Sensing *Subjective Well-being* from Social Media

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**Abstract.** Subjective Well-being (SWB), which refers to how people experience the quality of their lives, is of great use to public policy-makers as well as economic, sociological research, etc. Traditionally, the measurement of SWB relies on time-consuming and costly self-report questionnaires. Nowadays, people are motivated to share their experiences and feelings on social media, so we propose to sense SWB from the vast user generated data on social media. By utilizing 1785 users’ social media data with SWB labels, we train machine learning models that are able to “sense” individual SWB from users’ social media. Our model, which attains the state-by-art prediction accuracy, can then be used to identify SWB of large population of social media users in time with very low cost.

**Keywords:** Subjective Well-being, Social Media, Machine Learning

The last decade has witnessed the explosion of social media, on which users generate huge volume of content every day. Because of its richness and availability, a lot of innovative research has been conducted on large scale social media data to discover patterns in sociology, economics, psychology etc., which provides a brand new way for conventional social science research. Studies have shown that, people’s personal traits and psychological features, such as gender, sexual orientation, personality, Intelligence Quotient and so on, can be automatically predicted through clues on social media, such as behavioral [1,2] and linguistic [3] patterns.

People pursue “good life” from ancient time to now, and the Quality of Life (QoL) is influenced by objective factors like income, jobs, health, environment, which can be measured directly with objective indicators like GDP or PM2.5. However, these objective factors cannot determine one’s QoL. The key indicator of QoL, is Subjective Well Being (SWB), encompassing emotional well-being and positive functioning [4], which refers to how people experience the quality of their lives and includes both emotional reactions and cognitive judgments.

Reliable and timely information of SWB, provides important intellectual opportunities to research scientists and policy-makers. By analyzing large population data, it will be possible to identify the trend of SWB within different

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3 Atmospheric Particulate Matter with diameter of 2.5 micrometers or less, which is an indicator of air pollution.
groups, and figure out why some people are happy and others are not. Many governments and organizations, such as U.S.A, France, OECD (Organization for Economic Co-operation and Development) etc., have been funding surveys and research to collect people’s SWB data regularly in order to support efficient decision making and furthermore improve people’s well-being.

Self-report survey is the conventional method which has been widely used to assess SWB. However, questionnaire surveys, no matter in the form of paper-and-pencil, on-line etc., are costly and time consuming. What’s more, due to stereotype and social desirability, participants may not provide accurate, honest answers since survey is conducted in an intrusive manner – asking questions to subjects. Besides, it is a big challenge to conduct questionnaire based surveys in large scale or carry out longitudinal study.

Recent studies focus on the prediction of psychological variables, and the predicting models are established by analyzing the features and patterns of social media users’ profiles, posts, likes, friends etc. Such methods have been applied to the prediction of personality, depression, etc. SWB prediction also attracts researchers’ attention, while current works on SWB prediction are limited to prediction of groups other than individuals. Some of these work even require costly census data like “income median”. Therefore, our goal in this work is to establish efficient SWB prediction model based on social media data, which is applicable for individuals.

1 Related Work

SWB and its Assessment

Different from mere sentiment or simply happiness – spontaneous reflections of immediate experience, SWB is a measurement of individual’s cognitive and affective evaluations of one’s own life experience. The structure of SWB we used in this paper, as listed in Table 1, is composed of emotional well-being and positive functioning. Emotional well-being represents a long-term assessment towards one’s life, which consists of two dimensions. Positive functioning includes multidimensional structure of psychological and social well-being, and psychological well-being encompasses six dimensions focusing on individual level.

Watson, Ryff et al., developed positive and negative affective scale (PANAS) and psychological well-being scale (PWBS), which are correspondent to emotional well-being and positive functioning respectively. The reliability and validity of PANAS and PWBS have been validated in long-term practices by numerous psychological studies. In this paper, we use these two scales for SWB assessment.

