

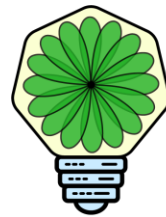


AI/ML in Wireless Networks: From Learning to Over-the-Air Computation

Carlo Fischione

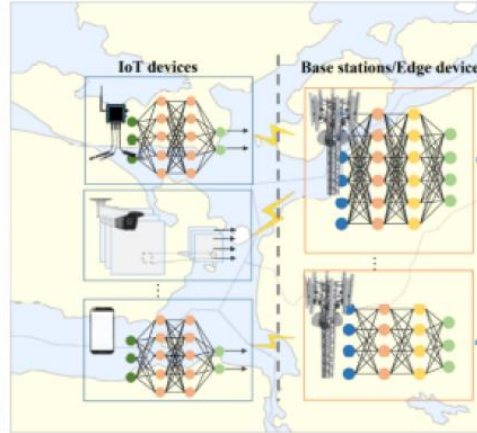
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SweWIN
Swedish Wireless Innovation Network

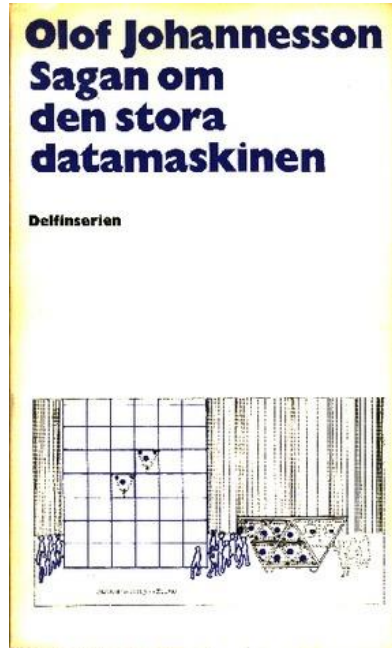
Many Use-cases of AI/ML in Wireless Networks



		Use cases	Future agenda item
Use cases for 6G Rel-20 study item	New use cases	AI/ML receivers for DM-RS overhead reduction	11.8 MIMO
		AI/ML based CSI-RS overhead reduction	11.8 MIMO
		AI/ML-based digital post-distortion (DPoD)	11.5 Energy efficiency
	Enhancement of existing 5G NR use cases	Beam management enhancement	11.8 MIMO
		CSI prediction enhancement	11.8 MIMO
Adopt in 6G without a study item phase		5G Rel-19 beam management	N/A
		5G Rel-19 positioning Case 1/3a/3b	
		5G Rel-19 CSI prediction	

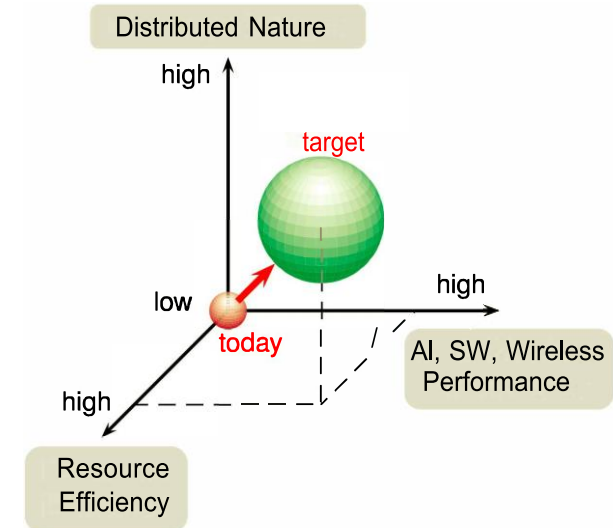
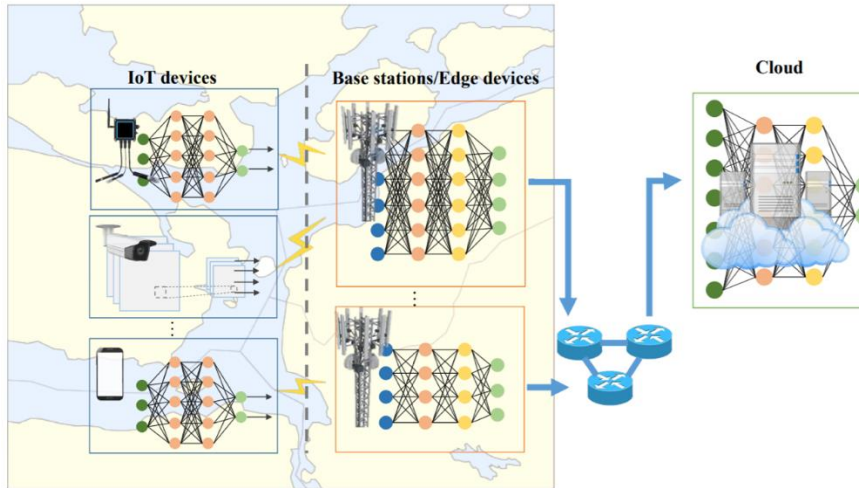
- Communication Infrastructures, Smart Cities, Smart Grids, Autonomous Vehicles...
- Several use cases in 3GPP standardization:
 - CSI management, beam management, positioning
 - Proprietary features with limited or without (extra) standards support: link adaptation
 - Network and Enterprise digital twins
 - ITU-R “beyond communications” features (ISAC, imaging, environmental reconstruction)

