

AI-assisted PHY technologies for 6G and beyond wireless networks

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Chair for Wireless Communication and Navigation

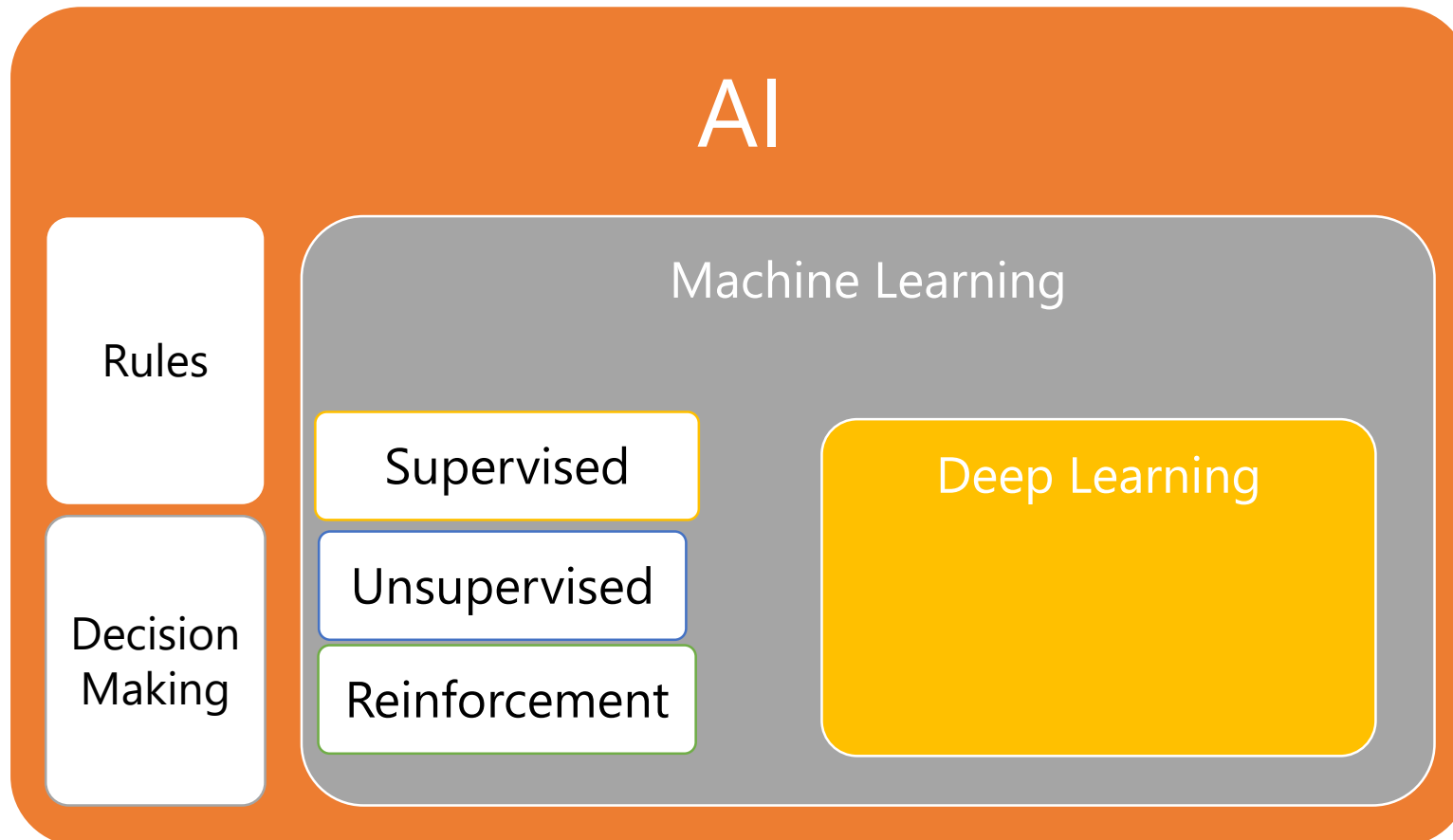
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Machine Learning

An ML algorithm learns the execution of a particular task T , maintaining a specific performance metric M , based on exploiting its experience E .



