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A time series taxonomy to identify the best suitable forecasting method

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Abbreviations

ACF	Autocorrelation Function
AIC	Akaike's Information Criterion
ANN	Artifical Neural Network
ARIMA	Autoregressive Integrated Moving Average
CART	Classification And Regression Trees
DTW	Dynamic Time Warping
ES	Exponential Smoothing
FS	Feature Selection
FSS	Feature Subset Selection
GBDT	Gradient Boosting Decision Tree
LE	Lyapunov Exponent
MAPE	Mean Absolute Percentage Error
MdAPE	Median Absolute Percentage Error
ML	Machine Learning
PACF	Partial Autocorrelation Function
RW	Random Walk
SVM	Support Vector Machine
TS	Time Series

Abstract

The time series forecasting method selection is often a very extensive and time consuming process. Also, the involved parties need a broad knowledge of the time series forecasting area in order to identify and implement all current methods. This extensive trial and error process is addressed by predicting the best suitable forecasting method for new time series without testing each method. The main question of this work is to examine if a descriptive time series taxonomy can be applied to predict the best suitable forecasting method. The taxonomy consists of different (statistical) time series features from the literature and is evaluated by the deployment of machine learning classification and rule models. The taxonomy classification as well as the forecasting model prediction process is automated by the development of the two R packages: *tstaxonomyr* and *tsfcmethodr*. The usefulness of the taxonomy is indicated by the two error measures *accuracy* and *F1-Score* of the classification models which return the best suitable forecasting method. In order to train these models 1,000 multivariate and univariate time series data of different kinds are collected and classified based on the developed taxonomy. Seven different forecasting methods are applied on the collected data to identify the best performing one for each of them. Thus, the evaluation prediction models predict for each inserted time series a method of the seven determined ones. The overall evaluation results for the time series taxonomy achieve an *accuracy* of *61%* to predict the best suitable forecasting method and an *accuracy* of *76%* to predict one of the three best performing ones for a time series. In comparison, the second error measure, the *F1-Score*, reaches a clearly lower score of *0.36* for the selection of the best suitable model. These results do not prove the application of a time series taxonomy to predict the best suitable forecasting method. Nevertheless, especially the medium high *accuracy* results indicate that the taxonomy may provides potentials to solve or support the trial and error forecating model selection problem by processing further work. Therefore, the research question is not clearly disproven by the results of this work. Although, the current set up of this thesis performs not good enough to apply the developed time series taxonomy and prediction models as a reliable forecasting model predictor. However, for end users with less knowledge of the time series forecasting area it can be used as a first quick decision supporter to identify a suitable technique.

1 Introduction

Forecasting has been an extensive research area for the recent years. It is applied as a key mean in a range of several areas like economics, industry, medicine and way more. Some application examples are governments or policy organizations which need forecasts of central economic values, like population growth or unemployment rates. Other application cases are continuous forecasts of product sales or demand to plan processes like production or personnel in the operations management. These cases represent by no means the extensive range of forecasting fields, but it makes clear that forecasts play a central role in good decision making today. Basically, forecasts are done on a data basis which commonly is a Time Series (TS). Since TS data represents historical data it is very consistent. This means, that statistical forecasting models are perfectly suited to apply forecasts based on the historical data basis (Montgomery et al. 2015, p. 2 f.).

Forecasting models represent a main part of the defined forecasting process from MONTGOMERY ET AL.. The process consists of seven steps, but only the two steps model *selection/fitting* and *model validation* are essential parts for the problematic of the forecasting method selection of this work. During the model selection stage several forecasting models are selected and adjusted in order to find the best performing method for the specific case later on in the model validation phase (Montgomery et al. 2015, p. 13 f.). This trial and error evaluation process of several models is often very extensive and time consuming. Likewise, the involved users need a broad knowledge in the forecasting domain in order to be able to identify and implement all existing models. Also, several new methods continuously are developed to improve forecasting performance by researchers which leads to an even larger method selection and evaluation process. Thus, the research field of forecasting model selection is handled by researchers for decades. First, research approaches provided general guidelines or checklists based on expert knowledge for selecting an appropriate model. The next step in literature was to build expert systems which generate and provide rules for the selection process. Lately, Machine Learning (ML) algorithms took place in the development of selection approaches. The meta learning concept is applied to use ML generated results as input for another learning algorithm. The study of PRUDÊNCIO AND LUDERMIR applied the k-nearest neighbor algorithm based on some simple beforehand generated TS characteristics. They provide the best performing forecasting method for each included TS from a collection of three traditional statistical techniques (Prudêncio and Ludermir 2004). Another work from WANG ET AL. extends the previous approach by including neural forecasting methods and applying several ML algorithms in order to generate rules, which define when methods perform the best (Wang et al. 2009). Therefore, this thesis partly ties in with the previous research approaches and aims to extend them in regard of their limited forecasting method scope, TS features and types of TS data.

However, currently no approach exists which manages different kinds of TS input data such as multivariate or univariate series and provides the best performing forecasting method from a broad collection of current prediction models. Furthermore, the recent meta learning approaches from the literature only apply raw feature values such as broad ranging numerical values for the selection process which leads to results that are difficult to understand for users. Therefore, the research question of the thesis is:

> *RQ: Is it possible to predict the best suitable forecasting method based on a descriptive TS taxonomy for any kind of TS such as multivariate and univariate series and from different domains?*

The first main goal is to develop a TS taxonomy based on several global key features to classify different types of TS and to identify similarities between them. The second main goal is to evaluate the taxonomy by a classification model that is based on the generated TS taxonomy results in combination with their evaluated best performing forecasting method. The model is used to predict the best suitable forecasting method for each given TS. The approach targets users with lacks of knowledge of the fast growing forecasting domain to enable them to quickly identify a suitable method.

The thesis is structured as follows: In chapter 2, theoretical backgrounds are explained in order to present a general knowledge about TS, TS features and forecasting, ML and taxonomies to enable the reader to understand the further chapters. Chapter 3 determines the process of the literature review in order to identify and select appropriate features to create a useful TS taxonomy. Then, the resulting features of the review process are listed and explained. The following TS taxonomy chapter contains the taxonomy conceptualization and its implementation as an R package to automate the classification process. Additionally, 1,000 TS are collected as representatives to build categories for each feature within the taxonomy. Chapter 5 analyses the current existing forecasting methods in order to identify the most relevant ones for the following model selection prediction process. In the next chapter, all experimental parts are set up in order to enable the evaluation of the developed TS taxonomy: First, a feature selection technique is applied to create a second ligther TS taxonomy. Second, the collected TS data is applied to the two developed taxonomies as well as to the selected forecasting methods in order to identify the best performing one for each individual TS. Then, an R package is created in order to provide ML prediction techniques to identify the best suitable forecasting method for a new classified TS based on the TS taxonomy. In chapter 7, the results for the model selection prediction are illustrated and evaluated. Also, some selection rules are derived from the classified TS taxonomy data and their best performing forecasting method. Finally, chapter 8 concludes the paper by a brief summary and provides the main results of this thesis. Additionally, the limitations of this work are discussed and guidelines of future work are proposed.

2 Background

2.1 Time series

A TS consists of a set of observations, which were recorded each at a specific point in time during a time period. This understanding of a TS is supported by the definition of Montgomery et al.:

> *A time series is a time-oriented or chronological sequence of observations on a variable of interest* (Montgomery et al. 2015, p. 2).

Additionally, brockwell2016 formulate a TS by a set of observations x_i, all individually recorded at a specific point in time t. They categorize a TS into two different types. First, a *discrete-time TS* contains observations made within a discrete set T_0 of times, for instance during a fixed time period. Second, *continuous-time TS* contain continuously observed observations over some time range, for example $T_0 = [0, 1]$. Furthermore, TS can be divided into univariate or multivariate ones. Univariate TS contain only one single time-dependent variable. For example, in figure 1 is the single variable represented by the population of the U.S.A. in millions on a ten year interval basis from the years 1790 to 1990. The set T_0 consists of 20 time points $\{1790, 1800, ..., 1990\}$. The time axis commonly is rescaled to a set of integers. In this case, it would be $T_0 = \{1, 2, ..., 20\}$ (Brockwell and Davis 2016, p. 1 f.).

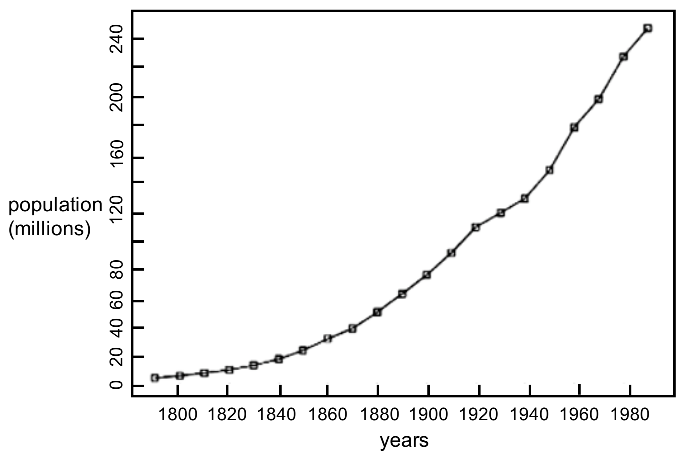

Figure 1 Univariate time series representing the population of the U.S.A. (cf. Brockwell and Davis 2016, p. 5)

Instead, multivariate TS exist of more than one time-dependent variable. Each included univariate series $\{X_t\}$ is a component of the overall multivariate series $\{X_{ti}\}$. Additionally, the several values can have dependencies between each other, $\{X_{ti}\}$ and $\{X_{tj}\}$ with $i \neq j$. Although, they can also be examined as two independently univariate series. Figure 2 shows an exemplary multivariate TS. The closing values of the Dow Jones Index of stocks and the Australian All Ordinaries Index of Share Prices at each trading day are combined within a defined time interval. Thus, the two series X_{t1} and X_{t2} build a series of two dimensional vectors (X_{t1}, X_{t2}) observed at 251 trading days until the 26th August 1994. In the example, the time set T_0 is rescaled to a time set of integer values $T_0 = \{1, 2, ..., 251\}$ (Brockwell and Davis 2016, pp. 227–231). For this thesis, both types of TS are considered as relevant in order to develop a TS taxonomy.

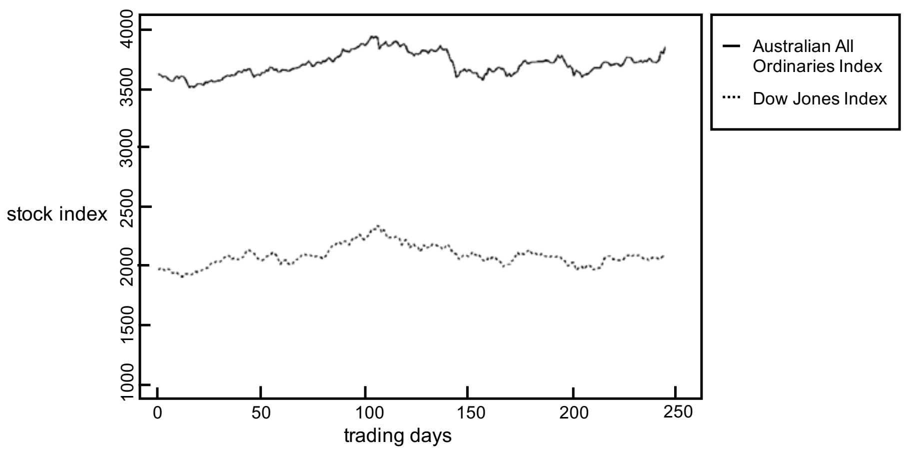

Figure 2 Multivariate time series representing combination of Dow Jones Index of stocks and the Australian All Ordinaries Index of Share Prices (cf. Brockwell and Davis 2016, p. 225)

2.1.1 Features

TS classification requires representation- or feature-based approaches. These illustrate a high structural information of the TS either by global or local features. In this thesis, only global features like statistical ones are considered because the taxonomy requires features that are valid for varying types of TS with different length of variables (Huang et al. 2018). Multivariate TS data usually embody a high dimensionality. This causes problems in regard of slowing down mining algorithms or making the data even unusable. Thus, feature extraction is applied in order to explore and extract different global TS features. Especially for classification tasks the extraction process is required to transform the different raw TS with varying dimensionality and varying length in a uniform format by the global features. This can lead to better classification results and higher algorithm speed performance. Furthermore, a small and uniform amount of features supports the human interpretableness of the results (Mörchen 2003). For instance, feature extraction methods for TS define statistical features such as stochastic trend or seasonality. Both terms aim to reduce noise and dimensionality of TS in order to only apply mining methods on the relevant data (Crone and Kourentzes 2010). In this thesis, all TS (global) features from the literature which are created by feature extraction or engineering methods are investigated in order to create an extensive TS taxonomy.

2.1.2 Forecasting

Forecasting represents the prediction of arbitrary future value(s). It is an important factor for decision making and future planning in several areas like economy or industry. For instance, governments require forecasts of unemployment or interest rates. Also, in the industry forecasting is an essential mean to support and improve the production processes. Almost all forecasts are applied based on TS data. Forecasting techniques are divided into two classes: qualitative or quantitative. Qualitative techniques require the recommendations of experts and often use none or only small parts of historical data. Whereas, quantitative methods predict based on historical data and by the mean of a forecasting model. The focus of this thesis is only on quantitative techniques since the goal is to identify the best suitable forecasting method for TS. Forecasting models try to identify patterns in the historical data in order to project these information into future values of a forecast. The form of a forecast is defined by the forecasting horizon and interval. The horizon describes the forecast period. It can be either short-term like days or weeks, medium-term like one or two years or even long-term such as for many years. Additionally, the interval determines the forecasting frequency. For instance, the forecast can be on a daily or weekly basis within the determined forecasting horizon of 30 days (Montgomery et al. 2015, pp. 1–6). All essential forecasting methods for the purpose of this thesis are collected and explained in chapter 5.

2.2 Taxonomy

Taxonomies are classifications of all kind of objects and information. In this paper, the TS represent the charactarized objects. The relationships between the objects allow the classification in similar groups. All taxonomies can either be shown as a table containing several attributes or as a hierarchical graph. The attributes consist of different values in order to assign a specific attribute value to each new classification object (Martin et al. 2007, p. 11 f.). In this paper, the different TS features are the attributes. The previously described meaning of a taxonomy is supported by the following two definitions from the online dictionaries Cambridge-Dictionary and Collins-Dictionary:

> *A system for naming and organizing things, especially plants and animals, into groups that share similar qualities* (Cambridge-Dictionary 2018).

> *Taxonomy is the process of naming and classifying things such as animals and plants into groups within a larger system, according to their similarities and differences* (Collins-Dictionary 2018).

Both definitions similarly understand the description and grouping of related things as the process of a taxonomy. A very simple example for this would be the classification of notebooks based on their brands. For instance, it could be either from Apple, Lenovo or Acer. This example illustrates that the attributes of the taxonomy do not have to be complete. Each taxonomy can be modified in his individual way. Some of the famous known taxonomies are the classification of living organisms from Carl Linnaeus and the periodic table of elements developed by *Dmitri Mendeleev* (Martin et al. 2007, p. 11 f.).

2.3 Machine Learning

ML successfully provides data analyses by identifying relationships between different input features in order to increase the efficiency of systems. ML techniques are divided into supervised and unsupervised methods. Unsupervised ML is used to discover the structure of unknown and unlabeled data, for instance by clustering algorithms. In this work, only supervised ML techniques are applied since only known data with labeled target variables is processed. These are trained by several predictor features and the labeled target variable. The resulting trained model is then able to predict the labels for new input data based on the given input features (Kotsiantis 2007).

Supervised ML techniques are divided into classification or regression methods. They differ in the way that classification methods predict discrete values whereas regression ones predict numerical values. In this thesis, a classification problem exists by identifying the best suitable forecasting method for each TS. The classification process consists of two steps: First, the taxonomy features for each TS are applied as input for the classification model. Additionally to the features, the best performing forecasting method is assigned for each time series. This information is used as the target variable for the training process. Then, the model is trained on the data by analysing the relationship between the features and target variable. Second, after the training process is completed, the model is able to predict the best suitable performing forecasting method for each new time series based on its features and their learned relationships (Hodeghatta and Nayak 2017, p. 131 f.).

In this thesis, only supervised ML classification methods are relevant for the evaluation process. The selection of the techniques is based on the two extensive supervised ML method evaluation papers from Kotsiantis and Caruana and Niculescu-Mizil. The techniques Support Vector Machine (SVM) and Artifical Neural Network (ANN) show the highest value regarding the evaluation metrics of accuracy and speed (Kotsiantis 2007).

The performance evaluation of Caruana and Niculescu-Mizil confirms with the high value of SVM and ANN. Additionally, their work ranks Gradient Boosting Decision Tree (GBDT) techniques very high based on the applied performance metrics (Caruana and Niculescu-Mizil 2006).

2.3.1 Support vector machine

The SVM is one of the newest supervised ML techniques. An essential aspect of SVM algorithms are hyperplane classifiers in order to separate the input data. Therefore, a maximal margin classifier considers all input features in the data. These form a n-dimensional space based on their total number. In this thesis, the input features are represented by all TS taxonomy features. Next, the dimensional space is split by a line into two different classes, this line is called hyperplane. As this thesis aims to identify the best suitable forecasting method, a multi-classification problem exists based on the number of labeled forecasting methods. Nevertheless, the explanation is continued based on a simple classification problem with two different classes in order to keep it simple (Kotsiantis 2007).

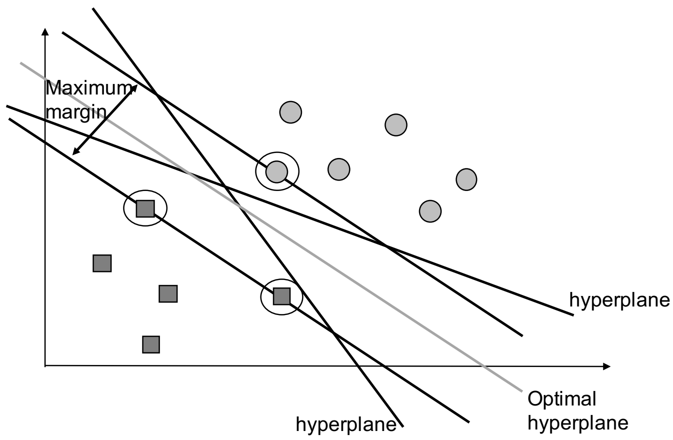

Figure 3 Support vector machine linear classification process (cf. Kotsiantis 2007, p. 15)

The figure 3 shows a linear classification process. Hyperplanes divide the input data above and below the line into two separate classes. Next, SVM algorithms identify the optimal hyperplane based on the one with the highest margin which is the distance of the closest data points for both classes in regard to the hyperplane. These essential points are called support vectors. They are repeatedly maximized until vectors with the largest possible distances between them and the hyperplane are reached. The formula for each hyperplane for linear separable data is defined as follows with the bias b and the weight vector w:

$$w^T x_i + b \geq +1, \textit{for all } x_i \in \textit{Positive group,} \tag{2.1}$$

$$w^T x_i + b \leq -1, \textit{for all } x_i \in \textit{Negative group.} \tag{2.2}$$

If it is possible to linearly divide the data into two clean classes, an optimum hyperplane is identified by minimizing the squared norm of the separating hyperplane. The minimization formula looks as follows:

$$\textit{Minimize } \Phi(w) = \frac{1}{2}||w||^2 . \tag{2.3}$$

The scenario of a linear hyperplane which is able to divide the overall data into two clear classes requires the assumption of perfect data. Whereas, real world data is always very complex and contains misclassified instances. Thus, it is almost never totally divisible. Therefore, SVMs apply soft margin classifier in order to manage the problem. Soft margin classifier adjust the training process of the method by accepting that several data points can lie on the incorrect side of the hyperplane. An additional tuning parameter is applied to define the acceptance ratio of violating data points. This is represented in the formula by the positive variable ζ with $\zeta \geq 0$:

$$w^T x_i + b \geq +1 - \zeta, \textit{for all } x_i \in \textit{Positive group,} \tag{2.4}$$

$$w^T x_i + b \leq -1 + \zeta, \textit{for all } x_i \in \textit{Negative group.} \tag{2.5}$$

Finally, a trained SVM method classifies new data points based on similarities to the support vector points. The measurement of the similarity is determined by the selected SVM kernel. In this thesis, only linear kernels are applied on the multi-classification problem (Kotsiantis 2007).

2.3.2 Artifical neural network

An ANN is a ML approach based on biological neural networks using perceptrons. A single perceptron is only able to linarly classify instances into two sets. Thus, ANNs consist of multilayered perceptrons in order to solve the problem of not linearly instances. This means, an arbitrary number of perceptrons are connected to represent an ANN. Figure 4 shows the basic structure consisting of an input layer, hidden layer(s), and a output layer.

The different layers represent neurons, which process input data based on their activation function. Therefore, the training process works as follows. First it requires labeled training data in order to define connections and their weights between the neurons. The specific weights are commonly generated by the Back Propagation algorithm. This algorithm repeatedly calculates the weights for all connections until it reaches the highest possible weight configuration. Then, during the classification of new data, the ANN propagates feed forward all the way from the input layer to the output layer. During this process, each neuron from the different layers calculates its own activation value based on the activation function and the assigned weights. This function sums up the values from all sending input relations and based on them it calculates its own activation value which commonly ranges between 0 to 1. Then, the value is sent to the neuron units from the next layer until the final output layer is reached. Furthermore, the number of neurons for each layer can be variable determined by the ANN modeler. This configuration is a very critical factor since an underestimation of neurons can lead to poor approximation. Whereas, a high number of neurons can lead to overfitting problems. In this case, the model is trained to excessive on the training data which leads to bad predictions using a new dataset. The model can also consist of more than one hidden layer. This configuration is mainly required for very complex classification problems. In this thesis, all configuration parameters are tested in order to develop the best performing ANN with the highest accuracy for the multi-classification problem of identifying the best suitable forecasting method (Kotsiantis 2007).

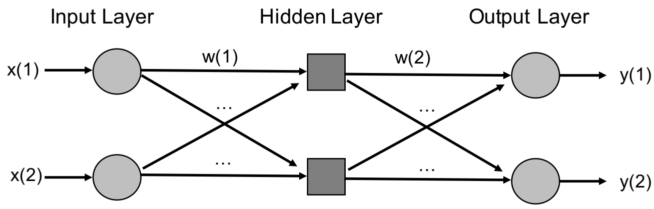

Figure 4 Artifical neural network structure (cf. Kotsiantis 2007, p. 9)

2.3.3 Gradient boosting decision tree

The GBDT is an ensemble ML technique which builds a strong learner model based on a number of integrated weak learners. The overall concept consists of three elements. First, the selection of a loss function is required. For instance, a classification problem can be handled by logarithmic loss. Second, a weak learner for the prediction process is essential. In the case of GBDT methods, decision trees are applied. Basically, decision trees classify data based on the sorted input features starting at the root node. Figure 5 shows that a tree consists of nodes which represent a classification feature and branches which are the value that a node can assume. Furthermore, a simple classification problem for each instance into the two classes *Yes* or *No* is shown.

Third, a strong learner model is applied to minimize the loss function. Gradient boosting is used in order to repeatedly generate weak learner models with marginally modified parameter settings. Finally, an additive model exists based on all generated weak learner models. The previous description of the ensemble process can be formulated as follows (Anghel et al. 2018). A common dataset D consists of n samples and m input features:

$$D = \{(x_i, y_i) \mid i \in \{1, .., n\}, x_i \in \mathbb{R}^m, y_i \in \mathbb{R}\}. \tag{2.6}$$

Next, the predicted outcome $y(\hat{x})^K$ of the ensemble of K trees is defined based upon the given dataset D for an input sample x. The parameter f_i represents the output of the ith tree of the ensemble process. This means, each f_i tree represents a weak learner for the ensemble strong learner model K:

$$y(\hat{x})^K = \sum_{i=1}^{K} f_i(x). \tag{2.7}$$

Finally, the generation of the final adaptive strong learner tree K is based on the minimization of a regularized objective function L. It consists of a loss function $l(y_i, \hat{y}_i^K)$ and the regularization function Θ in order to control the overfitting problem:

$$L = \sum_{i=1}^{n} l(y_i, y_i(\hat{x})^K + f_{K+1}(x_i)) + \Theta(f_{K+1}). \tag{2.8}$$

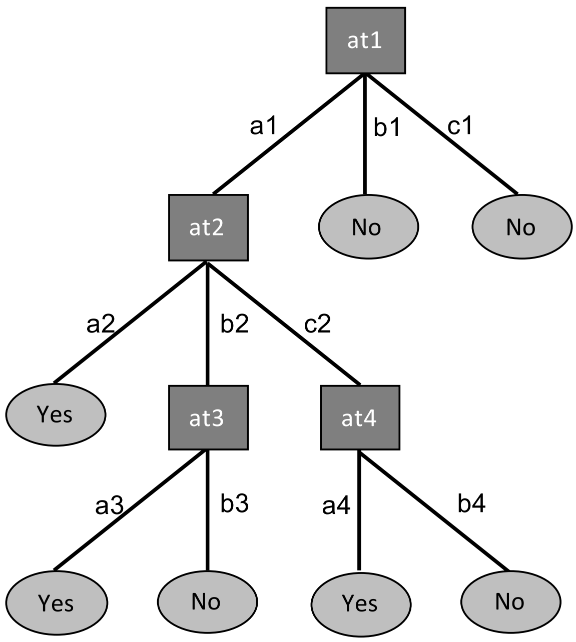

Figure 5 Decision tree classification example (cf. Kotsiantis 2007, p. 5)

In the work of ANGHEL ET AL. are the following two GBDT methods introduced and recommended (Anghel et al. 2018):

- <u>XGBoost</u>: In recent years, it is one of the state-of-the-art approaches in the ML area. Since 2015, it is very successful in many ML competitions, especially in the competitions from the common ML platform Kaggle. Major reasons for the outstanding competition success rate are high execution speed and high model performance. The method seems very promising for the classification problem of this thesis (Chen and Guestrin 2016) because of its succesful outcomes in categorization and classification cases in recent years.

- CatBoost: It is one of the newest appearances of GBDT techniques. Also, CatBoost coverages the management of categorical as well as numerical values. Usually, GBDT methods have to first convert categorical features into numbers before applying them in the training process. This is an essential advantage for the multi-classification problem based on the TS taxonomy since all taxonomy features are categorical. Furthermore, the method applies new concepts in order to generate leaf values of the boosted decision trees. This reduces the model overfitting problem (Dorogush et al. 2018).

3 Time series features

In this chapter, all different TS features from the literature that are essential and able to divide varying TS into different categories are identified. Thus, an extensive literature search is done. Afterwards the results are analyzed in order to identify and explain the relevant TS features. These essential results build the basis for the development of the TS taxonomy in the next chapter.

3.1 Literature review methodology

This section defines the process of conducting a structured literature research in order to identify all current essential TS features. The process partly bases upon the highly cited literature search process from Webster and Watson. The four suggested steps database search, keyword search, backward search and literature synthesis are adapted and defined as follows (Webster and Watson 2002):

The database search process is handled by databases which refer to journal and conference proceedings of high quality. Therefore, the two databases *SpringerLink* and *ScienceDirect* are selected and used. Next, the following keyword terms are defined in order to filter the findings during the database search:

> *Keyword-term 1: ("time series" AND ("global feature" OR "meta feature" OR "descriptive feature" OR"quantitavie feature")) OR "time series characteristic" OR "time series description" OR "time series describer"*
>
> *Keyword-term 2: ("time series" AND ("feature extraction" OR "feature engineering" OR "statistical feature") AND "time series classification") OR "time series feature"*

Additionally to the keyword term, the search process is restricted by the factor *Year*. This means, only publications up from the year 2008 are considered since this thesis is just interested in up-to-date features for TS from the last decade. Then, all as relevant identified findings are examined using the backward search process by checking the citations of each paper to find further relevant works from a prior time. In the last step, the previously relevant identified papers are analyzed. Webster and Watson determine a literature review as concept-centric. Thus, their adapted concept centric matrix for IS literature reviews is used (Webster and Watson 2002). Figure 6 shows that each row represents one article and each column one feature of the matrix:

Articles	Features				
	A	B	C	D	...
1	X		X		
2	X	X			
...					

Figure 6 Concept matrix structure (cf. Webster and Watson 2002, p. 17)

3.2 Literature review results

The literature search result evaluation based on the restrictions by the defined keyword term and year range is proceeded as following: First the titles of all outcomes are checked and for proper ones, the abstracts additionally are examined. In the next step, the full text of the resulting papers are checked in order to only identify the relevant works. Then, all citations of the relevant idenfitied paper are examined during the backward search.

In total, during the database search regarding to the keyword terms 1,389 findings from *SpringerLink* and 1,190 findings from *ScienceDirect* are checked based on their title and abstract. Based on that, 15 papers from *SpringerLink* and 21 papers from *ScienceDirect* remain for the full text examination. At the end, 18 papers are considered as relevant after duplicate checking. Next, during the backward search on the previous identified papers 17 further findings remain as relevant. Finally, 35 articles represent the relevant results from the overall literature search process.

The next step is the feature results synthesis. All identified papers and their including features are assigned into a concept matrix. All identified features represent the determined concepts in the columns of the matrix. The articles are listed in the rows of the matrix. One major aspect is, that the final findings can provide several features. For each article, the *number of citations* and the *average citations* per year are provided. All *number of citations* are adopted from the public web search engine of scholarly literature: *Google Scholar*. The *average citations* factor is calculated as follows:

$$Average\ citations = ROUND\left(\frac{Number\ of\ citations}{2019 - Year}\right). \tag{3.1}$$

The concept matrix rows are ascending ordered by the column *average citations* of the matrix. Results with a similar *average citations* number are ascending sorted by the papers *Year* in a second step. Therefore, the articles on the top of the concept matrix provide features with the highest relevance regarding to the *average citations* and the *Year*. Thus, the relevance is steadily decreasing until the bottom of the matrix. Furthermore, the *sum of citations* per feature is provided by the matrix. All assigned *average citations* for each feature are summarized. The features are ascending ordered from the left side to the right side based on their *sum of citations*. This means that the left features are the most relevant ones, whereas the right ones have the least relevance. Finally, the overall concept matrix is divided into two parts. First, a concept matrix for all relevant features in figure 7. Second, another matrix for all irrelevant features in appendix G:

Articles				Features																							
Reference	Year	Number of citations	Average citations	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non-linearity	Seasonality	Periodicity (Frequency)	Chaos	Entropy (Predictability)	Self-similarity	DTW distance	% of turning points	Partial autocorrelation	Variance	% of outliers	% of step changes	% of peaks	Durbin-Watson test	Quartile distribution	Coefficient of determination	Number of attributes
Smith-Miles 2009	2009	391	40	x	x			x	x	x					x												
Wang et al. 2006	2006	276	22	x	x	x	x				x	x	x	x		x											
Kate 2016	2016	61	21														x										
Lemke and Gabrys 2010	2010	105	12	x	x	x	x	x	x	x	x	x	x	x	x			x	x			x	x	x			
Nanopoulos et al. 2001	2001	214	12	x	x			x	x																		
Collopy and Armstrong 1992	1992	315	12			x														x	x						
Cui et al. 2016	2016	32	11	x	x		x	x	x		x								x						x		
Wang et al. 2009	2009	102	11	x	x	x	x				x	x	x	x		x											
Lahmiri 2014	2014	38	8														x										
Matijaš et al. 2013	2013	46	8	x	x	x	x	x	x	x			x														
Gudmundsson et al. 2008	2008	69	7														x										
Prudêncio and Ludermir 2004	2004	104	7	x	x	x	x			x								x									
Adya et al. 2001	2001	98	6			x															x	x					
Armstrong 2001c	2001	94	6			x						x															
Wang et al. 2007	2007	52	5	x	x	x	x				x	x	x	x		x											
Yang et al. 2017	2017	7	4			x	x	x			x				x					x		x					
Armstrong 2001b	2001	69	4			x						x									x						
Meade 2000	2000	61	4			x	x			x										x	x					x	
Scholz-Reiter et al. 2014	2014	12	3	x	x	x	x			x	x	x	x	x	x	x										x	
Graff et al. 2014	2014	11	3	x	x		x	x	x		x			x				x	x			x					
Graff et al. 2013	2013	14	3	x	x	x	x		x	x	x	x	x	x	x	x			x	x			x	x			
Prudêncio et al. 2004	2004	35	3	x	x		x			x								x		x							
Shah 1997	1997	47	3	x	x		x			x								x	x	x		x					
Drago and Scepi 2015	2015	6	2	x	x	x	x				x	x	x	x		x											
Davenport and Funk 2015	2015	5	2	x	x	x	x				x	x	x	x		x											
Prudêncio et al. 2011	2011	15	2			x	x			x								x									
Soares et al. 2009	2009	12	2	x	x					x										x	x						x
Arinze et al. 1997	1997	29	2			x	x											x								x	
Arinze 1994	1994	50	2			x	x	x										x								x	
Pimentel and de Carvalho 2019	2019	1	1	x	x			x	x	x										x	x				x		
Ali et al. 2018	2018	1	1	x	x	x	x		x	x	x								x			x	x				
Fulcher 2017	2017	1	1				x	x			x			x	x					x	x						
Ge and Ge 2016	2016	2	1					x									x	x		x			x				
Wang et al. 2008	2008	8	1	x	x	x	x				x	x	x	x		x											
Lemke and Gabrys 2008	2008	4	1	x	x	x	x		x	x	x		x						x				x				
Sum of average citations per feature				153	153	120	113	95	92	90	82	71	70	65	63	49	37	35	34	34	30	29	18	15	12	11	2

Figure 7 Concept matrix of relevant time series features

In figure 7, 24 features that are determined as relevant are represented. In order to be considered as relevant in this thesis, it is required that a feature is provided by at least two -or more articles since a feature that is only mentioned once in the current and past literature cannot be essential. Also, the *sum of citations* per feature has to be at least ten or higher. In this thesis a low number of citations represents nonrelevant findings because the citations of the articles define their importance in the research. Although, the feature *number of attributes* is an exception since it does not fullfil the previous defined requirements. It is part of the relevant features because almost all articles from the literature only handle univariate TS, whereas in this thesis multivariate TS are considered as well. Thus, it is an essential feature to enable the differentiation between univariate and multivariate TS.

The concept matrix in appendix G presents 32 features that are marked as irrelevant based on the requirements of at least two apperances and at least a *sum of citations* of ten or higher. The matrix contains two exceptions. These are the features *maximum value* and *minimum value* which actually fullfil the requirements but do not work for TS from different domains since several multivariate and univariate TS datasets from varying domains are used for evaluation in this thesis. Thus, the comparison is not useful of *maximum* or *minimum* values of TS with different units like currency or temperature. More information of the references from the relevant and irrelevant concept matrix in figure 7 and 14 are provided in appendix H.

3.3 Selected features

In this subchapter, all relevant TS features represented in the concept matrix in figure 7 are listed and explained. The explanation of each feature consist of the description and an exemplary calculation of it. Overall, all features are the basis for the taxonomy to classify the underlying TS datasets. In some findings from the concept matrix some features which consist of several subfeatures are mentioned. Also, the calculation or description of them is varying between the resulting articles sometime. In this thesis, all feature approaches are combined and aggregated to one final value calculation in order to be able to create descriptive features for the overall taxonomy. Moreover, the results of the previous literature search indicate that for some features different types of TS data are required. This necessary transformation process of the series data is called decomposition (Wang et al. 2006). Table 8 shows all three possible decompostion types for each feature, named: *raw*, *de-trended* or *de-trended and de-seasonalized* TS datasets. *de-trended* means a decomposed TS without trend and *de-seasonalized* one without seasonality. Also, some features can be measured on two or all different data types.

The overview in table 8 indicates that the feature *skewness*, *kurtosis*, *autocorrelation*, *partial autocorrelation* and *non-linearity* can be measured on all three different TS data types (Ali et al. 2018; Wang et al. 2006, 2008; Lemke and Gabrys 2010; Davenport and

Funk 2015; Wang et al. 2007; Scholz-Reiter et al. 2014; Wang et al. 2009). In this thesis, all three measurements are calculated and then summed and divided by three, the number of different data types, since for each feature only one final value should be provided to keep the taxonomy simple and readable. Next, the findings suggest to calculate the features *trend* and *seasonality* based on the raw and de-trended TS data (Wang et al. 2008; Davenport and Funk 2015; Wang et al. 2007; Scholz-Reiter et al. 2014; Wang et al. 2009). In this case, both values are generated for the two features and again summed and divided by two this time. However, *standard deviation*, *Durbin-Watson test* and *percentage of peaks* are only calculable on de-trended data (Ali et al. 2018; Lemke and Gabrys 2010; Collopy and Armstrong 1992). Also, the features *periodicity*, *chaos* and *self-similarity* require raw TS based on the literature review results (Wang et al. 2006; Davenport and Funk 2015; Wang et al. 2007; Scholz-Reiter et al. 2014; Wang et al. 2009). For the left eleven features no explicit requirements for the TS data type are provided. Thus for this thesis, it is assumed that these features are only measured based on raw series data.

Type of TS data	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non-linearity	Seasonality	Periodicity (Frequency)	Chaos	Entropy (Predictability)	Self-similarity	DTW distance	% of turning points	Partial autocorrelation	Variance	% of outliers	% of step changes	% of peaks	Durbin-Watson test	Quartile distribution	Coefficient of determination	Number of attributes
raw	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x
de-trended	x	x		x		x		x								x				x	x			
de-trended and de-seasonalized	x	x	x	x				x	x							x								

Figure 8 Type of time series data

Unless of the features *coefficient of determination* and *Durbin-Watson test*, all other as relevant defined features represent global statistical measures based on univariate TS structure. However, the taxonomy of this paper handles univariate as well as multivariate data. Thus, each multivariate TS is divided into its attributes where each of them represents a univariate structure in order to compute the feature values. In the next step, the literature suggest to concatenate the values for each feature in order to generate a single vector for a multivariate structure (Wang et al. 2007). However, for each feature one comparable final value is required in order to be able to classify it within the taxonomy of this thesis. Thus, the generated values of every feature for each component of the TS are combined by arithmetic addition to get a single vector with comparable values for the taxonomy classification. The only multivariate characteristics *coefficient of determination* and *Durbin-Watson test* cannot be computed for univariative TS data. Thus, for all one-dimensional series the value for the feature is set to -1.

3.3.1 Skewness

The *skewness* is a statistical measure for the lack of symmetry. In this thesis, it is applied to determine the level of asymmetry for each used TS. It identifies the extent to which the TS distrbution function skews to one side. Normal distributions and any other symmetrical distribution funtions have a value of zero. Positive values accord to datasets that tend to the right. In this case, the right tail is stronger then the left one. Moreover, distribution functions have a negative value that tilts to the left. The left tail is stronger than the right one. Overall, this means that every non-symmetric dataset is skewed in some degree. The *skewness* value is calculated as follows (Wang et al. 2006):

$$Skewness = \frac{1}{n\sigma^3}\sum_{i=1}^{n}(X_i - \mu)^3 \,. \tag{3.2}$$

The paramater μ is the mean of the TS while σ represents the standard deviation and n the number of observations of the dataset.

3.3.2 Kurtosis

Kurtosis is a measure of flatness or peakedness of a distribution relative to a normal distribution. The *kurtosis* of a normal distribution has a value of three. Thus the formula for the *kurtosis* coefficient is subtracted by a value of three. This results in a *kurtosis* excess that makes the assesment of a distribution very simple by examing its sign. A standard normal distribution is represented by the value zero. In case of a positive value, a peaked distribution can be assumed. Whereas, a negative value represents a flatter distribution. The excess *kurtosis* is computed as following (Wang et al. 2006):

$$Kurtosis = \frac{1}{n\sigma^4}\sum_{i=1}^{n}(X_i - \mu)^4 - 3 \,. \tag{3.3}$$

The paramater μ is the mean of the TS. σ represents the standard deviation and n the number of observations of the dataset.

3.3.3 Trend

The feature *trend* represents a long-term or dynamic movement in the mean level of a TS. It can occur in both directions, either upwards or downwards (Brockwell and Davis 2016, p. 14). The calculation of the *trend* can be performed by several different methods.

One example approach is provided by WANG ET AL.. Their work differentiates between two cases. If the dataset is nonseasonal, the work suggests to use a penalized regression spline to estimate the *trend*. Whereas the data is seasonal, a *seasonal-trend* decomposition approach is suitable which decomposes the series into trend, seasonal and irregular component. Finally, the *trend* is defined as follows (Wang et al. 2009):

$$Trend = 1 - \frac{Var(Y_t')}{Var(Z_t)}. \tag{3.4}$$

The first parameter is the variance of Y_t', this represents the transformed TS after *trend* and seasonality are excluded. The transformed series is defined by $Y_t' = Y_t^* - T_t - S_t$, where T_t is the *trend*, S_t denotes the seasonal factor, and Y_t^* represents the time series transformed in a normal distribution by a Box-Cox transformation process including the *trend*, seasonality and irregular component by $Y_t^* = T_t + S_t + E_t$. The second parameter of the ratio specifies the variance of the deseasonalized TS Z_t after the transformation process and is defined as $Z_t = Y_t^* - S_t$ (Wang et al. 2009).

3.3.4 Autocorrelation

The feature *autocorrelation*, also called *serial correlation*, indicates stationarity and seasonality by calculating the correlation of datapoints that are divided by an assigned timelag of the TS (Fulcher 2017). The *autocorrelation* coefficient ρ at k is defined as following with the two observations y_t and y_{t+k} which are divided by the same interval k, also known as lag (Brockwell and Davis 2016):

$$\rho_k = \frac{Cov(y_t, y_{t+k})}{Var(y_t)}. \tag{3.5}$$

It is defined by the ratio of the covariance between the two observations and the variance of y_t. The sum of all autocorrelation coefficients for $k = 0, 1, 2, ...$ represent the Autocorrelation Function (ACF). One essential attribute of the ACF is the symmetry around zero $\rho_k = \rho_{-k}$. Thus, only the negative or positive part is required to be computed (Brockwell and Davis 2016).

3.3.5 Mean

The feature *mean* μ represents the arithmetic average of the TS. All datapoints X_i are divded by the length of the TS n:

$$Mean = \frac{1}{n}\sum_{i=1}^{n} X_i \,. \tag{3.6}$$

Additionally, the resulting mean is normalized between the metric [0,1]. This is necessary to transform the feature *mean* in order to be comparable for all kind of TS data. X_{min} and X_{max} represent the minimum and maximum value of the TS. The parameter *mean* is the previous defined arithmetic average:

$$Normalized\, mean = \frac{mean - X_{min}}{X_{max} - X_{min}} \,. \tag{3.7}$$

3.3.6 Standard deviation

The descriptive statistic feature *standard deviation* σ is computed on the detrended TS data. It measures the amount of variation of the data. That means, a low value defines a TS close to the mean whereas a high value indicates a wider value distribution. It is defined as follows with the mean as μ and the number of observations as n (Ali et al. 2018):

$$Standard\, deviation = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (X_i - \mu)^2} \,. \tag{3.8}$$

3.3.7 Number of observations

Number of observations n represents the length of the TS.

3.3.8 Non-linearity

Nowadays, many types of TS data consist of non-linear behavior caused by recession. The measurement of *non-linarity* can be done by methods such as neural network theories. The work of Teräsvirta et al. provides a neural network test to detect neglected non-linearity. They suggest to exam whether the dataset is linear or not based on the null hypothesis of linearity. The rejection of the null hypothesis is checked by the application of their neural network approach to consider the TS as non-linear (Lemke and Gabrys 2010; Teräsvirta et al. 1993; Wang et al. 2009).

3.3.9 Seasonality

Seasonality of a TS are patterns that regularly repeat theirself by factors like each day of the week, each month of a year or even each year (Brockwell and Davis 2016, p. 15). Currently, a variety of methods exist to specify the *seasonality* of a dataset. The work of WANG ET AL. provides an examplary conceptual way. They suggest to follow a decomposition method such as a loess smoother to divide the original TS into the three parts trend, seasonal and remainder components. This decomposed series data is then used to extract the *seasonality* measure from it as follows (Wang et al. 2009):

$$Seasonality = 1-\frac{Var(Y_t')}{Var(X_t)}\,. \tag{3.9}$$

The first parameter is the variance of Y_t', it represents the transformed TS after trend and *seasonality* are excluded. The transformed series is defined by $Y_t' = Y_t^* - T_t - S_t$, where T_t is the trend, S_t denotes the seasonal factor, and Y_t^* represents the time series transformed in a normal distribution by a Box-Cox transformation process including the trend, seasonality and irregular component by $Y_t^* = T_t + S_t + E_t$. The second parameter of the ratio specifies the variance of the de-trended TS X_t after the transformation process and is defined as $X_t = Y_t^* - T_t$ (Wang et al. 2009).

3.3.10 Periodicity (Frequency)

The feature *periodicity* determines the cyclic patterns of the TS, which represent intervals of different length that repeat within the series (Davenport and Funk 2015). The difference to the feature *seasonality* are the cyclic patterns of varying length, whereas *seasonality* specifies a repeating fixed length. Amongst other existing methods, WANG ET AL. define a step-by-step approach for *periodicity* identification. The first steps are to exclude the trend of the TS and to find any peaks and troughs in their autocorrelation function with lags of at most one third of the series length. Next, an identified peak represents the frequency value if it fulfils the following requirements: a trough exist in the series before it, their difference is at least 0.1 and it regards to a positive correlation. In case none of the identified peaks fulfill this requirements, the frequency value is set to non-seasonal (Wang et al. 2009).

3.3.11 Chaos

Chaos is often shown by non-linear dynamic systems. These chaotic systems can be characterized by a positive Lyapunov Exponent (LE). Whereas, TS with a negative LE indicate a more stable system. In this thesis, LE is a quantitative value to measure the chaotic of a TS as in the work of WANG ET AL.. There are several calculation methods for the LE. In this thesis, the method presented by KANTZ is exemplary used for the calculation. Their method focuses on the distance between two trajectories. They exploit the assumption that the distance increases by the maximal TS λ_{max}. All distances are determined in a one dimensional space of the TS. $\omega_u(t)$ is the local eigenvector corresponding to the maximal *(LE)* λ_{max}. The average of all $\lambda_\tau(t)$ is the true *(LE)* (Kantz 1994; Wang et al. 2006):

$$\lambda_\tau(t) = \lim_{\epsilon \to 0} \frac{1}{\tau} ln\left(\frac{|x(t+\tau) - x_\epsilon(t+\tau)|}{\epsilon}\right),\ x(t) - x_\epsilon(t) = \epsilon\omega_u(t)\,. \tag{3.10}$$

3.3.12 Entropy (Predictability)

The feature *entropy* is a complexity measure from the information theory and can be applied to specify the *predictability* indications of a TS. One example is the *Approximate Entropy* $ApEn(m, r)$ method which specifies the logarithmic likelihood that the decomposed sequences of a series are close to each other and will stay close for the next decomposition of $m + 1$ (Fulcher 2017; Smith-Miles 2009):

$$ApEn(m, r) = \Phi^m(r) - \Phi^{m+1}(r)\,. \tag{3.11}$$

The parameters m and r are the length of the sequential patterns of the series and the threshold between them to be close. Moreover, $\Phi^m(r)$ is defined as following where A_i is the number of vectors within the distance threshold r of an arbitrary distance measure:

$$\Phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} lnC_r^m(i),\ where\ C_r^m(i) = \frac{A_i}{N - m + 1}\,. \tag{3.12}$$

A high value of $ApEn(m, r)$ determines an unstructured TS and indicates higher complexity and lower predictabilty of the series. Whereas a low value represents a series with several similar sequences which indactes a better *predictability* of the TS (Fulcher 2017).

3.3.13 Self-similarity

The feature *self-similarity* is determined by the application of the *Hurst exponent H*. WILLINGER ET AL. specify the *self-similarity* for TS data by seperating the original series into non-overlapping blocks of size m where each block is labeled by the index k.

This generates the following sequence with the level of aggregation m (Willinger et al. 1998):

$$X^{(m)}(k) = 1/m \sum_{i=(k-1)m+1}^{km} X(i), k = 1, 2, ..., n\,. \tag{3.13}$$

The defined sequence of the original TS is specified as *exactly self-similar* if equation (3.14) satisfies for all levels m or as *asymptotically self-similar* by $m \to \infty$ for equation (3.14).

$$X \stackrel{d}{=} m^{1-H} X^{(m)}\,. \tag{3.14}$$

In order to generate the *Hurst exponent H* for a specific TS several methods exist. Wang et al. suggest the estimation approach of autoregressive fractionally integrated moving-average, short ARFIMA. This method processes the maximum likelihood to fit the final model to estimate H (Wang et al. 2009).

3.3.14 DTW distance

The Dynamic Time Warping (DTW) is a well established distance measure for TS classification. Usually, it is directly used to find nearest neighbors because it is calculated between two TS. Recently, several works in the literature suggest to apply DTW as a feature to a machine learning method for classification. One example of the feature-based DTW approach is the paper of Kate. In his approach for every TS the DTW distances to different blocks which contain an arbitrary number of TS are calculated. He defines the DTW distance calculation by first finding the best suitable alginment between two TS Q and C. For the alignment, a n-by-m matrix is required with each cell (ith,jth) showing the cost to combine the point q_i of TS Q with point c_j of the series C by the equation $(q_i - c_j)^2$. Next, $W = w_1, ..., w_k, ..., w_K$ defines a contiguous warping path that specifies the alignment of two TS. Finally, the warping path that minimizes the total cost of the alignment between two points indictes to the corresponding minimal total cost which is determined as the DTW distance (Kate 2016):

$$DTW(Q, C) = argmin_{W=w_1,...,w_k,...,w_K} \sqrt{\sum_{k=1, w_k=(i,j)}^{K} (q_i - c_j)^2}\,. \tag{3.15}$$

3.3.15 Percentage of turning points

The feature *percentage of turning points* $X_t p$ checks the TS in order to measure their oscillating behavior. This means, a high number of turning points indicates a oscillating TS, whereas a lower number captures a more steady TS. A datapoint of the series is seen as one if it is a local maximum or minimum value for its two closest neighbors. Thus, a datapoint of the series X_i is a *turning point* if $X_{i-1} < X_i < X_{i+1}$ or $X_{i-1} > X_i > X_{i+1}$. The final number of turning points is divided by the number of observations *mathitn* to prevent the effect of the different TS sizes (Shah 1997; Lemke and Gabrys 2010).

3.3.16 Partial autocorrelation

The feature *partial autocorrelation* $\alpha(k)$ has the similar aim as the feature *autocorrelation* to capture the stationarity and sesonality of the TS, with lag $k \geq 2$. Moreover, the Partial Autocorrelation Function (PACF) is calculated by the two projections P and the two regression residuals X_{k+1} and X_1 as follows for a stationary TS (Brockwell and Davis 1986, p. 97 f.):

$$\alpha(k) = Corr(X_{k+1} - P_{\overline{sp}\{1,x_2,\dots,x_k\}} X_{k+1}, X_1 - P_{\overline{sp}\{1,x_2,\dots,x_k\}} X_1),\ k \geq 2\,. \tag{3.16}$$

3.3.17 Variance

The descriptive statistic feature *variance* σ^2 measures the distance from the mean for each datapoint in a dataset. It is calculated by the sum of all squared distances to the mean μ, which is further divided by the number of obersations n in a dataset (Ge and Ge 2016):

$$Variance = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2\,. \tag{3.17}$$

3.3.18 Percentage of outliers

Adya et al. defines an *outlier* as an isolated observation that strongly differs in his behavoir to the rest of the TS. For instance, non-recurring events or data transcription errors can be reasons for outliers in a dataset. Different statistical methods exist in order to identify them in a TS. Exemplary, Soares et al. defines the feature *percentage of outliers* as following, where the *number of outlier* represents all datapoints that are located further away as two times the standard deviation σ to the mean μ of the dataset and n is the number of observations of the TS (Adya et al. 2001; Soares et al. 2009):

$$\textit{Percentage number of outlier} = \frac{\textit{number of outlier}}{n}. \tag{3.18}$$

3.3.19 Percentage of step changes

Percentage of step changes within TS data represents heavy abrupt breaks. For the identification of these structural breaks the mean and standard deviation are required. *Step changes* are defined as following, where μ_{i-1} and σ_{i-1} represent the mean and standard deviation for all datapoints that occur before X_i (Shah 1997; Lemke and Gabrys 2010):

$$\textit{Step change at time } i \ = |X_i - \mu_{i-1}| > 2\sigma_{i-1}, \textit{ with } i = 5, .., n. \tag{3.19}$$

The final number of step changes is divided by the number of observations n of the TS to enable comparability between all datasets.

3.3.20 Percentage of peaks

The two articles of Lemke and Gabrys and Ali et al. define a *peak* as a datapoint of the overall TS with a value higher than 60 percent of the maximum value of the series. All peaks summed together provide the number of peaks which indicates the amount of strong recurring components in the TS. It is divided by the number of observations n of the series in order to provide it as a percentage of the overall TS length (Lemke and Gabrys 2010; Ali et al. 2018).

3.3.21 Durbin-Watson test

This feature represents the statistical test called *Durbin-Watson d*. It examines if an autocorrelation between two residuals from a regression analysis at lag one exist. In the work of Lemke and Gabrys, the calculation of the *Durbin-Watson* test is divided into two steps. First, the raw TS is detrended by applying a polynomial regression to order three. Second, the resulting regression residuals e are used in the following formula to check their first order autocorrelation, where $e_i = x_i - \hat{x_i}$ is defined with x_i as the observed values and $\hat{x_i}$ as the predicted values (Lemke and Gabrys 2010; Stephanie 2016):

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}. \tag{3.20}$$

The formula results in a value between zero and four. A value of two can be interpreted as no autocorrelation. Whereas a value of smaller than two indicates a positive autocorrelation and a value greater than two represents a negative autocorrelation (Stephanie 2016).

3.3.22 Quartile distribution

In this feature, the percentage of the values in a specific intervall of the dataset is calculated (Pimentel and de Carvalho 2019). For this thesis, the following four quartilies are defined:

- Q1: Percentage of values in the the first quartile [0, 0.25]
- Q2: Percentage of values in the the second quartile (0.25, 0.50]
- Q3: Percentage of values in the the third quartile (0.50, 0.75]
- Q4: Percentage of values in the the fourth quartile (0.75, 1]

The formula for the calculation of each quartile looks as follows. Where n is the number of observations for the specific quartile and m is the number of the overall observations from the TS:

$$Percentage\ of\ quartile = \frac{\sum_{i=1}^{n} X_i}{\sum_{i}^{m} X_i} * 100\,. \tag{3.21}$$

3.3.23 Coefficient of determination

The *coefficient of determination* R^2 measures in what degree the independet variables can explain the total variability of the dependent variable from the TS. It is established in classical regression analysis and represents normalized values ranging between zero and one. In the extreme case, $R^2 = 1$, the fitted regression equation explains the total variability of the values from the dependent variable. At the other extreme, $R^2 = 0$, none of the total scatter is explained by the regression equation. One way to calculate the *coefficient of determination* is defined by subtracting the ratio of the unexplained variabilty to the total variability from the value 1, where μ is the mean and $\hat{X}_i$ represents the predicted values of the regression of the dataset (Hahn 1973; Meade 2000):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (X_i - \hat{X}_i)^2}{\sum_{i=1}^{n} (X_i - \mu)^2}\,. \tag{3.22}$$

3.3.24 Number of attributes

The *number of attributes* represents the data dimensionality (Soares et al. 2009). In this thesis, it is very useful to identify whether a TS is univarite with only one attribute or the series is defined as multivariate by at least two or more attributes.

4 Time series taxonomy

In this chapter, the TS taxonomy is developed. The previously identified features from chapter 3 form the basis. Furthermore, an extensive amount of TS datasets is collected from different domains and types in order to have a broad representation of current and valid series data. Finally, these data collection in combination with the developed taxonomy is used to create an R package for the automated classification of TS data.

4.1 Collect time series datasets

In this section, a broad range of TS is collected to create a representation of the current real-world TS from varying domains like industry or finance. Likewise, the data should represent series of different characteristics such as stationary, nonstationary, cyclical or symmetric, etc. This data is used later on for the evaluation process of the taxonomy to predict the best suitable forecasting method for a TS in chapter 6 and 7. Right now, the data collection is required to get the max. and min. values of each feature for the feature scaling in section 4.2 in order to be able to determine the different classes for each feature during the taxonomy conceptualization.

Datasets	Series	Observations	Frequency	Type
M4-Competition (University of Nicosia 2018)				
M4-Yearly	54	19-87	Yearly	Demographic; Finance; Industry; Macro; Micro; Other
M4-Quarterly	54	39-188	Quarterly	Demographic; Finance; Industry; Macro; Micro; Other
M4-Monthly	54	63-522	Monthly	Demographic; Finance; Industry; Macro; Micro; Other
M4-Weekly	54	93-2,610	Weekly	Demographic; Finance; Industry; Macro; Micro; Other
M4-Daily	54	191-4,454	Daily	Demographic; Finance; Industry; Macro; Micro; Other
M4-Hourly	54	748-1,008	Hourly	Demographic; Finance; Industry; Macro; Micro; Other
NNGC-Competition (BIS-lab 2010)				
NNGC-A	11	22-37	Yearly	Airport data
NNGC-B	11	31-148	Quarterly	Sales data
NNGC-C	11	48-228	Monthly	Airport data
NNGC-D	11	527-1,181	Weekly	Production data
NNGC-E	11	377-747	Daily	Traffic data
NNGC-F	11	902-1,742	Hourly	Traffic data
NN3-Competition (BIS-lab 2009)	111	52-126	Monthly	Business data

Table 1 Univariate time series datasets

Overall, 1,000 different TS are collected. 500 multivarite and 500 univariate series. In table 1 all datesets of univariate data are shown. The first 324 series are provided by the *M4-Competition* from UNIVERSITY OF NICOSIA and MAKRIDAKIS ET AL.. The competition is published for forecasting model evaluation and contains overall 100,000 TS. The data have different types: *demographic, finance, industry, macro, micro and other* and are recored in varying frequencies: *yearly, quarterly, monthly, weekly, daily and hourly* (University of Nicosia 2018; Makridakis et al. 2018). In this thesis, for each frequency 54 TS are selected which are equally seperated into the six different types. As a result there are nine TS of each different type for a frequency. The only exception are hourly series, since they are only provided for the type *other*. Next, all 66 datasets of the *NNGC-Competition* are selected. For each of the six different frequencies eleven TS of varying length are provided. The frequencies are the same as in the *M4-Competition*. The TS have 22 to 1,742 observations and are part of different types of application like traffic or production data (BIS-lab 2010; Ali et al. 2018). The last 111 TS are from the *NN3-Competition* which contains monthly data (BIS-lab 2009; Ali et al. 2018).

The datasets for the entire 500 different multivariate TS are illustrated in table 2. The online platform *Kaggle* provideds public data sets for machine learning and data science problems. Currently, varying TS datasets are published by *Kaggle*. In this work, seven different datasets are chosen which provide 458 series together. The frequencies of the data vary between *hourly, daily and yearly*. Moreover, the data has dimensions of 4 to 21 attributes and a length of 5 to 92,246. Also, the seven datasets are from different types such as weather or stock data (Kaggle 2018). Next, the *University of Florida* provides different datasets which also partly contain TS data. From this source 35 series are collected with 4 to 15 attributes and frequencies of *yearly, monthly, weekly and daily* data (University of Florida 2018). The final seven TS are collected from the *UCI Machine Learning Repository* which is known for evaluation datasets for ML algorithms. They consist of *hourly and minutely* data with a large number of observations from 9,358 to 1,048,575 (Dua and Efi 2017).

