



Deep Learning for Physical Layer Communications: Opportunities and Challenges

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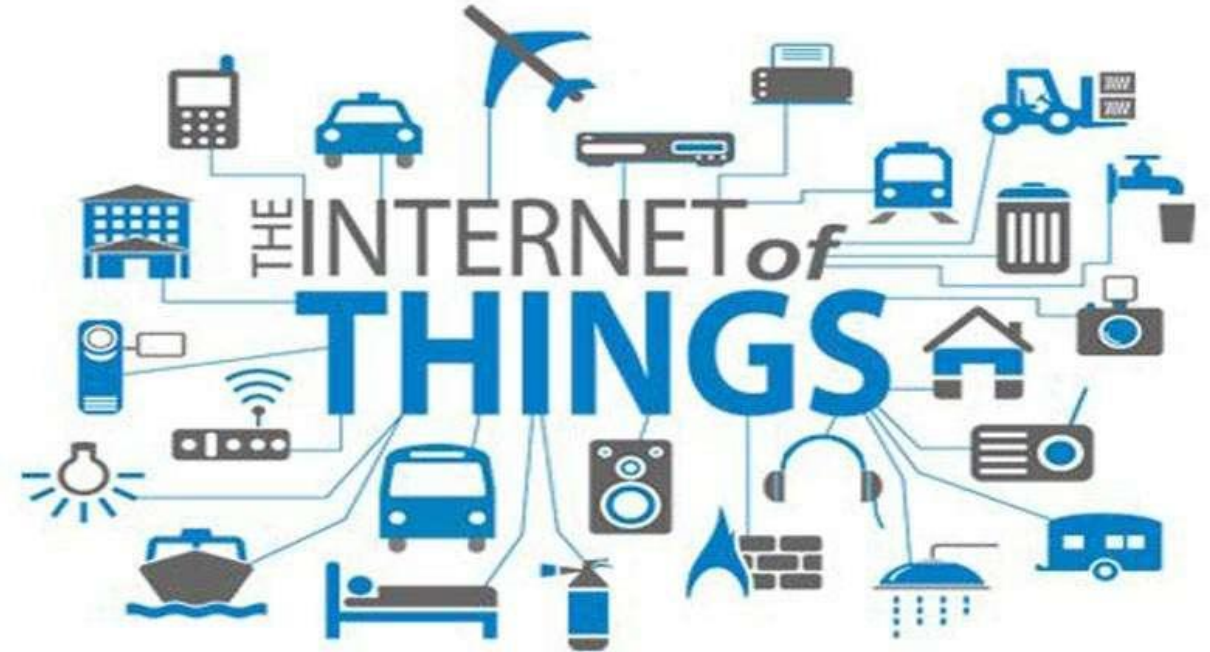
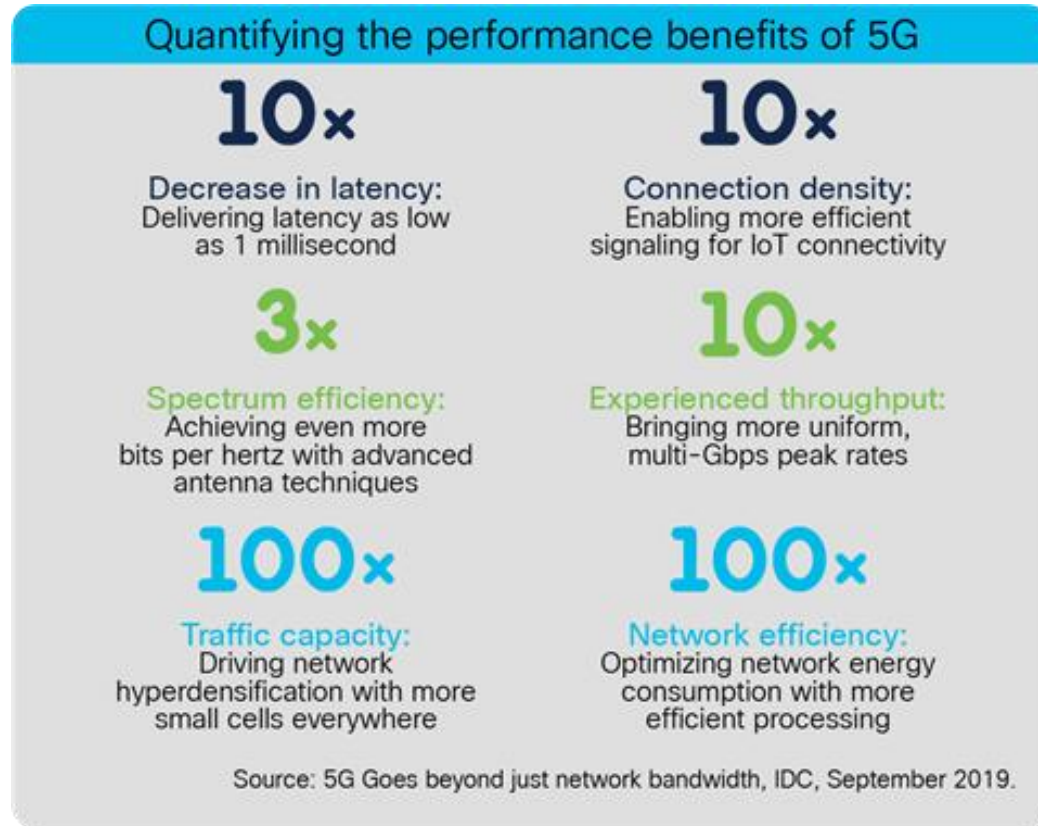
Heriot-Watt University, Edinburgh, UK

CHIST-ERA Call 2022
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Outline

- Why deep learning (DL)-based physical layer communication systems?
- Challenges & opportunities in designing DL physical layer communication systems:
 1. Designing communication blocks & tackling hardware impairments for wireless networks.
 2. Designing communication blocks for multi-user wireless networks.
 3. Designing communication blocks for optical fiber networks.
 4. Cell coverage planning for future wireless networks.
- Open issues in designing learning-based physical layer communication systems:
 1. How to perform online learning in DL-based frameworks?
 2. How to utilize feedbacks in designing DL frameworks?
 3. How to address latency & space (buffer) constraints?
 4. Model-based learning – a potential solution?
 5. Requirement for large scale experiments & data collection, could federated learning and transfer learning help?

Why deep learning (DL)-based physical layer communication systems?



Future Wireless Networks and its Requirements: Expectations on connection density, throughput and efficiency are expecting optimal solutions and novel ways are important!
Could Deep Learning Help?

Why Deep Learning?



Unprecedented Advances in Deep Learning



Advances in Computational Power



Data is the new Oil !!

David Parkins

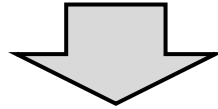
Key Issues of Traditional Digital Communication?

Model-based Communication Systems

$$\begin{array}{ll}\text{minimize}_x & f(x) \\ \text{subject to} & g_i(x) \leq 0, \quad i = 1, \dots, m \\ & h_j(x) = 0, \quad j = 1, \dots, p\end{array}$$

✓ Optimal Solution

✗ High complexity ✗ Various Assumptions

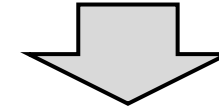


Protocol-based Communication Systems

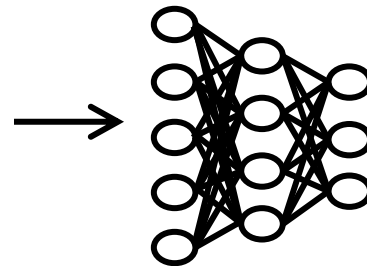
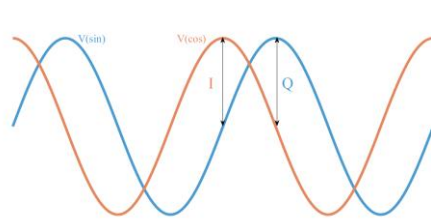


