A Weighted ML-KNN Model for Predicting Users' Personality Traits

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Abstract. Gaining insight into human personality and its impact on human behavior is very valuable in many applications, such as web information credibility prediction. In this paper, we explore using weighted ML-kNN model for automatic recognition of personality traits of web users, based on a given composition text. After extracting features through analysis of the content of user's Essays statues updates, we discretize contiguous attribute using Kohonen's feature-map algorithm, and assign weight to extracted features based on information entropy. The Essays dataset is partitioned into training dataset and test dataset. For a given test user, the weighted distance between test user and training user is calculated, and based on which the nearest neighbors are identified. The personality traits of test user are then predicted by using ML-kNN algorithm. Our experiment on the Essays dataset shows expected positive results.

Introduction

Social networks have become a most popular mediums for information dissemination as well as facilitators of social interactions [1]. Gaining insight into human personality and its impact on human behavior is very valuable in many respects [2]. Social connections among individuals can yield richer information than his/her isolated attributes [3]. Consequently, it is necessary to understand human behavior for the natural of social interactions.

In the Workshop on Computational Personality Recognition (Shared Task), different systems for personality recognition from text on a common benchmark have been compared. Considering the results on Facebook train-test split as a proof of concept, B. Verhoeven et al proposed a meta-learning approach which can be extended to certain component classifiers from other genres with other class systems, or even from other languages [4]. G. Farnadi et.al explored the use of ML techniques (SVM,kNN,NB) for automatic recognition of personality traits from users' Facebook statues updates [5], which outperform the majority class baseline algorithms even with a small set of training dataset. [6] achieved a high performance using ranking algorithms for feature selection, SVMs and Boosting (B) as learning algorithms. F. Alam et al explored the suitability and performance of several classification techniques based on a set of features extracted from Facebook data [2]. For automatic recognition, [1] studied different classification methods such as SMO, BLR and MNB. [7] employed features in five SVM classifiers for detecting five personality traits through Essays. D.S. Appling et al modeled dependencies between different personality traits using conditional random fields. [8,9] performed regression analysis to identify significant correlations between personality dimensions on the Big-5 Personality inventory and speech act labeling.

In this paper, we present a weighted ML-kNN model for predicting an individual's BIG-5 personality traits based on analysis of the content of his/her Essays text. At firstly, we extract features by analyzing the content of user's Essays statues updates. Then, we discretize the linguistic and emotional features of content that users produced on the basis of Kohonen's feature-maps algorithm. After that, we assign weights to extracted features based on information entropy theory. Finally, we apply weighted ML-kNN model to predict users' personality traits based on weighted feature set. We

run a set of experiments to investigate the performance of our model at predicting web user personality traits, and report system performances in terms of precision, recall and F1-meature.

Method

Extracting Features. The features for predicting uses' personality are complex, in this paper we mainly consider two aspects: linguistic features and emotional features which are based on linguistic features.

(1) Linguistic Features. In order to learn traits of content that user yields, we get word frequency statistics of 34 kinds of parts of speech with Stanford Parser (http://nlp.stanford.edu/software/lex-parser.shtml#About): *CC* (conjunction, coordination), *CD* (numeral, cardinal), *DT* (determiner), *EX* (existential there), *FW* (foreign word), *IN* (preposition or conjunction, subordinating), *JJ* (adjective or numeral, ordinal), *JJR* (adjective, comparative), *JJS* (adjective, superlative), *NN* (noun, common, singular or mass), *NNS* (noun, common, plural), *NNP* (noun, proper, singular), *NNPS* (noun, proper, plural), *PDT* (pre-determiner), *POS* (genitive marker), *PRP* (pronoun, personal), *RB* (adverb), *RBR* (adverb, comparative), *RBS* (adverb, superlative), *RP* (particle), *SYM* (symbol), *UH* (interjection), *VB* (verb, base form), *VBD* (verb, past tense), *VBG* (verb, present participle or gerund), *VBN* (verb, past participle), *VBP* (verb, present tense, not 3rd person singular), *WDT* (WH-determiner), *WP* (WH-pronoun), *WRB* (WH-adverb), *comma*, *period*, *exclamation* and *question*.

(2) Emotional Features. Based on the corpus for sentiment analysis of HowNet Knowledge (http://www.keenage.com/download/sentiment.rar),we extract emotional words whose part-of-speech tag is JJ (adjective or numeral, ordinal), JJR (adjective, comparative), JJS (adjective, superlative), RB (adverb), RBR (adverb, comparative) or RBS (adverb, superlative).

