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Low Dimensional Relevance Coding for Personalized Tag Recommendation in Image Tagging Applications

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Abstract—An approach of image coding for tag recommendation based on feature clustering and weighted coding is presented in this paper. The existing tag recommendation approach develops a decision based on correlation of image features and their tag annotated. The descriptive feature of the image sample defines the content of an image and is correlated with database features for tag recommendation. The feature dimension and its representation have a greater impact on the recommendation performance. The recent method tag recommendation developed CNN based visual features and proposed a tag recommendation based on weight factor. The dimensional feature and the isolated weight allocation limit the performance of presented tag recommendation system. This paper presents a new weight allocation and feature clustering method for tag recommendation. An approach of integral coding for weighted image-tag is presented to improve recommendation accuracy. The proposed recommendation system performance is tested on Flickr dataset for retrieval and recommendation accuracy.

Keywords-Tag Recommendation; Feature Clustering; Weighted Coding

I. INTRODUCTION

A large volume of data has constrained users from searching and retrieval of relevant information from an online source. With the rapidly increasing size of the image database, the search overhead is relatively increasing. A label annotated to an image termed 'tag' significantly helps in retrieving information more effectively compared to a direct search. Tags define the details of the image based on the content and user observations. The performance and accuracy of retrieval are effective with a proper tag detail. Hence, an automated tag recommendation system is developed. Automated tag recommendation performs a co-occurrence mapping of user-defined tags with the existing learned tag information and recommends the best-matched tags. The information retrieval in this large dataset is mainly dependent on tagging information. Hence, it is required to have accurate tagging to the image information to have better retrieval accuracy. Towards this requirement, research has been conducted on tag recommendation, where automatic tag generation is used to recommend appropriate tags. Automated tagging could overcome the issue of non-obvious and confusing tagging and relevant feedback from the user could improve this performance. To automate tag recommendation, a co-occurrence-based ontology approach was developed. The approach of co-occurrence tag recommendation is a process of the extraction of semantic relation between tags and the image content to recommend appropriate tags. For tag recommendation, images were analyzed for feature extraction, and various classification approaches were proposed. Wherein descriptive visual features are defined to represent an image, a large volume of feature descriptions and relative properties of the image-tag information has a crucial role in tag recommendation.

II. RELATED WORK

The development of a tag recommendation system has gained a lot of interest in the recent past with the development of a new approach for large image-sharing and information systems. In the context of analyzing the images for tag recommendation, a major issue is the dynamically growing distributed environment of data representation. Due to the emergence of new devices and new ways of communicating, image tagging has become a much broader issue [2]. In the process of tag recommendation in a diverse environment, speed and accuracy are prime needs. Optimal tagging based on semantic co-ranking can take a long time, resulting in non-convergence problems [3]. In the past, various methods were presented for optimized tag recommendation. In [4], the tag recommendation over a heterogeneous network has developed. The issue of co-ranking for tag recommendation has been defined as a Bergman divergence optimization by defining a random walk approach to an equivalent optimal kernel matrix learning problem. The co-ranking objective for tagging over a widely distributed environment has been addressed in [5,6]. It was optimized by solving the matrix learning problem. But the learning matrix derived from a defined hypergraph consist of shape information. The diversity of the distributed dataset and other variant parameters such as user characteristics were not considered. A new approach of tagging based on modified divergence optimization was applied over a distributed dataset to improve the accuracy of tag recommendation [7]. The relevance of the tag allocation has diversified in the approachability of not just allocating the tags but improving the relevance of the image tagging. A solution to the problem of tag diversity over a wide distribution of imaging information has been presented in [8]. In [9], user-annotated tags were

