HyperImpute:

Generalized Iterative Imputation with Automatic Model Selection

ICML2022

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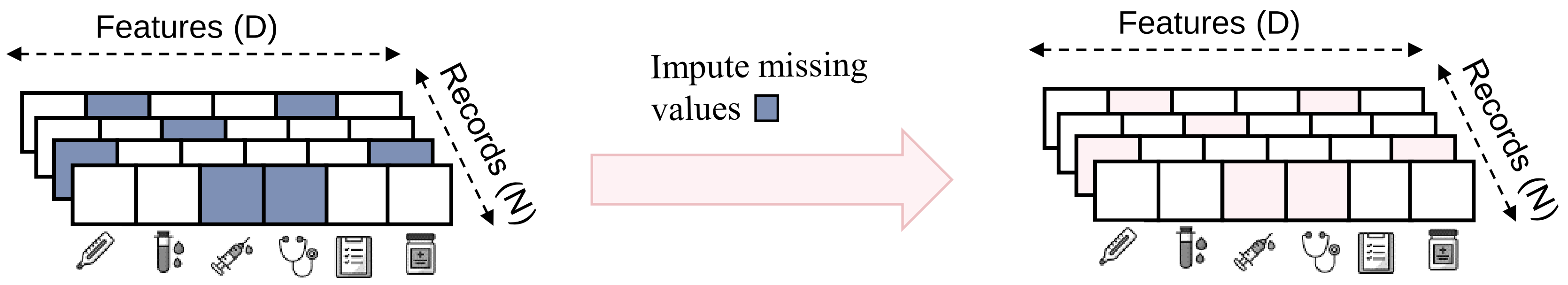
Setting: Missing data imputation

- **Motivation:** Missing data is a ubiquitous problem in real-life data collection
  - E.g. unrecorded patient characteristics, missing lab values
- **Goal:** Want to *know* likely values (regardless of downstream task)

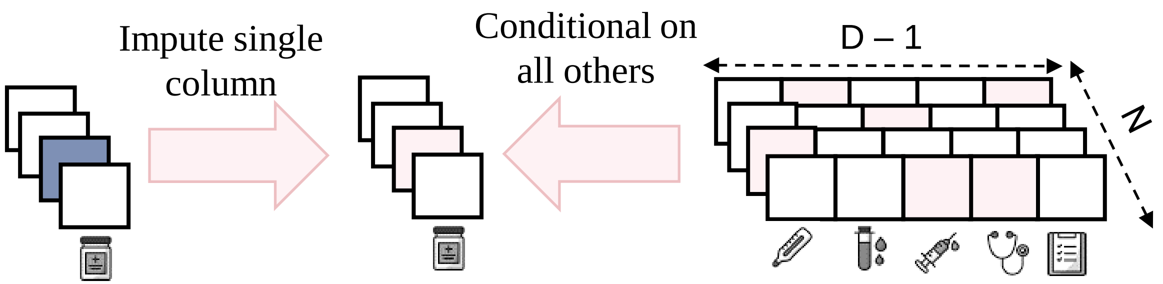
  → *Impute* values even when *no columns are complete*



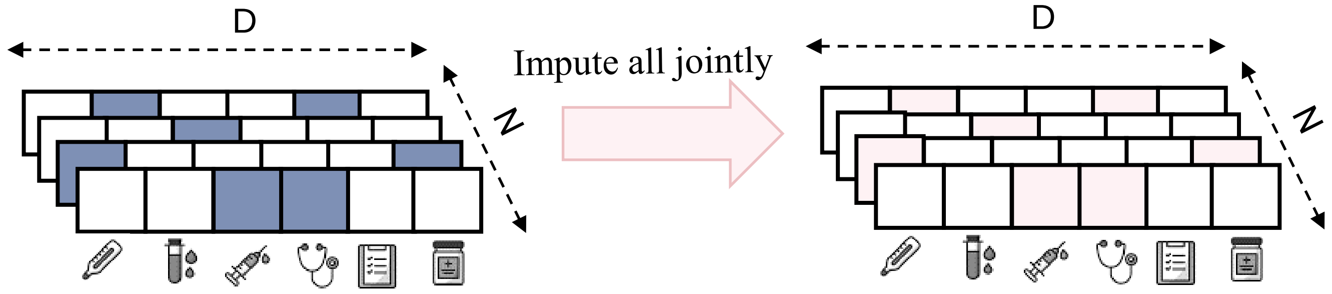
Related work: Much interest in imputation recently

