A Knowledge-based Recommendation System for Time Series Classification

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Abstract—**Time series data sets reflect the state and extent of things as they change over time. Information extraction based on such data plays an important role in many fields. The time series classification is a typical supervised learning problem, which is applied in speech recognition, image processing and so on. However, because the attributes of time series data don't make sense and the feature dimensions are particularly large, people can't treat them as general machine learning classification problems. Currently, many different time series classification problems have been proposed. But how to choose and use these methods is still a huge problem for non-computer professional researchers. This article uses the ontology technology to build a recommendation system that contains the details and features of such algorithms. When the users input the characteristics of the data and the task requirements, they can get reasonable suggestions and a description of the workflow of the algorithm. Such a system saves the user a lot of analysis and comparison time. It also makes such problems easier to understand.**

I. INTRODUCTION

Time series (TS) data analysis is an important topic in the field of machine learning and data mining. Time series classification (TSC) is a classic problem of time series analysis [1]. Currently, time series classification (TSC) has been applied to many different fields. At the beginning it was applied to speech recognition [2,3,4]. As more technologies are proposed, TSC is applied to more fields, such as classification of RNA data, ECG, Image processing, and so on.

The TSC problem is defined as follows: Given a data sample set: $\mathrm{D} = \{(X_1, c), (X_2, c) \dots (X_n, c)\}$, and its discrete labels: $\mathrm{C} = \{c_1, c_2 \dots c_k\}$,the timestamps are: $\mathrm{Y} = \{y_1, y_2 \dots y_m\}$ .Each data sample X_i includes: an n-dimensional time vector and an associated category c : $X_i = \{X_i^1, X_i^2 \dots . X_i^n, c\}$。TSC is to train a classifier on a dataset D in order to map from the space of possible inputs to a probability distribution over the class variable values.

However, TSC is different from general classification problems:

- The length of each sample is not equal, and each sequence cannot be regarded as an attribute vector as an input to the general classification algorithm.
- For sample sets with equal lengths, the attribute values at the same position may not match. So the result of directly using the general classification algorithm is uncertain

Due to the particularity of the TSC, the key issues in dealing with these tasks are the representation of the TS, the choice of the classification model, and the choice of the appropriate measure. These key points are different from the general classification problems and make many non-computer professional researchers confused. Currently, many researchers are working on the reviews which introduce the advantages and disadvantages of different TSC algorithms. In order to make such reviews friendly to users, the authors propose a knowledge-based recommendation system (KBRS) to intelligently generate appropriate representation methods, algorithms, and measures for the specific TSC process. Ontology technology is currently the most popular Semantic Web technology. It is flexible, extensible and easy to understand. The authors created classes of TSC-related technologies and defined a number of properties based on the relationships between them in the ontology. The users can use the characteristics of the TS dataset and the user's requirements as input of the system so that generates reasonable processing suggestions and provides details of the algorithm so that the user can better understand.

The main advantages of KBRS are:

- This recommendation system contains most of the TSC algorithms and data preprocessing methods and provides measurement and representation selection for some of these algorithms.
- This recommendation system is based on ontology technology so that it is easier to extend when a new TSC algorithm is proposed or a new data feature is considered.
- Data preprocessing technology is also an important part of the system. This is different from other recommendation systems that only consider classification or clustering. Especially this system describes the popular time series representation methods。
- This system creates an abstract class "process" to describe the details of each methods based on some defined properties so that users can understand the process of data processing very well.

The authors selected two typical time series experimental data sets for comparison between different algorithms. The results show that the algorithms recommended by this system have good performance.

The rest of this paper is organized as follow: Section 2 describes relevant knowledge involved in this paper. Section 3 presents the composition and structure of KBRS. Section 4 presents workflow of KBRS. Section 5 presents some experiments to indicate the rationality of this system. Section 6 presents the main conclusion and points directions for future work.

II. BACKGROUND

A. Time series representation

In order to effectively store and speed up the processing of time series, people need to adopt some methods to represent high-dimensional time series data. How to represent a time series is the basic problem of time series mining [1]. An effective time series representation method can not only allow similarity comparison between sequences, but also can be applied to different data mining tasks [29].

According to different conversion methods, Ratanamahatana and Ke-ogh classify different time series representations into three types: non-data adaptive, data adaptive, and model-based [5]:

i. non-data adaptive

In the non-data adaptive representation method, the conversion parameters of each time series are consistent. Spectrum analysis is a relatively common non-data adaptive representation. Agrawal firstly used the Discrete Fourier Transform (DFT) to map time series to the frequency domain [6]. This method effectively solves the two problems of "completeness of feature extraction" and "dimension disaster" in time series mining. Chan proposed the use of Discrete Wavelet Transform (DWT) to process time series [7].

