Enhancing LoRa Reception with Generative Models: Channel-Aware Denoising of LoRaPHY Signals

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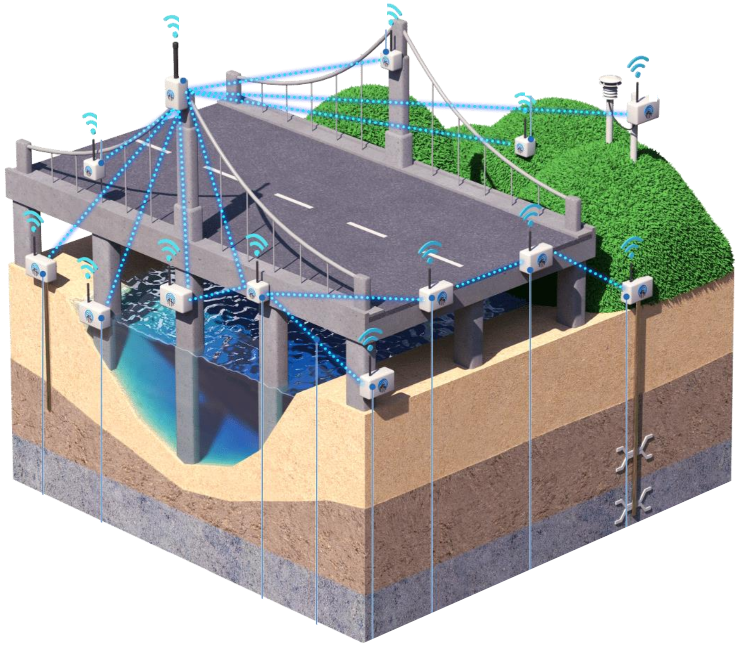
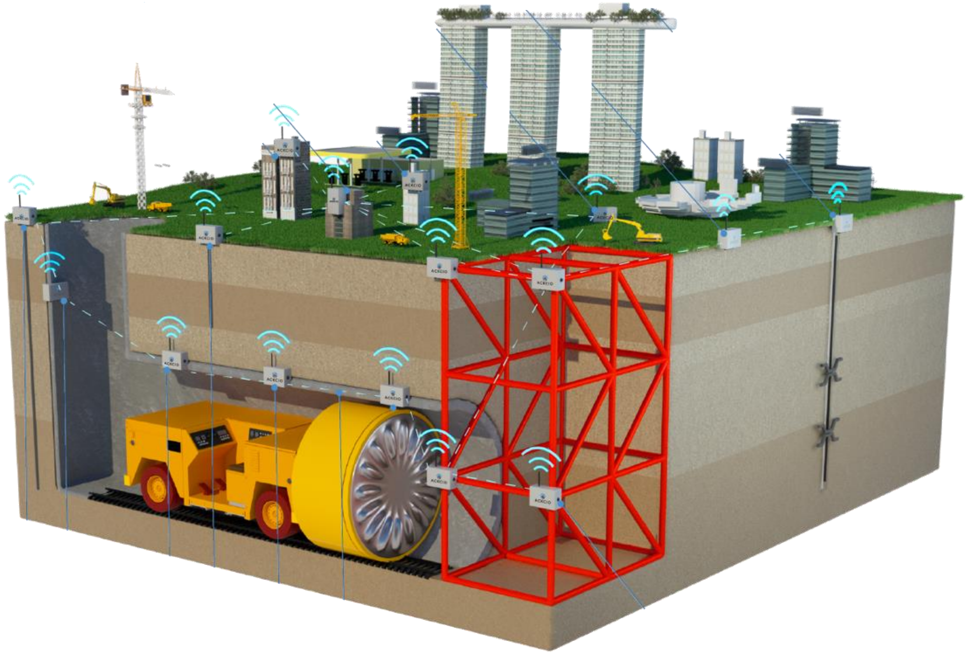
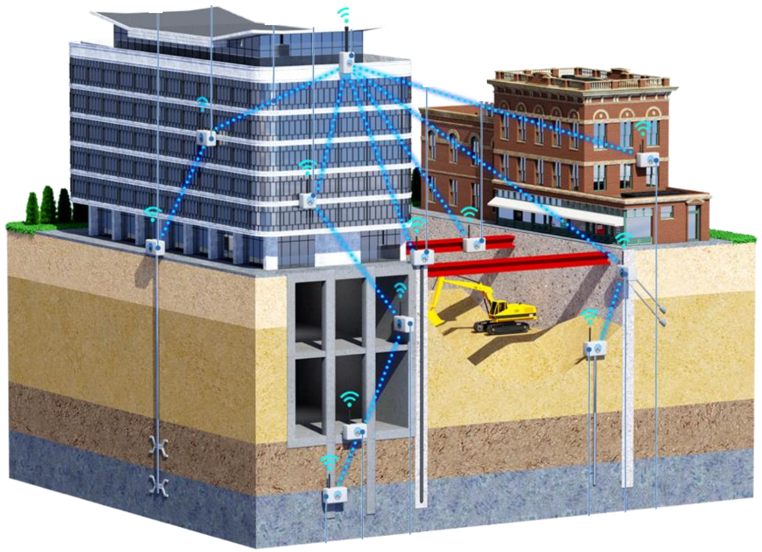
Wide Area Sensor Networks



Structural Monitoring



City Scale Tunnel Monitoring



Construction Site Monitoring

Low-Power Wide Area Networks (LP-WANs)

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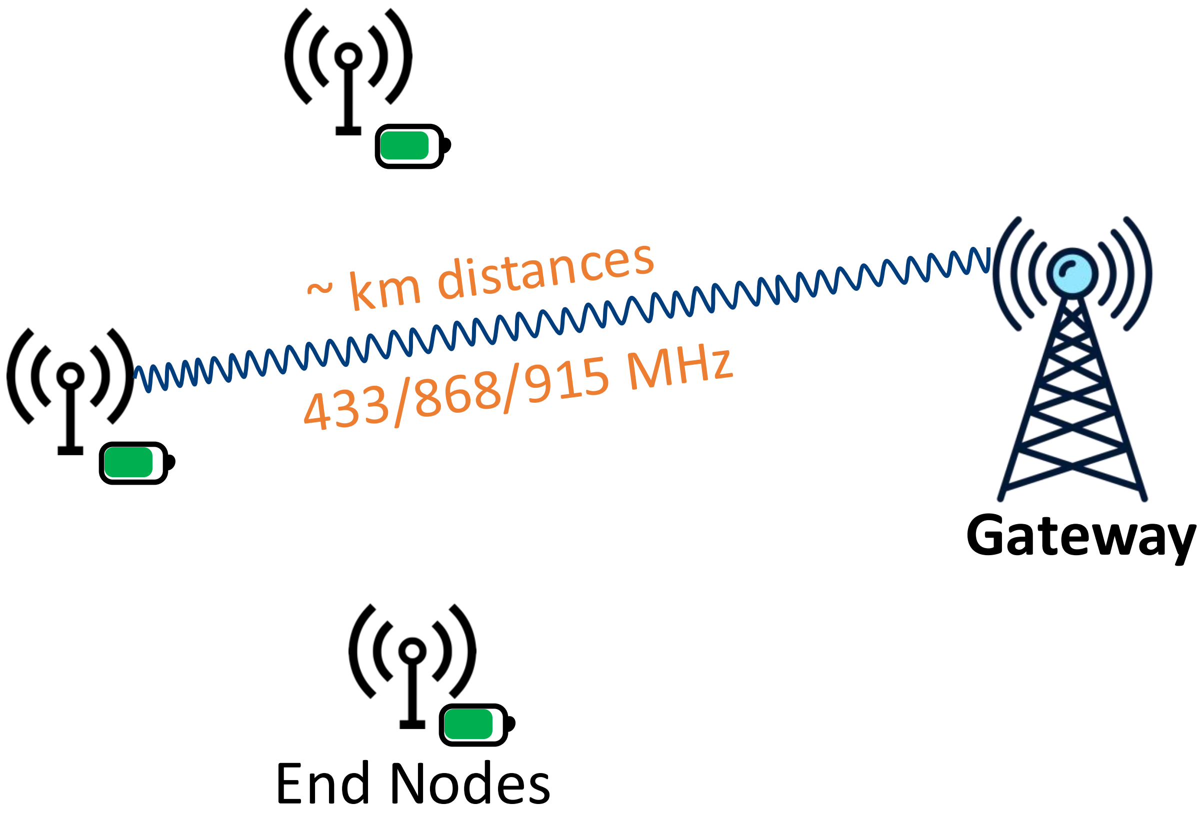
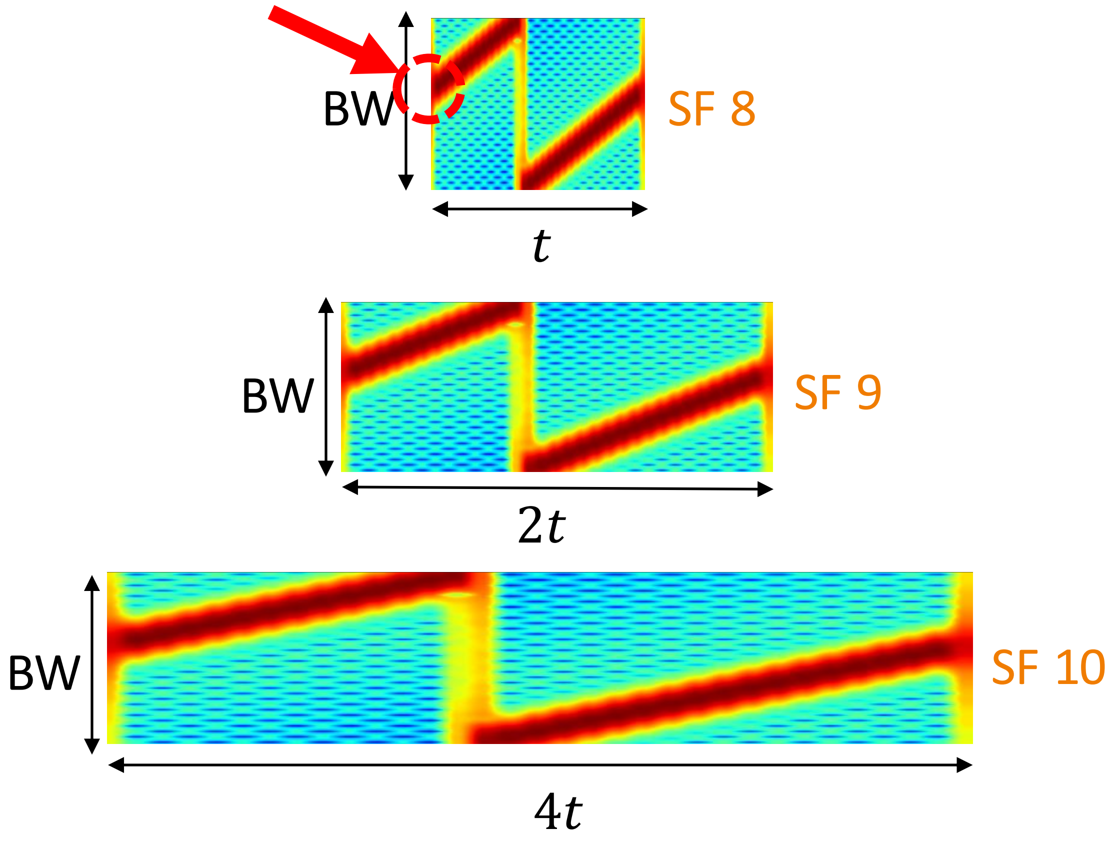
LoRa Network Characteristics

