# MACHINE LEARNING TECHNIQUES FOR PRIVATE 5G NETWORKS

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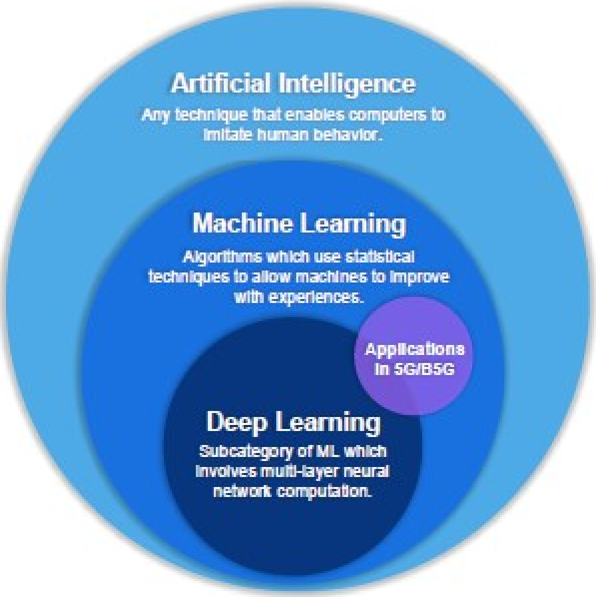
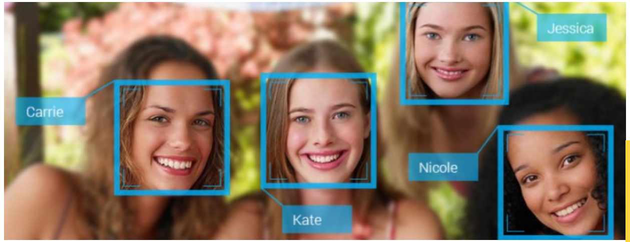
# Machine Learning – Fundamentals

- Machine Learning (ML) targets at solving complex problems where existing solutions require a lot of manual calculations and coordination, or at problems that have no solution using classical methods.
- These problems can be solved with machine learning techniques, replacing existing rule-based approaches with ML that are trained with historical data.

