ITU AI/ML in 5G Challenge 2021

Problem statements

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Contents

1 Summary table of problem statements for the ITU AI/ML in 5G Challenge 2021

This document contains the problem statements that have been curated for the 2021 edition of the ITU AI/ML in 5G Challenge.

Table 1: Summary of problem statements for the ITU AI/ML in 5G Challenge

No	Title	Affiliation
PS-001	Graph Neural Networking Challenge 2021: Creating a Scalable Network Digital Twin	Barcelona Neural Networking Center (BNN-UPC)
PS-002	WALDO (Wireless Artificial intelligence Location DetectiOn): sensing using mmWave communications and ML.	National Institute of Standards and Technology (NIST)
PS-003	Machine Learning for finding groups of BSSs (Basic Service Set) suitable for Coordinated Spatial Reuse	Universitat Pompeu Fabra (UPF)
PS-004	Federated Learning for Spatial Reuse in a multi-BSS (Basic Service Set) scenario	Universitat Pompeu Fabra (UPF)
PS-005	Network anomaly detection based on logs	China Unicom
PS-006	ML5G-PHY-Reinforcement learning: scheduling and resource allocation	Universidade Federal do Pará, (UFPA)
PS-007	Hardware-Efficient Modulation Classification with RadioML	Xilinx
PS-008	ML5G-PHY-Localization: Multidevice localization with mmWave signals in a factory environment	North Carolina State University (NCSU)
PS-009	RF-Sensor Based Human Activity Recognition	The University of Alabama
PS-010	Forecasting Model for Service Allocation Network Using Traffic Recognition	Saint Petersburg State Uni. of Telecommunications (SPbSUT)
PS-011	Delivery route optimization	ZTE

PS-012	Radio Link Failure Prediction	Turkcell
PS-013	Cross Layer user experience optimization – Radio link performance prediction	China Mobile
PS-014	Network resource allocation for emergency management based on closed loop analysis	ITU Focus Group on Autonomous Networks (FG-AN)
PS-015	Network failure detection and root cause analysis in 5GC by NFV-based test environment	KDDI, Japan
PS-016	Location estimation using RSSI of wireless LAN	RISING, Japan

2 Review of the ITU AI/ML in 5G Challenge – 2020

The ITU AI/ML in 5G Challenge brings together like-minded students and professionals from around the globe to study the practical application of artificial intelligence (AI) and machine learning (ML) in emerging and future networks.

- The first edition of the Challenge in 2020 welcomed over 1 300 participants from 62 countries, forming 911 teams.
- During the Grand Challenge Finale, held online, on 15-17 December 2020, teams selected from each problem statement competed for prizes totalling CHF 33 000. Global recognition and ITU certificates awaited the winners.
- Close to 30 webinars which accompanied the Challenge received over 10 000 views (live & replay; https://aiforgood.itu.int/ai-ml-in-5g-challenge/).
- The best peer-reviewed papers resulting from the Challenge will feature in a special issue of the ITU Journal “Future and evolving technologies” (https://www.itu.int/en/journal/j-fet/2021/005), to be published in June 2021.
- In December 2020, ITU NEWS Magazine (available in Arabic, Chinese, English, French, Russian, Spanish) featured in a 91-page dedicated edition to the Challenge (https://www.itu.int/en/itunews/Documents/2020/2020-05/2020_ITUNews05-en.pdf).

3 Call for problem statements: ITU AI/ML in 5G Challenge – 2021

If you plan to submit problem statements for the 2021 or future Challenges, please answer the following questions and submit your problem statement to ai5gchallenge@itu.int.

Name of the submitter:	*<<add your name here>>*
Affiliation:	*<<add your university or company or other affiliation here>>*
Contact email:	*<<add your email address here>>*
Country:	
Title of problem statement:	
Description of problem statement (provide as attachment, if needed):	

Is data set available? (public/private):	*<<yes/no/not needed>>* *<<if yes, please mention – public/private>>*
Would you offer prizes or incentives for winners of this problem statement?	*<<yes/no budget available>>* *<<if yes, please mention – amount or the incentive, e.g. internship opportunities>>*

NOTE 1 - Problem statements which require a dataset but the problem owner does not provide the required dataset will not be accepted.

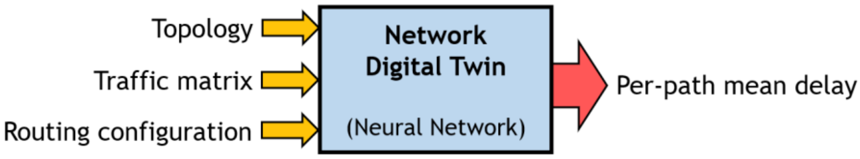
NOTE 2 - For description of problem statement, please fill in the information in the following template.

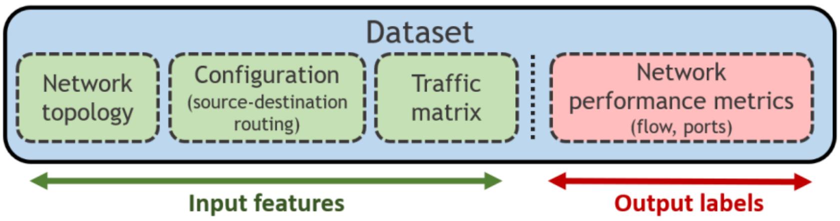
4 Template for problem statements

The table below is a template that can be used for submission of new problem statements for the ITU AI/ML Challenge.

Id	**ITU-ML5G-PS-TEMPLATE**
Title	Please do not modify this particular table, this serves as a template, use the one below.
Description	NOTE 1 - Include a brief overview followed by a description about the problem, its importance to IMT-2020 networks and ITU, highlight any specific research or industry problem under consideration.
Challenge Track/Theme	NOTE 2 - Include a brief note on why it belongs in this track/theme.
Evaluation criteria	NOTE 3 - This should include the expected submission format e.g. video, comma separated value (CSV) file, etc. NOTE 4 - This should include any currently available benchmarks. e.g. accuracy.
Data source	NOTE 5- e.g. description of private data which may be available only under certain conditions to certain participants, pointers to open data, pointers to simulated data.
Resources	NOTE 6- e.g. simulators, APIs, lab setups, tools, algorithms, add a link in clause 2.
Any controls or restrictions	NOTE 7- e.g. this problem statement is open only to students or academia, data is under export control, employees of XYZ corporation cannot participate in this problem statement, any other rules applicable for this problem, specific IPR conditions, etc.
Specification/Paper reference	NOTE 8- e.g. arxiv link, ITU-T link to specifications, etc.
Contact	NOTE 9 - Email id or social media contact of the person who can answer questions about this problem statement.

