Aggregating Conditionally Lexicographic Preferences Using Answer Set Programming Solvers

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Overview

- Introduction
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 - Positional Scoring Voting
 - Conditionally Lexicographic Preferences (LP Trees)
- Problems: Winner and Evaluation
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- 5 Solving the Problems Using Answer-Set Programming (ASP)
 - Experiments and Results
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Multi-Agent Decision Making

A group of students at UK are deciding a joint vacation in 2014 and they may consider the following issues:

- Time: spring, summer, fall, winter, etc
- Transportation: drive, fly, etc
- Destination: Chicago, Beijing, Miami, Brussels, etc
- Duration: three days, one week, ten days, etc

: :

Combinations of values from the domains of issues form vacation options (or alternatives); in such cases, alternatives come from combinatorial domains. Each student has her own preferences (linear ordering) over the alternatives. A solution is a vacation option considering students' preferences.

Multi-Agent Decision Making

Aggregating agents' individual preferences over alternatives to achieve collaborative decisions.

- Alternatives: in combinatorial domains
- Individual preferences: conditionally lexicographic preferences (LP trees)
- Aggregation: based on positional scoring voting rules
- Collaborative decisions: alternatives with the highest score

Contributions

- New computational complexity results for the winner and the evaluation problems based on a special class of positional scoring rules when votes are LP trees
- 2 Logic programs modeling the aggregation problems
- Insight into effectiveness of Answer-Set Programming (ASP) in modeling and solving these problems
 - Two ASP dialects compared

Voting in Combinatorial Domains

- Issues: $\mathcal{I} = \{X_1, X_2, \dots, X_p\}$, with $D(X_i) = \{0_i, 1_i\}$
- ② Alternatives: $\mathcal{X} = D(X_1) \times D(X_2) \times \ldots \times D(X_p)$, $|\mathcal{X}| = 2^p$ (denoted by m)
- ullet Vote: a strict total order on ${\mathcal X}$
- Profile: a finite set of votes collected from n voters



Positional Scoring Rules

- **1** Scoring vector: $w = (w_0, \dots, w_{m-1})$ of natural numbers, where $w_0 > w_1 > \ldots > w_{m-1}$ and $w_0 > w_{m-1}$.
- 2 Let $v = o_0 > o_1 > \ldots > o_{m-1}$ be a vote over \mathcal{X} , the score of alternative o_i in vote v is w_i , denoted by $s_w(v, o_i)$
- **3** Let \mathcal{V} be a profile of votes \mathbf{v} , the score of alternative \mathbf{o}_i in profile \mathcal{V} :

$$s_w(\mathcal{V}, o_i) = \sum_{v \in \mathcal{V}} s_w(v, o_i)$$

Positional Scoring Rules

- Borda: (m-1, m-2, ..., 0)
- k-approval: $(1, \ldots, 1, 0, \ldots, 0)$ with k being the number of 1's
- 2-valued (k, l)-approval: $(a, \ldots, a, b, \ldots, b, 0, \ldots, 0)$, where a and b are constants (a > b) and the numbers of a's and b's equal to k and l, respectively.

LP Trees

- **1** An LP tree ¹ \mathcal{L} over $\mathcal{I} = \{X_1, \dots, X_p\}$ is a binary tree
- ② Each node t in \mathcal{L} is labeled by an issue from \mathcal{I} , denoted by lss(t), and with preference information (0 > 1 or 1 > 0)
- Each issue appears exactly once on each path from the root to a leaf

Intuitively, the issue labeling the root of an LP tree is of highest importance. Alternatives with the preferred value of that issue (upper half) are preferred over alternatives with the non-preferred one (lower half).

¹Richard Booth, Yann Chevaleyre, Jérôme Lang, Jérôme Mengin, and Chattrakul Sombattheera. Learning conditionally lexicographic preference relations. 2010.

LP Trees: Example

$$D(Time) = \{summer(s), winter(w)\}, D(Dest) = \{Chicago(c), Miami(m)\}, D(Tran) = \{drive(d), fly(f)\}$$

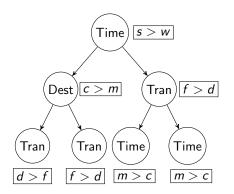


Figure: LP tree

 $scd \succ scf \succ smf \succ smd \succ wfm \succ wfc \succ wdm \succ wdc$

$$D(Time) = \{summer(s), winter(w)\}, D(Dest) = \{Chicago(c), Miami(m)\}, D(Tran) = \{drive(d), fly(f)\}$$

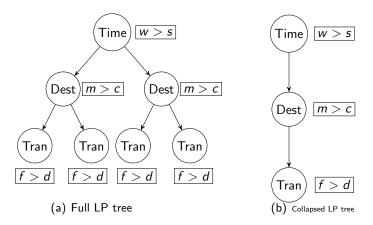


Figure: Collapse to UI-UP

$$D(Time) = \{summer(s), winter(w)\}, D(Dest) = \{Chicago(c), Miami(m)\}, D(Tran) = \{drive(d), fly(f)\}$$

