A neural clustering approach to iso-resource grouping for acute healthcare in Australia

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Abstract

Knowledge about resource consumption and utilisation is vital in modern healthcare environments. In order to manage both human and material resources efficiently, a typical approach is to group the patients based on common characteristics. The most widely used approach is driven by the Case Mix funding formula, namely to classify patients according to diagnostic related groups (DRGs). Although it is clinically meaningful, our experience suggests that DRG groupings do not necessarily present a sound basis for relevant knowledge generation. In this paper, we propose an alternative grouping of the patients based on a neural clustering approach, which generates homogeneous groups of patients with similar resource utilisation characteristics. Demographic information is used to generate the clusters, which reveal interesting differences in resource utilisation patterns. A detailed case study is presented to demonstrate the quality of knowledge generated by this process. The proposed approach can therefore be seen as an evidence-based predictive tool with high-knowledge generation capabilities.

1. Introduction

Public hospital systems face the problem of increasing cost in provision of health care and at the same time an increasing demand for its services due to the aging population. Adding to the pressure on hospitals are government budgets, which have not kept pace with those increasing costs and demands. Case Mix has been receiving growing attention because of its importance in terms of funding, budgeting, development of a benchmark of the best practice, improving health care and as a measure for analytical work. As more countries adopt a Case Mix approach as a measure, questions are raised regarding Case Mix's ability to correctly measure resources patient consume.

Case Mix is a system based on diagnostic related groups (DRGs), which groupings are based on clinical diagnostic categories. The basic premise of Case Mix is that those patients with similar DRGs should consume a similar amount of resources. Case Mix aims to use DRGs for funding public hospitals and other various management and analytical decisions [1].

Case Mix funding has been implemented in many different countries. The first country to implement it was the USA in 1983. By 1988, it was used by the Australian government to fund public hospitals

The role of DRGs, which are used by Case Mix as a predictor of resource consumption has been overestimated. In 1998, the Victorian Auditor General prepared a report on the Case Mix implementation in Victoria, Australia. Although, there were efficiency gains, there were also some major problems.

"Half of the networks, two-thirds of metropolitan hospitals and one-third of rural hospitals believed they seldom or never received adequate compensation for higher cost patients. The major concern was that casemix funding was based on an average." [1] [2]

"The group of people who would be expected to be disadvantaged under the casemix payment system are those requiring treatment that cost more than the average case due to a variety of factors. Such groups include the elderly, frail and aged, Aboriginal, and people with chronic illnesses and disabilities and from a non-English speaking or low socio-economic background. The average case complexity for these groups is higher due to the presence of co-morbidities or other clinical factors in their medical diagnosis." [2] [2]

Relying on DRGs alone is not a good indicator of resource consumption. This paper proposes a complementary measurement clustering technique based on demographics and admission characteristics to determine length of stay (LOS) as a proxy measure for resource consumption.

A proxy that measures resource consumption is used because directly measuring consumption is difficult, costly and time consuming. Using LOS as a proxy is

[1] (P15, Victorian Auditor's Special Report No.56, May 1998)
[2] *(p173, ibid)*

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nothing new [3]. Shahani et al. have used classification tress as an alternative method for grouping iso-resource consumption based on LOS.

This paper will also explore the role of DRGs in the analysis. It will look at the relationships between DRGs and each clusters and LOS. Knowledge that would be otherwise not be obtained from statistical methods can be generated from this clustering method. The knowledge can then be used for prediction of resource consumption by patients.

2. Case Study

The data was obtained from Frankston Hospital, a medium sized health unit in a region in the south-eastern suburbs of Melbourne, Australia. It is part of a network of hospitals which serves up to nearly 290,000 people, with a seasonal influx of visitors of up to 100,000. The area is a prime seaside retirement location where there is a high proportion of older people [3][4]. Demand for its services is exacerbated during holiday periods, when visitors impact heavily on emergency services. Frankston Hospital also provides health services to people across Victoria through programs such as the Mother/Baby Unit and Personal Alert Victoria.

The data consists of over 12,000 records of admitted patients from the 1 Oct, 1998 to 30 June, 1999. It contains information about demographics of patients and their LOS. In the later section, the procedure for obtaining the five different clusters will be explained.

Age, gender and initial admission information are known when the patient arrives. Most of the patients admitted into Frankston Hospital were elderly patients as shown in Table 6. This is further highlighted in Table 7 which shows the percentage age distributions of patients. Elderly patients tend to consume more than the "average" resources than do patients of the same DRG groupings. There was almost an equal number of male and female patients as shown in Table 1.

Patients can be admitted to: emergency (EMG), children (CHW), emergency department ward (EDW), cardiac care (C/C), short stay unit (SSU), post natal (PNA), health home unit (HHU), intensive care unit (ICU) and to various geographical areas of the hospital - W A refers to west wing block A, W B refers to west wing block B, S refers to the south wing and N refers to the north wing as shown in Table 2. EDW differs from EMG in that EDW patients are sent for observation. EDW is considered as a non-emergency ward but it consumes some emergency department resources as patients are looked after by emergency staff. HHU refers to older patients being looked after by hospital staff at home.

