Long Short Term Memory Networks for Bandwidth Forecasting in Mobile Broadband Networks under Mobility

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Abstract—Bandwidth forecasting in Mobile Broadband (MBB) networks is a challenging task, particularly when coupled with a degree of mobility. In this work, we introduce HINDSIGHT++, an open-source R-based framework for bandwidth forecasting experimentation in MBB networks with Long Short Term Memory (LSTM) networks. We instrument HINDSIGHT++ following an Automated Machine Learning (AutoML) paradigm to first, alleviate the burden of data preprocessing, and second, enhance performance related aspects. We primarily focus on bandwidth forecasting for Fifth Generation (5G) networks. In particular, we leverage 5Gophers, the first open-source attempt to measure network performance on operational 5G networks in the US. We further explore the LSTM performance boundaries on Fourth Generation (4G) commercial settings using NYU-METS, an open-source dataset comprising of hundreds of bandwidth traces spanning different mobility scenarios. Our study aims to investigate the impact of hyperparameter optimization on achieving state-of-the-art performance and beyond. Results highlight its significance under 5G scenarios showing an average Mean Absolute Error (MAE) decrease of near 30% when compared to prior state-of-the-art values. Due to its universal design, we argue that HINDSIGHT++ can serve as a handy software tool for a multitude of applications in other scientific fields.

Index Terms—Bandwidth Forecasting, Mobile Broadband Networks, Long Short Term Memory, Hyperparameter Optimization

1 INTRODUCTION

Over the recent years, the popularity of Mobile Broadband Networks (MBB) has shown a great rise, triggering research studies and activities from both academic and industrial parties. MBB networks sustain a huge portion of the global wireless telecommunications in the world, including video, voice, and Internet. Furthermore, indispensable society’s operations, including healthcare, security, transport, and education, highly rely on the reliable services of MBB networks. They are considered to be a vital element for people that seek to stay continuously connected.

According to the Cisco Annual Internet Report[1] the amount of human beings with Internet access will reach nearly two-thirds of the global population by 2023. In addition, the number of global mobile devices will surpass the world’s projected population by the same year, approaching a staggering 13.1B. The above numbers prognosticate that the need to effectively address tasks such as network traffic management, application provisioning, and bandwidth forecasting would greatly rise, particularly considering the occurring transition to the Fifth Generation (5G) era. Therefore, it is critical that mechanisms are developed to model and characterize the underlying features that define the behavior of bandwidth performance in next-generation MBB networks from an end-to-end perspective.

The topic of bandwidth forecasting in MBB networks has been in the spotlight for a long time. However, it has lately become more prominent due to the fast-expanding next generation network infrastructures, which in turn, yield to a larger exchange of network data, hence, increasing the need for higher and more accurate predictions. Furthermore, 5G introduces new frequency bands, such as the mmWave, which drives data rates to groundbreaking limits, thus, posing new challenges to the forecasting process. Research studies focus on integrating robust and effective algorithms, while maintaining the implementation and computational complexity in acceptable levels. Over the years, numerous solutions have been proposed ranging from traditional statistical methods, such as the Naive, Autoregressive Integrated Moving Average (ARIMA), and Vector Autoregression (VAR), to considerably higher complexity algorithms, namely dynamic linear models, TBATS [1] (i.e., based on exponential smoothing), and Prophet [2] (i.e., widely used by Facebook). Within the context of Artificial Intelligence (AI), both Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) networks have been projected as high efficient algorithms for time series modeling. Between the two, LSTM networks appears to be the most fitting solution for the bandwidth forecasting study, considering the complex long term dependencies and the unforeseeable behavior that mobile traces display due to mobility.

LSTM performance heavily relies on the selection of the model hyperparameters and the underlying dataset characteristics (i.e., periodic patterns and trends). Since these two aspects are tightly tied with each other, knowing how to efficiently tune an LSTM model becomes an important but rather challenging task, thus, urging for a hyperparameter optimization solution. Among the most popular approaches
are the Random Search (RS) and the Bayesian Optimization (BOA) [3, 4]. Furthermore, additional research studies have been published focusing on the implementation of novel hyperparameter optimization solutions [5, 6]. However, despite being critical, hyperparameter optimization is frequently ignored by the majority of LSTM related studies, since it is considered a time consuming process.

In this work, we present HINDSIGHT++, a novel, light-weight, versatile, and open-source R-based framework for bandwidth forecasting experimentation in MBB networks with LSTM networks. The main source of motivation behind the design of HINDSIGHT++ is two-fold. First, to limit the implementation complexity of LSTM networks, and second, to minimize the predictive error. Toward this goal, we adopt the concept of Automated Machine Learning (AutoML), an acronym used to describe the process of data pipeline automation. In particular, AutoML covers the complete learning routine, from raw data preprocessing to the final model production. Moreover, HINDSIGHT++ is compliant with parallel and multivariate data and supports a wide forecasting horizon. Last, it offers different hyperparameter optimization options and LSTM variants. The source code of HINDSIGHT++ is structured in a dynamic fashion, so it can accommodate new features and algorithms. Users are encouraged to integrate more libraries and software components to satisfy their cause, but also to enrich the capabilities of the framework.

