**CSC-450: Understanding Abstracts**

**Directions:** Each sentence (or part of a sentence) of an abstract corresponds to one of the sections of the paper (Introduction, Methods, Results, Discussion)

1. Relevant *background* required to understand the purpose or nature of the study (Introduction)
2. The *significance* of the project, the *problem* being addressed, the *objective*, or the *hypothesis* (question) under investigation (Introduction)
3. The *methods* used to address the problem, meet the objective, test the hypothesis, or answer the question.
4. *Results* obtained by following the methods (which may or may not be directly stated) of the investigation.
5. *Discussion* of the results, such as adding context or interpreting the results
6. *Not relevant* at all to the project at hand.

In the table below, state whether the sentence describes *background, significance,* an *objective,* or *hypothesis, methods*, or *results* (a sentence may describe more than one). A good abstract will contain at least one sentence corresponding to (1-4).

**2) Experimental evidence of massive-scale emotional contagion through social networks**

Emotional states can be transferred to others via emotional contagion, leading people to experience the same emotions without their awareness. Emotional contagion is well established in laboratory experiments, with people transferring positive and negative emotions to others. Data from a large real-world social network, collected over a 20-y period suggests that longer-lasting moods (e.g., depression, happiness) can be transferred through networks [Fowler JH, Christakis NA (2008) BMJ 337:a2338], although the results are controversial. In an experiment with people who use Facebook, we test whether emotional contagion occurs outside of in-person interaction between individuals by reducing the amount of emotional content in the News Feed. When positive expressions were reduced, people produced fewer positive posts and more negative posts; when negative expressions were reduced, the opposite pattern occurred. These results indicate that emotions expressed by others on Facebook influence our own emotions, constituting experimental evidence for massive-scale contagion via social networks. This work also suggests that, in contrast to prevailing assumptions, in-person interaction and nonverbal cues are not strictly necessary for emotional contagion, and that the observation of others’ positive experiences constitutes a positive experience for people.

Kramer, A. D. I., Guillory, J. E. & Hancock, J. T. Experimental evidence of massive-scale emotional contagion through social networks. *PNAS* **111,** 8788–8790 (2014).

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**2) Towards detecting influenza epidemics by analyzing Twitter messages**

Rapid response to a health epidemic is critical to reduce loss of life. Existing methods mostly rely on expensive surveys of hospitals across the country, typically with lag times of one to two weeks for influenza reporting, and even longer for less common diseases. In response, there have been several recently proposed solutions to estimate a population's health from Internet activity, most notably Google's Flu Trends service, which correlates search term frequency with influenza statistics reported by the Centers for Disease Control and Prevention (CDC). In this paper, we analyze messages posted on the micro-blogging site Twitter.com to determine if a similar correlation can be uncovered. We propose several methods to identify influenza-related messages and compare a number of regression models to correlate these messages with CDC statistics. Using over 500,000 messages spanning 10 weeks, we find that our best model achieves a correlation of .78 with CDC statistics by leveraging a document classifier to identify relevant messages.

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Culotta A. Towards Detecting Influenza Epidemics by Analyzing Twitter Messages. In: Proceedings of the First Workshop on Social Media Analytics [Internet]. New York, NY, USA: ACM; 2010. p. 115–22. Available from: <http://doi.acm.org/10.1145/1964858.1964874>

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