Urgency and time spent in emergency variables are obtained during the patient stay. Urgent patients are categorised from 1 to 5 (see Table 8), 1 being the most urgent while 5 being the least. Category 1 urgent patients are critical and must receive immediate treatment. Examples of cases in this category are intensive bleeding, gun shot wounds, patients requiring resuscitation and critical injuries and disease. On the other hand, Category 2 patients are to be treated within 10 minutes. The more critical the patients, the more intensive is the resource consumption. Category 1 patients require the most intensive resource usage. Likewise, the more time the patient spends in emergency the more resources the patient consume.

Information about patients' DRGs, LOS and last discharged wards are determined once the patient leaves the hospital. There are about a thousand different DRG classifications. They were coded using the 3 digit ICD-9 (International Classification Codes). LOS of patients are determined by difference in the time the patients are admitted to the time the patients are discharged. The last discharged wards refers to the final wards from which the patients are discharged (Table 3). Once patients are treated they may be transferred to other non-emergency wards for observation and are discharged when their condition has improved.

Before the data could be used, there was a need to preprocess the data. The neural network model could only accept numbers. The variable gender contains alphanumeric, "M" and "F" were converted to binary form; 1 being male and 0 female. Likewise other variables such as admission to wards and last discharged wards require columns representing the different wards with each column containing binary numbers "1" indicating the patient has entered the wards or otherwise a "0" is given. To assist further analysis we have divided the LOS into four categories: less than 12 hours, 12 hours to one day, one day to 5 days and over 5 days (Tables 4 and 5). This allows a distribution of the patient LOS to be closely examined.

3. A Clustering Approach

As stated in the previous section, DRG groupings alone do not necessarily present a sound basis for knowledge organization. We propose a neural clustering approach to iso-resource grouping that, in combination with DRG, could be used to provide a more detailed predictor and explanation of resource consumption.

Clustering is a more qualitative approach. The aim is to derive some insight into the factors influencing length of stay. The neural clustering used will be based on Kohonen's Self Organsing Map (SOM) [5]. Self organisation refers to a type of neural network which classifies data and discovers relationships within the data set without any guidance during learning. The basic principle of identifying those hidden relationships are that if input patterns are similar then they should be grouped

[3] *p19, Peninsula Health Annual Report, 2000*

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together. Two inputs are similar if the distance between the two inputs are close to each other.

A software package called Viscovery SOMine [6] was used to model the data. It provides a powerful visualization tool that maps a high dimensionality of inputs onto a two-dimensional map which shows a landscape of non-linear data distribution. Features of the data and the dependencies between the variables can be identified and evaluated from the map.

Experiments were carried out to determine the optimal number of clusters that could distinguish the data. During the experiments LOS was not used as an input to determine whether each cluster would exhibit different LOS characteristics. The criteria for picking the "optimal" number was whether:

- The clusters themselves were distinct in terms of LOS. If two groups could independently come up with two different average LOS, then chances are these two groups are different from one another.

- The variables that belong to each cluster make sense. The variables that each cluster have should be distinct and carry some information of their own. When each cluster is analysed, its profile should be unique and meaningful.

- The total size of the cluster. The size of each cluster needs to be monitored. If the cluster is too large then it is possible that more distinct groups could lie in the cluster. Likewise if it is too small, then there is high probability that the cluster is artificial.

Once the clusters are obtained, each cluster's profile is examined in detail. LOS of each cluster is highlighted and an examination of the relationship of DRGs with each cluster is carried out.

4. Results.

This section will present SOM maps followed by the profiles of each cluster. Tables and graphs will be used to support the descriptions. Figure 1 shows the resulting optimal clustering map of 5 distinct clusters. Experiments revealed that 5 clusters is the optimal balance between cluster size and distinguishing features. For example when a six cluster distinction was attempted, an additional group was formed that consisted of the different wards in cluster 4. However, this new cluster's LOS was no different from the previous cluster 4. And when a four cluster grouping was forced, it was found that the 5 clusters carries more information than the 4 cluster grouping. In a 4 cluster category, cluster 2 and 5 merge with each other. The information such as the distinct age group, different LOS, and admission and discharge from wards, is lost from merging these two groups.

Figure 2 shows how the different age distributions are partitioned across the clusters. The dark areas represent low values while the light areas represent high values. Cluster 5 seems to have the lowest age concentration. The other four clusters seem to have the same amount of dark and light areas.

Figure 3 shows the gender distribution of patients, Figure 4-time in emergency, Figure 5-distribution of urgency and Figure 6-LOS distribution. Cluster 1 seems to have the lowest LOS and time patients spent in emergency because of the high concentration of dark colour in the region. Cluster 5, although less darker than cluster 1, is darker than the other clusters. This tells us that Cluster 1 has the lowest LOS while Cluster 5 comes second lowest. However, it is difficult to clearly distinguish the gender concentration and urgency.

In summary, the map tells us there are some relationships between the variables involved and there are some interesting features in the data that warrant a more detailed examination. By representing the 36 dimensional clustering process on a two-dimensional plane for qualitative analysis, the visualisation of the clusters is greatly enhanced.

Table 1 gives a more quantitative feel to the clustering approach. From Table 1, there are five distinct clusters of which their variables are averaged. The distribution for each variable will be discussed later on. A detailed analysis of the tables, graphs and figures would reveal interesting profiles for each of the clusters.

