Adaptive Datastructures for Dynamic Graph Analysis

TECHNISCHE UNIVERSITÄT DARMSTADT

Defense talk

Outline

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Datastructures heavily influence the runtime performance of software

Runtime comparison
Performance of `contains`

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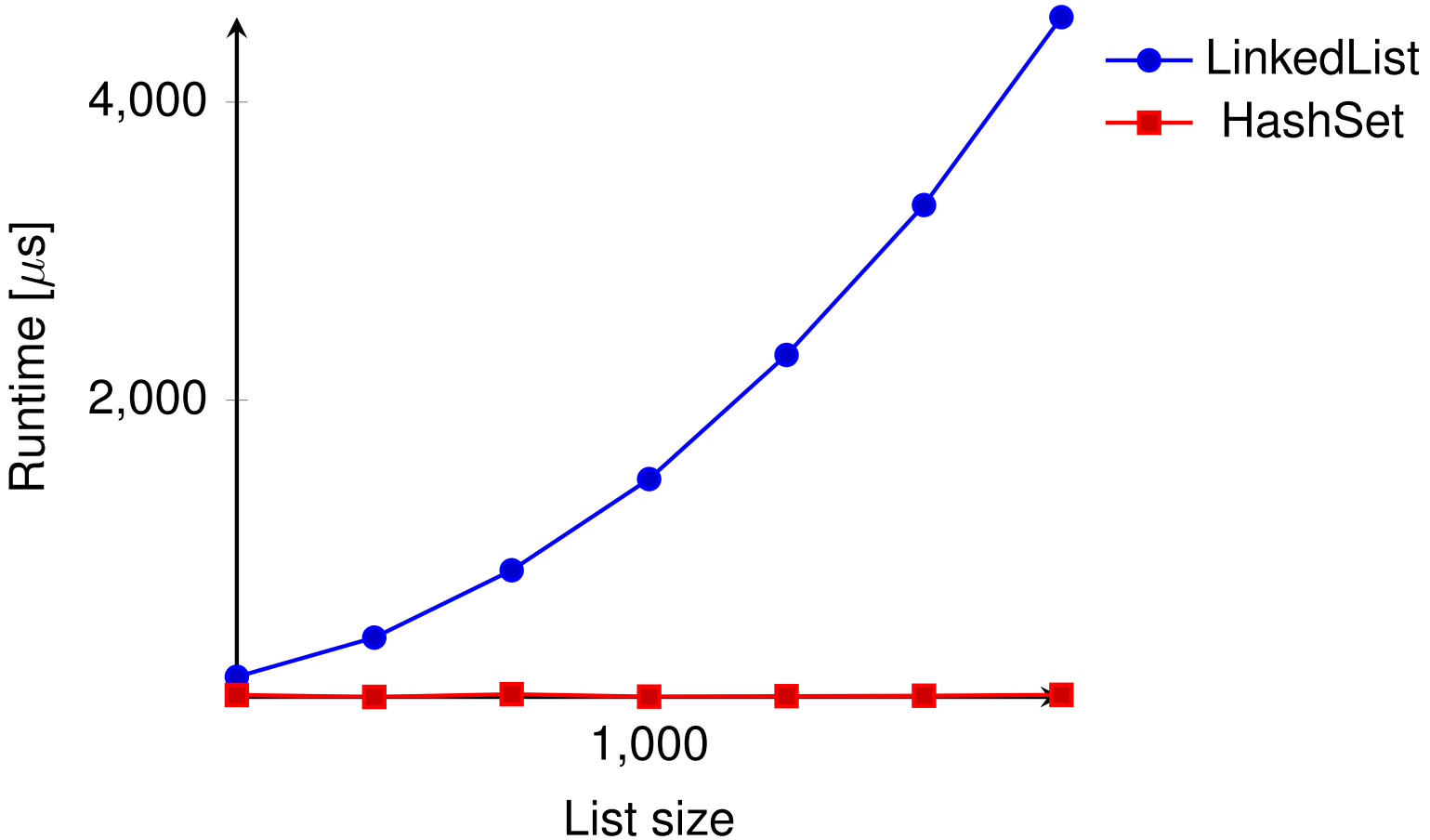

Runtime comparison
Performance of `add`

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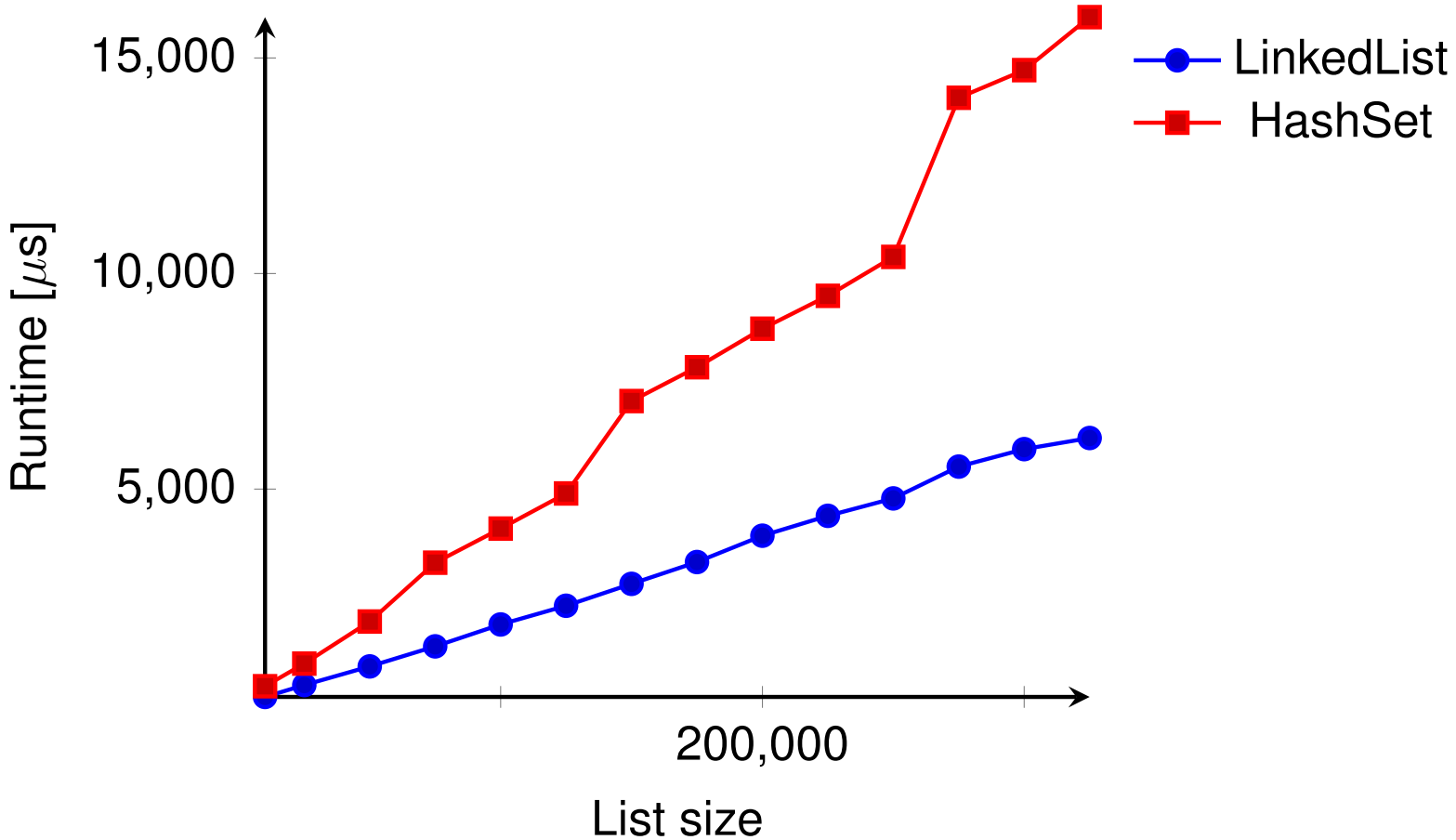

Outline

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Scope of our work

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- Implementation in Java, extending DNA

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- Dynamic part: batches that hold a set of updates for the graph

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- Implementation in Java, extending DNA
- Analysis of dynamic graphs
- Dynamic part: batches that hold a set of updates for the graph
- Multiple sequent batches form a run, multiple runs a series

How to influence performance?

