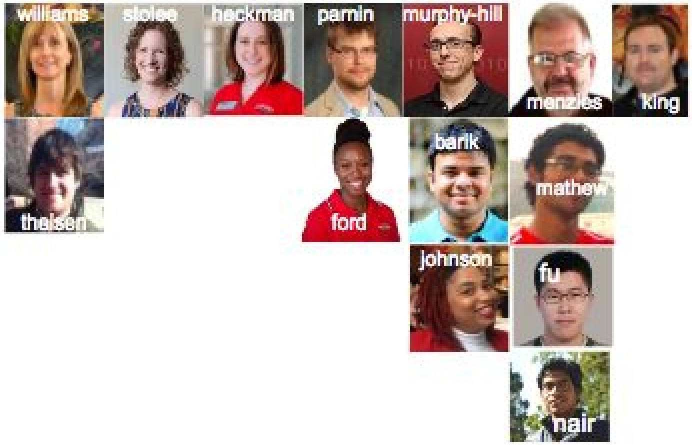
NC STATE UNIVERSITY

software
... if engineering then NC State ...



Using Bad Learners to find Good Configurations

Vivek Nair Tim Menzies
North Carolina State University

Norbert Siegmund
Bauhaus-Universität Weimar

Sven Apel
University of Passau

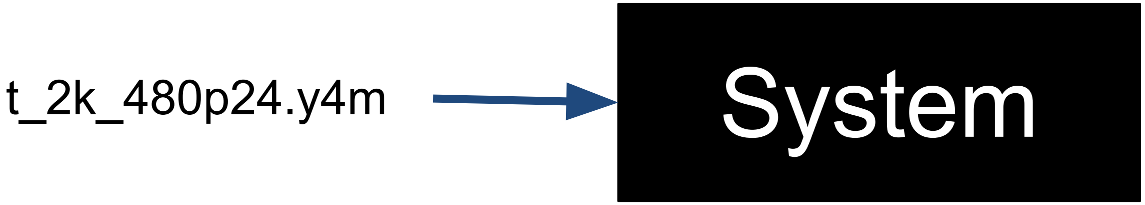
Bauhaus-Universität Weimar

UNIVERSITÄT PASSAU

Configurable Systems and Variability

System

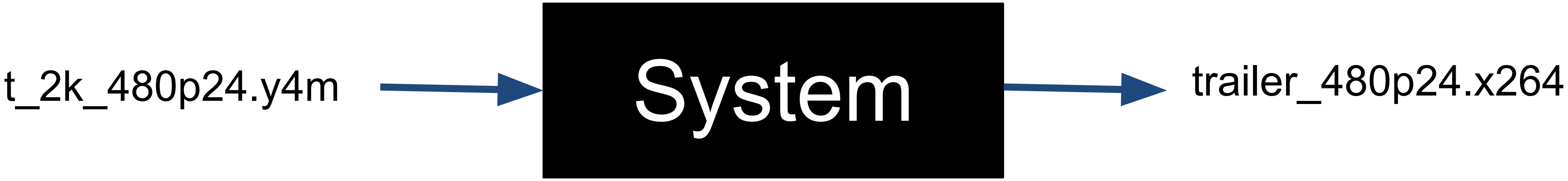
Configurable Systems and Variability



t_2k_480p24.y4m

System

Configurable Systems and Variability

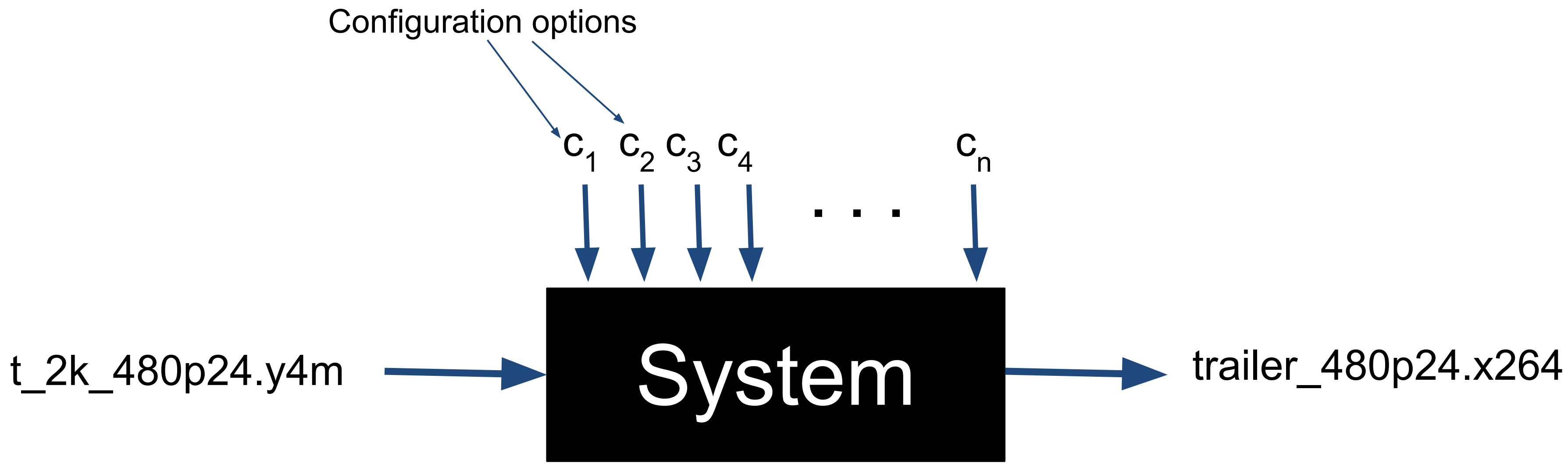


t_2k_480p24.y4m

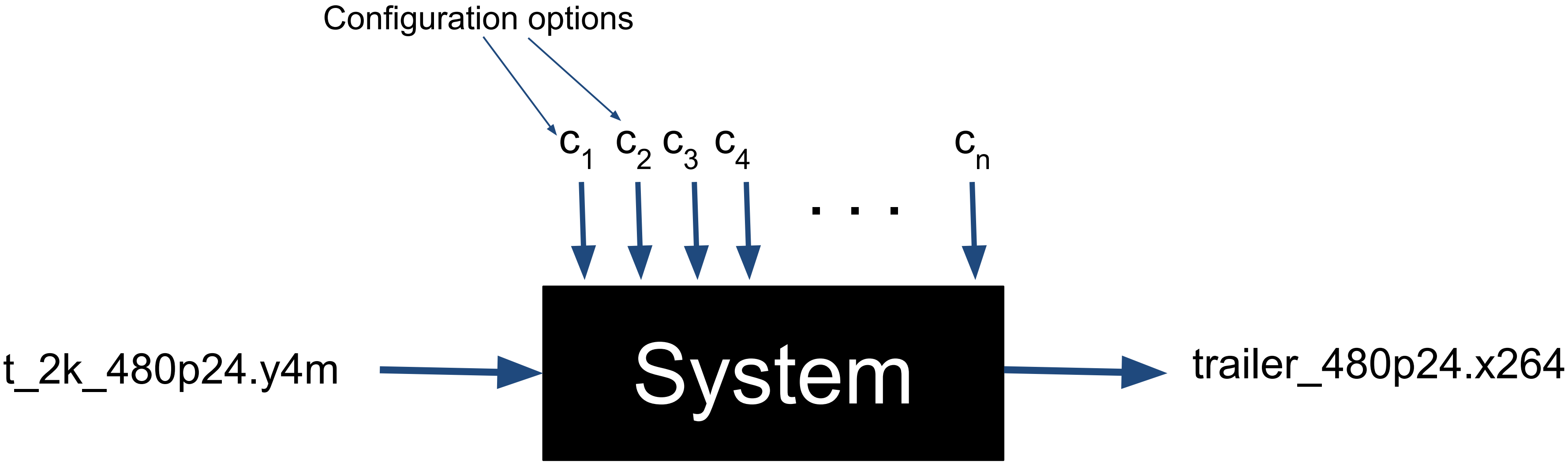
System

trailer_480p24.x264

Configurable Systems and Variability

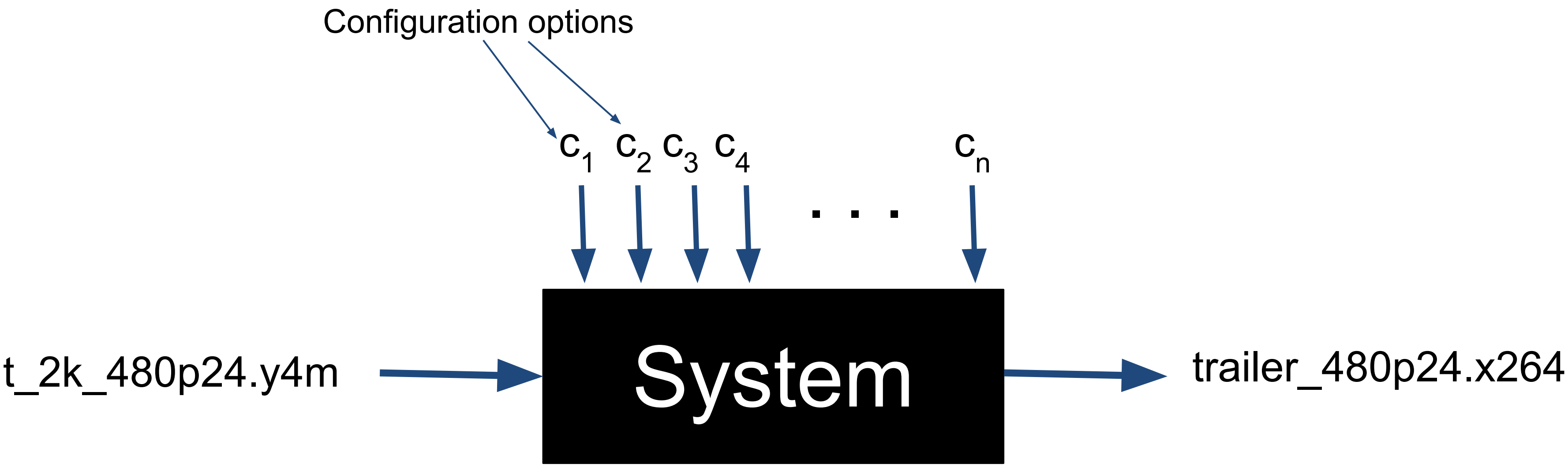


Configurable Systems and Variability



Non-functional behavior: response time, throughput, etc.

Configurable Systems and Variability



Non-functional behavior: response time, throughput, etc.

Objective: Find (near) **optimal configuration** of a system **with minimal effort**

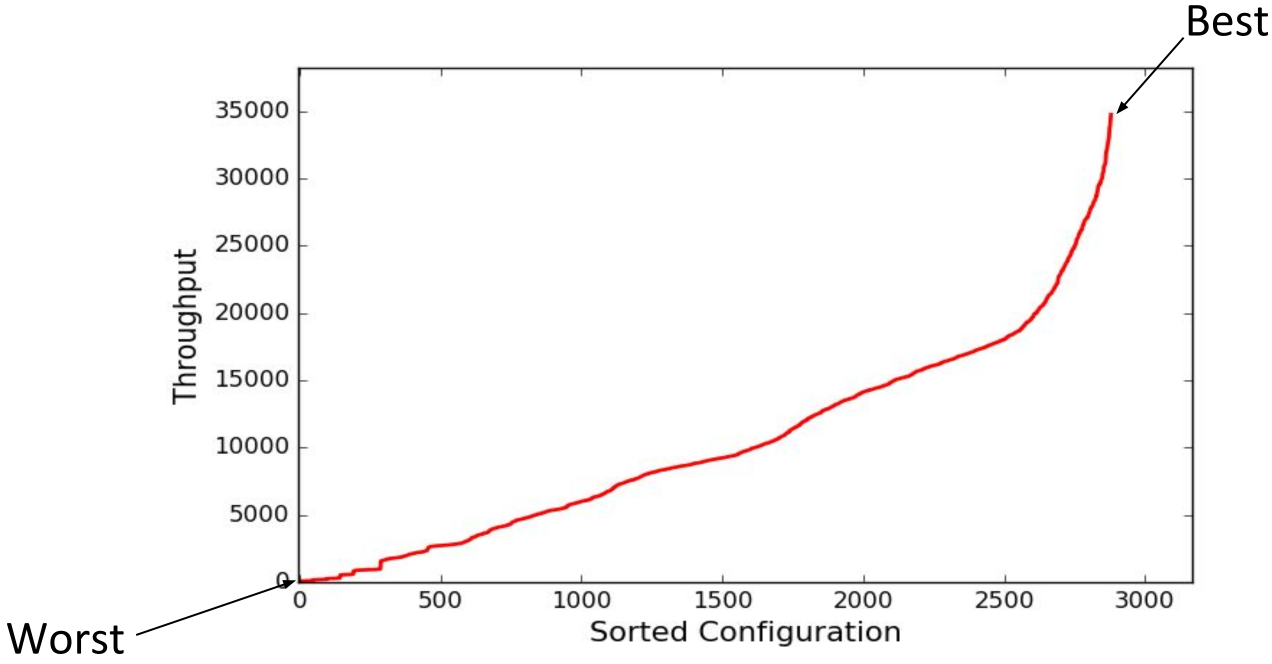
Performance Optimization is Necessary!

System: Apache Storm

Workload: Word Count

Performance: Throughput

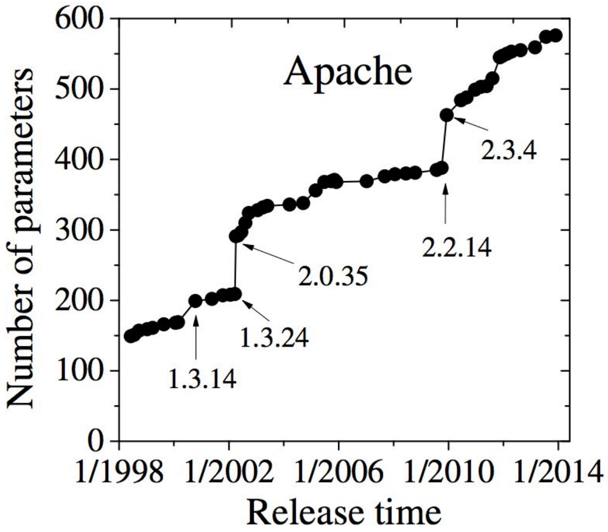
# Configurations: 6

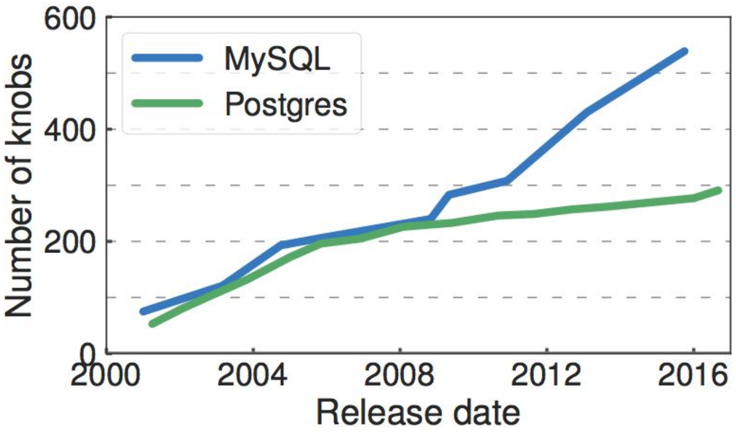


Best configuration is 480 times better than **Worst** configuration

Performance Optimization is getting more Complex!

✓ Necessary





200 new configuration options added to Apache HTTP server between 2010 and 2014

250 new configuration options added to MySQL between 2012 and 2016

[1] Xu et. al. 2015. Hey, you have given me too many knobs!: understanding and dealing with over-designed configuration in system software.FSE 2015
[2] Van Aken, Dana, et al. "Automatic Database Management System Tuning Through Large-scale Machine Learning." *International Conference on Management of Data*. ACM, 2017.

