe Depression	Treatment

Moodable[4]/EMU data: retrospectively-harvested crowd-sourced Smartphone & social media data. PHQ-9 was deployed to obtain a depression label. 151 participants sent texts within the last year[5].



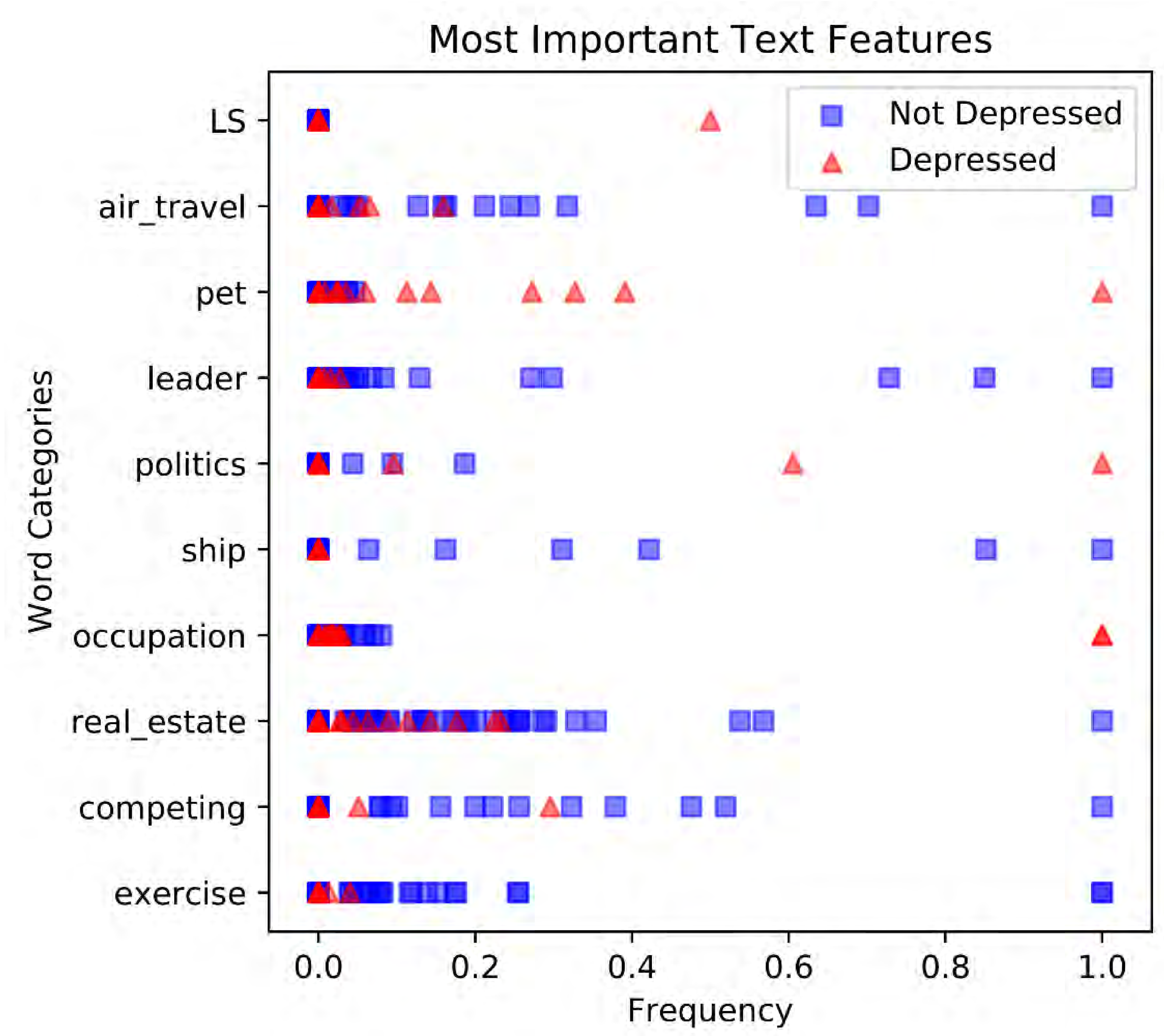


Screening with Text Messages

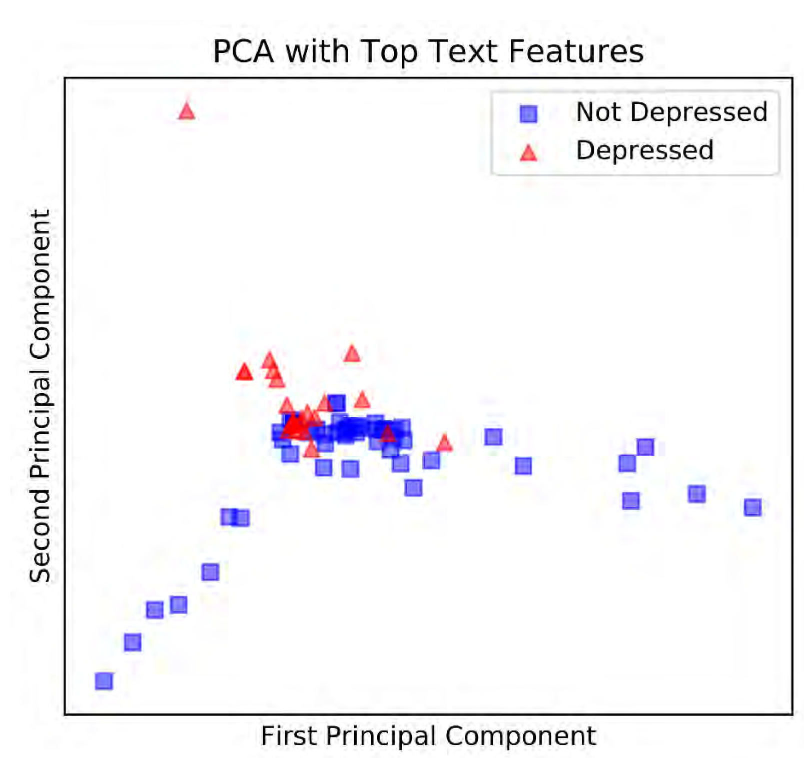


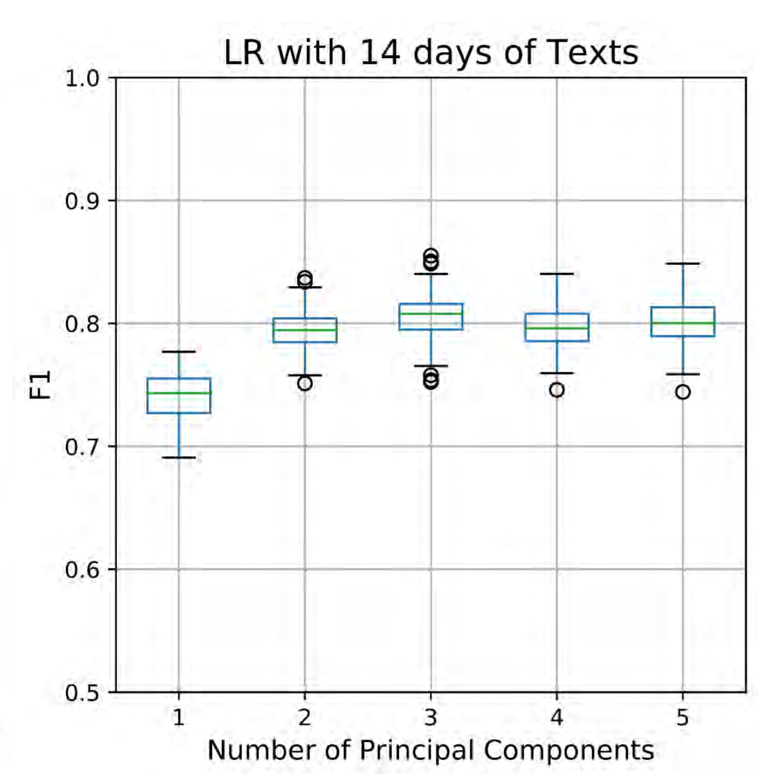
Machine learning methods selected from 245 content features involving:

- Word category frequencies
- POS tag frequencies
- Sentiment
- Volume



Logistic regression models only used 10 features from **two weeks** of texts, achieving an **F1 = 0.81** with three principal components[5].





Generating Text Messages

Goal: create a corpus of **public texts** from PHQ-9 labeled participants.

