Two Phase Implementation of MMMs-induced Fuzzy Co-clustering with Partially Exclusive Item Assignment

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Summary
Fuzzy co-clustering is a basic tool for extracting pair-wise clusters of familiar objects and items from cooccurrence information. A promising improvement of the conventional fuzzy co-clustering algorithms is achieved by introducing exclusive nature to item partition with the goal of the improvement of interpretability of co-clusters. However, in practice, some items are quite popular and to be shared by multiple clusters, and only a selected part of items should be exclusively assigned to unique clusters. In this paper, a partially exclusive item partition model is introduced into multinomial mixture models-induced fuzzy co-clustering and a two phase implementation is proposed for determining the optimal set of items to be exclusively assigned. Its characteristic features are demonstrated through a numerical experiment with a real-world benchmark data set.
Key words:
Fuzzy clustering, Co-clustering, Multinomial mixture, Exclusive partition, Classification.

1. Introduction

Cooccurrence information analysis is a basic step of many web system analysis and is utilized in such areas as document-keyword analysis or customer-product market analysis. Fuzzy co-clustering [1, 2] reveals the intrinsic pair-wise cluster structures of mutually familiar objects and items from cooccurrence information among them, such that two types of fuzzy memberships for objects and items are estimated for representing their cluster assignment. In a co-cluster, it is expected that objects and items that have high cooccurrences will have high memberships. In the same manner with fuzzy *c*-means (FCM) [3, 4], object memberships often represent the exclusive assignment to a cluster under the sum-to-one condition with respect to the cluster index, such that each object belongs to at most one cluster with a large membership. On the other hand, item memberships represent the relative typicality in each cluster under the sum-to-one condition with respect to the item index, such that the typicality of items is independently estimated in each cluster.

Fuzzy co-clustering induced from multinomial mixture models (FCCMM) [5] is a practical method that is motivated by multinomial mixture models (MMMs) [6] and can easily tune the degrees of fuzziness of object partition and item partition through comparison with the statistical MMMs.

In many fuzzy co-clustering models, however, because of the nonexclusive nature of item partitions, characteristics that are unique to particular clusters are often concealed by item sharing in multiple clusters. In order to improve the partition quality and interpretability, some previous works [7, 8] introduced the exclusive nature into item partition, where an additional penalty for exclusive item partition was added to the FCCMM objective function. By assigning some selected items to at most a single cluster with a large membership, typical items can be utilized to emphasize the peculiar features of each cluster.

In this paper, the FCCMM model is further investigated by introducing a two phase implementation procedure for selecting the optimal set of items to be exclusively assigned from the classification viewpoint. The first stage is devoted to selecting the items to be exclusively partitioned through an item-wise single penalization test. The second stage performs FCCMM by forcing the selected items to be exclusive.

The remaining parts of this paper are organized as follows: Section 2 reviews the FCCMM algorithm, and Section 3 proposes its extension with an exclusive item partition penalty in conjunction with its two phase implementation. Some experimental results are presented in Section 4, and summary conclusions are given in Section 5.

2. MMMs-induced Fuzzy Co-clustering

Assume that we have cooccurrence information for a set of objects and items, such as document-keyword cooccurrence frequencies in a document analysis, where $R = \{r_{ij}\}$ is an $n \times m$ cooccurrence information matrix for n objects and m items, and where r_{ij} is the degree of cooccurrence for object i and item j. The goal of co-clustering is to reveal the intrinsic information about co-cluster structures, in which mutually familiar objects are grouped into clusters that contain their typical items.

Honda *et al*. [5] proposed the fuzzy co-clustering algorithm known as FCCMM. MMMs [6] is a statistical co-clustering model for estimating mixtures of C component multinomial distributions, but it can also be interpreted as a soft partition model with an intrinsic fuzziness penalty. In the following discussion, the clustering models will be considered in the fuzzy co-clustering context.

