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Collaborative recommendation algorithm of semi-supervised learning in fusion of preference label of theme model

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Abstract. A kind of fuzzy correlated dimensional reduction and clustering method of text and multi-labels based on cluster classifying mapping was proposed here to realize multi-label classification of texts and reduce calculation complexity and keep classifying precision at the same time. Firstly, a theme model of preference label was constructed with the rating matrix of label preference to construct deduction and prediction process between users and label items; secondly, collaborative recommendation process was integrated with trust rating matrix to construct decomposition models of matrix probability, further construct collaborative recommendation trust models of matrix probability decomposition and then conduct model solution based on maximum-likelihood expectation-maximization; finally, there was more excellent absolute error mean index, coverage index, precision index and recall rate index and the calculation efficiency was higher to verify the effectiveness of the proposed method for the proposed algorithm compared with the selected contrasted algorithm through the actual display on test sets of Jester-data and MovieLens.

Key words. Theme model, Preference recommendation, Label learning, Collaborative recommendation.

1. Introduction

Information resources which can be provided are increasingly rich and and the needed information interesting users cannot be provided for them rapidly by traditional algorithms with rapid progress of Internet; and obtaining efficiency of information is also not high[1∼2]. There is difference of search engine between the recommended system and the traditional form so as to filter[3] information for users. The

[1]State

most common algorithm of the recommended system is collaborative filtering recommendation to filter and recommend user preferences. Currently, revenue increase by about 35% of Amazon P2P website caused by commodity filtering recommendation is reported in researches. But there are universal problems of collaborative algorithm, namely low[4] recommendation precision due to data sparseness and cold start.

Networks of socialization attributes have been widely researched and trust relation has been introduced into design process of recommendation system algorithm in recent years ; and filtering recommendation system[5] based on the trust relation has been proposed. For example, design principle of collaborative filtering recommendation system based on the trust relation is offered in Literature [6] and it is pointed out that there is difference between the model of "trust relation" on selection of reference users and adopted model of "collaborative filtering algorithm based on similarity evaluation" on traditional meaning. The information of trusted users can be fully used by users through the model of "trust relation" and efficient obtaining[7] of information can be realized through information processing. Coverage rate and quality of information recommendation can be increased by social networks among users to realize effective alleviation of the problem of data sparseness, which has been widely noticed by scholars recently. However, there are also some defects[8∼9] of the trust model of recommendation system: (1) exclusive problem of coverage rate index and recommendation precision to reduce recommendation precision due to binary mode, namely 0-1 expression method of adopted trust value of trust networks. (2) there is asymmetry of information between users for binary 0-1 expression way, so reasonable calculation of trust value is essential to improve performance of algorithms.

A kind of fuzzy correlated dimensional reduction and clustering method of text and multi-labels based on cluster classifying mapping was proposed here and deduction and prediction process between users and label items; secondly was constructed so as to construct models of matrix probability decomposition; and collaborative recommendation trust model of matrix probability decomposition was constructed further before model solution based on maximum-likelihood expectation-maximization and the effectiveness of the proposed method was verified by the experimental result.

2. Theme model of preference label

2.1. Sequencing of theme label

Label sequencing is similar to a kind of classification; for example, the classification objective is to determine label λ attribute of x in preset set $\boldsymbol{\lambda} = \{\lambda_1, \cdots, \lambda_n\}$, while LR problem is actually to predict label grade in $\boldsymbol{\lambda}$ in combination with x. Suppose the sequencing is total sequencing of $\boldsymbol{\lambda}$ defined on swap space Ω, set $\vartheta = \{1, 2, \cdots, n\}$, then total sequencing $\vartheta(a)$ is the position of λ_a in sequence set ϑ. LR problem is mainly to learn mapping $\mathbf{X} \to \Omega$, while the training set is[11]:

$$\mathrm{T} = \{\langle x_i, \pi_i \rangle\}, i = 1, 2, \cdots, n. \tag{1}$$

Where, x_i is the independent variable in example description and π_i is the corresponding target grade.

Example x, grade π and prediction grade $\hat{\pi}$ are offered to conduct value evaluation on prediction accuracy and cost function is defined in space Ω:

$$D\left(\pi, \hat{\pi}\right) = \left\{(i,j)\left|\pi\left(i\right) > \pi\left(j\right) \wedge \hat{\pi}\left(i\right) < \hat{\pi}\left(j\right)\right.\right\}\,. \tag{2}$$

If it is normalized to interval $[-1,1]$, then it is equal to Kendallτ coefficient; corresponding $D\left(\pi,\pi\right) = 1$, $D\left(\pi,\pi^{-1}\right) = -1$ and π^{-1} is the reverse sequence of π.

