

AutoML for Climate Change

A Call to Action

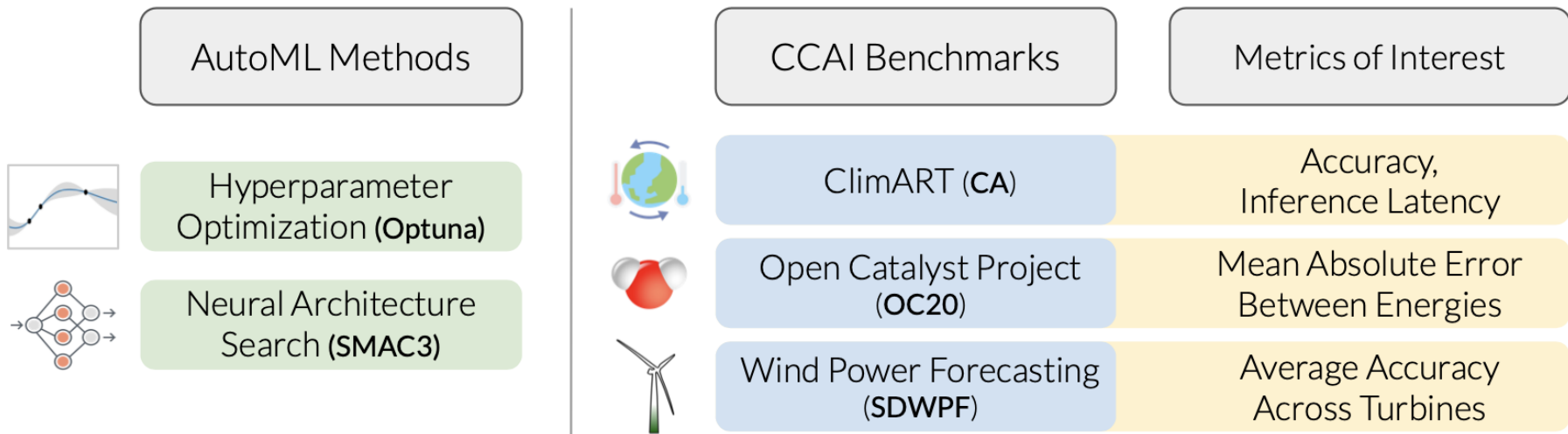
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A Call to Action

- ❖ Climate Change AI initiative presents diverse challenges
- ❖ Opportunity to use **AutoML techniques**
 - Hyperparameter optimization - HPO (*model training*)
 - Neural architecture search - NAS (*model selection*)
- ❖ Future challenge: **Spatiotemporal data / Physics-constrained settings**

Evaluating AutoML Out-of-the-box



Benchmark #1: ClimART (NeurIPS DBT 2021)

Multi-objective NAS with SMAC3 - 8.7% RMSE improvement over baseline*

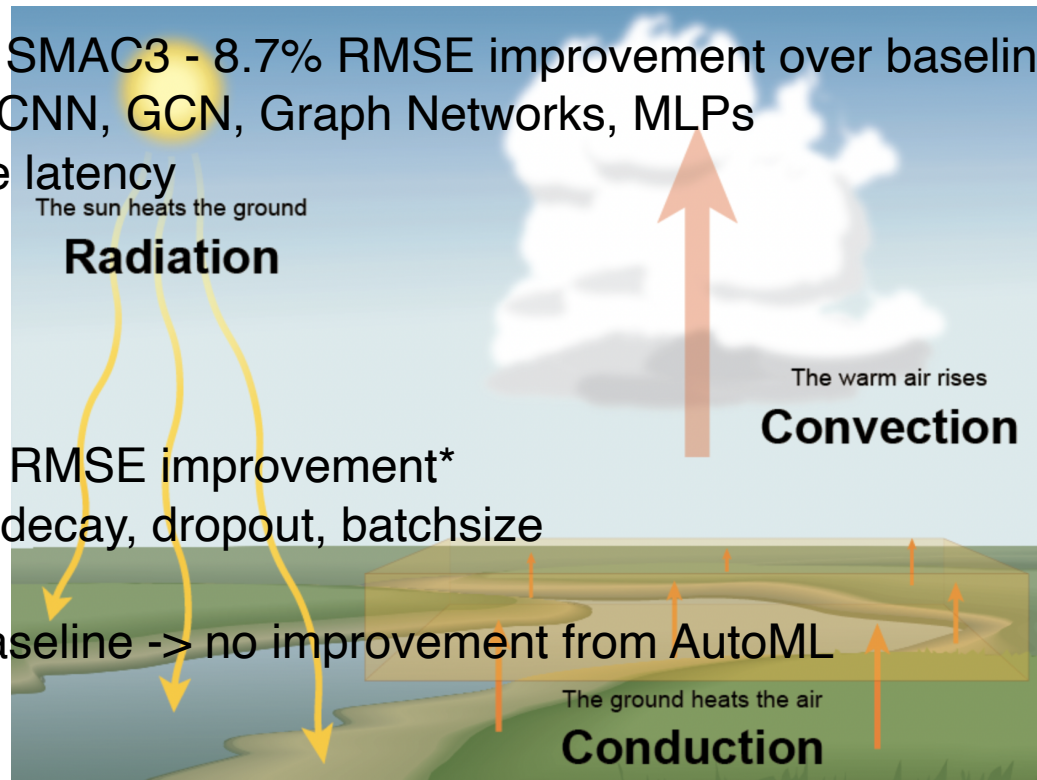
- ❖ Model selection from CNN, GCN, Graph Networks, MLPs
- ❖ Comparable inference latency

