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Weather Predication Using Classification Methods: An Experimental

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Abstract Weather data and specifically rainfall data contain streams of data that are collected hourly. These data can be used to identify the signatures of rivers and other areas. However, the process of discovering patterns from thousands of data information loss. Hence, precise data representation and pattern detection are crucial in ensuring that the patterns obtained have real meaning and can describe the weather signatures of certain areas accurately. In this paper, an experimental are carried out on classified rainfall sequences by case-based reasoning (CBR), with two other effective methods a support vector machine (SVM) and a naïve Bayes (NB).. The experimental results show that the incorporation of CBR gives both algorithms the capability to detect patterns of segmented rainfall with high accuracy and that SVM with CBR outperforms NB with CBR.

Keywords: Data mining; Classification; prediction and time series data.

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الملخص بيانات الطقس وبيانا ت هطول الأمطار على وجه التحديد تحتوي على تيارات من البيانات التي يتم جمعها كل ساعة. ويمكن استخدام هذه البيانات لتحديد توقيعات الأنهار ومناطق أخرى. ومع ذلك، فإن عملية اكتشاف أنماط من الآلاف من فقدان المعلومات البيانات. ومن ثم، فإن التمثيل الدقيق للبيانات وك شف الأنماط أمران حاسمان في ضمان أن يكون للأنماط التي تم الحصول عليها معنى حقيقي ويمكن أن تصف تواقيع الطقس لبعض المناطق بدقة. في هذا البحث تم إجراء تجربة تجريبية على تسلسلات هطول الأمطار المصنفة حسب المنطق القائم على الحالة CBR، مع طريقتين فاعلتين أخريين هما آلة ناقلات الدعم SVM و ساذجة بايس NB. وتبين النتائج التجريبية أن التضمين من كبر يعطي كل من الخوارزميات القدرة على الكشف عن أنماط هطول الأمطار المجزأة بدقة عالية وأن SVM مع CBR يتفوق NB مع CBR.

الكلمات المفتاحية: تنقيب البيانات، التصنيف، التنبؤ، بيانات السلاسل الزمنية.

I. Introduction

At the present, the time series data are being generated with extraordinary speed from almost every application domain. Among these data are related to the daily fluctuations of the stock market data, traces of dynamic processes and scientific experiments, medical field and daily rainfall occurrence. As a consequence, in the last decade there has been an increasing number of interests in querying and mining such data which, in turn had resulted active research to introduce the new methodology for indexing, classification, clustering and approximation of time series data [1], [2], [3], and [4]. However, The dynamic nature of the weather has led to much research n weather prediction, such as weather forecasting warning systems [1] and rainfall and flood forecasting [2-3]. The weather has an impact on many sectors and affects the power usage of industry, residential facilities, and agriculture [4-5]. Due to the continuous changes in the climate there is a need for weather prediction systems that is up to par with the current technology existed [6], including the Malaysian weather prediction system. Rainfall prediction is one of the areas being actively researched all over the world [7-9]. For instance, in Malaysia, rainfall data have been used to gauge the size of rainfall cells [10-11].

Neural network modeling has been a popular method for weather and climate prediction and classification [1-8]. However, classification is one of the data mining techniques that could potentially give new insights into weather prediction problems. It has been used in other applications, such as alarm log, financial events, and stock trend relationship analysis [11]. This paper reports on the use of two different classification algorithms, a support vector machine (SVM) and a naïve Bayes (NB) algorithm, that are compared with case-based reasoning (CBR) to classify patterns (rainfall signatures) in the Malaysian rainfall dataset and the results of an experiment to assess their performance

II. RALTED WORK

Classification is one of the most typical operations in supervised learning. There are two types of classification in temporal or time series data mining. The first is time series classification, which is similar to whole series clustering. Given a set time series with a single label for each, the task is to train a classifier and label new time series. The second is time point classification, where there are labels for each time point. A classifier is trained using the values and labels from the time points of the training set. Given a new time series, the task is to label all time points. This is known as sequential supervised learning and is related to prediction. Some examples of sequence classification applications are speech recognition, gesture recognition and handwritten word recognition[4]. Classification is relatively straightforward if generative models are employed to model the temporal data. However, according to a review by [7] studies on the use of classification in actual temporal applications is lacking in the literature.