Datasets	**Series**	**Observations**	**Features**	**Frequency**	**Type**
Kaggle-TS-Data (Kaggle 2018)					
S&P 500 stock data	150	1,259	7	Daily	Stock data
METAR weather TS	150	108	4	Daily	Weather data
Crypto-currencies	50	5-1,131	8	Daily	Currency data
Crime in the USA	100	14-16	17-21	Yearly	Crime data
Air pollution in Skopje	5	92,246	8	Hourly	Environmental data
Analise de Series Temporais	3	87-1,499	5-7	Daily	Weather data
University of Florida (University of Florida 2018)	35	13-365	4-15	Yearly, Monthly, Weekly, Daily	Economic data
UCI ML repository (Dua and Efi 2017)	7	9,358-1,048,575	8-14	Hourly, Minutely	Consumption data

Table 2 Multivariate time series datasets

Next, it is necessary that the collected data is properly formatted to process it in the R package in section 4.4 since almost all of the data is colleceted in *csv* or *xlsx* format or as a simple text file. Thus, the data is processed with R by first importing it and second adjusting it into a consistent format. For the univariate datasets from figure 1 and the multivariate from figure 2 a large list is respectively created. The univariate list is named from *UNI-TS-1* to *UNI-TS-500* and the multivariate one from *M-TS-1* to *M-TS-500*. Each TS consists of a *name, the data and a description* like in the example in figure 9. The *data* is represented by a R *data.frame* which always contains a *date* feature and then one to arbitrary further features. Those two lists are integrated as external data files into the R package from the upcoming section 4.4.

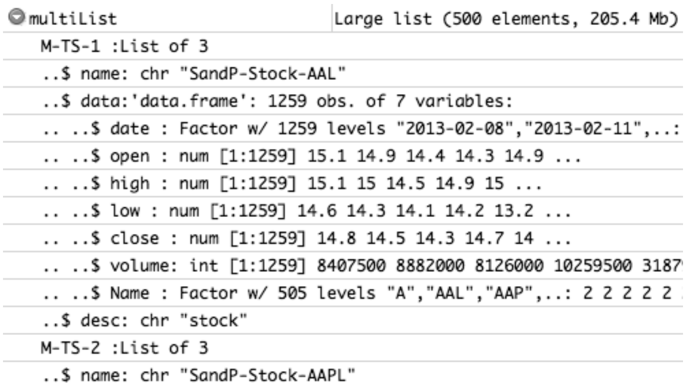
```
multiList                        Large list (500 elements, 205.4 Mb)
 M-TS-1 :List of 3
  ..$ name: chr "SandP-Stock-AAL"
  ..$ data:'data.frame': 1259 obs. of 7 variables:
  .. ..$ date : Factor w/ 1259 levels "2013-02-08","2013-02-11",..:
  .. ..$ open : num [1:1259] 15.1 14.9 14.4 14.3 14.9 ...
  .. ..$ high : num [1:1259] 15.1 15 14.5 14.9 15 ...
  .. ..$ low : num [1:1259] 14.6 14.3 14.1 14.2 13.2 ...
  .. ..$ close : num [1:1259] 14.8 14.5 14.3 14.7 14 ...
  .. ..$ volume: int [1:1259] 8407500 8882000 8126000 10259500 3187
  .. ..$ Name : Factor w/ 505 levels "A","AAL","AAP",..: 2 2 2 2 2
  ..$ desc: chr "stock"
 M-TS-2 :List of 3
  ..$ name: chr "SandP-Stock-AAPL"
```

Figure 9 Example of the multivarite time series list structure in R

4.2 Feature scaling

The final values can differ significantly for each previous described feature in chapter 3. This situation makes it difficult to determine descriptive classes for each feature in the taxonomy. Thus, the literature suggests to transform the values into a normalized span of [0, 1]. Therefore, a scale measure near zero indicates a very low presence of the feature. Whereas, a value near one shows a strong representation of the feature. Several methods exist for the transformation of data into a range of [0, 1] (Wang et al. 2009). In this thesis, the linear transformation scaling approach from WANG ET AL. is applied since it is able to process positive as well as negative values. x_i is a single measure of the feature X from one arbitrary TS and X_{min} and X_{max} represent the minimal and maximal value for the feature X from all collected TS from chapter 4.1 (Wang et al. 2006):

$$x_i \textit{ of feature } X = \frac{x_i - X_{min}}{X_{max} - X_{min}}. \tag{4.1}$$

All 24 relevant features are scaled into a span of [0, 1] based on the above formula, except the features *Durbin-Watson test* and *Number of attributes*. The *Durbin-Watson test* already delivers results in a determined range with an existing interpretation by a spread from [0, 4] with values greater or smaller two defining negative or positive autocorrelation.

More details are provided in chapter 3. Moreover, the feature *Number of attributes* is applied to define each TS either as univariate or multivariate.

4.3 Conceptionalize taxonomy

The feature scaling process from the previous section 4.2 enables the definition of descriptive classes for each feature in the taxonomy. Thus, for almost all features values the range of [0, 1] is divided into five different classes by steps of 0.2. That means, the first class ranges from [0, 0.2] and represents the lowest presence of the feature. Whereas, the last class shows the highest presence of a feature by containing all values between (0.8, 1]. The other three descriptive classes are (0.2, 0.4], (0.4, 0.6], (0.6, 0.8]. Exceptions are the features: *DTW distance*, *Durbin-Watson test*, *quartile distribution*, *coefficient of determination* and *number of attributes*. These follow an individual division:

The feature *DTW distance* consists of 13 sub-features. Each sub-feature represents the calculation of the DTW distance for a TS to a block of specific TS data. More details about the specific series blocks is given in section 4.4. Thus, 13 different scaled values are calculated for the *DTW distance*. Each of the 13 block values is divided into three descriptive classes: *less*, *medium* and *many* with the intervals of: [0, 0.33], (0.33, 0.66], (0.66, 1]. The same division of the previous three classes counts as well for the four quartiles of the feature *quartile distribution*. Furthermore, the feature *number of attributes* only distinguishes between univariate and multivariate TS data. Next, the *Durbin-Watson test* classifies a TS based on four different classes. Resulting values greater or smaller two defining negative or positive autocorrelation. The feature only works for multivariate series and therefore univariate ones are assigned to *none because univarite TS* and an exact value of two represents the class of *none autocorrelation*. The last individual division for the feature *coefficient of determination* consists of six descriptive classes. The scaled values are also divided into five different classes by steps of 0.2. Additionally, the class '*none because univarite TS*' exists because the calculation is only possible for multivariate TS.

All 24 features with their above defined descriptive classes build the final TS taxonomy in figure 10. The features are sorted ascending from high to low importance based on the sum of average citations per year from the concept matrix in figure 7:

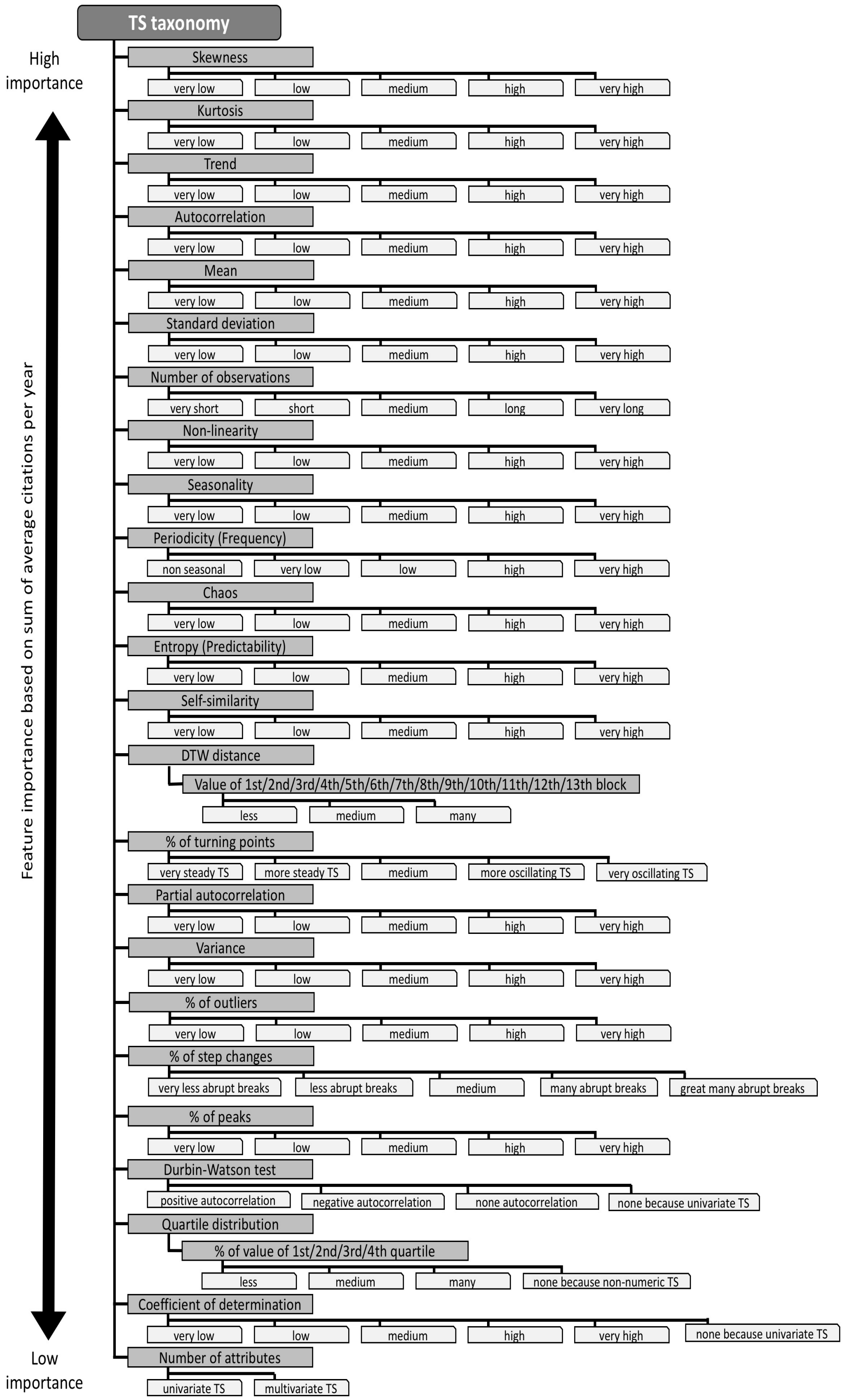

Figure 10 Time series taxonomy

4.4 Develop R package

In this chapter, the conceptualized TS taxonomy from the above chapter 4.3 is used to develop an R package for the automated classification of TS data. *R* is known as a free programming language and environment for statistical data analysis and visualization (R Core Team 2018). Furthermore, an *R package* provides reproducible R code by combining functions, external data and documentation and test files (Wickham 2015). In this thesis, the development process is based on the guideliness from the book of Wickham. He introduces suggestions how to transform code into packages to simplify the usage and documentation. Also, the deployment of the version control system for software developers *GitHub* is recommended. It is useful for tracking and management of code adjustments and package sharing to others.

4.4.1 Overview

The final released R package is called *tstaxonomyr*. It is licensed under *GPL-2* as free and open source software. Thus, the first version 1.0.0 is available for everyone on *GitHub* under: https://github.com/mowomoyela/tstaxonomyr. The main functionality is to classify univariate or multivariate time series on the developed taxonomy in section 4.3 through 24 different (statistical) time series features. Additionally, each feature can be calculated for its own. All provided functions of the package are described in detail in the following chapter 4.4.2. Moreover, the package can be simply installed in R from *GitHub*:

```
# Install the tstaxonomyr package
devtools::install_github("mowomoyela/tstaxonomyr")
```

Listing 1 Installation code for tstaxonomyr

After a succesful installation the package can be initialized for actual usage. In the following R code example a TS taxonomy classification and a single feature value calculation are illustrated:

```r
# Initialize the R package
library(tstaxonomyr)
# Use the univariate time series object 'BJsales'
ts_sales = datasets::BJsales
# Example of the TS taxonomy classification --------
  # Classify the time series based on the defined taxonomy
  # in 'classify_ts'
  classified_ts <- classify_ts(ts = ts_sales, na_option = "mean")
  # Get the classification factor results
  classified_ts
# Example of a single feature value calculation --------
  # Calculate the skewness of a time series object
  skewness = calculate_skewness(ts = ts_sales)
  # Get the resulting skewness factor
  skewness
```

Listing 2 Usage example for tstaxonomyr

4.4.2 Code

One important premice of Wickham is good coding stlye (Wickham 2015). Thus, in this thesis his coding guidelines based on *Google's R style guide* are followed. This styling supports readers of the code with a better understanding. For example, variable names should be defined as nouns and functions as verbs. Furthermore, underscore should be used for word seperation and only lowercase words. The other style suggestions like spacing or line length regulations are followed as well. For more details follow the *Code* section in the book of Wickham.

Another major recommendation is to store the entire package code into the directory *R/*. It should contain several files including all the different functions that are part of the package (Wickham 2015). In this work, the following three different files exist within the *R/* directory:

ts_features.R: This file contains 24 functions for the value calulcation of all features from chapter 3.3. Each function is briefly described in the following listing:

- *calculate_skewness(...)*: It generates the skewness of a TS object by applying the *skewness* function of the *e1071* R package (Meyer et al. 2018). This function provides three different equations for the calculation. In this thesis, *type 3* is chosen because it is similar to the equation suggested by Wang et al. (Wang et al. 2006).
- *calculate_kurtosis(...)*: This function creates the kurtosis for a TS object by deploying the *kurtosis* function of the *e1071* R package (Meyer et al. 2018). It offers three different types for the calculation. In this work, *type 3* is chosen

because it is similar to the equation suggested by WANG ET AL. (Wang et al. 2006).

- *calculate_trend(...)*: The trend value is calculated for a TS object based on the procedure described in section 3.3.3. The R code for the procedure of WANG ET AL. is provided by HYNDMAN. This code is directly used for the trend function and slightly transformed in regard to the previously mentioned code styling (Hyndman 2012; Wang et al. 2009).

- *calculate_autocorrelation(...)*: It generates the autocorrelation of a TS object by applying the *acf* function of the standard *stats* R package (R Core Team 2018). This function returns the coefficient of autocorrelation for each lag of the TS object. In this work, the procedure from PRUDÊNCIO ET AL. is applied. It generates the mean of the autocorrelation over all lags for each TS object since any TS object has his own length and therefore its own number of lags (Prudêncio et al. 2004).

- *calculate_mean(...)*: The mean of a normalized [0, 1] TS object is produced based on the *mean* function of the standard *base* R package (R Core Team 2018).

- *calculate_sd(...)*: This function generates the standard deviation of a TS object by the *sd* function of the standard *stats* R package (R Core Team 2018).

- *calculate_observationnumber(...)*: The number of observations of a TS object is calculated by applying the *length* function of the standard *base* R package (R Core Team 2018).

- *calculate_non_linearity(...)*: The non-linearity neural network test of TERÄSVIRTA ET AL. is applied. It is realized by the function *terasvirta.test* of the *tseries* R package (Trapletti and Hornik 2018). The code is also provided by HYNDMAN (Hyndman 2012; Teräsvirta et al. 1993).

- *calculate_seasonality(...)*: Here, the seasonality factor of a TS object is generated by the approach of WANG ET AL. introduced in section 3.3.9. The specific code already exist by HYNDMAN and is adopted with some transformations caused by the code styling of this work (Hyndman 2012; Wang et al. 2009).

- *calculate_periodicity(...)*: It applies the step-by-step approach of WANG ET AL. to get the periodicty of a TS object. The code for the approach is provided by HYNDMAN (Hyndman 2012; Wang et al. 2009).

- *calculate_chaos(...)*: LE is a quantitative value to measure the chaotic of a system. WANG ET AL. introduces it as an approach to measure the chaos of a TS object. HYNDMAN presents the code for the generation of the chaos factor of a TS. This code is adopted and slightly adjusted in regard to the code styling of this thesis (Hyndman 2012; Wang et al. 2009).

- *calculate_entropy(...)*: The *approximate entropy* method of FULCHER introduced in section 3.3.12 is deployed. The R package *pracma* provides the function *approx_entropy*. It is applied on every TS object with its default settings (Fulcher 2017; Borchers 2018).

- *calculate_selfsimilarity(...)*: The hurst exponent recommended by WANG ET AL. and described in section 3.3.13 is applied on TS objects. The *fracdiff* function of the *fracdiff* R package is used (Fraley et al. 2012). Also, the adopted code for the generation is provided online by HYNDMAN (Hyndman 2012; Wang et al. 2009).

- *calculate_dtw_blockdistance(...)*: The DTW distance is generated by the feature-based DTW method of KATE. In his approach for every TS object the DTW distances are calculated to each defined block containing an arbitrary number of TS. In this work, 13 different TS blocks are used. These are described in section 4.4.3. Therefore, a vector of 13 distances is returned by this function. The distances are calculated by the *dtwDist* function of the *dtw* R package (Kate 2016; Tormene et al. 2008).

- *calculate_turningpoint_percentage(...)*: This function generates the percentage of turning points of a TS object. Identified data points are significant turning points if their probability is smaller than the significance level of 5%. For the calculation the *turnpoints* function of the *pastecs* R package is deployed (Grosjean and Ibanez 2018).

- *calculate_partial_autocorrelation(...)*: The partial autocorrelation of a TS object is produced based on the *pacf* function of the standard *stats* R package (R Core Team 2018). This function returns the partial coefficient of autocorrelation for each lag of the TS object. In this work, the procedure from PRUDÊNCIO ET AL. is deployed. The mean of the partial autocorrelation is calculated over all lags for any TS (Prudêncio et al. 2004).

- *calculate_variance(...)*: It calculates the variance of a TS object by the *var* function of the standard *stats* R package (R Core Team 2018).

- *calculate_outlier_percentage(...)*: This function generates the percentage of outliers of a TS object. Identified data points are significant outliers if their probability is smaller than the significance level of 5%. For the calculation the *scores* function of the *outliers* R package is deployed. Three different tests of the *scores* function are used: *z*, *chisq* and *t*. The method *z* uses the differences between each TS value and the division of mean and standard deviation. *chisq* represents chi-squared scores and *t* t-Student scores (Komsta 2011). Finally, the mean over all three test results is returned as a percentage over all observations.

- *calculate_stepchange_percentage(...)*: The equation of the number of step changes for a TS is calculated by the approach of LEMKE AND GABRYS and SHAH introduced in section 3.3.19 (Lemke and Gabrys 2010; Shah 1997).

- *calculate_peak_percentage(...)*: The percentage of peaks within a TS object is calculated by the *findpeaks* function of the *stats* R package (R Core Team 2018). In the works of LEMKE AND GABRYS and ALI ET AL. peaks are defined with a value higher than 60% of the maximumum value of the TS. Thus the *minpeakheight* parameter of the *findpeaks* function is set to *0.6* (Ali et al. 2018; Lemke and Gabrys 2010)..

- *calculate_durbin_watson_test(...)*: This function is only usable for multivarite TS data. Thus, the method requires a data frame object and the name of the target variable from the TS. The resulting value is generated based on the approach of LEMKE AND GABRYS, described in section 3.3.21. First the data frame is detrended and second the durbin watson test is deployed. For the second step the *durbinWatsonTest* function of the *car* R package is used (Fox and Weisberg 2011; Lemke and Gabrys 2010).

- *calculate_quartile_distribution(...)*: The distribution is generated for the four TS quartiles which are determined in section 3.3.22. Thus, a vector of the four quartile distributions is returned by this function. This feature can only be generated for numeric TS. Otherwise, it is set to -1.

- *calculate_determination_coefficient(...)*: The function is just applicable for multivarite TS data. Therefore, the method requires a data frame object and the name of the target variable from the TS data. The resulting value is generated based on the *lm* linear regression function of the *stats* R package because it has attached the coefficition of determination value (R Core Team 2018). The *lm* function is used between the target variable and each feature of the data frame.

- *calculate_attributenumber(...)*: The number of attributes is only generated for data frames representing multivariate TS objects. It applies the *ncol* function of the standard *base* R package (R Core Team 2018).

ts_taxonomy.R: In this file only the extensive function *classify_ts(...)* is located. It is the main function of this package in order to finally classify a TS based on the developed taxonomy in section 4.3. The input parameter *ts* allows objects from the three different classes: time series, data.frame or vector. The last two classes are transformed into a TS object at the beginning of the function. This means for R *data.frame* objects that each feature is transformed into an own TS object. Moreover, the other input parameter *na_option* determines how to handle missing observations within the *ts* object. The selected imputation technique is handed over to the *predict_missing_observations(...)* function from the *misc.R* file in order to estimate the missing values and return them.

Feature	Min.; Max.	Feature	Min.; Max.	Feature	Min.; Max.
Skewness	-1.56; 1.29	Self-similarity	0.5; 1	DTW block 13	22,944.05; 2,369,047,000
Kurtosis	-1.23; 25.77	DTW block 1	2,876.91; 2,403,157,000	% turning points	0; 0.25
Trend	0; 1	DTW block 2	113,078.1; 3,160,719,000	Partial autocorrelation	-0.57; 0.15
Autocorrelation	-0.01; 0.65	DTW block 3	2,442,235; 7,390,375,000	Variance	0.03; 4.775906e+14
Mean	0.08; 0.73	DTW block 4	117,426.2; 3,375,461,000	% outliers	0; 0.14
Standard deviation	0; 26,217,230,000	DTW block 5	246,412; 4,528,558,000	% step changes	0; 0.85
Number of observations	13; 52,584	DTW block 6	123,634.1; 3,167,553,000	% peaks	0; 0.44
Non-linearity	0.22; 160.82	DTW block 7	719,995.2; 4,527,233,000	Quartile distribution Q1	0.02; 0.75
Seasonality	0; 1	DTW block 8	428,939.3; 4,321,836,000	Quartile distribution Q2	0.03; 0.45
Periodicity	0; 1	DTW block 9	570,058.6; 4,322,218,000	Quartile distribution Q3	0.05; 0.56
Chaos	0; 1	DTW block 10	78,383.39; 3,123,604,000	Quartile distribution Q4	0.04; 0.82
Entropy	-0.08; 0.98	DTW block 11	1,216.94; 2,393,432,000		
Coefficient of determination	0; 1	DTW block 12	927,905,600; 3,862,347,000		

Table 3 Minimum and maximum values for each feature of the collected 1,000 time series

After the input data check and transformation the actual feature values can be generated based on the above described functions from the file *ts_features.R*. The two features *calculate_determination_coefficient(...)* and *calculate_durbin_watson_test(...)* require multivariate TS. If a univariate series is the input the value -1 is assigned to them. Also, their resulting values are not required to be scaled afterwards as mentioned in section 4.2. All other 22 features are normally calculated based on the functions in *ts_features.R*. In figure 8 in section 3.3 is defined which feature is calculated on *raw*, *de-trended* or *de-trended and de-seasonalized* data. Thus, first for several features the TS data has to be decomposed by the *decompose_ts(...)* function before passing it to the feature calculation. Additionally, if a multivariate TS object is passed the 22 features are generated for each of the series attributes and combined by the mean afterwards. In the next step, all resulting values are scaled based on the function *scale_feature(...)* according to the defined linear transformation method from section 4.2. The *minimum* and *maximum* values for each feature are determined based on the 1,000 TS data which are collected in section 4.1. But, the *min-max* transformation is outlier sensitive. Therefore, all features that do not already return values between [0, 1] are preprocessed according to outliers before the identification of its *minimun* and *maximum* values. The *scores* function of the *outliers* R package is applied in order to remove all outliers from the 1,000 feature observations. The method *z* is applied which uses the differences between each value and the division of mean and standard deviation. An observation is marked as an outlier if its probability is smaller than the significance level of 1% (Komsta 2011). All removed outliers and their values are listed in the appendix D. After the outlier clearing process the defined *minimun* and *maximum* values are determined for each feature and are illustrated in table 3.

```
# Define descriptive classes of  the feature skewness
factor_levels <- c("very low", "low",
                  "medium", "high", "very high")
# If-else-clause to assign the final feature class
# ts_taxonomy[["feature_skewness"]] contains the
# previously scaled calculated skewness factor
# Add the result to the final ts_taxonomy_list list
if (ts_taxonomy[["feature_skewness"]] > 0.8) {
  ts_taxonomy_list[["Skewness"]] <-
        factor("very high", levels = factor_levels)
} else if (ts_taxonomy[["feature_skewness"]]  > 0.6) {
  ts_taxonomy_list[["Skewness"]] <-
        factor("high", levels = factor_levels)
} else if (ts_taxonomy[["feature_skewness"]]  > 0.4) {
  ts_taxonomy_list[["Skewness"]] <-
        factor("medium", levels = factor_levels)
} else if (ts_taxonomy[["feature_skewness"]]  > 0.2) {
  ts_taxonomy_list[["Skewness"]] <-
        factor("low", levels = factor_levels)
} else {
  ts_taxonomy_list[["Skewness"]] <-
        factor("very low", levels = factor_levels)
}
```

Listing 3 Taxonomy classification of a time series on the skewness feature

The final step is to assign each feature value to its matching descriptive class defined in the conceptualized TS taxonomy in section 4.3 of this work. This matching process is realized by if-else-clauses for each feature in order to assign the right factor value. An example for the feature *skewness* is presented in listing 3. Finally, the function *classify_ts(...)* returns the classified TS by a list containing 24 different factor values where each is representing one actual feature of the taxonomy from section 4.3.

misc_functions.R: This file only includes helper functions. That means, they are only internal methods and used by the other functions of the above files *ts_taxonomy.R* and *ts_functions.R*. Therefore, they are not externally available as part of this developed R package. In sum, the file consists of the following four functions:

- *get_ts_frequency(...)*: This function determines the frequency of an input vector representing a TS. For instance, the value for a daily TS is seven. The frequency factor is required by several functions like the trend oder seasonality calculation. It also is very useful within the taxonomy creation function to be able to create TS objects out of a vector or data frame attributes. The code is adopted from the online source of Hyndman. It is just slightly adjusted in regard of the code styling in this work (Hyndman 2012).

- *scale_feature(...)*: It scales a numeric value into a standardized interval of $[0, 1]$. The linear transformation method by min and max values of Wang et al. is applied to scale values of $(-\infty, \infty)$, described in section 4.2. This function is required for the taxonomy generation to scale all feature calculation results (Wang et al. 2006).

- *decompose_ts(...)*: The decomposition of a TS object is essential in order to get the trend, seasonality and the remainder of it. The remainder represents the series data reduced by the trend and seasonality. This functionality is mandatory since some features are calulated on the raw or decomposed data as illustrated in figure 8 from section 3.3. Hyndman provides already an extensive decompostion function in his code collection. His function is adopted and slightly modifed to the regulations of this work (Hyndman 2012).

- *predict_missing_observations(...)*: All missing observations of the inserted TS or vector object are replaced. The other input parameter *na_option* determines how to handle these missing observations. The first option is to replace the missing values by the simple imputation method using the mean value of the *ts* object. Or the more advanced imputation method *kalman* is applied to replace them. This method often delivers the best results but has a more intencive computation time. Whereas, the *mean* imputation reaches lower accuracy but a higher computation performance. In this package, the *na.mean* and *na.kalman* functions of the *imputeTS* R package are used to create values for missing observations (Harvey and Pierse 1984; Moritz and Bartz-Beielstein 2017). The kalman function applies a structural model adjusted by maximum likelihood. Structural models decompose TS data like explained in the function *decompose_ts(...)* in file *misc_functions.R*. Then, missing observation estimations are processed by the kalman filter which applies recursive estimation and smoothing. Recursive means that for each new state estimation corrections of the prediction error are taken into account based on previous predictions until the error is minimzed (Jalles 2009).

4.4.3 External data

Another essential aspect from the guideline of WICKHAM is to store all external data into the *data/* repository. That means, each file in the repository is available along the usage of this package (Wickham 2015). In sum, the following three datasets are provided:

- *uni_ts_list.rda* & *multi_ts_list.rda* : Both data files represent a list of 500 different TS represented in data frames. *uni_ts_list.rda* contains univariate series and *uni_ts_list.rda* multivariate ones. In section 4.1 the origin and structure of the data is described in detail. The files are provided to enable extensive testing of all functionalities of this R package. Also, the data is required to determine the *min* and *max* values of each feature for the scaling process within the *classify_ts* function.

- *matrix_block_list.rda*: This file is required for the DTW distance calculation. It is a list of 13 matrices containing several TS objects since the function *calculate_dtw_blockdistance(ts)* requires matrices in which each row represents a TS for the caculation process. The 1,000 multivariate and univariate series from the previously described two external data files are seperated into 13 blocks, more details are available in section 4.1. Block one to four represent the multivariate data from *kaggle*: *block 1: multivariate stock TS*, *block 2: multivariate weather TS*, *block 3: multivariate crime TS* and *block 4: multivariate crypto currency TS*. Additionally, block five contains all remaining multivariate series from *kaggle, university of florida and the uci machine learning repository*: *block 5: multivariate other TS*. Furthermore, block 6 to 11 consist of data from the *M4 competition*: *block 6: univariate finance TS*, *block 7: univariate micro TS*, *block 8: univariate demographic TS*, *block 9: univariate macro TS*, *block 10: univariate industry TS* and *block 11: univariate other TS*. Finally, block 12 and 13 contain series from the *NN3* and *NNGC competition*: *block 12: univariate NN3 TS* and *block 13: univariate NNGC TS*.

4.4.4 Object documentation

Another essential part in the R package development process of WICKHAM is *object documentation*. Especially, the documentation of functions is introduced by the application of *roxygen* comments. These start with a *#'* symbol and consist of a introduction and four tags. The introduction contains a short title and a more detailed description of the function. The first tag *@param* describes each input parameter of the function. The second tag *@return* defines which kind of output the function produces. The third tag *@example* shows useable R code to test the function. The last tag *@export* defines the function as external in order to provide it by the final R package. One exemplary function documentation is shown in listing 4. Finally, all documentations can be automatically converted into *.Rd* files. These are all located in the */man* directory of the package (Wickham 2015).

```
#' Generates the skewness of a ts object.
#'
#' This is a function to generate the skewness of a time
#' series object. As input is only required an object from
#' the class time series. Otherwise the function returns
#' an error message. Also, for \code{na_option} is only
#' required the string 'mean' or 'kalman' allowed. This
#' means, that all na values are either replaced by the
#' mean or kalman imputation of the ts. The standard
#' value of \code{na_option} is 'mean'.
#'
#' @param ts A time series object.
#' @param type integer of 1 to 3 defining one of the three
#' skewness algorithms
#' of the skewness function from the e1071 R package.
#' @param na_option A string value containing either 'mean'
#' or'kalman'; Standard values is 'mean'.
#' @return The skewness of \code{ts}.
#' If the above input params are wrong, an error message
#' is returned.
#' @examples
#' calculate_skewness(ts = datasets::BJsales)
#' @export
  calculate_skewness <- function(ts,
                                 na_option = "mean", type = 3){...}
```

Listing 4 Roxygen documentaion of function calculate_skewness(...)

5 Forecasting methods

In this chapter, established TS forecasting methods from the literature and practice are selected and explained. These are required for the evaluation of the conceptualized TS taxonomy in chapter 6 and 7 since this thesis aims to identify whether the forecasting method selection process can be automated by a defined taxonomy and classification problem. In recent decades, ML methods have become a serious alternative to classical quantitative forecasting techniques (Ahmed et al. 2010). The paper of Ahmed et al. provides an extensive overview and comparison of current ML methods for TS forecasting. Also, the work of Caruana and Niculescu-Mizil represents another essential performance comparison of ML techniques. Thus, the four methdos: *ANN*, *SVM*, *XGBoost* as *GBDT* model and *Classification And Regression Trees (CART)* are selected with regard to the two evaluation works (Ahmed et al. 2010; Caruana and Niculescu-Mizil 2006).

Additionally to ML approaches plenty classical quantitave TS forecasting methods exist. Several papers from the literature introduce and deploy different ones. The work of Wang et al. names the techniques: *Exponential Smoothing (ES)*, *Autoregressive Integrated Moving Average (ARIMA)* and *Random Walk (RW)* as the most popular ones (Wang et al. 2009). Additionally, Prudêncio and Ludermir select *ES* and *Box-Jenkins ARIMA* for forecasting scenarios (Prudêncio and Ludermir 2004). Likewise, in the comparison paper of Scholz-Reiter et al. five classical forecasting models are described: *ES*, *ARIMA*, *RW*, *locally constant* and *locally linear methods* (Scholz-Reiter et al. 2014). Another paper that handles the selection of appropriate forecasting techniques is from Arinze. It deploys the following six models: *moving average*, *single ES*, *holt's ES*, *winters ES*, *adaptive filtering* and *time series decomposition* (Arinze 1994). Finally, the three techniques: *ES*, *ARIMA*, *RW* are selected for the purpose of this work based on the intersections between the previously listed methods.

In sum, four ML and three classical TS foracsting models are selected for the purpose of this thesis. The three techniques: *ANN*, *SVM* and *XGBoost* are already described in detail for a classification problem in the background chapter in section 2.3. They can also be applied for a regression problem such as TS forecasting. Next, the other four methods are introduced in the following sections of this chapter:

5.1 Classification and regression trees

The *CART* method applies one single tree of a classification or regression problem to make decisions. The tree has a hierarchical shape and contains several partitions of the input data. It consists of decision nodes and of leaf nodes which conclude a tree path.

A path consists of arbitrary branches which run from the root node until it reaches a leaf node. Each node only has two outgoing branches. Thus, each node decision is binary. The construction of a tree is a recursive process until the smallest prediction error is reached. It starts at the root node of the tree. A splitting threhold value is recursivly defined until the smallest mean square error is achieved for the inserted testing data. This procedure is going down the entire tree for each decision node. Additionally, pruning is an essential setting to construct an optimal tree. It reduces the complexity of the tree by disposing uninformative nodes at the end of the tree since the more important a decision node is, the higher up in the tree it is located (Ahmed et al. 2010).

5.2 Exponential smoothing

The ES approach comprises plenty different prediction methods. The best fitting model depends on the data to forecast. The three parameters *error*, *trend* and *seasonality* are essential to identify the appropriate method for TS data (Scholz-Reiter et al. 2014). The work of Wang et al. suggests to follow the state space model approach of Hyndman et al. to automatically select the right ES method. That approach is based on the ES forecasting method classification work of Pegels. This handles twelve different ES models in total (Hyndman et al. 2002; Pegels 1969; Wang et al. 2009). Hyndman et al. allow to define the *trend* and *seasonality* either at none, additive or multiplicative. Furthermore, the parameter *error* is either additive or multiplicative. For instance, the Holt-Winters method is defined by a multiplicative error, an additive trend and a multiplicative seasonality. The three different parameters are automatically tested for the TS in order to find the best fitting method. This approach has done very well on the M-competition forecasting series, which is also part of the collected TS data in section 4.1 of this thesis (Hyndman et al. 2002; Wang et al. 2009). Following, the *single ES* is introduced to give an example of an ES model for a better understanding:

This method processes prior data points of the TS data in order to forecast. It is the simplest method of them because it does not include the parameters *trend* and *seasonality*, both are set as none. Thus, it is likely to be the best fit for nonseasonal and nontrended TS. The concept is to work with weights on the prior observations. These weights are exponentially declining from recent to more older ones. This weighting concept is reducing the influence of random fluctuations over time. The model works as follows (Arinze 1994):

$$F_t = F_{t-1} + \alpha(A_t - F_{t-1})\,. \tag{5.1}$$

F_t is representing the forecast value and A_t the actual value for the period t. Moreover, the parameter α constitues a smoothing factor between *0* and *1*. In the work of Arinze are applied the values *0.4*, *0.6* and *0.8* to fit the best model out of them (Arinze 1994).

5.3 Autoregressive integrated moving average

ARIMA is another classical linear forecasting method. There exist several different models because of the different combinations of its parameters. One example is the general non-seasonal model: $ARIMA(p, d, q)$. p is the order of autoregression, d represents the degree of first differencing and q denots the moving average order. An extension of that model is the seasonal method: $ARIMA(p, d, q)(P, D, Q)_s$. P, D and Q represent the seasonal equivalents of the previous defined lowercase parameters. Additionally, s defines the number of periods for each season. These different parameter settings enable many different model approaches. In order to identify the model that fits for a TS as best as possible the paramaters have to be estimated. Thus, the parameters p, P, q and Q are estimated and optimised by the maximum likelihood estimator Akaike's Information Criterion (AIC). It is defined as follows (Wang et al. 2009; Scholz-Reiter et al. 2014):

$$AIC = -2log(L) + 2(p + q + k + 1)\,. \tag{5.2}$$

L denotes the likelihood of the data, p and q are the above described parameters and k is either 1 or 0 if an intercept exist ($c \neq 0$) or not exist ($c = 0$) in the ARIMA model. Furthermore, the left paramters d and D are estimated by the KPSS and OCSB tests (Hyndman and Athanasopoulos 2018, p. 241 f.). The KPSS test identifies whether a TS is stationary according to its trend or not. Whereas the OCSB test determines if a series is stationary around its seasonality (Osborn et al. 1988; Kwiatkowski et al. 1992).

5.4 Random walk

This method is one of the simplest quantitative forecasting techniques. It requires no parameters to be maximized by any predictors. Thus, it is very simple to compute and has low performance costs. In the literature it is more often used for evalution works because it reaches very good results for some TS types. The model is defined as follows (Wang et al. 2009; Scholz-Reiter et al. 2014):

$$Y_t = Y_{t-1} + e_t\,. \tag{5.3}$$

The parameter Y_t represents the actual value and e_t a random error for the period t. Thus, a forecast for the next value is basically the last observation of the TS: $\hat{Y}_{t+1} = Y_t$.

6 Evaluation set up and implementation

In this chapter, all previous results and determined settings are combined and set up in order to generate results for the evalution process of the main goals from this thesis. The main goal is to examine if it is possible to predict the best suitable forecasting method for a TS based on a TS taxonomy which consists of several (statistical) features from the recent literature. Thus, in the TS model selection framework in figure 11 the interplay between all required parts is illustrated in order to answer the research question. This framework is inspired and partly based on the system's architecture from PRUDÊNCIO AND LUDERMIR and the meta-learning framework of WANG ET AL.:

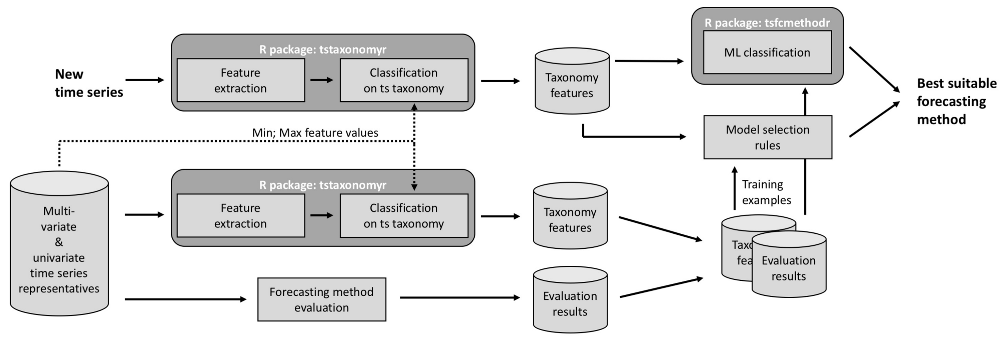

Figure 11 Time series model selection framework (cf. Prudêncio and Ludermir 2004, p. 125) and (cf. Wang et al. 2009, p. 2592)

The framework starts with the input of new TS. Therefore, for the evaluation process the collected 1,000 TS from subchapter 4.1 are divided into testing and training data by the well established *k-fold cross-validation* method. This approach divides the data into *k* random TS blocks of equal size. Then, each block is applied one time as testing data and the left blocks are used as training data. This ensures that each TS is deployed as training and testing data. In this thesis, the parameter *k* is determined as *10*. Thus, the testing process is running ten times and the results are averaged to get a single estimation at the end (Moreno-Torres et al. 2012). This settings are adopted based on the recommendations from the two papers of KOHAVI and RODRIGUEZ ET AL. which analyze different cross validation techniques and paramter setttings. They identified that 10-fold cross validation is less biased with an appropriate computional cost. Likewise, they propose the application of repeated cross validation if it is still computationally executable (Kohavi 1995; Rodriguez et al. 2010). In the next step, all feature values are calculated according to the defined features in section 3.3. Next, the generated values are classified based on the developed TS taxonomy from subchapter 4.3. These two steps are automated by the application of the created R package *tstaxonomyr* of section 4.4. The package returns the classified taxonomy features which are attached in the appendix A. The results are further processed either by a ML classification model or by descriptive model selection rules to predict the best suitable forecasting method for the inserted TS. However, these two possible predictors first require trainings examples to be fitted for the final prediction process:

The training data creation process starts with a data bundle of TS objects. 900 of the 1,000 multivariate and univariate TS representatives of section 4.1 are deployed as training data since the left 100 ones are already applied as testing data according to the above described *cross-validation* process. This training data is processed in two ways: First, each TS object is processed by the *tstaxonomyr* package which extracts the determinded features and then classifies it on the TS taxonomy from chapter 4.3. The results are listed in the appendix A. Second, each TS of the training data is forecasted by different methods to identify the best suitable one according to their performances. This evaluation step is explained in detail in the following section 6.1 and the results are attached in appendix C. Next, the resulting taxonomy features and the forecasting evaluation results are combined to use them as training examples. Now, two ways exist in order to predict the best suitable forecasting method. Either the trainings examples can be applied in the *tsfcmethodr* R package to fit a ML classification model or for a rule model to derive rules for the prediction of the best suitable forecasting method. The ML classification process is described in section 6.2 and the model selection rules process in section 6.3. The performance of the two predictors is evaluated in the next chapter 7.

Additionally, based on the training data a second evaluation is processed by adjusting the *tstaxonomyr* R package since the taxonomy features are only selected according to their number of citations. Thus, a feature selection technique is applied to measure the relevance of the selected features from the developed TS taxonomy from chapter 3.3 and 4.3 according to the collected 1,000 TS representatives from section 4.1. This process is described in the upcoming section 6.4.

6.1 Forecast method evaluation

In this section the *forecasting method evaluation* process from figure 11 is described. The determined seven forecasting models from chapter 5 are used. These include four ML and three classical TS forcasting techniques: *ANN*, *SVM*, *XGBoost*, CART, *ES*, *ARIMA* and *RW*. All seven of them are applied for each inserted TS for the training data bundle of figure 11. All objects of the collected 1,000 TS representatives is at some point training data since *cross-validation* is applied to split them into test and training data. The results of the seven forecasting methods have to be compared to identify the best performing one for each TS. In the work of Yokuma and Armstrong the evaluation of several criteria to select forecasting methods such as accuracy or computation performance by different study groups like practitioners or educators is illustrated. The results of the study show that *accuracy* is the most important factor in general (Yokuma and Armstrong 1995). Thus, only the criteria *accuracy* is applied in order to identify the best performing method for this thesis. Several different error measures that describe the *accuracy* of a forecast exist. In the work of ARMSTRONG several measures are described and evaluated. He suggest to use multiple error measures instead of only one. A rating of measures for TS data is provided on some criteria like *reliability* or *outlier protection*. Based on his rating the error measure *Median Absolute Percentage Error (MdAPE)* is selected for this thesis. Additionally, the *Mean Absolute Percentage Error (MAPE)* measure is chosen because he introduces an extensive study in which it was the most commonly used one. They are defined as follows (Armstrong 2001a):

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|F_t - A_t|}{A_t}}{n} * 100\,, \tag{6.1}$$

$$MdAPE = median\left(\sum_{t=1}^{n} \frac{|F_t - A_t|}{A_t}\right). \tag{6.2}$$

The paramters F_t and A_t are a forecast value and an actual value at time point t from the overall forecasting horizon number n.

6.1.1 Forecasting implementation

The seven selected forecasting methods from chapter 5 are implemented in R by seven different R functions. The entire code is available in the file *forecasting_methods.R* on *GitHub* under: https://github.com/mowomoyela/fcmodelevaluation. Each function is briefly described in the following listing:

- *forecast_rw(...)*: This function provides forecasts for a given TS or vector object based on the RW method which is explained in detail in section 5.4. The forecast is generated according to the input parameter: *horizon*. The method is realized by the function *rwf* of the *forecast* R package (Hyndman and Khandakar 2008).

- *forecast_arima(...)*: It generates a forecast of the inserted TS or vector object and the *horizon* by the application of the *auto.arima* and *forecast* functions from the *forecast* R package (Hyndman and Khandakar 2008). The *auto.arima* method is recursively determining the best fitting ARIMA model according to the input data. More information of the different ARIMA methods are provided in subchapter 5.3. The final forecast is generated by the *forecast* function.

- *forecast_es(...)*: The quantitave forecasting method ES which is defined in section 5.2 is implemented. The functions *ets* and *forecast* from the *forecast* R package are applied based on the function input objects: *data* and *horizon* (Hyndman and Khandakar 2008). During the forecasting process the best fitting ES model is determined according to the data.

- *forecast_svm(...)* & *forecast_cart(...)* & *forecast_xgboost(...)* & *forecast_ann(...)*: The four ML forecasting approaches from section 2.3 and chapter 5 are implemented by the *caret* R package (Kuhn et al. 2018). All of them require a TS or a data frame object and the forecasting horizon as input. Also, the parameters *cv_nfold* and *n_round* define the number of folds and number of runs for cross validation during the training model fitting process. The input parameters *data_features* and *data_label* determine the forecasting features and the target variable of the inserted data. The *forecast_svm(...)* function supports one linear and one complex non-linear SVM technique from the R package *caret*: *svmLinear* and *svmPoly*. Likewise, the *forecast_xgboost(...)* function supports the two different techniques: *xgbTree* and *xgbLinear*. The CART function applies the *rpart* method and the ANN one applies the *nnet* method (Kuhn et al. 2018).

6.1.2 Evaluation implementation

Now, the forecasting results of the seven different forecasting methods from the above subchapter 6.1.1 are evaluated in order to identify the best suitable one of them for the collected 1,000 TS from section 4.1. The two R functions *forecast_data_preparation(...)* and *forecast_evaluation(...)* are implemented. Their R code is provided on *GitHub* under: https://github.com/mowomoyela/fcmodelevaluation in the file *forecasting_methods _evaluation.R*. The final evaluation results for the 1,000 TS are stored in the appendix C. They build an essential part for the required training examples in figure 11. The functionality of both functions is precisely introduced:

- *forecast_data_preparation(...)*: This function prepares a TS or data frame object for the forecasting process. Missing observations in the dara are handled based on the input parameter: *na_option*. The two imputation techniques *mean* and *kalman* are provided. They are implemented by the *na.mean* and *na.kalman* functions of the *imputeTS* R package (Harvey and Pierse 1984; Moritz and Bartz-Beielstein 2017). They are also applied and explained in the created *tstaxonomy* R package in 4.4.2. All character features are transformed into factor values. Then, all factor features are transformed by the *one-hot-encoding* technique. It is a mandatory tool in ML to increase the prediction results. The factor values are divided by *binarization*. Thus, for each factor with *d* different values of a TS with *n* observations are created *d* binary factor variables. For each of them is defined whether it is assigned with *1* or not with *0*. This is required because for factor values ML techniques can assume the higher it is the better the value (Potdar et al. 2017). For the implementation in R the function *one_hot* from the package *mltools* is applied (Gorman 2018). Finally, the inserted data is further processed in a way that the function returns a data frame containing all data features and the target variable as numeric attributes.

- *forecast_evaluation(...)*: The results of the seven above defined forecasting method R functions from section 6.1.1 are compared. First, the *forecast_data_preparation()* function is applied to the inserted data in order to transform all attributes into numerical values and to replace missing observations. Second, the prepared data is used to generate forecasts for all seven different methods from chapter 5. For each inserted data the length of the last *10%* of the overall observations is defined as forecast horizon. But, if this number is greater than *30*, the horizon is set to *30* which represents the maximal forecasting horizon. Also, for data frame objects which represent multivariate TS the first numeric attribute is taken as target variable and the ohter ones as features. Additionally, the two functions: *forecast_svm()* and *forecast_xgboost()* provide each two different forecating techniques. For each of them both methods are applied to generate a forecast. Then, only the better technique of the two forecasting results regarding to the error measure MAPE is kept. Next, the generated seven forecasts of the different methods are compared by the previously defined error measures MAPE and MdAPE. The MAPE measure gets a weight of *0.6* because it is introduced as the most commonly used one in a study in the paper of Armstrong (Armstrong 2001a). The MdAPE is weigthed with *0.4*. Now, for example the best performing method according to the MAPE gets the weigth value: *0.6x7 = 4.2* and the lowest performing one: *0.6x1 = 0.6*. Whereas the best method is weighted with *0.4x7 = 2.8* based on the MdAPE. Next, for each method the two weighted values of the error measures are added togther. For instance, a method that performs best according to both error measures gets assigned *0.6x7 + 0.4x7 = 7*. Finally, the methods are ranked decreasingly from the best to the lowest performing one and then the ranking is returned.

6.2 Machine learning classification

The *ML classification* step is one of two opportunities to predict the best suitable forecasting method for a TS in the TS model selection framework in figure 11. It requires the training data consisting of the taxonomy classification results in appendix A or B and the model evaluation results from appendix C. It is implemented in a R package to automate the decision of the best suitable forecasting method for each TS. The four ML techniques which are described in section 2.3 of this thesis are applied: *ANN*, *SVM*, *XGBoost* and *CatBoost*. Furthermore, the entire package development process is based on the guidelines from the book of Wickham just like the developed R package in section 4.4 (Wickham 2015). The code style and documentation process which are described in subchapter 4.4.2 and 4.4.4 are adopted. Also, the final code is stored on the version control system *GitHub*.

6.2.1 Overview

The final version of the R package is licensed under *GPL-2* as free and open source software and is called *tsfcmethodr*. It is available for everyone on *GitHub* under: https://github.com/mowomoyela/tsfcmethodr. The main functionality is to predict the best performing forecasting method for a new TS based on four different possible ML techniques. All provided functions of the package are described in detail in the following chapter 6.3.2. The package can be simply installed in R from *GitHub*:

```
# Install the tsfcmethodr package
devtools::install_github("mowomoyela/tsfcmethodr")
```

Listing 5 Installation code for tsfcmethodr

After a succesful installation the package can be inizialized for actual usage. In the following R code two examples are shown for the prediction of the best suitable forecasting method for a new TS once based on the basic and once based on the ligther feature selected TS taxonomy of the *tstaxonomyr* R package:

```r
# Initialize the R package
library(tsfcmethodr)
# Example of a xgboost classification model with the basic ts
# taxonomy from tstaxonomyr R package --------
  # Train a xgboost model
  fitted_model <- tsfcmethodr::train_xgb(n_round = 10,
   cv_nfold = 10, tune_length = 10, ts_taxonomy = "v1")
  # Predict best performing forecasting method for a new ts
  ts_sales = datasets::BJsales
  prediction <- tsfcmethodr::predict_fc_model(fitted_model,
                ts_sales, "v1")
  prediction
# Example of a svm classification model with the ligther feature
# selected ts taxonomy from tstaxonomyr R package --------
  # Train a svm model
  fitted_model <- tsfcmethodr::train_svm(n_round = 10,
   cv_nfold = 10, tune_length = 10, ts_taxonomy = "v2")
  # Predict best performing forecasting method for a new ts
  ts_sales = datasets::BJsales
  prediction <-  tsfcmethodr::predict_fc_model(fitted_model,
                 ts_sales, "v2")
  prediction
```

Listing 6 Usage examples for tsfcmethodr

6.2.2 Code

The entire package code is stored in the package directory *R/*. It contains three different R files including all external and internal functions of the package: *train_ml_model.R*, *misc.R* and *predict_ml_model.R*. They are illustrated in detail in the upcoming paragraphs:

train_ml_model.R: This file contains 4 functions for the fitting process of each of the four ML techniques which are described in section 2.3 of this thesis. They are implemented by the *caret* R package (Kuhn et al. 2018): *train_svm(...)*, *train_ann(...)*, *train_catboost(...)* and *train_xgb(...)*. All of them require for *ts_taxonomy* as input *v1* or *v2* in order to define which classified TS data should be applied as training data. *v1* represents the external data file *ts_taxonomy_results.rda* of this package. Whereas, *v2* activates *ts_fs_taxonomy_results.rda* as training data. In both cases, the external file *ts_fc_taxonomy_results.rda* represents the target variable including for each TS the best suitable forecasting method. All three files are described in detail in the upcoming section 6.3.3. The input paramters *cv_nfold* and *n_round* define the number of folds and number of runs for cross validation during the training model fitting process. Also, the *tune_length* setting defines the number of model tuning intervals. During the model fitting process the textittrain_svm(...) function supports one linear and one complex non-linear classification technique from *caret*: *svmLinear* and *svmPoly*. Likewise, the *forecast_xgb(...)* function supports the two different techniques: *xgbTree* and *xgbLinear*. Moreover, the *catboost* function applies the *catboost.caret* method and the ANN one applies the *nnet* method (Kuhn et al. 2018).

misc.R: A data preparation and a TS classification function is included as internal helper functions. Both are briefly descriebed in the following listing:

- *fc_data_preparation(...)*: This internal function prepares a data frame object for the classification model training and prediction processes. All character features of the inserted data are transformed into factor values. Next, all factor features are transformed by the *one-hot-encoding* technique. It is a mandatory tool in ML to increase the prediction results and is described in detail in the previous data preparation function from section 6.1.2 of this thesis. For the implementation in R the function *one_hot* is applied from the package *mltools* (Gorman 2018). Also, any kind of date features within the inserted data are removed.
- *classify_new_ts_taxonomy(...)*: The function is required to classify a TS based on the two possible taxonomies from the *tstaxonomyr* R package which is developed in section 4.4. Either the basic or lighter feature selected taxonomy from subchapter 4.3 or 6.4 of this work can be selected by the input parameter: *ts_taxonomy*.

predict_ml_model.R: Only one function is stored in this file: *predict_fc_model(...)*. It predicts the best performing forecasting method for the inserted TS. As input is required a fitted classification model from the above defined training functions from file *train_ml_model.R*. Only the following six different ML techniques from the *caret* R package are allowed: *nnet*, *xgbLinear*, *xgbTree*, *svmLinear*, *svmPoly* and *catboost* (Kuhn et al. 2018). Before the final prediction, the inserted TS is classified by the *tstaxonomyr* R package. The parameter *ts_taxonomy* determines whether the basic or lighter feature selected TS taxonomy is applied. Finally, the classified series data is preprocessed by the above defined function: *fc_data_preparation(...)* and at the end the prediction result is returned.

6.2.3 External data

The entire external data of the package is stored in the *data/* repository. This package enables the usage of five different data files:

- *ts_taxonomy_results.rda* & *ts_fs_taxonomy_results.rda*: These two data files represent a data frame including 1,000 different univariate and multivariate classified TS according to the two taxonomies of the *tstaxonomyr* R package.

ts_taxonomy_results.rda is based on the basic taxonomy with 24 different statistical TS features developed in section 4.3. Whereas, *ts_fs_taxonomy_results.rda* is based on the ligther taxonomy of section 6.4. Each row represents one classified of the 1,000 collected series from subchapter 4.1.

- *ts_fc_evaluation_results.rda*: This file is a data frame which contains the best performing forecasting method for the 1000 TS from section 4.1 of this thesis. Each TS is evaluated in chapter 6.1 according to the seven possible forecasting techniques: *RW*, *ES*, *ARIMA*, *SVM*, *CART*, *xgboost* and *catboost*.

- *fitted_ts_taxonomy_xgb_model.rda* & *fitted_ts_fs_taxonomy_xgb_model.rda*: Both files represent a fitted classification *XGBoost* model from the *caret* R package: *xgbTree* (Kuhn et al. 2018). The combination of the two above files: *ts_taxonomy_results.rda* and *ts_fc_evaluation_results.rda* is applied by the first fitted model. Whereas, *fitted_ts_fs_taxonomy_xgb_model.rda* represents the merge of the files: *ts_fs_taxonomy_results.rda* and *ts_fc_evaluation_results.rda*. Each of them uses the forecating method evaluation results as target variable. Both files can be applied to predict the best performing forecasting model by the package function *predict_fc_model(...)*.

6.3 Model selection rules

In this section the training data from the model selection framework in figure 11 is processed in order to derive general model selection rules of it. The data set consists of the classified TS data from appendix A or B and the best fitting forecasting model of them from appendix C. The model selection rules are next to the ML classification predictors from section 6.3 a second opportunity to predict the best suitable forecasting method for a TS. In comparison to the complex ML classification models creates the rule model simple descriptive rules for the prediction. This enables users of the model selection framework from figure 11 to easy understand in which case which of the seven possible forecasting methods from section 5 is the best performing one. Whereas, the ML classification remains a black-box for the users. In the related work of Wang et al. the *C4.5* algorithm is used to derive forecasting model selection rules for univariate TS data (Wang et al. 2009). The *C4.5* concept from the highly cited work of Quinlan is adopted for this thesis as well. His approach is based on the concept of decision trees similar like the CART algorithm of section 5.1 (Quinlan 1993). For a detailed description of decision trees follow the sections 5.1 and 2.3.3. Both concepts are very similar but the *C4.5* follows the *divide and conquer* approach which differs in some ways. One major difference is that the tree node decision has an arbitrary output length instead of only binary one. Thus, the tree grows more in width than in length (Quinlan 1993, p. 17 f.). The next step of his approach is to transform the generated tree into rules since decision trees are quickly getting very large and complex which makes them very difficult to understand. Every path of the tree including all decision nodes to its leaves is one single rule. Every leaf represents one classification class. In our case the leaves contain one of the seven forecasting methods from section 5. Then, each single rule is fitted by removing node decision conditions which do not contribute to distinguish the leaf class from the other classes. Now, each class has an various amount of rules. These ruleset is further reduced by eliminating duplicating rules or the ones which have none positive influence on the class prediction accuracy. Finally, a set of rules and a default class build a classifier that can be seen as a pruned tree of the original entire tree. The default class is always selected if none of the rules fit to the new data case (Quinlan 1993, p. 45 f.).

The previously defined approach is implemented in R in order to derive the model selection rules of the training data from the model selection framework in figure 11. The *C5.0* function of the *C50* R package is applied (Kuhn and Quinlan 2018). This package provides the *C5.0* algorithm for decision trees and rule-based models which extends the above described algorithm of QUINLAN (Quinlan 1993). The rules are derived for the basic and ligther feature selected classified TS taxonomy data from the appendix A and B. As target levels the forecasting method evaluation results of the seven different techniques of the attachment C are applied. Furthermore, the *trials* setting of the *C5.0* function is set to *100* in order to define the number of possible boosting iterations to receive the most accuracte rule set (Kuhn and Quinlan 2018). The applied R code for the two taxonomies is presented in listing 7 and the resulting rules are stored in the appendix E.

```r
library(C50)
library(tsfcmethodr)
# Rule generation for the basic TS taxonomy
  # Get the classified TS data --------
  basic_taxonomy <-
   tsfcmethodr::ts_taxonomy_results[,
  which(colnames(ts_taxonomy_results) != "ts_name")]
  best_model <-
   tsfcmethodr::ts_fc_evaluation_results[, "best_model"]
  # Train a C5.0 rule model
  rule_model <- C50::C5.0(x = basic_taxonomy,
   y = best_model, rules = TRUE, trials = 100)
  # Get the rules
  summary(rule_model)
# Rule generation for the ligther feature selected ts taxonomy
  # Get the classified TS data --------
  fs_taxonomy <-
   tsfcmethodr::ts_fs_taxonomy_results[,
    which(colnames(ts_fs_taxonomy_results) != "ts_name")]
  best_model <-
   tsfcmethodr::ts_fc_evaluation_results[, "best_model"]
  # Train a C5.0 rule model
  rule_model <- C50::C5.0(x = fs_taxonomy,
   y = best_model, rules = TRUE, trials = 100)
  # Get the rules
  summary(rule_model)
```

Listing 7 Rule generation for the classified time series taxonomy data in R

6.4 Feature selection

Another step of the experimental setup is to run the TS model selection framework from figure 11 based on a feature selected TS taxonomy instead of on the basic developed one from section 4.3. The basic TS taxonomy is optimized by Feature Selection (FS). This means, only the features of the taxanomy from 4.3 that increase the performance of identifying the best perfoming forecasting method are taken into account. The FS step is additionally processed because the developed taxonomy from subchapter 4.3 is just based on TS features which have a high number of apperances in the literature. The previously computed results in section 6.1 enable the opportunity to apply a supervised FS technique on the entire training examples from figure 11. The well established works of Yoon et al. and Guyon and Elisseeff suggest the Feature Subset Selection (FSS) technique. It represents a subset of selected features by reducing irrelevant and redundant ones from the overall feature pool. The basic concept is to determine subsets that together lead to better results instead of ranking all features based on their individual relevance for the prediction problem. FSS mainly leads to a better prediction and runtime performance of the afterwards applied predictors. In this thesis, these predictors are listed and described in the sections 6.2 and 6.3 (Guyon and Elisseeff 2003; Yoon et al. 2005).