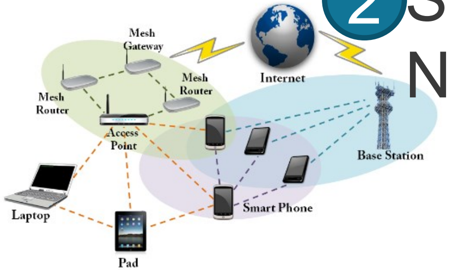


# ML Applications

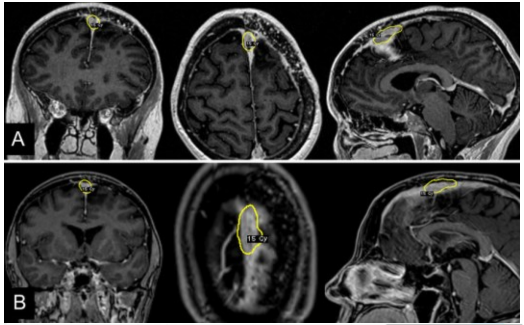
1 Facial Recognition




2 Smart Networking



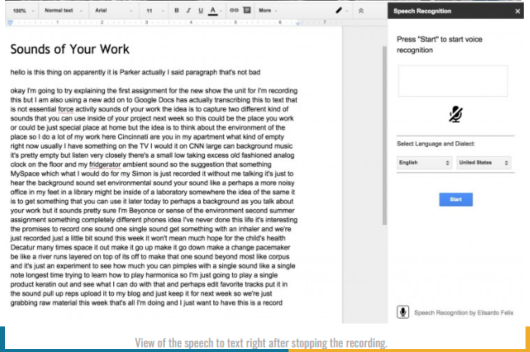

3 Brain Disease Prediction




4 Robot Dogs

5 Recommender System

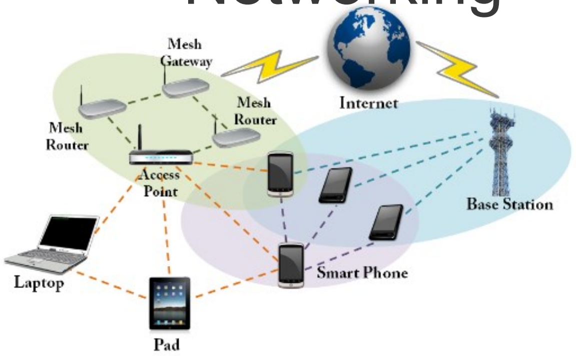

6 Speech2Text Generation



# Machine Learning in Networks

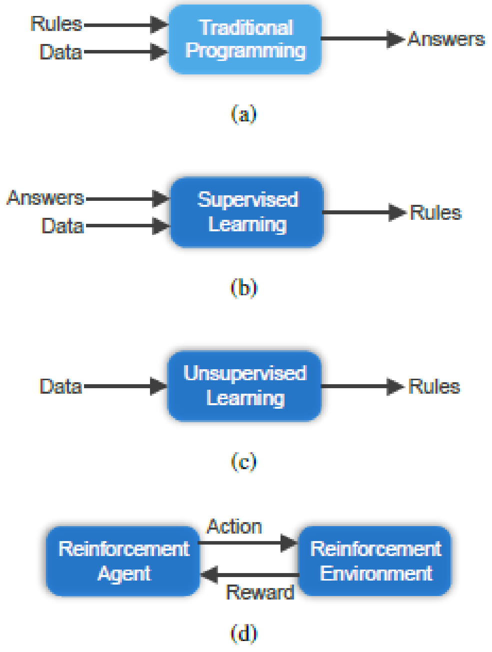
- There are many parameters in mobile and wireless networks, and there is no closed-form solution to optimize them.
- For such problems, an ML algorithm (eg a Neural Network - NN) can contribute by predicting parameters and estimating functions based on the available data.
- The next generation 5G/B5G mobile and wireless communication technologies also require the use of optimization techniques to minimize (or maximize) certain objectives (e.g. interferences, data rate).
- Many problems in mobile and wireless communications are nonlinear or polynomial, so they must be approximately solved

Smart Networking



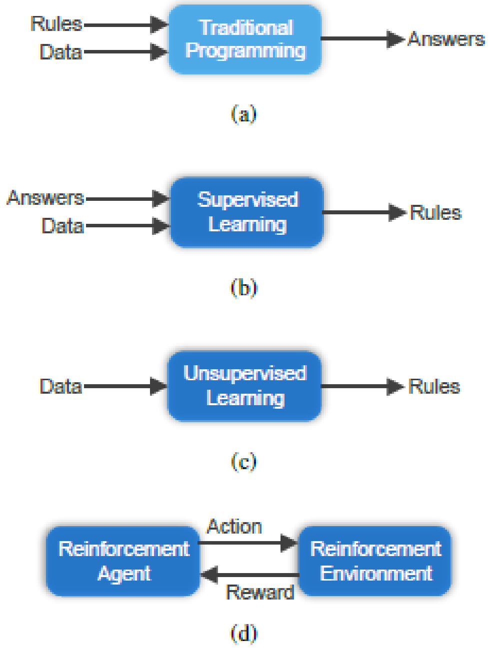
# ML Algorithms – Learning Process

- *A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance on tasks in T, as measured by P, improves with experience E.*



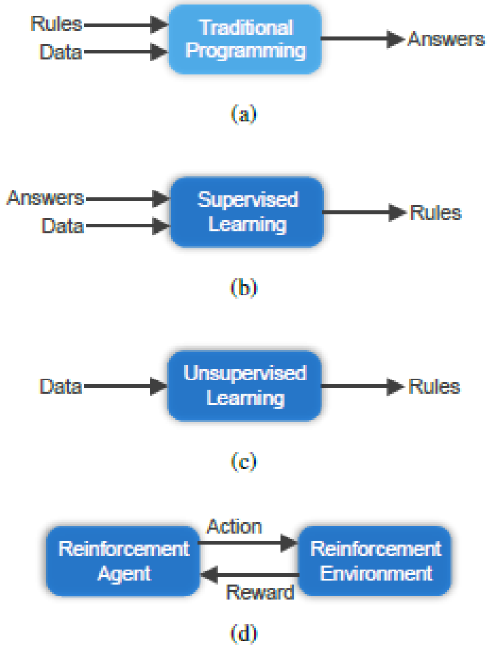
# ML Algorithms – Supervised Learning

- Supervised learning involves examining several examples of a random vector **x** and the label values of the vector **y**. The target is to predict **y** from an entirely new **x** by computing p(**y**|**x**), or certain properties of this distribution.



