



HOMER

New era of AutoML?

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MI²DataLab Winter Seminar 2022



Gartner Hype Cycle for Artificial Intelligence, 2019



gartner.com/SmarterWithGartner

Source: Gartner
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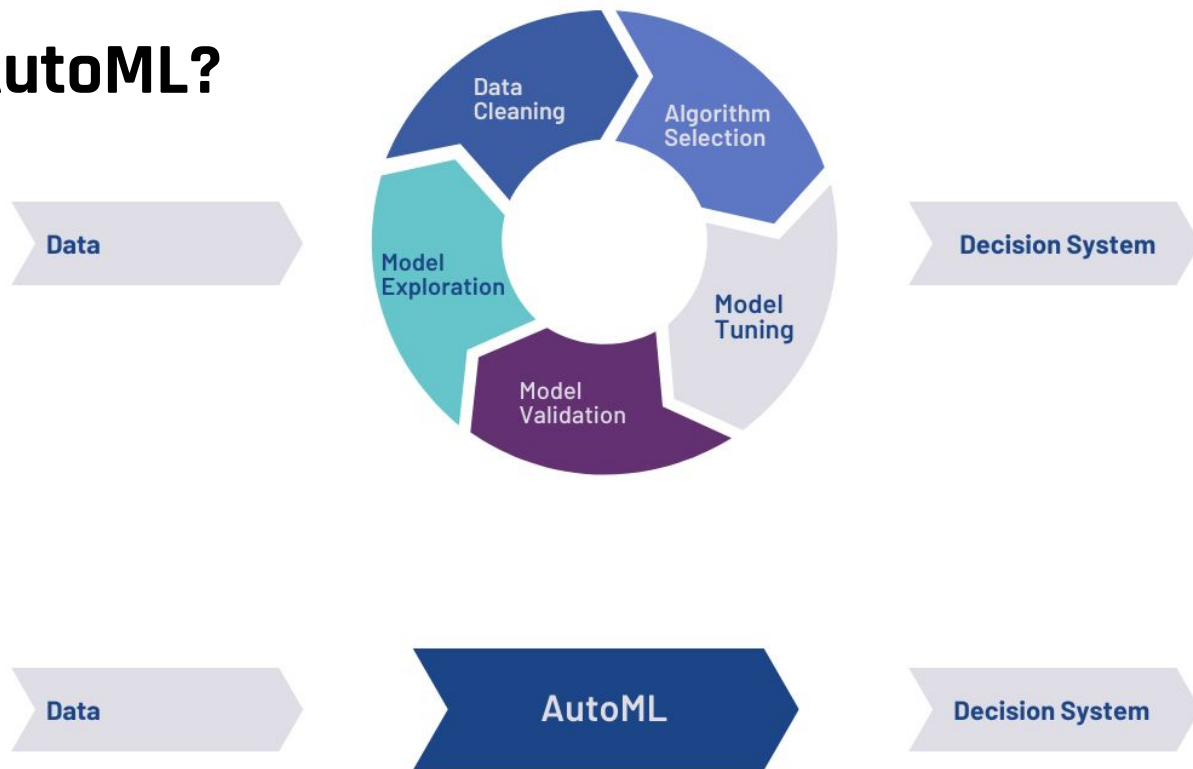
Gartner



What is AutoML?

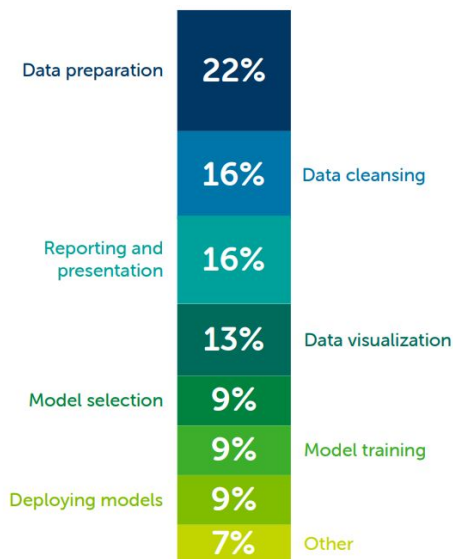


What is AutoML?



Who is AutoML end user?





n = 1,966

We asked our respondents how much time they spend on the above tasks, and for each item they entered a number reflecting the percentage of time spent relative to the other options. This is the average of the reported percentages.

1 Enable non-experts to train machine learning models (2.57)

2 Quickly and efficiently tune very many hyperparameters (2.75)

3 Help choose the best model types to solve specific problems (2.78)

4 Speed up the ML pipeline by automating certain workflows (data cleaning, etc.) (3.06)

5 Tune the model once performance (such as accuracy, etc.) starts to degrade (3.99)

6 Other (5.85)

We asked respondents to drag and rank the options from most to least important, with the first being most important.

n = 2,042



Who is AutoML end user?

Traditionally, application's developers using statistical and learning methods choose algorithms and tune their parameters empirically, commonly by trial and error; or in the best case, by using prior knowledge of experts on the domain.

[PSMS for Neural Networks, 2007]

*It can be challenging to make the **right choice** when faced with these degrees of freedom, leaving many users to select algorithms based on reputation or intuitive appeal, and/or to leave hyperparameters set to default values.*

[AutoWEKA, 2013]

*Automated Machine Learning (AutoML) supports **practitioners and researchers** with the tedious task of designing machine learning pipelines and has recently achieved substantial success.*

[Auto-sklearn 2.0, 2022]



o-WEKA

Started point: C. Thornton and F. Hutter and H.-H. Hoos and K. Leyton-Brown, *Auto-WEKA: Combined Selection and Hyperparameter Optimization of Classification Algorithms*, 2013

[illegible]

Started point: M. Feurer, A. Klein, K. Eggensperger, J. Springenberg, M. Blum and F. Hutter, *Efficient and Robust Automated Machine Learning*, 2015

BUT...



