

Learning Cooperative Solution Concepts From Voting Behavior

A Case Study on the Israeli Parliament

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Outline

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- Bottom Responsive Games

- Boolean Hedonic Games

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- Stochastic Block Model

Results & Discussion

Conclusion

Background

- ▶ Coalition formation games:
 - ▶ Mostly theoretical analysis
 - ▶ Most models require full information on player preference
 - ▶ Lack of large dataset with ground truth
- ▶ Clustering & community detection:
 - ▶ Data-driven analysis
 - ▶ Missing strategic behavior modelling

Data

- ▶ Israeli parliament (the Knesset) voting data
- ▶ Available since March 2017
- ▶ Contains 147 parliament members' votes on over 7500 bills in ~ 4 years
- ▶ Ground truth clusters: political party affiliations
 - ▶ 10 parties aligned along a left-right axis
 - ▶ Ideological agreement among the government (right) and the opposition (left) parties respectively

Probably Approximately Correct (PAC) Stability

Given m observations of formed coalitions S_1, \dots, S_m sampled i.i.d. from some distribution \mathcal{D} , and the cardinal valuations of players in S_j

$(v_i(S_j))_{i \in S}$

Local loss given a coalition structure π and a coalition $S \subseteq N$:

$$\lambda(\pi, S) = \begin{cases} 1 & \text{if } \forall i \in S : v_i(S) > v_i(\pi(i)) \\ 0 & \text{otherwise.} \end{cases}$$

The *expected loss* of π w.r.t. \mathcal{D} :

$$L_{\mathcal{D}}(\pi) = \Pr_{S \sim \mathcal{D}} [\lambda(\pi, S) = 1]$$

A *PAC stabilizing* algorithm:

- ▶ input: a set of i.i.d. samples $S_1, \dots, S_m \sim \mathcal{D}^m$
- ▶ output: a coalition structure π^* with the following guarantee:
 $\Pr_{(S_1, \dots, S_m) \sim \mathcal{D}^m} [L_{\mathcal{D}}(\pi^*) \geq \varepsilon] < \delta$
- ▶ The number of samples needed m grows linearly in the number of players, and polynomially in $\frac{1}{\varepsilon}$ and $\log \frac{1}{\delta}$

Research Questions

- ▶ Can we use hedonic games to model real-world collaborative activities?
- ▶ How well does the outcome compare to ground truth?
- ▶ How well does the outcome compare to that of canonical clustering and community detection models?

Methodology

Game Theoretic Models

- ▶ Assumes hedonic preferences
 - ▶ Top responsive
 - ▶ Bottom responsive
 - ▶ Boolean

Methodology

Game Theoretic Models

- ▶ Assumes hedonic preferences
 - ▶ Top responsive
 - ▶ Bottom responsive
 - ▶ Boolean
- ▶ Two approaches:
 - ▶ Full-information models: construct complete preference profile, then derive core stable solution
 - ▶ PAC models: learn a probably stable solution directly from partial preference relations

Methodology

Game Theoretic Models

- ▶ Assumes hedonic preferences
 - ▶ Top responsive
 - ▶ Bottom responsive
 - ▶ Boolean
- ▶ Two approaches:
 - ▶ Full-information models: construct complete preference profile, then derive core stable solution
 - ▶ PAC models: learn a probably stable solution directly from partial preference relations
 - ▶ Simulate i.i.d.: sampling with replacement $3/4$ of all bills
 - ▶ Repeat 50 times to check consistency of solution between runs
 - ▶ Select the “centroid” to represent model output: partition with minimum sum of information distance from other 49 partitions

Methodology

Comparisons

- ▶ Comparison machine learning models:
 - ▶ K-Means
 - ▶ Stochastic Block Model
- ▶ Comparing every hedonic & ML model output partition to ground truth party affiliations
 - ▶ Quantitatively: information theoretic measures
 - ▶ Qualitatively: political analysis

How different are two partitions, quantitatively?

Objectives

We want a measure that. . .

- ▶ has strong mathematical foundation: information theoretic measures
- ▶ is intuitive: satisfying metric property
 - ▶ non-negativity
 - ▶ symmetry
 - ▶ triangle inequality

How different are two partitions, quantitatively?

