Consideration of Site-wise Confidence in Fuzzy Co-clustering of Vertically Distributed Cooccurrence Data

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Summary
In advanced information and telecommunications network society, it is expected to utilize big data distributed among various organizations, such as cooperation groups, state organs and allied countries, with the goal of revealing intrinsic knowledge. In such collaborative data mining, however, personal privacy must be strictly preserved. This paper deals with a possible approach for utilizing distributed cooccurrence information in fuzzy co-clustering context under privacy consideration. Fuzzy Clustering for Categorical Multivariate data (FCCM) is a basic fuzzy co-clustering model and have been extended so as to perform privacy preserving data analysis. The secure model is further improved in this paper so that we can find robust knowledge, which is free from the influences of unreliable site, considering site-wise confidences. The applicability of the proposed model is demonstrated in several numerical experiments.

Key words:
Fuzzy Clustering, Co-clustering, Privacy preserving data mining.

1. Introduction

In advanced information and telecommunications network society, it is expected to utilize various big data, which are stored in various formats and in distributed sites. Cooccurrence information is a type of data formats and is common in such tasks as document-keyword frequencies in document analysis and customer-product purchase history in market analysis. Fuzzy co-clustering is a fundamental approach for analyzing cooccurrence information among objects and items, and has been utilized in document analysis [1], personalized recommendation [2,3], and so on. Fuzzy co-clustering divides objects and items into some co-clusters such that mutually familiar objects and items belong to same clusters in order to reveal co-cluster structures among them.

Fuzzy Clustering for Categorical Multivariate data (FCCM) [4] is a basic fuzzy co-clustering model, which was proposed by Oh *et al*. In FCCM, two different kinds of fuzzy memberships for objects and items are simultaneously estimated by alternately updating them.

In many real world data analysis tasks, it is expected to get much more useful knowledge by utilizing multiple databases stored in different organizations. In general, however, they cannot publish their databases to other organizations because of fear of privacy issues. In order to utilize multiple databases distributed in multiple sites under privacy consideration, FCCM was extended to FCCM for Vertically Distributed cooccurrence matrices (FCCM-VD) [5], in which site-wise information is securely stored in each site and is protected by encryption approach in collaborative data analysis. Common intrinsic object cluster structures are shared by multiple sites but site-wise item cluster structures are utilized only in each site.

FCCM-VD is useful for fairly merging distributed knowledge, however, some organizations may have harmful effects on co-cluster estimation because of low confidence. In order to solve this problem, this paper considers site-wise confidence based on the degree of coincidence between the whole object memberships and site-wise object memberships. Considering site-wise confidence, we can have more reliable knowledge by emphasizing intrinsic common co-cluster structures shared by reliable sites.

The remaining parts of this paper are as follows: Section 2 gives a brief review on Fuzzy Clustering for Categorical Multivariate data (FCCM). Section 3 describes FCCM for Vertically Distributed cooccurrence matrices (FCCM-VD). Section 4 proposes a novel approach for FCCM-VD considering site-wise confidence. In Section 5, the characteristics of the proposed algorithm is discussed through several numerical experiments with artificial matrices. Finally, summary conclusion is given in section 6.

2. Fuzzy Clustering for Categorical Multivariate Data (FCCM)

Fuzzy co-clustering is a fundamental approach for analyzing cooccurrence information among objects and items. A representative fuzzy co-clustering algorithm is Fuzzy Clustering for Categorical Multivariate data

Manuscript received February 5, 2016
Manuscript revised February 20, 2016

(FCCM) [4]. A brief review of FCCM is given in this section.

Assume that we have a cooccurrence matrix $R=\{r_{ij}\}$ on objects $i=1,\dots,n$ and items $j=1,\dots,m$, and each element $r_{ij}\in[0,1]$ shows the cooccurrence degree among user i and item j. For example, r_{ij} can be the amount of product j purchased by customer i in market analysis. FCCM divides objects and items into some co-clusters such that the degree of aggregations of each co-cluster is maximized. The objective function is as follows:

