ISSN 2776-8007

Intelligent POIs Recommender System based on Time Series Analysis with Seasonal Adjustment

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(Received: August 4, 2021; Revised: September 14, 2021; Accepted: October 5, 2021; Available online: December 16, 2021)

Abstract

Recommender systems have been applied on a variety of applications including movies, music, news, books, research articles, search queries, and travel information. Instead of searching travel information from the extremely huge amount of travel data, a personalized travel recommender system is desired. However, an inappropriate travel recommendation may result from a wrong season, even if it is already a correct location. The current recommender systems from time to time make an inappropriate commendation without considering the seasonal factor. In order to resolve the discrepancy, the seasonal factor should have been taken into consideration when making a good travel recommender system. Therefore, this study has taken the trend analysis, time series, and seasonal factor into considerations to cope with the above mentioned discrepancy and to make the travel recommender system renders a better fit.

Keywords: Recommender System, Time Series Analysis, Long-term Trend Analysis, Seasonal Adjustment

1. Introduction

People make their travel plans more frequently than ever when the widely used information usage has been accompanied with lower transportation cost. According to the Tourism Bureau of the Ministry of Transportation and Communications of the Republic of China, there were 13,182,967 [1] total outbound trips in 2015 while there were 10,439,785 [2] total inbound trips in the same year. Furthermore, the domestic trips of 156,260 [3] thousand hit the record high. A huge amount of international and domestic travel information makes it complicated to find out an optimal recommendation. The need is thereby establishing a recommender system to find out a better solution for people who need their own travel information [4].

The factors commonly adopted by the recommender system include distance, number of favors or followers, number of key-word searching, and number of visitors. The recommendation comes out as a result of the above mentioned factors [5]. However, the wrong timing may impact the appropriateness of the result if the timing factor was not taken into account. For example, maple travel is recommended to people during the summer season, is out of season, and even worse, is close to business. This study established a solution to cope with the time factor for an optimal recommendation for the travellers [6].

In this study, we adopt the time series method to distinguish the timing or the season. The distinguishing features include three portions. They are exclusion, transportation, and season systems. The exclusion mechanism is to exclude the close of business from the recommendation list. The transportation hour shall be taken into account when people start their travel. The distinguishing feature of season makes people an optimal recommendation. The mechanism of season is to distinguish whether it is the right timing to recommend a travel location for a specific time. Our study stimulates the three distinguishing features and is designed to eliminate the suggestion of visiting a right place but wrong timing. Our study trend to achieve a personalized optimal travel recommender system.

2. Methodology

The current travel recommender systems usually adopt geographic data, collaborative filtering and users' preference to sort the recommendation list. It is common to accommodate a feedback system to collect data from the experienced questionnaires (see Figure 1) [7], however, those feedback rankings are not always correct and the recommender systems may from time to time cause some "wrong" answer. Therefore, in this paper, we propose a seasonal judgment mechanism for improving accuracy of the recommendation. Our recommender system is constructed based on the system proposed in [8], which consists of a collaborative filtering module, user experience feedback module, public hobby gathering module, and recommender module.

First of all, let us start from collaborative filtering. It is a concept to start by collecting a huge amount of hobbits, interests, behavior etc. By computing the similarity among the data, a similar recommendation of interest product or information will come out from the recommender system to meet the request [9]. To make it simple, the recommender system will find out the people with the similar interests first and then predict the interest of the requester. Therefore, collaborative filtering is also named social filtering. Current internet business models often use social filtering to find their customers' interests, for example, Amazon [10], YouTube [11] and Kakaku [12] etc. They are typical examples of using social filtering.