We study the topic of bandwidth forecasting in commercial 5G networks under mobility, while we revisit Fourth Generation (4G) scenarios and draw additional insights by performing a comparative analysis between the two technology standards. Thereupon, we leverage two open-source datasets, 5Gophers, which features network measurements from operational 5G networks in the US, and NYU Metropolitan Mobile Bandwidth Trace (NYU-METS), a counterpart dataset that comprises of hundreds of 4G bandwidth measurements in the wild. We adopt systematic investigation to showcase the significance of hyperparameter optimization at each use case when compared to existing state-of-the-art approaches.

The main contributions of this work are:

- We design and implement HINDSIGHT++, a light-weight LSTM based framework for bandwidth forecasting in MBB networks.
- We carry out a large-scale study of bandwidth forecasting in MBB networks using HINDSIGHT++. We focus on different mobility scenarios and perform a comparative analysis between real-world operational 4G and 5G networks.
- We investigate the potential of hyperparameter optimization and explore the performance boundaries of different LSTM variants attempting to further improve their performance in a MBB environment.
- Last, we open-source HINDSIGHT++ to the community allowing for further experimentation with a variety of datasets and applications [8].

The rest of the paper is organized as follows. Section 2 provides background information on LSTM networks and summarizes related literature on network bandwidth forecasting and LSTM applications. Section 3 outlines the design of HINDSIGHT++, while Section 4 provides an overview of the software implementation and validation details. Performance evaluation takes place in Section 5, while the study is concluded in Section 6.

2 BACKGROUND AND RELATED WORK

In this section, we summarize literature work concerning bandwidth and performance forecasting tasks in mobile networks. In addition, we provide a brief background synopsis on LSTM networks and showcase how they are used within the context of networking.

2.1 Related Work on Performance Forecasting in Mobile Networks

Over the years, several studies have focused on modeling the performance of mobile networks. Even though most of them tackle the problem from slightly separate angles, they share a common objective, i.e., to minimize the error function and provide insights on the complexity of the mobile ecosystem.

A supervised Machine Learning (ML) solution for downlink throughput prediction in MBB networks is proposed in [9]. The authors argue that ML can be used as a tool for significantly reducing the data volume consumption over the network, while maintaining the predictive error in acceptable levels. Furthermore, in [10], Raida et al. leverage constant rate probing packets to estimate available bandwidth in a controlled Long-Term Evolution (LTE) environment, while in [11], they extend their work by further testing and validating the developed framework in live LTE networks. In [12], Maier et al. introduce a novel AI model with feed-forward neural networks for both downlink and uplink bandwidth forecasting. To find a fitting speed test duration, the authors investigate two scenarios. First, they train a model with a duration fixed to a value lower than the default, while second, they dynamically determine a duration by using the results of a pretrained neural network model. Experimental approaches studying the problem of bandwidth prediction have also been addressed in [13, 14, 15, 16, 17, 18, 19]. Beyond empirical-based studies, theoretical models have also been published. In [20], Gao et al. introduce a theoretical learning based throughput prediction system for reactive flows, while authors in [21] propose a novel stochastic model for user throughput prediction in MBB networks that considers fast fading and user location.

2.2 Background on LSTM Networks

The inception of RNNs was triggered by the ever-increasing need to effectively tackle time series forecasting applications with novel AI algorithms. Their central mechanism falls heir to artificial neural networks, a sophisticated and rather
complex ecosystem composed by a collection of connected nodes, known as artificial neurons, that was inspired by closely observing the core operations of the human brain. RNNs introduced revolutionary feedback loops that would allow information to persist or vanish as it flowed from one network to another. The innovative and unique architectural design of RNNs was embraced by communities in several fields spanning different applications, such as image captioning, speech and text recognition, and led to immensely increasing their popularity [23][24][25].

Despite the massive success and hype around RNNs though, it was not long after Bengio et al. addressed a critical flaw affecting tasks with long range dependencies [26]. In particular, by using both theoretical and empirical evidence, the authors showed that RNNs and gradient based algorithms lack the ability to learn sequences spanning long-intervals. The gradient descent shortcoming, also known as the problem of vanishing gradients, was also re-addressed seven years later by Hochreiter, Bengio et al. [27]. This finding launched research initiatives that led to the introduction of LSTM networks in 1997.

