

Discovering Behavior Patterns from Social Data for Managing Personal Life

Rui Pan[‡], Masanao Ochi[†], Yutaka Matsuo[§]

School of Engineering, The University of Tokyo,

Tokyo, 113-8656, Japan

[‡]pan@weblab.t.u-tokyo.ac.jp

[†]ochi@weblab.t.u-tokyo.ac.jp

[§]matsuo@weblab.t.u-tokyo.ac.jp

Abstract

In this thesis, we show the possibility of extracting personal behavior patterns from social data of integrated sources, namely Gmail, Facebook and Twitter, in order to help people understanding the causes and consequences of their behaviors for better managing the daily life.

First we show how behaviors affect the quality of the day by predicting daily performance and sentiment with behavior features built from social data. By using collective data in one year period, we can predict one's daily performance and sentiment versus one's personal average with accuracy of 83.7% and 73.0% respectively. We also found general behavior patterns such as, excessive social networking tend to affect the performance of the next day negatively, or people who sleep earlier and longer tend to be happier.

Next we further explore how factors such as performance or sentiment in return affect behaviors. We found general patterns such as people tend to tweet more when they are in a negative mood.

Finally we show that by using only individual data, we can extract behavior patterns of a particular person, which can be different from general behavior patterns extracted from collective data, also by using only the data of a certain period, we can find time-specific patterns such as higher humidity can affect personal performance in summer.

By extracting behavior patterns from social data, we show the possibility of helping people to better understand and control their behavior, in order to lead a more autonomous and fulfilled life.

Introduction

People have been pursuing ways to better manage our daily life, and the only thing we can directly control is our own behavior. So it is important to understand how our behaviors affect our day, and what affects our behaviors, in order to better choose our behaviors to improve the daily

life. But understanding our own behavior can be difficult because human behavior is a complex and personal differences are significant.

In Recent years, the rise of social media has provided us with abundant, easily accessible and real-time data of ourselves to analyze. And the advancement of machine learning technique has provided us with tools to analyze the hidden structure in large, complex and noisy social data. Many studies have been concentrating on the evaluation of a certain human trait, such as sentiment or personality, from a single data source. However, our daily life is a whole, and all the different parts can interact to affect each other, so understanding the links between behaviors and daily life in context can help us better change behavior and improve the day.

The ultimate goal of this study is to discover personal behavior patterns from social data to help people managing their daily life. This problem can be broken down to two parts. First, we need to find out how each behavior that can be observed from social data affects people's daily life. Then we need to know what elements in daily life affect the behaviors. When we think about the quality of the daily life, the output value of our daily life can be measured by our performance; and the income value can be measured by our subjective feeling, or sentiment.

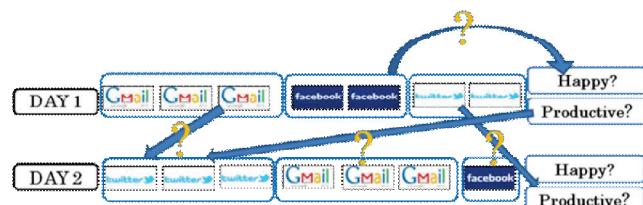


Figure 1 Main Problems to Solve

So the problems become: 1) How behaviors that can be observed from Gmail/Facebook/Twitter affect daily performance/ sentiment? For example, in Figure 1, how DAY1's Facebook activities affect the day's sentiment? 2) How elements in life affect these behaviors? For example, how is DAY2's twitter activities affected by DAY1's daily performance?

The contributions of this paper are as follows:

1. We show the possibility of extracting personal behavior patterns from social data of integrated sources;
2. We found behavior patterns that can potentially help people to better understand and control their behavior, in order to lead a more autonomous and fulfilled life.

Related Work

Previous study about e-mail behavior, social network and work performance (Bulkley and Alstyne 2006) shows that, e-mail behavior correlates with work performance, and different social ties (i.e. relationships) have different contribution on work performance. Therefore, we use e-mail behavior data to build daily performance indicators and differentiate e-mail exchange with a close contact (e.g. a team member) and a distant contact (e.g. a person one recently met at a conference) in the study.

