Friends' Influence Driven Users' Value Change Prediction from Social Media Usage

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Abstract. Basic human values represent a set of values such as security, independence, success, kindness, and pleasure, which we deem important to our lives. The value priority of a person may change over time due to different factors such as life experiences, influence, social structure and technology. In this study, we show that we can predict the value change of a person by considering both the influence of her friends and her social media usage. This is the first work in the literature that relates the influence of social media friends on the human value dynamics of a user. We propose a Bounded Confidence Model (BCM) based value dynamics model from 275 different ego networks in Facebook that predicts how social influence may persuade a person to change her value over time. Then, to predict better, we use a particle swarm optimization based hyperparameter tuning technique. We observe that these optimized hyperparameters produce more accurate future value score. We also run our approach with different machine learning based methods and find support vector regressor (SVR) outperforms other regressor models. By using SVR with the best hyperparameters of BCM model, we find the lowest Mean Squared Error (MSE) score as 0.00347.

Keywords: Values · Facebook Friends · Influence · BCM · Hyperparameters · PSO.

1 Introduction

In recent times, Social Networking Sites (SNS) have become a major platform of communications among users on the web. These SNS data provide a wide range of opportunities to identify cognitive and psychological attributes such as basic human values (aka *values*) [8], and personality [16] of users. Values represent one's attitudes, opinions, thoughts, and goals in life. Values of an individual might change over time due to the influence of her friends [10,14]. In this paper, we predict users' value dynamics (change of value scores over time) based on her social media usage (e.g., statuses and comments) and her friends' influence in an egocentric network such as Facebook[6].

Values are essentially a set of criteria such as security, self-enhancement, etc., that influence individuals to take different actions. Chen et al. [8] predict five higher-level values from user word usages in Reddit. In another study [19], authors predict users' values from generated (i.e., statuses) and supported (i.e., likes and shares) contents in Facebook. However, these approaches largely fail to capture the change users' value priorities (over time) from the social network usage. Several socio-psychological studies [9,14] show that values of a user might be reshaped by the influence of other members in the same interest group. To the best of our knowledge, no study has been conducted to identify the change of value scores of users that considers both the influence of her friends and her social network interactions. Identifying the change of values of an individual from friends' influence has a number of applications such as identifying university course major or career path shifting trends, prediction of customers' purchasing behavior, transforming customers' product selection preference or marketing policies, and understanding transition of economics and business.

Based on the above observation, we propose a technique to identify the changes of a user's value from her social network interactions with friends by using Bounded Confidence Model (BCM) [22,11,17]. Users' value might change due to other factors; however, for friends' influence calculation we use our modified version of popular BCM model. We observe the users' change of values in a time span of 10 years. Motivated by the work [8], first we collect data of 275 user networks from Facebook by using a google survey form. We mainly identify the ego networks with their close friends, i.e., $N \leq 5$ [1]. Since users' change of values are observed in terms of time intervals, we separate users' Facebook statuses, comments, and shares according to a time span of six months [21]. Then, we generate value scores from users' each six months interval Facebook statuses, comments, and shares by using IBM Watson Personality insight API [7]. From the computed value scores of users' writing content, we compute the hyperparameters such as convergent factor, μ and threshold, and σ, for our modified BCM model (see Equation 1). Then, we use particle swarm optimization (PSO) [4] method for finding the best hyperparameter configuration. Finally, we use these optimized hyperparameters of the BCM model to predict next value score by using support vector regressor (SVR) model [3]. In summary, our contributions in this paper can be highlighted as follows:

– We are the first to propose a value change identification technique that predicts user value change dynamics by considering the influence of friends and her social media interaction.

[6] Facebook is an example of an egocentric network [2] because the network provides interaction capability only among the friends while preventing any interactions from the external users to this network.

[7] https://cloud.ibm.com/catalog/services/personality-insightsabout

- We modify the BCM model and capture the friends influence in an ego centric network.
- We develop a PSO based best hyperparameter selection method that predicts user's future value score with less MSE score.