✓ Easy implementation

✗ Sub-optimal ✗ Hardly Generalizable



Learning-based Communication Systems



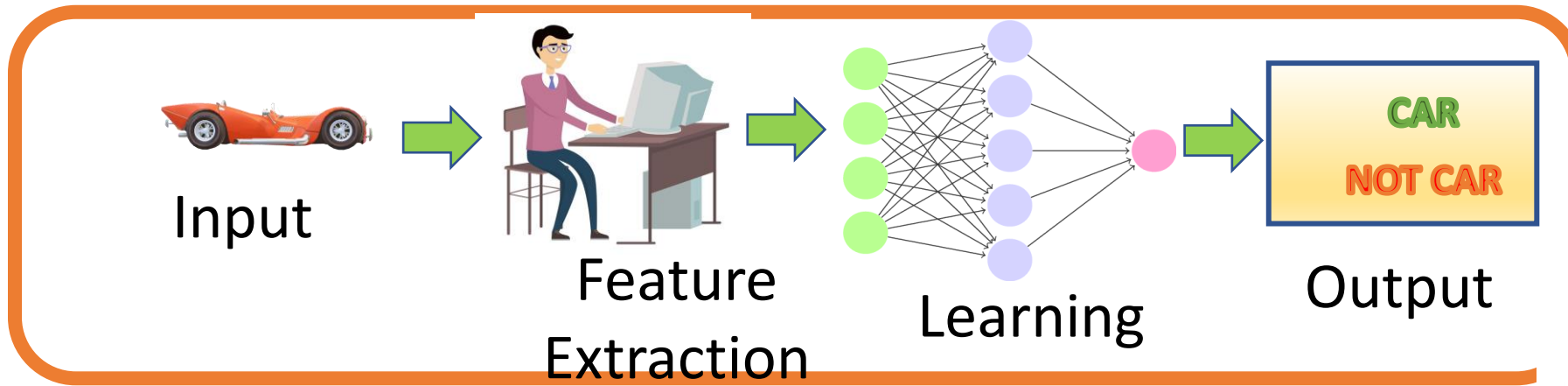
→ Spectrum State & Action

→ Decoded signal

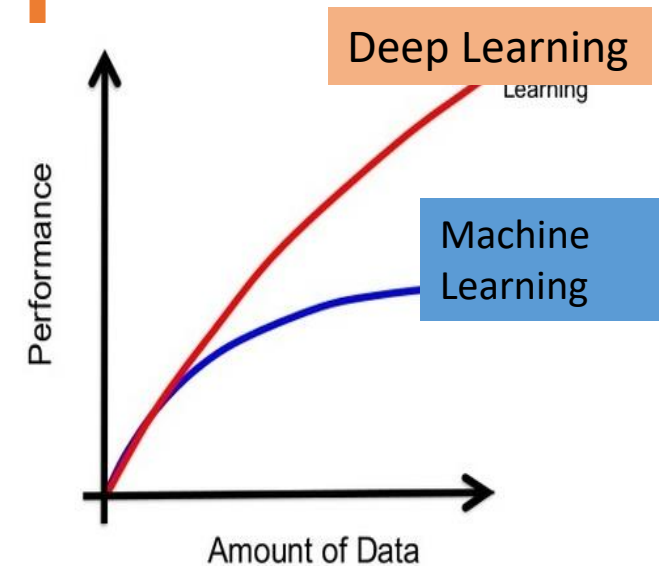
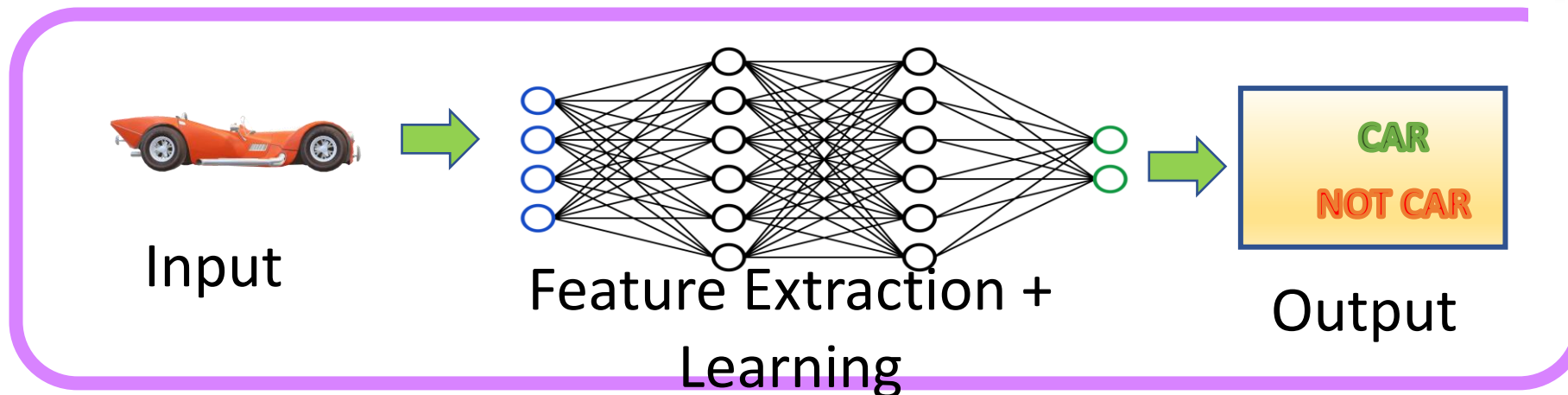
optimal solution in non-linear systems

✓ Highly versatile ✓ Highly accurate ✓ Low latency ✓ Low power

Machine Learning (ML)

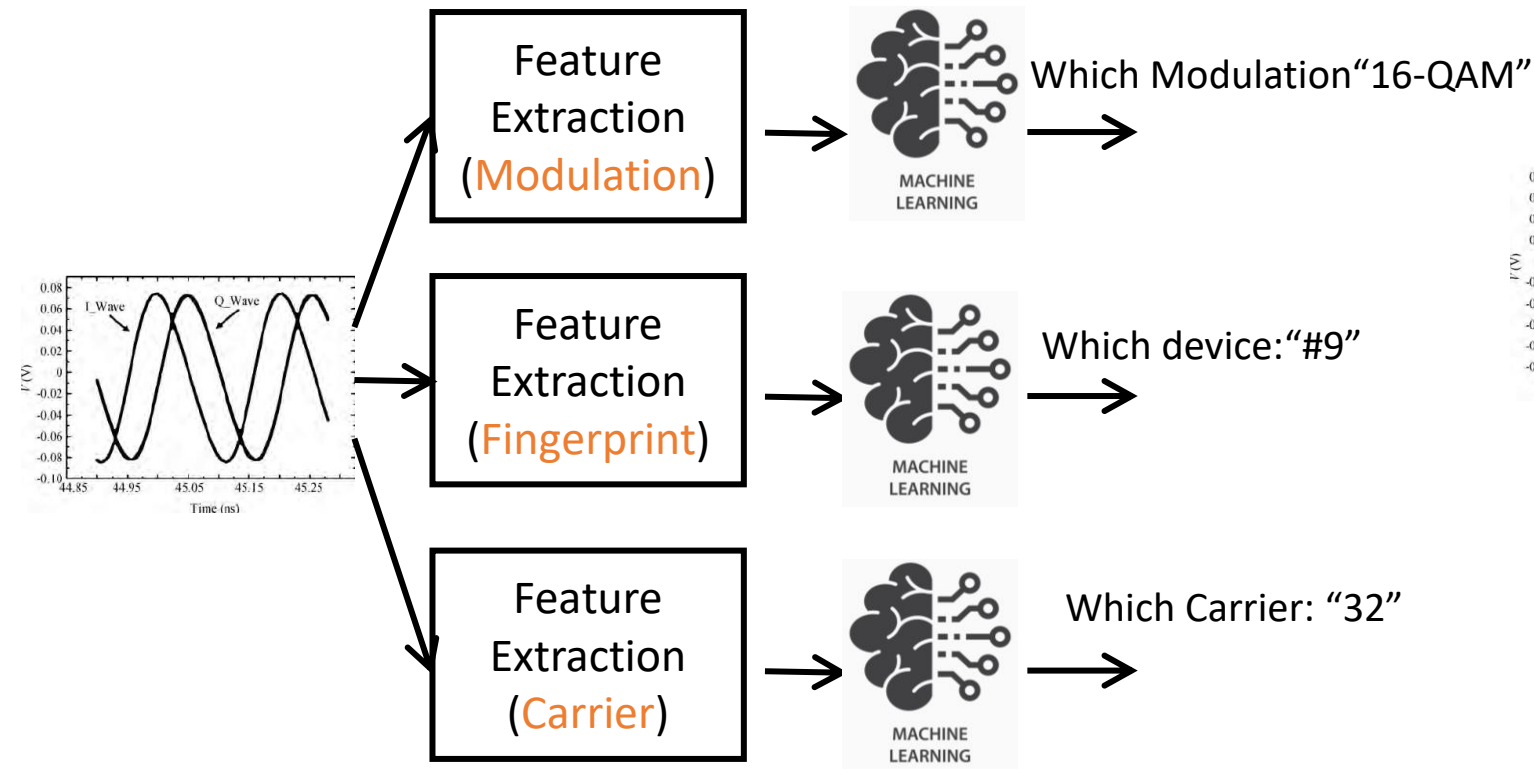


Deep Learning (DL)



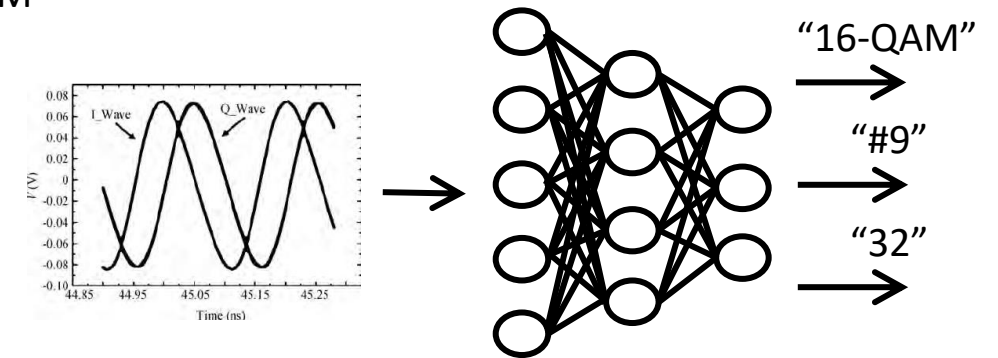
Why Deep Learning at Physical Layer Communication?

