Inferring Nationalities of Twitter Users and Studying Inter-National Linking

Wenyi Huang*
Information Sciences and Technology
Pennsylvania State University
University Park, PA 16802
harrywy@gmail.com

Ingmar Weber
Qatar Computing Research Institute
Doha, Qatar
iweber@qf.org.qa

Sarah Vieweg
Qatar Computing Research Institute
Doha, Qatar
svieweg@qf.org.qa

ABSTRACT

Twitter user profiles contain rich information that allows researchers to infer particular attributes of users' identities. Knowing identity attributes such as gender, age, and/or nationality are a first step in many studies which seek to describe various phenomena related to computational social science. Often, it is through such attributes that studies of social media that focus on, for example, the isolation of foreigners, become possible. However, such characteristics are not often clearly stated by Twitter users, so researchers must turn to other means to ascertain various categories of identity. In this paper, we discuss the challenge of detecting the nationality of Twitter users using rich features from their profiles. In addition, we look at the effectiveness of different features as we go about this task. For the case of a highly diverse country—Qatar—we provide a detailed network analysis with insights into user behaviors and linking preference (or the lack thereof) to other nationalities.

Categories and Subject Descriptors

Applied Computing [**Law, social and behavioral sciences**]: Sociology; Computing methodologies [**Machine Learning**]: Supervised learning by classification

Keywords

Twitter; Qatar; nationality inference; user classification

1. INTRODUCTION

The availability of large amounts of social media data has created new possibilities to study social phenomena at large scale through the lens of online behavior. To obtain insightful results and to "link" these online data to offline, "real-world" variables, it is often useful to have detailed social media user attributes such as gender, age or nationality. Though inferring gender and age from a user's social media presence has been studied before, the latter has, to the best of our knowledge, not been explored. A likely reason for this gap is that in most countries the population is dominated by the "native" nationality. Even in the US, which is often perceived as a country of immigrants, only about 13% of the population are foreign-born[1] and of those, about 45% are American citizens,[2] leaving just over 7% of "foreigners." Due to this nationality skew, even a trivial American-or-Not classifier would have an accuracy of 93% by always reporting "American." However, in Qatar, the *majority* of the population is foreigners, exceeding 85%. This creates a range of challenges related to the identification of national identity. We are interested in potential correlations between national identity and social capital [2], and are curious to know if asking questions about nationality as it manifests on Twitter can lead to different or better understandings of how the two are linked (or not).

To explore this question, we created a classifier that detects the likely nationality of Twitter users based on a range of features, including language, the hashtags they use, and the geographical location of their social ties. We then perform a feature analysis, which leads to an interesting discovery regarding patterns related to the use of particular hashtags, such as #disappointed or #takemeback. These hashtags have a negative connotation, and are linked to people of particular nationalities.

Regarding a definition of a "nationality," we take a simplified approach given our goal: you (a Twitter user) have the nationality that others (CrowdFlower workers) believe you have. We argue that this approach is acceptable for several reasons. First, challenges regarding perception of national origin and impartial treatment are known [22]. Regardless of how individuals self-identify as one nationality or another, the *impression* others have of them factors into conduct and actions (ibid.) Second, we also evaluated the quality of crowdsourced data on a subset of users who explicitly state their nationality in their Twitter profile as in "An American living in Doha" (details in Section 4.3). The agreement between self-stated nationality and crowdsourced labels was 91.86%, which validates the reliability of our crowdsourced data.

2. RELATED WORK

Related work involves user classification on Twitter for attributes ranging from political orientation to gender. In addition, researchers have explored the use of Twitter messages (and similar data) to study a wide range of cultural phenomena.

2.1 Twitter User Classification

Rao et al. [16] introduced the work of classifying latent user attributes including gender, age, regional origin, and political orientation using simple features such as n-gram models, presence of emoticons, number of followers/following and retweet frequency.

