Recommender System For Nursing Homes

By: Shafiur Chowdhury and Ashwin Verma

Project Code: https://github.com/Ashwin835/CIS-3715-Final-Project

Introduction

Healthcare is vital for the elderly and vulnerable, and nursing homes and skilled nursing facilities (SNFs) play a crucial role in providing long-term care. To improve the quality of care, it is important to examine the performance indicators of Medicare-certified SNFs and nursing homes. Inconsistencies in performance levels within the sector are a significant issue, and understanding the causes and key performance indicators (KPIs) is essential for improvement.

Several studies have evaluated the effectiveness of SNFs and nursing homes, focusing on aspects like patient outcomes, staffing ratios, and facility features. Higher nurse staffing levels are associated with better care quality, while nursing homes with more Medicaid residents have lower quality ratings due to limited resources. Infection control deficiencies are also common, emphasizing the need for better prevention practices.

This study aims to assess nursing home performance in specific care areas for Medicare-certified SNFs and nursing homes. It examined factors affecting care quality, using a large dataset of facility performance metrics to determine KPIs for comparison. A recommender system was developed, rating nursing home performance from 1-5 based on multiple factors. User-based, and item-based recommender methods were compared to find the best system, along with trying different preprocessing techniques to each system. Our recommender systems performance was evaluated using our own accuracy metric(discussed in the approach section further). After testing which model is the best fit for our data, we want to visualize various sample points that our system predicts correctly, all with different ratings given, to identify where higher rated homes are outperforming lower rated homes. We also want to conclude what are the most important features that can give any home a higher rating by our system. By analyzing features, we hope to conclude general features that lower rated nursing homes need to focus on improving, to get their ratings up and improve their quality for residents.

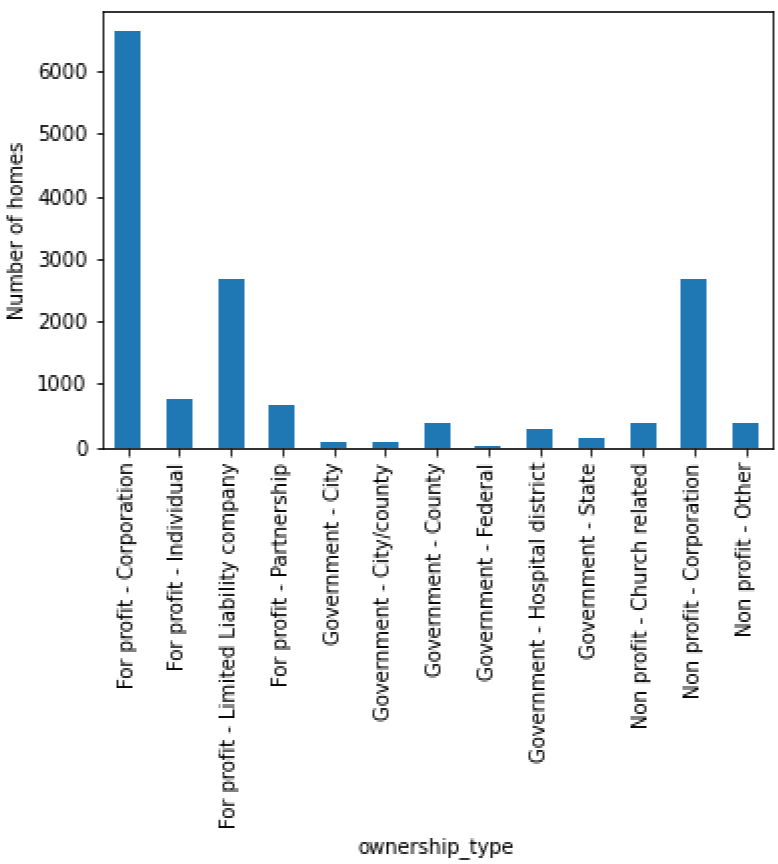
Approach

The research process has involved three weeks of work. In the first week, preprocessing and data cleaning were conducted, with insights drawn from state-based data. The user-based recommendation system was implemented, tested, and potentially tweaked. In the second week, the item-based recommendation system was implemented following the same outline. The final week involved finishing the item-based system, selecting the best-performing system, and identifying features that most affect nursing home ratings. Below, we'll provide a more detailed explanation of our approaches and results for each week.

