ITU AI/ML IN 5G CHALLENGE

Radio Link Failure (RLF) Prediction using Weather Information

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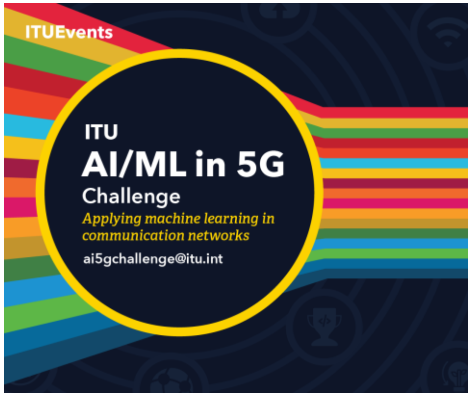

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AGENDA

1. Problem.
2. Strategy.
3. Model.
4. Performance.
5. Final remarks.
6. Q&A.

Problem

The challenge required using AI/ML for the prediction of future Radio Link Failure (RLF) occurrences (up to five days ahead).

Radio Link Failure is an anomalous condition of microwave LOS links defined by Turkcell using thresholds on standardized BBE and Unavailable Seconds key performance indicators (KPIs). Its prediction can result in mitigated downtime or reduced service degratation to the subscribers.

Problem

The dataset provided contains anonymyzed information associated to meteorological stations and RF-links, comprising:

- Weather forecasts/measurements.
- RF KPIs.
- Characterization of weather stations and RF site locations.
- Spatial information.

Particular challenges of the dataset:

- Significantly umbalanced dataset with small percentage of RLF occurrences.
- Uncertainty in regards to the origin of the weather predictions.
- Missing weather stations forecast data.
- Alignment of spatial and temporal data.

Problem

A Survey on Network Resiliency Methodologies against Weather-based Disruptions

Massimo Tornatore [*], Joao André [xiii], Péter Babarczi [¶], Torsten Braun [**], Eirik Følstad [‡‡], Poul Heegaard [‡‡], Ali Hmaity [*], Marija Furdek [§], Luisa Jorge [‡], Wojciech Kmiecik [xii], Carmen Mas Machuca [x], Lucia Martins [xiv], Carmo Medeiros [xiv], Francesco Musumeci [*], Alija Pašić [¶], Jacek Rak [‖], Steven Simpson [xi], Rui Travanca [††], Artemios Voyiatzis [†]

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Effect of sand and dust storms on microwave propagation signals in southern Libya

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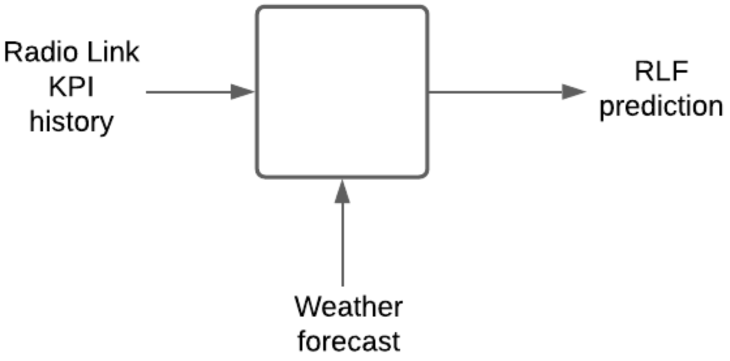
IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 58, NO. 8, OCTOBER 2009 4023

The Effects of Tropical Weather on Radio-Wave Propagation Over Foliage Channel

Yu Song Meng, *Student Member, IEEE*, Yee Hui Lee, *Member, IEEE*, and Boon Chong Ng, *Senior Member, IEEE*

Strategy

For this binary classification task, our team envisioned a simple model that would predict the occurrence of RLF per Mini-Link ID (MLID) in the next day(s) using the MLID's own **Radio Link KPI history** and its associated **weather forecast data** as inputs to produce **actionable information**.



The assumption here is that the KPI history of the Radio Link would provide short-term information concerning the susceptibility of the Radio Link to degradation/failure, while the forecast would provide information on the expected conditions the link would face in the immediate future.

Model

For simplicity when building our model:

- The KPI history used is the previous day's data only.
- The weather forecast used is the next day's only, and belongs to the closest meteorological station to the RF site of interest.

