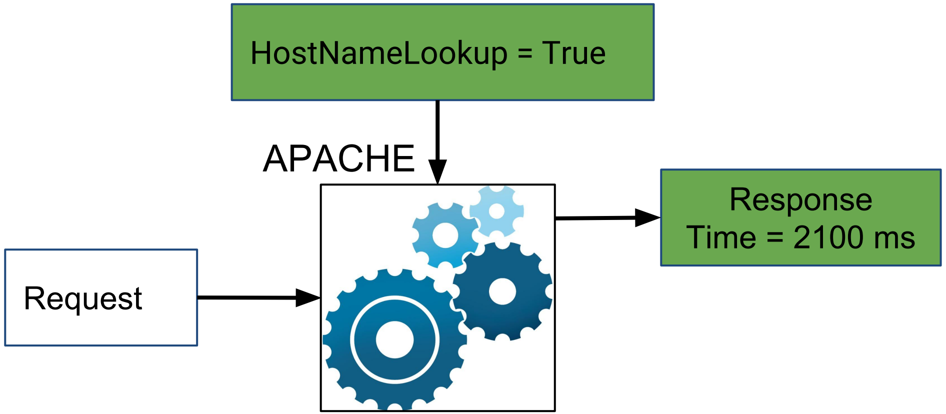
Frugal: Cheaper Methods for SBSE

Vivek Nair

Why configurations are so important?

- Software systems are configurable
- Configurations are parameters to control the behavior of a system
  - Configurations of ***Apache:***
    - HostNameLookups
    - FollowSimLinks
    - ….
- Different configurations of system will result in different performance



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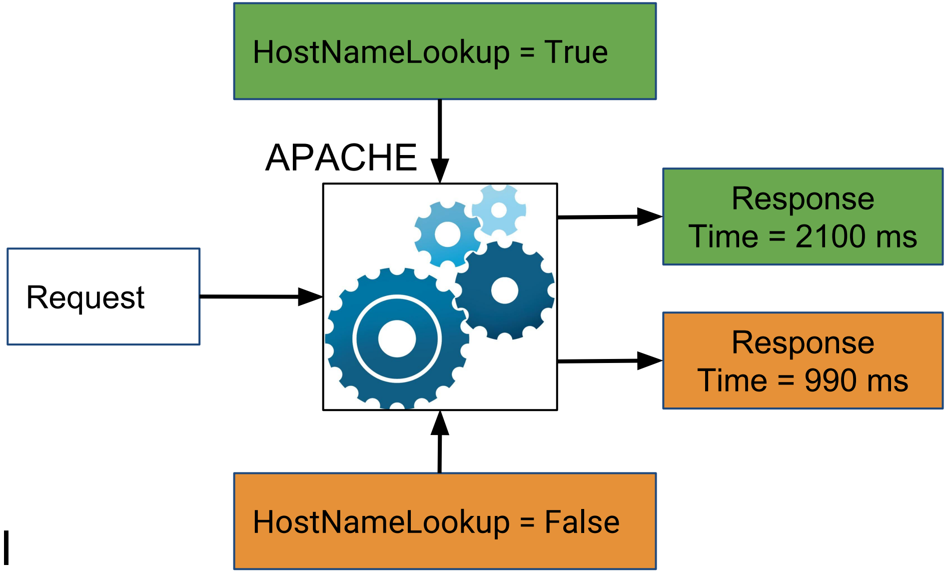

Example

Conf.	Features							
	x_1	x_2	x_3	..	x_i	..	..	x_N
1	1	0	1	0	0	0	1	1
2	0	1	1	1	1	0	0	1
3	1	0	0	1	0	1	0	0
4	1	1	0	1	0	1	0	1
5	1	0	1	1	0	1	1	0

Find the fastest configuration setting for given a sample program?

Just run it?

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.								
.								
3,932,160	1	0	1	1	0	1	1	0

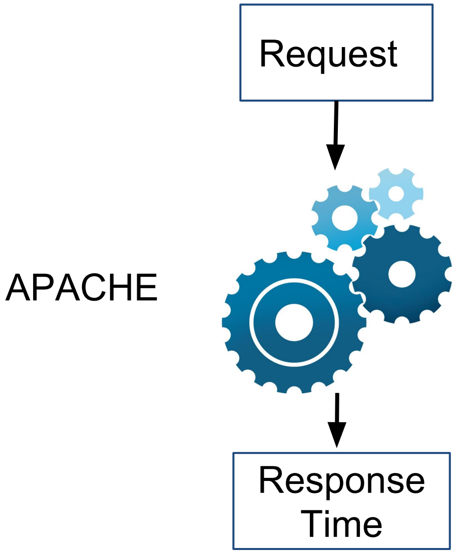
Find the fastest configuration setting for given a sample program?

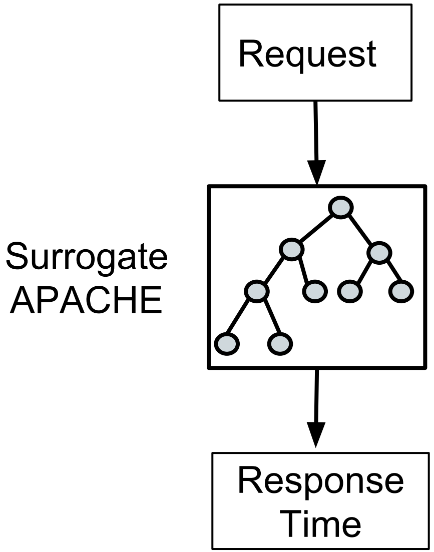
Just run it?

How about now?

We need a Surrogate!

Surrogate is a cheap version of the actual system





Who endorses Surrogates?

Other Communities

- Aerospace
  - Axial compressor blade shape optimization [Samad08]
  - Hydraulic turbine diffuser shape optimization [Marjavaara07]

- Engineering Design
  - Enhanced oil recovery process [Sanchez06]
  - Design of composite materials [Sakata08]
  - Alkaline-surfactant-polymer flooding processes [Zerpa05]

Software Engineering

No surrogates….

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Software Engineering

No surrogates….

Most Similar But ***NOT Surrogates***:

- Heuristic method to predict response times [Siegmund'12]
- Random Sampling to build a prediction model [Guo'13, Sarkar'15]

Our Surrogate Method!

Our method “WHAT” is better than the state of the art

- Similar result using 2 to 10 times less evaluations
- Predictions are more stable

Paper Submitted

Vivek Nair, Tim Menzies, Norbert Siegmund, Sven Apel. Faster Discovery of Faster System Configurations with Spectral Learning. Submitted to FSE - 2016

BACKGROUND

“*Search*” in Software Engineering

What is the: [Harman’12]

- best way to structure this system to enhance its maintainability?
- smallest set of test cases that covers all branches?
- fastest configuration of this system to run this benchmark program?

Software Engineering problems are

- MultiObjective [Mkaouer’15]
  - The are more than one objective to optimize
- Multi-Modal
  - There are more than one optimum solution
- Non-Separability
  - The optimum of one of the objectives is not the optimum for the other objective/s.
- High Dimensions
  - Number of dimensions of the search space is large

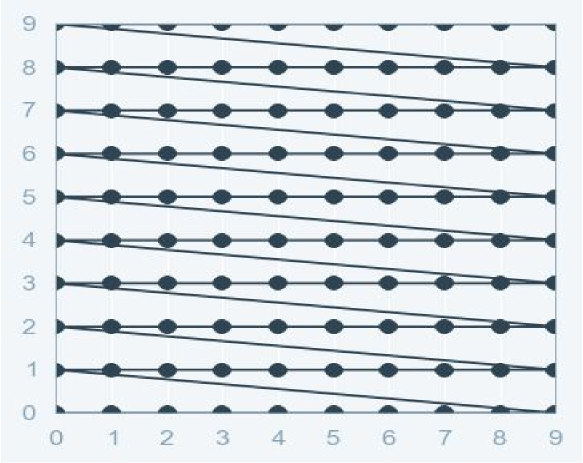
Which optimization algorithms can we use?

Mathematical optimization

- Based on the property of objective function and constraint function:
  - linear programing
  - non-linear programing
- Assumes properties like differentiability etc.

Grid Search

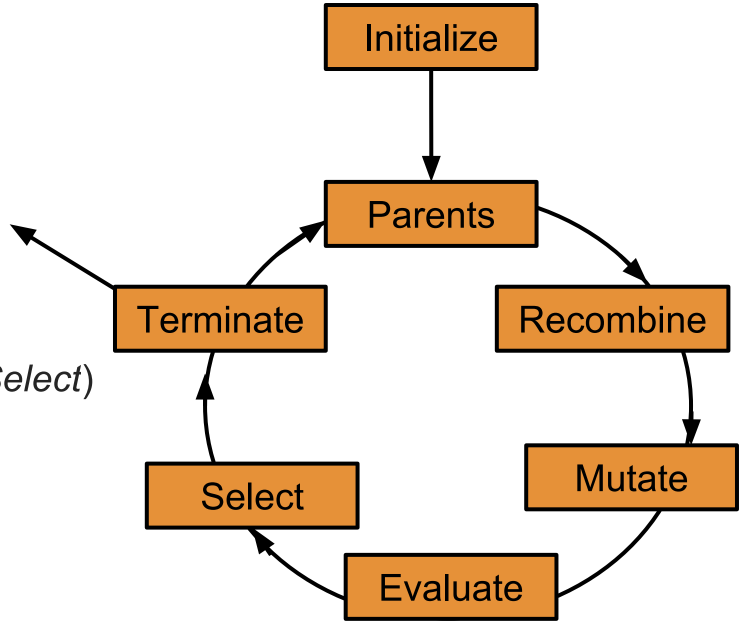
- Divide dimensions into bins
- Choose one from each bin
- Slow and can miss important optimization opportunities



Which optimization algorithms can we use?

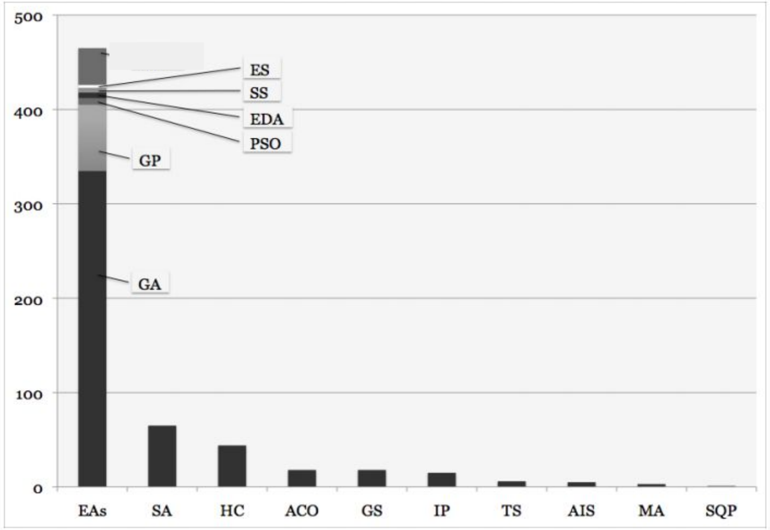
Evolutionary Algorithms

1. Initial Population (*Parent*)
2. While stoppingCriteria is True:
   a. Offspring = Reproduction (*Recombine* + *Mutate*)
   b. Evaluate Fitness (*Evaluate*)
   c. Replace least-fit population with new offspring (*Select*)
3. Return (Population)



Biased towards EA

- Simple implementation
  - Basic EA application can be coded up in 50 lines of python
- Distributed computation
  - Algorithms can be parallelized
- Generation of new ideas that have not been explored before



EA is most explored technique in SBSE [Harman'12]

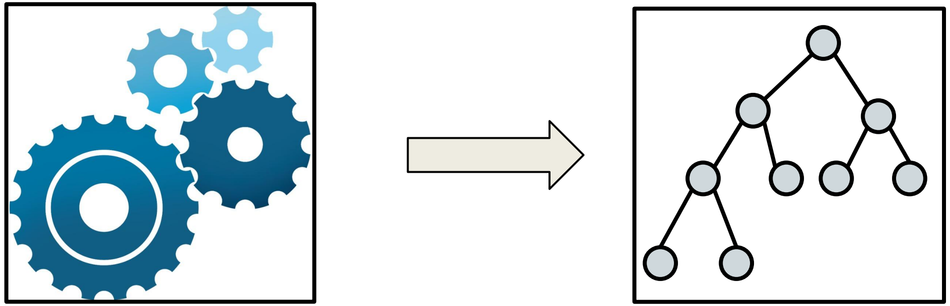
EA is really slow!

EAs require a *high number of objective function evaluations*

- Evaluation of single instance of software /hardware co-design problem can ***take weeks*** [Zuluaga'13]
- Test suite generation using EA can ***take weeks*** [Harman'12]
- Popular EA (NSGA-II) ***taking 7 days*** of execution time for Aviation Models [Krall'15]

Surrogate models might be the answer?

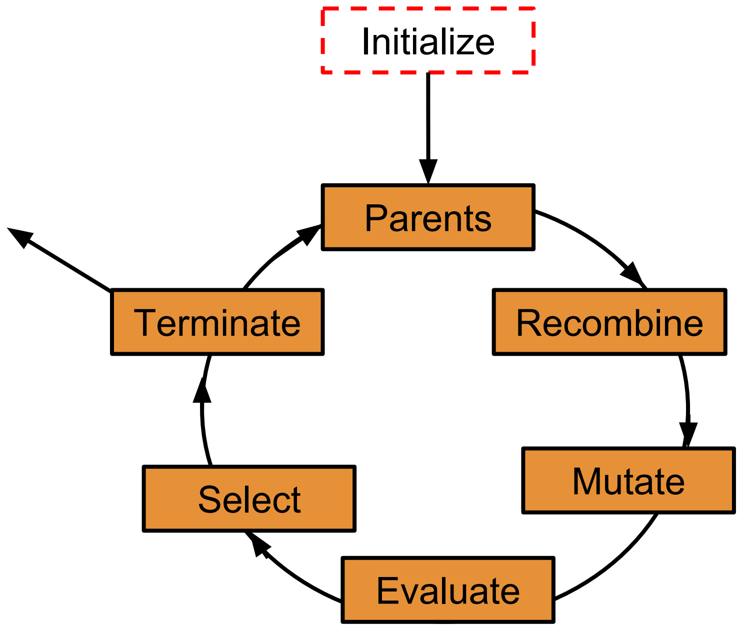
- Surrogates



- Motivation
  - Replacement of expensive function, evaluated many times
  - Widely used in Airfoil design, CFD, reservoir planning etc.
  - No known usage in Software Engineering

Surrogate can also be used to inform

- Initialization
    - Use only the best candidates evaluated using a surrogate [Rasheed'00]



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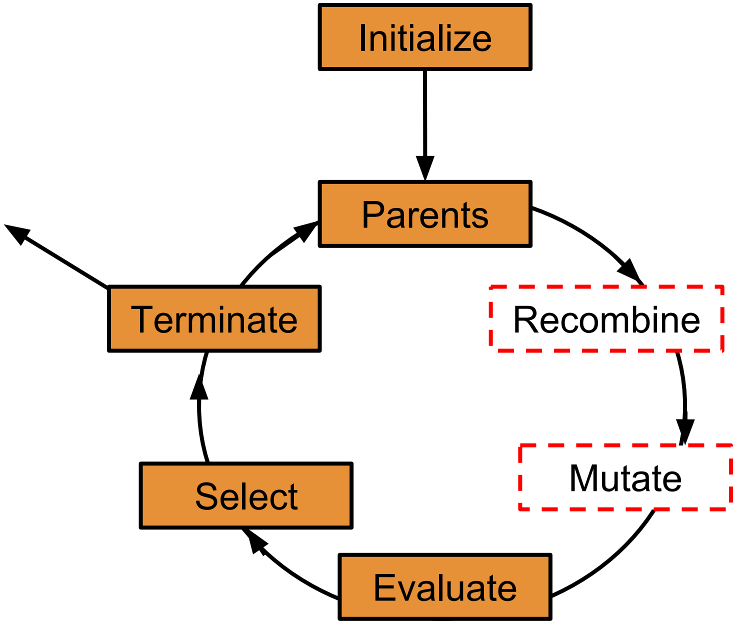
- Recombination + Mutation
    - Create multiple children and use the fittest of them all [Loshchilov'10]
    - Create local surrogate and and search locally [Abboud'01]



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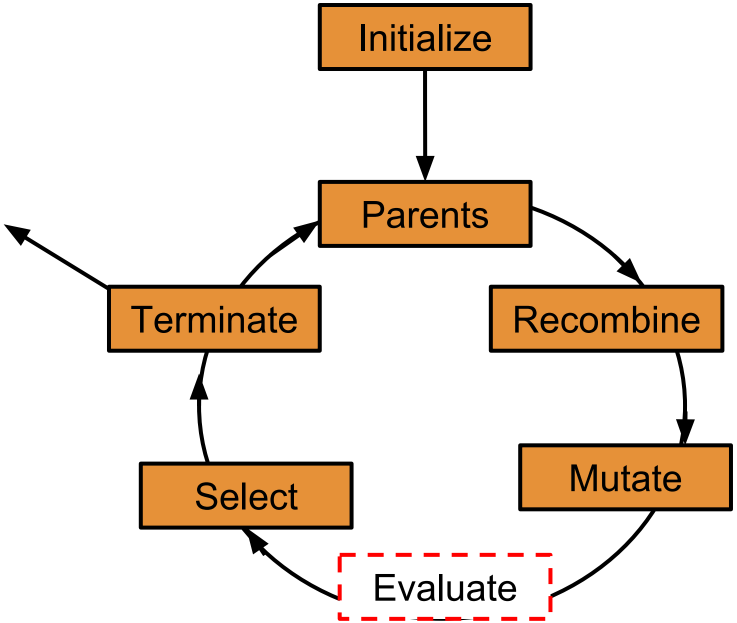
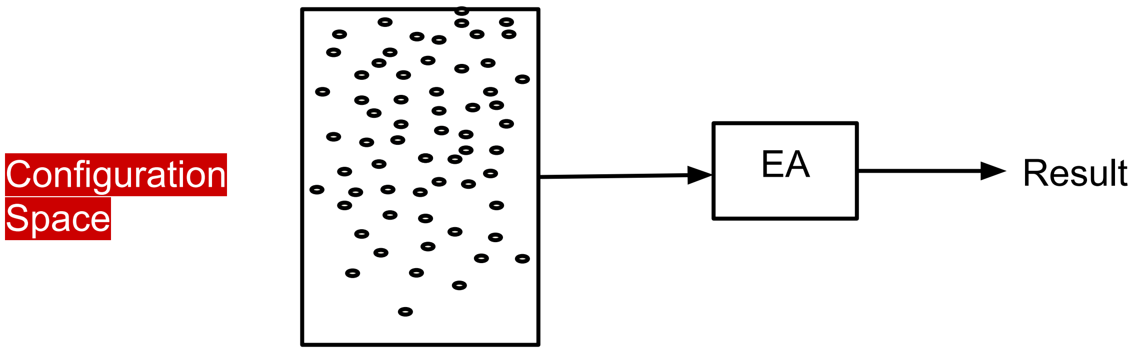
- Evaluate
    - Multiple Surrogates [Zhou'07]
    - **WHAT** is an evaluate surrogate



To Summarize



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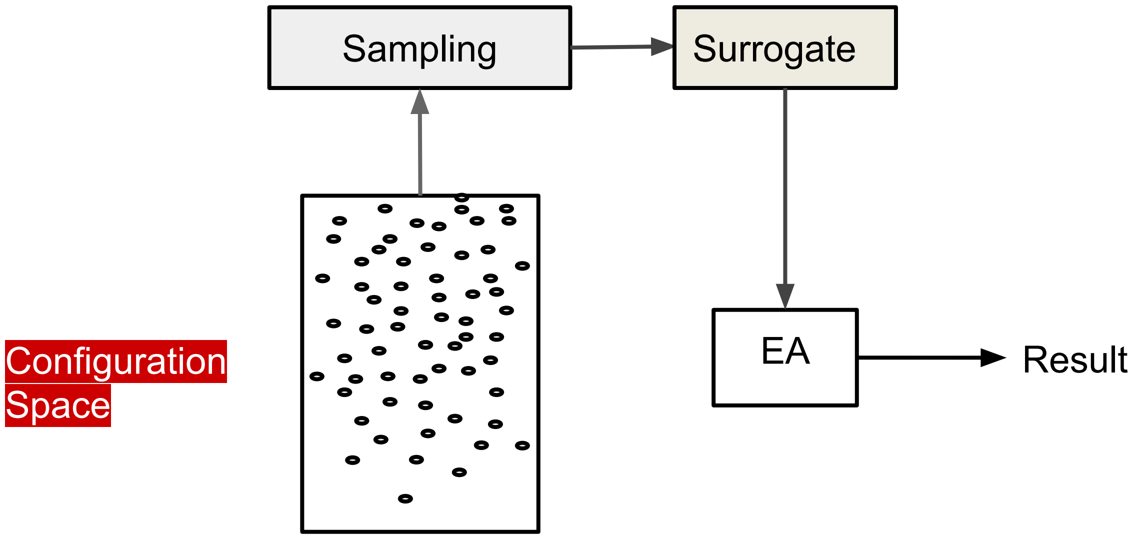

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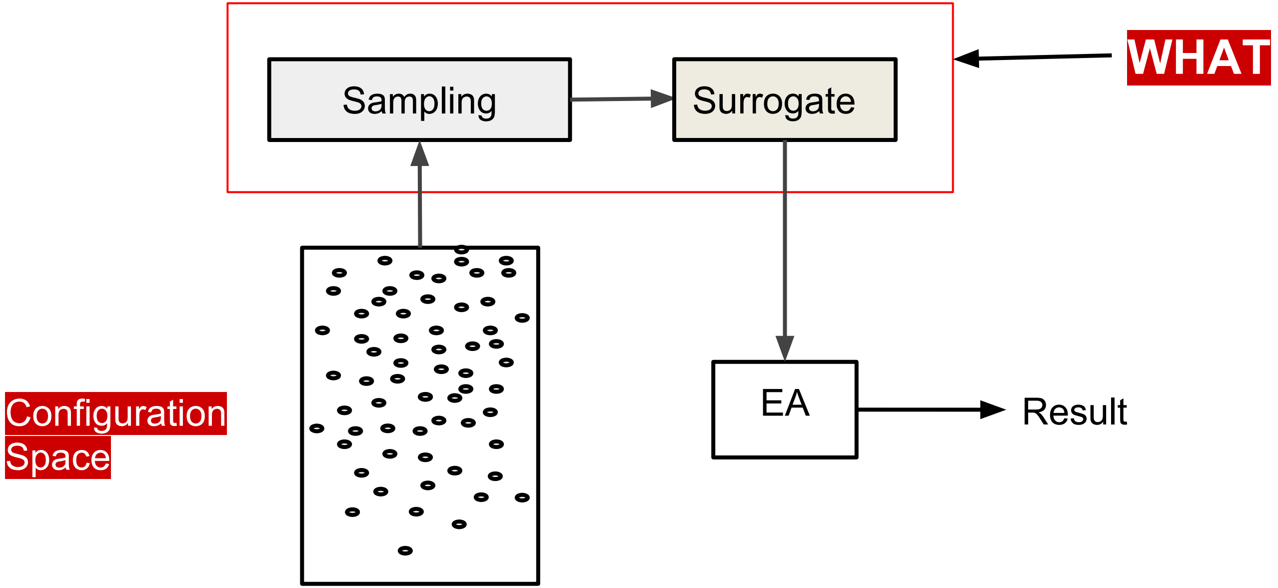
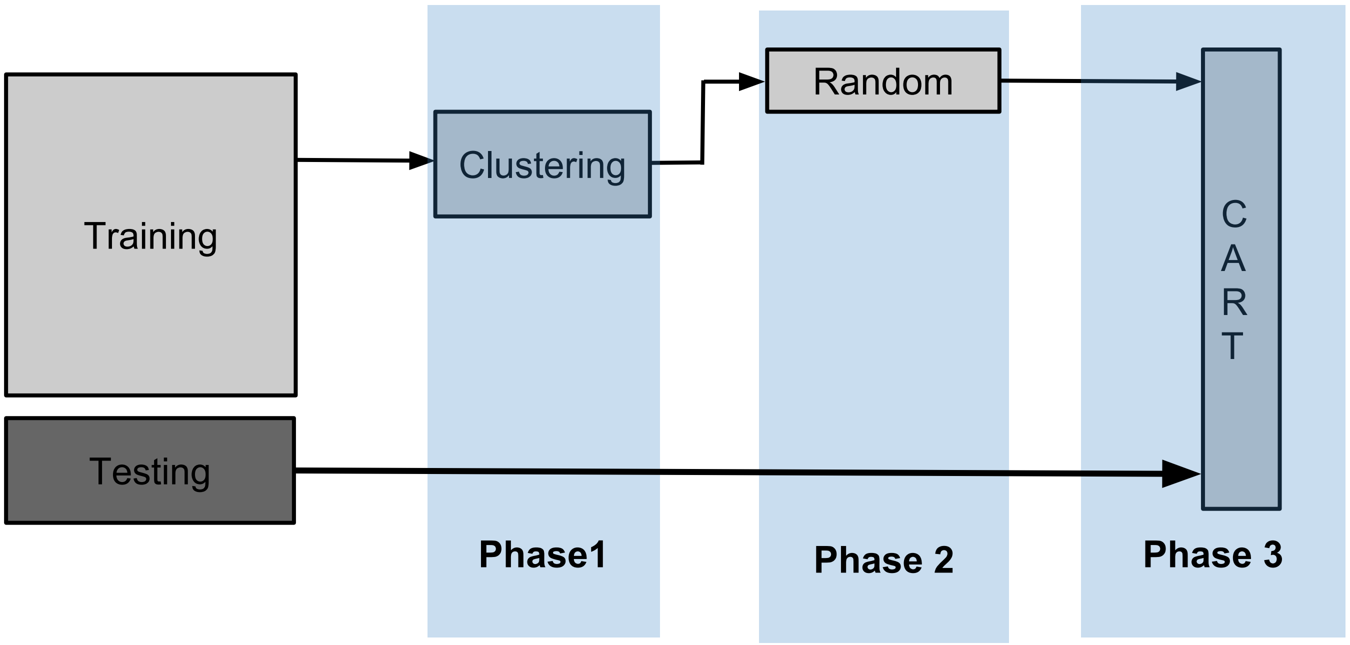


APPROACH

WHAT = Clustering + Sampling

- Phase 1: Clustering
  - WHERE
- Phase 2: Sampling
  - Random Sampling - Select any point at random
  - East West Sampling - Find extreme points on the dimension of highest variance
  - Exemplar - The point with minimum performance measure
- Phase 3: Generate Surrogate - CART
  - Samples selected by our sampler is used to train a CART model

WHAT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Testing
Clustering
Random
CART
Phase1
Phase 2
Phase 3