Existing work relies on:

a) Iterative Imputation (*Imputation by chained equations – ICE*) with correctly pre-specified per-column (prediction) models *OR*

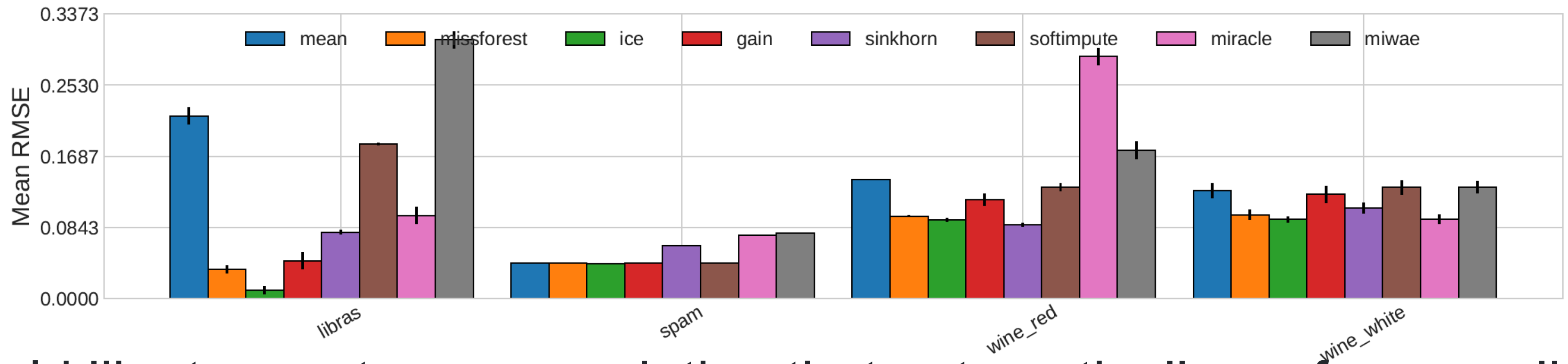


b) Deep Generative Models (*GAIN, MIWAE, MIRACLE*) as joint models for all features



Goal & desiderata for our new approach

Different methods do well across different datasets and settings…



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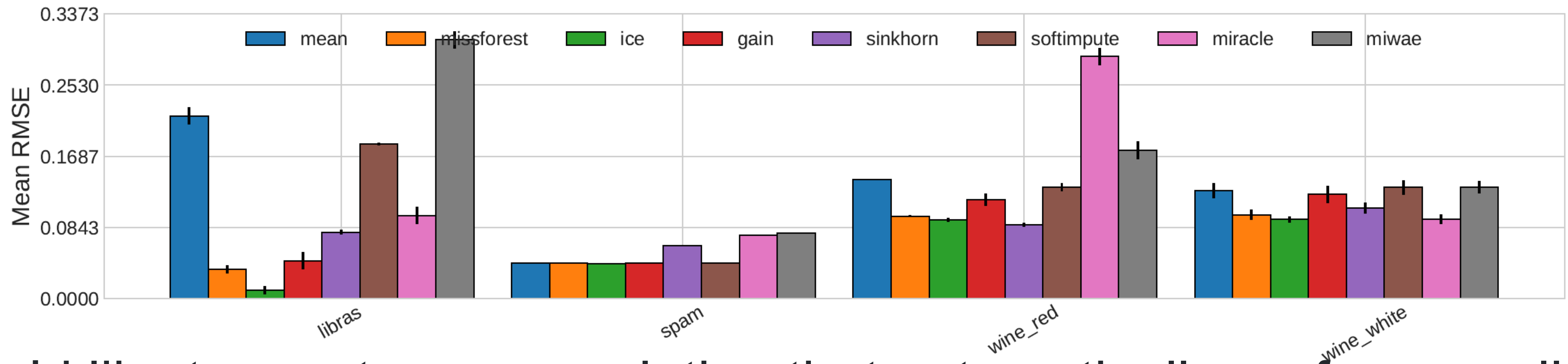

