Automated Linguistic Classification of Fake and Real News

Grayson Cupit[1], Leah Windsor[1], Danielle Clewley[1], Michael Boyd[1], & Alistair Windsor[1-2] • [1]Institute for Intelligent Systems • University of Memphis • [2]Department of Mathematics
jgcupit@memphis.edu • Leah.Windsor@memphis.edu • dnclwley@memphis.edu • mboyd6@memphis.edu • awindsor@memphis.edu • polx.weebly.com

Fake News

What is it? The deliberate spread of false information, satire, outdated or revived content, hoaxes, clickbait, propaganda, & disinformation

Why is it a problem? To date, real vs. fake differentiation relies on human moderation or social media integration.

How do we help? We develop an automated fake news classifier that relies only on linguistic features.

Research Question: What linguistic cues can be used to differentiate real news from fake news/propaganda?

Method

Text Corpora

11, 568 Fake news headlines
11,568 Fake news articles
10,998 Real news headlines
6,081 Real news articles

LIWC 2015 Differences

(Examples)

Table 1. *T-tests comparing fake and real headline language*

LIWC 2015 Variable	p	d
WC	≈ 0	0.52
Quote	1.36E-128	0.32
Exclam	5.78E-51	0.2
certain	1.72E-43	0.18
Analytic	7.43E-27	-0.14
swear	2.34E-17	0.11

Table 2. *T-tests comparing fake and real article language*

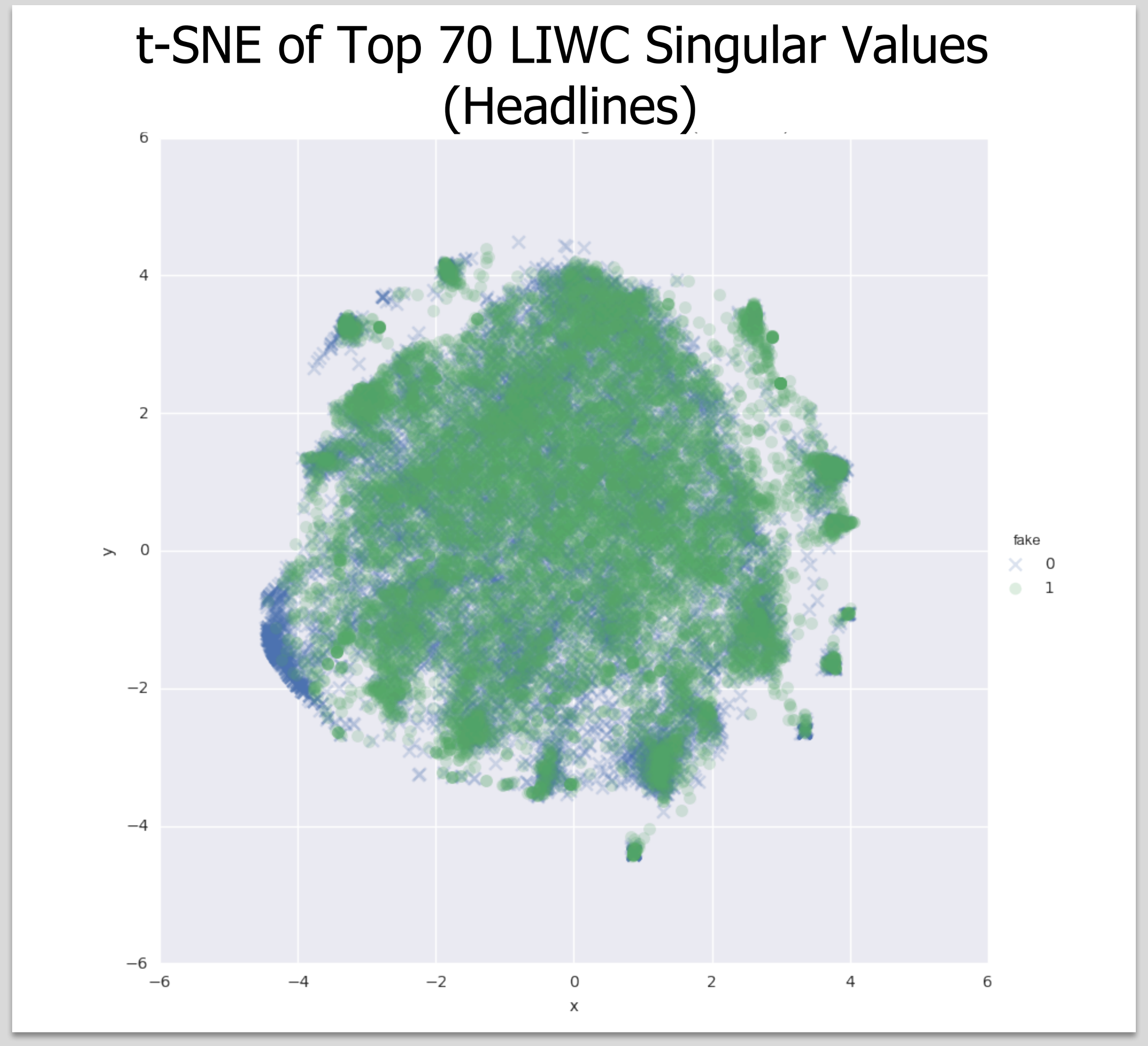
LIWC 2015 Variable	p	d
focuspast	≈ 0	-0.75
focuspresent	≈ 0	0.64
Analytic	1.98E-159	-0.43
you	1.09E-119	0.37
we	2.14E-112	0.36
they	2.09E-16	0.13

