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Link Quality Prediction Based On Gradient Boosting

Ameena Tijjani Jagamu[1], Shu Jian[2], Liu Linlan[3]

[1,2,3] *Software engineering, Nanchang Hang Kong University, Nanchang, China*
[1] *tijjaniameena@gmail.com*, [2] *shujian@nchu.edu.cn*, [3] *liulinlan@nchu.edu.cn*

Abstract

To predict the consistency of the connections in the Wireless Sensor Network (WSN), which can aid in the selection of links for the upper layer protocol. In this article we proposed a GBM (Gradient Boosting Machine)-based prediction of the relation efficiency. This measures the relation parameters (RSSI, LQI, SNR, and PRR) and trains the model to predict the future value of PRR based on real experimental data. Experimental findings suggest that our proposed LQP-GBM prediction accuracy indicates the efficacy of LQP-GBM as compared to CART AND LDA.

Keywords: *gradient boosting; link quality; prediction*

1. Introduction

WSNs consist of small sensors designed for specific purposes, with specialized applications and limitations. Wireless sensor (WSN) networks are a self-structured multi-hop network generated by several low-cost radio networking micro-sensor nodes. Wireless apps can make the contact with each other simpler for users. Nonetheless, complicating this perception is the fact that in all cases, no single wireless technology dominates the market nor offers the desired functionality. Nowadays, wireless, Wi-Fi, and Bluetooth devices are all used for various situations.Wireless systems are expected to continue to proliferate, and devices will continue to include numerous radios and stacks of networks.

Link Quality Prediction (LQP) is an essential strategy that allows the device to adapt proactively to the network context in order to alleviate output degradation. The researchers received significant attention from the LQP. Precise prediction, however, remains a difficult activity considering the complex complexity of wireless communication. Physical layer information, such as RSSI and SNR, is closely connected to the efficacy of wireless channel reception as the packets are released. PHY information is explicitly associated with a wireless channel's efficacy. LQP plays a critical function in WSNs routing procedures, topology monitoring and energy management etc. An effective prediction quality link mechanism, for example, can allow protocols to improve connect data transmission, and minimize the requisites for data retransmission and routing and to increase network performance and data reliability.

Gradients boosting are machine learning techniques in the context of a set of low predictive structures, typically decision trees, for regression and classification problems.It constructs the model step by step as do other boosting approaches, enabling them to be optimized by means of an undefined col-linear loss function. The single decision tree is a quick yet unpredictable algorithm that is easily influenced by small training data disturbances [16], But the efficiency of the ensemble techniques can be significantly improved[17]. In order to apply the capabilities of boosting algorithms to decision trees, gradient booster trees regression algorithm (GBDT) is called. Friedman[18] The gradient boost machinery (GBM) was suggested based on the application of gradient decrease boosting methods appropriate for reversal or gradation problems. Boosting method is basically a proactive technique of ensemble creation, introducing sequentially new weak base models that are trained for each iteration with respect to the error of the former entire ensemble model, and these simple learners generate only a marginally lower error rate than

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random guessing[19]. We give machine learning in the paper to predict the consistency of the relation to both physical layer information and PRR information. As input of the received packets and link PRR our models take the physical parameters and estimate the probability of obtaining the next packet. Our model approach involves the collection of quality data from the experimental scenarios, analysis, assessment, prediction, training and selection. We are creating and comparing two different methods of machine learning, namely CART, LDA. The contributions we make are:

- Analysis and evaluation of the need for accuracy of relations of PRR and physical layer information. In order to increase the consistency of the relation while preserving reliable relation estimation, we attach details on the PRR-based estimator.
- A method for predicting consistency of ties based on the GBM algorithm is proposed. Based on the model results we predict the degree of quality of the relation.
- The experimental results demonstrate that the suggestion link quality prediction approach is more predictive than the CART prediction model and the LDA prediction model in single-hop WSNs.

The rest of the paper is organized as following: Section II introduces the current work relevant to the estimation of relation efficiency. Parameter collection processes, data preprocessing and relation consistency are addressed in Section III.Boosting method as described in Section IV. Then, in Section V, we add the relation consistency predictor for WSNs.

2. Related Work

WSN methods link quality prediction fall into three category-based research, focused primarily on link characteristics, statistics, and machine learning.