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1. Buy new hardware

How to influence performance?

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2. Analyze usage and think about replacing datastructures

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3. Use datastructures optimized to special needs
   $\rightarrow$ general purpose database systems like MySQL or Oracle, or specialized graph data structures like STINGER

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3. Use datastructures optimized to special needs
   $\rightarrow$ general purpose database systems like MySQL or Oracle, or specialized graph data structures like STINGER
4. Use techniques that analyze and optimize automatically

How to influence performance?
Related work: automatic approaches

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- Chameleon: running on top of the JVM, giving optimization hints based on a fixed rule set
  $\rightarrow$ more than n calls of method $\mathcal{A}$? Use datastructure $\mathcal{X}$, it performs better!

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- CoCo: proxy datastructures for existing classes, running optimizations based on fixed rules

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- Drawback: How to control these optimizations?

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  - Should they be carried out only at specific points?
  - Should they adopt to each new situation?
  - Should there be any efficiency check for the optimization?
- Drawback: configuration / implementation overhead
  - Additional layer on top of a JVM might not be compatible with all current and future JVM implementations

Outline

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Our approach
Basic concepts

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1. Split up raw program and optimizing parts

Our approach
Basic concepts

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1. Split up raw program and optimizing parts
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Basic concepts

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2. Seperate counting of accesses (aggregated for list types), computing recommendations (based on the costs per call) and applying them
3. Compute recommendations based on counted data from longer time periods

Our approach
Basic concepts

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1. Split up raw program and optimizing parts
2. Seperate counting of accesses (aggregated for list types), computing recommendations (based on the costs per call) and applying them
3. Compute recommendations based on counted data from longer time periods
4. Avoid in-between swaps of datastructures

Our approach
Structural overview of our contribution to DNA

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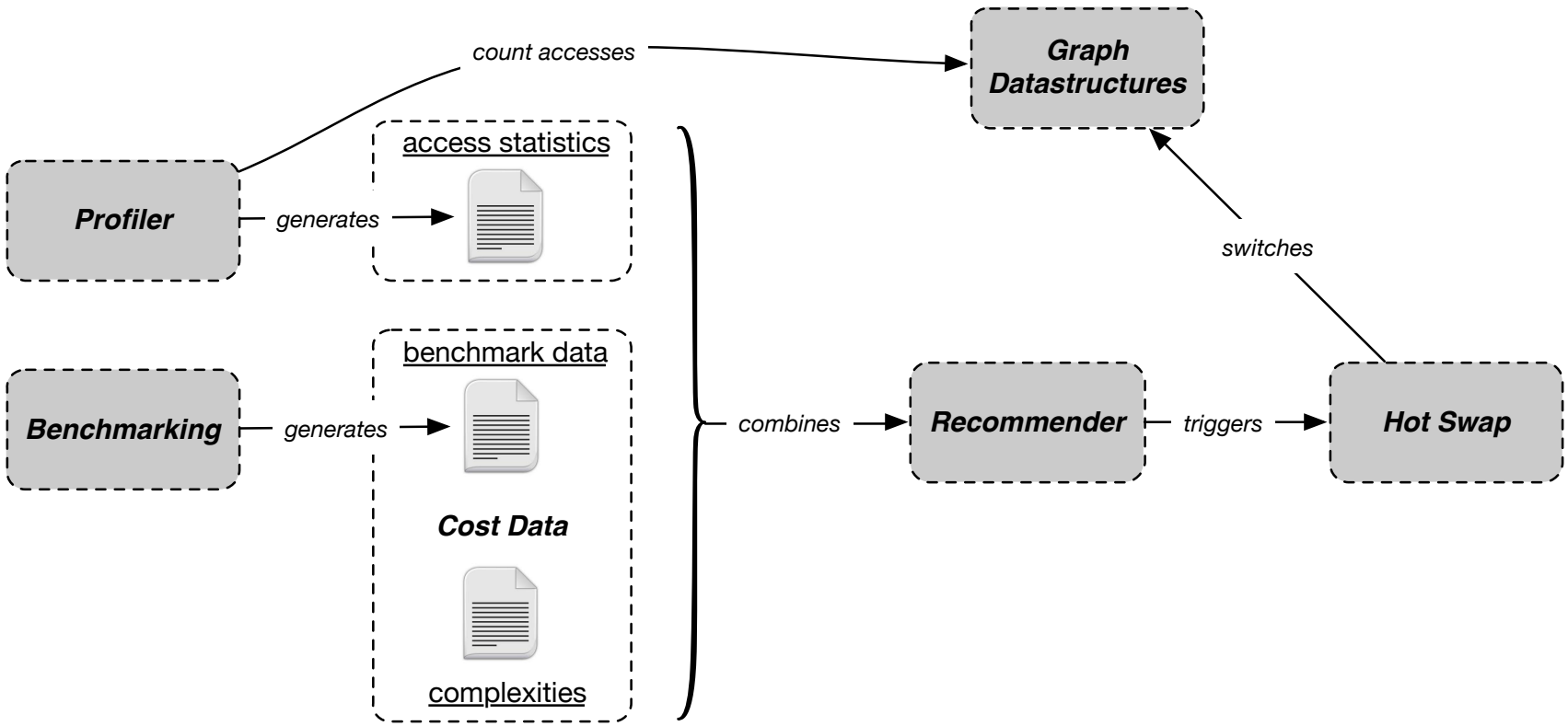

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Our approach
Graph datastructure - initial state

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- Datastructures were hardcoded into graph and node classes
  $\rightarrow$ one class for a node that uses `ArrayList` internally, another class that uses `HashSet`

Our approach
Graph datastructure - initial state

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- Datastructures were hardcoded into graph and node classes
  $\rightarrow$ one class for a node that uses `ArrayList` internally, another class that uses `HashSet`
- All combinations of datastructures needed to be hardcoded
  Example: `DirectedGraphAlHs` for storing nodes in a `ArrayList` and edges in a `HashSet`

Our approach
Graph datastructure - final state (1/2)

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- Split up graph's datastructures ("customer" classes for the graphs and nodes) and lists for storing nodes and edges

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Our approach
Graph datastructure - final state (1/2)

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- Split up graph's datastructures ("customer" classes for the graphs and nodes) and lists for storing nodes and edges
- Distinguishable list types for different needs $\rightarrow$ global node list, global edge list, node-local node and edge lists
- Define methods for all datastructures in a common interface

Our approach
Graph datastructure - final state (2/2)

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- A central factory class creates new lists on request
  $\rightarrow$ each “customer” class is able to request a new list without caring about the actual implementation

Our approach
Graph datastructure - final state (2/2)

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- A central factory class creates new lists on request
  $\rightarrow$ each “customer” class is able to request a new list without caring about the actual implementation
- Cost data for all accesses
  $\rightarrow$ runtime and memory costs per call for each access type, in terms of complexities and system-dependent measurements

  Complexity data example:

```
RUNTIMECOMPLEXITY_DARRAY_ADD_NODE = 1 Linear
```

Our approach
Graph datastructure - examples (1/2)

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```
EnumMap<ListType, Class<? extends IDataStructure>> listTypes =
  GraphDataStructure.getList(
    ListType.GlobalNodeList, DHashMap.class,
    ListType.GlobalEdgeList, DHashMap.class );
GraphDataStructure gds = new GraphDataStructure(listTypes,
  UndirectedNode.class, UndirectedEdge.class);