Definitions

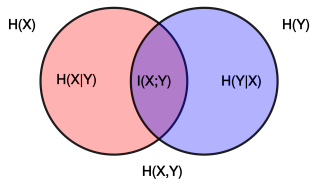


Figure: Venn diagram showing additive and subtractive relationships various information measures associated with correlated variables X and Y

► Entropy:

$$H(\pi) = - \sum_{j=1}^J \frac{|S_j|}{|N|} \log \frac{|S_j|}{|N|}$$

► Conditional entropy: $H(\pi|\pi')$ =

$$- \sum_{j=1}^J \sum_{k=1}^K \frac{|S_j \cap S'_k|}{|N|} \log \frac{|S_j \cap S'_k|/|N|}{|S'_k|/|N|}$$

► Mutual Information (MI):

$$I(\pi, \pi') = H(\pi) - H(\pi|\pi')$$

► Variation of Information (VI):

$$VI(\pi, \pi') = H(\pi) + H(\pi') - 2I(\pi, \pi'), \text{ metric!}$$

How different are two partitions, quantitatively?

Baseline Values

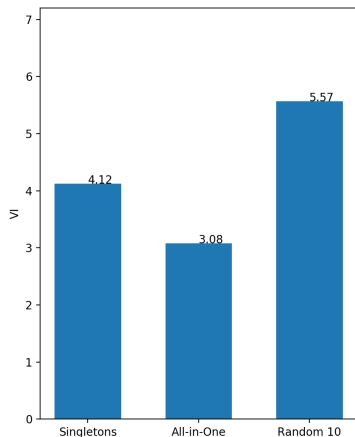


Figure: The Knesset partition baseline VI values

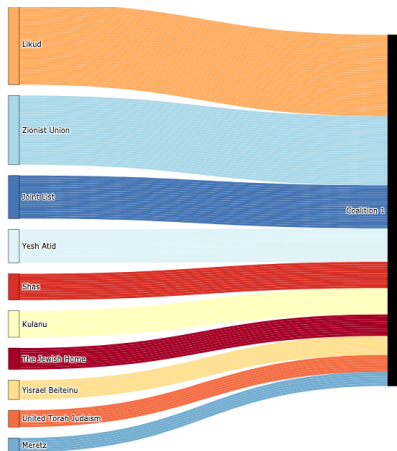


Figure: All-in-One partition of the Knesset

How different are two partitions, quantitatively?

Additional Measure: AMI

Adjusted Mutual Information (AMI):

$$AMI(\pi, \pi') = \frac{I(\pi, \pi') - E(I(\pi, \pi'))}{\max(H(\pi), H(\pi')) - E(I(\pi, \pi'))}$$

- ▶ Adjusted for chance
- ▶ Normalized: $[0, 1]$
- ▶ Not metric

Good for detecting “bad” (very different) partitions:

	Ajusted Mutual Information
Singletons	3e-14
All-in-One	-5e-16
Randome 10	0.007

Table: The Knesset partition baseline AMIs

Top Responsive Games

Definitions

Idea: for every player, the value of a coalition depends on the most preferred subset of players

► *Choice sets:*

$$Ch(i, S) = \{S' \subseteq S : (i \in S') \wedge (S' \succeq_i S'' \forall S'' \subseteq S)\}$$

When $|Ch(i, S)| = 1$, the unique choice set is $ch(i, S)$

► A *top responsive* preference profile requires that for any player $i \in N$, and any coalition that may contain player i :
 $S, T \in \mathcal{N}_i$:

1. $|Ch(i, S)| = 1$.
2. if $ch(i, S) \succ_i ch(i, T)$ then $S \succ_i T$
3. if $ch(i, S) = ch(i, T)$ and $S \subset T$ then $S \succ_i T$

Top Responsive Games

Example

Example 1

Consider a game of three players with the following choice sets:

$$ch(1, \{1, 2, 3\}) = ch(1, \{1, 2\}) = \{1, 2\}, ch(1, \{1, 3\}) = \{1, 3\}, ch(1, \{1\}) = \{1\}$$

$$ch(2, \{1, 2, 3\}) = ch(2, \{2, 3\}) = \{2, 3\}, ch(2, \{1, 2\}) = \{1, 2\}, ch(2, \{2\}) = \{2\}$$

$$ch(3, \{1, 2, 3\}) = ch(3, \{1, 3\}) = \{1, 3\}, ch(3, \{1, 2\}) = \{1, 2\}, ch(3, \{3\}) = \{3\}$$