Then the model precision can be estimated through average cost functions of a group of examples and pre-treatment method is defined so that LR problem can be realized through classifying way:

$$\forall \pi_i \in \Omega,\ \pi \to \lambda_i\,. \tag{3}$$

Though there are many defects of the method (elaborated in details hereinafter), it is allowed that pre-treated LR problem can be realized through classifying prediction method.

2.2. Similarity

Supporting similarity: similarity among different grades is $s\left(\pi_a, \pi_b\right)$, then supporting degree of rule $A \to \pi$ is[12]:

$$sup_{lr}\left(A \to \pi\right) = \sum_{i:A \subseteq desc(x_i)} s\left(\pi_i, \pi\right) \Big/ n\,. \tag{4}$$

The essence is to attach weight to all target grades in the training process. Common calculation methods of sequencing similarity are τ coefficient of Kendall and ρ coefficient of Spearman and similarity measurement equation in the thesis is as follows:

$$s\left(\pi_a, \pi_b\right) = \left\{ \begin{array}{ll} s'\left(\pi_a, \pi_b\right), & if\, s'\left(\pi_a, \pi_b\right) \ge \theta_{\sup} \\ 0, & otherwise \end{array} \right.\,. \tag{5}$$

Where, s' is similarity equation. Above forms indicate that the value has no effect on distinguishing different similarities when the similarity is lower than given threshold $\theta_{\sup}$.

Confidence similarity: the similarity definition is similar to that of supporting degree:

$$con_{lr}\left(A \to \pi\right) = sup_{lr}\left(A \to \pi\right)/sup\left(A\right). \tag{6}$$

Suppose sequencing grade similarity is measured with above given minimum cost function and τ coefficient method of Kendall is adopted; suppose threshold $\theta_{\sup} = 0$ to distinguish positive and negative contributions. An example of label sequencing in the method is given in Table 1 and it is for example 1 in Table 1 in details that:

$$\left(\{A1 = L, A2 = XL, A3 = S\}\right)\left(TID = 1\right)\,. \tag{7}$$

Vocabulary item of supporting degree contribution as one to π_3 is:

$$(\{A1 = L, A2 = XL, A3 = S\}, \pi_3) . \tag{8}$$

While supporting contribution degree of the vocabulary item to π_1 is 0.33:

$$(\{A1 = L, A2 = XL, A3 = S\}, \pi_1) . \tag{9}$$

Similarly, supporting contribution degree of the vocabulary to π_2 is zero:

$$(\{A1 = L, A2 = XL, A3 = S\}, \pi_2) . \tag{10}$$

2.3. Rating matrix of label preference

Deduction and prediction process between users and label items is constructed based on label deduction process of user preference. Users usually present two kind of behavior in resource accessing process: (1) seeking, adding and attention on labels. (2) user interaction process of resource browse, such as browse, clicking and collection, etc. Preferential behavior of users to information can be fully embodied by these two behaviors and better prediction of user preference can be realized if related features of the behavior is regarded as weight of algorithm prediction.

Calculation is conducted based on quality of Sigmoid function on labels and weight of adopted related features can be obtained based on label quality. If weight value form between items and corresponding label t is $\omega(i,t)$, then the calculation form is:

$$\omega(i,t) = \frac{1}{\exp(-m(i,t))} . \tag{11}$$

Where, m is quality of recommended label to satisfy relation $m = TF \times IDF$ and TF is word frequency parameter to indicate frequency of entry t in file d; IDF is inverse frequency parameter to indicate that there is inverse relation between file frequency and frequency of entry t.

Various ways can be adopted to conduct prediction and deduction of label preference in interaction process among system users and better expression of preference for user can be achieved through rating method. So, preferential relation between users and project resources is expressed in the method of numerical rating, which is also called item-ratings. The function of related weight in deduction process of label preference is fully considered, then:

$$IR(u,t) = \frac{\sum\limits_{i \in M_t} \omega(i,t) \cdot r_{u,i}}{\sum\limits_{i \in M_t} \omega(i,t)} . \tag{12}$$

Where $r_{u,i}$ is rating value of user u on item i and $\omega(i,t)$ is correlation weight between label t and item i; u is is a network user and M_t is all item sets of label .But non-evaluated items are not considered in above expression way in denominator and numerator. Precise prediction cannot be obtained for certain websites or test sets.

