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Lecture 10

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In the first lecture we discussed the **Max Cut problem**, which is NP-complete, and we presented a very simple algorithm that gives a 1/2 approximation. Today we will discuss the **Min Cut problem**, which is in P, and we will present a very simple randomized algorithm to solve it exactly.

My reasons for presenting this algorithm are: (1) it illustrates that non-trivial optimization problems can sometimes be solved by very simple algorithms, (2) the analysis is quite interesting, and (3) most importantly, it has useful consequences that will allow us to present an even more amazing result in the next lecture.

1 Minimum Cuts

Let G = (V, E) be an undirected graph. As before, for every $U \subseteq V$ we define

 $\delta(U) = \{ uv \in E : u \in U \text{ and } v \notin U \}.$

The Min Cut problem is to solve

$$\min\{ |\delta(U)| : \emptyset \neq U \subsetneq V \}.$$

Here we are minimizing over all subsets U of the vertices, except for $U = \emptyset$ and U = V because those two uninteresting sets have $|\delta(U)| = 0$. The Min Cut problem is equivalent to the problem

 $\min\{|F|: F \subseteq E \text{ s.t. } G \setminus F \text{ is disconnected } \}.$

To see the equivalence, note that any set $\delta(U)$ is a disconnecting set F, and given any disconnecting set F, we can find a cut $\delta(U) \subseteq F$ by letting U be any connected component in $G \setminus F$.

You should not confuse the Min Cut problem and the **Min** *s*-*t* **Cut problem**. In the latter problem, there are two distinguished vertices $s, t \in V$ and we must solve

$$\min\{ |\delta(U)| : U \subset V \text{ s.t. } s \in U, t \notin U \}.$$

This problem can be solved by network flow techniques, since the Max-Flow Min-Cut theorem tells us that the solution equals the maximum amount of flow that can be sent from s to t.

In fact, this gives us a solution to the Min Cut problem as well, because there is a reduction from the Min Cut problem to the Min *s*-*t* Cut problem. It is easy to see that the solution to the Min Cut problem equals the minimum over all pairs $s, t \in V$ of the solution to the Min *s*-*t* Cut problem. (There are more efficient reductions.)

We will present a remarkable randomized algorithm for solving the Min Cut problem which does *not* use a reduction to the Min s-t Cut problem. Instead it randomly contracts edges in the graph.

1.1 Edge Contractions

Let G = (V, E) be a multigraph, meaning that we allow E to contain multiple "parallel" edges with the same endpoints. Suppose that $uv \in E$ is an edge. To **contract** the edge uv means to apply the following operations:

- Add a new vertex w.
- For every edge xu or xv we add a new edge xw. This can create new parallel edges, because it might be the case that xu and xv both existed, in which case we will create two new edges xw.
- Every edge with an endpoint at either u or v is deleted.
- The vertices u and v are deleted.

The graph that results from this operation is written G/uv.



This process essentially "merges" the two vertices u and v into a "supervertex" w which corresponds to the pair of vertices $\{u, v\}$. After performing several contraction operations, a vertex w in the contracted graph is actually a supervertex corresponding to the set of nodes that were contracted together to form w. More formally, letting G = (V, E) be the original graph, each supervertex w in the contracted graph corresponds to a set of vertices $S_w \subseteq V$. These sets $\{S_w : \text{ supervertex } w\}$ form a *partition* of V, meaning that they are pairwise disjoint and their union is V.

The following figure shows the result of contracting the edges uv, vb and ad. In each supervertex we show the set of vertices from the original graph that were contracted together to form the supervertex.



Claim 1 Let w be a supervertex and suppose u and v are two vertices that were contracted into w (i.e., $u, v \in S_w$). Then there is a path P between u and v in the original graph G such that every edge in P was contracted.

PROOF: This follows by induction on the number of contraction operations. \Box

In the example above, u and b are in the same supervertex, and the path u-v-b in the original graph had all of its edges contracted.

Claim 2 If we contract some edge uv in a graph G, then the size of a minimum cut in the contracted graph G/uv is at least the size of a minimum cut in G.

