

重塑6G: 从信道到内容

Reshaping 6G: From Channel to Content

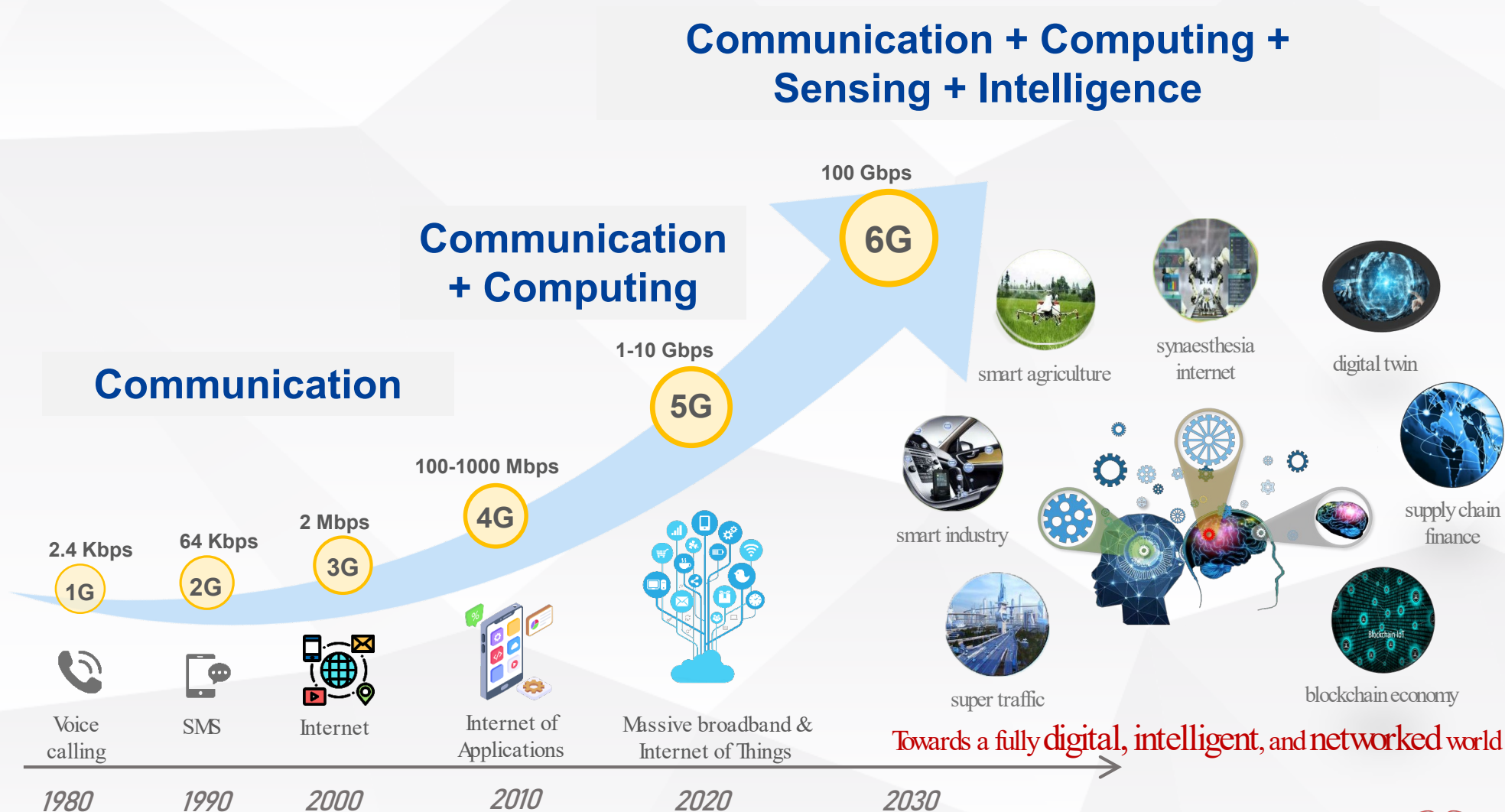
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2026年10月9日

饮水思源 · 爱国荣校



6G Vision: From Connectivity to Integration



Outline

Part 1

Rebuild Channel Foundation

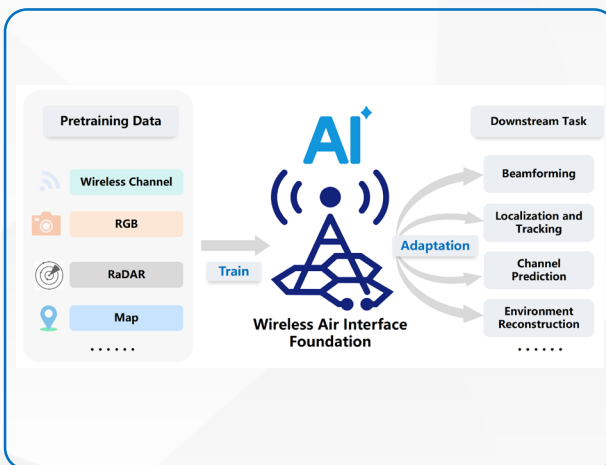
From traditional channel models to AI-driven prediction and digital twin



Part 2

Redesign Air Interface

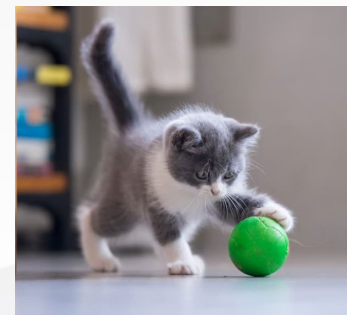
From task-specific AI to foundation models



Part 3

Redefine Communication Goal

From bit reconstruction to semantic delivery and content generation



"A cat is playing a ball"

A Full-Stack Reinvention From Channel Modeling to Content Delivery

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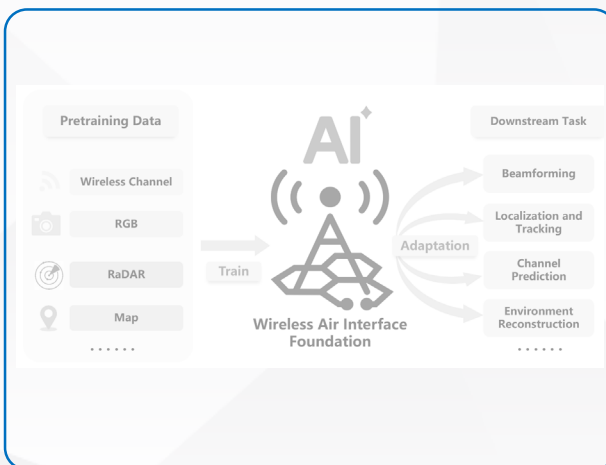
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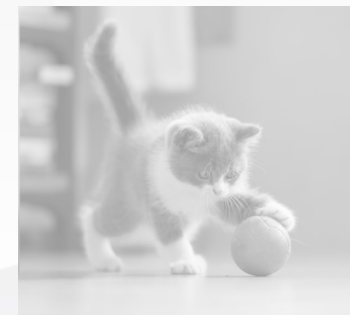
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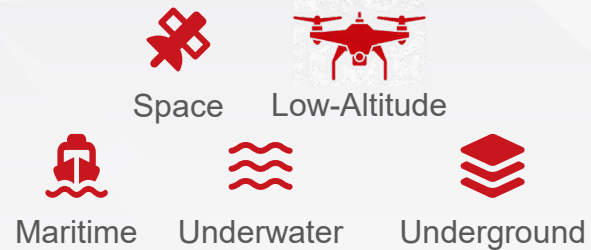
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A Full-Stack Reinvention From Channel Modeling to Content Delivery

Channel Modeling for 6G



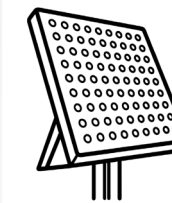
New Coverage



New Spectrum



New Antennas

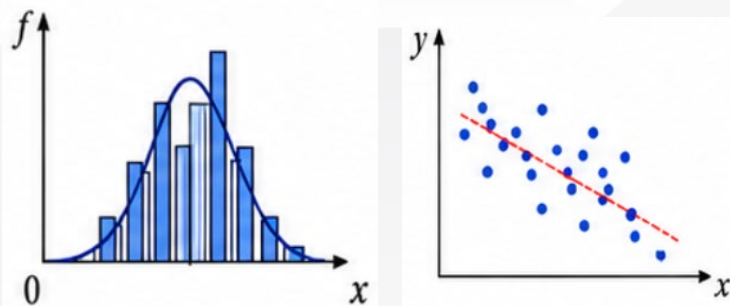


XL-MIMO · Holographic
MIMO · Fluid antenna ·
movable antenna · rotatable
antenna · RIS

- Channel models are the **foundation** for the design, analysis, optimization, and deployment of every wireless generation.
- 6G brings new opportunities and challenges for **accurate, efficient, and generalizable** channel modeling and prediction.

Channel Modeling: Traditional Approaches

Statistical Methods



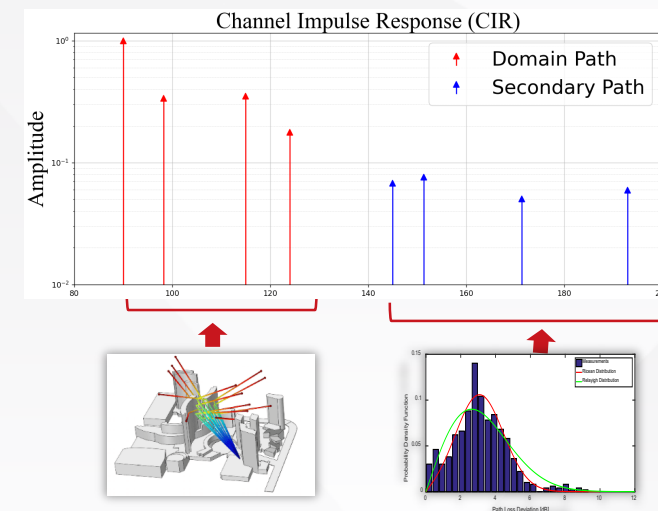
- ✓ Establish statistical distribution from empirical measurement, e.g. **3GPP, WINNER models**
- ✓ efficient, and serves as standardized benchmark for performance evaluation
- Fail to capture fine-grained channel variations in real environment

Deterministic Methods



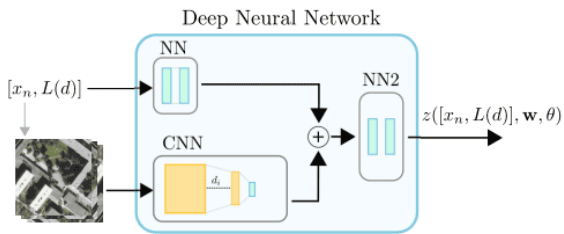
- ✓ Explicitly model environment-specific wave propagation via EM theory, e.g. **full-wave simulation, ray tracing**.
- ✓ Highly accurate and strong physical interpretability
- Computationally prohibitive for large-scale and real-time application
- Rely on precise 3D topology and material parameters.

