Machine Learning applied to Process Scheduling

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Definition of Machine Learning

Definition

Machine Learning is a field of Computer Science about the construction and study of systems that can learn from data.

Usual organizations of ML algorithms :

- Supervised learning (classification, ...)
- Unsupervised learning (clustering, ...)
- Semi-supervised learning
- ...

Notes about Machine Learning

We won't talk really about the theory. But:

- Pretreatment is **very** important.
- Usually, big tradeoff between speed and efficiency

In Process Scheduling, those factors will be limiting.

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What is Process Scheduling ?

Definition

Process Scheduling is the method by which processes are given access to processor time. It is used to achieved multi-tasking.

There is many well-known scheduling algorithms. For example:

- First In, First Out
- Round-Robin (fixed time unit, processes in a circle)

Main concerns

A scheduler has mainly 3 metrics: throughput, latency and fairness. We can simplify them (in practice) by:

- Speed (how much time the scheduler itself uses, number of context-switching, ...)
- Fairness (giving equal CPU time to each process)
- Reactivity (are interactive processes given any advantages ?)

A scheduler is complicated. Let's optimize one using ML !

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2. Our target: CFS
   - Inner workings
   - Advantages/Inconvenients

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Inner workings of CFS

- Stands for **C**ompletely **F**air **S**cheduler
- Scheduler of Linux since 2.6.23
- Just an RB-tree with elements indexed by the runtime of the process.
- Straightforward algorithm: just take the minimum of the tree.

CFS in Linux kernel is actually more complicated (handling Real-Time tasks, nice values, ...)

Why CFS ?

- Quite simple and works really well
- Most familiar (I implemented one in mikro)
- Already efficient. I wanted to see what ML could do.

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Advantages/Inconvenients

- ✓ Very simple to understand
- ✓ Works really well in general cases
- ✓ No real corner cases
- ✗ A little light on the handling of interactive processes.

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3 What can we do ?
- ML considerations
- Applying ML to the CFS

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ML considerations

- Restricted to supervised learning (classification and regression mainly)
- Scheduler must be as fast as possible. Its ML components too.
- Avoiding complex code in the kernel is often a good idea.

→ precomputed model/profile for each processes
→ no complex methods, results will be mitigated

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Applying ML to the CFS

Ojective: reducing the number of **context switchs**:

- A process time quantum should ideally not finish (process going to sleep)
- An estimation of the next quantum would help
- Based on the N lasts quantums
- Be careful not to be too unfair

Note: Many other objectives were possible...

Actual implementation

- Proof of Concept
- One using Taylor's Theorem and one using a classifier
- Need to extract real runtime quantums and to create profiles

Taylor's theorem

- The sequence of quantums can be seen as a function of the time.
- Taylor's theorem gives an approximation of a function on a point given its derivatives
- Discrete derivation is only substraction

→ an approximation of the next quantum is:

$$f(x+1) = f(x) + f'(x-1) + \frac{f''(x-1)}{2}$$

This method is simple and fast, but not very precise.

Classifier

Naive Bayes Classifier using the last 4 quantums:

- It is the best (found) compromise between speed and results
- Parameters and output are range of time, not the actual values
- Based on Bayes' theorem. Outputs the labels with most probability
- Only 4 multiplications are needed for each label (there is 10 of them).
- Using bit manipulation, we can avoid any conditionals

→ it is fast, but clearly not the most accurate

Plan

4. Results and analysis
   - perf and Linsched
   - Methodology and results
   - Analysis

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4 Results and analysis
- perf and Linsched
- Methodology and results
- Analysis

perf

- Performance analysis tools for Linux
- Based on kernel-based performance counters
- Can be used to extract **many** scheduling stats

Linsched

Linsched

- Linux Scheduler Simulator (in userland...)
- ✓ Easy to use (cycle of development, debugging, ...) and fast
- ✓ Can replay records from *perf*
- ✗ Hard to quantify how much time is used by the scheduler

