AI for Communication Networks, Communication Networks for AI

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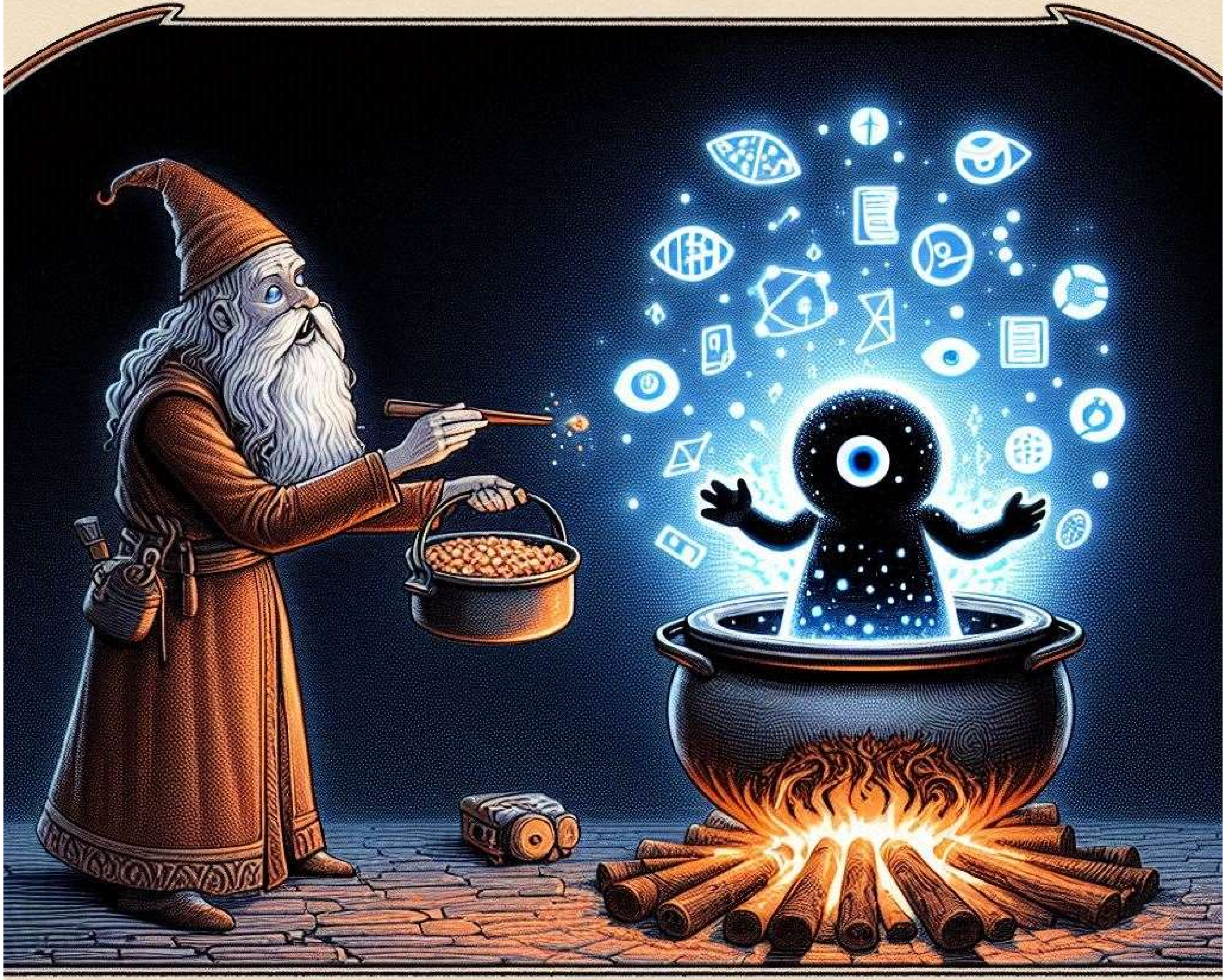
Outline

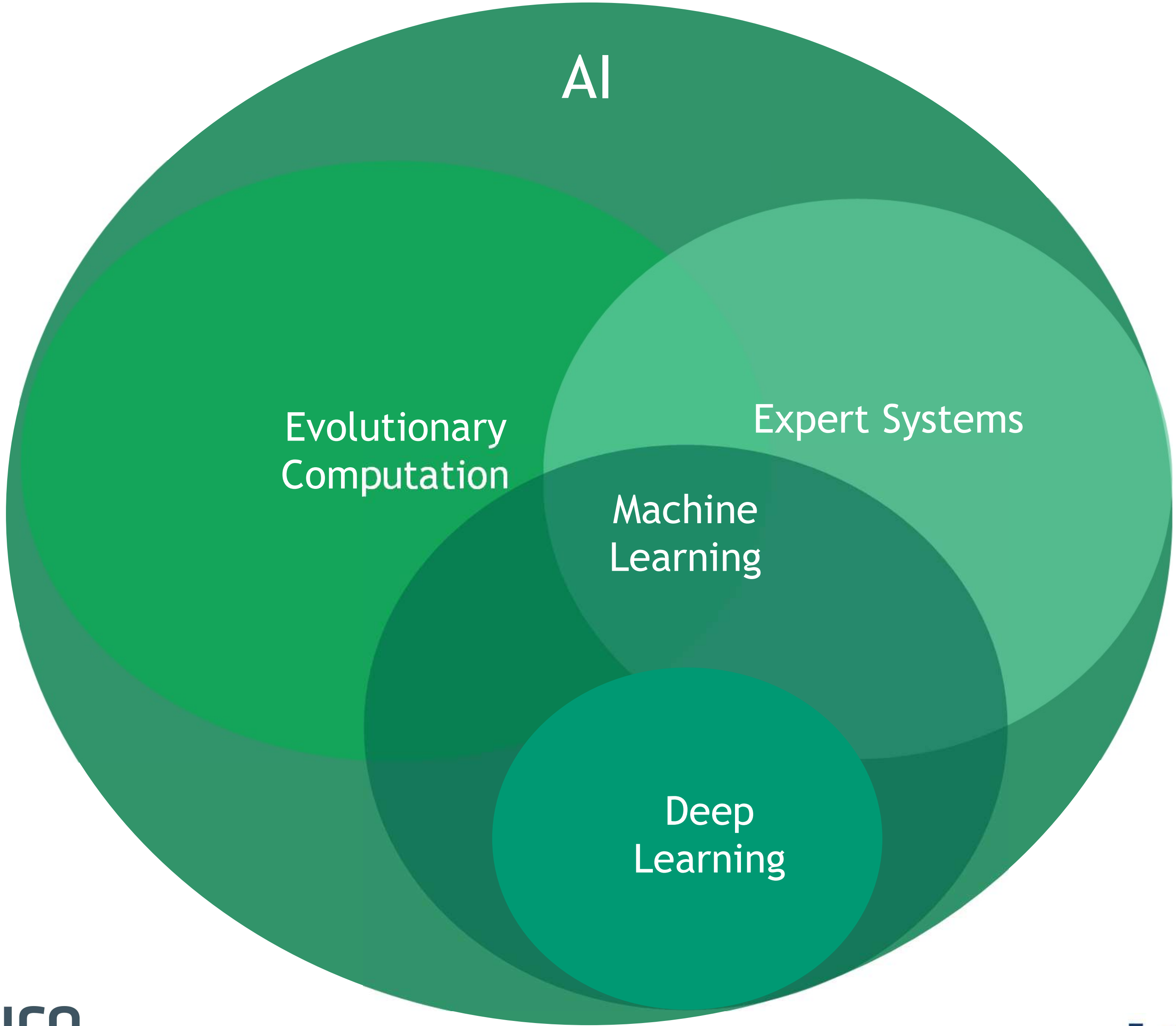
- AI and its Realms
- The AI-Enabled Communication Network
- Machine Learning-based Anomaly Detection and Root Cause Analysis in Mobile Networks
- Wrap-Up and Conclusions

