THESIS PROPOSAL

Economic Foundations of Practical Social Computing

by

Nisarg Shah
Carnegie Mellon University
nkshah@cs.cmu.edu


Other Thesis Committee Members:
Maria-Florina Balcan, Carnegie Mellon University.
Avrim Blum, Carnegie Mellon University.
Vincent Conitzer, Duke University.
Tuomas Sandholm, Carnegie Mellon University.

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Chapter 1

Introduction

What is social computing? It is a general term that denotes any process where inputs from multiple agents or users are used to guide the process of computing a social outcome. Social computing is ubiquitous today, from political elections where inputs of the voters are used to come up with a social decision, through crowdsourcing systems where inputs from workers are used to solve a task at hand, to multi-agent resource allocation problems where preferences of the users used to find an efficient allocation of resources.

On a very high level, social computing problems can be classified into two types: “inward” and “outward”. Inward (or aggregation) problems typically aim at collecting inputs from agents and aggregating them to compute the optimal decision. A typical example is that of multiple workers on a crowdsourcing platform offering their opinions regarding the appropriate label for an image; these opinions are aggregated to find the most appropriate label for the image. Outward (or allocation) problems, on the other hand, require allocating a set of resources to agents. In this case, preferences of the agents over allocations of resources are used to find an appropriate assignment of the resources. A typical example is dividing available computational resources between jobs in a shared cluster with different demands for the resources. Many organizations face both kinds of problems, inward problems that involve receiving feedback from the end-users or the employees and using it to make optimal data-driven decisions, and outward problems that involve allocating the organization’s resources to its employees.

We consider both form of social computing problems that arise in real-world scenarios. We focus on resource allocation in shared clusters (as well as some other resource allocation problems), and social choice problems that arise in human computation systems. We use tools and techniques from the extensive theory of fair division in economics literature, from the theory of incentives in game theory literature, and algorithmic computer science techniques to analyze present mechanisms as well as develop novel, compelling mechanisms for addressing such problems.

1.1 Resource Allocation

Perhaps the most important parameter in resource allocation problems (more generally, mechanism design problems) is the presence or absence of money in the system. Since the groundbreaking
results of Vickery [1961] and Myerson [1981], mechanism design with money (e.g., auction design) has been a hot research topic due to its relevance in many commercial applications. However, there are numerous settings where the use of money may be prohibited by normative considerations, e.g., many political decisions must be made without monetary transfers, and organ donations can be arranged by “trade” involving multiple needy patients and their relatives but monetary compensation is illegal. In such settings, the emphasis is on fairly dividing the available resources between the agents. In addition to fairness constraints, an important consideration is the game-theoretic desiderata known as strategyproofness, which requires that agents should not be able to manipulate the mechanism for their personal gain.

My previous work has focused on the allocation of divisible computational resources to agents who require them in a fixed proportion; such preferences are known as Leontief preferences. My earlier work [Parkes et al., 2014] generalized a recent compelling mechanism for Leontief preferences, known as the Dominant Resource Fairness mechanism (DRF) [Ghodsi et al., 2011], to two realistic settings. My subsequent work [Kash et al., 2014] focused on extending the static domain of Leontief preferences to a dynamic model where agents arrive over time, and agents’ private information is only revealed when they arrive. This work initiated the study of dynamic fair division; for centuries, fair division theory had only considered static settings. In future my goal is to design more robust mechanisms that can handle the full generality of a real-world cluster where the dynamics are more complex. Another line of research aims at designing allocation mechanisms for preferences other than Leontief preferences. In an ongoing work, we have designed a very compelling mechanism for allocating unused space in public schools of the Oakland (CA) unified school district to local charter schools. We prove that this mechanism satisfies attractive normative desiderata, and is to be used in December 2014 for the actual allocations.

1.2 Social Choice

Social choice theory aims at aggregating conflicting preferences of voters, and coming to a social decision which is arguably a good compromise given the preferences. For centuries, political elections were viewed as the raison d’Être of social choice theory, but it is essentially impossible to redesign political elections. On the other hand, the recent advent of crowdsourcing and human computation systems, where the designer of the system can freely choose a voting rule, have motivated a completely novel application of social choice theory. The goal is design voting rules in a principled way that would leads to performance improvement in such systems. Perhaps the most important way in which this setting differs from political elections is that, unlike political elections, there exists a truly best alternative (or a true ranking of the alternatives by their quality), which is unknown. Thus, the votes are not subjective preferences, but rather noisy estimates of this unknown ground truth.

In this thesis, my aim is to develop practical voting rules that accurately recover the underlying ground truth given noisy votes. The classical maximum likelihood approach is to assume a probabilistic vote generation model that governs the mistakes in the votes (a.k.a. a noise model), and select the voting rule that returns the most likely ground truth assuming that the votes are generated from this model. While traditional approach only considers standard objectives such as
predicting the ground truth or the best alternative, my earlier work [Procaccia et al., 2012] focused on alternative objectives that arise in real-world human computation systems [Lee et al., 2014].

However, the MLE approach to voting is rather constrained: First, it assumes that the votes are generated from a particular classic noise model, which can hardly predict the rather arbitrary noise present in votes collected from crowdsourcing systems [Mao et al., 2013], and second, for every noise model there is only a single voting rule that is optimal for the noise model. In my subsequent work [Caragiannis et al., 2013, 2014] we focus on designing robust voting rules that can accurately pinpoint the ground truth given a large number of votes from any noise model within a large enough family. This is in contrast to rules in the MLE framework that only work well for a single noise model. We propose two families of voting rules — which generalize the well-known notions of Condorcet consistent rules and positional scoring rules — that work well for two wide families of noise models, and pinpoint the unique, extremely robust voting rule that works well for an even wider family of noise models.

In ongoing research my aim is to take this framework to the next step by considering dependencies among input votes. For example, if votes are collected on a social network through a poll, the voters may have had interactions controlled by the social network structure. Thus, their votes may not be independent of each other. Independence of input votes is a standard assumption that is present in almost all of social choice research. My plan is to implement a voting post in the popular social network, Facebook, where complex opinions of users may be collected over a variety of questions, and the voting rules that emerge from this research may be implemented to design accurate systems for aggregating these opinions.

