A Dynamic Adaptation of AD-trees for Efficient Machine Learning on Large Data Sets

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Daily Pittsburgh Weather Data

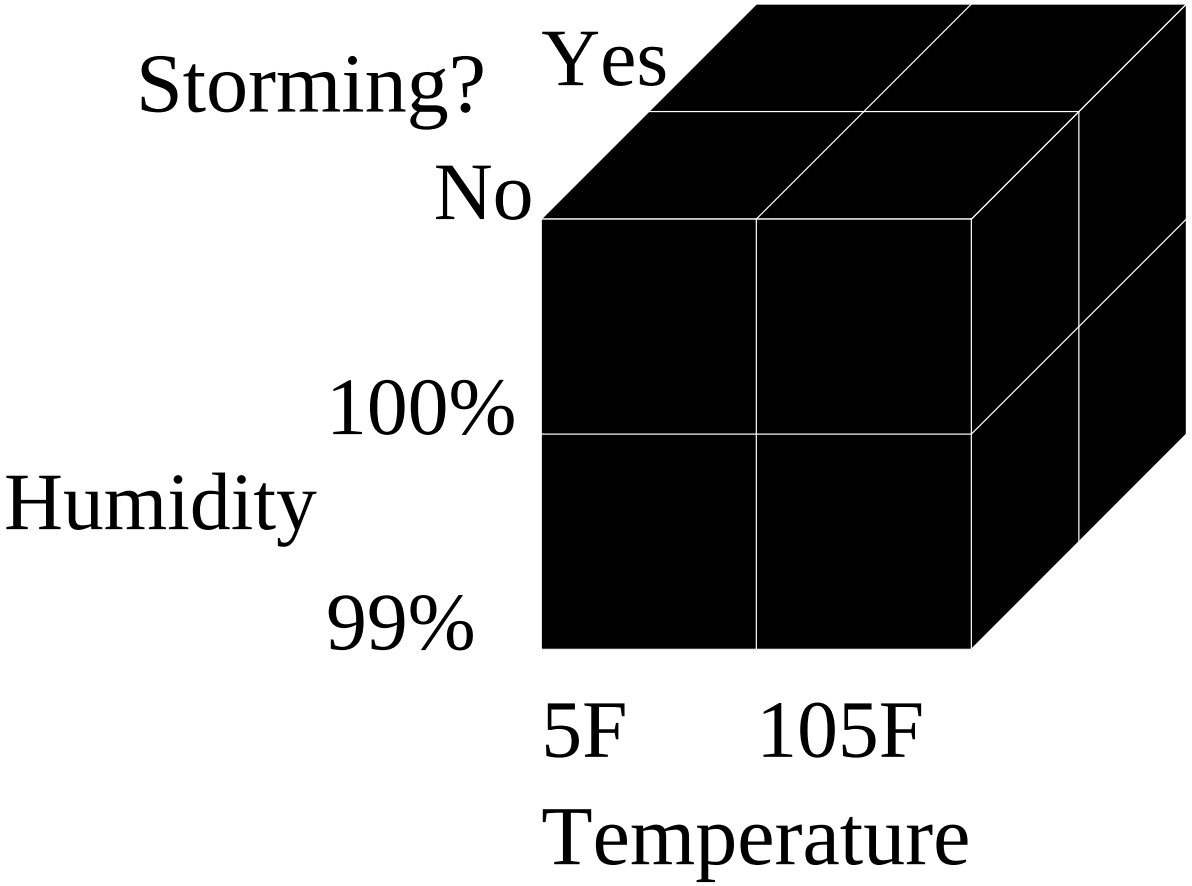
- Three attributes: “Temperature”, “Humidity” and “Storming”.

- Each attribute has only two discrete values in this example. The humidity, for instance, is either high (100%), or low (99%).

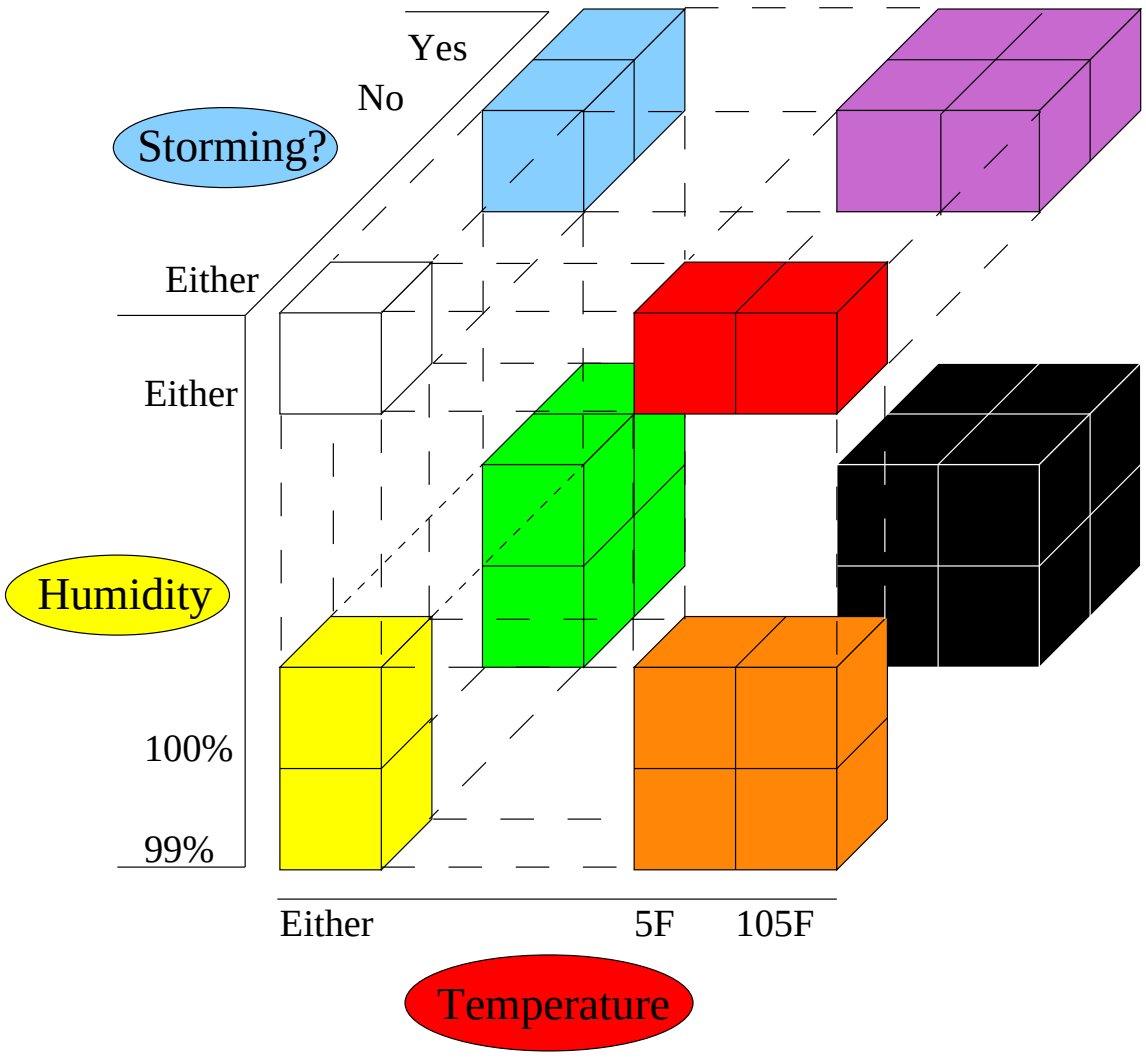
- Each horizontal row of the data set represents one day’s weather.

