



Metaheuristics for Smart Manufacturing

3. Random Sampling

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- 1 Introduction
- 2 Algorithm Concept
- 3 Experiment and Analysis
- 4 Summary

The slides and source code examples are available at
<http://iao.hfuu.edu.cn/teaching/lectures/metaheuristics-for-smart-manufacturing>



website



course material

- OK, so we can now represent a Gantt chart for m machines and n jobs as an integer string of length $m \times n$.

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- OK, so we can now represent a Gantt chart for m machines and n jobs as an integer string of length $m \times n$.
- How does this help us to search?
- Well, we can first try the trivial thing: create a random solution!

Listing: Creation of a single random $g \in \mathbb{G}$.

```
public class Representation {
    public int[] createRandom(final Random random) {
        final int jobs = this.m_jobTime.length;
        final int machines = this.m_machineTime.length;
        final int[] res = new int[jobs * machines];
        int index = -1;

        // first create a feasible string which contains each job index m times
        for (int i = 0; i < jobs; i++) {
            for (int j = 0; j < machines; j++) {
                res[++index] = i;
            }
        }
        // then we randomly shuffle the string: the values don't change, just
        // their positions,
        // i.e. we get a representation for a random schedule
        Tools.shuffle(random, res, 0, res.length);
        return (res);
    }
}
```

Listing: An algorithm which only creates one random sample.

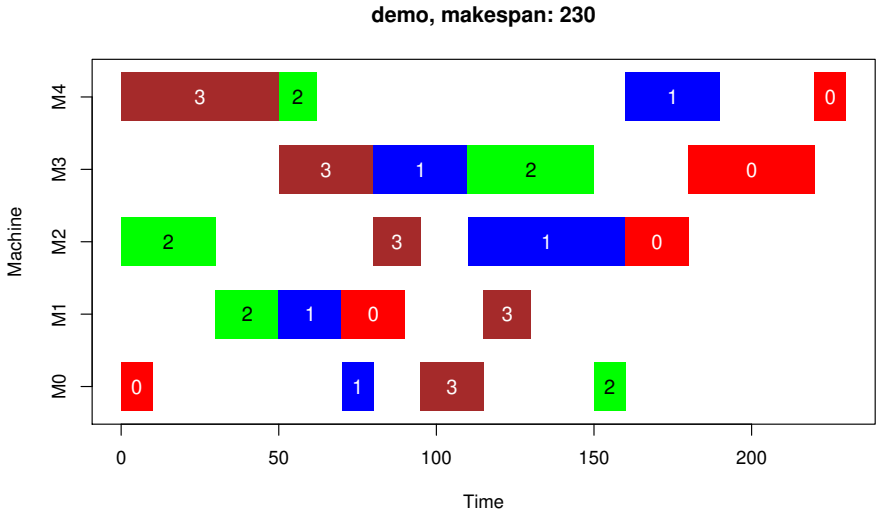
```
public final class SingleSample {  
  
    /**  
     * Generate a single random schedule.  
     *  
     * @param problem  
     *       the problem instance, i.e., the jobs and machines  
     * @param representation  
     *       the methods provided by our representation  
     * @param log  
     *       the log: simple class to collect/print results  
     * @return the Gantt chart data found  
     */  
    public static final int [][] run(final Problem problem,  
        final Representation representation, final Log log) {  
  
        final Random random = new Random();  
        final int [][] solution = problem.newEmptySolution();  
  
        // create a random point in the search space  
        int [] g = representation.createRandom(random);  
  
        // map the point to a solution  
        representation.map(g, solution);  
  
        // compute quality: actually calls problem.evaluate and remembers best result  
        log.evaluate(solution);  
  
        return log.getBestSolution(); // return best logged solution  
    }  
}
```

- I execute the program 100 times for each of the datasets demo, 1a24, swv15, and yn4