In addition to spectrum analysis, the researchers have proposed other methods specifically for time series representation. For example, Keogh [8] proposed a method based on Piecewise Linear Segments to represent the shape of a time series. This method is suitable for rapid time series classification and clustering. Later, Keogh [9] proposed a new dimension reduction technique - PAA (Piecewise Aggregate Approximation) and explained the advantages of PAA in time series similarity measure and index.

ii. data adaptive

Data Adaptive Representation - At the time of data conversion, the conversion parameters change as the time series data changes. Non-data adaptive representation methods can be transformed into data adaptive representation methods. For example, Keogh [10] proposed an adaptive Piece-wise Constant Approximation (APCA) for time based on PAA。

Lin [11] proposed a Symbolic Aggregate Approximation (SAX) representation method that converts initial real-valued high-dimensional data into discrete low-dimensional data.

Ye [12], [13] proposed the concept of time series shapelets which is a subsequence that best represents a category

iii. model based

The model-based representation assumes that a time series is an observation of a potential model. Azzouzi1 [14] firstly proposed the use of Hidden Markov Model (HMM) to define the relationship between time series variables. Kalpakis [15] used the Auto Regression Integrated Moving Average (ARIMA) to succinctly represent time series and defined a highly efficient similarity measure for this method. Nanopoulos [16] proposed a feature extraction method based on statistical models (such as mean, variance, etc.) to represent the entire time series.

Generally, the model-based representation has strong interpretability, when two time series may be represented by the same potential model of the same parameter set, they are considered similar [30].

B. Time series classification

The time series classification problem, as a branch of the sequence classification problem [17], has attracted wide attention in the field of time series mining. This problem is widespread in many areas of real life. Keogh specifically collected UCR data sets for time series classification/clustering.

All classification problems depend on the similarity between data, and the time series classification problem is no exception. For time series, the similarity between similar time series has the following three categories [18].

i. Similarity in Time:

Time series of the same category are the results of observing a potentially identical curve in the time dimension, and the difference between them may be caused by noise and phase drift. The 1-NN classifier is best suited to handle such problems, while the DTW metric mitigates the effects of noise.

ii. Similarity in Shape:

Time series of the same category are distinguished by some identical subsequences or shapes which may appear anywhere in the time series。 This is the main difference from the similarity in the time domain. The smaller the correlation of subsequences with time, the more difficult it is for time domain based 1-NN classifiers to deal with such problems. In this case, different categories can be distinguished by using time series feature-based methods.

iii. Similarity in Change:

The Similarity which is difficult to be observed appears in a highly autocorrelated sequence. This problem can be handled in a production mode such as Hidden Markov Model (HMM), Auto-Regressive Moving Average (ARMA) and so on [28].

Some researchers use other methods to classify these algorithms. The authors describe these different taxonomies in the recommendation system.

C. Existing Reviews for TSC

Due to the particularity of time series data, the problem of time series classification faces three major challenges. First, for most classifiers such as decision trees or neural networks, the input data is a feature vector, but the time series data has no clear features. Secondly, although the feature selection method can be used on the time series, due to the dimension of the feature space is very large, the process of feature selection is very cumbersome, and the amount of calculation is very large; finally, in some applications, in addition to accurate classification results, the user also wants to obtain an interpretable classifier. However, since time series data has no clear characteristics, it is very difficult to establish an interpretable classifier.

It is difficult for a non-computer professional to choose a method that meets the needs of the user. Many scholars are committed to presenting a comprehensive and understandable TSC taxonomy. Bagnall [19] implemented most common TSC methods and compared performance based on a large number of experiments. But model-based algorithms are not presented. Fortunately, Hassan [20] presents a review of deep learning for TSC and a detailed description and comparison of the model-based TSC algorithm. The experiments of these two reviews are based on a univariate TSC benchmark (the UCR/UEA archive [32],[33]) so that this article can summarize the performance of most TSC algorithms depending on their results [34].

Simultaneously, Bagnall [19] reviewed the common representation of time series to provide a basis for research on TSC. Lhermitte [22] states a comparison of similarity measures for major time series.

D. Ontology technology

As a modeling tool that can describe domain concepts at semantic and knowledge level, ontology aims to capture knowledge in related fields, identify common recognized terms in the domain, describe the semantics of concepts through the relations between concepts and provide the common understanding of knowledge in a field. This recommendation system is mainly based on ontology technology to be built. Its main feature is to make the information on the Web have the comprehensible semantics for computers, realize semantic interoperability between information systems with the support of ontology, and intelligently access and retrieve Web resources so that this system has a good scalability. In the future authors can connect the current basic system to other existing ontologies to extend it.

