Pain Project Report

December 14th, 2018

GitHUB repository:

https://github.com/MSIA/Team_Uptake

Team Members:

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AIM OF THE PROJECT

The aim of the project is to explore the self reported pain data as well as various surgery and patients related variables to analyze whether the pain experienced by patients with different characteristics have similarities. The initial hypothesis is that demographics data, such as age, weights and race, surgery types would have different effects on patients' pain level.

DATA CLEANING

Demographics data, pain data and information on morphine equivalents administered while inpatient for 70 minor patients undergoing either spine correction or Chest surgery was provided. Detailed steps for data cleaning are provided in Appendix 1 Section 1 (a).

PAIN SCORES NORMALIZATION

We are provided with pain scores that were collected by the hospital staff from the patients at 12 hr intervals. Since the perceived pain for different patients would be different, the pain scores were normalized.

- Normalization with mean
  For each patient, the pain scores were normalized by subtracting each 12 hr pain score by the mean of all 12 hr pain scores available for that patient. These normalized scores were utilized to study the pain trends across different patients.

- Normalization with VAS scores
  Since the time span of pain values collection was not very long post the operation, merely normalizing the pain scores by subtracting the mean of the given pain scores would not provide an accurate picture of the actual absolute pain values. We were also provided the results of APPT (Adolescent Paediatric pain Tool) results for the patient pool. Lot of literature exists which confirms the validity and reliability of the outcome of this tool as an accurate measure of the actual absolute pain [1,2]. So, the VAS (Visual Analog Scale) scores provided by this tool were used as a measure of the actual pain. We were provided the VAS scores for Post-Operative days 1 through 8 and subsequent 5 clinic visit. The hypothesis is that since the VAS scores have been proven to be good estimates of the actual pain, the difference in mean of the >0 VAS scores (divided by 10; since the VAS scale is 0-100) and the mean of the 12 hrs pain values provided to us for analysis would be a good metric to arrive at the absolute pain scores.

EXPLORATORY DATA ANALYSIS

The table given below summarizes the various key metrics for the 66 patients that have been considered for our analyses. Appendix 1 Section (b) shows the time trend for the discharge dates for the patients. It can be seen that the number of surgeries spiked win Jul - Sep. This coincides with the summer break and it makes sense for children to undergo a major surgery when they are on a break. Appendix 1 Section (c) summarizes the number of days that patients spend in hospital post Operation. It can be seen that the number peaks at

4 days both for spine and chest patients. Appendix 1 Section (d) illustrates the average pain trend across all 66 patients for both the type of normalizations.

Attribute	Spine		Nuss		Attribute	Spine		Nuss	
	#	%	#	%		#	%	#	%
Total	42	100%	24	100%	**PatientAge**				
Gender					< 10	0	0%	0	0%
Male	11	26%	21	88%	>=10 and < 14	14	33%	5	21%
Female	31	74%	3	13%	>=14 and < 18	23	55%	17	71%
PatientRace					>=18 and < 22	4	10%	2	8%
White	29	69%	19	79%	>=22	1	2%	0	0%
Black	3	7%	0	0%					
Asian	1	2%	0	0%	**PatientWeight in kgs**				
Hispanic	4	10%	2	8%	< 40	0	0%	1	4%
More than 1 race	5	12%	3	13%	>=40 and < 60	21	50%	11	46%
SurgeryHX					>=60 and < 80	18	43%	12	50%
History	9	21%	8	33%	>=80 and < 100	2	5%	0	0%
No History	33	79%	16	67%	>=100	1	2%	0	0%

ANALYSES

SURGERY HISTORY VS. PAIN LEVEL

During our EDA, we came across an interesting observation that patients with prior surgery history reported less pain as compared to those who did not. Appendix 2 illustrates our observations. We looked at Spine and Chest patients separately. For Spine patients, as evident from the graph, the pain trend line for the patients not having prior surgeries was consistently higher than the the trendline for patients with prior surgery history. Same trend was observed when we looked at average 0-24 hrs absolute pain and 0-72 hrs absolute pain scores. Looking at chest surgery patients, although the pain trendline did not show any pattern, the average 0-24 and 0-72 hrs average absolute pain scores were higher for patients without prior surgery history as compared to patients with prior surgery history.

PATIENT PREDICTIVE VS. PAIN LEVEL

Next we were interested in looking at whether the actual pain experienced by a patient is related to the pain that the patient predicted prior to his/her surgery. We looked at scatterplots and correlations among the predictive pain levels and mean absolute 24 hrs pain score. The scatter plots are illustrated in Appendix 3. The correlation value was -0.2 for spine patients and -0.17 for chest patients (both having p-value > 0.1). Hence, the correlations were not statistically significant.

CLUSTERING ANALYSIS FOR SPINE PATIENTS

We were interested in looking at evaluating whether we could segregate the patients into distinct groups on the basis of the features that were provided. Refer to Appendix 4 Section 4 (a) for the clustering analysis modeling details.

- **Visualization and Inferences from the four clusters for Spine**

We used parallel plots to visualise the four clusters because we have multivariate, numerical data. Parallel Coordinates Plots are ideal for such data. It helped us understand the spread of clusters across different variables. It also allowed us to compare many variables together and see the relationships between them. All parallel plots are illustrated in Appendix 4 Section 4(b).

Visualisation 1: Parallel coordinate plots across Demographic features for 4 clusters

Name of features: Gender, Age, Weight, Race

Inference across clusters from Visualisation 1:

Cluster	Gender	Age	Weight	Race
0	More males	Youngest patients	No pattern, even distribution	More non-white
1	More males	Ages in middle	No pattern, even distribution	More white
2	More females	Oldest patients	Heaviest patients	More white
3	More males	Ages in middle	Weights in middle	More white

Visualisation 2: Parallel coordinate plots across Non- Demographic features for 4 clusters

Name of features: Risser, Top level, Bottom level, Top degree, Bottom degree, Shape, # of levels

Inference across clusters from Visualisation 2:

Cluster	Risser	Top Level	Bottom Level	Top degree	Bottom degree	Shape	# of levels
0	very scattered values	low values (less scattered)	high values (less scattered)	average values (more scattered)	average values (more scattered)	average values (less scattered)	lowest value (less scattered)
1	lowest value (one risser value for all elements in cluster)	below average value (two values only for all elements in cluster)	low value (one bottom level value for all elements in cluster)	very scattered values	very scattered values	average value (one shape value for all elements in cluster)	average value (two values only for all elements in cluster)

2	highest value (one risser value for all elements in clusters)	low values (very scattered values)	very scattered values	very scattered values	very scattered values	highest value (one shape value for all elements in cluster)	above average values (scattered values)
3	more high values (less scattered)	highest values (less scattered)	high values (less scattered)	low values (scattered values)	low values (scattered values)	lowest value (one shape value for all elements in cluster)	lowest value (less scattered)

❖ **Time series across 4 clusters for spine data**

To understand the spread of pain values in the interval (0hrs , 192 hrs), we visualised pain trends for each cluster. We did two charts for following reasons:

1. Time Trend Line Chart of Average Normalised Pain scores:

   This chart helps us see the trend of pain for a particular cluster over a period of time. It also helps us identify the peak interval and low interval of pain for that cluster. (Appendix 4 Section 4 (c))

2. Box Plot Chart of Normalised Pain Score:

   This chart helps us understand the spread of values for all patients in the cluster for a particular hour interval. It also helps us identify outliers in each interval of hours. (Appendix 4 Section 4 (d))

❖ **Overall inference:**

- There were multiple outliers in pain data for cluster 0 and 1, this could be due to the fact that the features were not as indicative of the clusters. The pain trends were generally downward sloping but seemed random
- Cluster 2 was the most indicative cluster as the pain data showed a general increasing trend. This could be explained by the data having the heaviest and oldest patients and this could be flags for hospitals. There were no outliers in the box plots of the pain data and the features seemed to represent the group rather well. It was also interesting to note that cluster 2 had the heaviest concentration of patients who had surgery before. The average “starting pain” was the lowest. The patients could be used to the pain at first and did not expect much pain at first but because of their age/weight the pain gradually increased
- Cluster 3 had only one outlier in the boxplot. It also had the most number of individuals that have not had prior surgery. The average “beginning pain” was

the highest which suggests these patients who have not had prior surgery experienced the most pain in the beginning and gradually adapted to it

CLUSTERING ANALYSIS FOR CHEST PATIENTS

Similar to what we did with spine surgery patient, we decided to cluster chest surgery patients in order to gauge the pain trends over time and evaluate if we could segregate the patients into distinct groups on the basis of the features that were provided. Refer to Appendix 5 Section 5 (a) for the clustering analysis modeling details.

