AI & ENGINEERING COMMUNITY CALL

25. August 2023

WHAT CAN WE LEARN FROM EVOLUTION?

Nicklas Bekkevold (I&D Hamburg)

AGENDA

INTRODUCTION

EVOLUTIONARY ALGORITHMS

FEATURE SELECTION PROBLEM

CASE STUDY: AMBULANCE ALLOCATION IN NORWAY

Q&A

A BIT ABOUT ME

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Wrote a paper on applied EC this year

Comparing Metaheuristic Optimization Algorithms for Ambulance Allocation: An Experimental Simulation Study

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ABSTRACT

The optimization of Emergency Medical Services is a central issue in modern healthcare systems. With this in focus, we study a data set containing medical emergencies for the years 2015–2019 from Oslo and Akershus, Norway. By developing a discrete trace-based simulation model based on the data set, we compute average response times that are used to optimize ambulance allocations to stations in the region. We study several metaheuristics, specifically genetic, stochastic local search, and memetic algorithms. These metaheuristics are tested using the simulation to optimize ambulance allocations, considering response times. The algorithms are compared against each other and a set of baseline allocation models over different time periods. The main results of our experimental simulation study are that: (i) the metaheuristics generally outperform the simpler baselines, (ii) the best-performing metaheuristic is the genetic algorithm, and (iii) the performance difference between the metaheuristics and the simpler baselines increases in situations with high demand on ambulances. Finally, we present suggestions for future work that may help to further improve upon the current state-of-the-art.

CCS CONCEPTS

• **Computing methodologies → Randomized search; Discrete space search;** • **Theory of computation → Evolutionary algorithms; Randomized local search;** • **Applied computing → Health care information systems.**

KEYWORDS

vehicle fleet management, ambulance allocation, emergency medical service, response time, simulation, optimization, genetic algorithms, stochastic local search, memetic algorithms

*Both authors contributed equally to this research.

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1 INTRODUCTION

Handling emergency incidents efficiently is crucial for an Emergency Medical Service (EMS). Minutes, or even seconds, can often spell the difference between life and death [32]. During an emergency, the Emergency Medical Communication Center (EMCC) receives a call and quickly assesses the status of the situation. Then, medical resources are dispatched accordingly. For time-critical incidents like cardiac arrests, the *response time*—the time it takes for an ambulance to arrive at the scene as shown in Figure 1—is vital.

In Norway, response time is monitored and used to quantify the effectiveness of the EMS. A national goal is that 90% of acute incidents should have a response time of fewer than 12 minutes in densely populated areas and 25 minutes in sparsely populated areas [52]. Unfortunately, this report shows that almost none of the health regions in Norway could meet the response time goals in the period 2020–2022. Further, data from the central office of official government statistics, Statistics Norway, shows a rising trend in the number of ambulance assignments per year [48]. One possible part of a solution to mitigate these trends can be to use modern data-driven models and optimization techniques in order to use the limited EMS resources more effectively.

One such approach can be to attempt to minimize the response times of an EMS by dynamically redistributing emergency resources, i.e., optimize both when and where the ambulances should be located, based on a fixed number of ambulance base stations, in order to have the best preparedness. This problem is referred to as the ambulance allocation problem in the literature [57].

This paper develops a simulation-based approach for minimizing response times for the Oslo and Akershus EMS based on a unique real-world data set provided by the Oslo University Hospital (OUH).[1] The data set contains 754,811 EMS incident responses for the relevant region from 2015–2019. Each entry in the data set contains detailed information about an emergency event, like when

[1]This paper builds upon the MS thesis of Schjølberg and Bekkevold [40].

1454

EVOLUTIONARY COMPUTING

Field of AI (family of algorithms)

Encoded problem: metaheuristic

Simple programs with complicated behavior

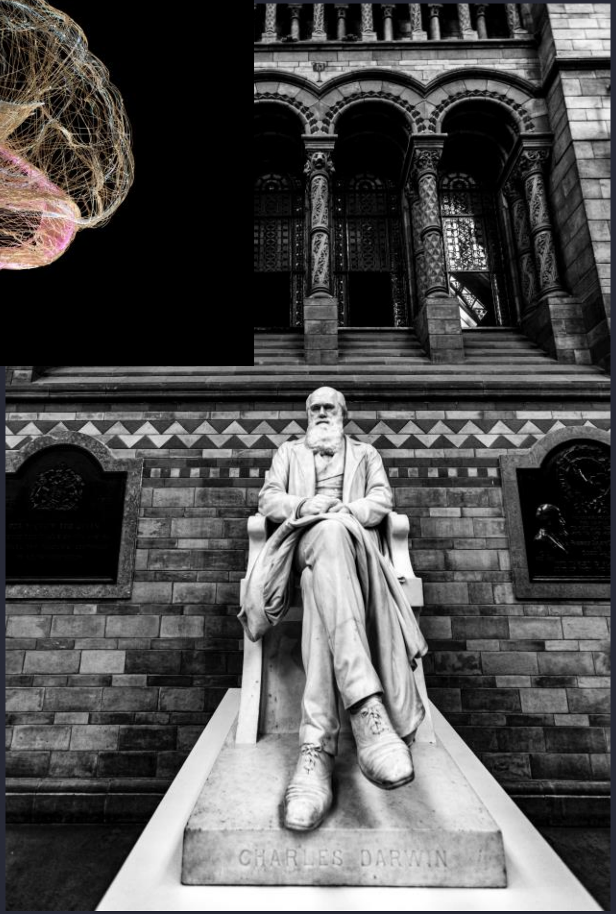
Lots of (optional) terminology from biology

Background:

Trade-offs between runtime and solution quality

Goal:

We want good enough solutions within reasonable time



EVOLUTIONARY ALGORITHMS

Genotype (encoded solution)

Population (collection of genotypes)

Phenotype (solution)

Fitness function (objective function)