Temperature	Humidity	Storming
105 F	100%	yes
105 F	99%	no
5 F	99%	no
5 F	99%	yes
⋮	⋮	⋮
⋮	⋮	⋮

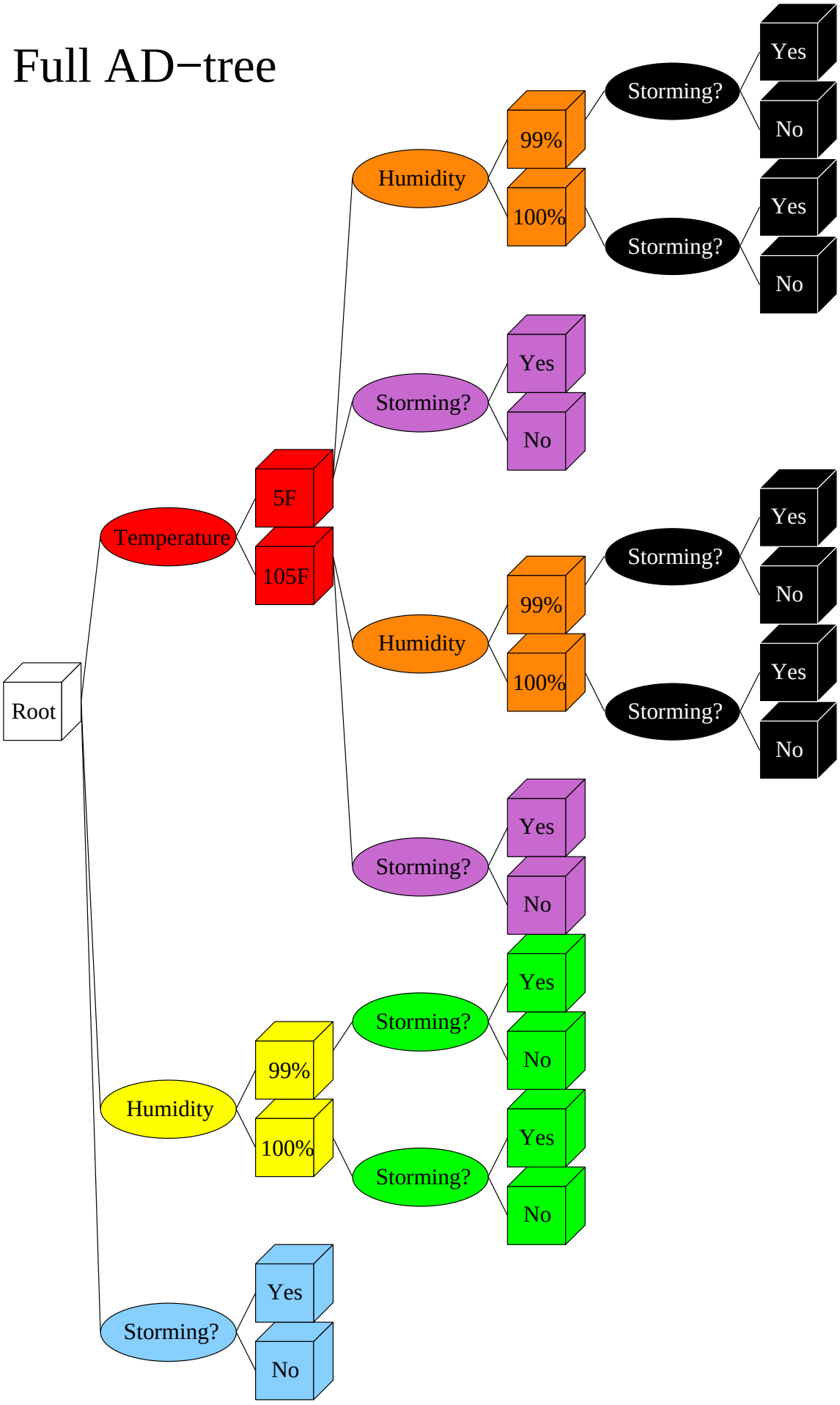
Datacube representation of data set



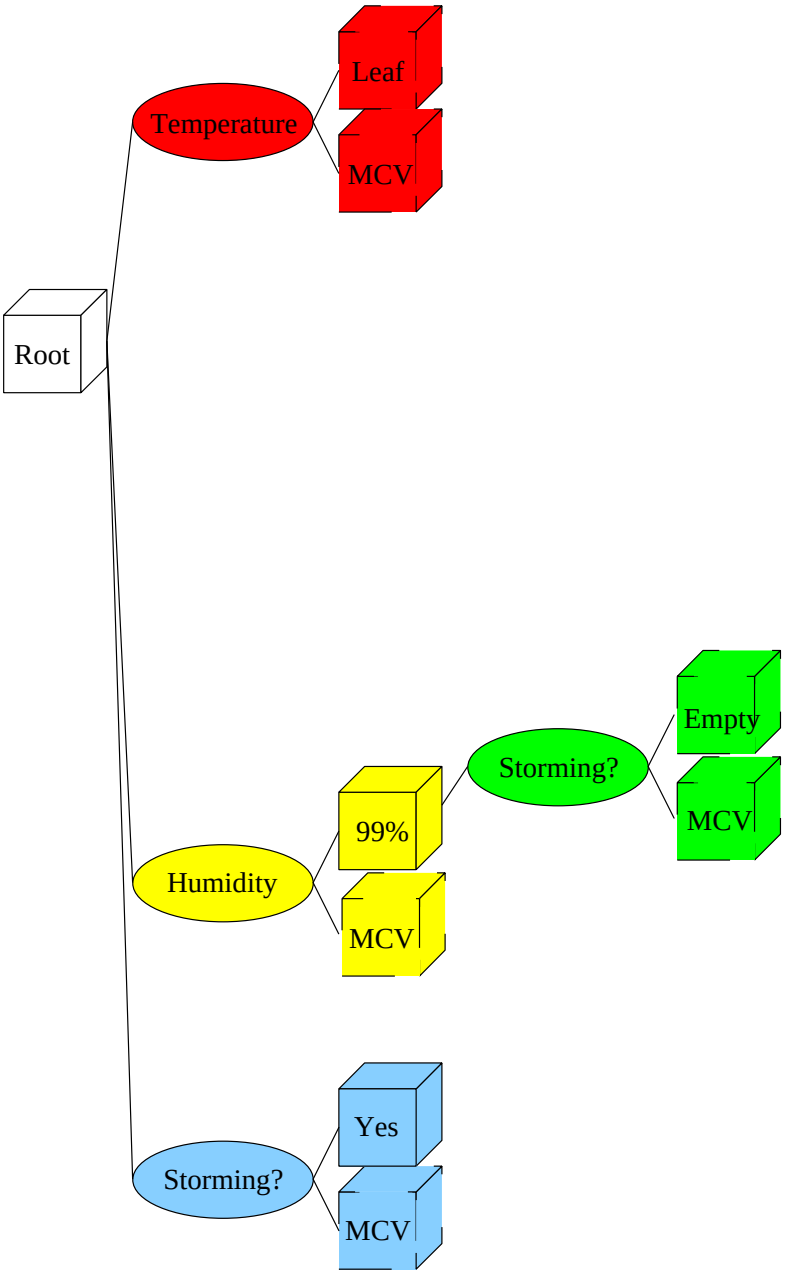
Datacube with marginalizations



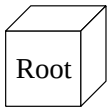
Full AD−tree


Root
Temperature
5F
105F
Humidity
99%
100%
Storming?
Yes
No
Storming?
Yes
No
Humidity
99%
100%
Storming?
Yes
No
Storming?
Yes
No
Storming?
Yes
No
Humidity
99%
100%
Storming?
Yes
No
Storming?
Yes
No
Storming?
Yes
No

Static AD−tree

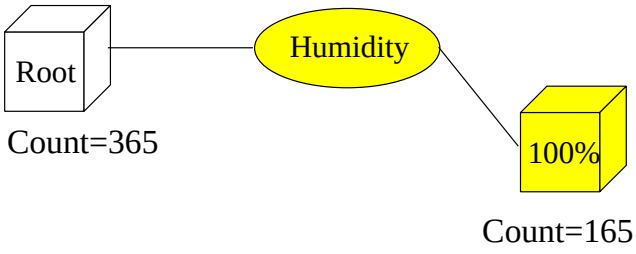


Dynamic AD−tree

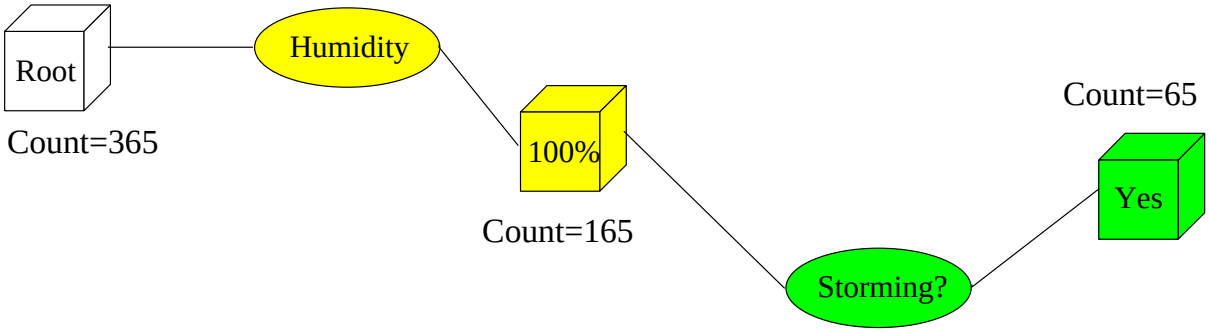


How Dynamic AD-trees Are Grown

Query 1: How many rows have Humidity = 100%?

