MedleySolver: Online SMT Algorithm Selection

Nikhil Pimpalkhare[1], Federico Mora[1],
Elizabeth Polgreen[1,2], and Sanjit A. Seshia[1]

[1] University of California, Berkeley

[2] University of Edinburgh

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Berkeley UNIVERSITY OF CALIFORNIA

THE UNIVERSITY of EDINBURGH

Where Are SMT Solvers Used?

Example Applications

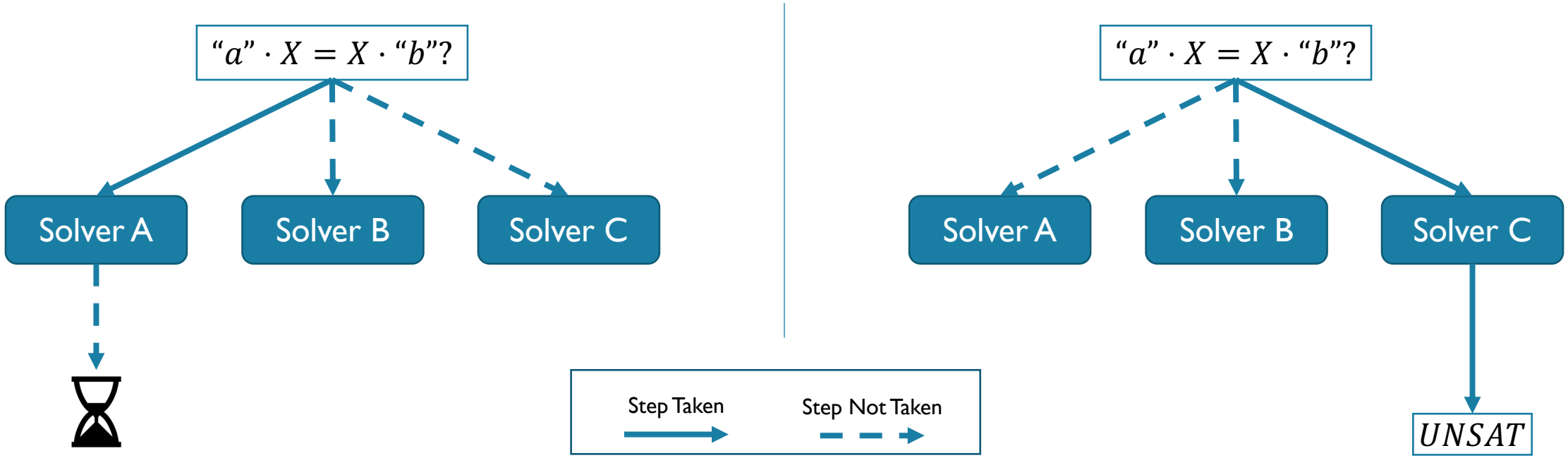
- Verification engines,
  - check many verification conditions.
- Symbolic execution engines,
  - check many path conditions.
- Program synthesis engines,
  - check many candidate programs.

Example Tools

The Rosette Language

What is SMT Algorithm Selection?

- For a given query, can we predict the solver that will perform best?



[1] J. R.Rice: The algorithm selection problem. Advances in Computers (1976).

Desired Features for Algorithm Selection

(End-User Perspective)

Feature \ Approach	Expert Encoded Decision Rule	Existing Methods (Offline Learning)	MedleySolver (Online Learning)
No Manual Input	☑	☑	☑
Minimal Upfront Costs			
No Data Requirements			
No Solver Requirements			
No Need to Repeat Upfront Costs			
Fine Grained Decisions			

