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A Comparison of Several Cluster Algorithms on Artificial Binary Data Scenarios from Travel Market Segmentation: Part 2

(Addition to Working Paper No. 7)

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1 Introduction

The search for clusters in empirical data is an important and often encountered research problem. Numerous algorithms exist that are able to render groups of objects or individuals. Of course each algorithm has its strengths and weaknesses. In order to identify these crucial points artificial data was generated—based primarily on experience with structures of empirical data—and used as benchmark for evaluating the results of numerous cluster algorithms. This work is an addition to Dolnicar et al. (1998), where hard competitive learning (HCL), neural gas (NGAS), k-means and self organizing maps (SOMs) were compared. Since the artificial data scenarios and the evaluation criteria used remained the same, they are not explained in this work, where the results of five additional algorithms are evaluated.

2 Description of Cluster Algorithms

Dolnicar et al. (1998) study the performance of well known cluster algorithms on artificial data scenarios from travel marketing. In this paper we compare these methods with some new approaches for data segmentation, namely the improved fixpoint method and hard competitive learning with binary distances.

2.1 The Improved Fixpoint Method

This family of clustering methods is a generalization of k-means-clustering in two ways: It is not restricted to the minimization of the inner variance and uses an improved fixpoint method.

Minimization of variance is equivalent to minimization of Euclidean distance. For the generalization of k-means-clustering the squared norm $||.||^2$ as objective function is replaced with an arbitrary convex function f (see below).

It is a well known fact that the standard k-means algorithm gets easily trapped in a local minimum. Steiner (1998) proposes the following approach in order to overcome this drawback:

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Consider we want a final solution with m centers. We start with more than m centers as initialization; after each iteration step the center of the smallest cluster is removed. We get the following pseudo-code for the improved fixpoint method:

1. Initialization: Let m^* be the desired number of centers. Then $m = \lceil 1.5m^* \rceil$ is the starting number of centers ($\lceil . \rceil$ rounds towards ∞). Draw a random sample of size m from the data set.
2. Determine the partition given by the current centers using the convex function f as distance measure.
3. Calculate the mean value for each cluster.
4. If $m > m^*$ remove the center with the fewest winning points and set $m = m - 1$.
5. If the positions of the centers or the number of centers has changed, continue with 2.

We used the following distance measures in combination with the improved fixpoint method:

st-1: improved fixpoint method with $f(.) = ||.||^2$. This exactly is the same as k-means with Euclidean distance (ED), but uses the improved method.

st-2: improved FPM with $f(.) = ||.||^{1.4}$. This method is less sensitive to outliers.

st-3: improved FPM with $f(.) = ||.||$; coincides with k-means used with absolute distance (AD). The only difference is the improved method.

st-4: improved FPM with $f(.) = \ln(\cosh(||.||))$ using scaling factor 3. The resulting solutions are comparable to st-1 around the center of the data and are equivalent to st-3 outside the center. The scaling factor determines the transition between these two behaviors.

The implementational details and a lot of experiments with several improved fixpoint methods can be found in Steiner (1998). A more formal treatment of the fixpoint method applied to a general class of optimization problems can be found in Pötzelberger & Strasser (1997).

2.2 Hard Competitive Learning with Binary Distance Measure

Another modification of a standard cluster algorithm is proposed by Leisch et al. (1998). They take hard competitive learning as base algorithm and replace the usual symmetric distances such as Euclidean or absolute distance by asymmetric binary distances. Binary distances can be useful, if a common '1' between two binary vectors is more important than a common '0'.

Consider two n-dimensional binary vectors $x = (x_1, \ldots, x_n)'$ and $y = (y_1, \ldots, y_n)'$. We define the 2×2 contingency table

		x = 1	x = 0	
y	1	α	β	$\alpha + \beta$
	0	γ	δ	$\gamma + \delta$
		$\alpha + \gamma$	$\beta + \delta$	n

where $\alpha = \#\{i : x_i = y_i = 1\}$ denotes the number of components where both x and y are one, $\beta = \#\{i : x_i = 0, y_i = 1\}$, $\gamma = \#\{i : x_i = 1, y_i = 0\}$, and $\delta = \#\{i : x_i = 0, y_i = 0\}$.