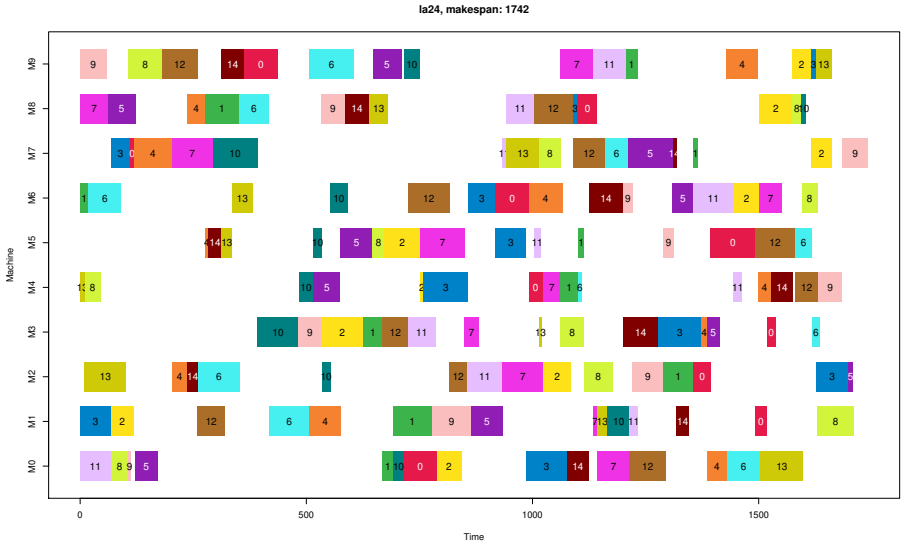
- I execute the program 100 times for each of the datasets demo, la24, swv15, and yn4

	makespan		
instance	mean	best	stddev
demo	249.04	180	36.067
la24	1853.02	1498	175.15
swv15	6516.36	5593	295.67
yn4	2053.39	1762	134.09

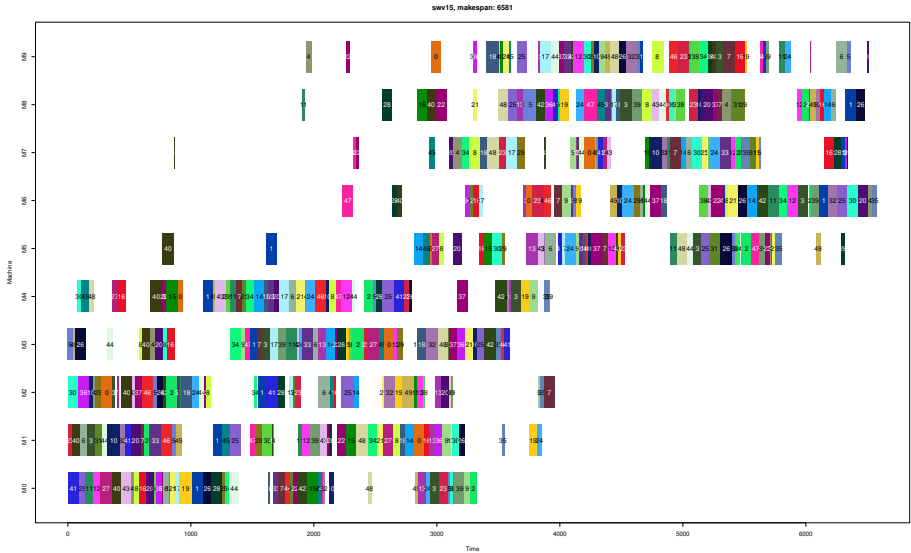
So what do we get?