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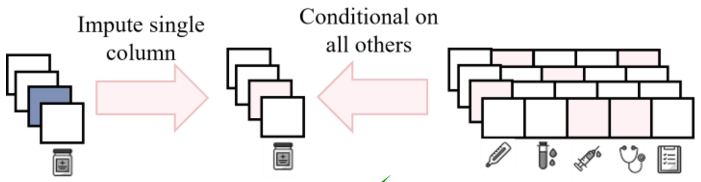
Three desiderata for our new solution:

1. *Weak assumptions:* Trainable without complete data, but not assume completely random missingness pattern
2. *Flexibility:* Combine flexibility of conditional specifications with capacity of deep approximators
3. *Easy Optimization:* Relieve burden of complete specification, and be easily & automatically optimized (tunable)

HyperImpute: A generalized iterative imputation approach

Why iterative imputation?



- *Weak assumptions*: Allows generic missing at random setting ✓
- *Flexibility:* Allows specifying different models for each column ✓
  → Easily incorporate different data-types and design-specifics, e.g. bounds
- *Easy Optimization:* column-wise perspective gives simple evaluation (prediction) criterion ✓

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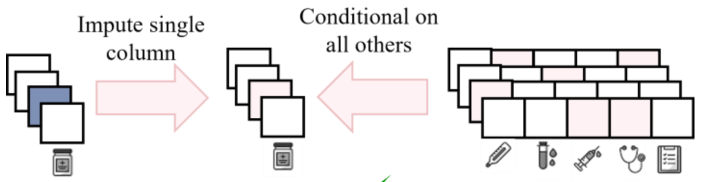

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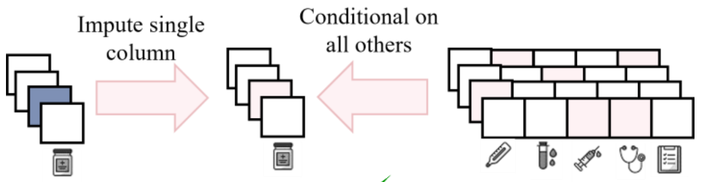

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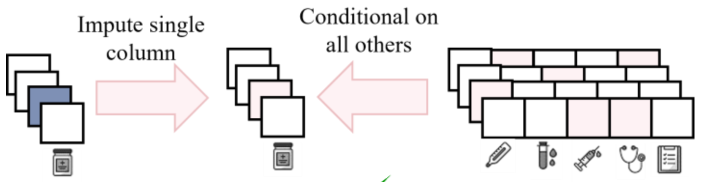

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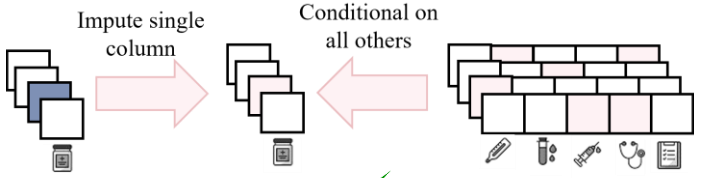

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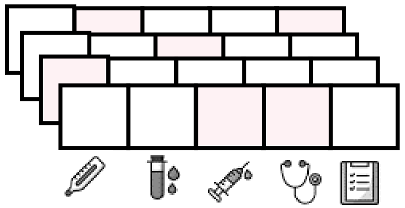
  → HyperImpute: Iterative model search ☺ ✓

The HyperImpute Framework



Given current
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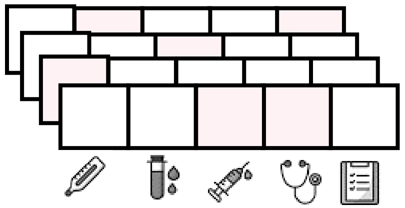