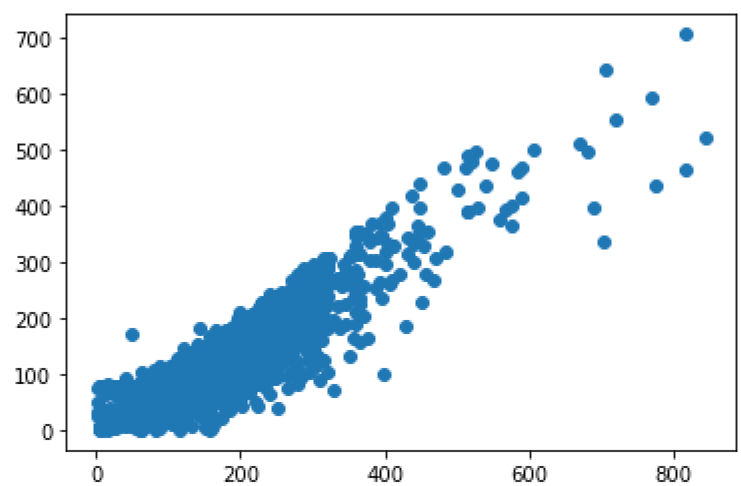
In the first week, the group has made significant progress, including in preprocessing, data understanding, and nearing completion of the user-based recommendation system. During preprocessing, irrelevant features were dropped, and missing values were handled by removing corresponding data points, leaving over 10,000 samples. Data understanding involved calculating averages by state, revealing most states had average nursing home ratings between 2.5-3.2, with Arkansas having the highest rating. However, when we looked at the value counts, we came to find out that the states with the highest overall rating were also the ones that have very insignificant amounts of data, making their high ratings meaningless.

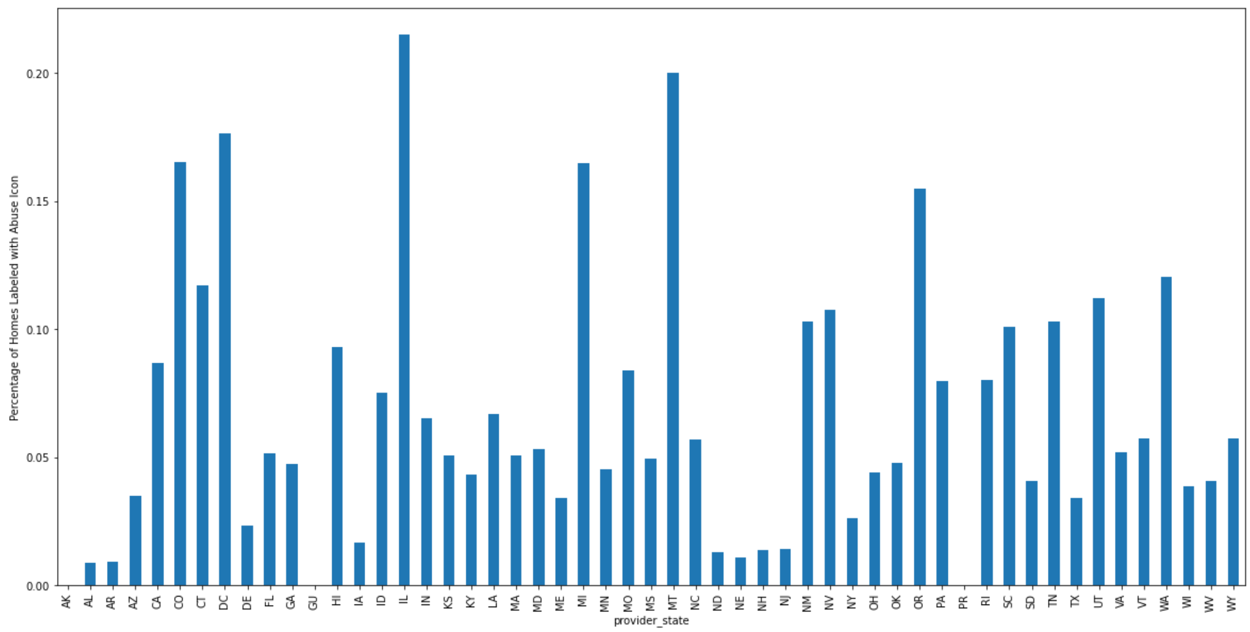
The correlation between the number of certified beds and ratings was explored, with a 90% correlation coefficient. The team also investigated the percentage of abusive nursing homes by state, finding it to be generally low, except for a few states with smaller populations. The ownership types of nursing homes were predominantly profit-seeking corporations.

