Exclusive Partition in FCM-type Co-clustering and Its Application to Collaborative Filtering

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Summary
The task of collaborative filtering has close relation to co-clustering, in which personalized recommendation is achieved by connecting users with items to be preferred. FCM-type co-clustering extracts user-item co-clusters, in which users are assigned to clusters in an exclusive manner while item partitions are not necessarily exclusive and each item can be shared (rejected) by multiple (all) clusters. In this paper, an exclusive constraint is introduced into FCM-type co-clustering and the clustering model is demonstrated to be useful in collaborative filtering task.

Key words:
Fuzzy clustering, Co-clustering, Collaborative filtering, Exclusive partition.

1. Introduction

A promising technique for enhancing Internet usability is collaborative filtering, in which personalized item recommendation is achieved by comparing user preferences [1-3]. In neighborhood-based recommendation models such as GroupLens [1], the user neighborhood of an active user is first estimated considering similarities among users and then, the applicability of un-selected items is calculated by the similarity-weighted average in his/her neighborhood. So, the concept has some connections with co-clustering.

Co-clustering is a technique for extracting user-item group structures from co-occurrence information of users and items. Fuzzy clustering for categorical multivariate data (FCCM) [4] is an FCM-type co-clustering model, in which fuzzy partition of both users and items are estimated based on the Fuzzy *c*-Means (FCM)-like concept [5]. The clustering criterion is given by the degree of aggregation to be maximized while different constraints are forced to the two memberships of users and items. User memberships are forced to be exclusive in a similar manner with FCM, in which the sum of memberships w.r.t. clusters are 1 for each user. On the other hand, the sum of item memberships w.r.t. items are forced to be 1 in each cluster. So, item memberships only play a role for evaluating the relative responsibility of items in each cluster and are not necessarily useful for revealing which cluster the item belongs to, i.e., items can be shared by multiple clusters or can be rejected from all clusters.

Oja [6] discussed co-clustering problems (biclustering problems) in the context of a modified principal component analysis (PCA) approach. In the neuro model, the exclusive feature of objects and items is not clearly discussed and the memberships of both objects and items are equally forced to be exclusive as much as possible.

Honda *et al*. [7-8] proposed a sequential co-clustering model, in which co-clusters are sequentially extracted by solving an eigenvalue problem in each phase. The sequential model is an extension of sequential fuzzy cluster extraction (SFCE) [9] for relational data matrices. In the sequential model, a full adjacency matrix of (users + items) is reformulated and the membership indicators of (users + items) are simultaneously estimated without distinguishing users and items. Avoiding multiple cluster assignment of elements, an element-wise penalty was used in a similar manner to SFCE, in which the penalty work for preventing a user or item already assigned to be assigned to second or later clusters. Based on the element-wise penalization scheme, the exclusive condition can be forced only to several selected items, so that partially exclusive partition is achieved [10]. Although the co-clustering model is useful for extracting co-clusters in a deterministic way, calculation of eigenvectors is often computationally expensive and is not suitable for large data sets.

In this paper, an extended model of FCCM is considered, in which item partition is also forced to be exclusive based on the element-wise penalization scheme of SFCE. The model is further modified in order to achieve partially exclusive partition of items. The applicability of the new model is demonstrated in a numerical experiment of a collaborative filtering task.

The remainder of this paper is organized as follows: Section 2 gives a brief review on the conventional co-clustering models. Section 3 introduces the exclusive condition of items to FCCM and extends it to a partially

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exclusive model. Section 4 presents several experimental results to demonstrate the characteristic features of the proposed approach. Section 5 summarizes the conclusions of this paper.

2. Brief Review on Conventional Co-clustering Models

Assume that we have a cooccurrence matrix $R = \{r_{ij}\}$ on n objects and m items and the goal is to extract C co-clusters of objects and items. For example, such task is popular in document analysis for finding the pairs of homogeneous document groups and keywords, in which r_{ij} can be the frequency of keyword j in document i.