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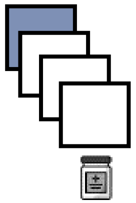

1 Find best model for next column d

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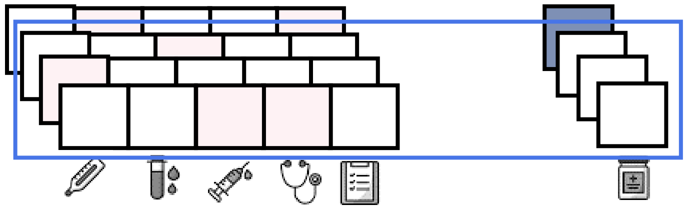

Using records $\mathcal{D}_d^{\text{obs}}$
with observed target

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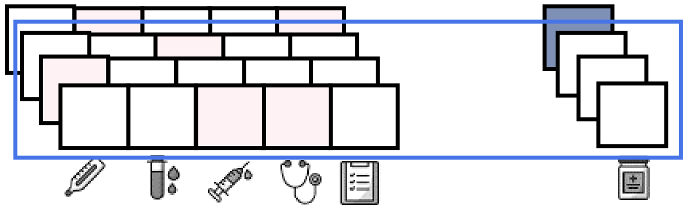

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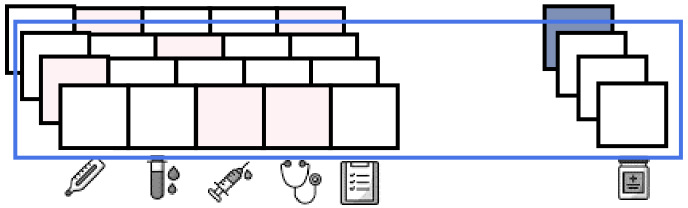

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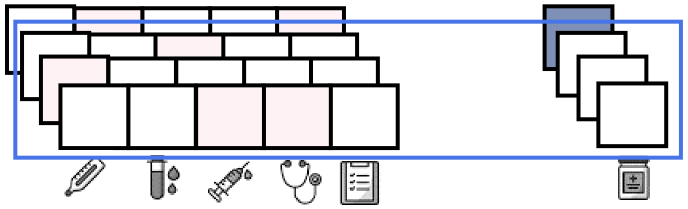
Optimizer

- Naive Search
- Bayesian Opt.
- Hyperband Opt.
- ...

The HyperImpute Framework



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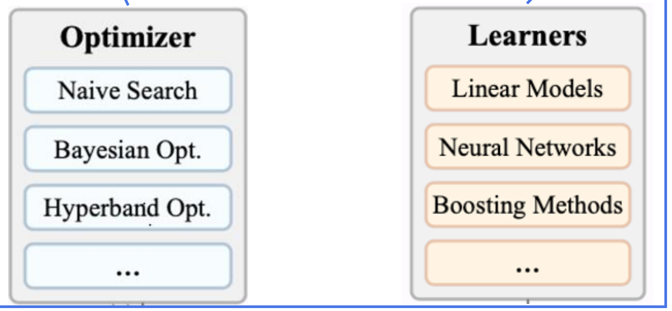