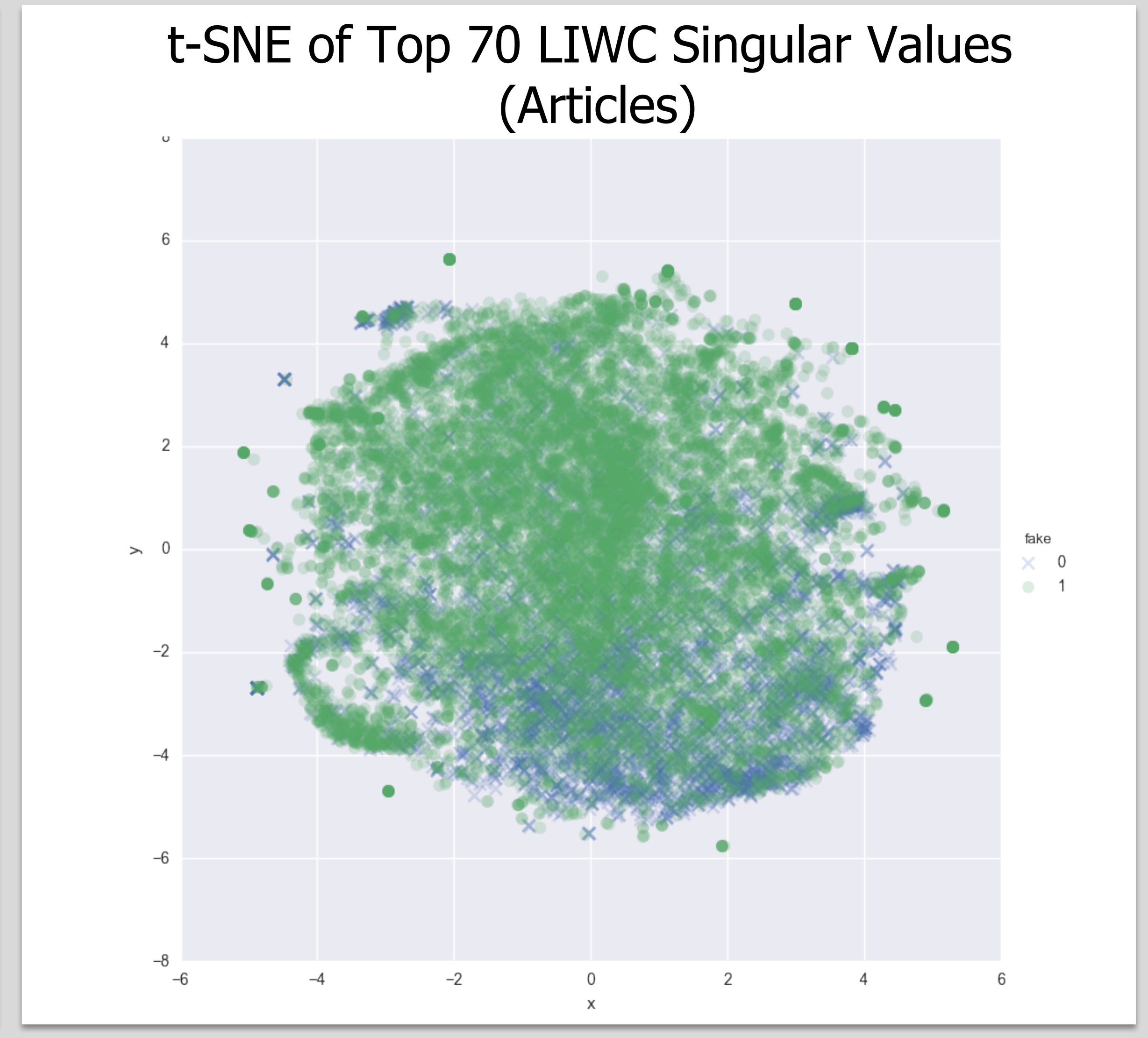
Cohen's *d* calculated using :

