Computational Social Choice Competition: Overview

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The field of computational social choice brings together principles, techniques, and tools from computer science and social choice theory to create a thriving multidisciplinary field. One of the most well-studied problems in computational social choice focuses on voting rules for selecting the winning candidate in an election. Recent research goes beyond classical voting rules by looking at rules that select multiple winners or drawing on the parallels between machine learning and voting. It is common to encounter voting paradoxes when implementing voting rules in electoral systems. Unfortunately, these paradoxes usually provide little information on the conditions that make them more or less likely to occur. Computer simulations and generative probabilistic models are practical approaches to address this problem. This introductory paper addresses the problem of evaluating voting rules in competitive computer simulations. Multiagent simulations can provide valuable insights into the performances of competing voting rules defined over parametrically generated problems and populations. The outcomes of this work could improve the designs of electoral systems in the absence of theoretical results to support the optimality of a voting method. This line of research could also bridge the gap between axiomatic and experimental analysis of voting systems, leading the way to enhanced explanations and predictions.

Keywords: Artificial Intelligence, Computational Social Choice, Voting, Multiagent Systems, Agents, Simulation

1. Introduction

The field of computational social choice (COMSOC) combines ideas, techniques, and models from computer science and social choice theory for aggregating collective preferences [12, 7]. This thriving and multidisciplinary field of research has numerous applications to group decision-making, resource allocation, fair division, and election systems [8]. One of the most well-studied problems in COMSOC focuses on designing voting mechanisms for selecting the winning candidates for an election. Paradoxes and impossibility results are commonly encountered when implementing voting rules in electoral systems [15]. Researchers are therefore exploring alternatives to classical voting mechanisms by incorporating, for instance, principles and techniques from machine learning [26, 2, 7, 6]. Agent-based simulations can also tackle such challenges, as evidenced by their successful applications in negotiation research [4, 9], supply chain management [22], and energy markets [20].

In line with this vision, we propose the COMPSOC (Computational Social Choice Competition) as a way to capitalize on the progress in agent research and computational social choice. In this introductory paper, we lay out the competition's goal, an overview of its flow, and some of its technical aspects.

2. Goal of the competition

Computational Social Choice Competition (COMPSOC) aims to advance the research in computational social choice by leveraging multiagent simulations [16, 19], and machine learning techniques [5, 26, 2]. The name of the competition, "COMPSOC", is an amalgamation of the words "COMSOC" and "COMPetition"

The competition will focus on the principled evaluation and analysis of voting rules in a competitive setting. The competitors will develop and submit the code of their voting rules, which will then be compared in a tournament based on social welfare and axiomatic satisfiability. The competition aims at providing valuable insights into the performances of voting mechanisms defined over parametrically generated voting problems, alternatives, and voters.

COMPSOC will bring together researchers from the fields of computational social choice, social sciences, political sciences, multiagent systems, and machine learning and provide a unique benchmark for evaluating voting mechanisms in various synthetic (or real) problem domains. The competition also aims at advancing the field by providing a systematic approach to designing and assessing voting mechanisms in the absence of established theoretical results. This advancement will help bridge the gap between axiomatic and experimental analysis of voting systems, ultimately leading to an improved explainability [10].

3. Guidelines of the competition

The flow of the competition is illustrated in figure 1. In step (1), the competitors implement their voting rules using a provided Python API. In step (2), synthetic voting profiles will be parametrically generated using various state-of-the-art voter models [27, 5]. In step (3), we will separately apply the competitors' voting rules to the generated baseline of profiles. In step (4), the optimal voting rules will be selected based on social welfare, and how well they satisfy anonymity, neutrality, monotonicity, Pareto optimality, unanimity, and non-imposition [25].

The top 3 winning competitors are the competitors with the voting rules that yield the highest social welfare for the multiagent voters (given the baseline ballots of the competition) while satisfying the properties mentioned above. Various sample codes of well-known voting rules will be provided to the participants to guide their implementations (including Borda, Copeland, Dowdall, etc.).

In addition to submitting the Python code of their voting mechanisms, the participants are expected to submit a report describing their mechanism, implementation, and expected results. This will

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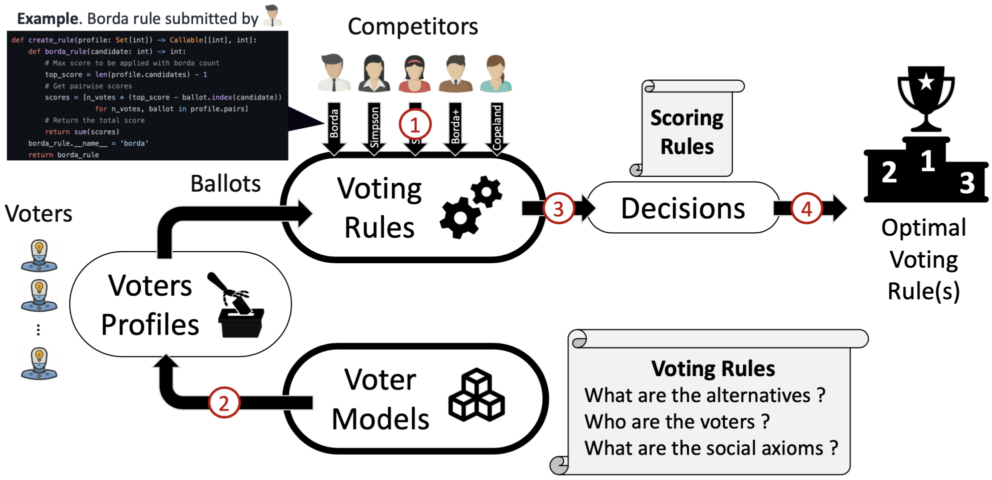