But operation such as collection is conducted by users on an item to indicate the preference, then it can be regarded that these items are preferred by users.

Implicit label can be further adopted to predict user rating of item resource upon completing the prediction process of user preference and the detailed process is as follows: firstly, user preference calculation is conducted on labels of item i to obtain the interest degree; then the weight $\omega(i,t)$ between labels and corresponding items is calculated. If calculation result of user interest degree for the label is $NTP(u,t)$, then preference evaluation value of user u on item i is:

$$IT(u,i) = \sum_{i \in T_i} NTP(u,t) \cdot \omega(i,t) \ . \tag{13}$$

3. Trust recommendation algorithm of matrix probability decomposition

3.1. Model and frame of the algorithm

General design thought of collaborative filtering recommendation is as follows: if two similar users on an item are scored and the score of the two users on other items is also similar, then this relation is actually limited to some degree. While design thought of trust recommendation algorithm of collaborative filtering is: trust relation among users is established based on similar preference and detailed recommendation process is shown in Fig. 1.

Different trust sources can be divided into implicit trust and direct trust. Full use of social attributes of network can be realized and user influence can be defined based on friend relation through collaborative recommendation of direct trust source.

Trust adopted in the thesis is mainly implicit trust and it can be calculated based on rating matrix of previous users. Suppose higher trust value between users is indicated by higher similarity of user preference and vice versa; there are many aspects of influence factors of trust degrees. Influence factor selection and model construction are constructed through full using user influence, preference similarity degree and professional degree for users in construction process of network trust model and adopted network trust model is shown in Fig. 2.

The essential linkage can be indicated by relation among nodes and trust relation is one of node relations in social attributes of network; user preference can be adopted to obtain trust information. A key factor for the traditional collaborative recommendation process is user similarity. Threshold is set in Literature [13] with similarity to establish user trust value:

$$T'_{u,v} = \begin{cases} sim(u,v), & if\ sim(u,v) \geq \theta_1 \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

As mentioned above, features of transitivity and directivity of user trust are indicated by asymmetry of user trust and alleviation of data sparseness problem can be realized through collaborative filtered process based on asymmetric trust

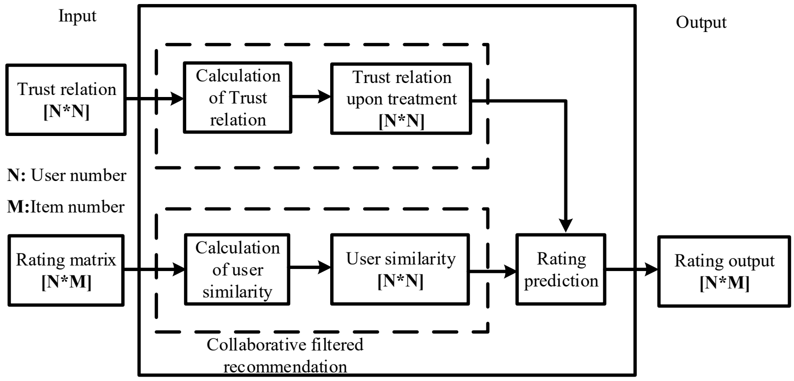

Fig. 1. Trust recommendation process of collaborative filtering

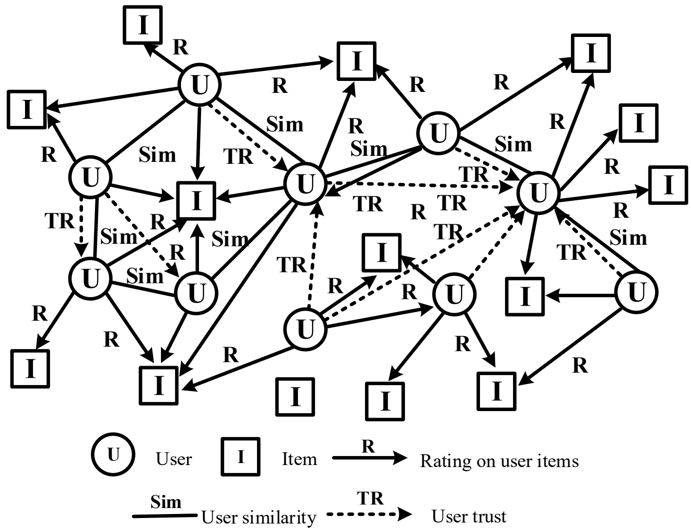

Fig. 2. Network trust model

information. So, asymmetric measurement of user trust can be realized based on influence relation among users and it can be characterized with Jaccard distance specifically:

$$T''_{u,v} = \frac{IT_u \cap IT_v}{IT_u}\,. \tag{15}$$

Calculation of user rating deviation can be realized based on set threshold of rating item and the calculation form is:

$$Tr\left(u\right) = \frac{\sum_{i=1}^{M}\left(R_{ui} - \hat{R}_i\right) I_{ui}}{\left|I_u\right|}, \left|I_u\right| \geq \theta\,. \tag{16}$$

Where, if the condition $R_{ui} = 0$ is satisfied, then $I_{ui} = 0$, or $I_{ui} = 1$. So final calculation form of trust value is:

$$T_{u,v} = \left(\lambda T'_{u,v} + (1-\lambda) T''_{u,v}\right) \cdot Tr(u)\ . \tag{17}$$

3.2. Analysis and calculation of the model

Maximum joint probability $P(R, T|\Lambda)$ of trust rating matrix should be ensured so as to ensure obtaining optimal similar forms $u_{1:N}$ and $v_{1:M}$ in calculation p[process of model parameters. The following conditions of joint probability should be satisfied by trust rating matrix:

$$\begin{aligned} &P(R, T|\Lambda) \propto P\left(R\left|U, V, \tau_R^2\right.\right) P(V|u_1, \Sigma_1) \\ &P(U|u_2, \Sigma_2) \times P(F|u_3, \Sigma_3) P\left(T\left|U, F, \tau_T^2\right.\right) \end{aligned} \tag{18}$$

Where, parameter set form of the model is $\Lambda = \left\{u_1, \Sigma_1, u_2, \Sigma_2, u_3, \Sigma_3, \tau_R^2, \tau_T^2\right\}$. Prior Gaussian probability distribution of users and labels in network models is for potential feature matrix:

$$P(V|u_1, \Sigma_1) = \prod_{j=1}^{M} N(v_j|u_1, \Sigma_1)\,. \tag{19}$$

$$P(U|u_2, \Sigma_2) = \prod_{i=1}^{N} N(u_i|u_2, \Sigma_2)\,. \tag{20}$$

$$P(F|u_3, \Sigma_3) = \prod_{s=1}^{N} N(f_s|u_3, \Sigma_3)\,. \tag{21}$$

Besides, calculation forms of $P\left(R\left|U, V, \tau_R^2\right.\right)$ and $P\left(T\left|U, F, \tau_T^2\right.\right)$ are:

$$P\left(R\left|U, V, \tau_R^2\right.\right) = \prod_{i=1}^{N}\prod_{j=1}^{M} P\left(R_{ij}\left|g\left(u_i^T v_j\right), \tau_R^2\right.\right)^{\sigma_{ij}}\,. \tag{22}$$

$$P\left(T\left|U, F, \tau_T^2\right.\right) = \prod_{i=1}^{N}\prod_{s=1}^{N} P\left(T_{i,s}\left|g\left(u_i^T f_s\right), \tau_T^2\right.\right)^{\sigma_{is}}\,. \tag{23}$$

So, the form of maximum joint probability of trust rating matrix is:

$$
\begin{aligned}
&P\left(R,T\left|\Lambda\right.\right)=\int_{u_{1:N}}\int_{v_{1:M}}\int_{f_{1:N}}\prod_{j=1}^{M}P\left(v_j\left|u_1,\Sigma_1\right.\right)\prod_{i=1}^{N}P\left(u_i\left|u_2,\Sigma_2\right.\right)\\
&\prod_{i=1}^{N}\prod_{j=1}^{M}P\left(R_{ij}\left|g\left(u_i^Tv_j\right),\tau_R^2\right.\right)^{\sigma_{ij}}\prod_{s=1}^{N}P\left(F_s\left|u_3,\Sigma_3\right.\right)\\
&\prod_{i=1}^{N}\prod_{s=1}^{N}P\left(T_{is}\left|g\left(u_i^Tf_s\right),\tau_T^2\right.\right)^{\sigma_{is}}d_{u_{1:N}}d_{v_{1:M}}d_{f_{1:N}}.
\end{aligned}
\tag{24}
$$

