Link Quality Estimation using Machine Learning

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Abstract—Since the emergence of wireless communication networks, quality aspects of wireless links have been studied for several technologies. By analyzing the rich body of existing literature on link quality estimation that uses models built from data traces, we have noticed that the techniques used for modelling are becoming increasingly complex. Several recent estimators use machine learning techniques, however it is sometimes difficult to understand the reported results as each model that relies on machine learning requires a complex design and development process. Each step of this process has the potential to significantly impact the final performance.

The aim of this paper is to provide an in depth study of how each step in the process of designing and developing a link quality estimator using machine learning affects its performance. Based on the analysis of the state of the art, we selected a representative subset of machine learning models used in the literature and a representative publicly available dataset and performed a systematic study on the influence of the design decisions taken in each step of the machine learning process on the performance of machine learning based link quality estimators. Our results show that measurement data pre-processing and feature engineering have a higher influence on the performance of the model than the choice of the algorithm.

Index Terms—link quality estimation, machine learning, data driven wireless networking, data driven optimization, data preprocessing, feature selection, model building, analysis

I. INTRODUCTION

In wireless networks the propagation conditions for radio signals may vary significantly with time and space, affecting the quality of radio links. In order to ensure reliable network performance, an effective estimation of link quality is needed so that the radio link parameters can be adapted or an alternative more reliable channel or route can be selected for wireless data transmission. Data driven Link Quality Estimator (LQE) research based on real measurement data start in late 90s, but related papers are being published also nowadays [1], [2]. Early papers on the topic used recorded traces and manually developed models [1]–[11]. In the recent years, several works on developing LQE are using machine learning algorithms [12]-[14]. The use of machine learning for LQE can have a significant impact on wireless networking procedures due to the ability of the technology to process and learn from large amounts of data traces, that can be collected across various technologies, topologies and mobility scenarios, having a potential to make them much more agile and adaptive.

Ideally, using machine learning, a more generic and macro level understanding of wireless links could be possible. A generic, automated mechanism to study links for any transceiver and any technology could also help better understand current operational aspects of wireless networks and open new horizons into wireless network design and optimization [15], [16]. Such mechanisms are being currently proposed

for instance for studying radio frequency (RF) spectrum usage [17], [18].

With the recently proposed estimators that use machine learning techniques, it is sometimes difficult to understand the reported results since each model that relies on machine learning assumes a complex building process [19], [20]. Each step of this process has the potential to significantly impact the final performance. Additionally, being able to reproduce the process and results [21]–[23], as should be the case in scientific publications, by sharing the data traces and source code could result in a more concentrated research effort.

The problem of different and sometimes contradictive observations coming from the large amount of research work on LQE based on different platforms, approaches, measurement sets, etc., has already been pointed out and addressed in [24]. The authors provided a comprehensive survey on empirical studies on low-power links in wireless sensor networks, but not paying any special attention to procedures using machine learning techniques.

In this paper, we complement that survey by analyzing the rich body of existing literature on link quality estimation with focus on models built from data traces. We also analyze publicly available data traces that are suitable for LQE research. Our analysis shows that the techniques used for LQE modelling are becoming increasingly complex. Several recent estimators use machine learning techniques, however it is sometimes difficult to understand the reported results as each model that relies on machine learning requires a complex design and development process. Each step of this process has the potential to significantly impact the final performance. Motivated by this finding, we provide an in depth study of how each step in the process of designing and developing a link quality estimator using machine learning techniques affects the performance of the final model by selecting a representative subset of machine learning models used in the literature and a representative publicly available dataset. Our results show that data pre-processing and feature engineering have a higher influence on the model performance than the algorithm selection.

The contributions of this paper are the following:

• The first major contribution of this paper is the in dept analysis of existing literature on link quality estimation with focus on models built from data traces. The analysis showed that link quality estimators are not only increasing their complexity but, the reported results are becoming more difficult to understand because each model that relies on machine learning requires a complex design and development process. The state of the art currently does not consider the effects of the data preparation on the final results.

- Motivated by the previous finding, the second major contribution of this paper is the extensive analysis on how the various steps of the machine learning process affect the final outcome. Our results show that measurement data pre-processing and feature engineering have a higher influence on the performance of the model than the choice of the algorithm. More precisely we show that:
 - Interpolation with domain knowledge improves the accuracy of the ML based LQE by 7% compared to not using any interpolation.
 - Feature selection improves the classification of *inter-mediate* links by 50% compared to using only raw data. Overall model improvement is 6%.
 - The sampling approach boosts the classification of intermediate links by 26% compared to no sampling used. The overall model accuracy has below 2% penalty.
 - We show that the choice of the algorithm yields only minor contribution in the final results. The difference is around 2%.
 - We also show that for this dataset, non-linear algorithms are only slightly better at classifying link quality than linear algorithms.

Our major finding that data preparation has a higher influence on the outcome than the algorithm selection are generic and do not depend on the choice of data traces and models. The figures of the improvements in each step of the data preparation can change with the dataset.

This paper is structured as follows. Section II summarizes and analyses related work, Section III summarizes and discusses freely available tracesets for link quality estimation and Section IV discusses the standard process used when designing a machine learning model. Section V analyzes the design choices of the data preparation on the performance of the model. More specifically, Sections V-A, V-B, V-D and V-C consider the contributions of cleaning and interpolation, feature selection, window size and sampling strategy respectively. Section VI then analyzes the contribution of the algorithm selection to the performance of the model. Finally, Section VII concludes the paper.

II. OVERVIEW OF DATA DRIVEN LINK QUALITY ESTIMATION

With the emergence and spreading of wireless technologies in the early 90s [25], it became clear that the packet delivery in these networks was inferior to that of wired networks [1]. Wireless transmission medium is characterized by significantly larger losses than wired. As a result, various techniques for estimating the quality of links based also on actual data traces, in addition to, or instead of simulated models emerged, some of them being summarized in Table I.

The work in [1] aimed to characterize the loss behavior of proprietary AT&T WaveLAN. It used packet traces with various configurations for transmission rate, packet size, distance

 $^{1}\mathrm{asterisk}$ (*) indicate experiment performed on public testbed, but no data available

and the corresponding packet error rate. Then they built a two-state Markov model of link behavior. The same model was used in [3], but with a different goal. In [3], they attempted to estimate the quality of the wireless links in order to improve congestion performance of the transmission control protocol (TCP). They used two Cumulative Distribution Functions (CDFs), computed from the collected traces, to model the transition probabilities in the two-state Markov model.

In [4], the authors aimed to improve the reactivity of routing tables in constrained devices such as sensor networks. They collected traces of transmissions for nodes located at various distances from each other. Then they computed reception probabilities as functions of distances and evaluated a number of existing link estimation metrics such as moving average. They also proposed a new estimation metric called window mean with exponentially weighted moving average (WMEWMA) and showed an improvement in network performance as a result of more appropriate routing table updates. The improvements were shown both in simulations and in experimentation. It also seems that this work was among the early ones introducing the three different regions of wireless links, i.e. good, intermediate and bad.