Twitter has been used as a source for analyzing sentiment in many recent studies, these studies usually focus on two sentiments: positive and negative. The main two methods of sentiment analysis with Twitter are lexicon method and distant supervision method. O'Connor et al.'s study (O'Connor et al. 2010) uses positive and negative word ratio to show sentiment in the Twitter, Read's study(Read 2005), Go's study (Go 2009) and following studies (Davidov et al. 2010, Marchetti-Bowick and Chambers 2012) use distant supervision method in which noisy labels, such as emoticons(e.g. a smiley face :) shows positive emotion) or hashtags(e.g. #happy shows positive emotion), are used as indicators of sentiment. We use twitter analysis as sentiment indicator of a person.

Previous study (Adali et al. 2012) show that with individual feedback, we can change people's behavior more effectively, so after using collective data to extract general behavior patterns, we use individual data to extract personal specific patterns.

The phenomenon of the object of prediction evolving over time is called Concept Drift in machine learning (Widmer and Kubat 1996). Recent studies addresses the problem of concept drift by using different techniques, such as retrain the data after a certain period (Neamtiu 2010), or incrementally update the feature/class co-occurrence counts. We use data from different time period to extract behavior patterns because people may change their behavior patterns over time.

Data Collection

We collect data from integrated source, namely Gmail, Facebook and Twitter.

We collect E-mail data shown in Figure 2 containing all the messages the user sent during the period and the messages the user received that are related to the sent messages: *From* shows the sender address encoded with hash function sha-1; *To* shows the encoded receiver address; *Messages-ID* shows the unique identifier of the e-mail; *References* are IDs of all the messages in the same thread prior to this e-mail; and *In-Reply-To* shows to which e-mail this mail replies; *Date* is the receive time.

```
{"From": "dbc0ce9052996550862ae27b2403202f83d09bf9",
"To": ["07d8e5d4ca258a9d54e3cdcecae7a3b543bf73d2"],
"Message-ID": "da3236f342dfab46cf602bb4505663c126953e1f",
"References": ["3e8b54ee1bac37a265e1d1bb0f1252bd4a101e5a"],
"In-Reply-To": "3e8b54ee1bac37a265e1d1bb0f1252bd4a101e5a",
"Date": "Thu, 30 Jun 2011 00:00:00 +0900",}
```

Figure 2 Gmail Data

We collect Facebook feeds data from each user. Each feed shows activities on Facebook shown in Figure 3, the main items are: *Story* gives a brief description of the activity; *from* shows the individual who initiated the activity, *type* shows the category of the activity.

```
{"story": "FBUser likes ABC Solutions.", "from": {"name": "FBUser", "id": "0123456789"}, "comments": {"count": 0}, "updated_time": "2012-06-30T00:00:00+0000", "story_tags": {"0": [{"length": 5, "offset": 0, "type": "user", "id": 0123456789, "name": "FBUser"}], "12": [{"length": 38, "offset": 12, "id": 987654321012, "name": "ABC Solutions: Solutions of ABC problem"}]}, "created_time": "2012-06-30T00:00:00+0000", "type": "status", "id": "0123456789_01234567890123"}
```

Figure 3 Facebook Feeds Data

Sat	Jun	30	00:00:00	+0000	2012
RT @DEF What a beautiful day! I just have to took a picture. Check it out! http://a.b/cdefgh #ABC					

Figure 4 Twitter Tweets Data

We collect the tweets data shown in Figure 4, Sometimes tweets contain links to pictures or other web contents which is shown in the form of a hyperlink; RT means the tweet is referring to another tweet; username started with @ shows to whom this tweet is especially addressed and hashtag start with # shows the topic of tweet

Weather is considered to have influence on individual's behavior. So we collect daily weather data, which contains temperature, humidity, precipitation and daylight hours.

Feature Construction

We build daily features relative to the personal average value. All the features are shown in Table 1. First we build the feature of the day we want to predict (named as TODAY_ in Table 1), then use also the feature from the previous day (LD_) and the day before the last day (LLD_). We use the time of the first online activity to indicate the time a person gets up (_UPTIME) and the last activity to indicate the time a person goes to bed (_BEDTIME). We also calculate how many hours the person sleeps that day (_SLEEP).

