Online Double Oracle

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Abstract

Solving strategic games with huge action spaces is a critical yet under-explored topic in economics, operations research and artificial intelligence. This paper proposes new learning algorithms for solving two-player zero-sum normal-form games where the number of pure strategies is prohibitively large. Specifically, we combine no-regret analysis from online learning with Double Oracle (DO) from game theory. Our method—*Online Double Oracle (ODO)*—is provably convergent to a Nash equilibrium (NE). Most importantly, unlike normal DO, ODO is *rational* in the sense that each agent in ODO can exploit a strategic adversary with a regret bound of $\mathcal{O}(\sqrt{k\log(k)/T})$, where k is not the total number of pure strategies, but rather the size of *effective strategy set*. In many applications, we empirically show that k is linearly dependent on the support size of the NE. On tens of different real-world matrix games, ODO outperforms DO, PSRO, and no-regret algorithms such as Multiplicative Weights Update by a significant margin, both in terms of convergence rate to a NE, and average payoff against strategic adversaries.

1 Introduction

Understanding games with large action spaces is a critical topic in a variety of fields from economics to operations research and artificial intelligence. A key challenge is in computing a Nash equilibrium (NE) Nash et al. (1950), where no player is better off by deviating from their current strategy. Unfortunately, finding a NE is generally intractable, and computing a two-player NE is known to be PPAD-hard Chen & Deng (2006). An exception is two-player zero-sum games where an NE can be tractably solved as a linear program (LP) Morgenstern & Von Neumann (1953). Despite the polynomial-time complexity of solving an LP van den Brand (2020), LP solvers are not adequate for games with prohibitively large action spaces. As a result, researchers have shifted their focus towards finding efficient approximation solutions McMahan et al. (2003); Lanctot et al. (2017); Brown (1951b); Zinkevich et al. (2007).

Double Oracle (DO) algorithm McMahan et al. (2003) and its extension Policy Space Response Oracles (PSRO) Lanctot et al. (2017) are efficient approaches to finding an approximate NE in games where the support of a NE is relatively small. In DO McMahan et al. (2003), players are initialised with a subset of the full strategy space, thus playing only a sub-game of the original game; then, at each iteration, a best-response strategy to the NE of the last sub-game, which is assumed to be given by an *Oracle*, is added into each agent's strategy pool. The process stops when the best-response is already in the strategy pool or the performance improvement of the sub-game NE becomes trivial. When an exact best-response strategy is not available, an approximate solution is often adopted. For example, PSRO Lanctot et al. (2017) applies reinforcement learning (RL) Sutton & Barto (2018) oracles to approximate a best response.

Whilst DO and PSRO both provide an efficient way to approximate the NE in large-scale zero-sum games, they still face two open challenges. **Firstly**, they require both players to *coordinate* in order to solve the NE in sub-games and update the strategy set; both players have to follow the same learning dynamics such as Fictitious Play (FP) Brown (1951a) or implement LP to solve the sub-game NE together. This contradicts many real-world scenarios where an opponent can play any (non-stationary) strategy in sub-games.

Secondly, and more importantly, DO methods are not *rational* Bowling & Veloso (2001), in the sense that they do not provide a learning scheme that can exploit an adversary (i.e., achieving no-regret). Whilst a

Table 1: Properties of existing solvers on two-player zero-sum games $\boldsymbol{A}_{n\times m}$. *:DO in the worst case has to solve all sub-games till reaching the full game, so the time complexity is one order magnitude larger than LP van den Brand (2020). †: Since PSRO uses approximate best-response, the total time complexity is unknown. ‡ Note that the regret bound of ODO can not be directly compared with the time complexity of DO, which are two different notions.

Method	**Rational (No-regret)**	**No Need to Know the Full Matrix $\boldsymbol{A}$**	**Time Complexity ($\tilde{\mathcal{O}}$) / Regret Bound ($\mathcal{O}$)**	**Large Games**
Linear Programming			$\tilde{\mathcal{O}}\big(n\exp(-T/n^{2.38})\big)$	
Generalised Fictitious Play		✓	$\tilde{\mathcal{O}}\big(T^{-1/(n+m-2)}\big)$	
Multiplicative Weight Update	✓	✓	$\mathcal{O}\big(\sqrt{\log(n)/T}\big)$	
Double Oracle		✓	$\tilde{\mathcal{O}}\big(n\exp(-T/n^{3.38})\big)^*$	✓
Policy Space Response Oracle		✓	$\times^\dagger$	✓
Online Double Oracle	✓	✓	$\mathcal{O}\big(\sqrt{k\log(k)/T}\big)^\ddagger$	✓