Have we failed to reach out to our target audience?

- Despite various attempts of our community to make other researchers aware of AutoML, it seems that the amount of people we have reached is still rather limited. With new activities, such as our AutoML fall school, we hope to change that in the future.
- The capabilities of our AutoML tools are not well aligned with their needs. In particular,
 - ◆ their capabilities are most likely not broad enough by offering only very limited support for data engineering – a task that often requires a significant amount of time and expertise,
 - ◆ and the black-box nature of most AutoML processes makes it hard to understand why a certain (ensemble of) model(s) is returned at the end of running AutoML.

Source: M. Lindauer, A. Tornede, *Rethinking AutoML: Advancing from a Machine-Centered to Human-Centered Paradigm*, November 30, 2022
<https://www.automl.org/rethinking-automl-advancing-from-a-machine-centered-to-human-centered-paradigm/>

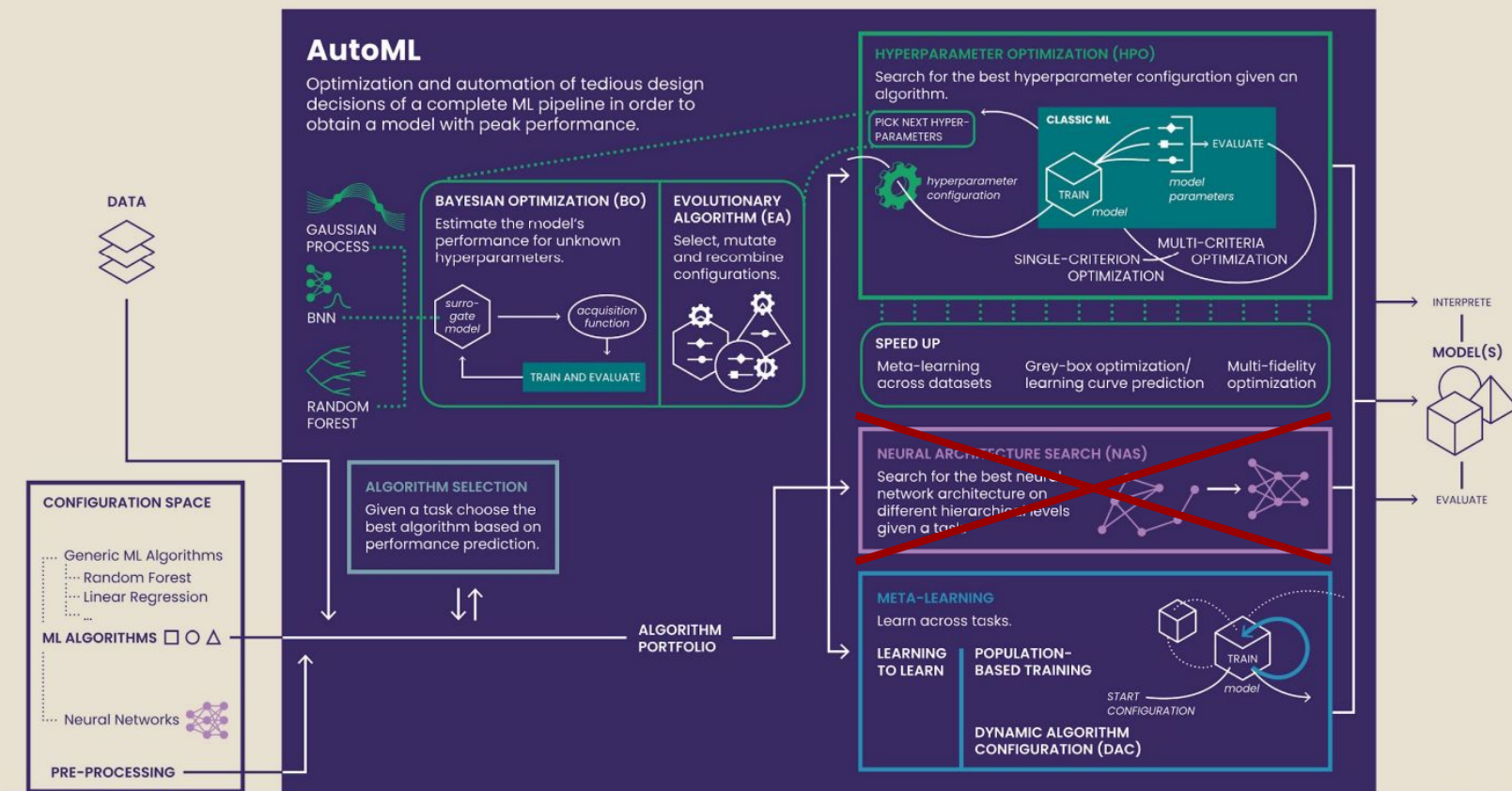


Ongoing research

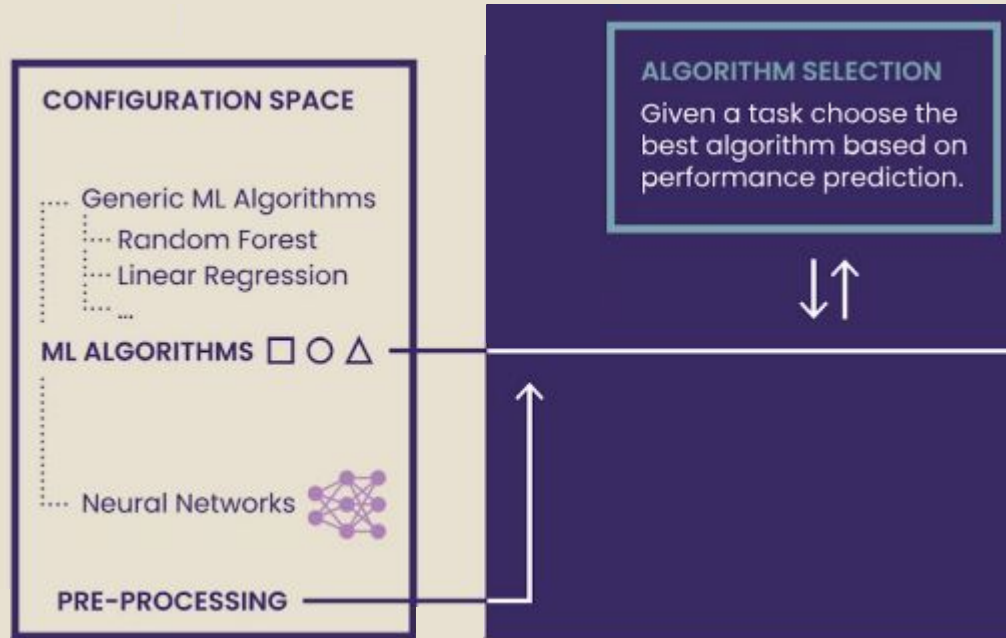
(mostly important for us)



What points have researchers focused on so far?



ML Algorithms for tabular data

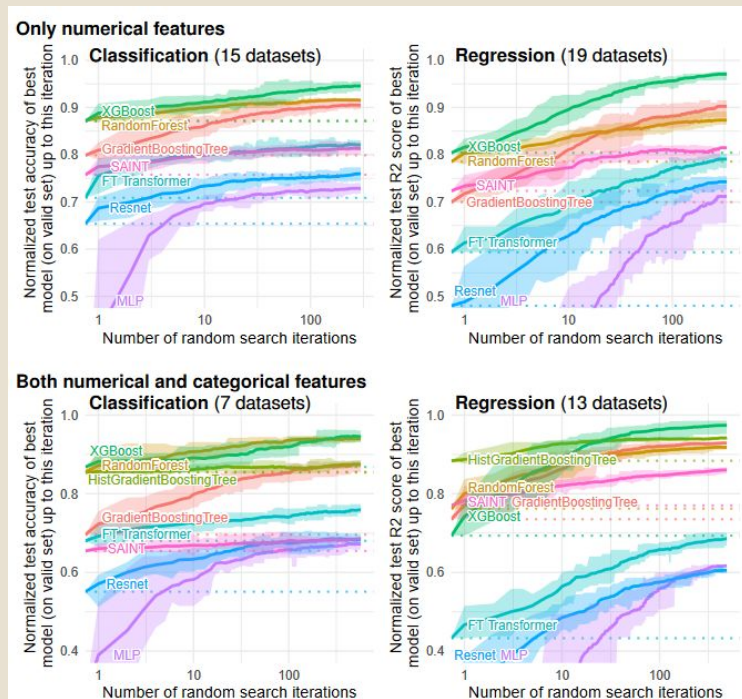


ML Algorithms for tabular data - latest works