Cluster 1 contains mostly patients who stay in emergency throughout their stay in the hospital as shown in Tables 2 and 3. These patients tend also to stay in emergency the shortest with an average of one hour (Table 1). They represent also one of the largest groups of the whole population. They have the shortest LOS of an average of 8 hours. Most of these patients stay in the hospital for less than 12 hours as can be seen by the distribution in Figure 7 which shows that it has the highest LOS under 12 hours. About 60% of the whole group stay less than 12 hours in the hospital while the other 36% stay between 12 hours to one day (Table 5). These groups of patients tend to be older (about 40% are above 65 years old as shown Table 7 and Figure 10). In short, these patients require prompt treatment before they are promptly discharged.

Since there were a few hundred DRG groups, the top 8 largest DRGs are only shown in Tables 9 to 13. The DRG reveal diagnosis of patients that need to be initially admitted to emergency and are urgently treated and discharged. These patients do not consume a large amount of resources as evidenced by their lowest length of stay of all clusters. The main DRG group is chest pain and abdominal pain which accounts for more than 10% of the whole of Cluster 1.

Cluster 2 represent patients who are admitted to emergency (Table 2) but are transferred elsewhere to other wards (Table 3) after they are treated for observation and recovery. These patients tend to have a very short stay in the emergency department with the second shortest time of an average of 1.3 hours (Table 1). They represent also one of the smallest groups of the whole population. They have the second longest LOS with an average of 7 days and 3 hours. Almost all of these patients stay in the hospital for more than a day. About 48% of the whole group stay between one to five days while the other 48% stay over five days (Table 5). These groups of patient tend to be older (about 50% are over 65 years old as shown in Table 7 and Figure 11).

Most patients in Cluster 2 suffer from obstructive airway disease and heart failure as shown in Table 10. These Cluster 2 patients consume the second most extensive resources in terms of LOS and yet two of the top 8 diagnoses appears in Cluster 1 as seen in Table 9. DRG code 177 and 252 are the top 8 groups in Cluster 1 and yet they appear to be in Cluster 2. This shows that relying on DRGs alone is not a good indicator of resource consumption.

Cluster 3 tends to be cardiac care(C/C) and emergency department ward (EDW) patients. These patients require the longest treatment in emergency of about 4 hours. They also stay in the hospital for a very long time, almost 8 days on average.

Most of the DRGs in this group appear to be in Table 10 as well. This patient Cluster spends three times longer in emergency than Cluster 2. So this patient Cluster consumes more resources even though their LOS is similar to Cluster 2. LOS does have its limitation as a proxy for resource consumption. On the other hand, it is widely used in the literature as a proxy and is the easier variable to measure and obtain.

Cluster 4 represent patients who go to the short stay unit (SSU) and postnatal unit (PNA). These patients stay in the hospital on average less than 6 days. These groups also have a high proportion of urgent patients. As can be seen from Figure 8 and 9, Cluster 3 has twice as many category 1 urgent patients than most of the other clusters. As stated, earlier Category One patients consume the most intensive resources.

From Table 12, Cluster 4 DRGs appear to be more spread out than the other clusters. The DRGs appear distinct from the other clusters as well. Most of the injuries involve hands, legs, mental disorder, abortion and appendectomy which may require further observation.

If DRGs are a good indicator of resource consumption, one would expect similar LOS to have similar DRGs and different LOS to have different DRGs. Although Clusters 3 and 4 have similar LOS, their DRGs are quite different from each other.

Cluster 5 represents children who are admitted to, and discharged from, the children's ward (Table 2 and Table 3). The patients for this group are 7 year olds on average. These patients spend an average of 1.8 hours in the emergency department (Table 1). They spend on average about a day and a half in the hospital. Almost all of these patients stay in the hospital for more than a day. Most of the LOS distribution falls between 12 hours to 5 days. (Table 5) which is the second shortest stay in hospital of all the clusters.

From Table 13, the top two DRGs account for more than 20% of the total cluster. Cluster 5 has the second shortest stay and yet its top two DRG group; DRG 473 and DRG 187 appear in both Cluster 4 and 2 respectively. Those two clusters have a different LOS from Cluster 5 (Table 1).

5. Conclusion

This paper highlights that DRGs alone should not be used to estimate resource consumption by patients. The weights used in DRGs have too many averages that hide the fact that there may be patients who consume more than the average. It is shown that knowledge generation by SOM, a neural data-mining tool, can be used to complement DRGs in estimating the resource consumption of patients. The knowledge generation tool creates clusters that reveal homogeneous groups of patients. Even though LOS was not used as an input, each cluster exhibits different LOS characteristics. When profiling each cluster we see some contradictions in the DRG labelling with LOS. Therefore, DRGs should not be used alone for estimating resource consumption as other demographic information plays a role and should be considered.

The clustering information can be used as a prediction tool. When a new patient is admitted, it can be worked out which group the patient belongs to and the likely resource consumption.

There is also a clear need to address and improve on the capabilities of DRGs. There are plenty of grounds for further research in this area. Other alternative techniques need to be invented to complement DRGs.

