Minimizing the Cost of Iterative Compilation with Active Learning

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Finishing his PhD soon :)

Performance tuning is hard!

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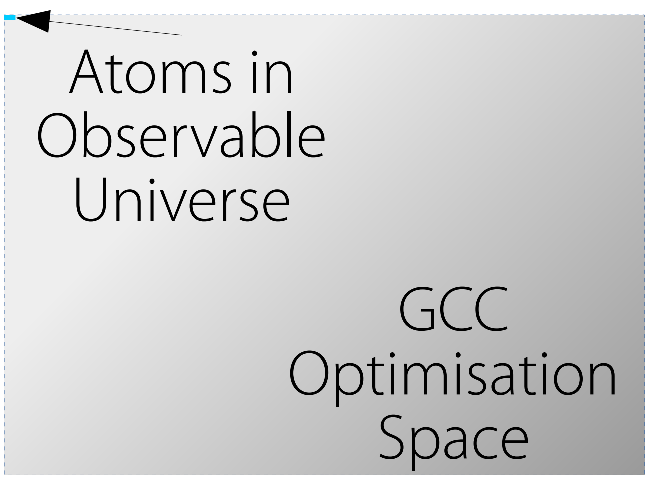
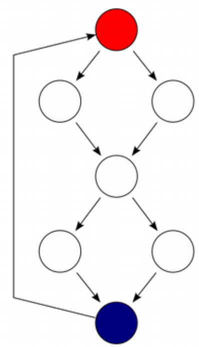
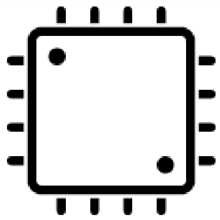


Performance tuning is hard!

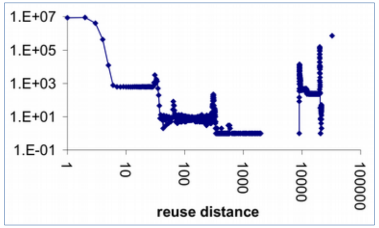
Atoms in Observable Universe

GCC Optimisation Space





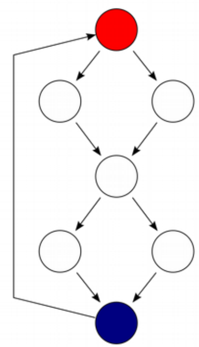
Runtime: …
Memory Usage: …
DL1 misses: …
L2 misses:…
…
…

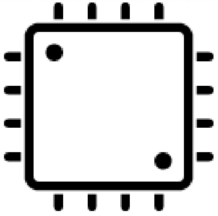


Performance tuning is hard!

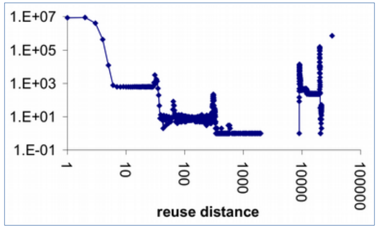
Atoms in Observable Universe

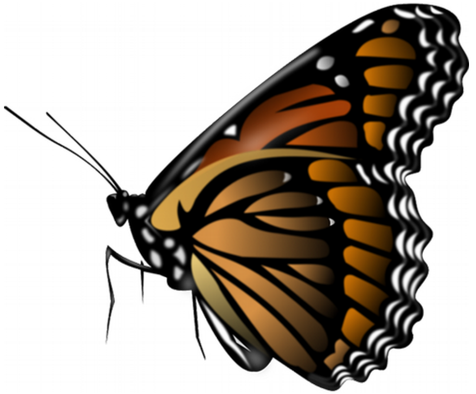
GCC Optimisation Space





Runtime: …
Memory Usage: …
DL1 misses: …
L2 misses:…
…
…





Performance tuning is hard!

ML to the rescue

Heterogeneous mapping

Heterogeneous mapping

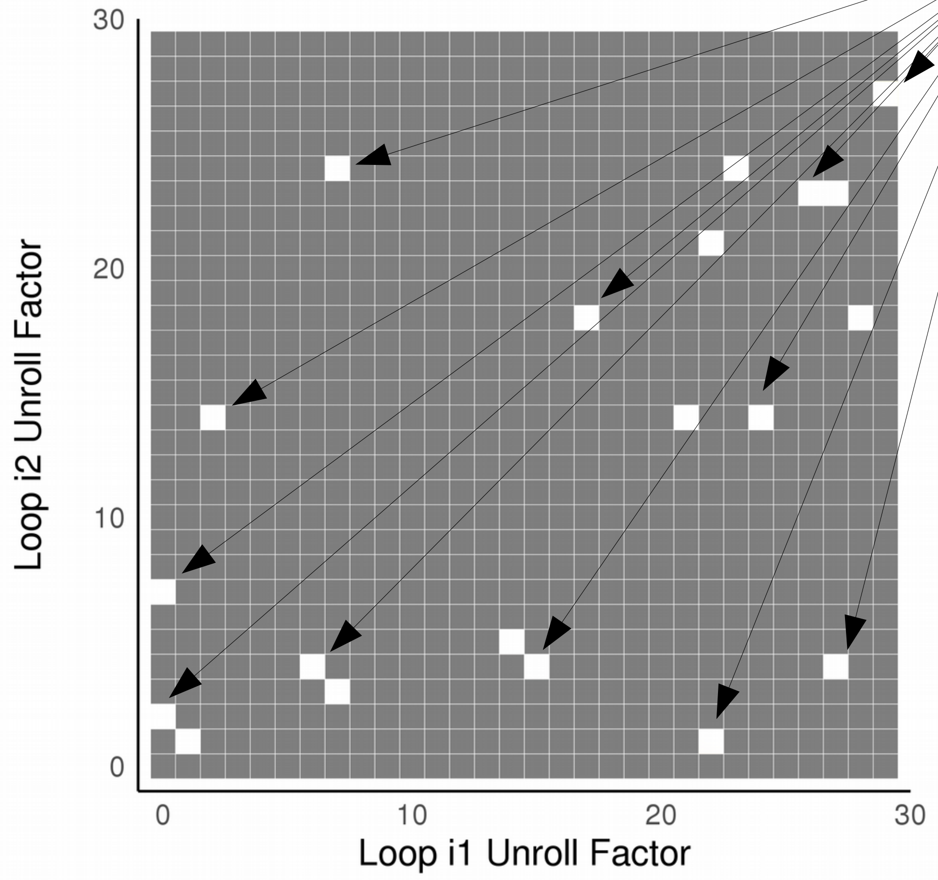
Workgroup size autotuning

Heterogeneous mapping

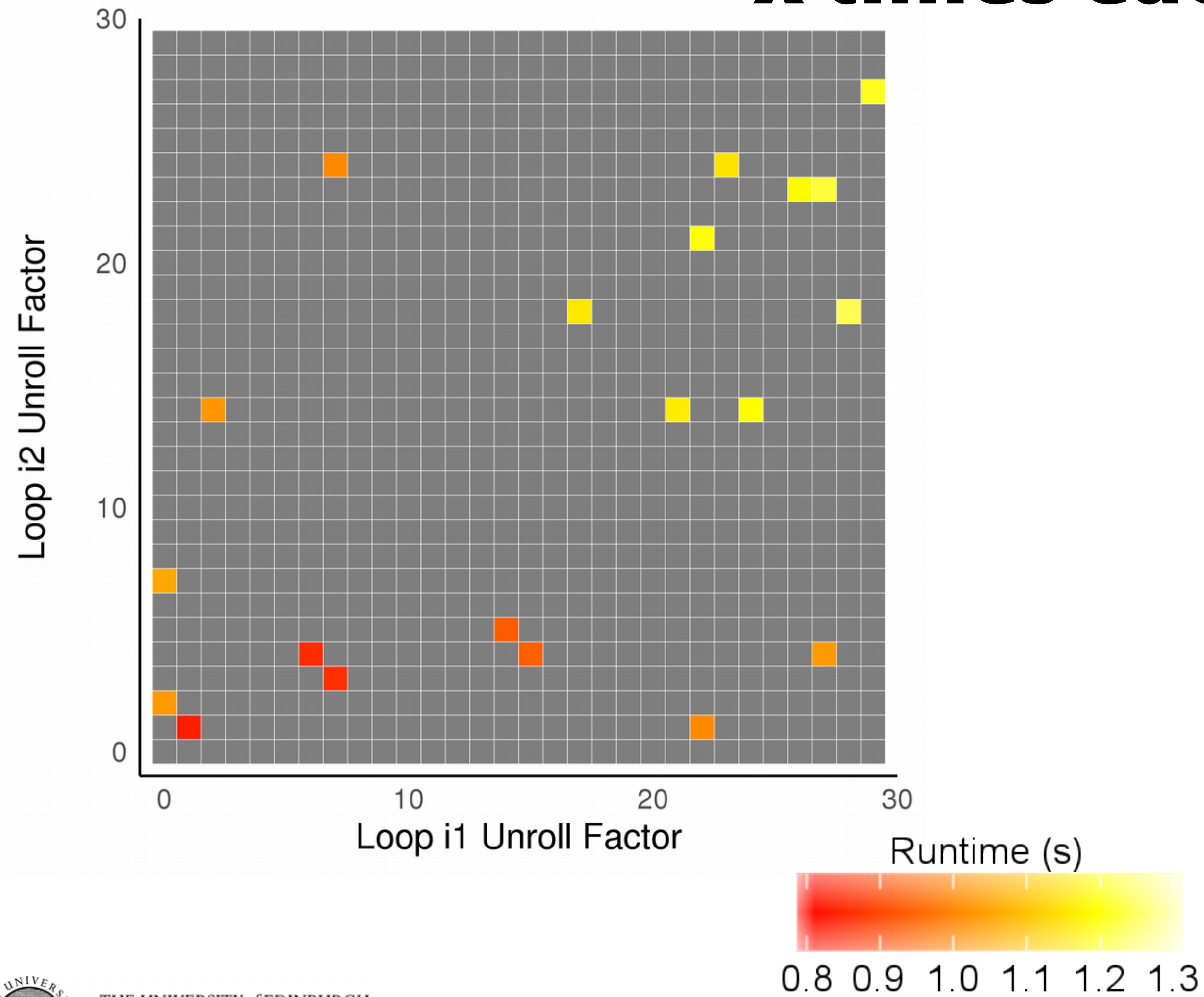
Workgroup size autotuning

Compiler optimizations

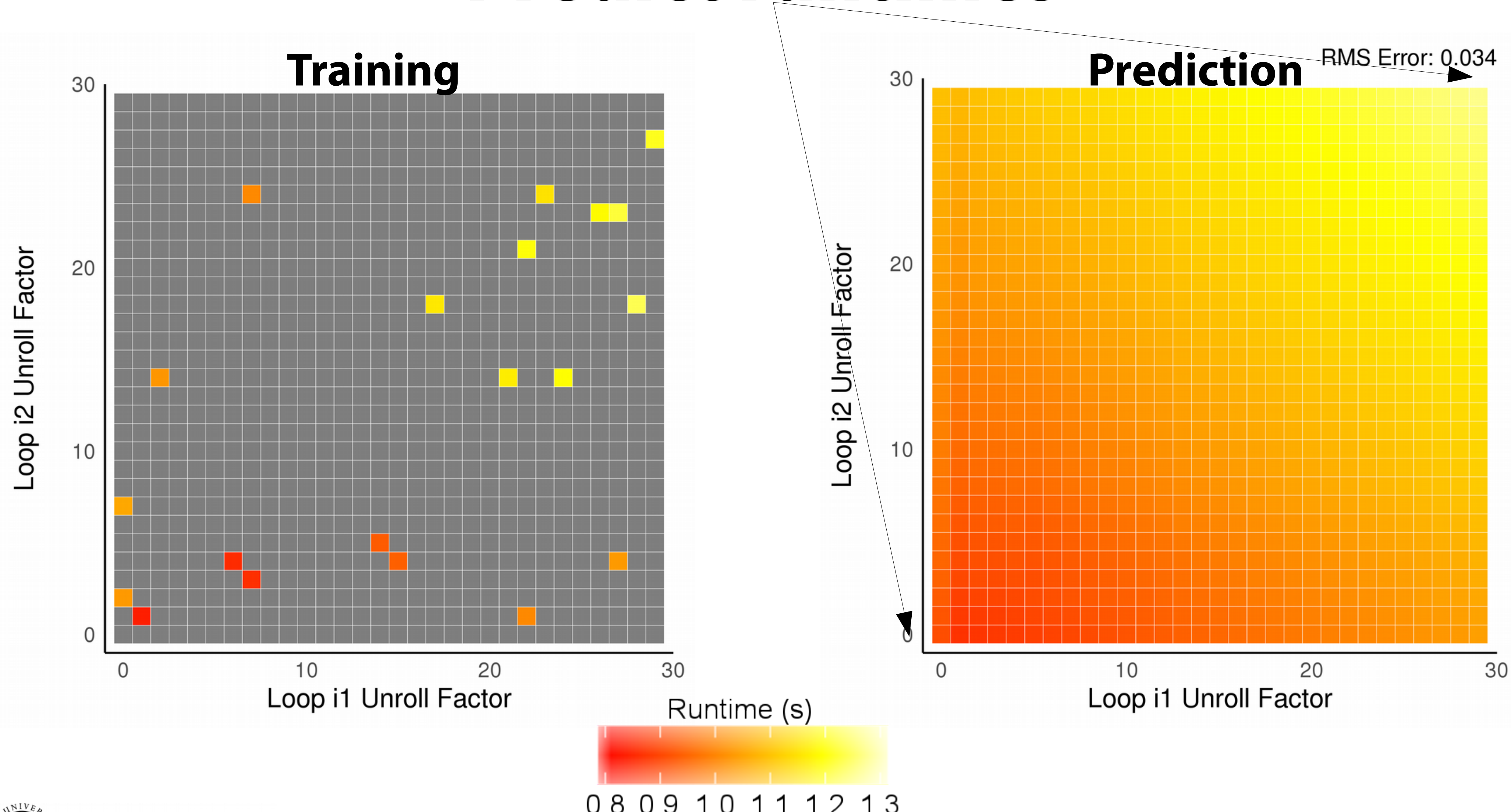
Select Points



Profile
x times each



Predict runtimes



Too slow!

1Ks to1Ms of points
10s of observations for each

Faster?

Faster?

	Machine Learning		
Training Points	Random, preselected		
Profiling runs	Fixed, preselected		

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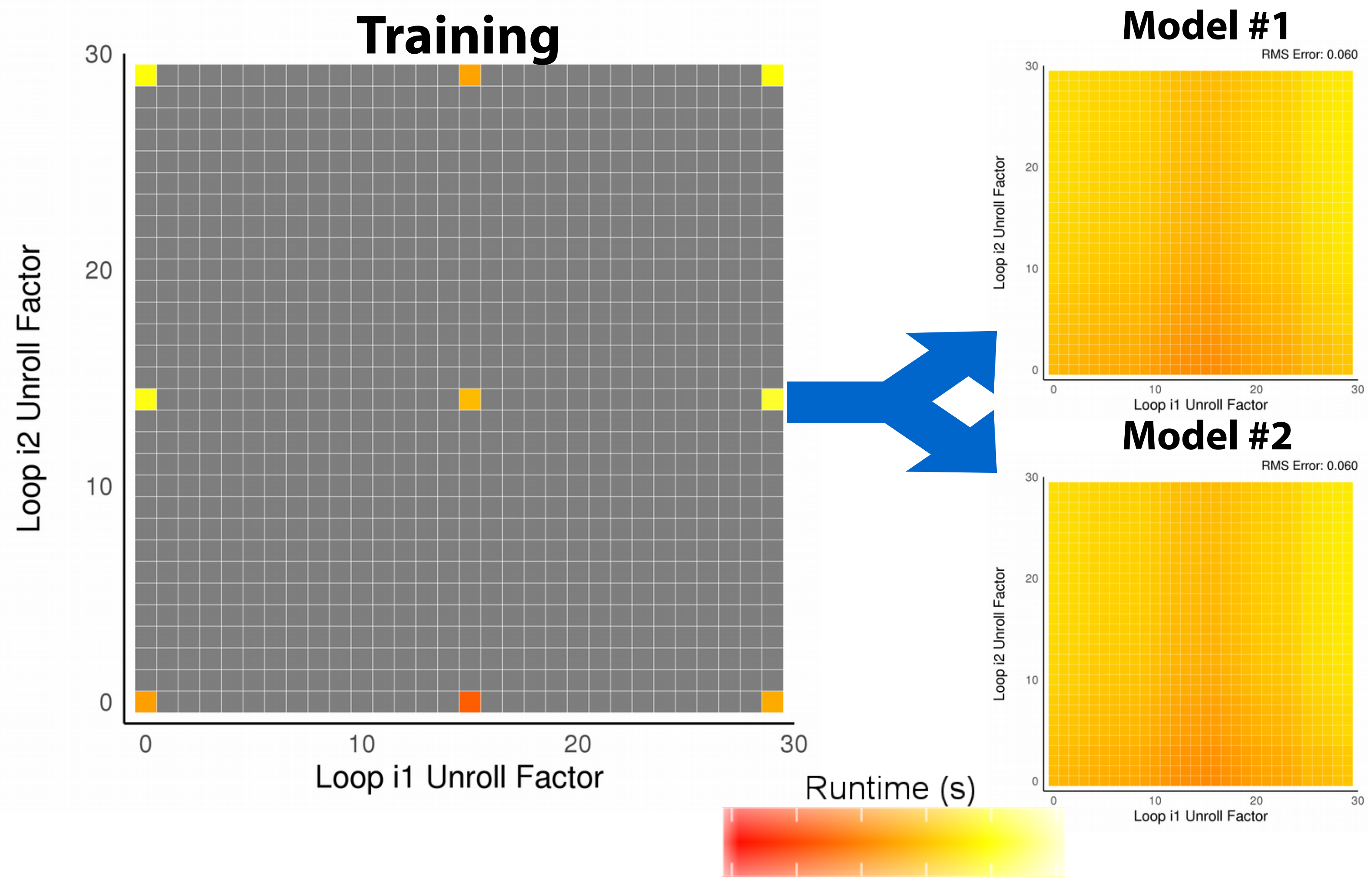
Faster?

	Machine Learning	**?**	
Training Points	Random, preselected	**High info points**	
Profiling runs	Fixed, preselected	Fixed, preselected	

Faster?

	Passive Learning	**Active Learning**	
Training Points	Random, preselected	**ML-guided selection**	
Profiling runs	Fixed, preselected	Fixed, preselected	