- Open source
- Long Range transmissions
- Sub-GHz unlicensed ISM band
- Battery constrained end nodes



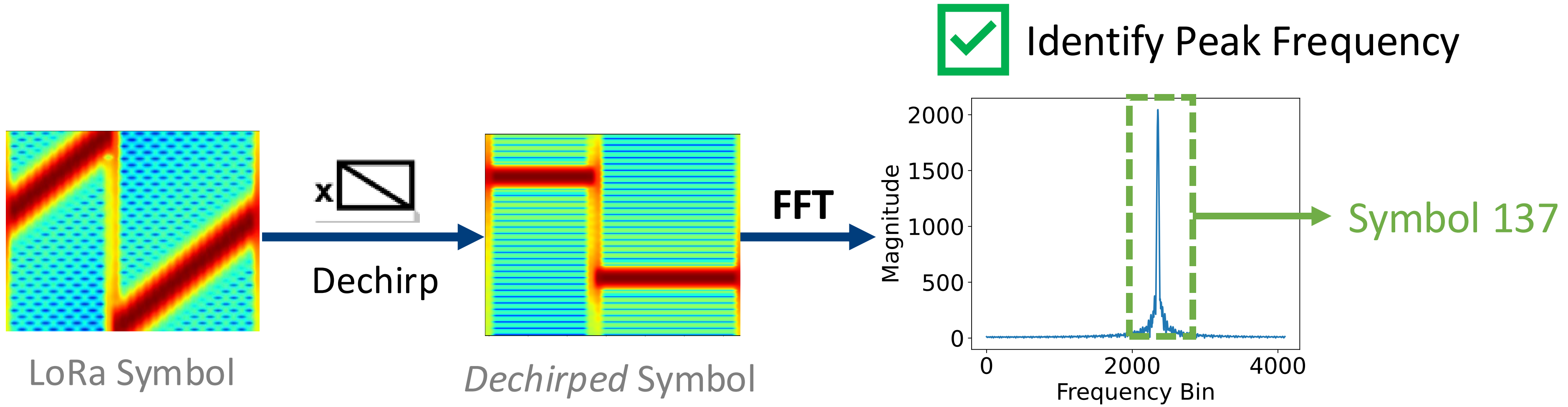
LoRaPHY – LoRa's Physical Layer

- Uses Chirp Spread Spectrum (CSS) for signal modulation
  - *Chirp*: frequency sweep across bandwidth over time
- Spreading Factor (SF)
  - Each SF increase doubles ToA
  - SF ranges 7-12
- Each symbol encodes SF bits
  - 2^{SF} start frequencies encode data



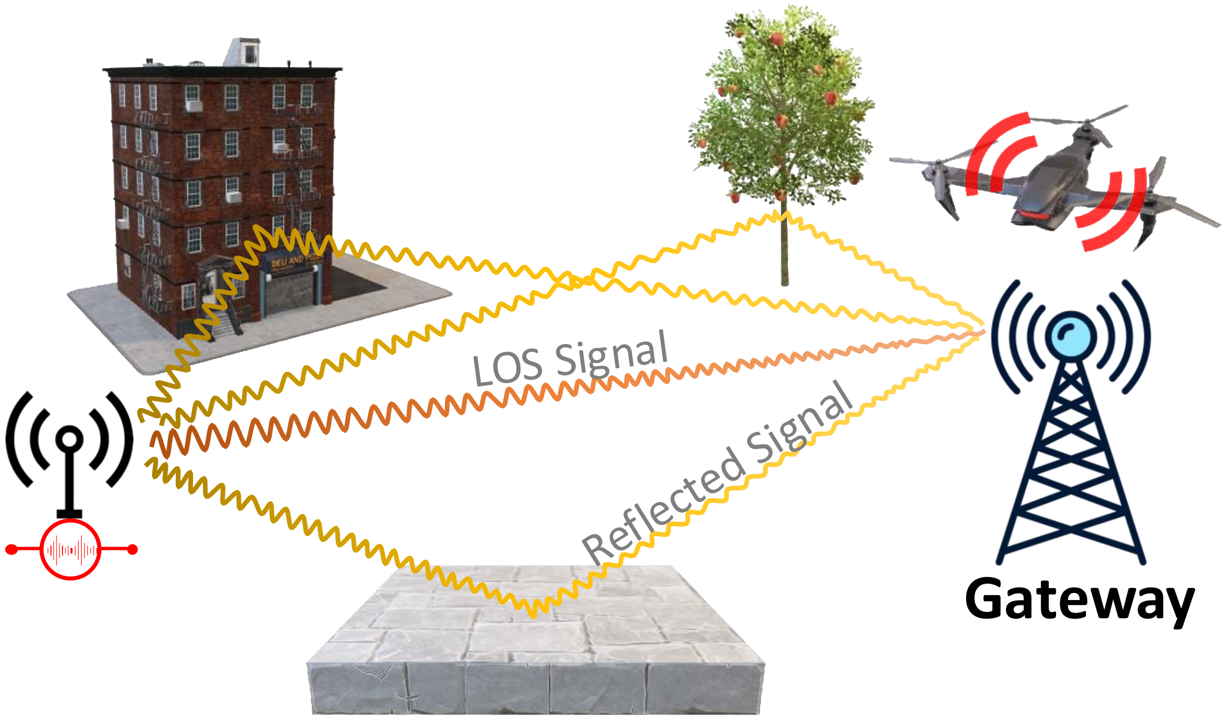
LoRa PHY Demodulation

Need to identify the “starting frequency”



Challenge: Channel Impairments

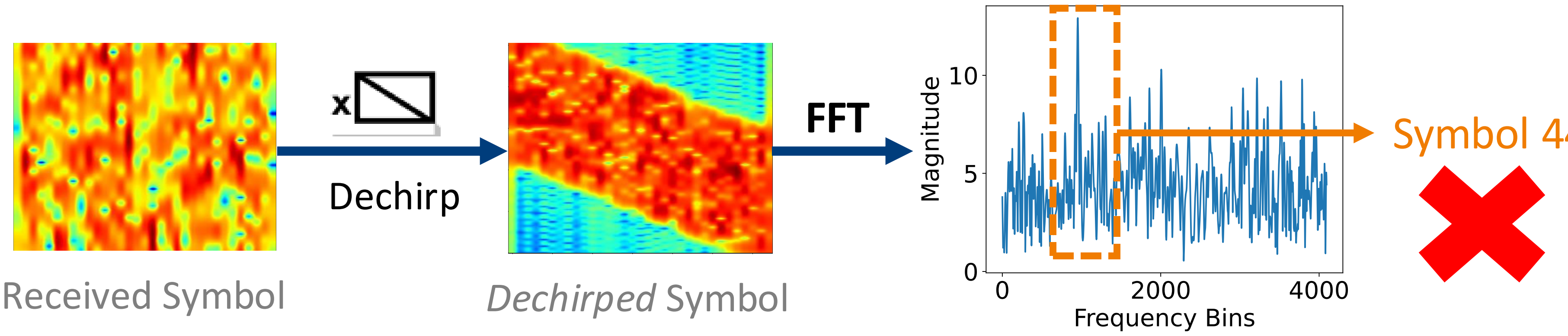
- Attenuation
  - From long distance transmission
- Multi-path Fading
  - From fleeting and static reflectors
- Interference
  - From other transmissions in ISM band
- Hardware Frequency and Time Offsets
  - Cheap hardware



High-Rate Packet Corruption!

Urban Channel Impairments

Real-world Noisy Environments



Received Symbol

Dechirped Symbol

- Shifted Peak
- Overwhelmed by Noise

High-Rate Packet Corruption!