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investigated and discovered to be biased with descriptions based on the user's personal information. The allocation of tags in a noisy environment was addressed in [10] for image tag recommendation. To minimize the issue of noise and over-biased tagging, a semantic similarity retagging approach has been proposed [11]. The image semantics-tag relevance fusion method for tag recommendation was described in [12-14]. To rerank and retag the image dataset, relevant and diverse parameter values for the assigned tags were used. While fusion methods present a simple approach to tag allocation improvement, they do not consider the diversity of the web-scale of the image dataset. In [15], a practical application where images were added or removed at a random interval was observed with the quality of the input given. In the tag recommendation process, the effect of representation on web scaling was considered. The diversity in data collection and online recommendations for re-tagging was presented in [16] which has developed a robust method for attackers to minimize false tagging issues. The allocated tag in such a case was modified by an attacker to minimize its represent ability from the relevance clustering. A similar issue is addressed in [17] where privacy concern about tag forgery was focused. A content-based coding for the enhancement of tag recommendation was proposed in [18]. In [19], an approach for the content-based representation of adding a new feature to tagging approach was presented. The computation and selection of these content features are often limited and wrongly selected. As in images the representing features are of a large count, the selection and mapping for a tag search is an overhead process. Hence, to improve the performance of image tagging, a new lower-dimension representative feature based on clustering and content information with relevant feedback is proposed. The approach of feature representation and image tag correlation is presented, and the system is analyzed and validated for the accuracy of tag recommendation. In tag recommendation, an approach of convolution feature representation (CNN) and weighted random walk method has developed in [1]. This approach presented a method for image feature representation and tag recommendation on the Flickr dataset using a weighted-based approach. However, the feature dimensions are large and distributed which has a constraint of a large delay in retrieval and tag recommendation. To overcome the addressed issue, a new improved weighted image-tag coding and clustering approach is proposed in this paper.

The rest of the paper is organized as follows: The existing feature clustering and tag recommendation approach are described in section 3. Section 4 presents the proposed tag recommendation using a weighted clustering approach. Section 5 describes the results obtained for the developed system. A conclusion is described in section 6.

III. TAG RECOMMENDATION SYSTEM USING WEIGHTED RANDOM WALK [1]

The process of tag recommendation is developed based on the feature vector and the mapped tag inputs. The representation of image feature and the recommended tag is developed by a Convolutional neural network (CNN). CNN is applied to an image under recognition for local feature based on visual feature. The feature representation based on CNN is applied in improving the accuracy of tag recommendation. The process of CNN based coding is used in a recent work [1] where the image is processed for tag recommendation based on the extracted feature. The process transforms the image into n × n dimension and a process of pre training approach with L layers.

The features are processed using convolutional layer, the feature of multiple layers are mapped where the feature is mapped to feature graph is processed through convolutional kernel. The feature vector is mapped to obtain $nl \times nl$ feature vector based on convolution layer Li, where the feature is represented by a set of

$$Fl = \{f\,l_{1,1}, f\,l_{1,2}, \ldots , fl_{nl,nl}\} \tag{1}$$

For the selection of neighbor, the tag recommendation is not effective in visual semantic image. The correlation approach of the image feature relate to a semantic image is used for the tag recommendation. The approach used in presented work is based on the visual feature similarity and the user group to which a image belong to. The image tagging has a higher influence with the user group detail used in tag recommendation. Images with a similar visual has a common tag recommendation belonging to a common group. This indicate a similar group which indicate a similar group which are more relative to each other. The correlation factor for visual similarity is computed by a Euclidian distance given by,

$$Dst = \min(d_i) \tag{2}$$

where

$$d_i = \sqrt{\sum_{i=1}^{k} T - Df_i} \tag{3}$$

T is test sample,
Df_i is the database feature used for training.

A Min-Max approach based on normalization is developed based on visual distance of multiple image sample defining visual similarity given by

$$S(f_{qi}, f_{di}) = 1 - \frac{d(f_{qi}, f_{di}) - d_{min}(f_{qi}, F)}{d_{max}(f_{qi}, F) - d_{min}(f_{qi}, F)} \tag{4}$$

Here, d represents Euclidian distance of multiple images of test sample and database images. d_{max} indicate maximum Euclidian distance of two image sample. The visual distance of similar group based on Euclidian distance a linear weighting for the visual feature is developed given as below.

$$y = \delta \times (1 - \rho) + (1 - \delta) \times j \tag{5}$$

Here, y is given as the correlation matrix and ρ define the weight coefficient. The nearest neighbors are given with highest rank in database and the samples are arranged in descending order. The best k samples' having highest correlation is then used for declaring the recommendation of tag.