Performance Optimization is required since Default Configuration is Bad!

✓ Necessary

✓ Complex

Default **MySQL** configuration in 2016 assumes that machine has only 160 MB of RAM[1]

Rule-of-thumb settings for WordCount (in **Hadoop**) gave one of its worst execution times[2]

[1] Van Aken, Dana, et al. "Automatic Database Management System Tuning Through Large-scale Machine Learning." *International Conference on Management of Data*. ACM, 2017.
[2] Herodotou, Herodotos, et al. "Starfish: A Self-tuning System for Big Data Analytics." *CIDR*

Performance Optimization can be Expensive!

✓ Necessary

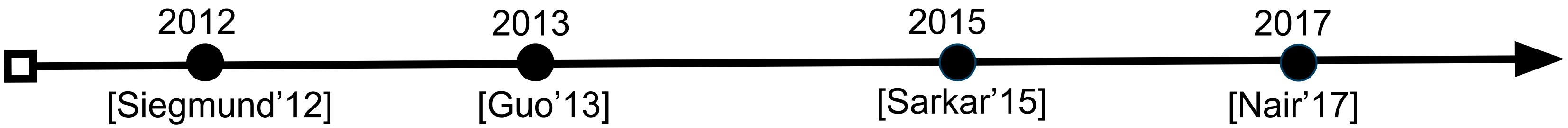
✓ Complex

✓ Default is bad

- Evaluation of single instance of their hardware/software co-design problem can take weeks[1]
- Rolling Sort use-case required 21 days, within a total experimental time of about 2.5 months[2]
- Test suite generation using Evolutionary Algorithm can take weeks[3]
- Image recognition workload and speech recognition workload, jobs ran for many hours or days[4]

[1] Zuluaga, Marcela, et al. "Active learning for multi-objective optimization." *International Conference on Machine Learning*. 2013.
[2] Jamshidi, Pooyan, and Giuliano Casale. "An uncertainty-aware approach to optimal configuration of stream processing systems."*MASCOTS-2016*
[3] Wang, Tiantian, et al. "Searching for better configurations: a rigorous approach to clone evaluation." *FSE-2013*
[4] Venkataraman, Shivaram, et al. "Ernest: Efficient Performance Prediction for Large-Scale Advanced Analytics." *NSDI*. 2016.

Existing Solutions



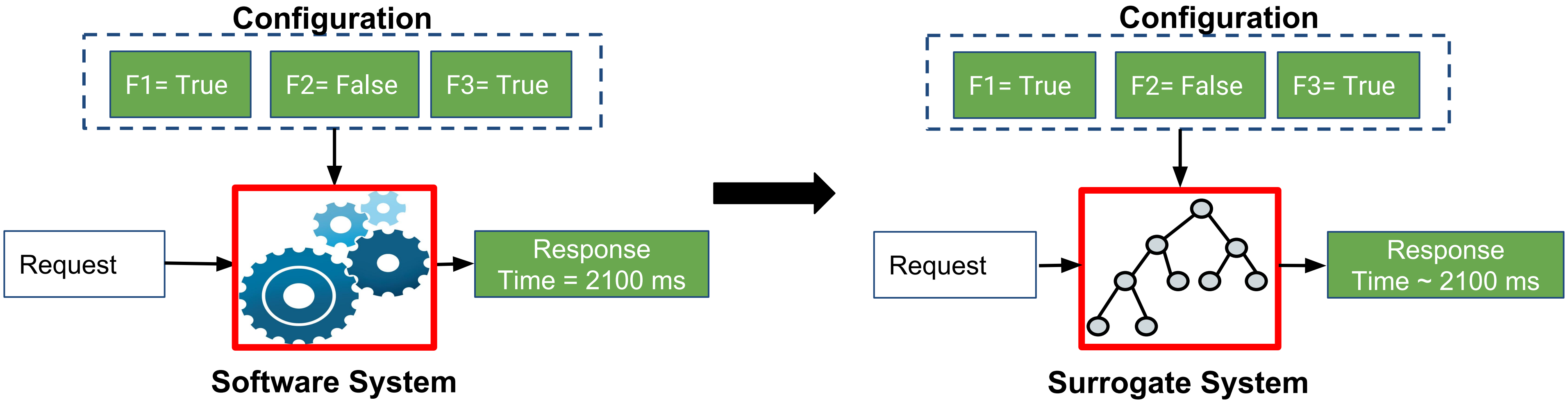
2012 [Siegmund'12]

2013 [Guo'13]

2015 [Sarkar'15]

2017 [Nair'17]

Accurately Model the configuration space



Configuration

F1= True

F2= False

F3= True

Request

Response Time = 2100 ms

Software System

Configuration

F1= True

F2= False

F3= True

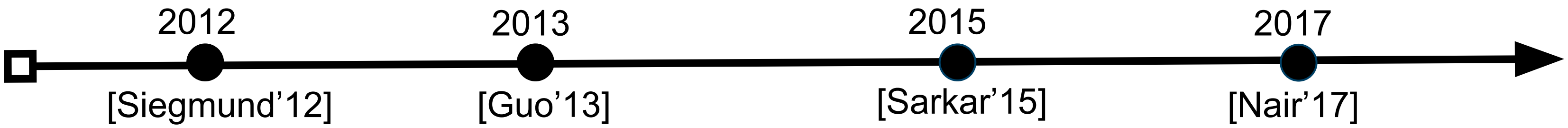
Request

Response Time ~ 2100 ms

Surrogate System

[Siegmund'12] Siegmund, Norbert, et al. "Predicting performance via automated feature-interaction detection." ICSE- 2012
[Guo'13] Guo, Jienmei, et al. "Variability-aware performance prediction: A statistical learning approach". ASE-2013
[Sarkar'15] Sarkar, Atri, et al. "Cost-efficient sampling for performance prediction of configurable systems (t)." ASE-2015
[Nair'17] Nair, Vivek, et al. "Faster discovery of faster system configurations with spectral learning." ASE Journal-2017 - to appear.

Existing Solutions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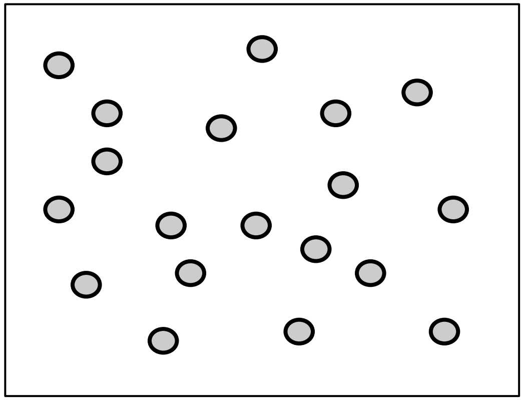
Configuration Space

[Siegmund'12] Siegmund, Norbert, et al. "Predicting performance via automated feature-interaction detection." ICSE- 2012
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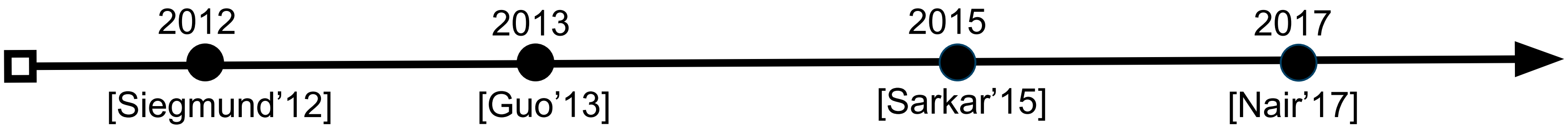
Existing Solutions



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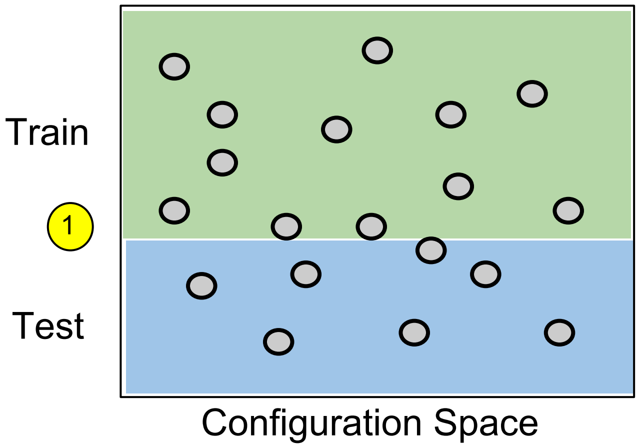

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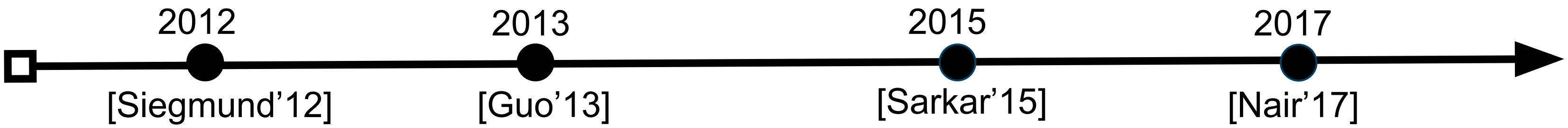
Existing Solutions



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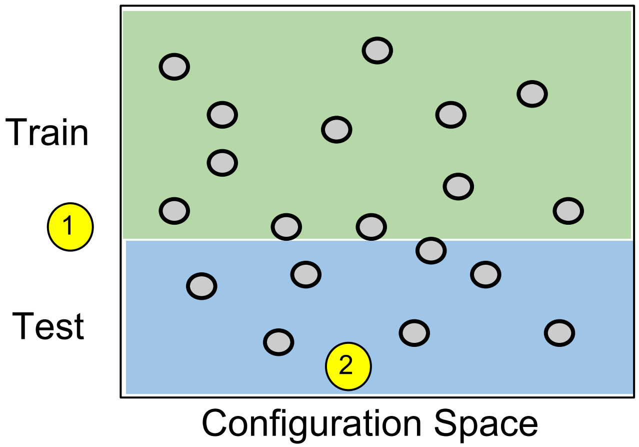

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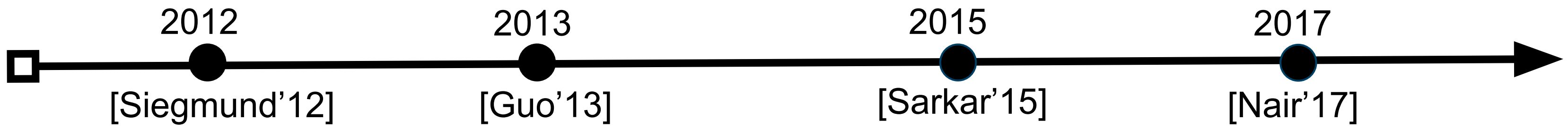

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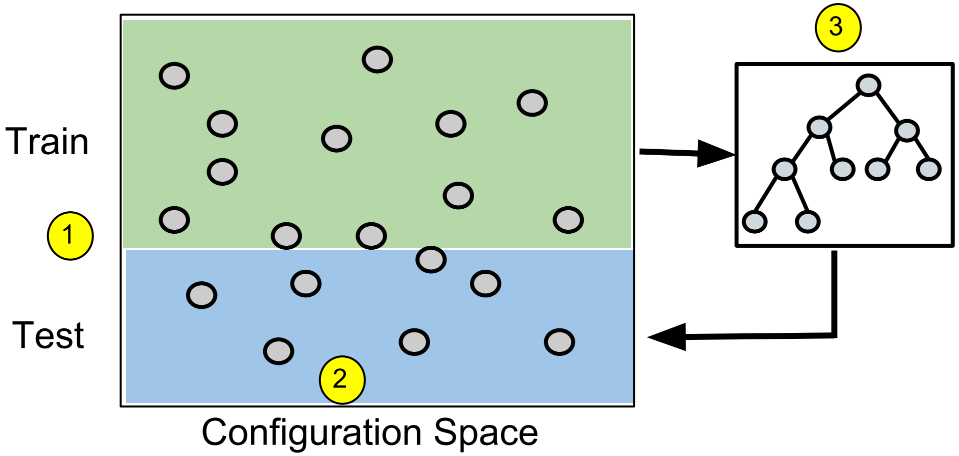

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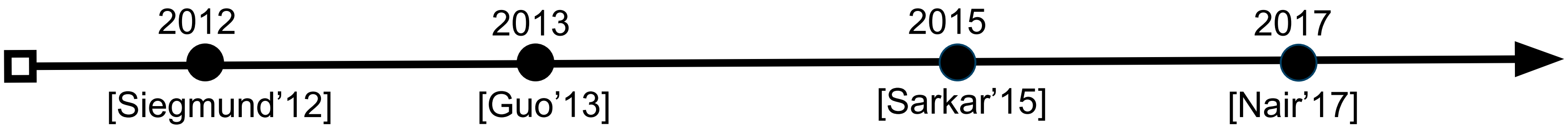
Existing Solutions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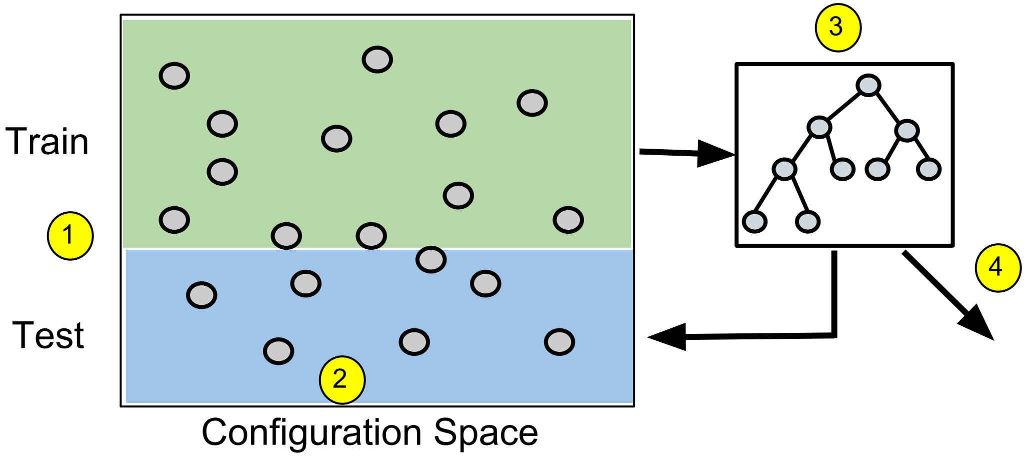

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4. *Exit* when an accurate model is built (e.g., error = 0.1)

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Limitation of Existing Solutions

Assumes, an Accurate Model of a software system can be built

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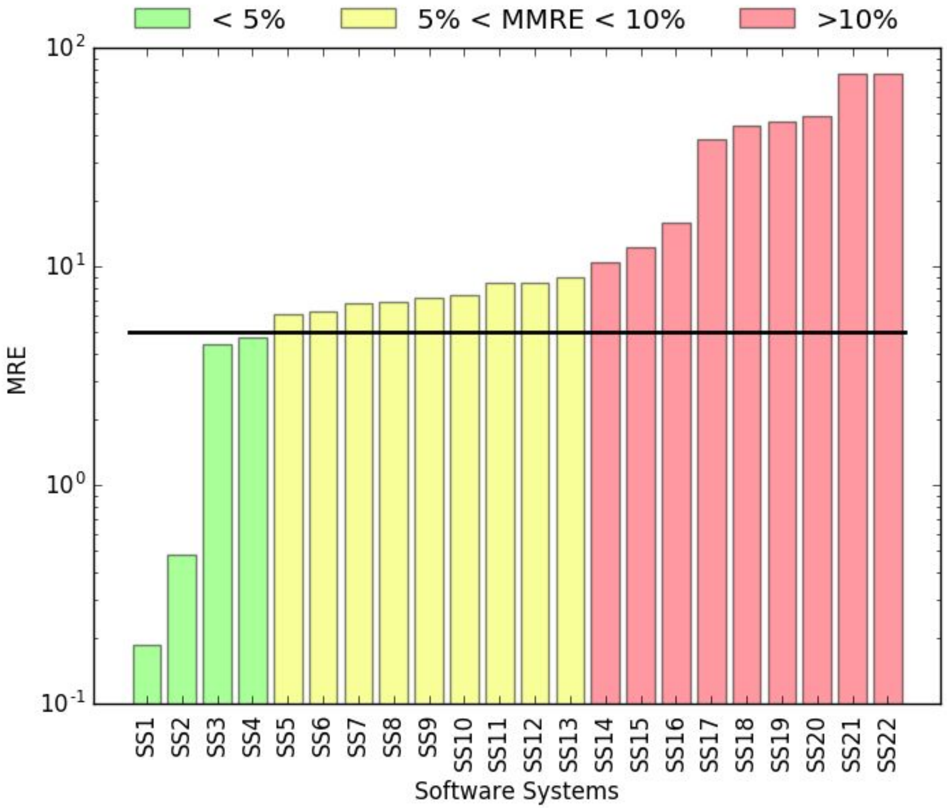

