

Detection of User Demographics on Social Media: A Review of Methods and Recommendations for Best Practices

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ABSTRACT

Researchers in fields such as sociology, demography and public health, have used data from social media to explore a diversity of questions. In public health, researchers use data from social media to monitor disease spread, assess population attitudes toward health-related issues, and to better understand the relationship between behavioral changes and population health. However, a major limitation of the use of these data for population health research is a lack of key demographic indicators such as, age, race and gender. Several studies have proposed methods for automated detection of social media users' demographic characteristics. These range from facial recognition to classic supervised and unsupervised machine learning methods. We seek to provide a review of existing approaches to automated detection of demographic characteristics of social media users. We also address the applicability of these methods to public health research; focusing on the challenge of working with highly dynamical, large scale data to study health trends. Furthermore, we provide an overview of work that emphasizes scalability and efficiency in data acquisition and processing, and make best practice recommendations.

Keywords

Social media; public health; social science; demography

1. INTRODUCTION

The wide use of social media sites such as, Facebook, Instagram and Twitter [1] have resulted in an unprecedented availability of social data that may be used to study human behavior across research domains. While some sites collect demographic information on users (e.g., gender on Facebook), others (e.g., Twitter) do not. This lack of demographic data, which is typically available in more traditional sources such as surveys, has ushered in a new focus on developing methods for inferring these traits as a means of expanding Big Data research. In this paper, we provide a critical assessment of existing approaches for automated detection of users' demographic traits and address how public health researchers may adopt these methods when working with social media data.

1.1 Social Media and Public Health Research

Digital traces generated by social media users offer a wealth of data for public health research. For example, studies using these data have focused on attitudes toward tobacco use [2]–[6] and vaccines [7]–[10], the onset of postpartum depression [11], sleep disorders [12], suicide risk [13], patient-perceived quality of care in hospitals [14], the dynamics of infectious diseases [15]–[21], neighborhood level trends in health, diet and weight loss [22], [23], mapping of the presence of food deserts [24],

monitoring of foodborne illness [25]–[28], the geographic distribution of fitness activity (specifically, cycling) [29], population representation [30], [31] etc.

There are several benefits to using social media data for public health research. First, social media data provide real-time updates on users' thoughts, feelings and experiences, allowing researchers to track users' attitudes and behaviors as they emerge. Both the population and individual-level scale of these data create the opportunity to study behaviors that are difficult to assess through traditional means of data collection [32]. Second, because social media posts are unsolicited, users may report opinions and behaviors with greater fidelity than they would in the context of interviews or surveys. Well-documented forms of response bias such as, social desirability bias, present in the context of surveys and interviews [33], may be weaker within social media spaces. Factors that influence the emergence of response bias (e.g., a desire to withhold poor behaviors from someone conducting a study) may be absent or lessened within social media spaces. Third, compared to surveys and other traditional means of data collection, these data are low cost and the process of data collection can be automated.

However, there are some limitations regarding the use of these data. For example, similar to traditional data streams, social media data are not always representative of the population of interest. While researchers have proposed methods for minimizing this limitation - such as probabilistically adjusting the data to match the population under study [34] - identifying and quantifying Big Data bias is challenging. This is partly due to a lack of demographic indicators - such as age, race and gender. The ability to accurately and reliably detect users' demographic traits would expand the use of social media as a research tool for social and behavioral sciences and public health. Additionally, linking demographic information to social media data would allow researchers to study disparities and trends in health-related attitudes and behaviors. It should be noted that there are privacy and ethical concerns associated with the use of social media data and the application of methods to infer user demographics, which we discuss in a later section.

2. METHODS FOR AUTOMATED DETECTION OF USER DEMOGRAPHICS

We focus on studies that address both profile-based social media spaces and blogs, with more emphasis on the former. Though blogs may be structured differently than social media sites – particularly in regard to the amount of personal data associated with users' posts versus their profiles – the methods for demographics inference are often similar. Additionally, we exclude studies that draw upon the linguistic structure of languages other than English to build predictive models, as well as those that correlate known demographic data with site use.

2.1 Data Extraction

We queried Google Scholar during October of 2016 using combinations of methodological terms: “prediction,” “classification,” and “machine learning”; terms related to user traits: “age,” “race,” “ethnicity,” “gender”, and platform-related terms: “social media” and “Twitter” and “blog.” On average, each search returned 121,120 articles. Within the first 20 pages of each search (ordered by relevance), an average of approximately 16 articles appeared relevant based on title and summary text. We then read through the abstracts of the potentially relevant articles and identified 60 studies that proposed methods for inferring or predicting users' demographic characteristics. All identified studies were published between 2006 to 2016. For each study, we extracted the year of publication, a brief description of the methods used, if and how the researchers obtained ground truth data, which metadata fields were used for classification, the precise features extracted from these metadata fields, the intended audience of the

paper (i.e. computer science, social science, etc.) and the demographic characteristic detected (i.e. age, race/ethnicity or gender) (See Appendix Table 1).

2.2 Methods and Social Media Platforms

The 60 selected studies focused on different social media platforms; 39 (65%) studies focused on Twitter, two on Facebook, two on Livejournal, one on Yelp, one on YouTube, and one on Pinterest. The remaining studies focused on other social media sites (e.g., Netlog, Fotolog) and blogs. Additionally, 44 (73%) studies explored supervised or semi-supervised machine learning methods, one (2%) used unsupervised learning, three (5%) used facial evaluation (human or automated), and 11 (18%) used raw or adjusted data matching. The machine learning methods considered include support vector machines [35]–[45], naïve Bayes [43], [46], modified balanced winnow [47], neural networks [48], maximum entropy [49], naïve Bayes decision tree hybrid [50], [51], gradient boosted decision trees [52], [53], as well as regularized linear, logistic or log-linear regression [43], [54]–[59]. Additional details on these methods can be found in the cited articles and in [60].

