

MULTI-OBJECTIVE OPTIMIZATION

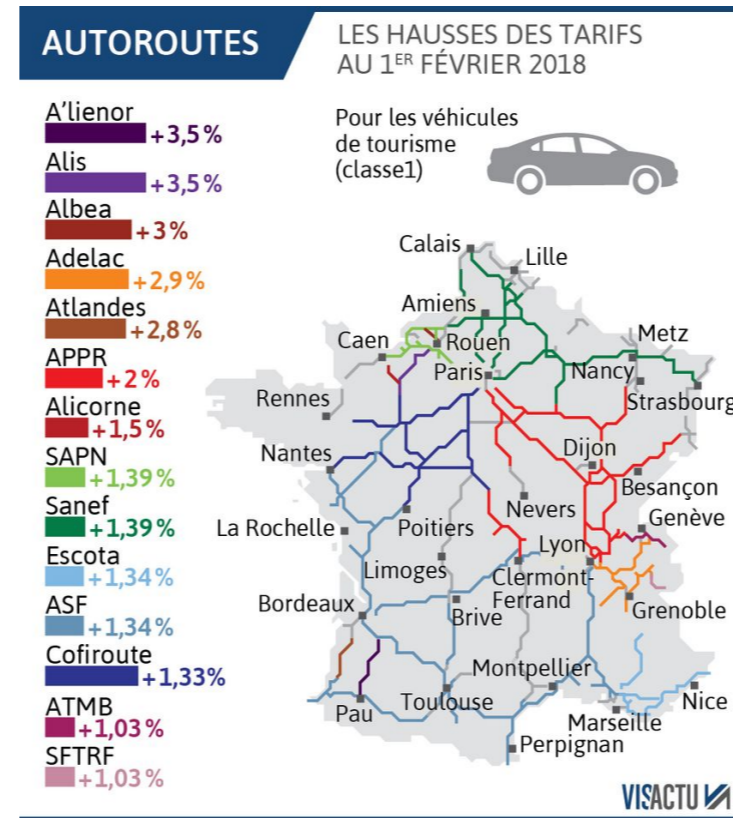
Pareto dominance, NSGA-II, MOEAs for RL

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Part of the [2021 RLVS](#).

MULTI-OBJECTIVE OPTIMIZATION

Optimizing **more than one** objective function **simultaneously**.



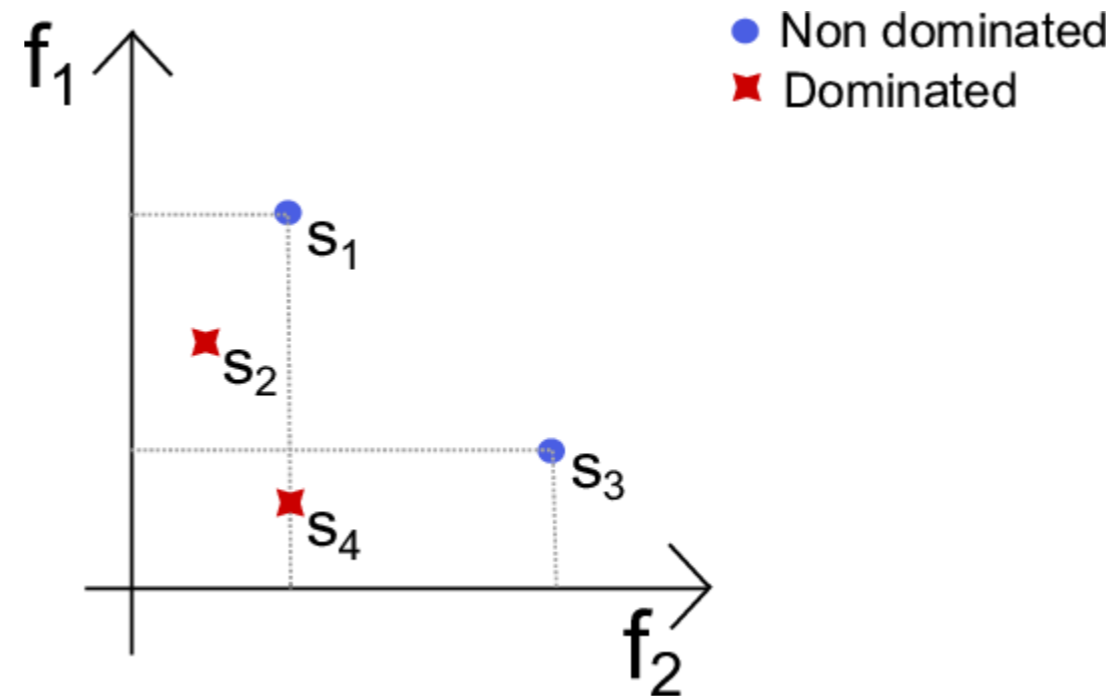
For example, when planning a trip, we want to minimize total distance travelled and toll fare.

