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Abstract

This paper presents an analysis of entries in the first TAC *Market Design Competition that compares the entries across several scenarios. The analysis complements previous work analyzing the 2007 competition, demonstrating some vulnerabilities of entries that placed highly in the competition. What's more, we provide a general approach to conducting experimental analysis of similar competitive games. The paper also suggests a simple strategy that would have performed well in the competition.*

1. Introduction

Auctions are special markets with restricted rules. Different auction designs may vary significantly in properties including efficiency, profit, and transaction volume. Well designed auctions result in desired economic outcomes and are widely used in solving real-world resource allocation problems, and in structuring stock and futures exchanges. As a result, the field of auction mechanism design has drawn much attention in recently years from economists, mathematicians, and computer scientists [2, 13].

In traditional auction theory, auctions are viewed as games of incomplete information, and traditional analytic methods from game theory have been successfully applied to some *single-sided auctions*, where a single seller has goods for sale and multiple buyers bid for the goods, and some simple forms of *double-sided auctions* (DAs), where there are multiple sellers and multiple buyers and both sides may make *offers* or *shouts*.

However, as, for example Friedman [6], has pointed out, DAs, particularly *continuous double auctions* (CDAs),[1] are too complex to analyze in this way since at every moment, a trader must compute expected utility-maximizing shouts based on the history of shouts and transactions and the time remaining in the auction. This difficulty led researchers to seek experimental approaches. Smith [26] pioneered this field and showed, through a series of experiments with human subjects, that even CDAs with just a handful of traders can give high allocative efficiency and quick convergence to the theoretical equilibrium. Software agents armed with various learning algorithms and optimization techniques have been shown to produce outcomes similar to those obtained by human subjects [4, 10] and are capable of generating higher individual profits [5].

In parallel with the automation of traders, computer scientists have started to take the approach of automated auction mechanism design. Thus, Cliff [3] explored a continuous space of auction mechanisms by varying the probability of the next shout (at any point in time) being made by a seller, denoted by Q_s, and found that a Q_s that corresponds to a completely new kind of auction led to faster transaction price convergence. Phelps *et al.* [22] showed that genetic programming can be used to find an optimal point in a space of pricing policies, where the notion of optimality is based on allocative efficiency and trader market power. Niu *et al.* [17] presented a mechanism that minimizes variation in transaction price, confirming the mechanism through an evolutionary exploration. Pardoe and Stone [18] suggested a self-adapting auction mechanism that adjusts auction parameters in response to past auction results.

Although these evolutionary or adaptive approaches involve automatic processes, they can only be feasible with the existence of an array of candidate auction rules or parameterizable frameworks that are conceived by human minds. What's more, the superiority of the result of an evolutionary exploration or an adaptive process, essentially a combination of auction rules, relies at least partly on the number of candidate auction rules and the superiority of individual rules. Phelps *et al.*[19, 20] showed how to acquire better strategies through evolutionary computation based on existing heuristic strategies. Without the candidate heuristic strategies, the approach may lead to no finding. On the other hand, all this work has one common theme — it all studies single markets or compares different market

*This is an extended version of [16].

[1] A CDA is a continuous DA in which any trader can accept an offer and make a deal at any time during the auction period.

mechanisms indirectly. In contrast, not only do traders in an auction compete against each other, real market institutions face competition [24]. For example, company stock is frequently listed on several stock exchanges. According to [25], the Indian National Stock Exchange or NSE claimed much of the trade volume from the established Bombay Stock Exchange or BSE only several months after the former opened in the mid 1990s. In addition, previous studies usually present comparison of auction mechanisms in different proprietary settings which differ in available information, computational resources and so on. As a result, mechanisms are difficult to compare. It is desirable to have some platform that models the scenarios in the real world, allows multiple markets to compete against each other, and evaluates market mechanisms in a uniform way.

The Trading Agent Competition (TAC) Market Design Tournament [8], also known as the CAT game, addresses these very issues.[2] Prior TAC competitions have competing trading agents that aim to maximize their payoffs by interacting in a single market. CAT games do just the opposite. Each entrant in the competition provides a *specialist* that regulates a market with a set of auction rules, and these specialists compete against each other to attract traders and make profit. Traders in CAT games are provided by the competition platform and each of them learns to choose the best market to trade in.

In a previous paper, we analyzed those entries from the first CAT competition (CAT 2007) that are available in the TAC agent repository,[3] and tried to identify effective auction rules [15]. In this paper, we extend this previous work by more closely examining the relative strength and weakness of the specialist agents.

2. The CAT competition

CAT games are designed to allow markets to compete against each other in a direct fashion. Each market serves a set of *traders*, each of which makes shouts indicating either what it is prepared to pay to buy some good (a *bid)*, or what it expects to be paid to sell such a good (an *ask*).

A CAT game lasts a certain number of *days*, each day consists of *rounds*, and each round lasts a certain number of *ticks*, or milliseconds.

Each trading agent is assigned private values for the goods it will trade. For buyers the private value is the most it will pay for a good. For sellers, the private value is the least it will accept for a good. The private values and the number of goods to buy or sell make up the demand and supply of the markets. Private values remain constant during a day, but may change from day to day, depending upon the configuration of the game server. Each trading agent is endowed with a *trading strategy* and a *market selection strategy*. The first specifies how to make offers, the second specifies which market to choose to make shouts in.