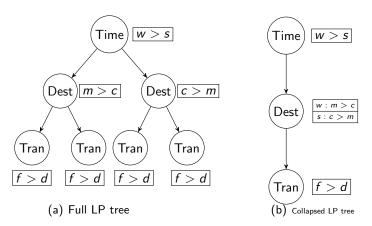


Figure: Collapse to UI-CP

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$$D(\mathit{Time}) = \{\mathit{summer}(s), \mathit{winter}(w)\}, \ D(\mathit{Dest}) = \{\mathit{Chicago}(c), \mathit{Miami}(m)\}, \\ D(\mathit{Tran}) = \{\mathit{drive}(d), \mathit{fly}(f)\}$$

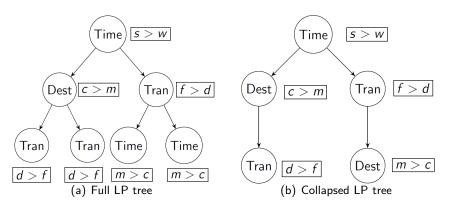


Figure: Collapse to CI-UP



$$D(Time) = \{summer(s), winter(w)\}, D(Dest) = \{Chicago(c), Miami(m)\}, D(Tran) = \{drive(d), fly(f)\}$$

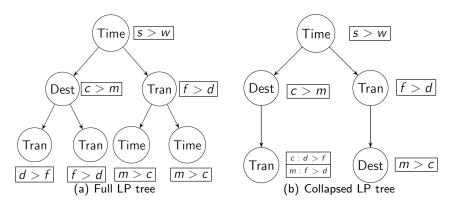


Figure: Collapse to CI-CP

Voting Rules Studied

Effective Implicit Positional Scoring Rules

Let r be a positional scoring rule, and w its underlying scoring vector. Rule r is effective implicit if, given m and i ($0 \le i \le m-1$), there is an algorithm that computes the value w_i in time polynomial in the sizes of m.

- Borda: $w_i = m i 1$
- k-approval: if $i \le k-1$, $w_i = 1$; otherwise, $w_i = 0$
- (k, l)-approval: if $i \le k 1$, $w_i = a$; if $k \le i \le l 1$, $w_i = b$; otherwise, $w_i = 0$

Problems

The Winner Problem

Let r be an effective implicit positional scoring rule with a scoring vector w. Given a profile \mathcal{V} of n LP trees over p issues, the *winner* problem is to compute an alternative $o \in \mathcal{X}$ with the maximum score $s_w(\mathcal{V}, o)$.

The Evaluation Problem

Let r be an effective implicit positional scoring rule with a scoring vector w. Given a profile $\mathcal V$ of n LP trees over p issues and a positive integer R, the *evaluation* problem is to decide whether there exists an alternative $o \in \mathcal X$ such that $s_w(\mathcal V, o) \geq R$.

Computational Complexity

- The computational complexity of the winner and the evaluation problems for positional scroing rules has not been fully understood
- Some computational complexity results are known for some special cases, we aim at expanding the space of known results for more general positional scoring rules

Computational Complexity: Borda

	CP	UP
CI	NPC	NPC
UI	NPC	Р
(a) Evaluation		

	CP	UP
CI	NP-Hard	NP-Hard
UI	NP-Hard	Р
(b) Winner		

Figure: Borda ²

² Jérôme Lang, Jérôme Mengin, and Lirong Xia. Aggregating conditionally lexicographic preferences on multi-issue domains, 2012.

Computational Complexity: k-Approval

- if $k = 2^{p-1}$, the winner and the evaluation problems are in P.
- ② if $k = c \cdot 2^{p-M}$ (c and M are constants) and $k \neq 2^{p-1}$, we have

	CP	UP
CI	NPC	NPC
UI	NPC	NPC
(a) Evaluation		

	CP	UP
CI	NP-Hard	NP-Hard
UI	NP-Hard	NP-Hard
(b) Winner		

Figure: k-approval ³

Computational Complexity: (k, l)-Approval

Our research considers yet another class of positional scoring rules: (k, l)-approval

$(2^{p-2}, 2^{p-2})$ -Approval Evaluation Problem

Let w be the scoring vector for $(2^{p-2}, 2^{p-2})$ -approval. The problem to decide for a given $\{UI, CI\} \times \{UP, CP\}$ profile $\mathcal V$ and an integer R whether there is an alternative o such that $s_w(\mathcal V, o) \geq R$ is NP-complete.

Proof.

Hardness follows from a polynomial reduction from the NP-complete problem *2-MINSAT*.