1.3 Overview of the Proposal Format

In this chapter I provided a high level overview of the part of my research that will constitute the core of my thesis, and some necessary background. Chapters 2 and 3 provide detailed summaries of my research on resource allocation problems and social choice problems, respectively, and include a section on the research that I am planning to do in the respective fields which will be included in my thesis. Chapter 4 outlines the lines of research I have worked on (and will work on) that will not be a part of my thesis.
Chapter 2

Resource Allocation without Money

We consider a variety of resource allocation problems that arise in practice. Our focus is restricted to settings where the use of monetary transfers is prohibited due to normative constraints. Imagine a shared computational cluster in a university or a research institute. The resources of the cluster must be divided fairly among the faculties or researchers who need them for performing computational tasks; however, payments cannot be used for allocating the resources. Usually, payments make it easier to enforce truth-telling, as lying and receiving more resources typically translates to a greater payment too. Hence, the absence of monetary transfers make it harder to design mechanisms that are efficient, and yet agents are naturally incentivized to report truthfully. We begin by considering our primary motivation — fair division of computational resources.

2.1 Fair Division of Computational Resources

Resource allocation is a fundamental issue in the design and implementation of computing systems, which are naturally constrained in terms of CPU time, memory, communication links, and other resources. We are interested in settings where these resources must be allocated to multiple agents with different requirements. Such situations arise, e.g., in operating systems (where the agents can be jobs) or in cloud computing and data centers (where the agents can be users, companies, or software programs representing them). To take one example, federated clouds [Rochwerger et al., 2009] involve multiple agents that contribute resources; the redistribution of these resources gives rise to delicate issues, including fairness as well as incentives for participation and revelation of private information, which must be carefully considered.

2.1.1 Background

Despite the growing need for resource allocation policies that can address these requirements, state-of-the-art systems employ simple abstractions that fall short. For example, as pointed out by Ghodsi et al. [2011], Hadoop and Dryad—two of the most widely-used cluster computing frameworks—employ a single resource abstraction for resource allocation. Specifically, these frameworks partition the resources into bundles—known as slots—that contain fixed amounts of
different resources. The slots are then treated as the system’s single resource type, and at this point the allocation can be handled using standard techniques that were developed by the systems community. However, in a realistic environment where agents have heterogeneous demands, the single resource abstraction inevitably leads to significant inefficiencies.

Ghodsi et al. [2011] suggest a compelling alternative. Their key insight is that even though agents may have heterogeneous demands for resources, their demands can be plausibly assumed to be highly structured, in maintaining a fixed proportion between resource types. For example, if an agent wishes to execute multiple instances of a job that requires 2 CPUs and 1 GB RAM, its demand for these two resources has a fixed ratio of 2. Given 5 CPUs and 1.8 GB RAM, the agent can run only 1.8 instances of its task (note that Ghodsi et al. allow divisible tasks) despite the additional CPU, hence the agent would be indifferent between this allocation and receiving only 3.6 CPUs and 1.8 GB RAM.

Preferences over resource bundles that exhibit this proportional structure are known as *Leontief preferences* in the economics literature. There are some positive results on resource allocation under Leontief preferences [Nicolò, 2004], but more often than not Leontief preferences are drawn upon for negative examples.

Leveraging this model, Ghodsi et al. [2011] put forward the *dominant resource fairness (DRF)* mechanism. Briefly, DRF allocates resources according to agents’ proportional demands, in a way that equalizes the shares that agents receive of their most highly demanded resource. Ghodsi et al. demonstrate that DRF satisfies a number of prominent desiderata:

1. **Pareto optimality (PO):** No alternative allocation keeps every agent at least as happy, and makes at least one agent strictly happier.

2. **Sharing incentives (SI):** Agents are at least as happy as they would be under an equal split of the resources.

3. **Envy-freeness (EF):** Agents do not wish to swap their allocated resources with other agents.

4. **Strategyproofness (SP):** Agents cannot gain by misreporting their demands.

### 2.1.2 Related Work

The work of Ghodsi et al. [2011] has inspired a number of publications in this area. Li and Xue [2011] characterize mechanisms that satisfy desirable properties under Leontief preferences. While their results imply group strategy-proofness (GSP, a much stronger property than SP) of various mechanisms, curiously, DRF is not captured by their results. More importantly, Li and Xue also assume strictly positive demands.

Friedman et al. [2011] explore the relations between resource allocation under Leontief preferences and bargaining theory. They introduce a family of *weighted* DRF mechanisms, but the weights in their case are only means for computing variations of DRF that are all provably group-strategyproof with *unweighted* agents.

Dolev et al. [2012] also study resource allocation under Leontief preferences. But they consider an altogether different fairness criterion, which they call *no justified complaints*. They show
existence of an allocation that satisfies no justified complaints; later, Gutman and Nisan [2012] gave a polynomial time algorithm for computing such allocations.

2.1.3 Weighted and Quantized DRFs

Despite the significant step forward made by Ghodsi et al. [2011], their model is only a stylized model of the reality, and lacks many key practical parameters. In a previous work [Parkes et al., 2014], we consider two generalizations of this setting, and propose mechanisms closely related to DRF that achieve desirable properties.

Our first generalization introduces exogenous agent weights that represent their priorities. Unlike related work in the literature where such weights were artificially introduced [Friedman et al., 2011], our setting requires us to define new fairness desiderata that reflect agent priorities. To that end, we define weighted versions of sharing incentives (informally, the utility of every agent is at least as much as its normalized weight) and envy-freeness (informally, no agent wants to swap its allocation with another agent after the allocation of the other agent is scaled appropriately to reflect the difference in the weights of the two agents). We also remove the restricting assumption that every agent demands all resources.

First, we formalize the mechanism intuitively described by Ghodsi et al. [2011] in terms of a water-filling process, and formulate it in terms of concrete linear programs. We observe that the mechanism is maximizing the minimum utility when every agent demands all the resources. For the general case when some agents may not demand some resources, we propose the leximin mechanism that maximizes the minimum probability, and subject to that, maximizes the second minimum probability, and so on. We then propose a natural weighted leximin mechanism that handles agent weights, and show that it satisfies weighted versions of the desiderata considered by Ghodsi et al. [2011] (in fact, we improve the strategy-proofness to group strategy-proofness even in the weighted setting).

**Theorem 1.** Weighted leximin mechanism satisfies weighted sharing incentives, weighted envy-freeness, Pareto optimality, and group strategy-proofness with weighted agents having Leontief preferences.

Motivated by the extensive literature on the price of fairness, we investigate the “price” of achieving various properties in the Leontief domain. The price of achieving a property is defined as the worst-case ratio of the utilitarian welfare (sum of utilities) of a mechanism achieving the given property over the maximum possible utilitarian welfare, worst-case taken over all possible agent profiles, and optimized over all mechanisms achieving the given property.