We use the Jaccard coefficient (see, e.g., Kaufman & Rousseeuw, 1990)

$$D(x, y) = \frac{\beta + \gamma}{\alpha + \beta + \gamma},$$

as distance D between x and y. Since D does not depend on δ, dimensions where both vectors are 0 are ignored. This distance counts the number of different components in x and y and divides it by the number of components, where at least one '1' appears.

See Leisch et al. (1998) for technical details. Note that the combination of hard competitive learning with binary distances is still work in progress and that the proposed algorithm is not fully mature yet.

		st-1	st-2	st-3	st-4	total average
dependent	1a	6.0	6.0	6.0	6.0	6.0
dependent	2	6.0	6.0	6.0	6.0	6.0
dependent	3b	6.0	6.0	6.0	6.0	6.0
dependent	4	6.0	6.0	6.0	6.0	6.0
independent	1a	6.0	6.0	6.0	6.0	6.0
independent	2	6.0	6.0	6.0	6.0	6.0
independent	3b	5.9	6.0	6.0	5.9	6.0
dependent	1b	5.4	5.3	5.7	5.2	5.4
independent	1b	4.3	4.5	4.7	4.7	4.6
dependent	3a	0.9	1.1	1.2	1.2	1.1
independent	3a	0.5	0.2	0.4	0.4	0.4

Table 1: Average number of clusters correctly identified

3 Results for the Improved Fixpoint Method

3.1 Reproduction Capability of Cluster Methods

Using the number of prototypes found (see Table 1 for details) as criterion for the quality of clusters found by the algorithms, no systematic difference between the four algorithms (st-1, st-2, st-3, st-4) under consideration can be detected. The simpler scenarios 1a and 2 for both the independent and dependent data as well as the scenarios 3b and 4 (dependent data) were correctly analyzed in each computation by all algorithms. Scenario 1b—more difficult due to the fact that one very small segment was defined with only 300 members—was never correctly reconstructed by the algorithms in the independent data set case because the small cluster was systematically ignored. This was not the case for the same scenario in the dependent data case. In Scenario 3b (independent) two of the four algorithms (st-2 and st-3) recognized all segments represented in the data, while st-1 and st-4 failed to find one segment in the worst case.

The classification rates (Table 2) also rendered very homogeneous results. In general the differences among the algorithms are in the range of one to three percent if the same amount of clusters was correctly identified and thus not worth pointing out especially. Very low differences between the classification rates and the Bayes classifiers are achieved when analyzing the independent data sets 1a, 2 and 3b and the dependent data sets 1a, 3b and 4.

3.2 Difficulty Levels of Artificial Data Scenarios

Based on the classification results, it is not only possible to evaluate the strengths and weaknesses of cluster algorithms but also the complexity of scenarios. In Table 1 the first criterion used to gain insight into the 'difficulty' of scenarios is the average number of segments found by each algorithm over all replications. Since this information does not have the power to differentiate between all (especially the easier) data sets, the difference between the Bayes classifier (percentage of theoretically possible cases identified correctly) and the average classification rate over all segments is given in Table 2. In both tables the scenarios are ordered according to their results, indicating that the dependent scenarios 1a, 2, 3b, and 4 as well as the independent scenarios 1a and 2 do not cause any reconstruction trouble for the algorithms under consideration as far as the average number of correctly identified clusters is concerned. Judging by the deviation from the Bayes classifier percentage the dependent data sets 1a, 3b and 4 as well as the independent data sets 1a, 2 and 3b seem to be the easiest exercise for the algorithms. Taking both criteria into account, 1a, 3b and 4 (dependent) and 1a and 2 (independent) may be called the simplest, 3a in both data generation versions causes serious trouble reconstructing followed by the scenario with a tiny segment of 300 cases (1a dependent and independent).