6. References

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[4] Peninsula Health Annual Report, 2000

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7. Appendix of Tables and Figures

Table 1. Average values representing cluster centres

Cluster	Urgency	Sex	Age	Time in Emergency (hr)	LOS	Total Size
1	3.28	0.50	52	1.0	8 hr	5187
2	3.37	0.45	59	1.3	7 days 3 hr	904
3	3.54	0.45	61	3.9	7 days 22 hr	2927
4	3.43	0.44	48	3.0	5 days 21 hr	1893
5	3.11	0.60	7	1.8	1 day 17 hr	1265

Table 2 Initial ward admissions

	Initial Ward Admissions											
Cluster	EMG	CHW	EDW	C/C	SSU	PNA	W A&B	HHU	S	N	ICU	Other
1	5183	0	0	0	0	1	0	0	0	1	0	2
2	904	0	0	0	0	0	0	0	0	0	0	0
3	0	2	1131	433	21	10	0	1	442	784	87	16
4	0	5	0	4	275	284	191	143	518	352	94	27
5	0	1260	0	0	2	0	0	0	1	0	0	2

Table 3. Last discharge wards

	Last Discharged Ward											
Cluster	EMG	CHW	EDW	C/C	SSU	PNA	W A&B	HHU	ICU	S	N	Other
1	5187	0	0	0	0	0	0	0	0	0	0	0
2	0	30	43	49	39	36	0	16	9	341	336	5
3	1	3	110	416	19	24	0	43	23	958	1322	8
4	3	0	0	0	254	273	191	160	77	527	387	21
5	0	1253	0	0	3	0	0	0	0	2	6	1

Table 4. Distribution of LOS

	LOS			
Cluster	< ½ day	1/2-1 day	1-5 days	> 5 days
1	3256	1891	40	0
2	1	41	432	430
3	18	152	1172	1585
4	28	273	906	686
5	42	519	662	42

Table 5. % distribution of patient LOS

	LOS %			
Cluster	< ½ day	1/2 – 1 day	1-5 days	> 5 days
1	63	36	1	0
2	0	4	48	48
3	1	5	40	54
4	1	14	48	36
5	3	41	52	3

Table 6. Distribution of age.

	AGE							
Cluster	0 to 10	11 to 15	16 to 20	21 to 30	31 to 40	41 to 50	51 to 65	Over 65
1	236	119	278	618	633	554	733	2016
2	17	6	25	90	86	88	157	435
3		5	70	179	217	272	612	1572
4	1	2	174	393	319	205	247	552
5	960	225	29	18	25	5	2	1

Table 7. % Age distribution.

	AGE %							
Cluster	0 to 10	11 to 15	16 to 20	21 to 30	31 to 40	41 to 50	51 to 65	Over 65
1	4.55	2.29	5.36	11.91	12.20	10.68	14.13	38.87
2	1.88	0.66	2.77	9.96	9.51	9.73	17.37	48.12
3	0.00	0.17	2.39	6.12	7.41	9.29	20.91	53.71
4	0.05	0.11	9.19	20.76	16.85	10.83	13.05	29.16
5	75.89	17.79	2.29	1.42	1.98	0.40	0.16	0.08

Table 8 % distribution

	Urgency %				
Cluster	1	2	3	4	5
1	1.10	7.36	36.76	54.29	0.48
2	0.88	6.64	47.79	43.81	0.88
3	1.95	8.92	48.00	40.83	0.31
4	1.37	6.44	39.99	51.40	0.79
5	0.87	12.09	61.90	25.06	0.08

Table 9. Cluster 1 DRG

Top 8 DRGs for Cluster 1		%
261	Chest pain	6.19
347	Abdominal pain/mesenteric adentis wo cc	4.45
889	Poisonning/toxic effect-drugs <60 wo cc	3.66
349	Oesophag, GE, misc diag age 10-74 wo cc	3.41
885	Injuries age <65	3.35
270	Unstable angina w cc	3.32
252	Heart failure and shock	2.33
177	Chronic obstructive airways disease	2.16

Table 10. Cluster 2 DRG

Top 8 DRGs for Cluster 2		%
177	Chronic obstructive airways disease	4.98
252	Heart failure and shock	3.10
37	Cerbrovascular d'o except ta w cc	2.65
170	Respiratory infect/inflam age > 54 w cc	2.43
171	Respiratory infect/inflam (> 54 w/o cc /	2.10
187	Bronchitis & asthma age <50 w/o cc	1.88
249	Circulation d'o ami w/o invasive invest pr	1.88
269	Unstable angina w cc	1.77

Table 11. Cluster 3 DRG

Top 8 DRGs for Cluster 3		%
177	Chronic obstructive airways disease	4.27
249	Circulation d'o ami w/o invasive invest pr	4.07
252	Heart failure and shock	3.69
270	Unstable angina w cc	3.25
261	Chest pain	3.04
37	Cerbrovascular d'o except ta w cc	2.56
170	Respiratory infect/inflam age > 54 w cc	2.32
269	Unstable angina w cc	2.19

Table 12. Cluster 4 DRG.