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Assume that each object i belongs to cluster c with fuzzy membership u_{ci} under the probabilistic constraint of $\sum_{c=1}^{C} u_{ci} = 1$. Additionally, each item j is also assumed to have fuzzy membership w_{cj} to cluster c but obeys a different constraint of $\sum_{j=1}^{m} w_{cj} = 1$, i.e., w_{cj} corresponds to the typicality of item j in cluster c rather than to its cluster indicator. The pseudo-log-likelihood to be maximized in MMMs is given as:

$$L_{mmms} = \sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{j=1}^{m} u_{ci} r_{ij} \log w_{cj} + \sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci} \log \frac{\alpha_c}{u_{ci}}. \quad (1)$$

α_c is the a priori probability (volume) of component c under $\sum_{c=1}^{C} \alpha_c = 1$. Using the EM algorithm [9], α_c, u_{ci} and w_{cj} are iteratively updated until convergence.

In the same way as in Gaussian mixture models [10], MMMs can also be interpreted as a soft partition model. $\sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{j=1}^{m} u_{ci} r_{ij} \log w_{cj}$ is an aggregation measure for object-item pairs in co-clusters, and mutually familiar pairs will have large memberships u_{ci} and w_{cj} in a particular cluster c. This is maximized in $u_{ci} \in \{0,1\}$ because of the linearity of the objective function with respect to u_{ci}; i.e., the hard clustering principle. Then, $\sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci} \log \frac{\alpha_c}{u_{ci}}$ is used for the fuzzification of u_{ci}. On the other hand, the fuzzy feature of w_{cj} is due to the nonlinearity of the log function.

Following the soft partitioning interpretation, FCCMM introduces additional fuzziness tuning penalties in the same manner as used in the entropy-based or K-L information-based fuzzification schemes in FCM [11, 12], in conjunction with nonlinearity tuning of the log function:

$$L_{fccmm} = \sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{j=1}^{m} \frac{1}{\lambda_w} u_{ci} r_{ij} ((w_{cj})^{\lambda_w} - 1) + \lambda_u \sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci} \log \frac{\alpha_c}{u_{ci}}. \quad (2)$$

In this objective function, the nonlinear degree is tuned by two types of adjustable penalty weights. λ_u tunes the responsibility of the K-L information-based penalty. Note that $\lambda_u = 0$ implies a crisp object partition, and a larger value for λ_u results in a fuzzier object memberships. On the other hand, λ_w tunes the nonlinear degree of the aggregation criterion. Following the definition of the log function:

$$\log w_{cj} = \lim_{t \to 0} \frac{1}{t} ((w_{cj})^t - 1), \quad (3)$$

the objective function in Eq.(2) reduces to MMMs with $\lambda_w \to 0$ while $\lambda_w = 1$ implies a crisp linear objective function. Then, $\lambda_w < 0$ results in fuzzier item memberships.

3. Exclusive Item Partition

3.1 Exclusive Partition Penalty on Item Memberships

Because item memberships are independently estimated for each cluster, some items may have large memberships in multiple clusters and others may not belong to any clusters. This item-sharing feature often results in the concealing of items unique to a particular cluster. In order to improve the quality of the partitions and the interpretability, some previous studies [7, 8] have made the item partitions exclusive.

In order to evaluate the degree of sharing of item j in cluster c, the sharing penalty weight is calculated as:

$$s_{cj} = \exp\left(-\beta \sum_{t \neq c} w_{tj}^{*}\right). \quad (4)$$

Note that s_{cj} is small when item j belongs to other clusters, and β tunes the sensitivity, such that a large β causes a rapid decrease in s_{cj}, while a small β brings a small change in s_{cj}.

In many co-clustering tasks, some items are quite popular and should be shared by multiple clusters, while others should be unique to a particular cluster. For example, in document analysis, some general terms are quite common, but topic-sensitive terms should be used for emphasizing features of particular clusters. This exclusive nature should be applied to only certain items. Assume that *EI* is a set of items to be exclusively assigned to co-clusters, and other items can be shared by multiple clusters. The item-sharing penalty s_{cj} is assumed to be

$$s_{cj} = \begin{cases} \exp\left(-\beta \sum_{t \neq c} w_{tj}\right) & ;\ j \in EI \\ 1 & ;\text{otherwise} \end{cases}. \quad (5)$$