Feature Support

- ☑ Strong
- ☐ Medium
- ☒ Weak

Existing Approaches

Expert Encoded

E.g., Z3's quantifier-free bit-vector solver tactic

```
(preamble_st,
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 // symbols. In this case, we should not use the `sat', but instead `smt'. Alternatively,
 // the UFs can be eliminated by eager ackermannization in the preamble.
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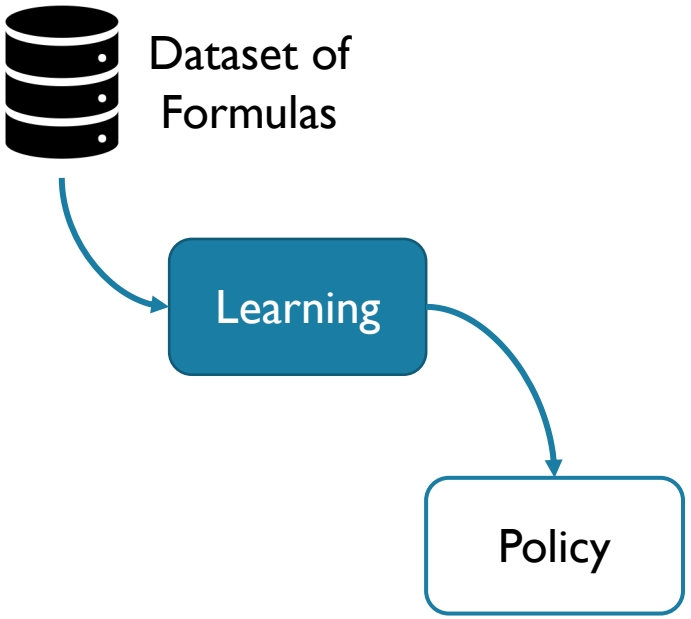
Machine Learned

E.g., SatZilla [2], MachSMT [3], FastSMT [4], …



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[4] Balunovic, M., Bielik, P., Vechev, M.T.: Learning to solve SMT formulas. NeurIPS (2018)

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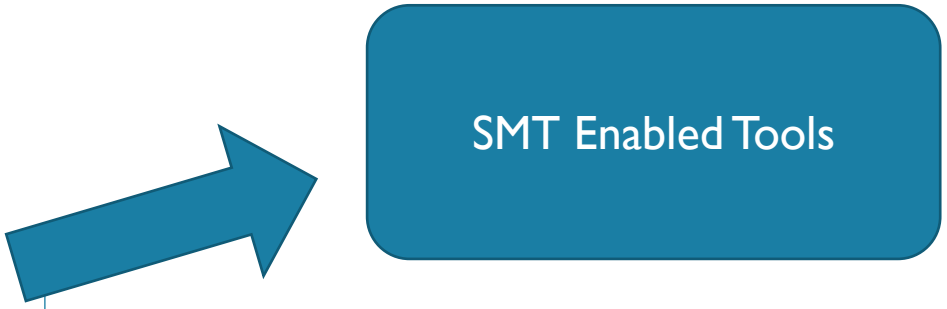

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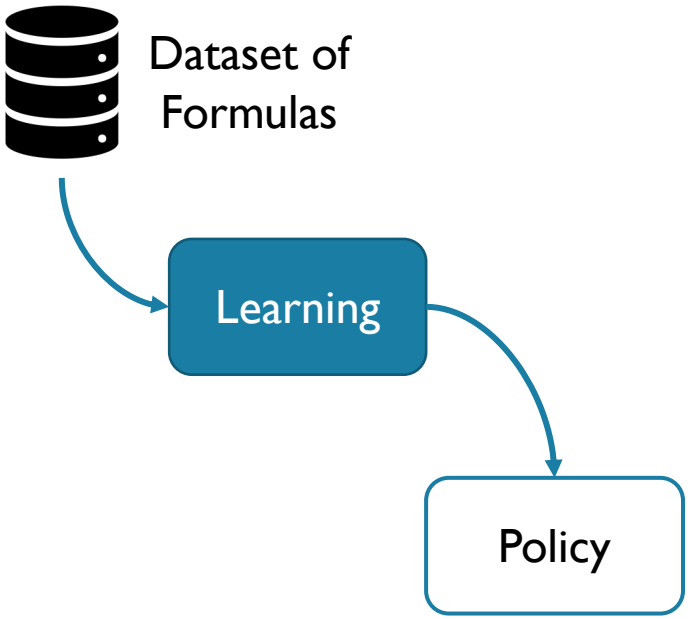

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Existing Approaches

SMT Enabled Tools

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```

1. Tailored to specific solvers
2. Not fine grained (takes time to engineer)

Machine Learned