*The work was done while the author was an intern at QCRI.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
HT'14, September 1–4, 2014, Santiago, Chile.
Copyright is held by the owner/author(s). Publication rights licensed to ACM.
ACM 978-1-4503-2954-5/14/09 ...$15.00.
http://dx.doi.org/10.1145/2631775.2631825 .

[1] http://www.census.gov/how/infographics/foreign_born.html
[2] http://www.migrationinformation.org/datahub/state.cfm?ID=US\#3

In [9], the authors extended this work by introducing a two phase architecture for classifying Twitter users. The first part is using basic features for classification, and the second part is to use social graph-information to update classification result. The interesting result is that the first phase alone achieves good performance which is hard to improve by the social graph information. The idea of using information from neighborhood context for classification was first introduced by Pennacchiotti and Popescu [12]. Zamal, Liu, and Ruths extended the previous work by augmenting the user features and neighboring features and boosted the performance of gender, age, political orientation classifications [23]. Burger, Henderson, and Zarrella [3] conducted a study that used only text content for determining the gender of Twitter users. They also included a human performance study using Amazon Mechanical Turk and claimed that the trained model performed better than human assessment. In addition, Cheng et al. [4], Hecht et al. [7] and Mahmud et al. [8] have looked at inferring Twitter user location based on tweet text. Unlike previous research, our study begins to explore the question of nationality detection—a new classification task.

2.2 Social Media and Social Studies

Poblete et al. [13] analyzed and compared Twitter user language, sentiment, content, and network properties in the ten most active countries. In [6], the authors study behavioral patterns on Twitter and associated them with three different cultural dimensions: pace of life, individualism, and power distance. They found that country-level behavior derived from Twitter strongly correlates with said dimensions. Santani and Gatica-Perez [17] presented an analysis of languages used in Switzerland to examine multiculturalism. They used Foursqaure data, and presented a descriptive analysis of linguistic differences and similarities in multiple cities. In our analysis we also came across negative sentiments and worries. This is related to work that looks at the geographical differences in well-being and happiness [14, 15, 18, 10].

3. DEMOGRAPHICS OF QATAR

Geographically, Qatar is located in the center of the Middle Eastern Countries. Although it is a small country, Qatar is one of the wealthiest countries in terms of per-capita income in the world due to oil and gas exploitation. Qatar is currently in a job and construction boom, partly related to the 2022 FIFA World Cup, which is attracting a lot foreign workers. As a result, the country has experienced a significant shift in its population composition, doubling in size to about 2 million in 7 years. Figure 1 shows the population as of 2012, according to the Qatar Statistics Authority and Qatar's Permanent Population Committee [11]. We can see that the demographic composition is very diverse with only 15% of the total population being Qataris, while the rest is mixed, and includes large fractions of Indians, Nepalese, and Filipinos. These statistics show the "offline" demographics of Qatar. Conversely, in our study, we analyze "online" nationalities as found on Twitter.

4. DATASET CONSTRUCTION

To study the online nationality distribution of Qatar, we chose Twitter as a platform due to its wide popularity and relative ease of data access through public APIs. To find a significant number of Twitter users based in Qatar, we made two constraints when querying the APIs: Users should either (i) explicitly state in their profile that they are located in Qatar (in the free text "location" field) or (ii) have at least one geo-tagged tweet originating from Qatar.

A total number of $51,449$ candidate Twitter user profiles were collected between April 2013 and June 2013. For these users, we