AI and its Realms

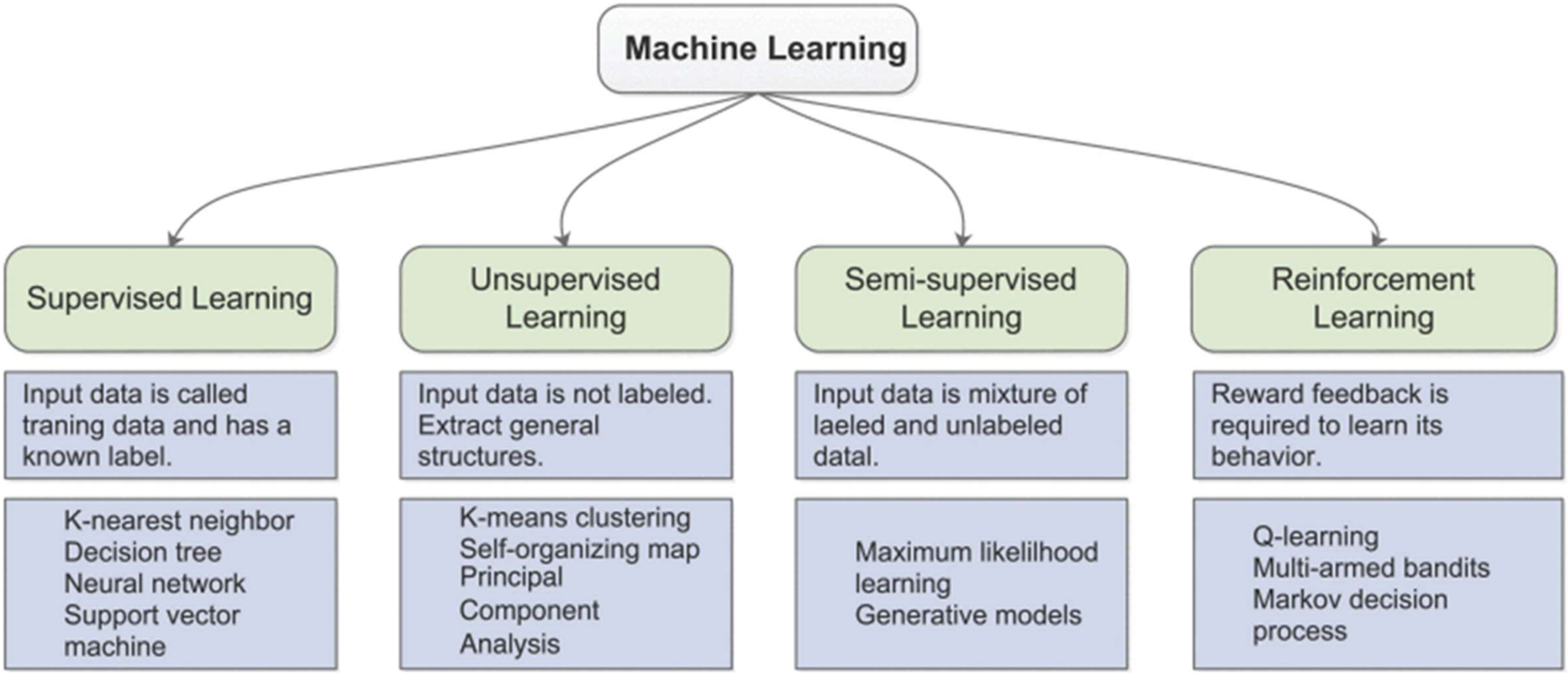


Feed the AI creature with enough data, so that it will speak the Oracles.

AI Domains


AI
Evolutionary Computation
Expert Systems
Machine Learning
Deep Learning

Machine Learning Algorithms



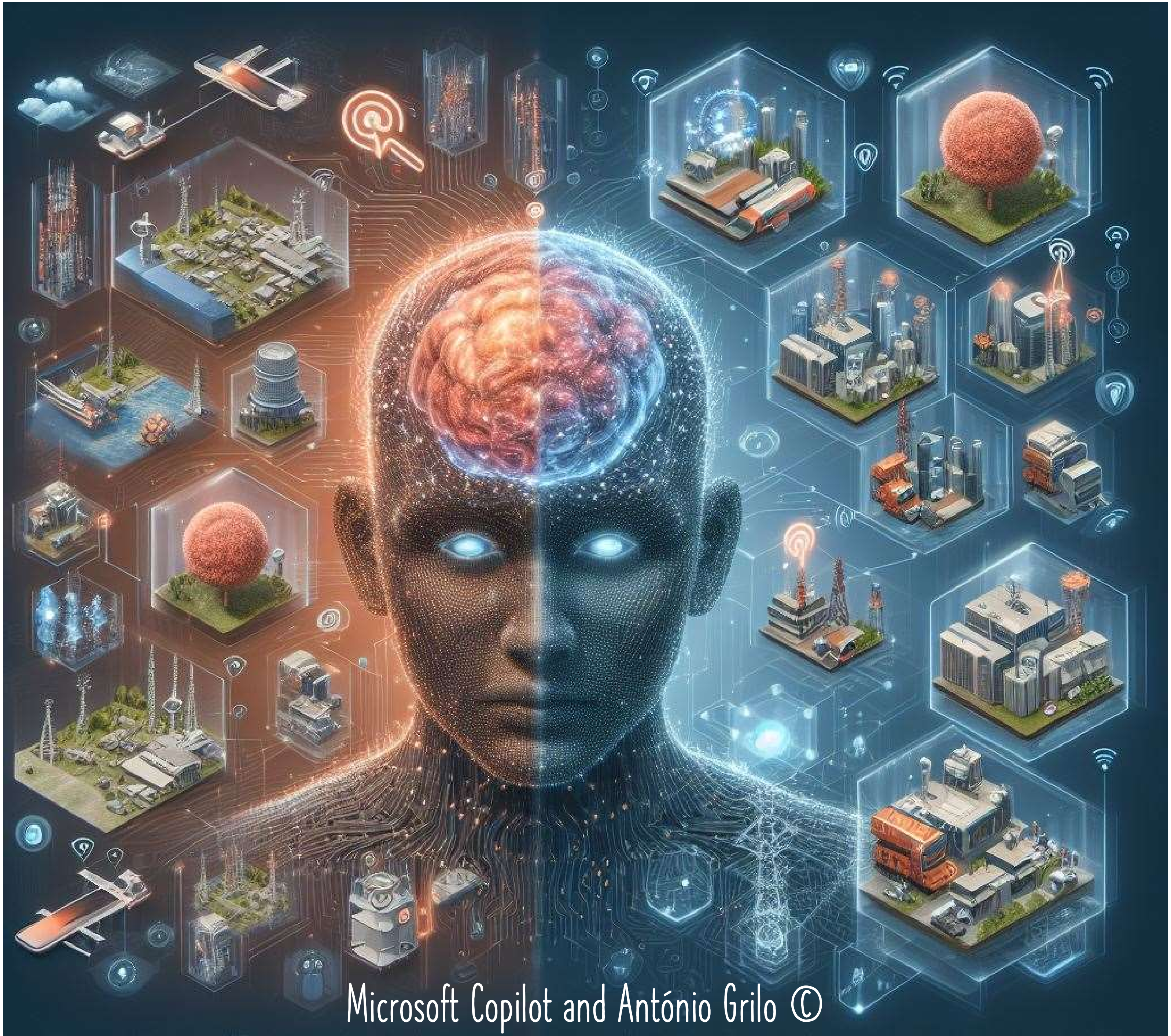
Adapted from Y. Liu, F. R. Yu, X. Li, H. Ji and V. C. M. Leung, "Blockchain and Machine Learning for Communications and Networking Systems," in *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, pp. 1392-1431, Secondquarter 2020, doi: 10.1109/COMST.2020.2975911.

