Bayesian Deep Belief Networks for Climate Anomaly Forecasting

Project Idea

Climate anomalies such as heatwaves and floods are becoming increasingly frequent due to climate change. These events are difficult to predict accurately due to the chaotic, nonlinear dynamics of the climate system. Traditional numerical weather models often lack the ability to express uncertainty in forecasts, which is crucial for risk-sensitive decision making.

We propose to use a Deep Belief Network (DBN) to model high-dimensional spatiotemporal climate data. The DBN will be enhanced with Bayesian inference—specifically, Stochastic Variational Inference (SVI)—to capture uncertainty in anomaly forecasts. The network will generate probabilistic predictions for extreme weather events, and the uncertainty of those predictions will be quantified via Bayesian posterior distributions. Our results will be compared against traditional ensemble-based climate forecasting methods in terms of accuracy and uncertainty calibration.

Methodology

1. **Data Acquisition & Preprocessing**
   - Ingest historical climate variables (e.g., daily surface temperature, precipitation) from NASA/NOAA APIs and CSV archives.
   - Regrid and align all datasets to a common spatiotemporal resolution.
   - Normalize each variable and, if needed, compute anomaly fields by subtracting long-term climatology.
2. **Deep Belief Network (DBN) Design**
   - Stack multiple Restricted Boltzmann Machine (RBM) layers to learn hierarchical features of spatiotemporal inputs.
   - Pretrain each RBM layer greedily with contrastive divergence on historical anomaly maps.
   - Fine-tune the full DBN with backpropagation to predict the probability of an anomaly in a future time window (e.g., 7-day heatwave).
3. **Bayesian Uncertainty Modeling**
   - Integrate Stochastic Variational Inference (SVI) into the DBN's weight learning: replace point-estimate weights with learned distributions.
   - Use amortized variational posteriors to approximate the true weight posterior; optimize the Evidence Lower Bound (ELBO) via minibatch stochastic gradients.
   - At inference, draw multiple weight samples to generate a predictive distribution for each grid cell's anomaly probability.
4. **Evaluation & Baseline Comparison**
   - Evaluate point forecasts (e.g., ROC-AUC, Brier score) and uncertainty calibration (e.g., reliability diagrams, prediction interval coverage).

- Compare against a traditional ensemble climate model (e.g., multi-member GCM ensemble) on the same forecast tasks.
- Perform ablation: DBN without Bayesian inference (deterministic) vs. Bayesian DBN.

5. **Visualization & Interpretation**

   - Map the spatial distribution of forecast mean and standard deviation to identify high-risk regions and quantify confidence.
   - Generate case studies of notable extreme events (e.g., a recent heatwave) to illustrate how Bayesian DBN uncertainty aligns with observed outcomes.

Dataset

We will use publicly available datasets from NASA (e.g., POWER Climate Data, MERRA-2) and NOAA (e.g., Global Historical Climatology Network - GHCN). These datasets include temperature, precipitation, and pressure data across multiple spatiotemporal resolutions. Web scraping may be done for additional real-time data feeds from national meteorological services.

Software Required

We will implement the DBN using Python with PyTorch. Bayesian inference will be carried out using Pyro or TensorFlow Probability. Additional tools include NumPy, SciPy, pandas for data handling, and Matplotlib/Seaborn for visualizations.

Papers to Read

- Salakhutdinov, R. & Hinton, G. (2009). Deep Boltzmann Machines. *AISTATS*. `https://www.cs.toronto.edu/~rsalakhu/papers/dbm.pdf`
- A Bayesian Deep Learning Approach to Near-Term Climate Prediction Xihaier Luo, Balasubramanya T. Nadiga, Ji Hwan Park, Yihui Ren, Wei Xu, Shinjae Yoo (2022) *ICML*. `https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2022MS003058`
- Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*. `https://doi.org/10.1038/nature14541`

Teammates

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Domain of Interest

Spatiotemporal climate anomaly forecasting, with a focus on extreme events such as heatwaves, heavy precipitation/floods, and droughts. We target global to regional scales using gridded temperature, precipitation, and pressure fields from NASA (POWER, MERRA-2) and NOAA (GHCN).

Motivation

Motivated by the urgent need to improve prediction and risk assessment of increasingly frequent extreme weather events under climate change, this project integrates probabilistic reasoning with deep learning to deliver interpretable, uncertainty-aware forecasts of heatwaves, floods, and other climate anomalies.