LITERATURE SURVEY

Mechanism Design and Approximation

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1 Introduction

Impressive growth in the intersection between computer science and economics in the past century has afforded economists new methods for studying classical economic theory. A major goal of these studies is to analyze and predict the behaviour of parties within economic systems. The study of game theory, originally formed as a branch of applied mathematics in the 1930s, aimed to develop these analytic models. In the following decades, the field of theoretical computer science sparked algorithmic research to solve traditional problems of routing, resource allocation, and optimization, with a focus on computational tractability.

Algorithmic game theory (AGT) combines the formulation of these algorithms with the power of predictive economic models. The strength of these economic models is restricted by the effectiveness of the system, so the theory behind designing accurate systems is at the core of AGT. The theory behind the design of these systems is called mechanism design. Over the last few decades, mechanism design theory has become ubiquitous in the study of the economy. Mechanism design theory explores how to produce optimal outcomes by accounting for competing incentives and incomplete information within a system. In this paper, we'll survey research done on mechanism design and give a historical context for the emergence of the field. We'll analyze the study from both a theoretical standpoint as well as its applications. Studying the triumphs of well-designed mechanisms and the downfalls of poorly-designed mechanisms will provide us with a baseline from which we will conjecture the future of the field.

2 Overview

In this section, we'll discuss why mechanism design is studied and how researchers classify economic situations as mechanism design problems. We'll draw answers from the birth of the field in the 1940s to the reverence garnered by researcher's in the 2000s. To highlight why mechanism design is important, let us first present a couple simple design problems to highlight some basic economic structures. We'll see that even simple economic systems contain interesting properties that can be abstracted across different systems.

Example 2.1: Single Item Auctions

Let us briefly compare two simple mechanisms: The First-Price Auction and The Second-Price (or Vickrey) Auction for a single item. In both the First-Price Auction and The Second-Price Auction, there are n agents competing for a single item, where each agent i values the item with value v_i, and places a bid on the item b_i. Each bid is hidden from one another, and the highest bidder wins. In the First-Price Auction, the highest bidder pays their own bid. In the Second-Price Auction, the highest bidder pays the second highest bid.

The price reduction in the Second-Price Auction gives this mechanism an important property. Unlike the First-Price Auction, the Second-Price Auction is *truthful*: every bidder should bid exactly what they value the item at, i.e. $b_i = v_i$. Contrast this with the structure of the First-Price Auction, where the agent's incentive is to bid only slightly more than the value held by the agent below him. This means the First-Price Auction is not **Dominant Strategy Incentive Compatible** (DSIC), the mechanism does not support truth-telling [1].

The DSIC property of a mechanism relates to a key concept of economic systems - **social welfare**. Social welfare is the collective wealth, or utility, of the agents in the system. The First-Price Auction in the previous example was not DSIC, and therefore did not maximize social welfare. Maximizing social welfare is usually a good heuristic to guide an algorithm. As we'll see in the next example, an algorithm that is successful when guided by social welfare maximization, may not maintain its properties when guided by a different heuristic.

Example 2.2: Matching Markets

Consider a housing market, where two buyers I, II wish to buy two houses a, b, with the following preference matrix:

$$\left(\begin{array}{c|cc} & a & b \\ \hline I & 12 & 2 \\ II & 2 & 5 \end{array}\right)$$

An algorithm that maximizes social welfare will produce a **perfect matching** for this example, wherein no two buyers who would both rather have each others houses than their current houses. The perfect matching for this example is $I \to a, II \to b$ [2].

Now consider an algorithm that aims to minimize inequality, or minimize the difference between the prices paid by each buyer in a match. The minimum inequality matching here is $I \to b, II \to a$. However, this is not a perfect matching: buyer I prefers house a, and buyer II prefers house b. We see that whether or not an algorithm returns a perfect match depends on the heuristic used to guide it.

The previous two examples outline different properties we can use to discuss mechanisms. We see that a poorly designed mechanism may not produce an optimal solution, or it may support lying. Now that we've introduced some fundamental concepts that guide mechanism design, let's discuss how the pioneers of the field understood these concepts and tested them empirically.