The ontology technology as a method of implementing this system is mainly due to the following advantages:

- In ontology in addition to the relation "has-a", authors define more relationships to represent the relationships between the algorithms and the characteristics of the dataset. Flexible and clear relationships allow users to find the right solution more accurately and quickly.
- The implemented ontology is a more complex mind map for the user. Users do not need to understand any computer language. Each input can get relevant information according to the relationships in the ontology. So this recommendation system is completely suitable for non-computer professional researchers.
- To date data classification problems, too much knowledge is involved. The recommendation system in this paper deals with the performance of 45 classification algorithms on a variety of data sets with different attributes and the description of the algorithm process. The flow chart cannot describe so much knowledge. The general taxonomy cannot describe such complex information.

III. KNOWLEDGE-BASED RECOMMENDATION SYSTEM

The authors build this knowledge-based recommendation system (KBRS) based on the reviews of existing TSC algorithms. The main method is to create the ontologies of topics associated with TSC and to define new properties to represent the connections between them. Based on the characteristics of the algorithm and a large number of experiments the authors link the characteristics of the data set to the algorithms, measures, and representations which are suitable for them.

Time series classification is different from the general data classification. In this new system, the time series representation methods are considered. And for time series classification algorithms measure, representation and model are the most important factors for choosing the classification solutions

A. Structure of KBRS

This high-level OWL ontology has been developed. The overall structure of the ontology is presented in Fig. 1.

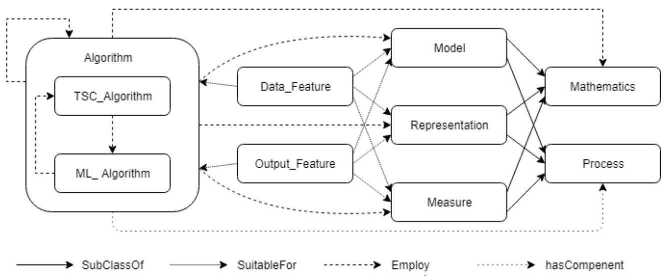

Fig. 1. Main structure of KBRS

Bagnall [19] did a lot of experiments to compare the performance of most of the TSC algorithms. Hassan [20] is mainly devoted to the application of deep learning in TSC. Based on these experimental results, the authors summarize the common characteristics of data sets and users' requirements and connect them to the algorithms which are suitable for them. This is the basis for the recommendation system to provide advice about how to choose the best algorithm.

The authors use ontologies of representation methods, measure, mathematics, and process to describe the principles of the algorithm. The ontology "process" is an abstract concept to make the description of the algorithm clearer, which contains the content of math, algorithm, measure. It defines each step of the algorithms such as ‘standardization’, ‘regularization’, ‘Normalization’. They link the algorithms which contain these steps. Depending on the relationship "has(n)thComponent" users can know the sequence of operations of the selected algorithm.

B. *Classes in KBRS*

The classes in ontology are the main components of this system. They are:

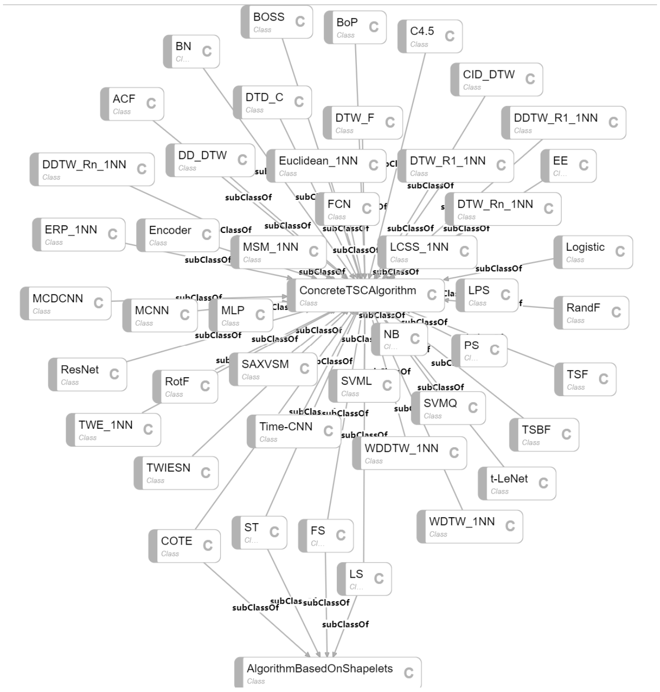

Fig. 2. TSC algorithms and class “AlgorithmBasedOnShapelets” in ontology

Algorithm – algorithms for data processing that can be common machine learning algorithms (ML_Algorithm) [27] and special algorithms oriented on time series classification (shown in table I). The main TSC algorithms are shown in Fig. 2.