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In tag recommendation, neighbor tag bipartite graphs are commonly used. This graph defines the k nearest image derived from the correlation vectors. The value of matching is used in defining the weight value for an image. The recent work of tag ranking outlined in [1] defines a random walk approach for recommendation based on PageRank approach. The presented approach derives a weighted random walk defined as follows:

$$PR(i) = (1-d)r_i + d\left(\sum_{j\epsilon in(i)} \frac{\omega_j \times PR(j)}{|out(j)|}\right) \quad (6)$$

$$r_i = \begin{cases} 1, i = u \\ 0, i \neq u \end{cases} \quad \omega_j = \begin{cases} 1 & j \in tag \\ y & j \in image \end{cases} \quad (7)$$

Here u represents the target image and when the weight value is obtained as 1 for node j is a tag. The presented correlation-based approach gives a finer representation of feature using CNN and a mapping approach of defining tag and image detail. The developed approach is however limited with the complexity of training and testing process in terms of accuracy and speed. The wide distribution of image feature and with no process of tag alignment the recommendation accuracy is constraint. To overcome the addressed issue an approach of image clustering and relevance feedback approach is proposed. The presented approach of clustering and tag mapping is presented.

IV. WEIGHTED CLUSTERING AND TAG RECOMMENDATION

The large size of feature vector and wide distribution of tag information constraint the performance of auto tag recommendation system. In minimizing the dimension of the representative feature various dimensional reduction approaches were proposed in the image retrieval system. However, a selection of random count leads to constraint accuracy where the probability of feature selection is constraint. To enhance the accuracy of the recommendation system with a wide distributed image and tag details a clustering approach is proposed. The process of clustering is illustrated in the given figure 1.

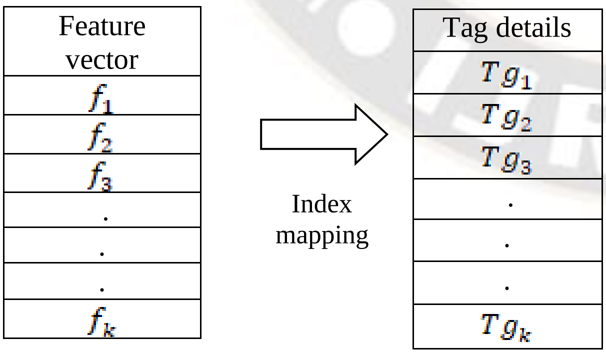

Figure 1. Mapping process of image and tag in an image tagging system

The process of tagging is performed by using a linear map of image to feature map. A set of learning images is processed for image feature defining the image content of visual features of color, shape and texture. The CNN model is used in deriving visual features after layer merging [1]. The features are listed as descriptive details to an image which eliminate the storage overhead of storing complete image. In the mapping process the tag given by users are mapped with the image feature. The retrieval process of image information is based on the correlative mapping of image feature of a query image with the features of trained feature into the database. The retrieval process is illustrated in figure 2.

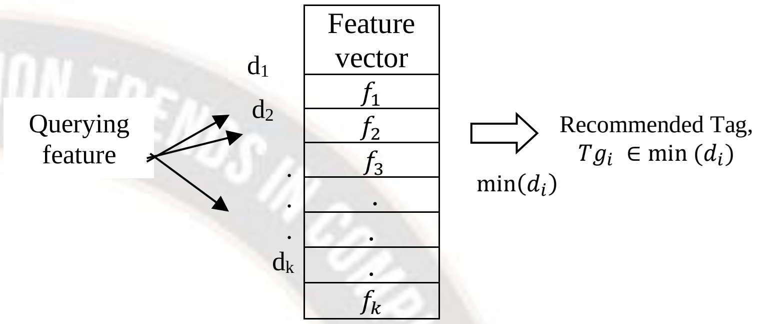

Figure 2. Correlation process of image mapping and Tag recommendation

The feature of query is correlated in a linear process where each image details is linearly correlated to compute feature distance. The feature with minimum distance is considered as best match which is then processed to extract the related tag for recommendation. Tags which are not found in the definition of user tags are recommended to given sample.

