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A Perspective On Test Methodologies For Time Series Forecasting As Supervised Learning

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Abstract – Supervised Machine Learning algorithms are widely used to predict the outcomes of the future dataset. It is the learning method to map from input values to output values. The aim is to predict the output values approximately when new input datasets are given. We discuss test methods on time series forecasting as supervised learning in this work. In time series forecasting, a sequence of time series datasets is rearranged to form like supervised learning problem. This model is trained using input as previous timestamp and output as next timestamp. Therefore, testing time series forecasting is demanded to find improper rearrangement of dataset and window width in sliding window method to ensure accurate prediction. Sliding window method uses the previous timestamp to predict the next time step. The added previous time steps by increase window width are required to check relevant dataset to reduce the false prediction.

Keywords–Time series forecasting, supervised learning, sliding window method.

1. Introduction

Machine learning algorithms is mainly of two types – supervised and unsupervised machine learning algorithms. Supervised machine learning algorithms is widely used in many researches such as educational, healthcare, industry etc. and also used majority in practical machine learning. Supervised machine learning algorithms is applied where we have a set of input and output dataset, then algorithm is used to map the input data to the output data by function. The objective is to maximize the accuracy of mapping function so that when we have new set of inputs that can predict the expected output for that input. Supervised machine learning algorithms can be further categorized into classification and regression. Classification is to give the output as category such as true or false or yes or no while regression is to give the output is real value such as units of the measurement. Time series forecasting can be regression that give the outputs as real value. Time series forecasting is applied when we have set of output data with the time set and to predict output of next time step. In time series forecasting as supervised learning, the sequence of time series dataset is required to rearrange to form like supervised learning problem. So, the machine learning practitioners require testing methodologies of time series forecasting model in order to find improper rearranged of dataset and added previous time steps by increase window width are required to check relevant dataset to reduce the false prediction.

2. SCOPE

Testing methodologies for time series forecasting as supervised learning is very useful to build the supervised machine learning model as it eliminates the unseen factors that may lead to reduce the accuracy of the model, so it enhances the prediction of the outcomes of the next time step in time series forecasting. The testing methodologies of the time series forecasting as supervised learning is well defined in this work that useful for the machine learning practitioners. Supervised machine learning is often used in the prediction of stock market, natural disaster, disease, etc.

3. OBJECTIVE

Testing methodologies for time series forecasting can be practiced to enhance the outcome of the predictions than traditional predictions in time series forecasting. The accuracy of the prediction that used testing methodologies should be higher than traditional predictions. Testing methods include find and eliminate missing values in the dataset, disarrangement in the sequence time series dataset to maximize the mapping function accuracy so that accuracy of the prediction of the outcomes from new input dataset can be achieved.

4. RELATED WORKS TO TEST METHODOLOGIES FOR TIME SERIES FORECASTING

The variations of the existing and desired behaviors of the machine learning system is referred to bug in machine learning [1]. Testing methods identify the bug in machine learning which specify the desired condition, component of machine learning and testing methods. The properties of machine learning testing glance what to test in machine learning testing, what criteria need to be considered. Testing methods are classified into two groups such as functional and non-functional requirements. Basic functional requirement includes correctness and relevance of the model and non-functional requirement includes efficiency, robustness and interpretability and fairness.

The testing technique called metamorphic testing that compare the several implementations of an algorithm process the same input and the results, then one or both of the implementations contains a fault if the results are not the same [2]. Testing methods to find out conceptual errors in machine learning models that carried out by black box and white box approaches [3]. The goal of these methods to identify all neurons in the neural network model. Black box referred to focus only external behaviors of the model that ensures the accuracy of the prediction whereas white box testing referred to consider the internal implementation of the model.

Machine learning testing methodology is often observed by the two communities such as Machine learning community and software testing community [4]. These two communities described their own definition of the methods i.e. their interpretation is distinct each other. In software testing community, machine learning system is tested to observe any given input that does not have its expected output while in system level testing of machine learning system, system is tested the interaction of different modules to meet functional requirement includes correctness and relevance of the model and non-functional requirement includes efficiency, robustness and interpretability and fairness.