First, we show that DRF (the leximin allocation) achieves sharing incentives, envy-freeness, and strategy-proofness by only sacrificing welfare by a factor of $m$, where $m$ is the number of resources. It is easy to check that for Leontief preferences, the price of achieving sharing incentives as well as the price of achieving envy-freeness are $m$ individually. While these observations are disappointing, they are not entirely unexpected. Indeed, fairness axioms like SI and EF force the mechanism to allocate resources to agents who contribute little to the utilitarian welfare, and hence are at direct odds with welfare-maximization. Strategy-proofness is an altogether different
matter. A priori the constraints imposed by SP seem less obstructive to welfare-maximization than SI or EF, and indeed in some settings SP mechanisms (even without the use of payments) provide optimal, or nearly optimal, social welfare [Procaccia and Tennenholz, 2009]. Nevertheless, we show that achieving SP also implies loss of utilitarian welfare by a factor of $m$ in the worst-case.

**Theorem 2.** The price of sharing incentives, the price of envy-freeness, and the price of strategy-proofness is $m$ for Leontief preferences.

Finally, we consider another realistic extension of DRF to the case where an agent’s utility only reflects the integral number of instances of its task that it can execute given the resources that it is allocated. For example, if to run a task an agent needs 2 CPUs and 2 GB RAM, and it is allocated 3 CPUs and 3 GB RAM, its utility would be 2 rather than $3/2$ in the standard Leontief domain. In this quantized Leontief domain, there are some basic impossibilities. For example, it is easy to check that envy-freeness is impossible to achieve together with Pareto optimality. As an easy example, consider two agents, both requiring 1 CPU (the only resource in the system) where only 1 CPU is available overall. One of the agents must receive the CPU, and it would leave the other agent envious. We show that strategy-proofness is incompatible with various combinations of desiderata, and therefore seek mechanisms that simply achieve sharing incentives and Pareto optimality, along with a slightly relaxed notion of envy-freeness.

Directly motivated by an approximate notion of envy-freeness proposed by Budish [2011], which he calls *envy bounded by a single good*, we define envy-freeness up to one bundle.

**Definition 1.** A mechanism is envy-free up to one bundle (EF1) if for an agent cannot run more than one additional instance of its task under another agent’s allocation than under its own allocation. Hence, an agent may only envy another agent’s allocation up to one bundle of its reported demands (i.e., up to one instance of its task).

Several generalizations of DRF fail to achieve the proposed desiderata. For example, maximizing the minimum dominant share (more generally, performing a leximin allocation in dominant shares), which is a natural generalization of DRF, does not work. However, we propose a rather unintuitive generalization of DRF. The new mechanism, which we call **SEQUENTIALMINMAX**, allocates bundles of agents’ demanded resources via an iterative process: In each iteration, it looks at the set of agents that can be allocated one more bundle of their demands, and chooses an agent such that allocating one more bundle to the agent minimizes the maximum dominant share of any agent after the allocation. That is, it assigns a score to each agent $a$, which is the maximum dominant share any agent would have if $a$ were allocated an additional bundle of its demands. Surprisingly, we show that this mechanism achieves the required properties.

**Theorem 3.** **SEQUENTIALMINMAX** achieves sharing incentives, envy-freeness up to one bundle, and Pareto optimality.

### 2.2 Dynamic Fair Division: A New Era

While the previous work extends the basic setting of Leontief preferences to include realistic considerations, some crucial aspects of real-world computing systems are beyond the current scope of
fair division theory. Perhaps most importantly, the centuries-old fair division literature does not capture the dynamics of these systems. Indeed, it is typically not the case that all the agents are present in the system at any given time; agents may arrive and depart, and the system must be able to adjust the allocation of resources. Even on the conceptual level, dynamic settings challenge some of the premises of fair division theory. For example, if one agent arrives before another, the first agent should intuitively have priority; what does fairness mean in this context? In a subsequent work [Kash et al., 2014], we initiate the study of fair division in dynamic environments, and propose and study the first compelling model for addressing this challenge.

### 2.2.1 Related Work

Previous to our work, Walsh [2011] proposed the problem of fair division of a single heterogeneous resource (traditionally termed cake) where agents arrive, take a piece of the cake, and immediately depart. This is in contrast with our setting where multiple homogenous resources are divided among the agents. More importantly, Walsh suggested several desiderata for fair cake cutting, and showed that adaptations of classic mechanisms achieve these properties. But these properties can also be satisfied by giving the whole cake to the first agent. Hence, the setting is not very compelling for fair division of resources. His notion of forward envy freeness, which is discussed below, is related to (strictly weaker than) our notion of dynamic envy freeness.

Resource allocation in a dynamic environment is studied extensively in settings where monetary payments are allowed, under the name of dynamic mechanism design (see, e.g., [Gershkov and Moldovanu, 2010] for a closely related setting where agents with private preferences arrive over time). However, to the best of our knowledge, no compelling model of dynamic fair division has been proposed for settings without money.

### 2.2.2 Proposed Mechanisms

In the dynamic setting that we study, agents arrive one-by-one over time, but do not depart (we provide some implications of our results for the setting where agents may depart as well). In step $k$, agent $k$ arrives and reports its Leontief demand vector. The mechanism can choose to allocate some resources between the first $k$ agents that have arrived till then. However, we assume that the mechanism cannot take back resources it already allocated; hence, it must be conservative and save some resources for future arrival as well. Our assumption is motivated by settings where resources are committed to long-term projects (and thus cannot be revocated) or by settings where consumable resources are allocated to agents which they may consume upon allocation.

In this setting, we first consider the abovementioned desiderata for static settings, and propose their natural extensions for our dynamic setting.

1. **Sharing Incentives (SI):** At every step $k$, the agents present in the system (agents 1 through $k$) must be at least as happy with their current allocation as an equal split of their collective entitlements (i.e., a $k/n$ fraction of each resource).

2. **Envy Freeness (EF):** In any step, no present agent should prefer the allocation of another present agent over its own allocation.
3. **Strategyproofness (SP):** An agent should not be able to gain at any step by misreporting a false demand vector, even at the expense of losing in other steps. Note that this is an extremely strong notion because it also prevents manipulations that make an agent slightly better off in one step but significantly worse off in other steps.

4. **Dynamic Pareto optimality (DPO):** The standard notion of Pareto optimality requires an allocation to compete with all possible alternative allocation; this is too stringent in a dynamic setting where an allocation must preserve resources to allocate to future agents. Hence, we only require that in step $k$ the allocation should not be Pareto dominated by any allocation that divides the collective entitlements of the present $k$ agents (i.e., a $k/n$ fraction of each resource) among the $k$ agents.

While the natural definitions of the desiderata are compelling, they lead to an immediate incompatibility. In particular, we prove the following.

**Theorem 4.** Envy-freeness and dynamic Pareto optimality are incompatible in a dynamic setting with Leontief preferences.

We show that dropping either of the two properties lead to simple and undesirable mechanisms. Hence, we relax both EF and DPO one-at-a-time, and propose mechanisms that satisfy the relaxed desiderata in conjunction with the other three desiderata in tact.