AI/ML and Networks: a Vision from 1966



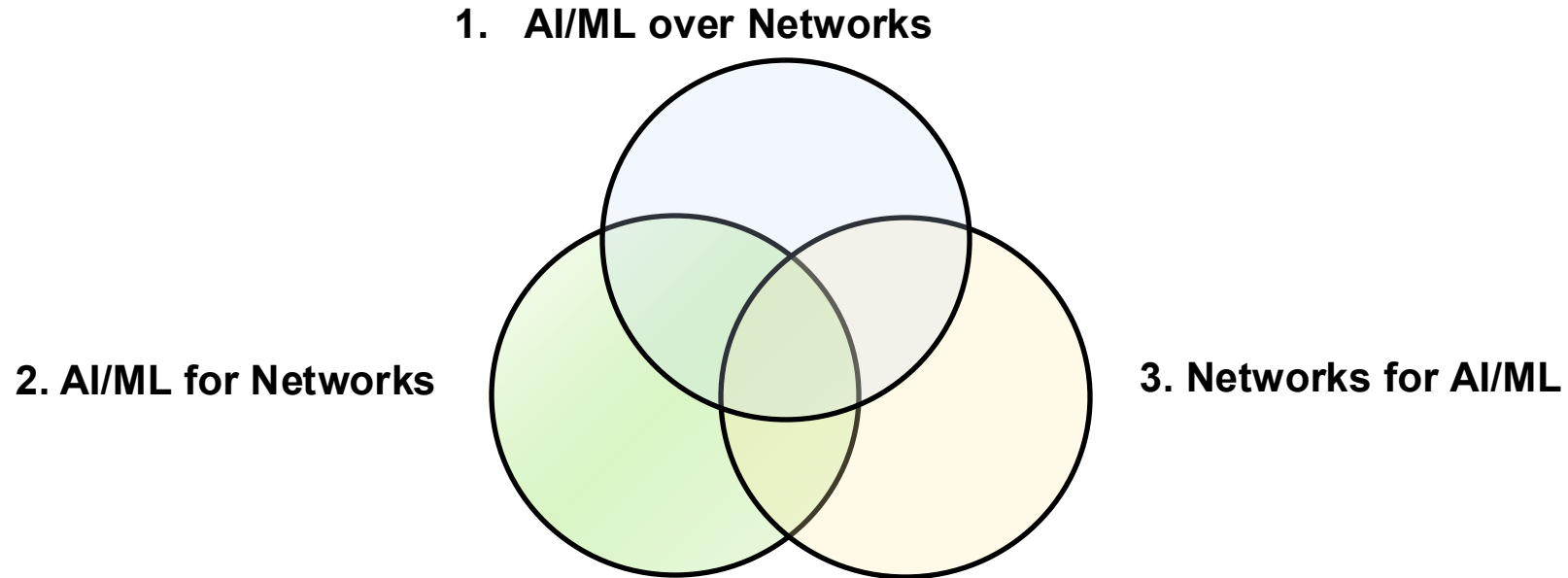
- “A great step forward came with the **teletotal**, which in principle was a combination of automatic telephone, radio, and TV.”
- In Alfven’s vision, **teletotal** was an omnipresent communication and computing network, capable of automating decision making, commerce, education, justice etc., via central computers.