Graph g = gds.newGraphInstance("Graph", 0, 50, 200);
Node node1 = gds.newNodeInstance(1);
Node node2 = gds.newNodeInstance(2);
Edge e = gds.newEdgeInstance(node1, node2);

g.addNode(node1);
g.addNode(node2);
g.addEdge(e);
```

Listing 1: Sample code for instantiating a new graph datastructure

Our approach
Graph datastructure - examples (2/2)

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```
public Graph(String name, long timestamp, GraphDataStructure gds) {
  this.name = name;
  this.timestamp = timestamp;
  this.nodeList =
      (INodeListDatastructure) gds.newList(ListType.GlobalNodeList);
  this.edgeList =
      (IEdgeListDatastructure) gds.newList(ListType.GlobalEdgeList);
  this.gds = gds;
}
```

Listing 2: Sample code for instantiating lists for a new graph

Our approach
Benchmarking (1/3)

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- We want to gather performance data for all actions on all defined datastructures

Our approach
Benchmarking (1/3)

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- We want to gather performance data for all actions on all defined datastructures
- System-dependent performance data: even if runtime complexities are equal, real performance shows huge differences

Our approach
Benchmarking (2/3)

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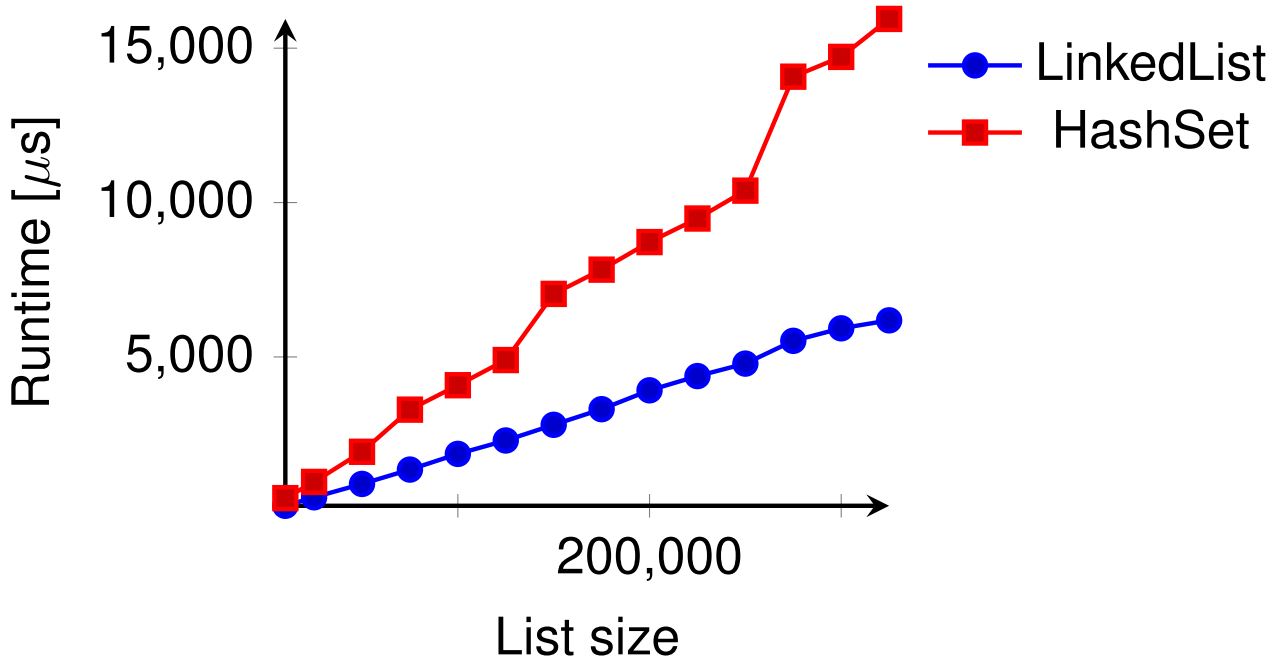

Different runtimes, but common complexity of $\mathcal{O}(1)$

Our approach
Benchmarking (3/3)

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- We want to gather performance data for all actions on all datastructures
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- For all methods defined through the common interface: measure the time and memory consumption of several executions with several sizes

Our approach
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- We want to gather performance data for all actions on all datastructures
- System-dependent performance data: even if runtime complexities are equal, real performance shows huge differences
- For all methods defined through the common interface: measure the time and memory consumption of several executions with several sizes
- Write data to files without aggregating them
  Example:

```
RUNTIMEBENCHMARK_DARRAY_ADD_NODE =
  50=1161.312,1119.687,1200.125,1194.062,1153.062;
  500=1042.22,813.54,1111.3,1151.6,1166.46;
  2000=3581.8,2770.64,4125.96,3247.1,4504.38
```

Our approach
Structural overview of our contribution to DNA

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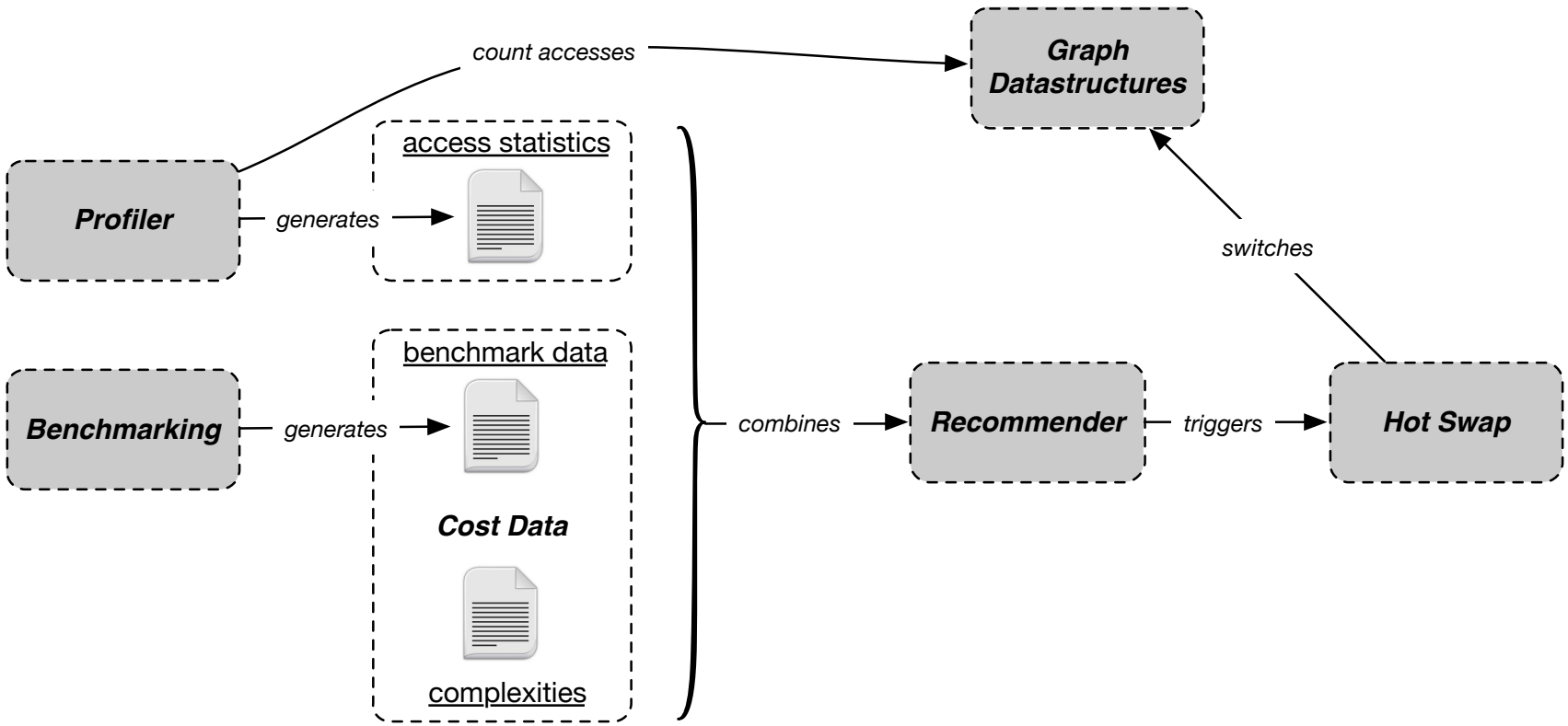

