Multi-Objective AutoML

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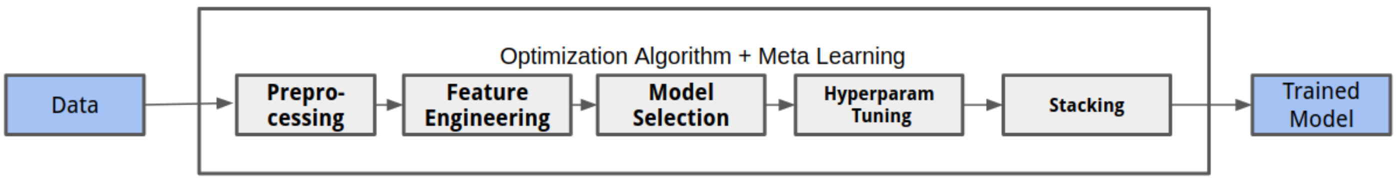
2019/07/23

A short intro to AutoML

- Automatically obtain an *"optimal"* model for a dataset
- The system performs model selection, tuning, ...
- Many different flavors exist!



Why?

- Many steps in the typical ML pipeline can be easily automatized!
- Computers are efficient in trying out many possibilities and searching through complex spaces.

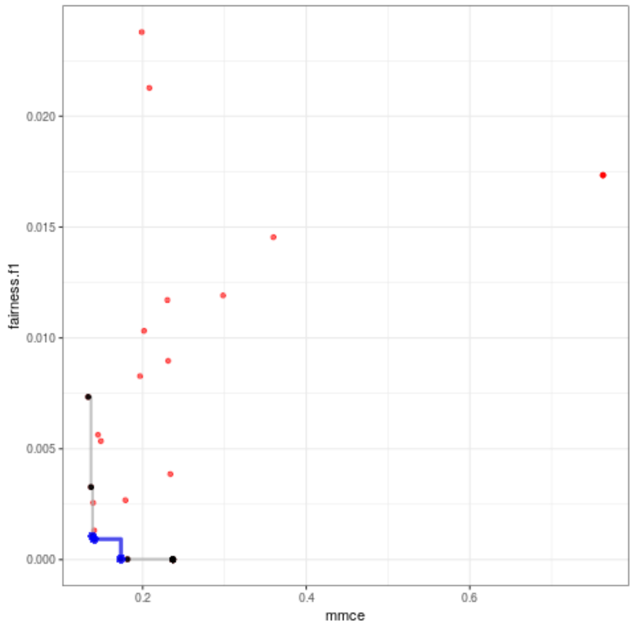
Multi-Objective AutoML - Why?

- Current AutoML approaches are **very good** at optimizing predictive performance!
- **But:** Many applications require models that trade of or are *good* with respect to multiple objectives.

Problem:

Too narrow focus on a single measure for predictive performance!

Users either use AutoML without considering other objectives, or do analysis manually!



Interesting Objectives:

Fairness

… usually means that our model f_θ trained on a dataset X and target y does not discriminate between a set of protected attributes A, such as ethnicity and gender.

There are many (often conflicting) definitions of fairness, to give two examples:

- Equalized Odds (Hardt, 2016)

  $$Pr\{\hat{Y} = 1 | A = 0, Y = y\} = Pr\{\hat{Y} = 1 | A = 1, Y = y\}, y \in \{0, 1\}$$

- Equal Opportunity (Hardt, 2016)

  $$Pr\{\hat{Y} = 1 | A = 0, Y = 1\} = Pr\{\hat{Y} = 1 | A = 1, Y = 1\}$$

- Further desideratum: Calibration

Interesting Objectives II:

Interpretability

Many post-hoc interpretability methods allow us to understand what our model learns. But: They mostly rely on **local** and **linear** explanations.

- Main Effect Complexity (Molnar, 2019)

  $\rightarrow$ How well can main effects be approximated by linear segments?

- Interaction Strength (Molnar, 2019)

  $\rightarrow$ How much of a model's prediction can **not** be explained by main effects?

- Sparsity

  Even simple models with $1000's$ of predictors are hard to grasp

Interesting Objectives III:

Robustness

- Robustness to adversarial examples, perturbations , distribution shift, …

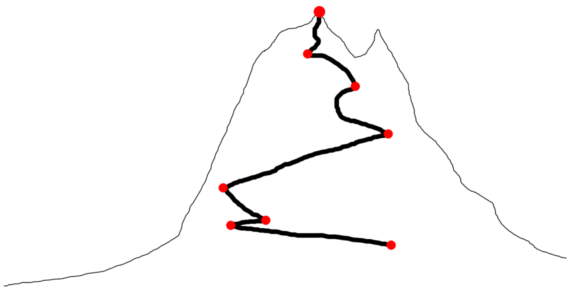
Memory and Inference Time

- Deploying on mobile devices, scoring *http* requests

…

Open Challenges

- **Awareness** for other objectives is often lacking. If they are not easily accessible users might just neglect them.
- **Fairness** measures are often not well-defined and highly depend on context
- Measures for **robustness** do not really exist and require more research.
- Research into **interpretability** measures has just started!
- New pre- and post-processing methods might be required.



- Interesting Datasets and Benchmarks are required to compare systems.
- Tools to increase **transparency** and **trust** in AutoML systems are important! Human-in-the-loop approaches can help here!

References

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