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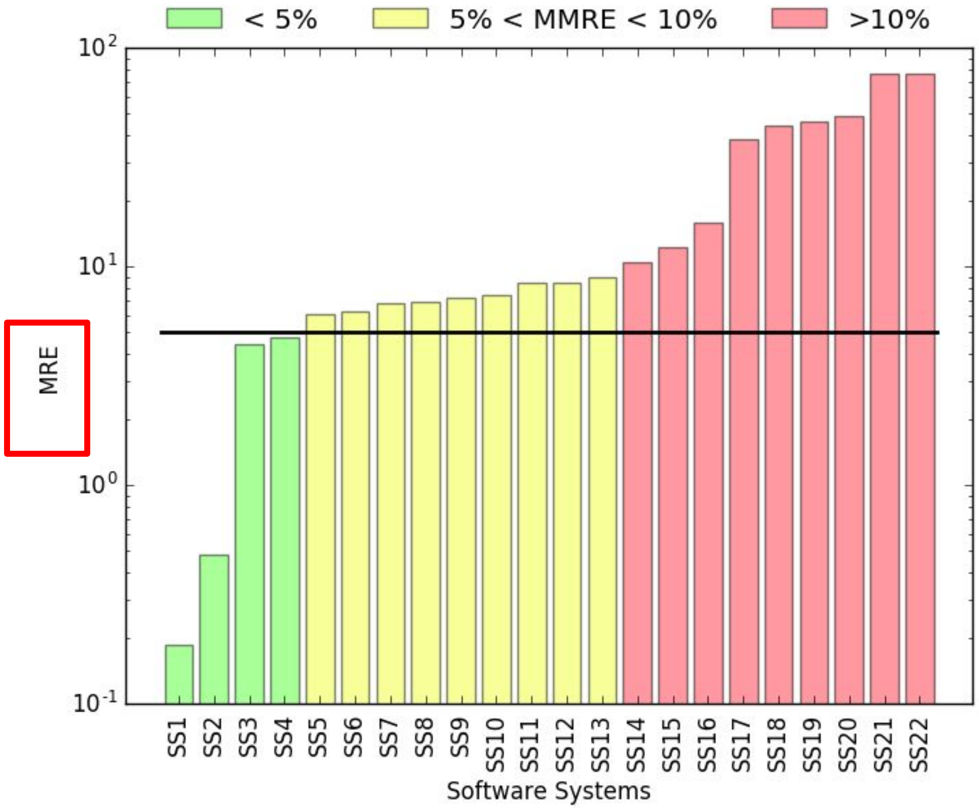

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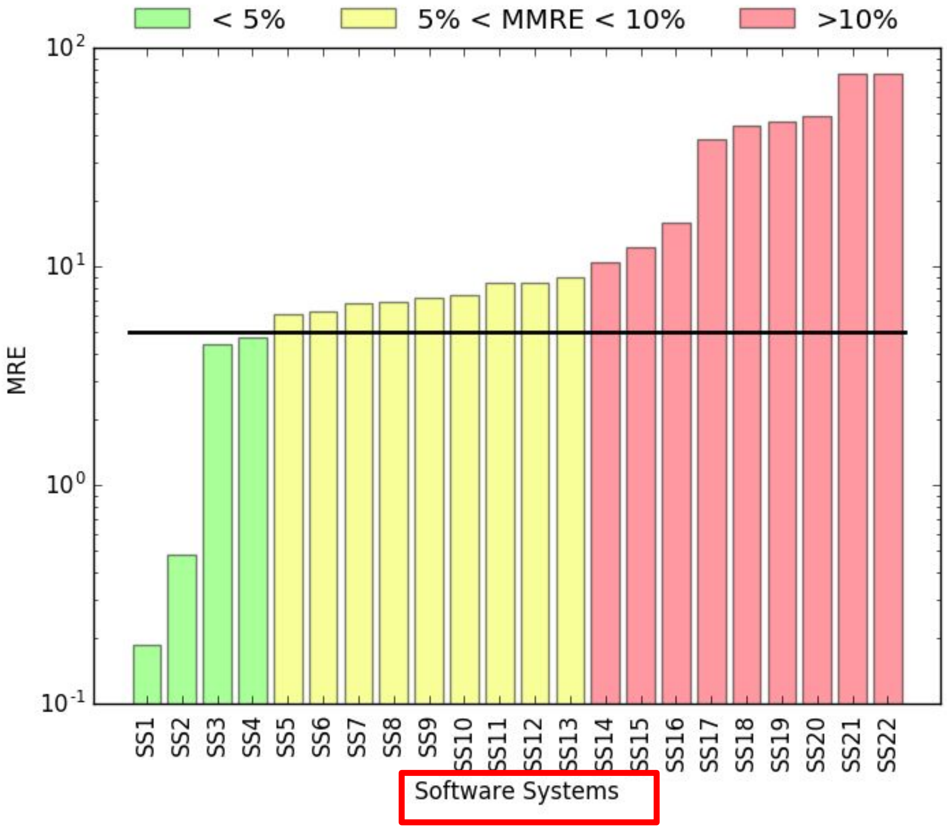

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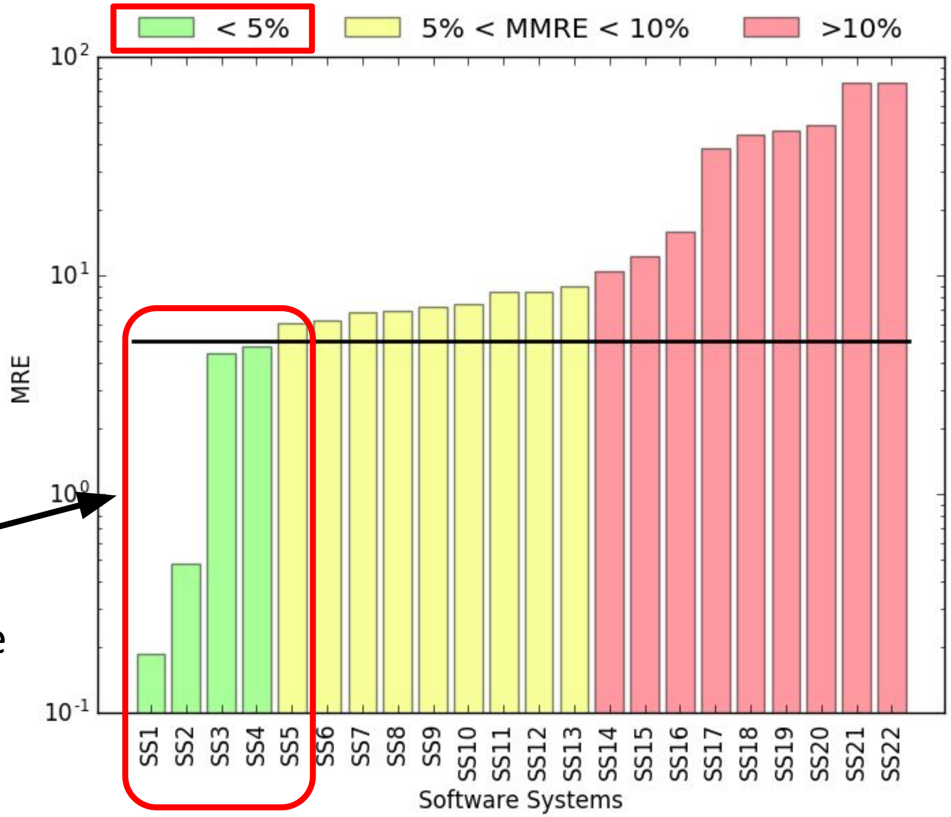

Software Systems used in existing works can be accurately modelled by CART

Limitation of Existing Solutions

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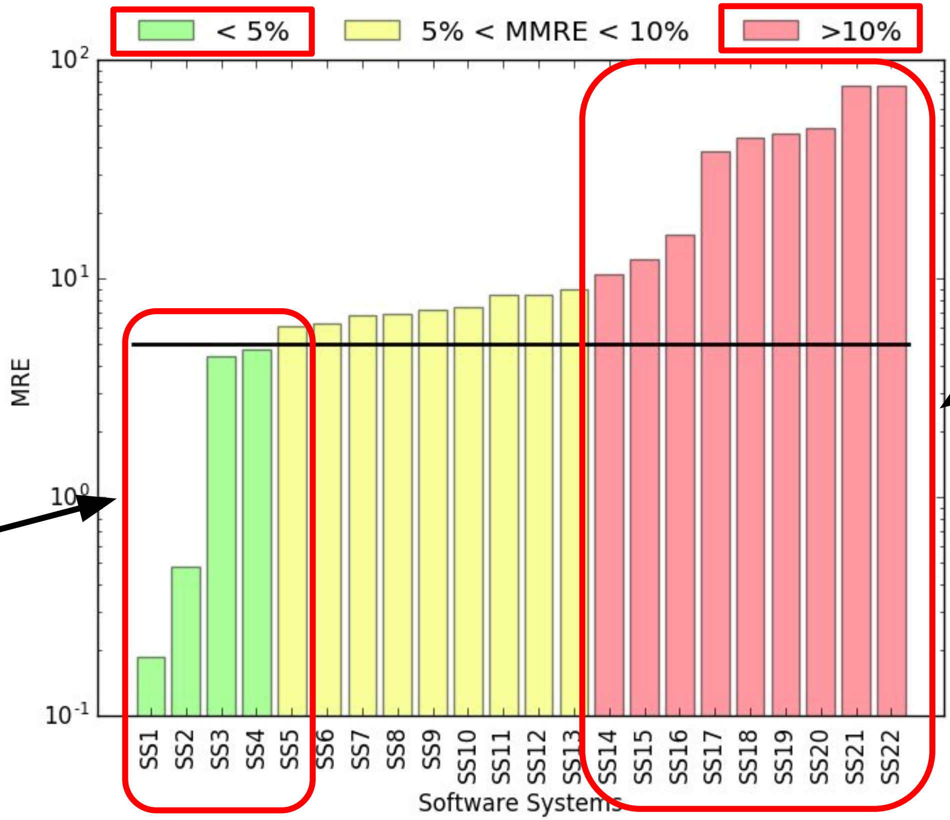


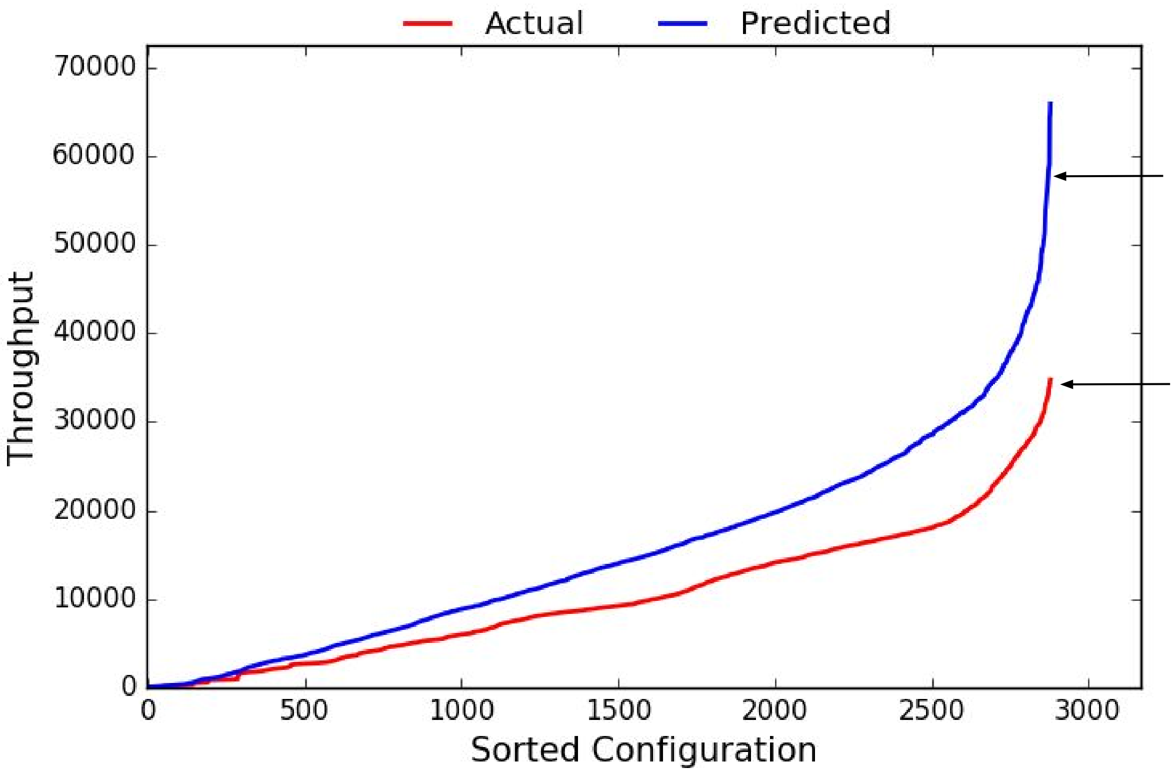
Some software systems cannot be accurately modelled