ML-based Communication Systems



- ✗ Feature Extraction
- ✗ Excessive H/W Utilization
- ✗ No Real-Time Fine-Tuning

DL-based Communication Systems



- ✓ All-in-one Solution
- ✓ Fixed H/W Utilization
- ✓ Simple Real-Time Fine-Tuning

Challenges in Physical Layer Communications & Opportunities using Deep-Learning

Challenge 1 - Designing Optimal Communication Systems

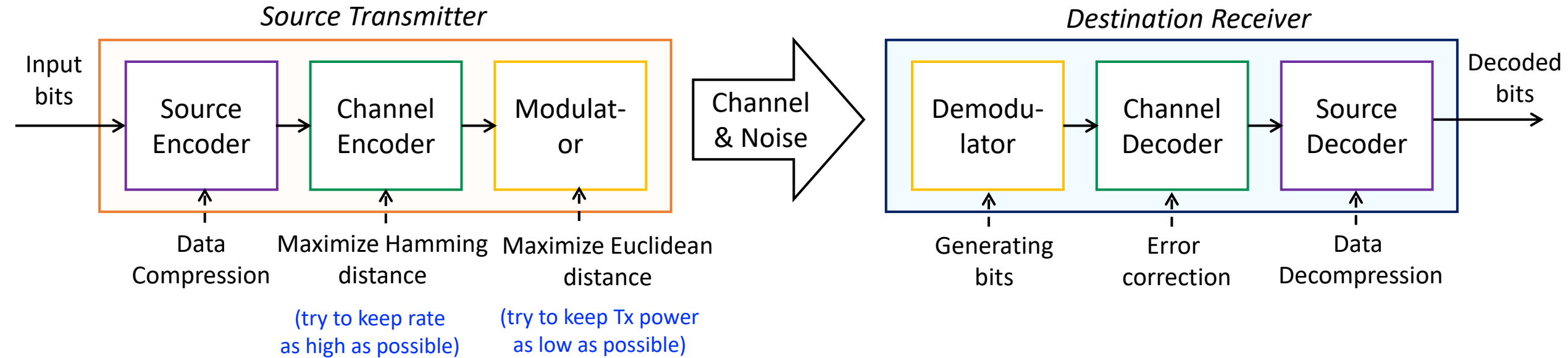
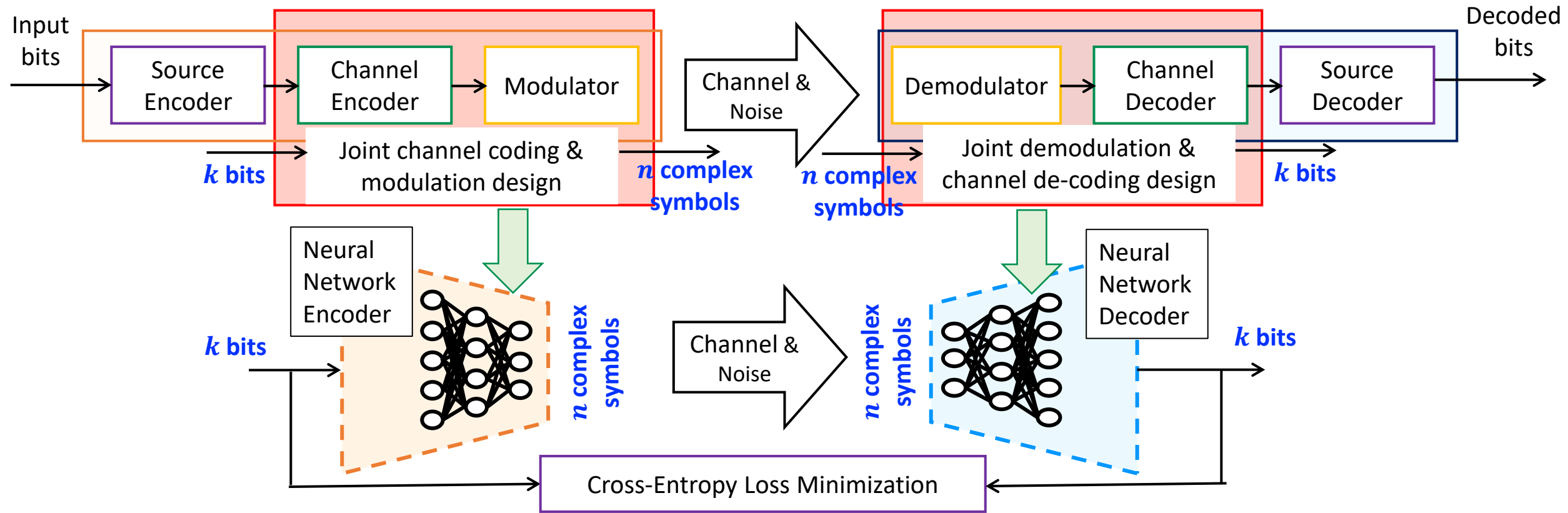


Fig: Traditional Communication blocks

✗ **Designing the source coding, modulation schemes and error-correcting codes** in a traditional digital communication system **are viewed as three separate problems**. However, the separate source and channel coding and the separate channel coding and modulation designs are **known to be suboptimal**.

✗ A practical system faces **multiple distortions** because of the non-linear elements and hardware imperfections that a **conventional algorithm cannot capture**.

Opportunity 1 – Designing Communication Blocks by End-to-End Learning-based Autoencoder (AE) Frameworks

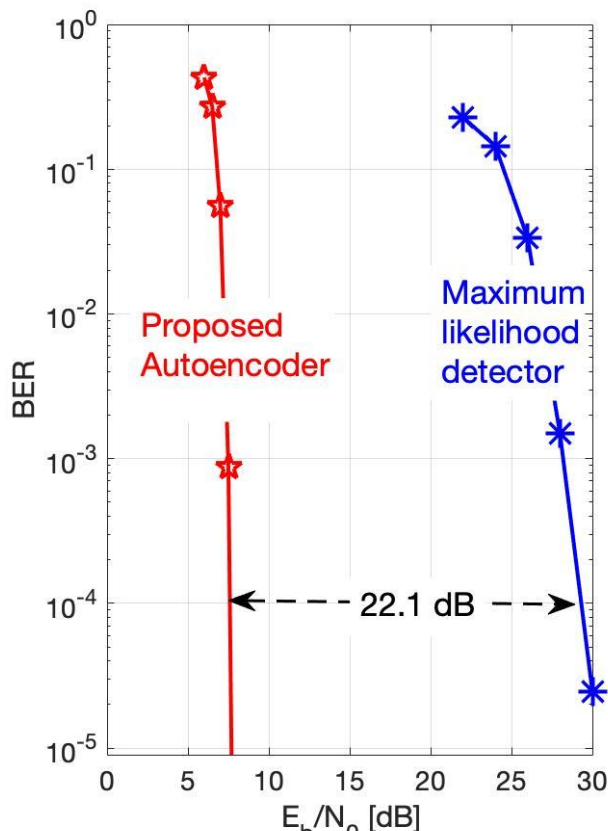


❑ **Channel AE** – adds redundancy to input data [Oshea17], while **Vision AE** – removes redundancy from input data.

❑ **Channel AE frameworks do not require detailed waveform design, constellation mapping, and/or reference signals. Further, can combine various signal processing blocks and implicitly tackle the hardware impairments.**

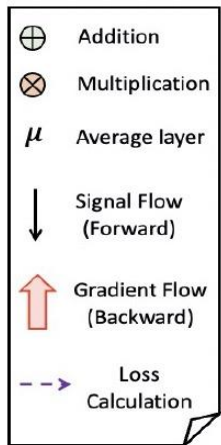
Opportunity 2: AE-based Joint Channel Coding & Modulation Design under Hardware impairments (non-linearity)

We propose AE-based joint channel coding and modulation ((block coded modulation (BCM)) design that removes the deteriorating impacts of the I/Q imbalance.