NE strategy guarantees the best performance in the worst scenario, it can be too pessimistic as a strategy compared to a rational strategy. For example, in a repeated Rock-Paper-Scissors (RPS) game, playing the NE of $(1/3, 1/3, 1/3)$ every iteration makes one player un-exploitable. However, if the adversary acts irrationally and sticks to one strategy, say "Rock", then the player should exploit the adversary by consistently playing "Paper" to achieve larger rewards than playing the NE. No-regret algorithms Cesa-Bianchi & Lugosi (2006); Shalev-Shwartz et al. (2011) prescribe a learning scheme in which a player is guaranteed to achieve minimal regret against the best fixed strategy in hindsight when facing an unknown adversary (either rational or irrational). Notably, if both players follow no-regret algorithms, then it is guaranteed that their time-average policies will converge to a NE in zero-sum games Blum & Monsour (2007) . However, the regret bounds of popular no-regret algorithms Freund & Schapire (1999); Auer et al. (2002) usually depend on the game size; for example, Multiplicative Weights Update (MWU) Freund & Schapire (1999) has a regret bound of $\mathcal{O}(\sqrt{\log(n)/T})$ and EXP3 Auer et al. (2002) in the bandit setting has a regret of $\mathcal{O}(\sqrt{n\log(n)/T})$, where n is the number of pure strategies (i.e., experts). As a result, directly applying no-regret algorithms, though rational, is not computationally feasible in solving large-scale games.

In this paper, we present a scalable solution to two-player zero-sum normal-form games where the game size (i.e., the number of pure strategies) is prohibitively large. Our main analytical tool is no-regret analysis from online learning Shalev-Shwartz et al. (2011). Specifically, by conducting no-regret analysis Freund & Schapire (1999) within the DO framework (McMahan et al., 2003), we propose the *Online Double Oracle (ODO)* algorithm which inherits the key benefits from both sides. It is the first DO method that enjoys the no-regret property and can exploit unknown adversaries during game play. Importantly, ODO achieves a regret of $\mathcal{O}(\sqrt{k\log(k)/T})$ where k, the size of effective strategy set, is upper-bounded by the total number of pure strategies n and often $k \ll n$ holds in practice. We test our algorithm on tens of games including random matrix games, real-world matrix games Czarnecki et al. (2020), and Kuhn and Leduc Poker. Results show that in almost all games, ODO outperforms both DO and PSRO variants Lanctot et al. (2017); McAleer et al. (2020), and the online learning baseline: MWU Freund & Schapire (1999) in terms of exploitability (i.e., distance to an NE) and average payoffs against different types of strategic adversaries.

2 Related Work

ODO contributes to both the game theory and online learning domains. To summarise our contribution, we present a list of existing game solvers for comparison in Table 1.

Approximating a NE has been extensively studied in the game theory literature. Fictitious Play (FP) Brown (1951b) and generalised FP Leslie & Collins (2006) are classical solutions where each player adopts a strategy that best responds to the time-average strategy of the opponent. Although FP is provably convergent to NE in zero-sum games, it is prohibited from solving large games due to the need to iterate through all pure strategies at each iteration; furthermore, the convergence rate depends exponentially on the game size Brandt et al. (2010). In terms of large-scale zero-sum games, DO McMahan et al. (2003); McAleer et al. (2021)

and PSRO methods Lanctot et al. (2017); McAleer et al. (2020); Feng et al. (2021) have shown remarkable empirical success. For example, a distributed implementation of PSRO can handle games of size 10^{50} McAleer et al. (2020). Yet, both FP and DO methods offer no knowledge about how to exploit an adversary in a game (i.e., no-regret property) Hart & Mas-Colell (2001), and thus are regarded as not *rational* Bowling & Veloso (2001). Modern solutions that are rational such as CFR methods Zinkevich et al. (2007); Lanctot et al. (2009) are efficiently designed for extensive-form games only.

Algorithms with the no-(external) regret property can achieve guaranteed performance against the best-fixed strategy in hindsight Shalev-Shwartz et al. (2011); Cesa-Bianchi & Lugosi (2006), thus they are commonly applied to tackle adversarial environments. However, conventional no-regret algorithms such as Follow the Regularised Leader Shalev-Shwartz et al. (2011), Multiplicative Weights Update (MWU) Freund & Schapire (1999) or EXP-3 Auer et al. (2002) have regret bounds that are based on the number of pure strategies (i.e., experts). Moreover, these algorithms consider the full strategy set during updates, which hinders their applicability to large-scale games. In this paper, we leverage the advantages of both DO and no-regret learning to propose ODO. ODO enjoys the benefits of both being applicable to solving large games, and being able to maintain the no-regret property (i.e., being rational).

3 Notations & Preliminaries

A two-player zero-sum normal-form game is often described by a payoff matrix $\boldsymbol{A}$ of size $n \times m$. The rows and columns of $\boldsymbol{A}$ are the pure strategies of the row and the column players, respectively, and we consider n and m to be prohibitively large numbers. We denote the set of pure strategies for the row player as $\Pi := \{\boldsymbol{a}^1, \boldsymbol{a}^2, \dots \boldsymbol{a}^n\}$, and $C := \{\boldsymbol{c}^1, \boldsymbol{c}^2, \dots, \boldsymbol{c}^m\}$ for the column player.

