Federated traffic prediction for 5G and beyond

An introduction to a problem statement for the ITU AI Challenge

Centre Tecnològic de
Telecomunicacions de Catalunya

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About us

Paolo Dini
(RU leader)

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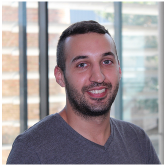

Francesc Wilhelmi
(Researcher)

- Sustainable AI (SAI) research unit
  - Multidisciplinary team: data/computer science, energy, communications
  - Main areas: edge intelligence, sustainable comp., MLops
  - Supercom initiative

Our office!

Previous Experience in Organizing a PS

- 2020 & 2021 editions[a]
  - Channel Bonding (CB) WLANs
  - Spatial Reuse in IEEE 802.11ax WLANs
- Webinars, hands-on, personal feedback...
- Joint contributions (ITU Journal)

[a] All the details can be found at **https://www.upf.edu/web/wnrg/ai_challenge**

MACHINE LEARNING FOR PERFORMANCE PREDICTION OF CHANNEL BONDING IN NEXT-GENERATION IEEE 802.11 WLANS

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Abstract – *With the advent of Artificial Intelligence (AI)-empowered communications, industry, academia, and standardization organizations are progressing on the definition of mechanisms and procedures to address the increasing complexity of future 5G and beyond communications. In this context, the International Telecommunication Union (ITU) organized the first AI for 5G Challenge to bring industry and academia together to introduce and solve representative problems related to the application of Machine Learning (ML) to networks. In this paper, we present the results gathered from Problem Statement 13 (PS-013), organized by Universitat Pompeu Fabra (UPF), which primary goal was predicting the performance of next-generation Wireless Local Area Networks (WLANs) applying Channel Bonding (CB) techniques. In particular, we overview the ML models proposed by participants (including Artificial Neural Networks, Graph Neural Networks, Random Forest regression, and gradient boosting) and analyze their performance on an open dataset generated using the IEEE 802.11ax-oriented Komondor network simulator. The accuracy achieved by the proposed methods demonstrates the suitability of ML for predicting the performance of WLANs. Moreover, we discuss the importance of abstracting WLAN interactions to achieve better results, and we argue that there is certainly room for improvement in throughput prediction through ML.*

Keywords – channel bonding, IEEE 802.11 WLAN, ITU Challenge, network simulator, machine learning

1. INTRODUCTION

The utilization of Artificial Intelligence (AI) and Machine Learning (ML) techniques is gaining momentum to address the challenges posed by next-generation wireless theless, the adoption of AI/ML in networks is still in its initial phase, and a lot of work needs to be done. In this regard, standardization organizations are undertaking significant efforts towards fully intelligent networks. An outstanding example can be found in the Interna-

FEDERATED LEARNING FOR SPATIAL REUSE OPTIMIZATION IN FUTURE IEEE 802.11 WLANS

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Abstract – *As wireless standards evolve, more complex functionalities are introduced to address the increasing requirements in terms of throughput, latency, security, or efficiency. To unleash the potential of such new features, Artificial Intelligence (AI) and Machine Learning (ML) are currently being exploited for deriving models and protocols from data, rather than by hand-programming. In this paper, we explore the feasibility of applying ML in next-generation IEEE Wireless Local Area Networks (WLANs). More specifically, we focus on the IEEE 802.11ax Spatial Reuse (SR) problem and predict its performance through Federated Learning (FL) models. The set of FL solutions overviewed in this work is part of the 2021 International Telecommunication Union (ITU) AI for 5G Challenge.*

Keywords – Federated learning, IEEE 802.11ax, ITU Challenge 2021, machine learning, network simulator, spatial reuse

1. INTRODUCTION

Wireless networks are evolving towards Artificial Intelligence (AI) / Machine Learning (ML)-driven systems able to address the overwhelming requirements of future mobile communications [1, 2], namely the fifth generation (5G) and Beyond 5G (B5G). The application of ML for networking can be found at different communication layers ent fields, such as medicine [8], autonomous driving [9], UAV-based wireless networks [10]. FL has become a suitable paradigm to foster collaboration among different parties interested in solving a common problem. Under the management of a central server (typically, a neutral entity), FL participants contribute to building a general ML model, each one using local data, by sharing model weights, rather than raw training data.