Data_Feature – characteristics of input datasets, including size, length etc.

Output_Feature – features of the output data and users’ requirements.

Mathematics – mathematics base of the algorithms.

Measure – measures for estimating expected and actual results of data processing and corresponding similarity functions.

Model – basic algorithms models;

Representation – The common time series representation methods. The authors summarize the comparation of these methods in Table II and describe them in ontology. The KBRS describes the difference in system. So sometimes users can consider these comparations as the conditions to choose suitable algorithms.

TABLE I ALGORITHMS IN KBRS

No.	Name in KBRS	Full Name
1	ACF	Autocorrelation function
2	BN	bayesian network
3	BoP	Bag of Patterns
4	BOSS	Bag of SFA Symbols
5	C45	C4.5
6	CID_DTW	Complexity-Invariant Distance
7	COTE	Collection of Transformation E
8	DD_DTW	Derivative Dynamic Time Warping
9	DDTW_R1_1NN	Derivative Dynamic Time Warping with full warping window
10	DDTW_Rn_1NN	Derivative Dynamic Time Warping with warping window set through cross validation
11	DTD_C	Derivative Transform Distance
12	DTW_F	Dynamic Time Warping Features
13	DTW_R1_1NN	Dynamic Time Warping with full warping window
14	DTW_Rn_1NN	Dynamic Time Warpingwith warping window set through cross validation
15	EE	Elastic Ensemble
16	Encoder	Encoder
17	ERP_1NN	Edit Distance for Real Sequences_1-nearest neighbor algorithm
18	Euclidean_1NN	Euclidean_1-nearest neighbor algorithm
19	FCN	Fully Convolutional Neural Network
20	FS	Fast Shapelet Tree
21	LCSS_1NN	Longest Common Subsequence_1-nearest neighbor algorithm
22	Logistic	Logistic regression
23	LPS	Learned Pattern Similarity
24	LS	Learned Shapelets
25	MCDCNN	Multi Channel Deep Convolutional Neural Network
26	MCNN	Multi-scale Convolutional Neural Network
27	MLP	Multi-layer Perceptron
28	MSM_1NN	Move-Split-Merge
29	NB	Naïve Bayes
30	PS	power spectrum transform
31	RandF	Random_Forest
32	ResNet	Residual Network
33	RotF	Rotation_Forest
34	SAXVSM	Symbolic Aggregate approximation and Vector Space Model
35	ST	Shapelet Transform
36	SVML	Support Vector Machine with linear kernel
37	SVMQ	Support Vector Machine with quadratic kernel
38	Time-CNN	Time Convolutional Neural Network
39	t-LeNet	Time Le-Net
40	TSBF	Time Series Bag of Features
41	TSF	Time Series Forest
42	TWE_1NN	Time Warp Edit Distance
43	TWIESN	Time Warping Invariant Echo State Network
44	WDDTW_1NN	Weighted Derivative Dynamic Time Warping
45	WDTW_1NN	Weighted Dynamic Time Warping

TABLE II THE COMPARATION OF TIME SERIES REPRESENTATION

(Methods in table: DFT- Discrete Fourier Transform; DWT- Discrete Wavelet Transform; SVD- Singular Value Decomposition; PAA- Piecewise Aggregate Approximation; APCA- Adaptive Aggregate Constant Approximation; PLA- Piecewise Linear Approximation; PRA-Piecewise Regression Approximation; SAX-Symbolic Aggregate approximation.
Columns in table: 1- Time domain frequency domain transform; 2-Dimensionality reduction; 3-Linear computational complexity; 4-Symbolization; 5-Processing variable length sequences; 6-Dynamic insertion/deletion; 7- Understandable; 8- Maintaining local feature.)

Representation Method	1	2	3	4	5	6	7	8
DFT	√	√	×	×	√	×	×	×
DWT	√	√	×	×	×	×	×	×
SVD	√	√	×	×	√	×	×	×
PAA	×	√	√	×	√	√	√	×
APCA	×	√	×	×	√	√	√	×
PLA	×	√	×	×	√	√	√	×
PRA	×	√	√	×	√	√	×	×
Polynomial fitting	×	√	×	×	√	×	×	×
Clipper Data	×	×	√	√	√	√	√	×
SAX	×	√	√	√	√	√	√	×
Landmarks	×	√	√	×	√	√	√	√
Important point	×	√	√	×	√	√	√	√

C. Properties in KBRS

Custom properties make ontology more flexible than taxonomy. The authors define some necessary properties to describe the relationship between classes.