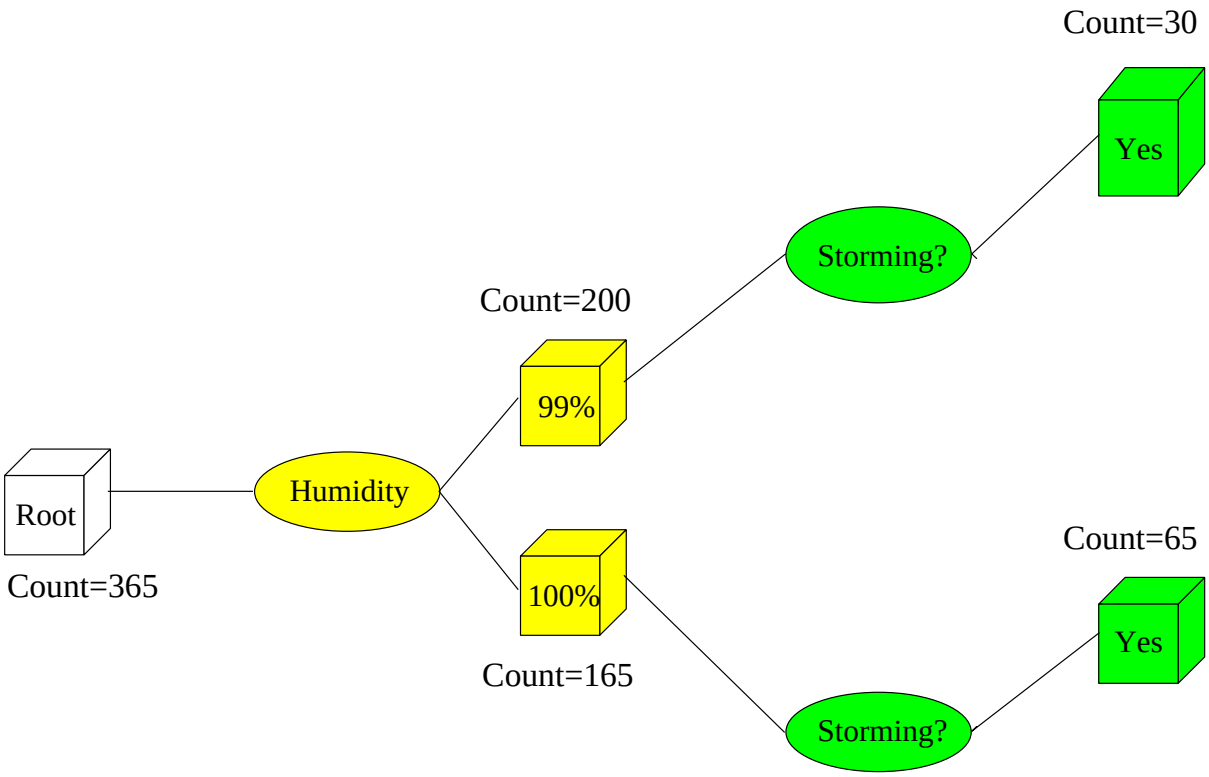


Query 2: How many rows have Humidity = 100% and Storming = Yes?



How Dynamic AD-trees Are Grown (slide 2)

Query 3: How many rows have Humidity = 99% and Storming = Yes?



Additional Dynamic AD-tree Benefit

- Amortized updates of AD-nodes to accomodate row additions to the data set.
- Accomplished with a tiny bit of extra state in each AD-node.
- Can be done with Static AD-trees, but more hassle.

Tests with the `e29.fds` Data Set

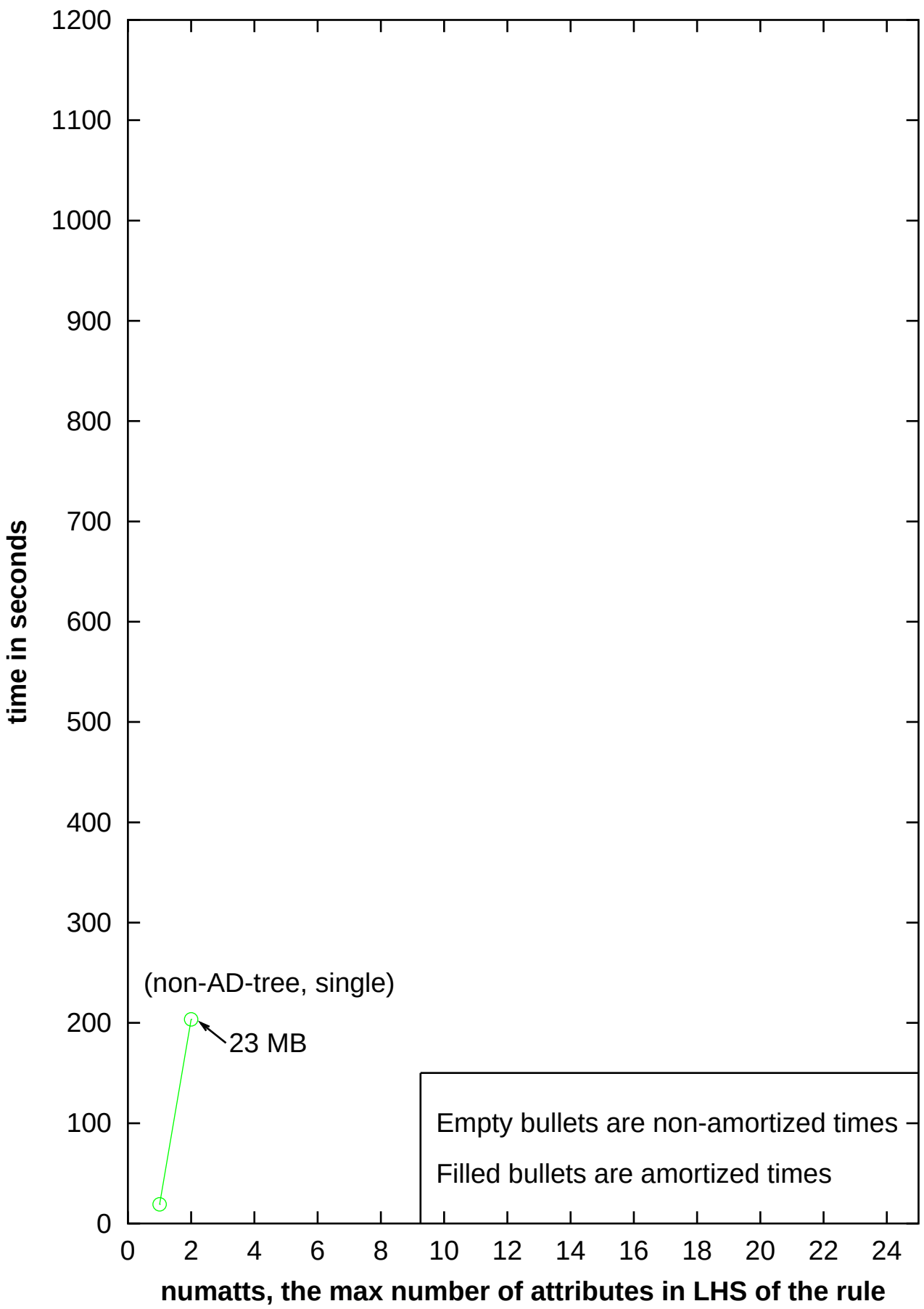
The `e29.fds` data set is a relatively small dataset. It comes from the Sloan Digital Sky Survey, and the attributes represent information about galaxies.

