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Medical Reviews Analysis from social media data

Date of Performance:

Date of Submission:



Aim: To use social media data to analyse medical reviews

Objective: Given a dataset with social media data analyse, and interpret information and feedback about medical products, services, treatments, or healthcare facilities as expressed by individuals on social media platforms.

Theory:

Medical reviews analysis from social media data refers to the process of collecting, analyzing, and interpreting information and feedback about medical products, services, treatments, or healthcare facilities as expressed by individuals on social media platforms. This analysis is often conducted to gain insights into the effectiveness, safety, patient experiences, and public perceptions related to various aspects of healthcare. Here are the key components of medical reviews analysis from social media data:

Data Collection: Data is collected from various social media platforms such as Twitter, Facebook, Reddit, online forums, and healthcare-specific websites. This data can include text, images, videos, and other forms of user-generated content.

Text Mining and Natural Language Processing (NLP): Text mining and NLP techniques are used to extract and process the textual information within the collected data. This involves sentiment analysis, named entity recognition, and other linguistic and semantic analyses to understand the content and context of medical reviews.

Sentiment Analysis: Sentiment analysis is a critical component of this analysis. It helps categorize the sentiment of reviews as positive, negative, or neutral. Sentiment analysis can reveal the overall satisfaction of patients and the areas where improvements are needed.



Topic Modeling: Topic modeling techniques are used to identify and categorize common themes or topics discussed in the medical reviews. This can help healthcare organizations understand what aspects of their services or products are frequently mentioned and which areas require attention.

Adverse Event Detection: In the case of medical products or treatments, adverse event detection is crucial. By analyzing social media data, it's possible to identify potential adverse events associated with certain drugs or medical interventions.

Patient Experience Analysis: Analysis of social media data can provide insights into the patient experience, including factors like wait times, staff behavior, facility cleanliness, and the overall quality of care provided by healthcare facilities.

Public Perceptions and Trends: Social media data can reveal public perceptions about healthcare issues, emerging trends in medical treatments, and the popularity of different healthcare providers or services.

Insights for Healthcare Providers and Regulators: The findings from social media data analysis can be used to improve the quality of healthcare services and products, identify areas for improvement, enhance patient satisfaction, and ensure compliance with regulatory standards.

Data Privacy and Ethics: It's important to handle social media data with sensitivity to privacy and ethical considerations. Anonymization and consent are crucial aspects when collecting and analyzing such data.

Reporting and Decision-Making: The results of the analysis are typically reported to healthcare providers, pharmaceutical companies, regulatory agencies, and other stakeholders to inform decision-making and improve the healthcare system.

Overall, medical reviews analysis from social media data is a valuable tool for gaining insights into the real-world experiences and perceptions of patients, consumers, and the general public regarding various aspects of healthcare, which can ultimately drive improvements in healthcare quality and patient care.

Code: -

!pip install pandas numpy matplotlib seaborn nltk sklearn gensim import pandas as pd



import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation as LDA

from sklearn.model selection import train test split

from sklearn.naive bayes import MultinomialNB

from sklearn.metrics import classification_report, confusion_matrix

from wordcloud import WordCloud

import gensim

from gensim import corpora

import re

nltk.download('punkt')

nltk.download('stopwords')

from google.colab import files

file_path = 'social_media_reviews.csv'

df = pd.read csv(file path)

df.head()

print(df.isnull().sum())

df.dropna(inplace=True)

def preprocess text(text):



```
text = text.lower() # Lowercase the text
  text = re.sub(r'\d+', ", text) # Remove numbers
  text = re.sub(r'[^\w\s]', ", text) # Remove punctuation
  tokens = word tokenize(text) # Tokenize the text
  tokens = [word for word in tokens if word not in stopwords.words('english')]
# Remove stopwords
  return ''.join(tokens)
df['cleaned reviews'] = df['review text'].apply(preprocess text)
# Display the cleaned reviews
df[['review text', 'cleaned reviews']].head()
X = df['cleaned reviews']
vectorizer = CountVectorizer(max features=1000)
X vectorized = vectorizer.fit transform(X)
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word tokenize
def preprocess text(text):
  # Remove URLs and special characters
  text = re.sub(r'http\S+|www\S+|https\S+', ", text, flags=re.MULTILINE)
  text = re.sub(r'\@w+\#', ", text)
  # Tokenize and remove stopwords
  tokens = word tokenize(text)
```



tokens = [word.lower() for word in tokens if word.isalpha()]

filtered_words = [word for word in tokens if word not in stopwords.words('english')]

return ''.join(filtered words)

Apply preprocessing to the 'review_text' column

df['cleaned_reviews'] = df['review_text'].apply(preprocess_text)

Inspect cleaned data

df[['review_text', 'cleaned_reviews']].head()
!pip install vaderSentiment
!pip install sklearn
!pip install seaborn

 $from\ vader Sentiment.vader Sentiment\ import\ Sentiment Intensity Analyzer$

Initialize VADER sentiment analyzer analyzer = SentimentIntensityAnalyzer()

