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Beyond Connectivity

Explainable and Robust AI for 6G Control Systems

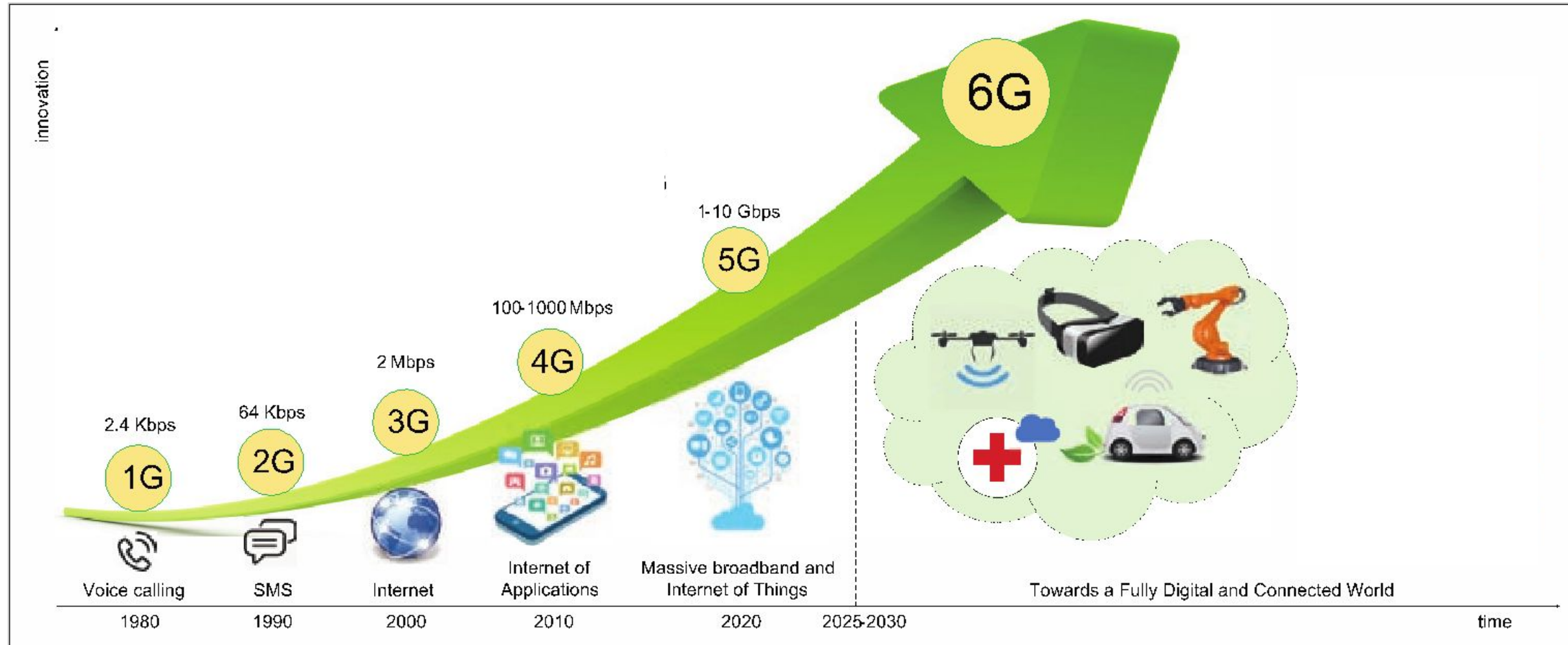
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Electrical and Electronics Engineering · Koç University