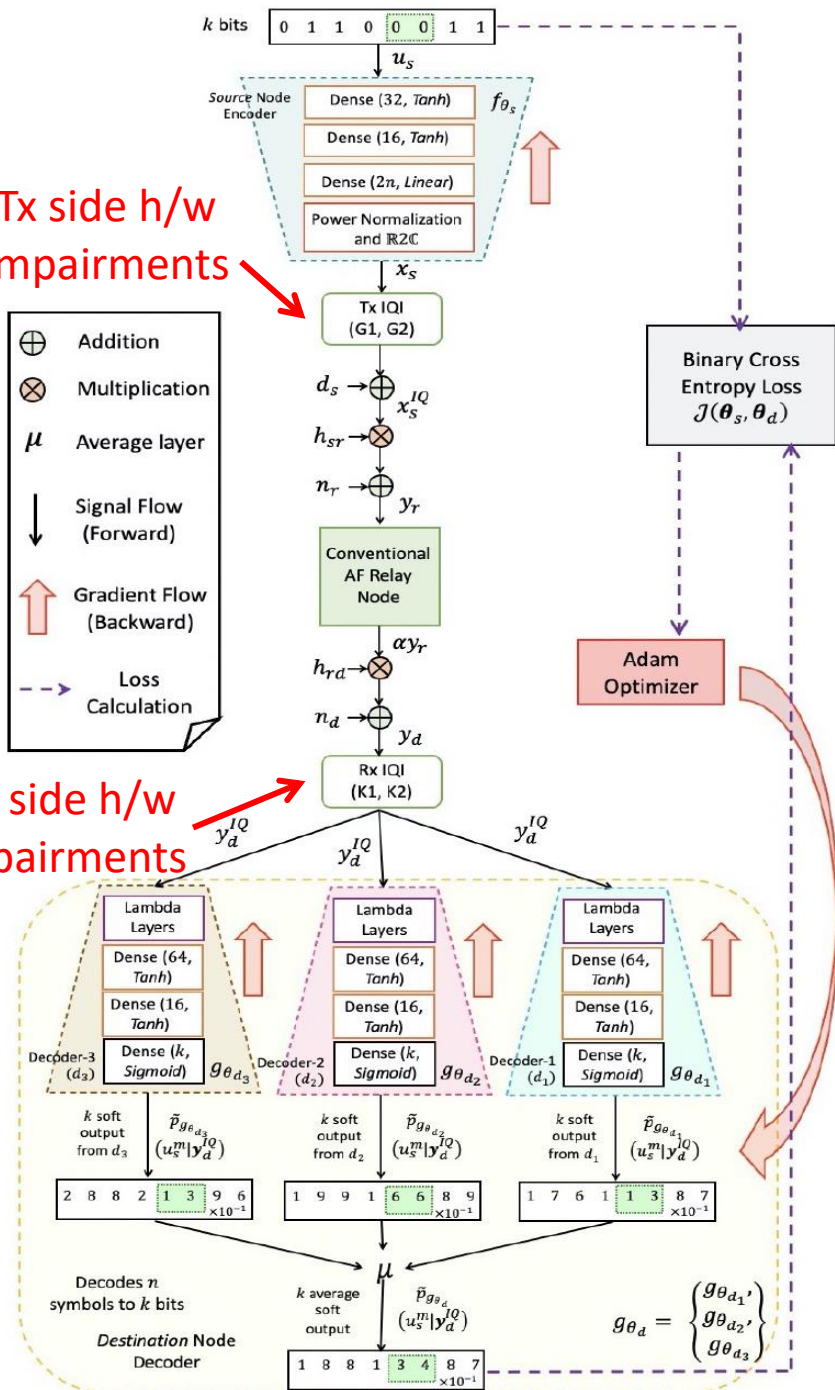


- A. Gupta and M. Sellathurai, "A Novel Average Autoencoder-based Amplify-and-Forward Relay Networks with Hardware Impairments," IEEE Trans. Cognitive Commun. Network., vol. 1, pp. 1-16, 2022.
- A. Gupta and M. Sellathurai, "End-to-End Learning-Based Framework for Amplify-and-Forward Relay Networks," in IEEE Access, vol. 9, pp. 81660-81677, 2021.
- A. Gupta and M. Sellathurai, "End-to-End Learning-based Two-Way AF Relay Networks with I/Q Imbalance," in Proc. International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), pp. 1-5, 2021.

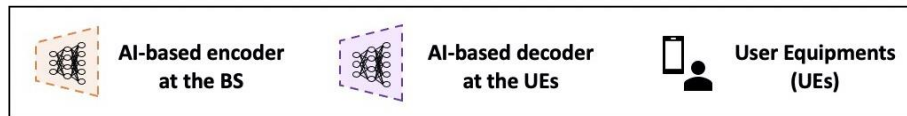
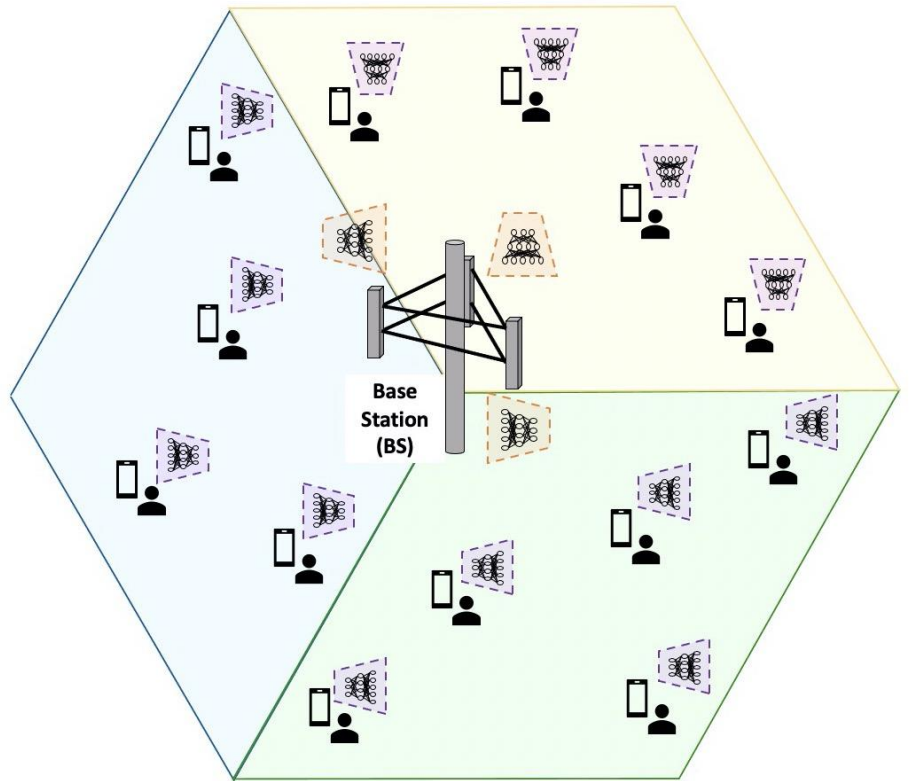
Tx side h/w impairments



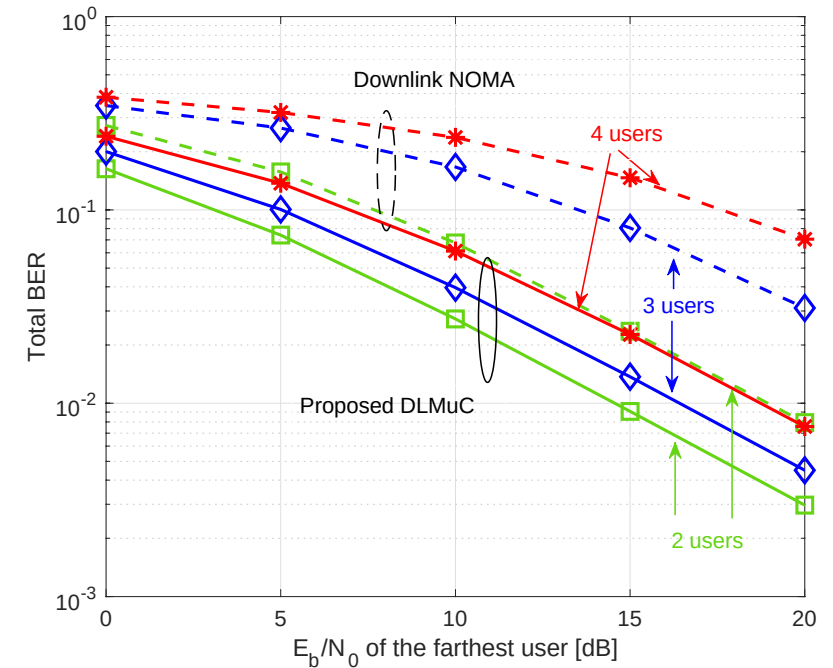
Rx side h/w impairments



Opportunity 3 – Designing Communication Blocks for Multi-User Wireless Networks (“Non-linearities due to interference”)



Until now, there is no optimal method for designing communication blocks, such as dirty-paper coding for wireless networks.