MOEAS

MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

- **NSGA:** Srinivas, Nidamarthi, and Kalyanmoy Deb. "Multiobjective optimization using nondominated sorting in genetic algorithms." *Evolutionary computation* 2.3 (1994): 221-248.
- **SPEA2:** Zitzler, Eckart, Marco Laumanns, and Lothar Thiele. "SPEA2: Improving the strength Pareto evolutionary algorithm." TIK-report 103 (2001).
- **NSGA-II:** Deb, Kalyanmoy, et al. "A fast and elitist multiobjective genetic algorithm: NSGA-II." *IEEE transactions on evolutionary computation* 6.2 (2002): 182-197.
- Deb, Kalyanmoy (2001) *Multi-objective optimization using evolutionary algorithms*. John-Wiley, Chichester
- **MOEA/D:** Zhang, Qingfu, and Hui Li. "MOEA/D: A multiobjective evolutionary algorithm based on decomposition." *IEEE Transactions on evolutionary computation* 11.6 (2007): 712-731.
- Emmerich, Michael TM, and André H. Deutz. "A tutorial on multiobjective optimization: fundamentals and evolutionary methods." *Natural computing* 17.3 (2018): 585-609. [pdf](#)

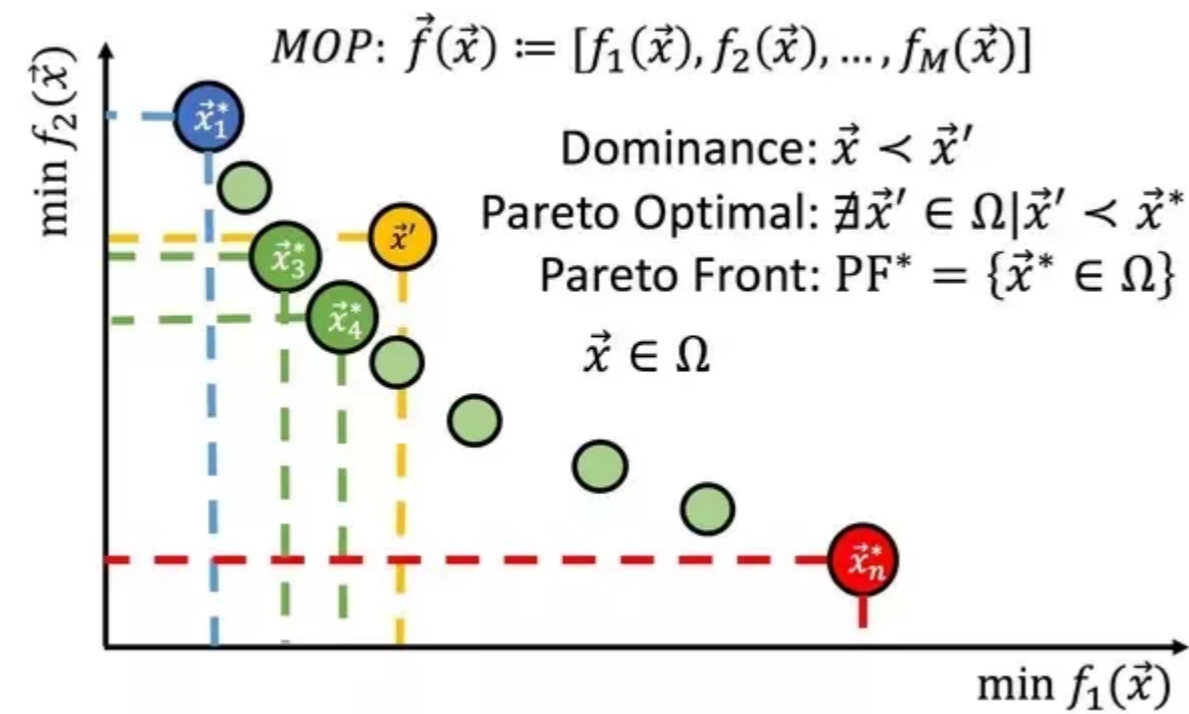
PARETO DOMINANCE



A solution is said to Pareto dominate another if it is more optimal in all dimensions.