The authors of [6] noticed that by considering additional metrics, also from higher levels of the protocol stack, the link estimation can be better coupled with data traffic. Therefore, they introduced a new estimator referred to as Four-Bit (4B) where they combined information from Physical (Packet Reception Ratio (PRR), Link Quality Indicator (LQI), Link (ACK count) and Network layers (routing) and showed that it performs better than a baseline they chose for evaluation.

The same research group then proposed another link quality estimator [7]. They used PRR and the Gillbert-Elliott model of a channel. The Gillbert-Elliott model is a 2-state Markov process: *good* and *bad* states with 4 transition probabilities. The output of the model is the channel memory parameter that describes the "burstiness" of a link. They evaluated the proposed channel memory parameter on 4 different traces both for IEEE 802.15.4 and IEEE 802.11 technologies. They concluded that the model starts to converge at about 40,000 packets.

In [5], the authors aimed at developing a new link quality estimator by predicting the likelihood of successfully receiving a packet. To achieve that, they established a relationship between Packet Success Ratio (PSR), which is similar to PRR, and Received Signal Strength (RSS). First they used a Kalman filter to model the correct value of the RSS, then they extracted the noise floor from it to obtain Signal-to-Noise Ratio (SNR), and finally they used a pre-calibrated table to map the SNR to a value for the PSR. Through experimentation, the authors showed that link degradation can be detected even with a single received packet.

Another new link quality metric has been proposed in [8]. The new TRIANGLE metric used the Pythagorean equation and computed the distance between the instant SNR and LQI vectors in a 2D space where the origin corresponds to the worst SNR and the worst LQI (0,0). Then they used three empirically set thresholds to identify four different link types: very good, good, average or bad. The metric required around

 $\begin{tabular}{l} TABLE\ I\\ Existing\ work\ on\ Link\ Quality\ Estimation\ using\ actual\ data\ traces \end{tabular}$

Title	Tech.	Goal	Input	Model	Output	Data	Reproduce ¹
A trace-based approach for modeling wireless channel behavior [1], 1996	WaveLAN, BARWAN testbed, BSD 2.1	Maximize throughput, channel error model	SNR, signal quality, throughput(PRR)	improved two-state Markov model	probability of error to occur and persist	Not specified (<1500 bytes/- packet, 1000 s/trace)	No*
Explicit Loss Notification and Wireless Web Performance [3], 1998	WaveLAN, University of California testbed	Improve TCP Reno on wireless links, maximize throughput	bitrate, packet size, no. bits, throughput, Bit Error Rate (BER)	CDF of error and error-free durations	probability of error to occur and persist	800 000 packets (100 000 packets/- experiment, 8 experiments)	No*
Taming the Underlying Challenges of Reliable Multihop Routing in Sensor Networks [4], 2003	proprietary, Mica Mote, TinyOS	Improve routing table management	WMEWMA(PRR)	Shortest Path, Minimum Transmission, Broadcast, Destination Sequenced Distance Vector	Decision on keep/remove routing table entry	≈600 000 packets (8 packets/s, 200 packets/P _{Tx})	No*
(4B) Four-Bit Wireless Link Estimation [6], 2007	Intel Mirage: 85x MicaZ; USC TutorNet: 94x TelosB; IEEE 802.15.4, TinyOS	improve routing table management	LQI, PRR, broadcast, ACK count	Construct 4-bit score of link state	Estimated link quality	Mirage: ???, 40-69 min/experi- ment; TutorNet: ???, 3-12h/experiment;	No*
A Kalman Filter Based Link Quality Estimation Scheme for Wireless Sensor Networks [5], 2007	probably TelosB, IEEE 802.15.4	PRR estimation	SNR(RSSI, noise floor)	Kalman filter + SNR to PRR mapping	estimated PRR	25 200 000 (500 samples/s, 14 h)	No
PRR Is Not Enough [7], 2008	IEEE 802.11, IEEE 802.15.4	Link state estimation	PRR	Gilbert-Elliott Model (2-state Markov process); good and bad state	link quality transition probability	Rutgers and Mirage tracesets	Yes
The Triangle Metric: Fast Link Quality Estimation for Mobile Wireless Sensor Networks [8], 2010	Tmote Sky, Sentilla JCreate, IEEE 802.15.4, Contiki OS	new LQE	SNR(RSSI, noise floor), LQI	Pythagorean equation maps to distance from the origin (hypotenuse)	Estimated link quality as very good, good, average or bad	30 000 + ???, (64 packets/s, all channels, unicast)	No
F-LQE: A fuzzy link quality estimator for wireless sensor networks, [9] 2010, [26] 2011	RadiaLE testbed, 49x TelosB, IEEE 802.15.4, TinyOS	link quality estimation, improve routing	WMEWMA(PRR), SF(PRR), ASL(PRR), ASNR(SNR)	Fuzzy logic maps current to estimated link quality	binary high/low quality (HQ/LQ) link estimation	??? (bursts, packet sizes, 20-26 channel)	No*
Foresee (4C): Wireless link prediction using link features [12], 2011	54x Tmote (local), 180x Tmote Sky (Motelab), IEEE 802.15.4,	Improve Routing	WMEWMA(PRR), RSSI, SNR, LQI	Logistic regression model	Probability of receiving next packet	80 000 + 80 000 noise floor (≈10 packets/s)	No*
Temporal adaptive link quality prediction with online learning, [27] 2012, [13] 2014	Motelab, Indriya and (local) 54x Tmote testbed, IEEE 802.15.4	link quality estimation, improve Routing	WMEWMA(PRR), RSSI, SNR, LQI	Logistic regression with SGD and s-ALAP adaptive learning rate	binary, estimates if link quality above desired threshold	480 000, (30 bytes size, 6 000 per exp., 10/sec.), Rutgers and Colorado tracesets	No [27] Yes [13]
Fuzzy Logic Based Multidimensional Link Quality Estimation for Multi-Hop Wireless Sensor Networks [10], 2013	(local) 15x TelosB, TinyOS, IEEE 802.15.4	improve routing, minimize topology changes	$D_{\alpha}(PRR),$ CV(PRR)	Fuzzy logic link quality estimator	binary high/low quality link estimation	???, (20 min/ex- periment, 12h)	No
Low-Power link quality estimation in smart grid environments [11], 2015	IEEE 802.15.4	Improve routing, LQE reactivity	RNP, SNR, ASL(PRR)	optimized F-LQE [9] with better reactivity	binary high/low quality link estimation	???, 500kV substation env. data, TOSSIM 2	No
WNN-LQE: Wavelet- Neural-Network-Based Link Quality Estimation for Smart Grid WSNs [14], 2017	10x CC2530 WSNs, IEEE 802.15.4	Improve routing, estimate PRR range	SNR	Wavelet-Neural- Network-Based Link Quality Estimator	Upper and lower bound of confidence interval for PRR	2 500 (20 bytes size, 3.33 per second)	No
Quick and Efficient Link Quality Estimation in Wireless Sensors Networks [2], 2018	Grenoble testbed FIT-IoT, 28x AT86RF231, IEEE 802.15.4	Analysis of LQI, fast decisions, improve routing	LQI	classification based on arbitrary values	Classify link as good, uncertain or weak	??? (2 000 per link, 16 channels)	No*

10 packets to provide the estimation in either static or mobile scenario.

