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Analysing the patient sentiments in healthcare domain using Machine learning

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Abstract

Emotion AI deals with the sentiments of human beings at various domains. It is named emotion AI as using the capabilities of AI the emotions of humans would be interpreted and analysed. The objective of this paper is to learn from the experience of patients towards the healthcare facilities by studying and analysing the sentiments of the patients using machine learning. This paper focus on training the machine for reading the reviews given by patients who have used various healthcare facilities. The machine will be trained to understand the polarity for each healthcare facility in terms of cleanliness, availability of doctors, interaction of doctors with patients etc. The code is implemented in python with various libraries required for machine Learning. The code is able to extract the polarity and is able to handle the emotions of the patients for questions answered in the dataset by patients. The paper would contribute and help the patients decides which healthcare facility they shall choose based on the experiences of various other patients. For this the goodness score for every healthcare facility is calculated and implemented using Machine learning. It's the contribution of artificial Intelligence and machine learning for healthcare Domain.

Keywords: Patient Experience, Quality, Sentiment Analysis, Artificial Intelligence, Polarity, Machine Learning, Python Implementation

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1. Introduction

Sentiment analysis is the quantitative study of people's opinions, sentiments and their attitudes towards any specific domain. This problem is important in various domains now a days. It offers various challenges to researchers but also provide useful information to anyone interested in understanding emotions. It refers to the emotional aspects of human behaviour, such as moods, attitudes, feelings, and expressions. The process of ML(Machine Learning) aims to create machines and software which can simulate human emotions, whether through speech, facial expressions, or other non-verbal cues. This technology has numerous applications, including healthcare, education, marketing, and entertainment. Some examples of sentiment analysis include emotion recognition software, which can analyse facial expressions to detect emotions like happiness, sadness, anger or fear. Sentiment analysis can also analyse written or spoken language to determine the writer or speaker's emotional state, and affective gaming which uses biometric sensors to detect players' emotional responses and hence can adjust the game accordingly. Machine learning helps machines to learn the concepts, interpret data, and provide desired outputs independently. ML models learn and analyse various conditions and clauses using various knowledge learning techniques such as unsupervised and supervised. Machine learning is thus a good tool for generating predictive insights. Also, Machine Learning helps in patient's interactions and recovery by sending out timely messages and notifications to patients regarding their visits, report collection and other activities. There are other Machine Learning applications like disease diagnosis which is of utmost importance like cancer which can be recognised by predictive analytics and with the help of machine learning[[i]]. We have used machine learning capabilities using python for the reviews given by patients towards the use of healthcare facilities availed by patients. We have written the code to comprehend the polarity given by patients and analyse the goodness score of various hospitals. By seeing the results, the patients would be able to decide which healthcare facility has better facilities and hence can go and visit the doctor in that specific healthcare facility. we have used the textBlob Library of machine learning which helps us to comprehend the polarity of the reviews given by patients. Thus the experience of patients towards the healthcare facility helps many other patients to decide on which hospital they should use as it will determine the quality of that healthcare facility. [ii,iii]

2. Related work

Patient feedback for healthcare facilities is an area for concern. Quite a lot of research is concentrated in the domain of sentiment analysis for healthcare. In the following paragraphs we have discussed the findings by various researchers in this specific domain of sentiment analysis for healthcare facility. The authors in [iv] have made comparison for different features sets. It's important to understand the polarity of outcomes to treat patients' illness. The authors have analysed this information and studied it as a classification problem. They have used Machine learning and NLP technique to study the various outcomes in medical text such as positive, negative, neutral and zero outcome. The authors have applied supervised model. The results showed generalization using the domain knowledge base Unified Medical Language System is effective in the task. Information about the context is important. Combining linguistic features and domain knowledge leads to the highest accuracy. This paper [v], applied sentiment analysis to design real-time satisfaction surveys. The author focused on paediatrician and obstetrician/gynaecologist physicians in District of Columbia, Maryland, and Virginia. They were able to classify patients' reasons for dissatisfaction and could generalise on how practices can improve their care. The paper also discusses and reported the accuracy of classifications. There are various machine learning approaches which are implemented by [vi,vii,viii]. The authors in these paper used sentiment analysis which are tweeted by patients for healthcare. Author have suggested that there is a need for an accurate and tested tool for sentiment analysis of tweets trained using a health care setting specific corpus of manually annotated tweets[ix]. The authors in[x] have mentioned that sentiment analysis is an important tool for various domains, such as politics, marketing etc. As mentioned by the authors healthcare domain brings a great area of opportunity using sentiment analysis such as obtaining information about the patients' mood, diseases, adverse drug reactions etc. As mentioned by the authors healthcare domain has been very little explored. Therefore, they proposed a module based on sentiment analysis to obtain sentiments and emotions and entity levels from texts related to the healthcare domain. The authors in [xi] have presented an unsupervised framework based on deep learning to process heterogeneous electronic health records and derive patient representations that can efficiently and effectively enable patient stratification at scale.