Machine learning testing methods involve the testing architecture of the machine learning component evaluation for correctness and relevance of the model [5]. Machine learning testing levels is divided into machine learning system, software, component, data testing. In each level of testing, correctness and robustness are to be maintained while developing the machine learning model.A systematic method for acquiring a metamorphic properties and functions for machine learning classifiers and support vector machine is approached [7]. Dataset coverage is a new test coverage, explicitly a notion of a quasi-testable core and obtaining a translation functions from the support vector machine are introduced. The dataset coverage is successful model the derivation of metamorphic properties and translation functions.

Automation the testing methods can accomplish the successful testing to reduce the costing and software testing is very important in software engineering discipline [9]. The tools for software testing are developed rapidly but testing the machine learning applications is still challenges. Deep learning is applied now to self-driving car that required lots of tasks to secure the model for false functional [10]. It still remains challenges in deep learning to how to setup inputs that activate different types of functions in deep learning and how to detect behavior of the deep learning system without giving manual checking.

Deep Neural Network testing coverage criteria from different perspective to enhance the deep learning system is proposed [11]. It will be useful in industry to be applied to large range of deep learning system. The behaviors of Deep neural network can be categorized into major function behaviors and corner-case behaviors. The automated testing methodology for deep neural network such as auto driven car is approached [12] to describe the parameter need to be considered. Systematic testing with neuron coverage way of partitioning between the neurons as a mechanism for target deep neural network behaves similarly for inputs. The adversarial robustness of deep neural network designed for image classifications is tested using combinatory testing criteria [13] [15]. In this approach, for the given input i that can be correctly classified by the neural network, the adversarial robustness property is interest with if there is similarity of input i with input j with respect to some distance where i and j are classified to different classes by neural network. This input j is called an adversarial example of i and deep neural network is not locally robust at i.

The different approaches as software testing approach in machine learning are considered [14] as analyzing the problem domain, analyzing the algorithm as defined and analyzing the runtime options. The first approach considered by the algorithm designers such as dataset size, range and label values. The second approach is to create test cases that considered the algorithm as it is defined. Then the approach analyzing the runtime options is to generate test case for machine learning algorithm that considered at their runtime options.

The approach for validation and identifying the bug in machine learning based applications such as hand-written digit recognition from photo using support vector machine and image classifications using convolutional neural network [16]. The challenges for testing in machine learning application such as generating reliable test oracles, generating effective corner cases, improving test coverage, testing the machine learning applications with millions of parameters are considered [17]. Many techniques are used in testing the machine learning application such as approaches for alleviating the oracle problems, multiple implementations with same inputs, metamorphic testing.

Machine learning and deep learning are widely applied in image recognition and cognitive computing, safety verification and evaluating the robustness of the neural networks system need to be considered [18] [19] [20]. In this experiments that involve trained the model until the model met its accuracy with original model. It observed that deep contractive network are more robust compared to standard neural network that are trained with Gaussian input noise and can be freely developed by adding Gaussian input noise to increase the minimum distortion of adversarial noises [21].

5. Proposed Testing Methodology for Time Series Forecasting as Supervised Learning

In time series forecasting dataset, testing is required to enhance the accuracy of the prediction next time step.