The set of mixed strategies for the row-player is $\Delta_\Pi := \left\{\boldsymbol{\pi} | \boldsymbol{\pi} = \sum_{i=1}^n x_i \boldsymbol{a}^i,\ \sum_{i=1}^n x_i = 1, x_i \geq 0, \forall i \in [n]\right\}$, and for the column player it is $\Delta_C := \{\boldsymbol{c} | \boldsymbol{c} = \sum_{i=1}^m y_i \boldsymbol{c}^i, \sum_{i=1}^n y_i = 1, y_i \geq 0, \forall i \in [m]\}$. The support of a mixed strategy is written as $\text{supp}(\boldsymbol{\pi}) := \{\boldsymbol{a}^i \in \Pi | x_i \neq 0\}$, with its size being $|\text{supp}(\boldsymbol{\pi})|$.

We consider $\boldsymbol{A}_{i,j} \in [0, 1]$ to represent the (normalised) loss of the row player when playing a mixed strategy against the mixed strategy of the column player. At the t-th round, the expected payoff for the joint-strategy profile $(\boldsymbol{\pi}_t \in \Delta_\Pi, \boldsymbol{c}_t \in \Delta_C)$ is $(-\boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t, \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t)$. In this paper, we consider the online setting in which players **do not** know the matrix $\boldsymbol{A}$, or the adversary's policy, but instead only receive a loss value after their strategy is played: e.g., at timestep $t+1$, the row player observes $\boldsymbol{l}_t = \boldsymbol{A}\boldsymbol{c}_t$ from the environment and plays a new strategy $\boldsymbol{\pi}_{t+1}$. The goal of the players is to reach a Nash equilibrium.

Nash Equilibrium. A NE of a two-player zero-sum game can be defined by the minimax theorem Neumann (1928):

$$\min_{\boldsymbol{\pi} \in \Delta_\Pi} \max_{\boldsymbol{c} \in \Delta_C} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c} = \max_{\boldsymbol{c} \in \Delta_C} \min_{\boldsymbol{\pi} \in \Delta_\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c} = v, \tag{1}$$

for some $v \in \mathbb{R}$. The $(\boldsymbol{\pi}^*, \boldsymbol{c}^*)$ that satisfies Equation (1) is a NE of the game. In general, one can apply LP solvers to find the NE in small games Morgenstern & Von Neumann (1953). However, when n and m are large, the time complexity is not affordable. A more general solution concept is the ϵ-Nash equilibrium.

ϵ-Nash Equilibrium. For $\epsilon > 0$, we call a joint strategy $(\boldsymbol{\pi}, \boldsymbol{c}) \in \Delta_\Pi \times \Delta_C$ an ϵ-NE if it satisfies

$$\max_{\boldsymbol{c} \in \Delta_C} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c} - \epsilon \leq \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c} \leq \min_{\boldsymbol{\pi} \in \Delta_\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c} + \epsilon. \tag{2}$$

3.1 Double Oracle Method

The pseudocode for DO McMahan et al. (2003) is listed in Appendix A.1. The DO method approximates a NE in large-scale zero-sum games by iteratively expanding and solving a series of sub-games (i.e., games with a restricted set of pure strategies). Since the sets of pure strategies of the sub-game are often much smaller than the original game, the NE of the sub-games can be easily solved via approaches such as FP. Based on the NE of the sub-game, each player finds a best-response to said NE, and expands their strategy set with this best-response. PSRO methods Lanctot et al. (2017); McAleer et al. (2020) are a generalisation of DO in which RL methods are adopted to approximate the best-response strategy. In the worst case scenario (e.g.,

the support size of NE is large), DO may end up restoring the original game and will maintain no advantages over LP solutions.

Although DO can solve large-scale zero-sum games, it requires both players to *coordinate* by finding a NE in the sub-games; this is a problem for DO when applied in real-world scenarios, as it cannot exploit the opponent who can play any non-stationary strategy (see the example of RPS in the Introduction). ODO addresses this problem by combining DO with tools in online learning.

3.2 Online Learning

Solving for a NE in large-scale games is demanding, so an alternative approach is to consider learning-based methods. We believe that by playing the same game repeatedly, a learning algorithm can approximate the NE asymptotically. A common metric, *(external)-regret*, to quantify the performance of a learning algorithm is to compare its cumulated payoff with the best fixed strategy in hindsight.

Definition 1 (No-Regret Algorithms)**.** *Let $\boldsymbol{c}_1, \boldsymbol{c}_2, \dots$ be a sequence of mixed strategies played by the column player, an algorithm of the row player that generates a sequence of mixed strategies $\boldsymbol{\pi}_1, \boldsymbol{\pi}_2, \dots$ is called a no-regret algorithm if we have the following property hold.*

$$\lim_{T\to\infty} \frac{R_T}{T} = 0, \qquad R_T = \max_{\boldsymbol{\pi}\in\Delta_\Pi} \sum_{t=1}^{T} \left(\boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t - \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c}_t\right).$$

If both players in a game follow a no-regret algorithm (not necessarily the same one), then the average strategies of both players converges to a NE Cesa-Bianchi & Lugosi (2006); Blum & Monsour (2007). For example, a well-known learning algorithm for games that has this no-regret property is the MWU algorithm Freund & Schapire (1999):

