PANEL: Emerging Technologies for NextG Networks

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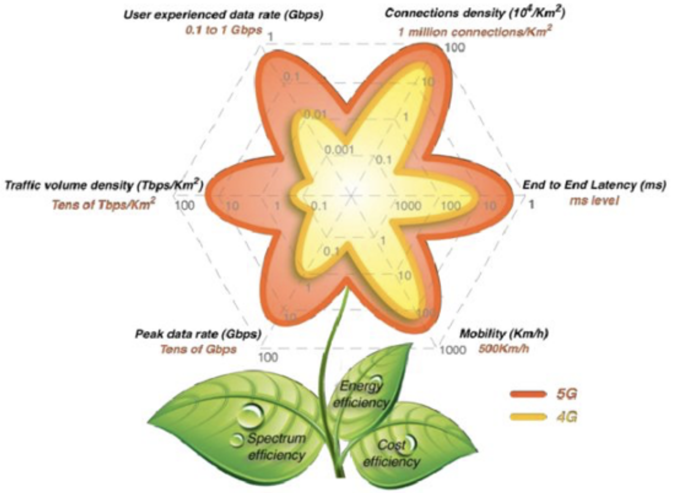
G = Generation

- **Generation**: new, fundamental, disruptive technology, a paradigm shift, for most devices (e.g., cellphones).
- 1G to 4G: each has its key technologies (FM radio, GSM/GPRS, WCDMA, LTE)
- 5G is different:
  - Technology's view: Full duplex, cognitive radio, SDN/NFV, non-orthogonal multiple access (NOMA), small cells/HetNet, massive MIMO, mmWave communications; **OR**: spectrum expansion, spectrum efficiency enhancement, network densification
  - Standardization's perspective: Enhanced Mobile Broadband (eMBB), URLLC (Ultra Reliable Low Latency Communications), mMTC (massive Machine Type Communications)
- How about 6G?
  - Spectrum, Terahertz Communications, light (VLC, FSO), blockchain, satellite, under water, …, intelligence
  - AI is *disruptive*: ML vs. model based; seems highly suitable for wireless systems, which are historically based on probabilistic models



