Neural Networks for Predicting Algorithm Runtime Distributions

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Motivation

Algorithm portfolios yield state-of-the-art performance for SAT, ASP, Planning, …

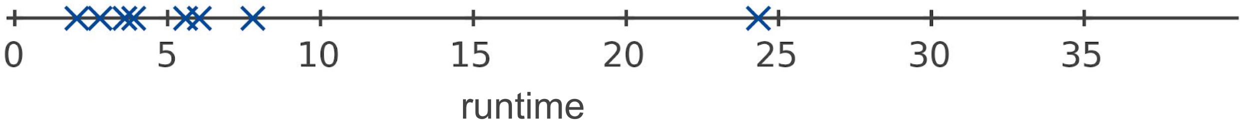
→ to build these we can make use of runtime predictions

Other applications:

- Optimal restarts
- Algorithm selection
- Algorithm configurations

Describing the Runtime of an Algorithm?

```
solve(instance, seed):
    # do something
    return solution, runtime
```



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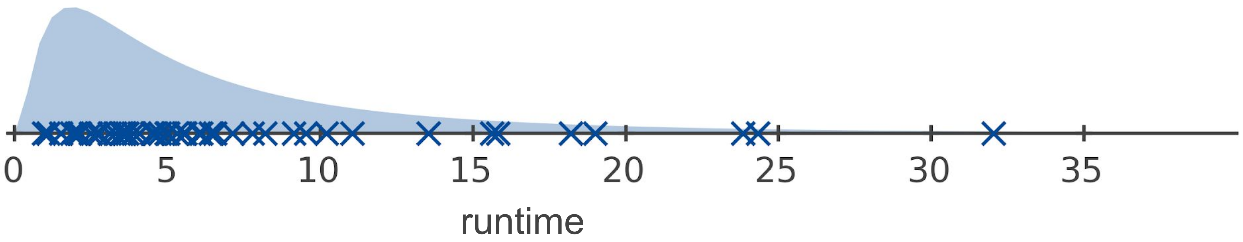


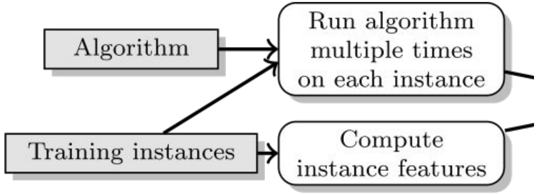
Contributions

1 Study how to **predict parametric RTDs**

2 Propose **DistNet**, a practical neural network for predicting RTDs

3 Evaluate DistNet and show that it can **learn from only a few samples per instance**

Typical Pipeline for Runtime prediction



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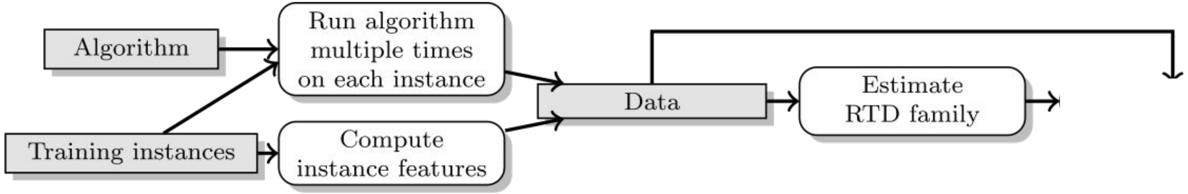

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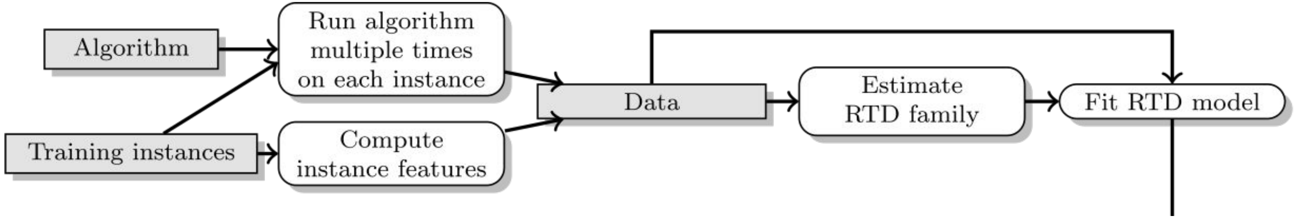