Solutions which are not dominated by any other are called "non-dominated".

PARETO FRONT



The Pareto Front is the set of Pareto Optimal solutions.
In Multi-Objective Optimization, we will search for the Pareto Front.

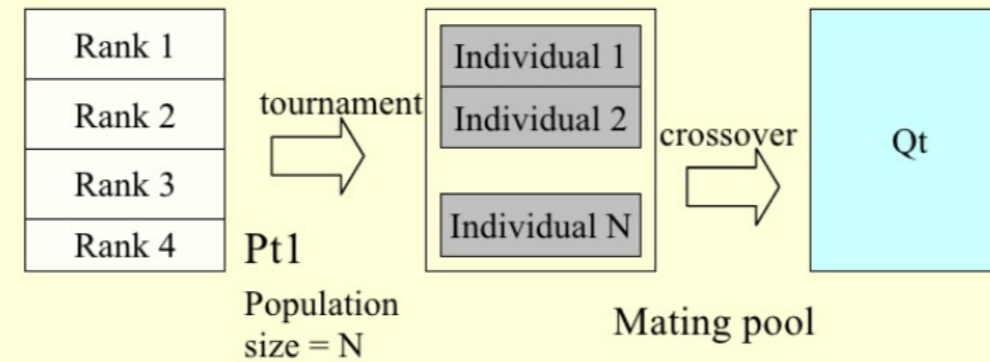
NSGA-II

NSGA2: Mainloop

Pt: Selected Parents at generation t
 Qt: the offspring that are generated from Pt

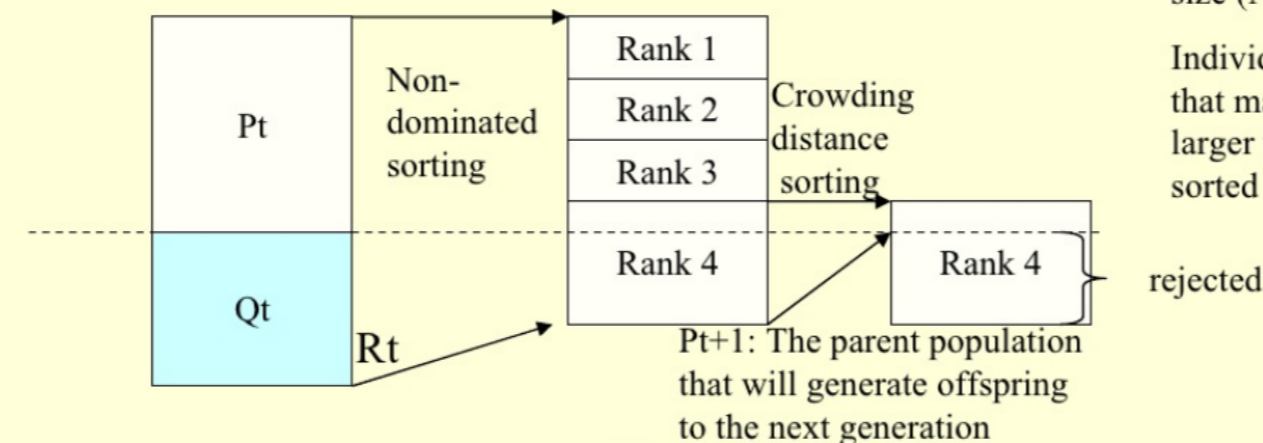
Step 1: Tournament

Each individual is compared with another randomly selected individual. (niche comparison)
 The copy of the winner is placed in the mating pool



Step 2: Apply crossover rate for each individual in a mating pool, and select a parent (s). Two parents perform crossover and generate two offspring. Two offspring will be placed in the offspring population Q_{t+1}