- **Visualization and Inferences from the four clusters for Chest**

  We again used Parallel Coordinate Plot to plot such data (Appendix 5 Section 5 (b)).

  Visualisation: Parallel coordinate plots across all features for 4 clusters

  Name of features: Grouping, Genetics, Patient Age, Patient Weight, Patient Race, Gender , Haller Index, Surgery HX

  Inference:

Cluster/Feature	Gender	Age	Weight	Race
0	All Males	Ages in middle	Weights in middle	More white
1(outlier)	Male	151 Months	44.4	Mixed race
2	All Male	Oldest patients	Heaviest patients	More white
3	Half Half	Youngest patients	Lightest patients	Half white half non white

- **Time series across 4 clusters for chest data**

  As done for Spine data, we tried to visualize trends for chest data in the interval (0hrs , 192 hrs) using time Trend Line Charts of Average Normalised Pain scores(Appendix 5 Section 5 (c)) and Box Plots of Normalised Pain Score (Appendix 5 Section 5 (d)).

- **Overall Inference:**
  - The trends of pain level of the heaviest group and the lightest group during the first 24 hours are exactly the opposite. The pain level of patients with larger weights decreased significantly during the first 24 hours whereas the pain level for the lighter patients increased a lot. Overall, the average pain level for cluster 1 patients is the highest among the three groups. This is very interesting because cluster 1 patients are in the middle range of age and

weight, meaning they were expected to have a middle ranged pain score as well. However, the result is counterintuitive

- Furthermore, the normalized pain score score for cluster 3 and 4 are quite close to zero. Cluster 4 patients' pain scores show a general decreasing trend, which aligns with our initial assumption since they are the youngest and lightest among all groups. More data and variables are needed here to draw further conclusions

RELATIONSHIP BETWEEN TOTAL MORPHINE EQUIVALENCE AND PATIENTS' PERCEIVED PAIN LEVELS

The initial expectation was that perceived pain before surgery could be correlated to amount of pain or painkillers needed. We started our analysis by plotting a scatter diagram for Average Actual Morphine equivalent taken and Patient's predicted pain for both groups of patients undergoing - Spine and Chest Surgery. The scatter plots are illustrated in Appendix 6 Section 6 (a).

As it is seen in the scatterplots, there is no trend between Average Actual Morphine equivalent taken and Patient's predicted pain for Spine Surgery or for Chest Surgery. Looking at the correlation values, we see that the correlation for Spine surgery patients is 0.09 and for Chest surgery patients, its 0.52 with the p-value > 0.1 for both. So the correlations were not statistically significant.

Next we looked at the relationship between the amount of painkillers taken and the actual pain values experienced. To analyse this, we grouped our morphine equivalents in two main categories: Main Drugs and Other Drugs.

Main drugs: Morphine, Dilaudid, Fentanyl

Other drugs: Supplemental opioids, NSAID(oral/IV), Acetaminophen(no/oral/IV), Epidural/OnQ, Other meds (methocarbamol, diazepam, neurontin, klonopin, clonidine)

All categories of drugs were combined into one "morphine equivalence", so that we could take a look at the total morphine equivalence from main drugs and other drugs and how it related to the pain level.

Appendix 6 Section 6 (b) illustrates the Pain level vs the morphine equivalent administered for patients 560 and 550. As we can see that these patients demonstrate higher pain levels when less dose of morphine equivalents was administered and lower pain levels when higher doses are administered. Looking at the plots for patients 556 and 522 (Appendix 6 Section 6 (c)), we see that these patients experienced sudden drop in their pain levels when a high dosage of morphine equivalent is administered. Although we see certain expected trends when we look at individual patients, we did not observe a common trend. Furthermore, the treatment for each patient was specific in terms of the drug or the group of drugs administered with minimum overlap with other patients. Hence, it was difficult to measure the ROI on individual drugs. In order for us to effectively determine the returns for specific drugs or drug groups, we recommend conducting test and control experiments.

REGRESSION ANALYSIS

For our final analysis, we decided to look at whether we could derive any relationship between the various attributes and the absolute (VAS normalized) pain scores through multiple linear regression. We looked at what are the factors that most significantly impacted average pain scores for each interval: 0-24 hrs and 0-72 hrs. We were also curious to see if significant factors changes in the period 0-24 hrs vs 0-72 hrs, in respect to understanding factors which affect pain immediately(0-24 hrs) and factors which affect overall in 72 hrs. Therefore, we fit a full model using all the response variables and ran a backward subset regression minimizing AIC to arrive at the most significant variables. As done for other analyses, we looked at spine and chest data separately. A level of 10% was chosen as the level of significance as the dataset is small.

Refer to Appendix 7 for the regression analysis results.

Spine Surgery Patients Analysis

It is interesting to note that the pain a patient experiences depends on Genetics (whether enrolled in genetics testing), Top Level, Bottom Level and SurgeryHX both immediately (first 24 hours) and in the 3 day duration post operation (0-72 hrs). In contrast, ASA and Complementary Therapy are significant for 0-72 hrs but not for 0-24 hrs.

For 0-24 hrs, the pain that a patient experiences is affected by whether the patient has had prior therapy. A complementary therapy has shown reduce the pain experienced by the patients with guided imagery and massage being the most effective amongst the three therapies provided. Surprisingly, the ASA rating for the surgeon also significantly impacts the pain observed by the patient, with higher ASA ratings corresponding to higher pain scores during the first 24 hours. For 0-72 hours, we see that whether the patient is enrolled in genetics testing or not impacts the pain experienced by the patient in a positive way. Top level has a negative coefficient and bottom level has a positive coefficient. This implies that a surgery in upper back is less painful than a surgery in lower back. Furthermore, observed pain is also more if the number of levels of spine involved in the surgery are higher, which makes sense. Finally, if the patient predicted a higher pain score, it is more likely that the patient experienced lower amount of pains post operation.

Chest Surgery Analysis

Similar to spine surgery, different set for variables are significant for the mean pain experienced in the first 24 hrs vs the first 72 hrs post surgery. For the first 24 hrs post Operation, patient gender, age and race significantly impact the pain experienced by the patient. Furthermore, it is seen that massage greatly reduces the pain. Looking at overall 0-72 hrs pain levels, only patient age (higher age => higher pain experienced) and whether the patient has had surgery or not (lower pain scores for patients having had prior surgeries) significantly impact the pain experienced by the patient.

The overall variables that come out to be significant in our regression analysis overlap with what we saw from the clustering analysis.