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The Problem of Traffic Prediction

Traffic prediction

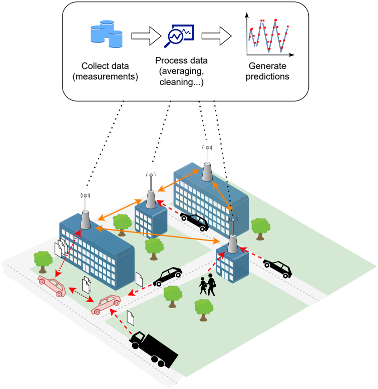
- Key in modern communications systems
- Useful for planning, optimization, management...

Problems

- Requirements: edge data has to be transmitted to central servers
- Implications in security (leaks), efficiency (high costs for transmission), and communication (big overheads)

Novel trends

- MEC: edge intelligence, distributed learning, transfer learning...
- **Federated Learning (our focus)**



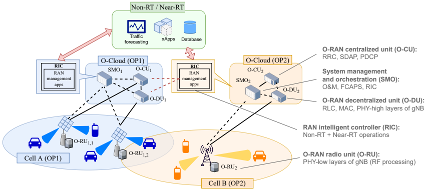
Traffic Prediction & ML

Classical ML

- Autoregressive Integrated Moving Average (ARIMA), Random Forests (RF), logistic regression, K-Nearest Neighbor (KNN), Support Vector Regression (SVR)...
- **Problem:** fail at capturing complex interactions (seasonality, irregular patterns)

Suitable DL methods

- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)
- Long Short-Term Memory units (LSTMs)



- Popular application for intelligent controllers (e.g., RIC in O-RAN)
- Used for traffic steering, slice SLA assurance, resource allocation, QoE/QoS optimization, dynamic handover...

Jiang, W. (2022). Cellular traffic prediction with machine learning: A survey. Expert Systems with Applications, 117163.

Outline

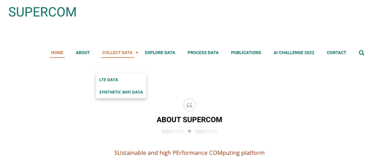
The Supercom Initiative

Supercom

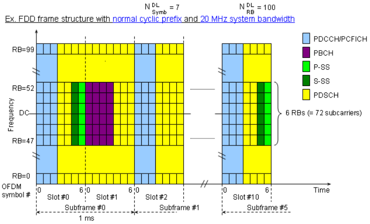
- SUstainable and high PErformance COMputing platform:
  - Data collection
  - Data exploration
  - Data processing

LTE/PHY measurements

- OWL framework [BW16]
- Downlink Control Information (DCI) messages
- Features: RNTI, MCS, RBs per frame...



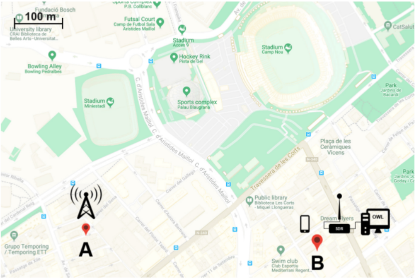
www.supercom.cttc.es



Source: *ShareTechnote*

Data Collection Campaigns at Supercom

- Cell sites in the metropolitan area of Barcelona
- Two main outputs:
    - Labeled (YouTube, Vimeo, Spotify...)
    - **Unlabeled (our focus)**
- Datasets oriented to academic & research purposes



