Cheers to Untappd! Preferences for Beer Reflect Cultural Differences Around the World

Completed Research

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Abstract

Common methods to collect data to perform cross-cultural studies, such as interviews or surveys, can be costly, thus, not scaling easily. Recently, studies have found evidence that data collected from location-based social networks (LBSNs) have the potential to revolutionize the study of urban societies. In this study, we investigate if preferences for beers shared in Untappd, an LBSN specialized in beer, reflect cultural differences. We explore an approach for identifying cultural similarities between groups of users considering preferences for beers. Using a large dataset of several cities in different countries worldwide, we found evidence that preferences for beers shared in Untappd reflect cultural differences that could be used to extract similarities between cultures, which could enable new services and applications.

Keywords

Location-based social network, Untappd, Cross-cultural study, Large scale assessment.

Introduction

Differences between cultures and their influence on urban social behavior is a challenging topic of study. This is because the concept of culture is so complex that simple definitions cannot capture it easily. There are several definitions of culture and we share the view of culture expressed by Matsumoto: "the set of attitudes, values, beliefs, and behaviors shared by a group of people, but different for each individual, communicated from one generation to the next" (Matsumoto, 1996).

To study urban social behavior, traditional approaches are typically used, including interviews, surveys, and observations, which can be costly when carried out on a large scale (Mocanu et al., 2013; Silva et al., 2017). Recently, researchers found evidence that data collected from location-based social networks (LBSNs) have the potential to change fundamentally the study of urban social behavior (Cranshaw et al., 2012; Mocanu et al., 2013; Silva et al., 2017). One of the reasons for that is because users act as a sort of social sensors using portable devices to generate large amounts of data related to several social and urban aspects, which can be a valuable source of information for different sorts of studies (Silva et al., 2017, Mueller et al., 2017).

Nowadays, there are several kinds of LBSNs available, for example, Instagram[1], to share pictures and short videos among contacts in the network, Waze[2] to share traffic related data, including problems in the traffic, and Untappd[3], a system that enables users to share beer preferences among their friends. Untappd is a social

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[1] http://www.instagram.com

[2] http://www.waze.com

[3] http://www.untappd.com

network for beer drinkers, which helps users to keep track of what they have tried and what they thought of it by given a check-in in a beer and rating it. It is possible to find similar LBSNs to Untappd, such as TapHunter[4], but Untappd is perhaps the most popular one, having around five million users around the world (Untappd, 2018).

Cross-cultural studies have identified significant differences in preferences across societies (Henrich et al., 2001; Henrich et al., 2010). In the food context, previous studies found that people form their beliefs, perceptions, and attitudes about food based on cultural values (Almli et al., 2011; Pieniak et al. 2009). More specifically about drinking, there are studies, such as the ones proposed by Labrie et al. (2012) and Brooks-Russell et al. (2014), suggesting that cultural beliefs and norms are important predictors of drinking patterns.

When considering cross-cultural studies, look at the beer consumption is interesting because beer is one of the most consumed beverages worldwide and has several types (World Health Organization, 2014). In addition, beer is typically consumed socially. This is relevant because there is evidence that socialization might influence consumer preferences (Mehta and Belk, 1991). In this direction, Mccluskey and Shreay (2011) surveyed international students to understand how their preferences and consumption habits for beer changed as they spent time in the United States. Their findings suggest that culture, indeed, might affect beer preferences.

Based on that, in this study, we hypothesize that preferences for beers shared in Untappd can reflect cultural differences. To investigate this hypothesis, we explore an approach for identifying cultural similarities between urban societies considering preferences for beers. To test our hypothesis, we collected a large dataset of beer preferences shared by users worldwide. In this study, we considered several cities in different countries. As a result, we found that cities belonging to the same country presented a smaller difference in preference for beer compared to cities in other countries, suggesting that beer preferences shared in Untappd reflect significant cultural differences, which could be used to extract similarities between cultures regarding this aspect.

