Automatically Infer Human Traits and Behavior from Social Media Data

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Abstract
Given the complexity of human minds and their behavioral flexibility, it requires sophisticated data analysis to sift through a large amount of human behavioral evidence to model human minds and to predict human behavior. People currently spend a significant amount of time on social media such as Twitter and Facebook. Thus, many aspects of their lives and behaviors have been digitally captured and continuously archived on these platforms. This makes social media a great source of large, rich, and diverse human behavioral evidence. In this paper, we survey the recent work on applying machine learning to infer human traits and behavior from social media data. We will also point out several future research directions.

1 Introduction
People currently spend a significant amount of time on social media to express opinions, interact with friends and families, share ideas and thoughts, provide status updates and organize/participate in events and activities. According to Nielsen’s 2016 Social Media report, on average, Gen X (ages 35-49) spent 6 hours and 58 minutes and Millennials (ages 18-34) spent 6 hours and 19 minutes per week on social media in the US. As a result, many aspects of their lives have been digitally captured and continuously archived on social media.

With recent advent of big data analytics and the availability of a large amount of user-generated content, data-driven human trait and behavioral analysis has increasingly been used to better understand human minds and predict human behavior. Prior research has demonstrated that by analyzing the information in a user’s social media account, we can infer many latent user attributes such as political leaning [Pennacchiotti and Popescu, O’Banion and Birnbaum, Kosinski et al., Benton et al.], brand preferences [Pennacchiotti and Popescu, Yang et al.,], emotions [Kosinski et al.,], mental disorders [De Choudhury et al., Vedula and Parthasarathy], personality [Kosinski et al., Schwartz et al., Liu et al.], substance use [Kosinski et al., Ding et al.], and sexual orientation [Kosinski et al.,]. In addition, understanding individual traits and behavior has numerous real life applications including public health [Giota and Kleftaras, 2013], marketing [Yang et al.,] and politics [Chirumbolo and Leone].

We believe user generated data on social media is ideal for data-driven user trait and behavior analysis due to its unique characteristics: (1) large scale: it includes behaviors of a large number of social media users (e.g., millions); (2) comprehensive: it contains a large number of behavioral markers from diverse sources (e.g., text posts, image posts, likes, and friendship); (3) longitudinal: it follows behaviors of social media users continuously over a long period of time (e.g., years); (4) objective: the analysis is based on the natural behavioral data automatically, continuously and objectively collected in an open environment.

In this survey, we summarize the recent advances in automated human traits and behavior inference from social media data. We included 24 studies published as full-length papers at one of the top AI, data mining, social media and multidisciplinary behavior conferences and journals in the last ten years. We focus on papers that employ machine learning techniques to automatically infer or predict latent attributes or behaviors of individuals from public social media data.

2 Overview of Studies
Table I lists the 24 papers included in our survey. For each paper, we summarize information related to the dataset such as the “Platform” from which the social media data were collected (e.g., Twitter, Facebook, Reddit, Instagram and Quora) and “Size”, which is the number of people with ground truth labels in the dataset. In addition, we also lists “Source Data Type”, to indicate the different types of social media data used in the study. Here, text refers to user-generated text data that include user posts (e.g., tweets or status update on Facebook), profile description, and comments; like refers to things a social media user likes such as books, people, music, movies, TV shows, photos and products; user profile includes demographic information (gender, age, occupation, relationship status etc.) and aggregated statistics of a user account (the number of friends, followers, followings etc.); posting activity which includes a set of statistics describing a user’s posting behavior on social media such as the total number of tweets/retweets, the average number of posts per day, the number of likes/replies for each post; image which includes the profile and background photos and also the image posts shared on social media; social network which refers to social
connections between different user accounts such as friendship networks on Facebook and follower/following relations on Twitter.

Although social media provide us an opportunity to easily track a large number of heterogeneous user behavioral data, the characteristics of social media data also bring significant challenges to data analysis. For example, the text and images are unstructured data. Making sense out of unstructured data is always a big challenge. User likes is very sparse and high dimensional. For example, the likes data in [Ding et al.,] includes 10 millions unique like dimensions. It is also not easy to search and analyze a large social network graph efficiently.

Finally, “Predicted Target” in Table 1 describes the predicted individual characteristics. We categorize them into either explicit user characteristics or latent user characteristics. 