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

u_{ci} and w_{cj} are the fuzzy memberships of object i and item j to cluster c, respectively. The entropy terms are the fuzzification penalty in the entropy-based fuzzification approach [6]. λ_u and λ_w are the penalty weight for tuning the degree of partition fuzziness and larger weights bring fuzzier partitions. In order to extract co-cluster structures, u_{ci} and w_{cj} are iteratively optimized using updating rules of memberships derived considering the optimality of the objective function. The updating rules are as follows:

$$u_{ci}=\frac{\exp\left(\lambda_u^{-1}\sum_{j=1}^{m}w_{cj}r_{ij}\right)}{\sum_{l=1}^{C}\exp\left(\lambda_u^{-1}\sum_{j=1}^{m}w_{lj}r_{ij}\right)}, \tag{2}$$

$$w_{cj}=\frac{\exp\left(\lambda_w^{-1}\sum_{i=1}^{n}u_{ci}r_{ij}\right)}{\sum_{l=1}^{m}\exp\left(\lambda_w^{-1}\sum_{i=1}^{n}u_{ci}r_{il}\right)}. \tag{3}$$

Object memberships u_{ci} is forced to be exclusive such that $\sum_{c=1}^{C}u_{ci}=1$. On the other hand, in order to avoid trivial solutions, item memberships w_{cj} are responsible for representing the mutual typicality in each cluster such that $\sum_{j=1}^{m}w_{cj}=1$.

3. FCCM for Vertically Distributed Cooccurrence Matrices (FCCM-VD)

If we can utilize multiple databases distributed in multiple sites, it is expected that we find more useful common knowledge rather than site-wise independent analysis. In utilizing personal information, however, personal privacy must be strictly preserved [7]. The remaining parts of this paper consider extraction of common co-cluster structures from distributed cooccurrence matrices.

Assume that T sites ($t=1,\dots,T$) share common n objects ($i=1,\dots,n$) and have separate cooccurrence information on different items, which are summarized into $n\times m_t$ matrices $R_t=\{r_{ij}^t\}$, where m_t is the number of items in site t and $\sum_{t=1}^{T}m_t=m$. This type of data are called vertically distributed cooccurrence matrices in contrast to horizontally distributed matrices, in which multiple sites gathers information on same items (attributes) on different objects [8]. A sample of vertically distributed matrices is shown in Fig. 1.

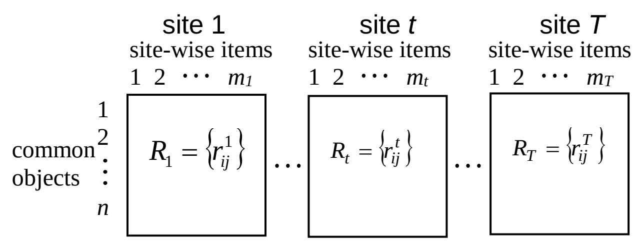


Fig. 1 A sample of vertically distributed matrices [5]

If we do not care about privacy issues, such distributed matrices should be gathered into a whole data set without information losses. Taking the privacy preservation into account, however, cluster analysis should be performed by concealing each data element within each site [8,9,10].

FCCM-VD [5] shares object partition information without broadcasting each cooccurrence matrix $R_t=\{r_{ij}^t\}$. Because Eq. (2) implies that $w_{cj}r_{ij}$ plays a role for tuning the contribution of the cluster structure of item j in u_{ci}, the site-wise structural information can be reflected through the sum of site-wise object partition information $\sum_{j=1}^{m_t}w_{cj}^t r_{ij}^t$. Then, each site should share $\sum_{j=1}^{m_t}w_{cj}^t r_{ij}^t$ and common u_{ci} can be calculated by the sum of site-wise information $\sum_{t=1}^{T}\sum_{j=1}^{m_t}w_{cj}^t r_{ij}^t$ without revealing each cooccurrence element r_{ij}^t. Furthermore, in order to share object partition considering personal privacy, the encryption approach can be adopted by concealing the actual values of $\sum_{j=1}^{m_t}w_{cj}^t r_{ij}^t$. The encryption approach is summarized in Fig. 2.

