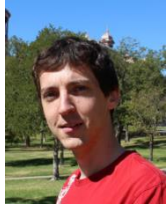


Performance-Influence Models: Prediction, Optimization, Debugging



Norbert Siegmund



Alexander Grebhahn

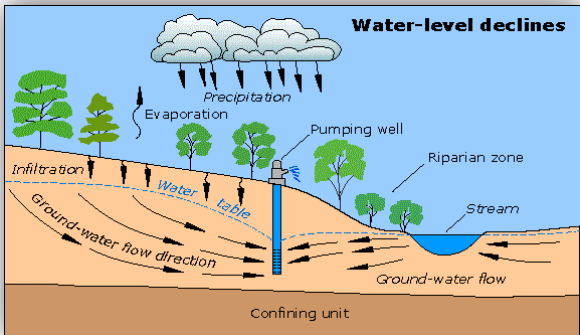


Sven Apel

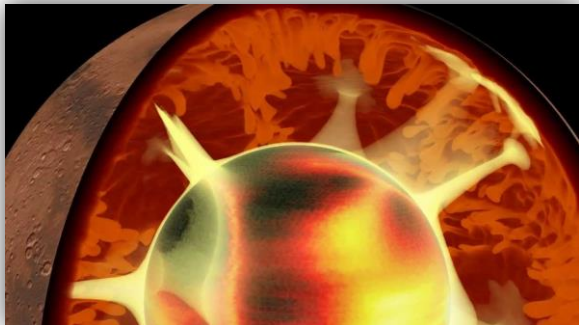
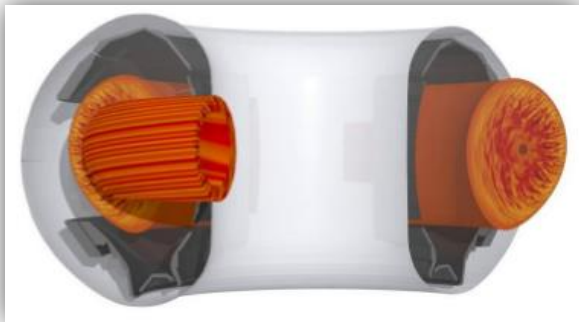
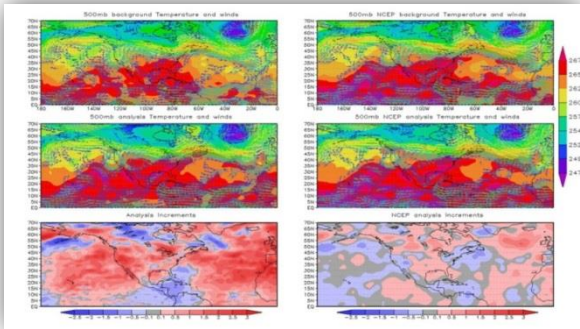


Christian Kästner

Even Domain Experts Struggle with Performance!



HPC Experts Meeting at Dagstuhl



Their Problem: Finding the Optimal Configuration for a Given Hardware Platform?

Binary configuration options

Coarse-grid solver

- ☐ IP_CG
- ☐ RED_AMG
- ☒ IP_AMG

Smoother

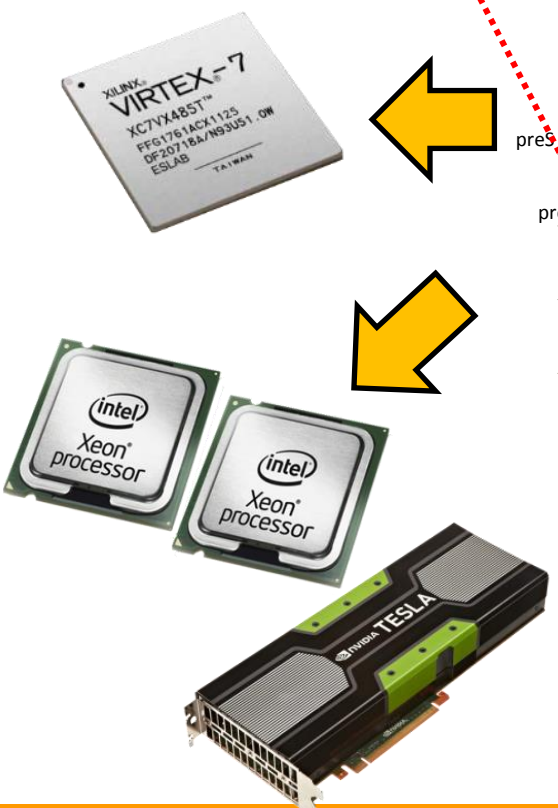
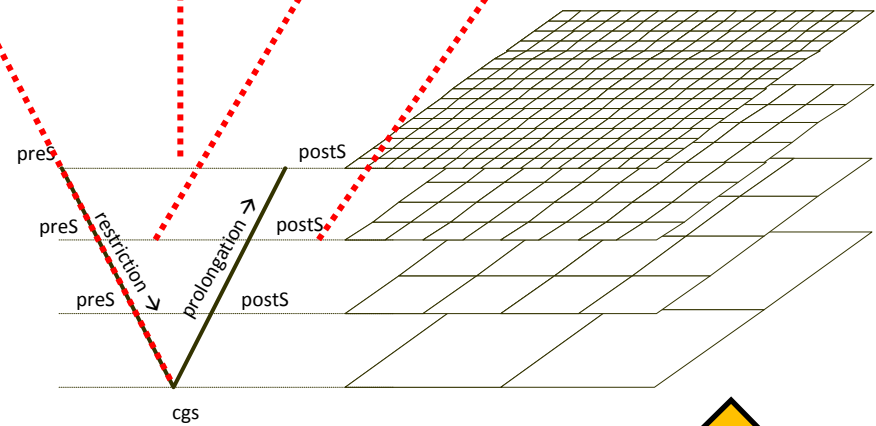
- ☒ Jac
- ☐ GS
- ☐ GSAC
- ☐ RBGS
- ☐ RBGSAC
- ☐ BS

