Forecasting Spread F at Jicamarca

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Introduction

Ionospheric dynamics are governed by the interaction of non-linear mechanisms. Equatorial Spread F (ESF) is one of the phenomena that occurs in this region and it may have a negative impact on radiowave propagation related to satellite communications and radio navigation systems. Thus, it is crucial to develop a predictive tool that leverages the vast data captured by different radar systems in order to give estimates of when Spread F events will occur. Even though some tools exist for this task, most of them are based on statistical models that capture the climatological behavior of ESF occurrence but may be incapable of capturing day-to-day variability.

Measurements

JULIA (Jicamarca Unattended Long-term Investigations of the Ionosphere and Atmosphere) radar observations were used to determine ESF occurrences. The geophysical parameters used as inputs consist of Jicamarca's digisonde measurement as well as global parameters. The dataset used spans the years from 2000 to 2020.

Data processing

We followed the same ESF characterization process as in Zhan, Rodrigues and Milla (2018). Furthermore, since all of the relevant information for our supervised learning algorithm lies on the time axis, we collapsed the height axis.

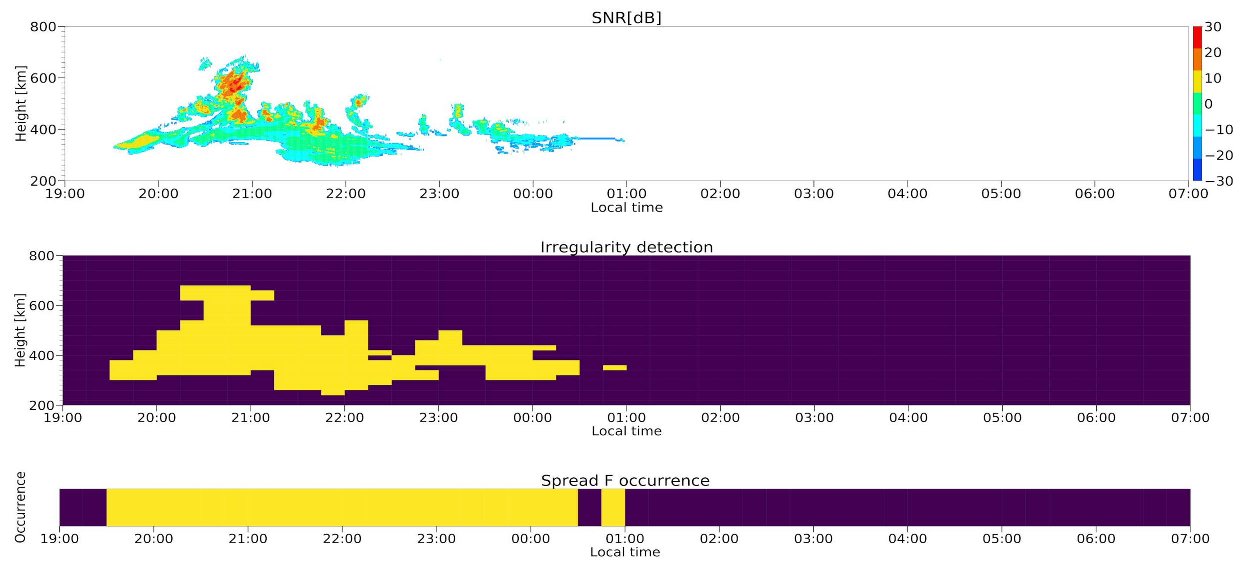

Figure 1. ESF occurrence characterization for January 2nd, 2000.

ESF occurrences for each day were stored as a time series and later merged with digisonde measurements and global parameters.

Datasets

We split our entire dataset in 3 subsets: Training, Validation and Testing datasets.

Figure 2. The entire dataset, sorted by date and time, was split in 70% training, 20% validation and 10% testing.