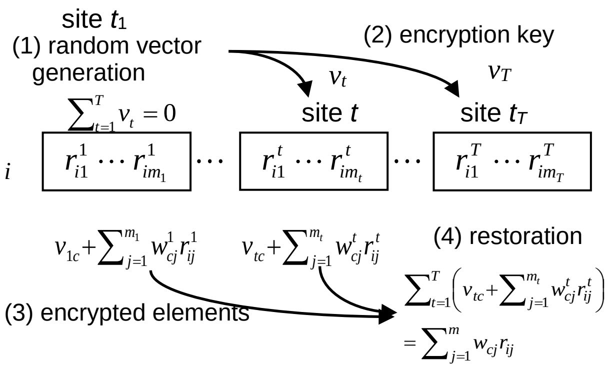


Fig. 2 Encryption operation [5]

First, Site t_1 generates length C random vector $\mathbf{v}_t = (v_{t1},\ldots,v_{tC})^T, t = 1,\ldots,T$ such that $\sum_{t=1}^{T} \mathbf{v}_t = 0$. Second, Site t_1 sends the encryption key to each of other sites. Third, Site $t_1,\ldots,t_{T-1}$ send their encrypted information $v_{tc} + \sum_{j=1}^{m_t} w_{cj}^{t} r_{ij}^{t}$ to site t_T. Finally, Site t_T calculates $\sum_{t=1}^{T}(v_{tc} + \sum_{j=1}^{m_t} w_{cj}^{t} r_{ij}^{t}) = \sum_{t=1}^{T}\sum_{j=1}^{m_t} w_{cj}^{t} r_{ij}^{t}$ for estimating common u_{ci}.

FCCM-VD algorithm is depicted as follows.

[**Algorithm 1: FCCM-VD** ($T > 2$) [5]]
Given $n \times m_1$ matrix R_1, ... , $n \times m_T$ matrix R_T, and let C be the number of clusters. Choose the fuzzification weights λ_u and λ_w.

Step1. [Initialization] In site t_1, randomly initialize u_{ci} such that $\sum_{c=1}^{C} u_{ci} = 1$ and broadcast them to all other sites.

Step2. [Iterative process] Iterate the following process until all u_{ci} are convergent.

(2-a) In site $t_1,\ldots,t_T$, update w_{cj}^{t} using the current values of u_{ci}.

(2-b) For $i = 1,\ldots,n$

(i) In site t_1, generate length C random vectors $\mathbf{v}_t = (v_{t1},\ldots,v_{tC})^T, t = 1,\ldots,T$ such that $\sum_{t=1}^{T} \mathbf{v}_t = 0$, and send $\mathbf{v}_t$ to each site.

(ii) In each site, calculate $v_{tc} + \sum_{j=1}^{m_t} w_{cj}^{t} r_{ij}^{t}$, and in site $t_1,\ldots,t_{T-1}$, send their own values to site t_T.

(iii) In site t_T, calculate $\sum_{t=1}^{T}\sum_{j=1}^{m_t} w_{cj}^{t} r_{ij}^{t}$,and update common u_{ci} using the sum.

(iv) Broadcast u_{ci} to all sites.

(2-c) Check the convergence condition.

In the case of $T = 2$, object memberships u_{ci} is alternately updated in each site without the encryption approach.

4. FCCM-VD Considering Site-wise Confidence

FCCM-VD provides common object memberships and site-wise item memberships securely from vertically distributed databases. Although some sites may have unreliable data for cluster estimation, FCCM-VD deals with separate matrices equally. In the case with unreliable sites, we want to weaken the responsibility of such sites on co-cluster estimation.

So, in this paper, "site-wise confidence" is introduced into FCCM-VD. Brief definition of "site-wise confidence" is given in next subsection.

4.1 Site-wise Confidence

In order to weaken the harmful effects of the unreliable sites on cluster estimation, this paper considers "site-wise confidence", which is measured by the degree of coincidence between site-wise object memberships and the global ones, and is defined as follows.

[**Definition 1: Calculation of Site-wise Confidence**]
Given $n \times m_1$ matrix R_1, ... , $n \times m_T$ matrix R_T, let C be the number of clusters.

Step1. In site $t_1,\ldots,t_T$, update site-wise object memberships u_{ci}^{t} using current values of w_{cj}^{t}.

Step2. In site $t_1,\ldots,t_T$, defuzzify u_{ci}^{t} such as max $u_{ci}^{t} = 1$ and otherwise $u_{ci}^{t} = 0$ for $i = 1,\ldots,n$.

Step3. In site $t_1,\ldots,t_T$, defuzzify the global object memberships u_{ci} such as max $u_{ci} = 1$ and otherwise $u_{ci} = 0$ for $i = 1,\ldots,n$.

Step4. In site $t_1,...,t_T$, count the number of coincidence between site-wise object memberships u_{ci}^t and the global ones u_{ci}, and calculate $\alpha_t = (\textit{number of coincidence}) / n$, where α_t is the site-wise confidence in site t.

