Enhancing DtS-IoT Uplink Success Probability through Transformer-Based Machine Learning in FLoRaSat

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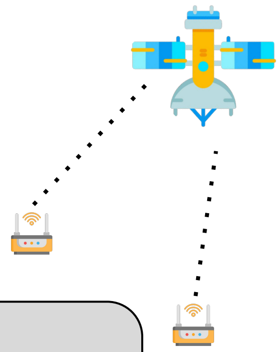
Introduction



Context and Challenge

DtS-IoT scenarios operate under changing conditions that depend on satellite trajectories, channel variability, transmission timing, simultaneous transmissions (collisions), etc.

Temporal and Sequence Models

Attention and recurrent models (LSTM, Transformers, etc) can capture and learn these temporal dependencies, helping the network predict and adapt conditions, thus improving the network performance.

Current trend

Most state-of-the-art works rely on Reinforcement Learning (RL), making sequential sequence models a highly attractive novel paradigm for DtS-IoT.

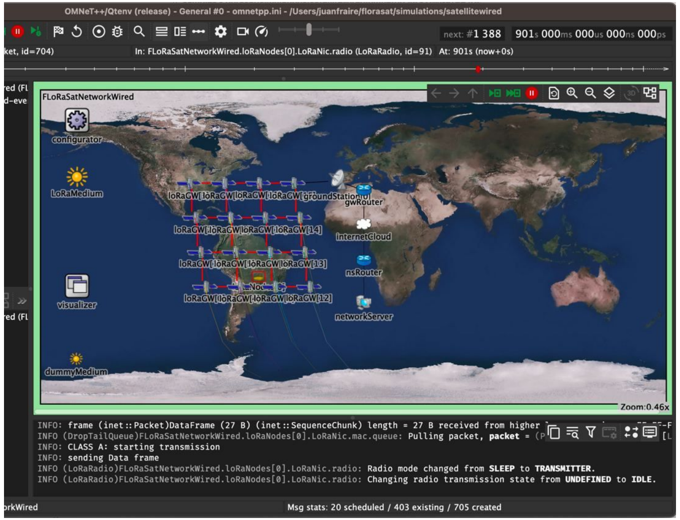
FLoRaSat

Overview

Open-source, event-driven, end-to-end simulation tool implemented in OMNET++. It is undergoing a constant process of development and improvement.

Capabilities

Capable to model : IoT terminals (LoRa PHY/MAC) LEO satellite links, Orbital dynamics, Interference and collisions, among others.



Problem Statement

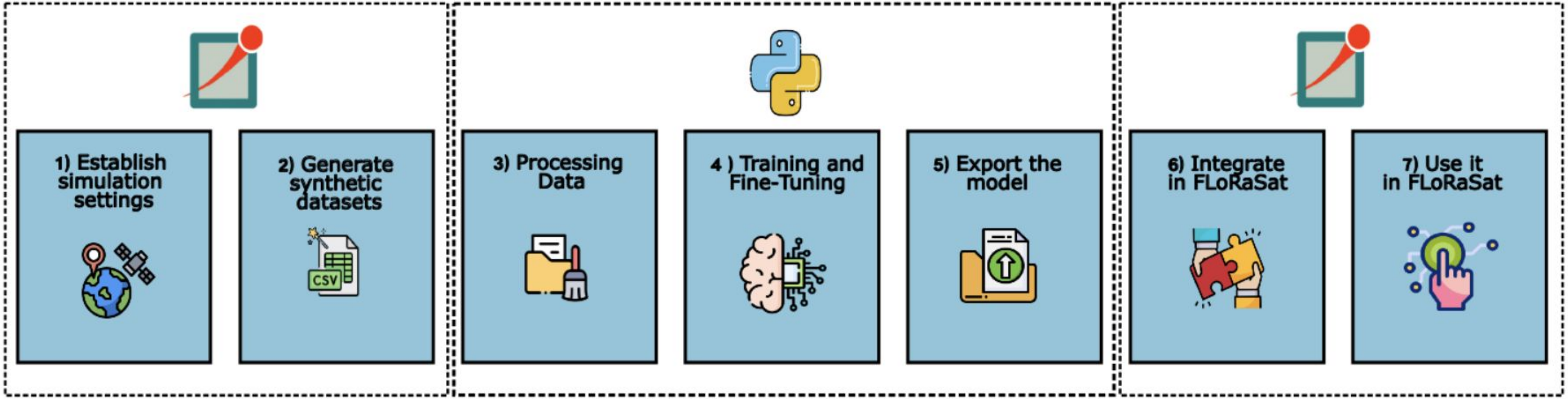
Problem definition and context:

Dts-IoT communications experience highly dynamic and time-varying link conditions. This work **combines** the effects of **well-know analytical factors** —such as satellite movement and doppler effects — **with unmodelled phenomena**, including traffic patterns from **isolated nodes** and unpredictable interference.