Authors have considered EHRs (Electronic Health records) of 1,608,741 patients from a diverse hospital cohort comprising a total of 57,464 clinical concepts. They then evaluated these representations as broadly enabling patient stratification by applying hierarchical clustering to different multi-disease and disease-specific patient cohorts. The authors have proposed a deep learning model which can perform sentiment analysis [xii] on electronic health records (EHRs) to identify patients' emotional states. They used a large dataset of EHRs and achieved high accuracy in sentiment classification. Another paper [xiii] provides a comprehensive review of the existing studies on sentiment analysis of patient feedback in healthcare They have analysed the limitations of the existing techniques and provide suggestions for future. Another machine learning approach for sentiment analysis in healthcare which uses a combination of supervised and unsupervised learning [xiv] techniques. They tested their approach on a dataset of patient reviews and achieved high accuracy in sentiment classification. The paper [xv]focuses on sentiment analysis of social media data for healthcare applications, such as patient opinions on healthcare services. Various approaches and challenges ae also discussed in this paper. This authors in [xvi] have examined the topics and sentimental change rules of user review. They compared the topics and sentimental change characteristics of user review texts before and after the COVID-19 pandemic. They employed the latent Dirichlet allocation method to cluster topics and the ROST content mining software to analyse user sentiments. Finally, they identified the most important topics and their trends over time. The authors in [xvii] have provided and worked on diabetic detection and diagnosis. They also concluded that CNN and support vector machines have outperformed in ML. Many researchers have developed different intelligent assistants like chatbots and robots which can be used to supports the daily DM management processes of patients like insulin management, diet monitoring, etc.Various accuracy methods like confusion matrix, R1 score and other indicators like sensitivity etc have been used. In this paper, the authors [xviii] have reviewed five classifiers (one being a variant of the TAN model) and assessed their performance with two Twitter datasets from two different critical events, the 2010 Chile earthquake and the 2017 Catalan independence referendum. They have done sentiment analysis for physician reviews on online platforms. The dataset is being used and a high accuracy is being achieved. The authors also provide insights into the factors that influence physician reviews and sentiments. Thus, from the above related work we can feel the importance of sentiment analysis in the area of healthcare domain and the various aspects and approaches related to sentiment analysis has been touched by various authors in the different domains of healthcare. Overall, these papers highlight the importance of sentiment analysis in the healthcare domain and hence motivates us to apply robust machine learning techniques which can provide accurate results and provide insights into the latest techniques and approaches used in this area.

3. Sentiment analysis from patient’s comments

Mining sentiments from text using Natural Language Processing is a common task in the field of artificial Intelligence and machine learning. Sentiment analysis determines the sentiments from a piece of text, or a review, tweet, or email by analysing the words and phrases used in it.

One can apply techniques for sentiment analysis, such as rule-based methods, machine learned algorithms, and deep learning techniques. Generally, the sentiment analysis starts with pre-processing the text (e.g., tokenization, stemming), feature extraction (e.g., bag-of-words, word embeddings) and classification (e.g., binary or multiclass classification). In rule-based methods, analysis of sentiment is performed by defining a set of rules based on keywords which gives the sense of positive or negative sentiments. In contrast, machine learning algorithms and deep learning techniques learn to identify sentiments from examples of labelled data.