Next we evaluate daily personal performance by analyzing the e-mail interactions of the person. We extract behavioral features from e-mail interactions between the person and each contact, we use the similar features as the related study which analyzes twitter interaction to classify relationships (Adali et al. 2012) to cluster a person's contacts to 2 groups: Cluster E has distinctively high reciprocity and high priority, means they have closer relationship (embedded ties in Uzzi's definition(Uzi 1997)) to the person; Cluster A has low reciprocity and low priority and the attention is in the minus direction, which shows distant relationship(arm's length ties in Uzzi's definition(Uzi 1997)).

Then we build indicator of each day's performance (named as _PERFORM in Table 1) as the number of messages sent to embedded contacts considering response time plus the messages sent to arm's-length contacts in each day.

We analyze twitter data for sentiment indicators (named as _SENTI in Table 1). We use distant supervision with emoticon as noisy label. We use unigram and bigram features to train Naive-Bayes classifier to classify all the collected twitter data as positive or negative. Then we use the difference of positive and negative tweets count to calculate personal daily sentiment.

We also build the features that show daily online social activity of each data source. For Gmail, _PRESSURE means the count of messages received from embedded contacts; for Facebook, FB_COUNT is the count of feeds posted that day; for Twitter, TT_COUNT is the tweet posted that day.

Finally we build features from each day's weather data collected from Japan Meteorological Agency website, including the length of day light hours (DAYLIGHT), the day's highest temperature (HIGH_TEMPER) and lowest temperature (LOW_TEMPER) and humidity (HUMIDITY).

Table 1 Features List

	The Day Predict	Day to	The Day Before	Two Days Before	Days Average
Timeline	TODAY_BEDTIM	LD_BEDTIME	LLD_BEDTIM	AVER_BEDTI	ME
	TODAY_UPTIME	LD_UPTIME	LLD_UPTIME	AVER_UPTIM	E
	TODAY_SLEEP	LD_SLEEP	LLD_SLEEP	AVER_SLEEP	
Performance	TODAY_PERFOR	LD_PERFORM	LLD_PERFOR	AVER_PERFO	RPM
Sentiment	TODAY_SENTI	LD_SENTI	LLD_SENTI	AVER_SENTI	
Activity	TODAY_PRES	LD_PRES	LLD_PRES	AVER_PRES	
	TODAY_FBCO	LD_FBCOUN	LLD_FBCOUN	AVER_FBCOU	NT
	TODAY_TTCO	LD_TTCOUNT	LLD_TTCOUN	AVER_TTCOU	NT
Weather	DAYLIGHT	HIGH_TEMPER			
	HUMIDITY	LOW_TEMPER			

Pattern Discovery

First we analyze collective data to find out general rules of how behaviors affect daily performance.

We reframe the question as a 2-class classification problem: given the behavioral features of a certain day, the day before, and two days before the day, is the day's performance/sentiment good (better than personal average) or bad (worse than personal average)? The object to predict is *TODAY_PERFORM*, or *TODAY_SENTI*, which is discretized to class of {-1, +1}, in which -1 means worse than personal average and +1 means better than personal average.

We also calculate the weight of each feature used in the prediction to extract behavior patterns that affect daily performance/sentiment the most. If we can get some mundane and easy to understand behavior patterns, it shows the validity and robustness of our study. If we can get some unexpected patterns, it would be more helpful for people to manage their daily life.

After discovering behavior patterns that affect daily performance and sentiment, we explore further about how elements in the daily life affect each behavior. We use the method of predicting each behavioral feature with all other features.

Next we also use each person's data to find patterns specific to the person. We compare the pattern extracted from personal data to the pattern extracted from collective data to see if the behavior pattern of the individual is different from the general pattern by looking at weighted features from the prediction of the individual data.

Then, because people can change over time, the behavior patterns of people may evolve during a certain time period. We use data from different time windows to check whether by shortening time windows, different patterns would emerge.

Finally we use the individual data within the shorter time window to extract personal behavior patterns.

Experiments and Results

We evaluate the method proposed in the previous chapters by experiment it on real data.