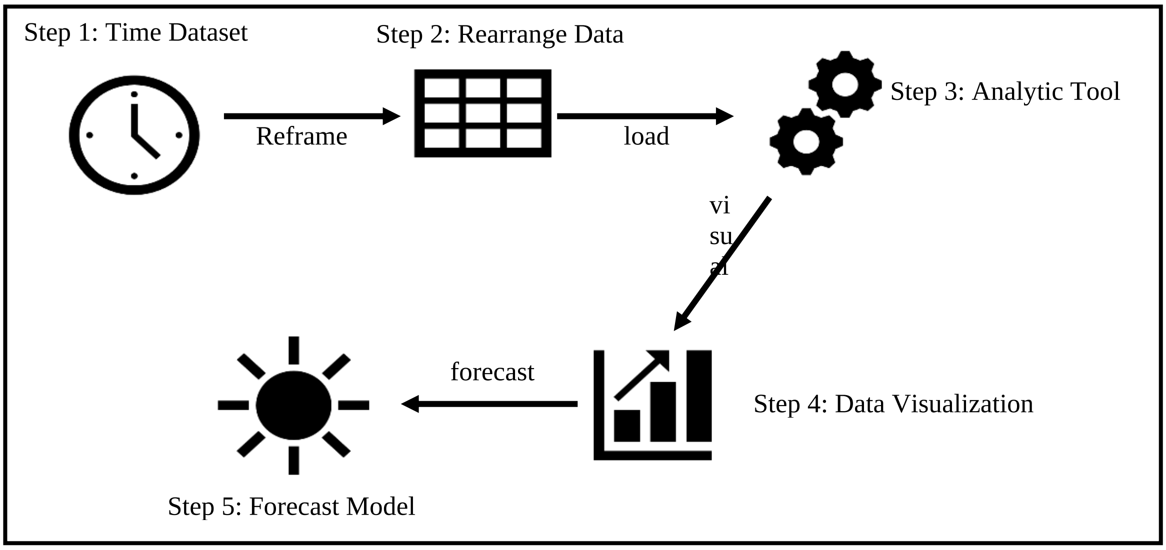

Figure 1: Sequential processing in Time Series Forecasting as supervised learning

Test methodologies in Time Series Forecasting are suggested in this work. The applicable test methods in the steps of time series forecasting model are introduced.

In step 1, the time related dataset are cleaned for data missing

In step 2, According to the numbers of future time steps prediction, there should be checked for proper number of the columns to be made and number of past values to be considered.

In step 3, proper analytic tool can be selected and used to perform the operations with the rearrange dataset to find the correlation between the attributes. The selected methods are performed for reasonable observation, then considering the alternate methods to compare with the selected methods.

In step 4, Using analytic tool, the visualization such as histogram, chi-test, plot etc. should be produced to verify the desired dataset.

In step 5, evaluation of the model should be considered by observing the various visualization and methods using analytic tool. The inputs and outputs are examined to reconsider the model. Testing the outputs gives the evaluation of model while testing the inputs gives the improvement in the model.

Advantages of Proposed Model

- The accuracy of the prediction using testing methodologies is higher than the
  - traditional prediction.
- Bad Dataset can be identified easily. This enhances the accuracy of the prediction.
- Testing methodologies for time series forecasting as supervised learning avoids the
  - disarrangement in the sequence time series dataset.
- The proper adjustment of window width in Sliding window method to check relevant dataset to reduce the false prediction.

LIMITATIONS OF PROPOSED MODEL

- The proper arrangement in the sequence of the dataset is the challenging task.
- Testing methodologies of the time series forecasting may not be useful to unsupervised machine learning.
- These testing methodologies need to be modified for other supervise machine learning algorithms except time series forecasting.

6. APPLICATIONS

- Testing methodologies for supervised learning can be used in many researches such as healthcare, educational, natural disaster and stock market.
- Thetesting methodologies can be applicable to various machine learning applications such as self-driving car system, image recognition.
- The use of these testing methodologies enhances the accuracy of weather forecasting and other prediction of disease in health care.

7. CONCLUSION AND FUTURE ENHANCEMENT

We found that testing is needed in time series forecasting for evaluating the forecasting model. Comparing the dissimilar methods with purposed methods observed that alternate solutions are found reasonable. The challenges testing in the steps of time series forecasting are described.

According to my study, there are still other methods to apply with time series forecasting, for example, backcast, competing hypotheses, predictive validity. We can find more reasonable alternative methods other than selected methods in order to find the accuracy level of the forecast model. Simple method may give the better accuracy of the forecasting.

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