Specialists facilitate trade by matching shouts and determining the trading price in an exchange market. Each specialist operates its own exchange market and may choose its own auction rules — the aim of the CAT competition is to create a specialist that optimizes a particular set of measures, including *market share*,[4] *profit share*,[5] and *transaction success rate*.[6] The specialist having the highest cumulative score — the sum of these three metrics — is the winner of a game. Specialists may have adaptive strategies such that the policies change during the course of a game in response to market conditions.

We developed JCAT [14], the platform that is used in the CAT competition.

2.1. Parameterized market mechanisms

An auction mechanism can be parameterized into components that each regulates an aspect of the market. The following gives a framework extending that in [32]:

- *Matching* policies define the set of matching shouts in a market at a given time.
- *Quoting* policies determine the ask quote and bid quote — indicators of where traders need to place asks and bids in order to trade — from existing asks and bids.
- *Shout accepting* policies judge whether a request by a trader to place a shout in the market should be accepted or rejected.
- *Clearing* conditions define when to clear the market and execute transactions between matched shouts.
- *Pricing* policies are responsible for determining transaction prices for matched shouts.
- *Charging* policies determine the charges a specialist imposes on traders and other specialists using the market. In JCAT, a specialist can set fees for registration with a specialist, for market information, for making a shout, for completing a transaction, and impose a tax on profit.

For example, the classic CDA mechanism is a combination of the following auction rules (without considering the charging component):

[2] The first competition was held in July 2007 and a second competition was held in July 2008.

[3] http://www.sics.se/tac/showagents.php.

[4] The number of traders attracted to the market relative to the total number of traders.

[5] The amount of profit made by a specialist relative to the total amount of profit made by all the specialists in a game.

[6] The number of shouts matched by the market relative to the total number of shouts that placed in the market.

- the market is cleared whenever a new shout is placed;
- the market matches the highest bid with the lowest ask that it exceeds;
- the pricing policy picks the midpoint of a matching ask-bid pair;
- the quoting policy uses the lowest unmatched ask as the ask quote and the highest unmatched bid as the bid quote; and
- the shout accepting policy only allows shouts to place that beat the corresponding market quote.

2.2. A simple, but powerful market design

We developed `MetroCat`, a market mechanism that instantiates this parameterized framework, based on the insights about the CAT game:

- It is crucial to maintain a high transaction success rate, since this rate is not immediately affected by the performance of other markets in contrast to market share and profit share. Thus a strong shout accepting policy, which only allows those shouts that are likely to match with other shouts, is desirable.
- Registration and information fees should be avoided, for these fees cause losses to extra-marginal traders[7] and drive them away. Keeping extra-marginal traders in the market allows them to contribute through their impact on market share.
- Moderate charges on shouts, transactions, and trader profit only impact intra-marginal traders, and because of this they still stay with the market as long as they can make a considerable amount of profit through transactions after covering fees.

These insights led us to develop a CDA-based market mechanism, which uses a history-based shout accepting policy, denoted as AH. AH is based on the GD trading strategy [9]. GD selects a price that maximizes the expected payoff, assuming that, for a given ask price a,

- if another ask price $a' < a$ was offered and was not accepted by a seller, a would not be accepted either;
- if another ask price $a' > a$ was offered and accepted by a seller, a would have been accepted as well; and
- if a bid price $b > a$ was offered in the market, a would have been accepted.

[7] Traders that theory says should not trade at market equilibrium and will not trade in efficient markets.

Based on these assumptions, the probability of a being matched is calculated as:

$$Pr(a) = \frac{\sum_{d \geq a} MA(d) + \sum_{d \geq a} B(d)}{\sum_{d \geq a} MA(d) + \sum_{d \geq a} B(d) + \sum_{d \leq a} RA(d)}$$

where

- $MA(d)$ is the number of asks with price d that have been matched;
- $RA(d)$ is the number of asks with price d that were not matched; and
- $B(d)$ is the number of bids with price d.

It is not realistic to keep a full history of shouts and transactions, so GD maintains a sliding window and only considers those shouts and transactions in the window. Computed like this, $Pr(a)$ is a monotonic decreasing function, since the higher a is, the lower $Pr(a)$. It is also assumed that when $a = 0.0$, $Pr(a) = 1$, and there is a certain value u_a, when $a > u_a$, $Pr(a) = 0$. The probability $Pr(b)$ of a given bid being accepted is computed analogously.

AH uses exactly $Pr(a)$ and $Pr(b)$ to estimate how likely a shout would be matched, and only accepts those shouts with a probability higher than a specified threshold $\lambda \in [0, 1]$. When it is close to 1, the restriction may become too tight for intra-marginal traders to be able to place shouts in the market. When it is close to 0, the restriction may become so loose that extra-marginal traders are able to place shouts that do not stand much chance of being matched. The former would cause both the market and the traders to lose part of the expected profit and lead those traders to leave, and the latter would cause a low transaction success rate. `MetroCat` uses $\lambda = 0.5$, which we found to be optimal for a game configuration similar to CAT 2007.

In addition to AH, `MetroCat` uses a simple charging policy that imposes low, fixed fees on shouts, transactions, and trader profit, and no charges on registration and information.[8]

Since we developed the competition platform, `MetroCat` was not an entry in the competition,[9] but we have used it as a benchmark in our post-tournament experiments.

[8] The fees `MetroCat` imposes on shouts, transactions, and trader profit are respectively 0.1, 0.1, and 10% during the post-tournament experiments described in later sections.