ML Applications in today's networks

Network Layer

Resource Allocation

RAT Selection

Handover & Mobility
Management

Network Slice
Selection & Allocation

MAC Layer

Multiple Access

Link adaptation

Error Correction

PHY Layer

Channel Coding

Channel Estimation

MIMO Precoding

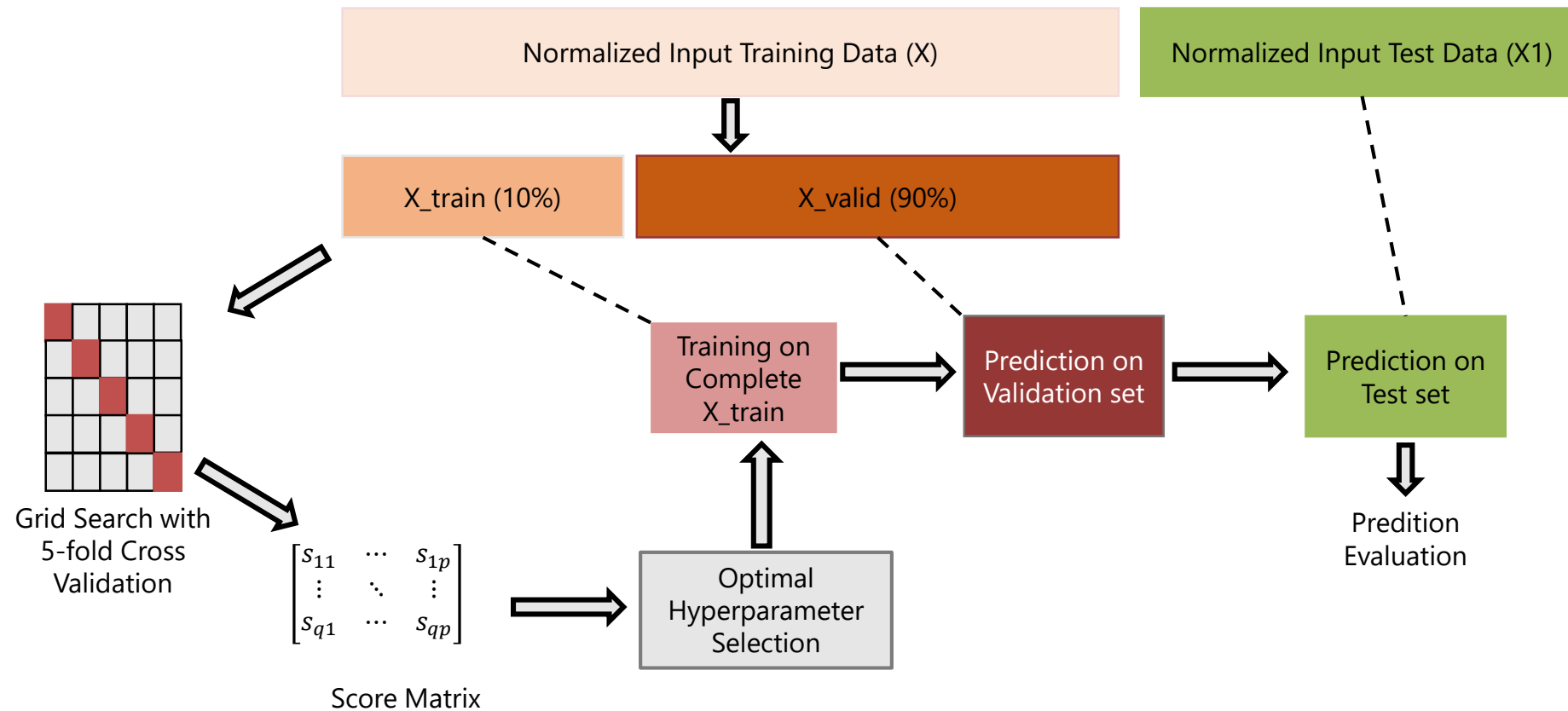
- Ranging & Localization
- Obstacle Detection
- PHY layer Security

Why ML for PHY?