Urban Channel Impairments

Real-world Noisy Environments

Can *channel impairments* be mitigated by **denoising** the LoRaPHY signal at the gateway?

- Shifted Peak
- Overwhelmed by Noise

High-Rate Packet Corruption!

Current State-of-the-Art:
Neural Demodulation

Neural Demodulation – Current SoTA

- NELoRa[SenSys '21] introduced Neural Demodulation
- Replace LoRa Demodulation

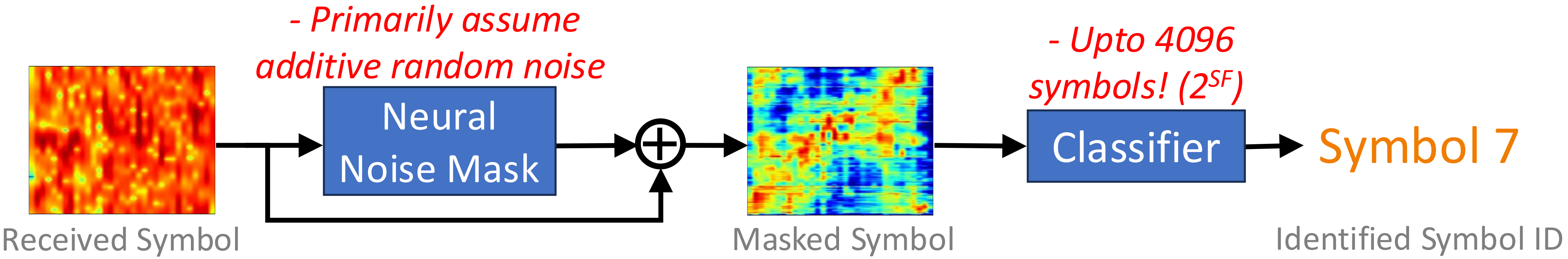
Key Challenges:

A. Channel Aware denoising
B. Compact model with fast inference

Drawbacks: ① Lack Channel Awareness ⇨ Training Data Dependent
② *Large Model Size* ⇨ Long Inference Time

Neural Demodulation – Current SoTA

- NELoRa[SenSys '21] introduced Neural Demodulation
- Replace LoRa Demodulation



Drawbacks: ① Lack Channel Awareness ⇨ Training Data Dependent
② *Large Model Size* ⇨ Long Inference Time

GLoRiPHY

Channel-Aware Neural Denoising framework for LoRaPHY

Focus of This Talk

A. Channel Aware denoising
B. Compact model with fast inference

How do we integrate ***channel awareness*** in GLoRiPHY?

Challenge: Integrating channel awareness

Why do we need to model the channel?

Received Signal

$$y = h * x$$

Convolved Noise

- Attenuation
- Multipath Fading

Environment-dependent statistical **patterns!**

LoRa highly susceptible to multipath

Error Rate shown to increase by orders of magnitude under multipath

Challenge: Modelling Channel Response h

Convolved Noise

$h * x$

- Attenuation
- Multipath Fading

Environment-dependent statistical **patterns!**

- Environment Variability
  - Countless unique combinations of channel *patterns.*
  - E.g., delay profile, attenuation, etc.
- Temporal Variability:
  - Channel changes over time.

Channel changes with environment and time

Challenge: Modelling Channel Response h

Convolved Noise

- Environment Variability

Can we estimate the Channel h from the received packet?

- Channel changes over time.

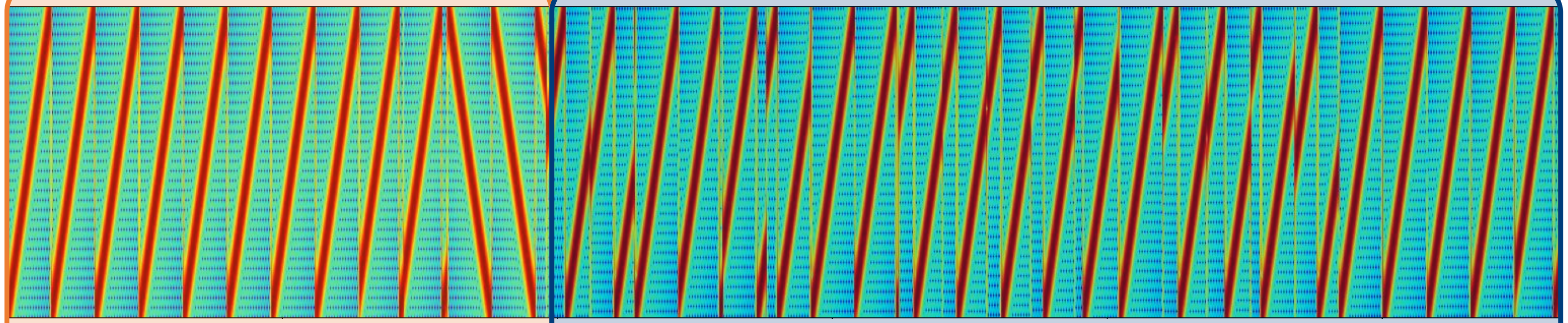
Environment-dependent statistical **patterns!**

