

HOWARD UNIVERSITY

**Identifying Subgroups of Minority
Diabetes Type II Data Using Cluster Analysis**

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Tacuma Kwabena Solomon

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**HOWARD UNIVERSITY
GRADUATE SCHOOL
DEPARTMENT OF ELECTRICAL ENGINEERING
AND COMPUTER SCIENCE
THESIS COMMITTEE**

Peter Keiller, D.Sc.
Chairperson

Legand Burge Ph.D.

Mugizi Robert Rwebangira, Ph.D.

Gloria Washington Ph.D.

Mugizi Robert Rwebangira, Ph.D.
Thesis Advisor

Candidate: Tacuma Solomon
Date of Defense: May 11, 2017

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ABSTRACT

Diabetes type 2 occurs in African Americans at a rate higher than Non-Hispanic whites. They are characterized by higher rates of the disease, with higher rates of mortality than other ethnic groups. With advancements in medical and computational technology, more information than ever exists in the form of medical data.

The objective of this project is to perform cluster analysis on anonymized diabetes type II data from Howard University Hospital's electronic health records.

The data was first extracted from SQL, cleaned, and preprocessed. It was then uploaded into R. Four algorithms were chosen to create two, three, four, and five clusters of the data, which was then subject to comparative analysis. It was then determined that DIANA (Divisive ANALysis) clustered the data best, and from which results were extrapolated.

It was discovered that there were high correlations between type II diabetes, hypertension, hyperlipidia, and cholesterolemia, which validated existing knowledge about African Americans most at risk for diabetes. There was also evidence of higher rates of benign neoplasm of the colon; non-cancerous colon tumors. Distinctions about other chronic diseases were made by gender and marital status. There were significantly more cases of acquired hypothyroidism cases occurring in women who are black, female, and non-single. There were elevated incidences of prostate cancer (neoplasm, malignant, of the prostate) in men who are black and non-single. Incidences of Tobacco use disorder also had higher occurrences in clusters featuring mostly single men and women. Many of these relationships remain unexplored.

Performing cluster analysis on electronic health records has enormous potential as a method of research. With advances in computational power and the proliferation of data, there is huge opportunity in mining medical data for knowledge.

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LIST OF SYMBOLS AND ACRONYMS

FFSGCDB	Fibromyalgia and Chronic Fatigue Syndrome Spanish Genetic Data Bank
GML	Generalized Linear Model
ICD-9	The International Classification of Diseases, Ninth Revision
WHO	World Health Organization
SAS EM	Statistical Analysis System Enterprise Manager
WEKA	Waikato Environment for Knowledge Analysis
PAM	Partitioning Around Medoids
MST	Minimum Spanning Tree
PCA	Principal Component Analysis
I2B2	Informatics for Integrating Biology and the Beside
SQL	Structured Query Language
Hclust	An agglomerative hierarchical clustering algorithm
DIANA	Divisive ANALysis
t-SNE	t-disbributed stochastic neighbor embossing

CHAPTER 1. INTRODUCTION

1.1 Background

Type II diabetes is a metabolic disease which affects more than 29 million Americans. It is the more common form of diabetes, accounting for 90% of diabetes cases, with occurrence rates even higher over the age of 45 [1]. It is typically characterized by high levels of blood sugar, and can lead to further complications, such as stroke, heart disease, amputations in the extremities, and death. Healthy treatment and disease management is critical.

Diabetes type II is especially prevalent in the African-American community. The ethnic group is characterized by the American diabetes Association as having a higher risk of diabetes [1]. African-Americans suffer from higher rates - 1.4 to 2.3-fold compared to White Americans - suffer across a wider age group, and suffer higher morbidity and mortality rates than other ethnic groups. [1]

With the proliferation of Electronic Health Records and advances in computing power, we can utilize new methods of research to uncover new insights about diabetes. What do certain groups of diabetes sufferers have in common? How are we able to predict the likelihood that someone may have diabetes? What new treatments can we suggest? These questions and more can be answered by machine learning.

Machine learning is defined as the ability to fit existing data to models which can be used to predict the outcomes of new instances of Data. Machine learning may allow us to predict the probability that someone may have diabetes, based on characteristics from their Health Records and can provide new insights into existing Records. It can also group data by similarity, allowing

researchers to spot trends in the data. Using machine learning, clustering, specifically, is the aim of the research.

This research is exploratory. By performing clustering algorithms on anonymized Electronic Health Records, we may be able to learn more about how diabetes patients are grouped, and why.

A novel element of research is the data that is being worked on. The data is anonymized Electronic Health Records collected over the period 2009 – 2013, in the I2b2 system. There is unique opportunity since the Howard University Hospital serves a 90% minority population. This allows us to gather results specifically from minorities.

To maintain ethical standards, it is important to emphasize that all Electronic Health Records are anonymized. All records are stripped of anything that can identify a patient.

CHAPTER 2. STATEMENT OF THE PROBLEM

The objective is to find subgroups within Howard University's electronic health records using cluster analysis, and to discover what characteristics these subgroups may share. Four algorithms will be used, two partitioning, and two hierarchical. This research is done with the expectation that insights will be found, so that we may understand more about diabetes type II in minority populations.

CHAPTER 3. RELATED WORK

Finding subgroups of data using clustering algorithms is an analytic process that is often used to generate subgroups from data.

Researchers used clustering to find specialized patterns and insight by segmenting the data into smaller fragments, each with specialized attributes. Different approaches produced different results by leveraging different techniques in formatting the dataset, choosing features, collecting data, the types of clustering algorithms that were used, the methodology of determining the algorithm's effectiveness, and in interpreting the clusters that result.

3.1 Data Collection

Different researchers used different methods of data collection. Some researchers collected data from disparate sites, whereas other researchers collected data from one site only. In the paper 'Characteristic evaluation of diabetes data using clustering techniques', Padmaja, Vikkurty, et al. the researchers gathered their data from the National Institute of Diabetes, Digestive, and Kidney Diseases in India in their effort to evaluate characteristics of diabetes via clustering. The Fibromyalgia and Chronic Fatigue Syndrome Spanish Genetic and Clinical Data Bank (FFSGCDB), is an online dataset that was used to find subgroups of Fibromyalgia patients. Another common dataset used for diabetes research is the Pima Indian dataset, which was used in the paper "Clustering and Classifying Diabetic Data Sets using K-means Algorithm". Data sets can also range in size; the paper 'Hidden Patterns; Clustering Diabetes Data' uses a dataset with 185,000 observations ranging over 5 years, while the smallest found sample was 1,446 observations in the FFSGCDB.

3.2 Data Preprocessing

Before loading the data into the software package of choice, the data must first be formatted. This preprocessing ensures that the data is in a form that can be adequately used by software and algorithms. In many research papers, their work was assisted by software tools. In the paper ‘Hidden Patterns: Clustering Diabetes Data’, Hu and Cook had to consider both the problems of missing data, and variable conversion. They used a technique called ‘Tree Surrogate Imputation’, an effective and widely used method replacing missing values, to help format their CDC dataset. After solving the problem for formatting however, they came upon another problem; they had to deal with a mixed dataset. They had the task of converting categorical and ordinal variables to numeric variables, since the algorithms that they wanted to use only worked for interval data. They used rank ordering for the ordinal variables, and Generalized Linear Model (GLM) for nominal variables.

Specialized software can also assist in data preprocessing. In the paper “Mining Hospital Databases for Management Support”, Freitas, Alberto, et al., in their efforts to analyze a hospital inpatient database, they prepared their data by using SPSS; IBM’s predictive analytics software, before uploading it into R.

Choosing the most important attributes of this data is also of importance. This section of machine learning is called feature selection. The method depends on the researcher and can be as much of an art, as a science. The features chosen by a researcher can determine the quality of the clusters; careful consideration is required. Datasets generated by medical health records pose unique challenges; variables may be of many types, and can be sparse. They also tend to suffer from very high dimensionality, having to model real world objects and humans. Algorithmic tools can assist in making this task more manageable. The paper, ‘Feature Selection for unsupervised

learning through local learning’ tries to rectify this by posing a way to best choose the optimum level of features from a high-dimensional dataset. It does this by revealing the intrinsic structures of a high dimensional space, and using gap statistics and for parameter estimation and assess the statistical significance of the structure through permutation tests.

In many medical databases, disease categories are stored in codes. The most popular of these is the ICD-9 code, developed by the World Health Organization (WHO). The code is associated with an encounter in a database, and is often used as a condition to filter for certain diseases. In the paper ‘Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time-Series Analysis’, ICD-9 codes were aggregated into 802 categories. The researchers even counted the number of a certain code per patient, dropping an individual if the count was too high in a 6-month period, and only included categories that had at least 5% prevalence in the sample. In another paper titled, ‘Identification of Type 2 diabetes subgroups through topological analysis of patient similarity’ Li, Cheng, et.al used the technique of identifying individual records using these ICD-9 codes, and then aggregated the substantial number of codes to 281 single-level disease categories or 18 level 1 categories in multilevel disease categories. Once the data is processed, the data was then imported.

3.3 Software package Used

In the literature, many different software packages were used. The list includes

- ‘Mining Hospital Databases for Management Support’ – R
- ‘Hidden Patterns: Clustering Diabetes Data’ – SAS EM tool
- ‘Clustering and Classifying Diabetic Data Sets using K-means Algorithm – WEKA tool

- ‘Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time-Series Analysis’ – Matlab

While each paper uses software for their approach, each package contains similar algorithms that can find comparable results.

3.4 Clustering Algorithms Selected

In cluster analysis, many algorithms can cluster data, and researchers generally choose which is best for them through a variety of factors; the size of the dataset, the type of data used (numeric vs mixed), and runtime. Partitioning algorithms, like K-Means, tend to cluster faster than hierarchical algorithms, but their cluster centers are susceptible to false minima. In similar work, some researchers settle on a using single algorithm, while others use a more comparative approach. Different papers used different approaches depending on the data.

In ‘Characteristic evaluation of diabetes data using clustering techniques’, by Padmaja, Vikkurty, et al. used K-Means, Partitioning Around Medoids (PAM), Minimum Spanning Tree (MST), and Nearest Neighbor for generating clusters. At the end of the paper, they then evaluated each algorithm using an approach called Attribute Oriented Induction. When using this approach, they first identified the distinct counts of various features. The features with the maximum number of distinct values were then removed. The remaining maximum and minimum items were then grouped together using the set grouping. Set grouping can be found in the paper ‘Using Destination Set Grouping to Improve the Performance of Window-Controlled Multipoint Connections.’

Other approaches used singular algorithms. While the reasons for such were not stated, it can be speculated that the datasets that were chosen must have had some influence in their decision.

An example of this is in ‘Cluster Analysis of Clinical Data Identifies Fibromyalgia Subgroups’ where the dataset used is mixed. Docampo, Collado, et al. had a dataset that contained mostly continuous and dichotomous values. Dichotomous values are binary; taking the form of either 1, or 0. Due to the dataset being 75% dichotomous, they decided to convert their continuous variables to dichotomous ones. As a result, if they were to use a partitioning algorithm, it could not be K-Means, since the algorithm only functions on purely numeric data. Instead they used Partitioning around Medoids and Gower’s similarity measure. Gower’s general similarity measure is a technique that can calculate the distances between continuous variables, returning a distance matrix and contains the distances between each point of data in the dataset. As a parameter to PAM algorithm in R, the distance matrix can then be used to cluster the data.

In another example, ‘Clustering and Classifying Diabetic Data Sets Using K-Means Algorithm’, the Kothianayaki and Thangaraj used the K-means algorithm and remarked that it was used both because of its popularity, and because it worked given a set of numeric objects. Different algorithms were best given the discretion of the researcher, and the type of data that was used. Other approaches in related works include:

- ‘Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time Series Analysis’ – Hierarchical Clustering
- ‘Mining Hospital Databases for Management Support’ – Hierarchical Clustering (using Hclust, diana (Divisive Analysis) in R)
- ‘Hidden Patterns: Clustering Diabetes Data’ – Hierarchical Clustering (Ward method)

3.5 Visualization of Results

When the data had been processed, it was time to represent the data for interpretation. This is visualization. In some papers, researchers may not do this, and instead provide summary

statistics – tables that encapsulate cluster information - while others may choose to both visualize and summarize their findings. Due to the large feature set size of the data, methods are needed to compress the dataset down to 2 dimensions for viewing.

A widely-used method for visualization is using Principal Component Analysis (PCA). PCA compresses the dimensionality of data without changing its structure. Figure 3.1 shows an example of a 3-dimensional visualization of Fibromyalgia patients, while Figure 3.2 shows how clusters - with their differing sizes - can be recorded in tabular form.

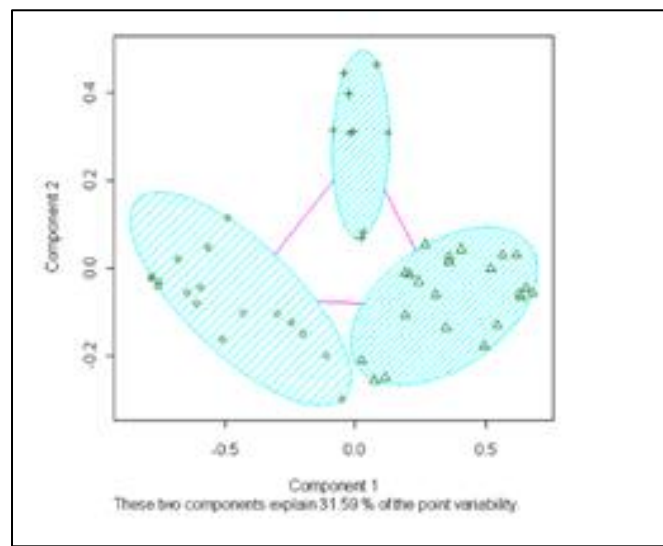


Figure 3.1 Clustering of variables into three dimensions
(Docampo, Elisa, et al. "Cluster analysis of clinical data identifies fibromyalgia subgroups." *PLoS One* 8.9 (2013): e74873.)

Table 3: Summary of clustering			
year	#clusters of size over100	size of largest cluster	size of smallest cluster
2004	6	16263	102
2005	11	9456	183
2006	10	10821	119
2007	7	18193	108
2008	5	26245	130

Figure 3.2 Example of Cluster Summary (Cook, Rachel, and Gongzhu Hu. "Hidden Patterns: Clustering Diabetes Data." *CAINE*. 2010.)

3.6 Discussion of Results

Discussion of results is where patterns and trends are extrapolated from the resulting clusters. Outlier clusters are often removed (“Hidden Patterns: Clustering Diabetes Data”) when they are too small (in that case, smaller than 100).

Attributes of a cluster that is noticeable higher can indicate novel observations. In the paper ‘Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time – Series Analysis, results were extrapolated from the number of codes, where one cluster contained over 5 times more codes than a larger subgroup, which lead to an observation. Sometimes proportions of features can lead to interesting findings. In the same paper, comparisons were made of the number of diagnoses of Asperger Syndrome in one subgroup versus the number of diagnoses of autism in another group.

Another study, in the paper ‘Characteristic evaluation of diabetes data using clustering techniques’ by Padmaja, Vikkurty, et al., researchers could predict the onset stage of diabetes by

looking at the percentages of a factor (the number of women), and comparing them to already established data.

In conclusion, this section should provide a comprehensive overview of related works in the field of cluster analysis for medical data. It shows how other approaches chose to gather data, pre-process data, choose software, choose the appropriate algorithm, and to visualize and interpret their results. Papers in this field are relatively sparse, as the field is still new. This is written with the intention that the reader has an idea of goings on in the field, and the procedure of steps should he/she choose to conduct research in it.

CHAPTER 4. TECHNICAL APPROACH

4.1 Feature Selection

Generating clusters that best describe the data depend heavily on feature selection. This is particularly difficult in medical data due to the sheer size and variety of information that can either be in the form of categorical, nominal, or ordinal variables, images, handwriting, etc. For this research, the medical data was accessed through the I2B2 schema [12]. The database provided a small enough range of features that algorithmic approaches were not needed. Features instead were hand-picked.

The features that were agreed on primarily included demographic information, the number of inpatient encounters, the average time of an inpatient stay, and the mode diagnosis of a patient.

4.2 Data Collection

Having an idea of what features were needed for the dataset, proper procedure was used to create and extract the dataset. The data was stored in the I2B2 format in an Oracle database and was accessed using Oracle SQL Developer.

4.2.1 I2B2 Schema

The data set for extraction was stored in the i2b2 system. I2b2 stands for Informatics for Integrating Biology and the bedside, and is a star schema (see Figure 4.1) for representing, storing, and retrieving medical Information. I2b2 came about as a means for standardizing the data repository for electronic health data. The i2b2 schema has 5 main tables:

- Observation Fact
- Patient Dimension

- Concept Dimension
- Visit Dimension
- Observer Dimension
- Modifier Dimension

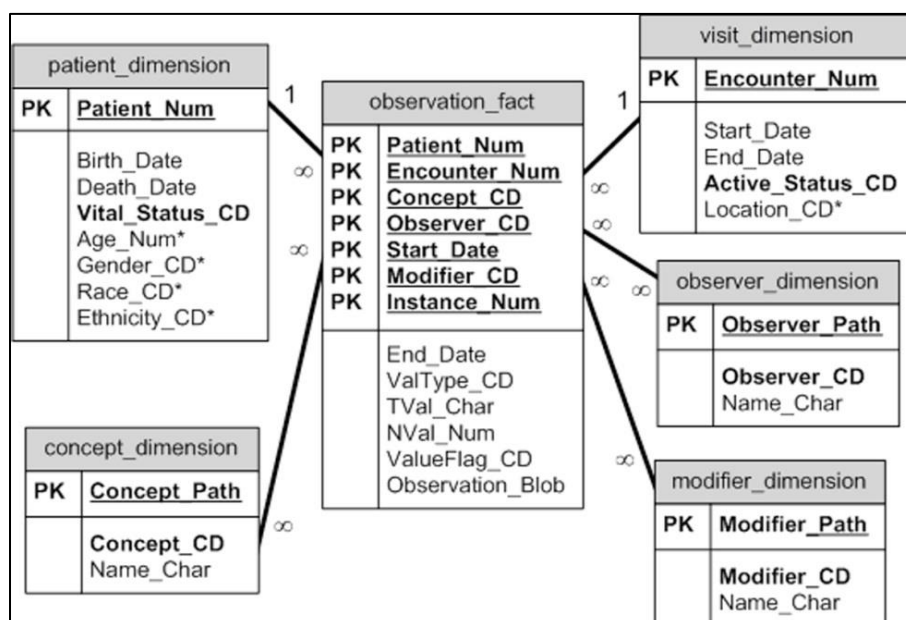


Figure 4.1 I2B2 Star Schema

4.2.1.1 Observation Fact

Observation fact is a table where each row is a record of an inpatient encounter. An inpatient encounter is any occurrence where a patient visits a hospital and is required to stay. In this case, a patient has an encounter number, which is the identification of the encounter and the primary key, the patient number, the patient's identification, a Concept CD, and a code that

classifies lab tests or diagnoses (Figure 4.2). It is based on the ICD-9 codes [24]. A single patient can have multiple observations here.

	ENCOUNTER_NUM	PATIENT_NUM	CONCEPT_CD	PROVIDE...	START_DATE	MODIFIE...
1	40266380	2594587	CTSA:HU	@	23-FEB-13	@
2	40266381	2594588	CTSA:HU	@	23-FEB-13	@
3	40266382	2594589	CTSA:HU	@	23-FEB-13	@
4	40266383	2594590	CTSA:HU	@	23-FEB-13	@
5	40266384	2594591	CTSA:HU	@	23-FEB-13	@
6	40266385	2594592	CTSA:HU	@	23-FEB-13	@
7	40266386	2594593	CTSA:HU	@	23-FEB-13	@
8	40266387	2594594	CTSA:HU	@	23-FEB-13	@
9	40266388	2594595	CTSA:HU	@	23-FEB-13	@
10	40266389	2594596	CTSA:HU	@	23-FEB-13	@
11	40266390	2594597	CTSA:HU	@	23-FEB-13	@
12	40266391	2594598	CTSA:HU	@	23-FEB-13	@
13	40266392	2594599	CTSA:HU	@	23-FEB-13	@
14	40266393	2594600	CTSA:HU	@	23-FEB-13	@
15	40266394	2594601	CTSA:HU	@	23-FEB-13	@
16	40266395	2594602	CTSA:HU	@	23-FEB-13	@
17	40266396	2594603	CTSA:HU	@	23-FEB-13	@
18	40266397	2594604	CTSA:HU	@	23-FEB-13	@
19	40266398	2594605	CTSA:HU	@	23-FEB-13	@
20	40266399	2594606	CTSA:HU	@	23-FEB-13	@

Figure 4.2 Screenshot of Observation Fact

4.2.1.2 Patient Dimension

In the Patient Dimension table, each row is a record of a patient (Figure 4.3). The row has an ID number, and categories for age, gender, religion, and ethnicity. The information on this table is anonymized (there are no identifiers that can in a row that can identify an individual).