2.1 1930s - Present

The desire to formulate a system that produces optimal solutions for self-interested agents traces back to the 1930s. During the late 30s, economists Oskar Lange and Abba Lerner presented arguments for a socialist market which could improve on the performance of private ownership market economies. However, these arguments often failed to detail the mechanics of their claims [3].

In response, Polish economist Leonid Hurwicz aimed to develop systems that could better formulate claims about market performance. The models he developed laid the foundations for the modern mechanism: given a set of of agents that (privately) communicate their incentives with a centralized coordinator, how can we produce an optimal solution? The concept of incentive compatibility, as outlined in our auction example, was coined by Hurwicz in 1972 to describe the success of these models [4]. For his role in the development of the field, Hurwicz was awarded the 2007 Nobel Prize along with Eric Maskin and Roger Myerson, two other pioneers of mechanism design [5].

In the last two decades, theoretical computer science has played a significant role in shaping the study of mechanism design. The scope of mechanism design has shifted to an algorithmic approach, where modern design problems involve optimization, approximation guarantees, and complexity bounds [6]. In the following section, we will use design theory to explain previous failed economic systems, as well as discuss some new focuses of the field.

3 Applications

Ad Auctions

The complexity of mechanism design is revealed when abstracting the single-item auction example (2.1) to an auction of multiple items. Two common strategies employed for multiple item auctions are the Vickrey-Clarke-Groves Auction (VCG) and the Generalized Second Price Auction (GSP). Search engines employ these auctions to select which advertisements to display; Google, Microsoft, Bing and Yahoo! use the GSP Auction, and Facebook uses the VCG Auction [7].

The structures of both systems are the same. Potential advertisers will enter keywords related to their product into the system. They also enter their valuation of each click. For each user's query, the search engine finds a set of ads related to the query's contents. The winning advertisers are presented and charged a cost relative to the bids of other advertisers.

The GSP Mechanism charges bidders as follows. The potential advertisers $a_1, a_2, ..., a_n$ are ordered by their bid-per-click times the predicted click through rate for the ad slot. Without loss of generalization assume $a_1 > a_2 > a_3 > ... > a_n$. Then the price paid by advertiser a_i is equal to the bid of advertiser a_{i+1}. It turns out the GSP Mechanism is not DSIC: there exists an equilibrium that incentivizes advertisers to bid lower than their true value-per-click. Furthermore, this equilibrium does not maximize social welfare.

The VCG Mechanism, alternatively, is DSIC and social-welfare maximizing. The mechanism charges each advertiser the marginal harm done to other participants by participating. In the previous example, advertiser a_1 will pay the bid-per-click times the predicted click through rate of all advertisers $a_2, ..., a_n$ in an auction where a_1 is not included [8].

3.0.1 The Effect of Collusive Bidding

Since 2011, the number of advertisers outsourcing their advertising strategies to digital marketing agencies (DMAs) has been rapidly growing. Furthermore, many of these DMAs belong to larger conglomerates that conduct all bidding activities through centralized agency trading desks (ATDs) [9]. Three researchers at the Barcelona Graduate School of Economics - Decarolis, Goldmanis, and Penta (2019) - analyzed the affect of these ATDs on the mechanisms. Since these centralized agencies have access to the bids of many different advertisers, they have the opportunity to lower the payments by coordinating the bids of the clients. As we will detail below, the researchers found that given a collusive bidding scenario, VCG would outperform the GSP auction, despite it's susceptibility to collusion.

First, the researchers defined a model for the game involving (i) the agency, or coalition of bidders and (ii) a set of independent bidders. The proposed bids by the agency can only be implemented if they follow two constraints:

1. The proposals are consistent with the independents' equilibrium bids
2. No member of the coalition has an incentive to abandon it and bid as an independent

A set of proposals that meets the above constraints will be known as the **Recursively Stable Agency Equilibrium (RAE)**. Now let us consider an example of five bidders with valuation $v = (40, 25, 20, 10, 9)$, and CTRs $\{20, 10, 9, 1, 0\}$. A truthful VCG mechanism will output a utility of $u = (441, 141, 91, 1, 0)$. Now consider that bidders 1 and 5 belong to the same agency, $C = \{1, 5\}$. Since the payment of 1 is strictly decreasing with bid 5, b_5, the agency has the incentive to lower b_5 as much as possible while ensuring bidder 1 gets the top position: So for any $b'_1 > 25$, the following bid profile $b' = (b'_1, 25, 20, 10, 0)$ will result in a utility of $u' = (450, 150, 100, 10, 0)$. Comparing u to u', it is clear no player in the coalition would rather be independent.