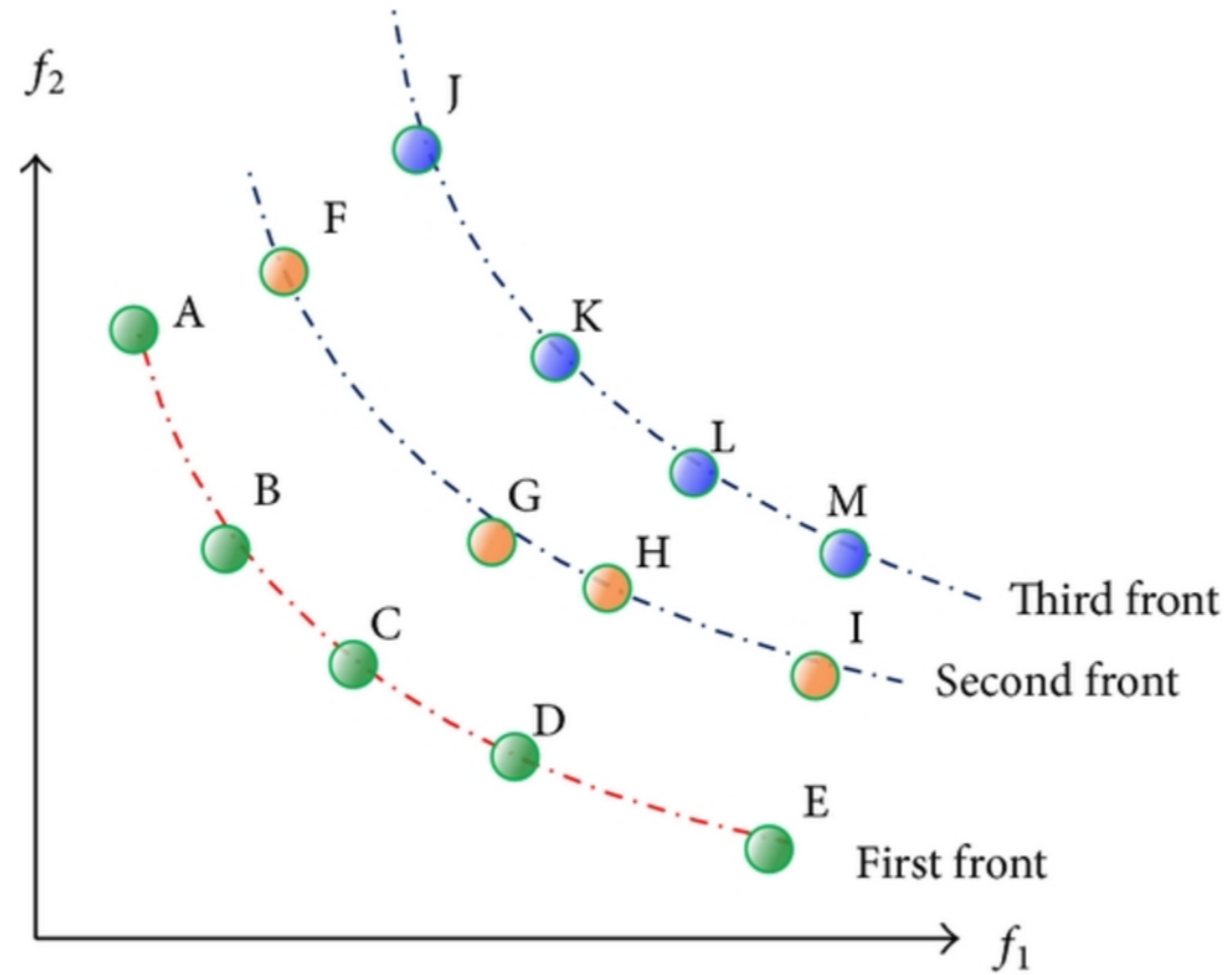
Step 3: Apply non-dominated sorting to R_t population. All non-dominated fronts of P_t+Q_t are copied to the parent population rank by rank.



Step 4: Stop adding the individuals in the rank when the size of parent population is larger than the population size (N)

Individuals in the last accepted rank, that make the parent population size larger than N (in example, rank 4), are sorted by crowding distance sorting.

