InTime

Boosting Convergence of Timing Closure using Feature Selection in a Learning-driven Approach

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Claim

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- Feature Selection helps boost AUC scores for Timing Closure ML models by ~10%

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- ML models predict timing closure of design by modifying CAD tool parameters — commercial tool InTime, by Plunify Inc.

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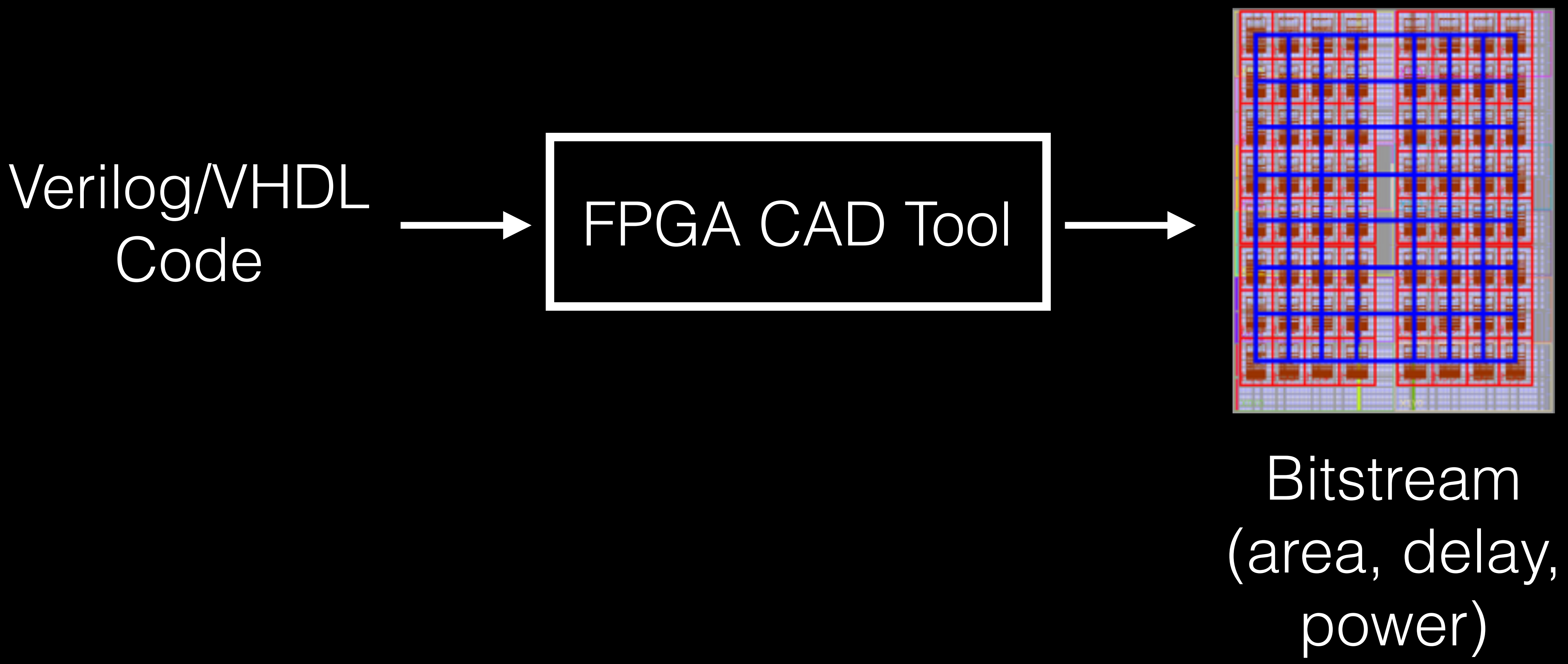
- For Altera Quartus
  — ~80 parameters to 8-22 influential parameters

FPGA CAD Flow

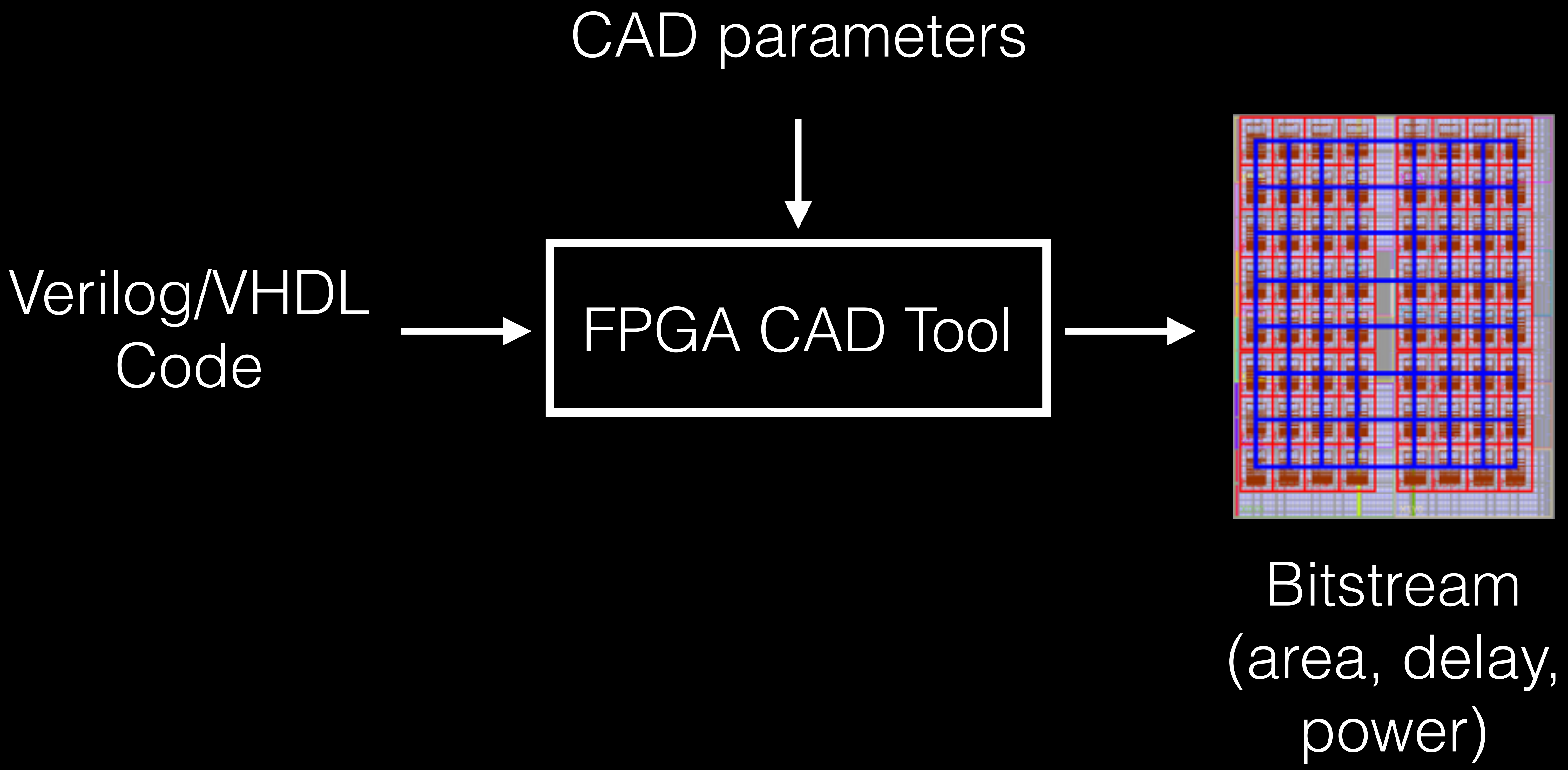


Verilog/VHDL Code

FPGA CAD Tool

Bitstream (area, delay, power)

FPGA CAD Flow



CAD parameters

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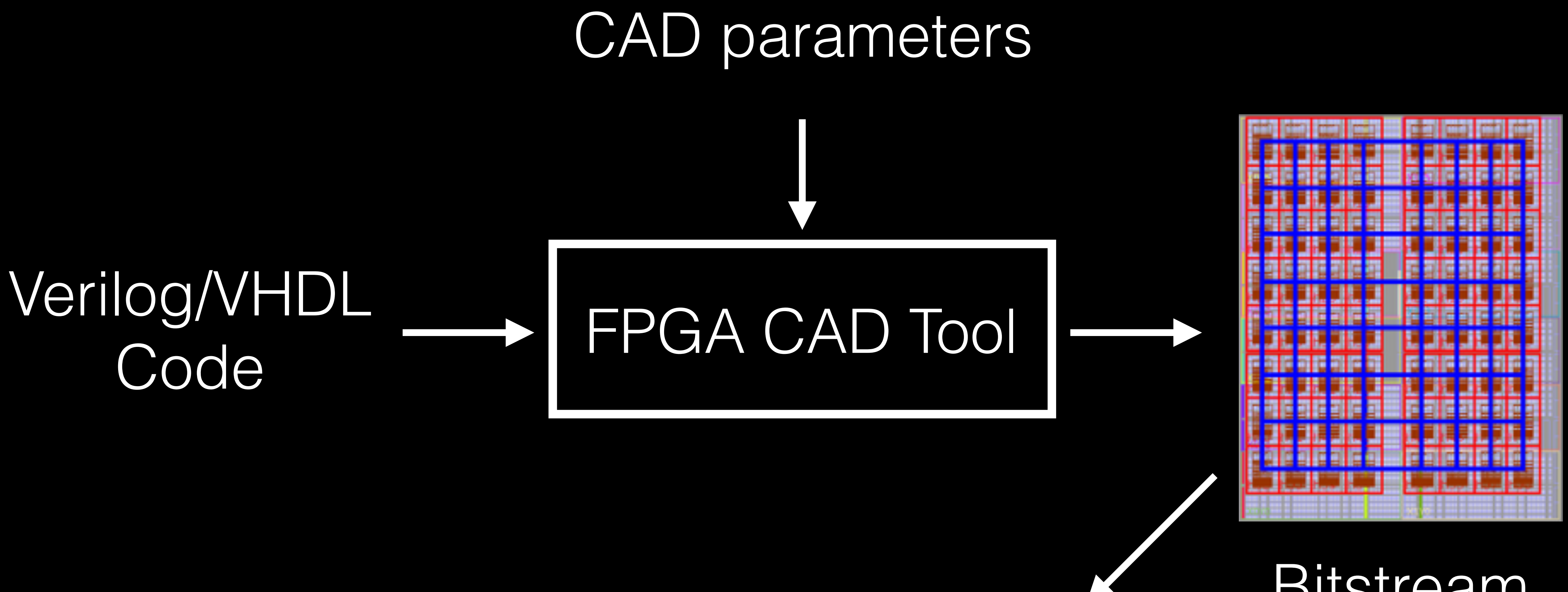

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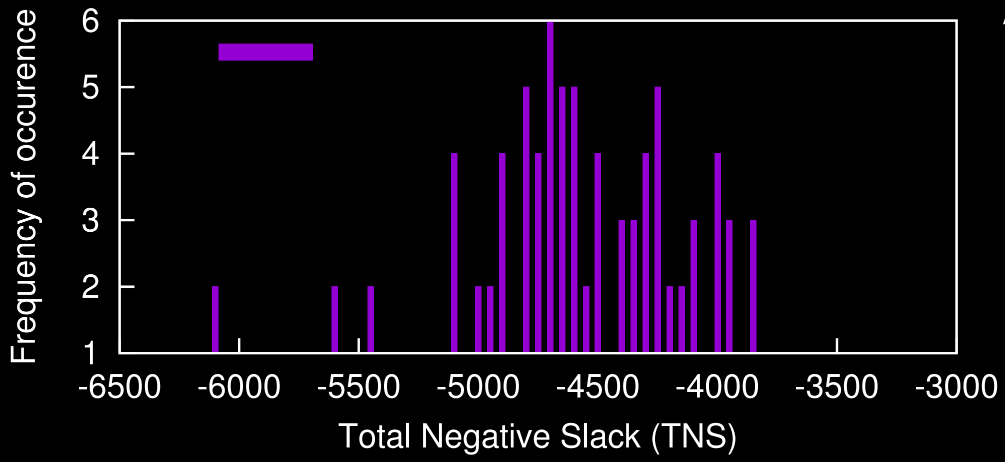

InTime High-Level View

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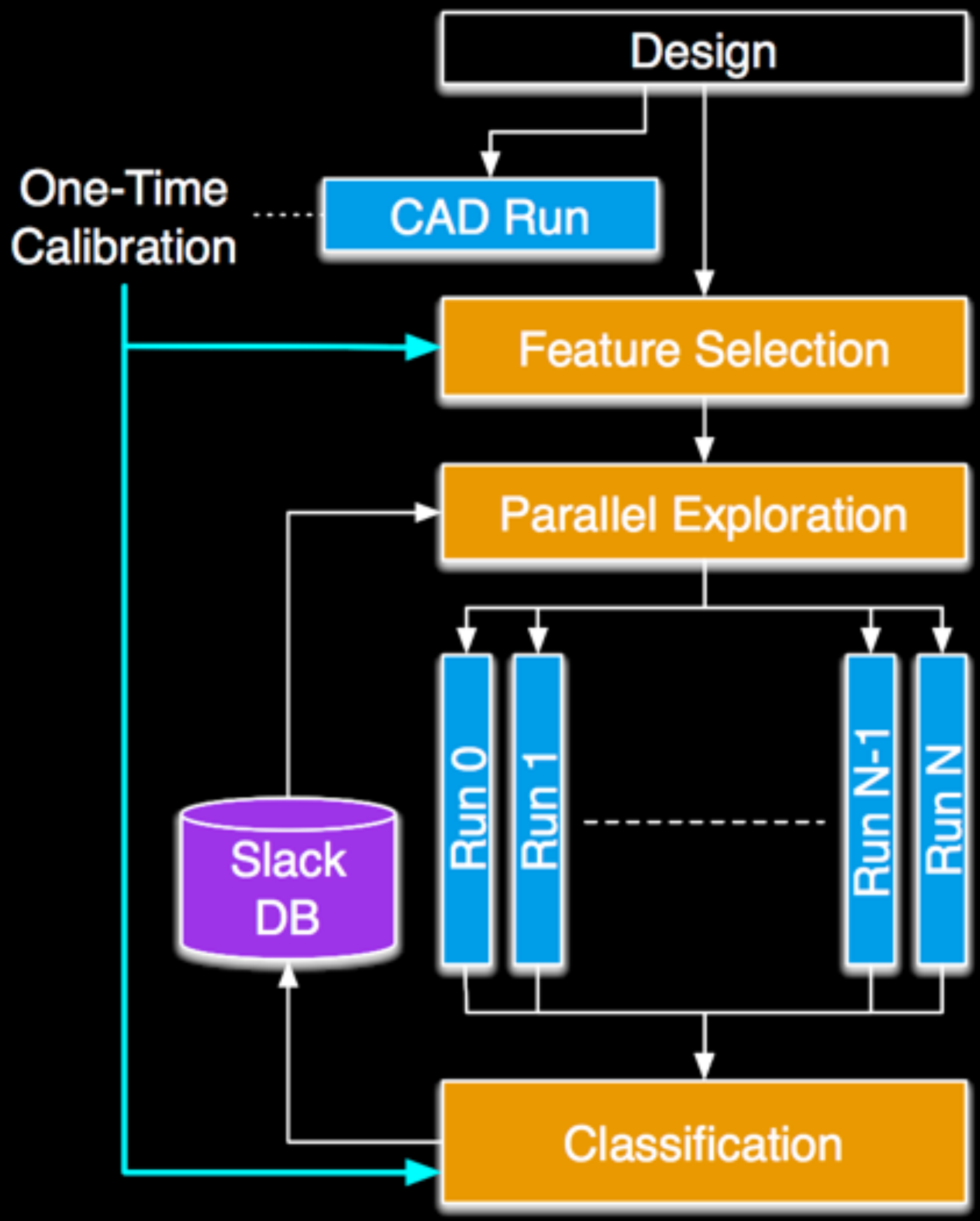

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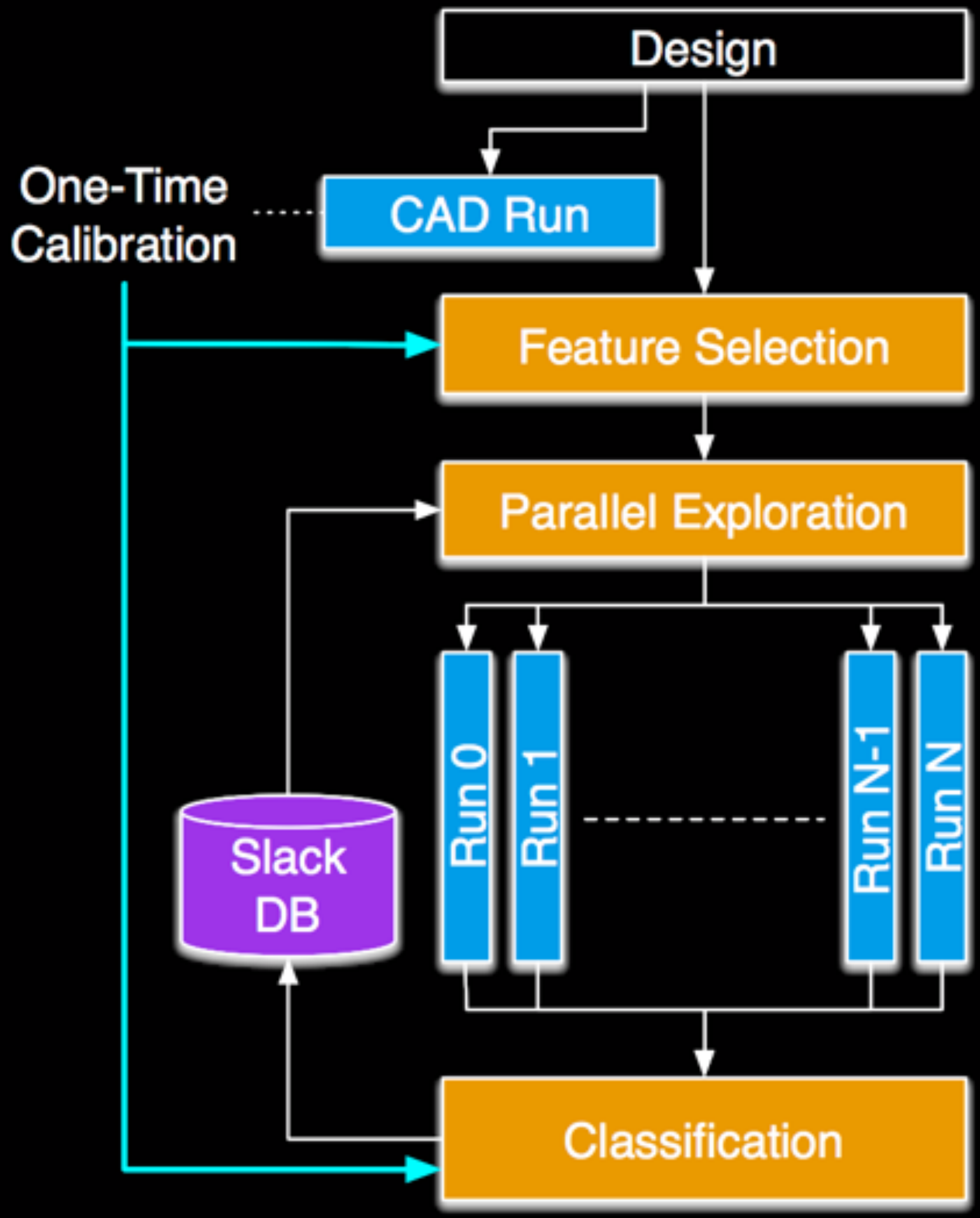
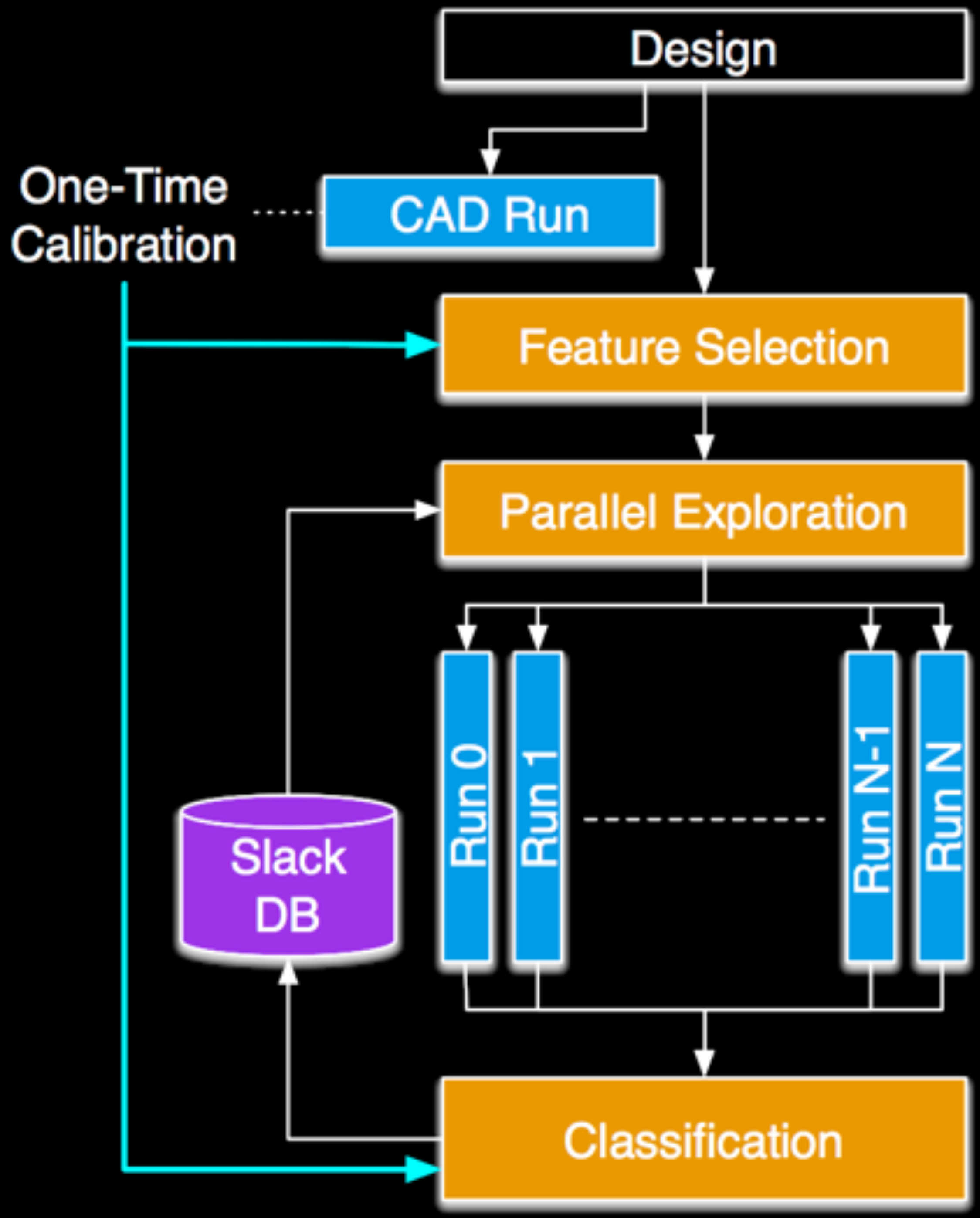


- **Position**:
  — Verified RTL designs expensive to edit
  — For timing closure, use CAD parameters

InTime High-Level View



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- InTime
  — free RTL, play with CAD tool parameters
  — **Problem**: exhaustive search intractable
  — **Solution**: use machine learning!