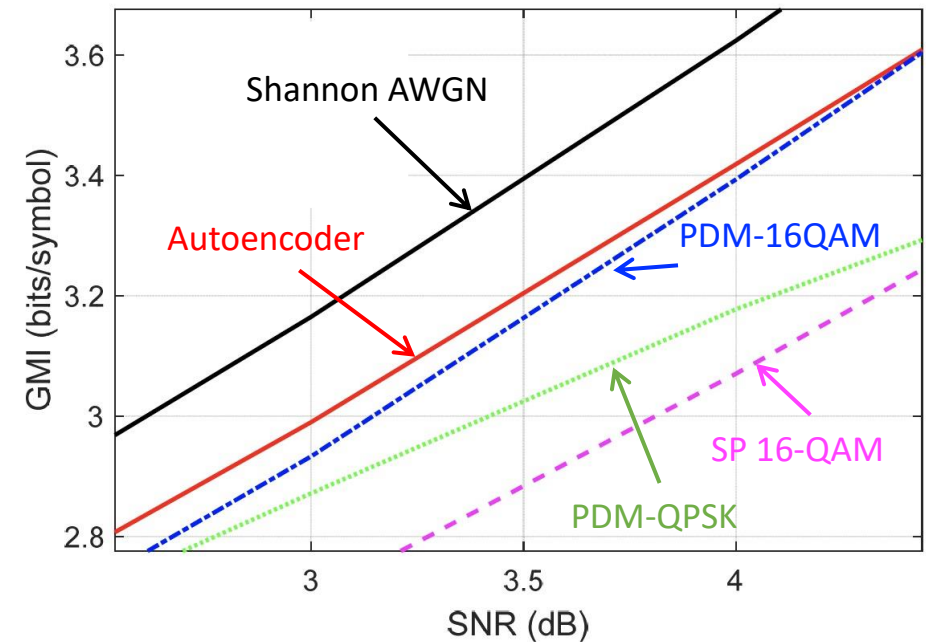
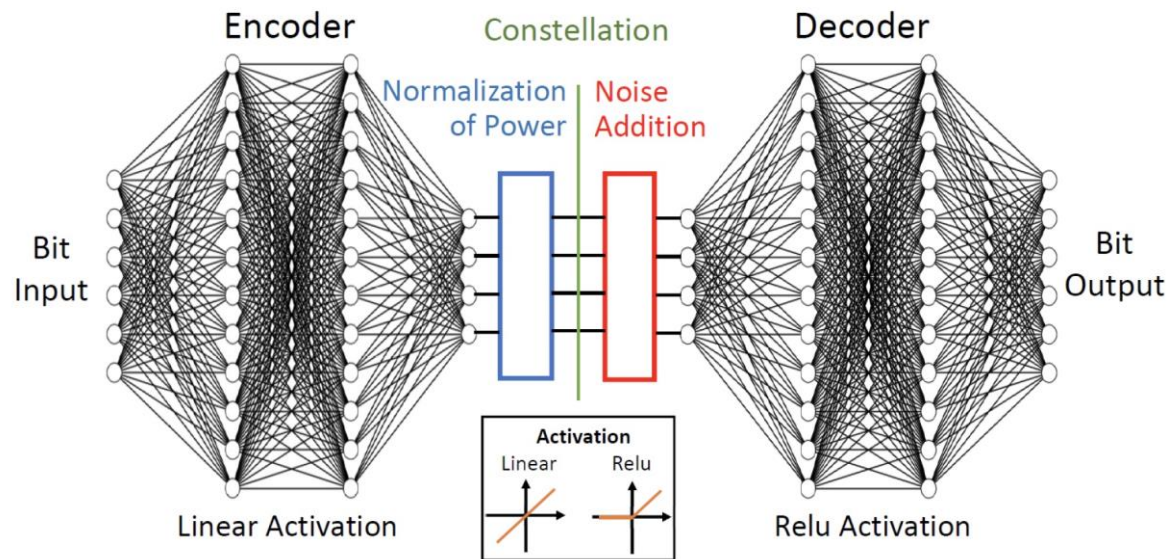


We propose a DL-based multi-user communication (DLMuC) network. Wherein at the same time-frequency block, ***we can pack at least twice the number of user equipments (UEs) at much higher rates in a beam or sector*** compared to currently supported 5G base station (BS) or Satellites, with low complexity UEs design.

Patent: A. Gupta and M. Sellathurai, “Deep learning multi-user communication,” Patent application submitted to UK, USA, GB2019616.8, Dec. 2020.

Opportunity 4 – Designing Communication Blocks in Optical Fibre Networks

Wireless communication networks suffer most from the “**wireless channel fading**”. While **optical communication networks** suffer most from the “**Non-linearities**”. Although designing high dimensional modulation formats exists as potential solution from 1990s, there exists no approach for its designing.

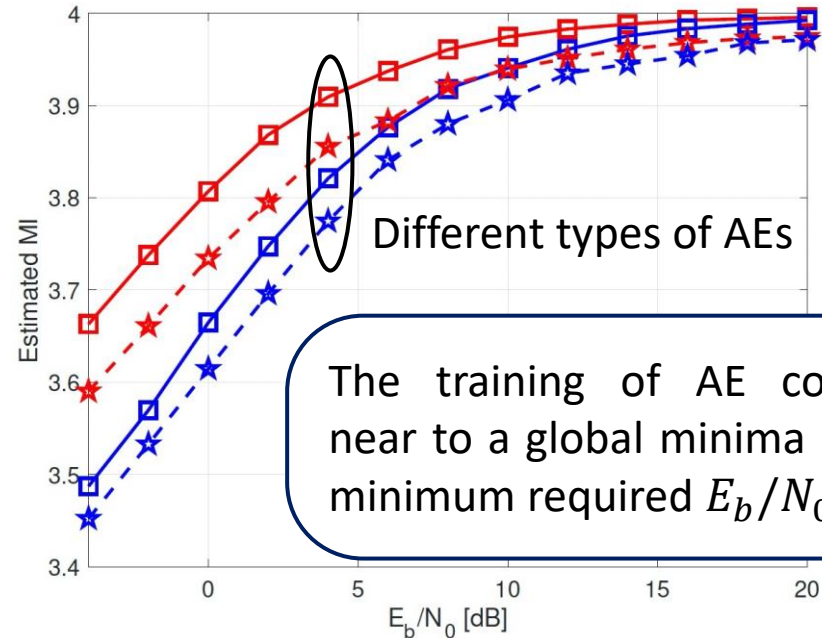


Demonstrated ultra long-haul transmission of a new four-dimensional (4D) modulation format having low generalized mutual information (GMI) gap to Shannon and designed using neural networks.

R. J. Essiambre *et. al.*, “Increased Reach of Long-Haul Transmission using a Constant-Power 4D Format Designed Using Neural Networks,” 2020 European Conference on Optical Communications (ECOC), Brussels, Belgium, 2020, pp. 1-4.

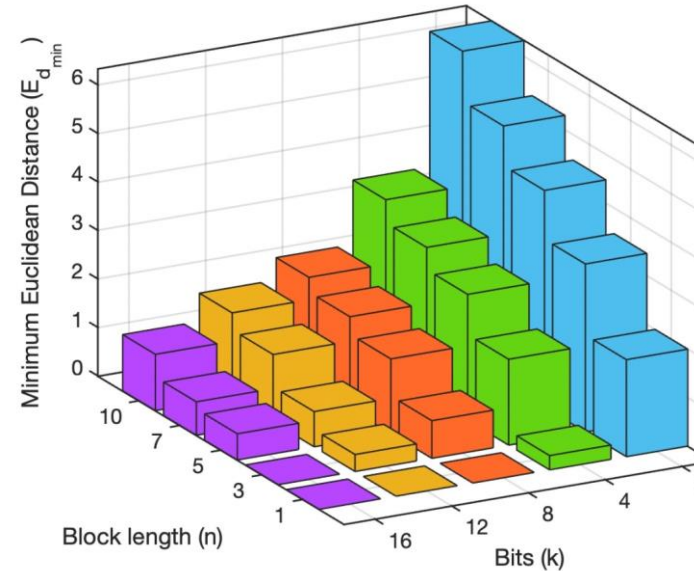
Opportunity 4 (Cont.) – Opening Black-box of DL-based Autoencoder (AE) Frameworks

Analyzing Training Convergence of AE performing BCM:



The training of AE converges near to a global minima above a minimum required E_b/N_0 .

