Unsupervised Wisdom Executive Summary, Mike Goldweber

Key Findings

There were several things that stood out. First, women were 66% of the injured. The majority of injuries occurred at home, and while the greatest number of diagnosed injuries were 'fractures' at 7K+. The single problem for both females and males were 'internal injuries' to the 'head' (17K total) (Table 1). Connect to the injuries is the single biggest product connection was to 'floor or flooring material'. Also, I discovered that there was a significant increase of ER visits in 2022, compared to the previous 3 years (Fig 1). Age, race, Hispanic surprisingly didn't have a significant impact on the distribution of injuries (Fig 3).

Summary of Project Approach

I decided early on there would be benefits to thorough data exploration. As a result, I decided to solely use on the primary dataset provide by the contest. My thought was that the categorical information would provide context for the falling injuries, which the narrative would provide insights into the reasons behind the falls. As a result, I looked at each column individually, followed by looking at combinations of the columns to find the combination(s) of categories from the key columns that would expose the problem. Admittedly, the approach was tedious and requires some patience; but by identifying the main factors behind the injuries, I believe an approach could be developed for mitigating these injuries across the elderly population.

One interesting approach to this project was the use of SQL on the dataset to explore these combinations of data categories. I believe the data exploration was enhanced, and it allowed me to find the biggest category combinations behind the injuries. For example, the mosaic plot shown in Figure 2 demonstrates the combination of the sex, diagnosis, location, and body part features of the dataset.

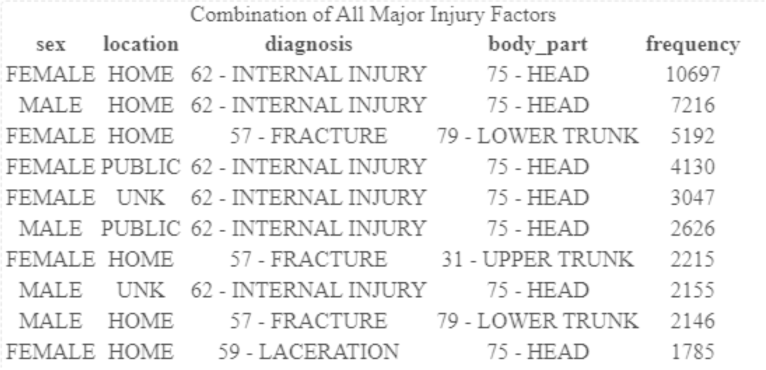
One problem was the significant number of unknown and unstated items in many of the data's features. This made it difficult to be certain that race and ethnicity was not a part of this problem, and it presents uncertainty with the location. I firmly believe many of the unknowns in the location column are home injuries, so I am sticking with this as a focus to any solution.

I used a *Partitioning Around Medoid* model because it works with a mix of continuous and categorical data[1]. The model's results I believe confirm what was discovered in the exploration. First, I split the set into two groups, one that covers 2019-2021, the second covers 2022. Initially this was due to model size limitations (max set of 65K). However, this was an unexpected opportunity to see if some insights into the higher injury counts could be discovered. The 2019-2021 PAM model shows a lot of similarities between the clusters (Table 2), and a distribution of the injuries and location. However, the 2022 PAM model shows one major cluster dominating this portion of the dataset. I was surprised to see that neither model focused on the injuries or location. In both sets, cluster 1 was heavy with the fracture and internal injuries.

A major limitation of my analysis is the failure to get aid from an LLM to analyze the narrative data. This was due to technical problems, rather than ignoring this aspect of the project.

[1] Preud'homme, G., Duarte, K., Dalleau, K. *et al.* Head-to-head comparison of clustering methods for heterogeneous data: a simulation-driven benchmark. *Sci Rep* **11**, 4202 (2021). https://doi.org/10.1038/s41598-021-83340-8

Data Exploration Visualization



Combination of All Major Injury Factors

sex	location	diagnosis	body_part	frequency
FEMALE	HOME	62 - INTERNAL INJURY	75 - HEAD	10697
MALE	HOME	62 - INTERNAL INJURY	75 - HEAD	7216
FEMALE	HOME	57 - FRACTURE	79 - LOWER TRUNK	5192
FEMALE	PUBLIC	62 - INTERNAL INJURY	75 - HEAD	4130
FEMALE	UNK	62 - INTERNAL INJURY	75 - HEAD	3047
MALE	PUBLIC	62 - INTERNAL INJURY	75 - HEAD	2626
FEMALE	HOME	57 - FRACTURE	31 - UPPER TRUNK	2215
MALE	UNK	62 - INTERNAL INJURY	75 - HEAD	2155
MALE	HOME	57 - FRACTURE	79 - LOWER TRUNK	2146
FEMALE	HOME	59 - LACERATION	75 - HEAD	1785

Table 1 - Showing the top 10 frequency of top injuries broken down by gender.