CONCLUSION AND ROI

Although detailed takeaways are presented in the individual analysis sections, we would like to highlight a few points:

1. For spine surgeries, Age is a great category to categories patients. Therefore incoming patients could be divided in groups and care strategies could be established based on their age. For instance, the older children(~18 years) experience highest pain so prior medication or treatment to reduce their pain could be strategized
2. For spine surgeries, on an average, most patients experience peak pain in 61- 72 hours and high pain in neighboring interval to it (49- 60 hrs and 73 - 84 hrs) . Hence, the hospital can make arrangements for a better experience for patients though providing post-operative therapies or other post-operative care during this period
3. Similarly, for chest surgery the first 24 hours are the most crucial and reported with highest pain. Therefore, similar steps can be taken to ease patients' pain
4. There is no relationship between perceived pain by patient and total morphine equivalence. There is also no visible relation between the morphine equivalents administered vs the actual pain experienced by the patient. Each and every patient shows a unique trend, and the need of the hour is to invest in researching and developing patient-centric treatments which are tailored to individual patients' needs
5. Therapy has an effect on Pain during the first 24 hours and significantly reduces pain between 24 - 72 hrs. The hospital could use this information and prescribe therapy to patients. They could also provide complementary therapy as one of their services. As pointed out, the effect of this would be significant and the marginal returns due to customer retention could be higher even with additional therapy costs

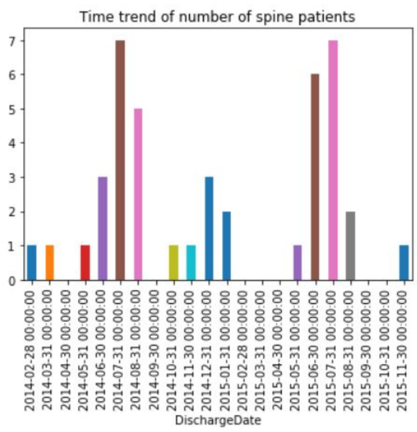
Appendix

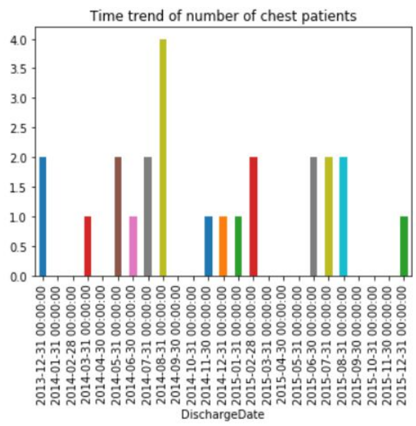
- **Appendix 1: Data Cleaning and Exploratory Data Analysis**
- **Appendix 2: Surgery History vs. Pain Levels**
- **Appendix 3: Patient Predictive vs Pain Level**
- **Appendix 4: Spine Data Clustering Visualization**
- **Appendix 5: Chest Data Clustering Visualization**
- **Appendix 6: Morphine Equivalent Visualization**
- **Appendix 7: Regression Analysis Details**

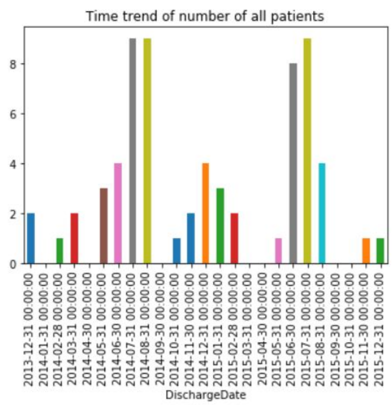
Appendix 1 : Data Cleaning and Exploratory Data Analysis

- **Section 1 (a): Data Cleaning**
  - Records for patients 513, 515, 544 and 547 were removed from analyses either due to Surgery cancelled and too few data points
  - For each patient, the intermediary missing pain values were imputed by taking the pain value for the previous 12 hrs window
  - Missing fields for patient 534, who underwent a spine surgery, were imputed using the median values of all other patients undergoing spine surgery
  - Missing values of Risser, Shape, and Bottom degree were imputed with the median for these fields for the spine patients

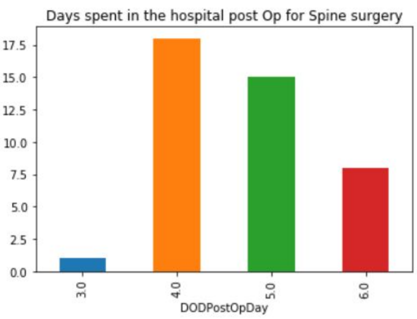
- **Section 1 (b): Timeline of Discharge Dates and Discharge Numbers**

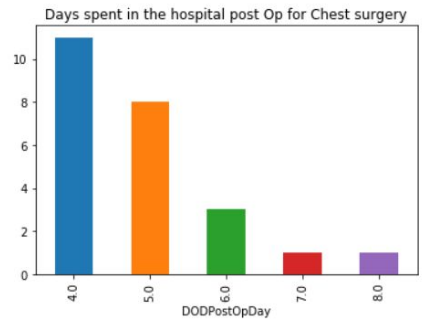


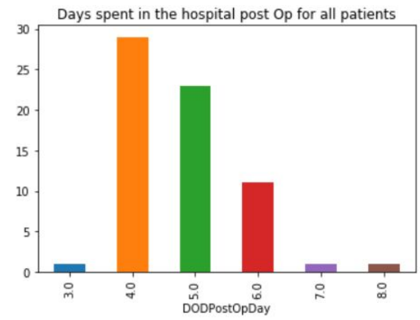




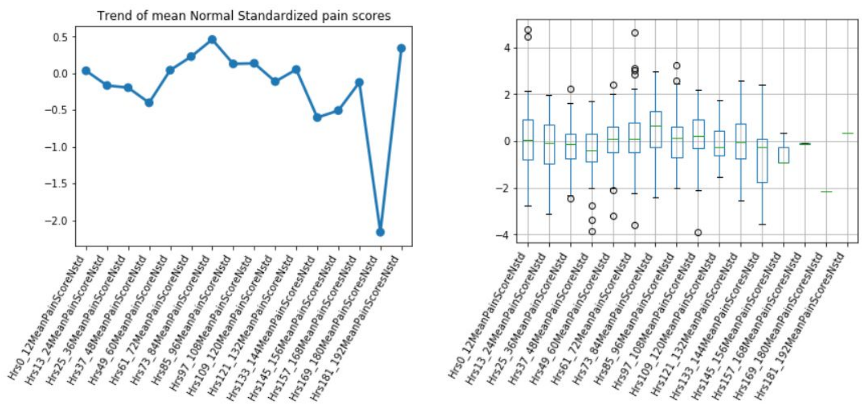
- **Section 1 (c): Days spent in hospital post-Operation**