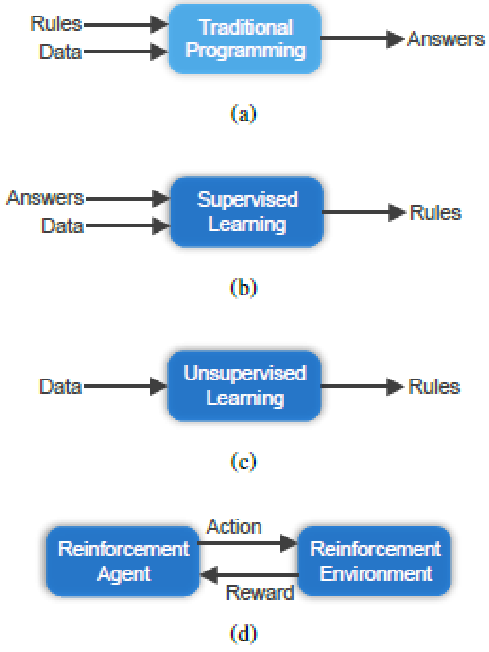
# ML Αλγόριθμων – Unsupervised Learning

- Unsupervised Learning involves observing different instances of a random vector **x** with the goal of learning its probability distribution p(**x**) and its properties



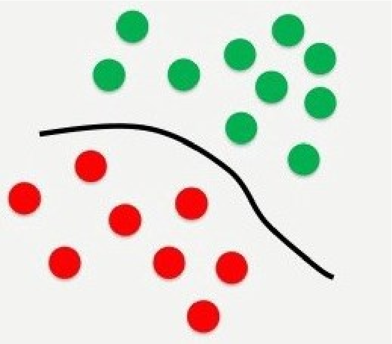
# ML Algorithms – Reinforcement Learning

- Reinforcement learning involves an agent interacting with an environment and receiving feedback (with rewards and punishments) based on the short or long-term benefits of his actions.

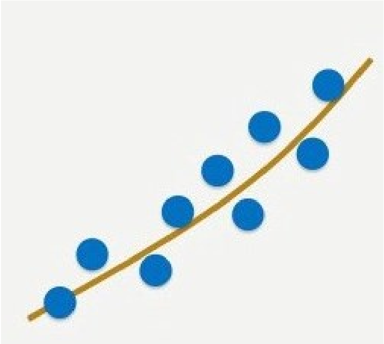


# Categories of ML Algorithms

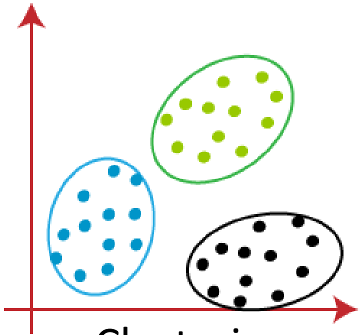
- **Classification**: Find the hyperplane that separates the known data classes (*Supervised Learning*).
- **Regression**: Find the mapping/equation that minimizes the error between model predictions and groundtruth values (*Supervised Learning*).
- **Clustering**: Find hidden clusters in the data based on distance criterions between data features (*Unsupervised Learning*).



Classification



Regression

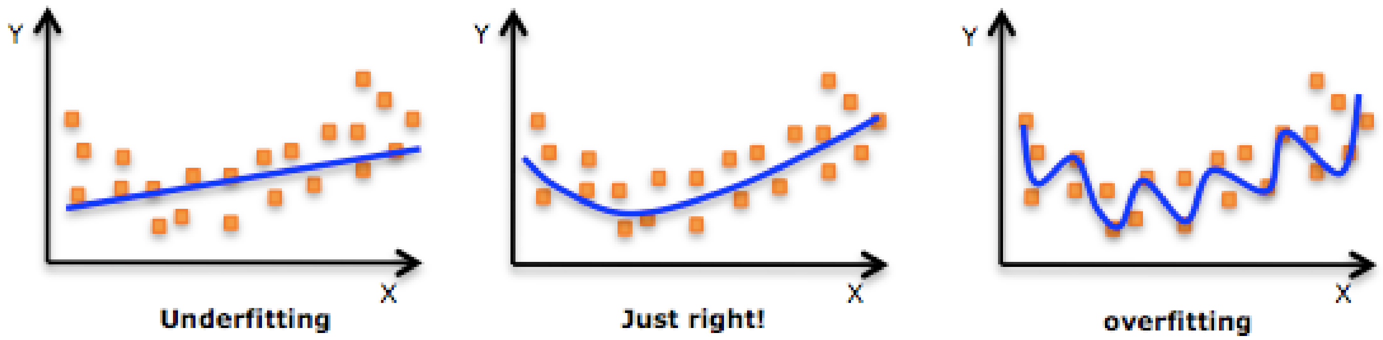


Clustering

# Overfitting vs Underfitting

- Overfitting: Your model performs extremely well on training set, but it has poor performance on testing set.
- Underfitting: Your model has further margins to improve its performance.