While LSTM networks are grouped under the big umbrella of RNNs, thus inheriting most of the latter’s key mechanisms, they introduce additional novel components explicitly added for capturing long term dependencies. The prime difference between the two algorithms is the number of neural network layers. The structure of a traditional RNN architecture is fairly simplistic and features a single neural network layer (i.e., tangent function). On the contrary, an LSTM architecture inserts additional complexity by engaging a total number of four neural networks (i.e., one tangent and three sigmoid functions) alongside a collection of interconnecting elements. The above components interact with each other in a unique manner resulting in a perplexed ecosystem that is known as LSTM cell. The main objective of an LSTM cell is to convey or remove information that flows along the neighbouring cells. Since LSTM cells establish a memory-wise mechanism, they are also referred in the literature as memory blocks. Figure 1 shows a schematic of an LSTM memory block.

![High-level representation of an LSTM memory block. Peephole connections are rendered by the blue dotted lines.](image)

The three central components responsible for exploiting the memory aspect of an LSTM cell are the forget, input, and output gates. As its name suggests, the forget gate is responsible for removing redundant information from the cell. Research studies have shown that alongside the output activation function, forget gate constitutes the most critical element of the cell [28]. Contrarily, the input gate acts as a regulator mechanism whose task is to preserve all vital information. Last, the output gate is used to decide the cell’s final state by using similar functionality as the forget gate. In other words, the output gate is the link between two consecutive LSTM memory blocks.

2.3 Network Performance Forecasting with LSTM Networks

Over the past years LSTM networks have been successfully applied for network performance related tasks. Cui et al. proposed a stacked bidirectional LSTM architecture for network-wide traffic estimation [29], while authors in [30] studied the applicability of LSTM for a real-time bandwidth prediction problem. Furthermore, Zhao et. al. focused on short-term traffic estimation by considering temporal–spatial correlation [31], whereas, authors in [32] proposed a hybrid framework that combines LSTM networks and an auto-encoder based model for network prediction from a spatio-temporal angle. Additional work on mobile traffic forecasting has been further proposed in [33][34][35].

Distinct from the preceding studies, this paper stands out and distinguishes itself by putting focus on the hyperparameter optimization aspect applied on data from different countries, network operators, technology standards, and mobility scenarios. In addition, to the best of our knowledge, this is the first study that attempts to perform a bandwidth forecasting comparative analysis between 4G and 5G networks under mobility with LSTM networks. Last, we make available to the community an open-source framework which follows an end-to-end AutoML paradigm and allows for ample experimentation with LSTM networks.

3 Framework Design

This section’s intent is to provide an overview of HINDSIGHT++. Figure 2 is a high-level control flow diagram that displays the interconnection of the different blocks, alongside complementary information, including matrix and parameter notation. We encourage the reader to use this diagram as a guideline or reference point when navigating through the current section.

HINDSIGHT++ is designed in a universal fashion so it supports both short and long range forecasts. As a result, we adopt an encoder-decoder scheme featuring two LSTM architectures that operate as a pair. The encoder-decoder design was originally introduced to address sequence to sequence (known as seq2seq) learning problems [36]. In a nutshell, encoder’s objective is to read and translate the input sequence into a sequence with a fixed length destined to be used as input to the decoder, which in turn, is responsible for generating an output value for each of the prediction steps. The number of Hidden Layers (HLs) and neurons across the two blocks can differ while additional HLs may be used (e.g., Bidirectional LSTM networks).

3.1 Initialization

The objective of this first phase is two-fold. First, to provide support with all required software components, and second, to initiate the data import process.
Fig. 2: A high-level representation of the HINDSIGHT++ control flow diagram. The operations for each block are described in Section 3 highlighted with a matching title. Dashed lines delimit the data preprocessing stage.

3.1.1 Load Prerequisites
HINDSIGHT++ relies on a number of open-source packages, or else, a collection of functions, compiled code, and data, available in CRAN. To guarantee software stability and robustness, it is critical that all dependencies are pre-installed in the system. Therefore, we enable a verification process that automatically locates, installs, and loads any missing packages and libraries.

3.1.2 Data Import
Next is the data import process where users select a number of $f \in [1, z]$ .csv files via an interactive window. Due to its universal design, HINDSIGHT++ operates under the assumption that the selected datasets are parallel. In addition, equidimensional datasets are required, since LSTM models expect input arrays with equal sizes. The last prerequisite is that the dependent variable locates in the first array position followed by any number of additional of regressors. We annotate the matrix dimensions for each dataset as $d_f \in \mathbb{R}^{n \times m}$, where $n$ and $m$ represent the number of samples and features, respectively.

3.2 Data Preprocessing
The process of data preparation in LSTM networks is rather perplexed time consuming. The complexity factor significantly increases considering the different data format combinations (e.g., multivariate, parallel) and parameters (e.g., lags, prediction steps). Figure 2(dashed frame) encloses all steps followed for providing compatibility with the LSTM models. In line with the AutoML concept, data preprocessing is treated as a black box.