Top 8 DRGs for Cluster 4		%
409	Hip and femur procs except major>54 w/o	2.85
683	Abortion d&c, aspir curettage, hysterotom	2.85
491	Cellulitis age < 60 w/o cc	2.75
314	Apendectomy w/o complicated p diag	2.64
473	fx, sprn, strn&disloc farm, HD, FT <75	2.64
408	Hip and femur procs except major joint w	2.43
841	Schizophrenia disorders	2.38
843	Major affective disorders	2.27

Table 13. DRG Cluster 5

Top 8 DRGs for Cluster 5		%
473	fx, sprn, strn&disloc farm, HD, FT <75	11.9
187	Bronchitis & asthma age <50 w/o cc	9.25
350	Gastroenteritis age < 10	5.06
135	Ottits media & uri age < 10	4.90
314	Apendectomy w/o complicated p diag	3.40
476	fx, sprn, strn&disloc uarm, lleg < 65 w cc	3.16
902	Other procedures for other injuries w/o cc	2.53
347	Abdominal pain/mesenteric adenitis w cc	2.45

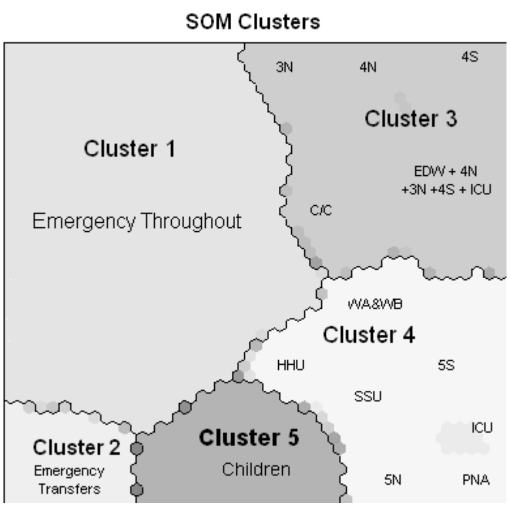

Figure 1. Map of 5 distinct clusters.

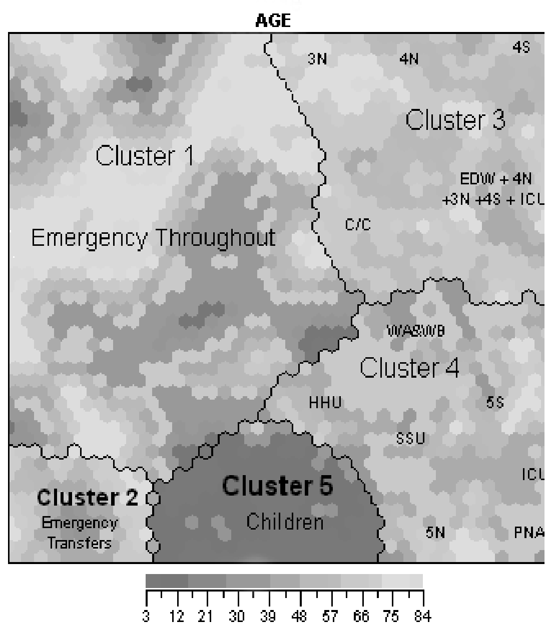

Figure 2. Age distribution.