Be noted that a site-wise cooccurrence information is reliable if it gives a similar co-cluster structure to the whole data case. Then, "coincidence" is measured by the degree of matching among u_{ci}^t and u_{ci} with respect to n objects. If the confidence α_t of site t is large, its structural information should be emphasized in u_{ci} calculation.

4.2 FCCM-VD Considering Site-wise Confidence

Considering the above site-wise confidence, the FCCM-VD algorithm is modified as follows.

[**Algorithm 2: FCCM-VD Considering Site-wise Confidence** ($T > 2$)]
Given $n \times m_1$ matrix R_1, ... , $n \times m_T$ matrix R_T, let C be the number of clusters. Choose the fuzzification weights λ_u and λ_w.

Step1. [Initialization] In site t_1, randomly initialize u_{ci} such that $\sum_{c=1}^{C} u_{ci} = 1$ and broadcast them to all sites.

Step2. [Iterative process] Iterate the following process until all u_{ci} are convergent.

(2-a) In site $t_1,...,t_T$, update w_{cj}^t using the current values of u_{ci}.

(2-b) In site $t_1,...,t_T$, update site-wise object memberships u_{ci}^t using the current values of w_{cj}^t.

(2-c) In site $t_1,...,t_T$, defuzzify u_{ci}^t such as max $u_{ci}^t = 1$, other $u_{ci}^t = 0$ for $i = 1,...,n$.

(2-d) In site $t_1,...,t_T$, defuzzify the global object memberships u_{ci} such as max $u_{ci} = 1$, other $u_{ci} = 0$ for $i = 1,...,n$.

(2-e) In site $t_1,...,t_T$, calculate α_t following Definition 1.

(2-f) For $i = 1,...,n$

(i) In site t_1, generate length C random vectors $\mathbf{v}_t = (v_{t1},...,v_{tC})^T, t = 1,...,T$ such that $\sum_{t=1}^{T} \mathbf{v}_t = 0$, and send $\mathbf{v}_t$ to each site.

(ii) In each site, calculate $v_{tc} + \alpha_t \times \sum_{j=1}^{m_t} w_{cj}^t r_{ij}^t$, and in site $t_1,...,t_{T-1}$, send their own values to site t_T.

(iii) In site t_T, calculate $\sum_{t=1}^{T} \alpha_t \sum_{j=1}^{m_t} w_{cj}^t r_{ij}^t$, and update common u_{ci} using the sum.

(iv) Send u_{ci} to all sites.

(2-g) Check the convergence condition.

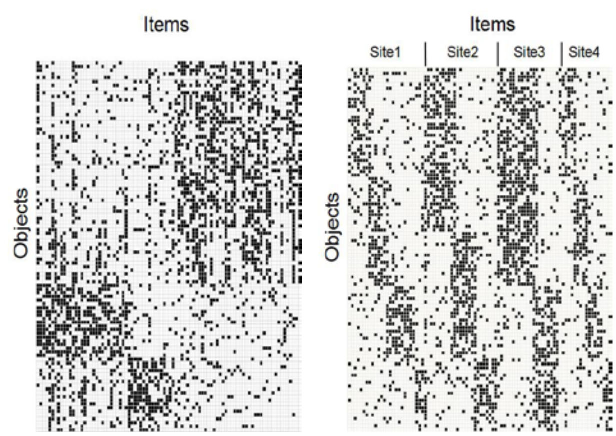
Using the above algorithm, the effect of unreliable sites is weakened in u_{ci} calculation, and it is expected to get much more reliable knowledge from vertically distributed databases than FCCM-VD.

5. Numerical experiments

We performed 3 numerical experiments with different artificial matrices.

5.1 Four Sites Collaboration with Encryption

An artificially generated 100×90 cooccurrence matrix $R = \{r_{ij}\}$ was used in this experiment, where 100 objects and 90 items form roughly 3 co-clusters. Figure 3(a) shows the original whole matrix, where black and white cells depict $r_{ij} = 1$ and $r_{ij} = 0$, respectively. Then, the matrix was arranged such that $m = 90$ items were vertically distributed into 4 sites with $(m_1, m_2, m_3, m_4) = (27,24,21,18)$ as shown in Fig. 3(b).



