Unleashing the potential of machine learning to address spatial reuse in future IEEE 802.11 WLANs

An introduction to two problem statements for the ITU AI Challenge

Universitat Pompeu Fabra Barcelona

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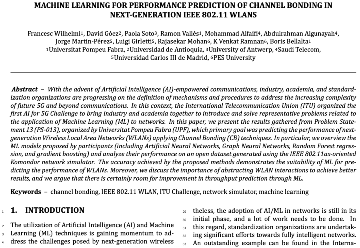
5 May 2021

2020 Edition

- Performance prediction of Channel Bonding (CB) WLANs[a]
- 5 teams, 3 finalists (students + professionals), 1 runner-up prize
- Webinars, hands-on, personal feedback...
- Joint contribution (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-

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1. Spatial Reuse
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Spatial Reuse in a nutshell

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Methods to address density in wireless networks

- **Time:** scheduling, medium access adaptation
- **Frequency:** Dynamic spectrum access, Dynamic channel bonding
- **Space:** Directional transmissions, Interference cancellation, *Transmit power control*, *Sensitivity adjustment*

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Network's goals

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- Improve efficiency
- More parallel transmissions

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Network's goals

- Increase spectrum utilization
- Improve efficiency
- More parallel transmissions

User's goals

- Increase transmission opportunities (TXOPs)
- Improve throughput
- Reduce delay

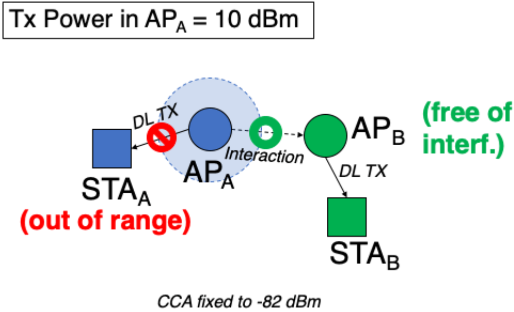
The CCA threshold

CSMA/CA Operation

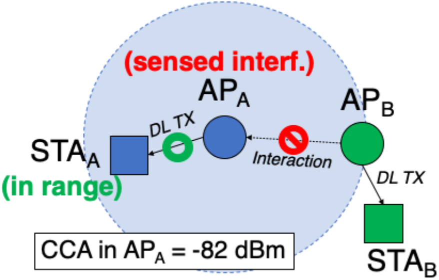
- Implement decreasing random backoff before transmitting
- Perform physical carrier sensing to assess whether the medium is busy or not
- Apply CCA mechanism:
  1. Check signal source (Wi-Fi or non-Wi-Fi)
  2. Apply threshold (e.g., -82 dBm)

For simplicity, we use the CCA as the unique threshold for detecting the channel busy/idle.

Effects of tuning the transmit power



Effects of tuning sensitivity



Tx Power fixed to 20 dBm

Spatial Reuse in IEEE 802.11ax

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- Two mechanisms:
  1. *OBSS/PD-based SR*
  2. *Parametrized SR*
- Common features: fast source identification, sensitivity adjustment, tx power limitation

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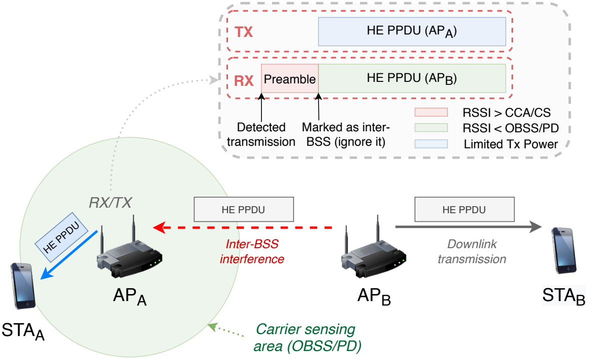

Spatial Reuse in IEEE 802.11be

Spatial Reuse in IEEE 802.11be

- Multi-AP coordination [Jas19]
- Exchange information and coordinate **simultaneous** Tx
- Two main proposals for IEEE 802.11be:
  1. **Coordinated SR (CSR)**
  2. PSR with beamforming/null steering