The artificial neural network (ANN) has been employed in time series applications for prediction and classification [2]. A class of ANN is the recurrent neural network (RNN), which is a widely used tool for the prediction of time series that has been used in several different applications[5]. The most common type of RNN is the dynamic system that makes efficient use of temporal information in the input sequence, both for classification as well as for prediction. This means that after training, interrelations between the current input and internal states are processed to produce the output and to represent the relevant past information in the internal states. During the supervised learning process the target values constitute a second source of information. These target values specify the relevant interrelations in the input sequence. For a RNN the input is typically a times series and the target is either a trivial sequence of constant values or another nontrivial time series. For the classification task the RNN classifies the sequence by class label; for instance, in a rainfall application a time series sequence would be classified as: No rain, Light, Moderate or Heavy, whereas in the prediction task a sequence would be classified into some time period.

In [2] the dynamic behavior of the RNN is used to categorize input sequences into different specified classes. These two tasks do not seem to have much in common. However, the prediction task strongly supports the development of a suitable internal structure, representing the main features of the input sequence, to solve the classification problem. Therefore, the speed and success of the training process as well as the generalization ability of the trained RNN are significantly improved. The trained RNN provides good classification performance and enables the user to assess efficiently the degree of reliability of the classification result.

Similar to [2] above, [3] applies two different types of neural network to classify time series data of single trial electroencephalograph (EEG) data. Standard multilayer perceptrons (MLPs) are used as a standard method for classification. They are compared to finite impulse response (FIR) MLPs, which use FIR filters instead of static weights to allow temporal processing inside the classifier. The authors address the classification of these signals using neural networks. Neural networks are used because they provide a well-established framework for pattern recognition problems. This type of network is known as a FIR MLP. The motivation for using a classifier capable of temporal processing is that the patterns to be recognized are not static data but time series. Thus, the temporal information of the input data should be used to improve classification results. This can be done with a static classifier like MLP and a mapping of the temporal input data to static data. Another way is to use a classifier with temporal processing like FIR MLP.

A time series classification method was also proposed by [10] in which a general framework of multi-view representation and representation-to-semantics mapping for sequence data are employed. Multi-view representation characterizes sequence data in a comprehensive manner. The primary representation depicts the temporal pattern of the sequence data. The multi-attribute representation identifies associated numerical attributes. After the representations at multiple views have been constructed, kernel fusion is used to combine similarity measures for different views (classification). For individual representations, two methods are applied to construct a valid sequence-data kernel via a prior distance function and compare their pros and cons.

Another method for time series classification was proposed by [11] for learning multivariate time series classifiers. Two types of background predicate are introduced: interval-based predicates such as “always”, and distance-based predicates such as the Euclidean distance. Special purposes techniques were presented that enable these predicates to be handled efficiently when performing top-down induction. Moreover, as boosting was employed, the accuracy of the resulting classifiers could be enhanced significantly.

Since EEG datasets are very well-known time series, and pattern classification plays an important role in the domain of the brain–computer interface, [12] presented methods for EEG pattern classification that jointly employed principal component analysis (PCA) and the hidden Markov model (HMM). Two methods were introduced: PCA+HMM and PCA+HMM+SVM. The usefulness of principal component features and the hybrid method was confirmed through the classification of EEGs that were recorded during the imagination of a left- or right-hand movement.

Case-based reasoning is an artificial intelligence approach for solving problems where a model of the domain knowledge is not available, and it displays basic machine learning capabilities. The CBR approach is widely used in different areas with good results. It has been used for mining tasks in different domains [13-19].