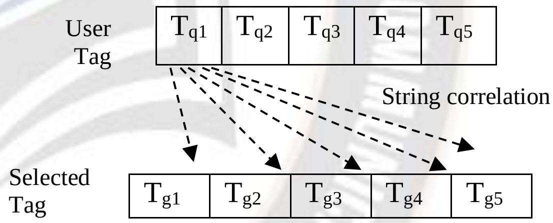

Figure 3. Process of tag recommendation

The process presented shows a large search overhead, as with increase in volume of image feature the search iteration increases which generate a delay in decision making. To overcome the addressed issue, a non-linear clustering based on correlation factor and relevance feedback is proposed. For a randomly distributed feature vector $f_{i,}$ and mapped tag tg_i presented as a set of $F \in (f_{i,} tg_i)$ is moralized to mean given by,

$$M(f_1, f_2, \dots \dots f_3) = \sum_{k=1}^{K} \sum_{f \in F} \left\| f - \bar{f} \right\|^2 \quad (8)$$

Here, f feature vector in database of ith cluster, and $\bar{f}$ is mean of set of data in the data base given as,

$$\bar{f} = \frac{1}{k} \sum_{f \in F} f \quad (9)$$

The correlation factor is a linear correlation distance of the data base feature with the input feature given as,

$$D(f,c) = \sqrt{\sum_{i=1}^{k}(f_i - c_i)^2} \quad (10)$$

The formation of cluster based on distance gives a similar characteristic image feature into a common group. The process of feature cluster grouping with tag map is illustrated in figure 4 below.

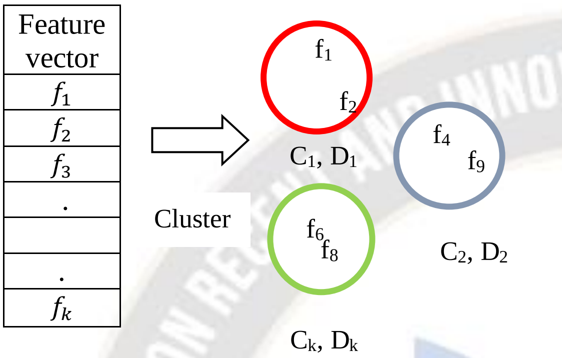

Figure 4. Illustration of cluster formation in tag recommendation

However, the information's mapped into the cluster has a magnitude correlation only. The information based on magnitudes may impact the cluster process and the accuracy of grouping. A improper cluster leads to higher false alarm in the detection process. To improve the accuracy of grouping, a gain-based information clustering is developed. The information's are computed with a cluster gain (CG) before updation defined by

$$CG = \frac{N(Q) - N(Q|f_i)}{N(f_i)} \quad (11)$$

Here, N defines the redundancy of a feature in the cluster for a updating attribute Q. the redundancy factor is given by,

$$N(Q) = -\sum_{i=1}^{k} Pr(C_i) log_2\left(Pr(C_i)\right) \quad (12)$$

Where Pr(.) define the probability operation of ith information going to a cluster C_i.

The mapping of cluster is developed as a weighted updation of the cluster center and the information. The distance factor of the information is updated with a weight value based on the relevance feedback of observation from tag detail and image feature distance. The updation is given as,

$$U(C,f) = \sqrt{\sum_{i=1}^{k} \omega_i (C_i - f_i)^2} \quad (13)$$

The weight is defined as the varying parameter of the observing input and the cluster values. The initial value of a weight is randomly set to a lower value of 0.1 to initiate and in each iteration the weight is updated for cluster convergence.

$$\left.\begin{array}{l} \omega_i = CG(C, f_i) \\ U_{convg} = \max\left(CG_{\omega_i, f_i, C}\right) \end{array}\right\} \quad (14)$$

An updation is converged for maximization of cluster gain with the updating feature. The information passed to the cluster is updated based on the feedback value of the correlation distance of image feature and tag distance.

$$\omega_{i+1} = \omega_i + dist(f_i, tg_i) \quad (15)$$

The cluster derived offer the advantage of lower correlation for tag recommendation with the search constraint to a selected cluster and the accuracy of tag recommendation is also improved due to the cluster formation of maximum cluster gain which is developed in reference to dual parameter of image feature and tag distance.