Channel changes with environment and time

Our Key Idea: Leveraging Preamble for Channel Estimation

Fixed Across Packets

LoRa Packet



Preamble

Payload Symbols

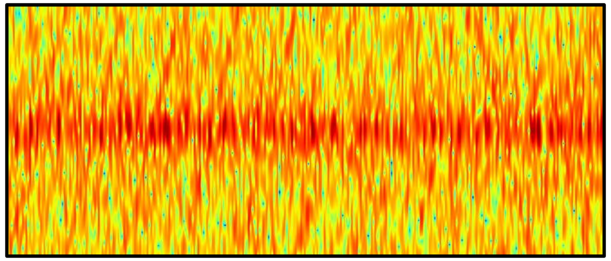
① Estimate How Channel Modifies Signal

Estimate Channel h

② **Channel Aware Denoising** of Payload

$$x = h^{-1} * y$$

Challenge: Extracting Channel Features

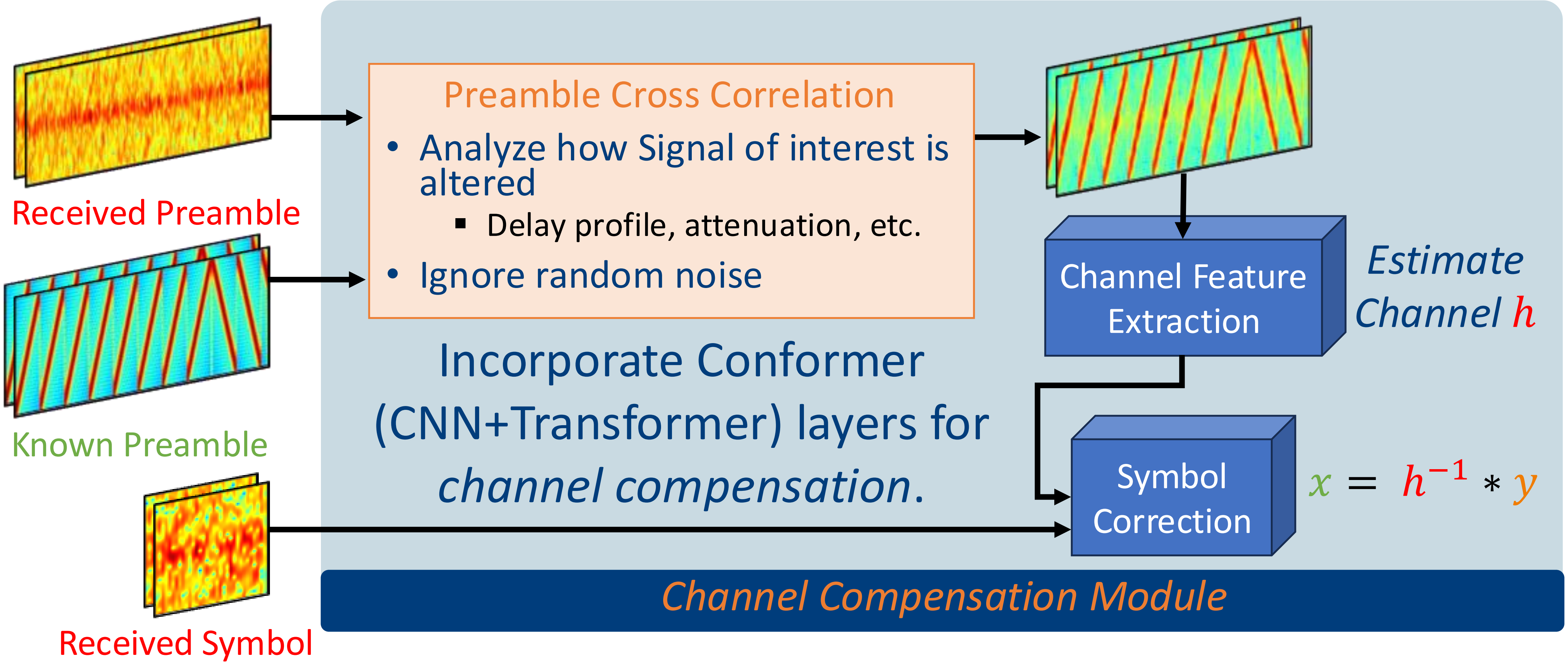

Real-world preamble

Preamble suffers from complex combination of noise

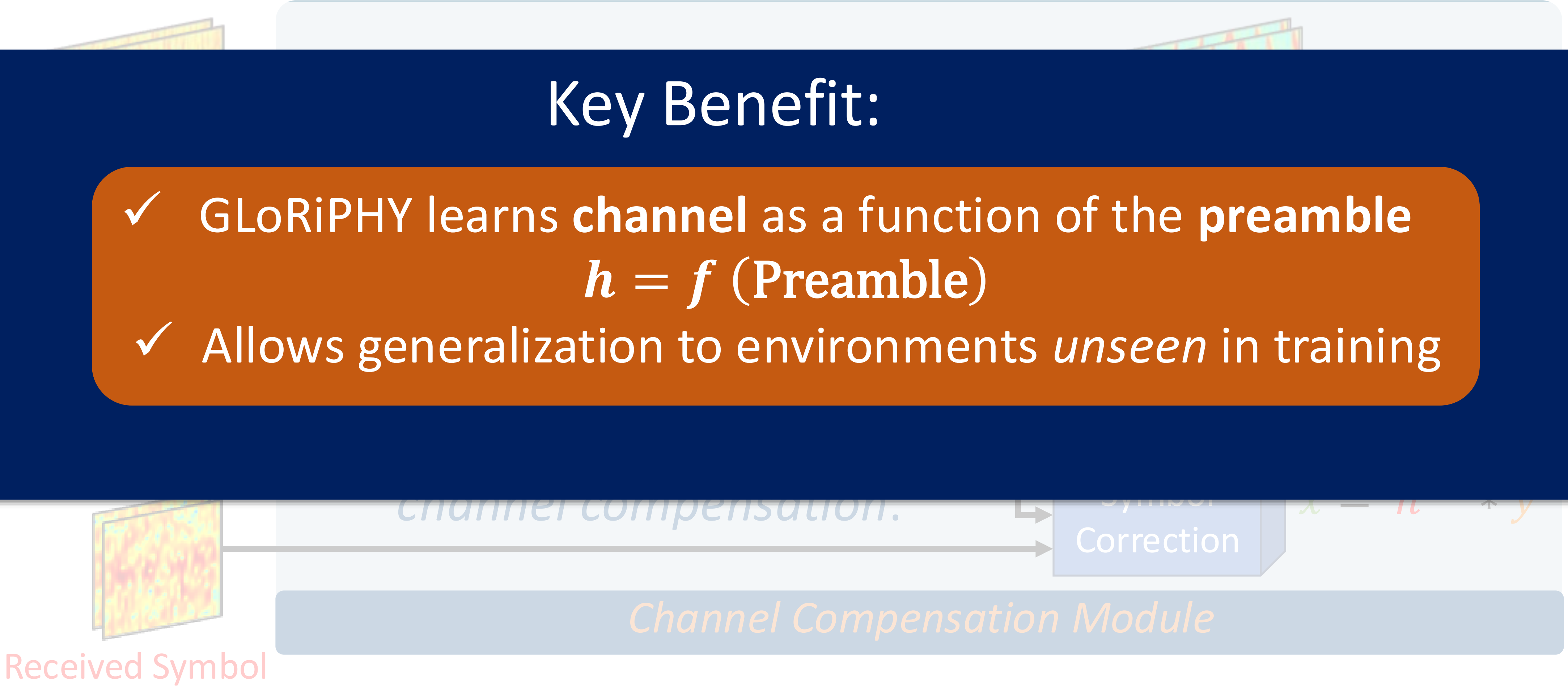
Received Signal		*Convolved* Noise		*Additive* Noise
y	$=$	$h * x$	$+$	n
		Environment-dependent statistical **patterns!**		Random Noise
		Channel Compensation Module		*Enhanced Symbol Generation Module*

GLoRiPHY **decouples** the processing of both noise components

Channel Compensation Module



Channel Compensation Module



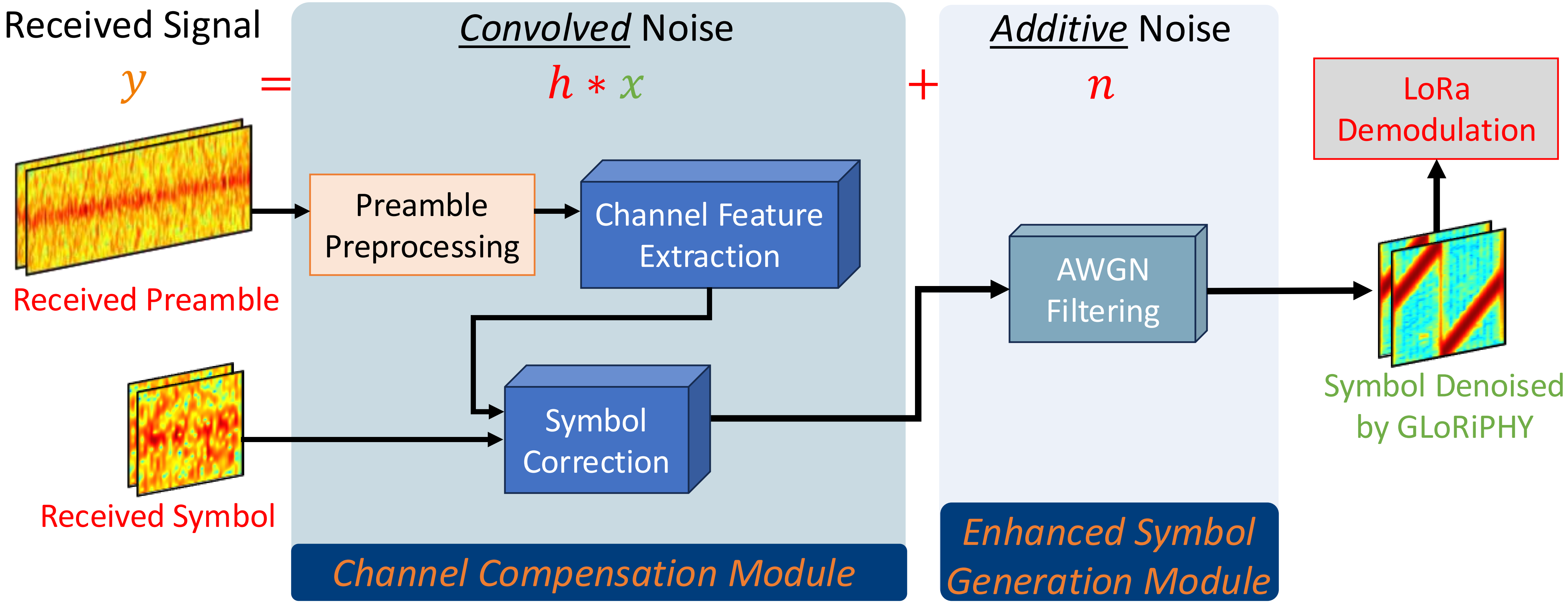
Key Benefit:

- ✓ GLoRiPHY learns **channel** as a function of the **preamble**

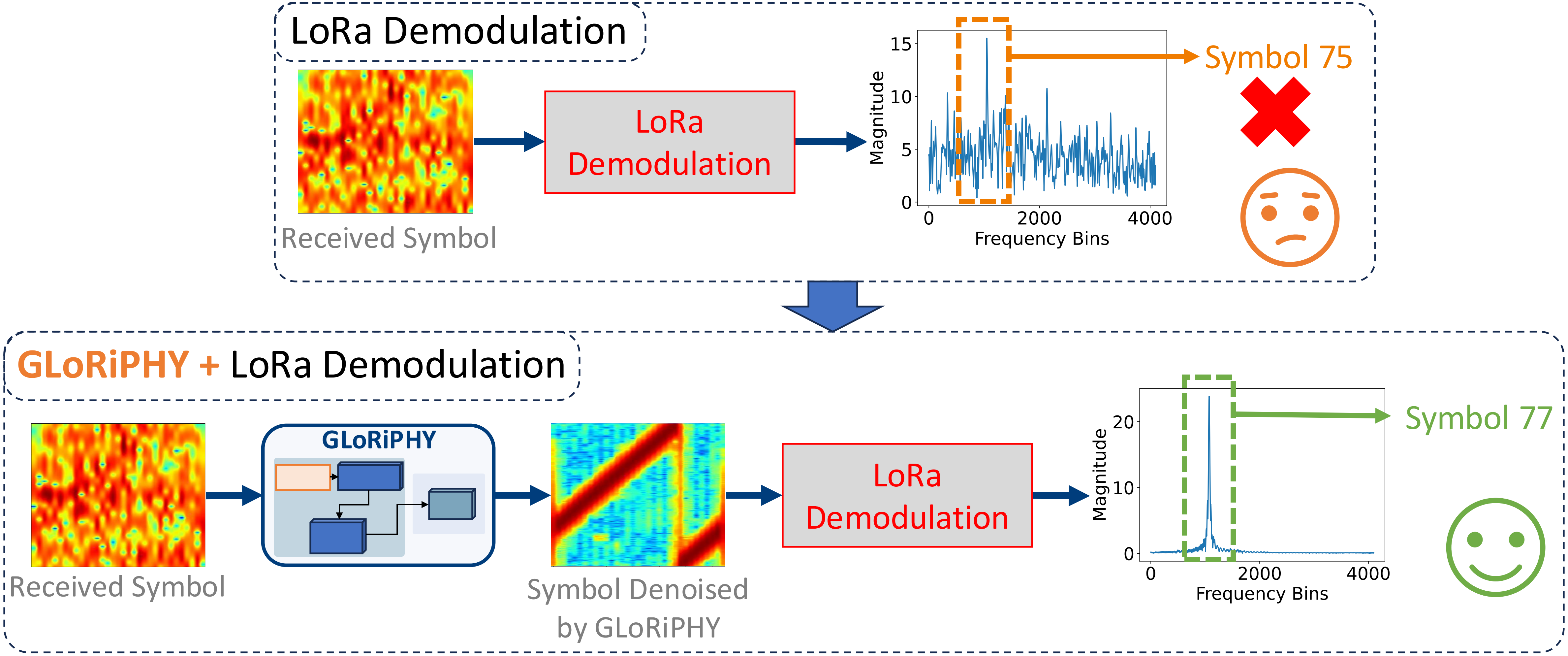
$$\boldsymbol{h} = \boldsymbol{f}\ (\textbf{Preamble})$$

