Probability of Successful Transmission of Uplink Messages in LoRaWAN

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Content

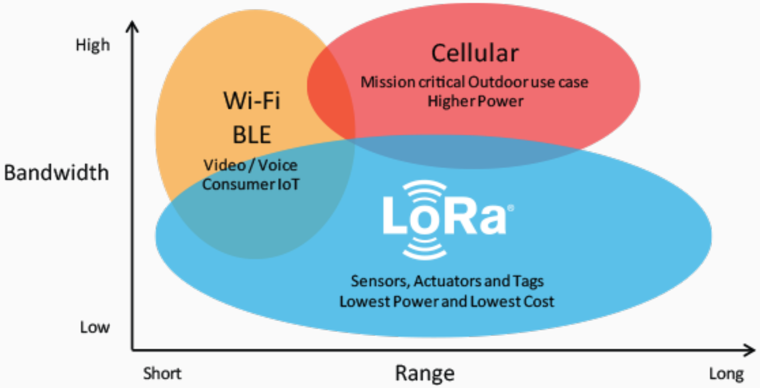
Introduction

LoRaWAN

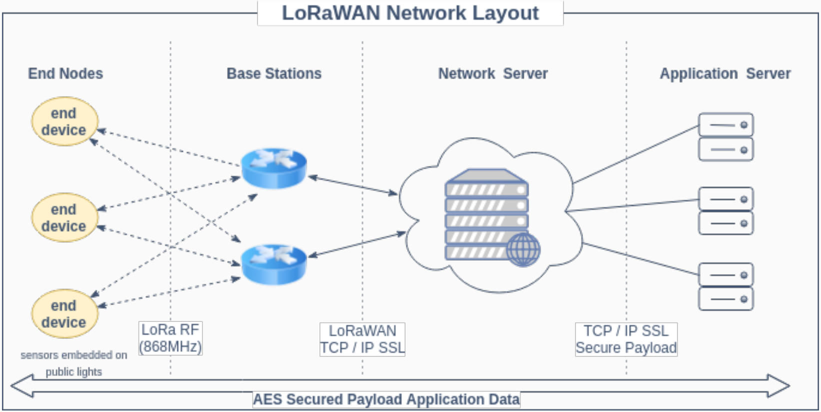
Long Range Wide Area Network - low power, wide area media access protocol built on top of LoRa designed to wirelesslly connect *things* to the Internet.

Perfect fit for network of IoT devices that:

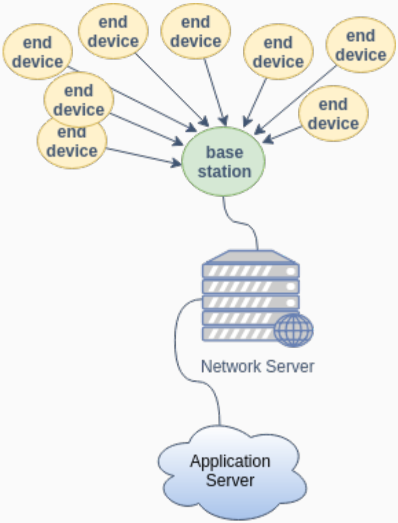
- are not power hungry
- require minimum bandwidth
- send data not to often


High
Bandwidth
Low
Wi-Fi
BLE
Video / Voice
Consumer IoT
Cellular
Mission critical Outdoor use case
Higher Power
LoRa
Sensors, Actuators and Tags
Lowest Power and Lowest Cost
Short
Range
Long