- R. Schwartz-Ziv and A. Armon, ***Tabular Data: Deep Learning is Not All You Need***, ICML 2021 Workshop AutoML Program Chairs
- L. Grinsztajn, E. Oyallon, and G. Varoquaux, ***Why do tree-based models still outperform deep learning on typical tabular data?***, NeurIPS 2022 Track Datasets and Benchmarks Program Chairs



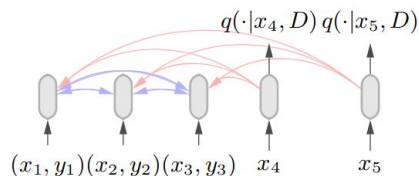
Forester Package @Anna.Kozak



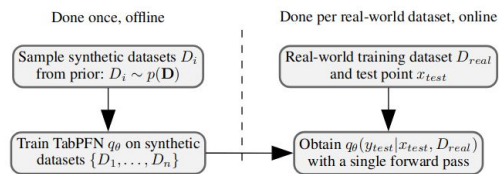
L. Grinsztajn, E. Oyallon, and G. Varoquaux, *Why do tree-based models still outperform deep learning on typical tabular data?*, NeurIPS 2022 Track Datasets and Benchmarks Program Chairs



TabPFN



(a) Architecture and attention mechanism



(b) Prior-fitting and inference

Figure 1: Left (a): Training samples $\{(x_1, y_1), \dots, (x_3, y_3)\}$ are transformed to 3 tokens, which attend to each other; test samples x_4 and x_5 attend only to the training samples. Right (b): The PFN learns to approximate the PPD of a given prior in the offline stage to yield predictions on a new dataset in a single forward pass in the online stage. Plots based on [24].

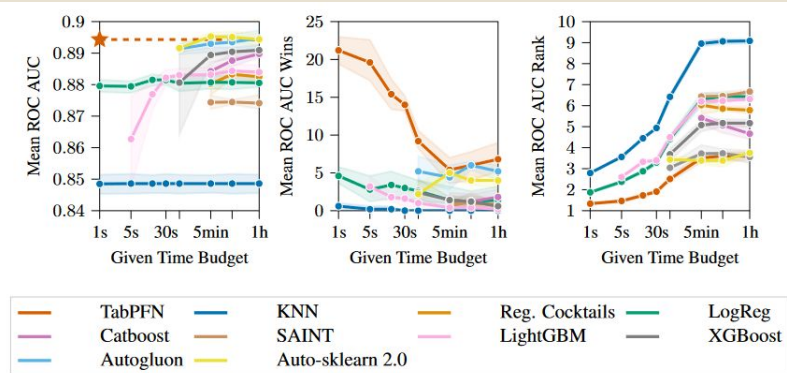


Figure 5: ROC AUC performance over time. We report mean ROC, mean wins and rank along with the 95% confidence interval across 5 repetitions for different time budgets (Unlabelled ticks: 1min, 15min).

The forester R package

What is **forester**?