3.2.1 Normalization
Multivariate data analysis often involves features with variable scales. Since LSTM weight allocation is prone to such data, it is critical that we consider a transformation function leveraging one of the following state-of-the-art normalization methods, known as min-max, z-score, and tanh.

3.2.2 Train-Test split
The next phase involves splitting each dataset into a training (80%) and a testing (20%) set. Both of these percentages can be configured as appropriate. We define the dimensions for each set as $d_f^{tr} \in \mathbb{R}^{n_{tr} \times m}$ and $d_f^{te} \in \mathbb{R}^{n_{te} \times m}$, where $n_{tr}$ and $n_{te}$ are the number of samples for the training and testing set, respectively, while $m$ represents the number of features.

| 2-D matrices | 3-D matrices |
|--------------|--------------|
| Training     | $X_{TR} \in \mathbb{R}^{n_{TR} \times nlags \times m}$ | $X_{TR} \in \mathbb{R}^{n_{TR} \times nlags \times m}$ |
|              | $Y_{TR} \in \mathbb{R}^{n_{TR} \times msteps \times z}$ | $Y_{TR} \in \mathbb{R}^{n_{TR} \times msteps \times z}$ |
| Testing      | $X_{TE} \in \mathbb{R}^{n_{TE} \times nlags \times m}$ | $X_{TE} \in \mathbb{R}^{n_{TE} \times nlags \times m}$ |
|              | $Y_{TE} \in \mathbb{R}^{n_{TE} \times msteps \times z}$ | $Y_{TE} \in \mathbb{R}^{n_{TE} \times msteps \times z}$ |

TABLE 1: Summary of the 2-D and 3-D matrix dimensions, where $n_{TR} = n_{te} - (nlags + msteps - 1)$ and $n_{TE} = n_{te} - (nlags + msteps - 1)$.

3.2.3 Transformation
Finally, data undergoes transformation and reshaping functions to comply with the LSTM input requirements. The outcome of this process are the 2-D and 3-D matrices summarized in Table 1. $X$ and $Y$ represent the LSTM input and output, respectively.

3.3 Hyperparameter Optimization
Even though hyperparameter optimization is a rather time consuming process, it can be key for achieving state-of-the-art performance and beyond. As human beings, we have a hard time to grasp, handle, and visualize multi-dimensional spaces, hence, manual hyperparameter tuning is often a rugged assignment. Notable hyperparameters examples include the HLs, neurons, Batch Size (BS), and Learning Rate (LR).

To the best of our knowledge, little research has been conducted to provide guidelines on the LSTM hyperparameter selection, since most studies focus on particular architectures and datasets [28]. Therefore, we are moving...
toward iterative based methods in an effort to improve the LSTM performance. In the following, we highlight the most popular hyperparameter optimization approaches.

- **Manual Search (MS).** Despite not being an optimization algorithm per definition, manual hyperparameter tuning is still possible in instances where prior knowledge about the system under study exists. MS is the least efficient option from the list since it is quite occasional and it usually requires extensive trial and error. On the positives, it is a very simplistic approach and involves minimum coding effort.

- **Grid Search (GS).** The brute force concept refers to the practice of trying out all possible solutions on the way to the global optimum. The equivalent algorithmic method within the context of hyperparameter optimization is known as GS. On the one hand, GS outperforms every optimization method in the market since it always tracks down the best solution. On the other hand, as the number of hyperparameters increases, it suffers from severe scalability issues. Additionally, it requires considerable computational resources, that even with a powerful computer, optimization can take days or even weeks. Due to the above, GS is not currently supported.

- **Random Search (RS).** Instead of evaluating all possible hyperparameter combinations, RS iterates over a smaller sample. As the number of iterations increase, the probability of converging to a better solution increases as well. The number of iterations required to reach to a good solution depends on several factors including the size of the hyperparameter space, search range, data complexity, and so forth. RS has a fairly simple implementation and does not require any scientific knowledge for the hyperparameters under study. In addition, it provides significant gains in terms of computational complexity, since it only tests a limited number of combinations, which is a safe approach under the assumption that non all hyperparameters are equally important. As a rule of thumb, there is a 95% chance that RS will reach to a good solution with only 60 iterations.

- **Bayesian Optimization (BOA).** A different alternative for complex and noisy objective functions is the BOA algorithm, a probabilistic approach that incorporates learning for hyperparameter optimization. BOA has its roots on the Bayes theorem which exploits the concept of conditional probability for making new predictions. Akin to RS, a number of iterations is required for converging to a good solution. Over the years, the popularity of BOA has increased, finding application to a wide range of problems including robotics, interactive animation, and Deep Learning (DL) related tasks.