		st-1	st-2	st-3	st-4	total average
dependent	1a	0.0	0.0	0.0	0.0	0.0
dependent	3b	0.0	0.0	0.0	0.0	0.0
independent	3b	1.0	0.0	0.0	1.0	0.5
independent	1a	0.0	1.0	1.0	1.0	0.8
independent	2	1.0	1.0	1.0	1.0	1.0
dependent	4	2.0	2.0	2.0	2.0	2.0
dependent	2	15.0	15.0	15.0	15.0	15.0
dependent	1b	14.0	18.0	15.0	17.0	16.0
independent	1b	30.0	28.0	25.0	26.0	27.3
dependent	3a	38.0	36.0	37.0	36.0	36.8
independent	3a	42.0	42.0	43.0	43.0	42.5

Table 2: Difference between Bayes classifier and average classification rate (in %)

		HCL-BD
independent	1a	6
dependent	4	5.6
independent	2	5.4
dependent	1a	5.4
independent	3b	5
dependent	3b	5
independent	1b	4.6
dependent	2	4.6
dependent	1b	3.1
dependent	3a	2.5
independent	3a	0

Table 3: Average number of clusters correctly identified

4 Results for HCL with Binary Distance

First it should be noted that HCL-BD cannot improve on the common algorithms on the datasets used in this paper, the algorithm has only been included for completeness and as reference results for further work. Almost all datasets in the used scenarios are symmetric in 0's and 1's in the sense that two common zeros between two cases provide as much discriminant information as two common ones. Hence using asymmetric distance measures for this type of data is simply the wrong thing to do. The binary distance uses not all available information by ignoring common zeros, although this is 50% of the available discriminant information. Hence, the performance can only be worse than for symmetric distance algorithms such as those of the previous section. One point of interest has to be how much the performance decreases by using a wrong distance concept.

One striking feature of HCL-BD (see Table 3) is that it cannot reproduce scenarios 3b (both dependent and independent). This is due to the fact that 3b contains one cluster where all components are zero. This cluster cannot be found by HCL-BD, as zeros are ignored by construction. The other 5 clusters are found in every repetition.

In terms of classification rate (Table 4), HCL-BD does of course bad on 3b, as one cluster (16% of the data) is always missing. If these 16% are not counted, the performance is comparable to other methods. Otherwise the method is comparable to the st-x methods, sometimes slightly better, in more cases worse (as expected).

		HCL-BD
independent	1a	0
dependent	1a	6
dependent	4	8
independent	2	11
dependent	3b	14
independent	1b	16
dependent	2	17
independent	3b	20
dependent	1b	26
dependent	3a	30
independent	3a	48

Table 4: Difference between Bayes classifier and average classification rate (in %)

	1a	1b	2	3a	3b	total average
TRN	6	5.9	6	0.9	6	4.96
HCL-AD	6	6	6	0.7	6	4.94
HCL-ED	6	5.8	6	0.4	6	4.84
Ngas-ED	6	5	6	0.8	6	4.76
Ngas-AD	6	5.7	6	0.4	5.6	4.74
St3	6	4.7	6	0.4	6	4.62
St4	6	4.7	6	0.4	5.9	4.60
St1	6	4.3	6	0.5	5.9	4.54
St2	6	4.5	6	0.2	6	4.54
k-means	5.8	4.7	5.5	0.8	5.5	4.46
SOM	6	3.4	5.8	1	5.4	4.32
HCL-BD	6	4.6	5.4	0.0	5	4.20

Table 5: Average number of correctly identified clusters (independent data sets)

5 Comparison with the Results from Working Paper #7

The comparison of all algorithms used is based on the same two main criteria: the average number of segments found by each algorithm in each scenario and the deviation of the classification rate from the Bayes classifier. As can be seen in Table 5, the algorithms introduced in this addition to working paper # 7 are less successful in identifying the segments of the independently generated data sets, which is mostly due to the inferior results in scenario 1b. On the other hand st1 to st4 render the best results when data is generated with interdependencies between variables (Table 6). The same is true when comparing the differences between the average classification rates and the Bayes classifiers (Tables 7 and 8).