2.1 FCM-type Co-clustering

Extending the *k*-Means-type fuzzy clustering model of Fuzzy *c*-Means (FCM) [5], Oh et al. [4] proposed fuzzy clustering for categorical multivariate data (FCCM), in which the objective function is defined by considering the aggregation degree of each cluster:

$$L_{fccm} = \sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{j=1}^{m} u_{ci} w_{cj} r_{ij} + \lambda_u \sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci} \log u_{ci} + \lambda_w \sum_{c=1}^{C}\sum_{j=1}^{m} w_{cj} \log w_{cj} \tag{1}$$

$U = \{u_{ci}\}$ and $W = \{w_{cj}\}$ are the fuzzy memberships of object i and item j to cluster c, respectively. The entropy terms are used for membership fuzzification [11]. In order to extract co-clusters having high aggregation degrees, u_{ci} and w_{cj} are iteratively optimized so that u_{ci} and w_{cj} become large if object i and item j are highly relevant.

Here, two different types of constraints are forced to u_{ci} and w_{cj}. u_{ci} is estimated under the condition of $\sum_{c=1}^{C} u_{ci} = 1$, which is also used in FCM for achieving exclusive partition where objects tend to be assigned to a solo cluster. On the other hand, w_{cj} should be estimated under a different constraint of $\sum_{j=1}^{m} w_{cj} = 1$ in order to avoid trivial solutions where all objects and items are assigned to one cluster. Using the constraint, w_{cj} represents the relative responsibility of item j in cluster c and item assignment is not necessarily exclusive, i.e., items can be shared (or rejected) by multiple (all) clusters.

2.2 Co-clustering Based on Neural PCA Model

Oja et al. [6] proposed a co-clustering model by extending Non-negative Matrix Factorization (NMF) model [12]. NMF approximately decomposes a matrix consisting of nonnegative elements into two non-negative matrices so that the columns of the matrices should be mutually orthogonal.

Because the columns of membership matrices U for objects and W for items are almost mutually orthogonal, both objects and items are to be assigned to a solo cluster, i.e., the exclusive partitions are forced to both objects and items without distinguishing them. Note that the weak exclusive constraints may make it difficult to estimate an explicit exclusive partition.

2.3 Sequential Fuzzy Co-cluster Extraction

A sequential algorithm for extracting co-clusters one by one was proposed [8], in which each cluster is independently handled and the second and later clusters are extracted by considering the penalty for avoiding multiple assignments of users and items that have already been assigned to a cluster.

In order to apply the sequential cluster extraction model from rectangular relational matrices [9] to cooccurrence matrices, Honda *et al*. reformulated an $(n+m)\times(n+m)$ full-rectangular matrix S as follows:

$$S = \begin{pmatrix} O & R \\ R^{\mathrm{T}} & O \end{pmatrix} \tag{2}$$

The membership indicators u_{1i} for user and w_{1j} for item are derived as the eigenvector corresponding to the largest eigenvalue of S in cluster 1.

In extraction of the second or later (c th) clusters, penalty weights for avoiding multiple assignment of users are added to the diagonal element s_{ii} ($1 \le i \le n$) of S.

$$s_{ii} = -\frac{1}{c-1}\sum_{t=1}^{c-1} \beta_t u_{ti}^2 \tag{3}$$

β_t is the weight parameter for tuning the degree of exclusive assignment and a large value brings an exclusive partition where each user can belong to only a solo cluster.

Each item, however, can be shared by multiple clusters and w_{cj} represent only the relative responsibility of items in cluster c if we do not add penalties to s_{jj} ($n+1 \le j \le n+m$). So, the clustering model is reduced to a similar one to FCCM although sequential clustering model may extract dense clusters only in early stages.

In collaborative filtering tasks, it is also possible that some typical items can be used to distinguish a small community having a special preference. Such typical items should be assigned to only a single cluster, while popular items can be shared by multiple clusters. Then, the above sequential co-clustering model was extended a partially exclusive partition model [10], in which additional penalty weights for the selected items are adopted as follows:

$$s_{ii} = -\frac{1}{c-1}\sum_{t=1}^{c-1}\beta_t w_{ti}^2 \tag{4}$$

Considering the additional penalties, only a part of items are forced to be exclusively assigned to clusters.

