MS&E 336/CS 366: Computational Social Choice. Win 2023-24

Course URL: http://www.stanford.edu/~ashishg/msande336/index.html.

Instructor: Ashish Goel, Stanford University.

Lecture 1, 1/8/2024. Scribed by Naman Gupta.

2 Prior reading

Chapter 1 and 2.1-2.4 of HCSC [1]

3 Introduction

• Course Name: Computational Social Choice MS&E 336/CS 366

• Instructor: Ashish Goel

• Location: 160-332

• Webpage: http://web.stanford.edu/ashishg/msande336/

• Books: Handbook of Computational Social Choice [1] and Algorithmic Game Theory [2]

• Deliverables:

- Each student will be asked to scribe one lecture (10%)
- Three homeworks which can be done in groups of 2-3 (40%). Given 1/25, 2/8, 2/22. Due 2/7, 2/21, 3/6 before midnight
- A take-home exam (20%)
- Project Report: in groups of 2-3, survey an open problem and possible directions. Please also show progress for some small special cases (or even the full problem). Preliminary report due 3/1, midnight (15%). Final report due 3/21, midnight (15%).
- Read 4-6 papers.

4 Motivating examples

Many modern systems rely on personalisation: advertising/marketing, content recommendation systems, etc. In contrast, social choice studies systems on the opposite end e.g. no personalisation. Instead of delivering a desirable result to every one participant, social choice systems aggregate the preferences of N voters across M candidates/alternatives. Examples include voting (350M voters, 1 president), jury trials (one decision for all jurors), etc.

While there are many impossibility theorems associated with this field of research, this class will only touch on them briefly. The remainder of the quarter will then focus on areas not invalidated by impossibility theorems.

5 Notation

Throughout this course, we will use f to refer to both a Social Choice Function (SCF) and a Social Welfare Function (SWF).

- A SCF takes in a profile and returns a (not-necessarily unique) winner.
- A SWF takes in a profile and returns a (non-strict) ranking of the candidates.

Moving forward, we will refer to both using f, which takes in a profile and returns a result.

We also use the notation $a \succcurlyeq b$ to indicate that a voter likes candidate/alternative a at least as much as candidate/alternative b.

6 Properties

We next introduce a series of properties that a designer may wish a social choice system (f) to satisfy.

- Fairness to voters: this includes multiple sub-properties. Note that there is no f that satisfies both reinforcement and the Condorcet criterion
 - Anonymity: exchanging the rankings of voters a and b does not change the output of
 - Condorcet criterion: If alternative a beats every other alternative b in a pairwise election (i.e. a is ranked above b more often than not), then a should be a winner. Also known as the "Pairwise Majority criterion". Such an a is called a Condorcet winner, which may not exist
 - **Reinforcement**: Suppose S and T are two profiles with disjoint voters but same alternatives. If f is a SCF, and f(S) and f(T) are intersecting, then f(S+T) must be contained in the intersection of f(S) and f(T)
- Fairness to candidates: this also includes multiple sub-properties. Two notes: (1) Note that non-imposition is a weaker guarantee of candidate fairness and (2) non-imposition and pareto optimality are both a form of "voter sovereignty"
 - **Non-imposition**: For each candidate/alternative a there exists a profile such that f(p) = a.
 - **Neutrality**: exchanging the positions of alternatives a and b in each voter's ranking exchanges a and b in the output of the SWF/SCF
 - Pareto Optimality: If every voter prefers a to b, then a is strictly above b in the output of the SWF, and b is not a winner in the output of the SCF
- Resolute: SCF outputs a single winner

- Strategy-proofness: No voter can benefit by misreporting preferences
- Unanimity: If every voter chooses alternative A over alternative B, then the overall preference should rank A above B

References

- [1] F. Brandt, V. Contizer, U. Endriss, J. Lang, and A.D. Procaccis. *Handbook of Computational Social Choice*. Cambridge University Press, 2016.
- [2] R. Motwani and P. Raghavan. Randomized Algorithms. Cambridge University Press, 1995.