# Time Series Forecasting

## USING LSTM

Marc Rodriguez Rodriguez
Isaac Pérez Anguiano

upf. Universitat Pompeu Fabra Barcelona

# OVERVIEW

1. Introduction
2. State of the Art
3. Methodology
   - Data analysis
   - Models and optimizations
4. Experiments
5. Results
6. Discussion
7. Conclusions
8. References

upf. Universitat Pompeu Fabra Barcelona

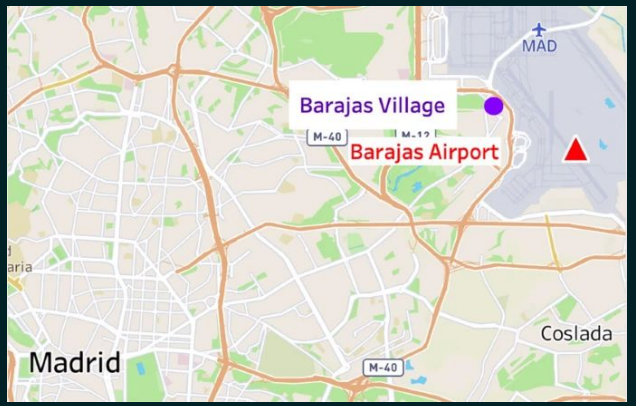
# INTRODUCTION

- Accurate daily weather prediction model using LSTM networks.
- Relevant for sectors like agriculture and urban planning.

upf. Universitat Pompeu Fabra Barcelona

# STATE OF THE ART

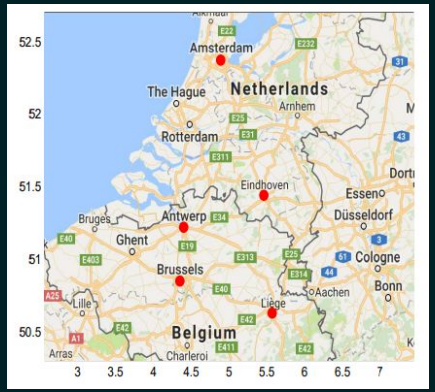
Modelling time series with multiple seasonalities: an application to hourly NO pollution levels (by M. Avila, A. Alonso & D. Peña) [1]




Air quality station in Barajas, Madrid

# STATE OF THE ART

Spatio-temporal Stacked LSTM for temperature Prediction in Weather Forecasting (by Z. Karevan & J.A.K. Suykens) [2]

