COMP251: Randomized Algorithms

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Based on (Kleinberg & Tardos, 2006)
Algorithm Design Techniques

- Greedy Algorithms
- Dynamic Programming
- Divide-and-Conquer
- Network Flows
- Randomization
Randomization

**Principle:** Allow fait coin flip in unit time.

**Why?** Can lead to simplest, fastest, or only known algorithm for a particular problem.

**Examples:**
- Quicksort
- Graph Algorithms
- Hashing
- Monte-Carlo integration
- Cryptography
Global Min Cut

**Definition:** Given a connected, undirected graph $G=(V,E)$, find a cut with minimum cardinality.

**Applications:**
- Partitioning items in database
- Identify clusters of related documents
- Network reliability
- TSP solver

**Network solution:**
- Replace every edge $(u,v)$ with 2 antiparallel edges $(u,v)$ & $(v,u)$
- Pick some vertex $s$, and compute min $s$-$v$ cut for each other vertex $v$.

**False Intuition:** Global min-cut is harder than min $s$-$t$ cut!
Contraction algorithm

Contraction algorithm. [Karger 1995]

- Pick an edge $e = (u, v)$ uniformly at random.
- **Contract** edge $e$.
  - replace $u$ and $v$ by single new super-node $w$
  - preserve edges, updating endpoints of $u$ and $v$ to $w$
  - keep parallel edges, but delete self-loops
- Repeat until graph has just two nodes $u_1$ and $v_1$.
- Return the cut (all nodes that were contracted to form $v_1$).
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Reference: Thore Husfeldt

Merging nodes is equivalent to build disjoint sets of increasing sizes
Contraction Algorithm

\textbf{Contraction}(V,E):

While \(|V| > 2\) do

\hspace{1cm} \textbf{Choose} \(e \in E\) uniformly at random

\hspace{1cm} \(G \leftarrow G - \{e\}\) // contract \(G\)

return \{ the only cut in \(G\) \}

Why are we doing that?
What is the likelihood to get a global min cut at the end?
**Contraction algorithm**

**Claim.** The contraction algorithm returns a min cut with prob $\geq 2/n^2$.

$(n = |V|)$

**Pf.** Consider a global min-cut $(A^*, B^*)$ of $G$.

- Let $F^*$ be edges with one endpoint in $A^*$ and the other in $B^*$.
- Let $k = |F^*| = $ size of min cut.
- In first step, algorithm contracts an edge in $F^*$ probability $k/|E|$.
- Every node has degree $\geq k$ since otherwise $(A^*, B^*)$ would not be a min-cut $\Rightarrow |E| \geq \frac{1}{2} k n$. $\iff \frac{k}{|E|} \leq \frac{2}{n}$
- Thus, algorithm contracts an edge in $F^*$ with probability $\leq 2/n$.

If a node $u$ has a degree $d_u < k$, we can make a partition $\{\{u\}, V-\{u\}\}$ whose cut is $d_u < k$ (and $F^*$ cannot be a global min-cut).

That’s the probability to pick a wrong edge...
Contraction algorithm

Claim. The contraction algorithm returns a min cut with prob $\geq 2 / n^2$.

Pf. Consider a global min-cut $(A^*, B^*)$ of $G$.

- Let $F^*$ be edges with one endpoint in $A^*$ and the other in $B^*$.
- Let $k = |F^*| = \text{size of min cut}$.
- Let $G'$ be graph after $j$ iterations. There are $n' = n - j$ supernodes.
- Suppose no edge in $F^*$ has been contracted. The min-cut in $G'$ is still $k$.
- Since value of min-cut is $k$, $|E'| \geq \frac{1}{2} kn'$.
- Thus, algorithm contracts an edge in $F^*$ with probability $\leq 2 / n'$.
- Let $E_j = \text{event that an edge in } F^* \text{ is not contracted in iteration } j$.

$$
\Pr[E_1 \cap E_2 \cdots \cap E_{n-2}] = \Pr[E_1] \times \Pr[E_2 | E_1] \times \cdots \times \Pr[E_{n-2} | E_1 \cap E_2 \cdots \cap E_{n-3}]
\geq (1 - \frac{2}{n}) (1 - \frac{2}{n-1}) \cdots (1 - \frac{2}{4}) (1 - \frac{2}{3})
= \left( \frac{n-2}{n} \right) \left( \frac{n-3}{n-1} \right) \cdots \left( \frac{2}{4} \right) \left( \frac{1}{3} \right)
= \frac{2}{n(n-1)}
\geq \frac{2}{n^2}
$$

$2/n^2$ is not much but it is still something...
Contraction algorithm

**Amplification.** To amplify the probability of success, run the contraction algorithm many times.

**Claim.** If we repeat the contraction algorithm $n^2 \ln n$ times, then the probability of failing to find the global min-cut is $\leq 1 / n^2$.

**Pf.** By independence, the probability of failure is at most

$$\left(1 - \frac{2}{n^2}\right)^{n^2\ln n} = \left(1 - \frac{2}{n^2}\right)^{\frac{1}{3}n^2} \leq (e^{-1})^{2\ln n} = \frac{1}{n^2}$$

with independent random choices, $(1 - 1/x)^x \leq 1/e$
Contraction algorithm: example execution

Reference: Thore Husfeldt
Global min cut: context

Remark. Overall running time is slow since we perform $\Theta(n^2 \log n)$ iterations and each takes $\Omega(m)$ time. Where $m = |E|$. Overall complexity $O(n^2 m \log n)$

Improvement. [Karger-Stein 1996] $O(n^2 \log^3 n)$.