NON-DOMINATED SORTING



FAST NON-DOMINATED SORT

fast-nondominated-sort (P)

for each $p \in P$

for each $q \in P$

if ($p \prec q$) then

$S_p = S_p \cup \{q\}$

else if ($q \prec p$) then

$n_p = n_p + 1$

if $n_p = 0$ then

$\mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}$

$i = 1$

while $\mathcal{F}_i \neq \emptyset$

$\mathcal{H} = \emptyset$

for each $p \in \mathcal{F}_i$

for each $q \in S_p$

$n_q = n_q - 1$

if $n_q = 0$ then $\mathcal{H} = \mathcal{H} \cup \{q\}$

$i = i + 1$

$\mathcal{F}_i = \mathcal{H}$

if p dominates q then

include q in S_p

if p is dominated by q then

increment n_p

if no solution dominates p then

p is a member of the first front

for each member p in \mathcal{F}_i

modify each member from the set S_p

decrement n_q by one

if n_q is zero, q is a member of a list \mathcal{H}

current front is formed with all members of \mathcal{H}

CROWDING DISTANCE ASSIGNMENT

crowding-distance-assignment (\mathcal{I})

$l = |\mathcal{I}|$

number of solutions in \mathcal{I}

for each i , set $\mathcal{I}[i]_{distance} = 0$

initialize distance

for each objective m

$\mathcal{I} = \text{sort}(\mathcal{I}, m)$

sort using each objective value

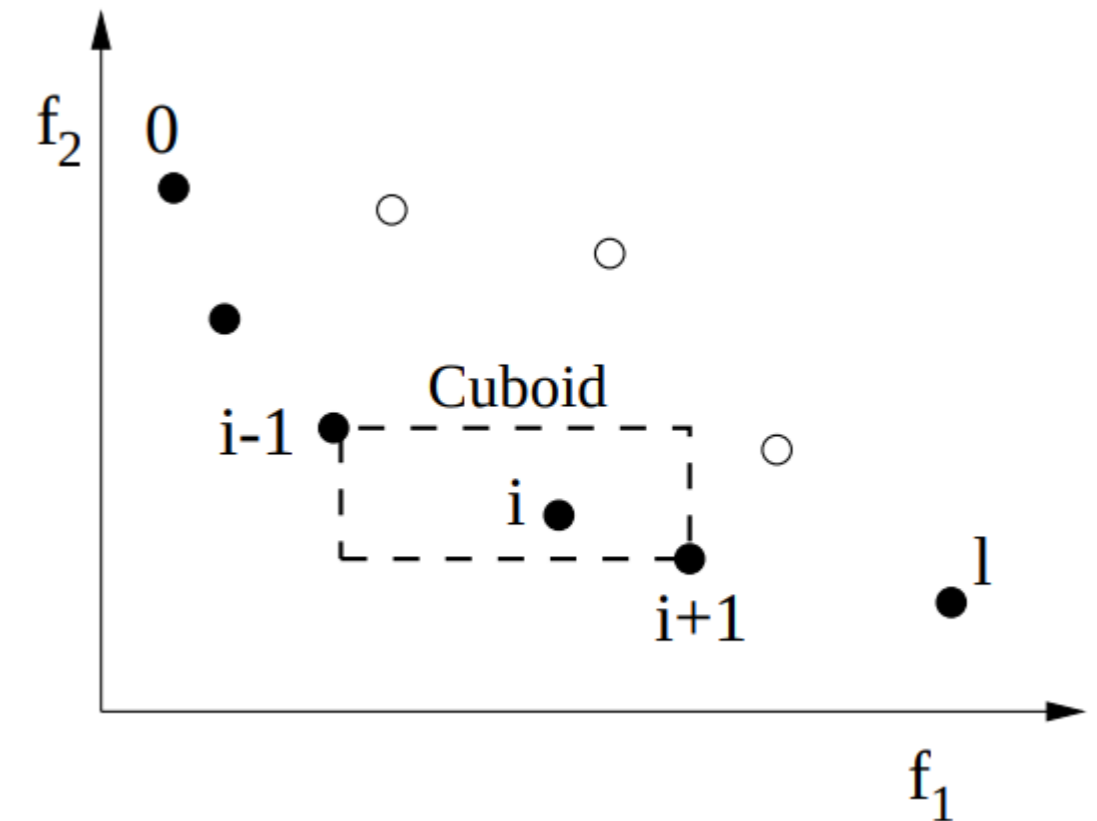
$\mathcal{I}[1]_{distance} = \mathcal{I}[l]_{distance} = \infty$