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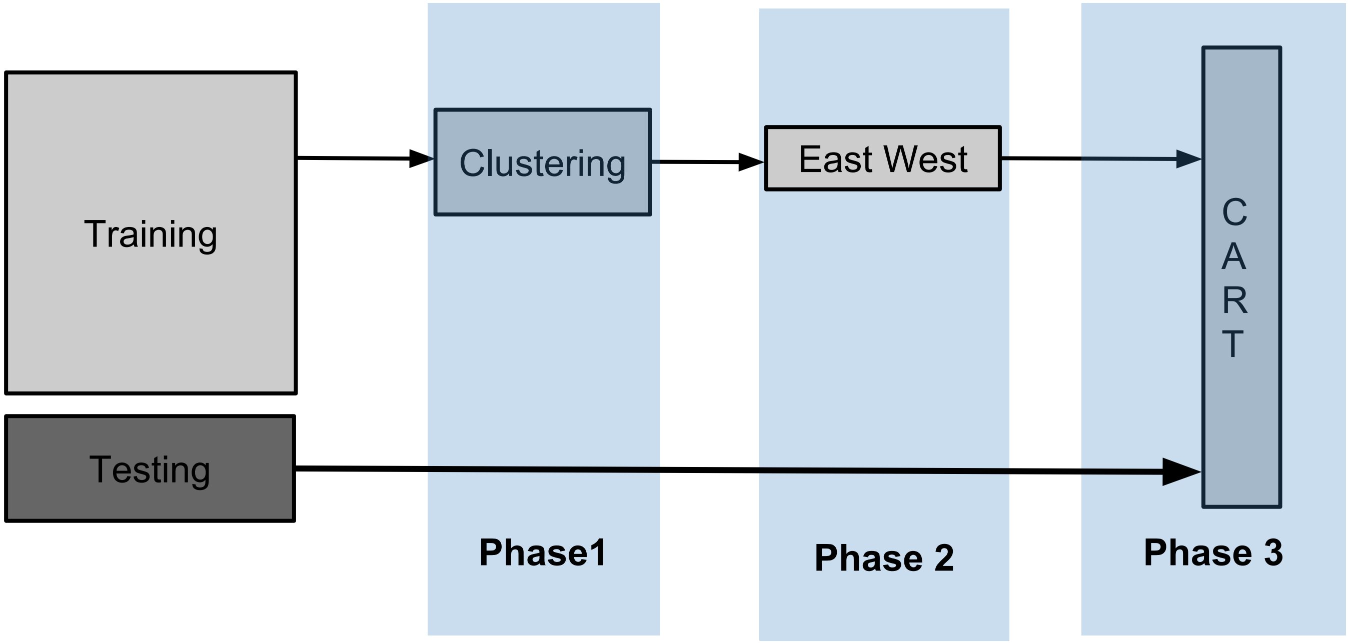
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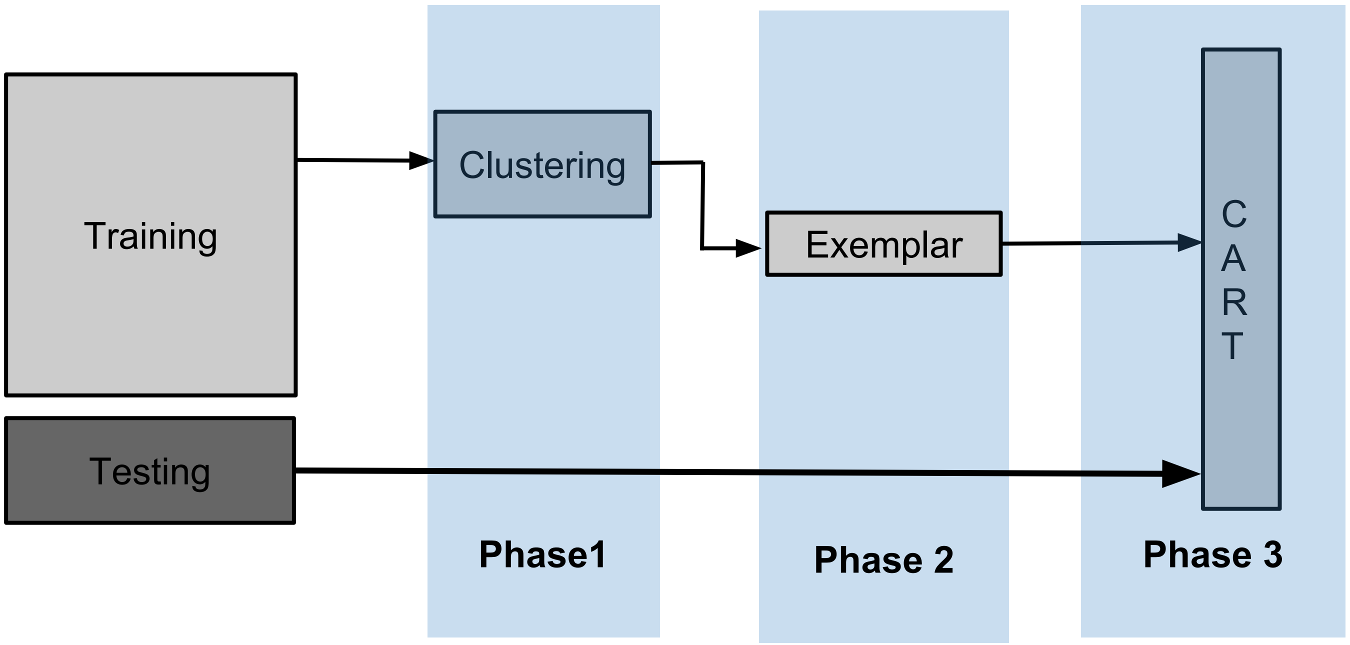
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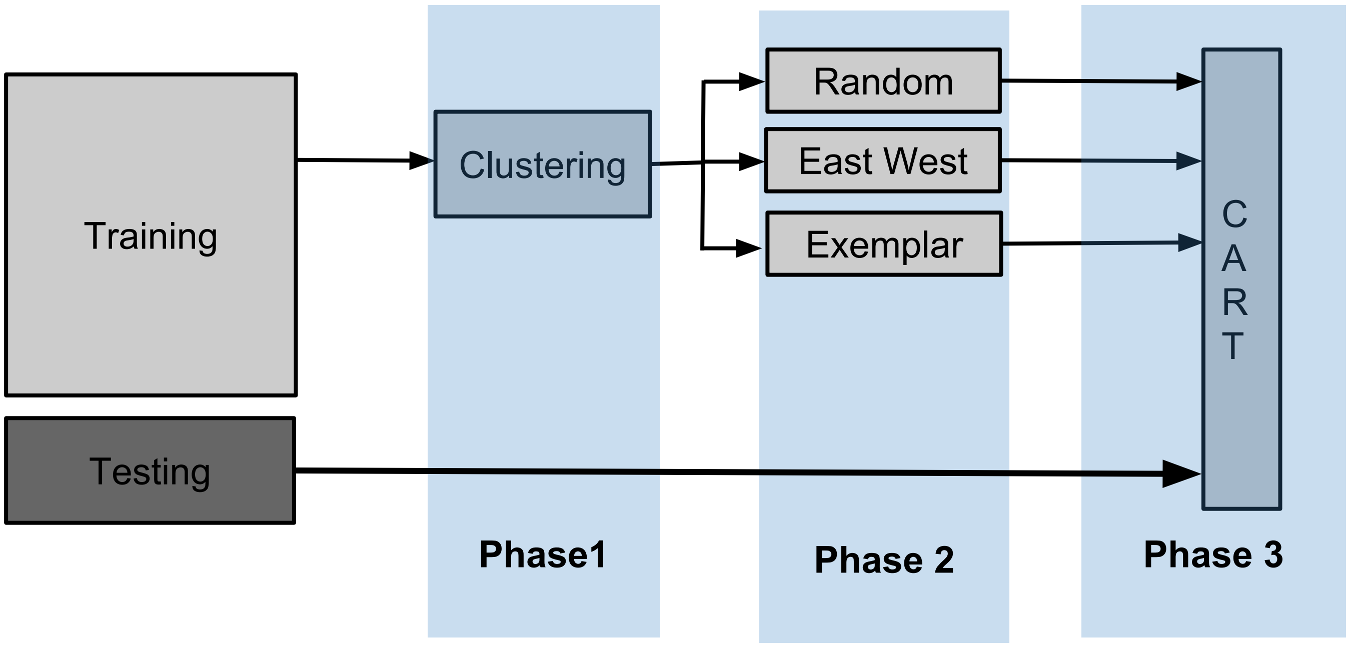

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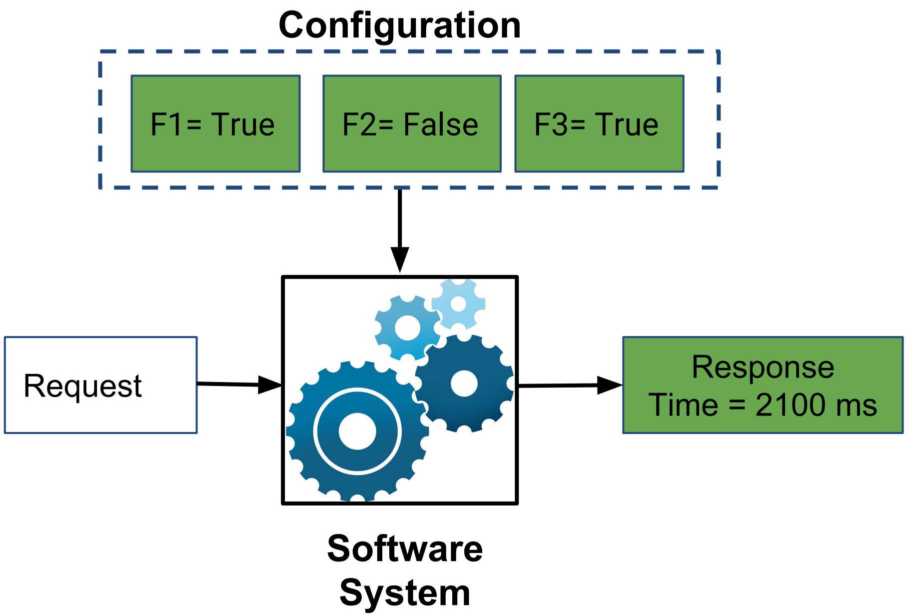
Definition

- Real System
  - Features can be either True or False
  - Configuration is a set of features
  - Each configuration has a corresponding response time or performance measure



Definition

- Real System
  - Features can be either True or False
  - Configuration is a set of features
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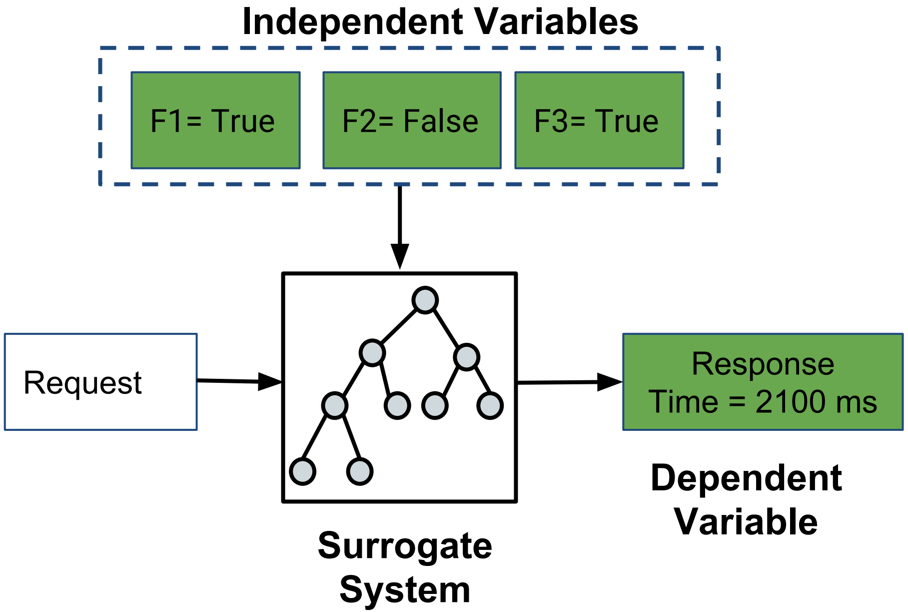
- Surrogate System
  - Configuration = independent variable
  - Performance measure = dependent variable



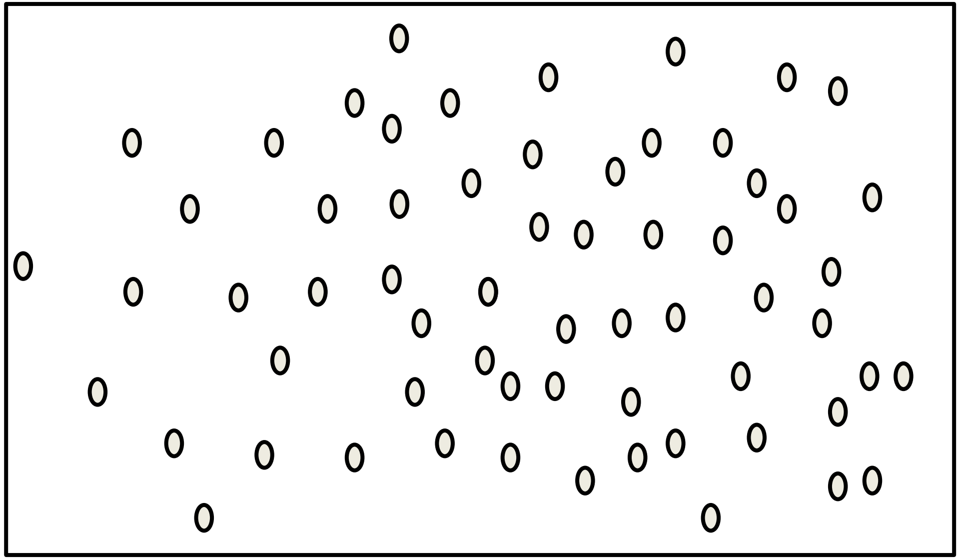
Phase 1: Clustering

- Clustering via WHERE
  - Novel near-linear time spectral learner
  - Exploits underlying lower dimensionality of search space

- In brief:
  - Find a dimension “d” with most variance
  - Project points to “d”
  - Split data at median “d”
  - Recurse
  - Stop when |n| < sqrt(N)

- ***Future work:***
  - Fast Spectral clustering [Yan’09]
- In brief:
  - Polynomial time operations
    - An initial k-means pass
    - O(N^2) operations on the centroids founds by K-means
    - Final pass: map all points to the centroids found in b

- Number of samples (N) = 64



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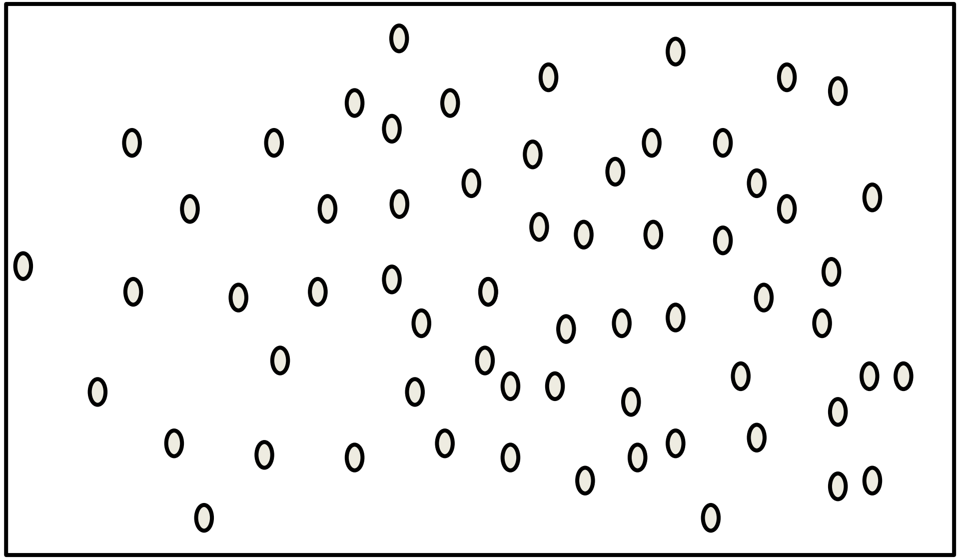

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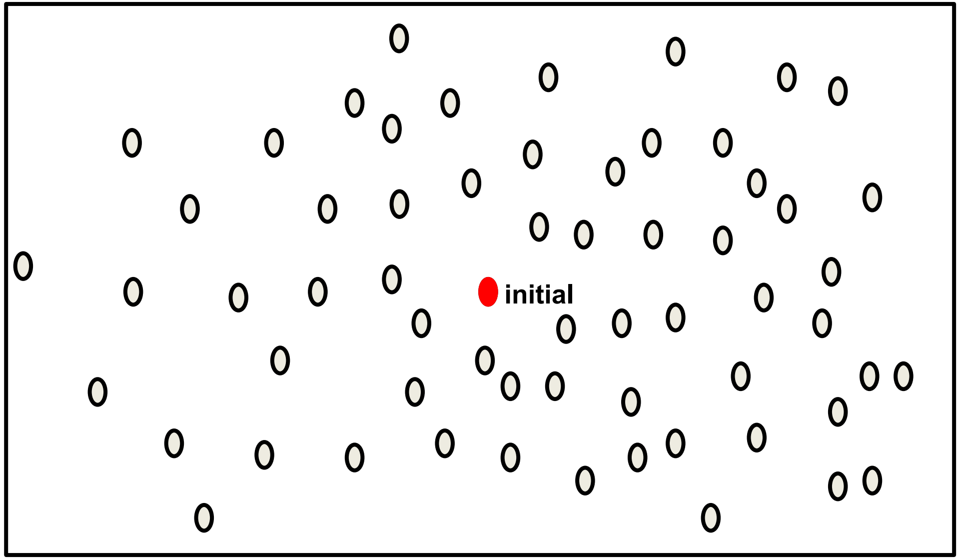

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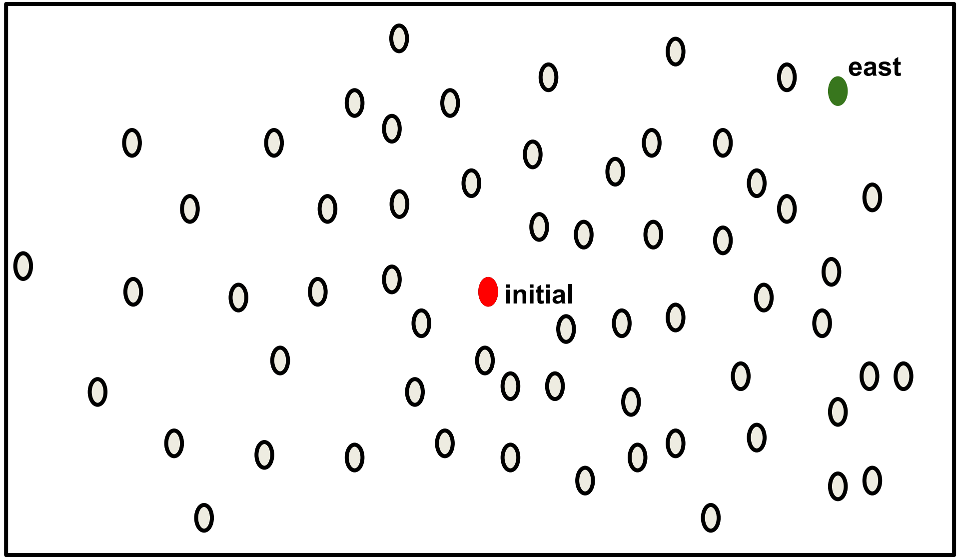

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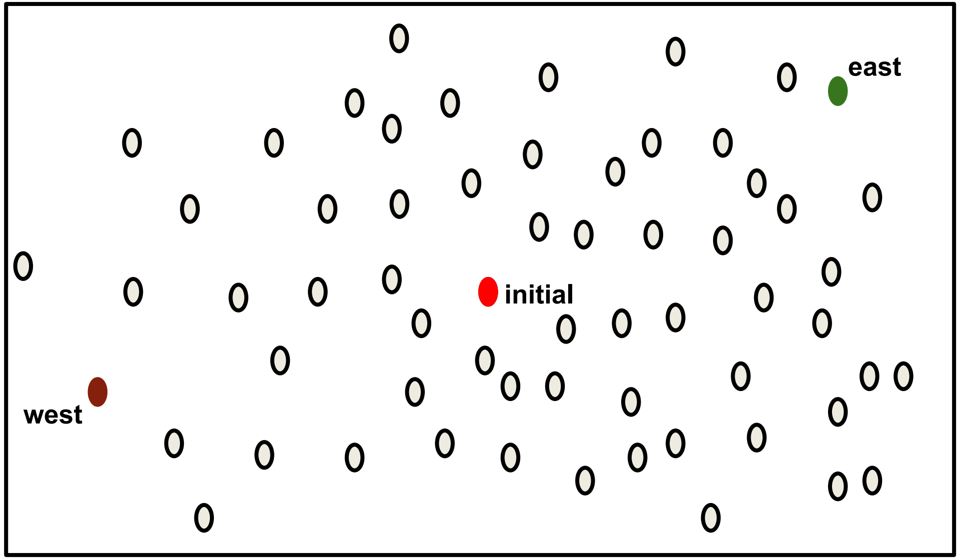

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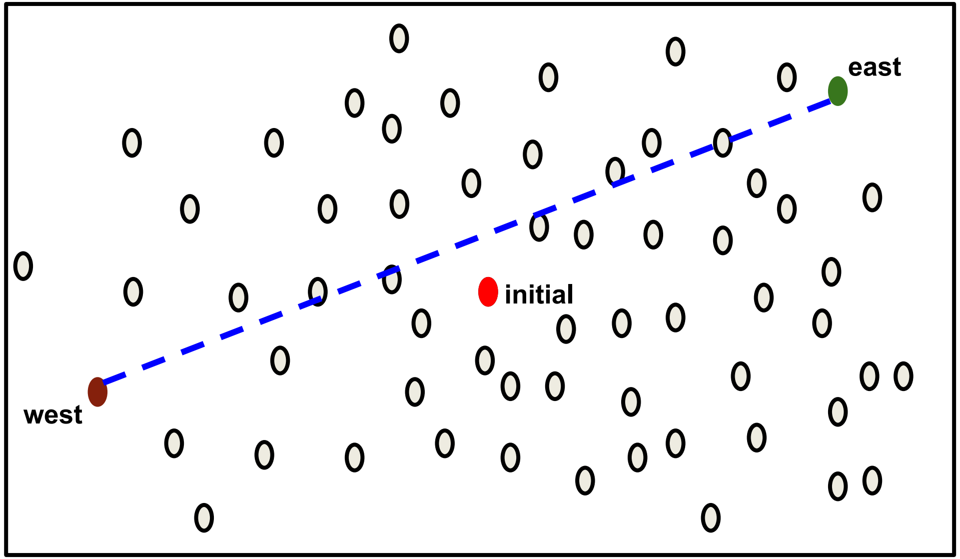

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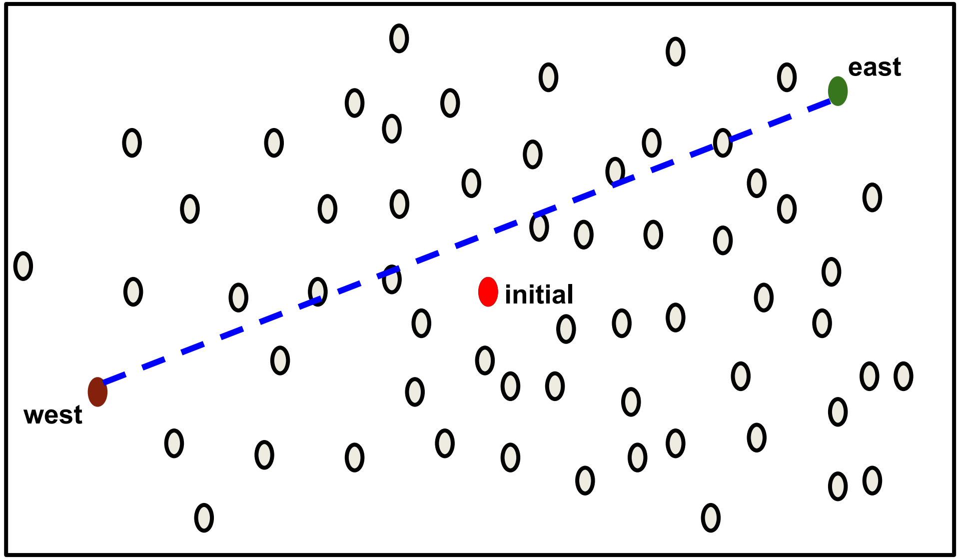

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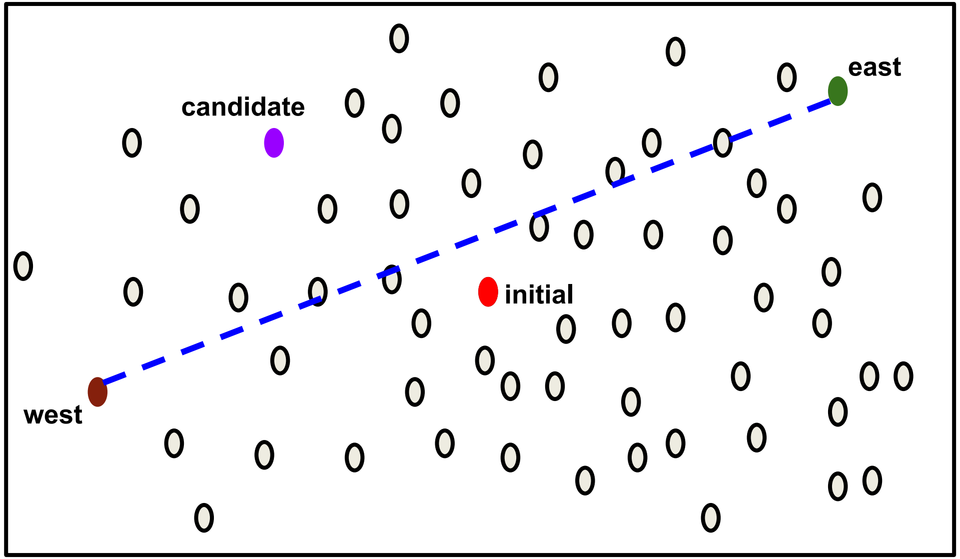

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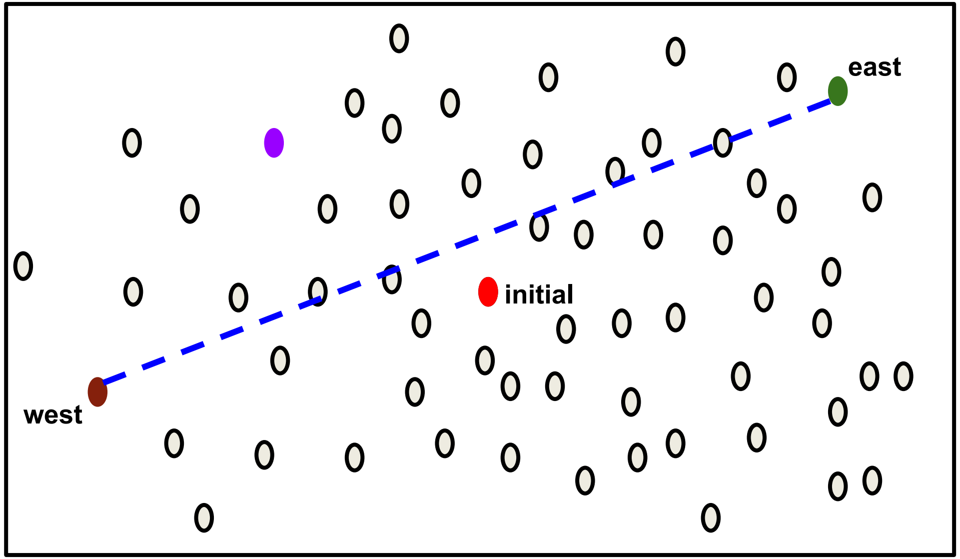

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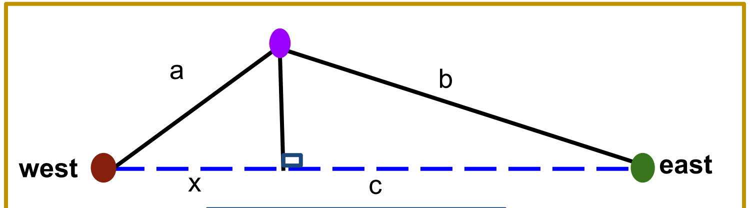

$$x = \frac{a^2 + c^2 - b^2}{2c}$$

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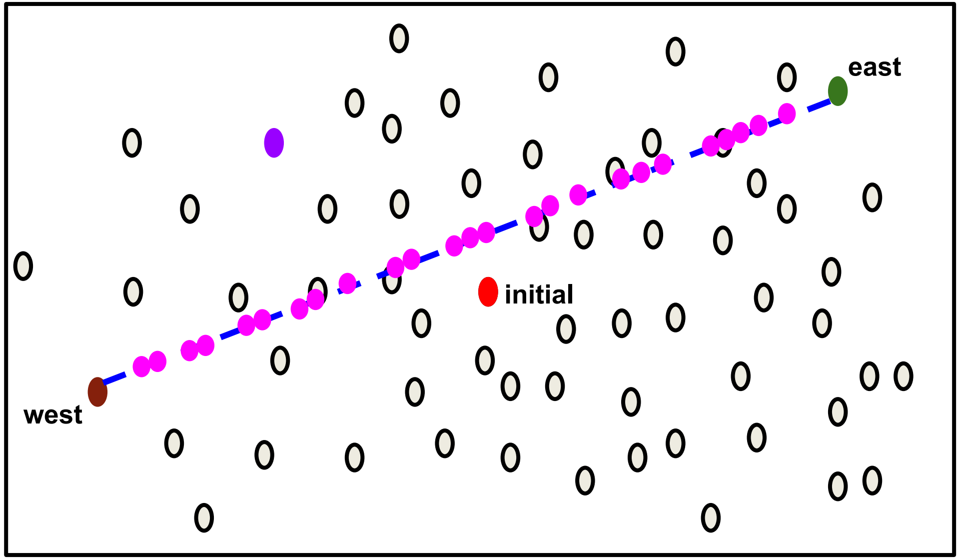