**Theorem 5.** DYNAMICDRF satisfies (the relaxed fairness notion) dynamic envy-freeness (DEF) along with DPO, SI, and SP.

**Theorem 6.** CAUTIOUS LP satisfies (the relaxed efficiency notion) cautious dynamic Pareto optimality (CDPO), along with EF, SI, and SP.

We perform simulations to test the performance of our proposed mechanisms on real data with respect to two metrics: the sum of utilities (utilitarian welfare), and the minimum utility (egalitarian welfare). As our data we use traces of real workloads on a Google compute cell, from a 7 hour period in 2011 [Hellerstein, 2010]. The workload consists of tasks, where each task ran on a single machine, and consumed memory and one or more cores; the demands fit our model with two resources. We compare our mechanisms against lower and upper bounds on the objective functions (upper bounds obtained by running unrealistically strong omniscient mechanisms that are aware of future demands). Comparing our two proposed mechanisms highlights the difference in performance when a fairness property is relaxed versus when an efficiency property is relaxed. In particular, CAUTIOUS LP performs surprisingly well for egalitarian welfare, and almost achieves the optimal welfare given by the omniscient mechanism.

### 2.3 Proposed Research for the Thesis

Our latest work [Parkes et al., 2014] proposes design of more realistic resource allocation mechanisms for multiagent systems with provable theoretical guarantees while expanding the scope of
fair division theory to capture dynamics of the systems at the same time. However, our discussions regarding resource allocation issues in shared clusters with David Pennock and Sébastien Lahaie from Microsoft Research New York, and with Alexey Tumanov and Greg Ganger from Carnegie Mellon University, as well as our observations from practical resource allocation problems (mentioned below) have highlighted that the current theoretical models need to be generalized in two key dimensions before mechanisms based on such models can be applied in practice.

Handling complex dynamics. The temporal dynamics in our current model [Parkes et al., 2014] are very restricted. In a real-world system, agents can arrive and depart over time. Further, while an agent is present in the system, it can submit multiple computational jobs whose resource demands would be different. Unlike our current setting, these jobs should have fixed workloads, and hence should finish in a finite amount of time.

I plan to take the model of Jain et al. [2012] (which only considers a single resource) as a starting point. I will first outline appropriate desiderata for this more involved setting, and seek to design a mechanism that satisfies the desiderata. If time permits, I am also interested in analyzing the “price” of such desiderata in terms of loss in social welfare. I plan to include this research in my thesis.

At present, the cluster at Carnegie Mellon University as well as the cluster at Microsoft Research use naïve mechanisms which directly ask agents to report the priority of their jobs, an explicit parameter that can easily be manipulated by the agent. My ultimate goal is to implement the mechanisms arising from my research in clusters at various universities and research organizations, and show that automatically aligning the incentives of individual agents leads to increased performance of the system. However, I am uncertain whether this would be achieved during my PhD.

Handling complex preferences. My more immediate interest is designing mechanisms for handling preferences of agents that arise from real-world applications (even in a static setting). In this regard, currently I am working on two independent projects, which I plan to include in my thesis.

For the first project, my motivation is the Microsoft Imagine Cup winner startup Food Bank Local, which distributes food items received from various sources to charities that need the items. I am working on a crisp theoretical model where the preferences of the charities are dichotomous (like / dislike each item) in a dynamic environment where the goods arrive over time. I have fixed several intuitive desiderata for this setting, and I am attempting to design a mechanism satisfying such desiderata. I would like to emphasize that this setting is a very natural dynamic extension of the static setting considered in the classic paper by Bogomolnaia and Moulin [2004].

Fair Allocation of Unused Classrooms. The second project, which I am personally more excited about, started when we were recently approached by Benjamin Brittain, a representative of the Oakland (CA) unified school district, for designing mechanism for a practical fair division problem. The Oakland school district has roughly 114 public schools. These schools sometimes have unused physical space (classrooms and shared facilities like gym, sports area, etc.). Local charter schools that need physical space can apply to claim this unused space. Law says that the space must be divided fairly across the charter schools, and no monetary payments can be used. The preferences of the charter schools are given by two parameters: the number of classrooms...
required, and the list of “acceptable” public schools where the demanded number of classrooms may be allocated. The charter schools have a dichotomous utility where they only care whether they receive at least their demanded number of classrooms at one of their acceptable sites. This is an extension of the dichotomous preference setting of Bogomolnaia and Moulin [2004] that has not been addressed in the literature.

Inspired by the performance of the leximin mechanism (DRF) in the Leontief preference domain, we looked at the leximin mechanism (one that maximizes the minimum utility, and subject to that maximizes the second minimum utility, and so on) for the classroom allocation setting. We were able to show that leximin satisfies all the desiderata in the classroom allocation setting that are satisfied by DRF in the Leontief preference domain, namely sharing incentives, ex-ante envy-freeness, ex-ante efficiency, and group strategy-proofness. By leveraging computational ideas from interior-point optimization methods, we have developed an efficient implementation of the leximin mechanism (which is provably $\mathcal{NP}$-hard to compute) that can handle a scale much larger than the current scale of OUSD. Our mechanism is going to be used for the coming round allocations in December 2014. If the experiment is successful, it may also be used on a larger scale for the Los Angeles Unified School District. I find it very exciting that the theory of fair division [Moulin, 2003], as exemplified by the leximin mechanism, provides an ideal, almost tailor-made framework for tackling modern fair division challenges that arise in real-world. I plan to include this research in my thesis.

Before concluding this chapter, I propose a research agenda that can be potentially transformative for many practical mechanism design problems. I have observed that the leximin allocation achieves attractive axiomatic properties, especially strategy-proofness, in numerous, completely different settings; besides the Leontief domain [Ghodsi et al., 2011], the weighted Leontief domain [Parkes et al., 2014], and the classroom allocation setting, several such examples can be found in the literature (see, e.g., [Bogomolnaia and Moulin, 2004, Roth et al., 2005, Chen et al., 2013, Bochet et al., 2012, Li et al., 2014]). These domains range from multi-agent resource allocation, through kidney exchange, to cake cutting. I suspect the possibility of a general result that shows the axiomatic properties of leximin under minimalistic assumptions on the domain. Such a result would be extremely important from a practical point of view: While many real-world settings may not satisfy the simplistic preferences studied in the fair division theory, they may satisfy such minimalistic assumptions. Such a result would alleviate the need to enforce preference reporting within a constrained domain, which may lead to significant loss of social welfare [Tumanov et al., 2012]. Rather, it would provide a compelling mechanism that can be directly applied to the practical setting of interest. I plan to work on this research problem during my PhD, but I am uncertain whether it will indeed yield a generic leximin mechanism with provable guarantees. As a first step, I plan to do further literature review to identify the use of the leximin mechanism in other settings. These settings in the literature would hopefully guide me towards the minimal assumptions required on the domain for the leximin mechanism to work. While my immediate goal would be to consider only static settings, my ultimate goal is to formulate a generalized leximin mechanism for dynamic settings (where agents as well as goods may arrive over time) and prove strong theoretical properties for the mechanism.
Chapter 3

When do Noisy Votes Reveal the Truth?