Software systems used in existing work can be accurately modelled

Core Insight

Rank-preserving model rather than highly accurate model

Rank Preserving Model

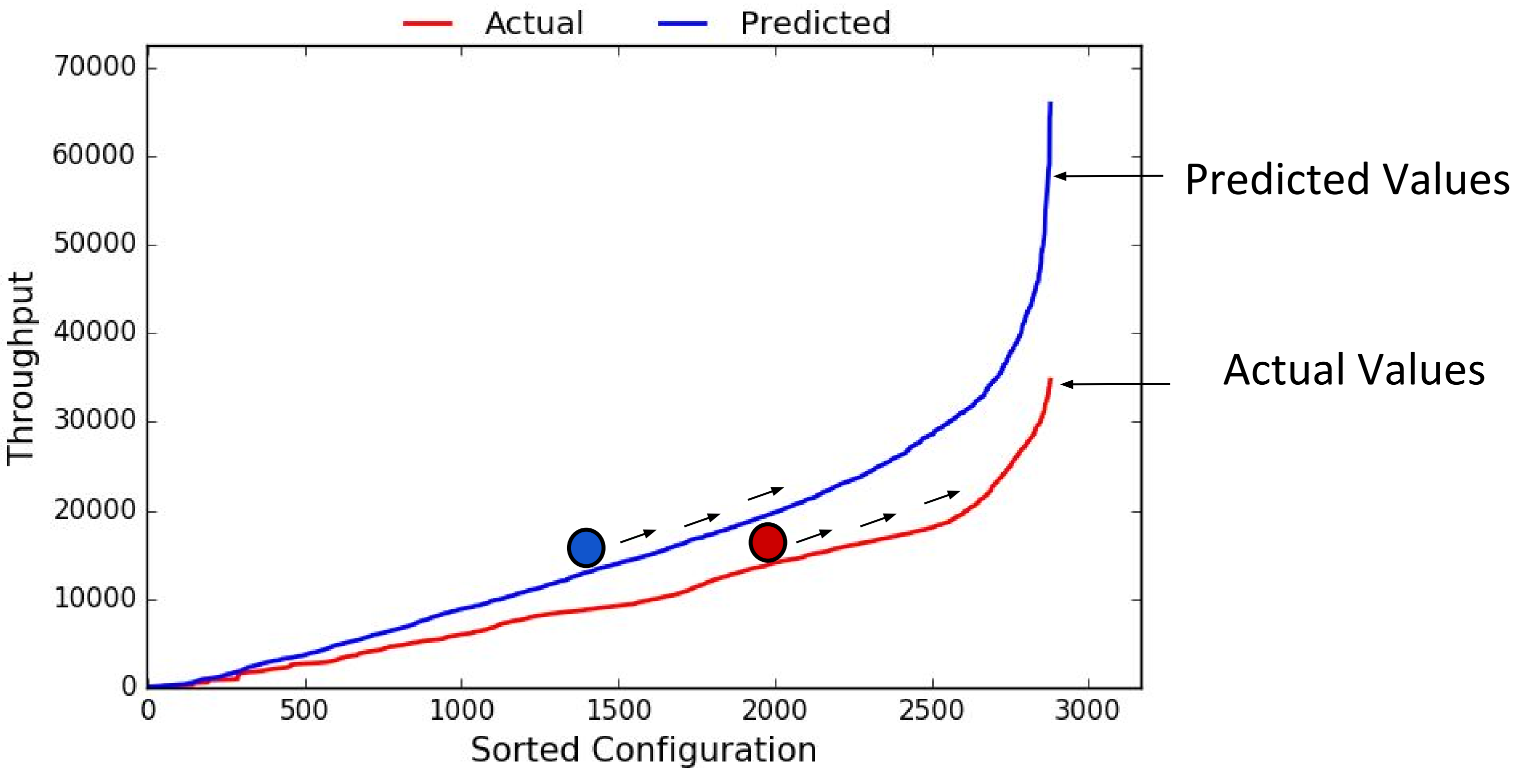


Predicted Values

Actual Values

Best Configuration obtained using actual and the predicted values is the same

Rank Preserving Model



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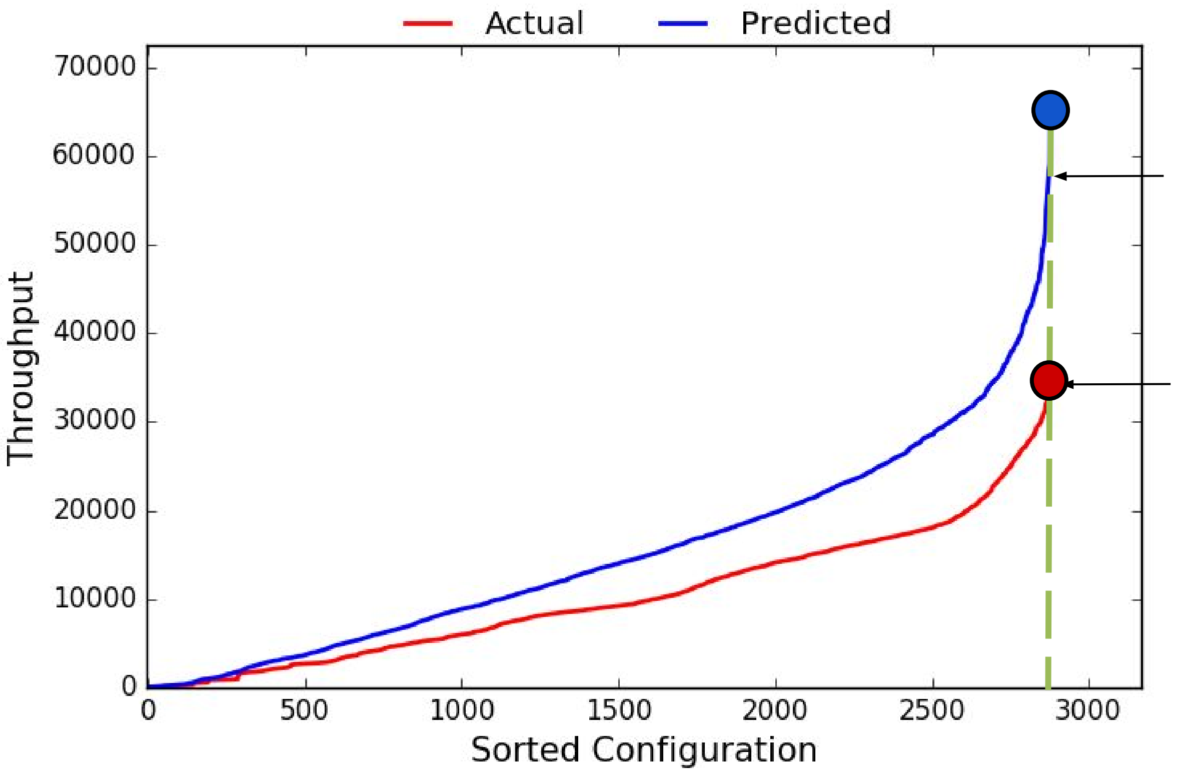

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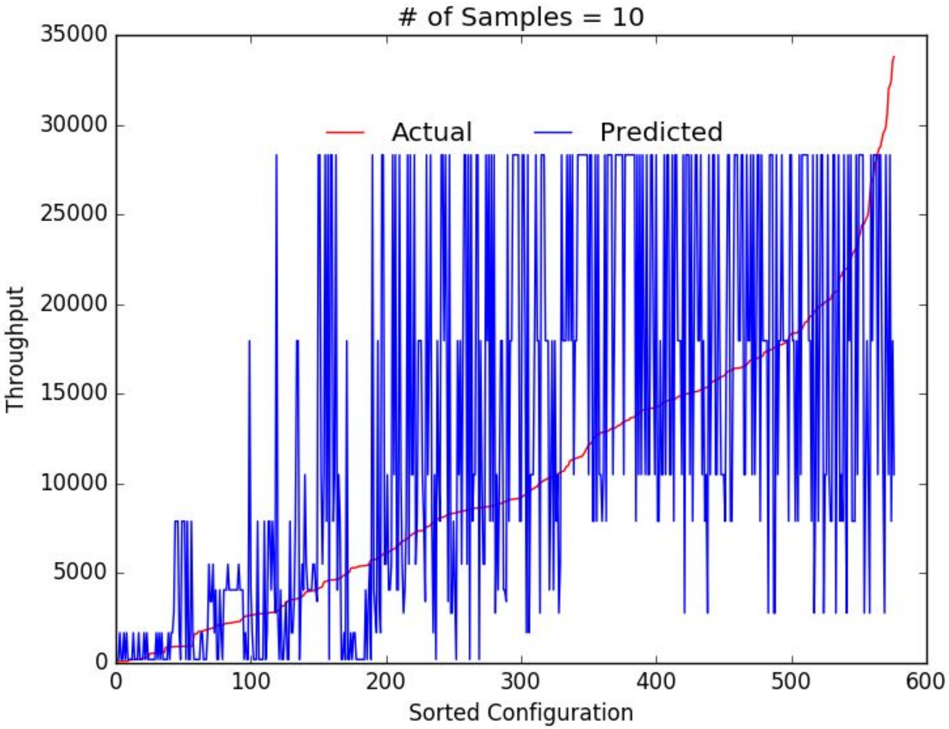

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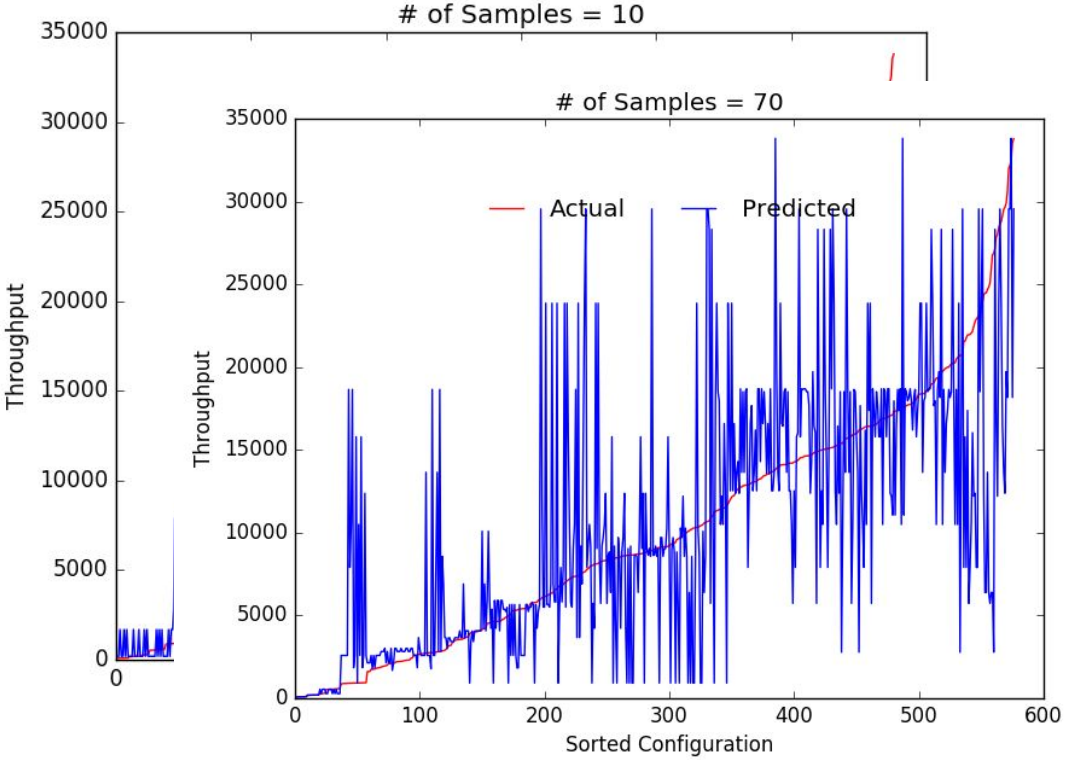

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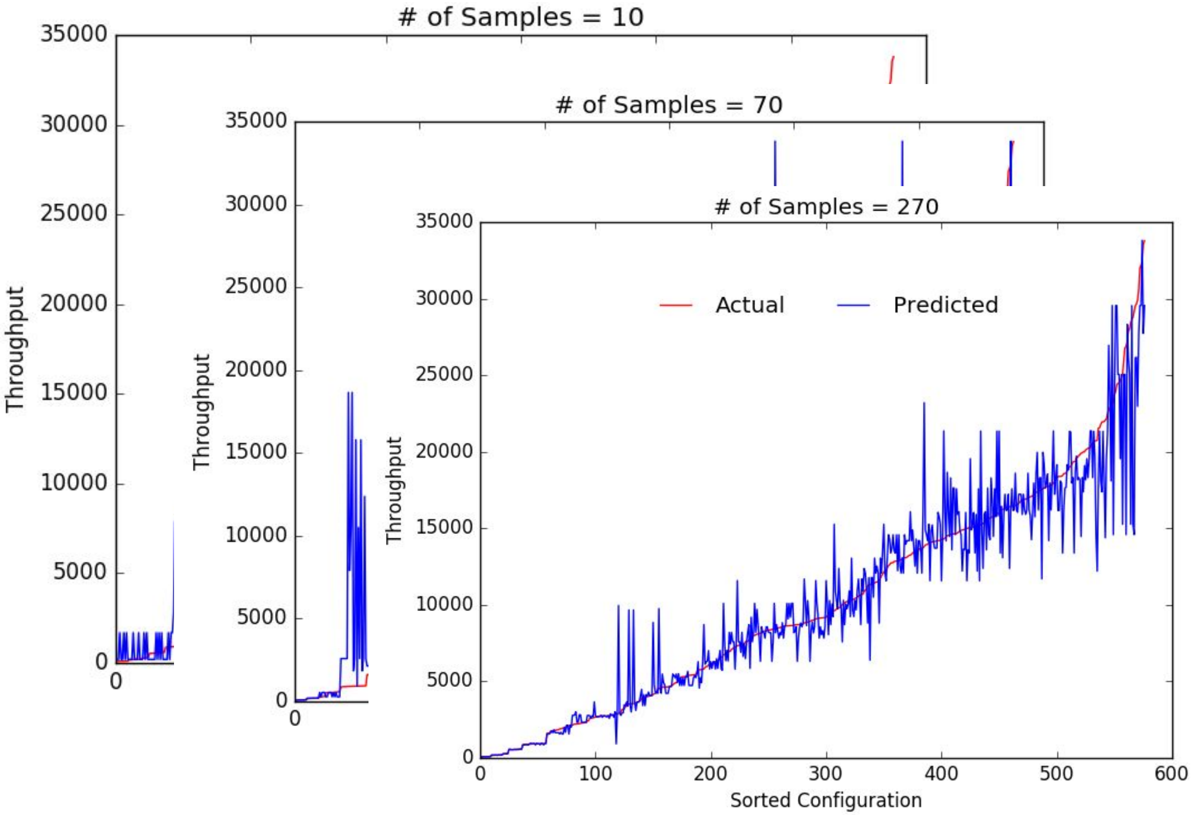

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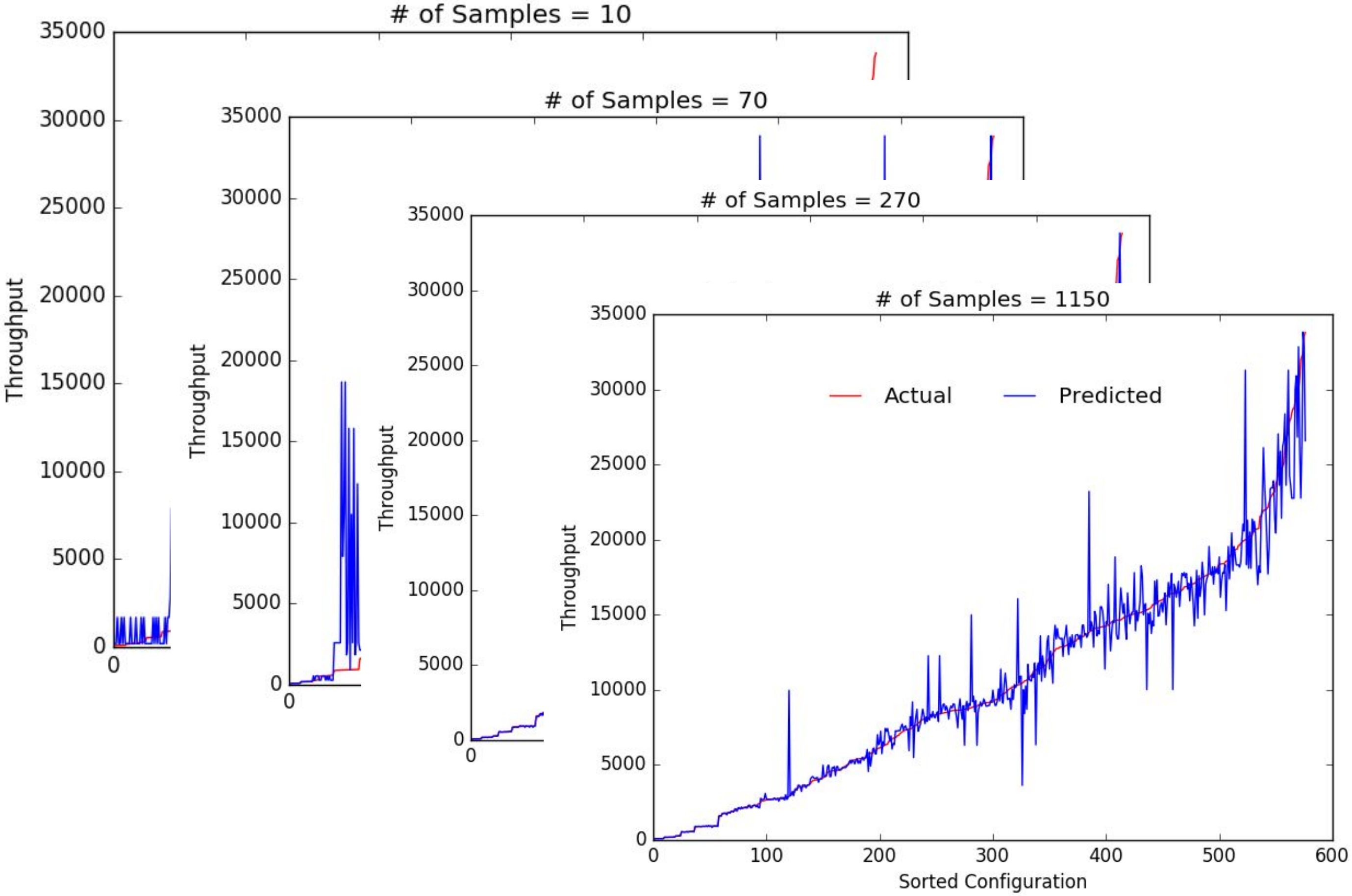