In the study of various FS techniques from Guyon and Elisseeff it is recommended to apply the combination of the FSS method types: *filter* and *wrapper*. *Wrapper* models use prediction machines as a black box without further adjustment to test several subsets of the overall features in order to reach the highest accuracy. It is a very simple method since the predictor is handled as a black box. In this thesis, the different prediction machines are the selected ML techniques: *ANN*, *SVM*, *XGBoost* and *CatBoost* from section 2.3. Whereas, *filter* methods select feature subsets independently from the following predictor model. It represents a pre-processing step for the afterwards prediction. Now, the combination of these two techniques looks as follows. First, a simple linear *wrapper* method is deployed as a filter to pre-process the overall features into a well performing subset. The best subset is determined by a recursive forward or backward elemination that compares the accuracy for each subset. As the names already suggest, it either starts by one feature and recursively tries to add more or it begins with all features and progressively eliminating the most irrelavant ones. Common *wrapper* methods are decision trees or linear SVM. Second, more complex predictor methods like a non-linear SVM or ANN are applied and adjusted on the pre-processed feature subset to fullfil the final prediction problem (Guyon and Elisseeff 2003).

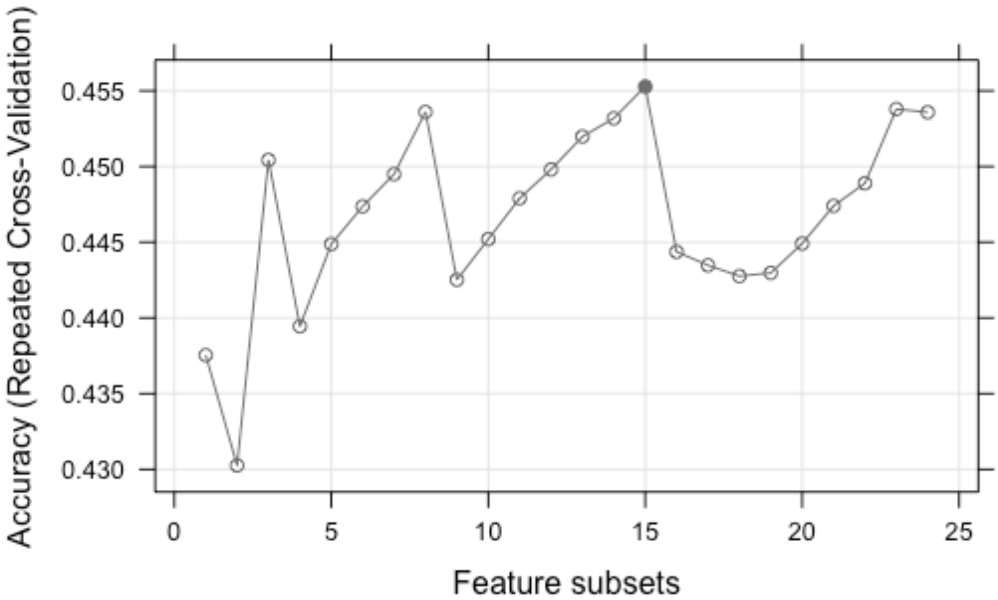

Figure 12 Recursive feature subset selection results

In this thesis, it exist a multi-class prediction problem by identifying for each TS the best forecasting method of the seven defined ones from chapter 5. Thus, a *wrapper* method that supports multi-class classifcation is required. The R package *caret* provides a function *rfe* which represents a recursive feature elimination technique. It applies a prediction method with backward FS based on the feature importances (Kuhn et al. 2018). As decision trees are common *wrapper* methods, the random forest model is applied in this work

(Guyon and Elisseeff 2003). Finally, this function is implemented in R based on the merged taxonomy results from appendix A and the forecasting method evaluation results in appendix C. The created R code is attached in the appendix F.

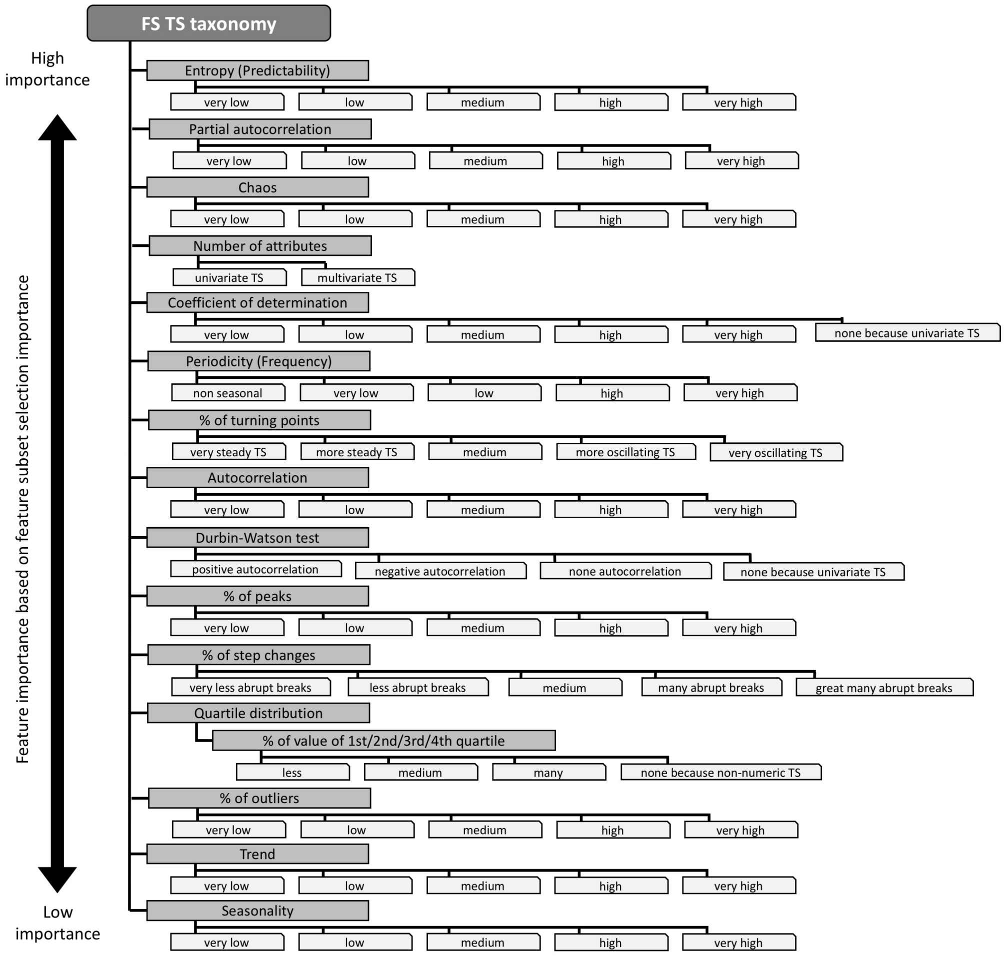

Figure 13 Feature subset selection time series taxonomy

In figure 12 the results of the previously defined recursive FSS process are shown. The *Y-axis* represents the accuracy for the different subsets and the *X-axis* all feature subset variations. The subset of 15 features generates the highest accuracy. Also, it is visible that a subset of eigth and the overall 24 features almost reaches comparable results. The *rfe* algorithm provides the decreasing importance for each feature of the best perfoming subset. Next, according to the final subset and feature importances the developed TS taxonomy from section 4.3 is rebuild in figure 13. The features are ordered by their FSS importance instead of their average citation number:

In order to automatically classify TS according to the FSS TS taxonomy the developed R package *tstaxonomyr* from section 4.4 is expanded based on the determined coding and documentation style of sections 4.4.2 and 4.4.4. The *classify_ts()* function from the file *ts_taxonomy.R* is extended by a new input paramater *taxonomy_type*. This new setting allows as input string either *v1* or *v2*. The first one classifies a new TS based on the basic taxonomy from figure 10. Whereas, *v2* determines the classification according to the ligther FSS taxonomy with only 15 features of this section. The code of the *tstaxonomyr* R package and specially of the new functionality is available on *GitHub* under: https://github.com/mowomoyela/tstaxonomyr. In the following R code example a TS classsification based on the above developed FSS taxonomy is illustrated:

```
# Initialize the R package
library(tstaxonomyr)
# Example of the TS taxonomy classification --------
# Use the univariate time series object 'BJsales'
ts_sales = datasets::BJsales
# Classify the time series based on the defined FSS taxonomy
# in 'classify_ts'
classified_ts <- classify_ts(ts = ts_sales, na_option = "mean",
taxonomy_type = "v2")
# Get the classification factor results
classified_ts
```

Listing 8 Usage example for the feature subset selection time series

7 Evaluation results

In this chapter, the results of the evaluation set up and implementation from the previous chapter 6 are collected and discussed. The developed TS taxonomies from chapter 4.3 and 6.4 are evaluated in order to check whether they are usable to predict the best suitable forecasting method for a TS or not. This prediction process is evaluated by the deployment of fitted ML classification techniques and a rule model. Their results are indicators for the usefulness of the TS taxonomies.

7.1 Machine learning classification results

The ML model evaluation from chapter 6.2 is based on 10-fold cross validation which is repeated ten times. These settings are recommended by the two works of Kohavi and Rodriguez et al. which are described more in detail in the explanation of the TS model selection framework in figure 11 from chapter 6 (Kohavi 1995; Rodriguez et al. 2010). As evaluation measures the *F1-score* and the *accuracy* of the multi-classification results are used. The *accuracy* represents the percentage of the testing data that was predicted correctly by the models. The *F1-score* provides an estimate between *0* and *1* on how well the classification models perform on a set of new testing TS which were not used during the training process. It consists on the the average of *precision* and *recall*. *Precision* handles the problem of correctly predicted positive outcomes of the predicted values. *Recall* handles the problem of correctly predicted positive outcomes of the actual values (Powers 2008; Davis and Goadrich 2006). The *F1-score* and *accuracy* have to be computed for all seven different classes and then the results are averaged to get a single error measurement for the ML predictors. Also, they can be compared well with each other since both range between *0* and *1*. The formal representation of them looks as follows:

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn}\,. \tag{7.1}$$

$$F1\ score = 2 * \frac{precision * recall}{precision + recall}\,, \tag{7.2}$$

$$Precision = \frac{tp}{tp + fp}\,, \tag{7.3}$$

$$Recall = \frac{tp}{tp + fn}\,. \tag{7.4}$$

Where *tp* represents all *true positive* results. It is the number of all correct classified prediction results. Whereas, *fp* is the number of results that are assigned to the class but belong correctly to another class. Also, *fn* is the amount of results that should have been assigned to the class but were predicted for another classes (Powers 2008; Davis and Goadrich 2006). The results of the final ML models according to the *F1-score* and *accuracy* are illustrated in table 4. These final models are the ones with the best error measure results from the automated model fitting process of the *tsfcmethodr* package and additional manual fitting trials to indentify the best parameter setting. In the table, the models beginning with *BT* are applied on the basic TS taxonomy and the ones with *FST* on the feature selected taxonomy:

Model name	Accuracy	F1-Score
BT-SVM	0.45	0.25
BT-ANN	0.45	0.29
BT-XGBOOST	**0.50**	0.27
BT-CATBOOST	0.48	0.25
FST-SVM	0.47	0.26
FST-ANN	0.44	0.25
FST-XGBOOST	0.48	**0.30**
FST-CATBOOST	0.48	0.29

Table 4 Machine learning models prediction results

The results of table 4 show that the models are close together according to the *accuracy* and the *F1-score*. The *BT-XGBOOST* model reaches the highest *accuracy* and the *FST-XGBOOST* one returns the highest *F1-score*. Both are stored as external data to the *tsfcmethodr* R package. Whereas, the *FST-ANN* method has the lowest *accuracy* and the models *BT-CATBOOST*, *FST-ANN* and *BT-SVM* reach the lowest *F1-score*. The difference between the best and the worst method for the *accuracy* and *F1-score* is only *0.05* for both measures. Furthermore, the average over all methods for the measures *accuracy* and *F1-score* are *0.47* and *0.27*. A significant difference between the two scores is visible since the *F1-score* is by an value of *0.20* smaller. The results do not show clear indications that the models perform better for one of the two taxonomies *BT* and *FST*. Next, the two best performing models *BT-XGBOOST* and *FST-XGBOOST* are analyzed more in detail by the evaluation of their confusion matrices.

		Reference						
		ANN	ARIMA	CART	ES	RW	SVM	XGB
Prediction	ANN	0.0	0.0	0.0	0.0	0.0	0.0	0.1
	ARIMA	1.5	9.5	0.7	2.9	3.7	4.6	1.9
	CART	0.2	0.3	0.9	0.1	0.1	0.2	0.2
	ES	0.3	0.1	0.0	0.4	0.0	0.2	0.1
	RW	0.4	0.7	0.3	0.7	1.6	1.3	0.6
	SVM	3.6	6.7	1.9	2.6	6.8	36.8	6.5
	XGB	0.2	0.2	0.1	0.2	0.3	0.1	0.4

Table 5 Confusion matrix of the best *accuracy* model: *BT-XGBOOST*

In table 5 is illustrated the confusion matrix of the overall ten times repeated 10-fold cross validation training cycles from the model with the highest *accuracy*: *BT-XGBOOST*. The confusion matrix contains in sum 100 elements since each training cycle is evaluated by 100 TS of the 1,000 collected ones from section 4.1. Each row represents the average number of predictions of all training cycles for one model. For instance, only *0.1* element is predicted for the ANN class in average. The columns represent the average number of reference values for the different classes. In average *6.2* actual elements of the class ANN are part of the validation data to test the prediction power of the trained model *BT-XGBOOST*. Thus, the confusion matrix enables the evaluation of the *accuracy* and *F1-score* error measures for each single class. These results are listed in table 7. The *accuracy* for the class ANN is *0* since the model predicts zero elements but in average *6.2* ANN reference objects exist. Also, the classes ES, RW and *XGB* reach very low *accuracy* with *0.06*, *0.13* and *0.04*. Whereas, the classes SVM and ARIMA have higher values with *0.85* and *0.54*. In sum, only two of the seven classes reaches an *accuracy* higher than *0.5*. The single class results according to the *F1-score* slightly differ to the *accuracy* ones. SVM is the only class that is higher than *0.5* with a score of *0.68*. Then, the ARIMA and CART classes are following with values of *0.44* and *0.39*. The other left four classes reaches *F1-scores* smaller than *0.2*. The comparison of the two measures shows that the class CART reaches a significant higher *F1-score* than *accuracy* with a difference of *0.16*. Furthermore, the classes SVM and ARIMA have a clearly smaller *F1-score* with a difference of *0.10* and *0.17*. The sums of each single row of the matrix deliver further essential observations since only for the three classes SVM, RW and ARIMA more than two elements are predicted in average. For the SVM class are predicted by far the highest number with an average of *65* objects. On the other side, the class ANN is almost never predicted during the overall training processes.

		Reference						
		ANN	**ARIMA**	**CART**	**ES**	**RW**	**SVM**	**XGB**
Prediction	**ANN**	0.3	0.0	0.5	0.2	0.3	0.7	0.3
	ARIMA	0.8	8.2	0.5	1.9	3.3	3.9	2.1
	CART	0.3	0.3	0.6	0.1	0.2	0.5	0.3
	ES	0.7	0.9	0.2	0.8	0.6	0.8	0.2
	RW	0.8	2.0	0.1	1.0	2.9	2.4	1.0
	SVM	3.0	4.8	1.7	2.6	4.8	32.8	5.2
	XGB	0.3	1.3	0.3	0.3	0.4	2.1	0.7

Table 6 Confusion matrix of the best *F1-score* model: *FST-XGBOOST*

In table 6 is shown the confusion matrix of the overall ten times repeated 10-fold cross validation training processes from the model with the highest *F1-score*: *FST-XGBOOST*. The *accuracy* of each single class can be evaluated. The classes ANN and *XGB* are the worst models with a small *accuracy* of *0.05* and *0.07*. Whereas, the SVM and ARIMA reach the highest values by far with *0.76* and *0.47*. The other left three classes have also smaller *accuracy* values between *0.12* and *0.23*. Overall, only one of the seven classes reaches an *accuracy* over *50%*. In comparison, the single class results for the *F1-score* only slightly differ. The scores for the classes *XGB*, CART, ES and RW are a bit higher than the *accuracy* ones. The values for the ARIMA and SVM classes are sligthly smaller. Also, the score for ANN is zero. Other informative factors are the rows which represent the average number of predictions of the training process for each class. It is conspicuous that for the two classes ANN and *XGB* are predicted the most objects for actual objects from the class SVM and not for their own class. For instance, the *XGB* class falsely predicts in average *2.1* objects that are actually from the SVM class and only truly predicts in average *0.7* elements that are *XGB* elements. Thus, it seems like that the *FST-XGBOOST* model wrongly identifies actual data from the SVM class as *XGB* or ANN objects. For the SVM class is predicted by far the highest number with an average of *54.9* objects. Whereas, the classes CART, ANN and ES are predicted very rarely with an average number of less than four elements.

		ANN	ARIMA	CART	ES	RW	SVM	XGB
BT-XGBOOST	**Accuracy**	0	0.54	0.23	0.06	0.13	0.85	0.04
	F1-Score	0	0.44	0.39	0.12	0.18	0.68	0.07
FST-XGBOOST	**Accuracy**	0.05	0.47	0.15	0.12	0.23	0.76	0.07
	F1-Score	0	0.43	0.19	0.15	0.25	0.67	0.09

Table 7 Error measure comparison between the best two machine learning models

The table 7 shows the comparison of the single class error measures for the best two performing models *BT-XGBOOST* and *FST-XGBOOST*. In sum, it seems like that the ML models are struggeling to predict the classes *ANN* and *XGB* since both have by far the worst error measure values. The comparison shows that ML models which apply the basic TS taxonomy reaches better predictions for the classes ARIMA, *CART* and *SVM* than the models according to the ligther feature selected TS taxonomy. On the other side, the *FST* models are better in estimating the other four left classes. Overall, the table shows that the ML models only perform well for the prediction of TS with the best performing forecasting models *ARIMA* or especially *SVM*. Thus, there are prediction problems with the five other single classes which is shown by their bad error measure results.

In the last step the two best performing ML methods *BT-XGBOOST* and *FST-XGBOOST* are further evaluated by the prediction of one of the top two or three best suitable forecasting methods for a TS. In appendix C the forecasting method evaluation is just a simple order according to the error measures MAPE and MdAPE. The distances between the measures of the seven models are not considered whether they are very close or far apart. For instance, it could be the case for some evaluated TS that the second best performing model is just slightly worse than the best suitable one. The results are presented in table 8. The highest *accuracy* for estimating one of the best two and three models are *0.66* and *0.72*. As expected the accuracy is increasing compared to the results from table 4 because now the prediction models only have to predict a model of the right two or three possible ones from the overall seven classes. Thus, the selection pool of the wrong classes is decreasing.

	Accuracy	
Model name	**Best two models**	**Best three models**
BT-XGBOOST	0.62	**0.72**
FST-XGBOOST	**0.66**	0.71

Table 8 Best machine learning models predicton results for one of the best two or three forecasting methods

7.2 Forecasting model selection rules

The overall generated forecasting model selection rules from section 6.3 are listed in the appendix E. The rules are created based on the classified 1,000 TS according to the basic or ligther feature selected TS taxonomy from section 4.3 and 6.4. For the first taxonomy the boosting process of the *C5.0* algorithm build three different trials. The first trial is the one with the lowest error rate. It consists of a decision tree with 387 leaf paths which are fitted to a final rule set of 62 different rules. The default class of the tree is the SVM forecasting model. Thus, if a new classified TS does not fit to one of the 62 rules the default class is predicted as final class. In table 9 for each of the seven possible forecasting methods of section 5 the rule with the highest *accuracy* is listed. For instance, *rule 8* expresses that a high *autocorrelation* and a low *seasonality* of a classified TS indicates ARIMA as the best suitable forecasting method by *83%*. For each class the best rule reaches an accuracy around *80%*. Additionally the number of rules and the average accuracy of each class are illustrated. The ARIMA class has the most rules by far despite the default class SVM. Whereas, the three ML models ANN, CART and *XGBoost* have the smallest amount of rules. Moreover, the methods ES and RW have the highest mean of the accuracy with *72%*. Although, the mean of all rules is very close by an difference not higher than *9%*.

Forecast model	**No. of rules**	**Mean of rules**	**Best rule**		
			No.	**Description**	**Acc.**
ANN	7	0.63	2	Skewness = medium & Chaos = medium & Entropy = very low & StepChanges = very less abrupt changes & DurbinWatsonTest = positive autocorrelation & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	0.75
ARIMA	16	0.61	8	Autocorrelation = high & Seasonality = low	0.83
CART	8	0.68	24	Kurtosis = low & Mean = medium & Seasonality in none seasonality, very low & StepChanges = very less abrupt changes & DurbinWatsonTest = none because univariate	0.83
ES	10	0.72	32	Kurtosis = low & Mean = medium & Seasonality in none seasonality, very low & StepChanges = very less abrupt changes & DurbinWatsonTest = none because univariate	0.83
RW	11	0.72	42	Skewness in high, low Periodicity = very low & Chaos = high & PartialAutocorrelation = very low & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	0.80
SVM	2 + default class	0.64	53	Trend = very low & TurningPoints = more oscillating & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	0.83
XGBoost	8	0.67	55	Kurtosis = very low & Autocorrelation = very high & DurbinWatsonTest = none because univariate & QuartileDistribution in Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less, Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	0.83

Table 9 Derived model selection rules of the basic time series taxonomy

Next, for the ligther feature selected TS taxonomy of section 6.2 the *C5.0* algorithm generated a decision tree with 361 different leaf paths and SVM as default class. During the rule optimization process its number was reduced to the final number of 73 rules. These are listed in the appendix E.2. In table 10 are shown the best rules, the number of rules and the average *accuracy* for each forecasting method. The class *XGBoost* reaches the highest mean *accuracy*. Whereas, the default class SVM has a very low *accuracy* for its single specified rule. Despite the default class, the ANN class shows an significant lower average of *accuracy* than the other models. Additionally, it contains the lowest number of rules together with the CART class. The RW and ARIMA classes have the highest numbers of rules.

Forecast model	No. of rules	Mean of rules	Best rule No.	Description	Acc.
ANN	7	0.58	1	Autocorrelation = very low & Seasonality = none seasonality & TurningPoints = more steady & PartialAutocorrelation = high & Outliers = low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	0.75
ARIMA	17	0.65	8	Entropy = medium & DurbinWatsonTest = none because univariate & Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 less	0.83
CART	7	0.71	25	Trend = very high & QuartileDistribution = Quartile1 medium & Quartile2 less & Quartile3 less & Quartile4 less	0.83
ES	11	0.67	32	Autocorrelation in low, very low & Seasonality = none seasonality & Outliers = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	0.83
RW	19	0.63	43	Trend = very high & Seasonality = none seasonality & Entropy in low, medium & Outliers = medium & Peaks = medium & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	0.80
SVM	1 + default class	0.45	62	Seasonality in high, low, medium, none seasonality, very low	0.45
XGBoost	11	0.77	63	Autocorrelation in high, very high & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 medium, Quartile1 less & Quartile2 many & Quartile3 less & Quartile4 less, Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	0.83

Table 10 Derived model selection rules of the ligther feature selected time series taxonomy

The comparison of table 10 and table 9 shows only slight differences. The *accuracy* of the best models just differs for the SVM method. Furthermore, for the feature selected taxonomy rules the average rule *accuracy* of the *XGBoost* and RW model significantly increases and decreases. At the same time, the overall number of rules for RW almost doubled. In total, it seems like that for the three ML techniques ANN, CART and *XGBoost* the rule models from section 6.4 cannot derive a very high amount of rules. The average rules *accuracy* for the ANN class is significantly lower than the other classes.

In the next step, the rule models for the two different TS taxonomies are evaluated according to the *F1-Score* and *accuracy* in order to be able to compare them with the ML results from the previous chapter 7.1. Both measures are defined and explained in the previous chapter. The rule models are also evaluated based on a 10-fold cross validation to enable the comparison with the ML models. In table 11, the rule model beginning with *BT* is deployed on the basic TS taxonomy and the one with *FST* on the ligther feature selected taxonomy. The highest *accuracy* with *61%* is reached by the *BT-C0.5* model. Whereas, the *BT-C0.5* model returns the best *F1-Score*. Thus, the *BT-C0.5* and *FST-C0.5* algorithm are integrated into the developed *tsfcmethodr* R package from section 6.3 since the results are higher than the previously illustraded ML results from chapter 7.1.

Model name	Accuracy	F1-Score
BT-C0.5	**0.61**	0.25
FST-C0.5	0.58	**0.36**

Table 11 Rule model prediction results

Next, the confusion matrices of the both models *BT-C0.5* and *FST-C0.5* are combined and their average values analyzed to get insights about the performance for the single outcome classes. In table 12 each row represents the average number of predictions of the two models. For example, only *0.5* objects are predicted for the *ANN* class in average. The columns represent the average number of reference values for the different classes. In average *6.5* actual objects of the class ANN are part of the validation data to test the prediction results of the two models. The two single classes SVM and ARIMA have the highest *accuracy* by far with *0.87* and *0.66*. On the other side, the single classes ANN and *XGB* achieve the lowest measures by very low values of *0.08* and *0*. The other three left classes also reach rather low *accuracies* ranging from *0.21* to *0.33*. Furthermore, the different *F1-Scores* of the single classes show identical patterns than the *accuracy* results with the same order from SVM as the best to *XGB* as the worst performing class. In sum, the table shows that the two rule models *BT-C0.5* and *FST-C0.5* perform very well in predicting SVM and are still good in predicting ARIMA as the best suitable forecasting method for a TS. On the other hand, they are very bad in estimating ANN or *XGB* and are also rather bad in predicting the other three left forecasting models as the best performing one.

		Reference						
		ANN	**ARIMA**	**CART**	**ES**	**RW**	**SVM**	**XGB**
Prediction	**ANN**	0.50	0	0	0.50	0	0	0.50
	ARIMA	0	9.50	0.50	1.50	2	2.50	0.50
	CART	0.50	0	0.50	0.50	0.50	0.50	0
	ES	1	0	0	1.50	1.50	0	0
	RW	0	1.50	0	0	2.50	2	0.50
	SVM	4.50	3	0.50	3	4.50	45.00	6.50
	XGB	0	0.50	0	0	0	1.50	0

Table 12 Combined confusion matrix of the two C5.0 rule models

In the next step, the rule models are further evaluated by the prediction of one of the top two or top three best suitable forecasting methods for a TS. The forecasting method evaluation results from the appendix C are just a simple order from the best to the worst performing model for a TS according to the error measures MAPE and MdAPE. Although, for example it could be the case that the second best performing model has just slightly worse error measures than the best performing one. Thus, the *accuracy* for the rule models is evaluated according to the prediction of one of the two or three best performing forecasting techniques of the seven possible ones. The results are presented in table 13. The *BT-C0.5* rule model reaches the highest *accuracy* for predicting a forecasting model of the best two ones for a TS. Furthermore, the *FST-C0.5* rule model achieves the highest *accuracy* with *0.76* for the top three forecasting method prediction. In comparison to the *accuracies* from table 11, the forecasting method prediction values are increased as expected because now the rule models only have to identify a method of the rigth two or three ones from the overall seven possible classes.

	Accuracy	
Model name	**Best 2 models**	**Best 3 models**
BT-C0.5	**0.67**	0.70
FST-C0.5	0.66	**0.76**

Table 13 Rule model prediction results for one of the best two or three forecasting methods

7.3 Discussion

In this chapter, the previously illustrated results from the ML predictions and the generated prediction rules are compared and discussed. In the first part, the best fitted ML model reaches an *accuracy* of *50%* to predict the best suitable forecasting method for a TS. The prediction is a multi-classification problem according to the defined seven forecasting methods from chapter 5. Thus, the chance to pick by random the best performing model of the seven is *14.29%*. In comparison, the ML prediction model of this thesis performs three and a half times better than just randomly select one of the possible forecasting methods. In the second part, the best performing rule model *BT-C0.5* achieves an *accuracy* of *61%* for the best suitable forecasting method prediction. This means that it is four and a half times better than randomly picking one method of the seven possible ones.

However, it is more common to select the class with the highest frequency within the trainings data instead of just totally picking a class by random. In table 14 is shown the distribution of each single class within the trainings data. SVM counts the highest number of TS for which it is the best suitable forecasting method. Thus, the simple selection of SVM as the best suitable method provides an *accuracy* of *43%* (*432/1000*) according to the 1,000 training representatives. In comparison, the best ML model performs better by *7%* and the best rule model is even better by *18%*.

ANN	ARIMA	CART	ES	RW	SVM	XGB
62	175	39	69	125	432	98

Table 14 Single class distribution of evaluation TS data

These results show that the rule model is clearly better performing than the best ML model according to the *accuracy* measure. The results provide the *accuracy* measures for each single prediction class. In both cases of the ML and rule models the only class that reaches very good prediction results is the SVM model with over *80%*. Also, the ARIMA class shows a decent predictably with an *accuracy* of around *60%*. The other five left classes have very poor results by *accuracies* around *20%* or even less for the ML models and *accuracies* around *30%* and lower for the rule models. In sum, both classification approaches only work for the SVM model and have positive potential for the ARIMA model. Whereas, the models are obviously struggeling to predict the other five classes.

The results of the second measure the *F1-Score* confirm the *accuracy* result findings. The single class prediction results show the same distribution with only appropriate results for the SVM model. In sum, the *F1-Score* results are certainly lower than the *accuracy* ones. According to the overall score the ML model predicts the best suitable forecasting model for a TS with *0.30*. This means, it is only twice as good as picking one out of the seven methods by random. The best rule model achieves a score of *0.36* and therefore it is two and a half times better than randomly picking one. Again, the best rule model shows a higher score for the *F1-Score* like for the *accuracy* measure. The *FST* models have a higher *F1-Score* and a lower *accuracy* than the *BT* models for the ML classification as well as for the rule model prediction. A low *F1-Score* often occurs through imbalanced prediction classes and thus may refer to a problematic of the trainings data class distribution of this thesis.

In the last step, the best two ML models and the two rule models are further evaluated. In the above tables 8 and 13 are shown the *accuracy* for the prediction of one of the best two or three performing forecasting methods for a TS. As expected the *accuracies* are higher than the one for the prediction of the best performing model. Although, the higher values have to be considered carefully because the selection pool of wrong classes is decreasing and that makes it easier to predict. The rule models show slightly higher results than the ML models with *67%* and *76%* for one of the best two and best three model prediction. Now, the *accuracies* for randomly picking a suitable forecasting method is increasing. In case of randomly selecting one of the top two of the seven possible models is *29%* and for one of the top three is *43%*. Thus, the best rule models perform approximately two times better for the top two or top three prediction than just randomly select one. Selecting one of the two or three models with the highest frequency from the trainings data leads to the classes SVM, ARIMA and RW according to table 14. Thus, the simple selection based on the frequency delivers an *accuracy* of *60%* for one of the top two models and *73%* for one of the top three. In comparison, the best prediction models perform better by *7%* for one of the top two and by *3%* for one of the top three models. The prediction returns only one of the best two or three models and perhaps not the best suitable one at the end. The difference between the performance of the third best and the best forecasting model may has a major impact of the forecasting results afterwards.

Finally, the research question of this paper is to check if it is possible to predict the best suitable forecasting method based on a descriptive TS taxonomy for any kind of TS such as multivariate and univariate series and from different domains. In sum, the overall evaluation results of the two TS taxonomies of this thesis show that the prediction of the best suitable and one of the top three forecasting methods achieves an *accuracy* of *61%* and *76%*. The *accuracy* results indicate sligthly promising results. Nevertheless, according to the second error measure the *F1-Score*, the prediction models achieve based on the two TS taxonomies a maximum score of *0.36* for the prediction of the best suitable method. This score is low and therefore a rather bad result. Overall, the combination of these results show that the current set up of this work does not allow a positive answer of the research question. However, especially the *accuracy* numbers provide indications that the TS taxonomies may have potentials to apply them for the forecasting model selection problem. Thus, the research question should also not be seen as disproven by the results. Rather the current evaluation set up and perhaps the TS taxonomies creation should be further analysed and processed in future work to exploit the identified potentials of this thesis. Thus, the question is: What could be the factors of the rather bad results and how could they be processed to further increase the results of the model selection problem?

One reason could be the distribution of the different prediction classes of the 1,000 evaluated TS from appendix C. In table 14, the number of objects for each of the seven different prediction classes are shown. It stands out that they are very imbalanced. The SVM class contains by far the most training objects. Whereas, the three classes ANN, CART and *XGB* have less than 100 representatives. The results from the evaluation chapters 7.1 and 7.2 show that the SVM and ARIMA classes are the best predicted ones. Maybe these results are achived because of the higher amount of training representatives. Therefore, the ML and rule models from chapter 6.3 and 6.4 are additionally tested by a more balanced amount of data with 60 representatives for each class. The only exception was the CART data which only consists of 39 training objects. However, the results do not show any better results than the one introduced in the aboves sections 7.1 and 7.2. This could be explained by the fact that only 60 representatives per class are too less training data.

One perspective to may increase the prediction results is to rebalance the training data by increasing the number of class represetantives for the classes with very few current objects like the three classes ANN, CART and *XGB*.

Another factor that perhaps is influencing the prediction performance are the collected 1,000 TS representatives from chapter 4.1 which are classified by the two different TS taxonomies. On the one hand, the amount of only 1,000 TS may is too less in order to cover all different descriptive classes of each feature from the TS taxonomy. In the appendix A.1 are listed the different descriptive class distributions for each feature of the basic TS taxonomy from chapter 4.3. The table for example shows that for the feature *number of observations* only data exists for two of the five possible descriptive classes: *very short* and *very long*. Also, the different levels of the features *DTW distance* or *standard deviation* are not completely covered by the collected 1,000 TS representatives. A higher number of classified TS data may improve the prediction models to identify further patterns between the descriptive taxonomy data. On the other hand, the quality and diversity of the 1,000 TS should be considered. It was very difficult to identify public availably multivariate TS data which is suitable as benchmarkig data. Therefore, the multivariate data does not show a very high diversity. One potential to increase the data quality and variety would be to create simulation data which represents more different characteristics like to cover all the different descriptive classes for the *number of observations* or *DTW distance* feature. Another way would be to request real existing multivariate TS from the practice of different areas such as manufacturing or retail.

The selection of the seven forecasting methods from chapter 5 and their evaluation process in section 6.1 are essentials parts for the prediction of the best suitable forecating method. The best method for the training data is identified according to the error measures *MAPE* and *MdAPE*. It might be the case that other error measures return different results for the best performing forecasting method for the evaluated 1,000 TS. Furthermore, perhaps the ML and rule models are struggeling to identify patterns for the different seven methods because some of them are too identical. This means that they perform well for the same kind of classified TS data and so the prediction models are not able to distinguish between them. Maybe the reduction or substitution of the seven models leads to an improvement in the prediction results.

The main factor for the prediction results is of course the conceptualized TS taxonomy containing the overall 24 features from chapter 4.3. It classifies each of the collected TS and provides them as training data for the prediction process. Maybe the features and their different descriptive classes of the taxonomy are not suited to predict the best performing forecasting method for a TS. Thus, the extention or adjustment by new features may achieve better prediction results. For example, in the concept matrix in figure 14 are listed

32 other TS features which were evaluated as irrelevant for this thesis. The reduction of the current 24 features does not seem very promising since the results of the ligther feature selected taxonomy from chapter 6.2 do not show better overall results than the basic one. However, the deployment of other feature selection approaches perhaps generates a new FSS that is better suited to predict the best suitable forecasting method.

8 Conclusion

Finally, all chapters and their results are concluded. Also, the limitations of this work are discussed and future work suggestions are provided. The main goal of this thesis is to build a TS taxonomy with different features in order to classify TS and then predict their best suitable forecasting method.

8.1 Summary

First, a theoretical background chapter was created to explain and define a TS and their features and forecasting. Also, the term taxonomy and the approach of ML was introduced. Furthermore, four different ML techniques were selected and explained based on evaluation works. Next, global TS features were collected by an extensive literature search. The final feature subset was selected based on a concept matrix and their number of citations. Overall, 24 different features were identified as relevant and then explained. Then, 1,000 univariate and multivariate TS of different types are collected as representatives of all kinds of existing TS data. Afterwards, the final TS taxonomy was conceptualized according to the selected features and the min max values for each feature of the collected series data. The taxonomy was implemented as an R package *tstaxonomyr* in order to enable automatically TS classification. In the next chapter, four ML methods (*ANN*, *SVM*, *CART* and *XGBoost*) and three classical forecasting methods (*ES*, *ARIMA* and *RW*) were identified and explained. Then, all previously developed work was combined and set up to enable the prediction of the best suitable forecasting method for new TS. Additionally, a FSS technique was applied according to the 24 taxonomy features and the classified 1,000 TS representatives. This was resulting in a subset of 15 features which were build as a second ligther TS taxonomy. Then, the collected 1,000 TS representatives were classified based on the developed taxonomy R package by either the basic or FSS taxonomy. For each TS the best performing forecasting method of the seven defined ones was identified through R. These two results were combined and then applied as training data for ML classification techniques which predict the best suitable forecasting method. For the prediction process an R package *tsfcmethodr* was developed. Finally, the results of the forecasting method prediction were evaluated based on the measures *accuracy* and *F1-score*. Additionally, *C5.0* rule models were applied based on the classified TS data from the two different TS taxonomies to derive descriptive prediction rules. These models were evaluated as well according to the two error measures *accuracy* and *F1-score*.

8.2 Results

The overall evaluation results of the TS taxonomy and a ligther subset of it achive an *accuracy* of *61%* to predict the best suitable forecasting method for a TS and *76%* to predict one of the three best performing ones. For a multi-classification of seven different forecasting methods the *accuracy* results provide slightly promising results. However, the second error measure the *F1-Score* reaches only relative low and therefore rather bad results since the best prediction model from the TS taxonomy evaluation process achives only a maximum score of *0.36*. This means that the prediction based on the TS taxonomy according to the *61%* of the *accuracy* measure performs four and a half times better than just picking randomly one of the seven possible forecasting methods as the best suitable one. In comparison, the value of *0.36* from the *F1-Score* expresses that the taxonomy based prediction just performs two and a half times better than a random selection. During the evaluation process the predictability of each forecasting method was analyzed. Both error measures equally showed that the predictors work well in predicting the best suitable model for TS that have either ARIMA or SVM as best performing one. However, the prediction models are struggeling in predicting TS of the other five forecasting methods.

In sum, the combination of all generated results and insights show that the current set up of this thesis does not allow to prove the research question positive. Nevertheless, especially the rather high *accuracy* results indicate that the developed TS taxonomy and its ligther subset may have potentials to solve or support the trial and error forecasting model selection problem. Therefore, the research question is also not clearly disproven by the results of this work. Rather the insights from the following chapter of future work could be applied in order to exploit the existing potentials and perhaps to further increase the prediction results to prove the TS taxonomy right for solving the TS forecasting model selection problem. Finally, the current implementations of this thesis *tstaxonomyr* and *tsfcmethodr* perform not good enough to be seen as reliable forecasting model predictor. Nevertheless, end users with less knowledge of the TS forecasting area can use it as a first quick decision supporter to identify a suitable technique. They can either use the prediction models from the *tsfcmethodr* R package or the derived descriptive prediction rules in order to identify the best suitable forecasting method.

8.3 Limitations and future work

The model selection prediction results are very dependet on the collected 1,000 TS representatives since they are applied as training data. Thus, the quality of these data may be increased with data of even higher quality or by extending the amount of TS. Especially, it was very difficult to identify public availably multivariate TS data which is suitable as benchmarking data. Thus, for some descriptive classes of the features from the developed TS taxonomy no training data exist. One opportunity would be to create simulation data which represent different characteristics to cover all classes of the current incomplete features like *Number of observations* or *Standard deviation*. Another one would be to request real existing multivariate TS from practice.

Another factor that has an influence on the prediction results is the best perfoming forecasting method specified for each TS of the prediction model training data. In this thesis the seven implemented forecasting methods are just a subset of the overall existing forecasting techniques. They can be expanded, reduced, adjusted or even substituted by other methods. This may leads to an improvement in the prediction results and in case of an expansion the choice of methods grows for the end user. Moreover, the best suitable forecasting method for the training data was identified based on the two error measures *MAPE* and *MdAPE*. Other error measures may lead to different results for the best performing forecasting method of each training TS.

Next, the computional performance of the two developed R packages *tstaxonomyr* and *tsfcmethodr* was not comprehensively considered. The focus was only on the accuracy and operability of the packages because of the rather limited processing period of this thesis. For instance, during the classification of a new TS the calculation of the DTW feature takes a long time. Thus, the packages should be revised according to a better computional performance.

Further future work can concern the conceptualized TS taxonomy containing the overall 24 features. It can be extended or adjusted by new features. Also, different feature selection methods can be applied in order to receive a well performing FSS. For instance, 32 further TS features which were marked as non relevant for the current set up of thesis are listed in the concept matrix of figure 14.

Another interesting next step would follow after the prediction of the best suitable forecasting method. The developed R package *tsfcmethodr* could be extended in order to directly forecast the values for the new inserted TS according to the model selection result. This means, that the end user just inputs his new TS and will get the forecast values from the best performing forecasting method as output.

Appendix

A Time series taxonomy results

A.1 Factor level descriptions

Table 15 Time series taxonomy results factor level description

Feature name	Levels	Level values
Skewness	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Kurtosis	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Trend	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Autocorrelation	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Mean	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Standard deviation	low; medium; very high; very low;	1; 2; 3; 4;
Number of observations	very long; very short;	1; 2;
Non linearity	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Seasonality	high; low; medium; none seasonality; very high; very low;	1; 2; 3; 4; 5; 6;
Periodicity	high; low; medium; none periodicity; very high; very low;	1; 2; 3; 4; 5; 6;
Chaos	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Entropy	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Self similarity	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Quartile distribution	Quartile1 less Quartile2 less Quartile3 less Quartile4 many; Quartile1 less Quartile2 less Quartile3 less Quartile4 medium; Quartile1 less Quartile2 less Quartile3 many Quartile4 less; Quartile1 less Quartile2 less Quartile3 many Quartile4 medium; Quartile1 less Quartile2 less Quartile3 medium Quartile4 less; Quartile1 less Quartile2 less Quartile3 medium Quartile4 many; Quartile1 less Quartile2 less Quartile3 medium Quartile4 medium; Quartile1 less Quartile2 many Quartile3 less Quartile4 less; Quartile1 less Quartile2 many Quartile3 less Quartile4 medium; Quartile1 less Quartile2 many Quartile3 medium Quartile4 less; Quartile1 less Quartile2 medium Quartile3 less Quartile4 less; Quartile1 less Quartile2 medium Quartile3 less Quartile4 many; Quartile1 less Quartile2 medium Quartile3 less Quartile4 medium; Quartile1 less Quartile2 medium Quartile3 many Quartile4 less; Quartile1 less Quartile2 medium Quartile3 many Quartile4 medium; Quartile1 less Quartile2 medium Quartile3 medium Quartile4 less; Quartile1 less Quartile2 medium Quartile3 medium Quartile4 medium; Quartile1 many Quartile2 less Quartile3 less Quartile4 less; Quartile1 many Quartile2 medium Quartile3 less Quartile4 less; Quartile1 medium Quartile2 less Quartile3 less Quartile4 less; Quartile1 medium Quartile2 less Quartile3 less Quartile4 medium; Quartile1 medium Quartile2 less Quartile3 medium Quartile4 less; Quartile1 medium Quartile2 many Quartile3 less Quartile4 less; Quartile1 medium Quartile2 many Quartile3 medium Quartile4 less; Quartile1 medium Quartile2 medium Quartile3 less Quartile4 less; Quartile1 medium Quartile2 medium Quartile3 less Quartile4 medium; Quartile1 medium Quartile2 medium Quartile3 medium Quartile4 less;	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13; 14; 15; 16; 17; 18; 19; 20; 21; 22; 23; 24; 25; 26; 27;

Continued on next page

Table 15 – continued from previous page

Feature name	Levels	Level values
DTW distance	Block1 high Block2 high Block3 high Block4 high Block5 high Block6 high Block7 high Block8 high Block9 high Block10 high Block11 high Block12 high Block13 high; Block1 high Block2 high Block3 medium Block4 high Block5 high Block6 high Block7 high Block8 high Block9 high Block10 high Block11 high Block12 high Block13 high; Block1 high Block2 high Block3 medium Block4 high Block5 high Block6 high Block7 high Block8 high Block9 high Block10 high Block11 high Block12 medium Block13 high; Block1 high Block2 high Block3 medium Block4 high Block5 medium Block6 high Block7 medium Block8 high Block9 high Block10 high Block11 high Block12 medium Block13 high; Block1 high Block2 medium Block3 medium Block4 medium Block5 medium Block6 medium Block7 medium Block8 medium Block9 medium Block10 medium Block11 high Block12 medium Block13 high; Block1 low Block2 high Block3 high Block4 high Block5 high Block6 high Block7 high Block8 high Block9 high Block10 high Block11 medium Block12 high Block13 medium; Block1 low Block2 high Block3 high Block4 high Block5 high Block6 high Block7 high Block8 high Block9 high Block10 high Block11 medium Block12 medium Block13 medium; Block1 low Block2 low Block3 high Block4 medium Block5 medium Block6 low Block7 medium Block8 medium Block9 medium Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 low Block3 low Block4 low Block5 low Block6 low Block7 low Block8 low Block9 low Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 low Block3 low Block4 medium Block5 low Block6 low Block7 low Block8 low Block9 low Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 low Block3 medium Block4 low Block5 low Block6 low Block7 low Block8 low Block9 low Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 low Block3 medium Block4 low Block5 medium Block6 low Block7 medium Block8 medium Block9 medium Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 low Block3 medium Block4 medium Block5 medium Block6 low Block7 medium Block8 medium Block9 medium Block10 low Block11 low Block12 low Block13 low; Block1 low Block2 medium Block3 high Block4 high Block5 high Block6 medium Block7 high Block8 high Block9 high Block10 medium Block11 medium Block12 medium Block13 medium; Block1 low Block2 medium Block3 high Block4 medium Block5 high Block6 medium Block7 high Block8 high Block9 high Block10 medium Block11 medium Block12 medium Block13 medium; Block1 low Block2 medium Block3 high Block4 medium Block5 medium Block6 low Block7 medium Block8 medium Block9 medium Block10 low Block11 low Block12 low Block13 low; Block1 medium Block2 low Block3 low Block4 low Block5 low Block6 low Block7 low Block8 low Block9 low Block10 low Block11 low Block12 low Block13 low; Block1 medium Block2 low Block3 low Block4 medium Block5 low Block6 low Block7 low Block8 low Block9 low Block10 low Block11 low Block12 low Block13 low; Block1 medium Block2 medium Block3 low Block4 medium Block5 low Block6 low Block7 low Block8 low Block9 low Block10 medium Block11 medium Block12 medium Block13 medium; Block1 medium Block2 medium Block3 low Block4 medium Block5 medium Block6 medium Block7 medium Block8 medium Block9 medium Block10 medium Block11 medium Block12 medium Block13 medium; Block1 medium Block2 medium Block3 medium Block4 high Block5 medium Block6 medium Block7 medium Block8 medium Block9 medium Block10 medium Block11 medium Block12 medium Block13 medium; Block1 medium Block2 medium Block3 medium Block4 medium Block5 medium Block6 medium Block7 medium Block8 medium Block9 medium Block10 medium Block11 medium Block12 medium Block13 medium;	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13; 14; 15; 16; 17; 18; 19; 20; 21; 22;
Turning points	medium; more oscillating; more steady; very oscillating; very steady;	1; 2; 3; 4; 5;
Partial autocorrelation	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Variance	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Outliers	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Step changes	great many abrupt changes; less abrupt changes; many abrupt changes; medium; very less abrupt changes;	1; 2; 3; 4; 5;
Peaks	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Durbin Watson test	negative autocorrelation; none because univariate; positive autocorrelation;	1; 2; 3;
Determination coefficient	high; low; medium; none because univariate TS; very high; very low;	1; 2; 3; 4; 5; 6;
Number of attributes	multivariate TS; univariate TS;	1; 2;

A.2 Classification results

Table 16 Basic time series taxonomy classification results

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-1	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-2	3	5	4	5	1	4	2	5	5	2	3	3	4	9	1	1	5	2	5	5	2	16	4	2
U-TS-3	2	5	3	5	2	4	2	2	5	2	3	1	4	9	1	1	5	3	5	5	2	16	4	2
U-TS-4	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-5	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-6	2	5	2	5	2	4	2	5	5	2	3	1	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-7	1	5	4	5	5	4	2	2	2	6	3	2	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-8	2	5	3	5	3	4	2	5	5	2	3	4	4	9	2	1	5	3	5	2	2	16	4	2
U-TS-9	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-10	3	5	4	2	1	4	2	5	5	2	3	1	4	9	1	1	5	2	5	5	2	16	4	2
U-TS-11	2	5	5	5	2	4	2	2	5	2	3	3	4	9	2	3	5	3	5	5	2	16	4	2
U-TS-12	2	5	2	5	5	4	2	2	5	2	3	4	4	9	2	1	5	5	5	5	2	16	4	2
U-TS-13	3	5	4	5	1	4	2	5	5	2	3	2	4	9	3	1	5	5	5	5	2	16	4	2
U-TS-14	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-15	3	5	2	2	5	4	2	5	6	2	3	1	4	9	2	3	5	3	5	5	2	25	4	2
U-TS-16	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	1	5	5	2	16	4	2
U-TS-17	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-18	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-19	2	5	2	5	2	4	2	5	5	2	3	1	4	9	2	3	5	3	5	5	2	16	4	2
U-TS-20	2	5	2	5	5	4	2	2	5	2	3	4	4	9	1	1	5	2	5	5	2	27	4	2
U-TS-21	2	5	5	2	3	4	2	5	4	2	3	1	4	9	1	1	5	3	5	5	2	16	4	2
U-TS-22	2	5	2	5	3	4	2	5	5	2	3	1	4	9	2	3	5	2	5	2	2	16	4	2
U-TS-23	2	5	1	2	1	4	2	5	5	2	3	1	4	9	2	1	5	2	5	5	2	16	4	2
U-TS-24	2	5	2	5	2	4	2	5	5	2	3	4	4	9	2	3	5	3	5	5	2	16	4	2
U-TS-25	3	5	1	5	1	4	2	5	5	2	3	1	4	9	1	1	5	2	5	5	2	16	4	2
U-TS-26	3	5	2	5	1	4	2	5	2	6	3	3	4	9	1	1	5	3	5	5	2	16	4	2
U-TS-27	3	5	2	2	5	4	2	5	1	2	3	1	4	9	2	1	5	2	5	2	2	17	4	2
U-TS-28	2	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-29	3	5	4	5	1	4	2	5	3	6	3	2	4	9	3	3	5	5	5	5	2	16	4	2
U-TS-30	3	5	4	5	1	4	2	5	5	2	3	2	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-31	1	5	4	5	1	4	2	5	5	2	3	2	4	9	3	1	5	5	5	5	2	16	4	2
U-TS-32	2	5	2	5	5	4	2	2	5	2	3	4	4	9	1	1	5	2	5	5	2	27	4	2
U-TS-33	1	5	4	2	3	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-34	3	5	1	5	3	4	2	5	5	2	3	3	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-35	2	5	2	5	5	4	2	2	5	2	3	3	4	9	4	1	5	3	5	5	2	16	4	2
U-TS-36	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-37	2	5	4	2	3	4	2	5	5	2	3	3	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-38	3	5	3	5	2	4	2	5	5	2	3	4	4	9	2	1	5	5	5	2	2	16	4	2
U-TS-39	3	5	4	5	1	4	2	5	5	2	3	2	4	9	3	1	5	5	5	5	2	16	4	2
U-TS-40	2	5	2	5	5	4	2	2	5	2	3	4	4	9	1	1	5	2	5	5	2	16	4	2
U-TS-41	2	5	2	5	2	4	2	2	5	2	3	1	4	9	2	3	5	3	5	5	2	16	4	2
U-TS-42	3	5	1	5	3	4	2	5	5	2	3	3	4	9	3	1	5	5	5	5	2	16	4	2
U-TS-43	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	2	5	5	2	16	4	2
U-TS-44	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-45	3	5	4	5	1	4	2	5	3	6	3	2	4	9	3	3	5	5	5	5	2	16	4	2
U-TS-46	1	2	5	5	3	4	2	2	5	2	3	3	4	9	3	1	5	5	5	5	2	16	4	2
U-TS-47	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-48	2	5	2	5	2	4	2	5	5	2	3	4	4	9	2	3	5	3	5	5	2	16	4	2
U-TS-49	2	5	2	5	2	4	2	5	5	2	3	4	4	9	2	1	5	1	5	5	2	16	4	2
U-TS-50	2	5	3	5	4	4	2	5	2	6	3	3	4	9	1	3	5	2	5	5	2	16	4	2
U-TS-51	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-52	3	5	4	2	1	4	2	5	5	2	3	3	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-53	3	5	2	5	2	4	2	2	5	2	3	4	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-54	2	2	4	4	3	4	2	2	4	4	4	5	4	9	1	4	5	5	5	5	2	20	4	2
U-TS-55	3	5	4	4	2	4	2	5	4	4	4	5	4	9	1	4	5	1	4	5	2	17	4	2
U-TS-56	2	2	4	4	3	4	2	2	4	4	4	5	4	9	1	4	5	5	5	5	2	20	4	2
U-TS-57	1	5	4	4	2	4	2	2	4	4	4	5	4	9	1	4	5	3	2	5	2	17	4	2
U-TS-58	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	1	4	5	2	7	4	2
U-TS-59	2	2	4	4	3	4	2	2	4	4	4	5	4	9	1	4	5	5	5	5	2	20	4	2
U-TS-60	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	1	4	5	2	7	4	2
U-TS-61	3	5	4	4	3	4	2	5	4	4	4	5	4	9	2	4	5	1	2	2	2	17	4	2
U-TS-62	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	1	4	5	2	7	4	2
U-TS-63	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	2	5	5	2	13	4	2
U-TS-64	3	5	1	4	3	4	2	5	4	4	4	3	4	9	2	4	5	3	5	5	2	16	4	2
U-TS-65	3	5	4	4	3	4	2	2	4	4	4	5	4	9	2	4	5	5	4	5	2	7	4	2
U-TS-66	3	5	4	4	1	4	2	5	4	4	4	5	4	9	2	4	5	1	2	2	2	17	4	2
U-TS-67	1	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	1	4	2	2	7	4	2
U-TS-68	2	5	4	3	3	4	2	5	6	6	1	5	4	9	2	1	5	2	2	5	2	17	4	2
U-TS-69	3	5	4	4	1	4	2	4	4	4	4	5	4	9	2	4	5	3	2	5	2	16	4	2
U-TS-70	3	4	4	3	1	4	2	3	6	6	4	5	4	9	1	3	5	3	5	1	2	22	4	2
U-TS-71	2	5	4	3	1	4	2	5	6	6	1	5	4	9	2	1	5	5	2	5	2	17	4	2
U-TS-72	3	5	4	2	3	4	2	5	4	6	1	1	4	9	1	3	5	3	5	5	2	16	4	2
U-TS-73	2	5	4	2	4	4	2	5	4	4	4	1	4	9	1	4	5	3	5	3	2	16	4	2
U-TS-74	3	5	4	4	3	4	2	5	4	4	4	2	4	9	1	4	5	4	5	2	2	27	4	2
U-TS-75	3	5	4	3	1	4	2	5	6	6	4	2	4	9	1	1	5	1	5	4	2	16	4	2
U-TS-76	1	2	4	3	5	4	2	5	6	6	4	5	4	9	1	3	5	3	2	5	2	12	4	2
U-TS-77	3	5	4	3	3	4	2	5	4	4	4	2	4	9	2	4	5	2	4	5	2	17	4	2
U-TS-78	3	5	4	3	1	4	2	5	4	4	4	2	4	9	1	1	5	3	2	2	2	27	4	2
U-TS-79	3	5	4	1	3	4	2	5	4	4	4	2	4	9	2	4	5	5	2	5	2	16	4	2
U-TS-80	1	5	4	3	3	4	2	5	4	4	4	2	4	9	2	1	5	5	2	5	2	27	4	2

