ForecastAI Project

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C951 PA Task 3

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Project Overview

A1. Organizational Need

At the Weather Company, we pride ourselves on our accurate forecasting that is enjoyed by thousands of Americans. One of our most popular offerings is the Weather Channel, an app that provides weather forecasts for the upcoming 10 days. This 10-day restriction is largely due to limits on how the physical models that drive our forecasting perform. A deep learning weather prediction algorithm would allow us to make fast and accurate predictions that could extend beyond that 10-day period.

A2. Context and Background

Meteorology and Weather Forecasting is an important part of the Weather Company's offerings. Our Weather Channel provides forecasting to Americans across the country, so it is important that our company is always ensuring that our forecasts are as accurate and up to date as possible. As with most predictions in the field of meteorology, our forecasts are made through physical models that simulate the Earth as if the atmosphere was a liquid. "The present state of the atmosphere is sampled, and the future state is computed" through differential equations and thermodynamics (Holmstrom et al., 2016). As the traditional method of forecasting, these physical models are used by meteorologists and weather forecasters across the globe to predict incoming weather. However, these models can be costly and time-consuming to use and fall apart when making long-term forecasts greater than 10 days (Holmstrom et al., 2016). This is an opportunity for us to implement a data-driven approach that uses AI, with the implementation of a deep learning weather prediction algorithm. This would allow us to make fast and accurate predictions about weather, especially when it comes to forecasting more than 10 days in advance.

A3a. Review of Outside Material

The implementation of a machine learning algorithm is an amazing opportunity for the Weather Company. Machine learning has been in use for weather forecasting since the 1990s, over time growing faster and more reliable (Olivetti & Messori, 2024). The Weather Company has over 30 years worth of data and examples to draw from when it comes to the development of our prediction AI. This AI could outperform the traditional models we have been using, as "at least seven different research groups… claim to have developed deep learning models able to forecast… with greater accuracy" than the leading physical models employed by the European Centre of Medium Range Weather Forecasts (Olivetti & Messori, 2024). With the growing strengths of AI-driven forecasting, many Americans will be looking to us as the leading American forecasters to implement AI prediction models into our app.

While in the past, deep learning models for forecasting may have been slow and inaccurate, recent developments in the field of AI and forecasting have made recent models faster and more accurate. One way AI-based forecasting has been improved is through the use of "ensembles," or bundles of multiple machine learning models that have their predictions averaged out in order to improve their accuracy (Holmstrom et al., 2016). By training multiple models of forecasting AI and having them work in unison, the Weather Company can enjoy accurate predictions without having to employ a physical model. These predictions would also be quicker than a traditional model. One key strength of a data-driven approach is that after training a machine learning algorithm, its predictions can be "orders of magnitude faster than [traditional physical models]" (Holmstrom et al., 2016). Between the speed and accuracy of machine learning, an AI-based approach is perfect for the Weather Company.

Deep learning models represent an opportunity for our company, as traditional physical models are very costly and time-consuming to build and run, while Ai-driven models are cheap and only require a short period of training before they can be used. When using a traditional model, "the computational cost… greatly hinders the improvements" that can be made to the system (Magnusson et al., 2024). Implementing a deep learning model would allow our company to spend less on physical models and divert that funding to other, more important places. AI models also offer "reasonable results beyond" the 10-day period that traditional physical models are constrained by (Magnusson et al., 2024). This means that our company could use AI to offer forecasts that extend well beyond the forecasts offered by our current systems or those of competing companies.

A4. Machine Learning Solution

The AI solution that the Weather Company should implement is an ensemble of machine learning models built to offer forecasts to customers, called ForecastAI. These models will be trained on the ERA5 dataset offered to the public by the European Centre for Medium-Range Weather Forecasts. The models will be implemented into our Weather Channel app in order to offer customers forecasts for their next 20 days.

A5. Machine Learning Solution Benefits

ForecastAI will be fast, cheap, and accurate. The machine learning models will be able to predict with greater speed and accuracy than the physical models we are currently employing. They will be cheaper as well, allowing the Weather Company to save both money and time when it comes to our predictions. These predictions will also be offered up to 20 days in advance, which will allow us to outperform our competitors who can only predict 10 days in advance.