Learning Objective:

Given a device's sequence of t transmissions, predict whether the **t uplink transmission** will be successfully received by a satellite.

End-to-End Pipeline



We need synthetic datasets because real datasets are either non-existent or proprietary.!!!

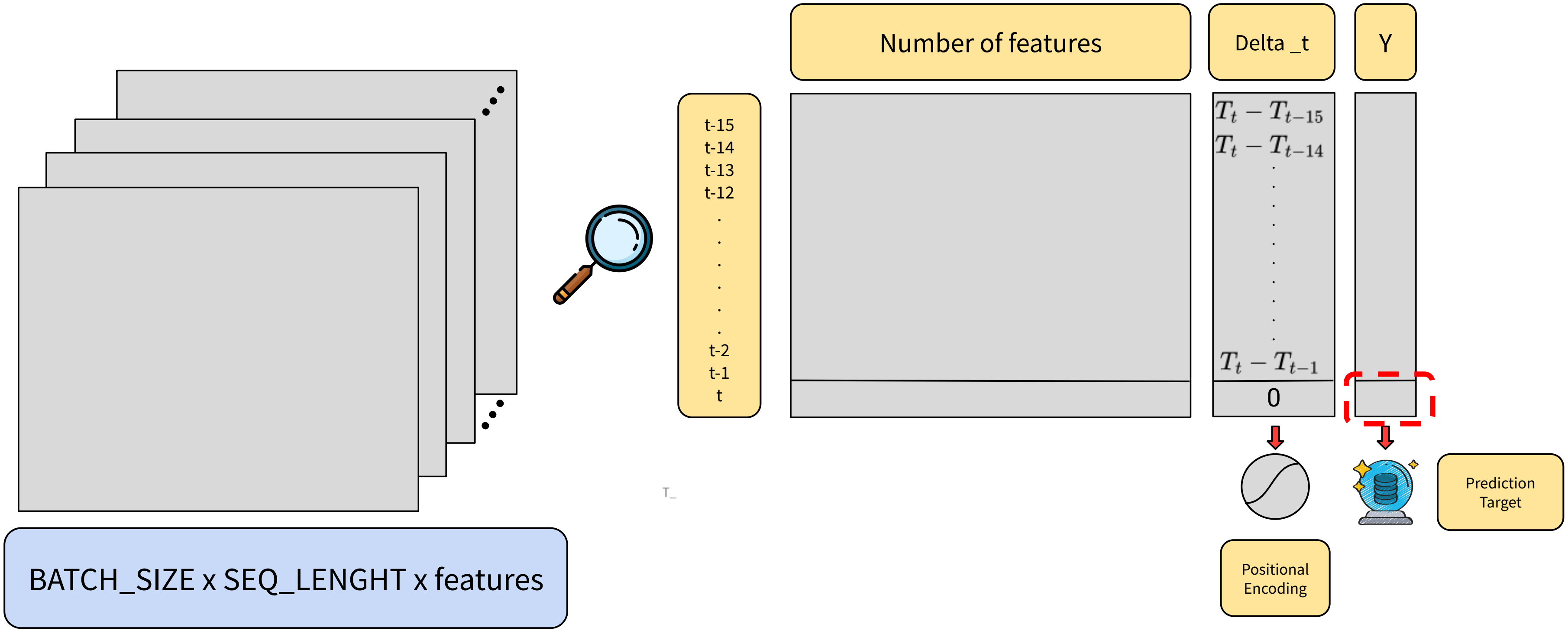
(1) Establish simulation settings

Parameter	Domain	Characteristic
Satellite Altitude	Orbital	Constant
RAAN		At Trx moment
Elevation Angle		At Trx moment
LoRa SF, LoRa TP	Radio	At Trx moment
Doppler Shift		At Trx moment
Latitude, Longitude	Device	Constant

Given scenario configurations and naturality from DtS-IoT scenarios, a challenging unbalanced dataset appears