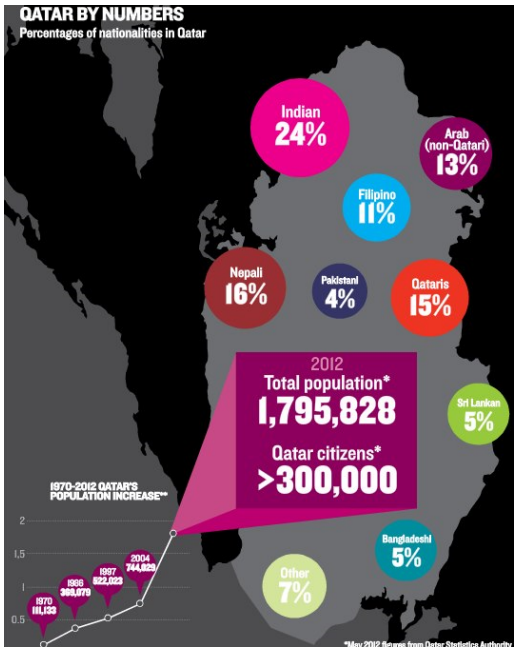


Figure 1: A Glimpse into Qatar's "offline" Demographic.

queried the API to collect all their publicly available tweets (up to 3,200). In total, $54,075,860$ tweets were collected. In addition to the tweets' content, we obtained additional meta information such as the (latitude, longitude) for geo-tagged tweets, and information about the device used to post the tweets. To filter out inactive profiles, we restricted our study to $35,780$ users who had at least 10 tweets and at least 5 followers and 5 friends.[3] Furthermore, we collect follower and friend user profiles of these $35,780$ users, yielding a total of $5,572,765$ profiles including their self-declared location. We also obtained profile pictures of the $35,780$ Twitter users.

4.1 Preprocessing

A user's nationality is rarely explicitly stated in the profile (e.g. "I am American"), making simple rule-based approaches inappropriate to build a training set. So, to obtain ground truth, and a reasonably sized training set, we turned to crowdsourcing to tag the data. To make the job easy for people to tag, we first preprocessed our data as follows:

- We use language detection tools by Shuyo, Nakatani [19] and run the code on all collected tweets. We calculated tweet language distributions for each Twitter user. In the crowdsourcing jobs, we show the top 3 languages used in tweets for every user.
- We use an R library to convert latitude/longitude pairs from geo-tagged tweets to countries. In the crowdsourcing jobs, we show the top 3 locations along with a small sample of geo-tagged tweets from each location for every user.
- Since most people state their location in natural language, e.g. "NYC," "New York City," and so on, we employed a state-of-the-art geo-coder to map these free texts to explicit countries. We used the Yahoo! Placemaker API[4] for this extraction. We show the top 3 self-stated countries of a user's followers and friends in the crowdsourcing jobs.

[3] We are using Twitter's terminology where a "friend" denotes a "followee," the compliment of a follower.

[4] `http://developer.yahoo.com/yql/console/\#`

- We also show other information about the Twitter users available from the Twitter API, such as their name, screen name, profile picture, biography, a link to a homepage, location, time zone, and interface language.

4.2 Data Labeling

We use the Crowdflower platform[5] for crowdsourcing. To create as-easy-as-possible micro-tasks for the contributors, we recreate Twitter profile pages and provide the preprocessed information about each user in the labeling interface. Figure 2 shows an example of our crowdsourcing job.

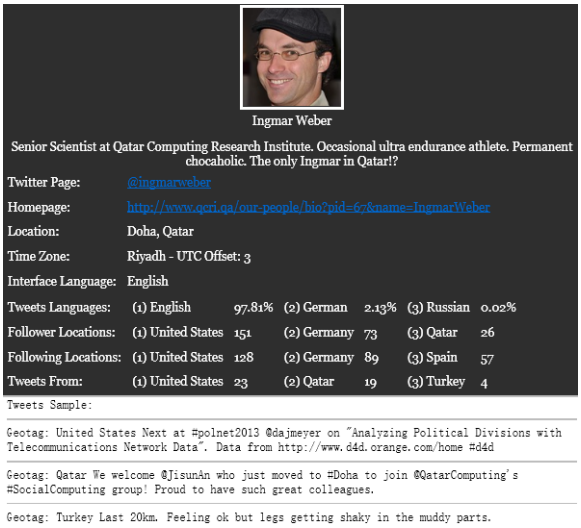


Figure 2: An example of a crowdsourcing task.

