

Drinks & Crowds: Characterizing Alcohol Consumption through Crowdsensing and Social Media

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The design of computational methods to recognize alcohol intake is a relevant problem in ubiquitous computing. While mobile crowdsensing and social media analytics are two current approaches to characterize alcohol consumption in everyday life, the question of how they can be integrated, to examine their relative value as informative of the drinking phenomenon and to exploit their complementarity towards the classification of drinking-related attributes, remains as an open issue. In this paper, we present a comparative study based on five years of Instagram data about alcohol consumption and a 200+ person crowdsensing campaign collected in the same country (Switzerland). Our contributions are two-fold. First, we conduct data analyses that uncover temporal, spatial, and social contextual patterns of alcohol consumption on weekend nights as represented by both crowdsensing and social media. This comparative analysis provides a contextual snapshot of the alcohol drinking practices of urban youth dwellers. Second, we use a machine learning framework to classify individual drinking events according to alcohol and non-alcohol categories, using images features and contextual cues from individual and joint data sources. Our best performing models give an accuracy of 82.3% on alcohol category classification (against a baseline of 48.5%) and 90% on alcohol/non-alcohol classification (against a baseline of 65.9%) using a fusion of image features and contextual cues in this task. Our work uncovers important patterns in drinking behaviour across these two datasets and the results of study are promising towards developing systems that use machine learning for self-monitoring of alcohol consumption.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing:** *Ubiquitous and mobile computing design and evaluation methods.*

Additional Key Words and Phrases: youth, social media, mobile crowdsensing, context, nightlife

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1 INTRODUCTION

Alcohol consumption in excess can lead to many adverse consequences, including violence and accidents [51], [57], [29]. These are serious problems in many countries, concerning both policymakers and the public [45], [7]. From the perspective of urban nightlife security, understanding patterns of drinking in urban areas is a relevant

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subject. Previous research [26], [20] has shown that young people drink alcohol both indoors (at home, bars, nightclubs) and outdoors (in parks or open streets). In the past, scientists investigating alcohol consumption traditionally conducted face-to-face interviews or used paper-and-pencil questionnaires to collect data. These methods have limitations, including recall limitations and the issue of scale [36], [27]. On the other hand, the booming of smartphones and social media are opening new channels for investigating alcohol consumption trends, through the integration of methods from social science and computer science.

Ubiquitous computing research has studied alcohol consumption in the last years from two main perspectives. In the first one, machine learning methods involving sensor data from a variety of wearable devices (wristbands, smart watches, earbuds, glasses) have been developed to detect fluid intake moments [59], [50], including alcoholic beverages [33], [11], [9]. These studies, using accurate on-body sensors and fine-grain temporal resolution, have typically involved a couple of tens of users in experiments that have ranged from controlled [47], [59] to in-the-wild settings [64], [23]. The second direction in ubicomp comes from crowdsensing [62], [22]. These works have used a combination of smartphone sensing and geolocalized human-generated input to collect data about everyday life habits, which has been used to document alcohol intake for a couple of hundred volunteers in [52] and [53]. This line of work focuses on understanding the real-life context in which drinking occurs, as a first step towards automatic recognition of drinking events, and can be seen as an evolution of more traditional methods in alcohol research, which have collected survey data via SMS on feature phones [37], as well as ubiquitous health research on food diaries and diet monitoring [59], [47], [15].

Mobile crowdsensing shares many aspects with the way in which social media is generated on Twitter, Facebook, and Instagram, involving deliberate human actions to take photos and add hashtags, combined with phone sensing to geolocalize content. In particular, social media research has been conducted to reveal a few aspects of alcohol consumption, mainly with data from the US or the UK. By using the location of users or their tweets, various alcohol intake patterns in urban and suburban areas and local and national levels can be extracted and compared to available public data [34], [48], [31]. Social media is generated at a global scale and potentially allows for studies with tens or hundreds of thousands of individuals. On the other hand, it is known that as a data source of behavioral traces, social media have limitations in terms of population bias and sparse temporal resolution.

To our knowledge, an important issue in ubicomp that has not been previously investigated is how these two threads of research (crowdsensing and social media) can be integrated, both to improve our understanding of their similarities as data sources informing the same phenomenon (alcohol consumption in everyday life), and to exploit their potential complementarities in machine learning approaches to classify drinking-related attributes. In this paper, we investigate this problem through two research questions:

RQ1: Given comparable datasets (with respect to country and time) generated by mobile crowdsensing and social media, what alcohol consumption patterns can be extracted with respect to temporal, place, and social context? What are the similarities and differences between these patterns depending on the data source?

RQ2: Can such complementarity be used to improve the performance of classification tasks applied to individual alcohol-consumption episodes, namely to infer alcohol categories?

The contributions of the paper are the following:

- (1) As a social media source, we curate new datasets of Instagram posts related to alcohol consumption, starting from a 1.6 million generic dataset of posts in Switzerland collected over five years. The resulting data, following a careful semi-automated curation process, includes alcohol-related hashtags, standardized alcohol categories (wine, beer, spirits), timestamps, images, venue information, user information, and other metadata. As a mobile crowdsensing source, we use the Youth@Night dataset first presented in [52], which comes from a large-scale mobile crowdsensing campaign that aimed at capturing nightlife activities

(including drinking) of young people over three months in Switzerland, and that we investigate under a novel comparative angle not previously studied.

- (2) We conduct new data analyses to reveal temporal, spatial, and social contextual patterns of alcohol consumption on weekend nights as captured by both crowdsensing and social media. Our analysis produces several relevant findings, including: (1) as a result of their respective population biases, both data sources show differences from general-population official statistics with respect to the distribution of consumed alcohol categories, with a significantly increased consumption of hard alcohol on weekend nights; (2) both sources show very similar temporal patterns, with a predominance of hard alcohol to be consumed in the late night; (3) crowdsensing can capture a significant amount of drinking in personal places like homes, while this practice is not common on Instagram; and (4) both sources show very similar social context patterns, with a strong predominance to drink with friends on weekend nights. These results paint a rich picture of young urban night dwellers consuming alcohol in the target country, and complement results from more traditional studies, which usually do not investigate time-specific trends.
- (3) Based on this analysis, we use a machine learning framework to classify individual drinking events according to alcohol categories, using contextual cues and image features from individual and joint data sources. We achieve classification accuracies up to 82.3% and 90.0% for the classification of alcohol categories and alcohol/non-alcohol, respectively, with contextual features being less discriminant than visual features. Combining the two datasets produces either marginal or no improvement in classification performance, which we hypothesize is due to the noisier nature of Instagram data. These results are encouraging for developing an automatic system towards self-monitoring of alcohol consumption.

The paper is organized as follows. Section 2 discusses related work. Section 3 presents the crowdsensing and Instagram datasets. Section 4 introduces the alcohol drink categories defined in our study. Section 5 presents the in-depth analysis of alcohol categories with respect to temporal, spatial, social, and occasion-related patterns for both crowdsensed and social media data sources. Section 6 presents and discusses the work on classification of alcohol categories and alcohol/non-alcohol episodes. Section 7 discusses the results. Section 8 concludes the paper.

2 RELATED WORK

In this section, we review work related to alcohol consumption research in social media and ubiquitous computing.

2.1 Social Media and Alcohol Consumption

Methods for automatic estimation of alcohol volume sales from Twitter streams were studied in [25]. Drinks, as a broad category next to fast food and slow food, were studied in [55] in the context of differences in check-in habits in food/nightlife Foursquare venues. These two works did not analyze types of alcoholic drinks in any detail. Other works on Twitter and Instagram that analyze food patterns have included alcoholic drink hashtags as part of their analyses but did not investigate specific alcohol drinking patterns [6], [46]. Our previous work [49] presented a descriptive analysis of patterns of food consumption on Instagram in the same target country, in which non-alcoholic and alcoholic drinks are treated as generic consumed items. Our paper significantly extends [49], both with an in-depth analysis of alcoholic drink types, and with an assessment of the objective utility of Instagram data to improve automatic inference of attributes from crowdsensed data.

Marczinski et al. [44] designed a 10-item alcohol-related Facebook activity (ARFA) questionnaire which asked 146 college students for past 30 day postings related to alcohol use and intoxication. By using regression analyses, they revealed that the ARFA scores were important predictors of recent drinking behaviors. In addition, they proposed that the ARFA scale can be a good tool for recognizing risky alcohol use. Boyle et al. [16] attempted to predict possible drinking from manual coding of past alcohol-related content on social media sites (Facebook,

Instagram, Snapchat) in a group of 408 first-year students during 6 weeks of college. This is different with respect to our work, which uses automatic feature extraction for classification of alcohol categories and alcohol/non-alcohol. This previous research also identifies that drinking with close friends, and drinking with a group of people of different gender could be predictive of later alcohol use, in case of not having previous information about alcohol-related posts on social media sites.

On Twitter, several works have used predefined alcohol-related hashtags to filter tweets containing alcohol items and to extract basic patterns [34], [18], [31]. Several of these works [34], [31] assume that all tweets containing alcohol-related hashtags are events of alcohol consumption or alcohol use. However, [18] proposed a more nuanced approach by manually classifying the themes of 5000 alcohol-related tweets into pro-alcohol tweets (79%), anti-drinking tweets (7%), and neutral tweets (13%). In addition, by extracting the location of users or location of tweets, various patterns of alcohol consumption in urban/suburban areas and local/national levels are discovered and compared to available public data in [34], [31].

Finally, Instagram photos can give visual cues to complement alcohol hashtags. The work in [48] extracted Instagram user demographics (age, gender, and race) by using Face++ (an online face processing toolkit) to automatically detect and analyze faces in selfie photos. The work then used a hashtag-driven approach to identify posts related to alcohol consumption in terms of time, under-age drinking patterns (using the demographics above), location-specific drinking patterns, and youth exposure to alcohol media. Our work also uses visual analysis of Instagram photos to extract content and profiles to infer basic demographics, but instead uses this information to investigate how social media datasets can complement mobile crowdsensing datasets and to automatically classify alcohol categories in individual posts.

2.2 Ubicomp and Alcohol Consumption

As a kind of hand-to-mouth activity, alcohol drinking is related to ubicomp research on recognition of eating and smoking occasions. Work on recognition of eating occasions includes [8], [59], [47]. First, Amft et al. [8] used multiple embedded sensors to collect data of an individual's food intake, which was used for building up personalized weight-loss plans for users. In the work of [59], Thomaz et al. implemented and evaluated methods to predict eating moments based on 3-axis accelerometer data from smartwatches. They collected data with 20 subjects of 2 groups and recognized eating moments in two conditions: 7 participants in 1 day (F-score: 76.1%) and 1 participant in 31 days (F-score: 71.3%). In the same line of research, Mirtchouk et al. [47] automatically estimated food type and amount of consumed food by using body-worn audio and motion sensors. Using 40 unique food types, the work reported a classification accuracy of 82.7% with a combination of sensors, compared to 67.8% for audio alone, and 76.2% for head and wrist motion.

There are also specific works studying drinking occasions [13], [50]. Bedri et al. [13] detected eating and drinking moments by using a wearable system. They discovered that inertial sensing is the best to detect eating events compared to two other features (optical and acoustic sensing features). The system can recognize chewing instances with the accuracy of 90.1% in a semi-controlled lab study, compared to 93% for outside-the-lab evaluation. Towards recognizing eating and drinking by using sound, BodyBeat [50] is a mobile sensing system capturing and detecting non-speech body sounds (food intake, breath, laughter, cough), that uses a microphone attached to a 3D printed neckpiece.

Other ubicomp works have focused on developing approaches to collect food and drink diaries, which have some similarities with photo-taking and tagging practices in social media [64], [23], [15]. Zepeda et al. [64] study logs of food through photo and text as interventions to create awareness and change dietary habits with 43 participants. Their results reveal that photo food consumption diaries can alter attitudes and food choice behaviors more than written diaries. Cordeiro et al. [23] examine and discuss the benefits of lightweight photo-based capture

in mobile food journals, compared to other existing journaling methods. Biel et al. recently studied a cohort of 128 college students who collected in-situ diaries of food, drinks, and context using a mobile application [15].

