

Multi-Objective AutoML

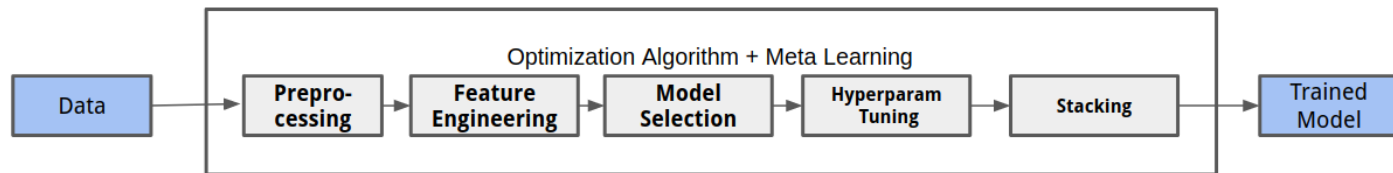
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A short intro to AutoML

- 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.

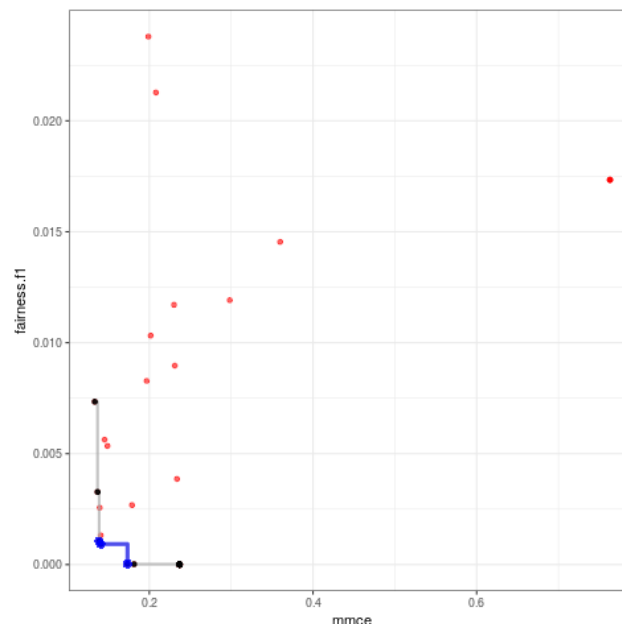
Multi-Objective AutoML - Why?

- Current AutoML approaches are **very good** at optimizing predictive performance!
- **But:** Many applications require models that trade off 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)
 - How well can main effects be approximated by linear segments?
- Interaction Strength (Molnar, 2019)
 - 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 II:

Robustness

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

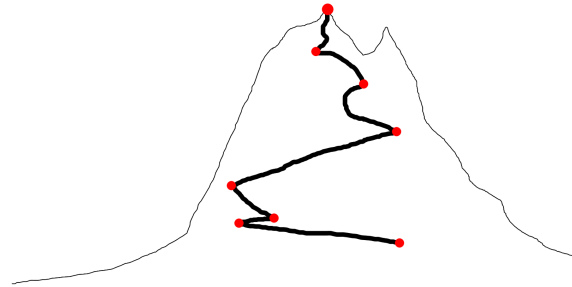
Memory and Inference Time

- Deploying on mobile devices, scoring *http* requests

...

Open Challenges

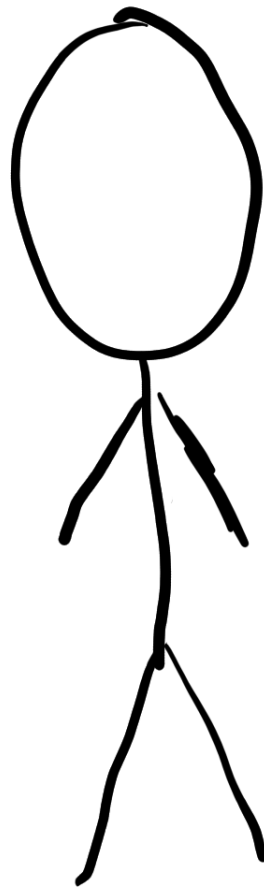
- **Awareness** for other objectives is often lacking. If they are not easily accessible users might just neglect them.
- **Fairness** measures are often not well-defined and highly depend on context
- Measures for **robustness** do not really exist and require more research.
- Research into **interpretability**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