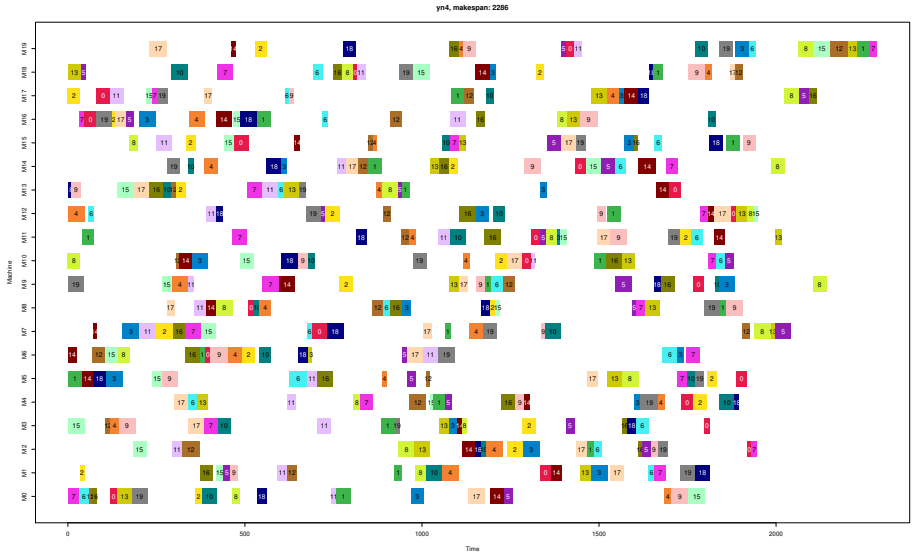
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- So the results are not good, there is lots of white space \equiv wasted time.

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- Notice 1. We can create and test the schedules very very fast.

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- So the results are not good, there is lots of white space \equiv wasted time. That was expected.
- Notice 1. We can create and test the schedules very very fast.
- Notice 2. There is a standard deviation in the results due to randomness.

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- If we can generate solutions fast and sometimes are lucky, sometimes not. . .

- If we can generate solutions fast and sometimes are lucky, sometimes not. . .
- then why don't we generate 1'000'000 schedules and keep the best one?

Listing: An algorithm which creates many random samples.

```
public class RandomSampling {  
  
    /**  
     * Solve a problem by generating many multiple random samples  
     *  
     * @param problem  
     *       the problem  
     * @param representation  
     *       the representation  
     * @param log  
     *       the log  
     * @return the result  
     */  
    public static int[][] run(final Problem problem,  
        final Representation representation, final Log log) {  
  
        final Random random = new Random();  
        final int[][] xbest = problem.newEmptySolution();  
  
        while (!log.shouldTerminate()) { // this becomes true after 1'000'000 steps  
            // create a random point in the search space  
            int[] g = representation.createRandom(random);  
  
            // map the point to a solution  
            representation.map(g, xbest);  
  
            // compute quality (and remember best in an internal variable)  
            log.evaluate(xbest);  
        }  
  
        return log.getBestSolution(); // return best logged solution  
    }  
}
```

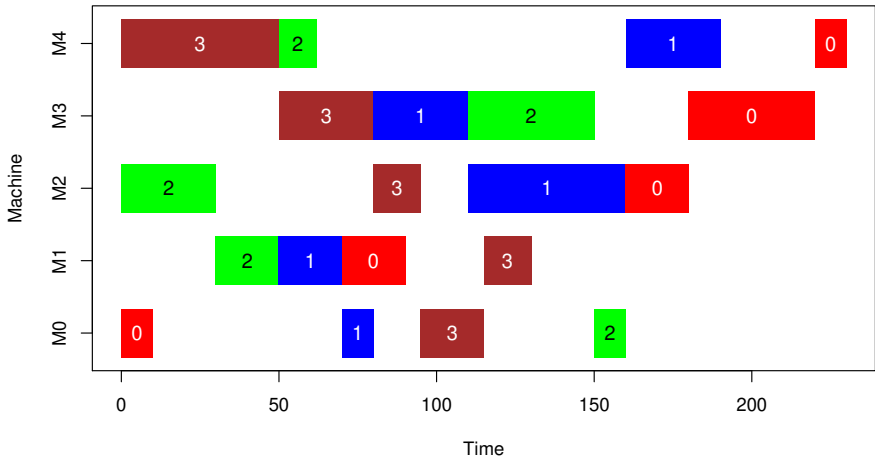
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		makespan		
algo	inst	mean	best	stddev
Random Sampling	demo	180	180	0
Single Sample	demo	249.04	180	36.07
Random Sampling	1a24	1254.03	1205	18.16
Single Sample	1a24	1853.02	1498	175.15
Random Sampling	swv15	5255.16	5038	52.06
Single Sample	swv15	6516.36	5593	295.67
Random Sampling	yn4	1532.79	1469	17.56
Single Sample	yn4	2053.39	1762	134.09