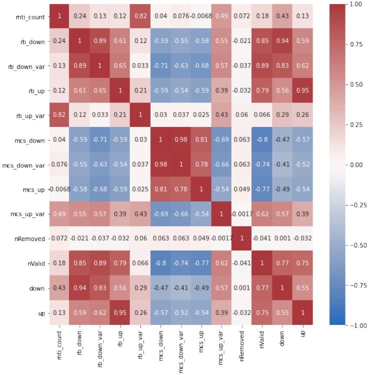
Data measurement campaign in Les Corts, Barcelona

Not Just Data

Supercom provides:

- Datasets
- Baseline ML models
- Data processing
- Data visualization
- Explainability (XAI) tools

→ Understand data & ML models

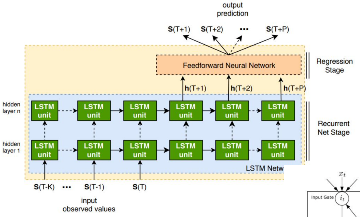


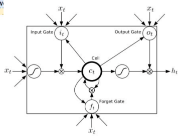
Previous Work at Supercom

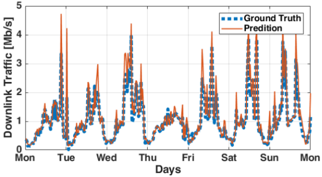
- Analysis & modeling [TBW+17]
- Traffic prediction [TGD18]
- Identification of patterns [RPT+19]
- Anomaly detection [TGD19]
- Traffic classification [TGG+20]
- Multi-task learning [RPBD20]

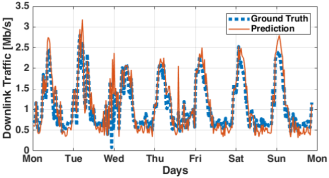
Traffic Prediction through LSTMs

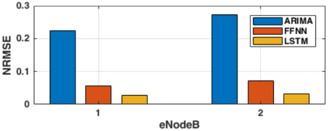
- LSTM are a kind of RNN
- Avoid long-term dependency (address vanishing-gradient)
- More details in [TGD18]...
- ... comparison with ARIMA, FFNN











Outline

Federated Learning

Google AI Blog

The latest news from Google AI

Federated Learning: Collaborative Machine Learning without Centralized Training Data

Thursday, April 6, 2017

Posted by Brendan McMahan and Daniel Ramage, Research Scientists

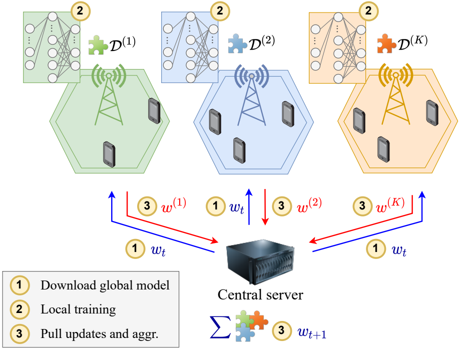
Standard machine learning approaches require centralizing the training data on one machine or in a datacenter. And Google has built one of the most secure and robust cloud infrastructures for processing this data to make our services better. Now for models trained from user interaction with mobile devices, we're introducing an additional approach: *Federated Learning*.

Federated Learning

- Introduced by Google
- Decentralized data distribution
- Some features:
  - Specialized training
  - High scalability
  - Fault-tolerant
  - Privacy

https://ai.googleblog.com/2017/04/federated-learning-collaborative.html

Federated Learning for Traffic Prediction



Goal

Generate a model able to predict $K+1, \ldots, K+n$ data points with K observations

FL procedure

1. Publish an initial global model w_0
2. Clients train on local data and submit local updates
3. Update the global model

Evaluation

Normalized Root Mean Square Error (NRMSE):

$$NRMSE = \frac{1}{\bar{x}} \sqrt{\frac{\sum_{t=1}^{N} (\hat{x}_t - x_t)^2}{N}}$$

Federated Learning Frameworks

TensorFlow Federated (TFF)