Hybrid Methods



- ✓ Combine the strengths of statistical and deterministic methods
- Introduce tradeoff between accuracy and complexity

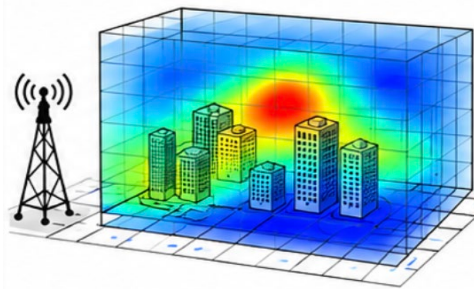
End-to-end Mapping



[Levie'2021] [Gupta'2022] [Wei'2024]

- Map environmental features (e.g. 3D maps, LiDAR) to channel parameters
- Suitable for large-scale channel prediction
- Lack physical explainability

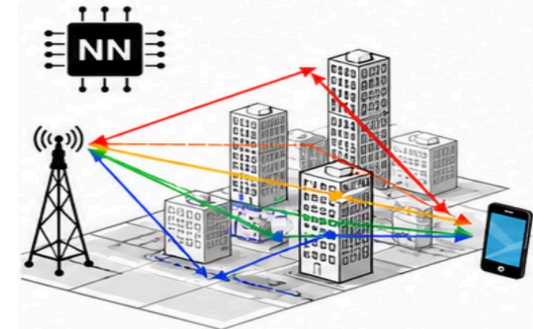
Wireless radiation field



[Zhao'2023] [Lu'2024] [Wen 2025]

- Reconstruct the 3D propagation environment via neural rendering
- Suitable for continuous-space channel modeling
- Require massive training data

Neural Ray Tracing

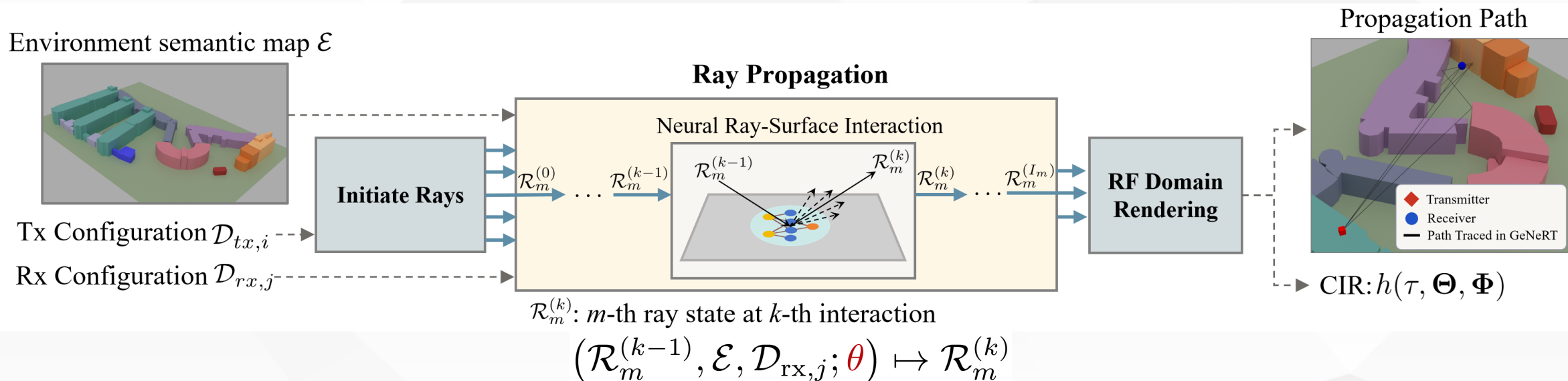


[Orekondy'2023] [Jia'2024] [Jiang'2025]

- Combine neural networks and RT framework to implicitly model radio-environment interaction
- **Great potential to achieve accuracy, efficiency, and generalization**

GeNeRT: Generalizable Neural Ray Tracing

- **Core idea:** inject neural networks in classic RT pipeline to learn **scenario-general ray-surface interactions**, e.g. reflection, diffractions, and scattering



Environment semantic map

— material-aware scene representation

Learnable ray propagation

— neural interaction at each bounce

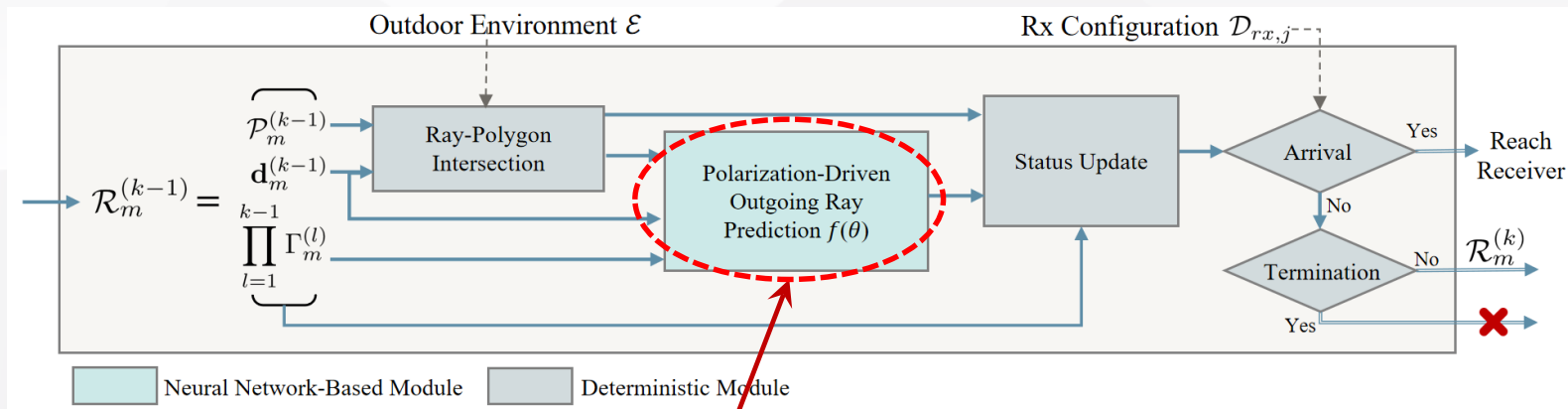
RF-domain rendering

— full CIR over delay, angle, and path



GeNeRT: Core Architectures and Training Strategy

Neural Ray-Surface Interaction



Polarization-Driven Outgoing Ray Prediction Network $f(\theta)$

- **Fresnel-inspired dual-branch:** Explicitly model parallel and perpendicular polarization components to prevent information loss
- **Relative geometry features:** reduce spatial dependency for cross-scenario transfer
- **Scatterer semantics:** material-aware interaction modeling

Stage 1 · Module-wise

pre-training on EM simulation

Polarization-driven modules learn general ray-surface interaction from simulation

Stage 2 · System-wise

end-to-end training on CIR

Receiver-side only CIRs are used to learn site-specific propagation characteristics

Stage 3 · Measurement

fine-tuning with real-world MPC

Sparse measured MPCs adapt polarization modules to real-world environments

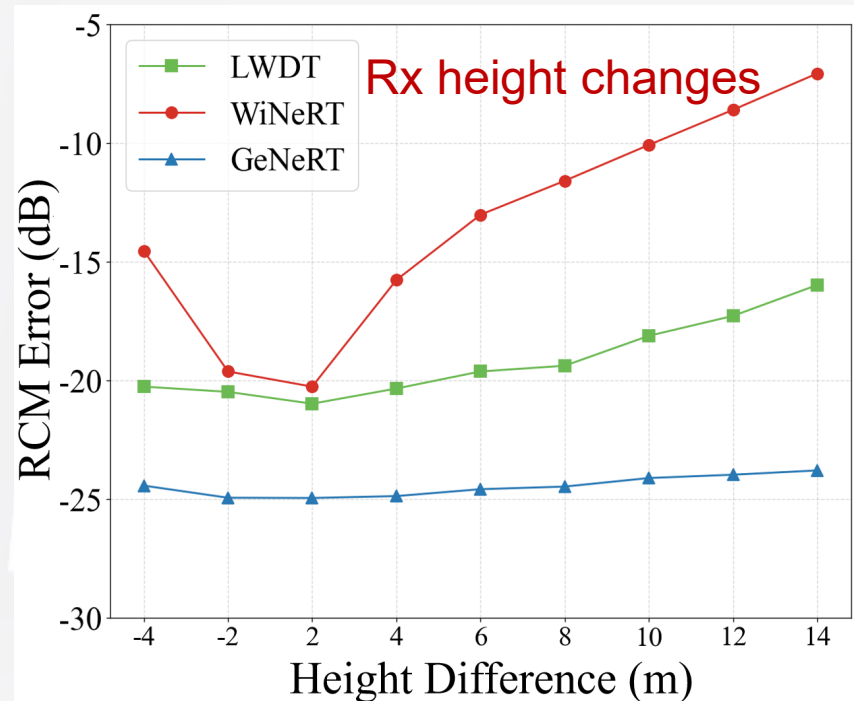


Generalization Test



Intra-scenario spatial transferability

	S_4 Rx horizontal shift			S_5		
	Overall Err.	RCM Err.	AvgDelay Err.	Overall Err.	RCM Err.	AvgDelay Err.
WiNeRT	-22.58 dB	-8.84 dB	28.45 ns	-20.89 dB	-7.14 dB	30.99 ns
LWDT	-25.58 dB	-13.01 dB	19.26 ns	-25.07 dB	-11.47 dB	22.35 ns
GeNeRT	-37.69 dB	-25.79 dB	3.96 ns	-36.29 dB	-24.69 dB	4.34 ns



Same scenarios as training set
 S_4 , S_5 : Rx horizontal shift
 S_6 – S_{14} : Rx height change

GeNeRT generalizes far better across Rx positions & heights

WiNeRT [Orekondy'2023] Qualcomm AI Research
Learnable Wireless Digital Twin (LWDT) [Jiang'2025] Arizona State Univ.

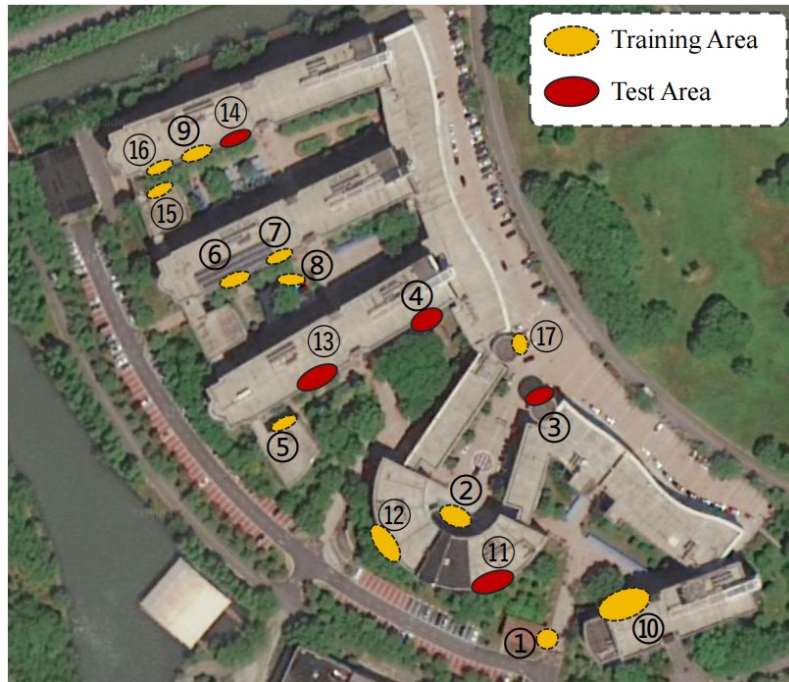
Inter-scenario generalization

	S_{15}		
	Overall Err.	RCM Err.	AvgDelay Err.
WiNeRT	-8.92 dB	-3.36 dB	35.18 ns
LWDT	-10.85 dB	-4.97 dB	32.38 ns
GeNeRT	-35.36 dB	-23.77 dB	4.91 ns

Entirely new scene S_{15} : different layouts & Tx/Rx distributions

GeNeRT keeps strong zero-shot performance, while baselines degrades sharply

Validation on Real-World Measurements



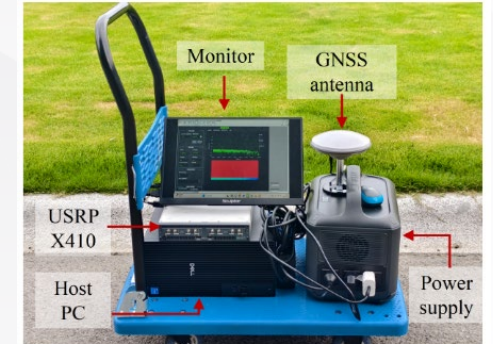
Measurement Campaign

- SJTU SEIEE campus
- 102 reflected paths were extracted
- Fine-tuning: 75 reflected paths (yellow areas)
- Test: 27 reflected paths (red areas)