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Towards 6G Networks

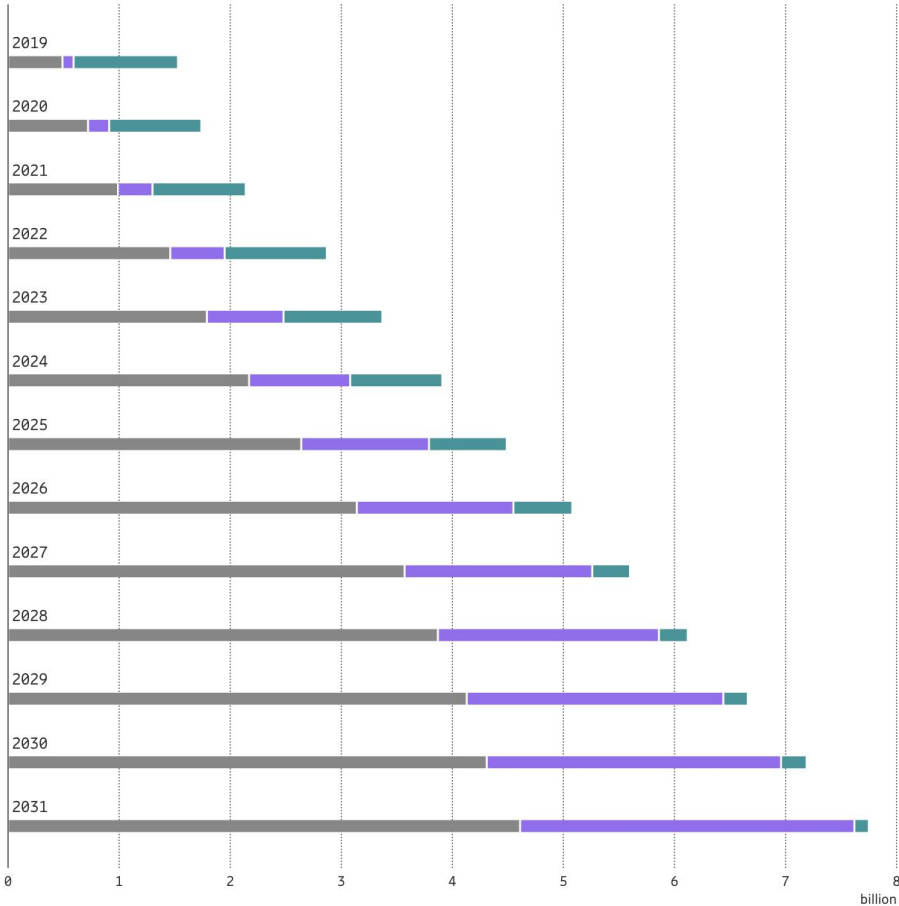


Source: M. Giordani, et al., "Towards 6G Networks: Use Cases and Technologies", IEEE Communications Magazine, 2020

IoT Connections Are Accelerating

Cellular IoT connections by segment and technology

● Broadband IoT(4G/5G) ● Massive IoT ● Legacy (2G/3G)



Source: Ericsson Mobility Report 2025

IoT connections (billion)

IoT	2025	2031	CAGR 2025-2031
Wide-area IoT	4.9	8.3	9%
Cellular IoT	4.5	7.8	10%
Short-range IoT	17.5	38.8	14%
Total	22.3	47.1	13%