A. Link quality prediction method based on link characteristics

Link quality prediction method based on link characteristics is passed Analyze the physical layer and link layer information to predict the Calculation of the link quality. Ansar and Dargie[1] suggest a protocol to approximate the duration of the positive or negative links from the obtained ACK packets. This protocol allows for the exchange of the link with nearby nodes such that the share channel usage is increased. The suggested method of analysis indicates that network performance can be efficiently improved and energy usage during transmission decreased. Liu et al.[2] By evaluating the effect of the asynchronous existence of the commonly accepted duty cycled radio control on the estimation of the efficiency of the links. Develop a distributed frame counter metre to independently count the successfully decoded and corrupted wake-up frames. The metre is applied to connect Four-Bit models of quality estimation. Experiments in indoor and outdoor scenarios show that the model for estimating the consistency of the connexions has improved. And Ghorpade and Aswale [3] propose a triangle link quality metric and minimum inter-path interference-based geographic multipath routing (TIGMR).By using the SNR and LQI averages as the right angle the hypotenuse value represents the metric of the triangle. The simulation results indicate that the TIGMR protocol optimises overall efficiency and increases the lifespan of the network compared to state-of - the-art two-phase geographic forwarding (TPGF) and link quality and energy-aware routing (LQEAR) protocols. In industrial monitoring and control applications of WSN, Sun et al.[4] suggest a robustrial relation estimation model for end-to-end data transmission. To order to represent the background noise correctly, the model utilises an alpha-stable distribution and a modified log-normal loss path model to more accurately describe the RSS. The communication quality is achieved through the mapping of the relationship between the physical channel and the PRR signal. Experimental results indicate that the estimate has a significant effect.

B. Statistics-based link quality prediction method

Statistically based link quality prediction approaches are based on a large number of link quality predictions that the data packet predicts. From a multidimensional viewpoint, characterization the consistency of the wireless link, Guo et al. [5] present the fuzzy logic based link quality indicator (FLI), and implement a FLI-based wireless link quality estimator in Collection Tree Protocol (CTP). By comparing the output between 4Bit-CTP and FLI-CTP, FLI-CTP decreases the average path length of various network configurations and topological changes. Sharma et al [6] Selected a good quality route with minimal hops dependent on accessibility node and variable channel conditions in a regional ad hoc network when transmitting data. This approach improves mobile ad hoc network connectivity capacity by changing the amount of prediction transmissions and incorporating the variation in the lack of access to the forecast. Experiments show that the approach dramatically improves performance, packet ranking, standardized routing and end--latency. Qin et al. [7] A three-layer impulse reaction framework is proposed to describe the decreasing impact of wireless contact in industrial environments. Including an expanded Kalman-based relation efficiency evaluator is constructed with a constant noise covariance matrix to track both specular and distributed power inside the space distribution parameter. Bildea et al [8] Split the efficiency of the links in three groups, good, mid and bad according to the PRR. The Gilbert-Elliot Markov two-state model is used for PRR analysis. Based on this, the LQI is transformed into two states by the threshold. The Gibert Elliot model is designed to approximate PRR according to LQI. Fonseca et al. [9] Propose a 4-Bit estimator which combines information on the physical layer, the link layer and the network layer. The physical layer contains immediate details about the efficiency of packet decoding. The link layer provides the ACK bit that is written to the transfer buffer upon positive receipt of the packet. The network layer includes the routing table with the compare bit and the pin bit. The experimental findings indicate major changes in the state of the art in terms of expense and production ratios.