5 Problem statements for the 2021 edition of the ITU AI/ML in 5G Challenge

Id	**ITU-ML5G-PS-001**
Title	Graph Neural Networking Challenge 2021
Description	Graph Neural Networks (GNN) have produced ground-breaking applications in many fields where data is fundamentally structured as graphs (e.g. chemistry, physics, biology, recommender systems). In the field of data networks, this new type of neural networks is being rapidly adopted for a wide variety of use cases, particularly for those involving complex graphs (e.g. performance modelling, routing optimization, resource allocation in wireless networks) [1]. The Graph Neural Networking 2021 problem statement brings a fundamental limitation of existing GNNs: their lack of generalization capability to larger graphs. In order to achieve production-ready GNN-based solutions, we need models that can be trained in network testbeds of limited size, and then be able to operate with guarantees in real customer networks, which are often much larger in number of nodes. In this challenge, participants are asked to design GNN-based models that can be trained in networks of limited size (up to 50 nodes), and then generalize successfully to larger networks not seen before, up to 300 nodes. Solutions with better scalability properties will be the winners. *<u>Problem statement:</u>* The goal of this challenge is to create a Network Digital Twin solution based on neural networks, which can accurately estimate QoS performance metrics given a network state snapshot. More in detail, this solution must predict the resulting source-destination mean per-packet delay given: (i) a network topology, (ii) a source-destination traffic matrix, and (iii) a network configuration (routing):  ***Figure 1:*** *Schematic representation of the neural network-based solution targeted in this challenge* Particularly, **the objective of this challenge is to achieve a Network Digital twin that can effectively scale to considerably larger networks** than those seen during the training phase. *<u>Baseline:</u>* As a baseline, we provide RouteNet [2], a Graph Neural Network (GNN) architecture recently proposed to estimate end-to-end performance metrics in networks (e.g. delay, jitter, loss). Thanks to its GNN architecture, RouteNet revealed an unprecedented ability to make accurate performance predictions even in network scenarios unseen during the training phase, including other network topologies, routing configurations, and traffic matrices.

	In this challenge, we extend the problem to modelling performance in networks considerably larger to those seen in the training phase. When RouteNet is trained in small-scale networks, such as those of the training dataset of this challenge, it is not able to produce accurate estimates in much larger networks, as those of the validation and test datasets. As a result, we need a model that offers better scalability properties. Nowadays, achieving scalable GNN models is a relevant open problem in the Machine Learning community. Participants are encouraged to update RouteNet or design their own neural network architecture from scratch. Check more details at: https://bnn.upc.edu/challenge/gnnet2021
Challenge Track/Theme	Network-track (design, train and test a neural network model for a networking use case).
Evaluation criteria	The objective is to test the scalability properties of proposed solutions. To this end, before the end of the challenge, we will provide a test dataset. This dataset will contain samples with similar distributions to the samples present in the validation dataset. Participants must label this dataset with their neural network models and send the results in CSV format. For the evaluation, we will use the Mean Absolute Percentage Error (MAPE) score computed over the delay predictions produced by candidate solutions: $$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left\lvert\frac{\hat{y}_i - y_i}{y_i}\right\rvert$$ Solutions with lower MAPE score will be the winners.
Data source	We provide a dataset generated with the OMNet++ network simulator, which is a discrete event packet-level network simulator. The dataset contains samples simulated in several topologies and includes hundreds of routing configurations and traffic matrices. Each sample is labelled with network performance metrics obtained by the simulator: per-flow performance statistics (mean per-packet delay, jitter and loss), and port statistics (e.g. queue utilization, size).  Data is divided in three different sets for training, validation and test. As the challenge is focused on scalability, the validation dataset contains samples of networks considerably larger (51-300 nodes) than those of the training dataset (25-50 nodes). Likewise, the test dataset will be released at the end of the challenge, just before the evaluation phase starts, and it will contain samples following the same distribution as in the validation dataset.

Resources	All the tools and resources can be found at the following link: https://bnn.upc.edu/challenge/gnnet2021/ - Datasets: Training, validation (released at the beginning) and test (unlabelled, released at the end) - Python API to easily read the datasets provided - RouteNet: baseline GNN-based Digital Twin (open-source implementations in TensorFlow and IGNNITION [3]) - Mailing list for questions and comments related to the challenge.
Any controls or restrictions	This challenge is open to all participants. To participate officially, it is mandatory filling the registration form at: https://bnn.upc.edu/challenge/gnnet2021/registration Please, find the specific rules of this problem statement at the website: https://bnn.upc.edu/challenge/gnnet2021
Specification/Paper reference	[1] Must-read papers on GNN for communication networks. https://github.com/BNN-UPC/GNNPapersCommNets [2] Rusek, K., Suárez-Varela, J., Mestres, A., Barlet-Ros, P., & Cabellos-Aparicio, A, “Unveiling the potential of Graph Neural Networks for network modelling and optimization in SDN,” In Proceedings of ACM SOSR, pp. 140-151, 2019. [3] IGNNITION: Framework for fast prototyping of Graph Neural Networks for communication networks. https://ignnition.net/
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Id	**ITU-ML5G-PS-002**
Title	WALDO (Wireless Artificial intelligence Location DetectiOn): sensing using mmWave communications and ML.
Description	The *Wireless Artificial Intelligence Location DetectiOn* challenge tackles one most promising applications of current 5G and future 6G wireless systems, which is the convergence of millimeter wave communication, sensing and localization [1]. Millimetre network are currently being deployed and new interesting use cases are being proposed, paving the way to new innovative and emerging applications. Indeed, millimeter wave spectrum offers not only large bandwidth for high throughput applications but also great opportunities for accurate localization to enable new applications such as presence detection, gesture recognition, or person identification. In this context, IEEE has recently started a new task group, TGbf, to enhance the reliability and efficiency of WLAN sensing, introducing IEEE 802.11bf, which extends the current IEEE 802.11ay functionalities. WLAN sensing utilizes the 802.11 deployed devices to conduct tracking and monitoring, thus alleviating the need for specific monitoring devices [2]. Participants are challenged to propose an AI/ML algorithm that estimates the location of moving targets, e.g. people, given a set of training data set consisting of received 802.11ay packets at different SNR levels and the corresponding wireless channel information. The challenge assumes an indoor multiple access points scenario. These devices will communicate using conventional IEEE 802.11ay packets, which consist of a preamble and a series of symbol blocks. This configuration enables a multi-static radar, since sensing can be performed by tracking changes on a wireless channel through the reception of multiple packets. A single-user multi-antenna elements architecture is adopted at each device, which means that a single RF chain is equipped with a uniform rectangular array and a single stream can be transmitted (SISO). The wireless channel variations in the room are introduced by the presence of people that can have different motion dynamics. We assume the room to be divided in multiple sectors. The participants need to estimate **how many people are present in each of these sectors**. This assumption represents practical applications such as in-store tracking to provide customized information and advertisement. The participant solutions can shed light on the sensing and localization performance and limitations of future 6G systems re-using current 5G infrastructure, provide future directions to IEEE standardization activities as well as quantify the impact of novel AI/ML techniques with respect to conventional signal processing.
Challenge Track/Theme	Network-track. The challenge considers the usage of AI/ML in 5G networks.

