CSC304 Lecture 17

Voting 4: Impartial selection

Recap

- The Gibbard-Satterthwaite theorem says that we cannot design strategyproof voting rules that are also nondictatorial and onto.
- Restricted settings (e.g., facility location on a line)
 - > There exist strategyproof, nondictatorial, and onto rules.
 - They can be used to (perfectly or approximately) optimize the societal goal
- Today, we will study another interesting setting called *impartial selection*

Impartial Selection

- "How can we select k people out of n people?"
 - Applications: electing a student representation committee, selecting k out of n grant applications to fund using peer review, ...

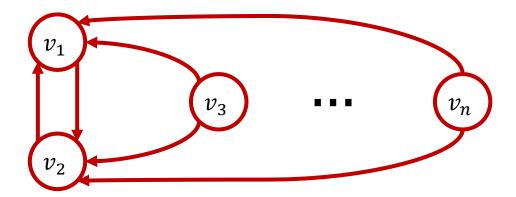
Model

- \triangleright Input: a *directed* graph G = (V, E)
- \triangleright Nodes $V = \{v_1, \dots, v_n\}$ are the n people
- \gt Edge $e = (v_i, v_j) \in E$: v_i supports/approves of v_j
 - \circ We do not allow or ignore self-edges (v_i, v_i)
- \triangleright Output: a subset $V' \subseteq V$ with |V'| = k
- $> k \in \{1, ..., n-1\}$ is given

Impartial Selection

- Impartiality: A k-selection rule f is impartial if $v_i \in f(G)$ does not depend on the outgoing edges of v_i
 - $>v_i$ cannot manipulate his outgoing edges to get selected
 - ▶ Q: But the definition says v_i can neither go from $v_i \notin f(G)$ to $v_i \in f(G)$, nor from $v_i \in f(G)$ to $v_i \notin f(G)$. Why?
- Societal goal: maximize the sum of in-degrees of selected agents $\sum_{v \in f(G)} |in(v)|$
 - > in(v) = set of nodes that have an edge to v
 - > out(v) = set of nodes that v has an edge to
 - \triangleright Note: OPT will pick the k nodes with the highest indegrees

Optimal ≠ Impartial



- An optimal 1-selecton rule must select v_1 or v_2
- The other node can remove his edge to the winner, and make sure the optimal rule selects him instead
- This violates impartiality

Goal: Approximately Optimal

- α -approximation: We want a k-selection system that always returns a set with total indegree at least α times the total indegree of the optimal set
- Q: For k=1, what about the following rule? Rule: "Select the lowest index vertex in $out(v_1)$. If $out(v_1) = \emptyset$, select v_2 ."
 - > A. Impartial + constant approximation
 - ▶ B. Impartial + bad approximation
 - > C. Not impartial + constant approximation
 - > D. Not impartial + bad approximation

• Theorem [Alon et al. 2011] For every $k \in \{1, ..., n-1\}$, there is no impartial k-selection rule with a finite approximation ratio.

• Proof:

- \triangleright For small k, this is trivial. E.g., consider k=1.
 - \circ What if G has two nodes v_1 and v_2 that point to each other, and there are no other edges?
 - \circ For finite approximation, the rule must choose either v_1 or v_2
 - \circ Say it chooses v_1 . If v_2 now removes his edge to v_1 , the rule must choose v_2 for any finite approximation.
 - Same argument as before. But applies to any "finite approximation rule", and not just the optimal rule.

• Theorem [Alon et al. 2011] For every $k \in \{1, ..., n-1\}$, there is no impartial k-selection rule with a finite approximation ratio.

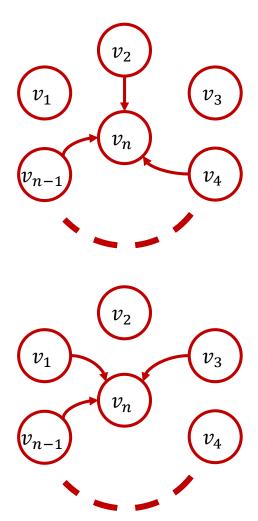
Proof:

- > Proof is more intricate for larger k. Let's do k = n 1. o k = n - 1: given a graph, "eliminate" a node.
- \triangleright Suppose for contradiction that there is such a rule f.
- \triangleright W.l.o.g., say v_n is eliminated in the empty graph.
- > Consider a family of graphs in which a subset of $\{v_1, \dots, v_{n-1}\}$ have edges to v_n .