There are also approaches to detect smoking episodes [54], [19]. Scholl et al. [54] evaluated two different prototypes which detected smoking behaviors based on augmenting a lighter. They studied the deployment of the systems, with 11 frequently-smoking participants. Interestingly, smokers were not aware of their daily smoking patterns and often mis-estimated their consumption. Chatterjee et al. [19] developed a model to estimate cigarette craving (during smoking abstinence) by using mobile sensor data. They found that stress and self-reported high craving are associated. By using this feature and other insights, they infer craving probabilities. In public health research, smoking can be associated with alcohol drinking [40]. Ma et al. examined relationships between cigarette smoking, alcohol use, and dietary intake. They reported that the use of cigarettes and alcohol are closely related [40].

Note that unlike these works, which exploit sound, motion, or inertial sensors, in our work we are interested in contextual and visual cues for recognition like semantic location, social context, and visual features. Furthermore, in some of these works there is also an interest in automatically detecting the moment of the eating/drinking/smoking occasion, whereas in our case we use timestamps voluntarily provided by people at the moment of documenting a drink (in the case of crowdsensing) or posting a photo (in the case of Instagram).

In the ubicomp literature, various alcohol consumption patterns have been studied by mobile crowdsensing, which collect data from installed phone applications and wearable devices. Researchers have asked participants to report every single drink event via text using feature phones in [36]. This approach shows that alcohol consumption increases on Saturday for males and females. Regarding using smartphones for daily logging of drinking behavior, [10] used a mobile health application to allow users self-report types of alcohol beverages, amount of consumed alcohol, and drinking time. Also using a smartphone app, Santani et al. investigated urban nightlife patterns for over 200 young people, collecting smartphone sensor and log data, alcohol drinking surveys, place drinking surveys, and videos of drinking environments [52]. Santani et al. also used the sensor and log data to automatically classify nights in which alcohol was consumed, with a reported accuracy of 76.6% [53]. This dataset, which is a large case study of crowdsensing research for alcohol consumption, will also be used in this paper. Other studies ask participants to carry wearable devices or bring along their smartphones before and during alcohol use [33], [11], [9]. In detail, they use mobile phone sensors (wifi, accelerometers, etc) to track drinking occasions, from non-drinking to heavy drinking [11], [9], [63]. Bae et al [11] defined a classification task for identifying non-drinking, drinking and heavy drinking episodes for 30 young adults aged 21-28 and reported an accuracy of 96.6%. The baseline was not explicitly mentioned, although it must be noted that the majority class, consisting of non-alcoholic drinking, constituted 90.7% of the data. You et al. proposed SoberDiary, a phone-based support system, which logged drinking through a Bluetooth breathalyzer connected to the mobile phone. According to quantitative and qualitative results, the system helped alcohol-dependent patients to self-track and self-manage their drinking behaviors [63]. None of the ubicomp works described conduct any comparisons to social media-based approaches.

Finally, relatively few comparative studies between basic patterns from smartphone sensing campaigns and social media data have been conducted in the past. It was shown in [42] that the hourly distributions of generic Foursquare check-ins and of automatically inferred place visits in the Nokia Mobile Data Challenge were similar. This similarity was used to learn a temporal model from Foursquare data in the context of cold-start phone applications [43]. These studies, however, did not focus on specific human activities as we do here for alcohol consumption. Furthermore, only time was studied as a variable, in contrast to our work that includes location, social context, alcohol categories, and gender in addition to temporal variations.

3 DATASETS

In this work, we use two data sources: (a) alcohol-related posts from Instagram, (b) self-reported alcohol drinking from smartphone-based crowdsensing. This section outlines the data collection and curation process.

3.1 Instagram Datasets

Instagram allows users to share pictures and videos and tag such posts with hashtags to express mood, location, social context, etc. For instance, a photo posted in Lausanne, Switzerland can have a caption: “#champagne with my family #summer #holiday #lausanne #sunshine #family #happiness”. In this example, #champagne is an alcohol hashtag, while references to the location (#lausanne), its social context (#family), its occasion (#summer, #holiday), and the user’s mood (#happiness) are also provided. In this work, we investigate alcohol consumption patterns using an initial corpus of 1.7 million Instagram posts consisting of pictures, hashtags, and metadata. This corpus was collected in our previous work [49] between November 1, 2010 and March 31, 2016 within the Swiss borders. This corpus will be referred to as *Instagram 1.7M dataset* in the rest of this paper.

From this data, we curated a dataset consisting of alcohol posts. This was done by manually defining a hashtag-based alcohol vocabulary suited for Switzerland. The alcohol vocabulary was generated in a two-step process. In the first step, all Instagram posts in the *Instagram 1.7M dataset* that matched 4sq nightlife venues (like bar, pub, or club) were examined. We assume that posts generated on nightlife places are a reasonable starting point to identify alcohol-related hashtags, resulting in a set of 76 alcohol hashtags. This vocabulary was further enriched by using 41 alcohol hashtags from our previous work [49] and a set of 149 hashtags from Pang et al. [48]. The three sets of alcohol hashtags contained some common elements that were filtered out, resulting in 199 unique hashtags. These 199 hashtags were then used to harvest a set of 30,192 Instagram posts from the *Instagram 1.7M dataset*, named as *Instagram alcohol dataset (30K)*. In the second step, we examined the alcohol hashtags in the *Instagram alcohol dataset (30K)* manually, and identified a further 249 alcohol hashtags not included in the 199 hashtag dictionary. We extracted all the posts which contained at least one of the 448 hashtags from the *Instagram 1.7M dataset*. This resulted in 34,856 posts that contain at least one alcohol-related hashtag, and is named *Instagram alcohol dataset (34K)*.

From the *Instagram alcohol dataset (34K)*, we filter the posts into three sub-datasets based on location, demographics, and both.

- **Spatial-driven Dataset:** This dataset consists of all Instagram posts in the *Instagram alcohol dataset (34K)* that have matching 4sq venues. The motivation behind this is to enrich the spatial description of drinking behaviour of youth. Towards this objective, Instagram venues are not detailed enough, as they only show the coordinates and the name of the place (i.e., name of the restaurant or pub). This lacks the details provided by 4sq, which also include a higher level view for each venue like Arts & Entertainment (0), College & University (1), Events (2), Food (3), Nightlife Spots (4), Outdoors & Recreation (5), Professional & Other Places (6), Residence (7), Shop & Services (8), Travel & Transport (9) and Other or None (-1)¹. Hence, we use the Instagram API with 4sq venue identities as inputs to match, and obtain a total of 84K Instagram-4sq matched venues. We keep all posts with Instagram-4sq matched venues, obtaining 19,409 posts, and name it the *Instagram alcohol spatial-driven dataset (19K)*.
- **Demographics-driven Dataset.** We keep those posts that belong to Instagram users having demographic information that can be inferred from their profile link. Among the 19,769 users in the *Instagram alcohol dataset (34K)*, there are 13,748 available user profile links, by examining the public availability of link “<https://www.instagram.com/username/>” where “username” is the self-declared user name. Many users had changed their usernames or closed their account when this was implemented. We also checked the public

¹<https://developer.foursquare.com/categorytree>

Table 1. Instagram datasets used in the rest of the paper.

Dataset	Instagram Alcohol dataset (34K)	Instagram Alcohol Spatial-driven dataset (19K)	Instagram Alcohol Demographics-driven dataset (11K)	Instagram Alcohol Spatio-demographics-driven dataset (6K)
# of images	34K	19K	11K	6.6K
# of users	19K	11K	5.8K	3.6K
# of venues	12K	5.3K	5.3K	2.7K
# of total hashtags	384K	205K	120K	69K
# of alcohol hashtags	49K	27K	15K	9.4K

availability of a hyperlink to the user profile picture. Then, we use the Face++ API² to infer attributes of users (gender and age). As a result, we obtained 5823 links containing one face, 274 with two faces, 19 with three faces, and 1 with four faces. We focus on the 5.8K results containing one face and obtain 11,050 posts. We call this dataset the *Instagram alcohol demographics-driven dataset (11K)*.

- **Spatio-demographics-driven Dataset.** We intersect the *Instagram alcohol spatio-driven dataset (19K)* and the *Instagram alcohol demographics-driven dataset (11K)*; we get 6,607 posts. Those 6K alcohol posts contain both users' demographics and drinking places. We call this dataset the *Instagram alcohol spatio-demographics-driven dataset (6K)*

Table 1 summarizes the details of the 4 datasets used in the rest of the paper. Depending on the specific analysis, we will use the corresponding dataset. Figure 1(a-f) illustrates typical content found on Instagram. Please note that in terms of numbers of users, these datasets involve one to two orders of magnitude more than what has been typically studied in the ubicomp literature discussed in Section 2.2.

3.2 Youth at Night Data

The Youth at Night (Y@N) crowdsensing study investigated nightlife behavior (including drinking) of young people in two Swiss urban areas: Lausanne and Zurich [52]. The study used an Android-based application to collect data including places, social context, and nightlife activities for Friday and Saturday nights from 8:00 PM to 4:00 AM for a period of three months. This data also included mobile sensor data like accelerometer, wifi, etc. as well as app logs.

Drink surveys asked participants to record the drink name, drink size, and social connection to surrounding people (e.g. family, friends, partner, etc.) whenever a participant had a new drink (alcohol or non-alcohol). Participants were also requested to fill in a place survey if a new place was visited. Place surveys collected city name, place categories (e.g. restaurants, private homes, etc.), and ratings of place. The Y@N crowdsensing campaign collected 2532 drink surveys from 218 participants and 1394 place surveys from 206 participants. For our work, we mainly focus on alcohol consumption and hence use the alcohol-related drink surveys. As a result, we obtain 1247 alcohol drink surveys provided by 204 participants. Figure 1(g-i) illustrates typical content found on the Y@N dataset. For more details of the data collection process, the readers are referred to [52].

3.3 Non-alcohol Datasets

In addition to investigating alcohol consumption, we examine non-alcohol consumption data in a classification setting in Section 6. For Instagram, we curated 16K non-alcohol posts by applying 51 non-alcohol hashtag vocabularies from our previous work [49] on the Instagram 1.7M dataset. In the context of classification of