[9] Instead it was included in the JCAT source code provided to entrants in CAT competitions to support the development of their entries.

3. The analysis of CAT entries

3.1. Strategy evaluation in competitive games

Trading competitions have been an effective tool in fostering innovative approaches and advocating enthusiasm and exchange among researchers [28, 31]. However, the competitions themselves usually cannot provide a complete view of the relative strength and weakness of entries. In a competition, the performance of one player closely depends upon the composition of its opponents and the competition configuration, and the scenarios considered are usually limited. Thus we typically turn to post-competition analysis to tell us which entries are most interesting.

Ideally, such an analysis will cover all possible scenarios, but this usually presents too large a possible space. As a result, a common practice is to deliberately select a limited number of representative strategies and run games corresponding to a set of discrete points or trajectories in the infinite space, assuming that the results are representative of what would happen in the whole space were one to explore it [27].

There are two common types of approaches to post-competition analysis: *white-box* approaches and *black-box* approaches.

A white-box approach attempts to relate the internal logic and features of strategies to game outcomes. In the Santa Fe Double Auction Tournament and post-tournament experiments [23], a thorough examination of auction efficiency losses indicated that the success of the KAPLAN trading strategy is due to its patience in waiting to exploit the intelligence or stupidity of other trading strategies. In Axelrod's Computer Prisoner's Dilemma Tournament [1], the strong showing of TIT FOR TAT is attributed to its friendliness and cooperativeness. A white-box approach is often domain-dependent, however the insights obtained in the concerned domain may still be extended to other domains. For instance, the payoff structure in the iterated Prisoner's Dilemma problem grasps the nature of many other issues that interest-conflicting parties face.

A black-box approach, on the other hand, considers strategies as atomic entities. One perspective is an *ecological* one based on *replicator dynamics*, from which the entities are biological individuals in an infinitely large population and a sub-population playing a particular strategy grows in proportion to how well that strategy performs relative to the whole population in average [7]. Walsh *et al.* [29] combines the game-theoretic solution concept of Nash equilibrium and replicator dynamics, turning a potentially very complex, multi-stage game of trading strategies into a one-shot game in normal form. What's more, a technique called *perturbation analysis* is used to evaluate the potential a strategy can be improved further. Phelps *et al.* [19] successfully applied this approach in acquiring a better trading strategy for DA markets. Jordan *et al.* [11] took a similar approach to the evaluation of entries in the TAC Supply Chain Management Tournament (SCM).

Niu *et al.* [15] performed a white-box analysis of CAT 2007, and examined how the dynamics in the CAT games are affected by the policies of each entry and their adaptation over time. This paper takes a complementary, black-box approach, and also examines the weakness and strength of CAT 2007 entries against `MetroCat`.

Although a black-box analysis abstracts away dynamics details during the interaction of strategies, it may still involve high complexity, due to the fact that a game may have an arbitrary number of players and an arbitrary number of strategies. The results of n-player, m-strategy games may not necessarily agree with the results of $(n+1)$-player, m-strategy games, or n-player, $(m+1)$-strategy games. For instance, player A beating player B in a bilateral game does not necessarily imply that A would still beat B when an additional player C is added, no matter C uses either of the strategies used by A and B, or a third, new strategy. This difficulty suggests, for example, that the replicator dynamics fields reported in [20] based on 6-agent auction games or in [11] based on 6-agent TAC SCM games may possibly change when a different set of game profiles are used to approximate the interaction of a player population with a certain composition of strategies.

To shed more light on the interaction of possible scenarios and limit the possible distortion brought by the sampled game profiles, we ran two sets of experiments to analyze entries of CAT 2007: multi-lateral simulation with games involving all the entries and bilateral simulation with games each involving two specialists. The two sets of experiments can be viewed as the two ends of a spectrum varying on the number of players and strategies in a game.

3.2. Multi-lateral simulation

A full analysis of a set of strategies can only be achieved by considering many runs (to eliminate randomness) of every possible combination of strategies. This is not feasible for the CAT competition where each game runs for around five hours (irrespective of the hardware — the length of each trading day is hard-coded at a constant that permits each specialist to take time to perform possibly complex computations — any reduction in this time would potentially distort the results). Inspired by ecological analyses like [1, 23] — in which more copies of successful strategies, and less copies of unsuccessful strategies are run for each successive game — but constrained by the number of specialists that we could have in a single game, we modified each strategy's playing time in proportion to its score. That is, in a game that included all specialists, we decreased the number of trading days for less successful strategies, and increased the days for more successful strategies.

Figures 1(a) and 1(b) show the result of this simulation. The distribution on the y-axis shows the proportion of the total number of trading days for all markets that are allotted to each market, indicating how this evolves in populations without and with MetroCat respectively.

Figure 1(a) shows that without MetroCat

- the results of this analysis agree with the results reported in [15], again confirming that IAMwildCAT was the strongest entry in the 2007 competition; and
- the days allotted to PersianCat shrink more slowly than those allotted to other losing specialists. This agrees with the results of bilateral games between IAMwildCAT and PersianCat (described below) and suggests that PersianCat was a strong entry.

Figure 1(b) shows that with MetroCat

- MetroCat quickly dominates the other entries, doing so faster than IAMwildCAT in Figure 1(a), and by generation 8 only MetroCat has any trading days; and
- the CAT 2007 champion, IAMwildCAT, loses trading days faster than other entries after generation 1, indicating some weakness in its design when facing an opponent like MetroCat.