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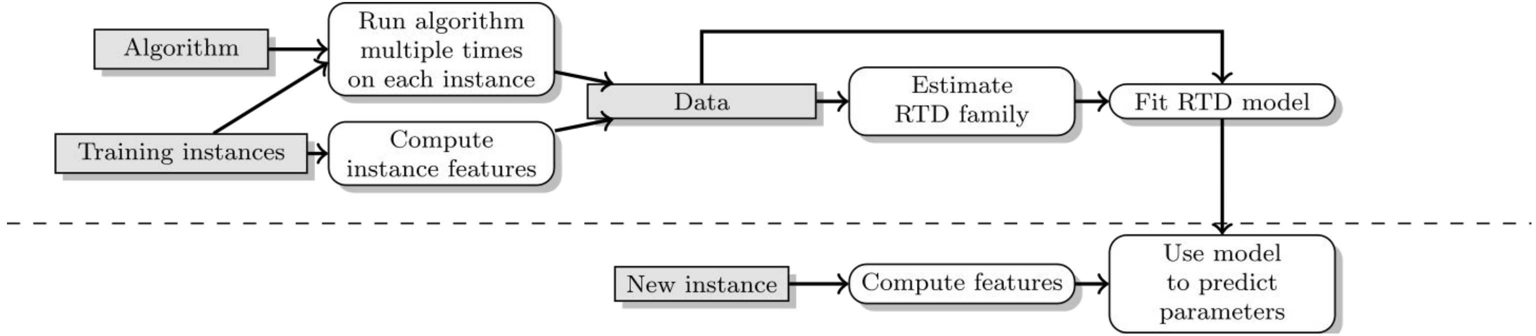

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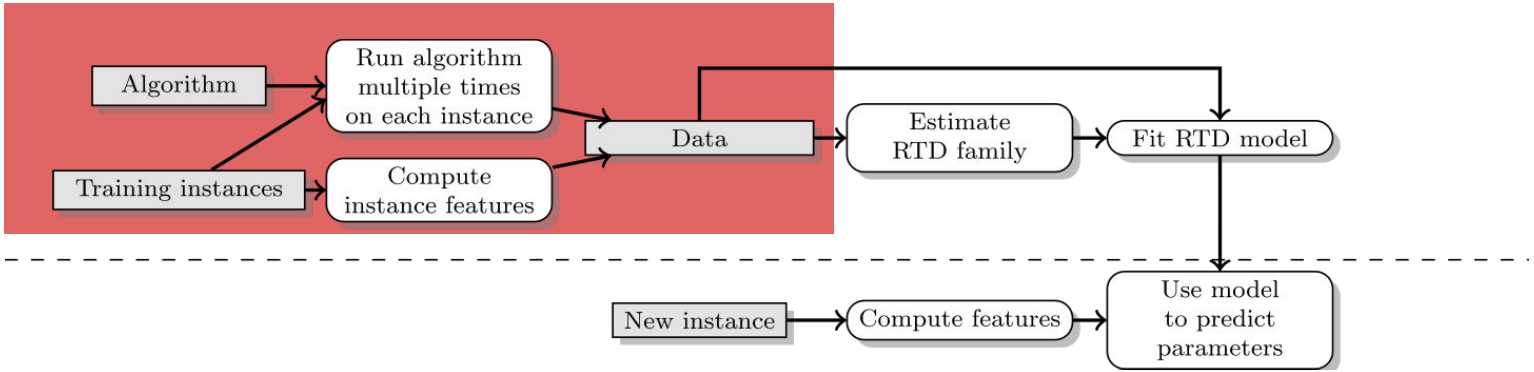
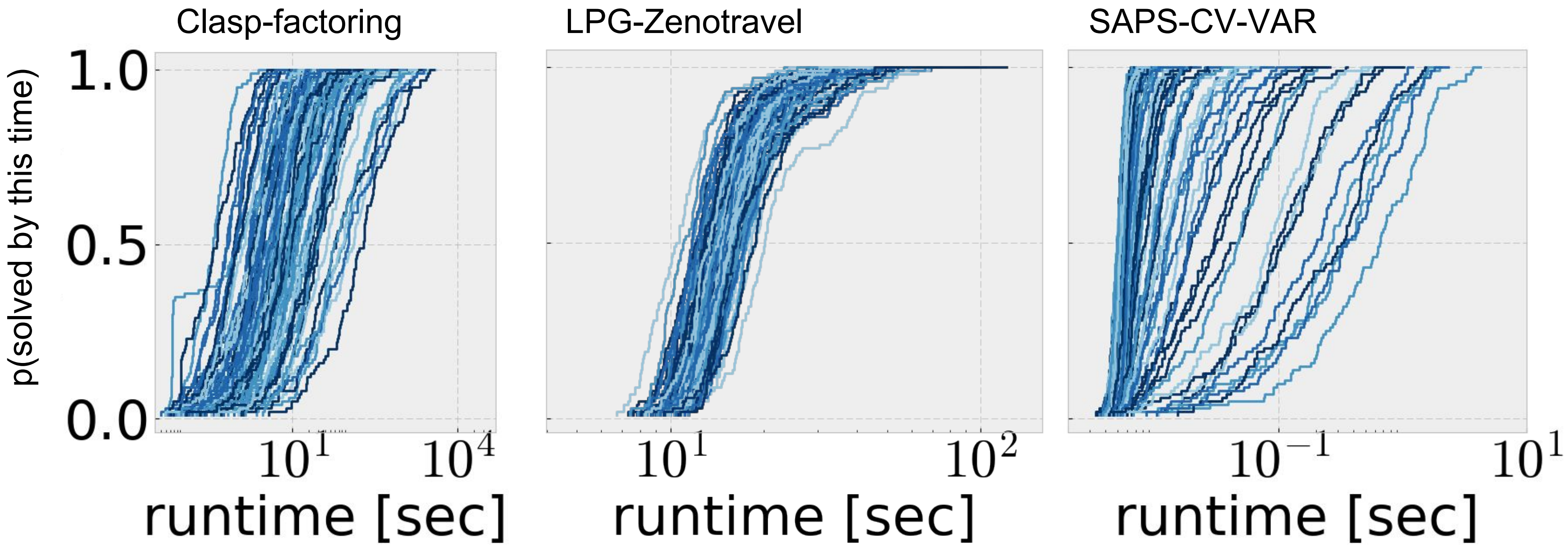


