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REGIONS GROUPING IN CENTRAL SULAWESI PROVINCE BY TRANSMITTED DISEASE USING FUZZY GUSTAFSON KESSEL

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ABSTRACT

Health is one of the main indicators in determining the human development index. This contradicts the situation in several areas in Indonesia where infectious diseases cause death and have become extraordinary events. It was recorded in Central Sulawesi that in 2020 there were 8 extraordinary events due to infectious diseases, which made this province become relatively high infectious diseases. One of the efforts that can be made to identify infectious diseases in an area is to form a grouping of locations into a group with similarities and the same characteristics. This is intended to provide information related to health in each region. Cluster analysis is one method that can be used to group the data. Cluster *analysis is dividing data into a group based on similarity. Data with similar characteristics will be gathered in one group. One of the algorithms in* cluster *analysis is Fuzzy Gustafson Kessel which can produce relatively better groupings than the basic algorithms in* cluster *analysis. This study will use data on infectious diseases in Central Sulawesi Province with several recorded infectious diseases. From 13 regions, 5* clusters *were formed.* Clusters *1, 2, and 3 each consist of 3 regions, while* clusters *4 and 5 each consist of 2 regions.*

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1. INTRODUCTION

Health is one of the indicators of the human development index. Given that the development of the health sector in Indonesia is being faced with a double burden where infectious diseases are still a problem that cannot be resolved, and there are still infectious diseases that were initially still able to be controlled, now reappear with spread without knowing regional or national boundaries [1]. Several infectious diseases are among the highest causes of death in Indonesia, such as diarrhea, acute respiratory infections (ARI), tuberculosis (TBC), dengue fever, HIV/AIDS, diarrhea, filariasis and other infectious diseases [2].

Extraordinary events (KLB) infectious diseases and poisoning are still a serious problem for people in Central Sulawesi. Several infectious diseases that still often cause outbreaks such as diarrhea, dengue fever, measles, and food poisoning. Several efforts have been made by the health ranks, but extraordinary events still continue to exist in Central Sulawesi, in 2020 8 outbreaks were reported with a total of 568 cases and 2 deaths [3].

Infectious diseases are diseases caused by various types of microorganisms that cannot be seen by the naked eye. Called an infectious disease because it can move from one person to another through the intermediary of insects, water, food and air. In addition to environmental intermediaries, it can also be transmitted through direct contact by touching the skin, kissing, or through the blood flow of a mother to a child while still in the womb [4]. Infectious diseases are divided into 3 groups based on the medium or mode of transmission, namely airborne (tuberculosis and pneumonia); through food, water and others (diarrhea, HIV/AIDS, diphtheria, leprosy, elephantiasis, measles, tetanus neonatorum, polio and AFP, rabies, and leptospirosis) as well as through vectors (dengue fever, malaria and chikungunya) [4].

Several health problems regarding communicable and non-communicable diseases that exist in Indonesia show that the Indonesian people are not aware of the importance of health. This should get more attention, especially for health authorities, regarding the spread of communicable and non-communicable diseases. Therefore, it is hoped that all parties should take better care of their own health. One effort that can be done is to form a regional grouping into a group that has similarities or almost the same characteristics. This is intended to provide information related to health in each region. One method that can be done in this grouping is using cluster analysis [5].

Cluster analysis is the process of dividing data into a group based on the degree of similarity [6]. Data that have similar characteristics will be gathered in one group, while data that have different characteristics will be gathered in different groups [7]. One approach in cluster analysis is Fuzzy Gustafson Kessel (FGK) which is the development of Fuzzy C-Means [8]. The matrix-forming values in the FGK will be updated in each iteration, so that they are able to adjust the geometric shape of the right membership function for a data set [9].

Based on the description described above, this study will group regencies/cities in Central Sulawesi Province based on infectious disease indicators using Fuzzy Gustafson Kessel.

2. RESEARCH METHODS

The data used in this study is secondary data obtained from the Regional Health Office of Central Sulawesi Province which contains data on the number of people with 8 variables of infectious diseases to humans, namely pulmonary tuberculosis, HIV/AIDS, acute respiratory infections, leprosy, diarrhea, malaria, rabies, and filariasis in 2020.