Affect and Life Satisfaction Metric on Social Media

Affect and Life Satisfaction (LS) reflect “happiness”, hence recent studies have investigated large scale social media data to metric people’s affect or LS. Quite a lot studies use LIWC (Linguistic Inquiry and Word Count), fruit carefully constructed over two decades of human research, or other similar psychological language analysis tool, to quantify psychological expression on social media. Representative works, like hedonometer (happiness indicator) through
Table 1. Dimensions of Subjective Well-being and their description.

| Dimension       | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Emotional       |                                                                             |
| well-being      |                                                                             |
| Positive        | P.A. Experience symptoms that suggest enthusiasm, joy, and happiness for life.|
| Affect          |                                                                             |
| Negative        | N.A. Experience symptoms that suggest that life is undesirable and unpleasant.|
| Affect          |                                                                             |
| Positive        |                                                                             |
| functioning     |                                                                             |
| Self            | S.A. Possess positive attitude toward the self; acknowledge and accept        |
| Acceptance      | multiple aspects of self; feel positive about past life.                    |
| Purpose in      | P.L. Have goals and a sense of direction in life; past life is meaningful;   |
| Life            | hold beliefs that give purpose to life.                                     |
| Environmental   | E.M. Feel competent and able to manage a complex environment; choose or     |
| Mastery         | create personally-suitable community.                                       |
| Positive        |                                                                             |
| Relations       | P.R. Have warm, satisfying, trusting relationships; are concerned about      |
| with others     | others welfare; capable of strong empathy, affection, and intimacy;         |
| Personal        | understand give-and-take of human relationships.                            |
| Growth          | P.G. Have feelings of continued development and potential and are open to     |
|                 | new experience; feel increasingly knowledgeable and effective.              |
| Autonomy        | A.I. Are self-determining, independent, and regulate internally; resist      |
| Items           | social pressures to think and act in certain ways; evaluate self by personal|
|                 | standards.                                                                 |

Twitter by Dodds et al. [12], twitter sentiment modeling and prediction of stock market by Bollen et al. [13], identify the sentiment (moods, emotions) in real time. By modeling people’s sentiment through statuses and posts on SNS, these works demonstrate that it is applicable to sense sentiment from social media.

Predict Personal Traits and Mental Status via Social Media
Kosińska [1], Schwartz [3] et al. analyzed the correlation between users' personal traits and behaviors or language usage on Facebook. Similarly works [2,14] are also conducted on social media like Twitter. Hao [15], Choudhury [16] et al. generalize this method to prediction depression, anxiety, etc.

Prediction of Group SWB through Social Media
Most recent work of Schwartz, Eichstaedt et al. generalize their method to LS prediction [8]. Their work used LS as a single indicator of SWB, and established model to predict the LS of each counties in the U.S.A through Twitter data. In their work, county is the unit to predict the LS, rather than individual. Their method, mainly analyze linguistic features on social media. Furthermore, their model introduced variables like “median age”, “median household income” and “educational attainment”, which can only be obtained via costly census.

In this work, our goal is to establish model which can predict multi-dimension SWB of individuals, considering both linguistic and behavioral features on social media. Model based on individual will provide better generalization ability to different groups, like groups with different ages, jobs and so on.

2 Method
In our study, we use both behavioral patterns and linguistic usage on social media, to identify their correlation with SWB. In order to establish models, we
conduct a user study to collect user’s social media data and SWB assessment. Then, we treat the modeling problem as a typical machine learning problem: to learn prediction model from social media data in which SWB is the label.

2.1 Data Collection
We ran our experiment on Sina Weibo (http://weibo.com), a Chinese leading social media platform with over 300 million users where more than 100 million microblogs are posted or reposted (retweeted) every day.

In the October of 2012, we randomly sent inviting messages to about twenty thousand Weibo users who fulfill our requirements of “active”. Active users are defined as users who have posted more than 500 microblogs before recruiting. Such active users have a relatively long term usage of social media, and their Weibo statuses provide adequate information for analysis.

Users who were willing to participate our experiment are guided to a web APP (http://ccpl.psych.ac.cn:10002). Participants were then guided to agree an informed consent and fill psychological questionnaire. Finally, 1785 adult volunteers (female:1136) filled the PANAS and PWBS survey to assess their Emotional Well-being and Positive Functioning as SWB, and their social media data were all downloaded through Sina Weibo API one month after the user study. Figure 1 illustrates the distribution of participants’ age and SWB distribution. Our dataset contains users’ social media data and SWB score.

Fig. 1. Distribution of Age and SWB Dimensions, where X-axis represents age or the score of each SWB dimension and Y-axis represents the number of participants.

2.2 Experiment Design
In previous studies, researchers proposed different indicators (indexes) based on social media data, and use psychological assessment as verification. These indexes are defined subjectively, and the procedure is always guided by researches’ intuition of what factors in social media data may be correlated to target variable. Actually, it is possible to build a prediction model by applying machine learning methods. In this paper, we take the task of predicting users’ psychological variable based on their social media behaviors as a typical machine learning
problem. To do so, we extract features from users’ social media data, and train a machine learning model to predict the target variable (i.e., users’ psychological variable).