V. RESULT

The result for the developed approach is performed over Flickr data set containing the data of image and its tag annotated. The proposed approach is developed on MATLAB tool and validated for variation in cluster density. The observations obtained for the developed approach is as outlined. In developing the simulation, the given data set is tested for k-fold test where k=4 is considered for the presented simulation. The dataset is divided into a set of training and testing, where 1/4 data are taken for testing ad reaming are considered for training. The simulation is developed for the proposed system compared with the existing approaches. The evaluation are carried out using the Accuracy (Acc), detection ratio (DR), sensitivity, false alarm rate and Recall Rate (RR) parameter. The metrics are defined by,

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

The detection ratio is given as

$$DR = \frac{TP}{TP+FN} \quad (17)$$

The ratio of false positive to the sum of true positive and false positive gives FAR given as follows:

$$FAR = \frac{FP}{TN+FP} \quad (18)$$

The parameter of observations is developed with the following observations.

TABLE 1: OBSERVATION FACTOR

(True Positive) TP	Correctly matched samples
(True Negative) TN	Truly detected false images
(False Negative) FN	False Samples detected as true matching

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(False positive) FP	True Samples detected as false matching

The matrix of confusion for the detection and tag recommendation is illustrated below.

TABLE 2: MATRIX OF CONFUSION FOR TAG RECOMMENDATION

Recognition	Recommended tag	Non recommendation
Matched sample	TP	FP
Non matched sample	TN	FN

The observation for the developed system is summarized for different test sample listed in table 3 below. The proposed method of weight tag recommendation (WTR) is compared with the existing approach of KNN method.

TABLE 3: OBSERVATION FOR SIMULATION SYSTEM DEVELOPED

TEST SAMPLE	APPROACH	ACCURACY (%)	DR	FAR	RR	TT(S)
S1	WTR	98.86	0.64	0.486	0.64	0.446
	KNN	98.08	0.94	0.468	0.91	0.146
S2	WTR	98.64	0.60	0.406	0.60	0.469
	KNN	98.06	0.64	0.4868	0.64	0.164
S3	WTR	98.66	0.64	0.446	0.64	0.468
	KNN	98.04	0.94	0.466	0.88	0.144
S4	WTR	98.64	0.64	0.441	0.64	0.466
	KNN	98.48	0.94	0.466	0.91	0.164

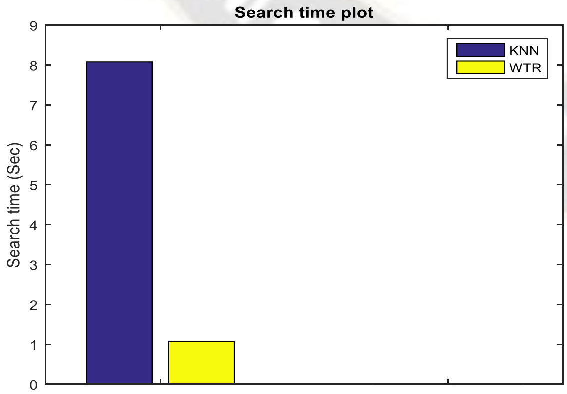

Figure 5. Observation of search time for the developed approach

Observation of search time indicates the time taken for making a decision of image mapping and tag recommendation. A clustered approach of search has a minimum search overhead due to lower searching data in a cluster compared to the whole data set. The observation illustrates a minimization of search time by 0.8sec compared to existing approach. This minimization results in faster tag recommendation and updation in real time interface.

