DM63
HEURISTICS FOR
COMBINATORIAL OPTIMIZATION

Lecture 7

Tabu Search,
Dynamic Local Search,
Iterated Local Search

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Outline

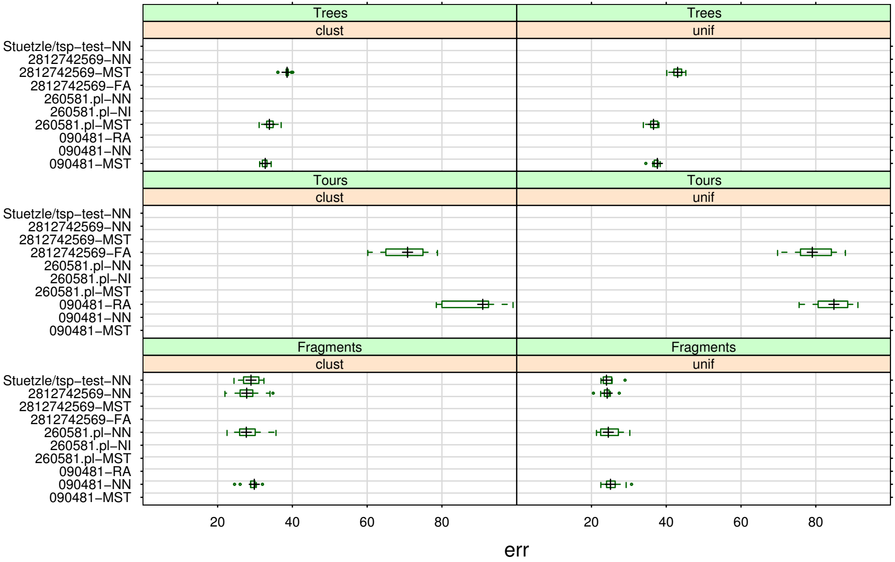
1. Competition

2. Tabu Search

3. Dynamic Local Search

4. Ejection Chains and Dynasearch

5. Iterated Local Search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Tabu Search

Key idea: Use aspects of search history (memory) to escape from local minima.

- Associate *tabu attributes* with candidate solutions or solution components.
- Forbid steps to search positions recently visited by underlying iterative best improvement procedure based on tabu attributes.

Tabu Search (TS):

determine initial candidate solution s
While *termination criterion* is not satisfied:
  determine set N' of non-tabu neighbours of s
  choose a best improving candidate solution s' in N'

  update tabu attributes based on s'
  $s := s'$

Example: Tabu Search for GCP – TabuCol

- **Search space:** set of all complete colourings of G.
- **Solution set:** proper colourings of G.
- **Neighbourhood relation:** one-exchange.
- **Memory:** Associate tabu status (Boolean value) with each pair (v, c).
- **Initialisation:** a construction heuristic
- **Search steps:**
  - pairs (v, c) are tabu if they have been changed in the last *tt* steps;
  - neighbouring colourings are admissible if they can be reached by changing a non-tabu pair or have fewer unsatisfied edge constr. than the best colouring seen so far (*aspiration criterion*);
  - choose uniformly at random admissible colouring with minimal number of unsatisfied constraints.
- **Termination:** upon finding a proper colouring for G or after given bound on number of search steps has been reached.

Note:

- Non-tabu search positions in $N(s)$ are called *admissible neighbours of s*.
- After a search step, the current search position or the solution components just added/removed from it are declared *tabu* for a fixed number of subsequent search steps (*tabu tenure*).
- Often, an additional *aspiration criterion* is used: this specifies conditions under which tabu status may be overridden (*e.g.*, if considered step leads to improvement in incumbent solution).
- Crucial for efficient implementation:
  - keep time complexity of search steps minimal by using special data structures, incremental updating and caching mechanism for evaluation function values;
  - efficient determination of tabu status: store for each variable x the number of the search step when its value was last changed it_x; x is tabu if $it - it_x < tt$, where $it =$ current search step number.

