WET-DRY CLASSIFICATION USING LSTM AND COMMERCIAL MICROWAVE LINKS

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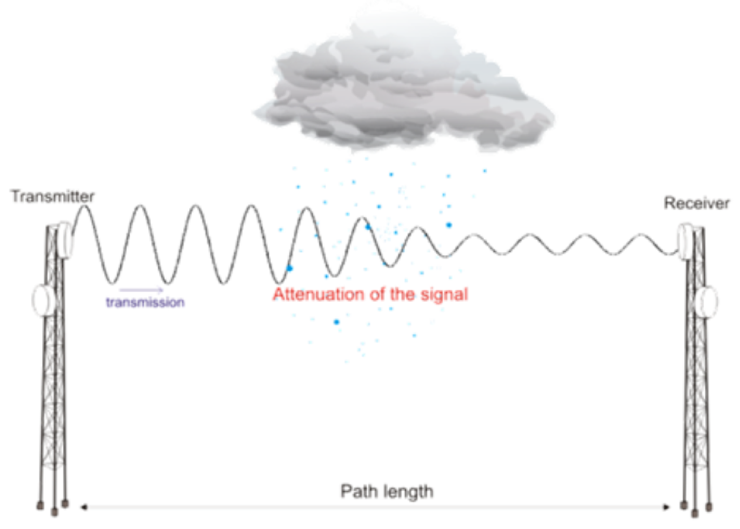
Introduction

The task of wet-dry classification using measurements from commercial microwave links (CMLs) is a subject that been studied in depth. In this work we present, for the first