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Linear Regressor Model for Internet of Things Automated Thermal Conditioning of a Smart Classroom Environment Using Limited dataset

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ABSTRACT: *This research paper presents a Linear Regressor (LR) modeling approach for automated thermal conditioning of smart spaces in a classroom environment using limited data constraints. Sensitive studies were performed in order to identify the breaking point of the LR model of polynomial-order-of-1 below which it will not be possible to obtain meaningful estimates and controllability actions, considering a range between 5% and 30% limited training data points. Based on several simulation experiments, it was found that the LR breaks at the 10% training data level. This result is valuable for recommender systems that may experience difficulty in obtaining enough primary dataset. Applications that provide early warning signals will also find this study useful.*
KEYWORDS: linear regressor, smart classroom, simulation experiment, recommender systems, primary dataset.

INTRODUCTION

Today's computer does not have the capacity to have an awareness of where it is (location-awareness). It cannot sense its physical environment in order to adapt its behavior accordingly. As a result of this, task initiated in one place cannot be re-established in another environment without re-configuration and user intervention. Also today's computer requires the operator to focus all his attention on it which has caused some social and health problems. In the context of automated smart conditioning for classroom environments, these issues may be addressed considering an optimized Linear Regressor (LR) approach.

In an Internet-of-Things (IoTs) based smart campus network, internet-enabled embedded devices offer automated services to support the teaching and learning operations at school. These device services provide a seamless interaction over a variety of platforms (platform technologies) including computing devices with people and their ambient environment. This is an essential ingredient of the semantic Web, since the future web must allow software agents to make use of one another's services without the need for continued user intervention (Berners-Lee, 2001). However, the complexity of existing techniques makes the LR technique attractive. In this research study, a model design and implementation of a smart classroom using an LR model and based on a limited data processing paradigm earlier introduced in (Osegi *et al*., 2023).

Related Works

There is a growing interest in thermal conditioning studies considering the automated conditioning of smart spaces. In (MacLeod *et al*., 2018), the efficacy of smart spaces for improving learning experiences had been investigated. They reported good improvement in the learning rate of students when adequate environmental conditioning was implemented.Shen *et al.* (2014) investigated how Near Field Communication (NFC) devices can be applied in the smart spaces' context for classroom attendance management automation. The benefits of such systems include real time feedback, intelligent location, intelligent monitoring of work progress, name visualization and remote check performance monitoring.

Uzelac *et al.* (2018), proposed a smart space system that allows the classification of student's satisfaction against work quality based on certain physical parameters. In Sutjarittham *et al.* (2019), a very interesting smart space system application for the prediction of classroom attendance and for optimally allocating classes so as to resolve the classroom underutilization problem was developed. Their proposed system used several machine learning artificial intelligence (ML-AI) techniques including Multiple Regression, Support Vector Regression for course attendance data prediction and a Constrained Programming (CP) optimization AI technique for optimal classroom allocation.

Bakken *et al.* (2017) studied the benefits of a smart classroom based Natural Text-to-Voice and Voice-to-Text software systems for supporting learners with disabilities. The authors reported better learning and understanding, as well as positive ratings for students with disabilities interacting with such natural smart sensing software compared to comparable Windows and Google Docs voice/text software.

Notwithstanding the existing and well applied body of research in this area of study, there are still issues affecting the various implementations pertaining smart classroom applications for smart campuses. Thus, there still room for improvement and research is still ongoing. One particular growing area of interest is in the area of smart classroom air-conditioning using automated tools and techniques (Aghniaey et al., 2019). This in turn have given rise to a number of key research studies in thermal conditioning such as in (Alberti et al., 2018a, Alberti et al., 2018b) where Non-linear Autoregressive Neural Networks (NARX-NETs) were used for precise air temperature prediction utilizing a combination of real and synthetic sequential temperature datasets obtained from the existing building structures of classrooms and in Paudel et al (2019) where the Long Short-Term Memory (LSTM) neural technique was used for the predicting some conditioning variables within a classroom such as temperature, humidity and luminance and in a context-aware energy saving system. Also in (Osegi *et al*., 2021) an Auditory Machine Intelligence (AMI) technique has been applied in the smart bed context for classroom conditioning automation

Proposed LR Method

LR models are simple, and straight-forward technique, but highly efficient in solving a large number of linearly separable problems. Indeed, it is the first choice when considering many scientific and engineering problems in nature and the most recommended for explaining the behaviour of simple to complex processes.