Then the resulting preference profile is top responsive:

$$\text{player 1: } \{1, 2\} \succ_1 \{1, 2, 3\} \succ_1 \{1, 3\} \succ_1 \{1\}$$

$$\text{player 2: } \{2, 3\} \succ_2 \{1, 2, 3\} \succ_2 \{1, 2\} \succ_2 \{2\}$$

$$\text{player 3: } \{1, 3\} \succ_3 \{1, 2, 3\} \succ_3 \{2, 3\} \succ_3 \{3\}$$

Top Responsive Games

Core Finding Algorithms - Full Information

Algorithm 1 Top Covering Algorithm

Input: A hedonic game satisfying top responsiveness.

```
1:  $R^1 \leftarrow N; \pi \leftarrow \emptyset$ .
2: for  $k = 1$  to  $|N|$  do
3:   Select  $S^k$ 
4:    $\pi \leftarrow \pi \cup \{S^k\}$  and  $R^{k+1} \leftarrow R^k \setminus S^k$ 
5:   if  $R^{k+1} = \emptyset$  then
6:     return  $\pi$ 
7:   end if
8: end for
9: return  $\pi$ 
```

Let $C^1(i, S) = ch(i, S)$ $C^{t+1}(i, S) = \bigcup_{j \in C^t(i, S)} ch(j, S)$

The *connected component* of i with respect to S : $CC(i, S) = C^{|N|}(i, S)$

Step 3: select $i \in R^k$ such that $|CC(i, R^k)| \leq |CC(j, R^k)|$ for each $j \in R^k$; and $S^k \leftarrow CC(i, R^k)$

Top Responsive Games

Core Finding Algorithms - PAC

Algorithm 2 PAC Top Covering Algorithm

Input: ε, δ , set \mathcal{S} of $m = (2n^4 + 2n^3) \lceil \frac{1}{\varepsilon} \log \frac{2n^3}{\delta} \rceil$ samples from \mathcal{D}

```
1:  $R^1 \leftarrow N, \pi \leftarrow \emptyset$ 
2:  $\omega \leftarrow \lceil 2n^2 \frac{1}{\varepsilon} \log \frac{2n^3}{\delta} \rceil$ 
3: for  $k = 1$  to  $|N|$  do
4:    $\mathcal{S}' \leftarrow$  take and remove  $\omega$  samples from  $\mathcal{S}$ 
5:    $\mathcal{S}' \leftarrow \{T : T \in \mathcal{S}', T \subseteq R^k\}$ 
6:   for  $i \in R^k$  do
7:     if  $i \notin \bigcup_{X \in \mathcal{S}'} X$  then
8:        $B_{i,k} \leftarrow \{i\}$ 
9:     else
10:       $B_{i,k} \in \arg \max_{T \in \mathcal{S}'} v_i(T)$ 
11:       $B_{i,k} \leftarrow \bigcap_{\{T \in \mathcal{S}' : ch(i,T) = ch(i,B_{i,k})\}} T$ 
12:     end if
13:   end for
14:   for  $j = 1, \dots, |R^k|$  do
15:      $\mathcal{S}'' \leftarrow$  take and remove  $\omega$  samples from  $\mathcal{S}$ 
16:      $\mathcal{S}'' \leftarrow \{T : T \in \mathcal{S}'', T \subseteq R^k\}$ 
17:     for  $i \in R^k$  do
18:        $B_{i,k} \leftarrow B_{i,k} \cap \bigcap_{T \in \mathcal{S}'' : ch(i,T) = ch(i,B_{i,k})} T$ 
19:     end for
20:   end for
21:   Select  $S^k$ 
22:    $\pi \leftarrow \pi \cup \{S^k\}$ ; and  $R^{k+1} \leftarrow R^k \setminus S^k$ 
23:   if  $R^{k+1} = \emptyset$  then
24:     return  $\pi$ 
25:   end if
26: end for
27: return  $\pi$ 
```

- Steps 1-3, 21-27: the same structure as Algorithm 1
- Steps 4-20: approximate player preferences from sample observations of coalitions formed
- [1] Step 21: select $i \in R^k$ such that $|CC(i, R^k)| \leq |CC(j, R^k)|$ for each $j \in R^k$; and $S^k \leftarrow CC(i, R^k)$
- Improved Step 21: select the largest Strongly Connected Component (SCC) in the graph induced by R^k as vertices and directed edges E , $(i, j) \in E$ if $j \in ch(i, R^k)$ for all $j \in R^k$; and $S^k \leftarrow SCC(R^k)$