3.3. Bilateral simulation

One-on-one games closely examine the strength and weakness of a specialist when it faces different opponents.

3.3.1 Payoff table

As a result, we ran 81 experiments in total between the nine specialists including MetroCat. Nine of these are self-play games. Table 1 shows the resulting payoffs of specialists — their average daily scores — in these CAT games. Each payoff is averaged over ten iterations and entry (i, j) is the payoff of specialist i in the game against specialist j.

Figure 3 compares these payoffs pictorially using a polar coordinate system. Each plot shows the nine specialists evenly distributed on the outer circle, the radial coordinates of the nine vertices of the solid-line polygon represent a given specialist's payoffs against all nine specialists, and the radial coordinates of the nine vertices of the dashed-line polygon represent its opponents' payoffs in these games. The solid-line polygon and the dashed-line polygon overlap on the vertex that corresponds to the self-play game of the particular specialist.

In Figure 3(a), the solid-line polygon completely encloses the dashed-line one, meaning MetroCat wins over all the other eight specialists in bilateral competitions.[10] Figure 3(i) shows the opposite situation in which Mertacor loses all the games. The two polygons for any other specialist intersect somehow, showing their advantages in some games and disadvantages in others.

Both Figure 3(b) and 3(h) show that IAMwildCAT, the CAT 2007 champion, surprisingly loses (although barely) against PersianCat that placed sixth. This explains why in Figure 1(a) the days for PersianCat shrink more slowly than those for other specialists. IAMwildCAT's loss, given the defeat of PersianCat by PSUCAT and jackaroo, suggests that IAMwildCAT has some particular weakness that is taken advantage of by PersianCat.

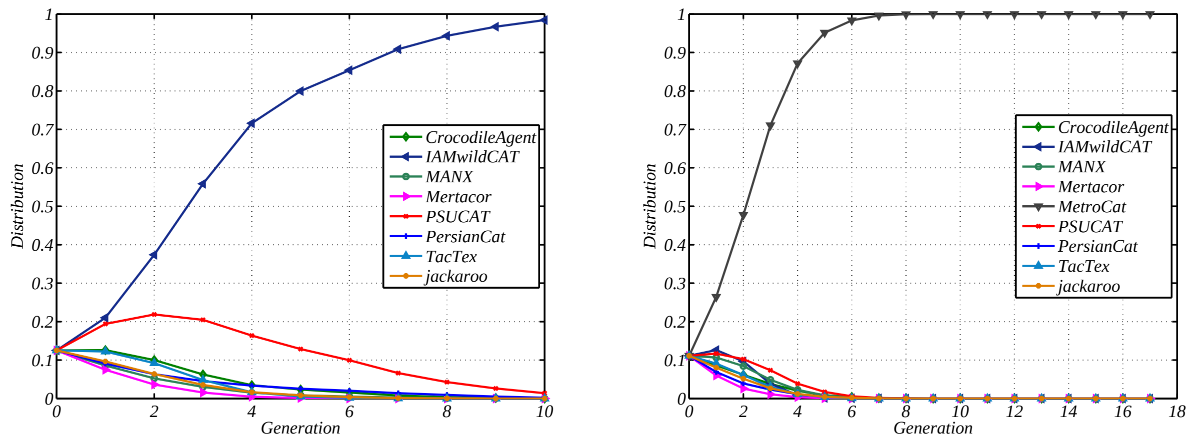
Other discrepancies, when compared to the results of the 2007 competition, include jackaroo (which placed fourth) winning over PSUCAT (second) and Crocodile (third). These may be significant, or may be caused by differences in the configurations for PSUCAT and Crocodile used in the simulations and CAT 2007 games.

3.3.2 Ecological simulation

The payoff table for the bilateral CAT games can be used to approximate ecological dynamics for populations involving more than two specialist types. The payoff of each specialist type for a certain population mixture is computed as the expected payoff for this specialist assuming that each specialist obtains the payoff it would have obtained had it computed one-on-one with each of the other specialists in the mix. Under this assumption, Figures 2(a) and 2(b) show how a population with an initial even distribution of specialists evolves over time when, as in [1], every specialist plays against every other specialist in every generation in bilateral games, and the number of specialists in any generation is proportional to the payoff achieved by that "breed" of specialist in the previous generation.