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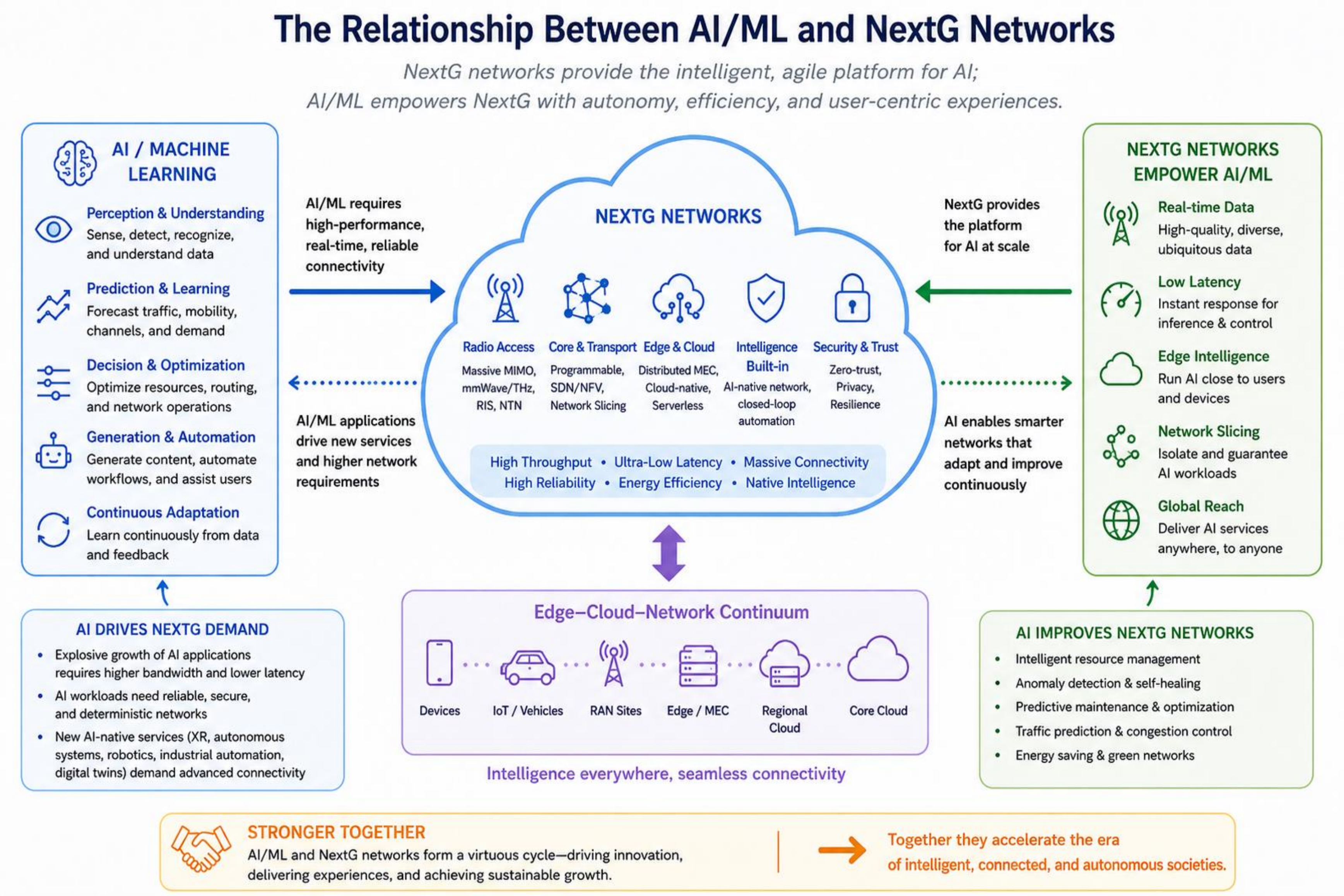
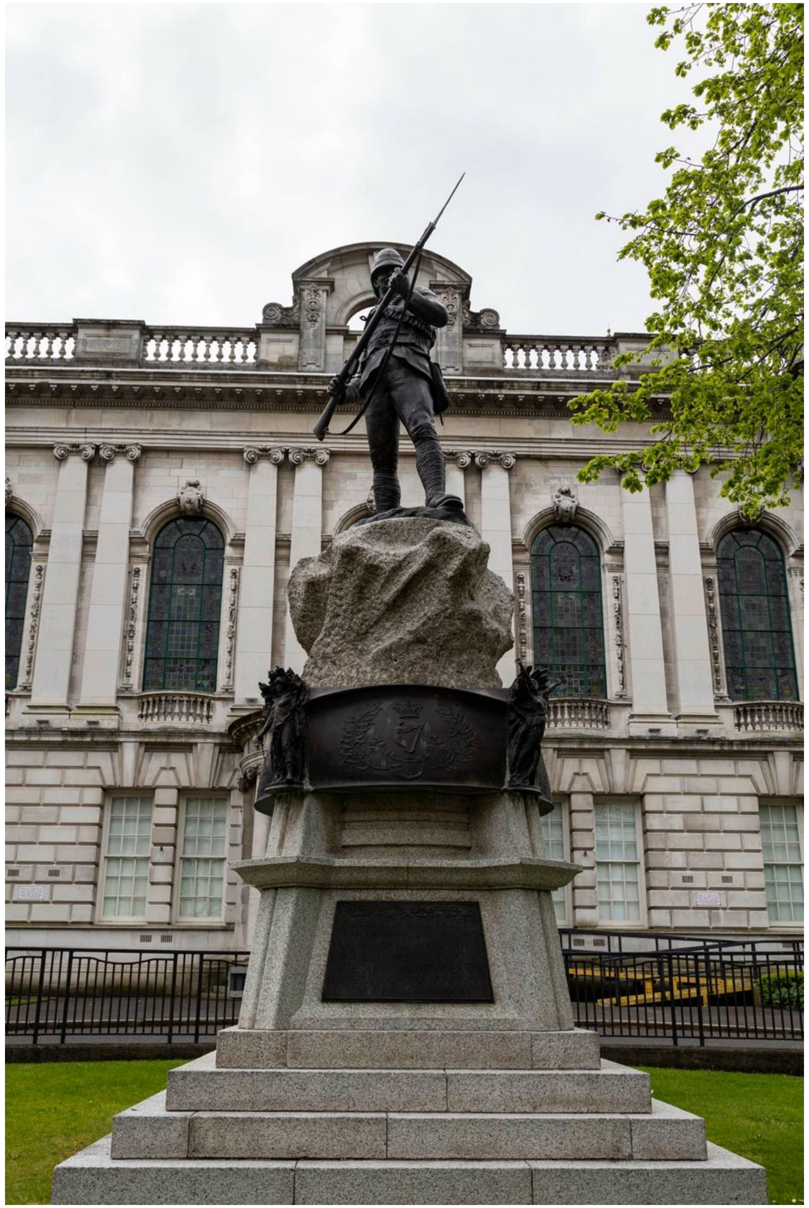
8/7/2019 Image source: IMT-2020 (5G) Promotion Group, "5G vision of IMT-2020 (5G) promotion group," Sep. 2014. 5