USRP X410
3.5GHz



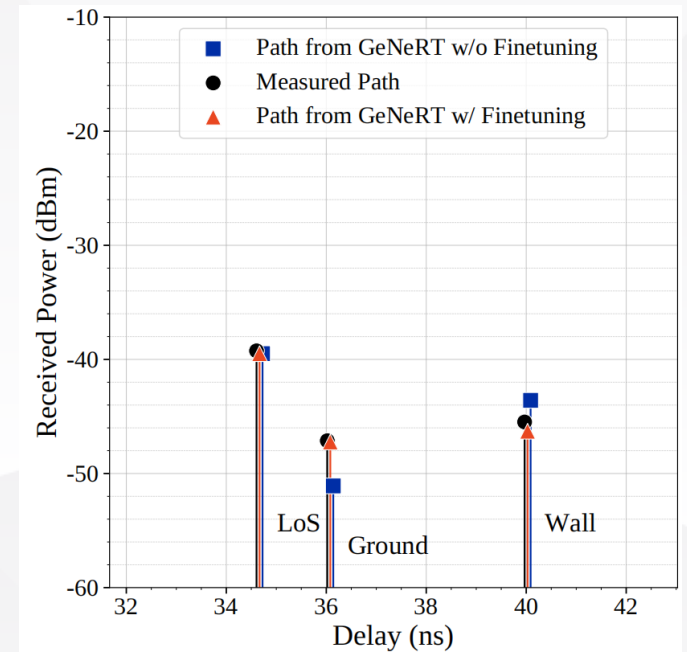
(a) Representative Tx-Rx deployment



(b) Hardware architecture of the Rx

Metric	w/o M.F.*	w/ M.F.*	Gain
Overall Error	-14.48 dB	-22.90 dB	8.42 dB
RCM Error	-0.90 dB	-9.32 dB	8.42 dB
AvgDelay Error	6.28 ns	3.58 ns	2.70 ns

* M.F. denotes measurement finetuning.



GeNeRT predicted paths match measured paths closely after fine-tuning with sparse measurements



LAMBDA: Low Altitude Multimodal Base Dataset

- A comprehensive dataset to empower research in low-altitude UAV Comm & Sensing
 - **High fidelity:** cm-level scene geometry with fine-grained material annotations
 - **Diverse modalities:** wireless CSI, RGB, depth, LiDAR, 4D radar, and IMU
 - **Rich scenarios:** urban/suburban/mountain/campus, rain/snow/fog, day/night, multi-UAV trajectories/multi-BS
 - **Flexible configurations:** support user-defined array size, bandwidths, & FMCW parameters
- **2.14 TB** of data with **540,000+** spatiotemporally aligned multimodal samples



Urban Area



Suburban & Mountainous Areas

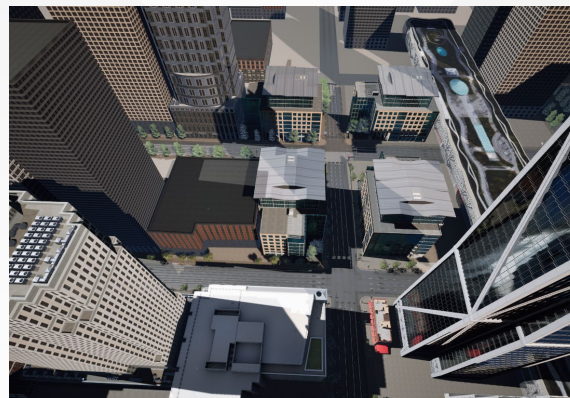
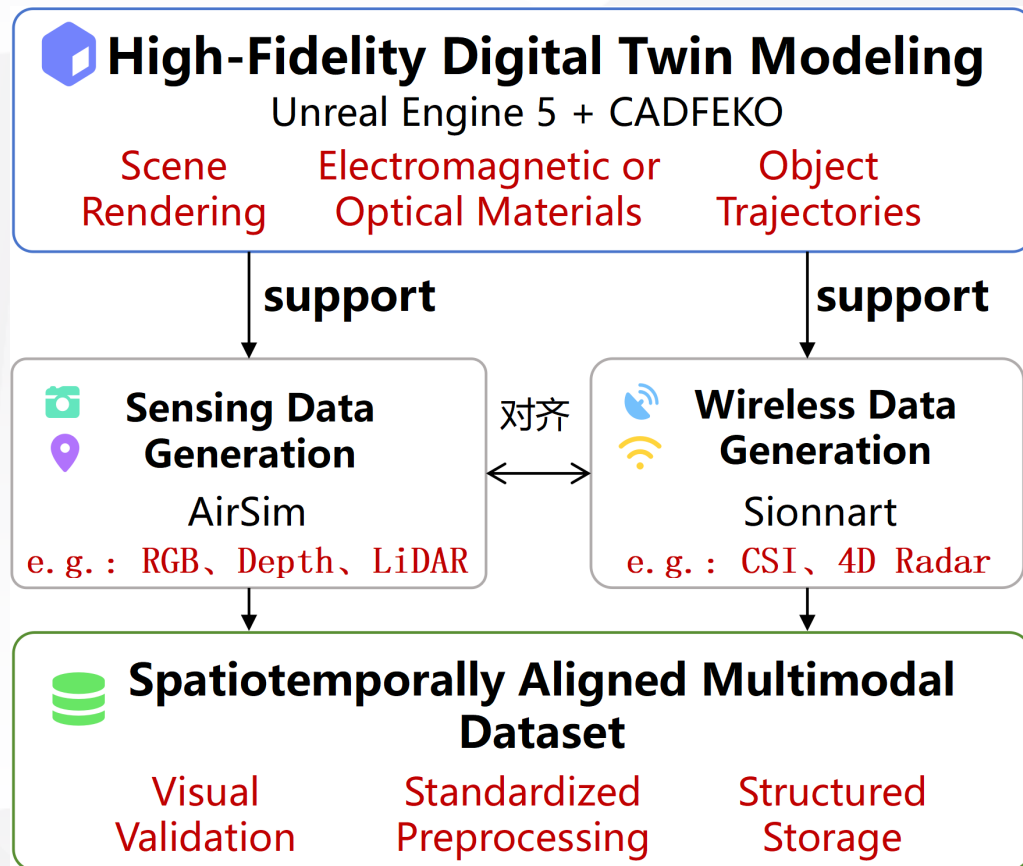


SJTU Campus

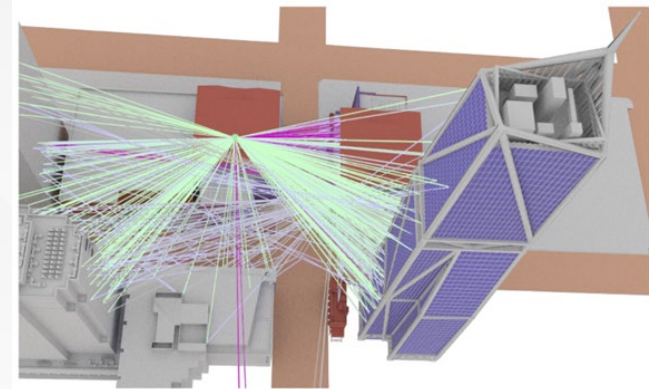


High-Fidelity Digital Twin Platform

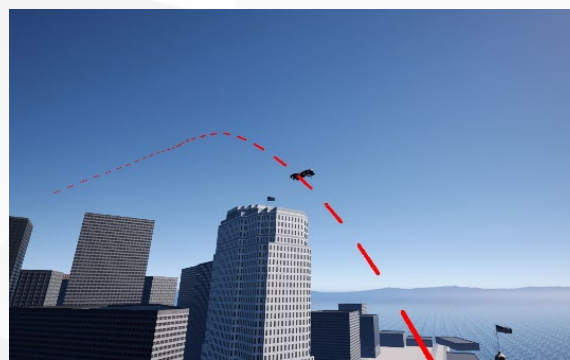
- Integrates 3D scene rendering, ray tracing, and object trajectory control to generate **spatiotemporally aligned** sensing and wireless channel data



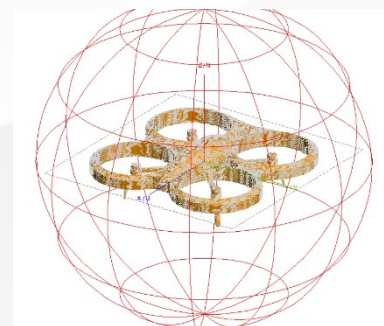
Unreal Engine 5 Scene Rendering



Sionna RT for CSI



UAV Trajectory Control

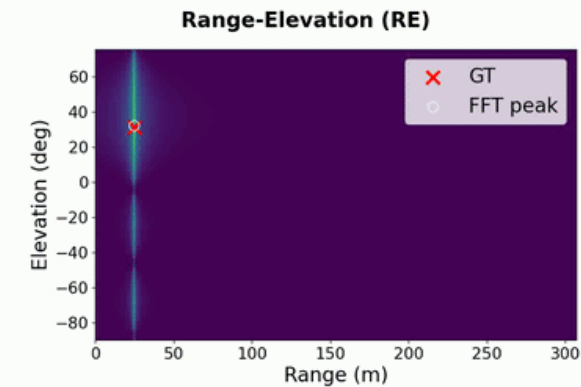
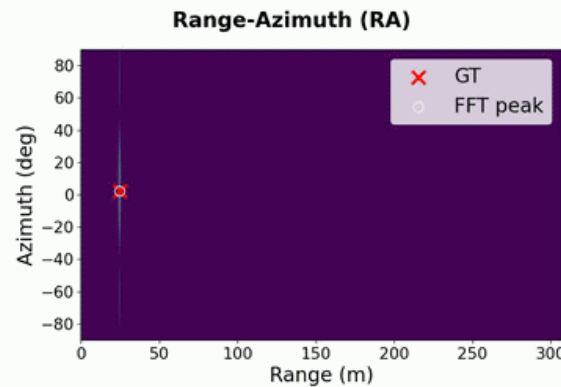
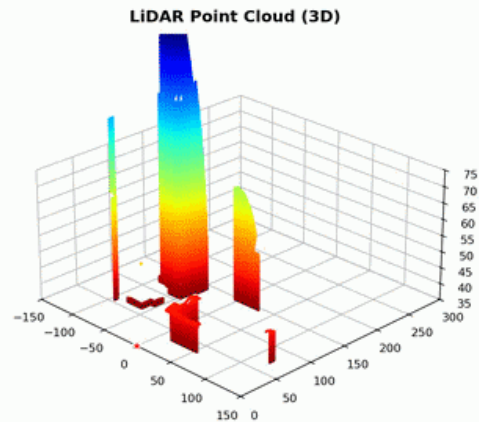
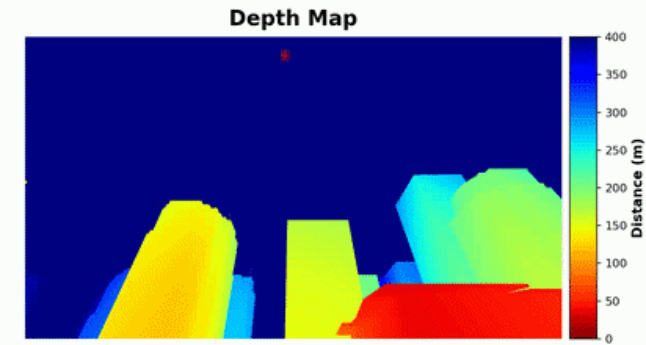
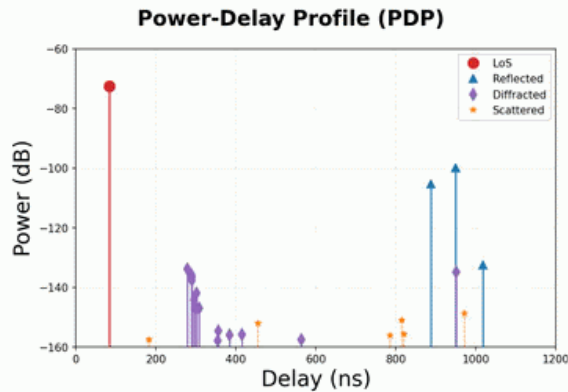