Now let us illustrate the effect agencies can have on revenue. Consider a set of 5 bidders with valuations $v = (5, 4, 3, 2, 1)$. The CTRs for the five positions are $\{20, 10, 5, 2, 0\}$. With only independent bidders, the VCG mechanism produces an outcome of 96. Now consider an agency $C = \{1, 3\}$. Applying the same logic as above, we have $b' = (b1', 4, 2+, 2, 1)$, with a resulting revenue of 86, and a corresponding loss in revenue of 10.

VCG mechanisms are more prone to collusion because a change in bid i affects *all* positions above them. In a GSP auction, on the other hand, a change to bid i affects only the payment of the bidder at $i - 1$. Despite this, researchers found a GSP auction susceptible to agencies can have greater affects on revenues. In our definitions of the auctions, we covered that the GSP mechanism is not truthful, and may output **inefficient allocations**. The most noteworthy finding of the researchers was that the affect of agencies on revenues in the GSP auction is independent of these distorted allocations. In fact, imposing efficiency on the system results in greater revenue loss from the VCG Mechanism.

Consider the profiles of the previous example, with 5 bidders values, $v = (5, 4, 3, 2, 1)$,, CTRs $\{20, 10, 5, 2, 0\}$ and an agency, $C = \{1, 3\}$. Applying the researcher's recursive GSP formula [1], the resulting efficiency-imposed RAE is $b' = (b1', 2.8, 1.6+, 1.6, 1)$, with a corresponding revenue 82. The agency-affected GSP output here incurs a loss of 4 from the agency-affected VCG.

The implications of these results stretch from both (i) the problems with advertising agencies across both types of auctions, as well as (ii) the specific issues with the GSP auction. Not only are these implications valuable to the revenue-interested search engines, but they may have implications into competition policy [9]. Ad agencies may be at risk of violations of antitrust policies that outlaw price coordination and collusion. However, these investigations may yield difficulties, as all price coordination would be done through bidding algorithms. These algorithms are void of explicit communication between parties that is required by the law to charge collusion, a clear indication that it is imperative for government agencies to revisit technology-related law. In the next subsection, we will present more research related to the performance of Auctions.

3.0.2 Measuring Incentive Compatibility

Incentive compatibility (IC) is one of the most important qualities of a mechanism: does the mechanism reward behaviour that is well-aligned with your true beliefs? As we've seen, incentive compatibility varies widely between mechanisms, and mechanisms which are not incentive compatible may yield suboptimal results. Facebook researchers Feng, Schrijvers, Sodomka (2019) investigated the use of machine learning in measuring Incentive Compatibility in Ad Auctions. Their focus was on minimizing IC regret:

[1] The specific GSP formula has been omitted as it is an extension of the description provided earlier. Inclusion would require extensive technical context without much to advance the argument. For further reference, see p12 of the corresponding research paper.

$$\text{IC regret}\,(v_i) = \max_{b_i} E_{b_{-i}}\left[u_i\left(b_i, b_{-i}\right) - u_i\left(v_i, b_{-i}\right)\right]$$

Where for advertiser i, v_i is the true value-per-click, b_i is their bid, b_{-i} is the bid of other advertisers, and u_i is the utility of advertiser i. Since the VCG Mechansim is DSIC, it has an IC regret of 0. For other mechanisms, IC regret can be thought of as the difference between the true value of the item, and the bid of the item. The model learned from repeated iterations of auctions across different time steps with the goal of selecting bids that minimize IC, for a true known value v. At each time step t, the test bidder participates n auctions and randomly partitions them into $m + 1$ blocks of equal size. For each time step, the algorithm:

1. computes an upper confidence bound (UCB) on the expected utility of each bid b
2. selects m bids corresponding to the m highest UCBs
3. uses the selected bids in the first m blocks of auctions, and uses the true value v in the final auction.
4. For each block, the algorithm observes the average allocation probability and payment

Using this algorithm, the researchers were able to derive the following upper-bound on the worst-case IC regret:

$$\sum_{b \in B : u^*(v,b) < u^*(v,b^*)} \frac{32(m+1)U^2 \ln T}{n\Delta(b)} + \frac{\pi^2}{3} \cdot \frac{\Delta(b)}{m}$$

Where U is the upper bound on utility, m is the number of auction blocks, T is the number of time steps, b is the bid, and n is the number of auctions. The theoretical result was supported by running simulations of GSP auctions. For a given m, IC regret decreased the more auctions were run. When holding for n, the number of auction blocks m seems to achieve best performance at 8 blocks. Any values higher incurs large variance from noisy information between auctions [10].

The above research has related to our ability to measure the success of mechanisms in closed environments. These theoretical results hold important conclusions about what conditions must be met for a mechanism to be successful in practice. In the following section, we'll reverse this approach. We'll discuss the theory behind a very real systemic failure: the subprime mortgage market of the 2008 crisis.

3.1 Subprime Mortgage Disaster

A crucial element for describing mechanisms involves the power of assumptions. The Facebook researchers running GSP simulations in the previous section assumed each advertiser's bid was independent and identically distributed on the Uniform distribution. In practice, however, a misguided assumption of independence may result in a poorly designed mechanism. As we've seen, a poorly designed mechanism is one that **misprices** items. The First-Price Auction over charges the winning bidder, incentivizing them to bid untruthfully. In this section, we'll show that the poorly designed mechanism causing the 2008 financial crisis resulted from a misguided assumption of the independence of loans, and we'll discuss the subsequent consequences of the mispricing of the housing market.

3.1.1 Collateralized Debt Obligations

Since 1968, big banks have traded Mortage-Backed Securities (MBS), collections of loans made to homeowners. Banks issue shares of these securities (tranches), to investors who collect dividends through the monthly mortgage payments. Some of these loans are risky, called subprime; the probability of the homeowner missing their payment and defaulting (losing the house) is high.

Consider a MBS with the probability that 1% of its loans will default. For a MBS of 1000 loans, 10 will default. For independent loans, the risk of this default rate increasing is extremely low. The banks used this assumption to create "smart" tranches, breaking the MBS into 10 shares. The lowest share absorbed all potential default loans (with a default rate of 10%) and the top nine were risk-free, sold for premium rates. However, the banks needed to figure out what to do with the lowest-performing tranche. Now enters the Collateralized Debt Obligation (CDO).

The banks applied the same logic from the MBS to large groups of the low-performing tranches. Again, 90% of the top tranches would be risk-free, while the lowest-performing tranche absorbed all of the default-rate. The banks were now dealing with tranches of tranches, and the assumption of independence no longer held. Each tranche was dependent on the group of tranches from which it came, each with high default rates. However, these shares were sold on the pretense that the top 90% were risk free [11].

3.1.2 Mispricing

Equipped with a method of selling subprime loans for premium rates, the banks needed to increase the demand for home loans. Mortgage lenders initially attracted homeowners by easing up on credit requirements and offering Adjustable Rate Mortages (ARMs) with extremely low initial rates. These ARMs were offered to both new homeowners as well as those with homes looking to refinance their mortgages.

Low rates push investors into risky investments, and the early 2000s interest rates were a nationwide misprice of risk. Leading up to the complications with CDOs and subprime loans, between 2000-2005, the US was experiencing an unsustainable growth in credit. Due to expanding funds from outside the US, banks had low interest rates and an increased desire to hand out long term loans [12]. The number of homeowners in the US began to climb. Coupled with the banks desire to handout subprime loans, these homeowners were often under-qualified for their loans. Relying on the appreciation of the housing market, homeowners planned to refinance their mortgages when the ARM rates adjusted or interest rates increased. However, the housing supply responded too strongly to the uptick in demand, resulting in a fall of housing prices. Refinancing was no longer viable, and the ARMs began to adjust. Homeowners could not meet interest rates and defaults sky-rocketed, bringing the CDO and CDO insurance market to a crash [13].