$$d = \frac{\bar{x}_{fake} - \bar{x}_{real}}{\sqrt{\frac{(n_{fake}-1)\sigma^2_{fake} + (n_{real}-1)\sigma^2_{real}}{n_{fake}+n_{real}-2}}}$$

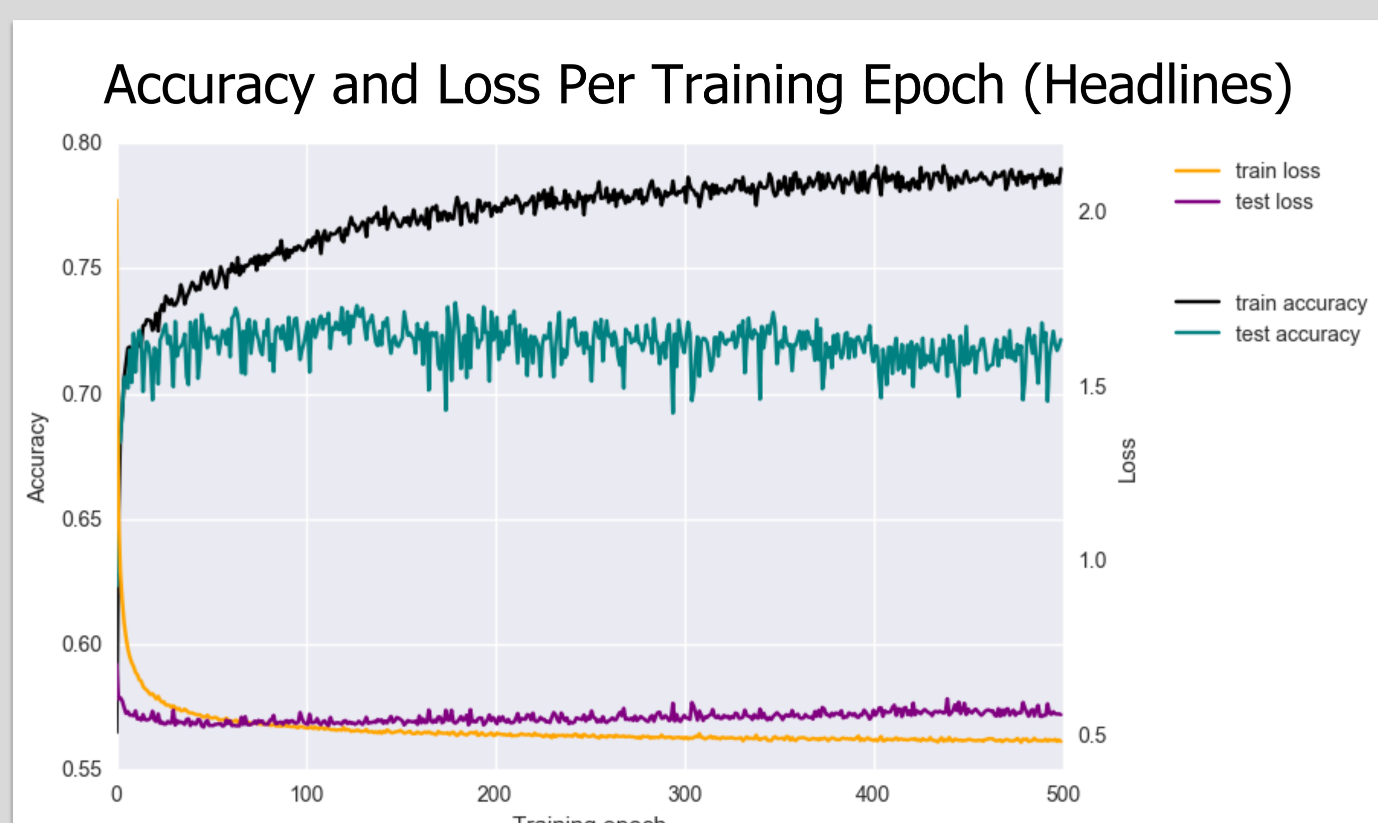
Figure 1 / Figure 2

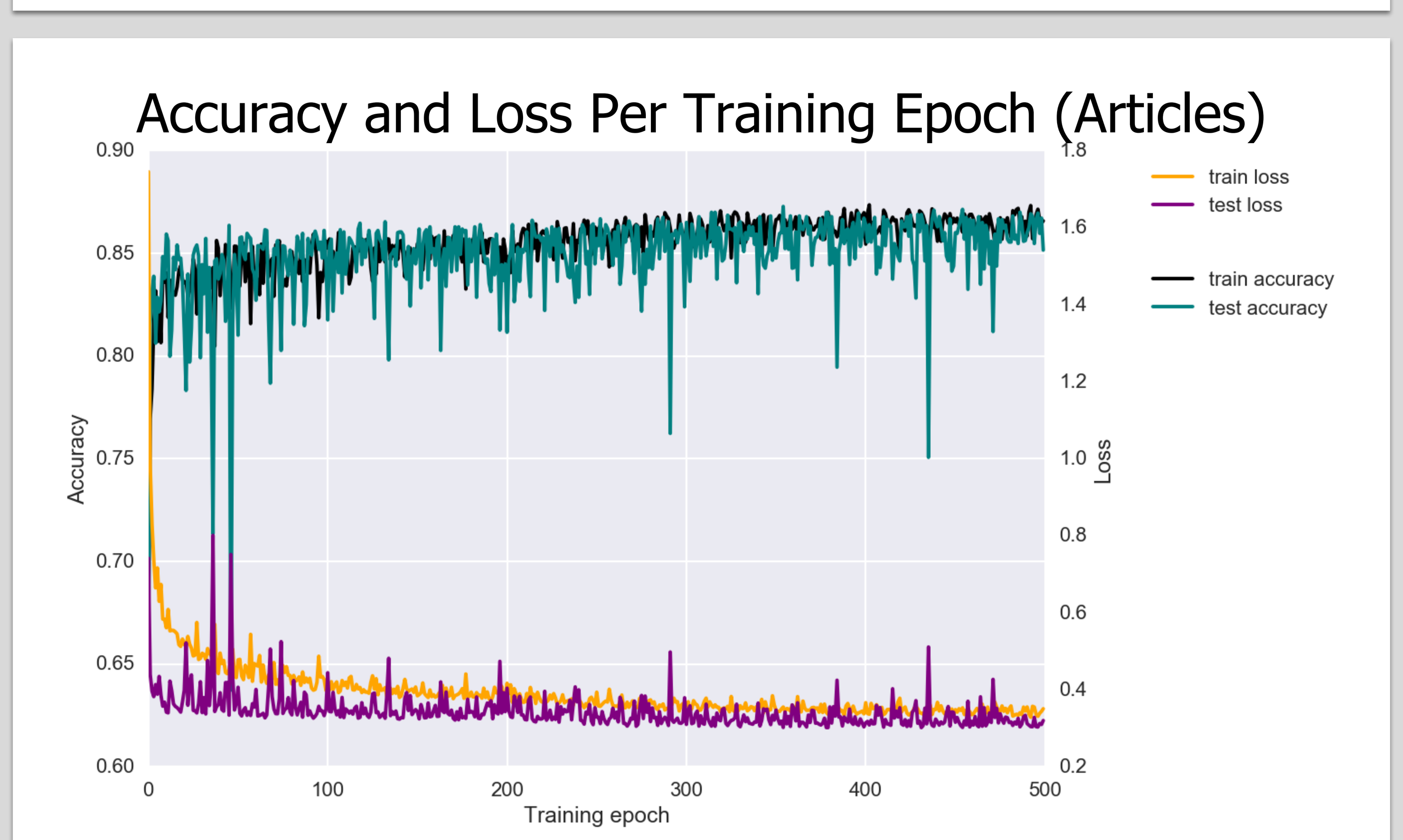
How do articles and headlines cluster in linguistic space?