Evaluation criteria	Two main metrics will be considered to evaluate the submission, i.e. counting and localization error. The counting error quantifies the accuracy in counting the total number of people present in the room. The localization error quantifies the accuracy in counting the number of people present in each sector. More weight will be given to the localization error.
Data source	The challenge relies on two open-source simulators: 1) NIST 802.11ay PHY [3] Used to generate 802.11ay packets 2) NIST Q-D channel realization software: https://github.com/wigig-tools/qd-realization Used to generate the millimetre wireless channel. **Training Data set** The training datasets consist of a collection of received packets and the relative wireless channels as well as the list of number of people per sector for each channel realization. These datasets are available for two different channel conditions. First a deterministic channel realization, which only includes the strongest reflections in the room. Second, a quasi-deterministic channel which includes the stochastic components that model the rough surface properties of the environment. The received packets in the datasets are available for different values of SNR. A MATLAB script is also provided to guide the participants to use directly the software used to generate the dataset. **Test** The test datasets consist of a collection of received packets at different SNR.
Resources	1) NIST 802.11ay PHY: This repository is now private, but it will be public by June 1st. Organizers of the challenge can be granted access to it, if requested. 2) NIST Q-D channel realization software: https://github.com/wigig-tools/qd-realization
Any controls or restrictions	Open
Specification/Paper reference	[1] C. D. Lima, "Convergent Communication, Sensing and Localization in 6G Systems: An Overview of Technologies, Opportunities and Challenges," IEEE Access, pp. 26902-26925, 2021. [2] T. X. Han, "IEEE 802.11bf Aims to Enable a New Application of WLAN Technology: WLAN Sensing," 5 12 2020. [Online]. Available: https://beyondstandards.ieee.org/ieee-802-11bf-aims-to-enable-a-new-application-of-wlan-technology-wlan-sensing/. [Accessed 11 03 2021]. [3] A. Bodi, "Physical-Layer Analysis of IEEE 802.11ay Based on a Fading Channel Model from Mobile Measurements," in ICC 2019 - 2019 IEEE International Conference on Communications (ICC), Shanghai, China, 2019.
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Id	**ITU-ML5G-PS-003**
Title	Machine Learning for finding groups of BSSs (Basic Service Set) suitable for Coordinated Spatial Reuse
Description	Beyond the IEEE 802.11ax Spatial Reuse operation, the upcoming IEEE 802.11be (11be) amendment [1] is expected to include features relying on multi-Access Point (multi-AP) coordination [2]. In this regard, Coordinated SR (C-SR) allows two or more APs to perform scheduled SR-based simultaneous transmissions, thus potentially improving the Signal-to-Interference plus Noise (SINR) ratio of individual links. In particular, coordination is achieved by defining two roles for APs: 1) a coordinator (or sharing) AP triggers one or more other APs to transmit simultaneously with appropriate power control, and 2) a coordinated (or shared) AP identifies SR opportunities announced by sharing APs and transmits with constrained transmission power during the transmission opportunity (TXOP). In C-SR, one relevant open issue lies in deciding the set of devices allowed to transmit simultaneously. For the sake of efficiency, it is therefore imperative to carefully select the best combinations of devices that can transmit in parallel. To address the SR problem in 11ax WLANs, we propose using Machine Learning (ML). ML allows capturing subtle information that cannot be predicted before-hand (for instance, regarding inter-BSS interactions). Such information enables conducting a learning-based procedure, which is aimed at increasing performance while reducing the number of undesired situations (e.g. poor fairness). In the context of the proposed problem statement, participants must propose ML models that, given a particular C-SR deployment, identify the best combinations of devices from different BSSs that are allowed to transmit simultaneously. A dataset will be provided for training these ML mechanisms.
Challenge Track/Theme	This problem statement is framed into the Networks-track because it gives rise to develop ML models based on a training dataset that will be provided to participants.
Evaluation criteria	Participants will submit a report explaining their solution, including the outcomes of their models.
Data source	A dataset generated with the Komondor simulator [3] will be provided to train ML models.
Resources	Besides the dataset, complementary material will be provided to participants, including references, detailed instructions, and guidelines.
Any controls or restrictions	This problem statement is open to any interested party.

Specification/Paper reference	[1] Garcia-Rodriguez, A., Lopez-Perez, D., Galati-Giordano, L., & Geraci, G. (2020). IEEE 802.11 be: Wi-Fi 7 Strikes Back. arXiv preprint arXiv:2008.02815. [2] TGbe document: AP coordination in EHT, 11-18-1926-02-0eht-terminology-for-ap-coordination. [3] Barrachina-Muñoz, S., Wilhelmi, F., Selinis, I., & Bellalta, B. (2019, April). Komondor: a wireless network simulator for next-generation high-density WLANs. In 2019 Wireless Days (WD) (pp. 1-8). IEEE. [Open-access version].
Contact	Francesc Wilhelmi (francisco.wilhelmi@upf.edu)

Id	**ITU-ML5G-PS-004**
Title	Federated Learning for Spatial Reuse in a multi-BSS (Basic Service Set) scenario
Description	The Spatial Reuse (SR) operation was firstly introduced in the IEEE 802.11ax (11ax) amendment [1] as a novel feature to improve spectral efficiency. SR allows Wi-Fi devices to identify transmission opportunities (TXOPs) even if noticing high interference, thus potentially increasing the number of parallel transmissions in an Overlapping Basic Service Set (OBSS). To accomplish that, SR uses Clear Channel Assessment (CCA) adjustment along with transmission power control. Several works have studied the potential gains of SR in the context of 11ax [1-4]. However, the potential gains of SR are limited by the rigidity of the mechanism introduced in the 11ax, which is too conservative and only considers local information. As a result, the definition of efficient policies for addressing SR remains open. To address the SR problem in 11ax WLANs, we propose using Machine Learning (ML). ML allows capturing subtle information that cannot be predicted before-hand (for instance, regarding inter-BSS interactions). Such information enables conducting a learning-based procedure, which is aimed at increasing performance while reducing the number of undesired situations (e.g. poor fairness). In particular, we ask for Federated Learning (FL) proposals, so that participants are expected to build a model that can be trained at different types of SR deployments. Such a model is expected to personalize its outcome according to the context (i.e. the deployment) to which it is applied. In this regard, clustering mechanisms are expected to be applied for aggregating nodes with similar characteristics.
Challenge Track/Theme	This problem statement is framed into the Networks-track because it gives rise to develop ML models based on a training dataset that will be provided to participants.
Evaluation criteria	Participants will submit a report explaining their solution, including the outcomes of their models.
Data source	A dataset generated with the Komondor simulator [5] will be provided to train ML models.
Resources	Besides the dataset, complementary material will be provided to participants, including references, detailed instructions, and guidelines.
Any controls or restrictions	This problem statement is open to any interested party.

Specification/Paper reference	[1] Wilhelmi, F., Barrachina-Muñoz, S., Cano, C., Selinis, I., & Bellalta, B. (2021). Spatial reuse in IEEE 802.11 ax WLANs. Computer Communications, 170, 65-83. [Open-access version]. [2] Wilhelmi, F., Barrachina-Muñoz, S., & Bellalta, B. (2019, October). On the performance of the spatial reuse operation in IEEE 802.11 ax WLANs. In 2019 IEEE Conference on Standards for Communications and Networking (CSCN) (pp. 1-6). IEEE. [Open-access version]. [3] Rodrigues, E. D. C., Garcia-Rodriguez, A., Giordano, L. G., & Geraci, G. (2020). On the Latency of IEEE 802.11 ax WLANs with Parameterized Spatial Reuse. arXiv preprint arXiv:2008.07482. [4] Krotov, A., Kiryanov, A., & Khorov, E. (2020). Rate Control With Spatial Reuse for Wi-Fi 6 Dense Deployments. IEEE Access, 8, 168898-168909. [5] Barrachina-Muñoz, S., Wilhelmi, F., Selinis, I., & Bellalta, B. (2019, April). Komondor: a wireless network simulator for next-generation high-density WLANs. In 2019 Wireless Days (WD) (pp. 1-8). IEEE. [Open-access version].
Contact	Francesc Wilhelmi (francisco.wilhelmi@upf.edu)