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Our approach
Profiler (1/4)

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- We need to know how often a method is called to compute complete costs

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- Profiling parts should be kept seperated from the other parts
  $\rightarrow$ possible with AspectJ

Our approach
Profiler (1/4)

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- We need to know how often a method is called to compute complete costs
- Profiling parts should be kept seperated from the other parts
  $\rightarrow$ possible with AspectJ
- Using AspectJ, all calls from the common interface are wrapped with the profiling parts on compile time

Our approach
Profiler (2/4)

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```
pointcut contains(DataStructure list) :
  call(* IDataStructure+.contains(..)) && target(list);
pointcut size(DataStructure list) :
  call(* IDataStructure+.size()) && target(list);

boolean around(DataStructure list) : contains(list) {
  boolean res = proceed(list);
  if (res)
    Profiler.count(this.currentCountKey, list.listType,
      AccessType.ContainsSuccess);
  else
    Profiler.count(this.currentCountKey, list.listType,
      AccessType.ContainsFailure);
  return res;
}

after(DataStructure list) : size(list) {
  Profiler.count(this.currentCountKey, list.listType, AccessType.Size);
}
```

Listing 3: Pointcut and advice to monitor datastructure accesses (excerpt)

Our approach
Profiler (3/4)

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- Data is monitored through different counting keys to distinguish callees (graph generation, batch generation, metrics)

Our approach
Profiler (3/4)

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- Data is monitored through different counting keys to distinguish callees (graph generation, batch generation, metrics)
- Data is aggregated over different states of DNA: over one batch, over one run

Our approach
Profiler (4/4)

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```
NR.GlobalNodeList_Init=0
NR.GlobalNodeList_Add=0
NR.GlobalNodeList_Random=0
NR.GlobalNodeList_RemoveSuccess=5000
NR.GlobalNodeList_RemoveFailure=0
NR.GlobalNodeList_Size=0
NR.GlobalNodeList_Iterator=0

aggregated.GlobalNodeList_Init=2
aggregated.GlobalNodeList_Add=70000
aggregated.GlobalNodeList_Random=1005785
aggregated.GlobalNodeList_RemoveSuccess=5000
aggregated.GlobalNodeList_RemoveFailure=0
aggregated.GlobalNodeList_Size=205181
aggregated.GlobalNodeList_Iterator=0
```

Listing 4: Profiling results file (excerpt)

Our approach
Structural overview of our contribution to DNA

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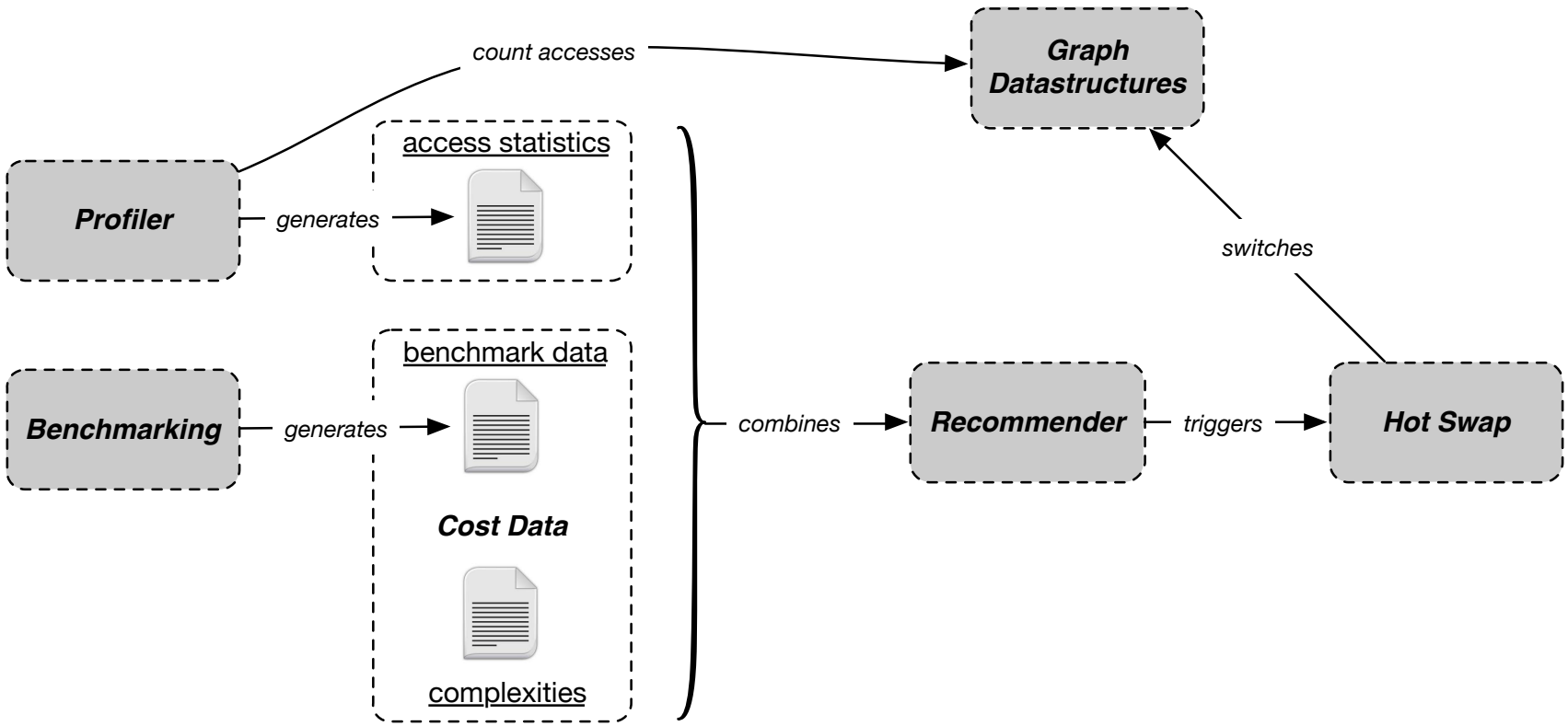

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Our approach
Recommender (1/3)

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- Recommender combines counted accesses with cost data for each datastructure

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Recommender (1/3)

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  - Complexities: static data, same value for all list sizes

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Recommender (1/3)

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- Recommender combines counted accesses with cost data for each datastructure
- First step: get the proper cost data
  - Complexities: static data, same value for all list sizes
  - Benchmarking results: depending on the current size

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- Recommender combines counted accesses with cost data for each datastructure
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  - On reading the data from files: preprocessing to aggregate the list of cost values for one size to one element, either minimum, maximum, or average

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  - Benchmarking results: depending on the current size
  - On reading the data from files: preprocessing to aggregate the list of cost values for one size to one element, either minimum, maximum, or average
  - On accessing the costs for a given list size: check which value to use, either the one for the next lower list size given, the next upper, or a linear interpolation

Our approach
Recommender (2/3)