2 Preliminaries and Related Work

2.1 Values

Basic human values define the goal, belief and behavior of an individual. Schwartz et al. [24] categorize the value dimension into five higher-level values. **Openness-to-change** mainly refers to the ability to "think outside of the box" which consists of two broad personal values: *self-direction* and *stimulation* [23]. **Self-transcendence** satisfies the motivational goal for preservation and enhancement of the welfare of people in the society [23]. **Self-enhancement** represents a person's interest to be socially recognized and attraction for control over other humans and resources in the society. **Conservation** emphasizes order, self-restriction, preservation of the past, and resistance to change. **Hedonism** basically means pleasure or sensuous gratification for oneself [23].

2.2 Modified Bounded Confidence Model (BCM)

BCM is a popular opinion dynamics model to determine the influence of a network of people over an individual. Motivated by the BCM devised by Deffuant et al. [12], we revise the model (see Equation 1) and introduce users' value change model. Considering the distance of the corresponding values between two users (i.e., an ego and each alter) is less than a given threshold σ, the updated value of each of the users can be computed by using the following equation:

$$BHV^{\mathrm{t+1}}{}_{\mathrm{i}} = BHV^{\mathrm{t}}{}_{\mathrm{i}} + \mu_{\mathrm{ego}} \frac{\Sigma_{j=1}^{N}(BHV^{\mathrm{t}}{}_{\mathrm{j}} - BHV^{\mathrm{t}}{}_{\mathrm{i}})}{N} \Theta(\sigma_{\mathrm{ego}} - |\frac{\Sigma_{j=1}^{N}(BHV^{\mathrm{t}}{}_{\mathrm{j}} - BHV^{\mathrm{t}}{}_{\mathrm{i}})}{N}|) \quad (1)$$

Here, $\mathrm{BHV_i}$ is the value score of the user i, j represents her friends, μ_{ego} is a convergence factor, σ_{ego} is the threshold within which the users interact or adapt with each other, and $\Theta()$ is a Heaviside's theta function [8]. According to Dunbar number, friends can influence who fall in the intimate sphere where $N \leq 5$ [2].

2.3 Values in Social Media

Chen et al. [8] identify values from Reddit, an online news sharing community. The authors identify five higher-level values from user's pattern of word using in social media. They predict the value scores by using linear regression. Boyd et al. [7] identify values from statuses of 767 Facebook users. They identify values with a data driven approach. Mukta et al. [19] identify values from both

[8] https://mathworld.wolfram.com/HeavisideStepFunction.html

user generated and supported contents in Facebook. Mukta et al. [21] predict the temporal change of values of Facebook users by using hybrid LSTM model. In this paper, we devise a novel technique to identify the value change of an individual by the social influence of her *friends* in Facebook.

2.4 Value Changing Influence Models

The value of a user might be changed due to different offline behaviors such as life experiences, life events, technological change, social structure, and life style of others [15] [10]. In previous studies [21,20], we find that value change of an individual reflects in their social media usage behavior, where authors capture the opinion change over time from social media. Quattrociocchi et al. [22] show that inner dynamics of information systems, i.e., TV, newspaper, social network platforms, - play a vital role on the evolution of the public network. In this paper, we compute value scores in different time intervals and analyze the interactions among users. Then, we measure how the value of one person may influence the change of value of others through social media interactions.

3 Methodology

In this section, we first describe the process of value change modeling by the influence of close friends using BCM model. Figure 1 shows the complete pipeline of our value change modeling and its hyperparameter optimization process. We discuss our methodology in the subsequent sections.

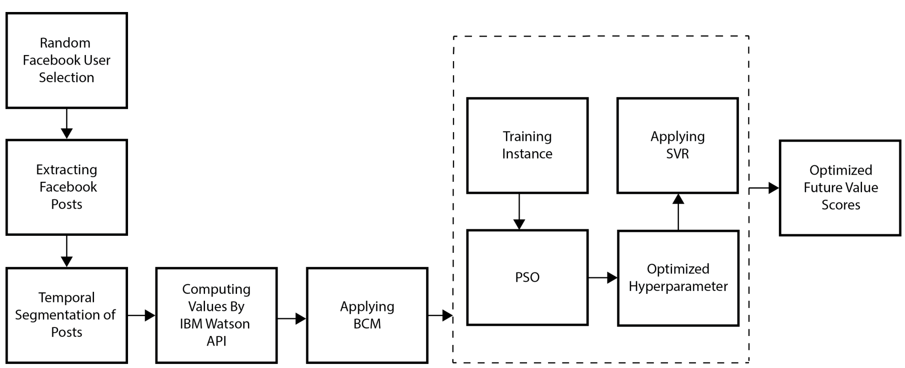

Fig. 1: Methodology of value change modeling and BCM hyperparameter optimization.