The HCL-version with binary distances does not identify the segments very successfully. Only in the case of scenario 1a (independent) the correct solution is found in all replications. The results concerning the deviation from the Bayes classifier are more promising. Again, if the unavoidable error for the zero-cluster of scenario 3b is taken into consideration, the classification rate is competitive.

Equally good results are achieved by TRN, st3 and st2 as far as the identification of types is concerned: only those scenarios with one little segment cause trouble. This statement is entirely correct for the dependent data sets, in case of the independent sets it has to be mentioned, that st2 and st3 were not able to find the segment with only 300 members in a single replication, whereas TRN did. In terms of deviation from the optimal classification rate there are no major differences. HCL-AD turns out to be the only algorithm that reliably finds the small segment in the independent data set 1b. On the other hand the dependent data sets 2 and 3b caused too

	1a	1b	2	3a	3b	4	total average
st3	6	5.7	6	1.2	6	6	5.15
st2	6	5.3	6	1.1	6	6	5.07
st4	6	5.2	6	1.2	6	6	5.07
st1	6	5.4	6	0.9	6	6	5.05
HCL-AD	6	4.7	5.6	2.1	5	6	4.90
TRN	6	4.2	6	1.1	6	6	4.88
Ngas	6	4.4	6	1.1	5.4	6	4.82
Ngas-AD	6	4.4	5.2	2.1	5	6	4.78
HCL-ED	6	4	5.3	1.1	6	6	4.73
SOM	5.8	3.6	5.6	2	4.6	6	4.60
HCL-BD	5.4	3.1	4.6	2.5	5	5.6	4.37
k-means	4.7	4	4.8	1.5	4.6	4.6	4.03

Table 6: Average number of correctly identified clusters (dependent data sets)

	1a	1b	2	3a	3b	total average
HCL-AD	1	5	1.0	42	0	9.8
TRN	1	11	1.0	41	0	10.8
HCL-ED	1	11	1.0	42	0	11.0
Ngas-AD	1	8	1.0	41	4	11.0
Ngas-ED	1	18	1.0	41	0	12.2
st3	1	25	1.0	43	0	14.0
st2	1	28	1.0	42	0	14.4
st4	1	26	1.0	43	1	14.4
st1	0	30	1.0	42	1	14.8
k-means	4	22	9.0	40	7	16.4
SOM	2	23	7.0	40	12	16.6
HCL-BD	1	16	12.0	49	20	19.6

Table 7: Difference between Bayes classifier and average classification rate in % (independent data sets)

	1a	1b	2	3a	3b	4	total average
st1	0	14	15	38	0	2	11.5
st3	0	15	15	37	0	2	11.5
st4	0	17	15	36	0	2	11.6
st2	0	18	15	36	0	2	11.8
TRN	0	23	15	37	0	2	12.8
HCL-AD	0	16	19	33	14	2	14.0
Ngas-ED	0	23	15	37	7	2	14.0
Ngas-AD	0	16	23	33	11	2	14.2
HCL-ED	0	24	23	37	0	2	14.3
HCL-BD	6	26	17	30	14	8	16.8
SOM	5	20	21	32	18	6	17.0
k-means	16	22	29	35	17	22	23.5

Table 8: Difference between Bayes classifier and average classification rate in % (dependent data sets)

much trouble for this algorithm to solve in every replication.

6 Conclusions

A broad range of different cluster-algorithms was tested using artificial data. The results not only give some insight into the difficulty-levels of data sets but also allow some conclusions about the abilities, strengths and weaknesses of cluster algorithms: K-means and SOMs seem to be rather unreliable in detecting the data structures under consideration, since k-means was not able to identify the segments of one single scenario in each replication and SOMs did so only in two out of nine data sets. HCL-AD is probably the best choice when aiming at the detection of small groups of homogeneous individuals. St-1 to St-4 cope very well with most of the problems encountered in this piece of research but are less recommendable for niche market situations. They are however very stable in the sense, that in most situation they reproduce the same results in many replications.

Finally it should be pointed out, that naming an overall winner does not make very much sense after this study. Obviously every algorithms has certain strengths and weaknesses and can therefore be recommended for analysis in specific data situations or in case of specific hypotheses about the data.