Table 2 summarizes the available hyperparameters alongside their search range and a short description, while Table 3 references all remaining framework parameters.

### 3.4 LSTM Variants

Over the years, a number of LSTM variants have been proposed targeting to further improve the performance of particular applications. Besides the Vanilla LSTM implementation, HINDSIGHT++ enables the experimentation with Bidirectional LSTM, a variant that enables a duplicate LSTM sequence for traversing the network using opposite directions. In the following, we provide a short reference summary for each of the two variants.

- **Vanilla LSTM:** A few years after the inception of LSTM networks back in 1997, the memory blocks underwent slight modifications. Within a two-year period, Gers et. al. proposed the integration of forget gate and peephole connections. In addition, in [41], Graves et al. presented the full Backpropagation Through Time (BPTT) training which finalized the Vanilla LSTM design.

- **Bidirectional LSTM:** Following the concept of Bidirectional RNNs, Bidirectional LSTM networks introduce an additional hidden layer to process each sequence both in a forward and a backward direction, ultimately training two sequences at once. Bidirectional LSTM networks are known to outperform the Vanilla counterpart networks in tasks such as phoneme, speech and audio recognition, while, they were also recently proposed for network traffic forecasting.

### 4 Framework Validation

We organize the following content into three main parts. First, we provide an overview of HINDSIGHT++ technical and implementation details. Next, we discuss the training, validation, and testing process, while we outline the key LSTM parameters. Last, we present the available benchmarking options alongside a brief visualization description.

#### 4.1 Implementation and technical concerns

The code of HINDSIGHT++ is exclusively written in R and a proof of concept implementation is available in [8].
backbone is the CRAN interface to Keras, a high-level, user-friendly Application Programming Interface (API) which enables quick and dynamic experimentation with DL algorithms, while it further allows for easy neural network architectural prototyping. Keras is designed to run on top of multiple back-end environments, including Theano, CNTK, and TensorFlow (default). Furthermore, it offers the option for executing the code either on top of CPUs or GPUs.

4.2 Learning Process
Training of neural networks is an iterative process that involves identifying unique data properties and learning the model parameters. At each iteration, we track both training and validation error, which we use as bias and variance measures, or else, indicators of underfitting or overfitting. The validation set always reflects the last portion of the initial training set. We test the final model on an never-seen-before testing set and use the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as our error metrics.

In the following, we enlist the core training parameters.

- **Activation functions**: HINDSIGHT++ supports four activation functions, i.e., tanh, relu, known for its fast convergence [45], sigmoid, and softmax, primarily used for classification related tasks.
- **HLs**: We limit the number of HLs between zero and three. Research studies have shown that they are sufficient for achieving top-level performance in the majority of tasks.
- **Epochs**: The number of epochs define the number of forward and backward passes during the training process. The default search range for epochs ranges between 50 and 100.
- **BS**: The term BS refers to the number of samples to be propagated in the network. Lower values significantly increase the Running Time (RT) complexity, therefore, we restrain it between 8 and 128.
- **LR**: Last, the LR determines to what extent newly acquired information overrides old information [46, 47]. Its search range is between 0.00001 and 0.01.

In addition, we use the Adam gradient descent optimization algorithm throughout all our experiments. However, users can experiment with other options, including Stochastic Gradient Descent (SGD), Adagrad, and RmsProp.

4.3 Benchmarking and Visualization
We enable dedicated timers to allow tracking the end-to-end RT complexity with high precision. Such a feature is particularly critical during large-scale studies where the hyperparameter search space can be large. In addition, timers can be used for measuring the impact of HLs or neurons during training, GPU/CPU performance benchmarking, and many more. We further provide an automated solution for storing the final models in an .hd5f format.

Time series visualization can be used to highlight certain phenomena at glance, including periodic patterns or trends, extreme outliers, odd observations, abrupt changes over time, and so forth. Moreover, it allows for visual inspection of the developed models to assess how well they fit the datasets under study. A different color scheme is used to distinguish the training, validation, and testing set.

5 PERFORMANCE EVALUATION
At present time, 4G networks are considered the norm of wireless telecommunication systems sustaining a big portion of society’s global network functions. However, the recent advances in technology indicate that in the upcoming decade 5G will become the next big thing with several network operators already moving toward its adoption. Therefore, it is dire that we identify the principal network characteristics and trends between the two technology standards and show to what extent they dictate the performance of LSTM networks. In addition, our experiments aim to identify the potential gains of hyperparameter optimization in delivering more efficient and robust models. Next, we provide a description of the two datasets under study.