Numeric configuration options

Pre-smoothing steps: 0 6

Post-smoothing steps: 0 6

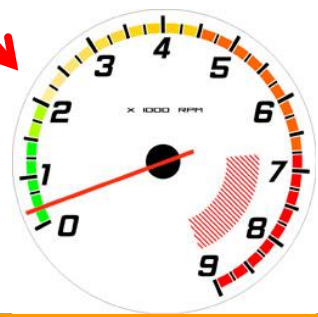
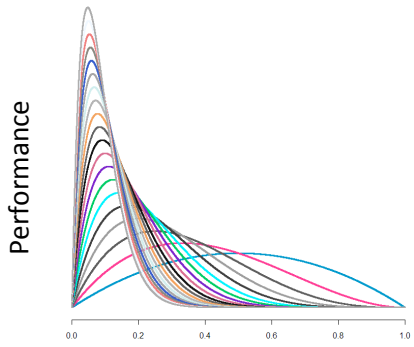
Stencil code



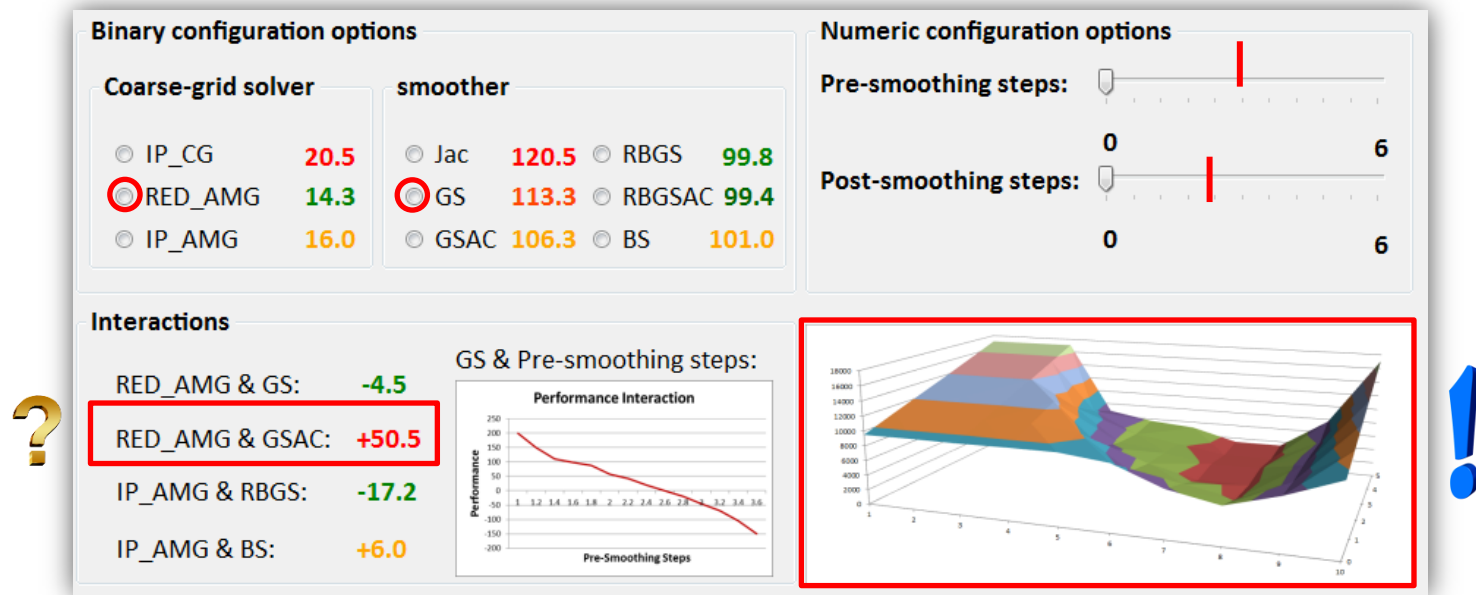
What is the Influence of Configuration Options on Performance?

Binary options

Numeric options



Vision: Performance-Influence Models

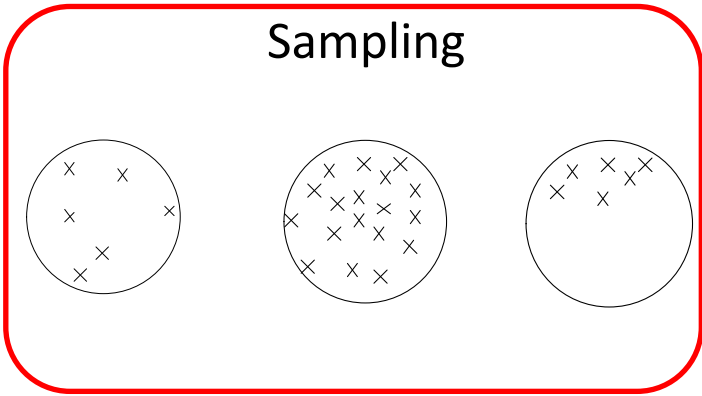


Determine the influence of configuration options and their interactions and use it for:

