PREDICTING ELECTRICITY OUTAGES CAUSED BY CONVECTIVE STORMS

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Introduction

Objective

Severe convective weather like thunder storms cause significant harm for electricity supply in Finland.

Prediction of damages caused by extreme weather events is crucial for operators.

We designed real-time prediction of short-term damage potential.

Overall Method

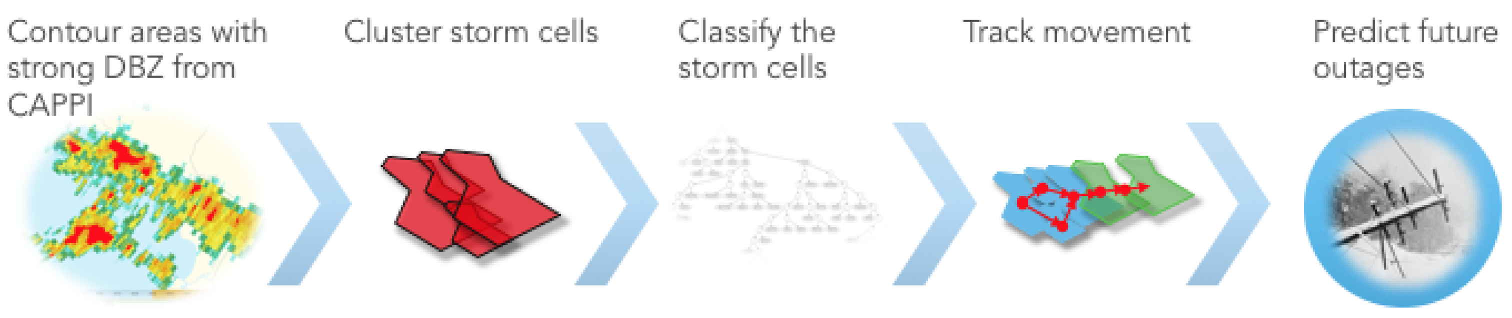

Figure 1: We have used the methods developed in [1] for overall process.

Classification

Convective weather are categorised based on how large share of transformers under the storm are without electricity.

Four categories listed in table 1.

Definition of categories convenient for the end user (power grid operators).

Table 1: Class definitions of the storm cells

Class	Share of transformers	Number of samples
0	no damage	551 029
1	0 - 10 %	4 919
2	10 - 50 %	4 286
3	50 - 100 %	3 337

Data

- Consists of two components: weather data by FMI and outage recordings by power grid operator
- Weather data collected by FMI during years 2012 to 2017 with 5 minutes resolution
- Contoured storm cells characterised by the list of features listed in Table 2
- The data is very imbalanced (see Figure 2)

Features

Table 2: Used input features

Feature	Explanation
Area	Area covered by the storm cell
Age	Age of the storm
Lightning density	Lightning density under storm cell
Max DBZ	Maximum radar reflectivity of the storm cell (spatially). Represents maximum rain intensity.
Min DBZ	Minimum radar reflectivity of the storm cell (spatially). Represents minimum rain intensity.
Mean DBZ	Mean radar reflectivity of the storm cell (spatially)
Median DBZ	Median radar reflectivity of the storm cell (spatially)
Std of DBZ	Standard deviation of radar reflectivity of the storm cell (spatially)
Lat	Storm center latitude
Lon	Storm center longitude
Temperature	Air temperature from ground observations
Pressure	Air pressure from ground observations
Wind speed	Wind speed from ground observations
Wind direction	Wind direction from ground observations
Precipitation amount	Precipitation amount from ground observations
Snow depth	Snow depth from ground observations

Labels

- Outage data and power grid description are fetched from two power distribution companies.
- The data set contains in total 33 858 observed outages.
  - Many of observed outages not related to weather (reason not known)
  - Severe storms cause hundreds of outages