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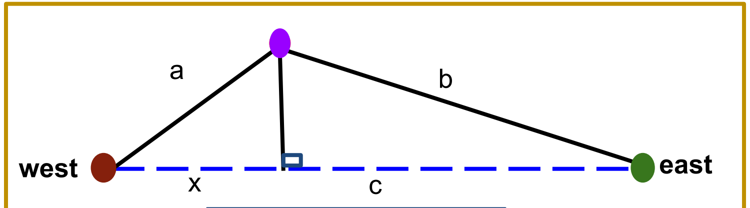

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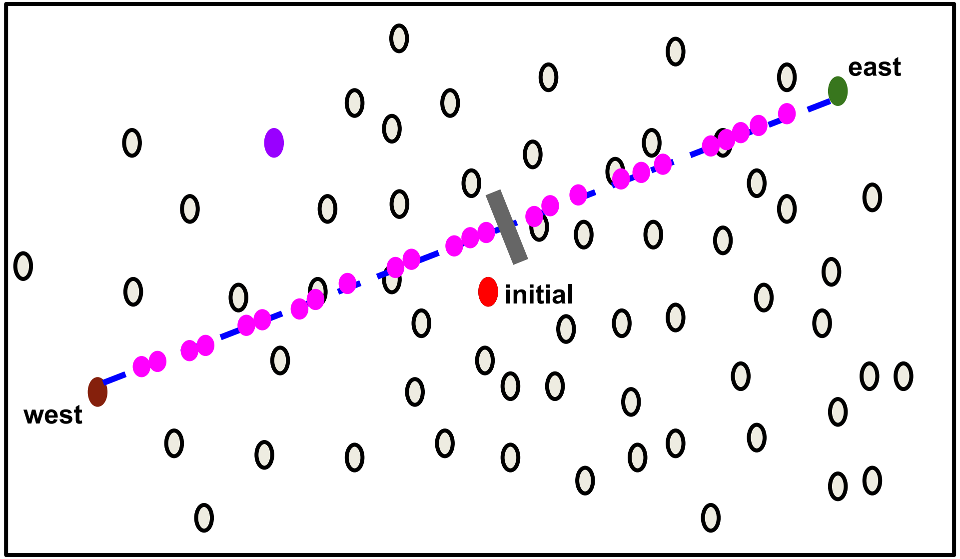

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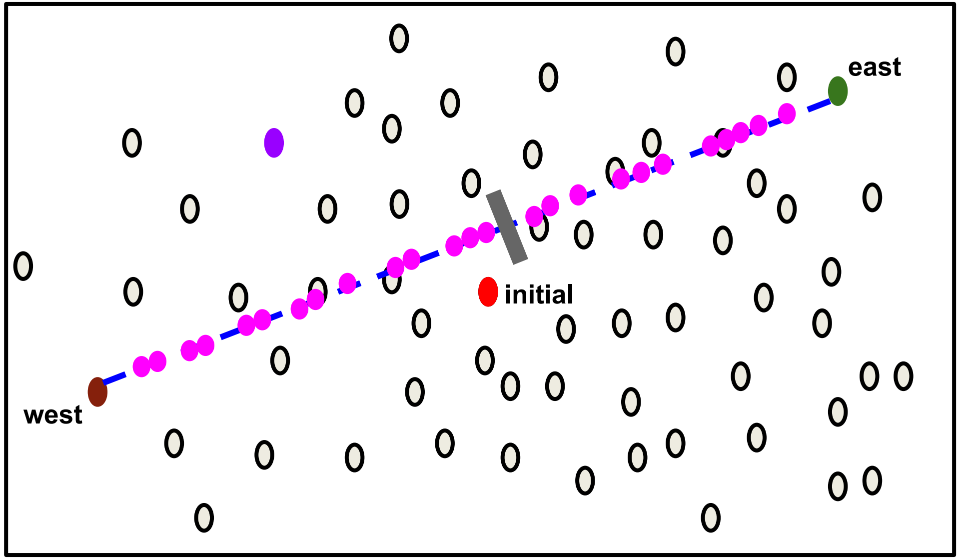

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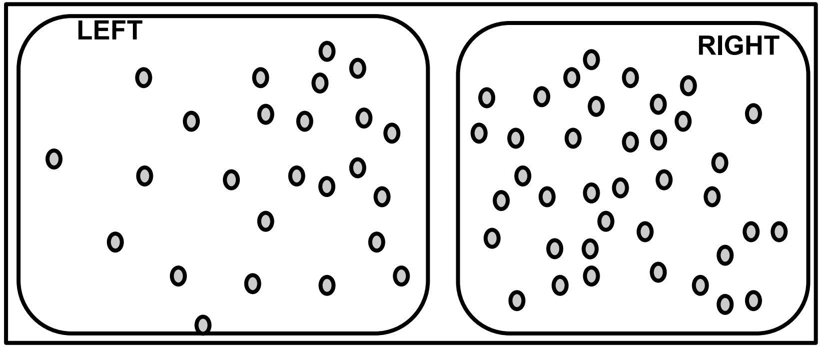

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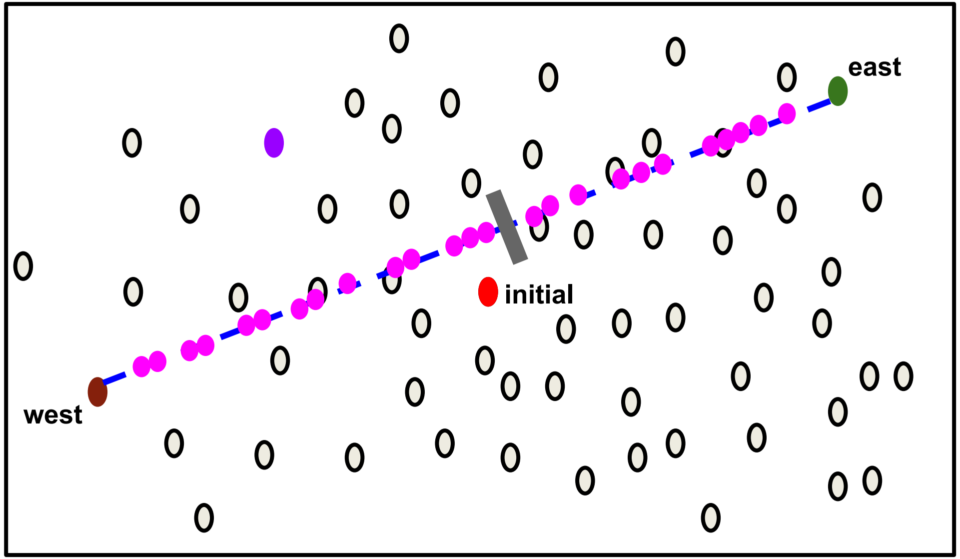

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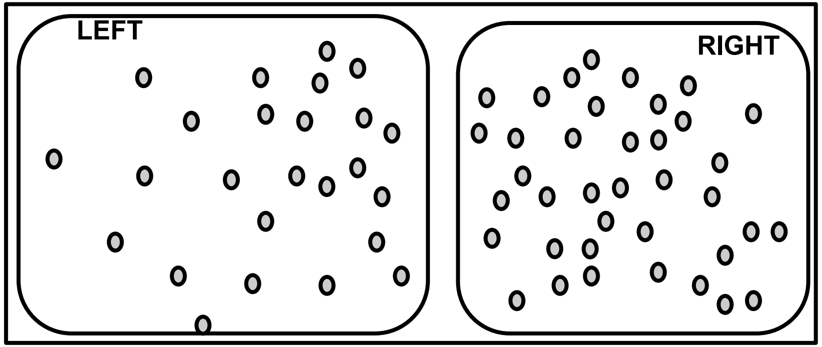

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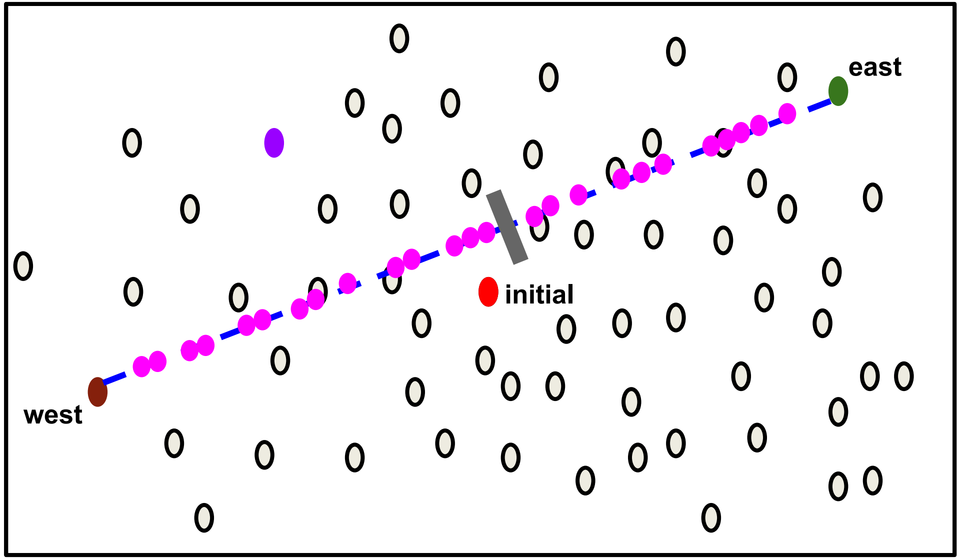

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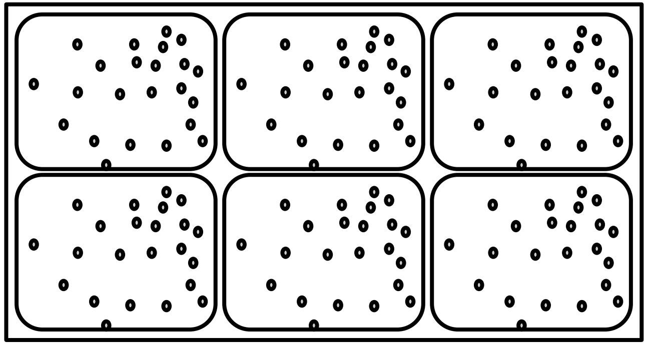
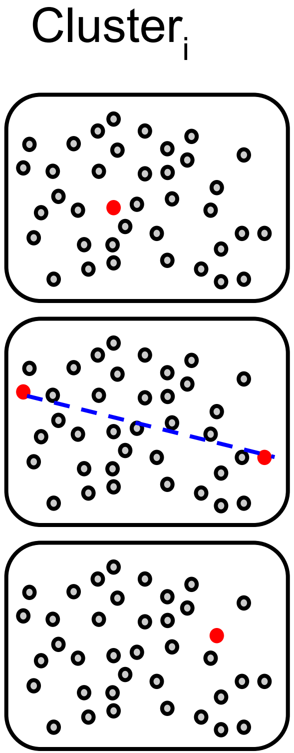
Configuration Space



Phase 2: Sampling

Choosing representative candidates from clusters

- Random
  - Choose a candidate at random
  - Number of evaluations/Cluster = 1
  - Point selected/Cluster = 1
- East-West
  - Choose extreme points in dimension of maximum variance
  - Number of evaluations/Cluster = 2
  - Point selected/Cluster = 2
- Exemplar
  - Choose the best candidate from the cluster
  - Number of evaluations/Cluster = n
  - Point selected/Cluster = 1



Phase 3: Generate Surrogate

- Use the configuration/s sampled from each cluster
- Run the configuration
  - In this work, we performed a table lookup
- Train a CART decision tree learner using:
  - Configurations (Independent Variable)
  - Performance Measure (Dependent Variable)

Experiments

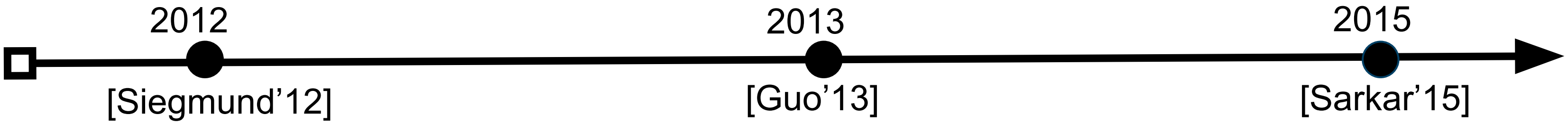
Collecting “Ground Truth” = 26 days of computation

Experiments

- **Datasets Used**:
  - Apache - *open-source Web server*
  - Berkeley DB C (**BDBC**) - *embedded database system written in C*
  - Berkeley DB Java (**BDBJ**) - *BDBC in Java with SQL support*
  - LLVM - *a compiler infrastructure written in C++*
  - SQLite - *embedded database system*
  - X264 - *is a video encoder in C*
- **Surrogate Used**: CART
- **Techniques compared against**:
  - Siegmund et al.
  - Guo et al.
  - Sarkar et al.
- **Performance Measure:**
  - MRE: Mean Relative Error

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

Techniques compared against



Techniques compared against

2012 — **[Siegmund'12]**

2013 — [Guo'13]

2015 — [Sarkar'15]

Uses Feature Wise heuristics:

- Find
  - a pair of configuration (C_1 and C_2)
  - has same features except for one (F_i)
- Performance score (PS) of F_i
  $PS(F_i) = PS(C_1) - PS(C_2)$
- Performance of a new C_i
  $PS(Ci) = \sum PS(F_i) \ \forall \ F_i \in C_i$

Techniques compared against

2012 — [Siegmund'12]

2013 — [Guo'13]

2015 — [Sarkar'15]

Progressive Sampling Approach:

While terminationCriteria() is True:

- Random Sampling
- Samples in step of |F|
- Build a CART tree

Techniques compared against

2012 [Siegmund'12]

2013 [Guo'13]

2015 **[Sarkar'15]**

Uses Feature Frequencies:

- Projective sampling to decide number of configurations to sample
- Random Sampling
- Build a CART tree

Research Questions

RQ 1: Can WHAT generate good predictions using only a small number of configurations?

RQ 2: Do less data cause larger variances in predicted values?

RQ 3: Can "good" surrogate models (to be used in optimizers) be built using WHAT?

RQ 4: How good is WHAT compared to the state of the art predictors?

RQ1 + RQ2

RQ1 + RQ2 explore

- if WHAT can generate good predictors with low variance
- how much of data should WHAT reflect upon

Comparison between:

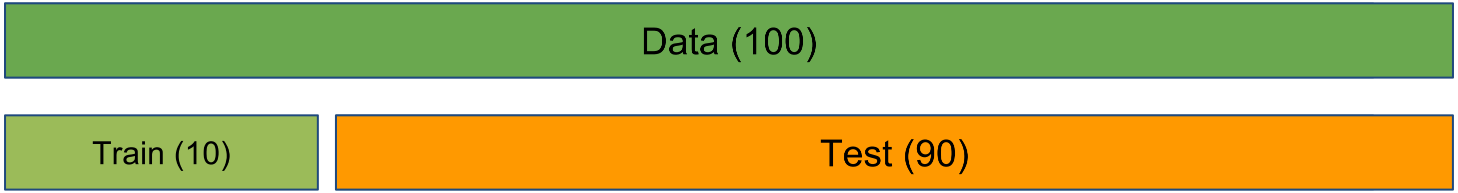
- Baseline (using all the data)
- WHERE + Random
- WHERE + EAST-West
- WHERE + Exemplar

Design of Experiment

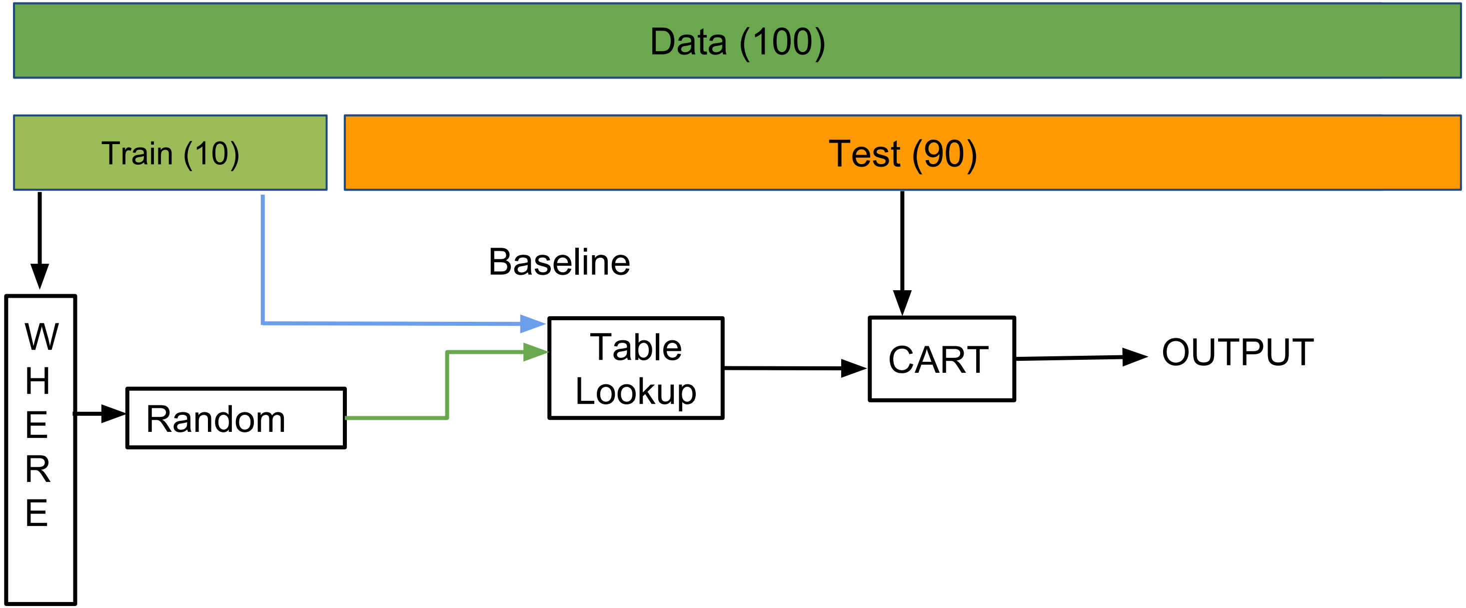
Design of Experiment

Data (100)