Mutation (p_m): $G \to G$

Crossover (p_c): $G \times G \to G \times G$

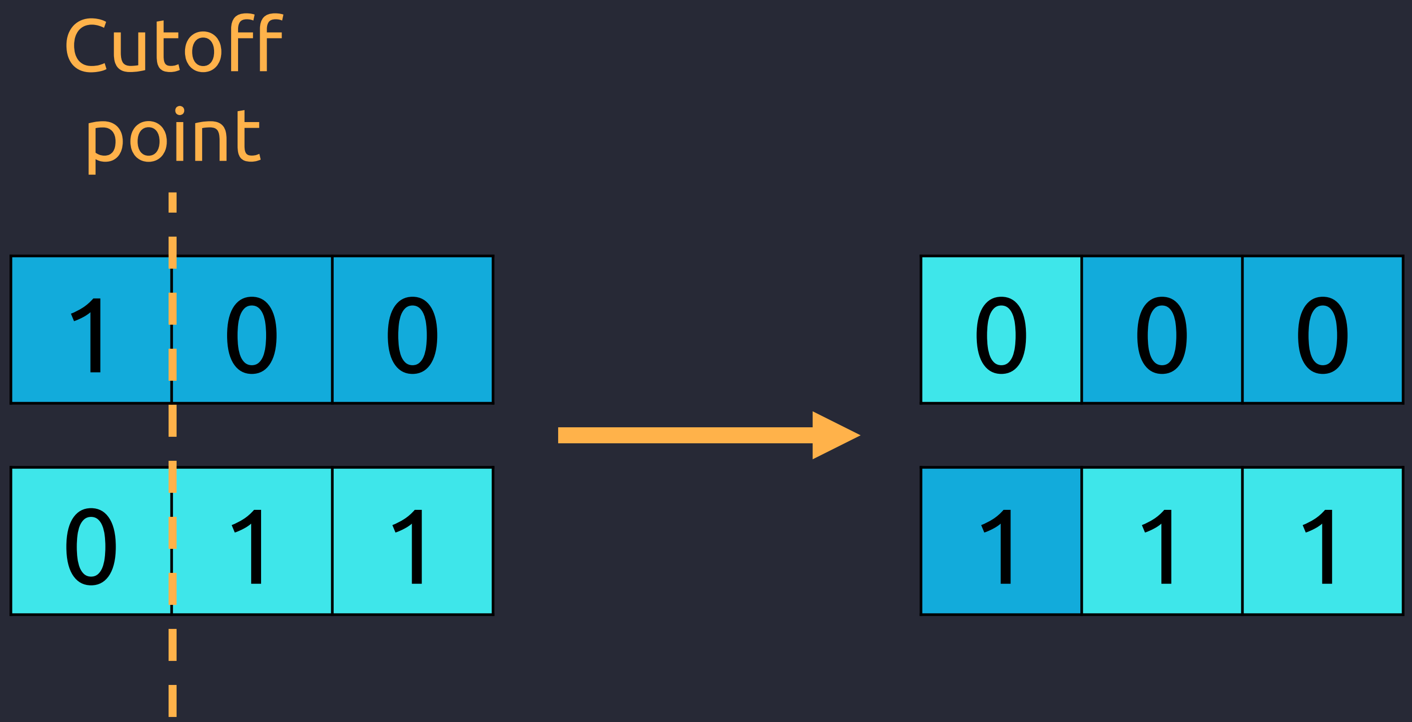
Selection: $G^n \to G$

- Roulette wheel (classic)
- Ranking
- Tournament selection

MUTATION (p_m): $G \to G$

(Random bit-flip)

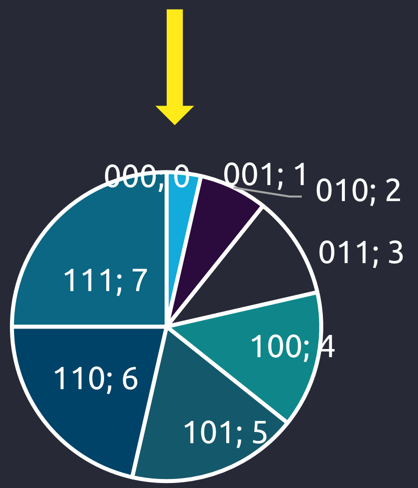
CROSSOVER (p_c): $G \times G \to G \times G$



(One-point crossover)

SELECTION: $G^n \rightarrow G$

Population			f
0	0	0	**0**
0	0	1	**1**
0	1	0	**2**
0	1	1	**3**
1	0	0	**4**
1	0	1	**5**
1	1	0	**6**
1	1	1	**7**



(Roulette wheel)

SELECTION: $G^n \rightarrow G$

Population			f
0	0	0	**0**
0	0	1	**1**
0	1	0	**2**
0	1	1	**3**
1	0	0	**4**
1	0	1	**5**
1	1	0	**6**
1	1	1	**7**

Tournament group

0	0	1	**1**
1	0	0	**4**

Winner

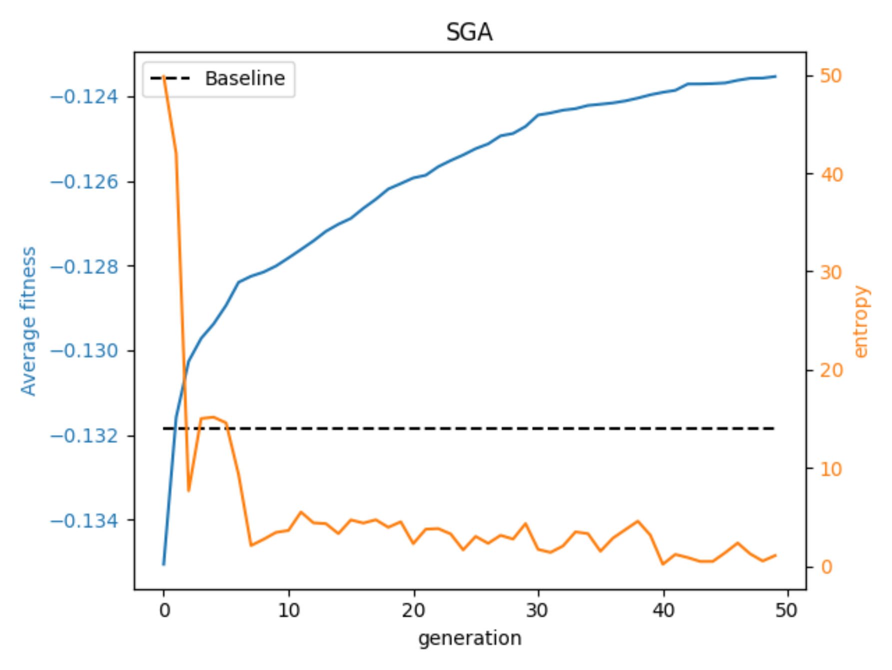
1	**0**	**0**	**4**

(Tournament selection $k = 2$)

WHEN TO STOP?