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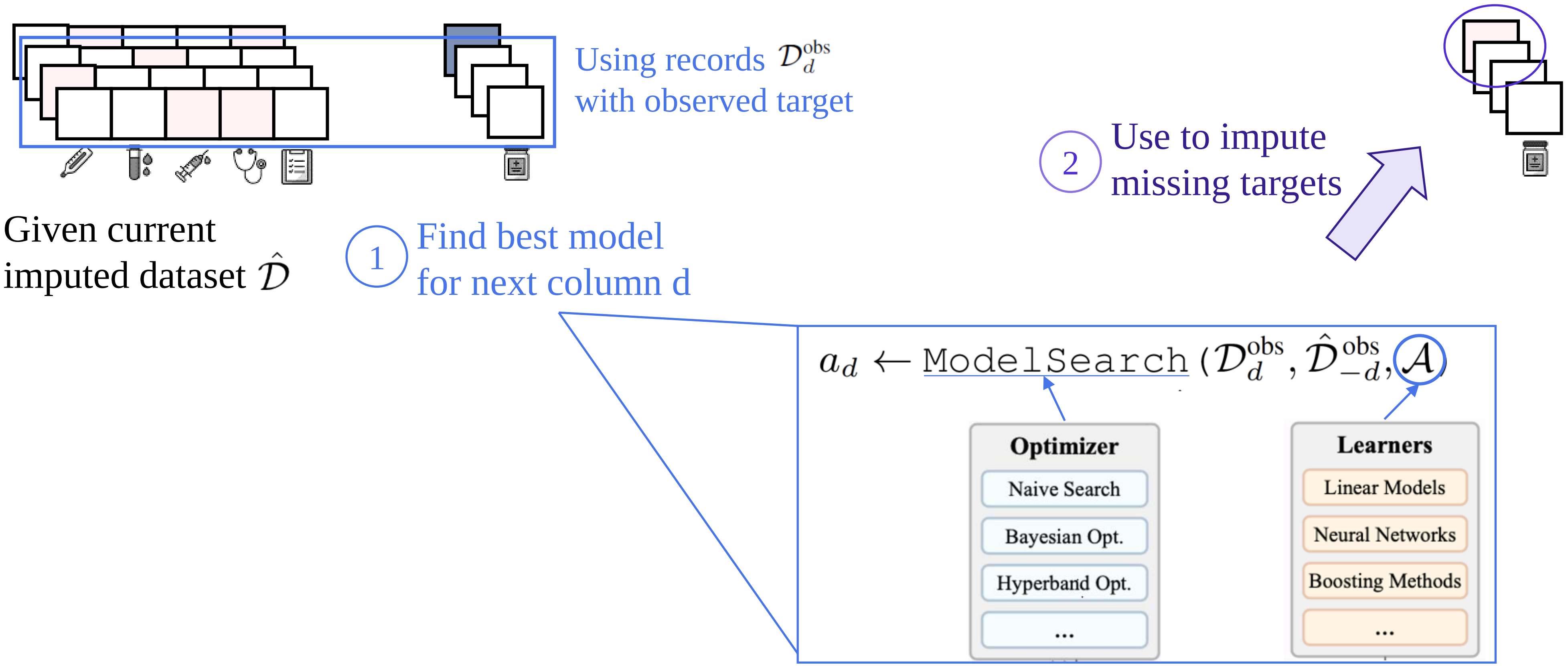