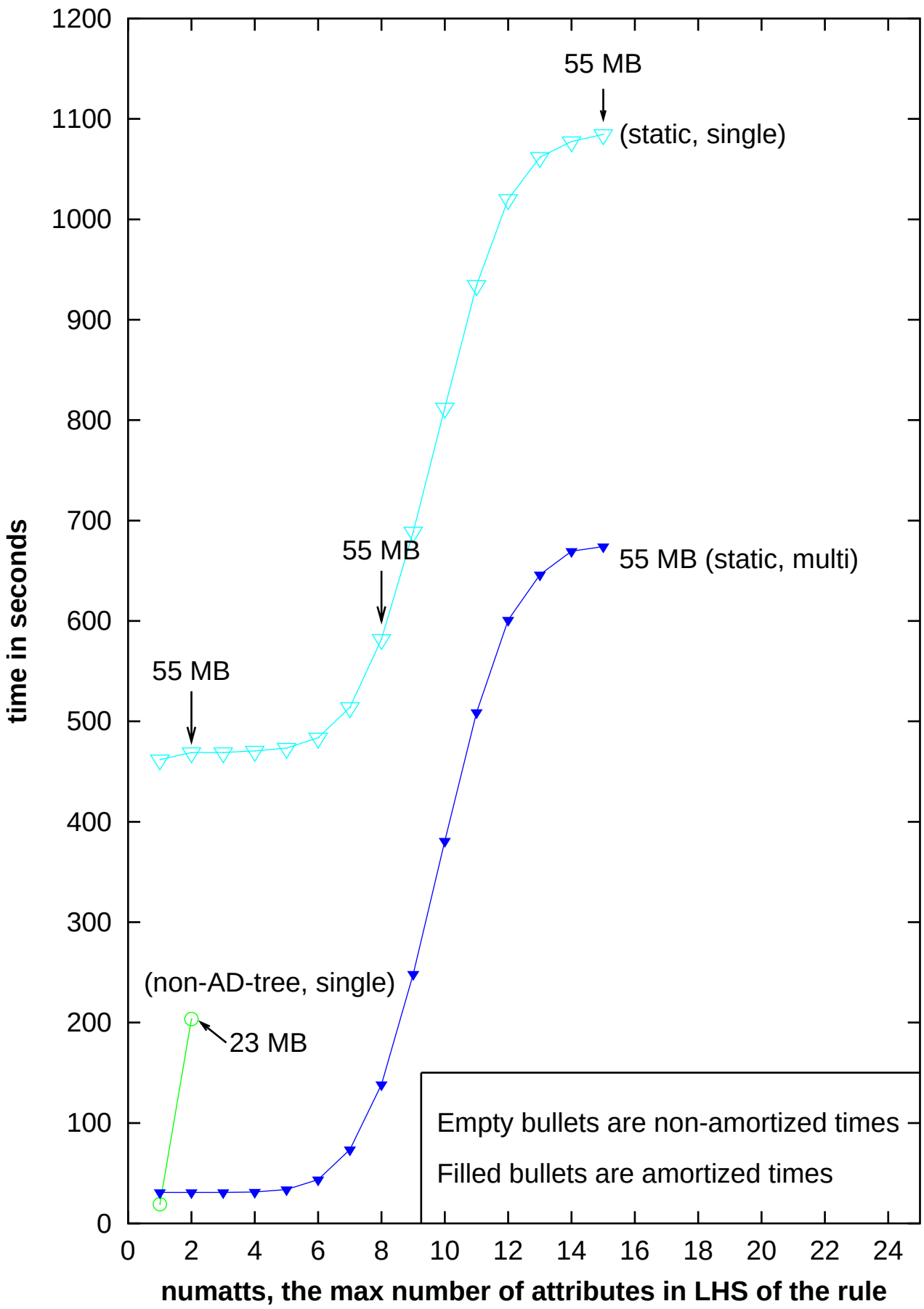
- 29 attributes
- Each attribute has low arity, i.e. between 2 and 6 possible values.
- 3079792 rows

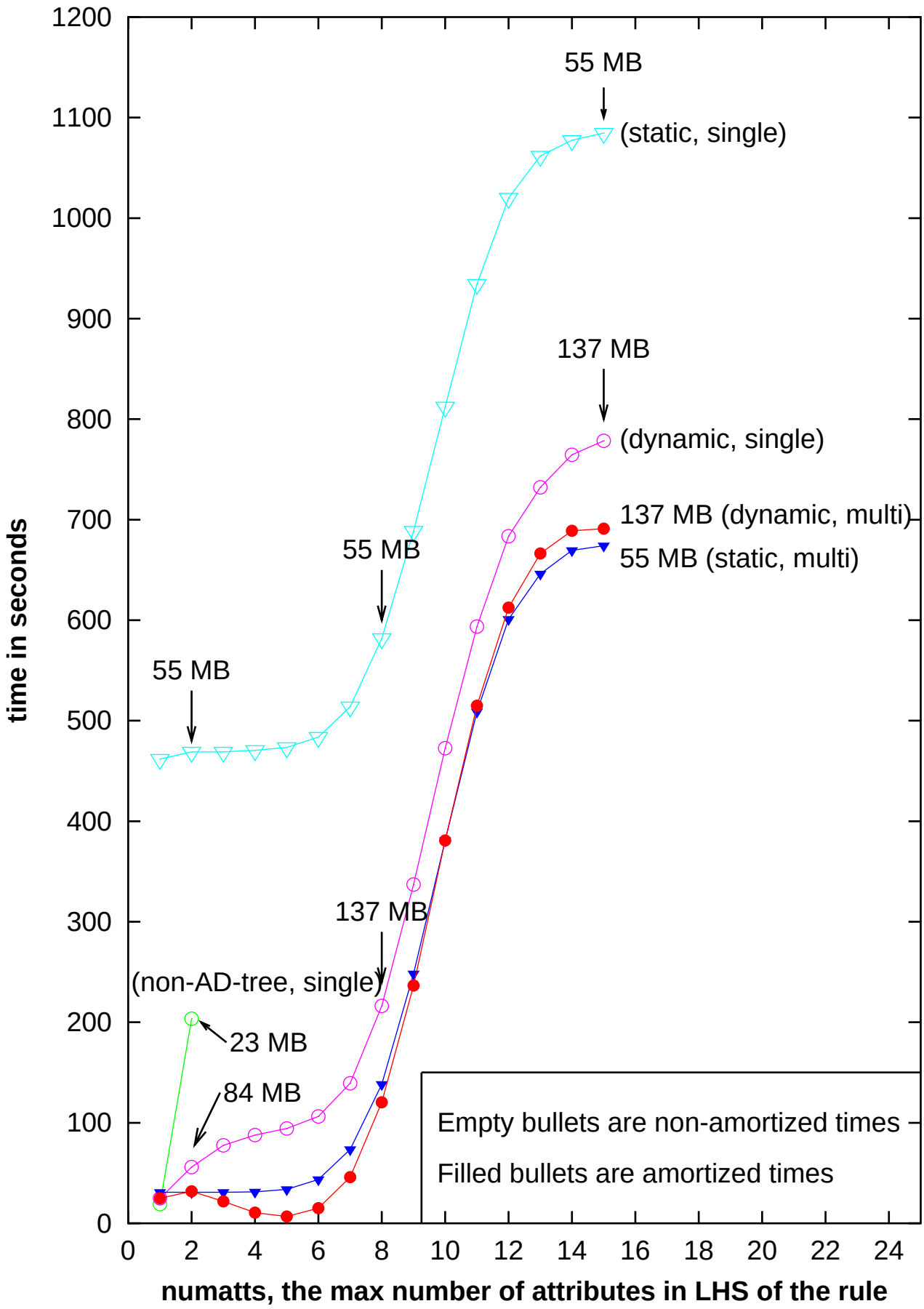
Rule Learner:

- chooses a set of attributes for the left-hand-side of the rule
- each new set of attributes is an incremental change from previous sets considered
- for various assignments of values to these attributes, it evaluates the accuracy of the resulting rule

As a result, successive queries are very similar to one another at all times. Therefore we expect the amortized performance of Dynamic AD-trees to be similar to that of Static AD-trees, if enough memory is allocated to the row caches and skinny AD-nodes. “One-off” performance of Dynamic AD-trees should of course be superior given enough memory.