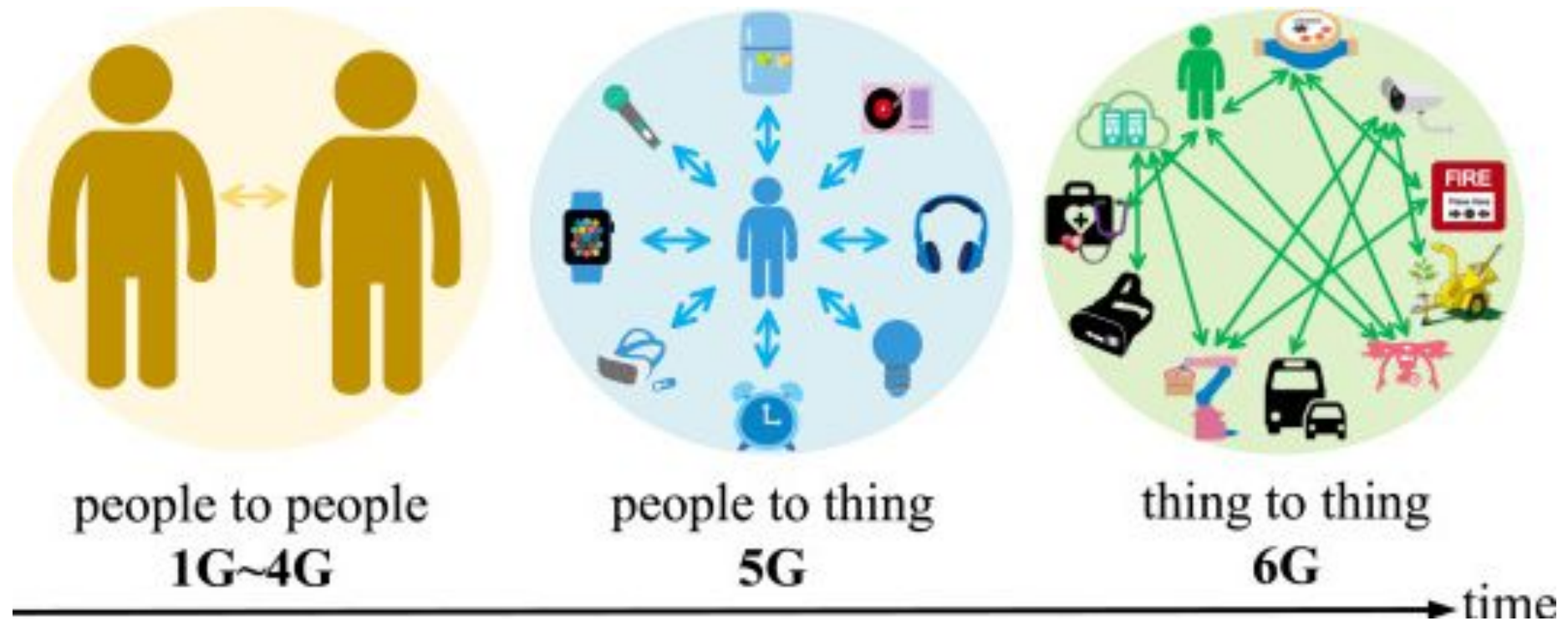
47.1B

total IoT connections by 2031

13%

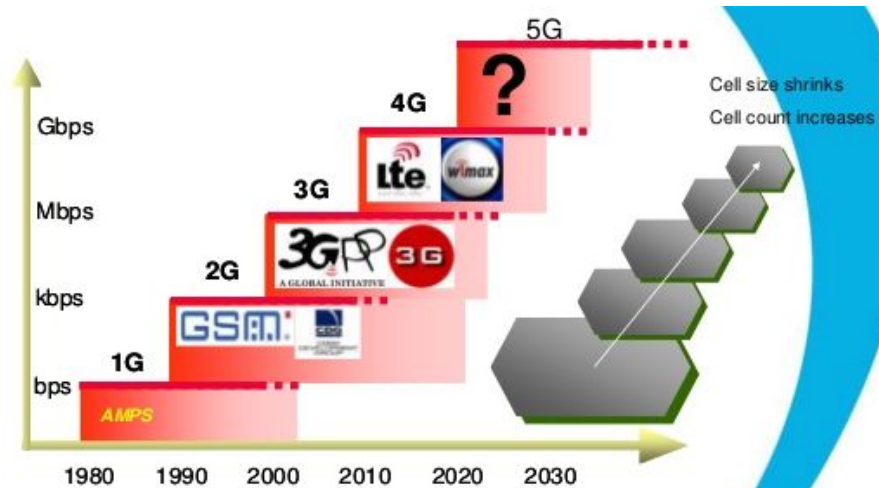
overall CAGR, 2025–2031

Networked Control Systems in 6G



Source: Y. Zhou, et al., "Service-aware 6G", Digital Communication and Networks, 2020

Wireless IoT Is a Multi-Objective Design Problem



Latency

Fast closed-loop response

Reliability

Dependable delivery for critical tasks

Energy

Battery and energy-harvesting limits

Scalability

Massive numbers of heterogeneous devices

AI in Wireless Networks

Conventional model-based design

LIMITATIONS

- Difficult to model nonlinear, time-varying environments
- Relies on predefined and static conditions
- High-complexity, high-latency decisions
- Limited predictive and multi-agent modeling



From models
to learned policies

AI-enabled design

CAPABILITIES

- Adaptive modeling and estimation
- Dynamic, nonlinear problem solving
- Low-latency predictive decision making
- Multi-objective, multi-agent intelligence

How to Make AI Smarter

01 Extreme-Value Theory Based Generative AI

EVT-based estimation and prediction of rare channel fades

02 Optimization Theory based AI

Optimization-guided and safe deep reinforcement learning for wireless networked control systems