Multiple models



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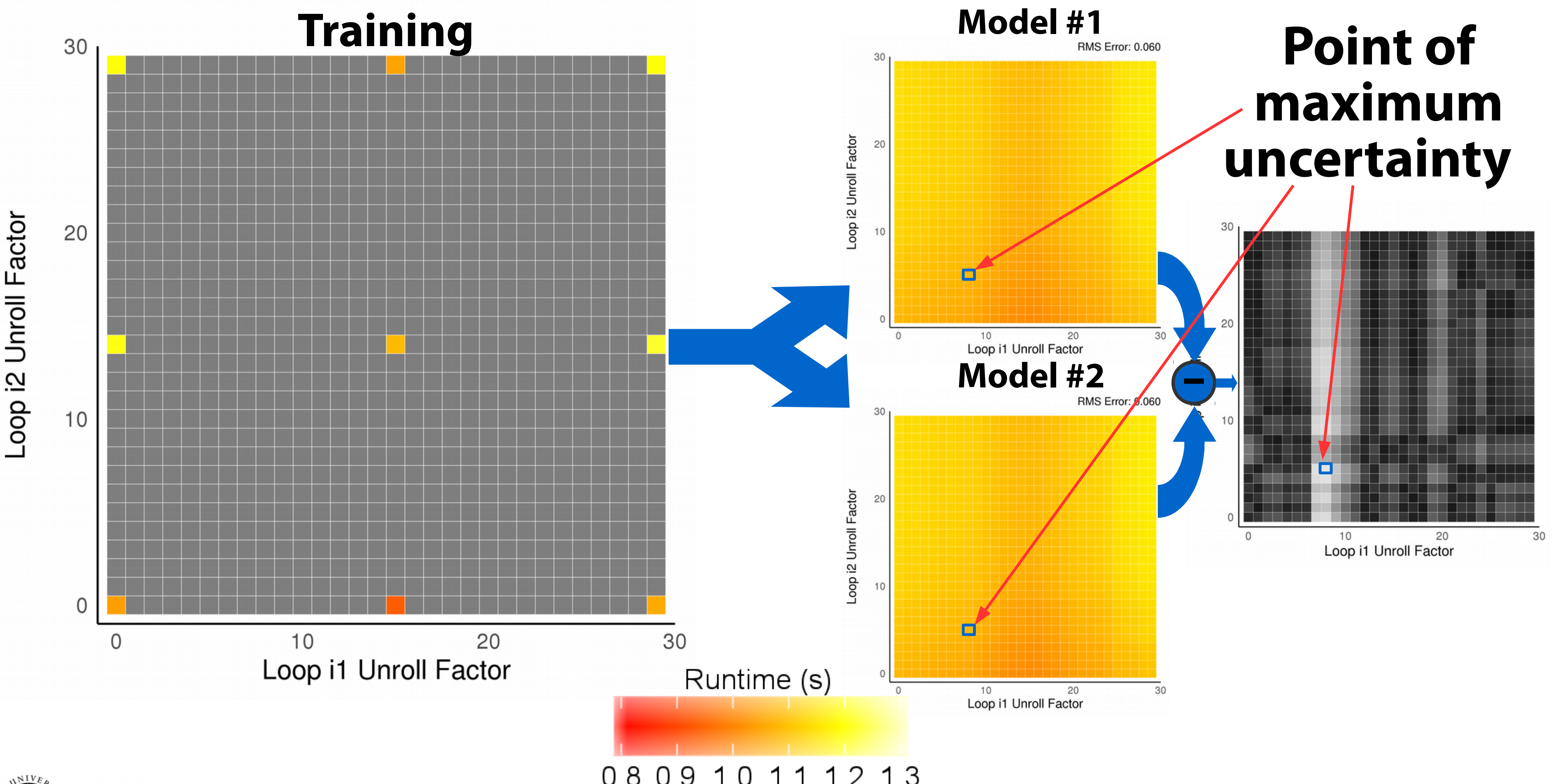
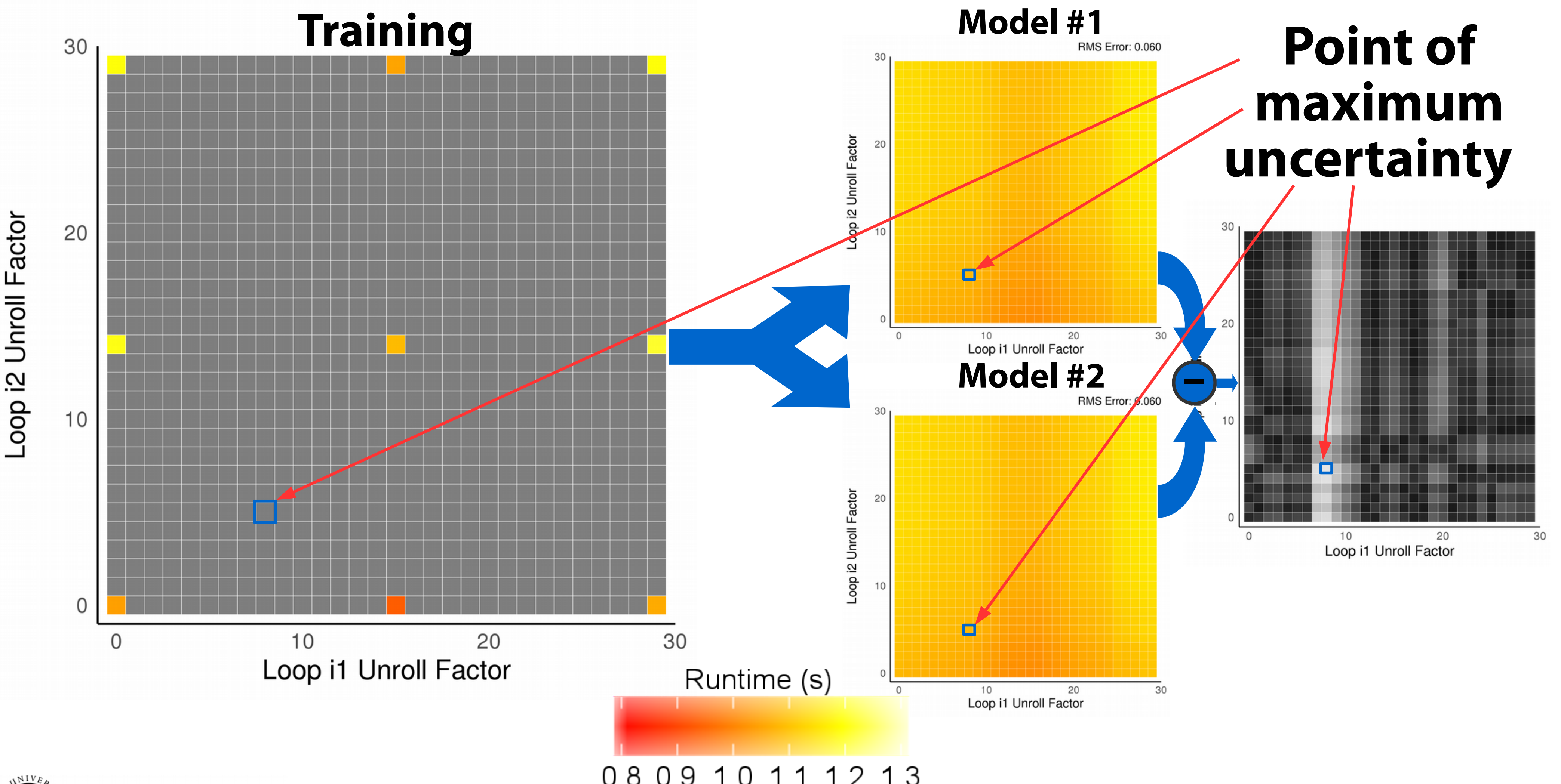
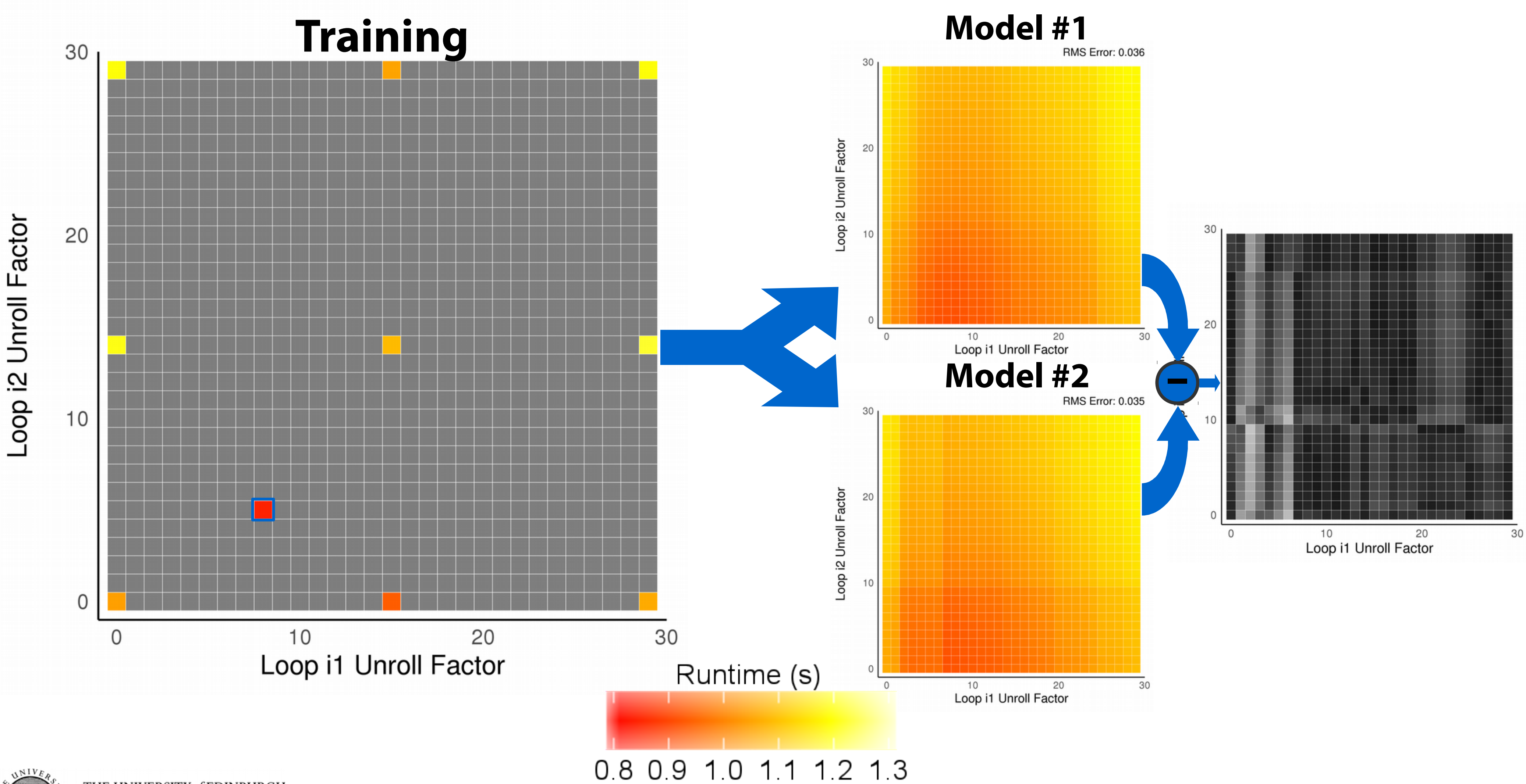
Find high uncertainty points



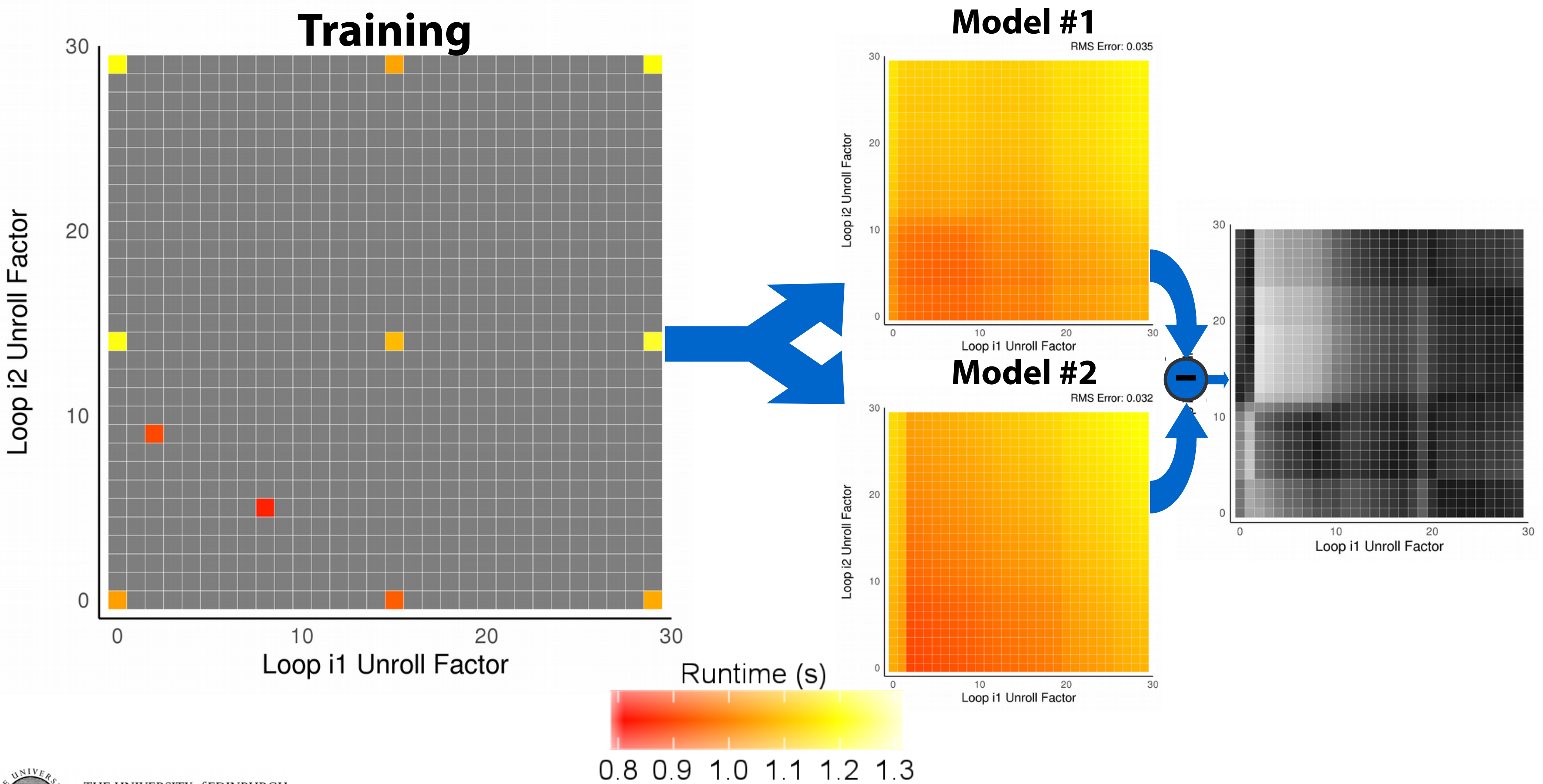
Select them


Training
Loop i2 Unroll Factor
Loop i1 Unroll Factor
0
10
20
30
Runtime (s)
0.8 0.9 1.0 1.1 1.2 1.3
Model #1
RMS Error: 0.060
Model #2
RMS Error: 0.060
Point of maximum uncertainty

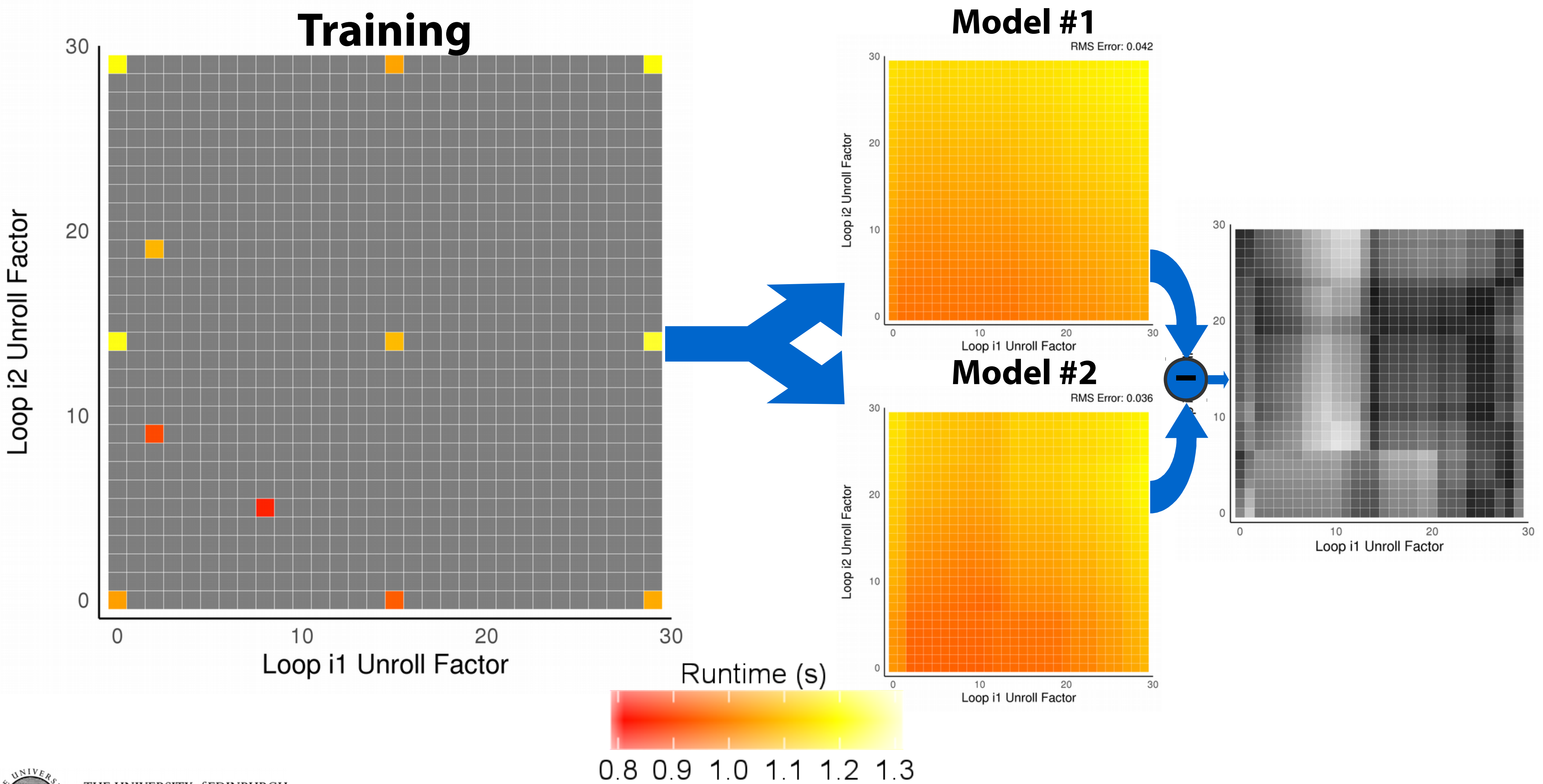
Profile them



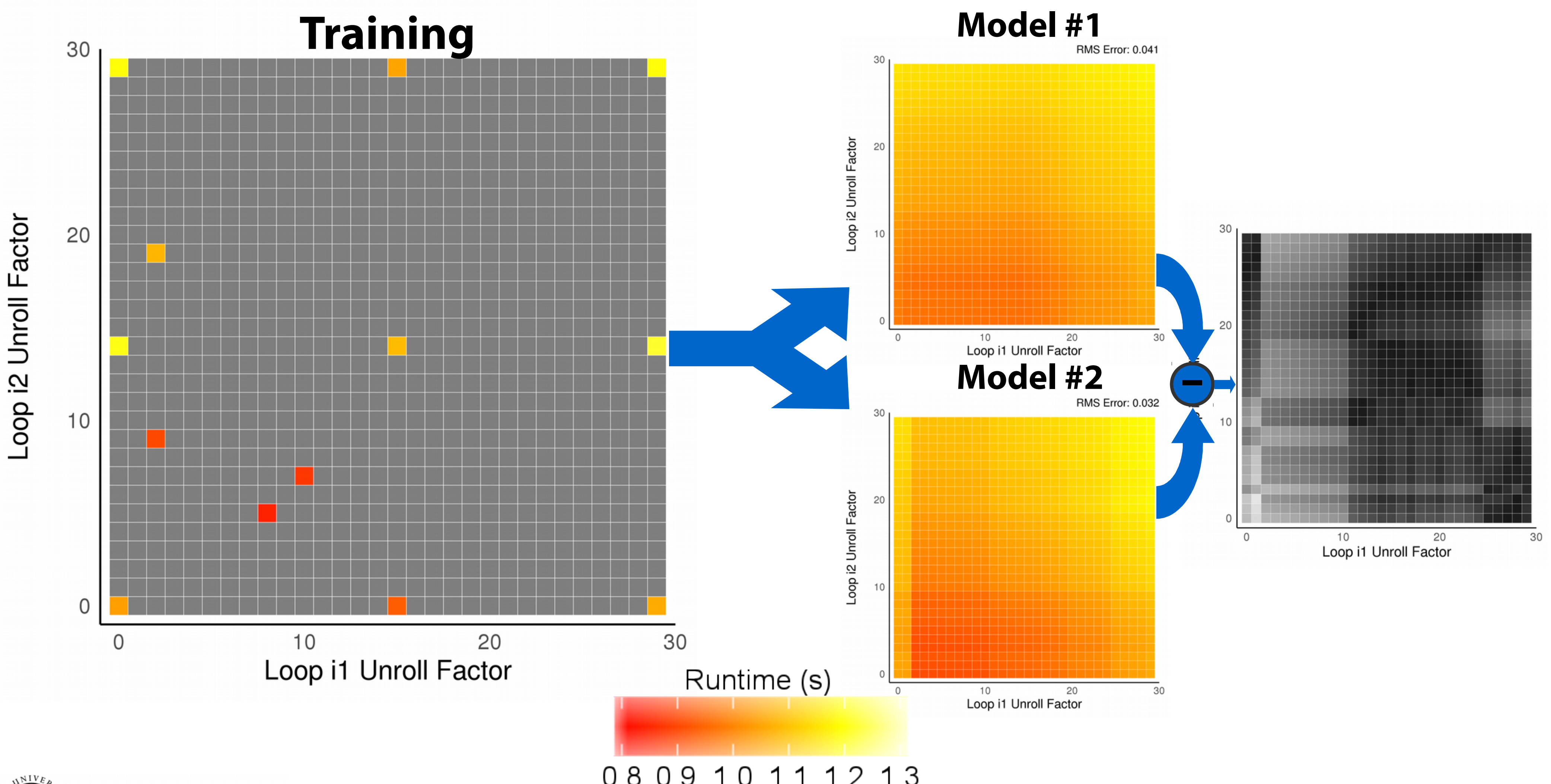
Repeat


Training
30
20
10
0
Loop i2 Unroll Factor
0
10
20
30
Loop i1 Unroll Factor
Runtime (s)
0.8 0.9 1.0 1.1 1.2 1.3
Model #1
RMS Error: 0.035
Loop i2 Unroll Factor
Loop i1 Unroll Factor
Model #2
RMS Error: 0.032
Loop i2 Unroll Factor
Loop i1 Unroll Factor
Loop i1 Unroll Factor

Repeat


Training
30
20
10
0
Loop i2 Unroll Factor
0
10
20
30
Loop i1 Unroll Factor
Model #1
RMS Error: 0.042
Model #2
RMS Error: 0.036
Runtime (s)
0.8 0.9 1.0 1.1 1.2 1.3

Repeat

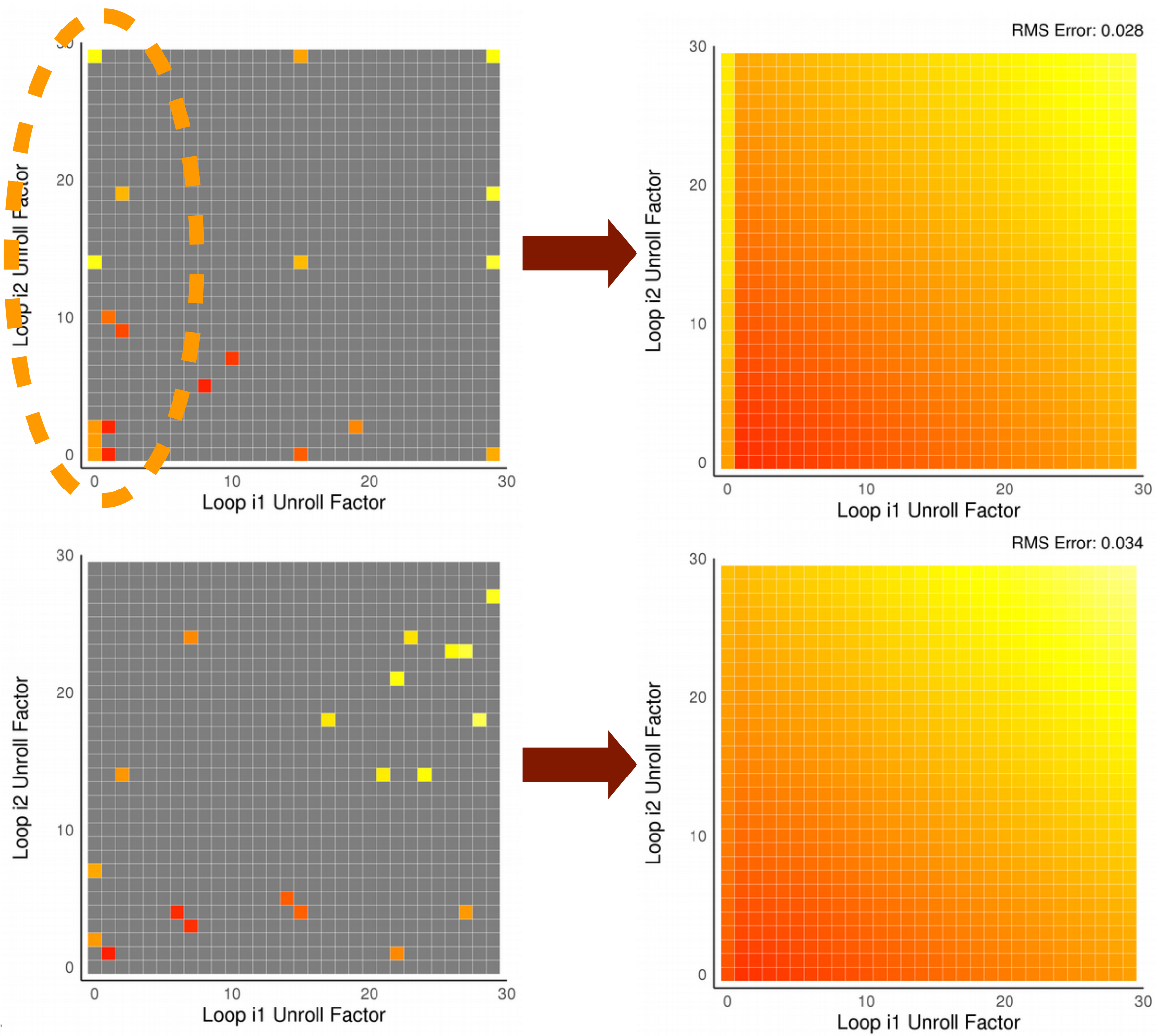


Training
30
20
10
0
0
10
20
30
Loop i2 Unroll Factor
Loop i1 Unroll Factor
Model #1
RMS Error: 0.041
Model #2
RMS Error: 0.032
Runtime (s)
0.8 0.9 1.0 1.1 1.2 1.3

