

Reading: *Algorithm Design* by Kleinberg and Tardos; *Introduction to Algorithms* by Cormen, Leiserson, Rivest, and Stein; *Approximation Algorithms* by Vazirani; *The Design of Approximation Algorithms* by Williamson and Shmoys

- A subset of edges $E' \subseteq E$ s.t. each vertex is adjacent to at most one edge in E'

Goal: MAX-MATCH: Maximize cardinality of E' .

Example: Draw a graph, a matching, and a max matching.

Flagship Problems

Minimum vertex cover

Given:

- A graph $G = (V, E)$

Output:

- A subset of vertices $V' \subseteq V$ s.t. for each edge $(i, j) \in E$, either $i \in V'$ or $j \in V'$

Goal: MIN-VC: Minimize cardinality of V' .

Example: Draw a graph, a vertex cover, and a min vertex cover.

Maximum matching

Given:

- A graph $G = (V, E)$

Output:

Approximation

Algorithm: Consider all possible solutions and output best.

[So check all subsets of vertices, eliminate subsets that aren't covers, output smallest; or check all subsets of edges, eliminate subsets that aren't matchings, output largest.]

Question: Quality of solution? Optimal.

Question: Run time? Exponential.

Note: Sometimes not possible to do better quickly (MIN-VC), or quick algs are complicated (MAX-MATCH).

We can try to approximate such problems:

- Let I be an instance of a min/max problem
- Let $C^{OPT}(I)$ be value of optimal solution
- Let $C^A(I)$ be value of alg A on instance I

Def: If I is a *minimization* problem, A is an *approximation alg* A with approximation ratio $\alpha \geq 1$ if for all input instances I ,

$$C^A(I) \leq \alpha C^{OPT}(I).$$

Def: If I is a *maximization* problem, A is an *approximation alg* A with approximation ratio $\alpha \leq 1$ if for all input instances I ,

$$C^A(I) \geq \alpha C^{OPT}(I).$$

Techniques

Charging arguments

Idea: Charge optimal soln. to alg. soln.

Example: MAX-MATCH:

Algorithm: Select legal edges arbitrarily until can't add any more.

Analysis:

- Consider an optimal solution OPT
- ALG owes each edge in OPT \$1
→ money owed = value of OPT
- Edges in ALG pay edges in OPT
→ max # guys an ALG edge must pay bounds approx ratio

Question: How much money does each edge in ALG need?

Idea: Payment scheme:

Each edge in ALG pays adjacent edges in OPT

- Everyone gets paid: each edge in OPT adj to some edge in ALG.
Why? If not, contradicts fact that matching is maximal (could add edge from OPT).

- ALG edges need at most \$2 each: each edge in ALG adj to at most two edges in OPT.

Draw picture.

Claim: ALG is a (1/2)-approx.

Question: Tight example?

Example: MIN-VC:

Algorithm:

- Set $C = \emptyset$
- While $E \neq \emptyset$
 - Select $e \in E$ and add an endpoint v of e to C
 - Set E to be $E \setminus \{e : v \in e\}$

Analysis:

- Consider an optimal solution OPT
- OPT lends each vertex in ALG \$1
→ money lent = value of ALG
- Vertices in OPT lend to vertices in ALG
→ max # guys an OPT vertex must pay bounds approx ratio

Question: How much money does each vertex in OPT need?

Idea: Lending scheme:

- Each vertex v in ALG is added because of some edge e
- Let v^* be an OPT vertex covering e
- v borrows \$1 from v^*
- Everyone gets \$1

- OPT vertices need at most $\$(n-1)$ each
Each vertex in OPT can cover at most $\$(n-1)$ edges (max degree).

Claim: ALG is an $O(n)$ -approx.

Question: Tight example?

Question: Improved algs?

- Greedy: iteratively select v of current max degree gives $O(\log n)$ -approx
- Maximal matching: use above alg, but select *both* endpoints gives 2-approx
Why 2-approx? Each edge in maximal matching borrows $\$2$ from covering vertex in OPT to pay for its endpoints; each vertex in OPT can cover at most one such edge since they are a matching.