- Early iterations are less risky than later ones: probability of contracting an edge in min cut hits 50% when $n / \sqrt{2}$ nodes remain.
- Run contraction algorithm until $n / \sqrt{2}$ nodes remain.
- Run contraction algorithm twice on resulting graph and return best of two cuts.

Extensions. Naturally generalizes to handle positive weights.

Best known. [Karger 2000] $O(m \log^3 n)$.

faster than best known max flow algorithm or deterministic global min cut algorithm
SAT formula

Boolean variables: \( x_i \) or \( \overline{x_i} \)

Clause: \( C_i = x_{i_1} \lor x_{i_2} \lor x_{i_3} \lor \cdots \lor x_{i_k} \)

Size of a clause = number of variables in the clause

SAT formula: \( \Lambda_i C_i \) (a formula is satisfied if all clauses are true)

Example (3 SAT formula):

\( (x_1 \lor x_2 \lor \overline{x_3}) \land (\overline{x_1} \lor x_2 \lor x_4) \)

\( x_1=1; x_2=1; x_3=1; x_4=1 \Rightarrow \text{True} \)

\( x_1=1; x_2=0; x_3=1; x_4=0 \Rightarrow \text{False} \)
Maximum 3-satisfiability

Maximum 3-satisfiability. Given a 3-SAT formula, find a truth assignment that satisfies as many clauses as possible.

\[ C_1 = x_2 \lor \overline{x_3} \lor \overline{x_4} \]
\[ C_2 = x_2 \lor x_3 \lor \overline{x_4} \]
\[ C_3 = \overline{x_1} \lor x_2 \lor x_4 \]
\[ C_4 = \overline{x_1} \lor \overline{x_2} \lor x_3 \]
\[ C_5 = x_1 \lor x_2 \lor x_4 \]

Remark. NP-hard search problem.

Simple idea. Flip a coin, and set each variable true with probability \( \frac{1}{2} \), independently for each variable.

Is it a good idea?
Maximum 3-satisfiability: analysis

Claim. Given a 3-SAT formula with $k$ clauses, the expected number of clauses satisfied by a random assignment is $7k / 8$.

Pf. Consider random variable $Z_j = \begin{cases} 
1 & \text{if clause } C_j \text{ is satisfied} \\
0 & \text{otherwise.}
\end{cases}$

- Let $Z = \text{weight of clauses satisfied by assignment } Z_j$.

$$E[Z] = \sum_{j=1}^{k} E[Z_j]$$

(linearity of expectation)

$$= \sum_{j=1}^{k} \Pr[\text{clause } C_j \text{ is satisfied}]$$

$$= \frac{7}{8} k$$

There is $2^3$ possible assignments for a clause of 3-SAT. Only one makes the clause false (all variable are false). Thus, $7/8$ return true.
The Probabilistic Method

Corollary. For any instance of 3-SAT, there exists a truth assignment that satisfies at least a $7/8$ fraction of all clauses.

Pf. Random variable is at least its expectation some of the time.

Probabilistic method. [Paul Erdös] Prove the existence of a non-obvious property by showing that a random construction produces it with positive probability!

Although the proof uses probability, the conclusion is determined for certain, without any possible error.

Not at the final!
Maximum 3-satisfiability: analysis

Q. Can we turn this idea into a $7/8$-approximation algorithm?
A. Yes (but a random variable can almost always be below its mean).

Lemma. The probability that a random assignment satisfies $\geq 7k / 8$ clauses is at least $1 / (8k)$.

Pf. Let $p_j$ be probability that exactly $j$ clauses are satisfied; let $p$ be probability that $\geq 7k / 8$ clauses are satisfied.

\[
\frac{7}{8} k = E[Z] = \sum_{j \geq 0} j p_j \\
= \sum_{j < 7k/8} j p_j + \sum_{j \geq 7k/8} j p_j \\
\leq \left( \frac{7}{8} k - \frac{1}{8} \right) \sum_{j < 7k/8} p_j + k \sum_{j \geq 7k/8} p_j \\
\leq \left( \frac{7}{8} k - \frac{1}{8} \right) \cdot 1 + k p
\]

Rearranging terms yields $p \geq 1 / (8k)$. 

\[\square\]
Maximum 3-satisfiability: analysis

**Johnson's algorithm.** Repeatedly generate random truth assignments until one of them satisfies $\geq \frac{7k}{8}$ clauses.

**Theorem.** Johnson's algorithm is a $7/8$-approximation algorithm.

**Pf.** By previous lemma, each iteration succeeds with probability $\geq \frac{1}{(8k)}$. By the waiting-time bound, the expected number of trials to find the satisfying assignment is at most $8k$. □

An approximation algorithm returns a solution provably close to the optimal.
Monte Carlo vs. Las Vegas algorithms

**Monte Carlo.** Guaranteed to run in poly-time, likely to find correct answer.  
*Ex:* Contraction algorithm for global min cut.

**Las Vegas.** Guaranteed to find correct answer, likely to run in poly-time.  
*Ex:* Randomized quicksort, Johnson's $\text{MAX}-3\text{-SAT}$ algorithm.

**Remark.** Can always convert a Las Vegas algorithm into Monte Carlo, but no known method (in general) to convert the other way.