Machine Learning Requirements

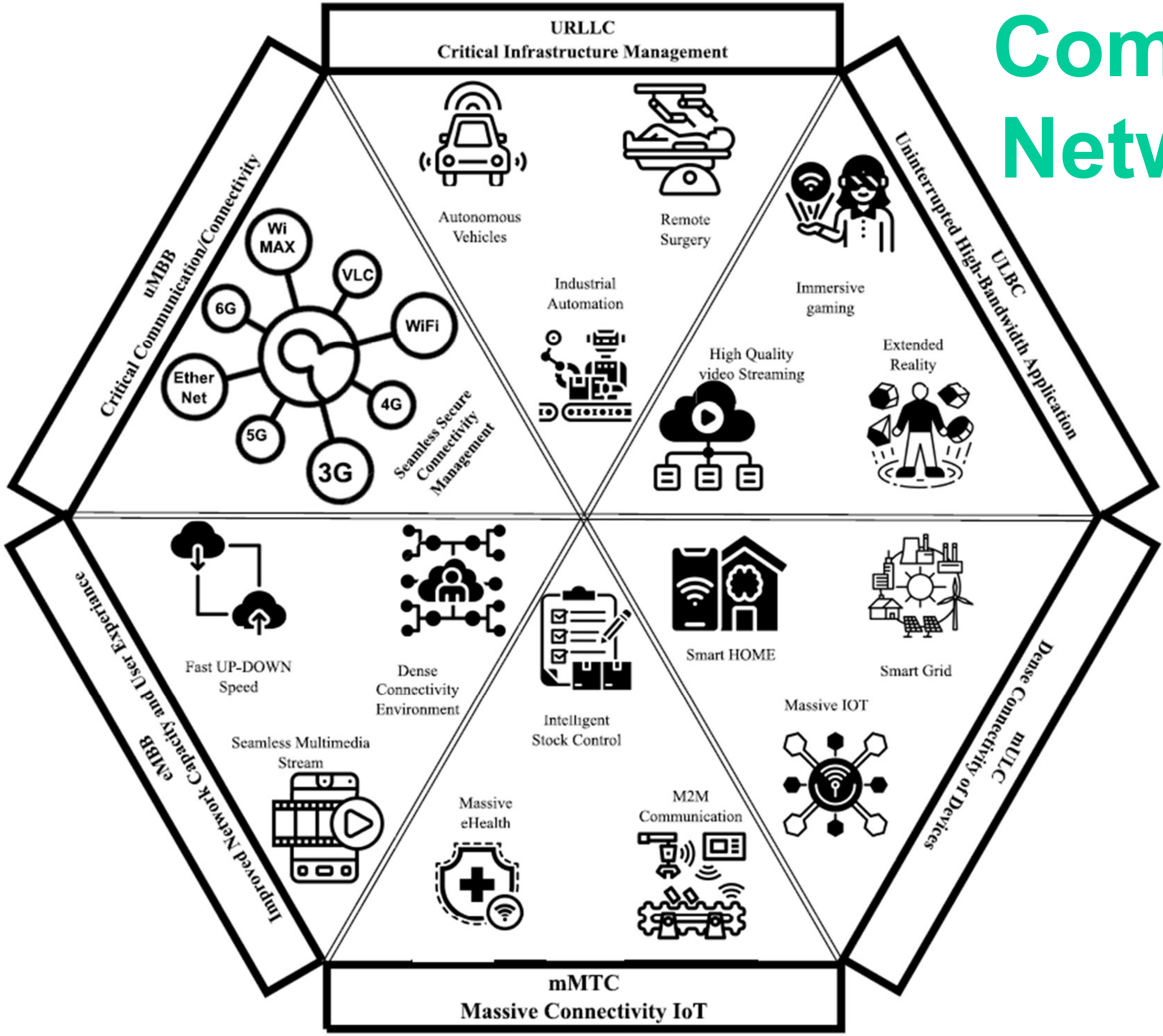
Supervised Learning	• Enough **labelled** data; • **The right data for the purpose.**
Unsupervised Learning	• Enough data; • **The right data for the purpose.**
Semi-supervised Learning	• Enough **partially labelled** data; • **The right data for the purpose.**

Reinforcement Learning	• A way to get Rewards from Actions (reward model or real system);
	• A suitable learning environment:
	  • Online Learning;
	  • Offline Simulation + Transfer Learning.

The AI-Enabled Communication Network



Communication Networks for AI



N. A. Khan and S. Schmid, "AI-RAN in 6G Networks: State-of-the-Art and Challenges, doi: 10.1109/OJCOMS.2023.3343069.

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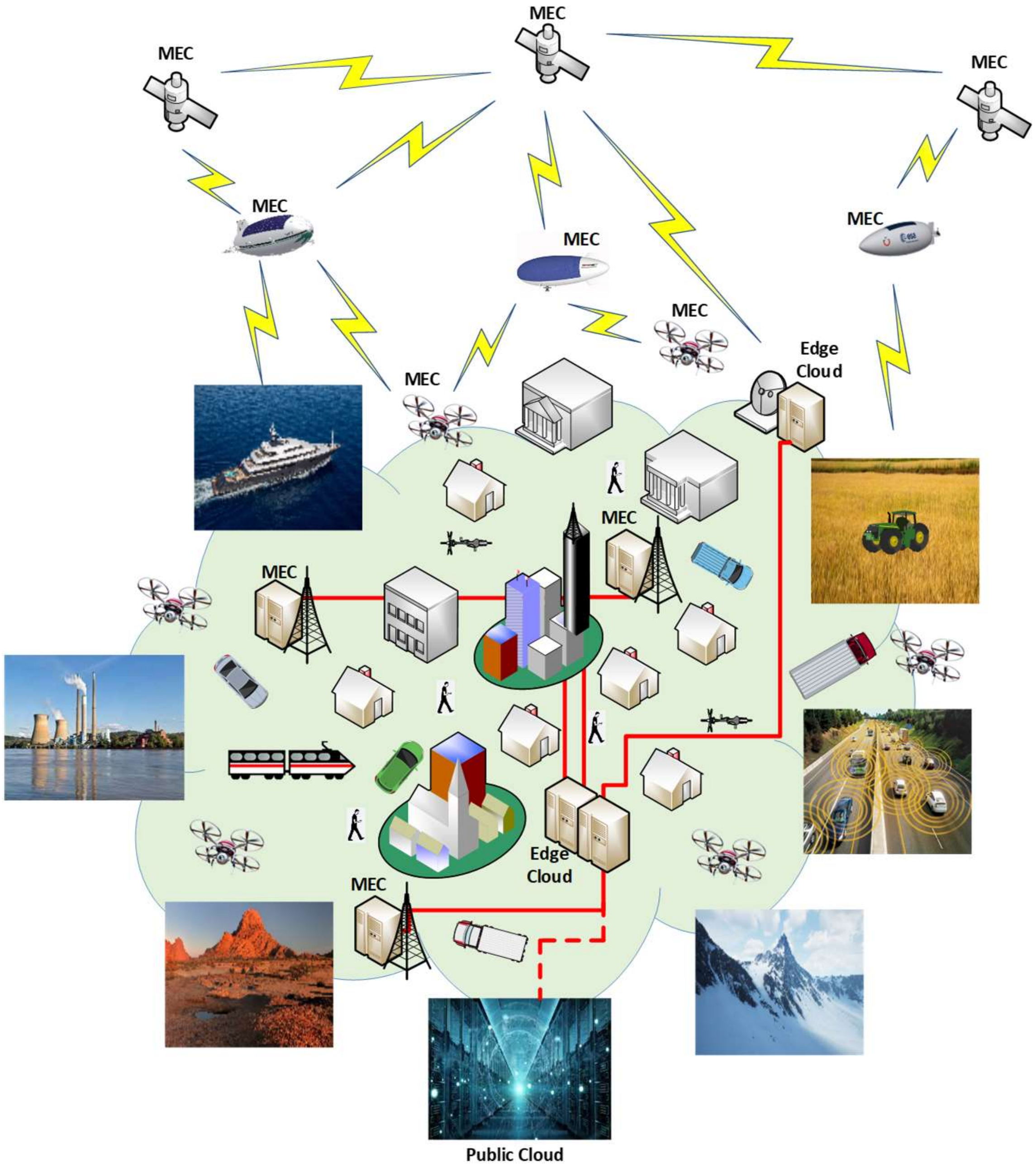
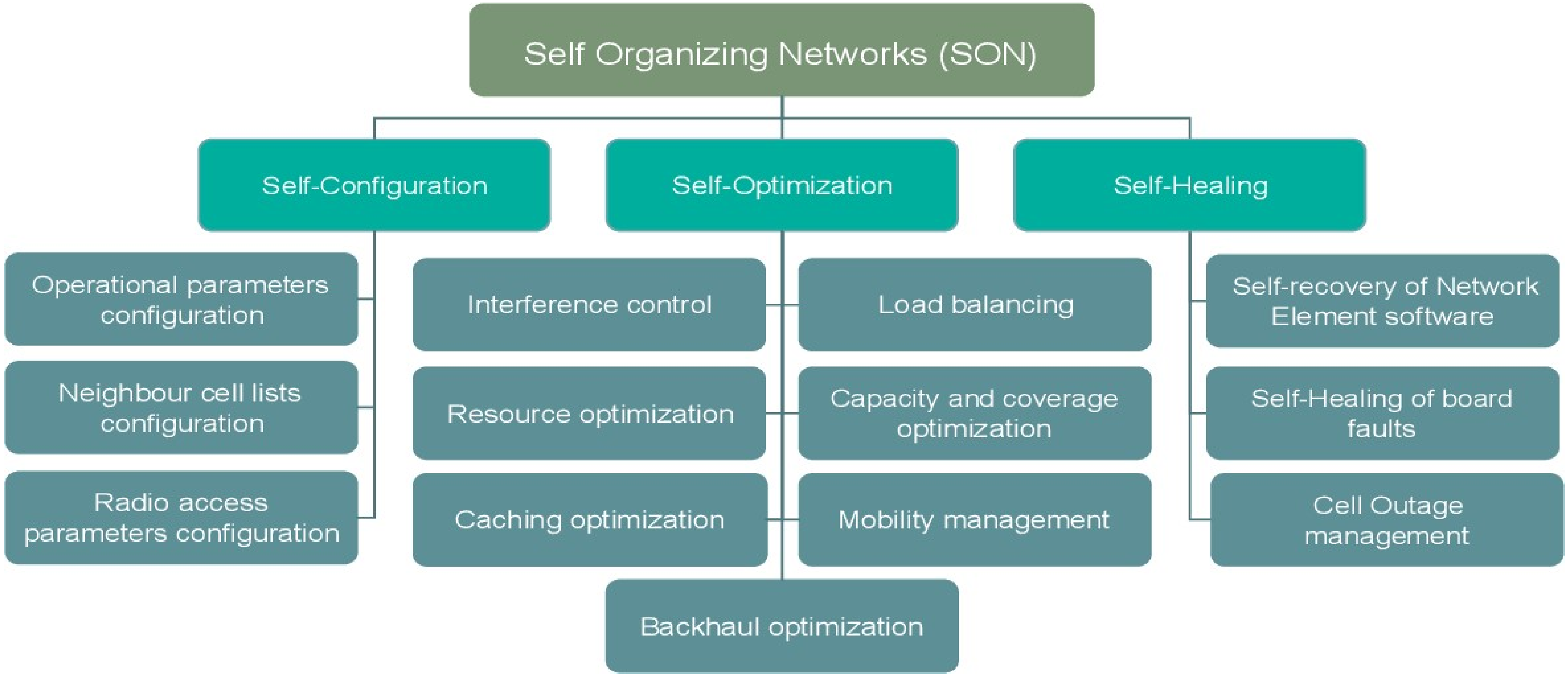
Edge-to-Cloud in the 6G SAGIN