In [9], the authors developed a new link quality estimator based on fuzzy logic. WMEWMA [4], averaged PRR value, stability factor (SF), asymmetry level (ASL) and average SNR (ASNR) are used as inputs to the model. As output, the model classifies links as high quality (HQ) or low quality (LQ). In a later paper [26], the same authors compared Fuzzy logic LOE (F-LQE) against PRR, expected transmission count (ETX) [28] Required Number of Packets (RNP) [29] and 4B [6] on the RadiaLE [26] testbed. The comparison of the metrics was performed using different scenarios including various data burst lengths, transmission powers, sudden link degradation and short bursts. Among their findings, they have shown that PRR, WMEWMA, and ETX, which are PRR-based LQEs, overestimate the link quality, while RNP and 4B underestimate the link quality. F-LQE was able to perform better estimation than other compared estimators.

While several of the metrics surveyed in this section use statistics to estimate the quality of the links, Foresee (4C) [12] is the first one to introduce statistical machine learning techniques. Such techniques are able to approximate the underlying distribution from the input data. Therefore, the authors used Received Signal Strength Indicator (RSSI), SNR, LOI and WMEWMA [4] and smoothed PRR as input features into the models. They trained three machine learning models: Naïve Bayes, neural networks and logistic regression. In their experiments, the three models were very close in performance. Because of its simplicity, they chose logistic regression for empirical implementation and validation in their testbed. Authors claim 20% to 30% improvement in end-toend delivery using this approach compared to TinyOS's vanilla ETX. The authors suggest that data gathered from 4-7 nodes for about 10 minutes should be sufficient to train their models offline.

The same research group then proposed a new machine learning based link quality estimator TALENT [27]. The first difference with respect to 4C from [12] is that it uses an online machine learning approach, where the model built on each device adapts with each new data point as opposed to being pre-computed on a server. The second difference is that TALENT has a binary output (i.e. PRR is above the predefined threshold or not) while 4C's has a multi-class output. The third difference is that TALENT uses new models for LQE: stochastic gradient descent (SGD) [30], smoothed AlmeidaLangloisAmaralPlakhov (ALAP) (s-ALAP) algorithm [31] for adaptive learning rate and Logistic Regression. The experiment ran on 18 intermediate quality links (0.45 < PRR < 0.89) on which TALENT was able to predict short high quality link intervals.

Similar to [9], the authors of [10] used a fuzzy logic and proposed Fuzzy-logic Link Indicator (FLI) for link quality estimation. While both share the goal of being used for link quality estimation in routing, they take into account different input features. The FLI model makes use of PRR, coefficient of variance of PRR and quantitative description of packet loss burst, which are gathered independently, while F-LQE [9] requires sharing PRR stats/information. FLI was evaluated in

a testbed for 12 hours worth of simulation time against 4B [6] and it was reported to perform better. Additionally, it reduced the frequency of topology changes while maintaining higher end-to-end success rate.

The authors of [11] proposed an optimized FLI [10] that is suitable for a specialized environment of smart grids. Such environments have higher than normal values for electromagnetic radiation, 50Hz noise and acoustic noise. The performance of the optimized FLI is evaluated against ETX, 4B and FLI by focusing on their stability, reliability and reactivity. The authors underlined that ETX often overestimates link quality, 4B is more reliable than ETX, and FLI is even more reliable than 4B. Furthermore, they reported that FLI is computationally expensive and not sufficiently reactive, and that 4B as a sender-side estimator is more reactive than FLI. The proposed optimized FLI omits the link stability factor at the cost of accuracy, and replaces it with smoothed required number of packets metric. In their simulations, such optimized FLI showed better reactivity.

Another proposal for estimating link quality in smart grid environments uses a wavelet neural network based LQE (WNN-LQE) [14]. WNN-LQE is designed to provide confidence intervals for the predicted SNR. The proposed solution is compared against several other approaches: Back Propagation Neural Network (BP-NN), Kalman algorithm (KF), ARIMA-based estimator and XCoPred. In their evaluation, the authors show that WNN-LQE is able to capture the link quality within the confidence intervals. They also show relative comparisons of the algorithms for stable and unstable links.

The most recent work [2] takes a step back from complex algorithms and reevaluates LQI as a prospective link quality estimator. The goal is to make fast decisions whether a wireless link should be established or maintained. The authors proposed an estimator that classified links as good, uncertain or weak, based on LQI. However, it is not clear from the paper how they defined the quality intervals (i.e. good: LQI=255; uncertain:165<LQI<255; weak: LQI<165). Using data collected from IoT-LAB testbed, they drew two conclusions. First, they reported that below -85dBm, RSSI becomes irrelevant and LQI becomes a valuable asset. Second, they reported that good directed links have 95.6% probability of keeping the quality in the opposite direction and 0% probability of degrading to bad in the opposite direction. Uncertain and weak directed links are slightly above 50% likely to keep the quality in the opposite direction.

A. Discussion

Our investigation focuses on data driven link quality estimation. In Table I we summarize the most related publications that use actual data traces recorded from actual devices. As a result, a large part of the proposed models and metrics are data driven - developed from raw data and then possibly fitted to a well-known or a newly proposed model. Considerable effort in the related work went into modeling, evaluation and quantifying the quality of wireless links.

The first column in Table I contains the title, reference and the year of publication. The second column provides the testbed, the hardware and the technology used in each of the papers. The third column lists the goals of the papers with respect to LQE. Columns four, five and six focus on the aspects of the estimators, particularly on their corresponding input(s), model and output. The last two columns give numbers about the size of data used and whether that data is publicly available for reproducibility of results.

Table I indicates that contributions span from the emergence of wireless communication technologies until nowadays. The majority of publications related to LQE are focused on sensor networks (IEEE 802.15.4) and only few target other types of wireless networks such as WiFi (IEEE 802.11) or Bluetooth (IEEE 802.15.1). This can be explained by the fact that IEEE 802.15.4-based wireless sensor networks at the time became relatively cheap to deploy and maintain, with sensor nodes open for implementing own proprietary solutions, resulting in a large wave of research focusing on ad hoc, mesh and multihop communications. The nodes implementing the selected technologies were deployed and maintained in various university testbeds.

With respect to the research goal, the surveyed papers can be categorized in two groups. The goal of the first group was to improve the performance of a protocol. Authors of [1], [3] investigated the TCP performance improvement while others looked at the routing protocol performance. This group of papers proposed new link quality estimators as an intermediate step towards achieving their goal. The goal of the second group of papers was proposing a new or improving an existing link quality estimator. For this class of papers, any protocol improvement in the evaluation process was obtained only a side effect.

With respect to the metrics used for estimating the quality of a link, we distinguish between single metric approaches used in [2], [4], [7], [14] and multiple metric approaches considered in [1], [3], [5], [6], [8]–[12], [27]. The most widely used metric, either directly or indirectly, is PRR. PRR values are used as model input in [1], [4]–[7], [9]–[12], [27], while categories derived from PRR values are used as model input in [5], [8]. Looking at the frequency of use, PRR is followed by hardware metrics i.e. RSSI, LQI and SNR in [2], [5], [6], [8], [12], [14], [27]. Other features are less common and tend to appear in single papers.