Note: Performance of Tabu Search depends crucially on setting of tabu tenure *tt*:

- *tt* too low $\Rightarrow$ search stagnates due to inability to escape from local minima;
- *tt* too high $\Rightarrow$ search becomes ineffective due to overly restricted search path (admissible neighbourhoods too small)

Advanced TS methods:

- **Robust Tabu Search** [Taillard, 1991]:
  repeatedly choose *tt* from given interval;
  also: force specific steps that have not been made for a long time.
- **Reactive Tabu Search** [Battiti and Tecchiolli, 1994]:
  dynamically adjust *tt* during search;
  also: use escape mechanism to overcome stagnation.

Further improvements can be achieved by using *intermediate-term* or *long-term memory* to achieve additional *intensification* or *diversification*.

Examples:

- Occasionally backtrack to *elite candidate solutions*, *i.e.*, high-quality search positions encountered earlier in the search; when doing this, all associated tabu attributes are cleared.
- Freeze certain solution components and keep them fixed for long periods of the search.
- Occasionally force rarely used solution components to be introduced into current candidate solution.
- Extend evaluation function to capture frequency of use of candidate solutions or solution components.

Tabu search algorithms algorithms are state of the art for solving many combinatorial problems, including:

- SAT and MAX-SAT
- the Constraint Satisfaction Problem (CSP)
- many scheduling problems

Crucial factors in many applications:

- choice of neighbourhood relation
- efficient evaluation of candidate solutions (caching and incremental updating mechanisms)

Example: Tabu Search for QAP

- **Solution representation**: permutation π
- **Initial Solution**: randomly generated
- **Neighbourhood**: interchange
  $\Delta_I : \quad \delta(\pi) = \{\pi' | \pi'_k = \pi_k \text{ for all } k \neq \{r,s\} \text{ and } \pi'_i = \pi_j, \pi'_j = \pi_i\}$
- **Tabu status**: forbid δ that place back the items in the positions they have already occupied in the last *tt* iterations (short term memory)

- Implementation details:
  - compute $f(\pi') - f(\pi)$ in $O(n)$ or $O(1)$ by storing the values all possible previous moves.
  - maintain a matrix $[T_{ij}]$of size $n \times n$ and write the last time item i was moved in location k
  - δ is tabu if it satisfies both:
    - $T_i\pi(j)$ + tabu list size $\geq$ current iteration
    - $T_j\pi(i)$ + tabu list size $\geq$ current iteration

Example: Robust Tabu Search for QAP

- **Aspiration criteria**:
  - allow forbidden δ if it improves the last π^*
  - select δ if never chosen in the last A iterations (long term memory)
- Parameters: *tt* $\in [\lfloor 0.9n \rfloor, \lceil 1.1n + 4 \rceil]$ and $A = 5n^2$

Example: Reactive Tabu Search for QAP

- **Aspiration criteria**:
  - allow forbidden δ if it improves the last π^*
- **Tabu Tenure**
  - maintain a hash table (or function) to record previously visited solutions
  - increase *tt* by a factor $\alpha_{inc}(= 1.1)$ if the current solution was previously visited
  - decrease *tt* by a factor $\alpha_{dec}(= 0.9)$ if *tt* not changed in the last $sttc$ iterations or all moves are tabu
- Trigger escape mechanism if a solution is visited more than $nr(= 3)$ times
- Escape mechanism $= 1 + (1 + r) \cdot ma/2$ random moves

Dynamic Local Search

- **Key Idea:** Modify the evaluation function whenever a local optimum is encountered.
- Associate *penalty weights* (*penalties*) with solution components; these determine impact of components on evaluation function value.
- Perform Iterative Improvement; when in local minimum, increase penalties of some solution components until improving steps become available.