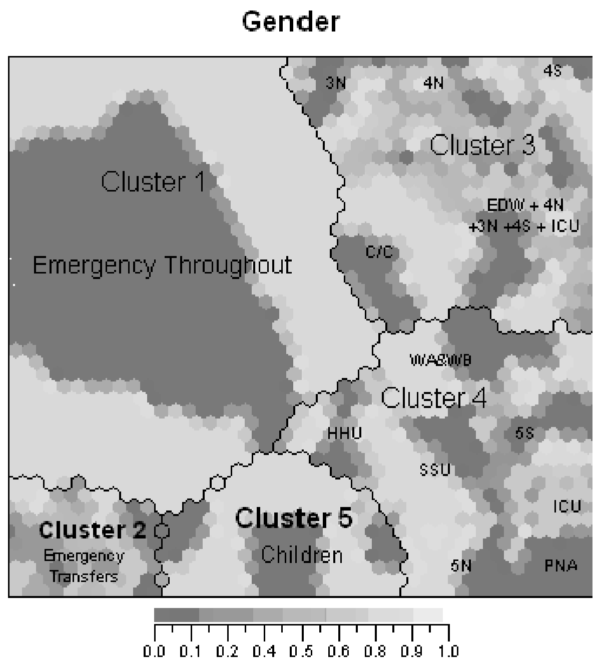

Figure 3. Gender distribution

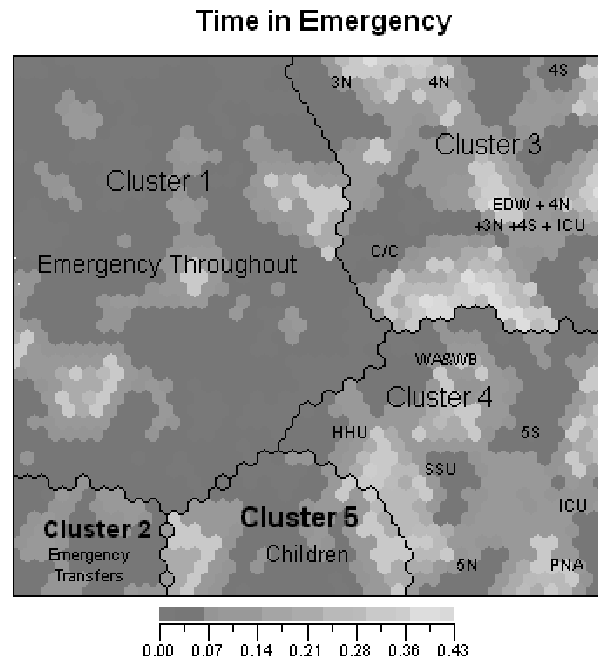

Figure 4. Time in emergency

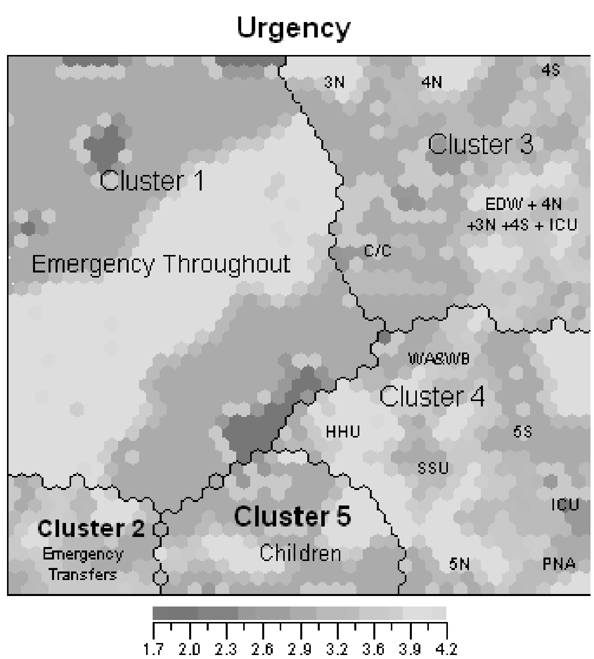

Figure 5. Distribution of urgency

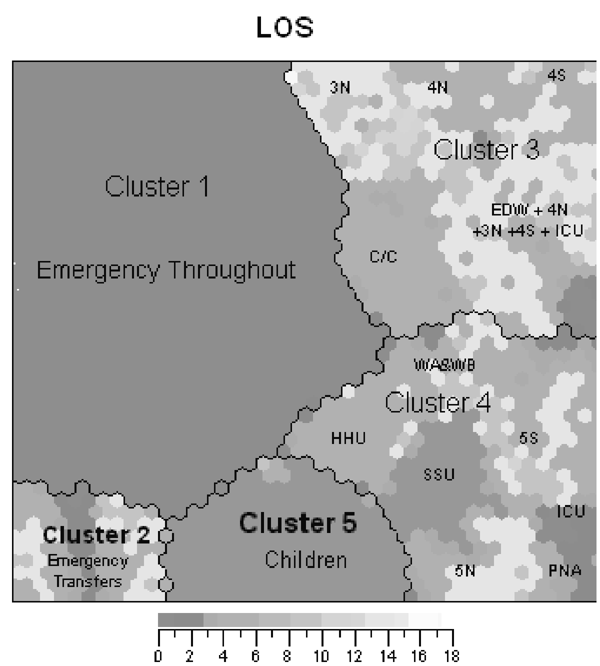