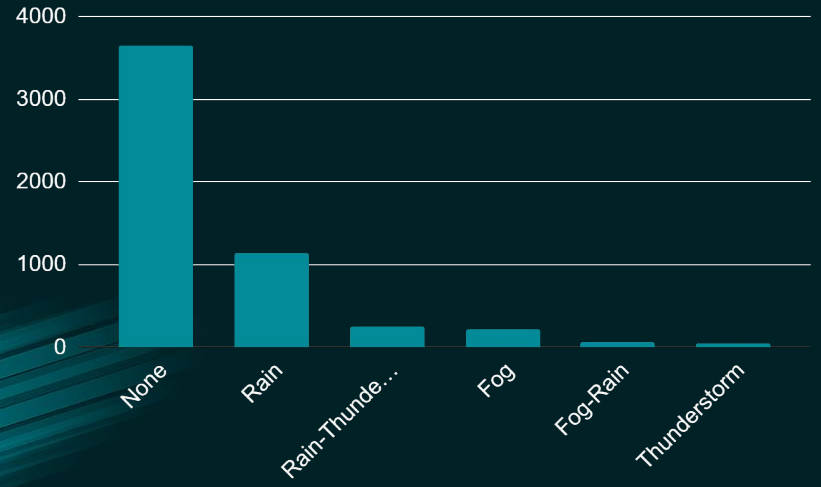


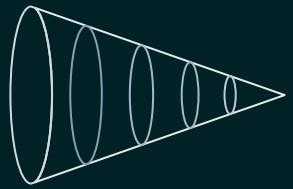

Map of weather stations in Belgium and Netherlands

upf. Universitat Pompeu Fabra Barcelona

# DATA ANALYSIS

## Cleaning events label:

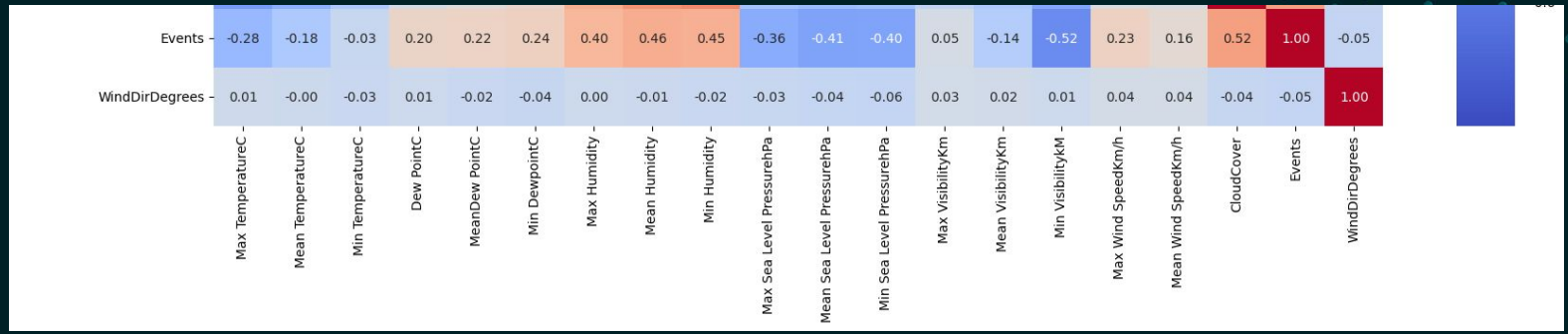


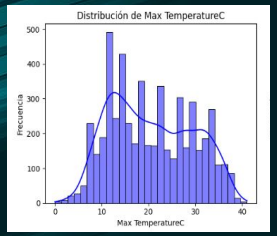

upf. Universitat Pompeu Fabra Barcelona

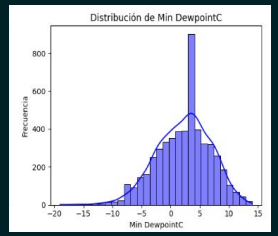
# DATA ANALYSIS

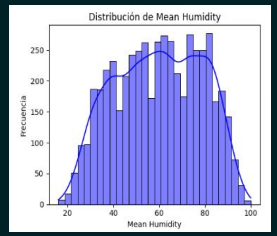
Deciding the features:

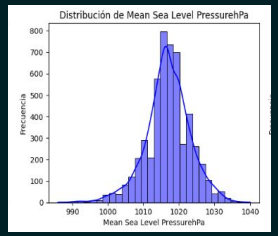


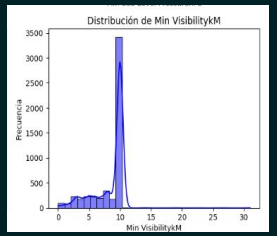

Part of correlation matrix

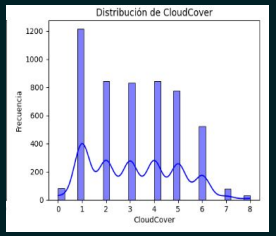


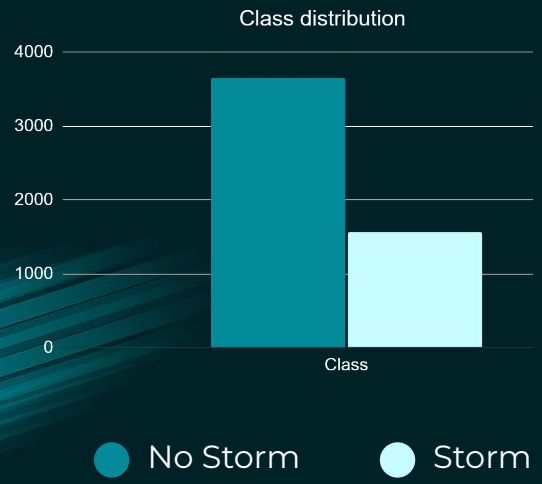



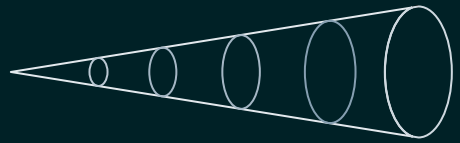

Distribution of features that have high correlation with Events

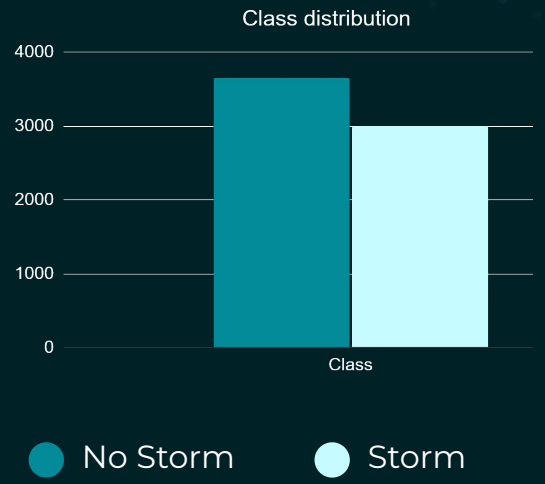
Universitat Pompeu Fabra Barcelona

# DATA ANALYSIS

Data augmentation:






upf. Universitat Pompeu Fabra Barcelona

# MODELS AND OPTIMIZATION

## Architecture

We implemented a LSTM architecture

## Training procedures

Supervised training using Adam optimizer with backpropagation over multiple epochs

## Loss functions

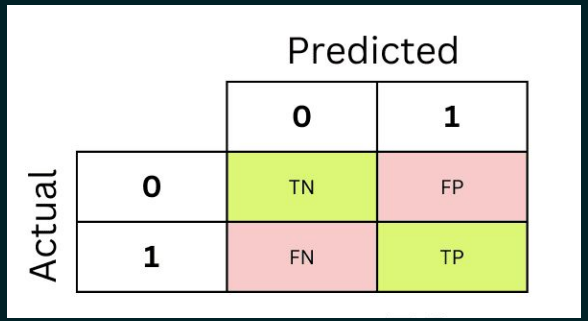
We used the binary cross entropy function

## Hyperparameters

Hyperparameters include input size, hidden size and number of layers

# EXPERIMENTS

- Cross Entropy vs Binary Cross Entropy
- Giving importance to recall
- Other metrics: loss, accuracy, precision, auc-roc




Example of confusion matrix

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Computation of precision and recall

# RESULTS

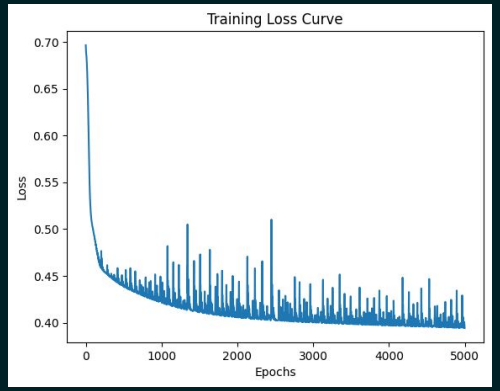
| Hidden size | Number of layers | Test loss | Test accuracy | Test recall |
|---|---|---|---|---|
| 32 | 1 | 0.4275 | 80.39% | 77.33% |
| 64 | 1 | 0.4033 | 81.74% | 80.33% |
| 128 | 1 | 0.4008 | 81.22% | 75.67% |
| 32 | 2 | 0.4208 | 81.67% | 79.67% |
| 64 | 2 | 0.4019 | 82.12% | 79.33% |
| 128 | 2 | 0.3953 | 81.44% | 81.83% |