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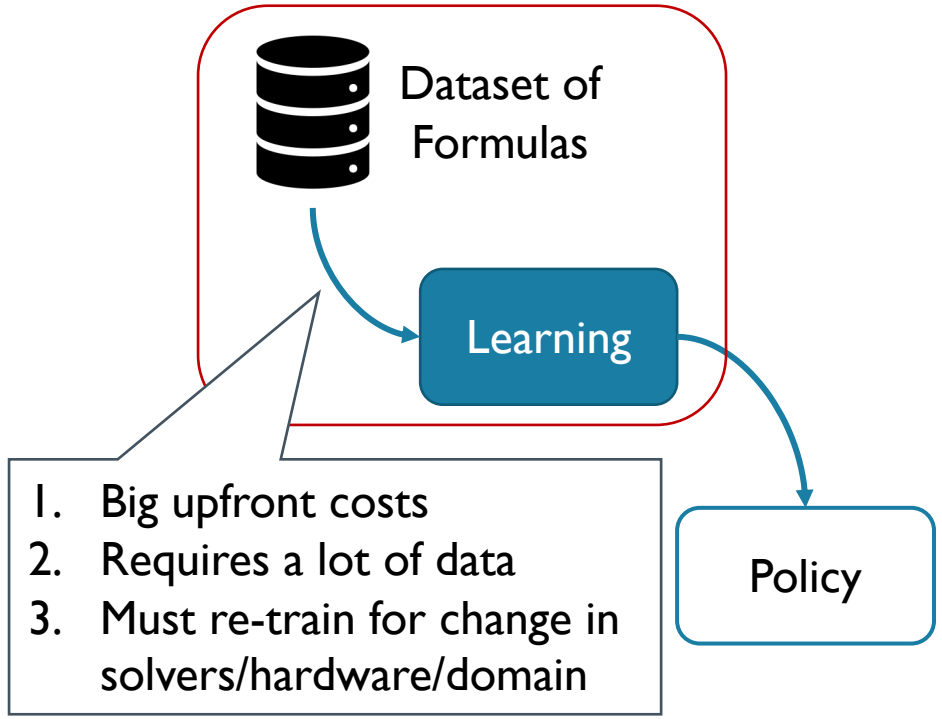

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Minimal Upfront Costs	✓	✗	
No Data Requirements	✓	▢	
No Solver Requirements	✗	✓	
No Need to Repeat Upfront Costs	✓	✗	
Fine Grained Decisions	✗	✓	

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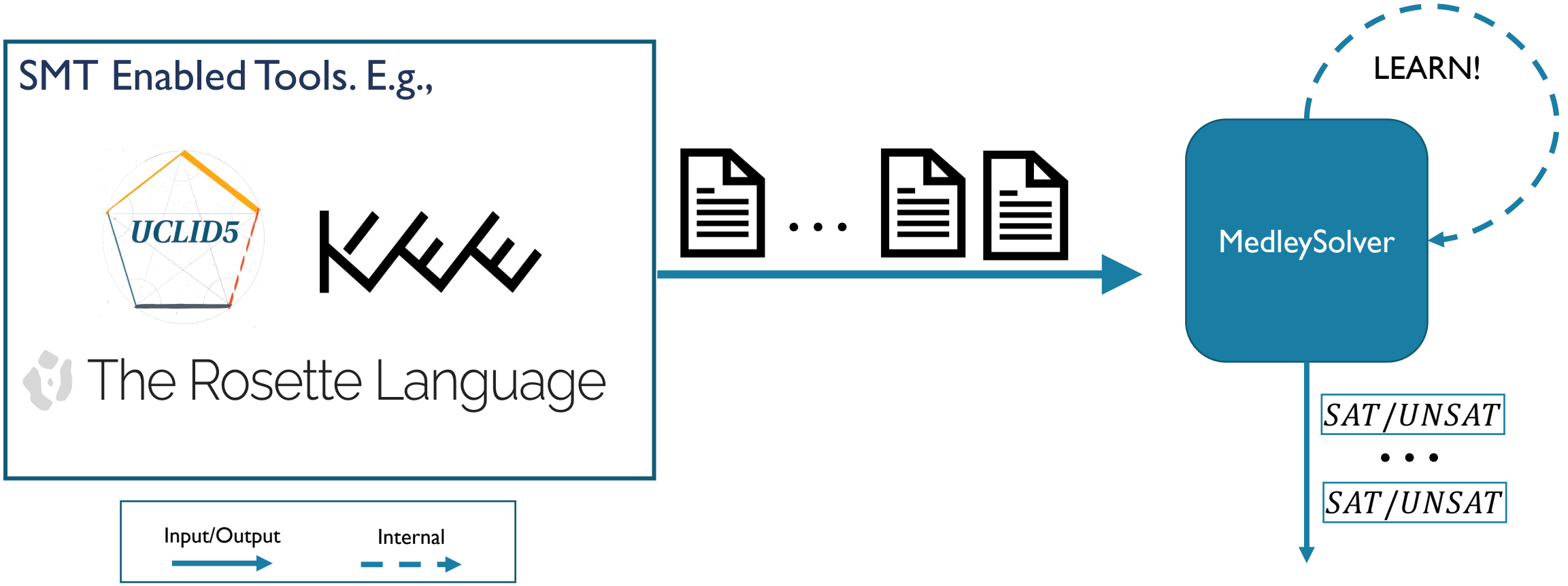
Our Proposal: Use *Online* Learning

- Learn as we go with what we have locally!



MedleySolver Overview

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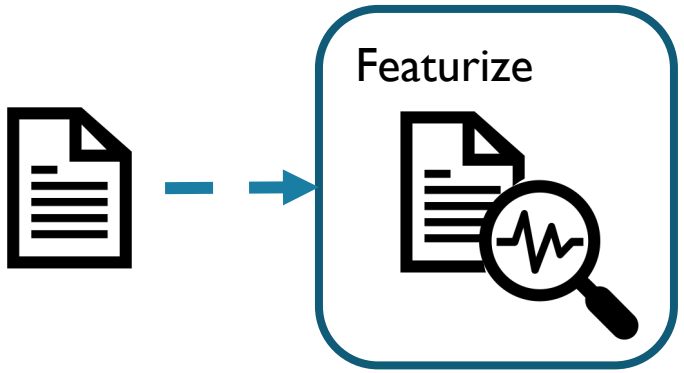

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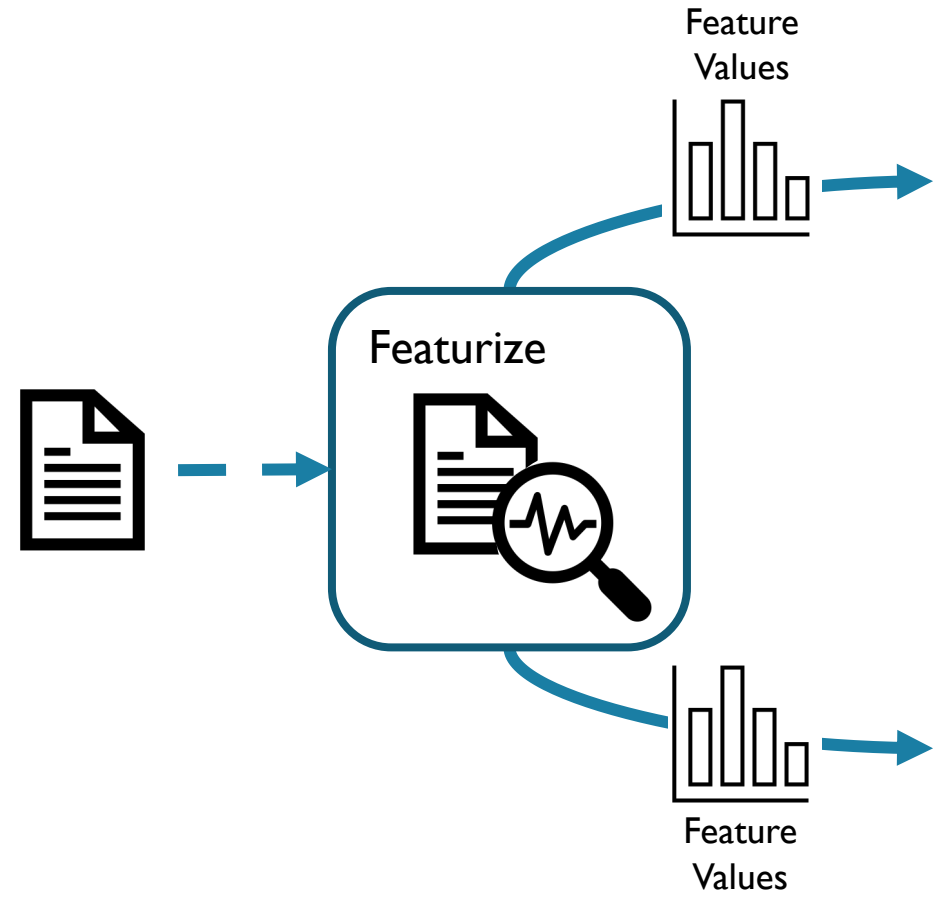

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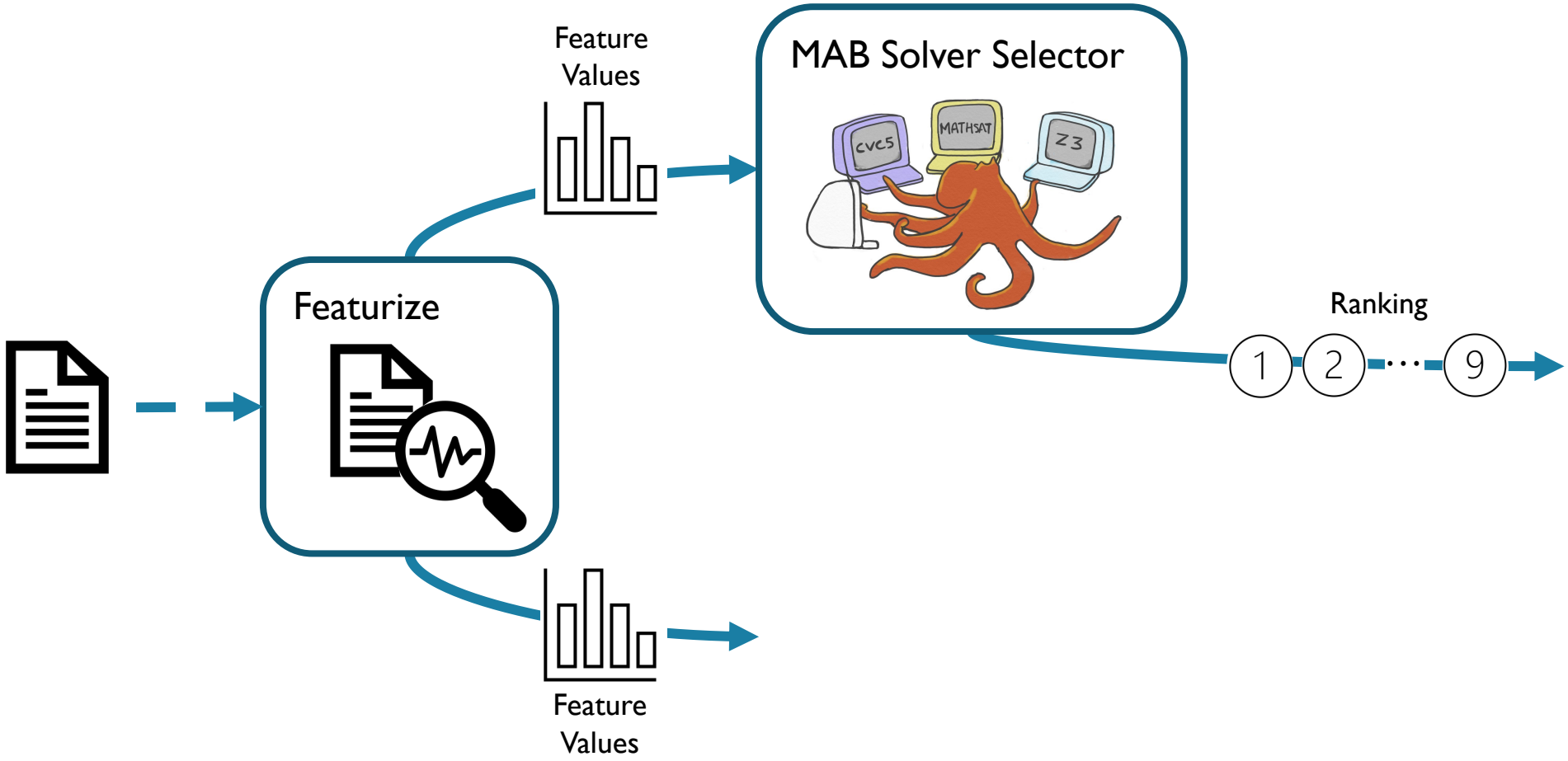

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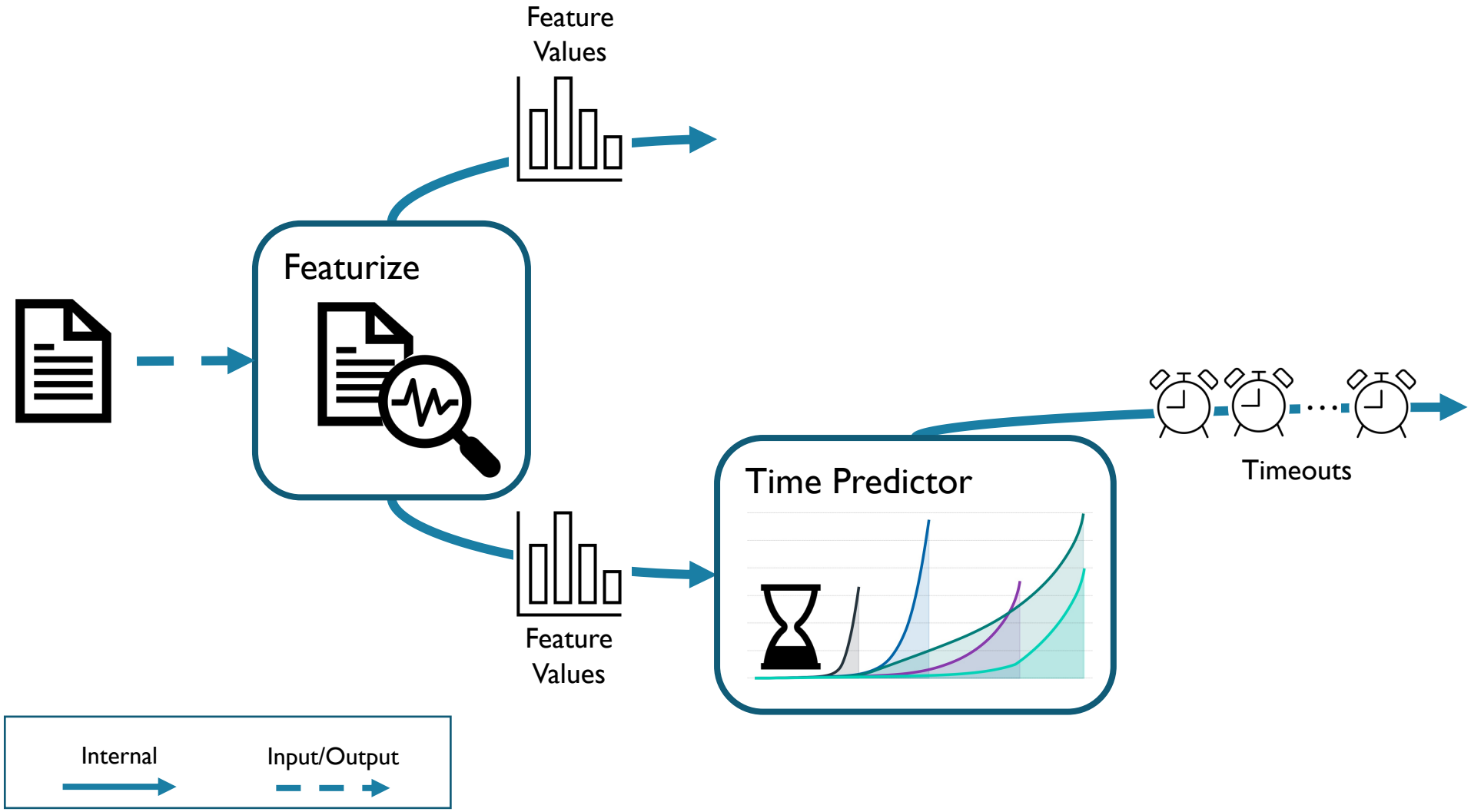

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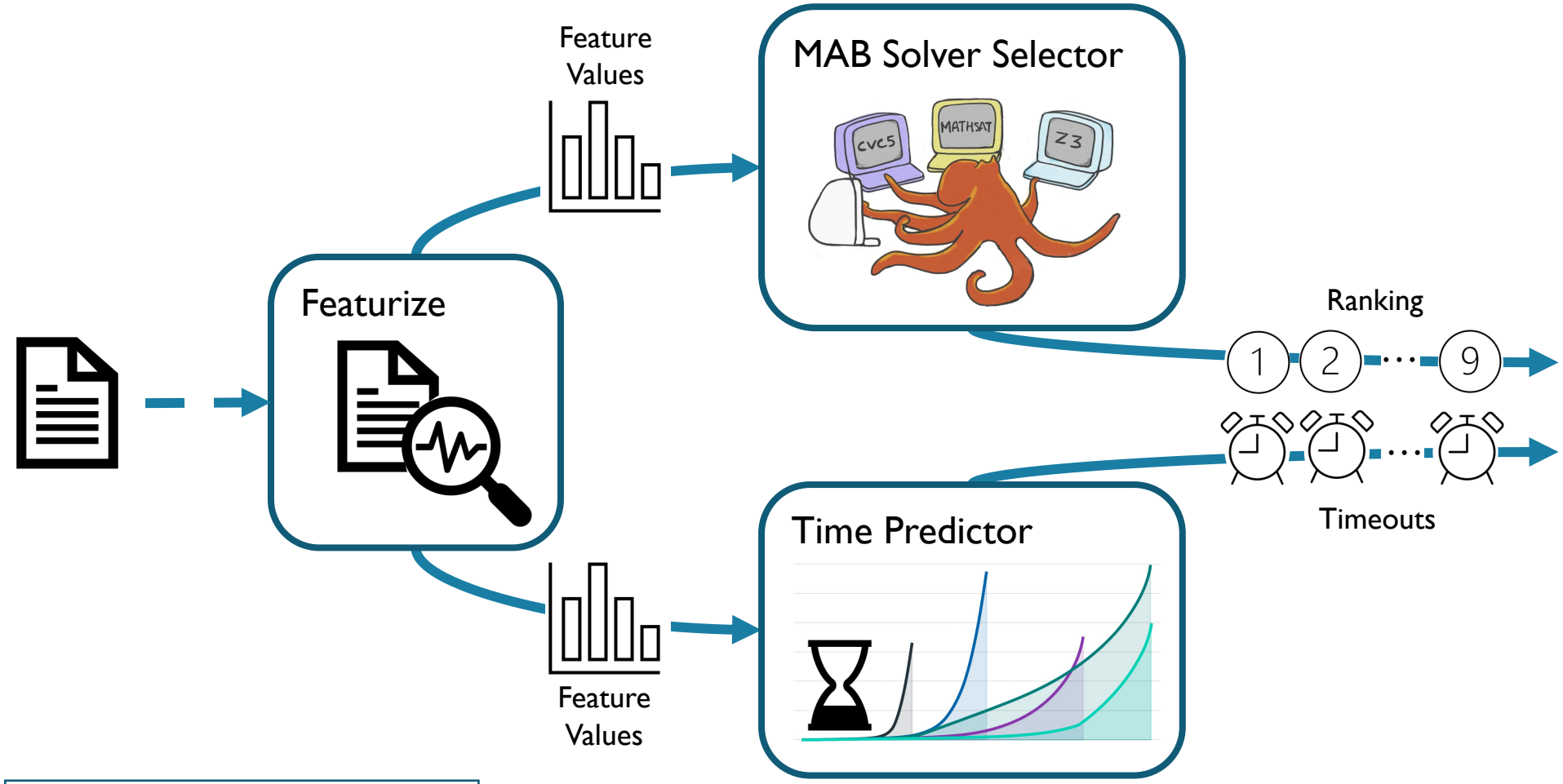

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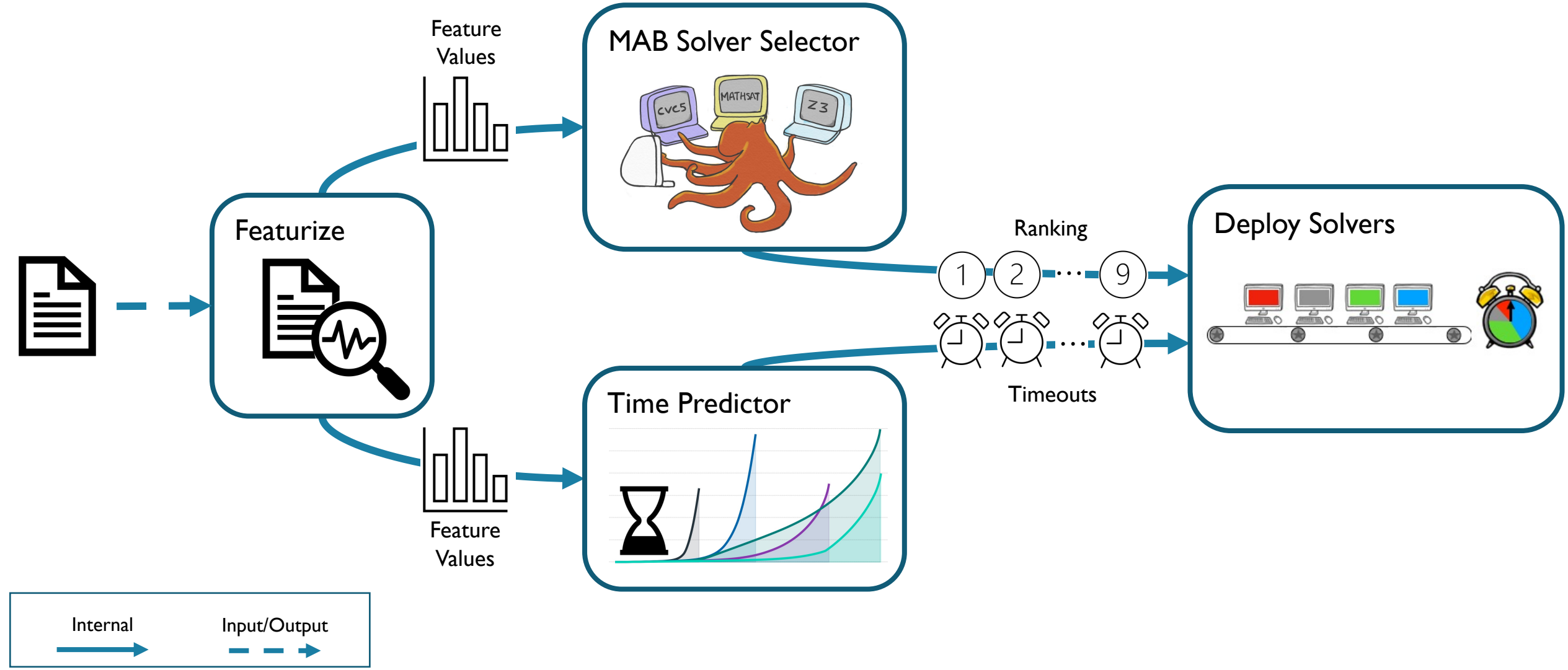