- full automation of the process of training tree-based models
- no demand for ML expertise
- powerful tool for making high-quality baseline models for experienced users

! The forester package is **designed for beginners** in data science, but also for more experienced users.

What do we need

without forester?

Modelling enthusiast
with tabular data



+



+

A list of installed
R packages

```
install.packages(  
  'ranger',  
  'xgboost',  
  'catboost',  
  'lightgbm',  
  'rpart',  
  'randomForest',  
  'partykit',  
  ...)
```

Time of writing code



x

7*

x

?

=

Best model



with forester?



+



+



```
install.packages('forester')
```

+



x

1

x

1

=



+



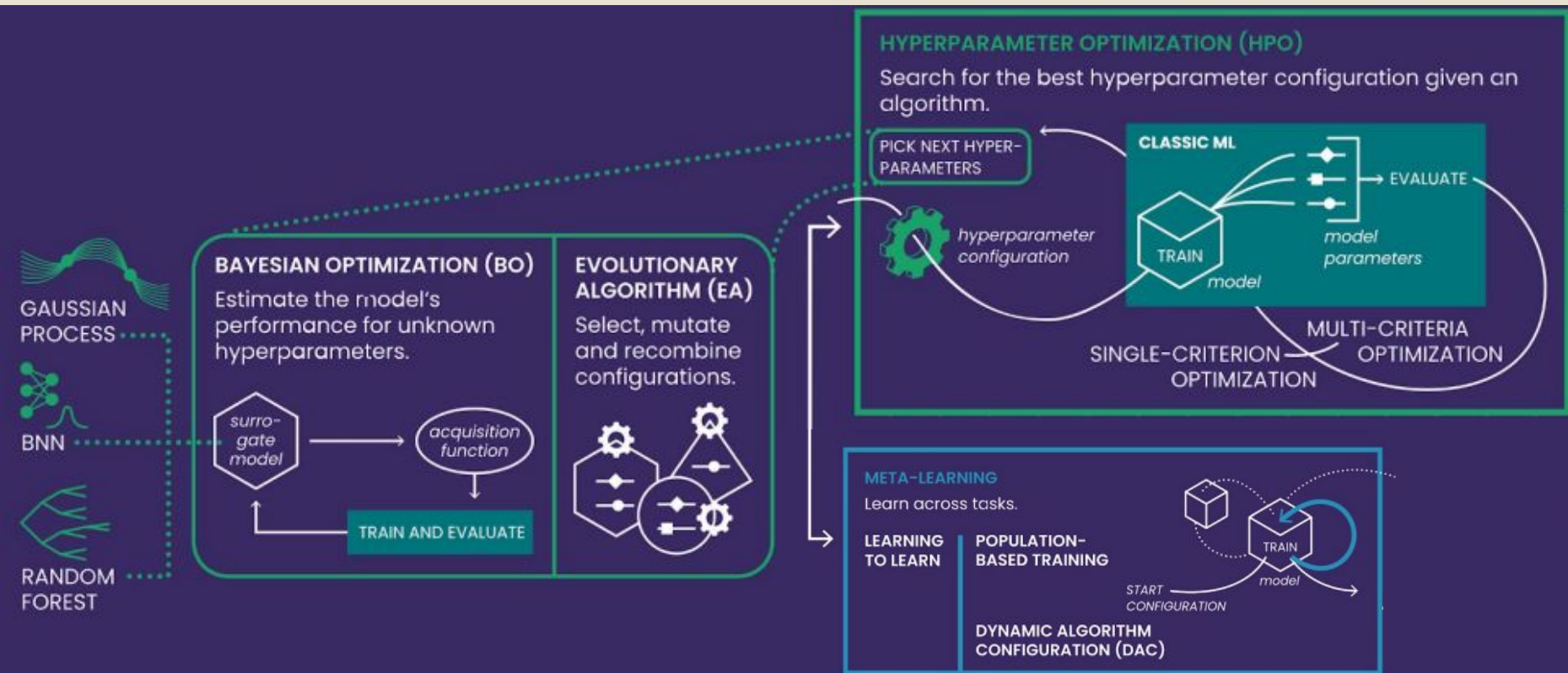
XAI + explaining tools
explain()



report()



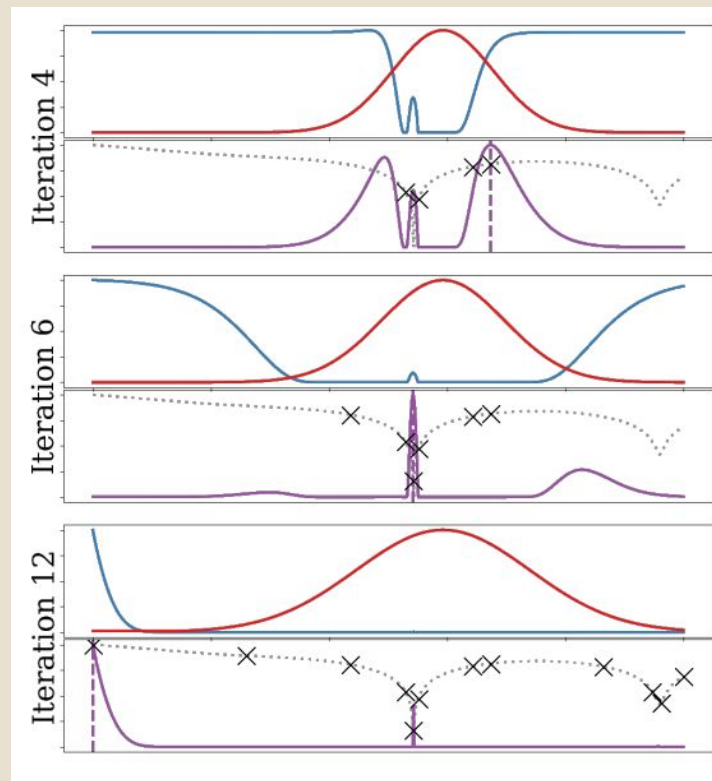
CASH & HPO (for tabular data and classic ML)