Neural Network Inputs

Rationale

h'F (1930 LT): "The height of the nighttime F layer is the single most important parameter controlling the generation of spread F" (Fejer et al, 1999). We use the time 1930 LT for two reasons: The onset time of spread F is usually around 1920 LT and 1945 LT for equinox and December solstice (Chapagain et al, 2009) and also because we compare our model with the FIRST.
h'F (prev. 30 min): This is the first value of h'F for which we have available data between 1900 LT and 1930 LT. This might indicate how fast the F layer has risen in the past 30 minutes.
F10.7: Correlates with onset altitude.
F10.7 (90 days): This is an average value of solar flux index in the last 90 days and it provides some information about the solar cycle.
Ap, Ap (24 h): Geomagnetic activity, depending on the local time, season and solar cycle, affects the occurrence of irregularities (Hysell and Burcham, 2002).
Day of the year: This is relevant mainly due to of the season-to-season variability.

Input pre-processing

All inputs passed to the model must be scaled because it makes a big difference when using steepest descent (Hinton et al). Geophysical parameters take a range of values that escape a small range such as [0, 1], so we applied `sklearn.preprocessing.MinMaxScaler` to fit the values into the desired range. The day of the year however, is a periodic variable and, as such, should not be dependent on the choice of origin (Bishop, 2011).

DNS = sin(2πD/365), DNC = cos(2πD/365), D: Day of year (1-365)

Model

Architecture

It consists of a Multilayer Perceptron with ELU as activation function. It outputs a real number which, when passed to a sigmoid function, can be interpreted as the probability of occurrence.

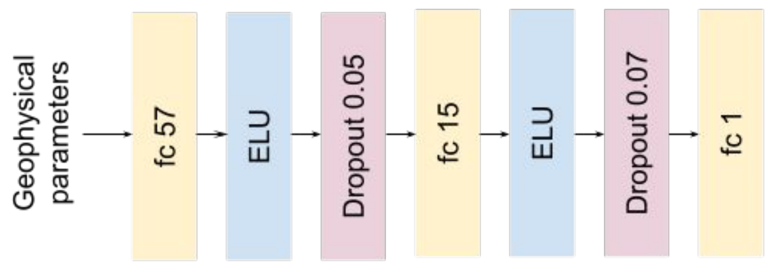

Figure 3. Neural Network Architecture.

In Figure 3, fc X is a fully-connected layer with X units. An activation function adds non-linearity to the network allowing it to learn from higher-level representations. Dropout p is a layer which, with probability p, sets to 0 the output of any unit.

Optimization

Training

Parameter optimization was carried out with the Adam algorithm for 30 epochs. The loss function used was `torch.nn.BCEWithLogitsLoss`.

Hyper-parameter configuration search

The model proposed corresponds to the best Optuna trial. This library implements the Sequential Model-Based Optimization algorithm that uses a Tree-structured Parzen Estimator as surrogate. We used a number of folds to partition the dataset by years and progressively added years one by one to the training dataset while shifting the validation dataset by one year. We aimed to maximize the average accuracy across all folds. The years used in this optimization process span from 2002 to 2018. As shown in Figure 5, we conducted 400 trials.