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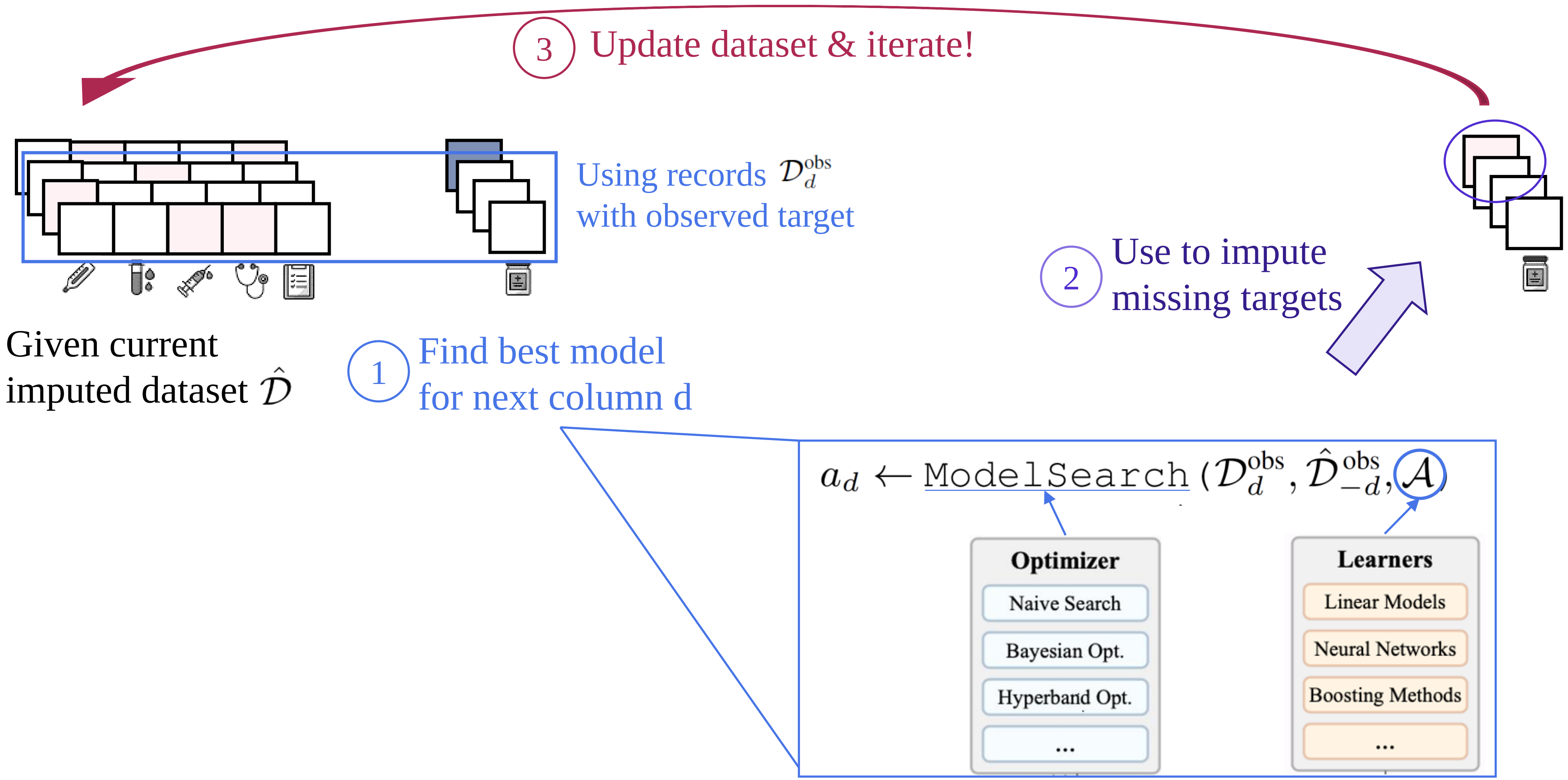
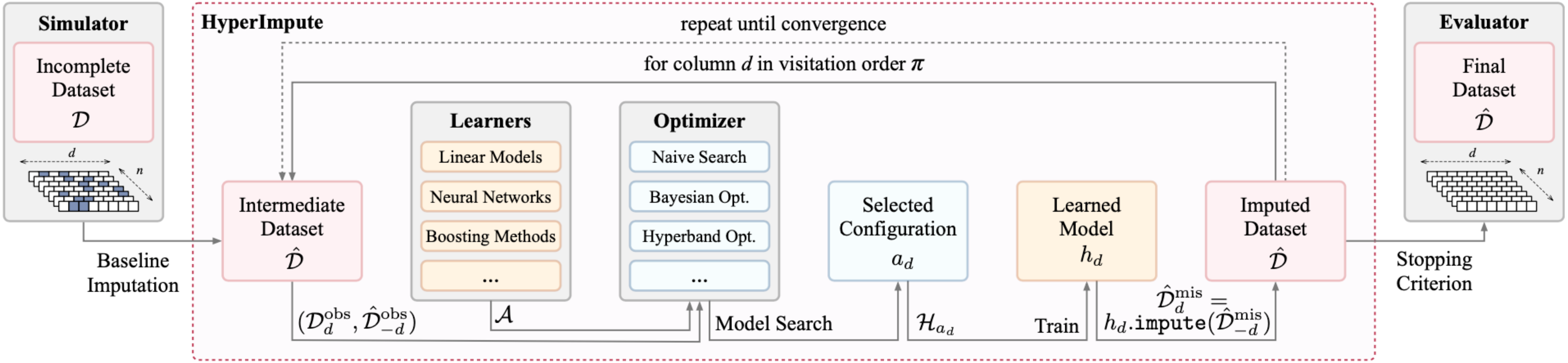


The HyperImpute package: A useful tool!