As to the model used for developing the link quality estimator, the surveyed approaches can be distinguished to those using statistical models [1], [3]–[5], [7], rule-based models [2], [6], [8], [10], [11], [26] and statistical machine-learning models [12]–[14].

Regarding the output of the link quality estimators, we identified binary estimators [4], [10], [11], [13], [26], multiclass estimators [2], [7], [8] and continuous-valued estimators [1], [3], [5], [6], [12], [14].

Finally, with respect to the reproducibility of the results in the analyzed papers, our investigation shows that only [7], [13] are easily reproducible, because they rely on publicly available traces. Studies reported in [1]–[4], [6], [12], [26] use open testbeds that, in principle, could be used to collect data and reproduce the results. However, it is not clear whether some of the testbeds are still operational 10-20 years after the

publication of the research. We did not find any evidence that the results in [5], [8], [10], [11], [14] can be reproduced as they rely on an internal one-time deployment and data collection.

As can be seen, the state of the art analyzed in Table I shows that the link quality estimators vary in the input signals from single input to multiple inputs, from instant values to values derived by various computational approaches. The algorithms used for model selection vary from averaging and smoothing to logistic regression, decision trees, fuzzy logic and neural networks. The output of the models also very from values to classes. In general, the above observation renders direct comparison of the performance of different estimators very difficult, in some cases additionally aggravated by the unavailable testing dataset or ill-defined validation setup, calling for a systematic approach and investigation proposed in this article.

III. OVERVIEW OF MEASUREMENT DATA SOURCES

To enable a better understanding of each of the steps involved in link quality estimation using real measurement data and machine learning models, we identified the most suitable publicly available sets of measurement data that can be used for a systematic study of each step. Measurement data comes in different shapes and forms and in most cases it cannot be directly used by machine learning algorithms. Mostly measurements are taken for a given period of time on a given radio link we refer to such measurements as traces. When we have a set of such traces for a number of links and/or periods of time in a given testbed we talk about a trace-set. Traces and trace-sets in general can have missing values or some other irregularities and need to be preprocessed for the use by machine learning algorithms; we refer to such preprocessed trace-sets as datasets.

In Table II we summarize publicly available trace-sets that, given the contained metrics, seem suitable for investigating link quality estimation. Other datasets that could be suitable, however not publicly available, are not considered. The first column lists the source of the trace-set and the estimated year of creation. The second column lists the hardware and technology used for the trace-set collection. The third column lists the information included in each trace, while the forth column gives details on the size of the trace/trace-set. The fifth column lists the type of the communication used in the measurement campaign and the last column contains notes about particularities of the trace-sets.

As shown in Table II, we identified nine candidate trace-sets for performing link quality estimation. These trace-sets were collected by teams in various universities world-wide using their testbeds ([32], [34], [38]) or one time deployments ([35]–[37], [39], [41]). Four of the traces are using IEEE 802.11, three are using IEEE 802.15.4, one is based on IEEE 802.15.1 and one is using a proprietary radio technology. The number of entries (i.e. measurement points) range from merely 6 thousand to 21 million, while the number of features per entry range from one to more than fifteen.

Two of the trace-sets, Rutgers [34] and Colorado [36], were used in two surveyed papers in Table I. The [13] used both Rutgers and Colorado, while [7] used only Rutgers.

TABLE II
PUBLICLY AVAILABLE TRACE-SETS FOR LQE INVESTIGATION

Source and year	HW & Tech.	Data	Size	Type	Notes
MIT, Roofnet, [32], [33], 2005?	Cisco Aironet 350, IEEE 802.11b, mesh, custom Roofnet protocol	source, destination, sequence, time, signal, noise,	21 258 359 (1725 links, 4 bitrates)	1-to-1, multihop?	not clear which packet were lost on a link
Rutgers University, ORBIT testbed, [34], 2007	29x PC + Atheros 5212, IEEE 802.11abg	seq. number, RSSI	611 632 (406 links, 300 packets/link, 1 packet/100ms, 5 levels of noise)	1-to-N	minor preprocessing
"packet-metadata", [35], 2015	2x TelosB, IEEE 802.15.4	RSSI, LQI, noise floor, packet size, no. retries, energy, Tx power, ACK, queue size,	14 515 200 (300 packets per 80646 runs per 6 distances)	1-to-1	requires minor pre-processing
Colorado, [36], 2009	5x listeners, IEEE 802.11	signal strength, data rate, channel, timestamp,	29 000 (500 packets per 58 locations,)	1-to-1	Wireshark PCAP format, require preprocessing
University of Michigan, [37], 2006	14x Mica2, proprietary protocol, sub-GHz ISM	RSSI	580 762 (1 packet/0.5s, 30 min/device, 3191 records/link)	1-to-N	MatLab binary format, dirty data (leading zeros, no units), can only assume link relations
EVARILOS, UGent, [38], 2015-03-11	6 nodes, Bluetooth	RSSI, timestamp	5 938 (<2 000 records/link)	N-to-1	Hospital environment, No Interference
EVARILOS, UGent, [38], 2015-03-11	5 nodes, IEEE 802.15.4	RSSI, Time-of-Arrival, timestamp	110 126 (<35 000 records/link)	1-to-N	Hospital environment, No Interference
University of Colorado, [39], [40], 2009 6x PC with omni antenna, 1x directional antenna, IEEE 802.11		seq. number, coordinates, direction, TX power, 5x RSSI values per log	5x 623 207 (500 packets per 180 positions per 4 directions per 11 Tx levels per 5 nodes)	1-to-N	3 types of antenna variable, Tx power, 4 directions, extensive documentation
Brussels University, [41], 2007	19x Tmote Sky, IEEE 802.15.4	seq. number, RSSI, LQI, timestamp	112 793 (<1 600 packet/link)	1-to-N	requires preprocessing, seq. number gaps; 3 other tracesets available

The Roofnet [32] is a well known WiFi based trace-set from MIT. It is the biggest (in number of entries) of all listed trace-sets. However, it is hard to find the exact Roofnet setup/configuration used for collecting the measurement data, since it evolved over time, and it is not clear whether links are multi-hop or not. One particularity of Roofnet that PRR can only be computed as an aggregate value per link and not in temporal sequence within a link.

Rutgers trace-set [34] was gathered in the ORBIT testbed and it is large enough, requires only moderate preprocessing and is properly formed for data-driven LQE. It exhibits the overall packet loss of 36.5%. However, RSSI is the only feature meaningful for LQE.

The "packet-metadata" [35] is a large dataset and comes with plenty of features useful for LQE. Beside the typical LQI and RSSI, it also provides information about the noise floor, transmission power, energy consumed and several network stack and buffer related parameters.

The Colorado trace-set [36] contains information from all network stack layers, therefore it is the most complete trace-set from the list.

Upon closer analysis, the last five trace-sets listed in Table II proved unsuitable for data-driven LQE. The trace-set from the University of Michigan [37] is incomplete and suffers from inconsistent format, lack of units, missing sequence numbers and lack of context and documentation. The two EVARILOS trace-sets [38] are in good shape, however they have less than 2,000 entries each and are thus too poor for the LQE evaluation study. In the Colorado trace-set [39] all links seem to be in good state as it has less than 1% packet loss, making it not representative for a general wireless network. Finally, the Brussels University trace-set [41] is too small and suffers from inconsistent structure and incomplete documentation.