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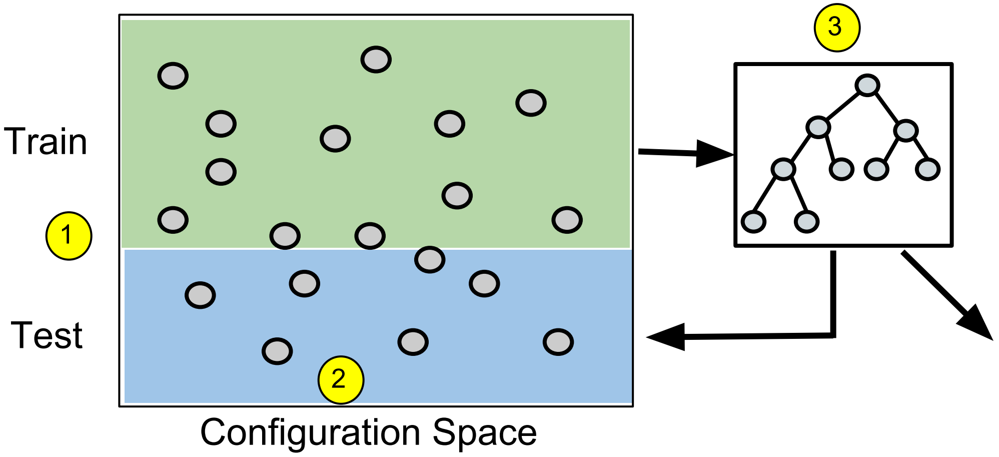

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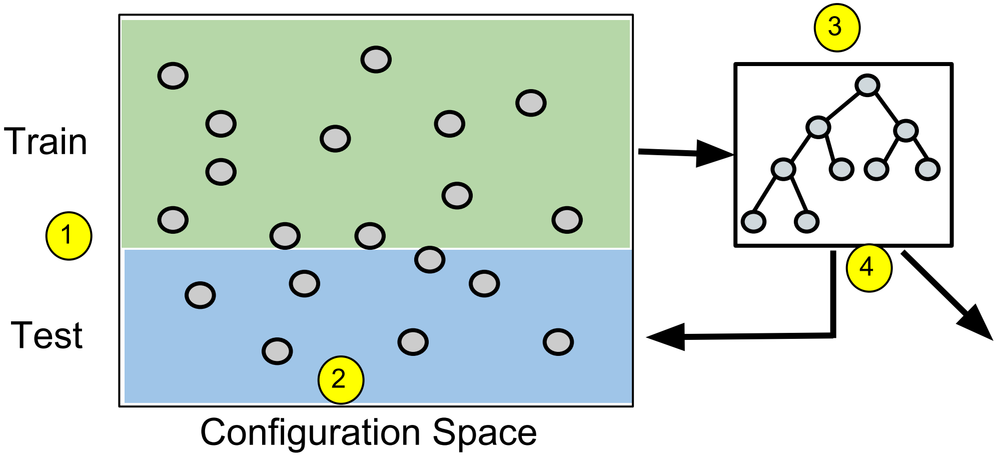

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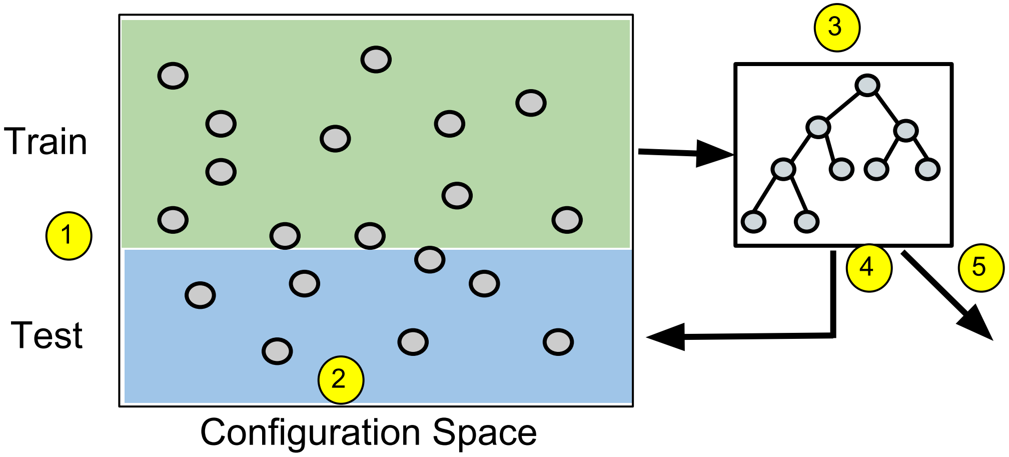
2. Measure all the configurations in the *testing* set;
3. Iteratively sampling configuration from *training* set to build a *model* and test the model against *testing* set;
4. Calculate accuracy □ model should get progressively more accurate

$$accuracy = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| rank(y_i) - rank(f(x_i)) \right|$$

Rank Preserving Model



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2. Measure all the configurations in the *testing* set;
3. Iteratively sampling configuration from *training* set to build a *model* and test the model against *testing* set;
4. Calculate accuracy model should get progressively more accurate
5. *Exit* when a model built does not improve (accuracy plateau)

$$accuracy = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| rank(y_i) - rank(f(x_i)) \right|$$

Evaluation

Baselines

- Progressive Sampling[1]
  - Sequentially (randomly) sample configuration to build a decision tree till threshold accuracy is reached
- Projective Sampling[2]
  - Using minimal set of initial sample configurations to project the sampling cost based on a threshold accuracy

[1] Guo, Jianmei, et al. “Variability-aware performance prediction: A statistical learning approach”. ASE-2013
[2] Sarkar, Atri, et al. "Cost-efficient sampling for performance prediction of configurable systems (t)." ASE-2015

Research Questions

RQ1

- Can inaccurate models accurately rank configurations?

RQ2

- How expensive is a rank-based method?

Subject Software Systems

Video Encoder	X264		
Databases	ORACLE BERKELEY DB	?	Grid benchmark
Utility	GNU wget	Apache HTTP SERVER	Web server
Compression	?	APACHE STORM	Data processing
Numerical	Dune		

Subject Software Systems

Pooyan Jamshidi

Sven Apel

Norbert Siegmund

X264

ORACLE
BERKELEY DB

GNU wget

Dune

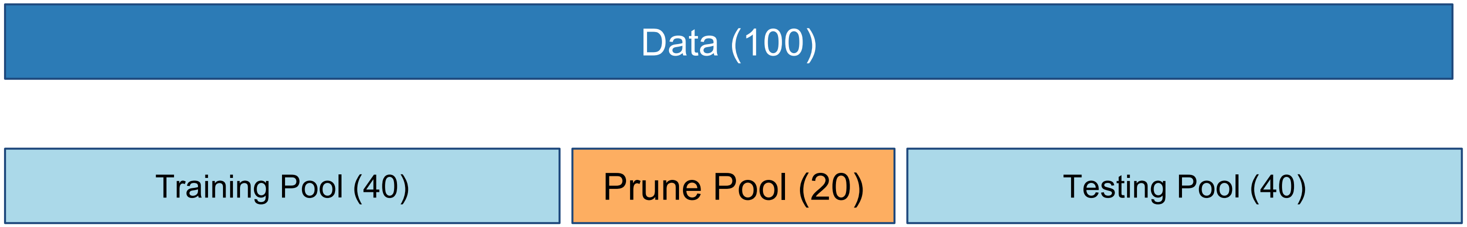
Apache
HTTP SERVER

APACHE
STORM

Combined effort = 6 computational months

Experimental Settings

Experimental Settings



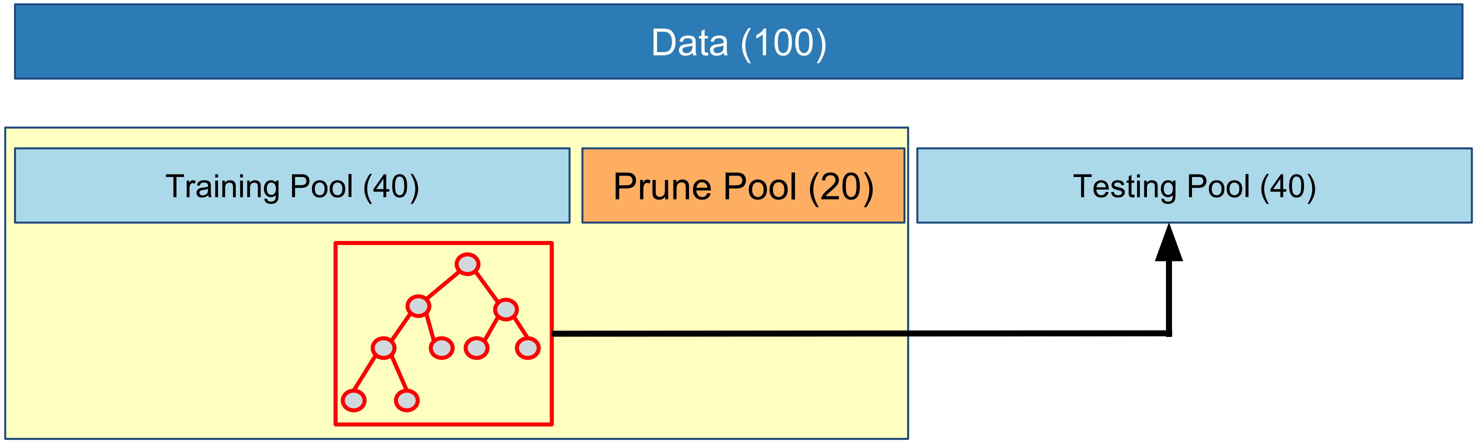
Data (100)

Training Pool (40)

Prune Pool (20)

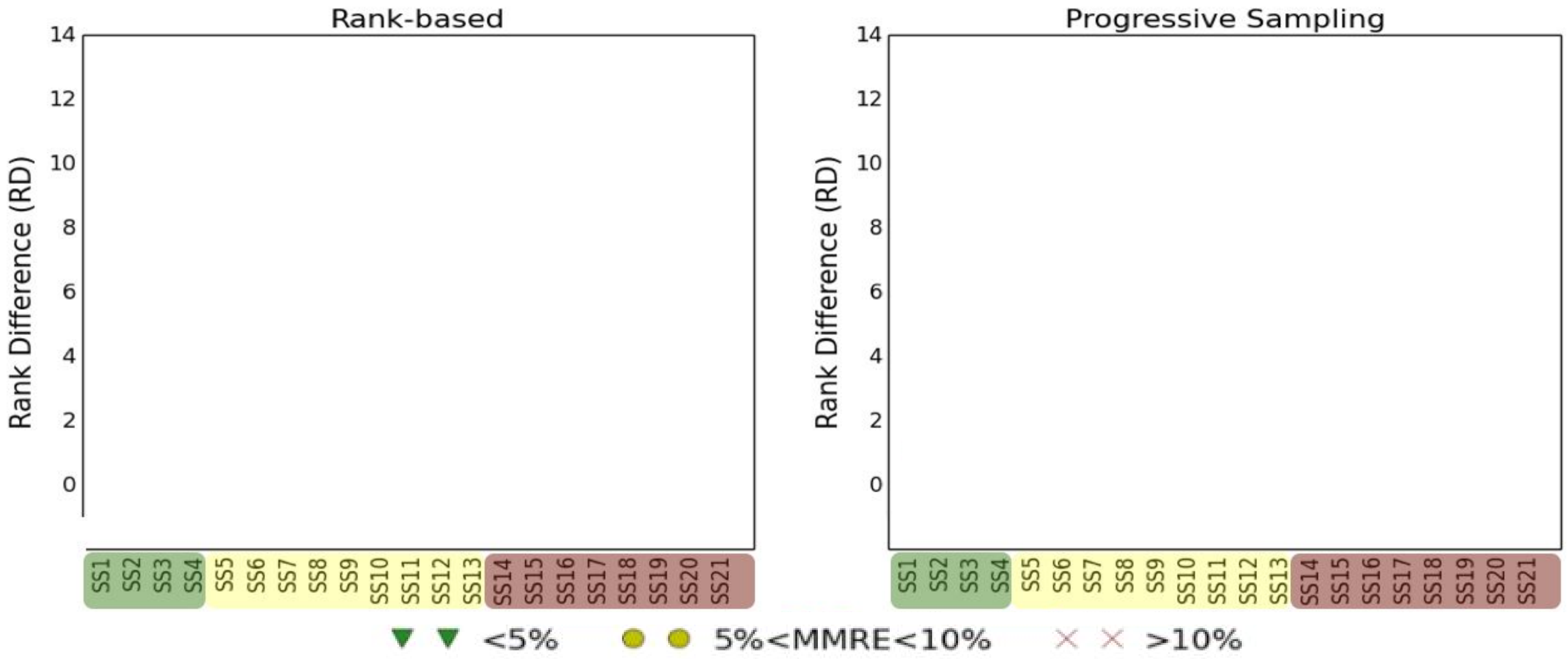
Testing Pool (40)

Experimental Settings



Results

RQ1: Can inaccurate models accurately rank configurations?