This study used cluster analysis with the Fuzzy Gustafson Kessel (FGK) approach. FGK will group objects, in this case regencies/cities into several clusters/groups, where each cluster member will have similarities with other members based on infectious disease indicators. The number of groups to be formed will be initialized at the beginning, then each object will be included in the group formed based on the distance of the object to the center of the cluster. FGK modifies the distance component in the minimized objective function by entering the covariance of the data so as to make the group formed more optimally [10]. Finally, the formed group will inform the profile and characteristics of each regency/city based on its infectious disease indicators.

The data were analyzed with the help of the Rstudio software. The stages of the research procedure are as follows [11]:

1. Input data
2. Performing the FGK algorithm steps as follows:
   a. Determining initialization of parameters, namely the number of clusters, weighting rank ($\boldsymbol{w > 1}$), maximum iteration ($\boldsymbol{t_{max}}$), termination criteria ($\boldsymbol{\varepsilon}$), initial objective function ($\boldsymbol{P_0 = 0}$), and the initial iteration ($\boldsymbol{t = 1}$). The optimum number of clusters with *fuzzy* method is measured using one of the validity indices, namely *Xie Beni* (XB). Optimal number of groups by minimizing the index value [12]. This index has a high accuracy in providing many optimum clusters [13].

   XB index can be calculated as follows [14]:

$$\boldsymbol{I_{XB(c)} = \frac{\sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^{w} d_{ik}^{2}}{n\min\|v_i - v_j\|^2}} \tag{1}$$

   Where :

   $\boldsymbol{I_{XB(c)}}$: index Xie Beni
   $\boldsymbol{c}$: number of clusters
   $\boldsymbol{n}$: number of research objects
   $\boldsymbol{w}$: rank weighting
   $\boldsymbol{\mu_{ik}}$: degree of membership of object $\boldsymbol{i}$ in cluster $\boldsymbol{k}$
   $\boldsymbol{d_{ik}^2}$: distance of the object $\boldsymbol{i}$ with the center of cluster k
   $\boldsymbol{v_i - v_j}$: distance between the center of clusters

   b. Generating a random value as the initial element of the partition matrix $\boldsymbol{U_0}$. Partition matrix element $\boldsymbol{\mu_{ik}}$; $\boldsymbol{i = 1, 2, 3, \cdots, n}$; $\boldsymbol{k = 1, 2, 3, \cdots, c}$ as initial membership degree with the number of elements in each row is 1.

$$\boldsymbol{U = \begin{bmatrix} \mu_{11}(x_1) & \mu_{12}(x_1) & \cdots & \mu_{1k}(x_1) \\ \mu_{21}(x_2) & \mu_{22}(x_2) & \cdots & \mu_{2k}(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{n1}(x_n) & \mu_{n2}(x_n) & \cdots & \mu_{nk}(x_n) \end{bmatrix}} \tag{2}$$

   c. Calculating the center of cluster $\boldsymbol{k}$ ($\boldsymbol{v_k}$) with $\boldsymbol{k = 1, 2, \cdots, c}$, from the partition matrix and grouped data.

$$\boldsymbol{v_k = \frac{\sum_{i=1}^{n}((\mu_{ik})^{w} x_i)}{\sum_{i=1}^{n}(\mu_{ik})^{w}}, 1 \le k \le c} \tag{3}$$

   Where :

   $\boldsymbol{\mu_{ik}}$: membership degree of data $\boldsymbol{i}$ in cluster $\boldsymbol{k}$
   $\boldsymbol{w}$: weighting exponent of the membership function. The value most often used by researchers for the value of $\boldsymbol{w}$ is 2 [15].
   $\boldsymbol{n}$: number of data
   $\boldsymbol{c}$: number of cluster
   $\boldsymbol{x_i}$: vector data i

   d. Calculating distance
   The objective function of the Gustafson-Kessel grouping is as follows:

$$\boldsymbol{D_{(i,k)A_i}^2 = \|x_i - v_k\|_{A_i}^2 = (x_i - v_k)^T A_i (x_i - v_k)} \tag{4}$$

$$\boldsymbol{A_i = [det(F_k)]^{\frac{1}{h}} (F_k^{-1})} \tag{5}$$

   Where :