Cultural similarities are an important feature in several international marketing studies (Cho and Padmanabhan, 2005). In fact, marketing managers often explore similarities between markets in a way to make better decisions. For instance, they could explore them to decide whether it is appropriate to standardize international marketing procedures (Karande et al., 2006). For this reason, finding cultural similarities among different societies has the potential to enable new services and applications. For example, it could be valuable for companies that have businesses in one location and want to verify the compatibility of preferences of users across different markets. This is particularly important in the beer market because big brewing companies tend to operate simultaneously in several locations worldwide with different cultural preferences and backgrounds.

The rest of the paper is organized as follows. First, related work is presented. Next, the dataset used in this study is described. After that, a proposal for the identification of cultural similarities is introduced. Next, the results are presented followed by its discussion. Finally, the study is concluded and future work is presented.

Related Work

There are several studies on LBSN data, showing their usefulness for several purposes. For instance, Cranshaw et al. (2012) and Karamshuk et al. (2013) has demonstrated that LBSNs data could be useful for urban planning and business strategies. Regarding the LBSN Untappd, recently, Chorley et al. (2016) performed a characterization of beer consumption expressed on this system, showing that its data carries valuable information about drinking patterns worldwide. Silva and Graeml (2016) demonstrated some of the possibilities in exploring Untappd data, for instance, to help entrepreneurs to make decisions and plan strategies.

Cross-cultural studies do not represent a new area of research and have been conducted by researchers for a long time, mainly in psychology and cultural anthropology (Murdock, 1949). There is a rich methodology

[4] https://www.taphunter.com

to perform these type of studies, such as traditional in-person participant observation, interviews, and surveys (Johnson, 2003). Another way of performing this type of study in digital communications contexts has been called Netnography, which is defined as a specific set of research practices rooted in participant observation. In netnography, a considerable quantity of the data comes from digital traces of spontaneously shared public messages in contemporary systems, such as online social networks (Kozinets, 1998). Netnography is less costly and can scale easier than some of the traditional approaches, for instance, interviews and focus groups. In addition, it can be less obtrusive because it is conducted exploring observations in a context that is not generated by the researcher (Kozinets, 1998; Kozinets, 2002).

In this direction, recently, some cultural differences studies are exploring social media data. For instance, Hochman e Schwartz (2012) studied color preferences in images shared on Instagram, showing considerable differences in the preferences across countries with distinct cultures. Garcia-Gavilanes, Quercia and Jaimes (2013) demonstrated that the culture of a country is associated with Twitter[5] usage. Reinecke et al. (2013) found that culture influences how we schedule events online in Doodle[6]. Mocanu et al. (2013) also identified cultural diversity exploring microposts of Twitter. Garcia-Gavilanes et al. (2014) perform a study of international Twitter communication which combines cultural information with other features, such as social and economic. Park et al. (2014) explore Twitter messages to investigate cultural differences in users' expression of emoticons. Mueller et al. (2017) demonstrate that Foursquare[7] check-in data in various regions of the world carry significant differences in preferences for venues between gender groups. Some of these differences reflect well-known cultural patterns. By also exploring data from Foursquare, Silva et al. (2017) proposed a methodology for identifying cultural boundaries and similarities across populations, considering eating patterns, for instance, what kind of food users prefer, as well as what time they often have their meals.

Our study differs from all previous efforts because we focus on studying if preferences for beers shared in Untappd can reflect cultural differences. Since beer is one of the most popular beverages consumed worldwide and has several types, we believe that this could be an important cultural trait that can be extracted from social media.

Dataset Description

About Untappd

Untappd was chosen because of its popularity among beer drinkers and enthusiasts (Untappd, 2018). The app allows its users to share information and interact on what beers they are drinking, making it a social network specifically for beer lovers. Users in Untappd can perform check-ins, which are the act of announcing in the system a beer consumed. If they desire, users can replicate their check-in performed in Untappd through Twitter messages, the so-called tweets, amplifying its reach between their contacts. With that, Untappd data becomes publicly available and can be easily collected and stored. This is due to the ease and free access to the Twitter API[8]. For this reason, this was the method used in this research.