- Understanding
- Debugging
- Prediction and optimization

$$14.3 + 113.3 - 4.5 - 73.9 + 171.7 = 219.9$$

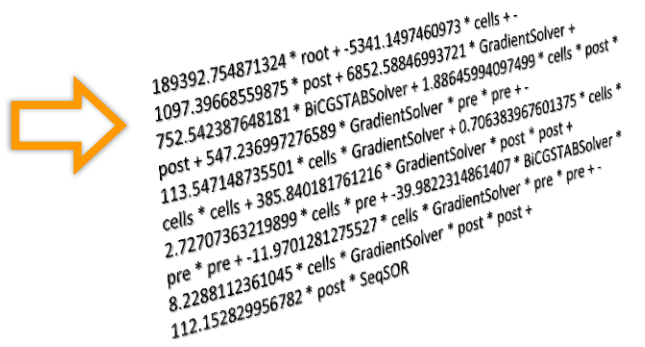
Learning Procedure



Learning

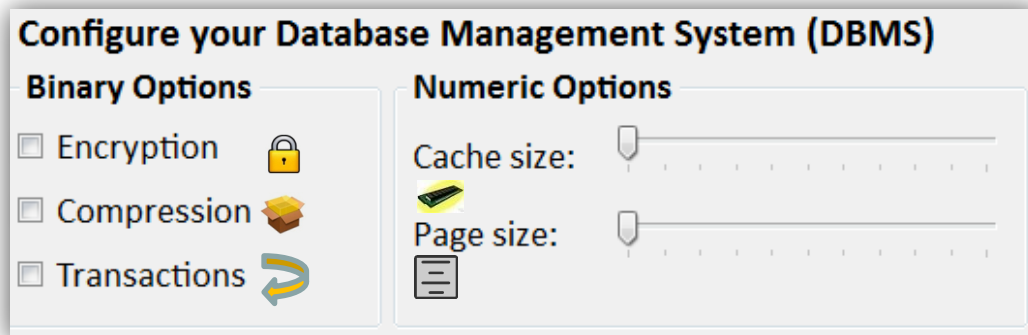


Performance-Influence Model

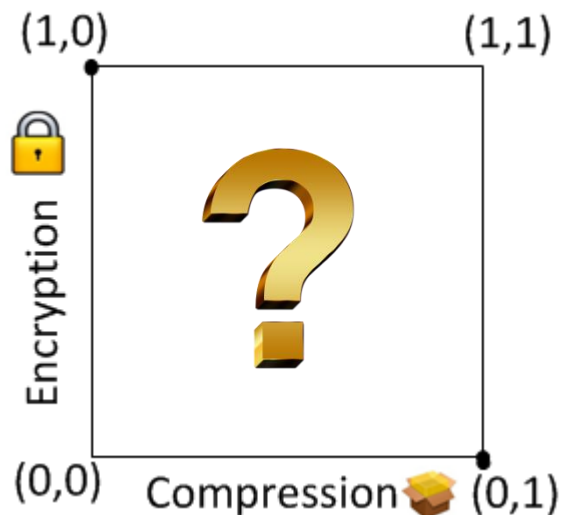


$$\begin{aligned} &189392.754871324 * \text{root} + -5341.1497460973 * \text{cells} + - \\ &1097.39668559875 * \text{post} + 6852.58846993721 * \text{GradientSolver} + \\ &752.542387648181 * \text{BiCGSTABSolver} + 1.88645994097499 * \text{cells} * \text{post} * \\ &\text{post} + 547.236997276589 * \text{GradientSolver} * \text{pre} * \text{pre} + - \\ &113.547148735501 * \text{cells} * \text{GradientSolver} + 0.706383967601375 * \text{cells} * \\ &\text{cells} * \text{cells} + 385.840181761216 * \text{GradientSolver} * \text{post} * \text{post} + \\ &2.72707363219899 * \text{cells} * \text{pre} + -39.9822314861407 * \text{BiCGSTABSolver} * \\ &\text{pre} * \text{pre} + -11.9701281275527 * \text{cells} * \text{GradientSolver} * \text{pre} * \text{pre} + - \\ &8.2288112361045 * \text{cells} * \text{GradientSolver} * \text{post} * \text{post} + \\ &112.152829956782 * \text{post} * \text{SeqSOR} \end{aligned}$$

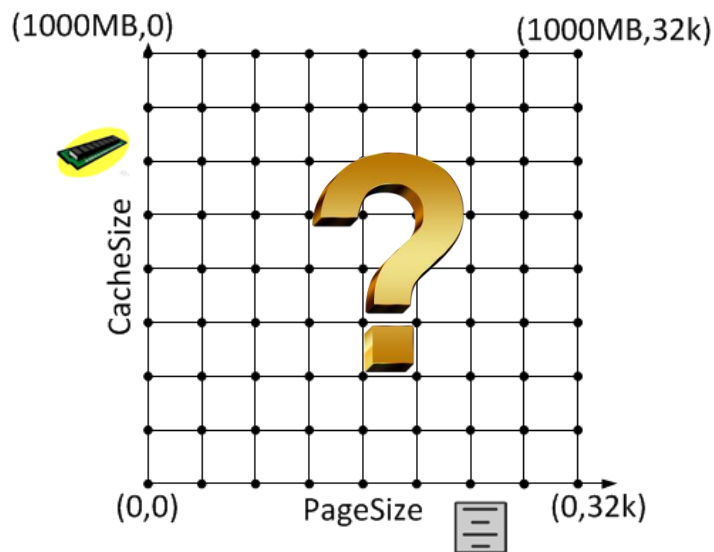
Sampling Binary and Numeric Options



Binary Options



Numeric Options



Exponential number!

Structured sampling approaches for the
different kinds of options

Heuristics for Binary-Option Sampling



Siegmund et al., ICSE'12

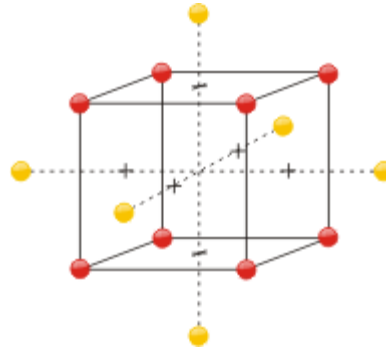
- Random?
 - Unlikely to select a valid configuration
 - Locally clustered solutions using SAT
- Heuristics
 - Option-Wise (OW): $\{\text{lock}, \{\text{box}\}, \{\text{arrow}\}, \{\text{cylinder}\}, \{\}$
 - Negative Option-Wise (nOW):

$$\{\text{lock}, \text{box}, \text{arrow}, \text{cylinder}\}, \{\text{lock}, \text{box}, \text{arrow}\}, \{\text{lock}, \text{box}, \text{cylinder}\}, \{\text{lock}, \text{arrow}, \text{cylinder}\}, \{\text{box}, \text{arrow}, \text{cylinder}\}$$
 - Pair-Wise (PW) : $\{\text{lock}, \text{box}\}, \{\text{box}, \text{arrow}\}, \{\text{arrow}, \text{cylinder}\}, \{\text{lock}, \text{arrow}\}, \{\text{lock}, \text{cylinder}\},$