Empirical RTDs



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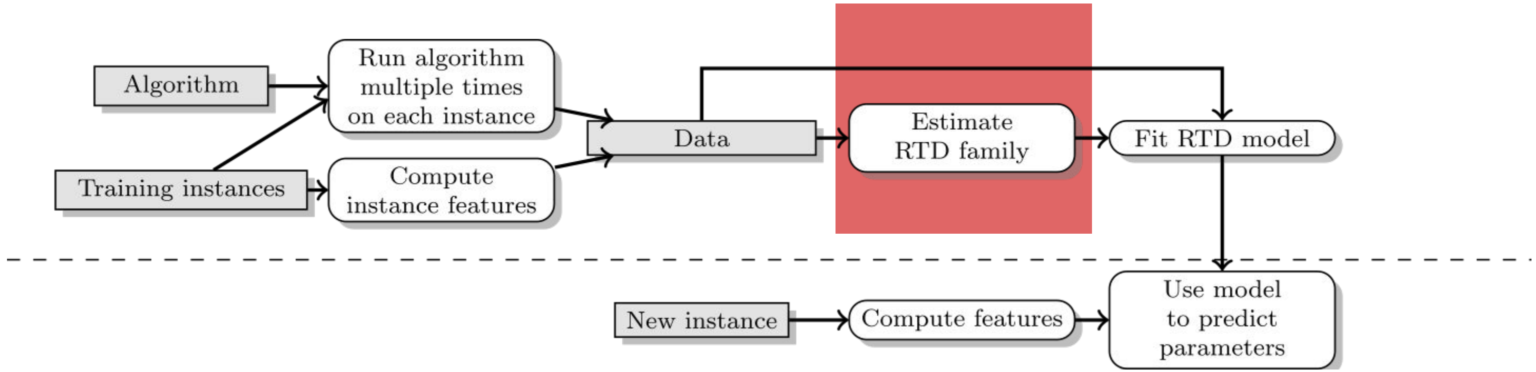
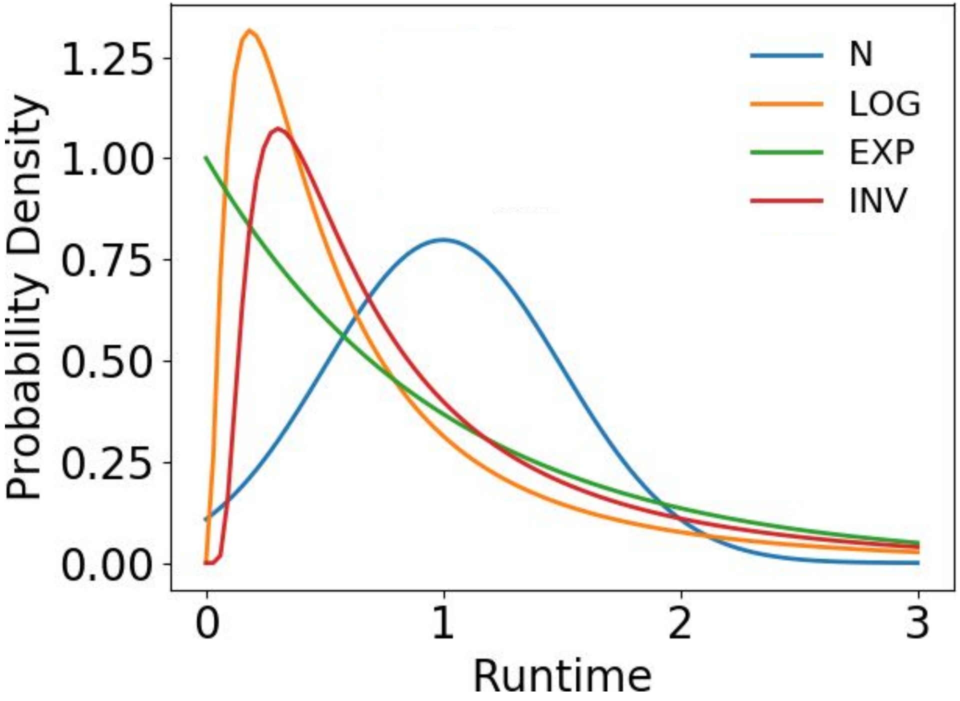