The calculation formulas of user$_i$'s positive, negative and neutral emotional features scores are shown in Eq.1, Eq.2, Eq3 respectively.

$$Positive_i = |Positive\ \ words|_i \ / \ |Emotional\ \ words|_i , \tag{1}$$

$$Negative_i = |Negative\ \ words|_i \ / \ |Emotional\ \ words|_i , \tag{2}$$

$$Neutral_i = 1 - Positive_i - Negative_i , \tag{3}$$

where |Emotional words|$_i$ represents the number of emotional words which user$_i$ uses in his/her contents; |Positive words|$_i$ and |Negative words|$_i$ represent the number of positive words and the number of negative words among all emotional words which user$_i$ uses respectively.

Discretizing Attribute Values. We partition contiguous attribute values into intervals based on Kohonen's feature-maps algorithm, the purpose of which is to assign weight to each attribute using fuzzy information entropy theory.

Calculating weighted *k* Nearest Neighbors. ML-kNN Model is derived from the traditional *k*-Nearest Neighbor (kNN) algorithm. For each unseen instance, its *k* nearest neighbors in the training set are firstly identified. For this purpose, we calculate the distance based on weighted features.

According to the different correlations between features and users' personality, we compute weight of each feature based on information entropy theory, in order to calculate the distance between two users. The calculation formula of feature f_j's weight is shown in Eq. 4.

$$Weight_j = IG(f_j) / \sum_{h=1}^{r} IG(f_h) , \tag{4}$$

where IG(f_j) represents information gain of feature f_j which is shown in Eq. 5.

$$IG(f_j) = -\sum_{k=1}^{n} p(y_k) \log p(y_k) + \sum_{val_j \in v_j} p(val_j) \times \sum_{k=1}^{n} p(y_k \mid val_j) \log p(y_k \mid val_j) , \tag{5}$$

where n stands for the number of personalities; val_j represents a certain value of feature f_j, while V_j represents the value set of feature f_j; $p(y_k)$ represents the probability that personality tag y_k appears in dataset; val_j represents the probability that feature $f_j = val_j$ appears in dataset; $p(y_k|val_j)$ represents the probability that personality tag y_k appears in dataset when feature f_j equals to val_j. The distance between test user t and user i in training dataset is calculated with Eq. 6.

$$d(x_t, x_i) = \sum_{j=1}^{r} Weight_j \times \| x_t^j - x_i^j \|, \tag{6}$$

where x_t^j and x_t^j represent feature f_j of test user t and user i in training dataset separately; $Weight_j$ represents weight of feature f_j, while, as we employ entropy based weight method to compute distance, $Weight_j$ equals to $1/r$ here; $\|\bullet\|$ denotes absolute value of returned real number. The calculation of distance is based on equivalent weight of features, which scales down less relevant features in the Euclidean axes. The algorithm is shown below.

Algorithm 1. Weighted k Nearest Neighbors

Input: test user t;
training dataset TD;
the number of neighbors n

Output: $N(x_t)$

```
for i∈TD do
    d(x_t,x_i)=Σ_{j=1}^{r} Weight_j×||x_t^j−x_i^j||
end for
Neighbors_List(x_t)←sort d(x_t,x_i) (i∈training dataset) in ascending order
N(x_t) ← get first n users in Neighbors_List(x_t)
return N(x_t)
```

Predicting Users' Personality based on ML-kNN Model. The weighted ML-kNN model for predicting users' personalities, which is adapted from [10], is shown as follows.

Algorithm 2. Weighted ML-kNN model for Predicting Users' Personality Traits

Input: training dataset;
the number of neighbors k;
test user t;
a smoothing parameter controlling the strength of uniform prior m.

