



## Research Article

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# Context Analysis of Customer Requests using a Hybrid Adaptive Neuro Fuzzy Inference System and Hidden Markov Models in the Natural Language Call Routing Problem

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**Abstract:** The context analysis of customer requests in a natural language call routing problem is investigated in the paper. One of the most significant problems in natural language call routing is a comprehension of client request. With the aim of finding a solution to this issue, the Hybrid HMM and ANFIS models become a subject to an examination. Combining different types of models (ANFIS and HMM) can prevent misunderstanding by the system for identification of user intention in dialogue system. Based on these models, the hybrid system may be employed in various language and call routing domains due to non-usage of lexical or syntactic analysis in classification process.

**Keywords:** Natural Language Call Routing, Text Mining, ANFIS, HMM, learning user intention

## 1 Introduction

Envision the modern life without telecommunications systems is simply unthinkable. Evolvement of landline and wireless phone systems has expanded the intensiveness of human lifetime activities. Due to telecommunications devices' extended solutions, it is more convenient to utilize telephone to receive data on flight connections or transactions regarding the product order. From this perspective, quantity of phone calls to cooperative service centers is in-

creasing drastically. As the amount of incoming phone calls is huge, calls should be automatically received, classified, and directed accordingly. Incoming call distribution is the routing of calling party appropriately to a live operator or an automated service. Call centers usually apply a touch-tone or speech-enabled menus to ensure the customer self-service utilizing Interactive Voice Response (IVR) that supports skill-based call routing. A touch-tone menu realizes call distribution based on calling party's selection through touch-tone keyboard.

In case of multiple call distribution terminals, various touch-tone menus are applied in hierarchical layers. By means of speech-enable IVR, touch-tone menus are substituted with speech-enable menus which enable calling parties to choose either speak a number (For example: "For ..., dial or say one") or a keyword ("Say credit cards, cash..."). In comparison with standard touch-tone IVRs, the speech-enable IVRs are more convenient in many areas, for example, information on flights, banking services and voice portals. Skill-based call routing filters and connects the caller to a customer service representative who has relevant competence to deal with a client inquiry. Utilization of touch-tone or speech-enabled IVRs' interfaces are usually challenging mainly when the quantity of menu commands is huge and they are not easy to memorize. Another frustrating feature is that calling parties frequently cannot define which touch-tone or voice option best of all corresponds to their question. It is obvious that a direct connect with a live operator is superior to menu-based systems. Notwithstanding this fact, recently, certain enterprises tried to apply natural language call routing systems to distribute incoming calls. Natural language (NLCR) allows callers to express the reason of their calls in own way, rather than giving them a closed list of menu commands. Through accurate routing of callers, NLCR saves time of both caller and operator. The perception of clients' purpose is one of the most significant issues in NLCR system. Hybrid Hidden Markov Model (HMM) and Adaptive

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Neuro Fuzzy Inference System (ANFIS) are offered by us as a method to solve this problem.

## 2 Related work

With the aim of discovering customer's purpose through dialogue mechanism, various methods have been developed. One of these methods is unsupervised learning approach: Hidden Topic Markov Modelling [1]. This method collects two methods of Latent Dirichlet Allocation and HMM with the aim of learning the document's topics.

In order to determine customer's purpose in NLCR, it was applied vector model based information retrieval application [2]. Within the vector model based approach, for every topic in the training corpus, inquiries are characterized as vectors of features (for example, words) indicating terms frequencies and then a distance between the inquiry and topic vector is calculated. The classifier selects the closest query [3, 4].

Topic unigram language model is developed on counting the quantity of each word occurrences for each topic as well as includes all words of each topic. The likelihood of the query in every topic is calculated and the topic which possesses the utmost resemblance is selected [5, 6].

For designing a conversational agent, it is employed a Markov Decision Process (MDP) framework. MDPs' assumption is that the system's current state and action determine the next state of the system. Partially MDPs substantiated their correspondence to be candidates for modelling conversational or dialogue agents [7, 8].

In the Discriminative Term Selection method, the discriminative power of the term is measured by measuring the average entropy variation on the topics when the term is present or absent. Each term is assigned a numeric value that indicates its importance [9].

With the aim of advancing single classifiers' functionality, it is possible to apply automated relevance feedback, boosting as well as discriminative training in [10].

