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TRAVEL AGENT SENTIMENT ANALYSIS USING DEEP LEARNING TECHNIQUES

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ABSTRACT:-

In this work the analysis about the travel data set. Then, in these three online travel agents such as Ticket.com, Agoda, Expedia use Facebook for supporting their business as customer service tool. moreover, the data will be analyzed in this deep learning algorithms. such as, convolutional neural networks (CNN), Naïve Bayes and support vector machines (SVM) to determine the sentiment analysis. however, the research consists about the deep learning techniques to implement that improve recommendation task is to predict that includes to design and testing in sentiment analysis.

Keywords: -

Aspect level sentiment classification (ALSC), target dependent sentiment classification, deep learning, decision making, Nvidia developer

INTRODUCTION: -

In this context, sentiment analysis is now this making the growth will be helpful. It is a branch of affective computing research. Moreover, it is the area is now widely recognized.

Understanding and interpreting the destination for destination management will thus provide opportunities for the creation of the brand value and image of the destination. It will also make an important contribution to the determination of tourist needs in the destination and meeting these needs. Tourists will be able to use it to make better travel plans.

Digital texts created in these new tourist processes are seen as an important opportunity for tourists and suppliers to get to know and understand each other. These opportunities should be evaluated in terms of suppliers, namely those offering touristic products (tourism enterprises, destination management), and tourists.

In this travelling about it is an informal and conversational. Moreover, it is an effective sentiment analysis that techniques are introduced in the process such as textual data. It is a significant construction that quality of tourism will be a great value. Furthermore, the experience that we can tell about that positive and negative thoughts on the online traveling experience. however, booking tickets in website ticket.com, Agoda, Expedia etc.

ASPECT LEVEL SENTIMENT CLASSIFICATION: -

In this aspect level classification have the several sub tasks. Just like, aspect extraction, opinion identification and Aspect sentiment classification.in this which we can use the deep learning method. moreover, it mainly focuses on the both the sentiment and target information. In this sentiment always as target. Furthermore, target is usually an entity or an aspect. however, it is the review of a target information in this task. Furthermore, it aims to determine towards the opinion target.it means that word or phrase (sequence of words). however, in the travelling website the people are typing in the search option about their destination and booking details etc.

In these other techniques which we need to implement that aspect level sentiment is scalable. Moreover, which it is support in the customer conversations & reviews.it targets mainly on the important tasks. Furthermore, it introduces the attention model that incorporates synthetic data. it tells about the customer payments by using credit or debit card of a transactions. Moreover, it is increasing the importance of global economy. However, it is an enough customer specific data to personalize them for each user. Finally, this aspect level sentiment should focus on the features of developed system in travelling area.

In this it is also tell about the aspect level classification is the method of working it is used to develop the tasks.

TARGET DEPENDENT SENTIMENT CLASSIFICATION: -

It is aims to given target. moreover, it talks about to identify the sentiment targets in the given sentence. which it means the information that we are searching about the destination that we are checking in the travelling. furthermore, this activation of the key industries. that will be handled more in the communities.

moreover, it is managing in the different ways for managing customer-brand relationships is currently essential with in this travelling trade. however, for extending the travelling business there doing promotions using SNS (social network sites). just like Facebook, twitter etc. In this more about target dependent sentiment classification talks about that particularly in the neural networks. Moreover, it is target dependent sentiment analysis (TDSA) method is useful to develop it. However, these neural networks which produce different results are multiple runs due to random results are there when it applies the neural networks. Finally, this TDSA method which it is helpful to improve and using these neural networks it will be easily developed.

In this target dependent sentiment classification talks about there are using the different sites that promotes the travelling business to increase the market.

LONG STHORT TERM MEMORY NETWORKS: -

In this I was discussing about the recurrent neural networks that it is related about the LSTM (long short-term memory). moreover, this long short-term memory which it is based on the artificial neural network in the field of deep learning. Furthermore, when the people are travelling to destination. generally, they have the GPS. It means that u can track your location where we are at certain point. furthermore, there is grid points which it means that we are moving in the correct way or not. So, this is about the GPS.

In this which it helps from the networks that is used to find out the route of destination from starting point to end point.

DATA SET:-

In this which I used the data set of travelling. moreover, in this which are having data set of users, destination, gender, accommodation.