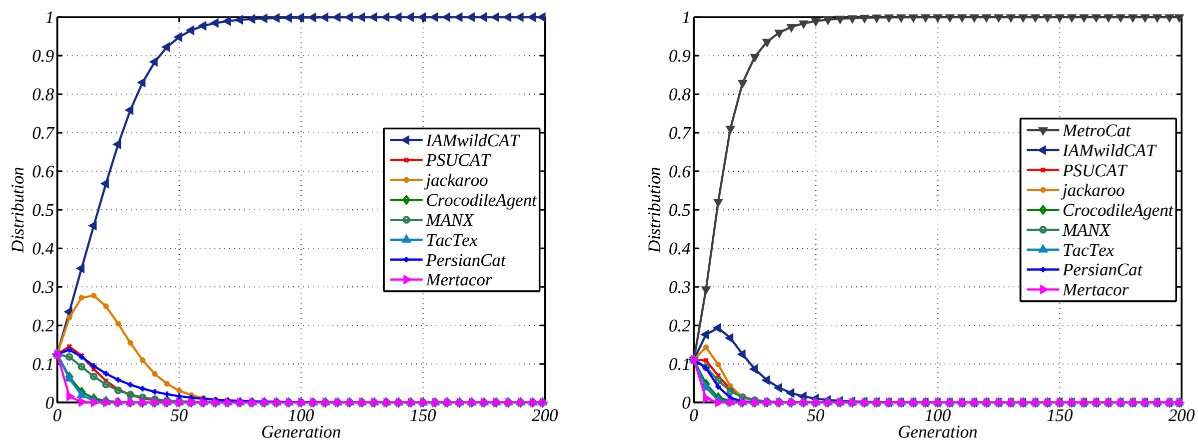
Comparing Figure 2(a) with Figure 1(a), and Figure 2(b) with Figure 1(b), shows that while the winning strategies are the same, the ecological simulations based on multi-lateral games converge much faster than those based on bilateral games. This may be explained by the more epidemic effects of the strength of particular specialists in multi-lateral games compared with bilateral games. Another noticeable phenomenon is that PSUCAT performs much worse in the simulations with bilateral games than those with multi-lateral games, while jackaroo and IAMwildCAT do the opposite. These discrepancies indicate that, as one might expect, different game setups may lead to very different results. However, our results may be helpful to identify the weakness in strategies by looking at the particular scenario

[10] MetroCat maintains a better balance than those CAT 2007 entries between market share and profit share by keeping extra-marginal traders and preventing them from placing uncompetitive shouts.



(a) Without `MetroCat` (b) Including `MetroCat`

Figure 1: Ecological simulation of CAT 2007 entries based on multi-lateral CAT games.



(a) Without `MetroCat` (b) Including `MetroCat`

Figure 2: Ecological simulation of CAT 2007 entries based on bilateral CAT games.

in which a strategy performs poorly.

3.3.3 Offense, defense, dominance, and equilibrium

To further reveal the strength and weakness of specialists, we compare specialists' payoffs — which we call *offense* — and the payoffs they allow opponents to make — which we call *defense* — when they face a same opponent.

Figure 4(a) puts all the solid-line polygons in Figure 3 into a single polar coordinate system and Figure 4(b) shows all the dashed-line polygons in a similar way. The comparison shows clearly that `MetroCat` has both the strongest offense and the strongest defense, while `Mertacor` exhibits almost the opposite.

In a normal-form game with both sides choosing their strategies from the nine specialists, we say a specialist *dominates* another if the former's offense is better than the latter for any same opponent.[11] Figure 5 shows the dominance relations between specialists. It represents each dominance relation with an arrow starting from the dominated specialist to the dominating one, and the unavailability of a dominance relation between two specialists with a dashed line. Our goal here is not to identify the dominating strategy as usual in a normal-form game, but to reduce the number of strategies of concern by gradually removing dominating and dominated strategies, so as to be able to obtain the relative strength and weakness of those left at a lower computational cost.[12] Figure 5(a) shows, as Figure 4 al-

[11]Defense may also be used to define dominance and may lead to different results and provide different insights into the strength and weakness of specialists.

[12]Imagine that a strategy may not the best in a competition, but its de-

specialist	Metro	IAM	PSU	jack	Croc	MANX	TacTex	Persian	Mertacor
MetroCat	0.6451	0.7134	0.7461	0.7804	0.8217	0.7524	0.8592	0.7773	0.8885
IAMwildCAT	0.5895	0.6568	0.7207	0.6793	0.7681	0.7070	0.8008	0.6145	0.7632
PSUCAT	0.5366	0.5687	0.6152	0.5534	0.6950	0.6121	0.6420	0.7409	0.8307
jackaroo	0.4786	0.5926	0.6989	0.6279	0.7537	0.7088	0.7839	0.6902	0.8602
CrocodileAgent	0.4357	0.5245	0.5420	0.5145	0.4865	0.4614	0.6210	0.5879	0.7257
MANX	0.5383	0.5930	0.6067	0.5790	0.5101	0.6434	0.7150	0.6166	0.6944
TacTex	0.3362	0.4123	0.5743	0.4344	0.6271	0.5369	0.5546	0.6126	0.7238
PersianCat	0.4326	0.6200	0.5155	0.5925	0.7041	0.6686	0.6399	0.6446	0.7710
Mertacor	0.2677	0.3831	0.2947	0.3172	0.5068	0.4026	0.4479	0.4650	0.5503

Table 1: The payoff matrix of bilateral CAT games between CAT 2007 entries and MetroCat.

ready does, that MetroCat dominates all the other specialists while Mertacor is almost dominated by all the rest except for CrocodileAgent. If we eliminate the dominating MetroCat and any specialist that is dominated by at least one specialist other than MetroCat, we will have four specialists left, PersianCat, IAMwildCAT, PSUCAT, and jackaroo. Figure 5(b) shows the dominance relations in the new scenario, where no specialist dominates another.

For any three specialists out of the four, we apply the heuristic strategy analysis method used in [20, 30], and Figure 6 shows the four replicator dynamics fields. The payoff of each specialist type for a certain population mixture is computed in the same way as in the ecological simulation above. Figures 6(a) and 6(c) show an unstable equilibrium between IAMwildCAT and PersianCat. Without considering this equilibrium and those pure profiles, all profiles lead to a homogeneous population, IAMwildCAT in Figures 6(a), 6(b), and 6(c), and jackaroo in Figure 6(d). This indicates strong dominance of the winning strategies in these 3-specialist scenarios. The landslide winnings may be due to the young age of CAT tournaments. As CAT competitions continue, the strategies for specialists evolve, and we expect that the relative strength between these strategies would become more complex and some mixed equilibrium may start to emerge.