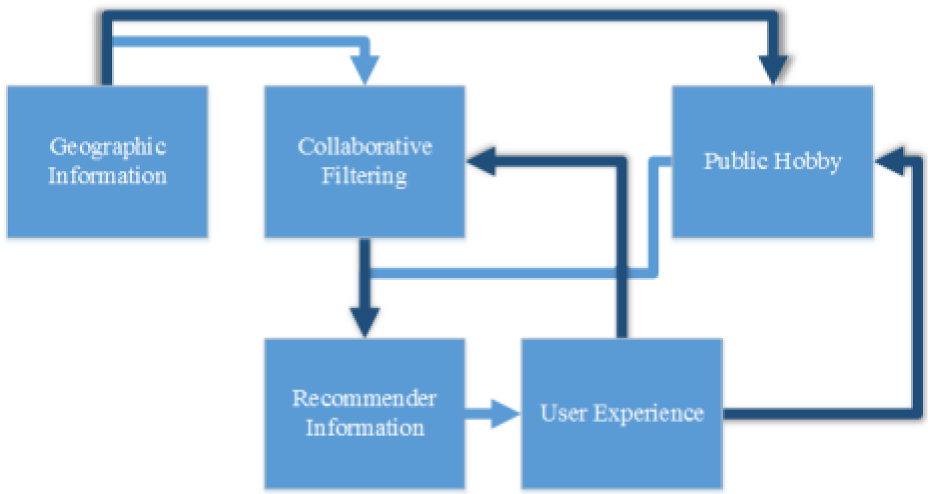

Figure. 1. Social filtering

Secondly, we would like to introduce a recommendation module. By utilizing the above mentioned collaborative filtering, the popular preference and the ranking are also included. The Recommender Ranking is made by putting two factors and finding the average of two factors [13], collaborative filtering data and popular preference as shown in Table 1.

Table. 1. Preference Range and Ranking

	Location A	Location B	Location C	Location D
Collaborative	1	2	4	3

 ISSN 2776-8007

Filtering Ranking				
Public Hobby Ranking	1	3	2	4
Conventional Recommender Ranking	1	2.5	3	3.5
Recommender Priority	1	2	3	4

In this study, we would like to introduce our recommender system where an optimal solution is made based on time series analysis with seasonal adjustment. The following is our flow chart (Figure 2).

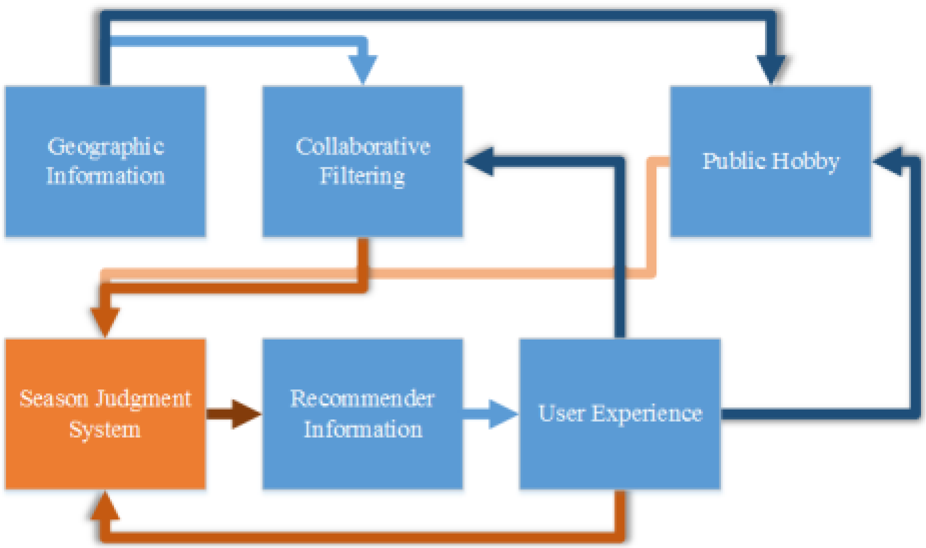

Figure. 2. Our Model-recommender system based on Time Series Analysis with seasonal adjustment

In our study, we include not only the traditional model but also adopt Time Series Analysis with seasonal adjustment. There are three portions to distinguish timing factors, they are exclusion, transportation, and seasonal system. The following sections will furthermore elaborate these three distinguishing factors.

- Exclusion System

When a visitor starts to move from one location to the destination [14], we need to consider the transportation time, counting by minutes, in order for the visitor to arrive on or before the close of business hours. Such transportation hour required is calculated through the Google transportation hour arrangement from start point to the destination.

- Transportation System

When a visitor starts to move from one location to the destination [15], we need to consider the transportation time, counting by minutes, in order for the visitor to arrive on or before the close of business hours. Such transportation hour required is calculated through the Google transportation hour arrangement from start point to the destination.