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Scenario	Algorithm	never	found	class. rate map.	class. rate all	$(\text{center-type})^2$	comp. range
1a	HCL-BD		4.00 / 5.40 / 6.00	0.67 / 0.69 / 0.70	0.46 / 0.63 / 0.70	0.39 / 0.53 / 0.58	0.00 / 0.00 / 0.00
1a	st-1		6.00 / 6.00 / 6.00	0.70 / 0.70 / 0.70	0.70 / 0.70 / 0.70	0.30 / 0.32 / 0.33	0.02 / 0.18 / 0.25
1a	st-2		6.00 / 6.00 / 6.00	0.70 / 0.70 / 0.70	0.70 / 0.70 / 0.70	0.30 / 0.32 / 0.33	0.02 / 0.18 / 0.25
1a	st-3		6.00 / 6.00 / 6.00	0.70 / 0.70 / 0.70	0.70 / 0.70 / 0.70	0.30 / 0.32 / 0.33	0.02 / 0.18 / 0.25
1a	st-4		6.00 / 6.00 / 6.00	0.70 / 0.70 / 0.70	0.70 / 0.70 / 0.70	0.30 / 0.32 / 0.33	0.02 / 0.18 / 0.25
1b	HCL-BD	2-5	3.00 / 3.10 / 4.00	0.79 / 0.83 / 0.85	0.49 / 0.52 / 0.57	0.28 / 0.29 / 0.38	0.00 / 0.00 / 0.00
1b	st-1		4.00 / 5.40 / 6.00	0.62 / 0.70 / 0.79	0.57 / 0.64 / 0.69	0.23 / 0.41 / 0.53	0.02 / 0.20 / 0.59
1b	st-2		4.00 / 5.40 / 6.00	0.62 / 0.70 / 0.79	0.57 / 0.64 / 0.69	0.23 / 0.41 / 0.53	0.02 / 0.20 / 0.59
1b	st-3		4.00 / 5.40 / 6.00	0.62 / 0.70 / 0.79	0.57 / 0.64 / 0.69	0.23 / 0.41 / 0.53	0.02 / 0.20 / 0.59
1b	st-4		4.00 / 5.40 / 6.00	0.62 / 0.70 / 0.79	0.57 / 0.64 / 0.69	0.23 / 0.41 / 0.53	0.02 / 0.20 / 0.59
2	HCL-BD		4.00 / 4.60 / 6.00	0.66 / 0.68 / 0.69	0.44 / 0.52 / 0.69	0.36 / 0.43 / 0.56	0.00 / 0.00 / 0.00
2	st-1		6.00 / 6.00 / 6.00	0.68 / 0.68 / 0.68	0.68 / 0.68 / 0.68	0.41 / 0.41 / 0.41	0.00 / 0.00 / 0.02
2	st-2		6.00 / 6.00 / 6.00	0.68 / 0.68 / 0.68	0.68 / 0.68 / 0.68	0.41 / 0.41 / 0.41	0.00 / 0.00 / 0.02
2	st-3		6.00 / 6.00 / 6.00	0.68 / 0.68 / 0.68	0.68 / 0.68 / 0.68	0.41 / 0.41 / 0.41	0.00 / 0.00 / 0.02