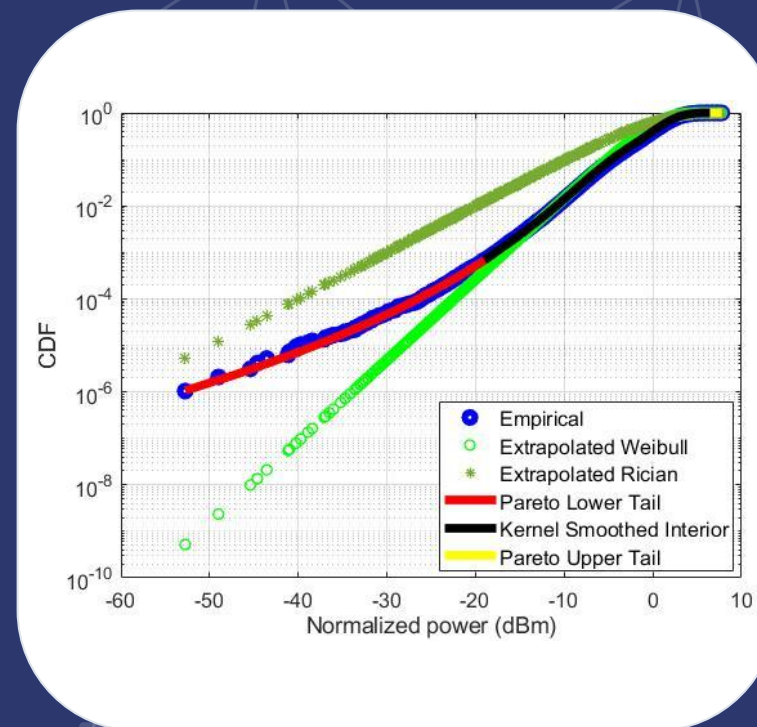
03 Explainable & Robust AI

Model reduction, confidence assessment, and trustworthy decisions

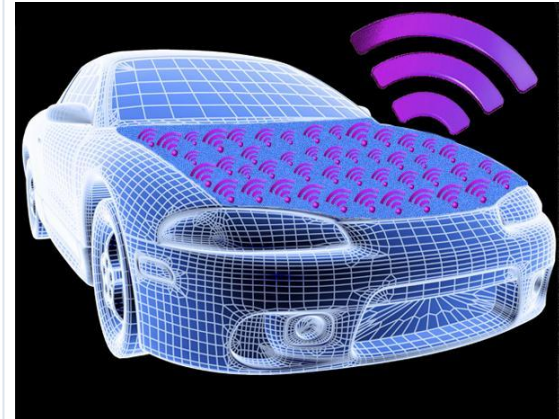
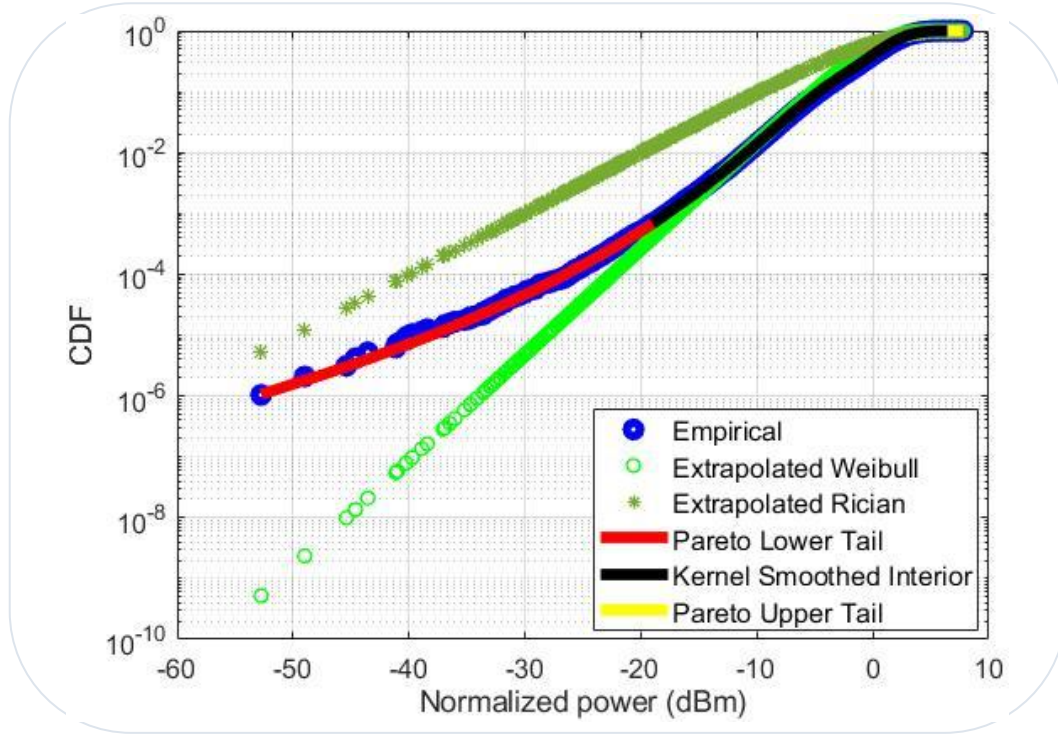
01

Extreme Value Theory Based Generative AI

Learn the rare channel events that determine ultra-reliability.



Why URLLC Requires New Channel Models



The ultra-reliable region is data-starved.

- Model the lower tail, not only the bulk distribution
- Learn from infrequent and severe channel fades
- Extrapolate safely beyond the observed samples