Top Responsive Games

Improved Core Finding Algorithm - PAC

- ▶ correctness proof hiteboarding, proof by picture
- ▶ running time improvements:
 - ▶ each iteration: from finding smallest CC 's $\mathcal{O}(|V|(|V| + |E|))$ to finding the largest SCC 's $\mathcal{O}(|V| + |E|)$
 - ▶ removing more players in the earlier iterations also reduces the amount of computation required for the later iterations

Top Responsive Games - Handcrafted Value Function

Let S_f be the set of members who voted “for” and S_a be the set of members who voted “against”. $S_p = S_f \cup S_a$.

$$v_i(S) = \begin{cases} 1 + \frac{1}{|S|} + \frac{|S_p|}{|N|}, & \text{if } S \text{ is the winning majority} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

- ▶ A winning coalition is always worth more than a losing coalition
- ▶ $\frac{1}{|S|}$ reflects that a win is more valuable when achieved with fewer members
- ▶ The participation term $\frac{|S_p|}{|N|}$ gives a win more value when there are more effective votes for a given bill
- ▶ Assign all unobserved coalition the value of zero

Top Responsive Games - Handcrafted Value Function

Let S_f be the set of members who voted “for” and S_a be the set of members who voted “against”. $S_p = S_f \cup S_a$.

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- ▶ Core stable partition: apply Algorithm 1 with partial reference profile as input
- ▶ PAC stable partition: apply improved Algorithm 2, sampling with replacement to make up for insufficient samples

Top Responsive Games - Appreciation of Friends

Let G_i be player i 's set of friends, and B_i the set of enemies.

$G_i \cup B_i \cup i = N$ and $G_i \cap B_i = \emptyset$. A preference profile P^f is based on *appreciation of friends* if for all player $i \in N$, $S \succeq_i T$ if and only if

1. $|S \cap G_i| > |T \cap G_i|$ or
2. $|S \cap G_i| = |T \cap G_i|$ and $|S \cap B_i| \leq |T \cap B_i|$

- Friends: anyone whose votes agreed with the given player's more often than they disagreed
- Agreed votes are only counted if the given player voted "for" or "against"
- Disagreed votes:
 1. Narrow disagreement (general friends): the other player's vote is different from mine, and is either "for" or "against"
 2. Broad disagreement (selective friends): the other player's vote is different from mine

Top Responsive Games - Appreciation of Friends

Examples

Example 2

Given 3 players and 3 bills, their votes are as follow:

	player 1	player 2	player 3
bill A	for	for	against
bill B	abstained	for	abstained
bill C	abstained	against	abstained

General friends preference profile:

player 1: $\{1, 2\} \succ_1 \{1, 2, 3\} \succ_1 \{1\} \succ_1 \{1, 3\}$

player 2: $\{1, 2\} \succ_2 \{1, 2, 3\} \succ_2 \{2\} \succ_2 \{2, 3\}$

player 3: $\{3\} \succ_3 \{1, 3\} \sim \{2, 3\} \succ_3 \{1, 2, 3\}$

Selective friends preference profile:

player 1: $\{1, 2\} \succ_1 \{1, 2, 3\} \succ_1 \{1\} \succ_1 \{1, 3\}$

player 2: $\{2\} \succ_2 \{1, 2\} \sim \{2, 3\} \succ_2 \{1, 2, 3\}$

player 3: $\{3\} \succ_3 \{1, 3\} \sim \{2, 3\} \succ_3 \{1, 2, 3\}$

Bottom Responsive Games

Definitions

Idea: for every player, the value of a coalition depends on **the absence of the least preferred** subset of players

► *Avoid sets:*

$$Av(i, S) = \{S' \subseteq S : (i \in S') \wedge (S' \preceq_i S'' \forall S'' \subseteq S)\}$$

► A *bottom responsive* preference profile requires:

1. if for all $S' \in Av(i, S)$ $T' \in Av(i, T)$, $S' \succ_i T'$ then $S \succ_i T$
2. if $Av(i, S) \cap Av(i, T) \neq \emptyset$ and $|S| \geq |T|$ then $S \succeq_i T$