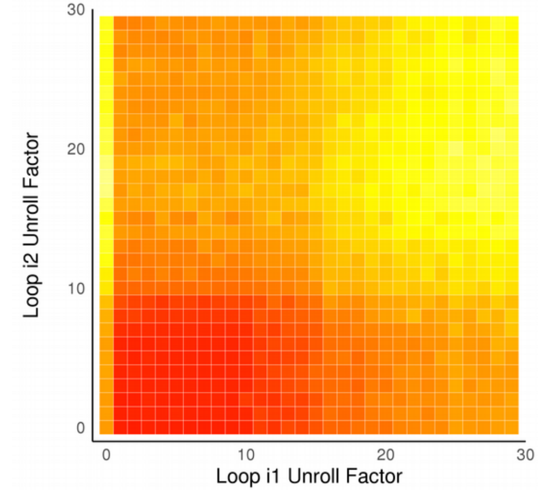
Training | Prediction

Active

Passive



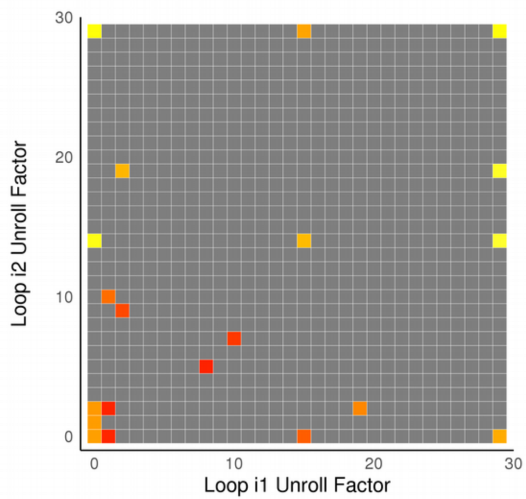
Runtime Measurements

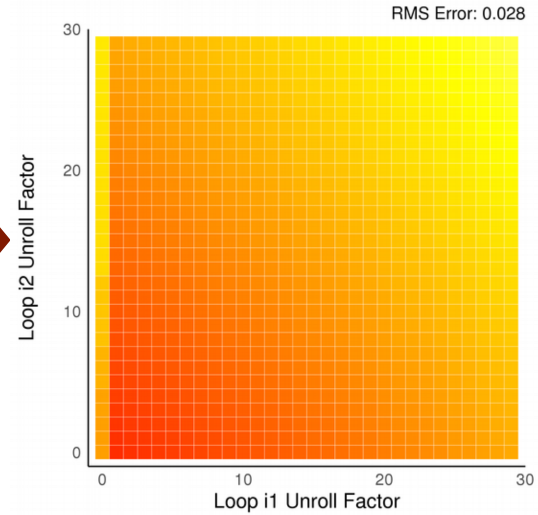


Training

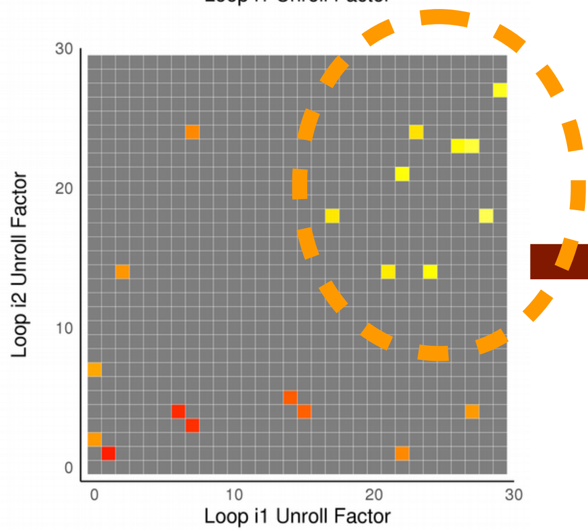
Prediction

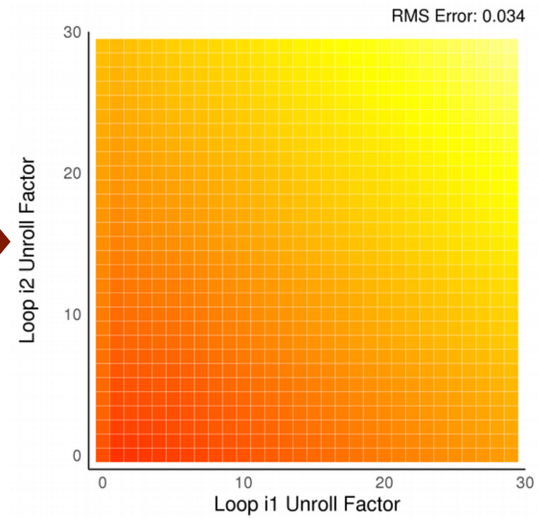
Active



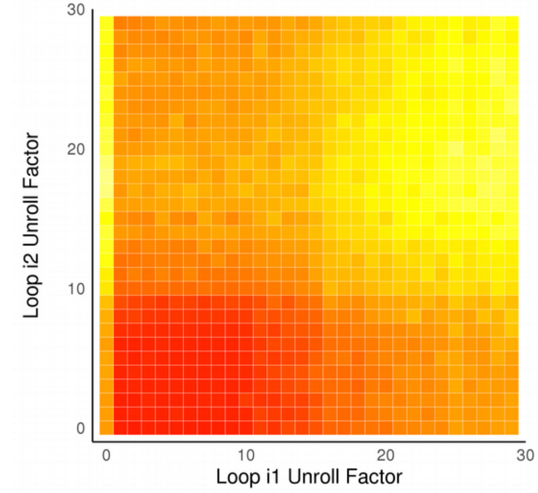


Passive





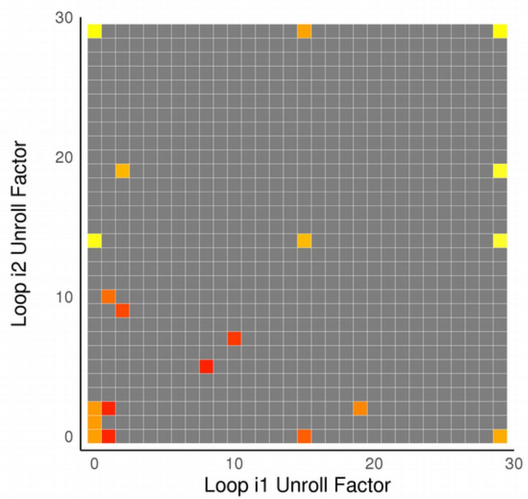
Runtime Measurements

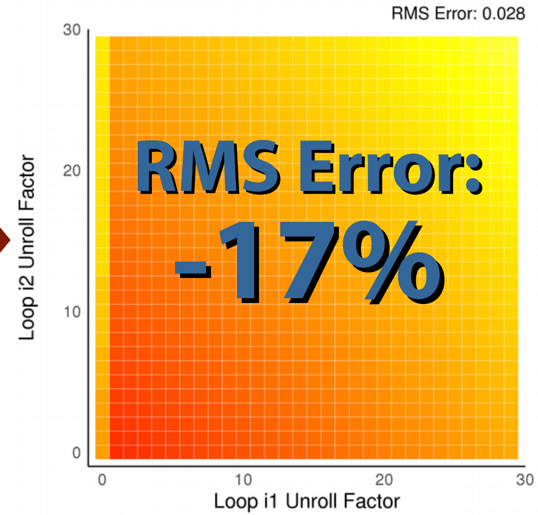


Training

Prediction

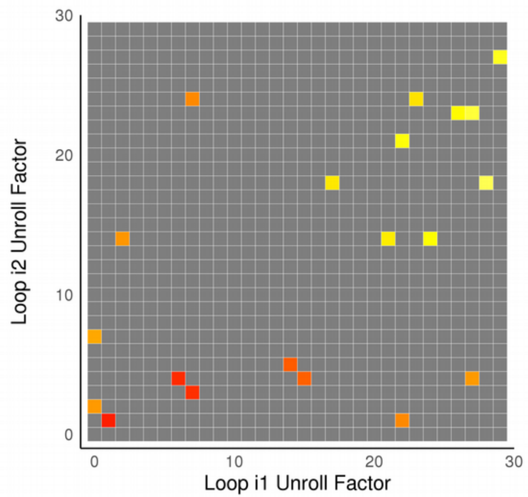
Active

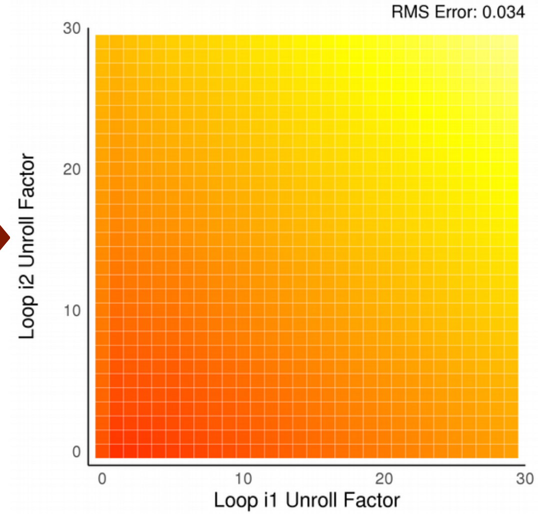




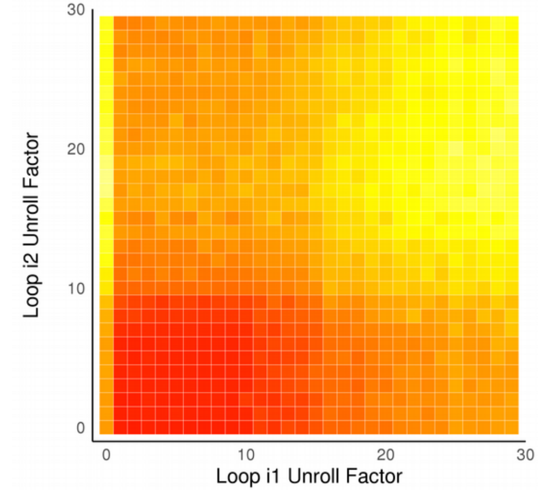
RMS Error: -17%

Passive





Runtime Measurements



3x faster

	Passive Learning	Active Learning	
Training Points	Random, preselected	ML-guided selection	
Profiling runs	Fixed, preselected	Fixed, preselected	

3x faster

	Passive Learning	Active Learning	**Something Better?**
Training Points	Random, preselected	ML-guided selection	**?**
Profiling runs	Fixed, preselected	Fixed, preselected	**?**

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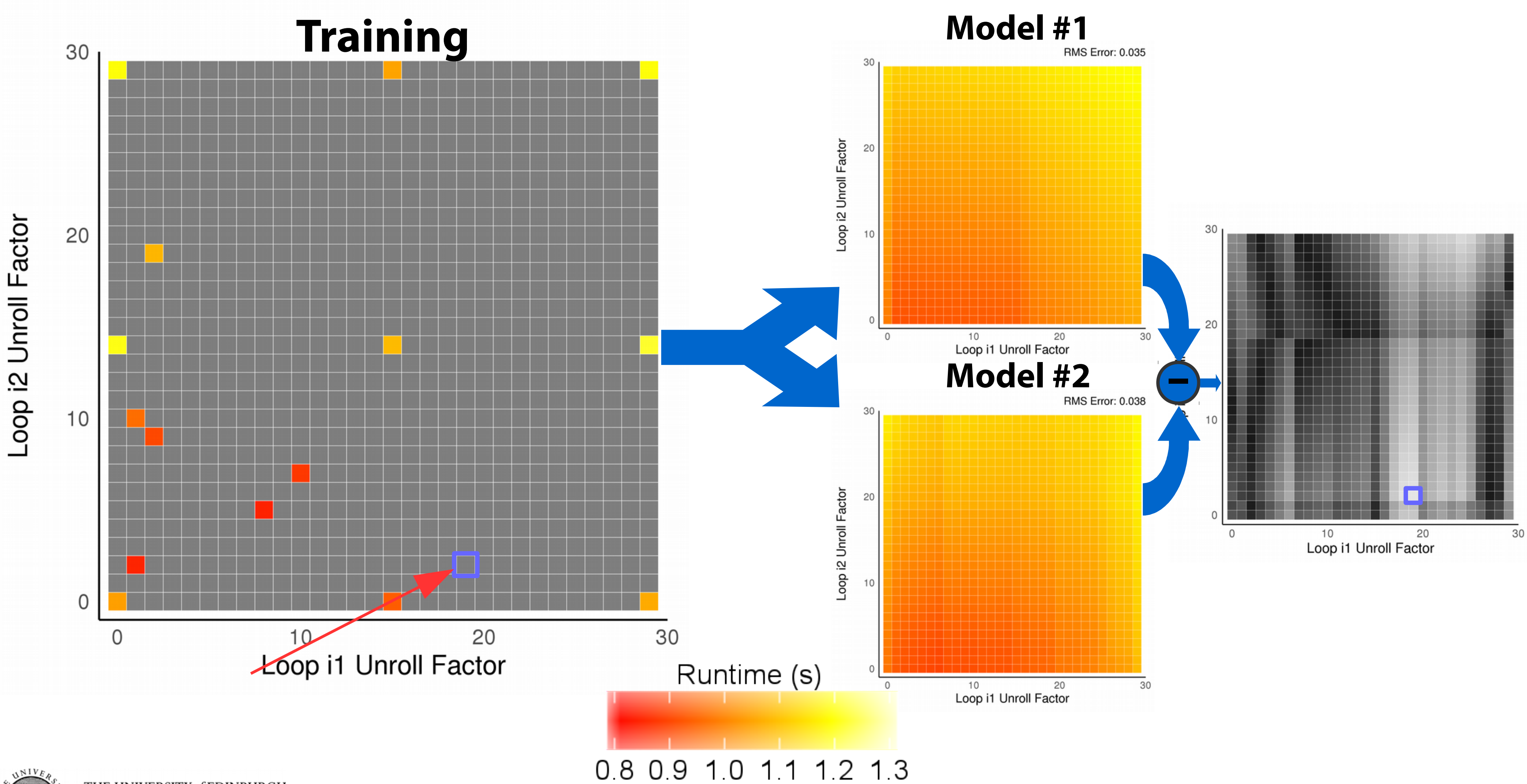
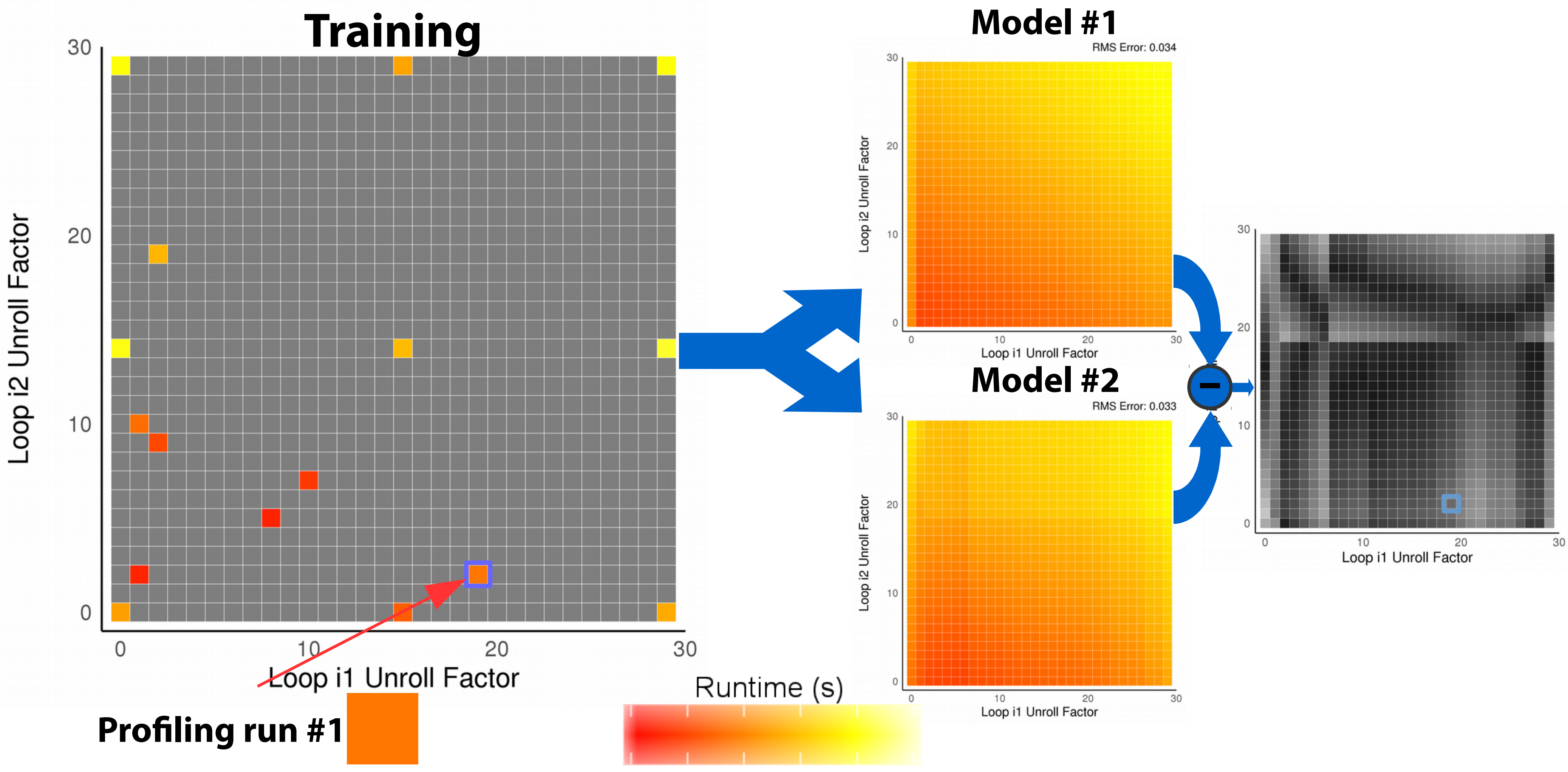
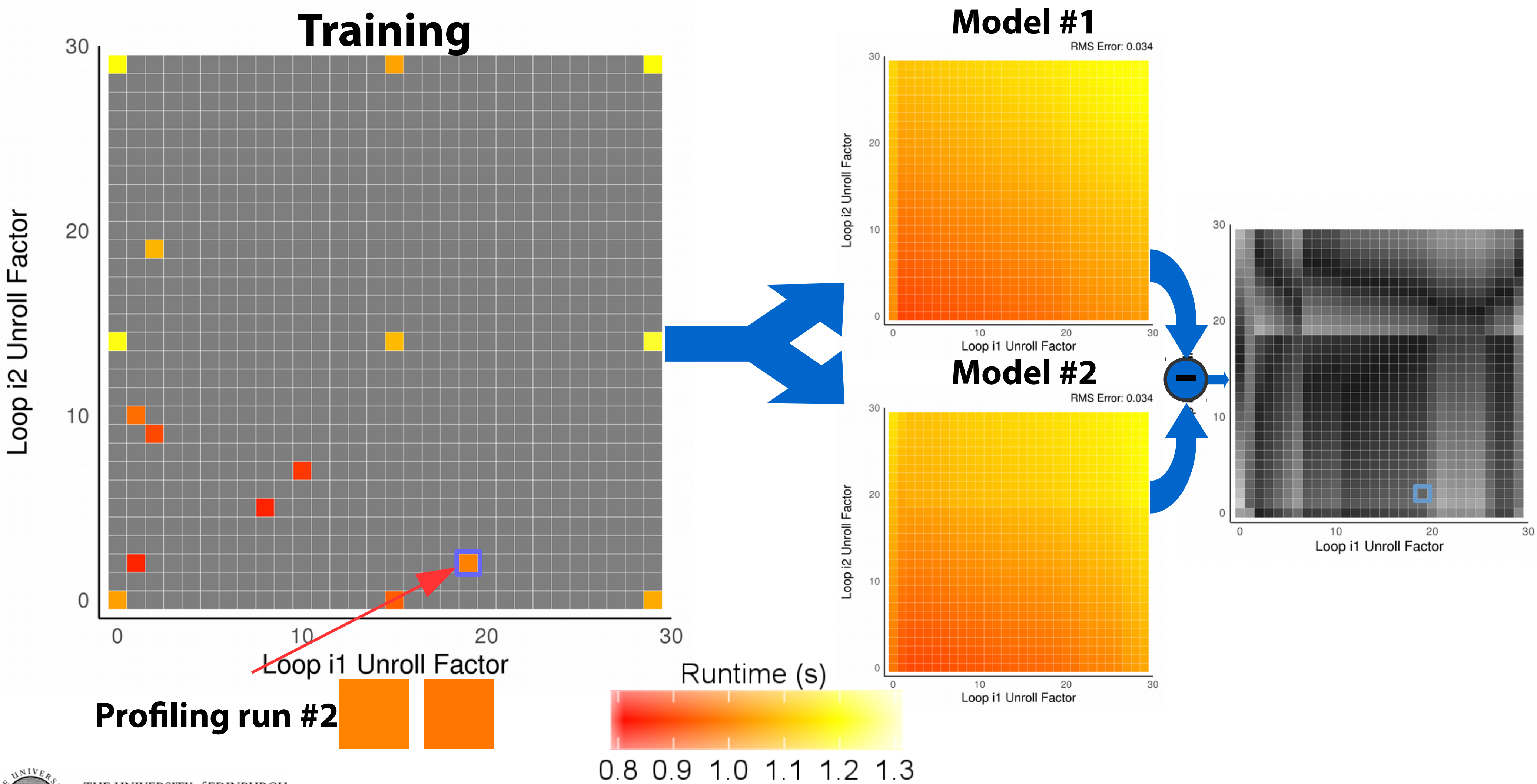
Can we do better?



Can we do better?



Can we do better?