Collection Details

Most tweets sent through Untappd follow a pattern. For example, one of the tweets collected had this message: "Gold Medal!!! - Drinking a Cocoa Wee by @bodebrown at @riodejaneiro - https://t.co/NQd7fI6xxx[9]". When analyzing this message, it is possible to identify that after the word "Drinking" it is informed the type of beer being consumed by the user. After the word "by" the brewing company is informed. Next, after the word "at" is informed where the user is consuming the beer. In the

5 http://www.twitter.com

6 http:// www.doodle.com

7 http://www.foursquare.com

8 http:// developer.twitter.com

9 This URL was anonymized to preserve user's identity

end, the message contains a link where more information about the check-in can be found in Untappd website. Furthermore, tweets provide metadata such as the coordinates where the check-in happened, identification from the user who tweeted, among other things.

Exploring that link in the check-in text, additional queries were made to the Untappd site for each tweet collected, in an effort to enrich the information of each check-in. Among the information obtained, we can mention: the date and time of the sharing (time); geographical coordinates (gps); user identification (userID); scores provided for certain beers (score); beer consumed (beer); and brewery of the beer consumed (brewery). Our dataset enables the extraction of rich information, such as beers with higher consumption in certain cities, which could be, for instance, valuable to companies in the field.

Our data were collected for approximately six months, totaling 1.7 million tweets. The collection period occurred from November 2016 to April 2017. Among the tweets collected, around 702 thousand tweets, or ~40% of the total, were georeferenced.

Data Treatment

After collected, the data were filtered and processed to reduce noise and generate information with higher quality. Check-ins with non-georeferenced information were eliminated and, after that, the remaining check-ins data were enriched trough publicly information available on Untappd's website, as we mentioned above. In addition, check-ins not containing a user score (personal rating) referring to a certain beer were also eliminated. This is important because our intention is to also use the score as a measure of preference for beers shared by the users.

Finally, in order to avoid biased results towards data that may characterize individual favoritism from frequent users, we disregarded check-ins that the user repeated the same beer. This happens when the tuple: userID, beer, and brewery repeats within the same city.

Overview of the Dataset

To better understand the user activity in Untappd and also identify which regions had the highest occurrences of check-ins, a heatmap was constructed, as presented in Figure 1. In this figure, the redder the color, the more data are available in that geographical area. This heatmap was constructed with parameters that allowed a useful data visualization, showing only regions with a high number of data, omitting areas with few data.

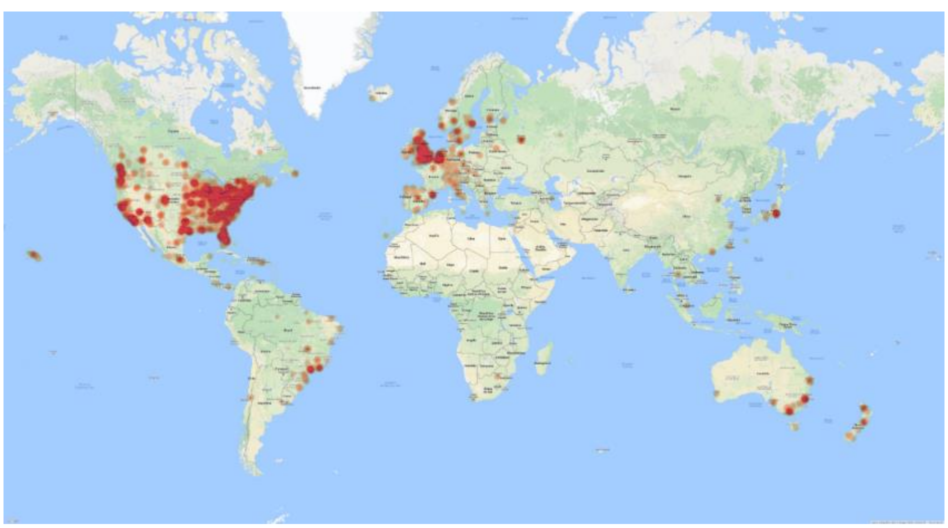

Figure 1. Heatmap of our dataset of beer preferences shared in Untappd.

