## Greedy Graph Algorithms

T. M. Murali

#### September 16, 21, 23, and 28, 2009

#### **Shortest Path Problem**

- G(V, E) is a connected directed graph. Each edge *e* has a length  $l_e \ge 0$ .
- ► V has n nodes and E has m edges.
- Length of a path P is the sum of the lengths of the edges in P.
- ▶ Goal is to determine the shortest path from a specified start node s to each node in V.
- ► Aside: If *G* is undirected, convert to a directed graph by replacing each edge in *G* by two directed edges.

#### **Shortest Path Problem**

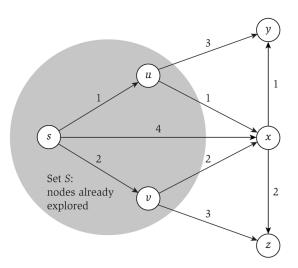
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- ► Aside: If *G* is undirected, convert to a directed graph by replacing each edge in *G* by two directed edges.

Shortest Paths

**INSTANCE:** A directed graph G(V, E), a function  $I : E \to \mathbb{R}^+$ , and a node  $s \in V$ 

**SOLUTION:** A set  $\{P_u, u \in V\}$ , where  $P_u$  is the shortest path in *G* from *s* to *u*.

#### Example of Dijkstra's Algorithm



**Figure 4.7** A snapshot of the execution of Dijkstra's Algorithm. The next node that will be added to the set *S* is x, due to the path through u.

- ► Maintain a set S of explored nodes: for each node u ∈ S, we have determined the length d(u) of the shortest path from s to u.
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While S \neq V
Select a node v \notin S with at least one edge from S for which
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Add v to S and define d(v) = d'(v)
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- d'(v) =length of shortest path from s to v using only nodes in S.
- To compute the shortest paths: store the predecessor u that minimises d'(v).

### **Proof of Correctness**

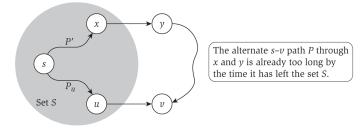
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  - Base case: |S| = 1. The only node in S is s.
  - Inductive step: we add the node v to S. Let u be the v's predecessor on the path P<sub>v</sub>. Could there be a shorter path P from s to v?

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**Figure 4.8** The shortest path  $P_v$  and an alternate *s*-*v* path *P* through the node *y*.

### **Comments about Dijkstra's Algorithm**

- Algorithm cannot handle negative edge lengths. We will discuss the Bellman-Ford algorithm in a few weeks.
- Union of shortest paths output form a tree. Why?

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▶ Running time per iteration is  $O(m) \Rightarrow$  overall running time is O(nm).

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- Store the minima d'(v) for each node  $v \in V S$  in a priority queue.
- ▶ Determine the next node *v* to add to *S* using EXTRACTMIN.
- After adding v to S, for each neighbour w of v, compute  $d(v) + l_{(v,w)}$ .
- If  $d(v) + l_{(v,w)} < d'(w)$ ,
  - 1. Set  $d'(w) = d(v) + l_{(v,w)}$ .
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### **Network Design**

- Connect a set of nodes using a set of edges with certain properties.
- Input is usually a graph and the desired network (the output) should use subset of edges in the graph.
- Example: connect all nodes using a cycle of shortest total length.

### **Network Design**

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# Minimum Spanning Tree (MST)

- Given an undirected graph G(V, E) with a cost c<sub>e</sub> > 0 associated with each edge e ∈ E.
- ► Find a subset T of edges such that the graph (V, T) is connected and the cost ∑<sub>e∈T</sub> c<sub>e</sub> is as small as possible.

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**INSTANCE:** An undirected graph G(V, E) and a function  $c : E \to \mathbb{R}^+$ 

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- Claim: If T is a minimum-cost solution to this network design problem then (V, T) is a tree.
- A subset T of E is a spanning tree of G if (V, T) is a tree.

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Which of these algorithms works?

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Decreasing cost order Delete edges in order of decreasing cost as long as graph remains connected. Reverse-Delete algorithm

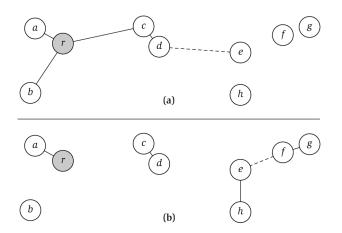
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- Which of these algorithms works? All of them!
- Simplifying assumption: all edge costs are distinct.

### **Example of Prim's and Kruskal's Algorithms**



**Figure 4.9** Sample run of the Minimum Spanning Tree Algorithms of (a) Prim and (b) Kruskal, on the same input. The first 4 edges added to the spanning tree are indicated by solid lines; the next edge to be added is a dashed line.

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  - Which edge should we add to join them?
- Which edges cannot belong to an MST?
  - What happens when we add an edge to an MST?
  - We obtain a cycle.
  - Which edge in the cycle can we be sure does not belong to an MST?