single random sample

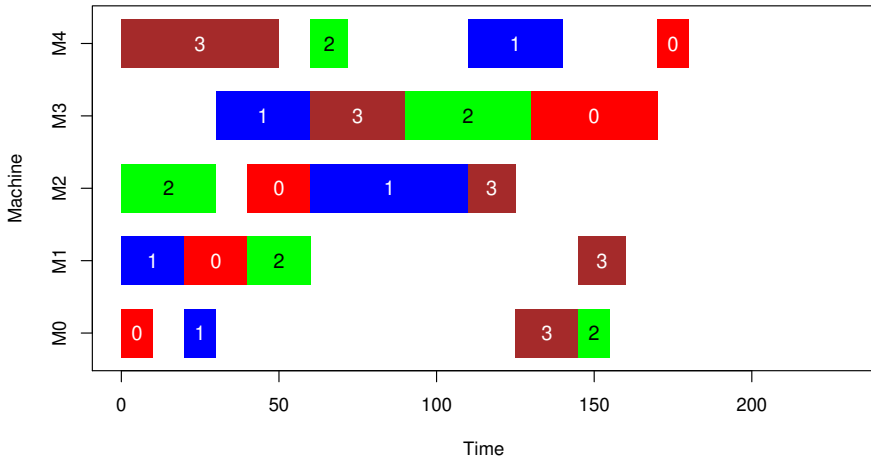
demo, makespan: 230



So what do we get?