InTime High-Level View

[FPGA’15 Designer’s Day] Preliminary results on customer designs (limited ability to discuss specifics)
[FCCM’15 Full] Extended results quantifying ML effects on open-source benchmarks
[FPGA’16 Short] Case-for “design-specific” learning instead of building a generic model
[FCCM’16 Short] Classifier accuracy exploration across ML strategies, and hyper-parameter tuning

Outline

- Brief intro of InTime flow and ML techniques

- Justifying the approach
  — Opportunity for using ML (Slack distribution)
  — The need for running ML (Entropy/Correlation)

- Review of Feature Selection

- Experimental results
  — Impact of features/run samples
  — ROC curves across designs
  — Comparing vs. FCCM'16 results

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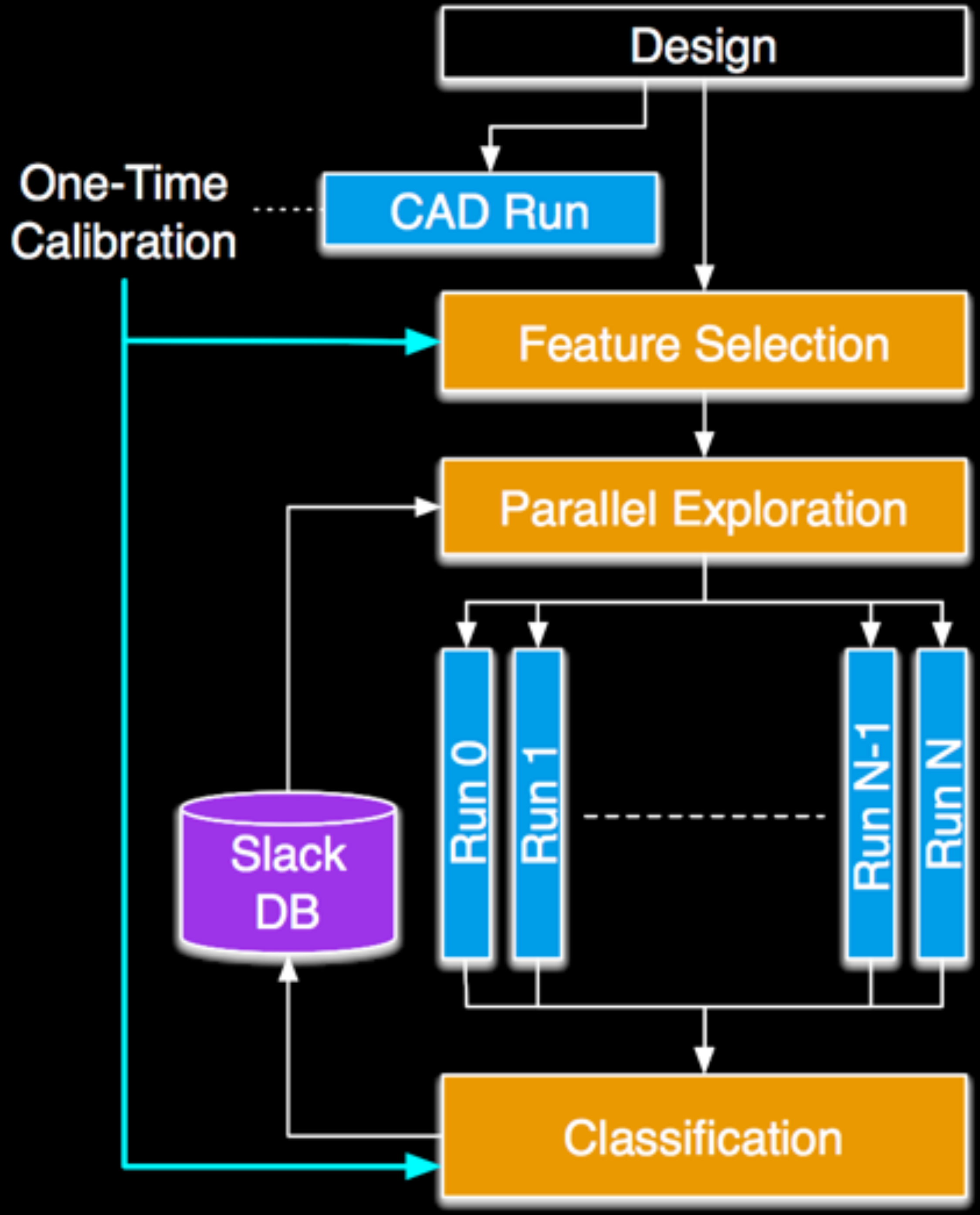

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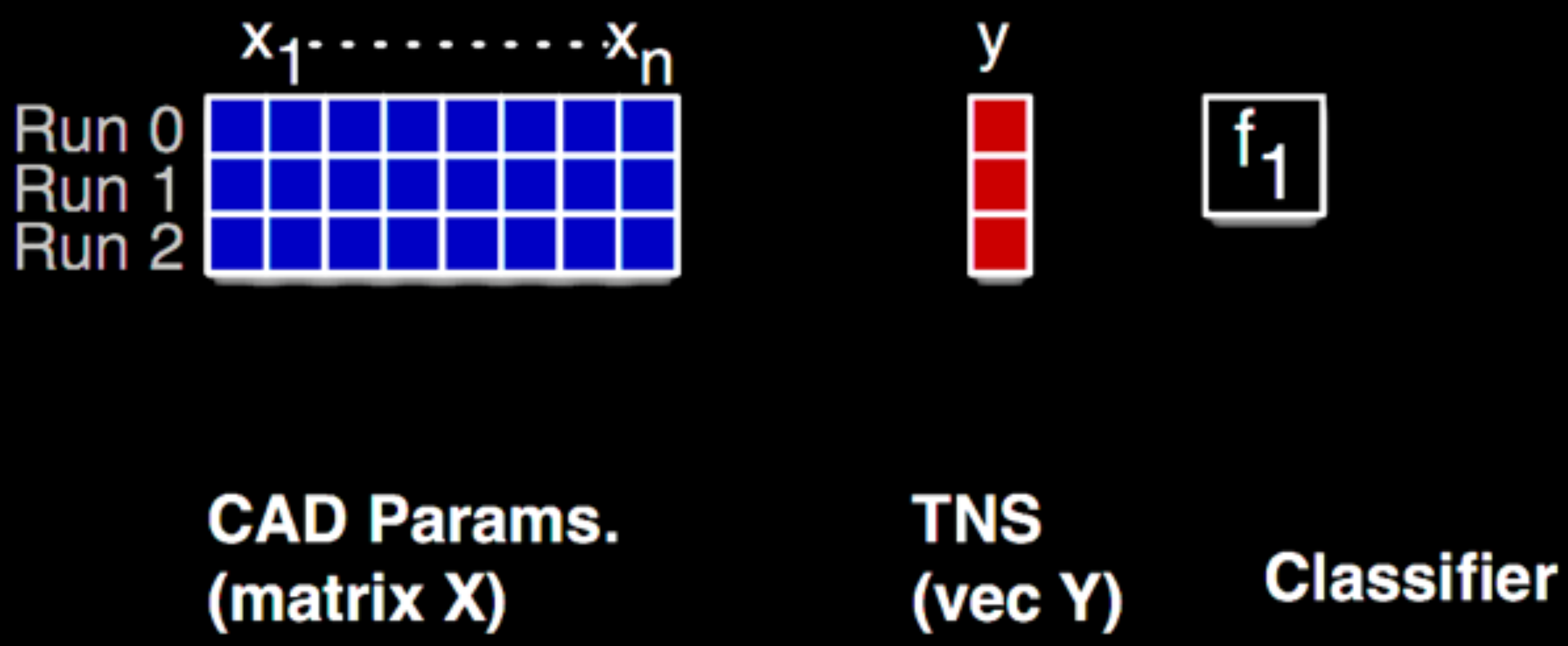
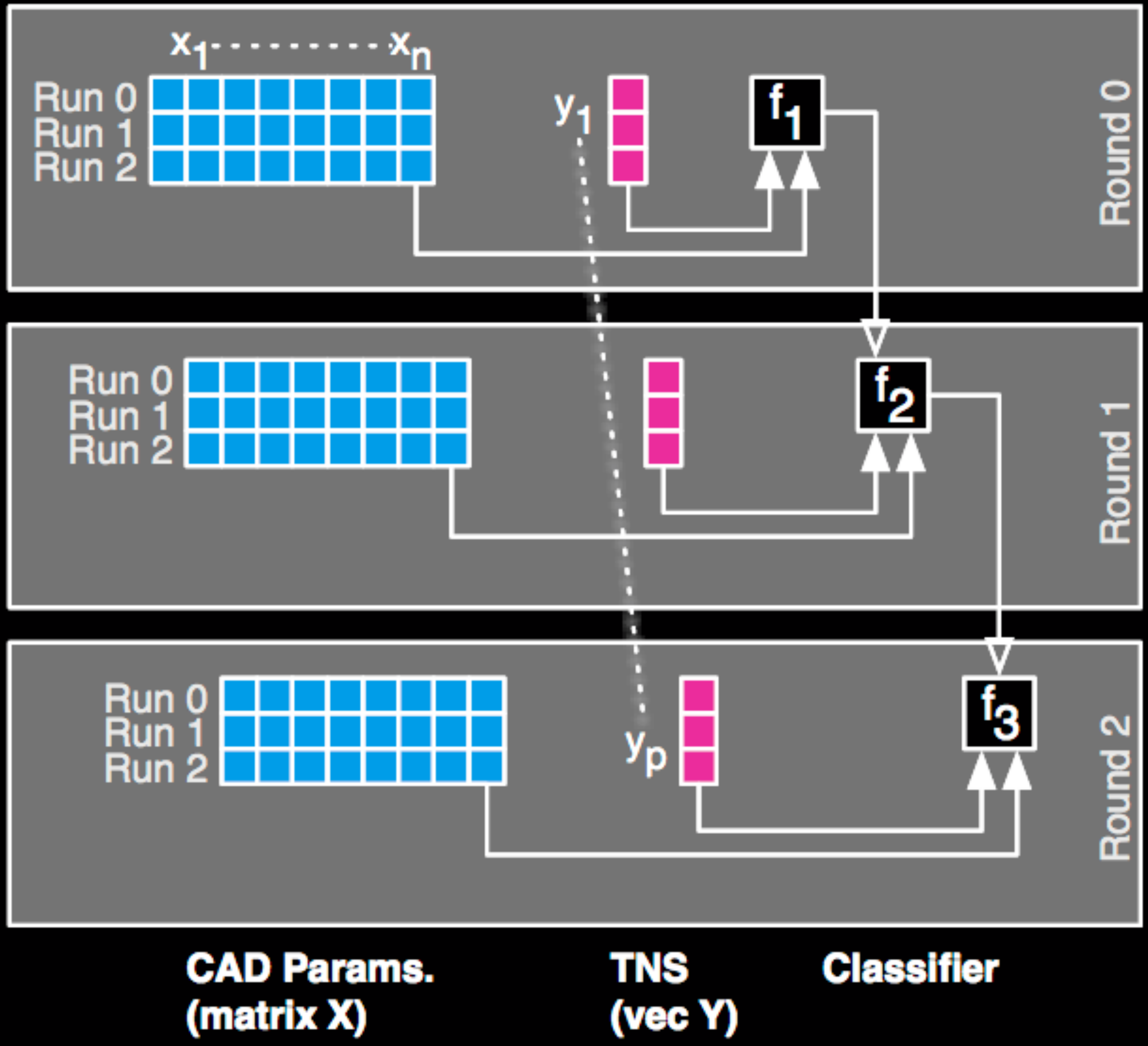
How InTime works



- Simply tabulate results
  — record input CAD parameters + timing slack

- Build a model for predicting [GOOD/BAD]

How InTime works



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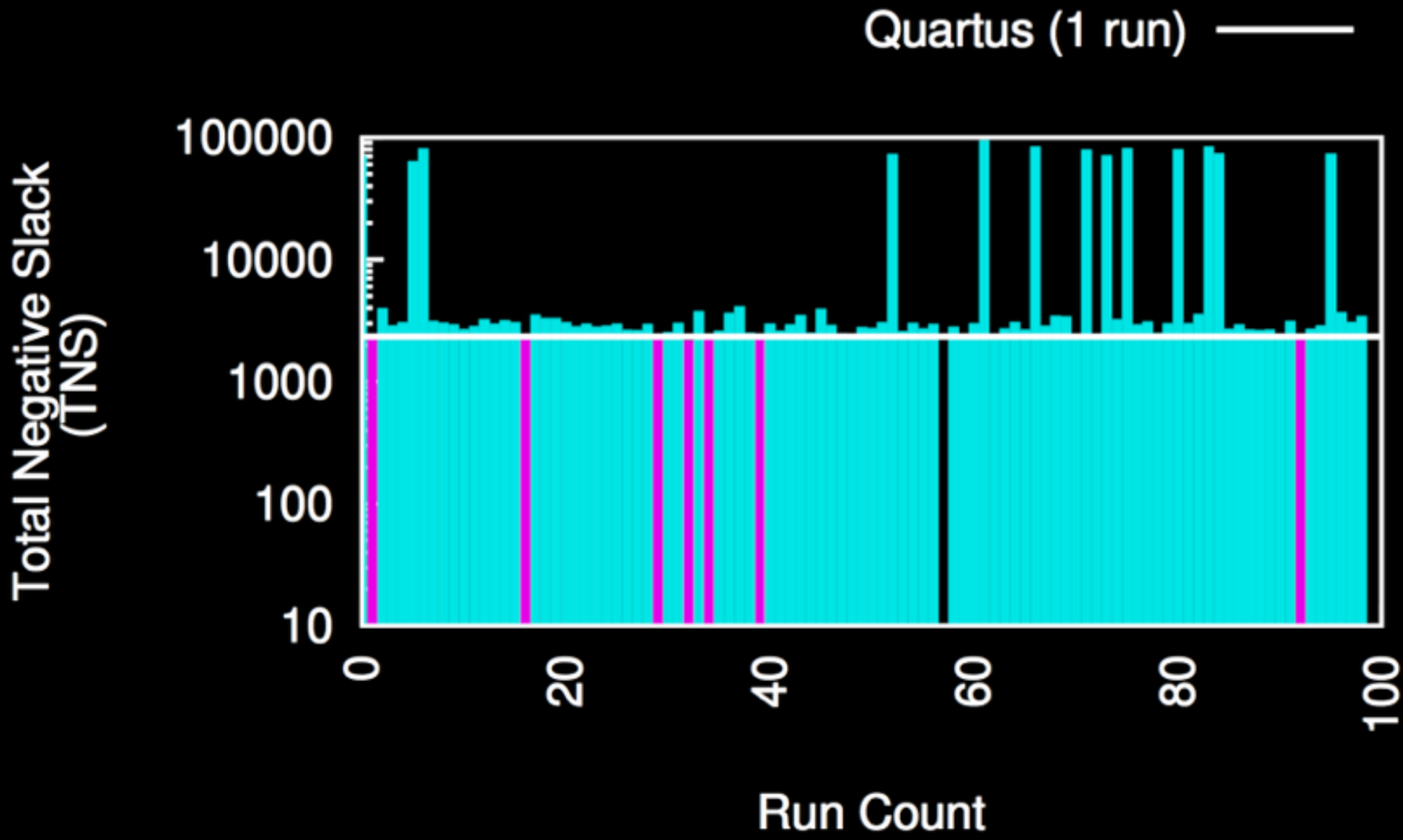
Q&A

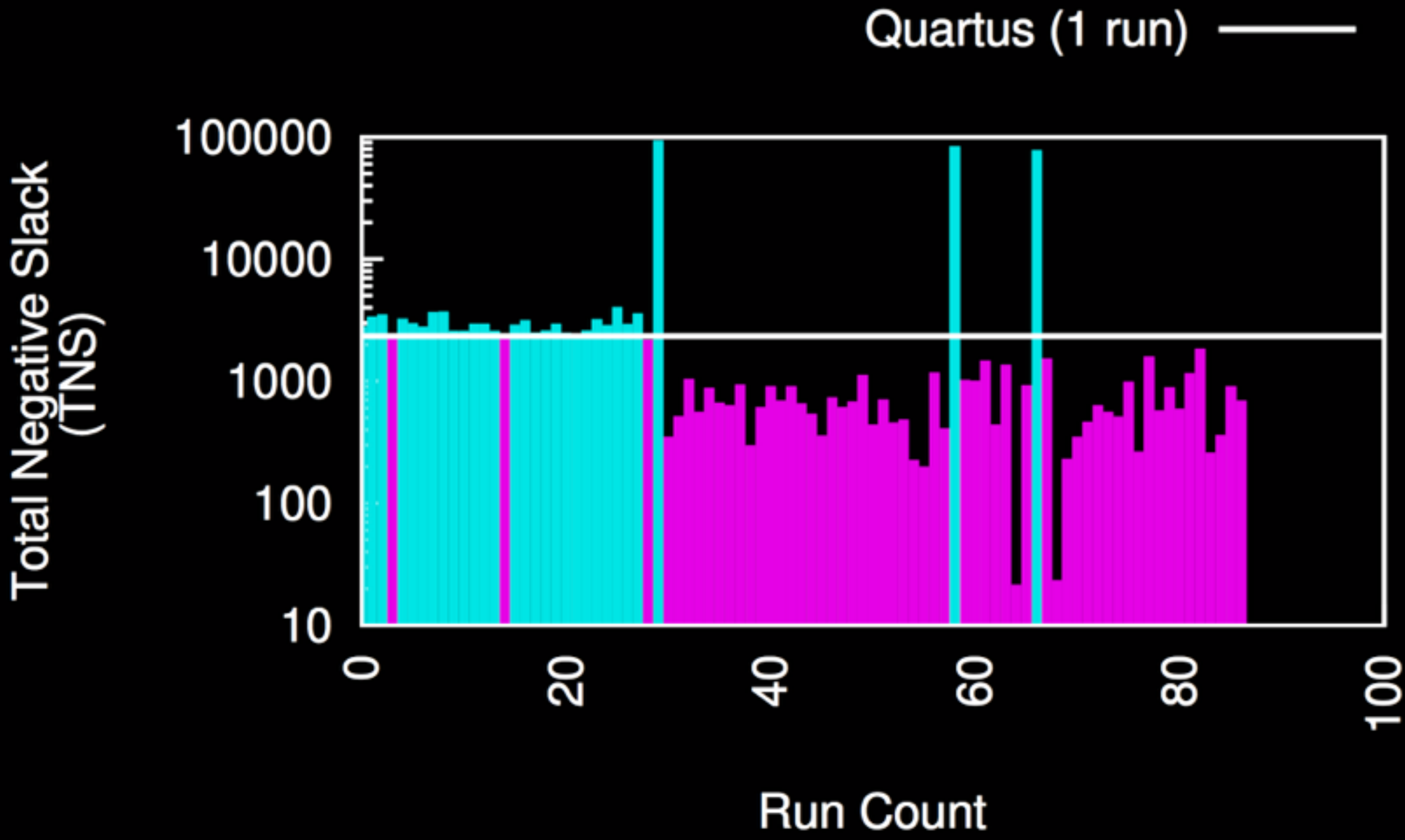
- Do this really work?
- What's the opportunity in timing slack spread?
- Do we really need machine learning?
- How unique are the final converged solutions?
- What is the coverage scope of our tool?