- ✓ Allows generalization to environments *unseen* in training

GLoRiPHY - Overview

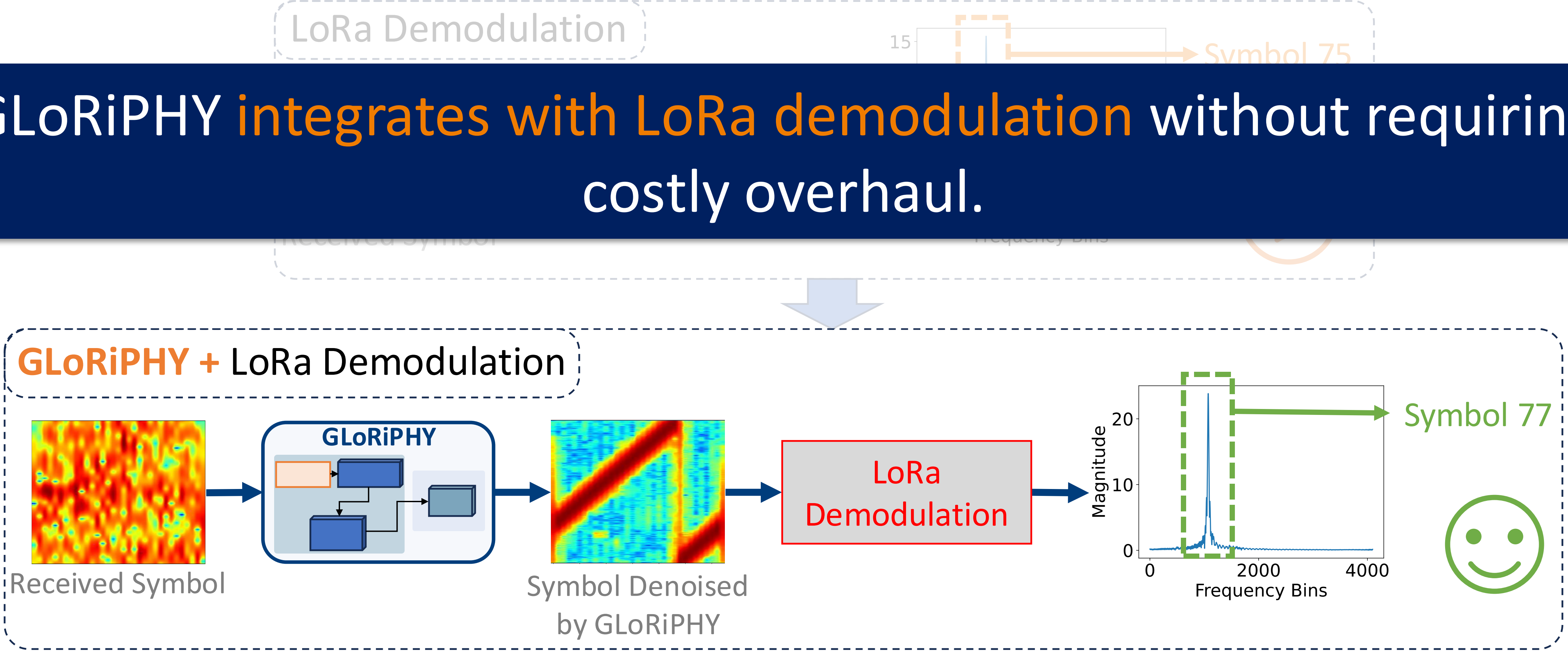


Enhanced Demodulation with GLoRiPHY



Enhanced Demodulation with GLoRiPHY

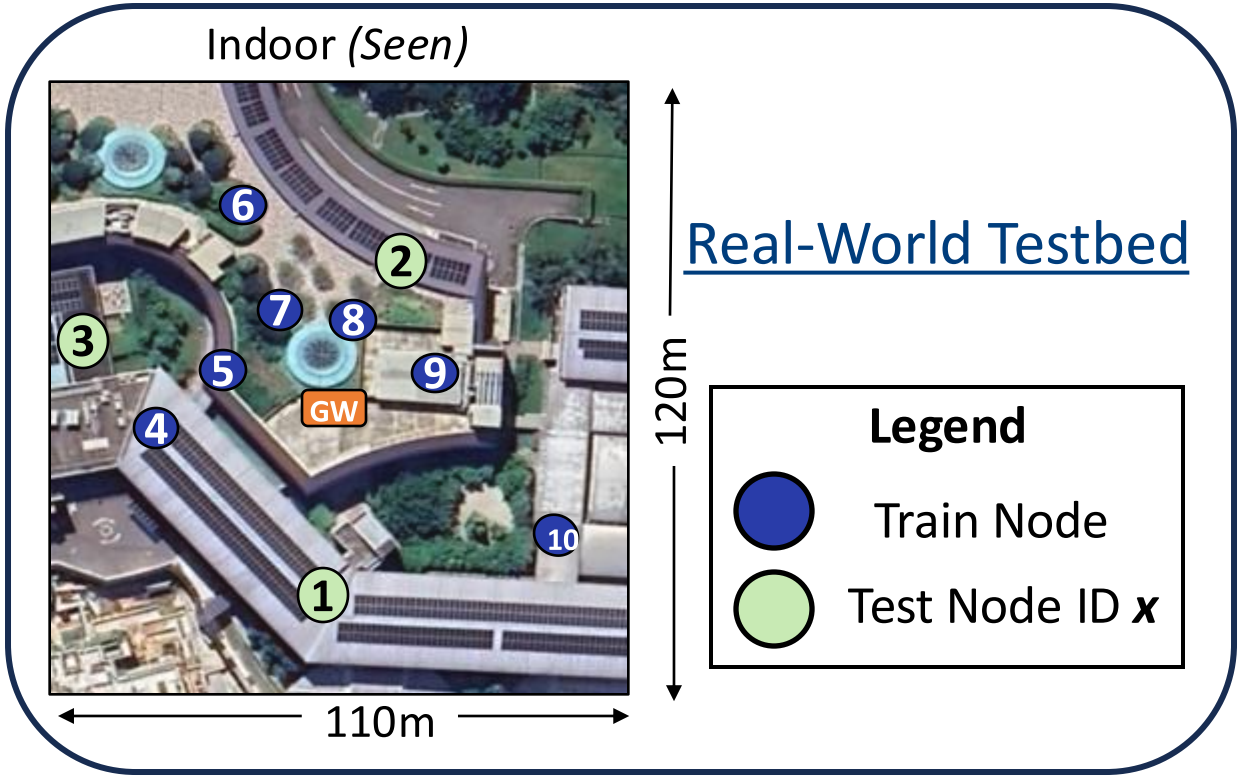
GLoRiPHY integrates with LoRa demodulation without requiring costly overhaul.



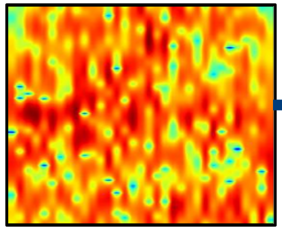
Evaluations

Setup -Datasets

- Real-world Tested
  - Transmitter: SX1272- based
  - Gateway: USRP B210
  - f_c = 868 MHz; BW = 125 KHz
  - SF 8
  - Random Payload
- Simulation Framework
  - Simulate SF 8-11
  - Simulate several theoretical channels