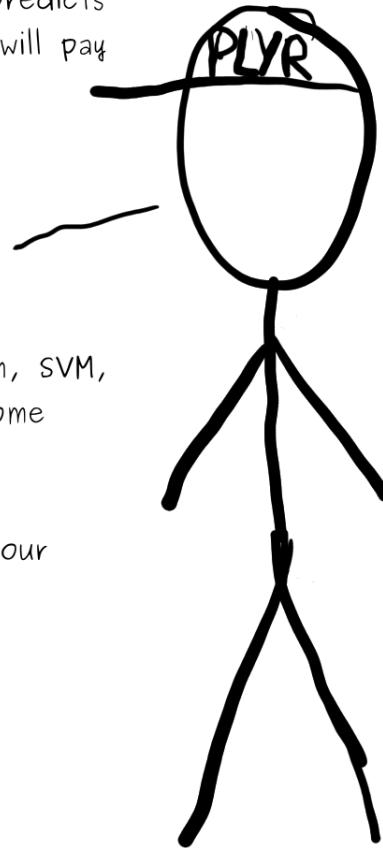
References

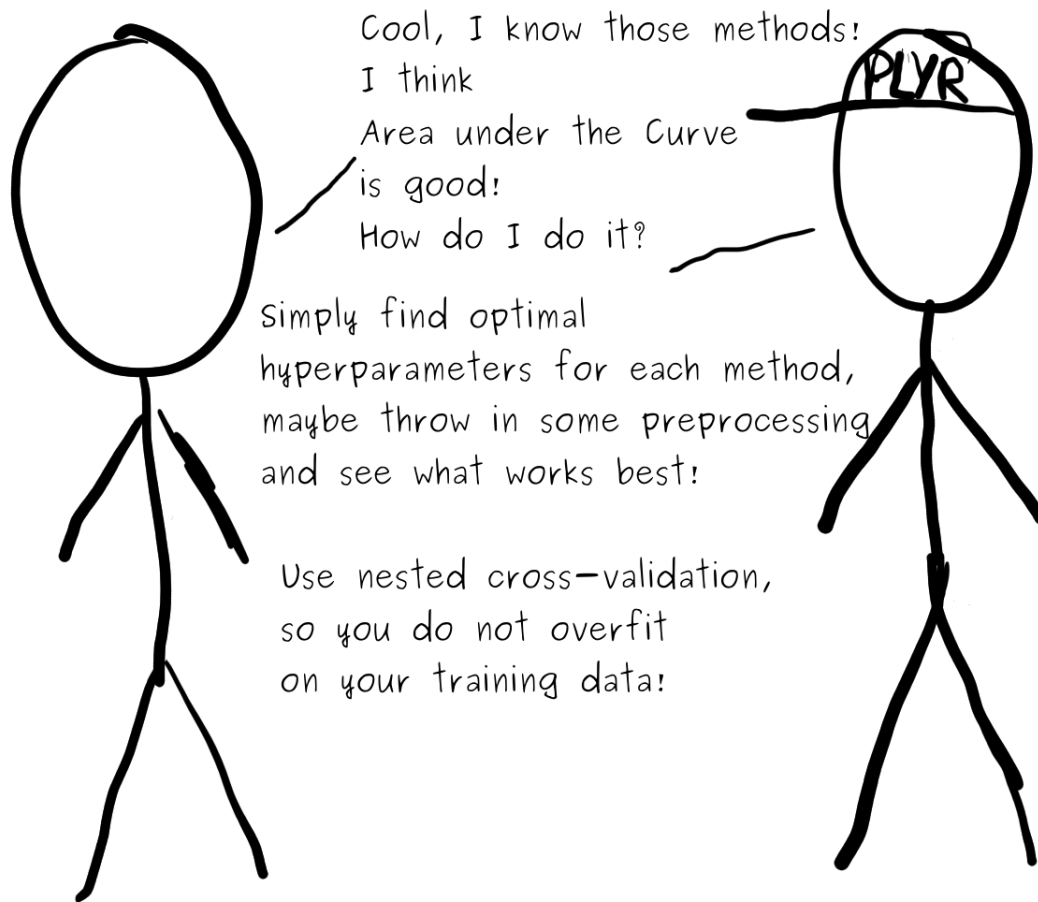