IV. DATA-DRIVEN LINK QUALITY ESTIMATION THROUGH CLASSIFICATION

To classify the quality of the link, we chose the 3-class distinction model (*good*, *bad* and *intermediate*) based on PRR. This distinction was extensively used by [24], however it also appears in [9], [29], [42]. Some articles [43]–[45] also use terminology of regions, i.e. *connected*, *transitional* and *disconnected* regions.

To perform a systematic study of the influence of the various processing steps in classifying the quality of the links, we start from the well established Knowledge Discovery Process (KDP) [46] illustrated on Figure 1. We study the influence of data preprocessing steps such as data cleaning, data interpolation, feature generation and resampling on the performance of the learned model. There is no fixed, predetermined order of executing these steps, and when searching for best settings of the process some of the steps may need to be iteratively repeated. We use one possible ordering of steps, however this should not affect the outcomes of the study. We also investigate the relative performance of a selected set of various linear and non-linear learning models. The aspects subject to the investigation are depicted in Figure 1 under the respective steps of the KDP.

The influence of each step on the results of the learned model is discussed in the following sections. After analyzing existing publicly available trace-sets in Section III, the Rutgers trace-set seemed the most appropriate for further consideration in this study. This trace-set includes 4,060 separate link traces, collected on 812 unique links with 5 different noise levels (i.e. 0, -5, -10, -15 and -20 dBm). Directly available trace-set features include raw RSSI and sequence number, source node ID, destination node ID and artificial noise level. From the experiment description we know that packets were sent every

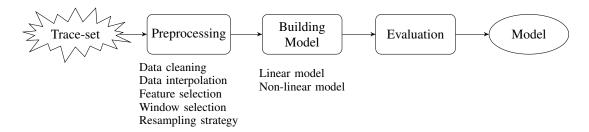


Fig. 1. Diagram of classification task

100 milliseconds for the period of 30 seconds. Therefore, every trace consists of 300 packets. An example of a trace with an overall intermediate quality of the link from the Rutgers traceset is depicted in Figure 3. Based on the specifications of the used radio, each RSSI value is defined between 0 and 128, where the value of 128 indicates error and is therefore invalid.

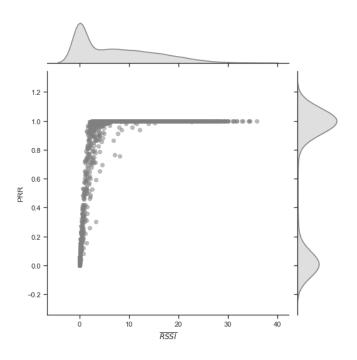


Fig. 2. Rutgers trace-set PRR distribution

A statistical analysis of the Rutgers trace-set reveals that 960 link traces out of 4,060 (23.65%) are completely empty (no packet received) and that out of total 1,218,000 packets sent only 773,568 (63.51%) were correctly received. Figure 2 illustrates distribution of Rutgers trace-set. It show correlation between average RSSI and overall PRR on each link.

Throughout the study we used scikit-learn toolkit [47]. We make all the scripts available for the community to use, reproduce improve and to build on top publicly available on GitHub repository².

V. DATA PRE-PROCESSING

As pointed out in Section III, a close look at publicly available trace-sets reveals missing values, inappropriate formatting, unaligned samples, unnecessary or missing features, etc. Thus, before being fed to machine learning algorithms or used to build a link quality model, these trace-sets need to be preprocessed. Typical preprocessing steps, depicted also in Figure 1, and their impact on the performance of a data driven link quality estimator are explained in the following subsections on the example of the Rutgers trace-set. It is worth noting that many of the design choices in the preprocessing steps depend on the purpose of using the data, however steps themselves are general and applicable to any use of the obtained dataset.

A. Cleaning & interpolation step

Before building a data driven model for link quality estimation, the selected Rutgers trace-set has to be examined and prepared for model building. First, a valid time series describing each link has to be extracted. By a valid time series we refer to a series of ordered tuples where each tuple contains a packet sequence number and a corresponding measured or calculated link metrics. The values in the tuples have to be within valid ranges. For instance, sequence numbers have to be in correspondence with the packets sent during the trace collection, and the link metrics values have to be in the valid ranges specified by the transceiver datasheets or other corresponding documentation. In general, link metrics related to received radio signal, i.e. signal-level link metrics such as RSSI, LQI, etc., can be obtained directly from the hardware registers of the corresponding transceivers, whereas link metrics related to packet data transmission, i.e. packetlevel link metrics such as PRR, PSR, etc., is calculated with suitable software procedures.

As described in Section IV, the Rutgers trace-set has some invalid values and a considerable number of missing sequence numbers due to lost packets. Models created automatically using machine learning algorithms can be significantly biased by invalid and missing data. Many out-of-the-box data mining algorithms cannot handle invalid values (e.g. NaN and $\pm\infty$ from IEEE 754 specs), or they ignore them. After analyzing the link quality estimators from Table I that use machine learning models, it is unclear what strategy, if any, was used for handling invalid and missing data nor their effect on the final model. Therefore, in this section we investigate the effects of missing data on model performance. With respect to other influencing parameters evaluated and discussed in Sections V-B, V-C and V-D we assumed the use of non-linear decision trees algorithm trained with trio of instant RSSI,

²https://github.com/sensorlab/link-quality-estimation

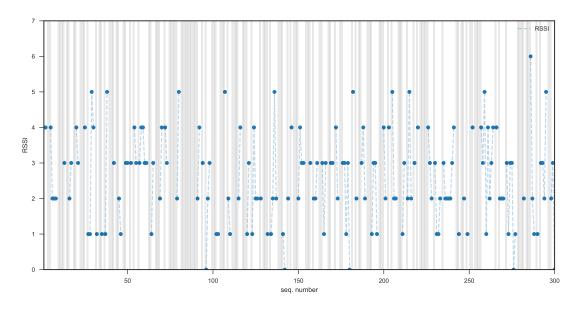


Fig. 3. A sample with overall intermediate quality from the Rutgers trace-set (gray: missing/gap, dot: valid RSSI, dashed line: consecutive data points)

averaged RSSI and standard deviation RSSI values, standard normalization and the random over-sampling approach.

In the machine learning community, there are many approaches on how to handle missing data [48], [49]. To analyze the impact of the approach to missing values on link quality classification, we trained the same model (i.e. decision trees), with the same feature set, once without any handling of missing values, once using a simple time series specific approach where we interpolate missing data with Gaussian noise, and once by using domain knowledge. In the case of interpolation with Gaussian noise, gaps of missing data were filled with random values based on previous and next valid value. In the case of using domain knowledge, we replaced the missing RSSI values with 0, which represents a very bad link with no received signal, yielding PRR equal to 0. The possible RSSI values are integers ranging between 0 (bad link with no signal) and 127 (good link with good signal), while value 128 is an invalid value or an error.