Bottom Responsive Games - Aversion to Enemies

A preference profile P^e is based on *aversion to enemies* if for every player $i \in N$, $S \succeq_i T$ if and only if

1. $|S \cap B_i| < |T \cap B_i|$ or
2. $|S \cap B_i| = |T \cap B_i|$ and $|S \cap G_i| \geq |T \cap G_i|$

It is a proper subclass of bottom responsive games

- ▶ Friends: anyone whose votes agreed with the given player's more often than they disagreed
- ▶ Agreed votes are only counted if the given player voted "for" or "against"
- ▶ Disagreed votes:
 1. Narrow disagreement (general friends/selective enemies): the other player's vote is different from mine, and is either "for" or "against"
 2. Broad disagreement (selective friends/general enemies): the other player's vote is different from mine

Top Responsive Games - Aversion to Enemies

Examples

Example 3

Given 3 players and 3 bills, their votes are as follow:

	player 1	player 2	player 3
bill A	for	for	against
bill B	abstained	for	abstained
bill C	abstained	against	abstained

General friends / selective enemies preference profile:

player 1: $\{1, 2\} \succ_1 \{1\} \succ_1 \{1, 2, 3\} \succ_1 \{1, 3\}$

player 2: $\{1, 2\} \succ_2 \{2\} \succ_2 \{1, 2, 3\} \succ_2 \{2, 3\}$

player 3: $\{3\} \succ_3 \{1, 3\} \sim \{2, 3\} \succ_3 \{1, 2, 3\}$

Selective friends / general enemies preference profile:

player 1: $\{1, 2\} \succ_1 \{1\} \succ_1 \{1, 2, 3\} \succ_1 \{1, 3\}$

player 2: $\{2\} \succ_2 \{1, 2\} \sim \{2, 3\} \succ_2 \{1, 2, 3\}$

player 3: $\{3\} \succ_3 \{1, 3\} \sim \{2, 3\} \succ_3 \{1, 2, 3\}$

Bottom Responsive Games

Core Finding Algorithms - Full Information

Algorithm 2 Bottom Responsive Game Core Finding Algorithm

Input: A bottom responsive game

```
1:  $S \leftarrow N; \pi \leftarrow \emptyset.$ 
2: while  $S \neq \emptyset$  do
3:   Set  $\Gamma \leftarrow \{S\}$ 
4:   Set  $\Phi \leftarrow \{X \in \Gamma \mid \{i\} \in Av(i, X) \text{ for each } i \in X\}$ 
5:   while  $\Phi = \emptyset$  do
6:      $\Gamma \leftarrow \bigcup_{X \in \Gamma} \bigcup_{i \in X} \{X \setminus \{j\} \mid j \in Y \text{ for some } Y \in Av(i, X)\}$ 
7:      $\Phi \leftarrow \{X \in \Gamma \mid \{i\} \in Av(i, X) \text{ for each } i \in X\}$ 
8:   end while
9:   Select a coalition  $X \in \Phi$ 
10:  Set  $\pi \leftarrow \pi \cup \{X\}$  and  $S \leftarrow S \setminus X$ 
11: end while
12: return  $\pi$ 
```

Bottom Responsive Games

Core Finding Algorithms - PAC

- ▶ Same structure as Algorithm 2
- ▶ Approximate player preferences $Av(i, X)$ from samples
 - ▶ Find friends from each set of sample coalitions
 - ▶ Take intersection of friend sets as “true friends”
 - ▶ Let each player’s avoid set be players outside the “true friends” set

Boolean Hedonic Games

Idea: a player either likes to be a member of a coalition or hates it

- ▶ A player is indifferent among all satisfactory coalitions, same for unsatisfactory coalitions
- ▶ Strictly prefers any satisfactory coalition over any unsatisfactory coalition
- ▶ Within each bill, “for” and “against” groups each forms a satisfactory coalition
- ▶ Assume unobserved coalitions as unsatisfactory

Boolean Hedonic Games

Examples

Example 4

Given a parliament with 3 players and 3 bills, their votes are as follow:

	player 1	player 2	player 3
bill A	for	against	for
bill B	abstained	for	for
bill C	for	against	against