Figure 1: Overview of the Computational Social Choice Competition (COMPSOC)

help disseminate the lessons learned from running the competition to the community and set the direction for future tournaments.

We will now cover the key aspects of the competition, that is, the voting rules, the voting models and the way the rules are compared.

4. Voting Rules

Social choice theory generally focuses on three types of social aggregation procedures: voting rules, social choice functions, and social welfare functions [25]. In this initial iteration of COMPSOC, we focus on non-resolute voting rules, that is, social aggregation functions that selection one or multiple winners given a set of voters and a set of alternatives. Formally, we start from a finite set of voters $N = \{1, 2, \ldots, i, \ldots, n\}$ and a finite set of alternatives $A = \{1, 2, \ldots, j, \ldots, m\}$. Each voter $i \in N$ has an order-able preference $\succsim_i$ over the alternatives in A.

If A is a finite non-empty set, then we define an $A-$ballot as a weak ordering of A. Additionally, if n is a positive integer, then an $(A, n)-$profile is an $n-$tuple of $A-$ballots. In the following, we refer to an $(A, n)-$profile as profile P. The voting rule V is a function whose domain is the collection of all $(A, n)-$profiles. For every P, the voting rule V produces an election outcome $V(P)$ that is a non-empty set of A, as illustrated in (1).

$$V : P \rightarrow V(P) \neq \emptyset \tag{1}$$

Each competitor k taking part in COMPSOC, will submit his voting rule V_k. In the competition, we will focus on linear ballots and voting rules that process desirable properties such as anonymity, neutrality, monotonicity, Pareto optimality, unanimity, and non-imposition. For example, the voting rule V could be implemented based on Dowdall, Copeland, or Borda rules [25].

5. Voter Models

The profile P that will be fed to a voting rule V needs to be defined based on models that describe a population of voters with various characteristics and distributions [5]. A profile P is generally decomposed into its ith components R_i defined as the ballot of the ith voter. Each R_i has components P_i and I_i denoting its derived relations of strict preference and indifference ($\succsim_i$). A profile P is therefore defined as in (2).

$$P = \langle R_1, R_2, \ldots, R_i, \ldots, R_n \rangle \tag{2}$$

We generally distinguish two methods to obtain the profiles. One is based on synthetically generated profiles and one uses empirical data from Websites like `www.preflib.org`. Herein, we will adopt the synthetic method for its scalability to the population characteristics we are interested in studying. In practice, we rely on generative models [5, 27, 26]. Next, we cover three possible ways to generate the profiles of the voters: random, gaussian, and hierarchical Bayesian.

5.1 Random Profiles

In this profile generation method, the ballots of the voters are generated by random permutations over the set A. This could be done either in a naive way or using more elaborate random utility models (RUM) [5].

5.2 Gaussian Profiles

Herein, we assign a Gaussian distribution over a support of randomly ranked alternatives. This method assigns a basic structure to the population of the voters and could be used to study different sub-populations and majority rules.

5.3 Hierarchical Bayesian Profiles

The third approach is based on data generation using a Dirichlet-Multinomial (DM) distribution. Such distribution is often used to model the distribution of counts in a categorical variable when the categories are not equally likely. DM distributions are commonly used in text mining, ecology, genetics, marketing, and finance. In our case, the components of profile P will be generated from multinomial distributions drawn from population-level preferences modeled using Dirichlet priors. In the Bayesian formulation of (3), the two distributions are coupled as conjugate and priors,

$$\mathbb{P}(n|\alpha) = \int_{\Omega} \mathbb{P}(n|\theta)\, \mathbb{P}(\theta|\alpha)\, d\theta \tag{3}$$
$$n|\theta \sim Multinomial(N; n, \theta)$$
$$\theta \sim Dir(\alpha)$$

where the prior α controls the concentration of the votes given the alternatives in A. The example in figure 2 illustrates a profile P_α set with prior $\alpha = (5, \frac{1}{2}, 2)$. The bottom part of the figure shows the resulting distribution of the votes. In this model, we distinguish different levels starting from the population of the voters down to the individual votes cast by each agent, or voter.