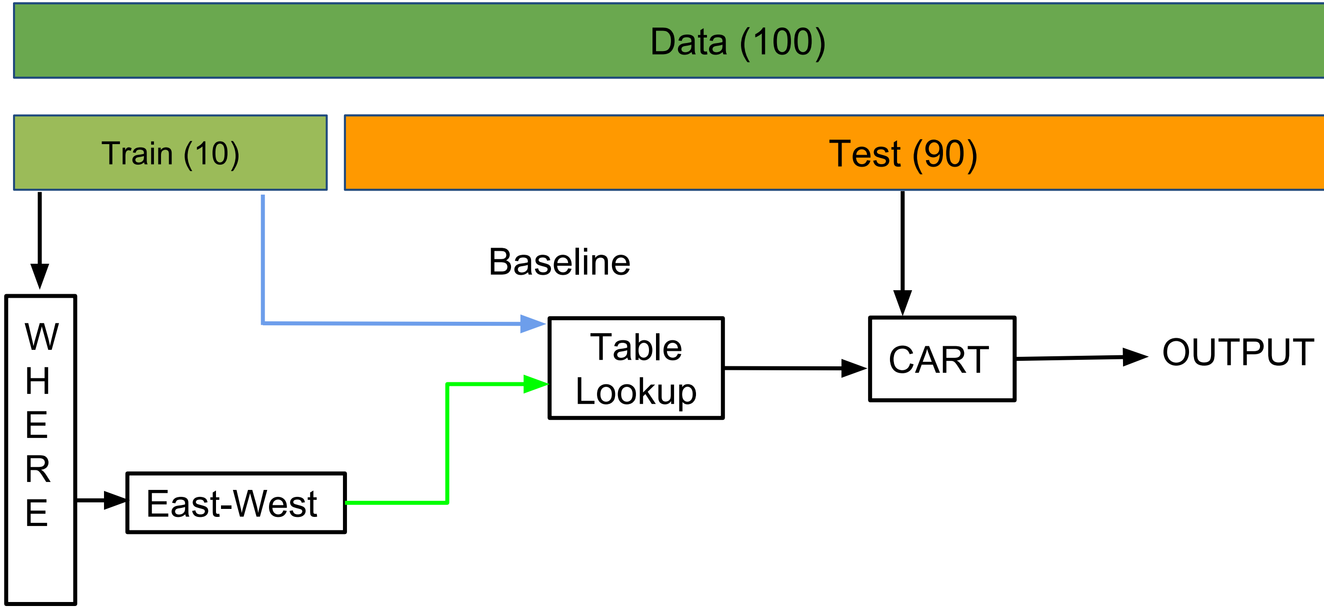
Design of Experiment



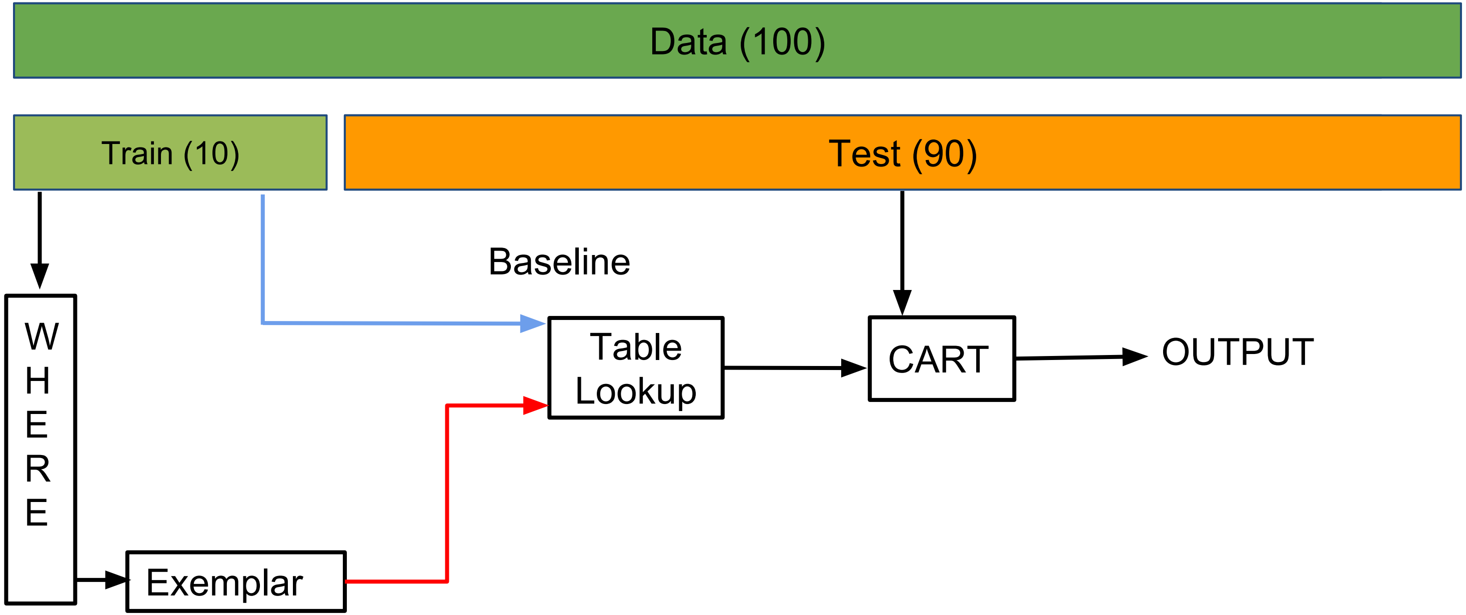
Design of Experiment



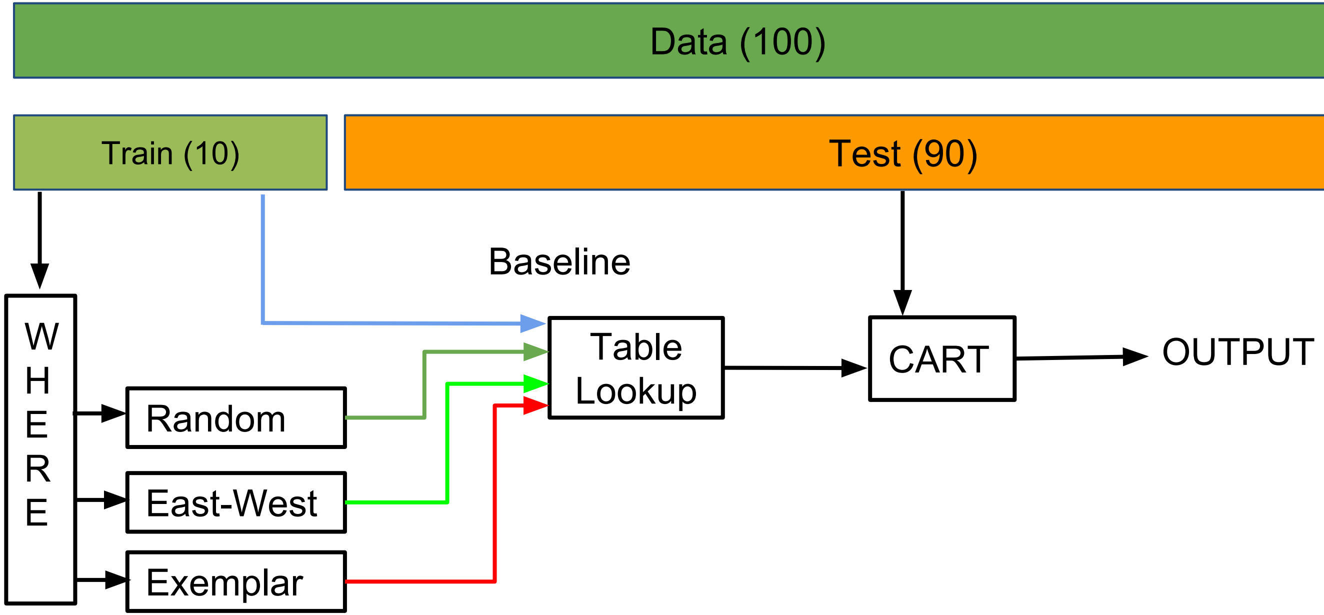
Design of Experiment



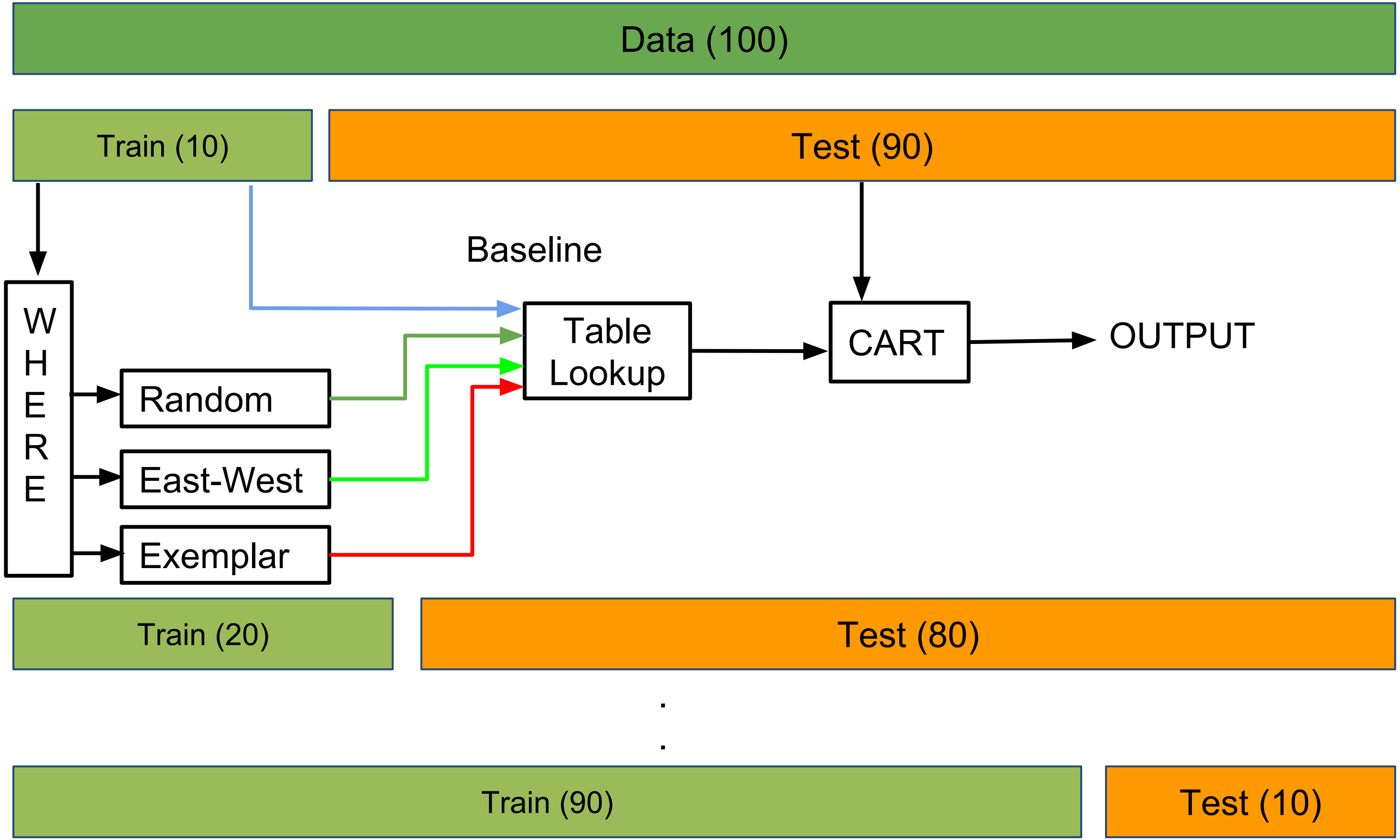
Design of Experiment



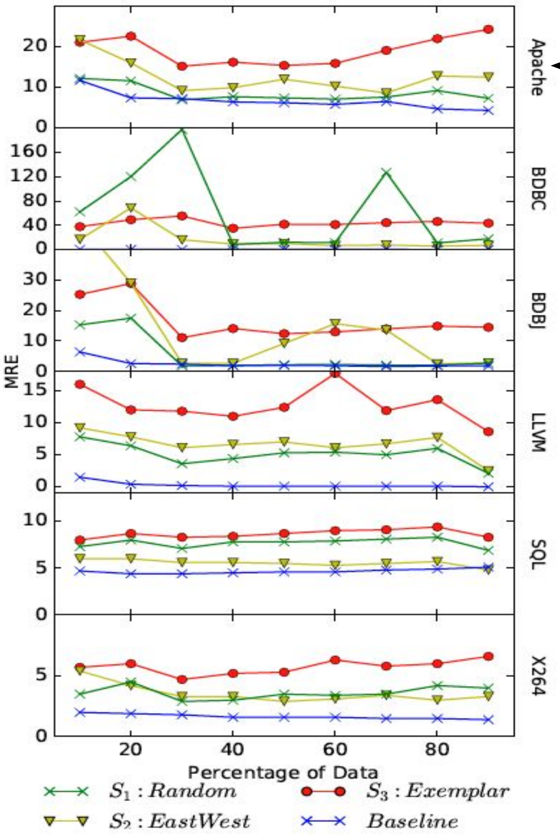
Design of Experiment



Design of Experiment

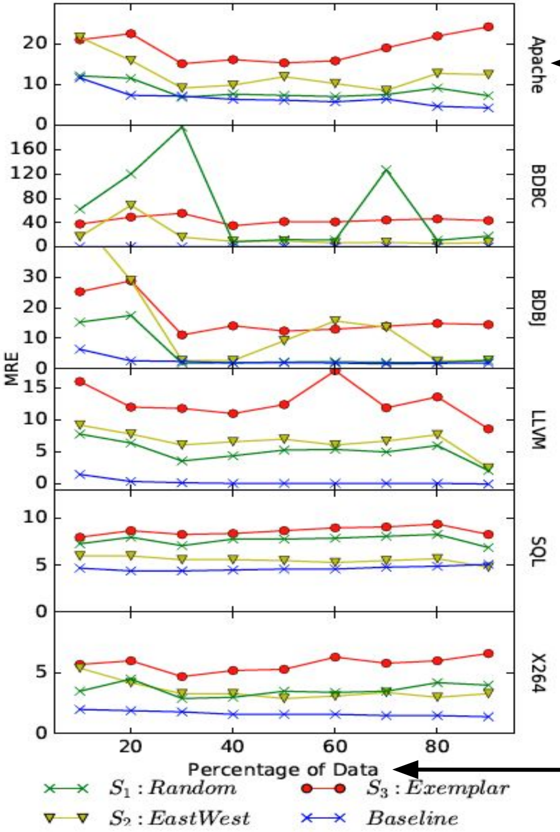


RQ1: Can WHAT generate good predictions using only a small number of configurations?



Software Systems

RQ1: Can WHAT generate good predictions using only a small number of configurations?



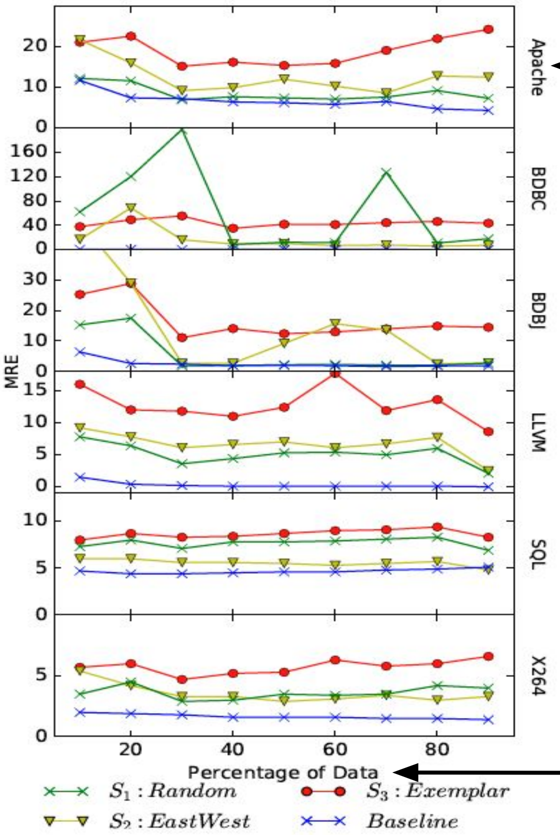
Software Systems

% of data reflected upon

RQ1: Can WHAT generate good predictions using only a small number of configurations?

Software Systems

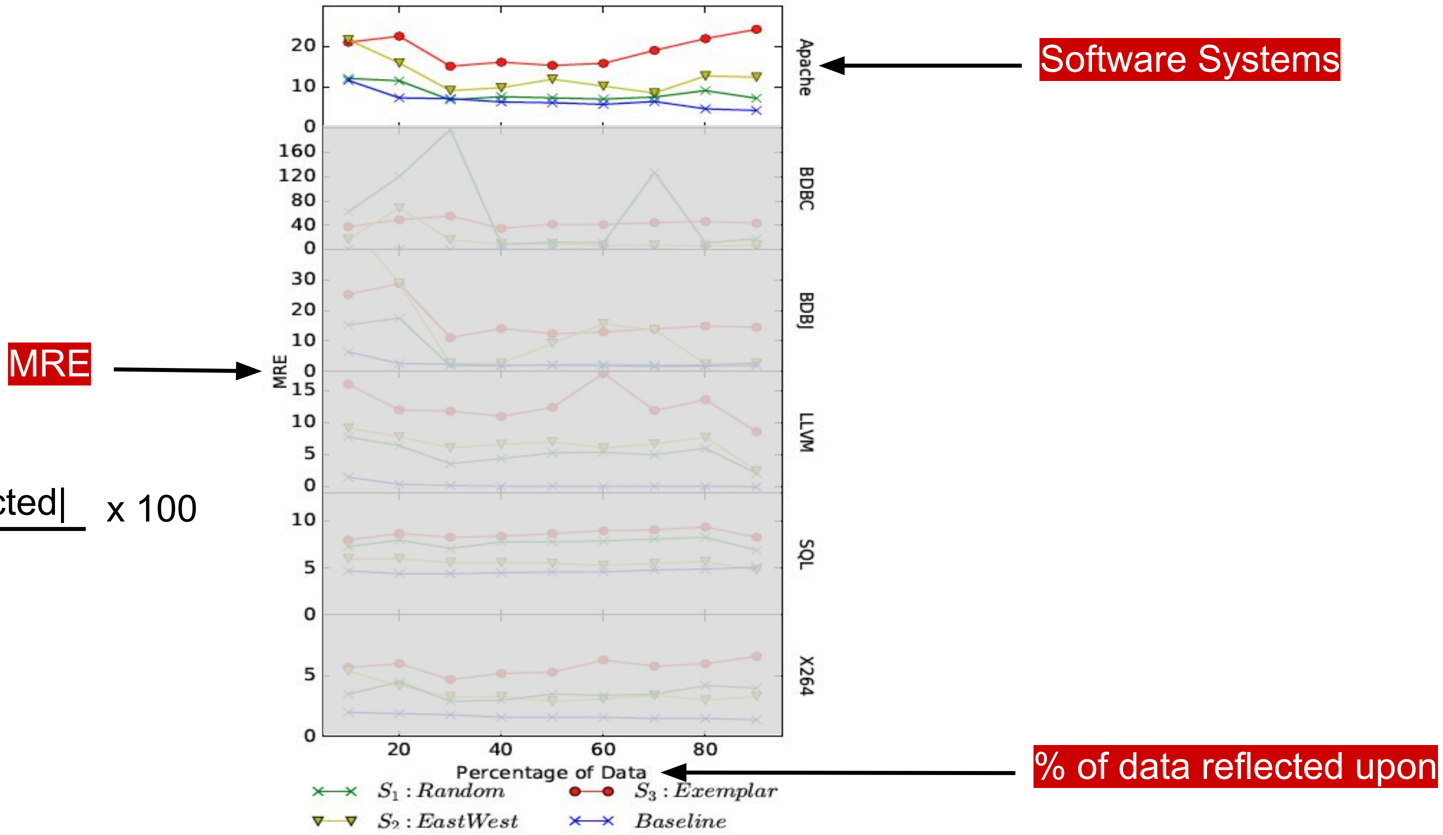
MRE



% of data reflected upon

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

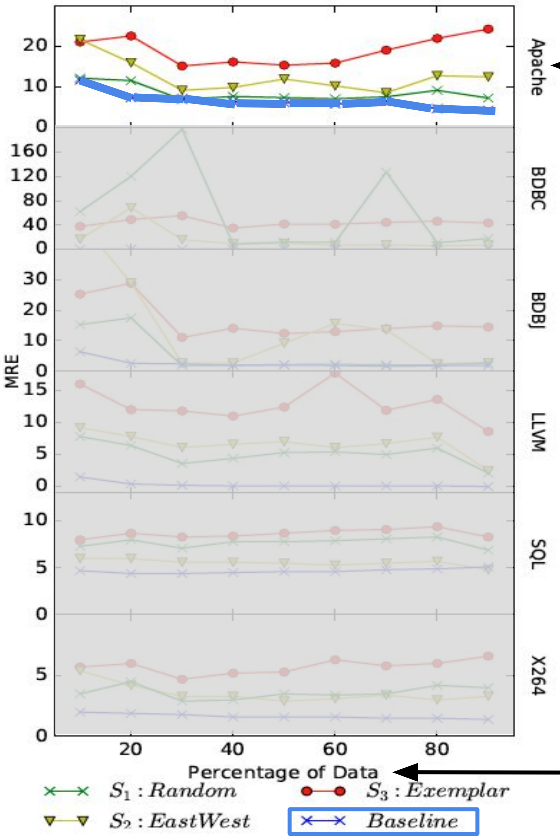
RQ1: Can WHAT generate good predictions using only a small number of configurations?



$$\text{MRE} = \frac{|\text{actual} - \text{predicted}|}{\text{actual}} \times 100$$

RQ1: Can WHAT generate good predictions using only a small number of configurations?

MRE

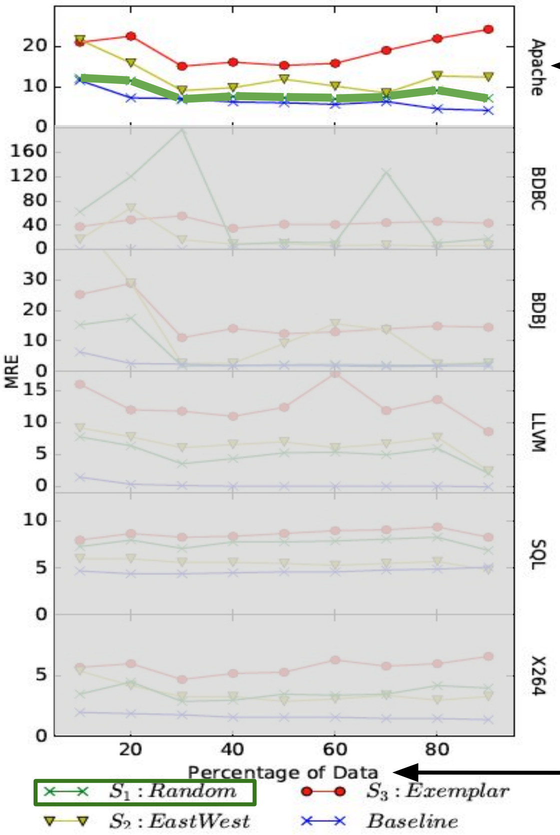


Software Systems

% of data reflected upon

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

RQ1: Can WHAT generate good predictions using only a small number of configurations?



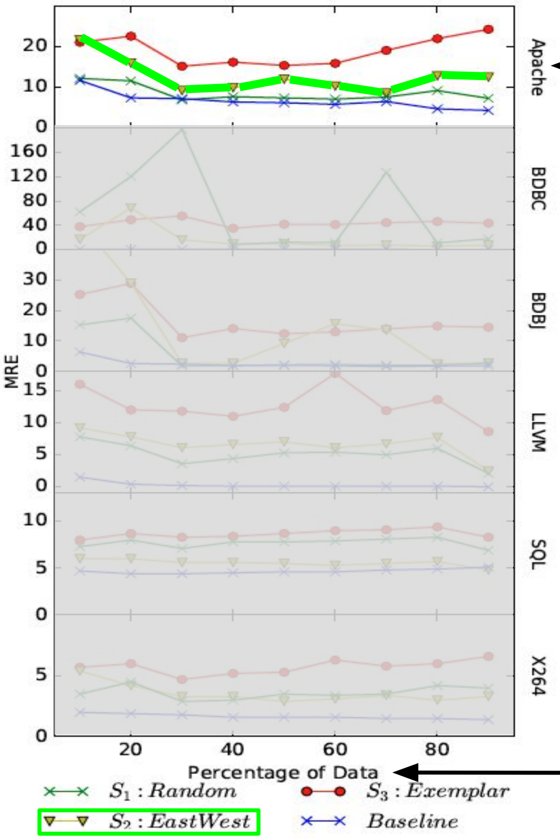
Software Systems

MRE

% of data reflected upon

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

RQ1: Can WHAT generate good predictions using only a small number of configurations?



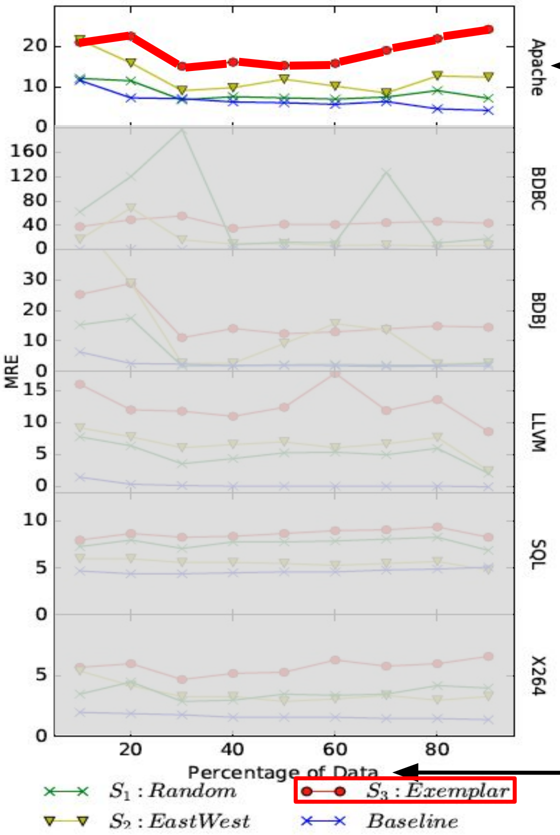
Software Systems

MRE

% of data reflected upon

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

RQ1: Can WHAT generate good predictions using only a small number of configurations?



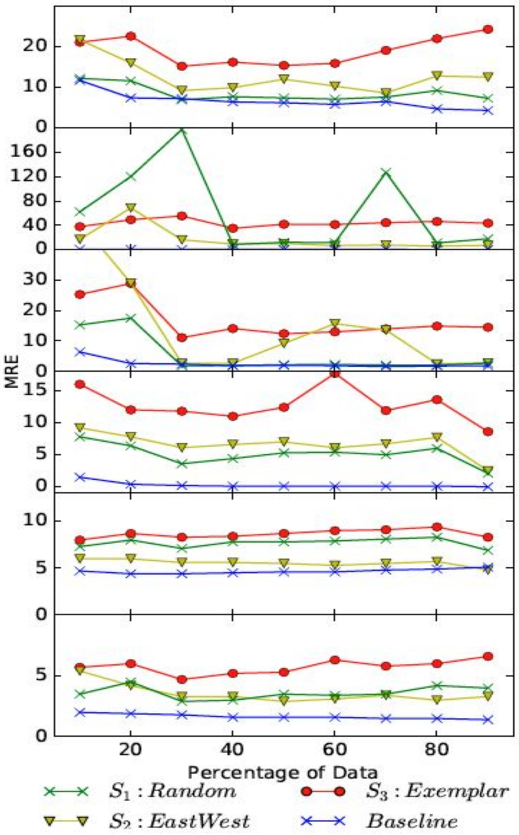
Software Systems

MRE

% of data reflected upon

$$MRE = \frac{|actual - predicted|}{actual} \times 100$$

RQ1: Can WHAT generate good predictions using only a small number of configurations?

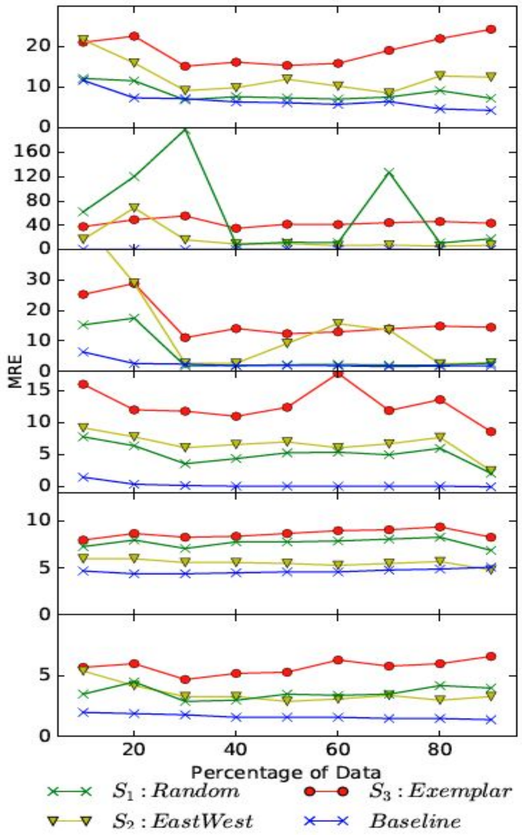


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	?	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	?	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	?	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

RQ1: Can WHAT generate good predictions using only a small number of configurations?

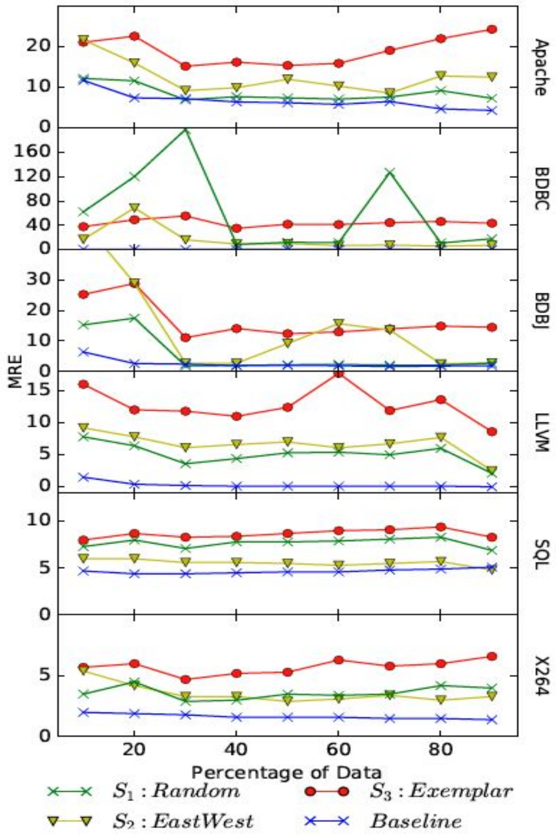


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✕	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✕	?	?	?	?	?
Standard Deviation	?	?	?	?	?	?

RQ1: Can WHAT generate good predictions using only a small number of configurations?

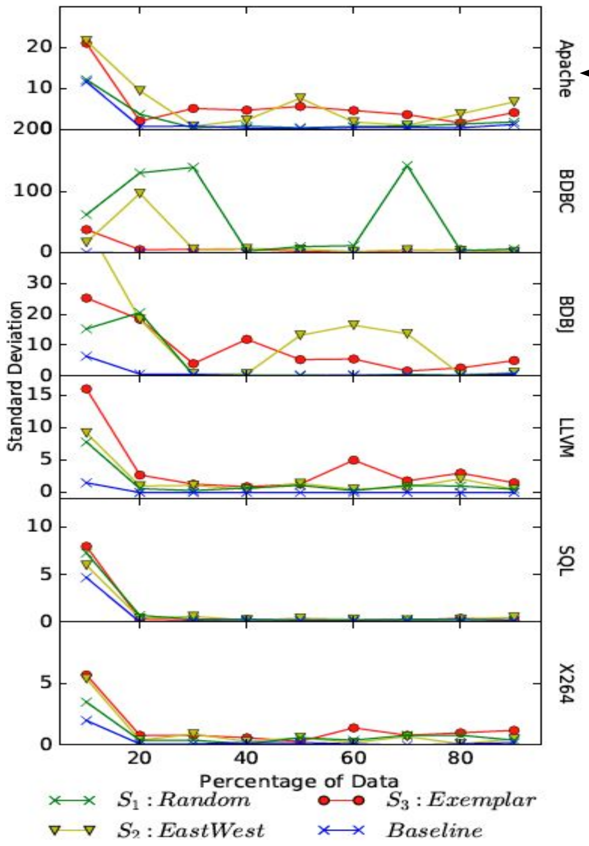


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✗	✔	✔	✗	✔
Standard Deviation	?	?	?	?	?	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✔	✗	✗	✔	✔
Standard Deviation	?	?	?	?	?	?

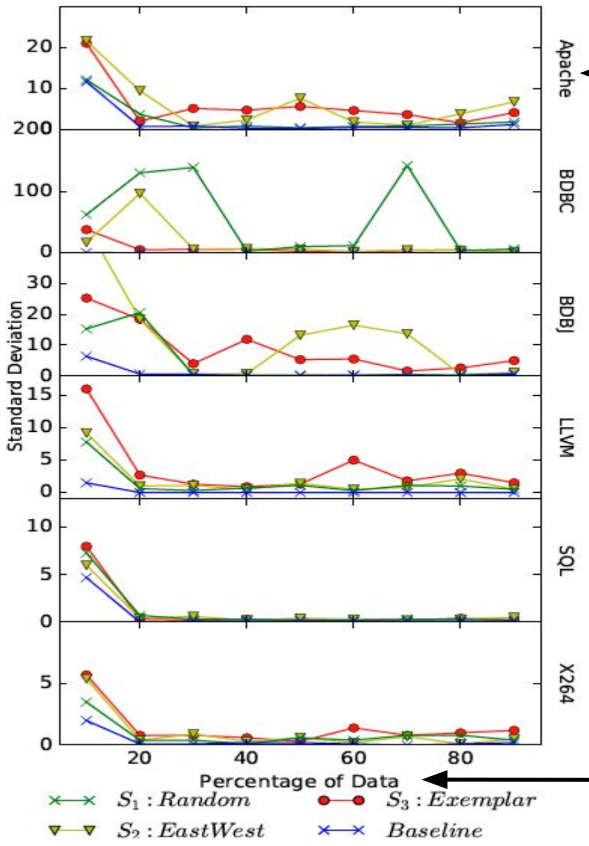
Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✗	✗	✗	✗	✗
Standard Deviation	?	?	?	?	?	?

RQ2: Do less data cause larger variances in predicted values?



Software Systems

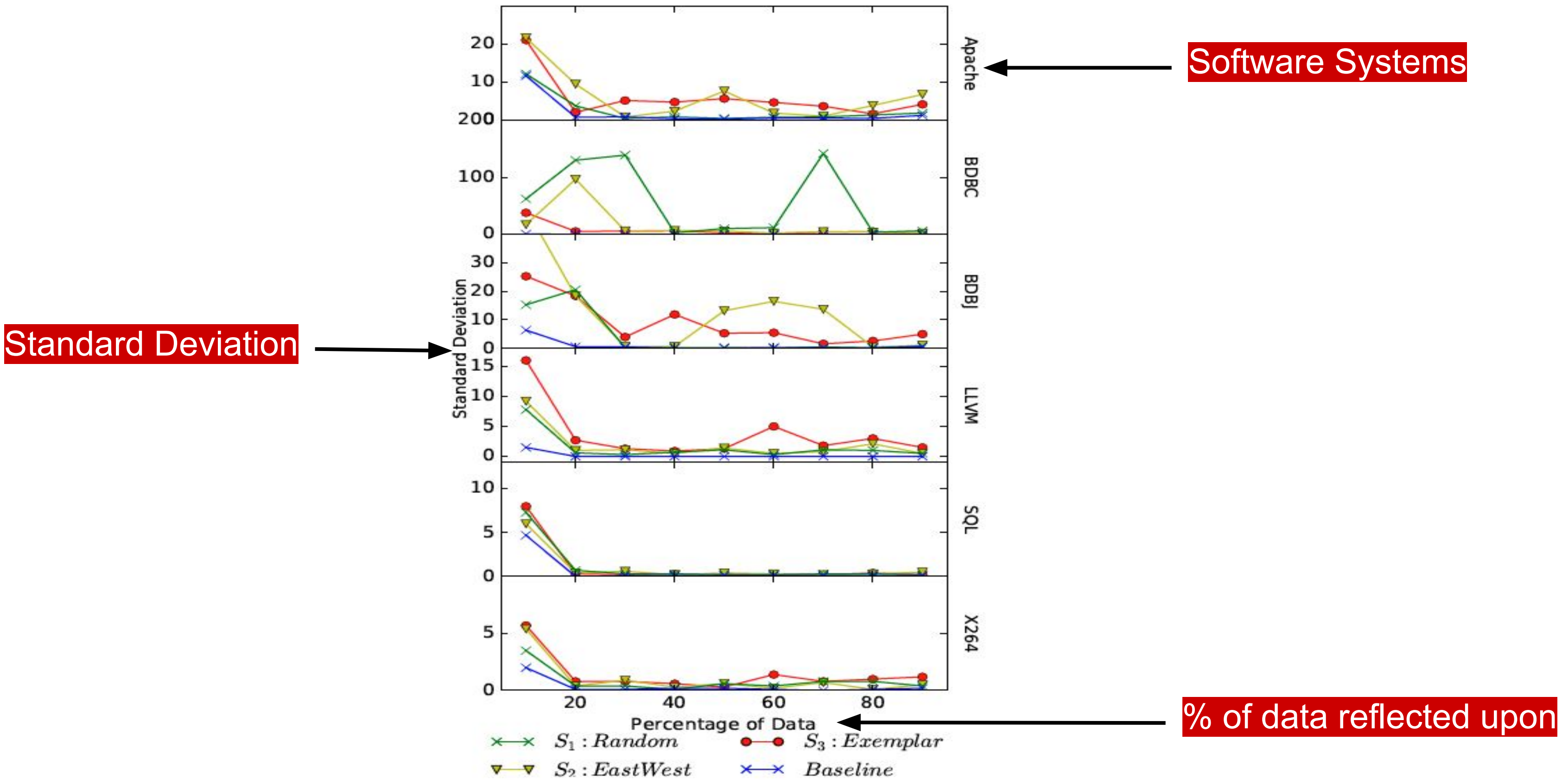
RQ2: Do less data cause larger variances in predicted values?