Boolean preference profile:

player 1: $\{1, 3\} \sim \{1\} \succ_1 \{1, 2\} \sim \{1, 2, 3\}$

player 2: $\{2\} \sim \{2, 3\} \succ_2 \{1, 2\} \sim \{1, 2, 3\}$

player 3: $\{1, 3\} \sim \{2, 3\} \succ_3 \{3\} \sim \{1, 2, 3\}$

Boolean Hedonic Games

Core Finding Algorithms - Full Information

Algorithm 3 Boolean Hedonic Game Core Finding Algorithm

Input: A Boolean hedonic game

```
1:  $N' \leftarrow N; \pi \leftarrow \emptyset.$   
2: while  $N' \neq \emptyset$  do  
3:   Find  $S \subset N'$  where all players in  $S$  find  $S$  satisfactory, and the size of  $S$  is the  
   largest if there are multiple such coalitions.  
4:    $\pi \leftarrow \pi \cup \{S\}$  and  $N' \leftarrow N' \setminus S$   
5: end while  
6: return  $\pi$ 
```

- ▶ Symmetry in preference profile implies the bill with the broadest support/disapproval also yields the largest coalition
- ▶ Symmetry further implies largest cross-party coalition will be part of the output partition
- ▶ Selecting any satisfactory coalition (not necessarily the largest) in Step 3 maintains core stability
- ▶ Our implementation: replace largest with median-sized coalition

Boolean Hedonic Games

Core Finding Algorithms - PAC

- ▶ Same as Algorithm 3
- ▶ Only difference: the input is satisfactory coalitions derived from sample bills
- ▶ The output is consistent with the observed samples, therefore PAC stable [2]

k-Means Clustering

k -means clustering[3] divides a given set of samples x_1, \dots, x_n into k disjoint sets C , each described by the mean μ_j of the samples in the cluster; it produces a partition minimizing the *within-cluster sum-of-squares* (WCSS):

$$\sum_{i=1}^n \min_{\mu_j \in C} (||x_i - \mu_j||^2)$$

- ▶ General purpose
- ▶ Only need to find the best k
- ▶ Runs fast
- ▶ Assumes similar sized clusters

k -Means Clustering

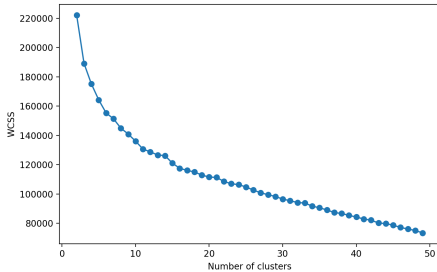
Model Construction

Distance between points

- ▶ Each politician correspond to a point
- ▶ Each bill acts as a feature
- ▶ A “for” vote takes value of 1, “against” -1, others 0

Finding the best k

- ▶ Elbow method:
 $k = 10$
- ▶ Average silhouette:
 $k = 2$



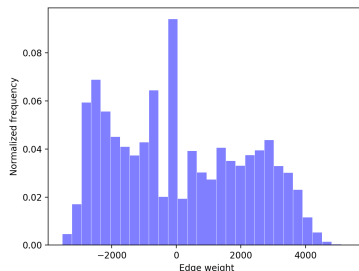
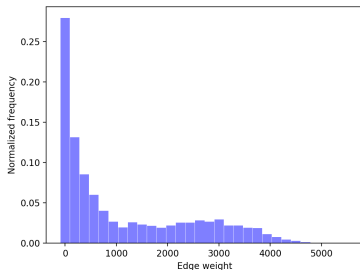
Stochastic Block Model

- ▶ A benchmark model in community detection
- ▶ Models dataset as a graph: parliament members as nodes, same/different votes as edge weights
- ▶ Assumes nodes in the same block shares same probability of being connected to other nodes
- ▶ Using Bayesian inference to find a partition that maximizes the likelihood of the observed network

Stochastic Block Model

Modeling Edge Weights

- ▶ Positive edge weight: the number of times a pair of politicians voted together, either “for” or “against” a bill.
 - ▶ Modeled as a geometric distribution
- ▶ Possibly negative edge weight: the difference between the number of times their votes agree and the number of times their votes disagree
 - ▶ Modeled as a normal distribution