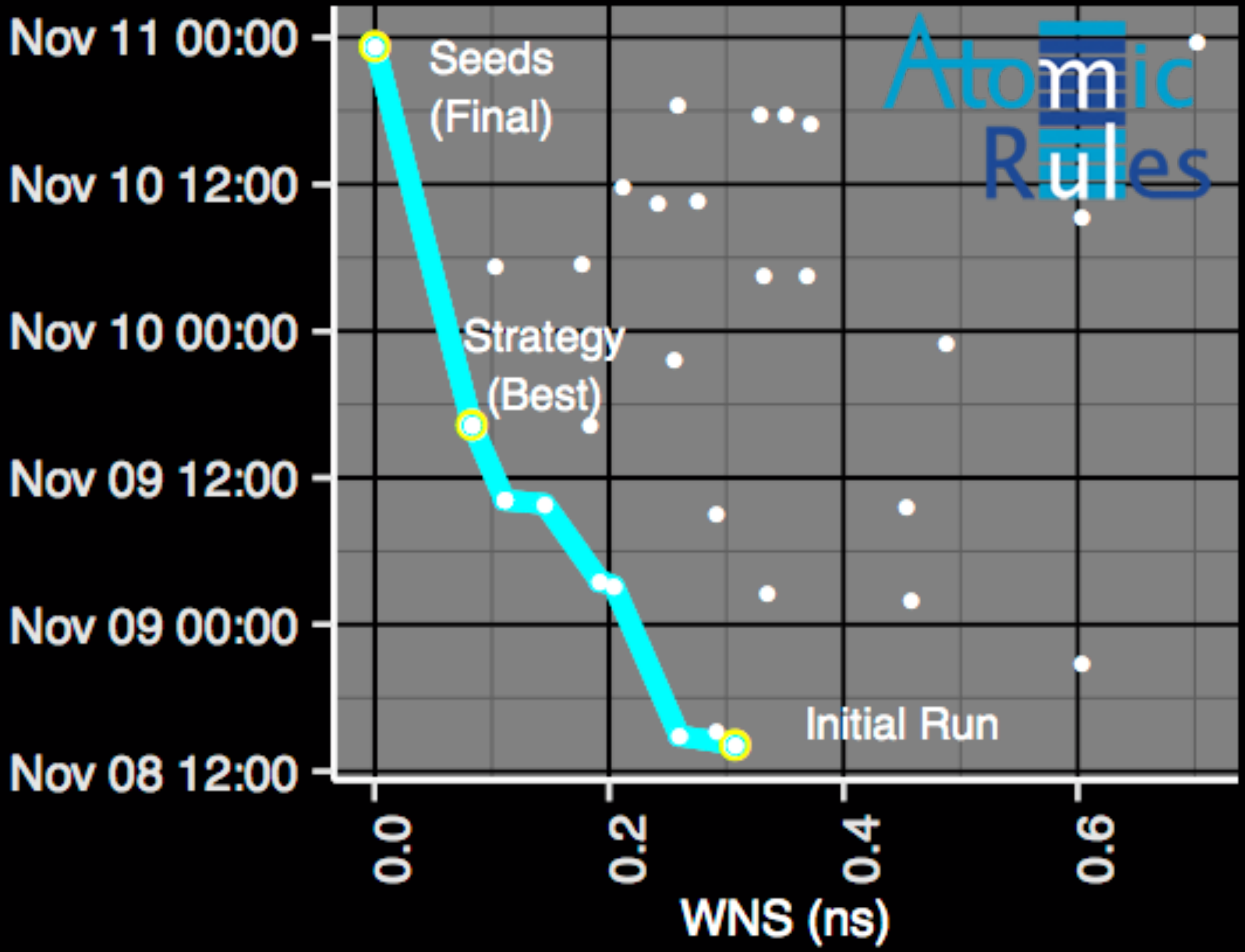
Do this really work?

Results — No Learning



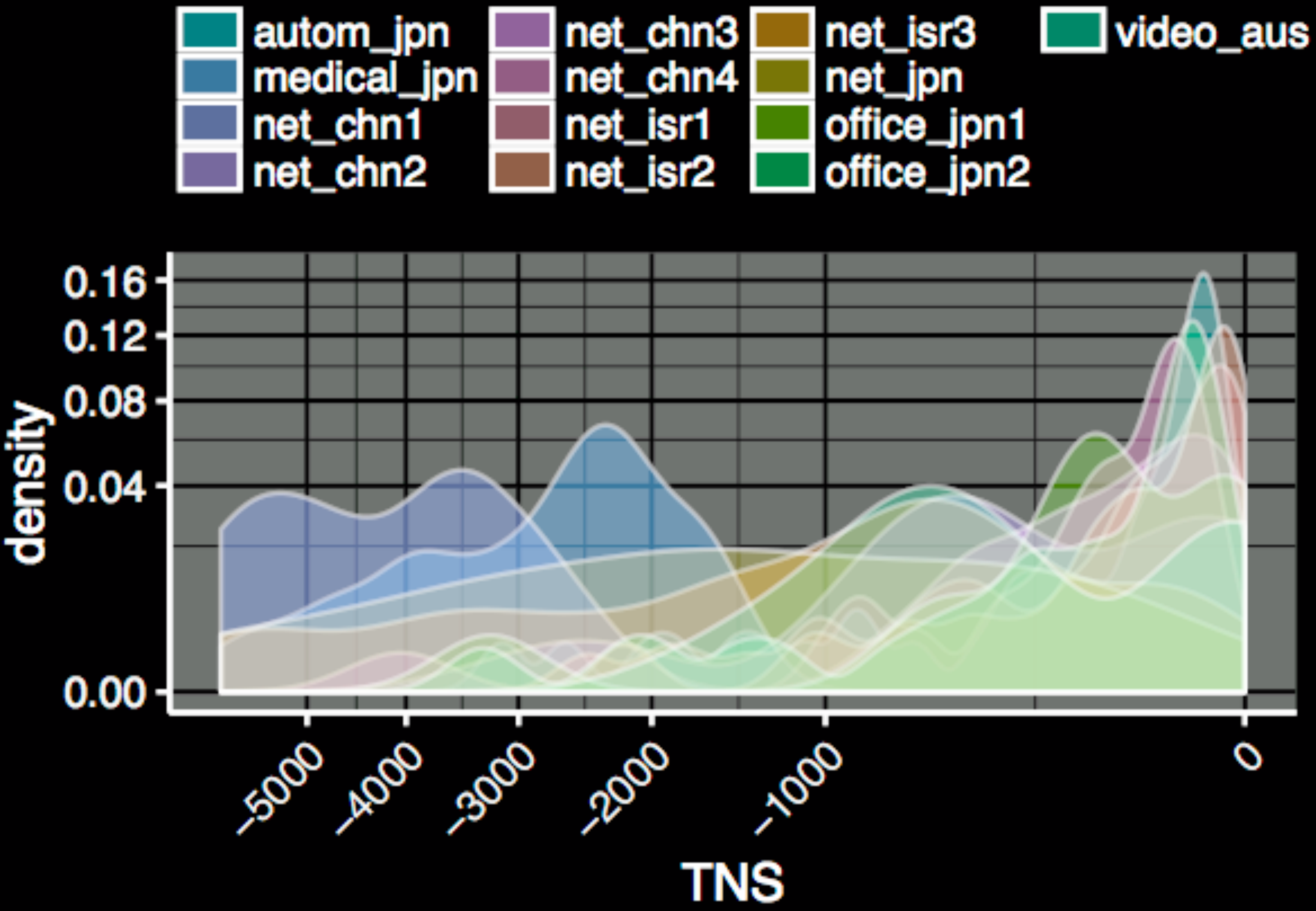
Results — with Learning




Nov 11 00:00
Nov 10 12:00
Nov 10 00:00
Nov 09 12:00
Nov 09 00:00
Nov 08 12:00
0.0
0.2
0.4
0.6
WNS (ns)
Seeds
(Final)
Strategy
(Best)
Initial Run
Atomic
Rules

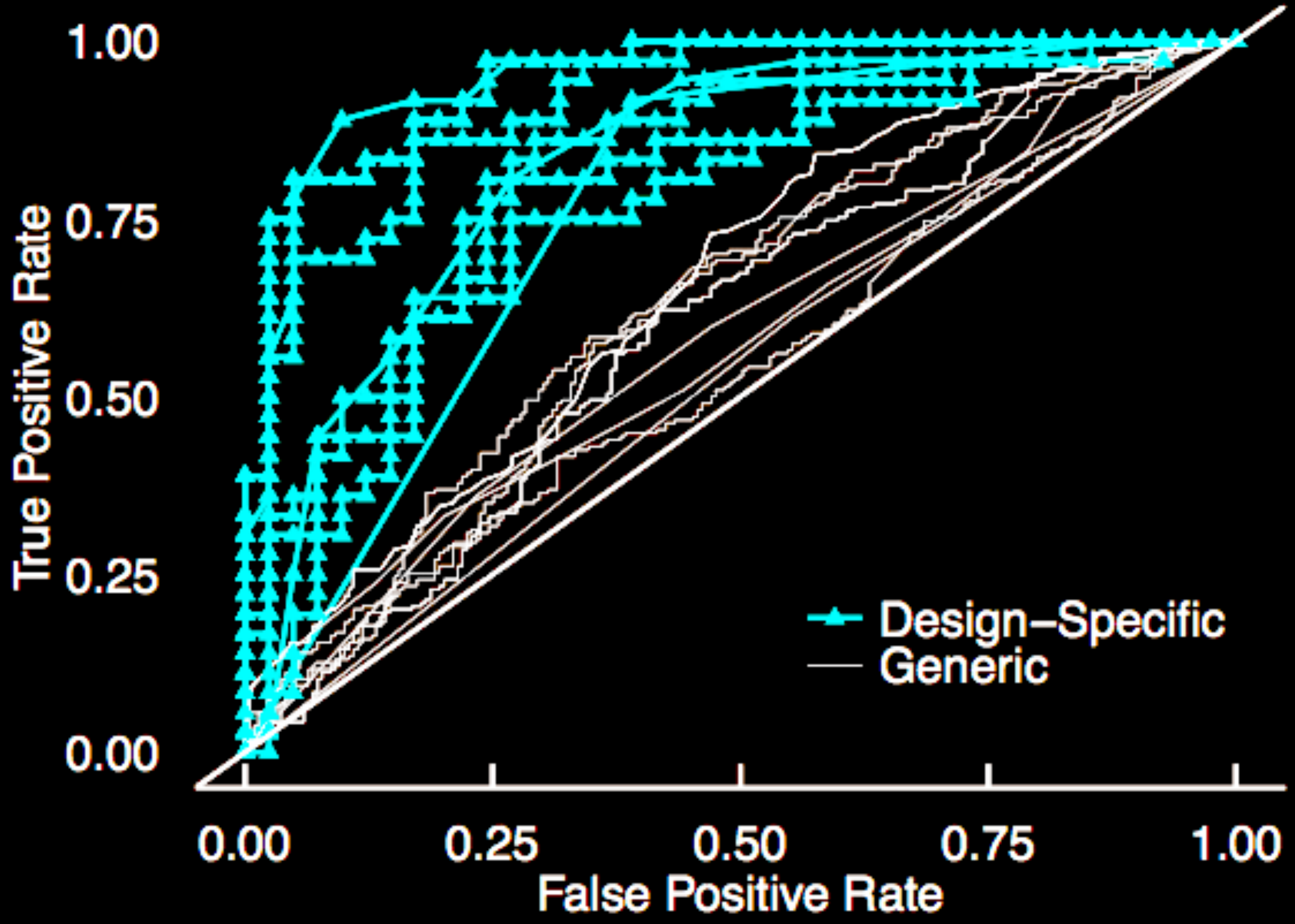
What's the opportunity in timing slack spread?

Parameter Exploration



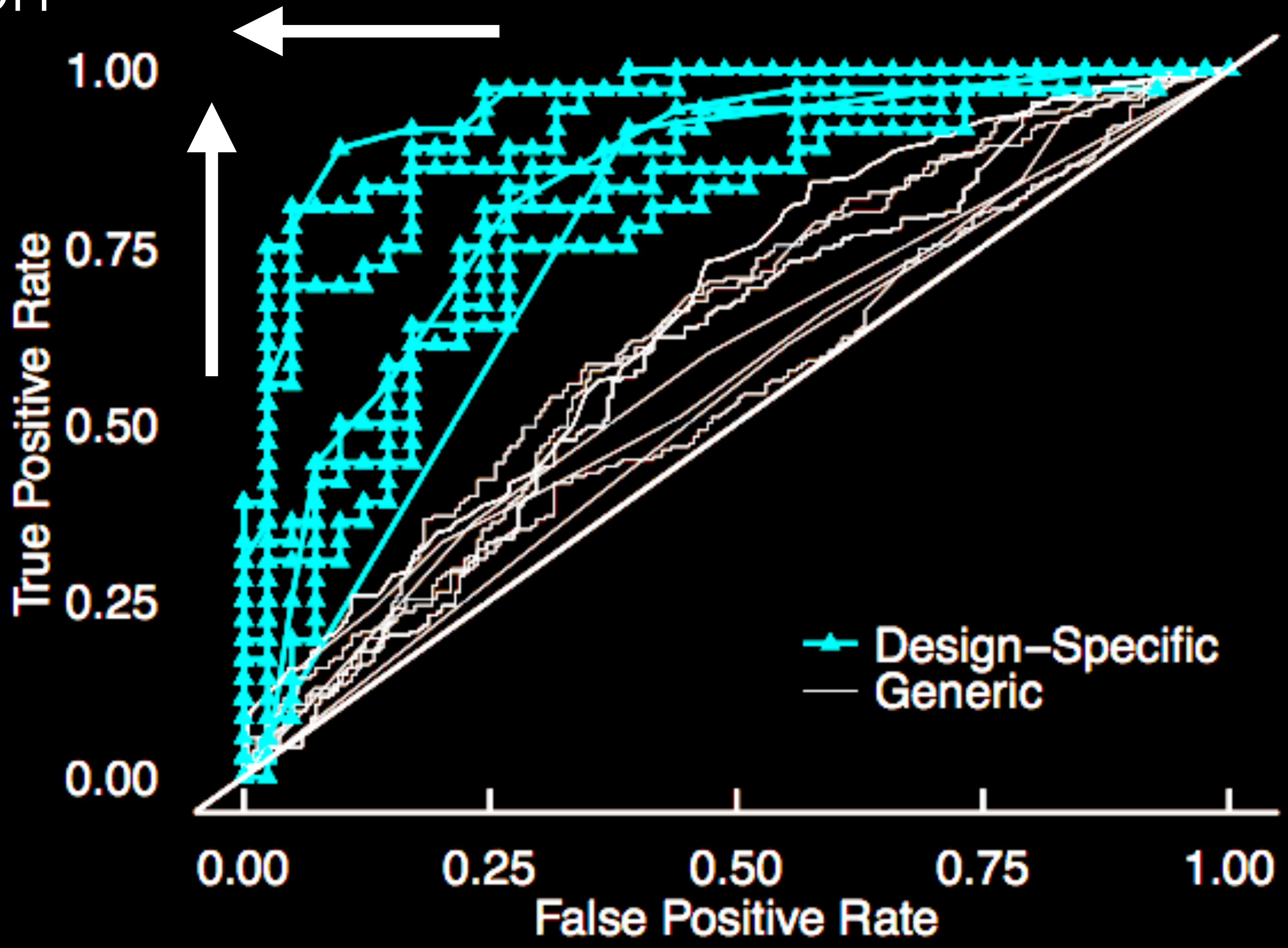
Do we really need machine learning?

Results (aes)


1.00
0.75
0.50
0.25
0.00
True Positive Rate
0.00
0.25
0.50
0.75
1.00
False Positive Rate
▲ Design–Specific
— Generic

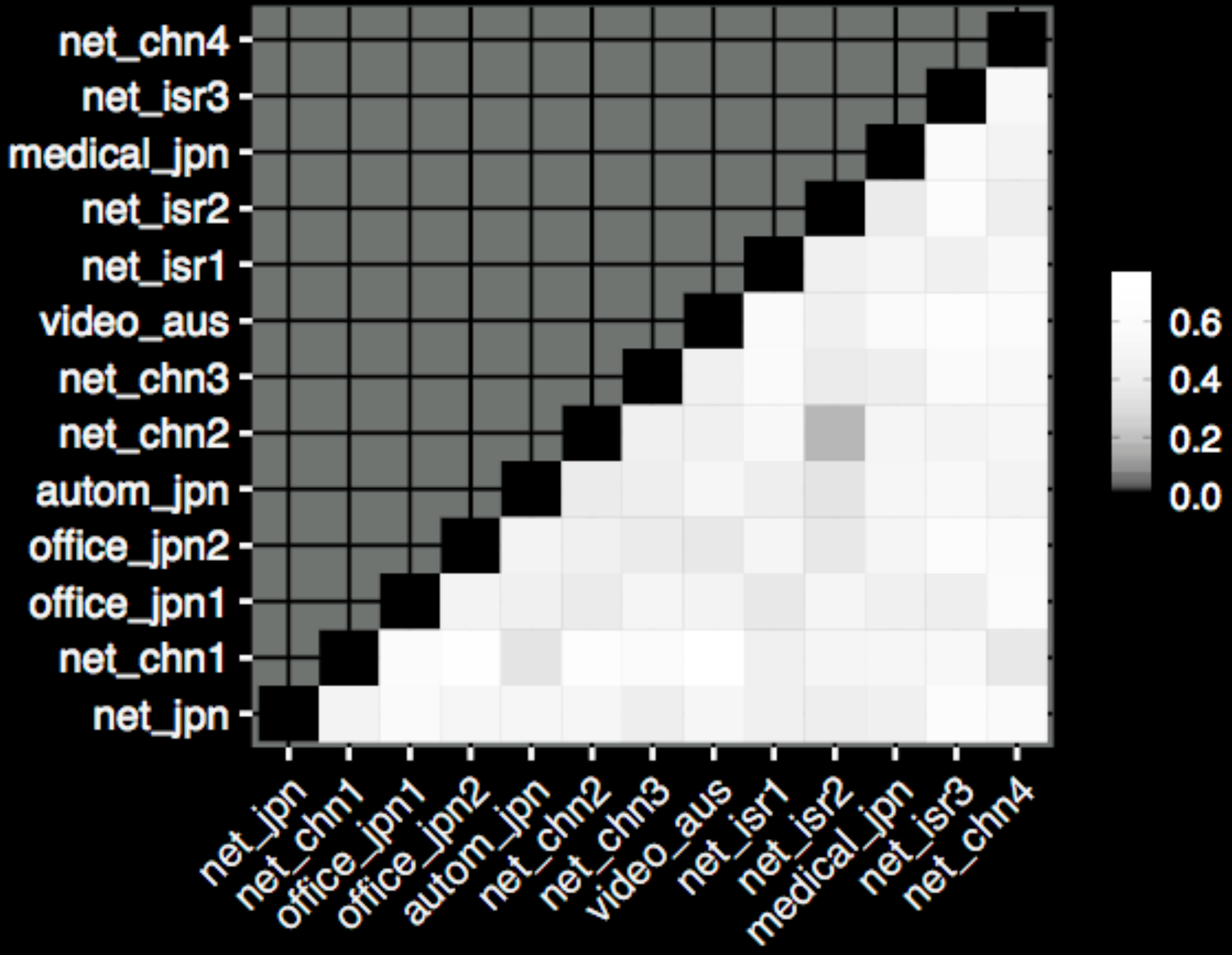
Results (aes)

best classification



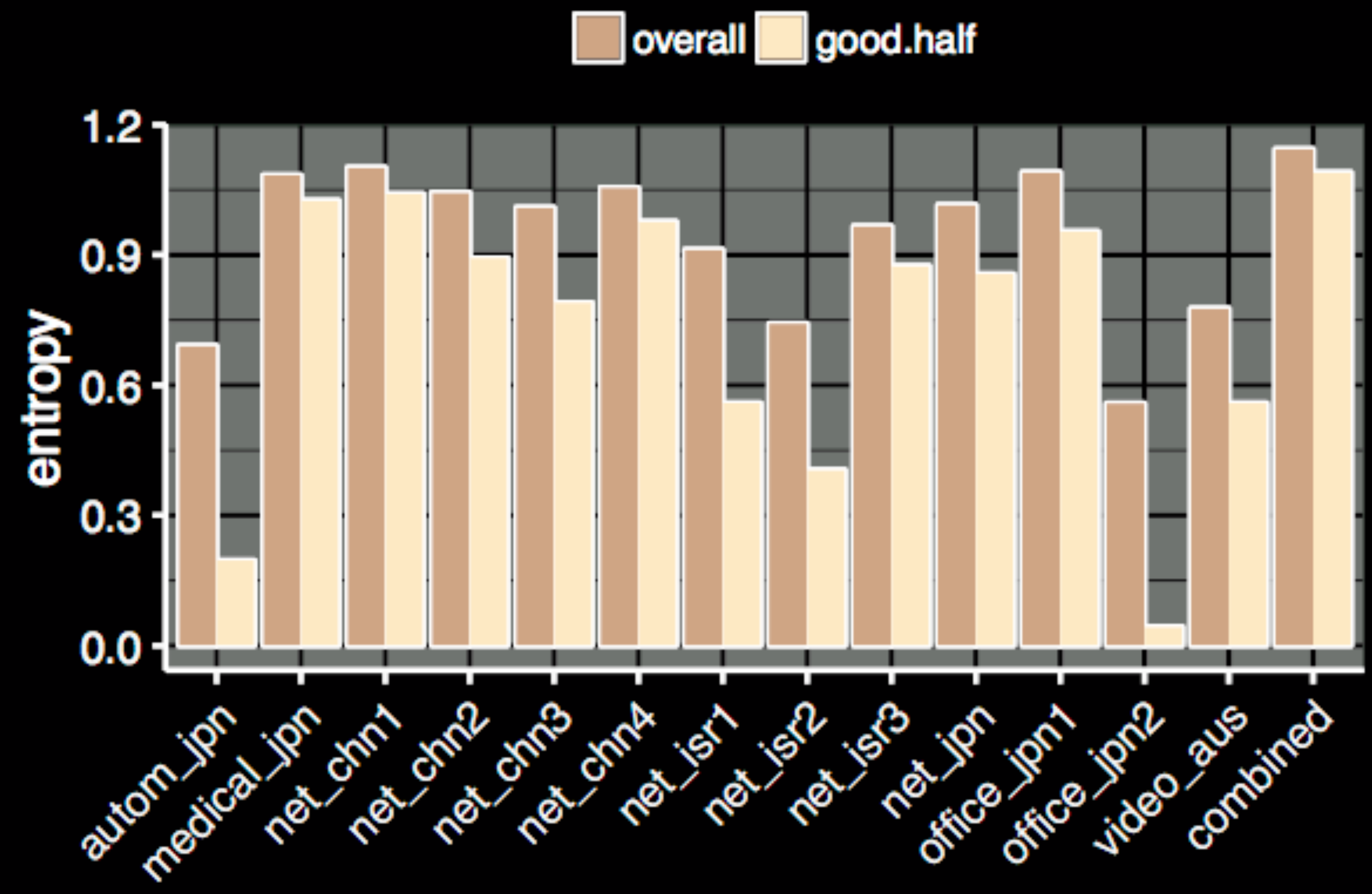
How unique are the final converged solutions?