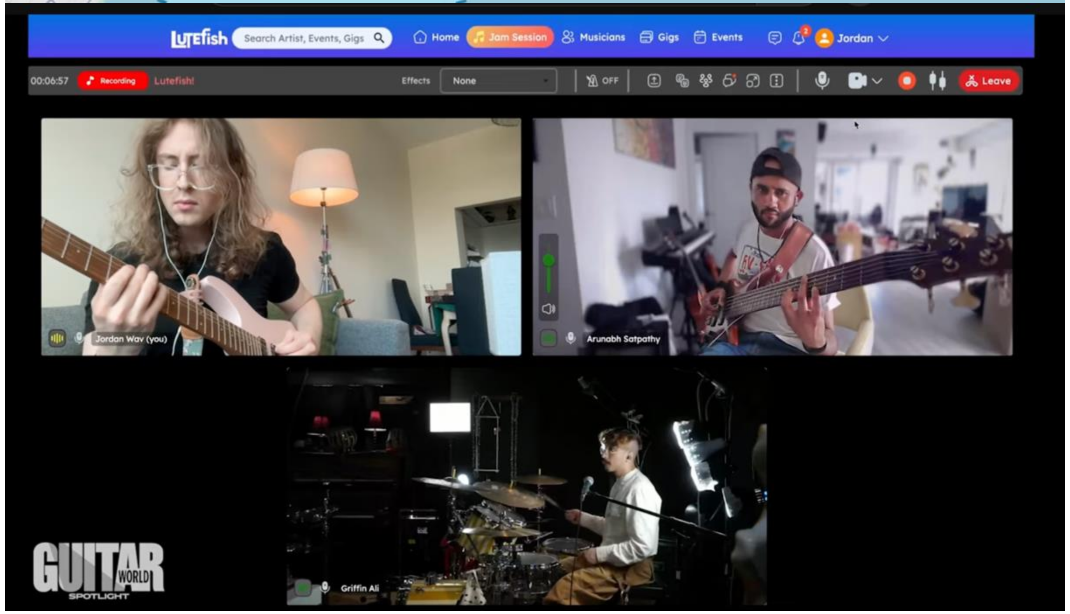
AI/ML and NextG



[Image generated by ChatGPT]

(i) New AI applications: need new mechanisms to support new traffic types





Human vs. Machine QoS

QoS requirements differ fundamentally between human-centric communication and Machine-to-Machine (M2M) communication due to human biological limits versus automated speed needs.

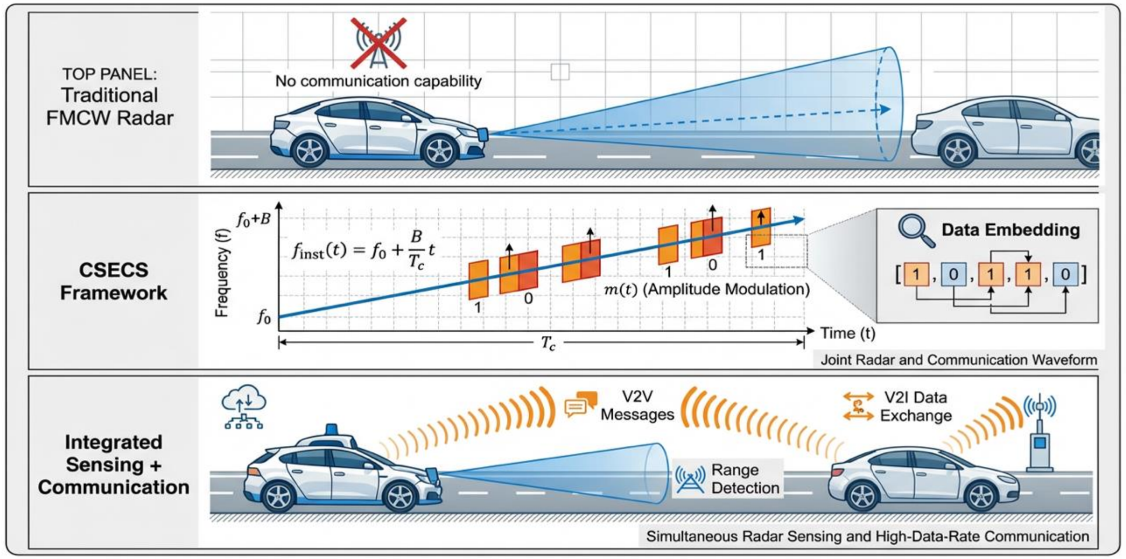
- Humans require smooth, continuous data delivery, while machines prioritize data integrity, massive scale, and deterministic timing.
- Human eyes are not sensitive to high frequency signals, which may be different from ML inference