CASH & HPO & Meta-learning

Bayesian Optimization with Priors

$$\mathbf{x}_n \in \arg \max_{\mathbf{x} \in \mathcal{X}} \alpha_{\pi}(\mathbf{x}, \mathcal{D}_n) = \arg \max_{\mathbf{x} \in \mathcal{X}} \alpha(\mathbf{x}, \mathcal{D}_n) \pi(\mathbf{x})^{\beta/n}$$



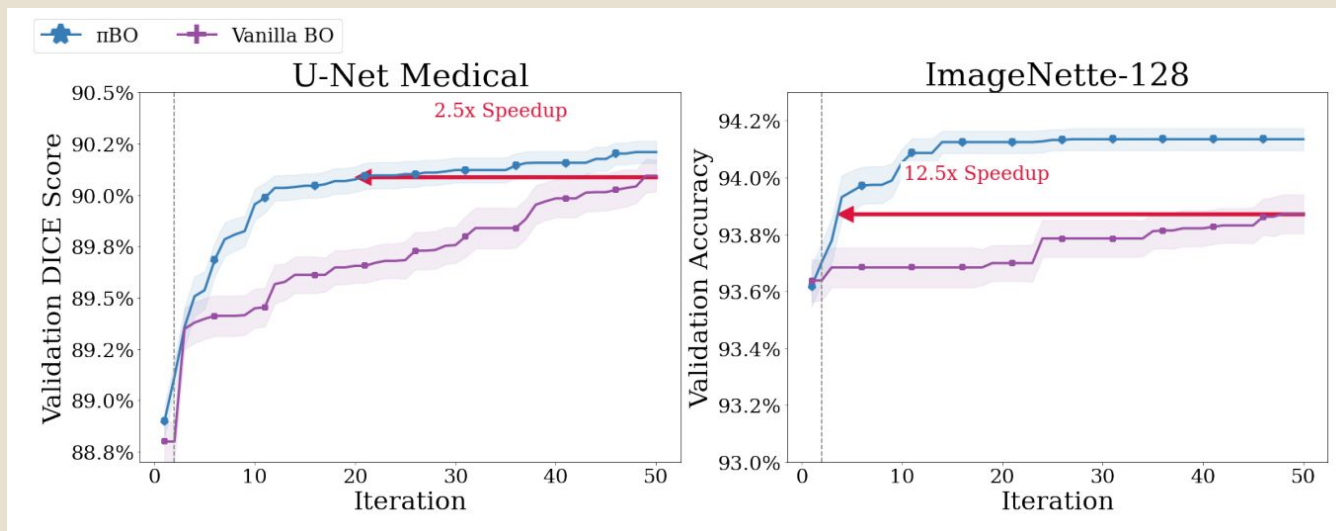
Consolidated learning @Katarzyna.Woźnica

Hvarfner, C., Stoll, D., Souza, A., Lindauer, M., Hutter, F. and Nardi, L. *piBO: Augmenting Acquisition Functions with User Beliefs for Bayesian Optimization*. 2022



CASH & HPO & Meta-learning

Bayesian Optimization with Priors



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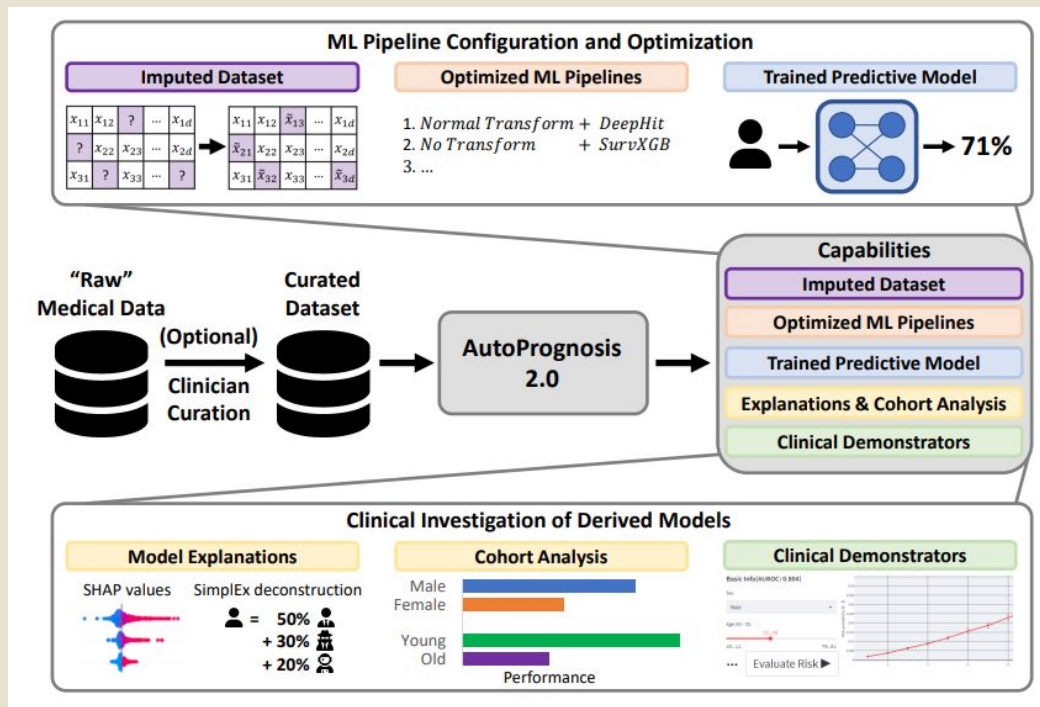



CASH & HPO & Meta-learning

AutoPrognosis 1.0 and 2.0

Patient data:

- UK BioBank
- UNOS
- MAGGIC
- SEER



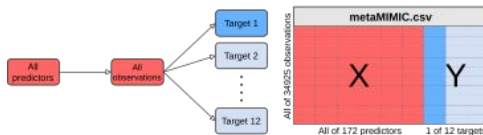
 **Consolidated learning @Katarzyna.Woźnica**

A M. Alaa and M. van der Schaar, *AutoPrognosis: Automated Clinical Prognostic Modeling via Bayesian Optimization with Structured Kernel Learning*, 2018

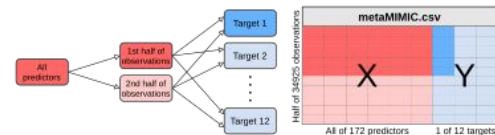
Consolidated learning

- Domain-specific meta-train collection regarding prior knowledge
- metaMIMIC benchmark
- the definition-based similarity of tasks is positively related to hyperparameters' transferability between them.

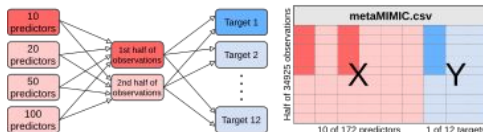
S1



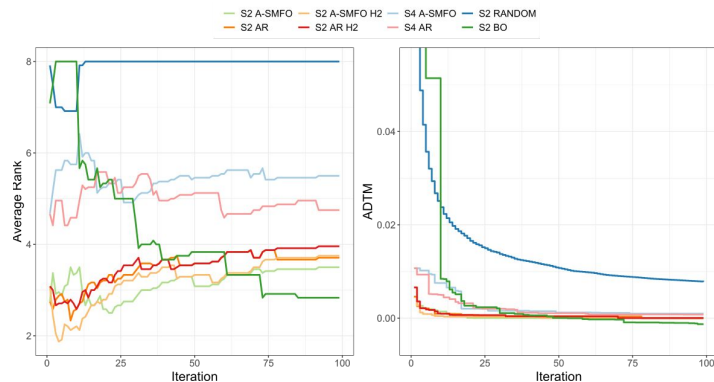
S2



S3



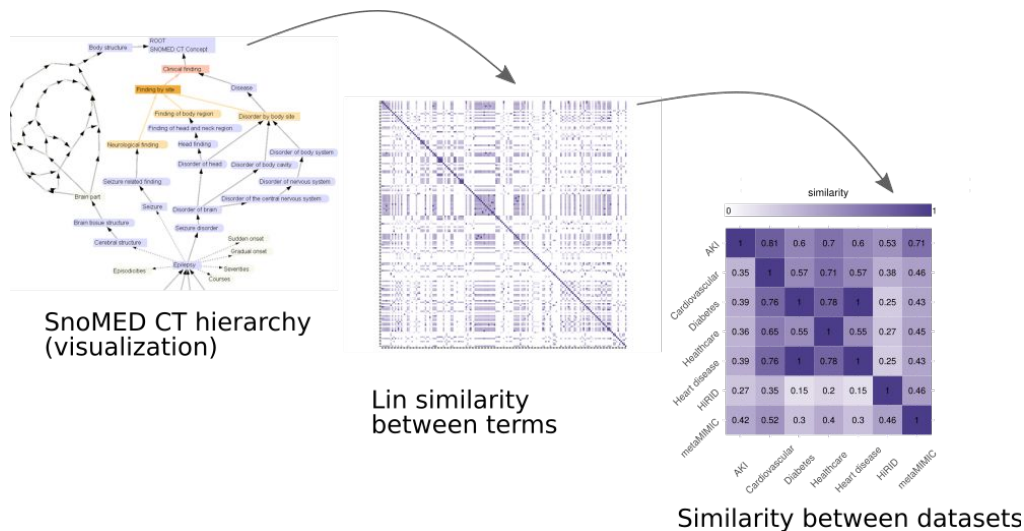
S4



K. Woźnica, M. Grzyb, Z. Trafas, and P. Biecek, *Consolidated learning - a domain-specific model-free optimization strategy with examples for XGBoost and MIMIC-IV*, 2022



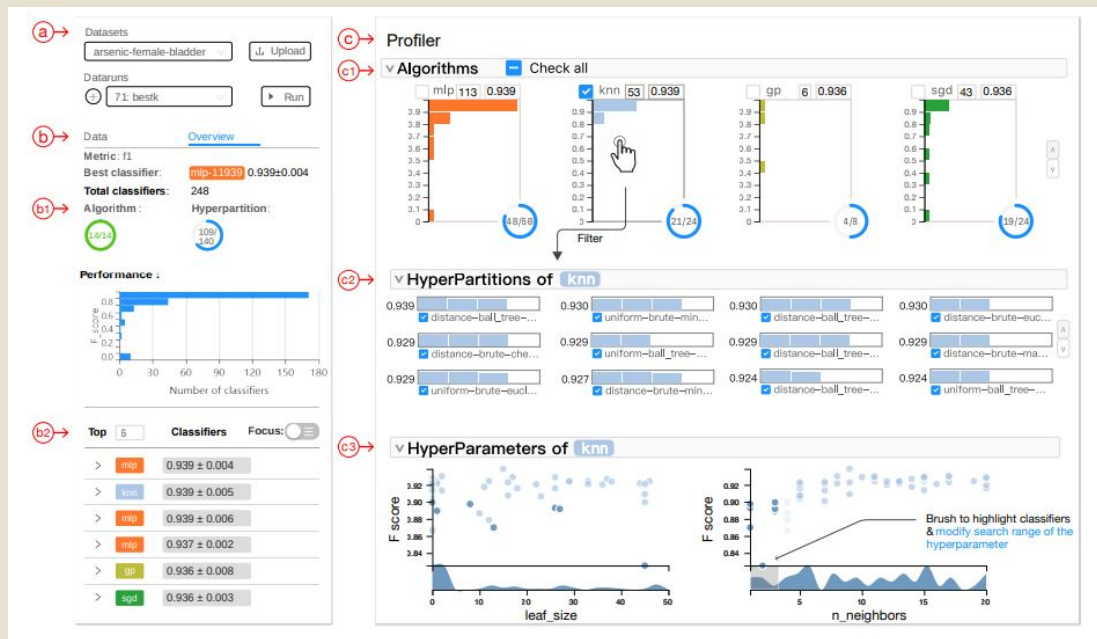
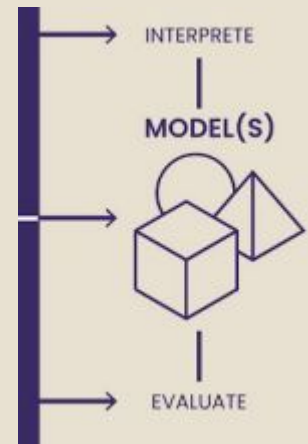
Ontology-based semantic meta-features