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• Proof (k = n - 1 continued):

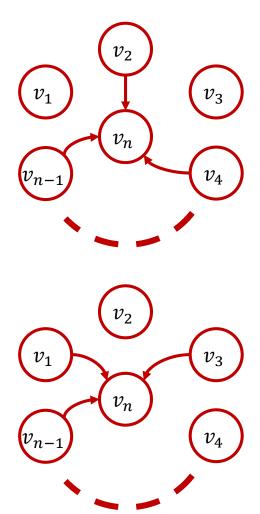
- > Consider star graphs in which a non-empty subset of $\{v_1, \dots, v_{n-1}\}$ have edge to v_n , and there are no other edges
 - \circ Represented by bit strings $\{0,1\}^{n-1}\setminus\{\vec{0}\}$
- $> v_n$ cannot be eliminated in any star graph
 - Otherwise we have infinite approximation
- > $f \text{ maps } \{0,1\}^{n-1} \setminus \{\vec{0}\} \text{ to } \{1, ..., n-1\}$
 - "Who will be eliminated?"
- > Impartiality: $f(\vec{x}) = i \Leftrightarrow f(\vec{x} + \vec{e}_i) = i$
 - \circ \vec{e}_i has 1 at i^{th} coordinate, 0 elsewhere
 - \circ In words, i cannot prevent elimination by adding or removing his edge to v_n



• Proof (k = n - 1 continued):

$$> f: \{0,1\}^{n-1} \setminus \{\overrightarrow{0}\} \rightarrow \{1, ..., n-1\}$$

- $f(\vec{x}) = i \Leftrightarrow f(\vec{x} + \vec{e}_i) = i$
 - $\circ \vec{e}_i$ has 1 only in i^{th} coordinate
- > Pairing implies...
 - \circ The number of strings on which f outputs i is even, for every i.
 - Thus, total number of strings in the domain must be even too.
 - o But total number of strings is $2^{n-1} 1$ (odd)
- > So impartiality must be violated for some pair of \vec{x} and $\vec{x} + \vec{e}_i$



Back to Impartial Selection

- Question: So what can we do to select impartially?
- Answer: Randomization!
 - > Impartiality now requires that the probability of an agent being selected be independent of his outgoing edges.
- Examples: Randomized Impartial Mechanisms
 - > Choose k nodes uniformly at random
 - Sadly, this still has arbitrarily bad approximation.
 - o Imagine having k special nodes with indegree n-1, and all other nodes having indegree 0.
 - Mechanism achieves $(k/n) * OPT \Rightarrow$ approximation = n/k
 - \circ Good when k is comparable to n, but bad when k is small.

Random Partition

• Idea:

> What if we partition V into V_1 and V_2 , and select k nodes from V_1 based only on edges coming to them from V_2 ?

Mechanism:

- \triangleright Assign each node to V_1 or V_2 i.i.d. with probability $\frac{1}{2}$
- \triangleright Choose $V_i \in \{V_1, V_2\}$ at random
- > Choose k nodes from V_i that have most incoming edges from nodes in V_{3-i}

Random Partition

Analysis:

- \triangleright We want to approximate I = # edges incoming to nodes in OPT.
 - Let $OPT_1 = OPT \cap V_1$, and $OPT_2 = OPT \cap V_2$.
 - Let I_1 = # edges incoming to OPT_1 from V_2 .
 - Let I_2 = # edges incoming to OPT_2 from V_1 .
- > Note that $E[I_1 + I_2] = I/2$. (WHY?)
- \blacktriangleright With probability $\frac{1}{2}$, mechanism picks k nodes from V_1 that have most incoming edges from V_2 (thus at least I_1 incoming edges).
 - \circ Because they're at least as good as OPT_1 .
- \triangleright With probability $\frac{1}{2}$, mechanism picks k nodes from V_2 that have most incoming edges from V_1 (thus at least I_2 incoming edges).
- > The expected total incoming edges is at least

$$\circ E\left[\left(\frac{1}{2}\right) \cdot I_1 + \left(\frac{1}{2}\right) \cdot I_2\right] = \left(\frac{1}{2}\right) \cdot E\left[I_1 + I_2\right] = \left(\frac{1}{2}\right) \cdot \frac{I}{2} = \frac{I}{4}$$

Random Partition

Improvement

- > The approximation ratio improves if we pick k/2 nodes from each part instead of picking all k from one part.
- \triangleright More generally, we can divide into ℓ parts, and pick k/ℓ nodes from each part based on incoming edges from all other parts.