CADFEKO-Based UAV RCS Simulation



Demo: Urban Block1 Scenario

LAMBDA Multimodal Visualization | Frame: 000003



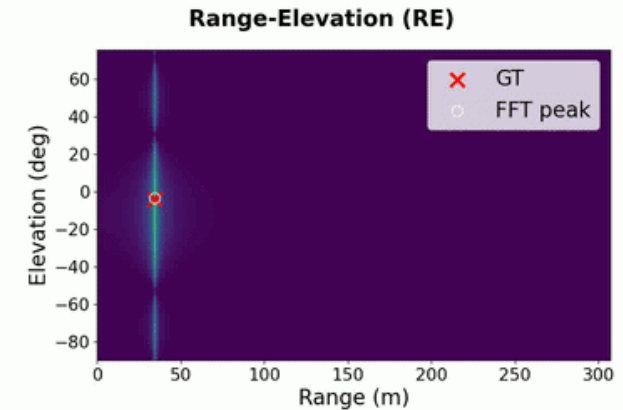
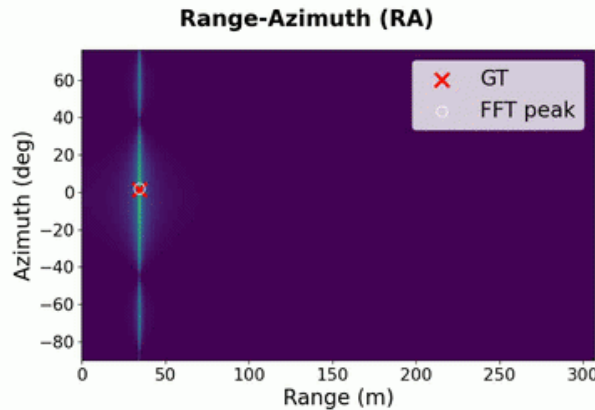
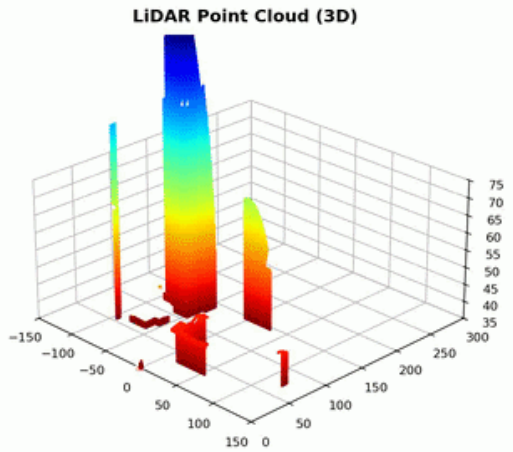
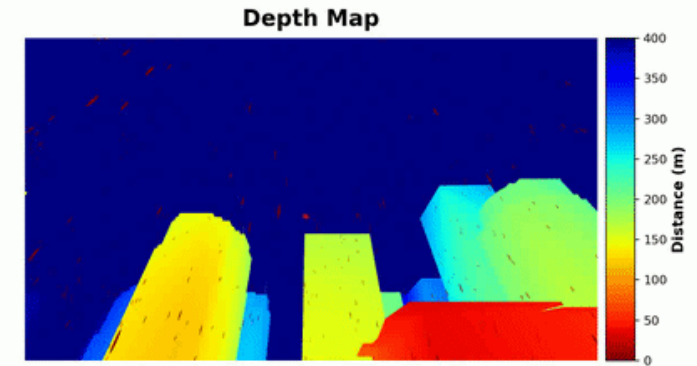
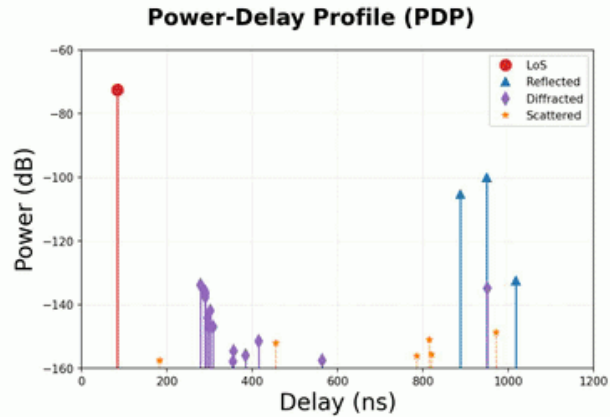
Spatiotemporal alignment across modalities





Demo: Urban Block1 Scenario Rainy Condition

LAMBDA Multimodal Visualization | Frame: 000003





Open-Source Release and Future Extension

- ◆ Our website: <https://lambda6g.net> (sample codes and documentation included)
- ◆ Total downloads so far: 14,000+
- ◆ Future extension
 - **Synthetic data:** enrich scenario, modality, UAV targets
 - **Measurement data:** to be collected at SJTU campus with a 32-TRX BS, a 512-line LiDAR, and 77GHz mmWave radar



LAMBDA paper



LAMBDA website



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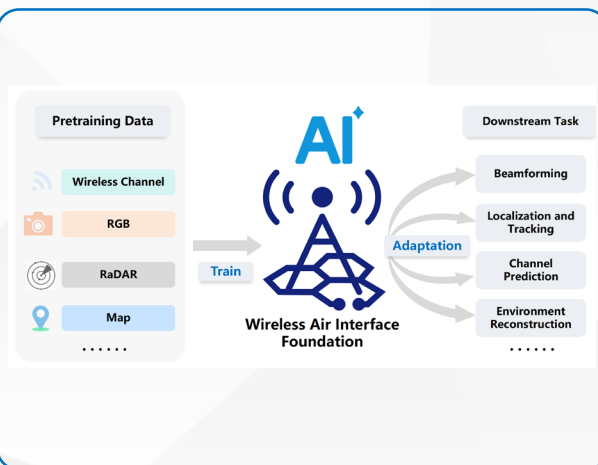
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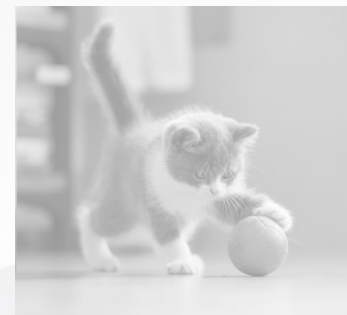
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From bit reconstruction to semantic delivery and content generation



"A cat is playing a ball"

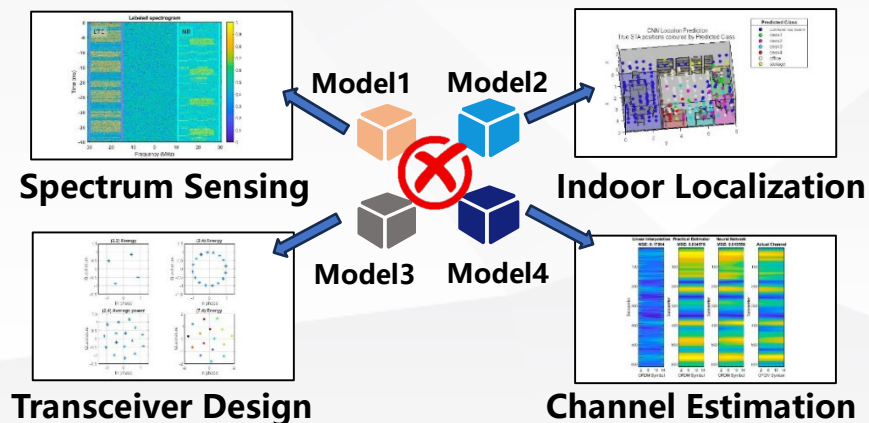
A Full-Stack Reinvention From Channel Modeling to Content Delivery

Foundation Models for Wireless Air-Interface

- **Wireless FMs: pre-trained on large-scale wireless data to learn universal representations of wireless propagation that are generalizable and transferable across scenarios and tasks**

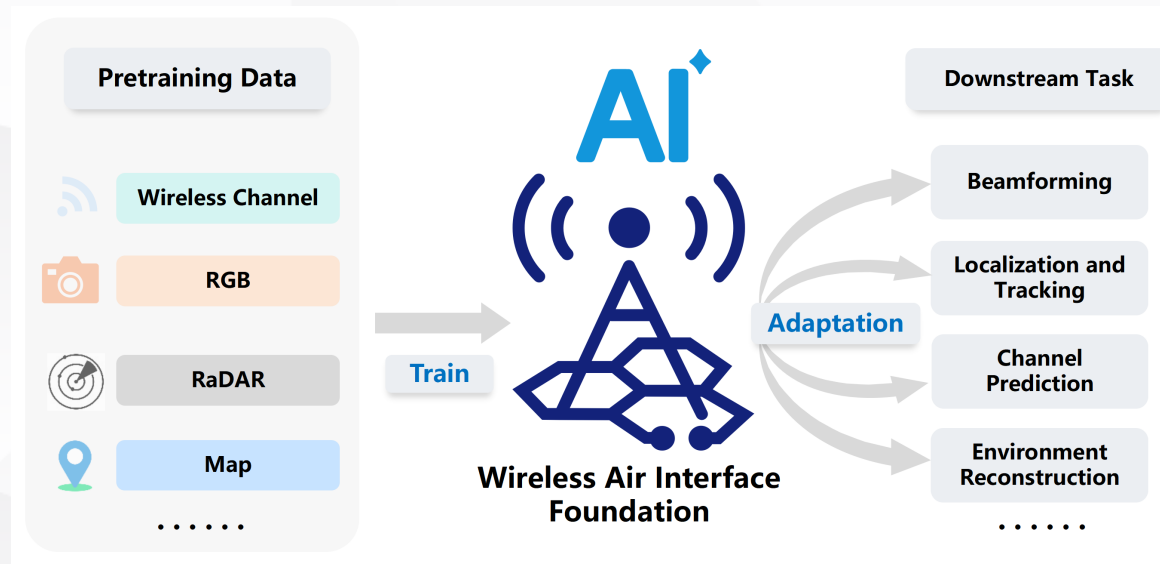
Fragmentation Issue with Task-Specific AI for Wireless

- Scenario- and task-specific, with limited generalization
- High maintenance cost



Vision of Wireless Foundation Models towards AI-Native 6G

- ✓ Cross-task transfer and cross-scenario generalization
- ✓ Lower maintenance cost





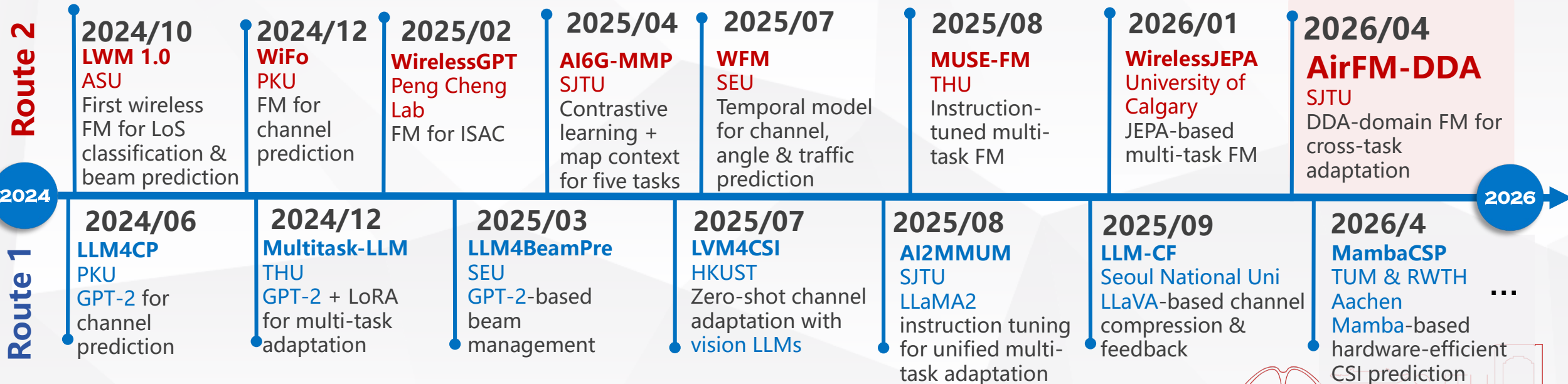
Roadmap of Wireless Foundation Models

Route 1: LLM-fined tuned models

- ✓ **Strength:** rapidly leverage the SOTA LLMs.
- **Fundamental limitation:**
 - Communication-irrelevant redundancy limits performance & deployment efficiency