C. Machine learning based link quality prediction method

The relation quality prediction method based on machine learning connects quality with volume prediction problems, primarily using patterns and modelling methods such as supervised learning. Shu et al. [10] Propose a multiple-class vector machine-based quality assurance method. The assessment parameters RSSI and LQI are chosen, and the consistency of the relation is divided in five PRR grades. Using a minimum amount of probe packets, the model will precisely estimate the current link efficiency. Lawrence et al. [11] Propose a specific approach using fuse logic that can lead to the conclusion of the LQ based on the cumulative performance and probabilities of a collection of offset c1assifiers. The conceptual model utilises machine learning to evaluate the functional relationships between the input and output variables. The results reveal that three of the six real-world indoor-and outdoor environments where the system is being used, had statistically important improvements relative to standard linear regression approaches. Liu and Cerpa [12] Propose 4C, A modern link estimator, which is implemented along with the relation output estimation. A prediction model is built by the authors using a logistic inverse that combines the PRRs with the data of the physical layer, i.e. RSSI, SNR and LQI, to input the likelihood of transmission of the next packet. The experimental results indicate that in single and multiple submit experiments increasing efficiency by more than 45 per cent, increases are between 20 and 30% compared to 4-Bit and STLE estimators. Ancillotti et al. [13] Propose a modern methodology for testing relation efficiency called a RL sample in the RPL that measures the consistency of links with a minimum overhead and energy usage consistently. In order to maintain current details about the consistency of the connexion and to respond rapidly to unexpected topological shifts, the RL study utilizes both synchronous and asynchronous monitoring schemes. A improving learning paradigm controls surveillance practises and reduces the overhead arising from effective training. The findings demonstrate that the RL sample helps to increase the rate of packet loss efficiently and enables nodes to easily react to changes in quality and connexion failures because of the node's versatility.

3. Lınk Qualıty Parameter

Indicators do not require a priori knowledge about protocol of communication and encryption of data. These indications may be detected, as a receiver gathers the signals passively. Therefore,whether it's there intrinsic trends connected to the topology of the network, it is a simple indication that helps a system to gain knowledge about the unknown topology of network. A level of linkage in wireless sensor networks used as major parameters in this paper to apply gradient boosting system techniques.

A. Selection of Link Quality Parameters

RSSI, LQI and SNR data are used in this paper as major parameters in wireless sensor networks as the measure of the consistency of the links. In this paper, the RSSI, SNR, and LQI uplink and downlink are Chosen as the link output prediction parameters.

B. State of Observation

RSSI (Received signal strength indicator)

Received signal strength indicator is a calculation of the strength of a received wireless signal as the name indicates. It's obvious that with space, The obtained signal frequency is projected to decrease. The strength of the transmitted signal is in inverse relation to the square of the interval between the transmitter and the receiver. The ratio of the received power to the reference power Ref can then be defined as RSSI. Usually, reference power Ref is taken as 1mW[20]. In RSSI the concept is as:

$$RSS = 10 \cdot \log \frac{P_{RX}}{P_{\mathrm{Ref}}} \tag{1}$$

Where P_{RX} is defining as:

$$P_{RX} = P_{TX} \cdot G_{TX} \cdot G_{RT}\left(\frac{9}{4\pi d}\right)^2 \tag{2}$$

Where P_{RX} is the transmitting power of the transmitter, P_{RX} is the wave's residual power at the receiver, G_{TX} and G_{TX} are the transmitter and receiver gain, 9 is the wave frequency, and finally the distance between the transmitter and the receiver.

LQI (link quality indicator)

The Link Quality Indicator (LQI) was used as a supplement to RSSI. LQI reflects the consistency of the packet received, and is not influenced by the climate as much as the RSSI. The LQI represents the number of retransmissions needed for correct reception of one radio packet[20]. LQI performs better than RSSI, depending on the device error rate and not the strength of the signal obtained. as reflections from artefact and electromagnetic fields are not significantly affected.

SNR (Signal to Noise Ratio)

Noise ratio not only takes the signal intensity into account but also the noise level in the signal. This can easily be calculated, in fact. General description of the Signal to Noise Ratio is:

$$SNR[dB] = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)[dB] \quad (3)$$

Where P_{Signal} the power is signal frequency, and P_{noise} is the noise power frequency, respectively. Many factors such as transmitting capacity, the loss of propagation, reflection, etc affect signal strength. The capacity of signal. In addition, noise is commonly based on the receptor noise, ambient noise and interference. For complete details see [21].

Pre-Processing of the Parameters

For the access to the expected variables of the underlying structure and relations. For the consistency parameters of the links we perform data pre-processing system.

Processing the Values of the Parameters

Considering the relation information parameters, the original value of each cycle is used to determine the consistency of the links. To conform to the GBM model, in WSN applications the tiesThese are asymmetric, i.e. the asymmetry of uplink and downlink performance attributable to empirical variables such as the specific processing capacity of the sensor nodes and the temporal and spatial features of the background noise. Physical layer parameters have the benefits of quick responsiveness to link consistency, simple interpretation of parameters and low overhead relative to WSNs link layer parameters. In this paper, RSSI, SNR, and LQI uplink and downlink are chosen as parameters for the efficiency of link prediction.