3.1 Data Collection

We randomly select a total of 275 (motivated by the study of Golbeck [16]) different Facebook ego networks where each user holds an ego network and his

Facebook friends are alters. Initially, we randomly invite a total of 320 Facebook friends to share their ego networks, but only a total of 275 users show their interest to share their data. After selection, we extract the list of users; then collect every comment of each user. Users' collect their data from their own profile [9] and download her data [10] in different time intervals with JSON format. Later, they share their data with us through the google form.

We extract public profile data like statuses, posts and shares that support comments and likes. Then, we divide the data into temporal segments. Each year is divided by 2 segments, each segment contains data of 6 months. In our experiment, we have Facebook posts of maximum 10 years for a single user, which we can divide into 20 segments. We select the users based on the number of their daily public interactions. Table 1 shows the statistics of our dataset.

Table 1: Statistics of our dataset

Attributes	**Values**
Number of ego Networks	275
Number of total Comments	75,625
Number of Maximum Comments of a User	237
Number of Minimum Comments of a User	25
Total Time Duration (years)	10
Maximum Time Span for a user (years)	10
Minimum Time Span for a user (years)	7

3.2 Influence Modeling for Value Change

Next, we propose a new technique to investigate the change of values over time. To do so, we apply the BCM model [12], where we use two hyperparameters: *convergence factor (μ)* and *threshold (σ)* of value difference. To optimize these hyperparameters, we use a machine learning based approach to determine the optimum values (i.e., solution) by using PSO algorithm (Figure 1). We actually tune the hyperparameters of the regression models. From these optimized hyperparameters, we find the *threshold (σ)* value for predicting the next value score through using SVR.

4 Experimental Evaluation

4.1 Ego Network Configuration

We consider the adjustment of the value score of an ego (u_i) by interacting all users u_j. We collect interaction data such as likes, comments, and sharing of object between an ego u, and their friends, u_j where $j \leq 5$ according to the *Dunbar number* [2]. We are interested in showing that when a number of users u_j influence to value score of a single user (e.g. an ego), her value score converges to a single unified score [6]. Hence, in this study, we assume that users may shift their value scores by the influence of close friends who fall in the sphere where $N \leq 5$ [2].

[9] https://www.facebook.com/settings?tab=your_facebook_information

[10] https://www.facebook.com/dyi/?referrer=yfi_settings

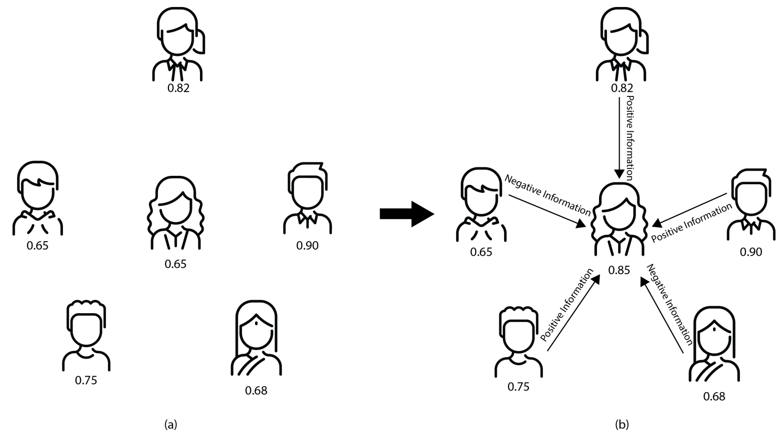

Fig. 2: Group wise influence based value change from time t_1 (Fig a) to t_2 (Fig b)

Similar to a group discussion, we select a primary user to detect his/her value change from the influence of other people of the group. Figure 2(a) shows that independent value scores for a total of 5 Facebook users. When they interact with each other in a group, value score for a user might be changed by the influence of other alters, i.e., Facebook friends. Figure 2(b) shows the final score for a value dimension after being influenced by the members of the group. We predict this change of user's value by using our modified BCM model. The model has different hyperparameters that we optimize by using Particle Swarm Optimization (PSO) method as discussed next.