**Golden Standard** Core part of SWB sensing system is the procedure of “learning” patterns of SWB from social media behavioral features. To evaluate reliability of established model, we use Pearson’s correlation coefficient. In social psychology, Pearson’s correlation coefficient is a well-recognized measurement for convergent validity, which is used to compare the relevance between two assessing instruments or methods [17][18]. Specifically, we calculate the correlation coefficient between psychological scales assessed SWB $Y$, and SWB sensed by a predicting model $\hat{Y}$.

$$\gamma = \rho(\hat{Y}, Y) = \frac{Cov(\hat{Y}, Y)}{\sqrt{Var(\hat{Y})Var(Y)}}$$

The higher a model’s $\gamma$ is, the closer the model can reach original scale. In the work of Schwartz, Eichstaedt et al. [8], they also adopted the same standard.

When measuring a psychological variable with different assessment instruments or methods, correlation coefficient between different instruments or methods, is typically around 0.39 to 0.68 [19], i.e.: $\gamma \in [0.39, 0.68]$. As a comparison, random guess (uniform distribution) yields $\gamma \in [-0.05, 0.05]$.

**Feature Extraction** Our assumption in this study is that, one’s SWB has impacts on one’s behavioral or linguistic patterns on social media. To predict SWB, we adopted demographic, behavioral and linguistic features to build the predicting model.

**Demographic Features (D, 3 features).** In our case, we use gender, age, and category of living place categorized by population density as demographic features. Although other demographic information, like “educational attainment”, can be quite useful for SWB prediction, they are actually unavailable on Weibo or many other social media platform. The three features we extracted from social media profile are available in users’ profile on most social media platform.

Notably, in our dataset, when applying Student’s t-test, we find that:

- Except for **Negative Affect**, people live in first-tier cities, score significantly higher than people live in other areas in 7 dimensions of SWB ($p < 0.005$);
- For **Positive Affect** and **Autonomy Items**, male users score significantly higher than female users ($p < 0.005$);
- For **Negative Affect**, male users score significantly lower ($p < 0.01$);
- Slight correlation occurs between users’ age and SWB dimensions: **Environmental Mastery** 0.15, **Autonomy Items** 0.15 and **Negative Affect** -0.11.

4 We categorize living place in mainland China to a) First-tier Cities: provincial capital and municipality cites, sample size $N_3 = 1009$; b) Other cities, $N_2 = 650$; c) Rural areas, $N_1 = 126$. When using this features for regression, we simply let: $(LivingPlace = 3, 2, 1)$ respectively, which can be seen as an indicator of population density. Similarly, gender are set to 1 (male) and 0 (female).
These findings have also been reported by previous research [20]. As found in our dataset, in China, living in first-tier city seems to offer a “happier” life, although it means to be in a more competitive environment. This might be caused by a comprehensive effect of income, education etc.

**Behavioral Features (B, 26 features).** We extract behavioral features from user profile and microblogs, including:

- Interaction with other users, like following, friends and bi-following count;
- Express patterns, like microblog count, repost ratio within all statuses;
- Privacy protection, like whether enable geographical information, whether allowing “strangers” to comment;
- Personalization to social media access, like the length of nickname (on Weibo, users can change their nickname at any time).

These features generally describe users’ implicit behavioral patterns on social media, and they are available in user’s detailed profile and microblog posts.

**Linguistic Features (L, 88 features)** SWB comprises abstract dimension like Autonomy Items, Purpose in Life, we believe such patterns might be implied in users’ linguistic expression in microblogs. Like many previous studies, we use an improved version of LIWC, SCLIWC – Simplified Chinese version LIWC optimized for microblog [21], to acquire users’ linguistic patterns. SCLIWC’s dictionary categorizes words by psychological attributes, like Social Process, Percept, Personal Concern, etc.

Since SWB may vary over time, we extract linguistic features according to particular time period – one week before and one week after the survey (denoted by ±1Week). This is because our preliminary trial on different time point, like 2 weeks before (−2Week), 2 weeks after (+2Week) filling questionnaire, with simple linear regression algorithm reveals ±1Week performs best.