Variability among PAC Partitions

Model	Partition Size Mean (SD)	CV
Value Function	87 (0)	0
General Friends	13 (1.29)	0.10
Selective Friends	20 (1.83)	0.09
Selective Enemies	10 (0)	0
General Enemies	34 (0.84)	0.02
Boolean	85 (16.92)	0.2

Table: PAC model partition size statistics across 50 runs per model

Model	Pairwise AMI Mean (Min)	CV
Value Function	1 (1)	0
General Friends	0.78 (0.6)	0.09
Selective Friends	0.84 (0.66)	0.08
Selective Enemies	0.99 (0.97)	0.01
General Enemies	0.97 (0.93)	0.01
Boolean	0.18 (-0.06)	0.86

Table: PAC Model Partition Pairwise AMI Statistics over 50 Runs per Model

Quantitative Analysis

AMI

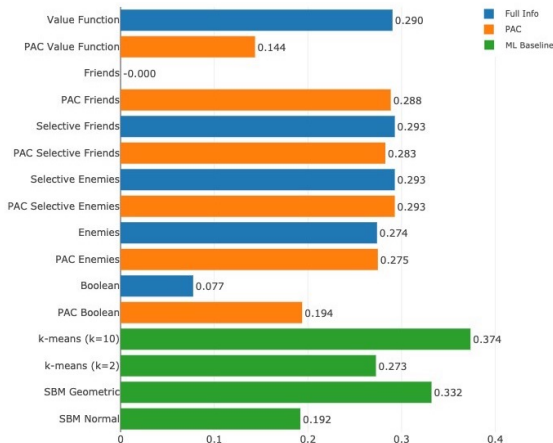


Figure: AMI between model partition and party affiliations

Quantitative Analysis

Friends Models - Full Information

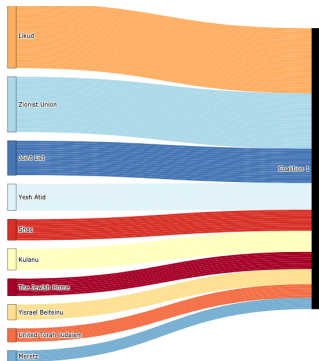
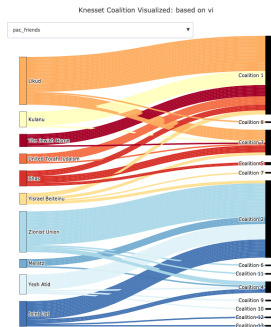


Figure: Partition produced by the general friends model

Full-information models

- ▶ $AMI_{\text{friends}} = 0$
- ▶ $AMI_{\text{selective friends}} = 0.293$
- ▶ More friendly \rightarrow more likely to have grand coalition as final partition
- ▶ Major drawback of the full-information friends models: sensitive to the definition of “friends”

Quantitative Analysis



- ▶ $AMI_{\text{PAC friends}} = 0.288$
- ▶ $AMI_{\text{PAC selective friends}} = 0.283$
- ▶ PAC models dampen their sensitivity to the definition of friends through sampling

Quantitative Analysis

Boolean Models

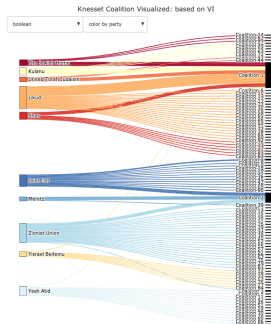


Figure: Partition produced by the Boolean model

Full-info model

- ▶ $AMI_{\text{Boolean}} = 0.077$
- ▶ Too many “stranded” singleton coalitions

PAC model

- ▶ $AMI_{\text{PAC Boolean}} = 0.194$
- ▶ Slightly better performance
- ▶ But of limited representativeness due to high variability