(a) original matrix (b) arranged matrix

Fig. 3 Artificial cooccurrence matrices 1

Here, the goal of collaborative analysis among 4 sites is to reconstruct the co-cluster structures, which are as similar to the whole data case as possible without publishing site-wise information. So, the FCCM-VD algorithm was applied with/without consideration of site-wise confidence, and the partition quality is evaluated by comparing the correlation coefficients of site-wise item memberships w_{cj}^t with the whole data case, which is given by the conventional FCCM with the original non-distributed data. Fuzzification parameters were set as $(\lambda_u = 0.001)$, $(\lambda_{w1}, \lambda_{w2}, \lambda_{w3}, \lambda_{w4}) = (100.0, 100.0, 100.0, 100.0)$ in FCCM-VD and the proposed model, respectively. In FCCM with the whole data, these parameters were set as $(\lambda_u, \lambda_w = 0.001, 100.0)$. Additionally, the partition quality is also compared with the case of site-wise independent analysis, where each site independently performed FCCM utilizing within-site information only. Fuzzification parameters were set as $(\lambda_u, \lambda_w) = (0.003, 100.0)$ in each site. Table 1 summarizes the results, in which the best and mean values in 100 trials with different random initializations are compared for each site.

The table shows that FCCM-VD with/without site-wise confidence achieved almost perfect performances in best while site-wise analysis could bring degraded performances only, i.e., this type of distributed information must be collaboratively analyzed. In comparison of mean performances, however, the proposed model with site-wise confidence outperformed the conventional FCCM-VD. The result indicates that considering “site-wise confidence” is meaningful.

Table 2: Correlation coefficient with the base item memberships (4 sites collaboration)

		Site1	Site2	Site3	Site4
FCCM-VD with Site-wise Confidence	Best	**0.99**	**0.99**	**0.99**	**0.99**
	Mean	**0.89**	**0.93**	**0.91**	**0.93**
FCCM-VD	Best	**0.99**	**0.99**	**0.99**	**0.99**
	Mean	0.85	0.89	**0.91**	0.90
Site-wise FCCM	Best	0.71	0.95	0.97	0.54
	Mean	0.62	0.84	0.89	0.60

Next, the characteristics of site-wise confidences are studied. Figure 4 shows the transition of site-wise confidence of each site. In the initialization phase, i.e., iteration 1, object partition is almost random and the site-wise confidences are all low, i.e., around $\alpha_t = 0.6$. But they became larger as co-cluster analysis proceeded. In the final phase, Site2 had a relatively smaller confidence than other three. It is because, as seen in Fig. 3(b), Site2 has somewhat different object partition from others. In this way, site-wise confidence is useful for reflecting differences among sites and can contribute to improving the performances of collaborative analysis.

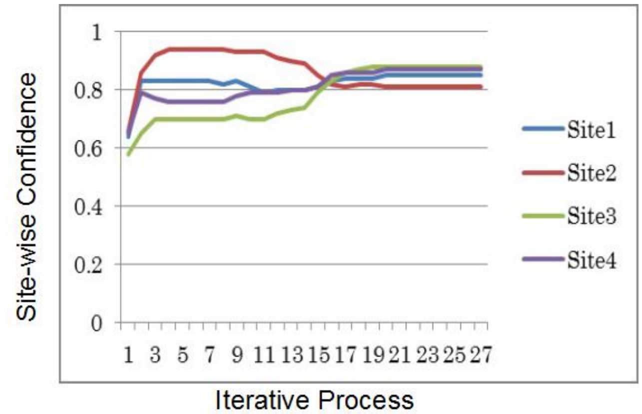
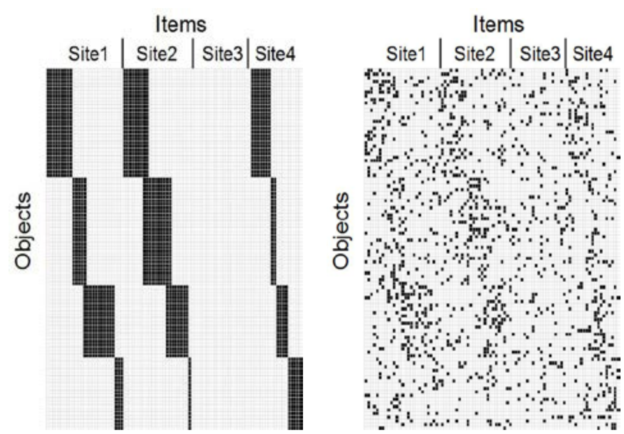


Fig. 4 The transition of "site-wise confidence" (4 sites collaboration)

5.2 Rejection of Meaningless Site

Second, the effect of meaningless site is studied, where one of four sites has no co-cluster structure. The noisy data matrix was generated from a noiseless matrix of Fig. 5(a), where sites 1, 2 and 4 has 4 co-cluster structures, but only site3 has no structure. A noisy cooccurrence matrix shown in Fig. 5(b) was generated by replacing '1' elements with '0' at a rate of 70% and '0' elements with '1' at a rate of 10%. Varied sparsely in noise, the co-cluster structures are only weakly recognized.