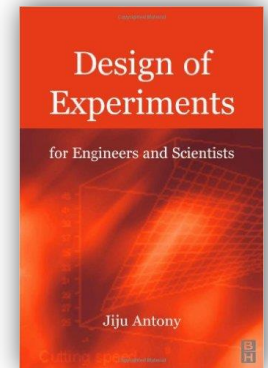
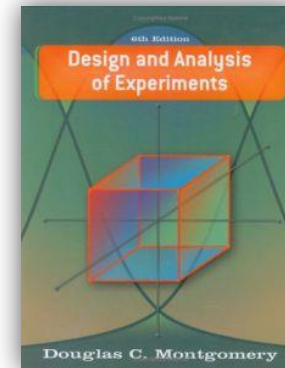
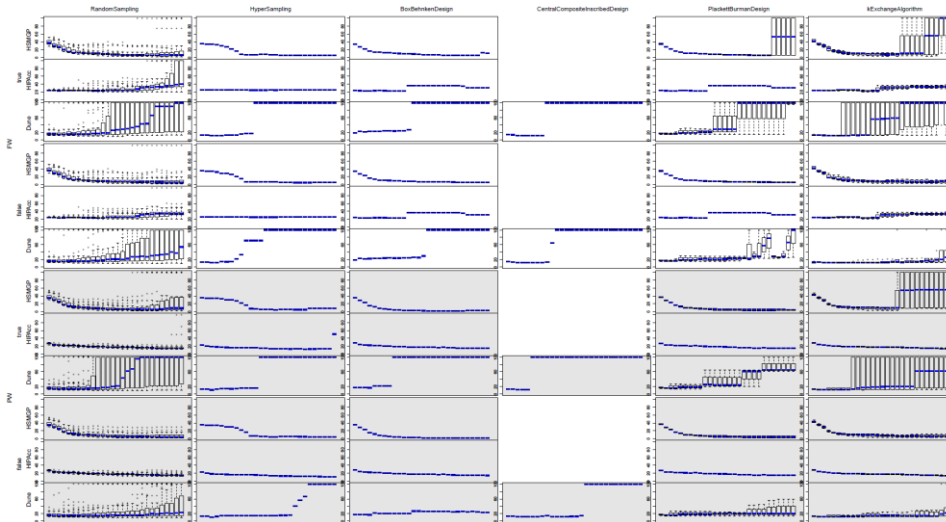
$$\{\text{box}, \text{cylinder}\}$$

Numeric-Option Sampling (Experimental Designs)

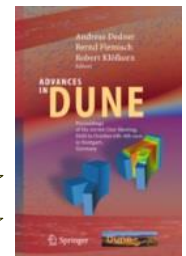
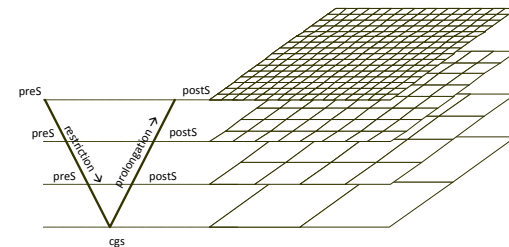
- Fractional factorial designs
- Optimal designs



- Pre-study:



Multi-grid solver as subject systems

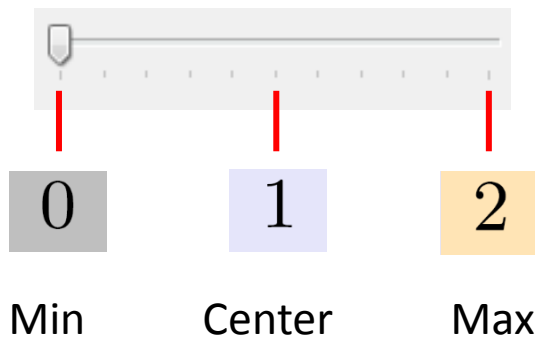


➞ Plackett-Burman Design as best design

Plackett-Burman Design (PBD)

- Minimizes the variance of the estimates of the independent variables (numeric options)
- ...while using a limited number of measurements
- Design specifies *seeds* depending on the number of experiments to be conducted (i.e., configurations to be measured)

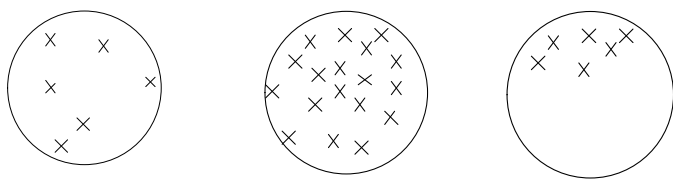
Value range of a numeric option



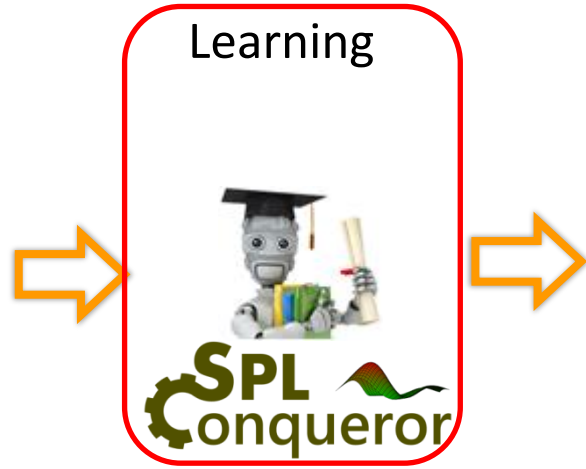
		Numeric options							
		o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8
Configurations	c_1	0	1	1	2	0	2	2	1
	c_2	1	0	1	1	2	0	2	2
	c_3	2	1	0	1	1	2	0	2
	c_4	2	2	1	0	1	1	2	0
	c_5	0	2	2	1	0	1	1	2
	c_6	2	0	2	2	1	0	1	1
	c_7	1	2	0	2	2	1	0	1
	c_8	1	1	2	0	2	2	1	0
	c_9	0	0	0	0	0	0	0	0

Learning Procedure

Sampling



Learning



Performance-Influence Model

$189392.754871324 * \text{root} + -5341.1497460973 * \text{cells} + -$
 $1097.39668559875 * \text{post} + 6852.58846993721 * \text{GradientSolver} +$
 $752.542387648181 * \text{BiCGSTABSolver} + 1.88645994097499 * \text{cells} * \text{post} *$
 $\text{post} + 547.236997276589 * \text{GradientSolver} * \text{pre} * \text{pre} + -$
 $113.547148735501 * \text{cells} * \text{GradientSolver} * \text{post} * \text{post} +$
 $\text{cells} * \text{cells} + 385.840181761216 * \text{GradientSolver} * \text{post} * \text{post} +$
 $2.72707363219899 * \text{cells} * \text{pre} + -39.9822314861407 * \text{BiCGSTABSolver} *$
 $\text{pre} * \text{pre} + -11.9701281275527 * \text{cells} * \text{GradientSolver} * \text{pre} * \text{pre} + -$
 $8.2288112361045 * \text{cells} * \text{GradientSolver} * \text{post} * \text{post} +$
 $112.152829956782 * \text{post} * \text{SeqSOR}$

Regression Learning

Exponential number!