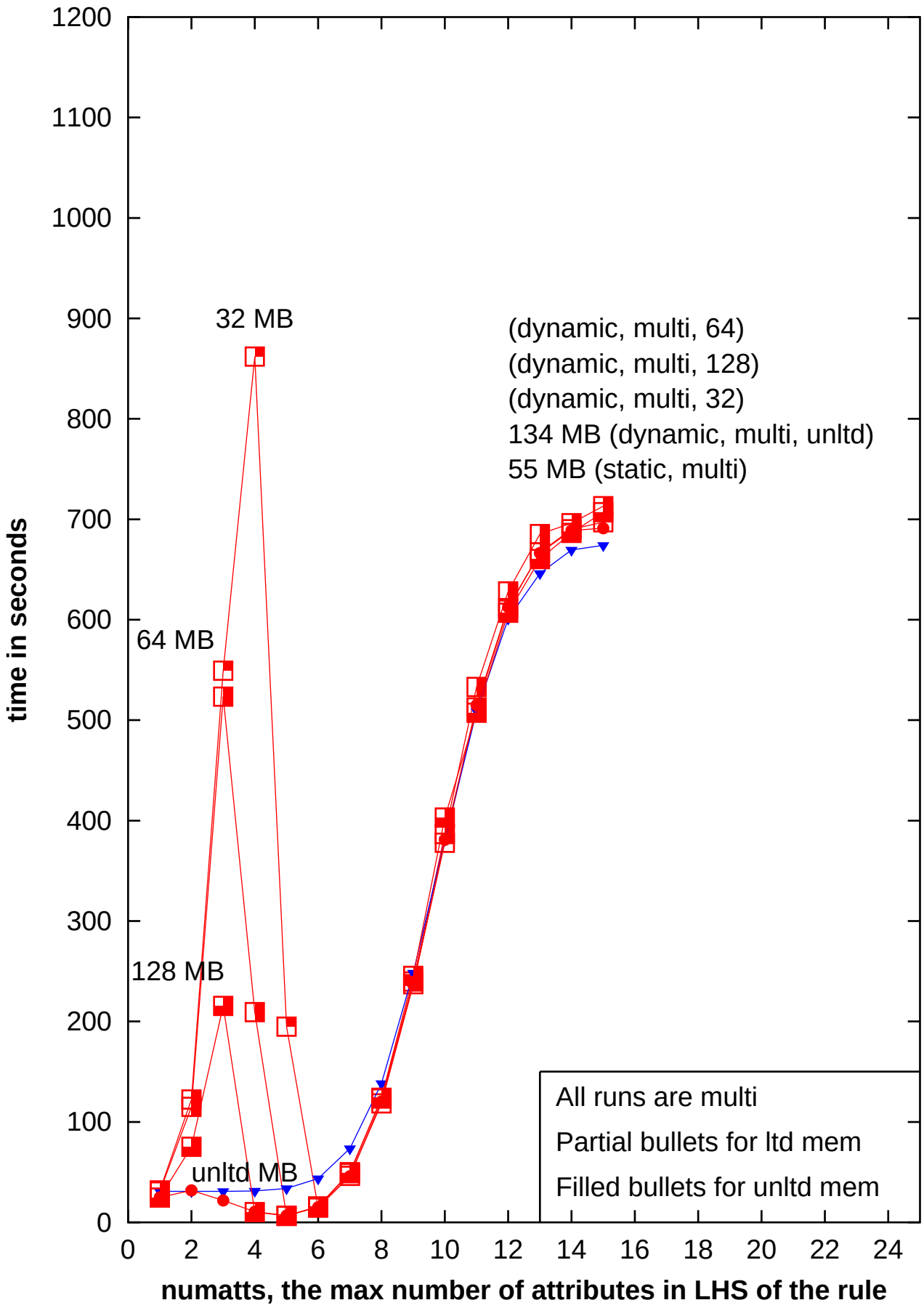

Rule Learner, unlimited memory, max time 1200s, on e29.fds
time in seconds
numatts, the max number of attributes in LHS of the rule
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
0
2
4
6
8
10
12
14
16
18
20
22
24
(non-AD-tree, single)
23 MB
Empty bullets are non-amortized times
Filled bullets are amortized times

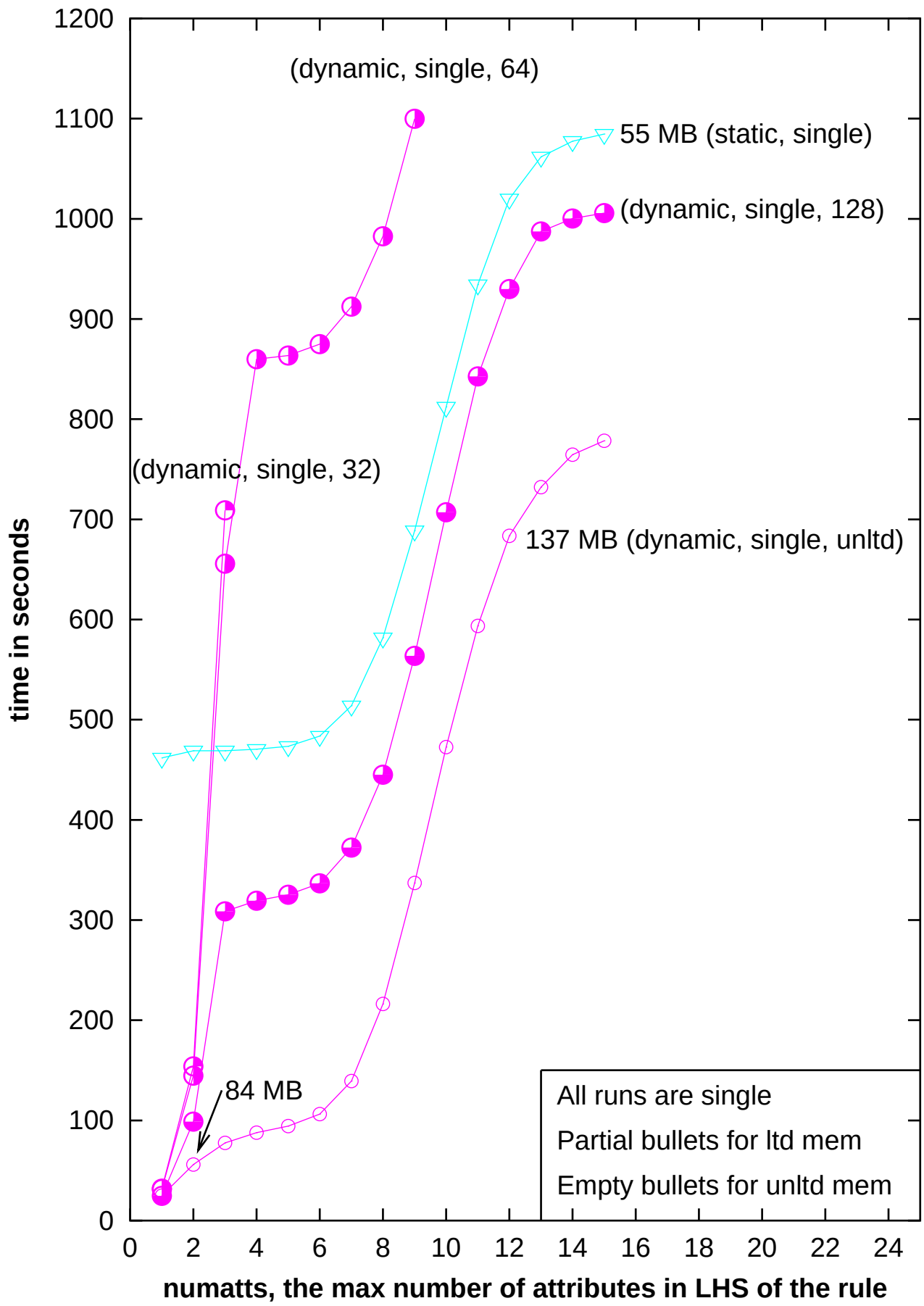

Rule Learner, unlimited memory, max time 1200s, on e29.fds
time in seconds
numatts, the max number of attributes in LHS of the rule
55 MB
(static, single)
55 MB
55 MB (static, multi)
55 MB
(non-AD-tree, single)
23 MB
Empty bullets are non-amortized times
Filled bullets are amortized times
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
0
2
4
6
8
10
12
14
16
18
20
22
24