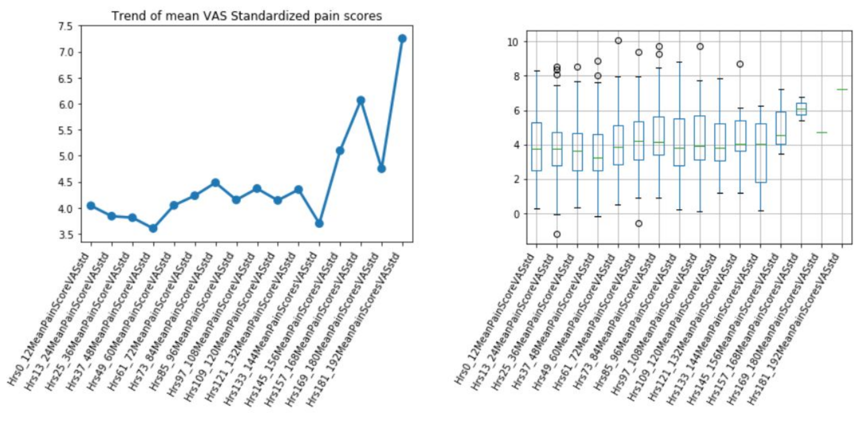




- **Section 1 (d): Trend Charts of standardized pain scores**



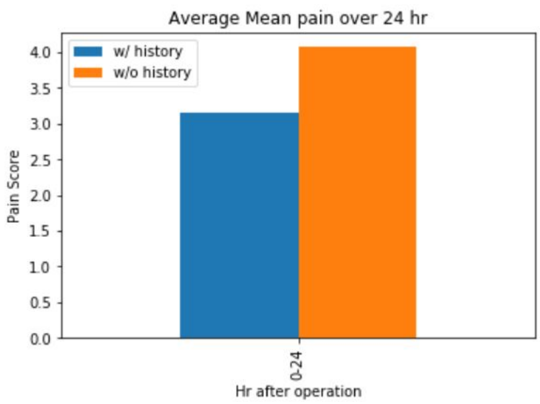
Mean Standardized

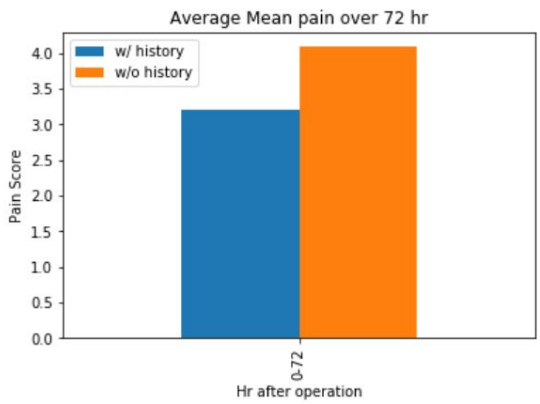


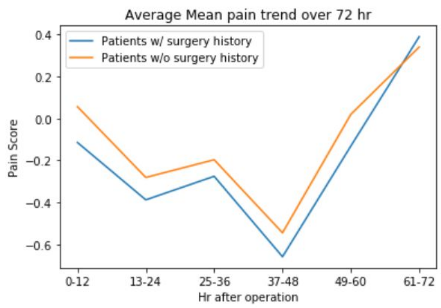
VAS Standardized

Appendix 2: Surgery History vs. Pain Levels

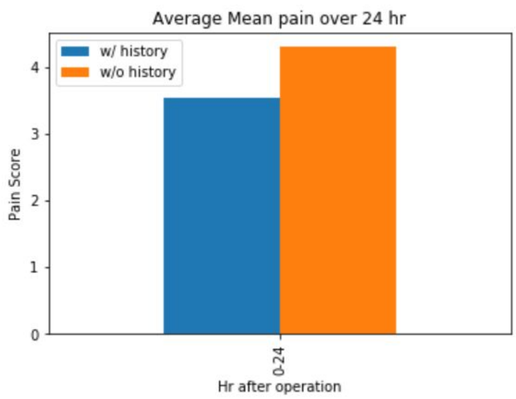
- ### Section 2 (a) Spine Surgery Patients

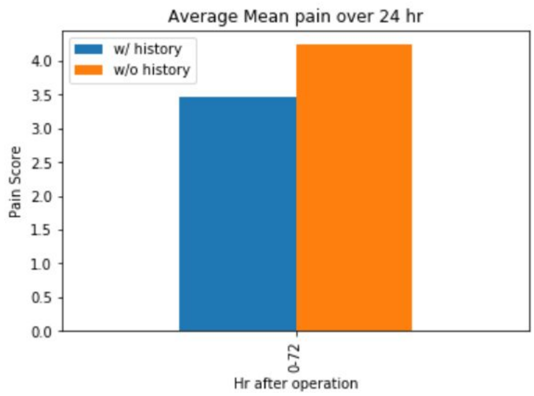


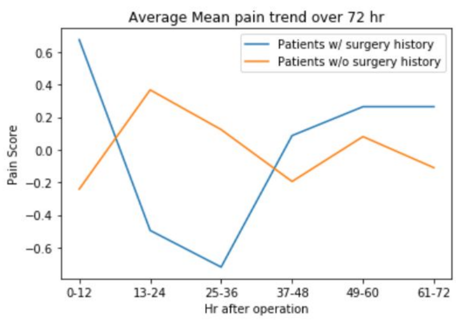




- ### Section 2 (b) Chest Surgery Patients

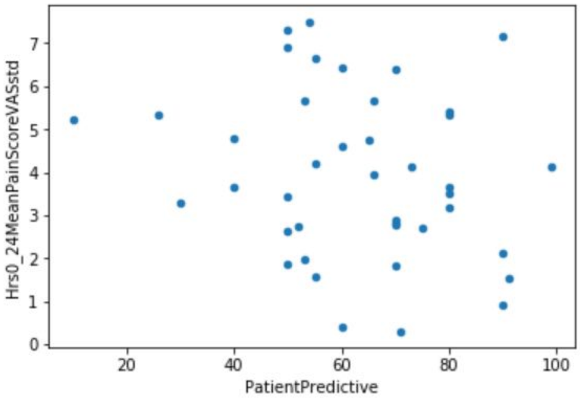




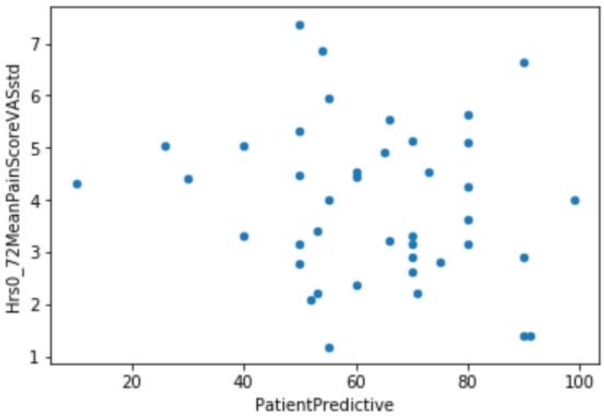


Appendix 3: Patient Predictive vs Pain Level

- **Section 3 (a): Average 24 hrs mean pain scores vs predicted pain scores for Spine surgery patients**



- **Section 3 (b): Average 24 hrs mean pain scores vs predicted pain scores for**



Appendix 4: Spine Data Clustering Visualization

Section 4 (a): Clustering Modeling details

Selection of K for K mean Clustering

Patient pain information was filtered out such that a data frame was extracted that included a patient's demographic information and spine surgery information. The number of descriptive features also meant that it was difficult to visualize the resulting clusters therefore a subset of features were used for clustering.

By an arbitrary choice of k = 3 and k = 5, we clustered our selected features and visualised it with age on the y-axis and weight on the x-axis. The plots are illustrated below.

No of features used for clustering: 16

Name of features: Grouping, Patient Age, Patient Weight, Patient Race, Risser, Top level, Bottom level, no of levels, Shape, Top degree, Bottom degree, Surgery HX, Top level categories, Bottom level categories.

PCA Dimensionality Reduction for Visualisation: To solve the problem of added dimensionality above, Principal Component Analysis was run on the feature data set to reduce the 16 features into eigenvectors and eigenvalues that are better visualized. This also tends to lead to more accurate labeling.

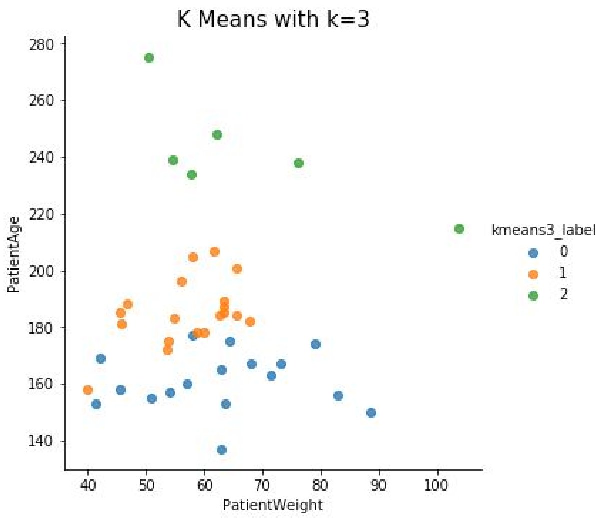
Comparing the two clusters, we see that:

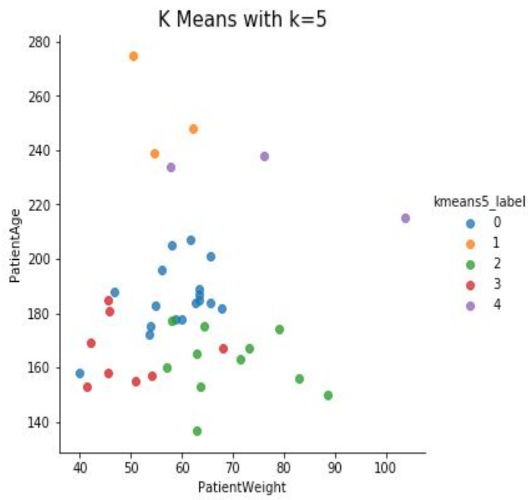
- For cluster with size = 3, we see a pattern of separation, with large variation in cluster 2 (green)
- For cluster with size = 5, we see overlap with a not very clear pattern of separation

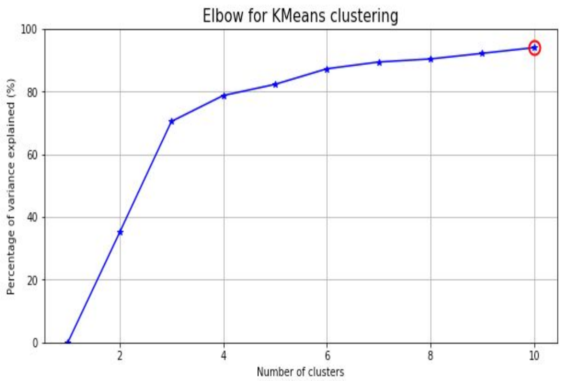
We were still not convinced with our cluster split. Therefore**,** we used the elbow method to visualize the optimum number of clusters that would explain up to 80% of variance. We concluded that 4 clusters explain up to approximately 80% of the variance.