2.3 Predicted Traits

Gender. Of the 60 studies selected, 47 (78%) predicted gender (see *Table 1* in the Appendix). Gender in most cases was treated as a binary outcome. Most studies utilized users' posts/tweets, profile colors, names, profile images, social network and preferences (e.g., likes on Facebook) independently or in combination to infer gender. The selection of features used for predicting gender assume that gender is heavily embedded in peoples' identity and may be implicitly expressed through factors such as speech, choices of colors in one's profile [51], or stated interests [55]. Thus, unsupervised learning methods could be adequate for separating features distinct to the two gender classes [61].

Studies that utilized users' posts proposed classification methods aimed at identifying gender differences reflected in linguistic patterns [38], [40], [49], [62]–[83]. In contrast, studies that leveraged users' first names either used these data to link user profiles to ground truth survey data [84]–[86], or to develop and improve upon classifiers that incorporate other features [35], [38], [43], [50], [75], [83], [84], [87], [88]. Although some sites – such as Twitter – do not require users to provide a valid first and last name in their profile, this technique may still capture a large sample of users. Mislove et al. [84], for instance, found that 64.2% of Twitter users elect to include at least a first name in their profile, however about 71.8% were males. The precision, recall and F1-score varied across studies, with some achieving values in the 90s. However, few studies have focused on non-binary gender identity presentations. Bamman et al. [76] and Liu and Ruths [38] address this concept but additional work is needed.

Age. We identified 29 studies that aimed to predict age (see *Table 1* in Appendix). Similar to gender, a variety of features – including profile photos, users' posts and names – have been used to infer age. Several of these studies use text features and supervised learning methods to predict exact numeric age, age category and/or life stage [44], [57], [58], [89]–[93]. Results of these studies indicated that age prediction is more challenging compared to gender. Nguyen et al. [90] suggested that text-dependent classification techniques may have a tendency to conflate numeric age with life stage, and rely on coarse predictions of age such as “above or below 25” [39].

Some studies have suggested that human labelers could be highly reliable when assessing a user's age range or category [94], but accuracy of this method based on ground truth data has yet to be determined and the labeling process could be cumbersome and costly. Studies by An and Weber [95] and Zaghenni et al. [96] utilized facial recognition software Face ++ (www.faceplusplus.com) – a free facial recognition

service that can estimate a user's age within a 10-year span – and found promising results. However, further work is needed to assess the reliability, accuracy and best applications of facial recognition tools.

Additionally, simple approaches - such as mentions of age or birthday within a user's post or matching first names to trends in popularity over time [97] - are promising but not widely employed within existing literature beyond the development of a training dataset [44], [62]. For the former, the available data might be limited to teenagers or milestone birthdays, and the latter could be limited to popular names.

Race and ethnicity. Of the papers that address race or ethnicity, eight used supervised learning approaches [35], [36], [52], [53], [53], [56], [83], [98], two used adjusted data matching [84], [99] and two relied on facial recognition [94], [95]. Some studies focused on user names or posts, or both to predict race or ethnicity [52], [53], [56], [83]. The classification performance among these papers – while promising – did not vary significantly. Three studies obtained maximum F-scores between approximately 0.70 and 0.76 [36], [53], [54], and two obtained accuracy between 0.78 and 0.84 [35], [36].

Certain profile features could potentially improve predictions of race and ethnicity. First, profile photos appear to be a good indicator of race or ethnicity. Pennacchiotti and Popescu [53] for instance, obtained a higher precision (0.878) using profile photos to evaluate race, compared to a gradient boosted decision tree classifier that incorporated a combination of lexical features from users posts, and user activity measures (0.629). Second, user profile descriptions could improve methods for predicting race and ethnicity. For example, Chen et al. [36] observed that adding user descriptions into classifiers consistently improved accuracy, precision and recall for n-gram and name based models. Third, Chang et al. [86], and Mislove et al. [97] also found user location to improve predictability of surnames, and Mohammady and Culotta [56] used location as a feature for calibrating supervised learning models.

One challenge associated with the prediction of race and ethnicity is the need to create a clear, bounded definition. Racial and ethnic identity is complex and evaluations by others may not match an individuals' self-identification. Most of the selected studies were vague and varied significantly in their definition of race or ethnicity. Pennacchiotti and Popescu [53] claimed to predict ethnicity, but classified users as African American or not. Chang et al. [99] and Chen et al. [36] both used the term ethnicity to refer to a classification system that includes both racial and ethnic identities (black, white, Asian, Hispanic), and Mohammady and Culotta [56] used the same classification system but addressed it as race. Future work should directly address this challenge.

2.4 Challenges

A major limitation of existing approaches for demographic prediction in social media spaces is the unavailability of ground truth data. Demographic data is often difficult to collect due to factors such as, changes in social media membership, restrictions against solicitation within social media sites and low survey response rates [100]. This lack of ground truth information means that studies that rely on data matching cannot reliably assess predictive accuracy. Studies that apply supervised learning techniques to infer the demographic characteristics of users must build training sets that include 'true' measures of the characteristics predicted. Often these studies depend on name matching or manual labelling to evaluate user traits; approaches that are rough approximations and subject to human bias. A second limitation is in comparing the different studies due to inconsistency in the performance metrics emphasized. Several studies focused on accuracy, which although useful, is not always the best measure for performance. A combination of other measures, such as precision, recall and F-score would be best

[66], [101]. Another limitation is the need to balance the pursuit of improving predictions with ensuring that methods proposed are useful and accessible to a variety of research domains.