Tail analysis

Novel lower-tail distributions for ultra-reliability

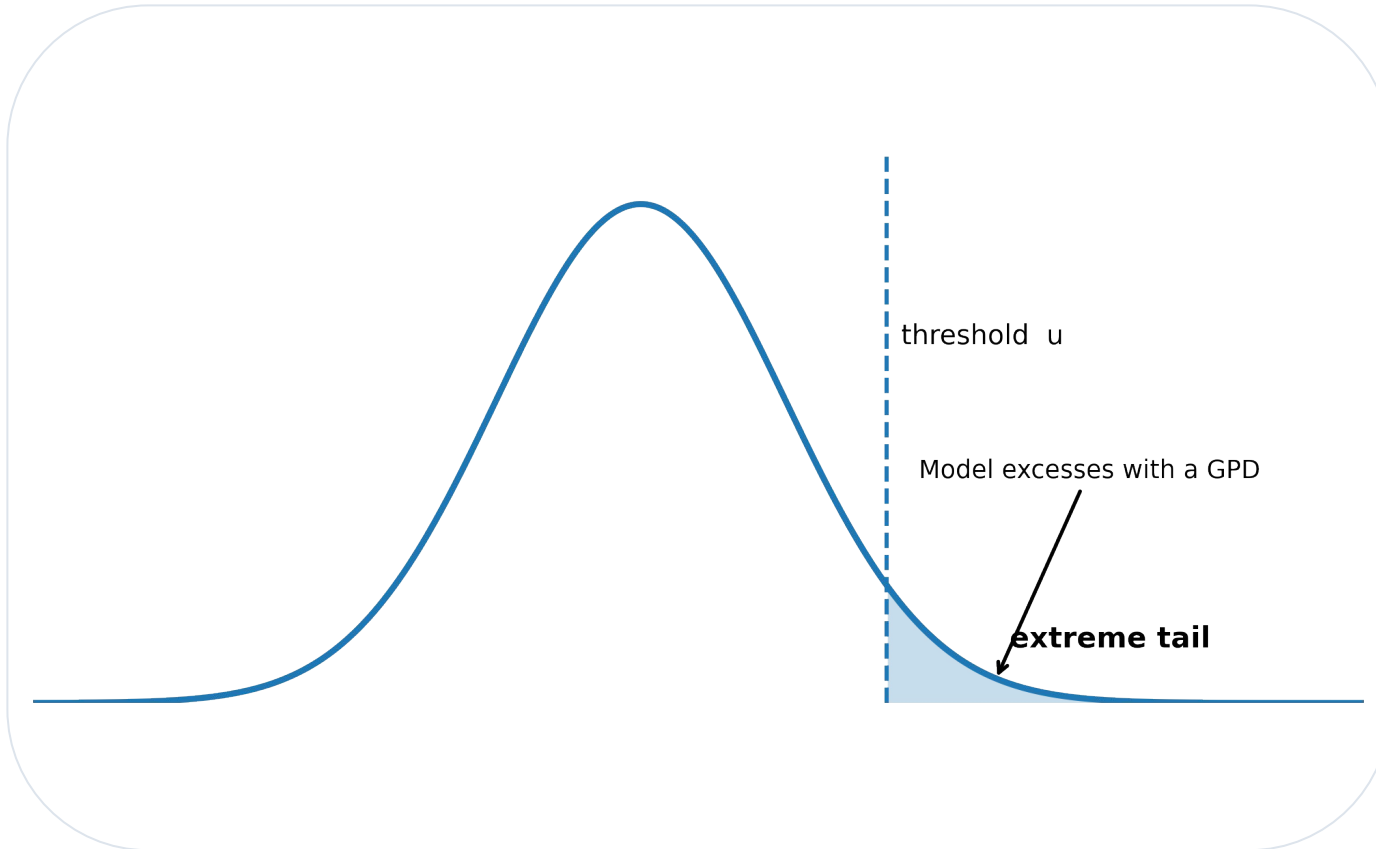
Rare-event data

Efficiently use limited observations of extreme fades

Decision making

Turn tail estimates into proactive communication actions

Extreme Value Theory



CORE IDEA

Focus the model on the rare events that control reliability.

- Choose a threshold that separates the tail from the bulk
- Model threshold exceedances with a Generalized Pareto Distribution (GPD)
- Estimate probabilities far beyond the directly observed range

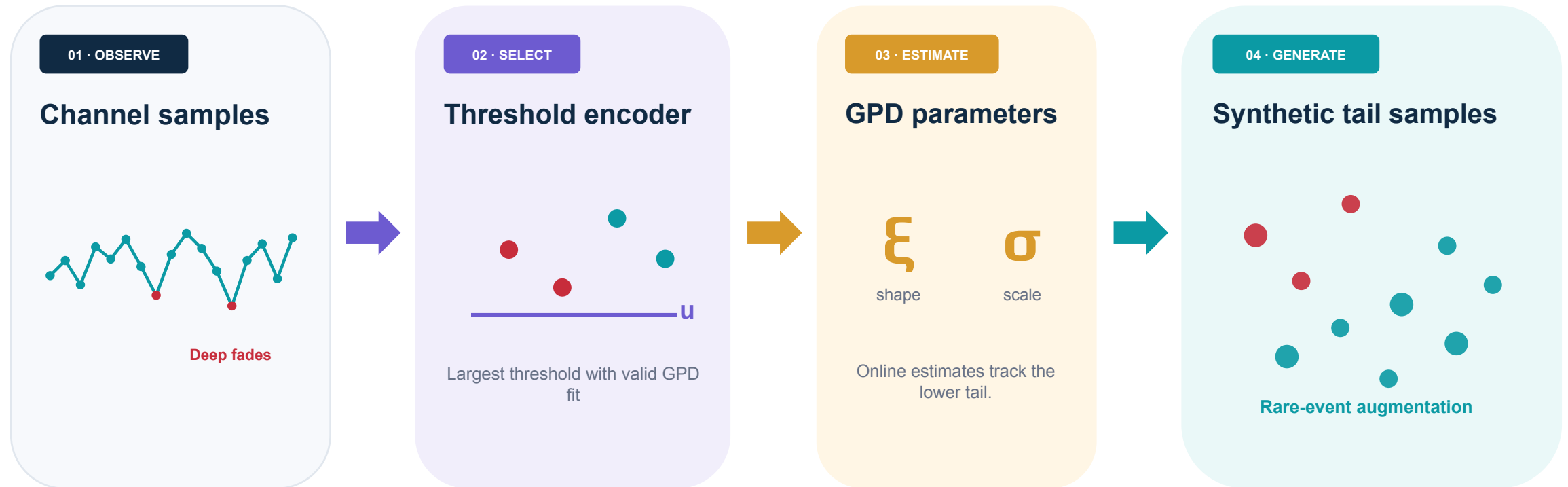
URLLC design becomes a tail-modeling problem, not an average-channel problem.