   $\boldsymbol{X}$: matrix of data that will be grouped
   U : matrix of initial membership degree
   V : matrix of cluster's center
   $\boldsymbol{A_i}$: group distance matrix (adaptive distance norm)
   $\boldsymbol{F_k}$: covariance matrix

e. Calculating the objective function
The objective function of the Gustafson-Kessel grouping is as follows:

$$J_{FGK}(X;U,V,A_i) = \sum_{i=1}^{c}\sum_{k=1}^{n}(u_{ik})^{w}\, D_{(i,k)A_i}^{2} \tag{6}$$

The optimum partition matrix is obtained when the objective function reaches its minimum.

f. Calculating the new membership degree to improve the partition matrix U_0 to obtain a partition matrix U_t with elements μ_{ik} calculated

$$\mu_{ik} = \left[\sum_{j=1}^{c}\left(\frac{D_{ikA_i}}{D_{jkA_i}}\right)^{\frac{2}{(w-1)}}\right]^{-1} \tag{7}$$

g. Check the stop condition with $P_t - P_{t-1} \vee$ or $(t > t_{max})$

3. Obtain cluster results from FGK analysis
4. Interpreting and make conclusions

3. RESULTS AND DISCUSSION

3.1. Parameter Initialization

In the FGK method first determine the initialization of parameters to be used, including determining the value of the weighting power (w), initial iteration, maximum iterations (t_{max}), initial objective function, termination criteria (ε) and number of clusters (k). Determination of the number of weighting powers (w) is by using ($w > 1$), the best weighting rank used is 2 so that in this study $w = 2$. The initial iteration is 1 and the maximum iteration is 1000, in terms of determining the number of limits from the maximum iterations there is no rule that regulates the limits of the maximum number of iterations. The initial objective function is 0. The termination criteria or error value used is 1×10^{-5} or 0.00001. Furthermore, for the number of clusters used, namely 5 clusters obtained from the test results using the *Xie Beni* (XB) index method. The determination of the optimum number of clusters is indicated by the minimum XB validity index value. The value of the weighting rank, initial iteration, maximum iteration, initial objective function, termination criteria and number of clusters can be seen in the following **Table 1**:

Table 1. Parameter Initialization

Weighting Rank	Initial Iteration	Maximum Iteration	Initial Objective Function	Termination Criteria	Number of Cluster
$w = 2$	1	$t_{max} = 1000$	$P_t = 0$	$\varepsilon = 0{,}00001$	5

3.2. Determination of Initial Membership Degree

Determination of initial membership degree value with a size where n is the data, while $\mu_{i,k}$ is the membership value in each cluster. The data used are 13 data as many as the number of regencies/cities in Central Sulawesi Province and the cluster to be formed is 5 clusters. Things to do in generating random numbers partition matrix U with components, with 1,2,3,,13; $k = 1,2,3,4,5$; as the value of $\mu_{i,k}$ initial membership degrees. The value is determined randomly with the condition that the number of element values in each row is 1. The initial membership degree value is obtained as follows:

Table 2. Initial Membership Degree

Regency/City	$\mu_{i,1}$	$\mu_{i,2}$	$\mu_{i,3}$	$\mu_{i,4}$	$\mu_{i,5}$	$\sum\mu_{i,k}$
1	0.194444	0.555556	0.152778	0.0625	0.034722	1
2	0.157025	0.066116	0.016529	0.404959	0.355372	1
3	0.271903	0.21148	0.238671	0.23565	0.042296	1
4	0.380952	0.421769	0.027211	0.027211	0.142857	1

5	0.115274	0.242075	0.161383	0.193084	0.288184	1
6	0.310458	0.303922	0.01634	0.215686	0.153595	1
7	0.152672	0.320611	0.183206	0.01145	0.332061	1
8	0.142857	0.348432	0.250871	0.111498	0.146341	1
9	0.189427	0.008811	0.348018	0.237885	0.215859	1
10	0.219608	0.2	0.023529	0.192157	0.364706	1
11	0.40678	0.207627	0.241525	0.033898	0.110169	1
12	0.082524	0.305825	0.038835	0.466019	0.106796	1
13	0.142857	0.167347	0.326531	0.012245	0.35102	1

3.3. Center of Cluster

The aim of center of cluster determination is to determine the distance of a data to the center of the cluster. A data object is included in a cluster if it has the shortest distance to the center of the cluster. Calculating the center of cluster i, $\boldsymbol{v}_i$ ($i = 5$) by using **Equation (3)**. The value of the cluster in the 12th iteration can be seen in the following **Table 3**.