Baseline and Metrics



Received Symbol

Baseline 1: LoRa Demodulation

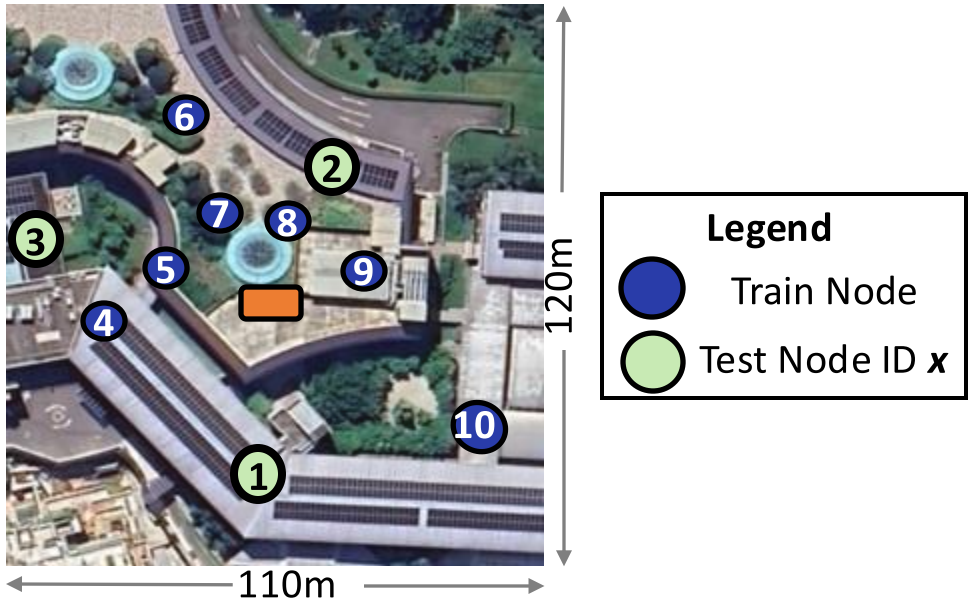
Baseline 2: NELoRa

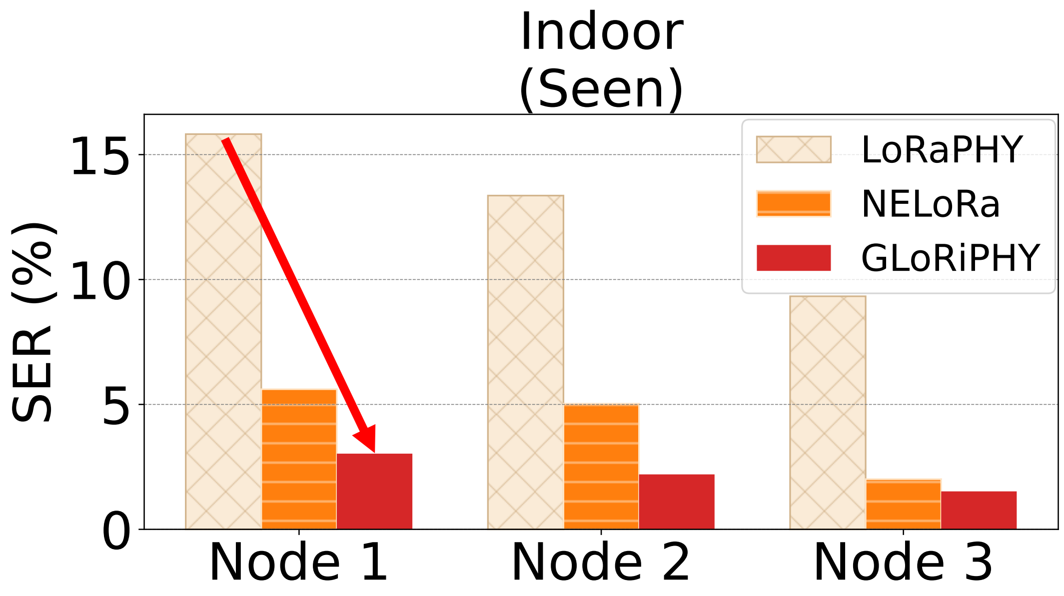
A. Trained on AWGN
B. Tuned with scenario-specific training data

Evaluation Metric: Symbol Error Rate (SER %) $= \frac{\text{Incorrectly Identified Symbols}}{\text{Total Received Symbols}} \times 100$

Real-world Test

- Trained on *indoor* testbed
- Tested with leave-one-out approach





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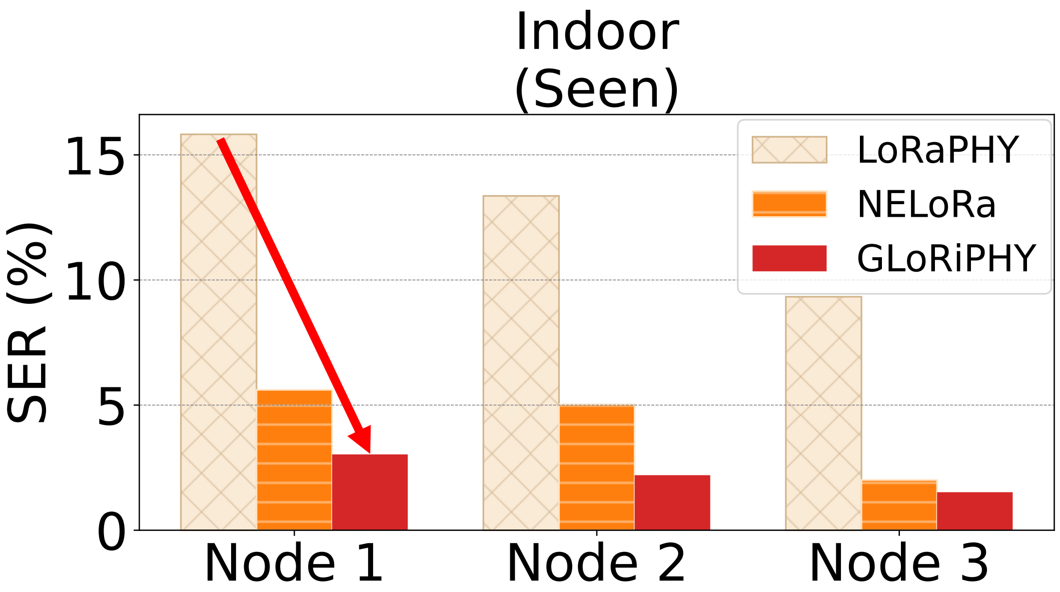
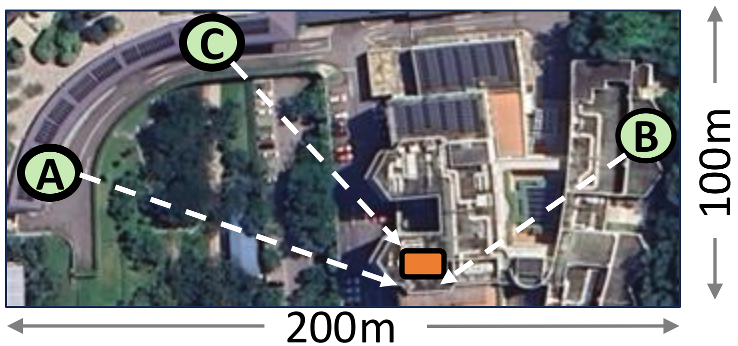


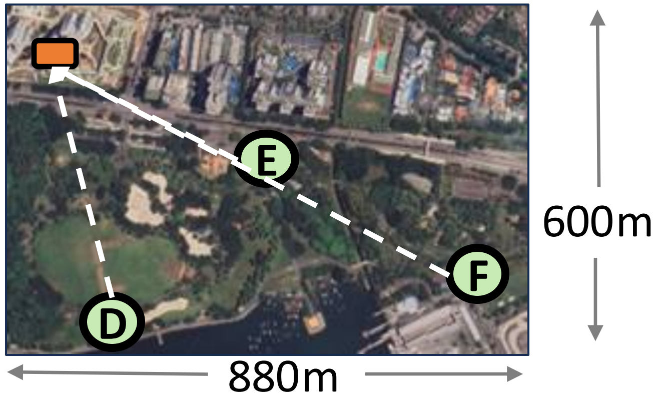
GLoRiPHY maintains **lowest SER** by effectively *compensating* for channel impairments.

Real-world Generalizability Test

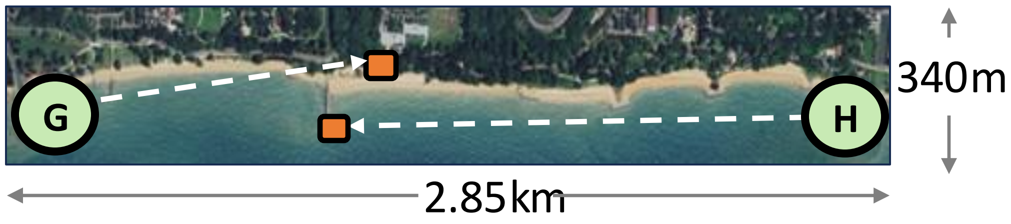
- Train on *Indoor* Testbed
- Testing Data collected
  - using hardware unseen during training.
  - from diverse environments