4. Conclusions and future work

This paper reports results of post-competition simulations of entries in the First TAC Market Design Competition based on both bilateral games and multi-lateral games. The results basically agree with those in [15] and the result of the actual tournament, and also unveil weaknesses of specialists in particular scenarios, including the defeat of IAMwildCAT by PersianCat in bilateral games and the poorer relative performance of jackaroo in multi-lateral scenarios than in bilateral scenarios.

Some simulations also consider an additional specialist, MetroCat, which uses a history-based shout accepting policy that is derived from the GD trading strategy for double auctions. MetroCat claims victories in all the scenarios addressed in this paper, showing the importance of a shout accepting policy in a market mechanism. This also indicates, together with the landslide winnings of specialists in the 3-specialist replicator dynamics simulations, that entries for CAT competitions may need significant improvement in the future.[13]

The bilateral games and multi-lateral games can be viewed as the two ends of a spectrum of CAT games. The aim of running simulations based on both configurations is to explore whether the different competition configurations lead to results that differ much. It is hoped that if they make no much difference — and our results suggest that they do not — the low cost of bilateral games can be used to approximate the games involving more different individual types and different population distributions.

A related work is by Kaisers *et al.* [12]. They explored the acquisition of the payoff table for n-player games based on the payoff table for 2-player games and vice versa, both involving a same set of strategies for players. They showed that the linear-programming-based approximation approach works fine in games between trading strategies. Our simulation shows that an approximation approach may work but would need additional tuneup so as to reduce the distortions incurred. The discrepancies observed in this paper suggest that additional simulations may need to run to obtain more

signer may still want to improve it rather than simply adopting the winning strategy designed by others. This reduction based on dominance may help to zoom into those scenarios that are more worthy of examination.

[13] Other experiments and some CAT trial games show that some entries of prior CAT competitions — which we assume have taken at least months for a team to design — are beaten by classic double auction mechanisms that we use as benchmarks. This again suggests that we have yet to obtain more insights into market mechanisms and their interaction dynamics so as to design better ones.

accurate approximation. The problem they try to solve can actually be extended into a more general one: how to build (approximately) the payoff table for n-player games based on a set of complete or partial payoff tables each for games involving no more than n players. Suppose, in a n-player game, each player may choose one of s strategies. There are thus totally C^s_{n+s-1} possible match-ups. If each match-up is simulated, a heuristic payoff table would become available to generate a replicator dynamics field for the s strategies, where possible equilibria can be identified as well as the relative strength of each strategy. If the C^s_{n+s-1} match-ups be viewed as the C^s_{n+s-1} discrete points along the dimension denoted as $\mathcal{D}(n, s)$, the above problem becomes to run simulations for points scattering along lower dimensions, e.g., $\mathcal{D}(2, s)$ for 2-player games in [12], so as to approximate the results for the C^s_{n+s-1} points along $\mathcal{D}(n, s)$. This approach would have more flexibility and allow gradual distortion reduction over time.

This future work is desirable because, even if the approximation is not quantitatively accurate, it may provide qualitative guidance on what scenarios should be investigated further and help to reduce the overall computational complexity. For example, the replicator dynamics fields in both [11] and [21] suggest that if there is a mixed equilibrium between three strategies, there may be at least one mixed equilibrium between two of these strategies. In addition, for a space of heuristic strategies that still expands gradually, like the one for CAT games, it is no less important to be creative — focusing on creating better strategies — than to be fair — finding a better way to evaluate existing strategies. Shedding light on weaknesses of a strategy and directions to improve may be even more important for strategies that are of practical importance.

Another possible future work is to consider the evolution of trading agents in addition to that of specialists. To make the situation simple, the simulations in this paper use a same trading agent composition that does not evolve at all. It is however more realistic to have simulations with intervening CAT competitions and trading agent competitions, so that trading agents learn to adapt their strategies as they interact with each other and with the specialists.

A further extension is to view a market mechanism as a combination of atomic auction rules rather than an atomic entity itself. From this point of view, there would be multiple populations, each for a type of auction rule. Multiple individuals, one from each population, need to collaborate to form a complete market mechanism, and compete against other combinations. The payoff of a market mechanism from a simulation would be used as the payoff for each individual component of the market mechanism. This multi-population simulation may be considered as a *grey-box* approach, a mixture of black-box approach and white-box approach, since it involves internal logic of strategies. Such a grey-box approach can be used to explore a solution space, enabling an automated solution design method, as long as a modular strategy design is available. The parameterized framework for specialists presented in Section 2.1 forms an ideal foundation for further work along this line.