5.1 Datasets
We exploit 5Gophers [48, 49], the first open-source dataset that attempts to study the performance of 5G in commercial settings, featuring three operational operators (two mmWave and one mid-band carrier) in the US. 5Gophers allows for a wide range of analyses, including impact of mobility, handoffs, network operator performance, and many more. In this study, we focus on a single walking, and two driving traces (i.e., medium mobility between 20 to 50Km), since we are primarily interested in the mobility aspect. The walking trace comprises from both 4G and 5G readings, followed by additional features, such as cell and handover identifiers. The experimental setup under medium mobility features three SGS10 devices mounted on a vehicle’s front windshield and measuring the iPerf performance for three major operators in Atlanta, i.e., Sprint, T-Mobile, and Verizon. A bandwidth estimation measure is recorded every 120sec. All traces alongside the number of available samples are reported in Table 4.

| Trace | RT | RSvL | RSvB | BOAVL | samples |
|-------|----|------|------|-------|---------|
| SprintA | 9  | 16   | 52   | 120   |         |
| SprintB | 8  | 19   | 45   | 120   |         |
| VerizonA | 16 | 49   | 19   | 120   |         |
| VerizonB | 16 | 49   | 19   | 120   |         |
| Walking  | 37 | 29   | 58   | 603   |         |

TABLE 4: 5Gophers. i. Per trace RT complexity [in min] along the LSTM configurations under study, and ii. number of available samples.

We complement our study with NYU-METS [50], an open-source dataset that comprises of 4G LTE bandwidth measurements carried out in the New York University (NYU) metropolitan area. NYU-METS covers several transportation modes including bus, subway, and ferry. The experimental setup features an LTE-enabled mobile device and a remote server located at the NYU lab. Transmission Control Protocol (TCP) measurements are carried out using the iPerf cross-platform tool with a sampling rate of one second. Likewise, Table 5 lists the available bandwidth traces.

5. https://fivegophers.umn.edu/www20
6. We conducted an offline multivariate campaign to investigate whether the additional features have a positive impact in performance. Results revealed that the error improvement was insignificant. In addition, as expected, we observed a slight increase in the RT complexity.
In [30], Mei et al. introduce NYU-METS and conduct an LSTM related study for realtime bandwidth prediction in 4G networks. The authors exploit a simplified LSTM model that features two HLs for modeling the temporal behavior in each scenario. In addition, they adopt a walk-forward validation, or else, they are higher dispersed across the graph. In this regard, the average testing MAE improvement is around 64% with an average of 46% and testing (TE) sets.

At a glance, we observe that 5Gophers error show an ≈ 100-fold increase when compared to NYU-METS. This observation is in line with our expectations, considering the higher data rates that users experience in a 5G network environment (i.e., up to 1500Mbps, see Figure 5). Next, we follow up the results discussion per dataset.

NYU-METS: From Figure 3, we make the following observations. The operating points of all models associated with the same trace are visually overlapping, hence, creating a clear-cut number of clusters. This graph point distribution leads to a rather critical result. In particular, it shows that different hyperparameter optimization algorithms have similar LSTM performance across all 4G traces. We verify the significance difference between the models using Dunn’s non parametric pairwise test which outputs p-values > 0.95. We then quantify how much improvement hyperparameter optimization can bring compared to the selected hyperparameter MSVL which is optimized for 4G traces [30]. We observe testing MAE improvement up to 6.46% with an average of η ≈ 3.5%.

Furthermore, we observe that LSTM models operate on a low MAE region which is the result of the low-variance data rates experienced in 4G under mobility, thus restricting the room for vast performance improvement. Across the two dataset portions, we find that, in average, validation error is lower than testing error, which is the common scenario, since model tuning takes place in the former set. Last, Figure 5 illustrates the bandwidth time series graph of three NYU-METS traces [30]. Color is used for mapping the forecasting lines ((RSVL)) with the associated part of the trace, i.e., training, validation, and testing set. As evident, LSTM models follow the data trends along the traces with minimal error deviation.

5Gophers: As evident from Figure 4, LSTM models do not maintain the same clustering properties as in Figure 3 instead, they are higher dispersed across the graph. In particular, we observe that for each mobility trace, all MSVL configurations operate in a higher error region (i.e., upper right). In this regard, the average testing MAE improvement trends from different technology standards, mobility scenarios, and network operators holds. We annotate each configuration as $H_A$, where $H \in \{MS, RS, BOA\}$ represents the hyperparameter optimization algorithm and $A \in \{VL, BD\}$ denotes the LSTM variant. The number of iterations for both RS and BOA is set to 50, while we decide the final model using the MAE validation score.

### 5.3 Performance Analysis

Figures 5 and 6 portray the MAE versus RMSE for NYU-METS and 5Gophers, respectively. We use a diverging color palette and four point shapes to discriminate between the available traces configurations, respectively. Each individual point in the graph constitutes the model’s operating point. Since we study the performance from an error perspective, a good model operates on the bottom left area of the grid (and vice versa). We report results for both validation (VAL) and testing (TE) sets.