time an empirical study on rain classification using long short-term memory (LSTM) units with a multi-variable time series and CMLs, we demonstrate that LSTM can even be used for rain detection (wet-dry classification).

Background

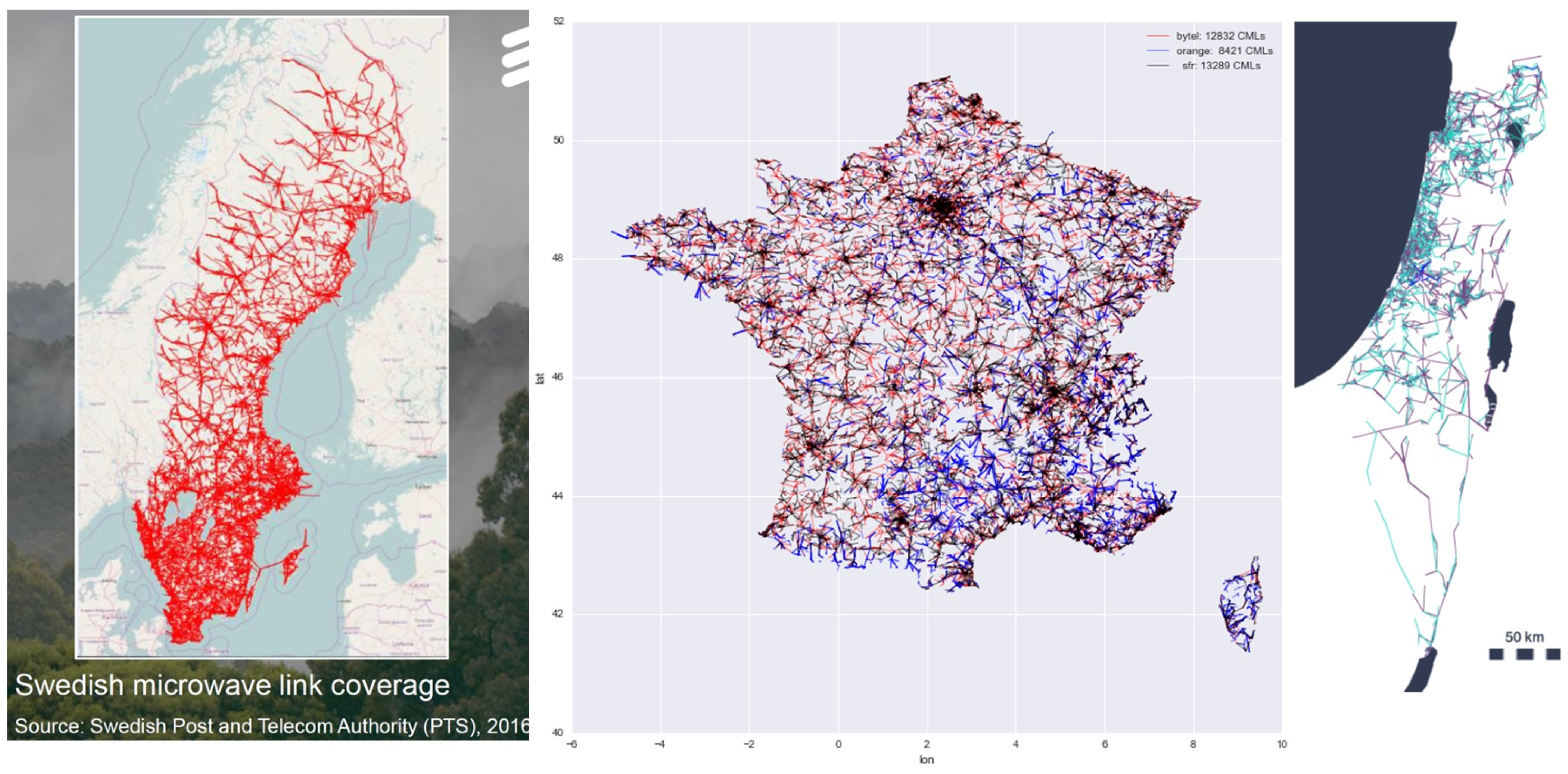
Commercial Microwave Links (CMLs) for rain detection and estimation