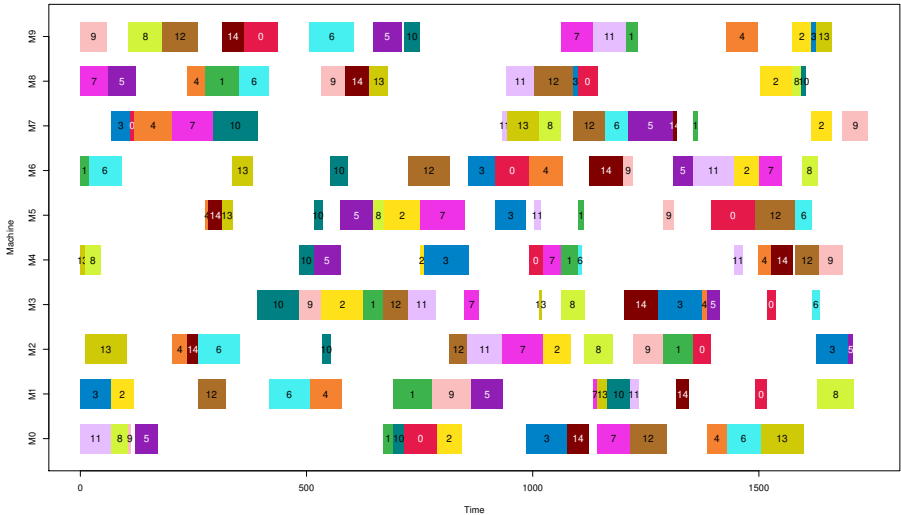
1'000'000 random samples

demo, makespan: 180



single random sample

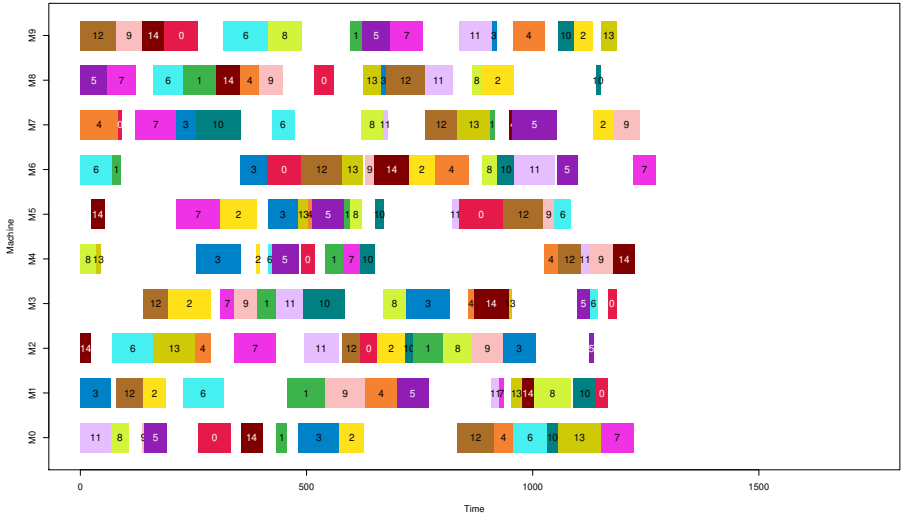
la24, makespan: 1742



So what do we get?

1'000'000 random samples

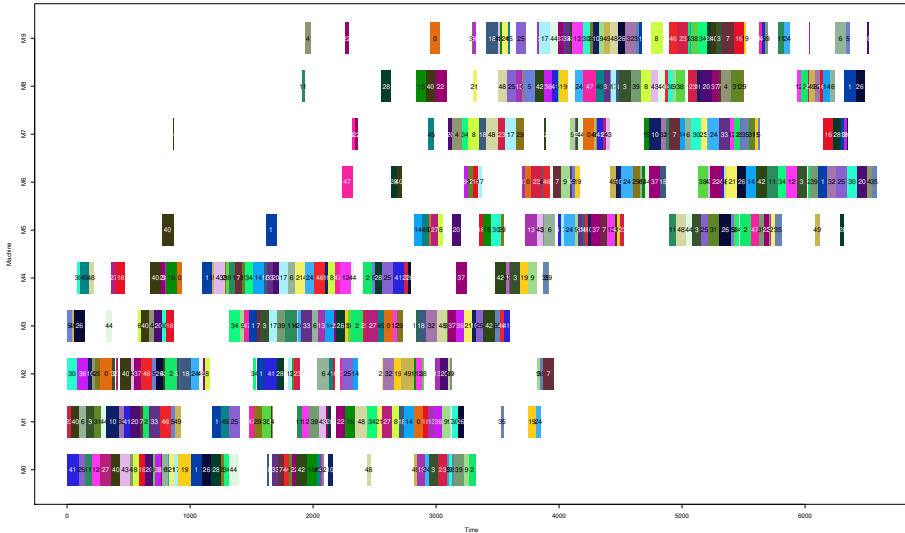
la24, makespan: 1272



So what do we get?

single random sample

swv15, makespan: 6581

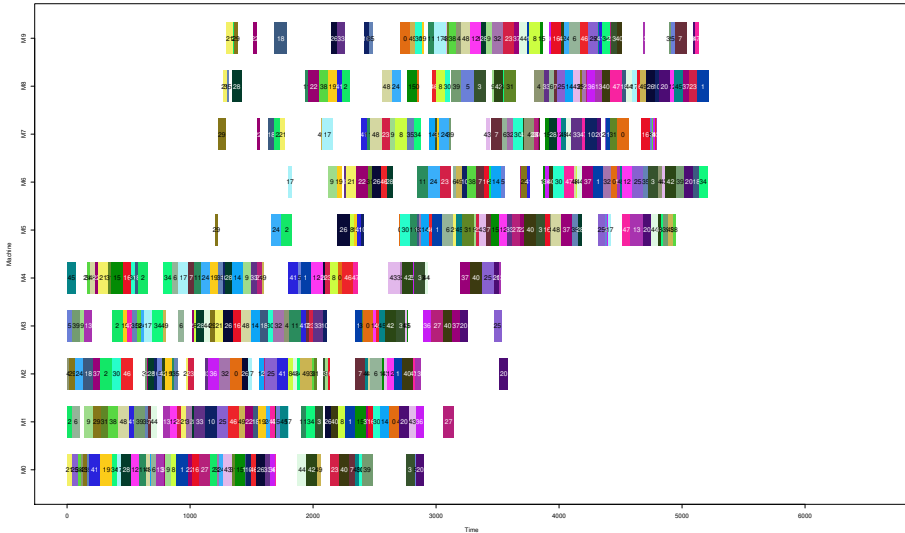


So what do we get?