Employ-links the algorithm and the measures, representation and other algorithm that can be used to explain the principle of algorithms;

hasComponent-links the algorithms considering them as the steps of data processing;

suitableFor-links input information and the algorithms, defining suitable algorithms for processing data with known characteristics.

hasSize-A data property in ontology is used to describe the value and range of the parameters of the classes.

IV. WORKFLOW OF THE KBRS

The main goal of KBRS is to synthesize the solution for TSC. So the ontology has been extended with information on time series processing. The whole process of solution synthesis consists of 4 steps and the flowchart is shown in Fig. 5:

1) Collect characteristics of datasets and requirements of the task and describe them with the ontology entities which are shown in Fig. 3.

2) Input each of characteristics and requirements and get the sets of suitable algorithms as the Fig. 4 shown;

3) Find the best choice among the suitable algorithms based on users' conditions (generally we extract the intersection of these sets);

4) (Optional) Describe the selected algorithm based on the outward links.

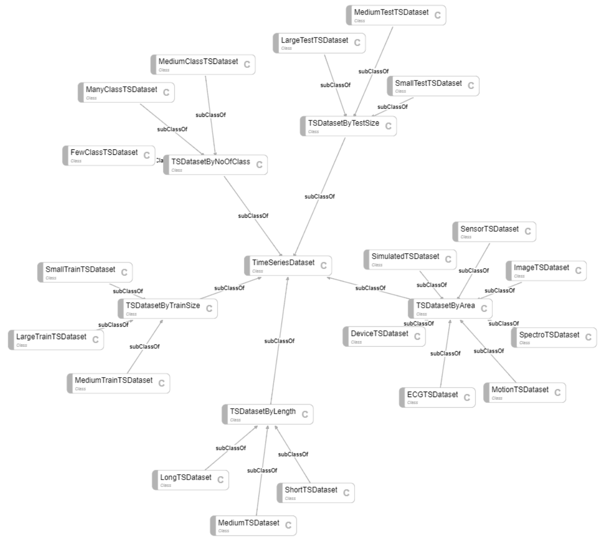

Fig. 3. The entities of data characteristics of the KBRS

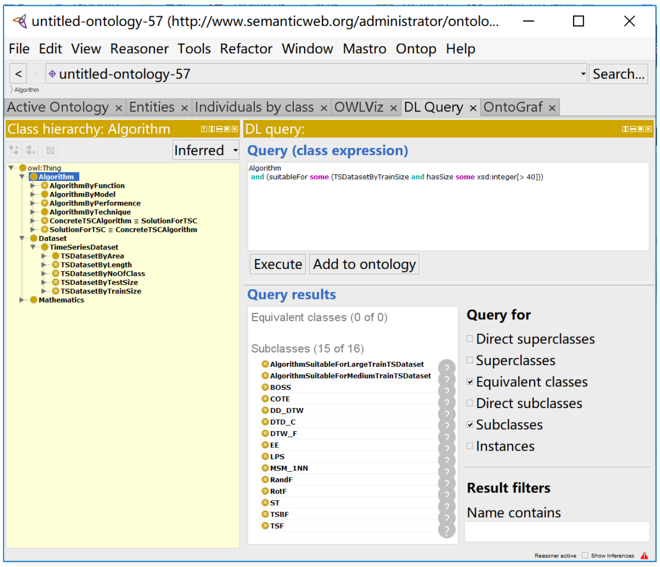

Fig. 4. An example for querying suitable algorithms in KBRS (The class expression describes a condition and KBRS could generate the suitable algorithms)

In this way the final output result is actually a reasonable data analysis process. The original dataset goes through a continuous conversion process-from disorderly to gradually regular. At last a TSC algorithm is applied to train the clear dataset to generate an efficient classifier. And it can provide users with relevant data analysis conclusions.

V. EXPERIMENTS

The ontology is written with OWL language and available at https://github.com/529492252/TSContology. It is edited in Protégé-5.5.0 and checked by HermiT 1.3.8.413 reasoner to make sure it is consistent.

This KBRS is applied on two classical TS data sets: ‘Meat’ and ‘CinCECGtorso’.

Food spectrographs are used in chemometrics to classify food types, a task that has obvious applications in food safety and quality assurance. The classes in data set ‘Meat’ are ‘chicken’, ‘pork’ and ‘turkey’. Duplicate acquisitions are taken from 60 independent samples. The data set is obtained using Fourier transform infrared (FTIR) spectroscopy with attenuated total reflectance (ATR) sampling [25].