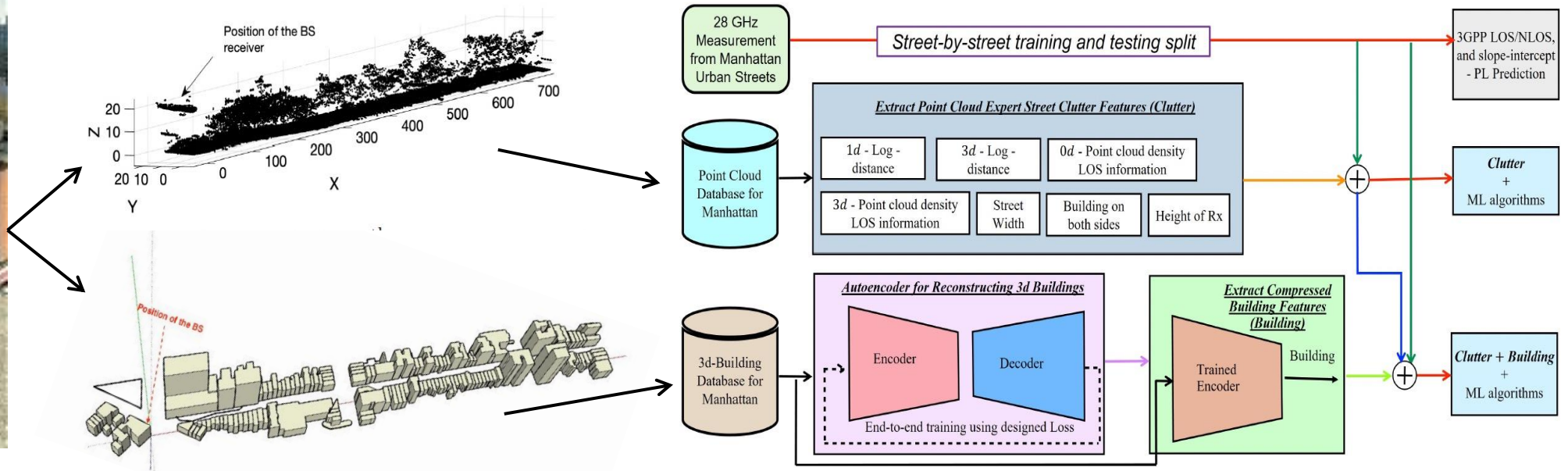
Interpretability of AE-based BCM Design



We open black box of AE-based BCM design by analyzing Euclidean distance, Hamming distance, Packing density, and Kurtosis.

- A. Gupta, M. Sellathurai and T. Ratnarajah, "End-to-End Learning-based Full-Duplex Amplify-and-Forward Relay Networks," IEEE Trans. Commun., Under Review, 2022.
- A. Gupta and M. Sellathurai, "A Stacked-Autoencoder Based End-to-End Learning Framework for Decode-and-Forward Relay Networks," ICASSP 2020 - 2020 IEEE Inter. Conf. Acoustics, Speech & Signal Process. (ICASSP), 2020, pp. 5–9.
- A. Gupta and M. Sellathurai, "End-to-End Learning-based Amplify-and-Forward Relay Networks using Autoencoders," ICC 2020 - 2020 IEEE International Conference on Communications (ICC), Dublin, 2020, pp. 1-6.

Opportunity 5 – Cell Coverage Planning for Future Networks



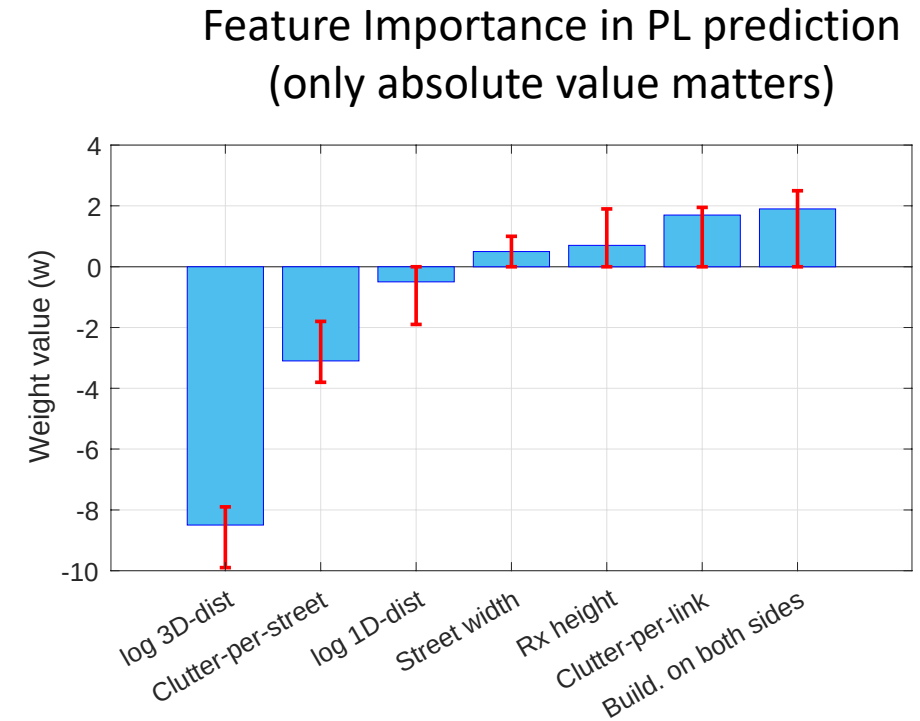
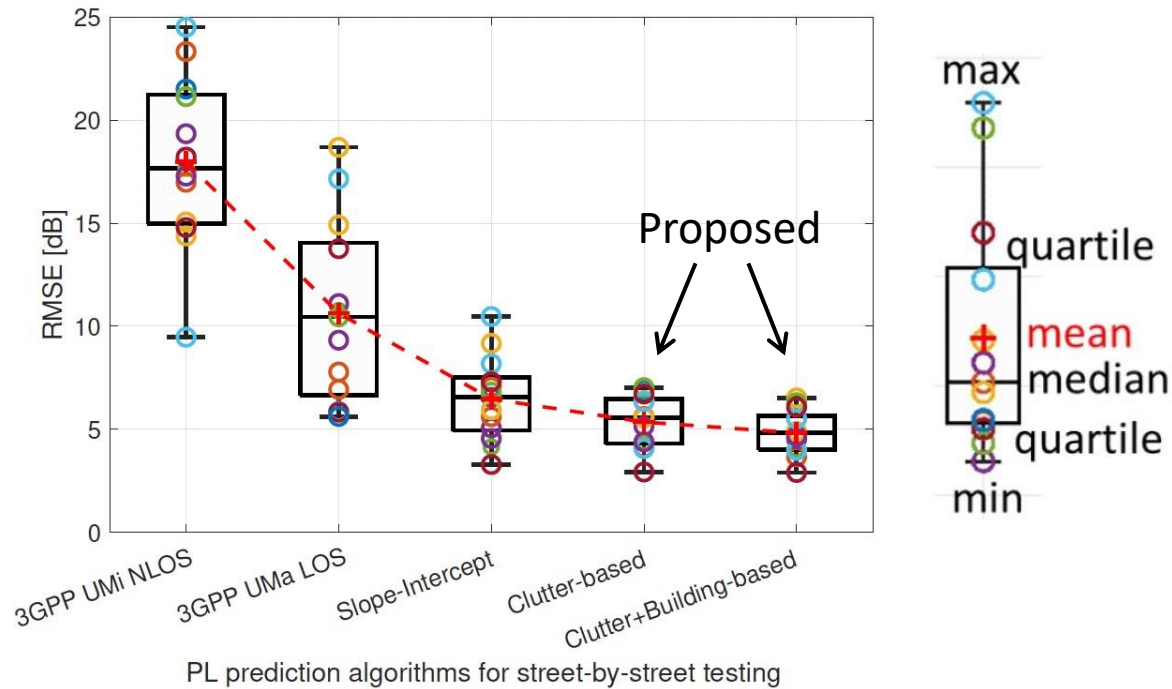
- ❑ **Highly accurate channel modelling and path loss (PL) prediction are essential in foretelling cell coverage, planning BS deployment.**
 - Mm-wave presents challenge of higher free-space, scattering, and diffraction losses from the propagation environment.
 - E.g. in a typical urban street, buildings and street clutter (wavelength of tens of cm) can significantly lower PL.
- ❑ For first time, we collectively utilize both street clutter and building information for mm-wave PL prediction using a large-scale real-world propagation measurement at 28 GHz in urban streets.

A. Gupta, J. Du, D. Chizik, R. A. Valenzuela and M. Sellathurai, “Machine Learning-based Urban Canyon Path Loss Prediction using 28 GHz Manhattan Measurements,” in IEEE Transactions on Antennas and Propagation, vol. 1, pp. 1-17, 2022.

Opportunity 5 (cont.) – Cell Coverage Planning for Future Networks

- For first time, we show ML-based PL prediction outperforms slope-intercept fit and 3GPP standard based models.

- We focus on interpretability: We adopt human-friendly environment features and quantify the significance of each feature in the PL prediction.