Despite having several tweets collected around the world, some cities do not have a considerable number of check-ins to compose a reliable database. Ensuring a minimum number of observations is important when selecting areas to study because the amount of data in a sample may interfere with the reliability of the results. In the selection process, we consider a minimum of 300 check-ins in the final dataset, i.e., after all data treatment steps.

Another important fact of our dataset is the lack of low scores attributed by users regarding the beers consumed. In general, 95% of all scores are between 2.25 and 5, on a scale from 0 to 5. One of the possible causes of this above-average scores concentration may be associated with the identification of qualitative criteria for scores. This is due to the difficulty in measuring what the score actually represents, considering the proposed scale. Similar problems can be found in surveys that use Likert scale concepts (Hodge; Gillespie, 2003).

Identification of Cultural Similarities

Studied Cities

In order to identify possible cultural aspects associated with beer consumption, we have selected popular cities in several parts of the world, aiming to benefit the cultural diversity (inside the parentheses we show the number of check-ins available for each location): Mexico City (1,004), Chicago (6,493), Los Angeles (2,210), New York (8,080), Portland (6,451), San Francisco (3,062), Belo Horizonte (436), Curitiba (465), Rio de Janeiro (1,070), São Paulo (2,555), Tokyo (2,764), Berlin (771), Brussels (1,160), Barcelona (1,877), Madrid (770), Paris (383), Amsterdam (1,556), Dublin (837), London (6,658), Prague (476), Moscow (857), Melbourne (1,808) and Sydney (2,597).

Paris is the city with the lowest number of check-ins, however, it is one of the biggest metropolises. Over the past decades "wine drinking" countries are consuming more beer (World Health Organization, 2014). Nevertheless, according to the most recent data shared by the World Health Organization, the wine consumption in France is more than twice the consumption of beer, trend not observed for most countries, where beer is usually more popular (World Health Organization, 2014). This fact might help to explain this result.

Proposed Approach

In order to identify cultural similarities between cities considering preferences for beers, we first grouped the data according to the 2017 beer style classification proposed by the Brewers Association (Association, 2017). Since 1979 the Brewers Association has provided beer style descriptions as a reference for brewers and beer competition organizers, and it is well accepted worldwide. This classification allows to group beers by ethnic characteristics: British Ale; Irish Ale; North America Ale; German Ale; Belgian and French Ale; Other Ales; Germanic Lager; North America Lager; Other Lager; Mixed or Other Types.

After that, we represent each city by a vector of preferences, reflecting a sort of cultural signature of each studied area. More formally, each area a, a city in our case, is represented by a preference vector composed of ten features $C^a = c_1^a, c_2^a, \dots, c_{10}^a$, each feature represents one of the ten beer categories mentioned above. Each category in C^a represents the total quantity of scores attributed for each beer category by users in a certain area a .

Next, we normalize the total number of check-ins attributed to each beer category by the highest number observed in a single beer category in the area $a(\max(C^a))$: each category c_i^a is equal to $c_i^a/\max(C^a)$. Thus, each area a is represented by a preference vector containing values from 0 to 1, indicating the preferences of beers of users from that area. In order to illustrate this process, consider city m with the following number of check-ins in the ten categories considered: $C^{\{m\}} = \{2, 3, 4, 2, 3, 1, 0, 5, 10, 1\}$. After the normalization step the values would be: $\{0.2, 0.3, 0.4, 0.2, 0.3, 0.1, 0, 0.5, 1, 0.1\}$.