3. Application of Exclusive Condition to Item Assignment in FCM-type Co-clustering

In collaborative filtering tasks, popular items should be shared without exclusive condition while typical items assigned to a solo cluster. So, in this paper, the FCM-type co-clustering model of FCCM is extended by introducing exclusive conditions for several selected items.

In sequential clustering models of relational matrices such as SFCE [9], each object was prevented to be assigned to multiple clusters by considering element-wise penalty weights. In the penalization scheme, a penalty weight is added to the corresponding diagonal element of the relational matrix in the sequential iteration.

Based on a similar concept, in this paper, penalty weights for the selected items to be exclusively assigned are introduced to the FCCM objective function.

$$\begin{aligned} L_{fccm} &= \sum_{c=1}^{C}\sum_{i=1}^{n}\sum_{j=1}^{m} u_{ci} w_{cj} r_{ij} - \beta \sum_{j\in EI}\sum_{c=1}^{C}\sum_{t\ne c} w_{cj}\cdot w_{tj}^{*} \\ &\quad + \lambda_u \sum_{c=1}^{C}\sum_{i=1}^{n} u_{ci}\log u_{ci} + \lambda_w \sum_{c=1}^{C}\sum_{j=1}^{m} w_{cj}\log w_{cj} \end{aligned} \tag{5}$$

The second term is the newly added penalty weights and EI is the set of items to be exclusively assigned. The weight parameter β tunes the degree of exclusiveness of partitions. When all items should be exclusively assigned, all items are included in EI and the co-clustering model is reduced to a full exclusive model. On the other hand, in the case of $EI = \{\phi\}$ or $\beta = 0$, the model is equivalent to the conventional FCCM algorithm.

If item j belongs to another cluster t and have a large membership w_{tj}^{*} ($t \ne c$), w_{cj} becomes small and is rejected by cluster c. So, the item can belong to only a solo cluster.

Here, w_{tj}^{*} is the current value of w_{tj} and is temporally fixed in the FCM-type iterative algorithm. In a similar manner to relational fuzzy *c*-means (RFCM) [13], in which the objective function includes 'dot products' of memberships and a part of memberships are temporally fixed, the updating rule for w_{cj} is given by using the temporally fixed w_{tj}^{*}.

The updating rules for two types of memberships are given considering the partial optimality of the above objective function. u_{ci} is updated in a same formula with the conventional FCCM model as:

$$u_{ci} = \frac{\exp\left(\lambda_u^{-1}\sum_{j=1}^{m} w_{cj} r_{ij}\right)}{\sum_{l=1}^{C}\exp\left(\lambda_u^{-1}\sum_{j=1}^{m} w_{lj} r_{ij}\right)} \tag{6}$$

On the other hand, w_{cj} is updated considering penalty as:

$$w_{cj} = \frac{\exp\left(\lambda_w^{-1} w_{cj}^{temp}\right)}{\sum_{l=1}^{m}\exp\left(\lambda_w^{-1} w_{cl}^{temp}\right)} \tag{7}$$

where w_{cj}^{temp} is given as follows: For $j \notin EI$,

$$w_{cj}^{temp} = \sum_{i=1}^{n} u_{ci} r_{ij} \ . \tag{8}$$

For $j \in EI$,

$$w_{cj}^{temp} = \sum_{i=1}^{n} u_{ci} r_{ij} - \beta \sum_{t\ne c} w_{tj}^{*} \ . \tag{9}$$

An iterative algorithm is repeated until convergent. Here, the weight β is first set as '0' and is gradually increased so that the cluster partition gradually transits from the conventional one to an exclusive one. This soft transition approach can achieve the clarification of co-cluster structure of the conventional FCCM by gradually forcing item memberships to be exclusive.