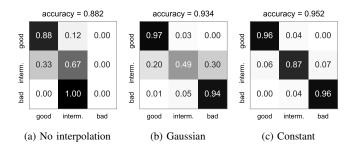


Fig. 4. Different interpolation variants with a non-linear decision trees algorithm and random oversampling

After the interpolation, the wireless link traces are described by a discrete series without missing values that is uniformly sampled. Figure 4 lists the results for all three interpolation cases using the form of a confusion matrix³, i.e. indicating how well the used model classifies individual instances. The best performing model in terms of accuracy (95.2%) is the one using domain knowledge in Figure 4c. The model using interpolation with Gaussian noise depicted in Figure 4b achieves 93.4% accuracy. While the difference in accuracy between the two models is only about 2 percentage points, their respective confusion matrices indicate that the model using interpolation with domain knowledge correctly classifies all three link types in between 87% and 96% of instances. The model using interpolation with Gaussian noise is significantly weaker at classifying the intermediate class since it only classifies it correctly in 47% of instances.

The results from Figure 4 can be explained by the fact that interpolating the missing samples with 0 indirectly preserves the information about the packet reception and it does not modify the model towards Gaussian distribution. The model in Figure 4b, where interpolation was done with Gaussian noise, converges toward normal distribution and starts losing information about the *intermediate* class. The results of the worst performing model, where invalid data points are dropped, is shown in Figure 4a. This model is unable to recognize *bad* quality link cases as the information about those was discarded from the trace.

B. Feature selection step

Feature selection is the process of selecting relevant raw features and/or creating synthetic features to be used for training of machine learning algorithms. It is a fundamental process in Knowledge Discovery Process (KDP) and can be done manually or, in some cases, can be built by existing algorithms. The Rutgers trace-set has only one feature useful for LQE, the instant (raw) RSSI value, and the sequence

³Confusion matrix, https://en.wikipedia.org/wiki/Confusion_matrix

number, that is used to compute the label for training according to the following:

$$y = f(\text{PRR}) = \begin{cases} \text{good}, & \text{if } \text{PRR} \ge 0.9\\ \text{bad}, & \text{if } \text{PRR} \le 0.1 \\ \text{intermediate}, & \text{otherwise} \end{cases}$$
 (1)

$$\mathbf{y} = [y_1, y_2, \dots, y_n], \quad \forall y \in \{\text{good}, \text{intermediate}, \text{bad}\}$$
 (2)

TABLE III $\begin{tabular}{ll} {\it TABLE III} \\ {\it Regression analysis} \ (R^2) \ {\it of the predicted value of synthetic} \\ {\it features} \\ \end{tabular}$

Feature	PRI	PRR ⁺¹		
	\mathbf{R}^2	MSE		
PRR ⁺¹	1.000	0.000		
PRR	0.988	0.012		
RSSI _{avg}	0.483	0.517		
RSSI	0.476	0.524		
$RSSI_{avg} * RSSI_{std}$	0.355	0.645		
RSSI _{std}	0.327	0.673		
RSSI * RSSI _{std}	0.321	0.679		
RSSI ² _{avg}	0.030	0.970		
RSSI ²	0.029	0.971		
RSSI * RSSI _{avg}	0.028	0.972		
1	-0.000	1.000		
$RSSI_{avg}^2 * RSSI_{std}$	-0.057	1.057		
$RSSI * RSSI_{avg} * RSSI_{std}$	-0.066	1.066		
$RSSI^2 * RSSI_{std}$	-0.085	1.085		
RSSI ³ _{avg}	-0.243	1.243		
RSSI ³	-0.243	1.243		
RSSI * RSSI ² _{avg}	-0.244	1.244		
RSSI ² * RSSI _{avg}	-0.244	1.244		
RSSI ³ _{avg} * RSSI _{std}	-0.317	1.317		
RSSI * RSSI ² _{avg} * RSSI _{std}	-0.322	1.322		

A typical approach in machine learning for such trace-sets is to investigate whether synthetic features, such as average RSSI over a time window or polynomial interactions [50], could help in training more accurate models than with only instant RSSI values. To identify the influential features that have a statistically significant correlation with PRR⁺¹ from which we derive the three classes of link quality. For the analysis, the correlation was investigated in terms of coefficient of determination (R²) statistics and Mean Squared Error (MSE). Note that the R² statistic can be negative if the model is not appropriate for the data.

By looking at R² and MSE for the predicted PRR (indicated as PRR⁺¹) assuming different combinations of features in Table III, it can be anticipated that the average RSSI will be slightly more valuable in the model performance than the instant RSSI. Due to space limitations, we only show a subset of combinations of synthetic features, some with positive and some with negative predicted value. Table also shows that in

the case of the Rutgers trace-set, polynomial interactions are not likely to improve the model performance.

For evaluating the influence of various feature combinations on the performance of the machine learning based LQE, including polynomial interactions, we selected Logistic Regression as a representative of linear models and decision trees as a representative of non-linear models. Figures 5 and 6 show the influence of the best performing feature combinations on the classification performance. For these results we assumed interpolation based on domain knowledge (i.e. replacing missing values with zeroes as discussed in Section V-A), synthetic feature creation with the window sizes W_{PRR} and $W_{history}$ set to 10, standard normalization and the random over-sampling approach (see Section V-D and Section V-C). The goal was to predict the link quality as per Eq. 1 for the next prediction window W_{PRR} .

The best performing feature combination for the linear model are RSSI⁻⁴ and RSSI⁻³ with an accuracy of 94.6% (see Figures 5k and 5l). This is followed by the feature combinations (RSSI, RSSI_{avg}, RSSI_{std}), (RSSI, RSSI_{avg}) and (RSSI_{avg}) shown in Figures 5d, 5c and 5b, respectively, with only 0.1 to 0.2 percentage points worse accuracy. However, it can be seen in Figures 5k and 5l that the best performing model in terms of accuracy is poor at correctly discriminating intermediate and bad classes, yielding only 26% and 31% correct answers, respectively. The high accuracy in this case can be explained by the heavily unbalanced data where good links are in majority and dominate the accuracy value. While only 0.1 percentage point inferior in accuracy, the model with feature combination (RSSI, RSSI_{avg}, RSSI_{std}) depicted in Figure 5d correctly discriminates all three classes in 94%, 86% and 97% of instances.

For the linear model, it can also be seen in Figure 5a that an instant (interpolated) RSSI feature vector offers good classification result for good and bad classes (above 93%), but the model is unable to identify *intermediate* class, where it yields only about 31% of correct answers. The performance further degrades when experimenting with RSSI², RSSI³ and RSSI⁴, where with an increasing exponent the discrimination capabilities of the model between bad and intermediate classes decrease. Linear models trained with synthetic data that uses negative exponent for RSSI (i.e. RSSI⁻¹, RSSI⁻², RSSI⁻³, RSSI⁻⁴) (Figures 5i, 5j, 5k and 5l) offer high classification rate for good class (above 91%), however they largely confuse the *intermediate* and *bad* link quality classes.

Other feature combinations such as (RSSI, RSSI_{std}), (RSSI_{avg}, RSSI_{std}) do not show good results and are therefore omitted from Figure 5.