- **Ultimate goal of ML: Perform well on unknown data!**



# Supervised Learning in 5G

- The main feature of supervised learning that differentiates it from other types (Unsupervised and Reinforcement Learning) is the initial assumption that we have a set of data (**x, y** - Labeled data)
- Supervised learning is beneficial for applications that have access to large amounts of data for training the algorithms, as the number of instances directly affects the convergence of the algorithm.

| ML Technique | Learning Model | Applications in Mobile and Wireless Communication |
| --- | --- | --- |
| Supervised Learning | Linear Regression. | Predict and model energy availability to define scheduling policies of harvesting nodes, providing the harvesting node with adaptation to energy availability (as in [21]). |
| | Statistical Logistic Regression. | Dynamic frequency and bandwidth allocation in self-organized LTE dense small cell deployments (as in [22]). |
| | Supervised Classifier. | Predict the network demand, to dynamically allocate the amount of network resources, topology setup, and bit rate, according to the connectivity performance i.e., bandwidth, latency, and jitter. (as in [23]). |
| | Support Vector Machines (SVM). | Path-loss prediction model for urban environments (as in [24]). Classification of the training channel state information (CSI) to select the optimal antenna indices in MIMO (as in [25]). |
| | Neural-Network-based approximation. | Channel Learning to infer unobservable channel state information (CSI) from an observable channel (as in [26]). |
| | Probabilistic Learning. | Adjustment of the TDD Uplink-Downlink configuration in XG-PON-LTE Systems to maximize the network performance based on the ongoing traffic conditions in the hybrid optical-wireless network (as in [27]). |
| | Artificial Neural Networks (ANN), and Multi-Layer Perceptrons (MLPs). | Modelling and approximations of objective functions for link budget and propagation loss for next-generation wireless networks (as in [28]–[32]). |
| | Deep Neural Networks (DNN). | Prediction and coordination of beamforming vectors at the BSs by learning mapping functions related to the environment setup, by using uplink pilot signals (as in [33]). Channel estimation and direction of arrival (DOA) estimation in MIMO (as in [34]). |

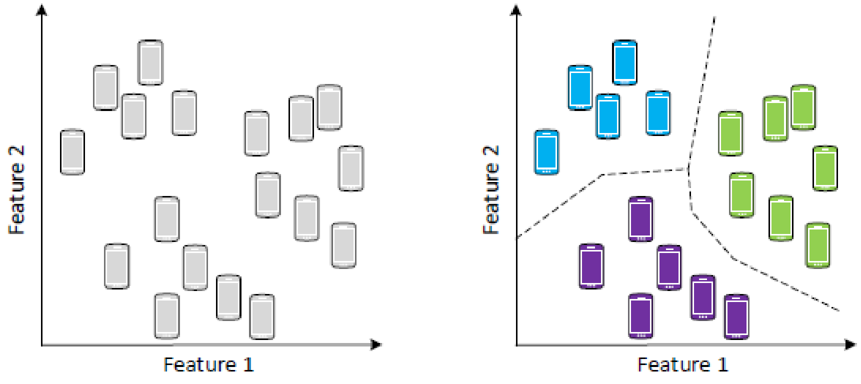
# Supervised Learning in 5G

AFFORDABLE 5G

- Self-organizing networks (SON) that learn to dynamically adapt to different environments
- Dynamic frequency and bandwidth allocation
- Evaluation of accurate path-loss models
- Evaluation of channel state information - CSI for decision making in network operation, as well as during signal processing
- Cell selection in multi-layer networks
- Device detection for device-to-device (D2D) communications

# Unsupervised Learning in 5G

- Clustering is a typical ML application that exhibits beneficial results when performed on edge devices in a mobile network




(a) (b)

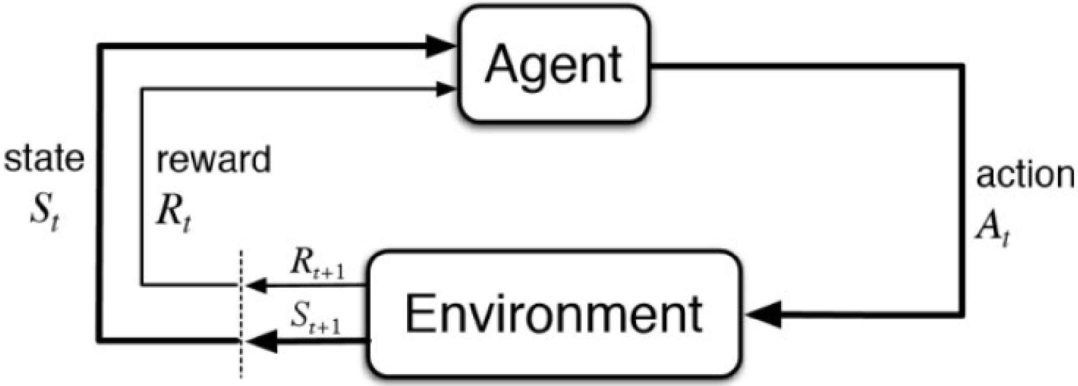
# Unsupervised Learning in 5G

- Unsupervised soft-clustering algorithm to detect fog nodes of the network and upgrade them from low power nodes (LPNs) to high power nodes (HPNs)
- Cooperative spectrum sensing algorithm using a combination of k-means clustering, Gaussian mixture model and expectation maximization (EM)
- k-means clustering and its classification capabilities are very useful for selecting an efficient relay node for urban vehicular networks
- Mobile network data for trafific anomaly detection using hierarchical clustering