4. Numerical Experiments

In this section, several experimental results are presented for demonstrating the characteristics of the proposed model.

4.1 Comparison of Exclusive Features

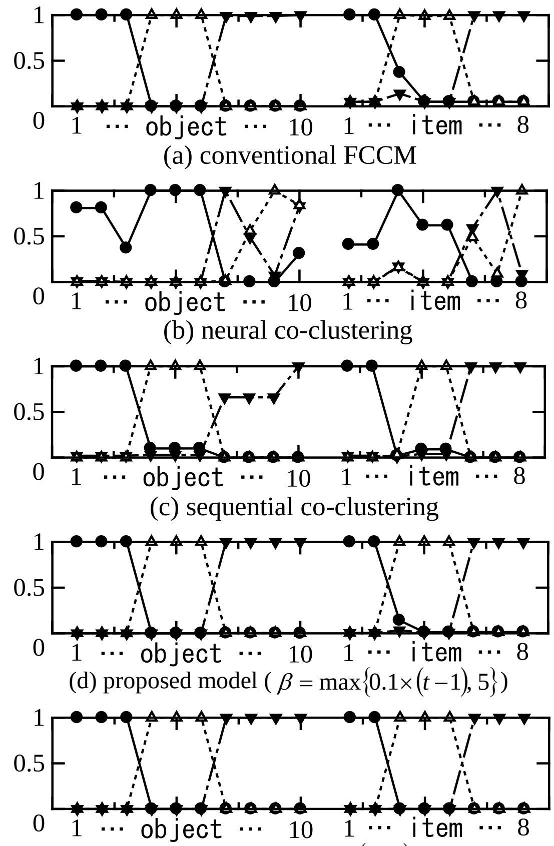
First, the exclusive features of the co-clustering models are compared in numerical experiments with an artificial data set. An artificially generated cooccurrence matrix composed of 10 object and 8 items ($n = 10, m = 8$) is shown in Table 1.

Table 1. Artificial cooccurrence matrix

	item	1	2	3	4	5	6	7	8
object	1	1	1	1					
	2	1	1	1					
	3	1	1						
	4			1	1	1			
	5			1	1	1			
	6			1	1	1			
	7						1	1	
	8							1	1
	9						1		1
	10			1			1	1	1

Clustering results by several co-clustering models are compared, in which cluster number is $C = 3$. In FCCM models, fuzzification weights were set as $\lambda_u = 0.1$ and $\lambda_w = 1.0$. In the proposed method, weight β was given by $\beta = 0.1 \times (t-1)$ where t is an iteration index.

Figure 1 compares the memberships of objects and items, in which all memberships are normalized so as to have maximum value of 1. First, FCCM assigned objects into clusters almost crisply while item 3 was shared by multiple clusters because FCCM does not force items to be exclusive. Second, Oja's neural co-clustering model merged the first two visual clusters into a big cluster because of the equally exclusive conditions for both objects and items. Third, sequential co-cluster extraction model with fully exclusive conditions failed to assign item 3 to any clusters because the item was severely shared and the sequential penalization rejected the item from all clusters so that all other items can fairly partitioned. Finally, the proposed co-clustering model with small $\beta_{\max}$ weaken the sharing degree of item 3 and the model without β limit could successfully partition all object and items almost crisply because the penalty for exclusive partition plays a role for clarifying the partition of FCCM.



(a) conventional FCCM

(b) neural co-clustering

(c) sequential co-clustering

(d) proposed model ($\beta = \max\{0.1 \times (t-1), 5\}$)

(e) proposed model ($\beta = 0.1 \times (t-1)$, $t = 166$)

Fig. 1 Comparison of memberships

4.2 Document Clustering with Fully Exclusive Partition

Next, the proposed co-clustering model was applied to a document clustering task. A data set to be analyzed was constructed from a Japanese novel "Kokoro" written by Soseki Natsume, which can be downloaded from Aozora Bunko (http://www.aozora.gr.jp). The data set was also used in [14]. The novel is composed of 3 chapters, each of which include 36, 18, 56 sections, respectively. In this experiment, the sections were given as objects ($n = 110$) and the cooccurrence frequencies with 83 most frequently used substantives and verbs were used for constructing a cooccurrence matrix ($m = 83$), whose elements are their tf-idf weights [15].