A general observation for the linear model is that RSSI_{avg}, followed by RSSI and RSSI_{std} are the most relevant features for training a well-performant model. The best model (RSSI, RSSI_{avg}, RSSI_{std}) in Figure 5d is followed by the (RSSI, RSSI_{avg}) in Figure 5c. Comparing the results of these two models, it can be seen that they perform comparably for the *good* and *bad* links, however, the addition of RSSI_{std} to the already existing (RSSI, RSSI_{avg}) improves the recognition of the intermediate class by 8 percentage points. These conclusions can also confirm the analysis from Table III where it

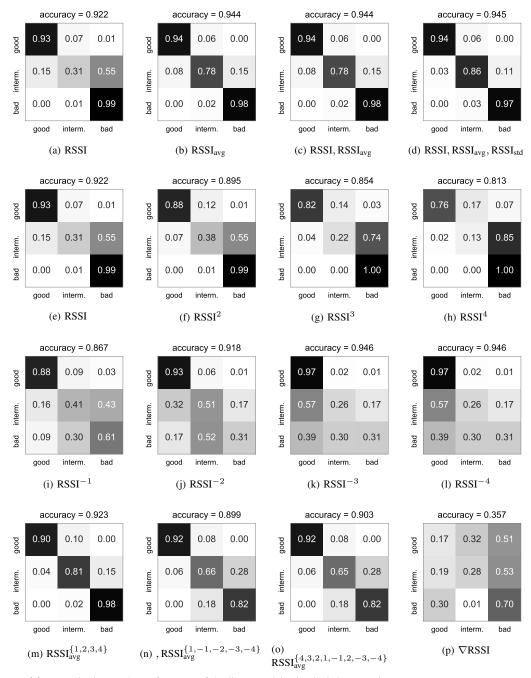


Fig. 5. The influence of feature selection on the performance of the linear model using logistic regression

can be seen that individual features explain the predicted PRR window because they have the highest R^2 values and small MSE.

For the non-linear model represented by the decision trees similar conclusions can be drawn as for the linear model. The best performing model shown in Figure 6d with an accuracy of 95.2% uses the feature combination (RSSI, RSSI_{avg}, RSSI_{std}). The second best model using the feature combination (RSSI, RSSI_{avg}) has an accuracy of 94.2% as shown in Figure 6c. By comparing these two best performing feature combinations for non-linear models, it can also be seen that adding RSSI_{std} to the already existing (RSSI, RSSI_{avg}) has only minor advantage

of 0.2 percentage points for the class of *good* links while the performance on the other classes remains the same.

Figure 6 also shows that $RSSI_{avg}$ alone with the non-linear model yields quite good results (87% for *intermediate*). Applying polynomials to RSSI or $RSSI_{avg}$ degrades the performance when comparing to RSSI or $RSSI_{avg}$. For instance, as can be seen in Figure 6h, $RSSI_{avg}^4$ drops the recognition of the *intermediate* class by 13% while the other two classes are unaffected.

The performance comparison of the same best performing feature vectors in the linear model in Figure 5 and the nonlinear model in Figure 6 shows that non-linear model slightly

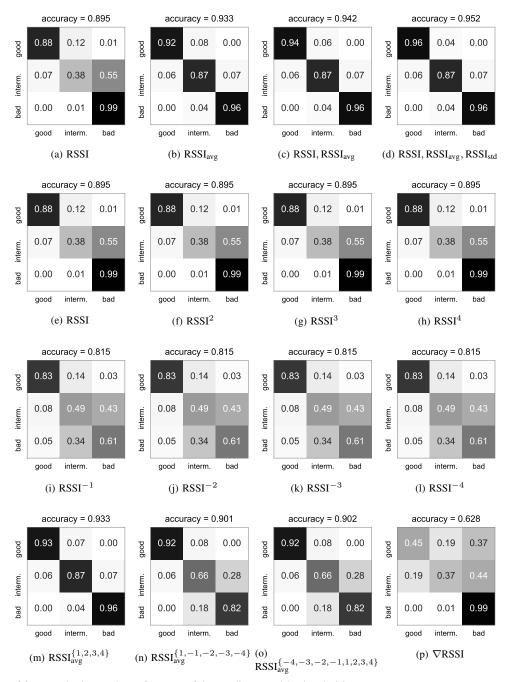


Fig. 6. The influence of feature selection on the performance of the non-linear model using decision trees

outperforms the linear model.

C. Window selection step

For studying the influence of the window selection on the performance of the model, we need to distinguish between two types of windows. The first is the historical window $W_{history}$ that is used for computing the features such as $RSSI_{avg}$. The second is the prediction window W_{PRR} that is used for computing the link quality labels. Given that the investigated trace-set consists of 300 packets per link, the size limits for the two windows are within [0,300] packets. However, choosing the value 0 implies no windowing, while choosing the value

300 implies per link labelling. Thus, we limited the range for the size of windows to [2,100] packets, within which we investigated the performance at the discrete set of nine values $\{2, 5, 10, 15, 20, 30, 50, 80, 100\}$. In this experiment we were predicting the link quality for the next prediction window $PRR(W_{PRR})$ considering the Rutgers trace-set with domain knowledge interpolation, the non-linear Decision Tree algorithm with the feature vector (RSSI, RSSI_{avg}(W_{history}), RSSI_{std}(W_{history})), standard normalization and the random over-sampling approach.

As graphically depicted in Figure 7, the best performing model uses $W_{PRR}=100$ and outperforms the models using

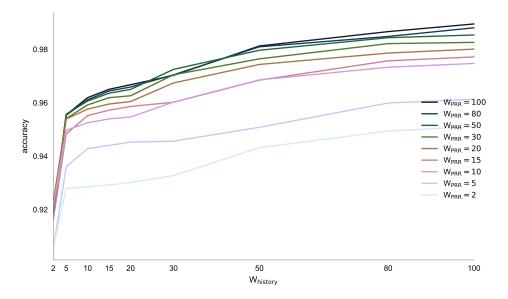


Fig. 7. The influence of window size on the accuracy of the non-linear model

other settings most of the time. Figure 8 shows a more indepth look at the per class performance of the models in the form of a confusion matrix for various window sizes. The accuracy for $W_{PRR} = 100$ and $W_{history} = 100$ goes up to 98.9% and the per class classification becomes 100% for good links, 96% for intermediate links and 98% for bad links. The results in general show that (i) looking historical window improves prediction because there is more information about how the link performed in the past, and (ii) increasing the prediction window (looking into the future) also increases the accuracy. Both observations, however, can also be a sideeffect of "smoothing"/averaging data from a relatively static trace-set. In particular, larger prediction windows are unable to inform on short term effects, although they better describe the overall link behavior. It needs to be pointed out that the optimal combination of values for historical and prediction windows is data specific, however the tradeoffs discussed in this section are general. While the Rutgers trace-set is relatively static, for a more dynamic trace-set the optimal window sizes are likely smaller.

For engineering a suitable link quality predictor, the agility of the estimator has to be specified by its user (e.g. the routing algorithm), but also the practical memory limitations of the devices have to be taken into account. More agile predictors use smaller window sizes, thus they tend to consume less memory, however they also yield lower accuracy. For large window sizes, the cold start period during which the historical window is initialized tends to be longer.