²<https://www.faceplusplus.com/attributes/>

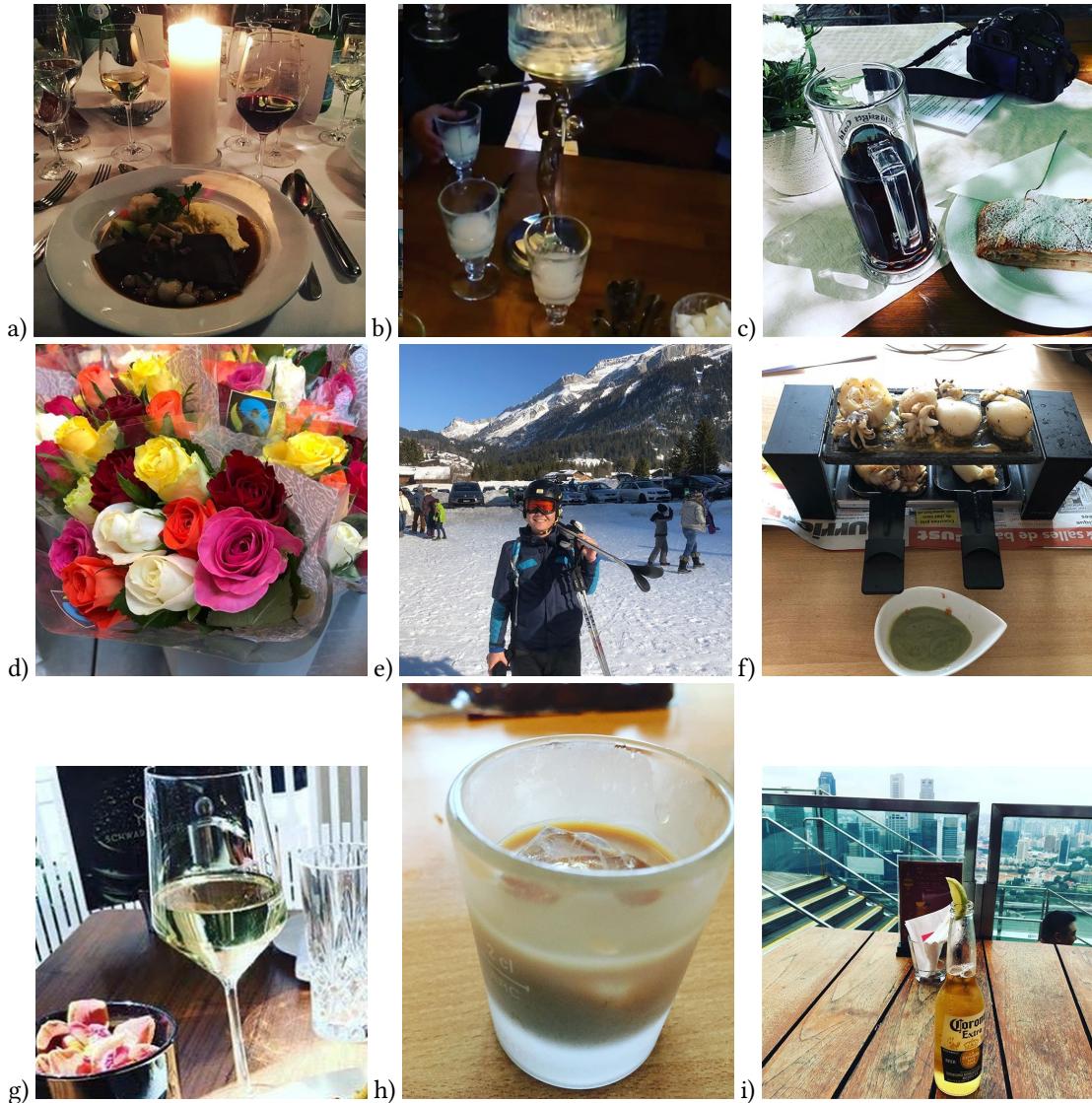


Fig. 1. Illustration of typical content of the Instagram and Y@N datasets. We use example photos taken by the authors (instead of original examples from the two datasets) for privacy reasons. Images (a-c) are similar examples to actual images from the Instagram 11K data, where hashtags clearly match image content (#wine, #cocktails, and #biere, respectively). Images (d-f) are similar examples to actual Instagram images in which hashtags do not match image content. Images (g-i) are similar examples to actual images from the Y@N data. The Y@N data is consistently focused on close views of drinks, while Instagram content is more diverse.

beverages consumed during the night, we only keep those pictures posted from 8 PM to 4 AM. As a result, we harvested 1431 *Instagram non-alcohol* posts from the 16K non-alcohol dataset. Meanwhile, Y@N also collected

Table 2. Result of manual coding of 449 alcohol hashtags into four alcohol categories.

Category	Wine	Beer	Spirit & Cocktail	Other
# of hashtags	152	141	128	28
Percent (%)	33.9	31.4	28.5	6.2

non-alcohol drink data in the same setting as for alcohol consumption. There were 644 non-alcohol drink reports that include similar information to that of alcohol drinks, i.e., picture, time, places, social context, etc.

4 ALCOHOL CATEGORY DEFINITION

There are four main categories of alcoholic drinks, as used by the World Health Organization (WHO) [4]: beer, wine, spirits, and cider. These categories reflect different methods to produce alcohol (brewing for beer; fermentation for wine and cider; distillation for spirits) and different taxing policies in many countries. However, the consumption of cider is marginal in Switzerland and the alcohol content is similar to beer, so the two categories can methodologically be combined. In the Y@N study, we had six different types of reported alcoholic drinks - the three main ones (beer/cider, wine, pure spirits) and three additional declinations of distilled alcohol that are associated with different risks among the target population: mixed drinks (with soda or energy drinks), aperitifs, and shots. However, at the coarser level, they all are spirit-based products. For our analysis, we use three main categories of alcoholic drinks: wine, beer, and spirits (including cocktails). Table 2 shows the distribution of the 449 alcohol hashtags (from the Instagram alcohol dataset 30K) over the three alcohol categories.

5 ALCOHOL CONSUMPTION ANALYSIS (RQ1)

In this section, we extract and compare alcohol consumption patterns from the three Instagram datasets, the Y@N corpus, and publicly available data (i.e. WHO [1],[4] and Swiss Federal Statistical Department [2]). Specifically, we study (1) types and quantities of alcohol consumed; (2) temporal patterns of drinking; (3) geospatial patterns of drinking; (4) social patterns of drinking; and (5) connection between occasions and alcohol drinking. With the Instagram datasets, we compute a four-dimensional vector of each user representing the four alcohol categories (wine, beer, spirit, and other). This method accounts for the issue of some alcohol items being dominantly mentioned by some users and/or some posts containing more than one alcohol category. The methodology was also adopted to compute a personal distribution of alcohol consumption for the same categories in the Y@N dataset.

5.1 Analysis of Alcohol Categories and Quantity

In this section, we analyze the distribution of quantities consumed for each alcohol category.

Federal alcohol board data: Figure 2a shows the percentage of alcohol beverage consumed (in liters) in the three categories (wine, beer, spirits). We observe that beer is the most consumed alcoholic beverage (59%), followed by wine (37%) and spirits the least (4%). In contrast, in terms of the amount of pure alcohol consumed, as estimated by the Swiss federal statistics, wine is the highest (48%) followed by beer (34%) as shown in Figure 2b. This is due to the amount of alcohol in these drinks, i.e. wine has 12-14% of alcohol, while for beer it is 4-7%. This also explains why the percentage of pure alcohol from spirits (18%) is greater.

Y@N dataset: Figure 2c illustrates the percentages of reported drinks over categories of alcohol consumed in the Y@N data, while Figure 2d shows the quantity of pure alcohol consumed for the same. The amount of pure alcohol consumed for this dataset was computed using the method proposed by [38]. Comparing these values with the data from the federal alcohol board, we observe several inconsistencies. Specifically, the federal data shows 48% of pure alcohol (liters) to be consumed from wine, but the Y@N data shows wine to contribute only 10%.

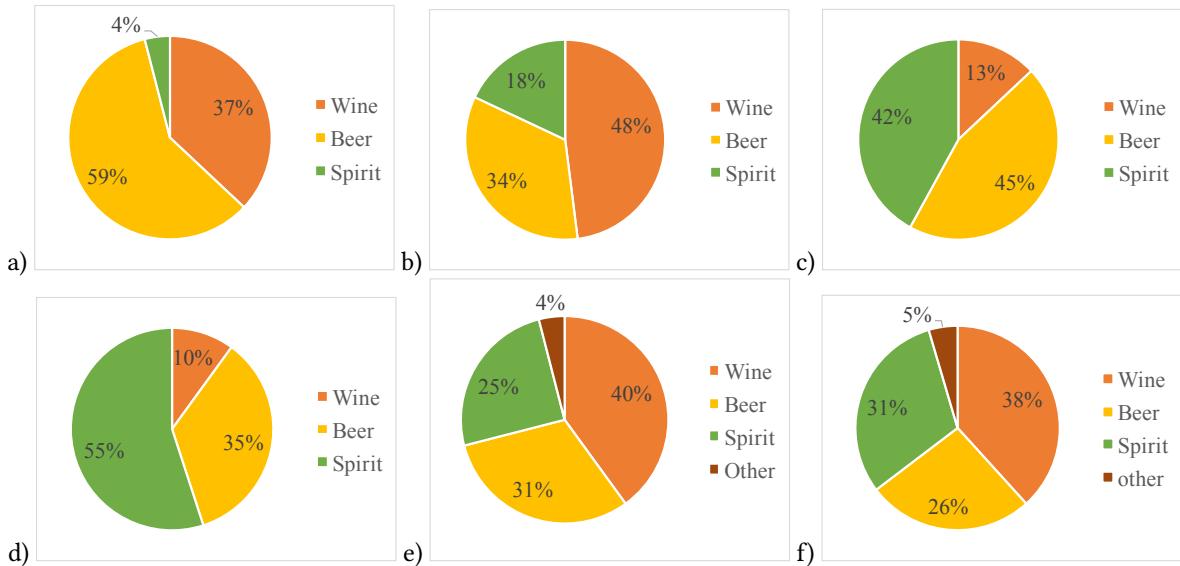


Fig. 2. Distribution of alcohol per person obtained from (a-b) Swiss federal statistics; (c-d) Y@N; and (e-f) Instagram. (a) Liters of effective alcohol estimated by the Swiss Federal Alcohol Board [2] (2010-2016). (b) Liters of pure alcohol estimated by the Swiss Federal Alcohol Board [2] (2010-2016). (c) Y@N alcohol drink survey 8PM-4AM on Friday and Saturday nights (Sep-Dec 2014). (d) Estimation of pure alcohol from Y@N drink survey on same period as (c). (e) Posts in the Instagram alcohol dataset (34K) (24-hour period and seven days a week) and seven days a week (2010-2016). (f) Posts in the Instagram alcohol dataset (34K) from 8PM-4AM on Friday and Saturday nights (2010-2016).

Similarly, the percentage of pure alcohol consumed from spirits as estimated by the federal board is 18%, while this value in the Y@N data is 55%. We hypothesize that these differences are due to the differences in the sampled population and time period. The federal survey is conducted over a larger representative population, while the Y@N dataset is restricted to young people drinking between 8pm-4am on Fridays and Saturdays (Sept-Dec 2014).

Instagram: Figure 2(e-f) shows the percentage of alcohol alcohol posts per person per category for Instagram 34K (24-hour and seven days a week) and Instagram 34K (8PM-4AM on Friday and Saturday nights), respectively. For the Instagram dataset for 8PM-4AM on Friday and Saturday night, we observe a higher percentage of spirit (31%) as compared to Figure 2e, and a corresponding decrease for wine and beer.

Overall, the distributions of alcohol categories in the three data sources are different. It must be noted that only Y@N and Instagram datasets can be directly compared (Figure 2c and Figure 2f) as they correspond to the distribution of alcohol posts per person over the same time of day and day of the week, while the federal board data is collected as a traditional survey. Specifically, we observe that in Y@N 42% was spirits, 45% was beer, and 13% was wine. The corresponding percentage in the Instagram dataset is 31%, 26%, and 38% respectively. One reason for this difference is the data sample; participants from Y@N were young Swiss people mostly from Lausanne and Zurich, while the Instagram dataset contains posts from different demographics including wider age ranges from all parts of the country and tourists.

In summary, the main observation is that trends of alcohol consumption reported in federal statistics, Y@N and Instagram do not match with respect to types and quantities of alcohol consumed. Furthermore, both Y@N and Instagram contain considerably more reports of hard drinks. As the “other” alcohol category comprises only 4% in the Instagram dataset, we will not be discussing this further.

5.2 Drinking Time Analysis

In this section, we analyze the temporal patterns of Instagram drinking with respect to time of day and day of the week. In addition, we also compare alcohol consumption between Y@N and Instagram through Friday and Saturday nights from 8 PM to 4 AM.

Instagram 34K distribution of alcohol consumption across time of day: We calculate the time distribution of alcohol categories per user. Then, we aggregate these values to obtain the average of all users (Figure 3). Figure 3a shows that alcohol posting increases from morning until noon (12AM-1PM); then, it keeps growing and peaks at night (7PM-10PM). At night, beer, wine, and spirits peak at 7 PM, 9 PM, 10 PM respectively. The difference in the peak time of these alcohol categories may be affected by the legal rules of selling alcohol in Switzerland. Specifically, the Swiss federal law [28], since January 2012, bans retail sales of alcohol from 10 PM to 6 AM. Particularly, spirits are observed to be consumed late at night as compared to beer and wine. Figure 3a shows that the spirits category is lower than wine and beer before 9PM, and dominates wine/beer after 9PM until early morning (also see Figures 4b and 4d discussed later in this section). These distributions follow the general trends of eating and drinking reported in the literature [49], and also follow more generally the trends of Instagram posting.