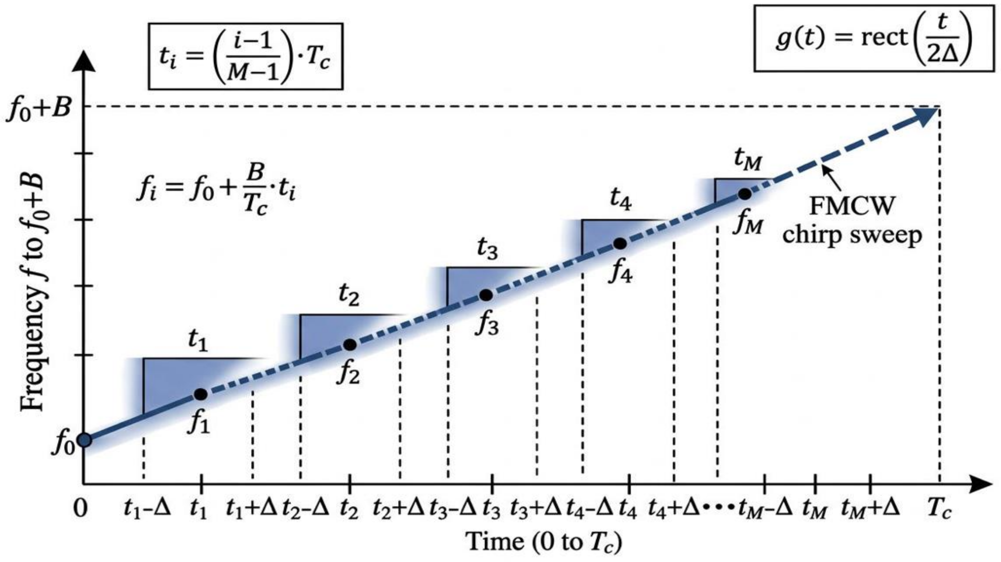
Metric	Human Users	M2M / IoT
Primary Focus	User Experience (QoE)	Absolute Reliability & Timing
Latency Tolerance	Low (<150 ms)	Ultra-low (<1 ms) OR Very High (Hours)
Packet Loss Tolerance	Moderate (1%–5%)	Zero (0%)
Traffic Pattern	Sustained, predictable	Burst, unpredictable, or scheduled
Typical Bandwidth	High (Mbps to Gbps)	Very Low (Kbps)

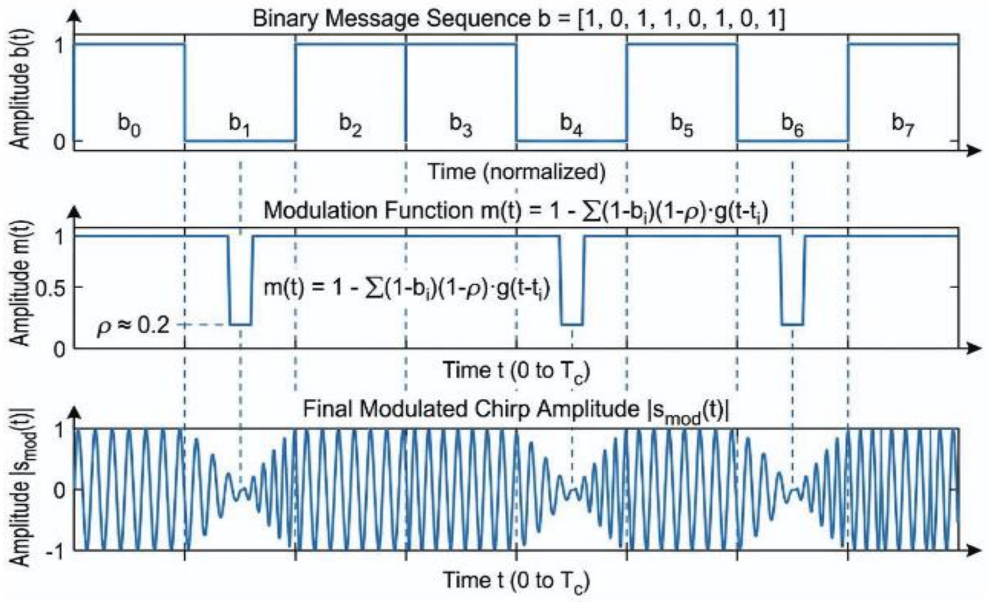
(ii) Integrated Sensing and Communications

Motivation:

- Stringent SWaP-C, latency, and spectrum constraints motivate shared sensing and communication on a common platform
- Three design philosophies: Communication-centric, Radar-centric, and clean-slate ISAC co-design
- Key trade-off: Communication data rate ↔ sensing fidelity ↔ legacy compatibility
- Radar-centric design: transforms legacy FMCW radars into dual-function sensing and communication nodes for 6G/NextG
- Firmware-only upgrades enable side communication channels without compromising the radar's safety-critical sensing mission