We collected social data of a total 50 users from Gmail, Facebook and Twitter since July 1, 2011 till June 30, 2012. The whole data set contains 74,246 E-mails from Gmail, 6,388 feeds from Facebook, and 29,175 tweets from Twitter.

Performance Related Patterns

First we evaluate performance prediction on collective data to find out general patterns of how behaviors affect daily performance. As a result, the accuracy of predicting a better/worse daily performance is 83.7 %.

We analyze features with top weight (ranking in the absolute value of weight) shown in Table 2 to find what affects daily performance the most.

The absolute value of the weight shows how strong the correlation between the feature and the daily performance is. Therefore, we can discover some general behavior patterns that lead to better or worse daily performance according to the weight.

Table 2 Top Weight Features (Collective-1-year)

Feature	Weight
TODAY_PRES	8.043
TODAY_TTCOUNT	1.231
TODAY_FBCOUNT	1.030
LLD_BEDTIME	-0.766
LD_SLEEP	0.712
LLD_PRES	-0.662

1. E-mail related behaviors: High pressure leads to a better performance because high pressure means more time-sensitive e-mails received and requires more time-sensitive response.
2. Social Networking: Facebook or twitter count today is positively correlated with performance, but more than average social networking on the day before would affect the performance negatively.
3. Sleep Time: If the day before last day sleeps earlier and longer, today's performance tend to be better.
4. Previous Performance: LD_PERFORM is positively correlated with today's performance. It shows that good performance or bad performance tend to last till the next day.

Sentiment Related Patterns

We evaluate sentiment prediction on collective data with the same method as performance prediction, as a result, the accuracy of predicting a better/worse daily sentiment is 73.0%.

We analyze features with top weight features shown in Table 3 in the daily sentiment prediction to find what affects daily sentiment the most.

From the weights of the feature, we can find some general behavior patterns that lead to better or worse daily sentiment.

1. Average sentiment: If the person usually has a positive mood, that day would tend to be positive too.
2. Sleep Time: If the person usually sleeps early and longer the person tends to have a better mood that day.

Table 3 Top Weight Features (Collective-1-year)

Feature	Weight
AVER_SENTI	0.933
AVER_BEDTIME	-0.133
AVER_SLEEP_TIME	0.067

Cross-Feature Patterns

Then we use all the features in Table 1 to predict each behavior feature of TODAY, namely BEDTIME, UPTIME SLEEP, PRESS, TTCOUNT, FBCOUNT. From the weight of features in the prediction, we discovered some connections between different behaviors from these weights as shown in Table 4:

Table 4 Top Weight of Features (Collective-1-year)

*Blanks are weight under 0.1

	TODAY_BEDTIME	TODAY_UPTIME	TODA_E	TODA_SS	TODA_T	TODAY_FBCOUNT
TODAY_UPTIME	0.725					
TODAY_SLEEP	-1.140	1.566				
TODAY_BEDTIME		1.361	-0.870			
LLD_UPTIME			0.634			
LLD_TTCOUNT				0.029		
LLD_PRESS				0.148		
LLD_FBCOUNT					0.491	
LLD_BEDTIME					0.172	
LD_TTCOUNT					0.066	
LD_FBCOUNT						0.508
Correlation coefficient	0.837	0.922	0.938	0.659	0.231	0.835

1. Tweets and sentiment: If a person feels a bit low (negative sentiment) that day, the person tends to tweet more.

2. Tweet and sleep time: If a person tweets more than other people, the person tends to sleep longer than other people. Maybe one has enough spare time.
3. Daylight and tweets: If the day is longer, as in summer, people tend to tweet more.
4. Social Networking: Comparing Facebook counts and twitter counts give us an unexpected result: Facebook usage are more consistent, meaning the Facebook count of the previous days would positively affect the Facebook count today. Twitter counts are more unpredictable. This is possibly one valid explanation for why thought both Facebook and twitter has a huge user base (approximately 9:5), much more Facebook user returns to Facebook everyday than active twitter users (approximately 4:1).

Personal Patterns

We use the data of individuals instead of collective data to extract personal patterns. The results show an improvement of accuracy in performance prediction but a decrease of accuracy in sentiment prediction. It shows that, sentiment is relatively stable state, general rules are more important than individual daily status. Performance is more dependent on the personal daily behaviors.