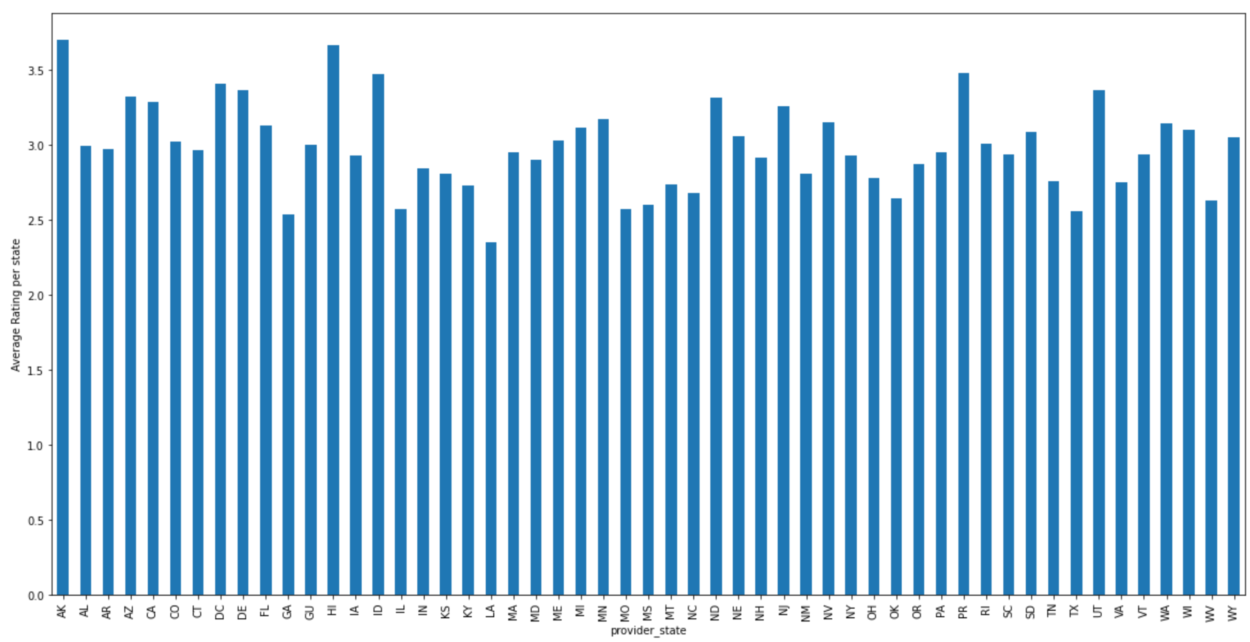
Here are the graphs visualizing these results



Residents and Certified Beds







After data understanding, the team proceeded with preprocessing by removing irrelevant features, encoding categorical features, splitting data, and scaling data using StandardScaler(). The user-based system was then implemented by mapping training data using the K nearest regressor and calculating similarity between each point's nearest neighbors, using Pearson correlation. The prediction formula was then applied to provide a rating.

In the second week, we picked off in finishing our user based recommender system. After using our nearest neighbors and similarity between each point's nearest neighbors, we used that information to predict its rating. After that, we needed to test the accuracy in its ratings prediction. We came up with our own accuracy metric, where we said that as long as the absolute difference between predicted and actual rating is less than or equal to 1, then it is a good rating. Our accuracy formula was good ratings divided by all ratings. We used this metric to assess both our user based and item based recommender systems accuracy.

In week 3 we implemented the item-based recommendation system. The team transposed the training data and calculated the cosine similarity between each feature and the target variable. Using the five greatest item similarities, predictions were made for each test sample, and the accuracy was calculated.