Different Ways to Embed Data and Results

Phase-Attached Modulation
Small shaped phase perturbation

$$s_{\mathrm{PAM}}(t) = \gamma\, e^{j\left(2\pi f_0 t + \pi \alpha t^2 + \psi_c(t;\mathbf{x})\right)}$$

$\psi_c(t;\mathbf{x})$ = communication phase, band-limited shaping

Mean-shift phase regime

Constrained Frequency Hopping
Admissible tone set offsets

$$f_{\mathrm{CFH}}(t) \;=\; f_0 + \Delta f^k + \alpha t, \qquad kT \;\le\; t \;<\; (k+1)T$$

$\Delta f_k \in F = \{\Delta f(1),\ldots,\Delta f(M\_F)\}$

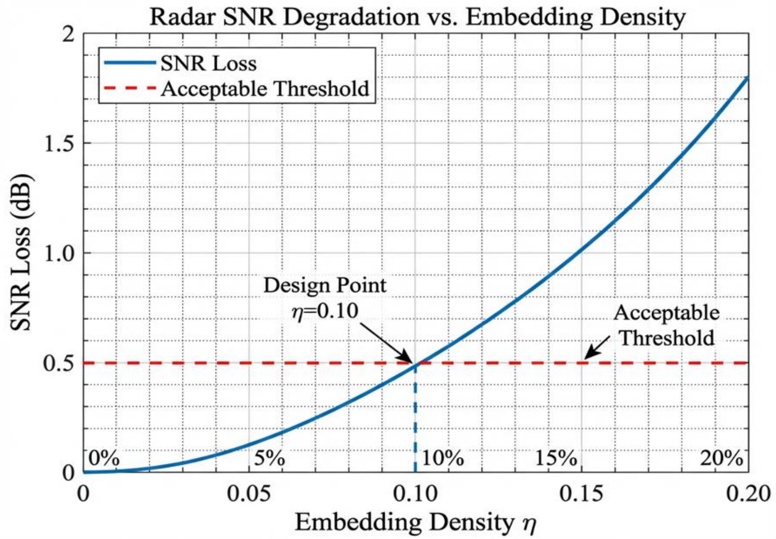
Empirical tone distribution

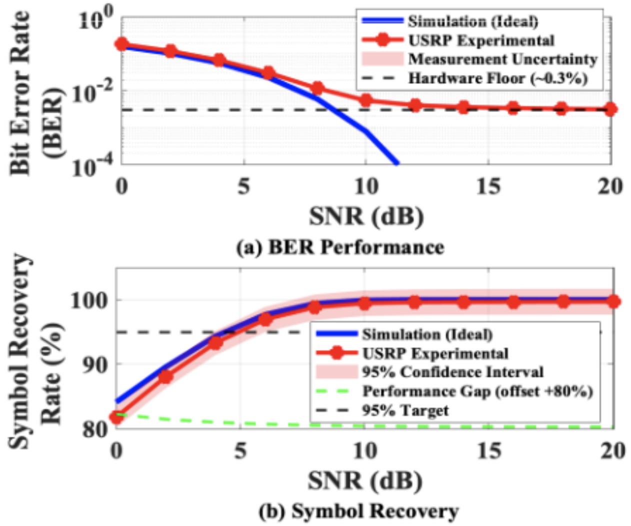
Phase-Coded Ortho. Sequences
Constant-modulus codes

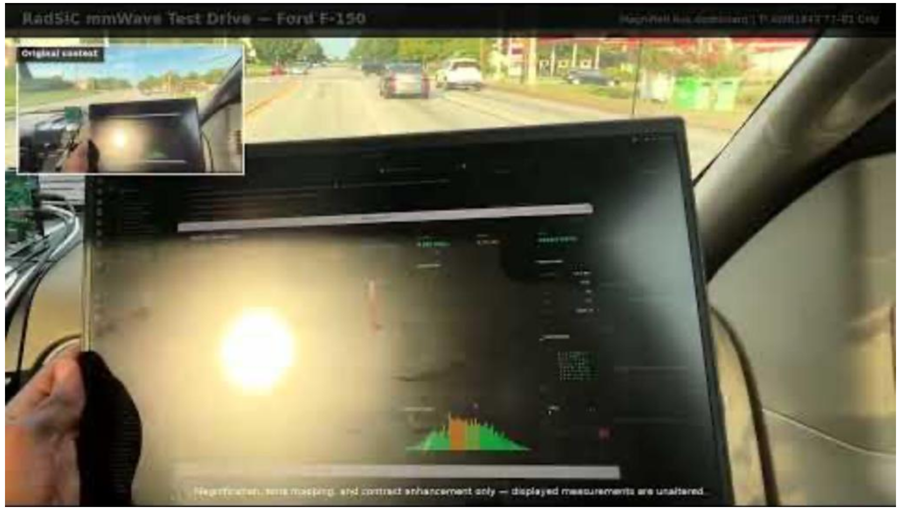
$$s_{\mathrm{PCOS}}(t) = \sum_{u=1}^{K} a_u(t)\, e^{j\phi_u(\mathbf{x})}\, s_u(t), \qquad |a_u(t)| \le 1$$