Dissimilarity

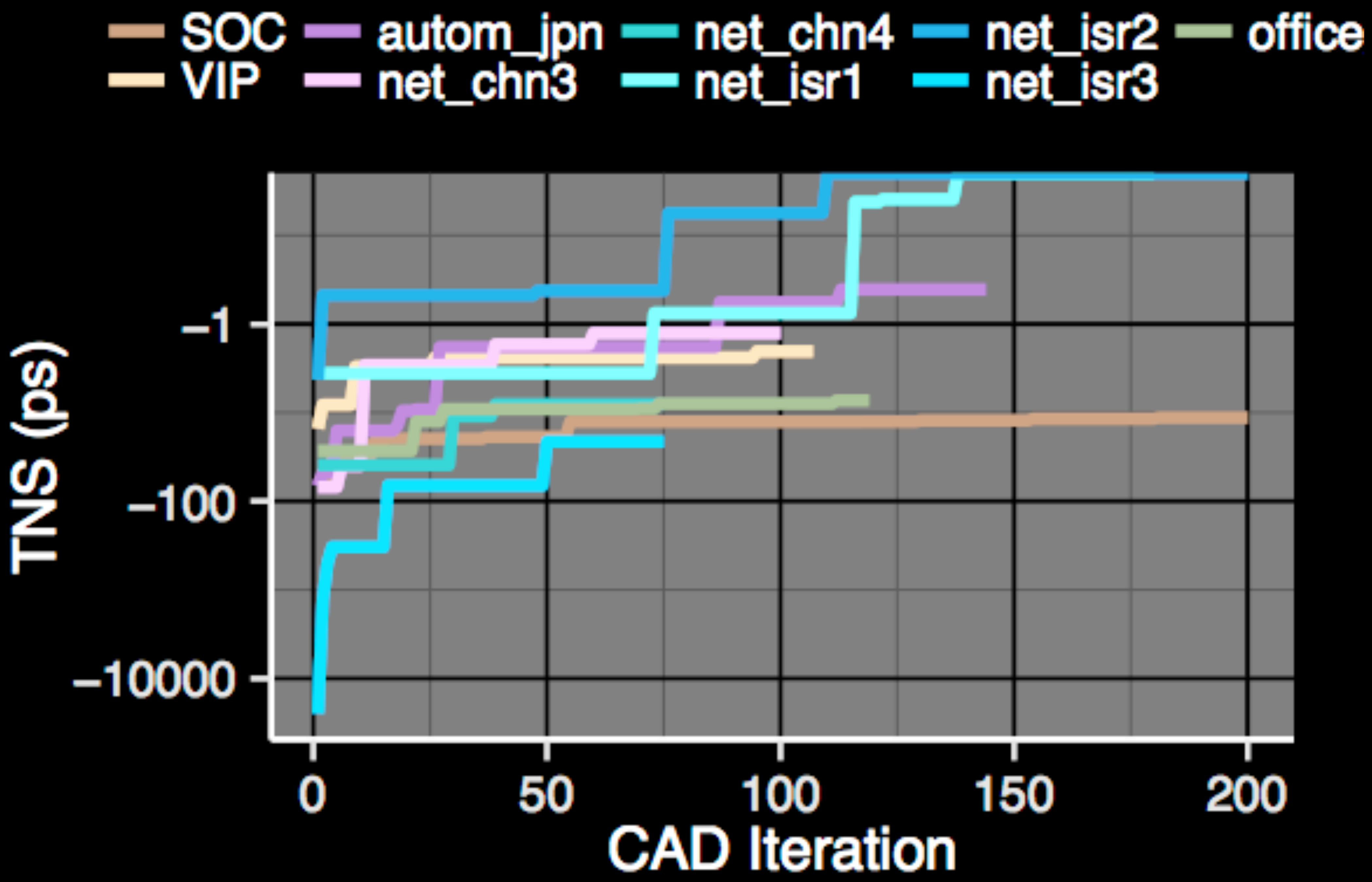


What is the coverage scope of our tool?

Entropy in solutions



So, what's the bottomline?


SOC
VIP
autom_jpn
net_chn3
net_chn4
net_isr1
net_isr2
net_isr3
office
TNS (ps)
−1
−100
−10000
0
50
100
150
200
CAD Iteration

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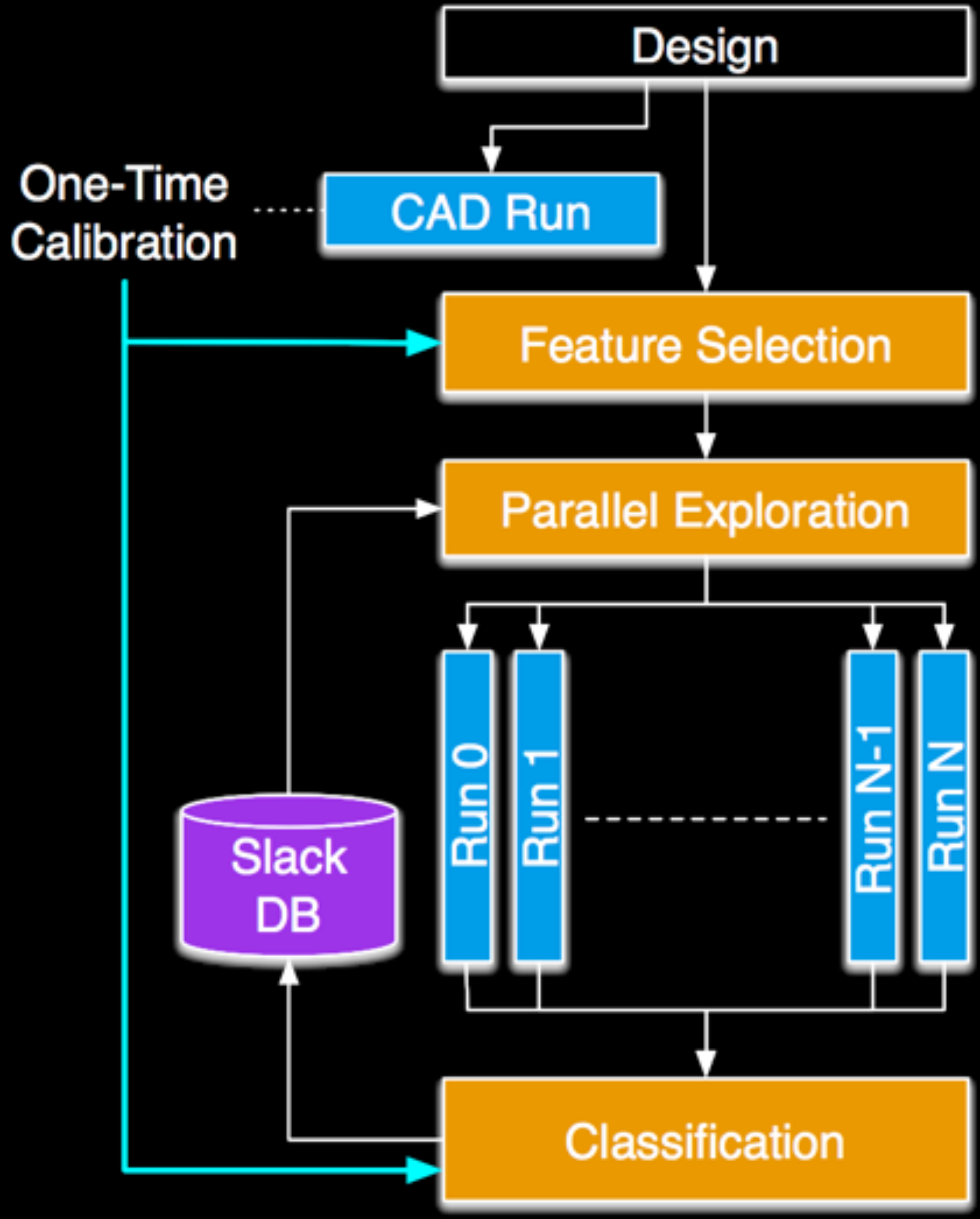
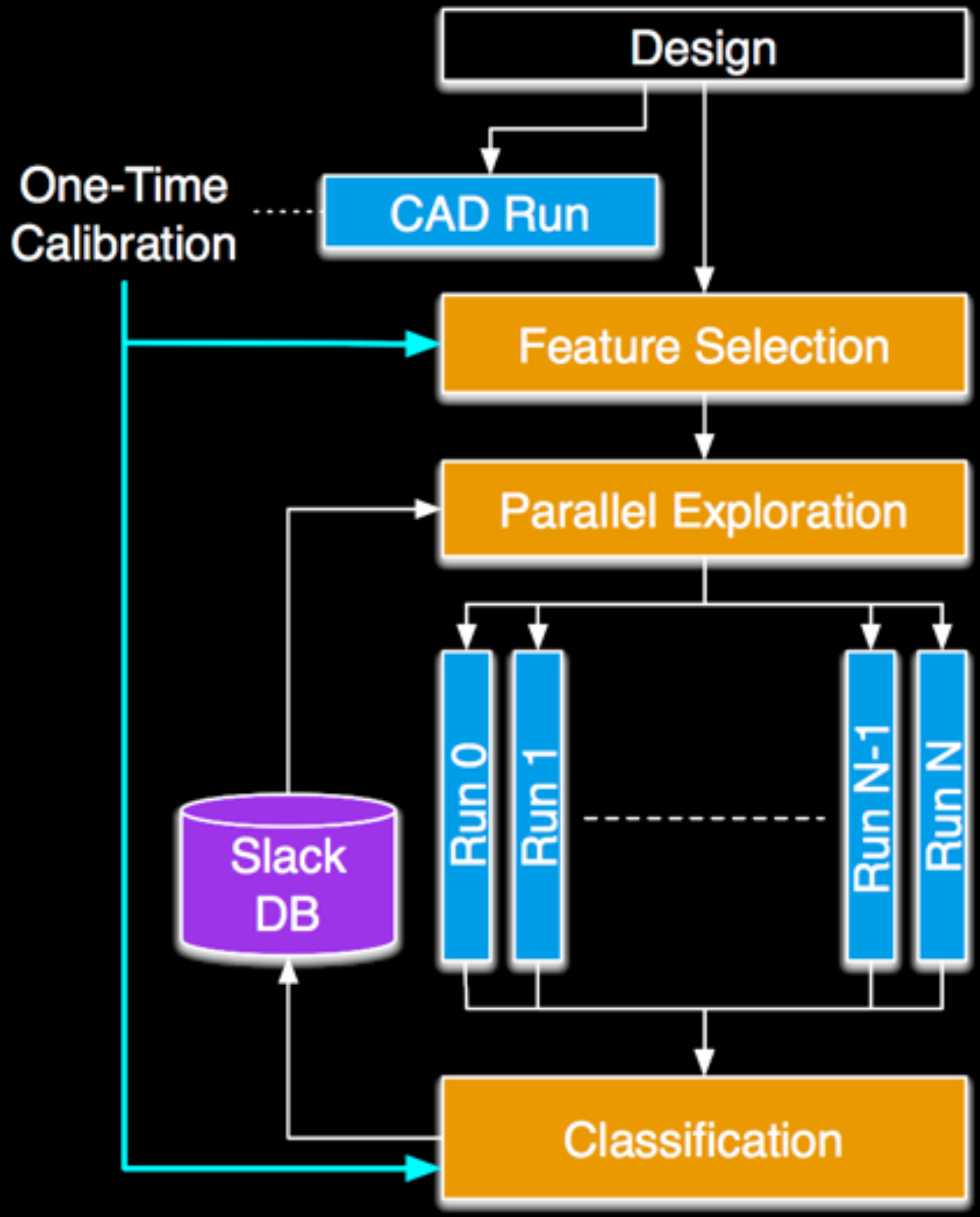
Feature Selection

Feature Selection

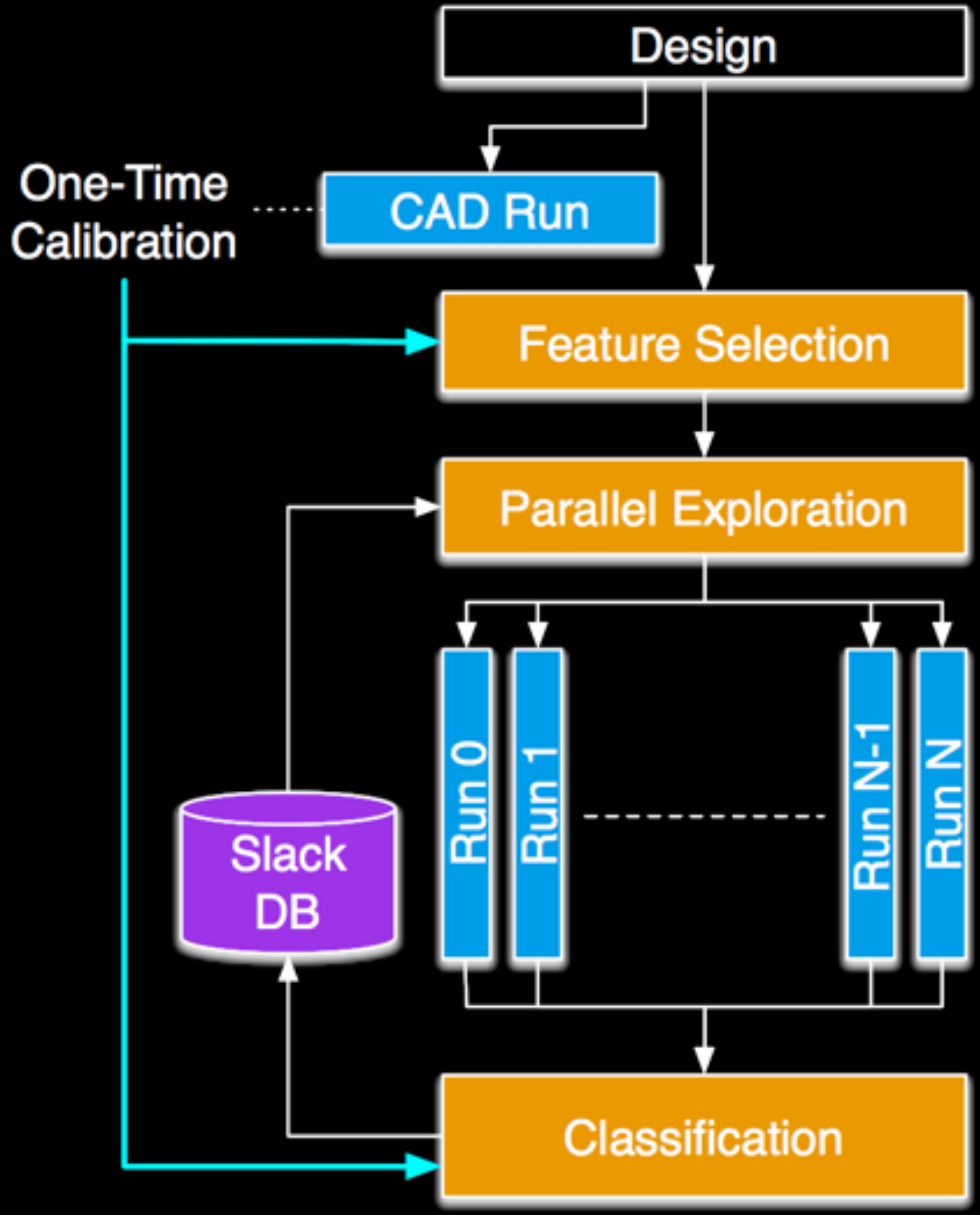


Feature Selection



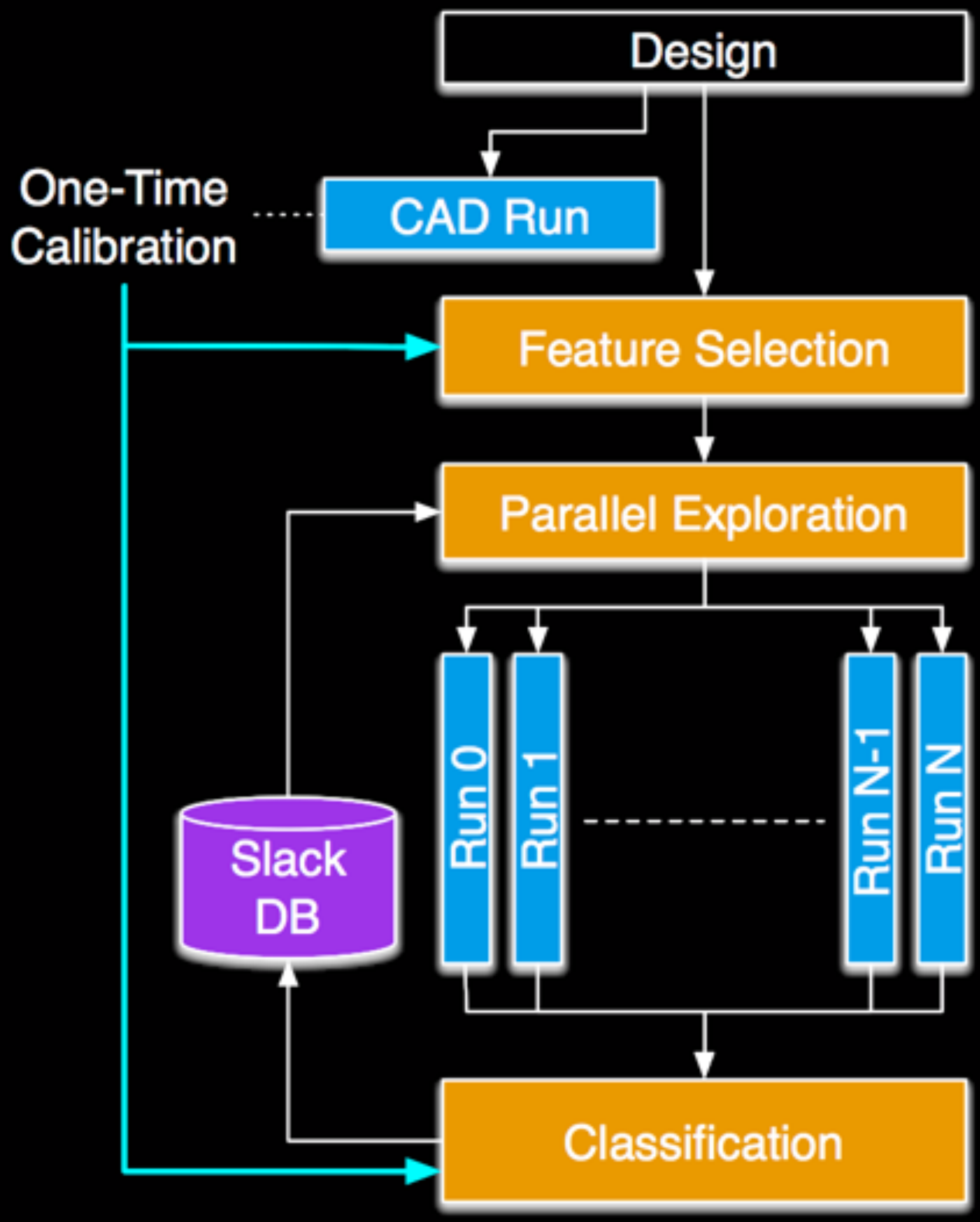
- **Hypothesis**: Not all CAD parameters affect timing outcome

Feature Selection



- **Hypothesis**: Not all CAD parameters affect timing outcome
- Can we find the most relevant parameters?