The relation between rain and signal attenuation is given by:

$$A = aR^bL \tag{1}$$

CMLs high coverage over land provide more than 4M sensors.



Our main contribution is in:

1. The use of records of errors in CMLs for rain monitoring.
2. The application of RNN techniques on CML data for rain monitoring.

Data description

Our data set based on actual CMLs measurements provided by the cellular company CELLCOM (Israel). Using CMLs static data $x^{(s)}$ and dynamic data RSL, TSL $x_n^{(2)}$ and Error $x_n^{(3)}$.

The link error types:

1. BBE(Background Block Error):An errored block not occurring as part of an SES.
2. ES(Errored Second):A one-second period with one or more errored blocks
3. SES(Severely Errored Second):A one-second period which contains $\geq$ 30 percentage errored blocks.
4. UAS(Unavailable Second):Intervals pertaining to an Unavailable Time.

$$x^{(s)} = [L, F_l, F_h, BW, h_s^{(n)}, h_s^{(f)}, h_a^{(n)}, h_a^{(f)}, h_b^{(n)}, h_b^{(f)}, g_a^{(n)}, g_a^{(f)}, b, C, a^{(n)}, a^{(f)}] \tag{2}$$

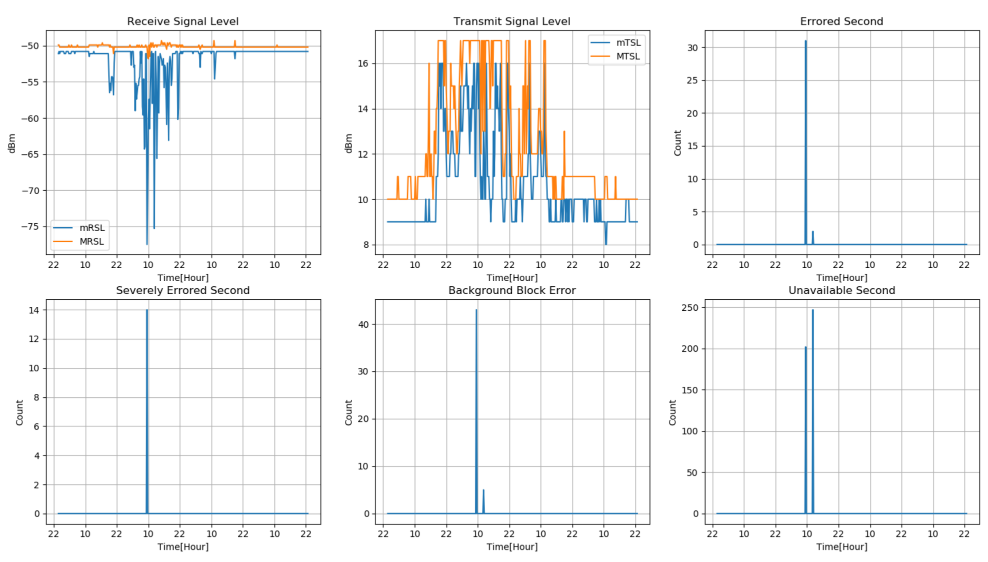
$$x_n^{(2)} = [mRSL, MRSL, mTSL, MTSL] \tag{3}$$

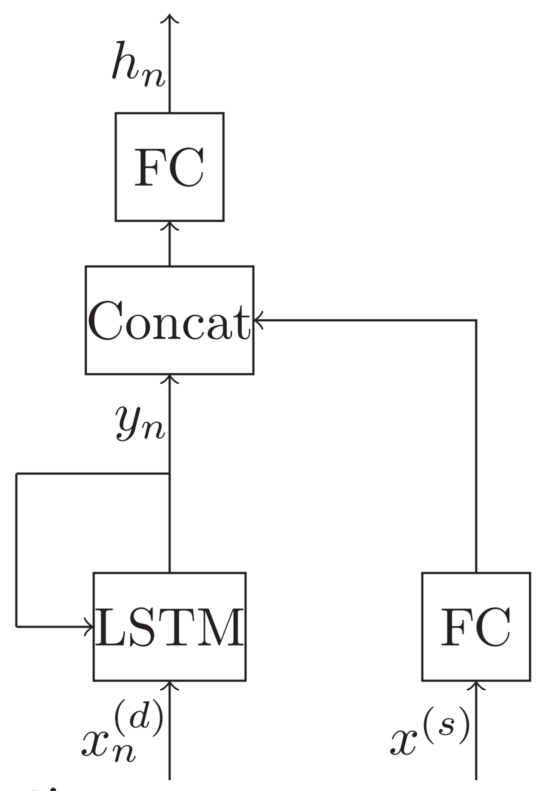
$$x_n^{(3)} = [BBE, ES, SES, UAS] \tag{4}$$

$$x_n^{(d)} = [\bar{x}_n^{(3)}, \bar{x}_{n-1}^{(3)}, \bar{x}_{n-2}^{(3)}, \bar{x}_{n-3}^{(3)}, \bar{x}_n^{(2)}, \bar{x}_{n-1}^{(2)}, \bar{x}_{n-2}^{(2)}, \bar{x}_{n-3}^{(2)}] \tag{5}$$

Method

The data preprocessing procedure:Normalization, concatenation, sub - sequences splitting and wet / dry sample alignment. The Network Architecture based on LSTM with dynamic and static inputs.





The loss function define via the flowing equations:

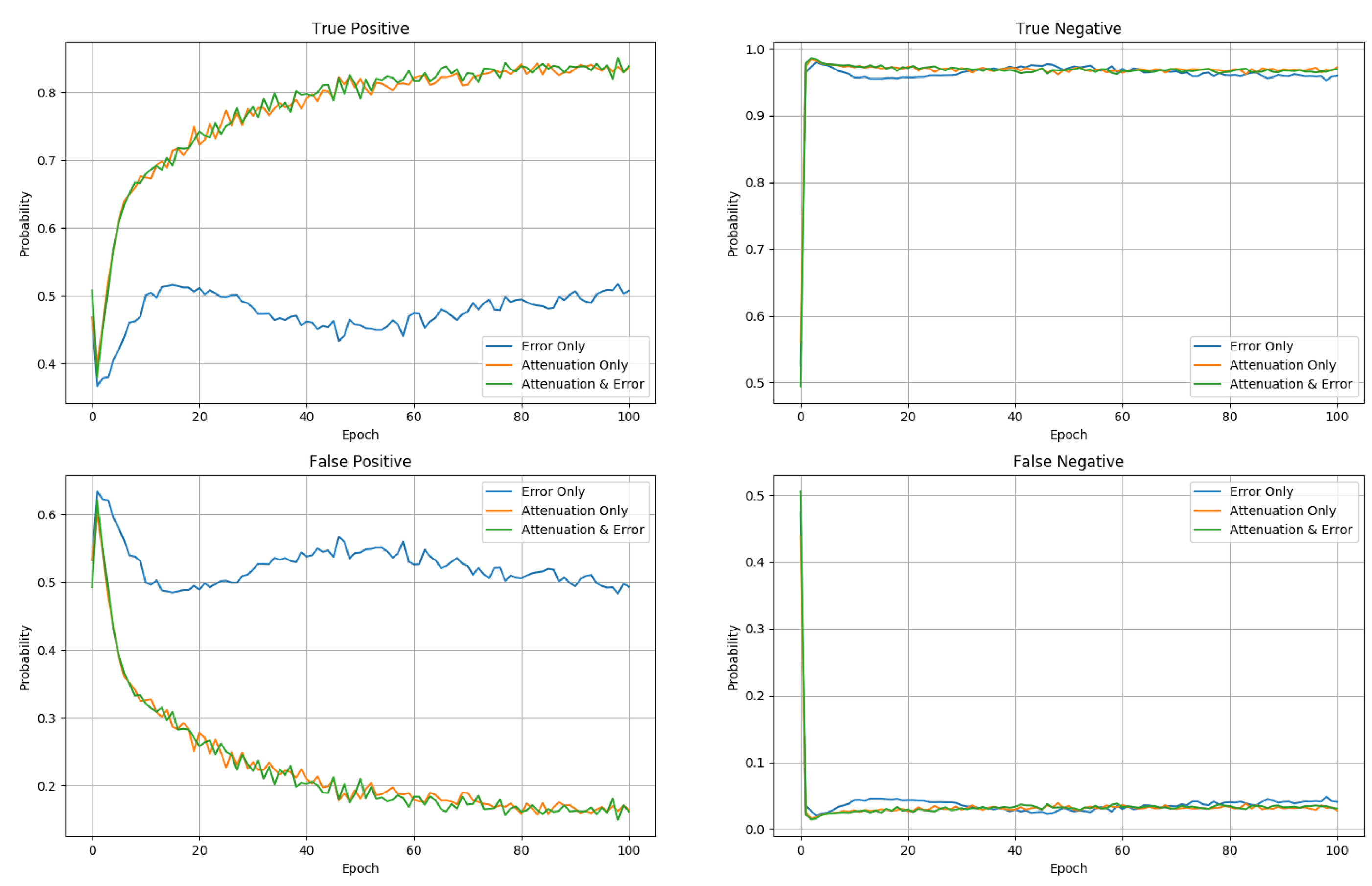
$$L = \sum_{n=0}^{N_s-1} \gamma_n \cdot L_n \tag{6}$$

Where L_n is standard Cross Entropy Loss

Experiments

We conducted three experiments, where in each case we used different dynamic input data: errors only (Eq. (4)), attenuations only (Eq. (3)), and both errors and attenuations.

The confusion matrix results over the three experiments



The experiments accuracy are shown in Table 1.

Table 1: Top epoch result

Dataset	Training	Validation
Error	76.7%	74%
Attenuation	91.5%	90.5%
Error and Attenuation	91.9%	90.8%

Acknowledgements

We would like to thank Cellcom for providing the link data that used for build the dataset, also we would like to thank the IMS for the rain gauge measurement and thank too all the research team member for there help.