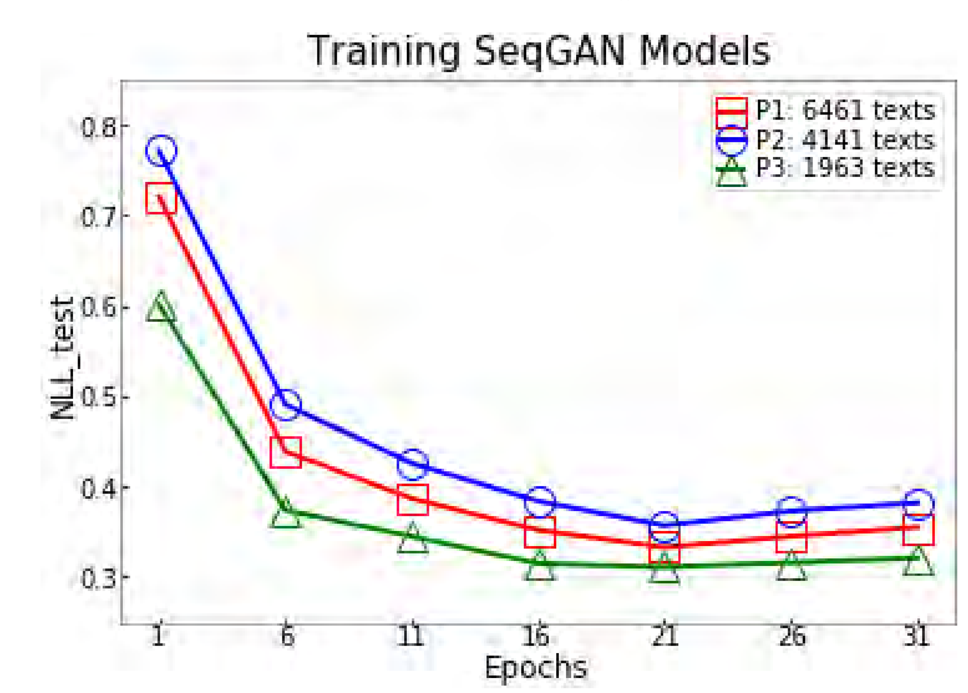
Generative Adversarial Networks (GANs) generate realistic data by using a **generator and a discriminator** engaged in a minimax game. GANs must be modified to generate sequences of discrete tokens[6] as

1. words are not differentiable leading to **no policy updates** and
2. sequences are only scored when complete so rewards are sparse.

Evolution of Text Generation Models

LSTM → SeqGAN → RankGAN → LeakGAN → RelGAN

We deploy **SeqGAN** to determine the impact of text quantity on generation quality measured by negative log-likelihood (NLL). SeqGAN
1. trains a stochastic parameterized policy with a policy gradient and
2. estimates rewards using a Monte Carlo search with a roll-out policy.



SeqGAN can still be **effective** when trained on around 2000 texts, though most of the participants have under 200 texts. We only need **20 epochs** to train.

Generated Text Message Examples

sure how much how awesome! ▪ *let me know when you see Monday* *aww they'll be like soon* ▪ *sure sound fine so* ▪ *ok. i can come tonight* *actually kids were on this way home* ▪ *should to make the toll on lol*

Future Work in Generating Texts

- Compare the screening ability of real texts with texts generated by GANs built on texts from **single and multiple participants**.
- Further anonymize generated texts by replacing named entities.
- Evaluate the appropriateness of popular metrics for this task.

References

[1] Evans, Bira, Gastelum, Weiss, Vanderford. "Evidence for a Mental Health Crisis in Graduate Education," Nature Biotechnology, 2018.
[2] Kroenke, Spitzer, William. "The PHQ-9: Validity of a Brief Depression Severity Measure," Journal of General Internal Medicine, vol. 16(9), 2001.
[3] National Alliance on Mental Health. "Mental Health By Numbers," 2019. Accessed 2020.
[4] Dogrucu, et al. "Instantaneous Depression Assessment using Machine Learning on Voice Samples and Retrospectively Harvested Smart-phone and Social Media Data," Smarthealth, accepted.
[5] Tlachac, Rundensteiner. "Screening for Depression with Retrospectively Harvested Private versus Public Text," IEEEjBHI, 2020.
[6] Yu, et al. SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient," AAAI, 2017.

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