Feature Selection

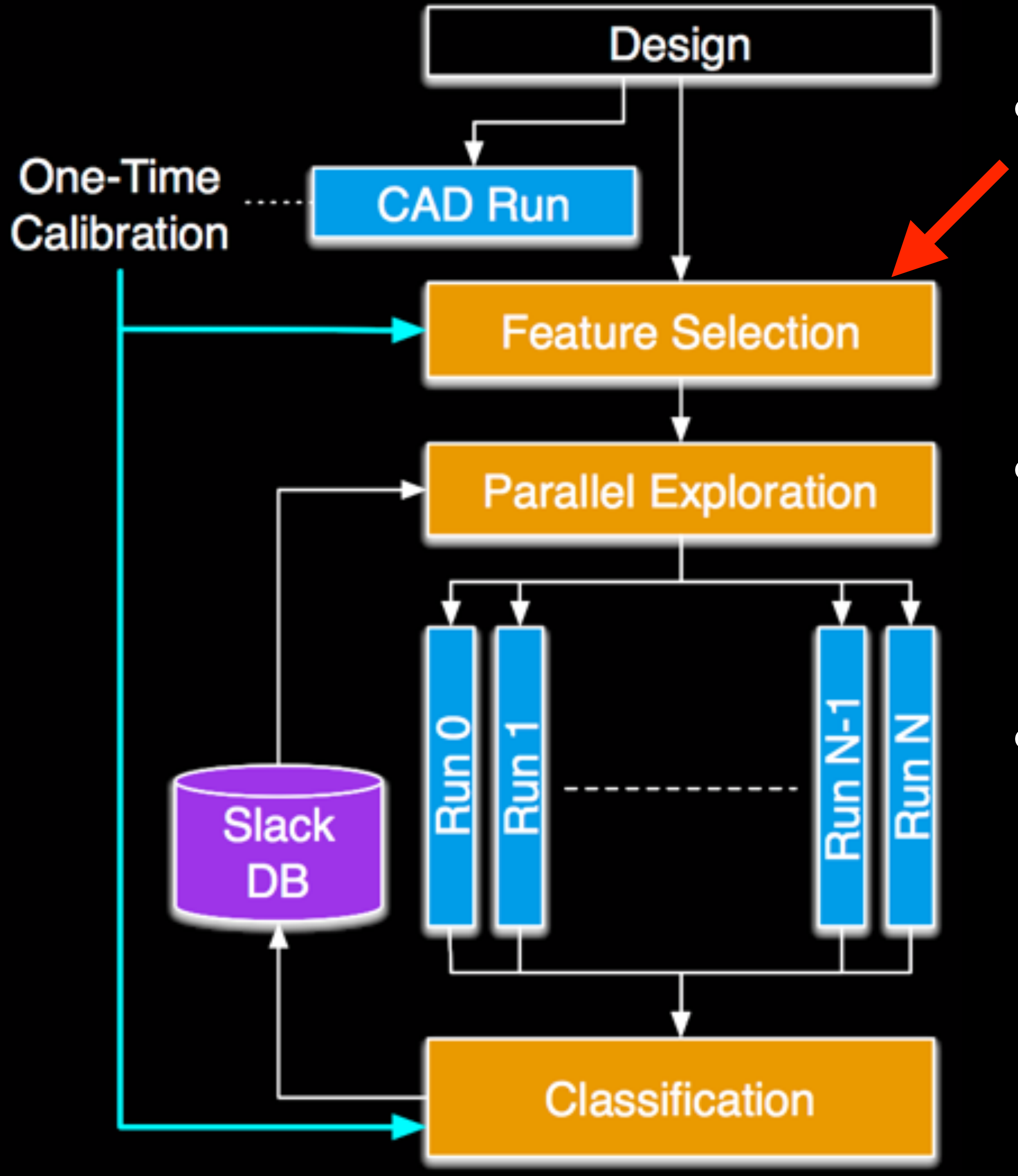


- **Hypothesis**: Not all CAD parameters affect timing outcome

- Can we find the most relevant parameters?

- Feature selection: known technique in ML circles
  — avoid noise during classification
  — avoid over-fitting

Feature Selection



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- Can we find the most relevant parameters?
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Techniques

- OneR — use frequency of class labels
- Information.Gain — uses entropy measure
- Relief — clustering of parameters
- Ensemble — combination of above…

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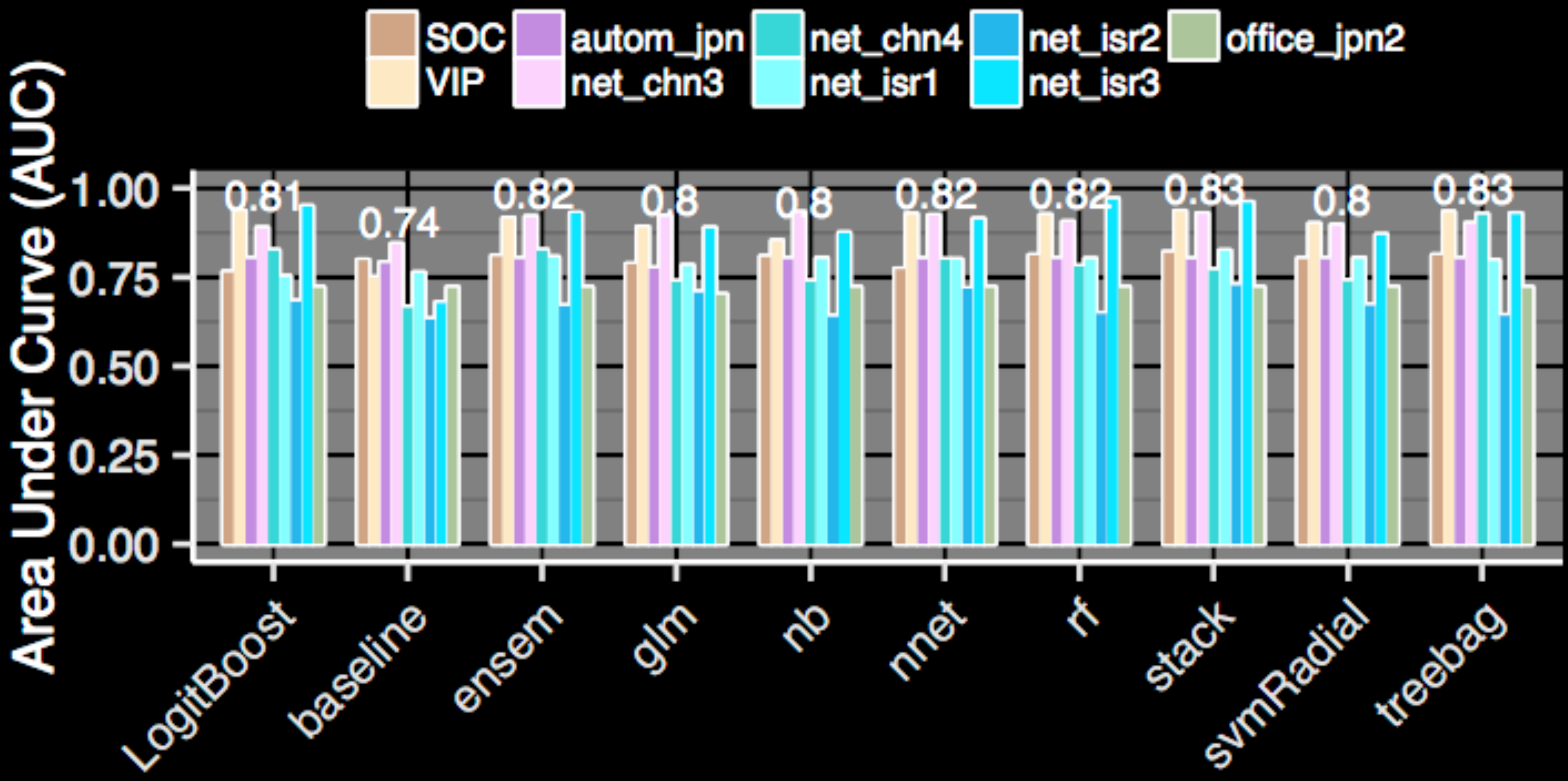
Q&A

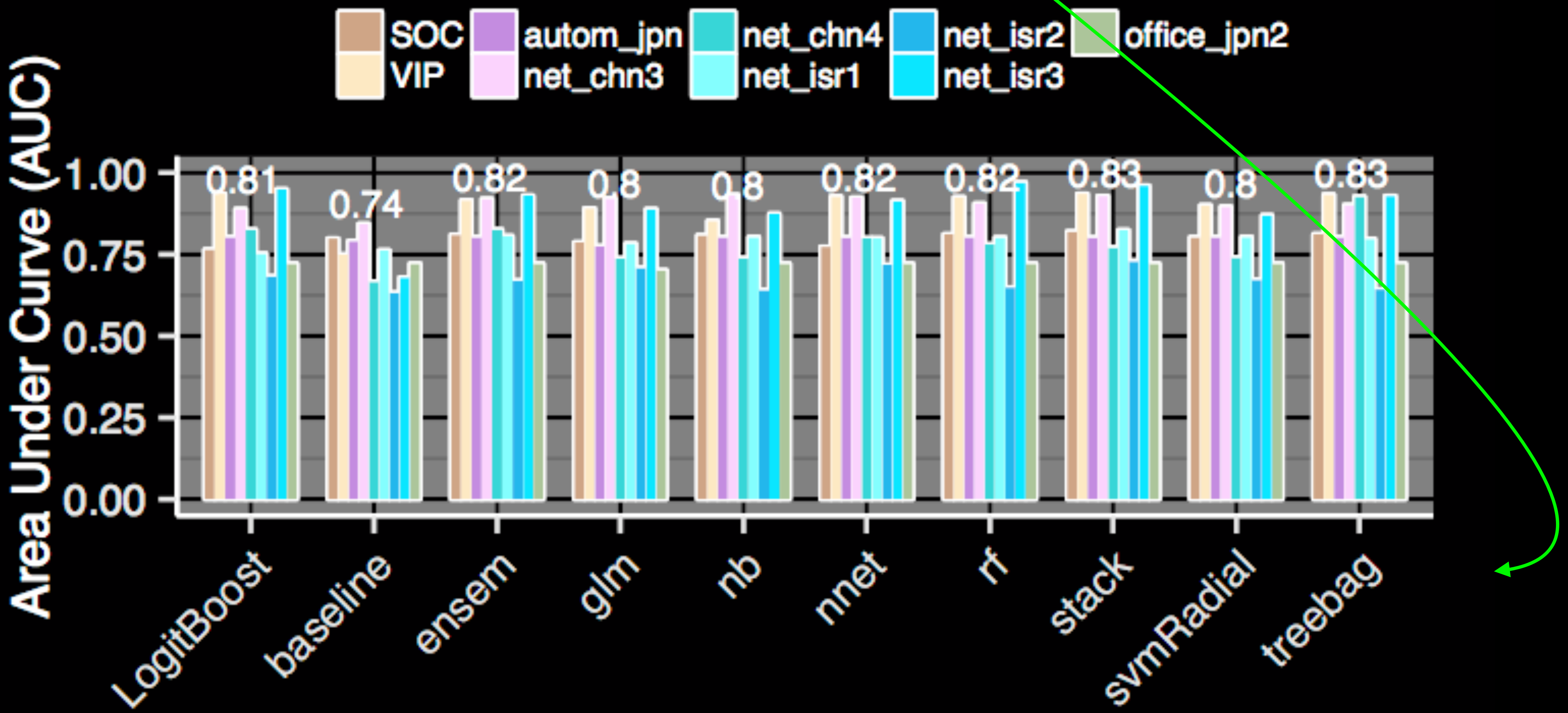
- How effective is feature selection?
- How long does the learning process take?
- What is the impact of choosing feature count?

How effective is feature selection?

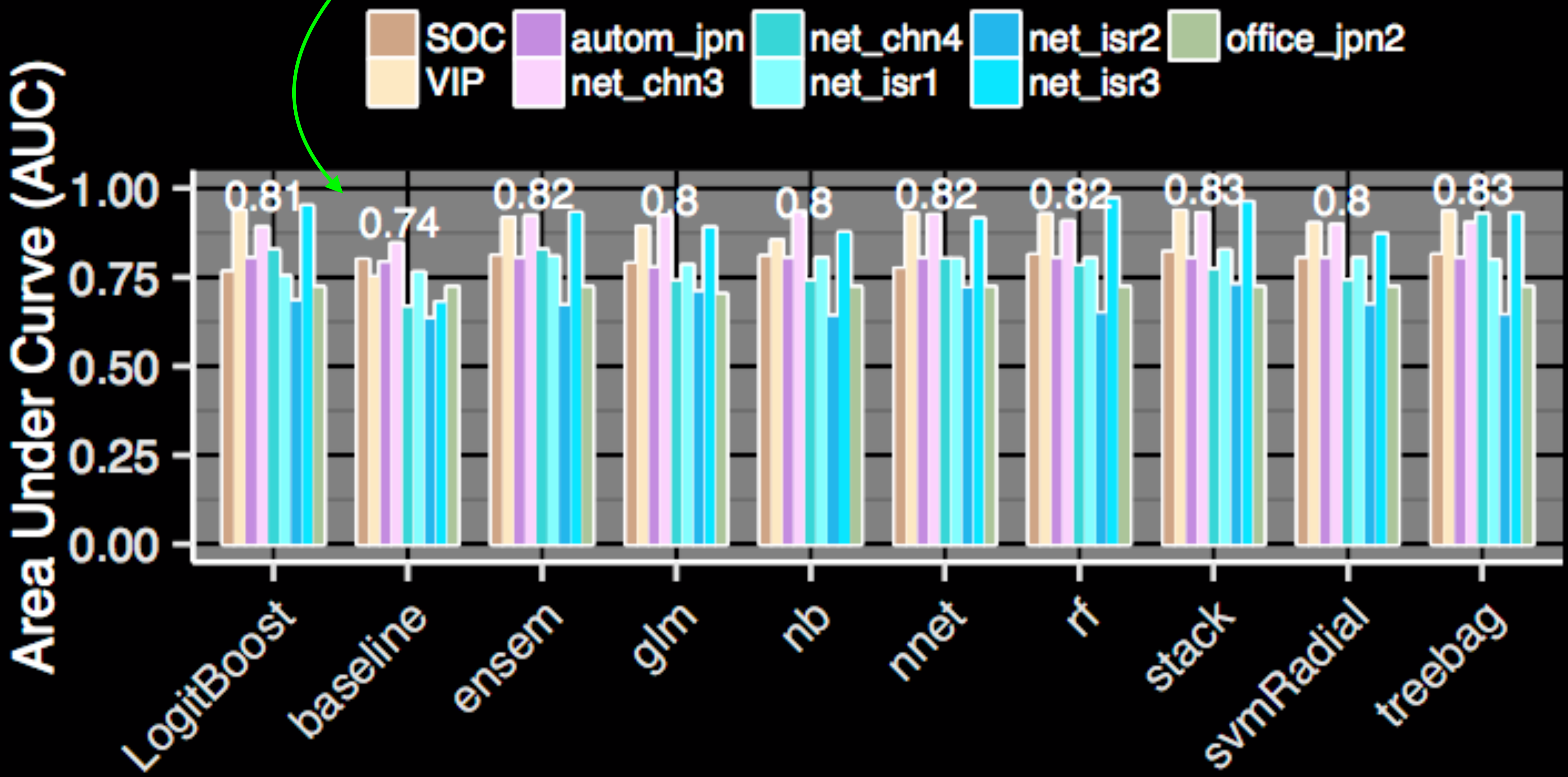


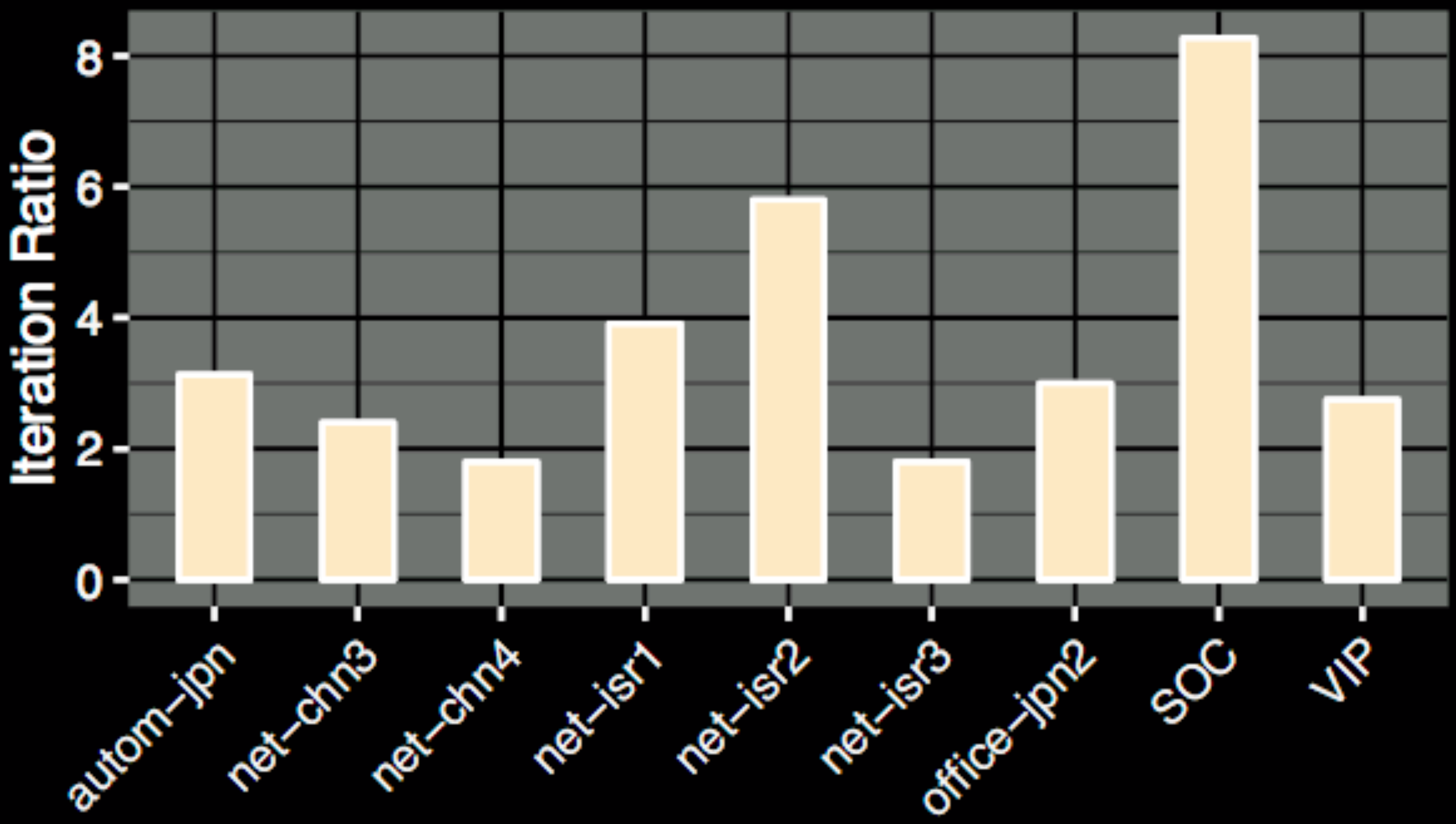
SOC
VIP
autom_jpn
net_chn3
net_chn4
net_isr1
net_isr2
net_isr3
office_jpn2
Area Under Curve (AUC)
1.00
0.75
0.50
0.25
0.00
0.81
0.74
0.82
0.8
0.8
0.82
0.82
0.83
0.8
0.83
LogitBoost
baseline
ensem
glm
nb
nnet
rf
stack
svmRadial
treebag