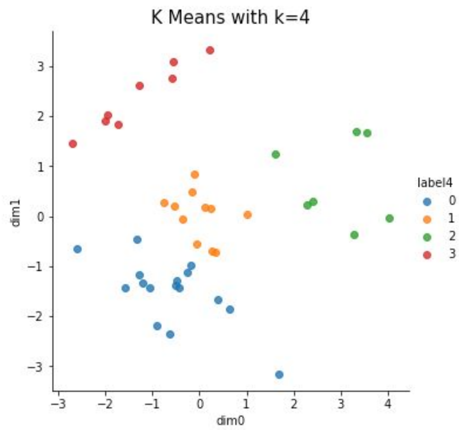
As K= 4 seemed the most optimum, we did K means with k=4. The elbow and the k-means chart for k = 4 are illustrated below.

Conclusion: K = 4 is the optimum choice

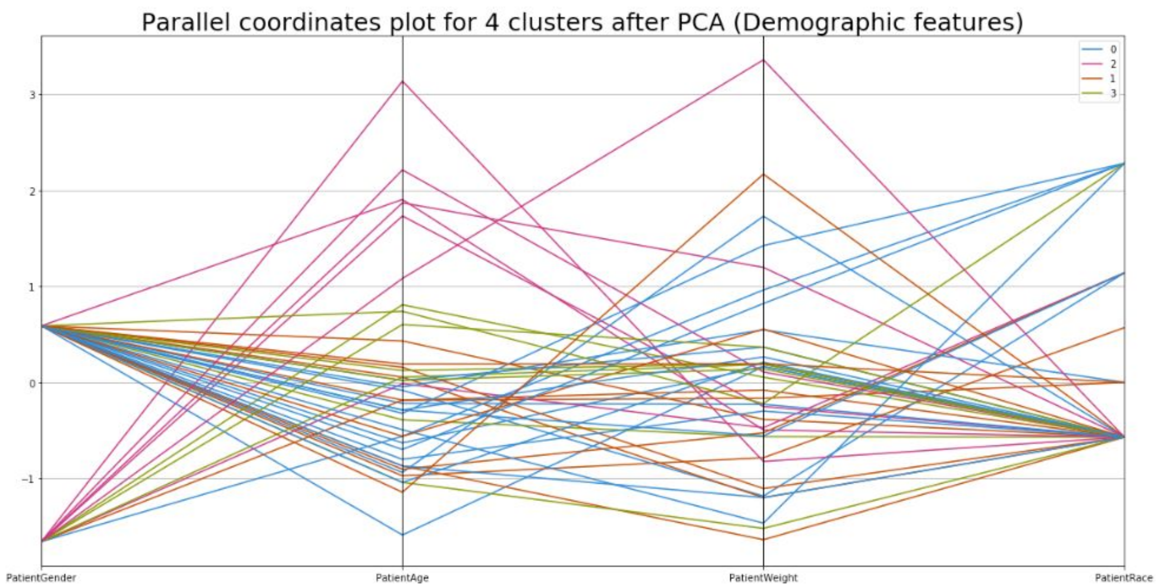


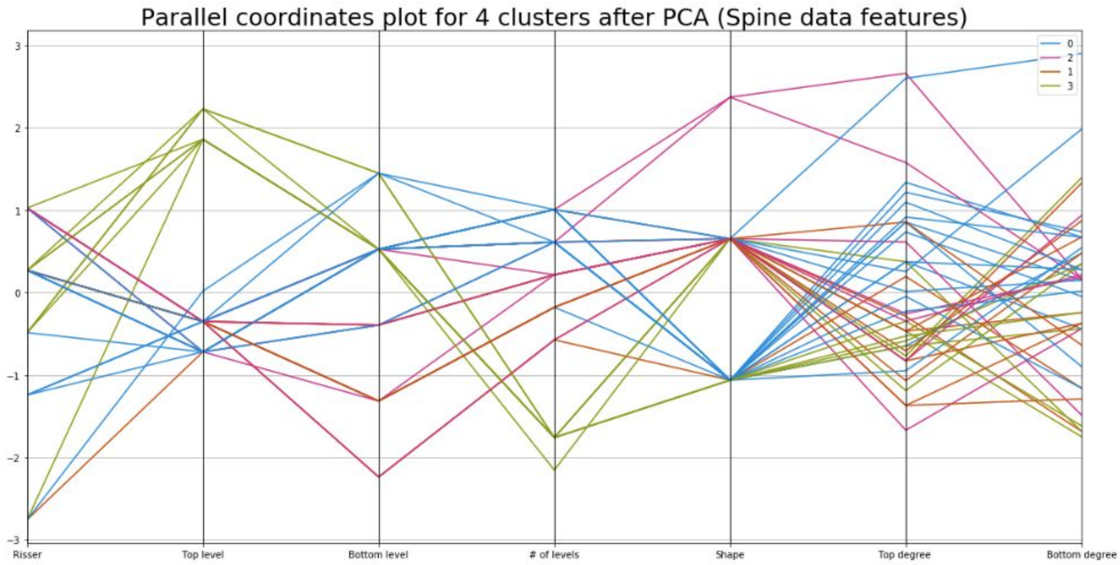




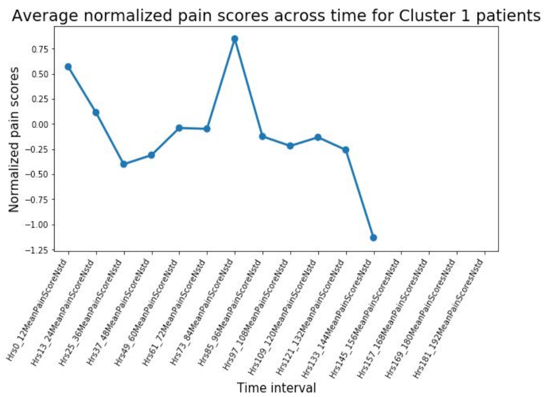


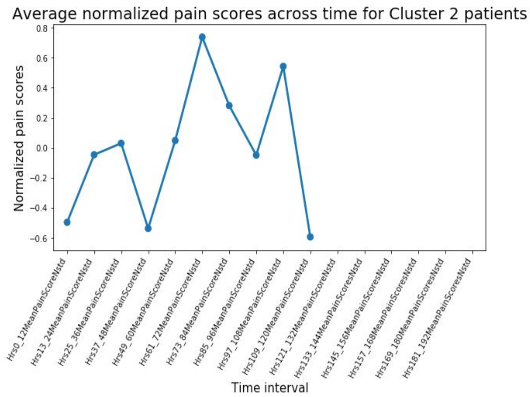
Section 4 (b): Parallel Plots for k = 4

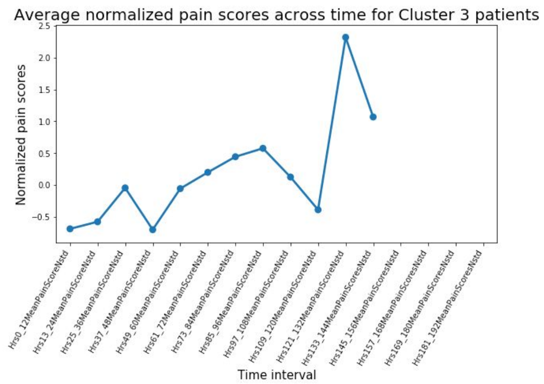


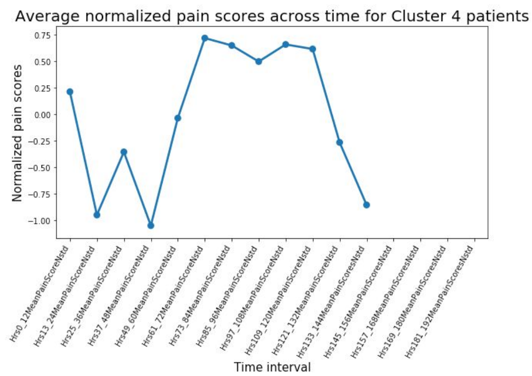


Section 4 (c): Time Trends for the clusters

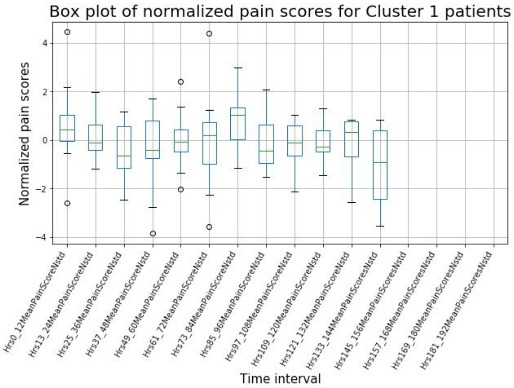


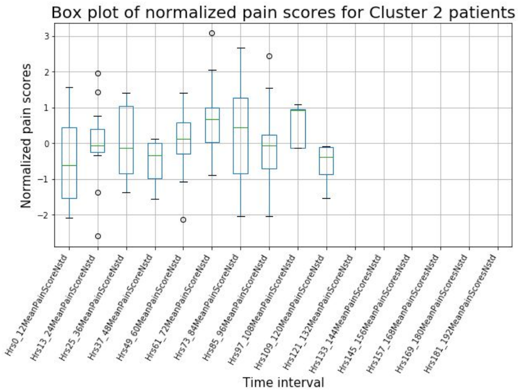


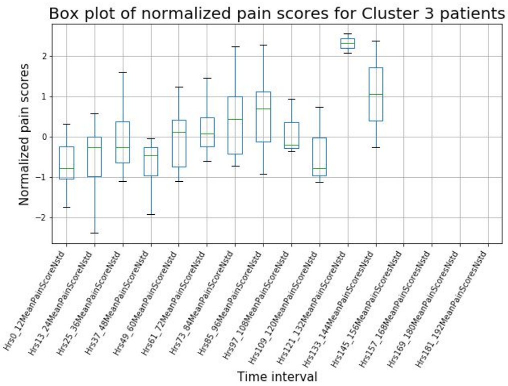


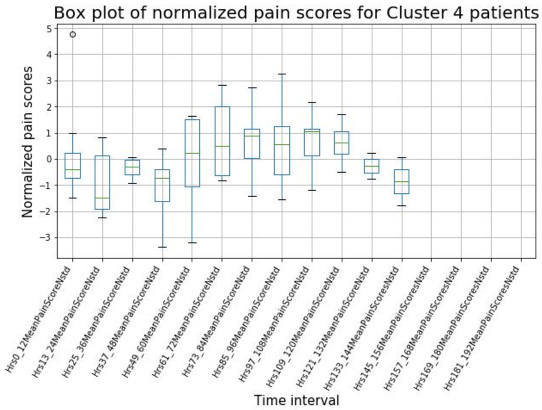


Section 4 (d): Box Plots for the clusters









Appendix 5: Chest Data Clustering Visualization

Section 5 (a): Clustering Modeling details

Selection of K for K mean Clustering

Patient pain information was filtered out from the original dataset and contained patient's demographic information and chest surgery related information.

By an arbitrary choice of k = 3 and k = 5, we clustered our selected features and visualised it as follows with age on the y-axis and weight on the x-axis. The plots are illustrated below.

No of features used for clustering: 8