Definition 2 (Multiplicative Weights Update)**.** *Let $\boldsymbol{c}_1, \boldsymbol{c}_2, \dots$ be a sequence of mixed strategies played by the column player. The row player is said to follow MWU if $\boldsymbol{\pi}_{t+1}$ is updated as follows*

$$\boldsymbol{\pi}_{t+1}(i) = \frac{\boldsymbol{\pi}_t(i)\exp(-\mu_t \boldsymbol{a}^{i\top}\boldsymbol{A}\boldsymbol{c}_t)}{\sum_{i=1}^{n} \boldsymbol{\pi}_t(i)\exp(-\mu_t \boldsymbol{a}^{i\top}\boldsymbol{A}\boldsymbol{c}_t)}, \ \forall i \in [n] \tag{3}$$

where $\mu_t > 0$ is a parameter, $\boldsymbol{\pi}_0 = [1/n, \dots, 1/n]$ and n is the number of pure strategies (a.k.a. experts).

Intuitively, MWU functions by putting larger weights on the experts who have lower losses in the long-run. Thus, compared to the best-fixed strategy in hindsight (i.e., the expert with the lowest average loss), MWU can achieve the no-regret property. However, since MWU requires updating the whole pure strategy set (of size n) at each iteration, it is not applicable to solving large-scale games.

4 Online Single Oralce

In this section, we introduce Online Single Oracle (OSO), a no-regret algorithm followed by individual players that can strategically exploit any non-stationary opponent unlike DO. Compared to the MWU algorithm, OSO can be applied to solving large zero-sum games as it only considers a smaller subset of the full pure strategy space. The following section is organised as follows: we start by setting out OSO, the key component of ODO. We then discuss the bound on the effective strategy set k, the key element in the regret bound of OSO. Finally, we set out two different questions on the effectiveness and efficiency of the best-response oracle, and analyse OSO's performance when the player only has access to *less-frequent* or *approximate* best-responses oracles.

4.1 Online Single Oracle Algorithm

One can think of OSO as an online counterpart to the *Single Oracle* in DO McMahan et al. (2003) which can achieve the no-regret property. In contrast to classical no-regret algorithms such as MWU Freund &

Algorithm 1: Online Single Oracle Algorithm

1: **Input:** Player's pure strategy set Π
2: Init. effective strategies set: $\Pi_0 = \Pi_1 = \{\boldsymbol{a}^j\}, \boldsymbol{a}^j \in \Pi$
3: **for** $t = 1$ to T **do**
4: **if** $\Pi_t = \Pi_{t-1}$ **then**
5: Compute $\boldsymbol{\pi}_t$ by the MWU in Equation (3)
6: **else if** $\Pi_t \neq \Pi_{t-1}$ **then**
7: Start a new time window T_{i+1} and
 Reset $\boldsymbol{\pi}_t = \big[1/|\Pi_t|, \ldots, 1/|\Pi_t|\big]$, $\bar{\boldsymbol{l}} = \boldsymbol{0}$
8: **end if**
9: Observe $\boldsymbol{l}_t$ and update the average loss in T_i: $\bar{\boldsymbol{l}} = \sum_{t \in T_i} \boldsymbol{l}_t / |T_i|$
10: Calculate the best-response: $\boldsymbol{a}_t = \arg\min_{\boldsymbol{\pi} \in \Pi} \langle \boldsymbol{\pi}, \bar{\boldsymbol{l}} \rangle$
11: Update the set of strategies: $\Pi_{t+1} = \Pi_t \cup \{\boldsymbol{a}_t\}$
12: **end for**
13: **Output:** $\boldsymbol{\pi}_T$, Π_T

Schapire (1999) where the whole set of pure strategies needs considering at each iteration, i.e., Equation (3), we propose OSO that only considers a *subset* of the whole strategy set. The key operation is that, at each round t, OSO only considers adding a new strategy if it is the best-response to the average loss in a time window (defined formally in the following paragraph). As such, OSO can save on exploration costs by ignoring the pure strategies that have never been the best-response to any, so far observed, average losses, $\bar{\boldsymbol{l}}$.

Our OSO is listed in Algorithm 1. We initialise the OSO algorithm with a random strategy subset Π_0 from the original strategy set Π. Without loss of generality, we assume that Π_0 starts from only one pure strategy (line 2). We call subset Π_t the **effective strategy set** at the timestep t, and define the period of consecutive iterations as one **time window** T_i in which the effective strategy set stays fixed, i.e., $T_i := \big\{t \;\big|\; |\Pi_t| = i\big\}$. At iteration t, we update $\boldsymbol{\pi}_t$ (line 5) whilst only considering the effective strategy set Π_t (rather than whole set Π); and the best-response is computed against the average loss $\bar{\boldsymbol{l}}$ within the current time window T_i (line 9). Adding a new best-response that is not in the existing effective strategy set will start a new time window (line 7). Notably, despite the design of effective strategy sets, the exact best-response oracle in line 10 still needs to search over the whole strategy set Π, which is a property that we relax through best-response approximation later.