Termination criterions:

1. Optimum value hit (when applicable)
2. Fixed amount of CPU time elapsed
3. Max number of fitness evaluations reached
4. No significant improvement after some time
5. Population diversity drops below a given threshold



PEN & PAPER EXAMPLE (SELECTION)

Individual	Genotype	Phenotype	Fitness $f(x) = x^2$	Probability	Expected count	Actual count
1	0 1 1 0 1	13	169	0.14	0.58	1
2	1 1 0 0 0	24	576	0.49	1.97	2
3	0 1 0 0 0	8	64	0.06	0.22	0
4	1 0 0 1 1	19	361	0.31	1.23	1
Sum			1170	1.00	4.00	4
Average			293	0.25	1.00	1
Max			576	0.49	1.97	2

PEN & PAPER EXAMPLE (CROSSOVER)

Individual	Parents	Cutoff point	Offspring	Phenotype	Fitness $f(x) = x^2$
1	0 1 1 0 1	4	0 1 1 0 0	12	144
2	1 1 0 0 0	4	1 1 0 0 1	25	625
2	1 1 0 0 0	2	1 1 0 1 1	27	729
4	1 0 0 1 1	2	1 0 0 0 0	16	256

PEN & PAPER EXAMPLE (MUTATION)

Individual	Offspring	Offspring (Mutated)	Phenotype	Fitness $f(x) = x^2$
1	0 1 1 0 0	1 1 1 0 0	26	676
2	1 1 0 0 1	1 1 0 0 1	25	625
2	1 1 0 1 1	1 1 0 1 1	27	729
4	1 0 0 0 0	1 0 1 0 0	18	324

PEN & PAPER EXAMPLE

Individual	Genotype	Phenotype	Fitness $f(x) = x^2$
1	1 1 1 0 0	26	676
2	1 1 0 0 1	25	625
2	1 1 0 1 1	27	729
4	1 0 1 0 0	18	324
Sum			2354
Average			588.5
Max			729

1. Generation

Fitness $f(x) = x^2$
169
576
64
361
1170
293
576

FEATURE SELECTION

Problem in machine learning & statistics

Simplify model

Fitness function = -Root Mean Squared Error (RSME)

101 features = 101 genes ⇔ 2^{102} possibilities

(5 070 602 400 912 917 605 986 812 821 504)

Genotype

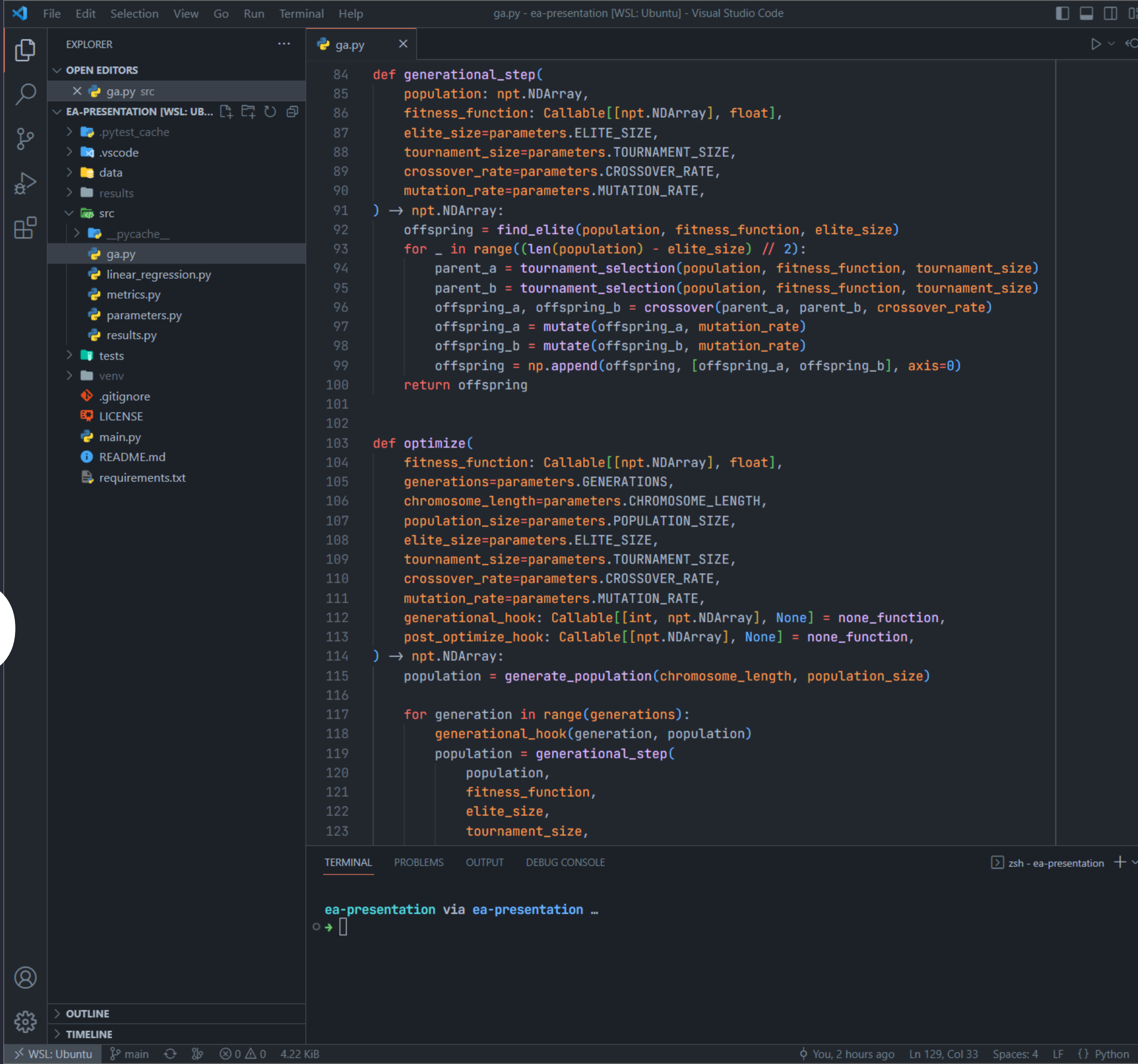
1 1 0 1 0

Phenotype

Feature 1	Feature 2	~~Feature 3~~	Feature 4	~~Feature 5~~
8.0	1.0	~~0.19~~	0.33	~~0.02~~
3.0	1.0	~~0.0~~	0.16	~~0.12~~
…	…	…	…	…