By applying the weight s_{cj} to the cluster-wise aggregation, the typicality of the items to be exclusively assigned can be adjusted, and the objective function of FCCMM is modified as follows:

$$L_{fccmm'} = \sum_{c=1}^{C}\sum_{i=1}^{n}\left(\sum_{j=1}^{m} \frac{1}{\lambda_w} u_{ci} r_{ij} s_{cj}\right)((w_{cj})^{\lambda_w} - 1) + \lambda_u \sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci} \log \frac{\alpha_c}{u_{ci}}. \quad (6)$$

The clustering algorithm uses a four-step iterative process to update s_{cj}, α_c, u_{ci}, and w_{cj} as follows:

$$\alpha_c = \frac{1}{n} \sum_{i=1}^{n} u_{ci}. \quad (7)$$

For $\lambda_w \neq 0$,

$$u_{ci} = \frac{\alpha_c \exp\left(\frac{1}{\lambda_u \lambda_w} \sum_{j=1}^{m} r_{ij} s_{cj} \left(w_{cj}\right)^{\lambda_w}\right)}{\sum_{l=1}^{C} \alpha_l \exp\left(\frac{1}{\lambda_u \lambda_w} \sum_{j=1}^{m} r_{ij} s_{lj} \left(w_{lj}\right)^{\lambda_w}\right)}. \quad (8)$$

For $\lambda_w = 0$, Eq.(3) gives

$$u_{ci} = \frac{\alpha_c \prod_{j=1}^{m} \left(w_{cj}\right)^{\left(r_{ij} s_{cj}\right)/\lambda_u}}{\sum_{l=1}^{C} \alpha_l \prod_{j=1}^{m} \left(w_{lj}\right)^{\left(r_{ij} s_{lj}\right)/\lambda_u}}. \quad (9)$$

$$w_{cj} = \left(\sum_{l=1}^{m} \left(\frac{\sum_{i=1}^{n} r_{ij} s_{cj} u_{ci}}{\sum_{i=1}^{n} r_{il} s_{il} u_{ci}} \right)^{\frac{1}{\lambda_w - 1}} \right)^{-1} \quad (10)$$

$$= \frac{\gamma_{cj}}{\sum_{l=1}^{m} \gamma_{cl}},$$

where

$$\gamma_{cj} = \frac{1}{\left(\sum_{i=1}^{n} r_{ij} s_{cj} u_{ci} \right)^{\frac{1}{\lambda_w - 1}}}. \quad (11)$$

Note that the penalty weight s_{cj} is also updated in the iterative process. This trick is often utilized in relational clustering, such as relational fuzzy *c*-means [13].

Here, it is obvious that as $\beta \to 0$, $s_{cj} \to 1$; i.e., the conventional FCCMM model without item exclusive penalty, while a larger β results in a local search for exclusive items. Thus, a practical approach for setting β is to start with $\beta = 0$ and gradually increase it until it reaches a prefixed maximum value $\beta_{\max}$, such that $\beta = \min\{0.1 \times (\tau - 1), \beta_{\max}\}$ with iteration index τ [7, 8]. In this way, the initial partitioning obtained by the conventional FCCMM is gradually relaxed until an exclusive item partition model is obtained.

3.2 Two Phase Implementation for Selecting Exclusive Items

The quality of the partitions obtained with the modified FCCMM algorithm is strongly influenced by which items have been selected to be exclusively assigned. In this paper, in order to find the cluster-wise unique items to be exclusive and improve the quality of the clusters, a two phase implementation procedure is proposed from the classification viewpoint by utilizing a priori information about the classes. The two phases include a single-penalization test to select the items and successive partial exclusive penalizations on the selected items.

Assume that we have cooccurrence information for a set of objects and items, and that the objects were drawn from C components with their supervised class labels. In the context of data mining, unsupervised clustering models are often better at revealing the natural data distribution than is a supervised class-wise analysis. In the following, the data distribution is obtained by unsupervised clustering, and the class labels are used only secondarily.

In the first phase, the applicability of an exclusive partition is evaluated for each item by forcing an item-wise exclusive penalty onto each item in a separate FCCMM trial; i.e., the effects of the exclusive penalty are tested separately for each item by item-wise penalization in FCCMM. The classifications can then be improved over those of the conventional nonexclusive model by forcing exclusive penalties onto items that are regarded as peculiar to a particular cluster.