Normalization

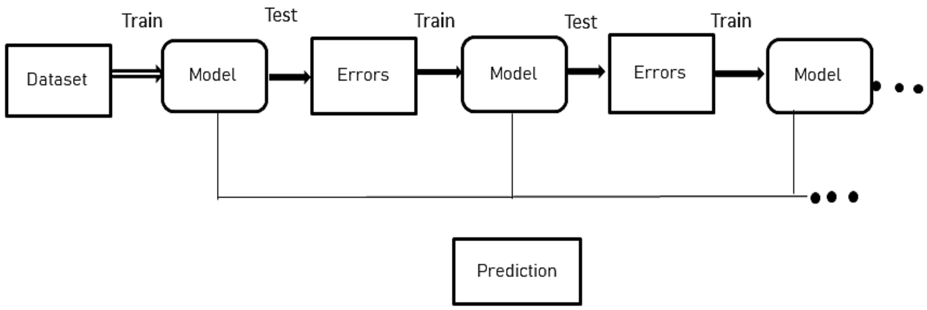
The data values can be scaled to the [0, 1] range that is called normalization. The range of parameters for each link quality is different in the network of wireless sensors. The data is structured to minimize the effect of variance and reduce model error, so that the data is between 0 and 1.

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (4)$$

When X denotes the quality parameter for the raw physical layer link, X* refer to the quality parameter of the normalized physical layer link, max(x) refers to the maximum value for the original physical layer link quality parameter, and min(X) refers to the minimum value of the quality parameter for the raw physical layer relation. [15]

4. Boostıng Machıne

Boosting is a loosely defined technique incorporating many basic models into one composite model. The aim is to become a stronger and stronger predictor as we add simpler models, the overall model. The basic models are called weak models, or slow learners, when boosting terminology. Some supervised models of machine learning are based on a single predictive model (i.e. linear regression, penalized models, naive Bayes, vector support machines). Instead, other methods such as bagging and random forests are based on the principle of constructing a series of models where each individual model predicts the outcome and then the ensemble simply averages the predicted values. The boosting methods family is based on a particular, positive ensemble forming technique that these key ideas of boosting are to sequentially introduce new models to the ensemble. A new low, base-learner model is trained at each specific iteration with respect to the entire ensemble's so far-learned mistake.



Sequential Approach to Ensemble.

Algorithm1 Friedman's Gradient Boost algorithm

Inputs:

- input data (x, y) $\mathrm{N}_{i=1}$
- Number of iterations M
- Choice of the loss-function (y, f)
- Choice of the base-learner model $\mathrm{h}(x, \theta)$

Algorithm:

1. initialize f_0 with a constant
2. for t = 1 to M do
3. compute the negative gradient $\mathrm{g_t(x)}$
4. fit a new base-learner function $\mathrm{h(x, \theta_t)}$
5. find the best gradient descent step-size ρ_t:
   $$\rho_t = \arg min_p \; \sum_{i=1}^{N} \Psi[y_i, \hat{f}_{t-1}(x_i)] + \rho h(x_i, \theta_t)$$
1. update the function estimate:
   $$\widehat{f}_t \leftarrow f_{t-1} + \rho_t \mathrm{h}(\mathrm{x}, \theta_t)$$
1. end for

The entry-side weights of each link are set directly after connecting to the network, as seen in algorithm 1. The entire process may be considered a GBM, where the base-learner process is just a link and the failure function is a normal quadrant fault. The algorithm also optimizes the association between the error of the entire network and the new link, thus rendering the comparison more apparent.