3.1.3 Prevention

Of the many factors contributing to the 2008 financial crisis, some human, some political, there are a few concrete regulatory actions could be taken to design a better loaning mechanism. Firstly, The Federal Reserve could have raised lending rates in order to properly reflect the risk of taking on debt and subsequently slowed the credit boom. The lack of government regulation on Wall Street, however, is the largest and most cynical piece of this puzzle. There are at two components that could have been regulated:

1. The Rating Agencies: There should have been a more stringent vetting process for the bond ratings assigned by rating agencies. Without regulation, the current system inherently incetivizes rating agencies to give banks top rates, whether deserving or

not. A regulatory system could have caught the fraudulent bonds before they were put on the market for trading.

2. The Credit Default Swaps: By the time hedge funds were shorting the industry billions of dollars and banks were issuing Credit Defualt Swaps, it may have been too late for government intervention. But the system that allows hedge funds to profit off of the collapse of a key industry reflects a system lacking proper channels of communication between government agencies and financial institutions.

The financial crisis was allowed by a market where financial institutions - banks, rating agencies, and hedge funds - are only incentivized to maximize revenue despite their actions affecting the millions of Americans involved in the market. When these institutions are void of regulation, the market no longer benefits those who it is meant to serve. Now let's see how we can apply our conclusions about the importance of regulation in a free market to new challenges.

3.2 Climate Change

The last section detailed how we can use mechanism design to describe how institutions interact with one another. Specifically, we saw that a poorly coordinated mechanism (and one guided by greed) resulted in years of a market that was mispriced and misguided by assumptions of its underlying components. Modeling the interaction between institutions, whether financial, political, or governmental, can answer important questions about why these institutions may agree and disagree on important issues. In this section, we'll look at why countries cannot seem to agree on one central issue: climate change. Climate change agreements are susceptible to the same issues that plagued the 2008 financial crisis: incentive compatibility and limitations on enforcement [14]. By analyzing the competing constraints placed on climate agreements, we can approximate an optimal mechanism countries will work to follow.

3.2.1 The Free Riding Problem

To frame climate change as an economic problem, let us consider pollution to be a pure public good, or a **nonexcludable externality**. For the most common forms of pollution, air and water, a polluter cannot control where their pollution goes or who consumes it. It follows that pollution reduction is a benefit to all, a pure public good.

Consider a set of communities that pollute, and that each of these communities would benefit from reducing their emissions. However, reducing pollution for an individual community is costly. If individual communities attempt to reduce emissions, there will not be enough reduction because the cost of reduction is handled only by that community, but the benefit of reduction is shared by each community.

The Coase Theorem explains that even in the presence of externalities, economic agents will ensure a Pareto-efficient outcome without government intervention [15]. A supporter of this theorem would argue that, for our polluted communities, a shared agreement of reduction would produce an equilibrium: nobody can leave the agreement to improve their own position, while leaving no others worse off. Baliga and Maskin (2002) show that a set of communities will not reach a Pareto-efficient agreement without a government mechanism. Any given community C will be better off by not participating. C will enjoy the benefits of all other communities participating, C^{-}, without paying the cost of reduction. The decrease in pollution reduction without C participating will be small relative to the cost saved by C. Each community will benefit by **free riding**, and no agreement or pollution reduction is reached. A government intervation is necessary to impose the agreement [15].

3.2.2 The Participation and Compliance Problems

Let's take an existing failed climate agreement, The Kyoto Protocol. Entering into force in 2005, the agreement set targets for greenhouse gas reductions individually for each country. It did not detail the technical means of cutting emissions, only supported a collective limit for which we should reduce emission. Barrett (2008) discusses that the main two issues with the Kyoto Protocol.