In the second phase, the partially exclusive FCCMM is implemented, and penalties are applied to each of the items selected in the previous phase. These items are emphasized by the penalties, and it can be expected that this will improve the quality of the clusters.

This two phase implementation procedure is summarized as follows:

[Two Phase Implementation for Selecting Items to be Exclusive]

I. Item-wise single-penalization test:

i. The conventional nonexclusive FCCMM is applied for deriving a base result.

ii. The partially exclusive FCCMM is applied by forcing an exclusive penalty on item j.

iii. If the classification quality is improved with penalty for j than the base result of the non-exclusive model, item j is selected to be exclusive:

$$j \to EI.$$

II. Partial exclusive penalization of the selected items:

The partially exclusive FCCMM is applied by forcing an exclusive penalty on each of the selected items in *EI*.

4. Numerical Experiment

4.1 Experimental Design

In this section, the proposed two phase implementation procedure is applied to a social network dataset, and the results are shown to demonstrate that the proposed approach is useful for selecting items peculiar to a cluster.

The Terrorist Attacks dataset, which is available from the LINQS webpage of the Statistical Relational Leaning Group at the University of Maryland, College Park (http://linqs.cs.umd.edu/project//index.shtml), consists of 1293 terrorist attacks, each of which is assigned to one of six labels that indicate the type of attack. Each attack is characterized by 106 distinct features, which are indicated in a vector of attributes that contains zero or unity for its absence or presence, respectively. The goal of this experiment is to use unsupervised co-clustering to reveal the intrinsic class distribution; note that the actual class information is withheld in distribution estimation. In this experiment, the minor classes were removed, and we considered only the three major classes of *bombing*, *kidnapping*, and *weapon attacks*; thus, $C = 3$.

In order to evaluate the best classification performances without initialization problems, fuzzy co-clustering models were operated in a supervised initialization scheme, where the initial object memberships were given following the correct class labels but they were updated in unsupervised manners.

In this experiment, three different FCCMM models were applied and compared as follows: (i) without an exclusive penalty on any items (Non-exclusive), (ii) with an exclusive penalty on all items (Fully exclusive), and (iii) with an exclusive penalty on selected items (Partially exclusive; note that this is the proposed two-phase implementation procedure).

The quality of the co-cluster partitions was evaluated by calculating the ratio of the number of correct matches among the supervised class labels and maximum membership classification in co-cluster solutions. In order to study the influence of both object and item fuzziness tunings, the FCCMM models were applied in three degrees of object fuzziness, $\lambda_u \in \{0.5, 1, 1.5\}$ and five degrees of item fuzziness, $\lambda_w \in \{-0.2, -0.1, 0, 0.1, 0.2\}$. For the exclusive partitions, the penalty weight $\beta_{\max} = 10$ was adopted.

Table 1: Comparison of unsupervised classification quality ($\lambda_u = 1$)

model	(λ_u, λ_w)				
	(1, 0.2)	(1, 0.1)	(1, 0)	(1, -0.1)	(1, -0.2)
Non-exclusive	0.816	0.673	0.663	0.788	0.792
Fully exclusive	0.617	0.608	0.628	0.595	0.718
Partially exclusive	0.691	0.871	0.862	0.805	0.847
The number of exclusive items	19	37	43	21	14

Table 2: Comparison of unsupervised classification quality ($\lambda_u = 0.5$)

model	(λ_u, λ_w)				
	(0.5, 0.2)	(0.5, 0.1)	(0.5, 0)	(0.5, -0.1)	(0.5, -0.2)
Non-exclusive	0.695	0.677	0.787	0.782	0.794
Fully exclusive	0.645	0.626	0.652	0.529	0.730
Partially exclusive	0.865	0.892	0.849	0.856	0.852
The number of exclusive items	37	31	14	16	5

Table 3: Comparison of unsupervised classification quality ($\lambda_u = 1.5$)

model	(λ_u, λ_w)				
	(1.5, 0.2)	(1.5, 0.1)	(1.5, 0)	(1.5, -0.1)	(1.5, -0.2)
Non-exclusive	0.733	0.676	0.657	0.794	0.789
Fully exclusive	0.586	0.602	0.599	0.453	0.651
Partially exclusive	0.688	0.857	0.855	0.809	0.838
The number of exclusive items	23	47	23	21	13

4.2 Comparison of Co-cluster Quality

The ratios of correct classification by maximum membership classification are compared in Tables 1-3.