Explicit User Characteristics refer to observable user attributes that can be easily collected from a social media platform. The most common explicit user characteristics include demographics (e.g., age, gender, race etc.), and user preferences (e.g., likes). Latent User Characteristics refer to user attributes that cannot be observed easily, and thus need to be assessed by more sophisticated psychometric evaluations. Typical latent user characteristics include personality, human values, depression and addiction. Since typical psychometric tests include dozens or even hundreds of questions (e.g., to assess detailed personality, the IPIP-300 test has 300 questions), it is often difficult to collect the ground truth to assess latent user characteristics at a large scale.
In summary, as shown in Table 1, Twitter is the most common social media platform used in these studies. This is mainly due to the relative ease of accessing user data on Twitter using its APIs. In terms of the type of user data involved in these studies, text (e.g., tweets or status updates on Facebook) is most common, followed by likes and social networks. Since different types of user data require different analysis techniques (e.g., using graph analytics for social networks and natural language processing for text data), user data type will have significant impact on the machine learning algorithms employed. The size of the datasets varies significantly from as many as 100K people to as few as 383.

In general, user attributes declared directly on social media (e.g., topic engagement on Twitter) can be obtained relatively easily at a large scale. In contrast, for user traits/behavior that require sophisticated psychometric evaluation (e.g., depression), their ground truth datasets tend to be smaller. Finally, the predicted user characteristics are quite diverse, ranging from demographics (e.g., age, gender, race, income and occupation), latent user traits (e.g., personality and values), mental disorders (e.g., addiction and depression) and online or real world behaviors (e.g., purchase behavior and cyberbullying).

In the following, we summarize the typical data analysis methods that are used to infer individual characteristics from social media data.

3 Inference Methods

Figure 1 shows the typical architecture of such a system. One or more types of user-generated data are extracted from a social media account. For each type of user data such as text or image, a set of features are extracted (we call this “single-view feature extraction/learning”). The features from each view are then combined together to form a single user representation (we call this “multiview feature learning”). Finally, the combined user features are used to predict various human traits and behaviors using typical machine learning methods such as SVM classification or linear/logistic regression.

There are three main challenges when inferring user traits and behavior from social media data: (1) small labeled training datasets since the ground truth human trait and behavior data are hard to collect at a large scale. (2) unstructured and high dimensional user data. For example, there could be millions of unigram and bigram features to represent the texts from a user. (3) heterogeneous user data. Frequently we need to combine user data from different modality (e.g., text and images) and types (e.g., structured and unstructured) to paint a complete picture of a user.

Based on how these challenges are addressed, we categorize the studies in our survey along three dimensions. As shown in Table 1, first, we categorize them based on whether they employ a separate unsupervised feature learning stage to take advantage of a large amount of unsupervised data (2-stage) or they simply use labeled data directly in supervised feature extraction and prediction (1-stage). In general, when the labeled ground truth dataset is small, unsupervised feature learning can boost a system’s performance significantly. To address the second challenge and avoid the “curse of dimensionality” problem, we categorize these systems based on how they extract, select and learn a small number of features from unstructured data (e.g., text and image). The features can be (a) “human engineered” where existing domain/linguistic knowledge is used to construct and select a small number of features or (b) constructed via “supervised selection”, which refers to systems that select relevant features based on their correlations with the ground truth; or (c) constructed via “unsupervised feature learning”, which refers to systems that automatically learn a small number latent features based on unlabeled social media data. In terms of the third challenge, we categorize these studies based on how they combine features from different views together. If they simply concatenate features from different views together, we label them as “concatenate”. If they employ machine learning to fuse information from different views together, we label them as “fusion”. We also list different machine learning algorithms employed for user traits and behavior prediction.

Since feature extraction, unsupervised feature learning and multiview fusion play important roles in developing such a system, in the following, we describe each topic in detail.

3.1 Basic Feature Extraction

Basic Feature extraction is often the first step that maps the information in one’s social media account into a meaningful and easy to manipulate feature representation. Here, we focus on extracting features from text and images since they are unstructured information and thus more difficult to represent. We will also briefly discuss how to extract features from social networks.