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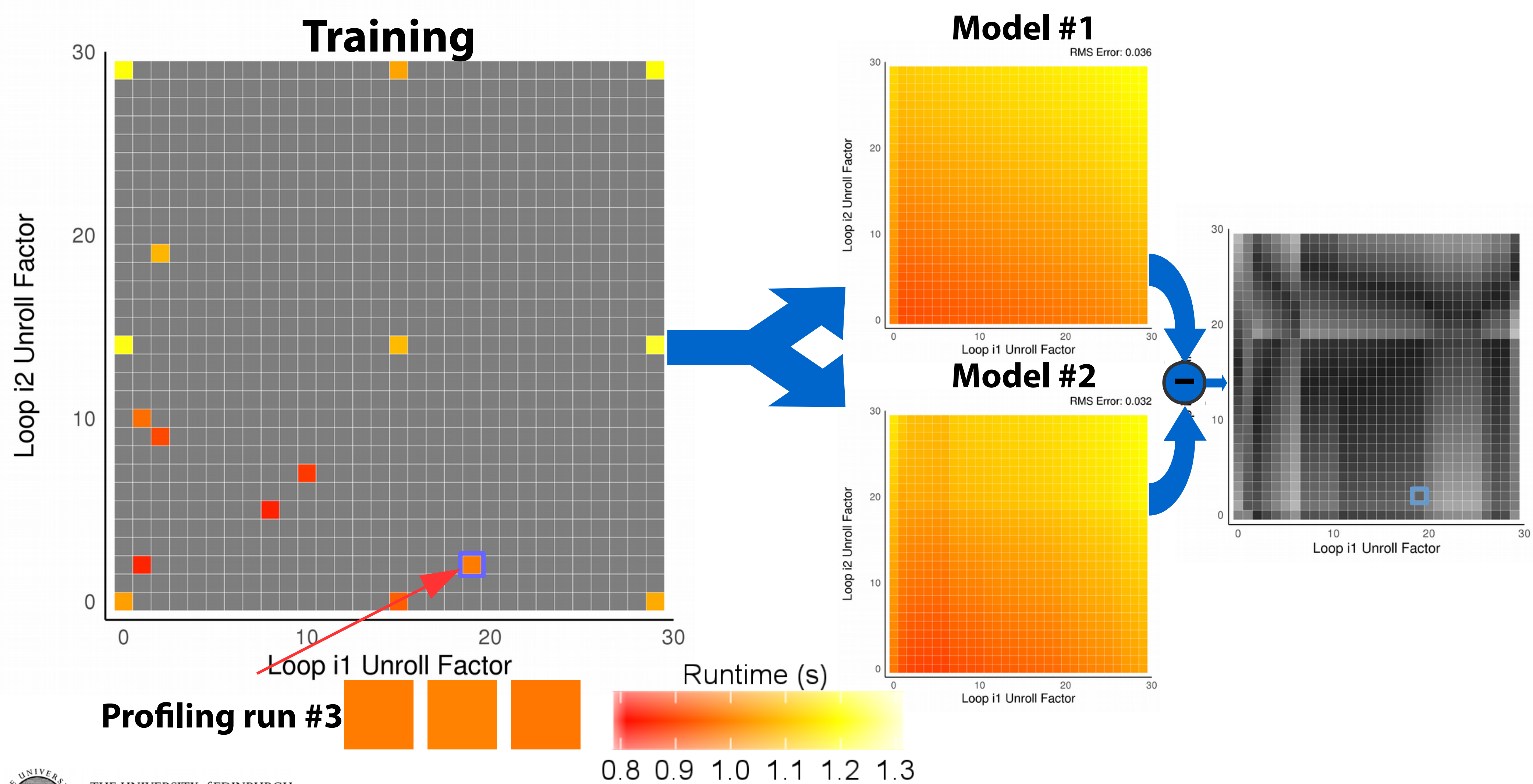
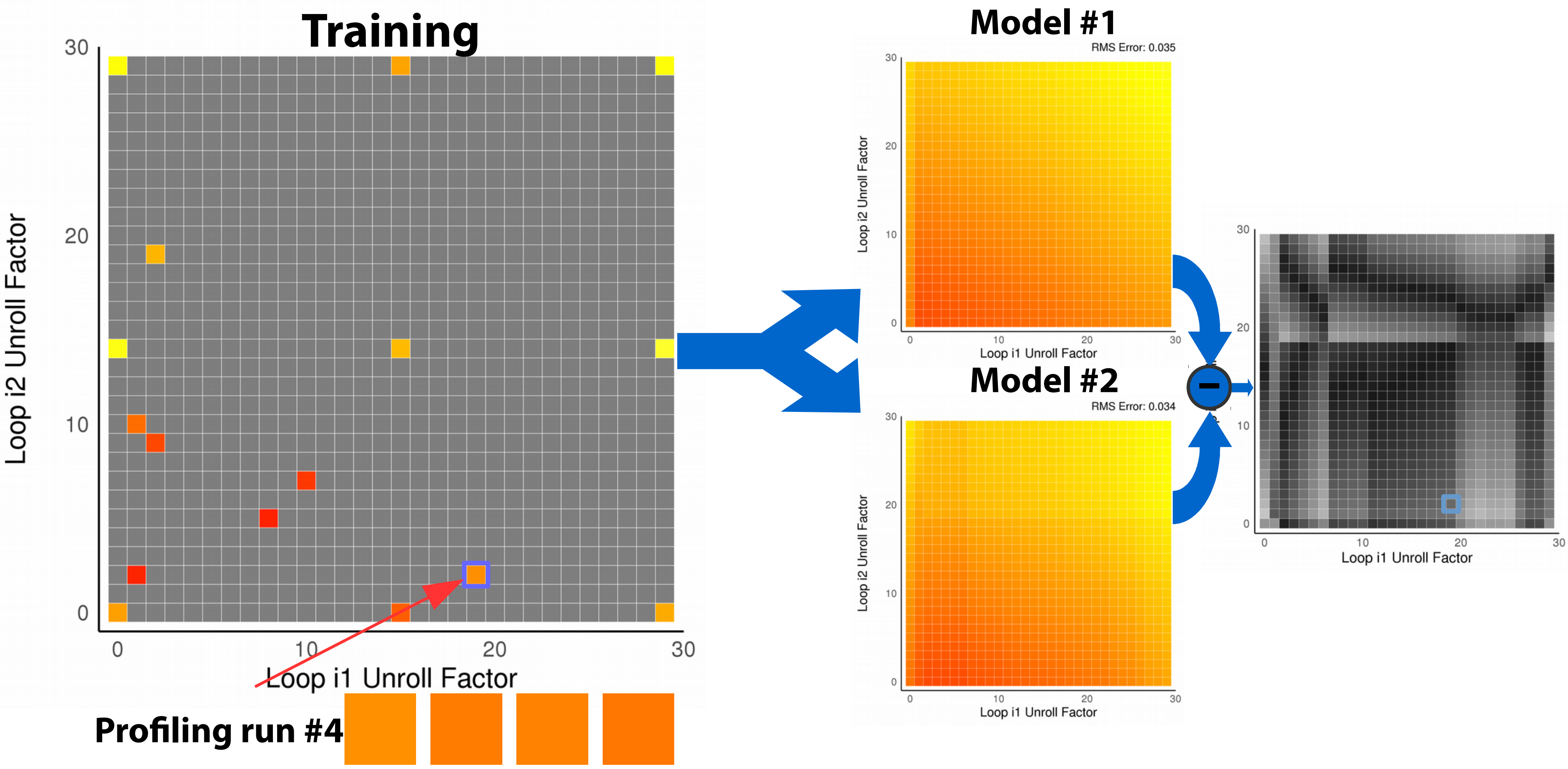
Can we do better?



Can we do better?



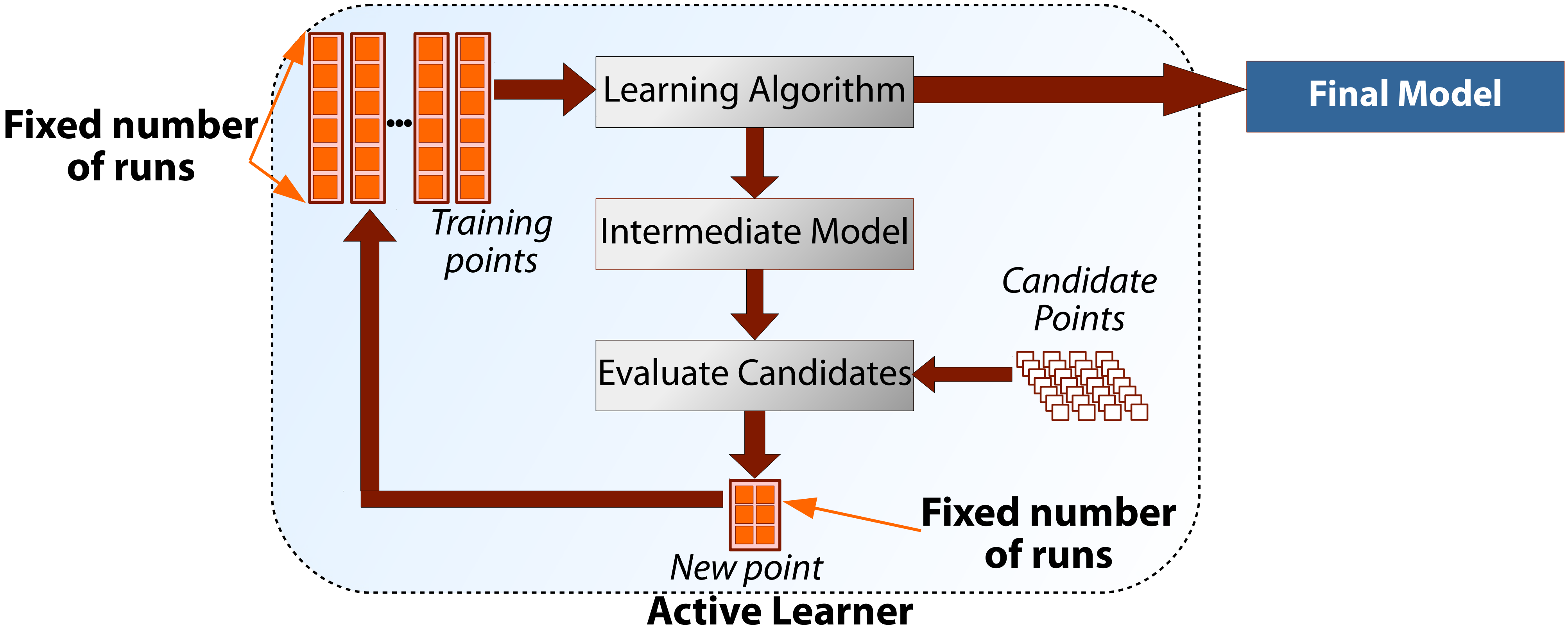
Noise

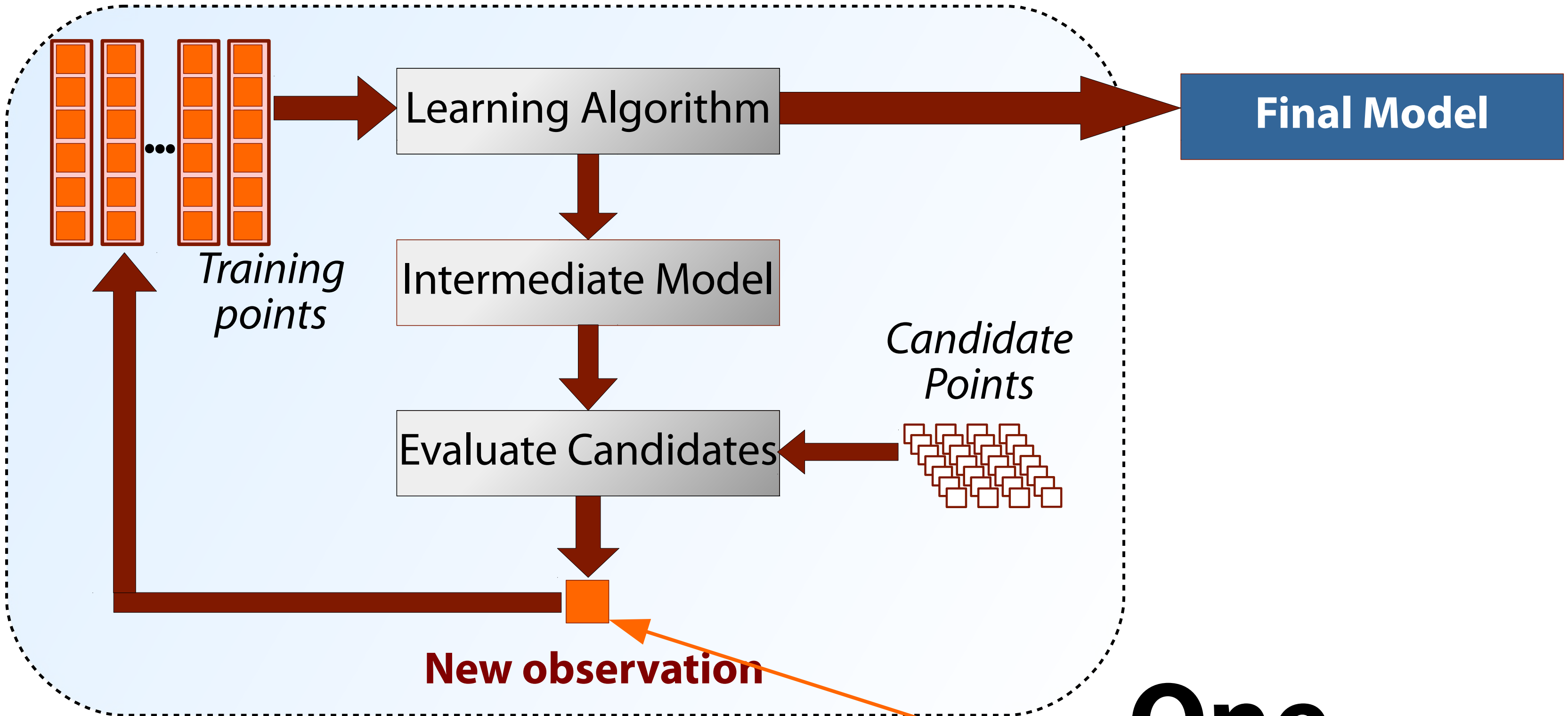
determines optimal # of observations

Noise
+ prediction uncertainty
determine optimal # of observations

	Passive Learning	Active Learning	**Our approach**
Training Points	Random, preselected	ML-guided selection	**ML-guided selection**
Profiling runs	Fixed, preselected	Fixed, preselected	**ML-guided selection**

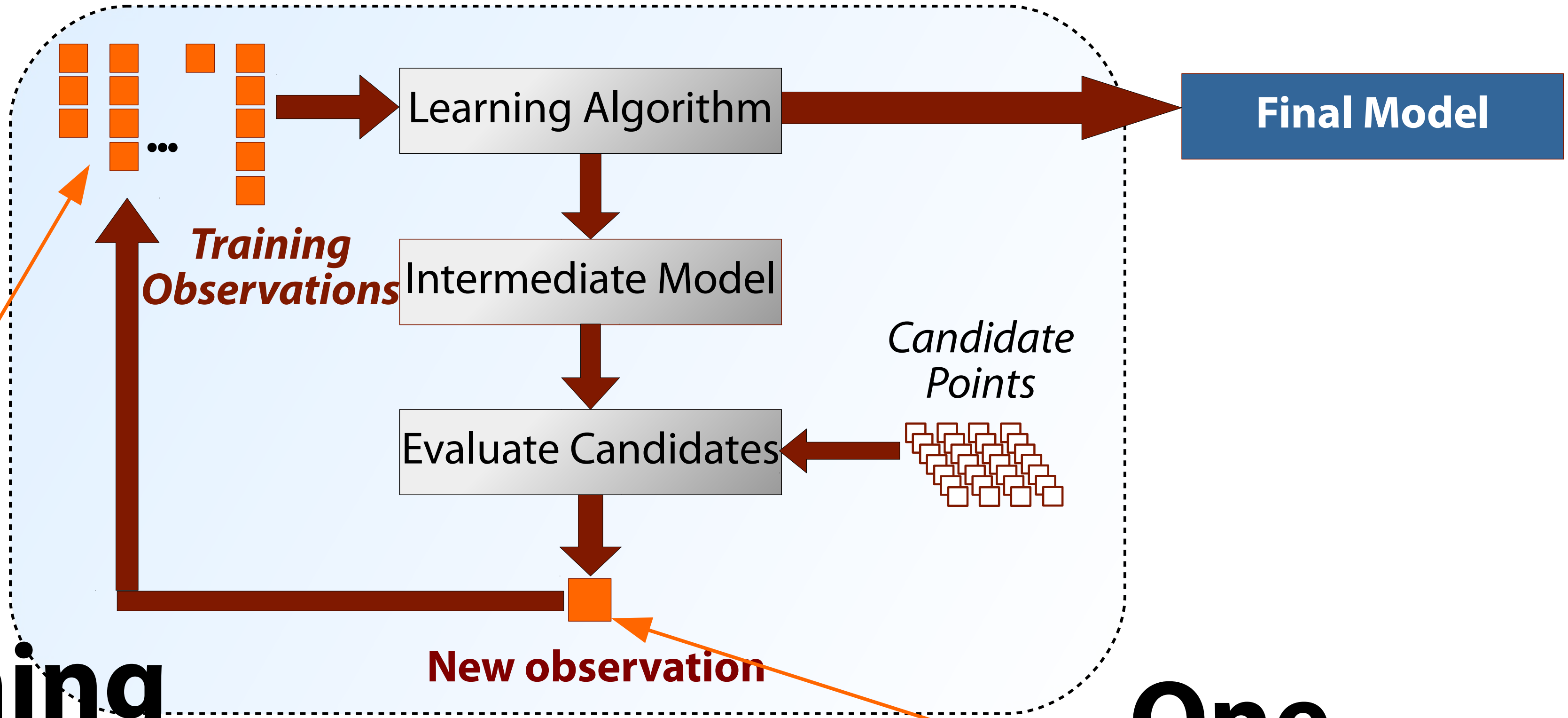
Sequential analysis with **noisy active learning**


Fixed number of runs
Learning Algorithm
Final Model
Training points
Intermediate Model
Candidate Points
Evaluate Candidates
New point
Fixed number of runs
Active Learner



Noisy Active Learner

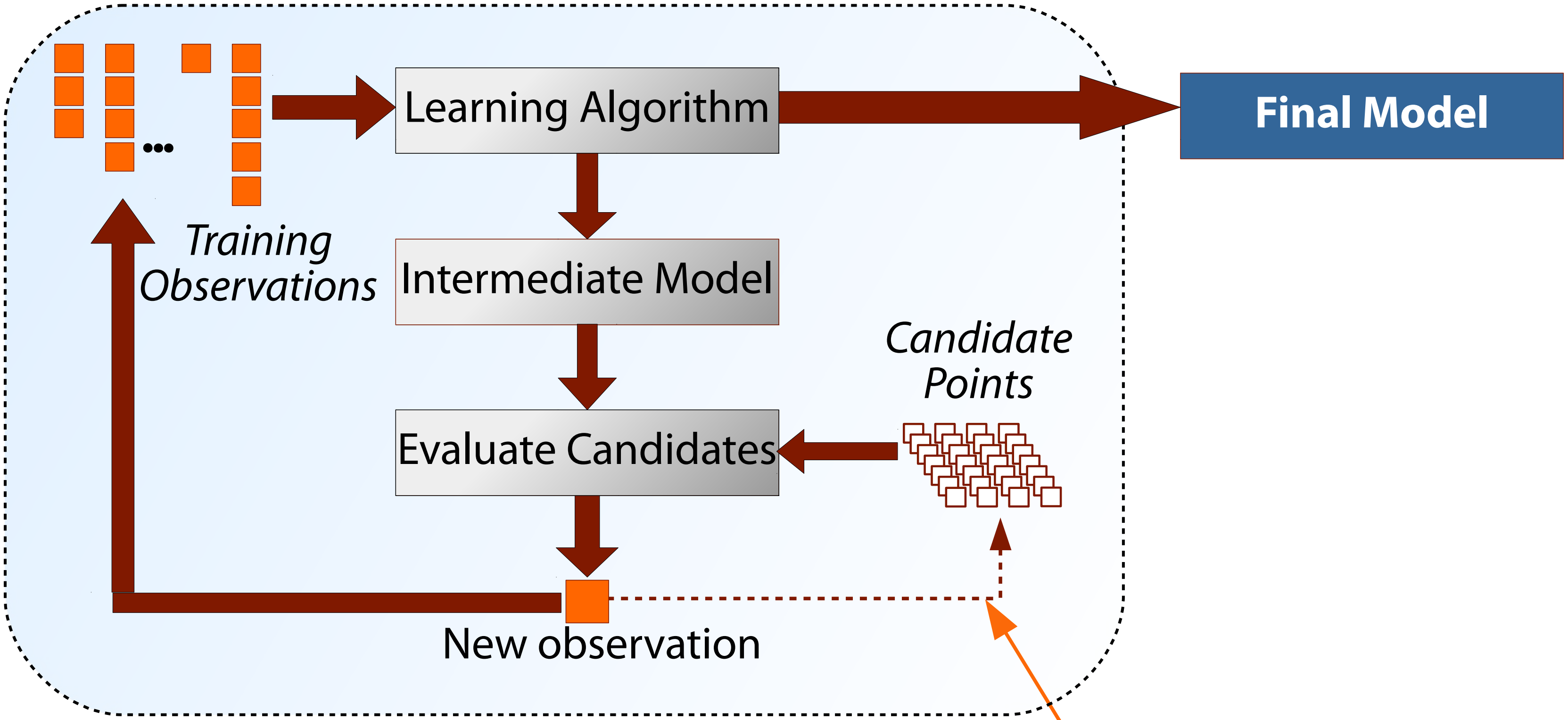
One observation at a time



Training data noisy

Noisy Active Learner

One observation at a time



Noisy Active Learner

Selected point stays in candidate set

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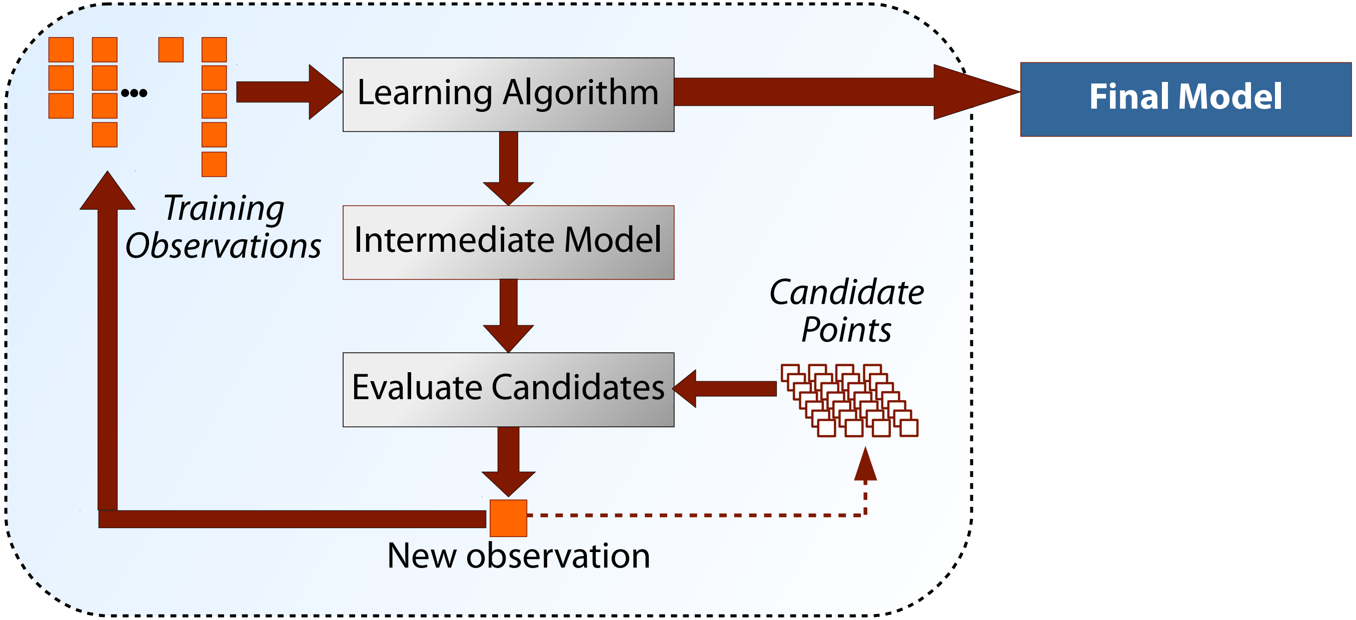
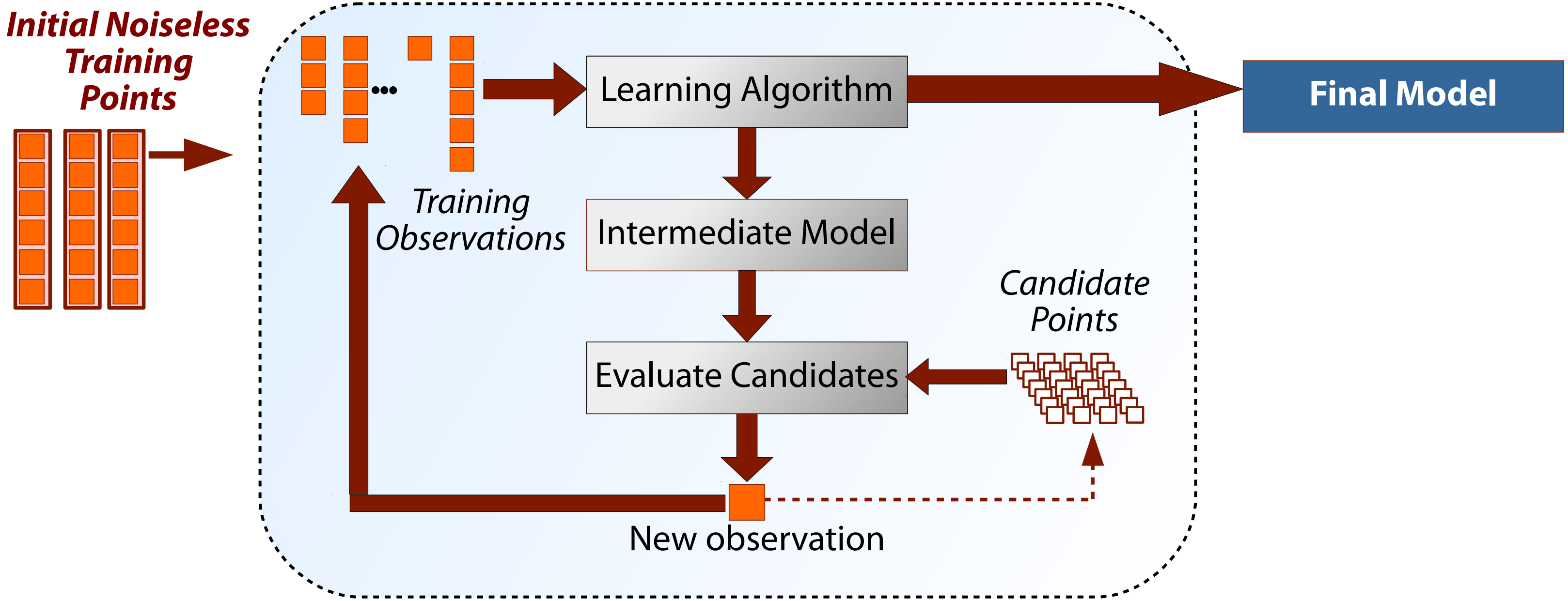