Also as table 5 shows, personal behavior pattern is different from the general pattern by looking at weighted features from the prediction of the individual data. For example, one person's daily performance is highly affected by twitter activities in the previous days and the person performance better in a sunny or longer day (longer daylight time), which was not obviously observed in the collective data.

Table 5 Top Weight of Features (Individual-1-year)

Feature	Weight in Individual Data	Weight in Collective Data
TODAY_PRES	5.738	8.043
LLD_TTCOUNT	-0.936	-0.225
TODAY_FBCOUNT	0.933	1.030
LLD_PRES	-0.915	-0.662
TODAY_TTCOUNT	0.824	1.231
LD_FBCOUNT	-0.546	-0.659
DAYLIGHT	0.365	0.257

Different Time Windows

People can change over time, so the behavior patterns of people may evolve during a certain time period. In this section, we use data from different time windows to train the classifier of performance/sentiment prediction in order to check how long the optimal time window to use in extracting behavior patterns is.

As Table 6 shows, we use individual data within 6 month time window to extract the following patterns of

shorter term data and compared it with the data from 1 year and found shorter term data can bring differences:

1. Individual patterns became much clearer than general patterns when extracted from a shorter time window. For example, the negative impact of last day's twitter activity gets stronger in 6 month data than 1 year data.
2. Temporary patterns emerge. For example, humidity affects performance much more in shorter term data than the 1 year data. That is because the recent 6 months data contains rainy season of Tokyo. If a person is sensitive to humidity, the pattern would emerge during this season when using short term data.

Table 6 Top Weight of Features (Individual-6-month)

Feature	Weight in 6 Month Data	Weight in 1 year Data
TODAY_PRES	4.736	5.738
LLD_TTCOUNT	-1.207	-0.936
TODAY_FBCOUNT	0.981	0.933
LLD_PRES	-0.964	-0.915
HUMIDITY	-0.691	-0.290
TODAY_TTCOUNT	0.669	0.824
LD_TTCOUNT	-0.481	-0.268

Discussion

There are several aspects in this study that are limited or have problems that can be further explored and improved. We will discuss them regarding each part of the method.

Firstly, we mainly used social data from Gmail, Facebook and Twitter to extract daily behavior patterns based on the assumption that these data have real life indications. But in some cases, these data may not reflect real life behavior. For example, people may set automatic responses for their e-mails.

Secondly, with more and more aspects of our life recorded by all kinds of device, we can use other data that indicates behavior patterns to improve daily life.

Also we use a data set of 50 people to show it is possible to extract behavior patterns from social data, but only with a much larger data set, we can truly acclaim the extracted patterns to be "general" human characteristics.

The result and method of the study can help people in real life, because by understanding our personal behavior patterns and general behavior patterns of people, we can understand ourselves better and monitor our behavior more effectively, especially in real-time. Also we can truly understand our unique characteristics and that gives us the knowledge of how we should strategically make life decisions such as career or personal relationship.

Conclusion

This study showed the possibility of discovering behavior patterns from social data.

Firstly, we collected social data from three sources: Gmail, Facebook and Twitter.

Secondly, we build performance indicator on Gmail behavior data and sentiment indicator on Twitter text analysis. We also built activity features according to the activity statistics of Gmail, Facebook and Twitter, and environment features according to the weather data.

Thirdly, we use these features to predict each indicator of performance and sentiment. We use collective data from the whole 1 year period first to get the general patterns, then further use the individual data and data with limited time window to see what the optimal condition for personal behavior pattern extraction is.

The results shows, by using collective data in one-year period, we can predict whether the daily performance would be higher or lower than the personal average with accuracy of 83.7% and daily sentiment is positive or negative comparing to personal average with accuracy of 73.0%. By using individual data, we can extract behavior patterns of a particular person, and by using data from different time period, we found that the best time window for prediction daily performance and sentiment is 6-month and temporary patterns emerge.

Overall, understanding our behavior patterns based on the objective evidence of data can lead us to a future world that our acts are more autonomous, our communication with others more effective and the effort to pursue a better life becomes a more rewarding game.

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