Being an iterative method, boosting is considered for improving any learning algorithm. Through integrating a set of "weak" or "simple" categorizers, the essence of boosting method is to construct a highly accurate classifier. The algorithm works by a study of the weak rule at each iteration to minimize the errors of training [11].

Cache modelling refers to the number of automatically chosen keywords for every topic and affiliated with a unigram statistical distribution. This distribution is being steadily compared with cache memory context [12]. The comparison is made on symmetric Kullback-Leibler diver-

gence [13]. A divergence measure is calculated between the inquiry and each topic, and the topic with the least value is chosen.

A statistical language model is utilized by Call Director of the BBN for speech recognition and a statistical topic identification system for identifying the topic from the phone calls. A polynomial model is used for keywords and combined two non-identical classifiers such as Bayesian and Log-Odds [14, 15].

Efficient mechanisms in topic identification problems are radial-basis function, Neural Networks, and Support Vector Machines [16].

With the aim of studying the caller's request through carrying conversation in transaction system, C.-H. Wu et al. used HMM model [17]. It was substantiated that by means of an accurate determination of callers' request, the conversation system's functionality as well as its conclusion reaching function significantly improves.

The theory of fuzzy sets are applied as an alternative approach in order to solve the NLCR problem [18–23].

A. Koromyslova et al. applied seven different term weighting techniques for feature selection and used k-NN, linear SVM and ANN methods for classification in NLCR problem. They found that feature selection with self-adaptive GA provides improvement of classification effectiveness and significant dimensionality reduction with all term weighting methods and with all classification algorithms [24].

Thien Khai Tran et al. presented EduCR - an Intelligent Call Routing system consists of telephone communication network; Vietnamese speech recognition; Text classifier/Natural language processor and Vietnamese speech synthesis and achieved more than 95% accuracy in real environment [25].

Dethlefs N. and Cuayáhuil, H. presented novel approach for situated Natural Language Generation in dialogue that is based on hierarchical reinforcement learning and learns the best utterance for a context by optimisation through trial and error [26].

Ferreira, T. C et al. introduced nondeterministic method for referring expression generation. They described two models that account for individual variation in the choice of referential form in automatically generated text: Naive Bayes model and Recurrent Neural Network [27].

Garoufi, K. surveyed several earlier and ongoing computational approaches to natural language that generate utterances by modelling speech acts or words as particular types of actions in planning a problem [28].

Goyal R. et al. used a character-level model, which unlike the word-level model makes it possible to learn to

“copy” information from the dialog act to the target without having to pre-process the input. In order to avoid generating non-words and inventing information not present in the input, they proposed a method for incorporating prior knowledge into the RNN in the form of a weighted finite-state automaton over character sequences [29].

Janarthanam, S. and Lemon, O. investigated the problem of dynamically modelling and adapting to unknown users in resource-scarce domains in the context of interactive spoken dialogue systems. They used a three-step process: collecting data using a Wizard-of-Oz method, building simulated users, and learning to model and adapt to users using Reinforcement Learning techniques [30].

Serban et al. investigated the task of building open domain, conversational dialogue systems based on large dialogue corpora using generative models. They proposed hierarchical recurrent encoder-decoder neural network to the dialogue domain, and demonstrate that this model is competitive with state-of-the-art neural language models and back off n-gram models [31].

With the aim of comprehending the caller’s request in the NLCR, Aida-zade K. et al., (including the current author) used a ANFIS [32]. This model was established and evolved and by us taking into consideration the below mentioned operations:

- applied HMM as the second classifier;
- developed two types of hybrid systems which one reduces error classification and other minimizes number of rejected requests.

Combination of different kinds of models (ANFIS and HMM) prevents misunderstanding of user intention. It is possible to employ the hybrid system (which based on these models) in various languages as well as call distribution domains, because there is not used lexical, grammatical, and syntactic analysis in comprehension process. The feature extraction algorithm developed by us computes a feature vector referred to statistical appearing words in the corpus without any lexical knowledge.

### 3 Automatic Call Routing by A Natural Language Call Router

NLCR aims to comprehend the caller’s intention and take one of the below mentioned relevant actions:

- Routing of calls to right places;
- Directing calls to a live operator;
- Asking clarification questions to eliminate ambiguity.