Id	**ITU-ML5G-PS-005**
Title	Network anomaly detection based on logs
Description	Modern communication network is becoming more and more complex. A large number of communication devices produce a large number of logs every day. From the logs, we can analyze the current health status of the devices and detect or predict the possible faults. Because the log data format is not uniform and unstructured, the traditional method of keyword search or rule matching to manually check the log is inefficient and not applicable. It is urgent to introduce AI-based log anomaly detection method to improve work efficiency and reduce operation and maintenance costs. We evaluate the effect by F1 value.
Challenge Track	Network-track
Evaluation criteria	According to the test set, the prediction result should be saved in a csv file and follow the required format. Within the scope of optimization objectives, we use F1 score to evaluate the results. F1 score is calculated based on the precision and recall of log anomaly detection. The higher the precision is, the higher the recall is, and the larger the F1 score value is, the better the effect of log anomaly detection algorithm is.
Data source	The data is the log data of network equipment, including time stamp, log information, etc. The log is in text format. The data is divided into training set and test set. The training set contains tag information, that is, with exception and without exception; it is a Boolean tag representing a true or false result. The test set comes from the same network equipment as the training set. The test set does not contain tag information. After modelling, the contestants predict the test set and get its tag. The data will be publicly available.
Resources	No
Any controls or restrictions	This Challenge is open to all participants.
Specification/Paper reference	No
Contact	xiongjs@chinaunicom.cn

Id	**ITU-ML5G-PS-006**
Title	ML5G-PHY-Reinforcement learning: scheduling and resource allocation
Description	This problem adopts a strategy named CAVIAR (Communication networks and Artificial intelligence immersed in Virtual or Augmented Reality). The problem is based on simulating a communication system immersed on a virtual world, using software such as AirSim and Unreal Engine. The problem is posed as a game that must be solved with reinforcement learning (RL). The goal is to schedule and allocate resources to unmanned aerial vehicles (UAVs) and terrestrial users. The RL agent is executed at the base station. It periodically takes actions based on the information captured from the environment, which includes channel estimates, images from cameras and positions from a Global Navigation Satellite System such as GPS. The communication system model is based on a multiple input/multiple output (MIMO) system, with the base station having a uniform array while the users have a single antenna. The agent receives a reward based on the service provided to the users.
Challenge Track	Network-track
Evaluation criteria	Agent reward, consisting of a weighted sum of key performance indicators, such as bit rate.
Data source	Raymobtime datasets - https://www.lasse.ufpa.br/raymobtime/
Resources	None.
Any controls or restrictions	This problem statement is open to all participants.
Specification/Paper reference	[1] 5G MIMO Data for Machine Learning: Application to Beam-Selection using Deep Learning, 2018 - http://ita.ucsd.edu/workshop/18/files/paper/paper_3313.pdf. [2] MmWave Vehicular Beam Training with Situational Awareness by Machine Learning, 2018 - https://ieeexplore.ieee.org/document/8644288. [3] Generating mimo channels for 6G virtual worlds using ray-tracing simulations. Submitted to IEEE Statistical Signal Processing Workshop 2021. [4] Simulation of machine learning-based 6G systems in virtual worlds. Submitted to the ITU Journal on Future and Evolving Technologies (submitted), 2021.
Contact	Aldebaro Klautau – aldebaro@ufpa.br. Tel: +55 91 3201-7181

Id	**ITU-ML5G-PS-007**
Title	Hardware-Efficient Modulation Classification with RadioML
Description	The ever-growing demand for wireless data is driving a need for improved radio efficiency, of which a key component is improved spectral allocation via high quality spectrum sensing and adaptation. A key component for solutions such as Dynamic Spectrum Access (DSA) and Cognitive Radio (CR) is Automatic Modulation Classification (AMC) [1, 2], where the high-level goal is to monitor the RF spectrum and determine the different modulations being used. This information is subsequently used to reach transmission decisions that transmit information more efficiently. Prior works have successfully applied deep learning to AMC, demonstrating competitive recognition accuracy for a variety of modulations and SNR regimes. However, to reap the benefits of AMC with deep learning in practice, an important challenge remains: modulation classification should be performed with low latency and high throughput to accurately reflect the current status of the transmissions. Inference with common deep neural networks can involve hundreds of millions of multiply-accumulate operations and many megabytes of parameters, which makes line-rate performance very challenging. A body of research [4, 5, 6] seeks to address these challenges applying quantization to weights and activations, pruning, novel topology design and pruning, which may be done in a co-designed fashion with hardware [7, 8] to provide the required system-level throughput. As this typically comes at the cost of some classification accuracy, multiple solutions offering different throughput at different levels of accuracy may be created. In this challenge, the participants will design neural networks with an awareness of both inference computation cost and accuracy to explore the landscape of compact models for AMC on the Deepsig RadioML 2018 dataset [3].
Challenge Track/Theme	Network-track, as the challenge consists of use cases related to signal decoding.
Evaluation criteria	Submissions will be required to specify both the accuracy of the provided solution and its hardware cost (as defined below). Each submission will be required to reach a hard threshold in terms of accuracy. Submissions that pass the threshold will be considered valid and will then be ranked according to a provided hardware cost function computed on: - Size of the trained model, both in regards to number of parameters and their bit precision. - Size of the overall number of activations generated during an inference pass through the trained network, again accounting for the effects of quantization. - Number of operations, normalized in terms of bit operations.

	Any trained model whose cost changes on a per-input basis will be evaluated by normalizing the cost w.r.t. to the dataset in a batch-1 setting. Valid submissions are required to include all the source code necessary to perform training from scratch and reach the required accuracy threshold. Because of inherent difficulty in reproducing training results exactly, a submission will be considered valid as long as it can be independently reproduced to reach the minimum required accuracy threshold, whether the reproduced accuracy matches the submitted one exactly or not. Valid submissions will be required to include all the source code necessary to compute the hardware cost. A reference implementation of the hardware cost function will be provided, and submissions will then be free to adapt it to their models (as long as the actual mathematical formulation is preserved). Submissions are encouraged to make their results as easy as possible to reproduce, e.g. by providing a single entry point to a predefined Docker image. Any submission that cannot be reproduced because of issues with setup, dependencies, etc. won't be considered valid, independently of what it claims to achieve.
Data source	This challenge relates to the RADIOML 2018.01A dataset published here: https://www.deepsig.ai/datasets.
Resources	We will provide a running training environment including training script in the pytorch library Brevitas available here: https://github.com/Xilinx/brevitas.
Incentives	Internships
Any controls or restrictions	Please ensure to adhere to the license agreement of the dataset: https://creativecommons.org/licenses/by-nc-sa/4.0/legalcode.
Specification/Paper reference	[1] Timothy J. O'Shea, Johnathan Corgan, and T. Charles Clancy. 2016. Convolutional Radio Modulation Recognition Networks. In Engineering Applications of Neural Networks. Springer International Publishing, Cham, 213–226. [2] T. J. O'Shea, T. Roy, and T. C. Clancy. 2018. Over-the-Air Deep Learning Based Radio Signal Classification. IEEE Journal of Selected Topics in Signal Processing 12, 1 (2018), 168–179. [3] Deepsig. RadioMLdatasets. https://www.deepsig.ai/datasets. [4] Sze, Vivienne, Yu-Hsin Chen, Tien-Ju Yang, and Joel S. Emer. "Efficient processing of deep neural networks: A tutorial and survey." *Proceedings of the IEEE* 105, no. 12 (2017): 2295-2329. [5] Park, Eunhyeok, Sungjoo Yoo, and Peter Vajda. "Value-aware quantization for training and inference of neural networks." In *Proceedings of the European Conference on Computer Vision (ECCV)*, pp. 580-595. 2018.