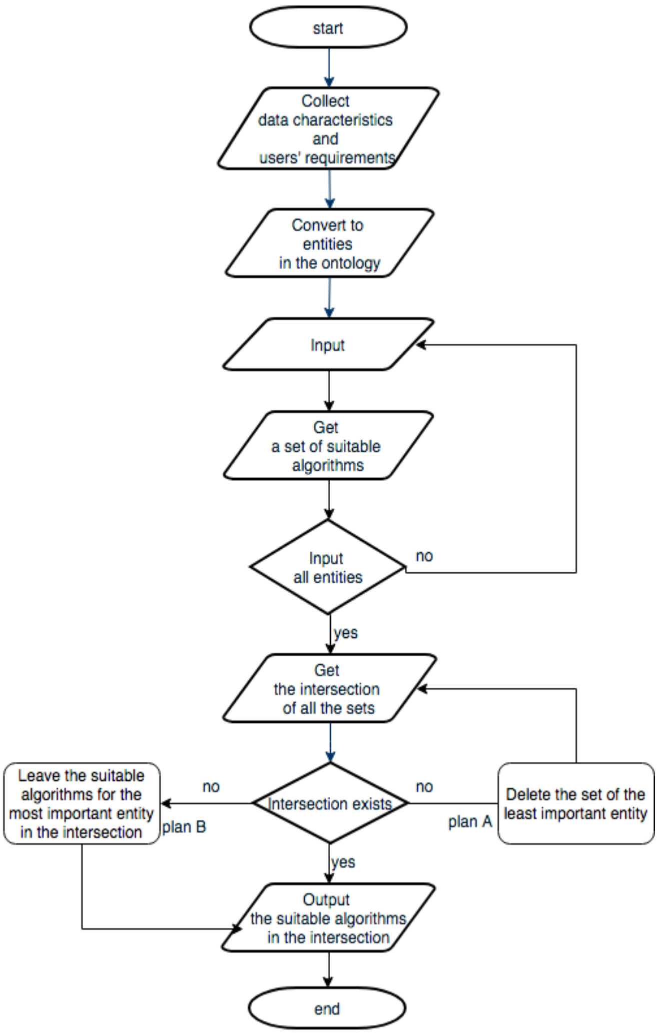

Fig. 5. The workflow of the KBRS

The data set ‘CinCECGtorso’ is derived from one of the Computers in Cardiology challenges, an annual competition that runs with the conference series of the same name and is hosted on physionet. Data is taken from ECG data for multiple torso-surface sites. There are 4 classes (4 different people) [26].

Firstly, the characteristics of these data sets should be summarized and described with the ontology entities, which are shown in TABLE III [32], [33].

TABLE III THE CORRESPONDING ENTITIES OF CHARACTERISTICS OF DATA SETS IN ONTOLOGY

Data Set	Category	Value of data set	Range of Class Value	Ontology Class
CinCECGtorso	Train size	40	hasSize some xsd:integer[< 100]	SmallTrainTSDataset
	Test size	1380	hasSize some xsd:integer[> 1000]	LargeTestTSDataset
	Length	1639	hasSize some xsd:integer[> 700]	LongTSDataset
	No. of classes	4	hasSize some xsd:integer[< 10]	FewClassTSDataset
	Data area	ECG	ECG	ECGTSDataset
Meat	Train size	60	hasSize some xsd:integer[< 100]	SmallTrainTSDataset
	Test size	60	hasSize some xsd:integer[< 300]	SmallTestTSDataset
	Length	448	Less_than_300	MediumTSDataset
	No. of classes	3	hasSize some xsd:integer[< 10]	FewClassTSDataset
	Data area	SPECTRO	SPECTRO	SPECTROTSDataset

These description entities are used to locate the suitable algorithms as inputs. In Fig. 5 the algorithms which are suitable for the characteristic ‘Small Train Data set’ are presented. Through this way, when users input some requirements or some characteristics, they can receive the suitable algorithms. Sometimes they can get more than one choice. But in KBRS the details of the algorithms such as model, measure and function are described. Users can make decision by themselves depending on these points. This is flexible and user-friendly design. The descriptions of the time series classification algorithms could provide information to make decisions such as the comparison of the data representation methods in TABLE II.