Unlimited candidates!

Individual Options

Interactions

Functions

Configurations

				
1	0	0	20	0
0	1	1	50	16
1	0	1	100	32
1	1	0	50	32
1	1	1	20	32
0	0	0	100	0
1	1	1	100	16

*

*

*

*

*

*

*

*

*

*

*

β_1

β_2

β_3

β_4

β_5

β_6

β_7

β_8

β_9

β_{10}

			
0	0	0	0
0	0	800	0
0	0	0	0
1	0	1600	0
1	1	640	0
0	0	0	0
1	1	1600	0

0

0

800

0

	
400	N/A
2500	1.2
10000	0.9
2500	1.5
400	1.5
10000	N/A
10000	1.2

400

N/A

2500

1.2

10000

0.9

2500

1.5

400

1.5

10000

N/A

10000

1.2

=

Perf.

833

411

290

799

753

514

416

Error:

41%

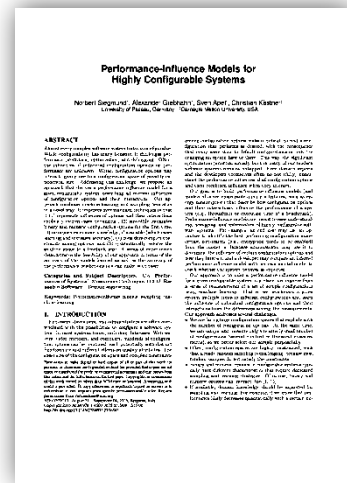
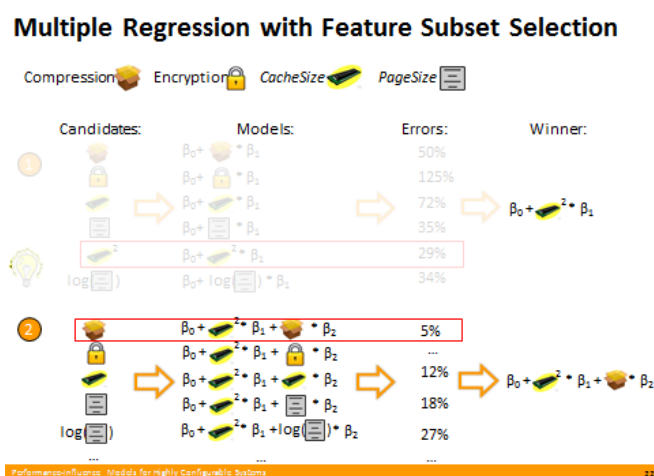
25%

7.4%



Multiple Regression with Feature Subset Selection

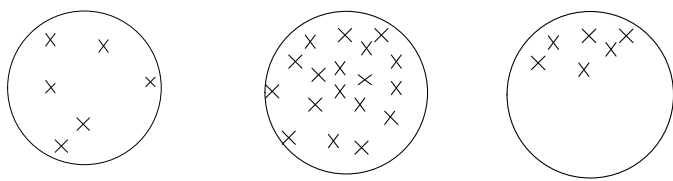
- Extend model in a stepwise manner
- Probe different candidates
 - Individual influences, interactions, functions



Siegmund et al., FSE'15

Learning Procedure

Sampling



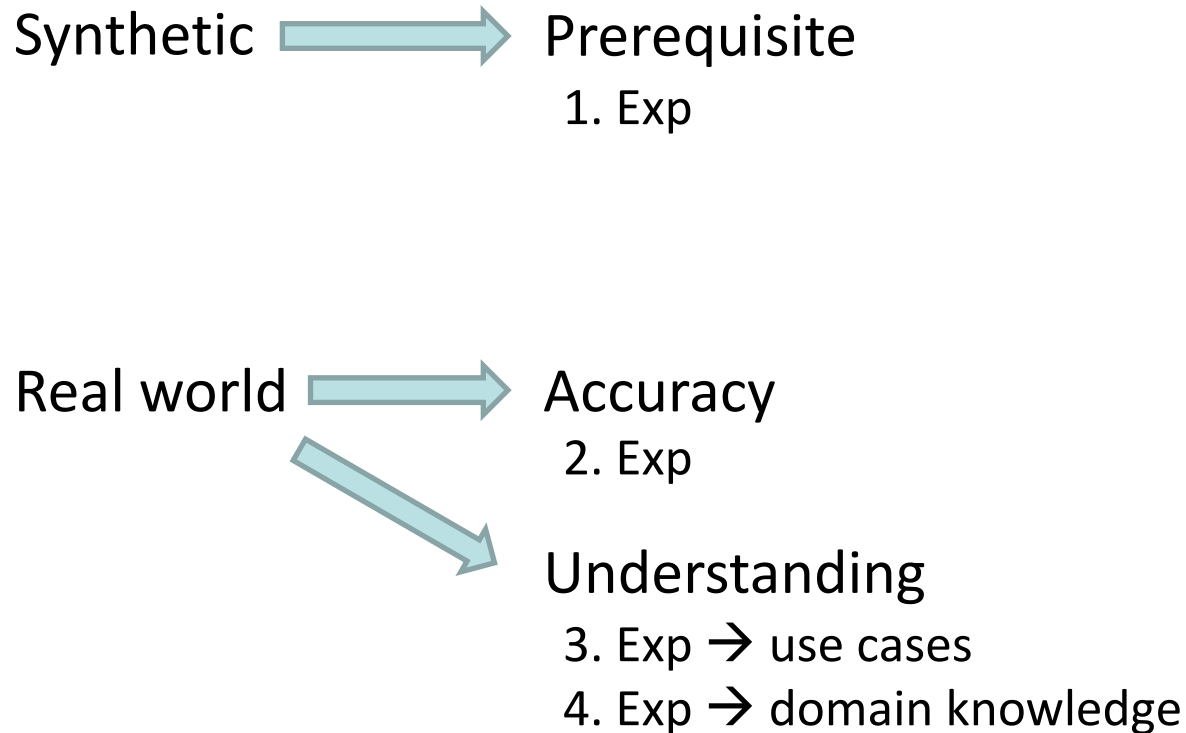
Learning



Performance-Influence Model

```
189392.754871324 * root + -5341.1497460973 * cells + -  
1097.39668559875 * post + 6852.58846993721 * GradientSolver +  
752.542387648181 * BiCGSTABSolver + 1.88645994097499 * cells * post *  
post + 547.236997276589 * GradientSolver * pre * pre + -  
113.547148735501 * cells * GradientSolver + 0.706383967601375 * cells *  
cells * cells + 385.840181761216 * GradientSolver * post * post +  
2.72707363219899 * cells * pre + -39.9822314861407 * BiCGSTABSolver *  
pre * pre + -11.9701281275527 * cells * GradientSolver * pre * pre + -  
8.2288112361045 * cells * GradientSolver * post * post +  
112.152829956782 * post * SeqSOR
```