- Seasonal System

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The last but not the least is the Seasonal System. The major concept is to collect the ranking from the experienced users. The top priority list of seasonal ranking makes the season more favorable season to visit [16]. For example, a location featured with cherry trees and maple trees may attract more visitors during spring and autumn season respectively than to visit during summer and winter season. The features of location information become the implications of the visiting season for travel recommendation systems. The following will elaborate more details about the seasonal system.

Let us make the Seasonal System into two steps. The first step is to set up a time series analysis for the rate from the evaluators to predict their future rating. Their rating is designed to be ranging from rate 1 to rate 5 points. The monthly average rate will be the rate points for the particular month. There are twelve months and twelve rates in a year. The second step in our system is to make a ranking for all information and to adjust the ranking to better fit and meet the request for the visitor. The following is the mechanism and the formula for the time series analysis The time series analysis we use is the long term trend and seasonal fluctuation. The details are as below:

- Long term trend analysis

$$Y_t = \alpha + \beta t + \varepsilon_t \tag{1}$$

  a. Y_t is the value of timing series
  b. t is time
  c. εt is residual value
- Seasonal fluctuation

Seasonal variation is measured in terms of an index, called a seasonal index. It is an average that can be used to compare an actual observation relative to what it would be if there were no seasonal variation. An index value is attached to each period of the time series within a year. This implies that if monthly data are considered there are 12 separate seasonal indices, one for each month [17].

We use the ratio-to-moving-average method in this project. The measurement of seasonal variation by using the ratio-to-moving-average method provides an index to measure the degree of the seasonal variation in a time series. The index is based on a mean of 100, with the degree of seasonality measured by variations away from the base [18].

a. Find the centered 12 monthly (or 4 quarterly) moving averages of the original data values in the time-series.
b. Express each original data value of the time-series as a percentage of the corresponding centered moving average values obtained in step(1).In other words, in a multiplicative time-series model, we get(Original data values)/(Trend values) *100 = (T*C*S*I)/(T*C)*100 = (S*I) *100. This implies that the ratio–to-moving average represents the seasonal and irregular components.
c. Arrange these percentages according to months or quarter of given years. Find the averages over all months or quarters of the given years.
d. If the sum of these indices is not 1200(or 400 for quarterly figures), multiply then by a correction factor = 1200/ (sum of monthly indices). Otherwise, the 12 monthly averages will be considered as seasonal indices [19].

We take 4 quarterly for example, because it's easier to show you how it works.

Table. 2. Data

Year/Quarters	I	II	III	IV
2012	2.1	3.3	4.2	2.8

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2013	2.5	3.4	4.3	3.0
2014	2.4	3.6	4.5	3.3
2015	2.3	3.5	4.6	3.2

Table. 3. 4 Quarterly moving averages and ratio-to-moving-averages.

Year	Quarter	Original Values(Y)	4 Figures Moving Total	4 Figures Moving Average	2 Figures Moving Total	2 Figures Moving Average(T)	Ratio-toMovingAverage(%)(Y)/(T)*100
2012	1	2.1					
	2	3.3					
			12.4	3.1			
	3	4.2			6.3	3.15	133.33
			12.8	3.2			
	4	2.8			6.425	3.2125	87.16
			12.9	3.225			
2013	1	2.5			6.475	3.2375	77.22
			13	3.25			
	2	3.4			6.55	3.275	103.82
			13.2	3.3			
	3	4.3			6.575	3.2875	130.80
			13.1	3.275			
	4	3.0			6.6	3.3	90.90
			13.3	3.325			
2014	1	2.4			6.7	3.35	71.64
			13.5	3.375			
	2	3.6			6.825	3.4125	105.49
			13.8	3.45			

	3	4.5			6.875	3.4375	130.90
			13.7	3.425			
	4	3.3			6.825	3.4125	96.70
			13.6	3.4			
2015	1	2.3			6.825	3.4125	67.40
			13.7	3.425			
	2	3.5			6.825	3.4125	102.56
			13.6	3.4			
	3	4.6					
	4	3.2					