Firstly, the Kyoto Protocol failed to widely attract participation, a crucial element of successful climate deals. Countries opting into climate deals may be susceptible to **trade leakage** should other countries not comply. Carbon-related industries in participating countries, will move to non-participating countries where emission regulations are lower. For fear of trade-leakage from the US, the US did not participate in the Kyoto Protocol. Similarly, China and India only opted-in to the agreement because they were mot required to reduce emissions. To compensate for the protocol's inability to garner widespread engagement, the emission standards were set far too low, and achieved no emission reduction [16].

Secondly, a climate agreement must ensure compliance. Once opted-in, the Kyoto Protocol did not require countries to meet their standards. Consider, for example, Canada's target of 6% reduction. In 2005, Canada's emissions were over 30% *above* this target. New Zealand and Japan suffered similar significant compliance gaps. In order to design a climate treaty that ensures both participation and compliance, methods of enforcement must be explored.

3.2.3 Enforcement

Martimort and Sand-Zantman (2013), define an enforceable mechanism such that the optimal option for each country is to obey the restrictions defined in the treaty. Then a country with efficiency type θ will abide by the mechanism whenever the following enforcement constraint holds, where $U(\theta)$ is the country's payoff at participation equilibrium and $U_N(\theta)$ is the country's payoff at non-participation equilibrium. $e(\theta)$ is the country's effort, and $(1-\alpha)$ scales the size of these effects on all other countries (α is the local effect). Finally we include discount factor δ to account for the repeated relationship between all countries.

$$U(\theta) \geq U_N(\theta) + (1-\delta)(1-\alpha)\left(E_{\tilde{\theta}}(e(\tilde{\theta})) - E_{\tilde{\theta}}\left(e_N(\tilde{\theta})\right)\right) \quad \forall\theta \tag{1}$$

The mechanism is also subject to two other constraints. First the mechanism must be **budget balancing**: The expected cost generated by all of the countries' efforts should be at least equal to their overall expected payoff. We write this as follows:

$$E_{\tilde{\theta}}\left(e(\tilde{\theta}) - \frac{e^2(\tilde{\theta})}{2\tilde{\theta}}\right) \geq E_{\tilde{\theta}}(U(\tilde{\theta})) \tag{2}$$

Where $\frac{e^2(\tilde{\theta})}{2\tilde{\theta}}$ is the **disutility of effort** for efficiency parameter $\tilde{\theta}$. Since the marginal cost of exerting effort depends on the country, Martimort and Sand-Zantman express the cost as a quadratic formulation per country.

The allocation of utility $U(\theta)$, or payoff for country of type θ, must also be **incentive compatible** with the effort given by that country, $e(\theta)$. An allocation $(U(\theta), e(\theta))$ is incentive compatible if and only if (i) $e(\theta)$ is non-decreasing and (ii) $U(\theta)$ is absolutely continuous where, at each point of differentiability,

$$\dot{U}(\theta) = \frac{e^2(\theta)}{2\theta^2} \tag{3}$$

From this lemma it follows that an incentive compatible mechanism will increase payoff as the efficiency of the country increases.

The optimization problem becomes $\max E_{\tilde{\theta}}(U(\tilde{\theta}))$ subject to (1), (2) and (3).

This optimization problem introduces inefficiencies due to restrictions on α, the local size of reduction effects [14]. When α is small, the size of reduction effects on other countries is high. A small α also increases incentives to free ride because the less benefits achieved by reduction efforts locally makes it hard to justify the cost of reduction. However, for a small enough α, the benefits of cooperation become attractive enough to compensate for the larger incentives to free ride, and the participation constraint can be met. In order to meet this requirement of participation, we place the following upper bound on α:

$$\text{Participation Requirement: } \alpha \leq \frac{\underline{\theta}}{2E_{\tilde{\theta}}(\tilde{\theta}) - \underline{\theta}}$$

$$\text{Enforcement Requirement: } \alpha \leq \frac{\underline{\theta}}{2E_{\tilde{\theta}}(\tilde{\theta}) - \underline{\theta}} - \frac{2(1-\delta)\left(E_{\tilde{\theta}}(\tilde{\theta}) - \underline{\theta}\right)}{\delta\left(2E_{\tilde{\theta}}(\tilde{\theta}) - \underline{\theta}\right)}$$

Since our enforcement constraint is stricter than the basic participation constraint, our minimum α becomes much smaller. Subsequently, the level of local effort required to overcome the incentive to free ride becomes much smaller, and much harder for countries to meet.