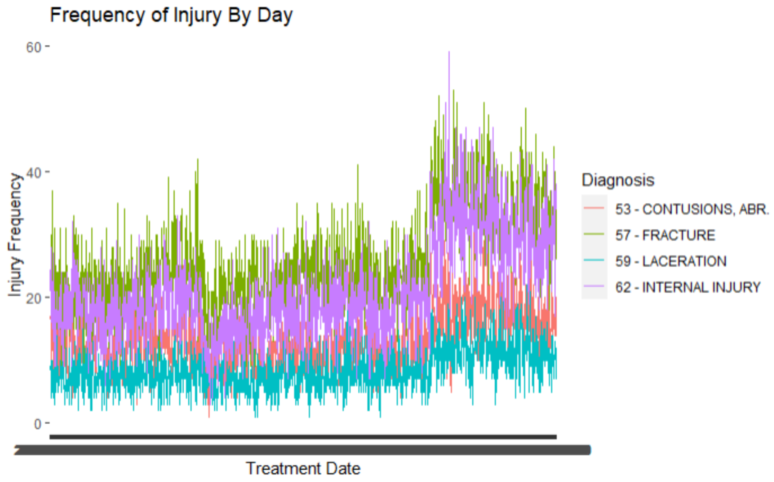


Figure 1 - Showing the frequency of injuries by day. Note the last quarter (2022) shows a major increase of daily injuries.

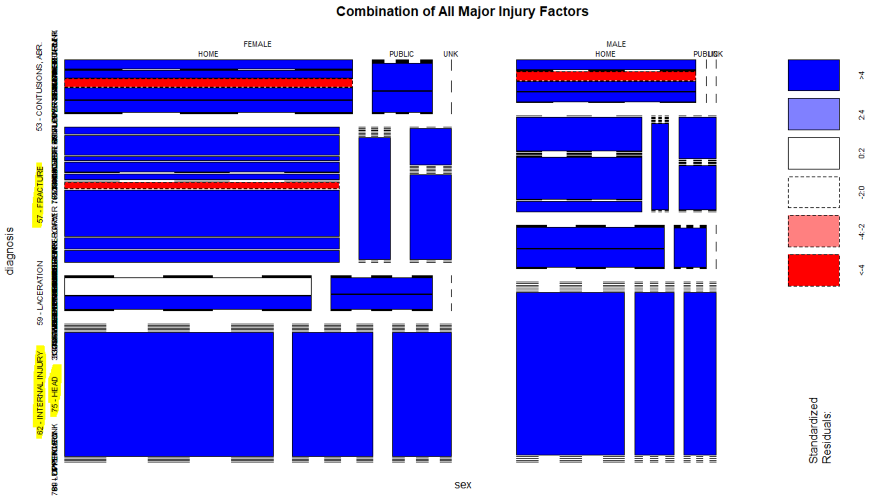
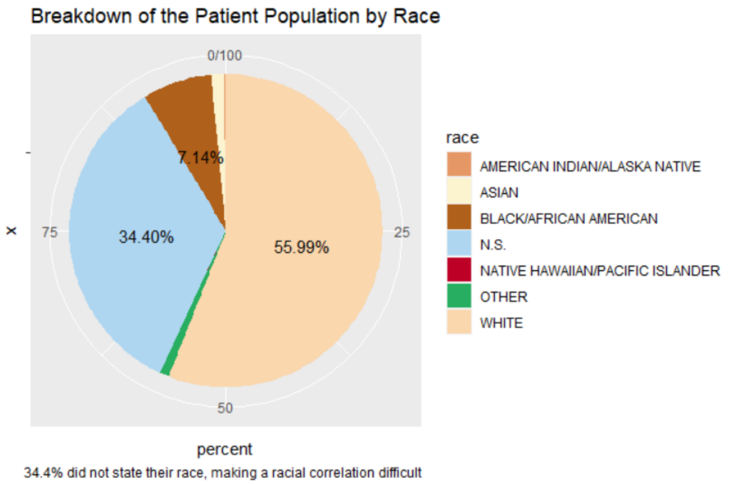


Figure 2 - This plot show all of the key elements of the data exploration brought together, sex, diagnosis, locations, and body parts.

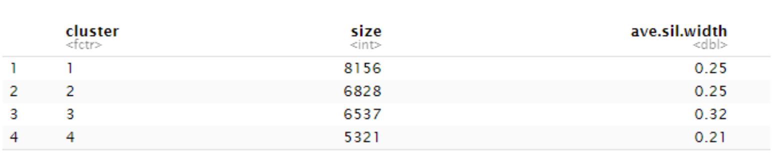


34.4% did not state their race, making a racial correlation difficult

Figure 3 - Breakdown of Pop by Race. N.S group spoils the possibity of being sure if race is a factor in the injuries.