PROOF: Consider any set W of supervertices in the contracted graph. Let $U = \bigcup_{w \in W} S_w$ be the corresponding set of vertices in G. The edges between W and \overline{W} in G/uv are in bijective correspondence with the edges between U and \overline{U} in G. Therefore the size of the cut $\delta(W)$ in G/uv equals the size of $\delta(U)$ in G. So every cut in G/uv has at least as many edges as the minimum cut in G. \Box

1.2 Computing Minimum Cuts by the Contraction Algorithm

The following randomized algorithm outputs a cut (possibly a minimum cut).

- Input: A graph G = (V, E).
- Output: A cut $\delta(U)$ for some non-empty set $U \subset V$.
- While the graph has more than two (super) vertices remaining
 - Pick an edge e uniformly at random
 - Contract e
- Let w be one of the two remaining supervertices. Output the cut $\delta(S_w)$, where S_w is the set of vertices in the original graph that were contracted together to form the supervertex w.

To analyze this algorithm we must show that it has decent probability of outputting a minimum cut. Our main result is: **Theorem 3** Fix any minimum cut C. The contraction algorithm outputs C with probability at least $\frac{2}{n(n-1)}$.

Continuing our example above, the algorithm might decide to contract one of the edges between $\{c\}$ and $\{u, v, b\}$ (say, the edge cv in the original graph). The resulting graph is shown below. Then the algorithm outputs the cut $\delta(\{a, d\})$, which is the same as the cut $\delta(\{u, v, b, c\})$, and which contains two edges. However, this is not a minimum cut of G as the cut $\delta(\{b\})$ contains just one edge.



Before proving the theorem we need two more preliminary claims.

Claim 4 Let G be a graph with n vertices in which the minimum size of a cut is c. Then G must have at least nc/2 edges.

PROOF: Every vertex must have degree at least c, otherwise the edges incident on that vertex would constitute a cut of size less than c. Any graph where the minimum degree is at least c must have at least nc/2 edges, since the sum of the vertex degrees is exactly twice the number of edges (by the handshaking lemma.) \Box

Claim 5 The cut $\delta(U)$ is output by the algorithm if and only if no edge in $\delta(U)$ is contracted by the algorithm.

PROOF: \Rightarrow direction: If an edge uv is contracted then the vertices u and v will belong to the same supervertex from that point onwards. Therefore the set U either contains both u and v, or neither of them. In either case $uv \notin \delta(U)$.

 \Leftarrow direction: Suppose no edge in $\delta(U)$ is contracted by the algorithm. Consider any pair of nodes $u \in U$ and $v \notin U$ in the original graph. If the algorithm contracts u and v into the same supervertex, then Claim 1 tells us that there is a u-v path P that consists entirely of contracted edges. But this path must intersect the cut $\delta(U)$, which contradicts our hypothesis that no edge in $\delta(U)$ was contracted.

So, for every pair of nodes $u \in U$ and $v \notin U$, these two nodes belong to different supernodes in the contracted graph. At the end of the algorithm there are only two supernodes, so one of them must correspond to U and the other to its complement \overline{U} . \Box

PROOF: (of Theorem 3) Recall that we fix an arbitrary minimum cut $C = \delta(U)$, and we must show that the algorithm has reasonable probability of outputting that particular minimum cut C. By Claim 5, this happens if and only if no edge in C is contracted. Since the contracted edges are randomly chosen, we can analyze the probability that any of those contracted edges lie in C.

Each contraction operation decreases the number of vertices by one. So in the *i*th iteration there are exactly n - i + 1 vertices. What can we say about the probability of contracting an edge in C during the *i*th iteration?

Let c denote the minimum size of any cut in the original graph, so c = |C|. The graph in the *i*th iteration has minimum cut size at least c, by Claim 2, and so it has at least (n - i + 1)c/2 edges, by Claim 4. So the probability that the randomly chosen edge in the *i*th iteration lies in C is at most

$$\frac{|C|}{(n-i+1)c/2} = \frac{2}{n-i+1}.$$

Formally, let \mathcal{E}_i be the event that in the *i*th iteration, the randomly chosen edge lies in C. Let $\overline{\mathcal{E}_i}$ be the complementary event. Unfortunately the \mathcal{E}_i 's are not independent! But this actually doesn't cause any problems. Regardless of whether the events $\mathcal{E}_1, \ldots, \mathcal{E}_{i-1}$ occur or not, there are no more than c remaining edges in C, so the probability that the *i*th random edge lies in C is at most 2/(n-i+1). In particular,

$$\Pr\left[\overline{\mathcal{E}_i} \mid \overline{\mathcal{E}_1} \land \dots \land \overline{\mathcal{E}_{i-1}}\right] \geq 1 - \frac{2}{n-i+1} = \frac{n-i-1}{n-i+1}.$$