Function to determine sentiment

HAIMLSBL701 AI&ML in Healthcare Lab

```
def get sentiment(text):
  score = analyzer.polarity scores(text)
  if score['compound'] \geq 0.05:
     return 'positive'
  elif score['compound'] <= -0.05:
     return 'negative'
  else:
     return 'neutral'
# Apply sentiment analysis to the cleaned reviews
df['sentiment'] = df['cleaned reviews'].apply(get sentiment)
# Inspect results
print(df[['cleaned reviews', 'sentiment']].head())
from sklearn.feature extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
# Vectorize the cleaned reviews
vectorizer = CountVectorizer(max df=0.9, min df=2, stop words='english')
X = vectorizer.fit transform(df['cleaned reviews'])
```



```
# Initialize LDA model
lda model = LatentDirichletAllocation(n components=5, random state=42)
lda model.fit(X)
# Display top words in each topic
terms = vectorizer.get feature names out()
for index, topic in enumerate(lda model.components ):
  print(f'Topic {index}:')
  print([terms[i] for i in topic.argsort()[-10:]])
import matplotlib.pyplot as plt
import seaborn as sns
# Sentiment distribution
sns.countplot(df['sentiment'])
plt.title('Sentiment Distribution')
plt.show()
# Visualize top terms in each topic
for index, topic in enumerate(lda model.components ):
  top words = [terms[i] for i in topic.argsort()[-10:]]
  plt.barh(top words, topic.argsort()[-10:])
  plt.title(f'Topic {index}')
```



plt.show()

Output:









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                             # Initialize VADER sentiment analyzer
analyzer = SentimentIntensityAnalyzer()
                                # Function to determine sentiment
                             # Function to determine sentiment
def get_sentiment(text):
    score = analyzer.polarity_scores(text)
    if score['compound'] > 0.05:
        return 'positive'
    elif score['compound'] <= -0.05:
        return 'negative'
    else:
        return 'neutral'</pre>
                            # Apply sentiment analysis to the cleaned reviews df['sentiment'] = df['cleaned_reviews'].apply(get_sentiment)
                            # Inspect results
print(df[['cleaned_reviews', 'sentiment']].head())
                                     cleaned reviews sentiment
staff greeted warmly positive
cleanliness facility stood
received call check progress
appointment well worth time
recommend clinic friends positive
 [33] from sklearn.feature_extraction.text import CountVectorizer from sklearn.decomposition import LatentDirichletAllocation

// (33) # Vectorize the cleaned reviews
    vectorizer = Countvectorizer(max_df=0.9, min_df=2, stop_words='english')
    X = vectorizer.fit_transform(df['cleaned_reviews'])

                                       # Initialize LDA model
                                    Ida_model = latentDirichletAllocation(n_components=5, random_state=42)
lda_model.fit(X)
                                    # Display top words in each topic
terms = vectorizer.get_feature_names_out()
for index, topic in enumerate(1da_model.components_):
    print(f'ropic (index):')
    print([terms[i] for i in topic.argsort()[-10:]])
                Topic 0:
['choose', 'reviews', 'long', 'wait', 'easy', 'place', 'worth', 'appointment', 'facility', 'staff']
Topic 1:
['improved', 'significantly', 'better', 'cautious', 'advise', 'rushed', 'thorough', 'diagnosis', 'visit', 'feel']
Topic 2:
['comfortable', 'hours', 'service', 'convenient', 'office', 'receive', 'charged', 'services', 'staff', 'felt']
                                     Topic 3:

['appreciate', 'definitely', 'listened', 'good', 'attentive', 'caring', 'staff', 'experience', 'come', 'concerns']
Topic 4:

['recommendations', 'options', 'excellent', 'recommend', 'doctor', 'care', 'clinic', 'experienced', 'effects', 'treatment']
     38 [34] import matplotlib.pyplot as plt
import seaborn as sns
                                     # Sentiment distribution
                                     sns.countplot(df['sentiment'])
     y [34] # Sentiment distribution
                                       sns.countplot(df['sentiment'])
plt.title('Sentiment Distribution')
plt.show()
                                     # Visualize top terms in each topic
for index, topic in enumerate(lda_model.components_):
    top.words = [terms[i] for i in topic.argsort()[-10:]]
    plt.bahr(top.words, topic.argsort()[-10:])
    plt.title(f'Topic (index)')
    plt.show()
                  ₹
                                                                                                                                                                              Sentiment Distribution
                                                         positive
                                                           neutral
```



Google Collaboratory Link: -

https://colab.research.google.com/drive/19mJ0cI4oJJZ-SuxzwZxuApPDO51z9Wja

Conclusion: -

Medical review analysis from social media data is crucial for understanding public sentiment and experiences related to healthcare products and services. It enables healthcare providers and organizations to gauge patient satisfaction, identify trends, and address concerns proactively. By analyzing these reviews, stakeholders can improve patient care, tailor services to meet consumer needs, and enhance overall healthcare communication strategies. Additionally, insights gained can inform policy decisions and help in the development of targeted health campaigns.