Self-Organizing Networks (SON)

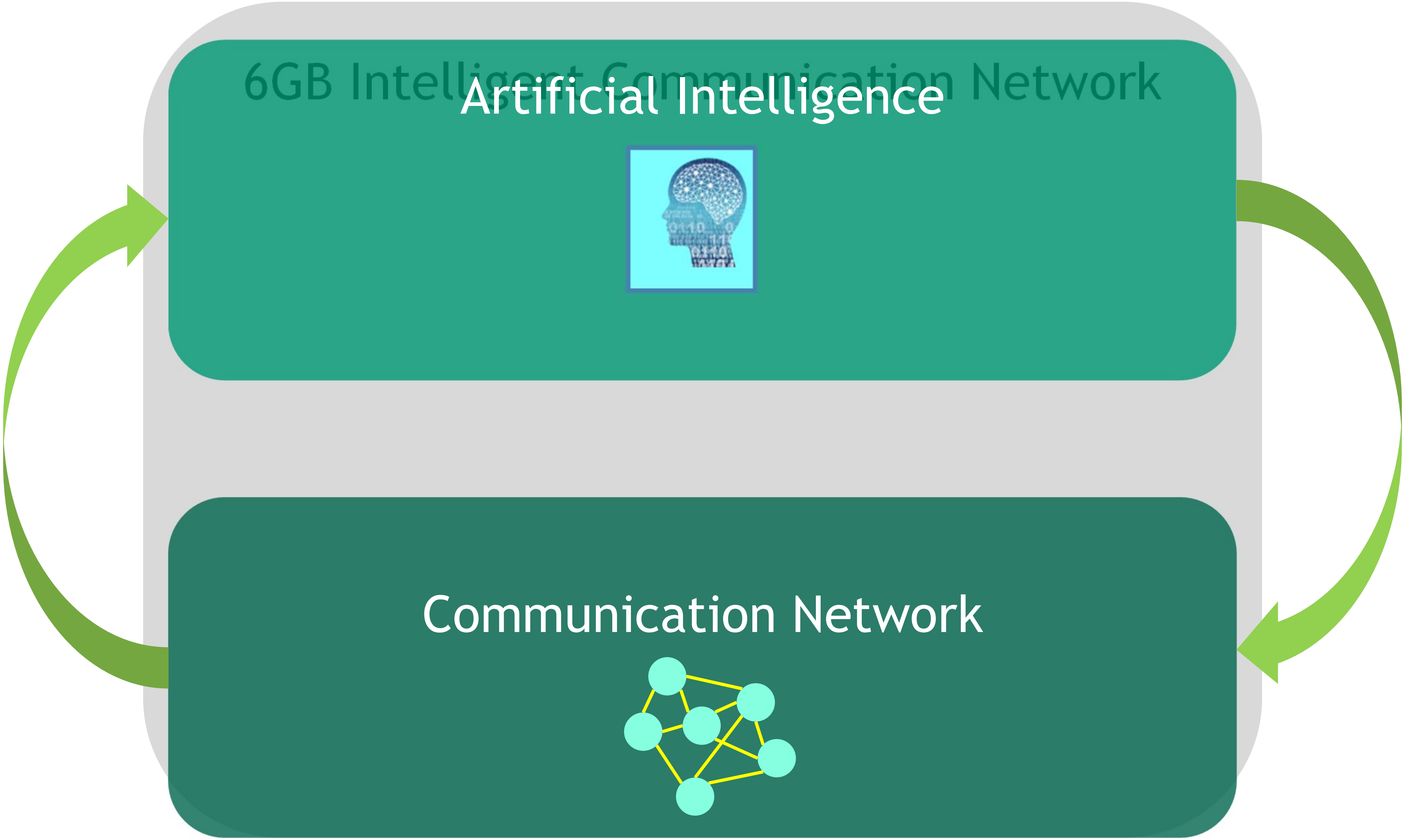


H. Fourati, R. Maaloul and L. Chaari, "Self-Organizing Cellular Network Approaches Applied to 5G Networks," 2019 Global Information Infrastructure and Networking Symposium (GIIS), Paris, France, 2019, pp. 1-4, doi: 10.1109/GIIS48668.2019.9044964.

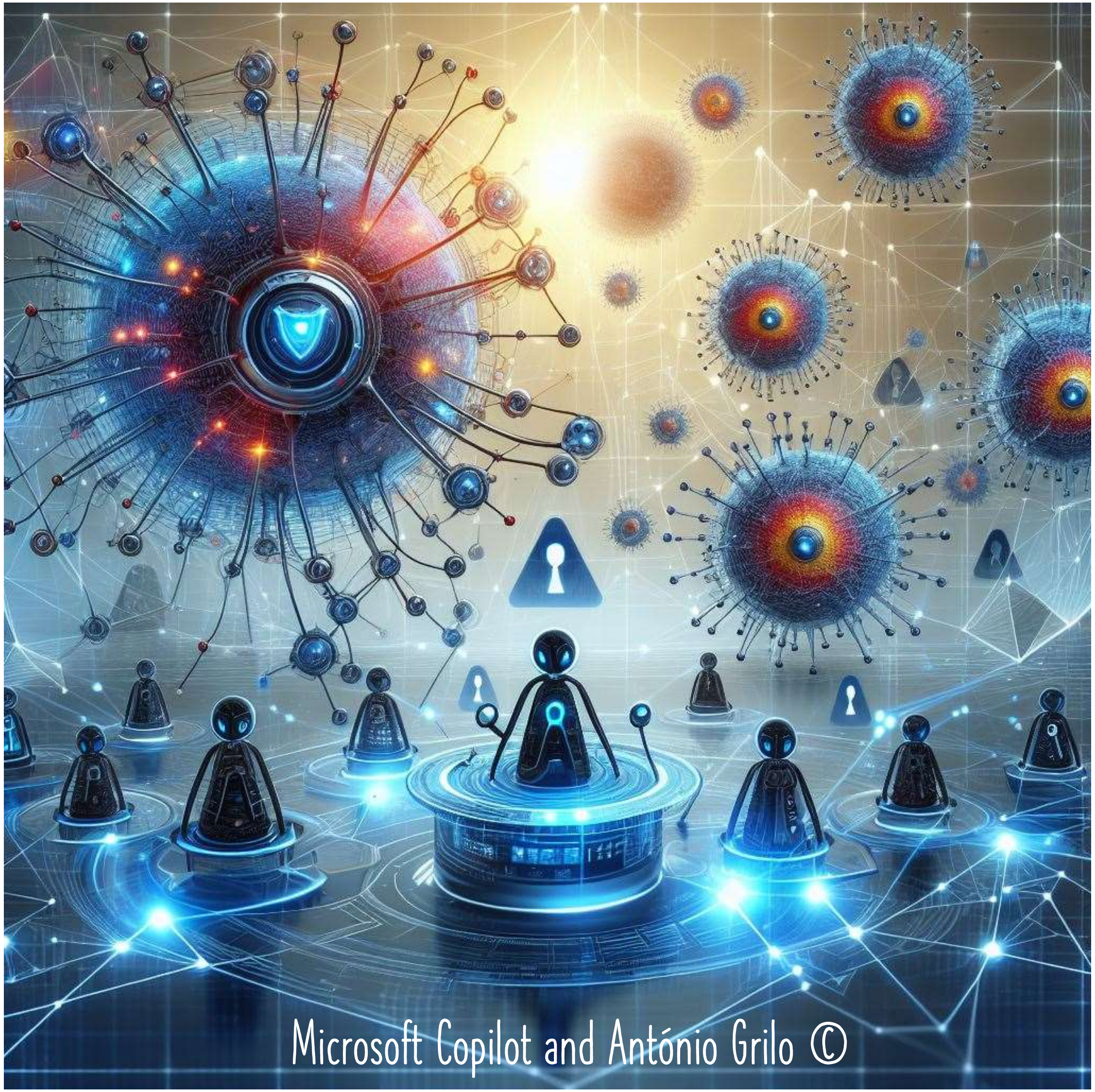
AI (ML) for Communication Networks

Supervised Learning	Unsupervised Learning	Semi-supervised Learning	Reinforcement Learning
• Traffic Classification • Intrusion Detection • Routing Optimization • **Traffic Prediction**	• Traffic Clustering • Filtering Algorithms • **Anomaly Detection and Root Cause Analysis**	• Resource Management • Network Behavior Analysis	• Network Reconfiguration • Resource Management • Decision-making • **Offloading Optimization** • **Energy Optimization**