LIVE DEMO

Feature selection



MEMETIC ALGORITHMS

GAs are considered *global* search algorithms

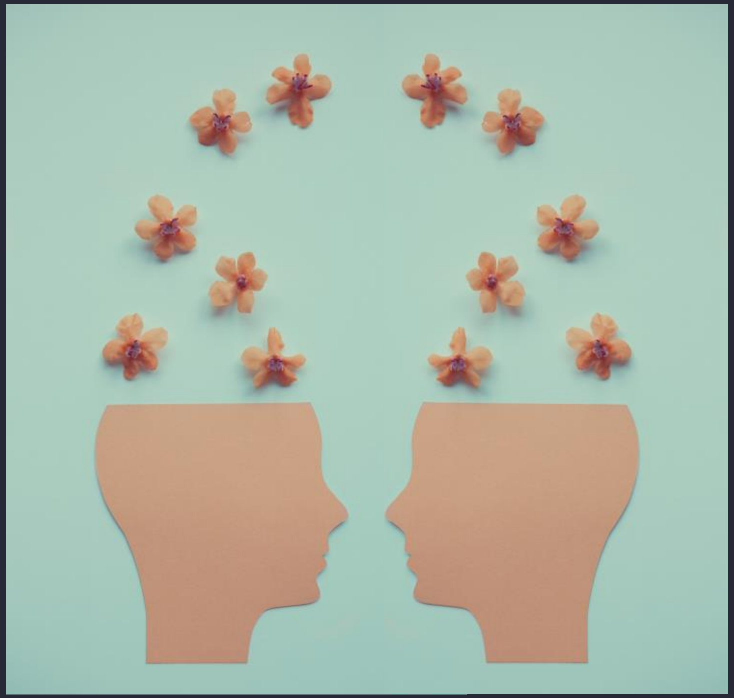
There are also *local* search algorithms:

- Hill climbing (greedy)
- Simulated annealing (stochastic)
- Stochastic Local Search (SLS)

We can also combine the two (hybridize) and get:

Memetic algorithms (MA)

- Seeding
- Selective initialization
- Domain-specific knowledge
- New operator: Improve (p_i): $G \rightarrow G$
- Adaptive



AMBULANCE ALLOCATION

Master's thesis evolved into a paper

Emergency medical service (EMS)

EMS incident dataset

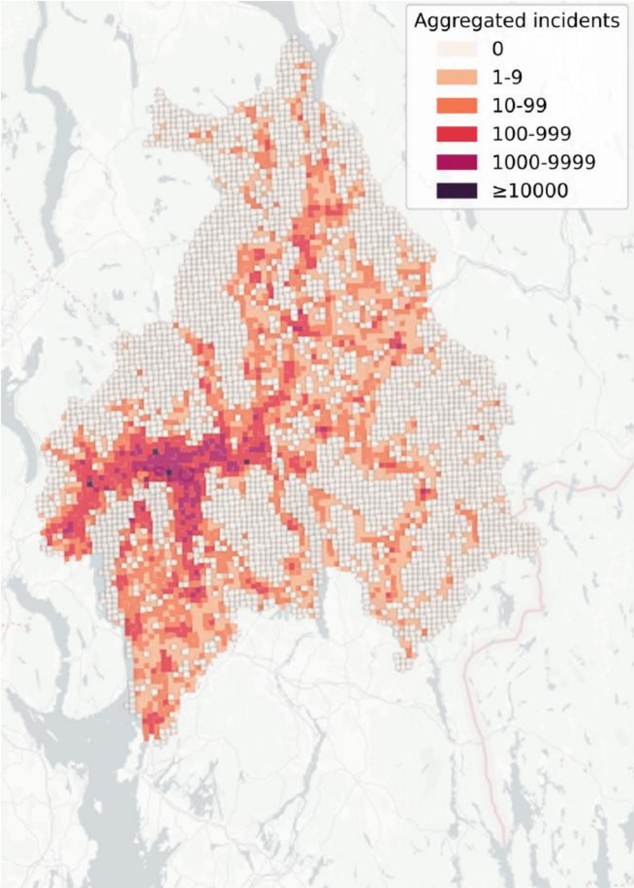
Simulation of Oslo & Akershus

Response time

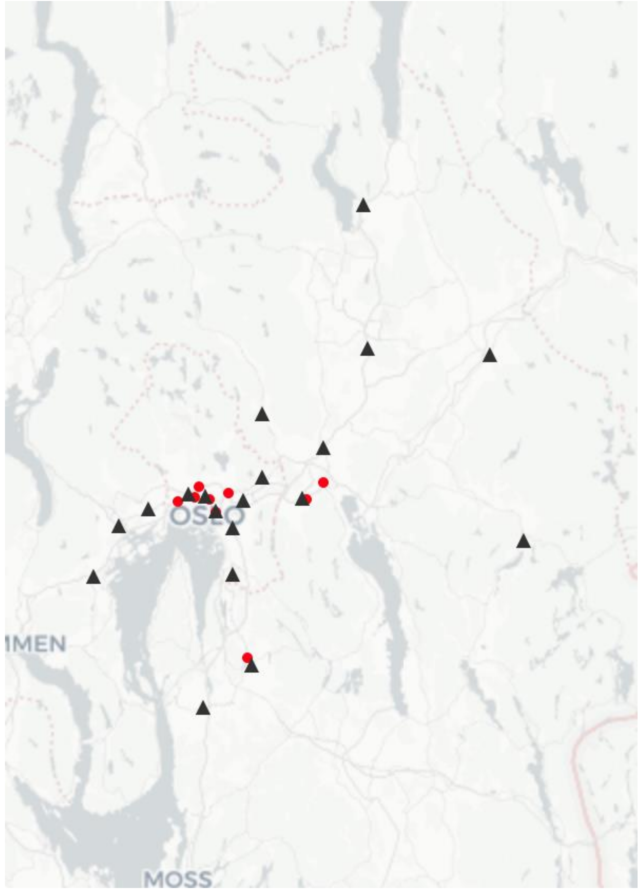
Statistical grids

Photo: Ole Kristian Andreassen (Oslo University Hospital)