First, the conventional nonexclusive FCCMM model was applied with all combinations of degree of object fuzziness and degree of item fuzziness. The classification ratios are shown in the top rows of Tables 1-3. For a particular degree of object fuzziness, the fuzzier and crisper item partition models achieved a slightly better classification quality than did the model with $\lambda_w = 0$, which is equivalent to the item fuzziness of MMMs.

Second, the fully exclusive FCCMM model was implemented by forcing the exclusive partition penalty on all 106 items. The classification ratios are shown in the second row of Tables 1-3. The quality of the classification was reduced for all degrees of fuzziness, because the fully exclusive penalty distorts the co-cluster structure. We note that this shows the importance of appropriately selecting the items that are to be exclusive.

Finally, the partially exclusive FCCMM was conducted using the proposed two phase implementation. In the item selection phase, the exclusive penalty was applied to each of the 106 items in a separate trial. The classification ratio was improved by at least 0.001 compared to that of the nonexclusive model; the numbers of items selected are shown in the last rows of Tables 1-3. In the next phase, the partially exclusive model was applied, and exclusive penalties were applied to only the items selected by the single-penalization test. The third rows of Tables 1-3 show that better classification ratios were obtained, except when $(\lambda_u, \lambda_w) = (1.5, 0.2)$. While the graph of the classification quality produced a valley shape with respect to λ_w in the conventional non-exclusive cases, it produced a mountain shape in the proposed partial model; the best result occurred when $(\lambda_u, \lambda_w) = (0.5, 0.1)$.

This shows that it is very important to select appropriate items to be exclusively assigned when estimating an intrinsic co-cluster distribution.

4.3 Evaluation of Selected Items

Finally, the validity of the item selection was intuitively evaluated through visual inspection of the degree of uniqueness of each item. Here, the best case with $(\lambda_u, \lambda_w) = (0.5, 0.1)$ is investigated, where 31 out of 106 items were selected to be exclusive. Figure 1 shows a visual comparison of the class-wise uniqueness of each item in the three supervised classes. The degree of shading indicates the percentage of the total number of degrees of co-occurrence in each class; black indicates 100%, and white indicates 0%. In this figure, 31 items are arranged in the order of their percentage in the *bombing* class.

We can see in Figure 1 that many of the selected items have large degrees of cooccurrence in only a single class, and thus these can be used to emphasize the peculiar characteristics of that class; i.e., they are meaningful in the context of data mining. These results show the advantage of the proposed two phase implementation procedure composed of the item selection based on item-wise penalization test and the successive partial exclusive penalization on the selected items.

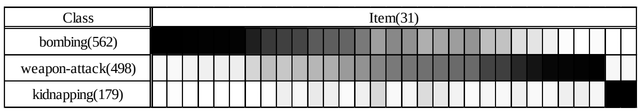

Figure 1: Percentage of cooccurrence degree for exclusive items ($\lambda_u = 0.5$, $\lambda_w = 0.1$)

5. Conclusion

In this paper, a two phase implementation procedure that selects items by using an item-wise penalization test and then applies partial exclusive penalization on the selected items was proposed for improving the MMMs-induced fuzzy co-clustering model. Some experimental results demonstrated that the peculiar items were selected and the classification quality was improved by placing an exclusive penalty on the selected items.

An area for future work is to investigate the results of this method for various applications, such as collaborative filtering based on fuzzy co-clustering [14]. Another direction is to develop a mechanism for automatically tuning the degree of fuzziness in conjunction with the exclusive penalty weight and based on the intrinsic fuzziness of the data.

Acknowledgments

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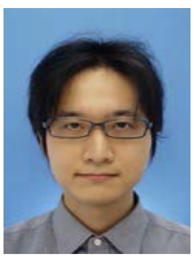

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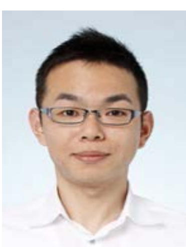

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