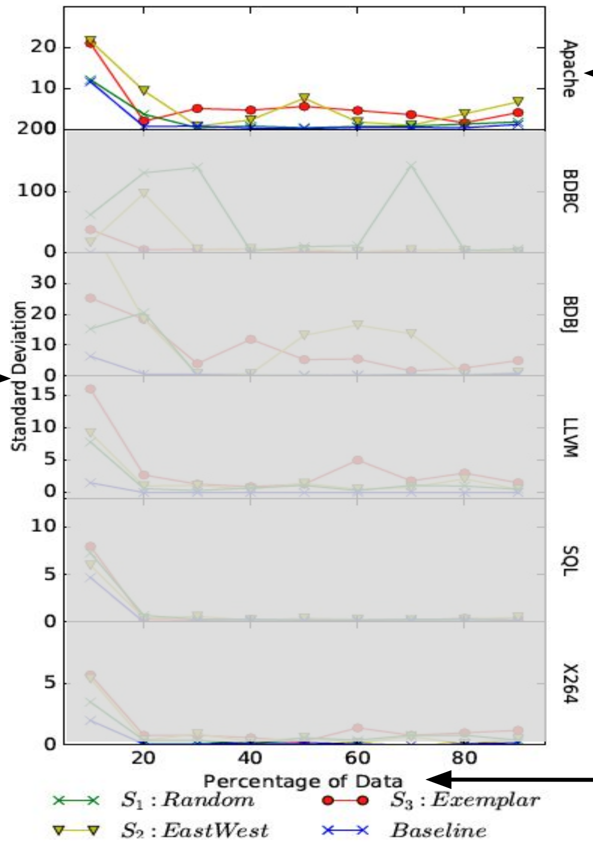
Software Systems

% of data reflected upon

RQ2: Do less data cause larger variances in predicted values?



RQ2: Do less data cause larger variances in predicted values?

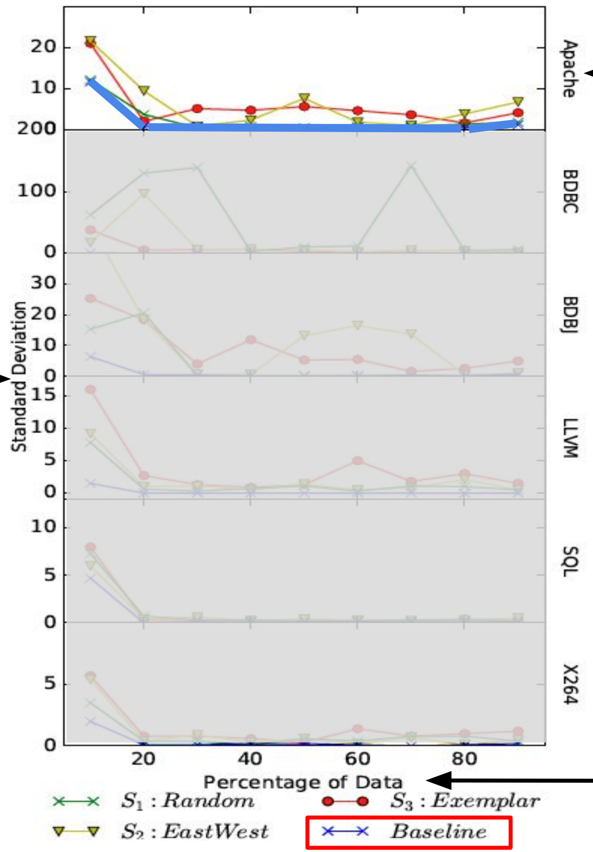


Software Systems

Standard Deviation

% of data reflected upon

RQ2: Do less data cause larger variances in predicted values?

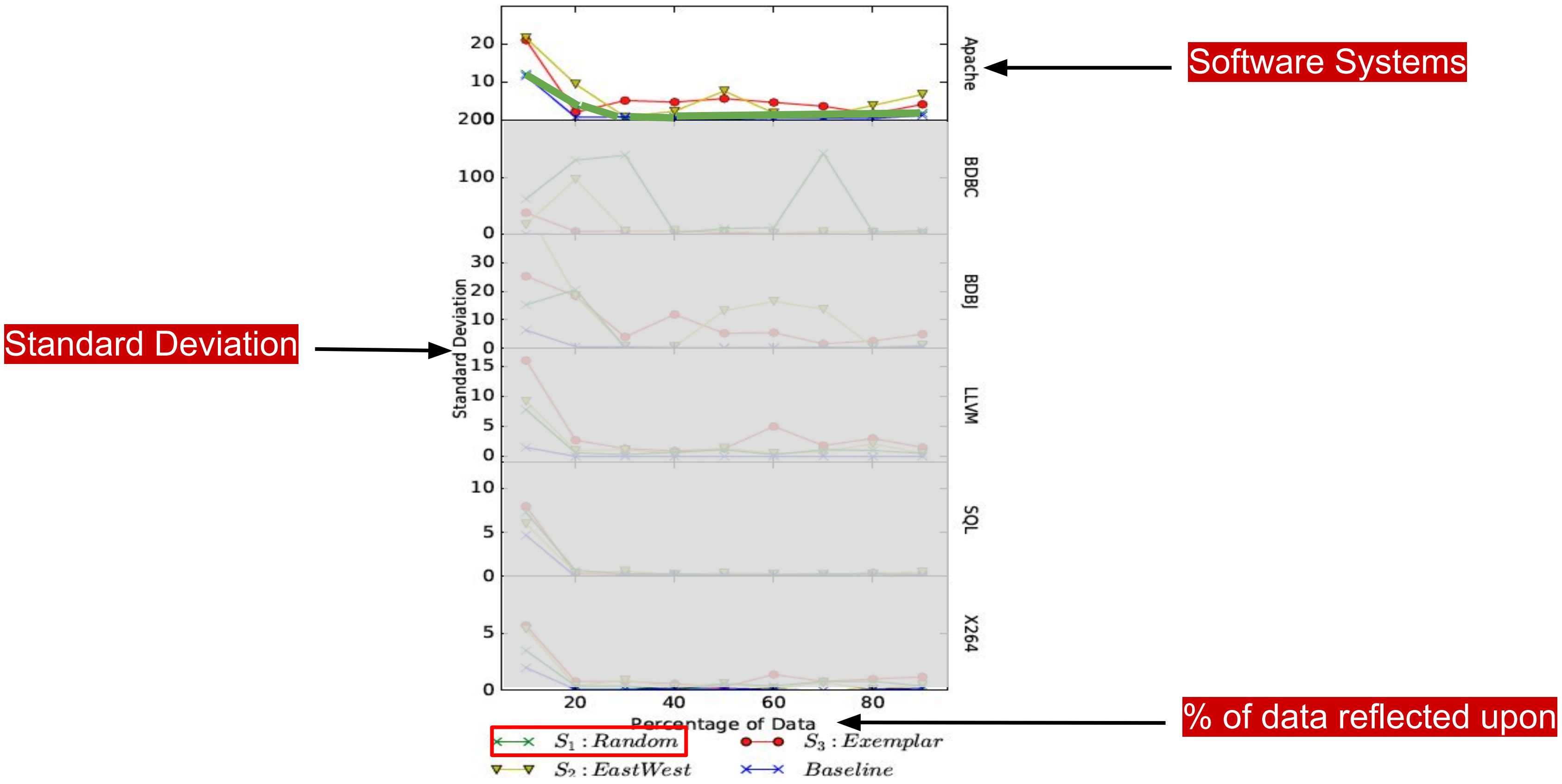


Standard Deviation

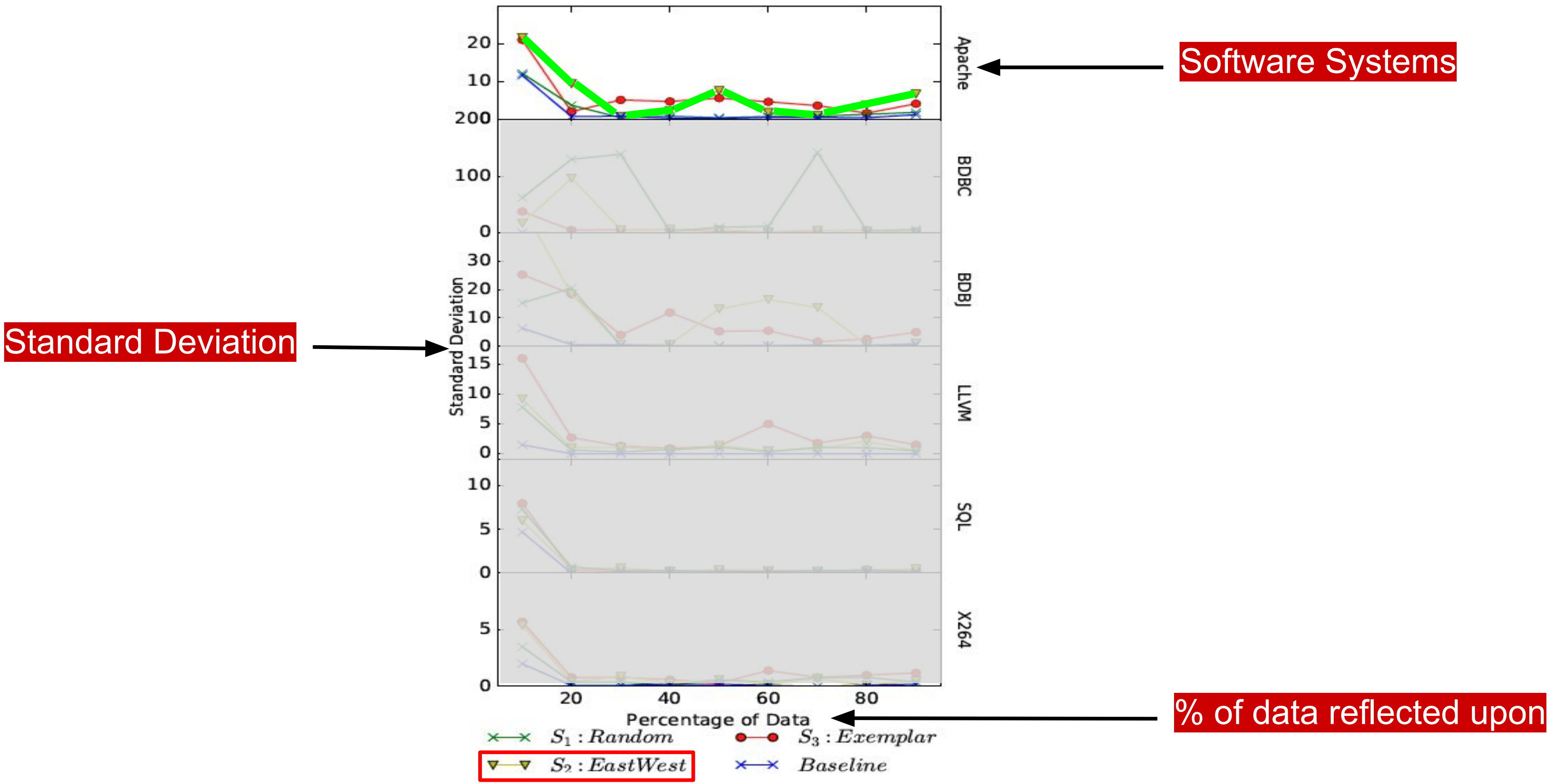
Software Systems

% of data reflected upon

RQ2: Do less data cause larger variances in predicted values?



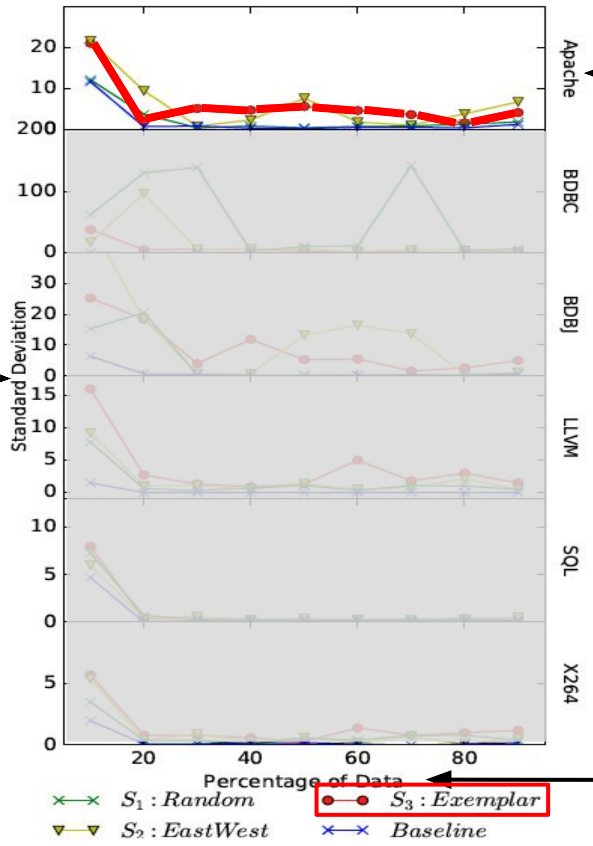
RQ2: Do less data cause larger variances in predicted values?



RQ2: Do less data cause larger variances in predicted values?

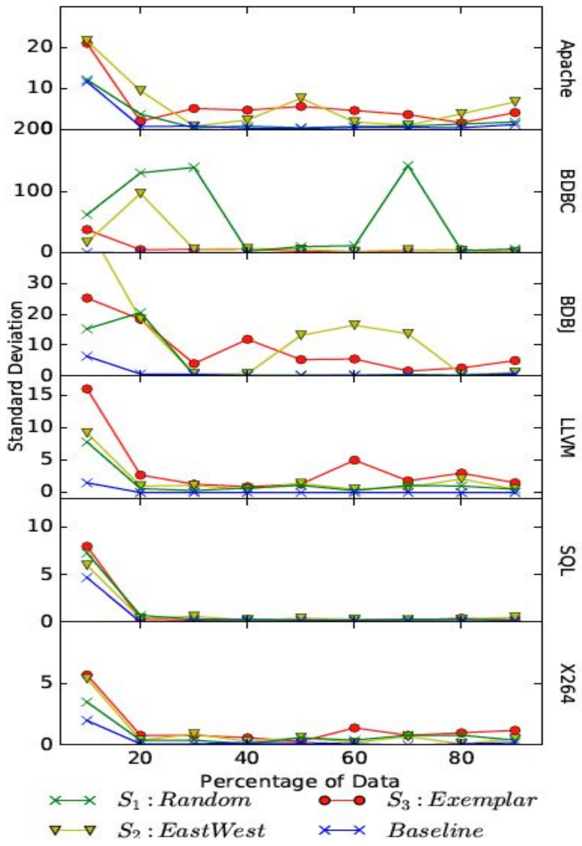
Software Systems

Standard Deviation



% of data reflected upon

RQ2: Do less data cause larger variances in predicted values?

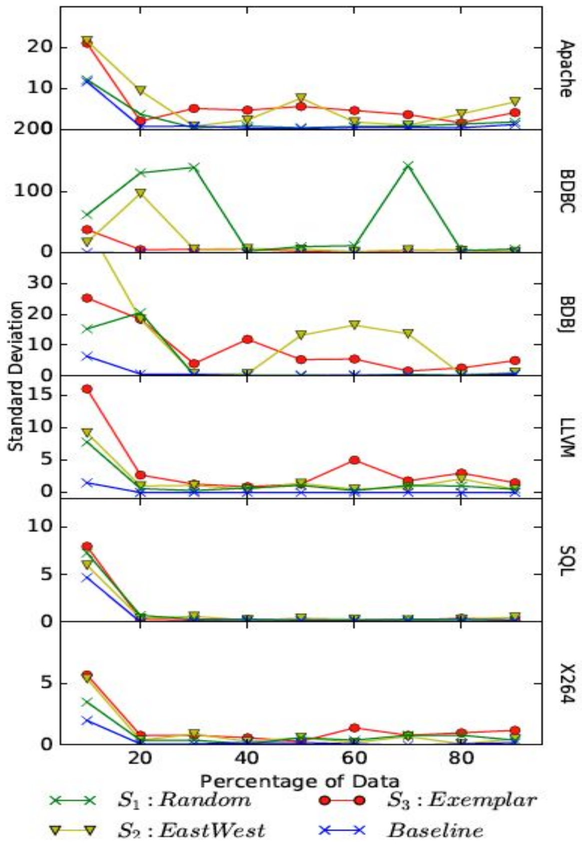


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✘	✔	✔	✘	✔
Standard Deviation	?	?	?	?	?	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✔	✘	✘	✔	✔
Standard Deviation	?	?	?	?	?	?

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✘	✘	✘	✘	✘
Standard Deviation	?	?	?	?	?	?

RQ2: Do less data cause larger variances in predicted values?

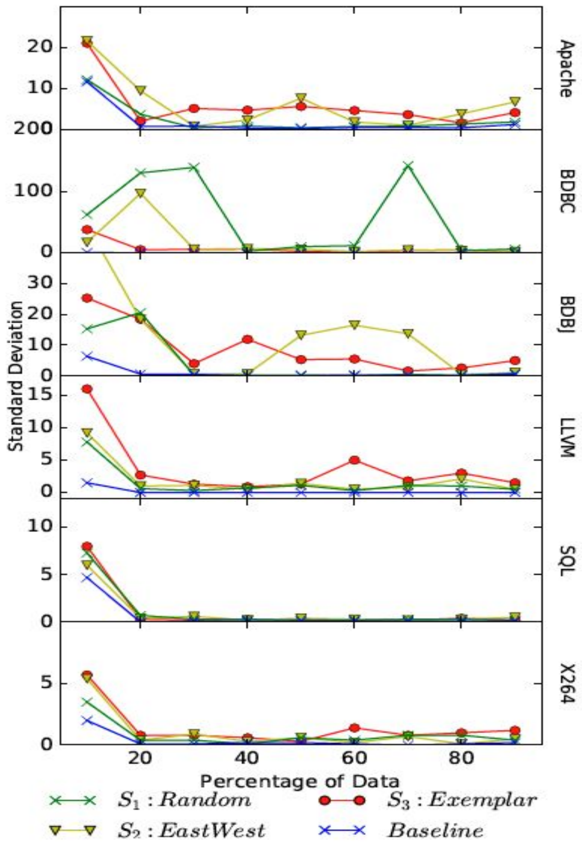


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✗	✔	✔	✗	✔
Standard Deviation	?	✗	?	?	?	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✔	✗	✗	✔	✔
Standard Deviation	?	✔	?	?	?	?

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✗	✗	✗	✗	✗
Standard Deviation	?	✔	?	?	?	?

RQ2: Do less data cause larger variances in predicted values?

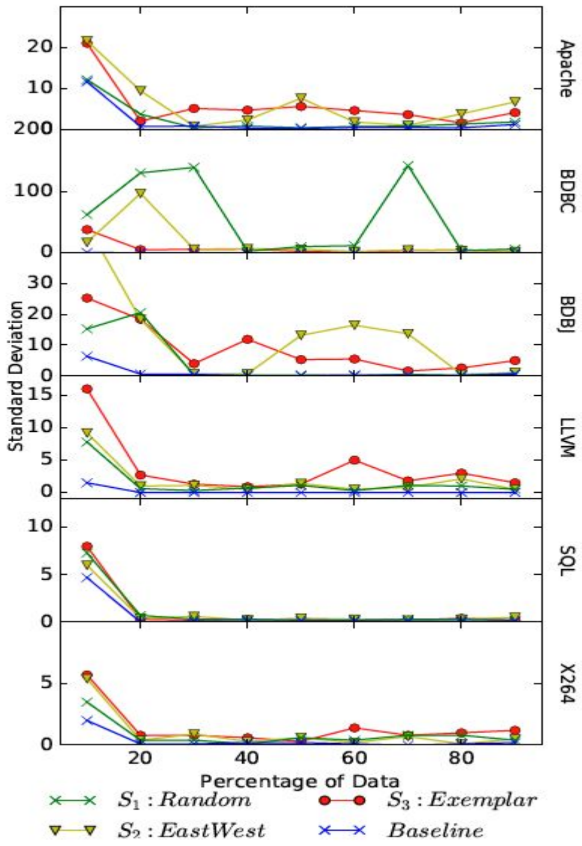


Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✘	✔	✔	✘	✔
Standard Deviation	?	✘	?	?	✔	?

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✔	✘	✘	✔	✔
Standard Deviation	?	✔	?	?	✔	?

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✘	✘	✘	✘	✘
Standard Deviation	?	✔	?	?	✔	?

RQ2: Do less data cause larger variances in predicted values?



Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✘	✔	✔	✘	✔
Standard Deviation	✔	✘	✔	✔	✔	✔

East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✔	✘	✘	✔	✔
Standard Deviation	✘	✔	✘	✔	✔	✔

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✘	✘	✘	✘	✘	✘
Standard Deviation	✘	✔	✘	✘	✔	✔

RQ1 + RQ2: Observations

- Baseline results is the best
  - It uses 100% of data
- Results plateaued after **40%**
- WHERE + Exemplar
  - largest Mean MRE
  - **Not Recommended**
- WHERE + East-West
  - MRE 3/6 times better/similar
  - Standard deviation is low
  - **Recommended**
- WHERE + Random
  - MRE 4/6 times better/similar
  - Standard deviation is low
  - **Recommended**

Random						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✔	✗	✔	✔	✗	✔
Standard Deviation	✔	✗	✔	✔	✔	✔

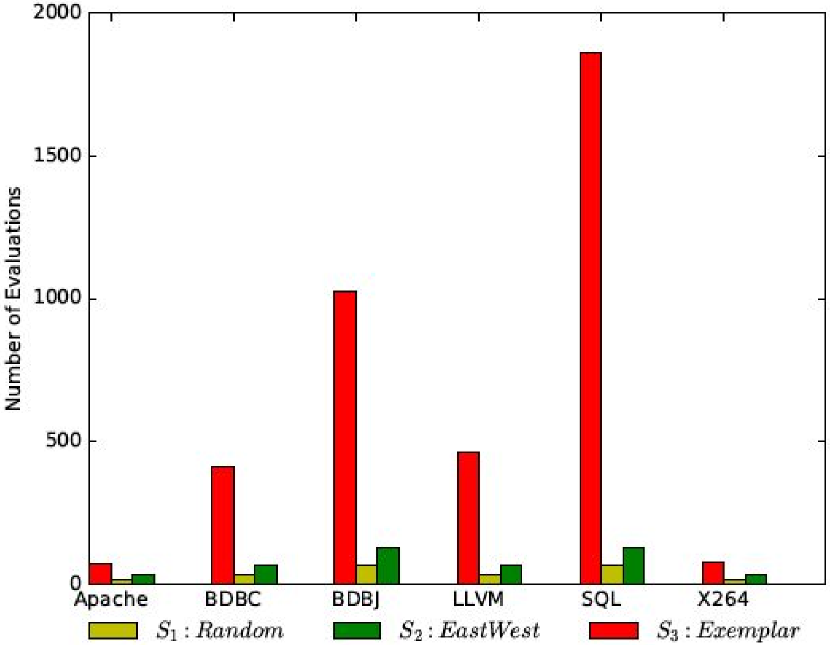
East-West						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✔	✗	✗	✔	✔
Standard Deviation	✗	✔	✗	✔	✔	✔

Exemplar						
Software System	Apache	BDBC	BDBJ	LLVM	SQLite	X264
Mean MRE	✗	✗	✗	✗	✗	✗
Standard Deviation	✗	✔	✗	✗	✔	✔

RQ1 + RQ2: Evaluation

- WHERE + East-West
  - MRE 3/6 times better/similar
  - Standard deviation is low
  - **Recommended**

- WHERE + Random
  - MRE 4/6 times better/similar
  - Standard deviation is low
  - **Recommended**



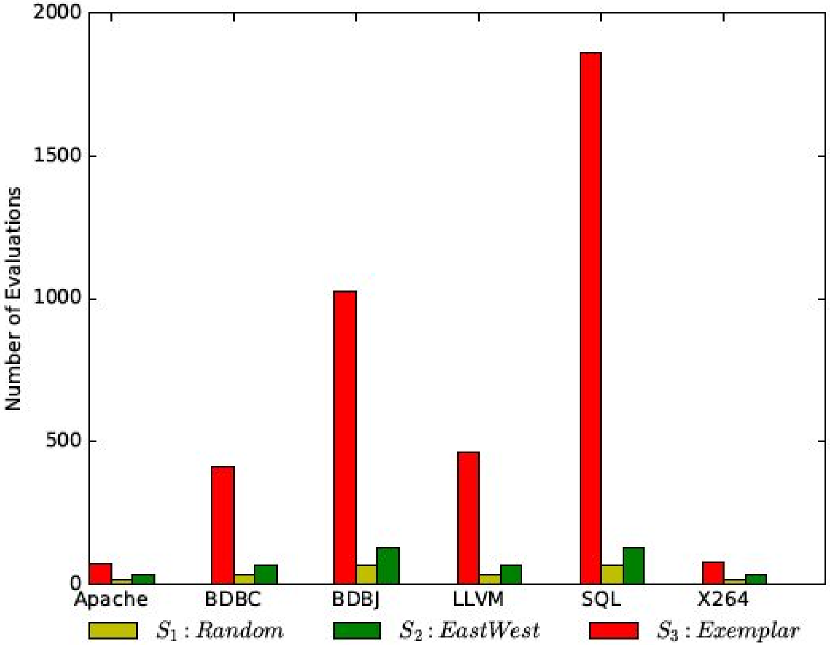
Software Systems

RQ1 + RQ2: Evaluation

- WHERE + East-West
    - MRE 3/6 times better/similar
    - Standard deviation is low
    - **Recommended**
- WHERE + Random
    - MRE 4/6 times better/similar
    - Standard deviation is low
    - **Recommended**

# of Evaluations

(When Training Data = 40%)



Software Systems

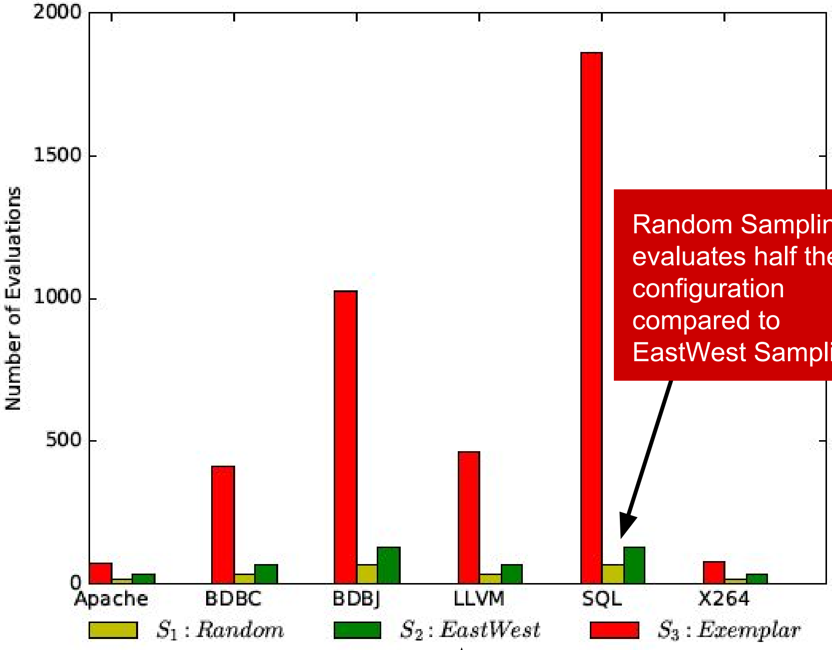
RQ1 + RQ2: Evaluation

- WHERE + East-West
  - MRE 3/6 times better/similar
  - Standard deviation is low
  - ~~**Recommended**~~

# of Evaluations

(When Training Data = 40%)

- WHERE + Random
  - MRE 4/6 times better/similar
  - Standard deviation is low
  - **Recommended**



Random Sampling evaluates half the configuration compared to EastWest Sampling

Software Systems

RQ1 + RQ2: Evaluation

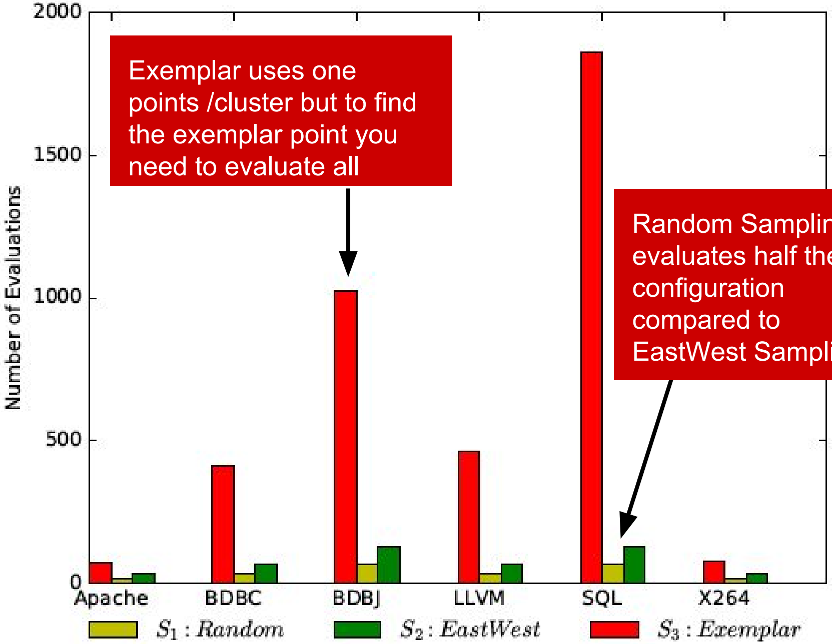
- WHERE + East-West
  - MRE 3/6 times better/similar
  - Standard deviation is low
  - **Recommended**
- WHERE + Random
  - MRE 4/6 times better/similar
  - Standard deviation is low
  - **Recommended**

# of Evaluations

(When Training Data = 40%)

Exemplar uses one points /cluster but to find the exemplar point you need to evaluate all

Random Sampling evaluates half the configuration compared to EastWest Sampling



Software Systems

RQ 3: Can "good" surrogate models (to be used in optimizers) be built using WHAT?