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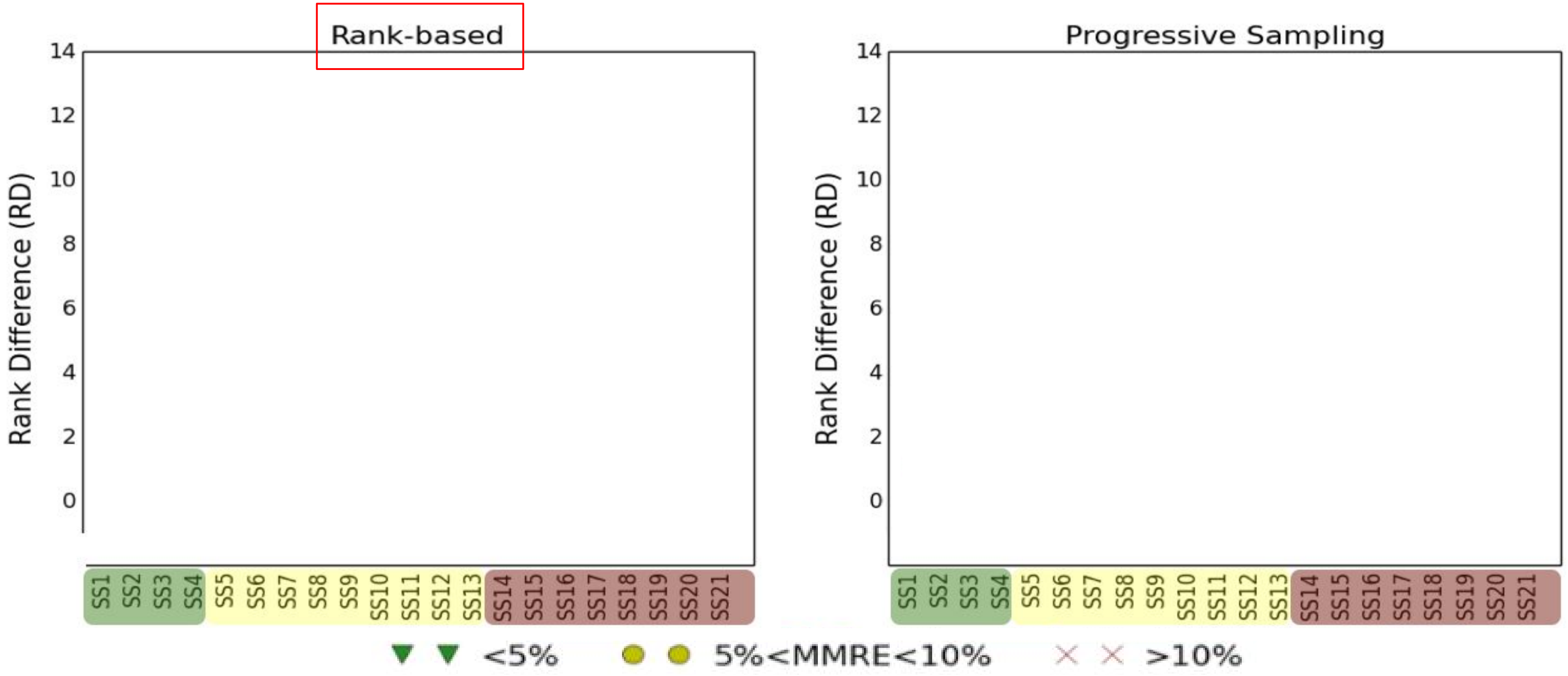

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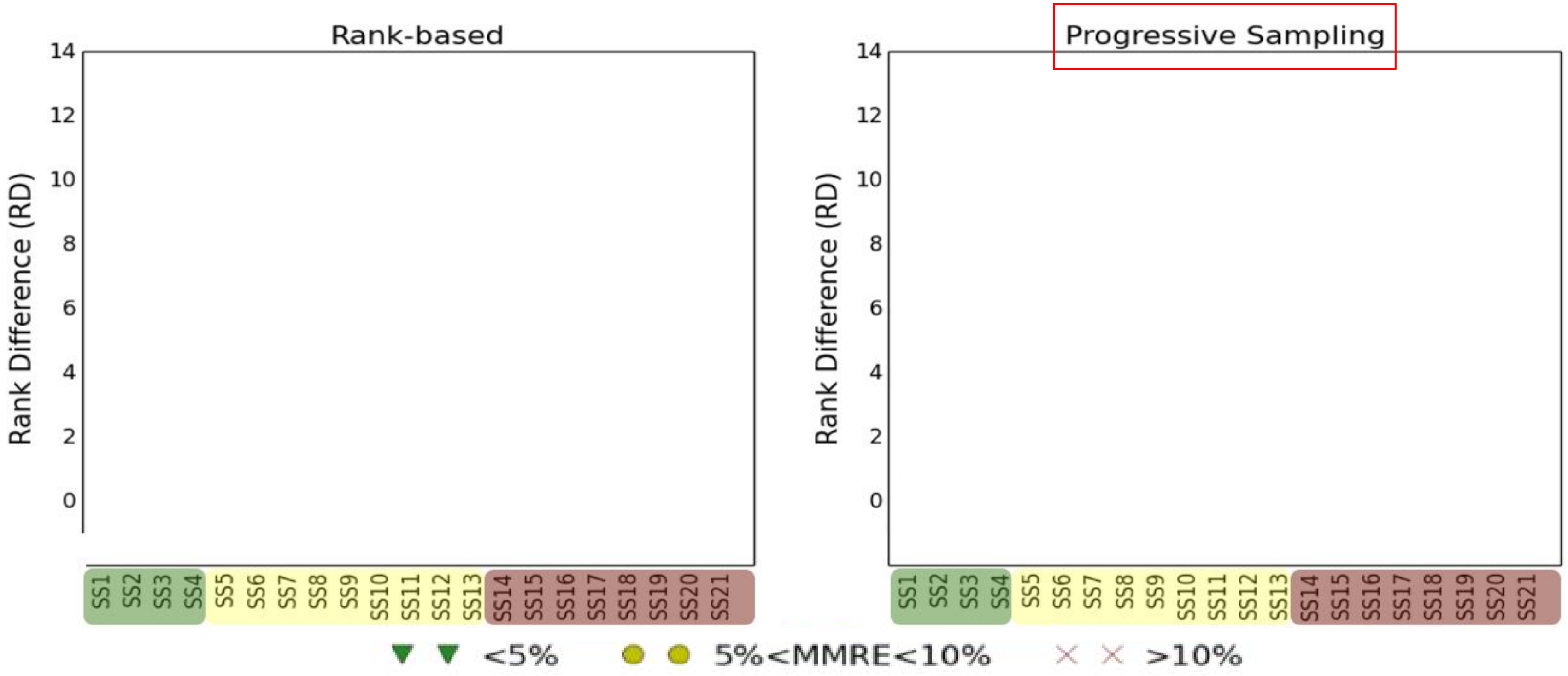

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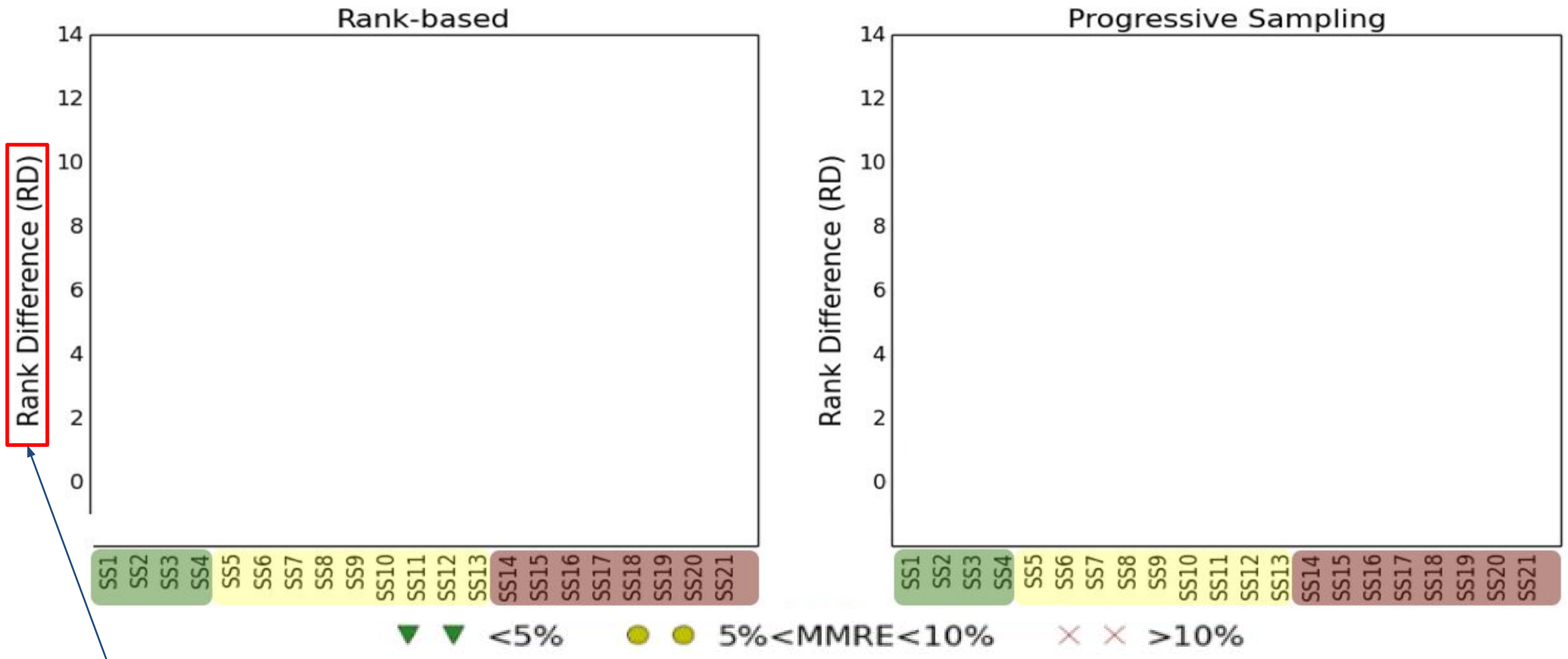
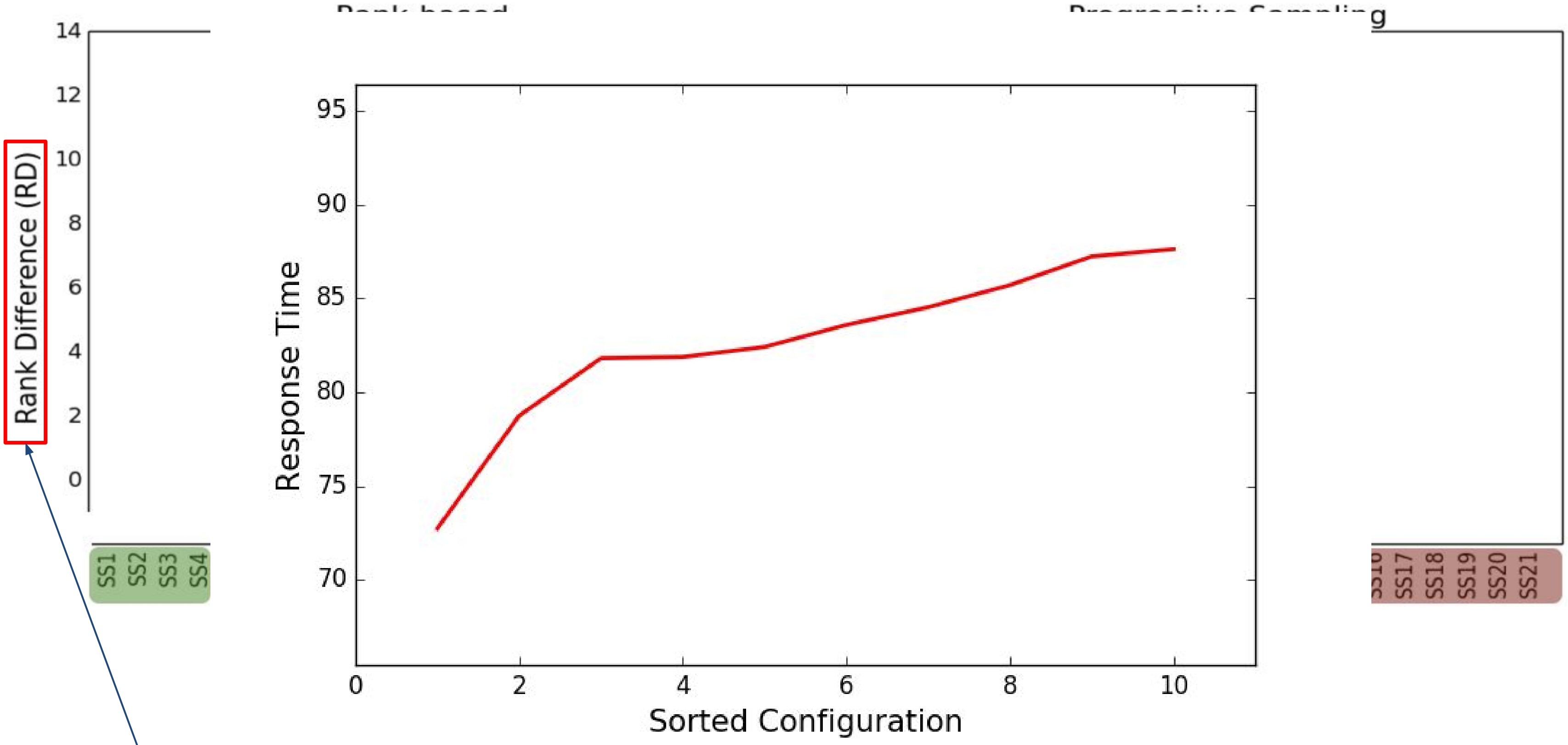


The lower the better

$$RD = |rank(actual_{optimal}) - rank(predicted_{optimal})|$$

RQ1: Can inaccurate models accurately rank configurations?



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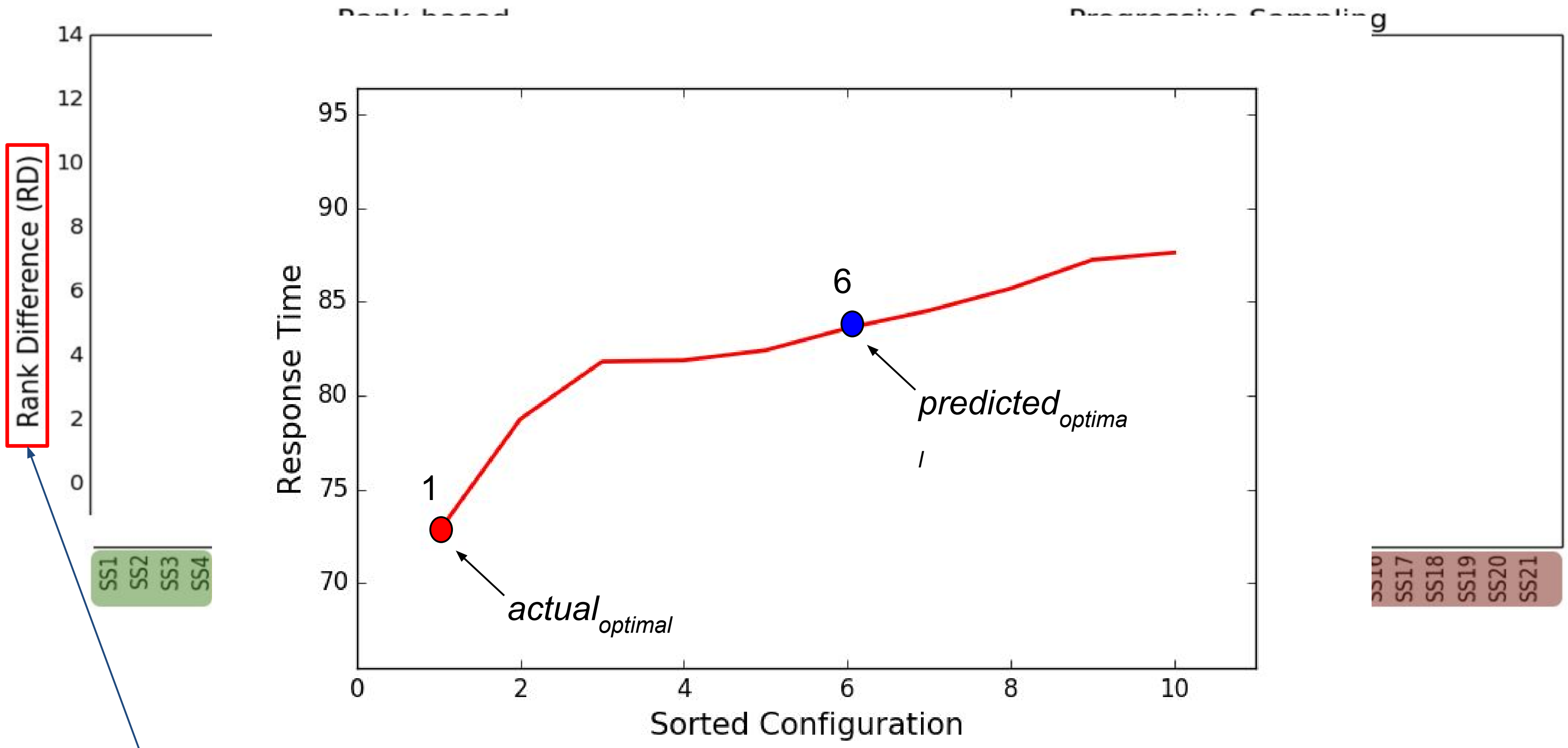