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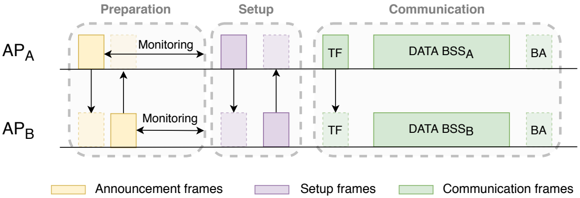

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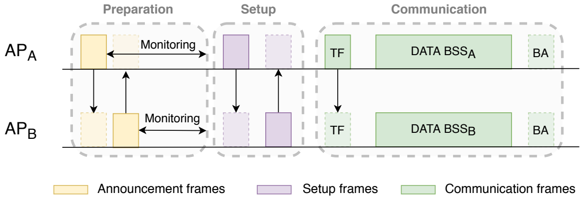
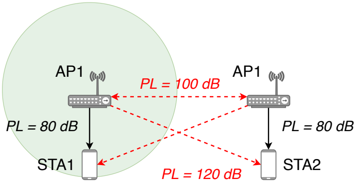


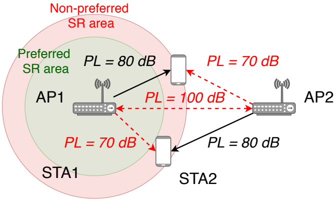
Open discussion points: extension to UL, measurement phase, role of OFDMA, optimization goals...

Some results - Toy scenario

(1)



(2)



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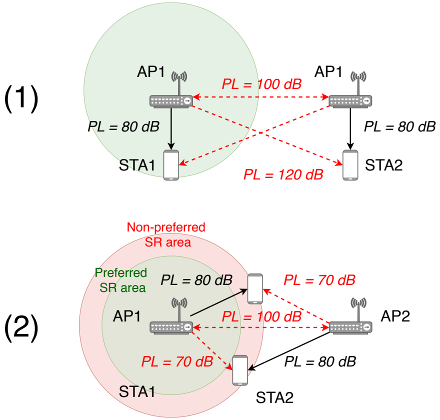
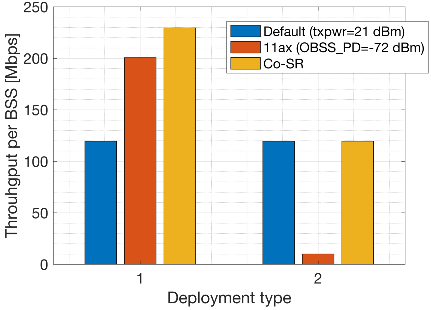
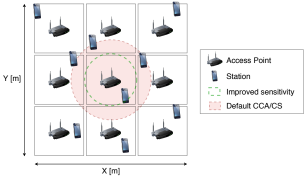


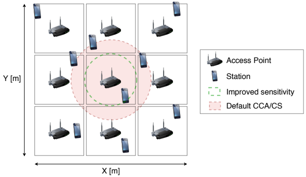


Some results - Dense scenario



- Random deployment
- Focus on BSS_A
- Analyze the impact of applying SR

Some results - Dense scenario



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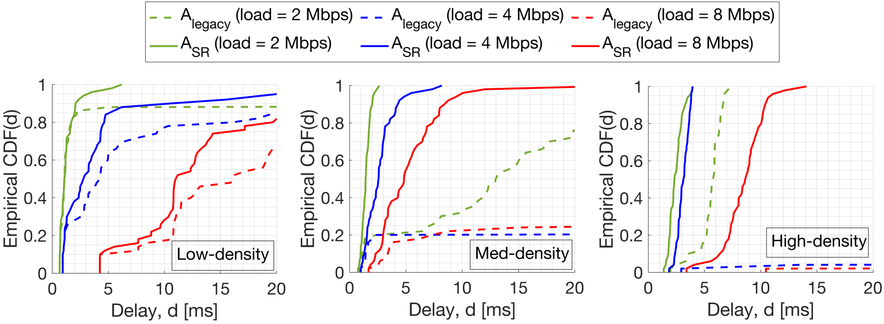

Outline

The emergence of AI for communications

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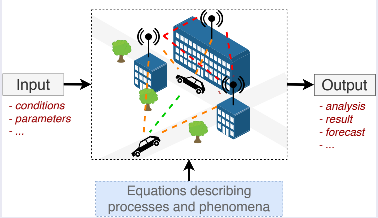
Model-based