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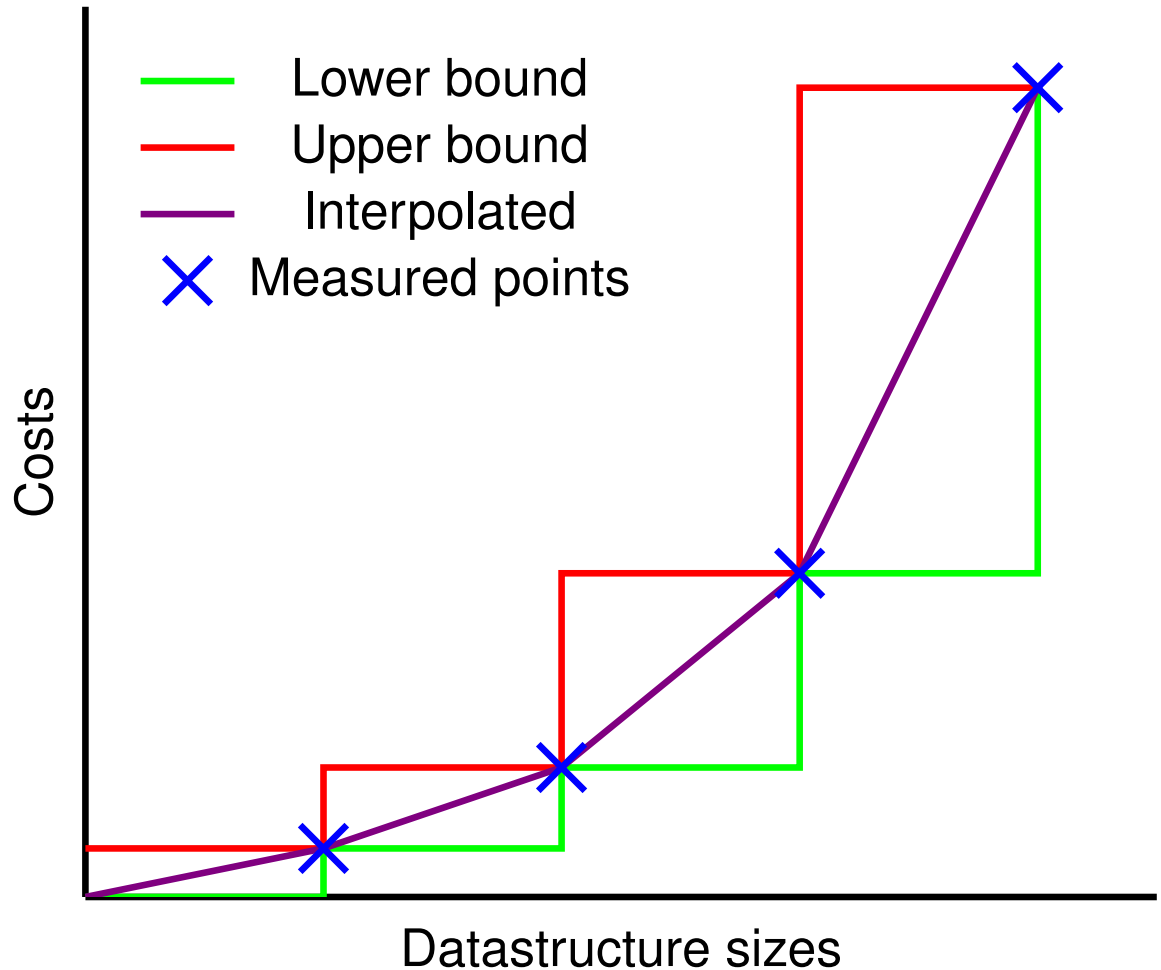

Our approach
Recommender (3/3)

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- Recommender combines counted accesses with cost data for each datastructure
- First step: get the proper cost data
- Second step: sum up the costs
  $\rightarrow$ for each counted access type, multiply the number of accesses with the costs per call
  $\rightarrow$ sum this up for all combinations of datastructures to get a sorted list of combinations that perform good

Our approach
Recommender - example (1/2)

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		Datastructure D_1	Datastructure D_2
Access type A_1	10 elements	1, 2, 2	10, 15, 11
	20 elements	10, 16, 24	20, 22, 21
Access type A_2	10 elements	5, 2, 9	2, 10, 9
	20 elements	5, 4, 5	5, 2, 5

Table: Cost matrix for the example datastructures and access types

Our approach
Recommender - example (1/2)

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		Datastructure D_1	Datastructure D_2
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Table: Cost matrix for the example datastructures and access types

		DS D_1	DS D_2
Access type A_1	10 elements	1	10
	20 elements	10	20
Access type A_2	10 elements	2	2
	20 elements	4	2

Table: Concrete costs for each access in an example scenario using minimum values

Our approach
Recommender - example (2/2)

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- Recorded accesses: 10 accesses for access type A_1 and 5 accesses for access type A_2
  $\rightarrow$ represented through $a_1 = 10$ and $a_2 = 5$

Our approach
Recommender - example (2/2)

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- Recorded accesses: 10 accesses for access type A_1 and 5 accesses for access type A_2
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- Costs for a datastructure with 15 elements, using the lower bound selector:

$$Costs(D_n) = \sum Costs(D_n, A_m, Size) * a_m$$

Our approach
Recommender - example (2/2)

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$$Costs(D_1) = Costs(D_1, A_1, 15) * a_1 + Costs(D_1, A_2, 15) * a_2$$

$$= 1 * 10 + 2 * 5 = 20$$

Our approach
Recommender - example (2/2)

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Costs(D_n) &= \sum Costs(D_n, A_m, Size) * a_m \\
Costs(D_1) &= Costs(D_1, A_1, 15) * a_1 + Costs(D_1, A_2, 15) * a_2 \\
&= 1 * 10 + 2 * 5 = 20 \\
Costs(D_2) &= Costs(D_2, A_1, 15) * a_1 + Costs(D_2, A_2, 15) * a_2 \\
&= 10 * 10 + 2 * 5 = 110
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Our approach
Recommender - example (2/2)

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- D_1 obviously performs better in this optimistic cost estimation

Our approach
Recommender - example (2/2)

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\end{aligned}
$$

- D_1 obviously performs better in this optimistic cost estimation
- Using a pessimistic approach (by aggregating the measured values by their maximum and using the upper bound selector), D_2 yields lower costs

Our approach
Structural overview of our contribution to DNA

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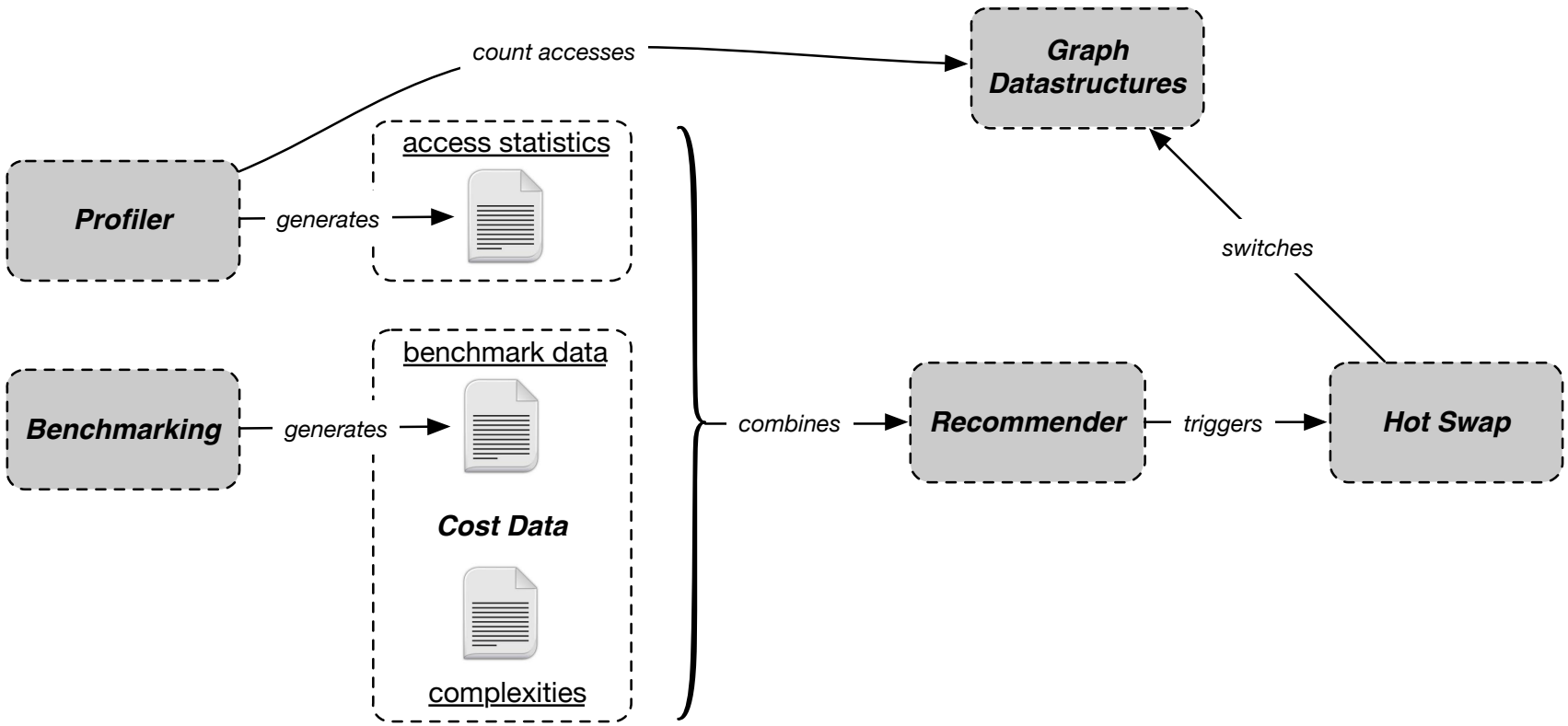