The most commonly used text features are unigrams [O’Banion and Birnbaum, b] and the LIWC (Linguistic Inquiry and Word Count) features. A unigram is the term frequency computed for each vocab-
| Paper                        | Stage   | Dimension Reduction   | Fusion          | Prediction Method                   |
|------------------------------|---------|-----------------------|-----------------|------------------------------------|
| Pennacchiotti and Popescu,   | 2-stage | human engineered      | concatenation   | Decision Trees                     |
| Yang et al., b               | 1-stage | human engineered      | NA              | SVM                                |
| De Choudhury et al.,         | 2-stage | human engineered      | concatenation   | SVM                                |
| Zhang and Pennacchiotti,     | 2-stage | human engineered      | concatenation   | SVM, Naive Bayes Logistic regression|
| O’Banion and Birnbaum,       | 1-stage | human engineered      | concatenation   | SVM                                |
| Kosinski et al.,             | 2-stage | human engineered      | NA              | Logistical/Linear regression        |
| Schwartz et al.,             | 2-stage | unsupervised learning | concatenation   | SVM, Linear regression              |
| Chen et al.,                 | 1-stage | human engineered      | NA              | Logistic regression                 |
| Gao et al., 2014             | 1-stage | supervised selection  | NA              | Lasso regression Least squares regression|
| Wu et al.,                   | 1-stage | human engineered      | NA              | Lasso regression                    |
| Yang et al., a               | 1-stage | human engineered      | NA              | SVM                                |
| Preotiuc-Pietro et al., a    | 2-stage | human engineered      | concatenation   | Gaussian Processes                 |
| Lee et al.,                  |         | human engineered      | concatenation   | SVM, Random Forest                  |
| Shen et al.,                 | 1-stage | human engineered      | concatenation   | Naive Bayes Adaboost Logistic regression|
| Bhargava et al., 2015        | 1-stage | human engineered      | NA              | Hierarchical clustering             |
| Song et al., b               | 2-stage | unsupervised learning | fusion          | SVM, Least squares regression Multi-view multi-task learning|
| Hu et al.,                   | 2-stage | human engineered      | NA              | SVM                                |
| Song et al., a               | 2-stage | unsupervised learning | fusion          | SVM, Decision Trees Random Forest Graph-based Learning|
| Liu et al.,                  | 1-stage | human engineered      | NA              | Linear Regression                   |
| Benton et al.,               | 2-stage | human engineered      | fusion          | SVM, Multi-task learning            |
| Ding et al.,                 | 2-stage | unsupervised learning | fusion          | SVM                                |
| Vedula and Parthasarathy,    | 1-stage | human engineered      | concatenation   | Decision Trees                      |
| Preotiuc-Pietro et al., b    | 2-stage | human engineered      | concatenation   | Logistic regression                 |
| Singh et al.,                | 1-stage | human engineered      | concatenation   | Bagging classifier                  |

Table 2: Summary of Analysis Methods

A word in a text corpus (e.g., a corpus of all the Facebook posts). Sometimes, unigrams can be weighted based on their informativeness (e.g., based on Inverse Document Frequency or IDF [Benton et al.]). Since robust inference often requires repeated word occurrence, low-frequency words are frequently filtered out. In addition to individual words, meaningful phrases can be extracted by keeping only ngrams (e.g., bigrams) with high point-wise mutual information (PMI) [Schwartz et al., Hu et al.].

LIWC features are human engineered features that are
constructed based on the psycholinguistic dictionary LIWC. It groups words into psychologically meaningful categories. Empirical results have confirmed that LIWC features are capable of detecting meaning and providing a broader range of social and psychological insights such as feelings, personality, values and motivations. LIWC includes 81 features in five categories such as psychological Processes (e.g., emotional, cognitive, sensory, and social processes), Relativity (e.g., words about time, the past, the future), Personal Concerns (e.g., occupation, financial issues, health), and other dimensions (e.g., punctuation and swear words). LIWC also includes writing style features such as word complexity (e.g., words with more than 6 characters). Many of the systems in our survey used LIWC features [Pennacchiotti and Popescu, 2010; Preotcu-Pietro et al., b].

Sometimes, customized vocabulary is used to extract informative words related to a prediction task. For example, [Preotcu-Pietro et al., b] defined 12,000 political terms in order to select informative unigrams pertaining to politics.