| ML Technique | Learning Model | Applications in Mobile and Wireless Communication |
|---|---|---|
| Unsupervised Learning | Gaussian Mixture Model (GMM), and Expectation Maximization (EM). | Cooperative spectrum sensing (as in [54]). |
| | Hierarchical Clustering. | Anomaly/Fault/Intrusion detection in mobile wireless networks (as in [55]). |
| | *k*-means Clustering. | Storing the data center contents in clusters to reduce the data travel among distributed storage systems (as in [56]). Optimal handover estimation by clustering the UEs according to their mobility patterns (as in [57]). Relay node selection in vehicular networks (as in [58]). |
| | Unsupervised Soft-Clustering. | Latency reduction by clustering fog nodes to automatically decide which low power node (LPN) is upgraded to a high power node (HPN) in heterogeneous cellular networks (as in [59]). |
| | Self-organizing map (SOM) Learning. | Planning the coverage of HetNets with dynamic clusters (as in [60]). |
| | Autoencoders (AE). | Channel characterization by interpreting a communication system design as an end-to-end reconstruction task, in order to jointly optimize transmitter and receiver components in a single process (as in [61]). |
| | Adversarial Autoencoders (AAE). | Detecting anomalous behavior in wireless spectrum by using Power Spectral Density (PDS) data in an unsupervised learning setting (as in [62]). |
| | Affinity Propagation Clustering. | Data-Driven Resource Management for Ultra-Dense Small Cells (as in [63]). |
| | Non-parametric Bayesian Learning. | Traffic reduction in a wireless network by proactively serving predictable user demands via caching at BSs and users' devices (as in [64]). |
| | Generative Deep Neural Networks (GDNN) | Capture the presence of traffic correlations that impact the readings of multiple sensors deployed in the same geographical area. (as in [65]). |

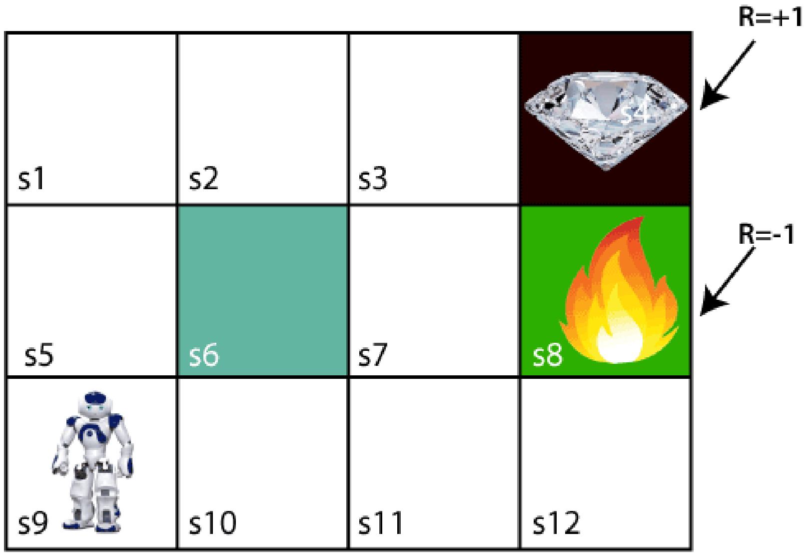
# Reinforcement Learning

- Reinforcement Learning(RL) is a type of machine learning technique that enables an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences.
- Though both supervised and reinforcement learning use mapping between input and output, unlike supervised learning where feedback provided to the agent is correct set of actions for performing a task, reinforcement learning uses rewards and punishment as signals for positive and negative behavior.



# Reinforcement Learning example

- Starting position: S9
- S6 block is a wall (cannot be crossed)
- S8 is a fire pit (reward -1)
- S4 is a diamond block (reward +1).
- Possible actions: up, down, left or right.
- Agent can follow any path, but it prefers the shortest one.