Challenges:
1) Noisy data→ Completely wrong IM
2) Overfitting
3) Too many updates to the IM

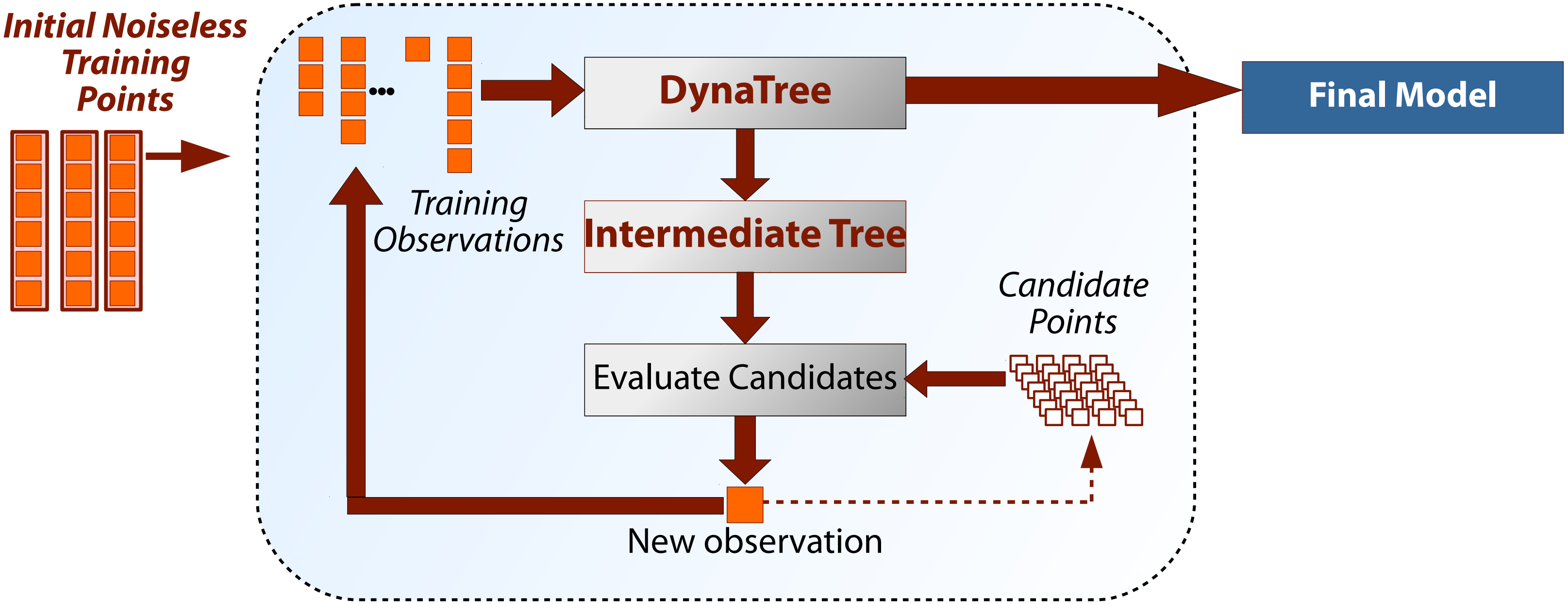


Challenges:

1) Noisy data→ Completely wrong IM

2) Overfitting

3) Too many updates to the IM



Challenges:

1) Noisy data → Completely wrong IM

2) Overfitting

3) Too many updates to the IM

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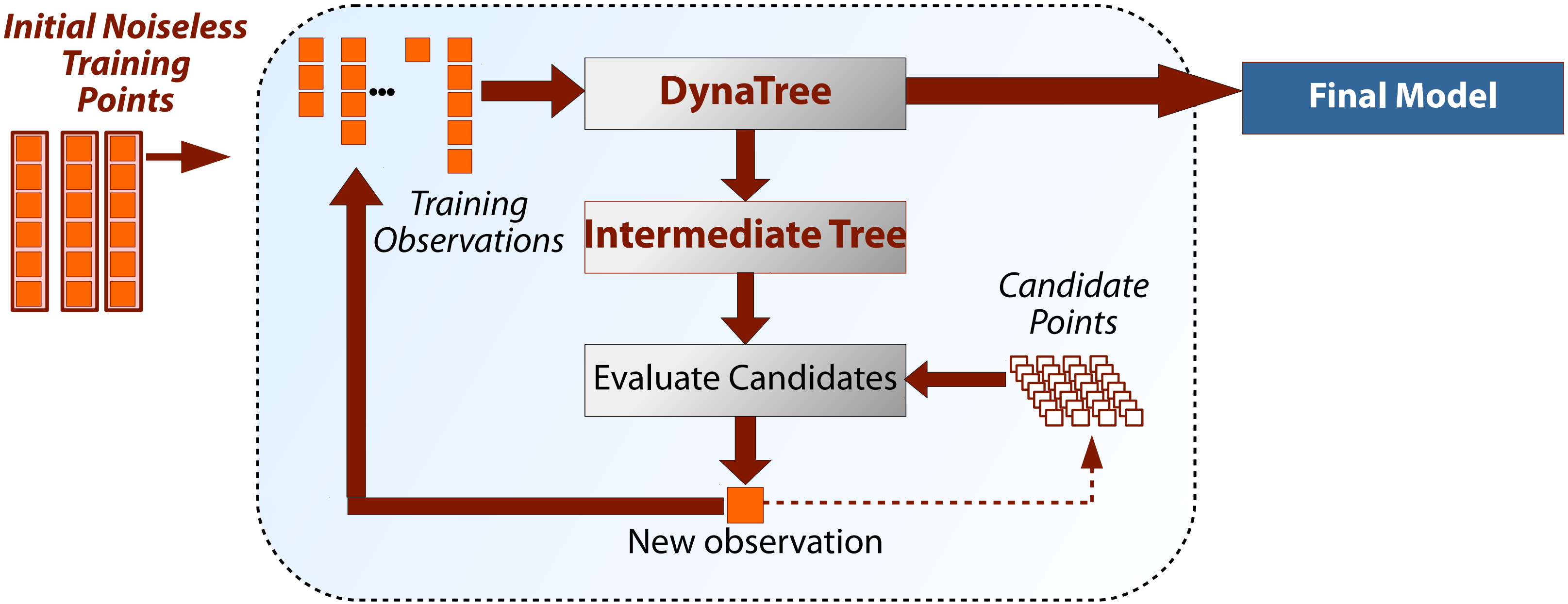
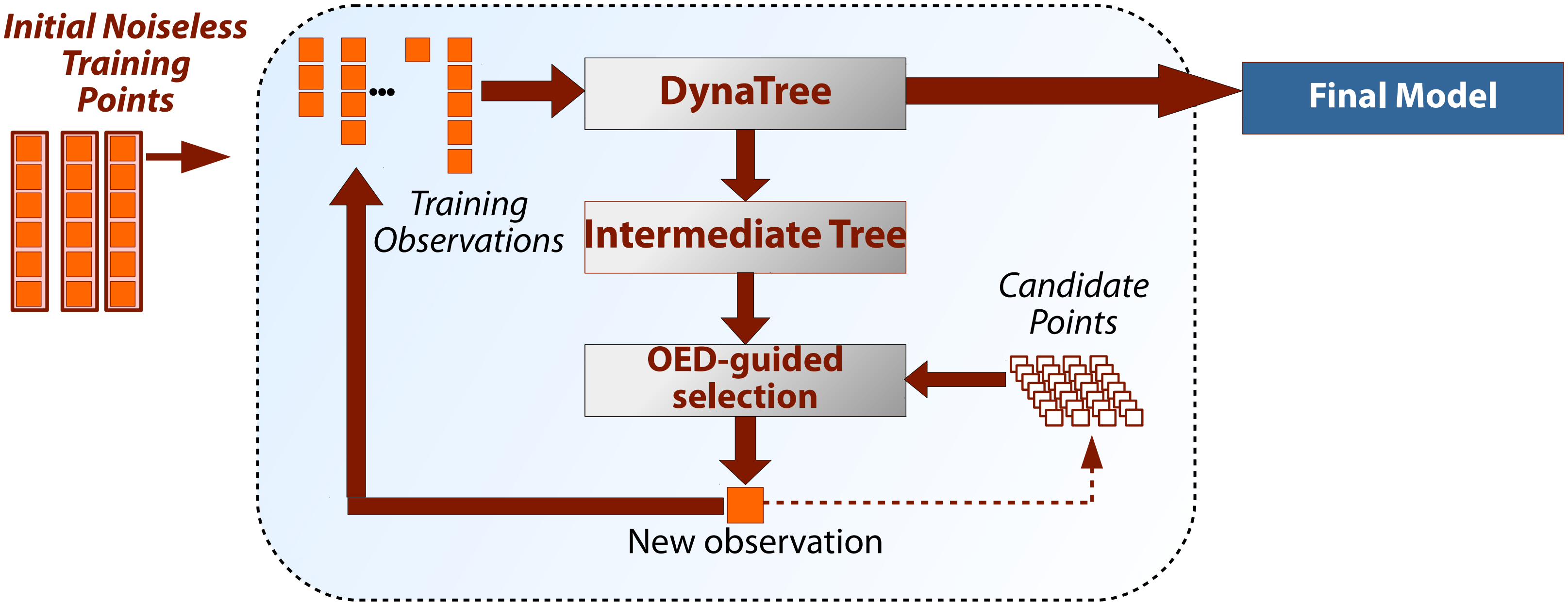


Challenges:
1) Noisy data→ Completely wrong IM
2) Overfitting
3) Too many updates to the IM



Challenges:
1) Noisy data→ Completely wrong IM
2) Overfitting
3) Too many updates to the IM

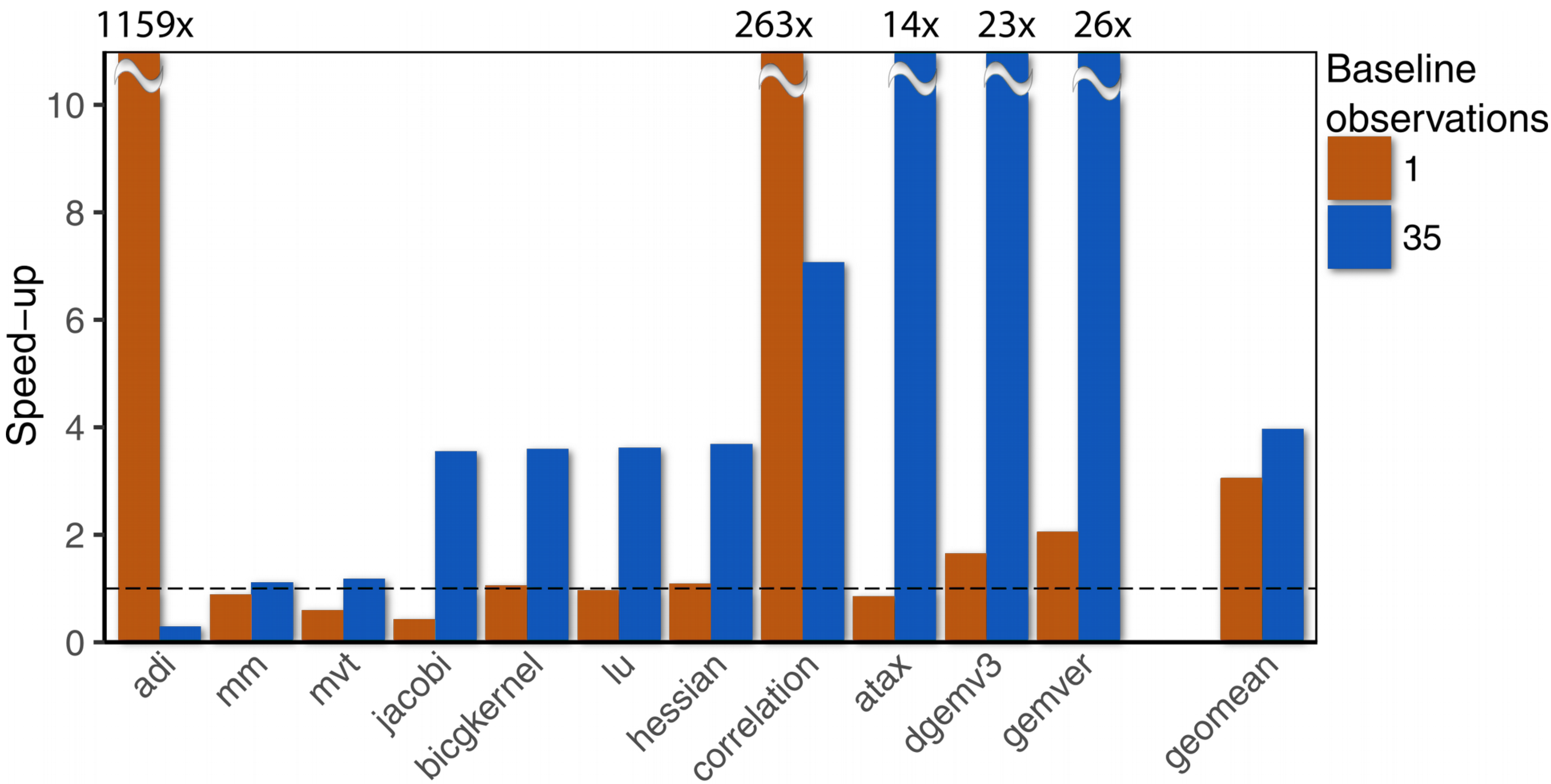
Test Case:

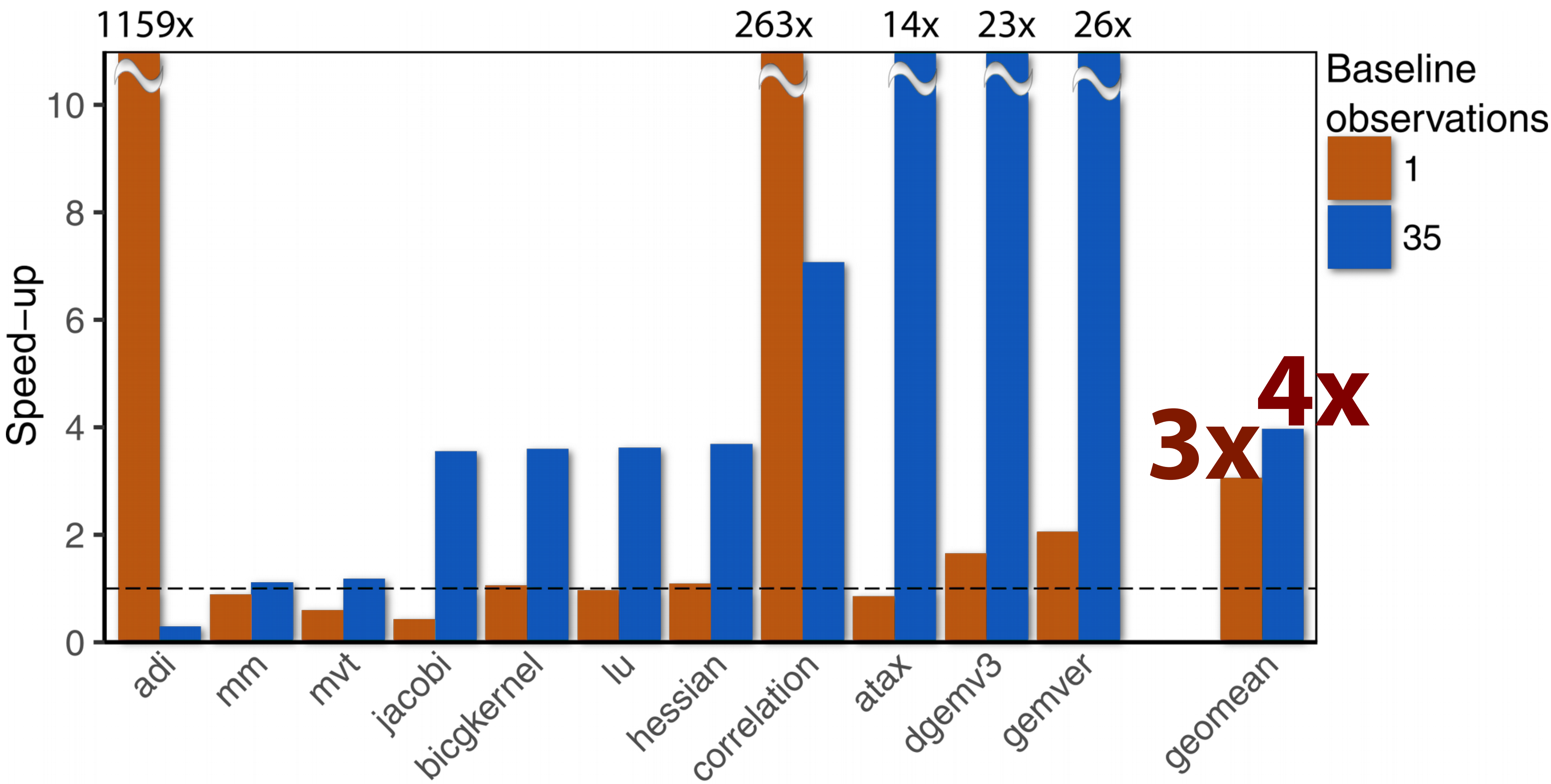
Prediction of runtime under different optimizations

SPAPT Benchmarks

Huge optimization space
$5x10^8$ to $1x10^{27}$

Benchmarks with both low and high noise


1159x
263x
14x
23x
26x
Speed−up
0
2
4
6
8
10
Baseline observations
1
35
adi
mm
mvt
jacobi
bicgkernel
lu
hessian
correlation
atax
dgemv3
gemver
geomean


1159x
263x
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23x
26x
Speed−up
0
2
4
6
8
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Baseline observations
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3x
4x
adi
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jacobi
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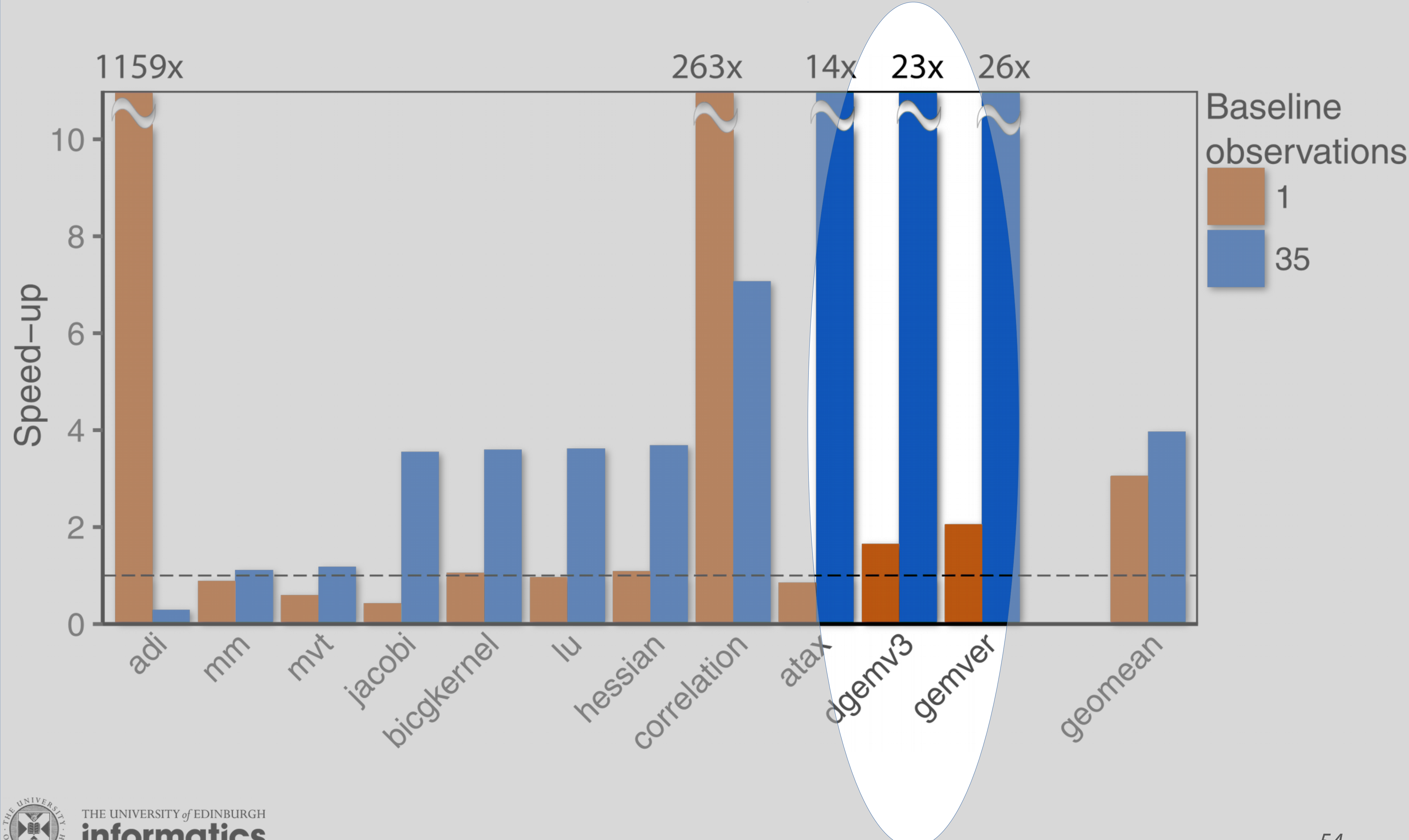