To ensure that the contributors correctly understood instructions, and to remove bots and spammers, we created 100 "gold" samples for the so-called "quiz mode." Potential contributors will first only see "gold" samples and must correctly tag at least 8 out of 10 gold samples before they can access non-gold units. For each contributor, we also require at least 3 trustful labels with higher than 66.6% agreement, which means at least two people agreed with each other. If such an agreement is not attained on the first 3 tags, we will require more people to tag the data until the agreement reaches 66.6%.

With respect to nationality group, we divided the Twitter users into 6 groups: Qatari (QA), non-Qatari Arab (ARA), Westerner (WES), Indian Subcontinent (IN), Southeast Asia (SA) and others (OTH). These simplified groups are based on the Social and Economic Survey Research Institute (SESRI) of Qatar University and in other statistics concerning the country's population. We assigned a group Unclear (UN) for Twitter profiles where Crowdflower contributors think there is not enough information to classify them into any of the 6 defined groups.

The tagging process lasted about a week. Figure 3 provides the results of the crowdsource tagging: The online demographics of Twitter users in Qatar is very different from the statistics in Figure 1. We attribute this difference to the fact that many expatriates from the Indian Subcontinent or from Southeast Asia come to Qatar to perform manual labor. Their salaries are often insufficient to permit purchases like smartphones or computers, and access to such devices is difficult. In addition, there is a possibility that unawareness and/or disinterest in Twitter leads to lack of tweet activity, and ability to post and/or read in native languages may not be available.

[5] http://crowdflower.com/

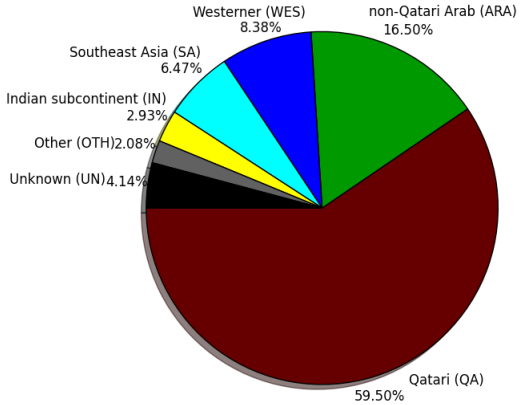


Figure 3: "Online" demographics of Twitter users in Qatar.

4.3 Data Validation

To validate the correctness of the crowdsourced data, we introduced "hidden gold" data to our crowdsource job. Among $35,780$ users, $1,210$ stated their own nationalities in the profiles. We randomly selected and hand-checked a subset of these users and got 467 profiles which we were 100% sure about their nationalities. For these users, we replaced the nationality words that appeared in their profiles with "XXX" and shuffled them into our crowdsource job. Contributors on Crowdflower.com will be assigned to tag these "hidden gold" data randomly.

After the tagging process was complete, we evaluated the correctness of these "hidden gold" data, which shows that 91.86% of the validation set were correctly tagged.

5. CLASSIFICATION MODEL

In this section, we describe how to build classifiers using the ground truth labels from the crowdsourced data. First, we introduce the features we use for training the classifiers.

5.1 Features

Twitter offers a range of user information with different characteristics, so we chose to first include as much information as possible when generating the features.

Location-related features. There are 4 types of location-related features: 1) Followers' Locations, 2) Friends' Locations, 3) Self-stated Location and 4) geo-tagged tweets' locations. Each feature vector is a 196 dimensional vector with each dimension representing a country;

Time zone. A vector of 24 dimensions with each dimension representing a possible time zone;

Language related features. Due to the limitation of language detection tools, there are 20 possible dimensions for the language-related vector covering the most prominently spoken languages, but it is missing many less-common languages;

HashTags. We collected $7,057$ different HashTages which appear more than 5 times in our dataset;

Profile picture features. We use Faceplusplus,[6] a facial recognition API, to estimate basic information from profile pictures. The feature is a three dimensional vector with one dimension representing gender, one representing race, and one for age;

Name ethnicity. We use a name ethnicity detection toolkit by [20] and get a 10 dimensional vector with each dimension representing an ethnicity;

[6] http://www.faceplusplus.com/

UTF-8 charset type We check the charset used by each user in their profile, and their tweets. A vector with 209 dimension was formed, with each dimension representing the percentage of a type of charset (in UTF-8).