1. ML algorithms (especially ANNs) are universal functional approximators and are Turing complete
2. Block optimality versus E2E Optimality
3. Rise of computation power through GPUs and DL frameworks

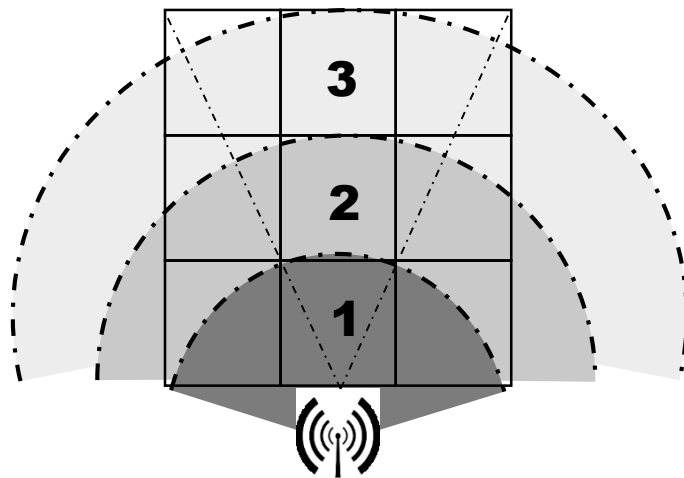
Examples

Learning Method



Ex 1 – Obstacle Detection

Objective : Detect the presence and the proximity of humans to the transmitter using only UWB baseband signals

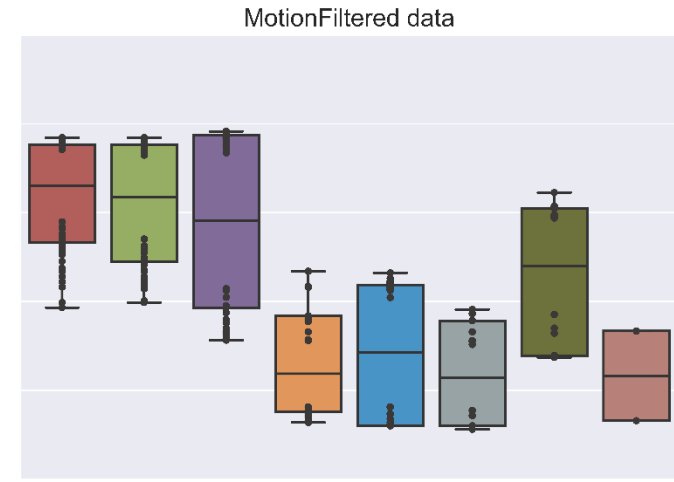
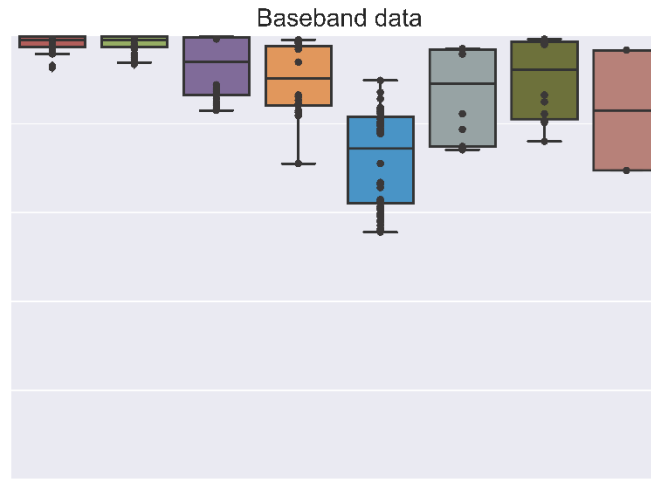
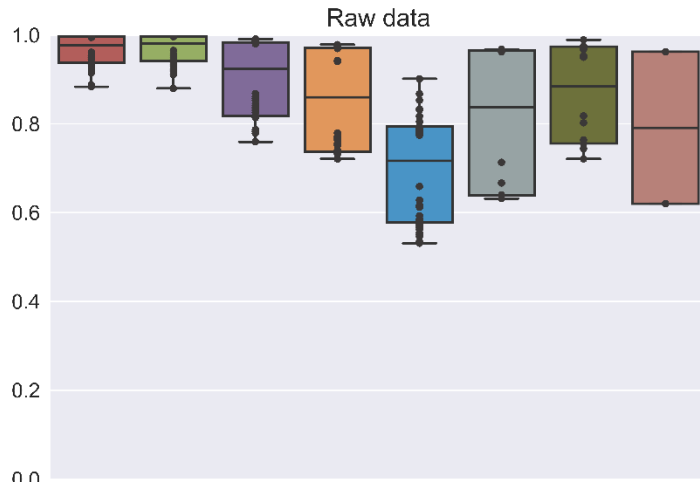