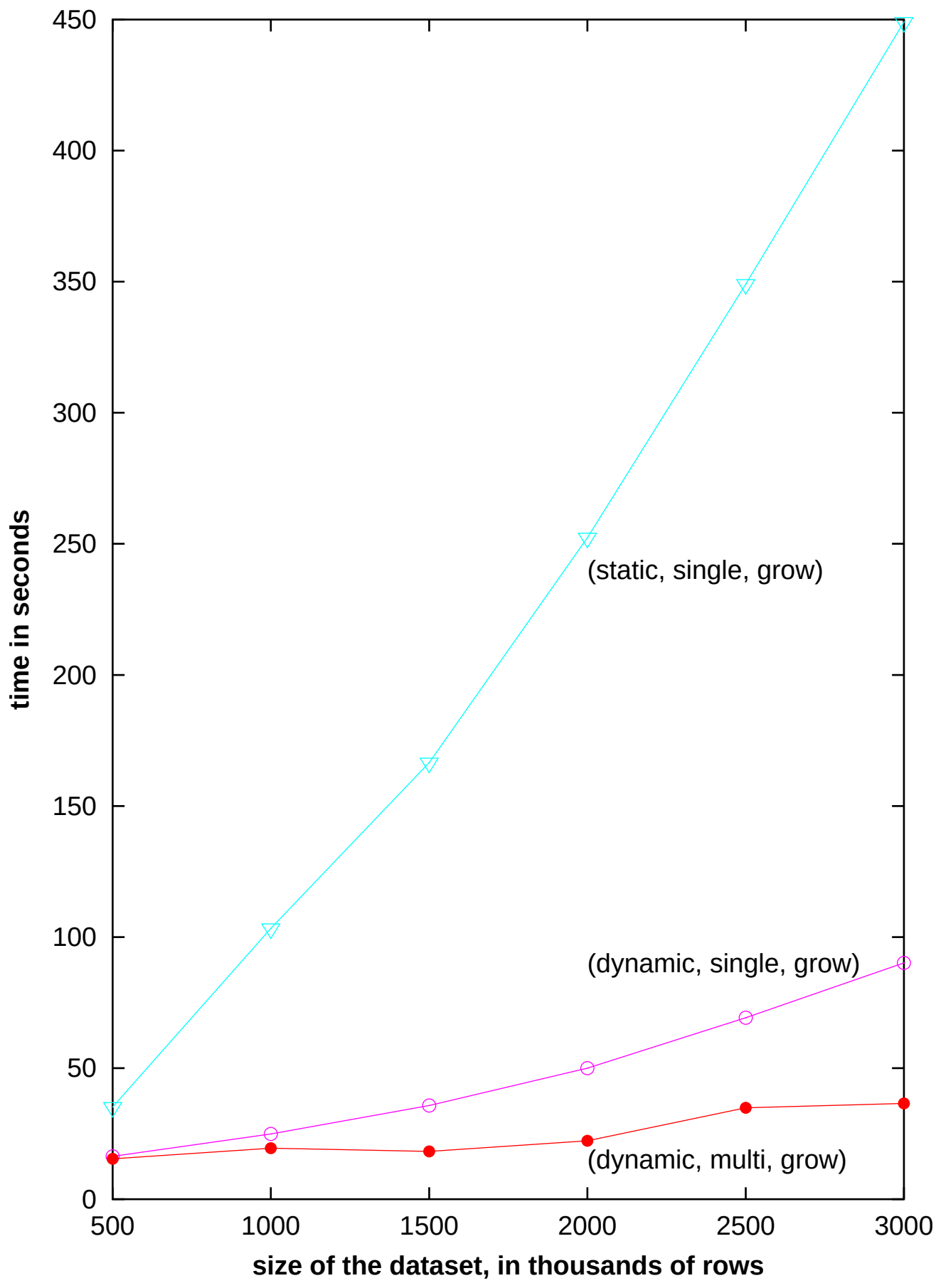

Rule Learner, unlimited memory, max time 1200s, on e29.fds
time in seconds
numatts, the max number of attributes in LHS of the rule
55 MB
(static, single)
137 MB
(dynamic, single)
137 MB (dynamic, multi)
55 MB (static, multi)
55 MB
55 MB
137 MB
(non-AD-tree, single)
23 MB
84 MB
Empty bullets are non-amortized times
Filled bullets are amortized times

Limited Memory Model gives 60% / 10% / 30% split to row caches, skinny AD-nodes, and the AD-tree itself:

- 32 MB model implies 19 MB / 3 MB / 10 MB split
- 64 MB model implies 38 MB / 6 MB / 20 MB split
- 128 MB model implies 77 MB / 13 MB / 38 MB split


Rule Learner, limited memory, multi, on e29.fds
time in seconds
numatts, the max number of attributes in LHS of the rule
32 MB
64 MB
128 MB
unltd MB
(dynamic, multi, 64)
(dynamic, multi, 128)
(dynamic, multi, 32)
134 MB (dynamic, multi, unltd)
55 MB (static, multi)
All runs are multi
Partial bullets for ltd mem
Filled bullets for unltd mem
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
0
2
4
6
8
10
12
14
16
18
20
22
24