AI-CN Binomial



Machine Learning-based Anomaly Detection and Root Cause Analysis in Mobile Networks



Miro-Markus Nikula, Luís M. Correia, António Grilo, Petri Mähönen, Luís Santo, Ricardo Dinis, “Machine learning-based anomaly detection and root cause analysis in mobile networks”, 2024, submitted paper.

Dataset

- Time series 4G network data from NOS network in Portugal.
- Data collected during 6 months from 25 base stations (BSs) with one-hour sampling rate -> 1 million data points.
- Each BS has three sectors, each with three cells representing different frequency bands (0.8 GHz, 1.8 GHz and 2.1 GHz) -> 9 cells per BS.
- No anomaly labels.

Abbreviation	Network KPI
USERS	Average number of users
PRB_DL	PRB DL average usage rate
PRB_UL	PRB UL average usage rate
HSR_INTRA	HSR intra frequency
HSR_INTER	HSR inter frequency
CELL_DL_TP	Cell DL average throughput
CELL_UL_TP	Cell UL average throughput
USER_DL_TP	User DL average throughput
USER_UL_TP	User UL average throughput
TVD	Traffic volume data
CA_TP	Carrier aggregation throughput
CQI	Average CQI
TIME_ADV	Average timing advance

Objectives and Research Questions

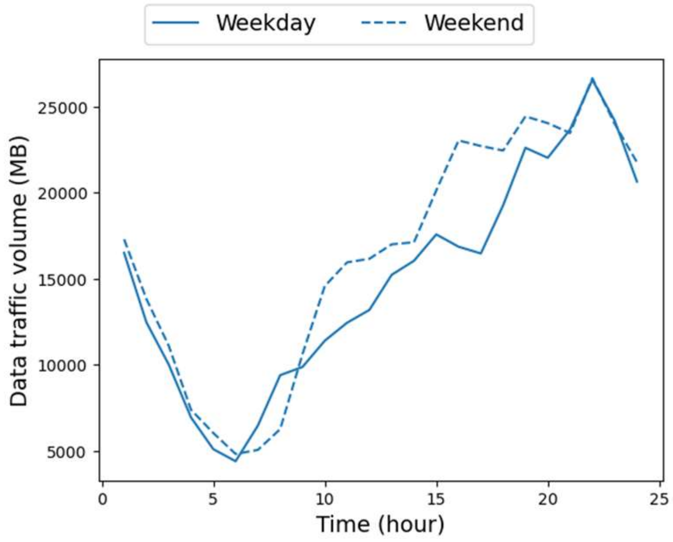
- To develop an unsupervised machine learning-based anomaly detection and RCA model able to automatically detect anomalies in unlabelled mobile network data.

1. How can anomaly detection and RCA be performed in the context of mobile networks?
2. How can they be performed using only unlabelled data?

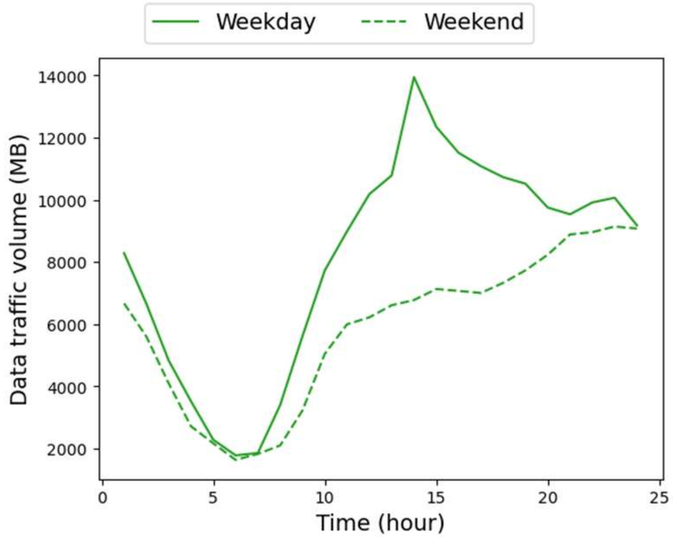
Sector traffic patterns

- Cells within a sector display similar behaviour (similar traffic mix).
- There are differences between weekdays and weekends.
- Sector 1 shows characteristics of residential area, whereas the traffic pattern of Sector 2 resembles an office area.
- Other traffic profiles seem to include transportation, entertainment and mixed profiles.

Sector 1



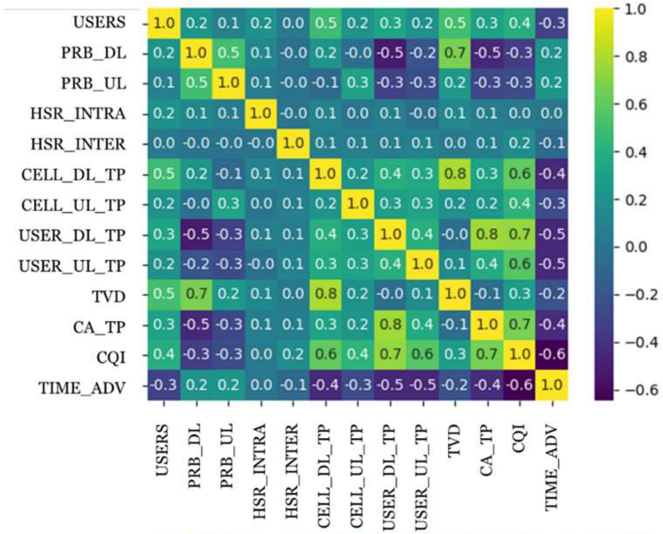
Sector 2



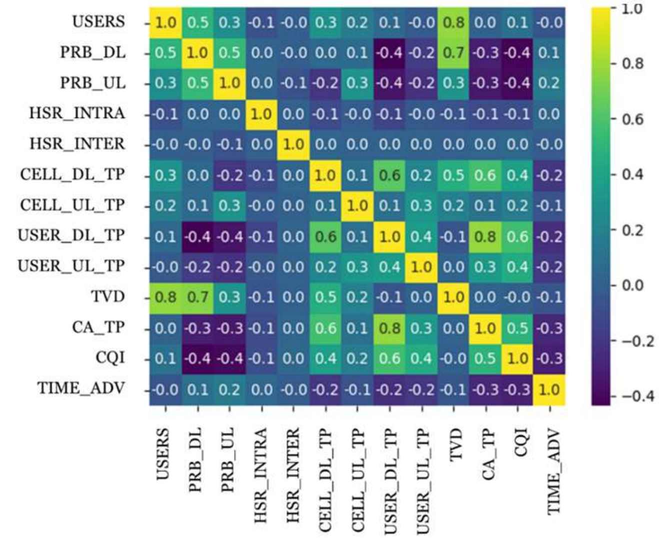
KPI correlations in different sectors

- **There are differences in correlations between different sectors.**
- **Traffic volume (*TVD*) in Sector 2 depends on the number of users more than it does in Sector 1.**

Sector 1

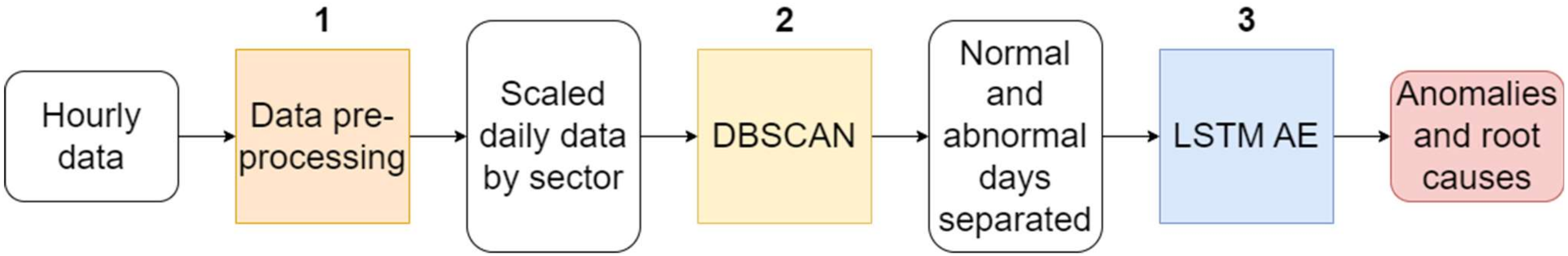


Sector 2



System pipeline

- The proposed system pipeline consists of three steps.