$|a_u(t)| \le 1$: weights; $s_u(t)$: K quasi-orthogonal codes; $\varphi_u(\mathbf{x})$: phase shifts determined by the data

Code sequence assignment





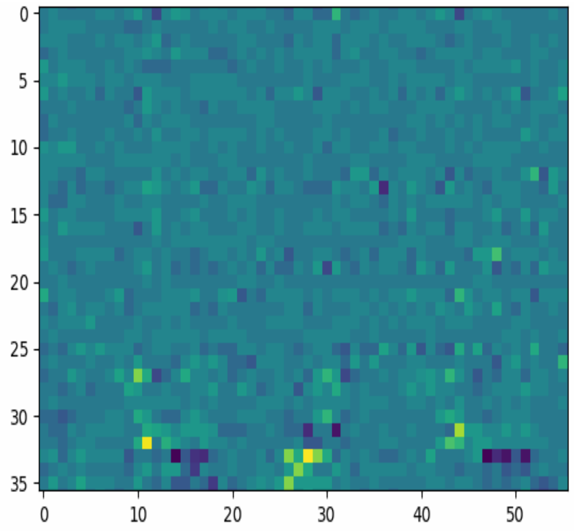


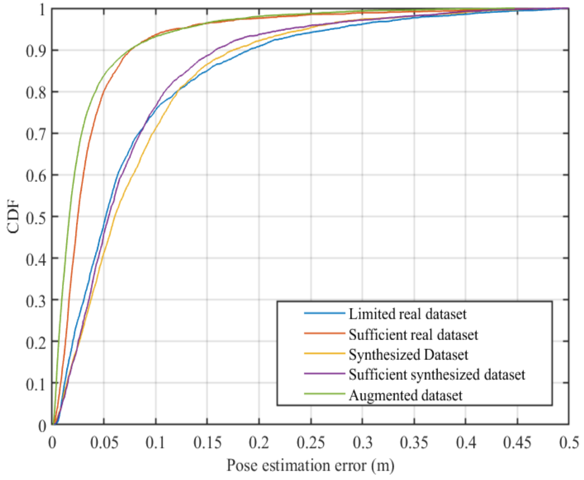
(iii) RF Data Augmentation

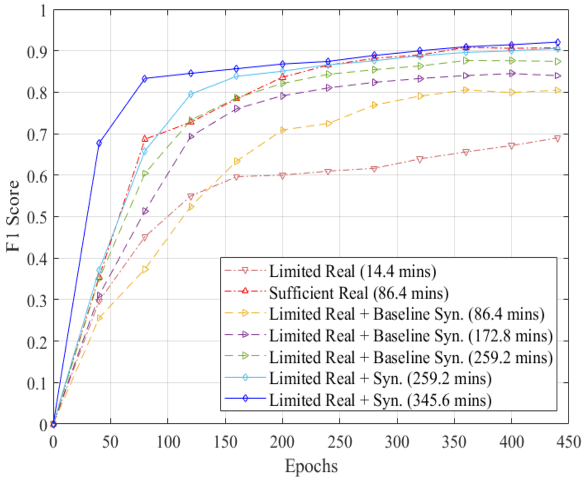
- Deep learning is powerful, but fundamentally limited by the availability, quality, and diversity of data

- Unlike CV and NLP, RF data collection is time-consuming and costly, with strong locality, and
  - ➔ Collected data is often noisy and sparse,
  - ➔ … spans spectral, temporal, and spatial dimensions
  - ➔ Diversity of environment is often limited
  - ➔ Variability in the RF signal representations across different types of devices
  - ➔ Difficult with generalization beyond training data