3. APPLICATION TO PUBLIC HEALTH RESEARCH

As noted, the availability of demographic characteristics in social media data would broaden the use of these data for public health research. However, the previously discussed studies highlight two potential challenges to applying existing methods for inferring social media user demographics to large-scale studies and during time-sensitive public health events (such as, infectious disease epidemics). The first is efficiency - defined here as the speed at which data may be collected, processed, and analyzed. The second is scalability - defined here as the feasibility of applying methods to very large datasets consisting of several hundreds of thousands or millions of users.

3.1 Scalability and Efficiency

Large quantities of Twitter metadata are required to apply many of the methods described in previous sections. Although having detailed user data – including data from users’ posts and friendship networks – can improve the performance of demographic classifiers, the collection, storage, and analyses of such data can be costly. For example, many of the studies reviewed in section two are text-dependent and rely on users’ posts – a strategy that Alowibdi et al. [51] described as “inefficient” and “not-scalable”. Additionally, Bergsma et al. [35] stated that while having information on Twitter users’ communication networks provide helpful details that amplify the predictive power of other profile indicators, this strategy is taxing on the Twitter API and may be unrealistic in some applications. For smaller studies, (i.e. sample sizes in the hundreds or thousands of users), these techniques might be relatively simple to implement. In contrast, those interested in broad topics such as US county-level exercise and wellbeing [102], may find these methods difficult or extremely time consuming to implement. Furthermore, researchers interested in studying time-sensitive phenomena – such as disease outbreaks [103] – may not have time to collect timeline or network data for all users within their data sample.

Challenges associated with scalability and efficiency may arise at several steps in the research process – including data collection, processing and analysis. For data collection, these issues may be linked to rate limits associated with the data collection tools. For example, Twitter’s public API which provides easy access to user metadata and tweets, includes measures designed to slow the collection of high volumes of data (see Table 1). Most calls to the Twitter API are limited to 180 calls per 15 minutes. This means that only 180 users’ metadata can be gathered within 15 minutes. The rate limit for user timelines is higher – 900 calls per 15 minutes – but each call may return only a portion of the timeline. To access data on users’ ties, one must first pull the IDs of friends and followers, and then link metadata to these IDs – a time-consuming, two-step process. Overall, though it may be appealing to include fine-grained, comprehensive, detailed information about the user, if the dataset contains tens of thousands or millions of users this process could take days, weeks or months. When studying time-sensitive health processes, this delay could be problematic.

In data processing, the challenge of scalability and efficiency could refer to the time and computing power needed to extract and organize information from these data. While the exact number of posts needed to produce quality predictions may vary from one study to another, some report collecting as many as 1000 tweets per user [58], which could lead to the generation of a very large dataset. For example, the study on vaccine sentiments by Salathé and Kandelwal used a sample of 101,853 twitter users. If we collected 1000 tweets per users, this would result in a dataset of over 100 million tweets. Extracting and interpreting features from these data – including breaking these data into unigrams or

identifying sociolinguistic indicators – an otherwise simple task – may become cumbersome when processing a dataset of this size.

Furthermore, text-dependent predictive models tend to be high-dimensional. Several of the models discussed in selected studies used unigrams as features, which present unique computational challenges. Burger et al. [30], for instance, developed a classifier that consists of 15.6 million features. These high-dimensional models not only require intense computational power to execute, but run the risk of overfitting.

Table 1. Scalability Illustrated: Gathering Data from Twitter

Feature	API Call	Calls per 15 Mins.	Data Returned
User Profiles	GET users/show GET users/lookup	180 1 user per call	Profile field data (user name, location, description, profile image, etc.) Profile aesthetic data (background color, banner image, etc.) Metadata for most recently posted tweet. Activity measures (location, status count, network counts)
User Timelines	GET statuses/user_timelines	900 32 tweets per call	Tweet text. Tweet sharing statistics. Metadata for tweet poster.
User Network	GET followers/ids GET friends/ids	15 1 user per call	ID values of friends ID values of followers

3.2 Efficient and Scalable Approaches to Demographic Prediction

A number of studies have attempted to identify user demographics without using computationally intense methods and metadata (Table 2). Some of these studies rely on detecting explicitly shared information (i.e. stating one’s age) or matching metadata to ground truth information. For example, Mislove et al. [84] inferred US-based Twitter users’ gender by matching first names to census data. Sloane et al. [104] determined user age by finding mentions or references to age within users’ profile descriptions (e.g. searching for phrases such as “years old”). Longley, Adnan and Lansley [86] proposed a process of parsing user names to extract embedded information on gender and ethnicity. The primary advantages of using a data matching approach is that it depends on simple, often easy to capture user information and allows researchers to categorize users with a high degree of certainty. However, this method excludes users who elect not to share directly identifiable information such as, real name or age. Longley and colleagues, for example, found that about 68% of users in their sample had an identifiable first and/or surname, and that only 47% of users were accurately classified as male or female using this metadata [86]. Though relying on this method may produce incomplete and biased data, researchers suggest that these techniques are effective for capturing a large swath of social media users.

For traits, such as race/ethnicity, the ground truth data matched to simple user metadata – such as names - may be overrepresented by a majority group. Some studies have proposed methods for overcoming this limitation. Chang et al. [99] and Mislove et al. [84] used Bayesian estimation to predict users’ ethnicity given: a.) racial/ethnic distribution of the website and b.) distribution of first and last names within each race/ethnicity as indicated by census data. Oktay, Firat and Ertem [97] built upon the work by Chang et al. [99] by expanding their methods to accommodate the detection of age.