Modeling Visualizations

2019-2021 On the left, 2022 model data on the right.



	cluster <fctr>	size <int>	ave.sil.width <dbl>
1	1	8156	0.25
2	2	6828	0.25
3	3	6537	0.32
4	4	5321	0.21

Table 3 - 2019-2021 Clusters

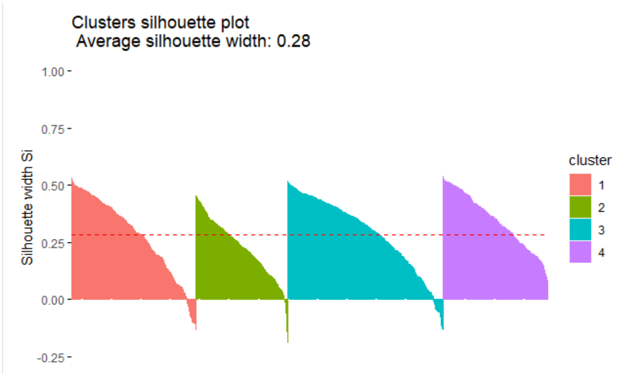


Figure 4 - 2019-2021 Clusters with sihouette of 0.28.

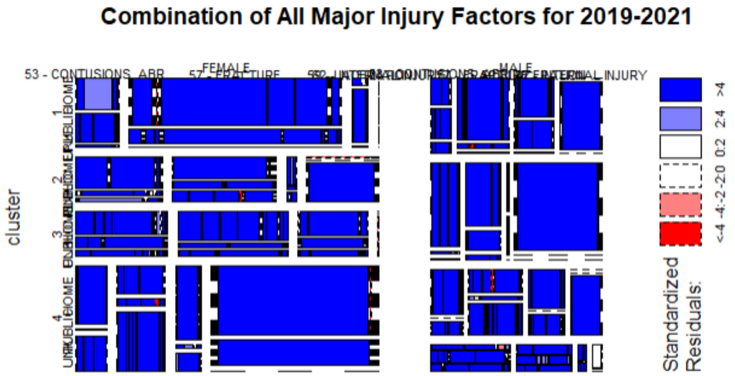
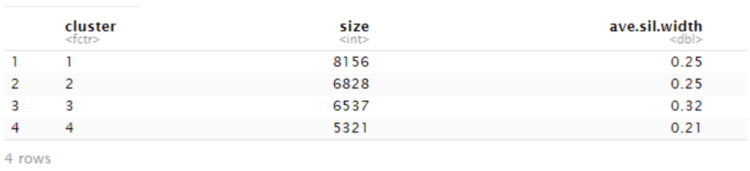


Figure 6 - Cluster and Injury factors from the PAM model for 2019 - 2021.



	cluster <fctr>	size <int>	ave.sil.width <dbl>
1	1	8156	0.25
2	2	6828	0.25
3	3	6537	0.32
4	4	5321	0.21

4 rows

Table 2 - 2022 Clusters

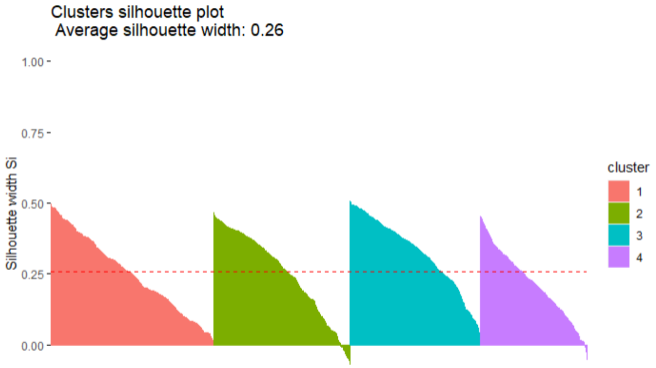


Figure 5 -2022 Clusters. Silhoutte of 0.26

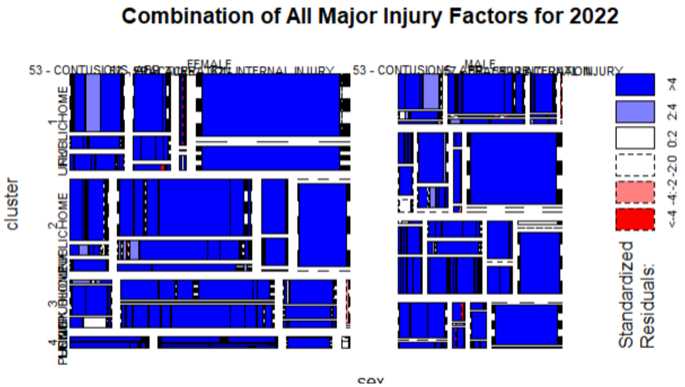


Figure 8 - Cluster and Injury factors from the PAM model for 2022.