AI/ML and Networks: Challenges



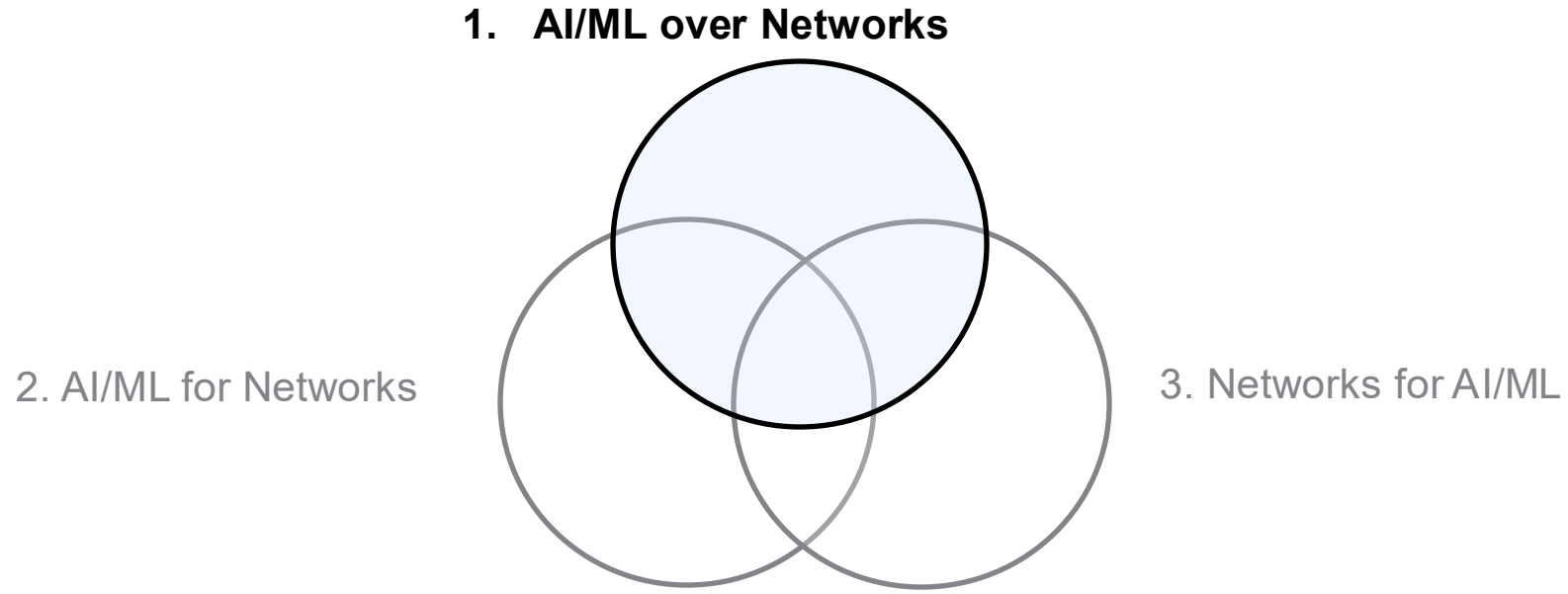
- In wireless networks, it is difficult to make AI/ML training and inference
- The networks and devices are distributed, heterogeneous, even using different communication protocols and software
- Inference on a device/access network needs data from other devices and network locations as a collaborative effort
- A major concern is energy-efficiency, **bandwidth limitations, software, and hardware constraints**

AI/ML and Networks Main Research Areas



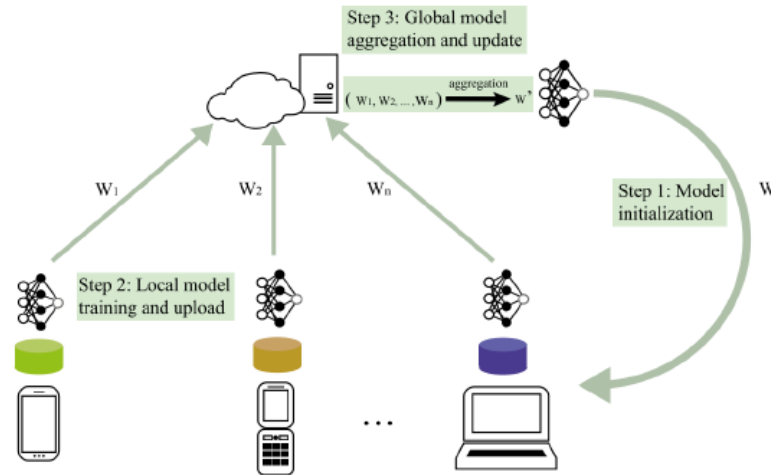
1. AI/ML over wireless networks;
2. AI/ML for networks;
3. Networks for AI/ML.

