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Technical Note

A robust heuristic method on the clustering-assignment problem model

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ABSTRACT

This research presents an effective way to generate the location rank for shelf space assignment. Instead of the time consuming mathematical programming techniques adopted in the CAPM by Chuang, Lee, and Lai (2012). This research provides satisfactory results with at maximum of 6.1% difference through a far more effective way.

1. Introduction

The clustering-assignment problem model (CAPM) employs the idea of between-item association (BIA) clustering to assign items into storage locations in order to shorten the picking distance compared with popular frequency-based techniques (Chuang, Lee, & Lai, 2012). In this note we propose a revised agglomerative clustering method based on BIA and a frequency-based storage assigning process. We examine the robustness of this method by alternating the order contents with various item-associations and find that the solution is stable.

Based on CAPM, the notations used in this note are as follows.

$P(i)$	number of orders for item i
$P(j)$	number of orders for item j
S_{ij}	item-index; index between item i and item j
K	number of groups
N	total number of stocked items
f_i	order frequency of item i
F_k	average order frequency of group k

1.1. Between-item association (BIA)

The BIA clustering involves clustering N items into K groups based on the between-item association. This study defines BIA as the chance that the items appear in the same orders. Based on that, we denote the item-association (S_{ij}) between items i and j as follows.

$$S_{ij} = \frac{P(i \cap j)}{[P(i) + P(j)]} \qquad (1)$$

Here, $P(i \cap j)$ is the number of orders containing both items. In other words, $S_{ij} = 1/2$ means that items i and j are always ordered simultaneously, while $S_{ij} = 0$ means that items i and j are never ordered together. Concerning the warehouse shelf layout and picking route, we follow the assumption in Chuang et al. (2012) that every picker executes one order when entering the storage location, follows the Z-type picking route to the item's storage location, and follows a straight line back to the I/O point.

1.2. Revised agglomerative clustering and allocating clusters

The BIA acquired herein constructs a symmetric $N \times N$ relationship matrix. Entries in the matrix represent the "relationship" between items. The pair-wise relation-oriented data violate the concepts in Euclidian space. Some of the non-Euclidian data can be translated into vectorial data through the processes of embedding and then clustering (Laub, Roth, Buhmann, & Müller, 2006). Research studies suggest a self-organizing map (Ritter, 1999) and data normalization (Doherty, Adams, & Davey, 2007) for pair-wise data clustering. Among the non-Euclidean clustering methods, the most common and intuitive selection is the hierarchical clustering technique, and it is hereby chosen for this step.

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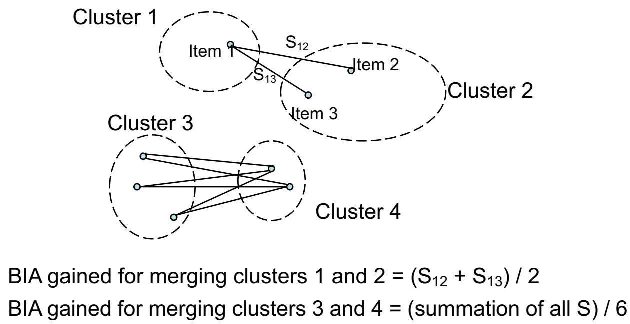

Fig. 1. The BIA gained for merger clusters.

In this research we take advantage of the BIA acquired and use it as the metric for combining clusters. We also add competing algorithms to re-examine the intermediate cluster during cluster-constructing procedures. The algorithms are described in the following steps.

Step 1: Acquire all BIAs and treat each item as a cluster.
Step 2: Scan through the pairs of clusters and find the maximum BIA gained. The BIA gained is defined as the average of BIA increases due to the merger of two clusters. Fig. 1 illustrates the idea of a BIA increase.
Step 3: Merge the two clusters with a maximum BIA gain.
Step 4: Examine the possible outliers. To avoid the effect of an outlier, the item that provides the least BIA gained is removed from the newly-merged cluster. Repeat Steps 2 and 3 until the removed item is the merging item.
Step 5: For each cluster, compute the average order frequency of group k (F_k) and then rank groups according to the frequencies.
Step 6: Assign a group with a larger order frequency to the storage region closer to the I/O depot.
Step 7: For each region, rank grouped items according to order frequencies of item i (f_i) and then place items with higher order frequencies into closer storage locations.
Step 8: Calculate the total picking distance.
Step 9: Go back to Step 2 and execute the merging process for $K - 1$ times (until all items belong to one cluster).