Table. 4. Seasonal index

Year/Quarters	I	II	III	IV
2012	-	-	133.33	87.16
2013	77.22	103.82	130.80	90.90
2014	71.64	105.49	130.80	96.70
2015	67.40	102.56	-	-
Total	216.26	311.87	395.03	274.76
Seasonal Average	72.09	103.96	6 131.68	91.59
Adjusted Seasonal Average	72.21	104.14	131.90	91.75

The total of seasonal averages is 399.32. The corresponding correction factor would be 400/399.32 = 1.0017. Each seasonal average is multiplied by the correction factor 1.0017 to get the adjusted seasonal indices as shown in the table 4 [20]. The trend value is multiplied by the seasonal adjusting index. The result is then taken as the predicted value of rating. Such ratings shall be sorted from high to low. The collaborative filtering and popular preference information are further calculated to come out with the final solution for the travel recommendation.

Table. 5. Recommendation with seasonal adjustment

	Location A	Location B	Location C	Location A
Forecast Pint	3.8	4.6	4.3	3.2

Season Ranking	3	1	2	4

Table. 6. Recommendation Range by Ranking with Seasonal Adjustment

	Location A	Location B	Location C	Location D
Collaborative Filtering Ranking	1	2	4	3
Public Hobby Ranking	1	3	2	4
Season Ranking	3	1	2	4
Recommender Information Point	1.67	2	2.67	3.67
Recommender Ranking	1	2	3	4

Having all three distinguishing factors available, the flow chart of the recommender system is modified. The following chart demonstrates the relationship flows for our study.

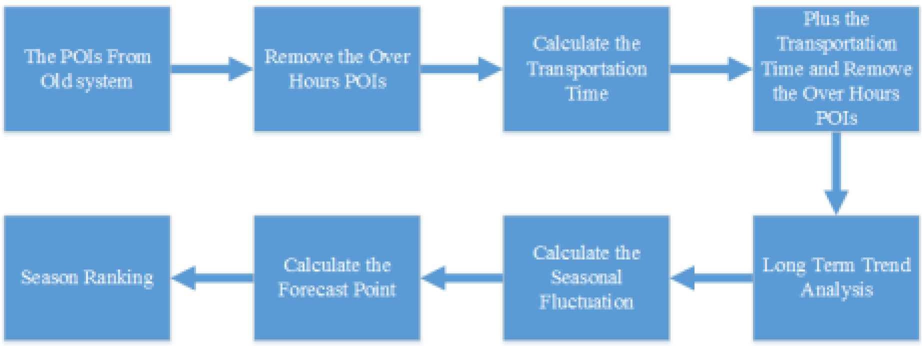

Figure. 3. Flowchart to accommodating timing distinguishing factors

3. Discussion

In this section, we give some examples to show the effectiveness of our study. We also compare the system that is based on time series analysis with seasonal adjustment with the traditional system that does not include time series analysis in recommendation. Because we cannot collect real data for a long time, we surmise every month the score of all POIs.

3.1. Scenario one

a. Purpose: To exclude out-of-business hours location from the recommendation list
b. Experimental place: TKU Main Engineering Bldg (E)
c. Experimental time: Feb 18, 2016 00:55 a.m

The unmodified traditional system recommends six stores to visit to the requestor who would like to find a store to buy food. However, after taking consideration of business hours, there are two stores left and are recommended to the requester. The out of business hours stores were excluded from the recommender system as a result of taking the Exclusion system into account.

Table. 7. Design one: the ranking change after taking exclusion system into consideration

Ranking	Ranking	Changes	New Ranking
1	椒麻雞大王	1→X	7-Eleven（淡大門市）
2	大吉祥香豆富	2→X	Family Mart（學城店）
3	吃乎義料	3→X	
4	火鍋世家（大忠店）	4→X	
5	7-Eleven（淡大門市）	5↗1	
6	Family Mart（學城店）	6↗2	

Figure. 4. The transportation time needed from start point to destination

3.2. Scenario two

a. Purpose: To test the time series analysis
b. Experimental place: TKU Main Engineering Bldg (E)
c. Experimental time: Feb 24, 2016 18:00 p.m.