Besides this way of constructing the preference vectors, we also propose another method, namely Hybrid. This method uses a similar structure to the one already described, a vector representing each city containing ten features, i.e., types of beer. However, users' preferences are calculated differently. Instead of considering only if a user gave or not a check-in in a certain beer category, we now also consider the score manually informed by the users. This score ranges from 0 to 5 representing how much one enjoyed a certain beer. This method envisions to better capture the relation between scores given by the users and the quantity of check-ins for each category of beer. In this way, uncommon beers with a low number of check-ins but high scores are less penalized in the overall users' preference description of a certain city.

With that, the Hybrid method considers the total sum of scores attributed to each beer category by users in a certain area a: $S^a = {s_1}^a, {s_2}^a, \dots {s_{10}}^a$. Next, we calculate the average scores times the total number of check-ins for each beer category in the area a: h_i^a=$(s_i^a/c_i^a\ )*\ c_i^a$. After that, we have all the new values of preference for each beer category $H^a = {h_1}^a, {h_2}^a, \dots {h_{10}}^a$. Next, we normalize the new values of preference at each beer category by the highest value observed in a single beer category in the area a . By doing that, each category with index i is equal to ${h_i}^a/max(H^a)$. In this way, each area a is also represented by a preference vector containing values from 0 to 1, indicating preferences of beers of users from that area.

After that, we use the preference vectors to group similar areas. For that, we perform a hierarchical clustering considering the Canberra distance (Everitt and Skrondal, 2006), to calculate the similarities between preference vectors for each city studied. The linkage criterion used was Ward's method (Ward, 1963). Other distances and linkage criteria could also be employed. In fact, we tested with other candidates but the best results were achieved with the combination presented (Canberra and Ward's method). A comparison of different combinations of strategies is out of scope of the present study.

Results

Figure 2 represents a dendrogram of the hierarchical clustering considering the method described in the previous section. It is possible to identify that ethnic identity was favored in these clustering. As we can see, all the cities from the same country have small distances between them, i.e., they have a smaller difference in preference for beer compared to cities in other countries, favoring being grouped together, as the image shows using red boxes. In this way, for instance, all cities considered in the United States remained in the same cluster.

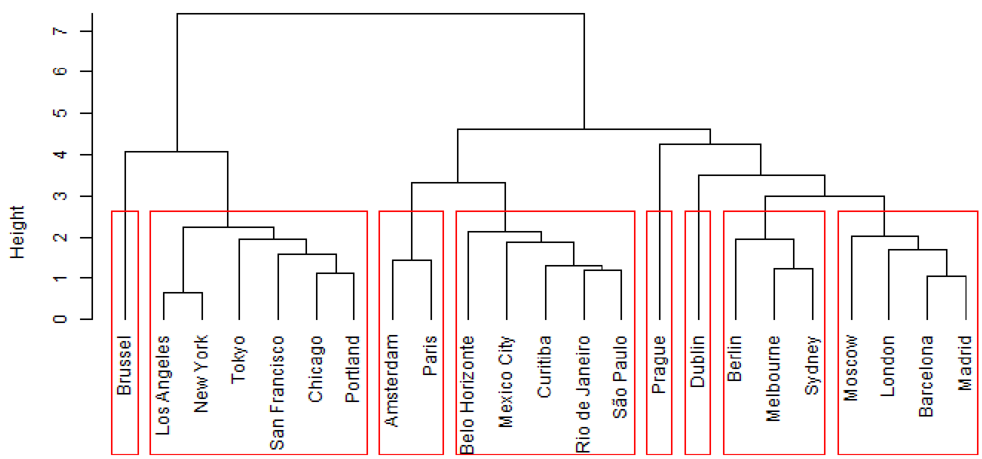

Figure** 2. **Dendrogram for the hierarchical clustering considering Canberra distance and Ward's linkage criteria.

A similar result was also observed with the Brazilian, Spanish and Australian cities. These are the only countries containing more than one city in our analysis. This result corroborates with the hypothesis of our study, that is, beer preferences shared in Untappd reflect significant cultural differences. This suggests a potential for exploring beer consumption as features for the study of cultural differences.