The framework of a natural language call router is described in Figure 1. Once a call has been placed by caller, it is heard an open-ended question “Please, tell us shortly, the reason of your call”. The caller respond is transmitted to speech recognition system and in their turn, natural language understanding modules classify the reason for the call. By means of speech recognition spoken response is converted to consecutive words chain. As a result of conversion, the speech recognizer excerpts one or some sentences as a user request. In accordance with the determined consecutive words chain, the language understanding device applies various subject recognition mechanism to identify the reason for the call. Based on the answer by the caller, the call is distributed via the system either to a customer service representative or to an automated order fulfillment system (self-service application) [33–36].

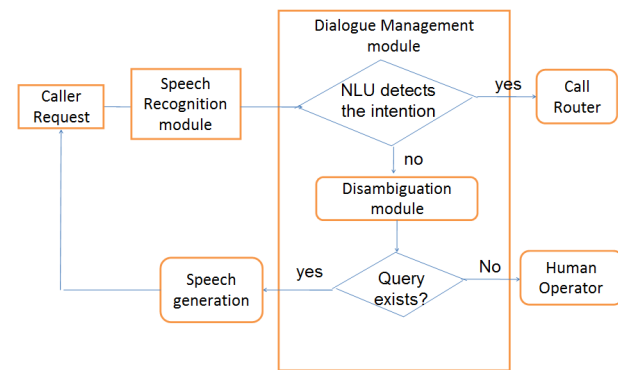


Figure 1: The general framework of a natural language call router.

The study of caller’s request for speech recognition is the most significant element within the conversation management module. Taking into consideration the utmost preciseness by speech recognition module, it is possible to use just written requisition. Two different mathematical models (classifiers) were employed by us in to solve this problem: HMM and ANFIS.

Result of our experiments reveals that in comparison with a separate classifier, the combination of multiple classifiers can lead to better productivity.

### 4 Application ANFIS for learning User intention in NLCR

Classification based machine learning demands two separate set of documents: a training and a test dataset. An automated classifier utilizes training dataset to learn the

differentiating parameters of documents. However, test dataset of documents is utilized to approve the functioning of automated classifier.

Main features which primarily specify texts are calculated for both document datasets. One of the important elements influencing performance of the next phase and preciseness of the system is the effectiveness of this phase. Due to fact that we are aiming not to utilize lexical knowledge, each of words is accepted as a single code word, i.e. the standard bag-of-features framework was used.

## 4.1 Feature extraction

Feature extraction algorithms are a significant part of all methods of machine learning. This algorithm is characterised by us as an instinctive and effective which does not demand any supplementary comment by human as well as lexical knowledge.

Below, we describe some of the parameters [32]:

- $N$  is the number of classes (destinations);
- $M$  is the number of different words (terms) in the corpus;
- $R$  is the number of observed sequences in the training process;
- $O^2 = [o_1^r, o_2^r, \dots, o_{T_r}^r]$  are the user requests in the training dataset, where  $T_r$  is the length of  $r$ -th request,  $r = 1, 2, \dots, R$ ;
- $\mu_{i,j}$  describes the association between  $i$ -th term (word) and the  $j$ -th class ( $i = 1, \dots, M; j = 1, 2, \dots, N$ );
- $c_{i,j}$  is the number of times  $i$ -th term occurred in the  $j$ -th class;
- $t_i = \sum_j c_{i,j}$  denotes the occurrence times of the  $i$ -th term in the corpus;
- frequency of the  $i$ -th term in the  $j$ -th class

$$\bar{c}_{i,j} = \frac{c_{i,j}}{t_i};$$

- Pruned ICF (Inverse-Class Frequency) [23]

$$ICF_i = \log_2 \left( \frac{N}{dN_i} \right),$$

where  $i$  is a term,  $dN_i$  is the number of classes containing the term  $i$ , which  $\bar{c}_{i,j} > q$ , where

$$q = \frac{1}{\delta \cdot N}.$$

The value of  $\delta$  is found empirically for the corpus investigated.