5. Lınk Qualıty Predıctıon

In various scenarios, LQ tracking has been used previously to select high-quality links which optimize the delivery rate and minimize traffic congestion. In addition to the LQ monitoring, LQ prediction / estimation is used to assess which ties are more likely to alter their actions beforehand. With each tree learning and improving on the previous one, the proposed model builds an ensemble of shallow and poor successive trees. Combined, these many poor successive trees produce a strong "committee" which is often difficult to overcome with other algorithms. This study utilizes the approach to systematically identify and concurrently obtain uplinks and downlinks during data collection. Instead of simply adding or detracting, GBM is used for gathering deep information regarding asymmetry between the relation up or down of each prediction parameter. In other words, the GBM is used for uplink and downlink extraction functionality for the SNR, RSSI and LQI respectively. [15]SNRup, SNRdown, LQIup, and LQI-down and RSSIup, RSSIdown are inputs. In this process, the uplink SNRup vector is SNR, the downlink SNR vector is SNRdown, the uplink LQI vector is LQIup and the downlink LQI vector is LQIdown. RSSIup denotes the RSSI vector for uplink, and RSSIdown denotes the RSSI vector for downlink.

Typically, The transmitting range is estimated by means of three PRR measured regions: the linked field, the transition field and the disconnected area. There are several common criteria in some literatures for separating consistency grades of ties according to the PRR. Bildea et al. [14] Divide the link rating into 3 PRR classes: excellent connexion where PRR is 80 per cent, fair link where PRR is less than 20 per cent < 80 per cent and bad link < 20 per cent.· Divide the link level into 3 stages Luo et al.[15] Divide the link norm into 5 classes according to PRR: really strong link where PRR is < 90 per cent; average link where 75 per cent < 90 per cent PRR; [22][15], Conversely demonstrated that the parameters of the link layer are the best indicator of the quality of the links. We are the data grade descriptor in this paper and the relation quality was graded according to the PRR ratio of the packet. In addition, the output in this paper is divided into 10 degrees according to the PRR, as shown in Table 1.

PRR Gradıng

Grade of Link Quality	**Rage of PRR**	**Label**
1	1.0	Extremely high
2	0.9	Very high
3	0.8	higher
4	0.7	high
5	0.6	Medium
6	0.5	Common
7	0.4	low
8	0.3	lower
9	0.2	Very low
10	0.1	Extremely low

As the input is used the asymmetric function extracted by the GBM. 70 percent of the data collection is used for training purposes, and 30% for model testing. The proposed prediction of the LQP-GBM relation quality is shown in Algorithm 2

Algorithm 2. LQP-GBM

Input: Data Set X, input node numbers n out, nodes number in every layer n, activation function, research rate X input

Output: The grade of link quality

Step 1: Load the dataset X, and with sets of SNRup, SNRdown, LQIup, LQIdown, RSSIup, RSSIdown and PRR.

Step 2:Convert in a data the (SNRup, SNRdown, LQIup, LQIdown, and RSSIup, RSSIdown). Frame and pre-processing, splicing and transforming {PRR} into a label collection reflecting the quality grade of the connection {label} as set out in the Table

Step 3: Data samples SNRup and LQIup, RSSIdown and label SNRdown and RSSIup. Check samples. Among these results, 70 percent consist of a training train and 30 percent comprise a model test.

Step 4: Train and test normalization

Step 5: Defines the concept of the gbm structure.

Step 6: Train the data sets train, using well-defined gbm method.

Step 7: Train the model using step6 as its input.

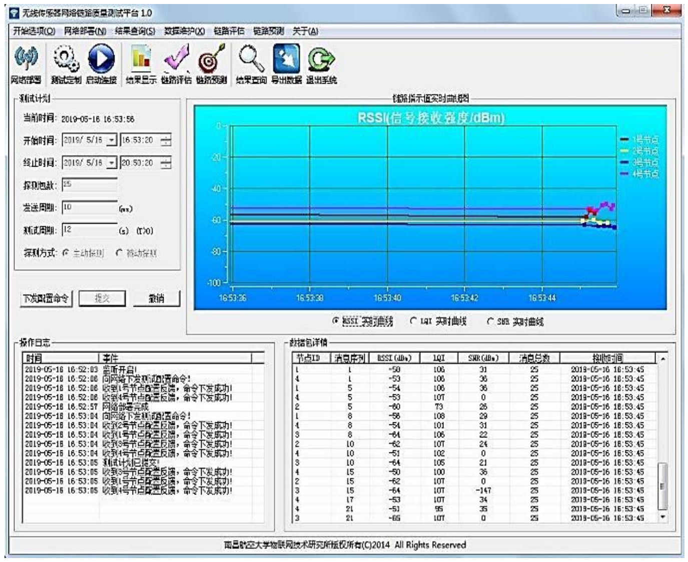
Step 8: Predict the train model using the test dataset and compare the predicted results with the (label) in test set

Step 9: Input process in step8 to find the accuracy of our model using confusion matrix.