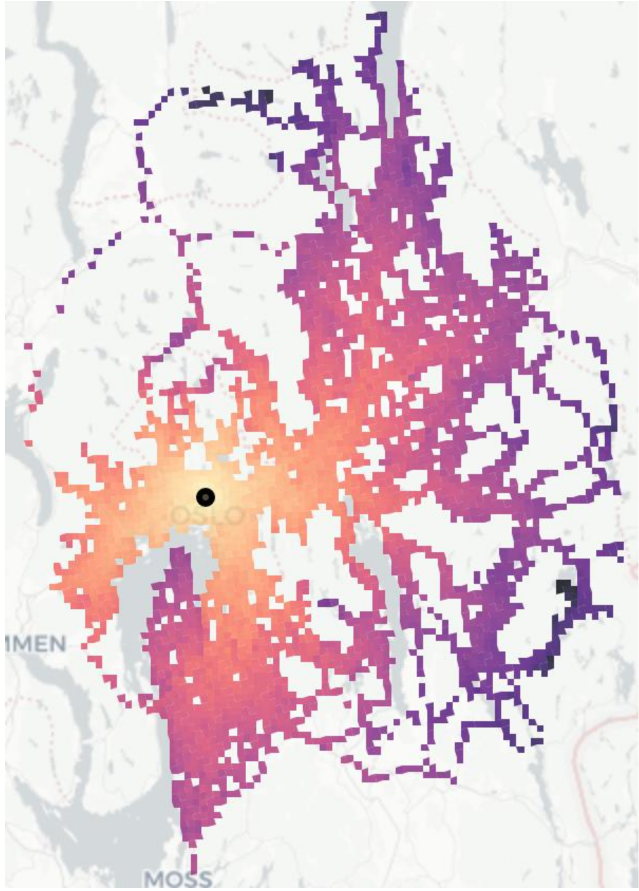
AMBULANCE ALLOCATION (DATA)



Aggregated EMS cases from 2015–2018 in Oslo and Akershus



The location of the 19 base stations (grey triangles) and the 11 hospitals (red circles) used in the experiments



The calculated time it takes from Ullevål Hospital to reach the other cells. Darker colors indicate longer travel times

AMBULANCE ALLOCATION (REPRESENTATION)

1 ambulance at base station 0

4 ambulances at base station 7

Genotype

Length: 34

0	1	2	3	4	4	4	5	6	6	6	7	7	7	7	8	8	8	8	9	9	10	10	11	11	11	12	12	13	14	15	17	17	18

Phenotype

1	1	1	1	3	1	3	4	4	2	2	3	2	1	1	1	0	2	1

Sum: 34

AMBULANCE ALLOCATION (BASELINES)

