CollectionSwitch: A Framework for Efficient and Dynamic Collection Selection

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Programs = Data Structures + Algorithms

Niklaus Wirth (1984)

Collections

- In Java, the Collections framework provides a reusable set of data structures
  - Widely used and well tested
  - One Interface → multiple implementations

- Developers rarely select/tune their collections [Cha++11]
  - Top-4 most used implementations are selected 95% of the cases [Cos++17]
  - Only 20% of the ArrayList instantiations specify the initial capacity [Cos++17]

Performance Impact of Collections

Inefficient selection of collections as the main cause of runtime bloat

Execution Time
+17% Improv.
Configuration of one HashMap alloc-site
[LS09]

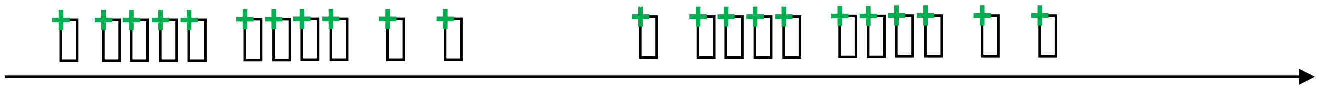
Memory Usage
+54% Improv.
Use of ArrayMaps instead of HashMaps
[OME09]

Energy Consumption
+38% Improv.
Use of ArrayList instead of LinkedList
[Sam++16]

How to better identify and fix such performance inefficiencies?

Motivational Scenario

```
List<T> myList = new ArrayList<>();

for(T elem : collection) {
    if(!myList.contains(elem)){
        myList.add(elem);
    }
}
```



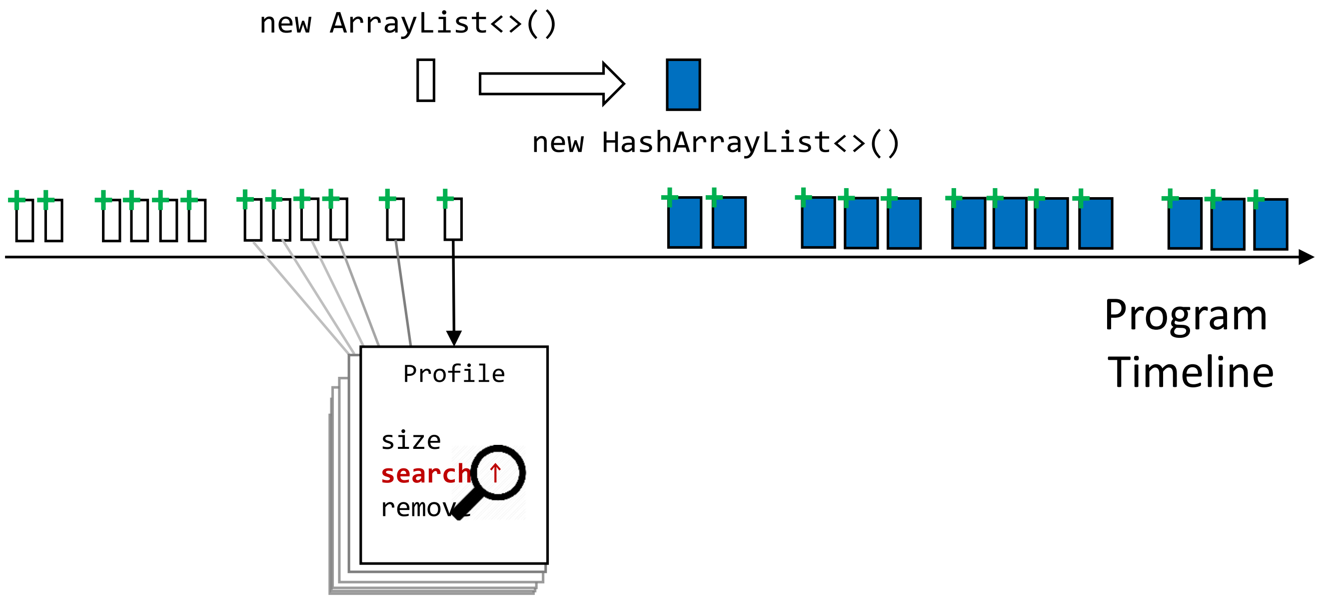
Program Timeline

```
List<T> myList = ctx.createList();

for(T elem : collection) {
    if(!myList.contains(elem)){
        myList.add(elem);
    }
}
```