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-81	3	5	4	1	1	4	2	5	4	4	4	5	4	9	1	4	5	3	5	2	2	17	4	2
U-TS-82	3	5	4	3	1	4	2	3	4	4	4	1	4	9	2	4	5	3	5	5	2	27	4	2
U-TS-83	2	5	4	1	1	4	2	5	4	4	4	5	4	9	2	4	5	5	2	5	2	17	4	2
U-TS-84	2	5	4	1	1	4	2	5	4	4	4	5	4	9	1	4	5	3	5	5	2	16	4	2
U-TS-85	1	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	3	3	5	2	17	4	2
U-TS-86	1	2	4	1	5	4	2	2	4	4	4	5	4	9	1	4	5	4	4	5	2	2	4	2
U-TS-87	3	5	4	2	3	4	2	5	4	4	4	3	4	9	2	1	5	3	2	5	2	16	4	2
U-TS-88	3	5	4	3	1	4	2	3	4	4	4	1	4	9	2	4	5	1	5	5	2	27	4	2
U-TS-89	3	5	4	1	1	4	2	5	4	4	4	3	4	9	1	4	5	1	5	2	2	16	4	2
U-TS-90	1	5	4	4	3	4	2	2	4	4	4	5	4	9	1	4	5	1	5	5	2	27	4	2
U-TS-91	3	5	4	2	3	4	2	5	4	4	4	1	4	9	1	1	5	2	5	5	2	16	4	2
U-TS-92	3	5	4	4	1	4	2	5	4	4	4	2	4	9	2	4	5	3	5	2	2	16	4	2
U-TS-93	1	5	4	2	3	4	2	5	4	4	4	1	4	9	1	1	5	1	2	5	2	16	4	2
U-TS-94	3	5	1	4	1	4	2	5	4	4	4	5	4	9	2	4	5	1	5	2	2	17	4	2
U-TS-95	1	5	1	4	2	4	2	5	4	4	4	2	4	9	1	4	5	3	5	2	2	25	4	2
U-TS-96	1	2	4	3	3	4	2	5	6	6	1	2	4	9	2	1	5	1	5	2	2	25	4	2
U-TS-97	3	5	4	4	1	4	2	5	4	4	4	2	4	9	1	4	5	5	2	5	2	16	4	2
U-TS-98	3	5	4	4	3	4	2	5	4	4	4	2	4	9	2	4	5	2	2	5	2	25	4	2
U-TS-99	3	5	4	2	1	4	2	5	4	4	4	1	4	9	1	1	5	4	2	3	2	16	4	2
U-TS-100	3	5	4	3	4	4	2	5	4	4	4	1	4	9	2	1	5	3	5	3	2	16	4	2
U-TS-101	3	5	4	3	1	4	2	5	4	4	4	3	4	9	2	4	5	3	2	3	2	16	4	2
U-TS-102	3	5	4	3	4	4	2	5	4	4	4	2	4	9	1	1	5	3	2	2	2	27	4	2
U-TS-103	3	5	4	2	3	4	2	5	4	4	4	1	4	9	2	1	5	2	5	5	2	16	4	2
U-TS-104	3	5	5	2	2	4	2	5	4	4	4	1	4	9	2	1	5	2	2	5	2	16	4	2
U-TS-105	1	5	4	2	2	4	2	5	4	4	4	3	4	9	1	4	5	1	2	2	2	17	4	2
U-TS-106	3	5	4	1	4	4	2	5	6	1	3	2	4	9	2	4	5	3	2	2	2	27	4	2
U-TS-107	1	5	4	2	2	4	2	5	4	4	4	2	4	9	2	1	5	1	4	5	2	16	4	2
U-TS-108	4	5	4	3	2	4	2	2	6	2	3	1	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-109	1	5	1	5	2	4	2	5	2	3	3	1	4	9	1	1	5	3	5	2	2	16	4	2
U-TS-110	1	5	4	2	2	4	2	4	3	2	3	3	4	9	2	1	5	2	5	5	2	16	4	2
U-TS-111	4	5	4	3	2	4	2	2	6	2	3	1	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-112	4	2	4	3	2	4	2	3	6	2	3	3	4	9	2	4	5	3	5	2	2	16	4	2
U-TS-113	5	3	4	3	3	4	2	3	2	2	3	1	4	9	3	4	5	3	5	5	2	26	4	2
U-TS-114	1	5	1	2	2	4	2	1	6	3	3	2	4	9	1	1	5	3	5	5	2	17	4	2
U-TS-115	1	5	3	5	5	4	2	4	6	3	3	1	4	9	1	1	5	2	5	2	2	27	4	2
U-TS-116	1	5	1	2	2	4	2	5	6	3	3	3	4	9	2	1	5	3	5	5	2	16	4	2
U-TS-117	3	5	4	3	3	4	2	5	6	6	1	5	4	9	2	3	5	2	5	5	2	23	4	2
U-TS-118	5	2	1	4	5	4	2	3	6	5	3	5	4	9	1	4	5	2	5	5	2	3	4	2
U-TS-119	3	5	4	3	2	4	2	5	6	6	1	5	4	9	1	3	5	2	4	5	2	17	4	2
U-TS-120	5	3	4	3	3	4	2	5	6	2	3	2	4	9	1	1	5	3	2	5	2	13	4	2
U-TS-121	3	5	4	3	2	4	2	4	6	6	1	5	4	9	2	1	5	1	3	5	2	6	4	2
U-TS-122	3	5	4	3	3	4	2	5	6	6	3	2	4	9	1	3	5	5	2	2	2	25	4	2
U-TS-123	3	5	4	3	3	4	2	5	6	6	1	2	4	9	3	1	5	3	5	5	2	17	4	2
U-TS-124	3	5	4	3	1	4	2	5	6	6	3	1	4	9	2	1	5	3	5	2	2	25	4	2
U-TS-125	3	5	4	3	3	4	2	5	6	6	1	5	4	9	2	1	5	3	2	3	2	17	4	2
U-TS-126	3	5	3	2	1	4	2	5	3	3	3	3	4	9	3	1	5	3	5	5	2	11	4	2
U-TS-127	3	5	1	2	3	4	2	5	4	4	4	4	4	9	1	4	5	3	5	3	2	27	4	2
U-TS-128	3	5	3	5	1	4	2	5	1	3	3	3	4	9	3	3	5	3	5	5	2	16	4	2
U-TS-129	3	5	4	3	2	4	2	5	6	6	1	2	4	9	2	1	5	1	2	5	2	7	4	2
U-TS-130	3	5	1	2	3	4	2	5	4	4	4	4	4	9	1	4	5	3	5	3	2	27	4	2
U-TS-131	3	5	1	2	3	4	2	5	4	4	4	4	4	9	1	4	5	3	5	3	2	27	4	2
U-TS-132	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	3	5	5	2	23	4	2
U-TS-133	3	5	3	2	1	4	2	5	3	3	3	3	4	9	3	1	5	3	5	5	2	11	4	2
U-TS-134	3	5	3	2	1	4	2	5	3	3	3	3	4	9	3	1	5	3	5	5	2	11	4	2
U-TS-135	1	5	3	2	5	4	2	2	6	2	3	4	1	9	3	4	5	3	5	5	2	16	4	2
U-TS-136	3	5	4	4	1	4	2	5	4	4	4	2	4	9	2	4	5	4	5	5	2	16	4	2
U-TS-137	3	5	4	3	3	4	2	5	6	2	3	5	4	9	1	4	5	5	2	5	2	17	4	2
U-TS-138	1	5	2	2	2	4	2	5	6	5	3	4	4	9	1	4	5	3	5	5	2	27	4	2
U-TS-139	3	2	4	3	3	4	2	5	6	6	1	5	4	9	2	1	5	3	2	5	2	10	4	2
U-TS-140	1	5	5	5	5	4	2	2	6	3	3	4	4	9	1	1	5	3	5	5	2	27	4	2
U-TS-141	1	5	3	2	5	4	2	2	6	2	3	4	1	9	3	4	5	3	5	5	2	16	4	2
U-TS-142	1	5	3	2	5	4	2	5	6	5	3	4	4	9	1	4	5	2	5	5	2	25	4	2
U-TS-143	3	5	4	3	2	4	2	5	6	6	1	5	4	9	2	1	5	4	3	5	2	7	4	2
U-TS-144	3	5	4	3	3	4	2	5	6	6	1	5	4	9	2	1	5	2	2	5	2	7	4	2
U-TS-145	3	5	3	5	3	4	2	5	4	4	4	1	4	9	1	3	5	3	5	1	2	16	4	2
U-TS-146	3	5	4	5	3	4	2	5	6	6	1	1	4	9	1	3	5	3	5	5	2	16	4	2
U-TS-147	3	5	4	4	3	4	2	5	4	4	4	5	4	9	1	4	5	5	4	2	2	7	4	2
U-TS-148	1	5	4	2	5	4	2	5	4	4	4	2	4	9	2	3	5	1	5	5	2	25	4	2
U-TS-149	2	5	3	5	3	4	2	5	4	4	4	1	4	9	1	3	5	3	5	5	2	16	4	2
U-TS-150	1	5	4	3	3	4	2	5	4	4	4	4	4	9	1	4	5	2	5	5	2	25	4	2
U-TS-151	1	5	1	2	5	4	2	5	6	6	1	4	3	9	1	3	5	2	5	5	2	17	4	2
U-TS-152	3	5	1	5	3	4	2	5	6	6	1	1	4	9	1	3	5	1	5	5	2	16	4	2
U-TS-153	1	5	4	2	2	4	2	5	3	2	3	4	4	9	1	1	5	3	5	5	2	16	4	2
U-TS-154	4	5	5	5	5	4	2	2	6	3	3	4	4	9	1	1	5	3	5	2	2	16	4	2
U-TS-155	1	5	3	2	5	4	2	4	2	2	3	4	1	9	1	1	5	2	5	5	2	27	4	2
U-TS-156	3	5	5	1	1	4	2	5	2	5	3	2	4	9	4	4	5	1	5	5	2	16	4	2
U-TS-157	3	2	4	3	2	4	2	5	6	6	1	5	4	9	1	1	5	1	4	5	2	1	4	2
U-TS-158	3	5	5	1	1	4	2	5	2	5	3	2	4	9	4	4	5	1	5	5	2	16	4	2
U-TS-159	3	2	4	3	2	4	2	5	6	6	1	5	4	9	1	1	5	1	4	5	2	1	4	2
U-TS-160	3	5	5	1	1	4	2	5	2	5	3	2	4	9	4	4	5	1	5	5	2	16	4	2
U-TS-161	1	5	4	2	2	4	2	5	3	2	3	4	4	9	1	1	5	3	5	5	2	16	4	2
U-TS-162	2	5	4	3	3	4	2	5	3	6	1	2	4	9	1	3	5	5	2	1	2	17	4	2
U-TS-163	1	5	4	5	2	4	2	5	1	6	3	4	4	9	3	1	5	3	5	3	2	16	4	2
U-TS-164	1	5	4	2	3	4	2	5	4	5	5	1	4	9	2	1	5	3	2	3	2	16	4	2
U-TS-165	3	2	4	3	1	4	2	5	2	6	3	2	4	9	1	1	5	5	2	3	2	16	4	2
U-TS-166	3	5	5	2	3	4	2	5	4	6	3	4	4	9	3	1	5	3	5	5	2	16	4	2

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ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-167	1	5	4	2	3	4	2	5	5	6	3	4	4	9	2	1	5	3	5	5	2	27	4	2
U-TS-168	3	5	5	3	1	4	2	5	4	1	3	4	4	9	1	4	5	2	5	5	2	16	4	2
U-TS-169	3	5	4	3	1	4	2	5	2	6	1	1	4	9	1	3	5	2	5	5	2	16	4	2
U-TS-170	3	5	4	3	3	4	2	5	2	6	3	5	4	9	2	1	5	2	5	5	2	17	4	2
U-TS-171	3	5	4	3	2	4	2	5	1	6	3	3	4	9	2	1	5	2	2	2	2	7	4	2
U-TS-172	1	5	4	3	5	4	2	5	6	6	1	2	4	9	3	1	5	1	5	5	2	16	4	2
U-TS-173	3	5	4	2	5	4	2	5	4	4	4	2	4	9	2	1	5	1	2	5	2	14	4	2
U-TS-174	2	5	4	2	3	4	2	5	4	4	4	2	4	9	4	1	5	1	2	5	2	16	4	2
U-TS-175	3	5	3	5	1	4	2	5	4	4	4	1	4	9	2	1	5	3	5	3	2	16	4	2
U-TS-176	5	3	2	5	2	4	2	5	6	6	1	1	5	9	3	2	5	3	5	5	2	26	4	2
U-TS-177	2	5	4	3	3	4	2	5	6	6	1	4	4	9	2	1	5	2	2	5	2	17	4	2
U-TS-178	3	5	4	3	3	4	2	5	4	4	4	5	4	9	3	3	5	5	3	5	2	7	4	2
U-TS-179	3	5	1	2	1	4	2	5	2	2	3	1	4	9	1	1	5	5	2	5	2	16	4	2
U-TS-180	3	5	3	2	3	4	2	5	4	4	4	4	4	9	1	4	5	3	5	5	2	27	4	2
U-TS-181	3	5	4	4	3	4	2	5	3	5	3	5	4	9	3	4	5	3	4	5	2	17	4	2
U-TS-182	3	5	4	3	2	4	2	5	6	6	4	2	4	9	3	3	5	1	2	5	2	1	4	2
U-TS-183	4	5	4	2	2	4	2	4	5	6	3	3	4	9	4	1	5	2	5	5	2	17	4	2
U-TS-184	1	5	4	3	3	4	2	5	4	4	1	2	4	9	3	4	5	5	2	2	2	17	4	2
U-TS-185	3	5	3	2	3	4	2	5	4	4	4	4	4	9	1	1	5	3	2	3	2	17	4	2
U-TS-186	4	5	1	5	4	4	2	5	4	4	4	1	4	9	5	1	5	3	5	1	2	16	4	2
U-TS-187	3	5	4	2	4	4	2	5	4	4	4	1	4	9	3	1	5	3	2	3	2	27	4	2
U-TS-188	3	5	4	3	2	4	2	5	6	6	1	1	4	9	3	1	5	2	2	5	2	7	4	2
U-TS-189	3	5	4	2	1	4	2	5	4	4	1	2	4	9	5	3	5	1	2	5	2	27	4	2
U-TS-190	3	5	4	3	2	4	2	5	6	6	4	4	4	9	3	3	5	2	2	5	2	17	4	2
U-TS-191	1	2	4	3	5	4	2	5	6	6	1	3	1	9	3	3	5	2	2	5	2	7	4	2
U-TS-192	3	5	4	3	2	4	2	5	1	3	3	5	4	9	5	1	5	4	5	5	2	23	4	2
U-TS-193	3	5	4	3	2	4	2	5	2	6	3	1	4	9	3	1	5	3	4	5	2	17	4	2
U-TS-194	3	5	1	5	2	4	2	5	6	6	1	4	4	9	3	3	5	2	5	5	2	22	4	2
U-TS-195	3	5	4	3	3	4	2	5	6	6	1	2	4	9	3	3	5	2	2	5	2	17	4	2
U-TS-196	4	3	4	3	3	4	2	2	4	4	4	3	4	9	2	4	5	1	2	2	2	11	4	2
U-TS-197	2	5	3	5	3	4	2	5	6	6	3	1	4	9	2	1	5	3	5	5	2	25	4	2
U-TS-198	1	5	4	2	2	4	2	5	4	4	4	3	4	9	1	3	5	3	2	2	2	17	4	2
U-TS-199	3	5	4	3	1	4	2	5	6	6	3	2	4	9	1	3	5	1	2	5	2	27	4	2
U-TS-200	1	5	4	2	3	4	2	5	6	6	1	1	4	9	3	3	5	1	2	2	2	16	4	2
U-TS-201	3	5	4	4	3	4	2	5	2	5	3	2	4	9	2	4	5	3	2	2	2	27	4	2
U-TS-202	1	5	1	2	2	4	2	5	4	4	4	1	4	9	4	3	5	2	5	2	2	27	4	2
U-TS-203	3	5	1	2	5	4	2	5	6	6	3	2	4	9	5	4	5	1	2	5	2	1	4	2
U-TS-204	3	5	4	2	3	4	2	5	4	4	4	3	4	9	1	3	5	3	5	3	2	25	4	2
U-TS-205	1	5	4	3	3	4	2	5	5	6	3	4	4	9	2	1	5	3	5	2	2	16	4	2
U-TS-206	3	5	4	2	3	4	2	5	4	4	4	2	4	9	2	1	5	5	2	2	2	21	4	2
U-TS-207	3	5	4	1	1	4	2	5	2	5	3	4	4	9	3	4	5	1	5	3	2	17	4	2
U-TS-208	3	5	4	2	4	4	2	5	4	4	1	2	4	9	3	1	5	1	5	5	2	17	4	2
U-TS-209	3	5	4	4	2	4	2	5	4	4	4	5	4	9	2	4	5	1	1	5	2	7	4	2
U-TS-210	3	5	2	5	1	4	2	5	4	4	4	3	2	9	5	1	5	1	5	1	2	16	4	2
U-TS-211	2	5	4	3	3	4	2	5	4	4	4	5	4	9	2	4	5	5	4	5	2	7	4	2
U-TS-212	3	5	4	2	1	4	2	5	6	6	1	1	4	9	2	3	5	4	5	4	2	16	4	2
U-TS-213	3	5	4	2	1	4	2	5	4	4	4	1	4	9	3	1	5	2	2	3	2	16	4	2
U-TS-214	1	5	3	5	3	4	2	5	6	6	1	3	5	9	5	3	5	3	5	5	2	27	4	2
U-TS-215	1	5	3	5	1	4	2	5	6	6	1	3	5	9	5	2	5	1	5	1	2	27	4	2
U-TS-216	3	5	4	2	3	4	2	5	4	4	1	5	4	9	3	3	5	3	5	2	2	16	4	2
U-TS-217	1	5	4	3	3	4	2	5	4	4	4	5	4	9	1	3	5	2	4	5	2	7	4	2
U-TS-218	3	5	4	2	1	4	2	5	3	6	1	3	4	9	3	2	5	3	5	5	2	17	4	2
U-TS-219	3	5	4	2	1	4	2	5	3	6	1	1	4	9	3	3	5	2	5	1	2	17	4	2
U-TS-220	1	5	4	2	3	4	2	5	2	6	1	3	4	9	2	3	5	2	2	5	2	16	4	2
U-TS-221	3	5	1	5	1	4	2	5	3	6	1	2	2	9	5	3	5	4	5	1	2	16	4	2
U-TS-222	3	5	4	3	3	4	2	5	4	4	4	2	4	9	2	3	5	3	3	5	2	17	4	2
U-TS-223	3	5	4	2	3	4	2	5	4	4	4	1	4	9	2	3	5	2	2	3	2	17	4	2
U-TS-224	3	5	3	5	3	4	2	5	4	4	4	2	1	9	5	1	5	2	5	5	2	16	4	2
U-TS-225	3	5	4	5	2	4	2	3	5	6	1	3	2	9	5	3	5	2	5	5	2	24	4	2
U-TS-226	1	5	4	2	3	4	2	5	1	6	1	3	4	9	3	3	5	1	2	3	2	17	4	2
U-TS-227	1	5	4	3	2	4	2	5	4	4	1	5	4	9	3	3	5	1	1	5	2	6	4	2
U-TS-228	3	5	4	3	3	4	2	5	1	6	4	3	4	9	5	3	5	2	2	5	2	17	4	2
U-TS-229	3	5	4	2	3	4	2	5	4	4	4	1	4	9	3	1	5	3	5	5	2	16	4	2
U-TS-230	3	5	4	2	2	4	2	5	3	6	1	1	4	9	1	3	5	2	2	1	2	17	4	2
U-TS-231	3	5	4	3	2	4	2	5	4	4	4	5	4	9	2	1	5	3	4	5	2	7	4	2
U-TS-232	3	5	4	3	1	4	2	5	4	4	4	2	4	9	3	3	5	2	2	5	2	17	4	2
U-TS-233	3	5	4	2	2	4	2	5	4	4	4	1	4	9	1	1	5	3	4	5	2	7	4	2
U-TS-234	5	2	4	5	1	4	2	5	6	6	1	3	3	9	3	3	5	1	5	5	2	10	4	2
U-TS-235	1	5	4	2	3	4	2	5	4	4	4	3	4	9	3	1	5	3	2	3	2	17	4	2
U-TS-236	3	5	4	2	3	4	2	5	4	4	4	1	4	9	1	3	5	1	2	5	2	16	4	2
U-TS-237	1	5	4	5	1	4	2	5	4	4	4	3	4	9	2	3	5	1	5	2	2	27	4	2
U-TS-238	1	5	4	5	1	4	2	5	4	4	4	3	4	9	1	2	5	3	2	3	2	16	4	2
U-TS-239	1	5	4	2	2	4	2	5	2	2	3	3	4	9	3	4	5	3	2	5	2	17	4	2
U-TS-240	3	5	4	2	3	4	2	5	6	6	1	1	4	9	3	3	5	3	5	5	2	16	4	2
U-TS-241	3	5	3	5	1	4	2	5	2	6	3	3	4	9	2	1	5	3	5	5	2	27	4	2
U-TS-242	1	5	4	2	3	4	2	5	4	2	3	2	4	9	3	2	5	1	2	3	2	16	4	2
U-TS-243	1	5	3	5	3	4	2	5	4	4	4	2	3	9	5	2	5	3	5	1	2	16	4	2
U-TS-244	3	5	1	2	2	4	2	5	2	2	3	1	4	9	2	4	5	3	2	5	2	17	4	2
U-TS-245	1	5	4	2	3	4	2	5	1	6	1	3	4	9	5	3	5	3	2	5	2	17	4	2
U-TS-246	1	5	4	5	3	4	2	5	5	6	1	2	5	9	5	3	5	3	5	3	2	16	4	2
U-TS-247	3	5	4	3	1	4	2	5	3	6	1	2	4	9	1	3	5	2	5	3	2	17	4	2
U-TS-248	3	5	4	2	1	4	2	5	2	6	1	1	4	9	5	3	5	5	2	5	2	17	4	2
U-TS-249	1	5	4	2	1	4	2	5	6	6	1	3	4	9	1	3	5	3	5	1	2	16	4	2
U-TS-250	3	5	4	2	3	4	2	5	1	2	3	2	4	9	2	1	5	3	2	5	2	17	4	2
U-TS-251	2	5	1	2	2	4	2	5	4	4	4	3	4	9	2	1	5	3	2	5	2	17	4	2
U-TS-252	3	5	4	2	3	4	2	5	4	4	4	3	4	9	2	3	5	2	4	5	2	16	4	2

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-253	1	5	4	2	3	4	2	5	4	4	4	4	4	9	3	1	5	3	5	5	2	27	4	2
U-TS-254	1	5	1	5	3	4	2	5	4	5	5	1	4	9	3	1	5	3	5	3	2	25	4	2
U-TS-255	3	5	4	2	3	4	2	5	4	4	4	2	4	9	2	1	5	3	2	5	2	7	4	2
U-TS-256	1	5	4	2	3	4	2	5	3	6	4	3	4	9	5	3	5	3	2	4	2	17	4	2
U-TS-257	3	5	4	2	1	4	2	5	4	4	4	3	4	9	1	2	5	2	2	3	2	16	4	2
U-TS-258	2	5	4	5	1	4	2	5	4	4	1	1	4	9	1	3	5	4	2	5	2	16	4	2
U-TS-259	1	5	4	2	3	4	2	5	4	4	4	3	4	9	2	3	5	2	2	5	2	17	4	2
U-TS-260	1	5	4	3	3	4	2	5	4	4	4	2	4	9	1	1	5	5	3	5	2	7	4	2
U-TS-261	3	5	4	2	3	4	2	5	4	4	4	1	4	9	3	3	5	3	5	5	2	25	4	2
U-TS-262	3	5	4	2	1	4	2	5	4	4	4	2	4	9	3	2	5	5	2	5	2	27	4	2
U-TS-263	1	5	4	2	2	4	2	5	4	4	4	2	4	9	2	3	5	3	5	5	2	23	4	2
U-TS-264	3	5	4	2	3	4	2	5	4	4	4	1	4	9	1	3	5	2	2	3	2	16	4	2
U-TS-265	1	5	4	5	2	4	2	5	4	4	4	3	4	9	2	2	5	2	5	5	2	16	4	2
U-TS-266	1	5	4	3	3	4	2	5	4	4	4	3	4	9	2	1	5	3	2	5	2	7	4	2
U-TS-267	3	5	4	3	1	4	2	5	6	6	3	2	4	9	2	1	5	5	2	3	2	17	4	2
U-TS-268	3	5	4	2	3	4	2	5	4	4	4	2	4	9	1	2	5	5	2	5	2	16	4	2
U-TS-269	3	5	4	2	3	4	2	5	4	4	4	2	4	9	1	2	5	2	4	5	2	17	4	2
U-TS-270	3	5	4	2	1	4	2	5	6	6	3	5	4	9	1	1	5	2	5	5	2	17	4	2
U-TS-271	3	5	4	5	3	4	2	5	4	4	4	2	4	9	2	5	5	2	2	5	2	17	4	2
U-TS-272	3	5	4	2	4	4	2	5	4	4	4	2	4	9	2	2	5	3	5	2	2	16	4	2
U-TS-273	3	2	4	2	1	4	2	2	4	4	4	2	4	9	1	2	5	1	5	5	2	17	4	2
U-TS-274	2	5	4	2	3	4	2	5	4	4	4	2	4	9	3	3	5	2	2	5	2	17	4	2
U-TS-275	2	5	1	5	3	4	2	5	4	4	4	2	4	9	3	3	5	1	2	5	2	2	4	2
U-TS-276	3	5	4	5	2	4	2	5	4	4	4	3	4	9	4	5	5	3	2	3	2	16	4	2
U-TS-277	1	5	4	2	2	4	2	5	4	4	1	3	4	9	3	2	5	4	4	3	2	2	4	2
U-TS-278	3	5	4	2	1	4	2	5	4	4	4	2	4	9	2	2	5	5	2	3	2	16	4	2
U-TS-279	3	5	4	2	3	4	2	5	4	4	4	2	4	9	1	2	5	1	4	5	2	17	4	2
U-TS-280	1	5	4	3	3	4	2	5	4	4	4	2	4	9	1	3	5	5	4	5	2	7	4	2
U-TS-281	1	5	4	2	3	4	2	5	4	4	1	2	4	9	2	2	5	5	4	5	2	17	4	2
U-TS-282	1	5	4	2	3	4	2	5	4	4	3	5	4	9	5	5	5	3	1	5	2	7	4	2
U-TS-283	2	5	1	5	1	4	2	5	4	4	4	3	4	9	1	2	5	4	2	5	2	27	4	2
U-TS-284	3	5	4	2	3	4	2	5	4	4	1	2	4	9	3	2	5	2	3	5	2	7	4	2
U-TS-285	3	5	4	2	1	4	2	5	4	5	5	2	4	9	5	2	5	5	2	2	2	17	4	2
U-TS-286	3	5	4	5	1	4	2	5	4	6	5	2	4	9	3	5	5	5	4	3	2	17	4	2
U-TS-287	2	5	4	5	3	4	2	5	4	6	3	2	4	9	1	5	5	5	4	1	2	7	4	2
U-TS-288	4	5	4	5	3	4	2	5	4	4	4	2	4	9	3	2	5	2	4	1	2	7	4	2
U-TS-289	3	5	4	5	2	4	2	5	4	2	3	2	4	9	1	5	5	4	2	3	2	2	4	2
U-TS-290	1	5	4	2	1	4	2	5	4	6	3	3	4	9	3	2	5	1	5	3	2	17	4	2
U-TS-291	3	5	4	5	1	4	2	5	4	3	5	2	4	9	1	5	5	2	4	1	2	27	4	2
U-TS-292	1	5	4	5	2	4	2	5	4	4	1	3	4	9	2	5	5	3	5	5	2	27	4	2
U-TS-293	3	5	4	2	3	4	2	5	4	4	3	5	4	9	5	3	5	3	3	2	2	7	4	2
U-TS-294	2	5	4	5	2	4	2	5	4	4	4	3	4	9	1	3	5	3	2	5	2	5	4	2
U-TS-295	1	5	4	5	2	4	2	5	4	4	4	2	4	9	2	5	5	3	2	5	2	13	4	2
U-TS-296	1	5	4	2	2	4	2	5	4	4	1	2	4	9	1	5	5	3	3	5	2	7	4	2
U-TS-297	3	5	4	2	2	4	2	5	4	4	1	5	4	9	3	5	5	3	1	5	2	7	4	2
U-TS-298	3	5	5	5	3	4	2	5	4	4	4	5	5	9	5	3	5	3	5	5	2	16	4	2
U-TS-299	3	5	4	5	1	4	2	5	4	4	1	3	4	9	1	5	5	5	5	2	2	16	4	2
U-TS-300	1	5	4	2	1	4	2	5	2	6	3	2	4	9	3	3	5	5	2	2	2	17	4	2
U-TS-301	1	5	5	5	1	4	2	5	4	4	1	5	1	9	3	3	5	5	2	5	3	16	6	1
U-TS-302	1	5	1	5	3	4	2	5	4	6	1	5	1	9	3	3	5	3	2	2	1	16	1	1
U-TS-303	3	5	1	5	3	4	2	5	4	6	1	5	1	9	5	3	5	3	2	2	1	16	5	1
U-TS-304	3	5	3	5	1	4	2	5	4	6	3	2	1	9	1	3	5	3	5	2	1	16	5	1
U-TS-305	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	5	3	1	16	5	1
U-TS-306	3	5	1	5	1	4	2	5	4	6	2	5	4	9	1	3	5	2	2	3	1	27	5	1
U-TS-307	3	5	3	5	3	4	2	5	4	6	1	5	1	9	3	3	5	2	5	2	1	16	5	1
U-TS-308	1	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	3	1	27	5	1
U-TS-309	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	3	5	5	5	2	3	16	5	1
U-TS-310	1	5	4	5	1	4	2	5	4	6	3	5	4	9	1	3	5	3	2	3	3	27	5	1
U-TS-311	1	5	1	5	3	4	2	5	4	6	3	5	1	9	3	3	5	3	5	3	1	16	5	1
U-TS-312	3	5	3	5	3	4	2	5	4	6	4	5	3	9	3	1	5	3	5	2	1	27	1	1
U-TS-313	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	2	2	2	1	16	5	1
U-TS-314	3	5	4	5	1	1	2	5	4	6	3	5	4	9	1	3	5	3	2	2	1	27	5	1
U-TS-315	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	3	1	16	5	1
U-TS-316	3	5	1	5	1	4	2	5	4	6	1	5	1	9	1	3	5	3	2	2	3	16	1	1
U-TS-317	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	2	5	2	1	16	5	1
U-TS-318	3	5	1	5	3	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	1	16	5	1
U-TS-319	2	5	1	5	1	4	2	5	4	6	1	2	1	9	3	3	5	3	5	3	1	27	5	1
U-TS-320	3	5	4	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	2	3	1	16	5	1
U-TS-321	3	5	4	5	1	4	2	5	4	6	3	2	4	9	1	3	5	2	2	2	1	27	5	1
U-TS-322	3	5	3	5	1	4	2	5	4	6	4	5	1	9	1	3	5	3	2	2	1	27	5	1
U-TS-323	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	3	5	2	2	1	1	27	5	1
U-TS-324	3	5	4	5	1	4	2	5	4	6	2	2	1	9	1	3	5	3	5	1	1	27	5	1
U-TS-325	3	5	4	5	3	4	2	5	4	6	1	5	1	9	1	3	5	3	5	3	1	27	5	1
U-TS-326	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	3	1	16	5	1
U-TS-327	3	5	3	5	3	4	2	5	4	6	1	5	3	9	5	3	5	3	5	2	1	16	5	1
U-TS-328	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	5	3	1	27	5	1
U-TS-329	3	5	4	5	1	4	2	5	4	6	2	5	1	9	1	3	5	3	5	3	1	16	5	1
U-TS-330	1	5	1	5	3	4	2	5	4	6	1	2	1	9	3	3	5	3	2	2	1	16	5	1
U-TS-331	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	3	5	3	2	3	1	27	5	1
U-TS-332	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	5	2	3	16	5	1
U-TS-333	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	1	5	3	5	3	3	27	5	1
U-TS-334	3	5	4	5	1	4	2	5	4	6	3	2	1	9	1	3	5	2	2	3	1	16	5	1
U-TS-335	3	5	1	5	3	4	2	5	4	6	1	5	4	9	1	3	5	2	2	2	1	17	5	1
U-TS-336	3	5	4	5	1	4	2	5	4	6	2	5	1	9	1	3	5	2	2	3	1	27	5	1
U-TS-337	3	5	3	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	1	16	5	1
U-TS-338	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	5	2	1	27	5	1

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ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-339	3	5	4	5	1	4	2	5	4	6	3	5	4	9	1	3	5	3	2	3	1	27	5	1
U-TS-340	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	5	3	1	27	5	1
U-TS-341	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	1	1	16	5	1
U-TS-342	1	5	1	5	3	4	2	5	4	6	1	5	1	9	3	3	5	2	2	2	1	16	5	1
U-TS-343	3	5	4	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	2	3	1	27	5	1
U-TS-344	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	2	2	3	1	16	5	1
U-TS-345	3	5	3	5	3	4	2	5	4	6	1	5	3	9	3	3	5	3	5	2	1	16	5	1
U-TS-346	3	5	4	5	1	4	2	5	4	6	3	2	1	9	3	3	5	3	5	1	1	16	5	1
U-TS-347	3	5	4	5	1	4	2	5	4	6	3	5	4	9	3	3	5	2	2	3	1	27	1	1
U-TS-348	1	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	2	5	3	1	16	5	1
U-TS-349	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	1	5	2	5	2	1	16	5	1
U-TS-350	3	5	4	5	1	4	2	5	4	6	2	5	1	9	1	3	5	3	5	3	1	16	5	1
U-TS-351	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	2	3	3	16	5	1
U-TS-352	3	5	3	5	1	4	2	5	4	6	1	5	1	9	5	3	5	3	5	5	1	27	5	1
U-TS-353	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	5	2	1	24	5	1
U-TS-354	1	5	3	5	3	4	2	5	4	6	1	5	3	9	3	3	5	2	2	2	1	27	5	1
U-TS-355	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	5	3	3	27	5	1
U-TS-356	3	5	1	5	1	4	2	5	4	6	2	5	4	9	1	3	5	2	2	3	1	27	5	1
U-TS-357	1	5	1	5	3	4	2	5	4	6	3	5	1	9	3	3	5	2	5	3	1	27	5	1
U-TS-358	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	3	27	5	1
U-TS-359	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	2	5	2	1	27	5	1
U-TS-360	3	5	1	5	3	4	2	5	4	6	3	5	1	9	1	3	5	3	5	3	1	27	2	1
U-TS-361	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	1	1	27	5	1
U-TS-362	1	5	3	5	3	3	2	5	4	6	3	5	1	9	3	3	5	2	5	2	3	27	5	1
U-TS-363	3	5	3	5	1	4	2	5	4	6	1	5	3	9	3	3	5	3	5	2	3	27	5	1
U-TS-364	3	5	3	5	3	4	2	5	4	6	3	5	1	9	3	3	5	2	2	2	1	27	5	1
U-TS-365	3	5	4	5	1	2	2	5	4	6	3	2	4	9	3	3	5	1	2	1	1	27	5	1
U-TS-366	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	1	3	27	5	1
U-TS-367	3	5	1	5	1	4	2	5	4	6	1	5	1	9	1	3	5	3	2	2	3	27	5	1
U-TS-368	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	5	2	1	27	5	1
U-TS-369	3	5	1	5	3	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	1	27	5	1
U-TS-370	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	5	3	3	27	5	1
U-TS-371	3	5	4	5	1	4	2	5	4	6	3	5	3	9	1	3	5	3	5	3	1	27	5	1
U-TS-372	3	5	4	5	1	4	2	5	4	6	3	5	4	9	3	3	5	2	2	3	1	27	5	1
U-TS-373	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	2	3	3	27	5	1
U-TS-374	3	5	1	5	1	1	2	5	4	6	1	5	1	9	1	3	5	2	2	3	1	27	5	1
U-TS-375	1	5	1	5	1	4	2	5	4	6	2	5	1	9	1	3	5	3	5	3	3	24	5	1
U-TS-376	3	5	1	5	1	4	2	5	4	6	1	5	1	9	1	3	5	2	5	2	1	27	5	1
U-TS-377	3	5	1	5	1	4	2	5	4	6	1	5	1	9	1	3	5	3	2	2	1	27	5	1
U-TS-378	1	5	3	5	3	4	2	5	4	6	3	5	2	9	5	3	5	3	5	2	3	27	5	1
U-TS-379	3	5	3	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	5	2	1	27	5	1
U-TS-380	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	5	2	1	24	5	1
U-TS-381	1	5	1	5	3	4	2	5	4	6	4	5	3	9	3	3	5	1	5	2	3	27	5	1
U-TS-382	3	5	4	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	5	1	1	27	5	1
U-TS-383	3	5	1	5	1	4	2	5	4	6	3	5	3	9	3	3	5	3	5	3	1	27	5	1
U-TS-384	1	5	1	5	3	4	2	5	4	6	1	5	1	9	3	3	5	3	5	2	1	27	1	1
U-TS-385	3	5	4	5	1	4	2	5	4	6	3	5	1	9	3	3	5	2	2	3	1	24	5	1
U-TS-386	3	5	4	5	3	4	2	5	4	6	3	5	1	9	3	3	5	3	2	3	1	16	5	1
U-TS-387	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	1	1	27	5	1
U-TS-388	3	5	3	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	1	27	5	1
U-TS-389	3	5	3	5	1	4	2	5	4	6	3	5	1	9	3	3	5	3	2	2	1	27	5	1
U-TS-390	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	3	5	3	2	3	1	27	5	1
U-TS-391	1	5	1	5	3	4	2	5	4	6	1	5	1	9	3	3	5	3	5	3	3	27	5	1
U-TS-392	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	3	5	3	2	3	3	27	5	1
U-TS-393	1	5	3	5	3	4	2	5	4	6	1	5	1	9	3	3	5	3	2	2	3	16	5	1
U-TS-394	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	3	5	3	2	2	1	27	5	1
U-TS-395	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	3	5	2	2	3	1	27	5	1
U-TS-396	3	5	3	5	1	4	2	5	4	6	3	5	3	9	3	3	5	3	5	2	1	27	5	1
U-TS-397	3	5	1	5	1	4	2	5	4	6	1	5	2	9	5	3	5	3	5	3	1	27	5	1
U-TS-398	3	5	1	5	1	4	2	5	4	6	3	5	4	9	3	3	5	2	2	3	1	27	5	1
U-TS-399	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	3	5	2	2	3	1	27	5	1
U-TS-400	3	5	3	5	1	4	2	5	4	6	1	5	3	9	3	3	5	2	5	2	1	27	5	1
U-TS-401	3	2	4	3	2	4	2	2	4	2	1	3	4	9	1	4	4	3	5	5	3	23	1	1
U-TS-402	3	5	3	5	1	4	2	5	4	6	1	5	5	9	5	3	5	4	5	5	3	27	5	1
U-TS-403	1	2	4	4	5	4	2	4	4	6	1	2	4	9	3	4	5	3	5	5	3	19	3	1
U-TS-404	3	5	1	5	3	4	2	5	4	4	4	3	4	9	1	1	5	1	5	5	3	17	5	1
U-TS-405	5	4	4	1	5	4	2	4	4	6	1	2	4	9	1	4	5	2	5	5	3	19	3	1
U-TS-406	5	3	4	3	2	4	2	2	4	6	1	3	4	9	3	4	5	2	5	5	3	8	3	1
U-TS-407	2	2	2	3	3	4	2	4	4	6	1	3	4	9	1	4	5	2	5	2	3	16	2	1
U-TS-408	2	2	4	1	5	4	2	1	4	6	4	2	4	9	1	4	5	2	5	2	3	8	3	1
U-TS-409	2	3	1	1	5	4	2	4	4	6	4	2	1	9	1	4	5	2	5	5	3	25	3	1
U-TS-410	3	2	4	2	5	4	2	2	4	4	4	2	4	9	1	1	5	3	2	5	3	4	3	1
U-TS-411	3	5	4	2	3	4	2	5	4	4	4	2	4	9	1	1	5	2	2	5	3	16	5	1
U-TS-412	1	5	4	2	2	4	2	2	4	6	1	3	4	9	3	1	5	3	2	5	3	15	3	1
U-TS-413	1	2	4	2	2	4	2	5	4	4	4	2	4	9	3	1	5	3	2	5	3	1	1	1
U-TS-414	3	5	1	2	2	4	2	5	4	4	4	3	4	9	1	1	5	3	2	5	3	17	1	1
U-TS-415	2	2	1	3	5	4	2	4	4	6	4	2	4	9	3	4	5	5	5	5	3	18	6	1
U-TS-416	3	2	4	2	2	4	2	2	4	6	4	3	4	9	1	1	4	2	5	5	3	27	3	1
U-TS-417	1	5	4	1	5	4	2	4	4	6	4	2	4	9	1	4	5	3	5	5	3	19	1	1
U-TS-418	2	2	4	2	3	4	2	5	4	4	4	3	4	9	1	1	5	2	2	5	3	17	3	1
U-TS-419	1	5	4	2	2	4	2	5	4	4	4	3	4	9	3	1	5	2	5	2	3	13	1	1
U-TS-420	2	5	1	2	2	4	2	2	4	6	4	3	4	9	1	1	5	3	5	5	3	16	2	1
U-TS-421	3	5	4	2	3	4	2	5	4	4	4	3	4	9	1	1	5	3	2	2	3	17	1	1
U-TS-422	1	5	4	5	2	4	2	5	4	6	4	3	4	9	1	1	5	3	2	5	3	16	3	1
U-TS-423	3	2	4	2	5	4	2	2	4	6	4	2	4	9	1	4	5	3	5	5	3	10	2	1
U-TS-424	3	2	1	3	5	4	2	2	4	6	4	2	4	9	1	4	5	2	5	5	3	8	6	1

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-425	3	1	3	3	5	4	2	4	4	6	1	3	4	9	3	4	5	2	5	5	3	27	2	1
U-TS-426	1	5	1	3	2	4	2	2	4	6	1	3	4	9	1	4	3	3	5	5	3	10	2	1
U-TS-427	3	5	3	1	5	4	2	4	4	6	4	3	4	9	1	4	5	2	5	5	3	25	3	1
U-TS-428	3	5	4	2	3	4	2	5	4	6	4	1	4	9	1	1	4	3	5	5	3	7	2	1
U-TS-429	5	4	4	4	5	4	2	4	4	6	3	2	4	9	1	4	5	3	5	5	3	18	3	1
U-TS-430	1	5	4	2	5	4	2	2	4	6	4	2	4	9	1	1	5	3	2	5	3	6	1	1
U-TS-431	3	2	4	2	5	4	2	2	4	6	4	2	4	9	1	1	1	2	2	5	3	14	3	1
U-TS-432	1	5	4	3	2	4	2	2	4	6	1	2	4	9	1	4	4	3	5	5	3	25	1	1
U-TS-433	3	5	4	3	5	4	2	2	4	6	4	3	4	9	1	4	5	3	5	5	3	16	6	1
U-TS-434	5	2	1	3	5	4	2	3	4	6	1	2	4	9	1	4	5	3	5	2	3	3	3	1
U-TS-435	3	2	4	2	2	4	2	5	4	6	4	2	4	9	1	1	5	3	2	5	3	2	5	1
U-TS-436	4	3	1	2	2	4	2	2	4	6	1	2	4	9	1	1	5	3	2	5	3	17	1	1
U-TS-437	3	2	4	2	2	3	2	2	4	6	4	2	4	9	1	1	5	3	2	5	3	17	3	1
U-TS-438	2	3	1	2	2	4	2	3	4	6	1	3	4	9	1	1	5	3	5	5	3	10	6	1
U-TS-439	1	5	4	2	5	4	2	5	4	6	4	5	4	9	1	1	5	2	4	5	3	1	1	1
U-TS-440	2	2	4	2	2	4	2	2	4	6	1	3	4	9	1	4	4	3	5	5	3	14	2	1
U-TS-441	3	5	1	3	5	4	2	2	4	6	1	2	4	9	1	1	1	3	5	5	3	14	6	1
U-TS-442	1	5	4	3	5	4	2	2	4	6	4	2	4	9	1	1	5	3	5	5	3	14	6	1
U-TS-443	3	2	4	3	5	4	2	2	4	6	4	5	4	9	1	1	5	2	4	5	3	1	2	1
U-TS-444	3	5	4	2	2	4	2	2	4	6	4	3	4	9	1	4	5	3	2	5	3	14	2	1
U-TS-445	1	5	4	2	2	4	2	5	4	6	4	2	4	9	1	1	4	2	5	5	3	25	5	1
U-TS-446	5	3	1	3	5	4	2	3	4	6	4	3	4	9	3	4	5	2	5	5	3	8	2	1
U-TS-447	2	2	4	1	5	4	2	1	4	6	4	2	4	9	3	4	5	2	5	5	3	27	2	1
U-TS-448	2	2	4	1	5	4	2	4	4	6	1	2	4	9	1	4	5	2	5	2	3	18	2	1
U-TS-449	1	5	1	2	2	4	2	5	4	6	4	3	4	9	1	1	5	3	5	5	3	13	1	1
U-TS-450	3	3	1	2	2	3	2	2	4	6	1	3	4	9	1	1	5	3	2	5	3	14	3	1
U-TS-451	5	4	5	2	5	4	2	4	4	2	3	4	4	9	1	4	5	3	5	5	3	25	1	1
U-TS-452	2	5	2	2	2	4	2	5	4	6	1	1	4	9	3	4	5	3	5	5	2	11	4	2
U-TS-453	3	5	5	2	2	4	2	5	4	2	3	4	4	9	1	4	5	3	5	2	3	17	2	1
U-TS-454	5	2	5	3	5	4	2	4	4	2	3	4	4	9	1	4	5	3	5	5	3	25	6	1
U-TS-455	2	1	5	1	5	4	2	5	4	2	3	3	4	9	3	4	5	2	5	5	3	10	6	1
U-TS-456	4	3	4	1	5	4	2	4	4	6	1	5	3	9	2	4	5	2	5	5	3	26	2	1
U-TS-457	3	5	1	2	3	4	2	5	4	4	4	3	4	9	1	1	5	5	2	2	3	17	1	1
U-TS-458	2	5	2	5	2	4	2	3	4	6	1	4	3	9	3	4	5	3	5	2	3	16	6	1
U-TS-459	1	5	1	2	3	4	2	5	4	4	4	2	4	9	3	1	5	1	5	5	3	27	5	1
U-TS-460	3	5	5	5	1	4	2	5	4	6	1	2	5	9	2	1	5	3	5	3	1	27	1	1
U-TS-461	3	5	4	5	1	4	2	5	4	4	4	2	4	9	1	1	5	3	5	5	3	16	5	1
U-TS-462	3	5	4	2	3	4	2	5	4	4	1	5	4	9	5	1	5	2	2	5	3	16	5	1
U-TS-463	2	5	4	5	3	4	2	5	4	6	1	2	4	9	3	1	5	2	2	5	3	17	5	1
U-TS-464	3	5	4	5	3	4	2	5	4	4	1	5	4	9	3	3	5	2	2	2	3	17	1	1
U-TS-465	3	5	4	5	2	4	2	5	4	6	3	5	4	9	5	3	5	1	4	2	3	6	1	1
U-TS-466	3	5	4	5	3	4	2	5	4	4	1	2	4	9	3	3	5	2	2	5	3	16	5	1
U-TS-467	3	5	4	5	3	4	2	5	4	4	1	5	4	9	3	1	5	2	5	3	3	17	5	1
U-TS-468	3	5	1	5	3	4	2	5	4	4	4	2	1	9	1	1	5	1	2	2	3	17	5	1
U-TS-469	3	5	4	5	3	4	2	5	4	4	1	5	1	9	3	3	5	3	2	5	3	17	1	1
U-TS-470	1	5	4	5	3	4	2	5	4	6	1	5	1	9	1	3	5	3	2	3	3	17	1	1
U-TS-471	3	5	1	5	3	4	2	5	4	6	1	2	1	9	1	3	5	1	2	2	3	17	5	1
U-TS-472	3	5	4	5	3	4	2	5	4	6	1	5	4	9	1	3	5	2	2	5	3	17	1	1
U-TS-473	1	5	4	5	2	4	2	5	4	4	1	2	4	9	3	3	5	3	4	5	3	7	5	1
U-TS-474	3	5	4	5	3	4	2	5	4	6	3	5	4	9	3	1	5	2	5	5	3	17	5	1
U-TS-475	2	5	4	5	3	4	2	5	4	6	1	5	1	9	1	3	5	3	5	5	3	17	1	1
U-TS-476	1	5	4	5	3	4	2	5	4	6	1	2	4	9	2	3	5	3	2	2	3	17	1	1
U-TS-477	1	5	4	5	2	4	2	5	4	4	4	3	4	9	1	1	5	3	5	5	3	17	5	1
U-TS-478	3	5	4	5	1	4	2	5	4	4	1	2	4	9	1	3	5	2	5	3	3	17	6	1
U-TS-479	2	5	4	2	1	4	2	1	4	4	1	2	4	9	5	1	5	3	5	5	3	27	3	1
U-TS-480	3	5	2	5	3	4	2	5	4	6	1	3	4	9	1	1	5	3	5	5	3	16	3	1
U-TS-481	1	5	3	5	3	4	2	5	4	6	1	5	2	9	5	3	5	3	5	2	1	27	5	1
U-TS-482	1	5	1	2	2	4	2	5	4	6	1	3	4	9	3	1	5	3	2	2	1	6	1	1
U-TS-483	2	5	1	5	3	4	2	5	4	6	1	2	4	9	1	3	5	3	5	5	3	8	2	1
U-TS-484	1	5	4	5	3	4	2	5	4	6	1	2	4	9	1	1	5	2	5	5	3	17	5	1
U-TS-485	3	5	4	2	3	4	2	5	4	2	3	2	4	9	3	1	5	2	2	2	1	17	5	1
U-TS-486	3	5	4	5	1	4	2	5	4	6	1	5	1	9	2	3	5	2	5	3	1	27	1	1
U-TS-487	3	5	4	2	1	4	2	5	4	4	4	2	4	9	2	1	5	3	2	5	3	16	5	1
U-TS-488	3	5	4	5	1	4	2	5	4	6	3	5	4	9	1	3	5	2	2	2	3	17	5	1
U-TS-489	3	5	4	5	1	4	2	5	4	4	1	2	1	9	3	1	5	2	5	2	3	16	5	1
U-TS-490	2	2	1	2	1	4	2	2	4	6	1	4	4	9	1	4	5	3	5	2	3	16	1	1
U-TS-491	2	4	5	5	1	4	2	2	4	6	1	5	2	9	5	1	5	2	5	5	3	16	5	1
U-TS-492	4	5	1	2	3	4	2	1	4	6	3	5	4	9	3	1	5	2	5	5	3	17	6	1
U-TS-493	3	5	3	5	3	4	2	5	4	6	1	5	5	9	3	3	5	3	5	2	1	16	5	1
U-TS-494	5	2	5	1	1	4	2	4	4	6	3	1	4	9	2	4	5	3	5	2	3	16	3	1
U-TS-495	4	5	5	4	2	4	2	4	4	6	1	3	4	9	3	4	5	2	5	5	3	27	5	1
U-TS-496	4	2	2	3	2	4	2	3	4	6	1	3	4	9	3	4	5	2	5	5	3	16	2	1
U-TS-497	1	5	5	5	1	4	2	1	4	6	3	4	2	9	1	1	5	2	5	3	2	16	4	2
U-TS-498	3	5	5	5	1	4	2	5	4	6	3	4	3	9	1	4	5	2	5	3	2	16	4	2
U-TS-499	1	5	5	5	1	4	2	3	4	6	3	1	3	9	2	1	5	2	5	3	2	16	4	2
U-TS-500	3	5	5	5	1	4	2	5	4	6	1	4	2	9	1	4	5	2	5	3	2	16	4	2
M-TS-1	2	5	4	4	3	4	2	5	6	6	4	3	4	1	2	4	5	1	5	5	3	16	5	1
M-TS-2	3	5	4	1	3	4	2	5	6	6	4	2	4	1	2	4	3	3	2	5	3	16	5	1
M-TS-3	3	5	1	4	3	4	2	5	4	4	4	3	4	9	1	4	5	2	5	5	3	16	5	1
M-TS-4	3	2	4	3	2	4	2	5	6	6	1	3	4	1	1	1	5	3	5	5	3	16	5	1
M-TS-5	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	1	5	1	5	5	3	16	5	1
M-TS-6	3	5	4	1	2	4	2	5	6	6	4	3	4	3	1	1	5	3	2	5	3	16	5	1
M-TS-7	3	5	4	1	2	4	2	5	4	4	4	3	4	9	1	4	5	2	2	5	3	17	5	1
M-TS-8	3	5	4	1	2	4	2	5	4	4	4	2	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-9	3	5	4	1	2	4	2	5	6	6	4	3	4	9	1	4	5	3	2	5	1	17	5	1
M-TS-10	3	5	1	1	3	4	2	5	6	6	4	1	4	20	1	4	5	1	5	5	3	16	5	1

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ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-11	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	4	5	1	2	5	3	17	5	1
M-TS-12	1	5	1	1	2	4	2	5	4	4	4	2	4	9	2	4	5	1	2	5	3	17	5	1
M-TS-13	3	5	4	1	1	4	2	5	6	6	4	3	4	9	1	4	5	3	5	5	1	16	5	1
M-TS-14	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-15	3	5	1	1	3	4	2	5	6	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-16	3	5	4	4	3	4	2	5	6	6	4	1	4	22	1	4	5	3	5	5	3	27	5	1
M-TS-17	2	5	1	1	2	4	2	5	6	6	4	3	4	9	2	4	5	3	2	5	3	17	5	1
M-TS-18	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	4	5	1	2	5	1	16	5	1
M-TS-19	3	5	4	1	3	4	2	5	6	6	4	3	4	9	2	4	5	3	5	5	3	16	5	1
M-TS-20	3	5	4	1	1	4	2	5	4	4	4	3	4	1	1	4	5	3	5	5	3	16	5	1
M-TS-21	3	5	4	3	3	4	2	5	6	6	4	3	4	9	1	1	5	2	5	5	3	16	5	1
M-TS-22	2	5	4	4	3	4	2	5	4	4	4	3	4	9	1	4	5	3	5	5	1	16	5	1
M-TS-23	3	5	4	3	2	4	2	5	6	6	4	2	4	9	1	1	5	3	2	5	3	16	5	1
M-TS-24	3	5	1	1	3	4	2	5	4	4	4	3	4	9	1	4	5	3	5	2	3	16	5	1
M-TS-25	3	5	4	4	2	4	2	5	6	6	4	2	4	9	1	4	5	3	4	5	3	17	5	1
M-TS-26	1	2	4	3	5	4	2	5	6	6	1	2	4	9	1	1	5	3	2	5	3	13	5	1
M-TS-27	3	5	1	1	3	4	2	5	6	6	4	3	4	9	1	1	5	2	2	5	1	17	5	1
M-TS-28	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	1	5	3	5	5	3	16	5	1
M-TS-29	3	5	4	3	2	4	2	5	6	6	1	3	4	9	1	1	5	3	2	5	3	17	5	1
M-TS-30	1	5	1	1	3	4	2	5	4	4	4	3	4	9	2	4	5	3	5	5	3	16	5	1
M-TS-31	3	5	1	3	2	4	2	5	6	6	1	2	4	1	1	1	5	3	2	5	3	17	5	1
M-TS-32	1	5	4	3	2	4	2	5	6	6	1	2	4	1	2	1	2	1	2	5	1	2	5	1
M-TS-33	3	5	4	3	2	4	2	2	6	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-34	3	5	4	1	3	4	2	5	6	6	4	3	4	22	1	1	5	2	5	5	3	16	5	1
M-TS-35	3	5	4	1	3	4	2	5	6	6	4	3	4	9	2	4	5	2	5	2	3	16	5	1
M-TS-36	2	2	4	3	3	4	2	5	6	6	4	3	4	9	1	1	5	1	5	5	3	16	5	1
M-TS-37	3	5	1	1	2	4	2	5	6	6	4	3	4	9	2	1	5	3	2	5	1	17	5	1
M-TS-38	1	2	1	3	2	4	2	5	6	6	1	2	4	22	2	3	5	2	4	5	3	17	5	1
M-TS-39	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	4	5	2	2	5	3	16	5	1
M-TS-40	1	5	4	1	5	4	2	5	6	6	4	2	4	9	2	4	5	3	2	5	3	17	5	1
M-TS-41	3	5	4	3	2	4	2	5	6	6	1	3	4	9	1	1	5	3	2	5	3	17	5	1
M-TS-42	3	5	4	1	3	4	2	5	6	6	4	3	4	9	1	4	5	1	5	5	3	17	5	1
M-TS-43	3	5	4	1	2	4	2	5	6	6	4	2	4	9	2	4	5	2	2	5	3	17	5	1
M-TS-44	3	5	4	4	3	4	2	5	6	6	4	3	4	22	2	1	5	2	5	2	1	25	5	1
M-TS-45	3	5	4	4	3	4	2	5	6	6	4	3	4	22	2	4	5	2	5	5	1	25	5	1
M-TS-46	2	5	4	1	3	4	2	5	6	6	4	3	4	9	1	1	5	3	5	5	3	16	5	1
M-TS-47	3	5	4	1	2	4	2	5	6	6	4	3	4	9	1	1	5	3	2	5	3	17	5	1
M-TS-48	3	5	4	2	1	4	2	5	4	4	4	3	4	9	1	2	5	5	5	2	3	16	5	1
M-TS-49	3	5	4	1	3	4	2	5	6	6	4	2	4	9	2	4	5	2	2	5	1	17	5	1
M-TS-50	3	5	4	1	3	4	2	5	6	6	4	3	4	4	2	4	5	1	5	2	1	10	5	1
M-TS-51	3	5	1	4	2	4	2	5	4	6	4	2	4	2	1	4	5	1	4	5	3	17	5	1
M-TS-52	2	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	2	5	5	3	16	5	1
M-TS-53	3	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	2	2	5	3	17	5	1
M-TS-54	3	5	1	1	2	4	2	5	4	6	4	3	4	9	1	4	5	3	4	5	3	17	5	1
M-TS-55	3	5	4	1	2	4	2	5	4	4	4	2	4	9	2	4	5	2	2	5	1	17	5	1
M-TS-56	2	5	1	1	3	4	2	5	4	6	4	3	4	22	1	4	5	3	5	5	3	16	5	1
M-TS-57	3	5	4	1	3	4	2	5	4	4	4	2	4	9	2	4	5	3	2	5	1	17	5	1
M-TS-58	3	5	4	4	3	4	2	5	4	6	4	3	4	9	1	4	5	2	5	5	3	16	5	1
M-TS-59	3	5	1	4	2	4	2	5	4	4	4	3	4	9	1	4	5	3	5	5	3	25	5	1
M-TS-60	1	5	1	4	2	4	2	5	4	6	4	3	4	1	1	4	1	3	2	5	3	17	5	1
M-TS-61	1	5	4	4	1	4	2	5	4	6	4	2	4	20	1	4	5	2	5	2	1	25	5	1
M-TS-62	3	5	1	1	2	4	2	5	4	6	1	2	4	22	1	4	5	1	2	5	3	17	5	1
M-TS-63	3	5	1	1	2	4	2	5	4	6	4	3	4	22	1	4	5	3	2	5	3	16	5	1
M-TS-64	1	5	1	4	2	4	2	5	4	4	4	2	4	22	1	4	5	3	2	5	3	17	5	1
M-TS-65	3	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	2	2	5	1	17	5	1
M-TS-66	3	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	2	5	2	3	27	5	1
M-TS-67	3	5	4	1	2	4	2	5	4	6	4	3	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-68	3	5	1	5	2	4	2	5	4	6	1	1	4	9	1	1	5	3	5	5	3	27	5	1
M-TS-69	4	4	1	5	5	4	2	1	4	6	1	1	4	11	2	1	5	5	5	5	3	16	5	1
M-TS-70	2	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	1	5	5	3	16	5	1
M-TS-71	3	5	1	1	3	4	2	5	4	6	4	3	4	22	1	4	5	3	2	5	3	16	5	1
M-TS-72	3	5	1	1	2	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-73	2	5	4	1	3	4	2	5	4	6	4	3	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-74	3	5	1	1	3	4	2	5	4	6	4	3	4	2	1	4	5	3	5	5	3	16	5	1
M-TS-75	3	5	1	1	2	4	2	5	4	6	4	3	4	22	1	4	5	3	2	5	1	16	5	1
M-TS-76	2	5	4	4	3	4	2	5	4	6	4	2	4	1	1	4	5	3	2	5	1	17	5	1
M-TS-77	3	5	1	4	3	4	2	5	4	6	4	3	4	9	2	4	5	2	5	5	3	16	5	1
M-TS-78	3	5	1	4	3	4	2	5	4	6	4	1	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-79	3	5	1	1	3	4	2	5	4	6	4	3	4	19	1	4	5	3	5	5	3	16	5	1
M-TS-80	3	5	1	1	1	4	2	5	4	4	4	3	4	9	1	4	5	1	5	5	1	16	5	1
M-TS-81	3	5	1	1	2	4	2	5	4	6	4	3	4	22	1	4	5	3	2	5	3	11	5	1
M-TS-82	2	5	1	3	3	4	2	5	4	4	4	1	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-83	3	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-84	3	5	4	4	2	4	2	5	4	6	4	2	4	9	2	4	5	3	2	5	1	17	5	1
M-TS-85	3	5	1	4	3	4	2	5	4	6	4	3	4	22	1	4	5	3	5	2	3	16	5	1
M-TS-86	3	5	4	1	3	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	1	16	5	1
M-TS-87	1	5	1	1	2	4	2	5	4	6	4	3	4	9	2	4	5	3	2	5	3	16	5	1
M-TS-88	3	5	4	1	2	4	2	5	4	6	4	3	4	22	2	4	5	1	2	5	3	17	5	1
M-TS-89	3	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	3	4	5	3	17	5	1
M-TS-90	2	5	1	1	3	4	2	5	4	6	4	3	4	22	1	4	5	3	5	5	3	16	5	1
M-TS-91	3	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-92	3	5	4	1	2	4	2	5	4	6	4	2	4	17	1	4	5	2	2	5	3	17	5	1
M-TS-93	3	5	4	1	3	4	2	5	4	6	4	3	4	22	2	4	5	2	5	5	3	24	5	1
M-TS-94	2	5	1	4	3	4	2	2	4	6	4	2	4	9	1	4	5	5	5	5	1	16	5	1
M-TS-95	3	5	4	1	3	4	2	5	4	6	4	2	4	1	1	4	5	5	2	5	3	23	5	1
M-TS-96	3	5	1	4	2	4	2	5	4	4	4	3	4	9	2	4	5	3	5	5	3	16	5	1