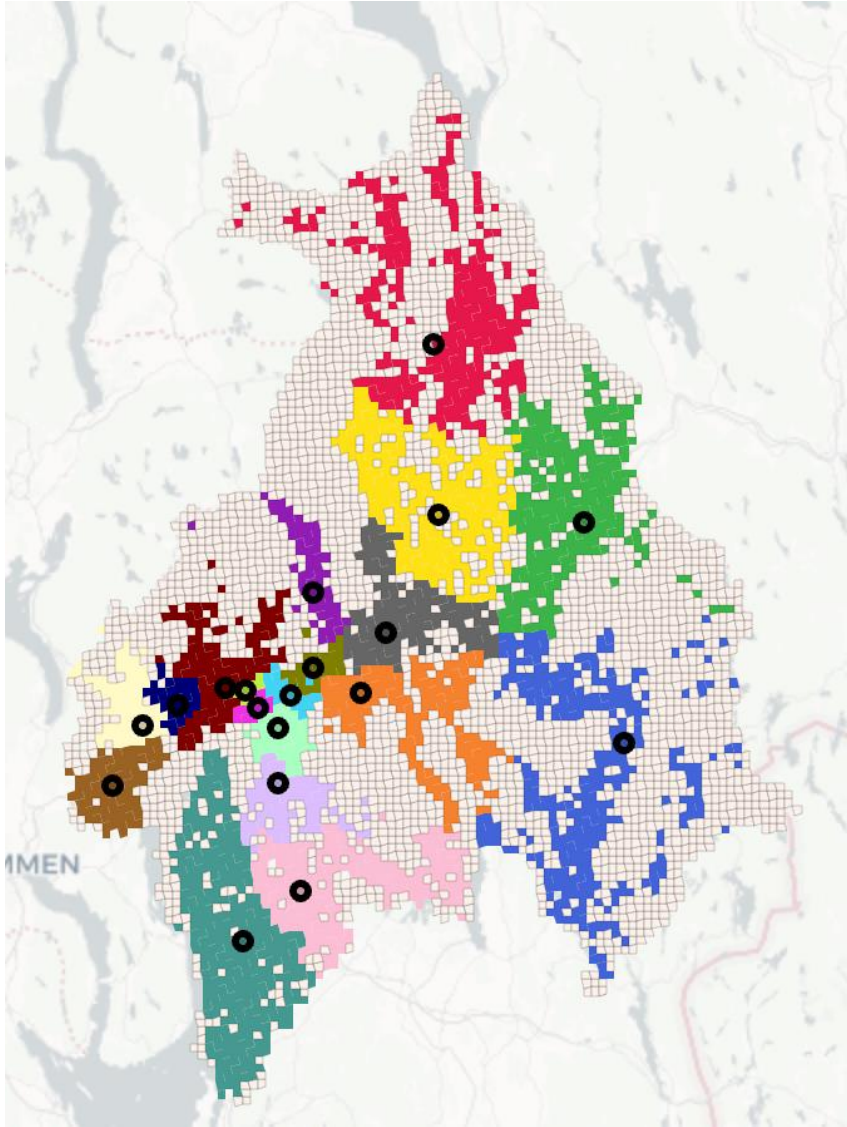
k-means clustering

Assign grid cells based on OSRM distances

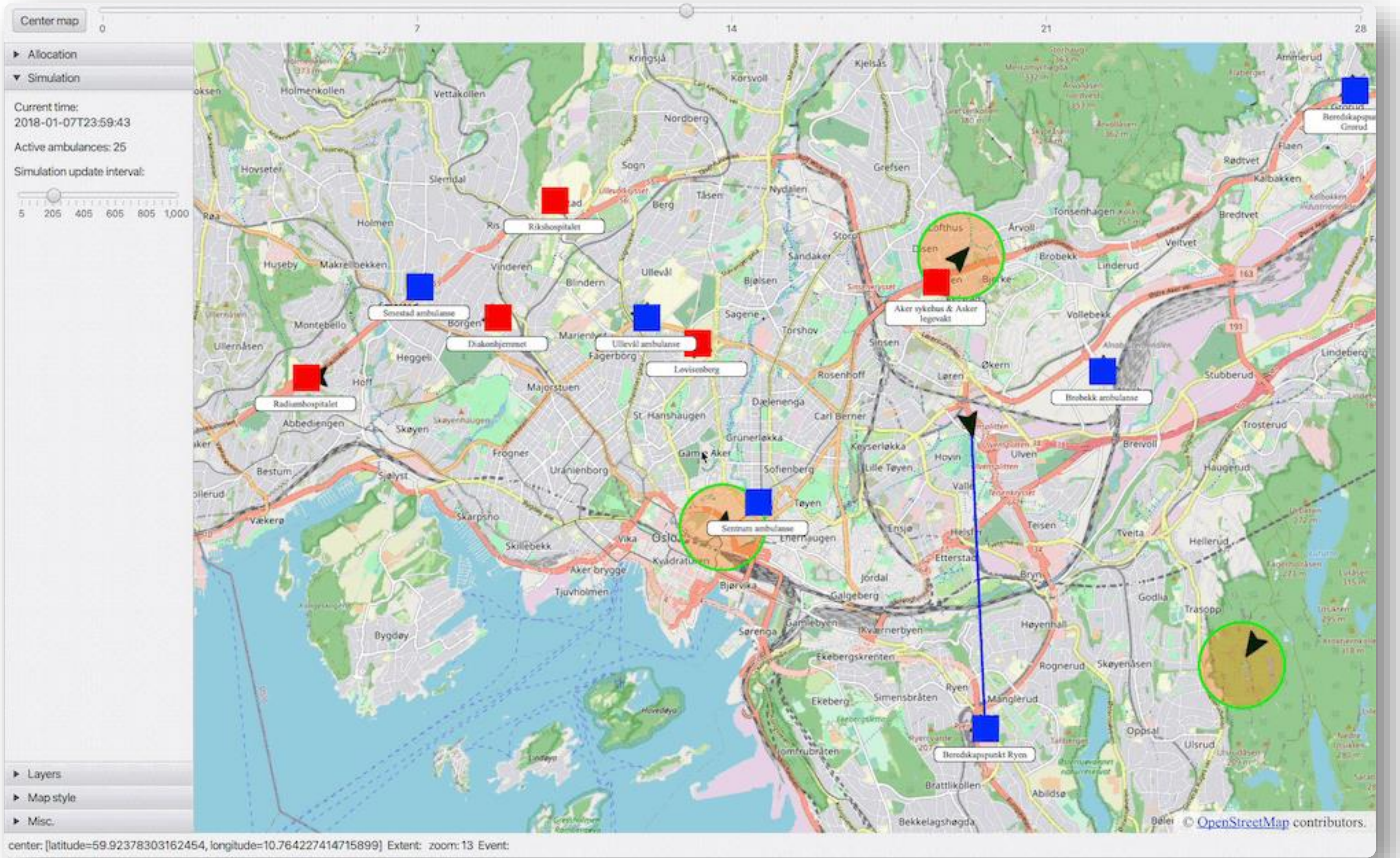
Allocate ambulances based on clusters population