	PATIENT_NUM	VITAL_STATUS_CD	BIRTH_DATE	DEATH_DATE	SEX_CD	AGE_IN_YEARS_NUM	LANGUAGE_CD
1	2451667	DEM VITAL:@	(null)	(null)	Male	59	DEM LANGUAGE:@
2	2451668	DEM VITAL:@	(null)	(null)	Female	61	DEM LANGUAGE:@
3	2451669	DEM VITAL:@	(null)	(null)	Female	55	* TRIAL * TRIA
4	2451670	DEM VITAL:@	(null)	(null)	Male	51	DEM LANGUAGE:@
5	2451671	* TRIAL * T	(null)	(null)	Female	40	DEM LANGUAGE:@
6	2451672	DEM VITAL:@	(null)	(null)	Female	23	* TRIAL * TRIA
7	2451673	DEM VITAL:@	(null)	(null)	Male	58	DEM LANGUAGE:@
8	2451674	* TRIAL * T	(null)	(null)	Female	79	DEM LANGUAGE:@
9	2451675	* TRIAL * T	(null)	(null)	Female	54	* TRIAL * TRIA
10	2451676	DEM VITAL:@	(null)	(null)	Male	78	DEM LANGUAGE:@
11	2451677	DEM VITAL:@	(null)	(null)	Male	71	DEM LANGUAGE:@
12	2451678	DEM VITAL:@	(null)	(null)	Female	57	DEM LANGUAGE:@
13	2451679	DEM VITAL:@	(null)	(null)	Female	36	* TRIAL * TRIA
14	2451680	DEM VITAL:@	(null)	(null)	Female	85	DEM LANGUAGE:@
15	2451681	DEM VITAL:@	(null)	(null)	Male	33	DEM LANGUAGE:@
16	2451682	DEM VITAL:@	(null)	(null)	Female	28	DEM LANGUAGE:@
17	2451683	DEM VITAL:@	(null)	(null)	Female	37	DEM LANGUAGE:@
18	2451684	DEM VITAL:@	(null)	(null)	Male	19	DEM LANGUAGE:@
19	2451685	DEM VITAL:@	(null)	(null)	Female	88	DEM LANGUAGE:@
20	2451686	DEM VITAL:@	(null)	(null)	Male	65	DEM LANGUAGE:@

Figure 4.3 Screenshot of Patient Dimension

4.2.1.3 Concept Dimension

The concept dimension table contains all the disease codes for every possible mappable illness. It contains fields for concept_cd, which is the code that is associated with an illness, name_char, which is the string attached to that code, and other characteristics (Figure 4.4).

These are the main three tables from which the data was extracted. The I2b2 schema was stored in oracle and accessible by Oracle SQL developer. Extracting the dataset that was needed required many SQL calls.

CONCEPT_CD	CONCEPT_PATH	NAME_CHAR	CONCEPT_BLOB	UPDATE_DATE	DOWNLOAD_DATE	IMPORT_DATE
1 DEM AGE:92	\i2b2\Demographics\Age\>= 85 years old\92\	92 years old	(null)	10-APR-07	10-APR-07	10-APR-07
2 DEM AGE:92	\i2b2\Demographics\Age\>= 65 years old\92\	92 years old	(null)	10-APR-07	10-APR-07	10-APR-07
3 DEM AGE:93	\i2b2\Demographics\Age\>= 85 years old\93\	93 years old	(null)	10-APR-07	10-APR-07	10-APR-07
4 DEM AGE:93	\i2b2\Demographics\Age\>= 65 years old\93\	93 years old	(null)	10-APR-07	10-APR-07	10-APR-07
5 DEM AGE:94	\i2b2\Demographics\Age\>= 85 years old\94\	94 years old	(null)	10-APR-07	10-APR-07	10-APR-07
6 DEM AGE:94	\i2b2\Demographics\Age\>= 65 years old\94\	94 years old	(null)	10-APR-07	10-APR-07	10-APR-07
7 DEM AGE:95	\i2b2\Demographics\Age\>= 85 years old\95\	95 years old	(null)	10-APR-07	10-APR-07	10-APR-07
8 DEM AGE:95	\i2b2\Demographics\Age\>= 65 years old\95\	95 years old	(null)	10-APR-07	10-APR-07	10-APR-07
9 DEM AGE:96	\i2b2\Demographics\Age\>= 85 years old\96\	96 years old	(null)	10-APR-07	10-APR-07	10-APR-07
10 DEM AGE:96	\i2b2\Demographics\Age\>= 65 years old\96\	96 years old	(null)	10-APR-07	10-APR-07	10-APR-07
11 DEM AGE:97	\i2b2\Demographics\Age\>= 85 years old\97\	97 years old	(null)	10-APR-07	10-APR-07	10-APR-07
12 DEM AGE:97	\i2b2\Demographics\Age\>= 65 years old\97\	97 years old	(null)	10-APR-07	10-APR-07	10-APR-07
13 DEM AGE:98	\i2b2\Demographics\Age\>= 85 years old\98\	98 years old	(null)	10-APR-07	10-APR-07	10-APR-07
14 DEM AGE:98	\i2b2\Demographics\Age\>= 65 years old\98\	98 years old	(null)	10-APR-07	10-APR-07	10-APR-07
15 DEM AGE:99	\i2b2\Demographics\Age\>= 85 years old\99\	99 years old	(null)	10-APR-07	10-APR-07	10-APR-07
16 DEM AGE:99	\i2b2\Demographics\Age\>= 65 years old\99\	99 years old	(null)	10-APR-07	10-APR-07	10-APR-07
17 HU_LAB:ZINC	\Custom Metadata\HU_LABTEST\ZINC\	ZINC	(null)	21-FEB-13	(null)	21-FEB-13
18 HU_LAB:WC	\Custom Metadata\HU_LABTEST\WOUND CULTURE (2 SWABS)\	WOUND CULTURE (2 SWABS)	(null)	21-FEB-13	(null)	21-FEB-13
19 HU_LAB:WBC	\Custom Metadata\HU_LABTEST\WHITE BLOOD CELL COUNT\	WHITE BLOOD CELL COUNT	(null)	21-FEB-13	(null)	21-FEB-13
20 HU_LAB:WZ	\Custom Metadata\HU_LABTEST\WHITE BLOOD CELL COUNT\	WHITE BLOOD CELL COUNT	(null)	21-FEB-13	(null)	21-FEB-13

Figure 4.4 Screenshot of Concept Dimension

4.2.2. Extracting the Dataset

To create the dataset, a table was first created, where all the columns represented the features of the dataset. The final dataset needed to contain:

- Patient ID number
- Gender
- Race
- Age
- Religion
- Marital Status
- Number of Inpatient Encounters
- Average Length of Stay
- Mode Concept CD

The mode concept_cd represented the ICD-9 code that appeared the most times in that patient's encounter records, that was not diabetes related. This was done to determine the chief co-morbidity for that patient. Since the data was stored in Oracle SQL server, the database needed to query and create a new table to export the final feature set.

4.2.2.1. Creating a preliminary feature set (Without Average Length of stay)

Creating a dataset with average length of stay fields, and mode concept cd required more elaborate SQL calls, so first a preliminary dataset was built. This preliminary Dataset contains all the previously mentioned fields, except for average length of stay, and mode concept cd.

The SQL code to produce that table in ORACLE SQL:

```
create global temporary table feature_set
on commit preserve rows

as select patient_dimension.patient_num Patient_number, patient_dimension.SEX_CD gender,
patient_dimension.AGE_IN_YEARS_NUM Age, patient_dimension.race_cd race,
patient_dimension.religion_cd religion,
patient_dimension.marital_status_cd marital_status, count(observation_fact.encounter_num)
Number_of_Inpatient_Encounters
from patient_dimension
join observation_fact
on patient_dimension.patient_num = Observation_Fact.Patient_Num
join concept_dimension
on observation_fact.concept_cd = concept_dimension.concept_cd
where (name_char like '%diabet%type%II%') or (name_char like '%type%II%diabet%') or
      (concept_path like '%diabet%type%II%') or (concept_path like '%type%II%diabet%')
group by patient_dimension.patient_num, patient_dimension.SEX_CD,
patient_dimension.AGE_IN_YEARS_NUM, patient_dimension.race_cd,
patient_dimension.religion_cd,
```

The code pulled the patient number, the gender, age, race, religion, marital status, and places it into a temporary table called feature_set.

4.2.2.2. Creating the Average Length of Inpatient Stay

To obtain the average length of stay for each patient, the end date was subtracted from the start date for all a patient's encounters in the encounter_dimension table, where they were all averaged and associated with a Patient Number. This result of this was then placed in table called average_length_of_stay.

The ORACLE SQL code appears in the following text:

```
create global temporary table average_length_of_stay
on commit preserve rows

as select patient_num, Round(avg(end_date - start_date),4) Average_length_of_stay
from observation_fact
join concept_dimension
on observation_fact.concept_cd = concept_dimension.concept_cd
where (name_char like '%diabet%type%II%') or (name_char like '%type%II%diabet%') or
      (concept_path like '%diabet%type%II%') or (concept_path like '%type%II%diabet%')
group by patient_num;
```

4.2.2.3. Joining the feature set and average length of stay

The next set of SQL queries then merged the feature_set and average_length_of_stay into one table:

```
create global temporary table final_feature_set
on commit preserve rows

as select patient_number, gender, race, age, religion, marital_status, Feature_Set.Zip_Code,
      Feature_Set.Number_Of_Inpatient_Encounters,
      Average_Length_Of_Stay.Average_Length_Of_Stay from feature_set
join average_length_of_stay
on Feature_Set.Patient_Number = Average_Length_Of_Stay.Patient_Num;
```

4.2.2.4. Creating mode concept_cd

The last step in creating the complete dataset was to append the mode concept_cd to the dataset. This showed the most frequent co-disease that each patient has.

The first thing that was done was to create a table called concept_count. In this temporary table, the database was queried so that for every patient, there would be a Patient Number, Concept_cd, Name_car, Max count of concept cds.

```
/* Creates a temporary able listing the Patient Number, Concept Cd, Name Char, Count, Max
count of concept cds */
create global temporary table concept_count
on commit preserve rows
as select observation_fact.patient_num, observation_fact.concept_cd,
concept_dimension.name_char, Count(observation_fact.concept_cd) cnt,
max(count(observation_fact.concept_cd)) over (partition by observation_fact.patient_num)
max_count
from observation_fact
join concept_dimension
on observation_fact.concept_cd = concept_dimension.concept_cd
where observation_fact.concept_cd not in (select observation_fact.concept_cd from
observation_fact where (concept_cd like 'DEM%') or (concept_cd like 'CTSA:%') or
(concept_cd like 'HU_LAB:%') or
(name_char like '%diabet%type%II%') or (name_char like '%type%II%diabet%') or
(concept_path like '%diabet%type%II%') or (concept_path like '%type%II%diabet%') )
group by observation_fact.patient_num, observation_fact.concept_cd,
Concept_Dimension.Name_Char;
```

This SQL code created a temporary table in oracle called concept_count. The table contains the mode ICD-9 codes for every patient in encounter fact. It is not complete however; there was still the problem of repeat rows per patient. What was needed was only one mode. This was solved with this code:

```
create global temporary table final_concept_count
on commit preserve rows
as select t.patient_num, t.concept_cd, t.name_char
from (select concept_count.patient_num, concept_count.concept_cd,
concept_count.name_char, ROW_NUMBER() OVER (PARTITION BY patient_num
ORDER BY patient_num ) as rnum
from concept_count) t
where t.rnum = 1;
```

This only returned one instance of a patient, the concept_cd / ICD-9 code of only one disease, and its associated name_char value.

4.2.2.5 Joining last feature set and final concept cd

Joining these two tables generated the final dataset for export. This is done with the following SQL code:

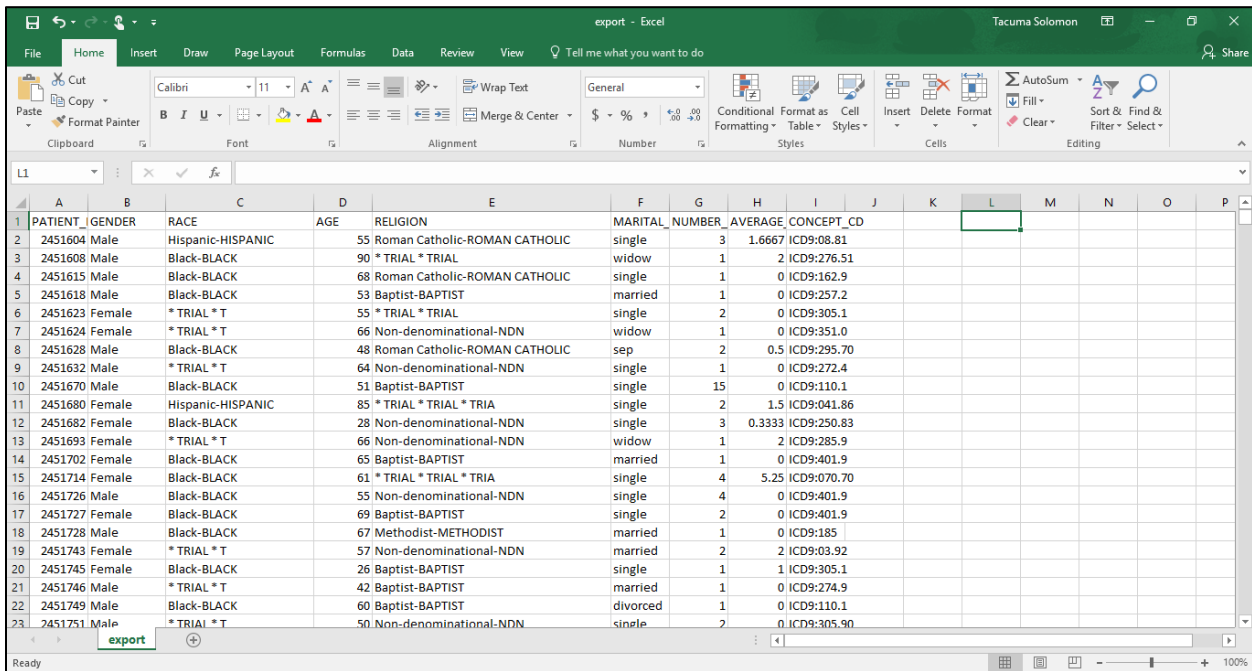
```
create global temporary table last_feature_set
on commit preserve rows
as select patient_number, gender, race, age, religion, marital_status,
Number_Of_Inpatient_Encounters, Average_Length_Of_Stay,
final_concept_count.concept_cd
from final_feature_set
join final_concept_count
on Final_Feature_Set.Patient_Number = Final_Concept_Count.Patient_Num;
```

4.3 Software Used

The software chosen for cluster analysis was R. From the related work section, and looking at requirements for cost, ease of obtainability, ease of use, results, popularity and support, it was determined that R would be the best choice. As a result, all data processing tasks were to make the data suitable for processing by R.

4.4 Preprocessing

Before the data can be uploaded into R, it first was made ready for use [13]. The dataset was exported to a csv file, and the changes made in Microsoft Excel. The data freshly exported from Oracle SQL developer is displayed in Figure 4.5:



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	PATIENT_ID	GENDER	RACE	AGE	RELIGION	MARITAL	NUMBER	AVERAGE	CONCEPT_CD							
2	2451604	Male	Hispanic-HISPANIC	55	Roman Catholic-ROMAN CATHOLIC	single	3	1.6667	ICD9:08.81							
3	2451608	Male	Black-BLACK	90	* TRIAL * TRIAL	widow	1	2	ICD9:276.51							
4	2451615	Male	Black-BLACK	68	Roman Catholic-ROMAN CATHOLIC	single	1	0	ICD9:162.9							
5	2451618	Male	Black-BLACK	53	Baptist-BAPTIST	married	1	0	ICD9:257.2							
6	2451623	Female	* TRIAL * T	55	* TRIAL * TRIAL	single	2	0	ICD9:305.1							
7	2451624	Female	* TRIAL * T	66	Non-denominational-NDN	widow	1	0	ICD9:351.0							
8	2451628	Male	Black-BLACK	48	Roman Catholic-ROMAN CATHOLIC	sep	2	0.5	ICD9:295.70							
9	2451632	Male	* TRIAL * T	64	Non-denominational-NDN	single	1	0	ICD9:272.4							
10	2451670	Male	Black-BLACK	51	Baptist-BAPTIST	single	15	0	ICD9:110.1							
11	2451680	Female	Hispanic-HISPANIC	85	* TRIAL * TRIAL * TRIA	single	2	1.5	ICD9:041.86							
12	2451682	Female	Black-BLACK	28	Non-denominational-NDN	single	3	0.3333	ICD9:250.83							
13	2451693	Female	* TRIAL * T	66	Non-denominational-NDN	widow	1	2	ICD9:285.9							
14	2451702	Female	Black-BLACK	65	Baptist-BAPTIST	married	1	0	ICD9:401.9							
15	2451714	Female	Black-BLACK	61	* TRIAL * TRIAL * TRIA	single	4	5.25	ICD9:070.70							
16	2451726	Male	Black-BLACK	55	Non-denominational-NDN	single	4	0	ICD9:401.9							
17	2451727	Female	Black-BLACK	69	Baptist-BAPTIST	single	2	0	ICD9:401.9							
18	2451728	Male	Black-BLACK	67	Methodist-METHODIST	married	1	0	ICD9:185							
19	2451743	Female	* TRIAL * T	57	Non-denominational-NDN	married	2	2	ICD9:03.92							
20	2451745	Female	Black-BLACK	26	Baptist-BAPTIST	single	1	1	ICD9:305.1							
21	2451746	Male	* TRIAL * T	42	Baptist-BAPTIST	married	1	0	ICD9:274.9							
22	2451749	Male	Black-BLACK	60	Baptist-BAPTIST	divorced	1	0	ICD9:110.1							
23	2451751	Male	* TRIAL * T	50	Non-denominational-NDN	single	2	0	ICD9:305.90							

Figure 4.5 Screenshot of Preprocessed csv file

4.4.1 Error Rates for Features

R requires that the data be clean when inserted, with null values appearing strictly as NA. Before this however, the task remained in finding the error counts of each dimension. In our method, if number of missing values was less than 40% it would be admissible for use in R. Each error rate was found by dividing the erroneous values in a dimension by the total number of elements in that dimension.

The error rates for 3 elements in the dataset were as follows:

- Error rates for race = 33.29%
- Error rates for religion = 31.76%
- Error rates for marital status = 2.56%

These errors were well below the upper threshold of availability, so they remained in the dataset.

4.4.2. Formatting Titles and Values

The dataset was formatted to remain in line with R standards and naming conventions. Rules must be followed with rows and column names:

- The first row must be used for headers. They generally represent variables.
- The first column should be used as row names; they represent observations
- Each row name should be unique. Remove duplications.
- Names with blank spaces should be avoided. 'First_name' or 'first.name' is acceptable, 'first name', is not.
- Avoid names with special symbols. Only underscore can be used.
- Variable names must not begin with a number. Letters should be used instead.

- Column names must be unique.
- R is case sensitive.
- Blank rows in data should be avoided
- Blank values should be replaced by NA (for not available)

To meet those requirements, erroneous values in the dataset were first be removed [13]. Values with ‘*Trial*’ – a value from the I2b2 database – were replaced with NA. Variable names were standardized for uniformity and readability. For example, values such as ‘Black – BLACK’, were changed to ‘Black’ in the race column, and values such as “Non-denominational – NDN” are changed to ‘Non-Denominational’. Blank spaces were changed to NA, falling in line with R’s policy of empty data cells.