The FCCM algorithm was applied to the cooccurrence matrix without chapter information for extracting three co-clusters ($C = 3$) of documents (sections) and keywords, and the purity of clusters (maximum membership assignment) are shown in Table 2. The table indicates that the FCCM algorithm could roughly estimate the three chapter structures without a priori chapter information. The selected keywords having the memberships of 0.2 or larger are summarized in the left half of Table 3. The keywords having large memberships are useful for characterizing and summarizing the contents of each cluster. However, some keywords were weakly shared by multiple clusters.

Table 2. Purity of clusters

	Cluster	1	2	3
Chapt.	1	32	4	0
	2	0	18	0
	3	1	12	43

Then, the proposed model with exclusive condition for all keywords was applied in order to clarify the belongingness of each keyword to clusters. The derived memberships are shown in the right half of Table 3. The table indicates that the proposed model could assign meaningful keyword almost crisply and clarify them. In this way, the proposed method is useful for characterizing co-clusters by clarifying membership assignment.

Table 3. Selected keywords and memberships

		conventional FCCM			exclusive partition		
c	word	w_1	w_2	w_3	w_1	w_2	w_3
1	sensei	**0.380**	0.002	0.000	**0.482**	0.000	0.000
	kore	**0.038**	0.004	0.001	**0.049**	0.000	0.000
	okusan	**0.025**	0.001	0.007	**0.031**	0.000	0.000
	mieru	**0.025**	0.001	0.004	**0.031**	0.000	0.000
	iku	**0.024**	0.006	0.001	**0.030**	0.000	0.000
	hito	**0.021**	0.005	0.001	**0.025**	0.000	0.000
	mondai	**0.021**	0.002	0.003	**0.025**	0.000	0.000
2	chichi	0.001	**0.191**	0.000	0.000	**0.234**	0.000
	haha	0.001	**0.147**	0.001	0.000	**0.179**	0.000
	tegami	0.002	**0.060**	0.001	0.000	**0.074**	0.000
	kaku	0.002	**0.054**	0.001	0.000	**0.066**	0.000
	tokyo	0.002	**0.044**	0.001	0.000	**0.054**	0.000
	byouki	0.005	**0.031**	0.001	0.000	**0.038**	0.000
	ani	0.003	**0.028**	0.002	0.000	**0.034**	0.000
	oji	0.003	**0.025**	0.002	0.000	**0.031**	0.000
	dasu	0.004	**0.022**	0.002	0.000	**0.025**	0.000
	shinu	0.008	**0.020**	0.001	0.001	**0.023**	0.000
3	K	0.001	0.001	**0.268**	0.000	0.000	**0.320**
	ojosan	0.001	0.001	**0.121**	0.000	0.000	**0.154**
	kare	0.001	0.001	**0.111**	0.000	0.000	**0.132**
	mukau	0.001	0.002	**0.071**	0.000	0.000	**0.086**
	shitsu	0.002	0.001	**0.056**	0.000	0.000	**0.068**

4.3 Application of Partially Exclusive Partition to Collaborative Filtering Task

A purchase history data set collected by Nikkei Inc. in 2000 is used in a collaborative filtering task. The data set used in [8] includes the purchase history of 996 users ($n = 996$) on 18 items ($m = 18$). The element r_{ij} of 996 × 18 relational data matrix $R = \{r_{ij}\}$ is 1 if user i has item j while otherwise 0. Randomly selected 1,000 elements of the data matrix was given as a test data set and the applicability of the proposed model to collaborative filtering task was evaluated by predicting the test elements based on co-clustering results.

