# Randomized Algorithms 2013A Lecture 8 – Edge Sparsification (cont'd) and Distance Oracles<sup>\*</sup>

# **Robert Krauthgamer**

We continue our plan from the previous class to prove the following theorem.

#### Theorem 7 [Benczur-Karger, 1996]:

For every weighted graph G = (V, E) on n vertices and error parameter  $\varepsilon > 0$ , there is a weighted subgraph G' = (V, E') with  $O(\varepsilon^{-2}n \log n)$  edges such that  $G' \in (1 \pm \varepsilon)G$ . Moreover, G' can be constructed in  $O(|E| \log^2 n)$  time.

We will actually prove a slightly weaker version, for unweighted graphs, with another  $\log^2 n$  factor, and without the near-linear time algorithm.

Main idea: Sample edges non-uniformly, each edge e with probability  $p_e$  that is inversely proportional to its "connectivity"  $c_e$ . So "dense" regions will be sampled with smaller probability, thereby reducing the number of edges there more aggresively.

#### **Definitions of Connectivity:**

A graph is k-connected if every cut in it has capacity  $\geq k$ .

A k-strong component is a maximal vertex-induced subgraph that is k-connected.

Example: Consider 3 cliques, connected by one cycle (triangle).

Exer: Prove there is a unique partitioning of the vertices into k-strong components. (Hint: If  $V_1$  and  $V_2$  are k-connected and have non-empty intersection, then also  $V_1 \cup V_2$  is k-connected.)

It follows that the k-strong components partition the vertices of the graph, obtained by repeatedly removing every cut of capacity  $\langle k$ . Moreover, a (k+1)-strong components is a refinement of that partition.

The strong connectivity of an edge  $e \in E$ , denoted  $c_e$ , is the maximum value k such that e is contained in a k-strong component. An edge is called k-strong if its strong connectivity is at least k; otherwise k-weak.

Note that strong connectivity differs from the usual definition of connectivity. (Example: n parallel paths between s, t.)

<sup>\*</sup>These notes summarize the material covered in class, usually skipping proofs, details, examples and so forth, and possibly adding some remarks, or pointers. The exercises are for self-practice and need not be handed in. In the interest of brevity, most references and credits were omitted.

#### Construction of sparsifier G':

Set  $q = q_{\varepsilon} := 4(d+2)\varepsilon^{-2} \ln n$ , and sample every  $e \in E$  with probability  $p_e = \min\{q/c_e, 1\}$ , in which case it is given weight  $1/p_e$ .

**Lemma 8:** With probability  $\geq 1 - O(1/n^d)$ , the resulting graph G' has O(qn) edges.

The proof for the expected number of edges was seen in class, using the following claim: A graph with total edge weight  $\geq k(n-1)$  has a k-strong component (which may be the graph itself).

Exer: Complete the high-probability proof using Chernoff bound.

**Lemma 9:** With high probability  $G' \in (1 \pm \varepsilon \log |E|)G$ .

Lemmas 8,9 together indeed prove (a weaker version of) Theorem 7, by simply using a smaller value  $\varepsilon_1 = \varepsilon / \log |E|$ .

**Idea of Proof:** The proof we seen in class using uniform sampling (Theorem 6). The idea is to describe the same algorithm in a different way, as if we divide the sampling process into phases, and phase  $i = 0, 1, \ldots$  flips the coins only for edges e with  $2^i \leq c_e < 2^{i+1}$ . The analysis then applies Theorem 6 separately on each  $2^i$ -strong component, which means that we basically "remove" edges with  $c_e < 2^i$ . Inside each such component, the edges from level i are chosen at random, but all edges with  $c_e \geq 2^{i+1}$  are kept (deterministically).

Exer: It is sometimes easier/faster to compute an approximation to  $c_e$ . So suppose we use in  $p_e$  an approximation to  $c_e$ , say within factor 3, i.e., values  $c'_e \in [c_e, 3c_e]$ . Explain how the theorem and analysis shown in class would extend.

# **Distance Oracles**

**Goal:** Preprocess a graph G = (V, E) with edge lengths  $l : E \to \mathbb{R}_+$  into a (small) data structure that can answer in time O(1) queries about the distance  $d = d_G$  (between any two vertices  $u, v \in V$ ).

