

DM811
Heuristics for Combinatorial Optimization

Lecture 13
Exercises: GCP

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- ✓ Combinatorial Optimization, Methods and Models
- ✓ CH and LS: overview
- ✓ Working Environment and Solver Systems
- ~ Methods for the Analysis of Experimental Results
- ✓ Construction Heuristics
- ✓ Local Search: Components, Basic Algorithms
 - Local Search: Neighborhoods and Search Landscape
 - Efficient Local Search: Incremental Updates and Neighborhood Pruning
- ~ Stochastic Local Search & Metaheuristics
 - Configuration Tools: F-race
 - Very Large Scale Neighborhoods

Examples: GCP, CSP, TSP, SAT, MaxIndSet, SMTWP, Steiner Tree, Unrelated Parallel Machines, p-median, set covering, QAP, ...

Outline

Recap.
GCP

1. Recap.

2. GCP

Outline

1. Recap.

2. GCP

Summary: Local Search Algorithms

(as in [Hoos, Stützle, 2005])

For given problem instance π :

1. search space S_π
2. neighborhood relation $\mathcal{N}_\pi \subseteq S_\pi \times S_\pi$
3. evaluation function $f_\pi : S \rightarrow \mathbf{R}$
4. set of memory states M_π
5. initialization function $\text{init} : \emptyset \rightarrow S_\pi \times M_\pi$
6. step function $\text{step} : S_\pi \times M_\pi \rightarrow S_\pi \times M_\pi$
7. termination predicate $\text{terminate} : S_\pi \times M_\pi \rightarrow \{\top, \perp\}$

After implementation and test of the above components, improvements in **efficiency** (ie, computation time) can be achieved by:

- A. fast incremental evaluation (ie, delta evaluation)
- B. neighborhood pruning
- C. clever use of data structures

Improvements in **effectiveness**, ie, quality, can be achieved by:

- D. application of a metaheuristic
- E. definition of a larger neighborhood

Outline

1. Recap.

2. GCP

Polynomial time reduction of the graph G to G' such that given a feasible k -coloring for G' it is straightforward to derive a feasible k -coloring for G .

Searching for a k -coloring (k fixed)

- Remove under-constrained nodes: $v \in V, d(v) < k$
- Remove subsumed nodes: $v \in V$, if $\exists u \in V, uv \notin E, A(v) \subseteq A(u)$
- Merge nodes that must have the same color: eg, if any nodes are fully connected to a clique of size $k - 1$, then these nodes can be merged into a single node with all the constraints of its constituents, because they must have the same color.

Local Search for Graph coloring

[Chiarandini et al., 2007]

Different choices for the **candidate solutions**:

decision vs optimization	assignment of colors to V	level of feasibility	
k -fixed	complete	proper	
k -fixed	partial	proper	+++
k -fixed	complete	improper	+++
k -fixed	partial	improper	-
k -variable	complete	proper	++
k -variable	partial	proper	-
k -variable	complete	improper	++
k -variable	partial	improper	-

imply different **neighborhood structures** and **evaluation functions**.

Scheme: k -fixed / complete / improper

Local Search

- Solution representation: `var{int} a[|V|](1..K)`
- Evaluation function: conflicting edges or conflicting vertices
- Neighborhood: one-exchange

Naive approach: $O(n^2k)$

Neighborhood examination

for all $v \in V$ **do**

```
┌ for all  $k \in 1..k$  do
└   ┌ compute  $\Delta(v, k)$ 
```

Better approach:

- V^c set of vertices involved in a conflict
- $\Delta(v, k)$ stores number of vertices adjacent to v in each color class k

Procedure Initialise_ $\Delta(G, a)$

$\Delta = 0$

for each v in V **do**

┌ **for** each u in $A_V(v)$ **do**
└ $\Delta(u, a(v)) = \Delta(u, a(v)) + 1$

Procedure Examine($G, N(a)$)

for each v in V^c **do**

┌ **for** each $k \in \Gamma$ **do**
└ compute $\Delta(v, k) = \Delta(v, k) - \Delta(v, a(v))$