In the co-clustering prediction procedure, each user cluster is first estimated by maximum membership assignment, and then, the membership of each item in the user cluster is drawn from co-clustering results. If the item has a large membership in the user cluster, the item is recommended to the user. The recommendation ability is assessed by ROC sensitivity [16]. The ROC curve is a true positive rate vs. false positive rate plots drawn by changing the threshold of the applicability level in recommendation, and the lower area of the curve becomes large as the recommendation ability is higher.

Using the FCCM clustering model, the users and items were partitioned into 5 co-clusters ($C = 5$). The fuzzification parameters were given as $\lambda_u = 0.1$ and $\lambda_w = 10.0$, respectively. In the model with exclusive condition for items, weight β was given by $\beta = \min\{1.0 \times (t-1), 1000\}$ where t is an iteration index.

First, the recommendation ability of the FCCM algorithm with fully exclusive partition of items is compared with the conventional FCCM algorithm without exclusive condition for items. Figure 2 compares the ROC sensitivity and implies that the recommendation ability of the full-exclusive model is severely inferior to that of the non-exclusive model because some popular items are not shared by multiple clusters.

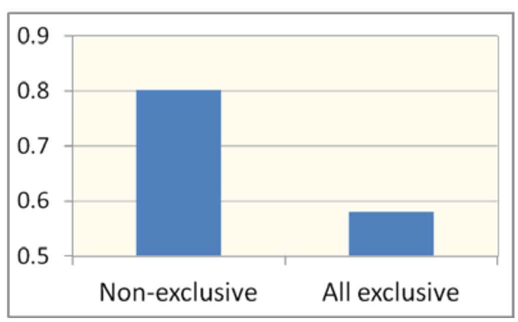


Fig. 2 ROC sensitivity: non-exclusive v.s. all-exclusive

Next, the exclusive condition was forced only to a selected item from 18 items and the ROC sensitivity is shown in Fig. 3. When the exclusive condition is forced only to a selected item, the recommendation ability of the model may significantly decrease, not changed, or slightly increase. For example, when item 4 was forced to be exclusive, the model had poor recommendation ability. On the other hand, by forcing item 13 to be exclusive, the recommendation ability of the FCCM-based model could be improved. In this way, the exclusive condition for item partition should be forced considering the characteristic feature of each item and the recommendation ability of the FCCM-based model can be improved by forcing the exclusive condition for appropriate items.

Here, a possible hypothesis is that the items owned by many users should be shared and the items owned by only a few users should be exclusively partitioned. Fig. 3 includes the number of users for each item in bracket. Unfortunately, the applicability of the exclusive condition was not related to the number of owners. So, we should construct a new criterion for selecting the items to be exclusive in our future works.

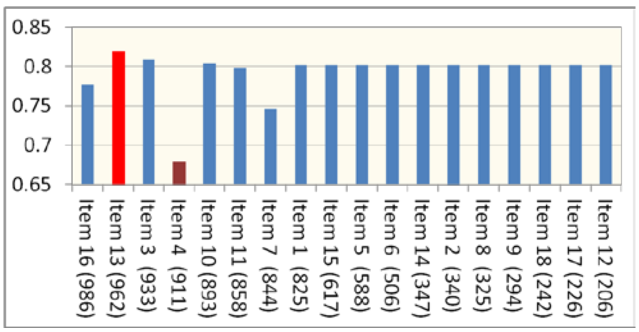


Fig. 3 ROC sensitivity: partially exclusive (num. of owners is shown in bracket)

5. Conclusions

In this paper, a new FCM-type co-clustering model was proposed by introducing an exclusive condition on items into FCCM. Although the conventional FCCM algorithm forces only objects to be exclusive, the exclusive partition is also given for items by considering a penalty for avoiding multiple cluster assignments. In order to force the selected items to be exclusively assigned, additional penalty for avoiding to be shared by multiple clusters was added in the FCCM objective function.

In a numerical experiment with a collaborative filtering task, the recommendation ability of the FCCM-based model can be improved by forcing the exclusive condition to appropriate items. Possible future works include the development of a criterion for selecting items to be exclusive and the study on the influence of combination of items when multiple items are forced to be exclusive.

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