AI/ML and Networks Main Research Areas



1. **AI/ML over wireless networks;**
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AI/ML over Networks: Federated Learning



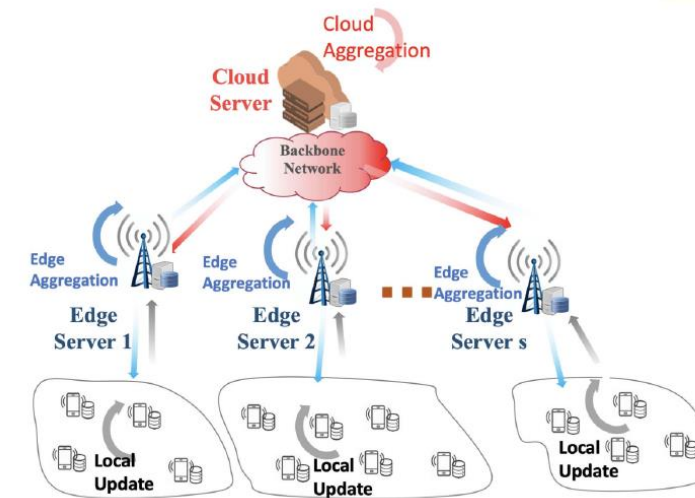
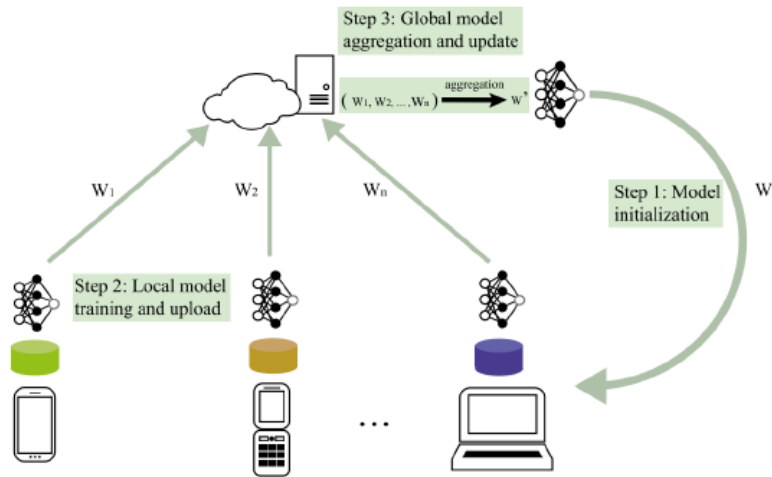
- In Federated Learning a subset of devices, sampled from K devices, participate in rounds to locally compute a global ML model
- Each device solves a local empirical risk problem

$$\mathbf{w}_k^{t+1} = \mathbf{w}_k^t - \gamma \nabla \ell_k(\mathbf{w}^t), \quad t = 1, 2, \dots$$

- where $\ell_k(\mathbf{w}^t) := \ell(f_k(\mathbf{x}_i : \mathbf{w}_k), y_i)$ is local loss function of local data
- The devices send the local model $\mathbf{w}_k^t$ to the Parameter Server
- The Parameter Server makes a global model as the average of the local models