The degree of membership for the words ( $\mu_{i,j}$ ) regarding the relevant classes may be evaluated by specialists or

may be computed by means of analytical formulas. As our primary target is not to utilize human annotation or lexical knowledge, the membership degree of every word was computed by us through below mentioned analytical formula.

$$\mu_{i,j} = \bar{c}_{i,j} \cdot ICF_i. \quad (i = 1, \dots, M; j = 1, 2, \dots, N) \quad (1)$$

## 4.2 Fuzzyfication operations

Maximum membership degree is found with respect to the classes for every term of the  $r$ -th request

$$\begin{aligned} \bar{\mu}_{s,j}^r &= \mu_{s,j_s}^r, \\ j_s &= \arg \max_{1 \leq v \leq N} \mu_{i,v}^r, \quad s = 1, \dots, T_r. \end{aligned} \quad (2)$$

Means of maxima are calculated for all classes:

$$\begin{aligned} \bar{\mu}_j^r &= \frac{\sum_{k \in Z_j^r} \bar{\mu}_{k,j}^r}{T_r}, \\ Z_j^r &= \left\{ i : \bar{\mu}_{i,j}^r = \max_{1 \leq v \leq N} \mu_{i,v}^r \right\} \\ j &= 1, \dots, N. \end{aligned} \quad (3)$$

For defuzzification process, we employed the method of Center of Gravity Defuzzification. This method prevents the obscurity of defuzzification in case of possible occurrence when output degree of membership emerges from multiple crisp output value [37, 39].

In the primary phase was used statistical evaluation of membership degree of words by (1) as a substitute for linguistic statements. Aftermath, fuzzy operations (2) and (3) were employed. We applied MANN in the output of the fuzzyfication process. Outputs of MANN are taken as indexes of classes appropriate to the query (Figure 2). MANN is trained by the back-propagation algorithm.

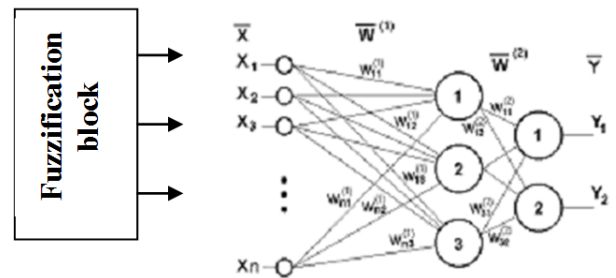


Figure 2: The structure of MANN in ANFIS.

## 5 Application HMM for learning User intention in NLCR

In one approach, discrete HMMs have been applied to defining user intention in a spoken dialogue system. Word Semantic Sets in [39] have been used as the states. In this work, we selected states in different fashion. We divided user requests into a number of states and collected words which included these states. Collection of such states gives us better results and avoids using any specific language knowledge [40].

The parameters of the HMM applied in the system currently introduced are as follows:

- $N_{HMM}$  is the number of states;
- $M_{HMM}$  is the number of different words (terms) in dialogues taking part in the training process for the given problem;
- $V$  includes all possible observations sets,  $V = \{v_1, \dots, v_{M_{HMM}}\}$ ;
- $\pi = \{\pi_i\}_{i=1}^{N_{HMM}}$  are initial state distributions:  $\pi_i = P(q_1 = i)$ ;
- $A = [a_{i,j}]$  is the state transition probability matrix,  $a_{i,j} = P(q_{t+1} = j | q_t = i)$ ,  $1 \leq i, j \leq N_{HMM}$ . We used ergodic and left-right HMMs in our system.
- $B = \{b_j(o_t)\}_{j=1}^{N_{HMM}}$  are the state-dependent observation probabilities. Here, for every state  $j$ ,  $b_j(o_t) = P(o_t | q_t = j)$  is the probability distribution of words occurring in states.
- $O^r = [o_1^r, o_2^r, \dots, o_{T_r}^r]$  are the observation sequences, where  $R$  is the number of observed sequences,  $T_r$  is the length of  $r$ -th observed sequence,  $T_r \leq T$ ,  $T$  is the given quantity,  $r = 1, 2, \dots, R$ .

Note that a HMM is compactly represented as  $\lambda = (A, B, \pi)$ .