Output: test user t's personalities $S_{predict}$

```
compute weighted N(x_t) with algorithm 1
for l∈{EXT,NEU,AGR,CON,OPN} do
    for x_i∈N(x_t) (i≠t) do
        if l∈x_i's label then
            l_num=l_num+1
        end if
    end for
end for
for x_i∈N(x_t) do
    l'_num=0
    for l∈{EXT,NEU,AGR,CON,OPN} do
        compute weighted N(x_i) with algorithm 1
        for a∈N(x_i) do
            if l∈a's label then
                l'_num=l'_num+1
            end if
```

```
        end for
        if l∈x_i's label and l'_num==l_num then
            l_sum=l_sum+1
        else if l∉x_i's label and l'_num==l_num then
                ¬l_sum = ¬l_sum+1
        end if
    end for
end for
P(H_1^l)=(s+l_num)/(s×2+m); P(H_0^l) =1-P(H_1^l)
P(E_j^l|H_1^l)=(s+l_sum)/(s×(k+1)+l_num)
P(E_j^l|H_0^l)=(s+¬l_sum)/(s×(k+1)+m-l_num)
S_predict ← arg max_{b∈{0,1}} P(H_b^l)P(E_j^l|H_b^l)
return S_predict
```

According to [10], the event that t has personality l is represented by H_1^l, while the event that t dosn't has personality l is represented by H_0^l; E_j^l ($j \in \{0,1,\ldots,k\}$) stands for the event that among the k nearest neighbors of t, there are exactly j instances which have personality l.

Experiment and Evaluation

Dataset. Personality traits are commonly expressed using five dimensions: EXT (extraversion), NEU(neuroticity), AGR(agreeableness), CON(conscientiousness), OPN(openness). Essays [11] is a large dataset of stream-of-consciousness texts (about 2400, one for each user), collected between 1997 and 2004 and labeled with personality classes. Texts have been produced by students who took the Big-5 test. The labels, that are self-assessments, are derived through z-scores computed by Mairesse et al [12] and converted from scores to nominal classes by us with median split. Since this corpus has been used by different scholars [12,13], it has been included in the shared task as a reference to previous works.

Weighted ML-kNN Classification. On the basis of information entropy theory, we calculate the unbalanced weights of features shown in Table 1.

Table 1. Weights of features

Feature	Weight	Feature	Weight
CC	0.027831087744011905	VB	0.029400552391457974
CD	0.02672996424430056	VBD	0.025643899880597544
DT	0.029758456002946024	VBG	0.02417241140121573
EX	0.03017380368734125	VBN	0.023472627251283764
FW	0.024390252225309453	VBP	0.03134910066504821
MD	0.023628038225530442	IN	0.031015555198166418
NN	0.03236128477834888	JJ	0.02544288143624376
NNS	0.01920016075292616	JJR	0.021902027192898844
NNP	0.028360053254371295	JJS	0.025614270721750324
NNPS	0.025828148558535914	WDT	0.022229268510149624
PDT	0.021052095077153526	WP	0.02377011942204686
POS	0.020592460748347193	WRB	0.023793616698004654
PRP	0.0312581791604354	PERIOD	0.03062577163640338
RB	0.028407651862704004	EXCLAMATION	0.02354746317144375
RBR	0.02128185054618292	QUESTION	0.02532700239203083
RBS	0.031278905210584323	OPSCORE	0.04410245513329516
RP	0.025666903200739062	MISCORE	0.04638371313119664
SYM	0.02085859049540904	AGSCORE	0.032295211382231154
UH	0.021254166609358104		

Then, we run the weighted ML-kNN algorithm to predict the personality traits of test users. Finally, we calculate the precision, recall and F-measure with *k* ranging from 5 to 180. The F1-meature for different parameter *k* is shown in Fig. 1.

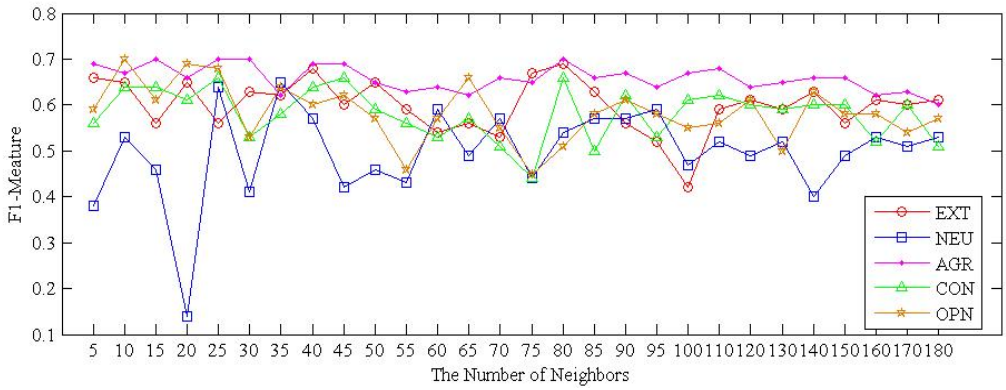

Figure 1. The F1-meature on the BIG-5 personality traits

The Workshop on Computational Personality Recognition (Shared Task) recommends participants to evaluate features and learning techniques, and compare the performances of their systems for personality recognition on a common benchmark. In this paper we compare our work with existing works on the standard Essays dataset in terms of average precision, recall and F1-measure. The result is shown in Table 2, from which we can observe that the recall of our method is significantly greater than existing methods, and as such, we get the best F1 measure.