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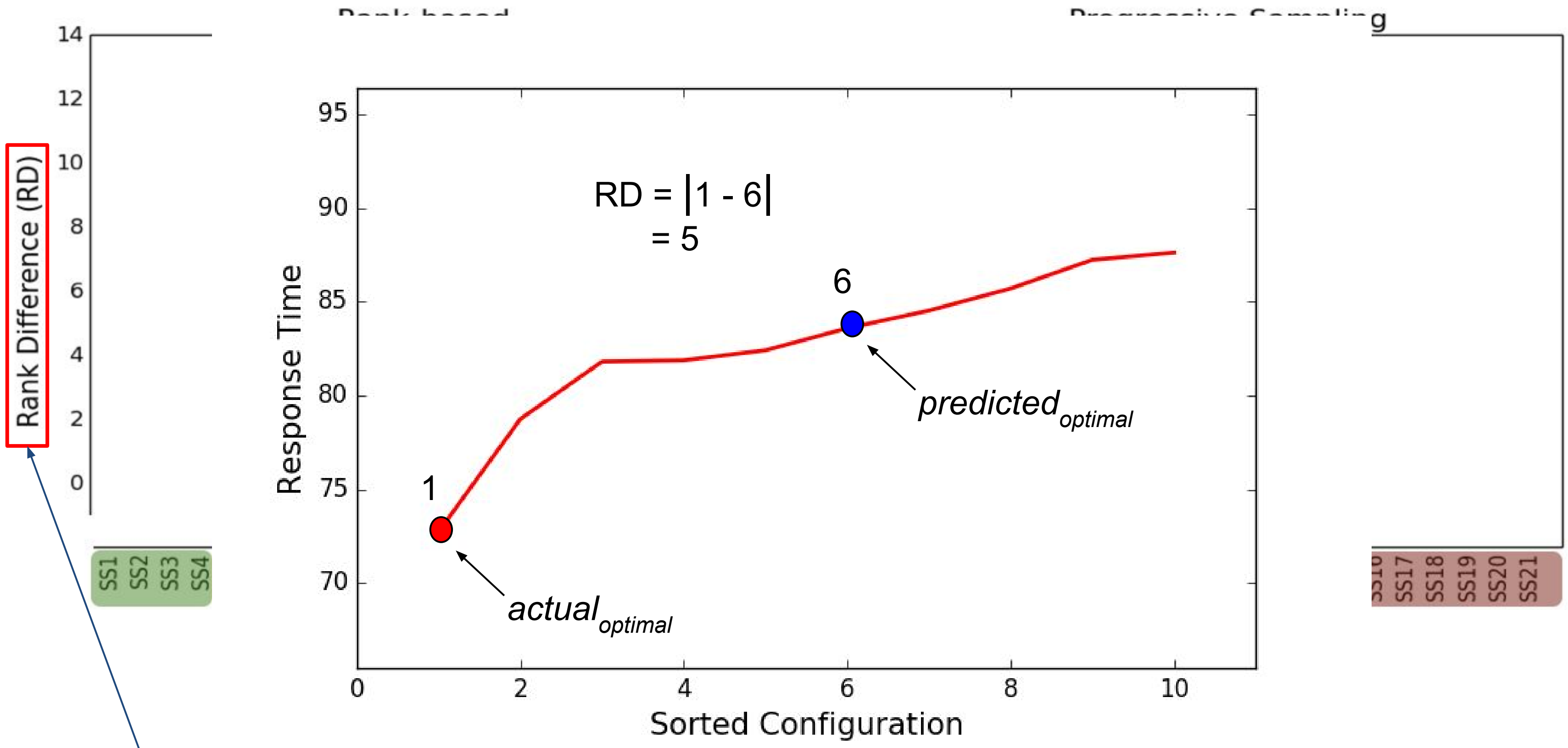
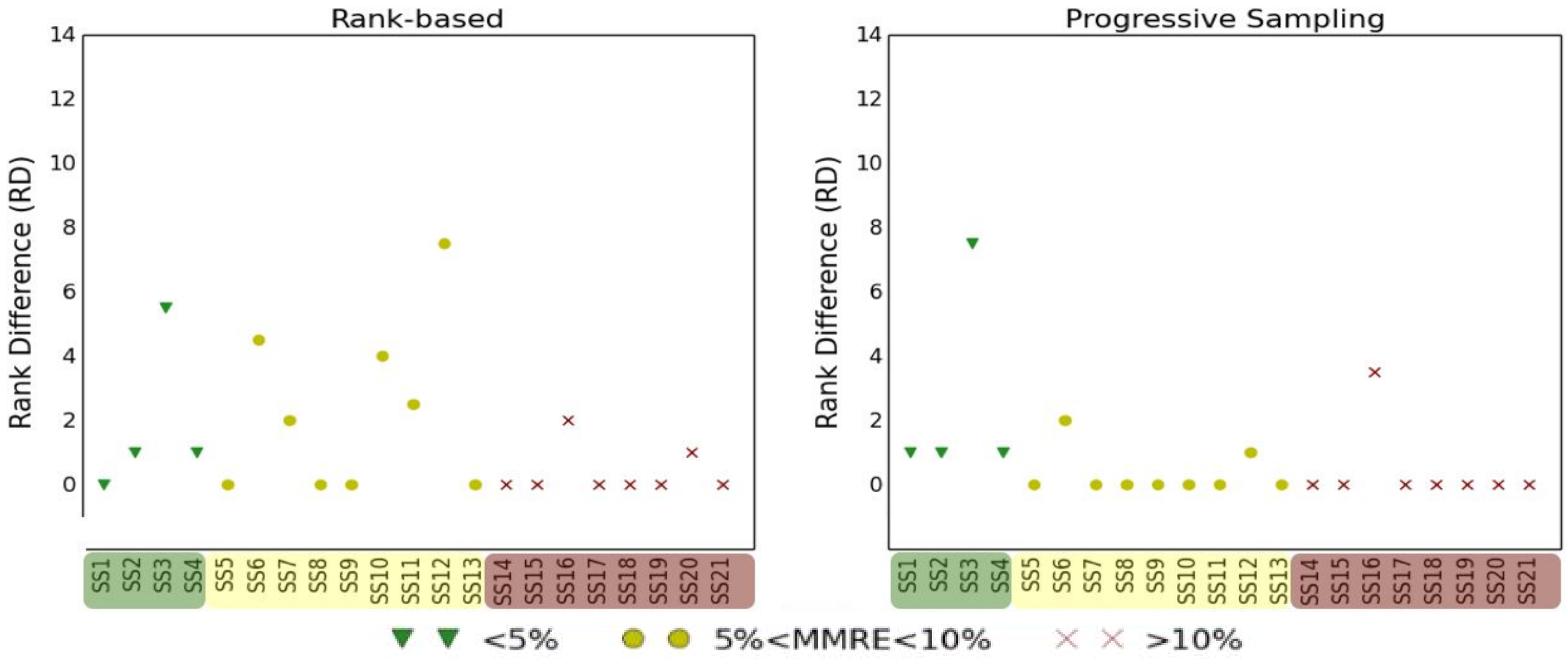


$$RD = |rank(actual_{optimal}) - rank(predicted_{optimal})|$$

RQ1: Can inaccurate models accurately rank configurations?



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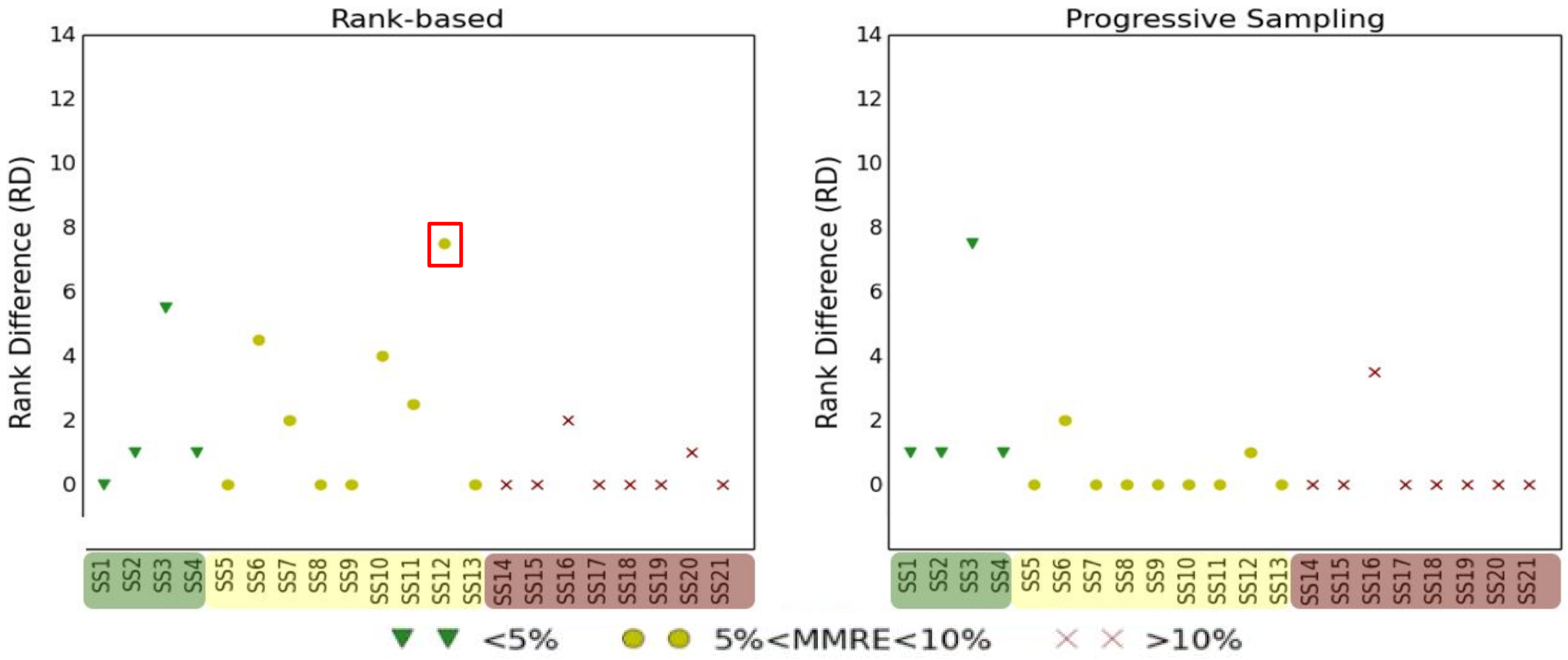

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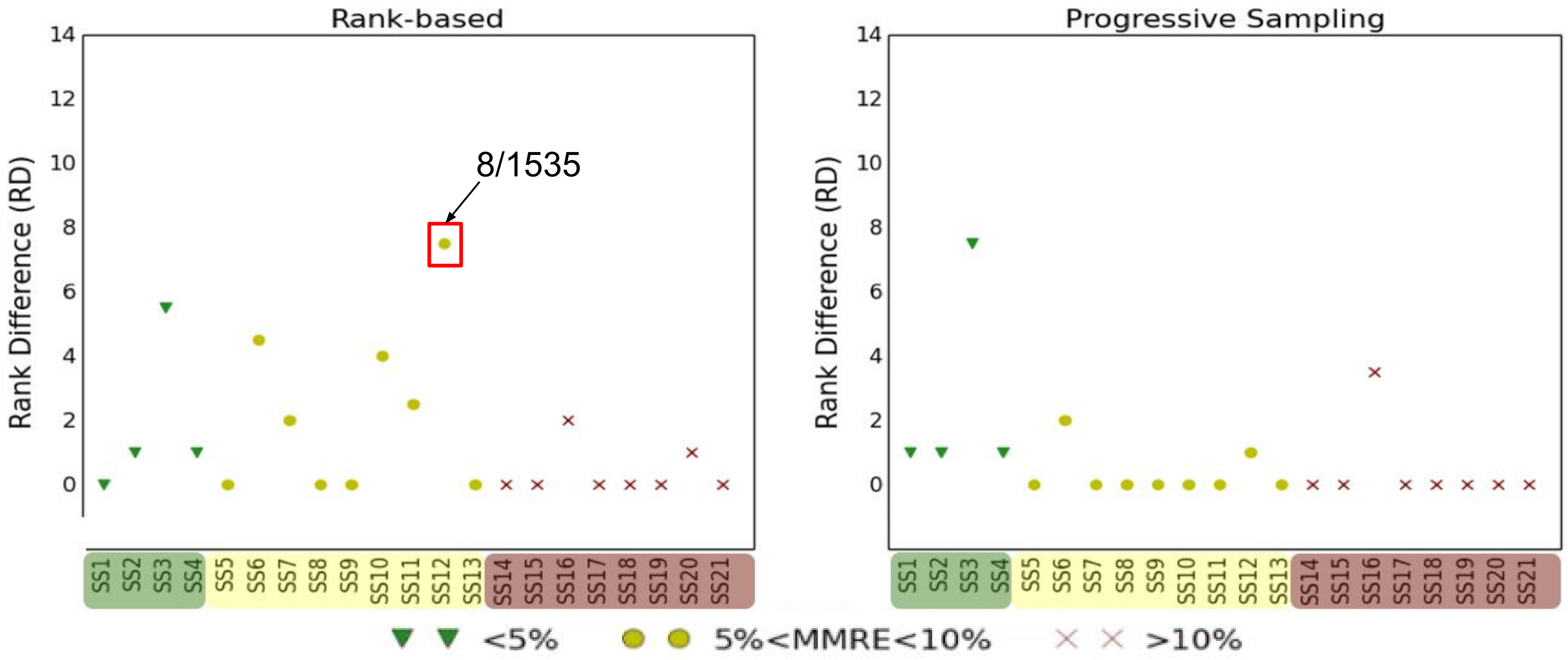

