

# CS 420: Advanced Algorithm Design and Analysis

## Spring 2015 – Lecture 13

Department of Computer Science  
University of British Columbia



February 24, 2015

# Announcements

## Assignments...

- ▶ Sample solutions to Asst 4 (and Midterm I) have been posted
- ▶ Asst5...due Thursday

## Midterm II...

- ▶ Q/A session...next Tuesday (March 03); 5:30-7:00; **DMPT 310**
- ▶ Exam...Wednesday (March 04); 5:30-7:00; **DMPT 310**
- ▶ ...on material up to and including this Thursday's class

## Readings...

- ▶ minimum-cost path problems [Erickson, Chapt 21, 22; Cormen+, Chapt 25 26; ...]
- ▶ edit-distance [Erickson, Chapt. 5.5, 6]

# Last classes...

## Graph algorithms

- ▶ path existence (connectivity) cont.
- ▶ optimization (minimum cost/shortest paths)
  - ▶ minimum length and minimum cost paths
  - ▶ properties of minimum cost paths
  - ▶ properties of edge relaxation
  - ▶ algorithms for *single source* min-cost paths
    - ▶ Bellman Ford
    - ▶ Dijkstra
    - ▶ comparison of Bellman-Ford and Dijkstra
  - ▶ all-pairs min-cost paths
    - ▶ Johnson's algorithm, using *edge re-weighting*

# Today...

## Min-cost path problems

- ▶ all-pairs of endpoints (cont.)
  - ▶ algorithms for dense graphs, using dynamic programming

## Edit distance problems

- ▶ dynamic programming solutions
- ▶ reformulation as (single source, single destination) min-cost path problem

# Coming up...

## Min-cost path problems

- ▶ issues related to real-world constraints
  - ▶ robustness (failure tolerance)
  - ▶ single-source single destination queries
- ▶ issues motion planning (continuous path problems)
  - ▶ paths on terrains
  - ▶ obstacle avoidance
  - ▶ curvature constraints

## Algorithms for all-pairs min-cost paths

Problem: Given  $G$ , determine  $\delta(u, v)$ , for all  $u, v \in V$ .

Johnson's algorithm (or repeated Dijkstra) is particularly efficient ( $O(n \cdot (m + n \lg n))$ ) for *sparse* graphs (graphs with  $m \ll n^2$ ).

What about dense graphs?

There are two straightforward *dynamic programming* solutions in this case, both of which involve solving the problem with progressively relaxed *structural constraints*.

1. path-length constraints
2. intermediate-vertex constraints

In both cases, we will assume the vertices are labeled  $1, 2, \dots, n$ .

## All-pairs min-cost paths, by dynamic programming

### path-length constraint relaxation

Let  $d_{ij}^{(r)}$  denote the minimum cost path from vertex  $i$  to vertex  $j$ , containing at most  $r$  edges. Then,

1.  $d_{ij}^{(0)} = 0$ , if  $i = j$  (and  $\infty$ , otherwise), and  $d_{ij}^{(1)} = c(i, j)$
2.  $d_{ij}^{(n-1)} = \delta(i, j)$

So, it suffices to see how to construct  $d_{ij}^{(r)}$  values given  $d_{ij}^{(r-1)}$  values.

*Key observation:*

$$\begin{aligned}d_{ij}^{(r)} &= \min\{d_{ij}^{(r-1)}, \min_{1 \leq k \leq n} \{d_{ik}^{(r-1)} + c(k, j)\}\} \\ &= \min\{d_{ij}^{(r-1)}, \min_{1 \leq k \leq n} \{d_{ik}^{(r-1)} + d_{kj}^{(1)}\}\} \\ &= \min_{1 \leq k \leq n} \{d_{ik}^{(r-1)} + d_{kj}^{(1)}\}\end{aligned}$$

# All-pairs min-cost paths, by dynamic programming

## path-length constraint relaxation (cont.)

This recurrence suggests the following dynamic programming solution:

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```
1: construct  $d_{**}^{(0)}$  and  $d_{**}^{(1)}$ 
2: for  $r = 2$  to  $n - 1$  do
3:   for  $i = 1$  to  $n$  do
4:     for  $j = 1$  to  $n$  do
5:        $d_{ij}^{(r)} \leftarrow \min_{1 \leq k \leq n} \{d_{ik}^{(r-1)} + d_{kj}^{(1)}\}$ 
6:     end for
7:   end for
8: end for
```

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Cost is  $O(n^4)$  in total.



## All-pairs min-cost paths, by dynamic programming path-length constraint relaxation (cont.)

But...

1.  $d_{ij}^{(r)} = d_{ij}^{(n-1)}$ , for all  $r \geq n - 1$ ; and
2.  $d_{ij}^{(2r)} = \min_{1 \leq k \leq n} \{d_{ik}^{(r)} + d_{kj}^{(r)}\}$

So we can compute:

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```
1: construct  $d_{**}^{(0)}$  and  $d_{**}^{(1)}$ 
2: for  $t = 1$  to  $\lceil \lg n \rceil$  do
3:   for  $i = 1$  to  $n$  do
4:     for  $j = 1$  to  $n$  do
5:        $d_{ij}^{(2^t)} = \min_{1 \leq k \leq n} \{d_{ik}^{(2^{t-1})} + d_{kj}^{(2^{t-1})}\}$ 
6:     end for
7:   end for
8: end for
```

---

Cost is reduced to  $O(n^3 \lg n)$  in total.

# All-pairs min-cost paths, by dynamic programming

## intermediate-vertex constraint relaxation

Let  $\hat{d}_{ij}^{(k)}$  denote the minimum cost path from vertex  $i$  to vertex  $j$ , using intermediate vertices in  $\{1, \dots, k\}$ . Then,

1.  $\hat{d}_{ij}^{(0)} = c(i, j)$
2.  $\hat{d}_{ij}^{(n)} = \delta(i, j)$

So, again it suffices to see how to construct  $\hat{d}_{ij}^{(k)}$  values given  $\hat{d}_{ij}^{(k-1)}$  values.

*Key observation:*

$$\hat{d}_{ij}^{(k)} = \min\{\hat{d}_{ij}^{(k-1)}, \hat{d}_{ik}^{(k-1)} + \hat{d}_{kj}^{(k-1)}\}$$

# All-pairs min-cost paths, by dynamic programming

## intermediate-vertex constraint relaxation (cont.)

This recurrence suggests the following dynamic programming solution:

---

---

```
1: construct  $\hat{d}_{**}^{(0)}$ 
2: for  $k = 1$  to  $n$  do
3:   for  $i = 1$  to  $n$  do
4:     for  $j = 1$  to  $n$  do
5:        $\hat{d}_{ij}^{(k)} \leftarrow \min\{\hat{d}_{ij}^{(k-1)}, \hat{d}_{ik}^{(k-1)} + \hat{d}_{kj}^{(k-1)}\}$ 
6:     end for
7:   end for
8: end for
```

---

Cost is  $O(n^3)$  in total.

# All-pairs min-cost paths, by dynamic programming

Note:

- ▶ space requirements
- ▶ path reconstruction
- ▶ similarities with Bellman-Ford...distributed implementation

## Edit distance Problem

Given two strings (over some fixed alphabet):

$$X = x_1 x_2 \dots x_n$$

$$Y = y_1 y_2 \dots y_m$$

we want to *transform*  $X$  to  $Y$  with the fewest primitive operations:

- ▶ *delete* a symbol:  $\text{cost}(x_i, -)$
- ▶ *insert* a symbol:  $\text{cost}(-, y_j)$
- ▶ *replace* a symbol:  $\text{cost}(x_i, y_j)$

Small total cost (edit distance) measures similarity of  $X$  and  $Y$   
(e.g. spell checking, sequence alignment)

# Edit distance Problem

optimal substructure:

Either (i)  $x_n$  is matched with  $y_m$ , (ii)  $x_n$  is matched with  $-$  (deleted), or (iii)  $y_m$  is matched with  $-$  (inserted).