### 5.2 Experimental Setup

We outline the experimental setup which we divide into two parts. The first part establishes the baseline LSTM performance, while the second part investigates the performance gains of hyperparameter optimization.

**Setting the Baseline:** For the baseline experiments ($MSVL$), we adopt a stacked Vanilla architecture with two HLs and the model hyperparameters reported in [30] and illustrated in Table 2. Note that these hyperparameters were prior optimized (e.g., by means of sensitivity analysis or by using indicative values based on previous experience with datasets of similar nature) on the same dataset [30].

| Trace | RSVL | RSBD | BOAVL | samples |
|-------|------|------|-------|---------|
| 7TrainA | 66  | 120  | 90  | 4910   |
| 7TrainB | 50  | 84   | 69   | 3316   |
| Bus57  | 38  | 83   | 77   | 2403   |
| Bus62A | 39  | 74   | 82   | 3293   |
| Bus62B | 28  | 45   | 66   | 1452   |
| NTrain | 44  | 68   | 95   | 2404   |
| LI     | 28  | 52   | 72   | 1447   |

**Toward Performance Optimization:** We repeat the experimental campaign by enabling hyperparameter optimization while testing the available LSTM variants. Our goal is to test whether the hypothesis stating that a set of fixed model hyperparameters is sub-optimal for modelling

7. The number of epochs alongside BS are not reported in the paper, therefore, we set them to a predefined value.

8. Statistical confidence can be strengthened by increasing the number of iterations. However, this would significantly add to the RT overhead.

9. For this work, we exclude T-Mobile since the reported measurements contain a multitude of invalid readings.

10. We do not report all seven traces due to space considerations.
between $MS_{VL}$ and the remainder LSTM configurations for Sprint and Verizon is 49% (33% for SprintA and 65% for SprintB) and 26.5% (38% for VerizonA and 15% for VerizonB), respectively. In addition, the testing MAE improvement for the walking trace is also substantial (≈37%), which highlights the need for hyperparameter optimization even in lower mobility scenarios. These results clearly show that 5G has very different characteristics compared to 4G and the set of hyperparameters optimized for 4G cannot be directly used in 5G settings.

Furthermore, we compare the average performance between the two hyperparameter optimization algorithms. To provide a fair comparison and remove any undesired biases, we only account for $RS_{VL}$ and $BOA_{VL}$. We find that across all traces, including the walking trace, BOA provides a slight performance boost of ≈4%.

Next, we study the performance of Bidirectional LSTM networks to infer whether they bring any significant benefits.
to the bandwidth forecasting problem. Likewise, we compare \( RS_{VL} \) and \( RS_{BD} \) to remove the hyperparameter optimization bias. On the one hand, we find that Bidirectional LSTM networks outperform the Vanilla counterpart in two out of the four driving traces (i.e., SprintA and VerizonA) with an average testing MAE improvement of \( \approx 15\% \). On the other hand, however, they seem to be performing worse in the other two driving traces (i.e., SprintB and VerizonB) by an average testing MAE percentage of \( \approx 15\% \). This finding verifies the fact that bidirectional LSTM networks are very dependant on the respective dataset underlying characteristics. Therefore, the question of whether or not they are fitting for a given application can only be answered after systematic empirical analysis.

Tables 4 and 5 provide additional insights with respect to the RT complexity. In particular, each row reports the RT [min] per trace and across the available configurations. In average, we observe that \( RS_{BD} \) present a higher RT of \( \approx 54\% \) when compared to the \( RS_{VL} \). The above result is not balanced across the two datasets due to the randomness bias during the hyperparameter selection process. For example, instances of the algorithm where higher values for HLs or neurons are selected will require more computational power to accomplish. On the other hand, the average increase in RT between \( BOA_{VL} \) and \( RS_{VL} \) reaches to a percentage of \( \approx 154\% \), which can be attributed to the following. First, since BOA leverages the Bayes Theorem for minimizing the gradient descent error, it requires more time to reach to a good solution, opposed to RS which randomly scans the search space. And second, the BOA implementation is not optimized to run on top of a GPU, which adds to the RT overhead.

**Takeaways:** The hyperparameter optimization paradigm is critical for improving several performance aspects in LSTM networks. However, its significance is highly dependant on the underlying data attributes. For example, sequences that display large signs of variance over time are notably harder to predict, thus requiring hyperparameter configurations of high precision. On the contrary, sequences that either meet the stationarity test requirements or show consistent trends across time have limited gains, since most combinations of hyperparameters within the predefined search range will provide comparable performance.

