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Iterated Local Search

迭代局部搜索

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Outline

- Introduction
- Iterated Local Search
- Relation to Other Metaheuristics

Introduction

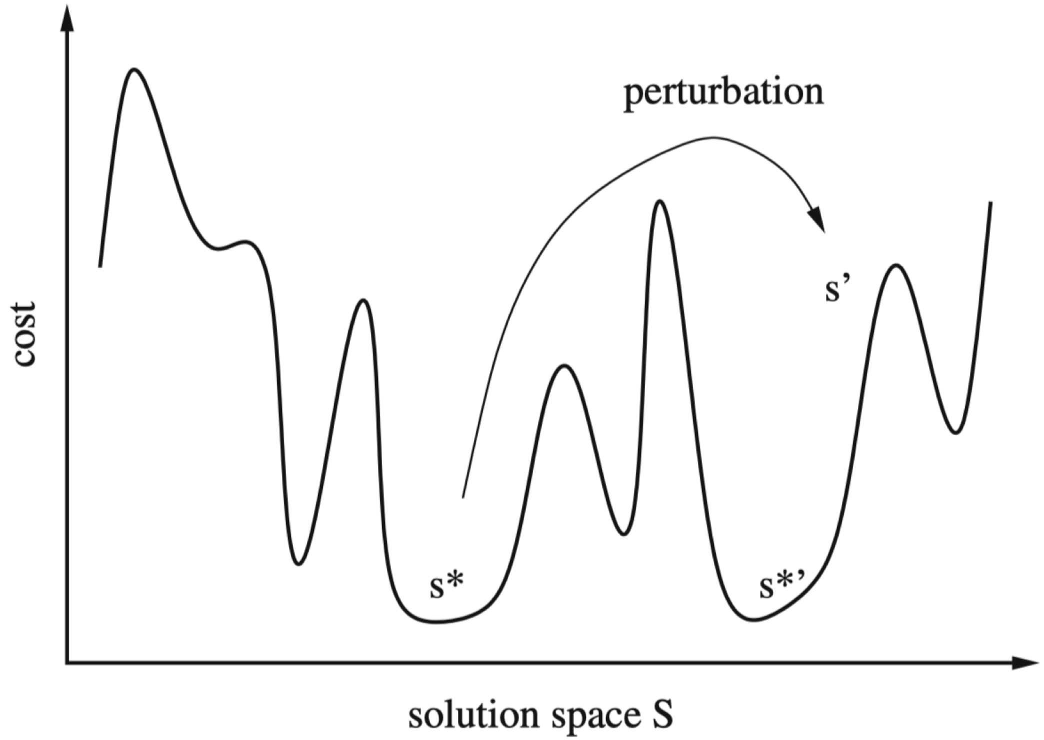
- **Iterated Local Search**
  - Key idea: focus the search on the solutions returned by a local search heuristic.
  - 4 Components:
    1. GenerateInitialSolution
    2. LocalSearch
    3. Perturbation
    4. AcceptanceCriterion

Algorithm 1 Iterated local search

$s_0 = \boxed{\text{GenerateInitialSolution}}$
$s^* = \boxed{\text{LocalSearch}(s_0)}$
repeat
    $s' = \boxed{\text{Perturbation}(s^*, \mathit{history})}$
    $s^{*\prime} = \text{LocalSearch}(s')$
    $s^* = \boxed{\text{AcceptanceCriterion}(s^*, s^{*\prime}, \mathit{history})}$
until termination condition met

Introduction

- **Iterated Local Search**
  - Starting with a local minimum s^*, we apply a perturbation leading to a solution s' . After applying LocalSearch, we find a new local minimum $s^{*\prime}$ that may be better than s^*.



Iterated Local Search

- **Generate Initial Solution:**
  - A random initial solution
  - A greedy initial solution
    1. Combined with local search, better quality solutions s_0^* ;
    2. Less improvement steps and the local search requires less CPU time.

  - Choice
    - Greedy initial solutions appear to be recommendable when one needs low-cost solutions quickly.
    - For longer runs, the initial solution seems to be less relevant, so the user can choose the easiest to implement.

