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Climate Model HPO

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Hyper parameter optimization for CCAI

Climate change poses a challenging threat to humanity which has spurred a rapidly developing field of artificial intelligence research focused on climate change applications.

Taking action towards climate change must come in many forms, such as reducing greenhouse gases effect, adaptation of renewable energy. A rapidly developing area in AI is the CCAI or Climate change AI, which is focused on applications to mitigate the effects of climate change.

Algorithms such as hyper parameter optimization have been studied deeply for the CCAI field.

In recent years, several techniques have been developed for atmospheric radiative transfer, wind power forecasting, and catalyst prediction. I mainly focus on AutoML algorithms, since they are emerging in recent years developing new techniques to solve climate based problems. Popular techniques include: neural architecture search and the hyper parameter optimization.

The real question is that: Since AutoML or the automated machine learning provides methods and processes to make machine learning available for non-machine learning experts, can current AutoML techniques can actually improve performance compared to human-designed models in high-leverage climate change AI applications?

**Topic of Interest:**

**Atmospheric Radiative Transfer.** Numerical weather prediction models, as well as global and regional climate models, give crucial information to policymakers and the public about the impact of changes in the Earth’s climate.

The ART (atmospheric radiative transfer) calculations are used to compute the heating rate of any given layer of the atmosphere. While ART has been calculated using physics simulations and other computationally intensive simulations.

We use the ClimART dataset from the NeurIPS datasets. It consists of global snapshots of the atmosphere across a discretization of latitude, longitude, atmospheric height and time from 1979 to 2014.

We can run HPO on the CNN baseline using the Optuna library (AutoML’s model). We can set a categorical hyperparameter to choose among MLP, CNN, GNN, GCN and L-GCN while also tuning learning rate and batch size.

Table 1

*Requirements and Current results:*

| Dataset | Type | Model | AutoML perf.% |
| --- | --- | --- | --- |
| ClimART | HPO | CNN | 1.534 |