Route 2: Wireless-native FMs

- ✓ **Strength:** capture the wireless data physical structure from ground-level design
- **Key challenge:**
 - Incorporate communication-domain knowledge to strengthen cross-scenario/task ability and reduce pre-training cost



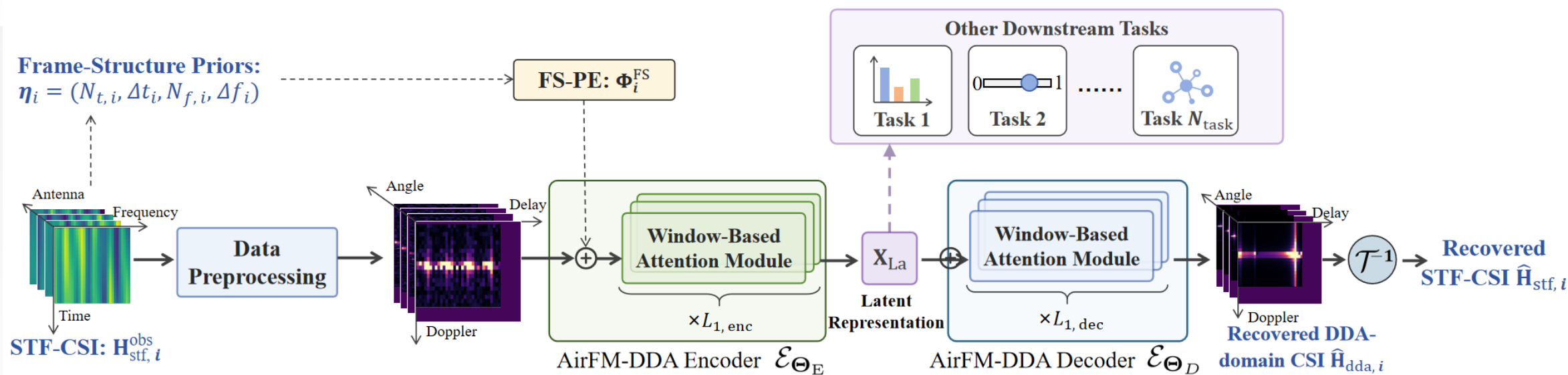


AirFM-DDA: Foundation Models in DDA Domain



Challenges

STF-domain CSI are **multipath-superimposed and entangled**, propagation physics hard to learn; global attention incurs **prohibitive computational complexity**.



Core Ideas

- ✓ Transform CSI into **Delay-Doppler-Angle (DDA)** domain to resolve multipaths
- ✓ **Window-based attention** reduces complexity from $O(n^2)$ to $O(n)$ while preserving locally-correlated multipath structures in DDA domain

AirFM-DDA (**A**ir-Interface **F**oundation **M**odel in the **D**elay-**D**oppler-**A**ngle Domain)

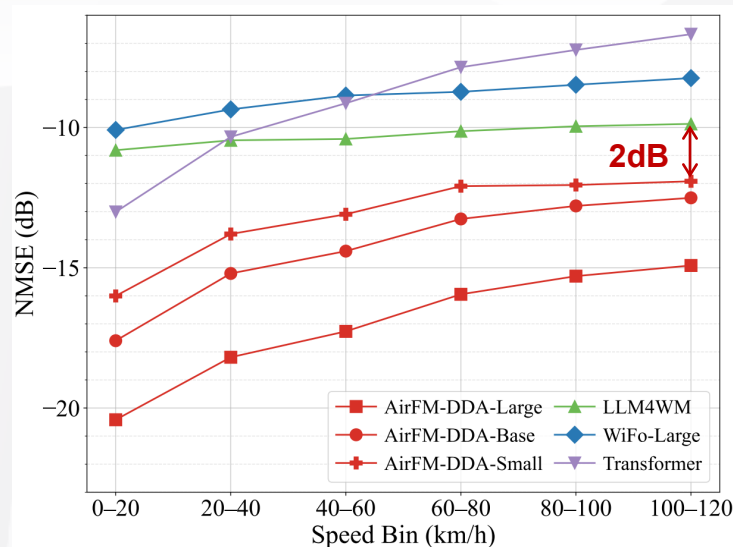




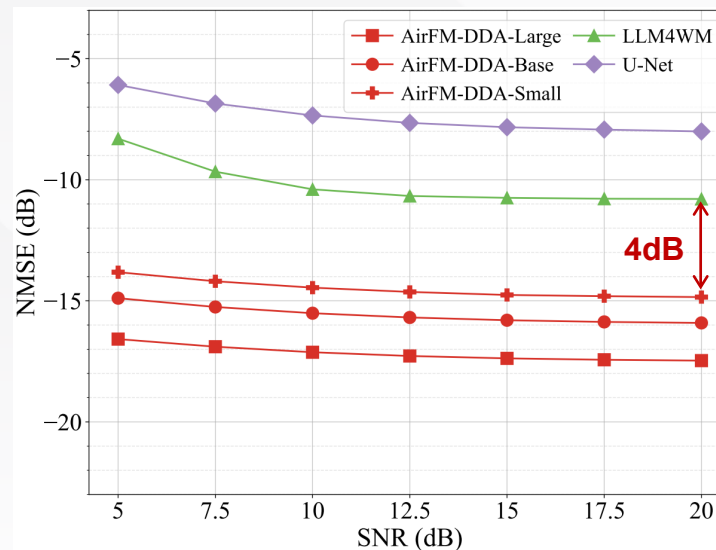
AirFM-DDA: Channel Reconstruction Performance



Channel Prediction across user speeds



Channel Estimation across SNR



Pretraining setup

- CSI data: 2.85M CSI samples on DeepMIMO across 22 cities, 18 for training, 4 for testing
- CSI config: 3.5GHz carrier; single-antenna UE; 8×4 BS array; two frame structures per city, FS-A (360 kHz SCS) and FS-B (1.44 MHz SCS)

Computing Efficiency: AirFM-DDA vs. WiFo

Metric	AirFM-DDA -Small	AirFM-DDA -Base	AirFM-DDA -Large	WiFo-Large (x = 0.5)	WiFo-Large (x = 0.75)
Params (M)	62.62	97.69	140.52	85.88	85.88
FLOPs (G)	656.96	1020.01	1462.59	1550	2100.19
Infer Latency (ms)	24.61	27.83	31.38	253.21	255.12
Peak GPU Mem (GiB)	1.44	1.68	1.95	13.66	14.61

- ✓ AirFM-DDA-base achieves **9x faster** inference and **88% lower** GPU memory than **WiFo-Large** at similar parameter scale





AirFM-DDA: Few-Shot Downstream Task Adaptation

LoS/NLoS-identification and Beam Prediction (3.5GHz → 28GHz BP)

Task	Metric	Training Ratio	AirFM -DDA-L	AirFM -DDA-B	AirFM -DDA-S	LLM4WM	LWM	Raw CSI	Task Spec.*	KNN
LoS	F1 Score (%)	10%	96.39	95.28	94.24	88.30	91.86	84.06	84.76	65.10
		25%	96.65	95.82	94.66	91.00	92.18	88.04	89.93	69.84
		50%	97.02	96.23	95.26	92.40	93.24	90.77	91.70	70.80
		100%	97.59	97.09	95.52	93.50	94.24	92.25	93.77	75.00
BP	Top-1 Acc. (%)	10%	65.95	61.43	57.41	49.62	44.75	32.44	35.18	21.08
		25%	70.24	67.00	62.25	55.97	52.16	38.41	45.83	28.81
		50%	76.86	72.68	67.50	60.60	58.04	43.44	51.57	34.66
		100%	82.82	79.51	77.16	66.38	64.59	47.31	56.84	38.41

* L, B, and S denote Large, Base, and Small, respectively. The task-specific baseline is ST-CNN for LoS identification and SPMM for BP.

Few-shot adaptation: freeze the pre-trained encoder; train only lightweight task heads with few labeled data

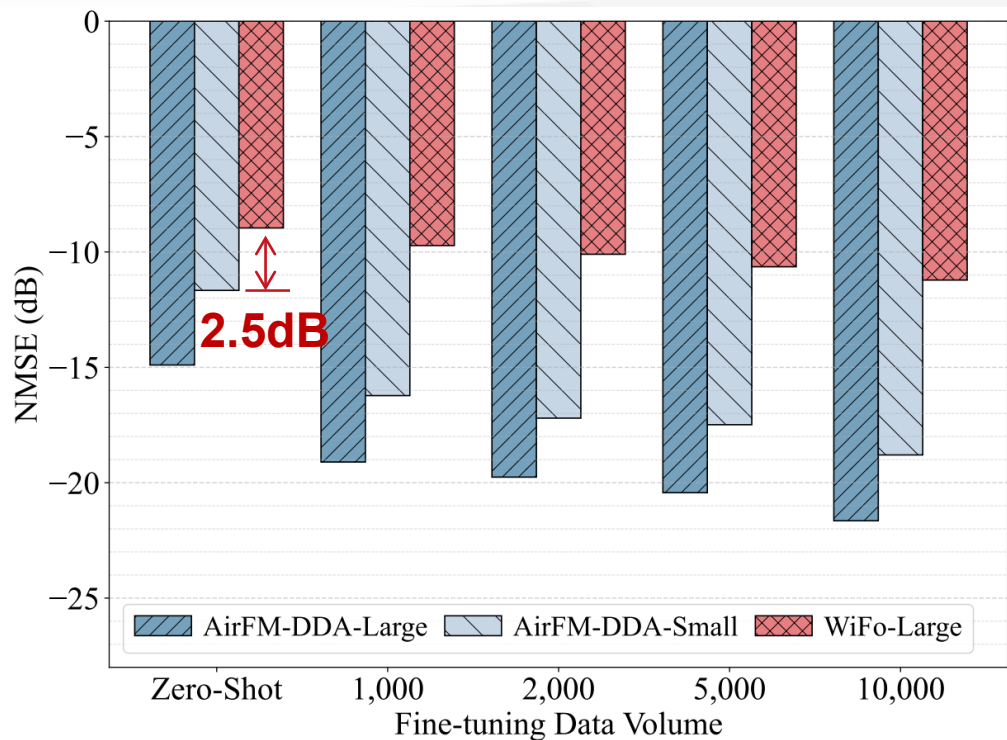
- ✓ **AirFM-DDA adapts well with few labels**, proving that that **DDA-domain** representation learned during pre-training captures a deep, transferable understanding of wireless channel physics.