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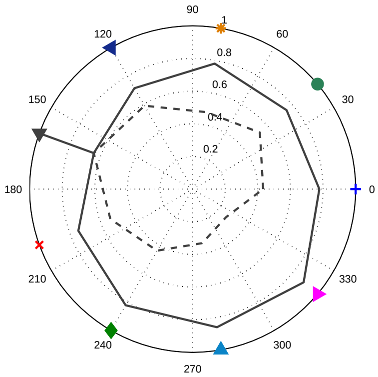
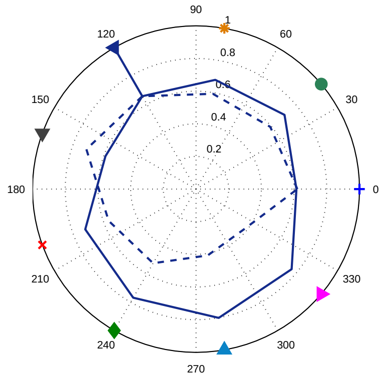
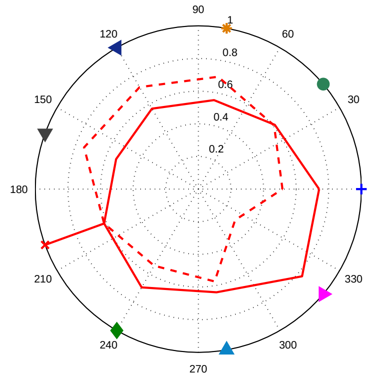