4.4.3. Checking for Errors

To validate the changes, each column was checked to ensure that values were within the stipulated guidelines. This was done by looking at the distinct values of every feature, using the advanced filter in the data tab of excel. The method for this is shown in Figure 4.6 and Figure 4.7:

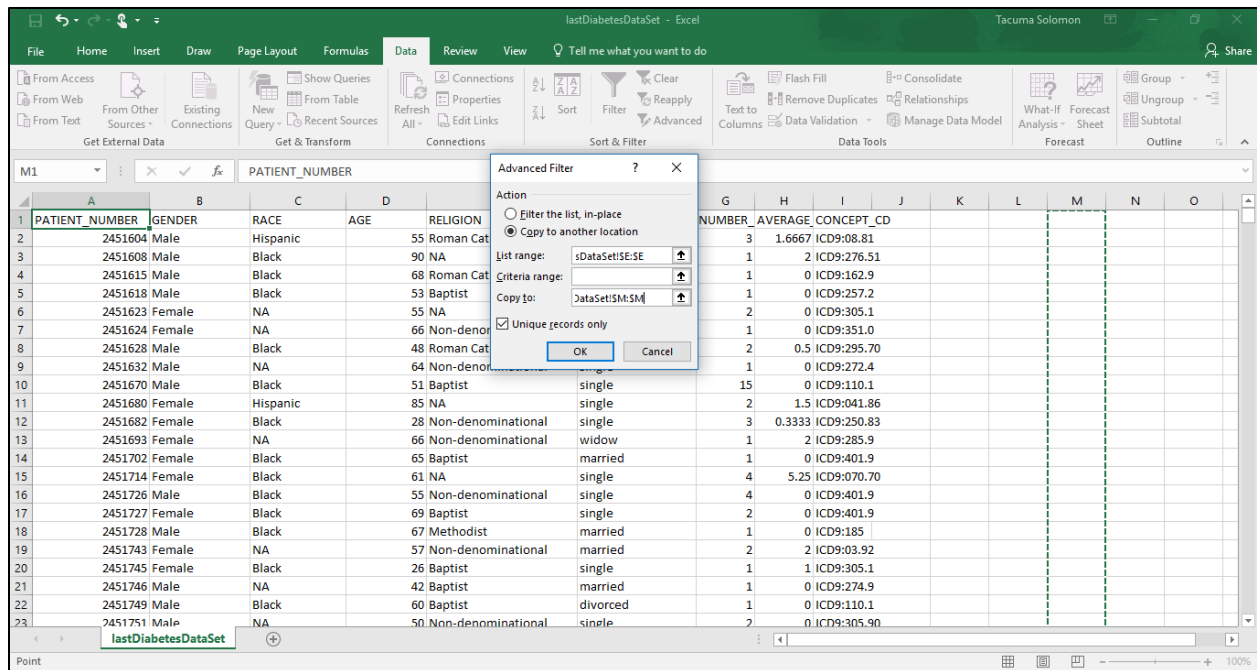


Figure 4.6 Screenshot of unique validation of data

PATIENT_NUMBER	GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER	AVERAGE	CONCEPT_CD	RELIGION
2451604	Male	Hispanic	55	Roman Catholic	single	3	1.6667	ICD9:08.81	Roman Catholic
2451608	Male	Black	90	NA	widow	1	2	ICD9:276.51	NA
2451615	Male	Black	68	Roman Catholic	single	1	0	ICD9:162.9	Baptist
2451618	Male	Black	53	Baptist	married	1	0	ICD9:257.2	Non-denominational
2451623	Female	NA	55	NA	single	2	0	ICD9:305.1	Methodist
2451624	Female	NA	66	Non-denominational	widow	1	0	ICD9:351.0	Other
2451628	Male	Black	48	Roman Catholic	separated	2	0.5	ICD9:295.70	Episcopal
2451632	Male	NA	64	Non-denominational	single	1	0	ICD9:272.4	Presbyterian
2451670	Male	Black	51	Baptist	single	15	0	ICD9:110.1	Christian
2451680	Female	Hispanic	85	NA	single	2	1.5	ICD9:041.86	Buddhist
2451682	Female	Black	28	Non-denominational	single	3	0.3333	ICD9:250.83	Lutheran
2451693	Female	NA	66	Non-denominational	widow	1	2	ICD9:285.9	Jehovah's Witness
2451702	Female	Black	65	Baptist	married	1	0	ICD9:401.9	Unknown
2451714	Female	Black	61	NA	single	4	5.25	ICD9:070.70	Church of God
2451726	Male	Black	55	Non-denominational	single	4	0	ICD9:401.9	Atheist
2451727	Female	Black	69	Baptist	single	2	0	ICD9:401.9	Hindu
2451728	Male	Black	67	Methodist	married	1	0	ICD9:185	Advent Christian
2451743	Female	NA	57	Non-denominational	married	2	2	ICD9:03.92	Orthodox
2451745	Female	Black	26	Baptist	single	1	1	ICD9:305.1	Protestant
2451746	Male	NA	42	Baptist	married	1	0	ICD9:274.9	Pentecostal
2451749	Male	Black	60	Baptist	divorced	1	0	ICD9:110.1	
2451751	Male	NA	50	Non-denominational	single	2	0	ICD9:305.90	

Figure 4.7 Screenshot of unique validation of data output

This is done for all features, to validate correctness.

At the end of the formatting process, the final processed dataset is show in Figure 4.8:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
	PATIENT_NUMBER	GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER	AVERAGE	CONCEPT_CD						
2	2451604	Male	Hispanic		55 Roman Catholic	single	3	1.6667	ICD9:08.81						
3	2451608	Male	Black		90 NA	widow	1	2	ICD9:276.51						
4	2451615	Male	Black		68 Roman Catholic	single	1	0	ICD9:162.9						
5	2451618	Male	Black		53 Baptist	married	1	0	ICD9:257.2						
6	2451623	Female	NA		55 NA	single	2	0	ICD9:305.1						
7	2451624	Female	NA		66 Non-denominational	widow	1	0	ICD9:351.0						
8	2451628	Male	Black		48 Roman Catholic	separated	2	0.5	ICD9:295.70						
9	2451632	Male	NA		64 Non-denominational	single	1	0	ICD9:272.4						
10	2451670	Male	Black		51 Baptist	single	15	0	ICD9:110.1						
11	2451680	Female	Hispanic		85 NA	single	2	1.5	ICD9:041.86						
12	2451682	Female	Black		28 Non-denominational	single	3	0.3333	ICD9:250.83						
13	2451693	Female	NA		66 Non-denominational	widow	1	2	ICD9:285.9						
14	2451702	Female	Black		65 Baptist	married	1	0	ICD9:401.9						
15	2451714	Female	Black		61 NA	single	4	5.25	ICD9:070.70						
16	2451726	Male	Black		55 Non-denominational	single	4	0	ICD9:401.9						
17	2451727	Female	Black		69 Baptist	single	2	0	ICD9:401.9						
18	2451728	Male	Black		67 Methodist	married	1	0	ICD9:185						
19	2451743	Female	NA		57 Non-denominational	married	2	2	ICD9:03.92						
20	2451745	Female	Black		26 Baptist	single	1	1	ICD9:305.1						
21	2451746	Male	NA		42 Baptist	married	1	0	ICD9:274.9						
22	2451749	Male	Black		60 Baptist	divorced	1	0	ICD9:110.1						
23	2451751	Male	NA		50 Non-denominational	single	2	0	ICD9:305.90						

Figure 4.8 Screenshot of processed dataset

4.5 Importing the Data Into R

Importing the data into R involved using the `read.csv()` command, specifically [13]:

```
diabetes_data -> read_csv(file.choose())
```

The imported data takes the appearance of Figure 4.9 in R:

```
> head(diabetes_data, 40)
```

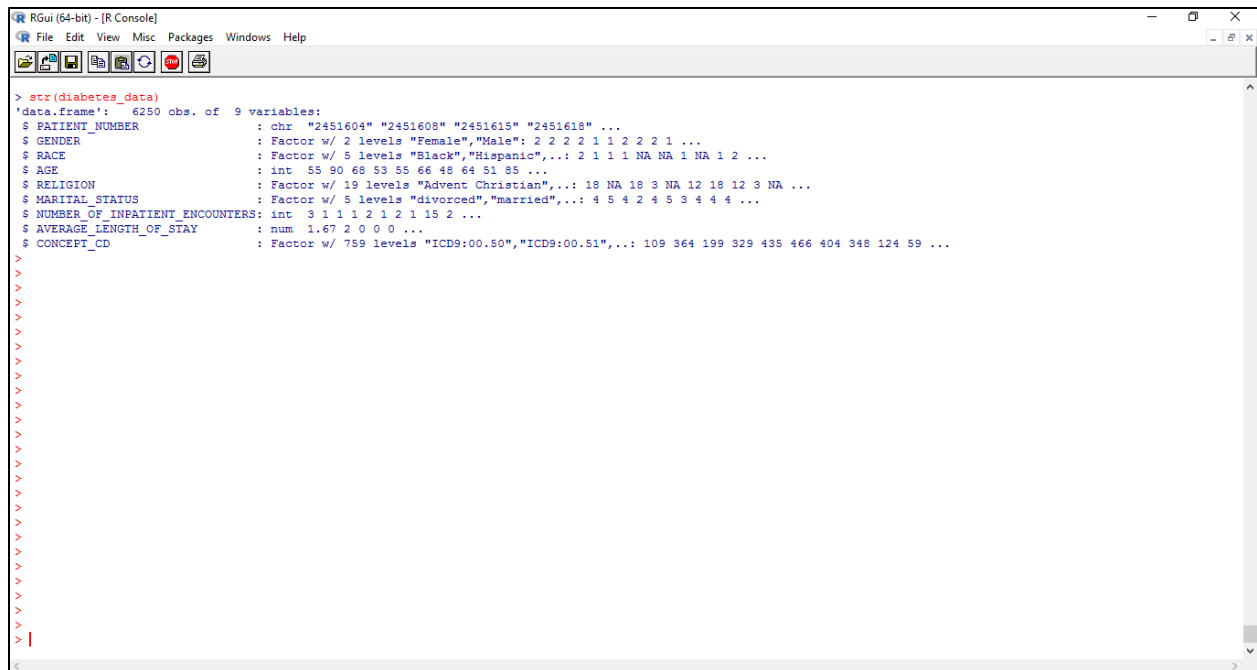
	PATIENT_NUMBER	GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD
1	2451604	Male	Hispanic	55	Roman Catholic	single	3	1.6667	ICD9:08.81
2	2451608	Male	Black	90	<NA>	widow	1	2.0000	ICD9:276.51
3	2451615	Male	Black	68	Roman Catholic	single	1	0.0000	ICD9:162.9
4	2451618	Male	Black	53	Baptist	married	1	0.0000	ICD9:257.2
5	2451623	Female	<NA>	55	<NA>	single	2	0.0000	ICD9:305.1
6	2451624	Female	<NA>	66	Non-denominational	widow	1	0.0000	ICD9:351.0
7	2451628	Male	Black	48	Roman Catholic	separated	2	0.5000	ICD9:295.70
8	2451632	Male	<NA>	64	Non-denominational	single	1	0.0000	ICD9:272.4
9	2451670	Male	Black	51	Baptist	single	15	0.0000	ICD9:110.1
10	2451680	Female	Hispanic	85	<NA>	single	2	1.5000	ICD9:041.86
11	2451682	Female	Black	28	Non-denominational	single	3	0.3333	ICD9:250.83
12	2451693	Female	<NA>	66	Non-denominational	widow	1	2.0000	ICD9:285.9
13	2451702	Female	Black	65	Baptist	married	1	0.0000	ICD9:401.9
14	2451714	Female	Black	61	<NA>	single	4	5.2500	ICD9:070.70
15	2451726	Male	Black	55	Non-denominational	single	4	0.0000	ICD9:401.9
16	2451727	Female	Black	69	Baptist	single	2	0.0000	ICD9:401.9
17	2451728	Male	Black	67	Methodist	married	1	0.0000	ICD9:185
18	2451743	Female	<NA>	57	Non-denominational	married	2	2.0000	ICD9:03.92
19	2451745	Female	Black	26	Baptist	single	1	1.0000	ICD9:305.1
20	2451746	Male	<NA>	42	Baptist	married	1	0.0000	ICD9:274.9
21	2451749	Male	Black	60	Baptist	divorced	1	0.0000	ICD9:110.1
22	2451751	Male	<NA>	50	Non-denominational	single	2	0.0000	ICD9:305.90
23	2451755	Male	Black	81	Non-denominational	divorced	1	0.0000	ICD9:401.9
24	2451794	Female	Black	60	Baptist	single	7	7.4286	ICD9:272.0
25	2451800	Female	Black	57	Baptist	single	1	0.0000	ICD9:401.9
26	2451803	Male	Black	41	Other	married	1	0.0000	ICD9:276.51
27	2451815	Male	<NA>	67	<NA>	separated	2	2.0000	ICD9:205.00
28	2451818	Male	Black	60	Baptist	single	45	1.4667	ICD9:070.70
29	2451820	Female	Black	40	<NA>	single	2	0.5000	ICD9:784.0
30	2451827	Male	Black	61	Baptist	single	3	0.0000	ICD9:110.1
31	2451832	Female	Black	29	Baptist	single	1	0.0000	ICD9:038.9
32	2451833	Female	Black	52	Non-denominational	single	3	0.3333	ICD9:042
33	2451835	Male	<NA>	58	Baptist	single	1	0.0000	ICD9:724.5
34	2451838	Female	Black	57	Non-denominational	single	3	1.3333	ICD9:070.32
35	2451842	Female	<NA>	64	Non-denominational	married	1	0.0000	ICD9:45.16
36	2451851	Female	Black	62	Roman Catholic	married	4	0.0000	ICD9:211.3

Figure 4.9 Screenshot of data imported into R

More processing was done on this data however. `str(diabetes_data)` displays the structure of the dataset, displaying the values of each type. R shows the 'PATIENT_NUMBER' is set as an int type. The following command changes the type:

```
diabetes_data$PATIENT_NUMBER<- as.character(diabetes_patient$PATIENT_NUMBER)
```

When the `str(diabetes_data)` command is entered, the structure of the dataset is shown in Figure 4.10:



```
> str(diabetes_data)
'data.frame': 6250 obs. of 9 variables:
 $ PATIENT_NUMBER      : chr  "2451604" "2451608" "2451615" "2451618" ...
 $ GENDER              : Factor w/ 2 levels "Female","Male": 2 2 2 1 1 2 2 2 1 ...
 $ RACE                : Factor w/ 5 levels "Black","Hispanic",...: 2 1 1 1 NA NA 1 NA 1 2 ...
 $ AGE                 : int   55 90 68 53 55 66 48 64 51 85 ...
 $ RELIGION            : Factor w/ 19 levels "Advent Christian",...: 18 NA 18 3 NA 12 18 12 3 NA ...
 $ MARITAL_STATUS      : Factor w/ 5 levels "divorced","married",...: 4 5 4 2 4 5 3 4 4 4 ...
 $ NUMBER_OF_INPATIENT_ENCOUNTERS: int   3 1 1 1 2 1 2 1 15 2 ...
 $ AVERAGE_LENGTH_OF_STAY : num   1.47 2 0 0 0 ...
 $ CONCEPT_CD        : Factor w/ 759 levels "ICD9:00.50","ICD9:00.51",...: 109 364 199 329 435 466 404 348 124 59 ...
```

Figure 4.10 Screenshot of structure of imported data

Representing the PATIENT_NUMBER in R ensures that the dimension is a factor or key, and not as a numeric value. The dataset was ready to be processed algorithmically.

4.6 Clustering Algorithms Used

To do the analysis, multiple algorithms were used. It was decided that to find the algorithm that can best cluster the dataset, partitioning and hierarchical algorithms will be implemented, with a comparative analysis on the results of each to determine the one most suitable to the task. From the research, it was decided that four algorithms will be used, two of a partitioning type, and two of a hierarchical type. Those algorithms were:

Partitioning:

- K-Modes algorithm [14] [16]
- PAM (Partitioning around Medoids) [16]

Hierarchical:

- Hclust – An agglomerative hierarchical clustering algorithm [17] [18]
- DIANA – A hierarchical algorithm that functions via Divisive Analysis [19]

To choose the algorithms, considerations were made based on the size and type of the dataset. K-means and K-means++, popular algorithmic approaches, were not used because the type of dataset gleaned from the database held both continuous and numeric data. K-means can only use numeric data. Before considering algorithms, much consideration was made on whether further processing on the data was needed. Should the data be converted to numeric? Were there algorithms that can effectively cluster mixed data? After trial and error, it was decided that mixed data would suffice. To further validate this reasoning, the dataset was modified in diverse ways and tested with PAM's package to determine what the visualizations of those clusters may look like. Figure 4.11 shows PAM clustering with different transformations of the data:

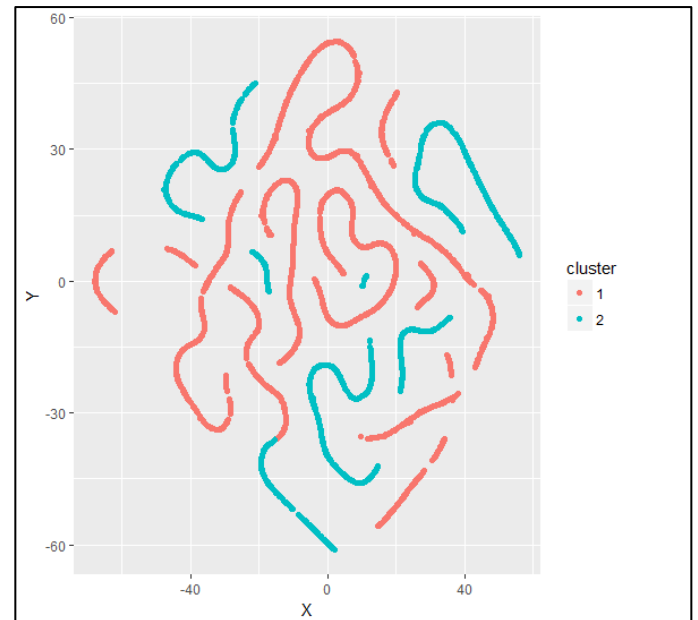
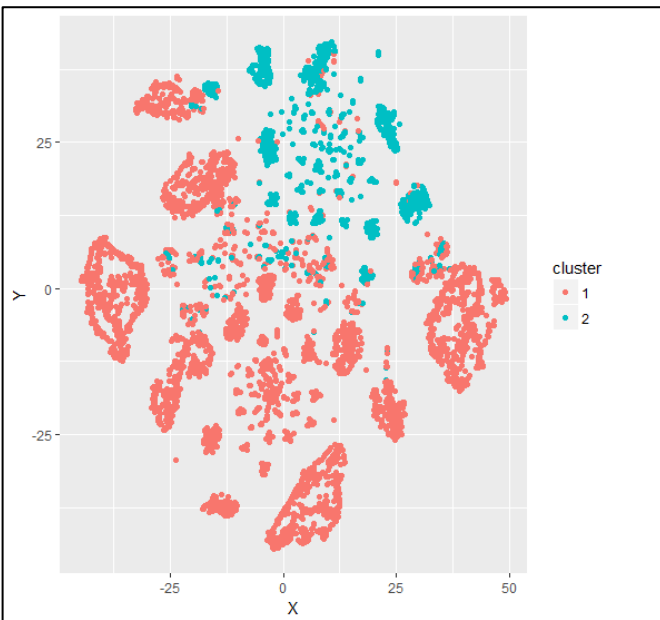
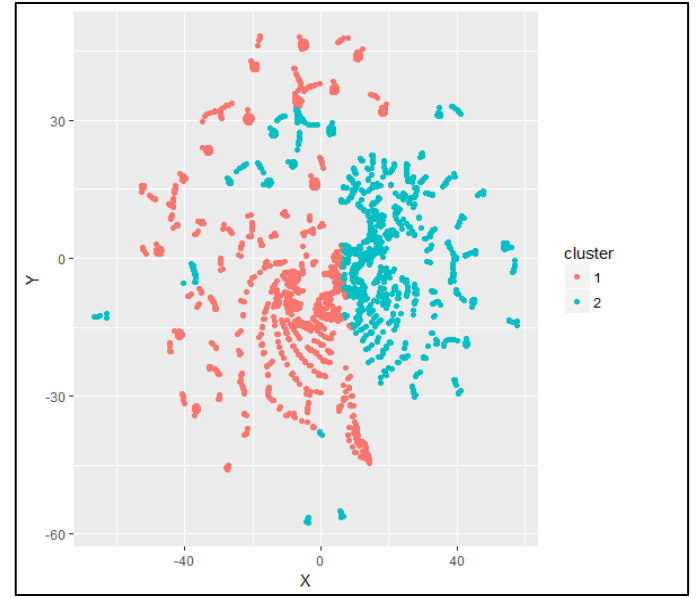
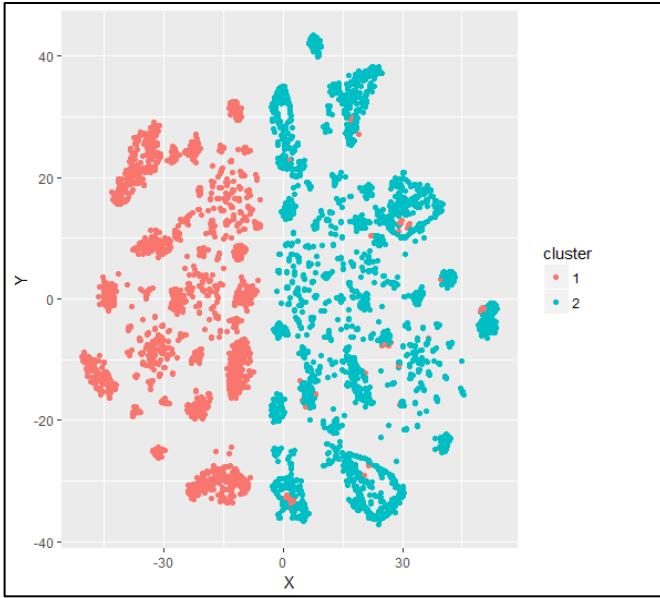


Figure 4.11 Figure of different visualizations from different data transformations

Eventually, the unaltered dataset was settled upon for further analysis. This however, presented a complication. How best to cluster a mixed dataset? Enter Gower dissimilarity measure [25]. Gower is a formula that measures the distance between two data points. It is contained in daisy, a R function that returns a dissimilarity matrix. While K-Means algorithms were unable to run mixed datasets, there existed partitioning algorithms that were able to do so, such as K-Modes.