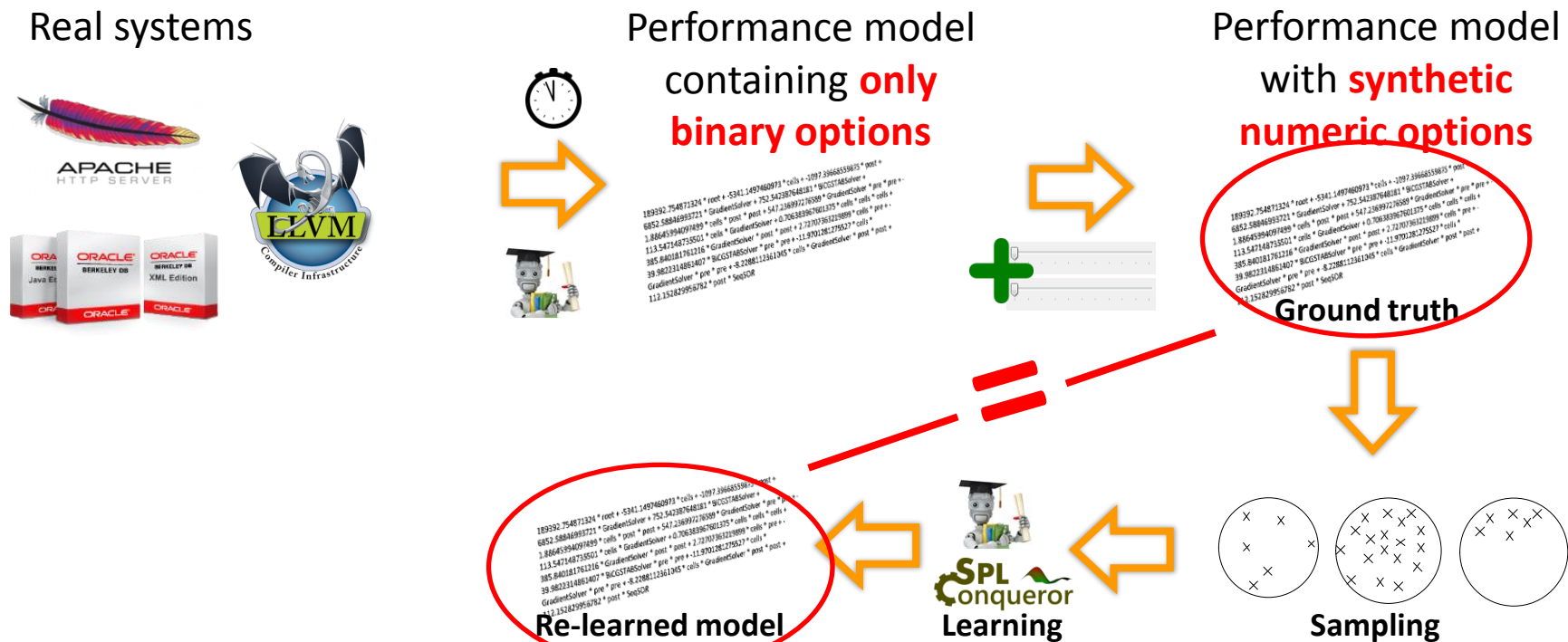

Experimental Evaluation



1. Experiment: Finding the Actual Influences

RQ: Do we find the actually existing influences and interactions?

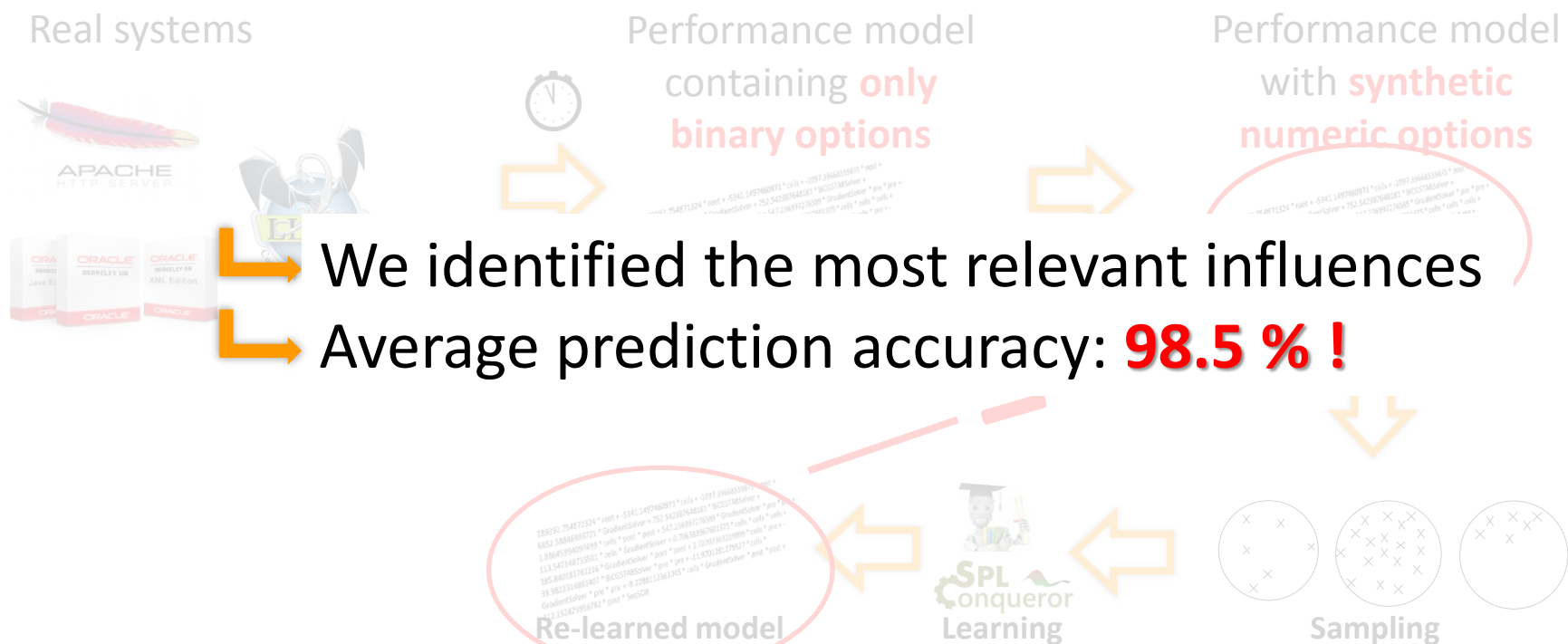
- Design:



1. Experiment: Finding the Actual Influences

RQ: Do we find the actually existing influences and interactions?