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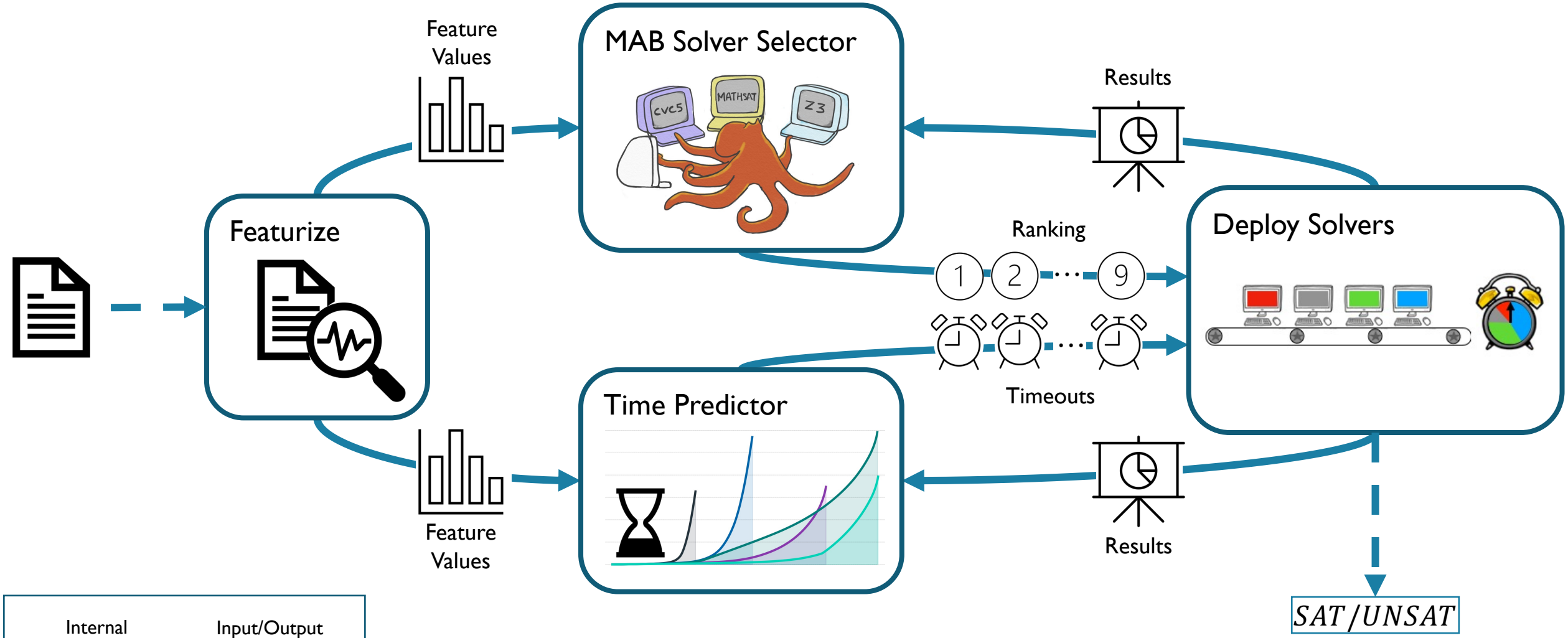
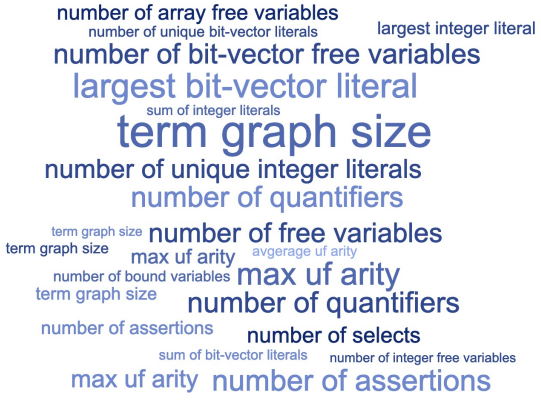


Computing Features

Feature Selection

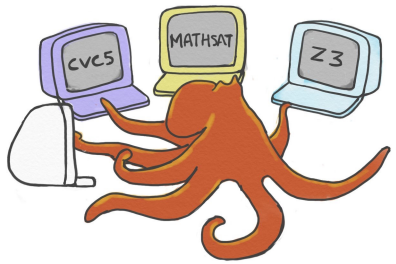
- Used a set of context-free features
  - E.g., "number of integer variables"
- Identified relevant features using Pearson R coefficient
  - Compute correlation of each feature against solving time, for each solver
  - Use 10 features with the highest average coefficient

Hypothetical feature correlation graphs (actual graphs are messier..)



Selecting Solver Order

MAB Solver Selector



Selecting Solver Order

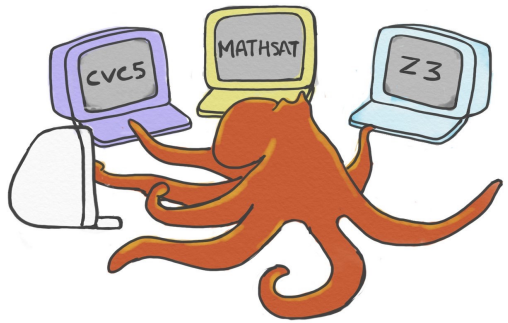
Multi-Armed Bandit Intuition

- Arms are slot machines
- Reward is payout
- Pick what slot machine to use

Our Multi-Armed Bandit Use

- Arms are solvers
- Reward is negative time taken
- Pick order of solvers to run

MAB Solver Selector



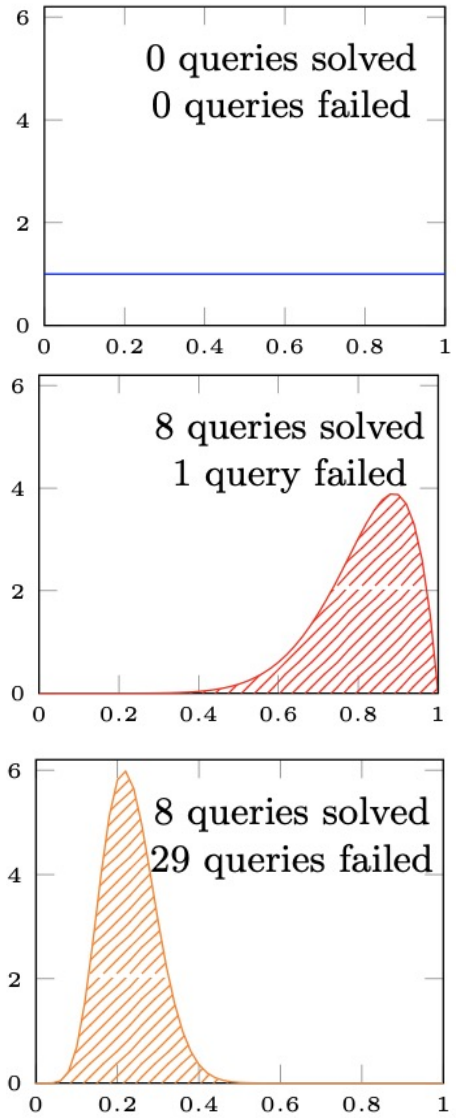
Implemented Algorithms

- Thompson Sampling
- k-Nearest-Neighbour Bandit
- Exp3
- Neural network bandit
- LinUCB

Thompson Sampling

Non-Contextual Algorithm 1

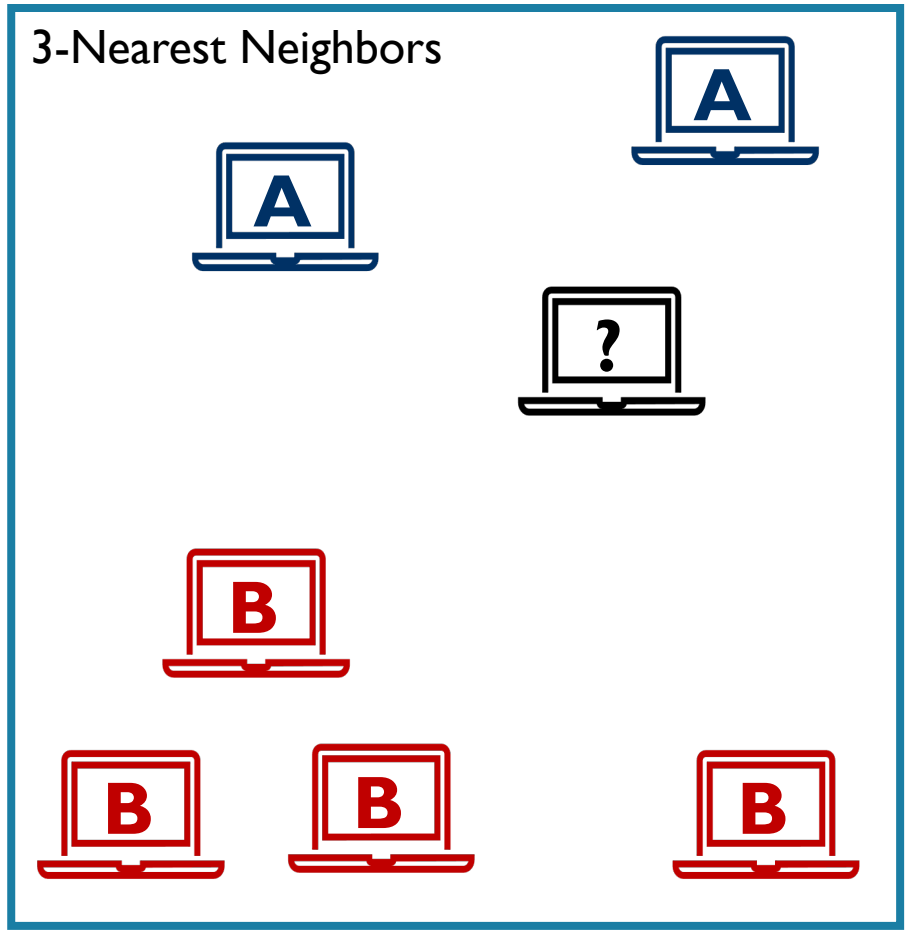