Atmospheric
Radiative
Transfer

HPO with Optuna - 15.9% RMSE improvement*

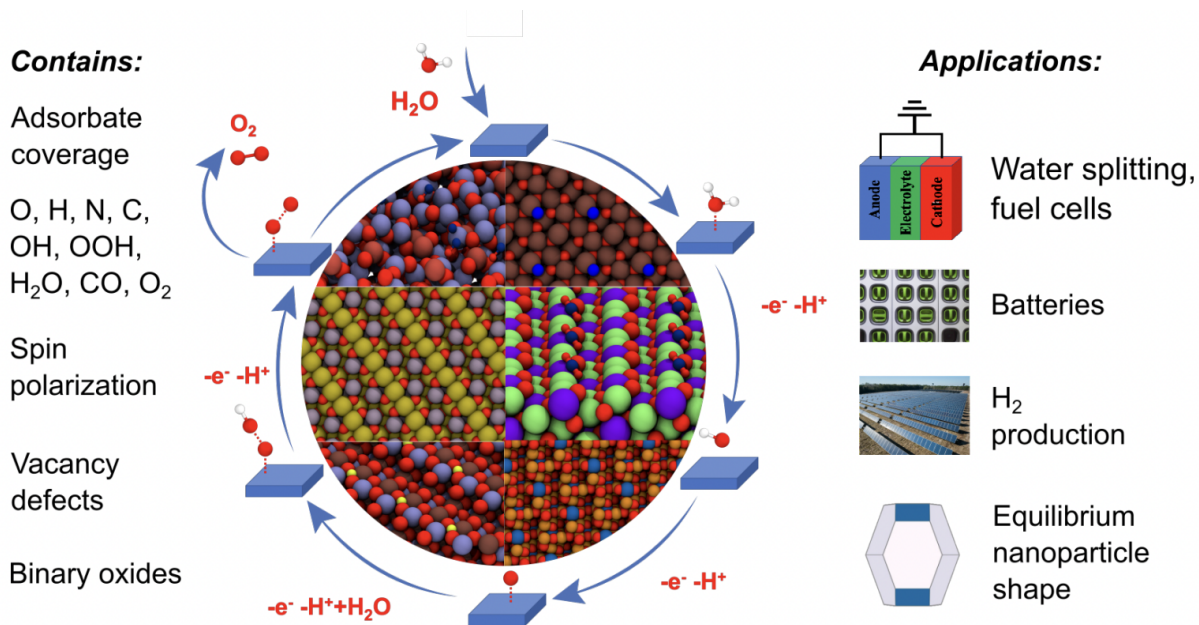
- ❖ Learning rate, weight decay, dropout, batchsize

*Authors report a better baseline -> no improvement from AutoML



Benchmark #2: Open Catalyst Project (NeurIPS competition 2021)

New Catalysts for Renewable Energy Storage



Benchmark #2: Open Catalyst Project

GraphNormer (SoTA approach)

+

HPO

{learning rate, warm-up steps, # layers, # attention heads, #blocks}

Only yields **0.65%** improvement in MAE

Benchmark #3: SDWPF - Wind Power Forecasting (KDD Cup 2022)

- ❖ **AutoML showed almost no improvement**
- ❖ HPO / NAS applied to two winning competition submission
 - Significant cost (up to 50 GPU hours) running AutoML

Promising Future Avenues

❖ NAS search spaces for **spatiotemporal data forecasting**

- Interpolation between model families: CNN, MLP, GCN, Graph Networks
- State-space models for longer sequences

❖ Architectures that incorporate **physical constraints**

- Drgoňa, Ján, et al. "*Physics-constrained deep learning of multi-zone building thermal dynamics.*"

Checkout our GitHub repo

<https://github.com/climate-change-automl/climate-change-automl>