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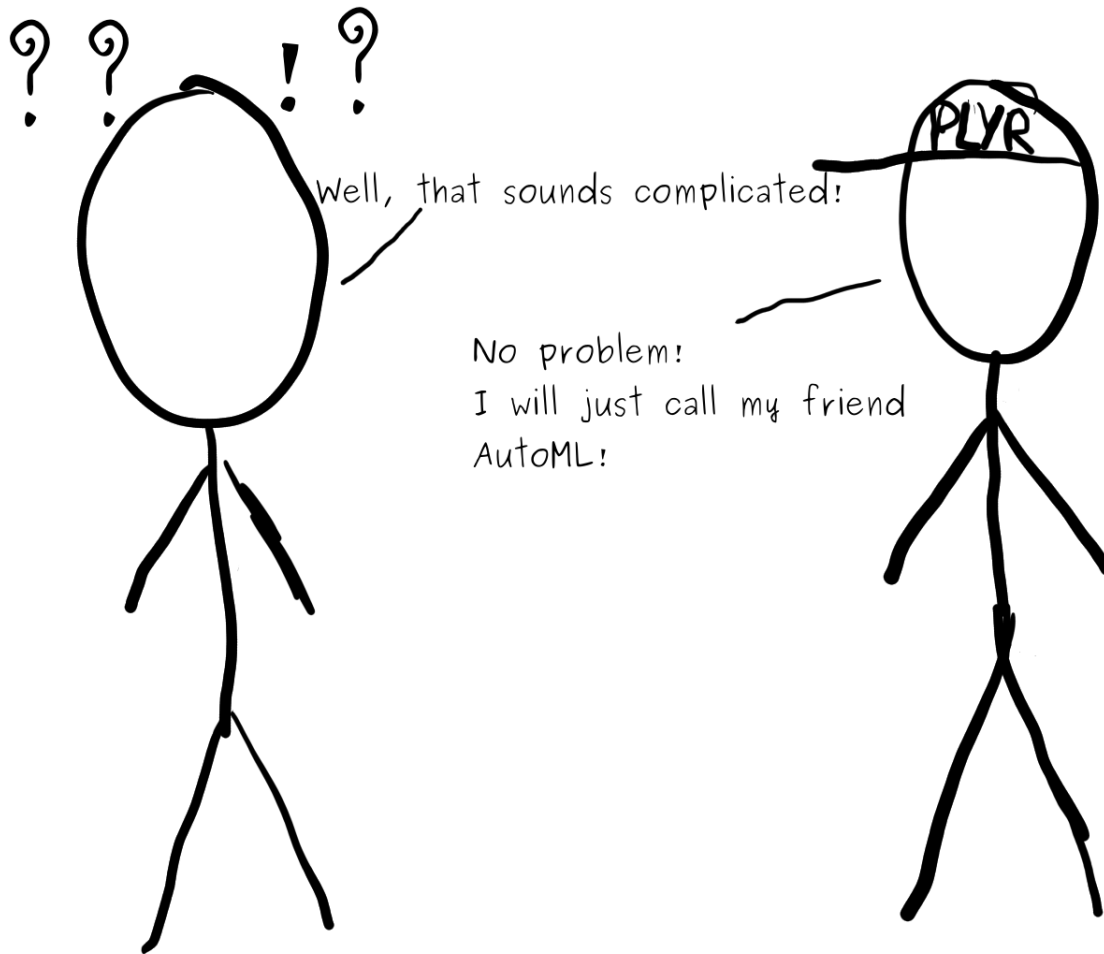