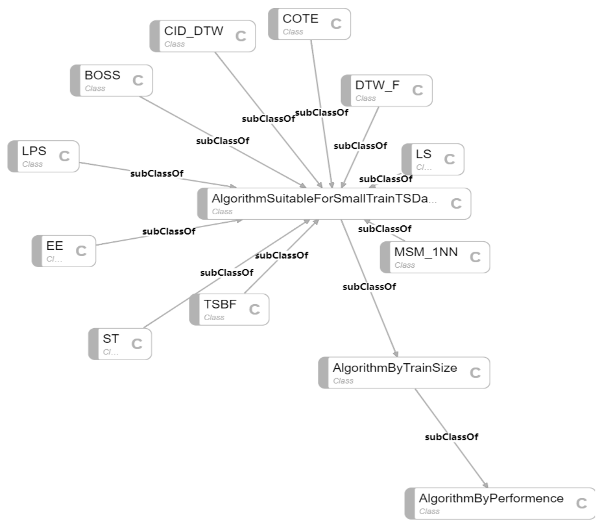

Fig. 5. Algorithms which are suitable for the data set with small size train data set

As the result of selection all the suitable algorithms are shown in TABLE IV (for ‘CinCECGtorso’) and TABLE V (for ‘Meat’).

TABLE IV ALL SUITABLE ALGORITHMS FOR ‘CINCECGTORSO’

(The symbol ‘√’ means this algorithm is suitable for the dataset in this Category. And the highlight algorithms are the selected algorithms which are suitable for all the requirements.)

Algorithm	Train size	Test size	Length	No. of classes	Data area
BOSS	√	√	√	√	√
CID_DTW	√	√	√		
COTE	√	√	√	√	√
DD_DTW			√		
DTD_C			√		
DTW_F	√	√	√	√	
EE	√	√	√	√	√
ERP_1NN					√
LCSS_1NN					√
LPS	√	√		√	
LS	√	√		√	
MSM_1NN	√	√	√	√	√
PS					√
ST	√	√	√	√	√
SVMQ					√
TSBF	√	√		√	
TSF			√	√	√

TABLE V ALL SUITABLE ALGORITHMS FOR ‘MEAT’

Algorithm	Train size	Test size	Length	No. of classes	Data area
BOSS	√	√	√	√	√
CID_DTW	√				
COTE	√	√	√	√	
DD_DTW			√		
DTW_F	√	√	√	√	
EE	√	√	√	√	
Logistic					√
LPS	√	√	√	√	
LS	√	√	√	√	
MLP					√
MSM_1NN	√		√	√	
RandF					√
RotF					√
SAXVSM		√			
ST	√	√	√	√	
SVML					√
SVMQ					√
TSBF	√	√	√	√	√
TSF		√		√	√

It’s worth noting that sometimes the user’s needs are so high that no algorithm can satisfy all the conditions. There are two solutions depending on the needs of the user:

1) Delete the conditions that the user thinks are least important, and then find the intersection.

2) Select the algorithms that are appropriate for the conditions that the user considers to be the most important in all the candidate algorithms.

In these two experiments BOSS, COTE, EE, MSM_1NN and ST are selected for data set ‘CinCECGtorso’ and BOSS and TSBF are selected for data set ‘Meat’ by KBRS, since these algorithms are suitable for all the conditions as the Fig. 6 and Fig. 7 shown.

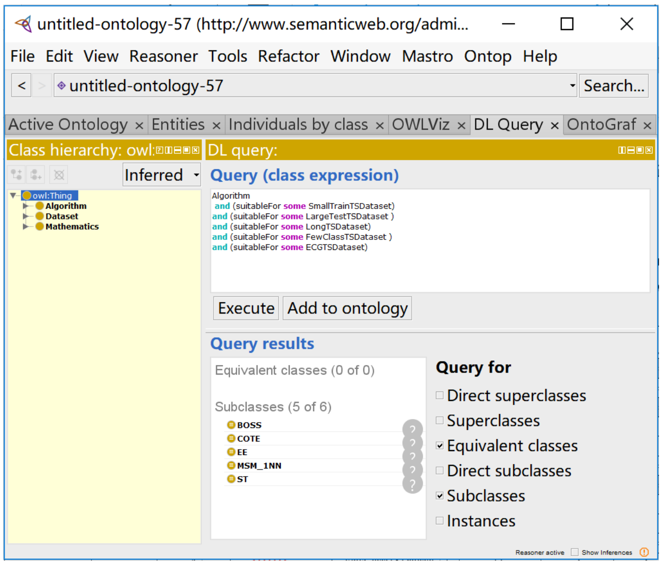

Fig. 6. Algorithms which are suitable for the data set ‘CinCECGtorso’