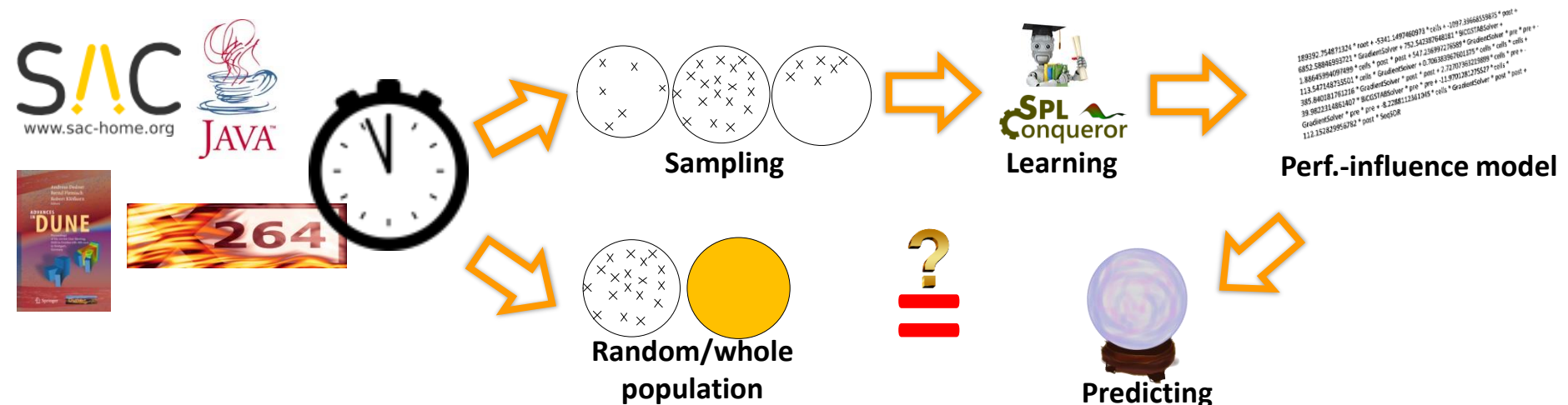
- Design:



2. Experiment: Performance Prediction

RQ: Which combination of sampling approaches achieve the highest prediction accuracy?

System	Domain	# Binary Opt.	# Numeric Opt.	# Constraints	# Configs
Dune MGS	Multi-Grid Solver	8	3	20	2 304
HIPAC ^{cc}	Image Processing	31	2	416	13 485
HSMGP	Multi-Grid Solver	11	3	45	3 456
JavaGC	Runtime Env.	12	23	4	10^{31}
SaC	Compiler	53	7	10	10^{23}
x264	Video Encoder	8	13	0	10^{27}



2. Experiment: Performance Prediction

RQ: Which combination of sampling approaches achieve the highest prediction accuracy?

System	Domain	# Binary Opt.	# Numeric Opt.	# Constraints	# Configs
Dune MGS	Multi-Grid Solver	8	3	20	2 304
HIPAcc	Image Processing	31	2	416	13 485
HSMGP	Multi-Grid Solver	11	3	45	3 456
JavaGC	Runtime Env	12	22	1	10 ³¹

→ Average prediction accuracy (PW+PBD): **86.8 % !**

→ Experimental designs are better than random sampling

SAC
www.sac-home.org

JAVA



Sampling



SPL
Conqueror
Learning



Perf.-influence model

```
017.20488320675 "grid" *  
"BCC073456400" *  
40 "GradGridSolver" * "grid" * "grid" *  
1011295 "cells" * "cells" * "cells" *  
1010223989 "cells" * "cells" * "grid" *  
101281275521 "cells" *  
"GradGridSolver" * "grid" * "grid" *  
385.840081 "grid" *  
38.182314481407 "BCC073456400" *  
GradGridSolver "grid" * "grid" * 5.220811336339e-  
11.3.332823958762 "grid" * "grid" *
```



Random/whole
population



Predicting



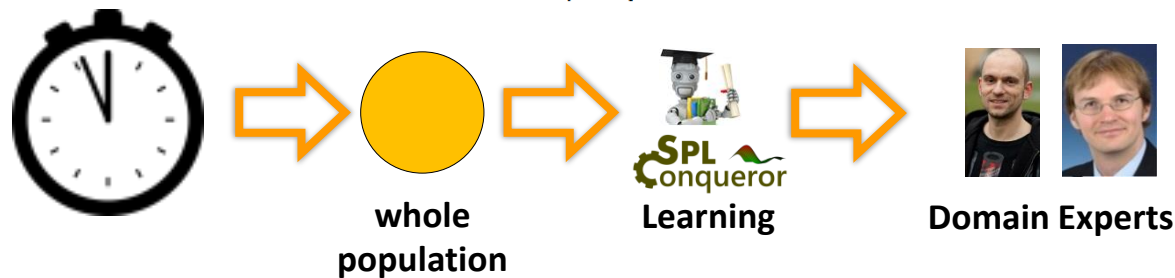
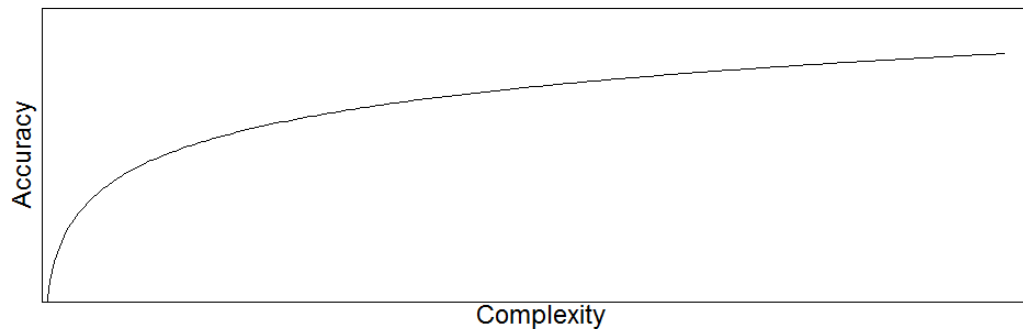
3. Experiment: Accuracy vs. Complexity

Collaboration with:



Sergiy
Kolesnikov

- RQ: Is it necessary to learn accurate but complex models?