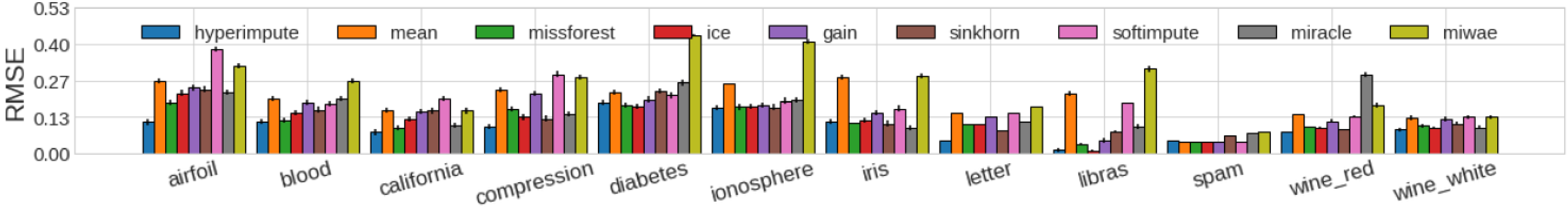


Implemented as an easy-to-use modular sklearn-style python package, incl. baselines and evaluation tools!

→ Available at https://github.com/vanderschaarlab/hyperimpute

Empirical investigation

HyperImpute outperforms existing baselines across different datasets and missingness mechanisms..



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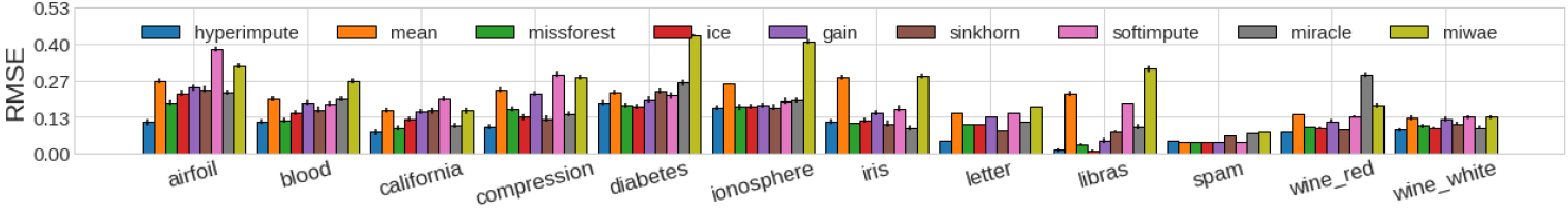
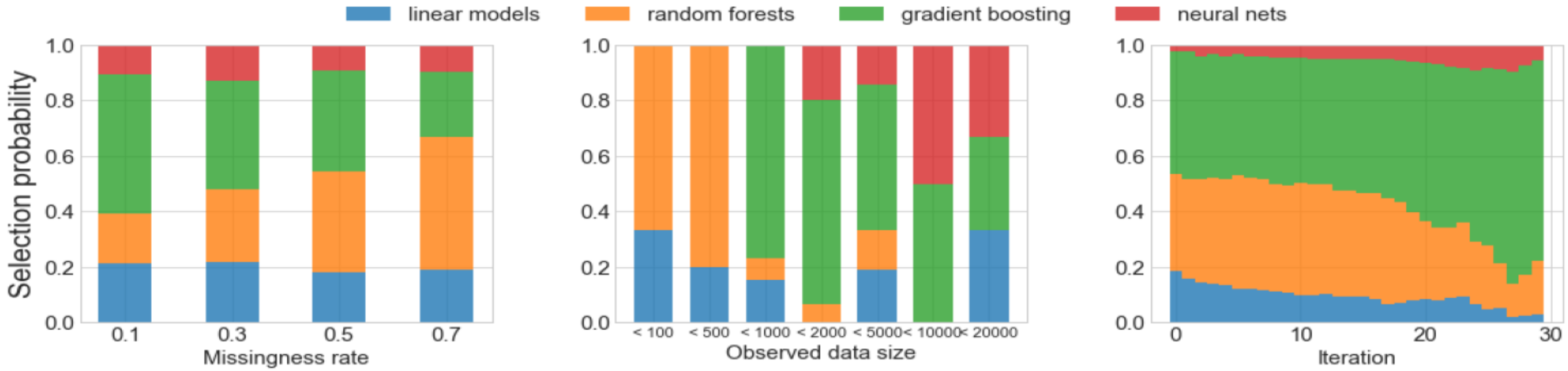