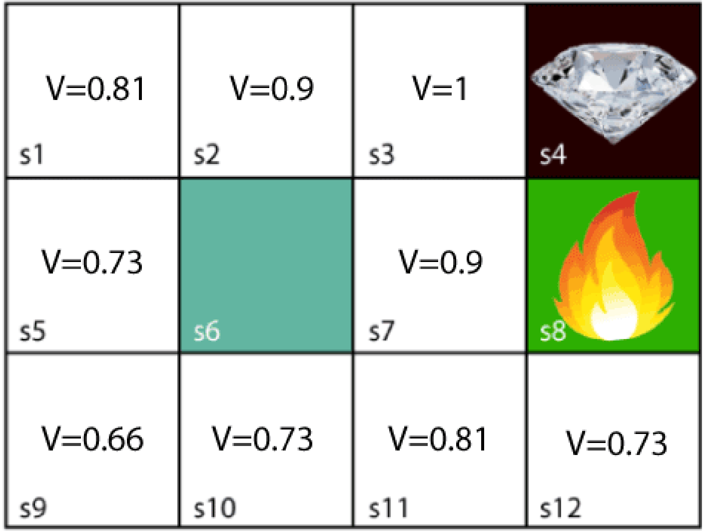
# Reinforcement Learning example

- Bellman Formula:

$$V(s) = \max_a [R(s,a) + \gamma V(s')]$$

where:

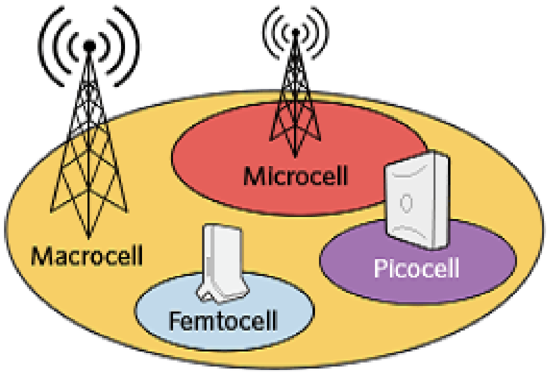
- V(s) = value calculated at a particular point.
- R(s,a) = Reward at a particular state s by performing an action.
- γ = Discount factor
- V(s') = The value at the previous state.




**Agent prefers the path with incremental V's.**

# Heterogeneous Networks

- Why HetNets? Cope with the ever-increasing need for bit-rate, bandwidth and massive devices.
- How to increase capacity? Wider radio spectrum, multi-antenna techniques and more efficient modulation and coding schemes.
- Limitation of capacity increment techniques: In crowded environments and cell edges, performance can significantly degrade
- Solution with HetNets: Densification is to add small cells within macro networks to spread traffic loads, widely maintain performance and service quality while reusing spectrum most efficiently.
- HetNet planning: addition of low-power base stations or Remote Radio Heads (RRH) within existing macro-cells.
- Advantage: Site acquisition is easier and cheaper.
- Disadvantage: Intra-cell and Inter-cell interferences and coordination becomes more stringent.

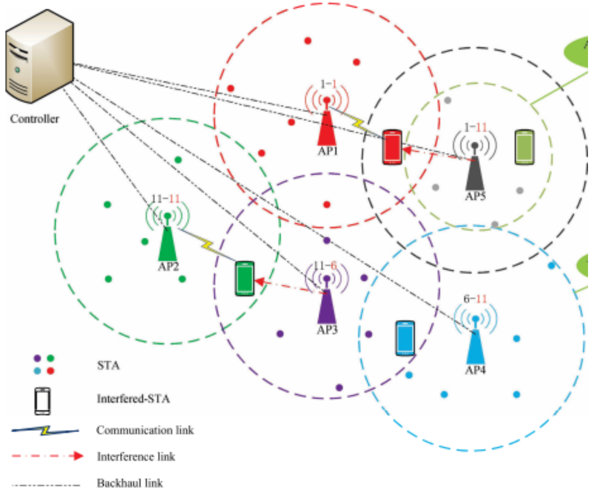


# Throughput Maximization Problem

- Throughput (in bits per sec) defines the extent to which a service is demanding (e.g. video needs high Throughput).
- Quality of Service (QoS): The degree to which the network satisfy the users' requirements.
- Why Throughput Maximization is timely? Network densification + large number of mobile devices lead to
  - Increased interference.
  - Degradation of devices QoS.
- Future networks: self-organization, self-configuration of radio resources and self-optimization of network parameters.
- Radio Resource Management (RRM) is strongly related to the coverage and capacity of wireless networks. Goal of Throughput Maximization:
  - Proactively adjust the power levels of HetNet transmitters, so as to mitigate interferences.
  - Fulfill the requested throughput of individual users and accommodate their needs.