**Feature Analysis** Among all the 117 features, we chose some features which are correlated with 8 SWB dimensions in relatively high level and listed them in Table 2. The table shows the correlation coefficient between features and SWB dimensions, from which we can see some behavioral and linguistic features on social media, are positively or negatively correlated with SWB dimensions. For example, users using more first pronoun word “I” in language tend to have lower Personal Growth; users who posted more statuses on social media tend to have higher Environmental Mastery. Such conclusions are in accordance with people’s intuition, which can also be seen as a face validation of our method.

**Learning Algorithm** SWB assessed by questionnaire survey comprises 8 dimensions, whose values are integers. To build the SWB prediction model, our goal is, for each SWB dimension, learn a function to maximize $\gamma$.

Since we didn’t find algorithms targeting on maximizing Pearson’s Correlation Coefficient, we treat this problem as regression and tried following algorithms:

- **Stepwise Regression**: Choose predictive variables Using F-test.
- **LASSO** (Least Absolute Shrinkage and Selection Operator): Using L1 norm to prevent overfitting, good at reducing feature space.
Table 2. Correlation coefficient between 8 SWB dimensions and some features.

| Feature Set | P.A. | N.A. | P.G. | P.L. | E.M. | P.R. | A.I. | S.A. |
|-------------|------|------|------|------|------|------|------|------|
| L: Usage of "I" | -.24 | -.13 | -.35 | -.25 | -.24 | -.22 | -.17 |      |
| B: N(BiFollowers) / N(Friends) | -.22 | -.17 | -.34 | -.25 | -.22 | -.22 | -.16 |      |
| L: Usage of Pronoun | -.24 | -.14 | -.34 | -.23 | -.25 | -.24 | -.22 | -.17 |
| B: N(BiFollowers)/N(Followers) | -.24 | -.17 | -.34 | -.25 | -.23 | -.24 | -.22 | -.18 |
| B: Domain Name Contains Digits (bool) | -.24 | -.17 | -.32 | -.23 | -.22 | -.23 | -.19 | -.17 |
| B: User Description Contains "I" (bool) | -.24 | -.15 | -.31 | -.24 | -.24 | -.23 | -.19 | -.17 |
| B: Using Personalized Avatar (bool) | -.22 | -.15 | -.30 | -.22 | -.21 | -.22 | -.19 | -.16 |
| B: Usage of Past Sense Words † | -.22 | -.13 | -.29 | -.21 | -.21 | -.22 | -.17 | -.17 |
| B: Usage of "We" | -.18 | -.13 | -.28 | -.17 | -.19 | -.18 | -.18 | -.13 |
| B: Allowing strangers' comments (bool) | -.19 | -.13 | -.26 | -.19 | -.19 | -.17 | -.17 | -.14 |
| L: Usage of Question Mark | -.19 | -.12 | -.26 | -.19 | -.19 | -.19 | -.16 | -.15 |
| L: Usage of Semicolon | -.19 | -.13 | -.26 | -.19 | -.19 | -.19 | -.16 | -.15 |
| B: N(Statuses) | +.23 | +.08 | +.25 | +.20 | +.23 | +.21 | +.21 | +.17 |
| B: Usage of Present Sense Words † | -.16 | -.11 | -.22 | -.17 | -.16 | -.17 | -.13 | -.13 |
| L: Usage of Anxiety Words | -.12 | -.07 | -.21 | -.18 | -.16 | -.15 | -.15 | -.10 |
| L: Usage of Friend Words | -.13 | -.09 | -.20 | -.15 | -.13 | -.10 | -.09 |      |
| L: Usage of Discrepancy Words | -.18 | -.10 | -.20 | -.15 | -.15 | -.17 | -.15 | -.11 |
| B: Allow Strangers to send Message (bool) | -.12 | -.11 | -.20 | -.16 | -.14 | -.14 | -.12 | -.11 |
| L: Usage of Negative Words | -.15 | -.09 | -.20 | -.15 | -.16 | -.10 | -.11 |      |
| D: Category of Living Place | +.20 | -.01 | +.19 | +.17 | +.23 | +.19 | +.20 | +.18 |
| D: Age | +.12 | -.05 | +.13 | +.11 | +.23 | +.18 | +.21 | +.15 |
| D: Gender (1 for male and 0 for female) | -.11 | -.03 | +.01 | +.05 | +.04 | +.05 | +.15 | +.04 |

† Tense marking words are only available in Chinese.

