

# Learning Voting Trees

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- Introductory notes (Computational Social Choice)
- Voting Rules and Voting Trees
- Automated design of Voting Rules by Learning
- Finding a Voting Tree
- Conclusions
- Applications

- Election: set of **voters**  $N = \{1, \dots, N\}$ ,  
**candidates/alternatives**  $A = \{x_1, \dots, x_m\}$ .
- Voters have linear preferences  $R^i$ .
- Winner: determined by a **voting rule**, a function  $\mathbf{f}$  from rankings to alternatives.

- Plurality: each voter gives one point to the alternative it ranks first (real-life elections).

## Pairwise elections

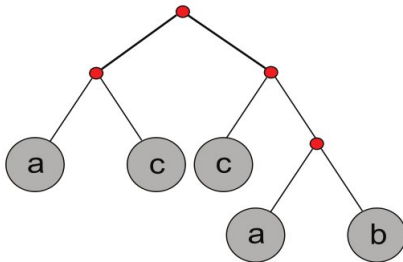
a **beats** b if the majority of voters prefers a to b.

- Copeland: candidate's score is the number of candidates that beats.
- Condorcet Winner: who he beats every other (does not always exist – condorcet paradox).

- A tournament ( $\succ$ ) over  $A$  is a complete binary irreflexive relationship ( $a \succ b$  iff a beats b).
- Example:  $N = \{1, 2, 3\}$ ,  $A = \{a, b, c\}$ 
  - Voter 1:  $c, b, a$
  - Voter 2:  $b, a, c$
  - Voter 3:  $a, c, b$
  - Overall:  $b \succ a$ ,  $c \succ b$ ,  $a \succ c$  (Condorcet paradox).
- (Pairwise) **voting rule** is a function from tournaments ( $T = T(A)$ ) to candidates ( $A$ ).
- $F : T \rightarrow A$ , the class of all voting rules.

# Binary Voting Trees

- Provide a succinct representation of voting rules.
- Not all voting rules can be represented by a voting tree (Copeland rule can be).



# Automated design of Voting Rules by Learning

- Designer:
  - knows the winner of every election, thus, knows the voting rule,
  - does not know how to represent it efficiently.
- Goal:
  - learn the designer's voting rule,
  - find a voting tree.
- Why?
  - Representing a voting rule is  $\text{EXP}(m)$ ,
  - voting trees make the procedure easier, more concise, incorporating desired properties (majority, robustness, ...).
- How many examples?

## Theorem

*An exponential training set is needed to learn voting trees.*

Restrict to the class of voting trees of polynomial size (at most  $k$  leaves).

## Lemma

*If the size of this class is exponential, the goal is achieved with polynomial training set.*



# Learning Results (2/2)

## Theorem

$| \text{Voting trees with } \leq k \text{ leaves} | \leq \text{EXP}(m, k)$

## Proof.

$\text{size} \leq (\# \text{possible structures} * \# \text{assignments to leaves}) * k =$   
 $(\# \text{possible structures} * m^k) * k = ((k-1)!) * m^k * k \quad \square$

# Finding a Voting Tree

## Definition (TREE-SAT)

- tree with partially labeled leaves,
- a training set

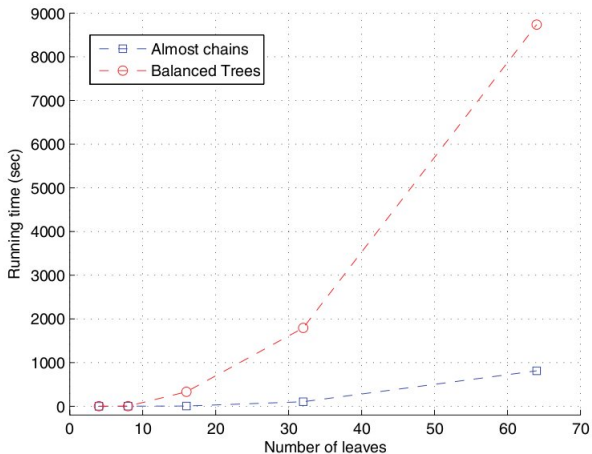
Find a consistent assignment of alternatives to the rest of the leaves.

## Theorem

*TREE-SAT is NP-complete.*

- Imagine the case in which the tree structure was unknown.
- In practice the complexity depends on the structure of the tree.

# Experiments



- For those voting rules that can be represented by a tree with polynomial number of leaves the learning process needs only a polynomial number of examples in the number of alternatives.
- Efficiently finding such a tree depends on its structure (almost chain, balanced tree).
- A designer can use this method to translate a cumbersome representation of its voting rule to a concise one which also satisfies desired properties.

- Compact representation of preferences in combinatorial domains (AI, logic).
- Development of computationally feasible mechanisms, and exploitation of computational intractability as a means against strategic manipulation.



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*In Proceedings of the Twenty-Two AAAI Conference on Artificial Intelligence.* July 22-26, 2007.



Ariel D. Procaccia, Aviv Zohar, and Jeffrey S. Rosenschein.  
Automated Design of Voting Rules by Learning from Examples.

*In Proceedings of the First International Workshop on Computational Social Choice,* 436-449. 2006.



1st International Workshop on Computational Social Choice  
Amsterdam, 6-8 December 2006.

*[http://staff.science.uva.nl/~ulle/COMSOC-2006/  
background.html](http://staff.science.uva.nl/~ulle/COMSOC-2006/background.html)*.



The LaTeX Beamer Class Homepage.

*<http://latex-beamer.sourceforge.net/>*.

Thank you!