AirFM-DDA: Cross-Dataset Generalization

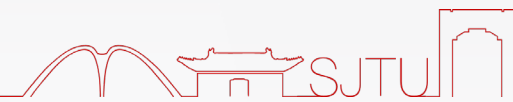
Time-domain Channel Prediction in NMSE on **WAIR-D** [Huangfu 2022] at 2.6GHz carrier with different fine-tuning size



Time-domain Channel Prediction in NMSE on **LAMBDA** [Zhou 2026] at 3.5GHz carrier with Zero-Shot

Model	TP ($x = 0.5$)	FP ($x = 0.5$)
WiFo-Large	-14.46	-8.38
AirFM-DDA-Small	-18.25	-17.92
AirFM-DDA-Base	-18.70	-18.54
AirFM-DDA-Large	-19.19	-19.48

- ✓ With zero-shot, **AirFM-DDA-Small** achieves **2.5dB** gain on **WAIR-D** and **3.8dB** gain on **LAMBDA** over **WiFo-Large**



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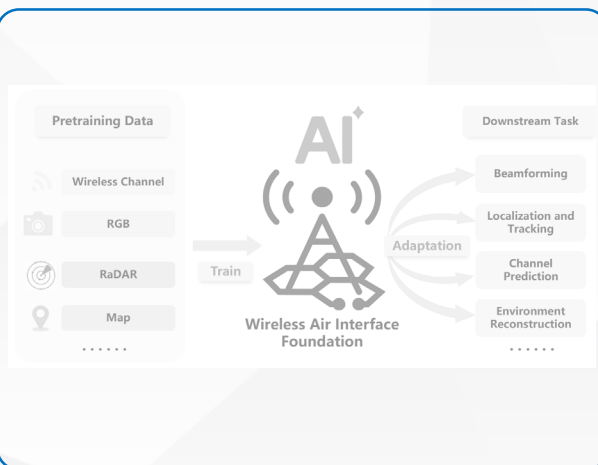
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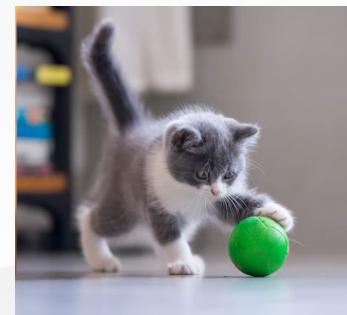
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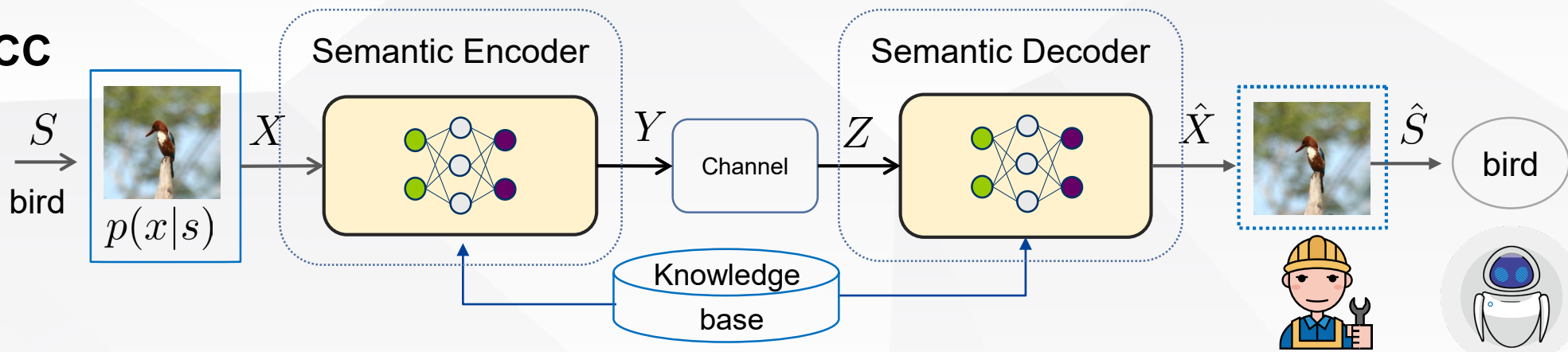
"A cat is playing a ball"

A Full-Stack Reinvention From Channel Modeling to Content Delivery

Semantic Communications

Paradigm shift: from bit transmission to the transmission of SEMANTICS

DeepJSCC



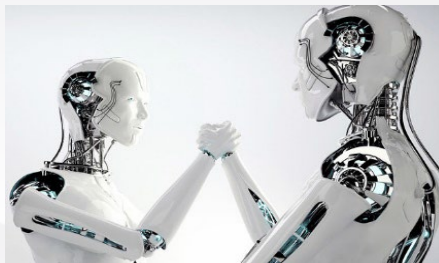
Application scenarios:
resource-constrained, task-oriented, and generative



Satellite Communications



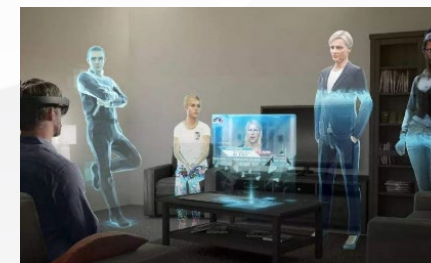
UAV Inspection



Communication between Agents



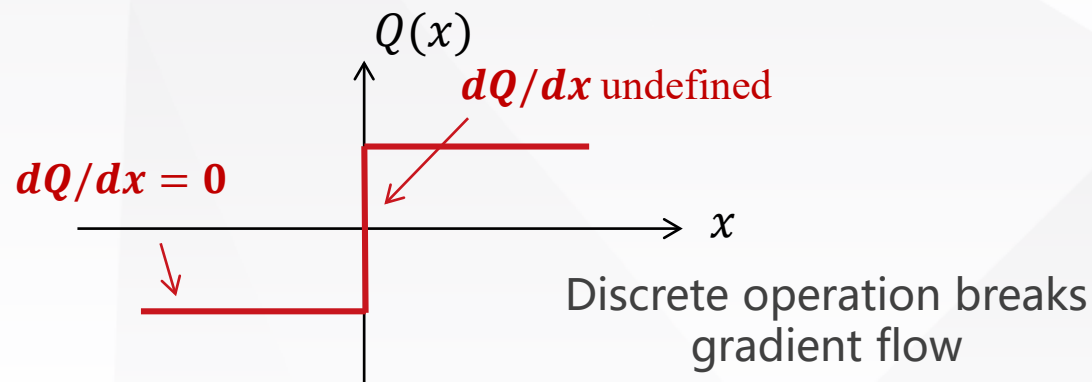
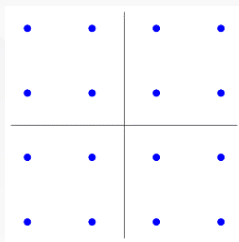
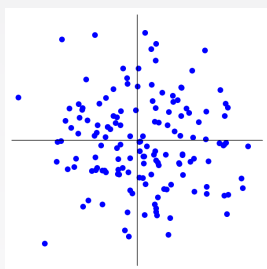
Immersive Virtual Reality



Holographic conferencing

■ Key challenge

- **Digital incompatibility:** direct transmission of **continuous semantic features** over the air conflicts with digital protocols & devices
- **Optimization barrier:** **non-differential** digital modulation prevents gradient-based learning



■ Traditional digitalization methods

- **Quantization+modulation:** fail to adapt to varying channel condition
- **Codebook-based methods (VQ-VAE):** high training cost for large codebook size

Question: How can do we make SemCom systems compatible with digital systems while preserving the benefits of end-to-end learning?