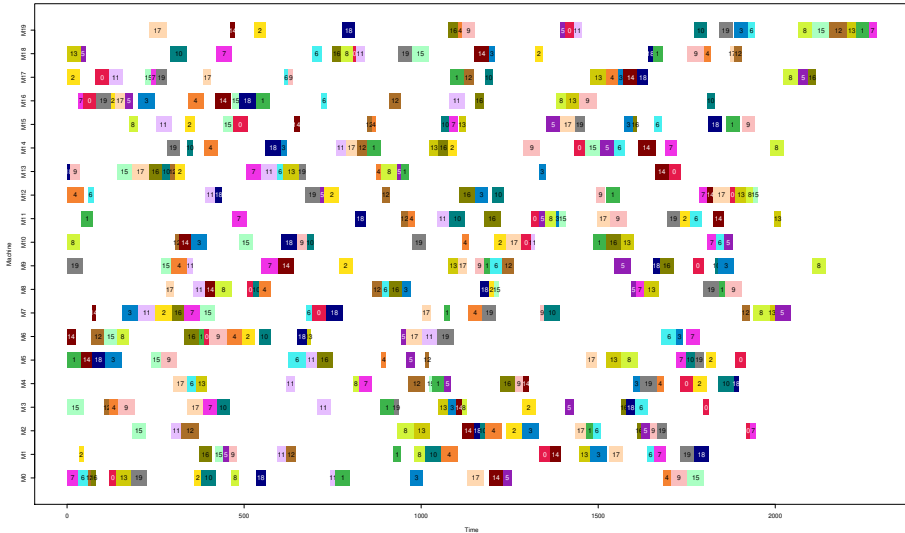
1'000'000 random samples

swv15, makespan: 5217



single random sample

yn4, makespan: 2286

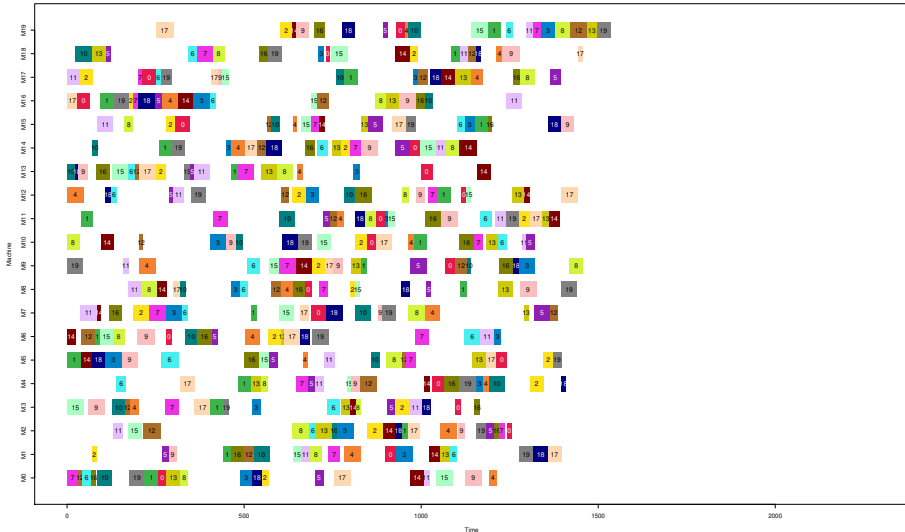


So what do we get?