Name of features: Grouping, Genetics, Patient Age, Patient Weight, Patient Race, Gender , Haller Index, Surgery HX

PCA Dimensionality Reduction for Visualisation: To solve the problem of added dimensionality above, Principal Component Analysis was run on the feature data set to reduce the 8 features into eigenvectors and eigenvalues that are better visualized. This also tends to lead to more accurate labeling.

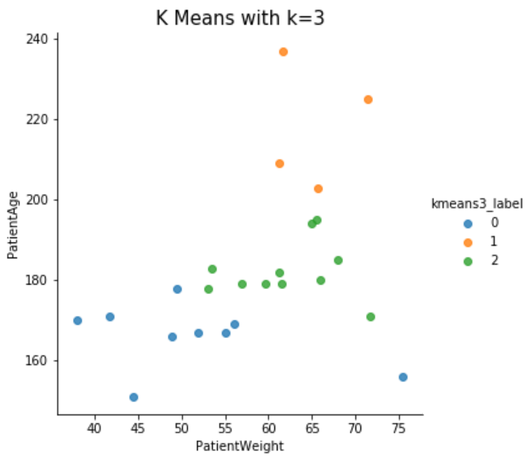
From the two plots below,

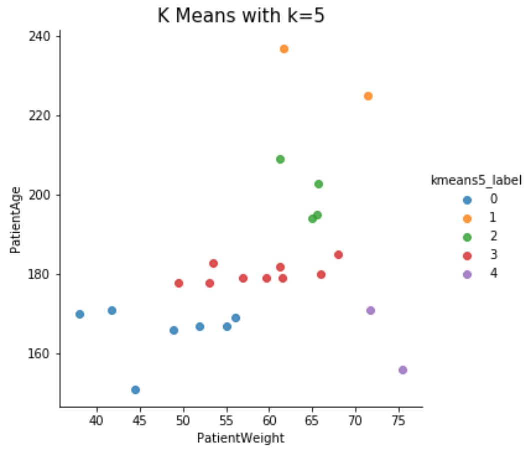
- We can see that although there are clear clustering with both choice of K, due to the limited number of observation in the dataset, group 1 and group 5 within the 5 clusters only has two patients.
- Therefore, between k= 3 and k=5, we think 3 clusters would be a better choice.

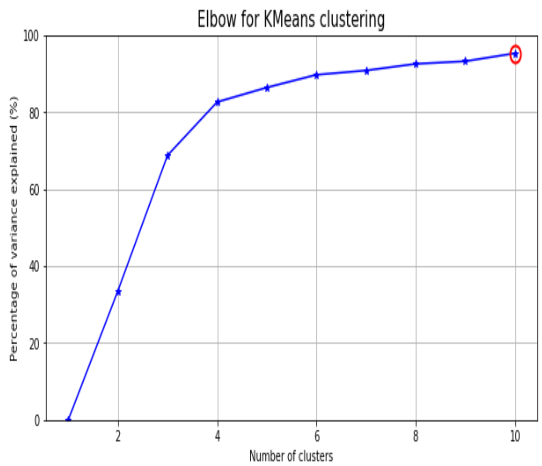
We were still not convinced with our cluster split. Therefore**,** we used the elbow method to visualize the optimum number of clusters that would explain up to 80% of variance. We concluded that 4 clusters explain up to approximately 80% of the variance.

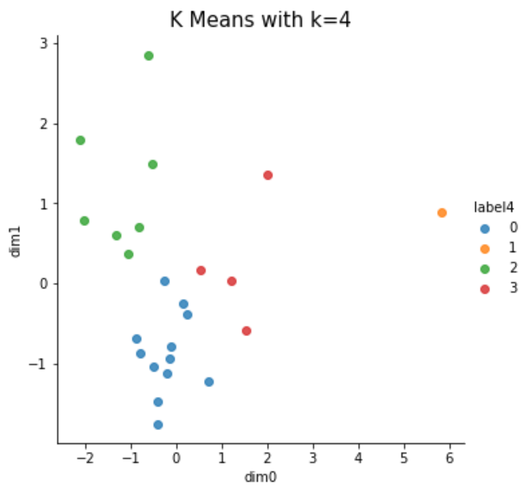
As K= 4 seemed the most optimum, we did K means with k=4. The elbow and the k-means chart for k = 4 are illustrated below.