Dynamic Local Search (DLS):

determine *initial candidate solution* s
initialise penalties
While *termination criterion* is not satisfied:
  compute *modified evaluation function* g' from g
    based on *penalties*
  perform *subsidiary perturbative search* on s
    using *evaluation function* g'
  update penalties based on s

Dynamic Local Search (continued)

- **Modified evaluation function:**

$$g'(\pi, s) := g(\pi, s) + \sum_{i \in SC(\pi', s)} penalty(i),$$

  where $SC(\pi', s) =$ set of solution components
  of problem instance π' used in candidate solution s.

- **Penalty initialisation:** For all i: $penalty(i) := 0$.

- **Penalty update** in local minimum s: Typically involves *penalty increase* of some or all solution components of s; often also occasional *penalty decrease* or *penalty smoothing*.

- **Subsidiary perturbative search:** Often *Iterative Improvement*.

Potential problem:

Solution components required for (optimal) solution
may also be present in many local minima.

Possible solutions:

A: Occasional decreases/smoothing of penalties.

B: Only increase penalties of solution components that are least likely to occur in (optimal) solutions.

Implementation of **B**:

[Voudouris and Tsang, 1995] Only increase penalties of solution components i with maximal utility:

$$util(s', i) := \frac{g_i(\pi, s')}{1 + penalty(i)}$$

where $g_i(\pi, s') =$ solution quality contribution of i in s'.

Example: Guided Local Search (GLS) for the TSP

[Voudouris and Tsang 1995; 1999]

- **Given:** TSP instance G
- **Search space:** Hamiltonian cycles in G with n vertices;
- **Neighbourhood:** 2-edge-exchange;
- **Solution components** edges of G;
  $f(G, p) := w(p)$; $f_e(G, p) := w(e)$;
- **Penalty initialisation:** Set all edge penalties to zero.
- **Subsidiary perturbative search:** Iterative First Improvement.
- **Penalty update:** Increment penalties for all edges with maximal utility by

  $$\lambda := 0.3 \cdot \frac{w(s_{\textit{2-opt}})}{n}$$

  where $s_{\textit{2-opt}}$ = 2-optimal tour.

Ejection Chains

- Attempt to use large neighborhoods without examining them exhaustively
- Sequences of successive steps each influenced by the precedent and determined by myopic choices
- Limited in length
- Local optimality in the large neighborhood is not guaranteed.

Example (on TSP): successive 2-exchanges where each exchange involves one edge of the previous

Example (on GCP): successive 1-exchanges: a vertex v_1 changes colour from $\varphi(v_1) = c_1$ to c_2, in turn forcing some vertex v_2 with color $\varphi(v_2) = c_2$ to change to another color c_3 (which may be different or equal to c_1) and again forcing a vertex v_3 with colour $\varphi(v_3) = c_3$ to change to colour c_4.

Dynasearch

- Iterative improvement method based on building complex search steps from combinations of simple search steps.
- Simple search steps constituting any given complex step are required to be *mutually independent*, *i.e.*, do not interfere with each other w.r.t. effect on evaluation function and feasibility of candidate solutions.

  Example: Independent 2-exchange steps for the TSP:

  Therefore: Overall effect of complex search step = sum of effects of constituting simple steps; complex search steps maintain feasibility of candidate solutions.
- **Key idea:** Efficiently find optimal combination of mutually independent simple search steps using *Dynamic Programming*.

Hybrid LS Methods

Combination of 'simple' LS methods often yields substantial performance improvements.

Simple examples:

- Commonly used restart mechanisms can be seen as hybridisations with Uninformed Random Picking
- Iterative Improvement + Uninformed Random Walk = Randomised Iterative Improvement

Iterated Local Search

Key Idea: Use two types of LS steps:

- *subsidiary perturbative (local) search* steps for reaching local optima as efficiently as possible (intensification)
- *perturbation steps* for effectively escaping from local optima (diversification).

Also: Use *acceptance criterion* to control diversification *vs* intensification behaviour.