Classifier method doesn’t matter

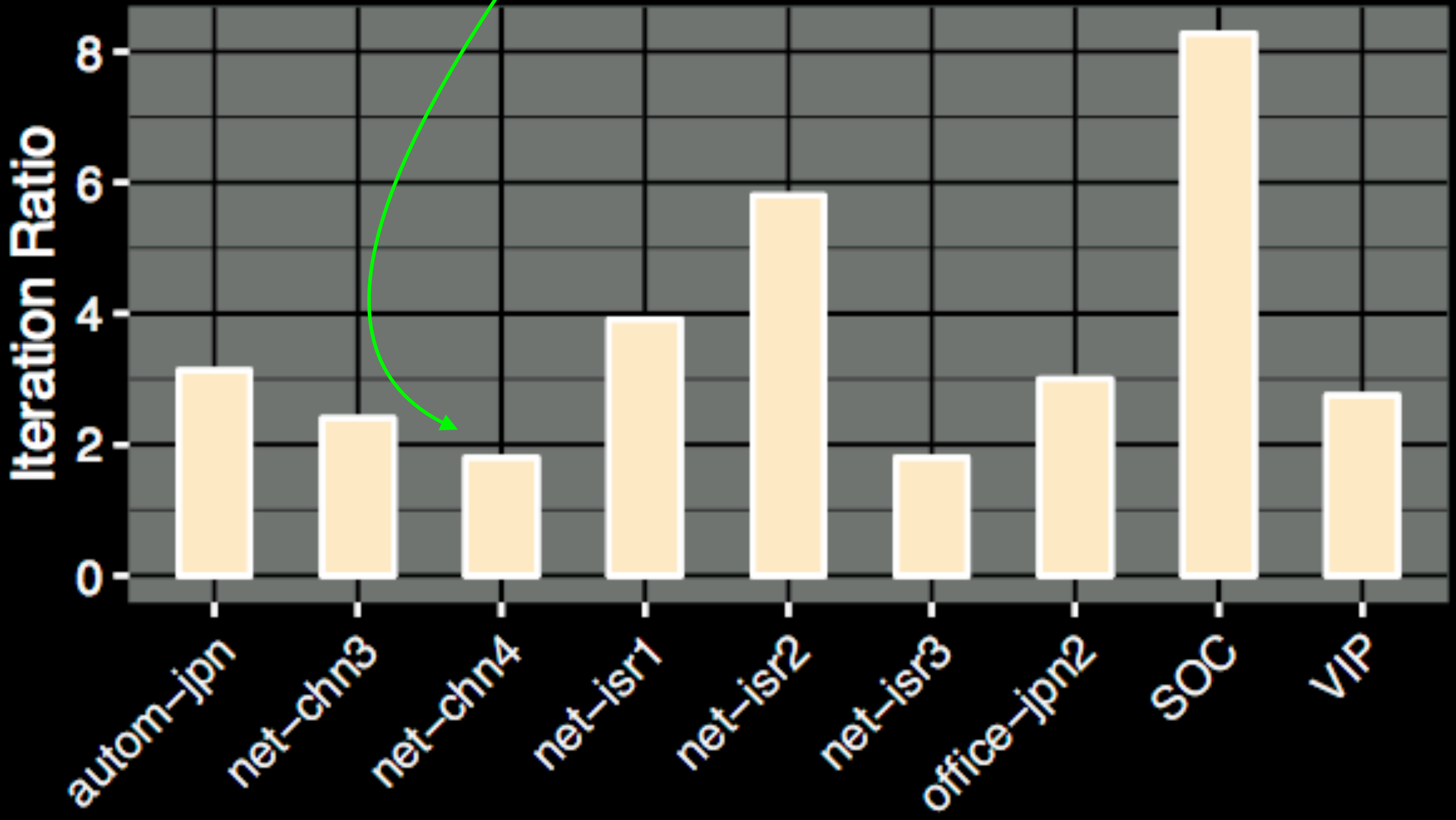


Baseline FCCM 2016 result

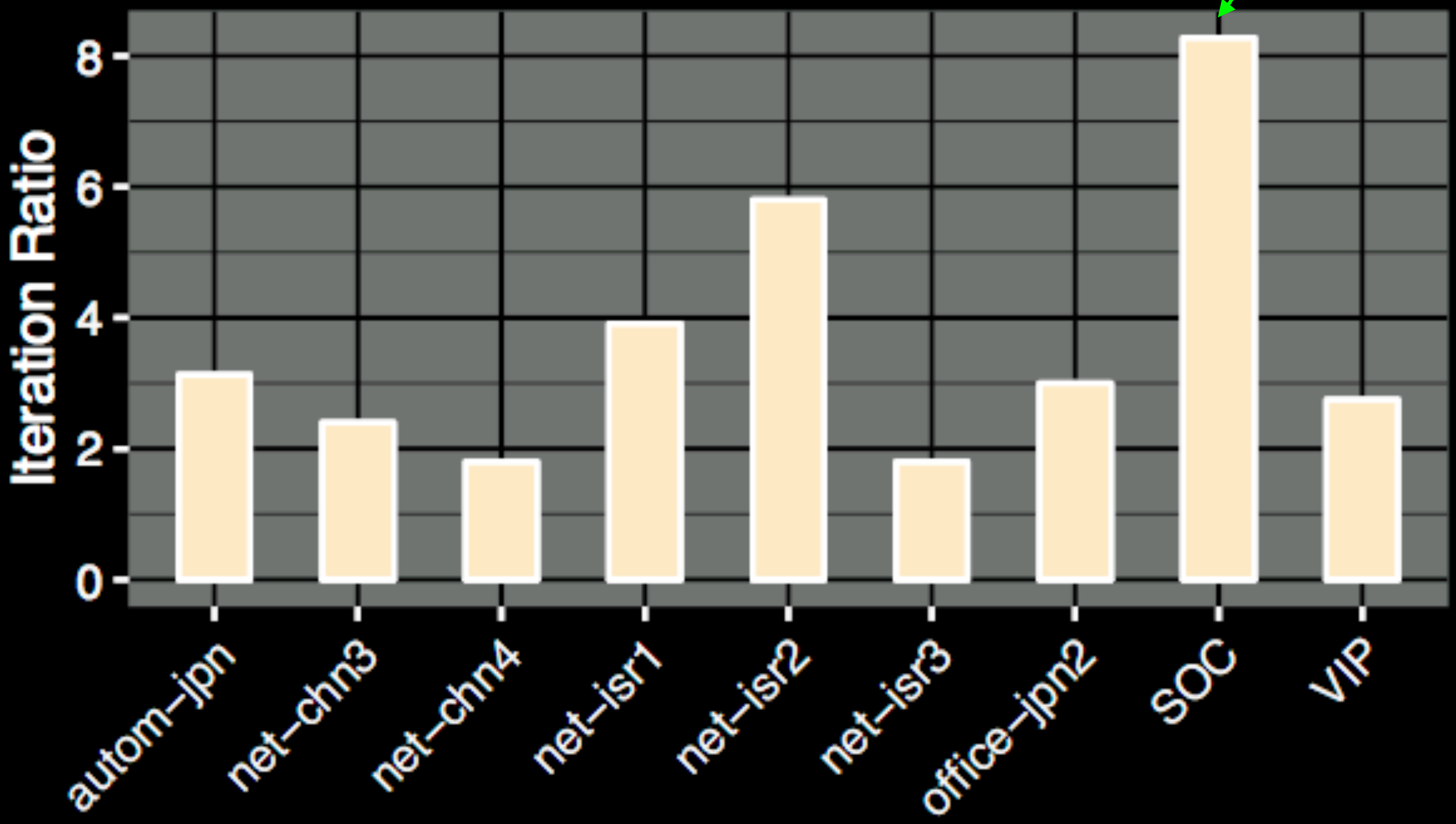



Iteration Ratio
0
2
4
6
8
autom–jpn
net–chn3
net–chn4
net–isr1
net–isr2
net–isr3
office–jpn2
SOC
VIP

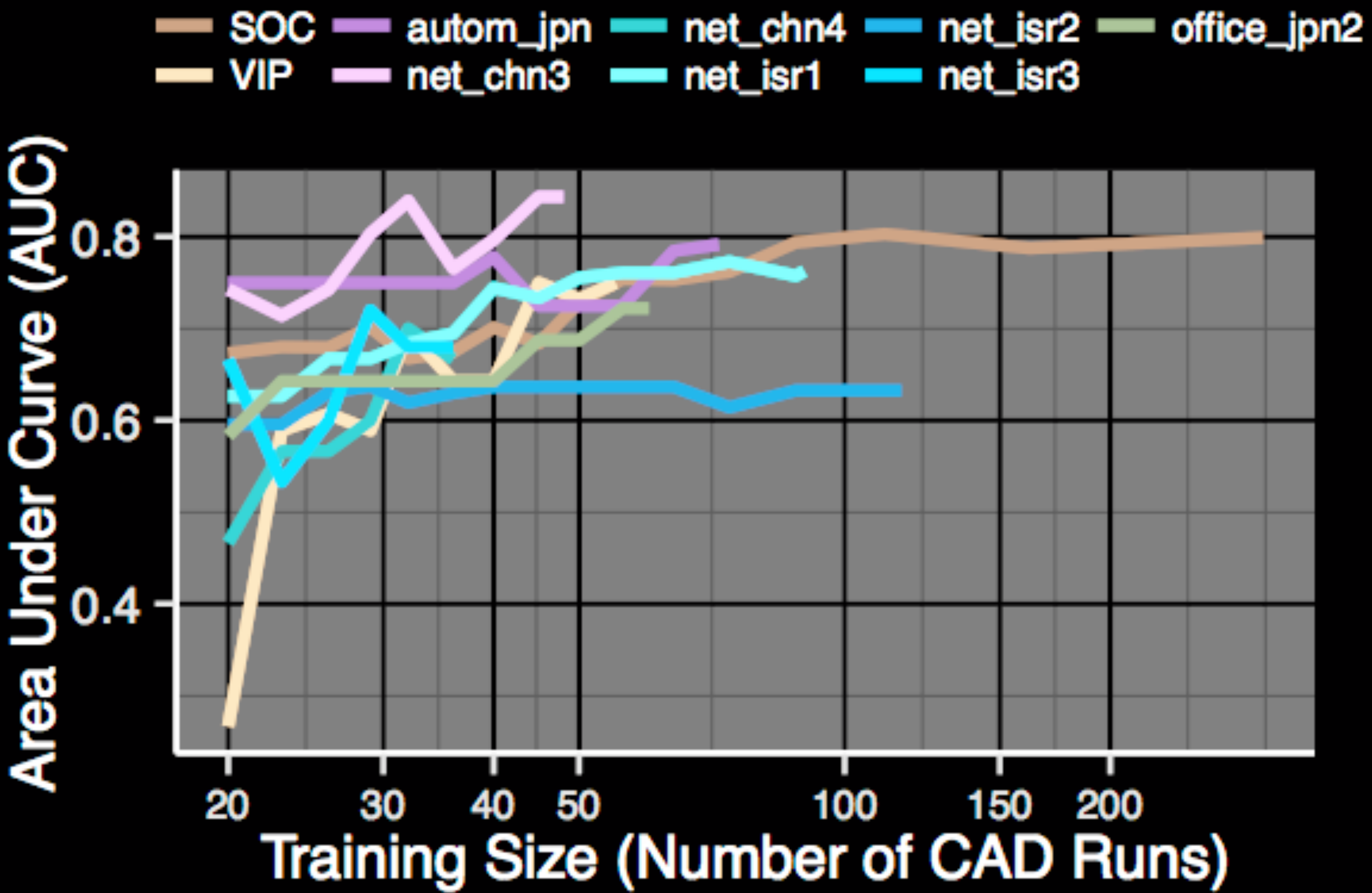
2-3x reduction in parallel FPGA CAD runs



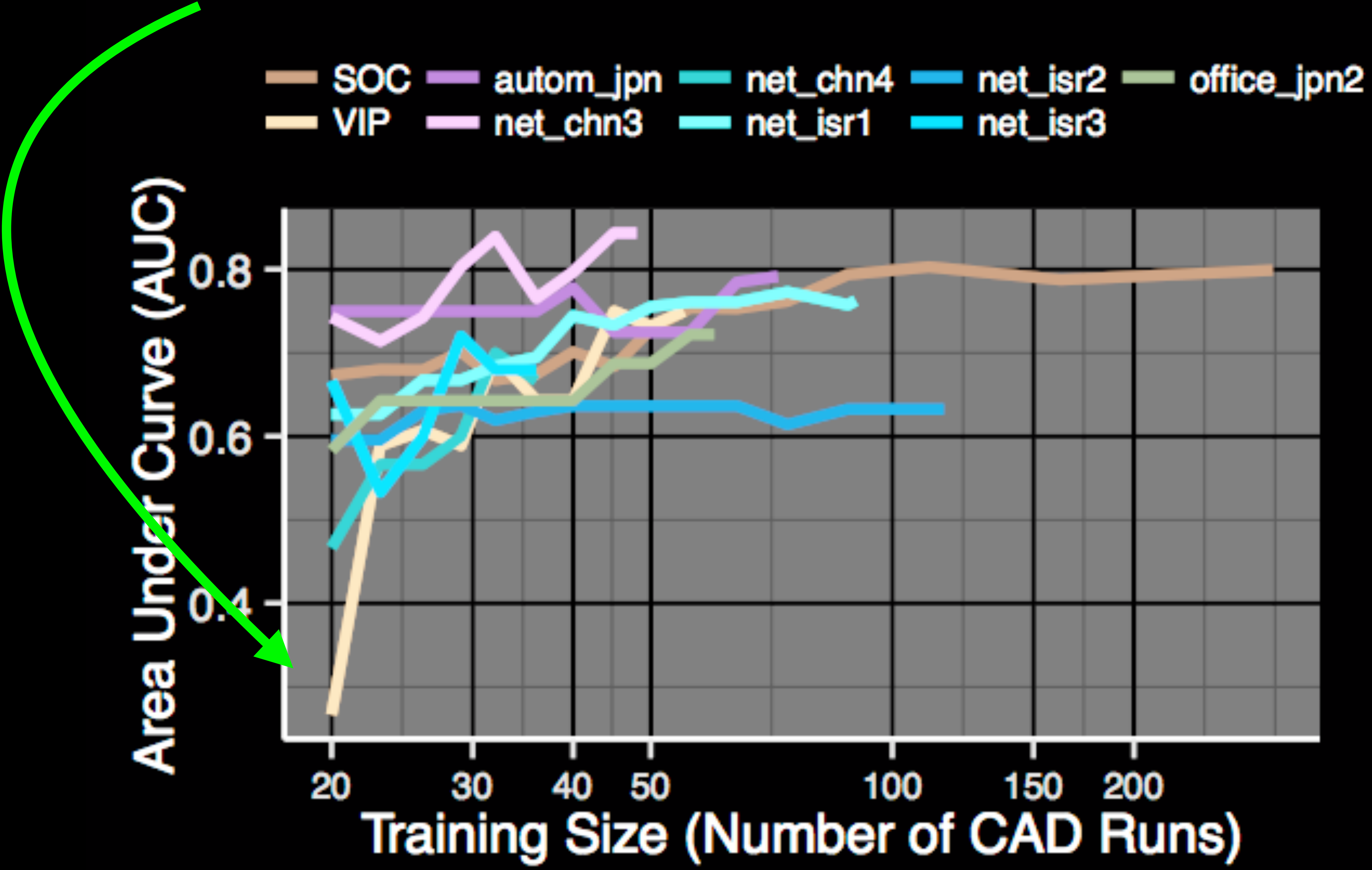
Outlier — fails to meet timing and quits



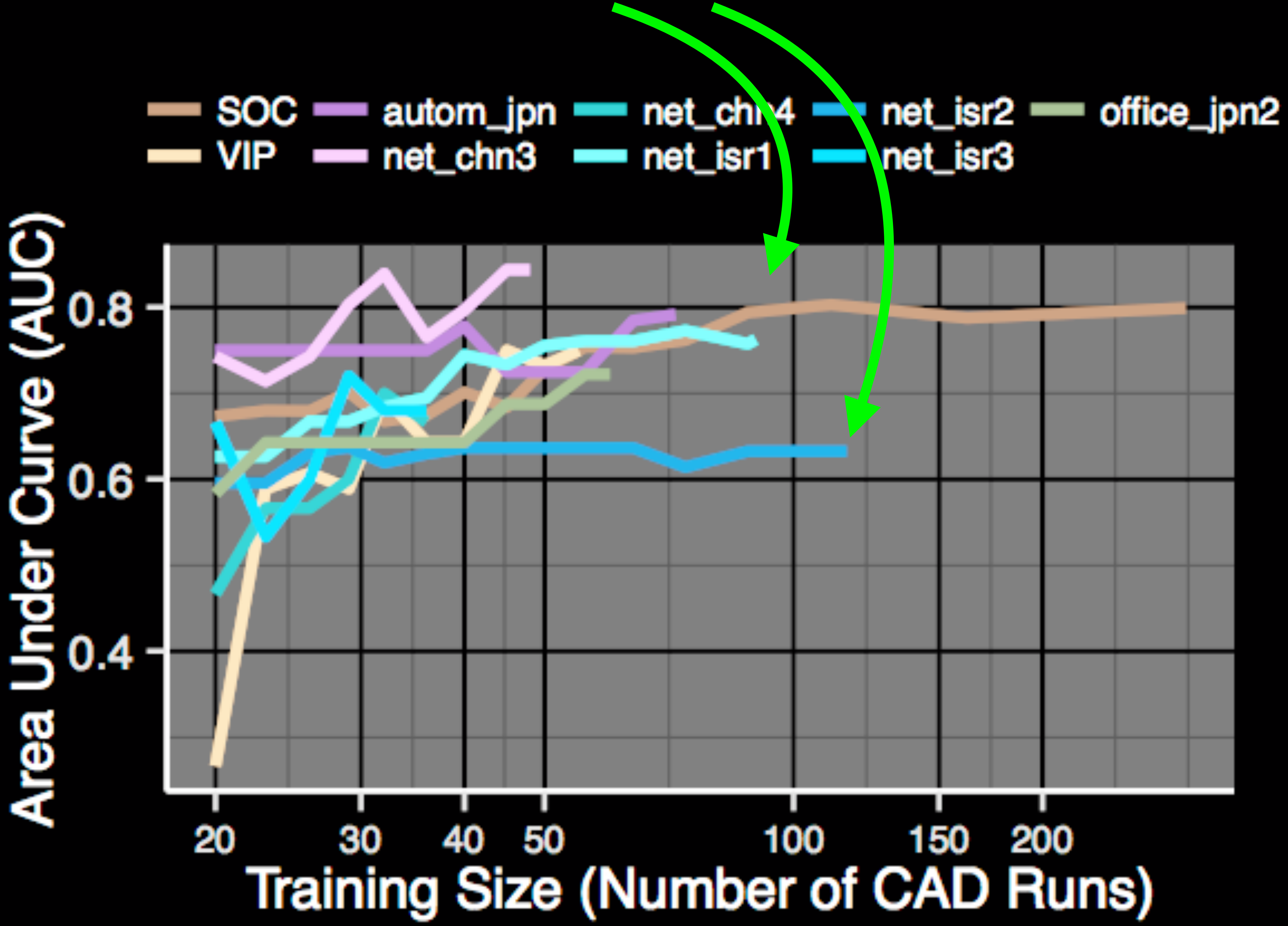
How long does it take to learn?


SOC
VIP
autom_jpn
net_chn3
net_chn4
net_isr1
net_isr2
net_isr3
office_jpn2
Area Under Curve (AUC)
0.8
0.6
0.4
20
30
40
50
100
150
200
Training Size (Number of CAD Runs)