$$H = \begin{cases} 0, & \text{If there is no person} \\ 1, & \text{High Risk person} \\ 2, & \text{Medium Risk person} \\ 3, & \text{Low Risk person} \end{cases}$$

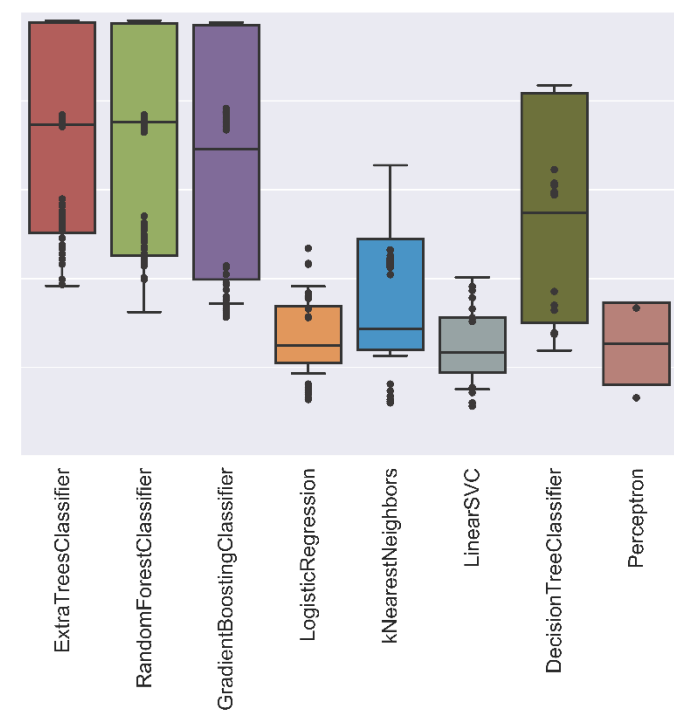
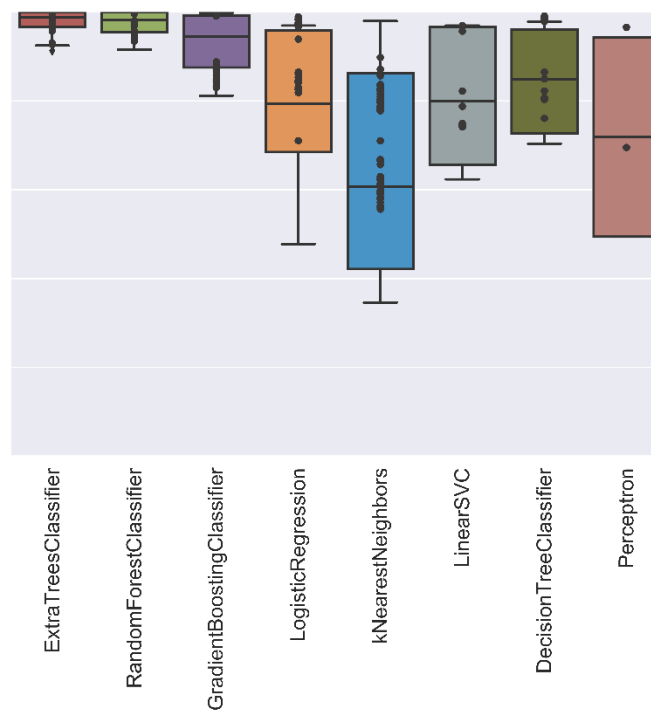
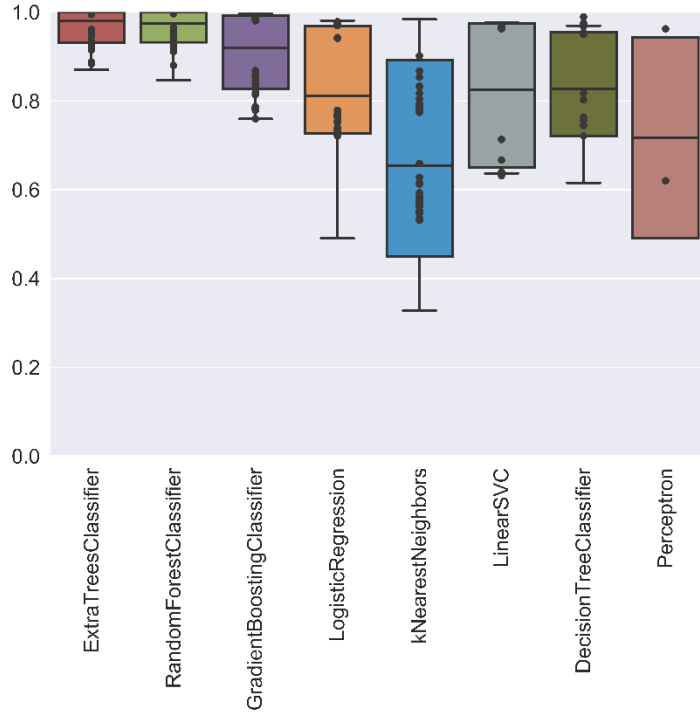
Name	Underlying Model	Parameters	Values
Logistic Regression	Linear	Regularization parameter (C)	[0.001, 0.01, 0.1, 1, 10, 100, 1000]
		Solver	[lbfgs, sag, newton-cg]
Perceptron	Linear	Regularization parameter (Alpha)	[0.0001, 0.001, 0.01, 0.1, 1]
K-Nearest neighbors	Nearest neighbors	Number of neighbors to consider (N)	[1, 2 ,....., 30]
Linear SVC	Support Vector Machine	Regularization parameter (C)	[0.001, 0.01, 0.1, 1, 10, 100, 1000]
Decision Tree	Tree Based	Splitting Quality Measure	[gini, entropy]
		Max_features to consider for splitting	[auto, sqrt, log2]
Random Forest Classifier Extra Trees Classifier	Tree based ensemble	Number of estimators, n	[16, 32, 64, 128, 256]
		Splitting Quality Measure	[gini, entropy]
		Max_features to consider for splitting	[auto, sqrt, log2]
Gradient Boosting Classifier	Tree based boosting	Number of estimators, n	[16, 32, 64, 128, 256]
		Learning Rate	[0.2, 0.5, 0.8, 1.0]