	[6] Gholami, Amir, Sehoon Kim, Zhen Dong, Zhewei Yao, Michael W. Mahoney, and Kurt Keutzer. "A Survey of Quantization Methods for Efficient Neural Network Inference." *arXiv preprint arXiv:2103.13630* (2021). [7] Umuroglu, Yaman, Nicholas J. Fraser, Giulio Gambardella, Michaela Blott, Philip Leong, Magnus Jahre, and Kees Vissers. "Finn: A framework for fast, scalable binarized neural network inference." In *Proceedings of the 2017 ACM/SIGDA International Symposium on Field-Programmable Gate Arrays*, pp. 65-74. 2017. [8] Blott, Michaela, Thomas B. Preußer, Nicholas J. Fraser, Giulio Gambardella, Kenneth O'Brien, Yaman Umuroglu, Miriam Leeser, and Kees Vissers. "FINN-R: An end-to-end deep-learning framework for fast exploration of quantized neural networks." *ACM Transactions on Reconfigurable Technology and Systems (TRETS)* 11, no. 3 (2018): 1-23.
Contact	Michaela Blott (mblott@xilinx.com)

Id	**ITU-ML5G-PS-008**
Title	ML5G-PHY-Localization: Multidevice localization with mmWave signals in a factory environment
Description	Cellular and Wi-Fi communication systems are incorporating millimeter wave spectrum into the possible operation bands. This, together with the introduction of MIMO systems with a large number of antennas, provides the key ingredients to operate with a very good angle and delay resolution, which offers the potential of accurate position and orientation estimation of a device. The ML5G-PHY-Localization challenge addresses the problem of estimating the 3D position and orientation (P/O) of active devices in a factory assuming a realistic hybrid MIMO architecture, both at the access point (AP) and the device. We consider the P/O estimation problem at the access point when several devices are trying to establish the link with the access point. The maximum number of active devices connected to the same AP is fixed. Participants are encouraged to design either a ML-based approach or a hybrid model/data-driven algorithm that can learn some priors from the provided training data set to provide high accuracy estimates with low training overhead during the testing phase. A set of training channels and training received pilots specific for the simulated factory are available during off-line training. These data sets can be used either to train a given network or to learn priors that can be leveraged by a hybrid algorithm. In the testing phase, a different set of received signals, still corresponding to the same factory, will be used to evaluate the performance of the proposed approaches. The acquired training data will correspond to a frequency selective hybrid millimeter wave MIMO-OFDM system as described in [1], where both the transmitter and receiver are equipped with a hybrid architecture. Approaches in the challenge will lead to important insights into what can be achieved using data-driven and/or model-based approaches.
Challenge Track	
Evaluation criteria	Normalized mean square error for position and orientation estimation; maximum error, minimum error, error for 50%, 75% and 90% of estimates with smallest error.
Data source	The training data set consists of a collection of channels associated to the links between devices and access points in a factory environment and also their associated positions in the room. The factory environment has been simulated by ray tracing, with 12 access points (AP) located at the ceiling. The devices are randomly placed at the room and assigned to the best AP. Only two possible heights for the devices are considered. The channels will be grouped to generate multidevice channels that allow the simulation of the uplink of the multiuser mmWave MIMO communication system. The number of devices per AP is limited.

	We will also provide the Matlab code to generate the received signals at the AP from the provided channels for different system parameters. The received signals will be the input to the position and orientation estimation algorithm to be developed. As test datasets, we provide three collections of the received training pilots obtained at SNRs ranging from -20 to 0 dB. The channels used to generate these received signals are different from the ones in the training datasets, but have been obtained in the same simulated factory.
Resources	None
Any controls or restrictions	This Challenge is open to all participants.
Specification/Paper reference	[1] J. P. González-Coma, J. Rodríguez-Fernández, N. González-Prelcic, L. Castedo and R. W. Heath, "Channel Estimation and Hybrid Precoding for Frequency Selective Multiuser mmWave MIMO Systems," in IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 2, pp. 353-367, May 2018. [2] A. Shahmansoori, G. E. Garcia, G. Destino, G. Seco-Granados and H. Wymeersch et al., "Position and Orientation Estimation through Millimeter Wave MIMO in 5G Systems," IEEE Trans. Wireless Commun., March 2018. [3] W. Zheng and N. González-Prelcic, "Joint Position, Orientation AND Channel Estimation in Hybrid mmWave MIMO Systems," 2019 53rd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 2019, pp. 1453-1458.
Contact	Prof. Nuria Gonzalez Prelcic, NC State University, USA ngprelcic@ncsu.edu Tel: +1 512 574 1604

Id	**ITU-ML5G-PS-009**
Title	RF-Sensor Based Human Activity Recognition
Description	RF sensors, or radar (radio detection and ranging), have become increasingly widespread due to proliferation of low-cost, low-power, small RF transceivers. Commercially available RF sensors have typically been devised for biomedical applications of heart rate or respiration measurement, indoor human sensing (e.g. detection and tracking), or automotive sensing applications. Their costs can range from just a few dollars to as much as several thousand dollars, depending on whether it is a chip or evaluation board and whether it comes with its own user interface and processing software. The architectures of the transceivers can also vary from simple continuous-wave (CW) transceivers, to single-channel or multi-channel frequency modulated CW, and even ultra-wide band (UWB) impulse radars. Depending on the architecture, RF sensors can thus provide a rich dataset with information about human presence and movements, including range, velocity, and angle as a function of time. RF sensor data can also be used for the purposes of human activity recognition, by applying a time-frequency transformation (e.g. short-time Fourier transform) to generate a plot of a subject's radial velocity versus time – also known as a micro-Doppler signature. Different activities generate different patterns in the micro-Doppler signature; thus, machine learning can be applied to classify these patterns and thus identify different activities. Accurate monitoring of human activities is a task critical to many applications of human ambient intelligence, including remote health monitoring, energy efficiency, smart environments, and human-computer interfaces. In this regard, RF sensing can be a great modality, as it is non-contact, is effective in the dark, and at low frequencies can even penetrate walls. RF sensors also are less personally invasive, as no imagery of the face or environment is obtained. However, there are a number of challenges in achieving high classification accuracy; to name a few: the relatively small amount of data available for training, generalization to people whose data is not in the training dataset, recognition of activities not in the training data set (open set problem), degradation in performance when observation angle nears 90 degrees, and modulation of Doppler spread incurred when an individual walks in arbitrary directions. This challenge addresses just the first of these challenges: how to most effectively train and classify RF human micro-Doppler signatures for activity recognition. Data from a multi-frequency RF sensor network comprised of three RF sensors with different transmit waveforms at center frequencies is provided at the Github link (https://github.com/ci4r/CI4R-Activity-Recognition-datasets). Participants should use a random selection of 50% of these samples for training and the remaining 50% of the samples for testing.