Motivational Scenario

It is possible to find and switch the collection type to a more suitable variant?

```
List<T> myList = ctx.createList();

for(T elem : collection) {
    if(!myList.contains(elem)){
        myList.add(elem);
    }
}
```



Profile Instances Behavior

Exemplary Results

- The DaCapo benchmark of Lucene and Avrora
  - Few allocation sites generate millions of collection instances

- **Lucene:** By augmenting 12 allocation sites with our adaptive behavior
  - Reduce execution time by **15%**

- **Avrora:** By augmenting 10 allocation sites with our adaptive behavior
  - Reduce peak of memory consumption by **10%**

CollectionSwitch

A framework for Dynamic Adaptation of Java Collections

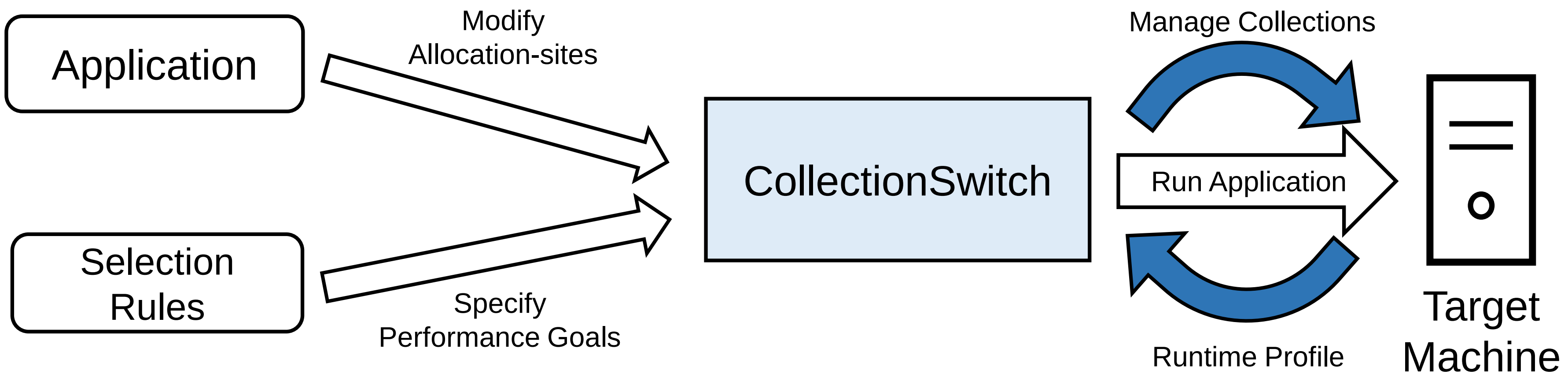
Combines two techniques:

1. Adaptive Allocation-Site
    - Profiles collection instances
    - Searches for a better variant
    - Switches future instantiations to the best variant type
2. Adaptive Collections
    - Instances that switch themselves to the appropriate implementation

Framework Overview

A) How to Enable Adaptive Collections?

C) How to Find a Better Implementation?

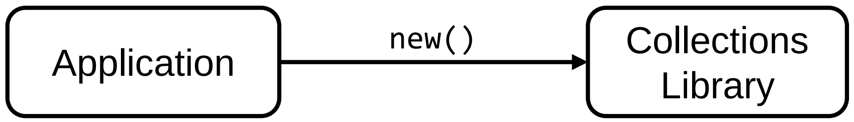


B) How to Define the Performance Goals?

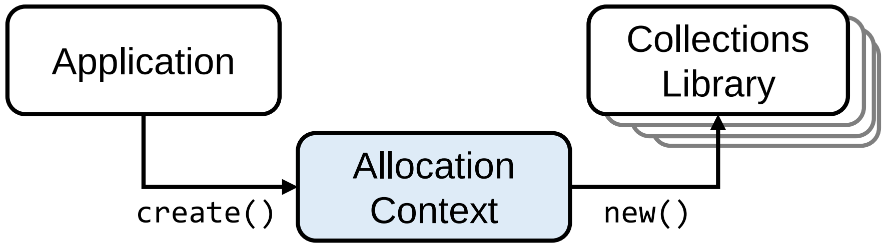
A) How to Enable Adaptive Collections

- Using CollectionSwitch in your project

```
// Original Allocation-Site
List<T> myList = new ArrayList<>();
```




```
// Using CollectionSwitch
static ListContext ctx = Switch.createContext(ARRAY);
List<T> myList = ctx.createList();
```



Allows same-interface transformations

B) How to define the Performance Goals?