- **Abnormal** days are outputted by Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering, whereas **anomalies** are outputted by Long Short-Term Memory Autoencoder (LSTM AE).

1. Data preprocessing

1. **Data sampling**

   Full days of data (01:00 – 24:00)

2. **Data cleaning**

   Remove days with less than 24 hours

3. **Data scaling**

   Standard scaling -> Each KPI has zero mean and unit variance across all days within a sector.

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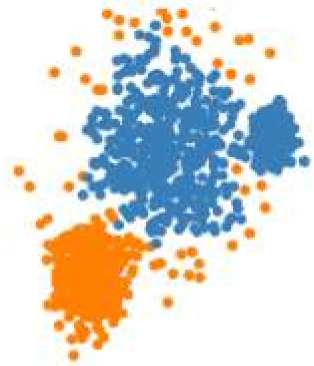
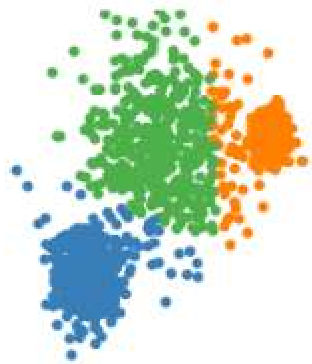
2. DBSCAN clustering

- Clustering was based only on traffic volume data.
- Weekdays and weekends are clustered separately.
- Two parameters:
  1. Eps: Distance radius from a data point
  2. MinPTS: Number of data points to form a cluster

DBSCAN

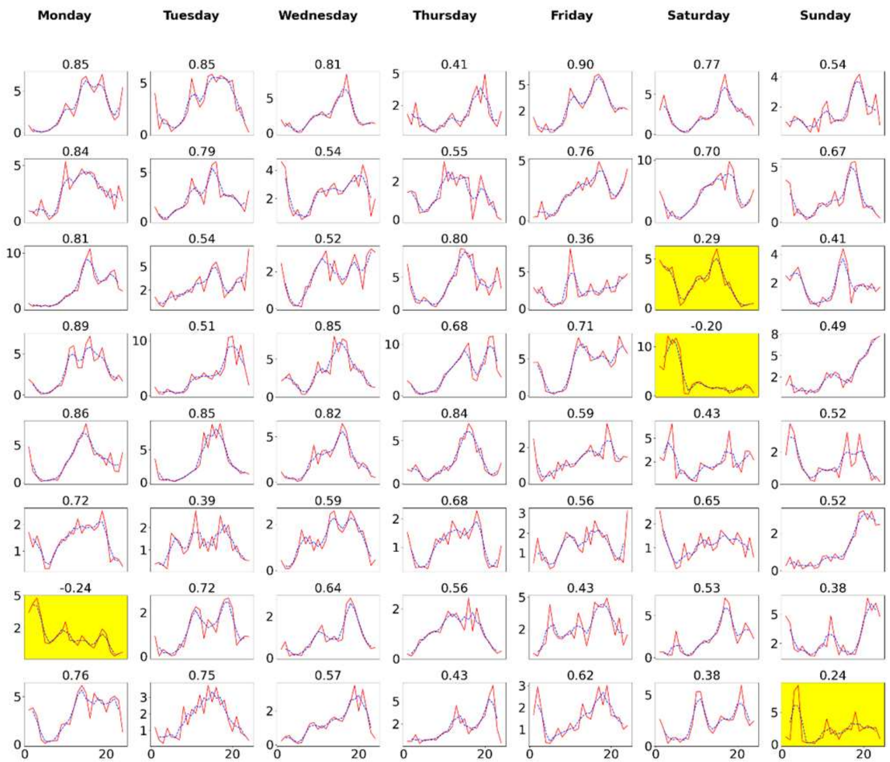


k-means

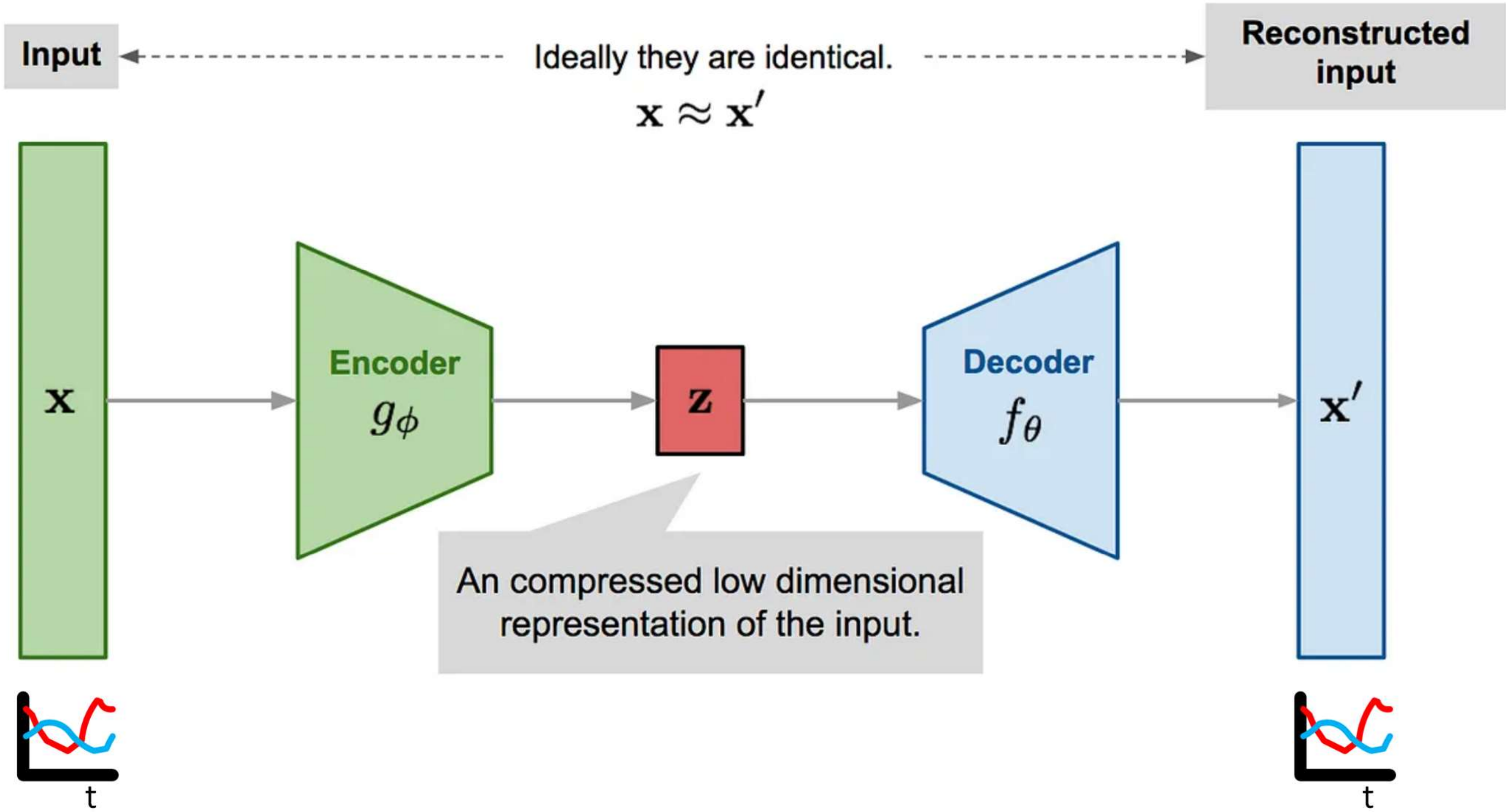


DBSCAN results

- Comparing clustering results with correlations between each day and the average day (weekday and weekend) shows promising similarities.
- Abnormal days also have lowest correlation values.
- Why is DBSCAN used instead of correlations?