RQ 3 explore

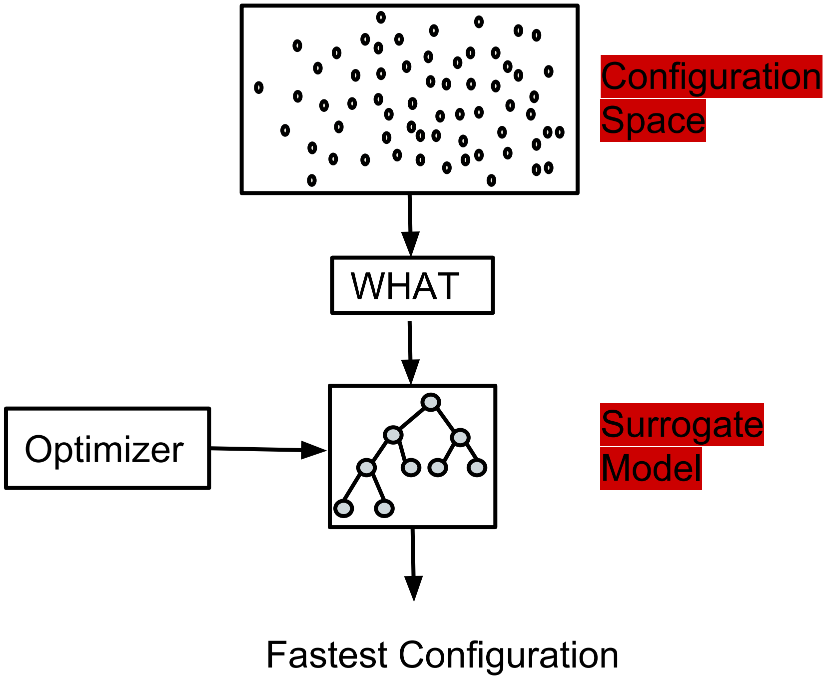
- if predictors generated using samples from WHAT can find faster performance scores (eg. Response time)

Optimization Goal

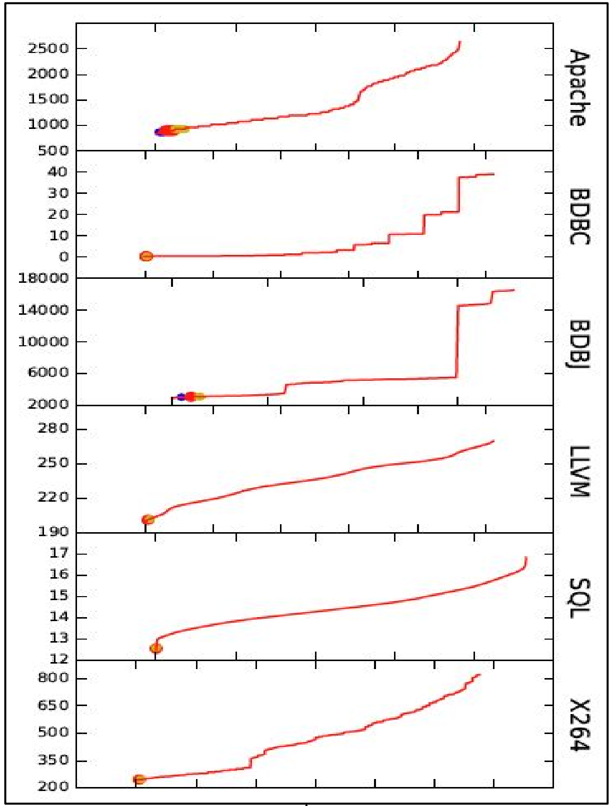
- Minimize the performance score of the system

Comparison between:

- GALE [Krall'15]
- DE [Storn'95]
- NSGA-II [Deb'02]



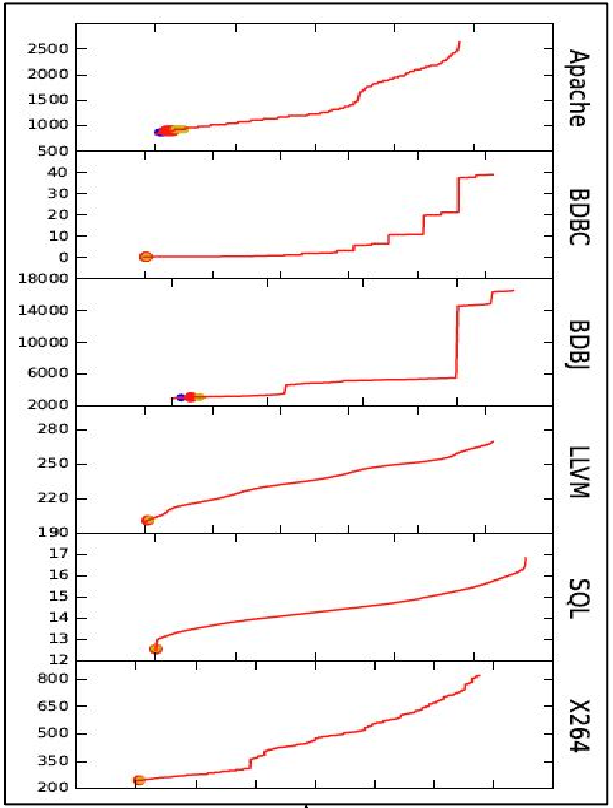
RQ 3: Can “good” surrogate models (to be used in optimizers) be built using WHAT?



Instances sorted based on Performance Scores

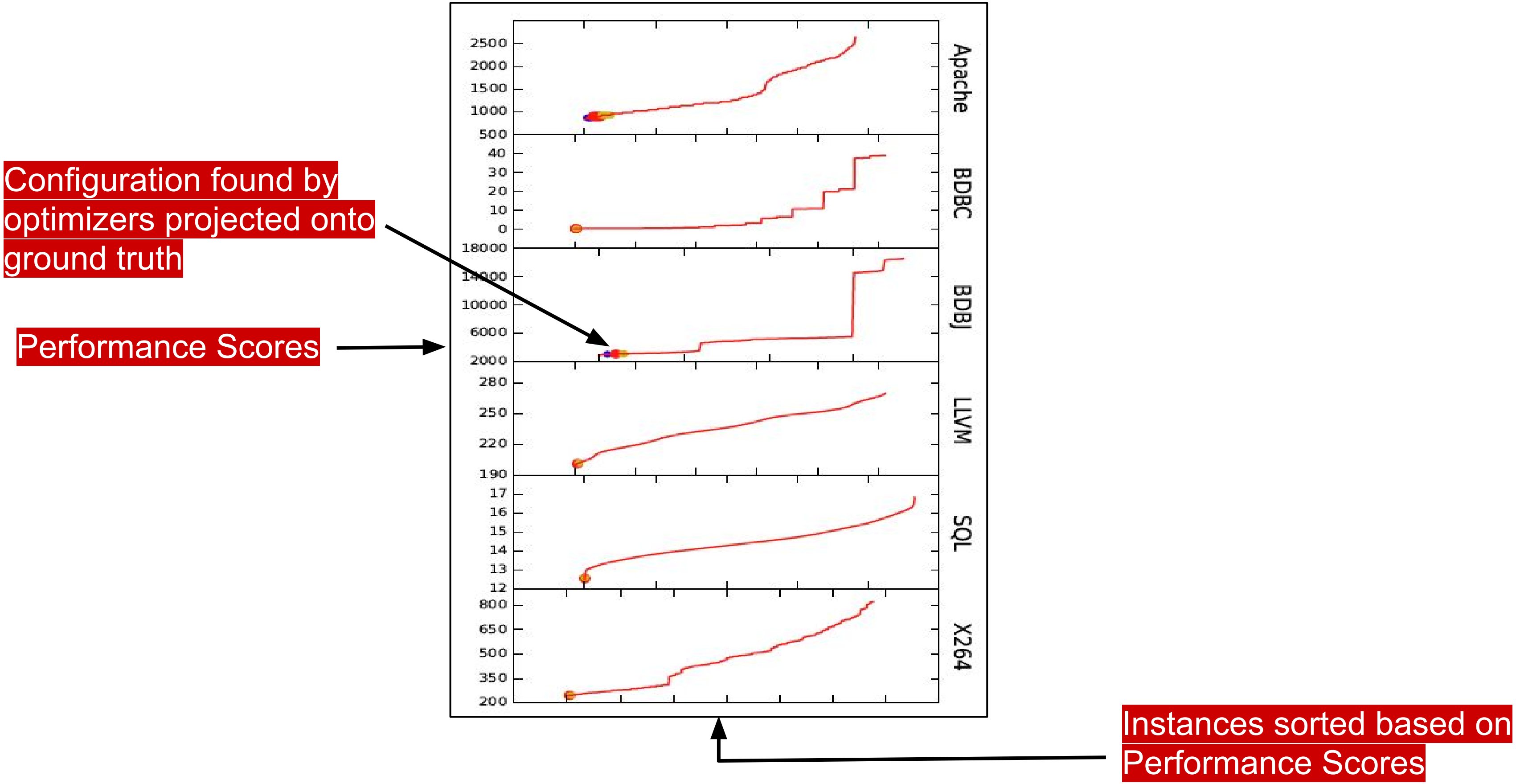
RQ 3: Can “good” surrogate models (to be used in optimizers) be built using WHAT?

Performance Scores



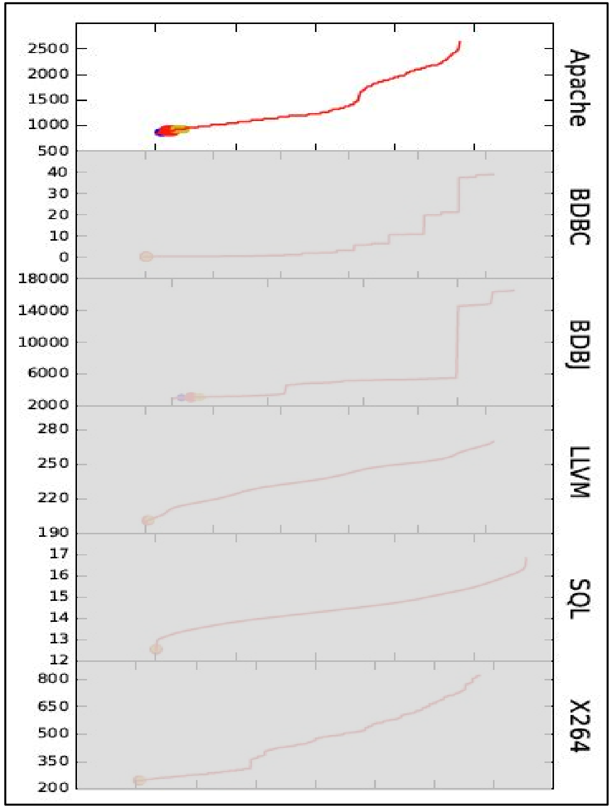
Instances sorted based on Performance Scores

RQ 3: Can "good" surrogate models (to be used in optimizers) be built using WHAT?



RQ 3: Can “good” surrogate models (to be used in optimizers) be built using WHAT?

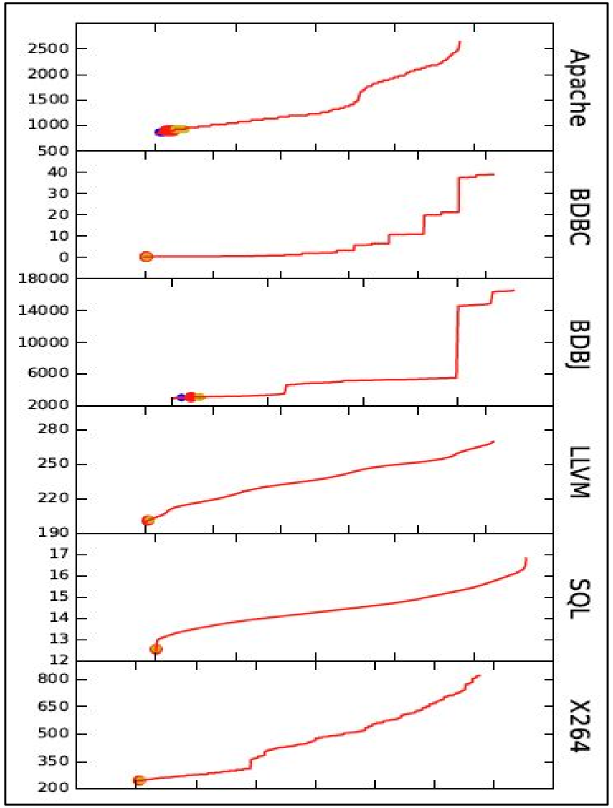
- Optimization Goal: Minimization



RQ 3: Can “good” surrogate models (to be used in optimizers) be built using WHAT?

- Optimization Goal: Minimization

- Optimized configurations
  - within 1% of the fastest configuration



RQ 4: How good is WHAT compared to the state of the art predictors?

RQ 4 explores

- If WHAT is better than state-of-the-art techniques
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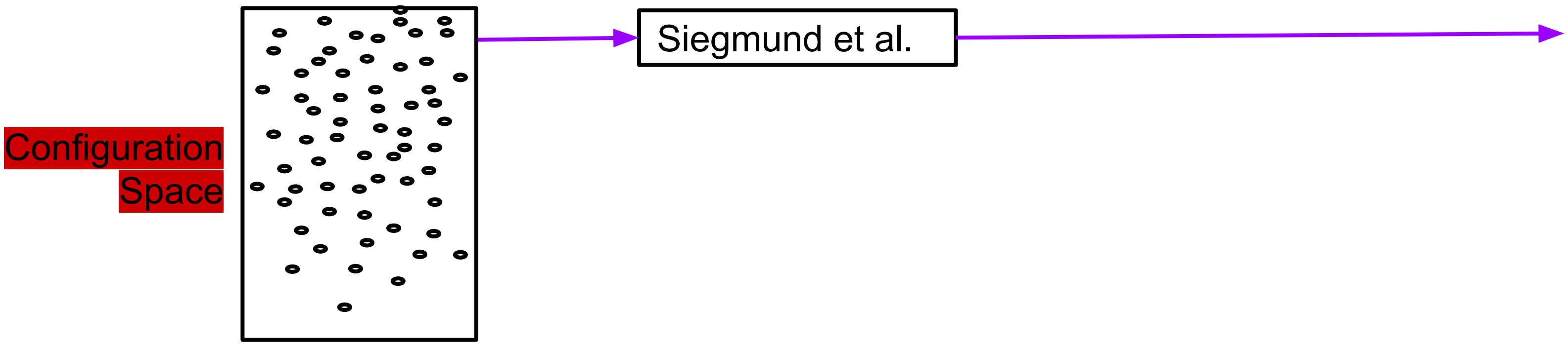

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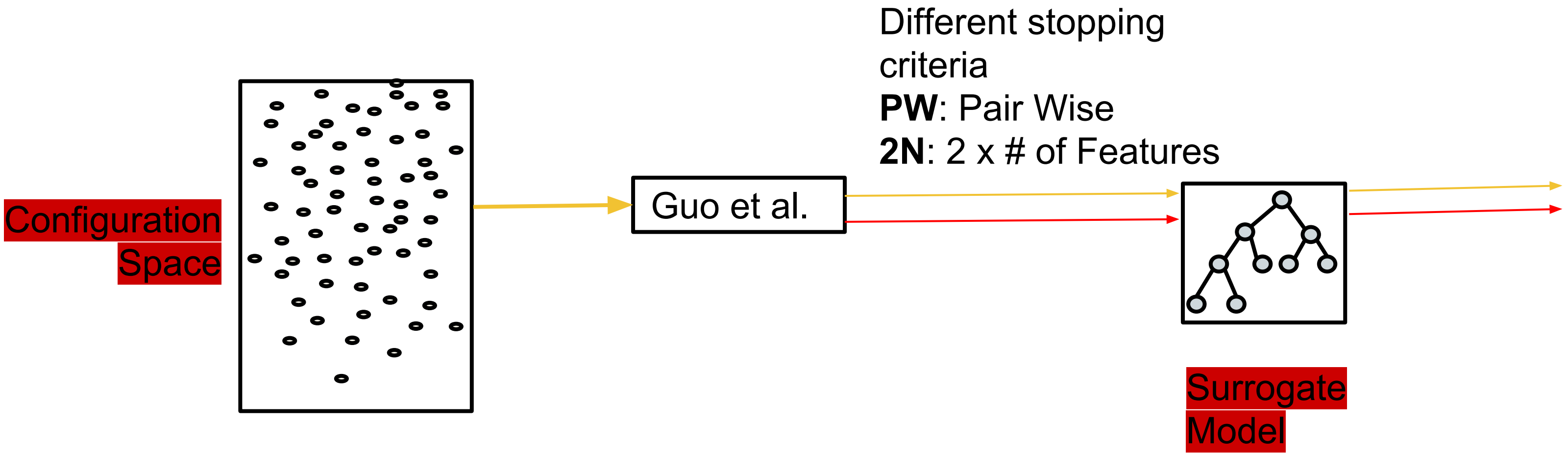

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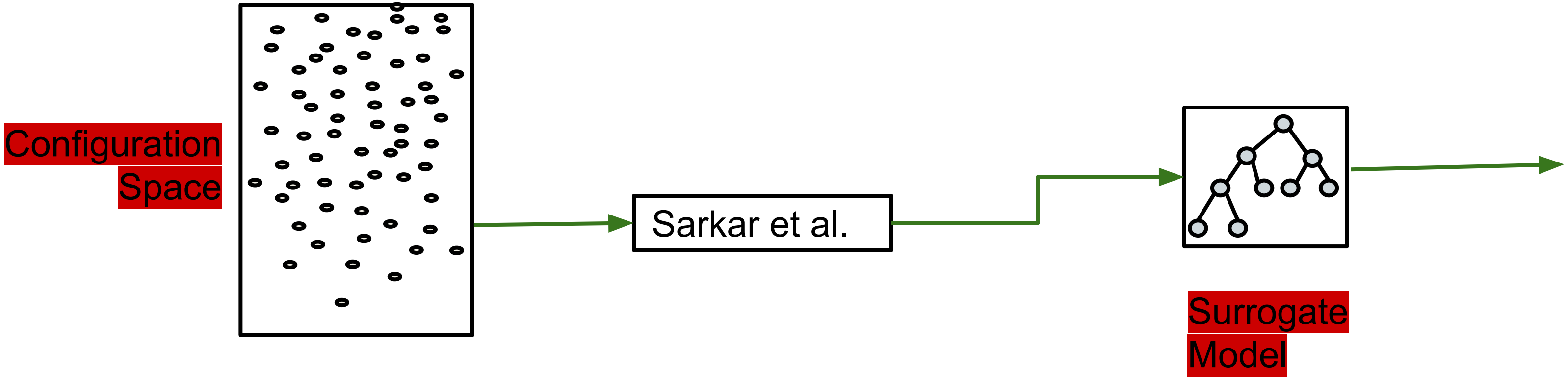

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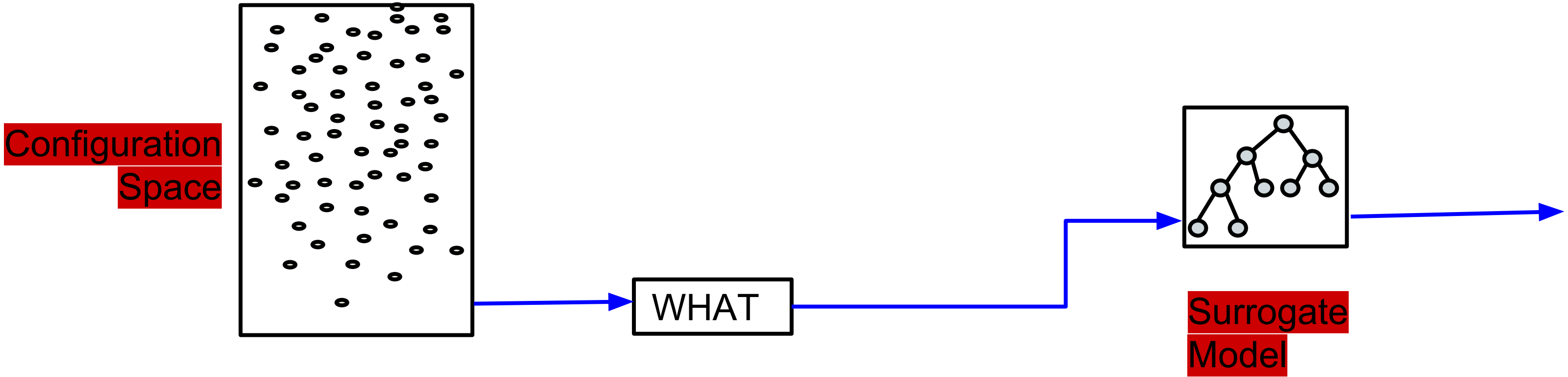

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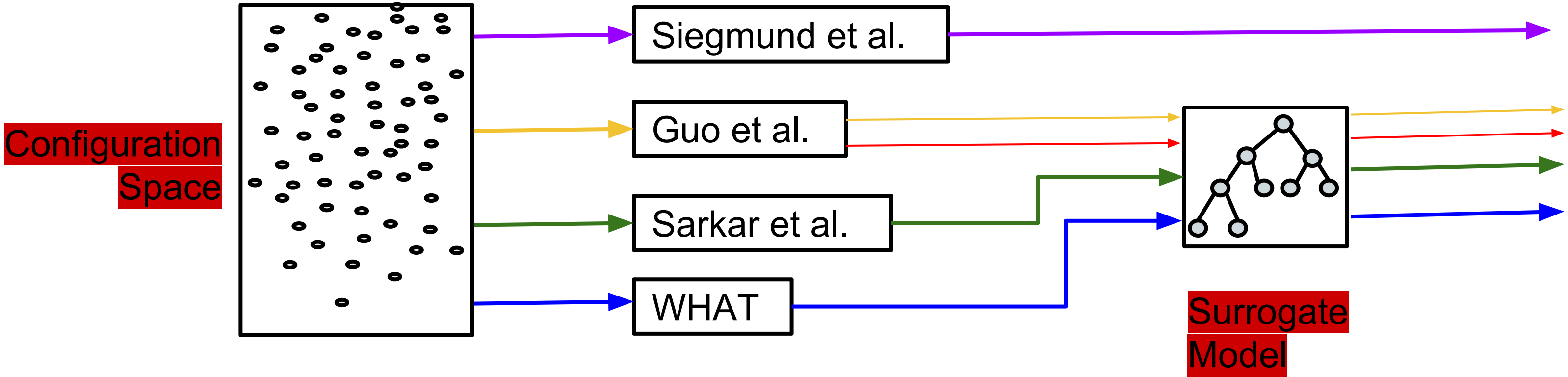

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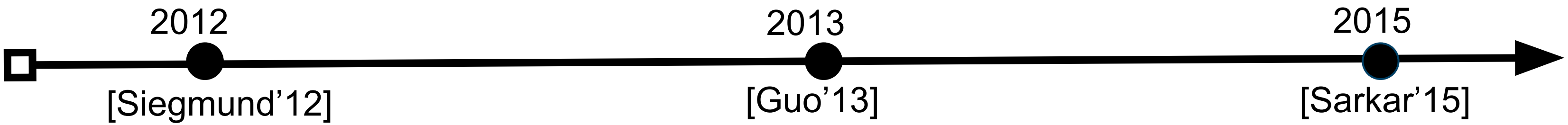

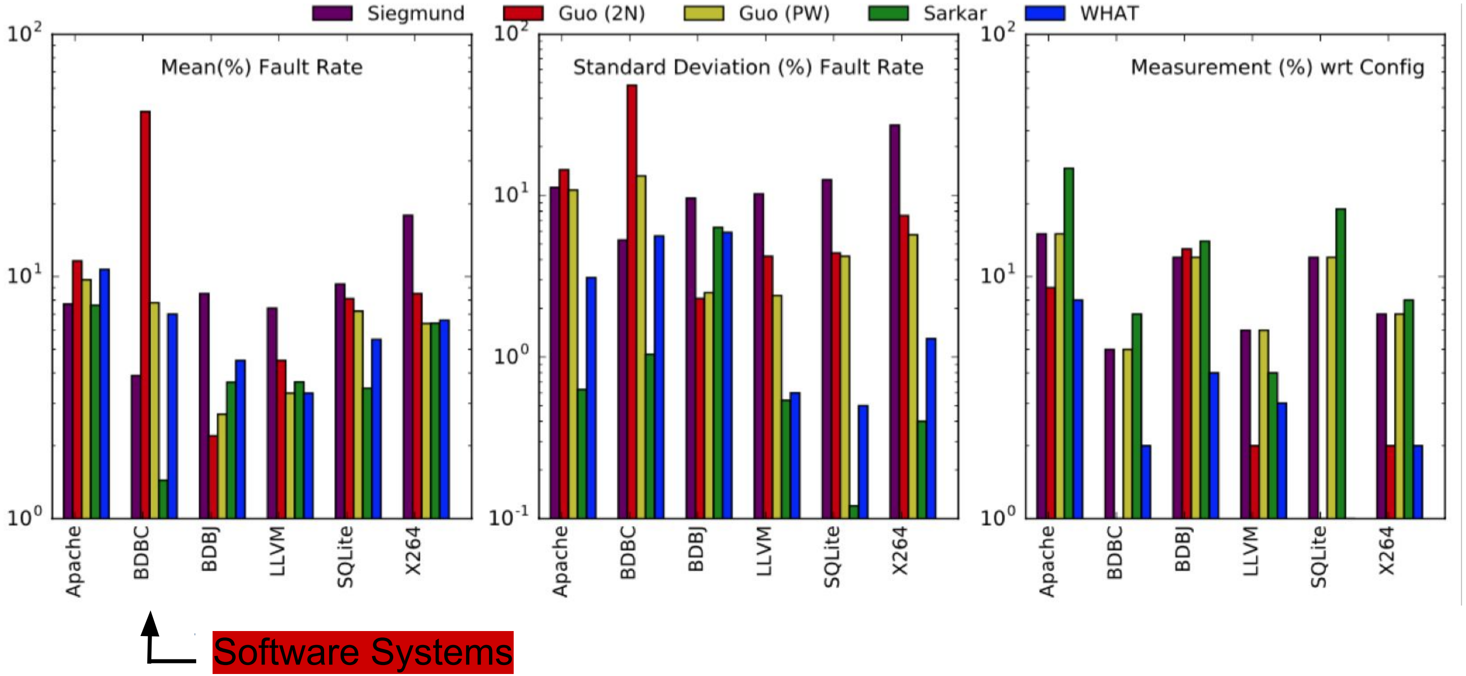

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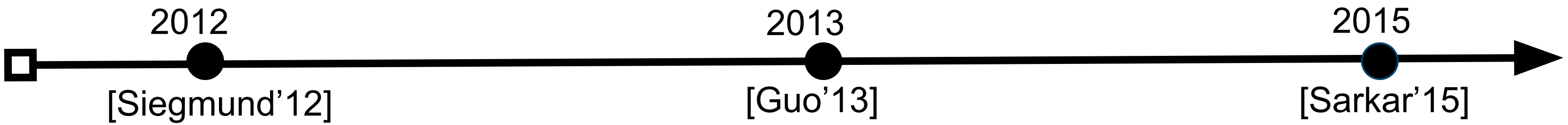