Configurable Selection Rules

- Space and time trade-offs
- Developers input the threshold for selecting a different variant

Rule	Improvement	Max Penalty
R_{time}	Time -20%	
R_{alloc}	Allocation -20%	Time +125%

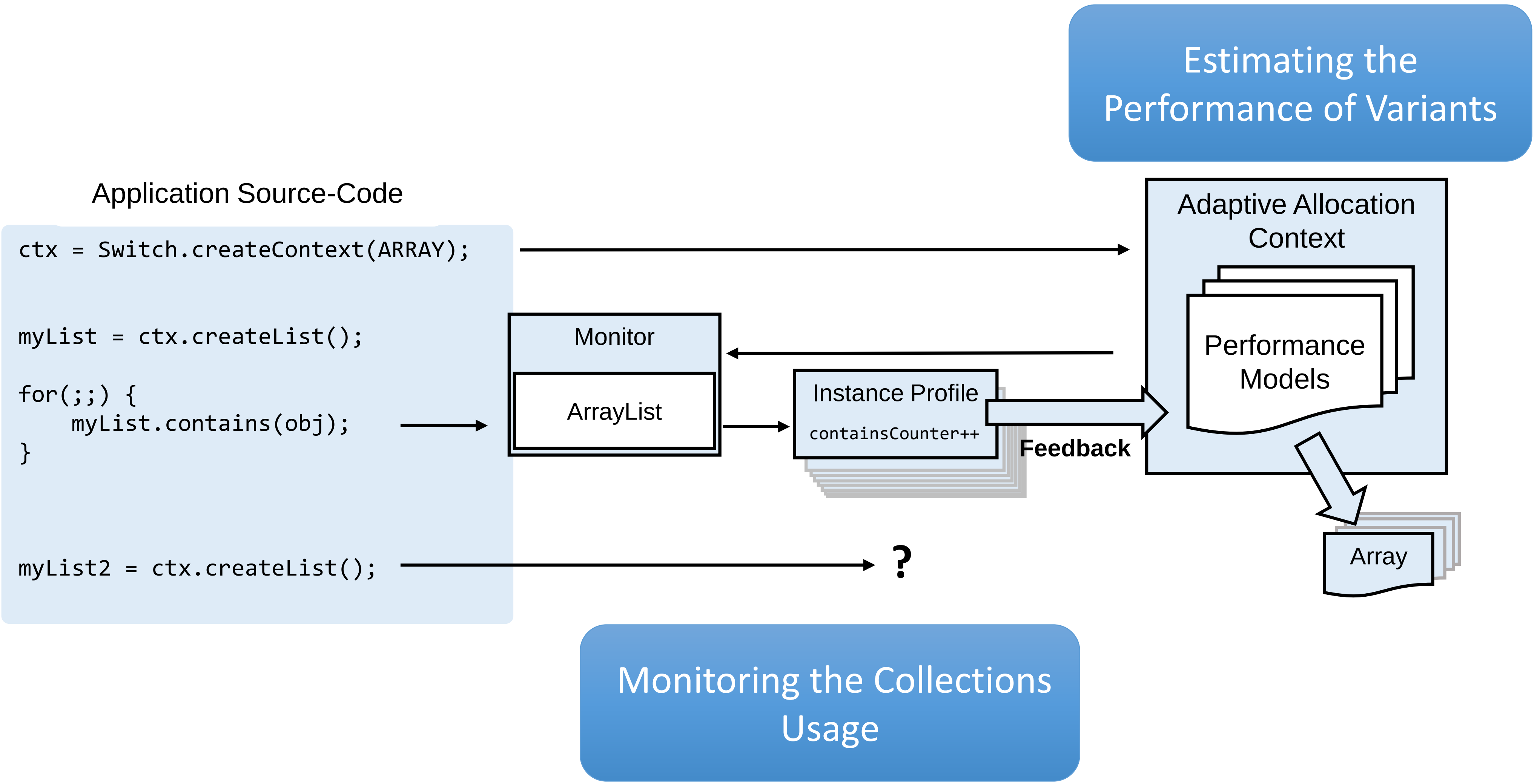
Selects a variant when its predicted time performance is at least 20% better