N. Mehrnia and S. Coleri, "Wireless Channel Modeling based on Extreme Value Theory for Ultra-Reliable Communications", IEEE Trans. on Wireless Communications, 2022.

N. Mehrnia and S. Coleri, "Non-Stationary Wireless Channel Modeling based on Extreme Value Theory for Ultra-Reliable Communications", IEEE Trans. on Vehicular Technology, 2021.

Generative AI for Real-Time URLLC: Tail Estimation

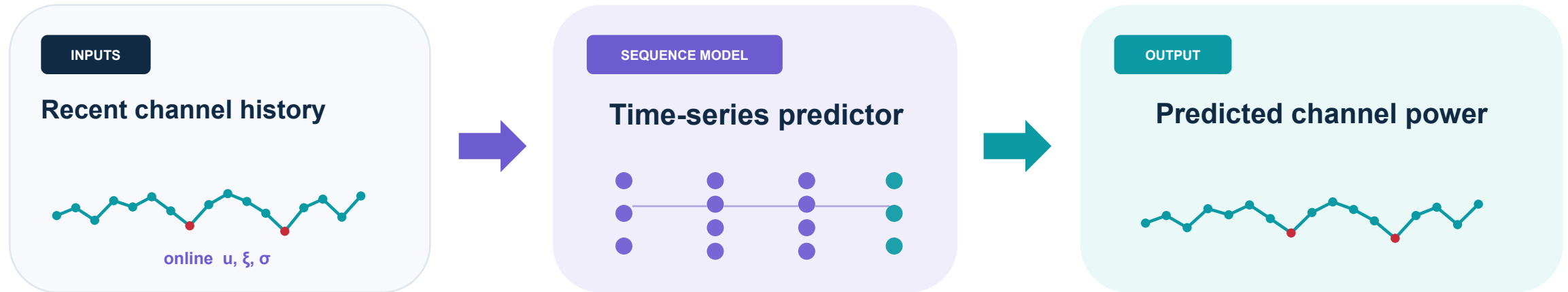
A structured pipeline turns limited channel observations into a real-time model of rare fades.



Threshold selection + generative parameter estimation enables real-time tail learning.

Tail-Aware Channel Prediction

Online tail estimates become part of the forecasting objective.



Standard MSE loss

AVERAGE FIT

Optimizes average prediction error across the full channel distribution.

Adaptive GPD loss

TAIL-AWARE

Uses online tail estimates to place additional emphasis on errors in the ultra-reliable region.

The same forecasting architecture can be trained to protect the rare fades that dominate URLLC reliability.

N. Mehrnia, P. Valiahd, S. Coleri and J. Gross, "Channel Prediction using deep recurrent neural network with EVT-based adaptive quantile loss function", IEEE Comm. Letters, 2025.

Tail-Aware Channel Prediction: Model Backbones

Four sequence-model backbones are evaluated within the same tail-aware prediction workflow.