Theorem [Alon et al. 2011]:

> $\ell = 2$ gives a 4-approximation.

> For $k \ge 2$, $\ell \sim k^{1/3}$ gives $1 + O\left(\frac{1}{k^{1/3}}\right)$ approximation.

Better Approximations

- [Alon et al. 2011] conjectured that for randomized impartial 1-selection...
 - > (For which their mechanism is a 4-approximation)
 - > It should be possible to achieve a 2-approximation.
 - > Recently proved by [Fischer & Klimm, 2014]
 - > Permutation mechanism:
 - \circ Select a random permutation $(\pi_1, \pi_2, ..., \pi_n)$ of the vertices.
 - \circ Start by selecting $y = \pi_1$ as the "current answer".
 - \circ At any iteration t, let $y \in \{\pi_1, ..., \pi_t\}$ be the current answer.
 - From $\{\pi_1, ..., \pi_t\} \setminus \{y\}$, if there are more edges to π_{t+1} than to y, change the current answer to $y = \pi_{t+1}$.

Better Approximations

- 2-approximation is tight.
 - > In an n-node graph, fix u and v, and suppose no other nodes have any incoming/outgoing edges.
 - > Three cases: only $u \to v$ edge, only $v \to u$, or both.
 - \circ The best impartial mechanism selects u and v with probability $\frac{1}{2}$ in every case, and achieves 2-approximation.
- But this is because n-2 nodes are not voting!
 - > What if every node must have an outgoing edge?
 - > [Fischer & Klimm]:
 - \circ Permutation mechanism gives $^{12}/_{7} = 1.714$ approximation.
 - \circ No mechanism gives better than 2/3 approximation.
 - \circ Open question to achieve better than $^{12}/_{7}$.

The rest of this lecture is not part of the syllabus.

PageRank

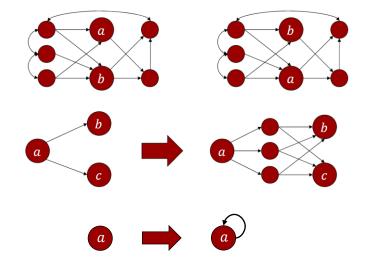
- An extension of the impartial selection problem
 - \triangleright Instead of selecting k nodes, we want to rank all nodes
- The PageRank Problem: Given a directed graph, rank all nodes by their "importance".
 - > Think of the web graph, where nodes are webpages, and a directed (u, v) edge means u has a link to v.
- Questions:
 - > What properties do we want from such a rule?
 - What rule satisfies these properties?

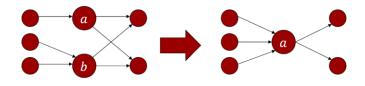
PageRank

- Here is the PageRank Algorithm:
 - > Start from any node in the graph.
 - > At each iteration, choose an outgoing edge of the current node, uniformly at random among all its outgoing edges.
 - > Move to the neighbor node on that edge.
 - > In the limit of $T \to \infty$ iterations, measure the fraction of time the "random walk" visits each node.
 - > Rank the nodes by these "stationary probabilities".
- Google uses (a version of) this algorithm
 - > It's seems a reasonable algorithm.
 - What nice axioms might it satisfy?

Axioms

- Axiom 1 (Isomorphism)
 - Permuting node names permutes the final ranking.
- Axiom 2 (Vote by Committee)
 - Voting through intermediate fake nodes cannot change the ranking.
- Axiom 3 (Self Edge)
 - > v adding a self edge cannot change the ordering of the *other* nodes.
- Axiom 4 (Collapsing)
 - > Merging identically voting nodes cannot change the ordering of the *other* nodes.
- Axiom 5 (Proxy)
 - \succ If a set of nodes with equal score vote for v through a proxy, it should not be different than voting directly.







PageRank

- Theorem [Altman and Tennenholtz, 2005]:
 The PageRank algorithm satisfies these five axioms, and is the unique algorithm to satisfy all five axioms.
- That is, any algorithm that satisfies all five axioms must output the ranking returned by PageRank on every single graph.