- Model rewards using probability distributions
  - (beta distribution)
- One distribution per solver
- Sample from each beta distribution
  - execute solvers in order of sample value
- Update using Bayes' rule
- Arms which are not thoroughly explored will have higher variance, making them more likely to be explored in the future



k-Nearest Neighbor

Contextual Algorithm I

- Given a query, k-NN looks at the k closest past solved queries and orders solvers by their number of appearances in these k, breaking ties randomly
- Update: if query k was solved, we put it into our list of past solved queries with the corresponding solver label



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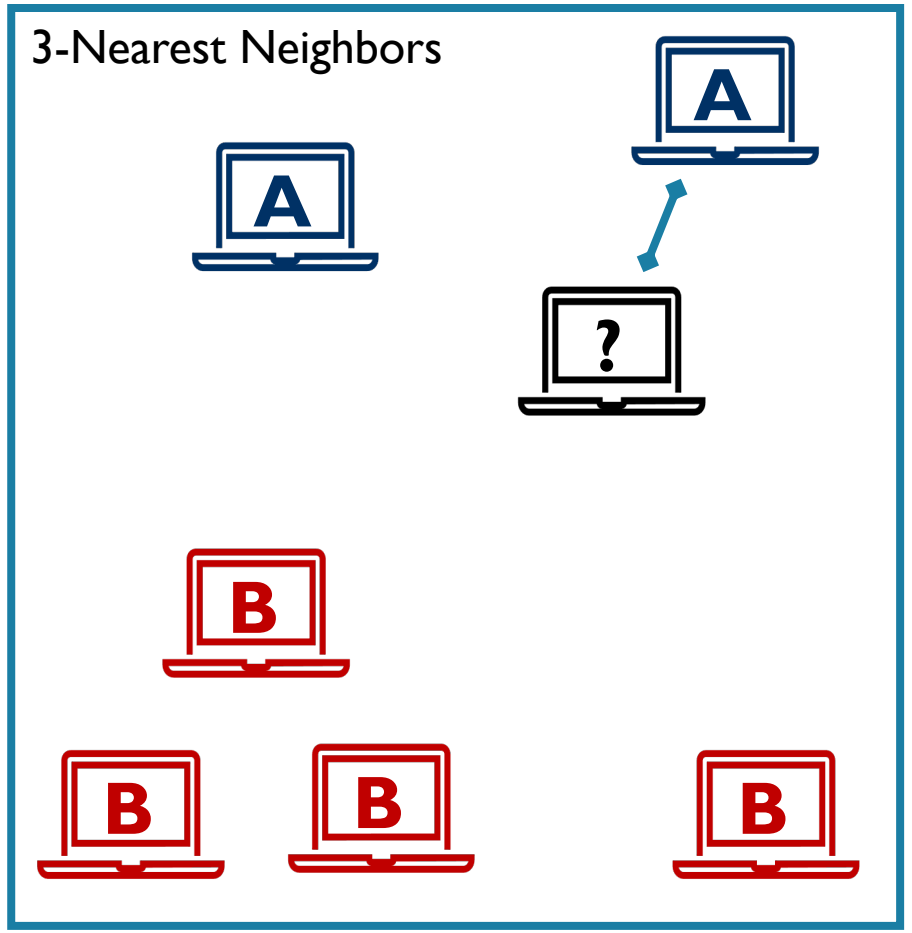

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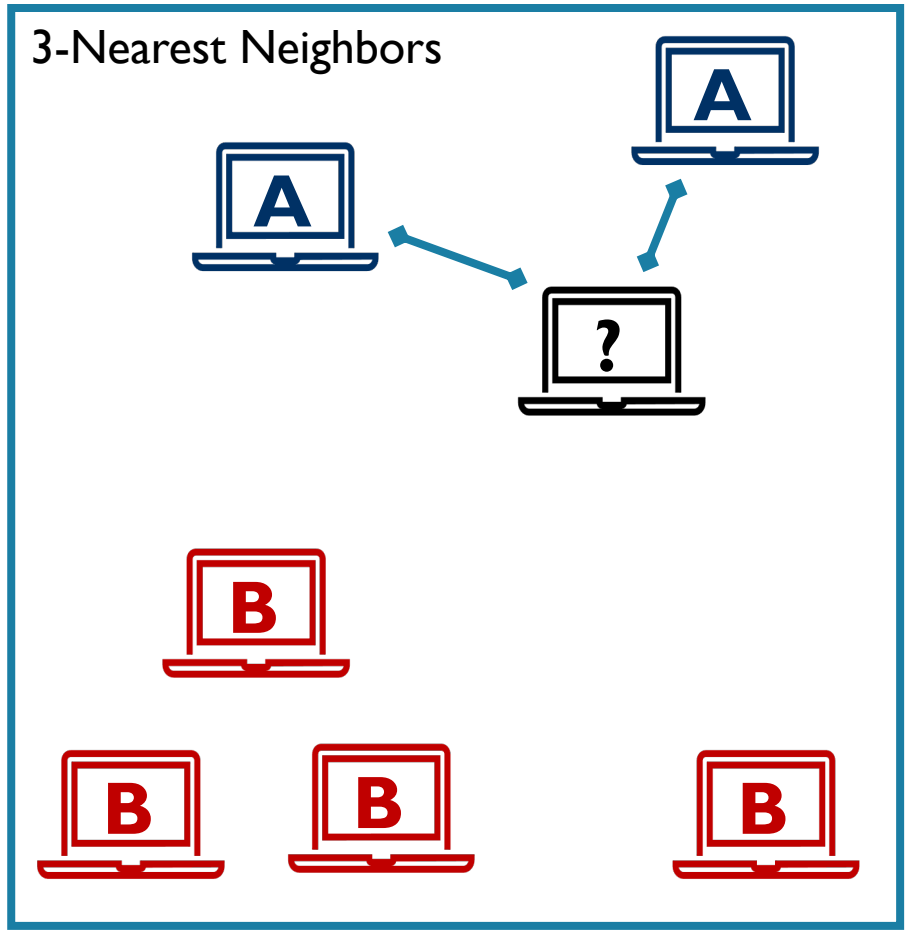

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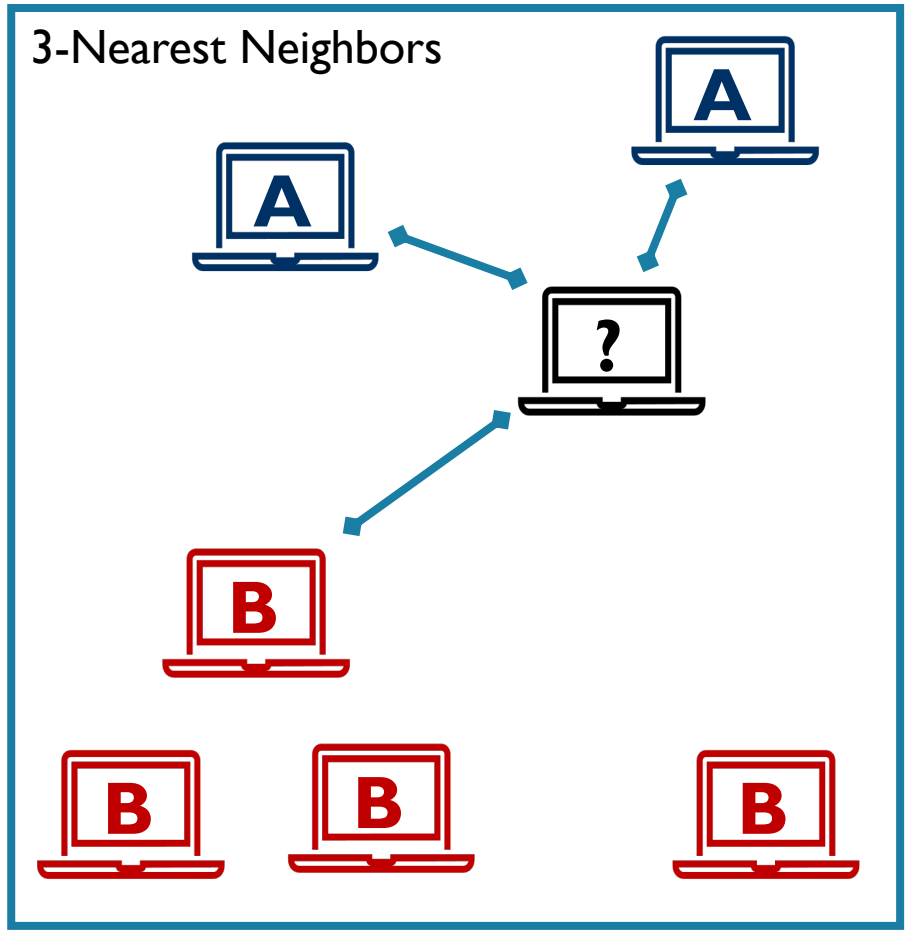

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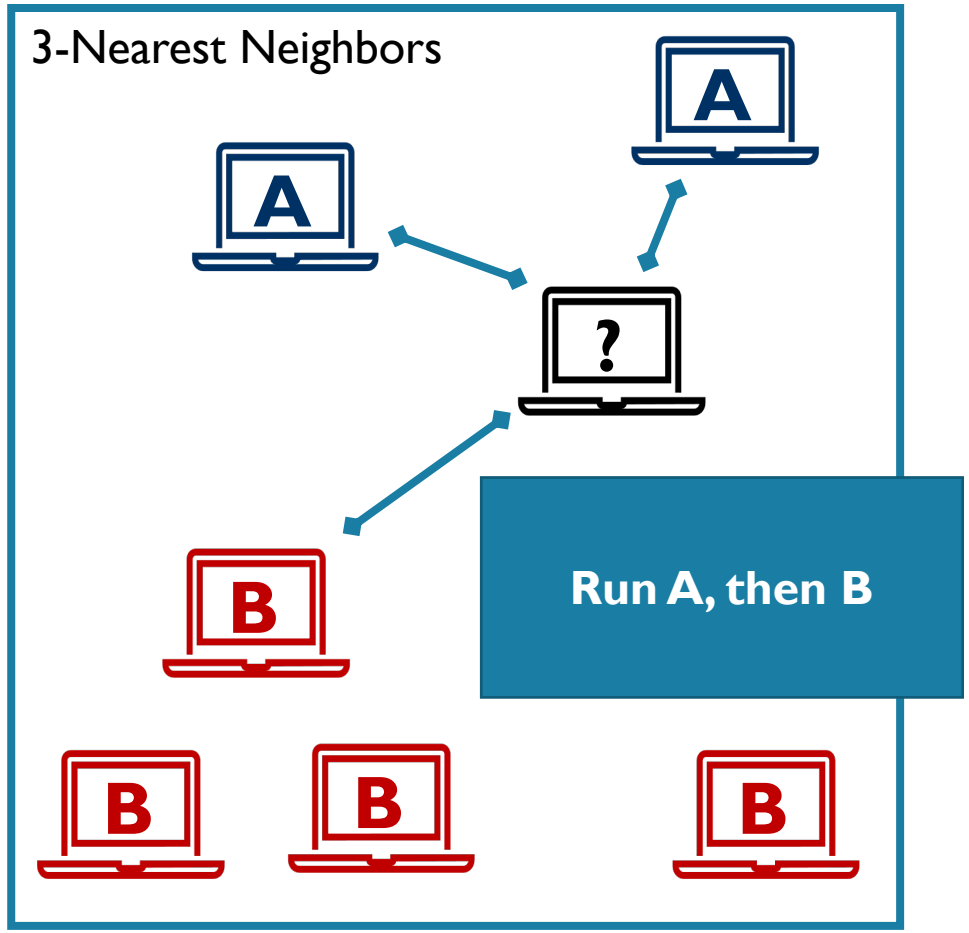

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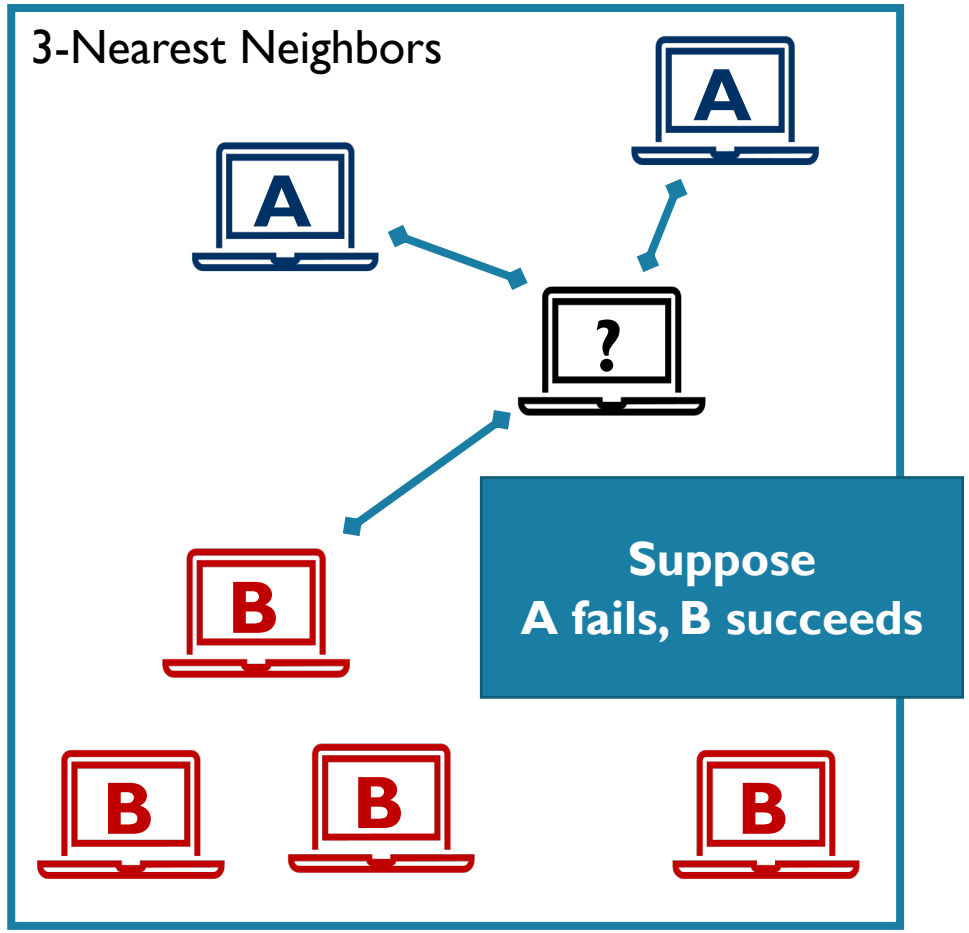