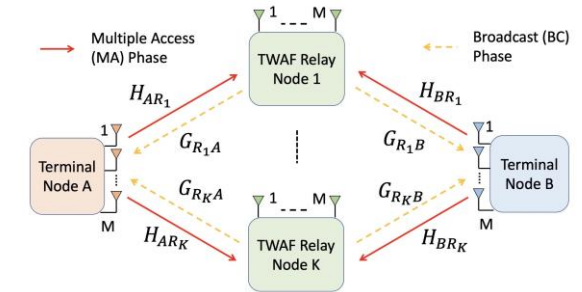


Open Issues in Designing Learning-based Physical Layer

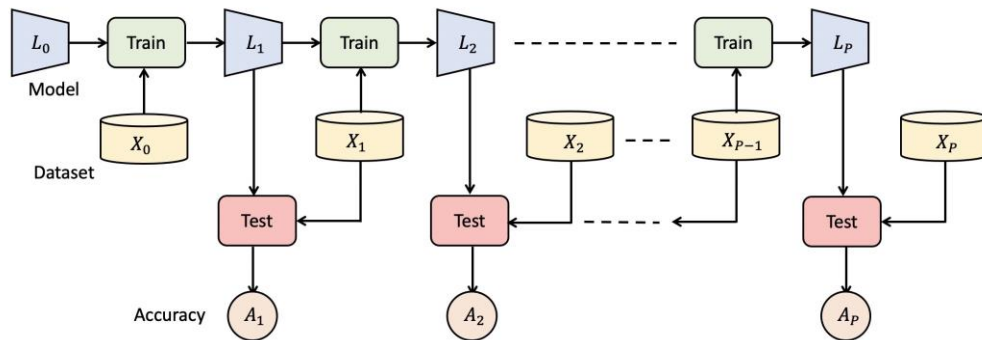
Issue 1– How to Perform Online Learning in DL?

Incremental Learning (IL) – Re-train old ML model again for only new data.

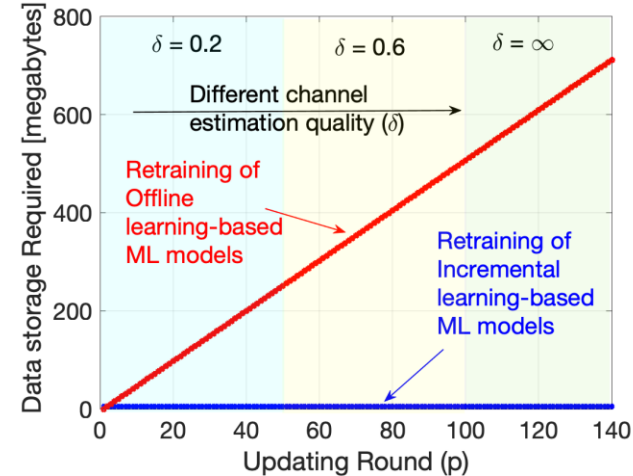
Consider a simple problem of relay selection



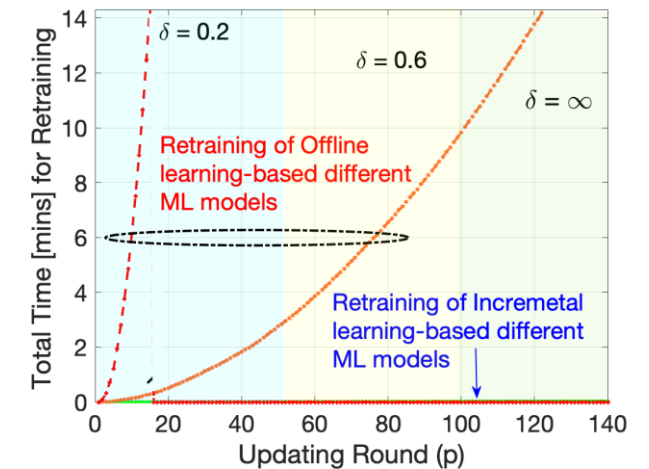
For similar mean accuracy b/w OL & IL:



Data storage cost



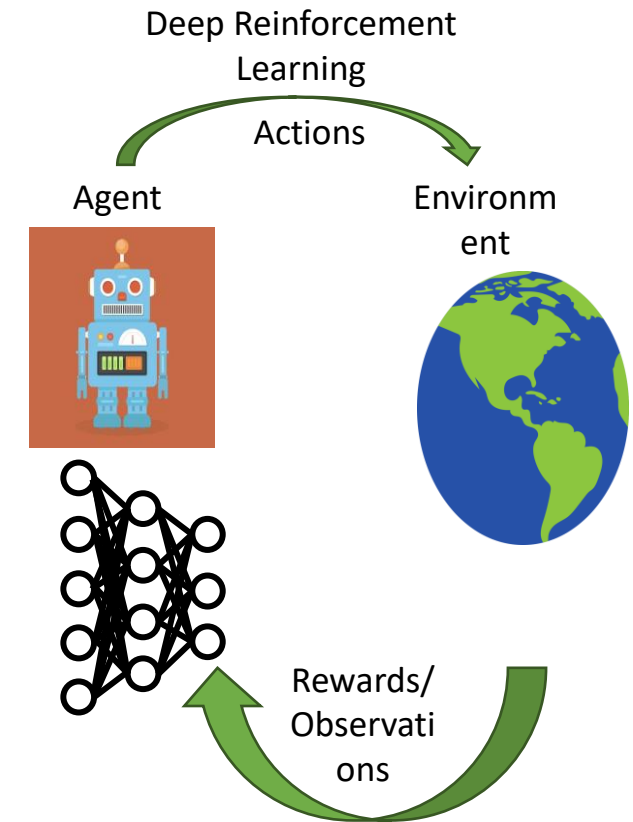
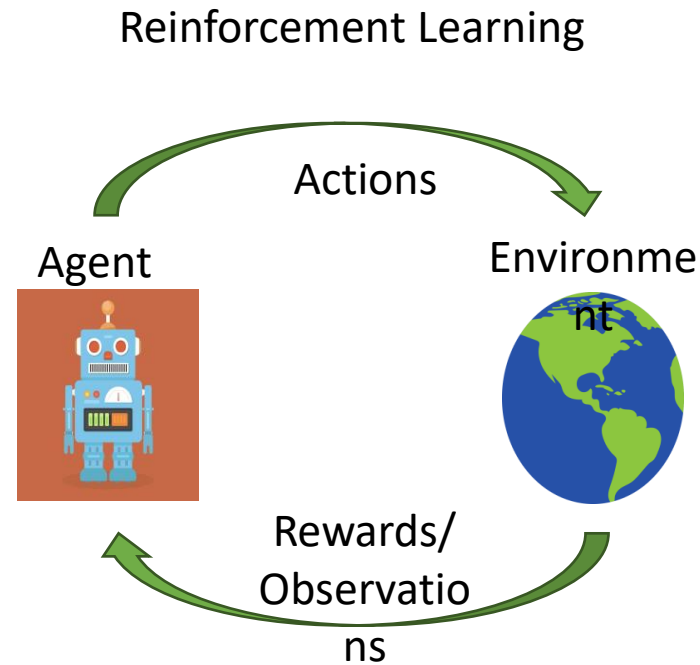
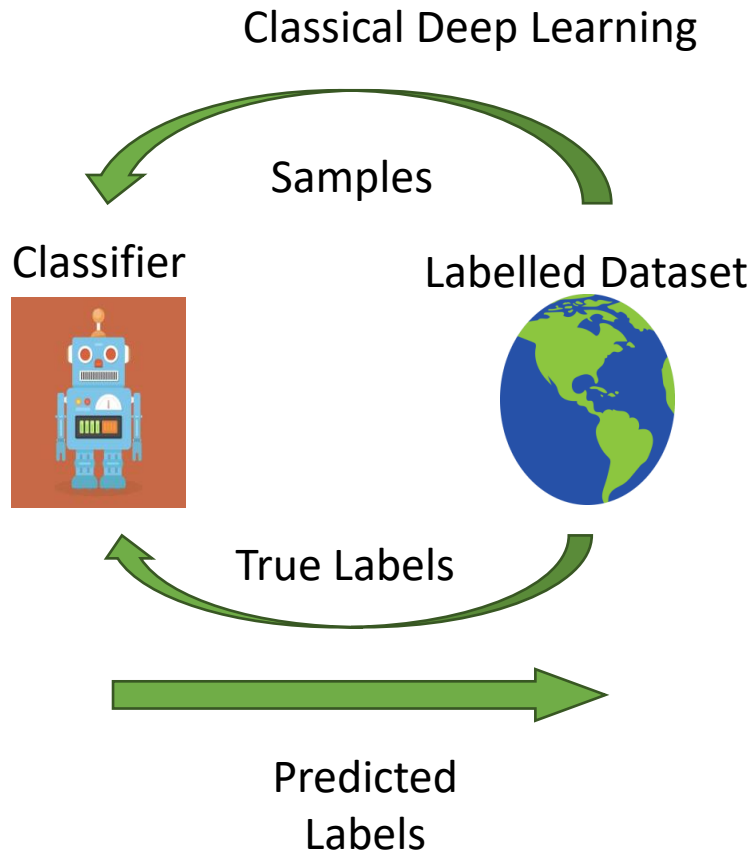
Training time cost