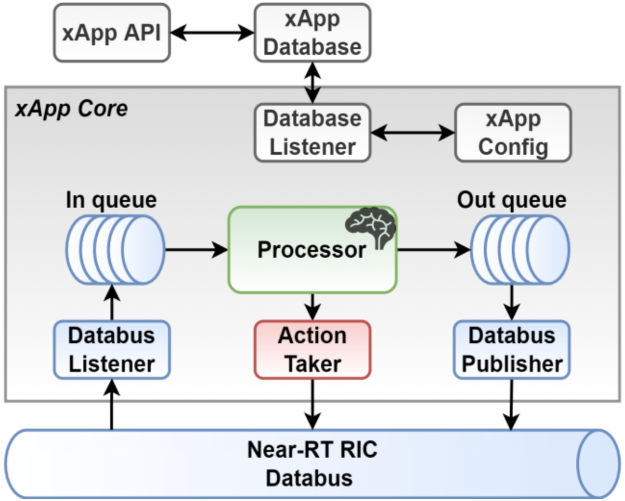
# System Model & Parameters

- Urban 5G network area
- $K$ macro (UMa) and/or micro UMi cells. Each cell has one Radio Unit (RU) with a total bandwidth $B$.
- $N$ Physical Resource Blocks (PRBs) for transmissions with bandwidth $W$.
- OFDM modulation scheme.
- $U$ UEs are located inside the network area.
- Each UE can connect to a single PRB of an RU.
- Sum-power constraint over all transmitting PRBs: $\sum_{n=1}^{N} P_{n,k} < P^{max}$
- Minimum power constraint for each PRB: $P_{n,k} > P^{min}$
- SINR of each connected UE: $SINR_u^{n,k} = \frac{P_{n,k} \cdot G_{k,u}}{(\sum_{k' \neq k}^{K} P_{n,k'} \cdot G_{k',u}) + N_0}$
- Throughput of each connected UE: $R_u^{n,k} = W \cdot log_2\left(1 + SINR_u^{n,k}\right)$



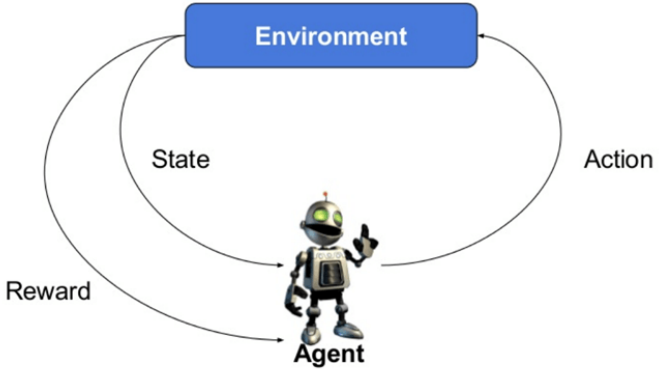
# Supporting xApps: Near-RT RIC Architecture

- O-RAN is controlled by a centralized controller (near-RT RIC), capable of regulating the power levels to maximize the network-wide throughput.
- The intelligent module of the xApp core is the Processor (code for ML).



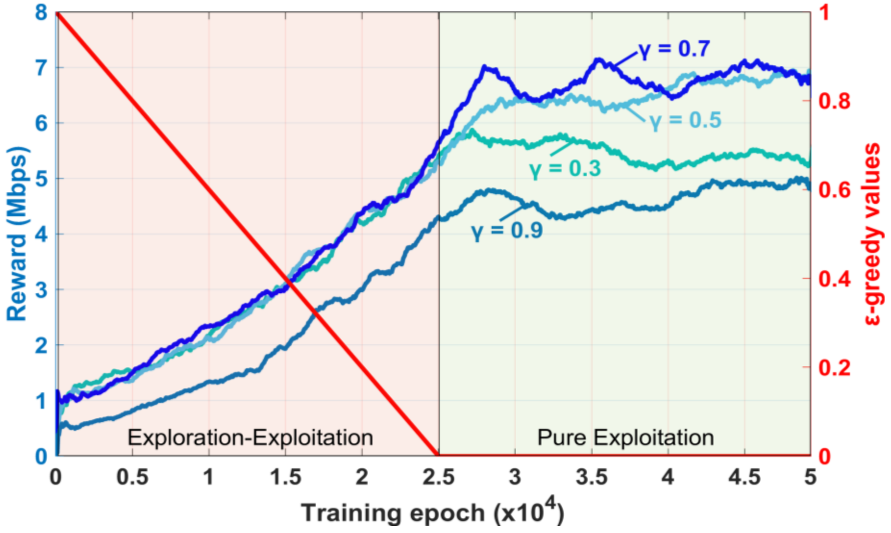
# Throughput Optimization algorithm

- Network-wide throughput maximization through power regulation.
- Proper adjustment of power levels, while simultaneously mitigating the co-channel interferences.
- Objective function: $\max_{p\epsilon P} \sum_{k\in K} \sum_{n\epsilon N} W \cdot log_2\left(1 + SINR_u^{n,k}\right)$
- DRL terminology: The centralized **agent** (the near-RT RIC) interacting with a telecom **environment** (cellular areas) aims to maximize the **objective function** (the network throughput) by observing the **state space** (the measurement reports) and taking **actions** (power level adjustments).
- Following a **trial-and-error** approach, the agent gradually converges in power control policy that ensures increased network utility.