Grid Scores - Accuracy

Indoor



Outdoor

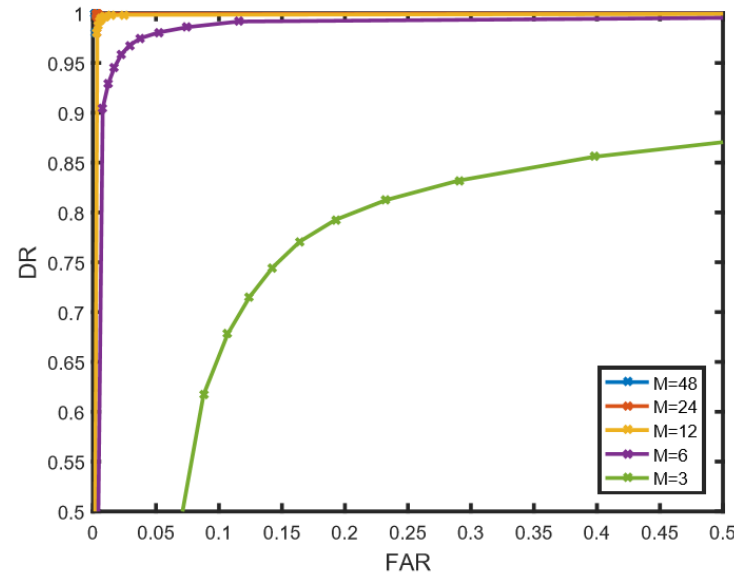


Ex 2 – PHY Layer Security

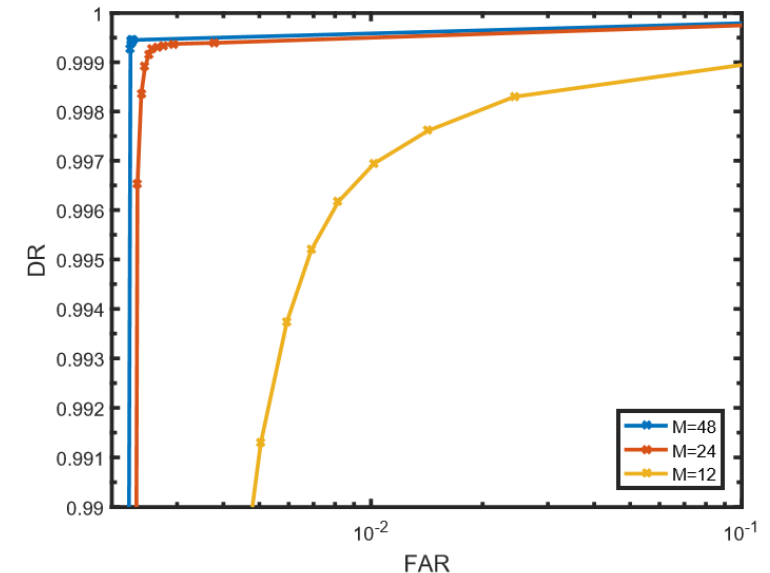
Objective: Use the channel impulse or frequency response to indicate the origin of transmitted data packets

If a receiver needs to authenticate a packet from a specific transmitter, it checks whether the respective channel estimation matches with the previous ones based on the received packets of that user