4.6.1 K-Modes

K-modes is an algorithm which partitions a dataset into discrete clusters. K-Modes was first introduced in the 1997 paper, ‘A Fast Clustering Algorithm to Cluster Very Large Categorical Data Sets in Data Mining’, Huang. The algorithm overcomes the main limitation of the K-Means, which only manipulates numeric data. This is due to the algorithm using Euclidean Distance [25]. To prepare the dataset, the code na.omit was run to remove all of the rows that contained NA values in the dataset.

```
dd_for_kmodes <- na.omit(dd_random)
```

Removes rows with any NA values

```
cluster_fit <- kmodes(dd_for_kmodes[,-1], 2, iter.max = 10, weighted = FALSE )
```

4.6.2 Gower Dissimilarity Matrix

K-Modes can handle mixed datasets. The other algorithms in the list require a dissimilarity measure. A dissimilarity measure is a mathematical formula used to describe the distances between data points. Gower, unlike other distance measures, such as Euclidian, can calculate the distance values between data points in mixed datasets. The output of the Gower function in daisy is a

dissimilarity matrix. The other algorithms in this list accept it as a parameter, and subsequently performs the requisite cluster analysis.

To produce the dissimilarity matrix in R for the dataset, the following code was used:

```
gower_dist <- daisy(diabetes_data[, -1],  
  metric = "gower",  
  type = list(symm = 1))
```

This creates a dissimilarity matrix, stored in the variable `gower_dist`

4.6.3 PAM – Partitioning Around Medoids

PAM, or Partitioning Around Medoids, is an algorithm that functions by picking points in a dataset of medoids. The algorithm then clusters on certain data points in the center and including the values that have points that are closest to it. Silhouette width can be used to determine the optimum number of clusters. To visualize PAM, like other partitioning algorithms, requires Principal Component Analysis or similar dimensionality compression algorithms to reduce the number of dimensions to either 2 or 3, which enables human-readable plots.

```
pam_fit <- pam(gower_dist, diss = TRUE, k = 8)  
#where k = the number of clusters.
```

4.6.4 HClust

Hclust is an agglomerative hierarchical algorithm that works by treating each data point as a cluster. It groups individual clusters to the cluster nearest to them, using the dissimilarity measure created using gower. This process happens recursively, connecting larger and larger clusters until the entire dataset is connected. As it is a Hierarchical means of clustering, there is no need for

transformations in order to view how the clusters converge. Hclust, like other hierarchical clustering algorithms, represent their results on a dendrogram. A dendrogram is a long, tree-like representation of the data, represented by levels. To derive cluster statistics, one must “cut” the tree at a certain level. That level corresponds to the number of clusters. Hclust, while generating more accurate results, can be sensitive to noise, and has a longer running time than Partitioning Methods.

To perform hclust on data. The dissimilarity matrix was used as a parameter.

```
hgroup <- cutree(d.hclust, 4)
```

To cut the tree, the first parameter is the hclust variable, and the second is the level, or number of clusters.

```
d.hclust = hclust(gower_dist)
```

Command to plot the dendrogram

```
plot(d.hclust)
```

4.6.5 DIANA - Divisible Analysis

The second hierarchical clustering algorithm that is being is DIANA, also known as Divisive Analysis [19]. Diana groups the entire dataset as a cluster, and does the opposite of HCLUST, splitting into sub clusters based on the distances of the points that are farther away. It does this by using the gower dissimilarity matrix that is fed to it as a parameter. In R, Diana has both a banner and dendrogram representation.

It's banner representation enables the user to tell what the most distinct cluster groupings are in the dataset. Then as, with hclust, the user can "cut" the tree, ascertaining the number of nodes.

```
d.dclust = diana(gower_dist)
```

To perform DIANA on data. The dissimilarity matrix is used as a parameter.

```
dgroup <- cutree(d.dclust, 4)
```

To cut the tree, the first parameter is the DIANA variable, and the second is the level, or number of clusters.

4.6.6 Visualization

To make the results of cluster partitioning readable to the eye, compression was needed. Electronic health records typically suffer from high dimensionality, which makes them difficult to map visually, requiring dimensions of either 2, or 3. An algorithm is need to do that compression of dimensionality, without compromising the value and structure of the data. For this research, the algorithm chosen was t-distributed stochastic neighbor embossing (t-SNE). [22]

T-SNE works by creating a probability distribution among data in the high-dimensionality set. Similar points of data are given a higher probability, less similar points are given a lower probability. The algorithm does again to points in a low-dimensional map, and then proceeds to minimize the Kullback-Leibler divergence. This algorithm is used by R, which is utilized here for our visualizations. The R code is shown below.

```
tsne_obj <- Rtsne(gower_dist, is_distance = TRUE)

tsne_data <- tsne_obj$Y %>%
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_fit$clustering),
         name = diabetes_data$PATIENT_NUMBER)

ggplot(aes(x = X, y = Y), data = tsne_data) +
  geom_point(aes(color = cluster))
```

CHAPTER 5. RESULTS

This section provides the result visualizations and clusters for each algorithm used on the data. Each algorithm clusters the data into 2 clusters, 3 clusters, 4 clusters, and 5 clusters.

While silhouette analysis (shown in Figure 5.1) determined that optimum number of clusters to be two, the silhouette widths were still sufficient that more information can be gleaned for up to 5 clusters. In this section, Figure 5.2, Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6 each show visualizations of K-Mode, PAM, Hclust, and DIANA respectively, along with results of each of their one, two, three, four, and five cluster sets.

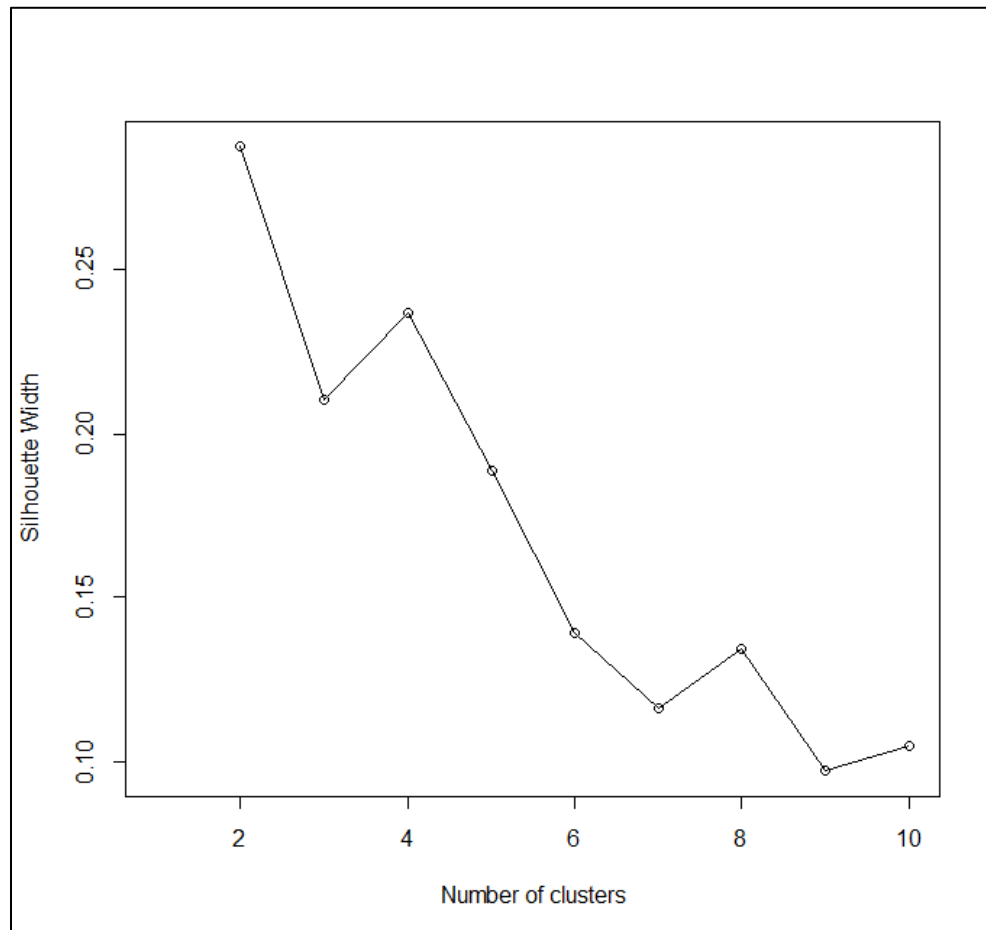
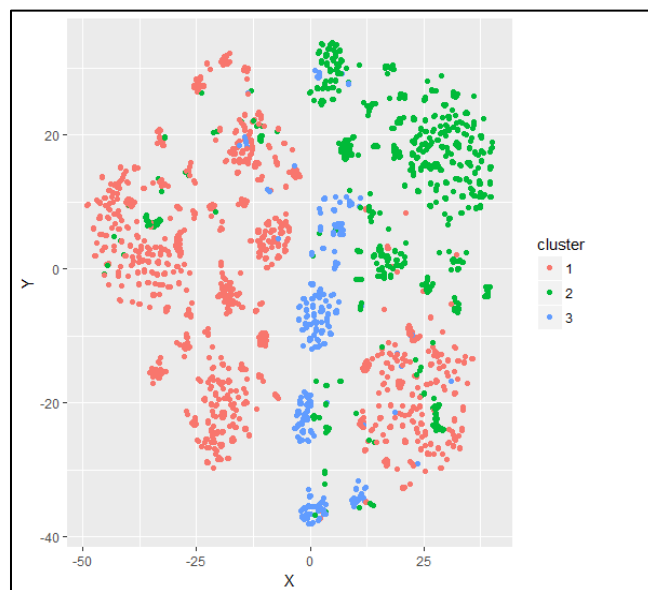
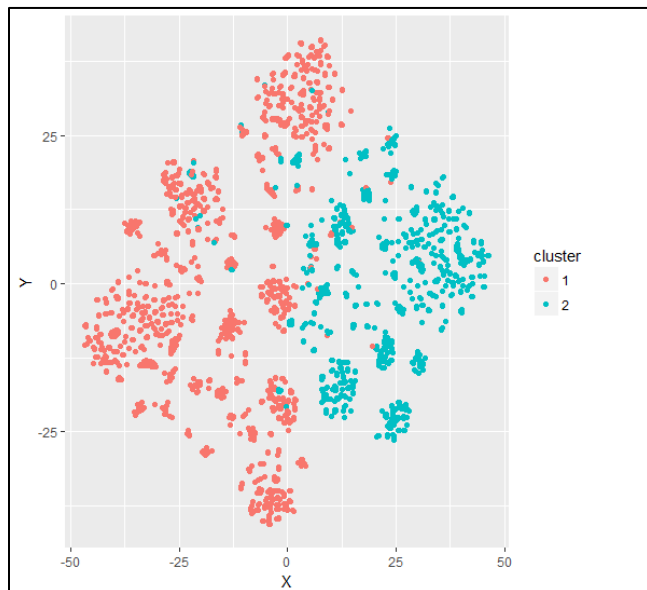


Figure 5.1 Silhouette width of PAM clusters

5.1 K-Modes Clusters



F

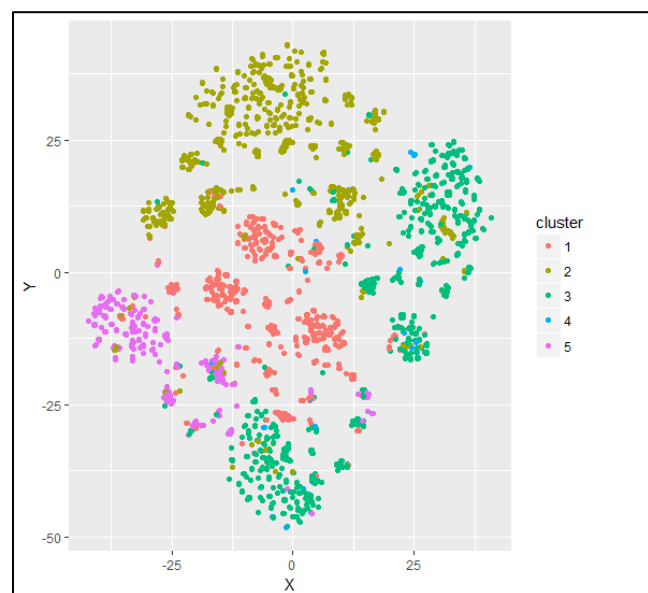
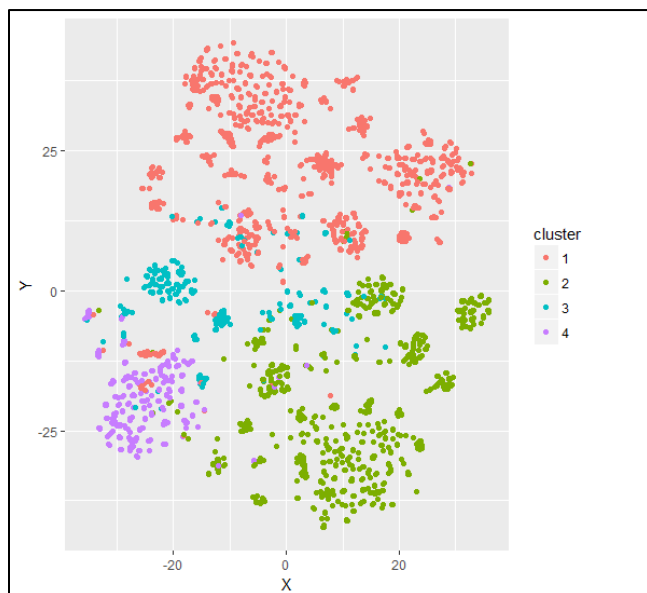


Figure 5.2 Visualizations of K-Modes clusters

2 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 582   Black      :1583   Min.    :12.00   Non-denominational:1185   divorced : 75   Min.    : 1.000   Min.    : -0.6429
Male :1225   Hispanic    : 107   1st Qu.:50.00   Baptist      : 321   married  : 430   1st Qu.: 1.000   1st Qu.: 0.0000
      Native American: 1   Median :58.00   Roman Catholic : 151   separated: 31   Median : 1.000   Median : 0.0000
      Other          : 50   Mean   :58.82   Other         : 42   single   :1217   Mean   : 3.041   Mean   : 2.0356
      White          : 66   3rd Qu.:68.00   Methodist     : 34   widow    : 54   3rd Qu.: 3.000   3rd Qu.: 1.2500
      Max.          :90.00   Christian      : 29   Max.    :64.000   Max.    :340.0000
      (Other)       : 45

  CONCEPT_CD      cluster
ICD9:401.9 : 222   Min.    :1
ICD9:272.4 : 100   1st Qu.:1
ICD9:305.1 : 84   Median :1
ICD9:110.1 : 69   Mean   :1
ICD9:272.0 : 69   3rd Qu.:1
ICD9:276.51: 56   Max.    :1
(Other)    :1207
```

```
[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1129   Black      :1103   Min.    :21.00   Baptist      :804   divorced : 79   Min.    : 1.000   Min.    : -0.5000   ICD9:272.4:178
Male : 41     Hispanic    : 38   1st Qu.:54.00   Roman Catholic :147   married  :225   1st Qu.: 1.000   1st Qu.: 0.0000   ICD9:401.9: 70
      Native American: 0   Median :61.00   Non-denominational: 68   separated: 45   Median : 2.000   Median : 0.0833   ICD9:272.0: 67
      Other          : 15   Mean   :61.89   Methodist     : 50   single   :713   Mean   : 3.606   Mean   : 1.9461   ICD9:211.3: 46
      White          : 14   3rd Qu.:71.00   Other         : 29   widow    :108   3rd Qu.: 4.000   3rd Qu.: 2.0000   ICD9:110.1: 42
      Max.          :90.00   Unknown       : 26   Max.    :40.000   Max.    :95.0000   ICD9:305.1: 41
      (Other)       : 46                                     (Other)    :726

  cluster
Min.    :2
1st Qu.:2
Median :2
Mean    :2
3rd Qu.:2
Max.    :2
```

3 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 432   Black      :1438   Min.    :12.00   Baptist      :768   divorced : 55   Min.    : 1.000   Min.    : -0.6429
Male :1171   Hispanic    : 79   1st Qu.:52.00   Non-denominational:553   married  :295   1st Qu.: 1.000   1st Qu.: 0.0000
      Native American: 1   Median :58.00   Roman Catholic :144   separated: 25   Median : 1.000   Median : 0.0000
      Other          : 37   Mean   :59.22   Other         : 38   single   :1212   Mean   : 3.325   Mean   : 2.0463
      White          : 48   3rd Qu.:68.00   Christian      : 30   widow    : 16   3rd Qu.: 3.000   3rd Qu.: 1.5000
      Max.          :90.00   Methodist     : 30   Max.    :64.000   Max.    :308.0000
      (Other)       : 40

  CONCEPT_CD      cluster
ICD9:401.9 : 172   Min.    :1
ICD9:305.1 : 84   1st Qu.:1
ICD9:110.1 : 77   Median :1
ICD9:272.0 : 74   Mean   :1
ICD9:272.4 : 66   3rd Qu.:1
ICD9:211.3 : 51   Max.    :1
(Other)    :1079
```

```
[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:886   Black      :873   Min.    :19.00   Non-denominational:671   divorced : 45   Min.    : 1.000   Min.    : 0.000   ICD9:272.4:198
Male : 81     Hispanic    : 49   1st Qu.:51.00   Roman Catholic :109   married  :126   1st Qu.: 1.000   1st Qu.: 0.000   ICD9:401.9: 52
      Native American: 0   Median :59.00   Baptist      : 67   separated: 22   Median : 1.000   Median : 0.000   ICD9:272.0: 39
      Other          : 20   Mean   :59.25   Methodist     : 43   single   :698   Mean   : 3.035   Mean   : 1.756   ICD9:305.1: 29
      White          : 25   3rd Qu.:70.00   Unknown       : 24   widow    : 76   3rd Qu.: 3.000   3rd Qu.: 1.679   ICD9:211.3: 25
      Max.          :90.00   Other         : 23   Max.    :35.000   Max.    :95.000   ICD9:110.1: 22
      (Other)       : 30                                     (Other)    :602

  cluster
Min.    :2
1st Qu.:2
Median :2
Mean    :2
3rd Qu.:2
Max.    :2
```



```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:393  Black      :375  Min.   :34.00  Baptist      :290  divorced : 54  Min.   : 1.00  Min.   : 0.0  ICD9:401.9: 68
Male : 14   Hispanic  : 17  1st Qu.:59.00  Roman Catholic : 45  married :234  1st Qu.: 1.00  1st Qu.: 0.0  ICD9:272.0: 23
Native American: 0  Median :63.00  Non-denominational: 29  separated: 29  Median : 1.00  Median : 0.0  ICD9:211.3: 18
Other      : 8  Mean   :65.04  Methodist     : 11  single  : 20  Mean   : 3.56  Mean   : 2.4  ICD9:272.4: 14
White      : 7  3rd Qu.:74.00  Other          : 10  widow   : 70  3rd Qu.: 4.00  3rd Qu.: 1.5  ICD9:110.1: 12
Max.      :90.00  Christian      : 8  Max.    :38.00  Max.    :340.0  ICD9:305.1: 12
              (Other) : 14  Max.    :340.0  (Other) :260

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3