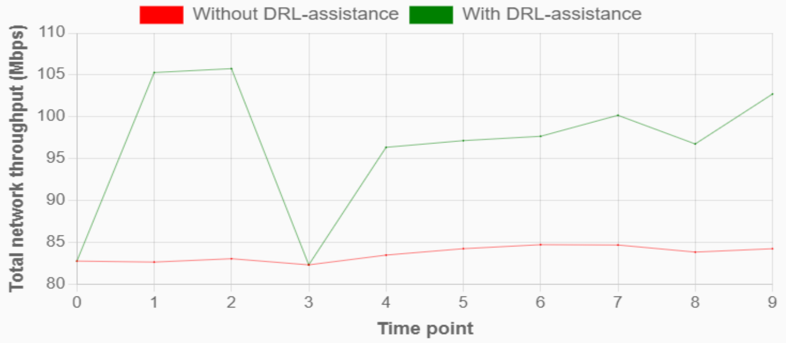


# Throughput Optimization algorithm

- Offline training prior deployment as xApp.
- Training process was performed with simulated measurements by the POSS simulator.
- In each training episode, the initial power levels are set to the average power level.
- Discount factor ($\gamma$) is associated with the extent to which the agent prefers immediate ($\gamma = 0$) or future ($\gamma = 1$) rewards.
- Learning curve of the training with $\varepsilon$-decaying



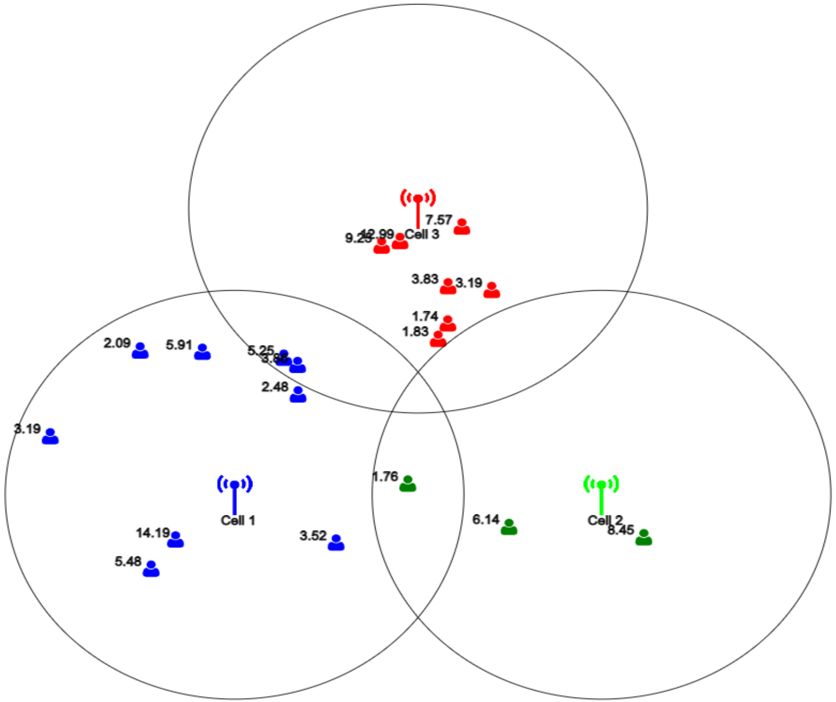
# ML algorithm rollout




**Instantaneous Power Levels**

0 Watt — 25 Watt

| | Rb1 | Rb2 | Rb3 | Rb4 | Rb5 | Rb6 | Rb7 | Rb8 | Rb9 | Rb10 | Rb11 | Rb12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ru1 | 1.27 | 2.34 | 0.78 | 2.06 | 34.33 | 5.88 | 5.57 | 4.32 | 1.98 | 4.36 | 5.87 | 6.48 |
| Ru2 | 5.69 | 6.51 | 0.10 | 4.09 | 0.10 | 3.86 | 6.21 | 3.48 | 3.14 | 5.59 | 0.10 | 2.60 |
| Ru3 | 2.38 | 4.35 | 2.01 | 1.53 | 4.83 | 5.59 | 5.43 | 0.10 | 35.82 | 5.73 | 0.10 | 0.10 |



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