Figure 6 LOS distribution

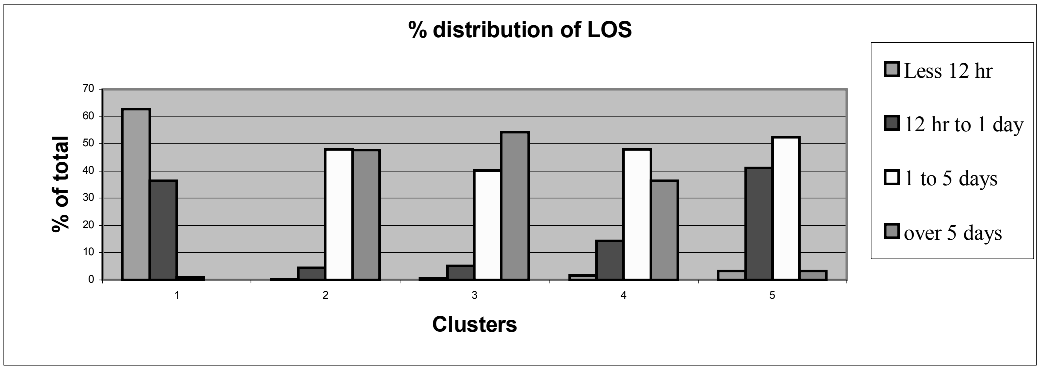

Figure 7 % distribution of LOS

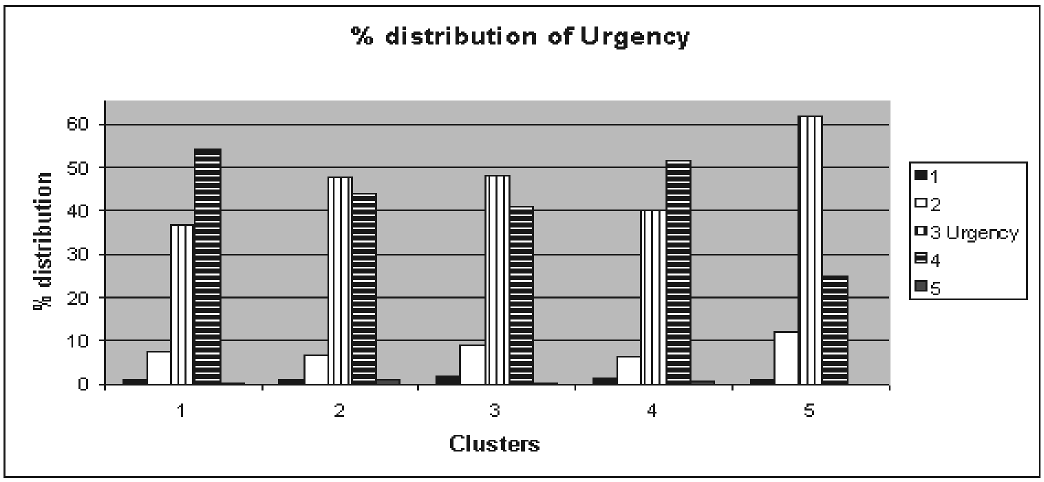

Figure 8. Distribution of urgency

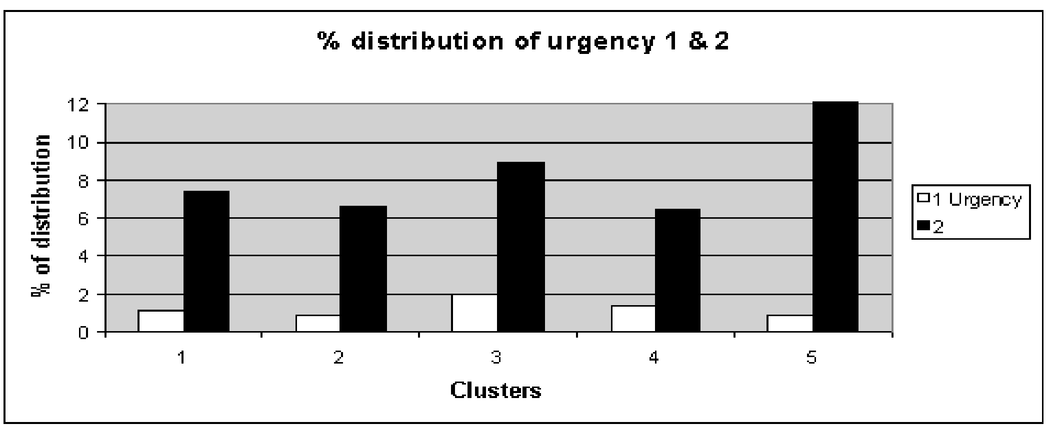

Figure 9. % distribution of urgency 1 and 2.