Semi Outdoor *(Unseeen)*

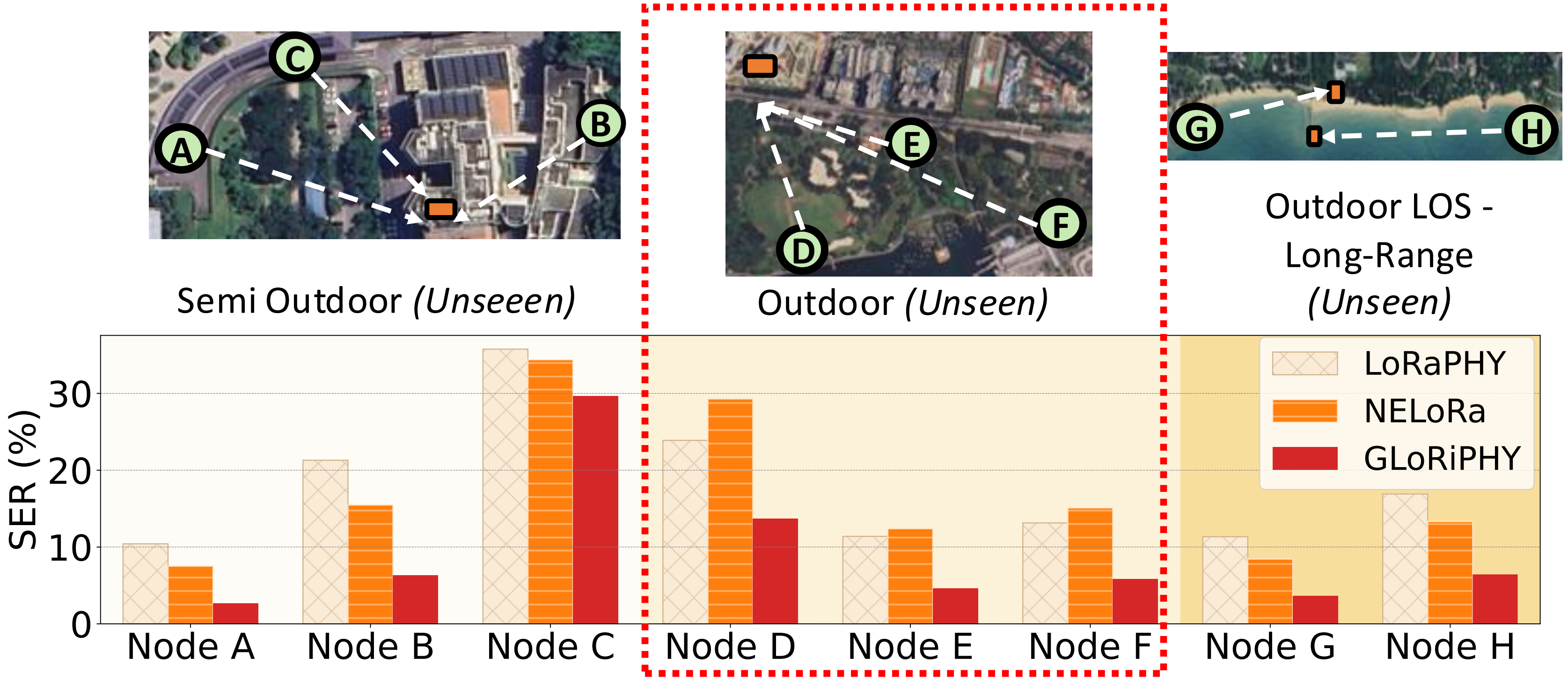


Outdoor *(Unseen)*



Outdoor LOS - Long-Range *(Unseen)*

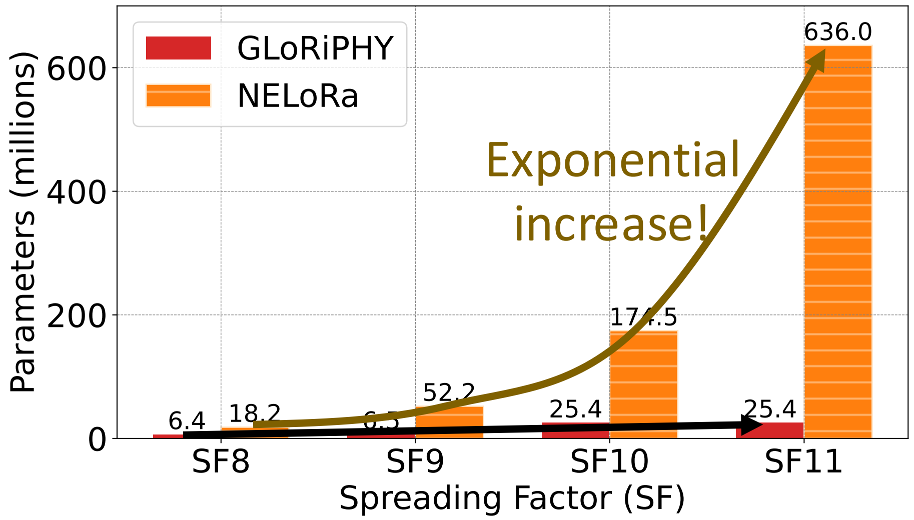
Real-world Generalizability Test

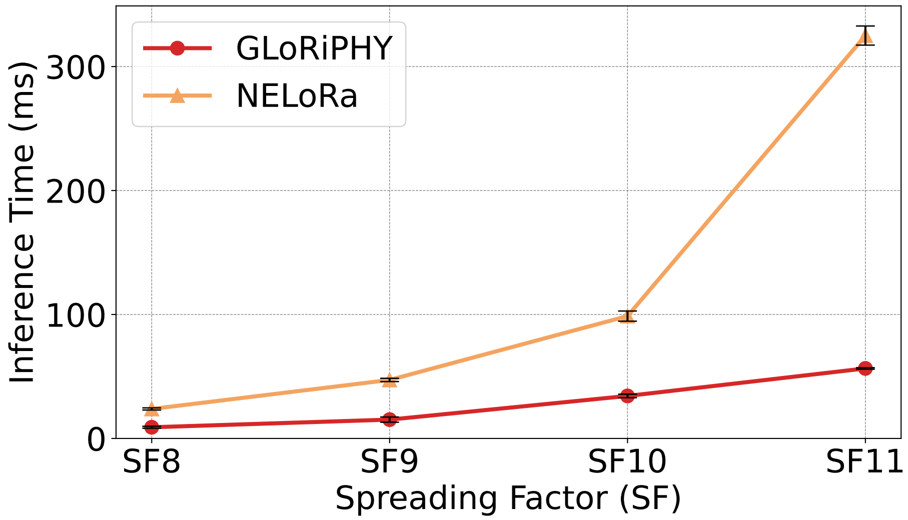


Demonstrates GLoRiPHY's **channel awareness** enabling **SER gain**, even in **environments vastly different** from the training setting.

Model Size and Inference Time

- Evaluate symbol identification time for 64 symbols

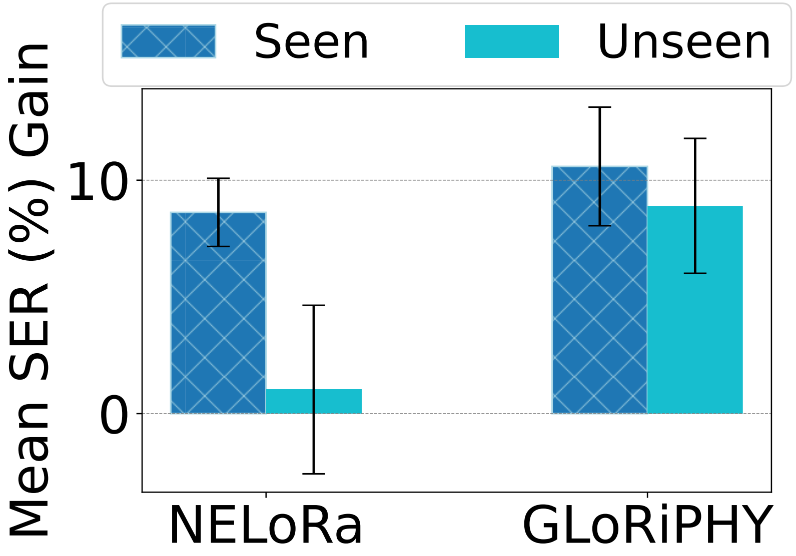




GLoRiPHY efficiently manages model size and inference time.

SER Gain in different Environments

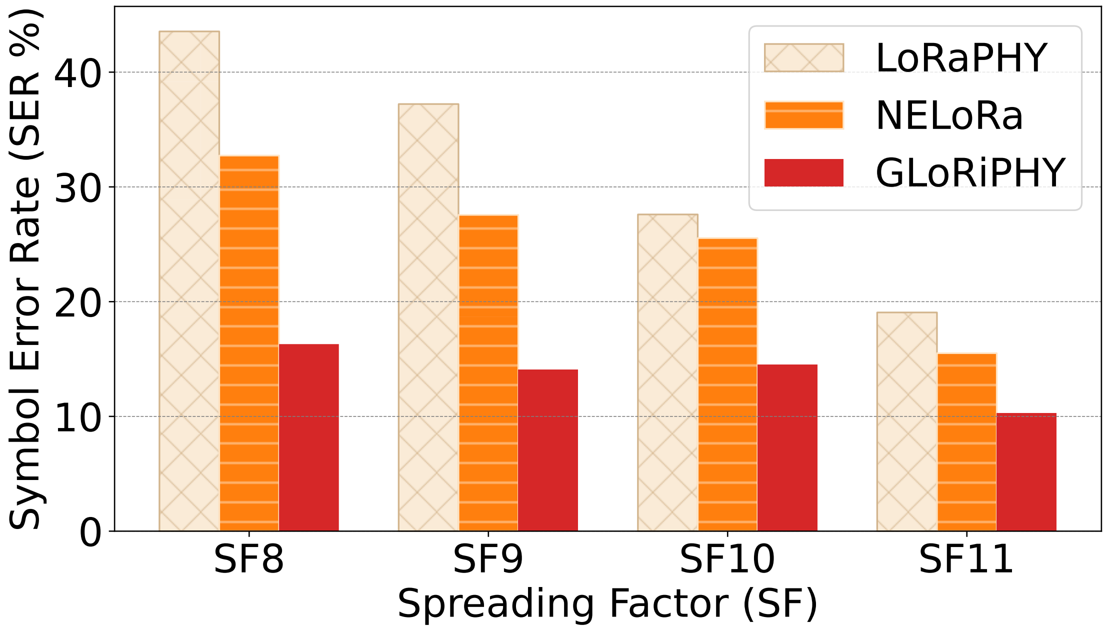
- In different environments
- SER Gain = SER reduction over LoRaPHY



Simulation Data Test

- Test if performance generalizes across SFs
- Generalization across diverse Rayleigh/Rician + AWGN Channels