Project Design

B1. Project Scope

The ForecastAI project will offer fast, accurate predictions up to 20 days in advance. It will allow us to reduce the money we are spending on the physical models we are currently employing. However, the ForecastAI project will not offer forecasts further than 20 days in advance, nor will it offer forecasts on extreme or unexpected weather events such as tornados.

In Scope:

- Development of an AI ensemble for forecasting weather
- Reduce costs of ongoing forecasting operations of the Weather Company
- Construction of a datacenter and office to house the ForecastAI project
- Allow the Weather Channel app to provide reports up to 20 days in advance, 10 days further than current Weather Channel capabilities
- Use of the ERA5 reanalysis dataset for accurate predictions

Out of Scope:

- Forecasts beyond 20 days in advance
- Prediction of extreme or unexpected weather events
- Integration with US Meteorological Satellite Systems
- Live Maps of weather conditions
- Use of early warning National Weather Service systems.

B2. Project Goals, Objectives, and Deliverables

These are the goals of the ForecastAI project:

- Improve the speed and reliability of Weather Channel forecasting
- Reduce spending on physical model forecasting
- Outperform competitors with 20-day predictions

These are the objectives of the ForecastAI project:

- Decrease costs of forecasts by 30%
- Increase forecast speed by 60%
- Increase forecast accuracy by 20%

These are the deliverables for the ForecastAI project:

- ForecastAI machine learning model ensemble
- ForecastAI integration with Weather Company API channels
- ForecastAI implementation into Weather Channel Application

B3. Project Methodology

The ForecastAI project will implement the standard SEMMA methodology as detailed below:

1. Sample: The ERA5 database will be sampled, extracting several representations of its entirety. Doing this will allow the training process to be expedited as the models will be trained on a subset of data rather than the whole dataset.
2. Explore: The representative samples extracted from the ERA5 database in step 1 will be examined for any outliers, such as extreme or unexpected weather events like tornados.
3. Modify: The representative samples will be modified, with certain outliers being removed and other data being grouped in order to allow the machine learning algorithm to read through the dataset easier.
4. Model: The representative samples will be read by machine learning algorithms, creating an ensemble that will allow for future predictions by extrapolating from the patterns in the representative samples.
5. Assess: The ensembles and their results will be compared against the physical models the Weather Company is already employing as well as the leading forecasts by the European Centre for Medium-Range Weather Forecasts to ensure that the predictions the ensemble is offering are reliable and make sense.

B4. Project Timeline

- From October 14th to October 15th of this year, the project will be in queue for approval.
- From October 15th to October 31st of this year, the company will hire new team members for the project.
- From November 1st to November 7th of this year, the ERA5 database will be sampled, extracting several representations.
- From November 8th to November 21st of this year, the representative samples will be explored, locating outlying weather and temperature conditions.
- From November 22nd to December 7th of this year, the representative samples will be modified in order to remove outliers and group the data for modelling.
- From December 8th to December 21st of this year, the data will be fed to the machine learning algorithms to create an ensemble that can be used for future predictions.
- From January 7th to January 21st of next year, the ensemble will be tested against the Weather Company's physical model as well as the one employed by the European Centre for Medium-Range Weather Forecasts to ensure that the newly created ensemble is accurate and ready for use.
- From January 22nd to February 14th of next year, the ensemble will be integrated into the Weather Company API.
- From February 15th to February 28th of next year, the ensemble will be implemented into the Weather Channel App.
- Starting March 1st of next year, the ForecastAI system will begin offering forecasts to customers as the project concludes.

B5. Project Resources and Costs

- ERA5 Dataset: Free
- ForecastAI Office: $342,000
    - Office Building: $72,000
        - Office Items: $2,000
        - Workstations: $20,000
            - Personal Computers: $15,000
            - Software Licenses: $5,000
    - Datacenter for ForecastAI ensemble: $270,000
        - Servers: $150,000

        - Infrastructure: $120,000
- Salary for team: $500,000
    - 1 Project Manager: $60,000
    - 2 Data Scientists: $130,000
    - 2 Meteorologist: $140,000
    - 1 Hardware Specialist: $50,000
    - 2 Software Engineer: $120,000

B6. Project Success Criteria

The ForecastAI project's success will be evaluated based on the criteria listed below:

- The accuracy of ForecastAI's predictions should be 20% better than that of the Weather Compay's preexisting traditional model.
- The speed of procuring forecasts from ForecastAI should be 60% faster than the Weather Company's preexisting traditional model.
- The cost of implementing ForecastAI should be 30% less than the cost of implementing the Weather Company's preexisting traditional model.