1. ACCOMODATION :-

   In this below figure shows the details of columns & rows

	travelCod	userCode	name	place	days	price	total	date
2	0	0	Hotel A	Florianop	4	313.02	1252.08	########
3	2	0	Hotel K	Salvador (	2	263.41	526.82	########
4	7	0	Hotel K	Salvador (	3	263.41	790.23	########
5	11	0	Hotel K	Salvador (	4	263.41	1053.64	########
6	13	0	Hotel A	Florianop	1	313.02	313.02	########
7	15	0	Hotel BD	Natal (RN	2	242.88	485.76	1/9/2020
8	22	0	Hotel Z	Aracaju (S	2	208.04	416.08	########
9	29	0	Hotel AU	Recife (PE	4	312.83	1251.32	########
10	32	0	Hotel AF	Sao Paulo	2	139.1	278.2	5/7/2020
11	33	0	Hotel K	Salvador (	4	263.41	1053.64	########
12	34	0	Hotel AF	Sao Paulo	3	139.1	417.3	########
13	38	0	Hotel BD	Natal (RN	2	242.88	485.76	########
14	39	0	Hotel K	Salvador (	1	263.41	263.41	########
15	42	0	Hotel BW	Campo Gr	3	60.39	181.17	########
16	43	0	Hotel K	Salvador (	4	263.41	1053.64	########
17	45	0	Hotel BD	Natal (RN	1	242.88	242.88	8/6/2020
18	51	0	Hotel K	Salvador (	1	263.41	263.41	########
19	53	0	Hotel BW	Campo Gr	2	60.39	120.78	########
20	54	0	Hotel AF	Sao Paulo	3	139.1	417.3	########
21	55	0	Hotel A	Florianop	2	313.02	626.04	########

hotels

7742	74	Hotel BP	Brasilia (D	4	247.62	990.48	#########
7748	74	Hotel AF	Sao Paulo	3	139.1	417.3	#########
7749	74	Hotel K	Salvador (	1	263.41	263.41	7/2/2020
7756	75	Hotel CB	Rio de Jan	3	165.99	497.97	#########
7759	75	Hotel BW	Campo Gr	2	60.39	120.78	#########
7761	75	Hotel CB	Rio de Jan	1	165.99	165.99	#########
7764	75	Hotel K	Salvador (	1	263.41	263.41	1/2/2020
7766	75	Hotel BW	Campo Gr	4	60.39	241.56	#########
7767	75	Hotel CB	Rio de Jan	3	165.99	497.97	#########
7768	75	Hotel AF	Sao Paulo	3	139.1	417.3	#########
7771	75	Hotel BW	Campo Gr	4	60.39	241.56	#########
7774	75	Hotel AF	Sao Paulo	3	139.1	417.3	#########
7775	75	Hotel BD	Natal (RN	1	242.88	242.88	#########
7776	75	Hotel K	Salvador (	3	263.41	790.23	#########
7777	75	Hotel BP	Brasilia (D	2	247.62	495.24	4/2/2020
7780	75	Hotel A	Florianop	3	313.02	939.06	#########
7781	75	Hotel AF	Sao Paulo	2	139.1	278.2	#########
7787	75	Hotel AF	Sao Paulo	4	139.1	556.4	#########
7793	75	Hotel K	Salvador (	3	263.41	790.23	#########
7796	75	Hotel BD	Natal (RN	2	242.88	485.76	#########
7798	75	Hotel BD	Natal (RN	3	242.88	728.64	#########
7801	75	Hotel BW	Campo Gr	3	60.39	181.17	#########

12964	126	Hotel Z	Aracaju (S	1	208.04	208.04	3/2/2023
12965	126	Hotel AU	Recife (PE	4	312.83	1251.32	3/9/2023
12968	127	Hotel K	Salvador (	2	263.41	526.82	########
12975	127	Hotel K	Salvador (	1	263.41	263.41	########
12979	127	Hotel K	Salvador (	1	263.41	263.41	########
12981	127	Hotel AU	Recife (PE	4	312.83	1251.32	1/9/2020
12983	127	Hotel BW	Campo Gr	4	60.39	241.56	########
12989	127	Hotel BD	Natal (RN)	2	242.88	485.76	3/5/2020
12995	127	Hotel BP	Brasilia (D	2	247.62	495.24	########
12998	127	Hotel AU	Recife (PE	4	312.83	1251.32	5/7/2020
12999	127	Hotel CB	Rio de Jan	4	165.99	663.96	########
13002	127	Hotel Z	Aracaju (S	2	208.04	416.08	6/4/2020
13005	127	Hotel BP	Brasilia (D	4	247.62	990.48	########
13006	127	Hotel K	Salvador (	3	263.41	790.23	7/2/2020
13007	127	Hotel Z	Aracaju (S	1	208.04	208.04	7/9/2020
13009	127	Hotel Z	Aracaju (S	4	208.04	832.16	########
13010	127	Hotel CB	Rio de Jan	1	165.99	165.99	########
13011	127	Hotel CB	Rio de Jan	2	165.99	331.98	8/6/2020
13013	127	Hotel A	Florianop	4	313.02	1252.08	########
13019	127	Hotel BW	Campo Gr	2	60.39	120.78	########
13020	127	Hotel AU	Recife (PE	2	312.83	625.66	########
13023	127	Hotel CB	Rio de Jan	2	165.99	331.98	########

