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Contents

Algorithmic Contract Theory: A Survey

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ABSTRACT

A contract is an economic tool used by a principal to incentivize one or more agents to exert effort on her behalf, by defining payments based on observable performance measures. A key challenge addressed by contracts — known in economics as *moral hazard* — is that, absent a properly set up contract, agents might engage in actions that are not in the principal's best interest. Another common feature of contracts is *limited liability*, which means that payments can go only from the principal — who has the deep pocket — to the agents.

With classic applications of contract theory moving online, growing in scale, and becoming more data-driven, tools from contract theory become increasingly important for incentive-aware algorithm design. At the same time, algorithm design offers a whole new toolbox for reasoning about contracts, ranging from additional tools for studying the tradeoff between simple and optimal contracts, through a language for discussing the computational complexity of contracts in combinatorial settings, to a formalism for analyzing data-driven contracts.

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This survey aims to provide a computer science-friendly introduction to the basic concepts of contract theory. We give an overview of the emerging field of "algorithmic contract theory" and highlight work that showcases the potential for interaction between the two areas. We also discuss avenues for future research.

1

Introduction

Imagine you are a website owner employing a website designer through an online freelancing platform. The most straightforward payment scheme for the designer's work, i.e., *contract*, is offering a fixed (lump sum) transfer t for completing the website's design. But is this the best in terms of incentives? Anecdotal evidence and everyday experience suggest this is not the case. In the words of an Upwork user: "Remember, Upwork [...] is more like a box of chocolates, you never know what you are going to get" (upwork.com, 2018). Rigorous empirical studies confirm the problem of low-quality, "careless" online work (Aruguete *et al.*, 2019), even when platforms use rating systems (as ratings are often inflated and thus not very informative) (Garg and Johari, 2021).

This problem stems from a basic misalignment of incentives: The designer (*agent*, he) is doing the hard work, while the owner (*principal*, she) is reaping the rewards. This misalignment is coupled with an information gap—the principal has no way of knowing how much effort the agent invested in designing her website. With misaligned interests and imperfect observability, the principal has to rely on the moral behavior of the agent. This effect, known as *moral hazard*, is a fundamental obstacle that any task delegation to human (or AI) agents must overcome.

Fortunately, studies also show that *pay-for-performance* contracts can have a significant impact on work quality (Mason and Watts, 2009; DellaVigna and Pope, 2017; Fest *et al.*, 2020; Kaynar and Siddiq, 2023; Wang and Huang, 2022). In our example, paying for performance means paying the agent based on information the principal can track and that determines her own rewards, such as the increase in the number of visitors to the website, the increase in the number of conversions, or the increase in revenue. Since the details of the payment scheme matter a lot towards the agent's incentives, this raises important economic design questions such as what should the payments be contingent on, or how high these payments should be.

The rising design challenge can thus be summarized as: compute an optimal (or near-optimal) pay-for-performance contract, where "optimal" is with respect to welfare and revenue implications of the cooperation. Questions like this are studied in economics under the umbrella of *contract theory* (Ross, 1973; Mirrlees, 1975; Holmström, 1979; Grossman and Hart, 1983; Innes, 1990; Carroll, 2015). Contract theory is one of the pillars of microeconomic theory, recognized by the 2016 Nobel Prize awarded to Hart and Holmström (nobelprize.org, 2016). However, unlike other well-established areas of microeconomic theory, such as mechanism design or information design, contract design has not seen much work from computer science until recently.

1.1 Motivation: Why Algorithms? Why Now?

We are motivated by a recent spike of interest from computer scientists in contract theory (e.g., Babaioff *et al.*, 2006; Feldman *et al.*, 2007; Babaioff *et al.*, 2012; Ho *et al.*, 2016; Dütting *et al.*, 2019). This spike of interest is caused by the fact that more and more of the classic applications of contract theory are moving online, growing in scale, and happening in data-rich environments. These include online labor platforms (e.g., Kaynar and Siddiq, 2023), delegating machine learning tasks (e.g., Cai *et al.*, 2015), pay-for-performance healthcare (e.g., Bastani *et al.*, 2017; Bastani *et al.*, 2019), and blockchain (e.g., Cong and He, 2019).

In addition, tools from contract theory are anticipated to play a crucial role in a world in which we increasingly rely on AI agents to perform complex tasks (Hadfield-Menell and Hadfield, 2019; Wang *et al.*, 2023; Saig *et al.*, 2024). This direction comes with a number of challenges, which are not addressed by classic contract theory. For instance, outcome and action spaces might be huge. Or, we may have to select a group of agents from a large pool of available agents. Also, naturally, all sides of the problem will involve (machine) learning. At the same time, the fact that the agents are programmed, might also open up new opportunities. For instance, it seems reasonable to assume programmed AI agents exhibit "hyper-rationality" that is harder to attribute to humans.

This naturally calls for a field that combines tools from *contract theory* with tools from *computer science* (specifically algorithm design and machine learning). Contract theory offers a well-established formalism to talk about incentives, and prevent detrimental behavior (such as shirking or free-riding). Computer science, in turn, provides a language to talk about computational complexity, offers tools for studying the tradeoffs between simple and optimal solutions, and has a natural focus on (machine) learning algorithms.

Indeed, similar to other economic areas where the computational lens has been applied (notably, mechanism and information design), the algorithmic perspective is already providing new structural insights, helping to map out the tractability frontiers, and leading to new tools for data-driven contracts. Ultimately, the algorithmic approach to contracts has the potential to inform better designs in practice, especially in computational environments.

