

# A Generalized Probabilistic Gibbard-Satterthwaite Theorem

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# Importance of Elections

- Political voting
- Electing board members
- Shareholders voting on company issues
- Artificial intelligent agent decision
- Search engine page-ranking



# Modeling an Election

- Each voter ranks the alternatives (*preference list*)
- All the preference lists make up a *preference profile*
- A *voting rule* (election system, social choice function) chooses a winner based on a profile

The interesting part is the voting rules.

This field of study is called social choice theory.

# Fairness in Election Systems

- Everyone should have an equal say
- Winner should accurately represent the group preference
- Simple with 2 alternatives; complicated with many

With two alternatives the one preferred by the most voters should win.



# Manipulation

A voter can get a better result by voting strategically, rather than voting his actual preferences.

Real Preferences

You	Others		Win
L	D	R	D
R	R	D	
D	L	L	



Manipulation

You	Others		Win
R	D	R	R
L	R	D	
D	L	L	

Manipulation is an enemy of fairness because the manipulative voter gets more influence than others.

Assume a simple plurality/first-past-the-post system.

In the first case it would be a tie, but lets assume our arbitrary tie breaking technique will choose the Democrats.

This is essentially the “wasted vote” problem.

This is a very simplistic example, but almost all voting systems are susceptible to manipulation.

# Gibbard-Satterthwaite Theorem

Voting rules are manipulable if they satisfy:

**Non-dictatorship** No single voter always dictates the group preference.

**Non-imposition** Every alternative has the possibility of winning.

We would like to devise an unmanipulable voting rule, but this theorem says it's impossible.

# Circumventing the Gibbard-Satterthwaite Theorem

- Searching for a computational barrier to manipulation
- Bartholdi, Tovey, and Trick studied the computational difficulty of finding a winner for various voting rules
- The Dodgson method is infeasible to manipulate because finding the winner is NP-hard
- Voting rules need to resist manipulation *and* make it feasible to find the winner

Many people have followed this line of research to great effect.

# Random Manipulation

- Friedgut, Kalai, and Nisan studied random manipulation
- Succeeds with non-negligible probability
- Shows the limits of a computational barrier to manipulation
- Only proved results for elections with 3 alternatives
- This is the work I attempted to generalize

If your alternative is not winning, randomly permute your preference list.



- Isaksson, Kindler, and Mossel have independently published a generalization in their paper *The geometry of manipulation: A quantitative proof of the gibbard-satterthwaite theorem*
- They proved that for a neutral social choice function, a uniformly chosen profile will be manipulable with probability at least  $2^{-1}\epsilon^2 n^{-4} m^{-6} (m!)^{-3}$
- Where  $\epsilon$  is the distance from dictatorship

As a disclaimer before a formal look at my work, others have published an independent generalization before I finished.

This is unfortunate for me, but fortunate for the field of social choice theory as a whole.

My work is still useful as:

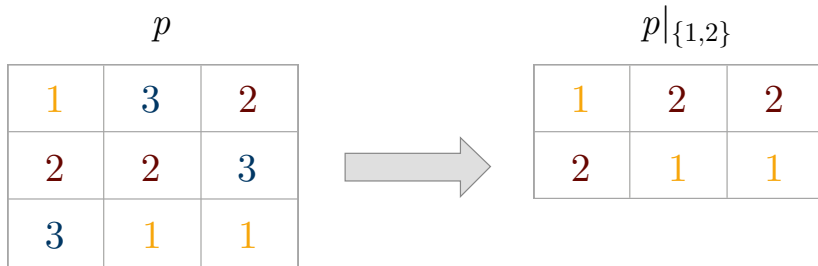
- A simpler proof
- A proof that closely follows the original
- An alternative proof

- $C = \{1, \dots, m\}$  is the set of alternatives.
- A preference list is a total ordering of the alternatives.
- The set of all preference lists is  $L(C)$ .
- A preference profile is a sequence of  $n$  preference lists.
- The set of all preference profiles is  $L(C)^n$ .
- A voting rule is a function that chooses a winning alternative from a profile, i.e.  $f : L(C)^n \rightarrow C$ .
- An election is a voting rule paired with a profile:  $(f, p)$ .