2. DESTINATION: -

In this which it helps through that which mode that people are travelling will be economic or business class.

travelCod	userCode	from	to	flightType	price	time	distance	agency	date
0	0	Recife (PE	Florianop	firstClass	1434.38	1.76	676.53	FlyingDro	########
0	0	Florianop	Recife (PE	firstClass	1292.29	1.76	676.53	FlyingDro	########
1	0	Brasilia (D	Florianop	firstClass	1487.52	1.66	637.56	CloudFy	########
1	0	Florianop	Brasilia (D	firstClass	1127.36	1.66	637.56	CloudFy	########
2	0	Aracaju (S	Salvador (	firstClass	1684.05	2.16	830.86	CloudFy	########
2	0	Salvador (	Aracaju (S	firstClass	1531.92	2.16	830.86	CloudFy	########
3	0	Aracaju (S	Campo Gr	economic	743.54	1.69	650.1	Rainbow	########
3	0	Campo Gr	Aracaju (S	economic	877.56	1.69	650.1	Rainbow	########
4	0	Recife (PE	Florianop	economic	803.39	1.76	676.53	Rainbow	########
4	0	Florianop	Recife (PE	economic	695.3	1.76	676.53	Rainbow	########
5	0	Brasilia (D	Aracaju (S	firstClass	1287.52	1.11	425.98	FlyingDro	########
5	0	Aracaju (S	Brasilia (D	firstClass	898.04	1.11	425.98	FlyingDro	########
6	0	Recife (PE	Florianop	premium	1070.54	1.76	676.53	Rainbow	########
6	0	Florianop	Recife (PE	premium	1013.4	1.76	676.53	Rainbow	########
7	0	Aracaju (S	Salvador (	economic	964.83	2.16	830.86	CloudFy	########
7	0	Salvador (	Aracaju (S	economic	811.73	2.16	830.86	CloudFy	########
8	0	Recife (PE	Sao Paulo	economic	513.06	1.26	486.52	CloudFy	########
8	0	Sao Paulo	Recife (PE	economic	829.91	1.26	486.52	CloudFy	########
9	0	Brasilia (D	Campo Gr	economic	583.6	0.72	277.7	CloudFy	########
9	0	Campo Gr	Brasilia (D	economic	506.56	0.72	277.7	CloudFy	########

5175	52	Brasilia (D	Campo Gr	firstClass	1009.71	0.72	277.7	FlyingDro	########
5175	52	Campo Gr	Brasilia (D	firstClass	847.83	0.72	277.7	FlyingDro	########
5176	52	Brasilia (D	Salvador (	economic	921.08	1.76	676.56	Rainbow	########
5176	52	Salvador (	Brasilia (D	economic	609.83	1.76	676.56	Rainbow	########
5177	52	Brasilia (D	Campo Gr	firstClass	1069.61	0.72	277.7	Rainbow	########
5177	52	Campo Gr	Brasilia (D	firstClass	870.91	0.72	277.7	Rainbow	5/1/2020
5178	52	Brasilia (D	Florianop	premium	1189.32	1.66	637.56	CloudFy	5/7/2020
5178	52	Florianop	Brasilia (D	premium	885.37	1.66	637.56	CloudFy	5/8/2020
5179	52	Aracaju (S	Florianop	economic	852.18	2.1	808.85	Rainbow	########
5179	52	Florianop	Aracaju (S	economic	819.41	2.1	808.85	Rainbow	########
5180	52	Recife (PE	Sao Paulo	firstClass	980.83	1.26	486.52	Rainbow	########
5180	52	Sao Paulo	Recife (PE	firstClass	1573.5	1.26	486.52	Rainbow	########
5181	52	Aracaju (S	Natal (RN	premium	427.25	0.46	176.33	Rainbow	########
5181	52	Natal (RN	Aracaju (S	premium	479.37	0.46	176.33	Rainbow	########
5182	52	Brasilia (D	Campo Gr	firstClass	1009.71	0.72	277.7	FlyingDro	6/4/2020
5182	52	Campo Gr	Brasilia (D	firstClass	847.83	0.72	277.7	FlyingDro	6/7/2020
5183	52	Aracaju (S	Salvador (	firstClass	1714.75	2.16	830.86	FlyingDro	########
5183	52	Salvador (	Aracaju (S	firstClass	1581.59	2.16	830.86	FlyingDro	########
5184	52	Recife (PE	Campo Gr	firstClass	1110.76	1.39	535.4	CloudFy	########
5184	52	Campo Gr	Recife (PE	firstClass	1244.73	1.39	535.4	CloudFy	########