2	st-4		6.00 / 6.00 / 6.00	0.68 / 0.68 / 0.68	0.68 / 0.68 / 0.68	0.41 / 0.41 / 0.41	0.00 / 0.00 / 0.02
3a	HCL-BD		1.00 / 2.50 / 4.00	0.47 / 0.50 / 0.52	0.04 / 0.11 / 0.18	0.21 / 0.53 / 0.85	0.00 / 0.00 / 0.00
3a	st-1	3-4	0.00 / 0.90 / 1.00	0.43 / 0.44 / 0.46	0.04 / 0.04 / 0.04	0.17 / 0.17 / 0.18	0.00 / 0.00 / 0.00
3a	st-2	3-4	0.00 / 0.90 / 1.00	0.43 / 0.44 / 0.46	0.04 / 0.04 / 0.04	0.17 / 0.17 / 0.18	0.00 / 0.00 / 0.00
3a	st-3	3-4	0.00 / 0.90 / 1.00	0.43 / 0.44 / 0.46	0.04 / 0.04 / 0.04	0.17 / 0.17 / 0.18	0.00 / 0.00 / 0.00
3a	st-4	3-4	0.00 / 0.90 / 1.00	0.43 / 0.44 / 0.46	0.04 / 0.04 / 0.04	0.17 / 0.17 / 0.18	0.00 / 0.00 / 0.00
3b	HCL-BD	2	5.00 / 5.00 / 5.00	0.59 / 0.60 / 0.61	0.54 / 0.57 / 0.59	0.52 / 0.52 / 0.53	0.00 / 0.00 / 0.00
3b	st-1		6.00 / 6.00 / 6.00	0.71 / 0.71 / 0.72	0.71 / 0.71 / 0.72	0.27 / 0.27 / 0.28	0.00 / 0.08 / 0.19
3b	st-2		6.00 / 6.00 / 6.00	0.71 / 0.71 / 0.72	0.71 / 0.71 / 0.72	0.27 / 0.27 / 0.28	0.00 / 0.08 / 0.19
3b	st-3		6.00 / 6.00 / 6.00	0.71 / 0.71 / 0.72	0.71 / 0.71 / 0.72	0.27 / 0.27 / 0.28	0.00 / 0.08 / 0.19
3b	st-4		6.00 / 6.00 / 6.00	0.71 / 0.71 / 0.72	0.71 / 0.71 / 0.72	0.27 / 0.27 / 0.28	0.00 / 0.08 / 0.19
4	HCL-BD		4.00 / 5.60 / 6.00	0.75 / 0.78 / 0.79	0.52 / 0.73 / 0.79	0.36 / 0.51 / 0.55	0.00 / 0.00 / 0.00
4	st-1		6.00 / 6.00 / 6.00	0.79 / 0.79 / 0.79	0.79 / 0.79 / 0.79	0.18 / 0.19 / 0.20	0.03 / 0.11 / 0.16
4	st-2		6.00 / 6.00 / 6.00	0.79 / 0.79 / 0.79	0.79 / 0.79 / 0.79	0.18 / 0.19 / 0.20	0.03 / 0.11 / 0.16
4	st-3		6.00 / 6.00 / 6.00	0.79 / 0.79 / 0.79	0.79 / 0.79 / 0.79	0.18 / 0.19 / 0.20	0.03 / 0.11 / 0.16
4	st-4		6.00 / 6.00 / 6.00	0.79 / 0.79 / 0.79	0.79 / 0.79 / 0.79	0.18 / 0.19 / 0.20	0.03 / 0.11 / 0.16