2. Numerical examples

2.1. The demonstrative example

2.1.1. Procedure of heuristics

Table 1 presents a set of random generated order information. The orders are labeled from E1 to E10, and the items are labeled from 1 to 10 as well. For instance, order E1 contains items 1, 2, 3, 8, and 9, and the order quantities are 5, 1, 5, 4, and 2, respectively. The average number of items for each order is 5. Tables 2 and 3 present the results of BIA and clusters' allocation, respectively.

The shortest distance appears when $K = 3$, and thus the 10 items are classified into 3 groups. The storage sequence of the 3 groups and their average order frequencies are $N_1 = \{1,3,2\}(F_1 = 5.67)$, $N_2 = \{8,10,9,7\}(F_2 = 5)$, and $N_3 = \{5,6,4\}(F_3 = 4.33)$, respectively. We assign the storage locations according to the IK values of each item within a group. Thus, the sequence of storage locations in this study is {1,3,2,8,10,9,7,5,6,4}, and the layout is illustrated in Fig. 2.

2.1.2. Comparison of solutions

The layout result from the popular IK method is {1,3,8,5,10,9,6,4,2,7}. A good illustration of picking distance improvement can be found by observing item 2. Item 2 with lower order frequency is assigned to the 9th position in the IK method, but a strong item association among items 1, 2, and 3 can be

Table 2
The BIA matrix.

Item	1	2	3	4	5	6	7	8	9	10
1	0.5	0.36	0.46	0.18	0.25	0.27	0.18	0.23	0.25	0.25
2	0.36	0.5	0.2	0	0.11	0	0.13	0.3	0.22	0.11
3	0.46	0.2	0.5	0.2	0.27	0.3	0.1	0.17	0.18	0.18
4	0.18	0	0.2	0.5	0.33	0.38	0.25	0.2	0.11	0.22
5	0.25	0.11	0.27	0.33	0.5	0.33	0.11	0.18	0.2	0.2
6	0.27	0	0.3	0.38	0.33	0.5	0.13	0.1	0.11	0.22
7	0.18	0.13	0.1	0.25	0.11	0.13	0.5	0.3	0.33	0.44
8	0.23	0.3	0.17	0.2	0.18	0.1	0.3	0.5	0.36	0.27
9	0.25	0.22	0.18	0.11	0.2	0.11	0.33	0.36	0.5	0.4
10	0.25	0.11	0.18	0.22	0.2	0.22	0.44	0.27	0.4	0.5

Table 3
Clustering results for each $K \leqslant N$.

$K =$	Result of clustering (result from stage 1)	Picking distance (result from allocating)
1	{1,3,8,5,10,9,6,4,2,7}	140
2	{1,3,5,6,2}, {8,10,9,4,7}	134
3	{1,3,2}, {8,10,9,7}, {5,6,4}	126
4	{8}, {1,3,2}, {10,9,7}, {5,6,4}	126
5	{8}, {1,3,2}, {5}, {10,9,7}, {6,4}	126
6	{1,3}, {8}, {5}, {10,9,7}, {2}, {6,4}	136
7	{1,3}, {8}, {5}, {10,9,7}, {2}, {4}, {6}	136
8	{1,3}, {8}, {5}, {9}, {10,7}, {2}, {4}, {6}	136
9	{1,3}, {8}, {5}, {9}, {10}, {2}, {4}, {6}, {7}	136
10	{1}{3}{8}, {5}, {10}{9}{6}, {4}{2}{7}	140

Table 1
The ordering data of numerical analysis.

Order	Item											
	1	2	3	4	5	6	7	8	9	10	EQ (order quantity)	EN (number of order items)
E1	5	1	5					4	2		17	5
E2	3	4					3	2	3	7	22	6
E3	1	3	1		5						10	4
E4	2		4	1		3	3			3	16	6
E5				7	9	3		1			20	4
E6	4		3		2	7			1	2	19	6
E7							4	1	3	4	12	4
E8	1		2	2	3	5					13	5
E9	6	5	3					4			18	4
E10				5	1		2	3	1	1	13	6
IQ (item quantity)	22	13	18	15	20	18	12	15	10	17	160	
IK (item frequency)	7	4	6	4	5	4	4	6	5	5		50