## **Graph Cuts**

- ► A cut in a graph G(V, E) is a set of edges whose removal disconnects the graph (into two or more connected components).
- Every set S ⊂ V (S cannot be empty or the entire set V) has a corresponding cut: cut(S) is the set of edges (v, w) such that v ∈ S and w ∈ V − S.

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- $\operatorname{cut}(S)$  is a cut because deleting the edges in  $\operatorname{cut}(S)$  disconnects S from V S.

### **Cut Property**

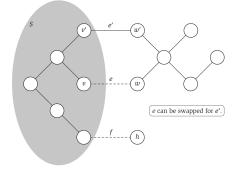
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#### **Cut Property**

- When is it safe to include an edge in an MST?
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- Let  $S \subset V$ , S is not empty or equal to V.
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- Claim: every MST contains e.
- Proof: exchange argument. If a supposed MST T does not contain e, show that there is a tree with smaller cost than T that contains e.



**Figure 4.10** Swapping the edge e for the edge e' in the spanning tree T, as described in the proof of (4.17).

## **Optimality of Kruskal's Algorithm**

- Kruskal's algorithm:
  - 1. Start with an empty set T of edges.
  - 2. Process edges in *E* in increasing order of cost.
  - 3. Add the next edge e to T only if adding e does not create a cycle. Discard e if it creates a cycle.
- Claim: Kruskal's algorithm outputs an MST.

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- Claim: Kruskal's algorithm outputs an MST.
  - 1. For every edge e added, demonstrate the existence of S and V S such that e and S satisfy the cut property.
  - 2. Prove that the algorithm computes a spanning tree.

#### **Optimality of Prim's Algorithm**

• Prim's algorithm: Maintain a tree (S, U)

- 1. Start with an arbitrary node  $s \in S$  and  $U = \emptyset$ .
- 2. Add the node v to S and the edge e to U that minimise

$$\min_{e=(u,v), u\in S, v\not\in S} c_e \equiv \min_{e\in \operatorname{cut}(S)} c_e.$$

- 3. Stop when S = V.
- Claim: Prim's algorithm outputs an MST.

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- 3. Stop when S = V.
- Claim: Prim's algorithm outputs an MST.
  - 1. Prove that every edge inserted satisfies the cut property.
  - 2. Prove that the graph constructed is a spanning tree.

### **Cycle Property**

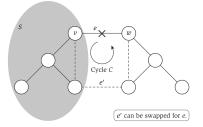
▶ When can we be sure that an edge cannot be in *any* MST?

#### **Cycle Property**

- ▶ When can we be sure that an edge cannot be in *any* MST?
- Let C be any cycle in G and let e = (v, w) be the most expensive edge in C.
- Claim: e does not belong to any MST of G.

#### **Cycle Property**

- ▶ When can we be sure that an edge cannot be in *any* MST?
- Let C be any cycle in G and let e = (v, w) be the most expensive edge in C.
- Claim: e does not belong to any MST of G.
- Proof: exchange argument. If a supposed MST T contains e, show that there is a tree with smaller cost than T that does not contain e.



**Figure 4.11** Swapping the edge e' for the edge e in the spanning tree T, as described in the proof of (4.20).

#### **Optimality of the Reverse-Delete Algorithm**

- Reverse-Delete algorithm: Maintain a set E' of edges.
  - ► Start with E' = E.
  - Process edges in decreasing order of cost.
  - Delete the next edge e from E' only if (V, E') is connected after deletion.
  - Stop after processing all the edges.
- ► Claim: the Reverse-Delete algorithm outputs an MST.

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  - Stop after processing all the edges.
- ► Claim: the Reverse-Delete algorithm outputs an MST.
  - 1. Show that every edge deleted belongs to no MST.
  - 2. Prove that the graph remaining at the end is a spanning tree.

## **Comments on MST Algorithms**

- ► To handle multiple edges with the same length, perturb each length by a random infinitesimal amount. Read the textbook.
- Any algorithm that constructs a spanning tree by including edges that satisfy the cut property and deleting edges that satisfy the cycle property will yield an MST!

#### **Implementing Prim's Algorithm**

• Maintain a tree (S, U).

- 1. Start with an arbitrary node  $s \in V$  and  $U = \emptyset$ .
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- 3. Stop when S = V.
- Sorting edges takes O(m log n) time.
- Implementation is very similar to Dijkstra's algorithm.
- ► Maintain S and store attachment costs a(v) = min<sub>e∈cut(S)</sub> c<sub>e</sub> for every node v ∈ V − S in a priority queue.
- ► At each step, extract minimum *v* from priority queue and update the attachment costs of the neighbours of *v*.
- ► Total of n − 1 EXTRACTMIN and m CHANGEKEY operations, yielding a running time of O(m log n).