There is also a small body of work that relies on text-independent machine learning techniques for classifying users. Using Naïve Bayes Decision Tree classification, Alowibdi, Buy and Yu [50], [51] utilized profile colors to detect user gender with 71% accuracy and phonemes/n-grams within user names to predict gender with 83% accuracy. Bergsma et al. [35] used location and name metadata to predict gender and race. Features in their model consisted of the presence or absence of location and name features, the n-gram length of these features, and a cluster ID value based on users’ names and communication. Though the presence of the cluster ID value improved their classifier, they obtained high accuracy for predicting gender (89.5), and race (82.4) without these features as well. Kosinski et al. [55] categorized users on Facebook according to what and who they “like.” Whereas this may be difficult to replicate in contexts such as Twitter, where “likes” may be analogous to “follows,” which requires the collection of network information, this strategy may be used within social media contexts structured similarly to Facebook. In contrast to supervised learning approaches, Vicente et al. [43] applied fuzzy c-means clustering to user names to predict user gender with up to 96% accuracy

Finally, work using automated facial detection [95], [96] and manual facial classification (e.g., employing workers on Amazon’s Mechanical Turk) [94] has provided promising estimates of Twitter users’ age, race and gender. While the scalability of crowdsourced methods is contingent upon the budget of the researcher, it nonetheless demonstrates efficiency as it requires only one piece of user metadata to process. Furthermore, additional work is needed to assess the ground truth accuracy of these methods.

There is obviously an imbalance in methods available to predict race/ethnicity and age versus gender. The latent factors that drive gender identity expression are strong and may manifest in a variety of ways, including seemingly peripheral factors such as profile color [51]. Whereas existing work has found a number of efficient and scalable gender-classification methods, the same cannot be said of race/ethnicity and age. As was described in section 2.2, the automated detection of age and race/ethnicity presents unique challenges. Racial identity is complex and may not match perceived race, and numeric age may be conflated with life stage [93]. Further exploration is needed to determine how these challenges can be overcome with less costly user metadata.

Table 2. Papers that Describe Scalable Approaches

Name	Characteristic detected	Method summary (short)	Metadata used	N
Sloan, L., et al. (2015) [104]	Age	Data detection	User descriptions	32K
Longley, P. A., et al. (2015) [86]	Age, Gender, Race/Ethnicity	Data matching	User names	230K
Zagheni, E., et al. (2014) [95] An and Weber (2016) [95]	Age, Gender, Race/Ethnicity	Facial evaluation (automated w/Face++)	Profile photos	345K
Chang, J., et al. (2010). [99]	Age, Race/Ethnicity	Bayesian estimation	User names	78K
Alowibdi, J. S., et al. (2013) [51] Alowibdi J. S., et al. (2013) [50]	Gender	Supervised classification (Naïve Bayes/Decision-Tree Hybrid).	Profile colors/User names	53K/180K
Mueller, J., & Stumme, G. (2016). [88]	Gender	Supervised classification (SVM algorithm with radial)	User names (not handles)	7K

Vicente, M., et al. (2015). [43]	Gender	Unsupervised classification (fuzzy c-means clustering)	User names	296K
Bergsma, S., et al. (2013). [35]	Gender, Race/Ethnicity	Supervised classification (SVM algorithm)	User location, user name	126M
Oktay, H., et al. (2014). [97]	Race/Ethnicity	Bayesian estimation	User names	100K
Kosinski, M., et al. (2013). [55]	Age/Gender	Supervised learning: OLS/logistic regression	User 'likes' on Facebook	58K

4. DISCUSSION

Researchers have sought to expand upon the use of social media data for research by developing methods for automated detection of key demographic features of users. This research is driven by the assumption that users leave behind clues regarding their offline identities – either implicitly or explicitly – and that it is possible to develop techniques to identify important demographic clues. This research has the potential to create opportunities to assess population representation and study disparities in social media data. Knowing key demographic information about users could, for instance, help researchers better understand gender, race or age-based inequality in information access or attitudes toward current events.

The existing approaches for demographics prediction have many advantages and caveats. Many simple methods have been shown to perform well in predicting age, gender and racial/ethnicity under certain assumptions. However, limitations exist in the adaptation of these methods to specific domains, e.g. public health, where studies might require large-scale datasets and may be time sensitive. The methods reviewed often emphasized the need to collect detailed user information to improve classifier performance without addressing issues in efficiency and scalability, which limits domain specific applicability.

4.1 Methodological Suggestions

First, we suggest that researchers develop an ensemble of methods appropriate for their data that draw on information-rich yet text-independent metadata. Second, methods that uncover and utilize latent identity attributes hidden within profile-specific metadata need further development. Profile metadata is rich and easy to access, and mining this resource may lead to the development of scalable predictive models. This is particularly needed for difficult to classify attributes such as race/ethnicity and age.

Additionally, we strongly recommend collaboration between computer scientists developing these tools and statisticians and domain specific, public health and social scientists who may use them to a.) ensure that methods used are appropriate for the data analyzed and b.) researchers understand how the data were generated and how this may impact the results of their research. For instance, particular demographic groups may be more or less likely to share specific types metadata. Social scientists may be consulted to better understand these biases.

We also encourage the development of open source tools aimed at demographic detection for large scale, time sensitive public health data. Those developing and improving methods for efficiently processing and extracting key demographic variables from social media data may consider making these tools available for other researchers to utilize and extend. The availability of such tools may help render data processing a more accessible, standardized and easily replicable process.