	In addition to the 40% of the real data samples provided, participants are also allowed to use any other source of RF or other sensor modality desired for training. This includes databases of optical imagery, such as ImageNet, motion capture data, synthesized RF data, or other measured RF data, such as the 4 GHz activity data provided at https://github.com/ci4r/4-GHz-Human-Activity-Dataset- . Data from one sensor may also be used to help classify data from another sensor in the network. The objective of the challenge is thus to encourage participants to advance the efficacy of DNN training in RF signature classification. In doing so, the participants are encouraged to think carefully about how the differences and similarities in the data acquired from each sensor can be exploited to maximize accuracy.
Challenge Track/Theme	Sensor Networks
Evaluation criteria	Overall classification accuracy and confusion matrix, reported for 1) each sensor in the network and 2) using all sensors in the network
Data source	Github with Data Download: https://github.com/ci4r/CI4R-Activity-Recognition-datasets
Resources	None.
Any controls or restrictions	All participants welcome.
Specification/Paper reference	Nothing specific, but if interested participants would like some pointers, contact szgurbuz@ua.edu with questions.
Contact	Dr. Sevgi Zubeyde Gurbuz, szgurbuz@ua.edu, Department of Electrical and Computer Engineering, The University of Alabama, Tuscaloosa, AL / USA

Id	**ITU-ML5G-PS-010**
Title	Forecasting Model for Service Allocation Network Using Traffic Recognition
Description	Focusing on the intelligent application demand of networking management and computing resource management, the artificial intelligence technologies such as machine learning and big data include the possibilities of the softwarized approach in IMT-2020 (SDN/NFV) are applied to digital upgrade of the internet infrastructure. The one of the main issues in this area - is the services traffic allocation, taking into account the users dynamics. Here we propose the problem statement with the services traffic forecasting based on the changing user needs for services. The suggestion of problem statement: - Proposal with ML model for recognizing the user demands based on the traffic services allocation; - Proposal with ML model for traffic forecasting, taking into account traffic types and user demands (in order to future service migration).
Challenge Track/Theme	Enables-track
Evaluation criteria	Solutions with lower MAPE and RMSE score for Task 2 and high probability in % of recognition in Task 1 will be the winners. The output format is the report (expected) which include the following: Problem analysis include the Gap analysis of current approaches for solve defined research problem (~2 pages); 1) Architectural scheme, models, algorithm in UML notation (~1 page); 2) Description of solution/suggestion (~1 page); 3) Results of modelling in the graphs and their explanation (~ 1-2 pages); 4) Source software with ML and Big data (if necessary) algorithms; 5) Trained ML-models; 6) Results in the CSV file, which contains results of training: necessary parameters (MAPE & RSME, Probability). *the ".docx" format is required for report.
Data source	Training and testing data sets will be able later on the site.
Resources	Netflow collector - was used; Python (version: 2.7 - 3.4) - for suggestions.
Any controls or restrictions	The problem statement is available for all participants.

Specification/Paper reference	None.
Contacts	Dr. Ammar Muthanna (e-mail: ammarexpress@gmail.com) Artem Volkov (e-mail: artemanv.work@gmail.com)' Abdukadir Khakimov (e-mail: Khakimov-aa@rudn.ru)

Id	**ITU-ML5G-PS-011**
Title	Delivery route optimization
Description	In 5G era where everything is connected, rapid growth of network traffic poses great challenge to traditional network. In this context, intelligent route planning of network service is essential for efficient network management. In particular, how to achieve balance between low latency, high data bandwidth of network service and better utilization of network resources is the key issue for network planning and optimization. This challenge is aimed to optimize the route planning in telecommunication network. Here the network is simplified as a high-speed transportation network due to its complexity, and then the problem is about how to optimize the delivery route planning in the transportation network. For a given transportation network, where some goods are to be delivered between certain starting and ending points, competitors is required to figure out the route for delivery with the lowest transportation cost. The features of the transportation network are as follows: 1) The network is an undirected graph, each transportation node is connected to no more than 10 other nodes. 2) There are no more than 300 transportation nodes in the network. 3) The transportation cost between 2 adjacent nodes depends on the distance between them. 4) There are multiple (no more than 40) lanes between 2 adjacent nodes, identified with numbers from 1 to 40. 5) There can be multiple deliveries on each lane simultaneously, but the total weight of goods delivered on each lane should be constrained within 10 tons. For example, each lane between adjacent nodes A and B can transport 10 tons of goods in total at most, regardless of the direction of the transportation. If 4 tons of goods is being delivered on a lane, then this lane can only carry another 6 tons of goods during the following deliveries. 6) The total number of the deliveries is no more than 1 000. 7) The weight of goods for each delivery can only be 1 ton, 4 tons or 10 tons. 8) Each delivery must use the lanes with the same identifier in the whole transportation network. For example, if the delivery uses lane 1 between nodes A and B, it can only use lane 1 between other nodes.

	It should be noted that: 1) The routes for all the deliveries should planned ahead of time, and cannot be changed once determined. 2) The solutions should be applicable to all given samples. 3) The solutions are not limited to machine learning, deep learning and traditional algorithms. 4) It should take less than 30 minutes for the solutions to figure out the results.
Challenge Track/Theme	Enabler track, since the problem is simplified and no domain knowledge is needed.
Evaluation criteria	Participants is required to submit runnable algorithms which plans the route for delivery with the lowest transportation cost, along with corresponding description document. These algorithms will be ranked by their total transportation cost on the datasets and duration of the calculation.

Data source	The dataset will be provided later.
	Each sample in the dataset is composed of 2 elements:
	1) A json object that describes the graph of the transportation network, see the below example:
	{
	nodes:[0,1,2] ,# id list of the transportation nodes
	edges:[
	(0,1):{ # (starting point, end point)
	lanes: [0,1,2], # id list of the lanes, the length of the array is the number of the lanes between the two adjacent nodes
	lane_weights:[10, 10, 20] # The weight that each lane can carry
	}
	]
	}
	2) An array composed of tuples that describes the information of each delivery, like: [(starting point, endpoint, weight), (starting point, endpoint, weight, …]

Resources	None
Any controls or restrictions	None
Specification/Paper reference	None
Contact	yuan.liya@zte.com.cn, yang.xikun@zte.com.cn

Id	**ITU-ML5G-PS-012**
Title	Radio Link Failure Prediction
Description	Cloud, rain, snow, and other weather-related phenomena affect the performance of radio links. This is especially applicable to backhaul links operating at GHz frequencies. A generic regional weather forecast data is available which lists expected conditions and coarse temperatures along with actual –precise– realizations. Adding to the complexity are the spatial nature of the data (regions of weather data and RLF needs to be aligned) as well as the time sync needed to correlate various occurrences. Over a period of time, we have compiled and anonymised region-wise data which corresponds to weather forecasts, radio link performances and radio link failures derived from our networks. Given the region-wise, historical data sets derived from our networks and weather forecasts from the meteorology stations predict the occurrence of radio link failures i) in the next day and ii) in the following 10 days
Challenge Track	Network
Evaluation criteria	f1-scores of identifying at least one radio link failure in the next day and the following 10 days will be used to evaluate solution proposals.
Data source	Data source can be reached at: https://lifeboxtransfer.com/s/b35bd3f5-fcf1-4af3-8348-968fc02f8c51 Zip file contains the following tab separated files (tsv): • **distances.tsv**: pair-wise distances • **met-forecast.tsv**: meteorology 5-day forecasts • **met-real.tsv**: meteorology historic realizations • **met-stations.tsv**: meteorology station information • **rl-kpis.tsv**: radio link KPIs and configuration parameters • **rl-sites.tsv**: radio link site information
Comparison to 2020 Problem statement	As compared to problem statement hosted by Turkcell in 2020, this problem statement offers a new data set (comprehensive and with very few missing values) and the data belongs to a new region. The evaluation criteria: predict any failures in the next day and the following 10 days as opposed to predicting failures for each of the following 5 days.
Resources	None