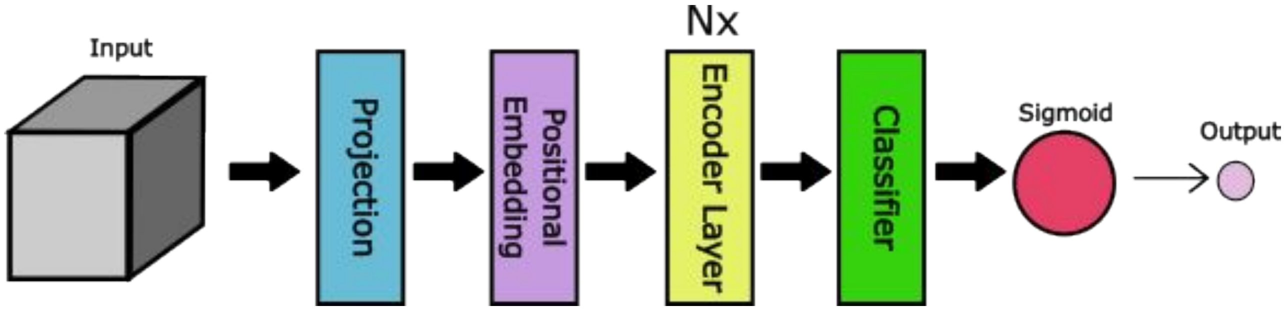
(2) Dataset generation and (3) preprocess

- A sliding window mechanism is used to convert simulation outputs into fixed-length temporal sequences for each device's transmissions.



(4) Model Building and (5) export it

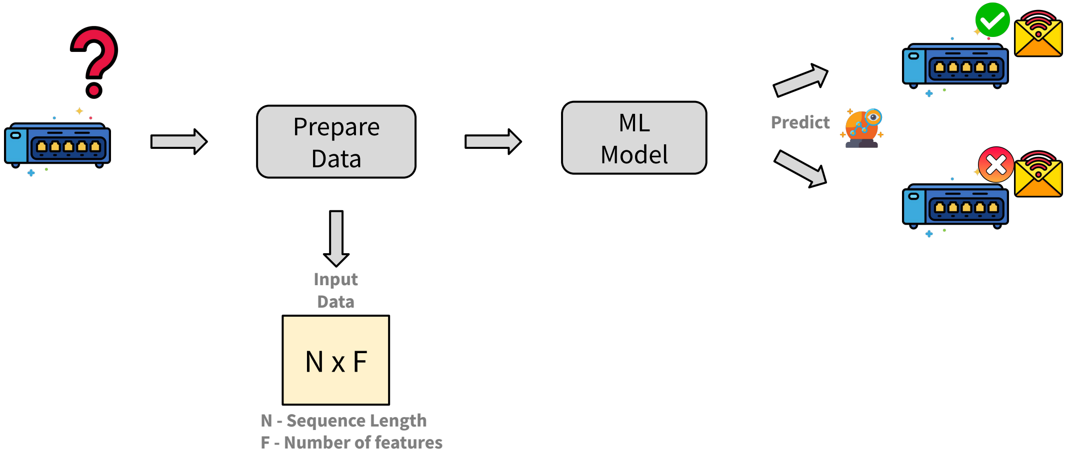
- Implementation of a **Encoder-Only Transformer** model to leverage bidirectional self-attention mechanisms to **captures full dependency** in both sides.
- **Class-weighted loss** addresses class imbalance by increasing the penalty for **positive-class misclassification**.



Proposed architecture

(6) Integration and (7) use in FLoRaSat

- The official binary distribution of **PyTorch (LibTorch)** is integrated into **FLoRaSat**.
- The **model runs on each device**, process the collected data, performs the **prediction** and based on the result, **decides** whether to transmit or not.



ML-Based Deployment Pipeline

Comparison

- A comprehensive **set of baselines** were implemented to validate the proposed model, categorized into two main approaches:
  - **Analytical Baseline**: A deterministic model based on probabilistic link budget, doppler effect, and collision theory.
  - **Machine Learning Baselines**: An architecture with similar characteristic such as Bidirectional LSTM (Bi-LSTM).
- **Bi-LSTM** uses the same sliding-window representation than the Transformer model , capturing the temporal dependencies within the dataset.