Instagram 34K distribution of alcohol consumption over day of week: We apply a method similar to the one described above for estimating the distribution of alcohol categories over the seven days of the week. Results are shown in Fig 3b. Our results are in line with those results reported by Kuntsche et al. [36] who used a traditional method based on questionnaires. These questionnaires were sent out as hypertext messages to all the participants hourly between 8 PM and midnight, and again at 11 AM the following day. The authors of [36] reported that consumption of alcohol increased slightly from Monday to Wednesday, and then dramatically increased, peaking on Saturday and decreasing on Sunday, as compared to the baseline percentage of drinks for men and women. In the Instagram alcohol dataset (34K), we observed similar patterns as shown in Figure 3b. Another interesting trend is that while wine and beer are slightly more common at the beginning of the week, hard alcohol is comparatively more prevalent on the weekends.

Joint distribution of alcohol consumption over time of day and day of week: This distribution is shown as a matrix of 7 days and 6 four-hour time slots in Figure 3c. Each entry corresponds to the relative frequency of posts and the color of the cell indicate the density of posts from lowest (green) to highest (red). Figure 3c shows that the density of alcohol posts is highest on the evenings of Friday/Saturday and late afternoon on Sunday. The time slot between 00 : 00 – 03 : 59 on Sunday is yellow as compared to the same time slot across the week, indicating that users drink at a comparatively higher density on Saturday night. On Sundays, people start drinking earlier than other days.

We are not aware of official Swiss statistics that report on the time consumption of alcohol across drink types. This result in itself shows that data from Instagram could be potentially useful to describe the population of social media users. In the next step, we compare the temporal trends of alcohol consumption in Y@N and Instagram. To make a fair comparison, we use Instagram data from Friday and Saturday night from 8 PM to 4 AM.

Comparison of Alcohol Consumption in Y@N and Instagram: Figure 4a and Figure 4c show the time distribution of alcohol consumption in Y@N, while Figure 4b and Figure 4d show the corresponding curves for Instagram alcohol dataset (34K). Figure 4a and Figure 4b show similar patterns for wine, beer, and spirits. In both datasets, the initial ranking early in the night (wine, beer, spirits) gets reversed in the 22:00 - 23:00 time slots, to (spirits, beer, wine). Figure 4c and Figure 4d show alcohol consumption patterns for Friday and Saturday night. In both Y@N and Instagram, wine, beer, spirits have overall lower probabilities on Friday night compared to Saturday night. Especially, spirits on Saturday nights have higher values than on Friday nights. Although wine, beer, and spirits peak at 10PM and 11PM on Friday nights (Figure 4c and Figure 4d), they have different peaks on

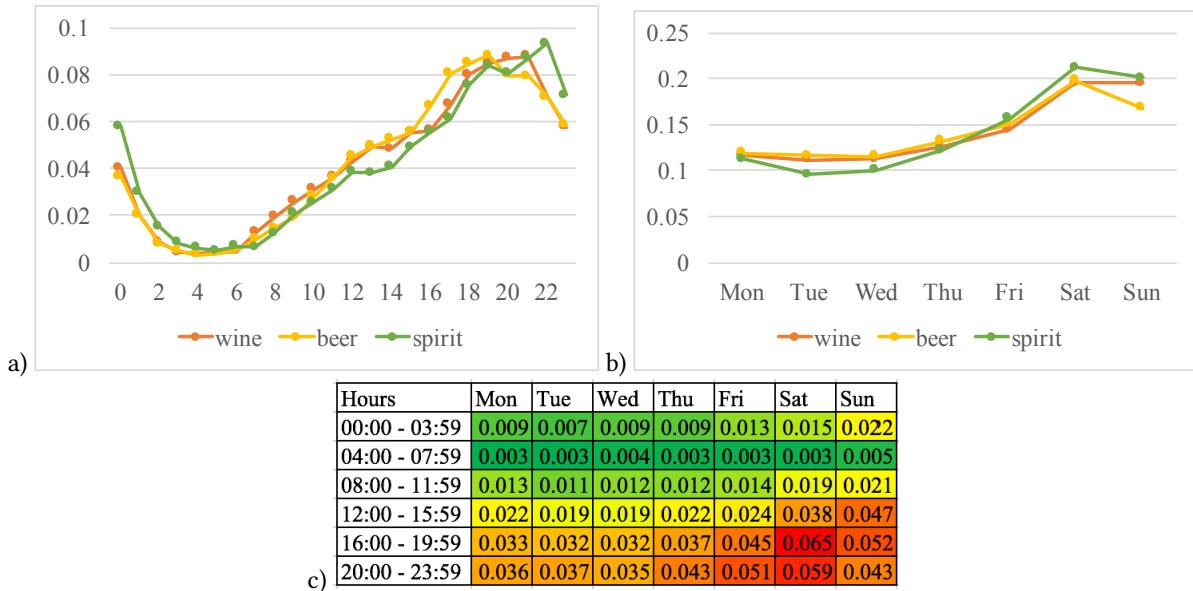


Fig. 3. Empirical time distribution of alcohol consumption on Instagram over a) time of day; b) day of week; c) joint time of day and day of week. The unit of the y-axis of a) and b) is probability.

Saturday. Wine peaks at 8 PM in both Y@N and Instagram, while beers and spirits swap the peak at 9 PM and 10 PM on Saturday nights in Y@N and Instagram.

In summary, we observe that (1) there is a higher relative number of posts about spirits as the night progresses on weekends as compared to wine and beer for which there is a higher relative number of posts earlier in the evening; (2) a comparison between Y@N reports and Instagram posts on Friday and Saturday nights (8 PM to 4 AM) share similar trends, with a greater amount of wine, beer, and spirits being posted/consumed on Saturdays than on Fridays.

5.3 Place Analysis

In this section, we compare patterns of drinking venues between Y@N and Instagram using the alcohol spatial-driven dataset (19K).

Y@N Places: study participants were asked to complete a place survey whenever they had a new drink in a new place. The place survey contains three kinds of values: city name, place category, and ambiance. In this paper, we focus on the place category. Participants could choose the following place categories: *coffee, bar, restaurant, personal, travel, plaza, school, events, club, park or lake, on board, other, and public*. In case participants chose “other”, they had to manually enter the name of the place in a text field. As we are interested in comparing place categories across datasets, we use the place hierarchy defined in Foursquare to find the equivalence across the two place category systems. After examining the hierarchy of ten Foursquare Venue Categories³, we match “coffee” and “restaurant” to Food, “bar” and “club” to Nightlife, “personal” to Residence, “travel” and “on board” to Travel & Transport, “plaza” and “park/lake” to Outdoor & Recreation, “school” to University & College, and “event” to Event. “Public” can correspond to ambiguous 4sq categories so it is matched to Unknown. Finally, for “other”

³<https://developer.foursquare.com/categorytree>

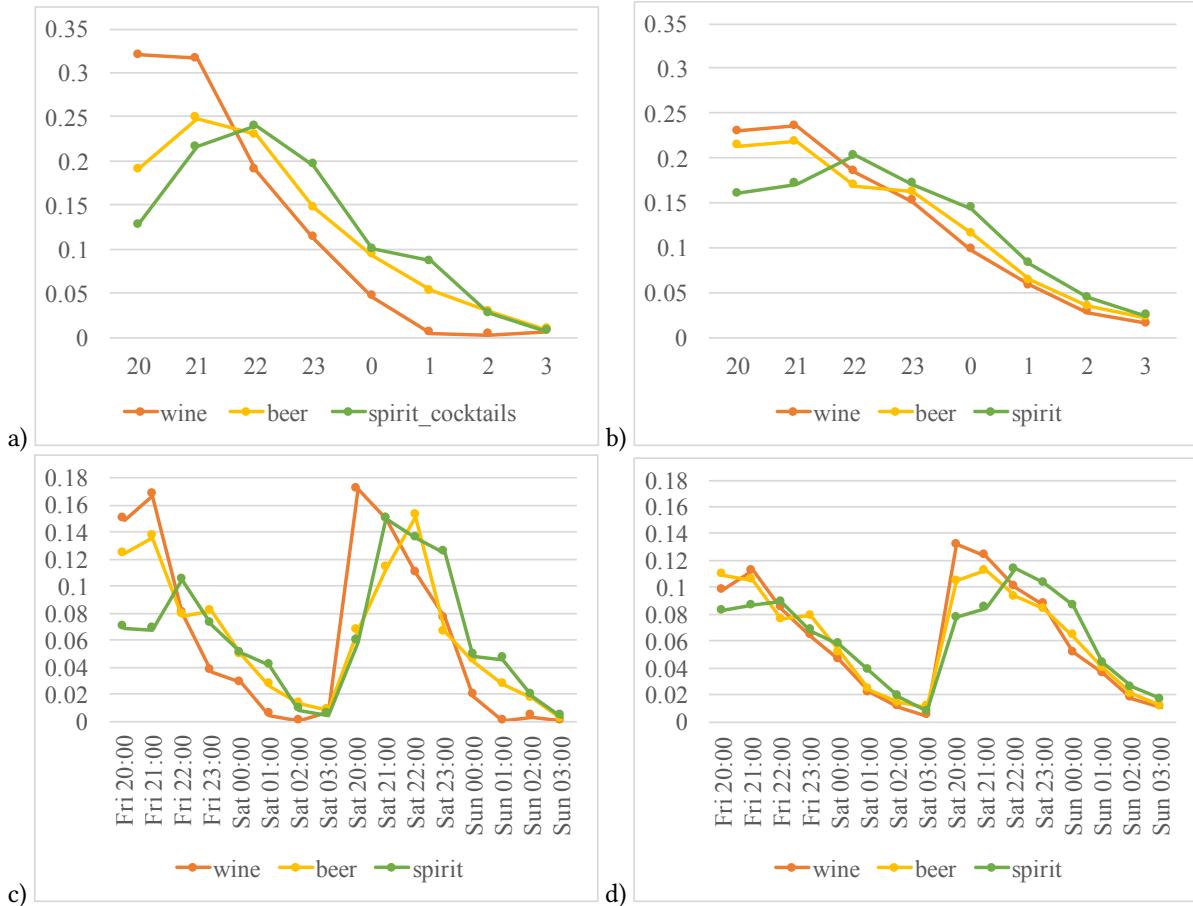


Fig. 4. Empirical time distribution of alcohol consumption over a) Combined Friday night and Saturday Night in Y@N. b) Combined Friday night and Saturday Night in the Instagram alcohol dataset (34K). c) Separate Friday night and Saturday Night in Y@N. d) Separate Friday night and Saturday Night in the Instagram alcohol dataset (34K). The unit of the y-axis of all figures is probability.

Y@N category, we collected 47 free text inputs and manually allocated them into one of the ten 4sq categories. Some cases are vague, so we allocated them into “unknown”. For each alcohol type, Figure 5a shows the average distribution per user for each place category. Wine is predominantly consumed at home (58%) followed by food venues (12%). In contrast, beer and spirits are mainly consumed at nightlife spots and home (65 to 70% of the probability mass). All other venues, individually, account for 10% or less.

Instagram Places: Figure 5b,c shows the distribution over places for each alcohol category with and without time filtering (8PM-4AM in Friday and Saturday nights) in the Instagram alcohol spatio-driven dataset (19K). We observe that four venue categories, namely Food, Nightlife Spots, Outdoor & Recreation, and Travel & Transport are the most predominant ones. Drinking categories in these four venues follow similar trends in the night-only and full-day conditions. Specifically on Friday and Saturday nights, wine has the highest probability mass at Food venues (0.29) followed by Outdoor & Recreation. Both beer and spirits are consumed in Nightlife Spots (0.47

for spirits, 0.36 for beer) and Food (around 0.25 for both alcohol categories). Importantly, drinking at Residence places is almost absent. This observation matches previous research in location-based social networks which found low rates of check-in at home [39].