A fundamental and widely utilized solution is to linear-regress the output state variable (response variable) say, *y* with the corresponding input state variable (predictor variable) say, *x*, as (Han & Kamber, 2006):

$$y = mx + c \tag{1}$$

Where,
m = slope or gradient of the regression line, and
c = the intercept of the line.

The parameters, *m* and *c*, are typically referred to as the coefficients of a Linear Regressor (LR) model. The Poly-1 model is a type of linear regression model that is typically solved using the well-known method-of-least-squares (*mols*).
The solution of the slope, *m*, by *mols* is represented by the generalized model in equation (2):

$$m = \frac{\sum_{i=1}^{|D|} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{|D|} (x_i - \bar{x})^2} \tag{2}$$

Where,
D = the number of feature data points,
$\bar{x}$ = the mean value of x, and
$\bar{y}$ = the mean value of y.

Also, from equation (1), the solution of c can then be obtained using equation (2) as:

$$c = \bar{y} - m\bar{x} \tag{3}$$

It is important to state that due to the inherent nature of a linear model, it may fail to capture patterns (features of data) that include certain non-linear characteristics. Thus, the results generated by LR models may be compromised leading to large errors in prediction; this has been attributed to the phenomenon of outliers (Osegi, 2021) which equally affects many types of models including Artificial Intelligence (AI) models but it is worst in the LR model.

RESULTS AND DISCUSSIONS

Simulation experiments were performed to gain insight into the effectiveness of the LR model considering varying the training data points between 5% and 30%. Considerations were given to two use cases. A first use case containing 50 data points of smart bed test data and another with a total of 100 data points.

(a) Results Using 50 data points

The Classification Accuracy (CA) on test data for 50 data points are as shown in Table 1. Also, as shown in Figure 1 is the distribution response considering the computed classification accuracies and using the feasible percentage data training points.

Table 1: Classification Accuracies of LR for feasible training using 50 data points

Feasible Training Data Points (%)	LR-CA$_{test}$ (%)
7	39.13
8	39.13
9	39.13
11	40.91
12	40.91
15	28.57
16	28.57
19	40.00
20	40.00
23	47.37
24	47.37
27	50.00
28	50.00

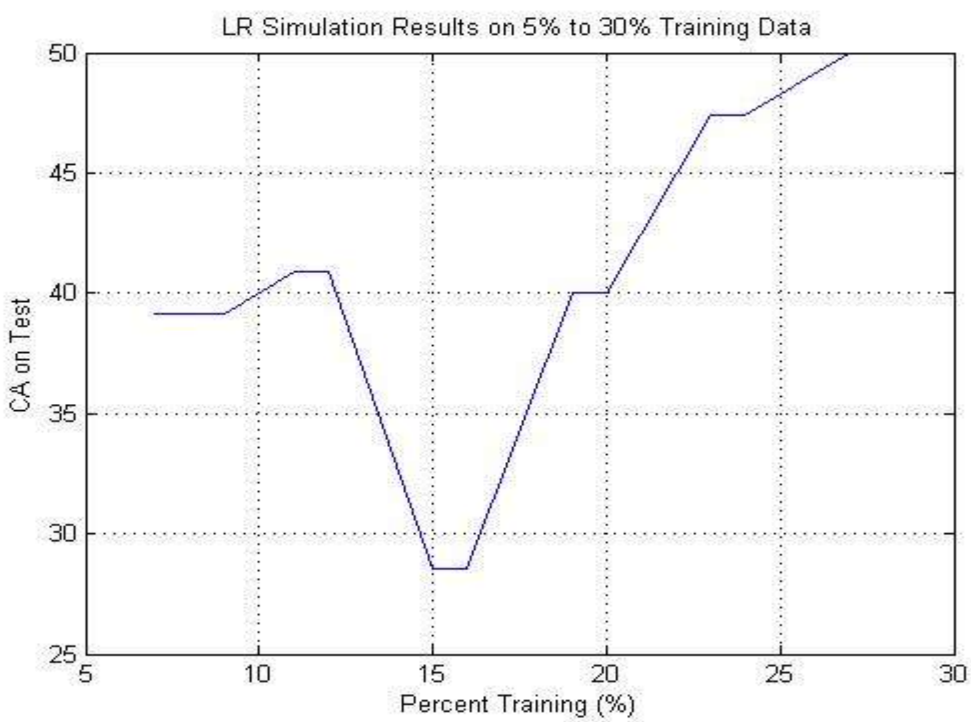

Figure 1: Distribution Response of Classification Accuracies Using LR Method for 50 data points.