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In this scenario, there were five locations suggested and prioritized from the traditional recommender system. After the time series analysis with seasonal adjustment, the top priority is changed to a better ranking. The locations with hot springs become better solutions and the Baishawan (Beach).

Table 8 shows the difference points we got between considering the seasonal factor or not, Old Points is the average of all scores every month. If the seasonal factor is not considered, we will get the unreasonable points and make the recommendations are not accurate. When the seasonal factor is considered by the system, we can get the forecast points of January and the recommendation clearly makes sense. The recommender system is more accurate after the seasonal factor is considered.

Table. 8. The old and new points we got

	Beitou Hot Spring Museum	Pulowan Recreation Area	Baishawan (Beach)	Lung Shan Temple	Bulao Hot Springs
Old Points (Average)	3.58	2.88	2.52	2.32	2.10
Old Ranking	1	2	3	4	5
Forecast Points (January)	4.38	3.59	1.51	3.40	4.26
Season Ranking	1	3	5	4	2

Table. 9. shows the ranking with seasonal factors or not. The ranking is from table 8.

Ranking	Old Ranking	Changes	New Ranking
1	Beitou Hot Spring Museum	1→1	Beitou Hot Spring Museum
2	Pulowan Recreation Area	2↘3	Bulao Hot Springs
3	Baishawan (Beach)	3↘5	Pulowan Recreation Area
4	Lung Shan Temple	4→4	Lung Shan Temple
5	Bulao Hot Springs	5↗2	Baishawan (Beach)

Table. 10. shows the data we surmise of POIs every month, the surmise are from the Government

Year	Month	Beitou Hot Spring Museum	Pulowan Recreation Area	Baishawan (Beach)	Lung Shan Temple	Bulao Hot Springs
1	1	3.34	2.25	1.53	1.15	1.95
1	2	3.19	2.25	1.74	1.16	2.76
1	3	2.91	1.99	2.05	1.08	1.81

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1	4	2.92	2.47	2.15	1.08	1.63
1	5	2.90	1.94	2.78	1.08	1.36
1	6	2.64	1.82	2.68	1.12	1.23
1	7	2.99	2.44	4.39	1.01	1.11
1	8	2.98	2.44	3.70	0.98	1.14
1	9	2.51	1.93	2.71	0.99	1.07
1	10	3.00	1.80	2.24	1.10	1.07
1	11	3.14	1.51	1.69	1.05	1.39
1	12	3.38	1.51	169	1.02	1.66
3	1	3.42	3.41	1.28	0.99	4.83
3	2	3.64	3.35	1.43	4.01	2.03
3	3	3.50	3.00	1.80	2.58	1.99
3	4	3.57	3.58	1.98	2.44	1.29
3	5	3.45	3.19	1.70	2.33	1.40
3	6	3.36	3.16	2.23	2.32	0.95
3	7	3.92	4.12	3.97	2.44	1.36
3	8	4.03	3.02	2.88	2.41	0.97
3	9	3.90	3.19	3.54	2.38	0.98
3	10	3.75	3.37	2.10	3.21	1.63
3	11	3.86	3.32	1.53	3.13	1.74
3	12	4.10	3.00	1.32	3.19	2.15
6	1	4.33	3.52	1.73	3.26	4.72
6	2	4.01	3.53	1.86	3.86	3.63
6	3	4.07	3.03	1.86	3.13	3.16
6	4	4.36	3.68	2.75	0.93	3.23

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6	5	3.83	3.62	2.72	2.91	3.11
6	6	3.35	3.69	3.68	2.79	2.70
6	7	3.64	3.68	4.39	2.88	2.60
6	8	3.67	3.22	4.06	3.00	2.14
6	9	3.64	3.08	4.62	2.94	2.61
6	10	4.42	2.88	2.87	3.15	3.27
6	11	4.21	2.87	2.18	3.10	3.40
6	12	3.13	2.93	1.62	3.10	3.77
Next Month		**Forecast Points**				
7	1	4.38	3.59	1.51	3.40	4.26

3.3. Scenario three

Compared to the famous amusement park, scenario three is similar to scenario two, table 11 shows the difference between considering the seasonal factor [21]. The data is from 2010 to 2014, we forecast the points in July of next year. Table 11 shows the difference points we got between considering the seasonal factor or not [22, 23], Old Points is the average of all scores every month. Clearly, the recommender system is more accurate after the seasonal factor is considered.