Selects a variant when its predicted allocation performance is at least 20% better with max time penalty of 25%

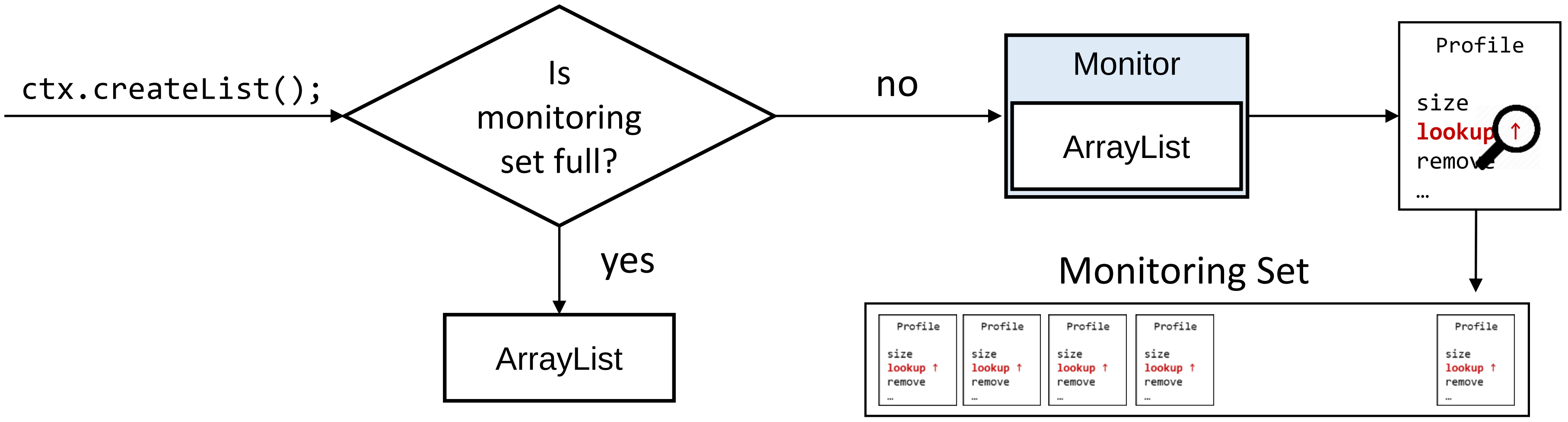
only Array variants!

- A variant is selected when it satisfies the rule
  - Criteria satisfied by multiple variants? Select the variant with biggest improvement

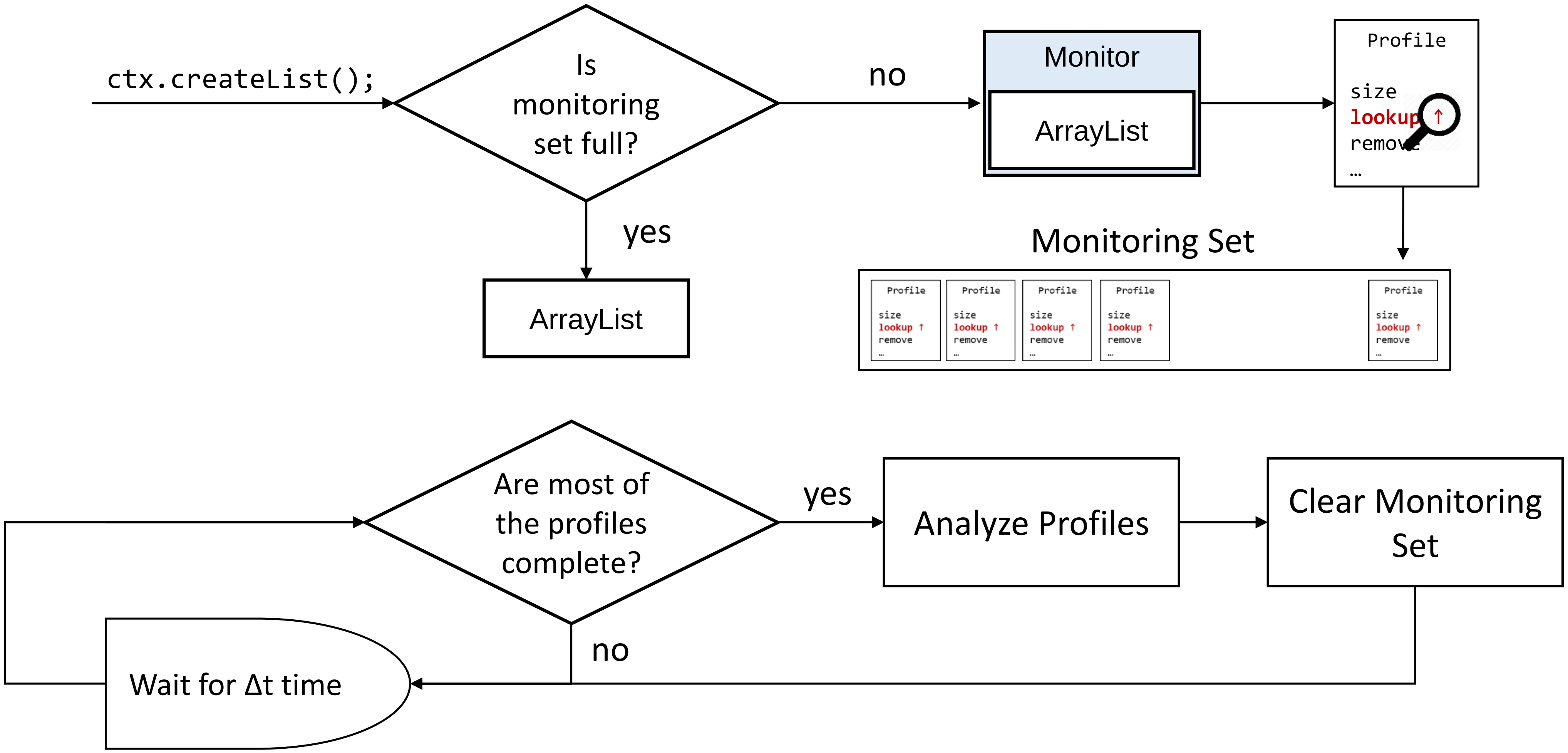
C) How to Find a Better Variant?