```

4 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 65  Black      :1102  Min.   :12.00  Non-denominational:673  divorced : 54  Min.   : 1.000  Min.   : -0.6429
Male :1200  Hispanic  : 75  1st Qu.:51.00  Baptist      :335  married :279  1st Qu.: 1.000  1st Qu.: 0.0000
Native American: 1  Median :58.00  Roman Catholic :129  separated: 25  Median : 1.000  Median : 0.0000
Other      : 40  Mean   :59.15  Other          : 38  single  :887  Mean   : 3.053  Mean   : 2.0101
White      : 47  3rd Qu.:68.00  Methodist     : 28  widow   : 20  3rd Qu.: 3.000  3rd Qu.: 1.2000
Max.      :90.00  Christian      : 27  Max.    :64.000  Max.    :308.0000
              (Other) : 35

CONCEPT_CD  cluster
ICD9:401.9 :168  Min. :1
ICD9:272.4 : 92  1st Qu.:1
ICD9:305.1 : 59  Median :1
ICD9:110.1 : 56  Mean :1
ICD9:272.0 : 46  3rd Qu.:1
ICD9:276.51: 39  Max. :1
(Other) :805

```

```

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1004  Black      :971  Min.   :21.00  Baptist      :763  divorced : 76  Min.   : 1.000  Min.   : -0.500  ICD9:401.9:105
Male : 15   Hispanic  : 31  1st Qu.:54.00  Roman Catholic:119  married :120  1st Qu.: 1.000  1st Qu.: 0.000  ICD9:272.4: 75
Native American: 0  Median :62.00  Methodist     : 45  separated: 43  Median : 2.000  Median : 0.000  ICD9:272.0: 63
Other      : 5  Mean   :62.04  Unknown       : 25  single  :679  Mean   : 3.692  Mean   : 1.873  ICD9:110.1: 40
White      :12  3rd Qu.:71.00  Other          : 21  widow   :101  3rd Qu.: 4.000  3rd Qu.: 2.000  ICD9:211.3: 38
Max.      :90.00  Christian      : 13  Max.    :57.000  Max.    :47.000  ICD9:305.1: 33
              (Other) : 33  Max.    :47.000  (Other) :665

cluster
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

```

```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:314  Black      :313  Min.   :25.00  Non-denominational:245  divorced : 18  Min.   : 1.000  Min.   : 0.000  ICD9:272.4 :110
Male : 47   Hispanic  : 25  1st Qu.:55.00  Roman Catholic : 46  married :254  1st Qu.: 1.000  1st Qu.: 0.000  ICD9:401.9 : 18
Native American: 0  Median :62.00  Baptist      : 26  separated: 8  Median : 1.000  Median : 0.000  ICD9:211.3 : 15
Other      : 13  Mean   :62.53  Christian     : 11  single  : 41  Mean   : 3.235  Mean   : 2.555  ICD9:272.0 : 11
White      : 10  3rd Qu.:71.00  Methodist     : 11  widow   : 40  3rd Qu.: 4.000  3rd Qu.: 1.400  ICD9:244.9 : 9
Max.      :90.00  Other          : 10  Max.    :26.000  Max.    :340.000  ICD9:276.51: 9
              (Other) : 12  Max.    :340.000  (Other) :189

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

```

```

[[4]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:328  Black      :300  Min.   :19.00  Non-denominational:324  divorced : 6  Min.   : 1.000  Min.   : 0.000  ICD9:305.1 : 28
Male : 4   Hispanic  : 14  1st Qu.:44.00  Roman Catholic : 4  married : 2  1st Qu.: 1.000  1st Qu.: 0.000  ICD9:272.0 : 16
Native American: 0  Median :53.50  Other          : 2  separated: 0  Median : 1.000  Median : 0.000  ICD9:276.51: 10
Other      : 7  Mean   :54.43  Baptist      : 1  single  :323  Mean   : 2.777  Mean   : 1.752  ICD9:038.9 : 9
White      :11  3rd Qu.:67.00  Unknown       : 1  widow   : 1  3rd Qu.: 3.000  3rd Qu.: 2.000  ICD9:110.1 : 8
Max.      :90.00  Advent Christian : 0  Max.    :26.000  Max.    :28.000  ICD9:285.9 : 8
              (Other) : 0  Max.    :28.000  (Other) :253

cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

```

5 Cluster Summary:

[[1]]									
GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD		
Female:222	Black :634	Min. :27.00	Baptist :291	divorced : 52	Min. : 1	Min. : -0.6429	ICD9:401.9 :150		
Male :505	Hispanic : 41	1st Qu.:56.00	Non-denominational:246	married :544	1st Qu.: 1	1st Qu.: 0.0000	ICD9:272.4 : 57		
	Native American: 0	Median :63.00	Roman Catholic : 97	separated: 22	Median : 1	Median : 0.0000	ICD9:272.0 : 32		
	Other : 29	Mean :63.25	Methodist : 30	single : 91	Mean : 3	Mean : 1.8655	ICD9:211.3 : 30		
	White : 23	3rd Qu.:71.00	Christian : 26	widow : 18	3rd Qu.: 3	3rd Qu.: 1.0000	ICD9:305.1 : 28		
		Max. :90.00	Other : 14		Max. :40	Max. :340.0000	ICD9:276.51: 15		
			(Other) : 23				(Other) :415		
cluster									
Min. :1									
1st Qu.:1									
Median :1									
Mean :1									
3rd Qu.:1									
Max. :1									
[[2]]									
GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD		
Female:926	Black :905	Min. :21.00	Baptist :645	divorced : 69	Min. : 1.000	Min. : -0.500	ICD9:401.9:134		
Male : 29	Hispanic : 27	1st Qu.:54.00	Roman Catholic :110	married : 11	1st Qu.: 1.000	1st Qu.: 0.000	ICD9:272.4: 65		
	Native American:0	Median :61.00	Non-denominational: 83	separated: 39	Median : 1.000	Median : 0.000	ICD9:272.0: 53		
	Other : 9	Mean :61.75	Methodist : 39	single :734	Mean : 3.562	Mean : 1.872	ICD9:110.1: 35		
	White : 14	3rd Qu.:70.00	Other : 23	widow :102	3rd Qu.: 3.000	3rd Qu.: 2.000	ICD9:211.3: 30		
		Max. :90.00	Unknown : 22		Max. :40.000	Max. :47.000	ICD9:305.1: 34		
			(Other) : 33				(Other) :600		
cluster									
Min. :2									
1st Qu.:2									
Median :2									
Mean :2									
3rd Qu.:2									
Max. :2									
[[3]]									
GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD		
Female:537	Black :805	Min. :12.00	Non-denominational:865	divorced : 27	Min. : 1.000	Min. : 0.000	ICD9:272.4 :140		
Male :381	Hispanic : 57	1st Qu.:48.00	Roman Catholic : 29	married : 93	1st Qu.:1.000	1st Qu.: 0.000	ICD9:305.1 : 47		
	Native American: 0	Median :56.00	Unknown : 7	separated:10	Median :1.000	Median : 0.000	ICD9:272.0 : 38		
	Other : 19	Mean :56.69	Methodist : 6	single :748	Mean : 2.844	Mean : 2.025	ICD9:276.51:33		
	White : 37	3rd Qu.:67.00	Other : 6	widow : 40	3rd Qu.: 3.000	3rd Qu.: 2.000	ICD9:211.3 :20		
		Max. :90.00	Christian : 3		Max. :64.000	Max. :105.000	ICD9:244.9 : 16		
			(Other) : 2				(Other) :624		
cluster									
Min. :3									
1st Qu.:3									
Median :3									
Mean :3									
[[4]]									
GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD		
Female:25	Black :35	Min. :27.00	Non-denominational:27	divorced : 2	Min. : 1.000	Min. :0.0000	ICD9:041.86:17		
Male :14	Hispanic : 2	1st Qu.:45.00	Roman Catholic : 7	married : 7	1st Qu.:1.000	1st Qu.:0.0000	ICD9:268.9 : 2		
	Native American:0	Median :45.00	Christian : 1	separated:2	Median :3.000	Median :0.3333	ICD9:276.51: 2		
	Other : 2	Mean :49.44	Orthodox : 1	single :27	Mean :4.231	Mean :0.9566	ICD9:276.8 : 2		
	White : 0	3rd Qu.:56.50	Other : 1	widow : 1	3rd Qu.:5.000	3rd Qu.:1.7500	ICD9:278.01: 2		
		Max. :76.00	Pentecostal : 1		Max. :23.000	Max. :8.0000	ICD9:305.1 : 2		
			(Other) : 1				(Other) :12		
cluster									
Min. :4									
1st Qu.:4									
Median :4									
Mean :4									
3rd Qu.:4									
Max. :4									
[[5]]									
GENDER	RACE	AGE	RELIGION	MARITAL_STATUS	NUMBER_OF_INPATIENT_ENCOUNTERS	AVERAGE_LENGTH_OF_STAY	CONCEPT_CD		
Female: 1	Black :307	Min. :21.00	Baptist :189	divorced : 4	Min. : 1.000	Min. : -0.1667	ICD9:110.1 : 49		
Male :337	Hispanic : 18	1st Qu.:50.00	Roman Catholic : 55	married : 0	1st Qu.:1.000	1st Qu.: 0.0000	ICD9:272.4 : 16		
	Native American:1	Median :58.50	Non-denominational:32	separated: 3	Median :2.000	Median : 0.0000	ICD9:305.1 : 14		
	Other : 6	Mean :58.51	Other : 27	single :330	Mean :4.009	Mean : 2.7045	ICD9:070.70: 13		
	White : 6	3rd Qu.:66.00	Unknown :13	widow : 1	3rd Qu.:4.000	3rd Qu.: 1.5000	ICD9:272.0 : 13		
		Max. :90.00	Methodist : 9		Max. :57.000	Max. :308.0000	ICD9:305.00: 11		
			(Other) : 13				(other) :222		
cluster									
Min. :5									
1st Qu.:5									
Median :5									
Mean :5									
3rd Qu.:5									
Max. :5									

5.2 PAM Clusters

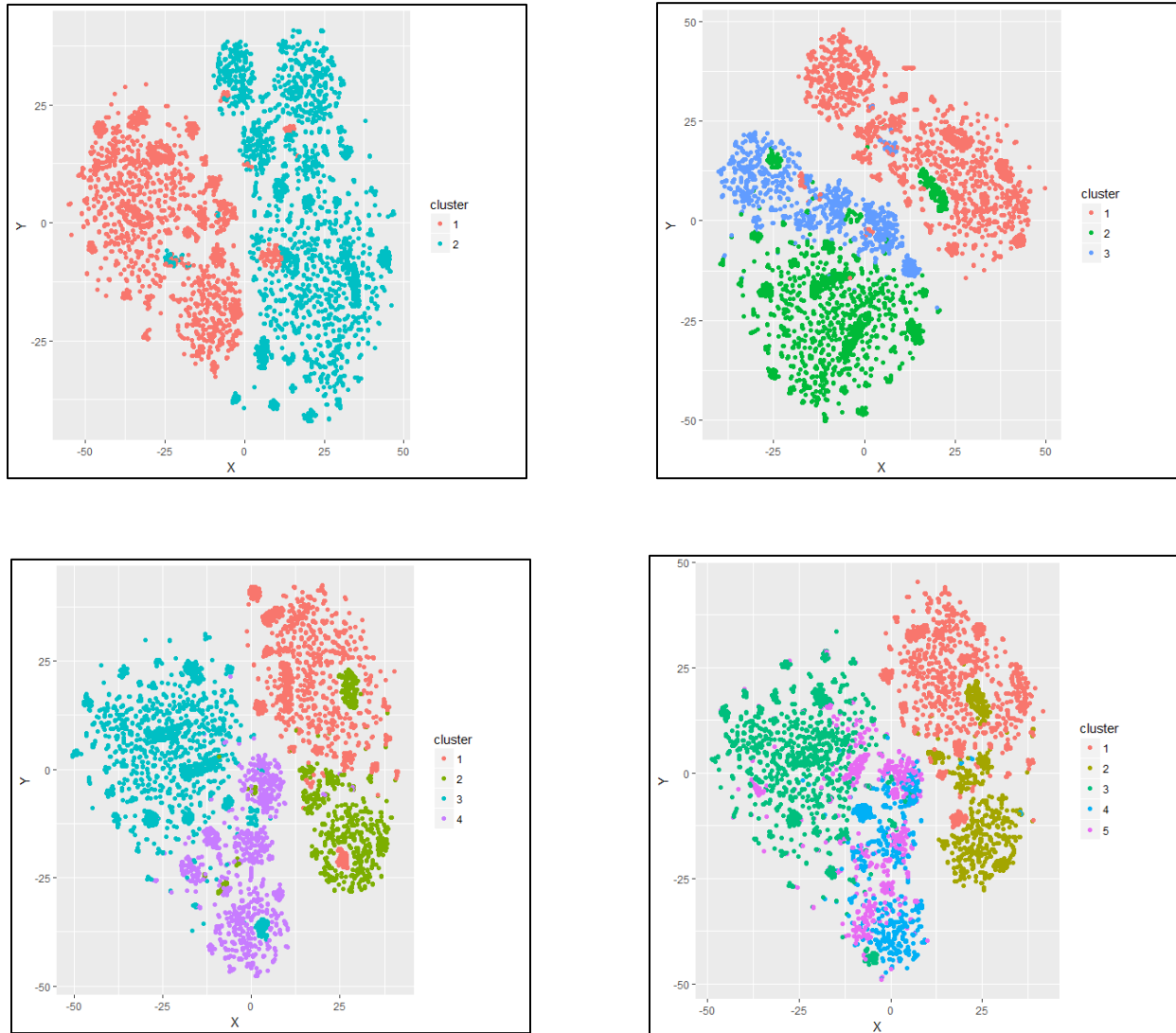


Figure 5.3 Visualizations of PAM clusters

2 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 166   Black      :1630   Min.    : 3.00   Non-denominational:963   divorced : 98   Min.    : 1.000   Min.    : -0.6429
Male :2585   Hispanic : 113   1st Qu.:52.00   Baptist      :595   married  : 726   1st Qu.: 1.000   1st Qu.: 0.0000
Native American: 2   Median :61.00   Roman Catholic :197   separated: 50   Median : 1.000   Median : 0.0000
Other      : 54   Mean :60.67   Other      : 65   single   :1763   Mean : 3.047   Mean : 2.1007
White     : 64   3rd Qu.:70.00   Methodist    : 49   widow   : 67   3rd Qu.: 3.000   3rd Qu.: 2.0000
NA's      : 888   Max. :90.00   (Other)     : 92   NA's    : 47   Max. :64.000   Max. :308.0000
NA's      :790

  CONCEPT_CD      cluster
ICD9:272.4 : 414   Min. :1
ICD9:401.9 : 261   1st Qu.:1
ICD9:305.1 : 126   Median :1
ICD9:272.0 : 102   Mean :1
ICD9:276.51: 88    3rd Qu.:1
ICD9:211.3 : 67    Max. :1
(Other)    :1693

[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:3448   Black      :2222   Min.    : 3.00   Baptist      :1111   divorced : 192   Min.    : 1.000   Min.    : -26.000
Male : 51     Hispanic : 95   1st Qu.:51.00   Non-denominational: 898   married  : 651   1st Qu.: 1.000   1st Qu.: 0.000
Native American: 0   Median :60.00   Roman Catholic : 245   separated: 86   Median : 1.000   Median : 0.000
Other      : 38   Mean :59.77   Methodist    : 81   single   :2186   Mean : 3.541   Mean : 1.780
White     : 51   3rd Qu.:69.00   Unknown      : 48   widow   : 286   3rd Qu.: 4.000   3rd Qu.: 1.556
NA's      :1093   Max. :90.00   (Other)     : 137   NA's    : 98   Max. :57.000   Max. :340.000
NA's      : 979

  CONCEPT_CD      cluster
ICD9:401.9: 332   Min. :2
ICD9:110.1: 178   1st Qu.:2
ICD9:272.0: 176   Median :2
ICD9:272.4: 161   Mean :2
ICD9:211.3: 113   3rd Qu.:2
ICD9:305.1: 110   Max. :2
(Other)    :2429
```

3 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 79   Black      :1482   Min.    : 3.00   Non-denominational:872   divorced : 98   Min.    : 1.000   Min.    : -0.6429
Male :2416   Hispanic : 102   1st Qu.:52.00   Baptist      :540   married  : 726   1st Qu.: 1.000   1st Qu.: 0.0000
Native American: 2   Median :60.00   Roman Catholic :188   separated: 50   Median : 1.000   Median : 0.0000
Other      : 50   Mean :60.27   Other      : 57   single   :1509   Mean : 3.194   Mean : 2.1496
White     : 60   3rd Qu.:69.00   Methodist    : 46   widow   : 67   3rd Qu.: 3.000   3rd Qu.: 2.0000
NA's      : 799   Max. :90.00   (Other)     : 85   NA's    : 45   Max. :64.000   Max. :308.0000
NA's      :707

  CONCEPT_CD      cluster
ICD9:272.4 : 327   Min. :1
ICD9:305.1 : 126   1st Qu.:1
ICD9:272.0 : 102   Median :1
ICD9:401.9 : 92    Mean :1
ICD9:276.51: 88    3rd Qu.:1
ICD9:211.3 : 67    Max. :1
(Other)    :1693

[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:2302   Black      :1562   Min.    : 3.00   Baptist      :742   divorced : 16   Min.    : 1.000   Min.    : -26.000
Male : 169    Hispanic : 78   1st Qu.:50.00   Non-denominational:702   married  : 72   1st Qu.: 1.000   1st Qu.: 0.000
Native American: 0   Median :58.00   Roman Catholic :158   separated: 7   Median : 1.000   Median : 0.000
Other      : 26   Mean :57.81   Methodist    : 41   single   :2322   Mean : 2.769   Mean : 1.838
White     : 38   3rd Qu.:67.00   Unknown      : 41   widow   : 25   3rd Qu.: 3.000   3rd Qu.: 1.333
NA's      : 767   Max. :90.00   (Other)     : 84   NA's    : 29   Max. :47.000   Max. :340.000
NA's      :703

  CONCEPT_CD      cluster
ICD9:401.9 : 501   Min. :2
ICD9:272.4 : 195   1st Qu.:2
ICD9:272.0 : 104   Median :2
ICD9:305.1 : 79    Mean :2
ICD9:211.3 : 58    3rd Qu.:2
ICD9:278.00: 52    Max. :2
(Other)    :1482
```

```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1233 Black      :808 Min. :22.00 Baptist      :424 divorced :176 Min. : 1.000 Min. : -0.1667 ICD9:110.1:178
Male : 51 Hispanic : 28 1st Qu.:56.00 Non-denominational:287 married :579 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:272.0: 72
Native American: 0 Median :64.00 Roman Catholic : 96 separated: 79 Median : 2.000 Median : 0.1742 ICD9:211.3: 55
Other : 16 Mean :64.52 Methodist : 43 single :118 Mean : 4.642 Mean : 1.6354 ICD9:272.4: 53
White : 17 3rd Qu.:74.00 Other : 20 widow :261 3rd Qu.: 5.250 3rd Qu.: 2.0000 ICD9:244.9: 38
NA's :415 Max. :90.00 (Other) : 55 NA's : 71 Max. :57.000 Max. :33.0000 ICD9:305.1: 31
                                NA's :359                                (Other) :857

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

```

4 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0 Black      :1008 Min. : 3.00 Non-denominational:632 divorced : 5 Min. : 1.000 Min. : -0.1667
Male :1672 Hispanic : 75 1st Qu.:50.00 Baptist :320 married : 78 1st Qu.: 1.000 1st Qu.: 0.0000
Native American: 2 Median :57.00 Roman Catholic :110 separated: 2 Median : 1.000 Median : 0.0000
Other : 24 Mean :57.14 Other : 50 single :1560 Mean : 3.027 Mean : 2.0611
White : 44 3rd Qu.:65.00 Unknown : 23 widow : 6 3rd Qu.: 3.000 3rd Qu.: 1.1354
NA's : 519 Max. :90.00 (Other) : 46 NA's : 21 Max. :64.000 Max. :308.0000

CONCEPT_CD      cluster
ICD9:401.9 : 261 Min. :1
ICD9:305.1 : 100 1st Qu.:1
ICD9:110.1 : 64 Median :1
ICD9:276.51: 63 Mean :1
ICD9:272.0 : 61 3rd Qu.:1
ICD9:305.00: 43 Max. :1
(Other) :1080