$L(C)^n$  is the Cartesian product of  $L(C)$  with itself  $n$  times,  
or the set of all  $n$ -tuples of elements of  $L(C)$

# Restricted Preference Profiles

- For a preference list  $v$ ,  $v|_D$  means  $v$  restricted to  $D$ , i.e.  $v$  with the alternatives not in  $D$  removed.
- For a preference profile,  $p$ ,  $p|_D$  means  $p$  with each preference list restricted to  $D$ .





# Manipulation Power

- Manipulation power  $M_i(f)$ , of voter  $i$  on a social choice function  $f$  is the probability that  $p'_i$  is a profitable manipulation by voter  $i$
- Where  $p$  is a profile and  $p'_i$  is a preference list which are both chosen uniformly at random





$$M^{a,b}(f) = \mathbb{P}[f(p) = a, f(p') = b]$$

- Describes the scenario where all voters together attempt to manipulate  $f$  to be  $b$  rather than  $a$
- $p$  and  $p'$  are chosen uniformly at random
- Voters don't alter their preference between  $a$  and  $b$

This definition does not require that anyone in particular gain from this, just that something “unexpected” happens.

Friedgut's proof is in three steps:

- Step 1** Application of a quantitative version of Arrow's impossibility theorem.
- Step 2** Reduction from an SCF with low dependence on irrelevant alternatives to a GSWF with a low paradox probability.
- Step 3** Reduction from low manipulation power to low dependence on irrelevant alternatives.



# Generalized Steps

Friedgut, was able to generalize Step 1 and Step 2 as follows:

## Lemma (Generalized Step 1)

*For every fixed  $m$  and  $\epsilon > 0$  there exists  $\delta > 0$  such that if  $F = f^{\otimes \binom{m}{2}}$  is a neutral IIA GSWF over  $m$  alternatives with  $f : \{0, 1\}^n \rightarrow \{0, 1\}$ , and  $\Delta(f, \text{DICT}) > \epsilon$ , then  $F$  has probability of at least  $\delta \geq (C\epsilon)^{\lfloor m/3 \rfloor}$  of not having a Generalized Condorcet Winner, where  $C > 0$  is an absolute constant.*

## Lemma (Generalized Step 2)

*For every fixed  $m$  there exists  $\delta > 0$  such that for all  $\epsilon > 0$  the following holds. Let  $f$  be a neutral SCF among  $m$  alternatives such that  $\Delta(f, \text{DICT}) > \epsilon$ . Then for all  $(a, b)$  we have  $M^{a,b}(f) \geq \delta$ .*

So we only need to generalize step 3 to get the whole proof.

# Step 3

## Lemma (Non-General Step 3)

*For every SCF  $f$  on 3 alternatives and every  $a, b \in C$ ,*

$$M^{a,b}(f) \leq \sum_i M_i(f) \cdot 6$$

## Lemma (Generalized Step 3)

*For every SCF  $f$  on  $m$  alternatives and every  $a, b \in C$ ,*

$$M^{a,b}(f) \leq \sum_i M_i(f) \cdot m!$$





# Combining Steps

- Step 3 is comprised of Lemma 6, Lemma 7, and Lemma 8 which we will generalize one at a time
- When we put together all 3 generalized steps we get our main result



# Statement of Lemma 6

## Lemma (Original Lemma 6)

$$M^{a,b}(f) = \mathbb{E}_p \left[ \frac{|A(p)|}{3^n} \cdot \frac{|B(p)|}{3^n} \right],$$

where  $p \in L(C)^n$  is chosen uniformly at random.

## Lemma (Generalized Lemma 6)

$$M^{a,b}(f) = \mathbb{E}_p \left[ \frac{|A(p)|}{\left(\frac{m!}{2}\right)^n} \cdot \frac{|B(p)|}{\left(\frac{m!}{2}\right)^n} \right],$$

where  $p \in L(C)^n$  is chosen uniformly at random.