Then, the team compared the performance of user-based and item-based systems to determine the best system for their dataset. They also explored additional techniques(tuning n neighbors, altering preprocessing steps), to improve the recommendation system's accuracy.

Below is the result for it:

	A	B	C
1	Model Tuning	TEST DATA ACCURACY	
2		User Based	Item Based
3	Dropped All Null Values, n neighbors=5	0.985	0.9558
4	Dropped All Null Values, n neighbors=8	0.986	0.826
5	Dropped All Null Values, n neighbors=1	0.961	0.98
6	Dropped All Null Values n neighbors=10	0.988	0.779
7	Fill Null with mean, n neighbors=5	0.988	0.95
8	Fill Null with mean, n neighbors=8	0.988	0.84
9	Fill Null with mean, n neighbors=1	0.96	0.98
10	Fill Null with mean, m neighbors=10	0.987	0.79

Given our results, we can see the best system for our dataset is to use the user based recommender system, that uses 5 nearest neighbors for the calculations, and has all null values filled with its feature mean.

Lastly, using the best system for our dataset, we tried to visualize and find influential features(discussed more in results section)

Results

A	B
Poorly rated Homes	Common Features that 5 star rated homes outperfrom on
1 star rated homes	health inspection ratings, staffing rating, staffing hours per resident(day), license staffing/resident hours, total nursing hours/resident (weekend)
3 star rated homes	heath inspection rating, staffing rating, staffing hours/resident per day, license staffing/resident hours, total nursing hours/resident (weekend)

With our chosen system, we finally tried to analyze what are the most influential features that our recommender system identifies, for it to give it the rating that it does. In order to do this, we graphed 9 samples that our recommender system predicted spot on.

We chose 3 samples that were 5 star rated, 3 that were 3 star rated, and 3 that were 1 star rated. The graphs are shown on the following pages, along with the key of what each number corresponds to what feature.

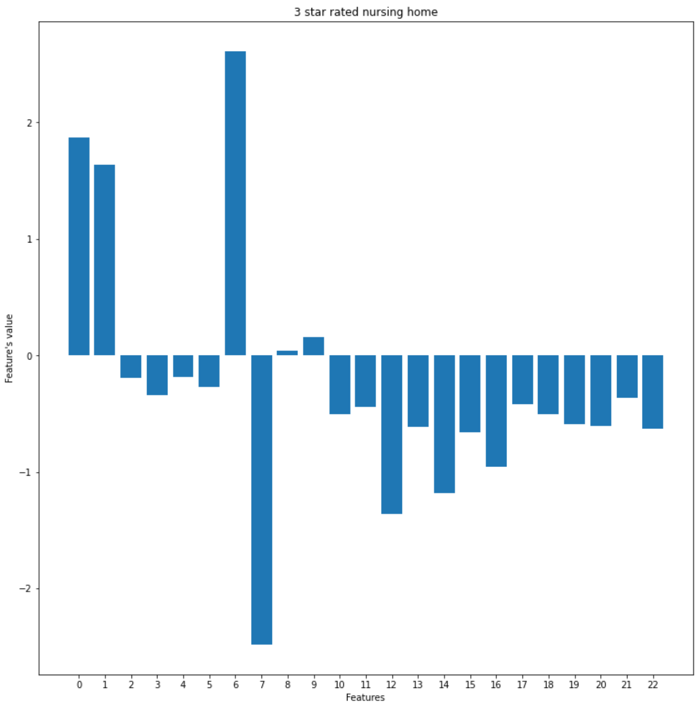
For each 5 star rated home, we wrote down what features the 5 star rated home performed drastically better than all 3 of the 1 star rated home. We repeated this process for the 3 star rated homes. Our results on the common features of our 5 star rated homes drastically outperforms the other lower rated homes, as shown in the picture above.