Seq2Seq-TF

Causal-TF

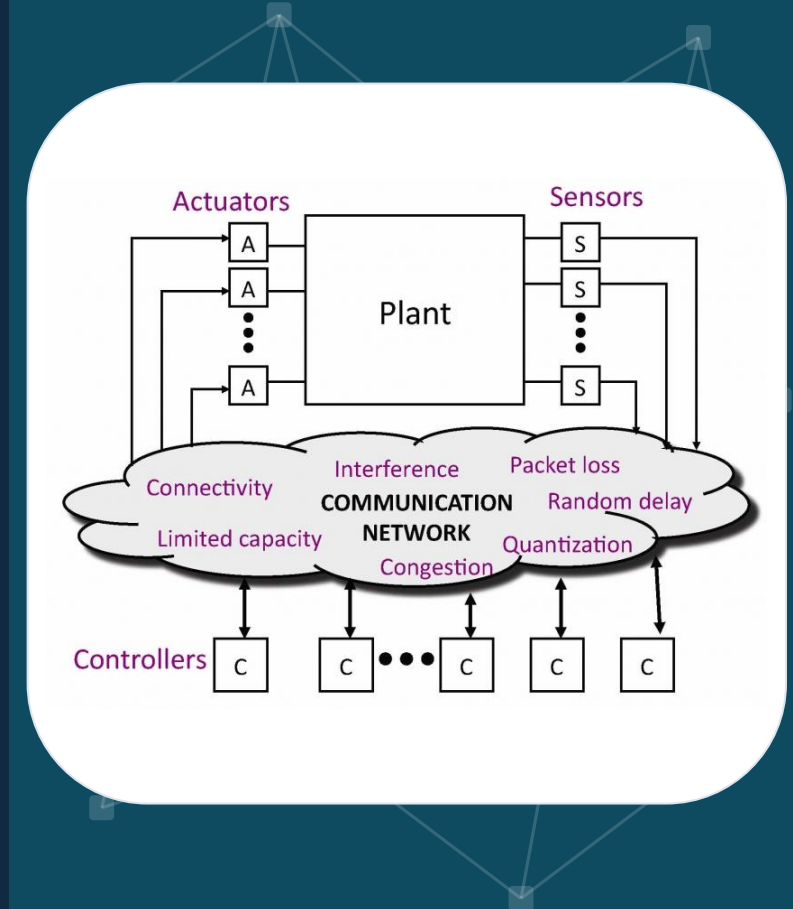
Attention-GRU

GRU

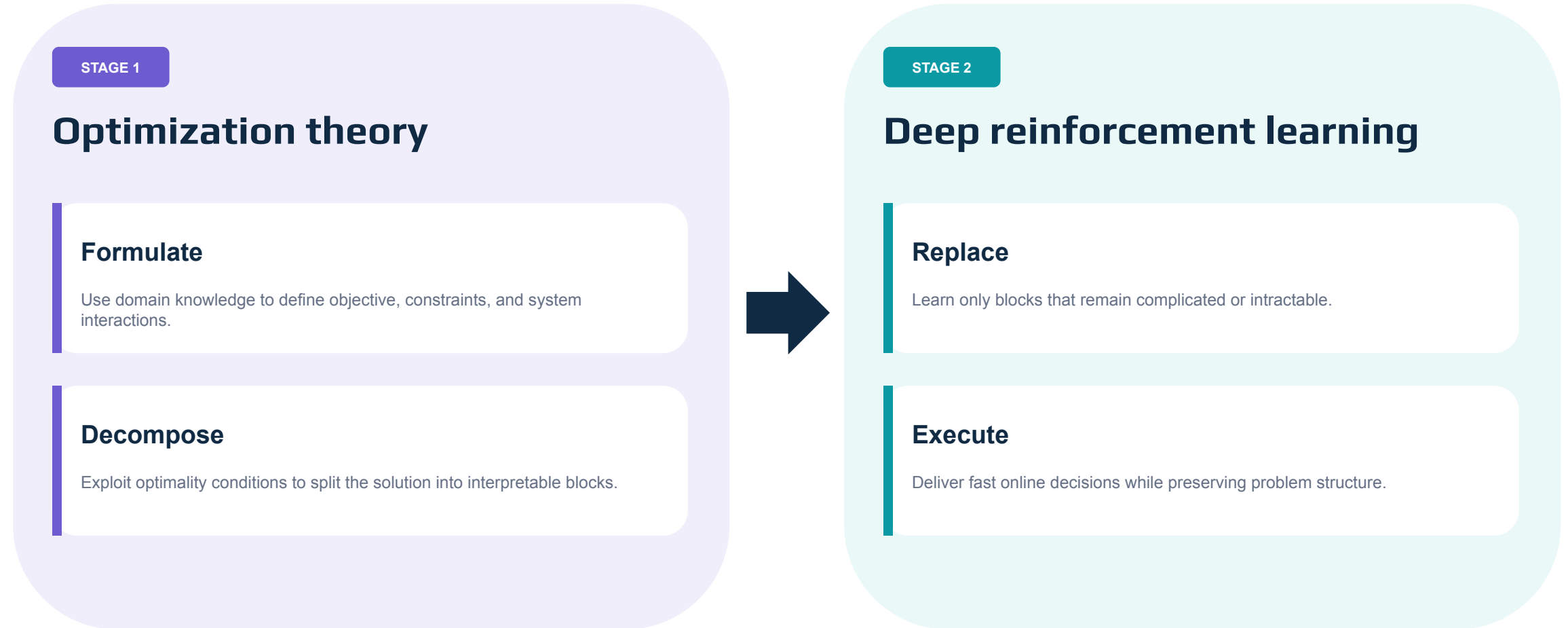
02

Optimization Theory Based AI

Optimization-guided and safe deep reinforcement learning for wireless networked control systems.



Optimization-Theory-Guided Learning Framework



Structured learning: accuracy and feasibility from optimization, speed and adaptability from AI.

H. Q. Ali, A. B. Darabi and S. Coleri, "Optimization Theory Based Deep Reinforcement Learning for Resource Allocation in Ultra-reliable Wireless Networked Control Systems", IEEE Trans. on Communications, 2024.
S. Coleri, A. G. Onalan and M. di Renzo, "Integrating Optimization Theory with Deep Learning for Wireless Network Design", IEEE Communications Magazine, 2025.

