Imperial College London

ITU AI/ML in 5G Challenge

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NN-Based mmWave Beam-Selection Utilizing LIDAR Data

Imperial_IPC1 Team

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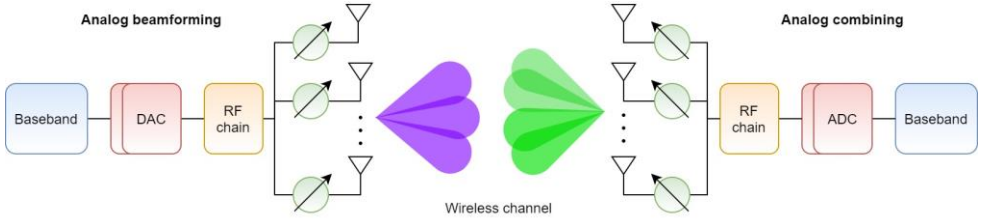
Imperial College London

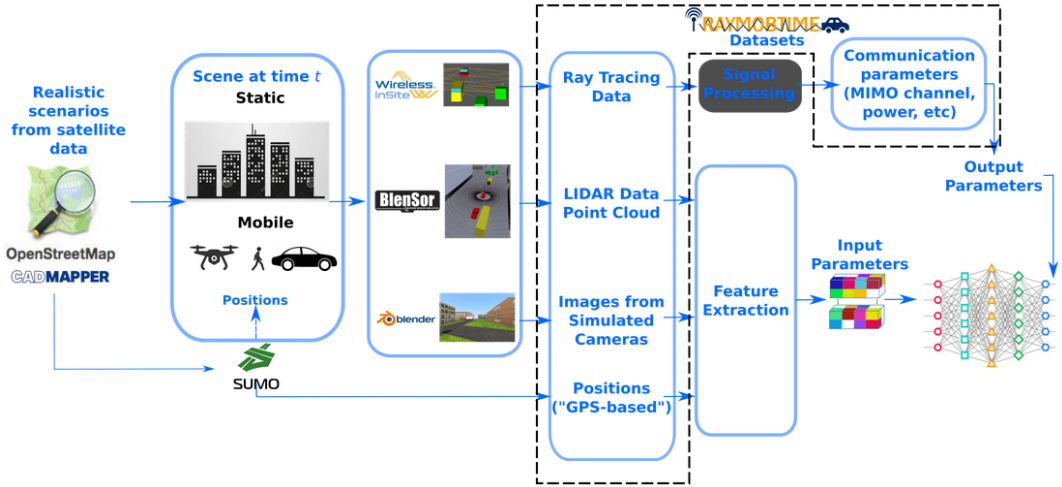
mm-Wave Beam Selection



- Very challenging due to pointy beams
- Of interest for both research and standards (e.g. IEEE 802.11 ad/ay [1], [2])

[1] https://www.ieee802.org/11/Reports/tgay_update.htm
[2] 1.11-14/0606r0, “Next Generation 802.11ad: 30+ Gbps WLAN”