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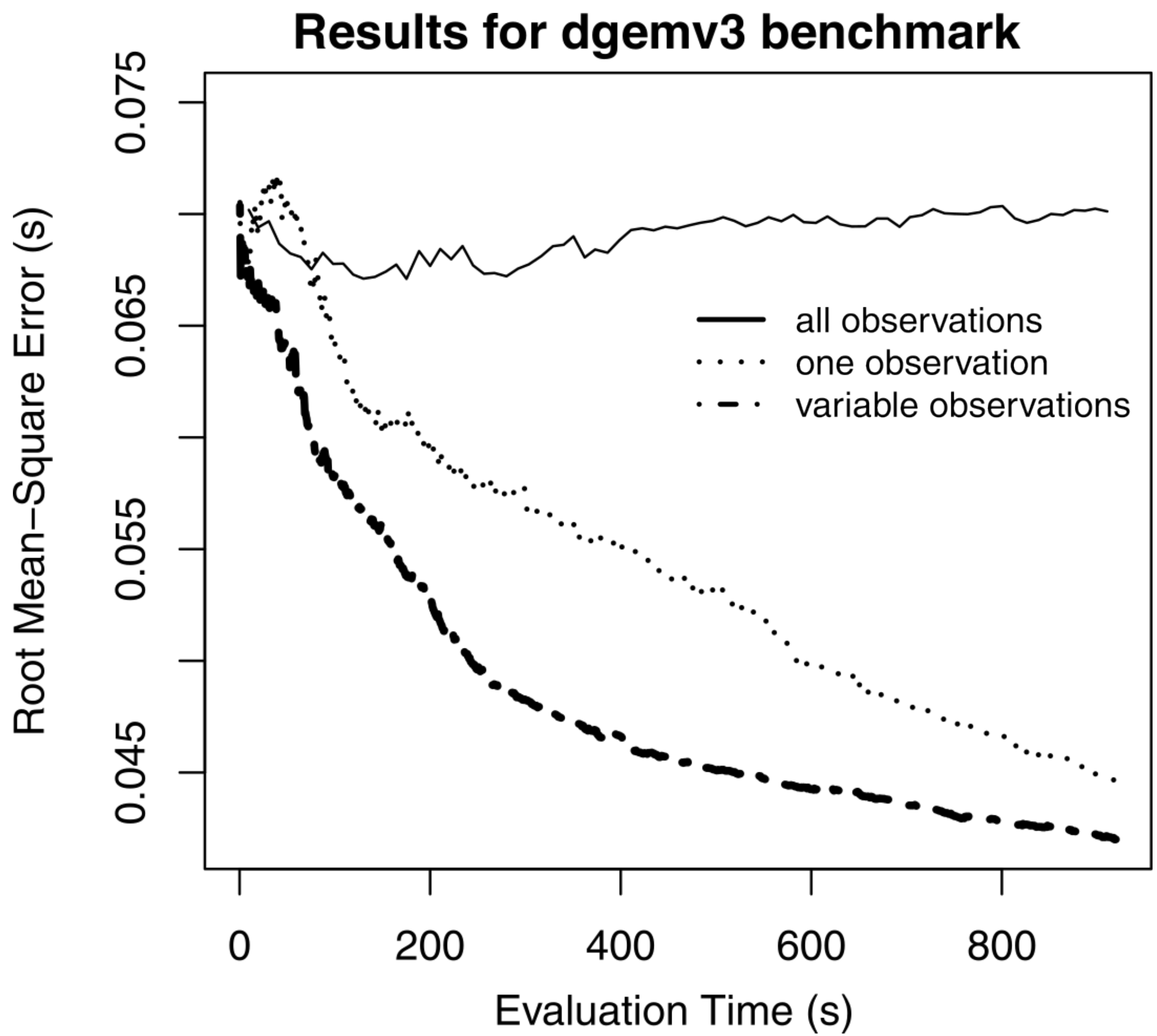
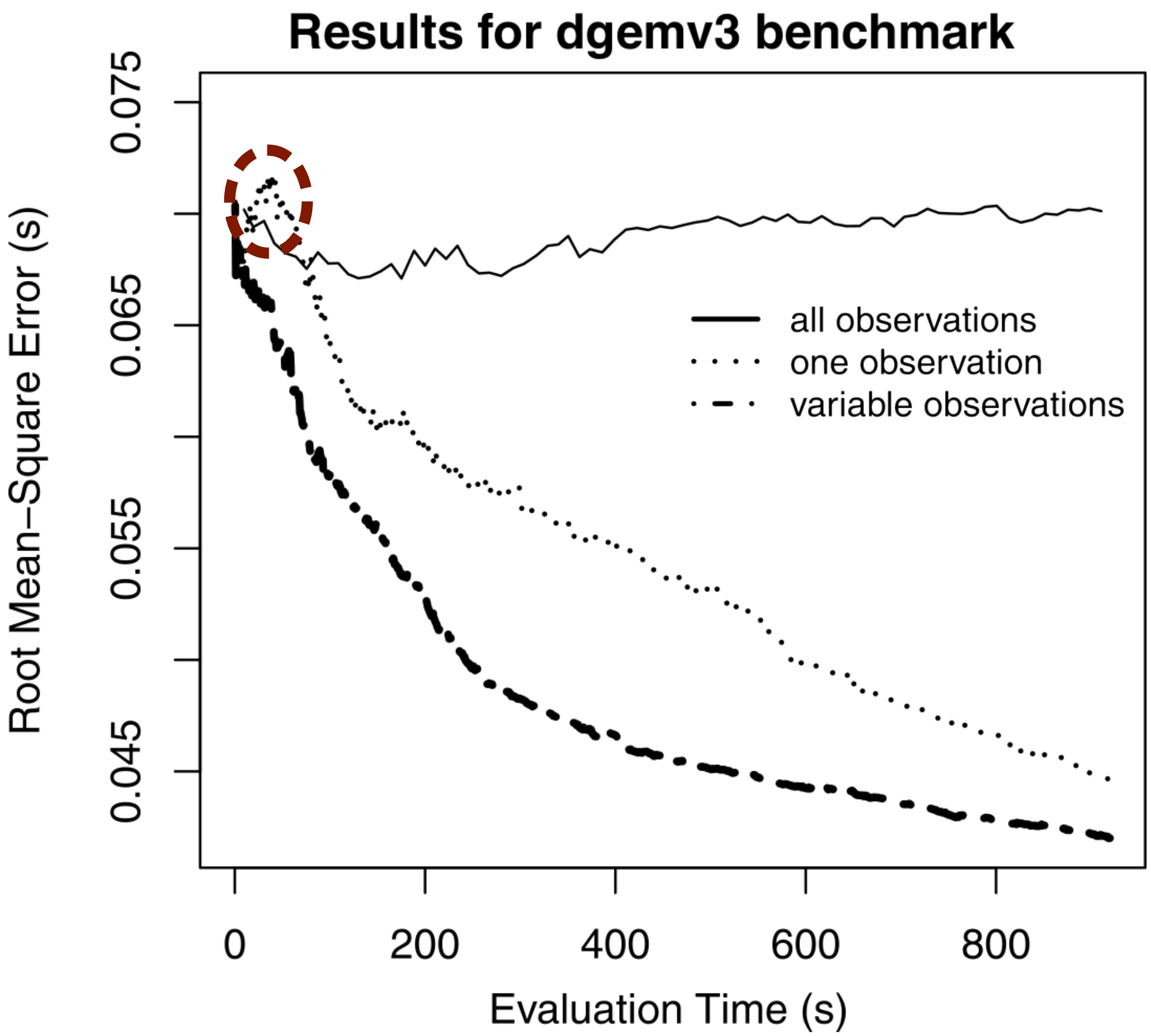


High noise for some points

Handles noisy points

Does not waste time for the rest



High noise for some points

Handles noisy points

Does not waste time for the rest

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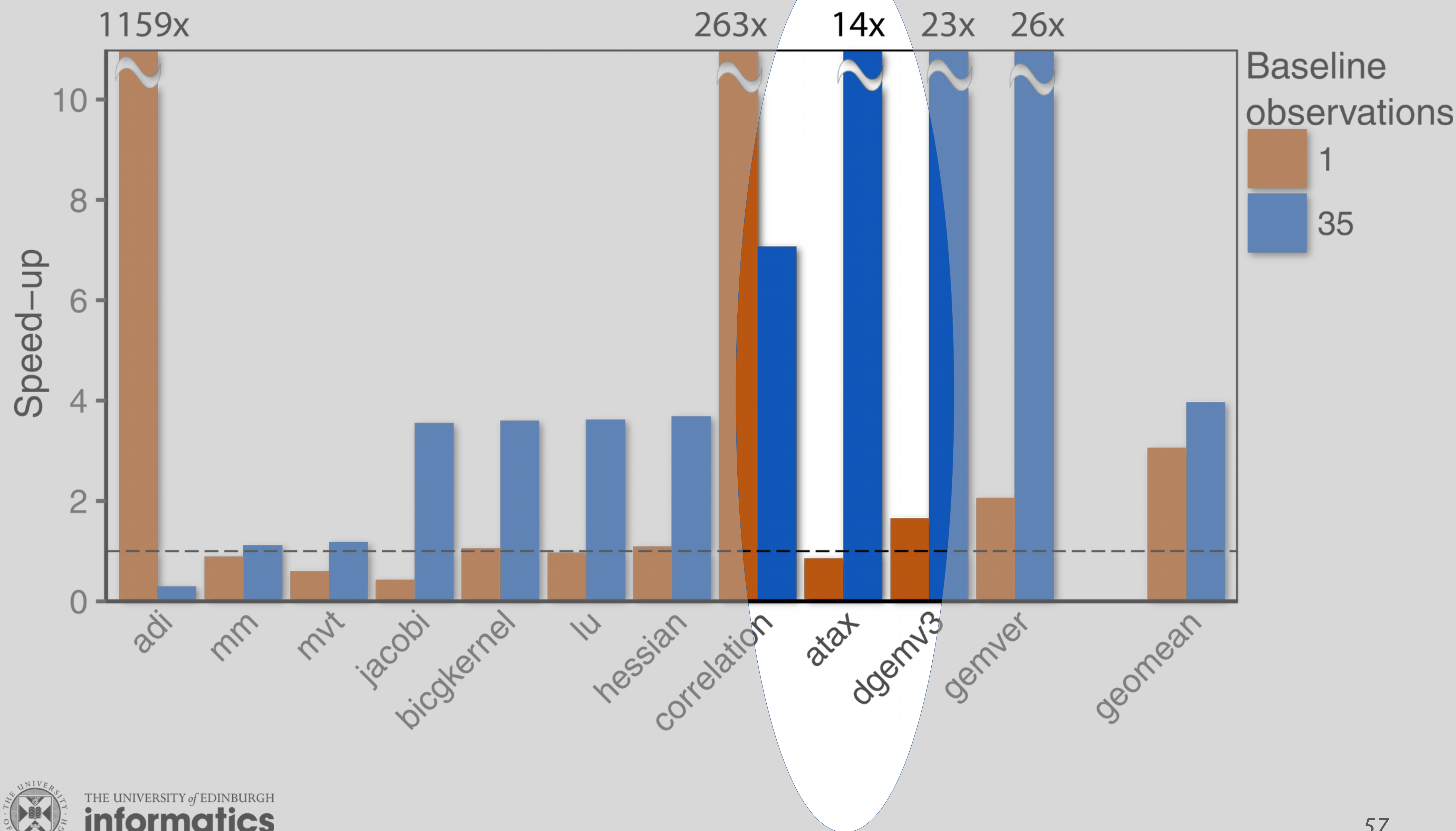

1159x
263x
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Baseline observations
1
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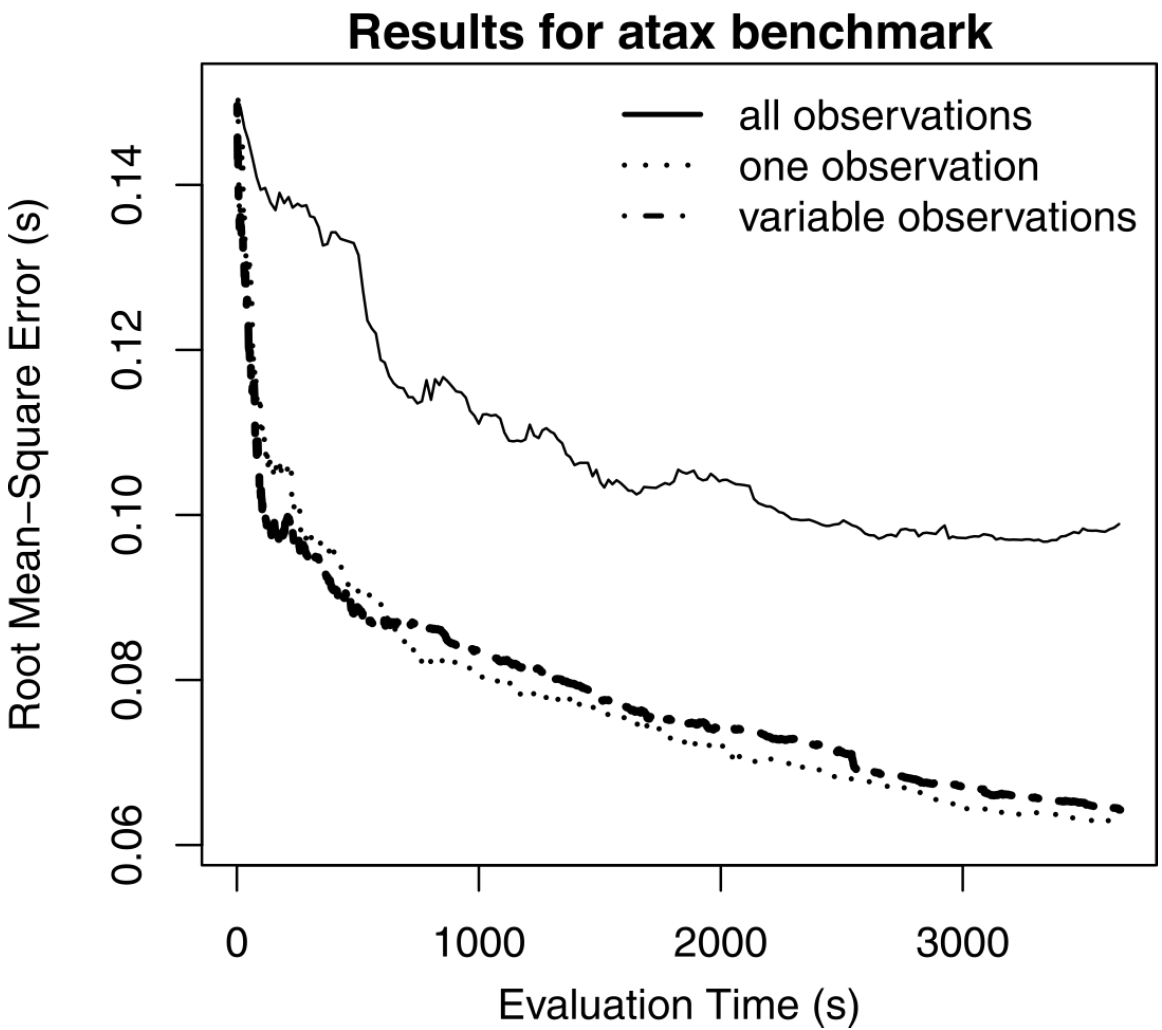
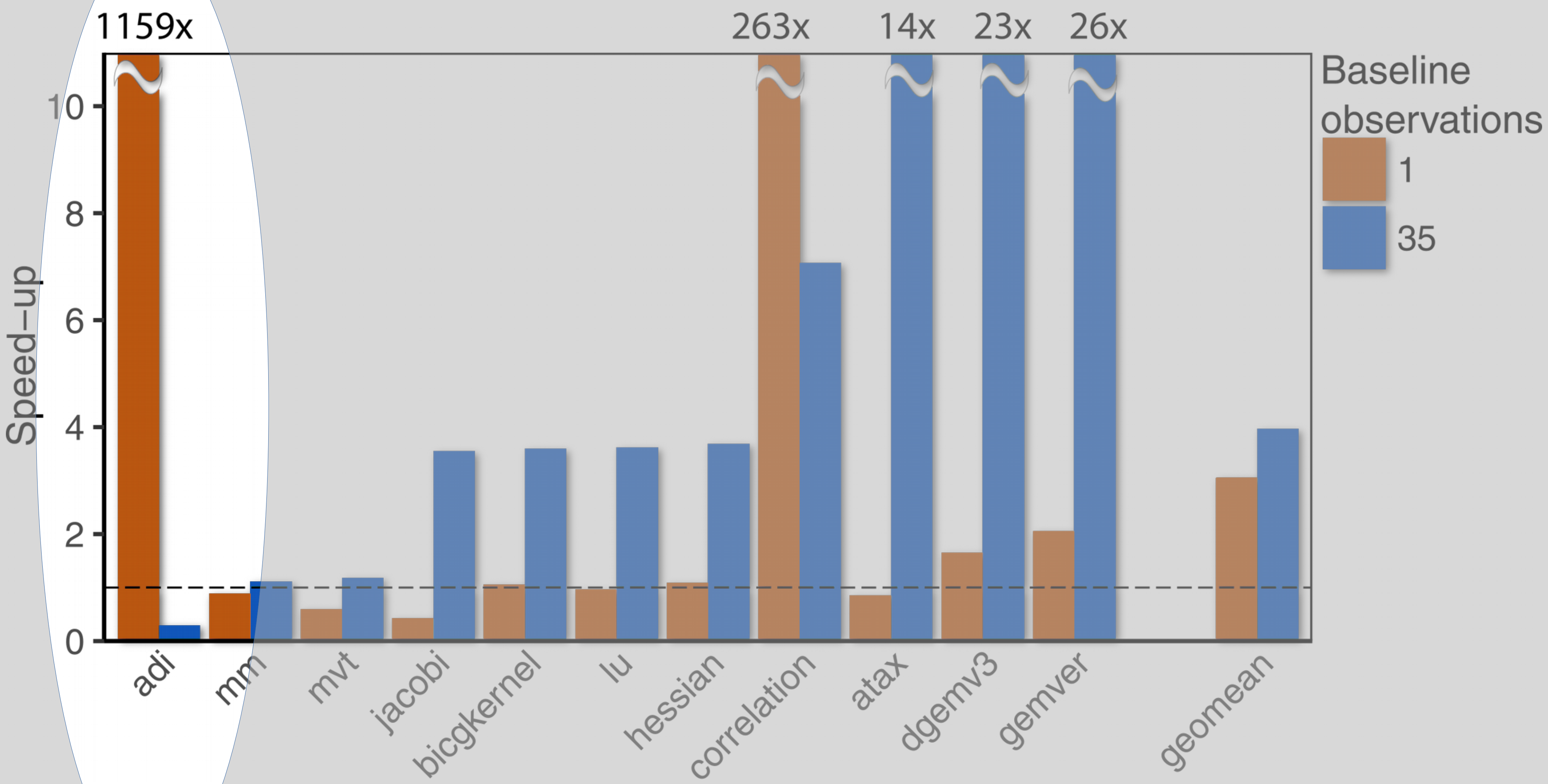


Low noise

Similar to one observation

No noise characterization needed


1159x
263x
14x
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Speed–up
0
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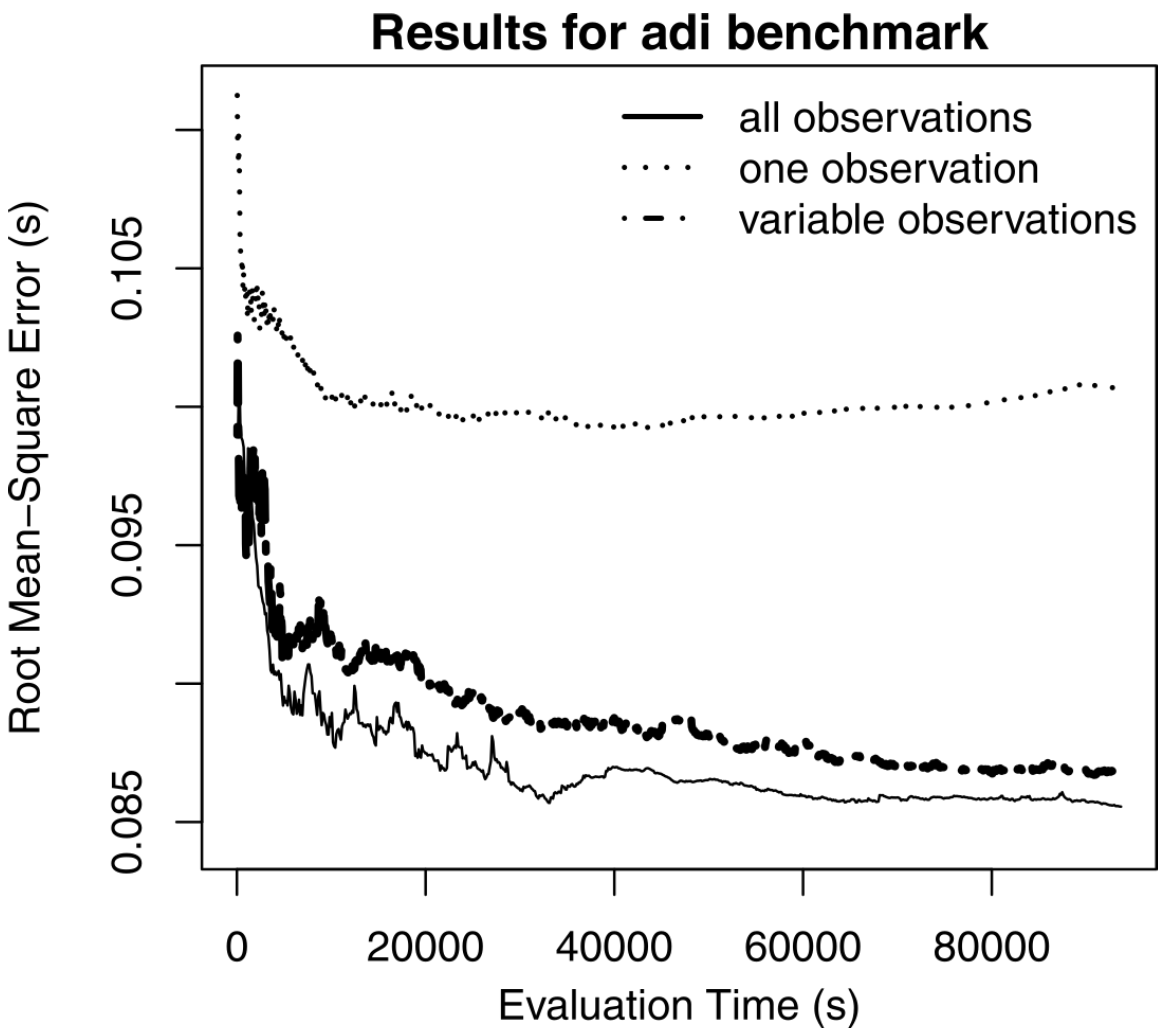
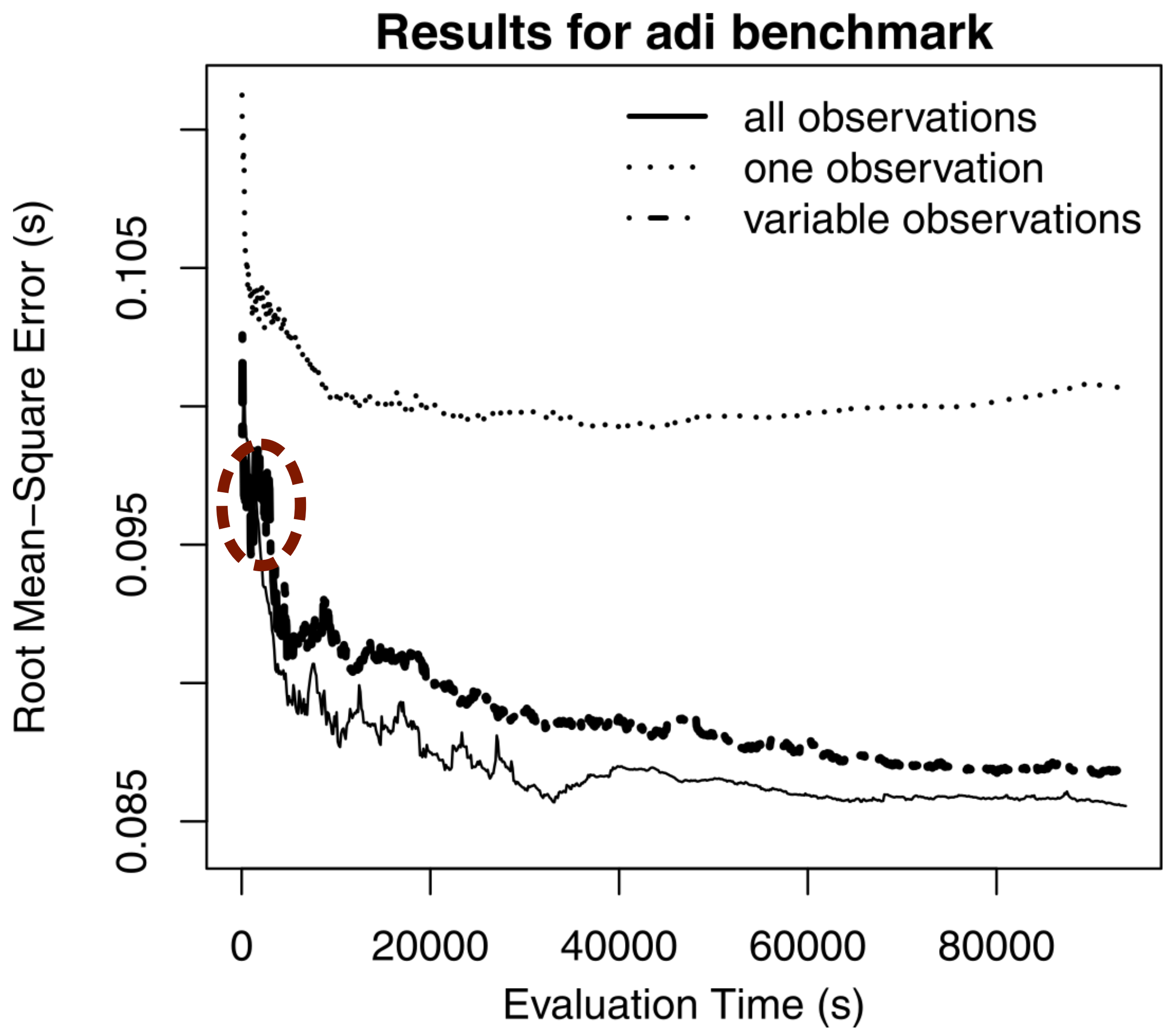
Baseline observations
1
35