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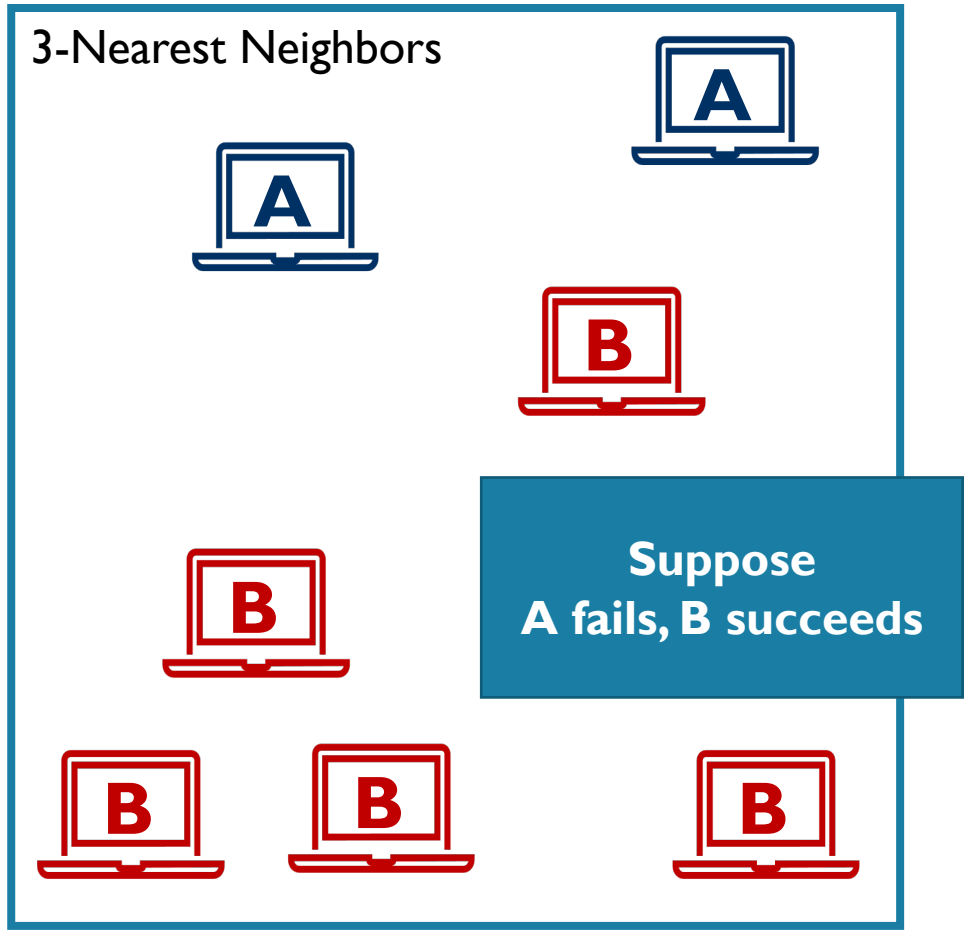

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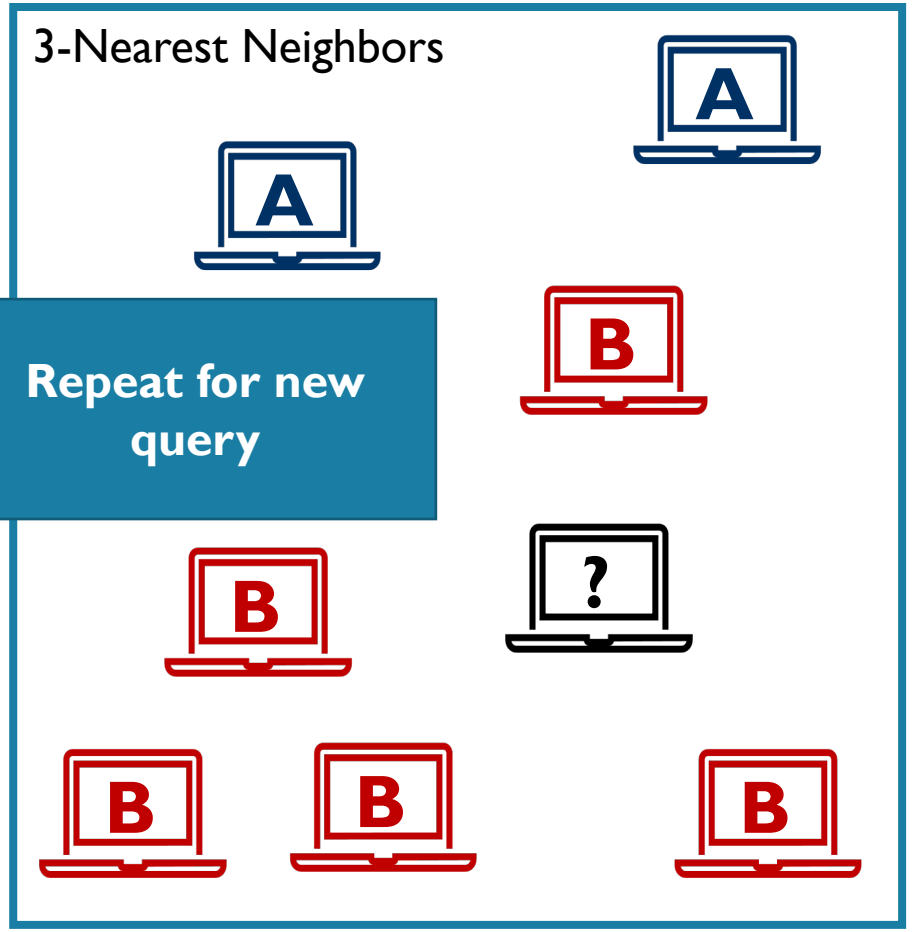
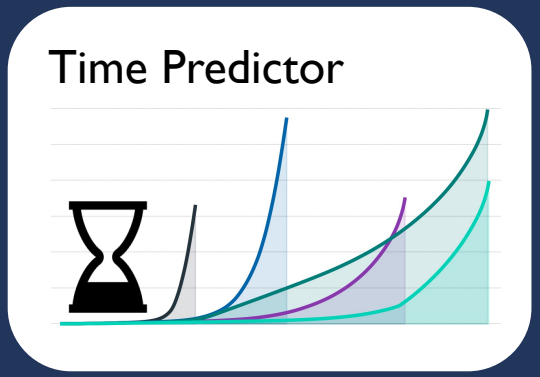
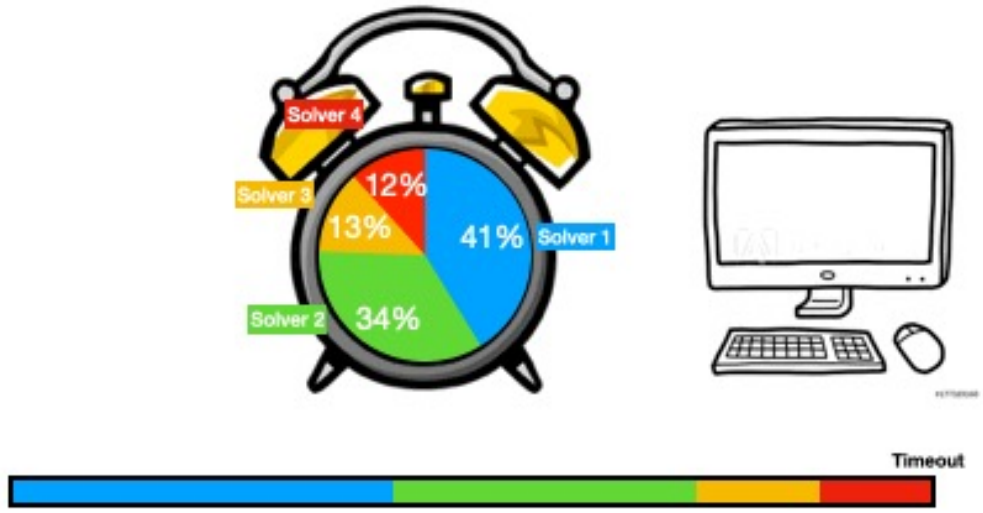


Allocating Timeouts



Allocating Timeouts

- Task: Split overall timeout T
  - allocate time to each solver in order.
- Cut off solver once we are confident it is unlikely to terminate



Modeling Execution Time as an Exponential

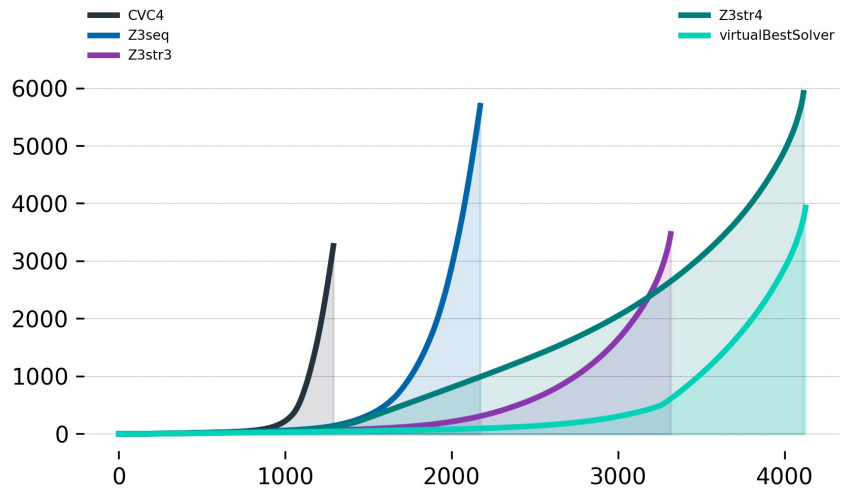
- Solver runtimes look like samples from an exponential distribution
- Estimate parameter λ using maximum likelihood estimation

$$\lambda^* = \frac{n}{\sum_i q_i}$$

- For a hyper-param δ, find t such that solver is δ% likely to terminate

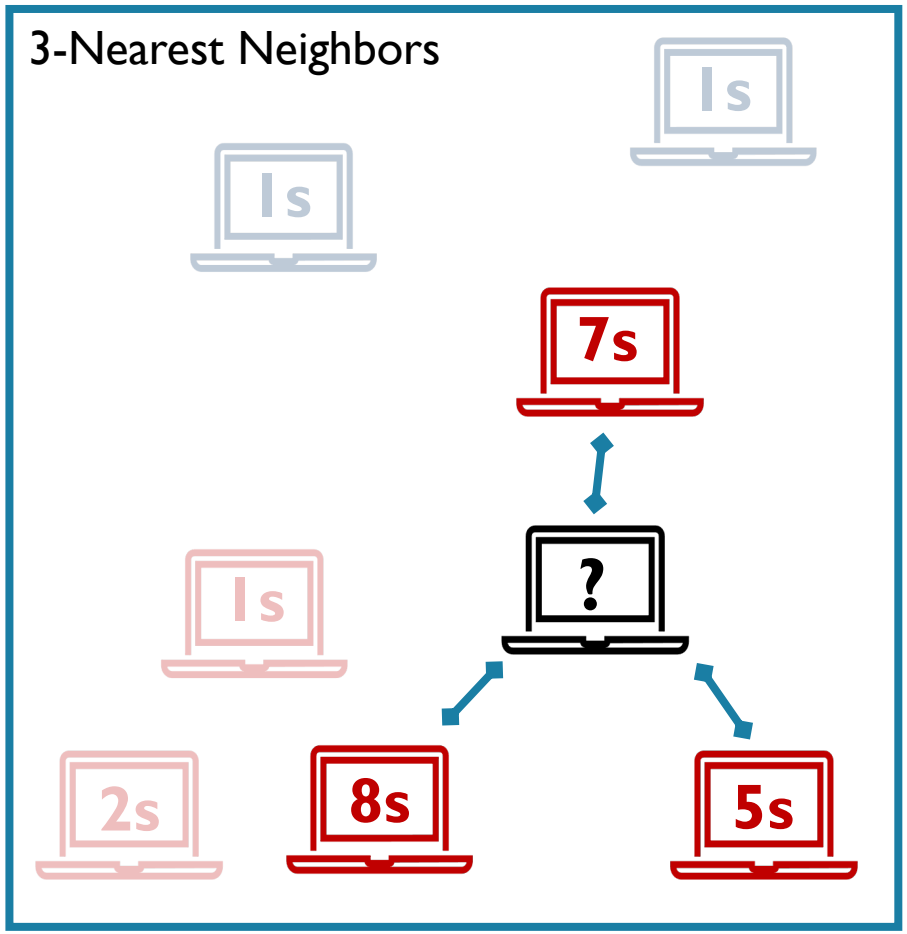
$$\mathrm{t} = \frac{-\ln(\delta + e^{-\lambda T})}{\lambda^*}$$

- After t seconds try the next solver!



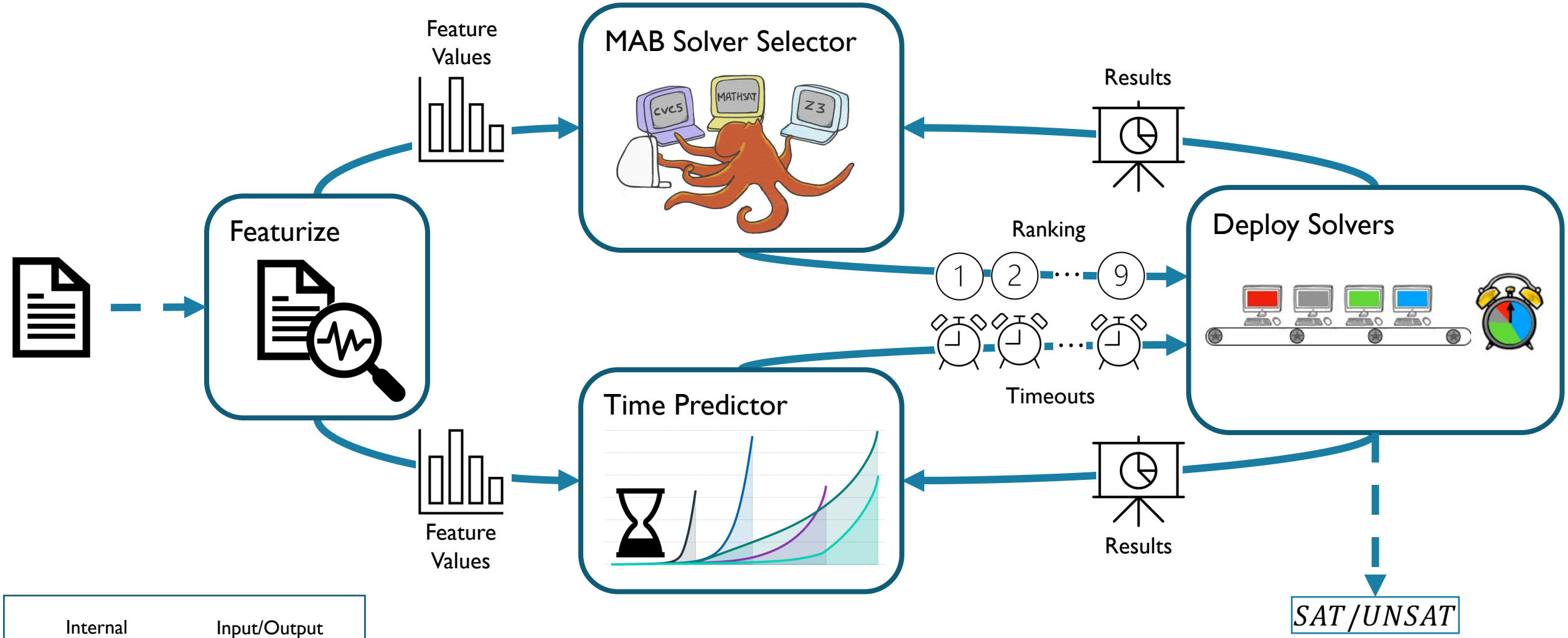
Contextual Time Allocation

- k-Nearest Neighbor Exponential:
  - Use the k-nearest queries to estimate λ
- Linear Regression:
  - Train a linear model which
    - takes in a query's feature vector as input,
    - outputs the expected runtime



Deploying Solvers and Recap

MedleySolver Overview



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No Manual Input	✓	✓	✓
Minimal Upfront Costs	✓	✗	✓ No pre-training
No Data Requirements	✓	▯	✓ No pre-training
No Solver Requirements	✗	✓	✓ No assumptions
No Need to Repeat Upfront Costs	✓	✗	✓ Adapt to changes as they come.
Fine Grained Decisions	✗	✓	✓ Complex, flexible decision rules

Feature Support

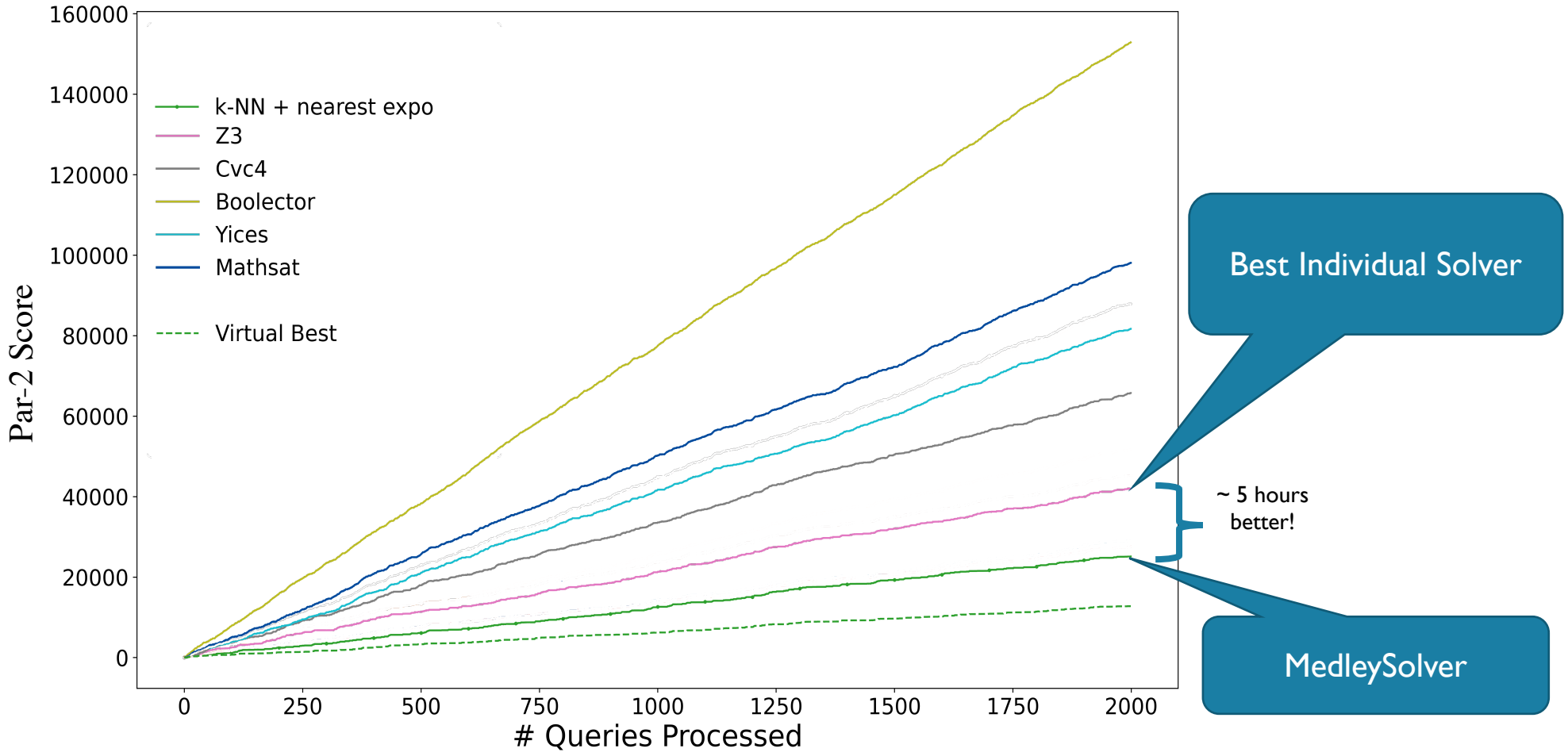
- ✓ Strong
- ▯ Medium
- ✗ Weak

Evaluation and Future Work

Experimental Setup

- 6 individual SMT solvers
  - CVC4, MathSAT, Z3, Boolector, Bitwuzla, and Yices
- 4 individual benchmark sets
  - BV, QF_ABV, Sage2, and Uclid5 (first 3 sets are from SMTCOMP)
  - 500 queries each (randomly sampled without replacement)
- 6 MedleySolver configurations in paper, 1 for presentation
  - 10-Nearest Neighbor for order selector
  - 10-Nearest Neighbor exponential distribution estimation for time predictor
- Dell PowerEdge C6220 server, 60 second timeout per query.