4.2 Hyperparameter Estimation

During hyperparamer estimation, for brevity and simplicity we only consider *hedonism* value dimension among all top-level 5 value dimensions. We collect users' pleasure seeking behavior, i.e., hedonism, by easily extracting their digital footprints (i.e., restaurant/movie check-ins, purchasing a gadget, etc.) from Facebook. We could also collect users' food related data from their check-ins of different restaurants. The convergence factor, μ indicates the momentum term of the influence dynamics. In our study, we consider μ= 0.4 following the study of [22]. However, to obtain the appropriate value of the threshold (σ) for the BCM model, we build a regression model. The regression model actually predicts the σ which minimizes the error to the least. To build the regression model, we consider four features for the training instances - i) value of user, u_i, at time t, ii) value of user's friend, u_j, at time t, iii) value of user, u_i, at time $t+1$, and iv) convergence Factor, μ. We perform several regression models with these features by a 10-fold cross-validation with 10 iterations. We use the following regressors: SVR, Gaussian Process Regressor (GPR), ElasticNet, BayesianRidge, and MLPRegressor (MLPR) [11].

For hyperparameter tuning, we apply PSO [12] by using Optunity Library [13]. PSO [4] is a typical algorithm of the swarm intelligence family. The algorithm is a population-based meta-heuristic optimization technique which initializes a number of individual search 'particles', each representing a possible solution. This population of particles change their positions by an evolutionary process. Each of these particles is in movement with a velocity allowing them to update their position over the iterations to find the global minimum. ParticleSwarm [14] has 5 parameters that can be configured: *num_particles, num_generations,* ϕ_1, ϕ_2, and *max_speed*. In our experiment, we use *num_particles* = 10 , *num_generations* = 15 ,*max_speed* = None, $\phi_1 = 1.5$, $\phi_2 = 2.0$ to initialize ParticleSwarm [15] solver in *Optunity*. In our case, we consider one set of hyperparameter configuration as a single particle.

We split the dataset into training, and test data by 70% (a total of 193 instances) and 30% (a total of 82 instances), respectively. Then, we define our objective function to minimize the cost of the model which in this case is, Mean Squared Error (MSE). We initialize different box constrained configuration sets of hyperparameters for different regressors. Each particle represents a configuration for hyperparameters of the machine learning model. All of the particles have MSE, i.e., fitness values, which are evaluated by the cost function to be minimized. The particles move through the problem space by following the current optimum particles. Table 2 shows the optimized hyperparameter configuration values for different regressors.

Table 2: Hyperparameters configuration for different regressors

Regression Model	Hyperparameter Configuration
SVR	kernel -RBF, gamma- [0, 50] , C-[1, 100] ;
	kernel -linear,C-[1, 100] ;
	kernel -poly, degree- [2, 5] , C-[1000, 20000], coef0-[0,1]
Gaussian Processes	normalize_y= [True,False], alpha = [1*e*-10 - 1*e*-2]
ElasticNet	alpha - [0, 1.0] , l1_ratio - [0, 1.0] , tol - [1*e*-4, 0.01]
BayesianRidge	alpha_1 - [1*e*-6, 0.01], alpha_2 - [1*e*-6, 0.01],
	lambda_1 - [1*e*-6, 0.01], lambda_2 = [1*e*-6, 0.01], tol -[1*e*-4, 0.01]
MLPRegressor	hidden_layer_sizes - [(50, 50, 50), (50, 100, 50), (100,)] ,
	activation - ['tanh', 'relu'], alpha - [1*e*-4, 0.01]

Since *Optunity* can optimize conditional search spaces, we set different hyparameters for SVR based on the kernel (e.g., *Radial Basis Function (RBF)*, *linear*, and *polynomial*. Table 2 shows the search space for *SVR* hyperparameters. Moreover, Table 3 shows the performance of the regressors over our test dataset.

[11] SVR: https://bit.ly/2OOBDZa, GPR: https://bit.ly/2OWxAKy, ElasticNet: https://bit.ly/3pDuh7M, BayesianRidge: https://bit.ly/3qJoyys, MLPR: https://bit.ly/3qEivez

[12] https://bit.ly/3ucqcLf

[13] https://homes.esat.kuleuven.be/ claesenm/optunity/

[14] https://bit.ly/37zcGYb

[15] https://bit.ly/3aBdSw3

Table 3: Strength (Low RMSE) of the regression model

Regression Algorithm	MSE
SVR	0.00334
Gaussian Process Regressor	0.07138
MLPRegressor	0.08912
ElasticNet	0.05312
BayesianRidge	0.01183

We find SVR regressor shows the best average performance (MSE-0.00337) to predict users' threshold value on the BCM model. Algorithm 1 presents the process of our PSO based hyperparameter optimization method.