So, the probability that the algorithm *never* contracts an edge in C is

$$\Pr[\overline{\mathcal{E}_{1}} \wedge \dots \wedge \overline{\mathcal{E}_{n-2}}] = \prod_{i=1}^{n-2} \Pr[\overline{\mathcal{E}_{i}} | \overline{\mathcal{E}_{1}} \wedge \dots \wedge \overline{\mathcal{E}_{i-1}}]$$

$$\geq \prod_{i=1}^{n-2} \frac{n-i-1}{n-i+1}$$

$$\geq \frac{n-2}{n} \cdot \frac{n-3}{n-1} \cdot \frac{n-4}{n-2} \cdots \frac{3}{5} \cdot \frac{2}{4} \cdot \frac{1}{3}$$

$$= \frac{2}{n(n-1)}.$$

So, by Claim 5, the probability that the algorithm outputs the cut C is at least 2/n(n-1).

Theorem 3 only proves that the algorithm has a very small probability of outputting the minimum cut C. As usual, we can boost the probability of success by performing independent trials.

Corollary 6 Fix any $\delta \in [0, 1]$. Running the contraction algorithm $n^2 \ln(1/\delta)$ times will find a minimum cut with probability at least $1 - \delta$.

PROOF: Fix a minimum cut C. The probability that we fail to find this cut during $n^2 \ln(1/\delta)$ trials is at most

$$\left(1 - \frac{2}{n(n-1)}\right)^{n^2 \ln(1/\delta)} \le \exp\left(-\frac{2}{n(n-1)}n^2 \ln(1/\delta)\right) \le \delta^2.$$

This gives a randomized, polynomial algorithm to compute a minimum cut.

1.3 Extensions

The contraction algorithm is interesting not only because it gives a simple method to compute minimum cuts, but also because there are several interesting corollaries and extensions. We now discuss a few of those.

Corollary 7 In any undirected graph the number of minimum cuts is at most $n(n-1)/2 = \binom{n}{2}$.

PROOF: Let C_1, \ldots, C_k be the minimum cuts of the graph. Let \mathcal{E}_i be the event that C_i is output by the algorithm. Since these are disjoint events, $\sum_{i=1}^k \Pr[\mathcal{E}_i] \leq 1$. We showed above that $\Pr[\mathcal{E}_i] \geq 2/n(n-1)$ for every i, which implies that $k \leq n(n-1)/2$. \Box

This bound is tight as the *n*-cycle has exactly $\binom{n}{2}$ minimum cuts. The next corollary proves a similar result for *approximate* minimum cuts. For any $\alpha \geq 1$, a cut is called an α -minimum cut if its number of edges is at most α times larger than a minimum cut.

Corollary 8 In any undirected graph, and for any real number $\alpha \geq 1$, the number of α -minimum cuts is less than $n^{2\alpha}$.

Finally, we state a generalization of the previous corollary which we will use next time. For every edge e let k_e denote the **edge-connectivity** of e, which is the minimum size of a cut containing e. Formally,

$$k_e := \min\{ |\delta(U)| : U \subset V \text{ and } e \in \delta(U) \}.$$

Theorem 9 Let G = (V, E) be a graph. Let $B \subseteq E$ be arbitrary and let $K = \min\{k_e : e \in B\}$. Then, for every real $\alpha \ge 1$,

$$|\{ \delta(U) \cap B : U \subseteq V \land |\delta(U)| \le \alpha K \}| < n^{2\alpha}.$$

The proof of this theorem is very similar to the proof of Corollary 8, except it needs one additional tool from graph theory called splitting off that we unfortunately don't have time to explain.