Tweet source. We collected 571 different utilities that Twitterers used to post tweets.

Mentioned users. Twitter users mentioned in Tweets (people you actually interact with)-this feature includes 3 sub features: 1) self-stated location of mentioned user, 2) interface language of mentioned user, 3) time zone of mentioned user.

Table 1 shows a complete list of features.

Feature	Description & Example
follower loc	[QA: 20, US: 1 , ...]
following loc	similar to follower loc
self loc	[UAE, UK, ...]
geo tag loc	similar to follower loc
time zone	[Abu Dhabi]
tweets lang	[EN: 70.7%, ES: 20.5%, UN: 8.8%]
interface lang	[EN: 1]
hashtag	[#love: 1 , : 1, #Mubarak: 1, ...]
race	[White: 91%, Yellow: 7%, Black: 2%]
age	[Age: 31, age_confidence: 83%]
gender	[Male: 1, gender_confidence : 98%]
name eth	[English: 89%, German: 9%, French: 2%]
charset	[Arabic: 25.1%, Basic Latin: 45.8% , ...]
source	[Twitter for iPhone: 312, Mobile Web: 3 ...]
mention loc	similar to follower loc
mention time zone	similar to time zone
mention lang	similar to interface lang

Table 1: Feature descriptions and examples.

5.2 Gradient Boosted Tree

Gradient Boosted Tree [5] is an effective off-the-shelf procedure for classification. The main advantages of Gradient Boosted Tree are that 1) it can handle data of mixed-type features, and 2) it is very robust regarding outliers in input space. In our case, we may have a lot of noisy data in our constructed feature space, and Gradient Boosted Tree can perform robustly in both training and predicting. Because the dataset is highly unbalanced, we performed our experiments and evaluations using stratified 5-fold cross-validation.

6. RESULT

The best performance of Gradient Boosted Tree was achieved with a number of trees$= 300$ and the best overall accuracy is 83.8%. In Table 2, we show the overall classification performance (Precision, Recall, F_1 score) for each nationality group. Due to the unbalanced data distribution, we can see that the performance for less populated groups is not very high.

	$Pre.$	$Rec.$	F_1
QA	86.67%	95.37%	90.81%
ARA	82.96%	71.16%	76.56%
WES	70.86%	70.62%	70.64%
SA	93.35%	90.48%	91.89%
IN	82.19%	71.13%	76.00%
OTH	78.67%	40.72%	53.54%
UN	30.78%	15.13%	20.16%

Table 2: The average Precision, Recall and F_1 scores for each nationality group.

For a detailed analysis of the trained model, we show the confusion matrix of the classification results in Table 3. Combining the results from Table 2 we can see that the low performance of classifying non-Qatari Arabs is due to the confusion with the group of Qatari citizens. In the following section, we explain why such classification is so challenging.

		Predicted Label						
		QA	ARA	WES	SA	IN	OTH	UN
True Label	QA	5439	143	63	10	9	2	37
	ARA	404	1125	25	1	5	4	17
	WES	125	28	567	12	12	14	45
	SA	24	5	16	561	2	0	12
	IN	41	2	16	2	200	1	19
	OTH	27	10	66	4	0	81	11
	UN	216	45	48	11	16	1	60

Table 3: The confusion matrix of the trained classifier.