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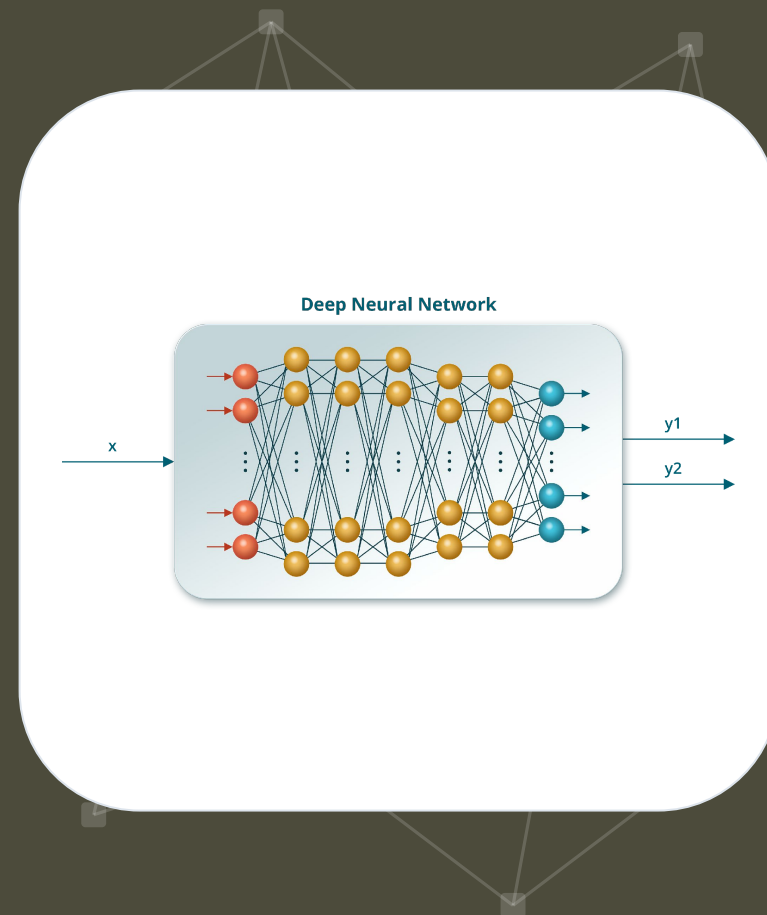
Explainable & Robust AI

Make 6G decisions smaller, safer, and easier to trust.

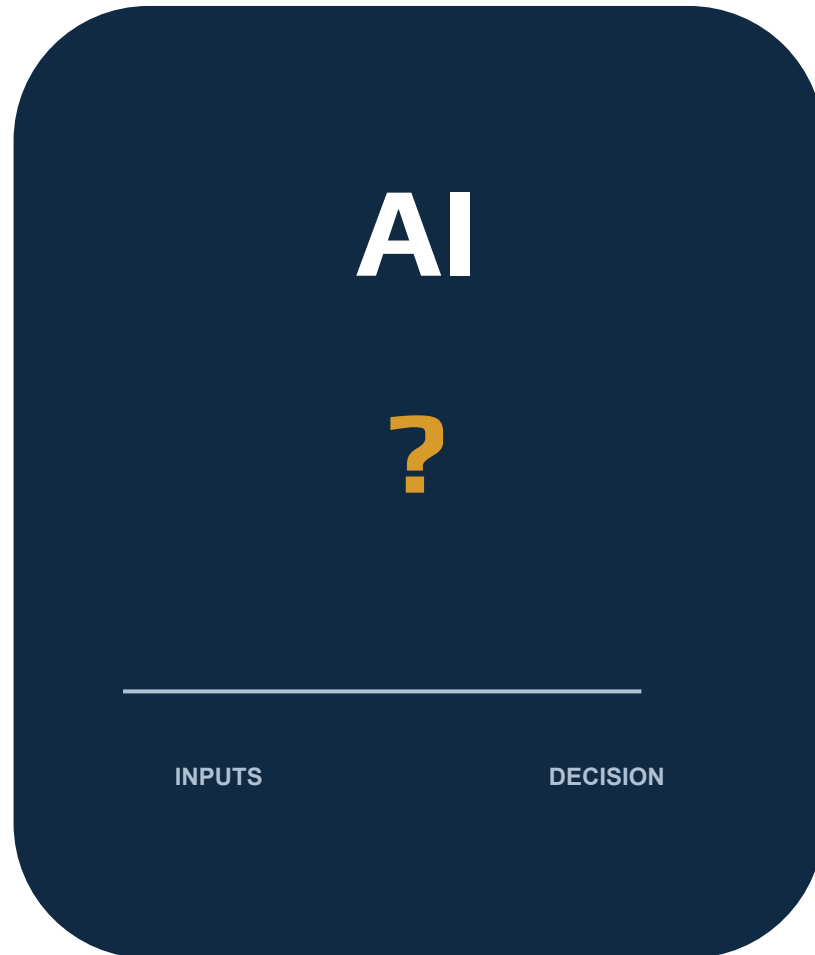
01 Extreme Value Theory Based AI

02 Optimization Theory Based AI

03 XAI



Why Explainable AI Matters for 6G



Feature influence

Which inputs actually drive the output?

Bias + generalization

Will the model remain reliable on new data?

Decision confidence

How strongly is a prediction supported?

Human control

Can we understand and override risky behavior?

XAI reveals how the algorithm works, where it is weak, and when it should not be trusted.

N. Khan, S. Coleri, A. Abdallah, A. Celik and A. M. Elwatil, "Explainable and Robust Artificial Intelligence for Trustworthy Resource Management in 6G Networks", IEEE Comm. Magazine, 2024.

Thank you

Questions & discussion

Sinem Coleri · Wireless Networks Laboratory · Koç University