Algorithm: Greedy:

- Set $C = \emptyset$
- While $E \neq \emptyset$
 - Find vertex v of highest induced degree $d(v)$ and add v to C
 - Set $E = E \setminus \{e : v \in e\}$

[[*Charging argument through a middle-*]]
[[*man.*]]

Analysis: Greedy: Let the “price” of an edge e covered by a vertex v in an iteration of the alg be $1/d(v)$ – all edges processed in one iteration pay for covering vertex v .

- Let e_k be k 'th edge covered. Then $price(e_k) \leq OPT/(m - k + 1)$.
At time k at least $m - k + 1$ edges left and OPT covers them all, so average cost-effectiveness is $OPT/(m - k + 1)$, so some such vertex exists.

- Greedy is $O(\log n)$ -approx.

Selected vertices totally paid for by edges, so cost of cover is

$$\sum_{k=1}^m price(e_k) \leq \sum_{k=1}^m OPT/k = O(\log n)OPT$$

Linear programming

Def: A *linear program* is a linear objective subject to a set of linear constraints.

Example:

minimize $x_1 + 2x_2 + x_3$

subject to $x_1 - x_2 + x_3 \geq 10$, $5x_1 + x_2 - x_3 \geq 3$,
 $x_1, x_2, x_3 \geq 0$

[[*Constraints are a polytope, objective is a*]]
[[*direction.*]]

Def: An *extreme point* of a linear program is a vertex of the polytope, i.e., a solution that cannot be written as a convex combination of other solutions.

Fact: The optimal solution is achieved by an extreme point.

Def: An *integer program* is a linear program in which variables are constrained to be 0 or 1.

Note: We can solve LPs efficiently, but not IPs.

Idea: LP-based approx algs:

- express problem as an IP
- relax to an LP and solve
- round solution
- show rounded solution is close in value to LP and hence to IP

Draw picture:

OPT LP — OPT IP — rounded solution

Example: MIN-VC:

- variables: x_i for each vertex i ($x_i = 1$ indicates vertex i is in cover)
- objective: $\min \sum_{i=1}^n x_i$ (cost of cover)
- constraints:
 - $\forall (i, j) \in E, x_i + x_j \geq 1$ (each edge is covered)
 - $x_i \in \{0, 1\}$ (integrality)
- for LP, relax last constraint to $x_i \in [0, 1]$.

[Any soln can be represented by setting variables appropriately; it's cost is described by objective. Hence, optimal soln to IP is optimal MIN-VC.]

Fact: LP for vertex cover is *half integral*: in an extreme point of LP, each variable $x_i \in \{0, 1/2, 1\}$ **Proof:**

- Let $V_- = \{i : 0 < x_i < 1/2\}$ and $V_+ = \{i : 1/2 < x_i < 1\}$.
- For $\epsilon > 0$, let
 - $y_v = \{x_v + \epsilon \text{ if in } V_+; x_v - \epsilon \text{ otherwise}\}$
 - $z_v = \{x_v - \epsilon \text{ if in } V_+; x_v + \epsilon \text{ otherwise}\}$
- $x \neq y, z$ since $V_+ \cup V_- \neq \emptyset$
- x convex comb of y and z since $x = \frac{1}{2}(y + z)$
- y and z are feasible for ϵ small enough since
 - positive
 - if $x_u + x_v > 1$ then $y_u + y_v > 1$ and $z_u + z_v > 1$ for ϵ small enough

- if $x_u + x_v = 1$ then if not half-integral either $u \in V_-$ and $v \in V_+$ or vice versa, so ϵ cancels and $y_u + y_v = z_u + z_v = 1$

Algorithm: MIN-VC

- Solve LP
- Let $C = \{i : x_i > 0\}$

Analysis:

$$\text{cost}(C) \leq 2 \sum x_i \leq 2OPT$$

Question: IP/LP for matching?

[Can add constraints to strengthen, e.g., odd cycles.]

Question: IP/LP for ranking tournaments?

[Sometimes multiple choices for variables; helps to pick right one.]