- Hand-crafted solution
- Accuracy vs tractability
- Generalization



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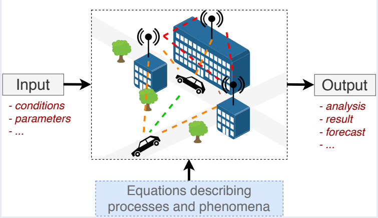
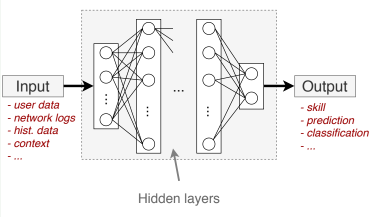


Data-driven

- Learn from data
- Address complexity
- Adaptability



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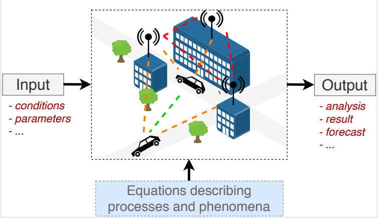

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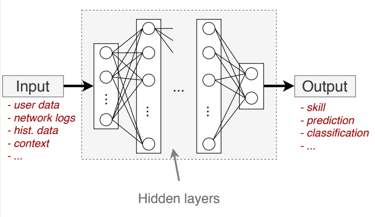
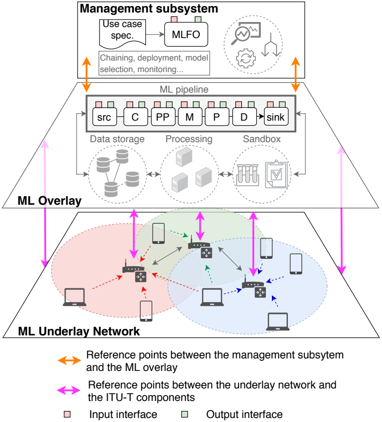


Enablers for adoption:

- Infrastructure (architecture, capacity, data)
- Reliability and trustworthiness

Machine-learning-aware communications



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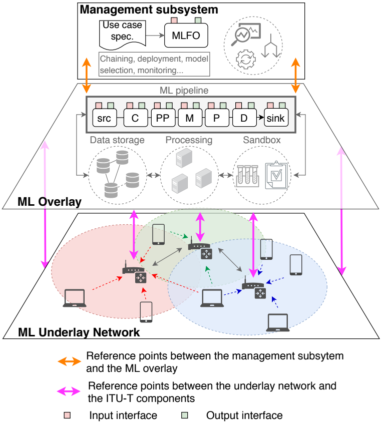
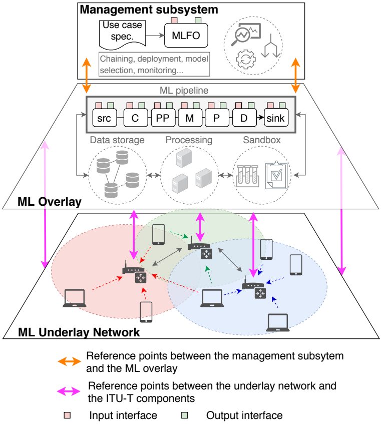


Architectural aspects

- Framework in ITU-T Y.3172 recommendation [ITU19]
- Flexibility required in WLANs

Machine-learning-aware communications



Architectural aspects

- Framework in ITU-T Y.3172 recommendation [ITU19]
- Flexibility required in WLANs

Reliability & Trustworthiness

- ML Sandbox
- Test, train, and evaluate ML models
- **Simulators in closed-loop ML-based optimization**

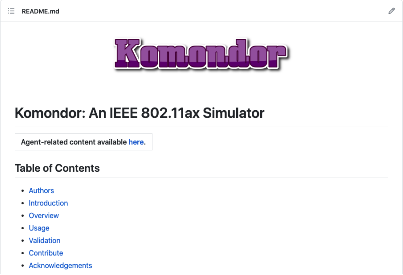
Generating synthetic training datasets

The Komondor simulator

- IEEE 802.11ax-oriented discrete-event simulator
- Fast performance & ML

Usage

- Simulate OBSS/PD-based SR
- Large-scale deployments
- Complete datasets hard to get from measurements


README.md

Komondor

Komondor: An IEEE 802.11ax Simulator

Agent-related content available here.