Considered Parametric Distribution



Distribution	Param.
Normal (N)	μ, σ
Lognormal (LOG)	s, σ
Exponential (EXP)	β
Inverse Normal (INV)	μ, λ

Quantifying the Quality of Runtime Distributions

$$\mathcal{L}_{\mathcal{D}}(\underbrace{\boldsymbol{\theta}}_{\text{distribution parameter}} \mid \underbrace{t(\pi)_1, \ldots, t(\pi)_k}_{\text{observed runtimes}}) = \prod_{i=1}^{k} p_{\mathcal{D}}(t(\pi)_i \mid \boldsymbol{\theta}) \qquad (1)$$

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observed runtimes

distribution parameter

$$-\log \mathcal{L}_{\mathcal{D}}(\boldsymbol{\theta} \mid t(\pi)_1, \ldots, t(\pi)_k) = -\sum_{i=1}^{k} \log p_{\mathcal{D}}(t(\pi)_i \mid \boldsymbol{\theta}) \tag{2}$$

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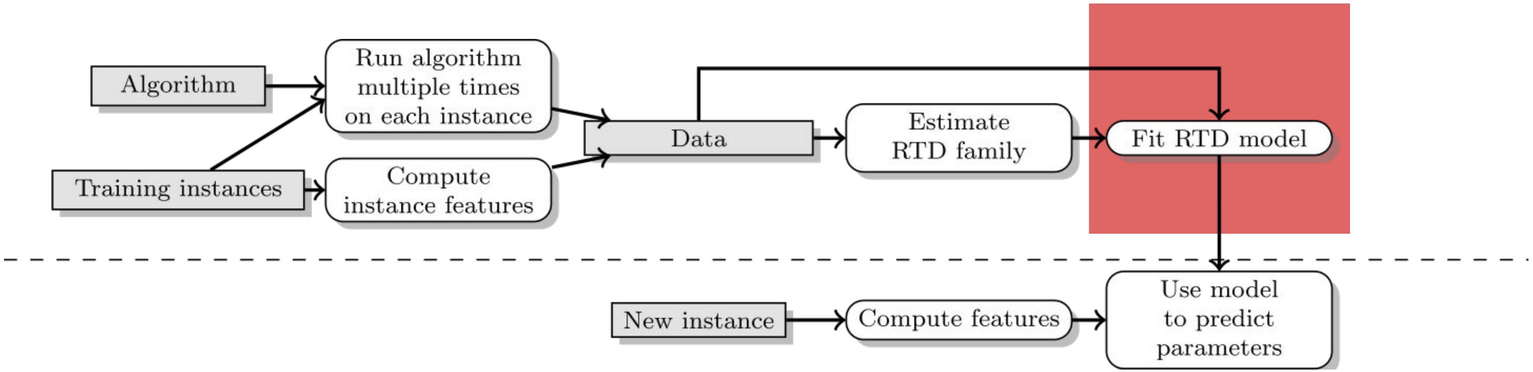

Predicting multiple Runtime Distributions

Option 1

For each training instance
→ fit the parametric distribution's parameter on observed runtimes.