Social choice theory studies the aggregation of individual preferences towards a collective choice. In one of the most common models, both the individual preferences and the collective decision are represented as rankings of the alternatives. A voting rule\(^1\) takes the individual rankings as input and outputs a social ranking.

One can imagine many different voting rules; which are better than others? The popular axiomatic approach suggests that the best voting rules are the ones that satisfy intuitive social choice axioms. For example, if we replicate the votes, the outcome should not change; or, if each and every voter prefers one alternative to another, the social ranking should follow suit. It is well-known though that natural combinations of axioms are impossible to achieve [Arrow, 1951], hence the axiomatic approach cannot give a crisp answer to the above question.

A different — in a sense competing — approach views voting rules as estimators. From this viewpoint, some alternatives are objectively better than others, i.e., the votes are simply noisy estimates of an underlying ground truth. One voting rule is therefore better than another if it is more likely to output the true underlying ranking; the best voting rule is a maximum likelihood estimator (MLE) of the true ranking. This approach dates back to Marquis de Condorcet, who also proposed a compellingly simple noise model: each voter ranks each pair of alternatives correctly with probability \(p > 1/2\) and incorrectly with probability \(1 - p\), and the mistakes are i.i.d.\(^2\) Today this noise model is typically named after Mallows [1957]. Probability theory was still in its infancy in the 18th Century (in fact Condorcet was one of its pioneers), so the maximum likelihood estimator in the Mallows model — the Kemeny rule — had to wait another two centuries to receive due recognition [Young, 1988].

Although Condorcet could have hardly foreseen this, his MLE approach is eminently applicable to crowdsourcing and human computation systems, in part because its main prerequisite (an underlying true ranking) is naturally satisfied by some of these domains. Further, these systems often employ voting to aggregate noisy estimates; EteRNA [Lee et al., 2014] is a wonderful example, as explained by Procaccia et al. [2012]. Consequently, the study of voting rules as MLEs has been gaining steam in the last decade [Conitzer and Sandholm, 2005a, Conitzer et al., 2009, Elkind

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1More formally known in this context as a social welfare function.

2Intuitively, if a ranking is not obtained because of cycle formation, the process is restarted.
3.1 Voting for Human Computation

While the MLE approach to voting derives its motivation from real-world human computation systems, it was only analyzed within the realm of traditional social choice — the focus was always on finding the best alternative, the true ranking, or top-$k$ alternatives. Many human computation systems usually have slightly different objectives. For example, consider EteRNA [Lee et al., 2014], a scientific discovery game developed by the collaboration of Carnegie Mellon University and Stanford University. The goal of this game is to design RNA molecules that fold into stable structures. Thousands of RNA designs are proposed weekly, but only a few can be synthesized in the lab to discover which one among them is truly the best. Since some designs are indeed more stable than others, this gives rise to a ground truth ranking of the proposed designs. To optimize the choice of the few designs to be synthesized, votes over proposed designs are collected from human players and then aggregated using a voting rule. Note that if a subset of designs is synthesized, the best among them is discovered easily. Hence, the aim of the voting rule used should be selecting a subset of designs such that the true best design is likely in the set.

This is exactly one of the objectives we considered in our earlier work [Procaccia et al., 2012]. We modeled human votes as samples drawn from Mallows’ model with an unknown noise parameter. Formalizing the abovementioned description of Mallows’ model, the probability of a ranking given the true ranking is exponentially decreasing in the Kendall tau distance of the ranking from the true ranking. Here, the Kendall tau distance measures the number of pairs of alternatives on which two rankings disagree. Under this model, we considered three different objective functions for selecting a subset of alternatives of a given size $k$. Let $A$ denote the set of alternatives.

**Definition 2** (Objective 1). Select a subset of alternatives of size $k$ that contains the best alternative.

**Definition 3** (Objective 2). Select a sequence of alternatives of size $k$ that is prefix of the true ranking of alternatives.

**Definition 4** (Objective 3). Select a subset of alternatives of size $k$ that coincides with the set of top $k$ alternatives in the true ranking.

Because we cannot achieve any of these objectives accurately, our goal is to achieve them with the highest probability. In other words, we seek to find the MLE subset of alternatives of size $k$ that best achieves the abovementioned objectives. The first objective is clearly motivated by EteRNA [Lee et al., 2014]. The second and the third objectives are useful in settings where $k$ alternatives are to be elected (e.g., forming a team or committee). The difference between the two objectives is the following: The second objective ranks the selected $k$ alternatives, and is therefore useful for selecting committees (where a president, a vice-president, etc. need to be distinguished). The third objective, on the other hand, does not distinguish between the selected alternatives, and is therefore useful when a team of members need to be selected to complete a task at hand. While at first glance it may seem that both alternatives would return identical subsets of alternatives, it is
not true: There may exist a subset of alternatives such that none of its permutations are as likely to be a prefix of the true ranking as the sequence that has the highest probability, but the sum of likelihoods of all its permutations being a prefix of the true ranking is the highest among all subsets of alternatives.

First, we observe the computational complexity of optimally solving for the three objectives.

**Theorem 7.** Objectives 1, 2, and 3 are \( \mathcal{NP} \)-hard for all non-trivial values of \( k \).

Inspired by crowdsourcing domains where the noise is extremely high, we analyze the limiting case of \( p \to 1/2 \), i.e., when the votes are only slightly better than random. We discover the optimal rules for the abovementioned three objectives; for the first and the third objectives, it turns out to be a classic social choice rule known as the Borda count, which works as follows: It assigns a score of \( m - i \) to the alternative at rank \( i \) in each vote, for all \( i \), and the overall score of an alternative is its total score across all votes. A subset of \( k \) alternatives is chosen by selecting the \( k \) alternatives with the highest score.

**Theorem 8.** Borda count is optimal for Objectives 1 and 3. The optimal rule for Objective 2 with a given value of \( k \) is an intuitive fusion of Borda count and Kemeny’s rule that coincides with Borda count when \( k = 1 \), and with Kemeny’s rule when \( k = m \), where \( m \) is the number of alternatives.

While our theoretical results use a value of \( p \) that is extremely close to \( 1/2 \) (\( p - 1/2 \) is exponentially small), our simulations show that Borda count achieves almost optimal probability as long as \( p \in (0.5, 0.6) \).