We now present the regret bound of OSO as follows,

Theorem 3 (Regret Bound of OSO)**.** *Let $\boldsymbol{l}_1, \boldsymbol{l}_2, \ldots, \boldsymbol{l}_T$ be a sequence of loss vectors played by an adversary, and $\langle \cdot, \cdot \rangle$ be the dot product, OSO in Algorithm 1 is a no-regret algorithm with*

$$\frac{1}{T}\Big(\sum_{t=1}^{T} \big\langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \big\rangle - \min_{\boldsymbol{\pi} \in \Pi} \sum_{t=1}^{T} \big\langle \boldsymbol{\pi}, \boldsymbol{l}_t \big\rangle\Big) \leq \frac{\sqrt{k \log(k)}}{\sqrt{2T}},$$

where $k = |\Pi_T|$ is the size of the effective strategy set in the final time window.

Proof. W.l.o.g, we assume the player uses the MWU as the no-regret algorithm and starts with only one pure strategy in Π_0 in Algorithm 1. Since in the final time window, the effective strategy set has k elements, there are exactly k time windows. Denote $|T_1|, |T_2|, \ldots, |T_k|$ be the lengths of time windows during each of which the subset of strategies the no-regret algorithm considers does not change. In the case of finite set of strategies, k will be finite and we have

$$\sum_{i=1}^{k} |T_k| = T.$$

In the time window with length $|T_i|$, following the regret bound of MWU in Definition 2 we have:

$$\sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \min_{\boldsymbol{\pi} \in \Pi_{|\bar{T}_i|+1}} \sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle \leq \sqrt{\frac{|T_i|}{2} \log(i)}, \quad \text{where } |\bar{T}_i| = \sum_{j=1}^{i-1} |T_j|. \tag{4}$$

In the time window T_i, we consider the full strategy set when we calculate the best response strategy in step 11 of Algorithm 1 and it stays in $\Pi_{|\bar{T}_i|+1}$. Therefore, the inequality (4) can be expressed as:

$$\sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \min_{\boldsymbol{\pi} \in \Pi} \sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle \leq \sqrt{\frac{|T_i|}{2} \log(i)}. \tag{5}$$

Sum up the inequality (5) for $i = 1, \dots k$ we have:

$$\begin{aligned}
&\sum_{i=1}^{k} \sqrt{\frac{|T_i|}{2} \log(i)} \geq \sum_{t=1}^{T} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \sum_{i=1}^{k} \min_{\boldsymbol{\pi} \in \Pi} \sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle \\
&\geq \sum_{t=1}^{T} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \min_{\boldsymbol{\pi} \in \Pi} \sum_{i=1}^{k} \sum_{t=|\bar{T}_i|+1}^{|\bar{T}_{i+1}|} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle = \sum_{t=1}^{T} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \min_{\boldsymbol{\pi} \in \Pi} \sum_{t=1}^{T} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle && \text{(6a)} \\
&\Rightarrow \sqrt{\frac{Tk \log(k)}{2}} \geq \sum_{t=1}^{T} \langle \boldsymbol{\pi}_t, \boldsymbol{l}_t \rangle - \min_{\boldsymbol{\pi} \in \Pi} \sum_{t=1}^{T} \langle \boldsymbol{\pi}, \boldsymbol{l}_t \rangle. && \text{(6b)}
\end{aligned}$$

Inequality (6a) is due to $\sum \min \leq \min \sum$. Inequality (6b) comes from Cauchy-Schwarz inequality and Stirling' approximation. Thus, we have the derived regret. □

We note here that in line 7 of Algorithm 1, each time OSO enters a new time window, it sets equal weight for every pure strategy in the current effective strategy. Since we assume a fully adversarial environment, the historical data that the agent learnt in the previous time window does not provide any advantages over the current time window, thus in order to avoid any exploitation, the agent needs to reset the strategy as stated in Algorithm 1. In situations where priority knowledge can be observed through historical data, our OSO algorithm can exploit this knowledge by updating the starting strategy in each time window. We leave this important extension to our future work.

Remark 1 (Worst-Case Regret Bound)**.** Similar to all existing DO type of methods, in the worst-case scenario, OSO has to find all pure strategies, i.e., $k = |\Pi|$. Thus, the regret in the worst case scenario will be: $\sqrt{|\Pi| \log(|\Pi|)}/\sqrt{2T}$. However, we believe $k \ll |\Pi|$ holds in many practical cases such as against strategic adversary Dinh et al. (2021). In later sections, we provide both theoretical and empirical evidence that real-world games tend to have $k \ll |\Pi|$.

In the next section, we discuss the relationship between the effective strategy set size k and the full game size.

4.2 Size of Effective Strategy Set k

Generally, the practical success of ODO and other discussed methods (e.g., DO McMahan et al. (2003) / PSRO Lanctot et al. (2017)) is based on the assumption that the support size of the NE is small. Intuitively, since OSO is a no-regret algorithm, should the adversary itself follow a no-regret algorithm, the adversary's average strategy would converge to the NE. Thus, the learner's best-responses with respect to the average loss will include all the pure strategies in the support of the learner's NE. Therefore, under the assumption of DO and PSRO that the support size of NE is small, the effective strategy set size k is potentially a far smaller number than the game size (i.e., n).

