Multi-Layer Perceptron for OBSS throughput prediction

Improving the capacity of IEEE 802.11 WLANs through ML
ITU-ML5G-PS-013

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About me

Ramon
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- Barcelona, Spain
- UPF student
- Undergraduate in computer science
- Interests in AI-ML in computer security

Problem description

Scenario

- Channel Bonding (aimed at next-generation WLANs).
- Complexity:
  - Distributed nature of WiFi.
  - Massively crowded scenarios.
  - High variability.
  - Spatial interactions among devices.

Goal

- Predict the performance of an Overlapping Basic Service Set (OBSS) throughput.
- Multilayer Perceptron (MLP)

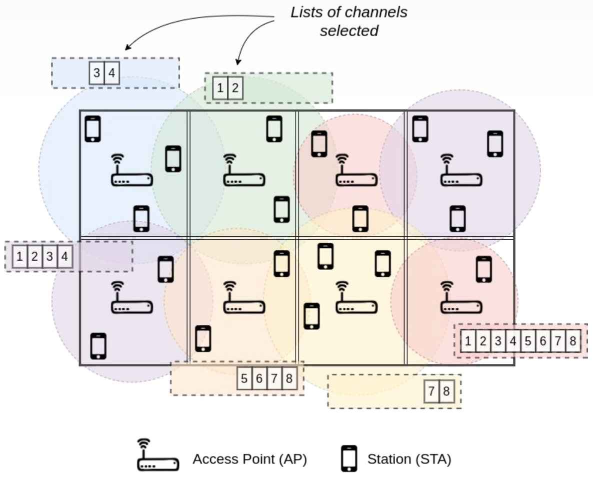
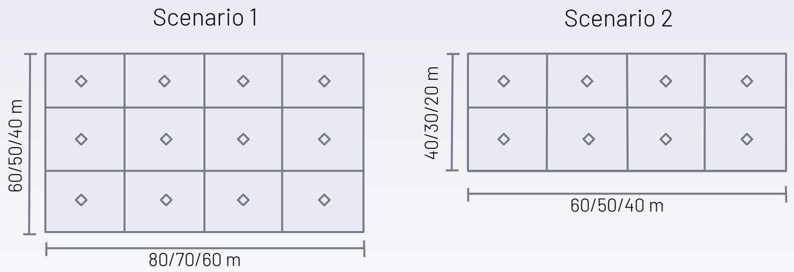
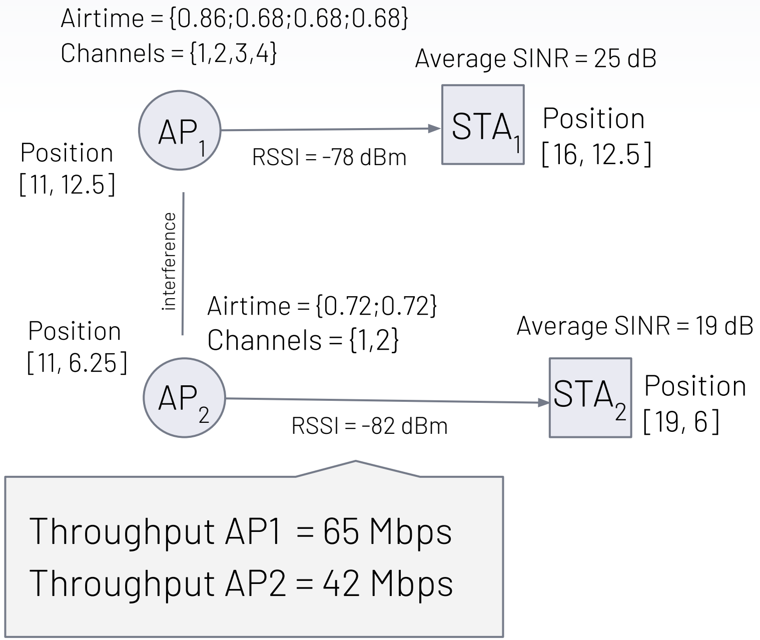


Illustration of an OBBS (provided by the Host)
https://www.upf.edu/web/wnrg/ai_challenge