### 3.2 Moving From MLE to Sample Complexity

As compelling as the MLE approach is, there are many different considerations in choosing a voting rule, and insisting that the voting rule be an MLE is a tall order (there is only one MLE per noise model); this is reflected in existing negative results [Conitzer and Sandholm, 2005b, Elkind et al., 2010a]. We focus on identifying the underlying true ranking of the alternatives, but relax the MLE requirement by asking: *How many* votes do prominent voting rules need to recover the true ranking with high probability? In crowdsourcing tasks, for example, the required number of votes directly translates to the amount of time and money one must spend to obtain accurate results. To classify voting rules by their sample complexity, we define two families of voting rules. For a ranking \( \sigma \) of alternatives, let \( a \succ_{\sigma} b \) denote that \( a \) is ranked higher than \( b \) by \( \sigma \). The pairwise-majority graph (PM graph) of a profile is the graph with alternatives as vertices, and an edge from alternative \( a \) to alternative \( b \) whenever the majority (strictly) prefers \( a \) to \( b \).

**Definition 5 (PM-c Rules).** A voting rule is called pairwise-majority consistent (or PM-c) if on all profiles with an acyclic PM graph, the rule returns the acyclic order of the PM graph.

**Definition 6 (PD-c Rules).** In a profile of votes, an alternative \( a \) is said to position-dominate an alternative \( b \) if \( a \) appears among the first \( k \) positions in at least as many votes as \( b \) does, for all values of \( k \), and the inequality is tight for some \( k \). Note that this relation is transitive. Hence, the
PD graph of the profile, where an edge is drawn from alternative \( a \) to alternative \( b \) if \( a \) position-dominates \( b \), is inherently acyclic. A voting rule is called position-dominance consistent (or PD-c) if on all profiles with a complete PD graph, the rule returns the acyclic complete order of the PD graph.

PM-c and PD-c rules intuitively generalize the families of Condorcet consistent rules and positional scoring rules, respectively. Together, they capture most well-known voting rules.

**Theorem 9.** The Kemeny rule, the Slater rule, the ranked pairs method, Copeland’s method, and Schulze’s method are PM-c. All positional scoring rules and the Bucklin rule are PD-c rules. The sets of PM-c and PD-c rules are disjoint.

We prove the following results, which crisply classify voting rules in terms of their sample complexity.

**Theorem 10.** Kemeny’s rule (with uniformly random tie-breaking) has the least sample complexity among all (randomized) voting rules, which is logarithmic in the number of alternatives. All PM-c rules have asymptotically logarithmic complexity in the number of alternatives. A wide family of scoring rules (including Borda count and the Harmonic rule [Boutilier et al., 2012]) have polynomial sample complexity, but some scoring rules (such as plurality and veto) have at least exponential sample complexity.

### 3.3 Moving From Sample Complexity to Robust Voting

While the exact or asymptotic sample complexity can help us distinguish between various voting rules, it relies on the assumption that the votes come from a specific distribution — in this case, Mallows’ model. Votes collected on crowdsourcing platforms and in other human computation systems have highly unpredictable noise that does not conform to the beautiful and elegant formulae of classic noise models [Mao et al., 2013]. Thus, proving interesting properties about voting rules for classic noise models does not tell us anything about the performance of these rules in practice. In fact, the MLE framework, or more generally, the sample complexity framework is fundamentally restricted to assuming a specific noise model.

One may overcome this problem by only assuming that the noise distribution in practice would satisfy some minimalistic constraint instead of pinning down the complete noise model. This gives rise to a family of noise models, and the goal is to design voting rules that are accurate with respect to all noise models in the wide family; in other words, the goal is to design robustly accurate voting rules. However, it is impossible for a single rule to be MLE for all the noise models in a wide enough family.

In a subsequent work [Caragiannis et al., 2013], we relax the MLE constraint by taking a normative point of view: given infinitely many samples, the rule should be able to reproduce the true ranking with probability 1. Rules that obey this condition are known as consistent estimators in statistics literature, but we avoid using the term consistency because it is traditionally used to describe another normative property in social choice. Instead, we call such rules accurate in the limit. The extremely relaxed requirement of accuracy in the limit is actually sufficient to guarantee
good performance in practical large-scale human computation systems where a plethora of votes are available.

We propose a family of noise models that satisfy a mild and intuitive property.

**Definition 7** (d-Monotonic Noise Models). Given a distance metric $d$ over rankings of alternatives, a noise model is called $d$-monotonic if the probability of a ranking decreases as the distance of the ranking from the true ranking increases.

Unlike Mallows’ model where the probability of a ranking decreases exponentially in its distance from the true ranking, the decrease is uncontrolled in a $d$-monotonic noise model. Our goal is to achieve accuracy in the limit with respect to all $d$-monotonic noise models for a family of distance metrics $d$. We fully characterize the distances $d$ such that all PM-c (resp. PD-c) rules are accurate in the limit for all $d$-monotonic noise models. We call these families of distances majority-concentric and position-concentric distances respectively.

**Theorem 11.** All PM-c (resp. PD-c) rules are accurate in the limit with respect to all $d$-monotonic noise models if and only if $d$ is majority-concentric (resp. position-concentric).

In practice, when votes are collected in a human computation system, one can check if the distribution is monotonic with respect to a majority-concentric or position-concentric distance, and if so, can apply any PM-c or PD-c rule, respectively. We show that standard distance functions are both majority-concentric and position-concentric.

**Theorem 12.** The Kendall tau distance, the footrule distance, and the maximum displacement distance are both majority-concentric and position-concentric.

While interesting distances are MC and PC, and therefore all PM-c and PD-c rules work well on distributions monotonic with respect to such distances, theoretically it is interesting to achieve accuracy in the limit with respect to all $d$-monotonic distributions for all distance metrics $d$. In our latest work [Caragiannis et al., 2014], we show that achieving this extreme robustness property is not an easy task.

**Theorem 13.** No PM-c or PD-c rule is accurate in the limit with respect to all $d$-monotonic distributions for all distance metrics $d$.

We search for rules that satisfy this property within the family of generalized scoring rules (GSRs) proposed by Conitzer and Xia [2008a], which contains almost all popular voting rules. We assume an additional technical condition of “no holes”, which intuitively says that if the output of a voting rule is a fixed ranking $\sigma$ almost everywhere in a small enough “neighborhood” of a profile in an appropriately defined Euclidean space, then the rule should also output $\sigma$ on that profile. We show that this condition is extremely mild in that no popular generalized scoring rules have any holes. Within this family of voting rules, we accurately pinpoint the unique voting rule that achieves the extreme robustness property; we term this rule the modal ranking rule.