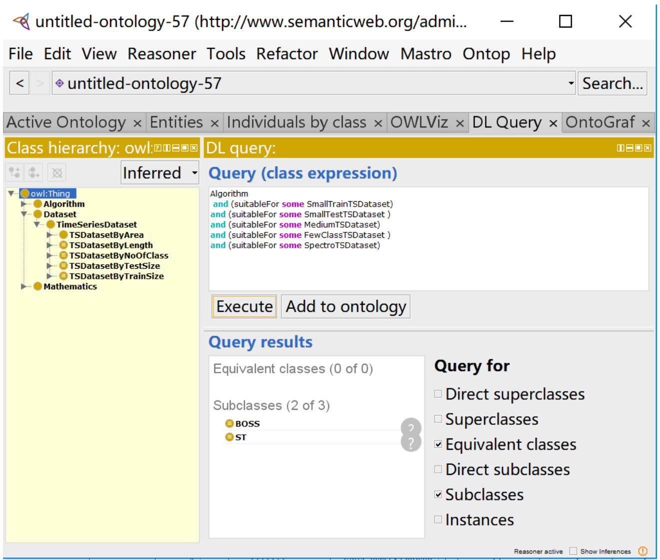

Fig. 7. Algorithms which are suitable for the data set ‘Meat’

Authors apply all the TSC algorithms on these two data sets and give a rank in TABLE VI and TABLE VII.

TABLE VI THE ACCURACY RANK OF ALL TSC ALGORITHMS ON 'CINCECGTORSO'

Rank	Algorithm	Accuracy	Rank	Algorithm	Accuracy
1	COTE	0.983	24	LPS	0.743
2	TSF	0.974	25	FS	0.741
3	CID_DTW	0.954	26	DD_DTW	0.731
4	EE	0.946	27	RandF	0.731
5	DDTW_Rn_1NN	0.944	28	SAXVSM	0.730
6	WDDTW_1NN	0.938	29	DDTW_R1_1NN	0.717
7	MSM_1NN	0.935	30	TSBF	0.716
8	LCSS_1NN	0.928	31	BoP	0.716
9	DTW_Rn_1NN	0.928	32	DTW_F	0.714
10	ST	0.918	33	RotF	0.712
11	WDTW_1NN	0.908	34	DTW_R1_1NN	0.674
12	BOSS	0.900	35	SVMQ	0.657
13	ERP_1NN	0.899	36	MCDCNN	0.643
14	Euclidean_1NN	0.891	37	C45	0.604
15	PS	0.888	38	Time-CNN	0.600
16	LS	0.855	39	Encoder	0.573
17	NB	0.847	40	TWIESN	0.553
18	TWE_1NN	0.846	41	MCNN	0.533
19	ResNet	0.844	42	t-LeNet	0.533
20	DTD_C	0.820	43	SVML	0.462
21	FCN	0.814	44	MLP	0.462
22	BN	0.803	45	Logistic	0.379
23	ACF	0.786			

TABLE VII THE ACCURACY RANK OF ALL TSC ALGORITHMS ON 'MEAT'

Rank	Algorithm	Accuracy	Rank	Algorithm	Accuracy
1	MLP	0.999	24	DD_DTW	0.969
2	SVML	0.997	25	LPS	0.968
3	SVMQ	0.996	26	ResNet	0.968
4	RotF	0.994	27	TWIESN	0.968
5	Logistic	0.993	28	ST	0.966
6	DTW_F	0.983	29	BoP	0.962
7	TSBF	0.983	30	SAXVSM	0.954
8	Euclidean_1NN	0.981	31	C45	0.940
9	ERP_1NN	0.981	32	ACF	0.927
10	COTE	0.981	33	FS	0.924
11	BOSS	0.980	34	PS	0.923
12	DTW_Rn_1NN	0.980	35	Time-CNN	0.902
13	CID_DTW	0.980	36	FCN	0.853
14	RandF	0.979	37	DDTW_Rn_1NN	0.821
15	EE	0.979	38	LS	0.814
16	TSF	0.978	39	WDDTW_1NN	0.790
17	DTD_C	0.978	40	DDTW_R1_1NN	0.759
18	BN	0.977	41	Encoder	0.742
19	MSM_1NN	0.977	42	MCDCNN	0.705
20	TWE_1NN	0.976	43	LCSS_1NN	0.611
21	DTW_R1_1NN	0.971	44	MCNN	0.333
22	WDTW_1NN	0.971	45	t-LeNet	0.333
23	NB	0.971			

As the tables shown all chosen algorithms are obviously in the upper half and have good performance. At least, with the help of KBRS they have not made bad choices.

VI. CONCLUSION

Obviously, the recommendation system based on ontology has better flexibility than a taxonomy. With the support of ontology technology authors flexibly define more relationships to describe the knowledge about TSC. Such a recommendation system effectively helps those non-computer science researchers choose and understand the appropriate TSC method.

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