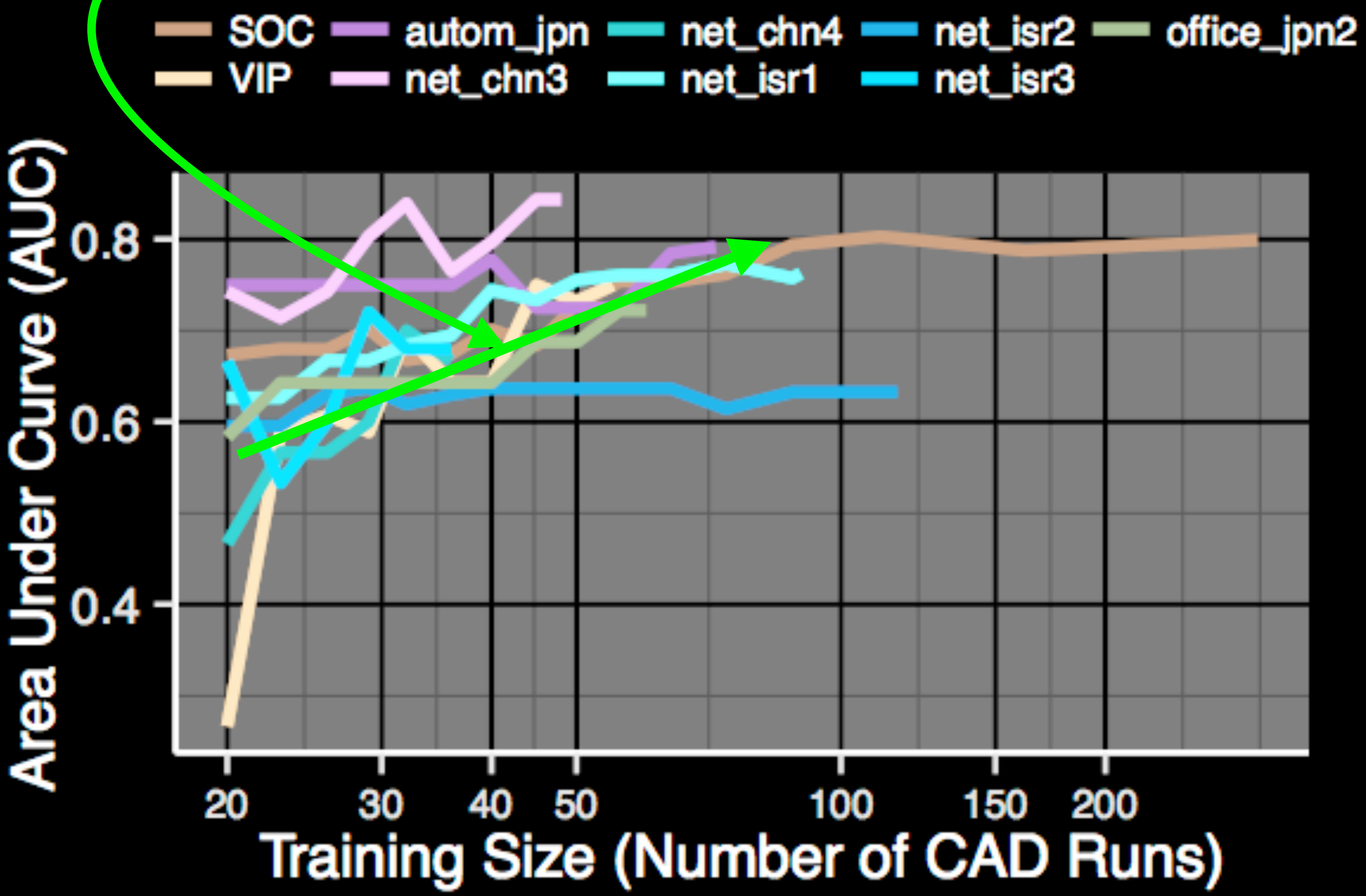
Need atleast 20 runs



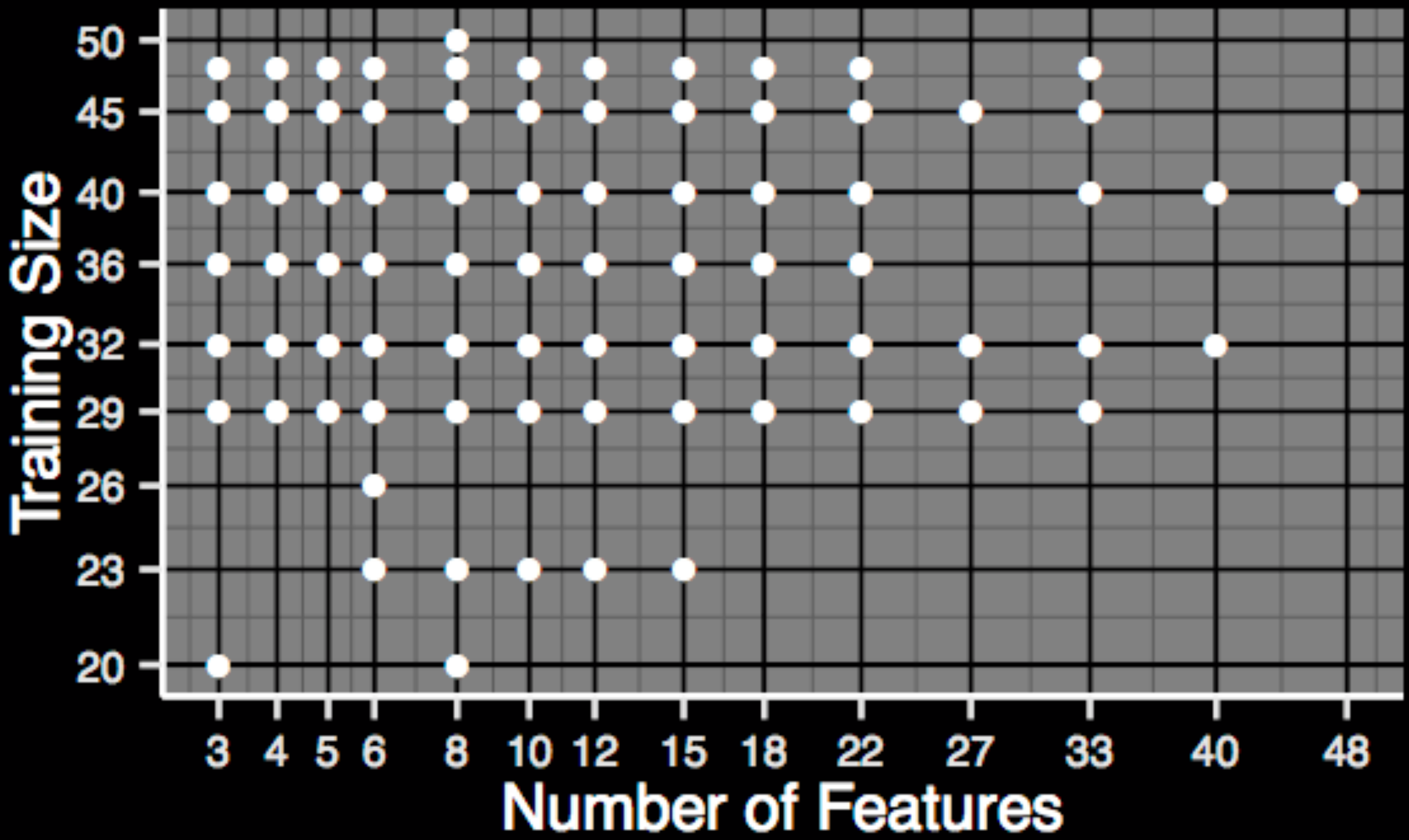
Need 3 rounds x 30 runs configuration

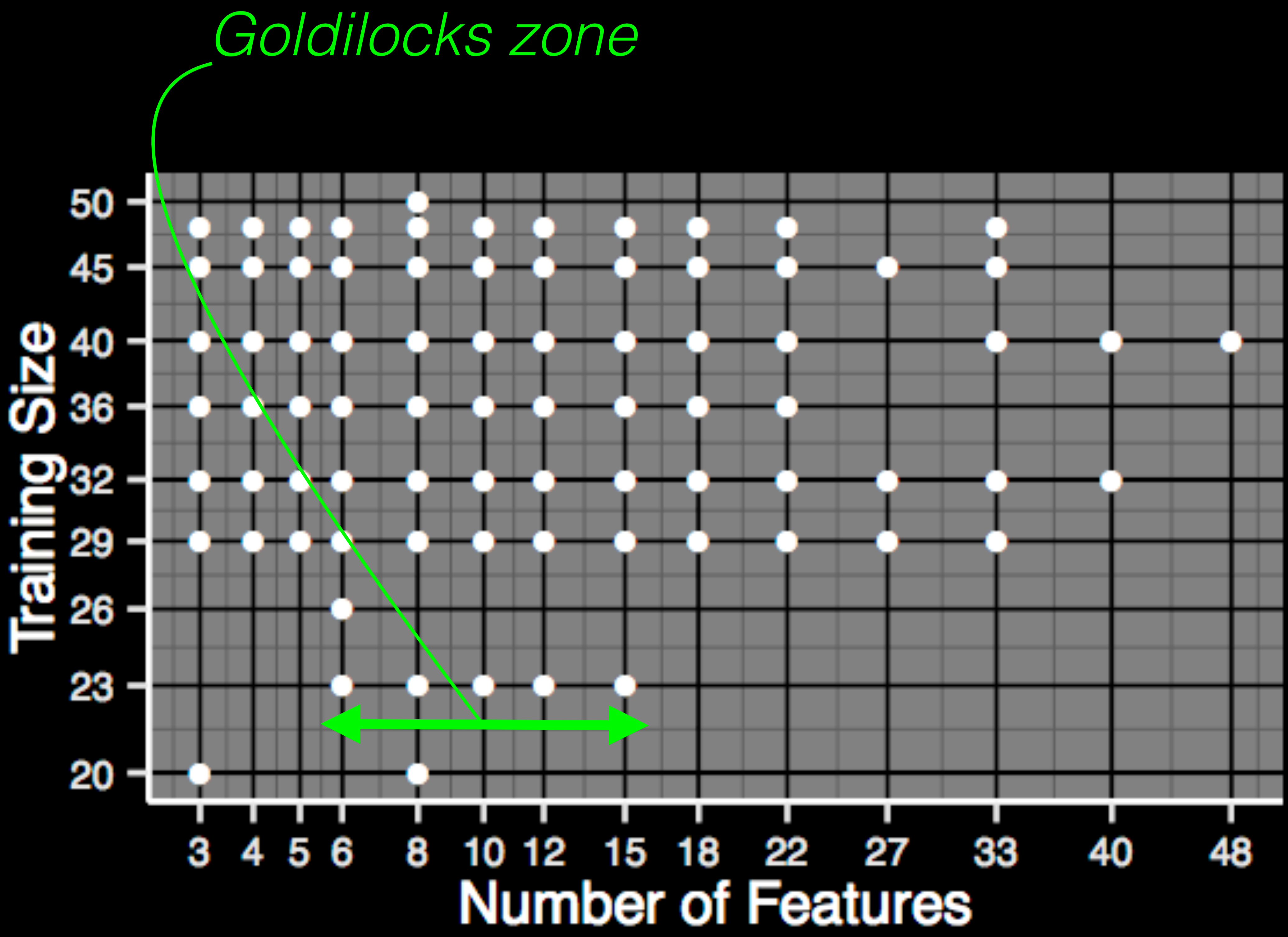


Better AUC the more we run

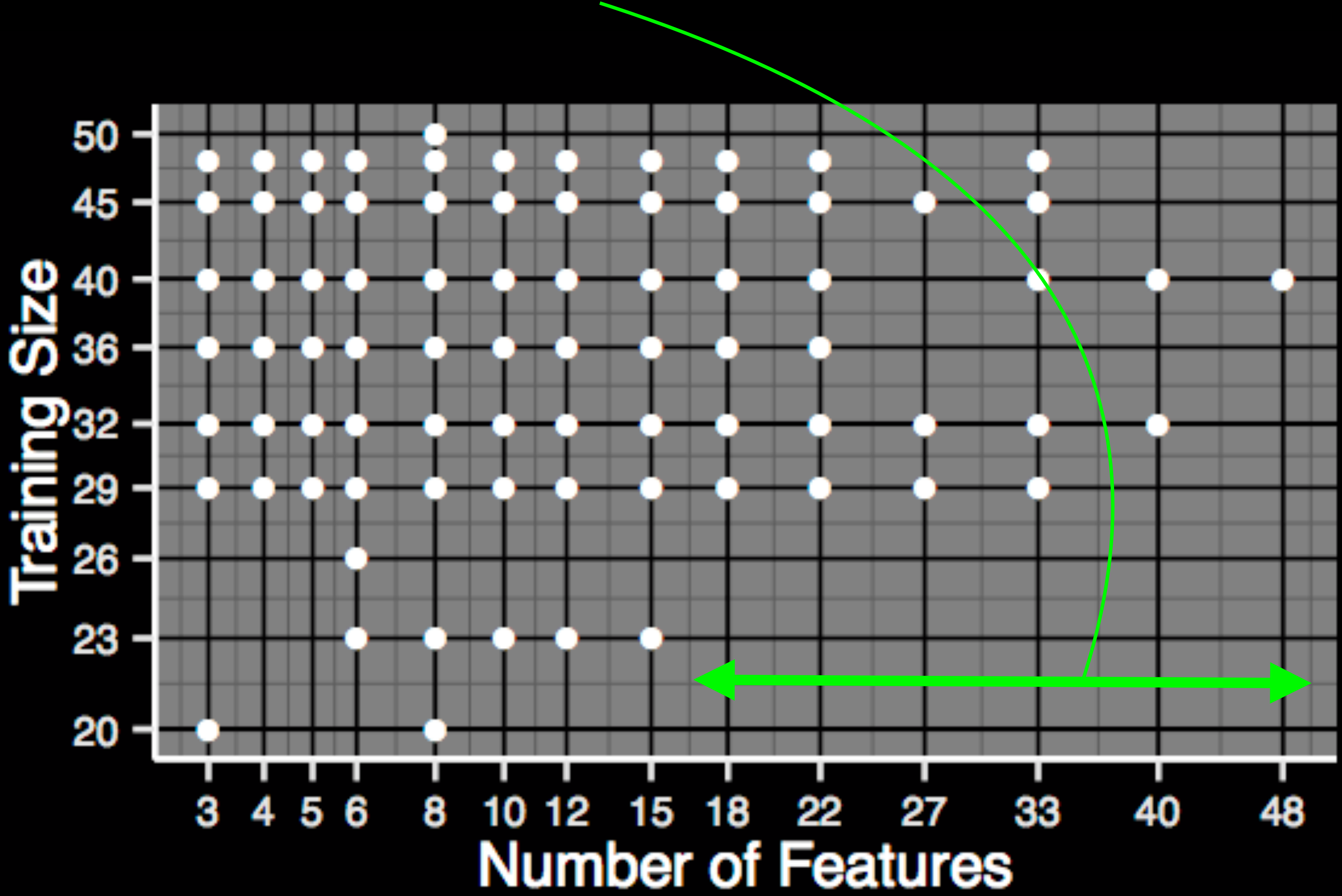


How do we choose the correct subset of features

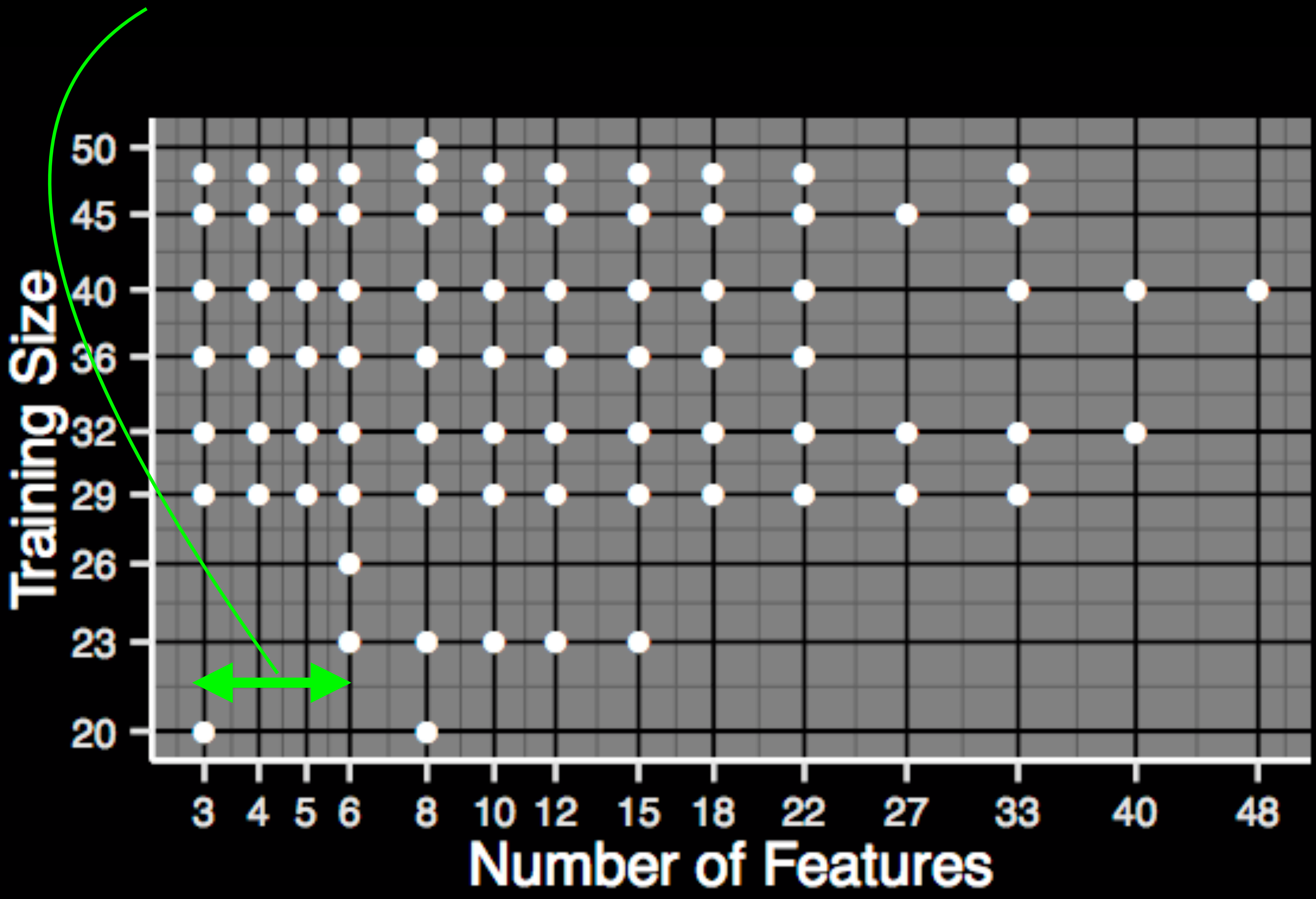

Training Size
50
45
40
36
32
29
26
23
20
3
4
5
6
8
10
12
15
18
22
27
33
40
48
Number of Features


Goldilocks zone
Training Size
50
45
40
36
32
29
26
23
20
3
4
5
6
8
10
12
15
18
22
27
33
40
48
Number of Features

Too many features — large training set



Too few features — more data required for other features



Conclusions

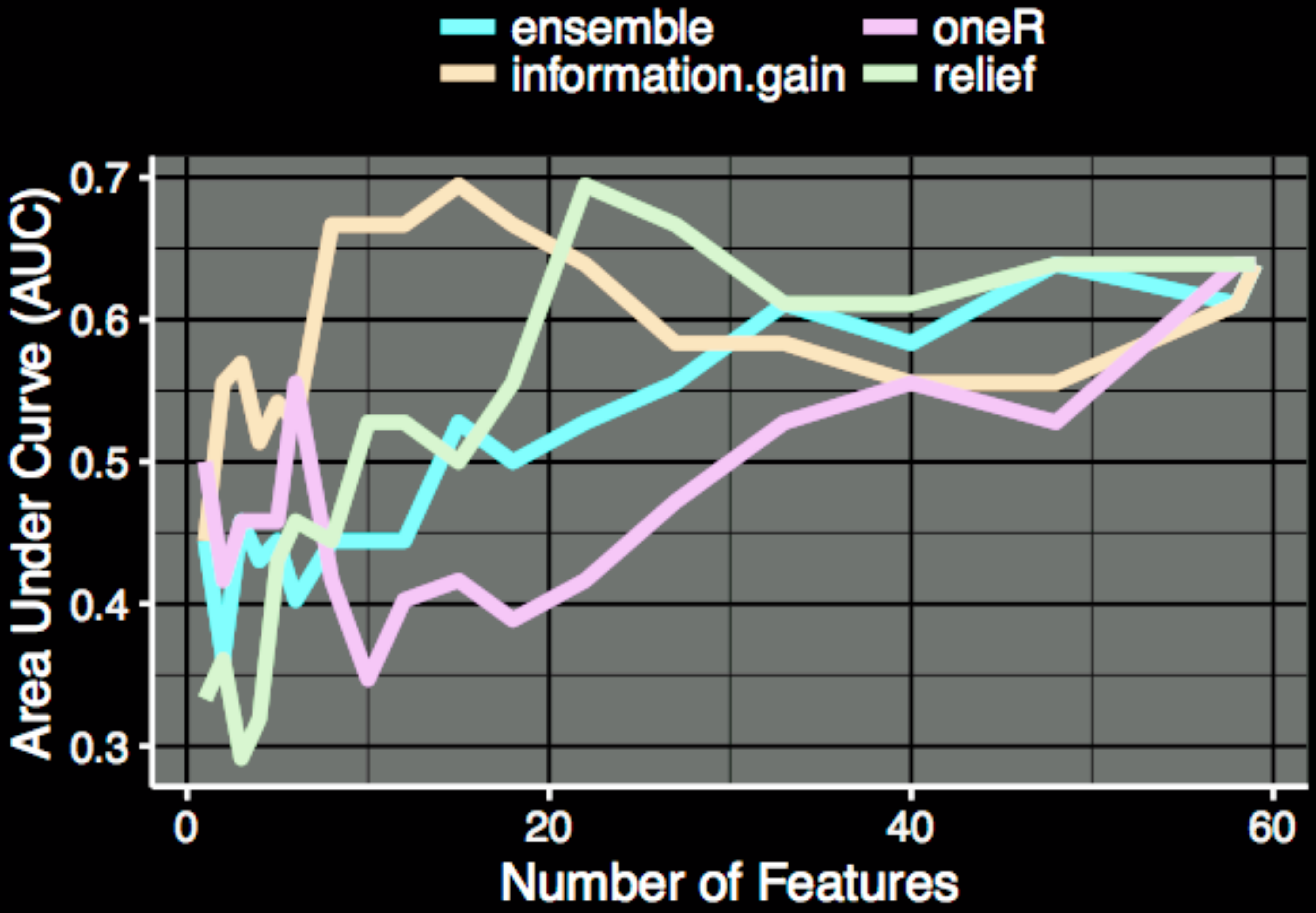
- Feature Selection helps boost AUC of InTime machine learning by ~10%
- Key idea — prune the set of Quartus CAD tool parameters to explore to <22
- Evidence continues to point towards design-specificity