so that boundary points are always selected

for $i = 2$ to $(l - 1)$

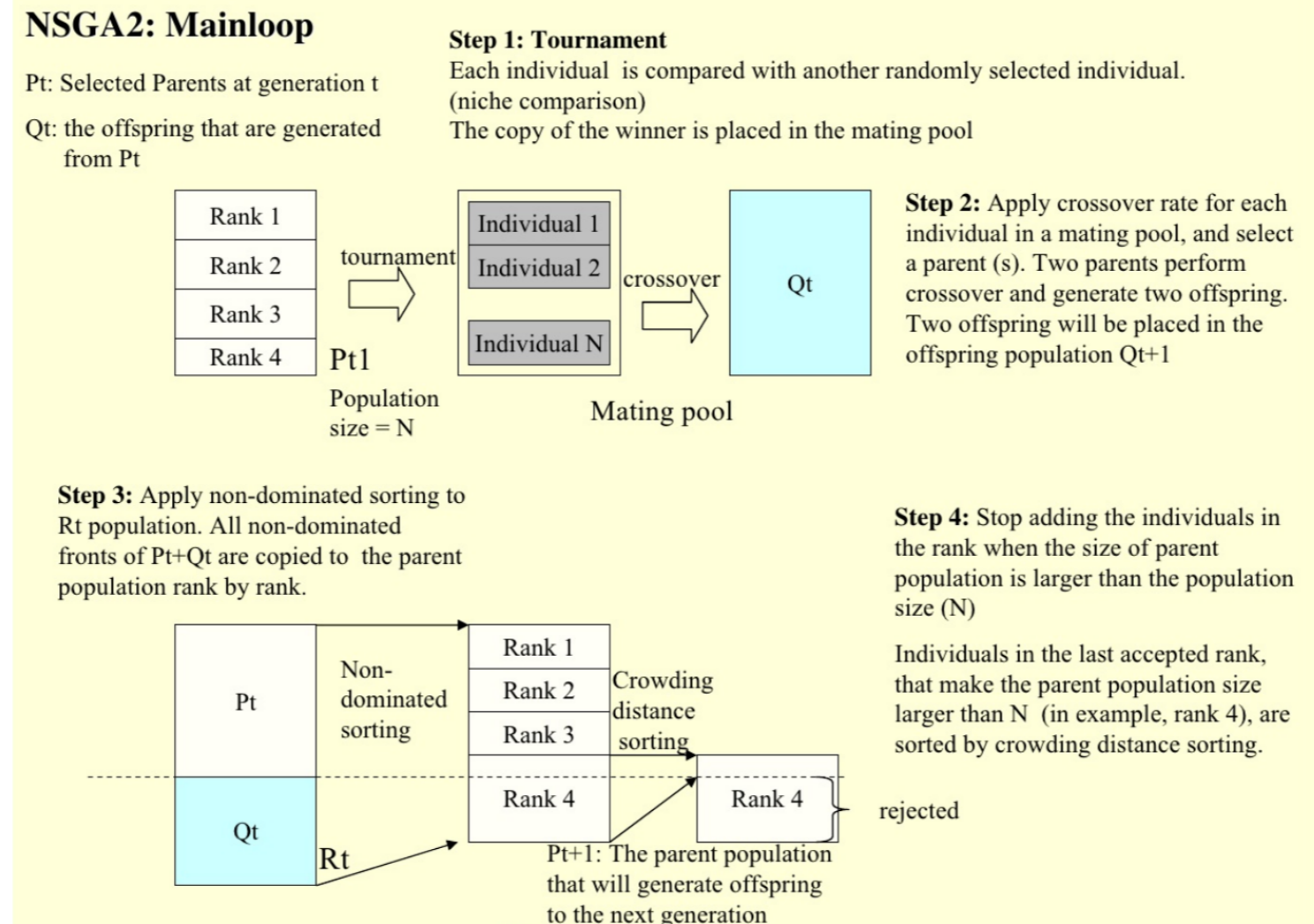
for all other points

$\mathcal{I}[i]_{distance} = \mathcal{I}[i]_{distance} + (\mathcal{I}[i + 1].m - \mathcal{I}[i - 1].m)$