Dataset

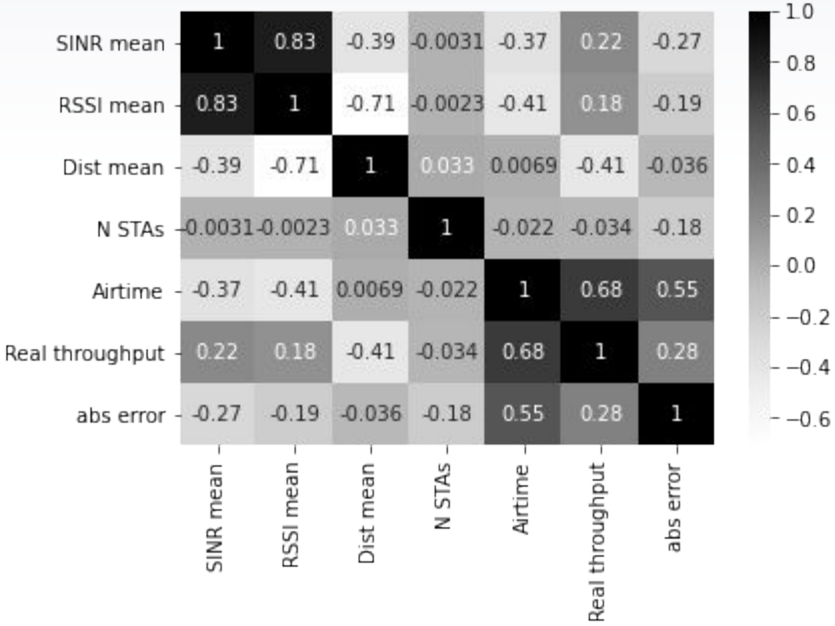
- Scenario 1 (12 APs, 10-20 STAs):
    - Scenario 1a (map size = 80 x 60 m): 100 random deployments
    - Scenario 1b (map size = 70 x 50 m): 100 random deployments
    - Scenario 1c (map size = 60 x 40 m): 100 random deployments
- Scenario 2 (8 APs, 5-10 STAs):
    - Scenario 2a (map size = 60 x 40 m): 100 random deployments
    - Scenario 2b (map size = 50 x 30 m): 100 random deployments
    - Scenario 2c (map size = 40 x 20 m): 100 random deployments



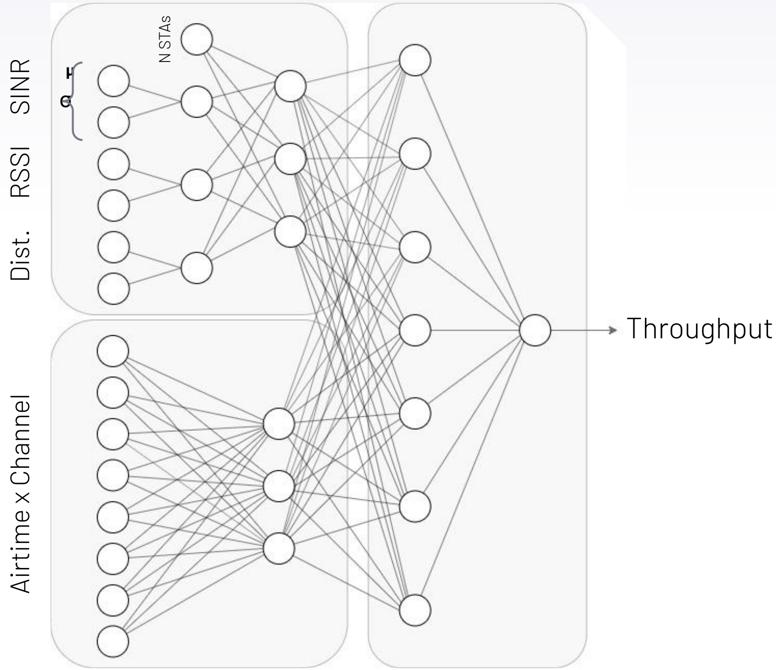


Analyzing Data

- Relevant data:
  - Received signal strength indicator (RSSI)
  - Signal-to-interference-plus-noise ratio (SINR)
  - Spatial coordinates
  - Number of Stations
  - Min and Max available channels (Bandwidth)
  - Airtime x Channel



Proposed Model: MLP



Block 1: Radio signal

- ❖ RSSI (μ,σ)
- ❖ SINR (μ,σ)
- ❖ Distance (μ,σ)
- ❖ N Stas

Structure:
2 hidden Layers + BatchNorm

Activation:
PReLU

Block 2: Airtime

- ❖ Channel 0
- ❖ Channel 1
- ❖ Channel ...
- ❖ Channel 7

Structure:
1 hidden Layer (input + 1)

Activation:
PReLU

Block 3: Throughput

Structure:
1 hidden Layer + output

Activation:
1st Layer: PReLU
+
2nd Layer: ReLU

The code of the proposed model is publicly available in https://github.com/VPRamon/MLP-Throughput-prediction

Training

Epochs	LR	Training loss	Validation loss
700	1E-2	13.14	13.25
500	1E-2	13.10	14.21
700	**2E-2**	**12.69**	**12.96**
500	2E-2	13.77	13.86
700	4E-2	13.15	13.48
500	4E-2	12.84	14.70

Criterion:

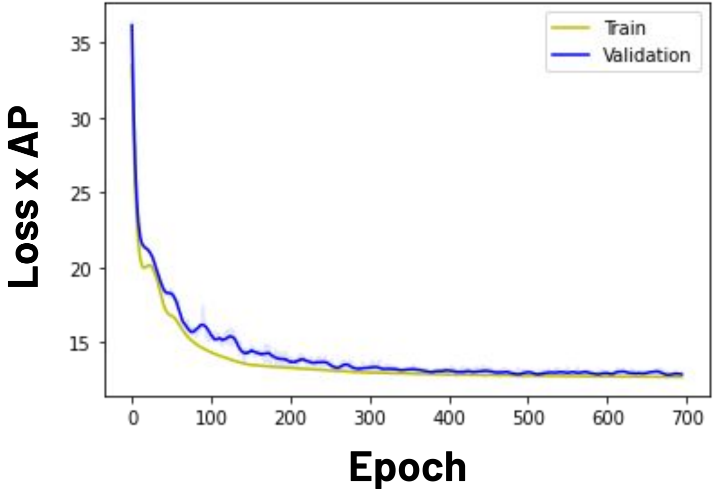
$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Optimizer:

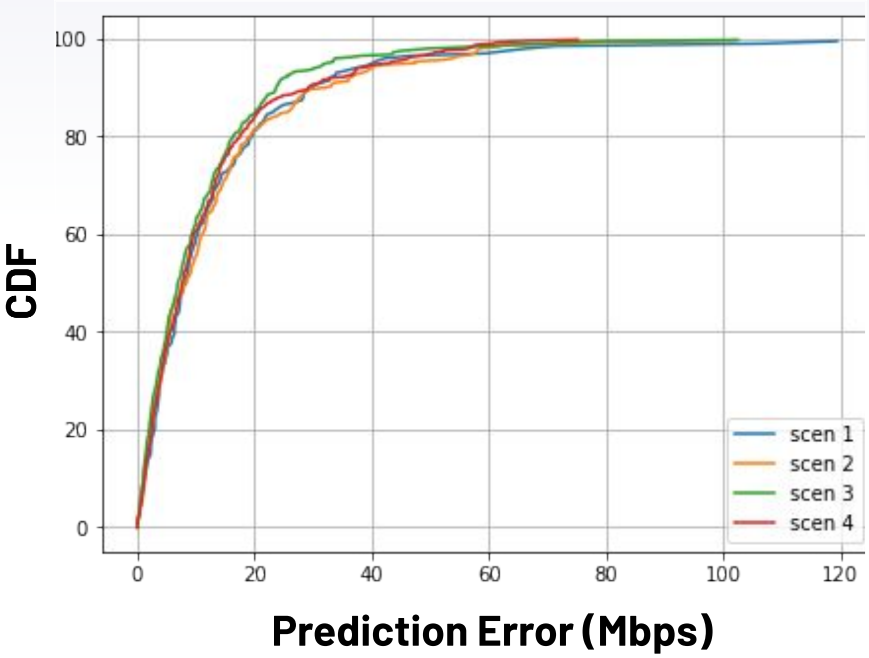
Adaptive moment estimation (Adam)

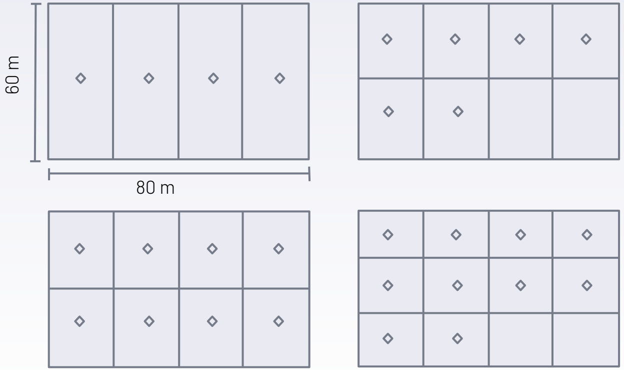
Training: 80%

Validation: 20%



Testing





Map size: 80x60m

Scenario 1 (4 APs) RMSE: 21.12 Mbps

Scenario 2 (6 APs) RMSE: 19.18 Mbps

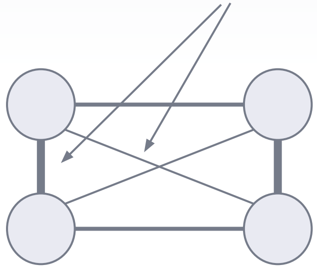
Scenario 3 (8 APs) RMSE: 15.92 Mbps

Scenario 4 (10 APs) RMSE: 17.38 Mbps

Conclusions

- Solution enabled by **Y.3172** [1]
- Usage of synthetic datasets for training ML models in a Sandbox [2]
- Further improvements (GNN)
  - Capture fine-grained inter-device interference details
  - APs receive different amount of interference
  - Neighbour with high interference → Freer Bandwidth → Better performance
- Very entertaining challenge.