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Our approach
Hot swap

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Currently known: a list of datastructure combinations and their performance costs

Our approach
Hot swap

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Currently known: a list of datastructure combinations and their performance costs

Which one to choose now for swapping?

Our approach
Hot swap - possible approaches

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- Switch whenever possible
  $\rightarrow$ same problem as with CoCo: it's easy to fool the system

Our approach
Hot swap - possible approaches

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- Switch whenever possible
  $\rightarrow$ same problem as with CoCo: it's easy to fool the system
- Other extreme: run a whole analysis and give recommendations afterwards
  $\rightarrow$ not feasible for long running programs

Our approach
Hot swap - possible approaches

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- Switch whenever possible
  $\rightarrow$ same problem as with CoCo: it's easy to fool the system
- Other extreme: run a whole analysis and give recommendations afterwards
  $\rightarrow$ not feasible for long running programs
- Solution for our context: collect data over some batches and find long-time candidates for the swap

Our approach
Hot swap - our approach

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- First step: collect data in a sliding window

Our approach
Hot swap - our approach

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- First step: collect data in a sliding window
- A item must be present in some of these slots (not sequently)
- Second step: check whether the swap is efficient
- Improvement to the naive algorithm: do not only use the best candidate from each list, but the first two or three

Outline

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Evaluation
Common setup

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- How does the automatic swap perform?

Evaluation
Common setup

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- How does the automatic swap perform?
- Compare performance of initial configuration, configuration with automatic swap and optimized configuration

Evaluation
Costs of profiling

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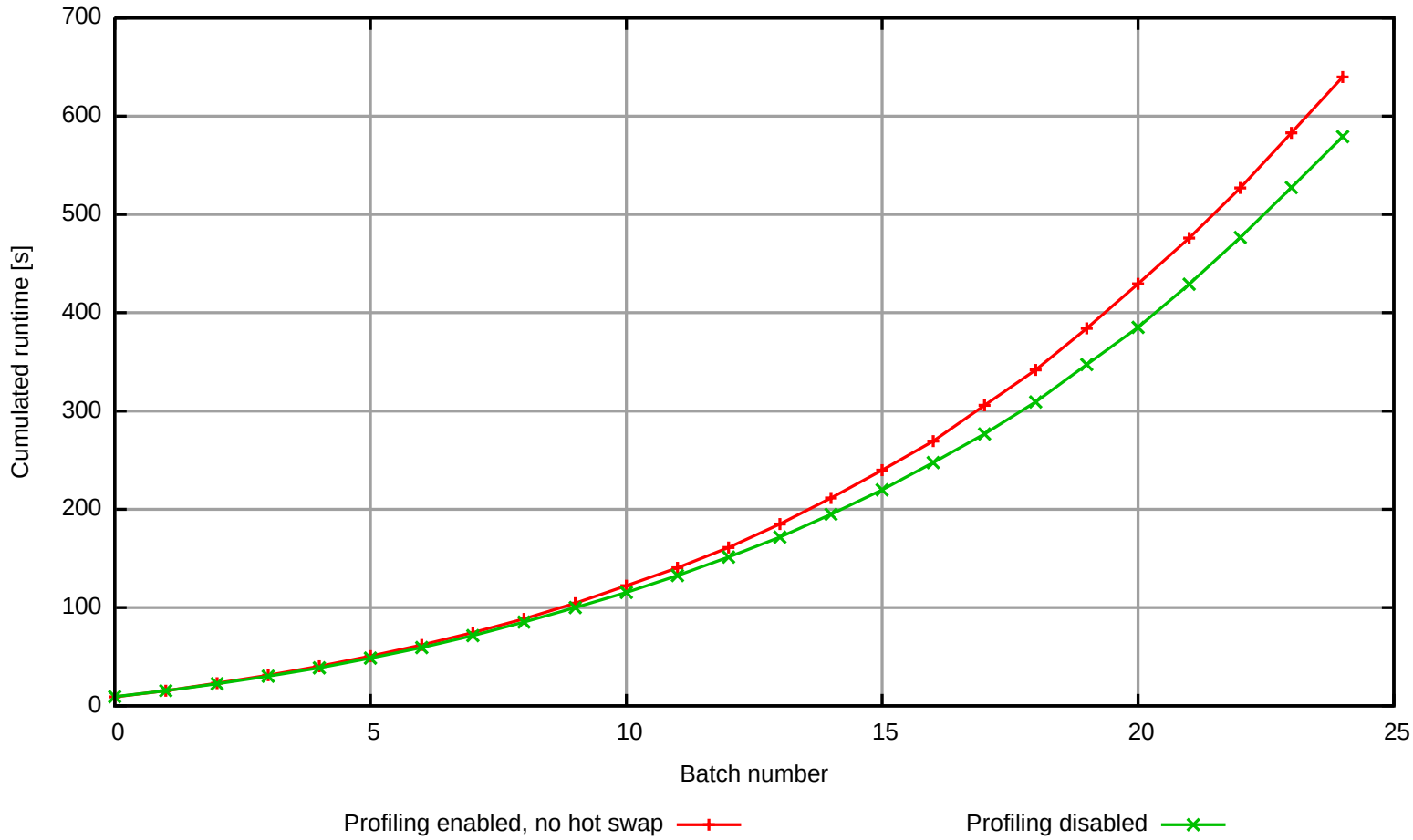

Profiling alone costs about +10% / ~2.5s per batch in this experiment

Evaluation
How fast can we go? (1/2)