$$\mathbf{w}^{t+1} = \sum_{k=1}^K \frac{N_k}{N} \mathbf{w}_k^t$$

Hierarchical Federated Learning



Problem: Traditional Federated Learning

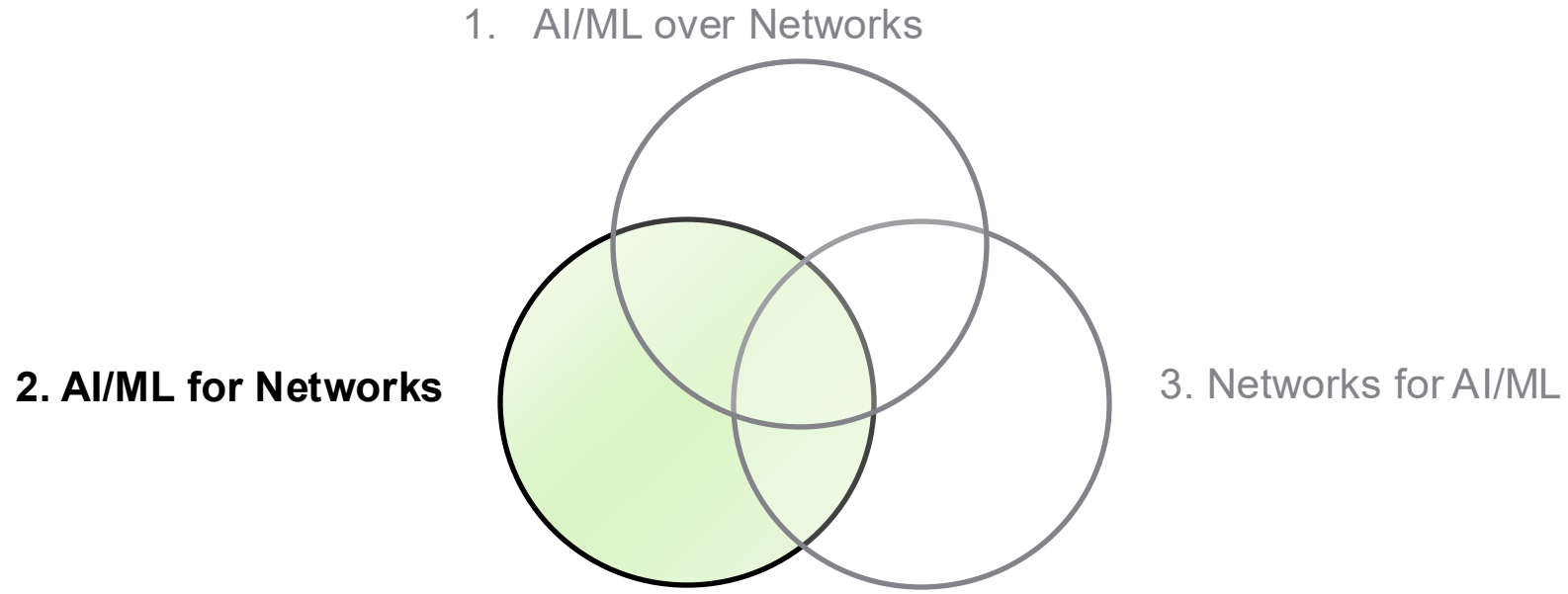
- **Scalability Issues:** Handling very large number of edge devices leads to scheduling, coordination, and reliability problems.
- **Communication Inefficiency:** Frequent transmission of high-dimensional model updates strains communication bandwidth.

Solution: Hierarchical Federated Learning

- **Introduce intermediate aggregators** (e.g., at cell towers or edge servers) to reduce server load.
- **Quantized Updates:** Send only quantized gradients instead of full-precision vectors

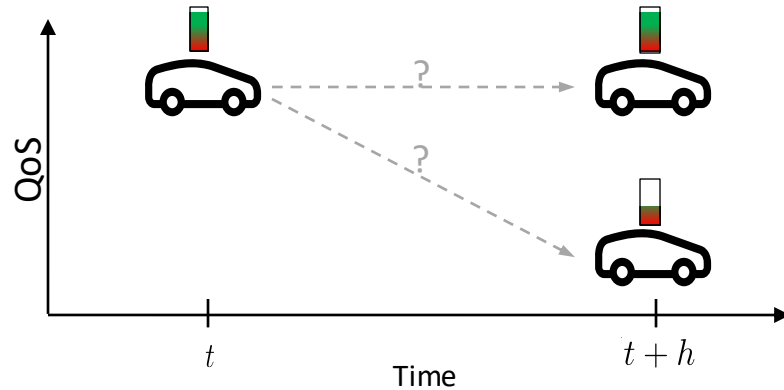
Results: reduces communication and computation costs .