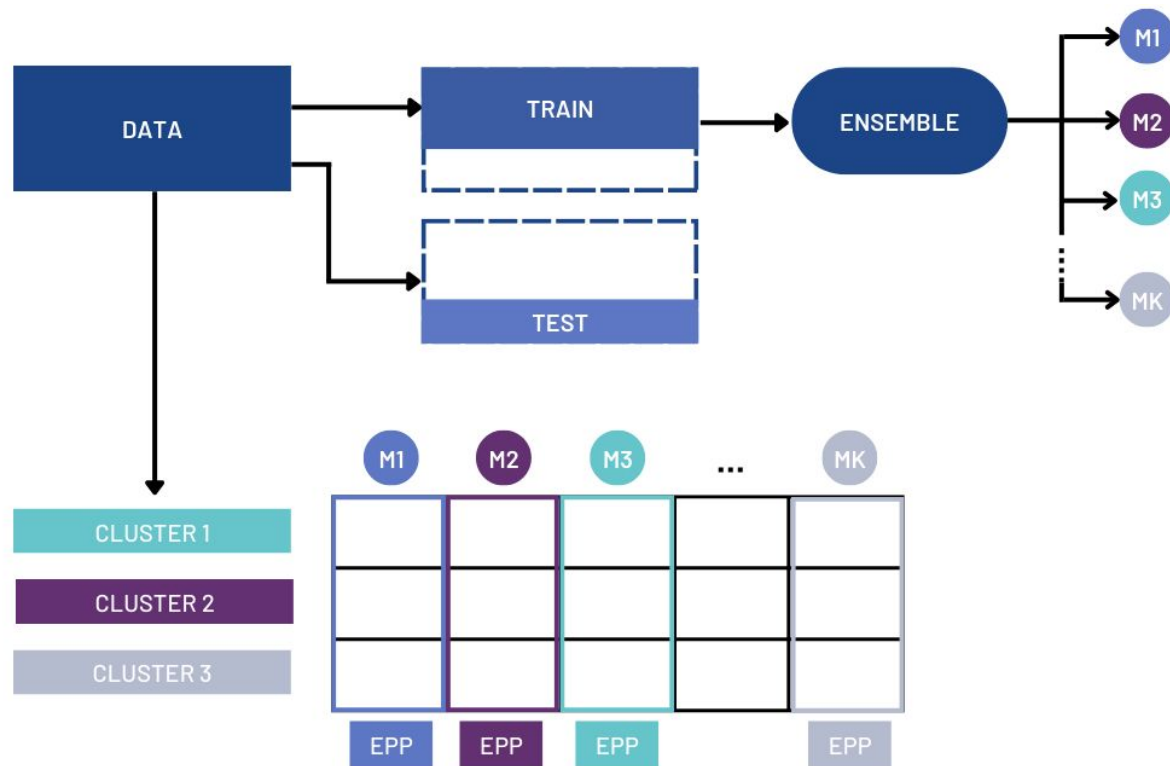
Hypothesis: semantic similarity of variables helps in meta-learning

➔ SnoMED annotated healthcare datasets (metaMIMIC + kaggle)

ATMSeer



EPP++



Questions?



Challenges



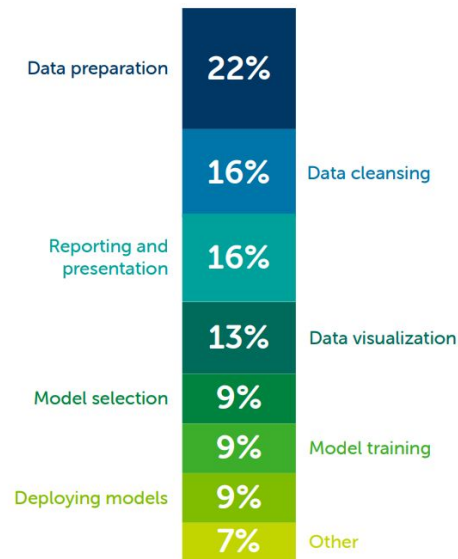
Two perspectives

- A. Automating Data Science** - Tijl De Bie, Luc De Raedt, José Hernández-Orallo, Holger Hoos, Padhraic Smyth, Christopher Williams
- B. Rethinking AutoML: Advancing from a Machine-Centered to Human-Centered Paradigm** - Marius Lindauer & Alexander Tornede



B.

AutoML actually only covers a rather small portion of the data science workflow and thus is only of limited use in practice.