Conclusion: K = 4 is the optimum choice. Also, Group 1 only had one patient. It was looked further into and this is the only patients who did not take genetic testing. Therefore, we think it is ideal to treat it as an outlier.

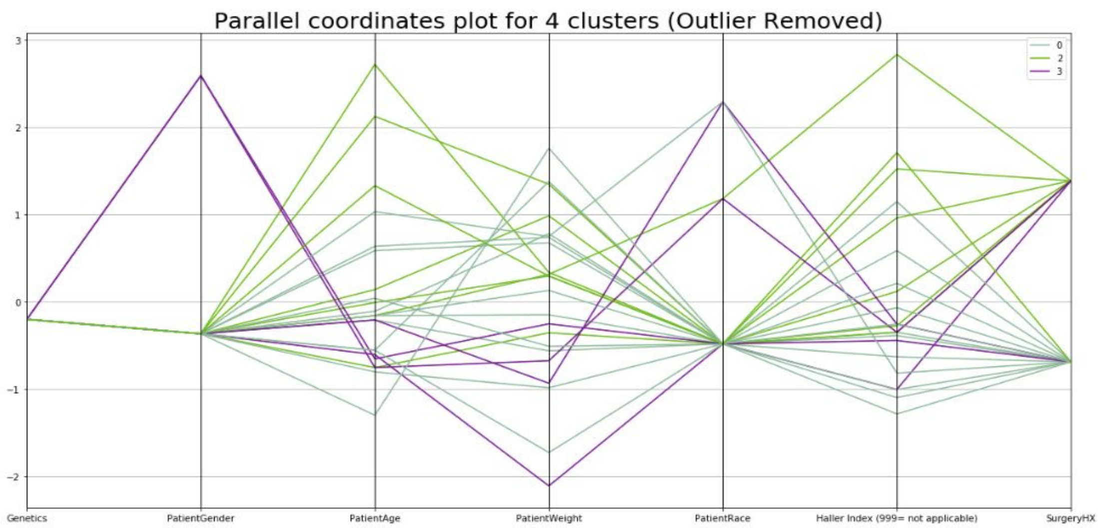




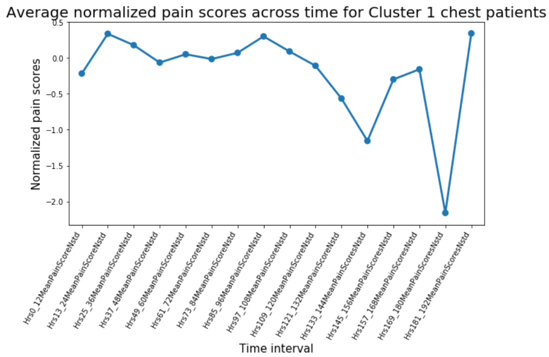


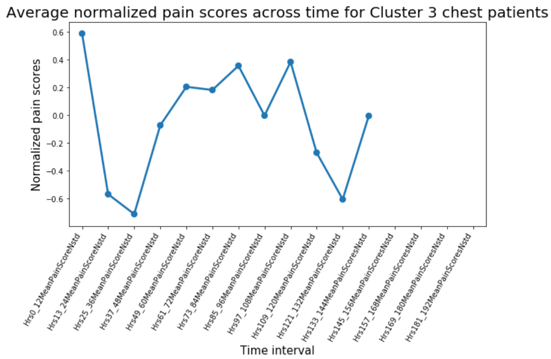


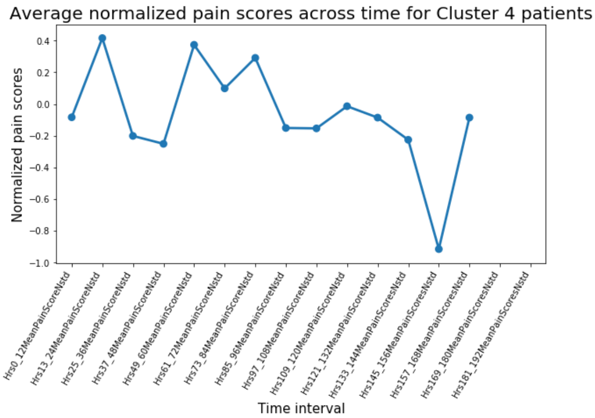
Section 5 (b): Parallel Plots for k = 4



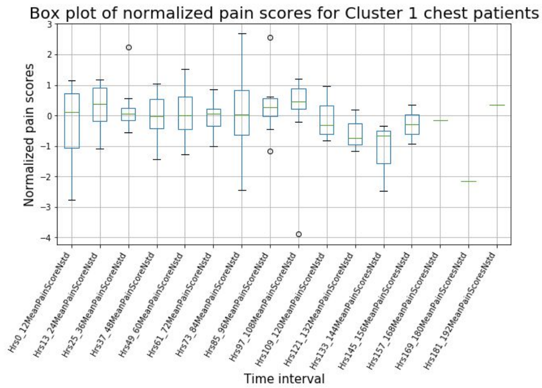
Section 5 (c): Time Trends for the clusters