Monitoring the Collections Usage



Monitoring the Collections Usage



Monitoring the Collections Usage

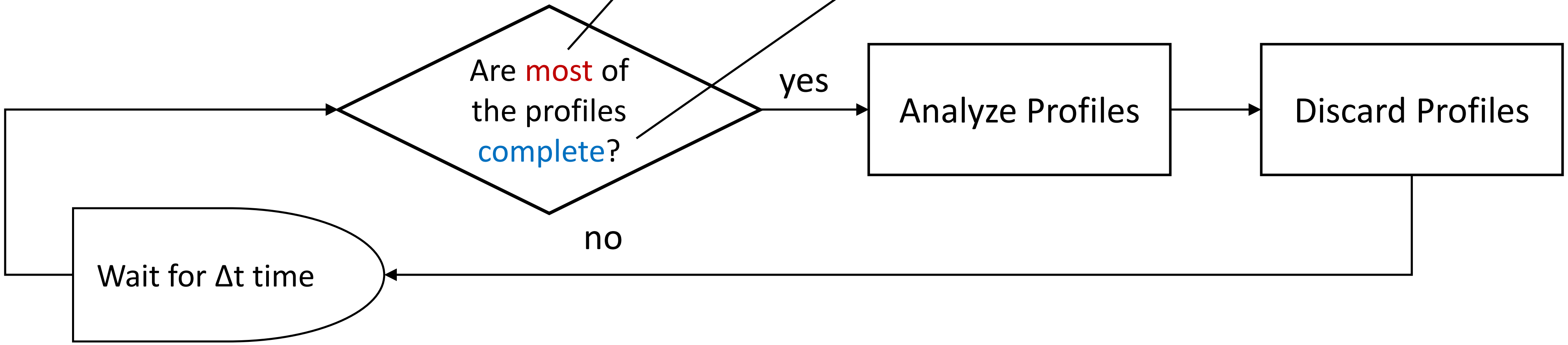
Parametrized ratio r

$r = 0.3$ too unstable

$r = 1.0$ too slow

$r = 0.6$ good compromise

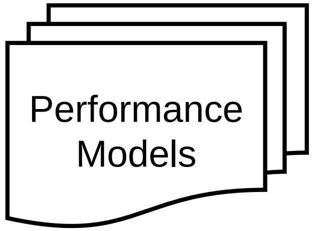
Instances have been assigned for garbage collection