3.USERS:-

code	company	name	gender	age
0	4You	Roy Braun	male	21
1	4You	Joseph Hc	male	37
2	4You	Wilma Mc	female	48
3	4You	Paula Dan	female	23
4	4You	Patricia Ca	female	44
5	4You	Trina Thor	none	47
6	4You	Jesse Dec	male	46
7	4You	Gregoria (	female	21
8	4You	Jack Sabo	none	41
9	4You	Debbie He	none	35
10	4You	Melvin Lo	male	36
11	4You	Virginia R	female	61
12	4You	David Tho	male	53
13	4You	Irene Tuck	none	36
14	4You	John Cody	male	37
15	4You	Janice Cuc	female	56
16	4You	Shane Hul	female	47
17	4You	Victor Trib	none	25
18	4You	Tanya Oro	none	65
19	4You	John Benr	male	22
20	4You	Sally Robe	female	65

21	19	4You	John Benr	male	22		
22	20	4You	Sally Robe	female	65		
23	21	4You	Julia Meir	female	56		
24	22	4You	Michele A	female	51		
25	23	4You	Leslie San	male	35		
26	24	4You	Calvin Cue	male	60		
27	25	4You	Elizabeth	female	64		
28	26	4You	Yolanda C	female	49		
29	27	4You	Sean Pear	male	62		
30	28	4You	April Mille	female	46		
31	29	4You	Lisa Nater	female	35		
32	30	4You	Alberta Bo	female	59		
33	31	4You	Christoph	none	40		
34	32	4You	Wesley Lo	male	44		
35	33	4You	Ida Turzak	female	56		
36	34	4You	Anita Pete	female	21		
37	35	4You	Helen Sell	none	34		
38	36	4You	Anna Rodi	none	56		
39	37	4You	Denise Ne	none	27		
40	38	4You	Nancy Dov	female	47		
41	39	4You	Billie Dwi	female	48		

42	40	4You	Carlos Car	none	42		
43	41	4You	Sandra Bis	female	62		
44	42	4You	Robert Co	male	61		
45	43	4You	Louise Jar	female	24		
46	44	4You	David Bris	male	21		
47	45	4You	Margaret I	female	54		
48	46	4You	Bobby Gar	male	42		
49	47	4You	Kevin Linc	male	28		
50	48	4You	Clyde Ruiz	male	46		
51	49	4You	Charles W	male	55		
52	50	4You	Monique '	female	56		
53	51	4You	Jenell Tor	female	39		
54	52	4You	Joyce Jacc	female	55		
55	53	4You	Carol Dixc	female	23		
56	54	4You	Dorothea	female	21		
57	55	4You	Ivory Shin	none	38		
58	56	4You	Lindsey Pi	none	39		
59	57	4You	Dorothy D	female	32		
60	58	4You	Ernie Wall	male	37		
61	59	4You	Katherine	none	29		
62	60	4You	Fred More	male	47		
63	61	4You	Susan Arn	female	61		

NIVIDIA DEVELOPER:

In this using this data sets that above images of users, accommodation & destination. Moreover, in this which have the Nvidia server of NGC catalog. However, it is having the option of vertex AI. moreover, it is used for the data set that we can write the code in Jupiter notebook, google colab etc. Finally, this is the way which it used the software for develop applications in deep learning.

ALGORITHMS:

In this I have used the algorithms of CNN & RNN

1.CONVENTIONAL NEURAL NETWORKS(CNN):

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
# undersampling
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter
from matplotlib import cm
# Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
```

Output:

```
/kaggle/input/argodatathon2019/users.csv
/kaggle/input/argodatathon2019/hotels.csv
/kaggle/input/argodatathon2019/flights.csv
```

```
df_user = pd.read_csv('/kaggle/input/argodatathon2019/users.csv')
df_hotel = pd.read_csv('/kaggle/input/argodatathon2019/hotels.csv')
df_flight = pd.read_csv('/kaggle/input/argodatathon2019/flights.csv')
```

```
df_user.isnull().sum()
```

Output:

```
code       0
company    0
name       0
gender     0
age        0
dtype: int64
```

```
df_user.head()
```

Output:

	code	company	name	gender	age
0	0	4You	Roy Braun	male	21
1	1	4You	Joseph Holsten	male	37
2	2	4You	Wilma Mcinnis	female	48
3	3	4You	Paula Daniel	female	23
4	4	4You	Patricia Carson	female	44