4.2 Privacy and Ethical Concerns

We acknowledge that there are privacy and ethical concerns associated with the use of social media data for research (noted in several publications [105]–[108]) and the development of tools for inferring user demographics. A major concern is the treatment of human subjects since research subjects no longer ‘participate’ in studies in a traditional sense [108]. This requires researchers to rethink how to implement standard ethical practices such as informed consent and anticipation of risks and harms. Currently, data ownership and within-site privacy guidelines help determine some research permissions. However, researchers should consider obtaining IRB approval for digital datasets [106], not linking social media data to other online information, and respecting the context – both cultural and situational [108] – in which the data were generated.

Ethical data use should also be considered in the publication and implementation of research results. As Boyd and Crawford [107] suggest, the practice and dissemination of Big Data research raises important questions about truth, power and control. Researchers may address these questions thoughtfully not only within the context of data collection and use, but in regard to study results and the relationship between these results and the perpetuation of inequality. It is important that researchers balance respect for privacy with research transparency and reproducibility, and ensure that findings are correct, reliable and interpretable for the public [105].

Given the breadth of ambiguity regarding the ethical use of social media data we urge researchers who use these data to closely follow the rapidly changing ethical landscape of social media data use, and to exercise beneficence when engaging in data use that does not fall neatly within existing institutional review board guidelines, or for which standard data management and analysis strategies do not exist.

5. CONCLUSION

The use of social media data offers unique, new opportunities to researchers interested in studying public health. Sites such as Twitter provide access to unsolicited attitudes on health topics and reports of health behaviors that are updated in real time. However, one limitation of these data is the usual lack of key demographic indicators – such as age, race and gender. Several studies have proposed methods for automated detection of these traits, but much of this work requires the collection of costly user metadata. The goal of this paper was to render this work more accessible to public health researchers interested in using large-scale and time-sensitive social media data by highlighting methods that do not rely on costly metadata and promote scalability and efficiency. The use of these methods could allow researchers to study demographic trends in health behaviors and attitudes toward topics of health or healthcare across broad geographic regions and within marginalized groups. Understanding these patterns could be of interest to researchers and policymakers interested in tracking diseases or understanding and alleviating health disparities – particularly in regard to poorly understood or stigmatized topics.

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APPENDIX

Table 1: Literature Reviewed				
Citation	Method	Metadata	Platform	Trait
Al Zamal, F., Liu, W., & Ruths, D. (2012). Homophily and Latent Attribute Inference: Inferring Latent Attributes of Twitter Users from Neighbors. In <i>Proceedings of the 6th International Conference on Weblogs and Social Media (ICWSM)</i> , 270.	Supervised learning : SVM classification	User tweets, neighbor tweets	Twitter	Age, Gender
Alowibdi, J. S., Buy, U. A., & Yu, P. (2013). Empirical Evaluation of Profile Characteristics for Gender Classification on Twitter. In <i>Proceedings of the 12th International Conference on Machine Learning and Applications (ICMLA 2013)</i> , 365–369. https://doi.org/10.1109/ICMLA.2013.74	Supervised learning: Naïve Bayes/Decision-Tree Hybrid (NB-Tree).	Profile colors, user name, user tweets	Twitter	Gender
An, J., & Weber, I. (2016). #greysanatomy vs. #yankees: Demographics and Hashtag Use on Twitter. In <i>Proceedings of the 10th International Conference on Weblogs and Social Media (ICWSM)</i> , 523–526.	Facial recognition: automated	Profile image, user descriptions	Twitter	Age (validated), Gender (validated), Race/ethnicity (not validated)
Argamon, S., Koppel, M., Pennebaker, J. W., & Schler, J. (2009). Automatically Profiling the Author of an Anonymous Text. <i>Communications of the ACM</i> , 52(2), 119–123. https://doi.org/10.1145/1461928.1461959	Supervised learning: Bayesian multinomial regression	User posts	Various blogging platforms	Age, Gender
Asoh, Hideki, Ikeda, Kazushi, & Ono, Chihiro. (2012). A Fast and Simple Method for Profiling a Population of Twitter Users. In <i>The Third International Workshop on Mining Ubiquitous and Social Environment</i> . Bristol, UK.	Adjusted data matching w/Bayesian estimation	User tweets	Twitter	Age (distribution), Gender
Bamman, D., Eisenstein, J., & Schnoebelen, T. (2014). Gender Identity and Lexical Variation in Social Media. <i>Journal of Sociolinguistics</i> , 18(2), 135–160. https://doi.org/10.1111/josl.12080/abstract	Supervised learning: expectation maximization framework	User tweets	Twitter	Gender
Benton, A., Raman, A., & Dredze, M. 2016. Learning Multiview Embeddings of Twitter Users. In <i>Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics</i> , Berlin, Germany, 14–19.	Supervised learning : SVM classification	User tweets, neighbor tweets	Twitter	Gender