Comparison between Y@N, and Instagram: Both datasets share a high occurrence of spirits, beer, and wine at nightlife spots (bar, club, etc.). In contrast, Residence in Y@N is one of the top venues for the three alcohol categories, while there are few posts on Instagram. If we compare Figure 5a and Figure 5c, beer and spirit both have over 30% probability mass at Nightlife Spots in both Y@N and Instagram, the next ones being Outdoor & Recreation, and Travel & Transport.

In summary, we observe that (1) Nightlife Spots and Food venues appear as important venues in Y@N and Instagram datasets for alcohol consumption, although in different relative order. (2) In contrast, Residence venues are *essentially absent* from Instagram, while they are the top venue for wine and spirits consumption and top-2 for beer. This illustrates the key value of crowdsensing as a potential way to “fill in” for the absence of social media reports made at home (which is the result of a number of factors and practices associated to the Instagram logic).

5.4 Social Context Analysis

In this section, we analyze patterns of drinking according to social context for the Y@N and Instagram alcohol datasets (34K).

Y@N: As mentioned in the previous sections, Y@N participants completed a survey whenever they had a new drink. In this survey, participants indicated their social context when the drink was consumed with five item choices: partner and spouse, female friends or colleagues, male friends or colleagues, family members, and other people. All items were asked for the specific number of people in each case. Based on the five items, we grouped female and male friends or colleagues into “friend_colleagues”. We also created “alone” when the counter values of all five choices are zero. In the end, we defined five types of social context, namely partner_spouse, friend_colleagues, family, alone, and other. As usual, we normalize at the level of the user and compute average distribution over all users. The distribution is shown in Figure 6a for each alcohol category. Friends and colleagues are the most common social context (55-65% of prob. mass). In particular, we observe that wine is consumed more than beer and spirits with family and partner & spouse (12-20% of prob. mass). In contrast, beer and spirits are predominantly consumed with friends & colleagues.

Instagram: As described in Section 4, we collected 151 social context hashtags. Due to issues of multiple forms of nouns, or multiple languages, we clustered these social hashtags into 39 social items. Based on the meaning of the items, we mapped these 39 social items into the five social context categories of Y@N. For example, items such as family, mom, parents, daughter, cousin are clustered into context “family”. The resulting average distribution is shown in Figure 6b (full day and all days of the week) and Figure 6c (Friday and Saturday nights). Overall, we observe a similar trend to what was observed in Y@N, with one main difference between full day and night timeslots, namely that during nights, alcohol is predominantly consumed with friends & colleagues with almost total absence of family. The predominance of friends & colleagues as drinking actors has some backing in the literature. Thrul et al. [60] concluded that the number of friends present is associated positively with hourly drinking frequency during the course of weekend evenings among young adults in Switzerland.

In summary, we observe two main trends: (1) friends and colleagues are the most common social context for alcohol drinking at night for all drink categories, and (2) this is the case for both datasets with a more pronounced trend for Instagram. This is not surprising given the overall young population captured in both datasets.

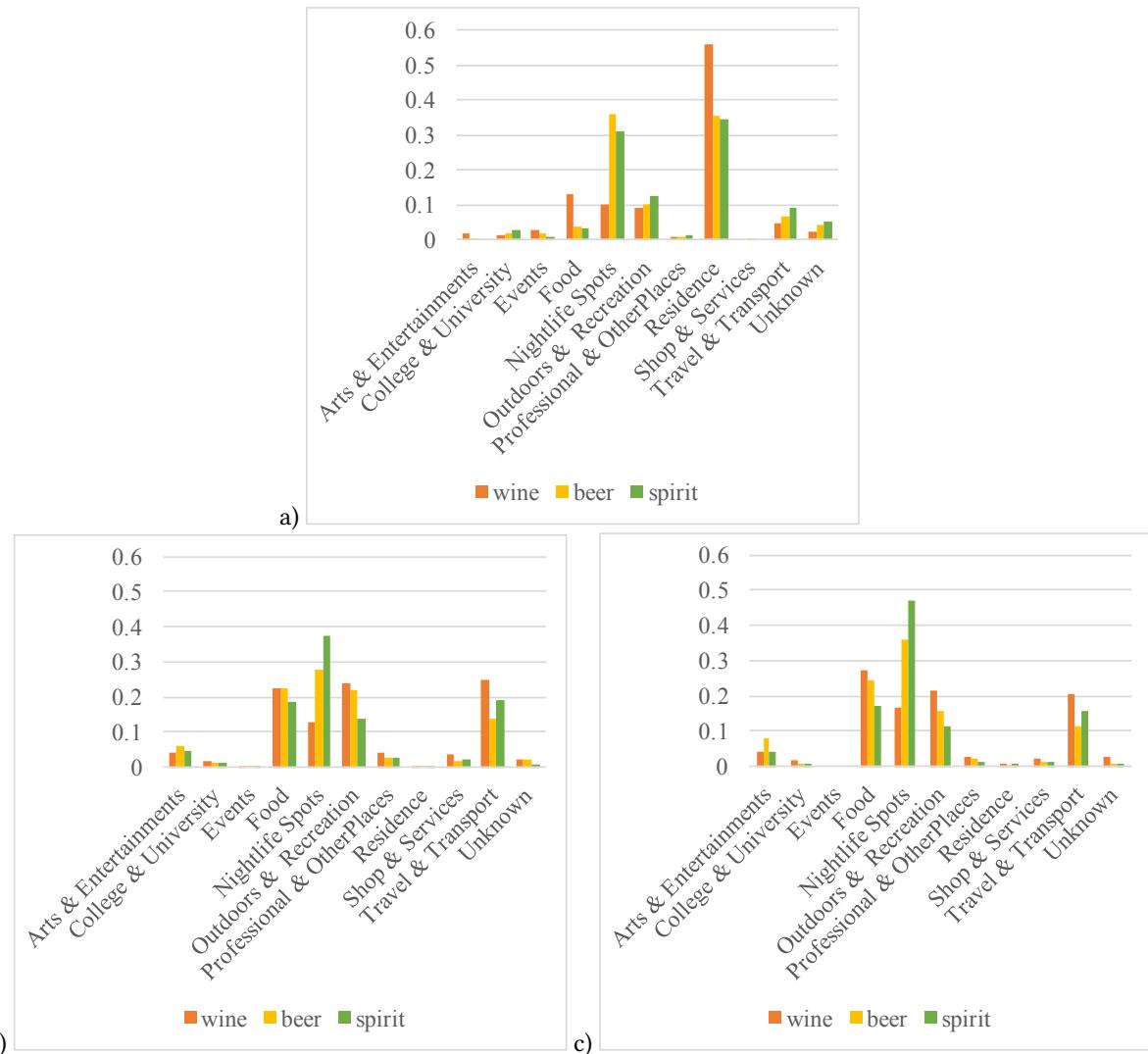


Fig. 5. Empirical distribution of alcohol consumption per place categories for each alcohol categories in a) Y@N b) The Instagram alcohol spatio-driven dataset (19K) c) The Instagram alcohol spatio-driven dataset (19K) from 8PM to 4AM in Friday nights and Saturday nights. The unit of the y-axis of all figures is probability.

5.5 Occasion Analysis

Here we present the analysis of the occasion context when users share alcohol consumption posts on Instagram. In Section 4, we obtained 152 occasion hashtags (showing the events when people drink) with a similar method of clustering hashtags as described in Section 5.4. We cluster these hashtags into 36 occasion items. Based on the meaning of each item, we manually group items into four categories, namely *party*, *holidays*, *events*, *festival*. As before, we first compute a user-level distribution over occasion categories. Then, we aggregate and estimate the average distribution over all users. Figure 7a and Figure 7b show how wine, beer and spirits are distributed in the

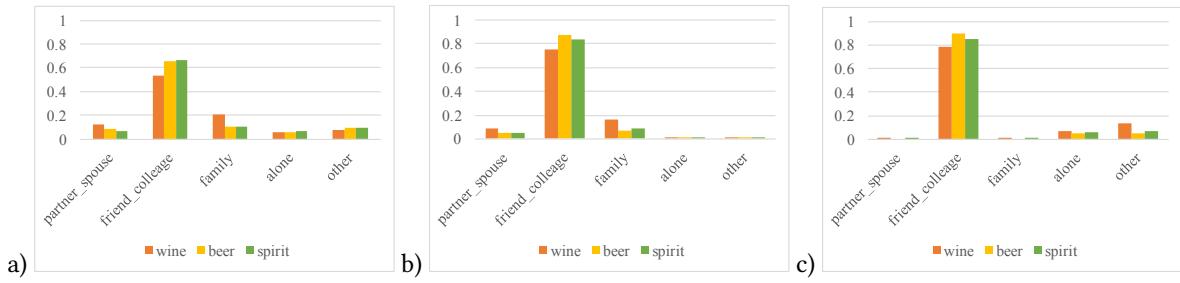


Fig. 6. Distribution of alcohol consumption per person with social relationship in a) Y@N b) The Instagram alcohol dataset (34K) c) The Instagram alcohol dataset (34K) from 8PM to 4AM on Friday and Saturday nights. The unit of the y-axis of all figures is probability.

full dataset and on Friday and Saturday nights. Furthermore, Figure 7c shows a comparison of the distributions for the more detailed occasion items. We observe that people drink at parties, during holidays, events, and festivals. On Friday and Saturday night, this party trend is more pronounced, especially with spirits. A party is not a location. It is an activity that takes place in any type of location (e.g. home, dorm, park, pub, club). According to the definition of Cambridge Dictionary [3], a party is a social event a social event where people meet to talk, eat, drink, dance, etc., often in order to celebrate a special occasion. For example, [14] showed that parties related to alcohol consumption included birthdays, weddings, and engagements. Based on Figure 7a, b, people drink spirits at parties, wine at parties and holidays, and beer at parties, festivals and events. Figure 7c shows the distribution for the detailed list of items for the full Instagram dataset, and for Friday and Saturday nights. From this, we first see that a few items dominate the kind of occasions, while the rest are rather marginal.

In summary, these results show that (1) partying is the predominant occasion context in which Instagram alcohol posts are produced, and (2) this trend is more pronounced for spirits, and slightly less so for wine and beer. As this information is not available for the Y@N study, a comparative analysis is not possible.

5.6 Gender Analysis

In this section, we analyze gender-based patterns of alcohol consumption in Y@N and the Instagram alcohol spatio-demographic-driven datasets (6K).

Y@N: We observe (Figure 8c and Figure 8d) that male participants reported consuming more beer (54%) and spirits (37%) than wine (9%). In contrast, female participants reported consuming more spirits (46%), followed by beer (36%) and wine (18%). We can thus see differences in consumption trends between males and females. An interesting observation is that female participants consumed alcohol more at Nightlife Spots (bars and clubs), Residence, and Travel and Transport (trains, on-board) venues as compared to males, who in addition to these three venue categories also consumed slightly more (in relative terms) in Outdoor & Recreation (plaza, park/lake) venues (Figure 9b).

Instagram: Figure 8a and Figure 8b show the distribution of alcohol posts of 2,824 males and 2,999 females extracted from the Instagram alcohol demographic-driven dataset (11K). We observe that the percentage of females' posts with wine is greater (47%) than males (38%), while males' posts about beer are higher (39%) than those for females (28%). For spirit and cocktails, females posted about the same (25%) as males (23%). In terms of posting venues, nightlife spots are the most popular venues for both males and females (with marginal difference in prob. mass) (Figure 9a).