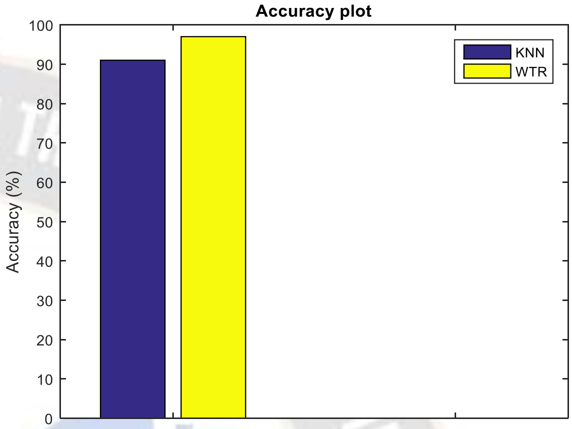

Figure 6. Observed accuracy for the developed approaches on sample1 testing

Accuracy is defined as the ratio of truly classified sample with recommend tag over the overall data set samples with tag annotated. Accuracy if the proposed system is observed to be higher than the existing approaches due the clustering of highly correlative samples to a cluster. This builds a higher probability of accurate recommendation compared to the distributed data set. The test sample features are mapped to the best correlative cluster center which has the advantage of minimum search overhead and higher accuracy to the system. To observe the tag recommendation performance over a dataset, the presented work is evaluated over Flickr dataset consisting of 1200 samples with tag annotated. The presented work divided the dataset into two parts for training and testing. Where, 200 samples are considered for testing and 1000 samples are taken for training. The system uses a one- many SVM classifier model in making decision. The test sample is passed for tag recommendation, where the features are extracted for the given query sample and correlated with the clustered data set for retrieval. Observations obtained for the developed recommendation approach is presented below.

Test image

Figure 7: Test sample from Flickr dataset for recommendation

Figure 7 illustrates the test sample used for testing the classification efficiency of the developed approach. The presented system is compared with a widely used KNN classifier. The cluster parameter (k) for the KNN based estimation is set to 2, where the whole data set is processed to select top 50% of the trained features for classification. This perform dimensional reduction; however, the observation of classification is limited to the considered training features. Figure 4 illustrates the obtained result for k=2.

Figure 8: Matched sample from the data based using KNN classifier for k=2

Due to 50% discard of feature vector the information is eliminated and hence the classification performance is degraded. Here, the dimensional reduction achieves a faster processing however the discarding of feature leads to misclassification. The obtained result for the given query sample using proposed weighted tag recommendation is presented in figure 9.

Figure 9: Retrieved sample

The retrieved sample is observed to be matching with the given test sample. The retrieval accuracy is due to the incorporation of required feature vector in the matching. The proposed approach offers dual enhancement of accuracy and minimization of search time. the retrieval accuracy is observed to be accurate due to the presence of feature vector in the cluster whereas the search time is reduced due to elimination of non-required search which are of farther distance. The computation time and the accuracy obtained for the developed system when compared to existing KNN approach is illustrated in figure 5 and 6 respectively. Similar testing is performed over a randomly picked sample from the data base and the results of retrieval for developed method is presented in figure 10.

(a) (b) (c)

Figure 10. (a) Original test sample, (b) matched sample at k=2 (c) Result for the proposed WTR method

The retrieval accuracy of the proposed system for varying K parameter is presented in table 4 for a given test sample shown in figure 11.

Figure 11. Test sample for analysis

TABLE 4: OBSERVATION OF DEVELOPED RECOMENDSTION SYSTERM

Matched sample @ K=	**2**	**3**	**4**
KNN approach			
WTR approach			

The observation of the developed approach for varying K value and compared to the WTR approach. the retrieval accuracy for the developed approach for different value of K is shown, where with increase in K value the information of the database is increased. The increase in details of the feature value increases the matching which is reflected in table 4. The tag recommended for the developed approach is illustrated in table 5. A true matching result in more accurate tag recommendation in reference to the cluster in matching. The user tag for the sample from the user is given by 'Leaf, green, small'.

TABLE 5. TAG RECOMMENDATION FOR THE MATCHING OF IMAGE

K	**Recommended tag using KNN**	**Recommended tag by WTR**
2	Nature, jungle, dawn	Leaf green, park, lawn
3	Small green leaf, hydrophobic	Park lawn green leaf, small leaf
4	Cluster green leaf, park	Green leaf, small leaf, green leaf

VI. CONCLUSION

The tag recommendation addressed is focused to minimize the computation overhead by minimize the search time and accuracy of retrieval. The tag recommendation system improves the accuracy of decision with minimal search time. The proposed approach of weighted cluster defines the accuracy by improving the clustering performance of a wide distributed data set. The proposed clustering approach performs the clustering with dual monitoring of image and tag for accurate classification based on cluster gain due to information updation. The retrieval performance and accuracy of tag recommendation is observed to be higher for the proposed approach.