Beretta, V., Maccagnola, D., Cribbin, T., & Messina, E. (2015). An Interactive Method for Inferring Demographic Attributes in Twitter. In Proceedings of the 26th ACM Conference on Hypertext & Social Media (HT '15), 113–122. https://doi.org/10.1145/2700171.2791031	Data matching/Supervised learning: SVM classification	User name, user tweets	Twitter	Age, Gender
Bergsma, S., Dredze, M., Van Durme, B., Wilson, T., & Yarowsky, D. (2013). Broadly Improving User Classification via Communication-Based Name and Location Clustering on Twitter. In Proceedings of the 2013 North American Chapter of the Association for Computational Linguistics: Human Language Technologies (HLT-Naacl), (June), 1010–1019.	Supervised learning: SVM classification	User location, user name,	Twitter	Gender, Race/Ethnicity
Burger, J. D., Henderson, J., Kim, G., & Zarrella, G. (2011). Discriminating Gender on Twitter. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, 1301–1309. https://doi.org/10.1007/s00256-005-0933-8	Supervised learning: Winnow	User tweets, user names, screen handles, user description	Twitter	Gender
Chang, J., Rosenn, I., Backstrom, L., & Marlow, C. (2010). epluribus: Ethnicity on Social networks. In <i>Proceedings of the Fourth International Conference on Weblogs and Social Media (ICWSM)</i> , 18–25.	Adjusted data matching w/Bayesian estimation	User names	Facebook	Race/Ethnicity
Chen, X., Wang, Y., Agichtein, E., & Wang, F. (2015). A comparative study of demographic attribute inference in twitter. In <i>Proceedings of the Ninth International Conference on Weblogs and Social Media (ICWSM)</i> , 590-593.	Supervised learning: SVM	User names, profile images, user descriptions, neighborhood info	Twitter	Gender, Race/Ethnicity
Culotta, A., Ravi, N. K., & Cutler, J. (2015). Predicting the Demographics of Twitter Users from Website Traffic Data. Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, 72–78.	Supervised learning: OLS regression	Following relationship	Twitter	Gender, Race/Ethnicity
Filippova, K. (2012). User Demographics and Language in an Implicit Social Network. In <i>Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning</i> , 1478–1488.	Supervised learning: Maximum entropy	Posts and social environment	YouTube	Gender
Fink, C., Kopecky, J., & Morawski, M. (2012). Inferring Gender from the Content of Tweets: A Region Specific Example. In <i>Proceedings of the 6th International Conference on Weblogs and Social Media (ICWSM)</i> , 459–462.	Supervised learning: SVM classification	User tweets	Twitter	Gender
Gadiya, M., & Jain, S. V. (2016). A Study on Gender Prediction using Online Social Images. <i>International Research Journal of Engineering and Technology</i> , 3(2), 1300–1307.	Supervised learning: SVM classification	Images	Pinterest	Gender
Goswami, S., Sarkar, S., & Rustagi, M. (2009). Stylometric Analysis of Bloggers' Age and Gender. In <i>Proceedings of the Third International Conference on Weblogs and Social Media (ICWSM)</i> , 214-2017.	Supervised learning: Naïve Bayes	User posts	Blogger	Age, Gender
Hofstra, B., Corten, S., Van Tubergen F., Ellison, N. (2016, April). “Segregation in Social Networks: A Novel Approach using Facebook.” Paper presented at the <i>International Sunbelt Social Network Conference (Sunbelt 2016)</i> , Newport Beach, CA.	Data matching /Supervised learning	User names	Facebook	Gender, Race/Ethnicity

Ikedo, D., Takamura, H., & Okumura, M. (2008). Semi-Supervised Learning for Blog Classification. In <i>Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence</i> , 1156–1161	Supervised learning: ASO algorithm	User posts	Blogs	Age, Gender
J. Alowibdi, U. Buy and P. Yu, "Language Independent Gender Classification on Twitter", In <i>Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM'13)</i> Niagara Falls, Canada, 2013	Supervised learning: Naïve Bayes/Decision-Tree Hybrid (NB-Tree).	Profile colors	Twitter	Gender
Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private Traits and Attributes are Predictable from Digital Records of Human Behavior. <i>Proceedings of the National Academy of Sciences of the United States of America</i> , 110(15), 5802–5. http://doi.org/10.1073/pnas.1218772110	Supervised learning: OLS/logistic regression	User 'likes' (could be translated to follows)	Facebook	Age, Gender
Liu, W., & Ruths, D. (2013). What's in a Name? Using First Names as Features for Gender Inference in Twitter. In <i>Analyzing Microtext: Papers from the 2013 AAAI Spring Symposium</i> , 10–16.	Supervised learning: SVM	User names, user tweets	Twitter	Gender
Longley, P. A., Adnan, M., & Lansley, G. (2015). The Geotemporal Demographics of Twitter Usage. <i>Environment and Planning A</i> , 47(2), 465–484. https://doi.org/10.1068/a130122p	Data matching	User names	Twitter	Gender, Ethnicity, Age
Ludu, P. S. (2014). Inferring gender of a Twitter user using celebrities it follows. arXiv Preprint arXiv:1405.6667. Retrieved from http://arxiv.org/abs/1405.6667	Supervised classification (SVM algorithm)	User tweets, User follows	Twitter	Gender
Mandel, B., Culotta, A., Boulahania, J., Stark, D., Lewis, B., & Rodrigue, J. (2012). A Demographic Analysis of Online Sentiment during Hurricane Irene. In <i>Proceedings of the Second Workshop on Language in Social Media (LSM 2012)</i> , 27-36.	Data matching	User names	Twitter	Gender
Marquardt, J., Farnadi, G., Vasudevan, G., Moens, M. F., Davalos, S., Teredesai, A., & De Cock, M. (2014). Age and Gender Identification in Social Media. In <i>Proceedings of CLEF 2014 Evaluation Labs</i> , 1129–1136.	Supervised learning: Logistic regression	Tweet content	Twitter	Gender, Age
McCormick, T. H., Lee, H., Cesare, N., Shojaie, A., & Spiro, E. S. (2015). Using Twitter for Demographic and Social Science Research: Tools for Data Collection and Processing. <i>Sociological Methods & Research</i> , 0049124115605339-. http://doi.org/10.1177/0049124115605339	Facial evaluation: Human	Profile photos	Twitter	Age, Gender, Race/Ethnicity
Mechti, S., Jaoua, M., & Belguith, L. H. (2014). Machine Learning for Classifying Authors of Anonymous Tweets, Blogs, Reviews and Social Media: <i>Notebook for PAN at CLEF 2014. CEUR Workshop Proceedings</i> , 1137–1142.	Decision table	User tweets	Twitter	Age/Gender
Miller, Z., Dickinson, B., & Hu, W. (2012). Gender Prediction on Twitter Using Stream Algorithms with N-Gram Character Features. <i>International Journal of Intelligence Science</i> , 2(24), 143–148. https://doi.org/10.4236/ijis.2012.224019	Supervised learning: Naïve Bayes and Perceptron	User tweets	Twitter	Gender