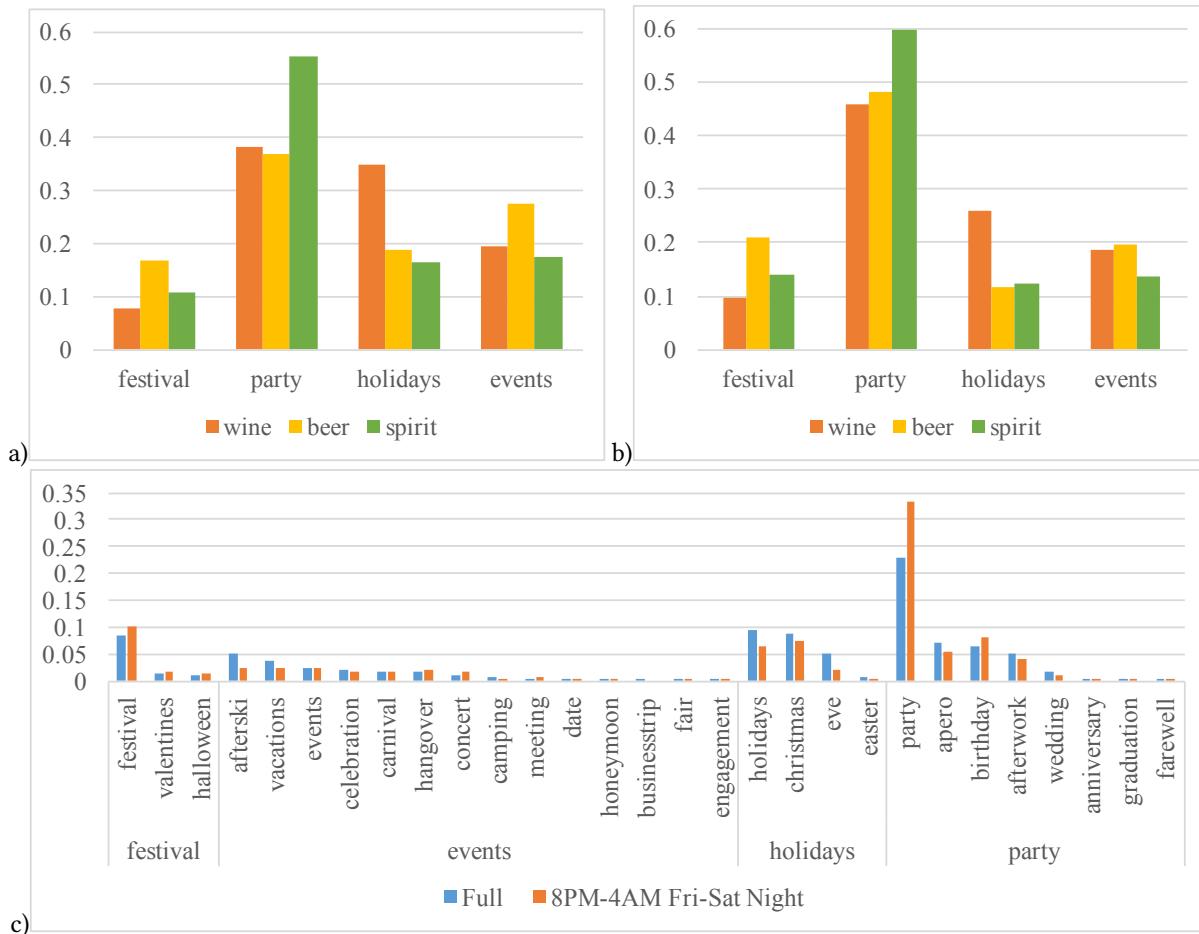


Fig. 7. Distribution of alcohol consumption with the occasion in a) The Instagram 34K. b) The Instagram 34K on Friday and Saturday nights. c) Detailed comparison of full, and Friday and Saturday nights for each detailed occasion. The unit of the y-axis of all figures is the probability.

Overall, the trends for gender across datasets are similar, with females posting more frequently about spirits and wine than males, and slightly more frequently from nightlife spots and travel and transport venues, while males comparatively post more about beer and slightly more from Outdoor & Recreation venues.

6 CLASSIFYING INDIVIDUAL EVENTS INTO ALCOHOL CATEGORIES (RQ2)

In the previous sections, we presented an analysis of temporal, spatial, and social context patterns of alcohol consumption on weekend nights as captured by both crowdsensing and social media. We now utilize these contextual cues, features extracted from images, and gender as input to a three-class classifier with the objective of classifying single reports/posts into their alcohol type (wine, beer, spirit). We examine the value of combining data from different sources to improve classification accuracy. Finally, we also implement and evaluate a binary classification task to discriminate alcohol and non-alcohol consumption from single events.

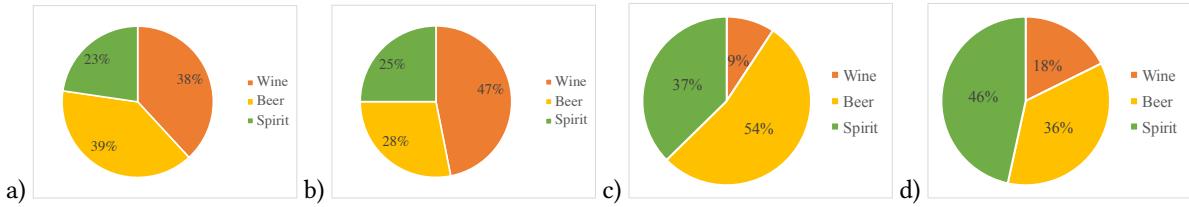


Fig. 8. Distribution of alcohol per person based on male and female obtained from (a-b) Instagram, and (c-d) Y@N. (a) Posts by males in the Instagram alcohol demographic-driven dataset (11K) (2010-2016). (b) Posts by females in the Instagram alcohol demographic-driven dataset (11K) (2010-2016). (c) Y@N alcohol drink survey 8PM-4AM on Friday and Saturday nights (Sep-Dec 2014) by males. (d) Y@N drink survey for females on the same period as (c).

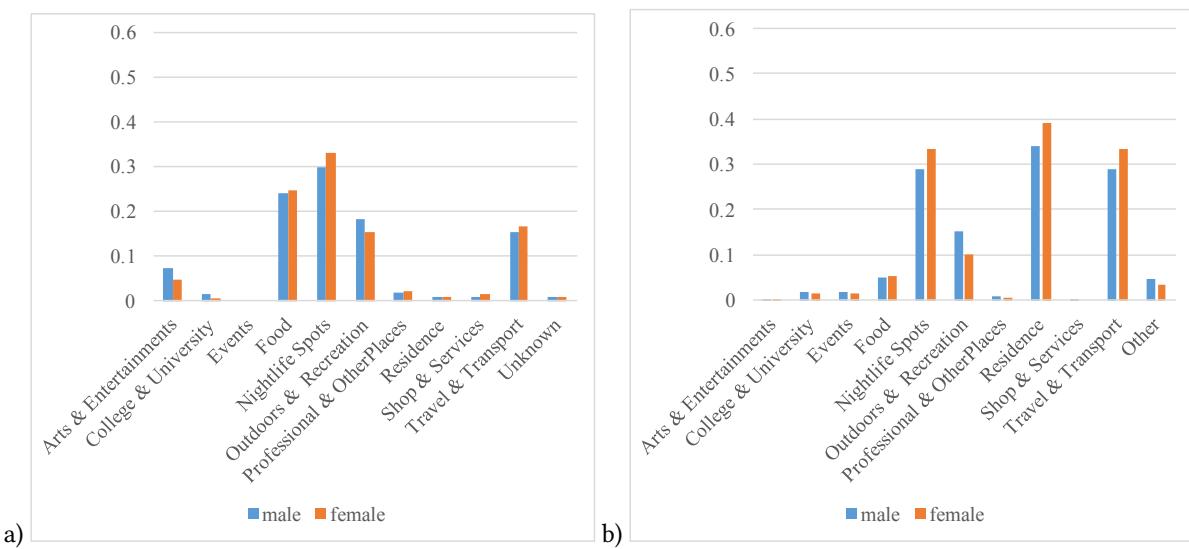


Fig. 9. Distribution of alcohol consumption per place category for males and females in a) Instagram alcohol spatio-demographic-driven dataset (6K) from 8PM to 4AM on weekend nights; b) Y@N dataset. The unit of the y-axis of all figures is probability.

6.1 Classification Method

Towards the objective stated above, we investigate two classifiers: random forest (RF) [17] and Support Vector Machines (SVM) [24], using the scikit-learn package for Python [5]. The classification tasks are conducted on individual and combined datasets. Specifically, we conduct classification of drink type (alcohol and non-alcohol) and alcohol categories using Instagram, Y@N and combined (Instagram and Y@N) datasets. In both classification tasks, when using the individual datasets, the hyper-parameters for the two machine learning algorithms were optimized using 10-fold inner cross-validation (CV), and the final performance was assessed using 5 independent runs of the 10-fold CV procedure and computing the average over the 5 runs. To study the effects of combining the datasets, we first partitioned each of the datasets into training and testing data. Specifically, we used 80% of data from Instagram to create the training set (Insta_Train), while the 20% was used as test set (Insta_Test). Similarly, we create Y@N_Train and Y@N_Test. We then fused the training sets Insta_Train and Y@N_Train

Table 3. Features for classification of drinking posts.

Feature	Description	Type	Group Feature
hour	Timestamp (in minutes) of Instagram post or Y@N survey	numeric	Time (T)
day	Day of the week of Instagram post or Y@N survey	numeric	Time (T)
Venue categories	4sq venue category of Instagram post or Y@N place survey	categorical (10)	Place (P)
Social categories	Social categories of Instagram post or Y@N survey	categorical (5)	Social (S)
Gender categories	Gender of user	categorical (2)	Gender (G)
Image features	Features from a convolutional neural network (CNN)	categorical (2048)	Image (I)

to create a combined training set. Using this combined training dataset, we learn a model using 10-fold inner cross-validation (CV), while final performance was assessed using the average of 5 independent runs of 10-fold CV. We report accuracy, precision, and recall (weighted precision and recall for the three-class task).

6.2 Feature Extraction

For Instagram, we extracted all posts from 8 PM to 4 AM on Friday and Saturday nights from the alcohol spatial-demographic-driven dataset (6K), which contains user information and 4sq place venues, giving a corpus of 1872 posts. Of these 1872 posts, 781 mentioned wine, 556 mentioned beer and 535 posts mentioned spirits. For Y@N, we used the 1247 surveys described in Section 3.2. 606 reports mentioned beer, 479 mentioned spirits, and 162 mentioned wine as the alcohol type being consumed.

For both datasets, we first extracted a number of contextual features including time (Section 5.2), place (Section 5.3), social context (Section 5.4) and gender (Section 5.6). We then grouped the features into 4 groups: context (C), social (S), time (T) and gender (G) (Table 3).

In addition, we extracted various image features utilizing a convolutional neural network model (CNNs) as feature extractor. Specifically, using Keras library with TensorFlow backend, we investigated the following architectures:

- InceptionResNet_V2 [56] is a competitive CNN that outperformed Inception_v3 in the ImageNet ILSVRC image classification benchmark and is considerably deeper. This model takes images of size 299x299 as input.
- MobileNet is a family of convolutional neural networks which are fast, small, and accurate [32]. The default input size for this model is 224x224.
- XceptionNet is based on depthwise separable convolution layers with residual connections [21]. This model takes images of size 299x299 as input.

All these models were pre-trained using ImageNet, a large corpus containing over 14 million images across 1,000 categories. After examining the above architectures, we choose InceptionResNet_V2 to extract the final features. The final features are obtained by applying max pooling to the output of the last convolutional layer and by removing the last fully-connected layer (this layer's outputs are the 1000-class cores) (Table 3). We used the default options in Keras for all the models investigated.

6.3 Alcohol Category Classification

As discussed in the introduction, alcohol category classification is a relevant problem from the standpoint of applications for public health and addiction research, as the three alcohol categories contain different amount of pure alcohol and a number of potential risks. This task is also important for ubicomp as it provides a framework to develop applications for self-tracking of alcohol consumption.

We first present the classification results when we train on individual datasets (Table 4). We observe that using contextual cues only, RF performs better than SVM for Instagram data. Specifically, the best classification accuracy (47.59%) using contextual cues is obtained using RF and the fusion of time and place (T+P) cues. This accuracy is moderately higher than the majority-class baseline. For Y@N, the performance of RF and SVM are very similar. The best classification accuracy (55.98%) is obtained using the fusion of social context and gender (S+G). We also observe that the best performance obtained for the Y@N data is 8-9% higher than the one obtained for Instagram, for both SVM and RF.