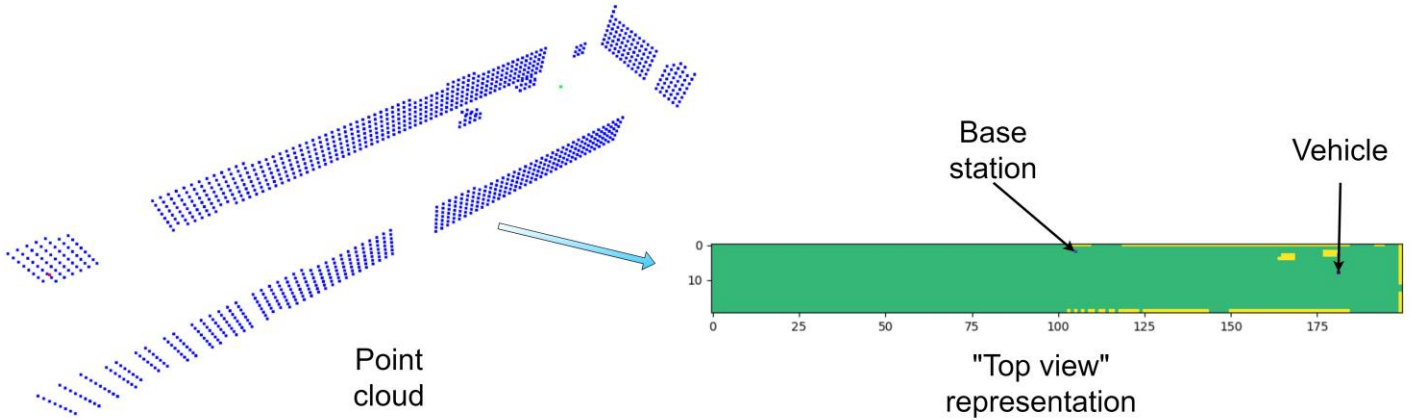
NN-based mm-Wave Beam Selection



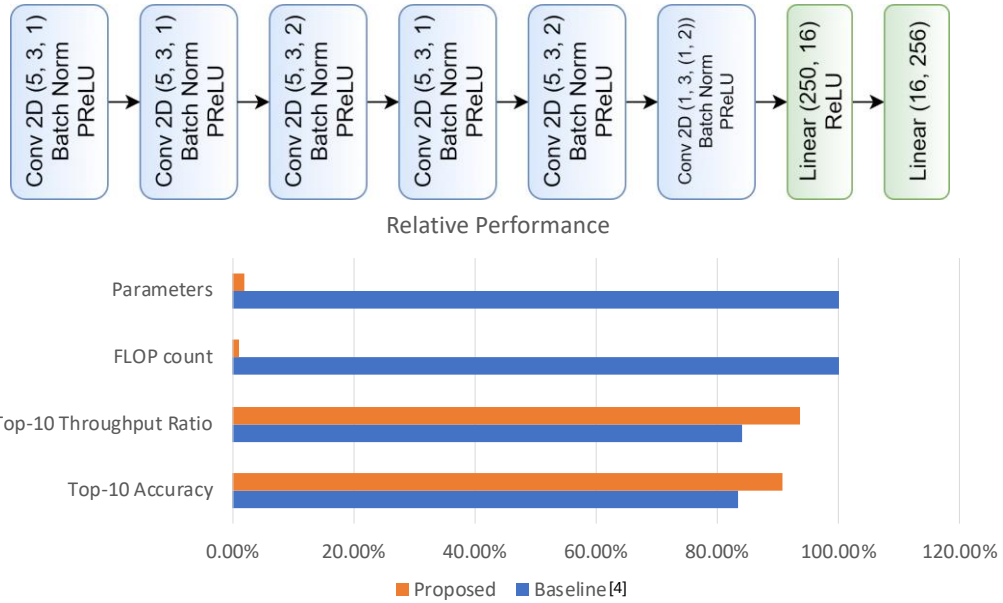
- We combine and use LIDAR and location data

[3] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang and R. W. Heath Jr., “5G MIMO Data for Machine Learning: Application to Beam-Selection using Deep Learning” in *2018 Information Theory and Applications Workshop (ITA)*

Data preprocessing



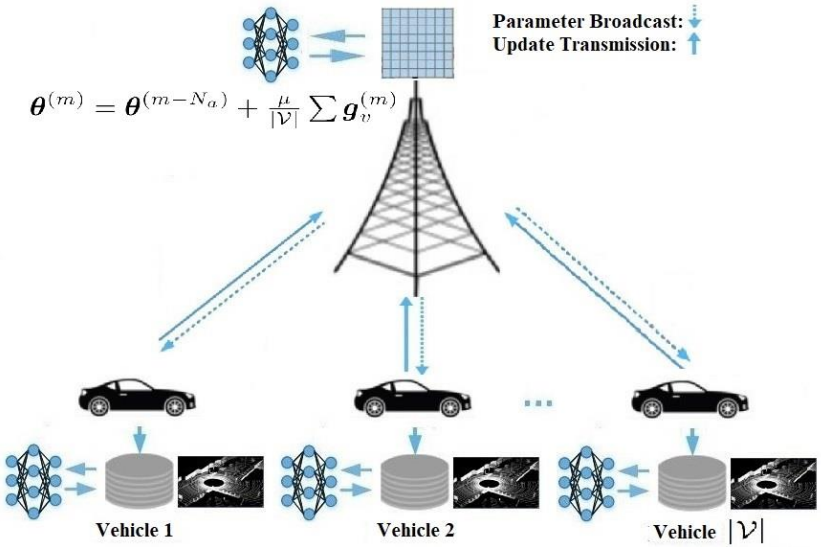
Neural network architecture



- Only 7460 parameters
- **55x** reduction in the number of parameters
- **100x** reduction in the number of FLOPs
- **7%** improvement in top-10 accuracy

[4] A. Klautau, N. González-Prelcic and R. W. Heath Jr., “LIDAR Data for Deep Learning-Based mmWave Beam-Selection” in *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 909-912, June 2019

