Toward Large-scale and Multi-facet Analysis of First Person Alcohol Drinking

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Introduction. Mining the vast quantities of online social communications has potential to deliver low-cost, high-resolution views into population behaviors that are relevant to prevention and health promotion efforts. In particular, there is an emerging literature examining alcohol use behaviors in social data, including temporal patterns[1] and behavioral nuances[2]. Furthermore, alcohol use is a significant source of global morbidity and mortality[3]. Established in the literature is the ability to detect - with 89% performance (AUC) - first-person reports of alcohol consumption[4]. There is a dearth of evidence as to whether the approach can identify solitary versus group drinking, and light versus heavy consumption. Both social context and volume dimensions of alcohol use are associated with likelihood of harm/disorder and have implications for prevention and response[5]. Accurate detection of such information about alcohol use behaviors has the potential to accelerate public health awareness, drive targeted responses, and identify opportunities for preventive interventions. The aim of our study is two fold: (1) to develop accurate classifiers to identify first person reports of alcohol use in Twitter data that would outperform existing standards, and (2) develop a classifier to precisely discern alcohol consumption level as well as drinking context using Twitter data.

Data Description. We developed a Twitter dataset consisting of 16 million (16M) GPS-tagged tweets that contained at least one of 600 alcohol-relevant keywords, the set of which was generated from expanding a list used previously[4] by drawing on terms in online alcohol dictionaries and the `word2vec` toolkit. A random sample of 10,000 (10K) of these keyword-matched tweets was manually annotated by three annotators through crowdsourcing. For quality assurance, three members of our team annotated 500 tweets and came to agreement about their gold labels; these tweets were then injected into 10K tweets and all annotations of crowdsource annotators who had less than 80% accuracy on the 500 tweets were ignored. Each tweet was first annotated as either first-person drinking or not first-person drinking where instructions described first-person drinking tweets as those in which "the text is indicative of alcohol consumption and describes the drinking activity of one or more individuals." For each first-person drinking tweet, annotators were further asked to label (a): the context of the tweet as either individual or group drinking, or unknown context; (b): the consumption level indicated in the tweet as heavy, light, unknown level; instructions described heavy level as either multiple drinks or intoxication, while light level as both single drink and no intoxication; and (c): the time of drinking as past, present, future, or unknown time. The overall annotator agreement on the resulting dataset was 76.1%, which indicates a fairly feasible task for humans.

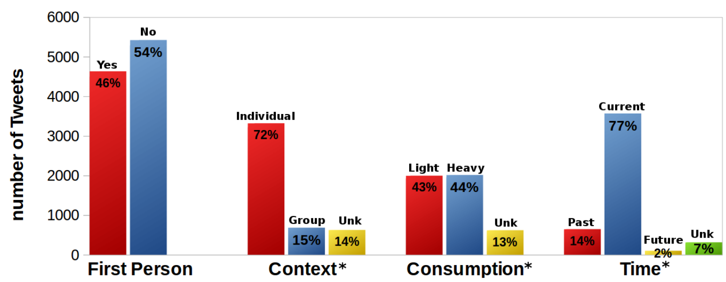
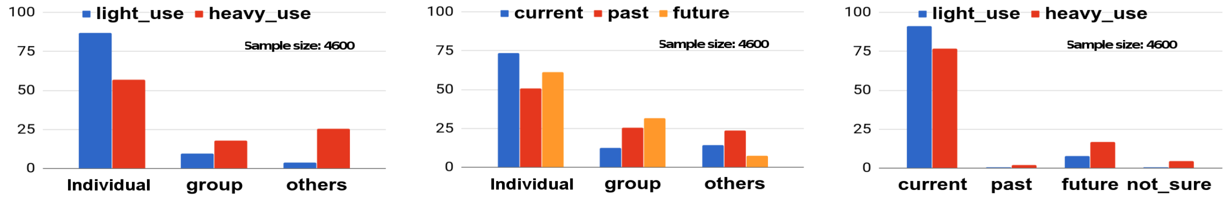


Figure 1: First person alcohol drinking Twitter dataset; *bars for context, consumption, and time are for first-person positive drinking tweets.