Algorithm 1: PSO_based_BCM_Hyperpar_Optimization

initialize:
u_{i} as value of a user
$u_{\mathrm{j...n}}$ as values of group users
$u_{\mathrm{i}} + t$ as value of a user in time t
μ as convergence factor (0.4)
σ as Threshold Value
Proc.: ***Dataset_ Prep_ BCM( )***
1: Calculate the threshold value via BCM Model
2: Set predictor variables (X) : u_{i}, $u_{\mathrm{j...n}}$, $u_{\mathrm{i}} + t$, μ
3: Set Dependent variable : σ
4: Divide the Data set by 70% and 30% as D1, and D2, Respectively
Proc.: ***Model _Training( )***
5: initialize D1 as train dataset
6: initialize D2 as test dataset
7: Run ML models to predict σ
Proc.: ***Hyperparam_ Optim( )***
PSO: Initialize
num_particles=10
num_generations=15
max_speed=None
ϕ_1=1.5
ϕ_2=2.0
8: Find the optimum σ for BCM model using PSO
9: Save ML model as M1
10: Calculate the $u_{\mathrm{i}} + t$ using M1
11: Calculate MSE on D2 dataset with respect to M1

5 Results and Discussion

In this experiment, we take Facebook interactions (i.e., statuses, comments, shares, and likes) of 275 users. By using PSO, we fine tune the parameters of the estimators to get the optimized threshold. With these parameters, we predict the best threshold, σ to predict the accurate value scores by using SVR.

Next, Figure 3 presents the amount of loss when compute the σ by using different models. Among these models, SVR shows the lowest loss to predict the hyperparameters. Use this threshold, σ value, we predict the best final values score of a user influenced by her close friends. Figure 4 shows the actual future value scores and predicted value scores using SVR for different users.

Berndt [5] describes that friendships have influence on user's attitude and behavior. For example, adolescents whose friends drink beer at parties likely to

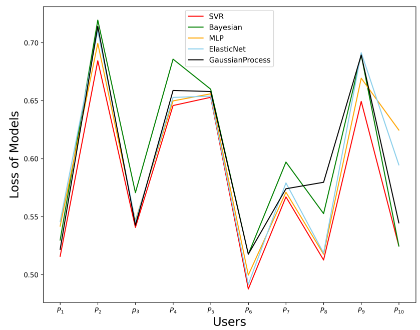

Fig. 3: Comparison of loss among the regression models.

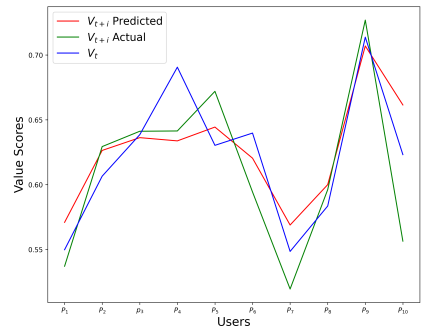

Fig. 4: Comparison between users' actual and predicted value scores.

start drinking. In contrast, user's value may influence negatively. For example, adolescents often have conflicts with others which might propagate among others. Epstein [13] and Hartup [18] describe that friends influence each other in different behaviors, including aspirations, achievements, values and attitudes. Our study also shows that friends' influence can persuade to change one's value which can even be predicable from the social media usage.

6 Conclusion

In this paper, we have extracted 275 different ego networks from a Facebook. Then, we have identified intimate friends ($N \leq 5$) for each of the ego networks. Later, we have segmented users' interaction in a time frame of 6 months. Then, we have computed users' value scores from their Facebook interactions by using IBM personality insight API. Based on the users' value scores, we have proposed a value dynamic technique based on modified BCM influence model. During modeling, we have also proposed a PSO based hyperparameter estimation technique. Our model have showed an outstanding performance (i.e., lower MSE) in predicting change of users' value from their Facebook interactions.

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