For the bandwidth prediction task under study, therefore, we find that hyperparameter optimization is especially vital in 5G networks, since they introduce higher data rates and larger variations over time. Coupled with the mobility aspect, a suboptimal hyperparameter set will fail to capture the intrinsic network characteristics. Among the two available optimization solutions under study, we observe that BOA provides slightly better results, since it utilizes probability theory concepts for minimizing the error. We further observe that 4G networks offer significantly lower data rates with a lower variation factor which significantly diminishes the need for advanced hyperparameter optimization solutions.

### 5.4 Impact of hyperparameters

The current subsection discusses the hyperparameter selection process and investigates potential trends or patterns across the available traces and datasets. Figures 7 and 8 illustrate the selected hyperparameters along the selected NYU-METS traces and 5Gophers datasets, respectively. The edges of each radar plot map to the maximum search range values across the seven hyperparameters, while color is used to discriminate between each configuration.

Overall, it is evident that the selected LSTM models adopt disparate strategies for minimizing the gradient descent error function, a result that verifies the high degree of complexity in the neural network ecosystem. Next, we isolate a number of use cases per dataset in an effort to discover any hidden patterns or trends alongside the pool of hyperparameters.

**NYU-METS:** One of the most notable remarks across all available 4G traces is that none of the LSTM models utilize more than two HLs. This observation infers that the addition of a third HL would add excessive noise to the learning model rather than minimizing the predictive error. The average number of neurons per HL across all traces equals to 258 and 81 for HL-1 and HL-2, respectively. In addition, more than half of the models feature a LR that rests around the 0.001 region with an average value of 0.002, the average BS is 43, while the average number of epochs equals to 65, revealing a relatively early error saturation point. The above numbers that LSTM networks opt to stray away from extreme hyperparameter values in an attempt to regulate the variance bias tradeoff.

**5Gophers:** Exploring potential patterns across the 5G bandwidth measurements, we observe that in some scenarios the optimized LSTM models feature a third HL. Again, this is a rather expected result considering the higher data rates and variation in 5G in addition with the challenging bandwidth trends over time and under mobility. Likewise, the average number of neurons per HL across all layers equals to 197, 79, and 32 for HL-1, HL-2 and HL-3, respectively. We observe that the number of neurons per HL for both datasets follow a decreasing trend across the network, which also coincides with the neuron selection from authors in \([30]\) (i.e., HL-1=256 and HL-2=128). Additionally, the average LR and BS across all traces equal to 0.004 and 28, respectively, while the number of epochs averages 76, which is an \( \approx 17\% \) increase comparing to the 4G counterpart result hinting a slower gradient descent convergence.

**Takeaways:** The designated results reveal that hyperparameter optimization is crucial for achieving superior performance in 5G networks, while trading computational resources. The above finding is further reinforced by the reported model hyperparameters, which significantly vary across technology standards, mobility scenarios, and to some extent network operators. Across the two datasets, we find that 5G data require LSTM configurations with an increased number of HLs and epochs, while featuring significantly lower BS values, which further reveals the challenging network conditions in such scenarios.

### 5.5 Challenges and Limitations

We further report a list of limitations and challenges that should be considered moving forward. First, the number of iterations for both hyperparameter algorithms is set to a constant value, i.e., 50 in both cases. This decision was
made after closely observing the fast saturation rate of the gradient descent error. However, we argue that future 5G applications may require a higher number of iterations to converge to a good solution, although, this would result to a substantial increase of the RT complexity. Second, the hyperparameter search range can be stretched to accommodate a higher pool of values, which could potentially add to the performance. The selected values were decided as a compromise to the performance versus RT complexity tradeoff. Last, both datasets are composed of traces with a limited number of samples which can have a negative effect on the LSTM performance since they are known to perform
6 Conclusions and Future Work

In this paper, we studied the challenging task of bandwidth forecasting in next-generation MBB networks under mobility. To ease our goal, we designed HINDSIGHT++, an open-source R-based framework that allows for LSTM experimentation in time series data. We specifically focused on the hyperparameter optimization aspect which is critical for achieving state-of-the-performance. We analysed and performed a comparative analysis between two open-source datasets of bandwidth measurements in operational 4G and 5G networks, respectively, aiming to quantify the LSTM performance improvement under different configuration setups. Results show that hyperparameter optimization provides significant benefits under 5G settings compared to 4G settings and the optimal parameters for 4G cannot be directly applied considering the substantially higher data rates and variation over time that users experience in 5G network conditions. As for the future, we plan on integrating feature selection algorithms, additional LSTM variants (e.g., Convolutional Neural Networks (CNN) LSTM and multiplicative LSTM), and provide support for supervised classification tasks. Furthermore, we will carry out a dedicated measurement campaign to collect additional network features (e.g., signal strength, latency, etc.). Using the new data, we aim to explore potential correlation or causation relationships and show whether or not they bring any significant gains to the LSTM performance.

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