“Fair repair” residue

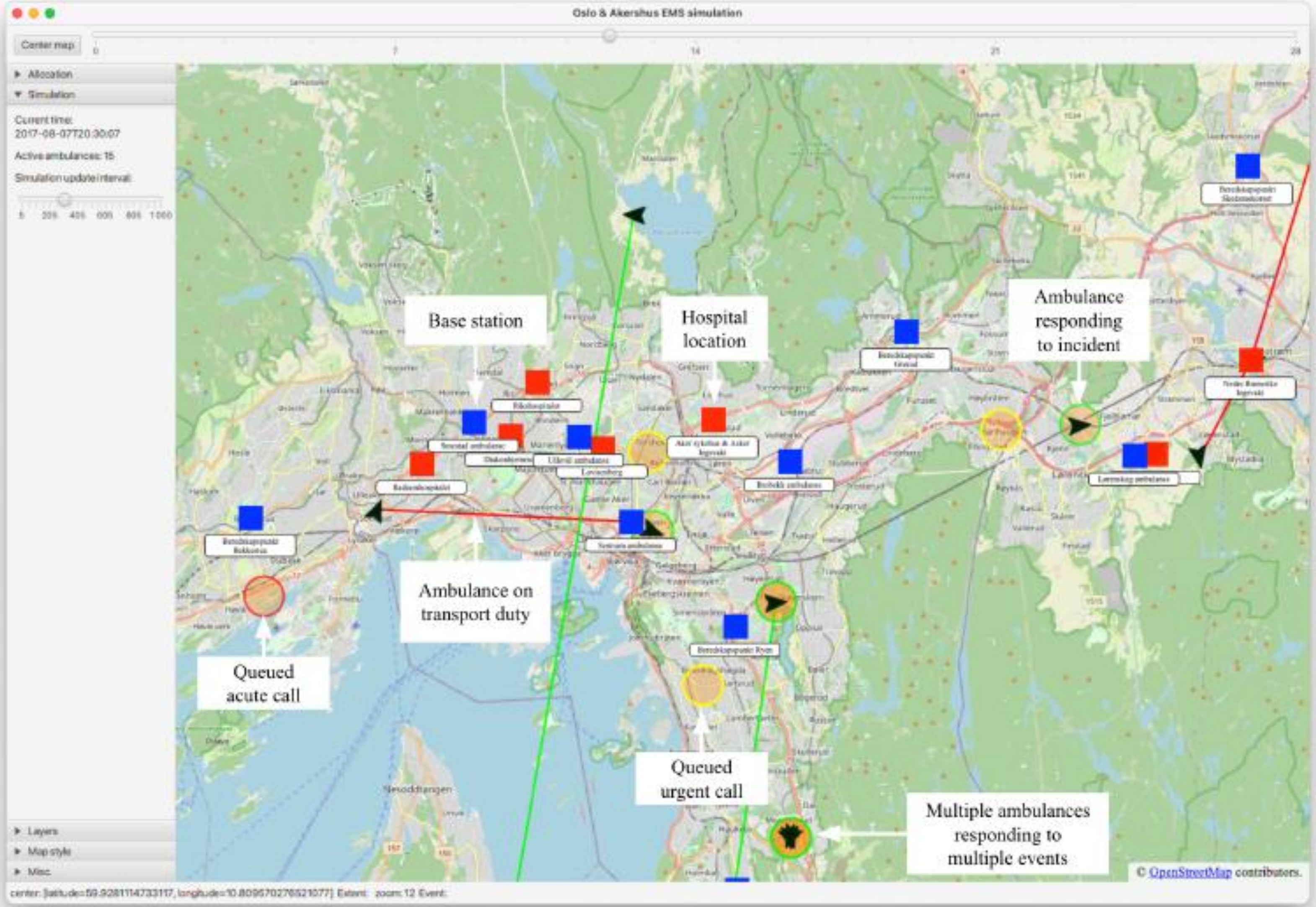
Best performing baseline



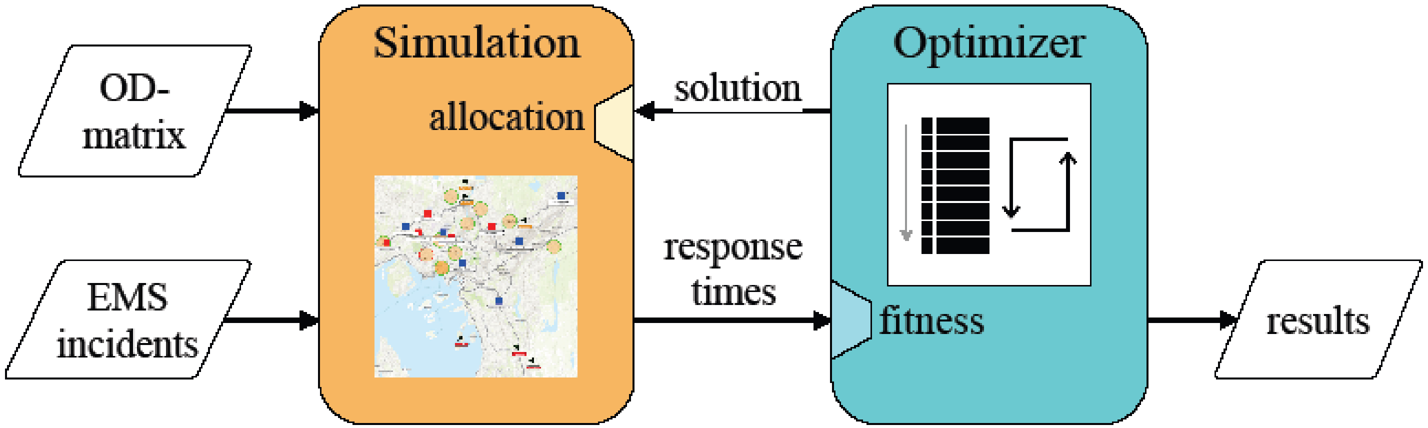
AMBULANCE ALLOCATION (SIMULATION)



AMBULANCE ALLOCATION (SIMULATION)



AMBULANCE ALLOCATION (ARCHITECTURE)



AMBULANCE ALLOCATION (RESULTS)