Table 3. Center of Cluster

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Cluster 1	0.81288	0.01386	0.6019	0.10494	0.70606	0.55917	−0.1003	1.13275
Cluster 2	0.27966	0.60721	−0.1113	−0.4774	−1.1174	−0.3092	−0.0899	−0.6611
Cluster 3	−0.7141	−0.4418	−0.5556	−0.9082	−0.4245	0.29867	0.45826	0.00753
Cluster 4	−0.2293	−0.4682	−0.5427	1.46916	0.76874	−0.365	−0.8732	−0.4572
Cluster 5	−0.3384	0.19928	0.64021	0.45198	0.48497	−0.458	−0.1003	1.13275

3.4. Distance Calculation

The similarity of characteristics between objects is used to measure the distance (*distance*). Calculate the distance $\boldsymbol{D}i^2_{(i,k)Ai}$ by using **Equation (1)** where is the row vector of the $\boldsymbol{X}$ matrix with 8 variables and $\boldsymbol{A}_i = [det(\boldsymbol{F}_k)]^{\frac{1}{h}}(\boldsymbol{F}_k^{-1})$ with value. After the calculation, the distance between data i and the center of cluster k with $i = 1,2,,13$ and $k = 1,2,3,4,5$ can be seen in the following **Table 4**:

Table 4. Distance

Regency/City	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
1	9.82×10^{4}	5.55×10^{-11}	8.44×10^{4}	2.12×10^{3}	1.13×10^{3}
2	4.64×10^{4}	2.85×10^{4}	2.57×10^{-11}	1.29×10^{3}	1.09×10^{3}
3	4.69×10^{4}	5.38×10^{-11}	5.19×10^{4}	6.45×10^{2}	1.39×10^{3}
4	3.81×10^{-11}	8.87×10^{4}	5.11×10^{4}	1.06×10^{3}	3.81×10^{1}
5	3.94×10^{-11}	5.96×10^{4}	4.37×10^{4}	6.49×10^{2}	1.32×10^{3}
6	3.31×10^{4}	1.63×10^{4}	9.51×10^{3}	7.54×10^{2}	3.57×10^{-13}

7	7.17×10^{4}	5.84×10^{4}	1.38×10^{4}	1.88×10^{-13}	7.72×10^{2}
8	4.25×10^{4}	5.49×10^{4}	2.72×10^{4}	3.69×10^{2}	3.66×10^{-13}
9	4.13×10^{4}	1.45×10^{4}	2.54×10^{-11}	4.05×10^{2}	3.83×10^{2}
10	4.54×10^{4}	3.61×10^{4}	2.66×10^{-11}	1.18×10^{3}	2.71×10^{2}
11	2.46×10^{4}	2.56×10^{4}	3.21×10^{4}	1.89×10^{-13}	6.94×10^{2}
12	3.62×10^{-11}	2.89×10^{4}	5.59×10^{4}	7.35×10^{2}	8.08×10^{2}
13	4.83×10^{4}	5.25×10^{-11}	5.91×10^{3}	4.99×10^{2}	9.78×10^{2}

3.5. Calculation of Objective Functions

Calculating functions the objective in the 12th iteration for the FGK method, using **Equation (6)**. After calculating, it was found that the iteration process ended in the 12th iteration. The process is declared to stop at $(P_t - P_{t-1} < \varepsilon)$. The objective function is fulfilled in the 12th iteration with an objective function value of 0.0001220437. This value describes the distance from the grouped data points to the cluster which is weighted by the degree of membership of the data points.

3.6. Calculation of Membership Degrees

Determination of the value of the degree of membership aims to determine the tendency of a data to enter a cluster. The value of the degree of membership of this study obtained the following results.