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4 Results and analysis
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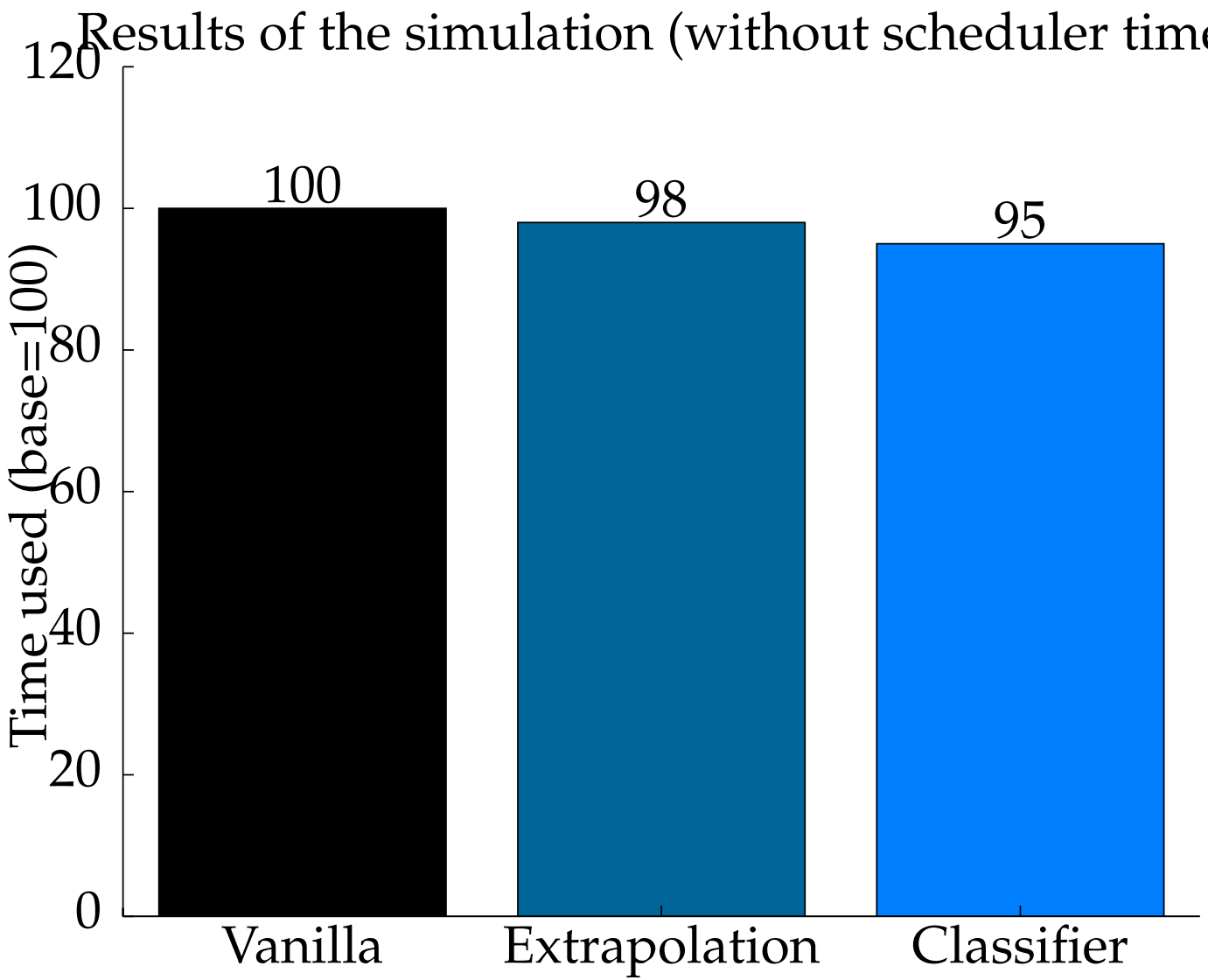
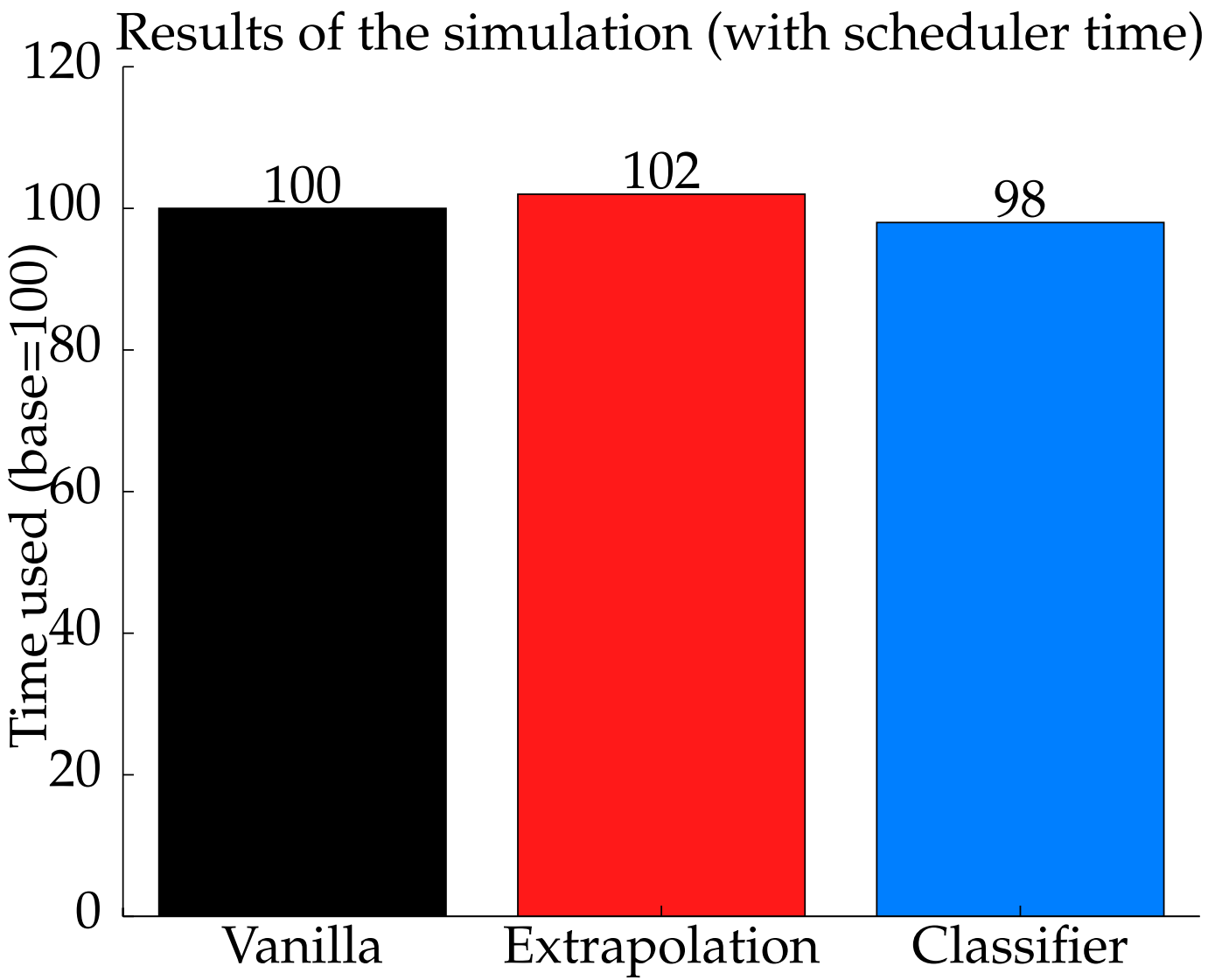
Methodology of the tests

- Use *perf* to extract records and datasets
- Use *WEKA* to compute profiles for each process
- Test using vanilla/modified linsched to see the gain
- Time the tests of vanilla/modified linsched to estimate how costly each method is

Results



Results



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Analysis

- CFS is already quite good
- ML results are positive but very limited
- More complex pretreatment/ML techniques would yield better results... at which cost ?

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Conclusion

- It was only **one** idea on **one** objective.
- Using ML in scheduling is hard, because of the speed/results tradeoff
- Difficulties for a real kernel integration (passing the models, limiting abuses, ...)
- Basic rule in scheduling: "Simpler is Better"
- Another idea: run a (kernel ?) process every X hours to compute new profiles...
- K. Kumar Pusukuri, A. Negi, *Applying machine learning techniques to improve Linux process scheduling*, Dec. 2005.

- Questions ?