Table 2. Comparison between our work and others' in average

Related Works	Methods	Precision	Recall	F1-measure
Our Work	Weighted ML-kNN	0.55	0.89	0.65
[4]	SVM	0.55	0.55	0.55
[5]	SVM,kNN,NB	0.62	0.62	0.57
[7]	SVM	NA	NA	0.57
[9]	NB	0.53	NA	NA

Summary

In this paper, we explored the feasibility of modeling user personality traits based on weighted ML-kNN. The reason behind our initiative in adopting ML-kNN, instead of classical kNN, is that there exist certain correlations among the Big-5 personality traits, and as such it is inappropriate to build 5 independent classifiers, one for each personality trait. We reported system performances in terms of precision, recall and F1-meature, and observed the expected positive effects.

Central to personality modeling are feature recognition and classification scheme. The features extracted and weighted in our method are based on information gain and information entropy, and the classifier is based on ML-kNN. It has been recognized that emotional features have great impact on user personality [7]. In this paper, we divide emotions into 3 categories: positive, neutral, and negative. We recognize that this partition is too coarse, and further research will be devoted to more fine-grained division of user emotions. Another ongoing work is to build ensemble of classifiers to improve precision.

References

[1] D. Markovikj, S. Gievska, M. Kosinski D. Stillwell, Mining Facebook Data for Predictive Personality Modeling. Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013. http://clic.cimec.unitn.it/fabio/wcpr13/markovikj_wcpr13.pdf.

[2] F. Alam, Stepanov, A. Evgeny, G. Riccardi, Personality Traits Recognition on Social Network–Facebook, Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013, 6-9.

[3] J.M. McGloin, D.S. Kirk, An overview of social network analysis. Journal of Criminal Justice Education, 21(2), 2010, 169-181.

[4] B. Verhoeven, W. Daelemans, T.D. Smedt, Ensemble Methods for Personality Recognition, Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013, 35-38.

[5] G. Farnadi, S. Zoghbi, M.F. Moens, M.D. Cock, Recognising Personality Traits using Facebook Status Updates. Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013. http://clic.cimec.unitn.it/fabio/wcpr13/farnadi_wcpr13.pdf.

[6] T.M. Tomlinson, D. Hinote, D.B. Bracewell, Predicting Conscientiousness through Semantic Analysis of Facebook Posts. Proc of Workshop on Computational Personality Recognition, Press, Melon Park, CA, 2013, 31-34.

[7] S. Mohammad, S. Kiritchenko, Using Nuances of Emotion to Identify Personnality, Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013,27-30.

[8] D.S. Appling E.J. Briscoe, H.Hayes R.L. Mappus, Towards Automated Personality Identification using Speech Acts. Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 2013, 10-13.

[9] F. Iacobelli, A. Culotta, Too Neurotic, not too Friendly: Structured Personality Classification on Textual Data, Proc of Workshop on Computational Personality Recognition, AAAI Press, Melon Park, CA, 19-22.

[10] M.L. Zhang, Z.H. Zhou. ML-kNN: A lazy learning approach to multi-label learning, Pattern Recognition, 40(7), 2007, 2038-2048.

[11] J.W. Pennebaker, L.A. King, Linguistic styles: Language use as an individual difference, Journal of Personality and Social Psychology, 77(1999)1296-1312.

[12] F. Mairesse, M.A. Walker, M.R.Mehl, R.K.Moore, Using Linguistic Cues for the Automatic Recognition of Personality in Conversation and Text. Journal of Artificial intelligence Research, 30(2007)457–500.

[13] S. Argamon, S. Dhawle, M. Koppel, J.W. Pennebaker, Lexical Predictors of Personality Type. In： Proc. of Joint Annual Meeting of the Interface and the Classification Society of North America, St. Louis, MO, 2005, 1-16.

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