End

6. Experimental Design and Analysis

Data from many design scenarios were gathered for the validation of the model. Using Crossbow's TelosB node for data transmission and reception, and use the Wireless Sensor Network Quality Testbed (WSNs-LQT) which was established by laboratory to collect connexion quality details, such as RSSI, SNR and LQI for uplink and downlink. The Test Platform WSNs-LQT is seen in Fig3 that analyses and progresses with the R Language and Jupyter Notebook for the collected link quality details.

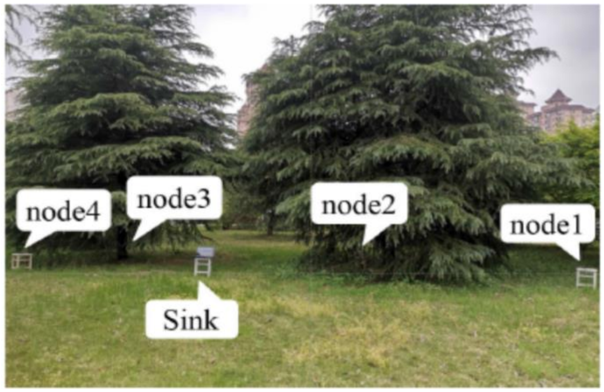


Link quality testbed platform

A. Experimental Scenarios

In this paper we use collected information from two experimental scenarios from indoor corridors, grove (which is also a campus forest) Fig4, 5. A miniature star WSNs network is installed in each scenario to test the consistency of the connexions. The corridor scene is mainly used to model WSN's smart home situation indoors. [23] showed that the WSN signal would be significantly affected if a Wi-Fi signal is in a WSN region. Thus indoor scenes are critical for evaluating the quality of the WSN links. The campus forest scene is used to model applications in field environments where signals are often influenced by barrier-caused multipath propagation.

A) Corridor scene



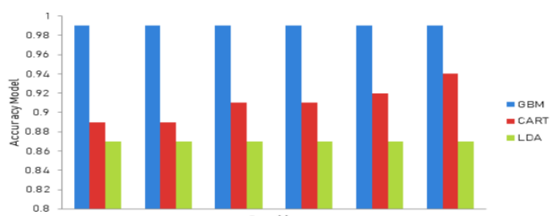
B). Grove(Campus Forest) scene

Experimental Scenarios

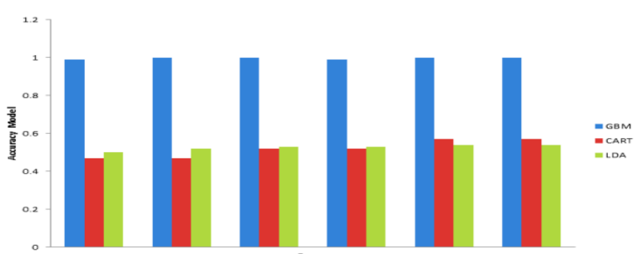
In every experimental scenario,Various networks with wireless sensors are used, as shown in Figure 4. Sensor nodes in these two experimental scenarios transmit packets through one hop The packet is submitted to the sink node and to the personal computer by the sink node.

B. Experimental Analysis

The experiment is structured primarily as follows: first, the validity of LQP-GBM (i.e. link quality prediction–gradient boosting machine) is checked by the model's approximate accuracy in two separate experimental scenarios and compared to two different models, classification regression tree (CART) and linear discrimination analysis (LDA). The preprocessed data set is divided into training set and test set according to the ratio of 70 per cent trainset, 30 per cent test set, to ensure the validity of the data set. Illustration 5. Illustrate the approximate precision as well as the 95 percent confidence interval (e.g. the range from the corridor scene to which 95 percent of the observed scores fell) in Figure 6. B) Describe the grove scene with an approximate precision.



Estimated Accuracy of Proposed LQP-GBM, CART, and LDA on Corridor Scene Data.



Estimated Accuracy of Proposed LQP-GBM, CART, and LDA on Grove (Campus Forest) scene Data.

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Table 2 shows the results from summarizing the distributions for each model (LDA, CART, and LQP-GBM).