… and allows to provide interesting insights into selected model classes!



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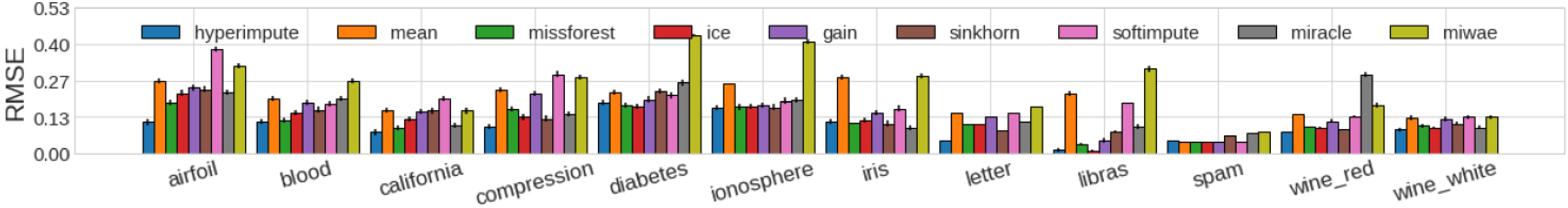

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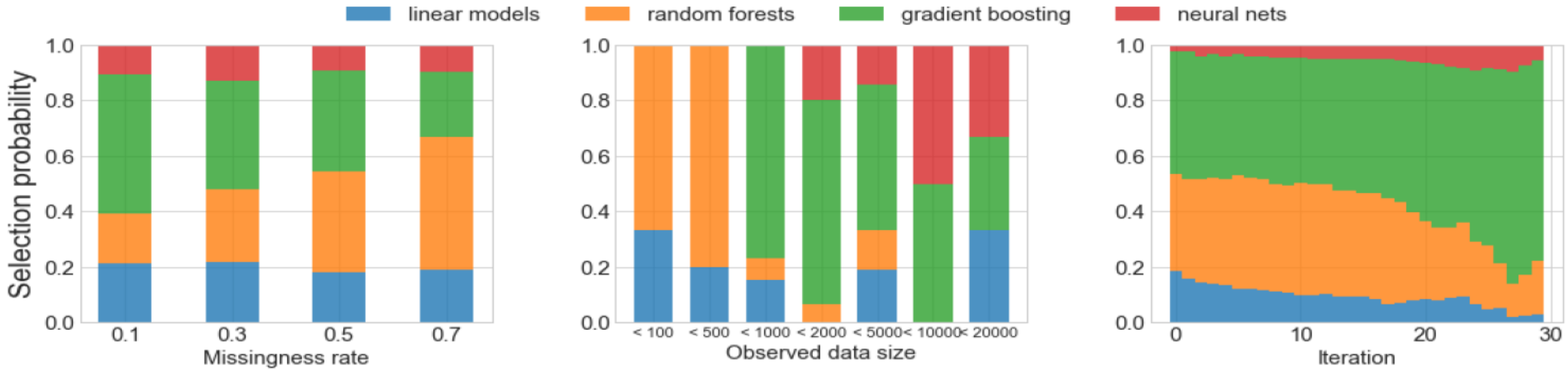

Sources of gain, convergence and other scenario analyses covered in full paper!

Try it out!

Code: https://github.com/vanderschaarlab/hyperimpute
Paper: https://arxiv.org/abs/2206.07769

This work was supported by:

AstraZeneca

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