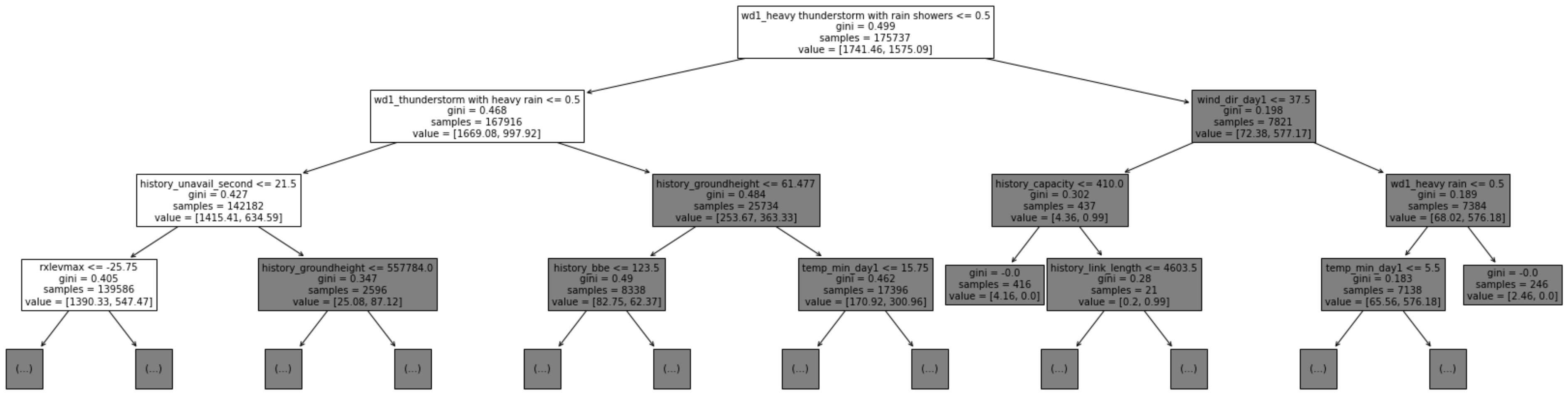
Our experiments and discussions supported the use of a Decision Tree Classifier as the preferred model in order to:

- Maximize interpretability.
- Make our model robust against feature scaling issues.
- Use the embedded feature importance capability for dimensionality reduction.

Model

Model details:

- Implemented using the ‘DecisionTreeClassifier’ from scikit-learn.
- Low Depth (i.e., 7 levels).
- Handling the unbalaced dataset required the use of class weights {FALSE:0.01, TRUE:0.99}.
- Only requires 29 input features for the prediction.



Performance over First Dataset

Accuracy:

Accuracy	0.9013
Cross-validation Accuracy	0.8608 (+/- 0.0740)
Test Set Error	0.8977

Confusion matrix for the validation subset:

	Predicted RLF = FALSE	Predicted RLF = TRUE
True RLF = FALSE	67222	7430
True RLF = TRUE	276	398

Classification report for the validation set:

Class	Precision	Recall	F1-score	Support
RLF = FALSE	1.00	0.90	0.95	74652
RLF = TRUE	0.05	0.59	0.09	674
Macro AVG	0.52	0.75	0.52	75326
Weighted AVG	0.99	0.90	0.94	75326

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Performance over Second Dataset

Accuracy:

Accuracy	0.9089

Confusion matrix:

	Predicted RLF = FALSE	Predicted RLF = TRUE
True RLF = FALSE	15668	1561
True RLF = TRUE	9	4

Classification report for the validation set:

Class	Precision	Recall	F1-score	Support
RLF = FALSE	1.00	0.91	0.95	17229
RLF = TRUE	0.00	0.31	0.01	13
Macro AVG	0.50	0.61	0.48	17242
Weighted AVG	1.00	0.91	0.95	17242

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Model

Final remarks:

- Our model is as good as the weather predictions. The source of the weather forecasts, their accuracy, and consistency are the most important characteristics exploited by our model.

- During the development we observed better results at trying to estimate the RLF occurence directly from the weather forecast, rather than for estimating intermediate KPIs. These results were counter-intuitive and require more analysis.

Questions