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ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-97	3	5	4	4	2	4	2	5	4	6	4	2	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-98	3	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	5	2	5	1	16	5	1
M-TS-99	3	5	4	1	2	4	2	5	4	6	4	3	4	9	2	4	5	3	2	5	1	17	5	1
M-TS-100	3	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	5	2	5	3	16	5	1
M-TS-101	3	5	1	1	1	4	2	5	4	4	4	1	4	22	1	4	5	3	5	5	3	16	5	1
M-TS-102	3	5	4	1	2	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-103	3	5	1	1	3	4	2	5	4	6	4	3	4	1	1	4	5	3	2	5	3	16	5	1
M-TS-104	3	5	1	1	2	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-105	3	5	4	4	3	4	2	5	4	6	4	2	4	9	1	4	5	2	5	5	1	16	5	1
M-TS-106	3	5	1	1	3	4	2	5	4	6	4	3	4	9	2	4	5	1	5	2	3	16	5	1
M-TS-107	3	5	4	1	3	4	2	5	4	4	4	3	4	9	1	4	5	2	2	5	1	16	5	1
M-TS-108	3	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	2	2	5	3	17	5	1
M-TS-109	3	5	1	1	3	4	2	5	4	6	4	3	4	20	1	4	5	1	2	5	1	16	5	1
M-TS-110	3	5	1	1	3	4	2	5	4	6	4	3	4	17	1	4	5	3	5	5	1	16	5	1
M-TS-111	3	5	1	4	3	4	2	5	4	6	4	3	4	22	1	4	5	2	5	2	3	25	5	1
M-TS-112	3	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	1	2	5	3	17	5	1
M-TS-113	3	5	1	4	2	4	2	5	4	6	4	2	4	9	2	4	5	1	2	5	3	17	5	1
M-TS-114	3	5	1	4	3	4	2	5	4	6	4	3	4	1	1	4	5	3	2	2	3	27	5	1
M-TS-115	3	5	1	4	3	4	2	5	4	4	4	3	4	9	2	4	5	2	2	5	3	17	5	1
M-TS-116	3	5	4	4	2	4	2	5	4	6	4	2	4	9	1	4	5	2	5	5	1	16	5	1
M-TS-117	3	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-118	3	5	1	1	3	4	2	5	4	6	4	3	4	22	1	4	5	3	2	2	3	17	5	1
M-TS-119	3	5	1	4	2	4	2	5	4	6	4	3	4	1	1	4	5	2	5	5	3	16	5	1
M-TS-120	2	5	1	3	1	4	2	5	4	6	4	1	4	9	1	4	5	2	5	2	3	16	5	1
M-TS-121	3	5	1	1	2	4	2	5	4	4	4	3	4	1	1	4	5	1	2	5	3	13	5	1
M-TS-122	1	5	4	1	2	4	2	5	4	6	4	2	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-123	2	5	4	1	3	4	2	5	4	4	4	3	4	5	1	4	5	3	5	5	3	27	5	1
M-TS-124	2	5	1	1	3	4	2	5	4	6	4	3	4	22	2	4	5	1	5	5	1	16	5	1
M-TS-125	3	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	2	5	5	1	16	5	1
M-TS-126	2	5	4	1	3	4	2	5	4	6	4	3	4	21	1	4	5	2	5	5	3	16	5	1
M-TS-127	3	5	1	4	1	4	2	5	4	6	4	3	4	1	2	4	5	3	5	2	3	16	5	1
M-TS-128	3	5	1	4	3	4	2	5	4	6	4	1	4	9	1	4	5	3	5	2	1	16	5	1
M-TS-129	3	5	1	1	3	4	2	5	4	6	4	3	4	1	2	4	5	1	2	5	3	16	5	1
M-TS-130	2	5	1	4	3	4	2	5	4	6	4	3	4	1	1	4	5	1	5	5	3	16	5	1
M-TS-131	1	5	1	4	5	4	2	5	4	4	4	3	4	10	1	4	5	3	2	5	3	17	5	1
M-TS-132	2	5	1	1	3	4	2	5	4	6	4	3	4	18	1	4	5	1	5	5	3	16	5	1
M-TS-133	3	5	1	4	2	4	2	5	4	6	4	2	4	9	1	4	5	3	2	5	1	17	5	1
M-TS-134	3	5	1	1	3	4	2	5	4	6	4	3	4	20	1	4	5	3	2	5	3	16	5	1
M-TS-135	1	5	1	4	2	4	2	5	4	6	4	3	4	22	1	4	5	3	2	5	3	17	5	1
M-TS-136	5	4	1	4	3	4	2	2	4	6	4	3	4	9	1	4	5	1	5	5	1	16	5	1
M-TS-137	3	5	4	4	2	4	2	5	4	6	4	2	4	9	1	4	5	2	5	5	3	25	5	1
M-TS-138	3	5	4	4	2	4	2	5	4	6	4	2	4	9	2	4	5	2	5	5	3	25	5	1
M-TS-139	3	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	1	5	5	3	16	5	1
M-TS-140	2	5	1	4	1	4	2	5	4	6	4	3	4	1	1	4	5	3	5	5	1	16	5	1
M-TS-141	3	5	4	1	3	4	2	5	4	4	4	2	4	9	2	4	5	2	2	5	1	17	5	1
M-TS-142	2	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	2	2	5	1	16	5	1
M-TS-143	3	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	3	5	5	3	16	5	1
M-TS-144	3	5	4	4	2	4	2	5	4	6	1	2	4	9	1	4	5	5	2	5	3	16	5	1
M-TS-145	3	5	1	1	3	4	2	5	4	6	4	2	4	9	1	4	5	5	2	5	3	17	5	1
M-TS-146	3	5	1	4	2	4	2	5	4	4	4	3	4	9	1	4	5	3	2	5	3	17	5	1
M-TS-147	1	5	1	1	3	4	2	5	4	6	4	3	4	9	1	4	5	3	2	5	3	16	5	1
M-TS-148	1	5	1	1	3	4	2	5	4	6	4	1	4	22	1	4	5	3	5	5	3	16	5	1
M-TS-149	3	5	1	4	3	4	2	5	4	6	4	3	4	9	1	4	5	3	5	2	1	16	5	1
M-TS-150	3	5	4	4	3	4	2	5	4	6	4	3	4	22	1	4	5	3	2	2	1	27	5	1
M-TS-151	2	5	2	5	4	4	2	5	4	4	1	4	2	9	5	1	5	3	5	1	3	16	6	1
M-TS-152	2	5	3	5	4	4	2	5	4	6	3	1	1	9	3	1	5	3	5	3	3	16	5	1
M-TS-153	3	5	3	5	1	4	2	5	4	6	3	1	1	9	3	3	5	3	5	3	3	16	5	1
M-TS-154	3	5	3	5	1	4	2	5	4	6	3	1	1	9	3	3	5	3	5	3	3	16	5	1
M-TS-155	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	1	5	1	3	11	3	1
M-TS-156	3	5	1	5	4	4	2	5	4	6	1	1	4	9	3	3	5	3	5	1	3	25	5	1
M-TS-157	3	5	3	5	4	4	2	5	4	2	1	1	1	9	5	3	5	3	5	1	3	27	5	1
M-TS-158	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	16	5	1
M-TS-159	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-160	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-161	3	5	1	5	1	4	2	5	4	2	3	4	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-162	3	5	1	5	1	4	2	5	4	2	3	1	1	9	3	3	5	2	5	3	1	27	5	1
M-TS-163	3	5	3	5	4	4	2	5	4	6	4	1	1	9	3	1	5	3	5	1	3	27	5	1
M-TS-164	3	5	3	5	1	4	2	5	4	6	1	3	1	9	3	1	5	3	5	3	3	16	5	1
M-TS-165	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	16	5	1
M-TS-166	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	3	3	16	1	1
M-TS-167	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	16	1	1
M-TS-168	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-169	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-170	3	5	3	5	1	4	2	5	4	6	3	1	1	9	3	3	5	2	5	3	3	27	5	1
M-TS-171	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	3	3	27	5	1
M-TS-172	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-173	3	5	1	5	1	4	2	5	4	6	1	1	4	9	3	3	5	2	5	1	3	27	5	1
M-TS-174	3	5	3	5	1	4	2	5	4	4	4	3	1	9	3	3	5	3	5	3	3	27	5	1
M-TS-175	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	27	5	1
M-TS-176	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	2	3	27	5	1
M-TS-177	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	3	5	3	5	1	1	11	5	1
M-TS-178	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	1	27	5	1
M-TS-179	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	27	5	1
M-TS-180	3	5	1	5	1	4	2	5	4	2	1	1	1	9	1	3	5	2	5	3	3	27	5	1
M-TS-181	3	5	1	5	1	4	2	5	4	6	1	1	4	9	3	3	5	2	5	1	3	11	5	1
M-TS-182	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	27	5	1

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-183	3	5	1	5	1	4	2	5	4	6	3	1	4	9	5	3	5	2	5	1	3	27	5	1
M-TS-184	3	5	3	5	1	4	2	5	4	4	4	3	1	9	5	1	5	3	5	1	3	11	5	1
M-TS-185	1	5	1	5	1	4	2	5	4	4	4	1	1	9	3	3	5	2	5	3	3	27	5	1
M-TS-186	3	5	3	5	1	4	2	5	4	6	1	3	1	9	3	3	5	2	5	3	3	16	5	1
M-TS-187	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	3	5	3	5	1	3	16	3	1
M-TS-188	3	5	1	5	1	4	2	5	4	2	3	1	4	9	3	3	5	3	5	1	3	25	5	1
M-TS-189	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	27	5	1
M-TS-190	3	5	3	5	1	4	2	5	4	4	4	1	1	9	1	3	5	3	5	2	3	27	5	1
M-TS-191	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	1	1
M-TS-192	3	5	1	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	16	5	1
M-TS-193	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-194	3	5	3	5	1	4	2	5	4	4	1	1	1	9	3	3	5	3	5	1	3	11	3	1
M-TS-195	3	5	3	5	1	4	2	5	4	6	4	1	1	9	3	1	5	3	5	1	3	27	5	1
M-TS-196	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	2	3	16	5	1
M-TS-197	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	1	5	3	5	3	3	27	5	1
M-TS-198	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-199	3	5	1	5	1	4	2	5	4	2	3	1	1	9	3	3	5	2	5	3	3	16	5	1
M-TS-200	3	5	1	5	1	4	2	5	4	6	1	1	1	9	3	3	5	2	5	1	3	16	5	1
M-TS-201	3	5	1	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-202	3	5	3	5	1	4	2	5	4	2	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-203	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-204	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	16	1	1
M-TS-205	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	3	3	27	5	1
M-TS-206	3	5	1	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-207	2	5	3	5	1	4	2	5	4	6	1	3	1	9	5	3	5	3	5	3	3	16	1	1
M-TS-208	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	2	3	27	5	1
M-TS-209	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	1	5	3	5	1	3	27	5	1
M-TS-210	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	27	5	1
M-TS-211	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	1	5	1	3	16	1	1
M-TS-212	3	5	1	5	1	4	2	5	4	6	3	1	4	9	3	3	5	3	5	1	3	11	5	1
M-TS-213	2	5	3	5	4	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	16	5	1
M-TS-214	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	1	5	3	5	3	3	11	5	1
M-TS-215	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	16	5	1
M-TS-216	2	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-217	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-218	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-219	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	2	3	25	5	1
M-TS-220	3	5	3	5	1	4	2	5	4	6	1	3	1	9	3	1	5	1	5	3	3	16	1	1
M-TS-221	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-222	3	5	3	5	1	4	2	5	4	6	1	3	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-223	3	5	3	5	1	4	2	5	4	2	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-224	3	5	1	5	1	4	2	5	4	2	1	1	1	9	3	3	5	2	5	3	3	27	5	1
M-TS-225	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	1	5	3	5	3	3	27	5	1
M-TS-226	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	27	5	1
M-TS-227	3	5	1	5	1	4	2	5	4	2	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-228	3	5	3	5	1	4	2	5	4	2	3	1	1	9	3	3	5	2	5	3	3	27	5	1
M-TS-229	3	5	3	5	4	4	2	5	4	6	1	1	1	9	3	3	5	3	5	2	3	25	5	1
M-TS-230	3	5	1	5	1	4	2	5	4	2	3	1	4	9	3	3	5	2	5	3	3	27	5	1
M-TS-231	3	5	3	5	1	4	2	5	4	6	4	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-232	3	5	1	5	1	4	2	5	4	2	3	1	4	9	3	3	5	2	5	1	3	27	5	1
M-TS-233	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	27	5	1
M-TS-234	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	3	5	3	5	3	3	25	5	1
M-TS-235	3	5	1	5	1	4	2	5	4	6	1	1	4	9	3	3	5	2	5	1	3	11	5	1
M-TS-236	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-237	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	2	5	2	3	27	5	1
M-TS-238	3	5	3	5	1	4	2	5	4	6	4	1	1	9	3	3	5	3	5	1	3	25	5	1
M-TS-239	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	16	5	1
M-TS-240	3	5	1	5	1	4	2	5	4	2	3	3	1	9	3	3	5	3	5	3	3	27	5	1
M-TS-241	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-242	3	5	3	5	1	4	2	5	4	2	1	3	1	9	3	1	5	3	5	1	3	27	5	1
M-TS-243	3	5	3	5	1	4	2	5	4	2	3	1	1	9	3	1	5	2	5	2	3	27	5	1
M-TS-244	3	5	3	5	1	4	2	5	4	4	1	1	1	9	3	1	5	3	5	1	3	16	1	1
M-TS-245	3	5	1	5	1	4	2	5	4	6	1	1	4	9	5	3	5	3	5	1	3	11	5	1
M-TS-246	3	5	1	5	1	4	2	5	4	2	3	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-247	3	5	3	5	1	4	2	5	4	6	4	1	1	9	5	1	5	3	5	3	3	16	5	1
M-TS-248	3	5	1	5	1	4	2	5	4	6	1	1	1	9	5	3	5	2	5	1	3	27	5	1
M-TS-249	2	5	3	5	4	4	2	5	4	4	4	1	1	9	3	1	5	3	5	1	3	16	3	1
M-TS-250	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	3	5	1	5	1	3	16	3	1
M-TS-251	3	5	3	5	1	4	2	5	4	2	1	1	1	9	5	1	5	3	5	1	3	16	5	1
M-TS-252	3	5	3	5	1	4	2	5	4	6	1	3	1	9	5	1	5	3	5	1	3	16	1	1
M-TS-253	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	3	3	16	1	1
M-TS-254	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	3	3	27	5	1
M-TS-255	3	5	1	5	1	4	2	5	4	6	4	1	1	9	3	3	5	3	5	1	3	25	5	1
M-TS-256	2	5	3	5	4	4	2	5	4	4	1	1	1	9	3	1	5	3	5	1	3	16	1	1
M-TS-257	2	5	3	5	4	4	2	5	4	6	1	1	1	9	3	1	5	3	5	3	3	16	1	1
M-TS-258	3	5	3	5	1	4	2	5	4	6	3	1	4	9	3	3	5	3	5	2	3	11	5	1
M-TS-259	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-260	2	5	3	5	4	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	27	1	1
M-TS-261	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	1	3	25	5	1
M-TS-262	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	3	1
M-TS-263	2	5	3	5	1	4	2	5	4	4	4	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-264	3	5	1	5	1	4	2	5	4	6	1	1	1	9	3	3	5	3	5	3	3	16	1	1
M-TS-265	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	3	5	3	5	1	3	16	3	1
M-TS-266	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	5	1
M-TS-267	1	5	1	5	1	4	2	5	4	2	3	1	1	9	1	3	5	2	5	3	3	27	5	1
M-TS-268	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	3	5	1	3	16	3	1

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ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-269	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	1	5	3	5	1	3	16	1	1
M-TS-270	3	5	1	5	1	4	2	5	4	6	1	1	1	9	1	3	5	2	5	1	3	27	5	1
M-TS-271	3	5	3	5	1	4	2	5	4	6	1	3	1	9	3	1	5	3	5	3	3	11	5	1
M-TS-272	3	5	3	5	1	4	2	5	4	4	4	1	1	9	3	1	5	3	5	2	3	27	5	1
M-TS-273	3	5	3	5	1	4	2	5	4	2	1	1	1	9	3	3	5	3	5	1	3	27	5	1
M-TS-274	3	5	1	5	1	4	2	5	4	6	1	1	4	9	5	3	5	3	5	1	3	11	5	1
M-TS-275	3	5	1	5	4	4	2	5	4	6	1	1	4	9	3	3	5	3	5	3	3	25	5	1
M-TS-276	3	5	1	5	1	4	2	5	4	2	3	1	4	9	3	3	5	2	5	1	3	27	5	1
M-TS-277	2	5	3	5	1	4	2	5	4	4	4	3	1	9	3	3	5	3	5	3	1	16	5	1
M-TS-278	3	5	1	5	1	4	2	5	4	6	3	1	4	9	3	3	5	3	5	1	3	11	5	1
M-TS-279	2	5	3	5	1	4	2	5	4	4	4	1	1	9	3	3	5	3	5	3	3	16	1	1
M-TS-280	3	5	3	5	1	4	2	5	4	6	4	1	1	9	5	1	5	3	5	1	3	27	5	1
M-TS-281	2	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	3	3	16	1	1
M-TS-282	3	5	3	5	1	4	2	5	4	6	1	1	1	9	5	3	5	3	5	1	1	27	5	1
M-TS-283	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-284	3	5	1	5	4	4	2	5	4	6	1	1	1	9	5	3	5	2	5	1	3	27	5	1
M-TS-285	3	5	3	5	1	4	2	5	4	6	1	1	1	9	3	1	5	1	5	1	3	16	1	1
M-TS-286	5	4	2	5	1	4	2	5	4	2	3	1	4	9	5	3	5	3	5	2	3	16	1	1
M-TS-287	3	5	3	5	3	4	2	5	4	6	1	4	4	9	3	3	5	3	5	2	3	16	1	1
M-TS-288	1	5	3	5	3	4	2	5	4	4	4	1	4	9	3	3	5	3	5	2	3	16	2	1
M-TS-289	3	5	3	5	1	4	2	5	4	6	1	3	4	9	3	3	5	3	5	3	3	16	3	1
M-TS-290	3	5	3	5	3	4	2	5	4	6	1	4	4	9	3	3	5	3	5	2	3	16	1	1
M-TS-291	3	5	3	5	1	4	2	5	4	6	1	1	4	9	3	3	5	3	5	3	1	16	5	1
M-TS-292	3	5	3	5	3	4	2	5	4	6	1	3	4	9	5	3	5	3	5	3	3	16	1	1
M-TS-293	3	5	3	5	3	4	2	5	4	6	1	1	1	9	3	3	5	3	5	3	3	16	3	1
M-TS-294	3	5	3	5	3	4	2	5	4	4	4	1	4	9	3	3	5	3	5	3	3	11	3	1
M-TS-295	3	5	3	5	3	4	2	5	4	4	4	1	4	9	3	3	5	3	5	2	3	16	3	1
M-TS-296	3	5	3	5	3	4	2	5	4	6	1	4	4	9	3	3	5	1	5	2	3	11	3	1
M-TS-297	3	5	3	5	3	4	2	5	4	6	1	4	4	9	3	3	5	3	5	2	3	16	5	1
M-TS-298	3	5	3	5	1	4	2	5	4	6	1	1	4	9	3	3	5	3	5	2	3	11	2	1
M-TS-299	3	5	3	5	3	4	2	5	4	4	4	4	4	9	3	3	5	1	5	2	3	16	3	1
M-TS-300	3	5	3	5	3	4	2	5	4	6	1	1	4	9	3	3	5	3	5	2	3	16	3	1
M-TS-301	2	5	4	5	4	4	2	5	4	4	1	5	4	9	3	5	5	1	5	1	2	16	4	2
M-TS-302	1	5	1	5	3	4	2	5	4	6	1	5	1	12	3	5	5	3	2	2	1	16	1	1
M-TS-303	3	5	1	5	3	4	2	5	4	6	1	5	1	9	5	5	5	3	2	2	1	16	5	1
M-TS-304	3	5	3	5	1	4	2	5	4	6	3	2	1	13	1	5	5	3	5	2	1	16	5	1
M-TS-305	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	5	5	3	5	3	1	16	5	1
M-TS-306	3	5	1	5	1	4	2	5	4	6	2	5	4	6	1	5	5	2	2	3	1	27	5	1
M-TS-307	3	5	3	5	3	4	2	5	4	6	1	5	1	12	3	5	5	2	5	2	1	16	5	1
M-TS-308	1	5	1	5	1	4	2	5	4	6	3	5	1	11	1	5	5	3	2	3	1	27	5	1
M-TS-309	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	5	5	5	5	2	3	16	5	1
M-TS-310	1	5	4	5	1	4	2	5	4	6	3	5	4	7	1	5	5	3	2	3	3	27	5	1
M-TS-311	1	5	1	5	3	4	2	5	4	6	3	5	1	15	3	5	5	3	5	3	1	16	5	1
M-TS-312	3	5	3	5	3	4	2	5	4	6	4	5	3	9	3	2	5	3	5	2	1	27	1	1
M-TS-313	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	5	5	2	2	2	1	16	5	1
M-TS-314	3	5	4	5	1	1	2	5	4	6	3	5	4	14	1	5	5	3	2	2	1	27	5	1
M-TS-315	3	5	1	5	1	4	2	5	4	6	3	5	1	8	1	5	5	3	2	3	1	16	5	1
M-TS-316	3	5	1	5	1	4	2	5	4	6	1	5	1	11	1	5	5	3	2	2	3	16	1	1
M-TS-317	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	5	5	2	5	2	1	16	5	1
M-TS-318	3	5	1	5	3	4	2	5	4	6	3	5	1	11	3	5	5	3	2	2	1	16	5	1
M-TS-319	2	5	1	5	1	4	2	5	4	6	1	2	1	12	3	5	5	3	5	3	1	27	5	1
M-TS-320	3	5	4	5	1	4	2	5	4	6	1	5	1	9	3	5	5	3	2	3	1	16	5	1
M-TS-321	3	5	4	5	1	4	2	5	4	6	3	2	4	13	1	5	5	2	2	2	1	27	5	1
M-TS-322	3	5	3	5	1	4	2	5	4	6	4	5	1	8	1	5	5	3	2	2	1	27	5	1
M-TS-323	3	5	4	5	1	4	2	5	4	6	3	5	1	14	1	5	5	2	2	1	1	27	5	1
M-TS-324	3	5	4	5	1	4	2	5	4	6	2	2	1	13	1	5	5	3	5	3	1	27	5	1
M-TS-325	3	5	4	5	3	4	2	5	4	6	1	5	1	11	1	5	5	3	5	2	1	27	5	1
M-TS-326	3	5	4	5	1	4	2	5	4	6	3	5	1	8	1	5	5	3	2	3	1	16	5	1
M-TS-327	3	5	3	5	3	4	2	5	4	6	1	5	3	9	5	5	5	3	5	2	1	16	5	1
M-TS-328	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	5	5	3	5	2	1	27	5	1
M-TS-329	3	5	4	5	1	4	2	5	4	6	2	5	1	9	1	5	5	3	5	3	1	16	5	1
M-TS-330	1	5	1	5	3	4	2	5	4	6	1	2	1	9	3	5	5	3	2	2	1	16	5	1
M-TS-331	3	5	4	5	1	4	2	5	4	6	1	5	1	15	1	5	5	3	2	3	1	27	5	1
M-TS-332	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	5	5	3	5	2	3	16	5	1
M-TS-333	3	5	1	5	1	4	2	5	4	6	1	5	1	7	3	2	5	3	5	3	3	27	5	1
M-TS-334	3	5	4	5	1	4	2	5	4	6	3	2	1	15	1	5	5	2	2	3	1	16	5	1
M-TS-335	3	5	1	5	3	4	2	5	4	6	1	5	4	9	1	5	5	2	2	2	1	17	5	1
M-TS-336	3	5	4	5	1	4	2	5	4	6	2	5	1	14	1	5	5	2	2	3	1	27	5	1
M-TS-337	3	5	3	5	1	4	2	5	4	6	3	5	1	11	3	5	5	3	2	2	1	16	5	1
M-TS-338	3	5	3	5	1	4	2	5	4	6	1	5	1	11	3	5	5	3	5	2	1	27	5	1
M-TS-339	3	5	4	5	1	4	2	5	4	6	3	5	4	14	1	5	5	3	2	2	1	27	5	1
M-TS-340	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	5	5	3	5	3	1	27	5	1
M-TS-341	3	5	4	5	1	4	2	5	4	6	3	5	1	12	1	5	5	3	2	3	1	16	5	1
M-TS-342	1	5	1	5	3	4	2	5	4	6	1	5	1	9	3	5	5	2	2	2	1	16	5	1
M-TS-343	3	5	1	5	1	4	2	5	4	6	3	5	1	8	3	5	5	3	2	3	1	27	5	1
M-TS-344	3	5	1	5	1	4	2	5	4	6	1	5	1	6	3	5	5	2	2	3	1	16	5	1
M-TS-345	3	5	3	5	3	4	2	5	4	6	1	5	3	9	3	5	5	3	5	2	1	16	5	1
M-TS-346	3	5	1	5	1	4	2	5	4	6	3	2	1	9	3	5	5	3	5	1	1	16	5	1
M-TS-347	3	5	4	5	1	4	2	5	4	6	3	5	4	16	3	5	5	2	2	3	1	27	1	1
M-TS-348	1	5	1	5	1	4	2	5	4	6	3	5	1	8	3	5	5	2	5	3	1	16	5	1
M-TS-349	3	5	3	5	1	4	2	5	4	6	1	5	1	9	3	2	5	2	5	2	1	16	5	1
M-TS-350	3	5	4	5	1	4	2	5	4	6	2	5	1	13	1	5	5	3	5	3	1	16	5	1
M-TS-351	3	5	1	5	1	4	2	5	4	6	1	5	1	9	3	5	5	3	2	3	3	16	5	1
M-TS-352	3	5	1	5	1	4	2	5	4	4	4	2	1	9	5	5	5	3	5	2	1	27	5	1
M-TS-353	3	5	4	5	1	4	2	5	4	4	1	2	4	9	1	5	5	3	2	2	1	27	5	1
M-TS-354	1	5	1	5	3	4	2	5	4	6	1	5	3	9	3	5	5	3	5	2	1	16	5	1

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-355	3	5	1	5	3	4	2	5	4	6	1	2	1	9	3	5	5	3	5	2	3	25	5	1
M-TS-356	3	5	1	5	1	4	2	5	4	6	3	5	1	9	1	5	5	2	5	2	1	16	5	1
M-TS-357	3	5	1	5	3	4	2	5	4	6	3	5	1	9	3	5	5	3	5	3	1	27	5	1
M-TS-358	1	5	1	5	3	4	2	5	4	6	1	2	1	9	3	5	5	3	2	2	1	16	5	1
M-TS-359	3	5	4	5	1	4	2	5	4	4	4	5	4	9	3	5	5	2	5	2	1	16	5	1
M-TS-360	1	5	4	5	3	4	2	5	4	6	1	2	1	9	1	5	5	2	5	2	1	27	5	1
M-TS-361	3	5	4	5	1	4	2	5	4	6	3	2	1	9	1	5	5	3	2	2	1	27	5	1
M-TS-362	3	5	1	5	1	4	2	5	4	6	2	5	3	9	3	5	5	2	5	3	1	27	5	1
M-TS-363	3	5	1	5	3	4	2	5	4	6	1	2	1	9	3	5	5	3	5	5	1	16	5	1
M-TS-364	3	5	1	5	1	4	2	5	4	4	1	5	1	9	3	5	5	2	5	2	1	27	5	1
M-TS-365	3	5	4	5	1	4	2	5	4	6	1	2	4	9	3	5	5	3	2	1	1	27	5	1
M-TS-366	3	5	4	5	1	4	2	5	4	6	3	5	1	9	1	5	5	2	2	3	1	27	5	1
M-TS-367	3	5	1	5	3	4	2	5	4	6	1	5	1	9	1	5	5	3	2	2	1	16	5	1
M-TS-368	3	5	1	5	3	4	2	5	4	6	1	2	3	9	3	5	5	2	5	5	1	27	5	1
M-TS-369	1	5	1	5	2	4	2	5	4	6	1	5	1	9	3	5	5	1	2	2	3	27	5	1
M-TS-370	3	5	1	5	3	4	2	5	4	6	3	2	3	9	3	5	5	2	5	2	1	27	5	1
M-TS-371	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	5	5	3	5	3	1	16	5	1
M-TS-372	3	5	4	5	1	4	2	5	4	6	3	5	4	9	3	5	5	2	2	3	1	27	5	1
M-TS-373	3	5	1	5	3	4	2	5	4	4	1	2	1	9	3	5	5	2	2	2	3	16	5	1
M-TS-374	3	5	4	5	1	4	2	5	4	6	1	2	1	9	1	5	5	2	2	3	1	16	5	1
M-TS-375	3	5	4	5	3	4	2	5	4	6	3	5	1	9	1	5	5	2	5	2	1	16	5	1
M-TS-376	3	5	4	5	3	4	2	5	4	6	1	2	1	9	3	5	5	2	5	2	1	16	5	1
M-TS-377	3	5	4	5	1	4	2	5	4	6	3	5	4	9	1	5	5	2	2	3	1	27	5	1
M-TS-378	1	5	3	5	3	4	2	5	4	6	1	2	2	9	5	5	5	1	5	2	1	16	1	1
M-TS-379	3	5	1	5	3	4	2	5	4	6	3	5	1	9	3	5	5	1	5	2	1	16	5	1
M-TS-380	3	5	1	5	3	4	2	5	4	6	1	5	3	9	1	5	5	3	5	2	1	27	5	1
M-TS-381	3	5	1	5	3	4	2	5	4	6	1	2	3	9	3	5	5	1	5	2	1	16	5	1
M-TS-382	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	5	5	3	2	3	1	27	5	1
M-TS-383	3	5	1	5	3	4	2	5	4	6	1	2	3	9	3	5	5	3	5	2	1	27	5	1
M-TS-384	1	5	4	5	3	4	2	5	4	6	3	2	4	9	3	5	5	3	2	3	1	16	5	1
M-TS-385	3	5	4	5	1	4	2	5	4	6	3	2	4	9	3	5	5	2	2	2	3	16	5	1
M-TS-386	3	5	1	5	3	4	2	5	4	6	1	2	1	9	3	5	5	2	5	2	1	27	5	1
M-TS-387	3	5	4	5	1	4	2	5	4	6	3	5	4	9	3	5	5	2	2	3	3	27	5	1
M-TS-388	3	5	1	5	1	4	2	5	4	6	1	2	3	9	5	5	5	3	5	2	1	16	5	1
M-TS-389	3	5	1	5	1	4	2	5	4	6	3	5	1	9	3	5	5	2	5	2	1	16	5	1
M-TS-390	3	5	4	5	1	4	2	5	4	4	1	5	1	9	1	5	5	3	2	2	1	27	5	1
M-TS-391	1	5	4	5	3	4	2	5	4	6	1	5	1	9	3	5	5	3	5	3	1	27	5	1
M-TS-392	3	5	4	5	1	4	2	5	4	6	1	5	1	9	1	5	5	3	2	3	3	27	5	1
M-TS-393	3	5	1	5	3	4	2	5	4	6	1	2	3	9	3	5	5	2	5	5	3	16	5	1
M-TS-394	3	5	4	5	1	4	2	5	4	4	1	2	1	9	3	5	5	3	2	2	1	27	5	1
M-TS-395	3	5	4	5	1	4	2	5	4	6	3	2	1	9	1	5	5	3	5	2	1	16	5	1
M-TS-396	3	5	1	5	1	4	2	5	4	6	3	5	3	9	3	5	5	3	5	2	1	27	5	1
M-TS-397	1	5	1	5	3	4	2	5	4	6	1	2	2	9	5	5	5	2	5	2	1	16	5	1
M-TS-398	3	5	4	5	1	4	2	5	4	6	1	5	4	9	3	5	5	2	2	2	1	16	5	1
M-TS-399	3	5	4	5	3	4	2	5	4	6	2	5	1	9	3	5	5	3	5	2	1	27	5	1
M-TS-400	3	5	1	5	1	4	2	5	4	6	1	2	1	9	3	5	5	3	5	3	1	27	5	1
M-TS-401	3	2	1	3	3	4	2	2	4	6	1	3	4	9	1	4	5	2	5	5	3	23	3	1
M-TS-402	3	5	3	5	1	4	2	5	4	4	1	5	2	9	5	5	5	4	5	5	3	16	5	1
M-TS-403	1	2	1	1	2	4	2	4	4	6	4	3	4	9	3	4	5	2	5	5	3	25	2	1
M-TS-404	3	5	1	5	3	4	2	5	4	4	4	3	4	9	1	3	5	3	5	5	3	16	1	1
M-TS-405	3	5	1	1	2	4	2	4	4	6	4	3	4	9	1	4	5	2	5	5	3	25	3	1
M-TS-406	2	2	1	2	3	4	2	2	4	6	1	1	4	9	3	4	5	2	5	5	3	8	1	1
M-TS-407	1	5	2	3	1	4	2	4	4	6	1	4	4	9	1	4	5	2	5	2	3	16	6	1
M-TS-408	3	5	1	3	2	4	2	1	4	6	4	1	4	9	1	4	5	2	5	2	3	9	6	1
M-TS-409	3	2	1	1	2	4	2	4	4	6	4	3	1	9	1	4	5	2	5	2	3	25	2	1
M-TS-410	3	2	1	2	2	4	2	2	4	4	4	3	1	9	3	1	5	2	2	2	3	7	3	1
M-TS-411	3	5	4	2	3	4	2	5	4	4	1	2	4	9	1	2	5	5	2	5	3	16	5	1
M-TS-412	1	5	1	2	2	4	2	2	4	6	1	1	4	9	3	4	5	3	2	5	3	16	2	1
M-TS-413	1	5	1	2	2	4	2	5	4	4	4	2	4	9	3	1	5	3	2	5	3	7	1	1
M-TS-414	3	5	1	2	2	4	2	5	4	6	4	3	4	9	1	1	5	2	2	5	3	17	3	1
M-TS-415	3	2	1	3	5	4	2	4	4	4	4	3	4	9	3	4	5	2	5	2	3	18	2	1
M-TS-416	3	5	1	2	2	4	2	2	4	6	4	3	4	9	1	1	5	2	5	5	3	16	2	1
M-TS-417	1	5	1	1	2	4	2	4	4	6	4	3	4	9	1	4	5	2	5	5	3	18	3	1
M-TS-418	2	2	1	2	3	4	2	5	4	6	4	3	4	9	1	1	5	2	2	5	3	17	3	1
M-TS-419	3	5	1	2	2	4	2	5	4	4	4	1	4	9	3	1	5	2	5	2	3	13	3	1
M-TS-420	2	5	1	2	2	4	2	2	4	6	4	1	4	9	3	4	5	3	5	2	3	16	3	1
M-TS-421	3	5	1	2	3	4	2	5	4	4	4	3	4	9	1	3	5	2	5	2	3	17	1	1
M-TS-422	1	5	4	5	2	4	2	5	4	4	4	2	4	9	3	2	5	3	5	2	3	10	3	1
M-TS-423	3	5	1	2	2	4	2	2	4	4	4	3	4	9	1	4	5	2	5	5	3	10	3	1
M-TS-424	2	5	1	3	2	4	2	2	4	4	4	3	4	9	1	4	5	2	5	2	3	8	6	1
M-TS-425	3	5	3	1	5	4	2	4	4	6	1	1	4	9	3	4	5	2	5	5	3	20	2	1
M-TS-426	1	5	1	2	3	4	2	2	4	6	1	3	4	9	1	4	5	2	5	5	3	10	6	1
M-TS-427	3	5	3	1	2	4	2	4	4	6	4	1	4	9	1	4	5	2	5	5	3	25	6	1
M-TS-428	2	5	1	2	3	4	2	5	4	4	4	1	4	9	1	1	5	2	5	5	3	17	2	1
M-TS-429	3	5	1	1	2	4	2	4	4	6	1	3	4	9	1	4	5	3	5	5	3	18	3	1
M-TS-430	3	5	1	2	2	4	2	2	4	4	4	2	4	9	1	1	5	2	2	2	3	1	3	1
M-TS-431	2	2	1	2	2	4	2	2	4	6	1	3	4	9	1	1	5	2	5	5	3	16	3	1
M-TS-432	1	5	1	3	3	4	2	2	4	6	1	3	4	9	1	4	5	3	5	5	3	25	1	1
M-TS-433	2	5	1	2	2	4	2	2	4	6	4	3	4	9	1	4	5	3	5	5	3	16	6	1
M-TS-434	2	5	3	3	2	4	2	3	4	4	4	3	4	9	3	4	5	3	5	2	3	14	6	1
M-TS-435	2	2	4	2	3	4	2	5	4	6	4	3	4	9	1	1	5	3	2	5	3	17	1	1
M-TS-436	3	2	1	2	2	4	2	2	4	6	4	3	4	9	1	1	5	2	2	5	3	17	3	1
M-TS-437	3	2	4	2	2	4	2	5	4	6	4	2	4	9	3	1	5	3	2	5	3	17	5	1
M-TS-438	2	2	4	2	2	4	2	2	4	6	1	3	4	9	1	4	5	3	5	5	3	16	2	1
M-TS-439	3	5	4	2	2	4	2	5	4	4	4	2	4	9	1	1	5	2	2	5	3	7	3	1
M-TS-440	3	5	1	2	3	4	2	2	4	6	1	3	4	9	1	4	5	2	5	5	3	16	3	1

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Table 16 – continued from previous page

ts_name	Skewness	Kurtosis	Trend	Autocorrelation	Mean	Standard deviation	Number of observations	Non linearity	Seasonality	Periodicity	Chaos	Entropy	Self similarity	DTW distance	Turning points	Partial autocorrelation	Variance	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-441	3	5	1	2	2	4	2	2	4	6	4	3	4	9	1	1	5	3	5	5	3	16	2	1
M-TS-442	3	5	1	2	2	4	2	2	4	6	4	3	4	9	1	1	5	2	5	2	3	14	6	1
M-TS-443	3	2	4	2	5	4	2	2	4	6	4	2	4	9	1	1	5	2	4	5	3	1	2	1
M-TS-444	3	5	1	2	3	4	2	2	4	6	4	3	4	9	3	4	5	3	5	5	3	16	2	1
M-TS-445	3	5	4	2	3	4	2	5	4	6	4	3	4	9	1	1	5	2	5	5	3	26	2	1
M-TS-446	3	5	1	2	2	4	2	3	4	6	4	1	4	9	3	4	5	2	5	5	3	8	2	1
M-TS-447	3	2	1	3	2	4	2	1	4	6	4	3	4	9	3	4	5	2	5	5	3	27	2	1
M-TS-448	2	5	1	1	5	4	2	4	4	6	1	3	4	9	1	4	5	2	5	2	3	18	3	1
M-TS-449	3	5	4	2	3	4	2	5	4	4	4	3	4	9	1	3	5	2	5	2	3	13	1	1
M-TS-450	1	3	1	2	2	4	2	2	4	6	1	3	4	9	1	1	5	3	2	5	3	14	6	1
M-TS-451	2	2	2	3	5	4	1	4	4	2	3	4	4	9	1	4	5	3	5	5	3	21	3	1
M-TS-452	2	5	2	2	2	4	1	5	4	6	1	1	4	9	3	4	5	3	5	5	3	11	3	2
M-TS-453	3	5	5	2	2	4	1	5	4	2	3	4	4	9	1	4	5	3	5	2	3	16	1	1
M-TS-454	5	3	5	5	2	4	1	1	4	2	3	3	4	9	5	4	5	1	5	5	3	16	1	1
M-TS-455	1	5	1	5	2	4	1	5	4	6	1	5	1	9	3	5	5	1	2	2	3	27	3	1
M-TS-456	2	2	1	4	3	4	2	2	4	6	1	5	4	9	5	4	5	4	5	5	3	16	2	1
M-TS-457	5	5	3	2	1	4	2	5	4	4	4	3	4	9	1	1	5	5	2	5	3	17	1	1
M-TS-458	3	5	2	5	2	4	2	3	4	6	1	4	3	9	3	4	5	3	5	2	3	16	6	1
M-TS-459	1	5	1	2	3	4	2	5	4	6	3	3	4	9	3	3	5	5	5	5	3	17	5	1
M-TS-460	2	5	5	5	1	4	2	5	4	6	1	5	5	9	3	3	5	2	5	3	1	16	2	1
M-TS-461	5	5	4	5	1	4	2	5	4	6	1	2	4	9	1	5	5	2	5	5	3	16	6	1
M-TS-462	3	2	4	5	1	4	2	5	4	4	3	5	4	9	3	2	5	2	5	5	3	16	6	1
M-TS-463	2	5	4	5	1	4	2	5	4	4	1	5	4	9	3	2	5	5	2	5	1	17	5	1
M-TS-464	3	5	4	5	3	4	2	5	4	4	1	5	4	9	3	5	5	5	5	5	3	7	3	1
M-TS-465	3	5	1	5	3	4	2	5	4	6	3	2	3	9	1	5	5	5	5	3	3	17	6	1
M-TS-466	3	5	4	5	1	4	2	5	4	6	1	5	4	9	3	2	5	5	5	2	1	16	5	1
M-TS-467	1	5	4	5	1	4	2	5	4	4	1	5	4	9	3	3	5	5	5	2	1	17	5	1
M-TS-468	5	5	2	5	1	4	2	5	4	6	1	2	3	9	1	2	5	5	5	5	3	16	6	1
M-TS-469	3	5	4	5	1	4	2	5	4	6	1	5	1	9	3	5	5	5	5	2	3	17	3	1
M-TS-470	3	5	3	5	1	4	2	5	4	6	1	5	3	9	3	2	5	5	5	2	1	17	6	1
M-TS-471	2	5	1	5	1	4	2	5	4	6	1	5	3	9	2	5	5	5	5	2	3	16	6	1
M-TS-472	3	5	4	5	1	4	2	5	4	6	1	5	4	9	1	5	5	5	5	2	3	17	1	1
M-TS-473	2	5	1	5	1	4	2	5	4	6	1	5	4	9	1	5	5	5	5	5	3	16	2	1
M-TS-474	3	5	4	5	1	4	2	5	4	4	1	5	1	9	5	2	5	5	5	5	3	17	5	1
M-TS-475	1	5	1	5	1	4	2	5	4	6	1	5	1	9	1	5	5	5	5	2	3	17	3	1
M-TS-476	3	5	1	5	1	4	2	5	4	6	1	5	3	9	2	2	5	5	5	2	3	16	6	1
M-TS-477	5	4	5	5	1	4	2	4	4	3	3	5	4	9	5	4	5	5	5	5	3	16	5	1
M-TS-478	5	5	1	5	1	4	2	5	4	4	1	2	1	9	1	5	5	5	5	5	3	25	1	1
M-TS-479	2	5	4	2	1	4	2	5	4	4	1	2	4	9	5	2	5	5	5	2	3	16	3	1
M-TS-480	3	5	3	5	1	4	2	5	4	6	3	3	4	9	1	1	5	5	5	2	3	16	3	1
M-TS-481	3	5	3	5	1	4	2	5	4	6	3	5	2	9	5	2	5	5	5	3	1	27	5	1
M-TS-482	3	5	2	5	3	4	2	5	4	6	1	3	1	9	3	3	5	2	5	5	3	26	6	1
M-TS-483	2	5	3	5	1	4	2	5	4	6	1	2	3	9	1	2	5	2	5	2	3	10	2	1
M-TS-484	3	5	4	5	1	4	2	5	4	4	1	5	4	9	2	3	5	5	2	5	2	15	4	2
M-TS-485	5	2	1	2	1	4	2	2	4	4	1	5	4	9	3	3	5	5	5	5	3	7	6	1
M-TS-486	3	5	4	5	1	4	2	5	4	6	1	5	1	9	2	5	5	5	5	3	1	23	3	1
M-TS-487	3	5	4	2	1	4	2	5	4	6	1	3	4	9	2	3	5	2	5	2	3	13	5	1
M-TS-488	3	5	4	5	1	4	2	5	4	6	3	5	4	9	1	5	5	2	5	2	3	17	1	1
M-TS-489	2	5	1	5	1	4	2	5	4	6	1	5	1	9	3	2	5	5	5	2	1	17	5	1
M-TS-490	3	5	3	5	1	4	2	5	4	6	1	4	4	9	1	1	5	2	5	2	3	16	3	1
M-TS-491	3	4	5	5	1	4	2	2	4	6	1	5	2	9	5	3	5	2	5	5	3	16	5	1
M-TS-492	4	5	1	2	3	4	2	1	4	6	3	5	4	9	3	1	5	2	5	5	3	17	6	1
M-TS-493	3	5	3	5	3	4	2	5	4	6	1	5	5	9	3	5	5	3	5	2	1	16	5	1
M-TS-494	5	5	5	1	4	4	2	4	4	6	3	1	4	9	2	4	5	1	5	2	3	17	3	1
M-TS-495	3	5	2	1	2	4	1	3	4	2	1	1	4	9	1	4	5	3	5	2	3	25	1	1
M-TS-496	3	5	3	4	2	4	1	5	4	6	1	3	4	9	1	4	5	2	5	5	3	26	2	1
M-TS-497	3	5	3	1	4	4	1	5	4	2	3	1	4	9	3	4	5	2	5	2	3	17	5	1
M-TS-498	2	5	2	4	4	4	1	5	4	2	3	3	4	9	1	4	5	3	5	2	3	16	5	1
M-TS-499	3	5	3	4	4	4	1	5	4	3	3	1	4	9	3	4	5	3	5	2	3	17	5	1
M-TS-500	3	5	3	1	1	4	1	4	4	2	3	4	4	9	3	4	5	2	5	2	3	26	5	1

B Feature selected time series taxonomy results

B.1 Factor level description

Table 17 Feature selected time series taxonomy factor level description

Feature name	Levels	Level values
Trend	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Autocorrelation	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Seasonality	high; low; medium; none seasonality; very high; very low;	1; 2; 3; 4; 5; 6;
Periodicity	high; low; medium; none periodicity; very high; very low;	1; 2; 3; 4; 5; 6;
Chaos	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Entropy	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Turning points	medium; more oscillating; more steady; very oscillating; very steady;	1; 2; 3; 4; 5;
Partial autocorrelation	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Outliers	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
Step changes	great many abrupt changes; less abrupt changes; many abrupt changes; medium; very less abrupt changes;	1; 2; 3; 4; 5;
Peaks	high; low; medium; very high; very low;	1; 2; 3; 4; 5;
DurbinWatson test	negative autocorrelation; none because univariate; positive autocorrelation;	1; 2; 3;
Quartile distribution	Quartile1 less Quartile2 less Quartile3 less Quartile4 many; Quartile1 less Quartile2 less Quartile3 less Quartile4 medium; Quartile1 less Quartile2 less Quartile3 many Quartile4 less; Quartile1 less Quartile2 less Quartile3 many Quartile4 medium; Quartile1 less Quartile2 less Quartile3 medium Quartile4 less; Quartile1 less Quartile2 less Quartile3 medium Quartile4 many; Quartile1 less Quartile2 less Quartile3 medium Quartile4 medium; Quartile1 less Quartile2 many Quartile3 less Quartile4 less; Quartile1 less Quartile2 many Quartile3 less Quartile4 medium; Quartile1 less Quartile2 many Quartile3 medium Quartile4 less; Quartile1 less Quartile2 medium Quartile3 less Quartile4 less; Quartile1 less Quartile2 medium Quartile3 less Quartile4 many; Quartile1 less Quartile2 medium Quartile3 less Quartile4 medium; Quartile1 less Quartile2 medium Quartile3 many Quartile4 less; Quartile1 less Quartile2 medium Quartile3 many Quartile4 medium; Quartile1 less Quartile2 medium Quartile3 medium Quartile4 less; Quartile1 less Quartile2 medium Quartile3 medium Quartile4 medium; Quartile1 many Quartile2 less Quartile3 less Quartile4 less; Quartile1 many Quartile2 medium Quartile3 less Quartile4 less; Quartile1 medium Quartile2 less Quartile3 less Quartile4 less; Quartile1 medium Quartile2 less Quartile3 less Quartile4 medium; Quartile1 medium Quartile2 less Quartile3 medium Quartile4 less; Quartile1 medium Quartile2 many Quartile3 less Quartile4 less; Quartile1 medium Quartile2 many Quartile3 medium Quartile4 less; Quartile1 medium Quartile2 medium Quartile3 less Quartile4 less; Quartile1 medium Quartile2 medium Quartile3 less Quartile4 medium; Quartile1 medium Quartile2 medium Quartile3 medium Quartile4 less;	1; 2; 3; 4; 5; 6; 7; 8; 9; 10; 11; 12; 13; 14; 15; 16; 17; 18; 19; 20; 21; 22; 23; 24; 25; 26; 27;
Determination coefficient	high; low; medium; none because univariate TS; very high; very low;	1; 2; 3; 4; 5; 6;
Number of attributes	multivariate TS; univariate TS;	1; 2;

B.2 Classification results

Table 18 Feature selected time series taxonomy results

ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-1	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-2	4	5	5	2	3	3	1	1	2	5	5	2	16	4	2
U-TS-3	3	5	5	2	3	1	1	1	3	5	5	2	16	4	2
U-TS-4	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-5	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-6	2	5	5	2	3	1	2	1	3	5	5	2	16	4	2
U-TS-7	4	5	2	6	3	2	2	1	3	5	5	2	16	4	2
U-TS-8	3	5	5	2	3	4	2	1	3	5	2	2	16	4	2
U-TS-9	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-10	4	2	5	2	3	1	1	1	2	5	5	2	16	4	2
U-TS-11	5	5	5	2	3	3	2	3	3	5	5	2	16	4	2
U-TS-12	2	5	5	2	3	4	2	1	5	5	5	2	16	4	2
U-TS-13	4	5	5	2	3	2	3	1	5	5	5	2	16	4	2
U-TS-14	4	2	5	2	3	3	3	1	2	5	5	2	16	4	2
U-TS-15	2	2	6	2	3	1	2	3	3	5	5	2	25	4	2
U-TS-16	4	2	5	2	3	3	3	1	1	5	5	2	16	4	2
U-TS-17	4	2	5	2	3	3	3	1	2	5	5	2	16	4	2
U-TS-18	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-19	2	5	5	2	3	1	2	3	3	5	5	2	16	4	2
U-TS-20	2	5	5	2	3	4	1	1	2	5	5	2	27	4	2
U-TS-21	5	2	4	2	3	1	1	1	3	5	5	2	16	4	2
U-TS-22	2	5	5	2	3	1	2	3	2	5	2	2	16	4	2
U-TS-23	1	2	5	2	3	1	2	1	2	5	5	2	16	4	2
U-TS-24	2	5	5	2	3	4	2	3	3	5	5	2	16	4	2
U-TS-25	1	5	5	2	3	1	1	1	2	5	5	2	16	4	2
U-TS-26	2	5	2	6	3	3	1	1	3	5	5	2	16	4	2
U-TS-27	2	2	1	2	3	1	2	1	2	5	2	2	17	4	2
U-TS-28	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-29	4	5	3	6	3	2	3	3	5	5	5	2	16	4	2
U-TS-30	4	5	5	2	3	2	3	1	2	5	5	2	16	4	2
U-TS-31	4	5	5	2	3	2	3	1	5	5	5	2	16	4	2
U-TS-32	2	5	5	2	3	4	1	1	2	5	5	2	27	4	2
U-TS-33	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-34	1	5	5	2	3	3	3	1	2	5	5	2	16	4	2
U-TS-35	2	5	5	2	3	3	4	1	3	5	5	2	16	4	2
U-TS-36	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-37	4	2	5	2	3	3	3	1	2	5	5	2	16	4	2
U-TS-38	3	5	5	2	3	4	2	1	5	5	2	2	16	4	2
U-TS-39	4	5	5	2	3	2	3	1	5	5	5	2	16	4	2
U-TS-40	2	5	5	2	3	4	1	1	2	5	5	2	16	4	2
U-TS-41	2	5	5	2	3	1	2	3	3	5	5	2	16	4	2
U-TS-42	1	5	5	2	3	3	3	1	5	5	5	2	16	4	2
U-TS-43	4	2	5	2	3	3	3	1	2	5	5	2	16	4	2
U-TS-44	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-45	4	5	3	6	3	2	3	3	5	5	5	2	16	4	2
U-TS-46	5	5	5	2	3	3	3	1	5	5	5	2	16	4	2
U-TS-47	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-48	2	5	5	2	3	4	2	3	3	5	5	2	16	4	2
U-TS-49	2	5	5	2	3	4	2	1	1	5	5	2	16	4	2
U-TS-50	3	5	2	6	3	3	1	3	2	5	5	2	16	4	2
U-TS-51	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-52	4	2	5	2	3	3	3	1	3	5	5	2	16	4	2
U-TS-53	2	5	5	2	3	4	2	1	3	5	5	2	16	4	2
U-TS-54	4	4	4	4	4	5	1	4	5	5	5	2	20	4	2
U-TS-55	4	4	4	4	4	5	1	4	1	4	5	2	17	4	2
U-TS-56	4	4	4	4	4	5	1	4	5	5	5	2	20	4	2
U-TS-57	4	4	4	4	4	5	1	4	3	2	5	2	17	4	2
U-TS-58	4	4	4	4	4	5	2	4	1	4	5	2	7	4	2
U-TS-59	4	4	4	4	4	5	1	4	5	5	5	2	20	4	2
U-TS-60	4	4	4	4	4	5	2	4	1	4	5	2	7	4	2
U-TS-61	4	4	4	4	4	5	2	4	1	2	2	2	17	4	2
U-TS-62	4	4	4	4	4	5	2	4	1	4	5	2	7	4	2
U-TS-63	4	4	4	4	4	5	2	4	2	5	5	2	13	4	2
U-TS-64	1	4	4	4	4	3	2	4	3	5	5	2	16	4	2
U-TS-65	4	4	4	4	4	5	2	4	5	4	5	2	7	4	2
U-TS-66	4	4	4	4	4	5	2	4	1	2	2	2	17	4	2
U-TS-67	4	4	4	4	4	5	2	4	1	4	2	2	7	4	2
U-TS-68	4	3	6	6	1	5	2	1	2	2	5	2	17	4	2
U-TS-69	4	4	4	4	4	5	2	4	3	2	5	2	16	4	2
U-TS-70	4	3	6	6	4	5	1	3	3	5	1	2	22	4	2
U-TS-71	4	3	6	6	1	5	2	1	5	2	5	2	17	4	2
U-TS-72	4	2	4	6	1	1	1	3	3	5	5	2	16	4	2
U-TS-73	4	2	4	4	4	1	1	4	3	5	3	2	16	4	2
U-TS-74	4	4	4	4	4	2	1	4	4	5	2	2	27	4	2
U-TS-75	4	3	6	6	4	2	1	1	1	5	4	2	16	4	2
U-TS-76	4	3	6	6	4	5	1	3	3	2	5	2	12	4	2
U-TS-77	4	3	4	4	4	2	2	4	2	4	5	2	17	4	2
U-TS-78	4	3	4	4	4	2	1	1	3	2	2	2	27	4	2
U-TS-79	4	1	4	4	4	2	2	4	5	2	5	2	16	4	2
U-TS-80	4	3	4	4	4	2	2	1	5	2	5	2	27	4	2

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Table 18 – continued from previous page

ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-81	4	1	4	4	4	5	1	4	3	5	2	2	17	4	2
U-TS-82	4	3	4	4	4	1	2	4	3	5	5	2	27	4	2
U-TS-83	4	1	4	4	4	5	2	4	5	2	5	2	17	4	2
U-TS-84	4	1	4	4	4	5	1	4	3	5	5	2	16	4	2
U-TS-85	4	4	4	4	4	5	2	4	3	3	5	2	17	4	2
U-TS-86	4	1	4	4	4	5	1	4	4	4	5	2	2	4	2
U-TS-87	4	2	4	4	4	3	2	1	3	2	5	2	16	4	2
U-TS-88	4	3	4	4	4	1	2	4	1	5	5	2	27	4	2
U-TS-89	4	1	4	4	4	3	1	4	1	5	2	2	16	4	2
U-TS-90	4	4	4	4	4	5	1	4	1	5	5	2	27	4	2
U-TS-91	4	2	4	4	4	1	1	1	2	5	5	2	16	4	2
U-TS-92	4	4	4	4	4	2	2	4	3	5	2	2	16	4	2
U-TS-93	4	2	4	4	4	1	1	1	1	2	5	2	16	4	2
U-TS-94	1	4	4	4	4	5	2	4	1	5	2	2	17	4	2
U-TS-95	1	4	4	4	4	2	1	4	3	5	2	2	25	4	2
U-TS-96	4	3	6	6	1	2	2	1	1	5	2	2	25	4	2
U-TS-97	4	4	4	4	4	2	1	4	5	2	5	2	16	4	2
U-TS-98	4	4	4	4	4	2	2	4	2	2	5	2	25	4	2
U-TS-99	4	2	4	4	4	1	1	1	4	2	3	2	16	4	2
U-TS-100	4	3	4	4	4	1	2	1	3	5	3	2	16	4	2
U-TS-101	4	3	4	4	4	3	2	4	3	2	3	2	16	4	2
U-TS-102	4	3	4	4	4	2	1	1	3	2	2	2	27	4	2
U-TS-103	4	2	4	4	4	1	2	1	2	5	5	2	16	4	2
U-TS-104	5	2	4	4	4	1	2	1	2	2	5	2	16	4	2
U-TS-105	4	2	4	4	4	3	1	4	1	2	2	2	17	4	2
U-TS-106	4	1	6	1	3	2	2	4	3	2	2	2	27	4	2
U-TS-107	4	2	4	4	4	2	2	1	1	4	5	2	16	4	2
U-TS-108	4	3	6	2	3	1	2	1	3	5	5	2	16	4	2
U-TS-109	1	5	2	3	3	1	1	1	3	5	2	2	16	4	2
U-TS-110	4	2	3	2	3	3	2	1	2	5	5	2	16	4	2
U-TS-111	4	3	6	2	3	1	2	1	3	5	5	2	16	4	2
U-TS-112	4	3	6	2	3	3	2	4	3	5	2	2	16	4	2
U-TS-113	4	3	2	2	3	1	3	4	3	5	5	2	26	4	2
U-TS-114	1	2	6	3	3	2	1	1	3	5	5	2	17	4	2
U-TS-115	3	5	6	3	3	1	1	1	2	5	2	2	27	4	2
U-TS-116	1	2	6	3	3	3	2	1	3	5	5	2	16	4	2
U-TS-117	4	3	6	6	1	5	2	3	2	5	5	2	23	4	2
U-TS-118	1	4	6	5	3	5	1	4	2	5	5	2	3	4	2
U-TS-119	4	3	6	6	1	5	1	3	2	4	5	2	17	4	2
U-TS-120	4	3	6	2	3	2	1	1	3	2	5	2	13	4	2
U-TS-121	4	3	6	6	1	5	2	1	1	3	5	2	6	4	2
U-TS-122	4	3	6	6	3	2	1	3	5	2	2	2	25	4	2
U-TS-123	4	3	6	6	1	2	3	1	3	5	5	2	17	4	2
U-TS-124	4	3	6	6	3	1	2	1	3	5	2	2	25	4	2
U-TS-125	4	3	6	6	1	5	2	1	3	2	3	2	17	4	2
U-TS-126	3	2	3	3	3	3	3	1	3	5	5	2	11	4	2
U-TS-127	1	2	4	4	4	4	1	4	3	5	3	2	27	4	2
U-TS-128	3	5	1	3	3	3	3	3	3	5	5	2	16	4	2
U-TS-129	4	3	6	6	1	2	2	1	1	2	5	2	7	4	2
U-TS-130	1	2	4	4	4	4	1	4	3	5	3	2	27	4	2
U-TS-131	1	2	4	4	4	4	1	4	3	5	3	2	27	4	2
U-TS-132	4	4	4	4	4	5	2	4	3	5	5	2	23	4	2
U-TS-133	3	2	3	3	3	3	3	1	3	5	5	2	11	4	2
U-TS-134	3	2	3	3	3	3	3	1	3	5	5	2	11	4	2
U-TS-135	3	2	6	2	3	4	3	4	3	5	5	2	16	4	2
U-TS-136	4	4	4	4	4	2	2	4	4	5	5	2	16	4	2
U-TS-137	4	3	6	2	3	5	1	4	5	2	5	2	17	4	2
U-TS-138	2	2	6	5	3	4	1	4	3	5	5	2	27	4	2
U-TS-139	4	3	6	6	1	5	2	1	3	2	5	2	10	4	2
U-TS-140	5	5	6	3	3	4	1	1	3	5	5	2	27	4	2
U-TS-141	3	2	6	2	3	4	3	4	3	5	5	2	16	4	2
U-TS-142	3	2	6	5	3	4	1	4	2	5	5	2	25	4	2
U-TS-143	4	3	6	6	1	5	2	1	4	3	5	2	7	4	2
U-TS-144	4	3	6	6	1	5	2	1	2	2	5	2	7	4	2
U-TS-145	3	5	4	4	4	1	1	3	3	5	1	2	16	4	2
U-TS-146	4	5	6	6	1	1	1	3	3	5	5	2	16	4	2
U-TS-147	4	4	4	4	4	5	1	4	5	4	2	2	7	4	2
U-TS-148	4	2	4	4	4	2	2	3	1	5	5	2	25	4	2
U-TS-149	3	5	4	4	4	1	1	3	3	5	5	2	16	4	2
U-TS-150	4	3	4	4	4	4	1	4	2	5	5	2	25	4	2
U-TS-151	1	2	6	6	1	4	1	3	2	5	5	2	17	4	2
U-TS-152	1	5	6	6	1	1	1	3	1	5	5	2	16	4	2
U-TS-153	4	2	3	2	3	4	1	1	3	5	5	2	16	4	2
U-TS-154	5	5	6	3	3	4	1	1	3	5	2	2	16	4	2
U-TS-155	3	2	2	2	3	4	1	1	2	5	5	2	27	4	2
U-TS-156	5	1	2	5	3	2	4	4	1	5	5	2	16	4	2
U-TS-157	4	3	6	6	1	5	1	1	1	4	5	2	1	4	2
U-TS-158	5	1	2	5	3	2	4	4	1	5	5	2	16	4	2
U-TS-159	4	3	6	6	1	5	1	1	1	4	5	2	1	4	2
U-TS-160	5	1	2	5	3	2	4	4	1	5	5	2	16	4	2
U-TS-161	4	2	3	2	3	4	1	1	3	5	5	2	16	4	2
U-TS-162	4	3	3	6	1	2	1	3	5	2	1	2	17	4	2
U-TS-163	4	5	1	6	3	4	3	1	3	5	3	2	16	4	2
U-TS-164	4	2	4	5	5	1	2	1	3	2	3	2	16	4	2
U-TS-165	4	3	2	6	3	2	1	1	5	2	3	2	16	4	2
U-TS-166	5	2	4	6	3	4	3	1	3	5	5	2	16	4	2

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-167	4	2	5	6	3	4	2	1	3	5	5	2	27	4	2
U-TS-168	5	3	4	1	3	4	1	4	2	5	5	2	16	4	2
U-TS-169	4	3	2	6	1	1	1	3	2	5	5	2	16	4	2
U-TS-170	4	3	2	6	3	5	2	1	2	5	5	2	17	4	2
U-TS-171	4	3	1	6	3	3	2	1	2	2	2	2	7	4	2
U-TS-172	4	3	6	6	1	2	3	1	1	5	5	2	16	4	2
U-TS-173	4	2	4	4	4	2	2	1	1	2	5	2	14	4	2
U-TS-174	4	2	4	4	4	2	4	1	1	2	5	2	16	4	2
U-TS-175	3	5	4	4	4	1	2	1	3	5	3	2	16	4	2
U-TS-176	2	5	6	6	1	1	3	2	3	5	5	2	26	4	2
U-TS-177	4	3	6	6	1	4	2	1	2	2	5	2	17	4	2
U-TS-178	4	3	4	4	4	5	3	3	5	3	5	2	7	4	2
U-TS-179	1	2	2	2	3	1	1	1	5	2	5	2	16	4	2
U-TS-180	3	2	4	4	4	4	1	4	3	5	5	2	27	4	2
U-TS-181	4	4	3	5	3	5	3	4	3	4	5	2	17	4	2
U-TS-182	4	3	6	6	4	2	3	3	1	2	5	2	1	4	2
U-TS-183	4	2	5	6	3	3	4	1	2	5	5	2	17	4	2
U-TS-184	4	3	4	4	1	2	3	4	5	2	2	2	17	4	2
U-TS-185	3	2	4	4	4	4	1	1	3	2	3	2	17	4	2
U-TS-186	1	5	4	4	4	1	5	1	3	5	1	2	16	4	2
U-TS-187	4	2	4	4	4	1	3	1	3	2	3	2	27	4	2
U-TS-188	4	3	6	6	1	1	3	1	2	2	5	2	7	4	2
U-TS-189	4	2	4	4	1	2	5	3	1	2	5	2	27	4	2
U-TS-190	4	3	6	6	4	4	3	3	2	2	5	2	17	4	2
U-TS-191	4	3	6	6	1	3	3	3	2	2	5	2	7	4	2
U-TS-192	4	3	1	3	3	5	5	1	4	5	5	2	23	4	2
U-TS-193	4	3	2	6	3	1	3	1	3	4	5	2	17	4	2
U-TS-194	1	5	6	6	1	4	3	3	2	5	5	2	22	4	2
U-TS-195	4	3	6	6	1	2	3	3	2	2	5	2	17	4	2
U-TS-196	4	3	4	4	4	3	2	4	1	2	2	2	11	4	2
U-TS-197	3	5	6	6	3	1	2	1	3	5	5	2	25	4	2
U-TS-198	4	2	4	4	4	3	1	3	3	2	2	2	17	4	2
U-TS-199	4	3	6	6	3	2	1	3	1	2	5	2	27	4	2
U-TS-200	4	2	6	6	1	1	3	3	1	2	2	2	16	4	2
U-TS-201	4	4	2	5	3	2	2	4	3	2	2	2	27	4	2
U-TS-202	1	2	4	4	4	1	4	3	2	5	2	2	27	4	2
U-TS-203	1	2	6	6	3	2	5	4	1	2	5	2	1	4	2
U-TS-204	4	2	4	4	4	3	1	3	3	5	3	2	25	4	2
U-TS-205	4	3	5	6	3	4	2	1	3	5	2	2	16	4	2
U-TS-206	4	2	4	4	4	2	2	1	5	2	2	2	21	4	2
U-TS-207	4	1	2	5	3	4	3	4	1	5	3	2	17	4	2
U-TS-208	4	2	4	4	1	2	3	1	1	5	5	2	17	4	2
U-TS-209	4	4	4	4	4	5	2	4	1	1	5	2	7	4	2
U-TS-210	2	5	4	4	4	3	5	1	1	5	1	2	16	4	2
U-TS-211	4	3	4	4	4	5	2	4	5	4	5	2	7	4	2
U-TS-212	4	2	6	6	1	1	2	3	4	5	4	2	16	4	2
U-TS-213	4	2	4	4	4	1	3	1	2	2	3	2	16	4	2
U-TS-214	3	5	6	6	1	3	5	3	3	5	5	2	27	4	2
U-TS-215	3	5	6	6	1	3	5	2	1	5	1	2	27	4	2
U-TS-216	4	2	4	4	1	5	3	3	3	5	2	2	16	4	2
U-TS-217	4	3	4	4	4	5	1	3	2	4	5	2	7	4	2
U-TS-218	4	2	3	6	1	3	3	2	3	5	5	2	17	4	2
U-TS-219	4	2	3	6	1	1	3	3	2	5	1	2	17	4	2
U-TS-220	4	2	2	6	1	3	2	3	2	2	5	2	16	4	2
U-TS-221	1	5	3	6	1	2	5	3	4	5	1	2	16	4	2
U-TS-222	4	3	4	4	4	2	2	3	3	3	5	2	17	4	2
U-TS-223	4	2	4	4	4	1	2	3	2	2	3	2	17	4	2
U-TS-224	3	5	4	4	4	2	5	1	2	5	5	2	16	4	2
U-TS-225	4	5	5	6	1	3	5	3	2	5	5	2	24	4	2
U-TS-226	4	2	1	6	1	3	3	3	1	2	3	2	17	4	2
U-TS-227	4	3	4	4	1	5	3	3	1	1	5	2	6	4	2
U-TS-228	4	3	1	6	4	3	5	3	2	2	5	2	17	4	2
U-TS-229	4	2	4	4	4	1	3	1	3	5	5	2	16	4	2
U-TS-230	4	2	3	6	1	1	1	3	2	2	1	2	17	4	2
U-TS-231	4	3	4	4	4	5	2	1	3	4	5	2	7	4	2
U-TS-232	4	3	4	4	4	2	3	3	2	2	5	2	17	4	2
U-TS-233	4	2	4	4	4	1	1	1	3	4	5	2	7	4	2
U-TS-234	4	5	6	6	1	3	3	3	1	5	5	2	10	4	2
U-TS-235	4	2	4	4	4	3	3	1	3	2	3	2	17	4	2
U-TS-236	4	2	4	4	4	1	1	3	1	2	5	2	16	4	2
U-TS-237	4	5	4	4	4	3	2	3	1	5	2	2	27	4	2
U-TS-238	4	5	4	4	4	3	1	2	3	2	3	2	16	4	2
U-TS-239	4	2	2	2	3	3	3	4	3	2	5	2	17	4	2
U-TS-240	4	2	6	6	1	1	3	3	3	5	5	2	16	4	2
U-TS-241	3	5	2	6	3	3	2	1	3	5	5	2	27	4	2
U-TS-242	4	2	4	2	3	2	3	2	1	2	3	2	16	4	2
U-TS-243	3	5	4	4	4	2	5	2	3	5	1	2	16	4	2
U-TS-244	1	2	2	2	3	1	2	4	3	2	5	2	17	4	2
U-TS-245	4	2	1	6	1	3	5	3	3	2	5	2	17	4	2
U-TS-246	4	5	5	6	1	2	5	3	3	5	3	2	16	4	2
U-TS-247	4	3	3	6	1	2	1	3	2	5	3	2	17	4	2
U-TS-248	4	2	2	6	1	1	5	3	5	2	5	2	17	4	2
U-TS-249	4	2	6	6	1	3	1	3	3	5	1	2	16	4	2
U-TS-250	4	2	1	2	3	2	2	1	3	2	5	2	17	4	2
U-TS-251	1	2	4	4	4	3	2	1	3	2	5	2	17	4	2
U-TS-252	4	2	4	4	4	3	2	3	2	4	5	2	16	4	2

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-253	4	2	4	4	4	4	3	1	3	5	5	2	27	4	2
U-TS-254	1	5	4	5	5	1	3	1	3	5	3	2	25	4	2
U-TS-255	4	2	4	4	4	2	2	1	3	2	5	2	7	4	2
U-TS-256	4	2	3	6	4	3	5	3	3	2	4	2	17	4	2
U-TS-257	4	2	4	4	4	3	1	2	2	2	3	2	16	4	2
U-TS-258	4	5	4	4	1	1	1	3	4	2	5	2	16	4	2
U-TS-259	4	2	4	4	4	3	2	3	2	2	5	2	17	4	2
U-TS-260	4	3	4	4	4	2	1	1	5	3	5	2	7	4	2
U-TS-261	4	2	4	4	4	1	3	3	3	5	5	2	25	4	2
U-TS-262	4	2	4	4	4	2	3	2	5	2	5	2	27	4	2
U-TS-263	4	2	4	4	4	2	2	3	3	5	5	2	23	4	2
U-TS-264	4	2	4	4	4	1	1	3	2	2	3	2	16	4	2
U-TS-265	4	5	4	4	4	3	2	2	2	5	5	2	16	4	2
U-TS-266	4	3	4	4	4	3	2	1	3	2	5	2	7	4	2
U-TS-267	4	3	6	6	3	2	2	1	5	2	3	2	17	4	2
U-TS-268	4	2	4	4	4	2	1	2	5	2	5	2	16	4	2
U-TS-269	4	2	4	4	4	2	1	2	2	4	5	2	17	4	2
U-TS-270	4	2	6	6	3	5	1	1	2	5	5	2	17	4	2
U-TS-271	4	5	4	4	4	2	2	5	2	2	5	2	17	4	2
U-TS-272	4	2	4	4	4	2	2	2	3	5	2	2	16	4	2
U-TS-273	4	2	4	4	4	2	1	2	1	5	5	2	17	4	2
U-TS-274	4	2	4	4	4	2	3	3	2	2	5	2	17	4	2
U-TS-275	1	5	4	4	4	2	3	3	1	2	5	2	2	4	2
U-TS-276	4	5	4	4	4	3	4	5	3	2	3	2	16	4	2
U-TS-277	4	2	4	4	1	3	3	2	4	4	3	2	2	4	2
U-TS-278	4	2	4	4	4	2	2	2	5	2	3	2	16	4	2
U-TS-279	4	2	4	4	4	2	1	2	1	4	5	2	17	4	2
U-TS-280	4	3	4	4	4	2	1	3	5	4	5	2	7	4	2
U-TS-281	4	2	4	4	1	2	2	2	5	4	5	2	17	4	2
U-TS-282	4	2	4	4	3	5	5	5	3	1	5	2	7	4	2
U-TS-283	1	5	4	4	4	3	1	2	4	2	5	2	27	4	2
U-TS-284	4	2	4	4	1	2	3	2	2	3	5	2	7	4	2
U-TS-285	4	2	4	5	5	2	5	2	5	2	2	2	17	4	2
U-TS-286	4	5	4	6	5	2	3	5	5	4	3	2	17	4	2
U-TS-287	4	5	4	6	3	2	1	5	5	4	1	2	7	4	2
U-TS-288	4	5	4	4	4	2	3	2	2	4	1	2	7	4	2
U-TS-289	4	5	4	2	3	2	1	5	4	2	3	2	2	4	2
U-TS-290	4	2	4	6	3	3	3	2	1	5	3	2	17	4	2
U-TS-291	4	5	4	3	5	2	1	5	2	4	1	2	27	4	2
U-TS-292	4	5	4	4	1	3	2	5	3	5	5	2	27	4	2
U-TS-293	4	2	4	4	3	5	5	3	3	3	2	2	7	4	2
U-TS-294	4	5	4	4	4	3	1	3	3	2	5	2	5	4	2
U-TS-295	4	5	4	4	4	2	2	5	3	2	5	2	13	4	2
U-TS-296	4	2	4	4	1	2	1	5	3	3	5	2	7	4	2
U-TS-297	4	2	4	4	1	5	3	5	3	1	5	2	7	4	2
U-TS-298	5	5	4	4	4	5	5	3	3	5	5	2	16	4	2
U-TS-299	4	5	4	4	1	3	1	5	5	5	2	2	16	4	2
U-TS-300	4	2	2	6	3	2	3	3	5	2	2	2	17	4	2
U-TS-301	5	5	4	4	1	5	3	3	5	2	5	3	16	6	1
U-TS-302	1	5	4	6	1	5	3	3	3	2	2	1	16	1	1
U-TS-303	1	5	4	6	1	5	5	3	3	2	2	1	16	5	1
U-TS-304	3	5	4	6	3	2	1	3	3	5	2	1	16	5	1
U-TS-305	1	5	4	6	3	5	1	3	3	5	3	1	16	5	1
U-TS-306	1	5	4	6	2	5	1	3	2	2	3	1	27	5	1
U-TS-307	3	5	4	6	1	5	3	3	2	5	2	1	16	5	1
U-TS-308	1	5	4	6	3	5	1	3	3	2	3	1	27	5	1
U-TS-309	4	5	4	6	1	5	1	3	5	5	2	3	16	5	1
U-TS-310	4	5	4	6	3	5	1	3	3	2	3	3	27	5	1
U-TS-311	1	5	4	6	3	5	3	3	3	5	3	1	16	5	1
U-TS-312	3	5	4	6	4	5	3	1	3	5	2	1	27	1	1
U-TS-313	1	5	4	6	3	5	3	3	2	2	2	1	16	5	1
U-TS-314	4	5	4	6	3	5	1	3	3	2	2	1	27	5	1
U-TS-315	1	5	4	6	3	5	1	3	3	2	3	1	16	5	1
U-TS-316	1	5	4	6	1	5	1	3	3	2	2	3	16	1	1
U-TS-317	1	5	4	6	3	5	3	3	2	5	2	1	16	5	1
U-TS-318	1	5	4	6	3	5	3	3	3	2	2	1	16	5	1
U-TS-319	1	5	4	6	1	2	3	3	3	5	3	1	27	5	1
U-TS-320	4	5	4	6	1	5	3	3	3	2	3	1	16	5	1
U-TS-321	4	5	4	6	3	2	1	3	2	2	2	1	27	5	1
U-TS-322	3	5	4	6	4	5	1	3	3	2	2	1	27	5	1
U-TS-323	4	5	4	6	3	5	1	3	2	2	1	1	27	5	1
U-TS-324	4	5	4	6	2	2	1	3	3	5	1	1	27	5	1
U-TS-325	4	5	4	6	1	5	1	3	3	5	3	1	27	5	1
U-TS-326	4	5	4	6	3	5	1	3	3	2	3	1	16	5	1
U-TS-327	3	5	4	6	1	5	5	3	3	5	2	1	16	5	1
U-TS-328	1	5	4	6	1	5	3	3	3	5	3	1	27	5	1
U-TS-329	4	5	4	6	2	5	1	3	3	5	3	1	16	5	1
U-TS-330	1	5	4	6	1	2	3	3	3	2	2	1	16	5	1
U-TS-331	4	5	4	6	1	5	1	3	3	2	3	1	27	5	1
U-TS-332	3	5	4	6	1	5	3	3	3	5	2	3	16	5	1
U-TS-333	1	5	4	6	1	5	3	1	3	5	3	3	27	5	1
U-TS-334	4	5	4	6	3	2	1	3	2	2	3	1	16	5	1
U-TS-335	1	5	4	6	1	5	1	3	2	2	2	1	17	5	1
U-TS-336	4	5	4	6	2	5	1	3	2	2	3	1	27	5	1
U-TS-337	3	5	4	6	3	5	3	3	3	2	2	1	16	5	1
U-TS-338	3	5	4	6	1	5	3	3	3	5	2	1	27	5	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-339	4	5	4	6	3	5	1	3	3	2	3	1	27	5	1
U-TS-340	1	5	4	6	3	5	1	3	3	5	3	1	27	5	1
U-TS-341	4	5	4	6	3	5	1	3	3	2	1	1	16	5	1
U-TS-342	1	5	4	6	1	5	3	3	2	2	2	1	16	5	1
U-TS-343	4	5	4	6	3	5	3	3	3	2	3	1	27	5	1
U-TS-344	1	5	4	6	1	5	3	3	2	2	3	1	16	5	1
U-TS-345	3	5	4	6	1	5	3	3	3	5	2	1	16	5	1
U-TS-346	4	5	4	6	3	2	3	3	3	5	1	1	16	5	1
U-TS-347	4	5	4	6	3	5	3	3	2	2	3	1	27	1	1
U-TS-348	1	5	4	6	3	5	3	3	2	5	3	1	16	5	1
U-TS-349	3	5	4	6	1	5	3	1	2	5	2	1	16	5	1
U-TS-350	4	5	4	6	2	5	1	3	3	5	3	1	16	5	1
U-TS-351	1	5	4	6	1	5	3	3	3	2	3	3	16	5	1
U-TS-352	3	5	4	6	1	5	5	3	3	5	5	1	27	5	1
U-TS-353	1	5	4	6	3	5	1	3	3	5	2	1	24	5	1
U-TS-354	3	5	4	6	1	5	3	3	2	2	2	1	27	5	1
U-TS-355	1	5	4	6	3	5	1	3	3	5	3	3	27	5	1
U-TS-356	1	5	4	6	2	5	1	3	2	2	3	1	27	5	1
U-TS-357	1	5	4	6	3	5	3	3	2	5	3	1	27	5	1
U-TS-358	1	5	4	6	3	5	3	3	3	2	2	3	27	5	1
U-TS-359	1	5	4	6	1	5	3	3	2	5	2	1	27	5	1
U-TS-360	1	5	4	6	3	5	1	3	3	5	3	1	27	2	1
U-TS-361	4	5	4	6	3	5	1	3	3	2	1	1	27	5	1
U-TS-362	3	5	4	6	3	5	3	3	2	5	2	3	27	5	1
U-TS-363	3	5	4	6	1	5	3	3	3	5	2	3	27	5	1
U-TS-364	3	5	4	6	3	5	3	3	2	2	2	1	27	5	1
U-TS-365	4	5	4	6	3	2	3	3	1	2	1	1	27	5	1
U-TS-366	1	5	4	6	3	5	1	3	3	2	1	3	27	5	1
U-TS-367	1	5	4	6	1	5	1	3	3	2	2	3	27	5	1
U-TS-368	1	5	4	6	3	5	3	3	3	5	2	1	27	5	1
U-TS-369	1	5	4	6	3	5	3	3	3	2	2	1	27	5	1
U-TS-370	1	5	4	6	1	5	3	3	3	5	3	3	27	5	1
U-TS-371	4	5	4	6	3	5	1	3	3	5	3	1	27	5	1
U-TS-372	4	5	4	6	3	5	3	3	2	2	3	1	27	5	1
U-TS-373	3	5	4	6	1	5	3	3	3	2	3	3	27	5	1
U-TS-374	1	5	4	6	1	5	1	3	2	2	3	1	27	5	1
U-TS-375	1	5	4	6	2	5	1	3	3	5	3	3	24	5	1
U-TS-376	1	5	4	6	1	5	1	3	2	5	2	1	27	5	1
U-TS-377	1	5	4	6	1	5	1	3	3	2	2	1	27	5	1
U-TS-378	3	5	4	6	3	5	5	3	3	5	2	3	27	5	1
U-TS-379	3	5	4	6	3	5	3	3	3	5	2	1	27	5	1
U-TS-380	1	5	4	6	3	5	1	3	3	5	2	1	24	5	1
U-TS-381	1	5	4	6	4	5	3	3	1	5	2	3	27	5	1
U-TS-382	4	5	4	6	3	5	3	3	3	5	1	1	27	5	1
U-TS-383	1	5	4	6	3	5	3	3	3	5	3	1	27	5	1
U-TS-384	1	5	4	6	1	5	3	3	3	5	2	1	27	1	1
U-TS-385	4	5	4	6	3	5	3	3	2	2	3	1	24	5	1
U-TS-386	4	5	4	6	3	5	3	3	3	2	3	1	16	5	1
U-TS-387	1	5	4	6	3	5	1	3	3	2	1	1	27	5	1
U-TS-388	3	5	4	6	3	5	3	3	3	2	2	1	27	5	1
U-TS-389	3	5	4	6	3	5	3	3	3	2	2	1	27	5	1
U-TS-390	4	5	4	6	1	5	1	3	3	2	3	1	27	5	1
U-TS-391	1	5	4	6	1	5	3	3	3	5	3	3	27	5	1
U-TS-392	4	5	4	6	3	5	1	3	3	2	3	3	27	5	1
U-TS-393	3	5	4	6	1	5	3	3	3	2	2	3	16	5	1
U-TS-394	1	5	4	6	1	5	3	3	3	2	2	1	27	5	1
U-TS-395	1	5	4	6	3	5	1	3	2	2	3	1	27	5	1
U-TS-396	3	5	4	6	3	5	3	3	3	5	2	1	27	5	1
U-TS-397	1	5	4	6	1	5	5	3	3	5	3	1	27	5	1
U-TS-398	1	5	4	6	3	5	3	3	2	2	3	1	27	5	1
U-TS-399	1	5	4	6	3	5	3	3	2	2	3	1	27	5	1
U-TS-400	3	5	4	6	1	5	3	3	2	5	2	1	27	5	1
U-TS-401	4	3	4	2	1	3	1	4	3	5	5	3	23	1	1
U-TS-402	3	5	4	6	1	5	5	3	4	5	5	3	27	5	1
U-TS-403	4	4	4	6	1	2	3	4	3	5	5	3	19	3	1
U-TS-404	1	5	4	4	4	3	1	1	1	5	5	3	17	5	1
U-TS-405	4	1	4	6	1	2	1	4	2	5	5	3	19	3	1
U-TS-406	4	3	4	6	1	3	3	4	2	5	5	3	8	3	1
U-TS-407	2	3	4	6	1	3	1	4	2	5	2	3	16	2	1
U-TS-408	4	1	4	6	4	2	1	4	2	5	2	3	8	3	1
U-TS-409	1	1	4	6	4	2	1	4	2	5	5	3	25	3	1
U-TS-410	4	2	4	4	4	2	1	1	3	2	5	3	4	3	1
U-TS-411	4	2	4	4	4	2	1	1	2	2	5	3	16	5	1
U-TS-412	4	2	4	6	1	3	3	1	3	2	5	3	15	3	1
U-TS-413	4	2	4	4	4	2	3	1	3	2	5	3	1	1	1
U-TS-414	1	2	4	4	4	3	1	1	3	2	5	3	17	1	1
U-TS-415	1	3	4	6	4	2	3	4	5	5	5	3	18	6	1
U-TS-416	4	2	4	6	4	3	1	1	2	5	5	3	27	3	1
U-TS-417	4	1	4	6	4	2	1	4	3	5	5	3	19	1	1
U-TS-418	4	2	4	4	4	3	1	1	2	2	5	3	17	3	1
U-TS-419	4	2	4	4	4	3	3	1	2	5	2	3	13	1	1
U-TS-420	1	2	4	6	4	3	1	1	3	5	5	3	16	2	1
U-TS-421	4	2	4	4	4	3	1	1	3	2	2	3	17	1	1
U-TS-422	4	5	4	6	4	3	1	1	3	2	5	3	16	3	1
U-TS-423	4	2	4	6	4	2	1	4	3	5	5	3	10	2	1
U-TS-424	1	3	4	6	4	2	1	4	2	5	5	3	8	6	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
U-TS-425	3	3	4	6	1	3	3	4	2	5	5	3	27	2	1
U-TS-426	1	3	4	6	1	3	1	4	3	5	5	3	10	2	1
U-TS-427	3	1	4	6	4	3	1	4	2	5	5	3	25	3	1
U-TS-428	4	2	4	6	4	1	1	1	3	5	5	3	7	2	1
U-TS-429	4	4	4	6	3	2	1	4	3	5	5	3	18	3	1
U-TS-430	4	2	4	6	4	2	1	1	3	2	5	3	6	1	1
U-TS-431	4	2	4	6	4	2	1	1	2	2	5	3	14	3	1
U-TS-432	4	3	4	6	1	2	1	4	3	5	5	3	25	1	1
U-TS-433	4	3	4	6	4	3	1	4	3	5	5	3	16	6	1
U-TS-434	1	3	4	6	1	2	1	4	3	5	2	3	3	3	1
U-TS-435	4	2	4	6	4	2	1	1	3	2	5	3	2	5	1
U-TS-436	1	2	4	6	1	2	1	1	3	2	5	3	17	1	1
U-TS-437	4	2	4	6	4	2	1	1	3	2	5	3	17	3	1
U-TS-438	1	2	4	6	1	3	1	1	3	5	5	3	10	6	1
U-TS-439	4	2	4	6	4	5	1	1	2	4	5	3	1	1	1
U-TS-440	4	2	4	6	1	3	1	4	3	5	5	3	14	2	1
U-TS-441	1	3	4	6	1	2	1	1	3	5	5	3	14	6	1
U-TS-442	4	3	4	6	4	2	1	1	3	5	5	3	14	6	1
U-TS-443	4	3	4	6	4	5	1	1	2	4	5	3	1	2	1
U-TS-444	4	2	4	6	4	3	1	4	3	2	5	3	14	2	1
U-TS-445	4	2	4	6	4	2	1	1	2	5	5	3	25	5	1
U-TS-446	1	3	4	6	4	3	3	4	2	5	5	3	8	2	1
U-TS-447	4	1	4	6	4	2	3	4	2	5	5	3	27	2	1
U-TS-448	4	1	4	6	1	2	1	4	2	5	2	3	18	2	1
U-TS-449	1	2	4	6	4	3	1	1	3	5	5	3	13	1	1
U-TS-450	1	2	4	6	1	3	1	1	3	2	5	3	14	3	1
U-TS-451	5	2	4	2	3	4	1	4	3	5	5	3	25	1	1
U-TS-452	2	2	4	6	1	1	3	4	3	5	5	2	11	4	2
U-TS-453	5	2	4	2	3	4	1	4	3	5	2	3	17	2	1
U-TS-454	5	3	4	2	3	4	1	4	3	5	5	3	25	6	1
U-TS-455	5	1	4	2	3	3	3	4	2	5	5	3	10	6	1
U-TS-456	4	1	4	6	1	5	2	4	2	5	5	3	26	2	1
U-TS-457	1	2	4	4	4	3	1	1	5	2	2	3	17	1	1
U-TS-458	2	5	4	6	1	4	3	4	3	5	2	3	16	6	1
U-TS-459	1	2	4	4	4	2	3	1	1	5	5	3	27	5	1
U-TS-460	5	5	4	6	1	2	2	1	3	5	3	1	27	1	1
U-TS-461	4	5	4	4	4	2	1	1	3	5	5	3	16	5	1
U-TS-462	4	2	4	4	1	5	5	1	2	2	5	3	16	5	1
U-TS-463	4	5	4	6	1	2	3	1	2	2	5	3	17	5	1
U-TS-464	4	5	4	4	1	5	3	3	2	2	2	3	17	1	1
U-TS-465	4	5	4	6	3	5	5	3	1	4	2	3	6	1	1
U-TS-466	4	5	4	4	1	2	3	3	2	2	5	3	16	5	1
U-TS-467	4	5	4	4	1	5	3	1	2	5	3	3	17	5	1
U-TS-468	1	5	4	4	4	2	1	1	1	2	2	3	17	5	1
U-TS-469	4	5	4	4	1	5	3	3	3	2	5	3	17	1	1
U-TS-470	4	5	4	6	1	5	1	3	3	2	3	3	17	1	1
U-TS-471	1	5	4	6	1	2	1	3	1	2	2	3	17	5	1
U-TS-472	4	5	4	6	1	5	1	3	2	2	5	3	17	1	1
U-TS-473	4	5	4	4	1	2	3	3	3	4	5	3	7	5	1
U-TS-474	4	5	4	6	3	5	3	1	2	5	5	3	17	5	1
U-TS-475	4	5	4	6	1	5	1	3	3	5	5	3	17	1	1
U-TS-476	4	5	4	6	1	2	2	3	3	2	2	3	17	1	1
U-TS-477	4	5	4	4	4	3	1	1	3	5	5	3	17	5	1
U-TS-478	4	5	4	4	1	2	1	3	2	5	3	3	17	6	1
U-TS-479	4	2	4	4	1	2	5	1	3	5	5	3	27	3	1
U-TS-480	2	5	4	6	1	3	1	1	3	5	5	3	16	3	1
U-TS-481	3	5	4	6	1	5	5	3	3	5	2	1	27	5	1
U-TS-482	1	2	4	6	1	3	3	1	3	2	2	1	6	1	1
U-TS-483	1	5	4	6	1	2	1	3	3	5	5	3	8	2	1
U-TS-484	4	5	4	6	1	2	1	1	2	5	5	3	17	5	1
U-TS-485	4	2	4	2	3	2	3	1	2	2	2	1	17	5	1
U-TS-486	4	5	4	6	1	5	2	3	2	5	3	1	27	1	1
U-TS-487	4	2	4	4	4	2	2	1	3	2	5	3	16	5	1
U-TS-488	4	5	4	6	3	5	1	3	2	2	2	3	17	5	1
U-TS-489	4	5	4	4	1	2	3	1	2	5	2	3	16	5	1
U-TS-490	1	2	4	6	1	4	1	4	3	5	2	3	16	1	1
U-TS-491	5	5	4	6	1	5	5	1	2	5	5	3	16	5	1
U-TS-492	1	2	4	6	3	5	3	1	2	5	5	3	17	6	1
U-TS-493	3	5	4	6	1	5	3	3	3	5	2	1	16	5	1
U-TS-494	5	1	4	6	3	1	2	4	3	5	2	3	16	3	1
U-TS-495	5	4	4	6	1	3	3	4	2	5	5	3	27	5	1
U-TS-496	2	3	4	6	1	3	3	4	2	5	5	3	16	2	1
U-TS-497	5	5	4	6	3	4	1	1	2	5	3	2	16	4	2
U-TS-498	5	5	4	6	3	4	1	4	2	5	3	2	16	4	2
U-TS-499	5	5	4	6	3	1	2	1	2	5	3	2	16	4	2
U-TS-500	5	5	4	6	1	4	1	4	2	5	3	2	16	4	2
M-TS-1	4	4	6	6	4	3	2	4	1	5	5	3	16	5	1
M-TS-2	4	1	6	6	4	2	2	4	3	2	5	3	16	5	1
M-TS-3	1	4	4	4	4	3	1	4	2	5	5	3	16	5	1
M-TS-4	4	3	6	6	1	3	1	1	3	5	5	3	16	5	1
M-TS-5	4	1	6	6	4	3	1	1	1	5	5	3	16	5	1
M-TS-6	4	1	6	6	4	3	1	1	3	2	5	3	16	5	1
M-TS-7	4	1	4	4	4	3	1	4	2	2	5	3	17	5	1
M-TS-8	4	1	4	4	4	2	1	4	3	2	5	3	17	5	1
M-TS-9	4	1	6	6	4	3	1	4	3	2	5	1	17	5	1
M-TS-10	1	1	6	6	4	1	1	4	1	5	5	3	16	5	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-11	4	1	6	6	4	3	1	4	1	2	5	3	17	5	1
M-TS-12	1	1	4	4	4	2	2	4	1	2	5	3	17	5	1
M-TS-13	4	1	6	6	4	3	1	4	3	5	5	1	16	5	1
M-TS-14	4	1	6	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-15	1	1	6	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-16	4	4	6	6	4	1	1	4	3	5	5	3	27	5	1
M-TS-17	1	1	6	6	4	3	2	4	3	2	5	3	17	5	1
M-TS-18	4	1	6	6	4	3	1	4	1	2	5	1	16	5	1
M-TS-19	4	1	6	6	4	3	2	4	3	5	5	3	16	5	1
M-TS-20	4	1	4	4	4	3	1	4	3	5	5	3	16	5	1
M-TS-21	4	3	6	6	4	3	1	1	2	5	5	3	16	5	1
M-TS-22	4	4	4	4	4	3	1	4	3	5	5	1	16	5	1
M-TS-23	4	3	6	6	4	2	1	1	3	2	5	3	16	5	1
M-TS-24	1	1	4	4	4	3	1	4	3	5	2	3	16	5	1
M-TS-25	4	4	6	6	4	2	1	4	3	4	5	3	17	5	1
M-TS-26	4	3	6	6	1	2	1	1	3	2	5	3	13	5	1
M-TS-27	1	1	6	6	4	3	1	1	2	2	5	1	17	5	1
M-TS-28	4	1	6	6	4	3	1	1	3	5	5	3	16	5	1
M-TS-29	4	3	6	6	1	3	1	1	3	2	5	3	17	5	1
M-TS-30	1	1	4	4	4	3	2	4	3	5	5	3	16	5	1
M-TS-31	1	3	6	6	1	2	1	1	3	2	5	3	17	5	1
M-TS-32	4	3	6	6	1	2	2	1	1	2	5	1	2	5	1
M-TS-33	4	3	6	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-34	4	1	6	6	4	3	1	1	2	5	5	3	16	5	1
M-TS-35	4	1	6	6	4	3	2	4	2	5	2	3	16	5	1
M-TS-36	4	3	6	6	4	3	1	1	1	5	5	3	16	5	1
M-TS-37	1	1	6	6	4	3	2	1	3	2	5	1	17	5	1
M-TS-38	1	3	6	6	1	2	2	3	2	4	5	3	17	5	1
M-TS-39	4	1	6	6	4	3	1	4	2	2	5	3	16	5	1
M-TS-40	4	1	6	6	4	2	2	4	3	2	5	3	17	5	1
M-TS-41	4	3	6	6	1	3	1	1	3	2	5	3	17	5	1
M-TS-42	4	1	6	6	4	3	1	4	1	5	5	3	17	5	1
M-TS-43	4	1	6	6	4	2	2	4	2	2	5	3	17	5	1
M-TS-44	4	4	6	6	4	3	2	1	2	5	2	1	25	5	1
M-TS-45	4	4	6	6	4	3	2	4	2	5	5	1	25	5	1
M-TS-46	4	1	6	6	4	3	1	1	3	5	5	3	16	5	1
M-TS-47	4	1	6	6	4	3	1	1	3	2	5	3	17	5	1
M-TS-48	4	2	4	4	4	3	1	2	5	5	2	3	16	5	1
M-TS-49	4	1	6	6	4	2	2	4	2	2	5	1	17	5	1
M-TS-50	4	1	6	6	4	3	2	4	1	5	2	1	10	5	1
M-TS-51	1	4	4	6	4	2	1	4	1	4	5	3	17	5	1
M-TS-52	1	1	4	6	4	3	1	4	2	5	5	3	16	5	1
M-TS-53	4	1	4	6	4	2	1	4	2	2	5	3	17	5	1
M-TS-54	1	1	4	6	4	3	1	4	3	4	5	3	17	5	1
M-TS-55	4	1	4	4	4	2	2	4	2	2	5	1	17	5	1
M-TS-56	1	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-57	4	1	4	4	4	2	2	4	3	2	5	1	17	5	1
M-TS-58	4	4	4	6	4	3	1	4	2	5	5	3	16	5	1
M-TS-59	1	4	4	4	4	3	1	4	3	5	5	3	25	5	1
M-TS-60	1	4	4	6	4	3	1	4	3	2	5	3	17	5	1
M-TS-61	4	4	4	6	4	2	1	4	2	5	2	1	25	5	1
M-TS-62	1	1	4	6	1	2	1	4	1	2	5	3	17	5	1
M-TS-63	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-64	1	4	4	4	4	2	1	4	3	2	5	3	17	5	1
M-TS-65	4	1	4	6	4	2	1	4	2	2	5	1	17	5	1
M-TS-66	1	1	4	6	4	3	1	4	2	5	2	3	27	5	1
M-TS-67	4	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-68	1	5	4	6	1	1	1	1	3	5	5	3	27	5	1
M-TS-69	1	5	4	6	1	1	2	1	5	5	5	3	16	5	1
M-TS-70	1	1	4	6	4	3	1	4	1	5	5	3	16	5	1
M-TS-71	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-72	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-73	4	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-74	1	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-75	1	1	4	6	4	3	1	4	3	2	5	1	16	5	1
M-TS-76	4	4	4	6	4	2	1	4	3	2	5	1	17	5	1
M-TS-77	1	4	4	6	4	3	2	4	2	5	5	3	16	5	1
M-TS-78	1	4	4	6	4	1	1	4	3	5	5	3	16	5	1
M-TS-79	1	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-80	1	1	4	4	4	3	1	4	1	5	5	1	16	5	1
M-TS-81	1	1	4	6	4	3	1	4	3	2	5	3	11	5	1
M-TS-82	1	3	4	4	4	1	1	4	3	5	5	3	16	5	1
M-TS-83	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-84	4	4	4	6	4	2	2	4	3	2	5	1	17	5	1
M-TS-85	1	4	4	6	4	3	1	4	3	5	2	3	16	5	1
M-TS-86	4	1	4	6	4	3	1	4	3	2	5	1	16	5	1
M-TS-87	1	1	4	6	4	3	2	4	3	2	5	3	16	5	1
M-TS-88	4	1	4	6	4	3	2	4	1	2	5	3	17	5	1
M-TS-89	4	1	4	6	4	2	1	4	3	4	5	3	17	5	1
M-TS-90	1	1	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-91	1	4	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-92	4	1	4	6	4	2	1	4	2	2	5	3	17	5	1
M-TS-93	4	1	4	6	4	3	2	4	2	5	5	3	24	5	1
M-TS-94	1	4	4	6	4	2	1	4	5	5	5	1	16	5	1
M-TS-95	4	1	4	6	4	2	1	4	5	2	5	3	23	5	1
M-TS-96	1	4	4	4	4	3	2	4	3	5	5	3	16	5	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-97	4	4	4	6	4	2	1	4	3	2	5	3	17	5	1
M-TS-98	1	1	4	6	4	3	1	4	5	2	5	1	16	5	1
M-TS-99	4	1	4	6	4	3	2	4	3	2	5	1	17	5	1
M-TS-100	1	4	4	6	4	3	1	4	5	2	5	3	16	5	1
M-TS-101	1	1	4	4	4	1	1	4	3	5	5	3	16	5	1
M-TS-102	4	1	4	6	4	3	1	4	3	2	5	3	17	5	1
M-TS-103	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-104	1	1	4	6	4	3	1	4	3	2	5	3	17	5	1
M-TS-105	4	4	4	6	4	2	1	4	2	5	5	1	16	5	1
M-TS-106	1	1	4	6	4	3	2	4	1	5	2	3	16	5	1
M-TS-107	4	1	4	4	4	3	1	4	2	2	5	1	16	5	1
M-TS-108	4	1	4	6	4	2	1	4	2	2	5	3	17	5	1
M-TS-109	1	1	4	6	4	3	1	4	1	2	5	1	16	5	1
M-TS-110	1	1	4	6	4	3	1	4	3	5	5	1	16	5	1
M-TS-111	1	4	4	6	4	3	1	4	2	5	2	3	25	5	1
M-TS-112	4	1	4	6	4	2	1	4	1	2	5	3	17	5	1
M-TS-113	1	4	4	6	4	2	2	4	1	2	5	3	17	5	1
M-TS-114	1	4	4	6	4	3	1	4	3	2	2	3	27	5	1
M-TS-115	1	4	4	4	4	3	2	4	2	2	5	3	17	5	1
M-TS-116	4	4	4	6	4	2	1	4	2	5	5	1	16	5	1
M-TS-117	1	4	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-118	1	1	4	6	4	3	1	4	3	2	2	3	17	5	1
M-TS-119	1	4	4	6	4	3	1	4	2	5	5	3	16	5	1
M-TS-120	1	3	4	6	4	1	1	4	2	5	2	3	16	5	1
M-TS-121	1	1	4	4	4	3	1	4	1	2	5	3	13	5	1
M-TS-122	4	1	4	6	4	2	1	4	3	2	5	3	17	5	1
M-TS-123	4	1	4	4	4	3	1	4	3	5	5	3	27	5	1
M-TS-124	1	1	4	6	4	3	2	4	1	5	5	1	16	5	1
M-TS-125	1	1	4	6	4	3	1	4	2	5	5	1	16	5	1
M-TS-126	4	1	4	6	4	3	1	4	2	5	5	3	16	5	1
M-TS-127	1	4	4	6	4	3	2	4	3	5	2	3	16	5	1
M-TS-128	1	4	4	6	4	1	1	4	3	5	2	1	16	5	1
M-TS-129	1	1	4	6	4	3	2	4	1	2	5	3	16	5	1
M-TS-130	1	4	4	6	4	3	1	4	1	5	5	3	16	5	1
M-TS-131	1	4	4	4	4	3	1	4	3	2	5	3	17	5	1
M-TS-132	1	1	4	6	4	3	1	4	1	5	5	3	16	5	1
M-TS-133	1	4	4	6	4	2	1	4	3	2	5	1	17	5	1
M-TS-134	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-135	1	4	4	6	4	3	1	4	3	2	5	3	17	5	1
M-TS-136	1	4	4	6	4	3	1	4	1	5	5	1	16	5	1
M-TS-137	4	4	4	6	4	2	1	4	2	5	5	3	25	5	1
M-TS-138	4	4	4	6	4	2	2	4	2	5	5	3	25	5	1
M-TS-139	1	1	4	6	4	3	1	4	1	5	5	3	16	5	1
M-TS-140	1	4	4	6	4	3	1	4	3	5	5	1	16	5	1
M-TS-141	4	1	4	4	4	2	2	4	2	2	5	1	17	5	1
M-TS-142	1	4	4	6	4	3	1	4	2	2	5	1	16	5	1
M-TS-143	1	4	4	6	4	3	1	4	3	5	5	3	16	5	1
M-TS-144	4	4	4	6	1	2	1	4	5	2	5	3	16	5	1
M-TS-145	1	1	4	6	4	2	1	4	5	2	5	3	17	5	1
M-TS-146	1	4	4	4	4	3	1	4	3	2	5	3	17	5	1
M-TS-147	1	1	4	6	4	3	1	4	3	2	5	3	16	5	1
M-TS-148	1	1	4	6	4	1	1	4	3	5	5	3	16	5	1
M-TS-149	1	4	4	6	4	3	1	4	3	5	2	1	16	5	1
M-TS-150	4	4	4	6	4	3	1	4	3	2	2	1	27	5	1
M-TS-151	2	5	4	4	1	4	5	1	3	5	1	3	16	6	1
M-TS-152	3	5	4	6	3	1	3	1	3	5	3	3	16	5	1
M-TS-153	3	5	4	6	3	1	3	3	3	5	3	3	16	5	1
M-TS-154	3	5	4	6	3	1	3	3	3	5	3	3	16	5	1
M-TS-155	3	5	4	6	1	1	3	3	1	5	1	3	11	3	1
M-TS-156	1	5	4	6	1	1	3	3	3	5	1	3	25	5	1
M-TS-157	3	5	4	2	1	1	5	3	3	5	1	3	27	5	1
M-TS-158	3	5	4	6	1	1	5	1	3	5	3	3	16	5	1
M-TS-159	3	5	4	6	1	1	3	1	3	5	1	3	16	5	1
M-TS-160	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-161	1	5	4	2	3	4	3	3	3	5	1	3	27	5	1
M-TS-162	1	5	4	2	3	1	3	3	2	5	3	1	27	5	1
M-TS-163	3	5	4	6	4	1	3	1	3	5	1	3	27	5	1
M-TS-164	3	5	4	6	1	3	3	1	3	5	3	3	16	5	1
M-TS-165	3	5	4	6	1	1	5	1	3	5	3	3	16	5	1
M-TS-166	3	5	4	6	1	1	3	1	1	5	3	3	16	1	1
M-TS-167	3	5	4	6	1	1	3	3	3	5	1	3	16	1	1
M-TS-168	3	5	4	6	1	1	5	1	3	5	1	3	16	5	1
M-TS-169	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-170	3	5	4	6	3	1	3	3	2	5	3	3	27	5	1
M-TS-171	3	5	4	6	1	1	3	3	3	5	3	3	27	5	1
M-TS-172	3	5	4	6	1	1	3	1	3	5	1	3	16	5	1
M-TS-173	1	5	4	6	1	1	3	3	2	5	1	3	27	5	1
M-TS-174	3	5	4	4	4	3	3	3	3	5	3	3	27	5	1
M-TS-175	3	5	4	6	1	1	3	1	3	5	1	3	27	5	1
M-TS-176	3	5	4	6	1	1	3	1	3	5	2	3	27	5	1
M-TS-177	3	5	4	2	1	1	3	3	3	5	1	1	11	5	1
M-TS-178	3	5	4	6	1	1	3	1	3	5	1	1	27	5	1
M-TS-179	3	5	4	6	1	1	5	1	3	5	3	3	27	5	1
M-TS-180	1	5	4	2	1	1	1	3	2	5	3	3	27	5	1
M-TS-181	1	5	4	6	1	1	3	3	2	5	1	3	11	5	1
M-TS-182	3	5	4	6	1	1	3	3	3	5	1	3	27	5	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-183	1	5	4	6	3	1	5	3	2	5	1	3	27	5	1
M-TS-184	3	5	4	4	4	3	5	1	3	5	1	3	11	5	1
M-TS-185	1	5	4	4	4	1	3	3	2	5	3	3	27	5	1
M-TS-186	3	5	4	6	1	3	3	3	2	5	3	3	16	5	1
M-TS-187	3	5	4	4	4	1	3	3	3	5	1	3	16	3	1
M-TS-188	1	5	4	2	3	1	3	3	3	5	1	3	25	5	1
M-TS-189	3	5	4	6	1	1	3	1	3	5	3	3	27	5	1
M-TS-190	3	5	4	4	4	1	1	3	3	5	2	3	27	5	1
M-TS-191	3	5	4	6	1	1	3	1	3	5	1	3	16	1	1
M-TS-192	1	5	4	6	1	1	3	3	3	5	1	3	16	5	1
M-TS-193	3	5	4	2	1	1	3	1	3	5	1	3	16	5	1
M-TS-194	3	5	4	4	1	1	3	3	3	5	1	3	11	3	1
M-TS-195	3	5	4	6	4	1	3	1	3	5	1	3	27	5	1
M-TS-196	3	5	4	6	1	1	3	3	3	5	2	3	16	5	1
M-TS-197	3	5	4	4	4	1	3	1	3	5	3	3	27	5	1
M-TS-198	3	5	4	2	1	1	3	3	3	5	1	3	27	5	1
M-TS-199	1	5	4	2	3	1	3	3	2	5	3	3	16	5	1
M-TS-200	1	5	4	6	1	1	3	3	2	5	1	3	16	5	1
M-TS-201	1	5	4	6	1	1	3	3	3	5	1	3	27	5	1
M-TS-202	3	5	4	2	1	1	5	1	3	5	1	3	16	5	1
M-TS-203	3	5	4	6	1	1	3	1	3	5	1	3	16	5	1
M-TS-204	3	5	4	6	1	1	3	1	3	5	3	3	16	1	1
M-TS-205	3	5	4	6	1	1	3	3	3	5	3	3	27	5	1
M-TS-206	1	5	4	6	1	1	3	3	3	5	1	3	27	5	1
M-TS-207	3	5	4	6	1	3	5	3	3	5	3	3	16	1	1
M-TS-208	3	5	4	6	1	1	3	3	3	5	2	3	27	5	1
M-TS-209	3	5	4	2	1	1	3	1	3	5	1	3	27	5	1
M-TS-210	3	5	4	6	1	1	5	1	3	5	3	3	27	5	1
M-TS-211	3	5	4	6	1	1	3	3	1	5	1	3	16	1	1
M-TS-212	1	5	4	6	3	1	3	3	3	5	1	3	11	5	1
M-TS-213	3	5	4	6	1	1	3	1	3	5	3	3	16	5	1
M-TS-214	3	5	4	4	4	1	3	1	3	5	3	3	11	5	1
M-TS-215	3	5	4	6	1	1	5	1	3	5	3	3	16	5	1
M-TS-216	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-217	3	5	4	6	1	1	5	1	3	5	1	3	16	5	1
M-TS-218	3	5	4	6	1	1	5	1	3	5	1	3	16	5	1
M-TS-219	3	5	4	6	1	1	3	1	3	5	2	3	25	5	1
M-TS-220	3	5	4	6	1	3	3	1	1	5	3	3	16	1	1
M-TS-221	3	5	4	6	1	1	5	1	3	5	1	3	16	5	1
M-TS-222	3	5	4	6	1	3	3	1	3	5	1	3	16	5	1
M-TS-223	3	5	4	2	1	1	5	1	3	5	1	3	16	5	1
M-TS-224	1	5	4	2	1	1	3	3	2	5	3	3	27	5	1
M-TS-225	3	5	4	2	1	1	3	1	3	5	3	3	27	5	1
M-TS-226	3	5	4	6	1	1	5	1	3	5	3	3	27	5	1
M-TS-227	1	5	4	2	1	1	3	3	3	5	1	3	27	5	1
M-TS-228	3	5	4	2	3	1	3	3	2	5	3	3	27	5	1
M-TS-229	3	5	4	6	1	1	3	3	3	5	2	3	25	5	1
M-TS-230	1	5	4	2	3	1	3	3	2	5	3	3	27	5	1
M-TS-231	3	5	4	6	4	1	3	1	3	5	1	3	16	5	1
M-TS-232	1	5	4	2	3	1	3	3	2	5	1	3	27	5	1
M-TS-233	3	5	4	6	1	1	3	1	3	5	3	3	27	5	1
M-TS-234	3	5	4	4	4	1	3	3	3	5	3	3	25	5	1
M-TS-235	1	5	4	6	1	1	3	3	2	5	1	3	11	5	1
M-TS-236	3	5	4	6	1	1	3	3	3	5	1	3	27	5	1
M-TS-237	3	5	4	6	1	1	3	3	2	5	2	3	27	5	1
M-TS-238	3	5	4	6	4	1	3	3	3	5	1	3	25	5	1
M-TS-239	3	5	4	6	1	1	3	1	3	5	3	3	16	5	1
M-TS-240	1	5	4	2	3	3	3	3	3	5	3	3	27	5	1
M-TS-241	3	5	4	6	1	1	3	3	3	5	1	3	27	5	1
M-TS-242	3	5	4	2	1	3	3	1	3	5	1	3	27	5	1
M-TS-243	3	5	4	2	3	1	3	1	2	5	2	3	27	5	1
M-TS-244	3	5	4	4	1	1	3	1	3	5	1	3	16	1	1
M-TS-245	1	5	4	6	1	1	5	3	3	5	1	3	11	5	1
M-TS-246	1	5	4	2	3	1	3	3	3	5	1	3	27	5	1
M-TS-247	3	5	4	6	4	1	5	1	3	5	3	3	16	5	1
M-TS-248	1	5	4	6	1	1	5	3	2	5	1	3	27	5	1
M-TS-249	3	5	4	4	4	1	3	1	3	5	1	3	16	3	1
M-TS-250	3	5	4	4	4	1	3	3	1	5	1	3	16	3	1
M-TS-251	3	5	4	2	1	1	5	1	3	5	1	3	16	5	1
M-TS-252	3	5	4	6	1	3	5	1	3	5	1	3	16	1	1
M-TS-253	3	5	4	6	1	1	3	1	1	5	3	3	16	1	1
M-TS-254	3	5	4	6	1	1	5	1	3	5	3	3	27	5	1
M-TS-255	1	5	4	6	4	1	3	3	3	5	1	3	25	5	1
M-TS-256	3	5	4	4	1	1	3	1	3	5	1	3	16	1	1
M-TS-257	3	5	4	6	1	1	3	1	3	5	3	3	16	1	1
M-TS-258	3	5	4	6	3	1	3	3	3	5	2	3	11	5	1
M-TS-259	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-260	3	5	4	6	1	1	3	1	3	5	1	3	27	1	1
M-TS-261	3	5	4	6	1	1	3	3	3	5	1	3	25	5	1
M-TS-262	3	5	4	6	1	1	3	1	1	5	1	3	16	3	1
M-TS-263	3	5	4	4	4	1	3	1	1	5	1	3	16	1	1
M-TS-264	1	5	4	6	1	1	3	3	3	5	3	3	16	1	1
M-TS-265	3	5	4	4	4	1	3	3	3	5	1	3	16	3	1
M-TS-266	3	5	4	6	1	1	3	1	3	5	1	3	16	5	1
M-TS-267	1	5	4	2	3	1	1	3	2	5	3	3	27	5	1
M-TS-268	3	5	4	6	1	1	3	1	3	5	1	3	16	3	1