Note that the assumption of a NE having a small support size holds true in many situations. In **symmetric** games with random entries (i.e., see Theorem 2.8 in Jonasson et al. (2004)), it has been proved that the

expected support size of a NE will be $(\frac{1}{2} + \mathcal{O}(1))n$ where n is the game size; showing that the support size of a NE strategy is only half of the game size. In **asymmetric** games with disproportionate action spaces (e.g., $n \gg m$), we provide the following lemma under which the support of a NE is small.

Lemma 1. *In asymmetric games $\boldsymbol{A}_{n\times m}, n \gg m$, if the NE $(\boldsymbol{\pi}^*, \boldsymbol{c}^*)$ is unique, then the support size of the NE will follow $|\operatorname{supp}(\boldsymbol{\pi}^*)| = |\operatorname{supp}(\boldsymbol{c}^*)| \leq m$.*

(We provide the full proof in the Appendix C.1.)

Empirically, we also show that the small support of a NE assumption holds on tens of real-world zero-sum games Czarnecki et al. (2020) (see Table 2 in Appendix D) and randomly generated games (see Figure 1).

In the case when a dominant strategy exists, we can theoretically bound k by the following lemma:

Lemma 2. *Suppose there exists a strictly dominant strategy for the player, then the size of the effective strategy set will be bounded by 2.*

Despite the practical success of our method and the DO/PSRO lines of work, there is no theoretical guarantee about the relationship between the support size of a NE and the performance of the algorithm. In this paper, we provide a negative result by constructing an example such that the size of the effective strategy set equals the size of the full strategy set, even when the support of NE is small.

Lemma 3. *Suppose the players start with the entry $\boldsymbol{A}_{1,1}$ and the game matrix $\boldsymbol{A}$ of the two-players zero-sum game is designed such as*

$$\boldsymbol{A}_{i,i} = 0.5 + \frac{0.1i}{n}\ \forall i \in [n];\quad \boldsymbol{A}_{i,i+1} = 0.9\ \forall i \in [n-1],$$
$$\boldsymbol{A}_{i,j} = 0.8\ \forall j \geq i+2, i \in [n],\quad \boldsymbol{A}_{i,j} = \boldsymbol{A}_{i,i} + \frac{0.1}{2n} \forall j \leq i, i \in [n],$$

where n is the size of the pure strategy set for both players. Then the game has a unique Nash equilibrium with support size of 1 (i.e., the entry $\boldsymbol{A}_{n,n}$) and the effective strategy set in both DO and OSO will reach the size of pure strategy set, that is, $k = n$.

We provide the full proof in Appendix C.3. The idea is that the the matrix $\boldsymbol{A}$ is designed such that the sub-game NE will change from $\boldsymbol{A}_{i,i}$ to $\boldsymbol{A}_{i,i+1}$ for $i \in [n]$, thus OSO will need to consider the full pure strategy set before reaching the game NE at $\boldsymbol{A}_{n,n}$. We would like to highlight that this negative result not only applies to our method, but also to **all** existing DO/PSRO algorithms and their variations.

However, as described in our experiments, we find that the extreme situation shown in Lemma 3 rarely occurs in practice. Later in Figure 1, we provide empirical evidence to support our claim that $k \ll |\Pi|$ and that there exists a linear relationship between k and the Nash support size in many real-world applications.

4.3 OSO with Less-Frequent Best-Response

The first adaptation to the best-response process that we consider is to make calls to the best-response oracle less frequently. Obtaining a best-response strategy can be computationally expensive Vinyals et al. (2019), and OSO considers adding a new best-response strategy at every iteration. A practical solution is to consider adding a new strategy when the regret in the current time window exceeds a predefined threshold α. To make OSO account for this, we denote $|\bar{T}_i| := \sum_{h=1}^{i-1} |T_h|$ as the starting point of the time window T_i, and write the threshold at T_i as $\alpha^i_{t-|\bar{T}_i|}$ where $t - |\bar{T}_i|$ denotes the relative position of round t in the time window T_i. We can make OSO add a new strategy only when the following condition is satisfied:

$$\min_{\boldsymbol{\pi}\in\Pi_t} \Big\langle \boldsymbol{\pi}, \sum_{j=|\bar{T}_i|}^{t} \boldsymbol{l}_j \Big\rangle - \min_{\boldsymbol{\pi}\in\Pi} \Big\langle \boldsymbol{\pi}, \sum_{j=|\bar{T}_i|}^{t} \boldsymbol{l}_j \Big\rangle \geq \alpha^i_{t-|\bar{T}_i|}. \tag{7}$$

Note that the larger the threshold α, the longer OSO takes to add a new strategy into Π_t. However, choosing a large α will prevent the learner from acquiring the actual best-response, thus increasing the total regret R_T

by α. In order to maintain the no-regret property, the α needs to satisfy

$$\lim_{T\to\infty} \frac{\sum_{i=1}^{k} \alpha^i_{T_i}}{T} = 0. \tag{8}$$

One choice of α that satisfies Equation (8) is $\alpha^i_{t-|\bar{T}_i|} = \sqrt{t - |\bar{T}_i|}$. We list the pseudo-code of OSO utilising Equation (7) and derive its regret bound of $\mathcal{O}\big(\sqrt{k\log(k)/T}\big)$ in Appendix B.1.