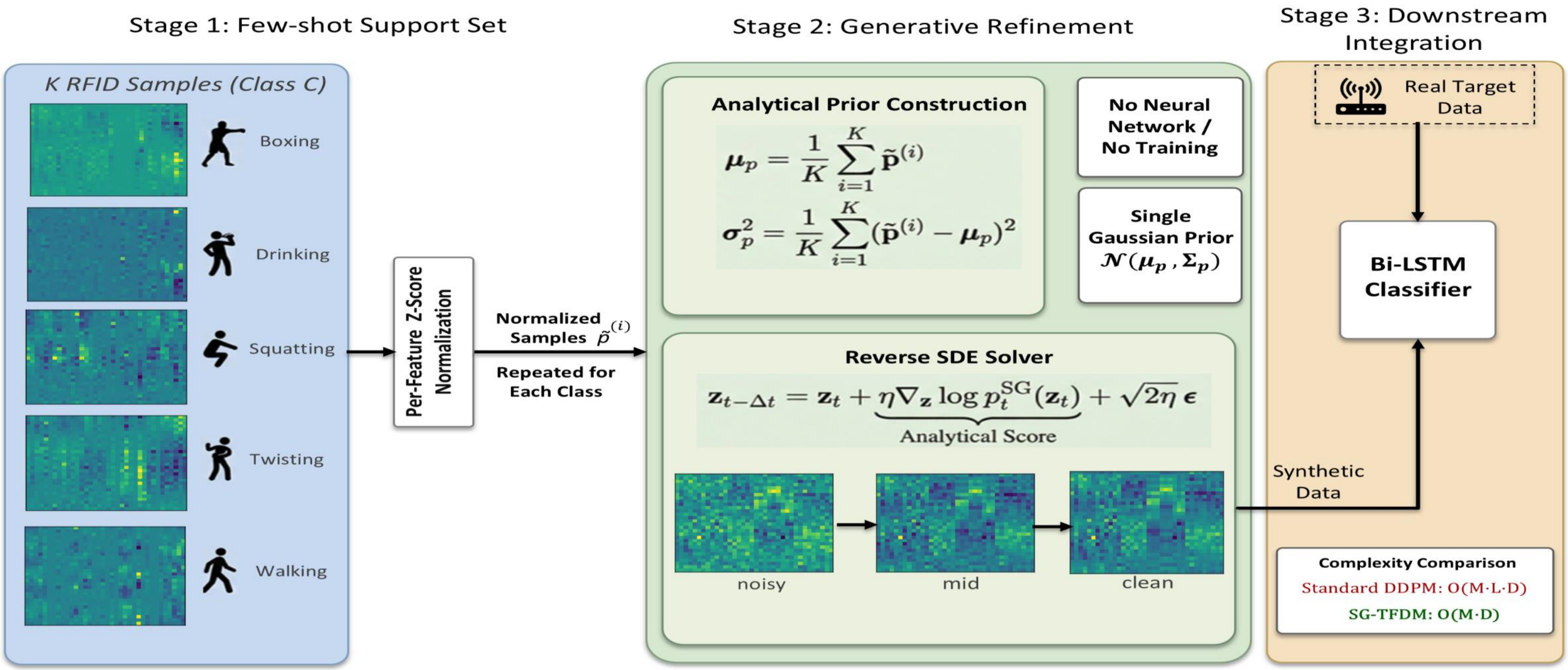
- A promising approach is to leverage AIGC for synthesizing RF data, with
  - ➔ Conditional GAN models
  - ➔ Diffusion and stable diffusion models
  - ➔ Domain knowledge remains crucial for model design and for assessing the quality of the synthesized datasets







Training-Free Diffusion for Fast Domain Adaptation



Three stages: (1) *K-shot support set + per-feature Z-score;* (2) *analytical Single-Gaussian prior + reverse-SDE;*
(3) *Bi-LSTM downstream classifier. Complexity: SG-TFDM = O(M*D) vs DDPM = O(M*L*D).*

Three stages, zero learned parameters in the inner loop | CPU at 3.2 ms / sample

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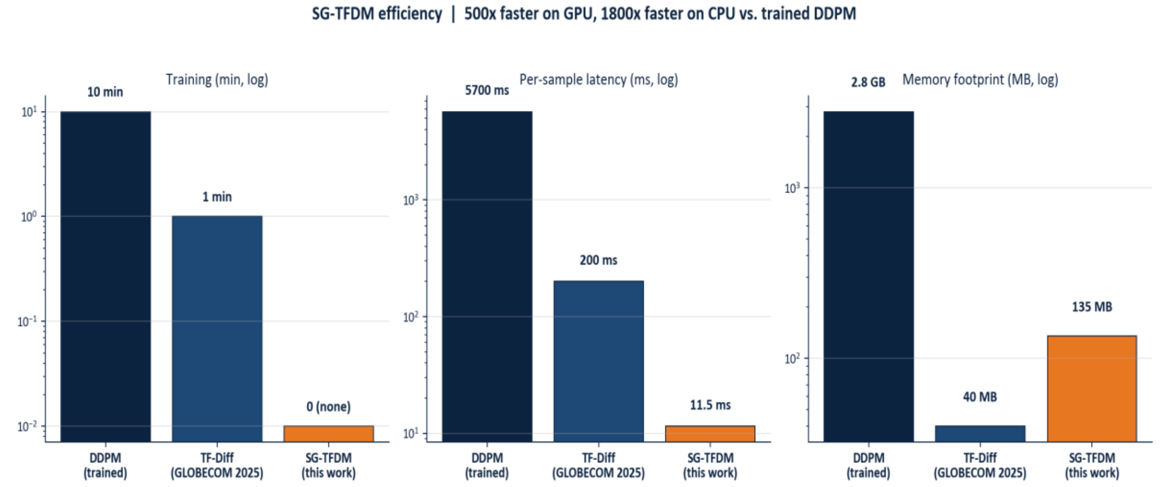