```

```

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 79 Black      :598 Min. :22.0 Non-denominational:323 divorced : 93 Min. : 1.000 Min. : -0.6429 ICD9:272.4:327
Male :951 Hispanic : 36 1st Qu.:56.0 Baptist :261 married :648 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:272.0: 41
Native American: 0 Median :65.0 Roman Catholic : 86 separated: 48 Median : 1.000 Median : 0.2745 ICD9:211.3: 32
Other : 30 Mean :64.9 Methodist : 31 single :153 Mean : 3.362 Mean : 2.0594 ICD9:185 : 30
White : 21 3rd Qu.:74.0 Christian : 25 widow : 61 3rd Qu.: 3.000 3rd Qu.: 2.0000 ICD9:305.1: 26
NA's :345 Max. :90.0 (Other) : 29 NA's : 27 Max. :40.000 Max. :95.0000 ICD9:110.1: 25
                                NA's :275                                (Other) :549

cluster
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

```

```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:2302 Black      :1464 Min. : 3.0 Baptist :712 divorced : 16 Min. : 1.000 Min. : -26.000
Male : 0 Hispanic : 70 1st Qu.:49.0 Non-denominational:631 married : 72 1st Qu.: 1.000 1st Qu.: 0.000
Native American: 0 Median :58.0 Roman Catholic :153 separated: 7 Median : 1.000 Median : 0.000
Other : 22 Mean :57.7 Methodist : 40 single :2155 Mean : 2.882 Mean : 1.906
White : 34 3rd Qu.:67.0 Unknown : 39 widow : 25 3rd Qu.: 3.000 3rd Qu.: 1.500
NA's : 712 Max. :90.0 (Other) : 76 NA's : 27 Max. :47.000 Max. :340.000

CONCEPT_CD      cluster
ICD9:401.9 : 332 Min. :3
ICD9:272.4 : 195 1st Qu.:3
ICD9:272.0 : 104 Median :3
ICD9:305.1 : 79 Mean :3
ICD9:211.3 : 58 3rd Qu.:3
ICD9:278.00: 52 Max. :3
(Other) :1482

```

```

[[4]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1233 Black      :782 Min. :25.00 Baptist :413 divorced :176 Min. : 1.000 Min. : -0.1667 ICD9:110.1:140
Male : 13 Hispanic : 27 1st Qu.:56.00 Non-denominational:275 married :579 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:272.0: 72
Native American: 0 Median :64.00 Roman Catholic : 93 separated: 79 Median : 2.000 Median : 0.1667 ICD9:211.3: 55
Other : 16 Mean :64.89 Methodist : 42 single : 81 Mean : 4.504 Mean : 1.6463 ICD9:272.4: 53
White : 16 3rd Qu.:74.00 Other : 20 widow :261 3rd Qu.: 5.000 3rd Qu.: 2.0000 ICD9:244.9: 38
NA's :405 Max. :90.00 (Other) : 51 NA's : 70 Max. :38.000 Max. :33.0000 ICD9:305.1: 31
                                NA's :352                                (Other) :857

cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

```

5 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0    Black      :1008    Min.   : 3.00    Non-denominational:632    divorced : 5    Min.   : 1.000    Min.   : -0.1667
Male :1672   Hispanic : 75    1st Qu.:50.00    Baptist    :320    married : 78    1st Qu.: 1.000    1st Qu.: 0.0000
Native American: 2    Median :57.00    Roman Catholic :110    separated: 2    Median : 1.000    Median : 0.0000
Other       : 24    Mean   :57.14    Other       : 50    single  :1560    Mean   : 3.027    Mean   : 2.0611
White      : 44    3rd Qu.:65.00    Unknown    : 23    widow   : 6    3rd Qu.: 3.000    3rd Qu.: 1.1354
NA's       : 519    Max.   :90.00    (Other)    : 46    NA's    : 21    Max.   :64.000    Max.   :308.0000
NA's       :491

CONCEPT_CD      cluster
ICD9:401.9 : 261    Min.   :1
ICD9:305.1 : 100    1st Qu.:1
ICD9:110.1 : 64    Median :1
ICD9:276.51: 63    Mean   :1
ICD9:272.0 : 61    3rd Qu.:1
ICD9:305.00: 43    Max.   :1
(Other)    :1000

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 0    Black      :550    Min.   :22.00    Non-denominational:304    divorced : 84    Min.   : 1.000    Min.   : -0.6429    ICD9:272.4:248
Male :951    Hispanic : 35    1st Qu.:55.00    Baptist    :235    married :615    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:272.0: 41
Native American: 0    Median :64.00    Roman Catholic : 82    separated: 43    Median : 1.000    Median : 0.2308    ICD9:211.3: 32
Other       : 29    Mean   :63.94    Methodist   : 28    single  :153    Mean   : 3.409    Mean   : 1.9305    ICD9:185 : 30
White      : 21    3rd Qu.:72.00    Christian   : 24    widow   : 33    3rd Qu.: 3.000    3rd Qu.: 2.0000    ICD9:305.1: 26
NA's       :316    Max.   :90.00    (Other)    : 28    NA's    : 23    Max.   :40.000    Max.   :69.0000    ICD9:110.1: 25
NA's       :250                                     (Other)    :549

cluster
Min.   :2
1st Qu.:2
Median :2
Mean   :2
3rd Qu.:2
Max.   :2

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:1943   Black      :1214    Min.   : 3.00    Non-denominational:611    divorced : 12    Min.   : 1.000    Min.   : -26.000
Male : 0       Hispanic : 65    1st Qu.:48.00    Baptist    :486    married : 60    1st Qu.: 1.000    1st Qu.: 0.000
Native American: 0    Median :56.00    Roman Catholic :149    separated: 6    Median : 1.000    Median : 0.000
Other       : 20    Mean   :55.19    Methodist   : 38    single  :1828    Mean   : 2.814    Mean   : 1.801
White      : 34    3rd Qu.:63.00    Unknown    : 37    widow   : 14    3rd Qu.: 3.000    3rd Qu.: 1.209
NA's       : 610    Max.   :90.00    (Other)    : 73    NA's    : 23    Max.   :47.000    Max.   :340.000

CONCEPT_CD      cluster
ICD9:401.9 : 304    Min.   :3
ICD9:272.0 : 87    1st Qu.:3
ICD9:305.1 : 77    Median :3
ICD9:278.00: 51    Mean   :3
ICD9:211.3 : 49    3rd Qu.:3
ICD9:272.4 : 46    Max.   :3
(Other)    :1329

[[4]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:714    Black      :444    Min.   :25.00    Non-denominational:266    divorced : 89    Min.   : 1.000    Min.   : -0.1667    ICD9:110.1:140
Male : 13     Hispanic : 22    1st Qu.:55.00    Roman Catholic : 92    married :363    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:211.3: 39
Native American: 0    Median :62.00    Baptist    : 62    separated: 44    Median : 2.000    Median : 0.0000    ICD9:272.0: 32
Other       : 13    Mean   :62.33    Methodist   : 40    single  : 81    Mean   : 4.708    Mean   : 1.2857    ICD9:244.9: 24
White      : 14    3rd Qu.:70.00    Other       : 18    widow   :114    3rd Qu.: 6.000    3rd Qu.: 1.3167    ICD9:305.1: 22
NA's       :234    Max.   :90.00    (Other)    : 48    NA's    : 36    Max.   :35.000    Max.   :33.0000    ICD9:13.41: 17
NA's       :201                                     (Other)    :453

cluster
Min.   :4
1st Qu.:4
Median :4
Mean   :4
3rd Qu.:4
Max.   :4

[[5]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:957    Black      :636    Min.   :34.00    Baptist    :603    divorced :100    Min.   : 1.000    Min.   : 0.0000    ICD9:272.4:278
Male : 0       Hispanic : 11    1st Qu.:63.00    Non-denominational: 48    married :261    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:272.0: 57
Native American: 0    Median :71.00    Roman Catholic : 9    separated: 41    Median : 2.000    Median : 0.8571    ICD9:401.9: 28
Other       : 6    Mean   :70.18    Methodist   : 7    single  :327    Mean   : 3.738    Mean   : 2.3933    ICD9:211.3: 25
White      : 2    3rd Qu.:78.00    Christian   : 4    widow   :186    3rd Qu.: 4.000    3rd Qu.: 3.0000    ICD9:038.9: 23
NA's       :302    Max.   :90.00    (Other)    : 8    NA's    : 42    Max.   :38.000    Max.   :95.0000    ICD9:13.41: 21
NA's       :278                                     (Other)    :525

cluster
Min.   :5
1st Qu.:5
Median :5
Mean   :5
3rd Qu.:5
Max.   :5

PATIENT_NUMBER GENDER RACE AGE RELIGION MARITAL_STATUS NUMBER_OF_INPATIENT_ENCOUNTERS AVERAGE_LENGTH_OF_STAY CONCEPT_CD
3785 2486617 Male Black 57 <NA> single 1 0 ICD9:401.9
6128 2537378 Male Black 68 <NA> <NA> 1 0 ICD9:272.4
5025 2511276 Female Black 56 <NA> single 1 0 ICD9:401.9
2150 2472768 Female Black 61 <NA> <NA> 1 0 ICD9:110.1
100 2452374 Female Black 75 Baptist <NA> 2 0 ICD9:272.4

```

5.3 HCLUST Summary

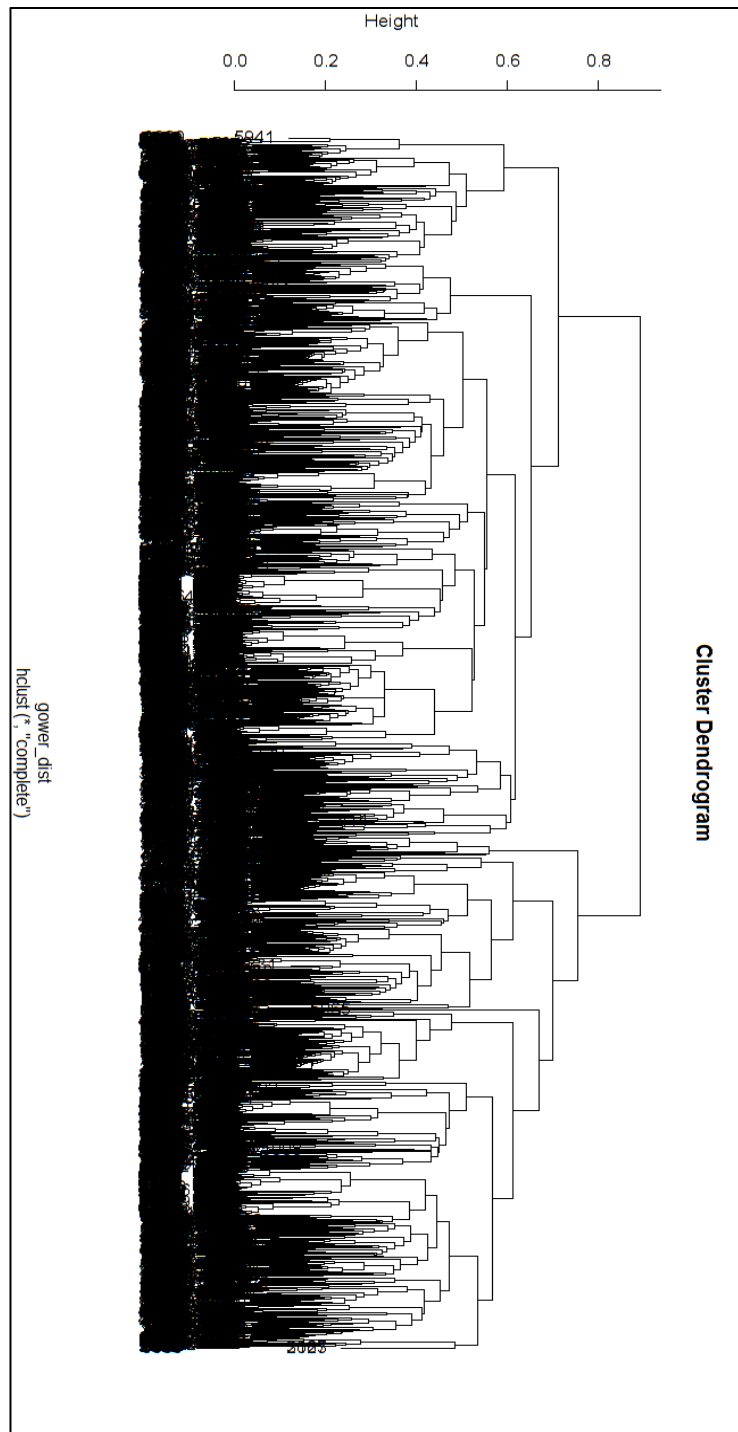


Figure 5.4 Visualization of clustered data through a Hclust dendrogram

2 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 5 Black      :1569 Min. : 3.00 Non-denominational:940 divorced : 96 Min. : 1.000 Min. : -0.6429
Male :2636 Hispanic : 111 1st Qu.:51.00 Baptist :560 married : 700 1st Qu.: 1.000 1st Qu.: 0.0000
Native American: 2 Median :59.00 Roman Catholic :193 separated: 47 Median : 1.000 Median : 0.0000
Other : 53 Mean :59.59 Other : 63 single :1714 Mean : 3.186 Mean : 2.0088
White : 65 3rd Qu.:68.00 Methodist : 45 widow : 39 3rd Qu.: 3.000 3rd Qu.: 1.6250
NA's : 841 Max. :90.00 (Other) : 92 NA's : 45 Max. :64.000 Max. :308.0000
NA's :748

  CONCEPT_CD      cluster
ICD9:401.9 : 261 Min. :1
ICD9:272.4 : 248 1st Qu.:1
ICD9:305.1 : 126 Median :1
ICD9:110.1 : 102 Mean :1
ICD9:272.0 : 102 3rd Qu.:1
ICD9:276.51: 91 Max. :1
(other) :1711
```

```
[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:3609 Black      :2283 Min. : 3.00 Baptist :1146 divorced : 194 Min. : 1.000 Min. : -26.000
Male : 0 Hispanic : 97 1st Qu.:52.00 Non-denominational: 921 married : 677 1st Qu.: 1.000 1st Qu.: 0.000
Native American: 0 Median :61.00 Roman Catholic : 249 separated: 89 Median : 1.000 Median : 0.000
Other : 39 Mean :60.59 Methodist : 85 single :2235 Mean : 3.424 Mean : 1.857
White : 50 3rd Qu.:70.00 Other : 48 widow : 314 3rd Qu.: 3.000 3rd Qu.: 1.750
NA's :1140 Max. :90.00 (Other) : 139 NA's : 100 Max. :47.000 Max. :340.000
NA's :1021

  CONCEPT_CD      cluster
ICD9:401.9: 332 Min. :2
ICD9:272.4: 327 1st Qu.:2
ICD9:272.0: 176 Median :2
ICD9:110.1: 127 Mean :2
ICD9:211.3: 113 3rd Qu.:2
ICD9:305.1: 110 Max. :2
(other) :2424
```

3 Cluster Summary:

```
[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 1 Black      :1506 Min. : 3.00 Non-denominational:917 divorced : 4 Min. : 1.000 Min. : -0.6429
Male :2545 Hispanic : 109 1st Qu.:51.00 Baptist :528 married : 700 1st Qu.: 1.000 1st Qu.: 0.0000
Native American: 2 Median :59.00 Roman Catholic :183 separated: 47 Median : 1.000 Median : 0.0000
Other : 49 Mean :59.41 Other : 63 single :1714 Mean : 3.127 Mean : 2.0153
White : 65 3rd Qu.:68.00 Methodist : 43 widow : 39 3rd Qu.: 3.000 3rd Qu.: 1.5594
NA's : 815 Max. :90.00 (Other) : 86 NA's : 42 Max. :64.000 Max. :308.0000
NA's :726

  CONCEPT_CD      cluster
ICD9:401.9 : 256 Min. :1
ICD9:272.4 : 240 1st Qu.:1
ICD9:305.1 : 124 Median :1
ICD9:272.0 : 98 Mean :1
ICD9:110.1 : 93 3rd Qu.:1
ICD9:276.51: 84 Max. :1
(other) :1651
```

```
[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:3609 Black      :2283 Min. : 3.00 Baptist :1146 divorced : 194 Min. : 1.000 Min. : -26.000
Male : 0 Hispanic : 97 1st Qu.:52.00 Non-denominational: 921 married : 677 1st Qu.: 1.000 1st Qu.: 0.000
Native American: 0 Median :61.00 Roman Catholic : 249 separated: 89 Median : 1.000 Median : 0.000
Other : 39 Mean :60.59 Methodist : 85 single :2235 Mean : 3.424 Mean : 1.857
White : 50 3rd Qu.:70.00 Other : 48 widow : 314 3rd Qu.: 3.000 3rd Qu.: 1.750
NA's :1140 Max. :90.00 (Other) : 139 NA's : 100 Max. :47.000 Max. :340.000
NA's :1021

  CONCEPT_CD      cluster
ICD9:401.9: 332 Min. :2
ICD9:272.4: 327 1st Qu.:2
ICD9:272.0: 176 Median :2
ICD9:110.1: 127 Mean :2
ICD9:211.3: 113 3rd Qu.:2
ICD9:305.1: 110 Max. :2
(other) :2424
```



```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 4    Black      :63    Min.   :39.00    Baptist      :32    divorced :92    Min.   : 1.000    Min.   : 0.000    ICD9:110.1 : 9
Male :91    Hispanic  : 2    1st Qu.:57.00    Non-denominational:23    married : 0    1st Qu.: 1.000    1st Qu.: 0.000    ICD9:272.4 : 8
Native American: 0    Median :64.00    Roman Catholic :10    separated: 0    Median : 2.000    Median : 0.250    ICD9:276.51: 7
Other       : 4    Mean   :64.45    Christian      : 5    single : 0    Mean   : 4.758    Mean   : 1.835    ICD9:070.54: 5
White       : 0    3rd Qu.:71.00    Methodist      : 2    widow  : 0    3rd Qu.: 4.000    3rd Qu.: 2.000    ICD9:401.9 : 5
NA's        :26    Max.   :88.00    (Other)        : 1    NA's    : 3    Max.   :38.000    Max.   :23.000    ICD9:272.0 : 4
                                NA's          :22    (Other)        :57

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3

```

4 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 1    Black      :1506    Min.   : 3.00    Non-denominational:917    divorced : 4    Min.   : 1.000    Min.   : -0.6429
Male :2545    Hispanic  : 109    1st Qu.:51.00    Baptist      :528    married : 700    1st Qu.: 1.000    1st Qu.: 0.0000
Native American: 2    Median :59.00    Roman Catholic :183    separated: 47    Median : 1.000    Median : 0.0000
Other       : 49    Mean   :59.41    Other        : 63    single :1714    Mean : 3.127    Mean : 2.0153
White       : 65    3rd Qu.:68.00    Methodist      : 43    widow  : 39    3rd Qu.: 3.000    3rd Qu.: 1.5594
NA's        : 815    Max.   :90.00    (Other)        : 86    NA's    : 42    Max.   :64.000    Max.   :308.0000

CONCEPT_CD      cluster
ICD9:401.9 : 256    Min. :1
ICD9:272.4 : 240    1st Qu.:1
ICD9:305.1 : 124    Median :1
ICD9:272.0 : 98     Mean :1
ICD9:110.1 : 93     3rd Qu.:1
ICD9:276.51: 84     Max. :1
(Other) :1651

```

```

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:2964    Black      :1904    Min.   : 3.00    Baptist      :962    divorced :194    Min.   : 1.000    Min.   : -26.000
Male : 0       Hispanic  : 77    1st Qu.:52.00    Non-denominational:752    married : 52    1st Qu.: 1.000    1st Qu.: 0.000
Native American: 0    Median :60.00    Roman Catholic :196    separated: 89    Median : 1.000    Median : 0.000
Other       : 27    Mean   :60.32    Methodist      : 71    single :2233    Mean : 3.483    Mean : 1.797
White       : 41    3rd Qu.:70.00    Unknown        : 41    widow  :314    3rd Qu.: 3.000    3rd Qu.: 1.800
NA's        : 915    Max.   :90.00    (Other)        : 98    NA's    : 82    Max.   :47.000    Max.   : 95.000

CONCEPT_CD      cluster
ICD9:401.9 : 261    Min. :2
ICD9:272.4 : 260    1st Qu.:2
ICD9:272.0 : 131    Median :2
ICD9:110.1 : 111    Mean :2
ICD9:305.1 : 95     3rd Qu.:2
ICD9:211.3 : 87     Max. :2
(Other) :2019

```