Table 4 shows the normalized confusion matrix of the human-tagged tweets. As described in section 4.2, the ground truth labels are based on majority votes from the crowdsource workers. This normalized confusion matrix describes the judging agreement among different people. This is trivially "biased" towards a low confusion and low error rate, as when two out of three judges agree on anything, correct or not, it is considered the gold standard. With this caveat in mind, the confusion matrix shows that the performance of human labeling is better than our classification model. However, we can also see from the matrix that it is difficult for humans to distinguish between the Qatari group (QA) and non-Qatari Arabs (ARA). In addition, compared to classification model, unclear labels (UN) appear more frequently when people are confused about the users' nationality (such as "Qatar born, Egyptian blood"). Overall, the human labeling confusion matrix also indicates that our data collection process is satisfactory for further studies.

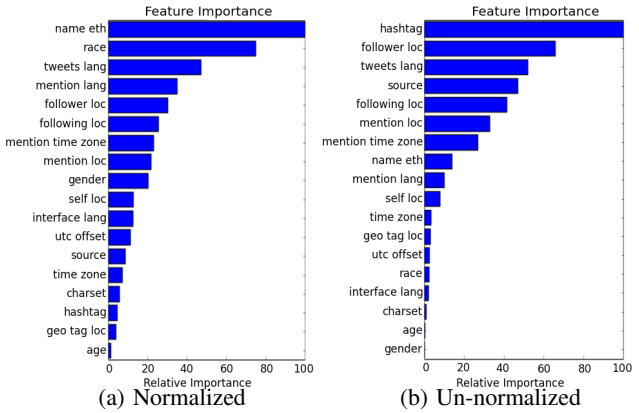
		Labeling Label						
		QA	ARA	WES	SA	IN	OTH	UN
True Label	QA	5158	259	92	8	7	7	169
	ARA	86	1418	16	1	1	2	53
	WES	27	8	721	3	1	7	32
	SA	13	1	10	578	0	2	12
	IN	8	2	11	2	239	2	12
	OTH	5	3	8	0	0	172	8
	UN	76	30	40	11	7	5	224

Table 4: The normalized confusion matrix of the human labelling.

6.1 Feature Analysis

All features do not contribute equally to the classification model. In many cases, the majority of the features contribute little to the classifier and only a small set of discriminative features end up being used. Here, we discuss the importance of different features.

The relative depth of a feature used as a decision node in a tree can be used to assess the importance of the feature. Here, we use the expected fraction of samples each feature contributes to as an estimate of the importance of the feature. By averaging all expected fraction rates over all trees in our trained model, we could estimate the importance for each feature. It is important to note that feature spaces among our selected features are very diverse. The impact of the individual features from a small feature space might not beat the impact of all the aggregate features from a large feature space. So apart from simply summing up all feature spaces within a feature (i.e. sum of all $7,057$ importance scores in hashtag feature), which is referred to as un-normalized in Figure 4, we also plot the normalized relative importance of each features, where each feature's importance score is normalized by the size of the feature space.



(a) Normalized (b) Un-normalized

Figure 4: Relative Feature Importance when training the models.

It is not surprising that the hashtag feature—with the largest ranked feature space—ranked first in the un-normalized plot. However, in the normalized plot, this feature ranked very low. One explanation is that *some* hashtags will be quite useful in classification, but the majority of hashtags are often not useful. To justify the explanation, we study the most popular hashtags when training the classifiers in Section 6.1.1. Location-related features like followers/following location and mentioned users' locations are often dominant features. These features, however, are only ranked second (for follower locations) and fifth (for following locations) in un-normalized ranking, being ranked fifth/sixth in normalized ranking. The relative ranking of these can potentially be explained by the fact that many people follow pop stars or international news agencies, but non-famous users are unlikely to be followed by many international users. Tweet language is the third most important feature in both evaluation metrics. We presume that most expatriates from non-Arab countries are unlikely to understand or tweet in Arabic. In the following sections, we take a look at the details of some of the most influential features.

By comparing these two figures, we provide a guideline of feature selection; if you want one feature (or small feature group) to work (to some degree) all the time, then name ethnicity and race are the best choice. But if you want more accurate result, features with a large feature space size (i.e. hashtags) will help improve classification models.