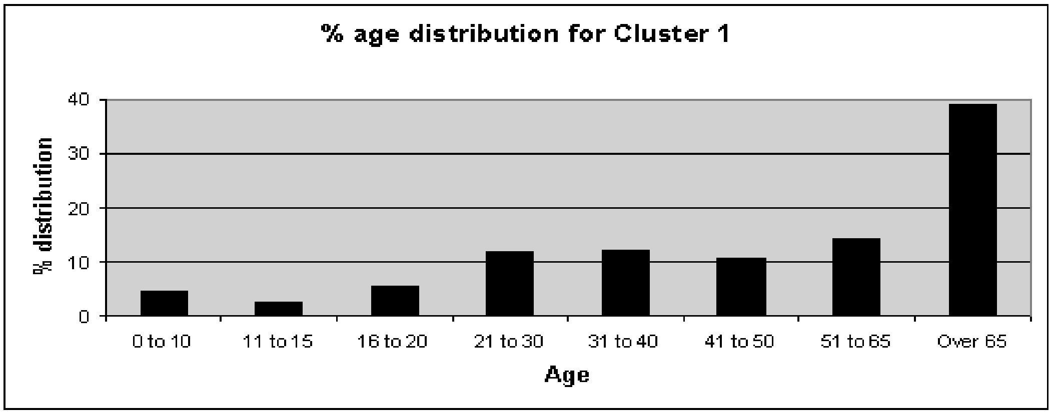

Figure 10. % Cluster 1 age distribution

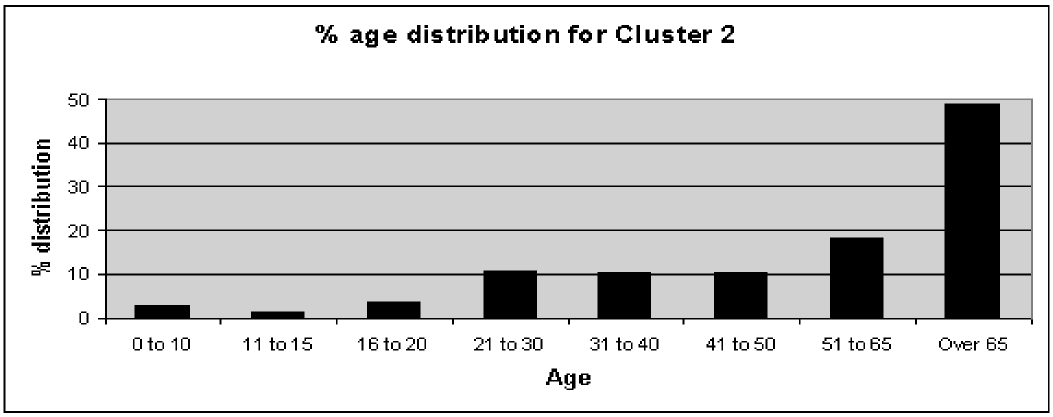

Figure 11. % Cluster 2 age distribution

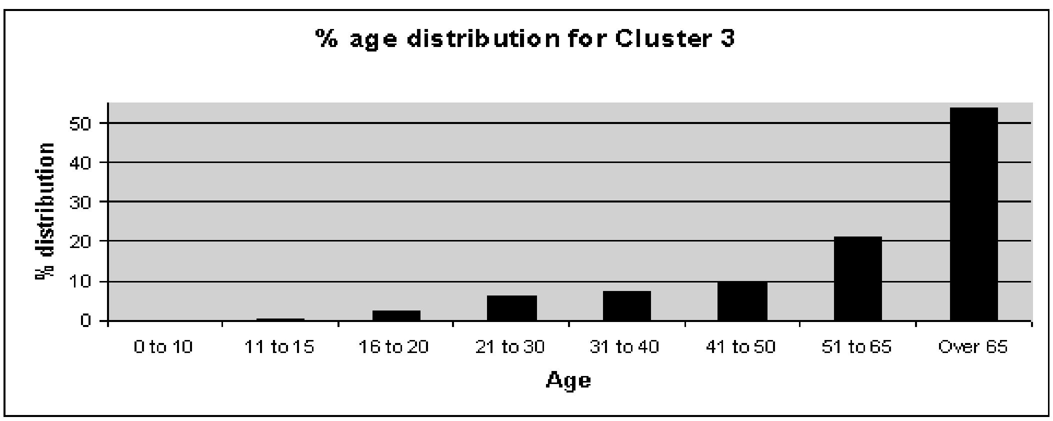

Figure 12. % Cluster 3 age distribution

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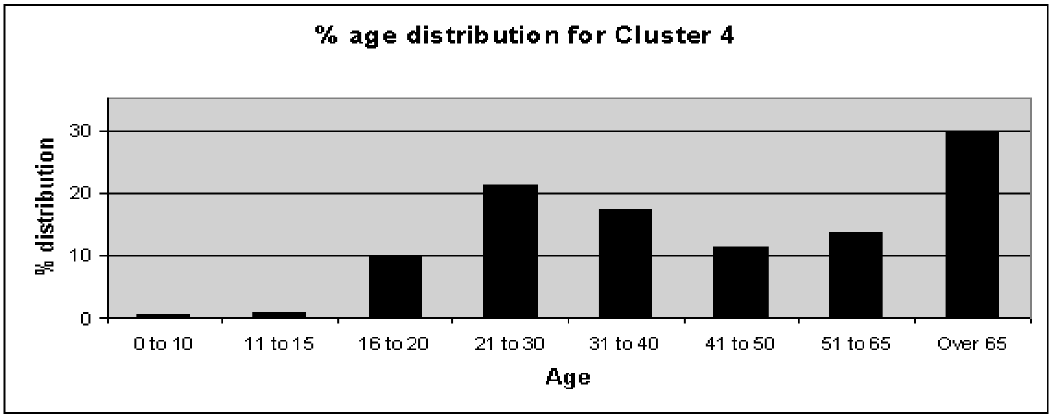

Figure 13.. % Cluster 4 age distribution

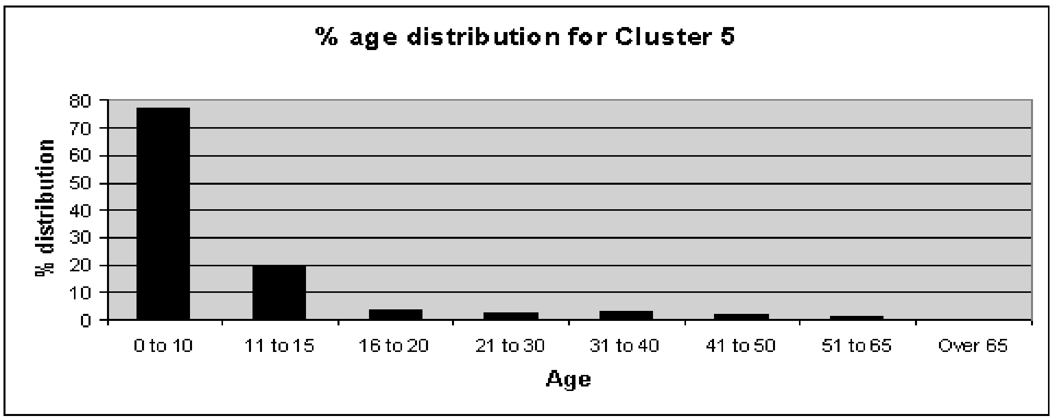

Figure 14. % Cluster 5 age distribution