Test results of the model with differents hyperparameters

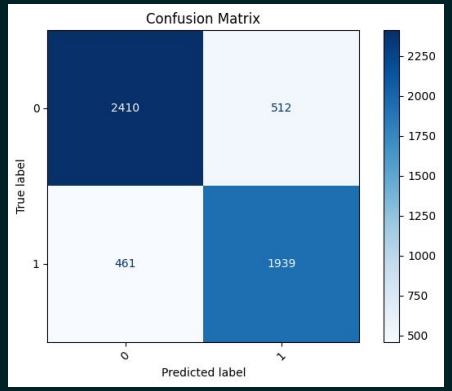
# RESULTS

Training results of LSTM with HS = 128 & L = 2:

| Loss | Accuracy | Precision | Recall | AUC-ROC |
|---|---|---|---|---|
| 0.3949 | 81.72% | 79.11% | 80.79% | 90.04% |




Training Loss Curve




Training Confusion matrix

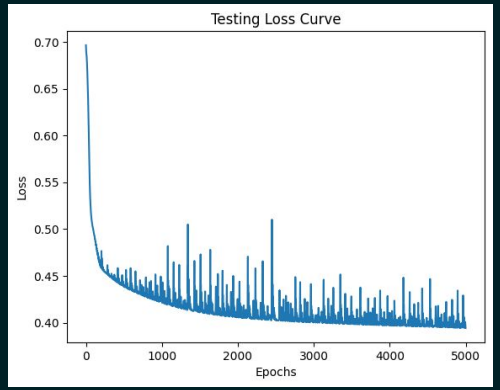
Loss, accuracy, precision, recall and AUC-ROC of training set

upf. Universitat Pompeu Fabra Barcelona

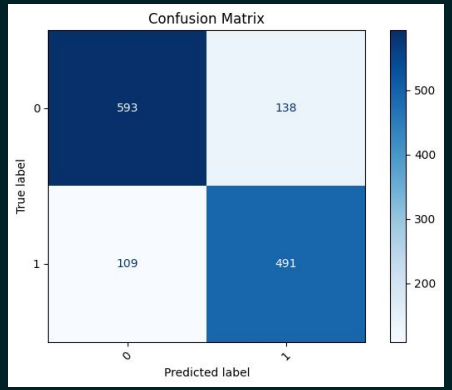
# RESULTS

Testing results of LSTM with HS = 128 & L = 2:

| Loss | Accuracy | Precision | Recall | AUC-ROC |
|---|---|---|---|---|
| 0.3953 | 81.44% | 78.06% | 81.83% | 90.11% |




Testing Loss Curve




Testing Confusion matrix

Loss, accuracy, precision, recall and AUC-ROC of testing set

upf. Universitat Pompeu Fabra Barcelona

# DISCUSSION

- Increasing hidden size (32 → 64) improved accuracy, recall, and reduced loss
- More layers (1 → 2) led to better recall and lower loss in most cases
- Best model: 2 layers, 128 hidden units

- Limitations:
  - Larger models didn't always outperform simpler ones
  - Limited size of the dataset

# CONCLUSION

- Main findings:
  - LSTM work for time series forecasting
  - Higher complexity usually leads to better performance
  - Importance of cleaning and prepare data

- Challenge: Balancing complexity vs. generalization

- Possible improvements:
  - Try different activation functions (tanh, ReLU, ...)
  - Test on more and better datasets to validate generalization

# REFERENCES


- [1] Avila, Matias & Alonso, Andres & Peña, Daniel. (2023). Modelling multiple seasonalities with ARIMA: Forecasting Madrid NO2 hourly pollution levels. https://doi.org/10.1007/s00477-025-02958-6
- [2] Karevan, Z., & Suykens, J. A. K. (2018). Spatio-temporal stacked LSTM for temperature prediction in weather forecasting. arXiv. https://doi.org/10.48550/arXiv.1811.06341



upf. Universitat Pompeu Fabra Barcelona

# THANKS!

Do you have any questions?




Universitat Pompeu Fabra Barcelona