- **MARS** (Multivariate Adaptive Regression Splines) non-parametric regression technique.
- **SVR** (Support Vector Regression) We used LibSVM implementation.

Since the range of different features values are quite different, data are normalized to keep features range in \([0, 1]\): \(X'_{i,j} = (X_{i,j} - \text{minValue}_j) / (\text{maxValue}_j - \text{minValue}_j)\). Besides, we apply **5-fold cross validation** to take most advantage of data and avoid potential overfitting on each algorithm.

### 3 Results

As shown in Table 3, we compare the performance of models trained by 4 algorithm on 6 combination of feature set. In the left part, column **Feature Set** refers to feature combination, for example, \(B + D\) means to use Behavioral Features and Linguistic Features for training and testing. Column **Algorithm** describes which algorithm is used to train learning model. In the right part, each cell shows the \(\gamma\) value. Darker cell background color means better performance.

At bottom of the table, there are “**Feature Set Baseline**” – models trained with only 3 demographic features. Feature set baseline model perform poorly on each dimension, the \(\gamma\) value is around 0.2, which is a very weak correlation. Additionally, performance in the case of random guess is basically \(\gamma \in [-0.05, +0.05]\).
Table 3. γ Values: Pearson’s Correlation Coefficient between SWB “sensed” by our model and assessed by PANAS/PWBS questionnaire scales.

| Feature Set | Algorithm | Emotional Well-being | Positive Functioning |
|-------------|-----------|----------------------|----------------------|
| B           | StepWise  | P.A. 0.24, N.A. 0.16, S.A. 0.21, P.L. 0.22, M 0.13, P.R. 0.18, P.G.A. 0.21 | |
|             | LASSO     | 0.16, 0.15, 0.00, 0.19, 0.14, 0.00, 0.16 | |
|             | MARS      | 0.16, 0.08, 0.14, 0.04, 0.05, 0.14, 0.07, 0.13 | |
|             | SVR       | 0.19, 0.13, 0.12, 0.06, 0.17, 0.13, 0.10, 0.15 | |
| [±1Week]    | StepWise  | P.A. 0.22, N.A. 0.16, S.A. 0.16, P.L. 0.14, M 0.10, P.R. 0.19, P.G.A. 0.16 | |
|             | LASSO     | 0.17, 0.10, 0.15, 0.16, 0.14, 0.10, 0.22 | |
|             | MARS      | 0.19, 0.10, 0.12, 0.14, 0.15, 0.14, 0.21, 0.12 | |
|             | SVR       | 0.11, 0.09, 0.08, 0.21, 0.20, 0.12, 0.17, 0.18 | |
| D+B         | StepWise  | P.A. 0.27, N.A. 0.22, S.A. 0.18, P.L. 0.23, M 0.20, P.R. 0.25, P.G.A. 0.25 | |
|             | LASSO     | 0.20, 0.16, 0.19, 0.11, 0.24, 0.18, 0.12, 0.25 | |
|             | MARS      | 0.19, 0.06, 0.17, 0.02, 0.20, 0.12, 0.06, 0.23 | |
|             | SVR       | 0.13, 0.13, 0.11, 0.21, 0.13, 0.17, 0.24, 0.07 | |
| [±1Week]    | StepWise  | P.A. 0.24, N.A. 0.19, S.A. 0.26, P.L. 0.26, M 0.20, P.R. 0.23, P.G.A. 0.28 | |
|             | LASSO     | 0.20, 0.13, 0.19, 0.23, 0.22, 0.20, 0.25, 0.25 | |
|             | MARS      | 0.16, 0.07, 0.04, 0.09, 0.06, 0.17, 0.14, 0.18 | |
|             | SVR       | 0.24, 0.11, 0.16, 0.30, 0.22, 0.19, 0.24 | |
| B+L         | StepWise  | P.A. 0.23, N.A. 0.21, S.A. 0.18, P.L. 0.22, M 0.19, P.R. 0.21, P.G.A. 0.26 | |
|             | LASSO     | 0.24, 0.20, 0.11, 0.20, 0.17, 0.18, 0.24, 0.20 | |
|             | MARS      | 0.10, 0.03, 0.09, 0.07, 0.04, 0.16, 0.00, 0.10 | |
|             | SVR       | 0.18, 0.13, 0.14, 0.11, 0.23, 0.19, 0.10, 0.22 | |
| [±1Week]    | StepWise  | P.A. 0.38, N.A. 0.26, S.A. 0.34, P.L. 0.35, M 0.34, P.R. 0.43, P.G.A. 0.35 | |
|             | LASSO     | 0.38, 0.26, 0.29, 0.34, 0.35, 0.34, 0.42, 0.35 | |
|             | MARS      | 0.40, 0.24, 0.30, 0.43, 0.45, 0.38, 0.60, 0.40 | |
|             | SVR       | 0.41, 0.27, 0.30, 0.35, 0.38, 0.39, 0.49, 0.34 | |
| Best Sensing Result | StepWise | P.A. 0.45, N.A. 0.27, S.A. 0.45, P.L. 0.45, M 0.45, P.R. 0.60, P.G.A. 0.40 | |
|              | LASSO     | 0.45, 0.26, 0.35, 0.45, 0.44, 0.45, 0.53, 0.40 | |
|              | MARS      | 0.40, 0.24, 0.30, 0.43, 0.45, 0.38, 0.60, 0.40 | |
|              | SVR       | 0.41, 0.27, 0.30, 0.35, 0.38, 0.39, 0.49, 0.34 | |