Table 5. Membership Degrees

Regency/City	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
1	3.36×10^{-15}	**1**	4.07×10^{-15}	2.63×10^{-14}	3.37×10^{-13}
2	2.10×10^{-15}	3.76×10^{-15}	**1**	2.70×10^{-14}	1.07×10^{-13}
3	2.61×10^{-15}	**1**	1.83×10^{14}	4.84×10^{-13}	7.00×10^{-13}
4	**1**	1.46×10^{-15}	1.71×10^{-15}	4.12×10^{-14}	8.14×10^{14}
5	**1**	1.78×10^{-15}	2.29×10^{-15}	6.75×10^{-14}	4.64×10^{-14}
6	2.07×10^{-17}	8.52×10^{-17}	6.54×10^{-16}	2.26×10^{-16}	**1**
7	9.62×10^{-19}	8.54×10^{-18}	7.91×10^{-17}	**1**	2.69×10^{-16}
8	4.85×10^{-17}	2.06×10^{-16}	1.81×10^{-16}	5.37×10^{-15}	**1**
9	3.79×10^{-15}	1.49×10^{-15}	**1**	1.26×10^{-13}	4.96×10^{-13}
10	1.08×10^{-15}	2.73×10^{-15}	**1**	1.20×10^{-14}	1.15×10^{-12}
11	1.48×10^{-18}	2.37×10^{-17}	8.42×10^{-18}	**1**	1.95×10^{-16}
12	**1**	5.45×10^{-15}	1.98×10^{-15}	2.02×10^{-14}	3.20×10^{13}
13	7.95×10^{-15}	**1**	1.64×10^{-13}	3.84×10^{-12}	7.56×10^{-13}

Based on **Table 5** shows the degree of membership of a regency/city to become a member of a cluster. Membership of a data (regency/city) is determined based on the value of the largest membership degree. The largest membership degree values in the table are indicated by numbers in bold. Based on the degree of membership, information is obtained about the tendency of a regency/city to become part of a cluster.

3.7. Cluster

Results The results of the FGK analysis formed 5 clusters with the number of members in each cluster as follows.

Table 6. Cluster Members

No	Regency/City	Cluster
1	Palu	2
2	Morowali Utara	3
3	Banggai Laut	2
4	Sigi	1
5	Tojo Una-Una	1
6	Parigi Moutong	5
7	Buol	4
8	Toli-Toli	5
9	Donggala	3
10	Poso	3
11	Morowali	4
12	Banggai	1
13	Banggai Kepulauan	2

Based on **Table 6** above, 5 clusters were obtained. Cluster 1 has three regions including Sigi, Tojo Una-una and Banggai. Cluster 2 has three regions including Palu, Banggai Laut and Banggai Kepulauan. Cluster 3 has three regions including Morowali Utara, Donggala, and Poso. Cluster 4 has two regions including Buol and Morowali. Cluster 5 consists of two regions, Parigi Moutong and Toli-Toli.

3.8. Cluster Interpretation in the Fuzzy Gustafson Kessel

After determining the number of clusters and their members formed, the next step is to give specific characteristics to describe the contents cluster. To interpret the results cluster used the value of the center cluster (centroid) which is the average value of each variable in each cluster. The value of the cluster is obtained as in **Table 7** as follows:

Tabel 7. Centroid Value

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Cluster 1	0.81288	0.01386	0.6019	0.10494	0.70606	0.55917	-0.1003	1.13275
Cluster 2	0.27966	0.60721	-0.1113	-0.4774	-1.1174	-0.3092	-0.0899	-0.6611
Cluster 3	-0.7141	-0.4418	-0.5556	-0.9082	-0.4245	0.29867	0.45826	0.00753
Cluster 4	-0.2293	-0.4682	-0.5427	1.46916	0.76874	-0.365	-0.8732	-0.4572
Cluster 5	-0.3384	0.19928	0.64021	0.45198	0.48497	-0.458	0.47125	-0.2615

Based on **Table 7** above, it can be seen that the highest average value of a cluster is marked in blue and the lowest average value of a cluster is marked in yellow. Based on this, it is known the characteristics of the five clusters formed, so that the following interpretation is obtained.