COMPARING THE ESTIMATED ACCURACY ON CORRIDOR SCENE

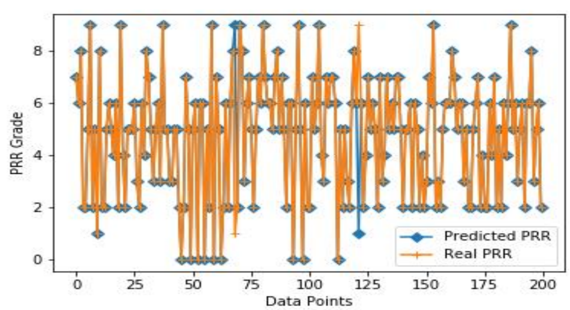
Accuracy	Min.	1stQu	Median	Mean	3rdQu	Max.
GBM	0.99	0.99	0.99	0.99	0.99	0.99
CART	0.89	0.89	0.91	0.91	0.92	0.94
LDA	0.87	0.87	0.87	0.87	0.87	0.87

COMPARING THE ESTIMATED ACCURACY ON GROVE1 SCENE

Accuracy	Min.	1stQu	Median	Mean	3rdQu	Max.
GBM	0.99	0.99	0.99	0.99	0.99	1.0
CART	0.48	0.48	0.52	0.52	0.57	0.57
LDA	0.51	0.51	0.53	0.53	0.54	0.56

We are added to a list after the models are equipped, and resample the models issued. We use the same training scheme (train control configuration) to test whether the models are equivalent, i.e. Object includes the evaluation metrics for each fold and each repeat for each algorithm to be evaluated. Figure 5 shows the accuracy of the corridor scene comparison model while Figure 6 shows the accuracy of the grove scene data.

Table 2&3, present the percentage of each evaluated model, based the tables the propose model accuracy for both scenes.in the above result the accuracy of the propose method is higher for experiments which mean the accuracy is pretty good.



Corridor Scene Dataset

As shown in Figure 5, the performance of the proposed model when train on Corridor dataset, and the experimental scenario was illustrated in Figure 4A. The prediction result shows that our predicted PRR data point and the real PRR points (which is the test data PRR) are align to each other but out of 1167 test data points only in data point 70 and 123 the proposed LQP-GBM grade was not align with the real PRR grading of the test data. We can conclude that the proposed model can be efficient in predicting feature

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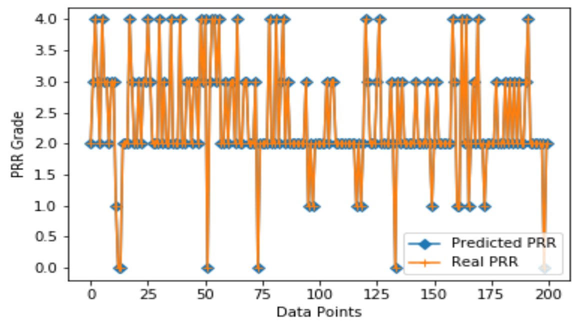
PRR.

We train the model on Grove's (Campus Forest) dataset to further verify the performance of the proposed model. The experimental example demonstrates Figure 4B.



Grove1 Scene

As shown in Figure 6, the outcome of the prediction shows that our expected PRR data point and the is the PRR test data are actually connected. We may conclude that the model proposed is effective for predicting PRR function.

From our observation the Grove (Campus Forest) scene dataset have 10972 data point and the Corridor scene dataset have 3900 data point. Because of the limited number of data in corridor scene dataset our model failed to perfectly grade and predicts the PRR.

7. Conclusıon

This study demonstrates that the gradient booster is ideal for predicting the link performance, providing a versatile framework for implementing various combinations of variables, i.e. predictive models details. gbm efficiency is affected by the setting of parameters. The key parameter is optimized for a better prediction output with less iterations to prevent overfitting, considering calculations and efficiency, the link is used as the input point and the uplink and downlink layer physical parameters are chosen.In order to determine the related standard, the grade is segregated according to the PRR and the LQP-GBM. Experiments in two conditions test the validity and reliability of the model. Experimental findings show that the LQP-GBM is more specifically dependent on the CART and LDA than the relation prediction. More specifically, the proposed model captures relation that contributes to more reliable Link quality predictions.

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