High noise

Similar to 35 observations



High noise

Similar to 35 observations

Conclusions

	Passive Learning	Active Learning	Our approach
Training Points	**Inefficient**	**Efficient**	**Efficient**
Profiling runs	**Inefficient**	**Inefficient**	**Efficient**

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	Passive Learning	Active Learning	Our approach
Training Points	Inefficient	Efficient	Efficient
Profiling runs	Inefficient	Inefficient	Efficient
Obser-vations	**Multiple and fixed**	**Multiple and fixed**	**One unless necessary**

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	Passive Learning	Active Learning	Our approach
Training Points	Inefficient	Efficient	Efficient
Profiling runs	Inefficient	Inefficient	Efficient
Obser-vations	Multiple and fixed	Multiple and fixed	One unless necessary
Assum-ptions?	**Enough runs for noise**	**Enough runs for noise**	**None**

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4x faster training

4x faster training
No assumptions

4x faster training
No assumptions
No risk

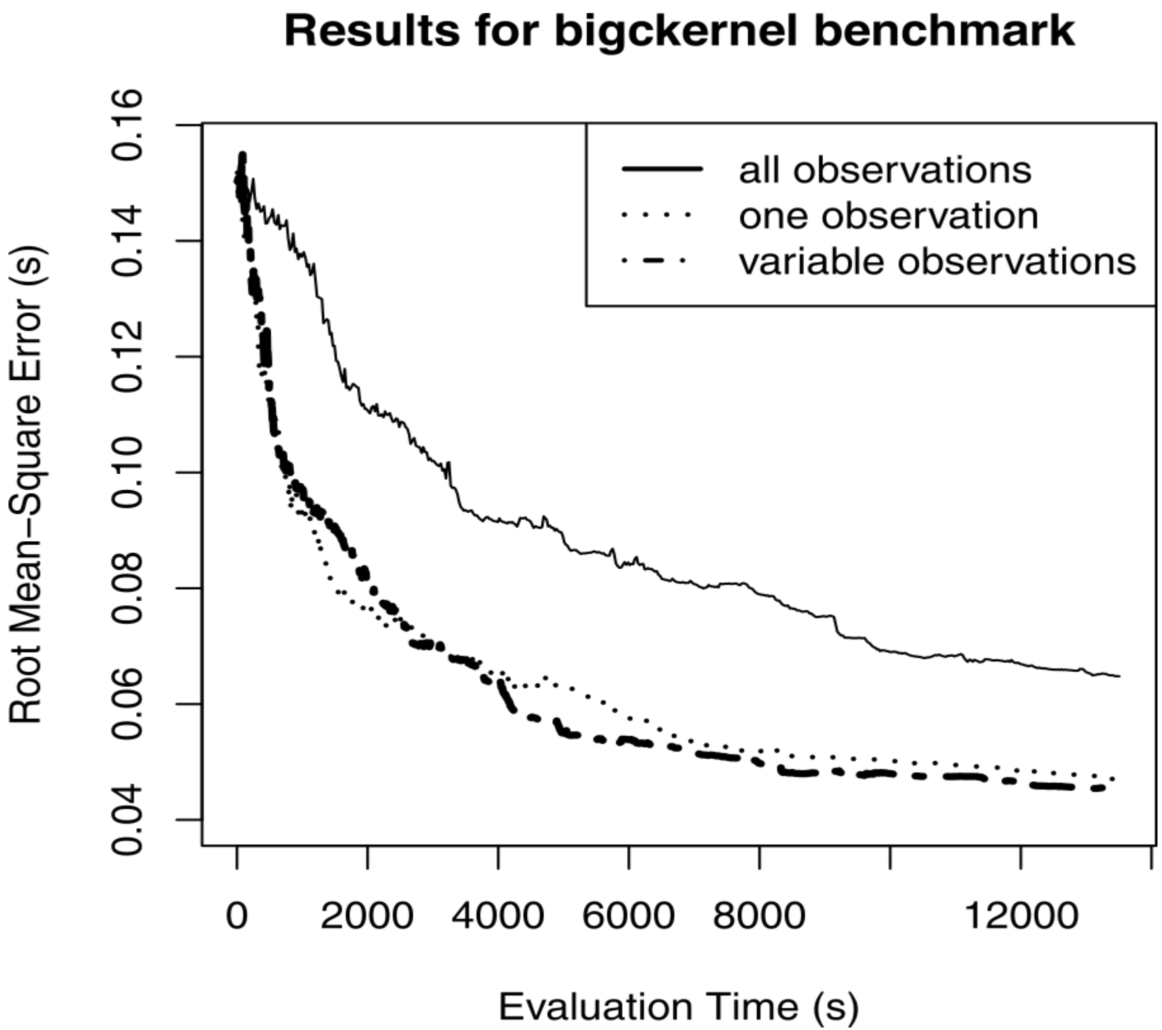
Thanks!

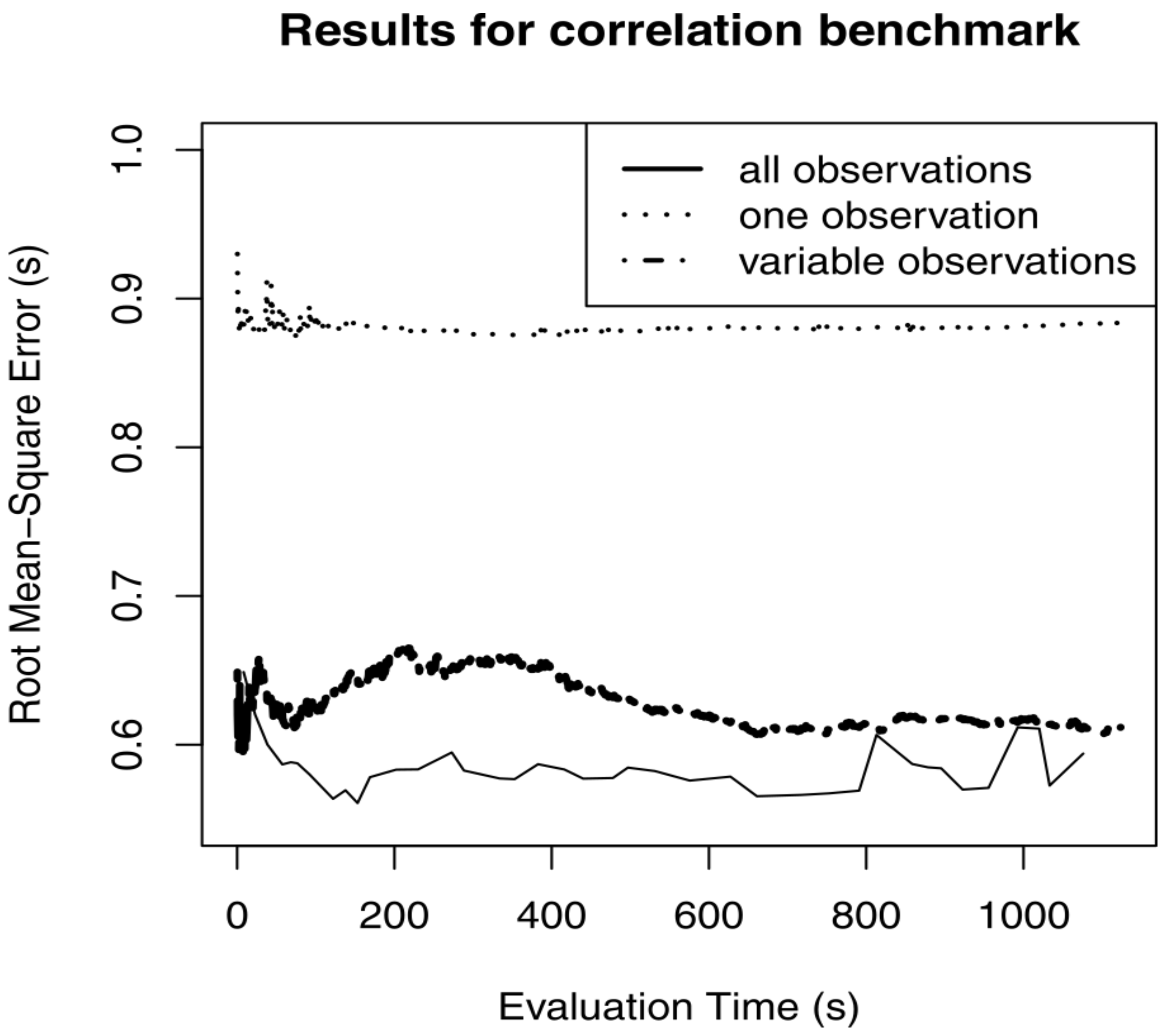

Minimizing the Cost of Iterative Compilation with Active Learning

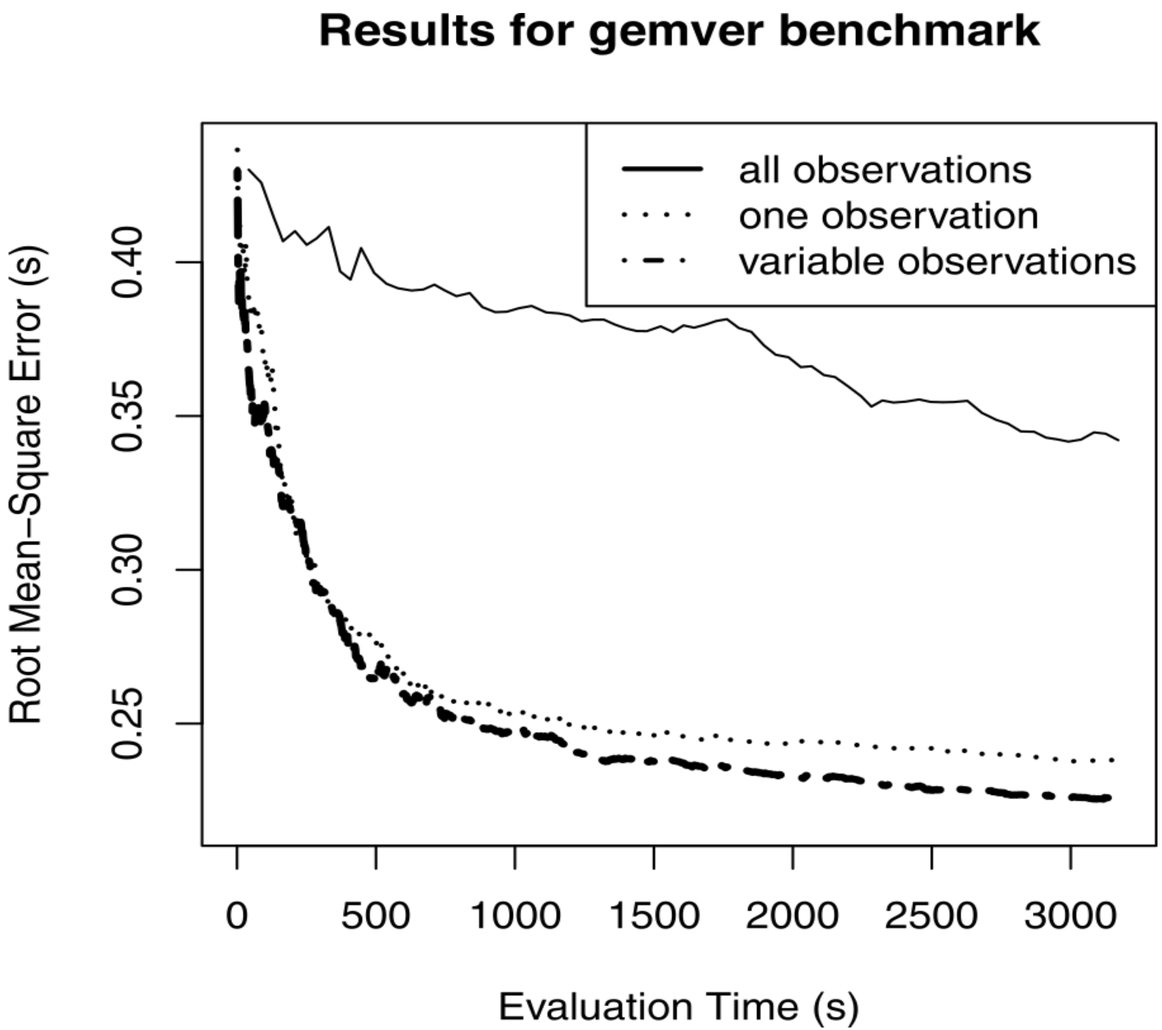
https://goo.gl/nG92CN

wfogilvie@gmail.com

ppetoumenos@gmail.com


Results for bigckernel benchmark
all observations
one observation
variable observations
Root Mean−Square Error (s)
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0
2000
4000
6000
8000
12000
Evaluation Time (s)


Results for correlation benchmark
all observations
one observation
variable observations
Root Mean−Square Error (s)
1.0
0.9
0.8
0.7
0.6
0
200
400
600
800
1000
Evaluation Time (s)



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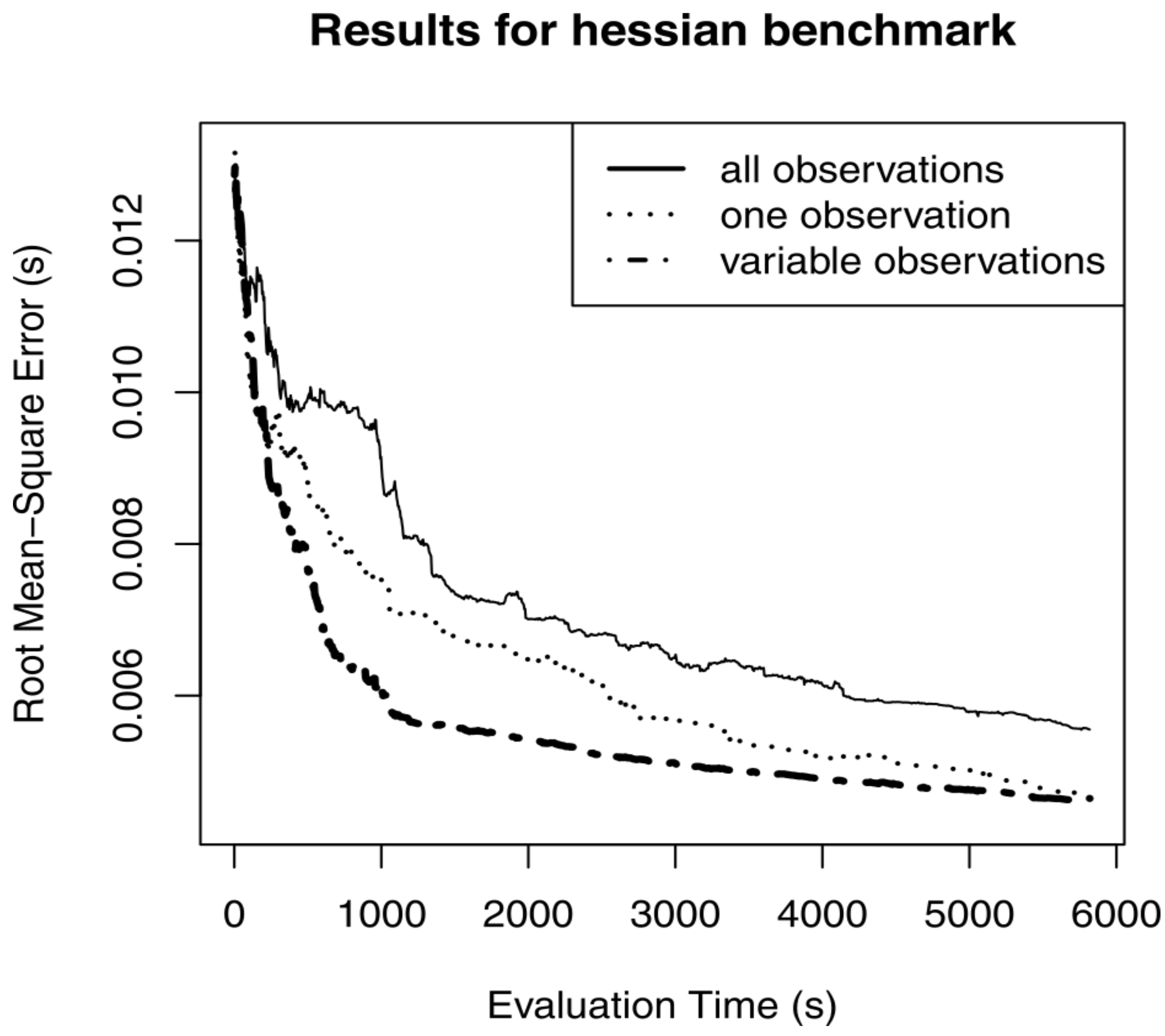
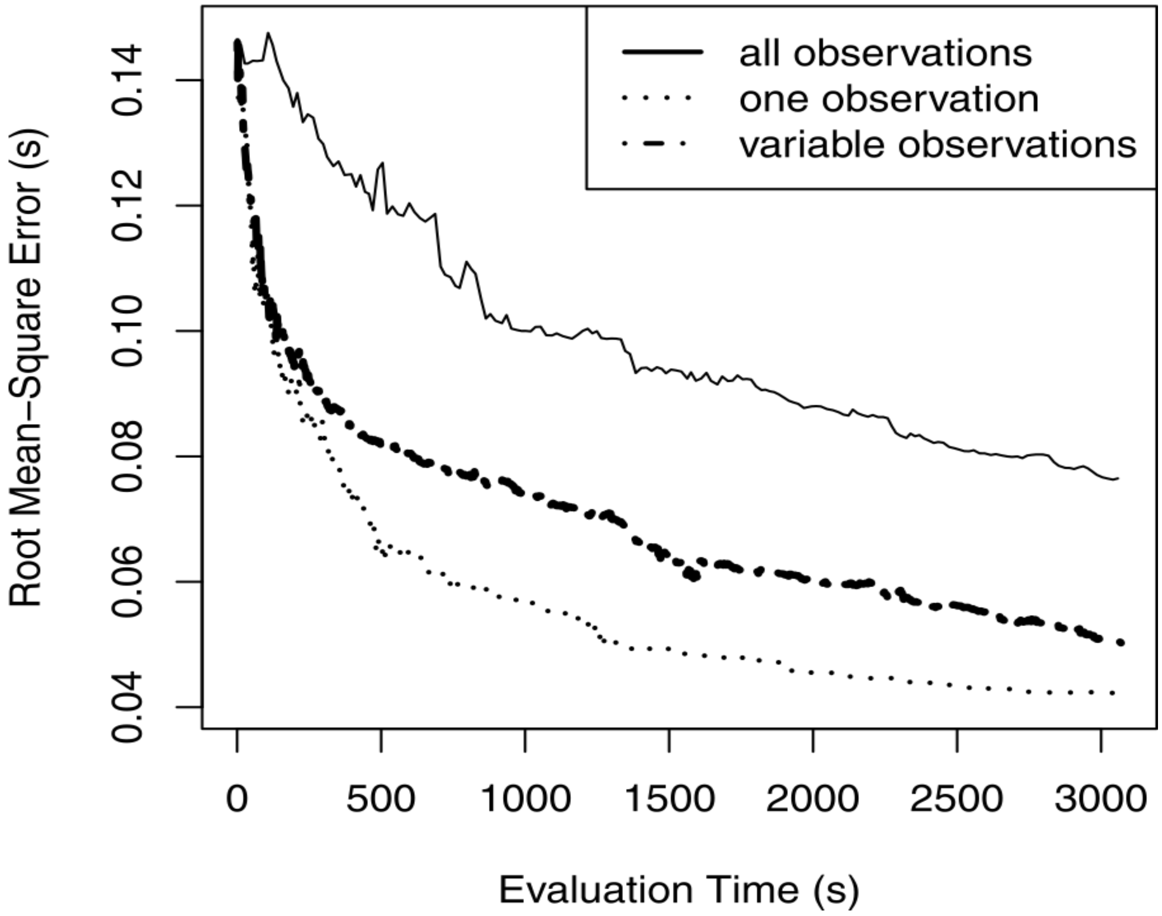

Results for hessian benchmark
all observations
one observation
variable observations
Root Mean−Square Error (s)
0.006
0.008
0.010
0.012
0
1000
2000
3000
4000
5000
6000
Evaluation Time (s)