**Definition 8** (The Modal Ranking Rule). On any given profile, the modal ranking rule simply returns the most frequent ranking in the profile, that is, the full ranking that is repeated the most number of times in the profile.
While at first glance it may seem weird because there are $m!$ rankings over $m$ alternatives, this rule is extremely intuitive in large-scale settings with only a few alternatives; in this case, every ranking is repeated sufficiently many times for the rule to make sense. Such settings have only become relevant in recent times due to the advent of human computation systems. Note that our requirement — accuracy in the limit — only imposes restrictions on the rule as the number of votes go to infinity. Hence, the difficulty of the result is in using the structure of generalized scoring rules (with no holes) to show that the rule must return the most frequent ranking on all profiles regardless of the number of votes.

**Theorem 14.** A generalized scoring rule without holes is accurate in the limit with respect to all $d$-monotonic distributions for all distance metrics $d$ if and only if it is the modal ranking rule.

In summary, we showed that among the union of GSRs without holes, PM-c rules, and PD-c rules, the modal ranking rule is the unique rule that achieves the extreme robustness property. This is pictorially depicted as follows.

### 3.4 Robustness++: From Statistical to Worst-Case Voting

The MLE approach as well as our robust voting approach has considered statistical models of social choice for aggregating noisy votes, where the noise is assumed to be coming from an underlying distribution. While robust voting framework places minimalistic constraints on the noise, in my latest work with my advisor Ariel D. Procaccia and Yair Zick, we take an even more pessimistic viewpoint and assume the noise to be adversarial instead of probabilistic. We present the first model of optimal voting under adversarial noise. From this viewpoint, voting rules are seen as error-correcting codes. One can think of the votes as a repetition code: each vote is a transmitted noisy version of a “message” (the ground truth ranking). How many errors can be corrected using this “code”?

It is very easy to see that recovering the true ranking is very unlikely. For example, suppose that we receive $n$ votes over the set of alternatives $\{a, b, c, d\}$, for an even $n$, and we know that the average Kendall tau distance between the votes and the ground truth is at most $1/2$. Can we always recover the ground truth? No: in the worst-case, exactly $n/2$ agents swap the two highest-ranked alternatives and the rest report the ground truth. In this case we observe two distinct rankings (each appearing $n/2$ times) that only disagree on the order of the top two alternatives. Both rankings have
an average distance of $1/2$ from the input votes, making it impossible to determine which of them is the ground truth.

Hence, instead of finding the true ranking, our goal is to find a ranking that is guaranteed to be at a small distance from the true ranking in the worst-case. Our main result is the following:

**Theorem 15.** If the average distance of the input votes from the true ranking (i.e., the average error in the profile) is guaranteed to be at most $t$ as measured by any distance metric $d$, one can always find a ranking that is guaranteed to be at distance at most $2t$ from the true ranking measured by $d$. Further, for four prominent distances — the Kendall tau distance, the footrule distance, the maximum displacement distance, and the Cayley distance — this bound is essentially tight.

While the worst-case optimal voting rules we propose require a bound on the average error as an input, we derive worst-case theoretical guarantees on the performance of our rules in the case where only an approximation of the average error bound is given to the rule. Our experiments using real data show that our proposed rules outperform all popular voting rules as long as a reasonable estimate of the bound (an over-approximation of the bound by a factor of at most 2) is provided.

### 3.5 Proposed Research for the Thesis

My research work develops voting rules that attain robustness properties at various levels of granularity, from robustness with respect to monotonic distributions for a wide family of distances, through robustness with respect to monotonic distributions for all distances, to robustness in the adversarial noise setting. My research on robust statistical voting leverages the fact that many practical human computation systems have a large number of input votes to overcome very high and unpredictable noise in the votes. This makes my research very pertinent to practical crowdsourcing systems. However, there are two key dimensions that should be incorporated in the modeling to make the voting rules more practical.

**Various, mixed data formats**: A bulk of social choice literature focuses on input votes in the format of top-votes (reporting the most favorite alternative) or full rankings. Recent work (see, e.g. [Procaccia et al., 2012, Xia and Conitzer, 2008b, 2011]) have incorporated other preference formats such as top-$k$ lists, pairwise comparisons, and partial orders. Another line of work attempts to study and reduce the communication complexity of the voting rules (see, e.g., [Conitzer and Sandholm, 2005a, Service and Adams, 2012, Kalech et al., 2011]). However, almost all research in social choice assumes that all input votes are in the same format.

In our previous work [Procaccia et al., 2012], we observe that our rules and our analysis only relies on the number of pairwise comparisons available in the data for various pairs of alternatives. We leveraged this observations to propose a model, which we called the *noisy choice model*, which is a generalization of Mallows’ model for producing extremely general datasets which may contain a mix of pairwise comparisons, partial orders, full rankings, top-$k$ lists, and possibly other formats, as well as *possibly a mixture of these formats*. In the same work, we also emphasized that the objective may not always be picking the best alternative or the best full ranking of the alternatives, which are the two standard objectives considered in the literature. However, my recent work has assumed that the input votes as well as the output of the voting rule are full rankings.
In future, I plan to work on designing voting systems (or in general, opinion aggregation systems) where complex opinion formats can be intuitively aggregated. I plan to look for realistic objective functions that may arise in existing crowdsourcing systems, and work on aligning the voting systems to optimize such objectives. My ultimate goal is to be able to apply such systems to real crowdsourcing systems (e.g., social networks — see the next paragraph), but I am not certain whether this will be achieved during my PhD. Nonetheless, I envision that in future crowdsourcing systems with complicated underlying objective functions would utilize various forms of preference elicitation, and would probably combine preferences gathered from various sources, which would give rise to datasets with heterogenous and complex formats. Thus, the voting systems I plan to develop are likely to be a crucial ingredient of such systems. In fact, I believe that there are already many crowdsourcing as well as organizational settings where social choice rules can be applied, and developing more practical voting rules would motivate the administrators of such systems to actually apply them and improve the performance of the system.

**Voting on Social Networks:** Currently, I am working on addressing social choice settings that arise in social networks, which, in my opinion, is a more interesting and practical direction today. I plan to include this research in my thesis.

Almost all research on social choice implicitly (or explicitly) assumes that the input votes are independent from each other. This assumption has its roots in traditional social choice settings (such as political elections), in which anonymous votes are aggregated with no additional information. In a human computation setting, however, the goal is to achieve the highest accuracy, and thus it is intuitive that more accurate voters must be given greater importance. Furthermore, when the voters are connected via an underlying social network structure, their votes may indeed have dependencies.