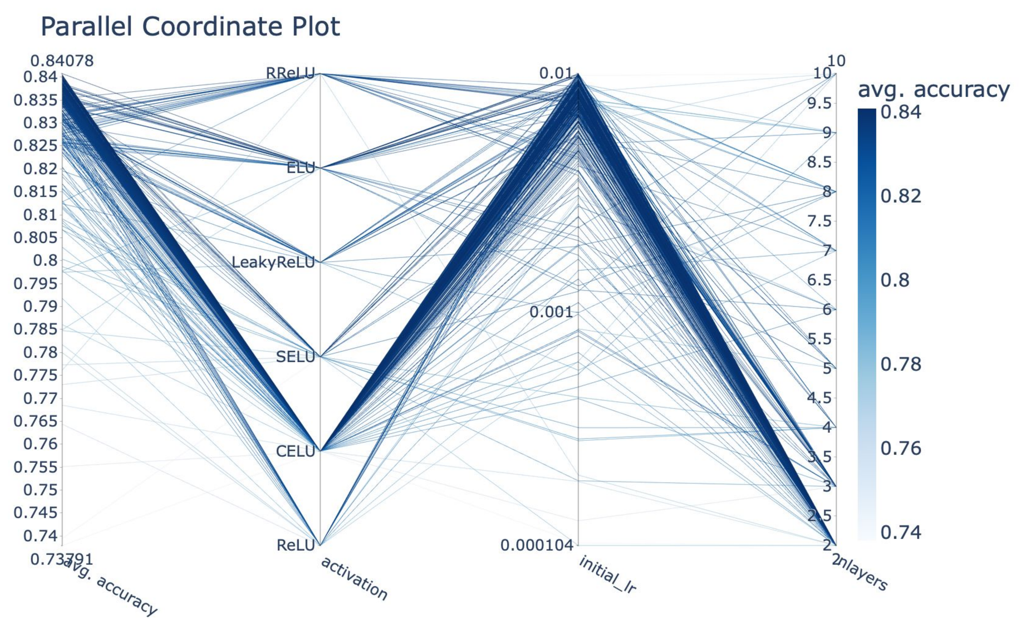

Figure 4. Hyper-parameter configurations and their corresponding average accuracy.

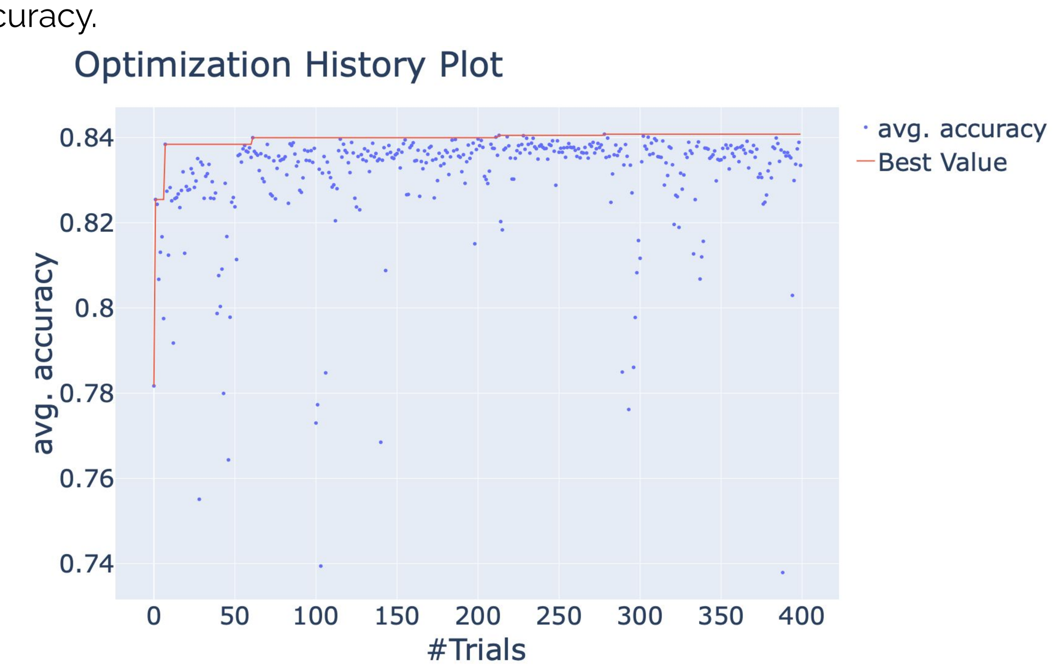

Figure 5. Optimization history.

Input Sensitivity

Figure 6 presents feature importance and the effect that each feature on the predictions made by the model for 300 instances from the dataset. Features are sorted in descending order according their importance.