A fuzzy logic-based methodology for knowledge acquisition was designed and utilized by [20] for the retrieval of temporal cases in a CBR system. The approach was used to obtain knowledge about what salient features of continuous-vector, unique temporal cases point out significant similarity between cases. The knowledge is determined in a similarity-measuring function and is thus used to retrieve 1-NNs from a large database. The present case is predicted based on the weighted median of the outcomes of related past cases. Past cases are weighted according to their degree of similarity to the present case.

Another approach based on CBR was suggested in [21] for fault detection of reinforced concrete bridges in polluted areas. The work aimed to present a new approach based on the CBR paradigm to solve the problem of bridge inspection and diagnosis, which is usually performed by civil engineers mainly through visual inspections, a type of activity involving subjective judgments and uncertainties. The architecture for data gathering and database storage was implemented in consideration of the above issues. The CBR paradigm was tested by using the jCOLIBRI platform

Case-based reasoning was applied by [13] to enable a system to learn from a variety of cases presented to it. The proposed method was tested on images taken from a large dataset. Case-based reasoning assisted in learning the fuzzy parameters for detection of salient regions by taking into account the features characterizing prominent boundary colors. In this approach a number of images are presented to the system and the parameters that supply the best match to the salient regions marked as ground truths are recorded. These images are grouped to form relevant cases, where each case includes all the images having similar image features, under the assumption that the same parameters will discover similarly good salient regions for all the test images. Case-based reasoning selects the top most relevant cases and thus helps in greatly reducing the rule-set. Thus CBR not only simplifies the problem of variations across a range of sample images, but also returns a set of characteristics defining the given dataset. This can be especially useful in making inferences about datasets containing similar types of images and can also aid in image retrieval.

Case-based reasoning was also used by [18] as part of an intelligent-based agent management system. The system uses information from previously managed situations to maintain quality of service in order to meet the requirements of a service level agreement. The results illustrated the performance of an agent in traffic pattern recognition in order to identify the specific type of problem and finally suggested the right solution.

A method for representation of temporal intervals in a CBR system was presented by [16] for case retrieval. The aim was to propose a method to support the prediction of events for industrial processes because many processes are too complex to be predicted by standard trend analysis. The authors showed how Allen's temporal intervals can be included in the semantic network representation of the Creek system. However, the representation has a weakness in that it only enables one fixed layer of intervals in the cases. Nevertheless, temporal interval-based CBR methods, as exemplified by [16], could have high potential for revealing such complex problems.

In addition, CBR has been used in a general framework to enable more compact and efficient representation of practical time series cases and thus capture the most important characteristics while ignoring irrelevant trivialities [23]. The aim of using CBR is to extract a set of qualitative, interpretable features from original time series data. These features should, on the one hand, convey significant information to human experts enabling potential discoveries/findings and, on the other hand, facilitate much-simplified case indexing and similarity matching in CBR. This goal is achieved in two consecutive stages. In the first, the time series of real numbers is transformed into a symbolic series by temporal symbolic approximation. A few different methods are used at this stage such FT, WT and symbolic approximation (SAX). In the second, a knowledge discovery method is used to identify key sequences from the transformed symbolic series in terms of their co-occurrences with certain classes.

In another work, CBR was employed for early fault diagnosis of continuous processes [19]. A laboratory plant was considered with 11 observed variables and 14 different classes of faults. The k-NN algorithm was also used to retrieve cases (similarity). It could also be used with several similarity methods such as Manhattan distance, Euclidean distance and DTW. The system was validated using a dataset obtained from simulations of fault classes in a laboratory plant. The accuracy of the classifiers using the different metrics with 10 different series lengths (from 10% to 100% of the series length) was compared. The proposed method seems to be feasible based on the experimental results. In fact, the system is able to provide an accurate fault classification with a small percentage of series length. The developed CBR system is able to work with time series, which is a problem not covered in most CBR systems.