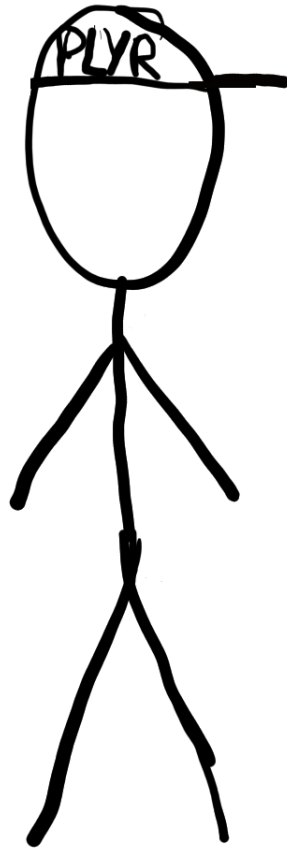
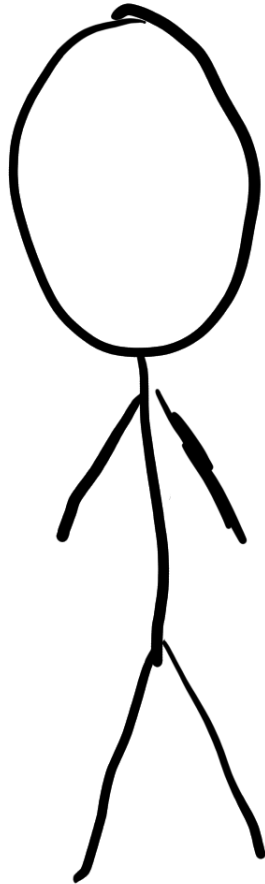
I need a model that predicts whether my customers will pay back their loans!

Sure, easy enough!
Try logistic regression, SVM, Random Forest and some Gradient Boosting.
How do you measure the performance of your model?



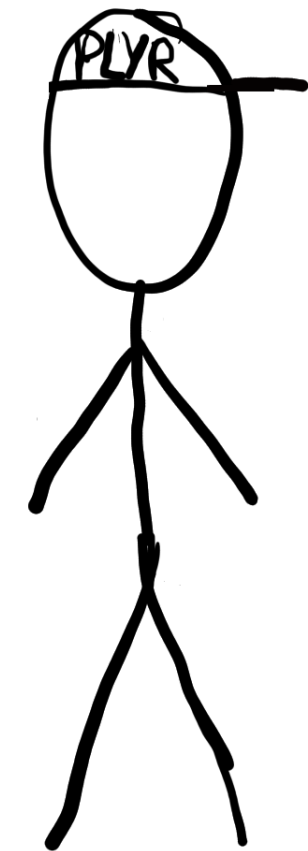
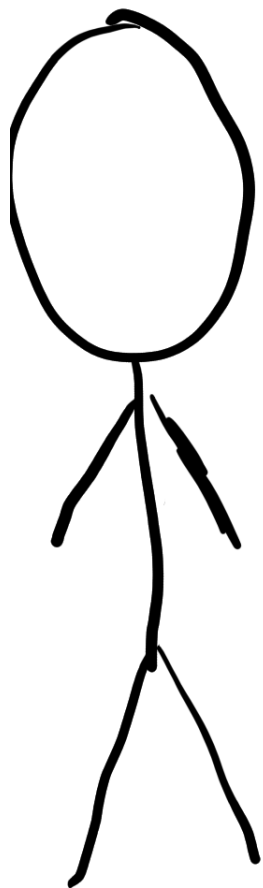






Sure!
Give me your data
and I will get back
to you!





Cool!

The model also can't discriminate
between men and women,
and

I need the model to be
interpretable!

Ahm ...

this is asking a lot!

I do not really know
how to help you there!