D. Resampling strategy

By analyzing the actual values in the considered trace-set it can be seen that there are 61% good, 34% bad and only 5% intermediate class entries. This distribution of data is largely due to the artifact of the experiment, where the nodes were relatively close to each other and the interference level was relatively low. Therefore, majority of links are actually good

and this is not due to missing values within one class category of link quality. Additionally, it is acnowleged in the literature [24], that the *intermediate* region of the receivers tends to be relative narrow compared to the *good* and *bad* regions, therefore naturally forming a minority class in most such tracesets.

Unbalanced trace-sets are often encountered in the machine learning and data mining communities, and they are typically solved by an appropriate resampling strategy. For studying the influence of the resampling strategy on the performance of the model for link quality classification, we employed the Random Over-Sample (ROS) and Random Under-Sample (RUS) approaches. ROS [51], [52] approach equalizes all class sizes to the size of the majority class by reusing the dataset entries of minority classes, therefore the resulting resampled trace-set is larger. The RUS [51], [52] approach on the other hand equalizes all class sizes to the size of the minority class by taking the smallest minority class and random samples from other larger classes. The new resampled dataset is therefore smaller. With both approaches (ROS and RUS), however, a training dataset is obtained with balanced classes.

Figure 9 shows that resampling strategies on the Rutgers trace-set decrease the overall accuracy of the classification model from 97.2% to slightly above 95%. However, when no resampling is performed, the minority class (i.e. *intermediate*) is only correctly detected in 61% of instances, meaning that the model is overfitted to majority classes. In the case of resampling, the minority class is correctly detected in over 87% of instances, yielding a 20 percentage points increase in performance. This improvement comes at a relatively small cost for the majority classes, a 3-4 percentage points decrease for the *good* links and a 2 percentage points decrease for the *bad* links.

Furthermore, the results for the selected trace-set also show that there is no significant difference between the two resampling strategies, RUS and ROS. This is probably due

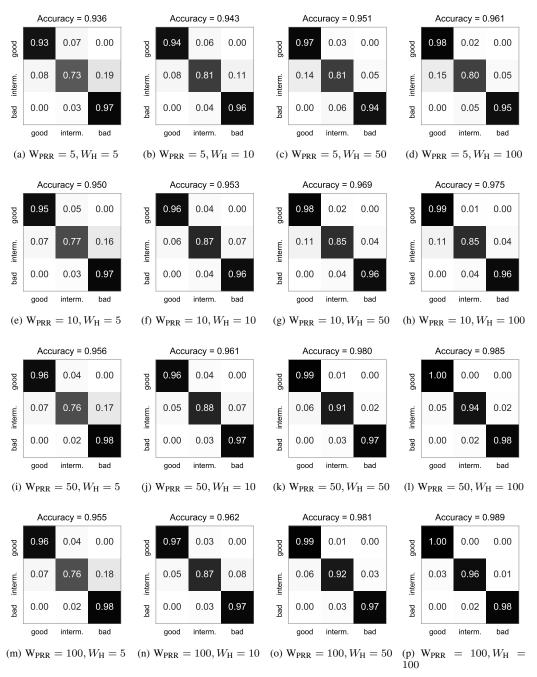


Fig. 8. The influence of window size on the non-linear model performance using decision trees - a detailed overview in the form of confusion matrices.

to relatively large size of the intermediate class. Although it only represents 5% of the population, it still contains more than 52,000 samples. However, looking beyond this particular trace-set, the RUS approach may suffer from excluding certain amount of majority class instances and may affect representativeness of remaining data points, especially for more dynamic datasets. On the other hand, due to enlarged number of data points the ROS approach requires more computing resources for building a model.

The results in this section are based on interpolation and cleaning using domain knowledge, instant RSSI, RSSI_{avg} and RSSI_{std} as a features and W_{PRR} and $W_{history}$ of size 10.

VI. BUILDING THE MODEL

The final step of this study concerns the influence of model selection on the performance of a link quality estimator. For this we selected logistic regression and linear SVM as representatives of linear models and decision trees, random forests and a multilayer perceptron, that is a class of feed-forward neural networks, as representatives of non-linear models. As a baseline reference model we assumed the majority classifier which in our case classifies all links in the *good* class.

The results in this section use the Rutgers trace-set with domain knowledge interpolation, the feature vector consisting of instant RSSI, RSSI_{avg} and RSSI_{std}, windowing with $W_{PRR} =$

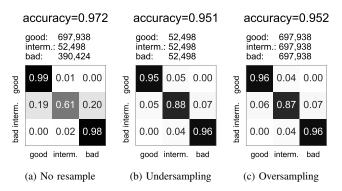


Fig. 9. Different resample strategies on pipeline with standard normalization and non-linear decision trees algorithm using (RSSI, RSSI_{avg} and RSSI_{std} features

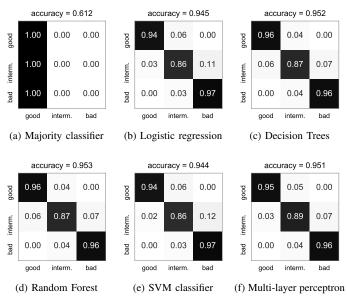


Fig. 10. The influence of the selected algorithm on the effectiveness of the model

10, $W_{history} = 10$, and random oversampling approach. The models were evaluated using 10-times stratified K-fold cross-validation [47], [53].

Figure 10 shows that all the selected models but the reference majority classifier have comparable performance. The difference in performance between algorithms is less than 3 percentage points for any class. The model with the highest accuracy of 95.3% is the random forest in Figure 10d, closely followed by decision trees in Figure 10c and a multi-layer perceptron in Figure 10f. The fact that linear models perform slightly worse is consistent with the findings in Section V-B. Looking at the ability of models to recognize the minority class, it can be seen that the multi-layer perceptron performs the best.

VII. CONCLUSIONS

In this paper, we first made in dept analysis of existing literature on link quality estimation with focus on models built from data traces. The analysis showed that link quality estimators are not only increasing their complexity but, the reported results are becoming more difficult to understand because each model that relies on machine learning requires a complex design and development process. We conclude that state of the art currently does not consider the effects of the data preparation on the final results.

Next, we selected a representative subset of machine learning models used in the literature and a representative publicly available dataset. Our conclusion is that Rutgers trace-set was suitable for our research.

Then followed a systematic study on the influence of the design decisions taken in each step of the machine learning process on the performance of machine learning based link quality estimators. We experimented with data cleaning and interpolation, feature selection, various window sizes, data-set sampling strategies and different algorithms in order to build a model. We conclude that trace-set preprocessing and feature engineering have a higher influence on the performance of the model than the choice of the algorithm.

We also conclude that interpolation with domain knowledge improves the accuracy of the ML based LQE by 7% compared to not using any interpolation. Feature selection improves the classification of *intermediate* links by 50% compared to using only raw data. Overall model improvement is 6%. The sampling approach boosts the classification of *intermediate* links by 26% compared to no sampling used. The overall model accuracy has below 2% penalty. We show that the choice of the algorithm yields only minor contribution in the final results. The difference is around 2%. We also show that for this data-set, non-linear algorithms are only slightly better at classifying link quality than linear algorithms.

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