III. Preliminary Discussion and Experiment

Preparation Classification is a class prediction technique, which is supervised in nature. This technique possesses the ability to predict the label for classes, provided that sufficient numbers of training examples are available [10]. There is a variety of classification algorithms available, including Support vector machines, k Nearest Neighbours, weighted voting and Artificial Neural Networks. All these techniques can be applied to a dataset for discovering set of models to predict the unknown class label. In classification, the dataset is divided into two sets, namely the training set (dependent set) and a test set (independent set). The data mining algorithm initially runs on the training set, than later the predicting model is applied on the test set [5, 12]. The dataset used in this experiment contains 15 attributes. From a large list of attributes, only twelve attributes are chosen. The chosen attributes are namely US state, population of community, median household income, median family income, per capita income, number of people under the poverty level, percentage of people 25 and over with less than a 9th grade education, percentage of people 25 and over that are not high school graduates, percentage of people 25 and over with a bachelor's degree or higher education, percentage of people 16 and over in the labour force and unemployed, percentage of people 16 and over in the labour force and unemployed, total number of violent crimes per 100K population. There are different methods available for attribute or feature selection. For this experiment, manual method was chosen for attribute selection [16] based on human understanding and intellect. It is practical, especially when dealing with a large number of attributes. It was also taken in account that only those attributes are chosen, which do not contain any missing values. Classification was applied using Decision Tree and Naïve Bayesian classifier. In the first step, the model is built on the training set with known class label and in the second step; the proposed model is applied by assigning class labels on the test set. After performing the experiment using the above mentioned classification algorithms, accuracy of both the algorithms is evaluated, for predicting the 'Rainfall Category' patterns.

1. Rainfall data

The time series rainfall data is gathered from Institute of Climate Change, University Kebangsaan Malaysia, Malaysia. The data set comes from 10 rainfall stations in Selangor state of Malaysia. The period covered is about 35 years from 1950 to 2006, with a stamped daily time and one variable of values. Table 1 shows the description of the rainfall data sets and shows examples of the dataset.

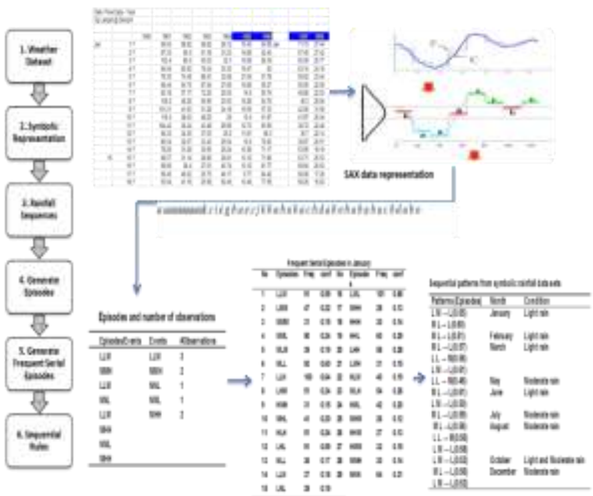
Table 1: Rainfall time series data characteristics

Code	Stations	Period of record	Time series length
1	Serdang: 5R- Mardi	1975-2003	10248
2	Ampang: 17R-JPS	1953-2003	18300
3	Janaletrik: 21R- Ponsoon	1953-2003	18300
4	Lenggeng_NS: 33R-Ldg	1947-2000	19398
5	Kajang_Sel: 28R	1975-2004	9882
6	Mantin_NS 32R-Setul	1960-2003	15738
7	UKM_Sel 51R-	1991-2004	4758
8	PemasokanAmpang_Sel 18R-	1947-1995	17568
9	Dominion 53R-Ldg	1970-2006	13176
10	LdgCairo NS 40R	1965-2000	12810