Gaussian Mixture Models as opposed to generalized likelihood ratio testing



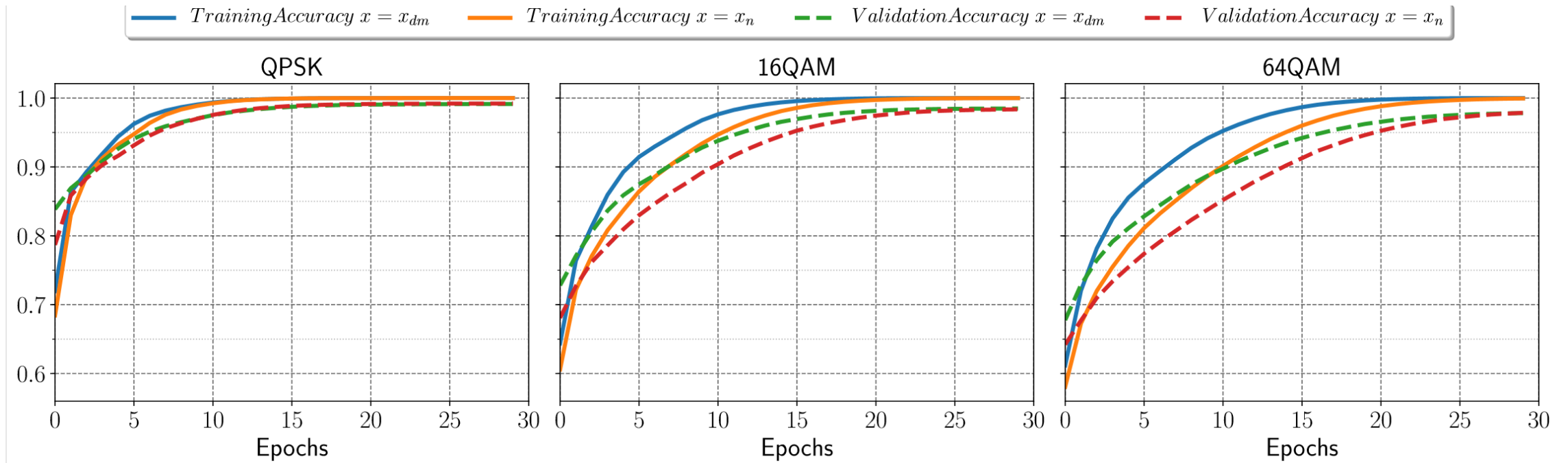
(a) Linear scale



(b) Log scale

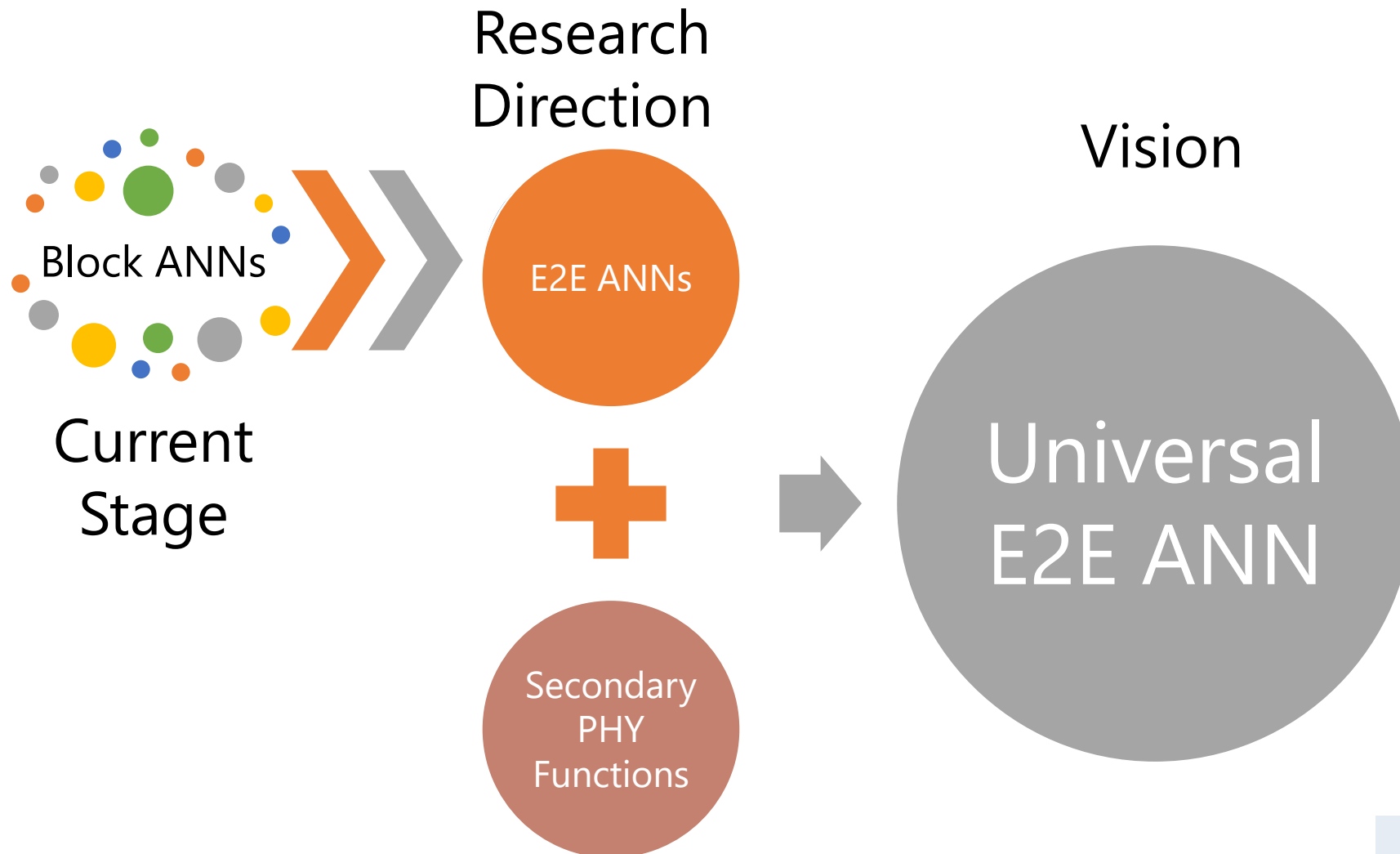
Ex 3 – Channel Coding

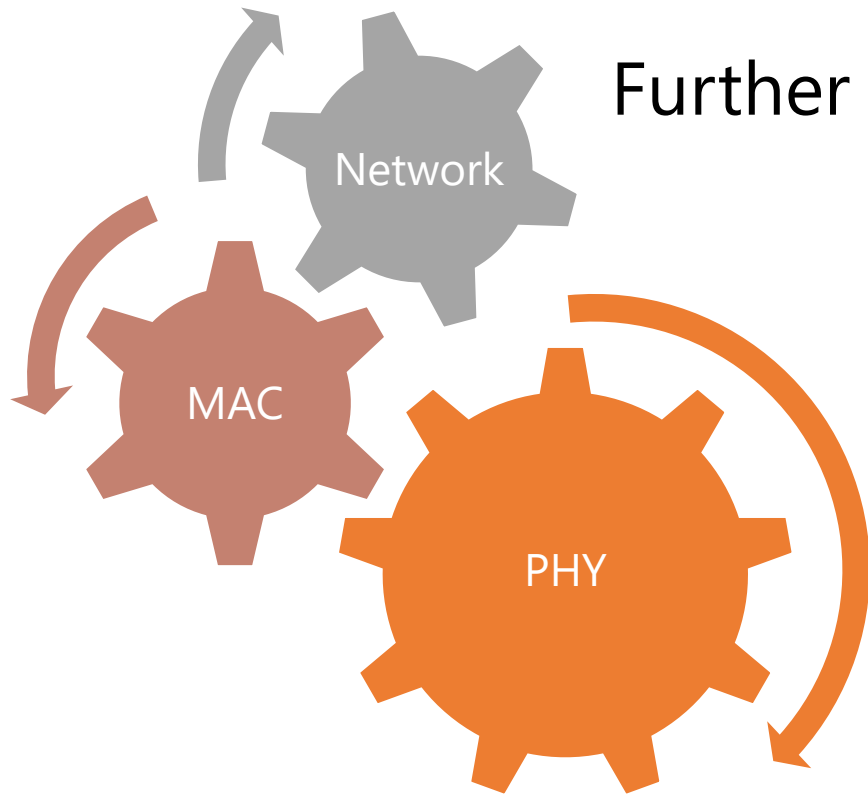
Objective: Study the feasibility of using Neural Network based architectures for decoding Turbo codes



Sattiraju, Raja, Andreas Weinand, and Hans D. Schotten. "Performance Analysis of Deep Learning based on Recurrent Neural Networks for Channel Coding." *arXiv preprint arXiv:1811.12063* (2018)

Conclusion & Vision





Further Evolution

Thank You

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