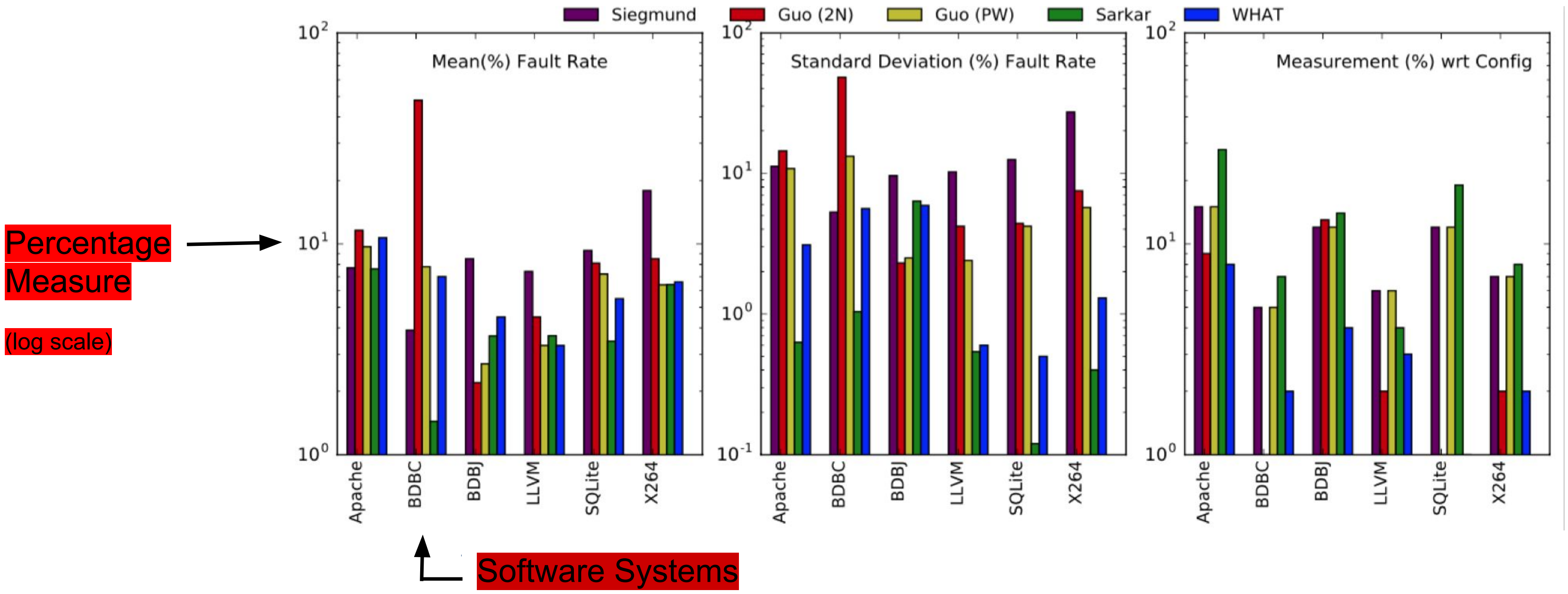

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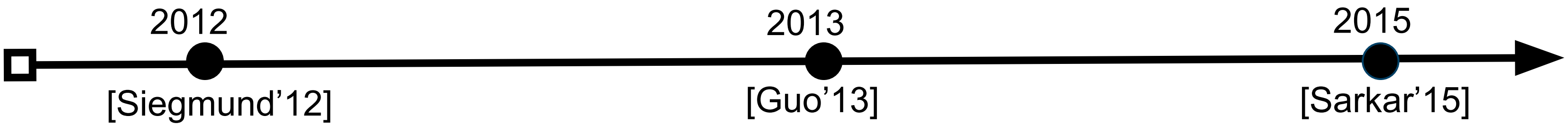
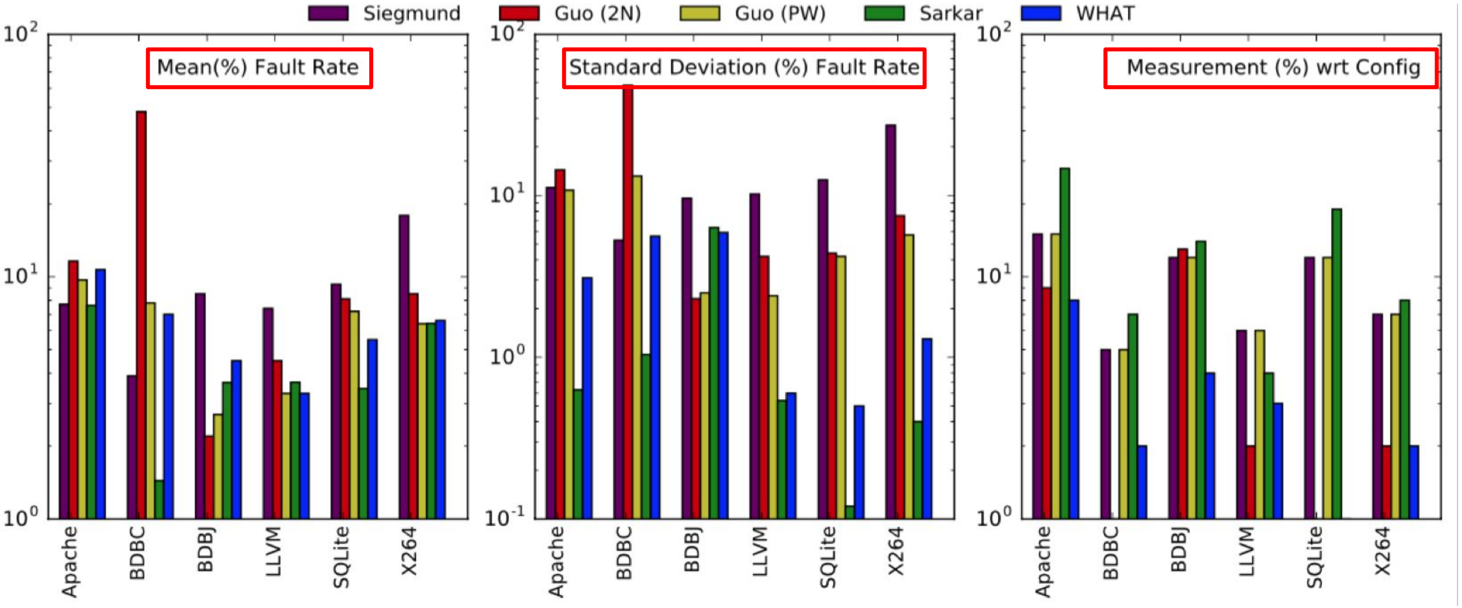


Percentage Measure

(log scale)



Software Systems

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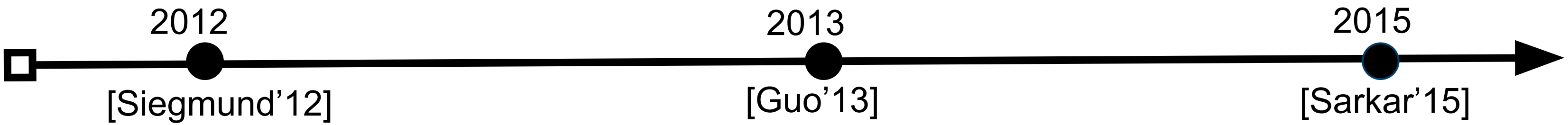

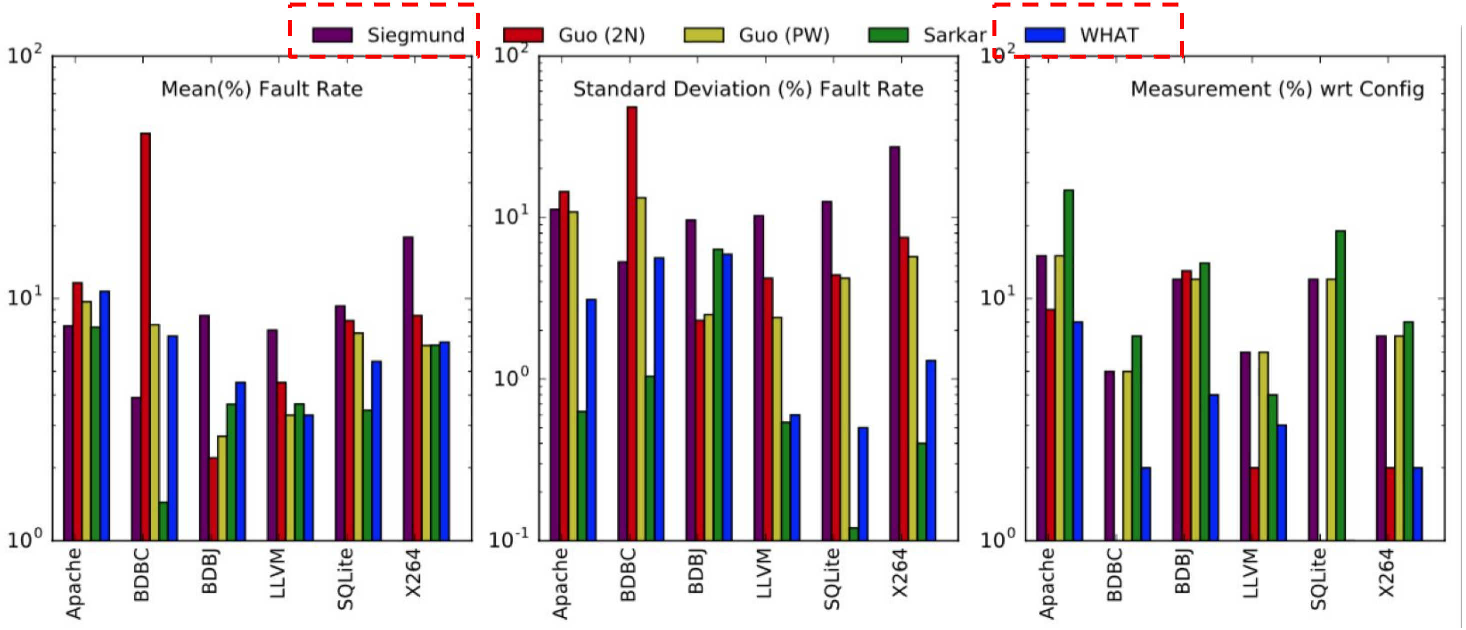

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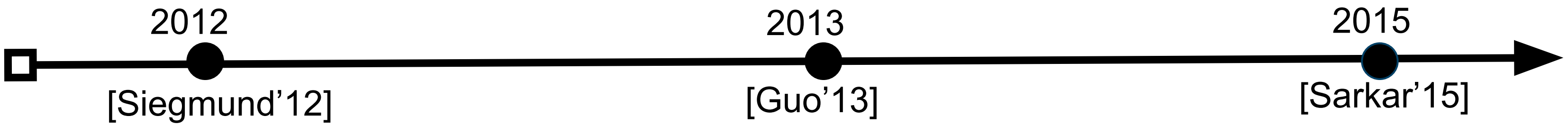

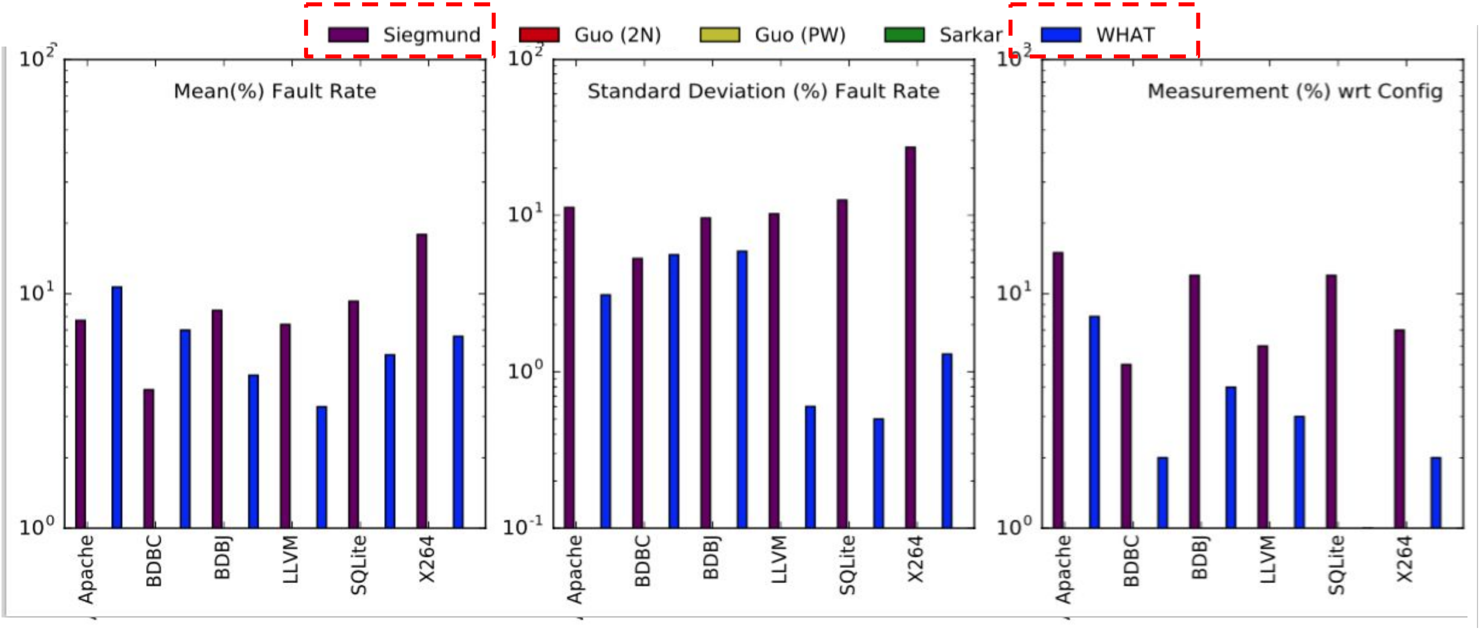

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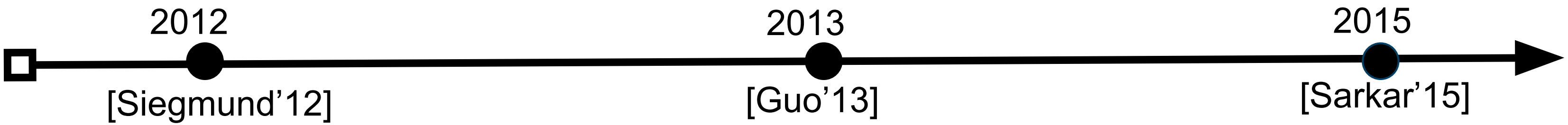

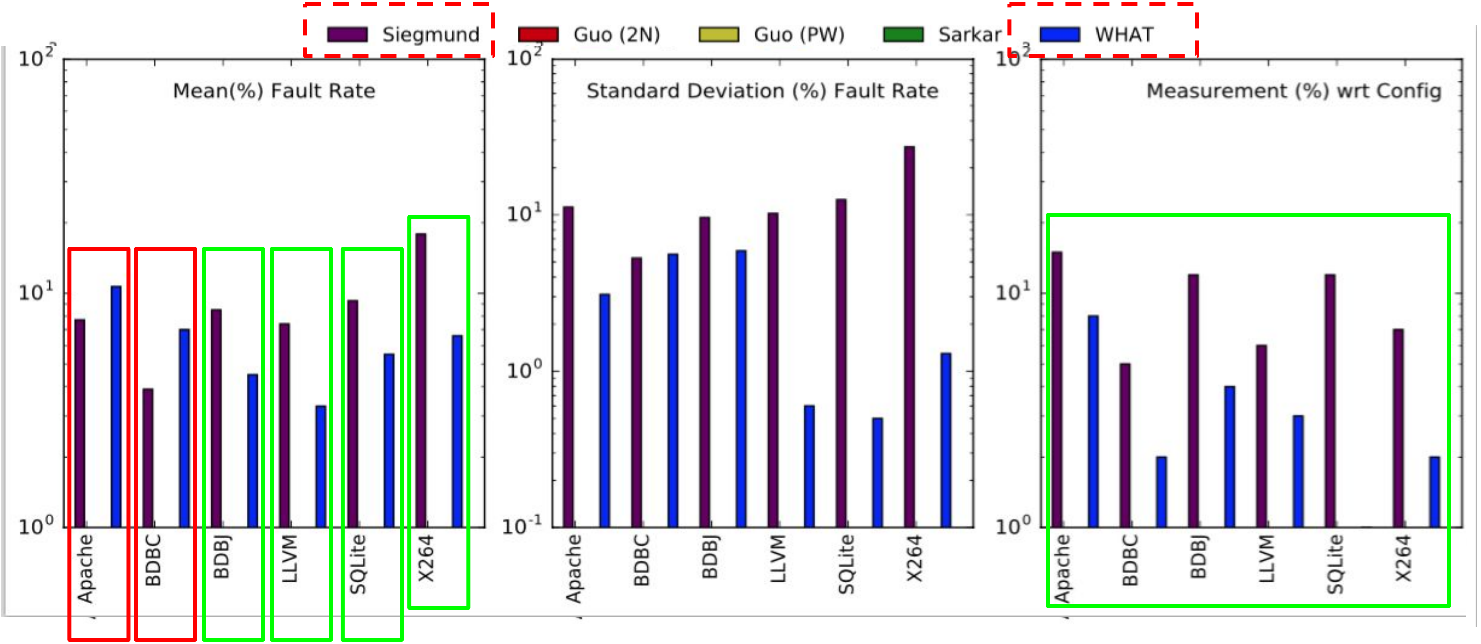

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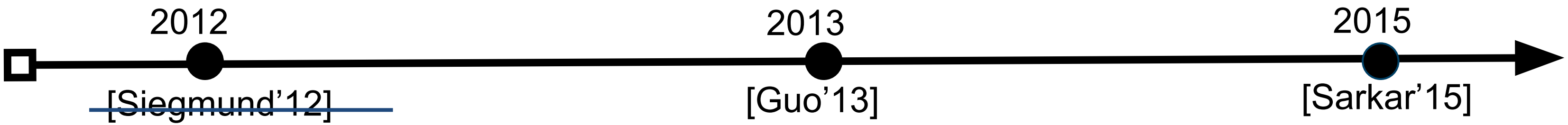

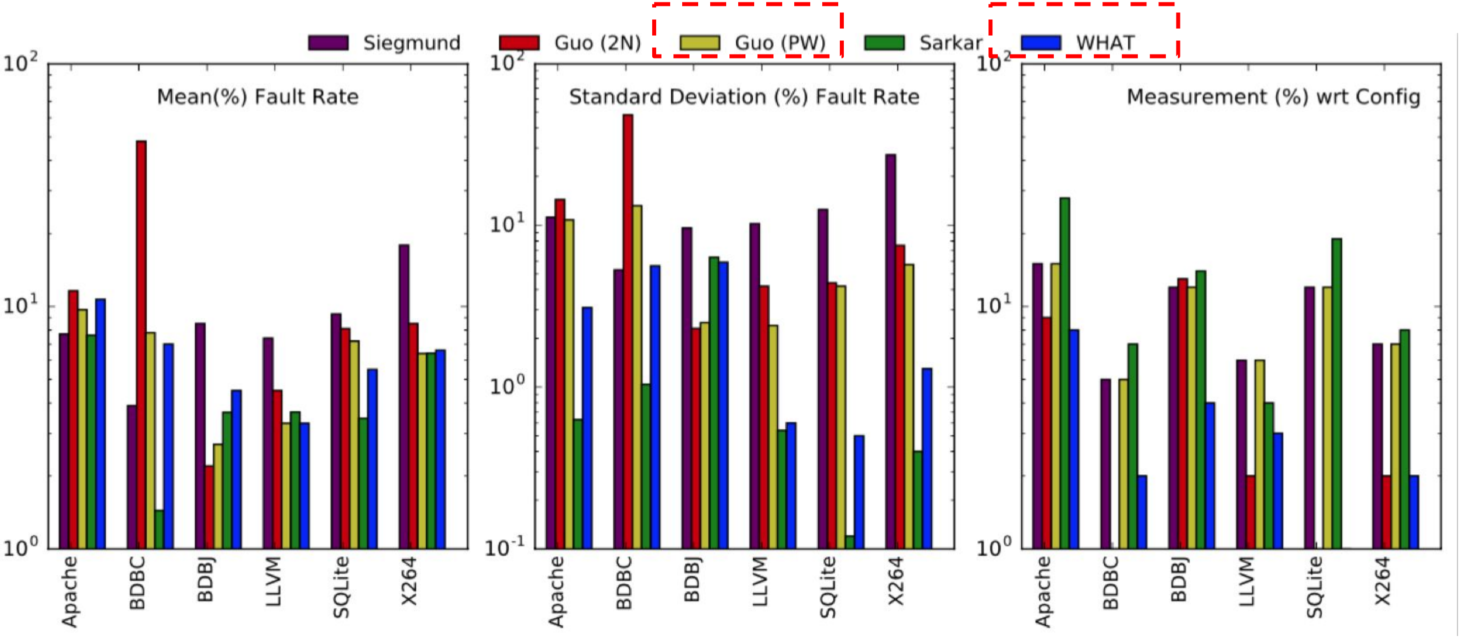

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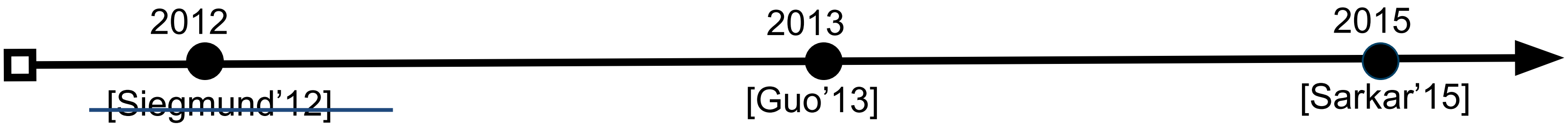

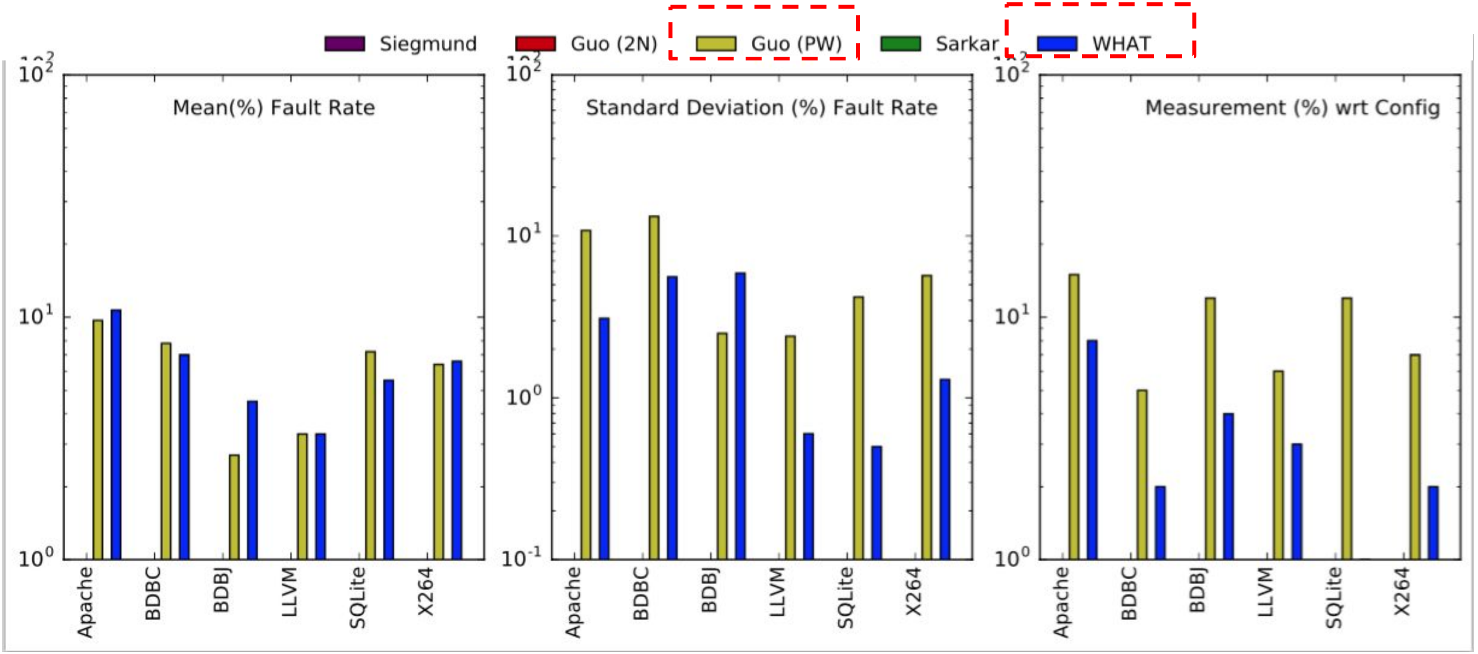

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2012 — ~~[Siegmund'12]~~

2013 — [Guo'13]

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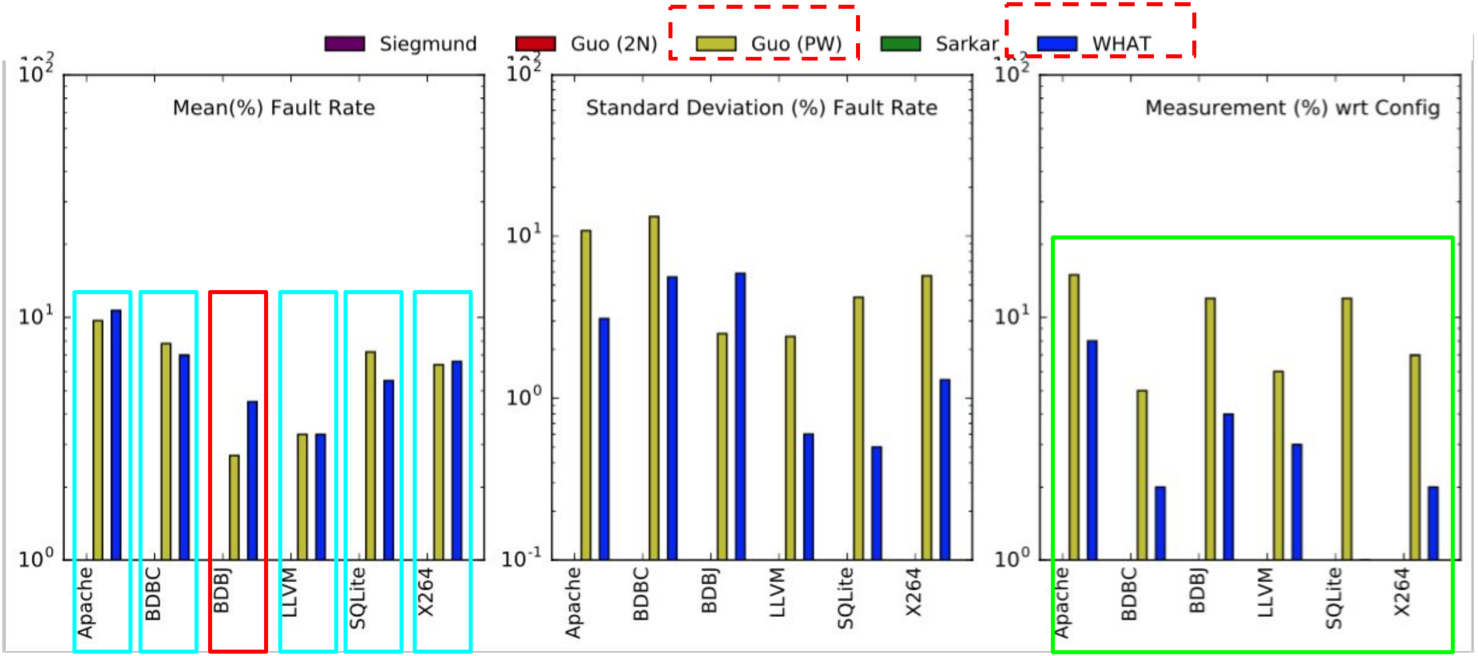