Thus, sentiment analysis can provide valuable feedback from patient experiences, treatment outcomes, and overall healthcare trends. It’s important to note that sentiment analysis may have limitations in accurately interpreting complex human emotions at times. There are many other examples where sentiment analysis has contributed which are as follows:

Patient feedback: Healthcare providers can use sentiment analysis to analyse patient feedback from surveys, online reviews, or social media platforms to understand patient satisfaction.

Clinical trial recruitment: Sentiment analysis can help researchers identify potential clinical trial candidates by analysing media posts, online forums for individuals who express interest in participating in clinical trials.

Mental health monitoring: Sentiment analysis can be used to monitor early signs of mental health issues due to excessive depression and anxiety.

Physician sentiment analysis: Healthcare providers can use sentiment analysis to analyze the language used in

physician notes to identify patterns in patient care and outcomes.
For working on any of these healthcare related issues we need the dataset to train and then analyse and work on different areas of sentiments analysis .There are several datasets available for healthcare monitoring for sentiment analysis. Here are few examples such as Sentiment 140(dataset of million of tweets), Affective text(dataset of 2500 sentences), EmoReact(Dataset of million of Facebook reactions) etc. Figure [1] below describes the generic process of sentiment analysis.

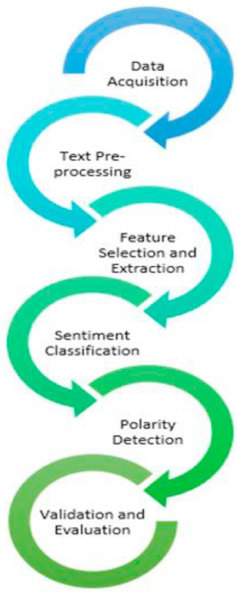


Fig. 1 Generic process for sentiment analysis (Source: Devopedia)

The Generic Process of sentiment analysis has to follow the underlined steps:
i)Data acquisition: It actually refers to the process of collecting and gathering the data required for sentiment analysis. This step is very important as the quantity and quality of the data we collect would definitely impact the accuracy and effectiveness of the sentiment analysis model. Data can be taken from sources like social media platforms, news, articles, opinions etc and the choice of data would also depend upon the objective of the research required for. It can also be taken using web scrapping i.e we can directly extract the data form various websites.
ii)Text Preprocessing: After acquiring data, it often requires preprocessing to clean and prepare it for sentiment analysis. Preprocessing steps may include text cleaning, tokenization, removing stop words, and handling special characters and emojis.
iii)Feature selection and extraction: These are two important techniques in ML to reduce the dimensionality of a dataset, improve model performance, and mitigate the curse of dimensionality. Both approaches aim to identify and use the most relevant and informative features while discarding irrelevant or redundant ones. In feature selection a subset of the most important features from the original set of features in the dataset. The aim is to retain the most informative features while eliminating those that do not contribute significantly.
In Feature extraction we can create new features from the original set by transforming, combining, or projecting them into a lower-dimensional space. We can apply Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for feature extraction.
iv)Sentiment classification:
Sentiment classification, is an NLP task that involves determining the sentiment or emotional tone expressed in a piece of text, typically classifying it as positive, negative and neutral. The goal of sentiment classification is to automate the process of understanding and categorizing the subjective opinions, emotions, and attitudes expressed in text data.