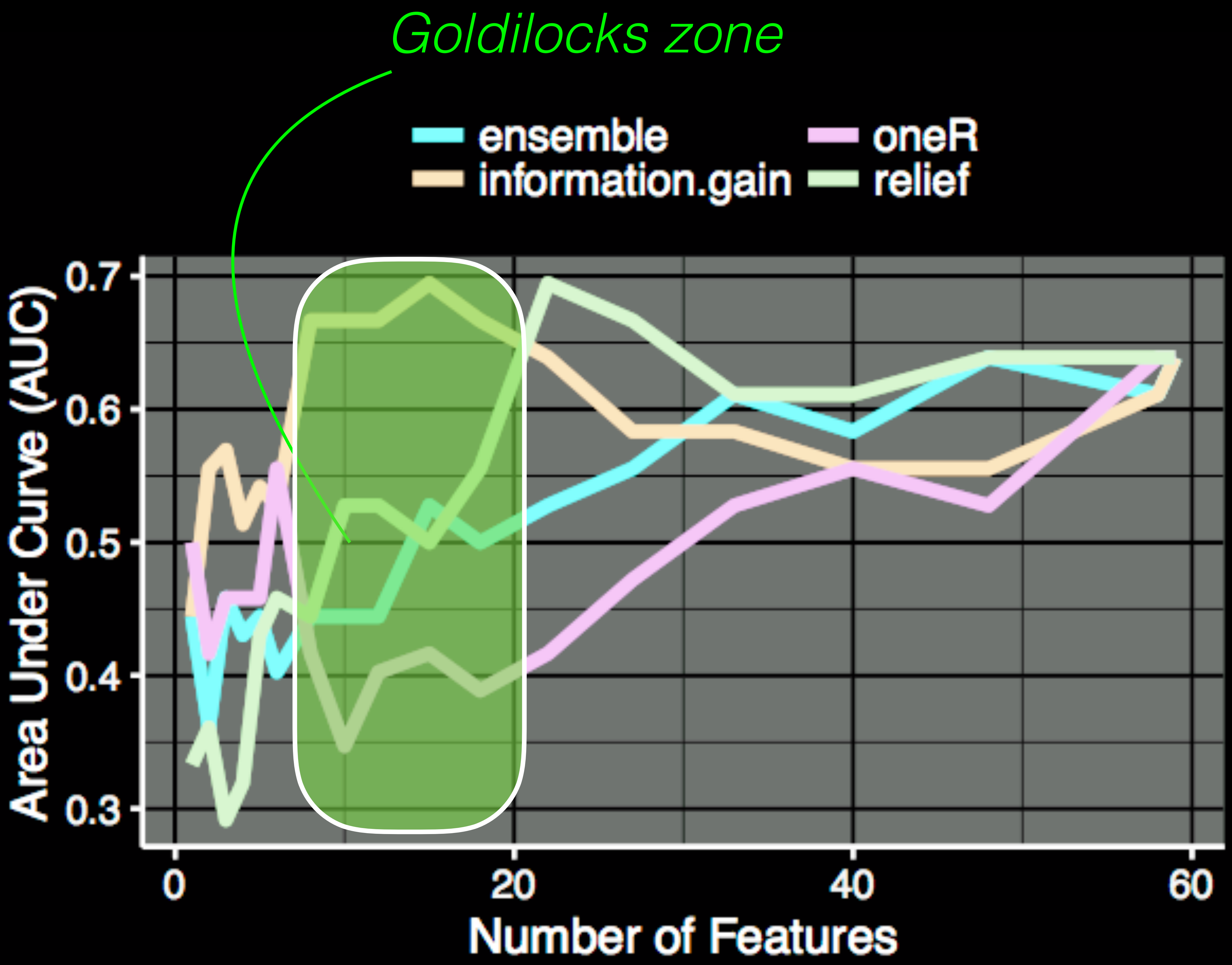
Open-source flow

- We are open-sourcing our ML routines
  — http://bitbucket.org/spinosae/plunify-ml.git
  — README.md contains instructions for installing and running on your machine

- Requires R (dependencies installed automatically)

Impact of feature count


ensemble
oneR
information.gain
relief
Area Under Curve (AUC)
0.7
0.6
0.5
0.4
0.3
0
20
40
60
Number of Features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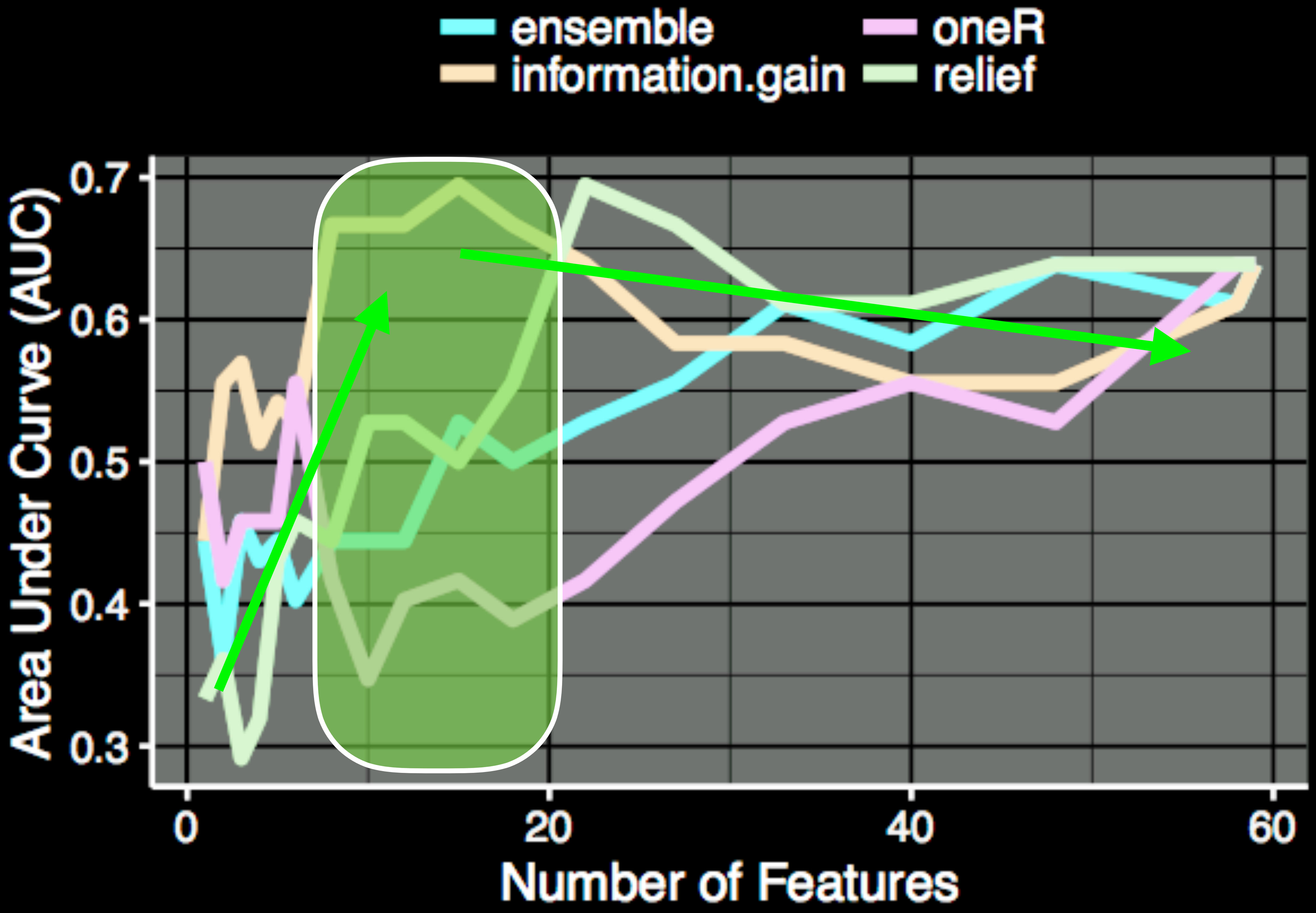
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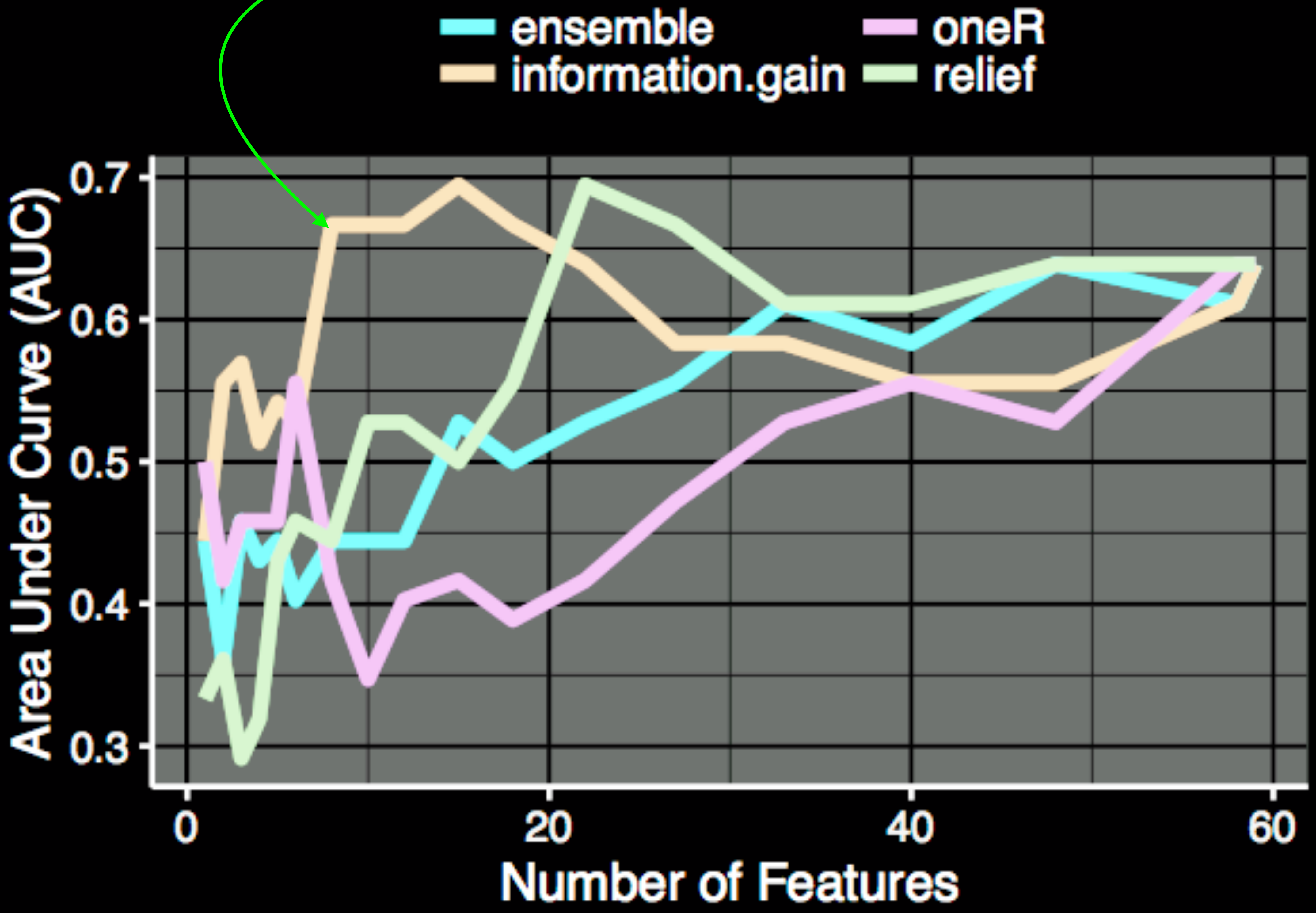
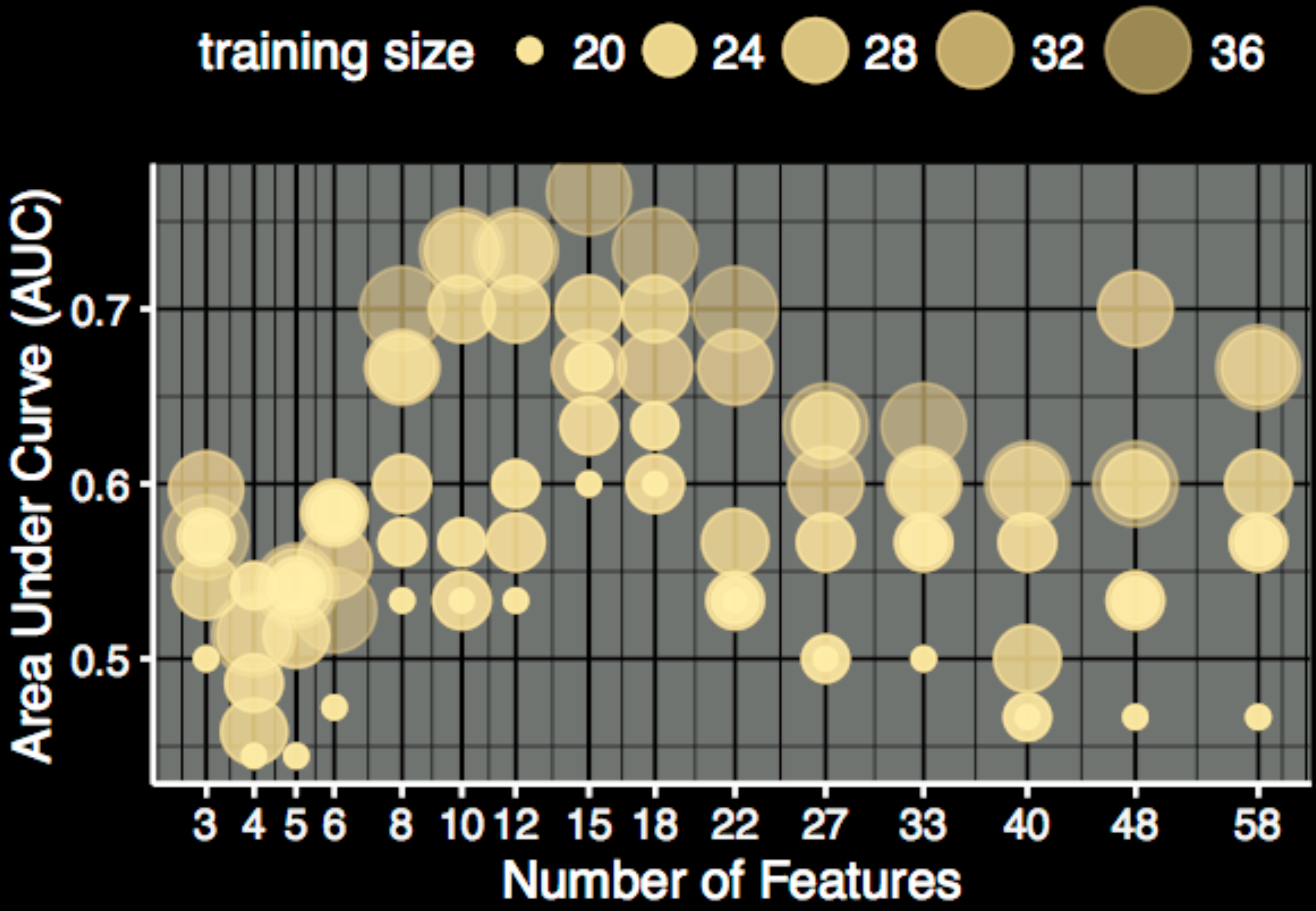
Information.Gain consistently best




training size
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24
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Area Under Curve (AUC)
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3
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10
12
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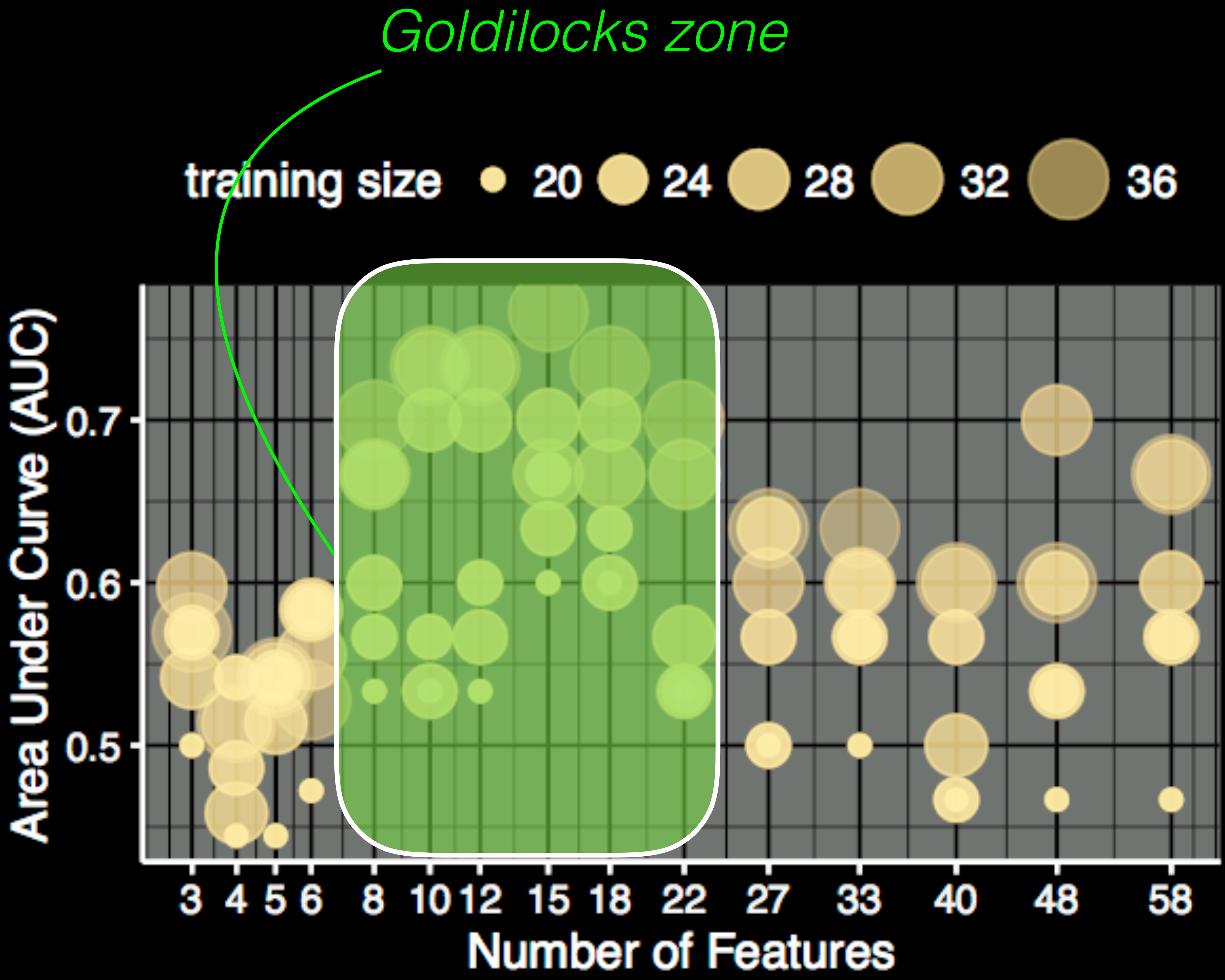
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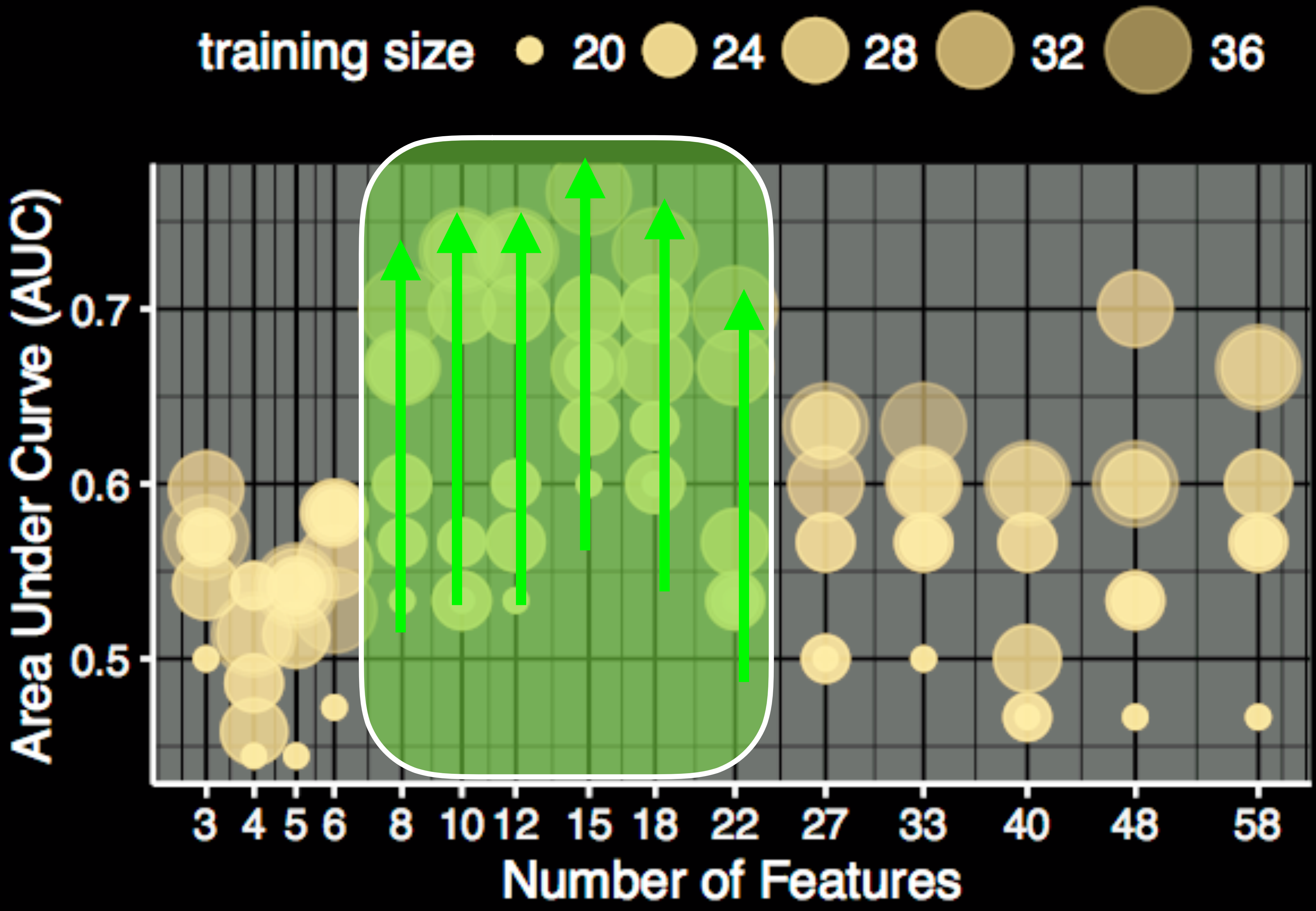
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