The parameters of the HMM are estimated according to each corresponding destination of the selected company, and are trained by Baum-Welch algorithm. Probabilities found on the basis of parameters of the HMM for all destinations corresponding to each query are calculated by the scaled-forward algorithm at the testing phase. The calculated probabilities are passed to a decision-making block. The probabilities of the HMMs are compared according to the destinations in the decision-making block (Fig. 3). If the calculated maximum probability is less than a threshold value found empirically as a result of experiments, the computer rejects the call and asks the user additional question or connects with human operator.

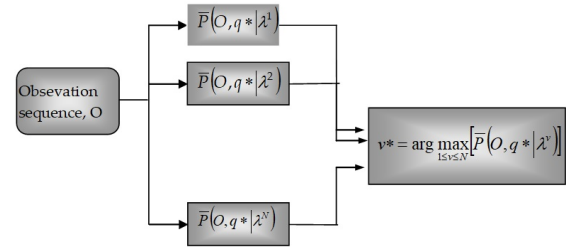


Figure 3: Learning user intention using HMM.

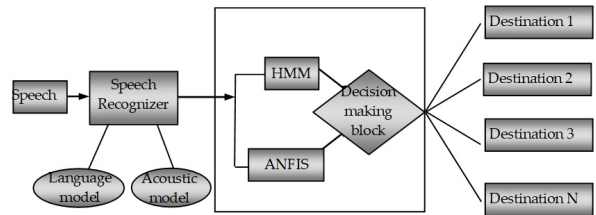


Figure 4: The structure of a hybrid system.

## 6 Structure of Hybrid Systems

We describe a combined system using the ANFIS and HMM approaches for understanding user intention, where every user request is analysed by both systems, which use the output of a speech recognizer. The results of ANFIS and HMMs are forwarded to the decision-making block and compared therein.

We suggest two types of hybrid system.

**Hybrid-I.** This system confirms the results verified by the ANFIS and HMM approaches. If either of these models rejects the decision, then the system does not accept any decision. This system reduces errors in the understanding process and is therefore is less prone to improper classification.

**Hybrid-II.** The method we suggest in this system is sequential. Initially, a trained first model for understanding is used, then a second model is applied to the rejected request that was not understood by the first model. This approach minimizes the number of rejected requests.

## 7 Experimental Results

The understanding of a request from an initial incoming call to an information center of an educational company in the Azerbaijani language, and routing according to its intention, was taken as the test problem to be solved.

Calls must be routed to one of the four departments of the company, or be connected to an operator, or be re-

jected. These departments are: 1) information center; 2) accounting department; 3) test exams center; 4) service departments.

We divided dataset randomly into 2 parts (training and testing) and made 8 folds. 350 queries have been taken for training process, 50 requests for testing process.

Words contained in the user request in human-computer dialogue are taken as observation sequence in HMM. HMMs have been built for every department of the company. The user queries are divided into the words and the parameters of HMM are estimated according to departments. The probabilities found on the basis of HMMs of all departments for each request are calculated, compared and result forwarded to a decision-making block. According to the result of experiments, the ergodic HMM with 3 states gives better accuracy (91.5%) than left-right HMM (90.75%).

With the aim of employing ANFIS in present experiment, words membership degree within the requisition is computed through the fuzzification model in the process of testing. The indexes of classes founded by trained neural networks parameters.

We set two boundary conditions for an acceptance decision:

$$1) \bar{y}_k \geq \Delta_1$$

$$2) \bar{y}_k - \tilde{y}_p \geq \Delta_2$$

where  $y_i$  is the output vector of MANN

$$\bar{y}_k = \max_{1 \leq i \leq N} y_i, k = \arg \max_{1 \leq i \leq N} y_i$$

$$\tilde{y}_p = \max_{1 \leq i \leq k-1; k+1 \leq i \leq N} y_i.$$

Below in Table 1 is shown the results of classification of user requests by ANFIS with different values of  $\Delta_2$  and  $\Delta_3$ .