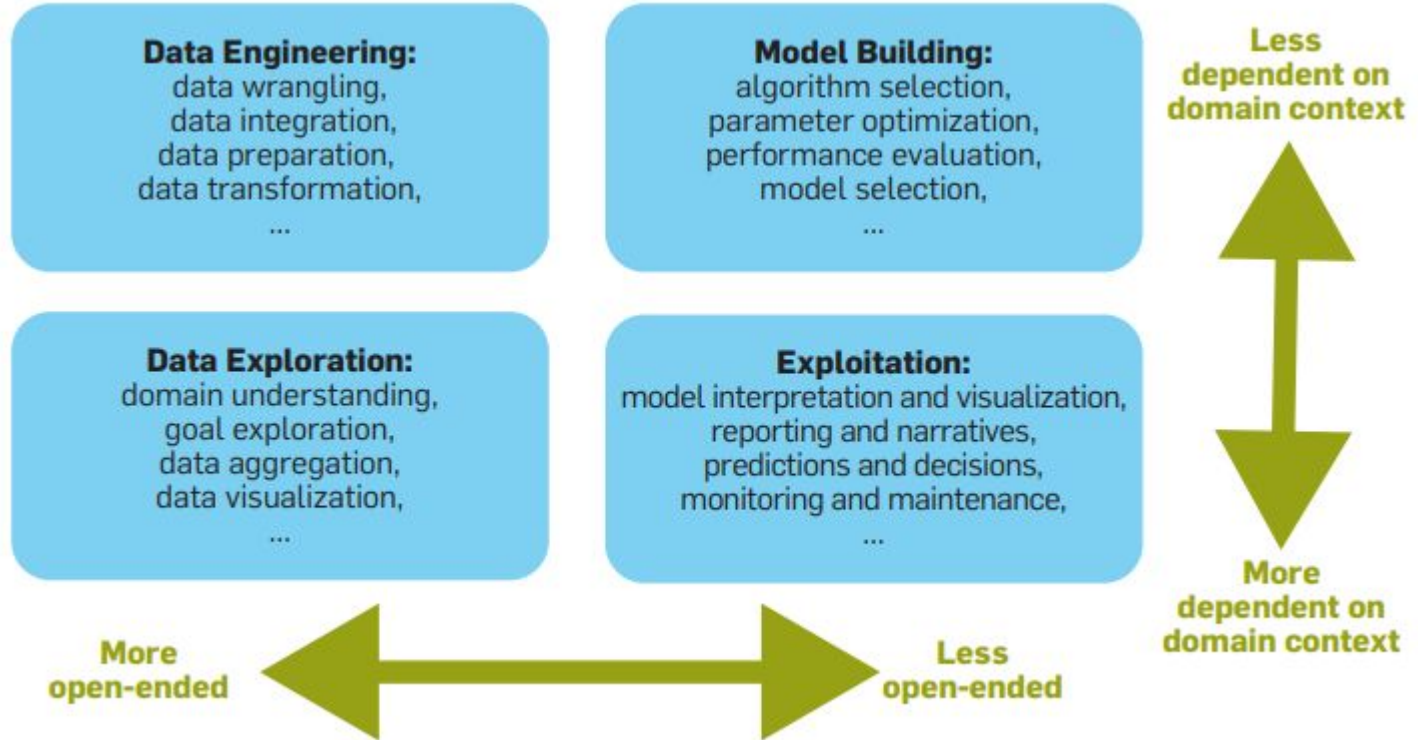
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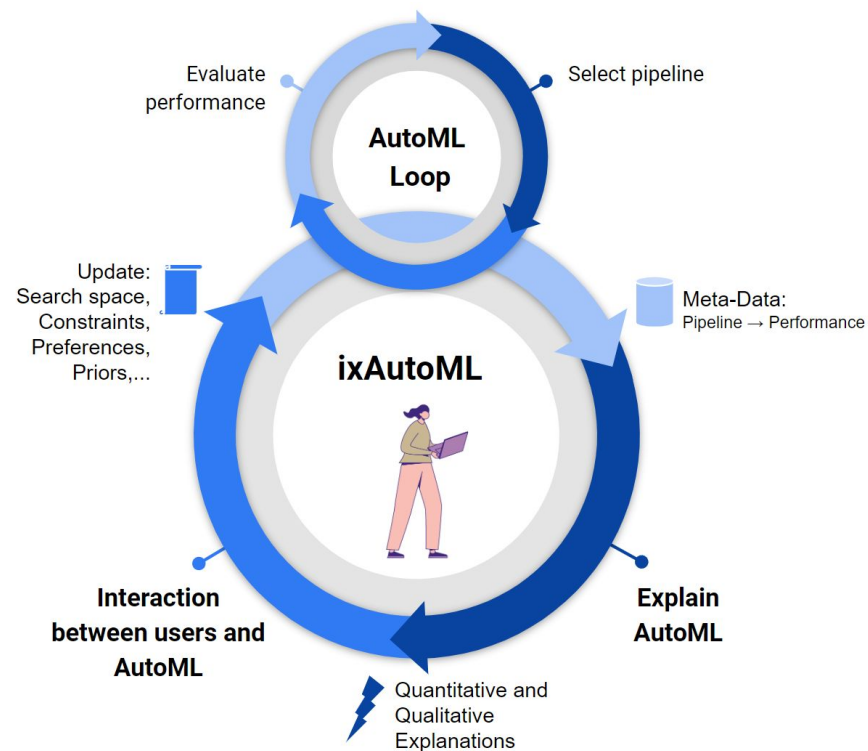
Automated Data Science

A.



Extension of target audience to data scientists

Both the internal process of AutoML tools and how their final result was constructed is often hard to understand, even for AutoML experts, let alone data scientists, leading to a lack of trust in AutoML systems.



Human-Centered AutoML

- Increasing the efficiency of AutoML by making use of the best of both worlds: a systematic search of efficient AutoML approaches and human expertise and intuition;
- A human-in-the-loop AutoML framework that is tailored to the needs of data scientists and thus leading to a more wide spread use of it;
- Insights into the design of ML applications and thus accelerating research on ML by reproducible and insightful tools;