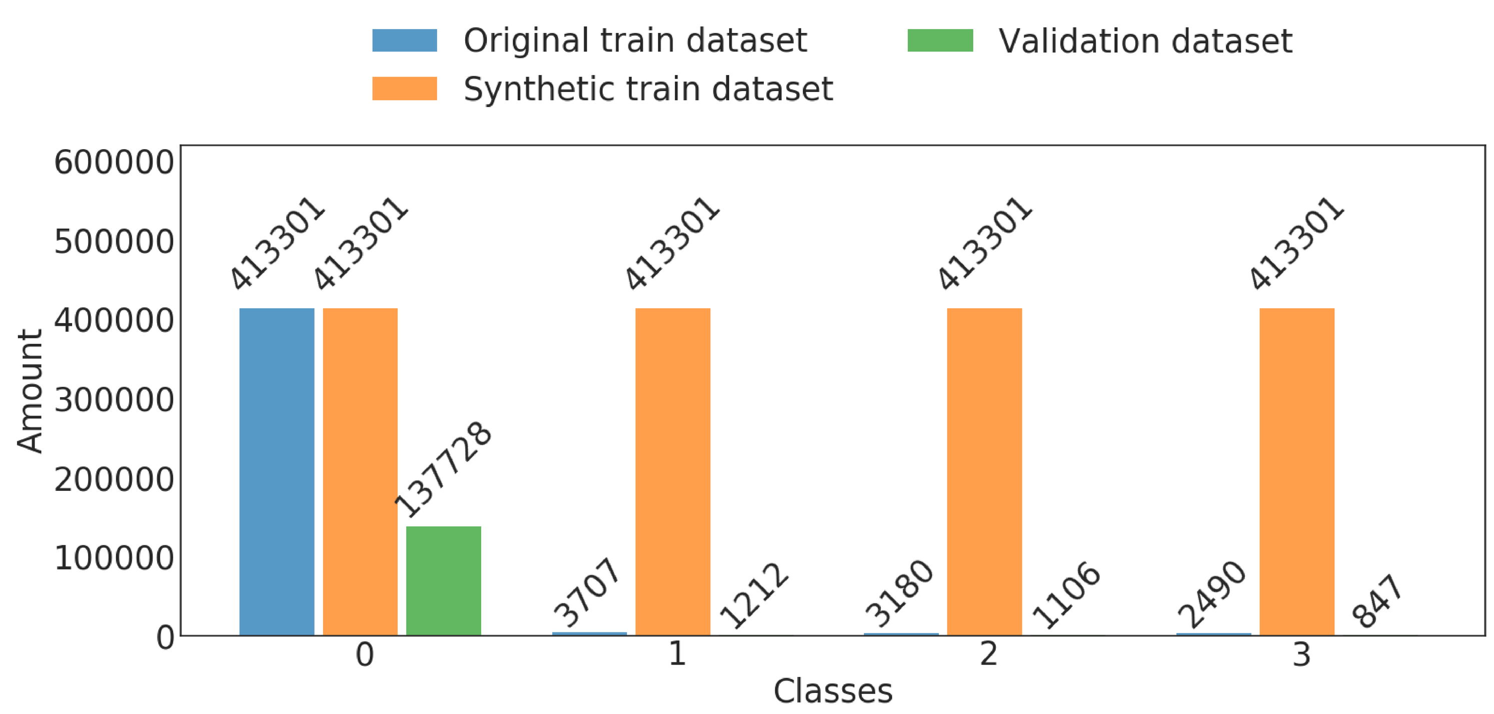

Figure 2: Histogram of storm cells belonging to different classes in train dataset

Classification Methods

Consider two alternative methods for classification.

1. **Random Forest Classificator** (RFC):
   - No limitations in tree size.
   - Forrest with 200 trees and equal class weights.
   - Gini impurity used as a loss function.
   - Works sufficiently with imbalanced data (no SMOTE or other techniques needed).
2. **Multi Layer Perceptron** (MLP):
   - Cross entropy used as loss function.
   - Imbalanced classes was handled with synthetic minority over-sampling technique (SMOTE) [2].
   - Hyper parameters shown in the table 3.