Any controls or restrictions	This Challenge is open to all participants.
Specification/Paper reference	
Contact	Evren Tuna, evren.tuna@turkcell.com.tr Salih Ergüt, salih.ergut@oredata.com

Id	**ITU-ML5G-PS-013**
Title	Cross Layer user experience optimization – Radio link performance prediction
Description	The radio condition of the mobile network can fluctuate on the order of milliseconds and may occasionally result in packet losses and network congestion, which may lead to non-effective usage of available radio resources and a degraded user experience. Therefore, it is highly desirable to introduce cross-layer optimization between the RAN and the application. By making the applications more aware of the network's behaviour predictions (bandwidth, latency, capacity, coverage holes, etc.), the application, take the video streaming as an example, is able to proactively adjusts the codec rate or resolution or dynamically control the user buffer based on the predicted radio link performance. The cross-layer coordination between application and RAN prediction is envisioned to significantly improve the user experience for the promising 5G services, e.g. 4K/8K HD Media, Cloud Gaming, AR/VR, etc. and may even enable new service scenarios in vertical industry. To enable the proactive application optimization, radio link performance prediction capability is desired. The task is radio link performance prediction by using both the radio access network (RAN) data and application data. The RAN data reflecting UE's network and radio status such as the signal quality, interference, resource, etc. and the label, application data rate, are provided. Machine learning/AI is expected be used to predict the application data rate with the RAN metrics.
Challenge Track/Theme	Network-track
Evaluation criteria	According to the test set, the prediction result should be saved in a csv file and followed the required format. We will compare the submission with true answer. The result will be ranked by the prediction accuracy. The prediction accuracy is measured by mean absolute error (MAE).
Data source	Training data from Radio Intelligent Controller (RIC) [1] testbed over wireless network with CellDLMACRate,DLOccupyPRBNum, ULSINR, DLMACRate, MCS, PDCPOccupBuffer, PDCPUnusedBuffer, DLPDCPSDUNum, DLOccupyPRBNum. Label data from the UE report which contains the application-level data rate.
Resources	None.
Any controls or restrictions	**TBD**
Specification/Paper reference	[1] O-RAN.WG3.RICARCH-v01.00: "O-RAN Working Group 3;Near-Real-time RAN Intelligent Controller; Near-RT RIC Architecture".
Contact	Qi Sun, Qiao Zhang, China Mobile

Id	**ITU-ML5G-PS-014**
Title	Network resource allocation for emergency management based on closed loop analysis
Description	Develop a prototype implementation of the following use case: Telecommunication systems are critical pillar of emergency management. A set of hierarchical AI/ML based closed loops could be used to intelligently deploy and manage slice for emergency responders in the affected area. A higher closed loop in the OSS can be used for detecting which area is affected by the emergency and deploy a slice for emergency responders to that area. It can then set a resource arbitration policy for the lower closed loop in RAN. The lower loop can use this policy to intelligently share RAN resources between the public and emergency responder slice. It can also intelligently manage ML pipelines across the edge and emergency responder devices by using split AI/ML models or offloading of inference tasks from the devices to the edge. Following are related steps in this use case scenario: 1. MNO may instruct OSS to detect certain set of emergencies and provide connectivity to emergency responders according to predefined SLA. NOTE- e.g. this input may be provided using an operator intent. 2. OSS might deploy a closed loop to achieve this. It might collect data from sources like network analytics data, social media scraping, input from emergency responders etc. NOTE- e.g. such inputs may be provided from nRT-RICs or other xNFs in the network. 3. OSS might use AI/ML models to detect emergency and deploy an ER slice to the location. It might also create high level strategy/policy to reallocate resources among the slices. NOTE- e.g. such closed loops may be hosted in non-RT RIC and may be used for predictive resource allocations to specific edge locations based on predicted needs, in turn based on detected emergency. NOTE- the policy to reallocate resources may depend, among other things, on the type of emergency e.g. a natural disaster, earth quake, a law and order situation, traffic accidents, etc. 4. RAN domain might use this high-level strategy/policy and possibly other inputs from emergency responders to create a closed loop to arbitrate resources among RAN NSSIs.

<table>
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NOTE- e.g. such closed loops may be hosted nearer to edge e.g. nRT RIC. The policy input from higher loop may indicate, among other things, the different sources of data for the lower loop.
5. RAN domain closed loop might also decide to offload inference tasks from ER devices to the edge or use split AI/ML model to run inference tasks on edge and ER device. This decision might be taken based on available network and compute resources.
NOTE- e.g. some layers of the AI/ML model may be hosted in the wearable devices of the emergency responders, which will help in say locating of persons under distress using various inputs.
Relation with autonomous behaviour-
1. Workflows for the closed loops are independent of each other. The only interaction between closed loops is via high level intents over the inter-loop interface.
2. Closed loops can create new closed loops in other network domains without human intervention.
3. Although loops are deployed in hierarchical fashion, each loop has the ability to evolve independently. It can use different models and ML pipelines as required. Each loop may move up or down the autonomy levels as defined in [ITU-T Y.3173].
4. Closed loops have ability to split and provision AI/ML models to other closed loops in automated fashion.
5. By making closed loops in edge domain autonomous, we also enable lesser orchestration delay, better privacy and flexibility for verticals (e.g., industrial campus networks).
6. Higher loops can use historical knowledge available to them to optimize and generalize lower loops using high-level intent. This increases efficiency of lower loops while preserving their autonomy. (e.g., higher loop might know certain kind of ML models are good for cyclone emergency management based on previous cyclones.)
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<tr><td>Challenge Track</td><td>PoC</td></tr>
<tr><td>Expected output and Evaluation criteria</td><td>
1. Well brought out relationship and mapping with discussions in FG AN use cases, and relationship with a focussed closed loop example(s).
2. Demonstration is focussed on a unique scenario (e.g. figure 1 below).
3. PoC (proof of concept) demonstrates the feasibility (or lack of it) of specific architecture approaches.
4. Quality of technical reports, papers and presentation of github code and demo.
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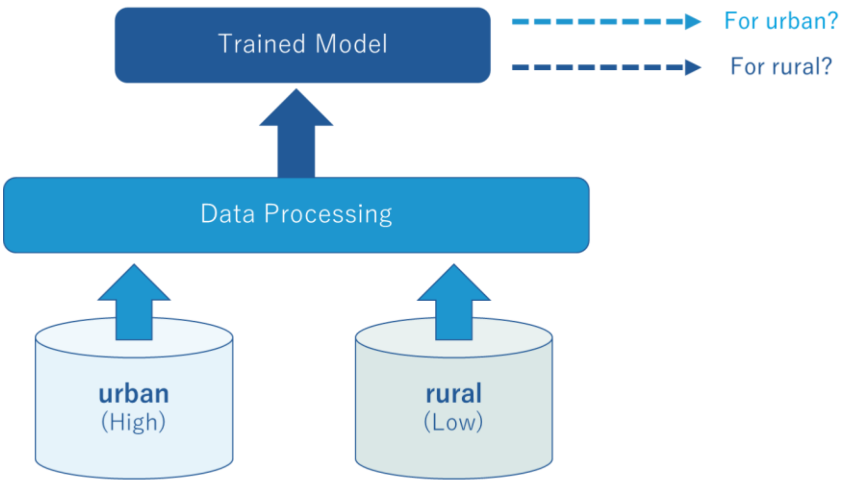
	5. Participation and engagement with mentors, regular and timely progress. Bonus points: for providing feedback to requirements/gaps: what are the impacts to existing reference points for enabling the AN key concepts?
Data source	Not applicable
Resources	1. Testbed and API description [FGAN-I-093] 2. Challenge resources [Build-a-thon resources]
Any controls or restrictions	The build-a-thon is open to all participants.
Specification/Paper reference	[ITU-T Y.3172], [ITU-T Y.3173], [FGAN-I-072], [FGAN-I-83-R2], [FGAN-I-088], [ETSI GS ZSM 001]
Contact	Abhishek Dandekar (Fraunhofer HHI, abhishek.girish.dandekar@hhi-extern.fraunhofer.de) Vishnu Ram Vishnu.n@ieee.org

