

CS 334: Machine Learning

Emory University

Fall 2023

Aadi Waghray and Joshua Sun

CS334 Final Report

Aadi Waghray and Joshua Sun

Abstract

Abstract text

Introduction

Predicting the weather has always been an important task in everyday life. From a simple decision of bringing an umbrella, to more complicated decisions of watering crops for agriculture or evacuating citizens for a flood, predicting precipitation is an important objective. Prior studies into predicting rainfall have been successful. The studies used models and techniques such as SVMs, Extreme Gradient Boosting, Decision Trees, and LSTMs. [3, 1, 5] We planned to use similar models in our study.

Our study is using the NOAA quality controlled datasets [2] as well U.S. Local Climatological Data from NOAA[4]. The quality controlled dataset is split up into monthly, daily, hourly, and sub-hourly datasets. Each dataset collects various atmospheric and earth data from various weather stations across the US. Similarly, the USLCD does the same, with more detail, but much more missing data. Prior studies into predicting precipitation used only one source of data. Our study is unique in attempting to augment the quality controlled datasets with more features. We specifically focus on data collected from Brunswick, GA.

Methodology

We first needed to preprocess our data. We first took the quality controlled data, and filtered the data to get rid of bad data. Conveniently, packaged with the data, were instructions on certain fields. For example, `ST_FLAG` is a field described such that, when the value is greater than 0, an error has occurred in the raw data gathering. Similarly, certain numeric fields, such as `P_PRECIP`, an extremely low value is written to the field if it is missing.

Continuing, certain fields are non-numeric, and needed to be removed, such as those fields. The fields removed without computation were

- `WBANNO`
- `LST_DATE`

- LST_TIME
- CRX_VN
- SUR_TEMP_TYPE
- SOLARAD_FLAG
- SOLARAD_FLAG
- SOLARAD_MAX_FLAG
- SOLARAD_MIN_FLAG
- SUR_TEMP_FLAG
- SUR_TEMP_MAX_FLAG
- SUR_TEMP_MIN_FLAG

Clearly the flags were removed, as they only gave error information. The station name is the same for all pieces of data. We removed the local time because we already have UTC time to extract information.

To extract more features, we converted `UTC_DATE` and `UTC_TIME` to a python `datetime` column labeled `DATE`.

Results

Results text

Conclusions

Conclusions text

Code

Code text

References

- [1] Ari Yair Barrera-Animas et al. “Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting”. In: *Machine Learning with Applications* 7 (Mar. 2022), p. 100204. ISSN: 26668270. DOI: 10.1016/j.mlwa.2021.100204. URL: <https://linkinghub.elsevier.com/retrieve/pii/S266682702100102X> (visited on 12/07/2023).
- [2] Howard J. Diamond et al. “U.S. Climate Reference Network after One Decade of Operations: Status and Assessment”. In: *Bulletin of the American Meteorological Society* 94.4 (Apr. 1, 2013), pp. 485–498. ISSN: 1520-0477. DOI: 10.1175/BAMS-D-12-00170.1. URL: <https://journals.ametsoc.org/doi/10.1175/BAMS-D-12-00170.1> (visited on 12/07/2023).
- [3] Chalachew Muluken Liyew and Haileyesus Amsaya Melese. “Machine learning techniques to predict daily rainfall amount”. In: *Journal of Big Data* 8.1 (Dec. 2021), p. 153. ISSN: 2196-1115. DOI: 10.1186/s40537-021-00545-4. URL: <https://journalofbigdata.springeropen.com/articles/10.1186/s40537-021-00545-4> (visited on 12/07/2023).
- [4] *Local Climatological Data (LCD) Publication*. URL: <https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00128> (visited on 12/13/2023).
- [5] Atta-ur Rahman et al. “Rainfall Prediction System Using Machine Learning Fusion for Smart Cities”. In: *Sensors* 22.9 (May 4, 2022), p. 3504.

ISSN: 1424-8220. DOI: 10.3390/s22093504. URL: <https://www.mdpi.com/1424-8220/22/9/3504> (visited on 12/07/2023).