```

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:645    Black      :379    Min.   :25.00    Baptist      :184    divorced : 0    Min.   : 1.000    Min.   : -0.1667    ICD9:401.9: 71
Male : 0       Hispanic  : 20    1st Qu.:54.00    Non-denominational:169    married :625    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:272.4: 67
Native American: 0    Median :62.00    Roman Catholic : 53    separated: 0    Median : 1.000    Median : 0.0000    ICD9:272.0: 45
Other       :12    Mean   :61.86    Christian      :15    single : 2    Mean : 3.152    Mean : 2.1281    ICD9:211.3: 26
White       : 9    3rd Qu.:71.00    Methodist      :14    widow  : 0    3rd Qu.: 3.000    3rd Qu.: 1.5556    ICD9:244.9: 22
NA's        :225    Max.   :90.00    (Other)        :33    NA's    :18    Max.   :37.000    Max.   :340.0000    ICD9:268.9: 17
                                NA's          :177    (Other)        :397

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

```

```

[[4]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 4    Black      :63    Min.   :39.00    Baptist      :32    divorced :92    Min.   : 1.000    Min.   : 0.000    ICD9:110.1 : 9
Male :91    Hispanic  : 2    1st Qu.:57.00    Non-denominational:23    married : 0    1st Qu.: 1.000    1st Qu.: 0.000    ICD9:272.4 : 8
Native American: 0    Median :64.00    Roman Catholic :10    separated: 0    Median : 2.000    Median : 0.250    ICD9:276.51: 7
Other       : 4    Mean   :64.45    Christian      : 5    single : 0    Mean   : 4.758    Mean : 1.835    ICD9:070.54: 5
White       : 0    3rd Qu.:71.00    Methodist      : 2    widow  : 0    3rd Qu.: 4.000    3rd Qu.: 2.000    ICD9:401.9 : 5
NA's        :26    Max.   :88.00    (Other)        : 1    NA's    : 3    Max.   :38.000    Max.   :23.000    ICD9:272.0 : 4
                                NA's          :22    (Other)        :57

cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

```

6 Cluster Summary

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 1    Black      :1050    Min. : 3.00    Non-denominational:660    divorced : 0    Min. : 1.000    Min. : -0.1667
Male :1748    Hispanic : 82    1st Qu.:50.00    Baptist :345    married : 2    1st Qu.: 1.000    1st Qu.: 0.0000
Native American: 2    Median :57.00    Roman Catholic :116    separated: 0    Median : 1.000    Median : 0.0000
Other : 27    Mean :57.03    Other : 54    single :1714    Mean : 3.119    Mean : 2.1612
White : 42    3rd Qu.:65.00    Unknown : 27    widow : 0    3rd Qu.: 3.000    3rd Qu.: 1.6667
NA's : 546    Max. :90.00    (Other) : 44    NA's : 33    Max. :64.000    Max. :308.0000
NA's :503

CONCEPT_CD      cluster
ICD9:401.9 : 169    Min. :1
ICD9:272.4 : 153    1st Qu.:1
ICD9:305.1 : 100    Median :1
ICD9:110.1 : 65    Mean :1
ICD9:276.51: 63    3rd Qu.:1
ICD9:272.0 : 62    Max. :1
(Other) :1137

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 0    Black      :456    Min. :27.00    Non-denominational:257    divorced : 4    Min. : 1.000    Min. : -0.6429    ICD9:272.4: 87
Male :797    Hispanic : 27    1st Qu.:56.00    Baptist :183    married :698    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:401.9: 87
Native American: 0    Median :64.00    Roman Catholic : 67    separated: 47    Median : 1.000    Median : 0.0000    ICD9:272.0: 36
Other : 22    Mean :64.63    Methodist : 26    single : 0    Mean : 3.143    Mean : 1.6951    ICD9:185 : 30
White : 23    3rd Qu.:73.00    Christian : 19    widow : 39    3rd Qu.: 3.000    3rd Qu.: 1.5000    ICD9:211.3: 29
NA's :269    Max. :90.00    (Other) : 22    NA's : 9    Max. :40.000    Max. :69.0000    ICD9:110.1: 28
NA's :223    (Other) :500

cluster
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:2964    Black      :1904    Min. : 3.00    Baptist :962    divorced :194    Min. : 1.000    Min. : -26.000
Male : 0    Hispanic : 77    1st Qu.:52.00    Non-denominational:752    married : 52    1st Qu.: 1.000    1st Qu.: 0.000
Native American: 0    Median :60.00    Roman Catholic :196    separated: 89    Median : 1.000    Median : 0.000
Other : 27    Mean :60.32    Methodist : 71    single :2233    Mean : 3.483    Mean : 1.797
White : 41    3rd Qu.:70.00    Unknown : 41    widow : 314    3rd Qu.: 3.000    3rd Qu.: 1.800
NA's : 915    Max. :90.00    (Other) : 98    NA's : 82    Max. :47.000    Max. : 95.000
NA's :844

CONCEPT_CD      cluster
ICD9:401.9: 261    Min. :3
ICD9:272.4: 260    1st Qu.:3
ICD9:272.0: 131    Median :3
ICD9:110.1: 111    Mean :3
ICD9:305.1: 95    3rd Qu.:3
ICD9:211.3: 87    Max. :3
(Other) :2019

[[4]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:645    Black      :379    Min. :25.00    Baptist :184    divorced : 0    Min. : 1.000    Min. : -0.1667    ICD9:401.9: 71
Male : 0    Hispanic : 20    1st Qu.:54.00    Non-denominational:169    married :625    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:272.4: 67
Native American: 0    Median :62.00    Roman Catholic : 53    separated: 0    Median : 1.000    Median : 0.0000    ICD9:272.0: 45
Other : 12    Mean :61.86    Christian : 15    single : 2    Mean : 3.152    Mean : 2.1281    ICD9:211.3: 26
White : 9    3rd Qu.:71.00    Methodist : 14    widow : 0    3rd Qu.: 3.000    3rd Qu.: 1.5556    ICD9:244.9: 22
NA's :225    Max. :90.00    (Other) : 33    NA's : 18    Max. :37.000    Max. :340.0000    ICD9:268.9: 17
NA's :177    (Other) :397

cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

[[5]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 4    Black      :63    Min. :39.00    Baptist :32    divorced :92    Min. : 1.000    Min. : 0.000    ICD9:110.1 : 9
Male :91    Hispanic : 2    1st Qu.:57.00    Non-denominational:23    married : 0    1st Qu.: 1.000    1st Qu.: 0.000    ICD9:272.4 : 8
Native American: 0    Median :64.00    Roman Catholic :10    separated: 0    Median : 2.000    Median : 0.250    ICD9:276.51: 7
Other : 4    Mean :64.45    Christian : 5    single : 0    Mean : 4.758    Mean : 1.835    ICD9:070.54: 5
White : 0    3rd Qu.:71.00    Methodist : 2    widow : 0    3rd Qu.: 4.000    3rd Qu.: 2.000    ICD9:401.9 : 5
NA's :26    Max. :88.00    (Other) : 1    NA's : 3    Max. :38.000    Max. :23.000    ICD9:272.0 : 4
NA's :22    (Other) :57

cluster
Min. :5
1st Qu.:5
Median :5
Mean :5
3rd Qu.:5
Max. :5

```

5.4 DIANA Summary

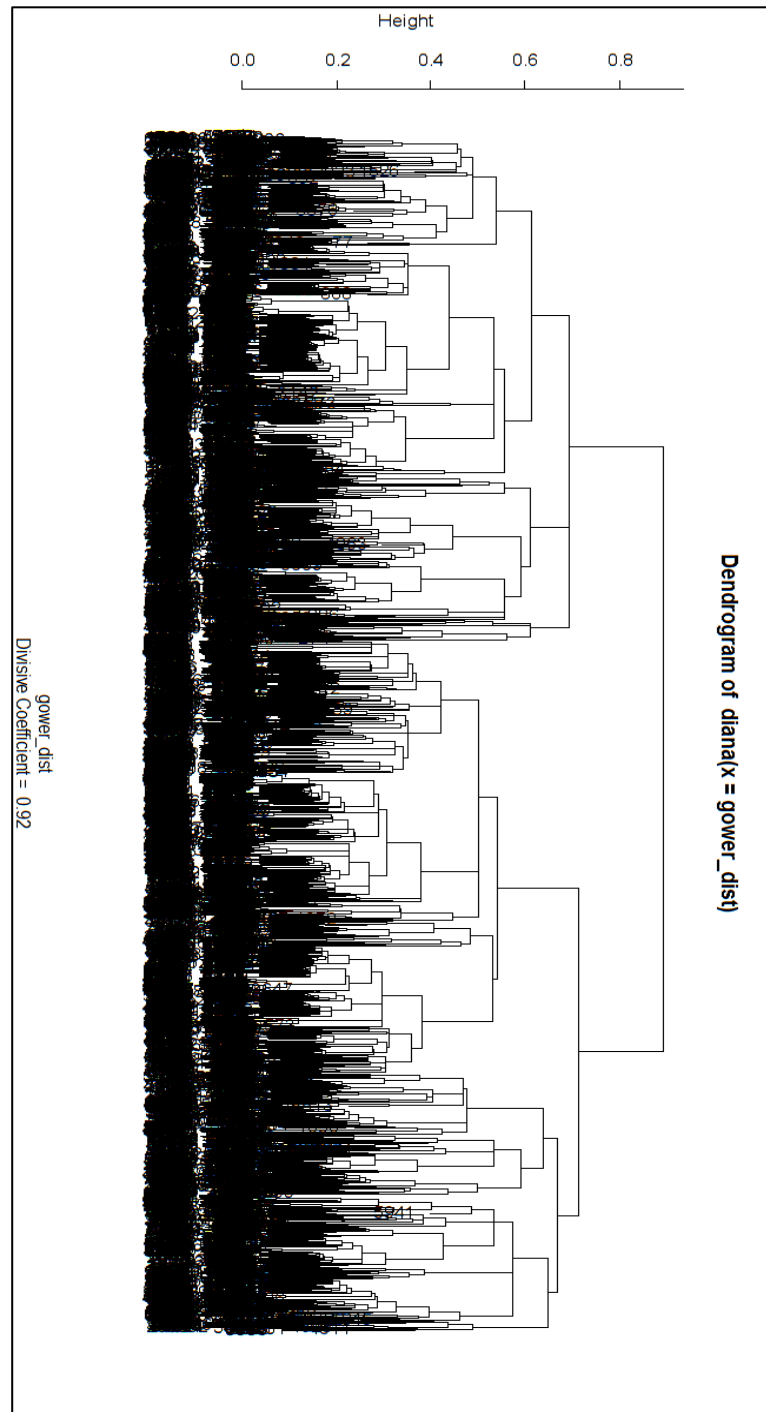
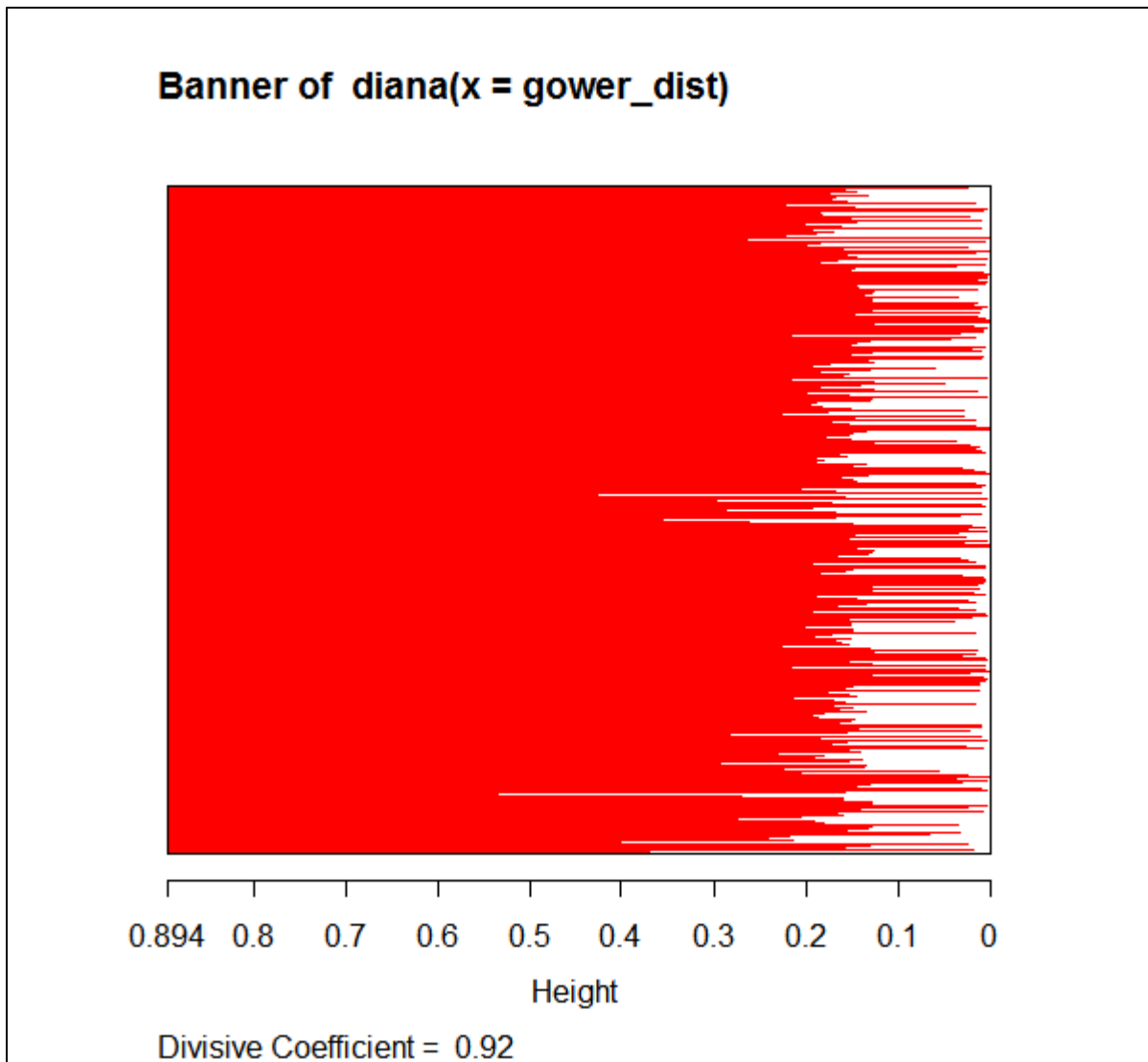


Figure 5.5 Visualization of clustered data through DIANA dendrogram



**Figure 5.6 Visualization of clustered data
though DIANA banner diagram**

2 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0    Black      :1567    Min.   : 3.00    Non-denominational:940    divorced : 92    Min.   : 1.000    Min.   : -0.6429
Male :2636    Hispanic  : 110    1st Qu.:51.00    Baptist      :559    married  :700    1st Qu.: 1.000    1st Qu.: 0.0000
Native American: 2    Median :59.00    Roman Catholic :192    separated: 47    Median : 1.000    Median : 0.0000
Other       : 53    Mean   :59.59    Other        : 63    single   :1713    Mean   : 3.187    Mean   : 2.0068
White       : 65    3rd Qu.:68.00    Methodist    : 45    widow    : 39    3rd Qu.: 3.000    3rd Qu.: 1.6178
NA's        : 839    Max.   :90.00    (Other)      : 91    NA's     : 45    Max.   :64.000    Max.   :308.0000
NA's        :746

CONCEPT_CD      cluster
ICD9:401.9 : 261    Min.   :1
ICD9:272.4 : 248    1st Qu.:1
ICD9:305.1 : 126    Median :1
ICD9:110.1 : 102    Mean   :1
ICD9:272.0 : 102    3rd Qu.:1
ICD9:276.51: 88    Max.   :1
(Other)    :1709

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female:3614    Black      :2285    Min.   : 3.00    Baptist      :1147    divorced : 198    Min.   : 1.000    Min.   : -26.000
Male : 0        Hispanic  : 98    1st Qu.:52.00    Non-denominational:921    married  : 677    1st Qu.: 1.000    1st Qu.: 0.000
Native American: 0    Median :61.00    Roman Catholic : 250    separated: 89    Median : 1.000    Median : 0.000
Other       : 39    Mean   :60.59    Methodist    : 85    single   :2236    Mean   : 3.422    Mean   : 1.858
White       : 50    3rd Qu.:70.00    Other        : 48    widow    :314    3rd Qu.: 3.000    3rd Qu.: 1.761
NA's        :1142    Max.   :90.00    (Other)      :140    NA's     :100    Max.   :47.000    Max.   :340.000
NA's        :1023

CONCEPT_CD      cluster
ICD9:401.9: 332    Min.   :2
ICD9:272.4: 327    1st Qu.:2
ICD9:272.0: 176    Median :2
ICD9:110.1: 127    Mean   :2
ICD9:211.3: 113    3rd Qu.:2
ICD9:305.1: 110    Max.   :2
(Other)    :2429

```

3 Cluster Summary:

```

[[1]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0    Black      :1567    Min.   : 3.00    Non-denominational:940    divorced : 92    Min.   : 1.000    Min.   : -0.6429
Male :2636    Hispanic  : 110    1st Qu.:51.00    Baptist      :559    married  :700    1st Qu.: 1.000    1st Qu.: 0.0000
Native American: 2    Median :59.00    Roman Catholic :192    separated: 47    Median : 1.000    Median : 0.0000
Other       : 53    Mean   :59.59    Other        : 63    single   :1713    Mean   : 3.187    Mean   : 2.0068
White       : 65    3rd Qu.:68.00    Methodist    : 45    widow    : 39    3rd Qu.: 3.000    3rd Qu.: 1.6178
NA's        : 839    Max.   :90.00    (Other)      : 91    NA's     : 45    Max.   :64.000    Max.   :308.0000
NA's        :746

CONCEPT_CD      cluster
ICD9:401.9 : 261    Min.   :1
ICD9:272.4 : 248    1st Qu.:1
ICD9:305.1 : 126    Median :1
ICD9:110.1 : 102    Mean   :1
ICD9:272.0 : 102    3rd Qu.:1
ICD9:276.51: 88    Max.   :1
(Other)    :1709

[[2]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:2264    Black      :1448    Min.   : 3.0    Baptist      :696    divorced : 0    Min.   : 1.000    Min.   : -26.000    ICD9:401.9: 203
Male : 0        Hispanic  : 65    1st Qu.:49.0    Non-denominational:626    married  : 0    1st Qu.: 1.000    1st Qu.: 0.000    ICD9:272.4: 194
Native American: 0    Median :58.0    Roman Catholic :149    separated: 0    Median : 1.000    Median : 0.000    ICD9:272.0: 105
Other       : 22    Mean   :57.4    Unknown      : 39    single   :2236    Mean   : 3.184    Mean   : 1.790    ICD9:110.1: 85
White       : 32    3rd Qu.:66.0    Methodist    : 37    widow    : 0    3rd Qu.: 3.000    3rd Qu.: 1.579    ICD9:305.1: 79
NA's        : 697    Max.   :90.0    (Other)      : 68    NA's     : 28    Max.   :47.000    Max.   : 52.000    ICD9:211.3: 59
NA's        :649    (Other)    :1539

cluster
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

[[3]]
GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1350    Black      :837    Min.   :25.00    Baptist      :451    divorced :198    Min.   : 1.000    Min.   : -0.1667    ICD9:272.4:133
Male : 0        Hispanic  : 33    1st Qu.:57.00    Non-denominational:295    married  :677    1st Qu.: 1.000    1st Qu.: 0.0000    ICD9:401.9:129
Native American: 0    Median :66.00    Roman Catholic :101    separated: 89    Median : 2.000    Median : 0.0889    ICD9:272.0: 71
Other       : 17    Mean   :65.94    Methodist    : 48    single   : 0    Mean   : 3.822    Mean   : 1.9734    ICD9:211.3: 54
White       : 18    3rd Qu.:75.00    Other        : 22    widow    :314    3rd Qu.: 4.000    3rd Qu.: 2.0000    ICD9:110.1: 42
NA's        :445    Max.   :90.00    (Other)      : 59    NA's     : 72    Max.   :38.000    Max.   :340.0000    ICD9:244.9: 37
NA's        :374    (Other)    :884

cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

```

4 Cluster Summary:

```

[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0 Black      :1078 Min. : 3.00 Non-denominational:693 divorced : 8 Min. : 1.00 Min. : -0.1667
Male :1772 Hispanic : 80 1st Qu.:50.00 Baptist :333 married : 0 1st Qu.: 1.00 1st Qu.: 0.0000
Native American: 2 Median :57.00 Roman Catholic :115 separated: 25 Median : 1.00 Median : 0.0000
Other : 26 Mean :56.92 Other : 52 single :1712 Mean : 3.12 Mean : 1.9743
White : 42 3rd Qu.:65.00 Unknown : 27 widow : 9 3rd Qu.: 3.00 3rd Qu.: 1.6542
NA's : 544 Max. :90.00 (Other) : 44 NA's : 18 Max. :64.00 Max. :105.0000
NA's :508