Where, $g(\cdot)$ is regularized logic mapping and the calculation form is $g(x) = 1/(1+\exp(-x))$ to ensure that value interval of $u_i^T f_s$ and $u_i^T v_j$ is $[0,1]$; if it is satisfied that $R_{ij} \neq \emptyset$, then $\sigma_{ij} = 1$, or $\sigma_{ij} = 0$. Similarly, if it is satisfied that $T_{is} \neq \emptyset$, then $\sigma_{uv} = 1$, or $\sigma_{uv} = 0$. the training target of TPMDM model is to obtain model estimation parameter Λ to maximize joint probability $P(R,T|\Lambda)$ for given trust matrix T and rating matrix R. The solution[14] process is based on maximum-likelihood expectation-maximization and the detailed process is:

(1) Posterior probability $P(u_{1:N}, v_{1:M}, f_{1:N}|R,T,\Lambda)$ of potential variables is calculated with E-step steps;

(2) Model estimation parameter Λ is used with M-step step. Approximate value $q(u_{1:N}, v_{1:M}, f_{1:N}|\Lambda')$ is introduced into actual value of posterior probability $P(u_{1:N}, v_{1:M}, f_{1:N}|R,T,\Lambda)$ and Λ' is change parameter in the approximate value to satisfy $\Lambda' = \left\{\lambda_{1i}, v_{1i}^2, \lambda_{2j}, v_{2j}^2, \lambda_{3s}, v_{3s}^2\right\}$, so q form is:

$$
\begin{aligned}
&q\left(u_{1:N},v_{1:M},f_{1:N}\left|\Lambda'\right.\right)=\prod_{i=1}^{N}q\left(u_i\left|\lambda_{1i},diag\left(v_{1i}^2\right)\right.\right)\\
&\prod_{i=1}^{N}q\left(v_j\left|\lambda_{2j},diag\left(v_{2j}^2\right)\right.\right)\prod_{i=1}^{N}q\left(f_s\left|\lambda_{3s},diag\left(v_{3s}^2\right)\right.\right).
\end{aligned}
\tag{25}
$$

So, maximization solution process of above joint probability $P(R,T|\Lambda)$ is converted to optimization process of target $L(\Lambda,\Lambda')$. Continual iteration and update of values Λ,Λ' can be realized so as to obtain values Λ,Λ' satisfying maximization of joint probability $P(R,T|\Lambda)$ upon repeated iteration and optimization of M-step and E-step. MAP process can be used for estimation in specific rating prediction process in the form of $\hat{R}_{ij} = \hat{u}_i^T\hat{v}_j$ and

$$
\begin{aligned}
\{u_i,v_j,f_s\}&=\underset{u_i,v_j,f_s}{\arg\max}\left(P\left(u_{1:N},v_{1:M},f_{1:N},R,T\right)\right)\\
&\approx\underset{u_i,v_j,f_s}{\arg\max}\left(u_{1:N},v_{1:M},f_{1:N}\left|\Lambda'\right.\right)=\left(\lambda_{1i},\lambda_{2j},\lambda_{3s}\right)
\end{aligned}
\tag{26}
$$

So, final rating estimation can be calculated as:

$$
\hat{R}_{ij}=\lambda_{1i}^T\lambda_{2j}\,. \tag{27}
$$

Comprehensively, training steps of decomposition trust model of matrix probability are shown in Algorithm 1.

Algorithm 1 training steps of decomposition trust model of matrix probability

Input: : trust matrix T, rating matrix R and number k of neighbors
Output: : prediction rating matrix $\hat{R}$
1: Random matrix $\lambda_{1i}, \lambda_{2j}, \lambda_{3s}$ are generated;
2: Training process: parameter $\Lambda = \left\{u_1, \Sigma_1, u_2, \Sigma_2, u_3, \Sigma_3, \tau_R^2, \tau_T^2\right\}$ is obtained according to Literature [10];
3: **if** prediction error of trust matrix T and rating matrix R conforms to set conditions that $e_1 \leq epsilon$ and $e_2 \leq epsilon$ and it is set that $epsilon = 0.0001$ with $t \geq minstep$, **then**
4: M-step:parameter updating $\Lambda' = \left\{\lambda_{1i}, v_{1i}^2, \lambda_{2j}, v_{2j}^2, \lambda_{3s}, v_{3s}^2\right\}$ is conducted;
5: E-step: parameter updating $\Lambda = \left\{u_1, \Sigma_1, u_2, \Sigma_2, u_3, \Sigma_3, \tau_R^2, \tau_T^2\right\}$ is conducted;
6: **end if**
7: **Predicted output:** $\hat{R}_{ij} = \lambda_{1i}^T \lambda_{2j}$