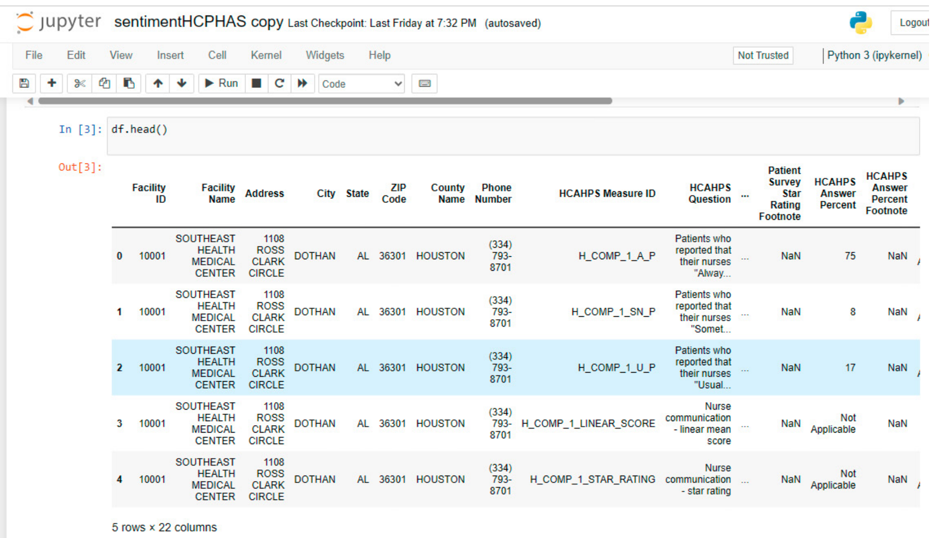
v)Polarity detection: Polarity detection is a subtask of sentiment analysis, where the primary objective is to determine the polarity of a piece of text, classifying it as positive, negative, or neutral based on the sentiment expressed.
vi)Validation and evaluation:
Validation is the process of checking and verifying the quality and integrity of data and models in sentiment analysis. We can apply data validation and cross validation too.
Evaluation: It involves assessing the performance and effectiveness of a trained model. It helps measure how well the model predicts sentiment on new, unseen text data. We can use the following metrics for evaluation purpose:

- Accuracy: The ratio of correctly classified sentiments to the total number of sentiments.
- Precision: The ratio of true positive predictions (correctly identified positive sentiments) to all positive predictions made by the model.
- Recall: The ratio of true positive predictions to all actual positive sentiments in the dataset.
- F1- Score: It provides a balance between precision and recall and is useful when we consider both false positives and false negatives.
- Confusion Matrix: It's a matrix that shows the number of true positives, true negatives, false positives and false negatives

We have also followed the above generic process of sentiment analysis. We have utilised the dataset for New York city health and hospitals corporation for patient satisfaction in which patients were asked questions related to healthcare facilities This dataset can be used for training and testing sentiment analysis models for reviewing the healthcare facility. All the questions are displayed as part of the snapshots in the figures below in implementation section. They had answered those questions with positive , negative and neutral sentiments. Based on the polarity of the sentiments, the dataset is analysed and the results are mentioned in the results and discussion section. We have implemented the code in python using the concept of NLP, we then analysed the polarity of each sentiment in python.

4. Discussion and Implementation Details

We have taken the dataset of the HCAHPS (Hospital Consumer Assessment of Healthcare Providers and Systems) and analysed the responses of the patients.
This is the snapshot of the dataset in figure [2] shown below. We have created a data frame named as df and with that data frame df we are using a head function which will display the first 5 rows from the entire dataset which is shown below.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In [3]:
```
df.head()
```

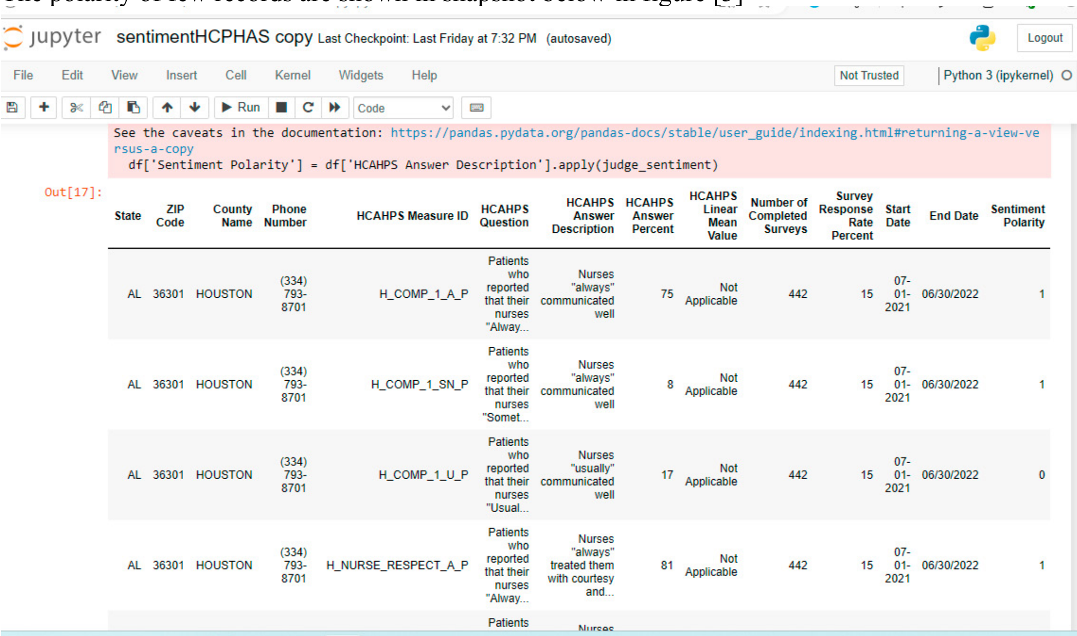
Out[3]:

	Facility ID	Facility Name	Address	City	State	ZIP Code	County Name	Phone Number	HCAHPS Measure ID	HCAHPS Question	...	Patient Survey Star Rating Footnote	HCAHPS Answer Percent	HCAHPS Answer Percent Footnote
0	10001	SOUTHEAST HEALTH MEDICAL CENTER	1108 ROSS CLARK CIRCLE	DOTHAN	AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_A_P	Patients who reported that their nurses "Alway...	...	NaN	75	NaN
1	10001	SOUTHEAST HEALTH MEDICAL CENTER	1108 ROSS CLARK CIRCLE	DOTHAN	AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_SN_P	Patients who reported that their nurses "Somet...	...	NaN	8	NaN
2	10001	SOUTHEAST HEALTH MEDICAL CENTER	1108 ROSS CLARK CIRCLE	DOTHAN	AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_U_P	Patients who reported that their nurses "Usual...	...	NaN	17	NaN
3	10001	SOUTHEAST HEALTH MEDICAL CENTER	1108 ROSS CLARK CIRCLE	DOTHAN	AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_LINEAR_SCORE	Nurse communication - linear mean score	...	NaN	Not Applicable	NaN
4	10001	SOUTHEAST HEALTH MEDICAL CENTER	1108 ROSS CLARK CIRCLE	DOTHAN	AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_STAR_RATING	Nurse communication - star rating	...	NaN	Not Applicable	NaN

5 rows × 22 columns

Fig 2 Snapshot of the HCAHPS dataset for Healthcare Domain

After applying the sentiment polarity algorithm, we have used the answer description column answered by patients and then it calculated the polarity of each response based on whether it was a positive, negative or a neutral comment.
The polarity of few records are shown in snapshot below in figure [3]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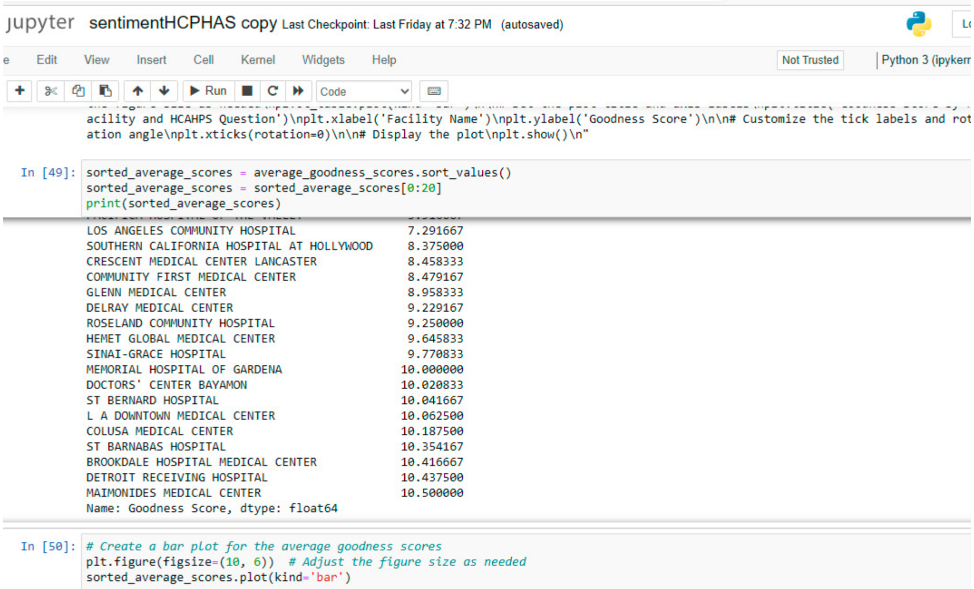
```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Sentiment Polarity'] = df['HCAHPS Answer Description'].apply(judge_sentiment)
```