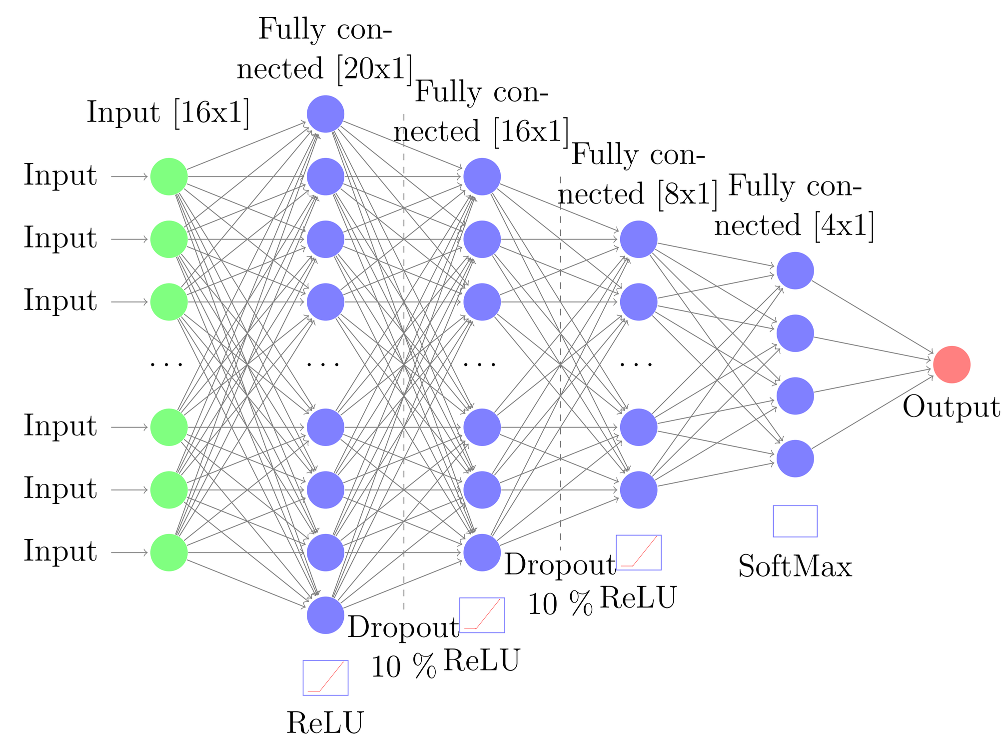

Figure 3: Network structure of MLP

Table 3: Hyperparameters of the MLP

Parameter	Value
Batch size	256
Epoch count	1000
Dropout probability	10 %
α (learning rate)	0.001
β_1 (exp decay for momentum)	0.9
β_2 (exp decay for momentum)	0.999
ϵ (stability constant)	10^{-8}
Initial decay	no decay

Results

RFC and MLP allow to reasonably predict amount of damage.

RFC shows slightly better performance.

Metrics	MLP SMOTE	RFC
AUC	96 %	99 %
Validation accuracy	89 %	96 %
F1 score micro average	71 %	99 %

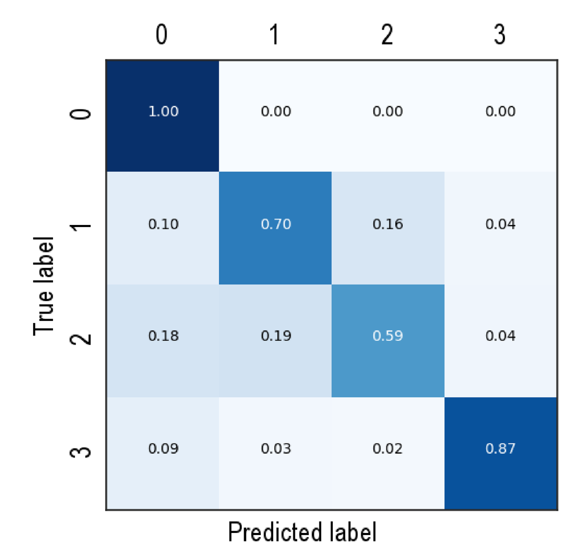

Figure 4: Confusion matrix of RFC

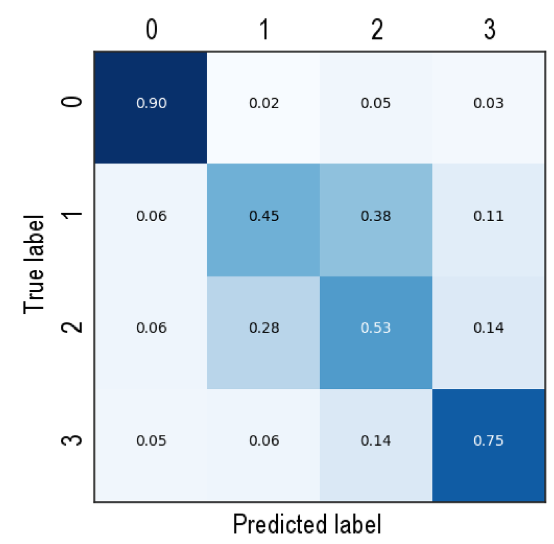

Figure 5: Confusion matrix of MLP

Conclusion

Random Forest Classifier allows for reasonable prediction of weather based electricity outages.

Future Work

- Use more advanced time-series models (recurrent neural networks)
- Combine our approach with Rate-Transfer algorithm [3] to cope with imbalanced data.

References

[1] Pekka Juhana Rossi, *Object-Oriented Analysis and Nowcasting of Convective Storms in Finland*, Ph.D. thesis, Aalto University, 2015.

[2] Nitesh V. Chawla, Kevin W. Bowyer, Lawrence O. Hall, and W. Philip Kegelmeyer, "Smote: synthetic minority over-sampling technique," *Journal of artificial intelligence research*, vol. 16, pp. 321–357, 2002.

[3] Samir Al-Stouhi and Chandan K Reddy, "Transfer learning for class imbalance problems with inadequate data," *Knowledge and information systems*, vol. 48, no. 1, pp. 201–228, 2016.

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