Results for jacobi benchmark



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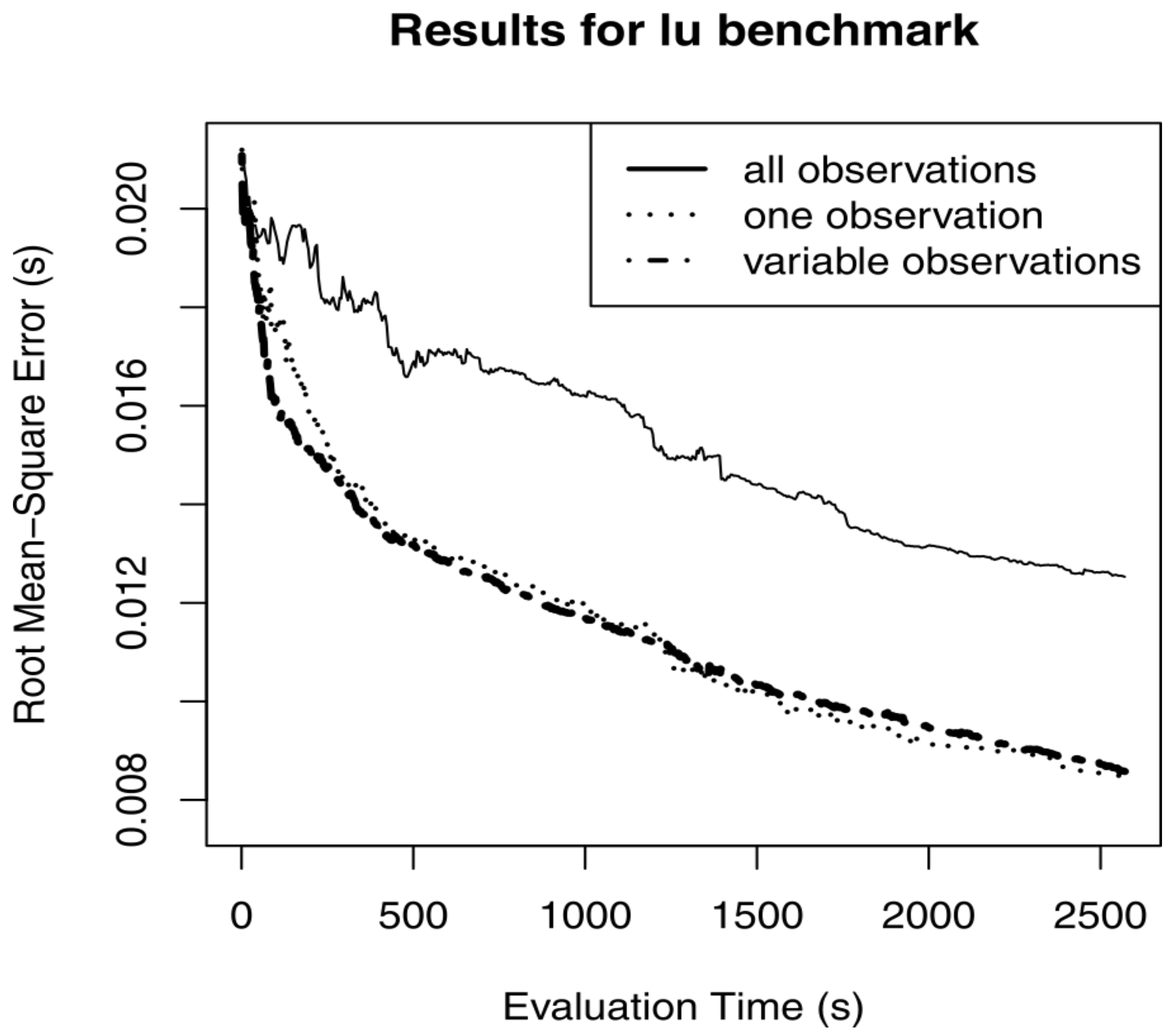
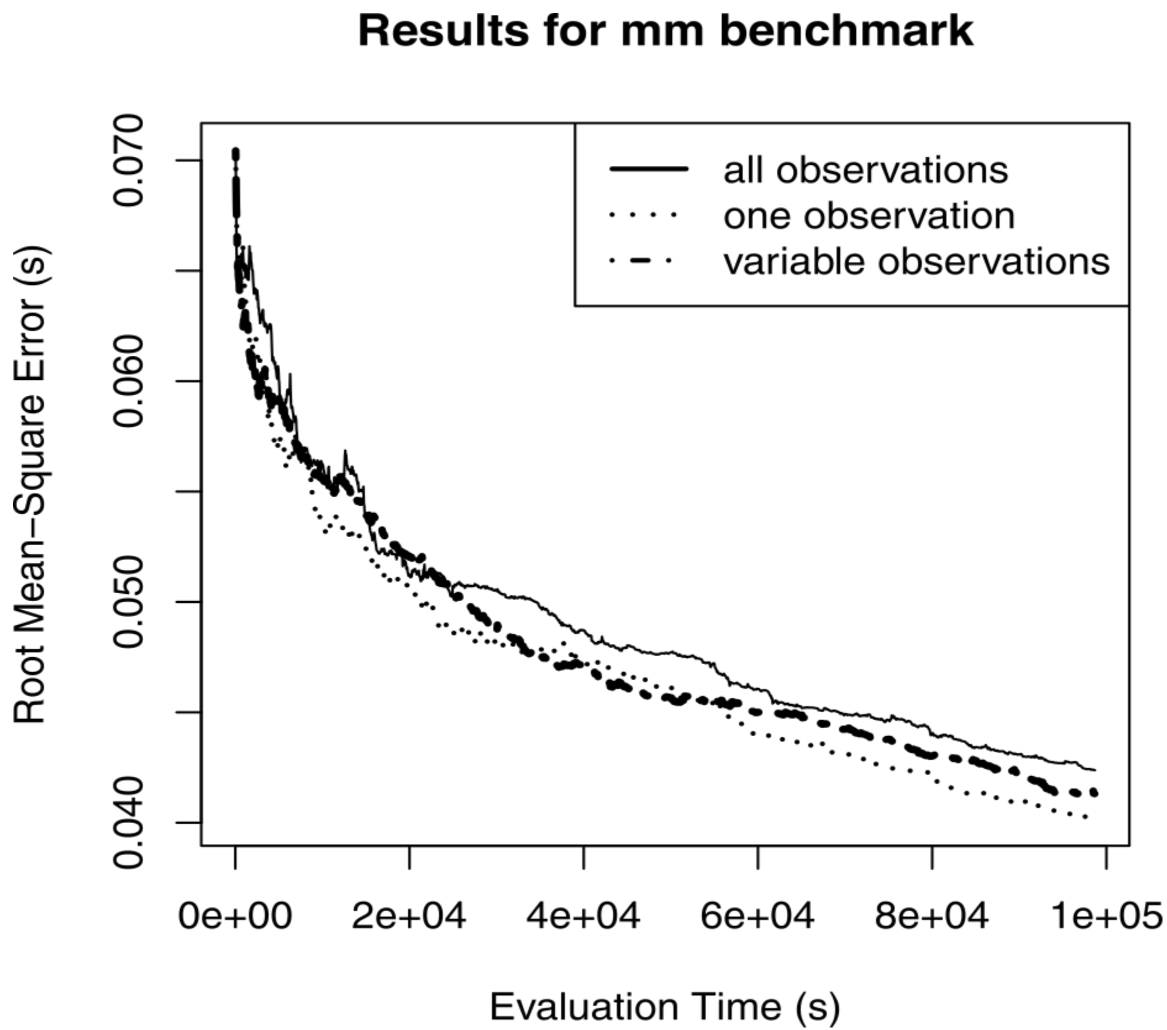


Results for lu benchmark
all observations
one observation
variable observations
Root Mean-Square Error (s)
0.008
0.012
0.016
0.020
0
500
1000
1500
2000
2500
Evaluation Time (s)



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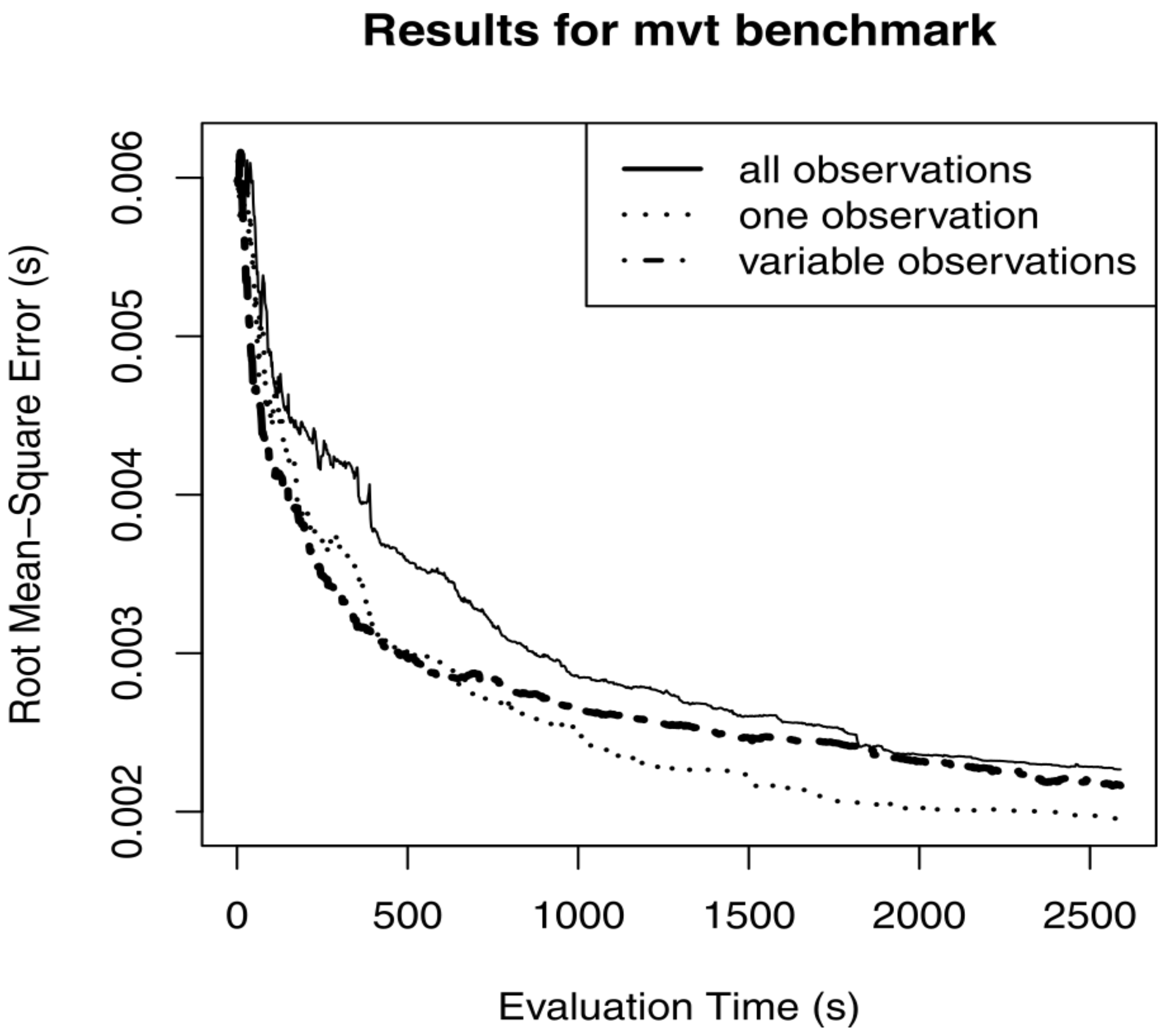
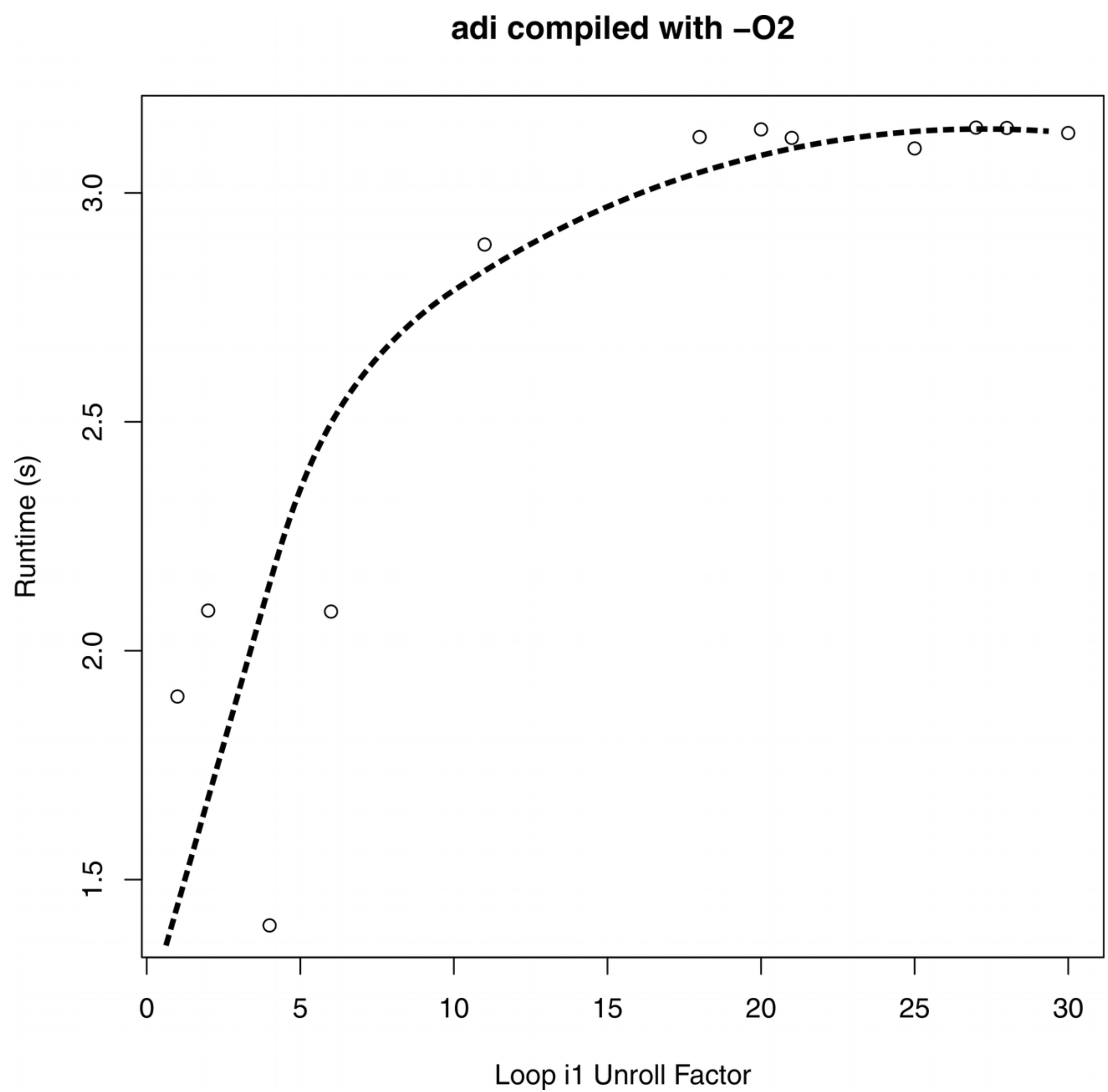
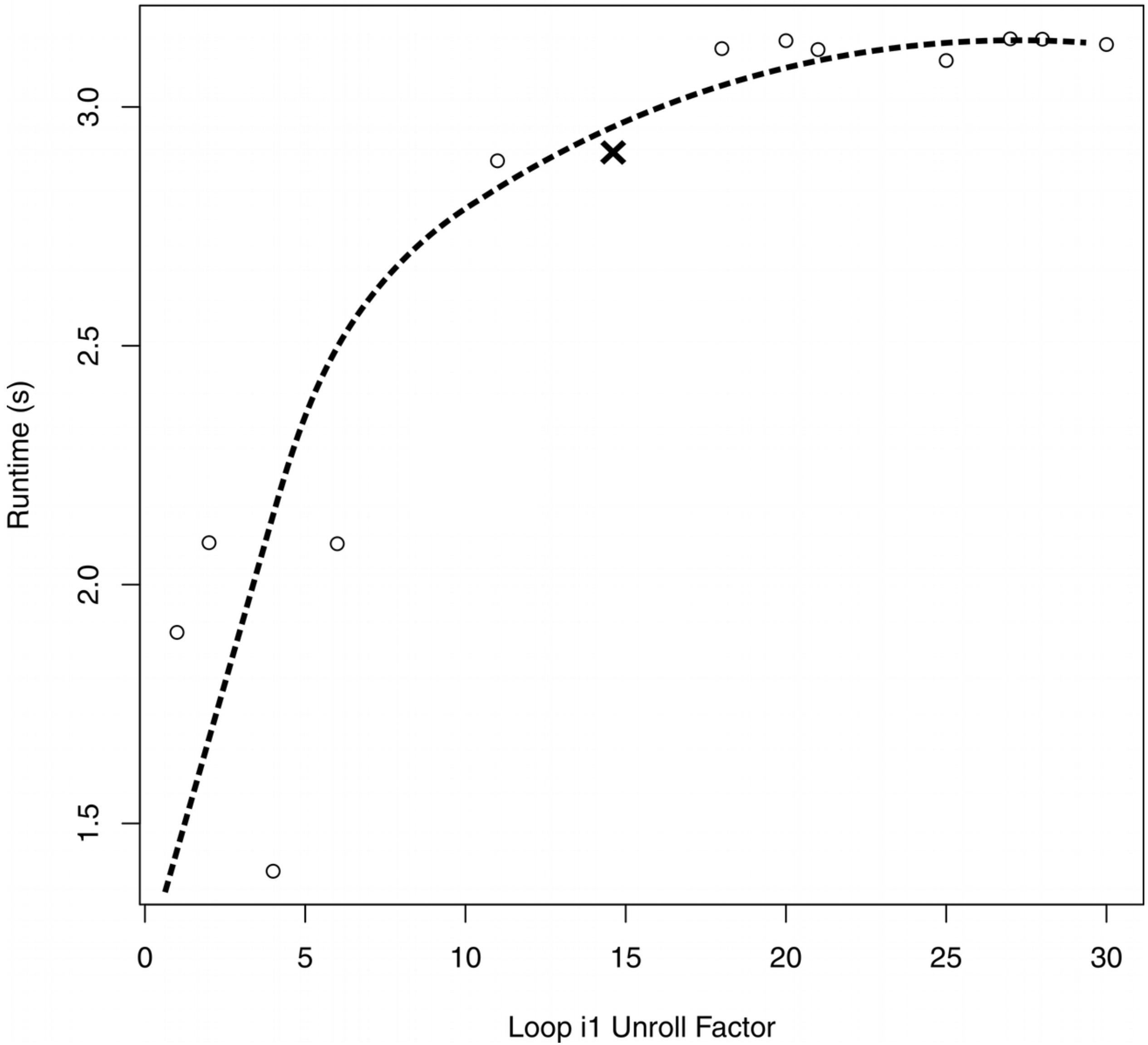
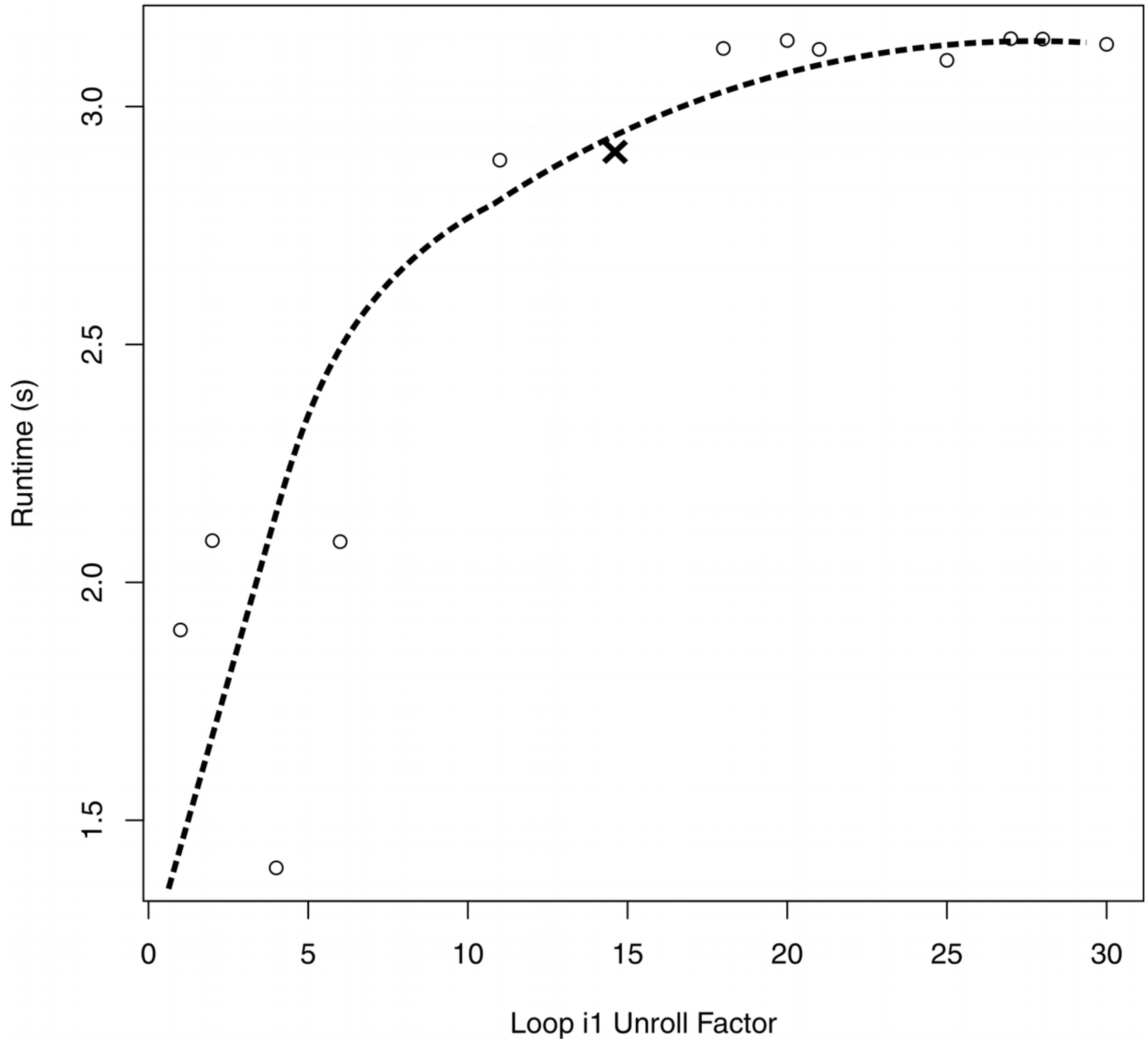

Results for mvt benchmark
all observations
one observation
variable observations
Root Mean−Square Error (s)
0.002
0.003
0.004
0.005
0.006
0
500
1000
1500
2000
2500
Evaluation Time (s)

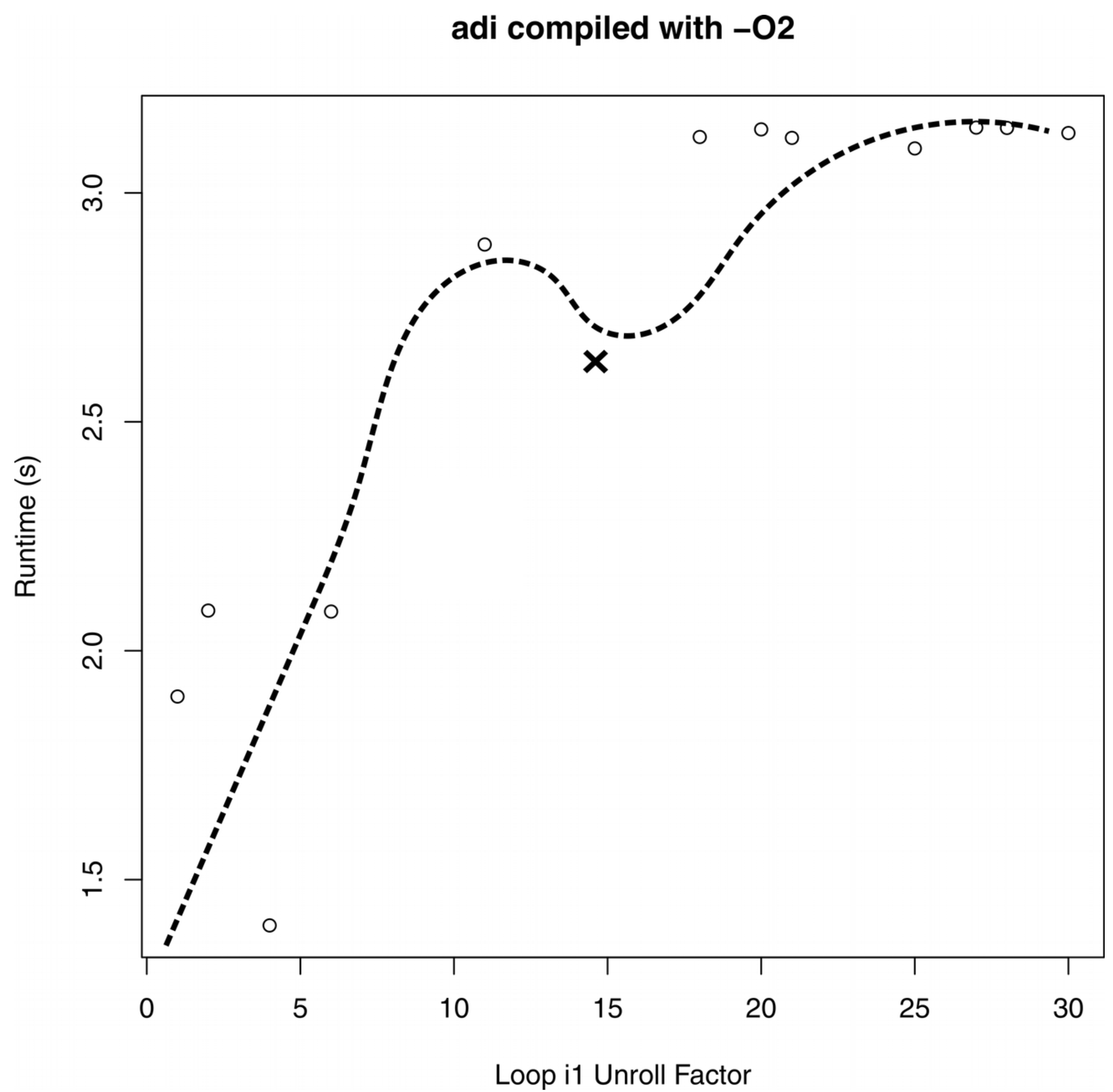

adi compiled with −O2
Runtime (s)
3.0
2.5
2.0
1.5
0
5
10
15
20
25
30
Loop i1 Unroll Factor

adi compiled with −O2



adi compiled with −O2





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