The image data such as profile pictures and photo posts, may contain rich information about individual characteristics. Each image is often represented as a vector of pixels, each pixel is represented by a number (in black and white photos) or three numbers using the RGB color scheme. In addition to the raw image features, meaningful high-level features such as color, facial expressions and postures can be extracted from images [Liu et al.,], which are then correlated with a user’s traits and behavior. Besides general image features, [Singh et al.,] extracts demographics and a taxonomy-based object categories (presence of tattoos, graffiti, drug) from Instagram images to facilitate the detection of cyberbullying.

Egocentric social network features are frequently used to characterize the social relations of a user [De Choudhury et al.,; Hong et al.,; Benton et al.,; Vedula and Parthasarathy,; Singh et al.,]. An egocentric network is defined as a network containing a single actor (ego), all the actors that an ego is connected to (alters), and all the links between the alters. For each ego, a set of network features are frequently extracted such as network size, betweenness centrality, normalized ego betweenness, cluster coefficient and normalized brokerage. We may also compute measures to assess network homophily such as average age difference between the ego and the alters.

3.2 Unsupervised Single View Feature Learning

Although the ground truth user traits and behavior data are costly to collect at a large scale, it is relatively easy to obtain a large amount of unlabeled user data from social media. The unsupervised feature learning algorithms are used to discover latent features from unlabeled social media data. Here we review typical unsupervised feature learning algorithms.

**Singular Value Decomposition (SVD)** is a mathematical technique that is frequently used for dimension reduction [De Lathauwer et al.,]. Given any $m \times n$ matrix $A$, the algorithm will find matrices $U$, $V$ and $W$ such that $A = U W V^T$. Here $U$ is an orthonormal $m \times n$ matrix, $W$ is a diagonal $n \times n$ metric and $V$ is an orthonormal $n \times n$ matrix. Dimensionality reduction is done by computing $R = U * W$, where $W_r$ neglects all but the $r$ largest singular values in the diagonal matrix $W$.

**Principal Component Analysis (PCA)** is a popular dimensionality reduction mechanism used to eliminate highly correlated variables. PCA can be implemented using SVD. SVD and PCA have been used to learn a low-dimension representation from a bag-of-word representation of social media posts [Benton et al.,; Ding et al.,;], likes [Kosinski et al.,; Ding et al.,;], and social networks [Benton et al.,;].

**Latent Dirichlet Allocation (LDA)** is a generative graphical model that allows sets of observations to be explained by unobserved latent groups [Blei et al.,]. In natural language processing, LDA is frequently used to learn a set of topics from a large number of documents. The topics are distributions of words that are frequently interpretable. In [Schwartz et al.,; Ding et al.,;], LDA is employed to learn topics from a user’s social media posts.

**GloVe** is an unsupervised learning algorithm originally designed to learn vector representations of words based on aggregated global word-word co-occurrence statistics from a text corpus [Pennington et al.,]. GloVe employs a global log bilinear regression model that combines the advantages of global matrix factorization with that of local context window-based methods. GloVe has been applied to Facebook status updates [Preotcu-Pietro et al., 2015; Ding et al.,;] and likes [Ding et al.,] to learn a dense feature vector for each word/like. To summarize all the words or likes from a user, we can use a vector aggregation functions such as average.

Recently, there is a new generation of neural network-based feature learning methods that employs self-taught learning to automatically derive a feature representation from examples automatically constructed from a large amount of unlabeled social media data.

**Autoencoder (AE)** is a neural network-based feature learning method [Hinton and Salakhutdinov,]. It learns an identity function so that the output is as close to the input as possible. Although an identity function seems a trivial function to learn, by placing additional constraints (e.g., to make the number of neurons in the hidden layer much smaller than that of the input), we can still force the system to uncover latent structures in the data.