Best performance of learning model is listed in the row of “Best Sensing Result”. It can be seen that, our model performs fairly well in 7 dimension of SWB (except for Negative Affect). As mentioned before, in social psychology research, to particular psychological variable, when a new developed assessing instrument or method achieves the standard of $\gamma \in [0.39, 0.68]$ with an existing reliable assessing method, it is fair to say the new developed method has equivalent utility with the existing one. As a comparison, work [8] predicts SWB of groups at the level of $\gamma \in [0.264, 0.535]$ using social media data, and work [5] predict SWB of groups at level of $\gamma = 0.598$ using objective data. Hence, our SWB prediction model has attained the state-by-art standard.

4 Discussion

In our experiment, we tried 4 algorithms on 6 feature set combinations to establish models. Experiment results show that, feature set combination is significant for model performance.

Comparison of Features Set Combinations Models using only $B$, $L$ or $B + L$ actually perform no better than baseline. While adding demographic features into training feature set will improve the model performance to different extents. Especially when using all feature set ($D + B + L$), sensing model achieve best performance. Although demographic feature set contain only age, gender
and category of living place, adopting these factors into feature set to train model will improve the model performance significantly. This phenomenon also echoes to work [8], when they and age, sex, monocytes, income and educational attainment control, the model accuracy accrue from 0.307 to 0.535.

**Comparison of Algorithms** We adopted algorithms of linear and non-liner, parametric and non-parametric, while in most cases, linear algorithm already perform fairly well. In the same feature set of $D + B + L$, StepWise Regression performs better than other algorithms on 4 dimensions. And MARS achieved $\gamma = 0.6$ on dimension of Personal Growth, which is the best performance in all combinations. Models trained using algorithm of LASSO contain relatively less features, for example, in the combination of $D + B + L$, 44 features enter the final model to predict dimension of Personal Growth.

**Limitation of This Work** Like many other studies on social media, our model also requires adequate user data for analysis. In our experiment, we set the standard of “active user” as posting more than 500 microblog posts. This limitation can be overcome along with users posting accumulating posts.

Weibo users accounts for more than a quarter of Chinese population, which means, there are Weibo users in, if not every village, nearly every county. SWB trends of different groups can provide practical opportunities to policy-makers. But social media users, surely cannot cover all population.

5 Conclusions

In this paper, we established models to sense individual social media users’ SWB, without survey or costly census data. The established models, which attain the state-by-art prediction standard, have equivalent utility with well-designed psychological scales. This approach of psychological assessment, can predict one’s SWB by automatically by analyzing his/her social media data in a non-invasive manner, and makes it feasible to assess users’ psychological features, in large scale and timely.

Core of the paradigm in this study, is to “learn” sensing (prediction) model from social media data and label data of psychological assessment. Patterns and the interaction structures of explicit or implicit variables in social media, can be automatically learned with algorithms (if they can be represented in the feature space). Such paradigm, avoids subjective bias of “designing an index” from numerous features, in which case significant patterns may be hard to be discovered and adopted in the final model. Besides, model is self-verified in the machine learning procedure using techniques like cross validation.

It is our will that the methods in this study can inspire subsequent research in the area of conventional psychology or social sciences. More empirical analysis on real data, leads to more reliable conclusion, and such conclusion can be used to improve the public welfare.

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