Deb, Kalyanmoy, et al. "A fast and elitist multiobjective genetic algorithm: NSGA-II." IEEE transactions on evolutionary computation 6.2 (2002): 182-197. [pdf](#)

NSGA-II OVERVIEW

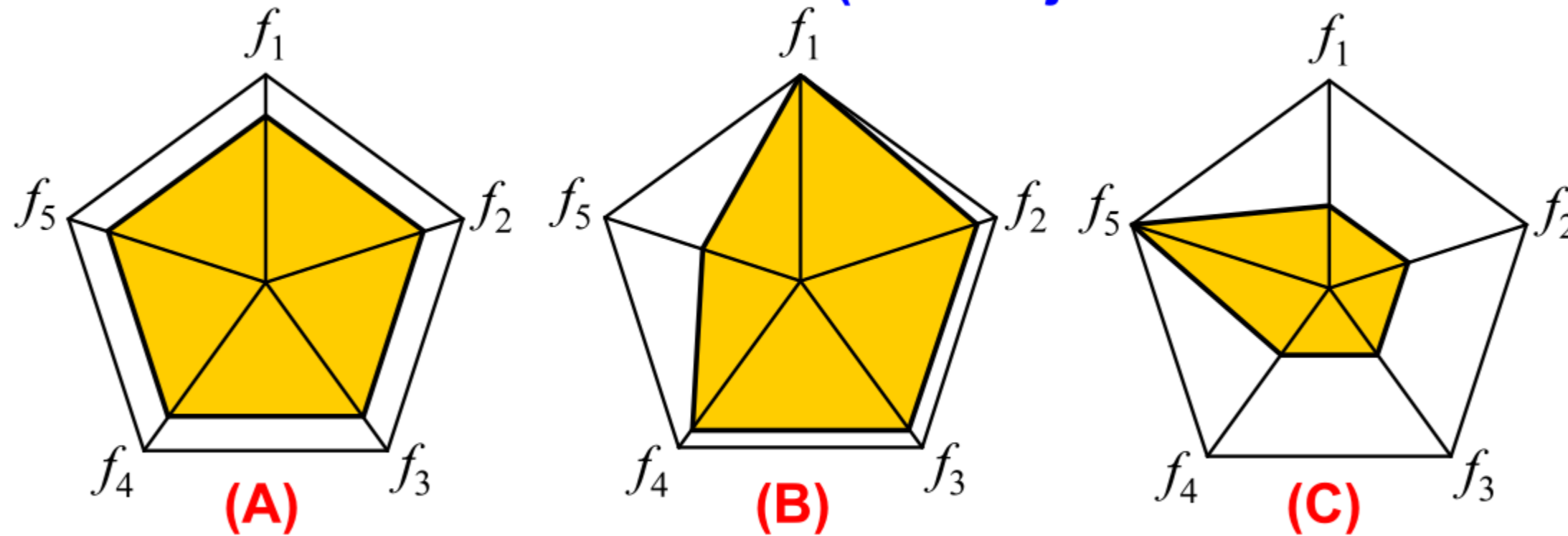


$$i \geq_n j \quad \text{if } (i_{rank} < j_{rank}) \text{ or } ((i_{rank} = j_{rank}) \text{ and } (i_{distance} > j_{distance}))$$

Deb, Kalyanmoy, et al. "A fast and elitist multiobjective genetic algorithm: NSGA-II." IEEE transactions on evolutionary computation 6.2 (2002): 182-197. [pdf](#)

PROBLEMS WITH NON-DOMINANCE

Three non-dominated solutions (Five-objective maximization)