Simulation as a fitness function

Algorithmic comparison

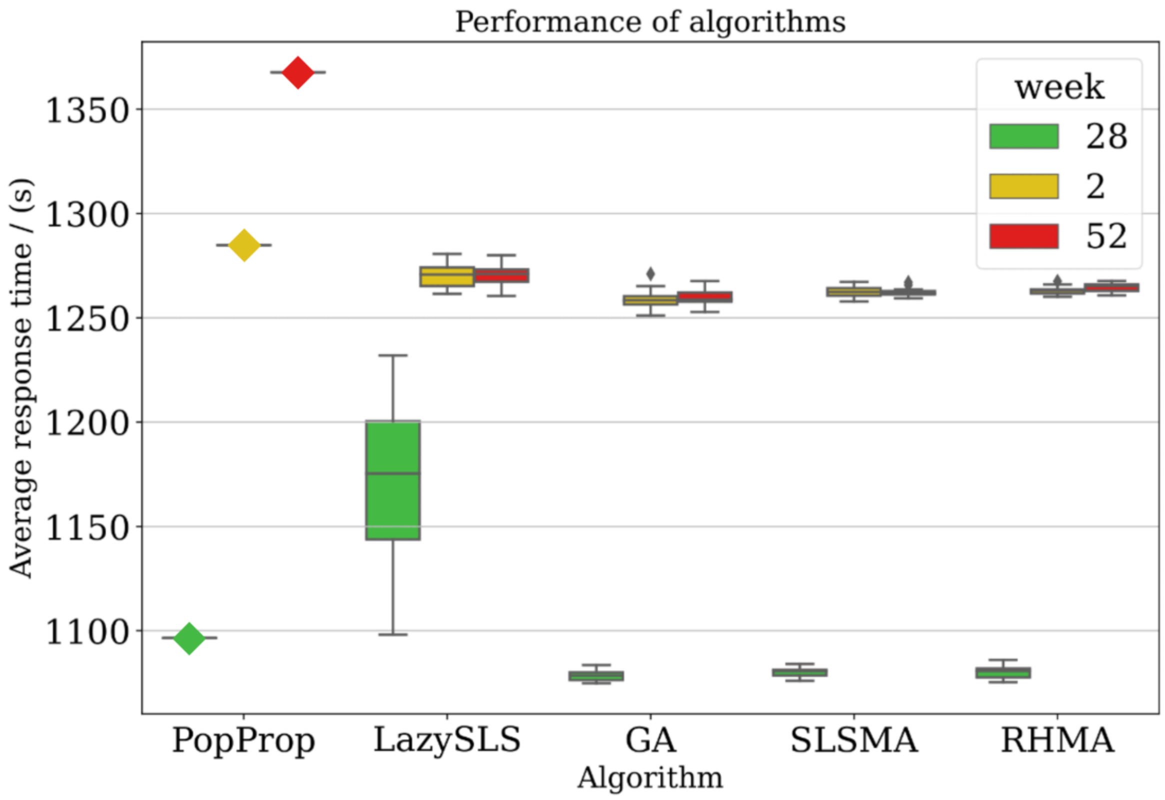
- Baselines
- SLS
- GA
- MA

Bit-flip-like mutation

One-point crossover

Tournament selection

Optimization more important during the "busy" weeks



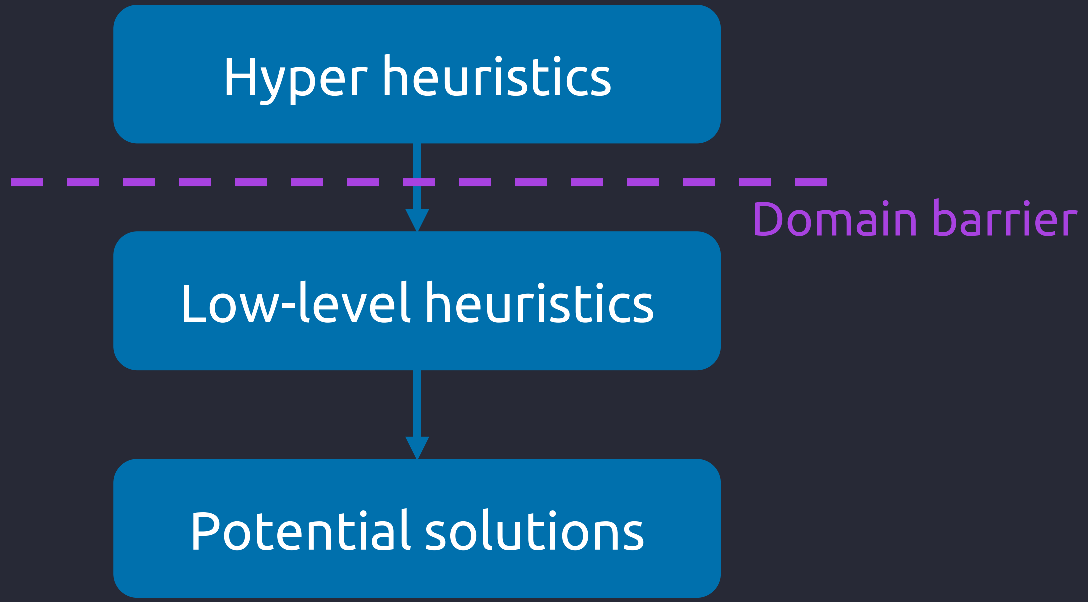
WHY DON'T YOU OPTIMIZE YOUR OPTIMIZER?

You can! (And you should)

(Hyper)parameter search also applies here,

but why stop there?

No free lunch (NFL) theorem



OTHER PROBLEMS

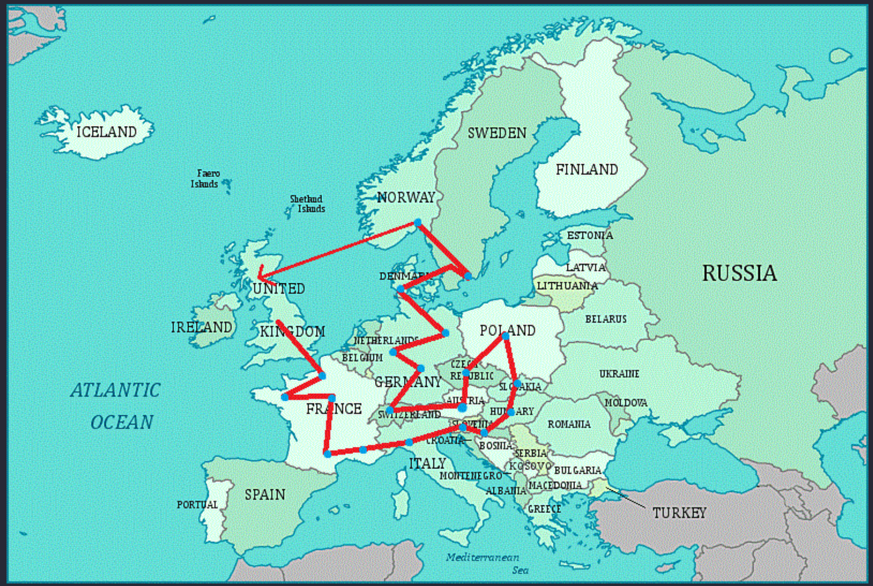
Traveling salesperson (TSP)

Multi depot vehicle routing problem (MDRP)

Job scheduling

Product design

Finding the optimal neural network architecture



CONTINUE YOUR LEARNING

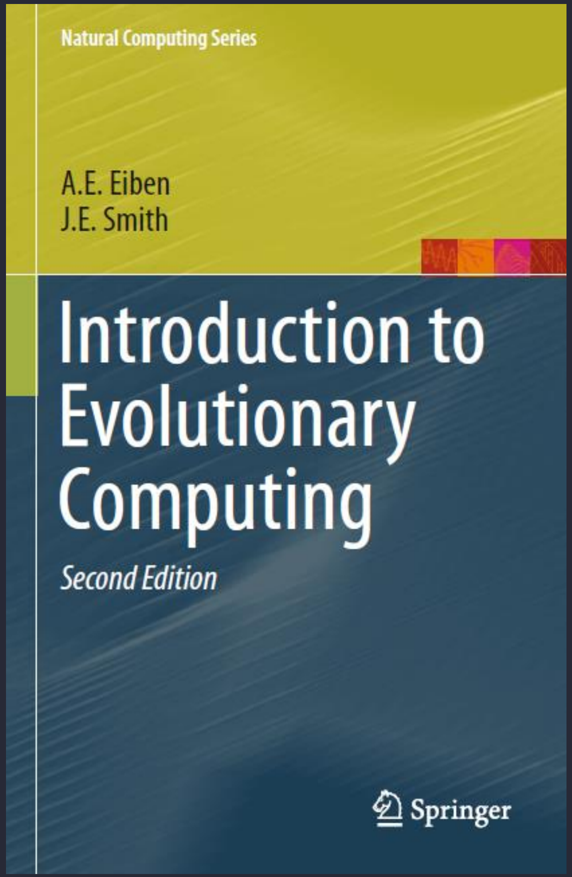
Reach out to me!

Check out the GitHub repository:

https://github.com/nicklasbekkevold/ea-presentation

Recommended literature:

- A. E. Eiben and J. E. Smith. 2003. *Introduction to evolutionary computing* (second edition ed.). Vol. 53. Springer, Berlin.
- T. Weise. 2009. Global optimization algorithms-theory and application available. Self-Published Thomas Weise, 361. (Link here)
- M. E. Schjølberg, N. Bekkevold, X. Sánchez-Díaz, and O. J. Mengshoel. 2023. *Comparing Metaheuristic Optimization Algorithms for Ambulance Allocation: An Experimental Simulation Study.* In Proceedings of the Genetic and Evolutionary Computation Conference (GECCO '23). Association for Computing Machinery, New York, NY, USA, 1454–1463. https://doi.org/10.1145/3583131.3590345



Q&A

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