# Choosing best shortcuts for a path

## Martin Pečar

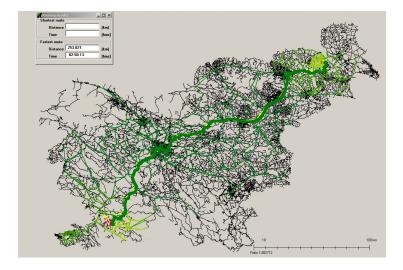
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# Motivation - example



- The Shortcut Problem: asks what is the best set of k additional edges (shortcuts) so that shortest paths will be preserved and the average hop length of paths will be minimal;
- Multi-Constrained Shortest Path: find a path from s to t with lowest cost, subject to constraints;
- Onstrained Network Optimization

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#### Weighted multiobjective network design problem

 $\mathbf{B} \in \mathbb{R}_0^{+d^2}$ a vector of constraints ("budget")G = (V, E)a directed (multi)graph $\mathbf{c} : E \mapsto \mathbb{R}_0^{+d^1}$ costs $\mathbf{b} : E \mapsto \mathbb{R}_0^{+d^2}$ "building" costs $\mathbf{w} : V \times V \mapsto \mathbb{R}_0^{+d^1}$ weightsDetermine  $E_0 \subset E$  such that it satisfies the constrains $\mathbf{b}(E_0) \leq \mathbf{B}$  and achieves

$$\min_{E^S \subset E} (\sum_{i,j} \mathbf{w}_{ij} \mathbf{c}(P_{G(V,E^S)}(i,j)))$$

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Weighted multiobjective network design problem

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a vector of constraints ("budget") a directed (multi)graph

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Weighted multiobjective network design problem  $\mathbf{B} \in \mathbb{R}_{0}^{+d2}$ 

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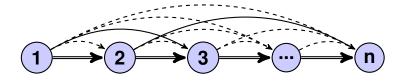
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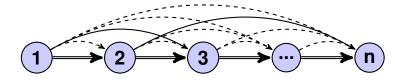
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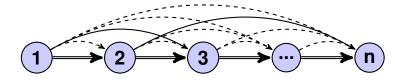
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- $b(e_s)$  can be different.

- $w_{1n} = 1$ , other  $w_{ij} = 0 \Rightarrow$  constrained shortest path;
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Subpath travelling costs

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<i>C</i> <sub>34</sub>	<b>C</b> 35		
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# b = 1 Constrained shortest path

$$c(1, n, B) = \min_{i,k} (c(1, i, k) + c(i, n, B - k))$$

 $k = \lfloor B \rfloor$ 

Algorithm 1 Dynamic Programming CSP

1: for l = 0 to k do 2: for i = 1 to n do 3: for j = i to n do 4:  $c(i, j, l) = \min_{v,s}(c(i, v, s) + c(v, j, l - s))$ 5:  $c(i, j, l) = \min(c(i, j, l), c_{ij}^{s})$ 6: end for 7: end for 8: end for

Complexity is  $O(k^2 n^3)$ 

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## Algorithm 2 Dynamic Programming CSP

1: <b>for</b> <i>I</i> = 0 to <i>k</i> <b>do</b>		
2:	for <i>i</i> = 1 to <i>n</i> do	
3:	for <i>j</i> = <i>i</i> to <i>n</i> do	
4:	$c(i,j,l) = \min_{v,s}(c(i,v,s) + c(v,j,l-s))$	
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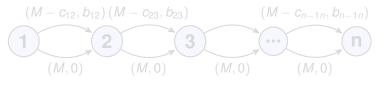
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## Algorithm 3 Dynamic Programming CSP

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Even the simplest form (each arc replaced by a shortcut) is NP-complete, can be translated to knapsack problem



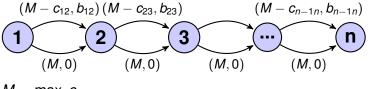
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# The set of used shortcuts uniquely defines the resulting shortest path.

Two shortcuts are *compatible*, if (interiors of) the intervals of the indexes of the end vertices are not overlapping. The shortest path can only contain compatible edges.

Example: (5,9) and (7,12) are not compatible, while (5,9) and (9,12) are.

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Gain of using a shortcut is

$$g(e_{ij}^{s}) = (\sum_{l=i}^{j-1} c_{ll+1}) - c_{ij}$$

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If the sets are compatible, then  $g(S_O) \ge g(S_S) \Rightarrow c(P_{S_O}) \le c(P_{S_S}).$ 

 $\begin{array}{l} \overline{P_{S_S}} \text{ are edges from } P \text{ which are skipped in } P_{S_S}.\\ c(P_{S_S}) = c(P) + c(S_S) - c(\overline{P_{S_S}}) = c(P) - g(S_S)\\ c(P_{S_O}) = c(P) + c(S_O) - c(\overline{P_{S_O}}) = c(P) - g(S_O)\\ g(S_O) \geq g(S_S) \Rightarrow c(P_{S_O}) \leq c(P_{S_S}) \end{array}$ 

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# Algorithm 4 Greedy CSP

- 1: Assign each shortcut  $e_S$  its normalized gain  $g_N(e_S)$
- 2: Sort shortcuts S by their normalized gain (descending)

```
4: while b(S_0) < B do
 5: if S(i) compatible with S_0 then
11: if g(S(j)) > g(S_0) then
13: end if
```

## Algorithm 5 Greedy CSP

- 1: Assign each shortcut  $e_S$  its normalized gain  $g_N(e_s)$
- 2: Sort shortcuts S by their normalized gain (descending)

3: 
$$S_O = \{\}, i = 1$$

- 4: while  $b(S_O) < B$  do
- 5: **if** S(i) compatible with  $S_O$  **then**

$$S_O = S_O \cup S(i)$$

- 7: end if
- 8: İ++

## 9: end while

```
      10: for j = 1 to m do

      11: if g(S(j)) > g(S_O) for ```

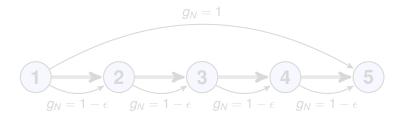
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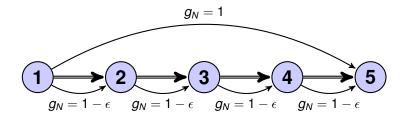
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8: i++  
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# 2-approximation?



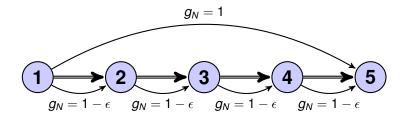
 $2\frac{B}{b_{max}}$ -approximation

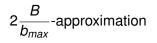
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# • Weighted multiobjective CNO was defined

• Special cases of CSP were discussed

Further work - find effective solutions for wider classes of graphs

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Further work - find effective solutions for wider classes of graphs

CSP is composed of 2 problems:

- find shortest path
- find path, cheaper than B

Both are in P, but the composed problem is NP-hard

What can we tell about the complexity of the composed problem, based on complexity of the subproblems and the type of composition? Questions, comments, ideas, ···?