Table. 11. The old and new points we got

	JanFuSun Fancyworld	Formosan Aboriginal Culture Village	Leofoo Village Theme Park	LihPaoLand	Formosa Fun Coast
Old Points (Average)	3.31	3.03	2.88	2.32	1.87
Old Ranking	1	2	3	4	5
Forecast Points (January)	3.57	2.02	3.56	4.94	4.17
Season Ranking	3	5	4	1	2

Table. 12. shows the ranking with seasonal factors or not. The ranking is from table 11.

Ranking	Old Ranking	Changes	New Ranking

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1	JanFuSun Fancyworld	1→3	LihPaoLand
2	Formosan Aboriginal Culture Village	2↘5	Formosa Fun Coast
3	Leofoo Village Theme Park	3↘4	JanFuSun Fancyworld
4	LihPaoLand	4→1	Leofoo Village Theme Park
5	Formosa Fun Coas	5↗2	Formosan Aboriginal Culture Village

Table. 13. shows the data we surmise of POIs every month, the surmise are from the Government.

Year	Month	JanFuSun Fancyworld	Formosan Aboriginal Culture Village	Leofoo Village Theme Park	LihPaoLand	Formosa Fun Coast
1	1	3.30	3.77	2.43	1.14	1.26
1	2	4.83	4.66	3.02	2.12	1.40
1	3	2.79	4.24	2.37	1.35	1.10
1	4	2.96	4.43	2.76	1.63	0.98
1	5	2.71	4.04	2.54	2.01	1.18
1	6	2.85	3.64	2.63	2.44	1.74
1	7	3.69	4.12	3.41	4.24	4.65
1	8	4.22	4.09	3.75	4.47	493
1	9	3.13	2.78	2.47	2.43	2.12
1	10	3.55	3.04	2.57	1.89	1.73
1	11	3.41	3.01	2.56	1.54	1.05
1	12	3.54	3.09	2.85	1.32	1.43
3	1	3.80	3.18	2.75	2.01	1.55
3	2	3.01	4.59	2.44	1.36	1.64

3	3	2.70	3.41	2.31	1.23	1.17
3	4	2.59	3.19	2.79	1.44	0.98
3	5	2.89	2.21	2.43	1.72	2.10
3	6	3.31	1.92	2.58	1.94	1.76
3	7	3.69	3.28	3.26	4.13	4.15
3	8	3.93	3.79	3.96	4.06	3.80
3	9	2.93	2.74	2.86	2.55	2.05
3	10	2.93	2.61	3.26	1.95	1.08
3	11	3.42	2.54	2.81	1.28	1.20
3	12	4.00	2.71	2.61	1.42	1.43
6	1	2.58	2.21	2.52	2.32	1.11
6	2	3.58	4.13	3.54	2.76	1.32
6	3	2.85	3.01	3.26	1.67	1.02
6	4	3.17	2.40	2.76	1.80	0.81
6	5	2.62	2.11	2.55	2.44	1.03
6	6	3.24	2.09	2.94	2.93	2.21
6	7	3.69	2.47	4.37	4.28	4.06
6	8	3.85	2.71	4.87	4.89	4.17
6	9	3.00	1.97	2.90	2.98	2.32
6	10	3.10	2.38	3.25	2.39	1.17
6	11	3.41	2.49	3.06	1.65	1.05
6	12	3.65	2.30	2.64	1.52	1.27
Next Month		**Forecast Points**				
6	7	3.57	2.02	3.56	4.94	4.17

4. Conclusion and Future Work

In our study, we accommodate time series analysis to the travel recommender system. Our time series analysis has made seasonal adjustments to better fit the request and is intended to come to an optimal solution. Based on the time series analysis, three system factors are incorporated, they are exclusion system, transportation system and seasonal factor system. The resolution has made our recommender system a personalized one to better fit and meet the request. In future study, we will collect more information pertaining to the stay hour the visitors have spent their time on the specific locations. Such information will make our analysis improved to even better fit to the visitors and meet their request.

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