Solution Design

C1. Project Hypothesis

If an ensemble of deep learning models are trained on a dataset of historically accurate weather data, it will be able to predict the weather up to 20 days in advance and with greater accuracy than traditional physical models.

C2. Project Algorithm

The ForecastAI project will implement a supervised learning algorithm. In a supervised learning algorithm, the model is provided with examples of inputs and outputs – in this case, historical weather data – and uses them to predict what would happen given a specific set of inputs. Several of these models will be combined together into an ensemble to improve accuracy.

C2a. Project Algorithm Strengths and Weaknesses

Supervised learning combined with the expansive ERA5 dataset will allow the ForecastAI models to learn the complex relationships between the atmosphere and future weather conditions and create accurate predictions. However, the size of the dataset and the nature of feeding the labeled data into the models will result in significant computational and power demands.

C3. Project Tools and Environment

- Programming Language: Java version 21
  - Library: Eclipse Deeplearning4j
- Development Environment: Apache Netbeans IDE version 27
- Version Control: Github
- Deployment Platform: Oracle Cloud Infrastructure
- Third-Party API:
  - Weather Company API
  - ECMWF Climate Data Store API

C4. Performance Measurement

- The accuracy of the ForecastAI project's predictions will be measured by comparing it to the predictions of the Weather Company's physical model by comparing the predictions of each over a period of two weeks to the actual weather conditions that end up occurring during that time in order to see which is more accurate.
- The speed of the ForecastAI project's predictions will be measured by comparing it to the Weather Company's physical model and timing how long it takes each of them to produce their forecasts.
- The cost of the ForecastAI project will be measured by comparing the cost of it over the course of two weeks to the cost of the Weather Channel's physical model over the course of two weeks in order to see which is cheaper.

Dataset

D1. Data Source

The dataset used in the ForecastAI project is the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts. It covers the atmospheric conditions of the world from January of 1940 to the present day. It is one of the largest and most accurate sets of atmospheric data in existence, and it is available for free.

D2. Data Collection

The data will be collected from the ERA5 reanalysis dataset using the ECMWF Climate Data Store API, allowing for regular retrieval of large amounts of updated climate data.

D2a. Strengths and Weaknesses of Data Collection

One advantage of the chosen data collection method is that the data can be continuously retrieved and updated without requiring any human intervention. This ensures that the ForecastAI project is always using the latest and most accurate weather data. One disadvantage to the chosen data collection method is that the ERA5 dataset is hosted by a third party, so if something happened to the Weather Company's ability to access ERA5, the ForecastAI project would be unable to function.

D3. Data Preparation

During the Explore phase of the project, the representative samples to be used in the ForecastAI models will be prepared by cleaning them of outliers, such as sensor anomalies or extreme weather events like tornados, allowing the data to be more accurately used for general long-term predictions.

D4. Sensitive Data Considerations

As the ERA5 reanalysis dataset is publicly available, there is no sensitive data involved in the ForecastAI project.

E. Sources

Holmstrom et al (2016). Machine learning applied to weather forecasting. Stanford University CS229 Project Report. https://cs229.stanford.edu/proj2016/report/HolmstromLiuVo-MachineLearningAppliedToWeatherForecasting-report.pdf

Olivetti & Messori (2024). Advances and prospects of deep learning for medium-range extreme weather forecasting. Geoscientific Model Development, 17(5), 2347–2358. https://doi.org/10.5194/gmd-17-2347-2024

Magnusson et al (2024). The rise of data-driven weather forecasting: A first statistical assessment of machine learning–based weather forecasts in an operational-like context. Bulletin of the American Meteorological Society, 105(6). https://doi.org/10.1175/BAMS-D-23-0162.1