(a) noiseless matrix (b) noisy matrix

Fig. 5 Artificial cooccurrence matrices 2

As is the case of Section 5.1, the correlation coefficient among site-wise item memberships derived from proposed model, FCCM-VD or site-wise FCCM and the ones from the whole data FCCM in order to investigate whether site3 can extract the similar co-cluster structures as the whole data case using proposed method, although site3 can't extract such structures only its own data.

In the whole data FCCM and site-wise FCCM in each site, fuzzification parameter were set as $(\lambda_u, \ \lambda_w) = (0.001, 100.0)$. In FCCM-VD and proposed model, object membership fuzzification was set as $(\lambda_u = 0.003)$, item membership fuzzification were set as $(\lambda_w = 100.0)$ in each site.

Table 2 compares the performances of the three models and implies that the collaborative analysis with FCCM-VD made it possible to share the whole data structure even when one site had no such structural information, i.e., site 3 can also exploit the structure information with FCCM-VD although it cannot in site-wise independent analysis. Especially, the partition quality of collaborative analysis was improved by considering site-wise confidence.

Table 2: Correlation coefficient with the base item memberships (rejection of meaningless site)

		Site1	Site2	Site3	Site4
FCCM-VD with Site-wise Confidence	Best	**0.99**	**0.99**	**0.98**	**0.99**
	Mean	**0.81**	**0.76**	**0.76**	**0.76**
FCCM-VD	Best	0.98	0.98	0.96	0.98
	Mean	0.76	0.72	0.70	0.72
Site-wise FCCM	Best	0.90	0.94	0.57	0.70
	Mean	0.64	0.64	0.52	0.53

Next, Fig. 6 shows the transition of "site-wise confidence". Starting from low-confidence situation with random partition, sites 1 and 2 successfully gained higher confidences while the confidence of site 3 (meaningless site) stayed with low value only. Here, site 4 had a medium confidence. It may because the size of site 4 is relatively smaller than sites 1 and 2, and co-cluster structure may be unclear.

These results indicated that the proposed method still useful for cases with meaningless sites.

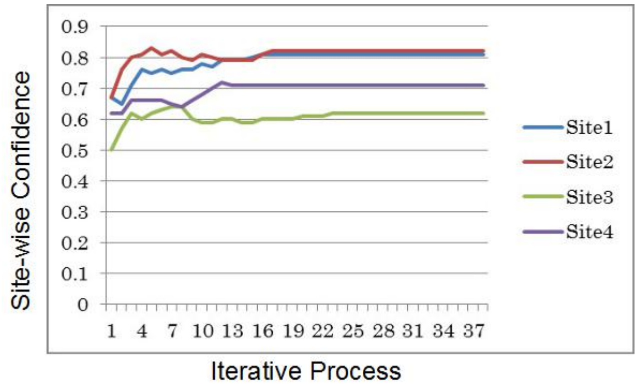


Fig. 6 The transition of "site-wise confidence" (rejection of meaningless site)

5.3 Dominant Structural Information Sharing

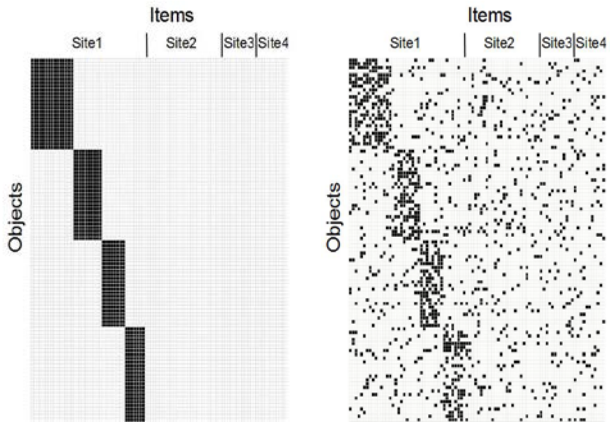
Third, a much extreme case is considered, where only one site has a dominant structural information while others do not. The intended co-cluster structure and a noisy data matrix to be analyzed are shown in Fig. 7. In these matrices, site1 has 4 co-cluster structures, but other sites has no clusters.