1. Cluster 1 has three regions including Sigi, Tojo Una-una and Banggai with the highest TBC disease (X_1) indicator with average of 0.81288. This means that regions in cluster have the highest status of TBC sufferers. Cluster also has the highest indicators of Malaria (X_3) and Filariasis (X_8) with each values of 0.55917 and 1.13275. In this cluster, also has the lowest indicator of HIV/AIDS (X_2) with average of 0.01386, and also has the lowest indicator of leprosy with an average of 0.10494.

2. Cluster 2 has three regions including Palu, Banggai Laut and Banggai Kepulauan with the highest indicator of HIV/AID disease (X_2) compared other cluster with average of 0.60721. The cluster has highest indicator of Diarrhea (X_5) with a value of 1.1174. It also has lowest indicators of ISPA (X_3) and Rabies (X_7) compared other clusters with an average of 0.1113 and 0.0899.
3. Cluster 3 has three regions including Morowali, Donggala and Poso with the lowest indicator of diarrhea disease (X_5) compared to other clusters with an average of 0.4245. This cluster also has indicators of Malaria Disease (X_6) and Filariasis (X_8) compared to clusters 0.29867and 0.00753 respectively.
4. Cluster 4 contains two regions including Buol and Morowali with the highest leprosy indicator (X_4) with an average of 1.46916. This means that regions in this cluster have the highest status of leprosy sufferers. In this cluster, also has the lowest indicator of TBC disease (X_4) compared to other clusters with an average of 0.2293.
5. Cluster 5 has two regions including Parigi Moutong and Toli-Toli with the lowest ISPA indicator (X_3) compared to other clusters with an average of 0.64021.

The results of the characteristics that have been obtained from each of clusters can be used as a reference by the government in making a policy. So from the results of grouping regions based on transmitted disease indicators using the Fuzzy Gustafson Kessel, it is able to provide an overview of the location or area in Central Sulawesi Province. This is expected to help the government in taking the right policies for health cases, especially communicable diseases based on clusters.

3.9. Visualization of Clustering Using a Map

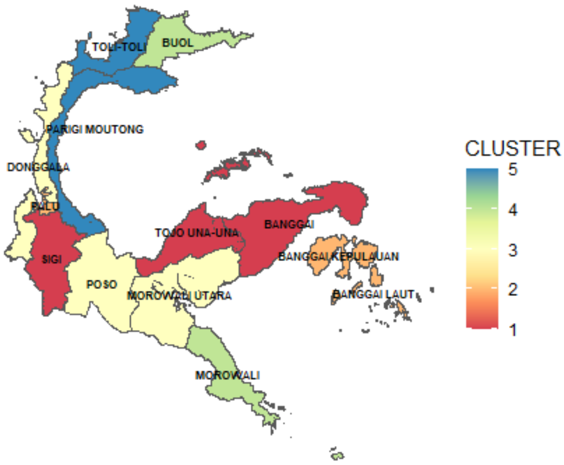

Figure 1. Mapping of Clustering Results

In **Figure 1**, you can see a map of Central Sulawesi from the results of cluster*ing* FGK analysis where the map of cluster 1 members is colored red, members of cluster 2 are colored orange, members of cluster 3 are colored yellow, cluster 4 are colored green and members of cluster 5 are given blue. This can make it easier for readers to find out which areas are in the cluster according to the results obtained from grouping using the FGK method.

4. CONCLUSIONS

The grouping of regions in Central Sulawesi based on infectious disease indicators using Fuzzy Gustafson Kessel obtained the optimum number clusters using the XB validity index as many as 5 clusters with the characteristics of each cluster being different based on the indicators. Cluster 1 consists of three regions with the highest characteristics of TBC, Malaria, and Filariasis. Cluster 2 consists of three regions with the highest characteristics of HIV/AID and diarrhea compared to other clusters. Cluster 3 consists of three regions that have the lowest characteristics of diarrhea, malaria and filariasis compared to other clusters. Cluster 4 consists of two regions with the highest indicators of leprosy and rabies. Cluster 5 consists of two regions with the highest indicators of ISPA compared to other clusters.

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