Despite grouping all cities from the same country, as expected, these groupings are marked by the presence of other cities as well. For instance, in the group formed by the United States cities, Tokyo was grouped together. This indicates that Tokyo shares a similar taste for beers with the studied cities of the United States. This might be an influence of a growth in the offer of American beers in Japan or even because of a higher acceptance in Japan of the Western culture and tastes (Hernandez, 2014). Another example is the group of Brazilian cities, which contains also Mexico City.

It is important to mention that this is not necessarily a problem with the approach or a bad result. For example, despite the close geographic proximity with the United States, Mexico City preference for beers can be, in fact, more similar to the Brazilian preference for beers. Besides the closer cultural similarity, Latin

Americans users, the cities studied have also a weather similarity, which is an important factor when talking about beer consumption (Dredge, 2010).

Nevertheless, in order to further investigate other possibilities to express the users' preferences for beers, we explore the Hybrid method for preferences calculation, as discussed in the previous section. Using the Hybrid method, cities sharing a similar culture are still expected to be grouped in the same cluster, according to our hypothesis. However, because the Hybrid method takes into account the scores given by users, not only the total number of check-ins, it may favor a better grouping given the users' preferences.

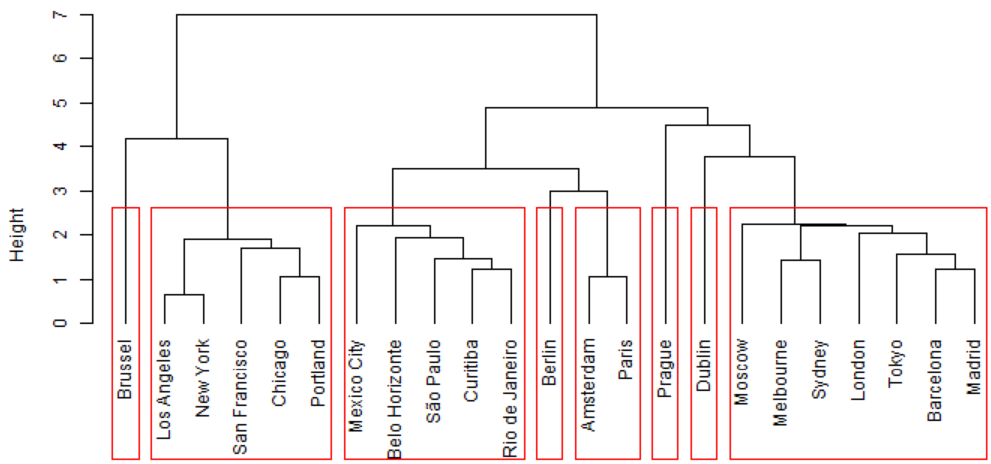

Figure 3. Dendrogram for the hierarchical clustering considering Canberra distance and Ward's linkage criteria for the Hybrid method.

Figure 3 presents a dendrogram for the hierarchical clustering considering Canberra distance and Ward's linkage criteria for the Hybrid method. Observing this figure, it is possible to note that the Brazilian cities remained in the same cluster along with Mexico City. Nevertheless, Mexico City, in this new clustering, has a higher difference in preference for beer compared the Brazilian cities, as we can see in the dendrogram. In addition, a cluster was formed with cities from the United States without cities of other countries.

Both methods presented surprising results regarding cultural similarities of beer preferences expressed in Untappd data. On the one hand, the first method of creating preference vectors for beers is based only on the total number of check-ins given for each category, providing insights also related to this aspect. This allows observing the consumption patterns for certain types of beer for each country. On the other hand, the Hybrid method aims to evaluate beer preferences of each country also through the lens of beer's scores given by users, envisioning to better capture the relation between scores and the quantity of check-ins for each category of beer. Perhaps, this method is more appropriate to capture ethnic and cultural characteristics as the taste and style of beer.

Both methods could be used in a complementary way but the idea of this study is not to directly compare them since they have different characteristics.