This survey aims to provide an introduction to contract theory that is accessible to computer scientists and give an overview of the emerging field of algorithmic contract theory.[1] We also discuss what we see as main directions for future work.

[1]Due to the large volume of recent work that takes an algorithmic approach to contracts, we present only a sample of papers from the current main trajectories of research.

1.2 Disambiguation: Contract Theory vs. Smart Contracts

We emphasize that the goals of the nascent area of algorithmic contract theory are orthogonal to those behind *smart contracts* (Szabo, 1997). While algorithmic contract theory, just as classic contract theory, aims to design contracts and provide tools to assess the pros and cons between different designs, smart contracts are a tool to *implement* contracts in an automated way, often relying on blockchain technologies to enable execution, control, and documentation. A shared theme of both is the use of computing technology to enable more efficient contracts.

1.3 Digression: Contracts within the Wider Context

In this survey, we follow Salanié (2017) in classifying incentive problems along two dimensions, as shown in Figure 1.1. This leads to three basic incentive problems (because the fourth combination does not seem to capture relevant applications). We adopt a terminology that identifies contract design, mechanism design, and information design with the three basic incentive problems that result from this classification.

	Uninformed party moves first:	**Informed party moves first:**
Private information is hidden type:	Adverse selection (Mechanism design)	Bayesian persuasion (Information design)
Private information is hidden action:	Moral hazard (Contract design)	Not studied

Figure 1.1: Salanié (2017, Chapter 1.1) proposes to classify problems where an informed party interacts with an uninformed party, along two dimensions: The first distinction is whether the private information bears on *who* the agent is ("hidden type"), or whether it bears on *what* action the agent takes ("hidden action"). The second distinction concerns the timing of the problem, and asks who moves first: the *uninformed* party or the *informed* party.

The division into three basic incentive problems results from viewing incentive problems as interactions between an uninformed party and an informed party, and classifying these interactions according to two criteria: The first is whether the private information concerns *who* the agent is ("hidden type"), or whether it concerns *what* action the agent takes ("hidden action"). The second is whether the *uninformed* party *moves first* and designs the incentive scheme, or whether it is the *informed* party who moves first.

This classification yields three important families of models:[2]

(1.) *Adverse selection* models: The uninformed party is imperfectly informed of the characteristics of the informed party; the uninformed party moves first. A canonical example is a first-price auction, where the auctioneer knows that the bidders' valuations are drawn from certain distributions, but only the bidders know the realized valuations. The auctioneer moves first by announcing the rules of the auction. Afterwards, the bidders submit their bids and based on this an allocation and payments are determined.

(2.) *Bayesian persuasion* models: The uninformed party is imperfectly informed of the characteristics of the informed party; the informed party moves first. A prototypical example here is one in which there is a hidden state drawn from a publicly known distribution, whose realization is known by only one of the two parties. For example, in a court case, the attorney representing a client, may know whether the client is guilty or innocent, and may seek to structure her arguments so as to convince the judge to acquit her client.

(3.) *Moral hazard* models: The uninformed party is imperfectly informed of the actions of the informed party; the uninformed party moves first. For example, a brand may seek to hire an influencer

[2] The fourth case is where the uniformed party cannot observe the actions of the informed party, and the informed party moves first. Salanié (2017, FN1 on p.4) argues that: "It is difficult to imagine a real-world application of such a model, and I do not know of any paper that uses it." Of course, it is also possible to consider problems that exhibit features of two or more of the "pure" problems, e.g., Bernasconi *et al.*, 2024.

on a social media platform to create sponsored content. The brand proposes a contract that defines how the influencer shall get paid. Payments can only be contingent on the observable but typically stochastic outcome of the agent's action (e.g., number of views the content receives). After signing the contract, the influencer creates the sponsored content and is paid according to the contract, based on the observed outcome.

Alternative names that can be found in the literature for (1.) and (2.) are *screening* and *signaling*, respectively. The majority of the work in computer science has focused on mechanism design (i.e., (1.)) and information design (i.e., (2.)). The focus of this survey is on (3.).

We note that while the division into three basic incentive problems is fairly standard and widely agreed upon, not all authors identify the three basic incentive problems with the terms mechanism design, information design, and contract design as we do here. We chose to adopt this terminology because it seems very natural from a computer science perspective (where mechanism design and information design/signaling are well established for (1.) and (2.), respectively), and because contracts are the main object of study in (3.).

1.4 Organization

This survey is organized as follows. In Section 2, we introduce the basic principal-agent model. In Section 3, we present the optimal contract problem, and discuss properties of optimal contracts. Section 4 introduces linear (a.k.a. commission-based) contracts, and studies the tradeoffs involved in choosing a simple rather than optimal contract from a worst-case approximation angle and a max-min optimality perspective. In Section 5, we explore the computational complexity of finding optimal and near-optimal contracts in complex scenarios. In Section 6 we study scenarios where agents have private types, and the goal is to construct contracts that incentivize agents to truthfully reveal their types, in addition to exerting effort. A modern algorithmic approach to contracts would not be complete without considering learning algorithms. In Section 7, we consider data-driven contracts, while in Section 8, we explore contracts and incentive-aware machine learning. Section 9 explores incomplete, vague, and ambiguous contracts. In Section 10, we discuss contract design for social good. Afterwards, in Section 11, we discuss approaches "beyond contracts," such as *delegation* and *scoring rule design*, that tackle related problems. We mention several open problems and additional directions throughout the survey, and conclude with a discussion in Section 12.

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