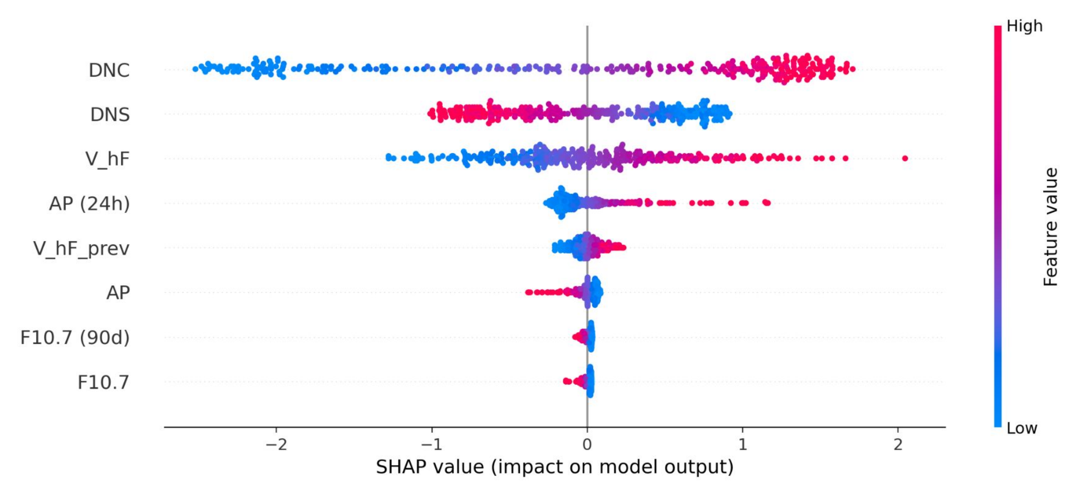

Figure 6. Shap summary plot.

Results

These results correspond to the evaluation and comparison of our model and FIRST on the testing dataset. It is important to point out that, in this work, FIRST is evaluated with occurrences obtained from the characterization presented earlier as opposed to the evaluation in Anderson and Redmon (2017), which apparently used occurrences from manually labeled ionograms. There were a total of 69 days for which FIRST did not make a prediction.

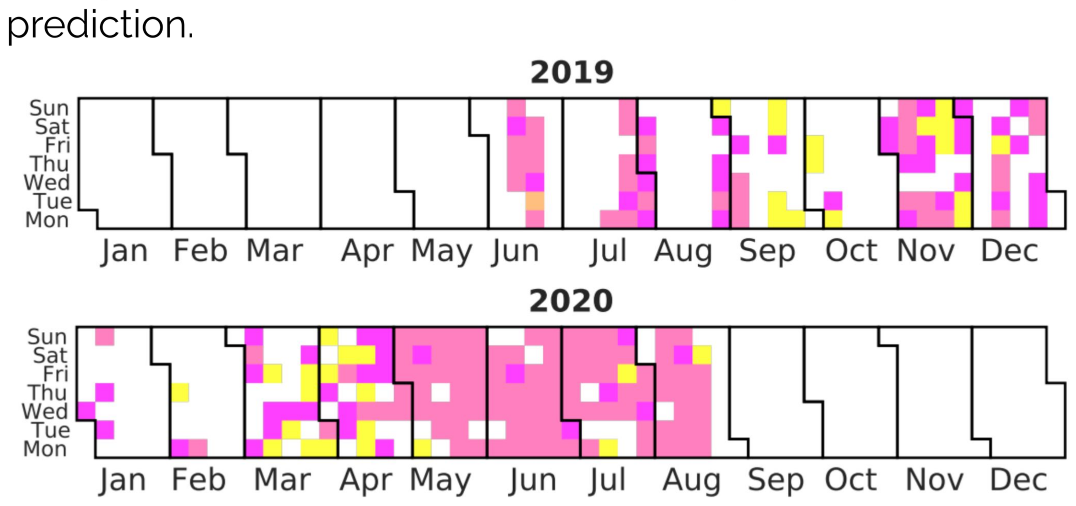

Figure 7. Evaluation of FIRST.