**Table 1:** Average Results of 8 Folds CV Accuracy Of ANFIS

Boundary conditions	Correct	Rejection	Error
No restriction	91.25%	0%	8.75%
$\Delta_1 = 0, 1; \Delta_2 = 0, 5$	87.5%	6.25%	6.25%
$\Delta_1 = 0, 3; \Delta_2 = 0, 5$	85.25%	9.5%	5.25%
$\Delta_1 = 0, 5; \Delta_2 = 0, 5$	82.75%	13.75%	3.5%

The results of Hybrid-I and Hybrid-II systems are given in Table 2. Hybrid-I confirms the results verified by the ANFIS and HMM approaches and prevents misunderstanding. Initially, the ANFIS model with high restriction ( $\Delta_1 = 0, 5; \Delta_2 = 0, 5$ ) was used for classification in Hybrid-II. Then HMM was applied to the rejected request that failed

to be understood by the first model. It must be emphasized that outputs are particular to depicted experiment and may be not similar in other test set.

**Table 2:** Average results of 8 folds CV accuracy of Hybrid systems

Methods	Correct	Rejection	Error
HMM	91.5%	0%	8.5%
ANFIS	91.25%	0%	8.75%
Hybrid-I	82.75%	13.75%	3.5%
Hybrid-II	93.25%	0%	6.75%

We collected our data from the information center of an educational company in the Azerbaijani language and its volume is very low. Here we addressed two important question: 1) How do other traditional text classification algorithms work for our data? and 2) How do our algorithms work for another dataset?

To answer first question, we checked naïve Bayes algorithm and received 89.2% results which is very close to our results.

For investigation of the second question we used subjectivity dataset 1v.0: 5000 subjective and 5000 objective processed sentences in movie reviews (<http://www.cs.cornell.edu/people/pabo/movie-review-data/>).

We applied both ANFIS and HMM to subjectivity dataset and achieved average results of 10 folds cross validation accuracy described in Table 3 and Table ??.

**Table 3:** Results of ANFIS for subjectivity dataset

	Correct (%)	Rejection (%)	Error (%)
$\Delta_2 = 0.8; \Delta_3 = 0.5$	78.66	18.84	2.5
$\Delta_2 = 0.5; \Delta_3 = 0.5$	85.77	8.62	5.61
No restriction	92.16	0.01	7.83

**Table 4:** Results of Ergodic HMMs for sentiment polarity and subjectivity datasets

	1	2	3	5
	state	states	states	states
Accuracy of 10 fold CV	89,35	89,63	89,33	89,13

When comparing the current system with others, it is necessary to emphasize that the use of linguistic knowl-

edge does improve accuracy. Since we do not use such knowledge, our results should only be compared with other methods having similar constraints, such as those which use features based on bags of words that are tested on the same data set. Examples include studies by Pang and Lee and Martineau and Finin [42, 43]. Pang and Lee report 92% accuracy on sentence-level subjectivity classification using Naive Bayes classifiers and 90% accuracy using SVMs on the same data set [43]. Martineau and Finin reported 91.26% accuracy using SVM Difference of TFIDFs [42]. The currently reported results: ANFIS (92.16%) are similar. We found that ergodic HMM with 2 states gives the best result for current Dataset. There are not available sufficiently many training samples in the Dataset. Therefore, the accuracy (89.7%) achieved in this work is less than state-of-the-art results. Powerful Markov models can be created only, if sample sets of considerable size available for the parameter training.

## 8 Conclusion

Two various classification system frameworks such as ANFIS and HMM models have been illustrated by us and these models have been employed in NLCR to comprehend a customer request. Our target through this investigation was to develop techniques which do not utilize linguistic knowledge as well as may be employed in other languages. The feature extraction operation is a significant element of these techniques. The study of informative features which evolve the system preciseness without language restrictions was the issue we concentrated.

We assume that in case of application of IF-THEN rules and specialists' expertise in ANFIS, accuracy of the system will advance and get abreast with human discernment.

It must be emphasized that utilization of linguistic knowledge does affect to evolvement of present system accuracy while comparing it with other systems. As we do not utilize linguistic knowledge within our technique, our outputs must exclusively be compared with those techniques which possess identical restrictions i.e. those utilizing features based on bags of words model that are experimented on the same data set. Due to this argument, objective comparison of our outputs with other results is unfair.

ANFIS classifies documents by means of occurrence of the terms in the corpus, whereas the HMM classifies documents based on the structure of the sentences. This interpretation can be used to build two different types of hybrid systems. The combination of multiple classifiers can result in better accuracy than that achieved by either individual

classifier. The Hybrid I system prevents certain errors in the understanding process, and the Hybrid II system increases accuracy from 91% to 93% for current dataset.

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