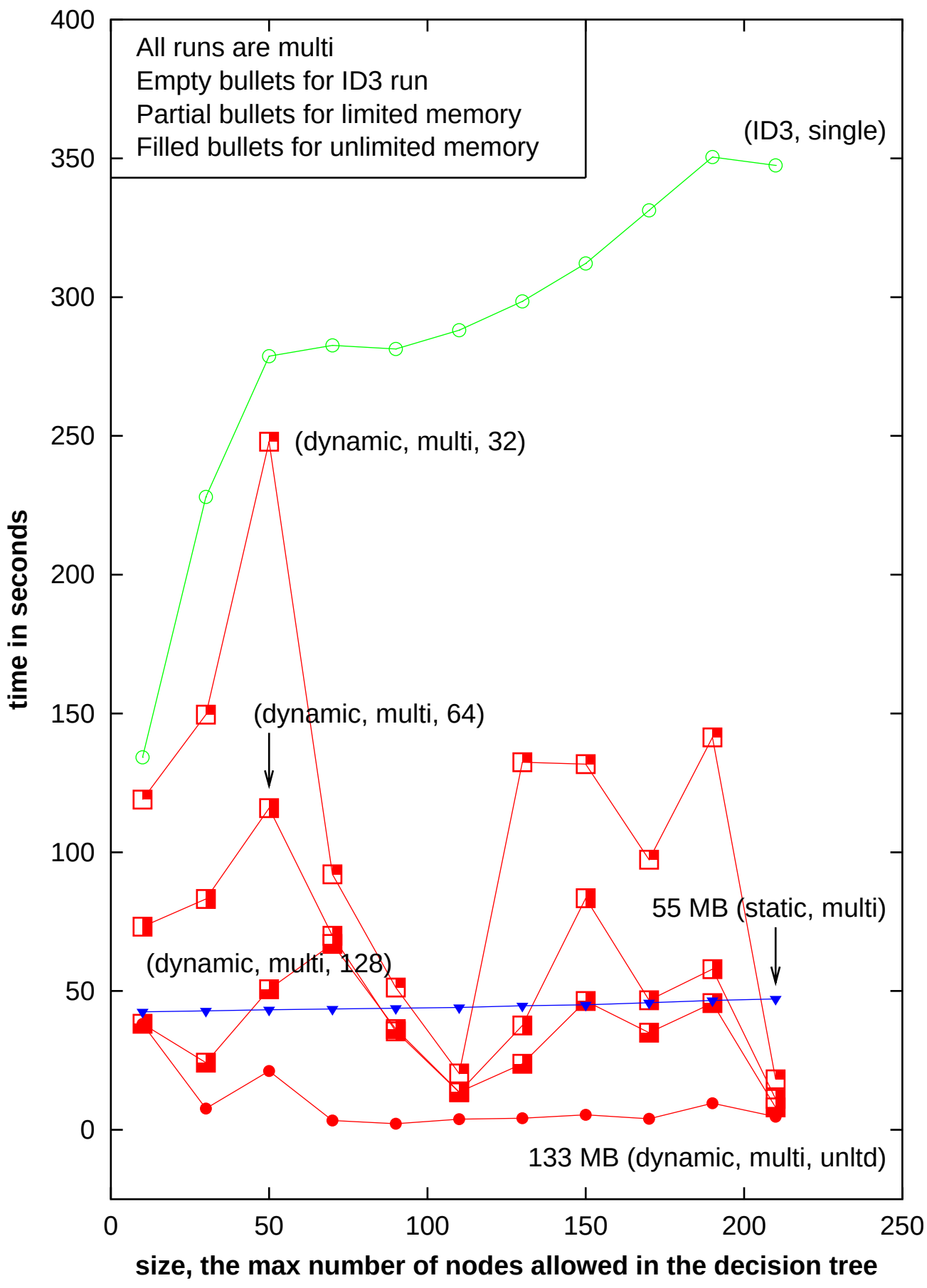

Rule Learner, limited memory, single, max time 1200s, on e29.fds
(dynamic, single, 64)
55 MB (static, single)
(dynamic, single, 128)
(dynamic, single, 32)
137 MB (dynamic, single, unltd)
84 MB
All runs are single
Partial bullets for ltd mem
Empty bullets for unltd mem
time in seconds
numatts, the max number of attributes in LHS of the rule
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
0
2
4
6
8
10
12
14
16
18
20
22
24

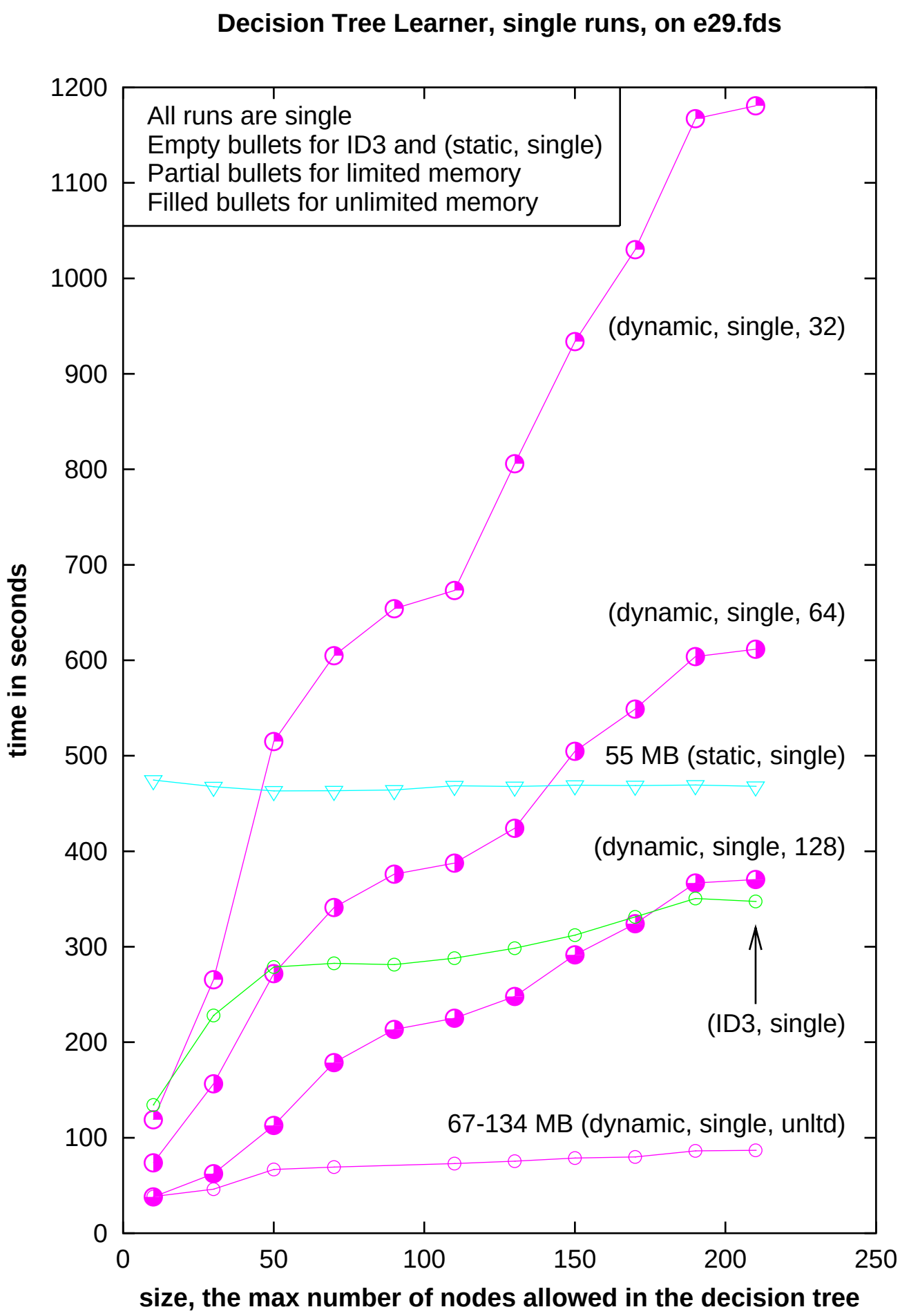

Rule Learner, growing e29.fds in 500,000-row chunks
time in seconds
size of the dataset, in thousands of rows
0
50
100
150
200
250
300
350
400
450
500
1000
1500
2000
2500
3000
(static, single, grow)
(dynamic, single, grow)
(dynamic, multi, grow)

The decision tree learner:

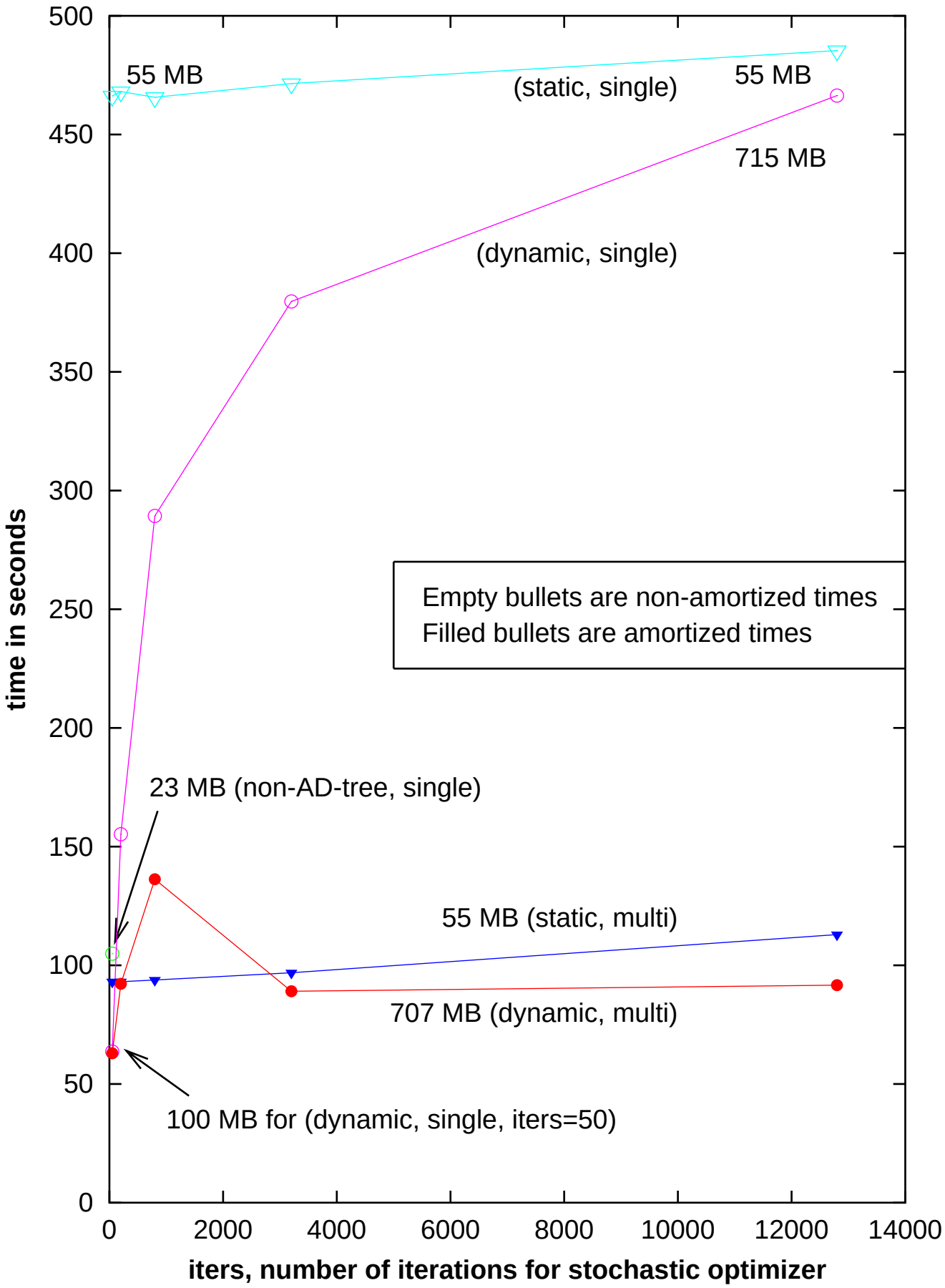
- given an existing node in the decision tree, it creates a child
- it chooses the “best” attribute to associate with the child
- to score potential attributes, queries are made which are identical to previously made queries, but with the addidition of the attribute being scored