Iterated Local Search

- **Perturbation:**
  - ILS escapes from local optima by applying perturbations to the current local minimum.

✦ **Strong perturbation:** usually determines a long local search phase but decreases the probability of hitting the same local optimum (in the limit, it results in a random restart)
✦ **Weak perturbation:** usually leads to a short local search phase but at the same time increases the probability of hitting the same local optimum over and over (stagnation)
✦ The objective is to find a perturbation function that can preserve the good aspects of the current solution while escaping from the current local optimum

- Adaptive perturbation
  - exploit the search history(e.g. TS)
  - change its strength during the search according to an a priori defined scheme.

Iterated Local Search

- **Acceptance Criterion :**
  - Intensification

$$\texttt{Better}(s^*, s^{*\prime}, \text{history}) = \begin{cases} s^{*\prime} & \text{if } \mathscr{C}(s^{*\prime}) < \mathscr{C}(s^*) \\ s^* & \text{otherwise.} \end{cases}$$

  - Diversification

$$\texttt{RW}(s^*, s^{*\prime}, \text{history}) = s^{*\prime}.$$

  - A simulated annealing type acceptance criterion

$$\texttt{LSMC}(s^*, s^{*\prime}, \text{history}) = \begin{cases} s^{*\prime} & \text{if } \mathscr{C}(s^{*\prime}) < \mathscr{C}(s^*) \\ \exp\{(\mathscr{C}(s^*) - \mathscr{C}(s^{*\prime}))/T\} & \text{otherwise.} \end{cases}$$

Iterated Local Search

- **Acceptance Criterion :**
  - If no improved solution has been found for a given number of iterations.
  - Then restart.

$$\texttt{Restart}(s^*, s^{*\prime}, \text{history}) = \begin{cases} s^{*\prime} & \text{if } \mathscr{C}(s^{*\prime}) < \mathscr{C}(s^*) \\ s & \text{if } \mathscr{C}(s^{*\prime}) \geq \mathscr{C}(s^*) \text{ and } i - i_{\text{last}} > i_{\text{r}} \\ s^* & \text{otherwise.} \end{cases} \quad (12.3)$$

Relation to Other Metaheuristics

- **Neighborhood-Based Metaheuristics**
  - Neighborhood-based Metaheuristics avoid local optimal by allowing moves to worse solutions in the neighborhood of the current solution.
    - SA: sample neighborhood randomly and accept worse solutions with a probability.
    - TS: avoid cycles by declaring tabu attributes of visited solutions.
    - GLS: penalize certain solution components to dynamically modify evaluation function.

  - All can be used as the local search procedure in ILS.
  - Trade-off between computation time and costs.

  - SA: an ILS without a local search phase (SA samples the original space S and not the reduced space S^*) and where the acceptance criteria are $\mathrm{LSMC}(s^*, s^{*\prime}, \mathrm{history})$.
  - TS: the use of memory inspires for deriving ILS variants.

Relation to Other Metaheuristics

- **Multi-start-Based Metaheuristics**
  - **Constructive metaheuristics:** ACO GRASP
    - Difference: ILS does not construct solutions.
    - ILS can be used instead of the embedded “local search” in ACO or GRASP.

  - **Perturbation-based metaheuristics:**
    - Population-based: EA MA SS
      - recombination of multiple solutions
        - EA: crossover
        - SS: recombination of multiple solutions
    - No population: ILS VNS
      - applying perturbations to single solutions.
      - Difference between ILS and VNS(closet to ILS)
        - ILS: explicit goal of building a walk in locally optimal solutions.
        - VNS: systematically change neighborhoods during the search.

Conclusion

- **Advantages:**
  - Simple, easy to implement, robust, and highly effective.
- **Essential idea:**
  - Focus the search not on the full space of solutions but on a smaller subspace defined by the solutions that are locally optimal for a given optimization engine.
- The success of ILS lies in the biased sampling of this set of local optima.
- Depend mainly on the choice of the local search, the perturbation, and the acceptance criterion.

Thank You !