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ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-269	3	5	4	6	1	1	5	1	3	5	1	3	16	1	1
M-TS-270	1	5	4	6	1	1	1	3	2	5	1	3	27	5	1
M-TS-271	3	5	4	6	1	3	3	1	3	5	3	3	11	5	1
M-TS-272	3	5	4	4	4	1	3	1	3	5	2	3	27	5	1
M-TS-273	3	5	4	2	1	1	3	3	3	5	1	3	27	5	1
M-TS-274	1	5	4	6	1	1	5	3	3	5	1	3	11	5	1
M-TS-275	1	5	4	6	1	1	3	3	3	5	3	3	25	5	1
M-TS-276	1	5	4	2	3	1	3	3	2	5	1	3	27	5	1
M-TS-277	3	5	4	4	4	3	3	3	3	5	3	1	16	5	1
M-TS-278	1	5	4	6	3	1	3	3	3	5	1	3	11	5	1
M-TS-279	3	5	4	4	4	1	3	3	3	5	3	3	16	1	1
M-TS-280	3	5	4	6	4	1	5	1	3	5	1	3	27	5	1
M-TS-281	3	5	4	6	1	1	3	1	1	5	3	3	16	1	1
M-TS-282	3	5	4	6	1	1	5	3	3	5	1	1	27	5	1
M-TS-283	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-284	1	5	4	6	1	1	5	3	2	5	1	3	27	5	1
M-TS-285	3	5	4	6	1	1	3	1	1	5	1	3	16	1	1
M-TS-286	2	5	4	2	3	1	5	3	3	5	2	3	16	1	1
M-TS-287	3	5	4	6	1	4	3	3	3	5	2	3	16	1	1
M-TS-288	3	5	4	4	4	1	3	3	3	5	2	3	16	2	1
M-TS-289	3	5	4	6	1	3	3	3	3	5	3	3	16	3	1
M-TS-290	3	5	4	6	1	4	3	3	3	5	2	3	16	1	1
M-TS-291	3	5	4	6	1	1	3	3	3	5	3	1	16	5	1
M-TS-292	3	5	4	6	1	3	5	3	3	5	3	3	16	1	1
M-TS-293	3	5	4	6	1	1	3	3	3	5	3	3	16	3	1
M-TS-294	3	5	4	4	4	1	3	3	3	5	3	3	11	3	1
M-TS-295	3	5	4	4	4	1	3	3	3	5	2	3	16	3	1
M-TS-296	3	5	4	6	1	4	3	3	1	5	2	3	11	3	1
M-TS-297	3	5	4	6	1	4	3	3	3	5	2	3	16	5	1
M-TS-298	3	5	4	6	1	1	3	3	3	5	2	3	11	2	1
M-TS-299	3	5	4	4	4	4	3	3	1	5	2	3	16	3	1
M-TS-300	3	5	4	6	1	1	3	3	3	5	2	3	16	3	1
M-TS-301	4	5	4	4	1	5	3	5	1	5	1	2	16	4	2
M-TS-302	1	5	4	6	1	5	3	5	3	2	2	1	16	1	1
M-TS-303	1	5	4	6	1	5	5	5	3	2	2	1	16	5	1
M-TS-304	3	5	4	6	3	2	1	5	3	5	2	1	16	5	1
M-TS-305	1	5	4	6	3	5	1	5	3	5	3	1	16	5	1
M-TS-306	1	5	4	6	2	5	1	5	2	2	3	1	27	5	1
M-TS-307	3	5	4	6	1	5	3	5	2	5	2	1	16	5	1
M-TS-308	1	5	4	6	3	5	1	5	3	2	3	1	27	5	1
M-TS-309	4	5	4	6	1	5	1	5	5	5	2	3	16	5	1
M-TS-310	4	5	4	6	3	5	1	5	3	2	3	3	27	5	1
M-TS-311	1	5	4	6	3	5	3	5	3	5	3	1	16	5	1
M-TS-312	3	5	4	6	4	5	3	2	3	5	2	1	27	1	1
M-TS-313	1	5	4	6	3	5	3	5	2	2	2	1	16	5	1
M-TS-314	4	5	4	6	3	5	1	5	3	2	2	1	27	5	1
M-TS-315	1	5	4	6	3	5	1	5	3	2	3	1	16	5	1
M-TS-316	1	5	4	6	1	5	1	5	3	2	2	3	16	1	1
M-TS-317	1	5	4	6	3	5	3	5	2	5	2	1	16	5	1
M-TS-318	1	5	4	6	3	5	3	5	3	2	2	1	16	5	1
M-TS-319	1	5	4	6	1	2	3	5	3	5	3	1	27	5	1
M-TS-320	4	5	4	6	1	5	3	5	3	2	3	1	16	5	1
M-TS-321	4	5	4	6	3	2	1	5	2	2	2	1	27	5	1
M-TS-322	3	5	4	6	4	5	1	5	3	2	2	1	27	5	1
M-TS-323	4	5	4	6	3	5	1	5	2	2	1	1	27	5	1
M-TS-324	4	5	4	6	2	2	1	5	3	5	3	1	27	5	1
M-TS-325	4	5	4	6	1	5	1	5	3	5	2	1	27	5	1
M-TS-326	4	5	4	6	3	5	1	5	3	2	3	1	16	5	1
M-TS-327	3	5	4	6	1	5	5	5	3	5	2	1	16	5	1
M-TS-328	1	5	4	6	1	5	3	5	3	5	2	1	27	5	1
M-TS-329	4	5	4	6	2	5	1	5	3	5	3	1	16	5	1
M-TS-330	1	5	4	6	1	2	3	5	3	2	2	1	16	5	1
M-TS-331	4	5	4	6	1	5	1	5	3	2	3	1	27	5	1
M-TS-332	3	5	4	6	1	5	3	5	3	5	2	3	16	5	1
M-TS-333	1	5	4	6	1	5	3	2	3	5	3	3	27	5	1
M-TS-334	4	5	4	6	3	2	1	5	2	2	3	1	16	5	1
M-TS-335	1	5	4	6	1	5	1	5	2	2	2	1	17	5	1
M-TS-336	4	5	4	6	2	5	1	5	2	2	3	1	27	5	1
M-TS-337	3	5	4	6	3	5	3	5	3	2	2	1	16	5	1
M-TS-338	3	5	4	6	1	5	3	5	3	5	2	1	27	5	1
M-TS-339	4	5	4	6	3	5	1	5	3	2	2	1	27	5	1
M-TS-340	1	5	4	6	3	5	1	5	3	5	3	1	27	5	1
M-TS-341	4	5	4	6	3	5	1	5	3	2	3	1	16	5	1
M-TS-342	1	5	4	6	1	5	3	5	2	2	2	1	16	5	1
M-TS-343	1	5	4	6	3	5	3	5	3	2	3	1	27	5	1
M-TS-344	1	5	4	6	1	5	3	5	2	2	3	1	16	5	1
M-TS-345	3	5	4	6	1	5	3	5	3	5	2	1	16	5	1
M-TS-346	1	5	4	6	3	2	3	5	3	5	1	1	16	5	1
M-TS-347	4	5	4	6	3	5	3	5	2	2	3	1	27	1	1
M-TS-348	1	5	4	6	3	5	3	5	2	5	3	1	16	5	1
M-TS-349	3	5	4	6	1	5	3	2	2	5	2	1	16	5	1
M-TS-350	4	5	4	6	2	5	1	5	3	5	3	1	16	5	1
M-TS-351	1	5	4	6	1	5	3	5	3	2	3	3	16	5	1
M-TS-352	1	5	4	4	4	2	5	5	3	5	2	1	27	5	1
M-TS-353	4	5	4	4	1	2	1	5	3	2	2	1	27	5	1
M-TS-354	1	5	4	6	1	5	3	5	3	5	2	1	16	5	1

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Table 18 – continued from previous page

ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-355	1	5	4	6	1	2	3	5	3	5	2	3	25	5	1
M-TS-356	1	5	4	6	3	5	1	5	2	5	2	1	16	5	1
M-TS-357	1	5	4	6	3	5	3	5	3	5	3	1	27	5	1
M-TS-358	1	5	4	6	1	2	3	5	3	2	2	1	16	5	1
M-TS-359	4	5	4	4	4	5	3	5	2	5	2	1	16	5	1
M-TS-360	4	5	4	6	1	2	1	5	2	5	2	1	27	5	1
M-TS-361	4	5	4	6	3	2	1	5	3	2	2	1	27	5	1
M-TS-362	1	5	4	6	2	5	3	5	2	5	3	1	27	5	1
M-TS-363	1	5	4	6	1	2	3	5	3	5	5	1	16	5	1
M-TS-364	1	5	4	4	1	5	3	5	2	5	2	1	27	5	1
M-TS-365	4	5	4	6	1	2	3	5	3	2	1	1	27	5	1
M-TS-366	4	5	4	6	3	5	1	5	2	2	3	1	27	5	1
M-TS-367	1	5	4	6	1	5	1	5	3	2	2	1	16	5	1
M-TS-368	1	5	4	6	1	2	3	5	2	5	5	1	27	5	1
M-TS-369	1	5	4	6	1	5	3	5	1	2	2	3	27	5	1
M-TS-370	1	5	4	6	3	2	3	5	2	5	2	1	27	5	1
M-TS-371	4	5	4	6	1	5	1	5	3	5	3	1	16	5	1
M-TS-372	4	5	4	6	3	5	3	5	2	2	3	1	27	5	1
M-TS-373	1	5	4	4	1	2	3	5	2	2	2	3	16	5	1
M-TS-374	4	5	4	6	1	2	1	5	2	2	3	1	16	5	1
M-TS-375	4	5	4	6	3	5	1	5	2	5	2	1	16	5	1
M-TS-376	4	5	4	6	1	2	3	5	2	5	2	1	16	5	1
M-TS-377	4	5	4	6	3	5	1	5	2	2	3	1	27	5	1
M-TS-378	3	5	4	6	1	2	5	5	1	5	2	1	16	1	1
M-TS-379	1	5	4	6	3	5	3	5	1	5	2	1	16	5	1
M-TS-380	1	5	4	6	1	5	1	5	3	5	2	1	27	5	1
M-TS-381	1	5	4	6	1	2	3	5	1	5	2	1	16	5	1
M-TS-382	1	5	4	6	3	5	3	5	3	2	3	1	27	5	1
M-TS-383	1	5	4	6	1	2	3	5	3	5	2	1	27	5	1
M-TS-384	4	5	4	6	3	2	3	5	3	2	3	1	16	5	1
M-TS-385	4	5	4	6	3	2	3	5	2	2	2	3	16	5	1
M-TS-386	1	5	4	6	1	2	3	5	2	5	2	1	27	5	1
M-TS-387	4	5	4	6	3	5	3	5	2	2	3	3	27	5	1
M-TS-388	1	5	4	6	1	2	5	5	3	5	2	1	16	5	1
M-TS-389	1	5	4	6	3	5	3	5	2	5	2	1	16	5	1
M-TS-390	4	5	4	4	1	5	1	5	3	2	2	1	27	5	1
M-TS-391	4	5	4	6	1	5	3	5	3	5	3	1	27	5	1
M-TS-392	4	5	4	6	1	5	1	5	3	2	3	3	27	5	1
M-TS-393	1	5	4	6	1	2	3	5	2	5	5	3	16	5	1
M-TS-394	4	5	4	4	1	2	3	5	3	2	2	1	27	5	1
M-TS-395	4	5	4	6	3	2	1	5	3	5	2	1	16	5	1
M-TS-396	1	5	4	6	3	5	3	5	3	5	2	1	27	5	1
M-TS-397	1	5	4	6	1	2	5	5	2	5	2	1	16	5	1
M-TS-398	4	5	4	6	1	5	3	5	2	2	2	1	16	5	1
M-TS-399	4	5	4	6	2	5	3	5	3	5	2	1	27	5	1
M-TS-400	1	5	4	6	1	2	3	5	3	5	3	1	27	5	1
M-TS-401	1	3	4	6	1	3	1	4	2	5	5	3	23	3	1
M-TS-402	3	5	4	4	1	5	5	5	4	5	5	3	16	5	1
M-TS-403	1	1	4	6	4	3	3	4	2	5	5	3	25	2	1
M-TS-404	1	5	4	4	4	3	1	3	3	5	5	3	16	1	1
M-TS-405	1	1	4	6	4	3	1	4	2	5	5	3	25	3	1
M-TS-406	1	2	4	6	1	1	3	4	2	5	5	3	8	1	1
M-TS-407	2	3	4	6	1	4	1	4	2	5	2	3	16	6	1
M-TS-408	1	3	4	6	4	1	1	4	2	5	2	3	9	6	1
M-TS-409	1	1	4	6	4	3	1	4	2	5	2	3	25	2	1
M-TS-410	1	2	4	4	4	3	3	1	2	2	2	3	7	3	1
M-TS-411	4	2	4	4	1	2	1	2	5	2	5	3	16	5	1
M-TS-412	1	2	4	6	1	1	3	4	3	2	5	3	16	2	1
M-TS-413	1	2	4	4	4	2	3	1	3	2	5	3	7	1	1
M-TS-414	1	2	4	6	4	3	1	1	2	2	5	3	17	3	1
M-TS-415	1	3	4	4	4	3	3	4	2	5	2	3	18	2	1
M-TS-416	1	2	4	6	4	3	1	1	2	5	5	3	16	2	1
M-TS-417	1	1	4	6	4	3	1	4	2	5	5	3	18	3	1
M-TS-418	1	2	4	6	4	3	1	1	2	2	5	3	17	3	1
M-TS-419	1	2	4	4	4	1	3	1	2	5	2	3	13	3	1
M-TS-420	1	2	4	6	4	1	3	4	3	5	2	3	16	3	1
M-TS-421	1	2	4	4	4	3	1	3	2	5	2	3	17	1	1
M-TS-422	4	5	4	4	4	2	3	2	3	5	2	3	10	3	1
M-TS-423	1	2	4	4	4	3	1	4	2	5	5	3	10	3	1
M-TS-424	1	3	4	4	4	3	1	4	2	5	2	3	8	6	1
M-TS-425	3	1	4	6	1	1	3	4	2	5	5	3	20	2	1
M-TS-426	1	2	4	6	1	3	1	4	2	5	5	3	10	6	1
M-TS-427	3	1	4	6	4	1	1	4	2	5	5	3	25	6	1
M-TS-428	1	2	4	4	4	1	1	1	2	5	5	3	17	2	1
M-TS-429	1	1	4	6	1	3	1	4	3	5	5	3	18	3	1
M-TS-430	1	2	4	4	4	2	1	1	2	2	2	3	1	3	1
M-TS-431	1	2	4	6	1	3	1	1	2	5	5	3	16	3	1
M-TS-432	1	3	4	6	1	3	1	4	3	5	5	3	25	1	1
M-TS-433	1	2	4	6	4	3	1	4	3	5	5	3	16	6	1
M-TS-434	3	3	4	4	4	3	3	4	3	5	2	3	14	6	1
M-TS-435	4	2	4	6	4	3	1	1	3	2	5	3	17	1	1
M-TS-436	1	2	4	6	4	3	1	1	2	2	5	3	17	3	1
M-TS-437	4	2	4	6	4	2	3	1	3	2	5	3	17	5	1
M-TS-438	4	2	4	6	1	3	1	4	3	5	5	3	16	2	1
M-TS-439	4	2	4	4	4	2	1	1	2	2	5	3	7	3	1
M-TS-440	1	2	4	6	1	3	1	4	2	5	5	3	16	3	1

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Table 18 – continued from previous page

ts_name	Trend	Autocorrelation	Seasonality	Periodicity	Chaos	Entropy	Turning points	Partial autocorrelation	Outliers	Step changes	Peaks	Durbin Watson test	Quartile distribution	Determination coefficient	Number of attributes
M-TS-441	1	2	4	6	4	3	1	1	3	5	5	3	16	2	1
M-TS-442	1	2	4	6	4	3	1	1	2	5	2	3	14	6	1
M-TS-443	4	2	4	6	4	2	1	1	2	4	5	3	1	2	1
M-TS-444	1	2	4	6	4	3	3	4	3	5	5	3	16	2	1
M-TS-445	4	2	4	6	4	3	1	1	2	5	5	3	26	2	1
M-TS-446	1	2	4	6	4	1	3	4	2	5	5	3	8	2	1
M-TS-447	1	3	4	6	4	3	3	4	2	5	5	3	27	2	1
M-TS-448	1	1	4	6	1	3	1	4	2	5	2	3	18	3	1
M-TS-449	4	2	4	4	4	3	1	3	2	5	2	3	13	1	1
M-TS-450	1	2	4	6	1	3	1	1	3	2	5	3	14	6	1
M-TS-451	2	3	4	2	3	4	1	4	3	5	5	3	21	3	1
M-TS-452	2	2	4	6	1	1	3	4	3	5	5	3	11	3	2
M-TS-453	5	2	4	2	3	4	1	4	3	5	2	3	16	1	1
M-TS-454	5	5	4	2	3	3	5	4	1	5	5	3	16	1	1
M-TS-455	1	5	4	6	1	5	3	5	1	2	2	3	27	3	1
M-TS-456	1	4	4	6	1	5	5	4	4	5	5	3	16	2	1
M-TS-457	3	2	4	4	4	3	1	1	5	2	5	3	17	1	1
M-TS-458	2	5	4	6	1	4	3	4	3	5	2	3	16	6	1
M-TS-459	1	2	4	6	3	3	3	3	5	5	5	3	17	5	1
M-TS-460	5	5	4	6	1	5	3	3	2	5	3	1	16	2	1
M-TS-461	4	5	4	6	1	2	1	5	2	5	5	3	16	6	1
M-TS-462	4	5	4	4	3	5	3	2	2	5	5	3	16	6	1
M-TS-463	4	5	4	4	1	5	3	2	5	2	5	1	17	5	1
M-TS-464	4	5	4	4	1	5	3	5	5	5	5	3	7	3	1
M-TS-465	1	5	4	6	3	2	1	5	5	5	3	3	17	6	1
M-TS-466	4	5	4	6	1	5	3	2	5	5	2	1	16	5	1
M-TS-467	4	5	4	4	1	5	3	3	5	5	2	1	17	5	1
M-TS-468	2	5	4	6	1	2	1	2	5	5	5	3	16	6	1
M-TS-469	4	5	4	6	1	5	3	5	5	5	2	3	17	3	1
M-TS-470	3	5	4	6	1	5	3	2	5	5	2	1	17	6	1
M-TS-471	1	5	4	6	1	5	2	5	5	5	2	3	16	6	1
M-TS-472	4	5	4	6	1	5	1	5	5	5	2	3	17	1	1
M-TS-473	1	5	4	6	1	5	1	5	5	5	5	3	16	2	1
M-TS-474	4	5	4	4	1	5	5	2	5	5	5	3	17	5	1
M-TS-475	1	5	4	6	1	5	1	5	5	5	2	3	17	3	1
M-TS-476	1	5	4	6	1	5	2	2	5	5	2	3	16	6	1
M-TS-477	5	5	4	3	3	5	5	4	5	5	5	3	16	5	1
M-TS-478	1	5	4	4	1	2	1	5	5	5	5	3	25	1	1
M-TS-479	4	2	4	4	1	2	5	2	5	5	2	3	16	3	1
M-TS-480	3	5	4	6	3	3	1	1	5	5	2	3	16	3	1
M-TS-481	3	5	4	6	3	5	5	2	5	5	3	1	27	5	1
M-TS-482	2	5	4	6	1	3	3	3	2	5	5	3	26	6	1
M-TS-483	3	5	4	6	1	2	1	2	2	5	2	3	10	2	1
M-TS-484	4	5	4	4	1	5	2	3	5	2	5	2	15	4	2
M-TS-485	1	2	4	4	1	5	3	3	5	5	5	3	7	6	1
M-TS-486	4	5	4	6	1	5	2	5	5	5	3	1	23	3	1
M-TS-487	4	2	4	6	1	3	2	3	2	5	2	3	13	5	1
M-TS-488	4	5	4	6	3	5	1	5	2	5	2	3	17	1	1
M-TS-489	1	5	4	6	1	5	3	2	5	5	2	1	17	5	1
M-TS-490	3	5	4	6	1	4	1	1	2	5	2	3	16	3	1
M-TS-491	5	5	4	6	1	5	5	3	2	5	5	3	16	5	1
M-TS-492	1	2	4	6	3	5	3	1	2	5	5	3	17	6	1
M-TS-493	3	5	4	6	1	5	3	5	3	5	2	1	16	5	1
M-TS-494	5	1	4	6	3	1	2	4	1	5	2	3	17	3	1
M-TS-495	2	1	4	2	1	1	1	4	3	5	2	3	25	1	1
M-TS-496	3	4	4	6	1	3	1	4	2	5	5	3	26	2	1
M-TS-497	3	1	4	2	3	1	3	4	2	5	2	3	17	5	1
M-TS-498	2	4	4	2	3	3	1	4	3	5	2	3	16	5	1
M-TS-499	3	4	4	3	3	1	3	4	3	5	2	3	17	5	1
M-TS-500	3	1	4	2	3	4	3	4	2	5	2	3	26	5	1

C Forecasting method evaluation results

Table 19 Forecasting method evaluation results

ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-1	arima	svm	ann	cart	rw	xgb	es
U-TS-2	arima	svm	cart	ann	es	xgb	rw
U-TS-3	arima	rw	svm	es	ann	cart	xgb
U-TS-4	arima	cart	svm	rw	ann	xgb	es
U-TS-5	arima	cart	rw	svm	ann	xgb	es
U-TS-6	arima	svm	ann	cart	rw	xgb	es
U-TS-7	es	arima	svm	xgb	ann	cart	rw
U-TS-8	arima	es	ann	svm	cart	rw	xgb
U-TS-9	arima	svm	ann	es	cart	rw	xgb
U-TS-10	rw	svm	xgb	cart	arima	ann	es
U-TS-11	svm	xgb	ann	rw	es	arima	cart
U-TS-12	arima	ann	es	svm	rw	xgb	cart
U-TS-13	arima	ann	rw	svm	xgb	es	cart
U-TS-14	arima	rw	svm	ann	xgb	cart	es
U-TS-15	rw	es	xgb	svm	arima	ann	cart
U-TS-16	arima	rw	svm	cart	ann	xgb	es
U-TS-17	arima	svm	ann	es	cart	rw	xgb
U-TS-18	cart	es	ann	svm	arima	rw	xgb
U-TS-19	rw	arima	svm	xgb	ann	cart	es
U-TS-20	svm	rw	arima	ann	cart	xgb	es
U-TS-21	arima	es	cart	svm	rw	ann	xgb
U-TS-22	rw	arima	es	svm	xgb	ann	cart
U-TS-23	rw	es	svm	xgb	arima	ann	cart
U-TS-24	arima	svm	ann	rw	cart	xgb	es
U-TS-25	arima	svm	ann	cart	xgb	rw	es
U-TS-26	arima	svm	rw	xgb	ann	cart	es
U-TS-27	svm	ann	rw	arima	xgb	es	cart
U-TS-28	svm	cart	es	ann	arima	rw	xgb
U-TS-29	arima	rw	svm	xgb	ann	cart	es
U-TS-30	cart	ann	svm	arima	xgb	rw	es
U-TS-31	arima	svm	rw	ann	xgb	cart	es
U-TS-32	arima	svm	ann	cart	xgb	rw	es
U-TS-33	arima	cart	svm	ann	rw	xgb	es
U-TS-34	arima	svm	cart	xgb	ann	rw	es
U-TS-35	rw	arima	es	svm	xgb	ann	cart
U-TS-36	arima	svm	ann	cart	es	rw	xgb
U-TS-37	arima	rw	xgb	ann	svm	cart	es
U-TS-38	arima	svm	ann	es	rw	xgb	cart
U-TS-39	arima	svm	cart	ann	es	rw	xgb
U-TS-40	arima	cart	rw	svm	ann	xgb	es
U-TS-41	arima	svm	cart	rw	es	xgb	ann
U-TS-42	arima	ann	svm	cart	xgb	rw	es
U-TS-43	arima	ann	cart	svm	es	rw	xgb
U-TS-44	arima	svm	ann	cart	es	rw	xgb
U-TS-45	arima	svm	rw	xgb	ann	cart	es
U-TS-46	arima	es	svm	ann	rw	xgb	cart
U-TS-47	arima	svm	ann	cart	es	rw	xgb
U-TS-48	arima	rw	es	svm	xgb	ann	cart
U-TS-49	svm	arima	ann	rw	es	cart	xgb
U-TS-50	ann	svm	cart	arima	xgb	rw	es
U-TS-51	arima	cart	svm	rw	ann	es	xgb
U-TS-52	arima	cart	rw	svm	ann	es	xgb
U-TS-53	arima	svm	ann	cart	xgb	rw	es
U-TS-54	cart	rw	es	xgb	arima	ann	svm
U-TS-55	xgb	es	rw	svm	ann	cart	arima
U-TS-56	cart	rw	es	xgb	arima	ann	svm
U-TS-57	ann	svm	cart	xgb	rw	arima	es
U-TS-58	ann	cart	rw	xgb	es	svm	arima
U-TS-59	cart	rw	es	arima	xgb	ann	svm
U-TS-60	cart	rw	xgb	es	svm	ann	arima
U-TS-61	rw	es	arima	xgb	cart	ann	svm
U-TS-62	cart	rw	xgb	ann	es	svm	arima
U-TS-63	cart	xgb	es	rw	svm	ann	arima
U-TS-64	xgb	rw	es	arima	ann	cart	svm
U-TS-65	ann	xgb	cart	es	rw	svm	arima
U-TS-66	arima	es	rw	ann	xgb	svm	cart
U-TS-67	ann	xgb	es	rw	cart	svm	arima
U-TS-68	xgb	rw	arima	es	svm	ann	cart
U-TS-69	cart	xgb	arima	rw	ann	es	svm
U-TS-70	ann	svm	rw	es	arima	xgb	cart
U-TS-71	es	cart	arima	ann	rw	xgb	svm
U-TS-72	arima	xgb	es	rw	cart	ann	svm
U-TS-73	xgb	es	rw	arima	cart	svm	ann
U-TS-74	xgb	es	rw	arima	cart	ann	svm
U-TS-75	svm	rw	arima	es	xgb	ann	cart
U-TS-76	xgb	es	rw	cart	svm	ann	arima
U-TS-77	cart	xgb	rw	es	svm	ann	arima
U-TS-78	arima	rw	es	xgb	svm	cart	ann
U-TS-79	cart	ann	rw	arima	es	xgb	svm
U-TS-80	cart	ann	xgb	rw	es	arima	svm
U-TS-81	xgb	es	rw	svm	arima	ann	cart
U-TS-82	rw	arima	es	xgb	svm	cart	ann
U-TS-83	arima	es	rw	xgb	svm	ann	cart
U-TS-84	svm	arima	es	ann	xgb	rw	cart
U-TS-85	arima	svm	es	rw	xgb	ann	cart
U-TS-86	xgb	es	cart	rw	arima	ann	svm
U-TS-87	ann	svm	arima	es	xgb	rw	cart
U-TS-88	rw	arima	es	xgb	svm	cart	ann

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Table 19 – continued from previous page

ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-89	svm	rw	es	xgb	arima	cart	ann
U-TS-90	xgb	arima	es	rw	cart	svm	ann
U-TS-91	rw	arima	es	xgb	ann	cart	svm
U-TS-92	rw	es	arima	xgb	cart	svm	ann
U-TS-93	cart	rw	arima	es	xgb	svm	ann
U-TS-94	rw	es	xgb	arima	ann	cart	svm
U-TS-95	svm	ann	cart	xgb	rw	es	arima
U-TS-96	cart	ann	rw	arima	es	xgb	svm
U-TS-97	svm	rw	arima	es	xgb	cart	ann
U-TS-98	cart	xgb	es	arima	rw	svm	ann
U-TS-99	rw	arima	es	xgb	svm	ann	cart
U-TS-100	xgb	es	rw	arima	ann	cart	svm
U-TS-101	rw	arima	es	xgb	svm	cart	ann
U-TS-102	svm	xgb	es	rw	arima	ann	cart
U-TS-103	svm	xgb	es	rw	arima	ann	cart
U-TS-104	svm	ann	cart	xgb	es	rw	arima
U-TS-105	rw	arima	es	xgb	ann	svm	cart
U-TS-106	svm	arima	ann	rw	es	xgb	cart
U-TS-107	arima	rw	es	xgb	svm	ann	cart
U-TS-108	arima	rw	es	xgb	svm	ann	cart
U-TS-109	xgb	rw	arima	svm	cart	es	ann
U-TS-110	xgb	rw	arima	es	svm	cart	ann
U-TS-111	arima	rw	es	xgb	svm	ann	cart
U-TS-112	es	rw	arima	xgb	ann	cart	svm
U-TS-113	ann	svm	rw	es	xgb	arima	cart
U-TS-114	xgb	rw	arima	svm	cart	ann	es
U-TS-115	xgb	svm	rw	ann	cart	arima	es
U-TS-116	xgb	arima	rw	es	svm	cart	ann
U-TS-117	arima	svm	rw	es	xgb	ann	cart
U-TS-118	cart	svm	xgb	rw	arima	es	ann
U-TS-119	es	xgb	arima	rw	svm	cart	ann
U-TS-120	cart	rw	xgb	es	svm	arima	ann
U-TS-121	arima	es	svm	rw	xgb	cart	ann
U-TS-122	arima	rw	es	ann	xgb	svm	cart
U-TS-123	es	svm	arima	xgb	rw	ann	cart
U-TS-124	arima	es	svm	xgb	ann	cart	rw
U-TS-125	svm	es	arima	rw	xgb	ann	cart
U-TS-126	arima	es	rw	xgb	svm	ann	cart
U-TS-127	arima	cart	ann	es	xgb	svm	rw
U-TS-128	xgb	ann	cart	rw	svm	es	arima
U-TS-129	svm	cart	ann	xgb	arima	es	rw
U-TS-130	arima	xgb	cart	ann	es	svm	rw
U-TS-131	arima	cart	xgb	ann	es	svm	rw
U-TS-132	xgb	rw	es	arima	ann	svm	cart
U-TS-133	arima	es	rw	xgb	svm	cart	ann
U-TS-134	arima	es	rw	xgb	svm	cart	ann
U-TS-135	svm	arima	cart	es	xgb	rw	ann
U-TS-136	svm	ann	cart	es	rw	arima	xgb
U-TS-137	ann	svm	cart	rw	xgb	arima	es
U-TS-138	svm	cart	xgb	arima	ann	rw	es
U-TS-139	ann	svm	es	arima	rw	xgb	cart
U-TS-140	svm	cart	ann	arima	rw	xgb	es
U-TS-141	svm	ann	arima	cart	es	xgb	rw
U-TS-142	svm	cart	arima	ann	xgb	rw	es
U-TS-143	ann	xgb	rw	es	arima	cart	svm
U-TS-144	arima	svm	es	rw	xgb	ann	cart
U-TS-145	xgb	es	rw	arima	cart	svm	ann
U-TS-146	arima	svm	xgb	es	rw	cart	ann
U-TS-147	rw	es	xgb	arima	svm	cart	ann
U-TS-148	arima	es	svm	rw	xgb	ann	cart
U-TS-149	cart	svm	es	rw	xgb	arima	ann
U-TS-150	es	xgb	ann	arima	cart	svm	rw
U-TS-151	ann	cart	rw	svm	arima	xgb	es
U-TS-152	cart	svm	xgb	arima	es	rw	ann
U-TS-153	svm	ann	arima	cart	xgb	rw	es
U-TS-154	svm	arima	cart	ann	xgb	es	rw
U-TS-155	rw	svm	cart	xgb	es	arima	ann
U-TS-156	arima	ann	svm	cart	es	xgb	rw
U-TS-157	es	rw	xgb	svm	ann	cart	arima
U-TS-158	arima	ann	svm	cart	es	rw	xgb
U-TS-159	es	rw	xgb	svm	ann	cart	arima
U-TS-160	arima	ann	svm	cart	xgb	es	rw
U-TS-161	svm	arima	cart	ann	xgb	rw	es
U-TS-162	es	arima	svm	ann	xgb	rw	cart
U-TS-163	xgb	arima	es	ann	rw	svm	cart
U-TS-164	rw	es	arima	xgb	cart	svm	ann
U-TS-165	rw	es	arima	xgb	svm	cart	ann
U-TS-166	cart	ann	xgb	arima	es	rw	svm
U-TS-167	arima	svm	cart	es	ann	rw	xgb
U-TS-168	rw	xgb	cart	ann	es	arima	svm
U-TS-169	rw	arima	es	xgb	cart	ann	svm
U-TS-170	svm	arima	es	ann	xgb	rw	cart
U-TS-171	ann	cart	es	svm	xgb	rw	arima
U-TS-172	xgb	rw	arima	es	cart	svm	ann
U-TS-173	rw	es	arima	xgb	cart	svm	ann
U-TS-174	rw	arima	xgb	cart	es	ann	svm
U-TS-175	svm	es	arima	ann	cart	xgb	rw
U-TS-176	xgb	es	ann	svm	arima	cart	rw
U-TS-177	arima	svm	xgb	rw	es	cart	ann
U-TS-178	arima	svm	es	rw	xgb	ann	cart
U-TS-179	svm	ann	xgb	cart	es	rw	arima
U-TS-180	rw	arima	es	xgb	svm	cart	ann
U-TS-181	es	arima	svm	rw	xgb	ann	cart
U-TS-182	cart	arima	xgb	ann	rw	es	svm

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-183	rw	ann	es	xgb	arima	svm	cart
U-TS-184	svm	ann	xgb	rw	arima	es	cart
U-TS-185	rw	arima	svm	cart	xgb	ann	es
U-TS-186	svm	rw	xgb	arima	es	ann	cart
U-TS-187	rw	svm	xgb	arima	es	cart	ann
U-TS-188	svm	ann	cart	es	arima	xgb	rw
U-TS-189	arima	es	svm	rw	xgb	ann	cart
U-TS-190	svm	ann	xgb	rw	arima	cart	es
U-TS-191	rw	svm	es	arima	xgb	cart	ann
U-TS-192	es	arima	svm	rw	xgb	cart	ann
U-TS-193	svm	es	rw	arima	ann	cart	xgb
U-TS-194	svm	cart	arima	xgb	ann	es	rw
U-TS-195	svm	es	arima	ann	rw	xgb	cart
U-TS-196	arima	rw	es	xgb	cart	svm	ann
U-TS-197	rw	arima	es	xgb	svm	ann	cart
U-TS-198	svm	xgb	es	rw	arima	cart	ann
U-TS-199	rw	es	xgb	arima	svm	ann	cart
U-TS-200	arima	es	ann	xgb	rw	svm	cart
U-TS-201	xgb	rw	cart	es	arima	ann	svm
U-TS-202	svm	arima	ann	xgb	rw	es	cart
U-TS-203	rw	es	xgb	svm	ann	cart	arima
U-TS-204	svm	es	cart	rw	xgb	arima	ann
U-TS-205	svm	ann	rw	es	arima	xgb	cart
U-TS-206	xgb	es	rw	svm	cart	arima	ann
U-TS-207	arima	xgb	es	svm	rw	ann	cart
U-TS-208	rw	xgb	cart	arima	es	ann	svm
U-TS-209	svm	arima	es	rw	xgb	ann	cart
U-TS-210	xgb	rw	es	cart	arima	svm	ann
U-TS-211	xgb	rw	arima	es	ann	cart	svm
U-TS-212	arima	xgb	es	rw	cart	svm	ann
U-TS-213	rw	svm	ann	cart	xgb	es	arima
U-TS-214	arima	rw	xgb	cart	es	svm	ann
U-TS-215	svm	rw	cart	es	xgb	arima	ann
U-TS-216	es	arima	rw	xgb	svm	ann	cart
U-TS-217	xgb	arima	rw	es	ann	cart	svm
U-TS-218	es	svm	xgb	ann	arima	rw	cart
U-TS-219	rw	svm	xgb	ann	arima	es	cart
U-TS-220	svm	ann	xgb	cart	es	arima	rw
U-TS-221	arima	cart	rw	svm	es	ann	xgb
U-TS-222	arima	es	svm	rw	xgb	ann	cart
U-TS-223	svm	ann	arima	cart	rw	es	xgb
U-TS-224	svm	es	rw	arima	xgb	ann	cart
U-TS-225	arima	rw	svm	xgb	ann	cart	es
U-TS-226	xgb	arima	rw	svm	ann	cart	es
U-TS-227	rw	xgb	svm	ann	arima	es	cart
U-TS-228	arima	rw	xgb	ann	cart	es	svm
U-TS-229	es	rw	svm	xgb	arima	cart	ann
U-TS-230	svm	ann	arima	cart	es	xgb	rw
U-TS-231	arima	es	rw	xgb	svm	ann	cart
U-TS-232	es	xgb	rw	arima	ann	svm	cart
U-TS-233	rw	arima	es	svm	xgb	ann	cart
U-TS-234	svm	ann	rw	arima	cart	es	xgb
U-TS-235	arima	es	rw	svm	xgb	ann	cart
U-TS-236	ann	svm	cart	rw	arima	es	xgb
U-TS-237	rw	es	arima	ann	xgb	cart	svm
U-TS-238	rw	es	svm	xgb	arima	cart	ann
U-TS-239	rw	xgb	cart	svm	ann	es	arima
U-TS-240	rw	es	xgb	svm	ann	cart	arima
U-TS-241	rw	arima	es	svm	xgb	cart	ann
U-TS-242	rw	xgb	arima	es	ann	svm	cart
U-TS-243	svm	xgb	cart	ann	es	rw	arima
U-TS-244	arima	rw	es	xgb	ann	svm	cart
U-TS-245	arima	xgb	cart	svm	rw	ann	es
U-TS-246	arima	svm	ann	cart	es	xgb	rw
U-TS-247	arima	es	svm	rw	xgb	ann	cart
U-TS-248	arima	ann	rw	xgb	svm	es	cart
U-TS-249	ann	cart	svm	xgb	rw	es	arima
U-TS-250	es	arima	svm	rw	xgb	cart	ann
U-TS-251	es	rw	xgb	arima	ann	svm	cart
U-TS-252	rw	arima	xgb	es	ann	cart	svm
U-TS-253	svm	xgb	es	arima	ann	rw	cart
U-TS-254	cart	rw	es	xgb	arima	svm	ann
U-TS-255	svm	es	arima	rw	xgb	ann	cart
U-TS-256	rw	xgb	arima	es	cart	ann	svm
U-TS-257	svm	ann	cart	rw	arima	es	xgb
U-TS-258	rw	arima	es	xgb	svm	cart	ann
U-TS-259	svm	rw	arima	es	ann	xgb	cart
U-TS-260	ann	rw	es	xgb	arima	svm	cart
U-TS-261	xgb	cart	es	ann	arima	rw	svm
U-TS-262	es	arima	rw	xgb	cart	ann	svm
U-TS-263	xgb	es	rw	arima	ann	cart	svm
U-TS-264	rw	es	svm	xgb	arima	ann	cart
U-TS-265	svm	rw	arima	es	xgb	cart	ann
U-TS-266	es	svm	rw	xgb	cart	arima	ann
U-TS-267	arima	ann	xgb	es	rw	svm	cart
U-TS-268	es	arima	rw	xgb	cart	svm	ann
U-TS-269	svm	rw	es	arima	xgb	ann	cart
U-TS-270	es	svm	arima	xgb	rw	ann	cart
U-TS-271	svm	es	arima	rw	xgb	ann	cart
U-TS-272	arima	rw	es	xgb	cart	ann	svm
U-TS-273	svm	rw	arima	es	xgb	ann	cart
U-TS-274	es	svm	ann	cart	xgb	rw	arima
U-TS-275	xgb	ann	es	rw	arima	svm	cart
U-TS-276	rw	arima	es	xgb	ann	svm	cart

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-277	arima	es	rw	xgb	ann	svm	cart
U-TS-278	es	arima	ann	cart	rw	svm	xgb
U-TS-279	arima	es	rw	xgb	ann	svm	cart
U-TS-280	ann	svm	cart	arima	es	rw	xgb
U-TS-281	rw	xgb	svm	es	ann	arima	cart
U-TS-282	arima	es	svm	rw	xgb	ann	cart
U-TS-283	svm	xgb	rw	ann	arima	cart	es
U-TS-284	svm	arima	es	rw	xgb	ann	cart
U-TS-285	cart	arima	es	rw	xgb	ann	svm
U-TS-286	arima	ann	es	xgb	rw	svm	cart
U-TS-287	svm	arima	ann	cart	es	rw	xgb
U-TS-288	arima	svm	rw	es	xgb	ann	cart
U-TS-289	xgb	es	ann	rw	arima	svm	cart
U-TS-290	rw	cart	xgb	ann	arima	es	svm
U-TS-291	cart	rw	es	xgb	arima	ann	svm
U-TS-292	svm	arima	xgb	rw	es	cart	ann
U-TS-293	arima	es	svm	rw	xgb	ann	cart
U-TS-294	ann	xgb	arima	rw	svm	cart	es
U-TS-295	cart	svm	ann	xgb	es	rw	arima
U-TS-296	svm	arima	es	rw	xgb	ann	cart
U-TS-297	svm	es	arima	rw	xgb	ann	cart
U-TS-298	xgb	ann	arima	cart	es	rw	svm
U-TS-299	es	rw	arima	xgb	cart	ann	svm
U-TS-300	es	arima	svm	rw	xgb	ann	cart
U-TS-301	es	arima	svm	rw	xgb	ann	cart
U-TS-302	es	arima	svm	rw	xgb	ann	cart
U-TS-303	xgb	es	svm	rw	arima	ann	cart
U-TS-304	rw	es	xgb	svm	arima	ann	cart
U-TS-305	svm	es	arima	ann	xgb	rw	cart
U-TS-306	es	arima	svm	ann	rw	xgb	cart
U-TS-307	svm	arima	es	rw	xgb	ann	cart
U-TS-308	arima	rw	svm	es	xgb	ann	cart
U-TS-309	svm	arima	es	rw	xgb	ann	cart
U-TS-310	arima	svm	es	ann	rw	xgb	cart
U-TS-311	arima	svm	es	rw	xgb	ann	cart
U-TS-312	es	svm	arima	ann	xgb	rw	cart
U-TS-313	svm	es	arima	xgb	rw	ann	cart
U-TS-314	svm	rw	arima	es	xgb	ann	cart
U-TS-315	svm	es	arima	rw	xgb	ann	cart
U-TS-316	es	arima	rw	svm	xgb	ann	cart
U-TS-317	es	arima	svm	rw	xgb	ann	cart
U-TS-318	rw	es	svm	xgb	ann	arima	cart
U-TS-319	arima	svm	es	rw	xgb	ann	cart
U-TS-320	arima	svm	rw	es	xgb	ann	cart
U-TS-321	ann	cart	xgb	rw	es	arima	svm
U-TS-322	ann	xgb	es	rw	arima	svm	cart
U-TS-323	arima	es	svm	ann	xgb	rw	cart
U-TS-324	svm	cart	ann	rw	arima	xgb	es
U-TS-325	arima	es	xgb	ann	cart	svm	rw
U-TS-326	ann	es	arima	rw	svm	xgb	cart
U-TS-327	arima	es	svm	ann	cart	rw	xgb
U-TS-328	svm	ann	cart	arima	es	rw	xgb
U-TS-329	rw	cart	arima	ann	es	svm	xgb
U-TS-330	svm	cart	arima	es	ann	xgb	rw
U-TS-331	svm	ann	cart	es	arima	xgb	rw
U-TS-332	es	xgb	svm	rw	arima	ann	cart
U-TS-333	ann	cart	es	arima	svm	rw	xgb
U-TS-334	cart	xgb	es	ann	arima	svm	rw
U-TS-335	svm	ann	xgb	rw	es	cart	arima
U-TS-336	xgb	es	svm	cart	rw	arima	ann
U-TS-337	svm	ann	arima	cart	es	xgb	rw
U-TS-338	arima	svm	ann	cart	es	rw	xgb
U-TS-339	rw	svm	arima	es	ann	cart	xgb
U-TS-340	xgb	cart	rw	es	ann	svm	arima
U-TS-341	rw	es	arima	xgb	svm	cart	ann
U-TS-342	rw	svm	es	xgb	arima	cart	ann
U-TS-343	arima	rw	svm	xgb	ann	cart	es
U-TS-344	rw	svm	arima	es	xgb	cart	ann
U-TS-345	rw	xgb	svm	arima	ann	cart	es
U-TS-346	cart	xgb	svm	ann	es	arima	rw
U-TS-347	rw	ann	cart	arima	es	xgb	svm
U-TS-348	svm	ann	rw	arima	xgb	cart	es
U-TS-349	ann	es	cart	arima	svm	xgb	rw
U-TS-350	cart	ann	svm	arima	es	rw	xgb
U-TS-351	svm	rw	arima	es	cart	xgb	ann
U-TS-352	rw	xgb	svm	es	ann	arima	cart
U-TS-353	arima	svm	xgb	es	rw	ann	cart
U-TS-354	rw	es	cart	arima	svm	ann	xgb
U-TS-355	rw	ann	arima	svm	xgb	es	cart
U-TS-356	es	ann	svm	rw	xgb	cart	arima
U-TS-357	svm	arima	es	cart	xgb	ann	rw
U-TS-358	cart	rw	es	svm	arima	xgb	ann
U-TS-359	svm	cart	rw	arima	es	ann	xgb
U-TS-360	ann	svm	cart	rw	arima	es	xgb
U-TS-361	arima	svm	es	xgb	ann	cart	rw
U-TS-362	xgb	rw	svm	cart	es	ann	arima
U-TS-363	rw	svm	arima	xgb	ann	cart	es
U-TS-364	arima	svm	es	cart	ann	xgb	rw
U-TS-365	svm	ann	arima	cart	es	xgb	rw
U-TS-366	svm	rw	xgb	ann	cart	es	arima
U-TS-367	arima	es	ann	cart	rw	svm	xgb
U-TS-368	svm	ann	arima	xgb	rw	cart	es
U-TS-369	svm	ann	cart	xgb	rw	es	arima
U-TS-370	es	ann	xgb	arima	cart	rw	svm

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-371	arima	es	svm	ann	cart	xgb	rw
U-TS-372	arima	es	svm	ann	cart	xgb	rw
U-TS-373	arima	rw	es	svm	ann	xgb	cart
U-TS-374	rw	arima	xgb	ann	es	cart	svm
U-TS-375	arima	xgb	es	svm	ann	rw	cart
U-TS-376	arima	svm	cart	xgb	ann	es	rw
U-TS-377	svm	ann	rw	es	xgb	arima	cart
U-TS-378	svm	ann	cart	xgb	arima	es	rw
U-TS-379	arima	svm	cart	rw	es	ann	xgb
U-TS-380	xgb	rw	svm	arima	ann	cart	es
U-TS-381	rw	es	xgb	arima	cart	ann	svm
U-TS-382	arima	xgb	es	rw	svm	ann	cart
U-TS-383	xgb	es	cart	rw	arima	ann	svm
U-TS-384	rw	es	arima	xgb	svm	cart	ann
U-TS-385	rw	svm	xgb	cart	arima	ann	es
U-TS-386	arima	es	svm	xgb	cart	rw	ann
U-TS-387	svm	arima	rw	es	cart	xgb	ann
U-TS-388	rw	xgb	es	cart	arima	svm	ann
U-TS-389	ann	rw	es	arima	svm	xgb	cart
U-TS-390	rw	es	svm	xgb	cart	ann	arima
U-TS-391	es	svm	rw	xgb	ann	arima	cart
U-TS-392	svm	rw	xgb	ann	arima	cart	es
U-TS-393	rw	es	xgb	cart	svm	arima	ann
U-TS-394	rw	arima	es	cart	xgb	ann	svm
U-TS-395	rw	es	ann	cart	svm	xgb	arima
U-TS-396	rw	es	arima	xgb	ann	cart	svm
U-TS-397	arima	rw	xgb	es	svm	cart	ann
U-TS-398	rw	svm	es	ann	cart	xgb	arima
U-TS-399	xgb	ann	cart	es	arima	svm	rw
U-TS-400	es	arima	rw	svm	xgb	ann	cart
U-TS-401	cart	arima	es	svm	rw	ann	xgb
U-TS-402	ann	cart	svm	xgb	es	arima	rw
U-TS-403	rw	arima	svm	es	xgb	cart	ann
U-TS-404	svm	xgb	arima	es	rw	ann	cart
U-TS-405	arima	rw	es	xgb	svm	cart	ann
U-TS-406	ann	svm	rw	arima	es	xgb	cart
U-TS-407	xgb	arima	es	cart	rw	svm	ann
U-TS-408	xgb	ann	arima	svm	cart	es	rw
U-TS-409	svm	cart	rw	xgb	es	ann	arima
U-TS-410	svm	cart	ann	xgb	es	rw	arima
U-TS-411	rw	es	xgb	arima	svm	cart	ann
U-TS-412	svm	ann	cart	xgb	arima	es	rw
U-TS-413	arima	svm	ann	cart	xgb	es	rw
U-TS-414	es	ann	rw	xgb	arima	cart	svm
U-TS-415	arima	rw	ann	xgb	svm	cart	es
U-TS-416	xgb	ann	rw	es	svm	cart	arima
U-TS-417	svm	ann	arima	rw	es	xgb	cart
U-TS-418	rw	arima	xgb	es	ann	cart	svm
U-TS-419	arima	xgb	rw	es	cart	svm	ann
U-TS-420	ann	es	svm	cart	arima	xgb	rw
U-TS-421	rw	cart	svm	ann	es	xgb	arima
U-TS-422	cart	xgb	es	arima	svm	rw	ann
U-TS-423	svm	ann	cart	es	rw	xgb	arima
U-TS-424	svm	arima	es	xgb	rw	ann	cart
U-TS-425	svm	ann	cart	rw	arima	es	xgb
U-TS-426	arima	svm	ann	cart	rw	es	xgb
U-TS-427	rw	arima	es	svm	xgb	ann	cart
U-TS-428	arima	cart	xgb	rw	svm	es	ann
U-TS-429	es	ann	cart	svm	xgb	rw	arima
U-TS-430	svm	cart	ann	xgb	es	rw	arima
U-TS-431	svm	cart	ann	arima	es	xgb	rw
U-TS-432	svm	rw	arima	ann	es	cart	xgb
U-TS-433	arima	ann	cart	xgb	es	svm	rw
U-TS-434	svm	es	ann	arima	cart	xgb	rw
U-TS-435	svm	es	arima	rw	xgb	ann	cart
U-TS-436	rw	es	xgb	arima	svm	ann	cart
U-TS-437	svm	arima	es	rw	xgb	ann	cart
U-TS-438	es	svm	ann	arima	rw	xgb	cart
U-TS-439	es	svm	rw	arima	xgb	ann	cart
U-TS-440	es	arima	svm	rw	ann	xgb	cart
U-TS-441	arima	rw	es	svm	xgb	cart	ann
U-TS-442	es	arima	svm	rw	xgb	ann	cart
U-TS-443	svm	cart	xgb	arima	es	rw	ann
U-TS-444	xgb	cart	arima	es	rw	svm	ann
U-TS-445	svm	ann	rw	arima	es	cart	xgb
U-TS-446	rw	es	xgb	arima	cart	svm	ann
U-TS-447	svm	xgb	ann	rw	arima	es	cart
U-TS-448	ann	cart	xgb	rw	svm	arima	es
U-TS-449	svm	ann	es	rw	xgb	arima	cart
U-TS-450	arima	es	ann	rw	svm	xgb	cart
U-TS-451	svm	ann	arima	cart	xgb	es	rw
U-TS-452	svm	es	ann	arima	cart	xgb	rw
U-TS-453	svm	rw	xgb	es	ann	arima	cart
U-TS-454	cart	ann	xgb	es	rw	svm	arima
U-TS-455	cart	svm	ann	xgb	rw	es	arima
U-TS-456	xgb	rw	arima	es	svm	cart	ann
U-TS-457	ann	arima	rw	svm	cart	es	xgb
U-TS-458	arima	es	xgb	ann	svm	cart	rw
U-TS-459	es	xgb	rw	ann	arima	svm	cart
U-TS-460	es	rw	xgb	arima	svm	ann	cart
U-TS-461	arima	svm	ann	cart	xgb	es	rw
U-TS-462	svm	cart	ann	xgb	es	rw	arima
U-TS-463	arima	svm	cart	xgb	ann	rw	es
U-TS-464	svm	arima	rw	es	xgb	ann	cart

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
U-TS-465	xgb	rw	svm	ann	arima	es	cart
U-TS-466	svm	xgb	cart	ann	arima	rw	es
U-TS-467	arima	es	xgb	svm	rw	cart	ann
U-TS-468	es	arima	rw	xgb	svm	cart	ann
U-TS-469	rw	svm	xgb	arima	es	ann	cart
U-TS-470	rw	arima	es	svm	cart	ann	xgb
U-TS-471	rw	arima	es	svm	xgb	ann	cart
U-TS-472	es	rw	xgb	cart	arima	svm	ann
U-TS-473	svm	cart	es	arima	ann	xgb	rw
U-TS-474	ann	arima	cart	svm	xgb	es	rw
U-TS-475	es	svm	xgb	arima	rw	ann	cart
U-TS-476	arima	svm	rw	ann	xgb	es	cart
U-TS-477	rw	es	xgb	svm	arima	ann	cart
U-TS-478	es	rw	arima	xgb	svm	cart	ann
U-TS-479	arima	ann	rw	es	xgb	cart	svm
U-TS-480	xgb	arima	es	rw	cart	svm	ann
U-TS-481	es	xgb	cart	svm	rw	arima	ann
U-TS-482	rw	xgb	svm	cart	ann	arima	es
U-TS-483	arima	es	rw	svm	xgb	ann	cart
U-TS-484	arima	es	xgb	rw	ann	cart	svm
U-TS-485	ann	cart	xgb	arima	es	rw	svm
U-TS-486	svm	ann	es	cart	arima	xgb	rw
U-TS-487	svm	cart	arima	es	xgb	ann	rw
U-TS-488	svm	ann	cart	es	xgb	arima	rw
U-TS-489	ann	rw	svm	cart	arima	xgb	es
U-TS-490	cart	svm	arima	ann	es	rw	xgb
U-TS-491	svm	ann	xgb	cart	es	arima	rw
U-TS-492	svm	arima	rw	xgb	cart	ann	es
U-TS-493	svm	arima	ann	rw	xgb	cart	es
U-TS-494	svm	xgb	ann	cart	rw	arima	es
U-TS-495	rw	arima	es	svm	xgb	ann	cart
U-TS-496	arima	svm	ann	cart	xgb	es	rw
U-TS-497	ann	svm	arima	cart	xgb	rw	es
U-TS-498	arima	ann	cart	xgb	svm	es	rw
U-TS-499	svm	arima	ann	xgb	rw	es	cart
U-TS-500	svm	arima	cart	rw	ann	xgb	es
M-TS-1	svm	xgb	ann	rw	cart	arima	es
M-TS-2	svm	arima	xgb	rw	es	cart	ann
M-TS-3	svm	xgb	ann	cart	rw	arima	es
M-TS-4	svm	xgb	arima	rw	es	cart	ann
M-TS-5	xgb	svm	arima	rw	ann	es	cart
M-TS-6	svm	xgb	es	rw	arima	cart	ann
M-TS-7	svm	arima	xgb	es	rw	cart	ann
M-TS-8	svm	es	arima	xgb	rw	cart	ann
M-TS-9	svm	xgb	arima	es	rw	cart	ann
M-TS-10	svm	xgb	arima	rw	ann	es	cart
M-TS-11	svm	xgb	ann	arima	rw	es	cart
M-TS-12	svm	xgb	rw	arima	es	cart	ann
M-TS-13	svm	xgb	ann	arima	rw	es	cart
M-TS-14	svm	xgb	ann	arima	rw	es	cart
M-TS-15	svm	xgb	es	rw	arima	cart	ann
M-TS-16	svm	xgb	rw	es	arima	cart	ann
M-TS-17	svm	arima	xgb	es	rw	cart	ann
M-TS-18	svm	arima	xgb	es	ann	rw	cart
M-TS-19	svm	xgb	cart	ann	rw	arima	es
M-TS-20	svm	xgb	cart	arima	es	rw	ann
M-TS-21	xgb	svm	cart	rw	arima	es	ann
M-TS-22	svm	xgb	ann	rw	cart	arima	es
M-TS-23	svm	xgb	es	arima	rw	cart	ann
M-TS-24	svm	xgb	cart	es	rw	ann	arima
M-TS-25	svm	arima	xgb	rw	es	cart	ann
M-TS-26	svm	es	rw	xgb	arima	cart	ann
M-TS-27	xgb	svm	cart	rw	ann	arima	es
M-TS-28	svm	xgb	ann	arima	rw	es	cart
M-TS-29	svm	arima	es	xgb	rw	cart	ann
M-TS-30	svm	xgb	cart	es	rw	arima	ann
M-TS-31	svm	xgb	arima	rw	es	cart	ann
M-TS-32	svm	xgb	cart	es	rw	arima	ann
M-TS-33	svm	xgb	es	rw	arima	cart	ann
M-TS-34	svm	xgb	rw	arima	es	cart	ann
M-TS-35	svm	xgb	cart	es	rw	arima	ann
M-TS-36	svm	ann	arima	xgb	es	rw	cart
M-TS-37	svm	arima	xgb	rw	ann	es	cart
M-TS-38	svm	xgb	arima	es	rw	cart	ann
M-TS-39	svm	xgb	cart	es	rw	arima	ann
M-TS-40	svm	xgb	ann	rw	arima	es	cart
M-TS-41	svm	es	arima	xgb	rw	cart	ann
M-TS-42	svm	xgb	rw	arima	es	cart	ann
M-TS-43	svm	xgb	es	arima	rw	cart	ann
M-TS-44	svm	xgb	ann	rw	arima	es	cart
M-TS-45	svm	xgb	es	rw	arima	cart	ann
M-TS-46	svm	xgb	es	arima	rw	cart	ann
M-TS-47	svm	arima	es	xgb	rw	cart	ann
M-TS-48	svm	xgb	cart	es	rw	arima	ann
M-TS-49	svm	xgb	es	rw	arima	cart	ann
M-TS-50	svm	xgb	rw	es	arima	cart	ann
M-TS-51	svm	es	xgb	arima	rw	cart	ann
M-TS-52	svm	xgb	cart	es	arima	rw	ann
M-TS-53	svm	xgb	es	rw	arima	cart	ann
M-TS-54	svm	ann	es	arima	xgb	rw	cart
M-TS-55	svm	xgb	arima	es	rw	cart	ann
M-TS-56	svm	xgb	cart	es	rw	arima	ann
M-TS-57	svm	xgb	ann	rw	cart	arima	es
M-TS-58	svm	xgb	cart	rw	ann	es	arima

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
M-TS-59	svm	ann	xgb	rw	es	arima	cart
M-TS-60	svm	ann	arima	xgb	rw	es	cart
M-TS-61	svm	xgb	es	rw	arima	ann	cart
M-TS-62	svm	es	arima	xgb	rw	cart	ann
M-TS-63	svm	xgb	arima	es	rw	cart	ann
M-TS-64	svm	xgb	es	rw	cart	arima	ann
M-TS-65	svm	arima	xgb	rw	es	cart	ann
M-TS-66	xgb	ann	svm	rw	arima	es	cart
M-TS-67	svm	xgb	cart	rw	arima	es	ann
M-TS-68	svm	xgb	ann	rw	es	arima	cart
M-TS-69	svm	xgb	cart	ann	arima	rw	es
M-TS-70	svm	xgb	cart	ann	rw	arima	es
M-TS-71	svm	xgb	rw	es	arima	cart	ann
M-TS-72	svm	ann	xgb	arima	rw	es	cart
M-TS-73	svm	xgb	es	rw	cart	arima	ann
M-TS-74	svm	xgb	cart	rw	arima	es	ann
M-TS-75	svm	arima	es	xgb	rw	cart	ann
M-TS-76	svm	xgb	arima	rw	es	cart	ann
M-TS-77	svm	xgb	cart	ann	es	rw	arima
M-TS-78	svm	xgb	rw	es	arima	ann	cart
M-TS-79	svm	xgb	rw	arima	es	cart	ann
M-TS-80	svm	xgb	es	arima	rw	cart	ann
M-TS-81	svm	rw	arima	es	xgb	cart	ann
M-TS-82	svm	ann	xgb	arima	rw	es	cart
M-TS-83	svm	xgb	rw	arima	es	cart	ann
M-TS-84	svm	es	arima	xgb	rw	cart	ann
M-TS-85	svm	xgb	ann	cart	es	rw	arima
M-TS-86	svm	xgb	rw	es	arima	cart	ann
M-TS-87	svm	xgb	es	rw	arima	cart	ann
M-TS-88	svm	xgb	es	rw	arima	cart	ann
M-TS-89	svm	arima	xgb	rw	es	cart	ann
M-TS-90	svm	xgb	cart	ann	arima	rw	es
M-TS-91	svm	xgb	ann	cart	rw	arima	es
M-TS-92	svm	xgb	arima	rw	es	ann	cart
M-TS-93	xgb	svm	cart	es	rw	arima	ann
M-TS-94	xgb	svm	cart	rw	es	arima	ann
M-TS-95	xgb	svm	rw	arima	es	cart	ann
M-TS-96	svm	xgb	ann	cart	es	rw	arima
M-TS-97	svm	xgb	rw	arima	es	cart	ann
M-TS-98	svm	xgb	cart	rw	es	arima	ann
M-TS-99	svm	ann	es	arima	xgb	rw	cart
M-TS-100	svm	xgb	ann	arima	rw	es	cart
M-TS-101	svm	xgb	ann	arima	rw	es	cart
M-TS-102	svm	xgb	arima	ann	es	rw	cart
M-TS-103	svm	xgb	rw	es	arima	cart	ann
M-TS-104	svm	es	arima	xgb	rw	cart	ann
M-TS-105	svm	xgb	rw	es	cart	ann	arima
M-TS-106	svm	xgb	rw	arima	es	cart	ann
M-TS-107	svm	xgb	rw	arima	es	cart	ann
M-TS-108	svm	es	xgb	arima	rw	cart	ann
M-TS-109	svm	xgb	rw	arima	es	cart	ann
M-TS-110	svm	xgb	rw	es	arima	cart	ann
M-TS-111	svm	xgb	ann	arima	es	rw	cart
M-TS-112	svm	arima	es	rw	xgb	cart	ann
M-TS-113	svm	xgb	cart	rw	arima	es	ann
M-TS-114	svm	xgb	cart	es	rw	arima	ann
M-TS-115	svm	xgb	rw	arima	cart	es	ann
M-TS-116	svm	xgb	cart	rw	arima	es	ann
M-TS-117	svm	xgb	ann	cart	es	rw	arima
M-TS-118	svm	arima	xgb	es	rw	cart	ann
M-TS-119	svm	xgb	es	rw	cart	arima	ann
M-TS-120	svm	xgb	cart	ann	arima	es	rw
M-TS-121	svm	xgb	arima	cart	rw	es	ann
M-TS-122	svm	arima	es	xgb	rw	ann	cart
M-TS-123	svm	rw	es	arima	xgb	cart	ann
M-TS-124	svm	xgb	es	rw	arima	cart	ann
M-TS-125	svm	xgb	cart	rw	es	arima	ann
M-TS-126	ann	svm	xgb	es	cart	rw	arima
M-TS-127	svm	xgb	cart	rw	arima	es	ann
M-TS-128	svm	xgb	ann	cart	es	arima	rw
M-TS-129	svm	xgb	arima	es	rw	cart	ann
M-TS-130	svm	xgb	es	rw	arima	cart	ann
M-TS-131	svm	xgb	rw	es	arima	cart	ann
M-TS-132	svm	xgb	cart	rw	arima	es	ann
M-TS-133	svm	xgb	cart	rw	es	arima	ann
M-TS-134	svm	xgb	cart	rw	es	arima	ann
M-TS-135	svm	xgb	es	rw	arima	cart	ann
M-TS-136	svm	xgb	ann	cart	arima	es	rw
M-TS-137	svm	xgb	es	rw	arima	cart	ann
M-TS-138	svm	es	rw	arima	xgb	cart	ann
M-TS-139	svm	xgb	cart	ann	rw	arima	es
M-TS-140	svm	xgb	cart	rw	es	arima	ann
M-TS-141	svm	xgb	es	arima	rw	cart	ann
M-TS-142	svm	xgb	ann	cart	rw	arima	es
M-TS-143	svm	xgb	ann	rw	arima	es	cart
M-TS-144	svm	xgb	arima	es	rw	cart	ann
M-TS-145	svm	xgb	es	arima	rw	cart	ann
M-TS-146	svm	xgb	es	rw	arima	cart	ann
M-TS-147	svm	xgb	ann	es	arima	rw	cart
M-TS-148	svm	xgb	ann	rw	es	cart	arima
M-TS-149	svm	xgb	cart	es	rw	arima	ann
M-TS-150	svm	xgb	cart	es	rw	arima	ann
M-TS-151	xgb	svm	rw	cart	arima	ann	es
M-TS-152	xgb	cart	svm	ann	es	rw	arima