  CONCEPT_CD      cluster
ICD9:401.9 : 170 Min. :1
ICD9:272.4 : 154 1st Qu.:1
ICD9:305.1 : 102 Median :1
ICD9:110.1 : 65 Mean :1
ICD9:272.0 : 65 3rd Qu.:1
ICD9:276.51: 64 Max. :1
(Other) :1152

[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 0 Black      :489 Min. :27.00 Non-denominational:247 divorced : 84 Min. : 1.000 Min. : -0.6429 ICD9:272.4: 94
Male :864 Hispanic : 30 1st Qu.:57.00 Baptist :226 married :700 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:401.9: 91
Native American: 0 Median :65.00 Roman Catholic : 77 separated: 22 Median : 1.000 Median : 0.0000 ICD9:110.1: 37
Other : 27 Mean :65.08 Methodist : 28 single : 1 Mean : 3.326 Mean : 2.0734 ICD9:272.0: 37
White : 23 3rd Qu.:74.00 Christian : 23 widow : 30 3rd Qu.: 3.000 3rd Qu.: 1.5000 ICD9:211.3: 31
NA's :295 Max. :90.00 (Other) : 25 NA's : 27 Max. :40.000 Max. :308.0000 ICD9:185 : 29
NA's :238 (Other) :545

  cluster |
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

[[3]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:2264 Black :1448 Min. : 3.0 Baptist :696 divorced : 0 Min. : 1.000 Min. : -26.000 ICD9:401.9: 203
Male : 0 Hispanic : 65 1st Qu.:49.0 Non-denominational:626 married : 0 1st Qu.: 1.000 1st Qu.: 0.000 ICD9:272.4: 194
Native American: 0 Median :58.0 Roman Catholic :149 separated: 0 Median : 1.000 Median : 0.000 ICD9:272.0: 105
Other : 22 Mean :57.4 Unknown : 39 single :2236 Mean : 3.184 Mean : 1.790 ICD9:110.1: 85
White : 32 3rd Qu.:66.0 Methodist : 37 widow : 0 3rd Qu.: 3.000 3rd Qu.: 1.579 ICD9:305.1: 79
NA's : 697 Max. :90.0 (Other) : 68 NA's : 28 Max. :47.000 Max. : 52.000 ICD9:211.3: 59
NA's :649 (Other) :1539

  cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

[[4]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1350 Black :837 Min. :25.00 Baptist :451 divorced :198 Min. : 1.000 Min. : -0.1667 ICD9:272.4:133
Male : 0 Hispanic : 33 1st Qu.:57.00 Non-denominational:295 married :677 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:401.9:129
Native American: 0 Median :66.00 Roman Catholic :101 separated: 89 Median : 2.000 Median : 0.0889 ICD9:272.0: 71
Other : 17 Mean :65.94 Methodist : 48 single : 0 Mean : 3.822 Mean : 1.9734 ICD9:211.3: 54
White : 18 3rd Qu.:75.00 Other : 22 widow :314 3rd Qu.: 4.000 3rd Qu.: 2.0000 ICD9:110.1: 42
NA's :445 Max. :90.00 (Other) : 59 NA's : 72 Max. :38.000 Max. :340.0000 ICD9:244.9: 37
NA's :374 (Other) :884

  cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

```

5 Cluster Summary:

```

[[1]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY
Female: 0 Black      :1078 Min. : 3.00 Non-denominational:693 divorced : 8 Min. : 1.00 Min. : -0.1667
Male :1772 Hispanic : 80 1st Qu.:50.00 Baptist :333 married : 0 1st Qu.: 1.00 1st Qu.: 0.0000
Native American: 2 Median :57.00 Roman Catholic :115 separated: 25 Median : 1.00 Median : 0.0000
Other : 26 Mean :56.92 Other : 52 single :1712 Mean : 3.12 Mean : 1.9743
White : 42 3rd Qu.:65.00 Unknown : 27 widow : 9 3rd Qu.: 3.00 3rd Qu.: 1.6542
NA's : 544 Max. :90.00 (Other) : 44 NA's : 18 Max. :64.00 Max. :105.0000
NA's :508

  CONCEPT_CD      cluster
ICD9:401.9 : 170 Min. :1
ICD9:272.4 : 154 1st Qu.:1
ICD9:305.1 : 102 Median :1
ICD9:110.1 : 65 Mean :1
ICD9:272.0 : 65 3rd Qu.:1
ICD9:276.51: 64 Max. :1
(Other) :1152

[[2]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 0 Black      :457 Min. :27.00 Non-denominational:247 divorced : 63 Min. : 1.000 Min. : -0.6429 ICD9:272.4: 84
Male :752 Hispanic : 6 1st Qu.:57.00 Baptist :226 married :633 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:401.9: 78
Native American: 0 Median :65.00 Methodist : 26 separated: 14 Median : 1.000 Median : 0.0000 ICD9:110.1: 34
Other : 17 Mean :65.03 Christian : 21 single : 0 Mean : 3.249 Mean : 1.7758 ICD9:272.0: 32
White : 18 3rd Qu.:74.00 Other : 10 widow : 21 3rd Qu.: 3.000 3rd Qu.: 1.6854 ICD9:185 : 29
NA's :254 Max. :90.00 (Other) : 12 NA's : 21 Max. :40.000 Max. :69.0000 ICD9:211.3: 24
NA's :210 (Other) :471

  cluster
Min. :2
1st Qu.:2
Median :2
Mean :2
3rd Qu.:2
Max. :2

[[3]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:2264 Black :1448 Min. : 3.0 Baptist :696 divorced : 0 Min. : 1.000 Min. : -26.000 ICD9:401.9: 203
Male : 0 Hispanic : 65 1st Qu.:49.0 Non-denominational:1626 married : 0 1st Qu.: 1.000 1st Qu.: 0.000 ICD9:272.4: 194
Native American: 0 Median :58.0 Roman Catholic :149 separated: 0 Median : 1.000 Median : 0.000 ICD9:272.0: 105
Other : 22 Mean :57.4 Unknown : 39 single :2236 Mean : 3.184 Mean : 1.790 ICD9:110.1: 85
White : 32 3rd Qu.:66.0 Methodist : 37 widow : 0 3rd Qu.: 3.000 3rd Qu.: 1.579 ICD9:305.1: 79
NA's : 697 Max. :90.0 (Other) : 68 NA's : 28 Max. :47.000 Max. : 52.000 ICD9:211.3: 59
NA's :649 (Other) :1539

  cluster
Min. :3
1st Qu.:3
Median :3
Mean :3
3rd Qu.:3
Max. :3

[[4]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female:1350 Black :837 Min. :25.00 Baptist :451 divorced :198 Min. : 1.000 Min. : -0.1667 ICD9:272.4:133
Male : 0 Hispanic : 33 1st Qu.:57.00 Non-denominational:295 married :677 1st Qu.: 1.000 1st Qu.: 0.0000 ICD9:401.9:129
Native American: 0 Median :66.00 Roman Catholic :101 separated: 89 Median : 2.000 Median : 0.0889 ICD9:272.0: 71
Other : 17 Mean :65.94 Methodist : 48 single : 0 Mean : 3.822 Mean : 1.9734 ICD9:211.3: 54
White : 18 3rd Qu.:75.00 Other : 22 widow :314 3rd Qu.: 4.000 3rd Qu.: 2.0000 ICD9:110.1: 42
NA's :445 Max. :90.00 (Other) : 59 NA's : 72 Max. :38.000 Max. :340.0000 ICD9:244.9: 37
NA's :374 (Other) :884

  cluster
Min. :4
1st Qu.:4
Median :4
Mean :4
3rd Qu.:4
Max. :4

[[5]]
  GENDER      RACE      AGE      RELIGION      MARITAL_STATUS      NUMBER_OF_INPATIENT_ENCOUNTERS      AVERAGE_LENGTH_OF_STAY      CONCEPT_CD
Female: 0 Black :32 Min. :34.00 Roman Catholic:77 divorced :21 Min. : 1.000 Min. : 0.000 ICD9:401.9:13
Male :112 Hispanic :24 1st Qu.:57.00 Christian : 2 married :67 1st Qu.: 1.000 1st Qu.: 0.000 ICD9:272.4:10
Native American: 0 Median :65.00 Methodist : 2 separated: 8 Median : 2.000 Median : 0.000 ICD9:211.3: 7
Other :10 Mean :65.36 Atheist : 1 single : 1 Mean : 3.848 Mean : 4.072 ICD9:272.0: 5
White : 5 3rd Qu.:72.25 Other : 1 widow : 9 3rd Qu.: 4.250 3rd Qu.: 1.050 ICD9:268.9: 4
NA's :41 Max. :90.00 (Other) : 1 NA's : 6 Max. :27.000 Max. :308.000 ICD9:110.1: 3
NA's :28 (Other) :70

  cluster
Min. :5
1st Qu.:5
Median :5
Mean :5
3rd Qu.:5
Max. :5

```

5.5 Discussion

Given the four algorithms, the next step was to compare the cluster patterns between the algorithms. Did the cluster the data similarly? Comparative analysis was done to determine whether the data clustered similarly, and to which algorithm clusters the data the best.

Table 5.1, Table 5.2, Table 5.3, and Table 5.4 shows the frequency of males and females in the instance where the data was split into four clusters, via the K-modes, PAM, Hclust, and DIANA algorithms. What was being observed here is the degree of overlap. The better the data is clustered, the more segregated it is by column; more data in one column, vs. another.

Table 5.1

K-MODES Clusters

	Male	Female	Mode Marital Status
Cluster 1	875	60	Single
Cluster 2	62	955	Single
Cluster 3	328	38	Married
Cluster 4	1	658	single

Table 5.2**PAM Clusters:**

	Male	Female	Mode Marital Status
Cluster 1	1672	0	single
Cluster 2	951	79	married
Cluster 3	0	2302	single
Cluster 4	13	1233	married

Table 5.3**HClust Clusters:**

	Male	Female	Mode Marital Status
Cluster 1	2545	1	Single
Cluster 2	0	2964	Single
Cluster 3	0	645	Married
Cluster 4	91	4	divorced

Table 5.4**DIANA Clusters:**

	Male	Female	Mode Marital Status
Cluster 1	1772	0	Single
Cluster 2	864	0	Married
Cluster 3	0	2264	Single
Cluster 4	0	1350	Married

In the small sample of features and their counts, of all the algorithms performed similarly except for HClust, clustering samples of single men, married men, single woman, married woman. Hclust presented a subgroup of married men.

The DIANA algorithm, however, stood out. It clustered data with very little overlap, as evidenced in the table. When splitting along the lines of gender, the algorithm delivered perfectly segregated gender findings. For this reason, all further analysis on the dataset was used by DIANA's interpretation of clustering.

5.6 Top Mode Diseases per Cluster

DIANA

2 CLUSTERS

1)

ICD9:401.9 - Hypertensive disease NOS – 9.9%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 9.4%

ICD9:305.1 - Tobacco use disorder – 4.78%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.87%

ICD9:272.0 – Cholesterolemia – 3.87%

ICD9:276.51 – Dehydration – 3.34%

2)

ICD9:401.9 - Hypertensive disease NOS – 9.19%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 12.4%

ICD9:272.0 – Cholesterolemia – 6.68 %

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.5%

ICD9:211.3 - Benign Neoplasm of Colon – 3.1%

ICD9:305.1 - Tobacco use disorder – 3.0%

3 CLUSTERS

1)

ICD9:401.9 - Hypertensive disease NOS – 9.9%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 9.4%

ICD9:305.1 - Tobacco use disorder – 4.8%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.9%

ICD9:272.0 – Cholesterolemia – 3.9%

ICD9:276.51 – Dehydration – 3.3%

2)

ICD9:401.9 - Hypertensive disease NOS – 9.0%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.6%

ICD9:272.0 – Cholesterolemia – 4.6%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.8%

ICD9:305.1 - Tobacco use disorder – 3.5%

ICD9:211.3 - Benign Neoplasm of Colon – 2.6%

3)

ICD9:272.4 - Hyperlipidemia, other and unspecified – 9.9%

ICD9:401.9 - Hypertensive disease NOS – 9.6%

ICD9:272.0 – Cholesterolemia – 5.3%

ICD9:211.3 - Benign Neoplasm of Colon – 4.0%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.1%

ICD9:244.9 - Acquired hypothyroidism NOS – 2.7%

4 CLUSTERS

1)

ICD9:401.9 - Hypertensive disease NOS - 9.6%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.7%

ICD9:305.1 - Tobacco use disorder – 5.8%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.7%

ICD9:272.0 – Cholesterolemia- 3.7%

ICD9:276.51 – Dehydration – 3.65

2)

ICD9:272.4 - Hyperlipidemia, other and unspecified – 10.9%

ICD9:401.9 - Hypertensive disease NOS – 10.5%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 4.3%

ICD9:272.0 – Cholesterolemia – 4.3%

ICD9:211.3 - Benign Neoplasm of Colon – 3.5%

ICD9:185 - Neoplasm, malignant, of prostate – 3.4%

3)

ICD9:401.9 - Hypertensive disease NOS – 9.0%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.7%

ICD9:272.0 – Cholesterolemia – 4.6%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.8%

ICD9:305.1 - Tobacco use disorder – 3.5%

ICD9:211.3 - Benign Neoplasm of Colon – 2.6%

4)

ICD9:272.4 - Hyperlipidemia, other and unspecified – 9.8%

ICD9:401.9 - Hypertensive disease NOS – 9.6%

ICD9:272.0 – Cholesterolemia – 5.3%

ICD9:211.3 - Benign Neoplasm of Colon - 4.0%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.1%

ICD9:244.9 - Acquired hypothyroidism NOS – 2.7%

5 CLUSTERS

1)

ICD9:401.9 - Hypertensive disease NOS – 9.6%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.7%

ICD9:305.1 - Tobacco use disorder – 5.8%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.7%

ICD9:272.0 – Cholesterolemia – 3.7%

ICD9:276.51 – Dehydration – 3.6%

2)

ICD9:272.4 - Hyperlipidemia, other and unspecified – 11.2%

ICD9:401.9 - Hypertensive disease NOS – 10.4%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 4.5%

ICD9:272.0 – Cholesterolemia – 4.3%

ICD9:185 - Neoplasm, malignant, of prostate – 3.9%

ICD9:211.3 - Benign Neoplasm of Colon – 3.2%

3)

ICD9:401.9 - Hypertensive disease NOS – 9.0%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.6%

ICD9:272.0 – Cholesterolemia – 4.6%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 3.8%

ICD9:305.1 - Tobacco use disorder – 3.5%

ICD9:211.3 - Benign Neoplasm of Colon – 2.6%

4)

ICD9:272.4 - Hyperlipidemia, other and unspecified – 9.8%

ICD9:401.9 - Hypertensive disease NOS – 9.6%

ICD9:272.0 – Cholesterolemia – 5.3%

ICD9:211.3 - Benign Neoplasm of Colon - 4.0%

ICD9:110.1 - Onychomycosis due to Trichophyton rubrum - 3.1%

ICD9:244.9 - Acquired hypothyroidism NOS – 2.7%

5)

ICD9:401.9 - Hypertensive disease NOS – 11.6%

ICD9:272.4 - Hyperlipidemia, other and unspecified – 8.9%

ICD9:211.3 - Benign Neoplasm of Colon – 6.3%
ICD9:272.0 – Cholesterolemia – 4.5%
ICD9:268.9 - Ergosterol deficiency – 3.6%
ICD9:110.1 - Onychomycosis due to Trichophyton rubrum – 2.7%

5.7 Findings

Doing analysis on the data, trends and recurrences appeared. Creating two clusters indicated larger trends while creating smaller clusters (a maximum of 5), showed more minute patterns. Each patient in the dataset was assigned an ICD-9 code of the mode comorbidity. Comorbidity is the presence of other chronic diseases in a patient. In the summary of each cluster, the frequencies of the comorbidities of each patient were tallied, and the clusters were parsed for insights.

In total six observations were made:

- 1) In each subgroup, whether in clusters of 2, 3, 4 and 5, the number of comorbidities were dominated by
 - a. Hypertensive Disease NOS – High Blood Pressure
 - b. Hyperlipidemia – Abnormally elevated levels of fat in the blood
 - c. Cholesterolemia – The presence of elevated levels of cholesterol in the blood.
- 2) Prevalence of Onychomycosis due to Trichophyton rubrum
- 3) Elevated rates of Benign Neoplasm of Colon
- 4) Acquired hypothyroidism cases showing up in women who are black, female, and non-single, with a median age of 66. (0 cases of single women).
- 5) Incidences of Neoplasm, malignant, of prostate in men who are black, non-single, with a mean age of 65.

- 6) Incidences of Tobacco use disorder showing up in clusters featuring mostly single men and women.

Chapter 6. CONCLUSION

Each of these observations either validate existing trends of diabetes patients or provide potential new areas of research on comorbidity, risk factors, and demographics. From using cluster analysis, we can use more specific demographic information to learn more about the disease.

Discussion of the conclusion can be described in two parts:

- Validation of existing knowledge of diabetes type II comorbidity,
- The effect of demographic features on co-morbidity, mainly gender and marital status.

Firstly, the data validates existing correlations of diabetes type II. These were the top three diseases in all of the clusters:

- Hypertensive disease – High blood pressure, and has a high correlation for African-Americans, and occurs more frequently among black than white Americans with diabetes [1]
- Hyperlipidemia - Is a result of heightened levels of fats and lipoproteins in the blood. It is commonly normally associated with diabetes and is the most common cause of diabetes death [23]
- Cholesterolemia - is the presence of elevated levels of cholesterol in the blood. According to the journal chapter, ‘Diabetes In African Americans’, by Eugene S. Tull and Jeffrey M. Roseman, they insist that ‘Individuals who have insulin-resistant diabetes have higher levels of cardiovascular disease risk factors, including LDL- cholesterol and triglycerides.

These three diseases, and their prevalence in the data, only served to prove that the research was on the right track. The fact that the primary three diseases uncovered by cluster analysis matches pre-existing notions for diabetes type II risk factors is an indication that the results were good.

Onychomycosis due to *Trichophyton rubrum* is a common disease and showed up frequently in results. It occurs in toenails and is caused by the fungus *Trichophyton rubrum*. According to the paper 'Prevalence of Toe Nail Onychomycosis in Diabetic Patients', by Saunte, Holgersen, et al., 'Male gender and old age are predisposing factors for fungal nail infection, as well as diabetes, psoriasis, peripheral arterial disease and immune suppression'. This shows that a correlation does exist, and the results validate this. What remains to be seen however, is the relationship that Onychomycosis has between age, diabetes type II, and African Americans. This relationship remains unexplored in research.

As more observations were made, more interesting correlations were discovered, mainly around marital status and gender. Hypothyroidism is the most common adult thyroid [28] disease in adults and is the most common in women. Results showed that the disease has a higher rate in women who are black, non-single, and with a mean age of 65. Diabetic patients have higher rates of thyroid disorders compared with the normal population, correlating with the results. This includes patients who are married, divorced, widowed or separated. They were all slightly at higher risk.

Men were not exempt. Non-single black men with a mean age of 35 showed elevated incidences of Neoplasm, malignant, of the prostate; prostate cancer. Again, this was also spread across men who are married, divorced, widowed or separated.

Marital status again played in a role in disease correlation. Clusters featuring mostly either single black men, or single black women, each at the mean ages of 56.92, and 57.4, respectively had higher incidences of Tobacco use disorder. What is important to note here for both previous examples is that there seemingly is a correlation between diseases and marital status. This is an indication of a potential pattern. Does marital status influence diabetes type II patients? Perhaps. Perhaps not. What matters is that a trend was spotted – a potential thread of investigation. This is the power of machine learning. Using cluster analysis, we were better able to observe that a seemingly innocuous demographic factor may affect what subsequent diseases a diabetes type II patient will suffer.

In conclusion, by using cluster analysis on minority health records, we were better able to understand comorbidities of diabetes type II in African Americans. Present correlations were validated, and new ones were found. Insights from demographic data can now spur further research on this disease and its effects.

Chapter 7. FUTURE WORK

Cluster analysis on minority health data is a field in its infancy. The work done in this thesis is only the start of what can be an established precedent of using machine learning algorithms on health data at Howard University.

Future work includes:

- Using cluster analysis to improve the accuracy rate in predicting whether someone has diabetes, by creating a “synthetic” feature for supervised learning.
- Using unused features in this project to provide additional information e.g. Clustering diabetes 2 patients around zip code data to find out the density of diabetes patients in different areas.
- Performing cluster analysis on established datasets (i.e. CDC) and comparing results to Howard University’s data to produce insights.
- Comparing cluster analysis results of people from other ethnic groups to Howard University’s results may uncover unforeseen relationships.

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