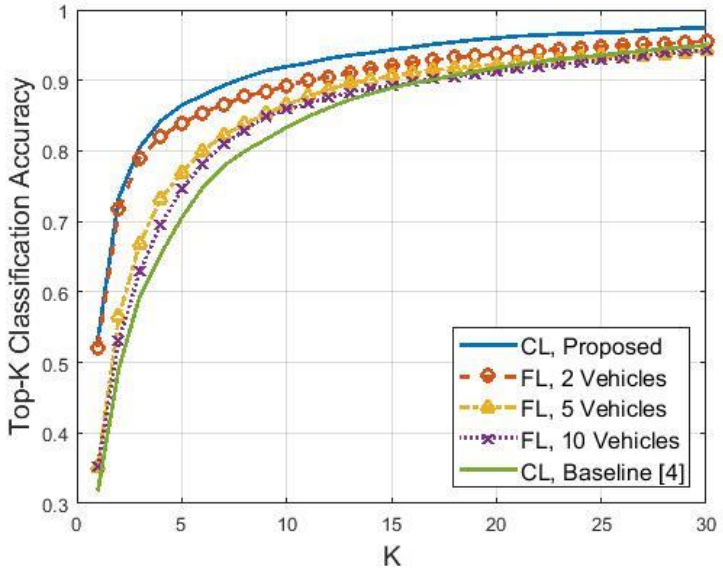
Federated learning (FL)



- [5] showed distributed beam inference outperforms localized inference at the BS
- However in [5], the NN is still trained on a large localized dataset offline

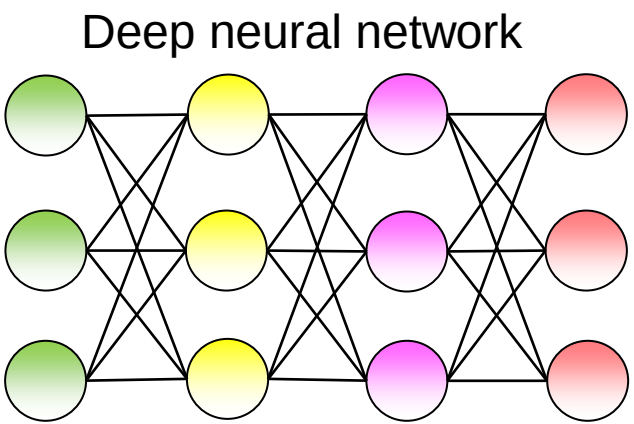
[5] M. Dias, A. Klautau, N. González-Prelcic and R. W. Heath, "Position and LIDAR-Aided mmWave Beam Selection using Deep Learning," in *2019 20th IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, Cannes, France, 2019, pp. 1-5

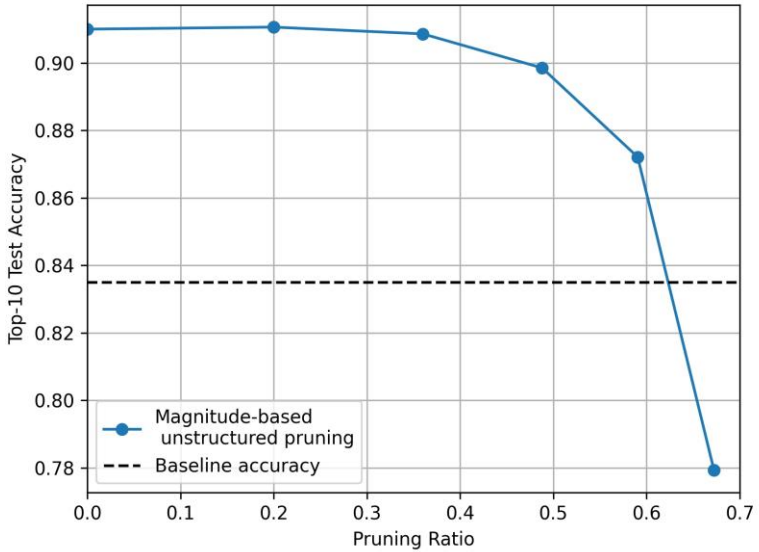
Federated learning - results



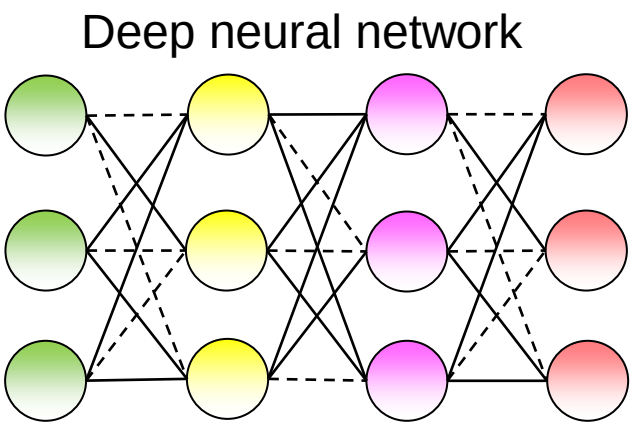
- FL enables distributed training and data collection during normal network operation
- Although FL results in some performance loss due to non-IID distribution of the local datasets, it still outperforms the baseline performance [4]