```
df_user.groupby("company").size()
```

Output:

```
company
4You             453
Acme Factory     261
Monsters CYA     195
Umbrella LTDA    194
Wonka Company    237
dtype: int64
```

In this using the travel agent to implement this deep learning algorithm by using convolutional neural networks. however, using this CNN model in this travelling.it consists of data collection, data segmentation. Moreover, it could provide accurate and energy efficient transportation mode in detection ability. Furthermore, it is based on the multiple smart phone sensor. However, it talks about the various type of sensing devices to gather data. moreover, using this data it will be guide through that about the ticket confirmation and your details will be there in it. moreover, in this deep learning algorithm which we are using that CNN. it contains huge data sets related to travelling. moreover, it talks about the recommendations that we can take from three aspects. just like recommendations system in travelling, community, user interface design. furthermore, more related information of this travelling it is destination places which u are selected, accommodations & weather of particular in this place. finally, this are the recommendations are there in this travelling.

```
df_user.groupby("gender").size()
```

Output:

```
gender
female    448
male      452
none      440
dtype: int64
```

```
df_flight.head()
```

Output:

	travelCode	userCode	from	to	flightType	price	time	distance	agency	date
0	0	0	Recife (PE)	Florianopolis (SC)	firstClass	1434.38	1.76	676.53	FlyingDrops	09/26/2019
1	0	0	Florianopolis (SC)	Recife (PE)	firstClass	1292.29	1.76	676.53	FlyingDrops	09/30/2019
2	1	0	Brasilia (DF)	Florianopolis (SC)	firstClass	1487.52	1.66	637.56	CloudFy	10/03/2019
3	1	0	Florianopolis (SC)	Brasilia (DF)	firstClass	1127.36	1.66	637.56	CloudFy	10/04/2019
4	2	0	Aracaju (SE)	Salvador (BH)	firstClass	1684.05	2.16	830.86	CloudFy	10/10/2019

```
df_flight.groupby("agency").size()
```

Output:

```
agency
CloudFy        116378
FlyingDrops     38758
Rainbow        116752
dtype: int64
```

```
df_flight.groupby(['travelCode', 'userCode']).size().max().min()
```

Output:

2

RECURRENT NEURAL NETWORKS(RNN):

In this recurrent neural network, which is the use for travelling is that analyze sequential data.it means that travelling customer details, accommodation etc. moreover, in this data talks about the text, images, customer information. Furthermore, in this recurrent neural network which it is having that memory which it is related through hidden layers. however, it is a step-by-step process in this travelling which we are select the exact location about your destination. then, sequential data which helpful to improve the features in travelling data.

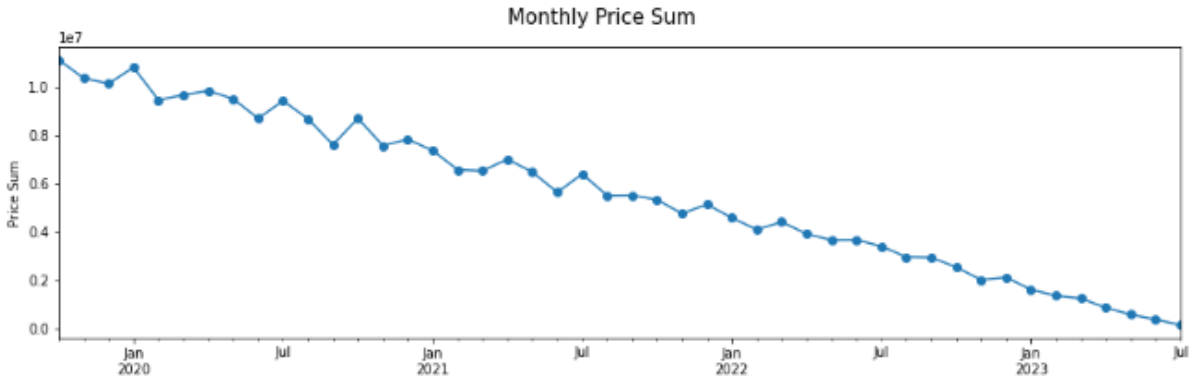
```
df_month_grow_rate.groupby('monthYear')["price"].sum().plot(kind='line', ax=ax1, marker="o")
df_month_grow_rate.groupby('monthYearInt')["MoM(%)"].sum().plot(
    kind='bar', ax=ax2,color="purple", alpha=0.3, label=True)

for a, b, in zip(range(45),df_month_grow_rate["MoM(%)"]):
    if b < 0:
        plt.text(a-0.5, b, str(b) + '%', rotation=0, fontsize='small')
    if b > 0:
        plt.text(a-0.5, b, str(b) + '%', rotation=0, fontsize='large', c = 'red')

fig1.suptitle('Monthly Price Sum', fontsize = '15')
fig2.suptitle('MoM', fontsize = '15')

ax1.set(xlabel=' ', ylabel='Price Sum')
ax2.set(xlabel='Year/Month', ylabel='MoM(%)')
```

Output:




```
df_flight.groupby("to").size()
```

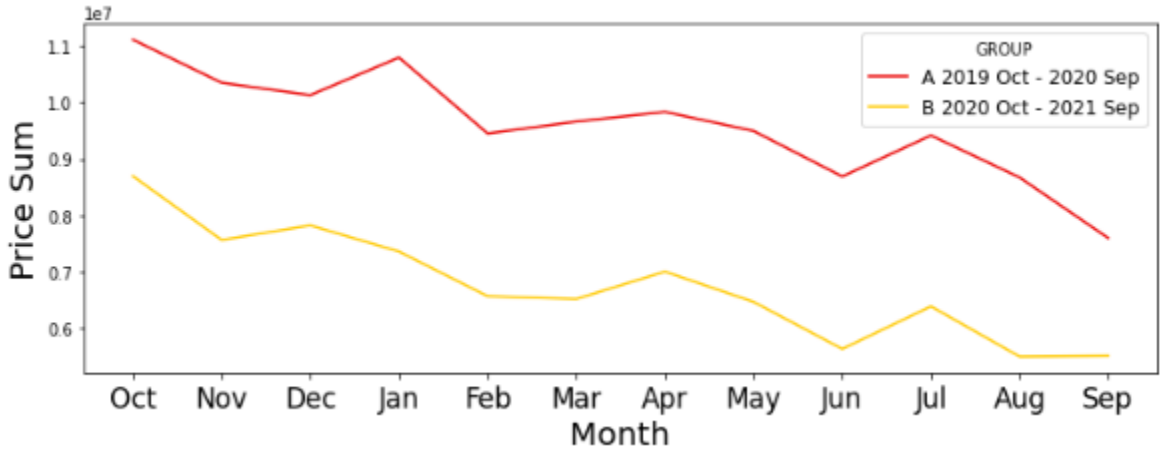
Output:

```
to
Aracaju (SE)          37224
Brasilia (DF)         30779
Campo Grande (MS)     34748
Florianopolis (SC)    57317
Natal (RN)            23796
Recife (PE)           30480
Rio de Janeiro (RJ)   16815
Salvador (BH)         17104
Sao Paulo (SP)        23625
dtype: int64
```

. In this travel data set using recurrent neural network algorithm it talks about that using which I was giving the input as about travel data set. moreover, which gives the output of the recurrent state. however, which tells about the hidden layers that applies the function of an initial weights which it effects then it gives the exact output. Furthermore, it will be used in the travel data set that set of inputs in layer of memory. however, the users which using the travel application that talks about the timeline of a person GPS is travelled. Finally, by using this RNN algorithm the output which will be visualize as graphs.

```
sns.lineplot(data=data, x='index', y='price', hue='group',markers= ["o","<"],palette = 'hot')
axs.set_xticks(range(1,13))
axs.set_xticklabels(['Oct','Nov','Dec','Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep'],fontsize = 17)
axs.set_xlabel("Month", fontsize = 20)
axs.set_ylabel("Price Sum", fontsize = 20)
plt.legend(title='GROUP', loc='upper right', labels=['A 2019 Oct - 2020 Sep', 'B 2020 Oct - 2021 Sep'],fontsize = 12)
plt.show()
```

Output:



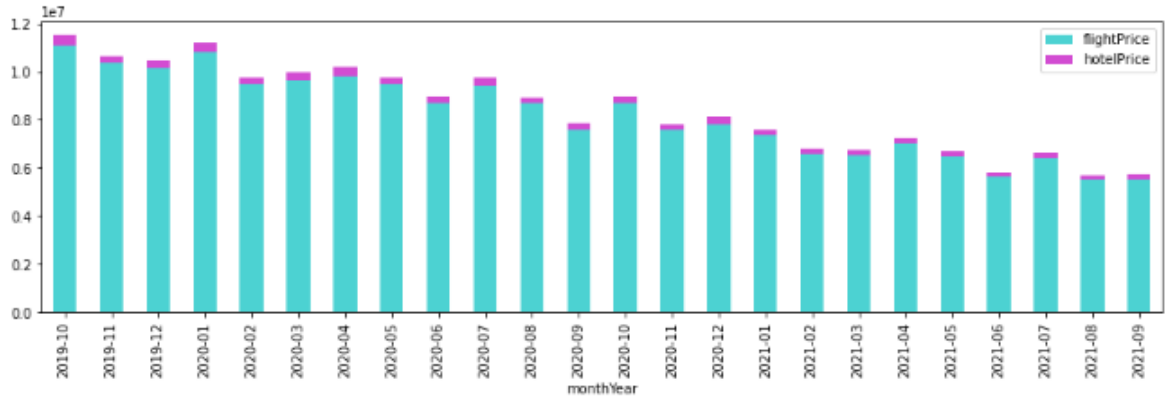