Procedure Update_ $\Delta(G, a, v, k)$

for each u in $A_V(v)$ **do**

┌ $\Delta(u, a(v)) = \Delta(u, a(v)) - 1$
└ $\Delta(u, k) = \Delta(u, k) + 1$

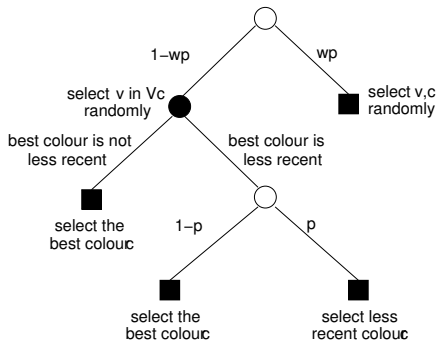
Comet examples

Tabu Search

Recap.
GCP

```
./coloring.co
```

Randomized Iterative Improvement



Guided Local Search

- evaluation function: $f'(s) = f(s) + \lambda \cdot \sum_{i=1}^{|E|} w_i \cdot I_i(\mathcal{C})$
 w_i is the penalty cost associated to edge i ;
 $I_i(s)$ is an indicator function that takes the value 1 if edge i causes a colour conflict in s and 0 otherwise;
parameter λ
- penalty weights are initialised to 0
- updated each time Iterative Improvement reaches a local optimum in f' ;
increment the penalties of all edges with maximal utility.

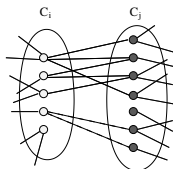
$$u_i = I_i(s) \cdot \frac{1}{1 + w_i}.$$

- once a local optimum is reached, the search continues for sw non-worsening exchanges (side walk moves) before the evaluation function f' is updated. Update of w_i and f' is done in the worst case in $O(k|V|^2)$.

Scheme: k -variable / complete / proper

Local Search

- Solution representation: $\text{var}\{\text{int}\} a[|V|](1..K)$
- Neighborhood: one-exchange restricted to feasible moves
Kempe chains



- Evaluation function: $f(s) = -\sum_{i=1}^k |C_i|^2$
favours few large color classes wrt. many small color classes

Local Search for GCP

Iterated Greedy

Scheme: k -variable / complete / proper

Local Search

- Solution representation: $\text{var}\{\text{int}\} a[|V|](1..K)$
- Neighborhood: permutation of color classes + greedy algorithm
- Evaluation function: number of colors

Theorem

Let φ be a k -coloring of a graph G and π a permutation such that if $\varphi(v_{\pi(i)}) = \varphi(v_{\pi(m)}) = c$ then $\varphi(v_{\pi(j)}) = c, \forall i \leq j \leq m$.

Applying the greedy algorithm to π will produce a coloring using k or fewer colors.

Scheme: k -variable / complete / improper

Local Search

- Solution representation: $\text{var}\{\text{int}\} a[|V|](1..K)$
- Neighborhood: one-exchange
- Evaluation function: $f(s) = -\sum_{i=1}^k |C_i|^2 + \sum_{i=1}^k 2|C_i||E_i|$

Ev. function chosen in such a way that an improvement in feasibility (in the worst case by coloring a vertex to a new color class) offsets any improvement in solution quality (in the best case by moving a vertex to the first color class).

Chiarandini M., Dumitrescu I., and Stützle T. (2007). **Stochastic local search algorithms for the graph colouring problem**. In *Handbook of Approximation Algorithms and Metaheuristics*, edited by T.F. Gonzalez, Computer & Information Science Series, pp. 63.1–63.17. Chapman & Hall/CRC, Boca Raton, FL, USA. Preliminary version available as *Tech. Rep.* AIDA-05-03 at Intellectics Group, Computer Science Department, Darmstadt University of Technology, Darmstadt, Germany.