4. Experimental analysis

Contrast test is conducted with four standard test databases including yeast, Image, Emotions and CAL500 in experimental verification phase and related description of experimental objects is shown in Table 1. Four indexes including classification accuracy mean, sequencing loss, hamming loss and coverage rate are adopted for algorithm evaluation index, which can be found in related description of Literature [12] and omitted. Above data sets are randomly divided into three parts: labeled sample, non-labeled sample and test sample.

Two algorithms in Literature [10] and Literature [13] are adopted for contrasted algorithm; Literature [10] is multi-label classification method based on Boosting and Literature [13] is multi-label classification method based on isometric log ratio conversion. Samples are selected randomly for classifier construction and only one selected sample is labeled in each step of iteration in the training start phase. Label quantity distribution in all data sets is given in Fig. 3.

Table 1. Description of data set

Text set	Sample set	Label quantity	Feature quantity
CAL500	501	173	67
Emotions	592	5	71
Image	1998	4	293
Yeast	1416	13	102

Comparison curve of above four data sets on selected four evaluation indexes can be obtained as quantity of samples to be classified increases, as shown in Fig. 3-6. Model performance can be improved as sample quantity increases for above several algorithms according to Fig. 3-6 and the specific manifestation is: classification precision mean of models is continually increased and indexes of coverage rate, hamming loss and sequencing loss are continually reduced.