# Define $A$ and $B$ Functions

Let  $a, b \in C$  be the first two alternatives, let  $p \in L(C)^n$  be a preference profile. We define

$$A(p) = \{x \in L(C)^n \mid x|_{\{a,b\}} = p|_{\{a,b\}}, f(x) = a\}$$
$$B(p) = \{x \in L(C)^n \mid x|_{\{a,b\}} = p|_{\{a,b\}}, f(x) = b\}.$$



## Recall $M^{a,b}$ Definition

Recall the definition of  $M^{a,b}(f)$ :

$$M^{a,b}(f) = \mathbb{P}[f(p) = a, f(p') = b]$$

where  $p, p'$  are chosen at random in  $L(C)^n$  with  $p|_{\{a,b\}} = p'|_{\{a,b\}}$ .





For any preference profile  $p \in L(C)^n$  there are  $(\frac{m!}{2})^n$  profiles  $x$  such that  $x|_{\{a,b\}} = p|_{\{a,b\}}$  because:

- There are  $m!$  possible preference lists
- Half of them will have the preference between  $a$  and  $b$  that agrees with  $p_i|_{\{a,b\}}$ , for any  $i$
- This gives  $\frac{m!}{2}$  possible preference lists for each voter
- So there are  $(\frac{m!}{2})^n$  profiles comprised of these preference lists



# Proof of Generalized Lemma 6

- First we fix a profile  $q$
- There are  $(\frac{m!}{2})^n$  profiles that agree with  $q|_{\{a,b\}}$
- $|A(q)|$  is the number of those for which the outcome is  $a$
- Randomly choose a profile,  $p$ , satisfying  $p|_{\{a,b\}} = q|_{\{a,b\}}$
- So the probability that  $f(p) = a$  is

$$\frac{|A(q)|}{\left(\frac{m!}{2}\right)^n}$$



# Proof of Generalized Lemma 6

- Likewise, randomly choose a profile,  $p'$ , satisfying  $p'|_{\{a,b\}} = q|_{\{a,b\}}$
- And the probability that  $f(p') = b$  is

$$\frac{|B(q)|}{\left(\frac{m!}{2}\right)^n}$$



# Proof of Generalized Lemma 6

Since  $p|_{\{a,b\}} = q|_{\{a,b\}}$  and  $p'|_{\{a,b\}} = q|_{\{a,b\}}$ , clearly we have that  $p|_{\{a,b\}} = p'|_{\{a,b\}}$ . Since  $f(p) = a$  and  $f(p') = b$  are independent events, the joint probability is

$$\frac{|A(q)|}{\left(\frac{m!}{2}\right)^n} \cdot \frac{|B(q)|}{\left(\frac{m!}{2}\right)^n}.$$





# Proof of Generalized Lemma 6

So we can rewrite

$$M^{a,b}(f) = \mathbb{P}[f(p) = a, f(p') = b]$$

as

$$M^{a,b}(f) = \mathbb{E}_q \left[ \frac{|A(q)|}{\left(\frac{m!}{2}\right)^n} \cdot \frac{|B(q)|}{\left(\frac{m!}{2}\right)^n} \right],$$





# Statement of Lemma 7

Lemma (Original Lemma 7)

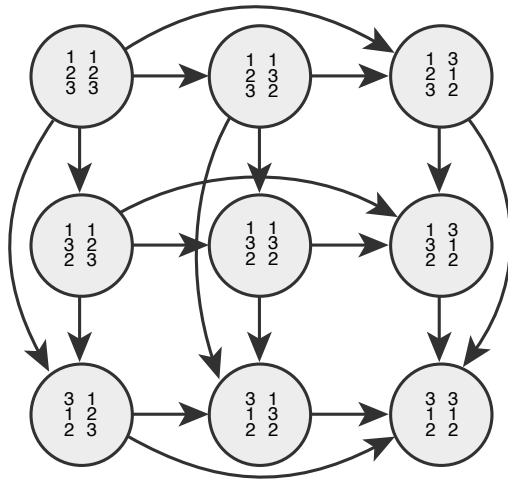
$$\sum_i M_i(f) \geq \frac{1}{6} 3^{-n} \mathbb{E}_p [|\partial A(p)| + |\partial B(p)|]$$

Lemma (Generalized Lemma 7)

$$\sum_i M_i(f) \geq \frac{1}{m!} \left( \frac{m!}{2} \right)^{-n} \mathbb{E}_p [|\partial A(p)| + |\partial B(p)|]$$