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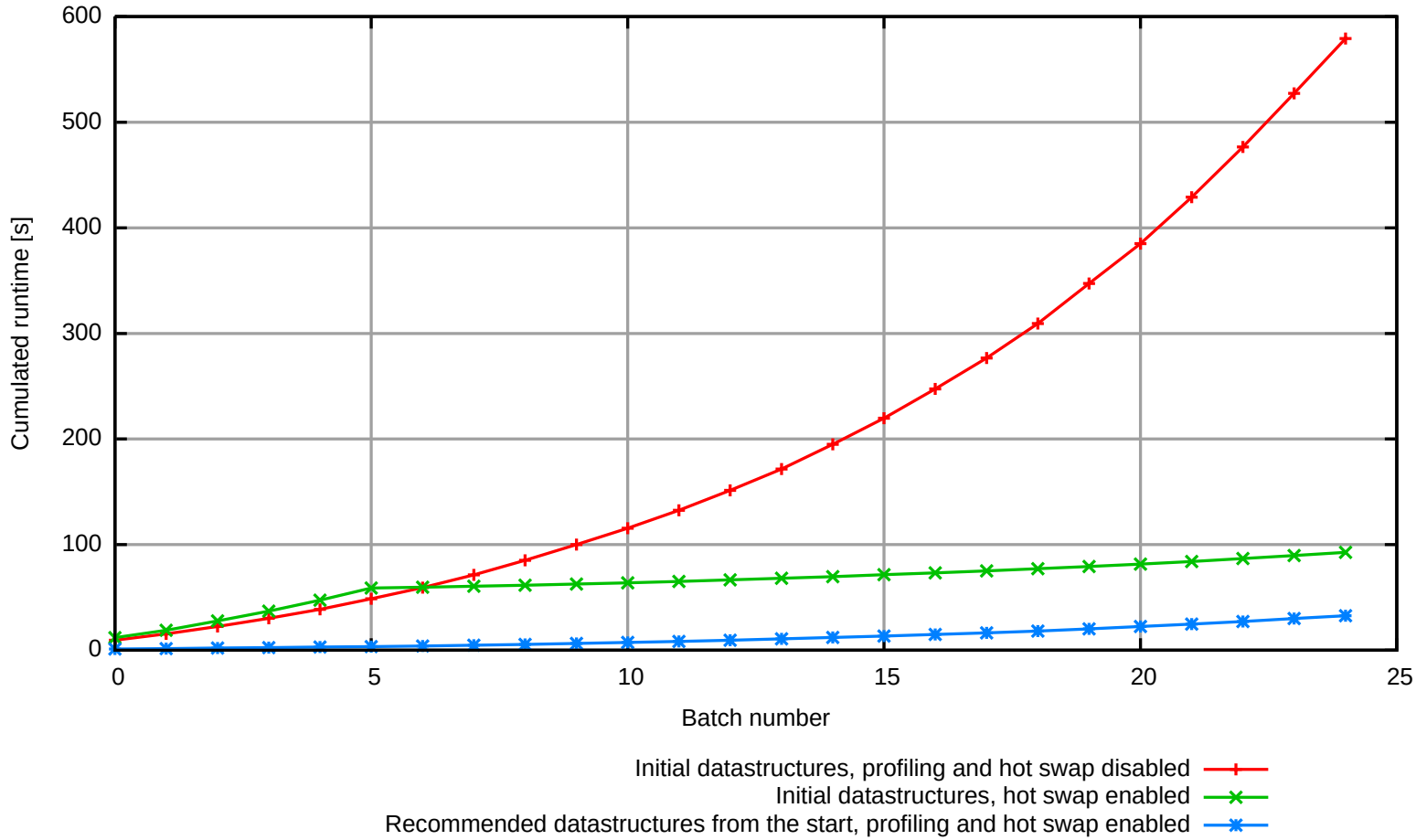

Evaluation
How fast can we go? (2/2)

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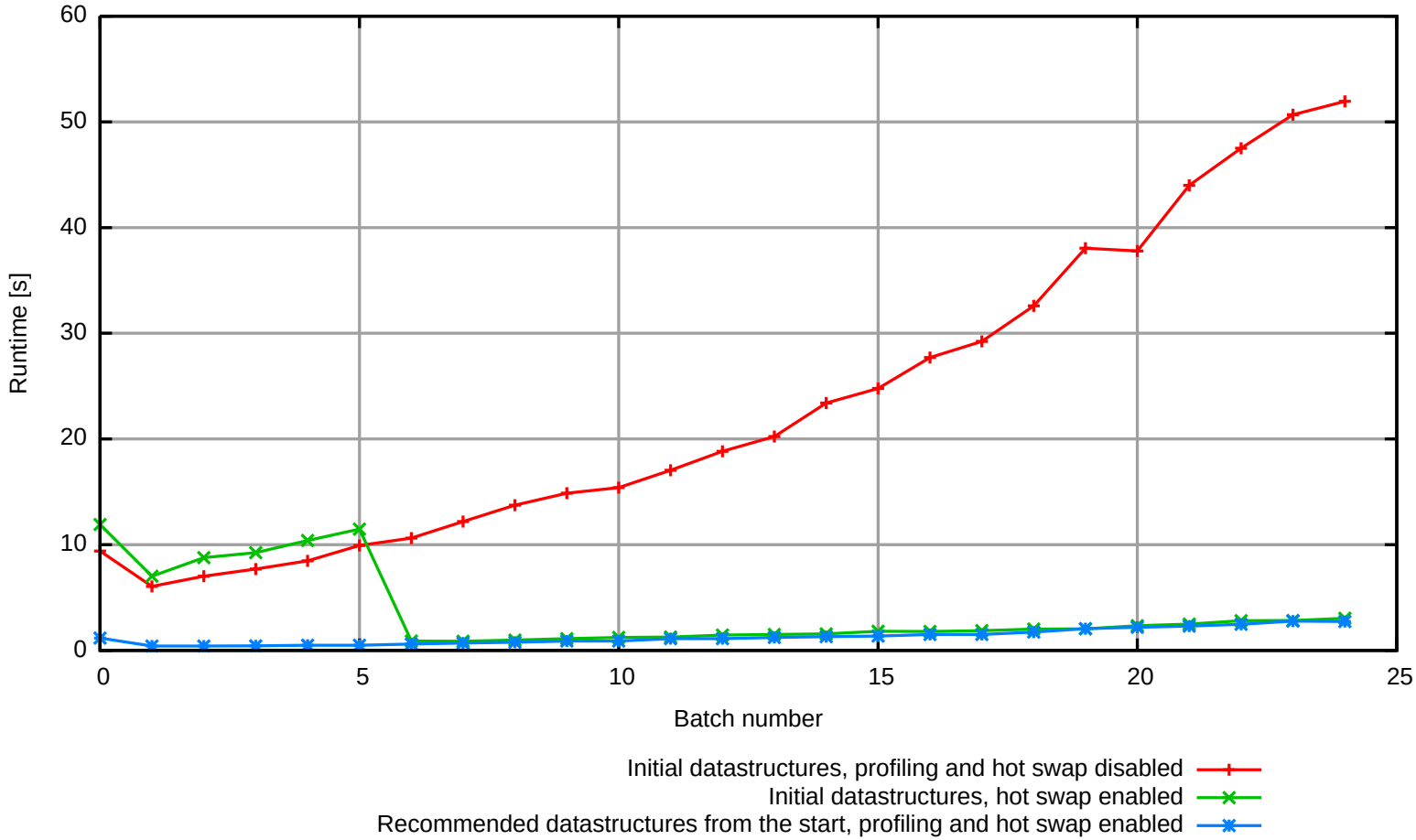