Pruning


Deep neural network


Top-10 Test Accuracy
0.90
0.88
0.86
0.84
0.82
0.80
0.78
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Pruning Ratio
Magnitude-based unstructured pruning
Baseline accuracy

Pruning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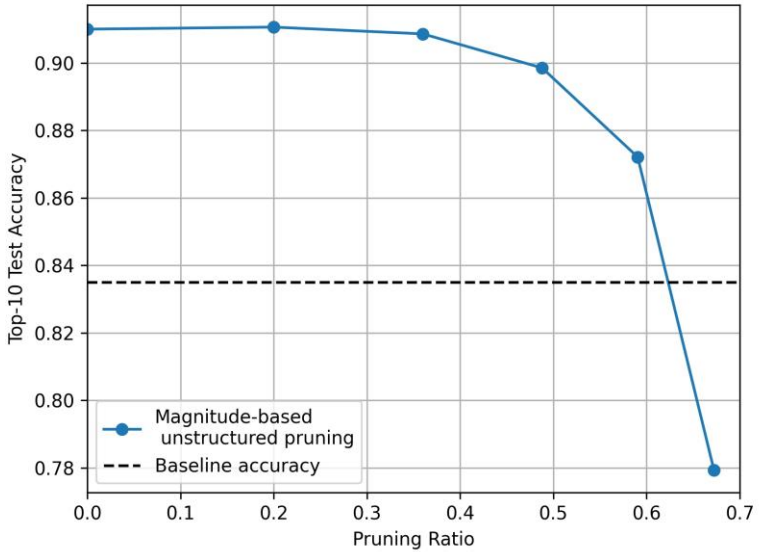
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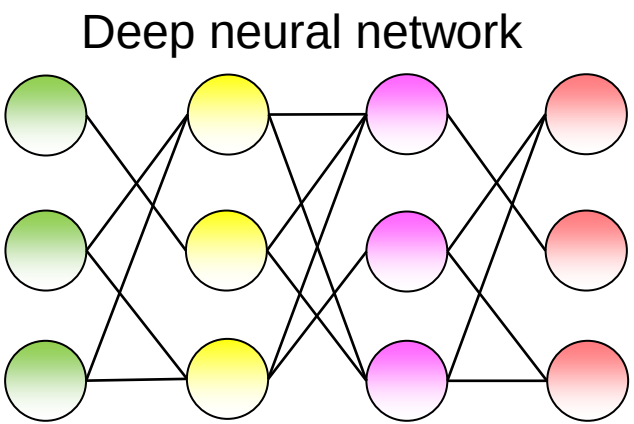
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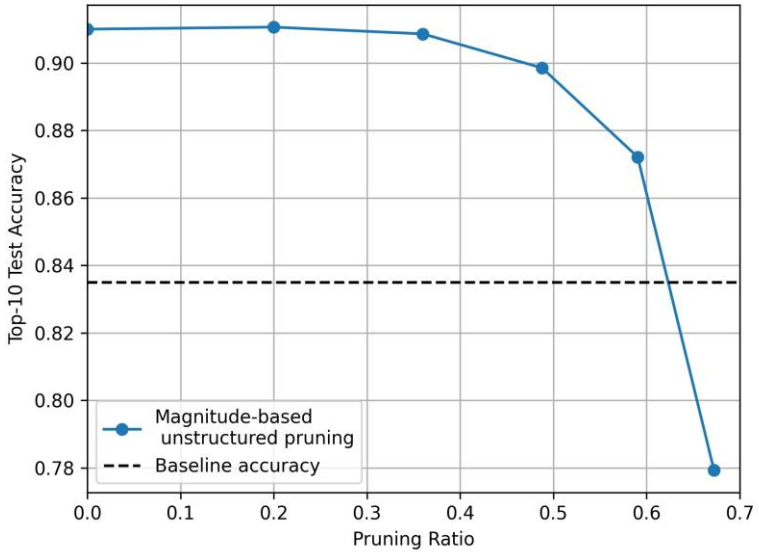
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Pruning Ratio
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Baseline accuracy

Main results

- **55x** reduction in the number of parameters
- **100x** reduction in the number of FLOPs
- **7%** improvement in top-10 accuracy
- Additional **50% reduction** of our NN parameters with **pruning**
- **Federated learning** for distributed training in practical scenarios

Ongoing work

- Propose NN-based solutions to design beamforming vectors from the Position+LIDAR+Image data in a regression scheme

Thank you for your attention

TensorFlow and PyTorch implementations of our solution are publicly available:

- PyTorch: github.com/ITU-AI-ML-in-5G-Challenge/PS-012-ML5G-PHY-Beam-Selection_Imperial_IPC1/pytorch
- TensorFlow: github.com/ITU-AI-ML-in-5G-Challenge/PS-012-ML5G-PHY-Beam-Selection_Imperial_IPC1/tensorflow

The paper with more federated learning results will be available on ArXiv soon.