Figure 1 shows that, in our dataset, 54% of the tweets that contain alcohol-relevant keywords do not indicate first-person drinking. Furthermore, a majority of first-person drinking tweets indicate individual drinking context and are posted close to the time of drinking (current). Such tweets also indicate almost balanced consumption level. Further analyses of the annotated results show that: in solitary contexts, consumption level tends to be light, whereas, in a group context, consumption level tends to be heavy, see Figure 2(a); in solitary contexts, the time of drinking is often current, whereas, in group context, it is often past or future, see Figure 2(b); and, current drinking often indicates light consumption while future and past drinking often indicate heavy consumption, see Figure 2(c).

Method. We investigate the performance of the state-of-the-art classification approach for first-person drinking, context, and consumption-level classification tasks. The state-of-the-art method for the first task is reported in[4]; the method is SVMs with linear kernel which uses character and word n-grams (weighted by TF-IDF) as well as features derived from standard topic modeling algorithms for the classification purpose. This publicly available tool



(a) Context vs. Consumption (b) Context vs. Time (c) Time vs. Consumption

Figure 2: Cross comparison of drinking context, consumption level, and time of drinking activity.

(https://github.com/jxnl/nyu-twipsy) is used for comparison purposes. The tool is implemented using the scikit-learn toolkit with grid search over hyperparameters for tuning purpose. Following[4], we develop our classifier using the same toolkit while we enhance its features by including syntactic features obtained from `TweeboParser`[6] and average word embeddings obtained from Google's pre-trained embeddings. We note that, although expensive to extract, syntactic features are important for accurate classification of posts with respect to the above tasks. Such features capture the (long-distance) relations between words which may not be effectively captured by n-grams. For example, in the tweet "I am drinking too much beer," it is important to know that the terms "I" and "beer" modify the verb "drinking" to accurately classify this tweet as a first-person alcohol drinking tweet. Were the direct object of the verb "water" instead of "beer," the post would be as not first-person alcohol drinking. Such information can be captured by syntactic features.

Results. We partitioned our 10K dataset into training data (80%), development data (10%) for parameter tuning, and test data (10%) for evaluation. We developed our classifier using SVMs with linear kernel implemented in scikit-learn toolkit and used grid search to optimize its parameters using development data. The AUC performance of SVMs with basic features developed in[4] and our enhanced features are reported in Figure 3. As the results show, enhanced features improved the performance of SVMs with basic features across all tasks. The difference was significant - measured by paired t-test with $\rho \leq 0.01$, and ablation analysis showed syntactic followed by word embedding features as key source of improvement (details are not reported due to space limit).

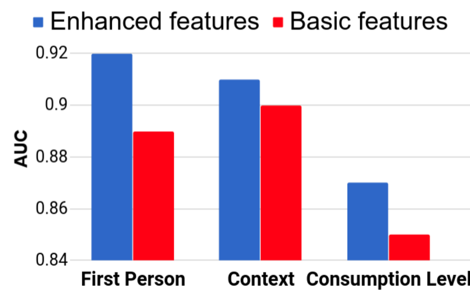


Figure 3: AUC classification performance.

Discussion. In this work, we developed effective classifiers to accurately detect first-person reports of alcohol use, social context and volume dimensions of alcohol use. Our work provides important information to complement traditional population health monitoring of alcohol use behaviors, including potentially identification of more nuanced dimensions reflecting heavy drinking, problems related to drinking, and information about the social context and setting around alcohol use behaviors. Such information has high value for informing targeted public health interventions and their evaluation, and may generate results with significant public health impact. Future analyses might explore associations among tweets evidencing first-person alcohol use and reports of problems such as indications of other substance use, fights or conflict, accidents or injury, and driving under the influence. Spatial and temporal resolution of such patterns could provide important information to further guide public health action.

Acknowledgments. This research was supported by funding from NIAAA R21AA023901 and NIGMS R01GM114355.

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