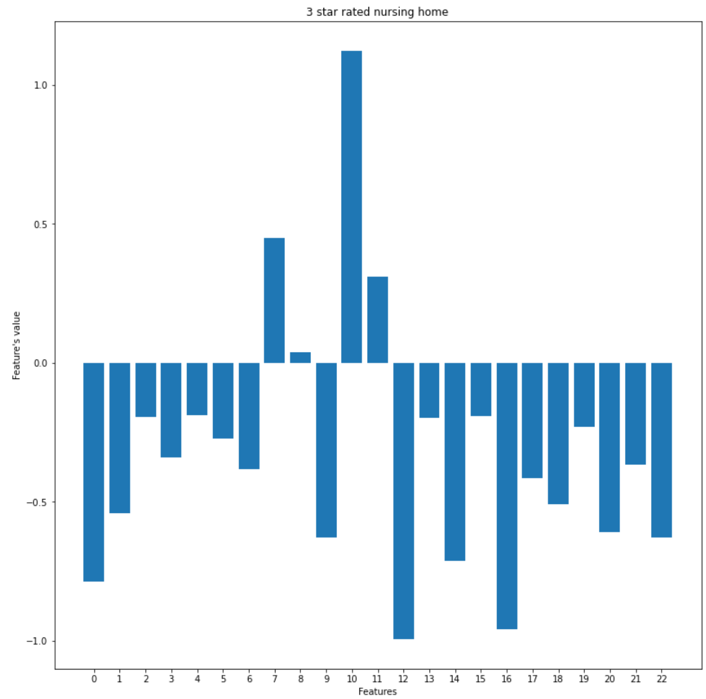
As shown in the picture, both our 3 star and 1 star rated homes are commonly performing poorly in features pertaining to health inspection ratings, and staffing hours of nurses per resident. The staffing hours per resident are poor in all standards as well such as day vs weekend, and licensed vs unlicensed hours. Our 5 star rated homes performed much better on these features.

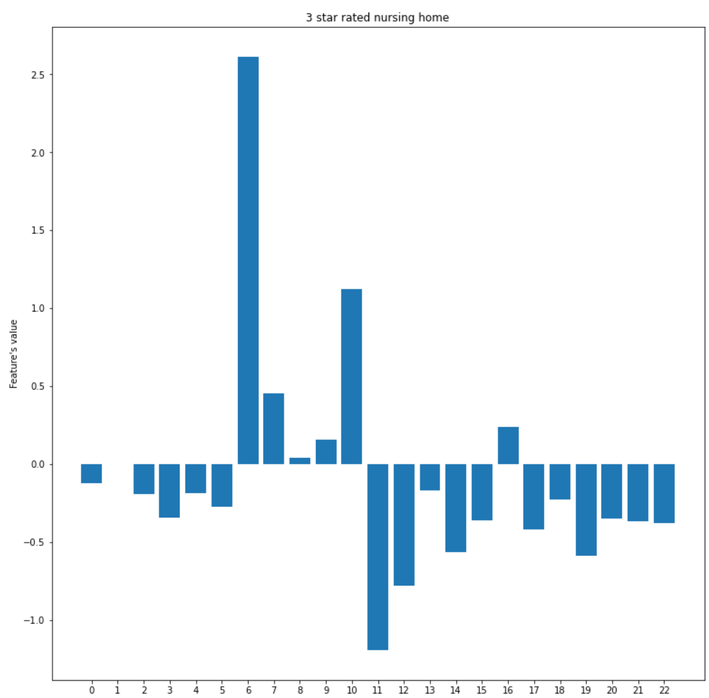
There were some features that the poorer rated homes generally did better on in comparison to 5 star rated homes, such as number of certified beds and armed forces status, but because they were poorly rated, it means that those features are not very influential in our recommender system. The influential features are really the health inspection rating, and the various staffing per resident features. If a poorly rated home wants to get their ratings up, improving these features will most likely get our system to give their home a higher rating.

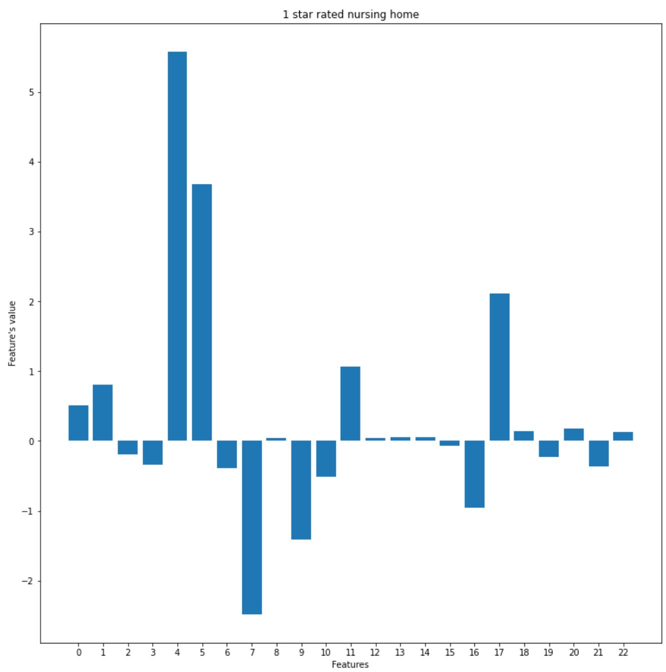
```
plot_labels=dict(zip(columns,labels))
print(plot_labels)
```