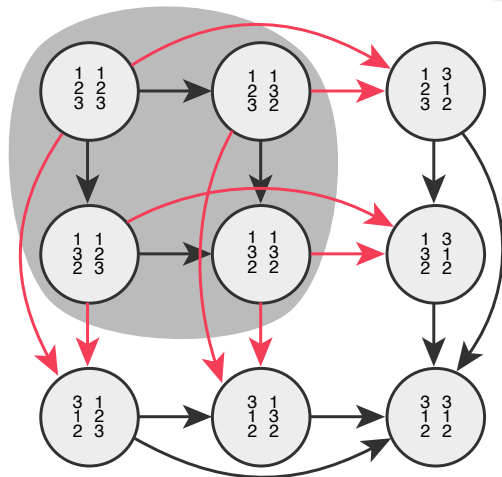
# Profile Lattice





# Upper Edge Border

- Set of edges whose tail is in  $A(p)$  and whose head is not in  $A(p)$
- Denoted  $\partial A(p)$
- Edge notation:  $(x_{-i}, x_i, x'_i)$  as shorthand for  $((x_{-i}, x_i), (x_{-i}, x'_i))$



$x_{-i}$  is  $x$  without the  $i$ th index.



# Formal Definition of Upper Edge Border

$$\begin{aligned}\partial_i A(p) = \{ & (x_{-i}, x_i, x'_i) \mid (x_{-i}, x_i) \in A(p), \\ & (x_{-i}, x'_i) \notin A(p), \\ & x_i|_{\{a,b\}} = x'_i|_{\{a,b\}}, \\ & x_i <_s x'_i\}\end{aligned}$$

$$\partial A(p) = \bigcup_j \partial_j A(p)$$

We don't have time to go into more of the lattice work I've done, including  $<_s$ .

$<_s$  means something like being close to the  $(1, 2, 3)$  ordering.

We define the upper edge border of  $B(p)$  analogously.

# Edges Correspond to Manipulations

## Lemma

*Each  $(x_{-i}, x_i, x'_i) \in \partial_i A(p) \cup \partial_i B(p)$  corresponds to at least one successful manipulation.*

We don't have time to show the proof, but it's in my paper.

# Proof of Generalized Lemma 7

- Randomly choose  $p$  and  $p'_i$
- $M_i(f)$  is the probability that  $p'_i$  is a successful manipulation
- We wish to come up with a lower bound for  $M_i(f)$
- We can think of these as two distinct profiles,  $p$  and  $p'$ , where  $p' = (p_{-i}, p'_i)$
- Clearly  $p_{-i}|_{\{a,b\}} = p'_{-i}|_{\{a,b\}}$
- We have  $p_i|_{\{a,b\}} = p'_i|_{\{a,b\}}$  with probability  $\frac{1}{2}$ , and we condition the following on this being the case
- So  $p|_{\{a,b\}} = p'|_{\{a,b\}}$



# Proof of Generalized Lemma 7

- Since every edge in  $\partial_i A(p) \cup \partial_i B(p)$  corresponds to at least one manipulation, we can lower bound  $M_i(f)$  by the probability that an edge is in  $\partial_i A(p) \cup \partial_i B(p)$
- The total number of possible edges of the form  $(x_{-i}, x_i, x'_i)$  is

$$(m!)^{n-1} \cdot m! \cdot m!$$

- But all edges in  $\partial_i A(p) \cup \partial_i B(p)$  must agree with  $p|_{\{a,b\}}$ . The total number of possible edges agreeing with  $p|_{\{a,b\}}$  is

$$\left(\frac{m!}{2}\right)^{n-1} \cdot \frac{m!}{2} \cdot \frac{m!}{2} = \frac{m!}{2} \left(\frac{m!}{2}\right)^n$$

- Since  $\partial_i A(p)$  and  $\partial_i B(p)$  are disjoint, no edge can be in both sets and so we have

$$|\partial_i A(p) \cup \partial_i B(p)| \leq \frac{m!}{2} \left(\frac{m!}{2}\right)^n$$





# Proof of Generalized Lemma 7

- Therefore, the probability that a randomly chosen edge is in either  $\partial_i A(p)$  or  $\partial_i B(p)$  is

$$\frac{2}{m!} \left( \frac{2}{m!} \right)^n \cdot \mathbb{E}_p [|\partial_i A(p)| + |\partial_i B(p)|]$$