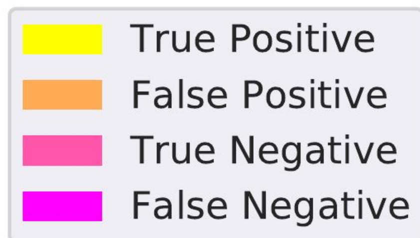

Figure 8. Color map for the confusion calendars and matrices.
True positive: The model predicted that Spread F would occur, and it did.
False positive: The model predicted that Spread F would occur, but it did not.
True negative: The model predicted that Spread F would not occur, and it did not.
False negative: The model predicted that Spread F would not occur, but it did.

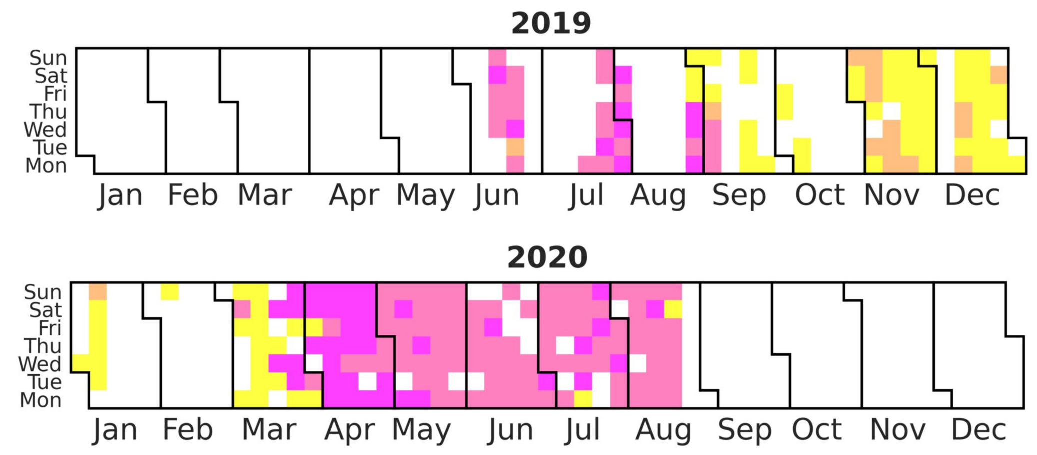

Figure 9. Evaluation of our model.

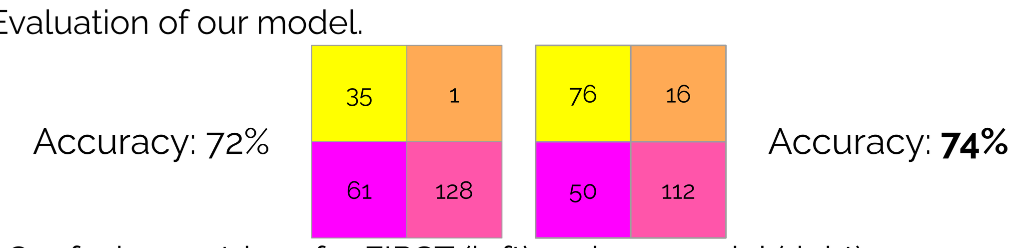

Figure 10. Confusion matrices for FIRST (left) and our model (right).

Conclusions

The most important geophysical parameters appear to be the day of the year and h'F. In addition, our preliminary results suggest that the predictive power of our model is slightly better than FIRST but further analysis is required to validate this claim. Previously, we trained a bigger model for which we did not conduct hyper-parameter optimization and obtained a higher accuracy. We hypothesize that might happen because the average accuracy is not the best metric to optimize and we should use a weighted average instead. Another hypothesis is that since we are using a different year for each fold to evaluate the model during the hyper-parameter optimization, the year-to-year variability becomes irrelevant and, as a result, the optimization algorithm chooses an oversimplified architecture.

Future work

- Extend the model to make predictions for different times of the night.
- Use GANs to model RTI evolution throughout the night.
- Explore proxies for the growth rate to evaluate if they could also be passed as inputs to a predictive model.
- Predict drifts from geophysical parameters such as h'F.

Acknowledgements

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