Estimating the Performance

We compare variants V performance according to the total cost metric $TC(V)$

$$tc(V) = \sum_{op} N_{op} * \underbrace{cost_{op,V}(s)}_{\text{avg. cost of operation } op}$$



$$TC(V) = \sum tc(V)$$

Collection Profile

- Maximum size s of the collection
- Amount of called operations N_{op}

Estimating the Performance

- Polynomial function of the collection size s

$$cost_{op,V}(s) = \sum_{k=0}^{d} a_k s^k$$

- We design a series of benchmarks to calculate the coefficients
  - + 30 variants
  - Single Operation Scenario
  - Measurement Variables
    - Execution Time
    - Memory allocation

Factor	Levels/Categories
Size	[10, 100,200,…,1M]
Operations	populate, contains, iterate, middle, remove
Data Type	Integer
Data Distribution	Uniform

Estimating the Performance

- Selects a variant V_{new} to replace the current V_{cur} when is satisfies the Performance Rule

R_{alloc}

Improvement	Max Penalty
Allocation = -20%	Time = +125%

$$\left(\frac{TC_{alloc}(V_{new})}{TC_{alloc}(V_{cur})} \leq 0.8\right) \land \left(\frac{TC_{time}(V_{new})}{TC_{time}(V_{cur})} \leq 1.25\right)$$

Adaptation on Instance Level

- CollectionSwitch can also switch to an adaptive variant
  - Second level of adaptation

- Adaptive Collections
  - Small sizes: Memory efficient implementation (array)
  - Large sizes: Time efficient implementation (hash)

Variant	Transition	Threshold
AdaptiveSet	Array -> Hash	40
AdaptiveMap	Array -> Hash	50

Transition is done by copying the elements

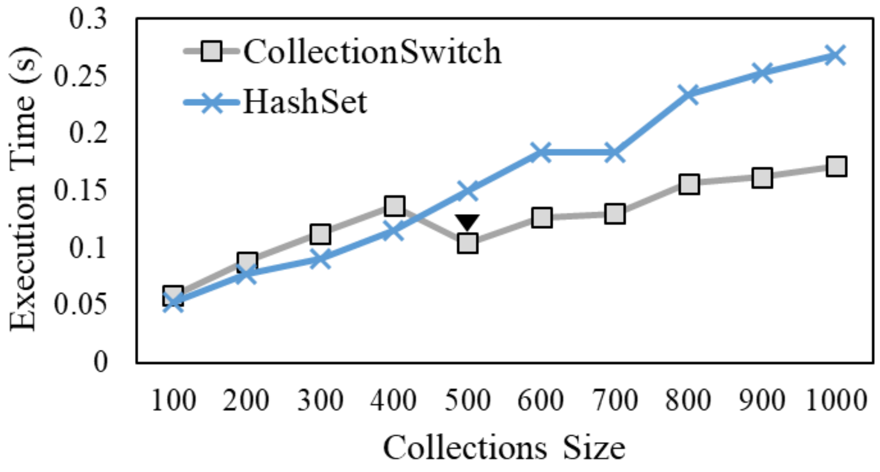
Evaluating the Model I

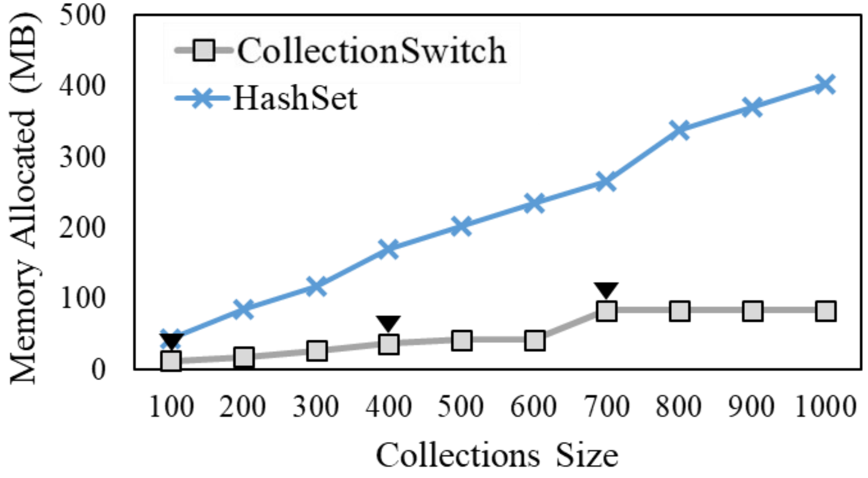
- Micro-benchmarks
  - Population of the collection
  - 100 searches of a random element