➤ It depends on the use case. Simple models help to identify the most relevant influences.

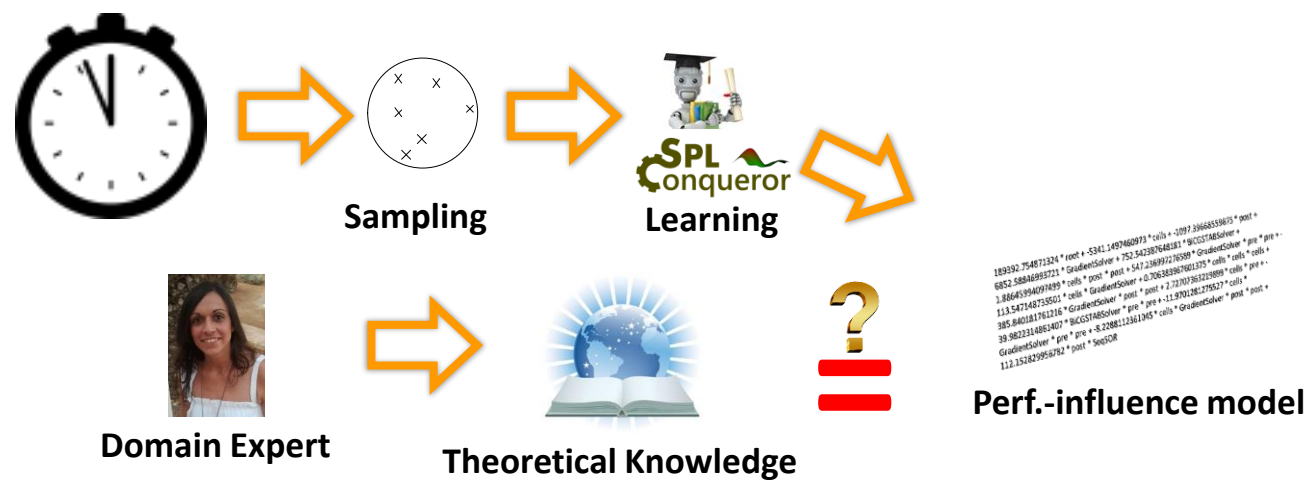
4. Experiment: Validation of Domain Knowledge

Collaboration with:



Carmen Rodrigo Francisco Gaspar

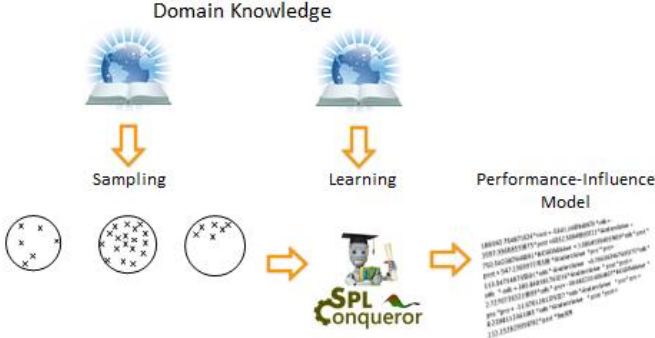
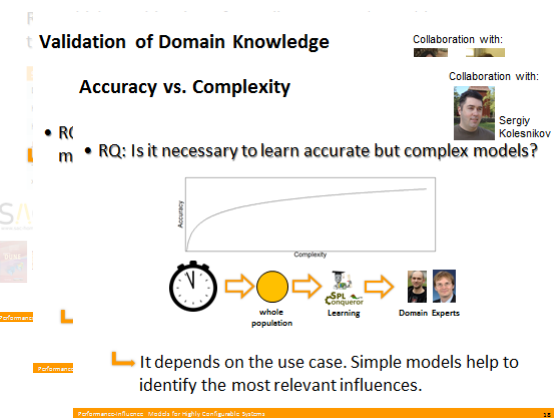
- RQ: Are we able to validate domain knowledge using a model?



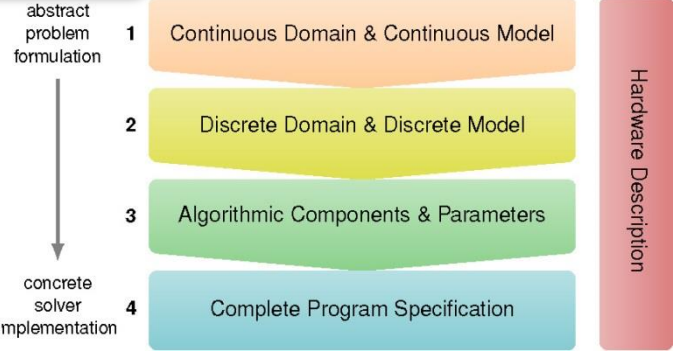
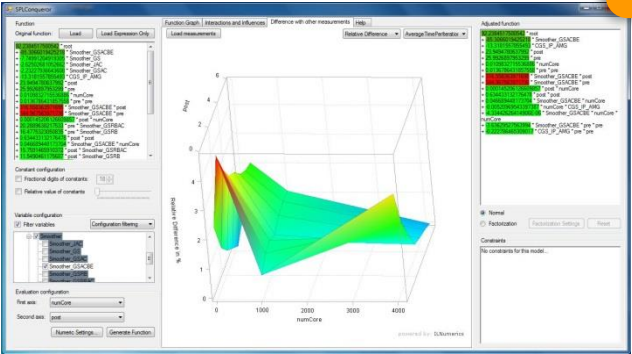
➡ Validate domain knowledge

Findings and Future Work

Evaluation: Performance Prediction



Thank You!



<https://github.com/nsiegmun/SPLConqueror>
<http://fosd.de/SPLConqueror/>