1. Framework for simulating FL
2. Ready-to-use
3. High-level (Federated Learning) and low-level (Federated Core) APIs

Pytorch

1. Custom implementation
2. PySyft
3. More deployment flexibility

```
import tensorflow as tf
import tensorflow_federated as tff

# Load simulation data.
source, _ = tff.simulation.datasets.emnist.load_data()
def client_data(n):
  return source.create_tf_dataset_for_client(source.client_ids[n]).map(
      lambda e: (tf.reshape(e['pixels'], [-1]), e['label'])
  ).repeat(10).batch(20)

# Pick a subset of client devices to participate in training.
train_data = [client_data(n) for n in range(3)]

# Wrap a Keras model for use with TFF.
def model_fn():
  model = tf.keras.models.Sequential([
      tf.keras.layers.Dense(10, tf.nn.softmax, input_shape=(784,),
                            kernel_initializer='zeros')
  ])
  return tff.learning.from_keras_model(
      model,
      input_spec=train_data[0].element_spec,
      loss=tf.keras.losses.SparseCategoricalCrossentropy(),
      metrics=[tf.keras.metrics.SparseCategoricalAccuracy()])

# Simulate a few rounds of training with the selected client devices.
trainer = tff.learning.build_federated_averaging_process(
  model_fn,
  client_optimizer_fn=lambda: tf.keras.optimizers.SGD(0.1))
state = trainer.initialize()
for _ in range(5):
  state, metrics = trainer.next(state, train_data)
  print(metrics['train']['loss'])
```

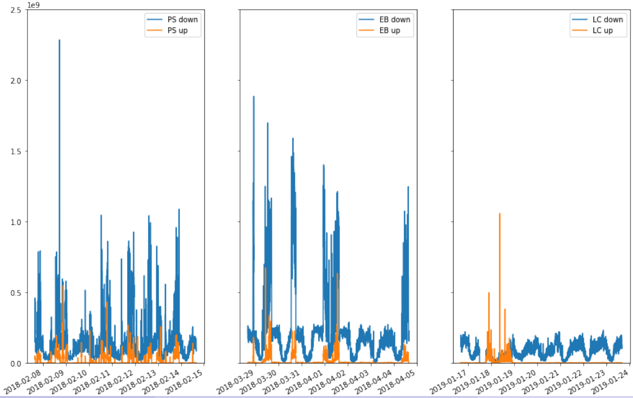
www.tensorflow.org

The Dataset (I)

1. [PS] Poble Sec (28 days)
2. [EB] El Born (7 days)
3. [LC] Les Corts (12 days)

$\Longleftrightarrow$

- 19909 + 5421 + 8615 samples in total
- Features are averaged every 120 seconds



The Dataset (II)

	rnti_count	rb_down	rb_down_var	rb_up	rb_up_var	mcs_down	mcs_down_var	mcs_up	mcs_up_var
2019-01-12 17:10:39	25	0.01231	2.143120e-08	0.00058	8.246154e-11	3.604651	69.747743	3.884615	22.906154
2019-01-12 17:10:40	23	0.01260	2.667215e-08	0.00031	6.666667e-12	4.050000	76.225316	2.933333	13.066667
2019-01-12 17:10:41	23	0.01064	2.160321e-08	0.00033	6.250000e-12	3.571429	67.741824	2.875000	12.250000
2019-01-12 17:10:42	17	0.00938	1.529747e-08	0.00013	1.666667e-11	2.894737	59.802105	4.333333	32.666667
2019-01-12 17:10:43	29	0.01359	3.007487e-08	0.00025	4.469697e-11	4.674419	77.304514	9.500000	88.272727

Problem Statement: Goals & Next Steps

Procedure

1. We will publish a dataset with LTE measurements
   - 3 Base Station (BS) locations
   - Features: RNTI, MCS up/down, RB up/down
   - Label: Up/down
   - Train vs Test datasets
2. Participants will design an FL model for traffic forecasting
3. The solution will be evaluated in a test dataset (with different measurements)

All the info will be found at `https://supercom.cttc.es/index.php/ai-challenge-2022`


STAY
TUNED

Questions

?

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