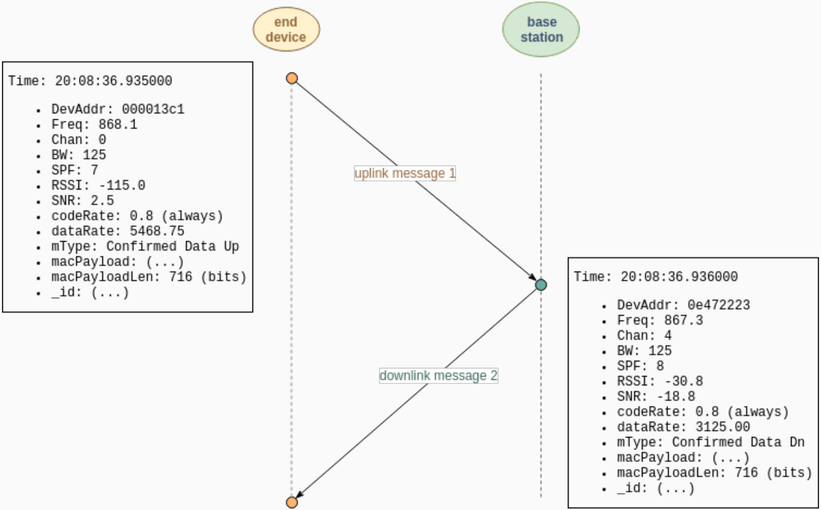
Infrastructure overview



Svebølle topology



Communication model for Svebølle deployment



Project goal

Is to apply forecasting methods on measured data from the single base station in Svebølle and examine whether there is a possibility of predicting successful transmission of LoRa messages for given future time interval.

Predicting future events

Structure of the measurement data

- Data was collected during the period of nearly 5 months
- 689k measurements are captured on a single base station
- Measured features
    - Time
    - DevAddr
    - Freq, Chan, BW, CR, DR
    - RSSI, SNR
    - crcStatus, mType,macPayload

Transformation to time-series

Time-series data is a series of data points indexed in time order and taken at successive equally spaced points in time.

To create time series data from given data set, the only important label is wheter the end device has successfully transmitted the message or not. For each time point, where every time point is observation in seconds there is activity flag assigned:

- 1 - device was active for observed time point
- 0 - device was not active for observed time point

Prediction models

- Moving average / weighted moving average
- Autoregressive integrated moving average (ARIMA)
- Holt's winter method
- Vector auto regression (VAR)
- Recurrent neural network (RNN)
- Reinforcement learning (RL)

Proposed RNN model

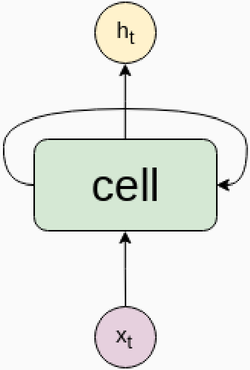
Artifical neural network

Recognizing regularities and patterns of the given data, learning from past experience and providing inference on the output.

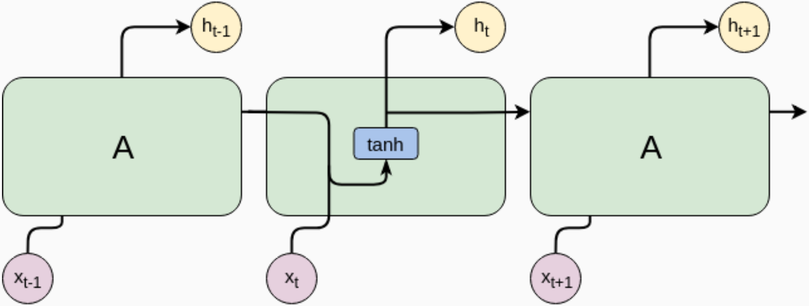
Vanilla ANNs are not perfectly suitable for time-series forecasting because they lack persistance.

Reccurent neural network

RNNs contain loops (feedbacks) allowing information to persist.



Unpacked RNN



Short-term memory problem

If a sequence is long enough, RNN will have a hard time carrying information from earlier time steps to later ones. The reason is that during back propagation, RNNs suffer from the vanishing gradient problem (gradient shrinks during back propagation time).

new weight = weight - learning rate * gradient

gradient $\rightarrow 0 \Rightarrow$ new weight $\rightarrow 0 \Rightarrow$ RNN stops learning

LSTM networks to the rescue

Model configuration

Probability of device activation for future time period

Conclusion

Future work

- **Multivariate time-series data** instead of univariate time-series data: observe not only previous historical events for specific device but also activation of other devices
- **Longer training sequences**
- Future **sequence predictions** instead of point-to-point predictions

Questions?