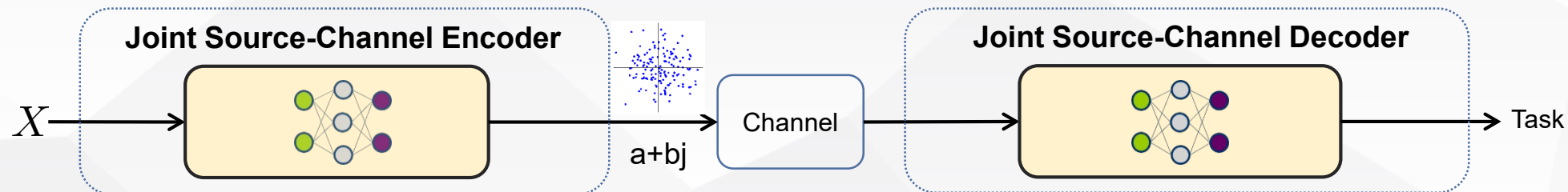


From Analog to Digital

DeepJSCC

□ analog modulation

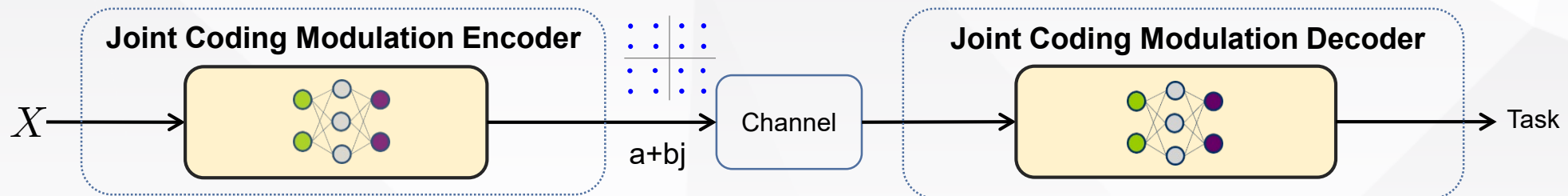
⚠ **signal-level** JSCC



Solution 1: JCM

□ digital modulation

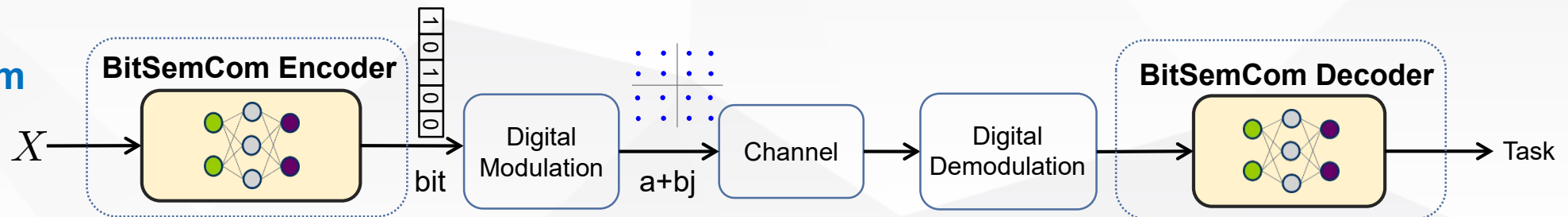
□ **symbol-level** JSCC



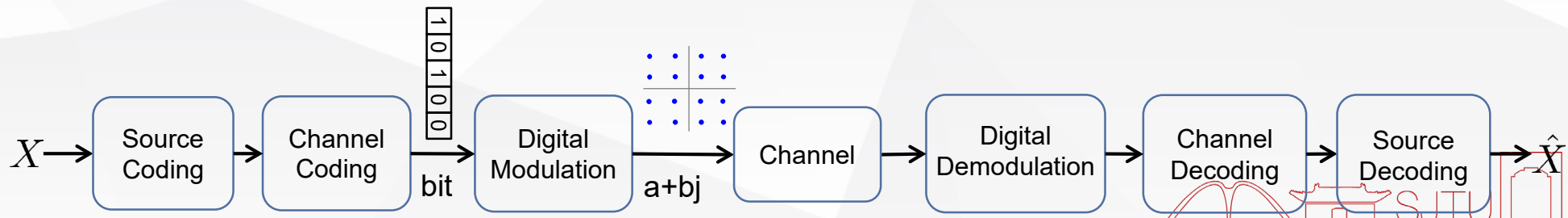
Solution 2: BitSemCom

□ digital modulation

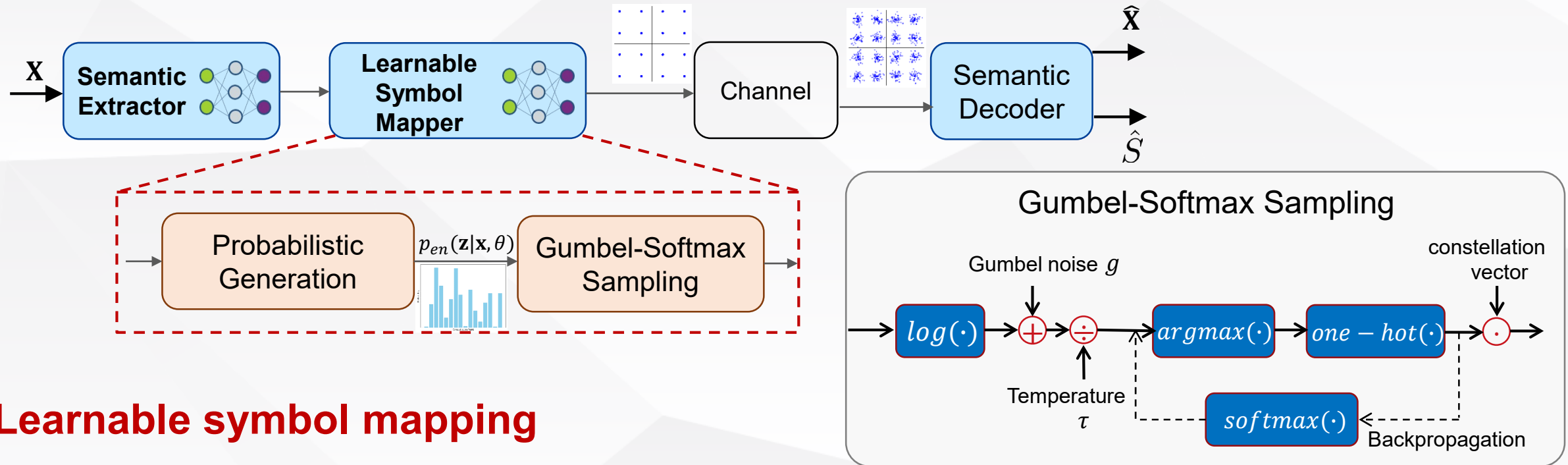
□ **bit-level** JSCC



Conventional digital system

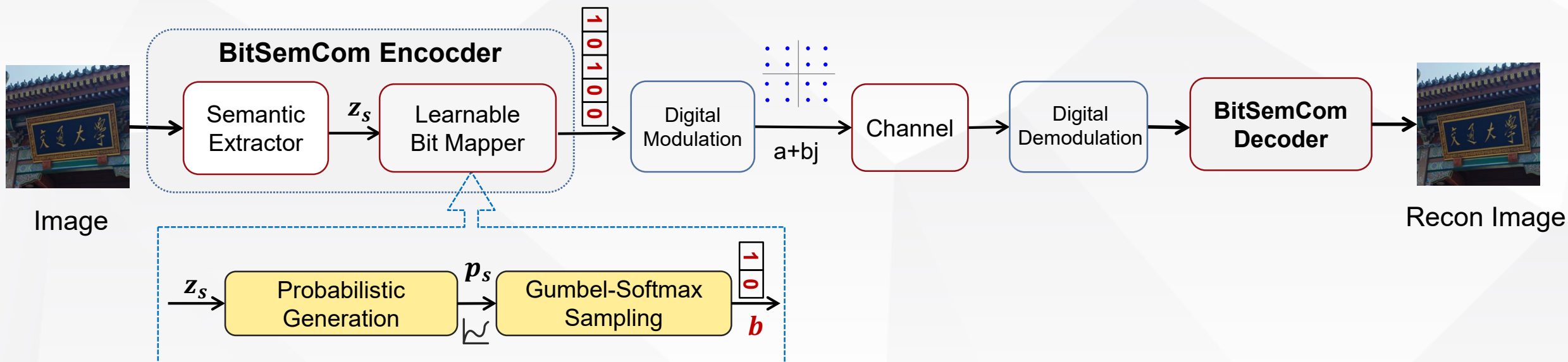


Symbol-level JSCC: Joint Coding-Modulation



Learnable symbol mapping

- **Probabilistic generation:** learn the transition probability of constellation symbols $p_{en}(\mathbf{z}|\mathbf{x}, \theta)$
- **Gumbel-Softmax sampling:** a reparameterization trick for differential constellation symbol generation based on $p_{en}(\mathbf{z}|\mathbf{x}, \theta)$
- Optimized via **end-to-end training** for channel adaptation



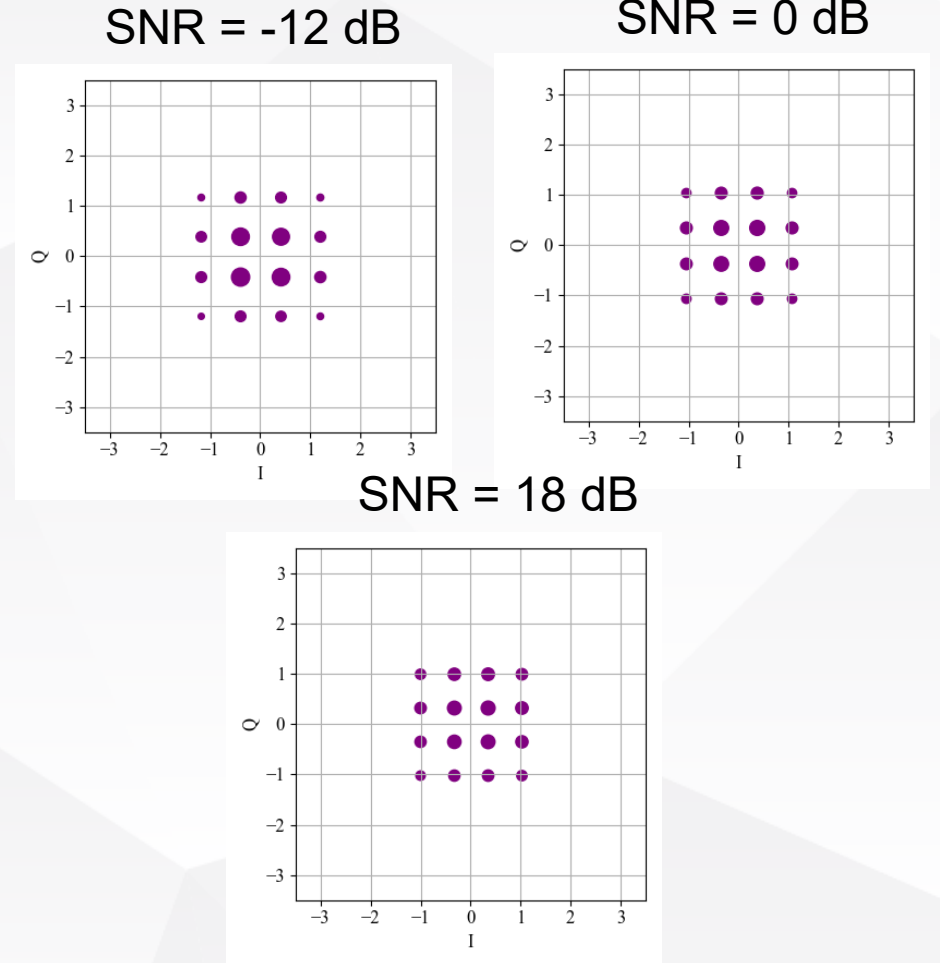
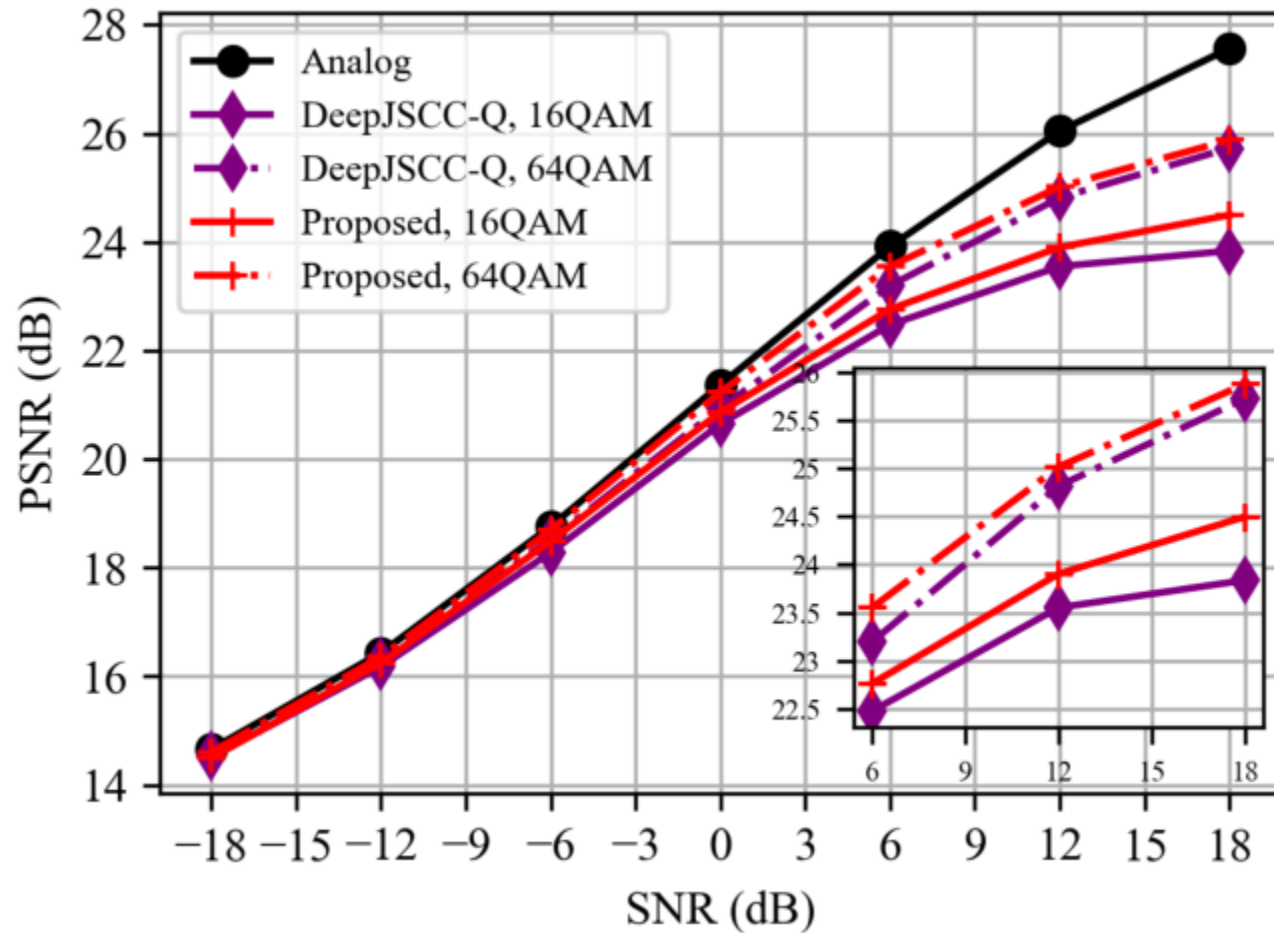
Learnable Bit Mapping

- Learn the **probability mapping** p_s from semantic features z_s to bit sequence b
- Use **Gumbel-Softmax sampling** to obtain b from p_s
- Optimized jointly with semantic extraction via **E2E-learning** by taking channel into account.