Mislove, A., Lehmann, S., & Ahn, Y. (2011). Understanding the Demographics of Twitter Users. In <i>Proceedings of the 5th International Conference on Weblogs and Social Media (ICWSM 11)</i> . Barcelona, Spain.	Data matching/Adjusted data matching w/Bayesian Estimation	User names, User location	Twitter	Gender, Race/Ethnicity
Mohammady, E., & Culotta, A. (2014). Using County Demographics to Infer Attributes of Twitter Users. In <i>ACL 2014 Joint Workshop on Social Dynamics and Personal Attributes in Social Media Proceedings of the Workshop Baltimore, Maryland, USA (pp. 7–17)</i> .	Supervised learning: OLS regression	User location, user tweets, User name	Twitter	Race/ethnicity
Mueller, J., & Stumme, G. (2016). Gender Inference using Statistical Name Characteristics in Twitter. <i>5th ASE International Conference on Social Informatics (SocInfo 2016)</i> , Union, NJ, USA, August 15-17, 2016. <i>Proceedings</i> , 47:1--47:8.	Supervised learning: SVM classification	User names (not handles)	Twitter	Gender
Mukherjee, A., & Liu, B. (2010). Improving Gender Classification of Blog Authors. In <i>Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing</i> , 207–217)	Supervised learning: SVM regression	User posts	A variety of blogging platforms	Gender
Nguyen, D., Gravel, R., Trieschnigg, D., & Meder, T. (2013). “How old do You Think I Am?”: A Study of Language and Age in Twitter. <i>Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media</i> , Cambridge, Massachusetts, USA, 439–448.	Supervised learning: OLS and logistic regression	User tweets	Twitter	Age (category, numeric, life stage)
Nguyen, D., Gravel, R., Trieschnigg, D., & Meder, T. (2013). TweetGenie: Automatic Age Prediction from Tweets. <i>ACM SIGWEB Newsletter</i> , 1–6. https://doi.org/10.1145/2528272.2528276	Supervised learning: Logistic regression	User tweets	Twitter	Age
Nguyen, D., Smith, N., & Rosé, C. (2011). Author Age Prediction from Text using Linear Regression. In <i>Proceedings of the 5th ACL-HLT Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities</i> , 115–123.	Supervised learning: OLS regression	User posts	blogger/online breast cancer forums	Age
Nguyen, T., Phung, D., Adams, B., & Venkatesh, S. (2011). Prediction of age, sentiment, and connectivity from social media text. In <i>International Conference on Web Information Systems Engineering (pp. 227–240)</i> . Springer. Retrieved from http://link.springer.com/10.1007%2F978-3-642-24434-6_17	Supervised learning: Logistic regression	User posts	Livejournal	Age
Nowson, S., & Oberlander, J. (2006). The Identity of Bloggers: Openness and Gender in Personal Weblogs. In <i>AAAI Spring Symposium: Computational approaches to analyzing weblogs</i> , 163–167.	Supervised learning: SVM classification	User posts	Blogs	Gender
Oktay, H., Firat, a., & Ertem, Z. (2014). Demographic breakdown of Twitter users: An analysis based on names. In <i>Proceedings of the ASE BIGDATA/SOCIALCOM/CYBERSECURITY Conference</i> , 1–11.	Adjusted data matching w/Bayesian estimation	User names	Twitter	Age, Race/Ethnicity