Out[17]:

State	ZIP Code	County Name	Phone Number	HCAHPS Measure ID	HCAHPS Question	HCAHPS Answer Description	HCAHPS Answer Percent	HCAHPS Linear Mean Value	Number of Completed Surveys	Survey Response Rate Percent	Start Date	End Date	Sentiment Polarity
AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_A_P	Patients who reported that their nurses "Alway...	Nurses "always" communicated well	75	Not Applicable	442	15	07-01-2021	06/30/2022	1
AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_SN_P	Patients who reported that their nurses "Somet...	Nurses "always" communicated well	8	Not Applicable	442	15	07-01-2021	06/30/2022	1
AL	36301	HOUSTON	(334) 793-8701	H_COMP_1_U_P	Patients who reported that their nurses "Usual...	Nurses "usually" communicated well	17	Not Applicable	442	15	07-01-2021	06/30/2022	0
AL	36301	HOUSTON	(334) 793-8701	H_NURSE_RESPECT_A_P	Patients who reported that their nurses "Alway...	Nurses "always" treated them with courtesy and...	81	Not Applicable	442	15	07-01-2021	06/30/2022	1

Fig 3 sentiment Polarity of records (sentiment Polarity column)

We had to see the responses state wise so we applied the group by clause on state and the sentiment polarity.
The results after applying group by clause is shown below in the snapshot in figure[4]. We can see from the figure below that Mamondies hospital has outperformed in terms of the responses so patients can comprehend that there are better healthcare facilities available here. The goodness score of other hospitals are also very close to this hospital so patients can review the hospital in terms of location and other parameters and hence decide which is the best suited healthcare facility for them.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```
acility and HCAHPS Question')\nplt.xlabel('Facility Name')\nplt.ylabel('Goodness Score')\n\n# Customize the tick labels and rot
ation angle\nplt.xticks(rotation=0)\n\n# Display the plot\nplt.show()\n"
```

In [49]:

```
sorted_average_scores = average_goodness_scores.sort_values()
sorted_average_scores = sorted_average_scores[0:20]
print(sorted_average_scores)
```

```
LOS ANGELES COMMUNITY HOSPITAL              7.291667
SOUTHERN CALIFORNIA HOSPITAL AT HOLLYWOOD   8.375000
CRESCENT MEDICAL CENTER LANCASTER           8.458333
COMMUNITY FIRST MEDICAL CENTER              8.479167
GLENN MEDICAL CENTER                        8.958333
DELRAY MEDICAL CENTER                       9.229167
ROSELAND COMMUNITY HOSPITAL                 9.250000
HEMET GLOBAL MEDICAL CENTER                 9.645833
SINAI-GRACE HOSPITAL                        9.770833
MEMORIAL HOSPITAL OF GARDENA               10.000000
DOCTORS' CENTER BAYAMON                    10.020833
ST BERNARD HOSPITAL                        10.041667
L A DOWNTOWN MEDICAL CENTER                10.062500
COLUSA MEDICAL CENTER                      10.187500
ST BARNABAS HOSPITAL                       10.354167
BROOKDALE HOSPITAL MEDICAL CENTER          10.416667
DETROIT RECEIVING HOSPITAL                 10.437500
MAIMONIDES MEDICAL CENTER                  10.500000
Name: Goodness Score, dtype: float64
```

In [50]:

```
# Create a bar plot for the average goodness scores
plt.figure(figsize=(10, 6))  # Adjust the figure size as needed
sorted_average_scores.plot(kind='bar')
```

Fig 4 Average Scores achieved by each healthcare facility

Below In Figure[5] We have plotted the results using the matplot library and used various functions of that library. We wanted to understand which hospital are providing better healthcare facilities so we calculated a goodness score based on the polarity for that hospital and we multiplied it with the no of people and used as the weight for the polarity. A goodness score is thus calculated which is the number of people who have given positive, negative and neutral polarity. Using the goodness score for each hospital, It would be easy for the patients to decide which hospitals they shall go which would provide great healthcare facilities in their respective state.

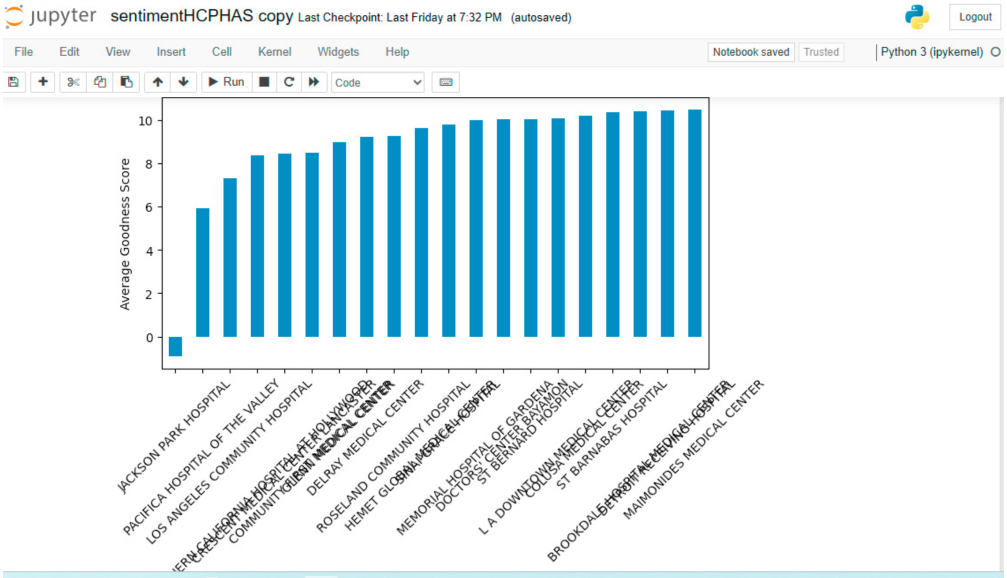

Figure [5] Results plotting the goodness values of all the hospitals

V Conclusion and future work

This paper reflects the contribution of Artificial Intelligence particularly machine learning using python in the area of healthcare and hence helping mankind and the society in deciding which healthcare facility they shall choose based on the responses by the patients who have used various healthcare facilities. Thus, this paper has contributed in term of patient's feedback towards the hospital and its facilities. The code is able to extract the polarity and is able to handle the emotions of the patients for questions answered in the dataset like cleanliness, patient recovery, availability. In future the concept of sentiment analysis can help other patients to decide on which is a better hospital in terms of availability and infrastructure facilities, cleanliness etc. we have taken the HCAHPS(Hospital Consumer Assessment of Healthcare Providers and Systems dataset). The same generic concept can be utilised to calculate the polarity of any given dataset for patients' feedback and hence it will address an important issue for patients to decide on any hospitals for their relatives and hence can take the advantage. In the future more emphasis can be laid on other paradigms for analysis of different aspects of the dataset available and further few optimisation techniques like genetic Algorithm [xix,xx,xxi,], ant colony optimisation etc can also be included as the hybrid model for sentiment analysis. By applying any of the optimisation algorithm [[xxii],[xxiii],[xxiv]]with machine learning, there will be less chances of getting stuck with local optimum solution and we can expect a global optimum solution. We can even apply ensemble technique of Machine learning which includes bagging and boosting and hence would boost the results by machine learning approaches and the results can be further improved.

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