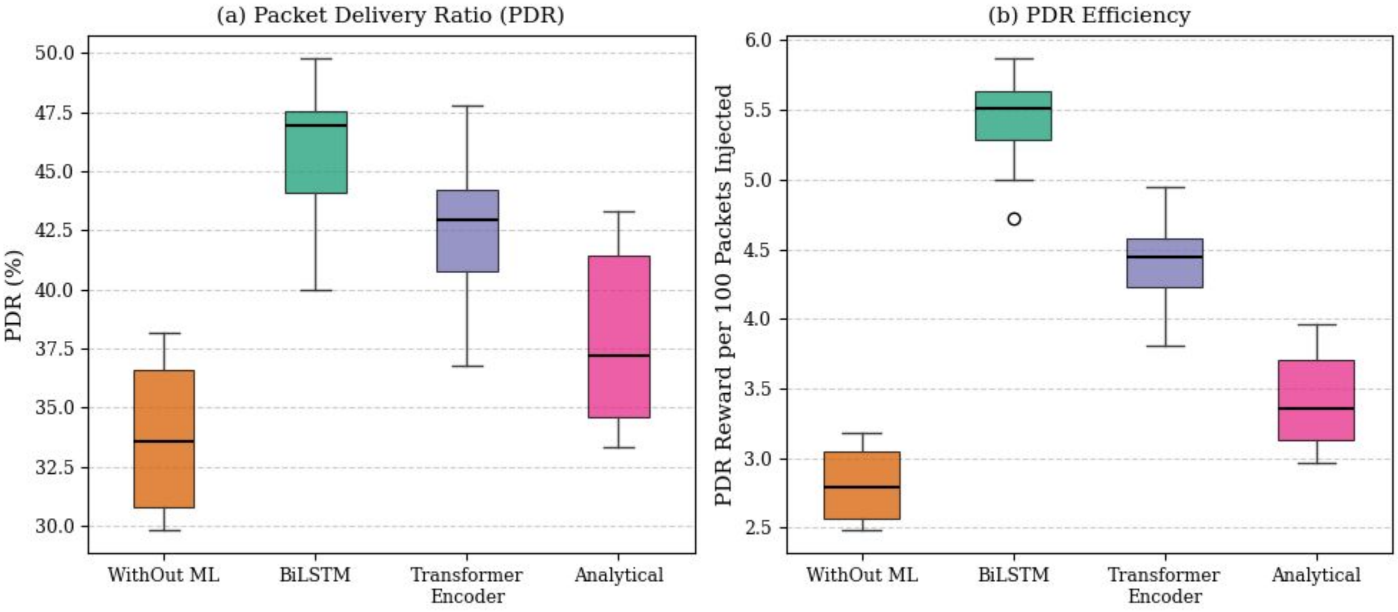
Preliminary results adjusted

Model	Metrics						
	General	Class 0 - No reception			Class 1 - Reception Ok		
	AUC-PR	Precision (%)	Recall (%)	F1-Score (%)	Precision (%)	Recall (%)	F1-Score (%)
Analytical. Baseline	0.5251	78.02	99.22	87.34	69.63	3.04	5.58
Analy. Baseline (best threshold)	0.5251	91.33	71.92	80.40	44.14	76.19	55.81
Bi-LSTM	0.7169	95.63	72.61	82.47	51.22	89.50	65.10
Bi-LSTM (best threshold)	0.7169	92.02	83.10	87.28	59.72	77.30	67.23
Transformer Encoder	0.7054	95.46	72.85	82.60	51.20	89.11	65.00
Transformer Encoder (best threshold)	0.7054	91.65	83.72	87.48	60.03	76.01	67.03

Bi-LSTM
- 357KB - 88385 params

Transformer Encoder
- 64.4KB - 14081 params

Preliminary results in FLoRaSat



Performance comparison of baseline models with adjusted decision thresholds in FLoRaSat

Conclusions

- **Analyt. Baseline**: The lowest Precision value in positive Class (44.14%) indicates that this approach does not distinguish correctly the positive and negative cases.
- **Transformer-Encoder**: It achieves the second best F1-Score in positive Class (67.03). Together with Bi-LSTM indicate that both architectures are an optimal selection to understand the complex patterns in comparison to baselines.
- **PDR and Efficiency**:The Transformer and Bi-LSTM significantly surpass alternatives in terms of PDR, whileBi-LSTM also maximizes efficiency, despite its larger model size.
- Although **Transformers and Bi-LSTM models** achieve comparable performance, the Transformer-Encoder stands out for its **lightweight architecture**, making it particularly suitable for highly resource-constrained devices.