### Implementing Kruskal's Algorithm

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- 2. Process edges in E in increasing order of cost.
- 3. Add the next edge e to T only if adding e does not create a cycle.
- Sorting edges takes  $O(m \log n)$  time.
- ▶ Key question in step 3: "Does adding e = (u, v) to T create a cycle?"
- ► Maintain set of connected components of *T* in a data structure that supports:
  - FIND(u): return the name of the connected component of T containing u.
  - UNION(A, B): merge connected components A and B.
- ► Implementing step 3: Adding e = (u, v) creates a cycle if and only if FIND(u) = FIND(v).
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  - 3. If  $\operatorname{FIND}(u) \neq \operatorname{FIND}(v)$ , execute  $\operatorname{UNION}(\operatorname{FIND}(u), \operatorname{FIND}(v))$  and add e to T.

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- Total running time of Kruskal's algorithm is  $O(m \log n)$ .

## **Union-Find Data Structure**

- Abstraction of the data structure needed by Kruskal's algorithm.
- ▶ Maintain disjoint subsets of elements from a universe *U* of *n* elements.
  - Think of each subset being a connected component of T.
- Each subset has a name. A subset's name will be the identity of some element in it.
- Support three operations:
  - 1. MAKEUNIONFIND(U): initialise the data structure with elements in U.
  - 2. FIND(u): return the identity of the subset that contains u.
  - 3. UNION(A, B): merge the sets named A and B into one set.

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  - Assume identities of elements are integers from 1 to *n*.
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  - 1. MAKEUNIONFIND(U): For each  $s \in U$ , set COMPONENT[s] = s in O(n) time.
  - 2. FIND(s): return COMPONENT[s] in O(1) time.
  - 3. UNION(A, B): merge B into A by scanning COMPONENT and updating each index whose value is B to the value A. Takes O(n) time.

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- UNION is very slow because we cannot efficiently find the elements that belong to a given set.

- ▶ Optimisation 1: Use an array ELEMENTS in addition to COMPONENT.
  - ▶ Indices of ELEMENTS range from 1 to *n*.
  - ELEMENTS[s] stores the elements in the subset named s in a list.
- Execute UNION(A, B) by merging B into A in two steps:
  - 1. For every element  $u \in B$ , set COMPONENT[u] = A in O(|B|) time.
  - 2. Append ELEMENTS[B] to ELEMENTS[A] in O(1) time.
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- ▶ Optimisation 2: Store size of each set in an array SIZE. If SIZE[B] ≤ SIZE[A], merge B into A. Otherwise merge A into B. Update SIZE.

# **Union-Find Data Structure: Analysis of Implementation 2**

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- ► FIND is fast in the worst case, UNION is fast in an amortised sense. Can we make both operations worst-case efficient?

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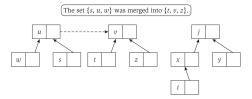


Figure 4.12 A Union-Find data structure using pointers. The data structure has only two sets at the moment, named after nodes v and j. The dashed arrow from u to v is the result of the last Union operation. To answer a Find query, we follow the arrows until we get to a node that has no outgoing arrow. For example, answering the query Find(i) would involve following the arrows it ox, and then x to j.

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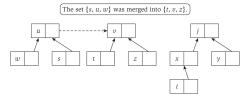


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- Implementing FIND(u): follow pointers from u to the root of u's tree.
- Implementing UNION(A, B): make smaller tree's root a child of the larger tree's root. Takes O(1) time.

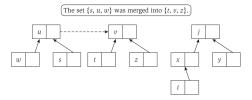


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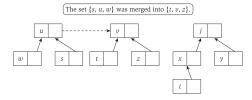


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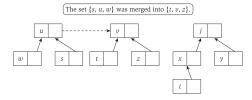


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- ▶ Why does FIND(*u*) take *O*(log *n*) time?
- Number of pointers followed equals the number of times the identity of the set containing u changed.
- ► Every time u's set's identity changes, the set at least doubles in size ⇒ there are O(log n) pointers followed.

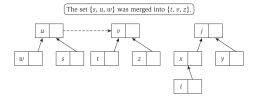


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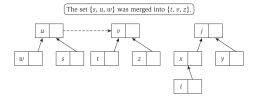


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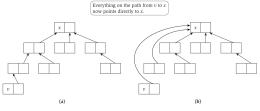


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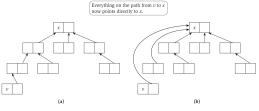


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- Can prove that total time taken by n FIND operations is  $O(n\alpha(n))$ , where  $\alpha(n)$  is the inverse of the Ackermann function, and grows e-x-t-r-e-m-e-l-y s-l-o-w-l-y with n.

### **Comments on Union-Find and MST**

- ► The UNION-FIND data structure is useful to maintain the connected components of a graph as edges are added to the graph.
- ► The data structure does not support edge deletion efficiently.
- ► Current best algorithm for MST runs in O(mα(m, n)) time (Chazelle 2000) and O(m) randomised time (Karger, Klein, and Tarjan, 1995).
- Holy grail: O(m) deterministic algorithm for MST.