

Min-Cut Algorithm

Input: A n node graph

Output: A minimal set of edges that disconnects the graph.

1. **repeat** $n - 2$ **times:**

- (a) Pick an edge uniformly at random.
- (b) Contract the edge.

endrepeat

2. **output** the set of edges connecting the two remaining vertices.

Theorem 1. *The algorithm outputs a min-cut set of edges with probability $\geq \frac{2}{n(n-1)}$.*

Lemma 1. *Contraction operation (step 1(b)) does not reduce the size of the min-cut set.*

Proof. Every cut set in the new graph is a cut set in the original graph. \square

Analysis of the Algorithm

Assume that the graph has a min-cut set of k edges.

We compute the probability of finding one such set C .

Lemma 2. *Let C be a min-cut set of G . If the run of the algorithm did not contract any edge of C , it also did not eliminate any edge of C .*

Since the minimum cut-set has k edges, all vertices have degree $\geq k$, and the graph has $\geq nk/2$ edges.

Let $E_i =$ "the edge contracted in iteration i is not in C ".

We want

$$\Pr(\cap_{i=1}^{n-2} E_i) = \Pr(E_1) \Pr(E_2|E_1) \Pr(E_3|E_2 \cap E_1) \dots \Pr(E_{n-2} | \cap_{i=1}^{n-3} E_i).$$

$$\Pr(E_1) \geq 1 - \frac{k}{nk/2} = 1 - \frac{2}{n}$$

$$\Pr(E_2|E_1) \geq 1 - \frac{k}{(n-1)k/2} = 1 - \frac{2}{n-1}$$

$$\Pr(E_i | \cap_{j=1}^{i-1} E_j) \geq 1 - \frac{2}{n-i+1}$$

$$\begin{aligned} \text{Thus, } \Pr(\cap_{i=1}^{n-2} E_i) &\geq \prod_{i=1}^{n-2} \left(1 - \frac{2}{n-i+1}\right) = \\ \prod_{i=1}^{n-2} \left(\frac{n-i-1}{n-i+1}\right) &= \frac{2}{n(n-1)} \end{aligned}$$

Min-Cut: High Probability Algorithm

Input: A n node graph

Output: A minimal set of edges that disconnects the graph.

1. **for** $i = 1$ **to** $n^2 \ln n$

1.1. **repeat** $n - 2$ **times:**

(a) Pick an edge uniformly at random.

(b) Contract the edge.

endrepeat

1.2 Let C_i be the set of edges connecting the two remaining vertices.

endfor

2. **output** the set with the minimum size among the C_i 's.

Theorem 2. *The high probability algorithm outputs a min-cut set with probability at least $1 - 1/n^2$.*

Random Variable

Let (\mathcal{S}, Pr) be a discrete probability space.

Let V be a set of values.

A random variable X defined on (\mathcal{S}, Pr) is a function

$$X : \mathcal{S} \rightarrow V$$

Let $\mathcal{E}(r) = \{s \in \mathcal{S} \mid X(s) = r\}$

$$Pr(X = r) = Pr(\mathcal{E}(r)) = \sum_{s \in \mathcal{E}(r)} Pr(s).$$

Two random variables X and Y (defined on the same sample space) are called independent if for all x and y

$$Pr\{X = x \text{ and } Y = y\} = Pr\{X = x\} Pr\{Y = y\}$$

Expectation

The **expectation** of a discrete random variable X :

$$E[X] = \sum_{i \in \text{range}((X))} i \cdot \text{Pr}(X = i).$$

Linearity of Expectation

Theorem 3. For any two random variables X and Y

$$E[X + Y] = E[X] + E[Y].$$

Proof.

$$\begin{aligned} E[X + Y] &= \\ \sum_{i \in \text{range}(X)} \sum_{j \in \text{range}(Y)} (i + j) \Pr((X = i) \cap (Y = j)) &= \\ \sum_i \sum_j i \Pr((X = i) \cap (Y = j)) + & \\ \sum_j \sum_i j \Pr((X = i) \cap (Y = j)) &= \\ \sum_i i \Pr(X = i) + \sum_j j \Pr(Y = j). & \end{aligned}$$

□

(Since we sum over all possible choices of i (j).)

Lemma 3. *If E_1, E_2, \dots, E_k are disjoint events such that $\sum_{i=1}^k \Pr(E_i) = 1$ then for any event B ,*

$$\sum_{i=1}^k \Pr(B \cap E_i) = \Pr(B).$$