

# Learning Cooperative Solution Concepts From Voting Behavior

A Case Study on the Israeli Parliament

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Jan 2020



# Outline

Introduction

Methodology

Hedonic Game Stability Models

Machine Learning Models

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

# 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

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- ▶ 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

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- ▶ 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

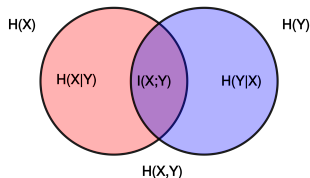


Figure: Venn diagram showing additive and subtractive relationships various information measures associated with correlated variables  $X$  and  $Y$

### ► 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

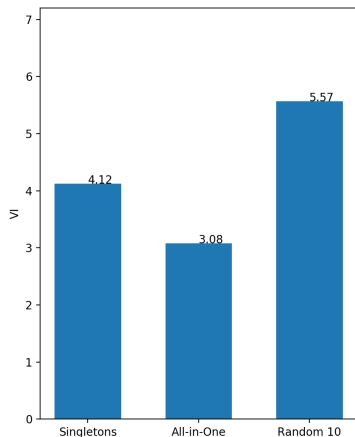


Figure: The Knesset partition baseline VI values

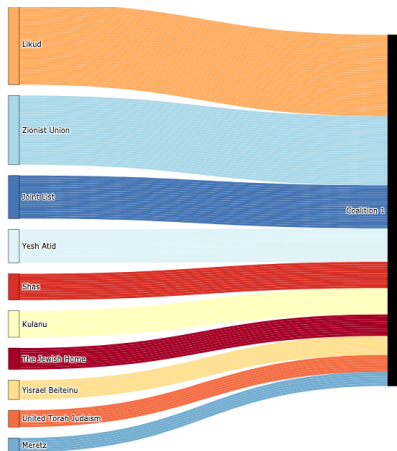


Figure: All-in-One partition of the Knesset

# 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

## Second Slide Title

- ▶ First item.

## Second Slide Title

- ▶ First item.



## Second Slide Title

- ▶ First item.
- ▶ Third item.

## Second Slide Title

- ▶ First item.
- ▶ Third item.

## Second Slide Title

- ▶ First item.
- ▶ Third item.
- ▶ Fifth item.

## Second Slide Title

- ▶ First item.
- ▶ Third item.
- ▶ Fifth item. Extra text in the fifth item.

# Main Theorem

## Theorem 1

*Theorem Statements. Example for citation [1].*

## Proof.

Proof of the theorem goes here.



# Summary

- ▶ The **first main message** of your talk in one or two lines.
- ▶ The **second main message** of your talk in one or two lines.
- ▶ Perhaps a **third message**, but not more than that.
- ▶ Outlook
  - ▶ Something you haven't solved.
  - ▶ Something else you haven't solved.

# Bibliography

- [1] A. Author.  
*Handbook of Everything*.  
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- [2] S. Someone.  
On this and that.  
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