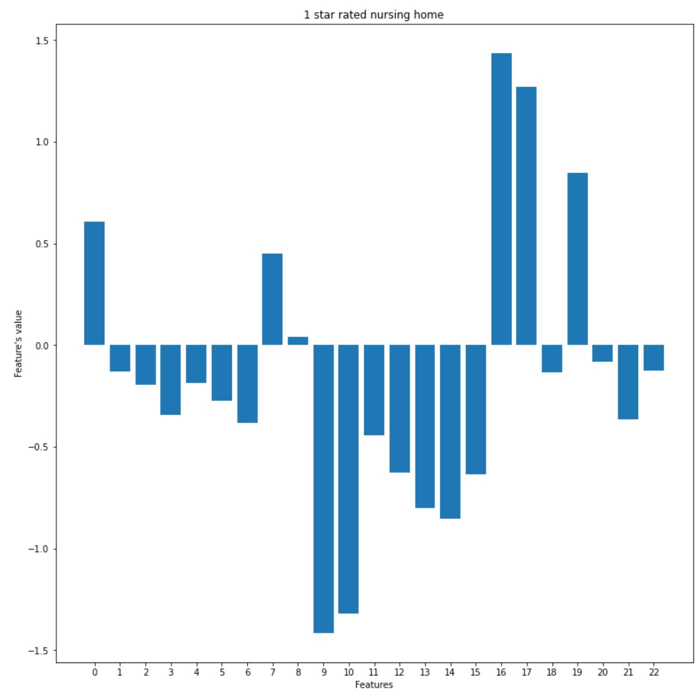
```
{0: 'number_of_certified_beds                                                                   ', 1: 'average_number_of_re
sidents_per_day                                                                      ', 2: 'provider_resides_in_hospital
', 3: 'continuing_care_retirement_community                                                                   ', 4: 'specia
l_focus_status                                                                       ', 5: 'abuse_icon
', 6: 'most_recent_health_inspection_more_than_2_years_ago
', 7: 'with_a_resident_and_family_council                                                                    ', 8: 'automati
c_sprinkler_systems_in_all_required_areas                                                                    ', 9: 'health_i
nspection_rating                                                                      ', 10: 'qm_rating
', 11: 'staffing_rating                                                                 ', 12: 'reported_nurse_aide_staff
ing_hours_per_resident_per_day                                                             ', 13: 'reported_licensed_
staffing_hours_per_resident_per_day                                                           ', 14: 'reported_tota
l_nurse_staffing_hours_per_resident_per_day                                                        ', 15: 'regis
tered_nurse_hours_per_resident_per_day_on_the_weekend                                                        ',
16: 'number_of_administrators_who_have_left_the_nursing_home
', 17: 'number_of_facility_reported_incidents                                                               ', 18: 'num
ber_of_substantiated_complaints                                                                ', 19: 'number_of_citatio
ns_from_infection_control_inspections                                                           ', 20: 'number_of_f
ines                                                                         ', 21: 'number_of_payment_denials
', 22: 'total_number_of_penalties                                                                 '}
```