We denote n = |V| and m = |E|.

**Naive solution:** Store all  $\binom{n}{2}$  distances in a matrix/array, with direct access in time O(1).

Can one "compress" the information, perhaps at the expense of accuracy, i.e., the distances are only approximated?

**Theorem 10** [Thorup-Zwick, 2001]: Let k > 1 be an integer. There is an algorithm that preprocesses the graph G in expected time  $O(kmn^{1/k})$ , and produces a data structure that can answer a distance query in time O(k) and with approximation factor 2k - 1.

Remark: We will ignore the preprocessing time, and focus on storage (space). In particular, we assume the shortest-path between every two vertices is computed, and essentially use only the fact that distances satisfy the triangle inequality.

### Algorithm Prep(G,k):

1.  $A_0 = V; A_k = \emptyset$ .

2. for  $i = 1, \ldots, k - 1$ 

3. Construct  $A_i$  by including each  $u \in A_{i-1}$  with probability  $1/n^{1/k}$ .

4. for every  $v \in V$ 

5. for 
$$i = 0, \dots, k - 1$$

6. store  $d(v, A_i) = \min\{d(v, w) : w \in A_i\}$  and the minimizer w as  $p_i(v)$ 

7. set  $d(v, A_k) = \infty$ .

8. store  $B(v) = \bigcup_{i=0}^{k-1} \{ w \in A_i \setminus A_{i-1} : d(v, w) < d(v, A_{i+1}) \}$  in a hash table that answers whether  $w \in B(v)$  and if so, what is its distance to v, in O(1) worst-case time.

Remark: We can use a two-level hash table of size O(|B(v)|).

# Intuition of preprocessing:

The sets  $A_i$  are subsamples of V at different "levels", and provide "landmarks".

Each  $p_i(v)$  is just the level *i* landmark closest to *v*.

What is a set B(v)? sort V by distance from v, and partition it into k levels (rings) at positions  $n^{1/k}, n^{2/k}, \ldots$ ; store  $n^{1/k}$  random vertices from each ring.

Analysis of preprocessing storage: The only concern is the  $\sum_{v} |B(v)|$ , and this was sketched in class.

Exer: Prove that for every  $v \in V$  and  $i \in \{0, \ldots, k-1\}$ ,

 $\mathbb{E}[|B(v) \cap A_i|] \le n^{1/k}.$ 

# Algorithm Query(u,v):

- 1. w = u; i = 0
- 2. while  $w \notin B(v)$
- 3. i = i + 1
- 4. (u, v) = (v, u) //swap

5. 
$$w = p_i(u)$$

6. return d(u, w) + d(w, v)

The runtime is obviously O(k).

Analysis of query algorithm: The entire  $A_{k-1} \subseteq B(v)$ , hence some answer is always returned, and the number of u - v swaps (the final *i*) is at most k - 1.

Let  $\Delta = d(u, v)$ . We claim that each swap of u, v increases d(w, u) by at most  $\Delta$ ; denoting by  $u_i, w_i$  etc. the values at the end of iteration i, we claim that  $d(w_i, u_i) \leq d(w_{i-1}, u_{i-1}) + \Delta$ . This will imply the approximation factor (strech bound), since we start with  $d(w_0, u_0) = 0$ , at the final i we have  $d(w_i, u_i) \leq i \cdot \Delta \leq (k-1)\Delta$ , and thus also  $d(w_i, v_i) \leq d(w_i, u_i) + d(u_i, v_i) \leq k\Delta$ .

Suppose iteration *i* passes the while loop's condition. Then  $w_{i-1} \notin B(v_{i-1}) = B(u_i)$ . By the construction of  $B(u_i)$ , there must be some vertex in  $A_i$  that is even closer to  $u_i$  than  $w_{i-1}$ , i.e.,  $d(u_i, A_i) \leq d(u_i, w_{i-1})$  hence

$$d(u_i, w_i) = d(u_i, A_i) \le d(u_i, w_{i-1}) \le \Delta + d(u_{i-1}, w_{i-1}).$$