Furthermore, under enforcement policy, only the most **efficient** countries strictly prefer opting into the treaty. The mismatches in incentives between efficient and inefficient countries are known as distortions. Because enforcement is the strongest bound on required payoff, the threshold for the level of efficiency required to meet that payoff is increased. The difference between efficient and inefficient countries grows, and the distortions are more pronounced.

3.2.4 A Working Mechanism?

Possible solutions to the complexities of the enforcement problem have employed the use of the international trade framework. Stiglitz, 2006, suggests the use of **trade restrictions** to force under-performing states to meet emissions standards. In the current worldwide market, most developed countries charge taxes on carbon-heavy industries. On the other hand, the goal, gas, and oil industries in the US are heavily subsidized by the government, and carbon-based energy prices are cheap. This results in an unfair trade advantage for American firms, who reap the benefit of international trade for their cheap energy, while the world suffers the effects of their pollution. The simple answer, outlined by Stiglitz, is to prohibit other countries importing energy-intensive goods produced in the US [17].

However, we must acknowledge the difficulties in the application of these trade restrictions in worldwide treaties. Strong trade restrictions can lack credibility and legitimacy [16]. Furthermore, the theories discussed in this section become hard to implement because the number of dependencies per country is so large. Government subsidies, pressure by lobbyists, slow moving agencies, bodies resistant to change, and a government run by a generation who will not feel the effects of climate change make these agreements difficult to pass. As stated by Stiglitz, we have the tools we need to solve the crisis. All we're missing is the political resolve [17].

4 Moving Forward

The applications of mechanism design which we have visited attempt to draw solutions to highly complex systems. For the 2008 financial crisis and climate change (dis)agreements, we see that optimal solutions may be out of reach due to bureaucracies that are difficult to model. Roughgarden and Cohen (2019) argue that despite these complexities, optimal solutions may serve an important role in approximation methods:

> Even when the theoretically optimal mechanism is not directly useful to the practitioner, for example because it is too complex, it is directly useful to the analyst. The reason is that the performance of the optimal mechanism can serve as a benchmark, a yardstick against which we measure the performance of other designs that stand a chance of being implemented (Roughgarden and Cohen, 2019).

Specifically, they highlight three specific areas for future research: (i) new applications for approximation, (ii) relationships between different notions of complexity, and (iii) narrowing the gaps between worst-case analysis and the average cases found in practice. In this literature survey, we've seen the growing impact of computer science on the field of mechanism design, specifically on approximation and optimization. The "worst-case" analysis approach to computer science algorithms works to classify the behaviour of systems in response to specific, valid inputs. The same approach may be used to analyze mechanisms. A possible new frontier could be the development of models that explain precisely why economic mechanisms may perform significantly worse than their worst-case approximations in practice [18].

As we saw in the enforcement policy of our climate change mechanism, introducing new constraints drastically increased the computational complexity of the model. However, the relationship between complexity and design patterns has not been researched extensively. In the future, there may be benefit in classifying these mechanisms according to their complexity, and providing a formal relationship between different methods of complexity, a description akin to that of incentive compatibility or social welfare maximization.

Finally, we must acknowledge the growing presence of data-driven computational methods. To mitigate the complexities that arise from competing incentives in a system, we may use behavioural data to employ preference models to supplement existing systems. Promising evidence for this method has been presented by Hartline (2019), who compares the performance of novel systems directly from behavioral data from the original system [19]. The insights found by these models compounds with the availability of data. As we continue to derive tractable economic models, the predictive capacity for data-informed mechanisms increases. The application of machine learning models to classical design problems holds promising results for complexity analysis, solution approximation, and subsequently, the performance of our economic mechanisms.

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