- We conditioned our analysis on  $p_{-i|_{\{a,b\}}} = p'_{-i|_{\{a,b\}}}$ , so our lower bound becomes

$$M_i(f) \geq \frac{1}{2} \cdot \frac{2}{m!} \left( \frac{2}{m!} \right)^n \cdot \mathbb{E}_p [|\partial_i A(p)| + |\partial_i B(p)|].$$



# Proof of Generalized Lemma 7

- Simplifying gives

$$M_i(f) \geq \frac{1}{m!} \left( \frac{2}{m!} \right)^n \cdot \mathbb{E}_p [|\partial_i A(p)| + |\partial_i B(p)|] .$$

- Summing over  $i$  gives

$$\sum_i M_i(f) \geq \frac{1}{m!} \left( \frac{2}{m!} \right)^n \cdot \mathbb{E}_p [|\partial A(p)| + |\partial B(p)|] .$$





# Lemma 8

Lemma (Original Lemma 8)

$$|\partial A(p)| + |\partial B(p)| \geq \left(\frac{1}{3}\right)^n |A(p)| \cdot |B(p)|$$

Lemma (Generalized Lemma 8)

$$|\partial A(p)| + |\partial B(p)| \geq \left(\frac{2}{m!}\right)^n |A(p)| \cdot |B(p)|$$

I got close, but wasn't able to complete the proof of this lemma.

In my thesis I give a partial proof and a detailed description of the things that would be required to make it work.

Because of lack of time, I won't go into it here.

# Combining Lemma 6, 7, and 8

Restatement of the lemmas:

$$M^{a,b} = \mathbb{E}[|A||B|] \cdot L_6 \quad \text{lemma 6}$$

$$L_7 \cdot \mathbb{E}[|\partial A| + |\partial B|] \leq \sum_i M_i \quad \text{lemma 7}$$

$$\frac{1}{L_8} \cdot (|\partial A| + |\partial B|) \geq |A||B| \quad \text{lemma 8}$$

Now we can solve for the result of step 3:

$$M^{a,b} = \mathbb{E}[|A||B|] \cdot L_6 \quad \text{lemma 6}$$

$$M^{a,b} \leq \mathbb{E}[|\partial A| + |\partial B|] \cdot \frac{L_6}{L_8} \quad \text{by lemma 8}$$

$$M^{a,b} \leq \sum_i M_i \cdot \frac{L_6}{L_7 L_8} \quad \text{by lemma 7}$$

Because it's *much* easier to read:

- $A \equiv A(p)$
- $M^{a,b} \equiv M^{a,b}(f)$
- $M_i \equiv M_i(f)$



## Combining Lemma 6, 7, and 8

The variables have the following values:

$$L_6 = \left(\frac{m!}{2}\right)^{-2n}$$

$$L_7 = \frac{1}{m!} \left(\frac{m!}{2}\right)^{-n}$$

$$L_8 = \left(\frac{m!}{2}\right)^{-n}$$

Substituting becomes:

$$\begin{aligned}\frac{L_6}{L_7 L_8} &= \left(\frac{m!}{2}\right)^{-2n} \cdot m! \left(\frac{m!}{2}\right)^n \cdot \left(\frac{m!}{2}\right)^n \\ &= \left(\frac{m!}{2}\right)^{-2n} \cdot m! \cdot \left(\frac{m!}{2}\right)^{2n} \\ &= m!\end{aligned}$$



## Step 3 Result

The final result for step 3 is:

$$M^{a,b}(f) \leq \sum_i M_i(f) \cdot m!$$

By combining it with Friedgut's step 1 and 2 we get the generalized main theorem:

### Theorem (Main Result)

*There exists a constant  $C > 0$  such that for every  $\epsilon > 0$  the following holds. If  $f$  is a neutral SCF for  $n$  voters over  $m$  alternatives and  $\Delta(f, g) > \epsilon$  for any dictatorship  $g$ , then  $f$  has total manipulability:*

$$\sum_{i=1}^n M_i(f) \geq \frac{(C\epsilon)^{\lfloor m/3 \rfloor}}{m!}.$$

In this case  $C$  is a constant, and not the set of the alternatives.