Table 9: Summary of the Results on the Dependent Data Sets

Scenario	Algorithm	never	found	class. rate map.	class. rate all	(center-type)^2	comp. range
1a	HCL-BD		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.83	0.82 / 0.82 / 0.83	0.66 / 0.67 / 0.68	0.00 / 0.04 / 0.15
1a	st-1		6.00 / 6.00 / 6.00	0.82 / 0.83 / 0.83	0.82 / 0.83 / 0.83	0.13 / 0.13 / 0.13	0.01 / 0.06 / 0.12
1a	st-2		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.83	0.82 / 0.82 / 0.83	0.13 / 0.13 / 0.13	0.02 / 0.07 / 0.12
1a	st-3		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.83	0.82 / 0.82 / 0.83	0.13 / 0.13 / 0.13	0.01 / 0.05 / 0.11
1a	st-4		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.83	0.82 / 0.82 / 0.83	0.13 / 0.13 / 0.13	0.01 / 0.07 / 0.12
1b	HCL-BD	2	4.00 / 4.60 / 5.00	0.85 / 0.87 / 0.89	0.63 / 0.72 / 0.80	0.46 / 0.53 / 0.58	0.00 / 0.00 / 0.01
1b	st-1	2	4.00 / 4.30 / 5.00	0.77 / 0.79 / 0.81	0.53 / 0.59 / 0.67	0.15 / 0.18 / 0.20	0.04 / 0.13 / 0.26
1b	st-2	2	4.00 / 4.50 / 5.00	0.74 / 0.77 / 0.80	0.49 / 0.61 / 0.71	0.16 / 0.17 / 0.19	0.03 / 0.11 / 0.30
1b	st-3	2	4.00 / 4.70 / 5.00	0.73 / 0.76 / 0.80	0.54 / 0.64 / 0.71	0.17 / 0.19 / 0.20	0.03 / 0.11 / 0.20
1b	st-4	2	4.00 / 4.70 / 5.00	0.73 / 0.76 / 0.79	0.54 / 0.63 / 0.71	0.17 / 0.19 / 0.20	0.02 / 0.09 / 0.22
2	HCL-BD		4.00 / 5.40 / 6.00	0.77 / 0.80 / 0.80	0.49 / 0.71 / 0.80	0.46 / 0.62 / 0.69	0.00 / 0.00 / 0.00
2	st-1		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.82	0.82 / 0.82 / 0.82	0.10 / 0.10 / 0.11	0.00 / 0.03 / 0.08
2	st-2		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.82	0.82 / 0.82 / 0.82	0.10 / 0.11 / 0.11	0.00 / 0.03 / 0.08
2	st-3		6.00 / 6.00 / 6.00	0.82 / 0.82 / 0.82	0.82 / 0.82 / 0.82	0.10 / 0.11 / 0.11	0.00 / 0.03 / 0.08
2	st-4		6.00 / 6.00 / 6.00	0.79 / 0.82 / 0.82	0.79 / 0.82 / 0.82	0.10 / 0.12 / 0.16	0.00 / 0.04 / 0.21
3a	HCL-BD	1-2-3-4-5-6	0.00 / 0.00 / 0.00	0.00 / 0.00 / 0.00	0.00 / 0.00 / 0.00	0.00 / 0.00 / 0.00	0.00 / 0.00 / 0.00
3a	st-1	1-2-4	0.00 / 0.50 / 1.00	0.35 / 0.37 / 0.40	0.06 / 0.07 / 0.07	0.09 / 0.10 / 0.10	0.00 / 0.05 / 0.36
3a	st-2	1-4-5-6	0.00 / 0.20 / 1.00	0.36 / 0.37 / 0.39	0.07 / 0.07 / 0.07	0.09 / 0.09 / 0.09	0.00 / 0.00 / 0.00
3a	st-3	1-4-6	0.00 / 0.40 / 1.00	0.34 / 0.37 / 0.39	0.04 / 0.06 / 0.07	0.09 / 0.10 / 0.13	0.00 / 0.07 / 0.63
3a	st-4	1-2-4-5-6	0.00 / 0.40 / 1.00	0.33 / 0.36 / 0.39	0.05 / 0.06 / 0.07	0.09 / 0.10 / 0.12	0.06 / 0.27 / 0.61
3b	HCL-BD	2	5.00 / 5.00 / 5.00	0.67 / 0.67 / 0.67	0.59 / 0.61 / 0.62	0.58 / 0.58 / 0.58	0.00 / 0.00 / 0.00
3b	st-1		5.00 / 5.90 / 6.00	0.75 / 0.81 / 0.82	0.67 / 0.80 / 0.82	0.11 / 0.11 / 0.14	0.00 / 0.05 / 0.25
3b	st-2		6.00 / 6.00 / 6.00	0.81 / 0.81 / 0.82	0.81 / 0.81 / 0.82	0.11 / 0.11 / 0.11	0.00 / 0.02 / 0.06
3b	st-3		6.00 / 6.00 / 6.00	0.81 / 0.81 / 0.81	0.81 / 0.81 / 0.81	0.12 / 0.12 / 0.12	0.00 / 0.02 / 0.05
3b	st-4		5.00 / 5.90 / 6.00	0.72 / 0.80 / 0.81	0.72 / 0.80 / 0.81	0.12 / 0.13 / 0.25	0.00 / 0.06 / 0.52

Table 10: Summary of the Results on the Independent Data Sets