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Open-source project: `https://github.com/wn-upf/Komondor`

Outline

Federated Learning for SR in a multi-BSS scenario (I)


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

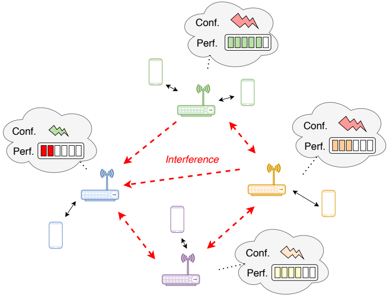
Standard machine learning approaches require centralizing the training data on one machine or in a datacenter. And Google has built one of the most secure and robust cloud infrastructures for processing this data to make our services better. Now for models trained from user interaction with mobile devices,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

Federated Learning

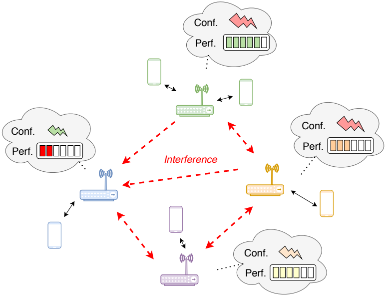
- Introduced by Google
- Decentralized data distribution
- Some features:
  - Specialized training
  - High scalability
  - Fault-tolerant
  - Privacy

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

Federated Learning for SR in a multi-BSS scenario (II)



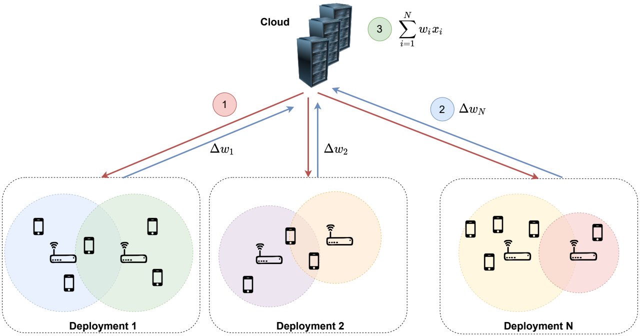
Federated Learning for SR in a multi-BSS scenario (II)



Motivation

- Distributed nature of WLANs
- Complexity of SR
- Split a big problem into sub-problems
- Personalized models

Federated Learning for SR in a multi-BSS scenario (III)



Procedure

1. Publish initial ML model (e.g., SGD)
2. Generate and submit local updates
3. Update the general model

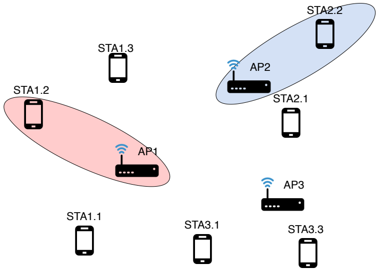
Federated Learning for SR in a multi-BSS scenario (IV)

Next steps

1. We will publish a dataset on 11ax SR
   - Multiple random deployments
   - Features: OBSS/PD-based threshold, transmit power, interference...
   - Label: throughput / delay
2. We will provide a general model as baseline
3. Participants need to (propose) train a FL model
   - Improve general model
   - Specialize model in each deployment
4. The solution will be evaluated in a test dataset

Outline

ML for finding groups of BSSs suitable for C-SR (I)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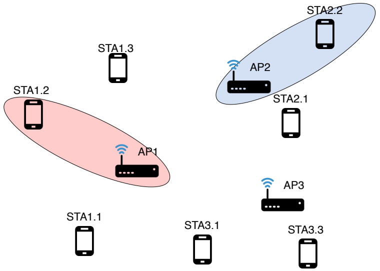

Goal

- Find best sets of devices for transmitting concurrently
- Adjust transmit power accordingly
- ML approach (clustering)

ML for finding groups of BSSs suitable for C-SR (II)

Next steps

1. We will publish a dataset on 11be C-SR
   - Multiple random deployments
   - Multiple sets of transmissions
   - Features: transmitting nodes, transmit power, interference...
   - Label: throughput / delay
2. Participants need to propose and train an ML model
3. The solution will be evaluated in a test dataset

Questions

?

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References I

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