Daily Flow Data - Year											
Sg Langat @ Dengkil											
		1960	1961	1962	1963	1964	**1965**	**1966**		**1967**	**1968**
Jan	1	?	69.93	58.92	68.62	29.72	15.43	64.05	Jan	71.73	27.44
	2	?	87.33	66.6	61.18	31.23	14.89	62.43		67.45	27.42
	3	?	103.4	80.6	65.03	32.1	16.58	58.18		65.09	25.77
	4	?	94.94	83.92	78.04	33.32	19.47	52		63.14	24.18
	5	?	78.35	74.48	88.41	32.68	21.54	51.78		59.62	23.44
	6	?	68.44	64.76	87.94	27.65	16.89	55.27		55.05	22.59
	7	?	83.18	57.17	72.26	25.56	14.9	56.74		49.88	22.53
	8	?	109.2	49.28	56.96	23.93	16.28	54.76		45.3	29.94
	9	?	131.21	41.93	51.28	24.18	15.59	57.33		42.96	31.58
	10	?	119.3	38.63	48.23	29	13.6	61.97		41.97	25.04
	11	?	104.42	36.24	43.48	25.99	12.73	65.56		38.72	22.48
	12	?	94.33	34.35	37.03	25.2	11.81	68.3		36.7	22.14
	13	?	86.54	32.67	33.43	25.54	10.9	70.93		39.97	20.51
	14	?	78.26	31.28	30.56	25.24	10.38	71.17		53.95	19.19
15	15	?	68.57	31.14	28.96	29.81	10.12	71.96		63.71	25.53
	16	?	58.96	38.4	27.01	40.74	10.12	81.77		69.64	20.63
	17	?	58.46	46.02	26.75	49.17	9.77	84.42		68.08	17.28
	18	?	53.94	41.16	25.99	52.46	10.49	77.55		58.26	15.83

Fig. 1:Original Rainfall Dataset

2. Rainfall data pre-processing



Fig, 2:Rainfall Pattern Discovery Framework

Building Classifiers and Measurements In this part pattern detection algorithm for a rainfall time series dataset is proposed. However, the adaptive sliding window algorithm (ASWA) and the improved case-based reasoning (CBR) approach namely; the data segmentation phase of pattern detection adapts the classical sliding window algorithm (SWA) to compute change points in time series rainfall data, where the ASWA improves the SWA with respect to two parameters, namely, error and window size. In pattern detection phase, the goal is to detect the class labels of the rainfall dataset. Two phases of CBR are improved: the retrieval phase is adapted to compute rainfall sequences with unequal window sizes and the revise phase is improving classification accuracy. Finally, rainfall sequences were classified and class label as following:

Table 2: Rainfall class Label

Rainfall Range	Class	Symbol
0-2mm/day	No rain	N
3-10mm/day	light	L
11-30mm/day	Moderate	M
31-60mm/day	heavy	H

IV. EXPERIMENTAL

In the experiment, a comparison was made of the performance of NB and SVM algorithms combined with CBR on weather data. During the experiment, the preprocessed rainfall signatures were converted into an .ARFF file, which is the standard file type for WEKA. Then 10-fold cross-validations were applied to the input dataset, separately for the NB and the SVM algorithms. The accuracy for 10-fold cross-validation for NB and SVM was 80.2209% and 81.1968%, respectively (see Table 3). Hence, SVM outperformed NB when combined with CBR.

Table 3: Accuracy (correctly classified instances)

Method	CBR	SVM	NB
Accuracy	90.6086	81.1968	80.2209

V. CONCLUSION

This paper presented a comparison of the performance of two classification algorithms, SVM and NB when combined with CBR in predicting the ‘rainfall. The experimental results showed that SVM, Support Victor Machine performed better than NB on the rainfall dataset, using WEKA. It is evident that CBR can take provide a great advantage to machine learning algorithms such as SVM in improving the effectiveness of prediction. In future research, it is planned to apply other classification algorithms with CBR as well to rainfall signatures and evaluate their prediction performance. Another direction for future work is to use other techniques for time series classification and prediction and study their effect on the prediction performance of different algorithms

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