More interference
=
More Contention



[1] Wilhelmi, Francesc, et al. "A flexible machine-learning-aware architecture for future WLANs." IEEE Communications Magazine 58.3 (2020): 25-31.
[2] Wilhelmi, Francesc, et al. "Usage of Network Simulators in Machine-Learning-Assisted 5G/6G Networks." *arXiv preprint arXiv:2005.08281* (2020).

Resources

- https://www.upf.edu/web/wnrg/ai_challenge
- https://zenodo.org/record/4059189
- https://github.com/VPRamon/MLP-Throughput-prediction

Thank you !

Questions?

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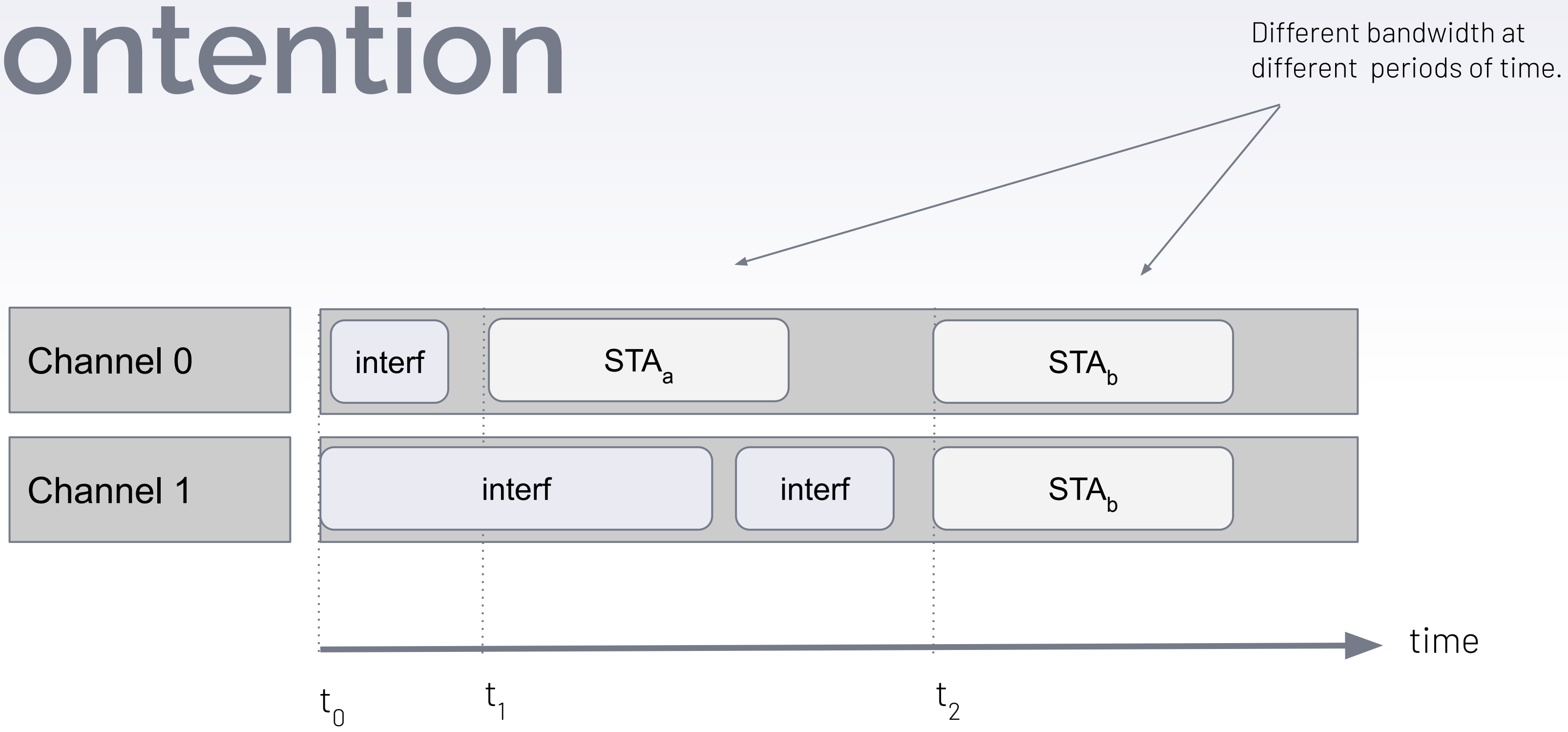
Contention



Different bandwidth at
different periods of time.
Channel 0
Channel 1
interf
STA$_a$
STA$_b$
interf
interf
STA$_b$
time
t_0
t_1
t_2