AI/ML and Networks Main Research Areas



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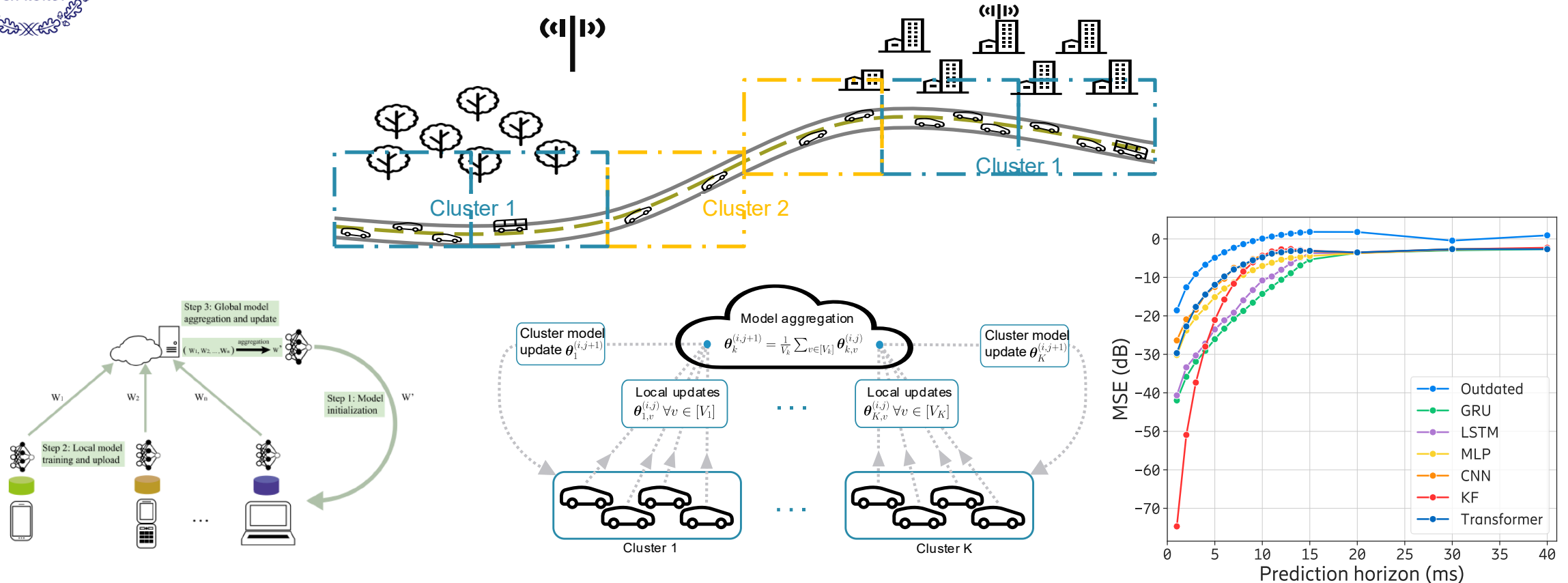
AI/ML for Network: Vehicular Networks



Application	Latency [ms]	Data rate [Mbps]	Reliability [%]	Prediction horizon
Teleoperated driving: Control of vehicles by a remote operator	≤ 50	30/50	99 (UL) 99.999 (DL)	seconds/ minutes
High-density Platooning: Enable vehicles to travel in close proximity	10-25	30/50	90-99.99	seconds/ minutes