Hence, if  $ED[i, j]$  denotes the edit distance of  $x_1 \dots x_i$  to  $y_1 \dots y_j$ ,

$$ED[i, j] = \min \left\{ \begin{array}{l} ED[i - 1, j - 1] + \text{cost}(x_i, y_j) \\ ED[i - 1, j] + \text{cost}(x_i, -) \\ ED[i, j - 1] + \text{cost}(-, y_j) \end{array} \right\}$$

dynamic programming solution:

Knowing all cost values, we can compute  $ED[i, j]$  values in increasing order of  $i + j$  (or by row, or column)

# Edit Distance Matrix

	1	2			$j$			$m$
1								
2								
$i$								
$n$								

# Edit Distance Matrix

	1	2			$j$			$m$
1								
2								
$i$								
$n$								

**New entry** depends on only



# Edit Distance Matrix

	1	2			$j$			$m$
1								
2								
$i$								
$n$								

**New entry** depends on only **three neighbouring entries**.

# Edit distance Problem

dynamic programming solution:

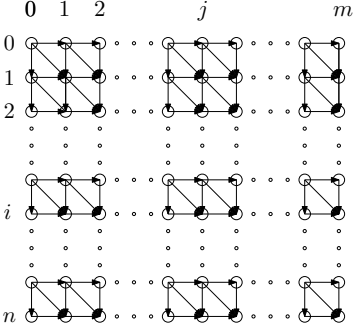
1. Total cost is  $O(nm)$ 
  - ▶ each ED-table entry is computed in  $O(1)$  time
2. Space can be reduced to  $O(n + m)$ 
  - ▶ it suffices to keep only *two* active columns of ED-table
3. Optimal edit script can be reproduced efficiently
  - ▶ by divide and conquer

# Edit Distance Matrix

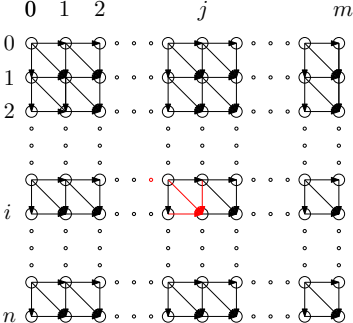
A grid representing an edit distance matrix. The columns are labeled 1, 2, ...,  $j$ , ...,  $m$  and the rows are labeled 1, 2, ...,  $i$ , ...,  $n$ . The cell at row  $i$  and column  $j$  is highlighted in blue. The cell at row  $i$  and column  $j-1$  is highlighted in green.

	1	2			$j$				$m$
1									
2									
$i$									
$n$									

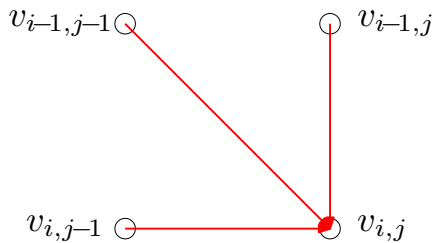
# Edit Distance Graph



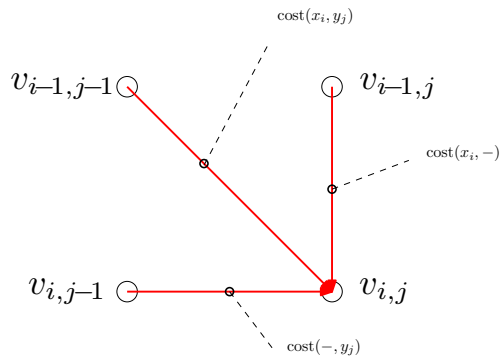
# Edit Distance Graph



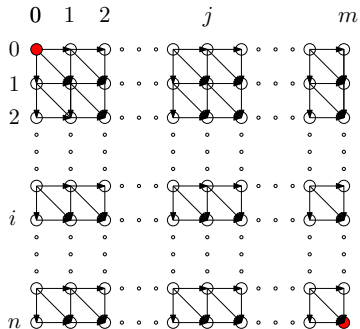
## Edit Distance Graph



# Edit Distance Graph



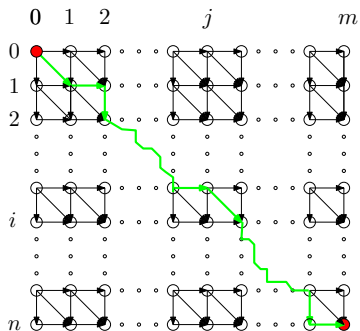
# Edit Distance Graph



We want to find the min-cost path from  $v_{0,0}$  to  $v_{n,m}$ .



# Edit Distance Graph



We want to find the min-cost path from  $v_{0,0}$  to  $v_{n,m}$ .