1'000'000 random samples

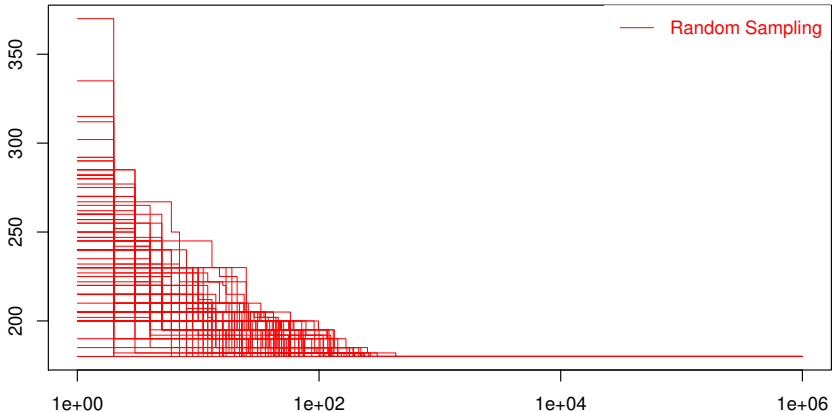
yn4, makespan: 1534



What progress does the algorithm make over time (measured in objective function evaluations, FEs)?

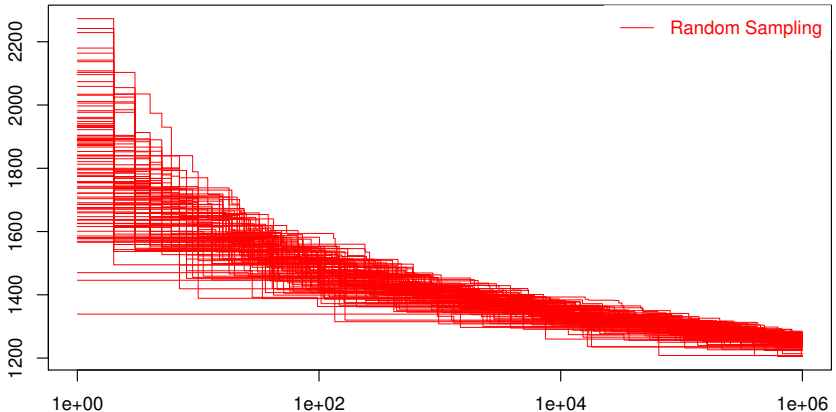
What progress does the algorithm make over time (measured in objective function evaluations, FEs)?

demo (log-scaled FEs)



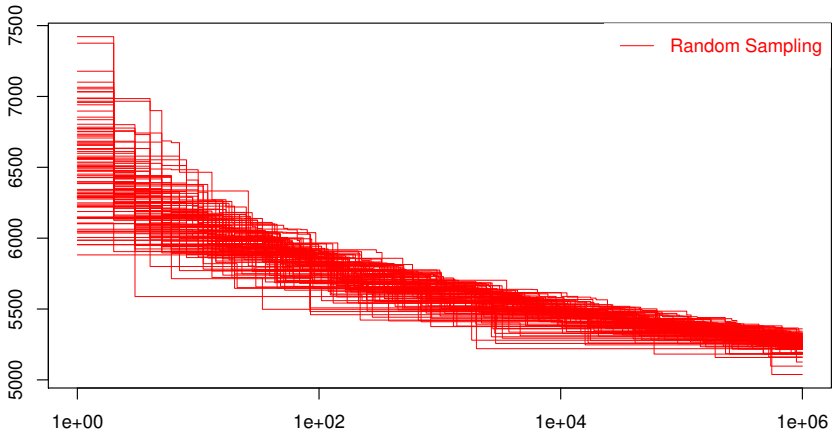
What progress does the algorithm make over time (measured in objective function evaluations, FEs)?

la24 (log-scaled FEs)