As is the case of Section 5.1 and 5.2, the correlation coefficient among site-wise item memberships derived from proposed model, FCCM-VD or site-wise FCCM and the ones from the whole data FCCM in order to investigate whether site2,3,4 can extract the intrinsic 4 co-cluster structures in separate matrices, they can't extract such structures using only its own data.

In the whole data FCCM, fuzzification parameters were set as $(\lambda_u, \ \lambda_w) = (0.001, 100.0)$, and in site-wise FCCM, these parameters were set as $(\lambda_u, \ \lambda_w) = (0.004, 100.0)$. In FCCM-VD and proposed model, object membership parameter was set as $(\lambda_u = 0.003)$, $(\lambda_u = 0.004)$, respectively. Item membership parameters were set as $(\lambda_w = 100.0)$ in each site.

The result of the same experiment is shown in Table 3, and implies that the proposed method is also useful for sharing a dominant information among all sites.

Fig. 8 shows the transition of "site-wise confidence". Only site 1 has high confidence. This implies site 2, 3 and 4 has less effect on cluster estimation, and site 1 has more informative. Thus, site 2, 3, 4 has larger (best and mean) correlation coefficients using proposed method because of sharing of the dominant information.



(a) noiseless matrix (b) noisy matrix

Fig. 7 Artificial cooccurrence matrices 3

Table 3: Correlation coefficient with the base item memberships (dominant structural information sharing)

		Site1	Site2	Site3	Site4
FCCM-VD with Site-wise Confidence	Best	0.98	**0.95**	**0.97**	**0.96**
	Mean	**098**	**0.95**	**0.97**	**0.96**
FCCM-VD	Best	**0.99**	0.94	0.86	0.94
	Mean	**0.98**	0.92	0.81	0.91
Site-wise FCCM	Best	0.96	0.50	0.41	0.48
	Mean	0.96	0.50	0.41	0.48

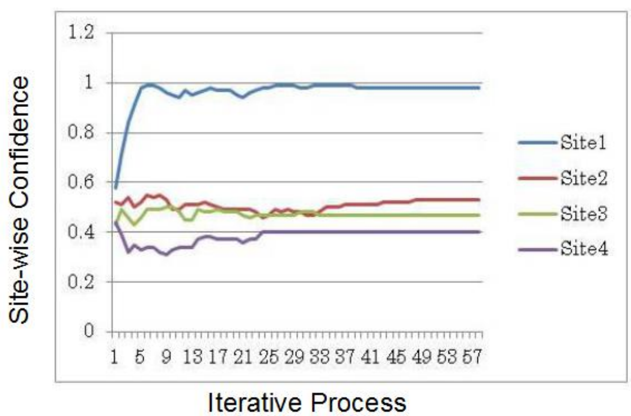


Fig.8 The transition of "site-wise confidence" (dominant structural information sharing)

These results indicate that the proposed model is still useful even if only a few sites has dominant structural information and the responsibility of each site can be effectively captured by site-wise confidence.

6. Conclusion

In this paper, a novel collaborative fuzzy co-clustering model for vertically distributed data was proposed considering "site-wise confidence". In numerical experiments, proposed model is more useful for estimating co-cluster structures in distributed matrices than the conventional collaborative model (FCCM-VD). Considering site-wise confidence, the effect of meaningless dataset is weaken, and the mechanism often work well on estimating the intrinsic co-cluster structures.

A possible future work is to adapt the proposed algorithm to other fuzzy co-clustering based on probabilistic models [11]. Another future work is hybrid use with some cluster validity measures [3].

Acknowledgments

This work was supported in part by the Ministry of Education, Culture, Sports, Science and Technology, Japan, under Grant-in-Aid for Scientific Research (#26330281).

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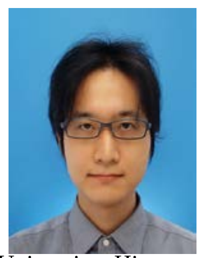

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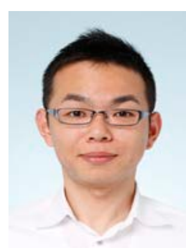

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