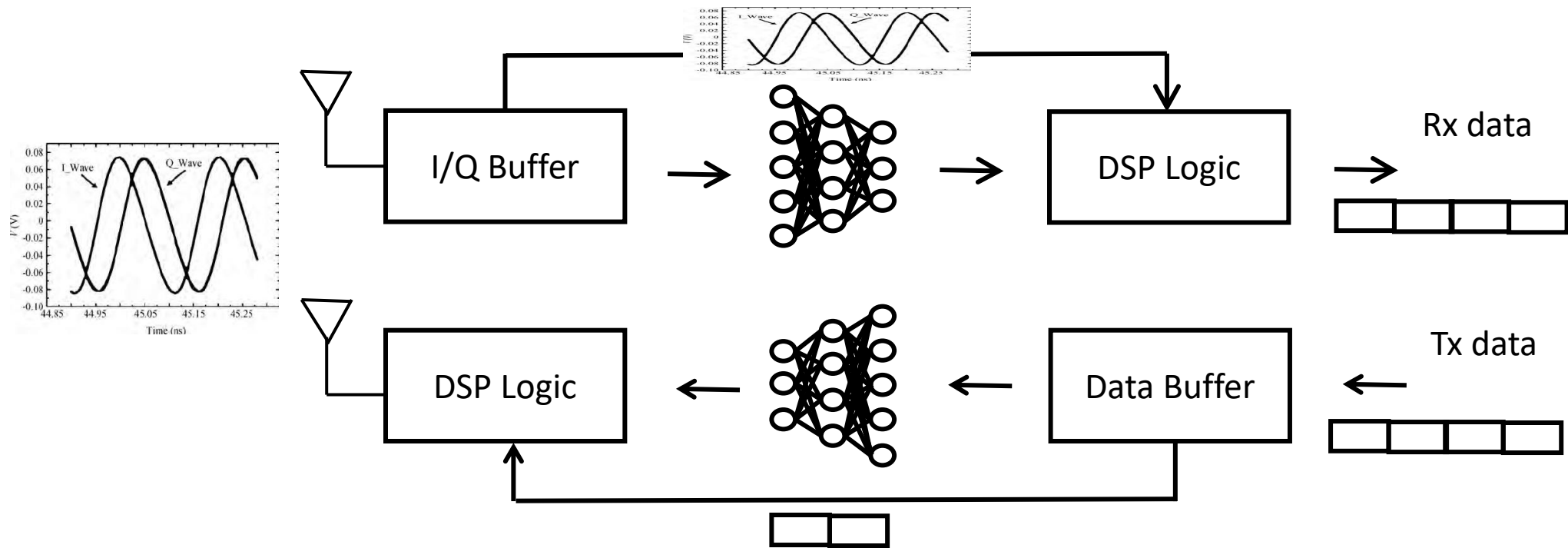
A. Gupta, M. Sellathurai, V. V. Mani, and T. Ratnarajah, "Incremental Learning-based MIMO Relay Selection", in *Proc. IEEE World Congress on Computational Intelligence (IEEE WCCI), AI6G Workshop*, pp. 1-9, 2022.

Issue 2 – How to Utilize Feedbacks in Designing DL Frameworks?

Deep Learning (DL) models are trained using a dataset & it's less linked with interactions. Reinforcement learning (RL) is closer to human brain where policy is learnt via trial-and-error using feedback mechanism.

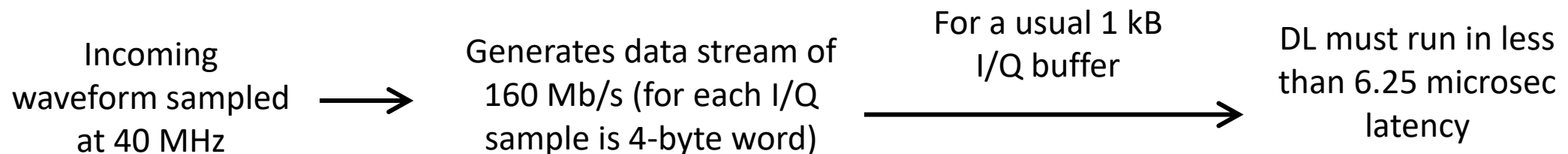


Issue 3– Addressing Latency and Space Constraints in real-time



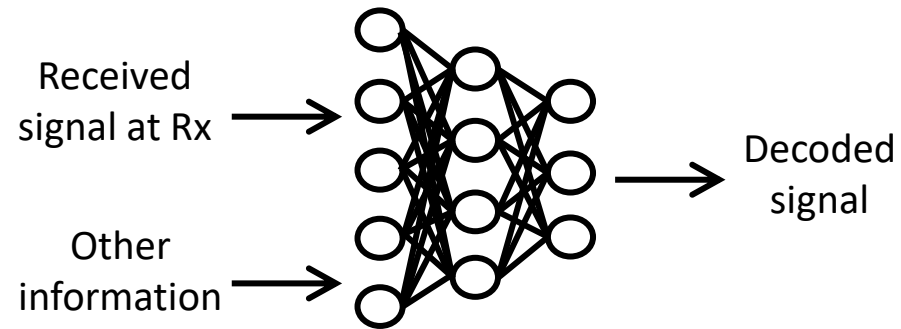
DL networks must run quickly enough to avoid overflowing the I/Q buffer and/or the data buffer.

Example (Wi-Fi Channel):



Issue 4: Model-based Learning: A Possible Solution?

Data-driven DL Frameworks



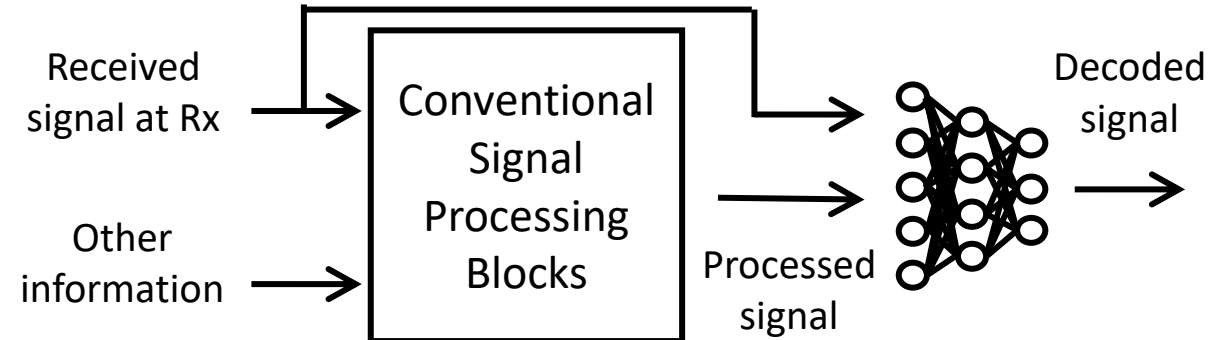
Advantages:

- Don't need any conventional signal processing block.
- Model scenarios without any mathematical model.

Disadvantages:

- Doesn't utilize wireless communication blocks designed after decades of research.
- Requires a very large dataset to train.
- Requires a very large NN architecture.
- Requires a very long training time.

Model-based DL Frameworks



Advantages:

- Utilize wireless communication blocks designed after decades of research.
- Requires a smaller dataset to train.
- Requires a smaller NN architecture.
- Requires a shorter training time.
- Can also model scenarios without any mathematical model.

The question is: Could this achieve the necessary performance required?

Issue 5— Requirement for Large Scale Experiments and Data Collection and Data Privacy

- ❖ Quality and quantity of training and testing data is vital for designing DL-based PHY layer.
- ❖ However, there are minimal to no large datasets like Vision community (such as ImageNet by Stanford). As a result, DL algorithms for the PHY layer are tested in controlled, lab-scale environments and with a limited number of wireless technologies. Thus, each work “can potentially claim to be better than prior work”.
- ❖ Could Transfer Learning Help to overcome data issue?
- ❖ Data Privacy Issue – could this be solved by Federated Learning framework?
- ❖ Thus, there is an urgent need for standardized dataset for validating the DL-based PHY layer models.

Some projects collecting large scale datasets for wireless communications research community:

- ❑ DeepSig (<https://www.deepsig.ai>)
- ❑ Platforms for Advanced Wireless Research (PAWR) (<https://advancedwireless.org>)
- ❑ Colosseum network emulator (<http://experiments.colosseum.net>)

Thank you

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