Quantitative Analysis

Handcrafted Value Function Models

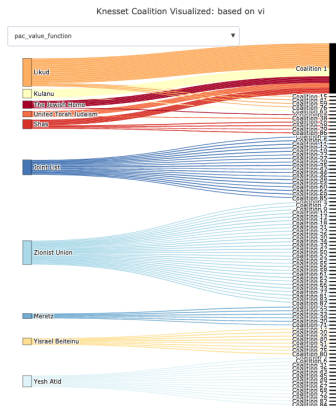


Figure: Partition produced by the PAC value function model

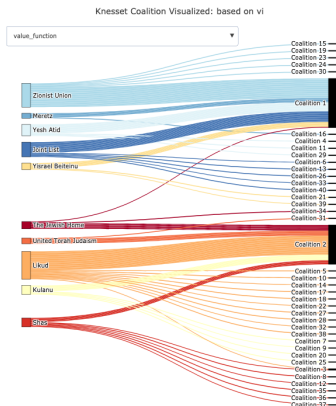


Figure: Partition produced by the value function model

Quantitative Analysis

Handcrafted Value Function Models

Full-info model

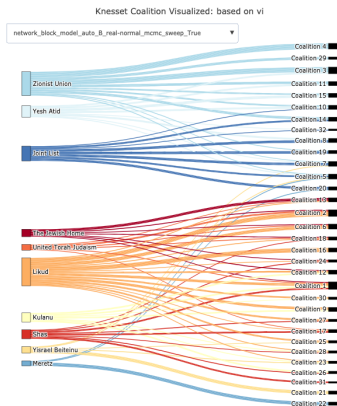
- ▶ $AMI_{\text{Value Function}} = 0.290$
- ▶ Identified a government coalition and an opposition coalition
- ▶ Presence of Yisrael Beiteinu members in coalition 1 (opposition parties) not in line with reality

PAC model

- ▶ $AMI_{\text{PAC Value Function}} = 0.144$
- ▶ Worst performing PAC model
- ▶ Many singleton coalitions
- ▶ Identified a government coalition
- ▶ Missing opposition coalition due to sampling more likely picking government majority bills — limitation of value function formulation

Quantitative Analysis

SMB - Normal Edge Weights



- ▶ $AMI_{SMB \text{ normal}} = 0.192$
- ▶ Many small coalitions
- ▶ Left-wing/right-wing grouping observed, but fails to distinguish the government from the opposition

Figure: Partition produced by the SBM normal model

Quantitative Analysis

Model Selection

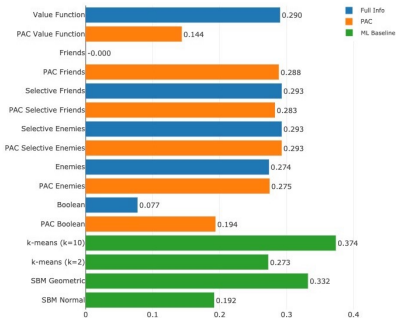


Figure: AML: higher means closer to ground truth

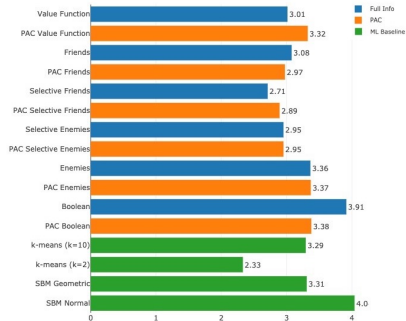


Figure: VI: lower means closer to ground truth

Qualitative Analysis

Selected Models

PAC Models

- ▶ Selective Friends
- ▶ Selective Enemies
- ▶ Boolean

Comparison ML Models

- ▶ 2-group k -means
- ▶ 10-group k -means
- ▶ SBM Geometric

Qualitative Analysis

Criteria

- ▶ Coherence: separate coalition and opposition parties cleanly? (no mixed coalitions)
- ▶ Overall Structure: able to distinguish between the main government and opposition groups?
- ▶ Party Sub-groups: able to identify subgroups within parties?

Model	Coherence	Structure	Sub-group
PAC Selective Friends	✓	✓	✗
PAC Selective Enemies	✓	✓	✗
PAC Boolean	✓	✓	✗
2-group k -means	✗	✓	✗
10-group k -means	✗	✗	✗
SBM Geometric	✗	✗	✗

Conclusion

Summary

- ▶ ML methods: do not consider players' preferences and strategic behavior
- ▶ Game theoretic research: mostly theoretical or prescriptive with simulated data
- ▶ This thesis: a “descriptive” study of hedonic game theoretical models using real-world data of scale, and with ground truth
 - ▶ PAC models are able to recover overall structure & more coherent than ML models
 - ▶ PAC approach result is more robust than full-info approach

Future Research

- ▶ Apply PAC models on other parliaments, e.g. Dutch, Brazilian, US congress
- ▶ Apply other hedonic uncertainty models, e.g. Bayesian core, on the Knesset dataset

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