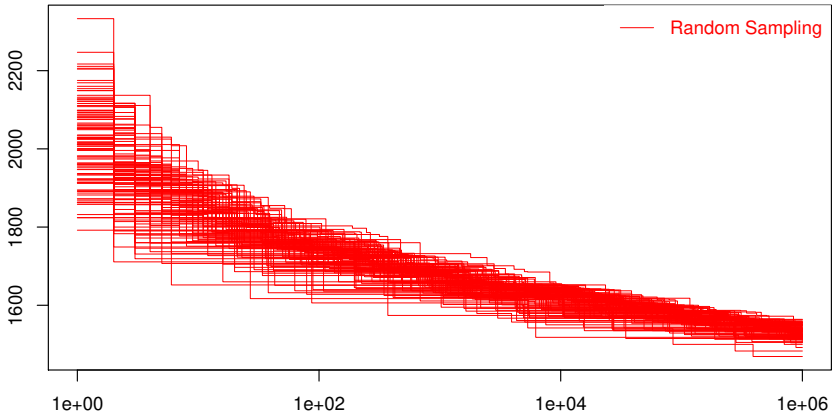
What progress does the algorithm make over time (measured in objective function evaluations, FEs)?

swv15 (log-scaled FEs)

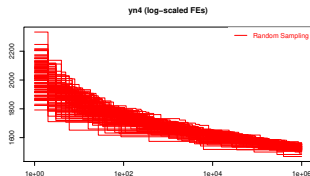
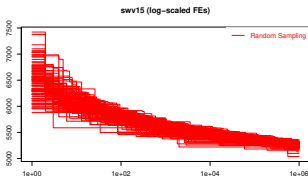
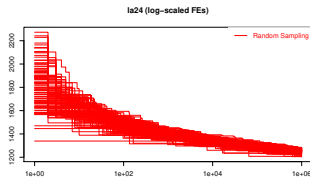
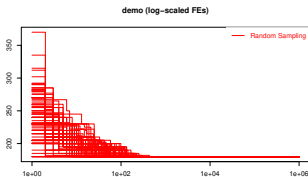


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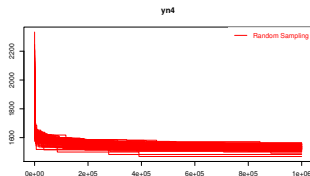
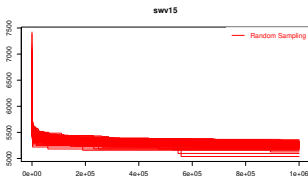
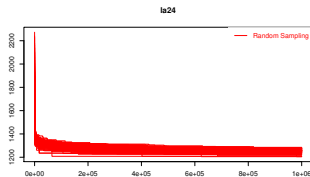
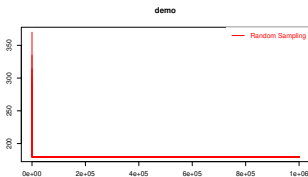
yn4 (log-scaled FEs)



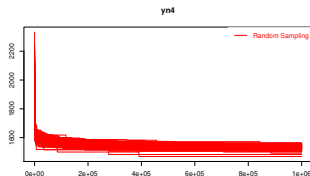
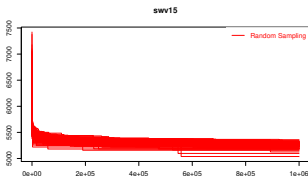
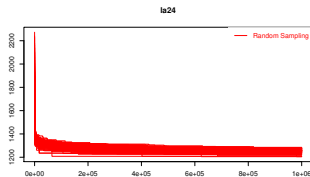
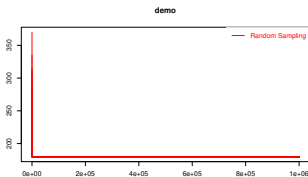
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- This holds for runtime, but also for improvements of algorithms.



- We have now a basic algorithm that provide some solutions.

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- But it is stupid and does not make any use of the information it has seen during the search.

谢谢

Thank you

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Caspar David Friedrich, "Der Wanderer über dem Nebelmeer", 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog



1. Paul Anthony Samuelson and William Dawbney Nordhaus. *Microeconomics*. Boston, MA, USA: McGraw-Hill Irwin, 17th edition, 2001. ISBN 0071-180664.