The use of image features improves classification accuracy, with the best performance obtained using SVM. Specifically, we observe an accuracy of 81.6% for Y@N and 62.76% for Instagram. We believe this difference in performance is due to Y@N being a “cleaner” data source and images being more representative of the alcohol being consumed by design of the crowdsensing mechanism. In contrast, Instagram is noisier due to the images not always being representative of hashtags and captions used, as illustrated in Figure 1. Overall the best performance is obtained by combining image features and contextual cues using SVM classifier. We obtain 82.30% and 63.63% for Y@N and Instagram which is moderately higher than using only image features. To understand the difference in performance between the two data sources, we examine the difference of visual content between Y@N and Instagram by extracting 1000 object features using the Inception model pre-trained on ImageNet. The 1000 object features as the last fully-connected layer correspond to the 1000-class scores. Then, we calculated the average score over all images in both Y@N and Instagram and filtered the top 30 objects for each dataset, as shown in Figure 10. We observe that the top-30 detected objects between Y@N and Instagram have important differences. Y@N images clearly tend to depict alcohol containers (e.g. beer bottle, wine bottle, beer glass) while Instagram, in addition to this, has eating-related concepts (e.g. restaurant, plate, candle, etc.). The cumulative scores also show that Y@N images are better described by drinks than Instagram images (see Figure 1). Thus, these results indicate that Y@N pictures are overall cleaner than Instagram photos. This potentially explains that using visual features to classify alcohol categories results in higher accuracies for Y@N data.

In the next step, we explore the impact of merging data from the two data sources on classification accuracy of alcohol type (see Table 5). Here, we combine 80% of data from both Instagram and Y@N for training the model and test individually on 20% of each of the datasets separately. The best classification performance for both datasets is obtained using SVM classifier and all the images and contextual cues (T+P+S+G), and is slightly higher (about 3-4%) than those from RF. The best performance achieved for Y@N is 81.5% and for Instagram is 62%. Comparing these classification results with those obtained for individual datasets (Table 4), we observe no improvement using SVM for Instagram and Y@N. The performance improvement using RF is only marginal (0.5% for Instagram, 1.5% for Y@N for I+T+P+S+G). This is slightly lower than those obtained for SVM when learned only on individual datasets. We also consolidate the highest accuracies of features of individual and combined dataset from Table 5 and Table 4 into Table 8.

In summary, we have shown that (1) Instagram alcohol posts are more challenging as a data source for classification compared to Y@N due to Instagram’s unconstrained nature, (2) that image features are significantly more effective than context for this task (yet context itself has some discriminative power), and (3) that the direct combination of datasets for training does not result in significant performance gains.

Table 4. Classification accuracy of alcohol categories for models trained/tested on individual datasets i.e., Instagram only, and Y@N only using RF and SVM classifiers. A denotes accuracy, P denotes precision, R denotes recall. Best performances for Y@N data are 8-9% higher than for Instagram for contextual features, and 17-19% higher for image features.

Features	Random Forest (RF)						SVM					
	1872 Insta			1247 Y@N			1872 Insta			1247 Y@N		
	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	41.72			48.59			41.72			48.59		
T	36.16	0.36	0.36	49.50	0.42	0.49	41.72	0.42	0.42	48.6	0.38	0.47
P	46.63	0.45	46.6	48.00	0.43	0.48	46.52	0.44	0.46	48.59	0.36	0.48
T+P	47.59	0.47	0.47	49.25	0.47	0.50	40.51	0.39	0.41	50.63	0.42	0.49
S	41.72	0.17	0.42	50.78	0.54	0.51	41.73	0.17	0.42	50.60	0.53	0.51
G	40.60	0.27	0.41	53.73	0.47	0.54	40.48	0.27	0.41	53.73	0.47	0.54
T+P+S	46.91	0.45	0.47	49.54	0.45	0.46	40.46	0.40	0.41	49.89	0.42	0.49
T+P+G	46.76	0.43	0.46	53.94	0.54	0.49	40.58	0.41	0.40	52.06	0.45	0.50
S+G	40.25	0.27	0.41	55.61	0.58	0.56	40.40	0.17	0.41	55.98	0.47	0.54
T+P+S+G	46.38	0.42	0.46	55.28	0.49	0.50	40.20	0.42	0.39	54.25	0.47	0.54
I	58.30	0.58	0.59	75.66	0.77	0.72	62.76	0.63	0.61	81.60	0.79	0.83
I+T+P+S+G	58.15	0.58	0.59	75.2	0.73	0.72	63.63	0.64	0.63	82.30	0.80	0.79

Table 5. Classification accuracy of alcohol categories for models trained on combined dataset (Instagram + Y@N) and tested on Instagram-only and Y@N-only data using RF and SVM classifiers. We observe that combining the data leads to improved SVM classification for Instagram but not for Y@N using contextual features (Table 4) but no improvement for Image + context features compared to individual datasets. In this setting, SVM performs moderately better than RF. A denotes accuracy, P denotes precision, R denotes recall.

Features	Random Forest (RF)						SVM					
	1872 Insta			1247 Y@N			1872 Insta			1247 Y@N		
	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	41.72			48.59			41.72			48.59		
T	37.10	0.37	0.37	50.00	0.43	0.5	42.12	0.42	0.42	48.9	0.40	0.49
P	47.23	0.45	0.47	49.00	0.43	0.49	46.92	0.45	0.47	49.19	0.42	0.49
S	38.33	0.39	0.38	47.67	0.48	0.47	39.00	0.40	0.38	49.22	0.49	0.49
G	44.90	0.45	0.45	38.90	0.38	0.40	45.90	0.46	0.46	37.39	0.37	0.37
T+P	45.80	0.45	0.46	46.00	0.45	0.47	44.90	0.43	0.45	47.55	0.46	0.48
T+P+S	45.10	0.45	0.45	48.40	0.48	0.49	45.50	0.46	0.44	50.12	0.51	0.50
T+P+G	46.20	0.46	0.46	53.81	0.54	0.54	46.10	0.46	0.46	53.53	0.54	0.53
S+G	37.42	0.34	0.39	55.10	0.56	0.54	38.20	0.38	0.38	54.10	0.53	0.55
T+P+S+G	47.40	0.44	0.49	54.38	0.55	0.55	48.42	0.48	0.48	54.96	0.56	0.56
I	57.80	0.54	0.62	77.00	0.77	0.77	62.10	0.60	0.64	81.00	0.82	0.80
I+T+P+S+G	58.70	0.55	0.60	76.88	0.76	0.76	62.00	0.61	0.63	81.50	0.84	0.80

Table 6. Classification accuracy of alcohol and non-alcohol on individual datasets (Instagram dataset including 1872 alcohol posts and 1431 non-alcohol posts; and Y@N dataset including 1247 alcohol reports and 644 non-alcohol reports). (A denotes accuracy, P denotes precision, R denotes recall).

Features	Random Forest (RF)									SVM								
	3303 Insta			1891 Y@N			3303 Insta			1891 Y@N								
	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	56.68			65.94			56.68			65.94								
T	61.03	0.61	0.61	65.94	0.46	0.66	61.30	0.62	0.61	65.94	0.44	0.66						
P	62.36	0.65	0.62	68.53	0.67	0.69	62.36	0.65	0.62	68.53	0.67	0.68						
T+P	63.76	0.63	0.64	68.3	0.67	0.68	64.72	0.65	0.65	68.50	0.67	0.68						
S	56.43	0.46	0.56	76.00	0.76	0.76	56.67	0.45	0.57	76.00	0.76	0.76						
T+P+S	63.03	0.63	0.63	76.80	0.76	0.77	65.03	0.65	0.65	76.00	0.76	0.76						
I	74.65	0.76	0.75	80.00	0.82	0.80	78.42	0.78	0.78	84.20	0.85	0.83						
I+T+P+S	74.62	0.76	0.75	80.11	0.83	0.80	79.74	0.80	0.80	90.00	0.90	0.90						

Table 7. Classification accuracy of alcohol and non-alcohol on combined datasets (Instagram + Y@N) using RF and SVM classifiers. (A denotes accuracy, P denotes precision, R denotes recall).

Features	Random Forest (RF)									SVM								
	3303 Insta			1891 Y@N			3303 Insta			1891 Y@N								
	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	56.68			65.94			56.68			65.94								
T	63.78	0.65	0.63	66.04	0.66	0.66	63.63	0.64	0.63	66.04	0.66	0.66						
P	62.72	0.64	0.62	64.45	0.64	0.64	60.90	0.60	0.60	65.51	0.57	0.65						
S	56.36	0.49	0.56	73.74	0.72	0.73	56.36	0.49	0.56	72.94	0.73	0.72						
T+P	65.45	0.65	0.65	66.31	0.64	0.66	60.75	0.60	0.60	66.31	0.65	0.66						
T+P+S	65.45	0.65	0.65	76.39	0.76	0.76	65.30	0.65	0.65	76.92	0.76	0.76						
I	74.54	0.79	0.74	79.04	0.8	0.79	77.12	0.77	0.77	86.47	0.86	0.86						
I+T+P+S	72.57	0.76	0.72	79.31	0.80	0.79	81.06	0.81	0.81	87.26	0.87	0.87						

6.4 Alcohol vs. Non-Alcohol Classification

For a practical application, alcohol drinking events first have to be distinguished from non-alcohol ones. In this section, we expand the work to study a binary alcohol/non-alcohol classification task. Toward this, we use the same 1872 Instagram posts and 1247 responses from Y@N for the alcohol class. For the non-alcohol class, we extract 1431 posts from Instagram and 644 reports from Y@N as mentioned in Section 3. We follow the same methodology as described in Section 6.1. The classification results using individual datasets are presented in Table 6 while those obtained by fusing the two datasets are presented in Table 7. The baseline method is again a majority-class classifier.

For the classification results based on individual datasets, Table 6 shows that contextual features alone can achieve 65% accuracy for Instagram and 76% for Y@N. Furthermore, the combination of contextual and image features can obtain the highest accuracy of classification (79.74% on Instagram and 90% on Y@N). The combination of context and visual information results in a better classifier than context-only and image-only cases. In general, the performance of SVM is better than RF.

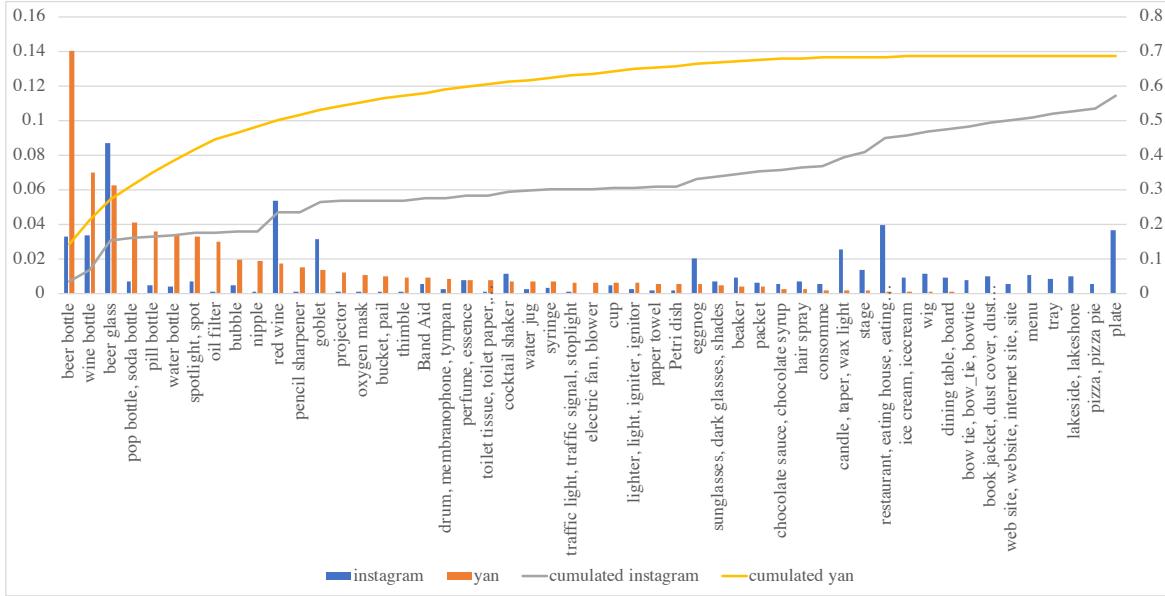


Fig. 10. Comparison between top 30 objects detected on Y@N and Instagram pictures. Average scores are ranked with respect to their value on the Y@N data. Continuous lines show the cumulative scores for both datasets.