Speedup of more than 90% per batch

Evaluation
Memory optimization

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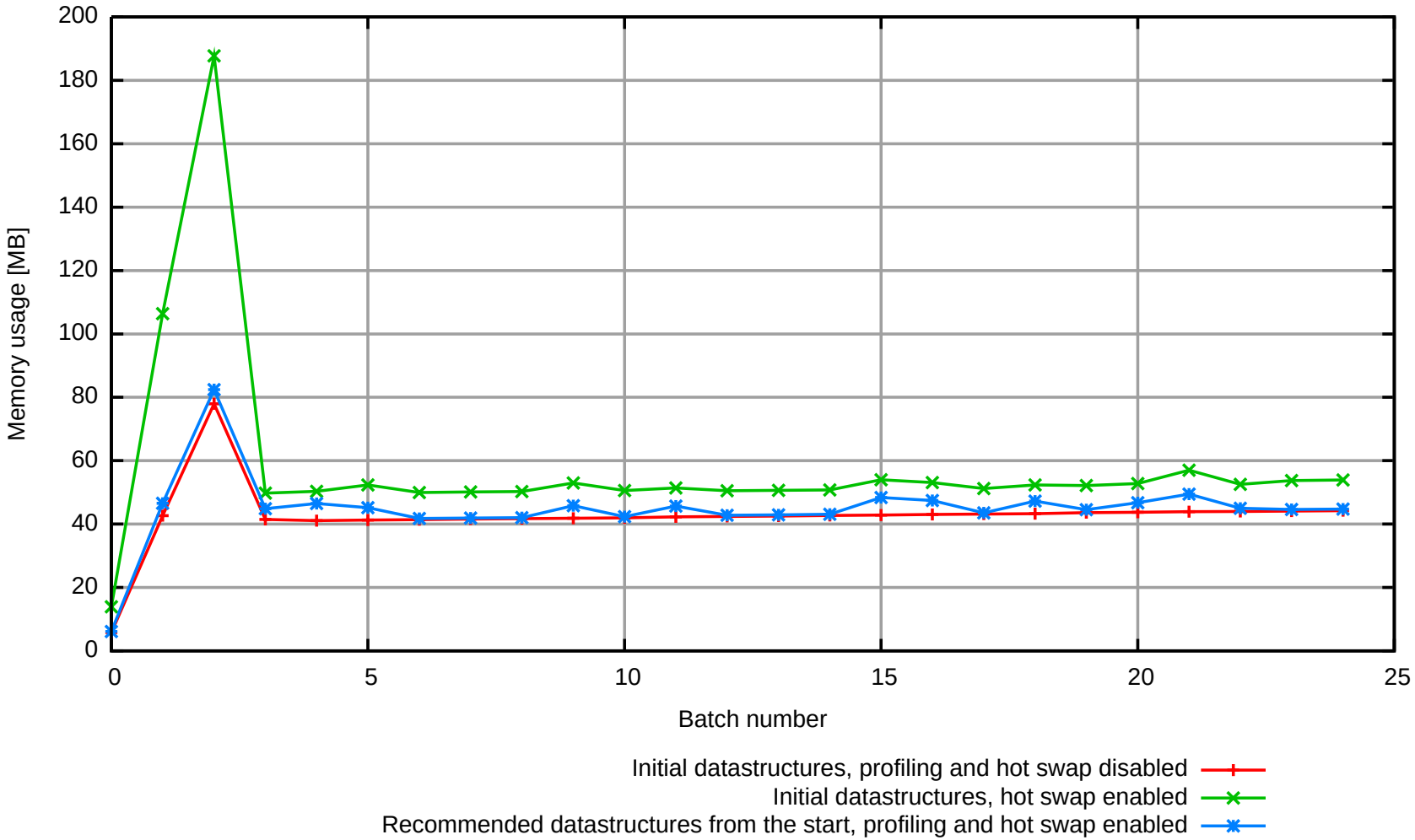

Evaluation
Optimization for a single access type

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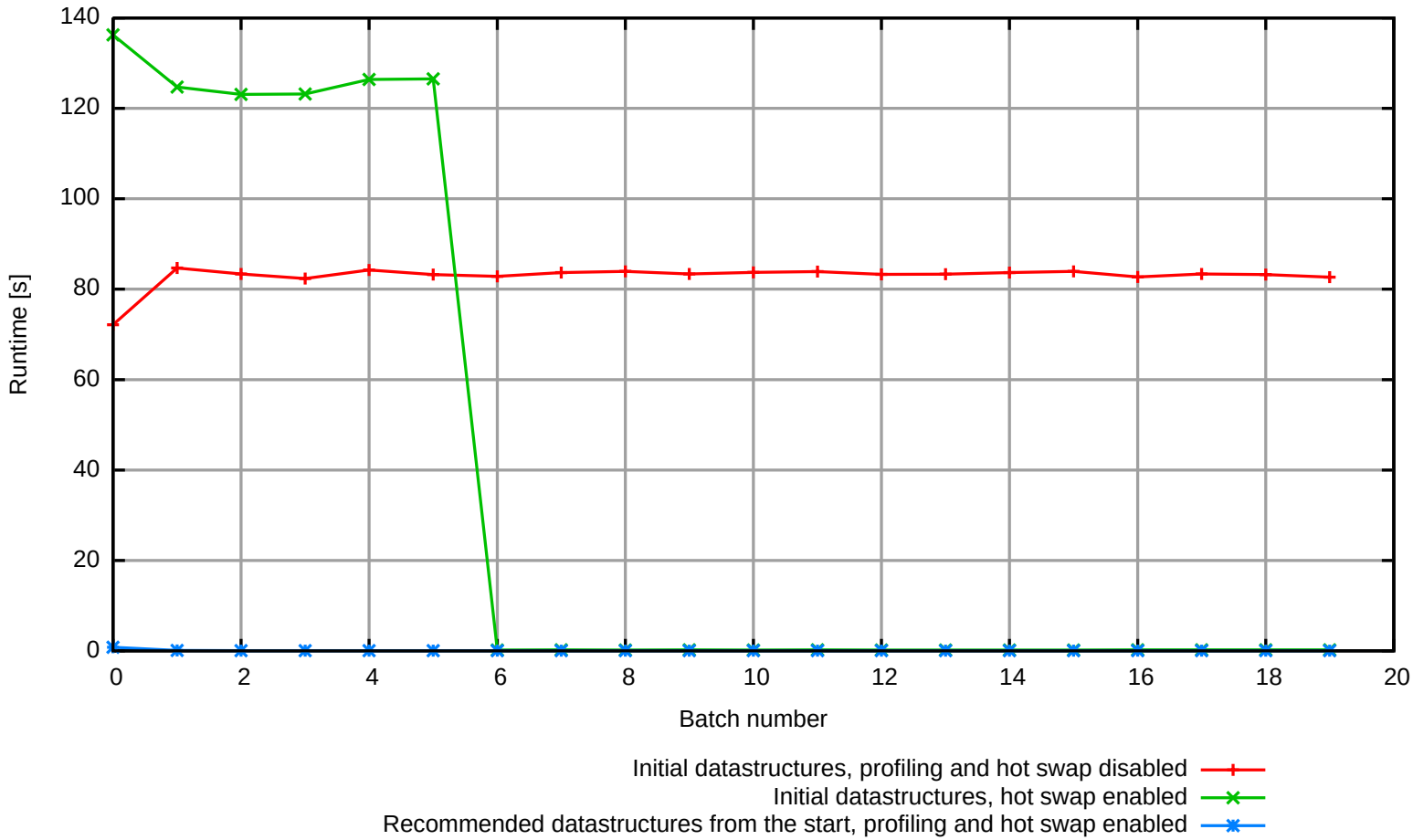

One access type dominates → use the datastructure with best performance

Evaluation
Summary of the results

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- Huge runtime optimizations possible

Evaluation
Summary of the results

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Evaluation
Summary of the results

TECHNISCHE UNIVERSITÄT DARMSTADT

- Huge runtime optimizations possible
- Memory recommendations disappointing
- Different combinations for different scenarios
- Recommended combinations evolve

Outline

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Summary

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- Developed a system for automatic datastructure optimizations

Summary

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- Lightweight runtime footprint

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- Obvious runtime results

Summary

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- Developed a system for automatic datastructure optimizations
- Lightweight runtime footprint
- Obvious runtime results
- Ease for further development of DNA: focus on the algorithms

Outlook
Open questions

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- Where did we go wrong with memory costs?

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Open questions

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- Can we use our approach in other parts of DNA too (metrics, updates,. . .)?

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Open questions

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- Address internal problems like hashing and accuracy of profiling

Outlook
Open questions

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- Where did we go wrong with memory costs?
- Can we use our approach in other parts of DNA too (metrics, updates,. . .)?
- Address internal problems like hashing and accuracy of profiling
- Is there a commonly good combination to start with?

Thanks for your attention!

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