Performance generalizes across SFs



Conclusion

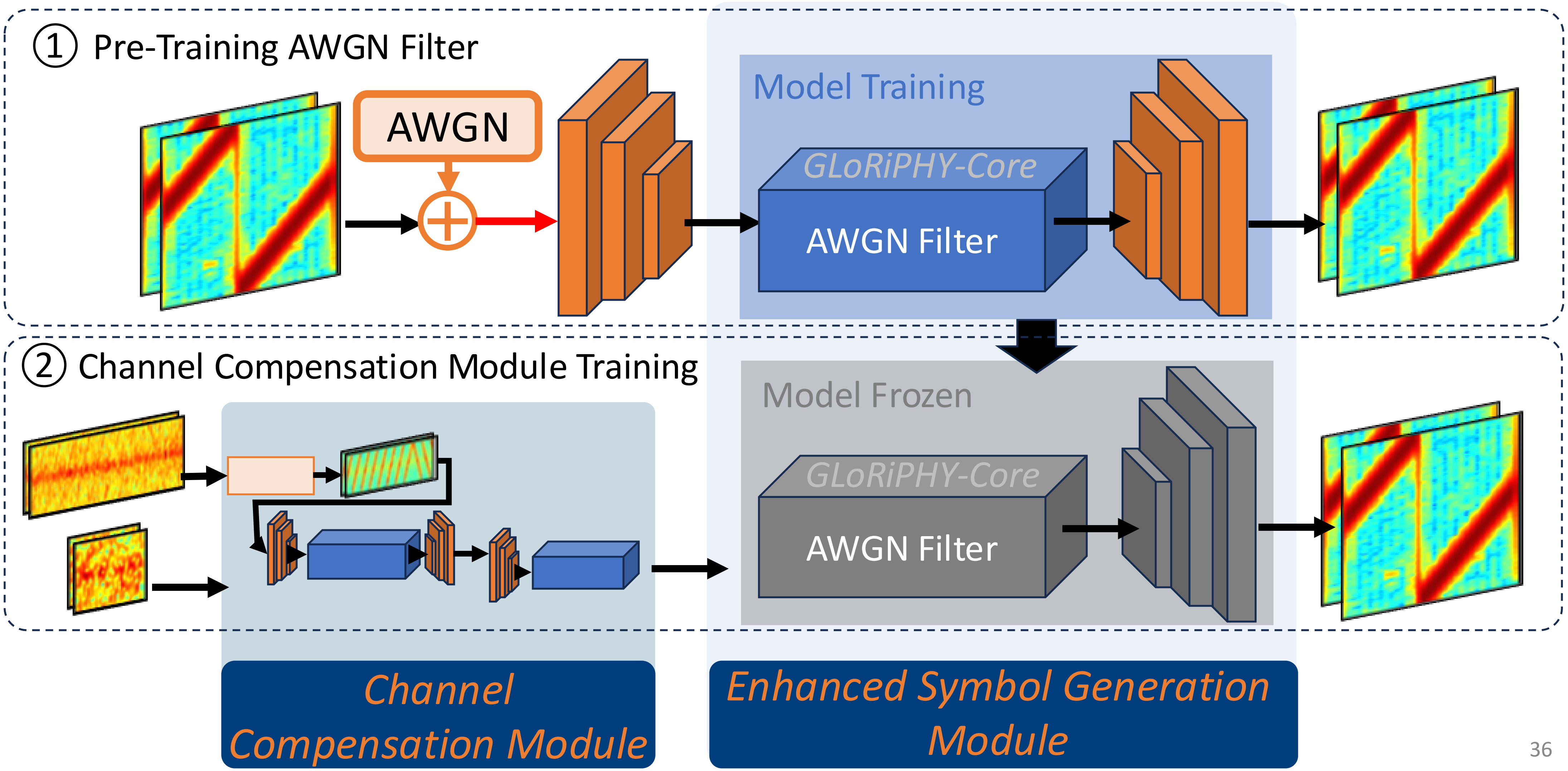
- We present **GLoRiPHY**, a preamble-based, channel-aware denoising framework that significantly enhances LoRaPHY demodulation.

- Compared to state-of-the-art, GLoRiPHY demonstrates:
  - Upto 2.85x improvement SER reduction
  - 8.64x SER improvement in *unseen* environements
  - Upto 5.75x faster inference times

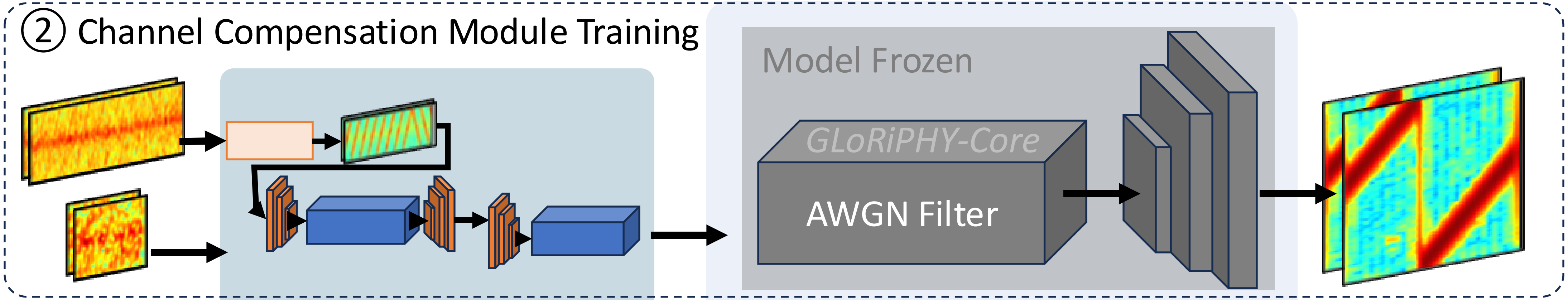
Key step towards broader applicability of neural solutions on Physical Layer.

More Information

GLoRiPHY Training



GLoRiPHY Training



Channel Compensation Module

Training Loss reduction requires handling convolved noise

Enhanced Symbol Generation Module

- Acts as a critic in *Channel Compensation Module* training
- AWGN filter can address only additive noise

GLoRiPHY Training

- Dual Component Loss
  - MSE to reduce error on generated STFT
  - CCE to reduce final demodulation errors

$$\text{Loss} = \alpha \cdot \text{MSE} + \beta \cdot \text{CCE}$$

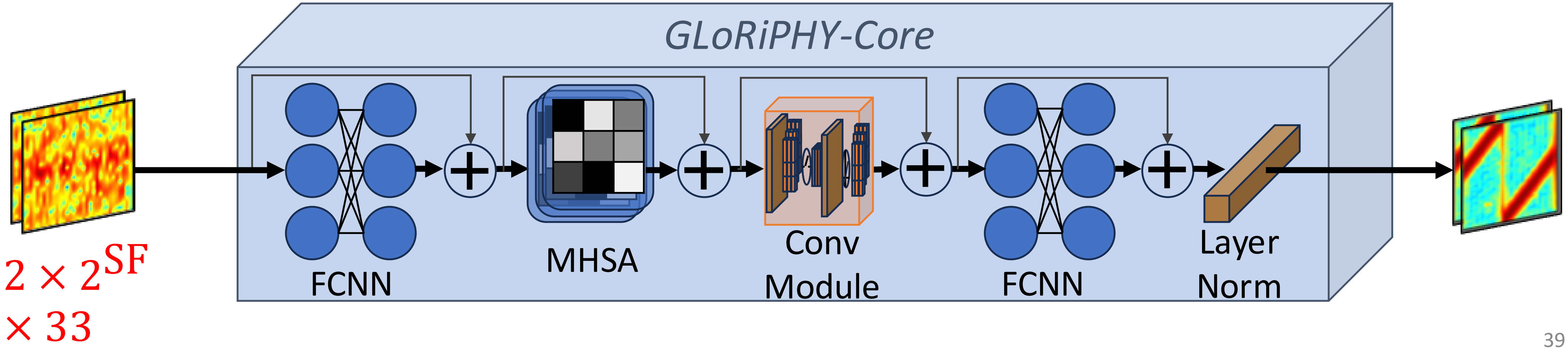
- Curriculum Learning
  - Input data complexity increases with training stage

GLoRiPHY Architecture

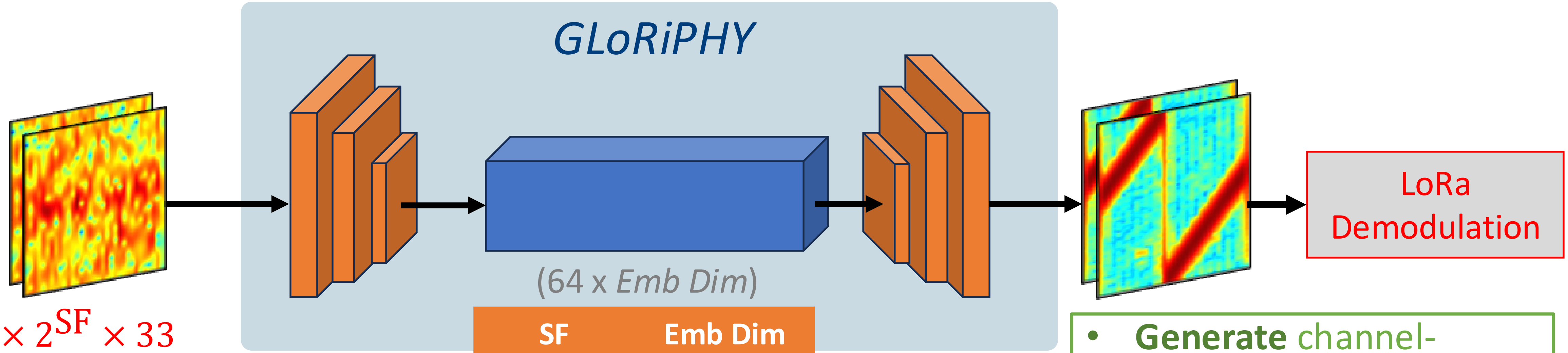
- *GLoRiPHY-Core*
  - Core learning model for GLoRiPHY
  - Based on Conformer architecture, combining:
    - MHSA – For long term features
    - CNN – For local features

Challenge!

- Minimal frequency resolution $= 2^{\mathrm{SF}}$
- Can lead to models with billions of parameters



Compact Model Size



$2 \times 2^{\mathrm{SF}} \times 33$

SF	Emb Dim
7/8/9	256
10/11/12	512

Challenge!

Minimal resolution in frequency to identify a symbol $= 2^{\mathrm{SF}}$

Manage **Compact** Embedding Representations

- **Generate** channel-compensated symbols
- Ensure **high fidelity** across amplitude, phase, frequency, and time
- Enables **direct LoRa demodulation**