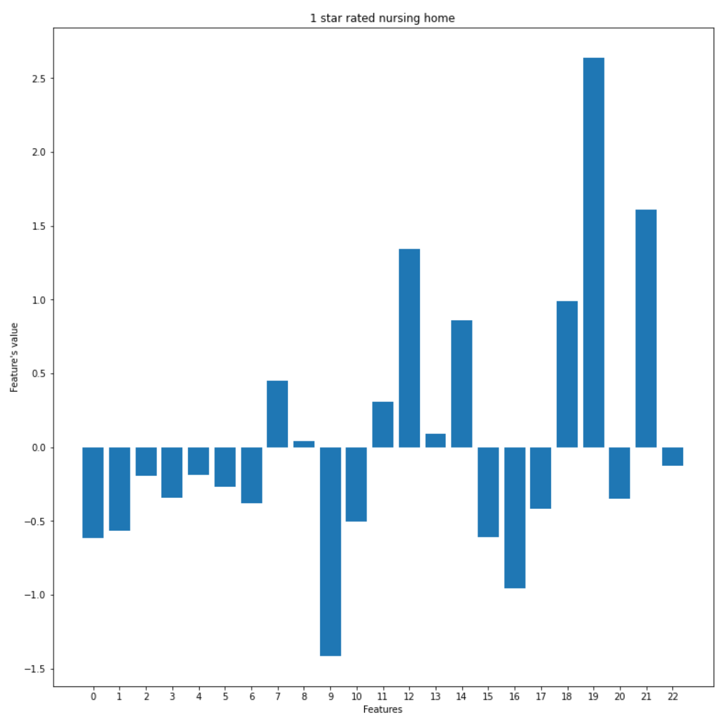

3 star rated nursing home
Feature's value
Features

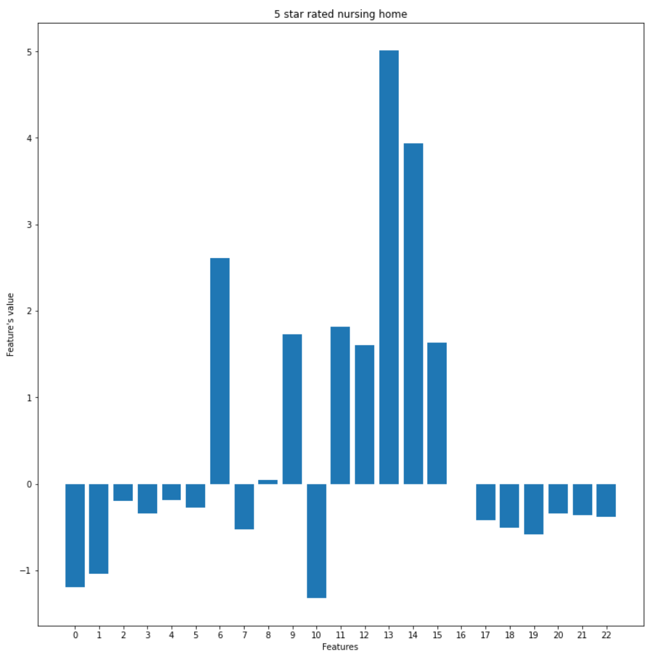

3 star rated nursing home
Feature's value
Features


3 star rated nursing home
Feature's value
Features

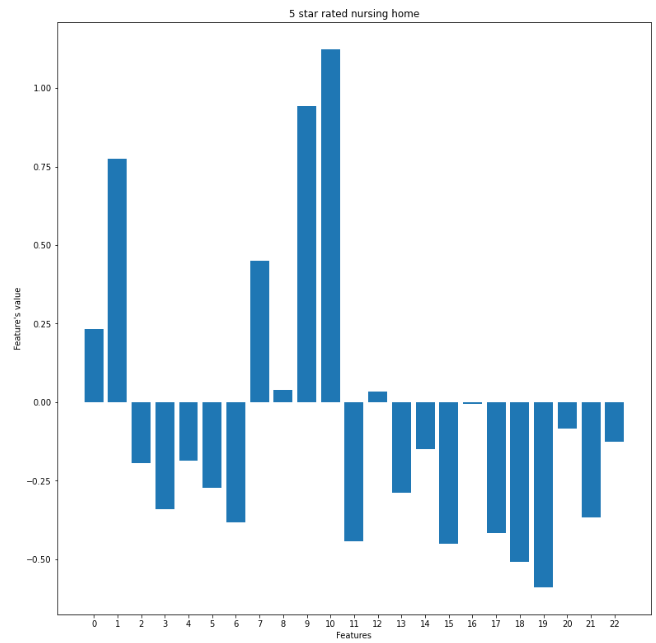

1 star rated nursing home
Feature's value
Features


1 star rated nursing home
Feature's value
Features

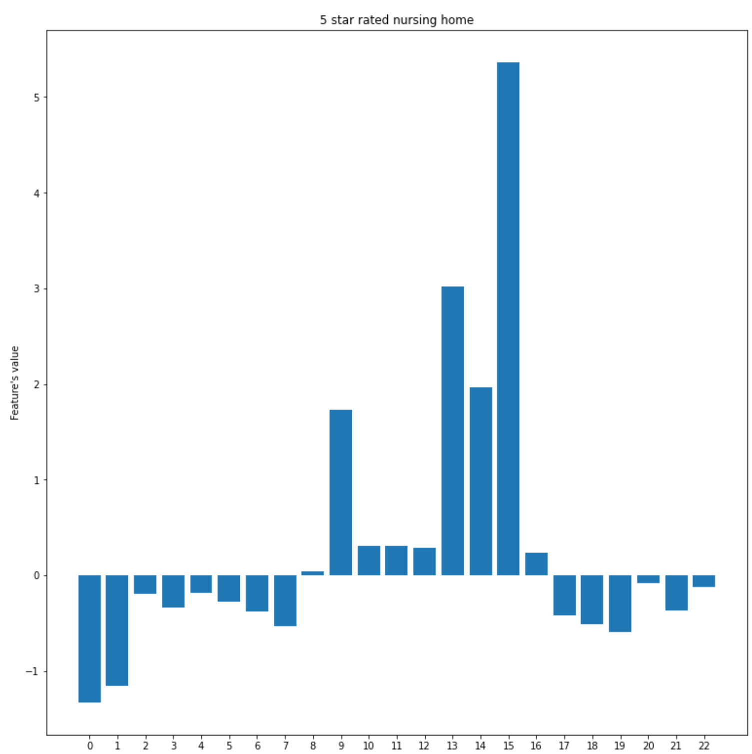

1 star rated nursing home
Feature's value
Features



5 star rated nursing home
Feature's value
Features
5
4
3
2
1
0
−1
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22



5 star rated nursing home
Feature's value
Features
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22



5 star rated nursing home
Feature's value
Features
5
4
3
2
1
0
−1
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

Conclusion

Overall, this project was a massive success. Not only were we able to build a highly accurate recommender system, but we were also able to analyze what poorly rated homes are lacking, and what high rated homes are excelling in.

We found out that some of the most influential features are the health inspection rating, and the various staffing hours per resident features. Obviously every home should strive to improve all the features as much as they can, but that can pose a challenge given there are over 25 features. So finding out the most influential features that each poorly rated home can focus on the most to highly improve their ratings in our recommender system, was a very big accomplishment. We are glad that we were able to help poorly rated homes increase their ratings, which in the end also helps to increase the quality of care for the residents that depend on these homes for living.