Rule	Improvement
R_{time}	Time = 20%

Evaluating the Model II

- Micro-benchmarks
  - Population of the collection
  - 100 searches of a random element





Rule	Improvement
R_{time}	Time = 20%

Rule	Improvement	Max Penalty
R_{alloc}	Allocation = 20%	Time = 20%

Evaluating the Performance Improvement

- DaCapo benchmarks
  - Real applications

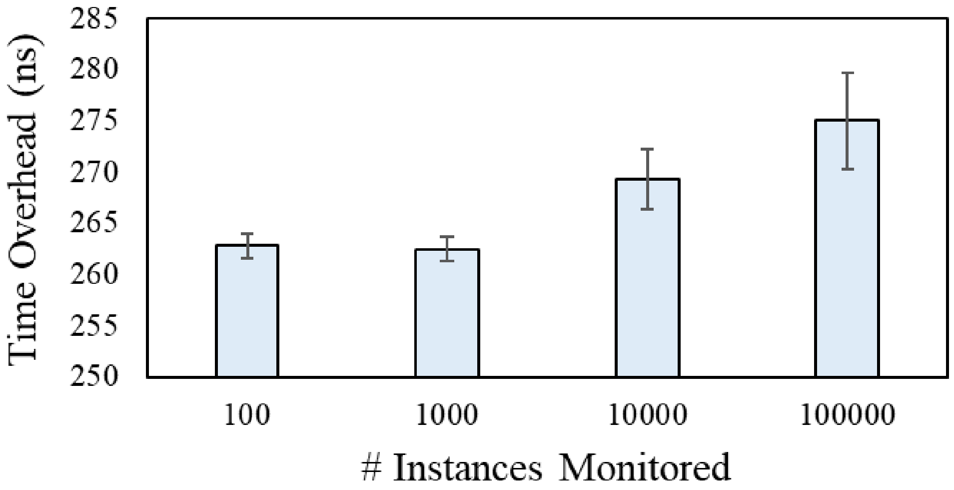
Bench	Input Size	#Target. Alloc.	Original Run T(s)	Original Run M(MB)	CollectionSwitch R_{time} $T_1(s)$		R_{time} $M_1(MB)$		R_{alloc} $T_2(s)$		R_{alloc} $M_2(MB)$	
avrora	large	7	4.1	72.4	4.2	–	72.1	–	4.4	+7%	65.4	-10%
bloat	large	17	30.3	96.7	28.9	–	96.9	–	26.6	-12%	89.4	-8%
fop	default	15	0.5	53.4	0.5	–	57.0	+7%	0.5	–	53.9	–
h2	large	10	40.1	509.0	38.3	-6%	508.7	–	44.6	+11%	470.1	-8%
lusearch	large	12	3.6	282.4	3.1	-15%	269.4	-5%	3.4	-6%	268.0	-5%

Evaluating the Overhead

- DaCapo
  - No significant overhead

Rule	Improvement
R_{imp}	Time = ∞%

- Estimation of Variants Performance
  - Below 300 ns



- Memory Overhead
  - Footprint of each Allocation Context ~1Kb.

Summary

- Selecting the appropriate collection is critical for designing efficient Java applications

- CollectionSwitch selects collection at runtime through:
  - Adaptive allocation-sites
  - Adaptive collections

- Improvement on execution time and memory of real applications

Thank You!

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References

- [Cha++11] Changhee Jung, Silvius Rus, Brian P. Railing, Nathan Clark, and Santosh Pande. 2011. **Brainy: effective selection of data structures.** (PLDI ‘11)

- [Cos++17] Diego Costa, Artur Andrzejak, Janos Seboek, and David Lo. **Empirical Study of Usage and Performance of Java Collections.** (ICPE '17)

- [LS09] Lixia Liu and Silvius Rus. 2009. **Perflint: A Context Sensitive Performance Advisor for C++ Programs.** (CGO '09)

- [OME09] Ohad Shacham, Martin Vechev, and Eran Yahav. **Chameleon: adaptive selection of collections.** (PLDI '09)

- [Sam++16] Samir Hasan, Zachary King, Munawar Hafiz, Mohammed Sayagh, Bram Adams, and Abram Hindle. 2016. **Energy profiles of Java collections classes.** (ICSE '16)