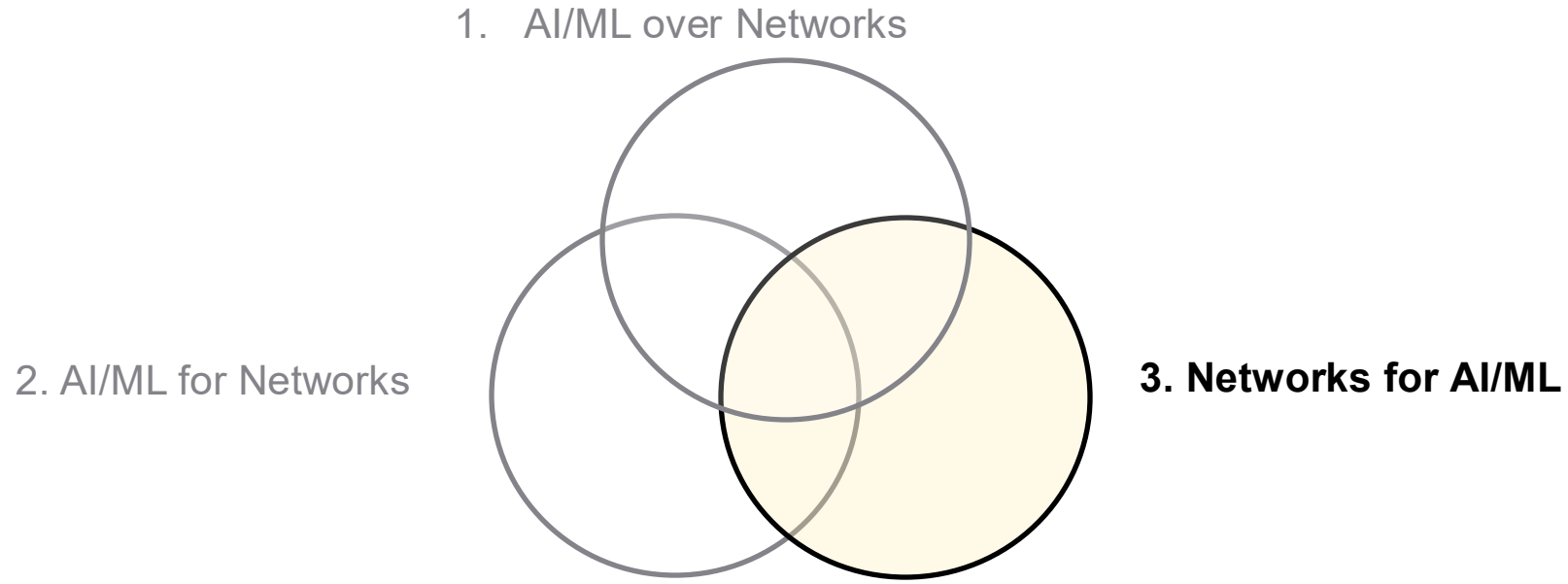
- QoS: network performance obtained by the users.
 - measured by throughput, latency, packet loss, or wireless channel quality.
 - affected by the propagation environment and the traffic load.
- Wireless protocols will use predictive QoS (pQoS) to ensure the actual QoS.
 - If not, the protocols must take countermeasures to satisfy the communication requirements.
- Can ML perform temporal predictions of the QoS?

AI/ML for Networks: Vehicular Networks pQoS



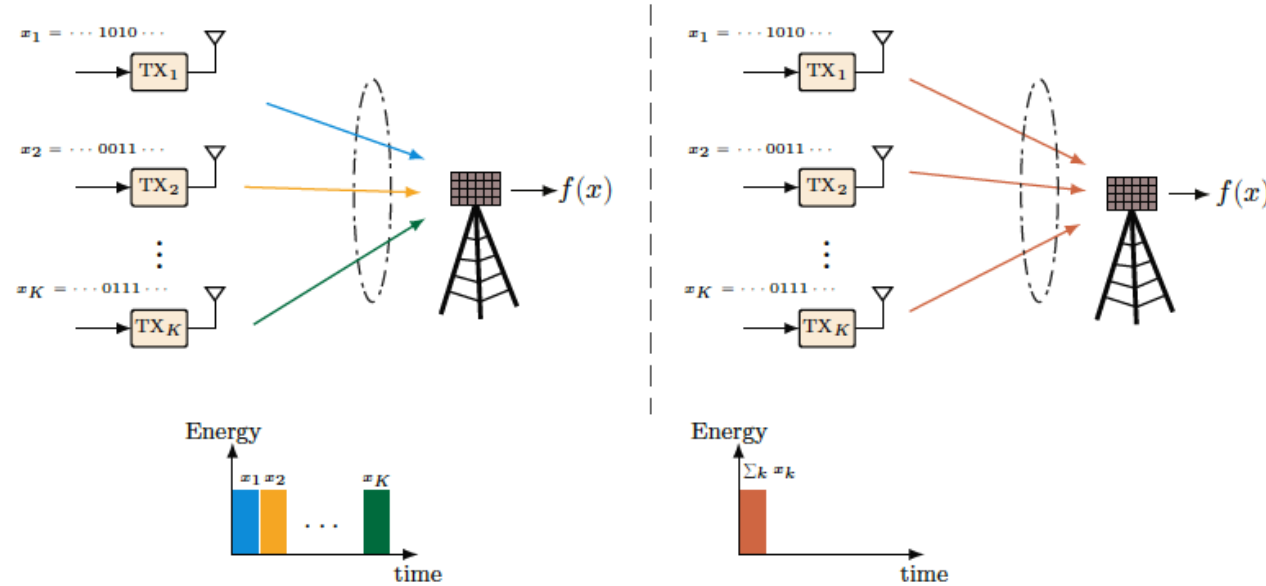
- The model-based Kalman filter performs well in the case with perfect channel knowledge on short prediction horizons.
- The GRU performs better in noisy scenarios and on long prediction horizons.