3. LSTM AE

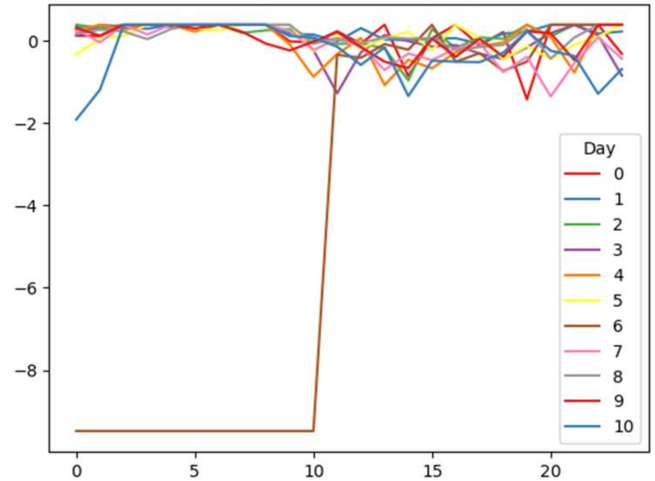


Adapted from https://medium.com/@jwbtmf/lstm-autoencoder-for-anomaly-detection-for-ecg-data-5c0b07d00e50

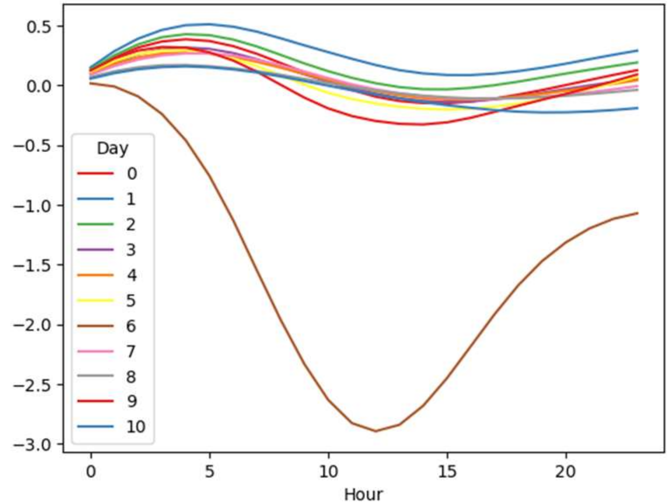
LSTM AE Anomaly Detection

- AE's encoder-decoder structure can reveal anomalous days based on reconstruction error.
- LSTM layers capture temporal dependencies.
- Reconstruction error is the difference between the original and reconstructed data.

Original Handover patterns



Reconstructed Handover patterns



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LSTM AE parameters

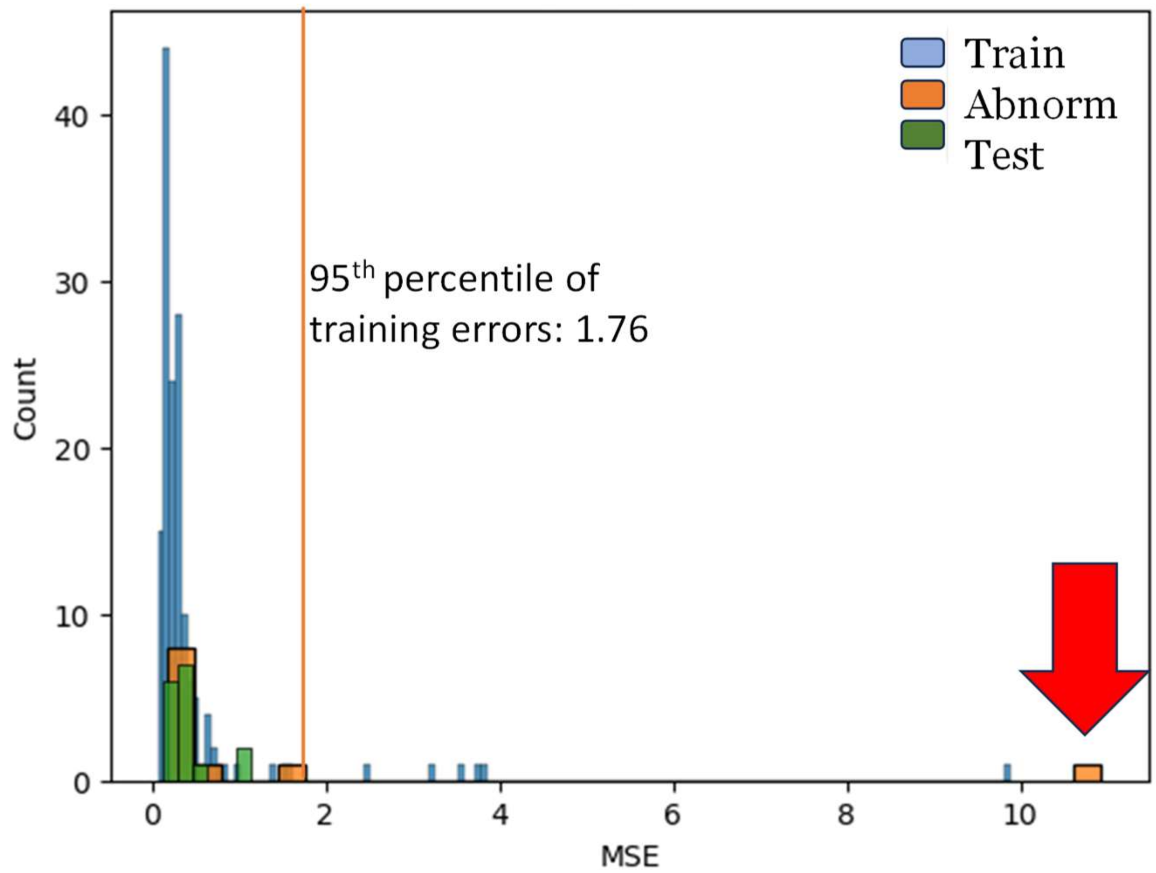
- Input shape: $n \times 24 \times 7$
- Trained with normal days only
- Adam optimizer
- Mean squared error (MSE) as loss function
- Anomaly threshold is the 95th percentile of training errors.
- KPIs increasing the error of anomalies -> potential root causes

Abbreviation	KPI	Used in
TVD	Traffic volume data.	DBSCAN
USERS	Average number of users.	LSTM AE
PRB_DL	PRB DL average usage rate.	LSTM AE
PRB_UL	PRB UL average usage rate.	LSTM AE
HSR_INTRA	HSR intra frequency.	LSTM AE
HSR_INTER	HSR inter frequency.	LSTM AE
CQI	Average CQI.	LSTM AE
CA_TP	Carrier aggregation throughput.	LSTM AE

Anomaly detection results

- Some abnormal days are below the threshold, some above
  - ➔Anomalies resulting from network errors?

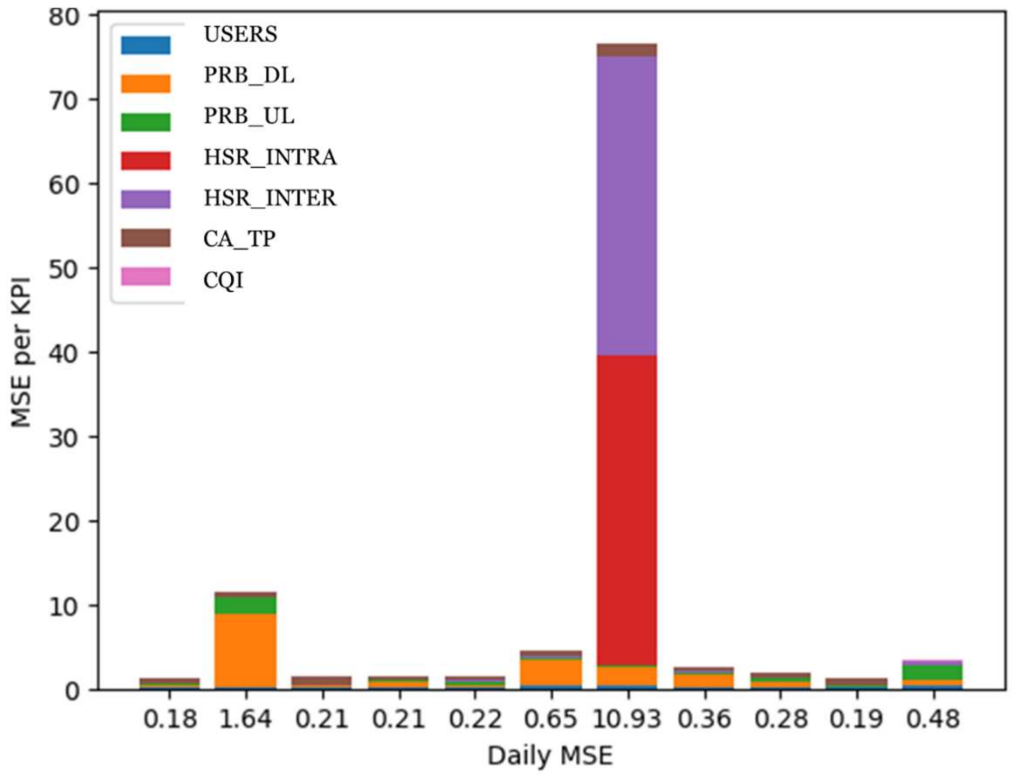
- Most normal days are below the threshold, a few above
  - ➔Network errors not visible in traffic volume?