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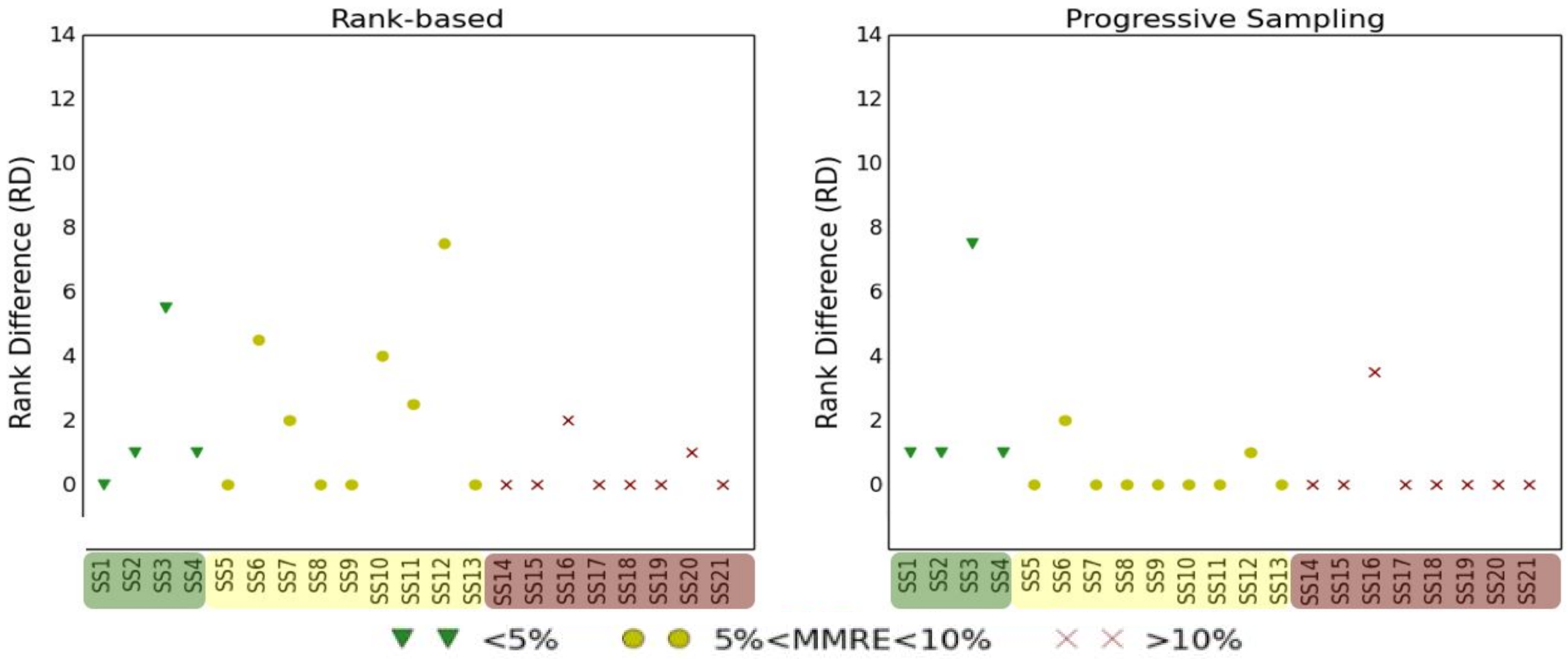
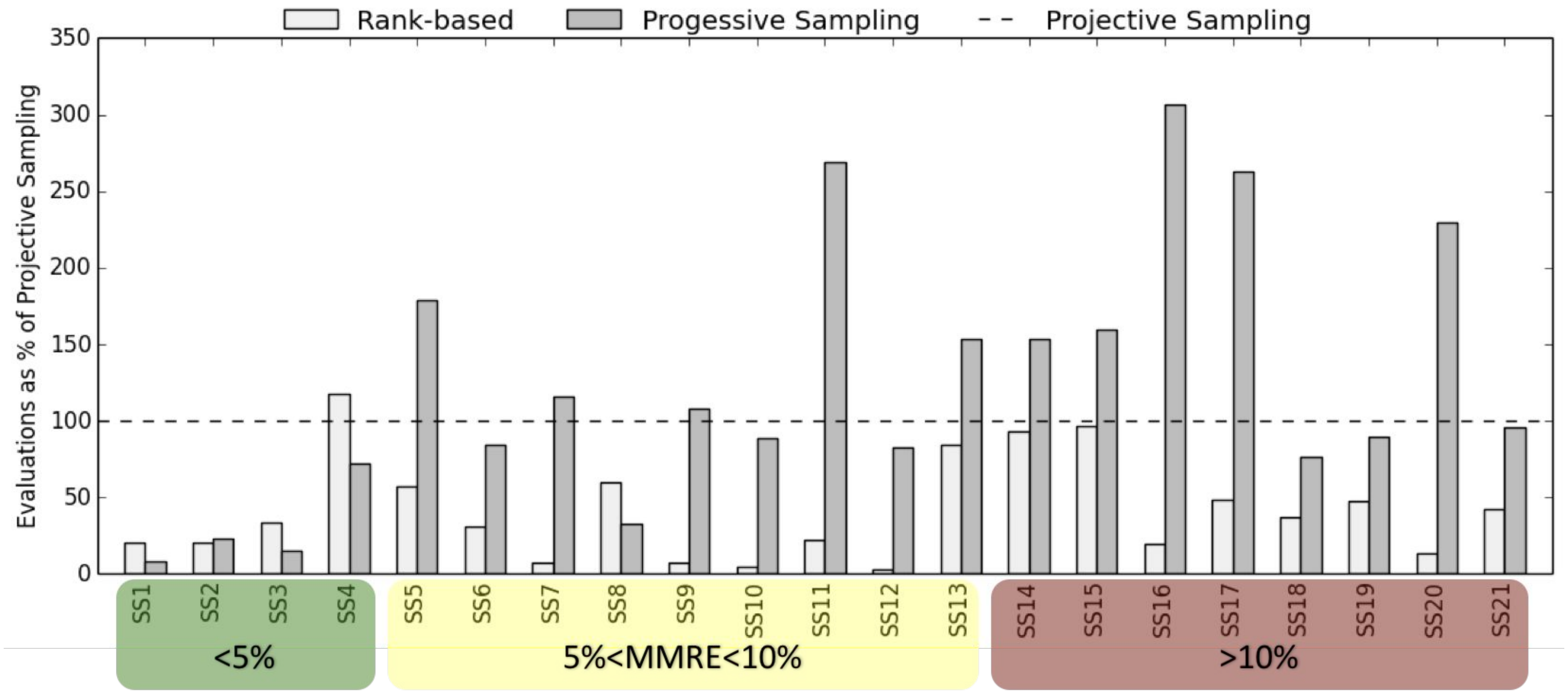
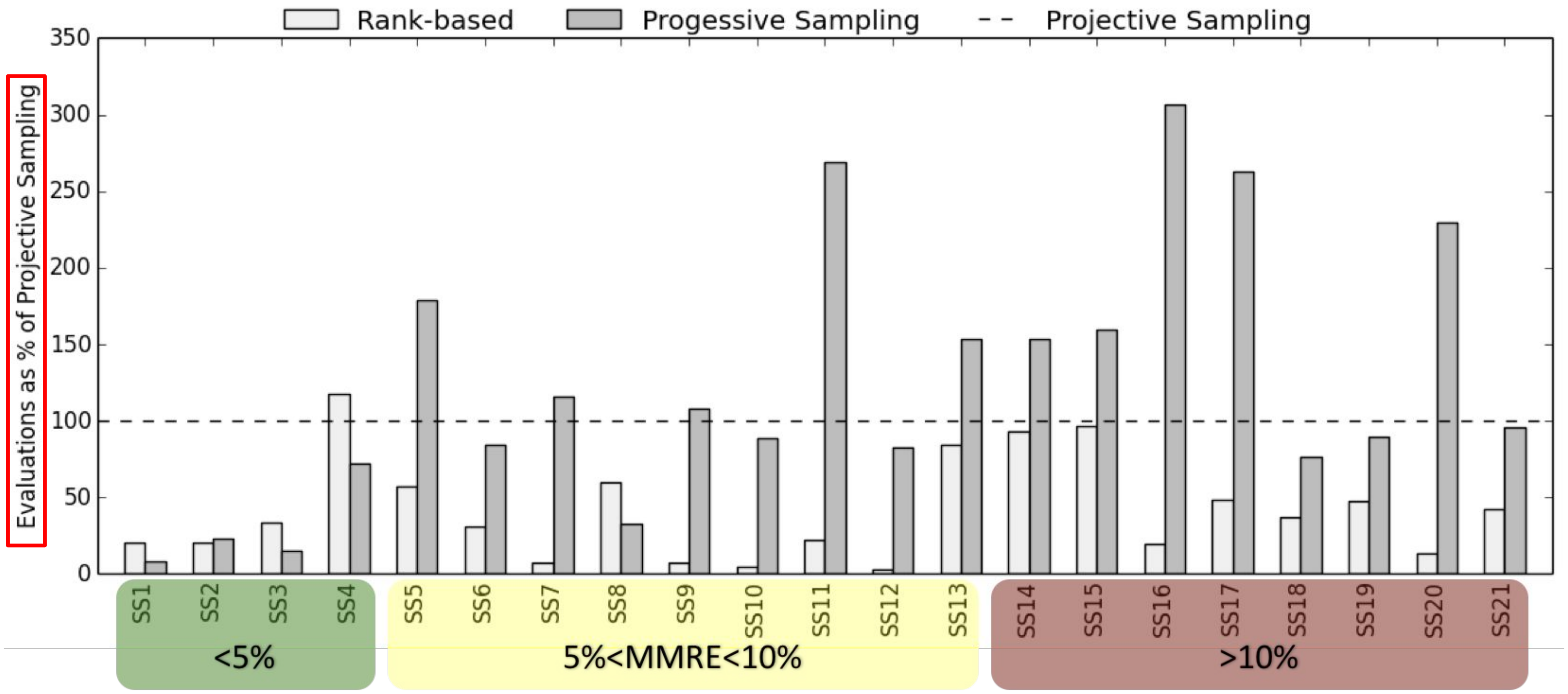


Yes, a rank preserving model can be useful in finding (near) optimal configurations!

RQ2: How expensive is a rank-based approach?

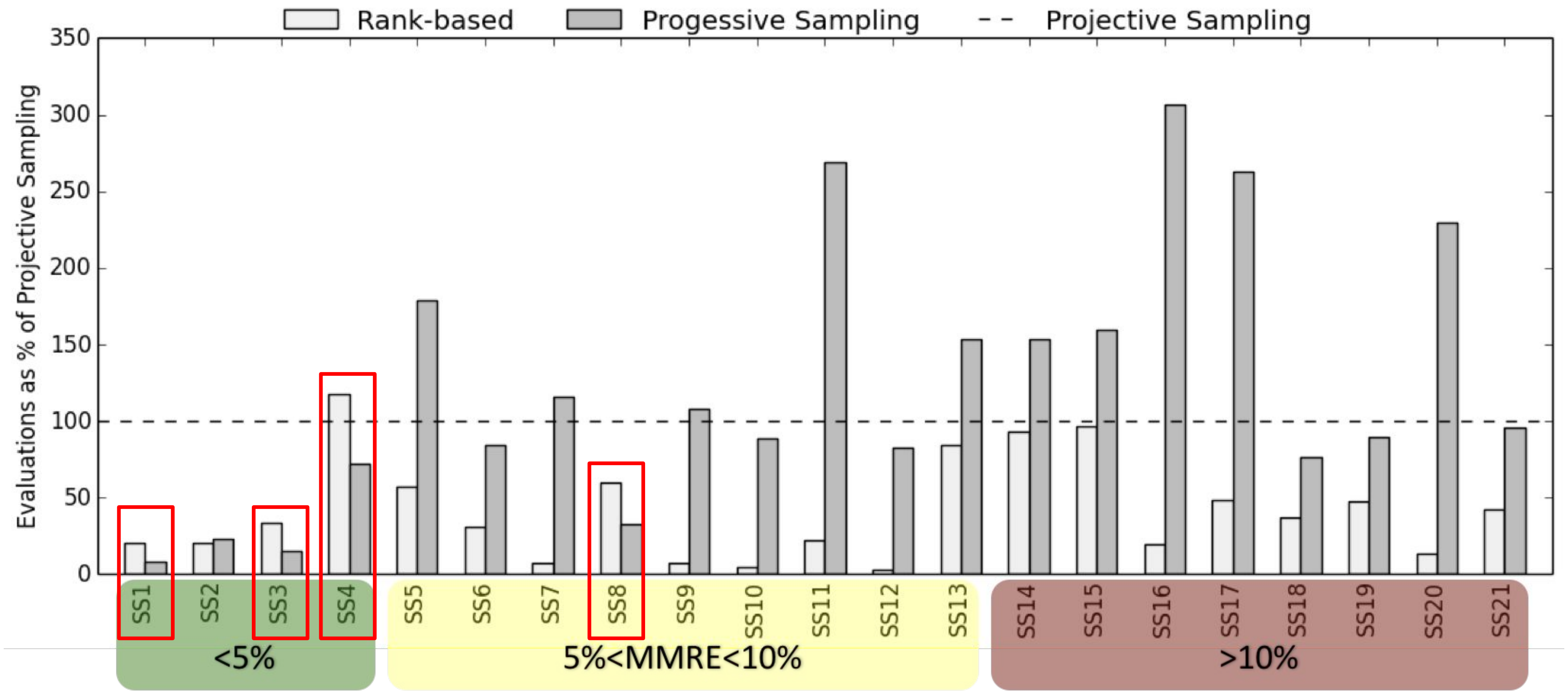


RQ2: How expensive is a rank-based approach?



The lower the better

RQ2: How expensive is a rank-based approach?



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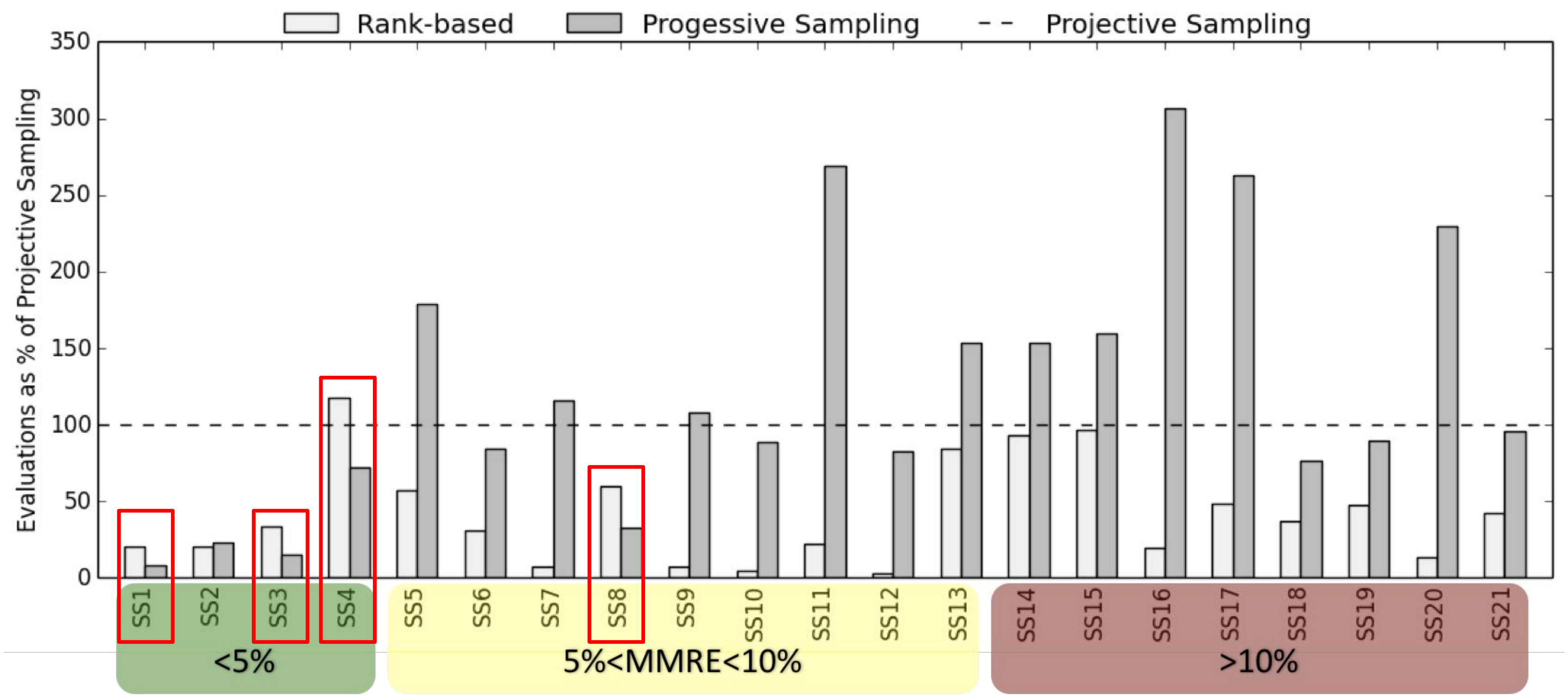

Yes, a rank-based approach requires fewer measurements!

Conclusion

- Rank-based method
  - a highly accurate model is not required for performance optimization;
  - performance optimization using predicted values correlated to actual values saves resources

- Future Work & Limitation
  - Relies heavily on testing pool (20%)
  - Bayesian based sequential sampling to reduce cost

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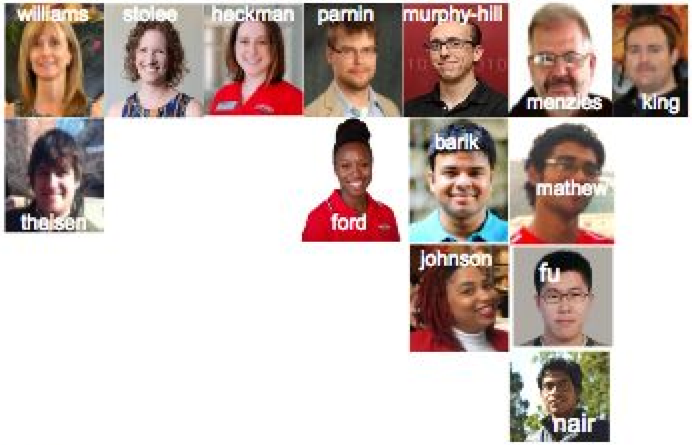

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Rank-preserving models

rather than

highly accurate models!

Expected Graduation: **May 2018**

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