Table 8. Best classification accuracy of alcohol categories on individual and combined datasets (Instagram + Y@N) using SVM classifiers. A denotes accuracy, P denotes precision, R denotes recall.

Features	Individual Dataset						Combined Dataset					
	1872 Insta			1247 Y@N			1872 Insta			1247 Y@N		
	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	41.72			48.59			41.72			48.59		
Contextual Features	46.52	0.44	0.46	55.98	0.47	0.54	48.42	0.48	0.48	54.96	0.56	0.56
All Features	63.63	0.64	0.63	82.30	0.80	0.79	62.00	0.61	0.63	81.50	0.84	0.80

For the classification results involving the combined datasets for training, Table 7 shows that the best accuracy (81.06% for Instagram or 87.26% for Y@N) is obtained using the fusion of image features and context features. Comparing the performance between individual and combined datasets, the performance on Instagram improves from 79.74% on individual in Table 6 to 81.06% on combination in Table 7, while Y@N decreases from 90.00% to 87.26%. In other words, the advantage of combining datasets for classification of alcohol vs. non-alcohol is marginal on Instagram (a noisier dataset), but decreases on Y@N (a cleaner dataset) as discussed earlier (Figure 10). We also consolidate the highest accuracies of features of individual and combined datasets from Table 6 and Table 7 into Table 9.

In summary, compared to the performance of alcohol category classification, alcohol vs. non-alcohol classification results in higher accuracy, and could be used as a first step towards an application that identifies consumed alcohol categories.

Table 9. Best classification performance of alcohol and non-alcohol on individual and combined datasets (Instagram + Y@N) using SVM classifiers. A denotes accuracy, P denotes precision, R denotes recall.

Features	Individual Dataset									Combined Dataset								
	3303 Insta			1891 Y@N			3303 Insta			1891 Y@N								
	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R	A	P	R
Baseline	56.68			65.94			56.68			65.94								
Contextual Features	65.03	0.65	0.65	76.00	0.76	0.76	65.30	0.65	0.65	76.92	0.76	0.76						
All Features	79.74	0.80	0.80	90.00	0.90	0.90	81.06	0.81	0.81	87.26	0.87	0.87						

7 DISCUSSION AND IMPLICATIONS

In this section we discuss the results previously presented and their implications.

For **RQ1**, we studied and compared the alcohol consumption patterns in data collected from social media (Instagram) and mobile crowdsensing (Y@N). Table 10 summarizes our observations about drinking patterns with focus on quantity, time, place, social context, occasion, and gender.

- (1) *Quantity*: The amount and type of alcohol consumed in Y@N and Instagram do not follow the same trends. In Y@N, we observed a predominant reporting of beer consumption, while the dominant post in Instagram for the same time period was wine. The observations made in these two datasets do not match those reported by the Swiss federal statistics [1, 2, 28] with a disproportionate amount of spirits consumption in both crowd-generated datasets. While the specific time covered by our datasets (nights on weekends) could partly explain these differences, other sources of bias are likely present. This is an important observation from the ubicomp point of view as most literature has relied on either crowdsensed data like Y@N or social media data like Instagram, and relatively little work so far has been conducted on how bias affects machine based inference in urban ubicomp systems [30, 58].
- (2) *Time*: We observed similar trends in both datasets. Specifically, more spirits were reportedly consumed as the night progresses and on weekends. Beer and wine were consumed earlier in the evening and in the week. These results are backed by the results reported by Kuntsche et al., who found that people drink the most on weekends, especially from Saturday night to the first hours of Sunday morning [36]. Furthermore, this observation could be affected by Swiss federal laws that ban the retail sales of alcohol from 10 PM to 6 AM [28]. This illustrates the complexity of nightlife affected by personal choices, regulation, and social practices.
- (3) *Place*: In our datasets, we observed that alcohol was consumed with some differences. In Y@N, alcohol was consumed in private spaces, while on Instagram the top venue was nightlife locations. Food locations, outdoor & recreation, and travel & transport are common across both datasets. In line with our results, the results reported by [35], [61] using traditional methods for data collection show that the top venue categories of alcohol consumption are bar/pub/nightclubs, private homes, events (festivals), public places (parks, streets), restaurants (food) and travel & transport. These observations have implications for ubicomp and alcohol research, as social media (possibly due to both performative aspects and privacy concerns) create a gap regarding the report of drinking at home. This could be mitigated by mobile crowdsensing methods, where participants share their data neither with their friends nor with online audiences.
- (4) *Social Context*: In both Y@N and Instagram, we showed that friends and colleagues were the most common social context. These results are backed up by previous research which found that the most common social context of alcohol consumption are friends and colleagues [12, 61]. More specifically, [61] reported that 63.8% of people drinking alcohol do so in the home of friends and family.

- (5) *Occasion*: As the Instagram data was collected over a five-year period, this allowed us to observe various patterns of alcohol consumption during festivals and holiday occasions. For instance, in this dataset we observed a greater relative frequency of posts about spirits in parties, wine during holidays, and beer on festivals and events. In line with our work, the work in [14] summarized the main occasions of alcohol drinking using a telephone survey . The list included birthdays, wedding parties, events, and festivals.
- (6) *Gender*: In our datasets we observed differences in alcohol consumption patterns (alcohol type and location) between males and females. Specifically, we observed that males reported to drink more beer than females and slightly more in Outdoor & recreation locations, while females reported a larger relative percentage of spirits and wine and slightly more at nightlife locations. These trends were observed in both Y@N and Instagram datasets and are in line with previously reported results using traditional methods [41].

For **RQ2** we developed and tested a method to classify alcohol categories using contextual features and visual features. The main results can be summarized as follows (also see Table 11).

- (1) *Context Features*. We consider time, place, social, gender as context features for classification. For classification of alcohol categories, context features improved performance by 5-7% compared to a majority-class baseline, as shown in Tables 4 and 5. For classification on alcohol and non-alcohol, context features generated a performance improvement of 9-11% compared to the majority-class baseline, as shown in Tables 6 and 7. For the alcohol/non-alcohol task, context-only features achieve 76% classification accuracy. On the other hand, context features do not produce better performance than visual features.
- (2) *Visual Features*. We consider image features and its combination with context features. Generally, the use of visual features to classify both alcohol categories and alcohol/non-alcohol substantially improves accuracy compared to the majority-class baseline (around 20% in both tasks), as shown in Tables 4 and 6. We also showed that the classification accuracy on Y@N is better than on Instagram. The results in Section 6 shows that fusing visual features with contextual features led to small improvements in classification accuracy for both the three-class alcohol category task and the alcohol/non-alcohol task. Specifically, this improvement was consistently observed for the SVM model, while for the RF model there was either no improvement or a small decrease in accuracy.
- (3) *Dataset Combination*. Overall we found that Y@N represents less noisy data for classification compared to Instagram (Figure 10) resulting in consistently higher accuracies for both contextual and visual features. Likely due to these differences, the combination of datasets for training did not produce major classification improvements. In other words, the performance improvement by combining the datasets was null or minimal. There was a marginal improvement in classification accuracy in some cases, while in others, the combined dataset has lower accuracy than the individual dataset. Specifically, for the alcohol category classification task, a minor improvement was observed for the RF model, while a decrease was observed for the SVM model. The result of combining the datasets for alcohol/non-alcohol classification is also mixed, with a small improvement in accuracy for Y@N using SVM, while for Instagram the improvement is seen with RF. We hypothesize that if the content of Instagram images used for dataset combination was filtered to only depict actual drinks and drink containers, the performance of a classifier trained on a combined dataset could increase. The use of machine learning to filter Instagram posts to obtain more focused content about drinking episodes could be part of future work.

8 CONCLUSION

In this paper, we conducted a comparative study using data from a crowdsensing campaign and social media to examine the phenomenon of alcohol consumption on weekend nights and to devise and evaluate contextual classifiers of alcohol categories, which is relevant for both ubicomp and alcohol research. We conclude the paper by reviewing the answers to our research questions and discussing directions for future research.

Table 10. Summary of findings related to RQ1.

Contextual factor	Instagram data	Y@N data
Quantity	The datasets do not follow the same trends. Such trends also depart from those reported in national statistics.	
Drinking Time	Time of day: wine 9pm; beer 7pm; spirit 10pm . Day of week: alcohol consumption are highest on Saturday	Time of day: wine 8pm; beer 9pm; spirit 10pm. Similarly to Instagram, the conditional distribution of spirits is higher than wine and beer after 10 PM.
Place	Food, Nightlife Spots, Outdoor & Recreation, and Travel & Transport are predominant while Residence places are almost absent	Residence is the predominant category followed by Nightlife Spots, and Outdoor & Recreation.
Social	Friend & colleagues are the most common category.	
Occasion	For parties, spirits are the dominant category. For holidays, wine is the top category. For festivals, beer is the top category.	Not available
Gender	In relative terms, women post more about wine; males post more about beer.	Same trend as the one for Instagram for males and beer, but a larger proportion of spirits and beer for both genders.

Table 11. Summary of findings related to RQ2.

Features	Individual	Combination
Context features	Improved performances compared to majority class baseline: - Alcohol categories: 5-7%. - Alcohol/non-alcohol: 9-11%. Best performance for Y@N data is 8-9% higher than for Instagram data for alcohol category classification, and 11-13% for alcohol/non-alcohol classification.	Minimal or no improvement using combined datasets.
Visual features	Improved performances compared to naive majority class baseline: - Alcohol categories: 22-31%. - Alcohol/non-alcohol: 23-24% Best performance for Y@N data is 17-19% higher than for Instagram data for alcohol category classification, and 5-6% for alcohol/non-alcohol classification.	Minimal or no improvement using combined datasets.

Our RQ1 inquired about alcohol consumption patterns on weekend nights that could be extracted from both data sources with respect to temporal, place, and social context, and about the similarities and differences revealed by examining the two sources jointly. Our work has provided specific answers to these questions for the specific case of young urban dwellers, with potentially novel ideas for ubicomp research regarding (1) thinking about the consumption of hard alcohol as a relevant issue in and of itself, specially given recent literature that discusses

how different emotions can be elicited by different types of alcoholic drinks, and (2) the importance of youth drinking in personal places. We believe that current ubicomp research on drinking episode recognition could make use of some of the findings from our contextual analysis.

Our RQ2 examined how image features and contextual cues could be used to classify individual drinking occasions according to alcohol category, and whether the complementarity of crowdsensing and social media sources could improve the performance of this classification task. Our work has provided answers to these questions, with best classification accuracies in Y@N data of 82.3% for wine/beer/spirits, and of 90% for alcohol/non-alcohol, obtained by fusing image and contextual features.

Future work could investigate a number of open issues. First, regarding pattern analysis, we would like to understand in more detail the possible effects that the local regulations on alcohol retail sales can have on the emerging trends we observed. Second, it would be relevant to investigate possible regional differences; in our case, this refers to the French-speaking and German-speaking regions of Switzerland, both of which are represented in the crowdsensed and social media data sources. Finally, regarding the use of contextual cues for classification, we would like to understand whether in specific cases (e.g. specific time slots or specific locations) we could observe a larger improvement when combining datasets. This could motivate the use of multiple models and more sophisticated transfer learning.

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