Then for all training instances, for each distribution parameter:
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- can only be as good as each fitted distribution
- do not know about interaction between their outputs
- typically minimize loss in the parameter space

Predicting multiple Runtime Distributions

Option 2

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Predicting multiple Runtime Distributions

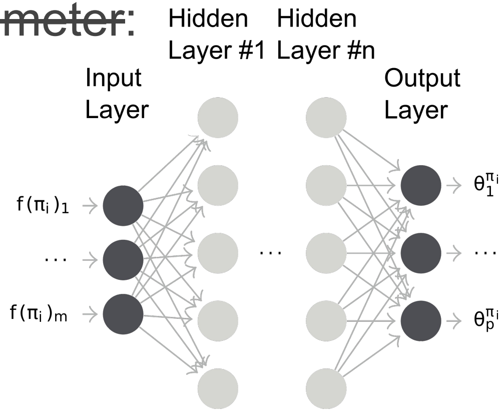
DistNet

~~For each training instance~~

~~→ fit the parametric distribution's parameter on observed runtimes.~~

Then for all training instances, ~~for each distribution parameter~~:

fit a neural network using negative log-likelihood as a loss function



Results

Scenario	dist	iRF	mRF	DistNet
Saps-CV-VAR	LOG	0.99	-0.29	**-0.52**

We compared

- DistNet
- independent Random Forests (iRF)
- multi-output Random Forests (mRF)

on 7 scenarios from SAT solving and AI planning.

Figure: Averaged negative log-likelihood. Smaller values are better.

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	INV	0.22	-0.09	**-0.54**
Clasp-factoring	INV	-0.04	-0.09	**-0.16**
	LOG	-0.14	-0.13	**-0.14**
[...]				
LPG-Zenotravel	LOG	**-0.85**	-0.84	**-0.85**
	INV	-0.72	-0.80	**-0.84**

Figure: Averaged negative log-likelihood. Smaller values are better.

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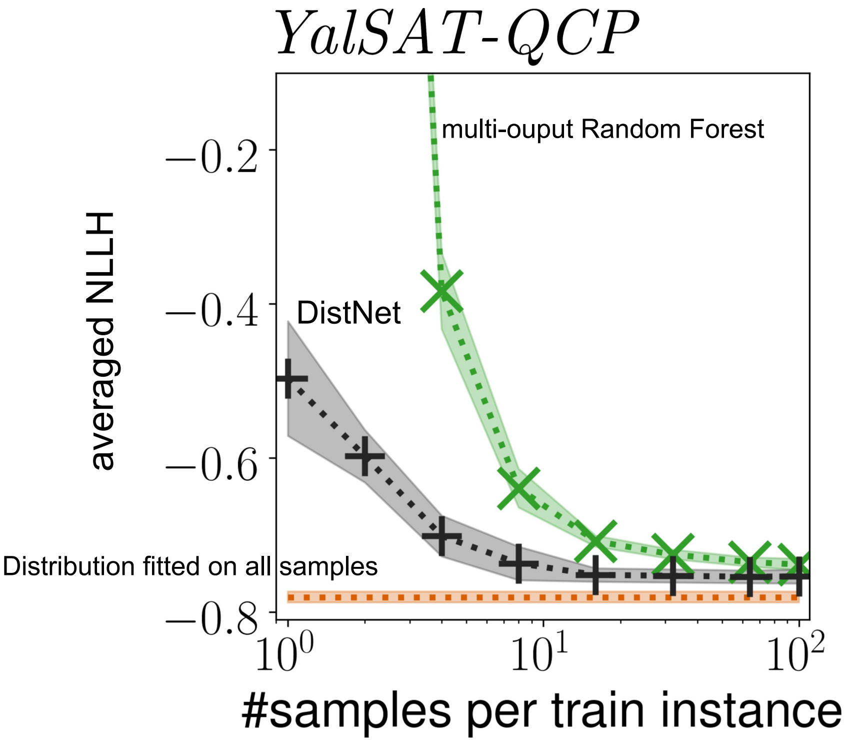
→ Predicting parameters for RTDs is possible
→ Joint predictions work better
→ DistNet provides more robust predictions which are often better than those of competitors

DistNet on a Low Number of Observations



Wrap-Up

We have proposed DistNet, which

- **jointly learns** distribution parameters
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- performs well even if **only few observations per instance** are available

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Open Questions:

- How to automatically determine a well fitting distribution family?
- How to handle heterogeneous datasets?

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We have proposed DistNet, which

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Code and data: https://www.automl.org/distnet/