Key remarks

- ✓ Joint source-channel coding at **bit** level
- ✓ **Seamlessly integrated** into existing digital system by reusing all standard modulation, waveform, and beamforming technique
- ✓ Support both **soft-/hard-decision** demodulator

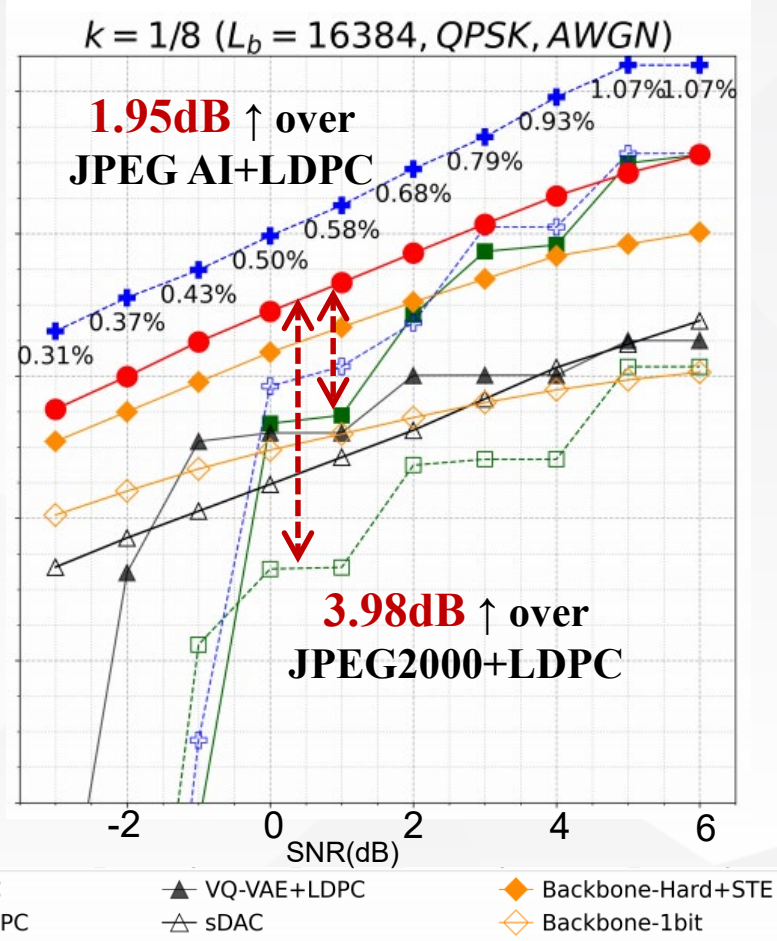
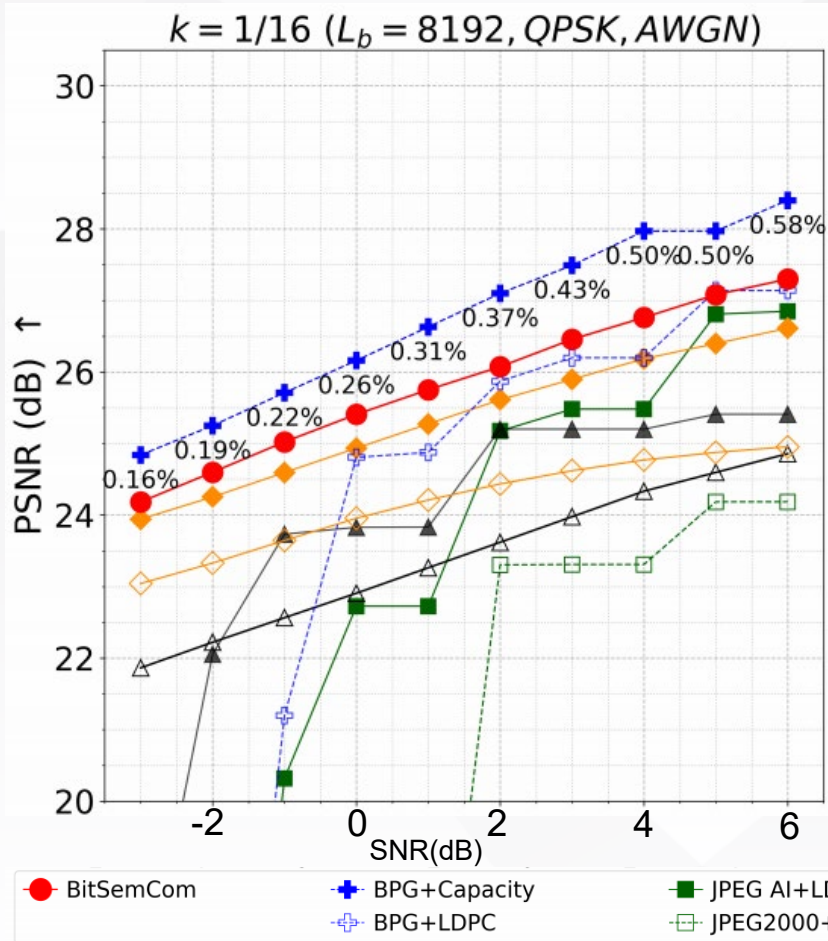
JCM Performance with QAM modulation



PSNR vs. SNR on Tiny ImageNet (16QAM / 64QAM)

Learned constellation distribution adapts to SNR

BitSemCom Performance



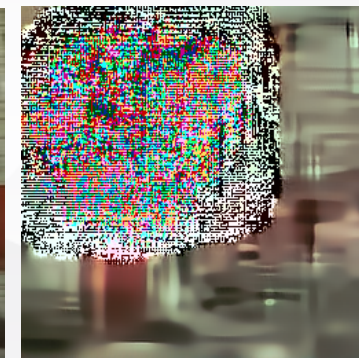
SNR = -1dB @AWGN, QPSK



Original



BitSemCom



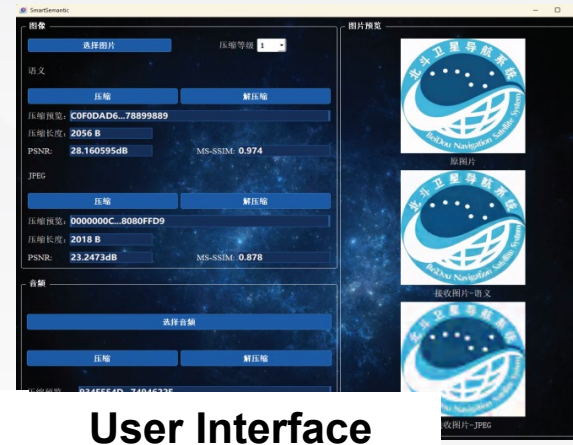
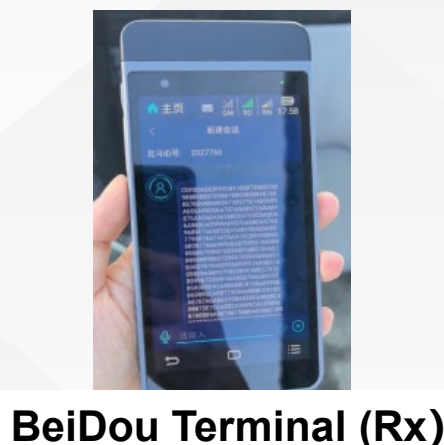
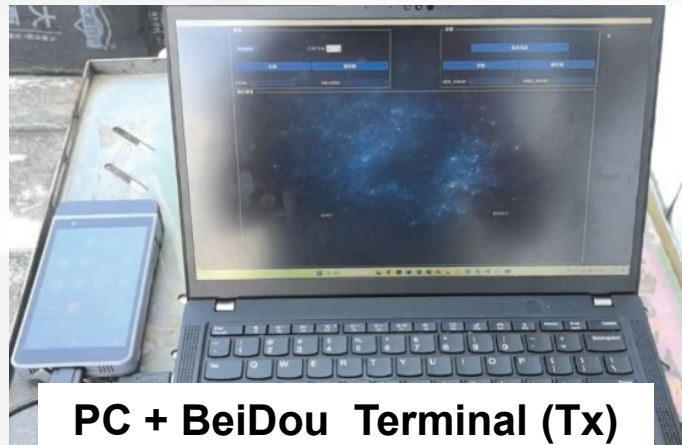
JPEG AI+LDPC

- Bit-level JSCC: robust to SNR variations
- Superior performance at lower SNR and channel cpp

Robust at low SNR



BitSemCom for Beidou Satellite Image Transmission



✓ 256 x 256 RGB image with single Beidou short message service ($\leq 12\text{Kbits}$) with PSNR $\geq 28\text{dB}$

Experiment 1: No bit error

8192bit, **1.23%** 16384bit, **2.47%** 32768bit, **4.93%**

Original **JPEG2000**



PSNR: 23.25 dB
SSIM: 0.8787



PSNR: 26.27dB
SSIM: 0.9403

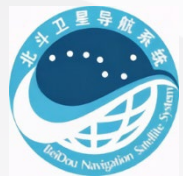


PSNR: 32.81dB
SSIM: 0.9872

BitSemCom



PSNR: 28.16dB
SSIM: 0.974



PSNR: 32.02dB
SSIM: 0.990

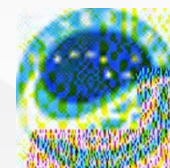


PSNR: 36.9dB
SSIM: 0.996

Experiment 2: Bit Error Rate 10^{-3}

8192bit, **1.23%** 16384bit, **2.47%** 32768bit, **4.93%**

JPEG2000



PSNR: 9.9001
SSIM: 0.4584



PSNR: 18.0269
SSIM: 0.7174



PSNR: 18.21dB
SSIM: 0.7781

BitSemCom



PSNR: 26.83dB
SSIM: 0.964



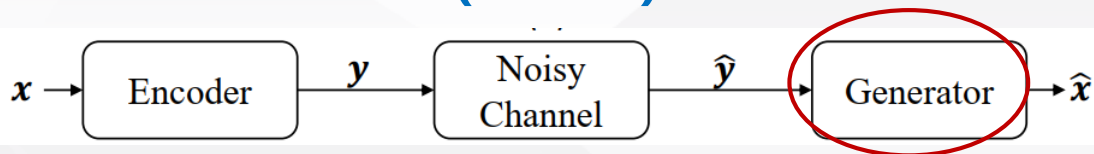
PSNR: 28.84dB
SSIM: 0.971



PSNR: 31.86dB
SSIM: 0.987

Generative AI for Semantic Communications

Joint Source-Channel-Generation Coding (JSCGC)



- The receiver design shifts from **deterministic reconstruction** to **controllable stochastic generation**

Problem Formulation

$$\max_{\theta, \phi} I(\mathbf{X}; \hat{\mathbf{Y}}),$$

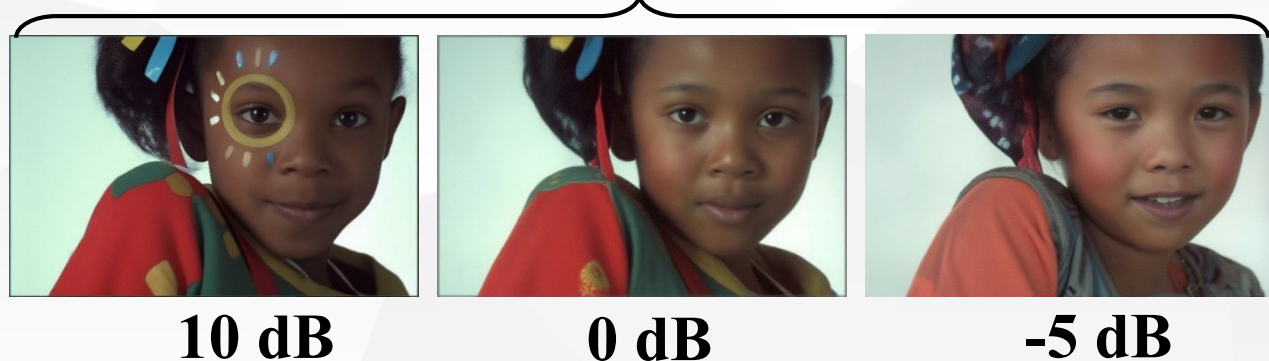
$$\text{s.t. } d_p(p(\mathbf{X}), p(G_\theta(\hat{\mathbf{Y}}))) \leq \zeta.$$

- MI preserves **source semantic** rather than enforce pixel-level matching
- Perceptual constraints for **realistic and high-quality** visualization

Deterministic Reconstruction



Controllable Stochastic Generation



[1] T. Wu, et al, "Joint source-channel-generation coding: From distortion-oriented reconstruction to semantic-consistent generation," *ISIT*, 2026.

[2] T. Wu, et al, "JSCGC: Joint Source-Channel-Generation Coding for Wireless Generative Communications," submitted to *IEEE TWC*, 2026.



Summary and Open Challenges

Reshape 6G through full-stack reinvention: **rebuild the channel foundation, **redesign** the air interface, and **redefine** what to transmit**

-- GeNeRT, LAMBDA, AirFM-DDA, JCM, BitSemCom, JSCGC



Scaling laws and benchmarks for wireless FMs

What is the 'ImageNet moment' of wireless foundation models? We need shared datasets, unified benchmarks, and scaling laws grounded in propagation physics.



A theory of semantic and generative communication

Rate–distortion theory guided 70 years of communication design. What is its counterpart when the goal is semantic consistency and content generation?



Open ecosystems for standardization

Open datasets (LAMBDA), open models (AirFM-DDA), and open interfaces — so that 6G intelligence is reproducible, comparable, and deployable.





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Thank you



飲水思源 愛國榮校