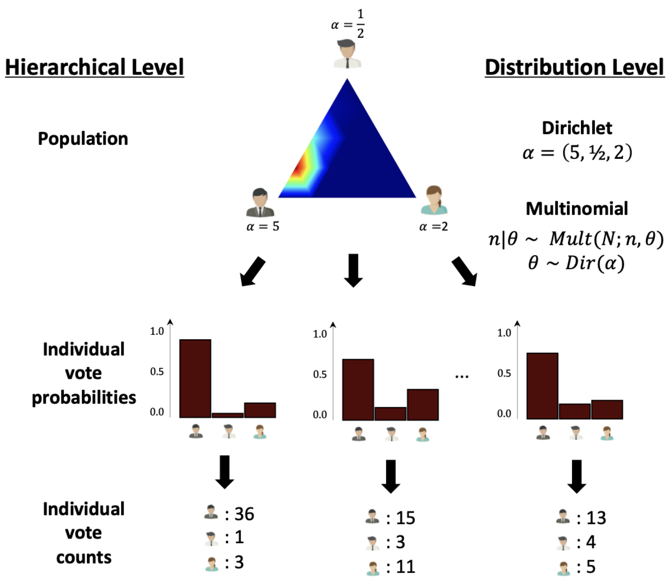

Figure 2: Generation of the votes from Dirichlet-Multinomial distributions

The generative model (3) could be refined by integrating additional levels of parametrization [5]. Additional hyper-parameters in (3) could be defined to attribute elaborate economic or political types to the voters. The voters could ultimately be implemented as a multiagent system with agents that can learn from repetitive elections and even form coalitions.

6. Comparing the voting rules

Once the profiles are generated and the voting rules submitted by the competitors, we need to comprehensively compare the rules given some criteria. It is possible to adopt axiomatic criteria as well as numeric ones that look at the induced social welfare. It is also possible to utilitarian distortion particularly when the rankings in P are incomplete [24, 14, 11]. Herein, we focus on a method that measures the social welfare induced from adopting different voting rules.

To evaluate a voting rule V, we start from the set of voters N and a finite set of alternatives A. Given a profile P, a voting rule V satisfies $V(P) \neq \emptyset$ and $V(P) = v \subseteq A$. The procedure starts by building a utility increment $U(P)$ with $U(P) \in [0, 1]$ from $V(P)$. This $V-$induced utility increment assigns to any winning vote $v = (c_1, c_2, \ldots, c_j, \ldots, c_m)$ the quantity $\frac{m-j}{m}$, $\forall c_j \in A$. In words, this utility function quantifies the level of happiness of a particular voter given the actual winner(s) of the elections.

Formally, given each voter i's top candidate $v_i \in A$, the score of the voting rule of competitor k, V_k, is defined as in (4).

$$Score(V_k) = \sum_{i=1}^{n} U(P_\alpha)(v_i) \tag{4}$$

Here, the profile P_α is taken to be a Dirichlet-Multinomial profile. Let us take an example of random profile P_{rand} defined for $n = 20$ voters and $m = 5$ alternatives. Let us define 4 voting rules $V \in \{Borda, Copeland, Dowdall, Simpson\}$. Figure 3 illustrates how the scoring is performed based on procedure (4).

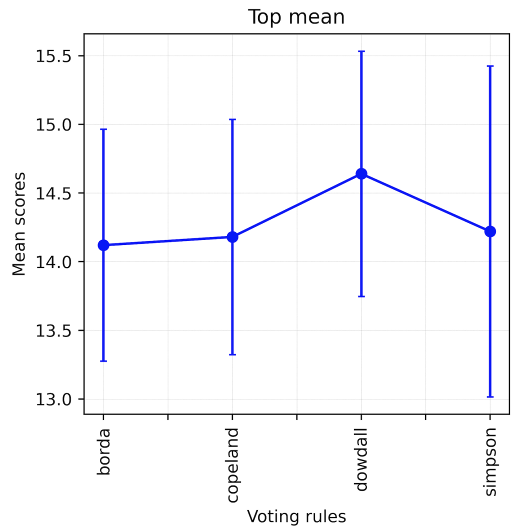

Figure 3: Scoring of 4 voting rules given a randomly generated profile

Comparing the voting rules should not uniquely rely on numerical scoring but should also be done with respect to the adopted axioms. This axiomatic interpretation could be done by testing the submitted voting rules against a grid of axioms. The selection of the winning rules could for example rely on a metric that accounts for social welfare as well as the satisfiability of these axioms.

7. Conclusion and Perpectives

In this introductory paper, we outlined the core ideas behind the Computational Social Choice Competition (COMPSOC). Computational social choice theory could largely benefit from agent development, multiagent systems, and computer simulations. The research outcomes of COMPSOC could help in the design of voting rules in the absence of theoretical results to support the optimality of a particular election systems. Most importantly, this line of work could bridge the gap between axiomatic and experimental analysis of voting systems, leading the way to enhanced explanations and predictions [10].

Ultimately, the long-term goal of COMPSOC is to drive the development of inclusive, robust, and fair election systems in line with liquid democracy [3, 1], crowdsourced governance [21, 23], deliberative democracy [18], and augmented democracy [17, 13]. One could even envision a simulation testbed of social functions that runs off-the-grid in the discovery of optimal social mechanisms. These voting rules could then be re-integrated into online AI-powered democratic platforms through agent mediation [17].

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