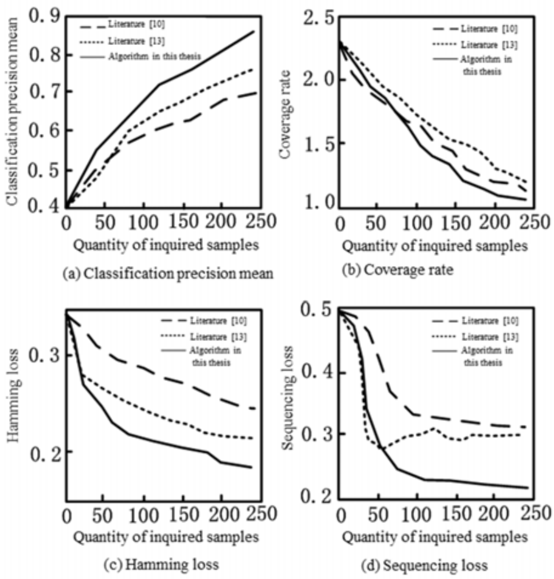

Fig. 3. Comparison result of four evaluation indexes in CAL500

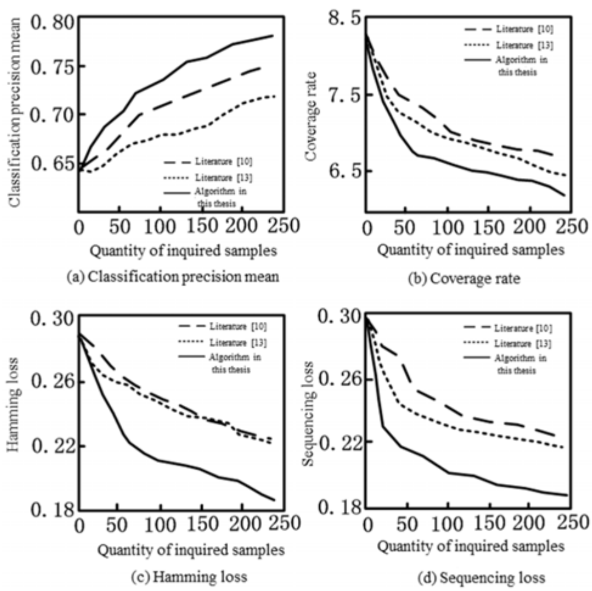

Fig. 4. Comparison result of four evaluation indexes in Emotion

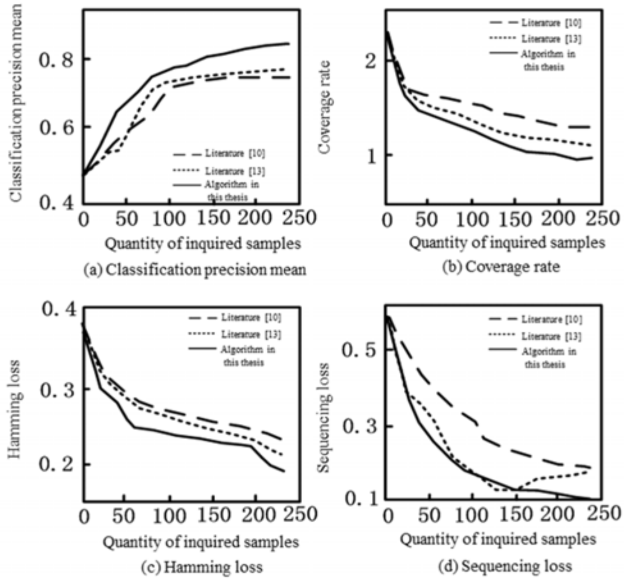

Fig. 5. Comparison result of four evaluation indexes in Image

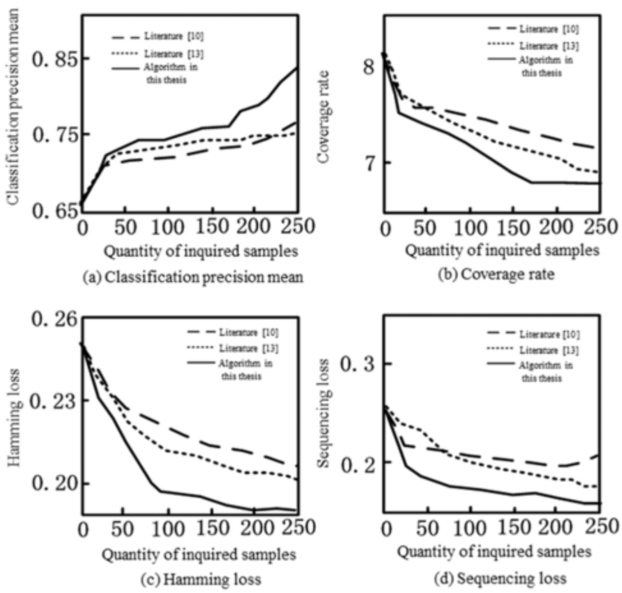

Fig. 6. Comparison result of four evaluation indexes in Yeast

Besides, four evaluation indexes of proposed algorithm are all better than those of comparison algorithm on horizontal comparison of the algorithm. Meanwhile, needed sample quantity of proposed method is less than that of comparison methods when classification precision of model classifier is the same. Experimental result indicates that requirement on labeled sample quantity in the training process can be lowered so as to avoid increasing manual labeling cost excessively on the condition of ensuring performance of classification models for the proposed algorithm.

Two algorithms in Literature [10] and Literature [13] are still adopted in efficiency comparison of algorithm calculation. Hardware: AMD four-core 2.8GHz, 6Gddr3-1600; the system is flagship version of win7 and comparison data of operation time is shown in Table 2.

Table 2. Time comparison of model classification

Test set	Calculation model	Time/min
CAL500	Algorithm in this thesis	6.5 6.5
	Literature [10]	35.8 35.8
	Literature [13]	15.7 15.7
Emotions	Algorithm in this thesis	7.8 7.8
	Literature [10]	41.3 41.3
	Literature [13]	20.6 20.6
Image	Algorithm in this thesis	5.3 5.3
	Literature [10]	28.6 28.6
	Literature [13]	17.4 17.4
Yeast	Algorithm in this thesis	8.3 8.3
	Literature [10]	41.2 41.2
	Literature [13]	32.6 32.6

It can be found through comparison data in Table 2 that operation time of proposed algorithm in this thesis is much less than that of selected contrast algorithms. It is consistent with analysis result of algorithm calculation complexity in Section 4. The calculation complexity in Literature [10] is the highest and the needed classification time is the longest due to adopted improved Boosting classification algorithm of multi labels. High calculation efficiency of the proposed algorithm is verified in the experiment.

5. Conclusion

A kind of drift excavation method of semi-supervision learning in fusion of preference label of theme model was proposed here. High-dimension text is converted to low-dimension fuzzy correlation vectors with fuzzy related evaluation so as to avoid disaster problem of dimension quantity and algorithm applicability can be increased because there is requirement on convexity of classification area for the proposed algorithm. Advantages of proposed algorithm on calculation efficiency and classification precision are verified by the experimental result.

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