Id	**ITU-ML5G-PS-015**
Title	Network failure detection and root cause analysis in 5GC by NFV-based test environment.
Description	As 5G mobile networks are getting to be spread globally, the stable and high-quality operation is a must to minimize the social impact caused by 5G service failure. In conjunction with 5G deployment, not only NFV (network virtualization function) but also CNF (cloud native function) is being deployed in service provider networks, adding complexity and uncertainty to operational environment. In that situation, network automation is a key to accelerate 5G network penetration, although highly experienced operators can tackle affected network failure and the anomaly detection is additionally desired to be automatically and rapidly performed by AI/ML. In this problem, the data sets in a 5G core network are provided along with network status information such as normal, a failure, mis-operation and so forth, as normal/abnormal labels. Participants are required to create the model to pinpoint the network status of failures and mis-operation using those data sets and evaluate the performance of the developed model. In order to align to the real operational environment, we provide the data sets in cases of low and high volume of calls assuming urban and rural environments (Fig. 1). Participants are asked to consider the common trained model or separate trained models to estimate. In addition to this, we provided very limited data set for learning just case (Fig. 2). The participants are requested to create model under this condition, for example, by intentionally generated complimentary data set, or by borrowing the data model in Fig. 1.  Fig. 1: Urban/rural models

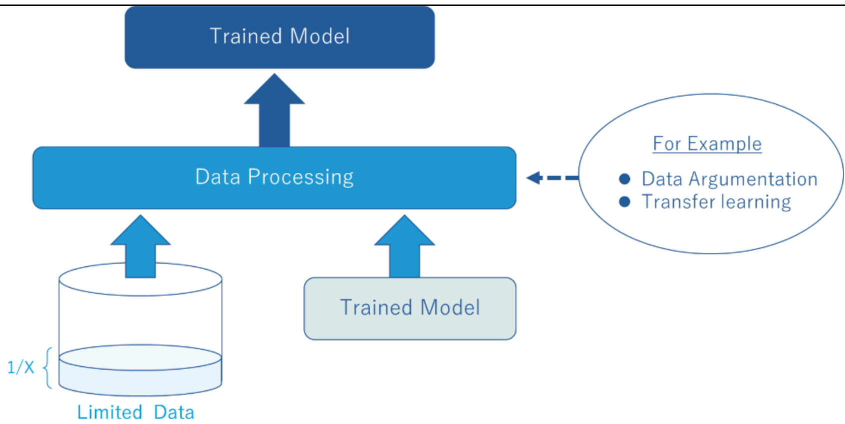


Fig. 2: Limited data case.

Challenge Track	Network Track This challenge focuses on the investigation how AL/ML is applied to detect the degradation and pinpoint network defect of 5GC.
Evaluation criteria	Participants must submit the presentation file containing the demonstration video in order to indicate the solution of the problem and the evaluated results of the solution. The evaluation must be done by an appropriate method for used AI/ML.
Data source	The data sets used for this challenge were created in the NFV-based test environment simulated for 5GC according to [1]. In this sense, they are synthetic data, but as similar as the real data, resulting from our NFV-based test environment. The data sets consist of normal/abnormal labels, performance monitoring data sets such as traffic volume of an user plane, various information of a control plane, HW and middleware performance data. Whilst the data sets were kept to be stored for a long period enough to be analysed, intentional network failures were applied to the network, leading to abnormal labels.
Resources	Participants must prepare for their own computing environment. Utilized tools are desired to be open source software (OSS)-based in order for other people to conduct additional experiments.
Any controls or restrictions	No restriction, but must be utilized only for this purpose.
Specification/Paper reference	[1] J. Kawasaki, et al, “Comparative Analysis of Network Fault Classification Using Machine Learning”, NOMS2020, 10.1109/NOMS47738.2020.9110454
Contact	info_itu5G_jp@lists.cc1g.kddi-research.jp

Id	**ITU-ML5G-PS-016**
Title	Location estimation using RSSI of wireless LAN
Description	The demand for location information is becoming more critical due to the emerge of map applications and augmented reality (AR). Global positioning system (GPS) is the leading steam of localization; however, its accuracy significantly degrades when the number of satellites can be seen from the receivers decreases or due to the impact of reflection from the structures. Thus, the sole use of GPS cannot guarantee ubiquitously accurate localization. As a substitution, localization techniques utilizing the radio signal received from access point (AP) of Wi-Fi and base station (BS) of cellular systems is promising. However, the typical triangulation approach suffers from the multipath fading channel, and hence it cannot achieve high accuracy. This challenge aims to verify if the AI/ML aided localization utilizing receives signal strength indicator (RSSI) observed at the terminal can achieve a similar accuracy as the GPS-based localization. In the traditional localization based on RSSI, it is necessary to have accurate modeling of the channel model that significantly impacts localization accuracy. This challenge explores the possibility if the data-oriented localization can replace the model-based location with the help of powerful AI/ML technique.
Challenge Track/Theme	１． Network Track
Evaluation criteria	Participants are requested to submit AI/ML program/parameters tuned. Average localization error, maximum error, algorithm performance (computational complexity, adaptability to dynamic environment) The top three teams are supposed to compete by using the data set provided just before the final competition.
Data source	The training data includes the location of AP, RSSI information within the coverage of the AP and its corresponding location.
Resources	N/A
Any controls or restrictions	N/A
Specification/Paper reference	[1] S. Hara and D. Anzai, “Use of Simplified Maximum Likelihood Function in a WLAN-Based Location Estimation” IEEE Conference on Wireless Communications and Networking, pp.1-6, May 2009 [2] S. Hara, “Statistical estimation theory in localization,” IEICE Fundamentals Review, vol.4, no.1, pp.32-37, 2010
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