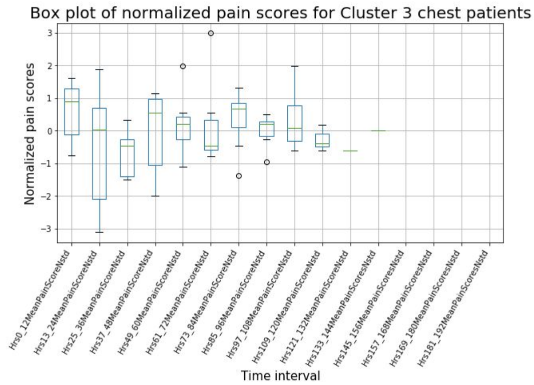


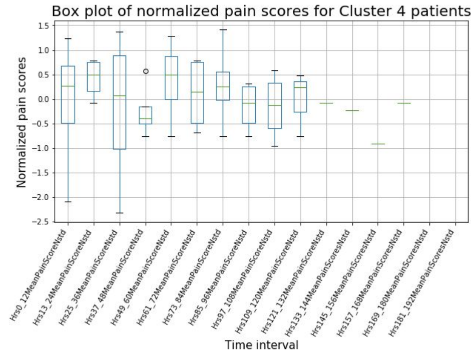




Section 5 (d): Box Plots for the clusters

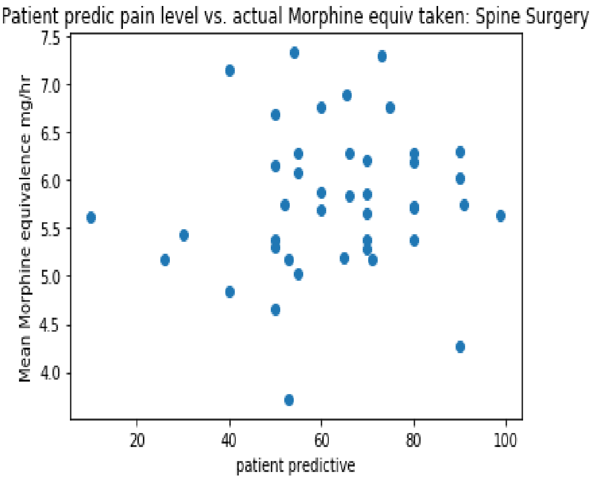


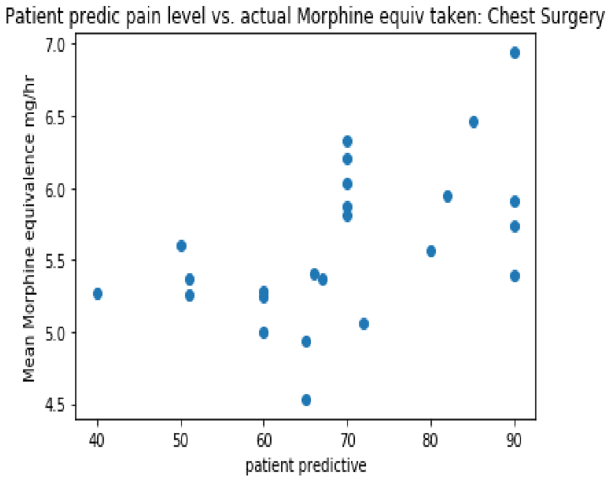




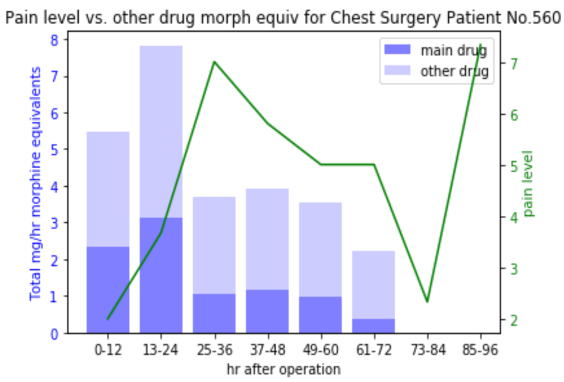
Appendix 6: Morphine Equivalent Visualization

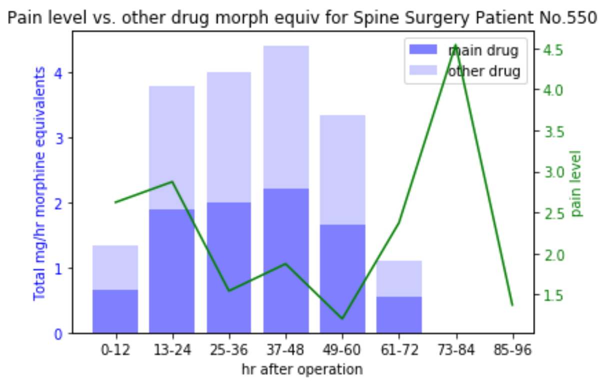
Section 6 (a): Scatterplots for Patient Predictive pain and mean morphine equivalents administered



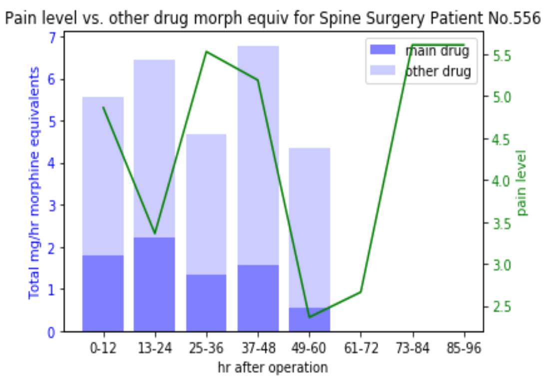


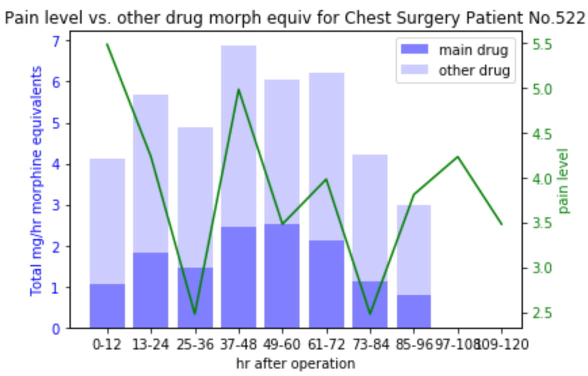
Section 6 (b): Morphine Equivalent administered vs Pain experienced (Trend 1)





Section 6 (c): Morphine Equivalent administered vs Pain experienced (Trend 2)





Appendix 7: Regression Analysis Details

Section 7(a): Regression Results for Spine Surgery patients

```
Call:
lm(formula = postOp0_24Hrs ~ Genetics + Toplevel + Bottomlevel +
    SurgeryHX + ParentPredictive, data = spine)

Residuals:
    Min      1Q  Median      3Q     Max
-2.7991 -0.9493  0.0462  1.0478  3.9094

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -2.91414    5.64175  -0.517   0.6087
Genetics          1.98676    0.94054   2.112   0.0419 *
Toplevel         -0.21045    0.11012  -1.911   0.0642 .
Bottomlevel       0.52223    0.27409   1.905   0.0650 .
SurgeryHX        -1.35921    0.70963  -1.915   0.0636 .
ParentPredictive -0.02454    0.01547  -1.586   0.1216
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.773 on 35 degrees of freedom
Multiple R-squared:  0.287,     Adjusted R-squared:  0.1852
F-statistic: 2.818 on 5 and 35 DF,  p-value: 0.03059
```

0-24 hrs

```
Call:
lm(formula = postOp0_72Hrs ~ Genetics + Toplevel + Bottomlevel +
    SurgeryHX + ASA + as.factor(ComplementaryTherapy) + ParentPredictive,
    data = spine)

Residuals:
    Min      1Q  Median      3Q     Max
-1.9554 -0.8784  0.2261  0.6431  2.3400

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                      -2.94677    4.62660  -0.637  0.52871
Genetics                          1.22579    0.66586   1.841  0.07492 .
Toplevel                         -0.19935    0.08018  -2.486  0.01832 *
Bottomlevel                       0.47246    0.21676   2.180  0.03676 *
SurgeryHX                        -1.45316    0.51272  -2.834  0.00789 **
ASA                               0.86065    0.38649   2.227  0.03312 *
as.factor(ComplementaryTherapy)2 -1.17811    0.65056  -1.811  0.07955 .
as.factor(ComplementaryTherapy)3 -2.66453    1.28543  -2.073  0.04632 *
ParentPredictive                 -0.02676    0.01102  -2.427  0.02103 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.232 on 32 degrees of freedom
Multiple R-squared:  0.4412,    Adjusted R-squared:  0.3015
F-statistic: 3.158 on 8 and 32 DF,  p-value: 0.009453
```

0-72 hrs

Section 7(b): Regression Results for Chest Surgery patients

```
Call:
lm(formula = postOp0_24Hrs ~ PatientGender + PatientAge + as.factor(PatientRace) +
    as.factor(ComplementaryTherapy), data = chest)

Residuals:
     Min       1Q   Median       3Q      Max
-1.74095 -0.54573 -0.01069  0.37330  2.80010

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                      -4.38083    3.19037  -1.373  0.18865
PatientGender                     1.94971    0.96328   2.024  0.06000 .
PatientAge                        0.04997    0.01603   3.118  0.00662 **
as.factor(PatientRace)4          -2.47622    1.04277  -2.375  0.03041 *
as.factor(PatientRace)6          -1.58290    0.85159  -1.859  0.08155 .
as.factor(ComplementaryTherapy)1 -0.54880    0.82727  -0.663  0.51653
as.factor(ComplementaryTherapy)2 -4.01722    1.53802  -2.612  0.01888 *
as.factor(ComplementaryTherapy)3  0.69315    1.26413   0.548  0.59104
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.28 on 16 degrees of freedom
Multiple R-squared:  0.6651,    Adjusted R-squared:  0.5186
F-statistic: 4.539 on 7 and 16 DF,  p-value: 0.005835
```

0-24 hrs

```
Call:
lm(formula = postOp0_72Hrs ~ PatientAge + SurgeryHX, data = chest)

Residuals:
    Min      1Q  Median      3Q     Max
-2.6110 -1.0007 -0.1668  0.9216  3.7019

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.99344    2.97570  -1.342   0.1939
PatientAge   0.04603    0.01649   2.791   0.0110 *
SurgeryHX   -1.24894    0.68978  -1.811   0.0845 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.546 on 21 degrees of freedom
Multiple R-squared:  0.3036,    Adjusted R-squared:  0.2373
F-statistic: 4.578 on 2 and 21 DF,  p-value: 0.02238
```

0-72 hrs

References

1. https://academic.oup.com/painmedicine/article/13/10/1284/1933008
2. http://anesthesiology.pubs.asahq.org/article.aspx?articleid=1944240