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ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
M-TS-153	xgb	ann	svm	cart	es	arima	rw
M-TS-154	svm	ann	xgb	cart	rw	es	arima
M-TS-155	svm	ann	xgb	cart	arima	es	rw
M-TS-156	svm	xgb	ann	rw	cart	arima	es
M-TS-157	svm	xgb	arima	cart	rw	ann	es
M-TS-158	svm	ann	xgb	arima	es	cart	rw
M-TS-159	svm	ann	xgb	rw	arima	es	cart
M-TS-160	cart	arima	rw	svm	ann	es	xgb
M-TS-161	xgb	svm	ann	cart	es	rw	arima
M-TS-162	svm	xgb	ann	cart	rw	arima	es
M-TS-163	svm	xgb	ann	cart	rw	arima	es
M-TS-164	svm	ann	rw	xgb	cart	arima	es
M-TS-165	svm	ann	xgb	rw	arima	cart	es
M-TS-166	svm	ann	es	xgb	cart	rw	arima
M-TS-167	svm	ann	xgb	cart	es	rw	arima
M-TS-168	ann	xgb	svm	cart	rw	es	arima
M-TS-169	xgb	rw	svm	cart	arima	ann	es
M-TS-170	ann	svm	xgb	cart	rw	es	arima
M-TS-171	svm	xgb	cart	arima	ann	rw	es
M-TS-172	cart	svm	rw	ann	xgb	arima	es
M-TS-173	svm	xgb	ann	cart	rw	arima	es
M-TS-174	xgb	rw	svm	ann	cart	arima	es
M-TS-175	ann	svm	xgb	cart	rw	arima	es
M-TS-176	svm	ann	xgb	cart	rw	arima	es
M-TS-177	svm	ann	xgb	rw	cart	arima	es
M-TS-178	arima	ann	xgb	es	svm	cart	rw
M-TS-179	svm	ann	arima	es	xgb	cart	rw
M-TS-180	ann	svm	xgb	cart	arima	rw	es
M-TS-181	svm	xgb	ann	rw	cart	arima	es
M-TS-182	svm	ann	rw	xgb	cart	arima	es
M-TS-183	ann	svm	cart	xgb	es	arima	rw
M-TS-184	svm	rw	xgb	ann	cart	arima	es
M-TS-185	svm	ann	xgb	es	rw	cart	arima
M-TS-186	ann	svm	xgb	rw	cart	arima	es
M-TS-187	svm	xgb	ann	cart	rw	arima	es
M-TS-188	svm	ann	cart	xgb	rw	arima	es
M-TS-189	svm	xgb	ann	rw	arima	es	cart
M-TS-190	svm	xgb	ann	cart	rw	arima	es
M-TS-191	arima	xgb	ann	es	rw	svm	cart
M-TS-192	svm	xgb	ann	cart	rw	arima	es
M-TS-193	xgb	arima	ann	rw	es	cart	svm
M-TS-194	xgb	svm	rw	ann	arima	cart	es
M-TS-195	svm	xgb	ann	cart	rw	arima	es
M-TS-196	ann	svm	arima	es	rw	xgb	cart
M-TS-197	xgb	cart	svm	ann	rw	arima	es
M-TS-198	svm	ann	xgb	rw	arima	cart	es
M-TS-199	ann	xgb	svm	cart	rw	arima	es
M-TS-200	svm	ann	xgb	cart	rw	arima	es
M-TS-201	svm	ann	rw	xgb	cart	arima	es
M-TS-202	svm	xgb	ann	cart	arima	rw	es
M-TS-203	svm	xgb	ann	rw	cart	arima	es
M-TS-204	svm	xgb	ann	cart	es	rw	arima
M-TS-205	svm	ann	xgb	rw	arima	es	cart
M-TS-206	svm	xgb	cart	rw	ann	arima	es
M-TS-207	svm	xgb	cart	rw	arima	es	ann
M-TS-208	ann	xgb	rw	arima	svm	es	cart
M-TS-209	svm	rw	xgb	ann	arima	cart	es
M-TS-210	svm	xgb	arima	es	ann	rw	cart
M-TS-211	ann	svm	xgb	rw	arima	es	cart
M-TS-212	svm	ann	xgb	rw	cart	arima	es
M-TS-213	svm	ann	xgb	cart	rw	es	arima
M-TS-214	svm	rw	xgb	cart	ann	arima	es
M-TS-215	svm	xgb	ann	es	arima	cart	rw
M-TS-216	svm	rw	ann	cart	arima	xgb	es
M-TS-217	rw	svm	xgb	ann	cart	arima	es
M-TS-218	cart	xgb	svm	ann	rw	es	arima
M-TS-219	svm	cart	xgb	es	rw	ann	arima
M-TS-220	svm	xgb	es	ann	arima	cart	rw
M-TS-221	ann	svm	cart	xgb	rw	arima	es
M-TS-222	svm	xgb	ann	cart	rw	arima	es
M-TS-223	svm	xgb	ann	cart	arima	rw	es
M-TS-224	ann	xgb	svm	cart	es	rw	arima
M-TS-225	xgb	ann	rw	svm	cart	arima	es
M-TS-226	svm	arima	ann	xgb	es	cart	rw
M-TS-227	svm	rw	xgb	ann	arima	cart	es
M-TS-228	svm	ann	xgb	rw	arima	es	cart
M-TS-229	svm	ann	xgb	cart	rw	arima	es
M-TS-230	svm	xgb	ann	cart	arima	rw	es
M-TS-231	svm	ann	rw	arima	xgb	es	cart
M-TS-232	svm	xgb	cart	arima	es	ann	rw
M-TS-233	svm	cart	es	xgb	ann	rw	arima
M-TS-234	svm	ann	xgb	cart	rw	arima	es
M-TS-235	svm	xgb	cart	ann	rw	arima	es
M-TS-236	svm	ann	rw	xgb	cart	arima	es
M-TS-237	xgb	svm	ann	rw	cart	arima	es
M-TS-238	svm	xgb	ann	cart	rw	arima	es
M-TS-239	svm	xgb	ann	cart	arima	es	rw
M-TS-240	svm	ann	xgb	rw	es	arima	cart
M-TS-241	svm	xgb	ann	cart	rw	arima	es
M-TS-242	svm	ann	xgb	es	arima	rw	cart
M-TS-243	svm	ann	xgb	es	cart	rw	arima
M-TS-244	svm	ann	xgb	cart	rw	arima	es
M-TS-245	ann	svm	xgb	cart	rw	arima	es
M-TS-246	svm	ann	xgb	cart	arima	es	rw

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Table 19 – continued from previous page

ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
M-TS-247	svm	ann	xgb	cart	arima	es	rw
M-TS-248	svm	xgb	arima	es	ann	cart	rw
M-TS-249	arima	rw	svm	ann	es	xgb	cart
M-TS-250	xgb	svm	ann	cart	rw	arima	es
M-TS-251	xgb	rw	svm	cart	ann	arima	es
M-TS-252	ann	cart	xgb	svm	rw	arima	es
M-TS-253	xgb	svm	cart	es	rw	arima	ann
M-TS-254	svm	ann	arima	xgb	cart	es	rw
M-TS-255	svm	ann	xgb	cart	rw	arima	es
M-TS-256	svm	rw	xgb	ann	arima	cart	es
M-TS-257	svm	xgb	ann	arima	cart	rw	es
M-TS-258	svm	xgb	cart	rw	ann	arima	es
M-TS-259	svm	ann	xgb	cart	rw	arima	es
M-TS-260	svm	xgb	ann	cart	arima	es	rw
M-TS-261	svm	xgb	ann	cart	rw	arima	es
M-TS-262	svm	xgb	arima	es	rw	ann	cart
M-TS-263	svm	ann	cart	rw	xgb	arima	es
M-TS-264	svm	xgb	cart	rw	es	ann	arima
M-TS-265	svm	ann	xgb	cart	rw	arima	es
M-TS-266	svm	ann	rw	xgb	cart	arima	es
M-TS-267	svm	xgb	ann	rw	cart	arima	es
M-TS-268	xgb	ann	arima	svm	cart	rw	es
M-TS-269	ann	rw	svm	xgb	cart	arima	es
M-TS-270	svm	xgb	ann	cart	arima	rw	es
M-TS-271	svm	ann	xgb	cart	es	arima	rw
M-TS-272	svm	xgb	ann	rw	arima	cart	es
M-TS-273	svm	xgb	ann	rw	cart	arima	es
M-TS-274	svm	ann	cart	xgb	rw	arima	es
M-TS-275	svm	xgb	ann	cart	rw	arima	es
M-TS-276	xgb	svm	ann	cart	es	rw	arima
M-TS-277	svm	xgb	ann	cart	rw	arima	es
M-TS-278	svm	xgb	ann	cart	rw	arima	es
M-TS-279	svm	xgb	ann	cart	arima	es	rw
M-TS-280	svm	ann	xgb	rw	arima	es	cart
M-TS-281	svm	ann	xgb	arima	es	rw	cart
M-TS-282	svm	arima	ann	xgb	rw	es	cart
M-TS-283	xgb	svm	ann	rw	cart	arima	es
M-TS-284	svm	xgb	ann	cart	arima	es	rw
M-TS-285	xgb	svm	ann	rw	arima	es	cart
M-TS-286	svm	ann	xgb	cart	rw	arima	es
M-TS-287	svm	xgb	ann	rw	cart	arima	es
M-TS-288	rw	svm	arima	cart	es	ann	xgb
M-TS-289	svm	ann	rw	xgb	cart	arima	es
M-TS-290	svm	ann	xgb	cart	rw	arima	es
M-TS-291	svm	xgb	cart	ann	rw	arima	es
M-TS-292	svm	ann	xgb	rw	cart	arima	es
M-TS-293	xgb	ann	rw	svm	cart	arima	es
M-TS-294	xgb	ann	svm	rw	cart	arima	es
M-TS-295	svm	xgb	ann	cart	rw	arima	es
M-TS-296	svm	xgb	rw	ann	cart	arima	es
M-TS-297	svm	ann	xgb	cart	rw	arima	es
M-TS-298	svm	rw	xgb	ann	cart	arima	es
M-TS-299	ann	svm	xgb	cart	rw	arima	es
M-TS-300	svm	rw	xgb	cart	ann	arima	es
M-TS-301	arima	cart	ann	rw	xgb	es	svm
M-TS-302	svm	xgb	arima	cart	ann	rw	es
M-TS-303	ann	cart	xgb	svm	es	rw	arima
M-TS-304	rw	svm	xgb	es	arima	cart	ann
M-TS-305	arima	svm	rw	es	xgb	cart	ann
M-TS-306	xgb	es	rw	arima	svm	cart	ann
M-TS-307	es	rw	svm	ann	cart	arima	xgb
M-TS-308	svm	rw	es	arima	xgb	ann	cart
M-TS-309	svm	arima	rw	es	xgb	cart	ann
M-TS-310	svm	xgb	arima	es	rw	cart	ann
M-TS-311	xgb	rw	arima	svm	es	cart	ann
M-TS-312	ann	arima	cart	es	rw	svm	xgb
M-TS-313	svm	xgb	es	rw	arima	cart	ann
M-TS-314	svm	ann	cart	rw	arima	es	xgb
M-TS-315	svm	cart	ann	xgb	es	rw	arima
M-TS-316	svm	rw	arima	es	xgb	cart	ann
M-TS-317	rw	arima	es	xgb	cart	ann	svm
M-TS-318	rw	es	arima	xgb	svm	ann	cart
M-TS-319	rw	arima	es	xgb	svm	ann	cart
M-TS-320	es	rw	arima	svm	xgb	ann	cart
M-TS-321	svm	rw	arima	es	xgb	ann	cart
M-TS-322	svm	rw	arima	es	xgb	ann	cart
M-TS-323	svm	rw	arima	es	xgb	ann	cart
M-TS-324	rw	es	arima	svm	xgb	cart	ann
M-TS-325	arima	svm	es	rw	xgb	ann	cart
M-TS-326	arima	rw	es	svm	xgb	cart	ann
M-TS-327	rw	arima	es	xgb	svm	cart	ann
M-TS-328	xgb	rw	es	arima	svm	ann	cart
M-TS-329	xgb	svm	es	rw	arima	cart	ann
M-TS-330	arima	ann	cart	svm	xgb	es	rw
M-TS-331	es	arima	rw	xgb	svm	ann	cart
M-TS-332	rw	es	arima	xgb	cart	ann	svm
M-TS-333	arima	es	rw	xgb	ann	cart	svm
M-TS-334	ann	cart	xgb	es	rw	arima	svm
M-TS-335	xgb	es	rw	arima	svm	cart	ann
M-TS-336	es	rw	arima	xgb	svm	cart	ann
M-TS-337	svm	es	rw	arima	xgb	ann	cart
M-TS-338	xgb	es	rw	arima	svm	ann	cart
M-TS-339	xgb	svm	rw	es	arima	cart	ann
M-TS-340	ann	xgb	rw	arima	es	svm	cart

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Table 19 – continued from previous page

ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
M-TS-341	xgb	rw	es	arima	svm	ann	cart
M-TS-342	arima	xgb	es	rw	svm	cart	ann
M-TS-343	arima	es	rw	xgb	svm	cart	ann
M-TS-344	arima	xgb	rw	es	svm	ann	cart
M-TS-345	ann	cart	rw	es	arima	xgb	svm
M-TS-346	svm	ann	cart	rw	arima	es	xgb
M-TS-347	es	rw	xgb	arima	svm	ann	cart
M-TS-348	rw	es	svm	xgb	cart	ann	arima
M-TS-349	rw	svm	arima	es	xgb	cart	ann
M-TS-350	svm	rw	arima	es	xgb	cart	ann
M-TS-351	es	rw	arima	svm	xgb	cart	ann
M-TS-352	rw	arima	es	xgb	svm	cart	ann
M-TS-353	arima	es	rw	xgb	svm	cart	ann
M-TS-354	rw	arima	svm	ann	cart	es	xgb
M-TS-355	rw	arima	es	cart	ann	xgb	svm
M-TS-356	arima	es	rw	xgb	ann	cart	svm
M-TS-357	es	arima	rw	xgb	svm	cart	ann
M-TS-358	svm	es	rw	xgb	arima	cart	ann
M-TS-359	arima	es	rw	xgb	svm	cart	ann
M-TS-360	rw	xgb	svm	ann	cart	arima	es
M-TS-361	arima	es	rw	xgb	svm	ann	cart
M-TS-362	es	arima	rw	svm	cart	ann	xgb
M-TS-363	arima	rw	es	xgb	svm	cart	ann
M-TS-364	arima	es	svm	rw	xgb	cart	ann
M-TS-365	es	rw	arima	xgb	cart	ann	svm
M-TS-366	xgb	arima	es	rw	svm	cart	ann
M-TS-367	arima	es	rw	xgb	svm	cart	ann
M-TS-368	arima	rw	es	xgb	svm	cart	ann
M-TS-369	xgb	rw	arima	es	ann	cart	svm
M-TS-370	rw	es	xgb	svm	arima	cart	ann
M-TS-371	arima	rw	es	xgb	svm	cart	ann
M-TS-372	es	arima	svm	rw	xgb	cart	ann
M-TS-373	arima	svm	rw	es	xgb	cart	ann
M-TS-374	svm	rw	arima	es	xgb	cart	ann
M-TS-375	arima	es	rw	svm	xgb	cart	ann
M-TS-376	rw	xgb	arima	es	svm	cart	ann
M-TS-377	xgb	es	arima	rw	svm	ann	cart
M-TS-378	xgb	rw	arima	svm	cart	es	ann
M-TS-379	arima	es	rw	svm	xgb	cart	ann
M-TS-380	arima	es	rw	svm	xgb	ann	cart
M-TS-381	arima	rw	es	svm	xgb	cart	ann
M-TS-382	arima	es	rw	xgb	svm	cart	ann
M-TS-383	rw	arima	es	cart	ann	svm	xgb
M-TS-384	rw	arima	svm	xgb	ann	es	cart
M-TS-385	arima	es	rw	xgb	cart	ann	svm
M-TS-386	xgb	arima	svm	rw	es	cart	ann
M-TS-387	es	arima	svm	rw	xgb	cart	ann
M-TS-388	arima	es	rw	svm	xgb	cart	ann
M-TS-389	arima	es	xgb	rw	svm	ann	cart
M-TS-390	rw	es	xgb	arima	ann	cart	svm
M-TS-391	rw	arima	es	ann	xgb	cart	svm
M-TS-392	es	arima	rw	svm	xgb	cart	ann
M-TS-393	es	arima	svm	rw	xgb	cart	ann
M-TS-394	arima	es	rw	xgb	svm	cart	ann
M-TS-395	es	arima	rw	svm	xgb	cart	ann
M-TS-396	arima	es	rw	xgb	svm	cart	ann
M-TS-397	es	rw	arima	ann	cart	svm	xgb
M-TS-398	svm	es	arima	rw	xgb	cart	ann
M-TS-399	es	arima	rw	xgb	cart	ann	svm
M-TS-400	rw	arima	es	xgb	svm	cart	ann
M-TS-401	svm	xgb	ann	cart	es	rw	arima
M-TS-402	rw	cart	arima	es	xgb	svm	ann
M-TS-403	svm	ann	arima	rw	es	cart	xgb
M-TS-404	svm	xgb	es	rw	cart	arima	ann
M-TS-405	es	rw	arima	xgb	svm	ann	cart
M-TS-406	svm	xgb	rw	arima	es	cart	ann
M-TS-407	svm	xgb	ann	cart	arima	es	rw
M-TS-408	svm	xgb	rw	es	arima	cart	ann
M-TS-409	ann	xgb	svm	cart	rw	arima	es
M-TS-410	svm	ann	xgb	es	arima	cart	rw
M-TS-411	ann	svm	es	rw	xgb	arima	cart
M-TS-412	svm	arima	xgb	es	ann	rw	cart
M-TS-413	svm	ann	es	xgb	rw	arima	cart
M-TS-414	svm	xgb	cart	es	ann	arima	rw
M-TS-415	rw	es	arima	xgb	svm	cart	ann
M-TS-416	svm	xgb	es	rw	arima	cart	ann
M-TS-417	svm	xgb	rw	arima	es	cart	ann
M-TS-418	svm	ann	xgb	rw	arima	es	cart
M-TS-419	rw	es	svm	xgb	arima	cart	ann
M-TS-420	svm	xgb	ann	cart	rw	arima	es
M-TS-421	svm	xgb	arima	es	cart	rw	ann
M-TS-422	svm	xgb	rw	es	cart	arima	ann
M-TS-423	xgb	svm	es	ann	rw	arima	cart
M-TS-424	rw	arima	svm	xgb	es	cart	ann
M-TS-425	arima	es	rw	xgb	svm	cart	ann
M-TS-426	svm	es	rw	arima	xgb	cart	ann
M-TS-427	xgb	svm	cart	rw	arima	es	ann
M-TS-428	svm	ann	xgb	cart	es	rw	arima
M-TS-429	es	ann	arima	rw	xgb	svm	cart
M-TS-430	svm	es	rw	xgb	arima	cart	ann
M-TS-431	svm	xgb	rw	es	cart	arima	ann
M-TS-432	svm	xgb	cart	ann	es	rw	arima
M-TS-433	svm	cart	rw	xgb	arima	ann	es
M-TS-434	xgb	ann	svm	rw	arima	cart	es

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Table 19 – continued from previous page

ts_name	best_model	second_model	third_model	fourth_model	fifth_model	sixth_model	seventh_model
M-TS-435	svm	xgb	arima	es	rw	cart	ann
M-TS-436	svm	xgb	cart	es	rw	arima	ann
M-TS-437	svm	xgb	cart	rw	es	arima	ann
M-TS-438	svm	rw	es	arima	xgb	cart	ann
M-TS-439	svm	xgb	es	rw	cart	arima	ann
M-TS-440	svm	es	arima	rw	xgb	ann	cart
M-TS-441	xgb	svm	rw	arima	es	cart	ann
M-TS-442	svm	ann	xgb	arima	es	rw	cart
M-TS-443	svm	ann	xgb	cart	rw	es	arima
M-TS-444	svm	xgb	cart	es	arima	rw	ann
M-TS-445	svm	xgb	rw	arima	es	cart	ann
M-TS-446	svm	xgb	ann	cart	rw	es	arima
M-TS-447	rw	arima	es	xgb	ann	svm	cart
M-TS-448	xgb	arima	es	rw	svm	ann	cart
M-TS-449	svm	rw	es	xgb	cart	arima	ann
M-TS-450	svm	xgb	es	rw	arima	cart	ann
M-TS-451	svm	xgb	arima	cart	ann	es	rw
M-TS-452	svm	rw	es	ann	arima	cart	xgb
M-TS-453	rw	es	arima	svm	xgb	ann	cart
M-TS-454	rw	es	arima	ann	svm	xgb	cart
M-TS-455	cart	rw	arima	svm	ann	es	xgb
M-TS-456	cart	es	xgb	rw	arima	svm	ann
M-TS-457	rw	xgb	svm	cart	ann	es	arima
M-TS-458	rw	arima	es	svm	ann	xgb	cart
M-TS-459	rw	ann	arima	es	svm	xgb	cart
M-TS-460	ann	svm	xgb	es	cart	arima	rw
M-TS-461	svm	ann	xgb	rw	es	arima	cart
M-TS-462	arima	es	svm	rw	xgb	ann	cart
M-TS-463	svm	es	xgb	rw	arima	cart	ann
M-TS-464	ann	xgb	rw	arima	es	svm	cart
M-TS-465	svm	rw	arima	es	xgb	cart	ann
M-TS-466	es	arima	rw	xgb	svm	ann	cart
M-TS-467	arima	es	ann	svm	rw	xgb	cart
M-TS-468	svm	ann	rw	arima	es	xgb	cart
M-TS-469	arima	es	rw	svm	xgb	cart	ann
M-TS-470	svm	rw	arima	es	ann	xgb	cart
M-TS-471	svm	arima	rw	es	xgb	cart	ann
M-TS-472	xgb	es	rw	arima	ann	svm	cart
M-TS-473	arima	rw	es	xgb	ann	cart	svm
M-TS-474	arima	es	svm	ann	rw	xgb	cart
M-TS-475	arima	es	rw	svm	xgb	cart	ann
M-TS-476	es	rw	arima	ann	xgb	svm	cart
M-TS-477	rw	arima	es	xgb	svm	cart	ann
M-TS-478	xgb	rw	arima	es	svm	cart	ann
M-TS-479	arima	es	rw	svm	ann	xgb	cart
M-TS-480	rw	svm	arima	xgb	ann	es	cart
M-TS-481	xgb	svm	rw	arima	es	cart	ann
M-TS-482	rw	arima	svm	ann	es	cart	xgb
M-TS-483	rw	es	arima	svm	xgb	ann	cart
M-TS-484	svm	ann	cart	rw	arima	es	xgb
M-TS-485	arima	es	svm	rw	xgb	cart	ann
M-TS-486	arima	svm	es	rw	xgb	ann	cart
M-TS-487	ann	arima	svm	rw	es	xgb	cart
M-TS-488	ann	svm	xgb	es	rw	arima	cart
M-TS-489	svm	es	arima	rw	ann	xgb	cart
M-TS-490	rw	svm	arima	ann	xgb	cart	es
M-TS-491	rw	cart	xgb	es	ann	svm	arima
M-TS-492	xgb	arima	rw	es	cart	svm	ann
M-TS-493	svm	es	rw	arima	cart	ann	xgb
M-TS-494	rw	es	arima	svm	xgb	cart	ann
M-TS-495	svm	xgb	ann	cart	arima	rw	es
M-TS-496	arima	ann	es	rw	svm	xgb	cart
M-TS-497	xgb	svm	rw	arima	es	cart	ann
M-TS-498	svm	xgb	ann	cart	rw	arima	es
M-TS-499	xgb	svm	ann	es	rw	arima	cart
M-TS-500	xgb	svm	arima	rw	cart	es	ann

D Time series feature outlier detection for minimum and maximum value generation

Table 20 Time series feature outlier detection

Feature name	Outliers	Outlier TS name	Outlier value
Skewness	10	U-TS-176; U-TS-196; U-TS-405; U-TS-429; U-TS-454; M-TS-69; M-TS-136; M-TS-286; M-TS-454; M-TS-477	-3.09; 2.02; -2.17; -1.93; -1.64; 2.97; -7.21; -2.45; -2.59; -13.51
Kurtosis	4	U-TS-405; U-TS-429; M-TS-136; M-TS-477	37.3; 42.83; 247.13; 298.63
Autocorrelation	20	U-TS-54; U-TS-55; U-TS-56; U-TS-57; U-TS-58; U-TS-59; U-TS-60; U-TS-61; U-TS-62; U-TS-63; U-TS-65; U-TS-66; U-TS-67; U-TS-69; U-TS-85; U-TS-90; U-TS-94; U-TS-95; U-TS-181; M-TS-456	0.88; 0.88; 0.88; 0.83; 0.89; 0.88; 0.89; 0.87; 0.89; 0.87; 0.86; 0.67; 0.87; 0.88; 0.66; 0.85; 0.81; 0.92; 0.75; 0.89
Standard deviation	2	U-TS-437; U-TS-450	3386322765770.26; 13973366414589.5
Number of observations	6	M-TS-451; M-TS-452; M-TS-453; M-TS-454; M-TS-455; M-TS-495	92246; 92246; 92246; 92246; 92246; 1048575
Non-linearity	23	U-TS-69; U-TS-115; U-TS-155; U-TS-183; U-TS-407; U-TS-409; U-TS-417; U-TS-425; U-TS-429; U-TS-451; U-TS-454; U-TS-456; U-TS-494; U-TS-495; M-TS-407; M-TS-409; M-TS-417; M-TS-425; M-TS-429; M-TS-451; M-TS-477; M-TS-494; M-TS-500	1517.46; 366.65; 229.8; 181.4; 321.71; 293.46; 265.65; 188.84; 188.75; 403.2; 192.89; 278.99; 221.18; 428.94; 303.57; 265.2; 250.45; 197.01; 185.63; 531.4; 459.19; 188.68; 339.22
Entropy	25	U-TS-12; U-TS-20; U-TS-24; U-TS-32; U-TS-40; U-TS-49; U-TS-53; U-TS-127; U-TS-130; U-TS-131; U-TS-135; U-TS-138; U-TS-140; U-TS-141; U-TS-142; U-TS-151; U-TS-153; U-TS-154; U-TS-155; U-TS-161; U-TS-166; U-TS-180; U-TS-451; U-TS-453; M-TS-451	1.06; 1.1; 1.02; 1.13; 1.17; 1.03; 1.12; 1.18; 1.18; 1.18; 1.31; 1.35; 1.29; 1.31; 1.04; 1.2; 1.1; 1.22; 1.17; 1.1; 1.03; 1.28; 1.05; 1.05; 1.09
Partial autocorrelation	37	U-TS-291; U-TS-292; M-TS-304; M-TS-305; M-TS-315; M-TS-316; M-TS-318; M-TS-323; M-TS-324; M-TS-325; M-TS-329; M-TS-335; M-TS-337; M-TS-339; M-TS-341; M-TS-344; M-TS-346; M-TS-347; M-TS-348; M-TS-350; M-TS-353; M-TS-355; M-TS-357; M-TS-360; M-TS-361; M-TS-364; M-TS-365; M-TS-366; M-TS-369; M-TS-372; M-TS-374; M-TS-375; M-TS-376; M-TS-390; M-TS-397; M-TS-455; M-TS-488	-0.61; -0.59; -0.63; -0.59; -0.62; -0.58; -0.59; -0.67; -0.62; -0.65; -0.58; -0.57; -0.6; -0.6; -0.61; -0.62; -0.61; -0.61; -0.61; -0.64; -0.69; -0.6; -0.59; -0.6; -0.62; -0.62; -0.62; -0.64; -0.58; -0.6; -0.57; -0.58; -0.65; -0.61; -0.58; -0.58; -0.65
Variance	4	U-TS-401; U-TS-428; U-TS-432; U-TS-440	11533819242944886; 2150451764761884; 8604401484807960; 1433225941591596
DTW block 1	10	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-76; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130	13937504562.56; 3413641079.02; 8262836998.16; 23985208243.32; 2765352022.07; 6342284541.22; 6288338756.93; 7391214539.06; 5342522505.16; 2823739594.64
DTW block 2	11	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130; M-TS-306; M-TS-344	17605342081.51; 4333677656.9; 9095971865.91; 28547114167.05; 6989783903.11; 8101283829.68; 9358689286.66; 6835561117.2; 3412288251.98; 5408430962.76; 3411965097.68

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Table 20 – continued from previous page

Feature name	Outliers	Outlier TS name	Outlier value
DTW block 3	16	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306; M-TS-310; M-TS-314; M-TS-323; M-TS-333; M-TS-336; M-TS-339; M-TS-344	36560973133.07; 9089429843.34; 13402698434.2; 52123111284.08; 10337184885.25; 17471357402.59; 19527415483.11; 14552455038.97; 30809410881.36; 14795292902.27; 10146861051.34; 8658703415.57; 14228617141.41; 10098190662.9; 10737035733.16; 19424884522.48
DTW block 4	13	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130; M-TS-306; M-TS-310; M-TS-333; M-TS-344	19597624386.01; 4833396057.85; 9548493895.89; 31025033013.38; 7341464549.96; 9086015160.23; 10427367482.15; 7646526290.41; 3731958635.5; 8078543902.92; 3880760804.39; 3730043097.38; 5095290939.04
DTW block 5	13	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306; M-TS-310; M-TS-333; M-TS-339; M-TS-344	23830133118.54; 5895065215.69; 10509882470.25; 36289230875.79; 8088638584.04; 11178059968.32; 12697749185.38; 9369431259.91; 13750886112.1; 6604561064.22; 6349873788.97; 4791912429.26; 8671281455.17
DTW block 6	10	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130; M-TS-306	17316165452.16; 4261179429.86; 9030330010.25; 28187461315.03; 6938779363.09; 7958381100.14; 9203601553.64; 6717872171.52; 3365925739.79; 5020776863.67
DTW block 7	13	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306; M-TS-310; M-TS-333; M-TS-339; M-TS-344	23830967804.85; 5896029459.65; 10510875220.28; 36290195012.93; 8089632952.74; 11179018732.31; 12698697976.7; 9370326625.52; 13749189868.04; 6602943423.36; 6348798438.91; 4790363370.33; 8669635564.96
DTW block 8	13	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306; M-TS-310; M-TS-333; M-TS-339; M-TS-344	23272584769.77; 5755404608.99; 10383432545.06; 35595740717.8; 7990433214.22; 10902608930.26; 12398777994.11; 9142617978.12; 13002986502.72; 6245237651.8; 6004378666.4; 4531015453.91; 8199651369.62
DTW block 9	13	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306; M-TS-310; M-TS-333; M-TS-339; M-TS-344	23272905107.66; 5755749032.41; 10383810826.99; 35596134105.78; 7990786662.49; 10902969451.38; 12399163921.96; 9142949849.86; 13002350021.25; 6244627427.3; 6003971570.25; 4530429095.69; 8199029577.4
DTW block 10	10	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130; M-TS-306	17261054132.24; 4247312951.77; 9017760939.31; 28118895598.43; 6928998614.2; 7931102926.7; 9174004098.3; 6695411850.14; 3357042332.19; 4947048342.6
DTW block 11	10	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-76; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130	13854922616.54; 3392923328.41; 8244076331.66; 23882446833.51; 2756455079.83; 6327704464.96; 6247506139.28; 7346901703.16; 5308908981.88; 2810495762.5
DTW block 12	9	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-306	16719084886.94; 4612343644.97; 9274180546.44; 27074579307.97; 7283316530.76; 7899945569.11; 9107273675.76; 6771880805.43; 4674527148
DTW block 13	10	M-TS-2; M-TS-31; M-TS-32; M-TS-60; M-TS-76; M-TS-95; M-TS-103; M-TS-119; M-TS-129; M-TS-130	13644271485.78; 3340469619.98; 8196614174.68; 23620315205.42; 2734190156.47; 6290943960.35; 6143648948.84; 7234143894.27; 5223452384.71; 2777125105.39

E Forecasting model selection rules

E.1 Rules for basic time series taxonomy

Table 21 Derived model selection rules of the basic time series taxonomy from the C5.0 decision tree model

Rule no.	Rule description	Forecast model	Rule acc.
1	DurbinWatsonTest = negative autocorrelation & calculate_determination_coefficient = low	ANN	0.75
2	Skewness = medium & Chaos = medium & Entropy = very low & StepChanges = very less abrupt changes & DurbinWatsonTest = positive autocorrelation & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ANN	0.75
3	Kurtosis = medium & NonLinearity = medium & DurbinWatsonTest = none because univariate	ANN	0.67
4	QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 less	ANN	0.67
5	Mean = medium & Periodicity = low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ANN	0.60
6	Kurtosis = very low & NonLinearity = low & Chaos = very high & DurbinWatsonTest in negative autocorrelation, none because univariate	ANN	0.60
7	Autocorrelation = very high & StepChanges = medium & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 medium	ANN	0.50
8	Autocorrelation = high & Seasonality = low	ARIMA	0.83
9	Seasonality = medium & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 less	ARIMA	0.80
10	Skewness = medium & Seasonality = medium & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.80
11	Entropy = low & Peaks = medium & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ARIMA	0.80
12	Periodicity = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	ARIMA	0.75
13	Kurtosis = low & Periodicity = none periodicity & Entropy = very low & DurbinWatsonTest = positive autocorrelation	ARIMA	0.75
14	Seasonality = very high	ARIMA	0.73
15	Chaos = high & feature_dtwdistance = Block1 low & Block2 high & Block3 high & Block4 high & Block5 high & Block6 high & Block7 high & Block8 high & Block9 high & Block10 high & Block11 medium & Block12 medium & Block13 medium	ARIMA	0.67
16	Skewness = medium & Autocorrelation in low, medium, very low & Mean in high, medium & NonLinearity = very low & Periodicity = none periodicity & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.64
17	Trend = very low & NonLinearity = very low & Chaos in medium, very high & DurbinWatsonTest = none because univariate	ARIMA	0.55
18	SelfSimilarity in low, very low & PartialAutocorrelation = medium & DurbinWatsonTest in negative autocorrelation, none because univariate	ARIMA	0.55
19	Autocorrelation in low, medium, very low & Entropy = very low & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 medium	ARIMA	0.54

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Table 21 – continued from previous page

Rule no.	Rule description	Forecast model	Rule acc.
20	Trend = high & SelfSimilarity = high & TurningPoints in medium, more steady & PartialAutocorrelation = very low & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less & calculate_determination_coefficient = very high	ARIMA	0.55
21	Kurtosis = very low & Trend = very high & Autocorrelation in low, medium, very low & Outliers in high, medium & StepChanges = very less abrupt changes & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.50
22	Trend = very high & Chaos in high, medium & PartialAutocorrelation = medium & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.48
23	Seasonality = medium	ARIMA	0.44
24	Kurtosis = low & Mean = medium & Seasonality in none seasonality, very low & StepChanges = very less abrupt changes & DurbinWatsonTest = none because univariate	CART	0.83
25	Skewness = high & Trend = very high & Seasonality = none seasonality & StepChanges = less abrupt changes & Peaks = very low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	CART	0.75
26	Kurtosis = low & Mean = very low & Chaos = medium & DurbinWatsonTest = none because univariate	CART	0.67
27	Kurtosis = very low & DurbinWatsonTest = none because univariate & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 many, Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 medium	CART	0.67
28	NonLinearity = very high & Chaos = very high & DurbinWatsonTest = none because univariate	CART	0.67
29	Autocorrelation = low & Periodicity = very high & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	CART	0.67
30	NonLinearity = very low & Periodicity = medium & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	CART	0.67
31	Kurtosis = medium & NonLinearity = very low	CART	0.50
32	Autocorrelation in low, very low & Seasonality = none seasonality & Outliers = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.83
33	Chaos = high & Entropy = very low & SelfSimilarity = high & PartialAutocorrelation = medium & Outliers = medium & StepChanges = very less abrupt changes & DurbinWatsonTest = positive autocorrelation	ES	0.83
34	Kurtosis = low & Mean = low & DurbinWatsonTest = none because univariate	ES	0.83
35	Kurtosis = very low & Mean = high & Seasonality = very low & Entropy = very low	ES	0.75
36	NonLinearity = low Seasonality = low	ES	0.67
37	Autocorrelation in low, medium & Periodicity = very low & Entropy = low & Peaks in high, low, very low & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ES	0.67
38	Periodicity = medium & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	ES	0.67
39	Chaos = low & Entropy = very low & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.67
40	Autocorrelation = very high & TurningPoints = more steady & DurbinWatsonTest = none because univariate	ES	0.67
41	Entropy = very low & Outliers in low, very low & StepChanges = less abrupt changes & Peaks in medium, very low & DurbinWatsonTest = positive autocorrelation	ES	0.67
42	Skewness in high, low & Periodicity = very low & Chaos = high & PartialAutocorrelation = very low & DurbinWatsonTest = negative autocorrelation & Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.80

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Table 21 – continued from previous page

Rule no.	Rule description	Forecast model	Rule acc.
43	NonLinearity = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 many, Quartile1 less & Quartile2 medium & Quartile3 many & Quartile4 less	RW	0.80
44	Mean = medium & Entropy = very low & Outliers = medium & StepChanges = less abrupt changes & DurbinWatsonTest = positive autocorrelation &	RW	0.80
45	Trend = medium & Periodicity = none periodicity & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	RW	0.75
46	Trend in low, medium & TurningPoints = more oscillating & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 less & Quartile4 less	RW	0.75
47	Autocorrelation = medium & Seasonality = low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.75
48	Trend = medium & TurningPoints = medium & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less & calculate_determination_coefficient = very high	RW	0.75
49	SelfSimilarity = medium & PartialAutocorrelation = medium & Peaks = low & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.71
50	Periodicity = very low & Chaos = medium & SelfSimilarity = very high & PartialAutocorrelation = medium & Peaks in medium, very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.71
51	Trend = very high & Autocorrelation in low, very low & Seasonality = none seasonality & PartialAutocorrelation in high, medium & Outliers in low, very high & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.70
52	Trend = very high & Autocorrelation in low, medium, very low & Seasonality = none seasonality & Outliers in high, medium & StepChanges = less abrupt changes & DurbinWatsonTest in negative autocorrelation, none because univariate QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.47
53	Trend = very low & TurningPoints = more oscillating & Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	SVM	0.83
54	Seasonality in high, low, medium, none seasonality, very low	SVM	0.45
55	Kurtosis = very low & Autocorrelation = very high & DurbinWatsonTest = none because univariate & QuartileDistribution in Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less, Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	XGBoost	0.83
56	Kurtosis = low & Mean = very low & Chaos = very high & DurbinWatsonTest = none because univariate	XGBoost	0.75
57	Skewness = low & Kurtosis = very low & Mean = medium & Entropy = very low & DurbinWatsonTest = none because univariate	XGBoost	0.75
58	Periodicity = none periodicity & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	XGBoost	0.75
59	Seasonality = high & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	XGBoost	0.75
60	Kurtosis = medium & Entropy = very low	XGBoost	0.67
61	DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 medium, Quartile1 medium & Quartile2 less & Quartile3 less & Quartile4 medium	XGBoost	0.63
62	NonLinearity = very high	XGBoost	0.22

E.2 Rules for ligther feature selected time series taxonomy

Table 22 Derived model selection rules of the ligther feature selected time series taxonomy from the C5.0 decision tree model

Rule no.	Rule description	Forecast model	Rule acc.
1	Autocorrelation = very low & Seasonality = none seasonality & TurningPoints = more steady & PartialAutocorrelation = high & Outliers = low & Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ANN	0.75
2	DurbinWatsonTest = negative autocorrelation & calculate_determination_coefficient = low	ANN	0.75
3	Autocorrelation = medium & Periodicity = low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ANN	0.67
4	PartialAutocorrelation = low & calculate_determination_coefficient = high	ANN	0.67
5	Autocorrelation = very high & TurningPoints = more oscillating & StepChanges = medium & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 medium	ANN	0.57
6	Autocorrelation in medium, very low & DurbinWatsonTest = none because univariate & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 less, Quartile1 less & Quartile2 many & Quartile3 medium & Quartile4 less, Quartile1 medium & Quartile2 less & Quartile3 medium & Quartile4 less, Quartile1 medium & Quartile2 medium &Quartile3 less &Quartile4 medium	ANN	0.56
7	Peaks = high	ANN	0.10
8	Entropy = medium & DurbinWatsonTest = none because univariate & Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 less	ARIMA	0.83
9	Autocorrelation = high & Seasonality = low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.80
10	Autocorrelation in low, very low & Periodicity = very low & Outliers = very high & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.75
11	Seasonality = medium & Outliers = very low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.75
12	Periodicity = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	ARIMA	0.75
13	Seasonality = very high	ARIMA	0.73
14	Chaos in high, very high & TurningPoints = very steady & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	ARIMA	0.71
15	Chaos = high & TurningPoints = medium & StepChanges = very less abrupt changes & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.71
16	Autocorrelation = very low & Chaos = medium & TurningPoints = medium & Outliers = low & StepChanges = very less abrupt changes & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.70
17	Autocorrelation in low, medium, very low & Seasonality in none seasonality, very low & TurningPoints in more oscillating, more steady & Outliers = high & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.67
18	TurningPoints = more steady & PartialAutocorrelation = very low & Outliers = low & StepChanges = less abrupt changes & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.63
19	Autocorrelation = very low & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 medium & Quartile4 less	ARIMA	0.57

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Table 22 – continued from previous page

Rule no.	Rule description	Forecast model	Rule acc.
20	Autocorrelation in low, medium & Entropy = very low & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 medium	ARIMA	0.55
21	Autocorrelation in low, medium, very low & Periodicity = none periodicity & TurningPoints in medium, very steady & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.53
22	Trend = very high & Autocorrelation in low, medium, very low & Chaos in high, medium, very high & Outliers = medium & Peaks in medium, very low & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.51
23	Trend in medium, very high & Chaos = medium & PartialAutocorrelation = medium & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ARIMA	0.47
24	Seasonality = low	ARIMA	0.33
25	Trend = very high & Quartile1 medium & Quartile2 less & Quartile3 less & Quartile4 less	CART	0.83
26	Trend = DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 medium	CART	0.80
27	Autocorrelation in high, very high & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 many & Quartile4 less, Quartile1 less & Quartile2 many & Quartile3 medium & Quartile4 less, Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 medium calculate_determination_coefficient in none because univariate TS, very low	CART	0.80
28	Autocorrelation in high, very high & TurningPoints = more oscillating & StepChanges = less abrupt changes & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less calculate_determination_coefficient = none because univariate TS	CART	0.75
29	Chaos = very high & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 many	CART	0.67
30	Autocorrelation in low, very low & Entropy = high & TurningPoints = medium & Outliers = high & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less &Quartile2 medium & Quartile3 medium & Quartile4 less	CART	0.60
31	Chaos = very low	CART	0.57
32	Autocorrelation in low, very low & Seasonality = none seasonality & Outliers = very low & DurbinWatsonTest in negative autocorrelation, none because univariate & Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.83
33	PartialAutocorrelation in high, very low & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less calculate_determination_coefficient = high	ES	0.80
34	Trend = very high & Chaos = medium & TurningPoints = more steady & PartialAutocorrelation = very low & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.80
35	Autocorrelation in high, very high & Outliers = medium & QuartileDistribution = Quartile1 many & Quartile2 less & Quartile3 less & Quartile4 less	ES	0.75
36	Periodicity = very low & Chaos = high & PartialAutocorrelation = very low & StepChanges = less abrupt changes & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.75
37	Chaos = low & TurningPoints = more steady	ES	0.75
38	Trend = very high & Autocorrelation in low, medium, very low & Seasonality in none seasonality, very low & Outliers = medium & Peaks = low & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	ES	0.67
39	Periodicity = medium & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	ES	0.67
40	Chaos = low & Outliers = low	ES	0.67

Continued on next page

Table 22 – continued from previous page

Rule no.	Rule description	Forecast model	Rule acc.
41	DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 many	ES	0.50
42	PartialAutocorrelation = low	ES	0.171
43	Trend = very high & Seasonality = none seasonality & Entropy in low, medium & Outliers = medium & Peaks = medium & Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.80
44	Autocorrelation in low, very low & TurningPoints = very oscillating & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.80
45	Autocorrelation in low, very low & Periodicity = none periodicity & Outliers = very high & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.80
46	Chaos = high & PartialAutocorrelation = very low & StepChanges = very less abrupt changes & Peaks = medium & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.80
47	Autocorrelation = medium & Outliers = low & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.75
48	Trend in low, medium & TurningPoints = more oscillating & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 less & Quartile4 less	RW	0.75
48	Trend in low, medium & TurningPoints = more oscillating & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 less & Quartile4 less	RW	0.75
49	Autocorrelation = low & Seasonality = very high & Entropy = high	RW	0.75
50	Seasonality = very high & TurningPoints = very oscillating	RW	0.75
51	Trend = high & Chaos in high, medium & PartialAutocorrelation = medium & Outliers = low & StepChanges = less abrupt changes & Peaks = medium	RW	0.71
52	Chaos = medium & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 many	RW	0.67
53	DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 medium & Quartile4 many, Quartile1 less & Quartile2 medium & Quartile3 many & Quartile4 less	RW	0.67
54	Trend = very high & Autocorrelation = low & Seasonality = none seasonality & Outliers = low & DurbinWatsonTest = none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.62
55	Trend = very low & calculate_determination_coefficient in high, very high	RW	0.60
56	Trend = medium & Periodicity = very low & Chaos = medium & Outliers = medium & DurbinWatsonTest in negative autocorrelation, none because univariate	RW	0.58
57	Periodicity = none periodicity & TurningPoints = more oscillating & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	RW	0.57
58	Autocorrelation = low & TurningPoints in more steady, very oscillating & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 medium	RW	0.46
59	TurningPoints = more steady & PartialAutocorrelation = very low & StepChanges = very less abrupt changes	RW	0.33
60	Seasonality = low	RW	0.25
61	Peaks = low	RW	0.19
62	Seasonality in high, low, medium, none seasonality, very low	SVM	0.45
63	Autocorrelation in high, very high & QuartileDistribution in Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 medium, Quartile1 less & Quartile2 many & Quartile3 less & Quartile4 less, Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	XGBoost	0.83

Continued on next page

Table 22 – continued from previous page

Rule no.	Rule description	Forecast model	Rule acc.
64	Autocorrelation in high, very high & QuartileDistribution in Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less, Quartile1 medium & Quartile2 many & Quartile3 medium & Quartile4 less	XGBoost	0.80
65	Trend = medium & Autocorrelation in high, very high & TurningPoints = more steady & calculate_determination_coefficient = very high	XGBoost	0.80
66	Autocorrelation = very high & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less calculate_determination_coefficient = none because univariate TS	XGBoost	0.80
67	Seasonality = high & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	XGBoost	0.75
68	Autocorrelation = very low & QuartileDistribution = Quartile1 less & Quartile2 less & Quartile3 less & Quartile4 medium	XGBoost	0.75
69	TurningPoints = very steady & Outliers = high & DurbinWatsonTest in negative autocorrelation, none because univariate & QuartileDistribution = Quartile1 less & Quartile2 medium & Quartile3 medium & Quartile4 less	XGBoost	0.75
70	Periodicity = none periodicity & QuartileDistribution = Quartile1 medium & Quartile2 many & Quartile3 less & Quartile4 less	XGBoost	0.75
71	DurbinWatsonTest = none because univariate & QuartileDistribution in Quartile1 less & Quartile2 medium & Quartile3 less & Quartile4 many, Quartile1 medium & Quartile2 less & Quartile3 less & Quartile4 medium	XGBoost	0.75
72	Trend = very high & Chaos = medium & TurningPoints = medium & PartialAutocorrelation = very low & Peaks = medium & DurbinWatsonTest = negative autocorrelation & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less	XGBoost	0.75
73	Periodicity = very low & Chaos = high & TurningPoints = more steady & PartialAutocorrelation = very low & Peaks = low & QuartileDistribution = Quartile1 medium & Quartile2 medium & Quartile3 medium & Quartile4 less calculate_determination_coefficient = very high	XGBoost	0.71

F Feature selection code

```
# Initialize required R packages
library(caret)
library(randomForest)
# Read the ts taxonomy feature results of the 1000 ts.
ts_taxonomy <- tsfcmethodr::ts_taxonomy_results
ts_taxonomy <- ts_taxonomy[, -which(colnames(ts_taxonomy) ==
"ts_name")]
ts_taxonomy[] <- lapply(ts_taxonomy, factor)
# Read in the forecasting method evaluation results of the 1000 ts.
fs_evaluation <- tsfcmethodr::ts_fc_evaluation_results
fs_evaluation[] <- lapply(fs_evaluation, factor)
# Define the model fitting parameters by using a random forrest with
# backward search and a 10-fold cross-validation that repeats 10 times.
fit_control <- caret::rfeControl(functions = rfFuncs,
method = "repeatedcv",
number = 10,
repeats = 10)
# Run the rfe algorithm based on the loaded data and defined paramaters
subset_results <- caret::rfe(ts_taxonomy,
fs_evaluation[, "best_model"],
sizes = c(1:ncol(ts_taxonomy)),
rfeControl = fit_control
, metric = "Accuracy")
# List the best subset features decreasing by importance.
predictors(subset_results)
# Plot the final results for the accuracy measure with grid
# and object lines.
plot(subset_results, type=c("g", "o"), xlab = "Feature subsets")
```

Listing 9 Feature selection of the time series taxonomy in R

G Concept matrix for irrelevant features

Articles				Features																															
Reference	Year	Number of citations	Average citations	Max value	Min value	Domain of the series	Granularity	Fickleness	Traversity	Exogenus	Missing values	Level of detail	Strength of curvature	Lumpiness (Changing variance)	Spikiness (Strength of spikness)	Flat spots using discretization	Number of crossing points	Kullback-Leibler score	Index of maximum KL score	Recurrence rate	Average diagonal length	Length of longest diagonal line	Length of longest vertical line	Transitivity	Embedding dimension	Delay time	Multivariate normality test	Maximum fractal dimension difference	Minimum fractal dimension difference	(discrete-time) Fourier transform	StatAv (mean stationarity)	Sign change measure	% of values with absolute Z-score	Ratio of TS length and no. attributes	% of attributes after attribute selection
Smith-Miles 2009	2009	391	40																																
Wang et al. 2006	2006	276	22																																
Kate 2016	2016	61	21																																
Lemke and Gabrys 2010	2010	105	12	x																															
Nanopoulos et al. 2001	2001	214	12																																
Collopy and Armstrong 1992	1992	315	12																																
Cui et al. 2016	2016	32	11	x	x																														
Wang et al. 2009	2009	102	11																																
Lahmiri 2014	2014	38	8																																
Matijaš et al. 2013	2013	46	8		x		x	x	x	x																									
Gudmundsson et al. 2008	2008	69	7																																
Prudêncio and Ludermir 2004	2004	104	7			x																													
Adya et al. 2001	2001	98	6																																
Armstrong 2001c	2001	94	6																																
Wang et al. 2007	2007	52	5																																
Yang et al. 2017	2017	7	4										x	x	x	x	x	x	x																
Armstrong 2001b	2001	69	4								x																								
Meade 2000	2000	61	4																																
Scholz-Reiter et al. 2014	2014	12	3																	x	x	x	x	x	x	x									
Graff et al. 2014	2014	11	3																																
Graff et al. 2013	2013	14	3	x																															
Prudêncio et al. 2004	2004	35	3																																
Shah 1997	1997	47	3																																
Drago and Scepi 2015	2015	6	2																																
Davenport and Funk 2015	2015	5	2																																
Prudêncio et al. 2011	2011	15	2			x																													
Soares et al. 2009	2009	12	2																								x								
Arinze et al. 1997	1997	29	2									x																							
Arinze 1994	1994	50	2									x																							
Pimentel and de Carvalho 2019	2019	1	1								x																x						x	x	x
Ali et al. 2018	2018	1	1	x																															
Fulcher 2017	2017	1	1																											x	x				
Ge and Ge 2016	2016	2	1																									x	x						
Wang et al. 2008	2008	8	1																																
Lemke and Gabrys 2008	2008	4	1	x																												x			
Sum of average citations per feature				27	19	9	8	8	8	8	5	4	4	4	4	4	4	4	4	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	1

Figure 14 Concept matrix of irrelevant time series features

H References of concept matrix for time series features

Table 23 Concept matrix references

Reference	Author(s)	Year	Title
(Smith-Miles 2009)	Smith-Miles, K. A.	2009	Cross-disciplinary Perspectives on Meta-learning for Algorithm Selection
(Wang et al. 2006)	Wang, X., Smith, K. and Hyndman, R.	2006	Characteristic-Based Clustering for Time Series Data
(Kate 2016)	Kate, R. J.	2016	Using Dynamic Time Warping Distances As Features for Improved Time Series Classification
(Lemke and Gabrys 2010)	Lemke, C. and Gabrys, B.	2010	Meta-learning for Time Series Forecasting and Forecast Combination
(Nanopoulos et al. 2001)	Nanopoulos, A., Alcock, R. and Manolopoulos, Y.	2001	Feature-based Classification of Time-series Data
(Collopy and Armstrong 1992)	Collopy, F. and Armstrong, J. S.	1992	Rule-Based Forecasting: Development and Validation of an Expert Systems Approach to Combining Time Series Extrapolations
(Cui et al. 2016)	Cui, C., Wu, T., Hu, M., Weir, J. D. and Li, X.	2016	Short-term building energy model recommendation system: A meta-learning approach
(Wang et al. 2009)	Wang, X., Smith-Miles, K. and Hyndman, R.	2009	Rule induction for forecasting method selection: Meta-learning the characteristics of univariate time series
(Lahmiri 2014)	Lahmiri, S.	2014	Wavelet Low- and High-frequency Components As Features for Predicting Stock Prices with Backpropagation Neural Networks
(Matijaš et al. 2013)	Matijaš, M., Suykens, J. A. K. and Krajcar, S.	2013	Load Forecasting Using a Multivariate Meta-learning System
(Gudmundsson et al. 2008)	Gudmundsson, S., Runarsson, T. P. and Sigurdsson S.	2008	Support vector machines and dynamic time warping for time series
(Prudêncio and Ludermir 2004)	Prudêncio, R. B. C. and Ludermir, T. B.	2004	Meta-learning Approaches to Selecting Time Series Models
(Adya et al. 2001)	Adya, M., Collopy, F., Armstrong, J. and Kennedy, M.	2001	Automatic identification of time series features for rule-based forecasting
(Armstrong 2001c)	Armstrong, J. S.	2001	Selecting Forecasting Methods
(Wang et al. 2007)	Wang, X., Wirth, A. and Wang, L.	2007	Structure-Based Statistical Features and Multivariate Time Series Clustering
(Yang et al. 2017)	Yang, D., Dong, Z., Lim, L. H. I. and Liu, L.	2017	Analyzing big time series data in solar engineering using features and PCA
(Armstrong 2001b)	Armstrong, J. S.	2001	Extrapolation for Time-Series and Cross-Sectional Data
(Meade 2000)	Meade, N.	2000	Evidence for the selection of forecasting methods

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Table 23 – continued from previous page

Reference	Author(s)	Year	Title
(Scholz-Reiter et al. 2014)	Scholz-Reiter, B., Kück, M. and Lappe, D.	2014	Prediction of customer demands for production planning - Automated selection and configuration of suitable prediction methods
(Graff et al. 2014)	Graff, M., Pena, R., Medina, A. and Escalante, H. J.	2014	Wind speed forecasting using a portfolio of forecasters
(Graff et al. 2013)	Graff, M., Escalante, H. J., Cerda-Jacobo, J. and Avalos Gonzalez, A.	2013	Models of Performance of Time Series Forecasters
(Prudêncio et al. 2004)	Prudêncio, R. B.C., Ludermir, T. B. and de Carvalho, F. de A.T.	2004	A Modal Symbolic Classifier for Selecting Time Series Models
(Shah 1997)	Shah, C.	1997	Model selection in univariate time series forecasting using discriminant analysis
(Drago and Scepi 2015)	Drago, C. and Scepi, G.	2015	Time Series Clustering from High Dimensional Data
(Davenport and Funk 2015)	Davenport, F. and Funk, C.	2015	Using time series structural characteristics to analyze grain prices in food insecure countries
(Prudêncio et al. 2011)	Prudêncio, R. B. C., de Souto, M. C. P., Ludermir, T. B.	2011	Selecting Machine Learning Algorithms Using the Ranking Meta-Learning Approach
(Soares et al. 2009)	Soares, R. G., Ludermir, T. B. and Carvalho, F. A.	2009	An Analysis of Meta-learning Techniques for Ranking Clustering Algorithms Applied to Artificial Data
(Arinze et al. 1997)	Arinze, B., Kim, S.-L. and Anandarajan, M.	1997	Combining and Selecting Forecasting Models Using Rule Based Induction
(Arinze 1994)	Arinze, B.	1994	Selecting appropriate forecasting models using rule induction
(Pimentel and de Carvalho 2019)	Pimentel, B. A. and de Carvalho, A. C.P.L.F.	2019	A new data characterization for selecting clustering algorithms using meta-learning
(Ali et al. 2018)	Ali, A. R., Gabrys, B. and Budka, M.	2018	Cross-domain Meta-learning for Time-series Forecasting
(Fulcher 2017)	Fulcher, B. D.	2017	Feature-based time-series analysis
(Ge and Ge 2016)	Ge, L. and Ge, L.-J.	2016	Feature extraction of time series classification based on multi-method integration
(Wang et al. 2008)	Wang, L., Wang, X., Leckie, C. and Ramamohanarao, K.	2008	Characteristic-based Descriptors for Motion Sequence Recognition
(Lemke and Gabrys 2008)	Lemke C. and Gabrys, B.	2008	On the Benefit of Using Time Series Features for Choosing a Forecasting Method

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