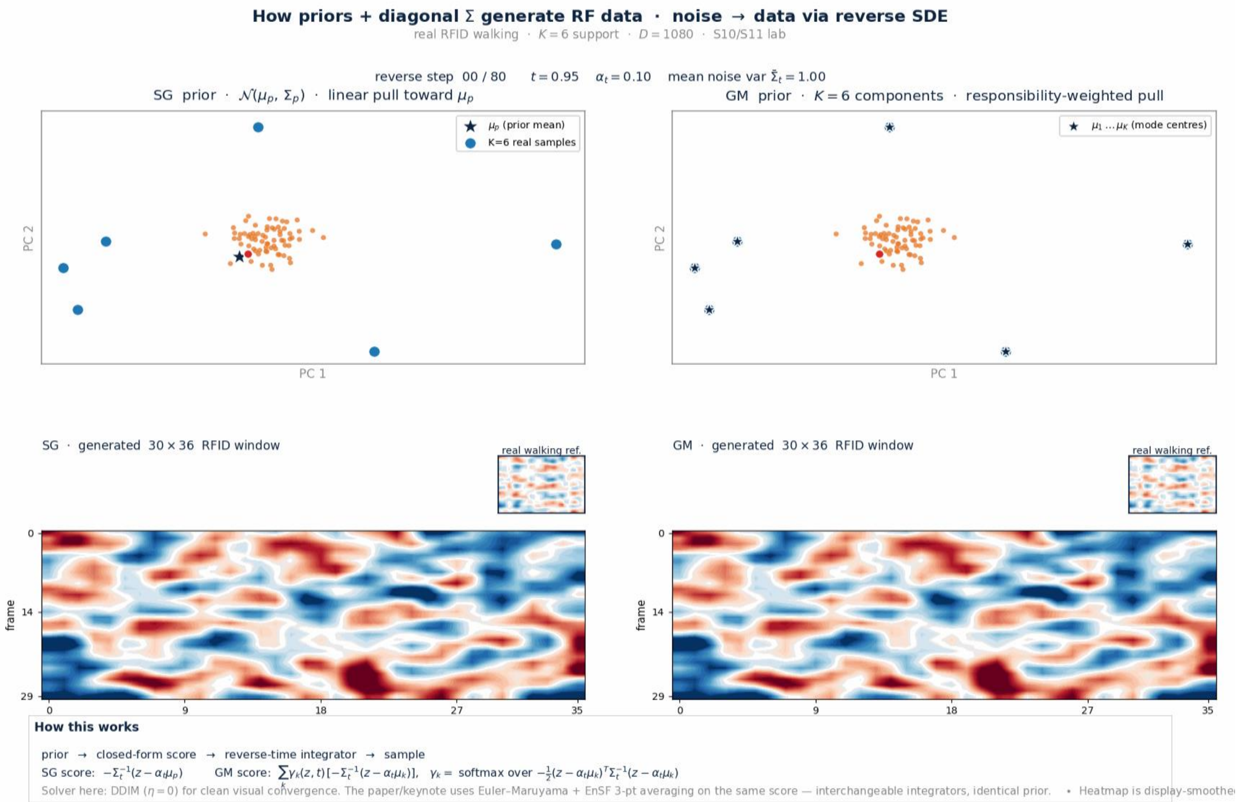

FID Scores (Inception, lower is better)

DDPM (trained): 30.2
SG-TFDM (this work): 6.9 - 7.9

➔ 4x sharper distribution match

SSIM Score (per-pair, higher is better)

DDPM (trained): 0.41
SG-TFDM (this work): 0.90 - 0.92

➔ 2x structural fidelity

AllData (S1-S9) → S10/S11 cross-session, accuracy (%) and macro-F1

Method	K=5 Acc	K=5 F1	K=10 Acc	K=10 F1	K=20 Acc	K=20 F1
Source-only	62.2	.583	60.7	.566	62.0	.579
From scratch	54.2	.472	63.8	.540	80.4	.764
Fine-tune (real-only)	75.6	.751	80.0	.798	83.8	.834
Fine-tune + SG-TFDM (ours)	**86.1**	**.857**	**92.4**	**.924**	**92.9**	**.928**