Computational Intelligence Master in Artificial Intelligence 2021-22

Multi-objective optimization

Nondominated Sorting Genetic Algorithm II (NSGA-II)

K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan *IEEE Trans. on Evolutionary Computation*, Vol.6, No.2, 2002





Multi-objective optimization

Problem

Let X be a search space of feasible solutions, also called a *feasible set*. Let $f: X \longrightarrow \mathbb{R}^M$, $f(x) = (f_1(x), \dots, f_M(x))$, $M \ge 2$, be the *multi-objective function* to optimize. We seek $\max_{x \in X} (f_1(x), \dots, f_M(x))$.

Domination relation and Pareto optimality

A feasible solution x_1 is said to *dominate* another solution x_2 , denoted $x_1 \succ x_2$, iff

- **1** $f_i(x_1) \ge f_i(x_2), \ \forall i : 1 \le i \le M, \text{ and } f_i(x_1) \ge f_i(x_2)$
- ② $f_j(x_1) > f_j(x_2)$ for at least one $j \in \{1, ..., M\}$.

A solution $x^* \in X$ is Pareto optimal if $\nexists x' \in X : x' \succ x^*$.

Intuitively, a solution is called nondominated or Pareto optimal if none of the objective functions can be improved in value without degrading some of the other objective values.

All Pareto optimal solutions are considered equally good.

Pareto fronts and nondominated sort algorithm

Pareto fronts

- The first Pareto front F₁ of a set P ⊆ X is the subset of all the nondominated solutions in P.
- For i > 1, the i-th Pareto front \mathcal{F}_i is the subset of all the nondominated solutions in $P \bigcup_{i < i} \mathcal{F}_j$.
- The naive method to compute sequentially the Pareto fronts of a set P following the above definition has a computational cost $O(MN^3)$, where N = |P|.
- The fast nondominated sort algorithm [Deb et al., 2002] is a clever method to compute all the Pareto fronts of a set P with computational cost O(MN²).

Fast-nondominated-sort(P) - First part

```
\mathcal{F}_1 = \emptyset
for p in P:
   S_p = \emptyset # solutions dominated by p
   n_p = \emptyset # domination counter of p
    for q in P:
       if p \succ q: # p dominates q
         S_p = S_p \cup \{q\}
       elif q \succ p: # q dominates p
          n_{p} = n_{p} + 1
    if n_p == 0:
       p_{rank} = 1 # p belongs to the first front
       \mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}
```

Fast-nondominated-sort(P) - Second part

```
i = 1
while \mathcal{F}_i \neq \emptyset:
    Q = \emptyset # members of the next front
    for p in \mathcal{F}_i:
       for q in S_n:
          n_{a} = n_{a} - 1
          if n_a == 0: # q belongs to the next front
             q_{rank} = i + 1
             Q = Q \cup \{q\}
    i = i + 1
    \mathcal{F}_i = Q
```

Crowding distance and crowded-comparison operator

Crowding distance

- Within a Pareto front \mathcal{F}_i , solutions with a less crowded surrounding should be given priority in the selection process, to guide the search toward a uniformly spread-out Pareto-optimal front.
- The *crowding distance* of p in \mathcal{F}_i is the sum of the (normalized) lengths of the edges of a hyper-rectangle of M-dim. formed by the two nearest neighbors of p in \mathcal{F}_i along each of the functions f_m .
- Hence, a greater crowding distance of a solution p means a lesser crowded region around p in \mathcal{F}_i .

Crowded-comparison operator

Given two individuals p, q (feasible solutions) of a set $P \subseteq X$, the crowded-comparison operator \succ_n is a partial order defined as:

$$p \succ_n q$$
 iff $p_{rank} < q_{rank}$ (i.e. $p \succ q$) or $(p_{rank} == q_{rank} \text{ and } p_{distance} > q_{distance})$

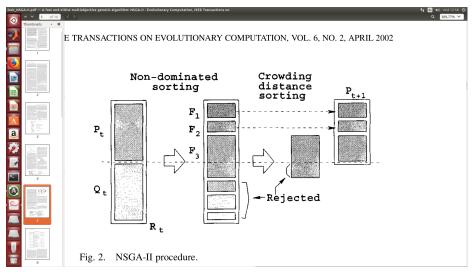
Crowding-distance-assignment(S)

```
I = |S| # number of solutions in set S
for i in range(1, l+1): # S[i] is an individual, 1 \le i \le l
   S[i]_{distance} = 0
for m in range(1, M + 1): # f_m is an objective function, 1 \le m \le M
   S = sort(S, m)
                   \# sort using m-th objective function
   S[1]_{distance} = S[I]_{distance} = \infty # extreme values must be kept
   for i in range(2,1): # for every non-extreme value, 2 \le i \le l-1
      if S[i]_{distance} \neq \infty:
         S[i]_{distance} = S[i]_{distance} + \# sum the normalized edge for m
                      (S[i+1].m - S[i-1].m) / (f_m^{max} - f_m^{min})
```

NSGA-II algorithm loop body

```
# Start with current population P_t at generation t
Q_t = \text{make-offspring}(P_t) # by tournament selection, recombination
                                    # and mutation (\lambda = \mu)
R_t = P_t \cup Q_t # mixed population to perform (\mu + \lambda) replacement
\mathcal{F} = \text{fast-nondominated-sort}(R_t) \# \mathcal{F} = (\mathcal{F}_1, \dots) \text{ set of Pareto fronts}
P_{t+1} = \emptyset
i = 1
while |P_{t+1}| + |\mathcal{F}_i| < \mu:
    crowding-distance-assignment(\mathcal{F}_i) # for later \succ_n comparison
    P_{t+1} = P_{t+1} \cup \mathcal{F}_i
    i = i + 1
crowding-distance-assignment(\mathcal{F}_i)
\mathcal{F}_i = \text{sort}(\mathcal{F}_i \succ_n) # sort in decreasing order using crowding distance
P_{t+1} = P_{t+1} \cup \mathcal{F}_i[1 : \mu - |P_{t+1}|]
t = t + 1
```

NSGA-II algorithm loop body (graphically)



taken from K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II". *IEEE Trans. on Evolutionary Computation*, Vol.6, No.2, 2002.