4.4 Considering ϵ-Best Responses

The second adaptation brings OSO more closely in line with the work of PSRO by considering a non-exact best-response oracle. So far, OSO agents compute the exact best-response to the average loss function $\bar{\boldsymbol{l}}$ (i.e., line 10 in Algorithm 1). Since calculating the exact best-response is often infeasible in large games, an alternative way is to consider an ϵ-best response (e.g., through a RL subroutine similar to PSRO Lanctot et al. (2017)) to the average loss.

By first analysing the convergence of DO, we can derive the regret bound as well as convergence guarantees for an OSO learner in the case of an ϵ-best response oracle.

Theorem 4. *Suppose an OSO agent can only access the ϵ-best response in each iteration when following Algorithm 1, if the adversary follows a no-regret algorithm, then the average strategy of the agent will converge to an ϵ-NE. Furthermore, the algorithm is ϵ-regret:*

$$\lim_{T\to\infty} \frac{R_T}{T} \leq \epsilon; \quad R_T = \max_{\boldsymbol{\pi}\in\Delta_\Pi} \sum_{t=1}^{T} \left(\boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t - \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c}_t\right).$$

(We provide the full proof in Appendix B.2.)

Theorem 4 justifies that in the case of approximate best-responses, OSO learners can still approximately converge to a NE. This results allows for the application of optimisation methods to approximate the best-response, which paves the way to use RL algorithm in solving complicated zero-sum games such as StarCraft Vinyals et al. (2019). Now that we have introduced the algorithms the individual player will follow, we can now discuss the outcomes when both competing players follow such algorithms.

5 Online Double Oracle

Algorithm 2: Online Double Oracle Algorithm

1: **Input:** Full pure strategy set Π, C
2: Init. effective strategies set: $\Pi_0 = \Pi_1, C_0 = C_1$
3: **for** $t = 1$ to T **do**
4: Each player follows the OSO in Algorithm 1 with their respective effective strategy sets Π_t, C_t
5: **end for**
6: **Output**: $\boldsymbol{\pi}_T, \Pi_T, \boldsymbol{c}_T, C_T$

Recall that if both players follow a no-regret algorithm, then the average strategies of both players converge to the NE in two-player zero-sum games Cesa-Bianchi & Lugosi (2006); Blum & Monsour (2007). Since OSO has the no-regret property, it is then natural to study the self-play setting where both players utilise OSO, which, we call Online Double Oracle (ODO), and to investigate its convergence rate to a NE in large games.

There are two major benefits of using ODO in comparison to DO: **Firstly**, ODO does not need to compute a NE in each sub-game which can become computationally expensive for large sub-games. **Secondly**, ODO produces rational agents which can exploit an adversary to achieve the no-regret property. The convergence rate of ODO to a NE follows:

Theorem 5. *Suppose both players apply OSO. Let k_1, k_2 denote the size of the effective strategy set for each player. Then, the average strategies of both players converge to the NE with the rate:*

$$\epsilon_T = \sqrt{\frac{k_1 \log(k_1)}{2T}} + \sqrt{\frac{k_2 \log(k_2)}{2T}}.$$

In the situation where both players follow OSO with a Less-Frequent Best-Response as in Equation (7) and $\alpha^i_{t-|\bar{T}_i|} = \sqrt{t - |\bar{T}_i|}$, the convergence rate to NE will be

$$\epsilon_T = \sqrt{\frac{k_1 \log(k_1)}{2T}} + \sqrt{\frac{k_2 \log(k_2)}{2T}} + \frac{\sqrt{k_1} + \sqrt{k_2}}{\sqrt{T}}.$$

Proof. Using the regret bound of OSO algorithm in Theorem 3 we have:

$$\sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t - \min_{\boldsymbol{\pi}\in\Pi} \sum_{t=1}^{T} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c}_t \leq \sqrt{\frac{Tk_1 \log(k_1)}{2}}; \quad \max_{\boldsymbol{c}\in C} \sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c} - \sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t \leq \sqrt{\frac{Tk_2 \log(k_2)}{2}}.$$

From the above inequalities we can derive that

$$\bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\bar{\boldsymbol{c}} \geq \min_{\boldsymbol{\pi}\in\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\bar{\boldsymbol{c}} \geq \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t - \sqrt{\frac{k_1 \log(k_1)}{2T}} \geq \max_{\boldsymbol{c}\in C} \sum_{t=1}^{T} \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\boldsymbol{c} - \sqrt{\frac{k_2 \log(k_2)}{2T}} - \sqrt{\frac{k_1 \log(k_1)}{2T}}.$$