REFERENCES

[1] Zheng, Liu, Zhao Tianlong, Han Huijian, and Zhang Caiming. "Personalized tag recommendation based on convolution feature and weighted random walk." International Journal of Computational Intelligence Systems 13, no. 1 (2020): 24-35.
[2] Fu, Jianlong, and Yong Rui. "Advances in deep learning approaches for image tagging." APSIPA Transactions on Signal and Information Processing 6 (2017).
[3] Wu, Lin, Yang Wang, and John Shepherd. "Efficient image and tag co-ranking: a bregman divergence optimization method." In Proceedings of the 21st ACM international conference on Multimedia, pp. 593-596. 2013.
[4] Liang, Tingting, Liang Chen, Jian Wu, and Athman Bouguettaya. "Exploiting heterogeneous information for tag recommendation in API management." In 2016 IEEE International Conference on Web Services (ICWS), pp. 436-443. IEEE, 2016.
[5] Sagha, Hesam, Nicholas Cummins, and Björn Schuller. "Stacked denoising autoencoders for sentiment analysis: a review." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 7, no. 5 (2017): e1212.
[6] Wu, Lin, Xiaodi Huang, Chengyuan Zhang, John Shepherd, and Yang Wang. "An efficient framework of Bregman divergence optimization for co-ranking images and tags in a heterogeneous network." Multimedia Tools and Applications 74, no. 15 (2015): 5635-5660.
[7] Squillero, Giovanni, and Alberto Tonda. "Divergence of character and premature convergence: A survey of methodologies for promoting diversity in evolutionary optimization." Information Sciences 329 (2016): 782-799.
[8] Vallet, David, Miriam Fernández, Pablo Castells, Phivos Mylonas, and Yannis Avrithis. "Personalized information retrieval in context." In 3rd International Workshop on Modeling and Retrieval of Context, Boston USA, pp. 16-17. 2006.
[9] Bozdag, Engin. "Bias in algorithmic filtering and personalization." Ethics and information technology 15, no. 3 (2013): 209-227.
[10] Fonseca, Eduardo, Manoj Plakal, Frederic Font, Daniel PW Ellis, and Xavier Serra. "Audio tagging with noisy labels and minimal supervision." arXiv preprint arXiv:1906.02975 (2019).
[11] Barbosa, Luciano, and Junlan Feng. "Robust sentiment detection on twitter from biased and noisy data." In Coling 2010: Posters, pp. 36-44. 2010.
[12] Guo, Kehua, Yayuan Tang, and Peiyun Zhang. "CSF: Crowdsourcing semantic fusion for heterogeneous media big data in the internet of things." Information fusion 37 (2017): 77-85.
[13] Benavent, Xaro, Ana Garcia-Serrano, Ruben Granados, Joan Benavent, and Esther de Ves. "Multimedia information retrieval based on late semantic fusion approaches: Experiments on a wikipedia image collection." IEEE Transactions on Multimedia 15, no. 8 (2013): 2009-2021.
[14] Sawant, Neela, Jia Li, and James Z. Wang. "Automatic image semantic interpretation using social action and tagging data." Multimedia Tools and Applications 51, no. 1 (2011): 213-246.
[15] Vandic, Damir, Flavius Frasincar, and Frederik Hogenboom. "Scaling pair-wise similarity-based algorithms in tagging spaces." In International Conference on Web Engineering, pp. 46-60. Springer, Berlin, Heidelberg, 2012.
[16] Milicevic, Aleksandra Klasnja, Alexandros Nanopoulos, and Mirjana Ivanovic. "Social tagging in recommender systems: a survey of the state-of-the-art and possible extensions." Artificial Intelligence Review 33, no. 3 (2010): 187-209.
[17] Bo, Cheng, Guobin Shen, Jie Liu, Xiang-Yang Li, YongGuang Zhang, and Feng Zhao. "Privacy. tag: Privacy concern expressed and respected." In Proceedings of the 12th ACM conference on embedded network sensor systems, pp. 163-176. 2014.
[18] Pudota, Nirmala, Antonina Dattolo, Andrea Baruzzo, Felice Ferrara, and Carlo Tasso. "Automatic keyphrase extraction and ontology mining for content-based tag recommendation." International Journal of Intelligent Systems 25, no. 12 (2010): 1158-1186.
[19] Lops, Pasquale, Marco De Gemmis, Giovanni Semeraro, Cataldo Musto, and Fedelucio Narducci. "Content-based and collaborative techniques for tag recommendation: an empirical evaluation." Journal of Intelligent Information Systems 40, no. 1 (2013): 41-61.