Exp. 1: Comparison to Individual Solvers



Exp. 2: Comparison to Pre-Trained Tools

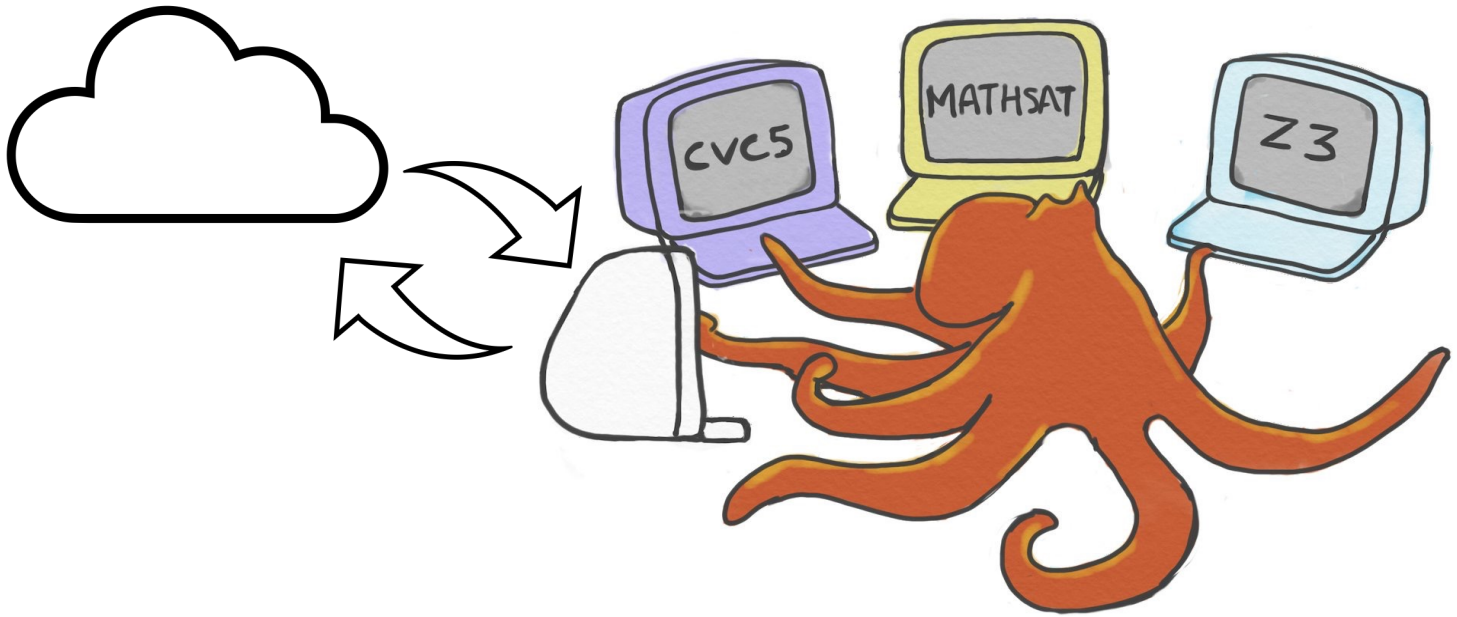
- Compare against MachSMT
  - State-of-the-art
- Report par-2 score for test
- Report time in seconds for training

- 40% of queries for training
  - Only used by MachSMT
- 60% of queries for testing
  - Used by both

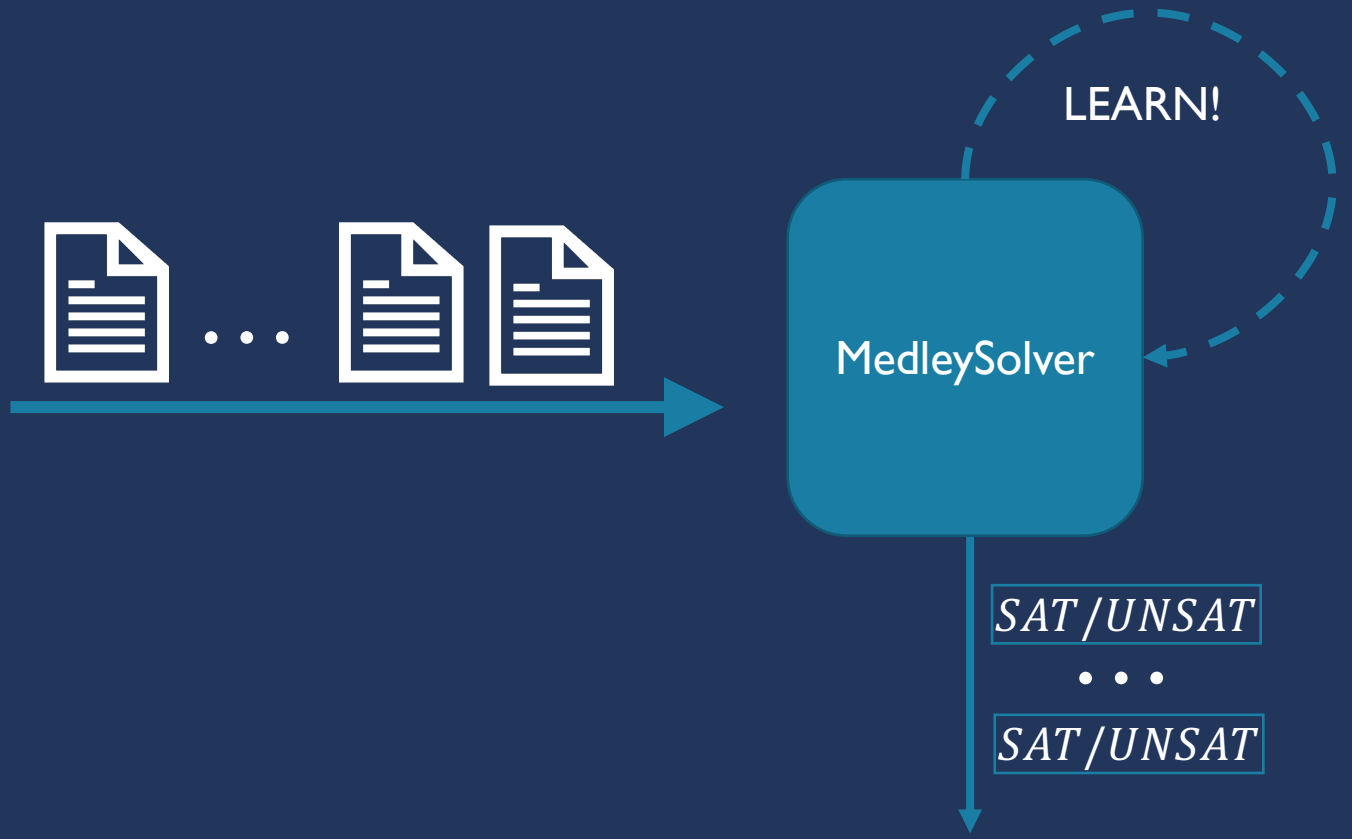
Benchmark / Tool	BV	QF_ABV	Sage2	Uclid5	Combined
MedleySolver	Test: 1638.7	Test: **310.5**	Test: 9245.3	Test: 4248.0	Test: 18565.5
MachSMT	Test: **1458.3** Train: 33895.5	Test: 919.2 Train: 4498.9	Test: **8516.1** Train: 55115.5	Test: **2430.9** Train: 276419.8	Test: **12539.1** Train: 300072.8
Virtual Best	Test: 801.7	Test: 184.3	Test: 5204.2	Test: 1464.7	Test: 6746.0

Future Work

- Whitebox monitoring techniques
  - instead of black box timeout estimation
- What if one of the solvers is a distributed solver in the cloud?
  - Front end to decide when to solve locally and when to query server



MedleySolver: Online SMT Algorithm Selection



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Code & Data