RCA results

- Daily MSE represents the reconstruction error of the full day.
- The daily MSE can be separated into KPI-wise MSE.
- The KPIs whose MSE is higher than the daily MSE are considered as root causes.

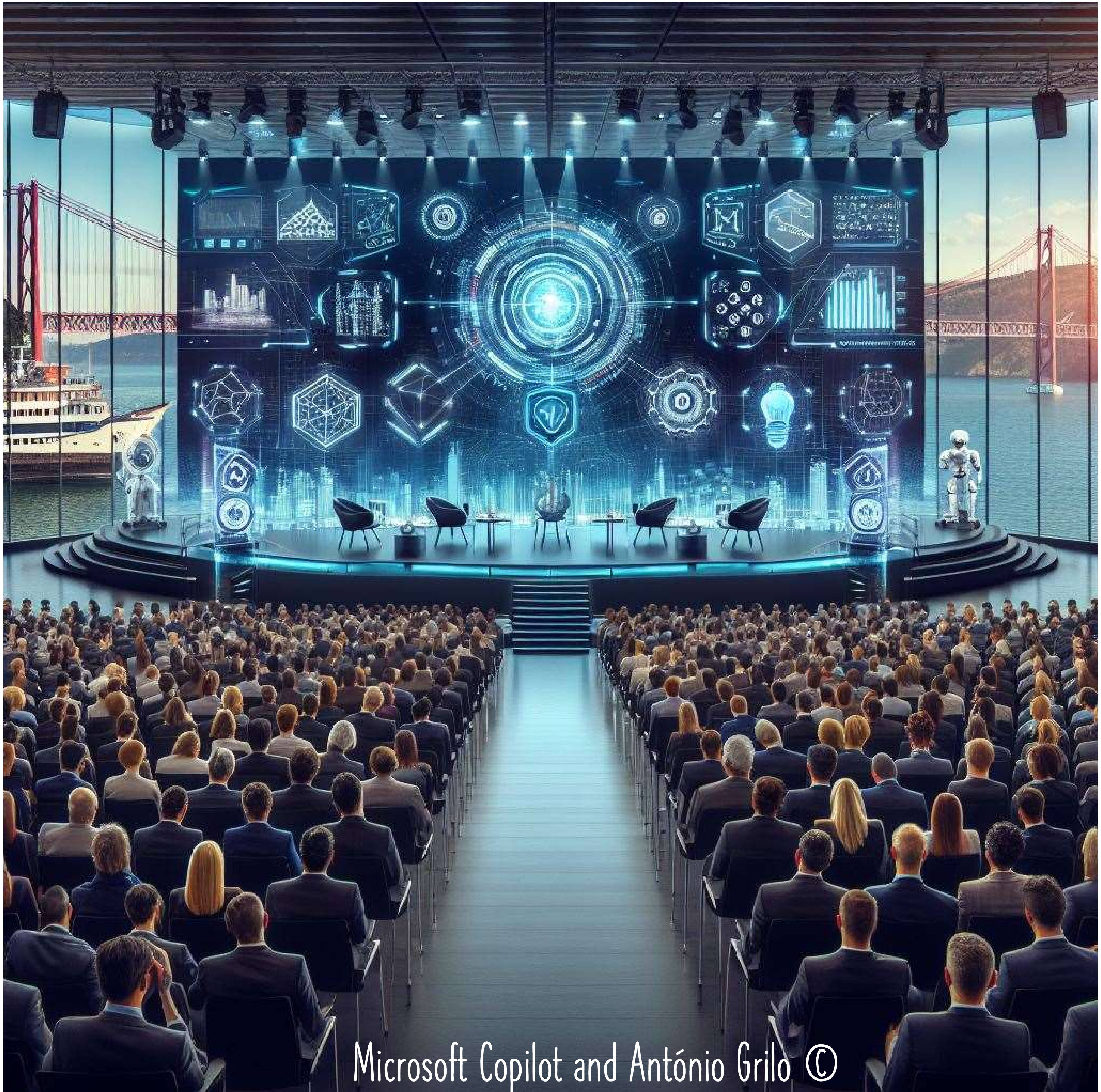
  ➔HSRs are the cause of this anomaly.



Future work

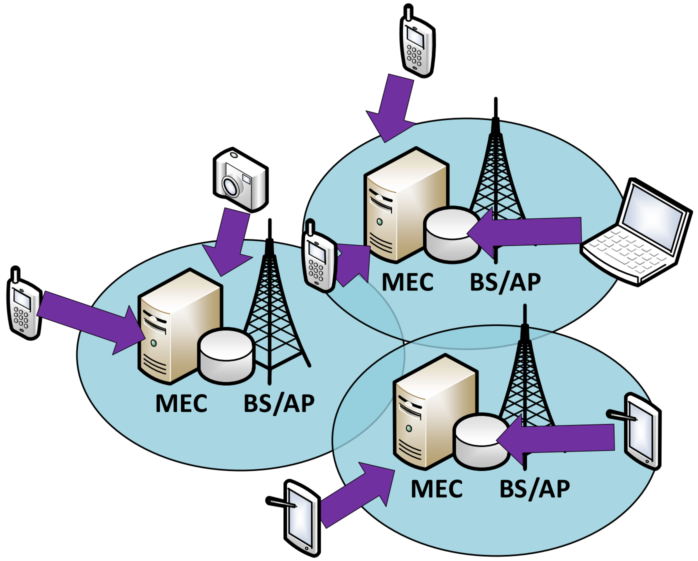
- Improving the results: Which KPIs would be nice to have?
- Experimenting with more granular data containing at least some anomaly labels.
- Comparing the system's computational overhead with different solutions to determine in which parts of the network it could be deployed.
- Deploying the system in a real-world mobile network to see the effect on QoE and operational costs.
- The development of automatic anomaly detectors and root cause analysis solutions will be crucial activities moving forward towards fully self-organising mobile networks in 5G and beyond.

Wrap-Up and Conclusions



MEC Offloading Optimization

- User Equipments (UEs) are limited in terms of resources, requiring them to offload computing tasks to Mobile Edge Computing (MEC) servers.
- Develop intelligent network management agents capable of making offloading decisions.
- Consider communication delay, processing delay, UE energy.
- Consider heterogeneous UEs, heterogeneous MEC servers.
- Deep Reinforcement Learning: Advantage Actor Critic (A2C).

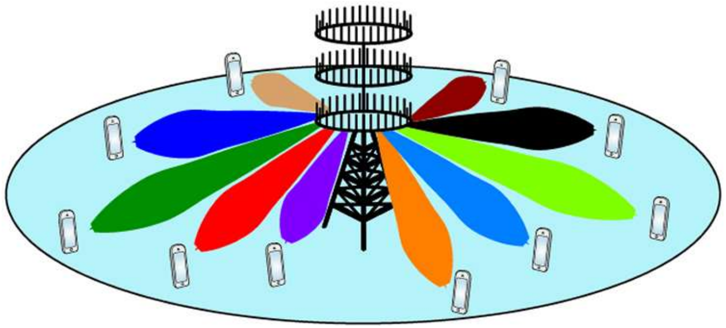


Carlos Silva, Naercio Magaia, and António Grilo. 2023. Task Offloading Optimization in Mobile Edge Computing based on Deep Reinforcement Learning. In Proceedings of the Int'l ACM Conference on Modeling Analysis and Simulation of Wireless and Mobile Systems (MSWiM ’23), ACM, New York, NY, USA, 109–118.

Network Energy Saving Techniques Aided by AI/ML in 5G Networks

(ongoing MSc thesis)

- Energy consumption constitutes a significant part of mobile operator OPEX.
- Reduce energy consumption by gracefully switching-off gNB functions: beam, sector, cell.
- Dataset with 5G data from two countries:
  - Romenia: 3 clusters x 2 gNB x 3 sectors x MIMO 64/32
  - Portugal: 4 clusters x 4 gNBs x 3 sectors x MIMO 64/32
- Traffic Prediction + Reinforcement Learning.



Conclusions

- **The communication networks of the future will necessarily be AI-enabled.**
  - **Support present and future user applications.**
  - **Self-Configuration, Self-Optimization, Self-Healing.**
  - **Seamless integration network functions and AI.**
- **Anomaly detection and root cause analysis are essential for SON reliability.**
  - **Huge amounts of data make manual analysis and labelling next to impossible.**
  - **Unsupervised Learning can be used to detect probable anomalies.**
- **AI-enabled Self-Organizing Networks is ripe for research, with many opportunities for operators, manufacturers and academia.**

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