AI/ML and Networks Main Research Areas



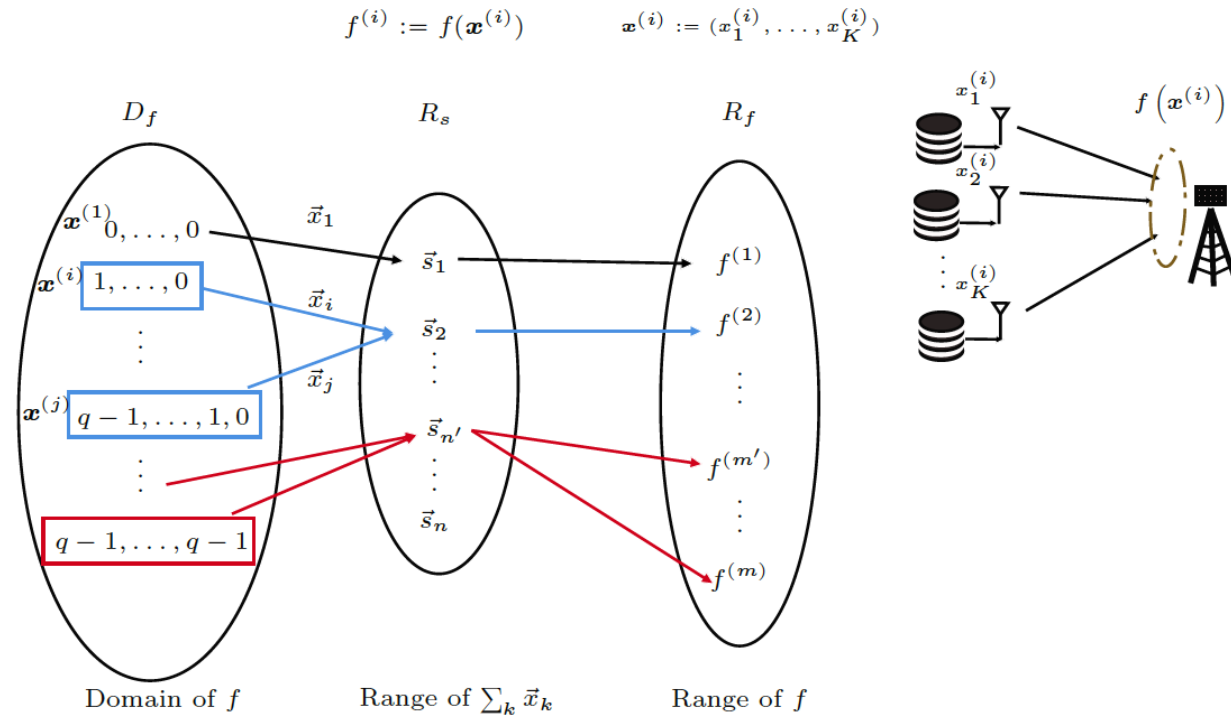
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Networks for AI/ML: Over-the-Air Computations



- Computation over-the-air in the wireless medium.
- Integrate communication and computation.
- Shared bandwidth among users in time, frequency, and code domain.
- Most of current research relies on **analog** communications.
- We have introduced **digital** communications for over-the-air computations

Networks for AI/ML: Digital Over-the-Air



- Key idea: make the overlappings of digitally modulated signals distinguishable

S. Razavikia, J.M.Barros Da Silva Jr., C. Fischione, *ChannelComp: A general method for computation by communications*, IEEE Transactions on Communications, 2023

Do We Need New Communication Protocols for AI/ML?



- *“The Americans have need of the telephone, but we do not. We have plenty of messenger boys”*. Sir William Preece, Chief Engineer of the British Post Office, 1876.
- *“Cellular phones will absolutely not replace local wire systems”*. Marty Cooper, the father of the cell phone, 1974

Conclusions: a Very Rich and Active Research Domain!

AI/ML TRENDS IN WIRELESS RESEARCH

AI-NATIVE 6G
& SEMANTIC/
GOAL-ORIENTED
COMMS



OPEN RAN
INTELLIGENCE
(rApps/xApps)
&
GREEN RAN

NEURAL PHY
(LEARNED
RECEIVERS/
CODECS)



AI-ENABLED
JOINT
COMMUNICATION-
SENSING &



EDGE
INTELLIGENCE
&
OVER-THE-AIR
FL



AI-DRIVEN
NETWORK TWINS
& SIMULATION
PLATFORMS