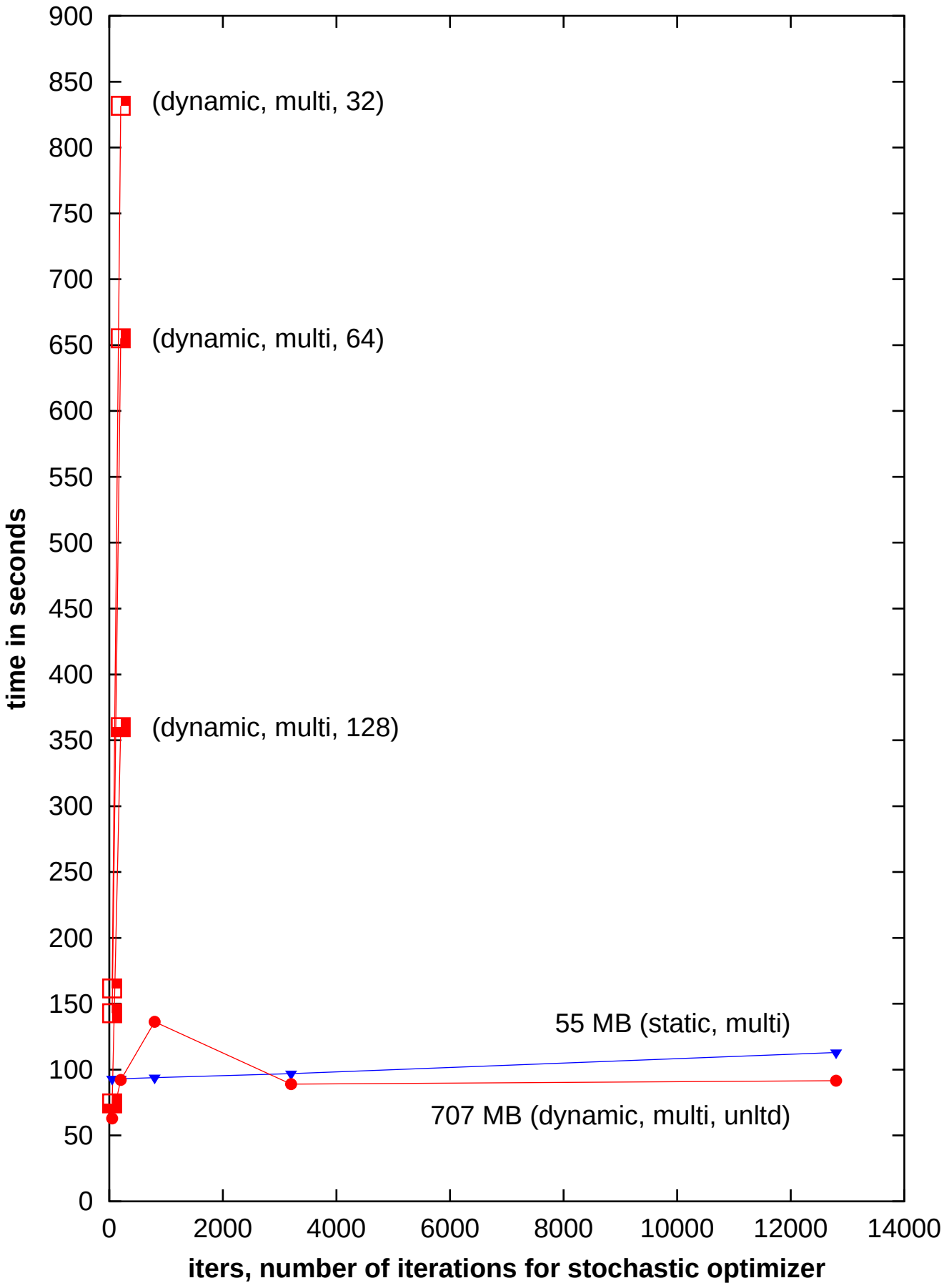
Again, successive queries are similar to one another. However, when changing which decision tree node is creating a child, a “jump” is made which reduces the applicability of the current row caches and skinny AD-nodes.


Decision Tree Learner, multi runs, on e29.fds
All runs are multi
Empty bullets for ID3 run
Partial bullets for limited memory
Filled bullets for unlimited memory
(ID3, single)
(dynamic, multi, 32)
(dynamic, multi, 64)
(dynamic, multi, 128)
55 MB (static, multi)
133 MB (dynamic, multi, unltd)
time in seconds
size, the max number of nodes allowed in the decision tree
0
50
100
150
200
250
300
350
400


Decision Tree Learner, single runs, on e29.fds
All runs are single
Empty bullets for ID3 and (static, single)
Partial bullets for limited memory
Filled bullets for unlimited memory
(dynamic, single, 32)
(dynamic, single, 64)
55 MB (static, single)
(dynamic, single, 128)
(ID3, single)
67-134 MB (dynamic, single, unltd)
time in seconds
size, the max number of nodes allowed in the decision tree
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
0
50
100
150
200
250

The Bayes net structure fi nder uses a stochastic hill-climbing algorithm to fi nd a Bayes net structure which approximately “explains” the data set. This stochastic element induces a query pattern which is seldom localized for more than a few successive queries.


Bayes Net Structure Finder, unlimited memory, on e29.fds
time in seconds
iters, number of iterations for stochastic optimizer
0
50
100
150
200
250
300
350
400
450
500
0
2000
4000
6000
8000
10000
12000
14000
55 MB
(static, single)
55 MB
715 MB
(dynamic, single)
Empty bullets are non-amortized times
Filled bullets are amortized times
23 MB (non-AD-tree, single)
55 MB (static, multi)
707 MB (dynamic, multi)
100 MB for (dynamic, single, iters=50)


Bayes Net Structure Finder, limited memory, on e29.fds
time in seconds
iters, number of iterations for stochastic optimizer
(dynamic, multi, 32)
(dynamic, multi, 64)
(dynamic, multi, 128)
55 MB (static, multi)
707 MB (dynamic, multi, unltd)
900
850
800
750
700
650
600
550
500
450
400
350
300
250
200
150
100
50
0
0
2000
4000
6000
8000
10000
12000
14000

Summary of Static and Dynamic AD-trees

- AD-trees pre-cache counting queries in an effi cient manner.

- The time to answer a query is independent of the number of data set rows, once the Static AD-tree is built. Static AD-trees thrive in amortized contexts.

- Dynamic AD-trees only grow the AD-tree where needed, when needed. Row caches and skinny AD-nodes are used to maintain performance, and hence are sensitive to query patterns.

- Dynamic AD-trees are flexible and effi cient in both amortized *and* “one-off” applications. They can serve as generic, high-performance replacements for more specialized structures.

Future Work

- Better management of row cache and skinny AD-node priority queues.

- Dynamic reordering and addition of data set attributes. Simple with Dynamic AD-trees.

- Localized variation of parameters within a Dynamic AD-tree. For instance, adding or hiding some attributes to/from an AD-node. More interesting is dynamic attribute resolution.

- The above items would allow dynamic, variable discretization of real-valued attributes.

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