Computational Complexity: (k, l)-Approval

	CP	UP
CI	NPC	NPC
UI	NPC	NPC
(a) Evaluation		

	CP	UP
CI	NP-Hard	NP-Hard
UI	NP-Hard	NP-Hard
(b) Winner		

Figure: $(2^{p-2}, 2^{p-2})$ -approval ⁴

Answer-Set Programming (ASP)

- Answer-Set Programming ^{5 6} is a language for modeling search and optimization problems defined by constraints
- Rich syntax
 - Constraints: :- not a, b.
 - Aggregates: $1\{b, c, d\}2$.
 - Definitions: goal : a. goal : b, c.
- Formal semantics is given by answer sets ⁷
- Fast solvers are available
 - DLV, Cmodels, clingo

⁵V.W. Marek and M. Truszczynski. Stable models and an alternative logic programming paradigm, 1999.

⁶Niemelä. Logic Programs with Stable Model Semantics as a Constraint Programming Paradigm, 1999.

⁷Michael Gelfond and Vladimir Lifschitz. The Stable Model Semantics For Logic Programming, 1988

ASP Dialects

- Some ASP extensions provide syntax to model numeric constraints directly
- There are solvers that collect numeric constraints and use specialized propagation techniques to solve them
 - clingcon: combines, based on Satisfiability Modulo Theories, ASP with non-Boolean Constraint Programming

Encodings in ASP

- Encoded LP trees as logic programs
- Encoded the winner and the evaluation problems in two ASP dialects
 - $\{winner, evaluation\} \times \{Borda, k-approval, (k,l)-approval\} \times \{clingo, clingcon\}$
- The answer sets computed correspond to the solutions to the winner and the evaluation problems

Random LP Profiles

 To experiment with LP profiles, we developed methods to randomly generate encodings of a special type of CI-CP LP tree of size linear in the number of issues

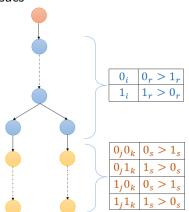


Figure: Random LP tree

Experimentation

- Focused on NP-hard cases
- The winner problem: $\{FI(10), FV(500)\} \times \{Borda, 2^{p-2}\text{-approval}, 2K\text{-approval}^8\} \times \{clingo, clingcon\}$
- The evaluation problem: for a randomly generated profile, computed winning score WS and solved the evaluation problem with various thresholds (percentages of WS): $\{5\%\cdot WS,\ 10\%\cdot WS,\ \dots,\ 100\%\cdot WS,\ WS+1\}\times \{Borda,\ 2^{p-2}\text{-approval},\ 2K\text{-approval}\}\times \{clingo,\ clingcon\}$

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 $^{^8 2 \}text{K-approval:} \ (2, \dots, 2, 1, \dots, 1, 0, \dots, 0)$ with the numbers of 2's and 1's equal to 2^{p-2}

Varying p and n

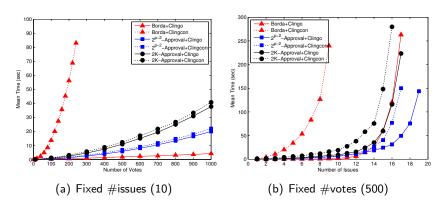


Figure: The winner problem

Evaluation: Borda

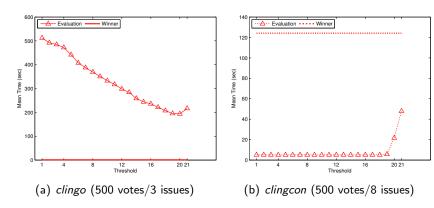


Figure: Borda

Evaluation: 2^{p-2} -Approval

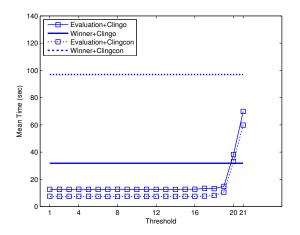


Figure: 500 votes/16 issues

Evaluation: 2K-Approval

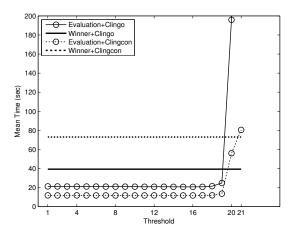


Figure: 500 votes/14 issues

Future Work

- Generate richer classes of random LP trees
- Aggregate preferences in other formalisms, such as conditional preference networks (CP-nets) ⁹ and answer set optimization preferences ¹⁰

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⁹C. Boutilier, R. Brafman, C. Domshlak, H. Hoos, and D. Poole. CP-nets: A tool for representing and reasoning with conditional ceteris paribus preference statements. 2004.

¹⁰Gerhard Brewka, Ilkka Niemela, and Miroslaw Truszczynski. Answer set optimization, 2003.