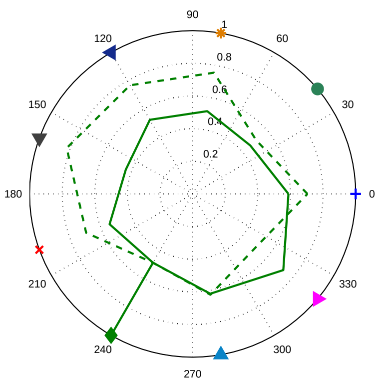
(a) MetroCat



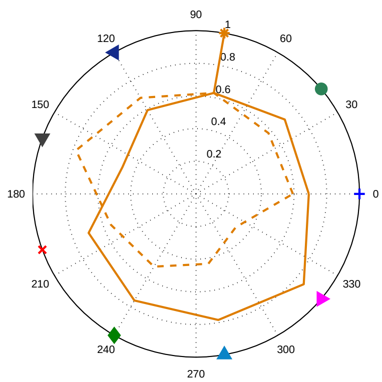
(b) IAMwildCAT



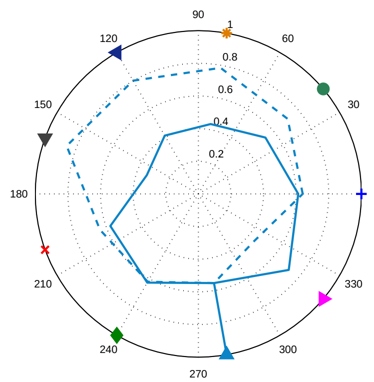
(c) PSUCAT



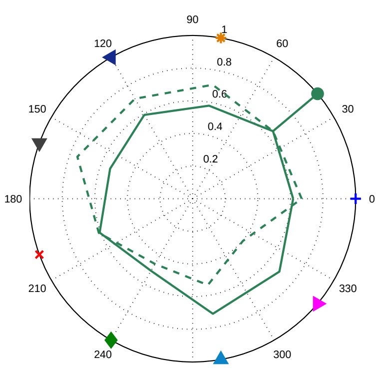
(d) CrocodileAgent



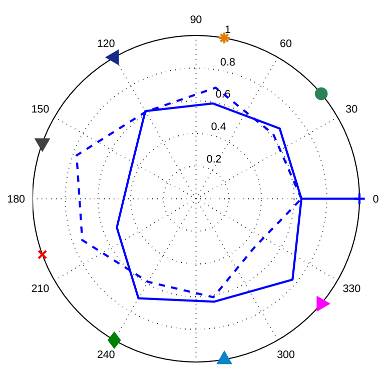
(e) jackaroo



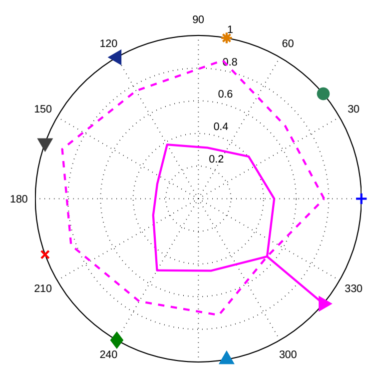
(f) TacTex



(g) MANX

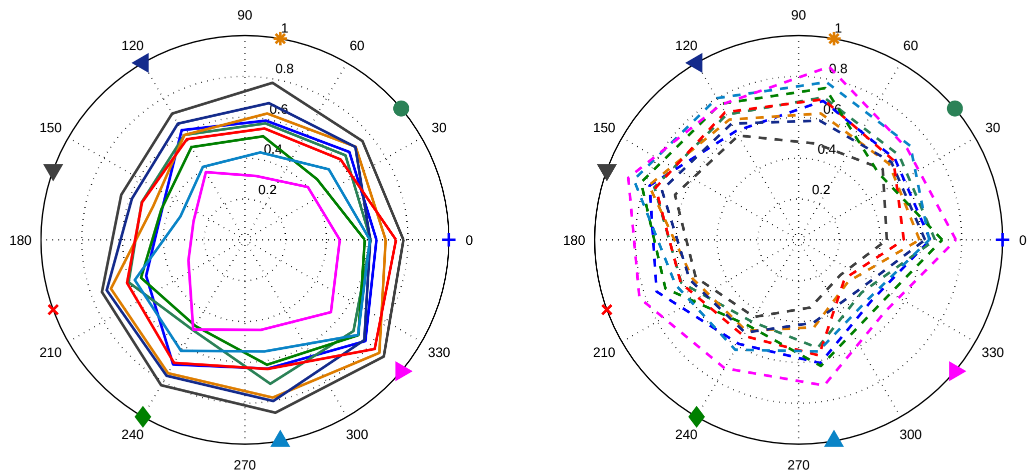


(h) PersianCat



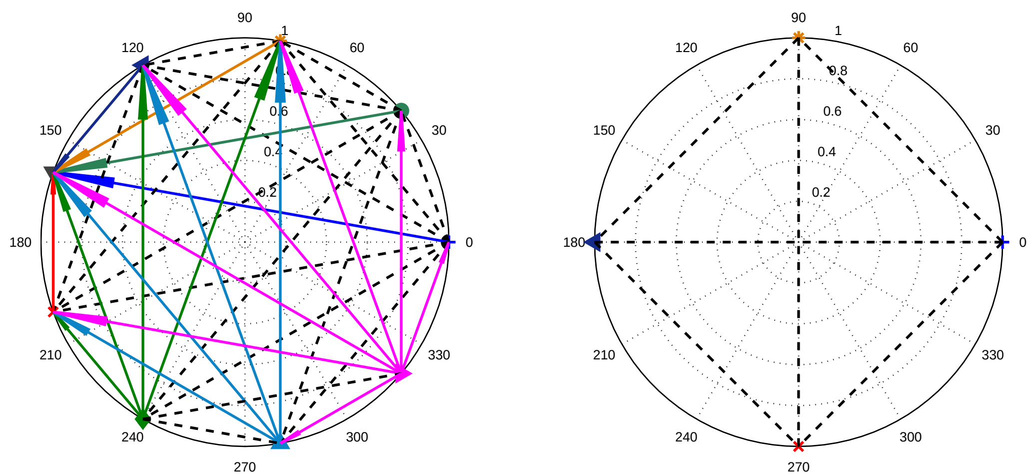
(i) Mertacor

Figure 3: Payoffs of self and opponents in bilateral CAT games. On the outer circles starting from polar angle 0° lists the nine specialists anti-clockwise : `PersianCat` (0°), `MANX` (40°), `jackaroo` (80°), `IAMwildCAT` (120°), `MetroCat` (160°), `PSUCAT` (200°), `CrocodileAgent` (240°), `TacTex` (280°), and `Mertacor` (320°). The radial coordinates of the nine vertices of the solid-line polygon represent a given specialist's payoffs against all nine specialists respectively, and those of the dashed-line polygon represent payoffs of its opponents. The overlapping vertex of the two polygons in each plot is the self-play game of the particular specialist.



(a) Offense (b) Defense

Figure 4: Comparison of the offense and defense of specialists.



(a) S_6,S_3,S_8,S_2,S_9,S_5,S_1,S_7,S_4 anti-clockwise from $0°$

(b) S_6,S_8,S_2,S_5 anti-clockwise from $0°$

Figure 5: Dominance relations based on offense. S_1: `CrocodileAgent`, S_2: `IAMwildCAT`, S_3: `MANX`, S_4: `Mertacor`, S_5: `PSUCAT`, S_6: `PersianCat`, S_7: `TacTex`, S_8: `jackaroo`, and S_9: `MetroCat`.

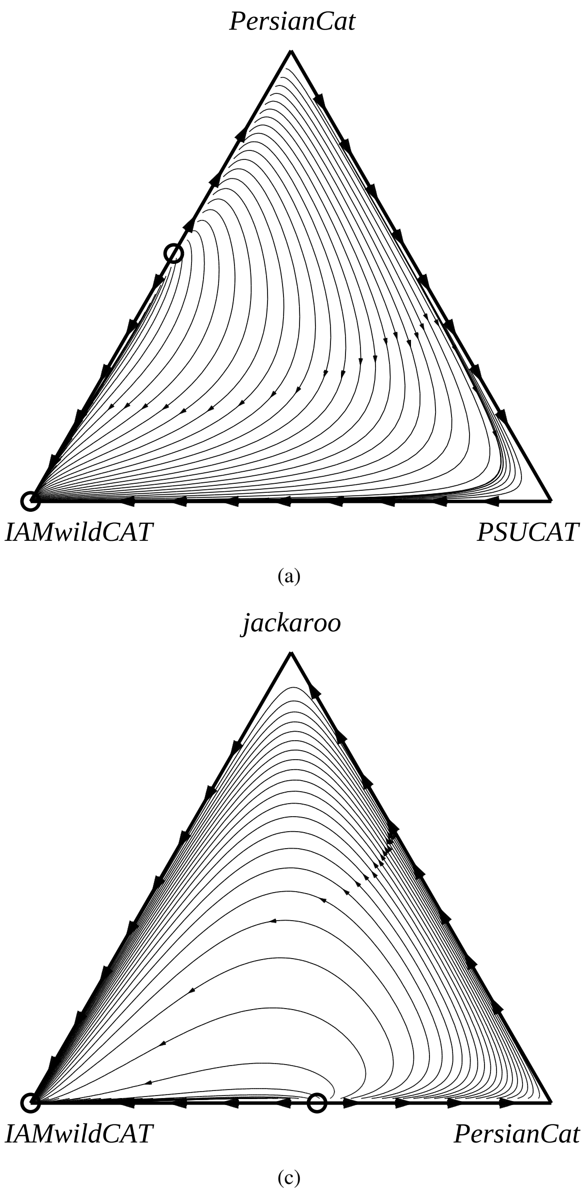


Figure 6: Replicator dynamics fields for any three specialists out of `PersianCat`, `jackaroo`, `IAMwildCAT`, and `PSUCAT`.