6.1.1 Hashtags

In Figure 5, we plot the most influential hashtags for training the classifier using the Gephi [7] toolkit. Red dots represent Twitter users labeled as Qatari, green dots represent non-Qatari Arabs, blue dots represent Westerners, cyan dots represent Southeast Asians, and yellow dots represent people from the Indian subcontinent. The large gray nodes (mostly overlapped by the textual hashtags) represent each hashtag. This color scheme will be used throughout the remainder of the paper.

From this figure, we observe that certain hashtags are only used by certain groups. For example #IPL (Indian Premier League) only appears among people from the Indian subcontinent, #ihatequotes is used among people from Southeast Asia, and #No_thirsty_in_Qatar are most used among Qataris. Such hashtags serve as "sufficient" features, which means that if such hashtags appear in one's tweets, the classifier will has sufficient information to infer your nationality group. However such "sufficient" features

[7] https://gephi.org/

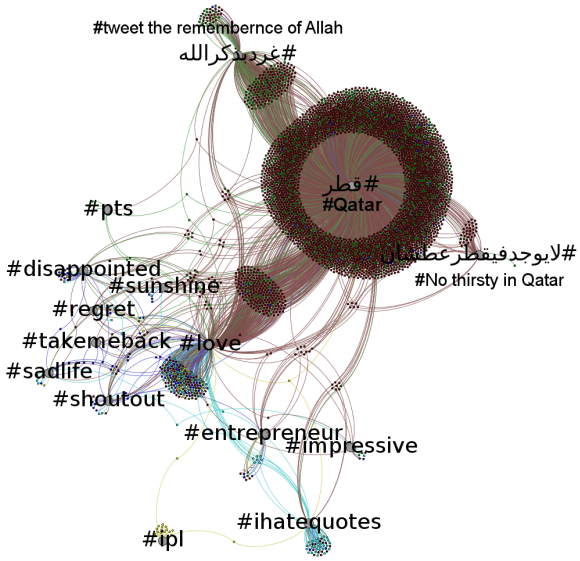


Figure 5: Top 15 important hashtags when training the classifers.

(hashtags) appear comparatively rare as we could see from the figure. Most hashtags provide little information about your nationality (for example #Qatar (in English) #Doha (in English)). This supports our findings in Section 6.1—that the hashtag feature plays an important role in training the classifier. However, if averaged by the size of the feature set, it is not that important because most hashtags contribute very little to the classifier.

Also, this figure shows that the language used in hashtags also provides important information about nationality groups as non-Arab people rarely use Arabic hashtags, and they rarely retweet Arabic hashtags. This is likely due to the language barrier. Also we see that if an Arabic hashtag is related to Qatar, it is most likely tweeted by Qataris.

Compared to Arabs, others are more willing to express personal feelings - at least in English. For example, the hashtag #love has a low percentage of Arab users attached to it when compared to the overall fraction of such users. In addition, foreign expatriates have a much higher probability of expressing negative emotions in tweets. Hashtags like #sadlife, #disappointed, #takemeback are mostly tweeted by this population.

7. CONCLUSIONS

We built a classification model to address the question of how to identify nationalities of Twitter users. We collected the Twitter user profiles from Qatar, and used crowdsourcing to label the dataset. We used Gradient Boosted Tree to model the data and trained a classifier to detect the nationality of Twitter users based on a number of features. A feature analysis study was performed, and we discovered some interesting patterns of user features. The distribution of the inferred online Twitter nationalities does not match the offline reality, mostly due to a selection bias of who is online and on Twitter. However, our methodology is useful for detecting general trends, and—importantly—will serve as a foundation for future work. Exploring the link between social capital, cultural capital [2], and Twitter use and relationships in Qatar are all rich areas of study. Going forward, we plan to combine traditional offline surveys with online data mining approaches. This combination may help unbias online results, e.g. through the use of appropriate re-weighting factors, and it could enrich more limited and structured surveys with rich and multi-faceted analyses.