Although this project was a success, there were definitely some things we could have done to be even more successful. One thing we could have done was graph more samples to have a stronger hypothesis on the influential features. Although 9 samples is a good number, we would have liked to have a stronger hypothesis, which would have been more meaningful. Another thing we wanted to do was try to alter more preprocessing steps, in order to see if our system could get better results.

Acknowledgements

Numpy
Scipy
Pandas

Harrington, C., Schnelle, J. F., McGregor, M., & Simmons, S. F. (2016). The Need for Higher Minim

Staffing Standards in U.S. Nursing Homes. Health Services Insights, 9, HSI.S38994.

https://doi.org/10.4137/HSI.S38994

Grabowski, D. C., Caudry, D. J., Dean, K. M., & Stevenson, D. G. (2017). Integrated Payment and

Delivery Models Offer Opportunities and Challenges for Residential Care Homes. Health Affairs, 3

1745-1751. https://doi.org/10.1377/hlthaff.2017.0360

Kaiser Family Foundation. (2020). Nursing Home COVID-19 Data and Inspections Results Availab

Nursing Home Compare. https://www.kff.org/coronavirus-covid-19/issue-brief/nursing-home-covid-
data-and-inspections-results-available-on-nursing-home-compare/
Dataset: https://data.cms.gov/provider-data/dataset/4pq5-n9py