Discussion and Limitations

In this study, we found evidence that beer preferences shared in Untappd reflect cultural differences. Cities belonging to the same country presented a smaller difference in preference for beer compared to cities in other countries. This finding indicates that preferences for beer could be used to extract similarities between cultures regarding this aspect. As an example of these similarities, Brussels is one city with close similarity with the cities of the United States. This result is mainly due to their similar taste in North American Ales, and Belgian and French Ales.

Our approach to identify cultural similarities based on beer preferences explored cities around the world. Note that our approach could be explored to any area granularity, such as neighborhoods and countries. The construction of the preference vectors remains the same, what changes are the data considered, for example, data shared by all users from a certain country.

Identify cultural similarities in an automatic fashion could enable new (or smarter) urban applications, services, and business opportunities. For instance, in certain business decision-making, the understanding of cultural aspects can be an important differential. To give an example, companies operating in a certain region of the planet might be interested in verifying the combability of its home market with different ones, thus, helping strategic expansions process, choosing more wisely where to invest money. Besides, while operating in a new market, those insights might ease the adaptation of the company's product to have a higher acceptation, for instance, producing specific market campaigns (Cho and Padmanabhan, 2005; Karande et al., 2006; Silva and Graeml, 2016).

In addition, our approach could help place recommendation systems, which might useful for visitors of a certain city. It is becoming more popular users performing searches within diverse categories, such as "brewery", not just specific places (Chaey, 2012). Based on this fact, applications like Foursquare and other search applications based on location, such as TripAdvisor[10], could explore the new cultural criteria in their recommendation algorithms. Perhaps, new services to suggest geographical areas, not just places, could be also proposed.

It is important to mention some of the limitations of our study. For instance, the availability and accuracy of the data. Only public Untappd check-ins shared through Twitter were captured, and this mode of publication is avoided by users who want to ensure greater privacy, thus, we do not have guarantees of having the opinion of all users. Besides, we are not able to ensure that a check-in was performed at the exact moment of the drink consumption (Chorley et al., 2016). This prevents us to consider the time dimension, a feature that might be of significant value when performing cross-cultural studies as the one performed in this study (Silva et al., 2017). In addition, there is no information on the amount consumed by the user, as reported by Chorley et al. (2016), preventing the improvement of our analysis considering this information.

When considering data by cities, we might be considering check-ins performed by tourists who visited those cities. This is because we only consider the geolocation of the check-in not assuring that a user is a resident of a specific city. With that, we might be finding the taste of tourists as opposed to the local taste. This might not be a problem because beer consumption is associated with availability (Mccluskey and Shreay, 2011), i.e., a tourist will consume what is available in a certain area and perhaps consume what is popular among locals, because peer consumption can be a significant factor when choosing a beer (Hayakawa, 2000). Anyway, in our dataset, we did not find a significant number of users performing check-ins in different countries, suggesting that this is not a problem. In order to prevent possible problems in this direction, one could also apply approaches to detect tourists, such as those performed by Paldino (2015).

The fact that Untappd is only available in English might be a limiting factor in countries that do not consider this language as an official one. Despite all these possible problems, our results suggest that the exploration of these type of data could be useful in the hard task of studying cross-cultural differences.

Conclusions and Future Research

By studying a large scale dataset collected from Untappd, a popular LBSN to share beer experiences, our results suggest that users' preferences for beer types are an important cultural feature. It was possible to identify the potential to explore beer preferences to the identification of cultural aspects that can be exploited, for example, in building new social Web applications and enable new services and business opportunities.

Future research in this direction includes to perform a user-level analysis. It is possible to obtain information related to users' preference for certain types of beer and the places where they prefer to have them. This may enable the better understanding of cultural aspects related to the consumption of beer, as well as to identify potential patterns, including geospatial ones, not explored before. These aspects may be beneficial when it is important to understand the consumer market of beers or behavioral patterns related to beer drinkers.

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[10] https://www.tripadvisor.com

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