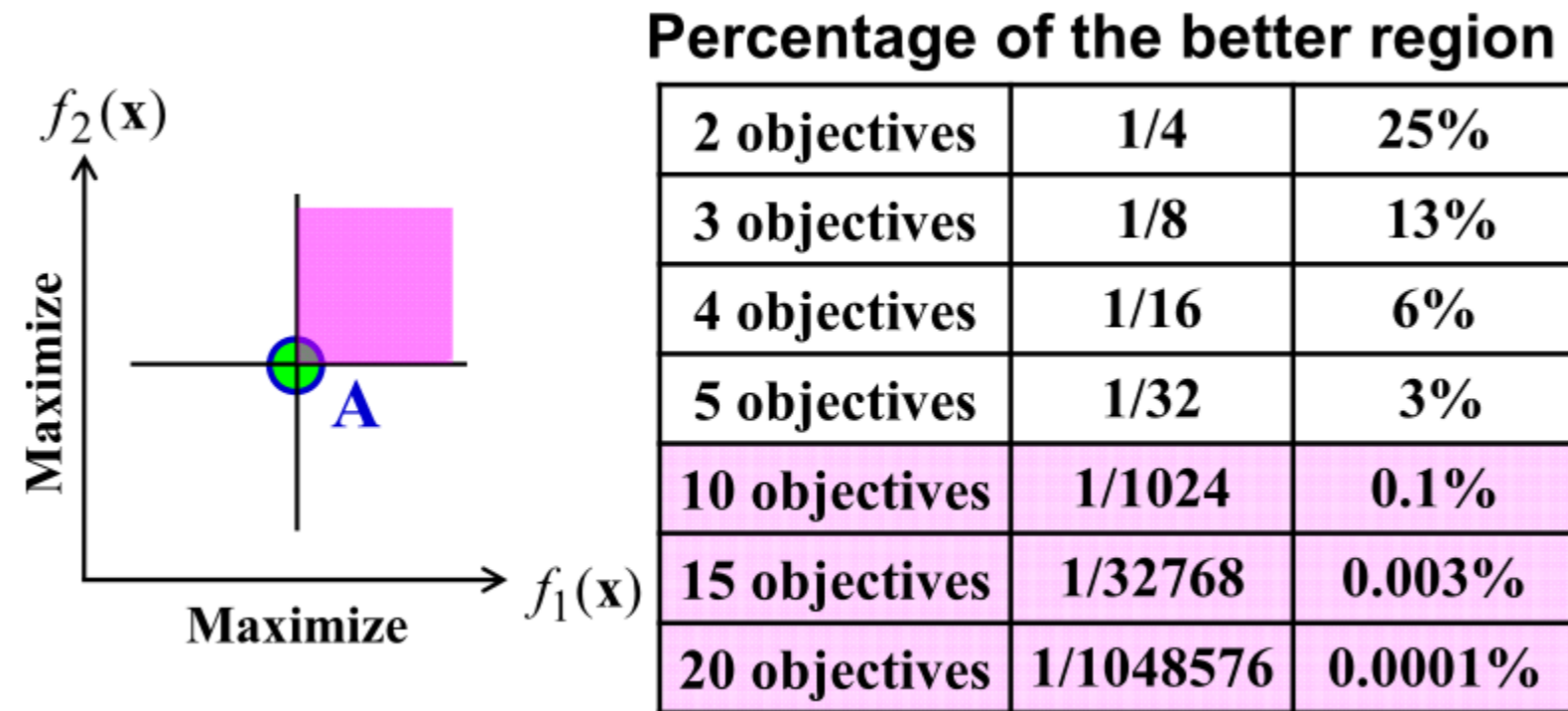


Good for all objectives. Very good except for f_5 . Only f_5 is good.

With more objectives, some objectives may be overrepresented in the non-dominated set.

Ishibuchi, Hisao, and Hiroyuki Sato. "Evolutionary many-objective optimization." [Proceedings of the Genetic and Evolutionary Computation Conference Companion](#). 2019.

MANY-OBJECTIVE OPTIMIZATION



When increasing beyond a small number (2-4) of objectives, the chance of fully non-dominated solutions decreases.

Different algorithms, visualization methods, convergence metrics are needed.

Ishibuchi, Hisao, and Hiroyuki Sato. "Evolutionary many-objective optimization." [Proceedings of the Genetic and Evolutionary Computation Conference Companion](#). 2019.

MOEAS FOR RL

An advantage of evolutionary RL:
multiple solutions along the Pareto front

Primary objective:
maximize total reward

secondary objective:
optimize different behaviors (use of specific robotic limb), increase efficiency.

Example: efficient robot locomotion

Prediction-Guided Multi-Objective Reinforcement Learning for Continuous Robot Control

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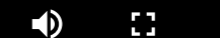
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Xu, J., Tian, Y., Ma, P., Rus, D., Sueda, S., & Matusik, W. (2020, November). Prediction-Guided Multi-Objective Reinforcement Learning for Continuous Robot Control. In International Conference on Machine Learning (pp. 10607-10616). PMLR. <http://pgmorl.csail.mit.edu/>