**Word Embedding with Word2Vec** is a neural network-based method originally designed to learn dense vector representations for words [Mikolov et al.,]. The intuition behind the model is the Distributional Hypothesis, which states words that appear in the same context have similar meanings. There are two models for training a representation of word: continuous bag of word (CBOW) and skipgram (SG) model. CBOW predicts target word from one or more context words, while SG predicts one or more context words from target word. The models are frequently trained using either a hierarchical softmax function (HS) or negative sampling (NS) [Mikolov et al.,]. To process social media posts, the word2vec model is applied to learn a vector representation of each word. Then a simple average of all the word vectors by the same user is used to represent all the posts of a user [Benton et al.,; Ding et al.,;]. In addition, word embeddings can be used to produce word clusters [Preotcu-Pietro et al., a; Preotcu-Pietro et al., b] and domain lexicons (e.g., depres-
3.3 Multi-view Feature Fusion

To obtain a single, comprehensive and coherent user representation based on all the social media data available, we need to combine user features from different views together. In addition to simply concatenating features extracted from different views, we can also apply machine learning algorithms to systematically fuse them together. We categorize these fusion methods into two types: (a) unsupervised feature learning that doesn’t require any supervised data and (b) supervised multi-task learning.

There are two types unsupervised learning algorithms for multiview feature fusion: (1) Canonical Correlation Analysis and (2) Deep Canonical Correlation Analysis.

Canonical Correlation Analysis (CCA) CCA is a statistical method that explores the relationships between two multivariate sets of variables (vectors). Given two feature vectors, CCA tries to find a linear transformation of each feature vector so that they are maximally correlated. CCA has been used in [Sargin et al., Chaudhuri et al., Kumar and Daumé, Sharma et al., Ding et al.].

Deep Canonical Correlation Analysis (DCCA) DCCA aims to learn highly correlated deep architectures, which can be a non-linear extension of CCA [Andrew et al.]. The intuition is to find a maximally correlated representation of two feature vectors by passing them through multiple stacked layers of nonlinear transformation [Andrew et al.]. Typically, there are three steps to train DCCA: (1) using a denoising autoencoder to pretrain each single view. (2) computing the gradient of the correlation of top-level representation. (3) tuning parameters using back propagation to optimize the total correlation.

The features learned from multiple views are often more informative than those from a single view. Comparing with single-view user feature extraction and learning, multi-view learning achieved significantly better performance in predicting demographics [Benton et al.], political leaning [Benton et al.], and substance use [Ding et al.].

Multi-task learning (MTL) is a supervised learning method to combine multi-view user data together. It tries to jointly train multiple prediction tasks at the same time to exploit the commonalities and differences across tasks. In [Song et al.,], the authors collected multi-view user data from different platforms (e.g., Twitter, Facebook, LinkedIn accounts of the same user) and predict volunteerism from two tasks: user-centric analysis and network-centric analysis. Finally, they linearly fused these two components to enhance the final prediction.

4 Discussion and Future Directions

Large-scale social media-based user trait and behavior analysis is an emerging multidisciplinary field with the potential to transform human trait and behavior analysis from controlled small scale experiments to large scale studies of natural human behavior in an open environment. This provides us a new opportunity to explore the interactions of a large number of individual, social and environmental factors simultaneously, which would not be possible with traditional methods that use small samples. The insight gained from these studies could be valuable to help better understand the human minds and decision-making process. It will also provide empirical evidence to help public health providers and policy makers to improve mental health care and to combat public health threats (e.g., addiction and obesity). Due to the privacy concerns on accessing user data on social media and the sensitive nature of the inferred user characteristics, if not careful, there could be significant privacy consequences and ethical implications. So far, most of the studies in our survey focused primarily on technical contributions. There should be more discussions on ethical considerations when conducting research in this field.

There are also several promising directions for future research. Since individual traits and behavior are highly correlated, building a prediction model that simultaneously infer multiple correlated traits and behavior should yield better performance than predicting each trait/behavior separately. Most existing studies only predict one user attribute/behavior at a time. More research should be conducted to jointly train and predict multiple user attributes together for better performance.

It is also common for a user to have multiple accounts on different social media platforms. Recently, new technologies have been developed to link different social media accounts of the same user together [Abel et al.]. With this linked data, it is possible to perform novel cross-platform user trait and behavior analysis such as (1) domain bias analysis that focuses on studying the impact of domain or social media platform on user trait and behavior prediction, (2) domain adaptation that addresses how to adjust prediction models trained on one platform (e.g., Twitter) to predict the traits and behavior on another platform (e.g., Facebook). So far, there is some initial work on domain bias analysis and correction in personality prediction [Kiliç and Pan,]. More research is needed in order to develop more robust tools for human trait and behavior analysis.
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