Iterated Local Search (ILS):

determine initial candidate solution s
perform *subsidiary perturbative search* on s
While termination criterion is not satisfied:

> $r := s$
> perform *perturbation* on s
> perform *subsidiary perturbative search* on s
>
> based on *acceptance criterion*,
> keep s or revert to $s := r$

Note:

- *Subsidiary perturbative search* results in a local minimum.
- ILS trajectories can be seen as walks in the space of local minima of the given evaluation function.
- *Perturbation phase* and *acceptance criterion* may use aspects of *search history* (*i.e.*, limited memory).
- In a high-performance ILS algorithm, *subsidiary perturbative search*, *perturbation mechanism* and *acceptance criterion* need to complement each other well.

Subsidiary perturbative search:

- More effective subsidiary perturbative search procedures lead to better ILS performance.
  Example: 2-opt *vs* 3-opt *vs* LK for TSP.
- Often, subsidiary perturbative search = iterative improvement, but more sophisticated LS methods can be used.
  (*e.g.*, Tabu Search).

Perturbation mechanism:

- Needs to be chosen such that its effect *cannot* be easily undone by subsequent perturbative search phase.
  (Often achieved by search steps larger neighbourhood.)
  Example: perturbative search = 3-opt, perturbation = 4-exchange steps in ILS for TSP.
- A perturbation phase may consist of one or more perturbation steps.
- Weak perturbation $\Rightarrow$ short subsequent perturbative search phase; *but:* risk of revisiting current local minimum.
- Strong perturbation $\Rightarrow$ more effective escape from local minima; *but:* may have similar drawbacks as random restart.
- Advanced ILS algorithms may change nature and/or strength of perturbation adaptively during search.

Acceptance criteria:

- Always accept the *better* of the two candidate solutions

  ⇒ ILS performs Iterative Improvement in the space of local optima reached by subsidiary perturbative search.

- Always accept the *more recent* of the two candidate solutions

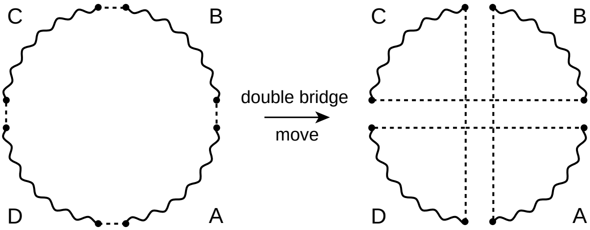
  ⇒ ILS performs random walk in the space of local optima reached by subsidiary perturbative search.

- Intermediate behaviour: select between the two candidate solutions based on the *Metropolis criterion* (*e.g.*, used in *Large Step Markov Chains* [Martin *et al.*, 1991].

- Advanced acceptance criteria take into account search history, *e.g.*, by occasionally reverting to *incumbent solution*.

Example: Iterated Local Search for the TSP (1)

- **Given:** TSP instance G.
- **Search space:** Hamiltonian cycles in G.
- **Subsidiary perturbative search:** Lin-Kernighan variable depth search algorithm
- **Perturbation mechanism:**
  'double-bridge move' $=$ particular 4-exchange step:



- **Acceptance criterion:** Always return the better of the two given candidate round trips.

Example: Iterated Local Search for the TSP (2)

Note:

- Double-bridge move perutrbation cannot be directly reversed by a sequence of 2-exchange steps as performed by "usual" LK implementations.
- This perturbation is empirically shown to be effective independent of instance size.

Note:

- This ILS algorithm for the TSP is known as *Iterated Lin-Kernighan (ILK) Algorithm*.
- Although ILK is structurally rather simple, an efficient implementation was shown to achieve excellent performance [Johnson and McGeoch, 1997].

Iterated local search algorithms ...

- are typically rather easy to implement (given existing implementation of subsidiary simple LS algorithms);
- achieve state-of-the-art performance on many combinatorial problems, including the TSP.

There are many LS approaches that are closely related to ILS, including:

- Large Step Markov Chains [Martin *et al.*, 1991]
- Chained Local Search [Martin and Otto, 1996]
- Variants of Variable Neighbourhood Search (VNS) [Hansen and Mladenovič, 2002]