Peersman, C., Daelemans, W., & Van Vaerenbergh, L. (2011). Predicting age and gender in online social networks. In <i>Proceedings of the International Conference on Information and Knowledge Management</i> , 37–44. https://doi.org/10.1145/2065023.2065035	Supervised learning: SVM classification	User posts	Netlog (Belgian social networking site)	Age, Gender
Pennacchiotti, M. (2011). Democrats, Republicans and Starbucks Aficionados: User Classification in Twitter. In <i>Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining</i> , 430–438. https://doi.org/10.1145/2020408.2020477	Supervised learning: Gradient Boosted Decision Trees	Name, location, description, user tweets	Twitter	Race/Ethnicity
Pennacchiotti, M., & Popescu, A. (2011). A Machine Learning Approach to Twitter User Classification. In <i>Proceedings of the Fifth International AAI Conference on Weblogs and Social Media</i> , 281–288.	Supervised learning: Gradient Boosted Decision Trees	User name, profile photo, friends/followers, date of creation, user tweets	Twitter	Race/Ethnicity
Rao, D., Paul, M. J., Fink, C., Yarowsky, D., Oates, T., & Coppersmith, G. (2011). Hierarchical Bayesian Models for Latent Attribute Detection in Social Media. In <i>Proceedings of the Fifth International Conference on Weblogs and Social Media (ICWSM)</i> , 598–601.	Semi-supervised classification (Hierarchical Bayesian models)	User posts, user names	Facebook	Gender/Ethnicity
Rao, D., Yarowsky, D., Shreevats, A., & Gupta, M. (2010). Classifying latent user attributes in Twitter. <i>Proceedings of the 2nd International Workshop on Search and Mining User-Generated Contents</i> , 37–44. http://doi.org/10.1145/1871985.1871993	Supervised learning: SVM classification	User tweets	Twitter	Gender
Reddy, S., Wellesley, M. A., Knight, K., & Marina del Rey, C. A. (2016). Obfuscating gender in social media writing. In <i>Proceedings of the 1st Workshop on Natural Language Processing and Computational Social Science</i> (pp. 17–26). Retrieved from http://www.aclweb.org/anthology/W/W16/W16-56.pdf#page=29	Supervised learning: Logistic regression	User posts	Twitter/Yelp	Gender
Rosenthal, S., & McKeown, K. (2011). Age prediction in blogs: A study of style, content, and online behavior in pre-and post-social media generations. <i>Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1</i> , 763–772.	Supervised learning: Logistic regression	Post content and network info	Livejournal	Age
Rustagi, M., Prasath, R. R., Goswami, S., & Sarkar, S. (2009). Learning Age and Gender of Blogger from Stylistic Variation. In <i>Pattern Recognition and Machine Intelligence</i> (pp. 205–212). Springer, Berlin, Heidelberg.	Supervised learning: Naïve Bayes	User posts	A variety of blogging platforms	Age, Gender
Santosh, K., Joshi, A., Gupta, M., & Varma, V. (2014). Exploiting Wikipedia Categorization for Predicting Age and Gender of Blog Authors. In <i>Proceedings of the UMAP 2014 Posters, Demonstrations and Late-Breaking Results</i> , 33-36.	Supervised learning: K-nearest neighbors and SVM	User posts	Undisclosed blog	Age, Gender
Sap, Maarten, Eichstaedt, Johannes, Kern, Margaret L., Stillwell, David, Kosinski, Michal, Ungar, Lyle H., & Schwartz, H. Andrew. (2014). Developing Age and Gender Predictive Lexica over Social Media. In <i>Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)</i> , 1146–1151.	Supervised learning: SVM, OLS regression	User posts	Facebook/ Twitter/Blogs	Age, Gender

Schler, J., Koppel, M., Argamon, S., & Pennebaker, J. W. (2006). Effects of Age and Gender on Blogging. In <i>AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs</i> , 199–205.	Supervised learning (multi-class real winnow)	User posts	Blogs	Age, Gender
Siswanto, E., & Khodra, M. L. (2013). Predicting Latent Attributes of Twitter User by Employing Lexical Features. In <i>Proceedings of the 2013 International Conference on Information Technology and Electrical Engineering (ICITEE)</i> , 176–180. https://doi.org/10.1109/ICITEED.2013.6676234	Supervised learning: SVM classification	User name, user tweet	Twitter	Age
Sloan, L., Morgan, J., Burnap, P., & Williams, M. (2015). Who tweets? deriving the demographic characteristics of age, occupation and social class from twitter user meta-data. <i>PLoS ONE</i> , 10(3), 1–20.	Data matching	User descriptions	Twitter	Age
Sloan, L., Morgan, J., Housley, W., Williams, M., Edwards, A., & Burnap, P. (2013). Knowing the Tweeters Deriving Sociologically Relevant Demographics from Twitter. <i>Sociological Research Online</i> , 18(3).	Data matching	User names, user tweets, user locations	Twitter	Gender
Smith, J. (2014). Gender Prediction in Social Media. arXiv Preprint. Retrieved from http://arxiv.org/abs/1407.2147	Data matching	User name	Fotolog	Gender
Tuli, G. (2015). Modeling and Twitter-based Surveillance of Smoking Contagion. Virginia Polytechnic Institute and State University. Unpublished Dissertation. Retrieved from https://vtechworks.lib.vt.edu/handle/10919/64426	Supervised learning: SVM classification	User tweets	Twitter	Age (above/under 18)
Vicente, M., Batista, F., & Carvalho, J. P. (2015). Twitter Gender Classification Using User Unstructured Information. In <i>Proceedings of the IEEE International Conference on Fuzzy Systems</i> , 1-7	Unsupervised learning: fuzzy c-means clustering	User names	Twitter	Gender
Volkova, S., Bachrach, Y., Armstrong, M., & Sharma, V. (2015). Inferring Latent User Properties from Texts Published in Social Media. In <i>Proceedings of the Twenty-Ninth Conference on Artificial Intelligence (AAAI)</i> , 4296–4297.	Supervised learning: log-linear regression	User tweets	Twitter	Age, Gender, Race/ethnicity
Wang, Y., Xiao, Y., Ma, C., & Xiao, Z. (2016). Improving Users' Demographic Prediction via the Videos They Talk About. In <i>Proc. of the Conference on Empirical Methods in Natural Language Processing (EMNLP16)</i> , 1359-1368.	Bayesian estimation	Keyword mentions	Weibo (Chinese platform similar to Twitter)	Gender, Age
Zagheni, E., Garimella, V. R. K., Ingmar, W., & State, B. (2014). Inferring International and Internal Migration Patterns from Twitter Data. In <i>Proceedings of the 23rd International Conference on World Wide Web</i> , 1-6	Facial evaluation: automated	Profile photos	Twitter	Age, Gender
Zhang, C., & Zhang, P. (2010). Predicting Gender from Blog Posts. Technical Report. University of Massachusetts Amherst, USA.	Supervised learning: SVM	User posts	A variety of blogging platforms	Gender