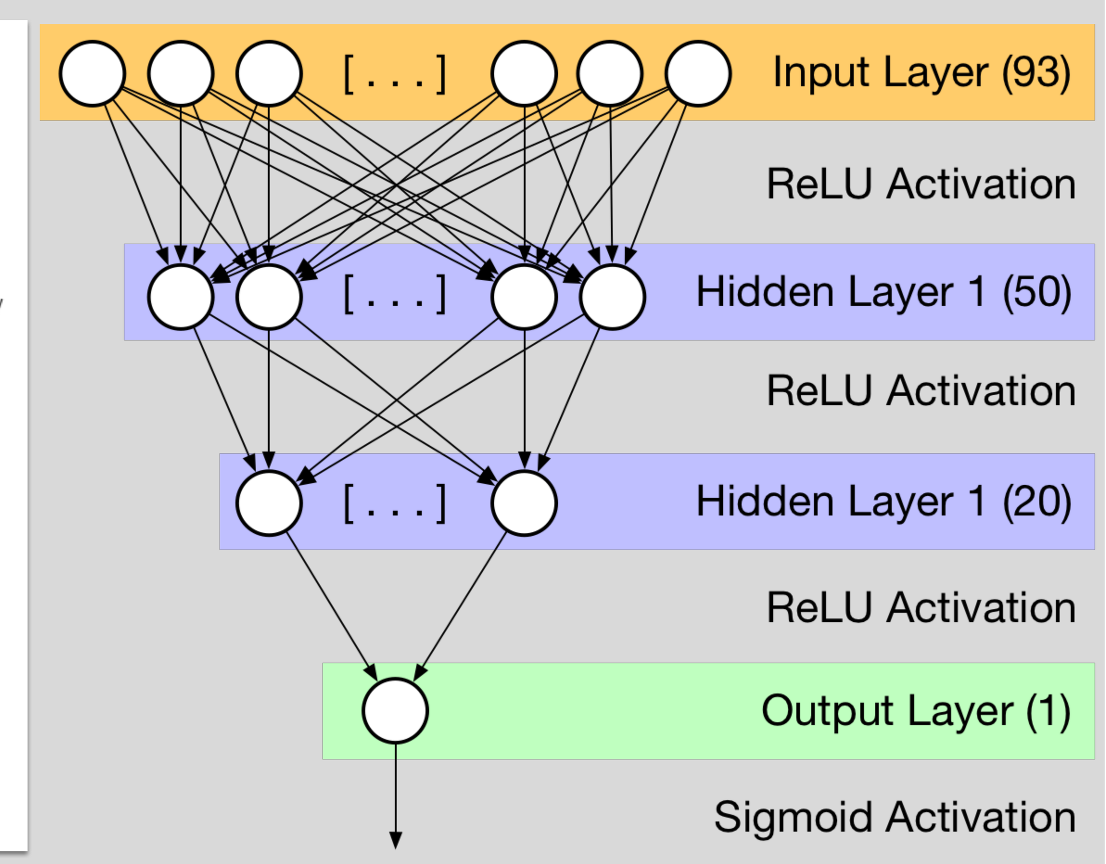




Model





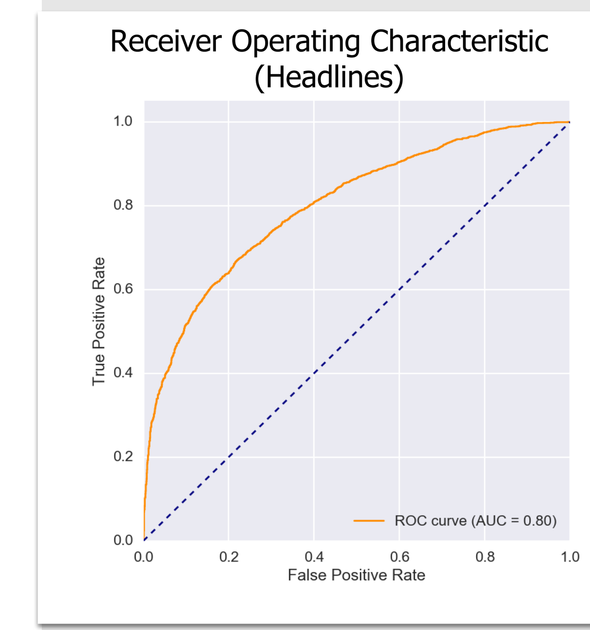


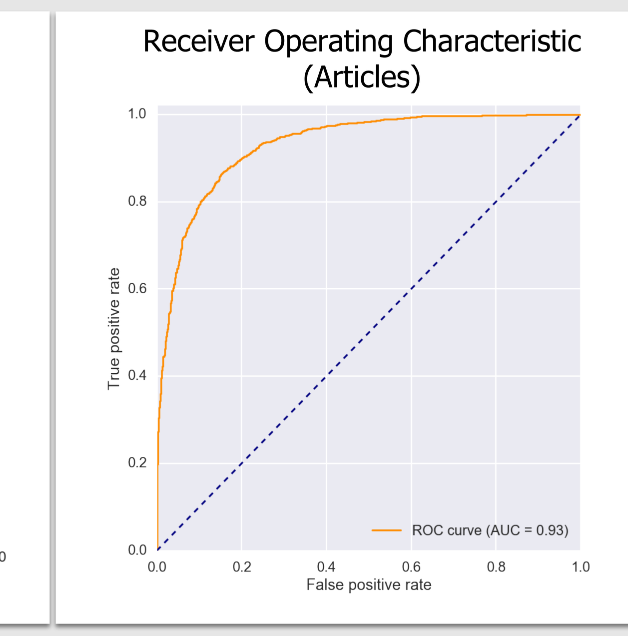
- Deep neural network model
- Input is 93 raw dimensions of LIWC 2015 output for a given article
- Weight update equations penalized using L2 regularization to prevent overfitting
- Output interpretable as classifier certainty

This research is supported by the Minerva Initiative, Department of Defense FA9550-14-1-0308

Results

- While there are statistically significant differences between real and fake news headlines, they do not give us the full story.
- Article texts are better for differentiating between real and fake news.
- Linguistic channels alone carry a strong signal that can be used to predict the credibility of online content.
- Article based classifier exhibited up to 86% accuracy on validation sets, AUROC = 0.93





Next Steps

- Identify which linguistic cues serve as the best predictors for social media engagement with a piece of news

Table 3. *F-tests for headline features predicting shares (fake)*

LIWC 2015 Variable	F	p
tentat	147.75	1.09E-33
differ	137.76	1.52E-31
OtherP	90.44	2.50E-21
conj	52.76	4.13E-13

Table 4. *F-tests for headline features predicting shares (real)*

LIWC 2015 Variable	F	p
WC	76.21	2.91E-18
WPS	51.50	7.60E-13
female	32.15	1.46E-08
social	27.10	1.97E-07

- Experimental approach examining and classifying EEG data of subjects reading fake vs. real news

References

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015.* Retrieved from https://repositories.lib.utexas.edu/handle/2152/31333
Risdal, M. (n.d.). Getting Real about Fake News. Retrieved June 9, 2017, from https://www.kaggle.com/mrisdal/fake-news
Maaten, L. van der, & Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*(Nov), 2579–2605.
Kunze, K., Shiga, Y., Ishimaru, S., & Kise, K. (2013). Reading Activity Recognition Using an Off-the-Shelf EEG–Detecting Reading Activities and Distinguishing Genres of Documents. In Document Analysis and Recognition (ICDAR), 2013 12th International Conference on (pp. 96–100). IEEE.