While there have been some publications on social choice that handle dependencies in the input votes [Shapley and Grofman, 1984, Berg, 1993a,b, Ladha, 1992, 1993, 1995, Dietrich and List, 2005], it was only recently that Conitzer [2012, 2013] considered an explicit model of voting where the voters are connected via an underlying social network structure. However, his model includes only two alternatives and extremely simple network interactions. Specifically, each edge is aligned with the “correct” alternative with probability $p > 1/2$, and a vertex votes according to the majority opinion of its edges. Conitzer acknowledges that his goal is to “give a simple model that helps to illustrate which phenomena we are likely to encounter as we move to more complex models” [Conitzer, 2013, p. 1483].

As a first step forward, I propose the following natural extension of his model to more than two alternatives. Given a graph $G = (V, E)$, a ranking $\sigma^e$ is drawn for each edge $e \in E$ from a noise model $g^e$ specific to $e$ centered around the ground truth ranking. The vote $\sigma^v$ of each vertex $v \in V$ is determined by applying a voting rule $f^v$ specific to $v$ to the set of rankings on the edges incident to $v$. We only observe the (inter-dependent) votes $\sigma^v$ submitted by the vertices, and need to aggregate them in order to recover the ground truth.

While one may follow the traditional MLE approach and compute the MLE voting rules at the “global” level given the noise models $g^e$ and the “local” voting rules $f^v$, I think the assumption that $g^e$ and $f^v$ are known would be a stringent assumption in practice. Rather, I am seeking to design robust voting rules that guarantee recovery of the ground truth with high probability in large social
networks with respect to a wide range of $g^e$ and $f^v$. I have obtained preliminary results which suggest that our modal ranking rule is robust — even with votes coming from a social network — when the edge distributions $g^e$ are $d$-monotonic for some distance metric $d$ and every $f^v$ is the modal ranking rule. However, the latter assumption is quite stringent.

I plan to work on designing voting rules that achieve greater robustness with respect to local rules $f^v$, potentially at the cost of reducing the (currently extremely general) scope of edge distributions $g^e$. Two direct and important generalizations of this simplistic model are incorporating the apriori opinions of the users, and considering more complex models where opinions may change over time (similar to models of diffusion).

I believe that this line of research can be potentially transformative for social computing in general. For example, I envision organizations that actively and systemically seek opinions of their members as well as users for taking macro-level decisions. Social networks, such as Facebook, provide a great platform for data-driven decision-making. In more detail, imagine an organization that needs to select among a few product prototypes, and posts an opinion poll on its Facebook page, which asks visitors about the relative chance of success of the different prototypes. I envision collection and aggregation of complex user opinions (including rankings over a set of alternatives) to be an essential feature of social networks in the near future.

I have ongoing discussion (and an upcoming visit to) researchers at Facebook. We plan to implement a voting post where any user or page can post an opinion poll and other users can submit their opinion, which can be aggregated in various possible ways. In particular, the poster would be able to view statistics about the votes collected, would be able to choose a voting rule appropriate for the format of data collected (here, general voting methods that can be applied to complex and heterogenous data formats would be extremely useful) as well as appropriate for the objective that the poster has in mind. The plan is to also collect feedback from the poster regarding the effectiveness of the results produced by various voting rules, which would help improve the system over time.

A side product of this experiment would be generation of a real-world dataset for voting where a ground truth exists; to the best of my knowledge, currently there are very few such datasets [Mao et al., 2013]. I am excited about exploring new ways of interacting with users, through voting applications that allow users to make joint decisions in small groups, and — more interestingly — allow users to participate in large-scale decision making.
Chapter 4

The Rest of My Research — In a Nutshell

Besides fair division of computational resources and computational social choice, I have worked on a number of topics including prediction markets, security games, cooperative game theory, and multi-agent systems, which will not be a part of my thesis. Below, I have briefly described the publications that constitute the core of my research in these areas.

• **Security Games:** The existing popular model of security games [Kiekintveld et al., 2009] model how a defender can allocate its security resources in a randomized fashion to prevent potential targets from an attacker. The solution concept used is that of a Stackelberg equilibrium where the defender first commits to its randomized allocation, and the attacker accordingly chooses a target to maximize its own utility. This simple model has had a substantial real-world impact: it lies at the core of game-theoretic algorithms that are regularly employed to aid the day-to-day operations of major security agencies, such as the US Coast Guard, the Federal Air Marshals Service, and the Los Angeles Airport Police. While some of these domains involve resource deployment by multiple agencies with overlapping sets of targets, these agencies typically do not coordinate with each other, primarily due to the need to share sensitive information, as confirmed to us by Craig Baldwin of the United States Coast Guard [Baldwin, 2014]. My initial work [Jiang et al., 2013] showed that in realistic settings, the defenders could lose from 30% to 70% utility in the worst-case by the lack of coordination, and my ongoing work [Procaccia et al., 2014] proposes privacy-preserving coordination mechanisms that share minimal sensitive information between defender agencies.

Our current results only show that optimal coordination can be achieved while sharing minimal private information, but use computationally inefficient algorithms. Also, our techniques are limited to coordination between two defender agencies. In future, my plan is to devise efficient coordination mechanisms for more than two agencies that have an underlying topology for communication by using ideas from the private distributed constraint optimization community (see, e.g., [Greenstadt, 2007]).

• **Cooperative Games:** A recent work by Bachrach et al. [2011] proposed an extension of classical cooperative games, which they call the reliability extension, where a cooperating agent may put in effort but ultimately fail to contribute to the team with a certain known
probability. It may still be possible to form ex-ante revenue sharing contracts which incentivizes an agent to put in effort by guaranteeing a positive payment even if the agent fails. My work [Bachrach et al., 2012, Bachrach and Shah, 2013, Bachrach et al., 2014] has focused on analyzing the effect of agent failures on various cooperative games, and developing efficient optimal or approximation algorithms for finding such contracts. The key finding of my research is that agent failures actually increase the possibility of existence of a stable contract such that no coalition of agent has an incentive to deviate.

- **Prediction Markets:** My work on prediction markets [Kets et al., 2014] focuses on the effect of betting strategies on the long-run wealth dynamics as well as on the accuracy of the limiting market price in predicting various events. The key message of the paper is that markets where multiple traders with heterogenous beliefs survive in the limit have more accurate prediction than markets where only the most accurate trader survives in the limit.

- **Multi-agent Systems:** In a recent work [Jiang et al., 2014], we investigate the power of voting among diverse, randomized software agents. With teams of computer Go agents in mind, we develop a novel theoretical model of two-stage noisy voting that builds on recent work in machine learning. This model allows us to reason about a collection of agents with different biases (determined by the first-stage noise models), which, furthermore, apply randomized algorithms to evaluate alternatives and produce votes (captured by the second-stage noise models). The main result of the paper proves that a large team of diverse but weak agents (where each agent has very low accuracy in choosing optimal decisions) outperforms a team of similar but strong agents (where every agent has very high accuracy). This is confirmed by our simulations with teams of popular Go solvers.
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