```
df_hotel["datetime"] = pd.to_datetime(df_hotel["date"])
df_hotel['monthYear'] = pd.to_datetime(df_hotel['datetime']).dt.to_period('M')
df_hotel['year'] = pd.to_datetime(df_hotel['datetime']).dt.year
df_hotel['month'] = pd.to_datetime(df_hotel['datetime']).dt.month
```

```
df_hotel.head()
```

Output:

	travelCode	userCode	name	place	days	price	total	date	datetime	monthYear	year	month
0	0	0	Hotel A	Florianopolis (SC)	4	313.02	1252.08	09/26/2019	2019-09-26	2019-09	2019	9
1	2	0	Hotel K	Salvador (BH)	2	263.41	526.82	10/10/2019	2019-10-10	2019-10	2019	10
2	7	0	Hotel K	Salvador (BH)	3	263.41	790.23	11/14/2019	2019-11-14	2019-11	2019	11
3	11	0	Hotel K	Salvador (BH)	4	263.41	1053.64	12/12/2019	2019-12-12	2019-12	2019	12
4	13	0	Hotel A	Florianopolis (SC)	1	313.02	313.02	12/26/2019	2019-12-26	2019-12	2019	12

```
df_flight_groupby = df_flight.groupby('monthYear')["price"].sum().to_frame()
df_hotel_groupby = df_hotel.groupby('monthYear')["price"].sum().to_frame()
df_flight_hotel = pd.merge(df_flight_groupby, df_hotel_groupby, on=['monthYear'], how='left')
df_flight_hotel = df_flight_hotel.rename(columns={'price_x': 'flightPrice', 'price_y': 'hotelPrice'})
```




```
df_flight_hotel.groupby(['days_hotel']).size()
```

Output:

```
days_hotel
1.0    7649
2.0    7659
3.0    7603
4.0    7639
dtype: int64
```

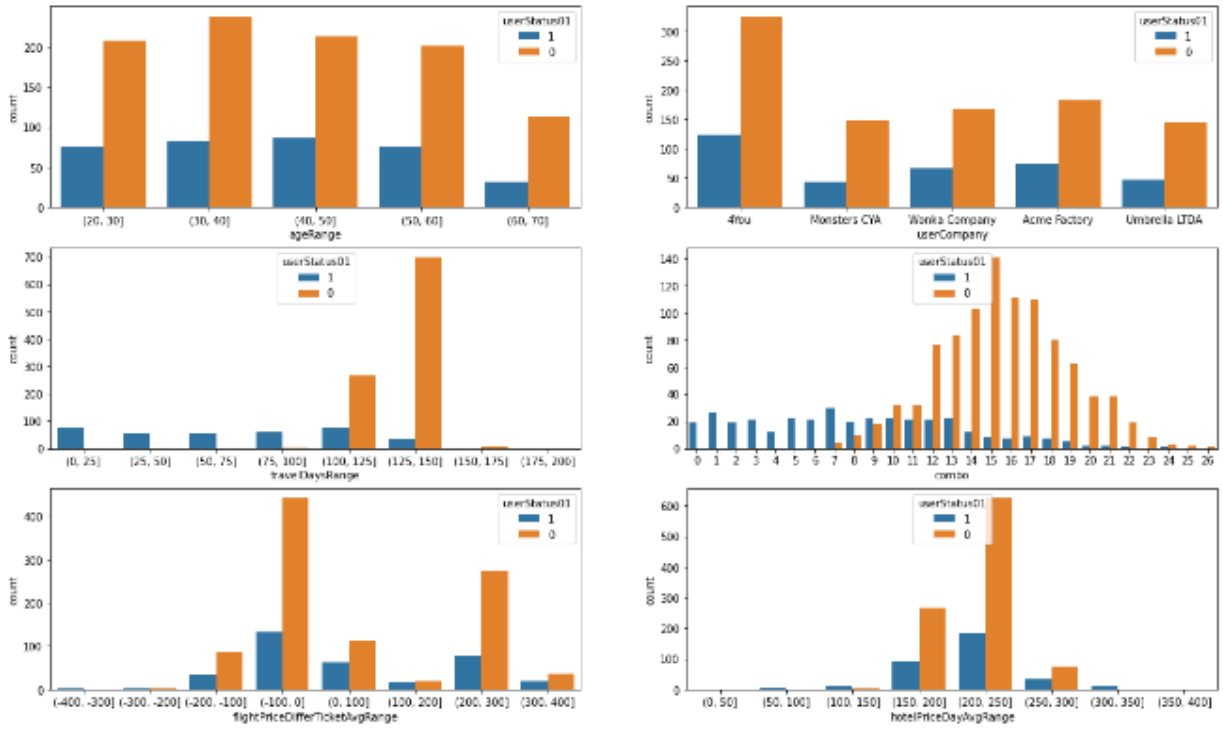
```
df_churned_groupby.groupby( ['userStatus'] ).size()
```

Output:

```
userStatus
churned      353
continued    971
dtype: int64
```

```
sns.countplot(x='ageRange', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[0][0] )
sns.countplot(x='userCompany', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[0][1] )
sns.countplot(x='combo', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[1][1] )
sns.countplot(x='travelDaysRange', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[1][0] )
sns.countplot(x='flightPriceDifferTicketAvgRange', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[2][0] )
sns.countplot(x='hotelPriceDayAvgRange', hue = "userStatus01", data = df_customer,
hue_order = [1,0], ax=axarr[2][1] )
```

Output:



CONCLUSION

In this paper improved that about the travel agent sentiment analysis using deep learning techniques. Moreover, which it is used through travel has the good or bad reviews. however, which I was implement this deep learning algorithms that it is used to improve the websites of travel. Furthermore, which it is also this sentiment analysis which describe about text processing, future selection & deep learning classification. Finally , in this travel data set which is used to develop it that can be expected.

REFERNCES:

.. Nguyen, Huy Thanh, and Minh Le Nguyen. "Effective attention networks for aspect-level sentiment classification." In *2018 10th International Conference on Knowledge and Systems Engineering (KSE)*, pp. 25-30. IEEE, 2018.

.. Zhou, Jie, Jimmy Xiangji Huang, Qin Chen, Qinmin Vivian Hu, Tingting Wang, and Liang He. "Deep learning for aspect-level sentiment classification: survey, vision, and challenges." *IEEE access* 7 (2019): 78454-78483.

.. Poernomo, A. D., and S. Suharjito. "Indonesian online travel agent sentiment analysis using machine learning methods." *Indones. J. Electr. Eng. Comput. Sci* 14, no. 1 (2019): 113.

..Chu, Kai Fung, Albert YS Lam, and Victor OK Li. "Travel demand prediction using deep multi-scale convolutional LSTM network." In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1402-1407. IEEE, 2018.

.. Puh, Karlo, and Marina Bagić Babac. "Predicting sentiment and rating of tourist reviews using machine learning." *Journal of Hospitality and Tourism Insights* ahead-of-print (2022).

.. Martín, Carlos Alberto, Jesús M. Torres, Rosa María Aguilar, and Sergio Diaz. "Using deep learning to predict sentiments: case study in tourism." *Complexity* 2018 (2018).

.. Cui, Yu, Qing He, and Alireza Khani. "Travel behavior classification: an approach with social network and deep learning." *Transportation research record* 2672, no. 47 (2018): 68-80.

.. Hou, Yi, and Praveen Edara. "Network scale travel time prediction using deep learning." *Transportation Research Record* 2672, no. 45 (2018): 115-123.

.. Mbunge, Elliot, and Benhildah Muchemwa. "Deep Learning and Machine Learning Techniques for Analyzing Travelers' Online Reviews: A Review." *Optimizing Digital Solutions for Hyper-Personalization in Tourism and Hospitality* (2022): 20-39.

.. Chen, Liang-Chu, Chia-Meng Lee, and Mu-Yen Chen. "Exploration of social media for sentiment analysis using deep learning." *Soft Computing* 24, no. 11 (2020): 8187-8197.

.. Chu, Kai-Fung, Albert YS Lam, and Victor OK Li. "Deep multi-scale convolutional LSTM network for travel demand and origin-destination predictions." *IEEE Transactions on Intelligent Transportation Systems* 21, no. 8 (2019): 3219-3232.

.. Muhammad, Putra Fissabil, Retno Kusumaningrum, and Adi Wibowo. "Sentiment analysis using Word2Vec and long short-term memory (LSTM) for Indonesian hotel reviews." *Procedia Computer Science* 179 (2021): 728-735.

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