From the results in Table 1, it can be seen that the best test CA occurred when the feasible training percent is set to 27% or 28%. It is also an average performance considering the classification data fitting task requirement. In addition, the worst performance can be seen when the feasible training points are at 15% or 16% (see yellow highlighting).

In general, it can be seen that lowering the percentage training data points does not necessarily imply a lower CA on the test set as is evidenced in the CA distribution response plot shown in Figure 1. Indeed, the test CA distribution is a non-linear representation of the percent training data. As an instance, the 7% training set gave a test CA of 39.13% which is about 10% higher than that using a training set of 15 or 16%.
This striking revelation goes to show the unique importance of limited data sampling in computational studies.

(b) Results Using 100 data points
The Classification Accuracy (CA) on test data for 100 data points are as shown in Table 2. As in previous sub-section (sub-section 3.1), the computed classification accuracies using the feasible percentage data training points are as shown in Figure 2.

Table 2: Classification Accuracies of LR for feasible training using 100 data points

Feasible Training Data Points (%)	**LR-CA$_{test}$ (%)**
6	36.17
8	45.65
10	51.11
12	52.27
14	53.49
16	54.76
18	43.90
20	30.00
22	56.41
24	52.63
26	48.65
28	38.88
30	37.14

As can be seen from Table 2, the best performing percent training setting is at the 22% (green highlighting) level and the worst at 20%. Interestingly, just as in the case of 50 data points, lower data training points does not imply a lower test CA.

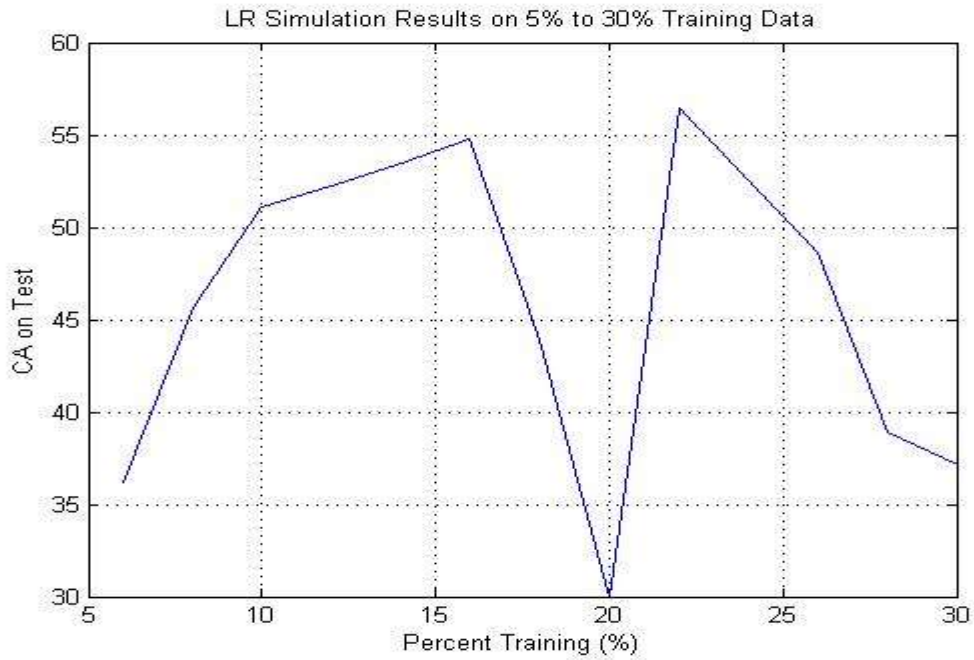

Figure 2: Distribution Response of Classification Accuracies Using LR Method for 100 data points.

CONCLUSION AND RECOMMENDATION

In this research study, the modeling of smart classroom based on the Linear Regressor (LR) approach is presented on the basis of a limited training data set which is much lower than the 50% average level used in many statistical machine learning research studies. Furthermore, through sensitivity studies, it was revealed that the test Classification Accuracy (CA) for the LR method is a non-linear function of its training percent data setting.

Also, it was seen that lowering the training percent data setting does not necessarily imply a lower test CA. Thus, this implies the LR is resilient in the face of limited data and can prove as a promising option for real time monitoring and control tasks in smart beds.In future, it will be expected to develop specific fine-tuning method for the LR to enhance its accuracy in the face of limited data. Further tests on a variety of thermal related data are also envisaged.

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