8. REFERENCES

[1] E. Badger. Map the iphone users in any city, and you know where the rich live, 2013.

[2] P. Bourdieu. *Distinction: A social critique of the judgement of taste*. Harvard University Press, 1984.

[3] J. D. Burger, J. Henderson, G. Kim, and G. Zarrella. Discriminating gender on twitter. In *EMNLP*, pages 1301–1309, 2011.

[4] Z. Cheng, J. Caverlee, and K. Lee. You are where you tweet: a content-based approach to geo-locating twitter users. In *CIKM*, pages 759–768. ACM, 2010.

[5] J. H. Friedman. Stochastic gradient boosting. *Computational Statistics & Data Analysis*, 38(4):367–378, 2002.

[6] R. O. G. Gavilanes, D. Quercia, and A. Jaimes. Cultural dimensions in twitter: Time, individualism and power. In *ICWSM*, 2013.

[7] B. Hecht, L. Hong, B. Suh, and E. H. Chi. Tweets from justin bieber's heart: the dynamics of the location field in user profiles. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 237–246. ACM, 2011.

[8] J. Mahmud, J. Nichols, and C. Drews. Where is this tweet from? inferring home locations of twitter users. In *ICWSM*, 2012.

[9] A. Mislove, S. Lehmann, Y.-Y. Ahn, J.-P. Onnela, and J. N. Rosenquist. Understanding the demographics of twitter users. In *ICWSM*, pages 554–557, 2011.

[10] L. Mitchell, M. R. Frank, K. D. Harris, P. S. Dodds, and C. M. Danforth. The geography of happiness: Connecting twitter sentiment and expression, demographics, and objective characteristics of place. *PLOS One*, 8, 2013.

[11] C. M. Paschyn. Anatomy of a globalized state. *Think. Issue 2*, 2012.

[12] M. Pennacchiotti and A.-M. Popescu. A machine learning approach to twitter user classification. In *ICWSM*, pages 281–288, 2011.

[13] B. Poblete, R. O. G. Gavilanes, M. Mendoza, and A. Jaimes. Do all birds tweet the same?: characterizing twitter around the world. In *CIKM*, pages 1025–1030, 2011.

[14] D. Quercia, J. Ellis, L. Capra, and J. Crowcroft. Tracking "gross community happiness" from tweets. In *CSCW*, pages 965–968, 2012.

[15] D. Quercia, D. Ó. Séaghdha, and J. Crowcroft. Talk of the city: Our tweets, our community happiness. In *ICWSM*, 2012.

[16] D. Rao, D. Yarowsky, A. Shreevats, and M. Gupta. Classifying latent user attributes in twitter. In *SMUC*, pages 37–44, 2010.

[17] D. Santani and D. Gatica-Perez. Speaking swiss: languages and venues in foursquare. In *ACM Multimedia*, pages 501–504, 2013.

[18] H. A. Schwartz, J. C. Eichstaedt, M. L. Kern, L. Dziurzynski, R. E. Lucas, M. Agrawal, G. J. Park, S. K. Lakshmikanth, S. Jha, M. E. P. Seligman, and L. H. Ungar. Characterizing geographic variation in well-being using tweets. In *ICWSM*, 2013.

[19] N. Shuyo. Language detection library for java, 2010.

[20] P. Treeratpituk and C. L. Giles. Name-ethnicity classification and ethnicity-sensitive name matching. In *AAAI*, 2012.

[21] W. Xie, C. Li, F. Zhu, E.-P. Lim, and X. Gong. When a friend in twitter is a friend in life. In *WebSci*, pages 344–347, 2012.

[22] I. P. Young and J. A. Fox. Asian, hispanic, and native american job candidates: Prescreened or screened within the selection process. *Educational Administration Quarterly*, 38(4):530–554, 2002.

[23] F. A. Zamal, W. Liu, and D. Ruths. Homophily and latent attribute inference: Inferring latent attributes of twitter users from neighbors. In *ICWSM*, pages 387–390, 2012.