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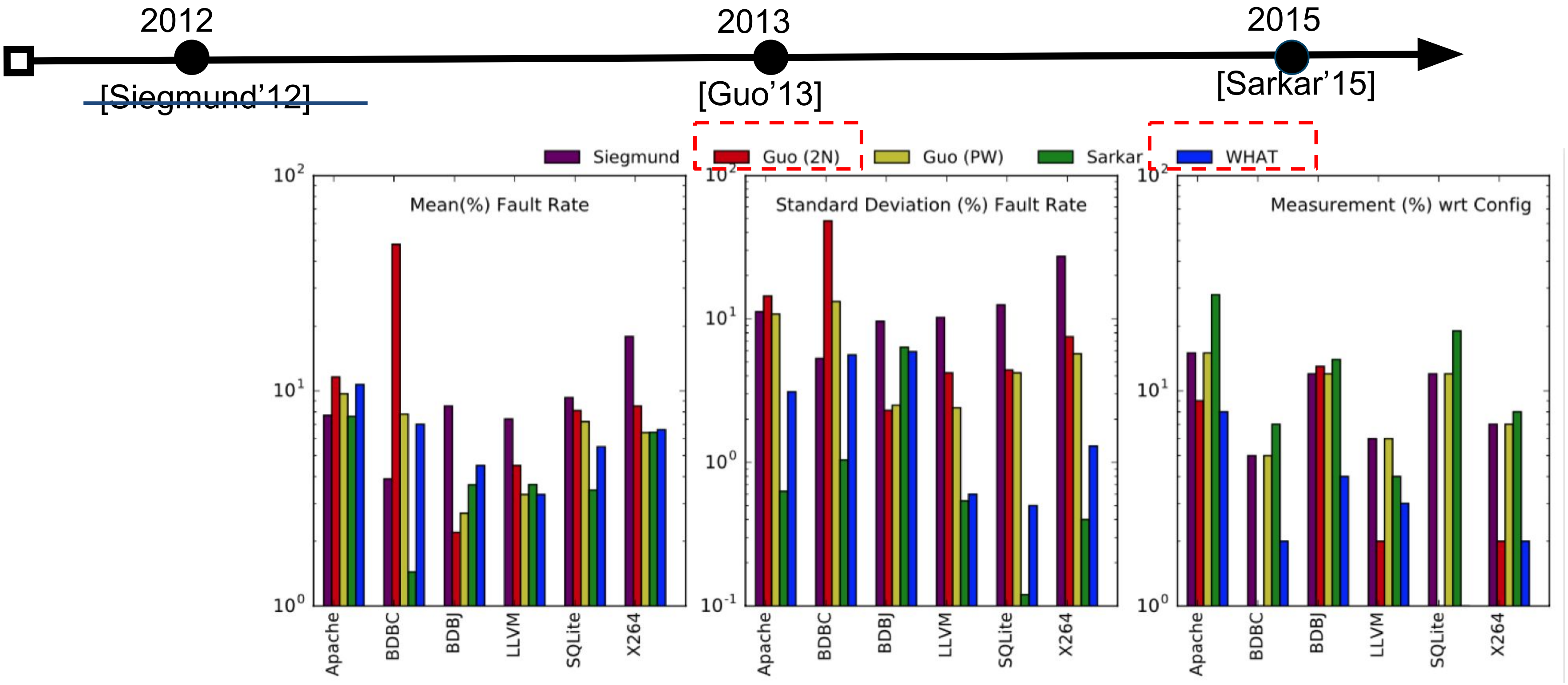

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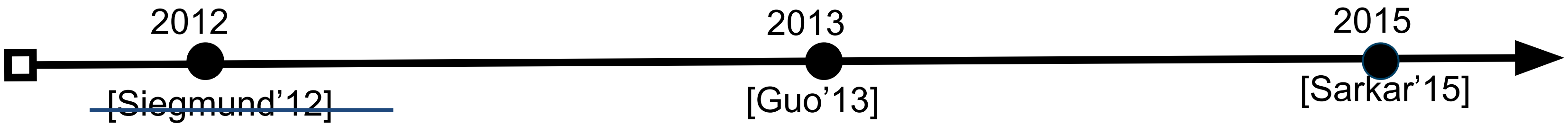

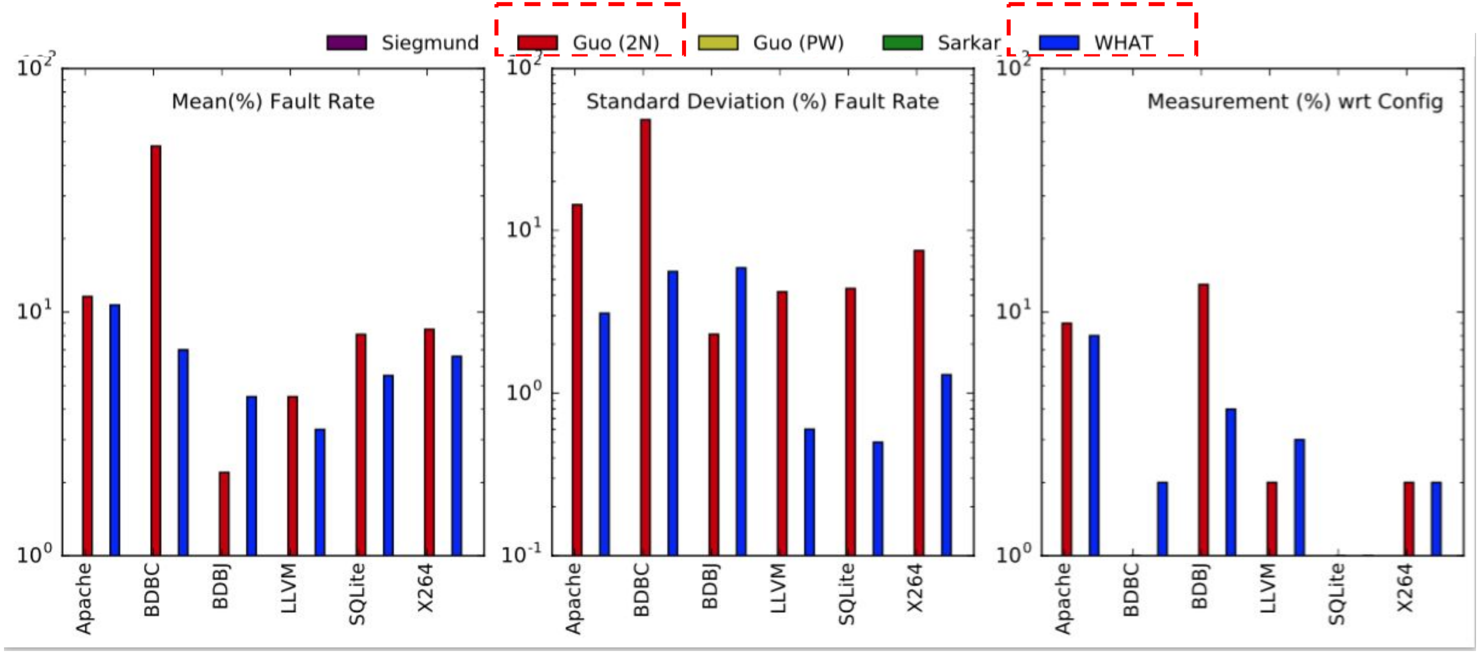

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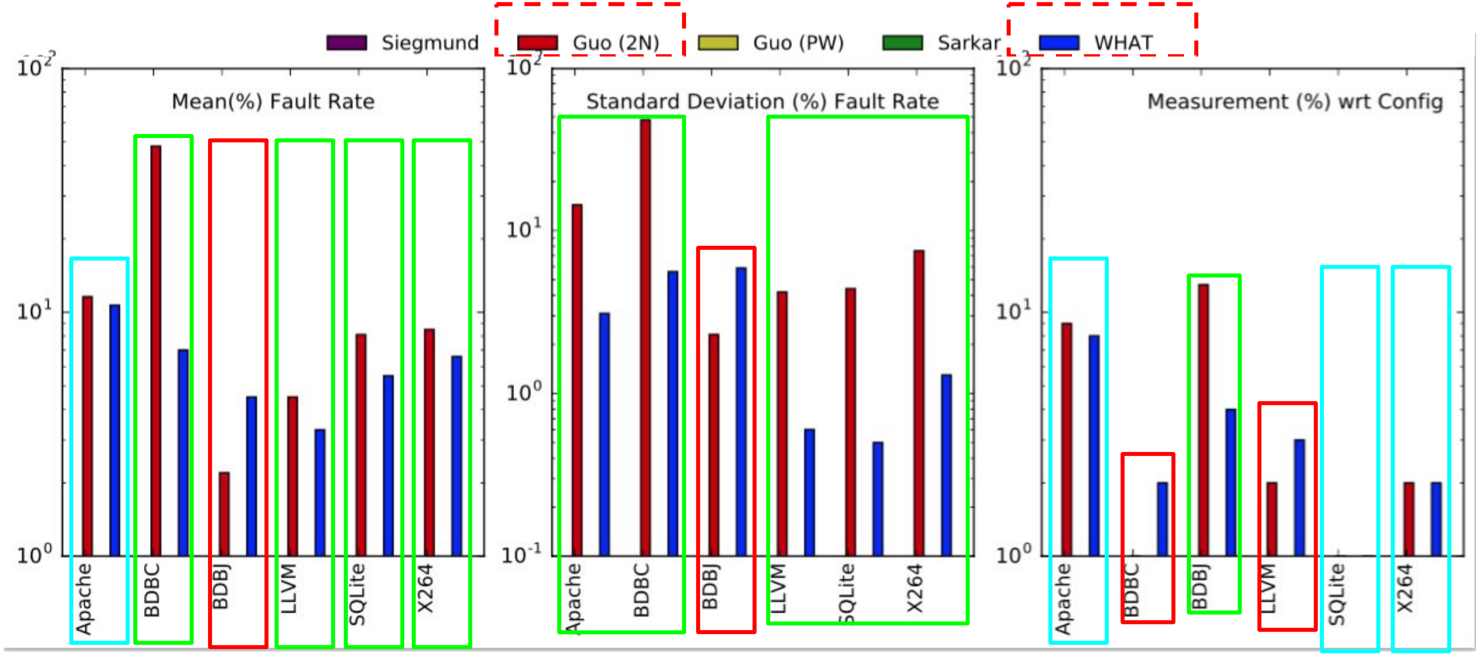

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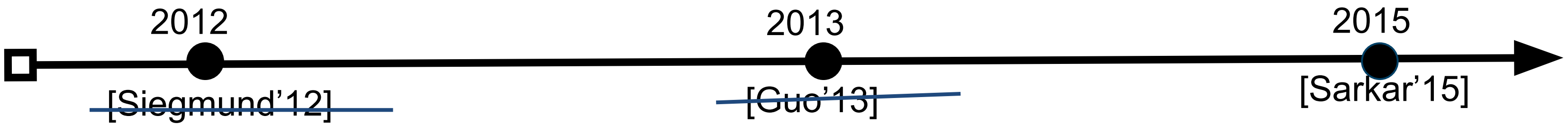

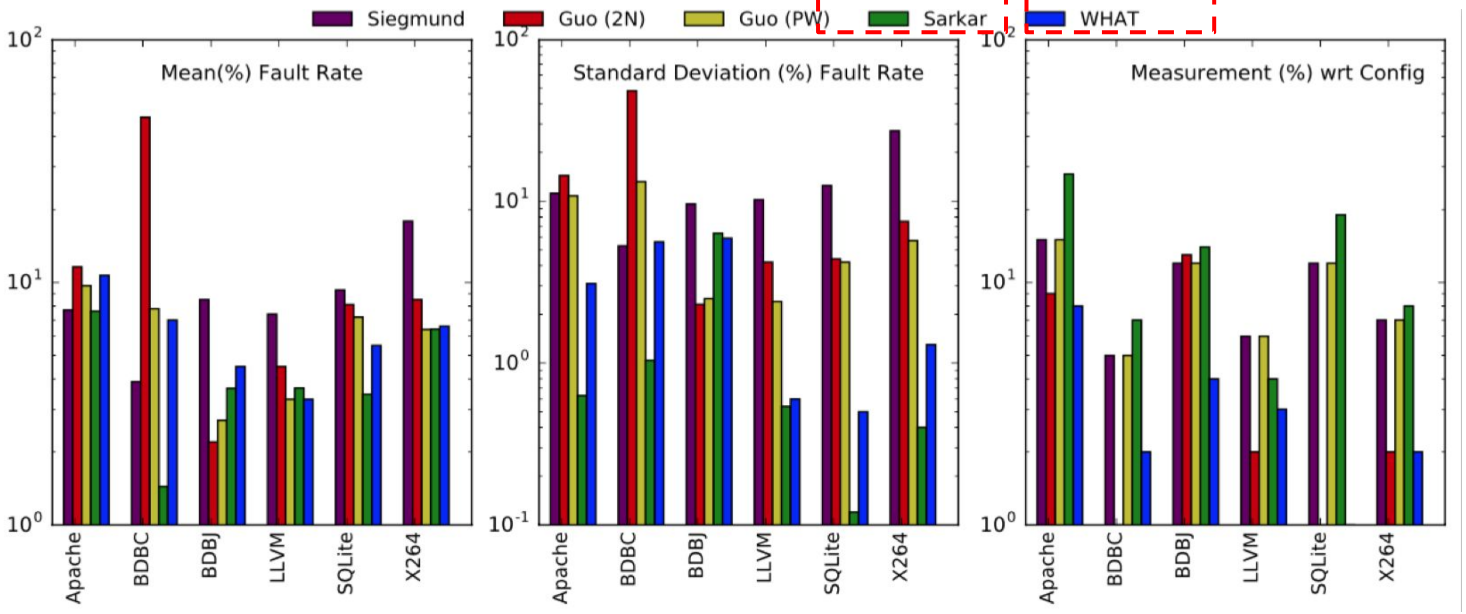

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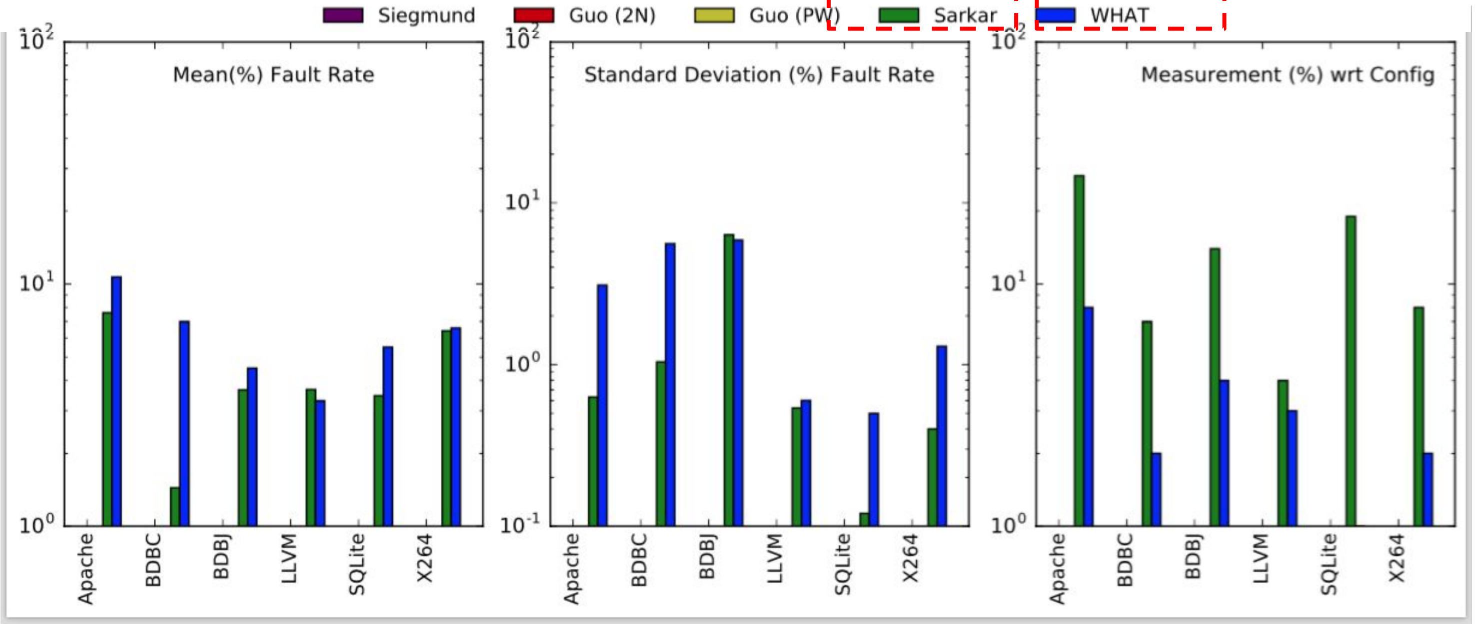

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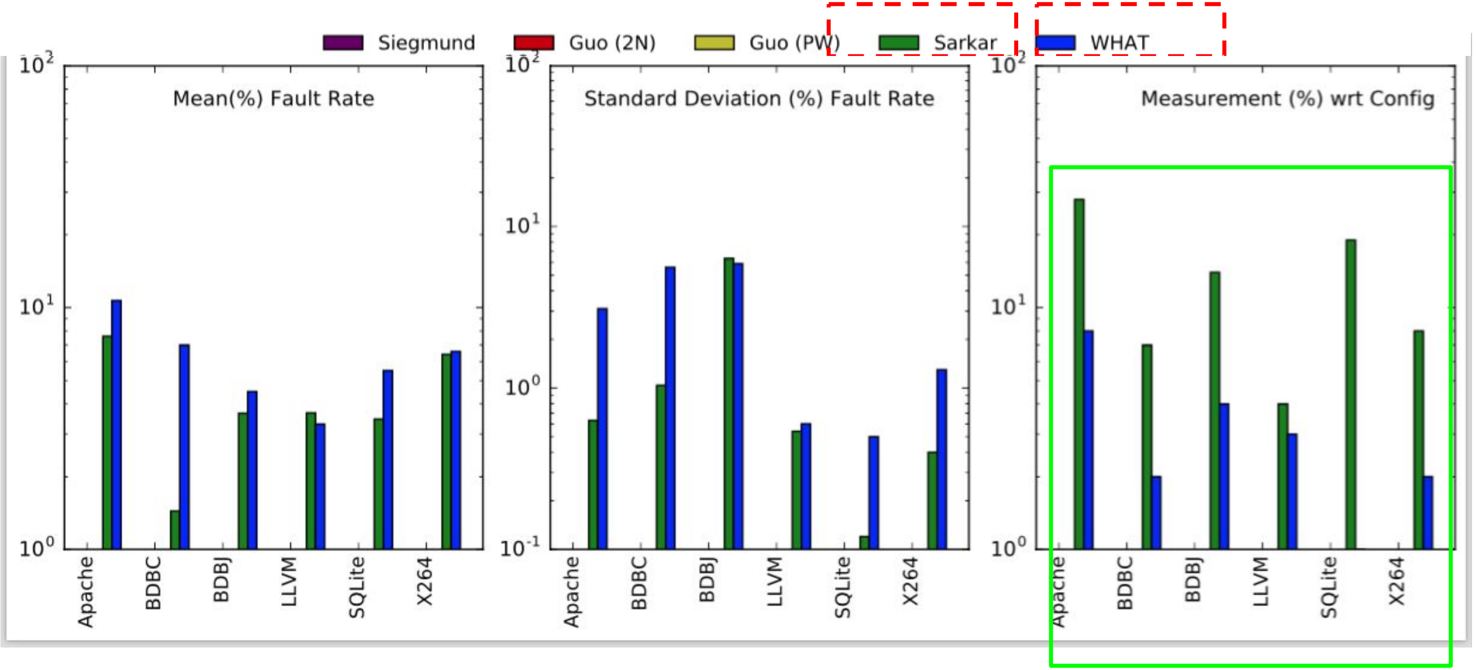

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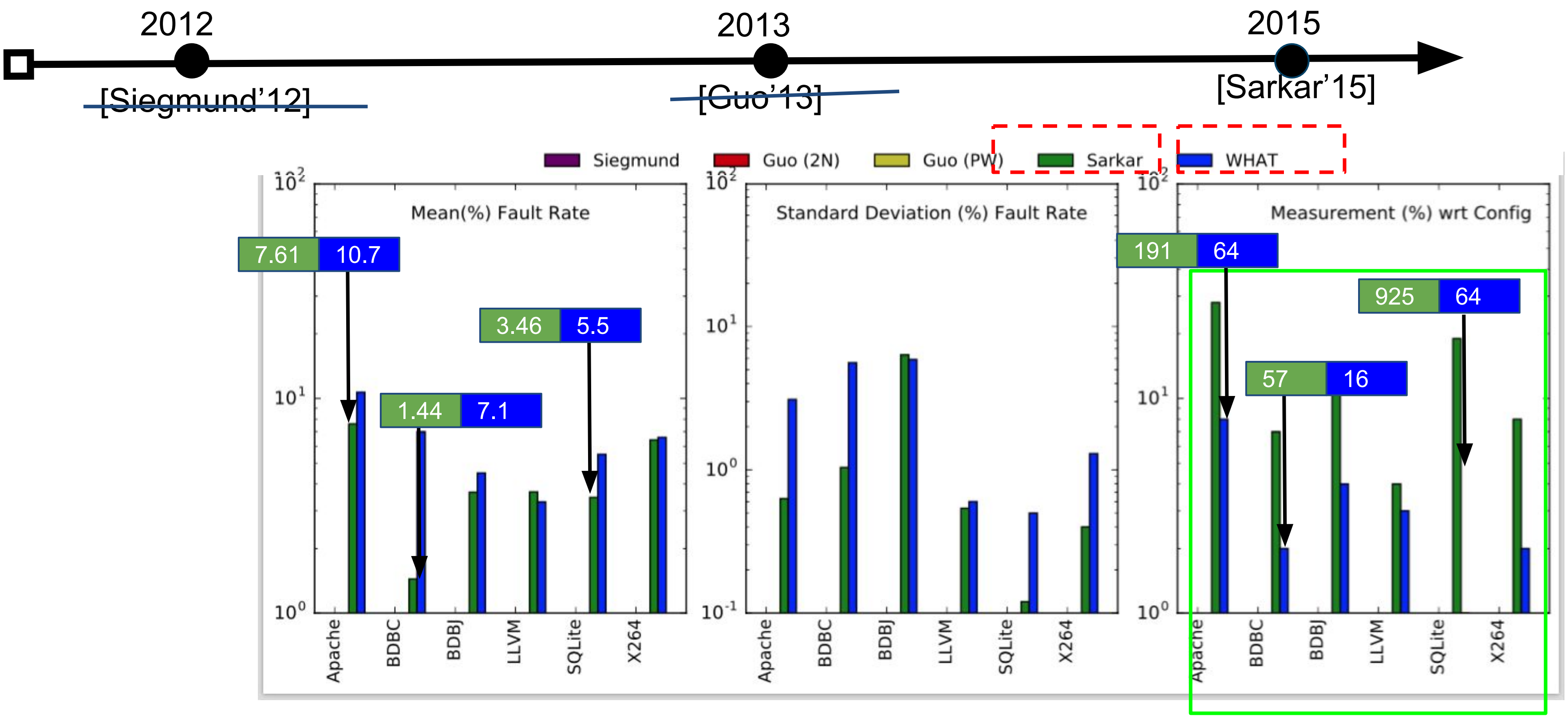

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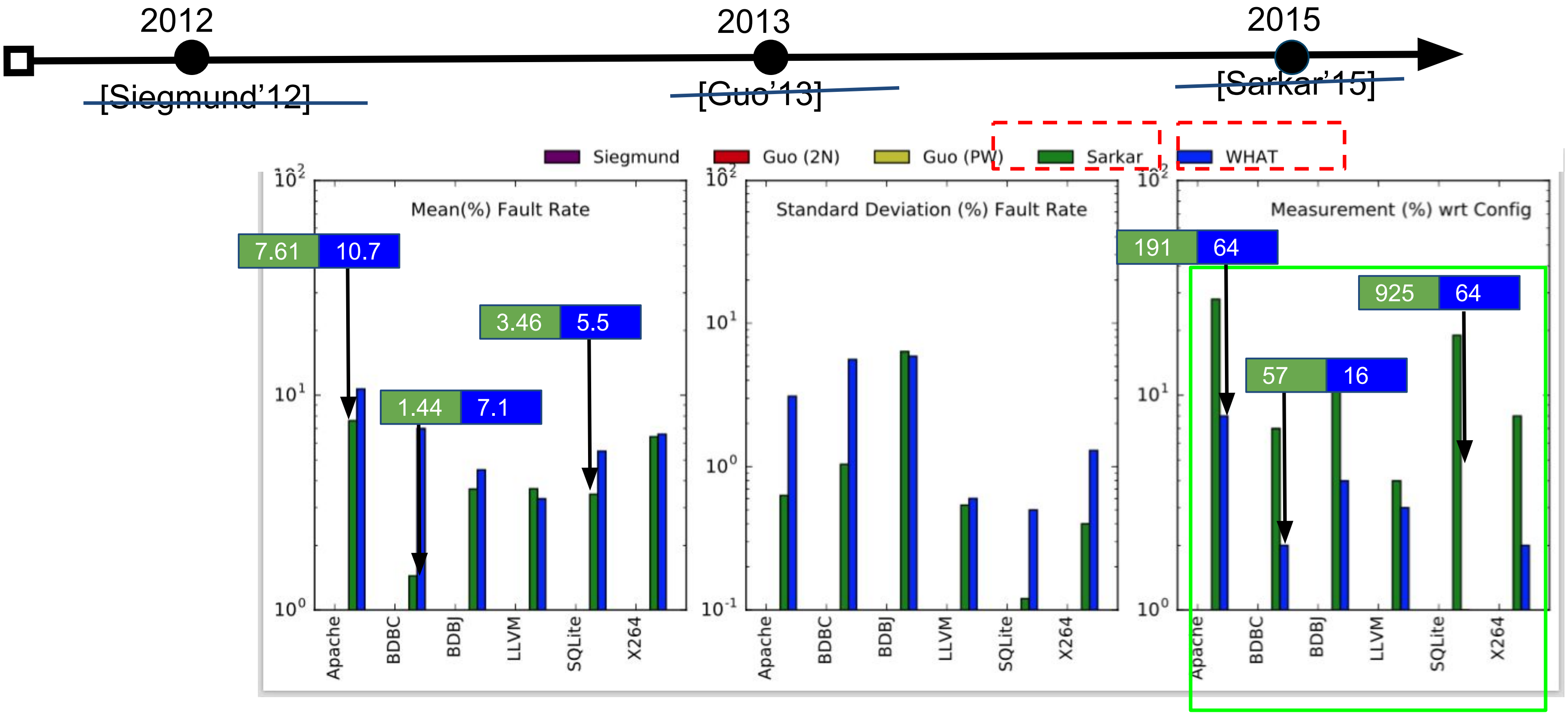

Research Questions

RQ 1: Can WHAT generate good predictions using only a small number of configurations?

RQ 2: Do less data cause larger variances in predicted values?

RQ 3: Can “good” surrogate models (to be used in optimizers) be built using WHAT?

RQ 4: How good is WHAT compared to the state of the art predictors?

Research Questions

RQ 1: Can WHAT generate good predictions using only a small number of configurations? **YES**

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RQ 3: Can "good" surrogate models (to be used in optimizers) be built using WHAT? **YES**

RQ 4: How good is WHAT compared to the state of the art predictors? **Comparable**

Future Work

Future Work

- Progressive WHAT
  - WHAT is rigid
  - Has no options of budget
  - Progressive Sampling using WHAT

- Multi-objective Problems
  - Problem are multi-objective
  - New surrogates required
  - New surrogate model update techniques

- Sampling Way
  - Sampling is preferable if evaluation is expensive
  - Initial results are competitive with other algorithms

- Spectral Grid Search
  - Exploit the underlying dimension while generating Grids

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Question and Comments

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