Similarly, we have

$$\bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\bar{\boldsymbol{c}} \leq \max_{\boldsymbol{c}\in C} \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\boldsymbol{c} \leq \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t + \sqrt{\frac{k_2 \log(k_2)}{2T}} \leq \min_{\boldsymbol{\pi}\in\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\bar{\boldsymbol{c}} + \sqrt{\frac{k_1 \log(k_1)}{2T}} + \sqrt{\frac{k_2 \log(k_2)}{2T}}.$$

Thus, with $\epsilon_T = \sqrt{\frac{k_1 \log(k_1)}{2T}} + \sqrt{\frac{k_2 \log(k_2)}{2T}}$ we have

$$\max_{\boldsymbol{c}\in C} \sum_{t=1}^{T} \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\boldsymbol{c} - \epsilon_T \leq \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\bar{\boldsymbol{c}} \leq \min_{\boldsymbol{\pi}\in\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\bar{\boldsymbol{c}} + \epsilon_T.$$

By definition, $(\bar{\boldsymbol{\pi}}, \bar{\boldsymbol{c}})$ is ϵ_T-Nash equilibrium.

In situation where both players follow OSO with Less-Frequent Best Response, following Theorem 6 in Appendix B.1 we have:

$$\sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t - \min_{\boldsymbol{\pi}\in\Pi} \sum_{t=1}^{T} \boldsymbol{\pi}^\top \boldsymbol{A}\boldsymbol{c}_t \leq \sqrt{\frac{Tk_1 \log(k_1)}{2}} + \sum_{i=1}^{k_1} \alpha^i_{|T_i|} \leq \sqrt{\frac{Tk_1 \log(k_1)}{2}} + \sqrt{k1}\sqrt{T}$$

$$\max_{\boldsymbol{c}\in C} \sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c} - \sum_{t=1}^{T} \boldsymbol{\pi}_t^\top \boldsymbol{A}\boldsymbol{c}_t \leq \sqrt{\frac{Tk_2 \log(k_2)}{2}} + \sum_{i=1}^{k_2} \alpha^i_{|T_i|} \leq \sqrt{\frac{Tk_2 \log(k_2)}{2}} + \sqrt{k_2}\sqrt{T}.$$

Thus, using the same above arguments in the case of OSO, with $\epsilon_T = \sqrt{\frac{k_1 \log(k_1)}{2T}} + \sqrt{\frac{k_2 \log(k_2)}{2T}} + \frac{\sqrt{k_1}+\sqrt{k_2}}{\sqrt{T}}$, we have:

$$\max_{\boldsymbol{c}\in C} \sum_{t=1}^{T} \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\boldsymbol{c} - \epsilon_T \leq \bar{\boldsymbol{\pi}}^\top \boldsymbol{A}\bar{\boldsymbol{c}} \leq \min_{\boldsymbol{\pi}\in\Pi} \boldsymbol{\pi}^\top \boldsymbol{A}\bar{\boldsymbol{c}} + \epsilon_T.$$

□

Theorem 5 suggests that, similar to OSO, the convergence rate of ODO will not depend on the game size, but rather the size of the effective strategy set of both players. As we studied in the OSO section, although we can not theoretically prove the linear relationship between the size of the effective strategy set and the size of the NE support, in many practical applications, such linear relationship holds true (shown in Figure 1). Thus, in the same way as DO, ODO will prove effective in solving large games where the size of the NE support is indeed much smaller than the full game size (e.g., also see Table 2 in Appendix D).

5.1 ODO *vs.* Double Oracle with MWU

It is important to highlight that ODO is markedly different from simply implementing DO with MWU to solve for the sub-game NE (i.e., running MWU till convergence in the sub-game). Firstly, ODO checks for a best-response that is outside of the current effective strategy set per MWU update, whereas DO adds a best-response every time a sub-game NE is solved, which often requires thousands of MWU iterations. Most importantly, the best-response target in ODO (i.e., the time-average loss $\bar{\boldsymbol{l}}$) is not necessarily a NE; this is in contrast to DO where the best-response is computed with respect to an exact NE. Intuitively, the convergence of DO only requires the best-response target in the last sub-game to be a NE, thus calculating the NEs in every sub-game to update the strategy set is not necessary. ODO tackles this problem by using the time-average loss as the new best-response target. As a result, ODO performs much better compared to DO in Figure 3. Finally, even if DO implements MWU to solve the sub-game NE, it is still not a no-regret algorithm. This also explains the performance gap between OSO and DO with MWU in Figure 4.

6 Experiments & Results

In this section, we aim to demonstrate the effectiveness of our practical use algorithms, OSO and ODO. However, we begin by looking at the major assumption of this work, and verify the linear dependence between the size of the effective strategy set and the NE support size in random matrix games. Next, over multiple real-world matrix games Czarnecki et al. (2020), we evaluate OSO in both the self-play setting (i.e., ODO) and when playing against a strategic adversary. Finally, to validate performance on very large games, we show the performance of ODO on Kuhn and Leduc Poker which have huge size of pure strategies. As we benchmark on OSO iterations against other baselines, for fair comparison, we implement plain OSO in Algorithm 1 without the less-frequent best-response mentioned in Equation (7) for all our experiments. All hyperparameter settings can be found in Appendix D.

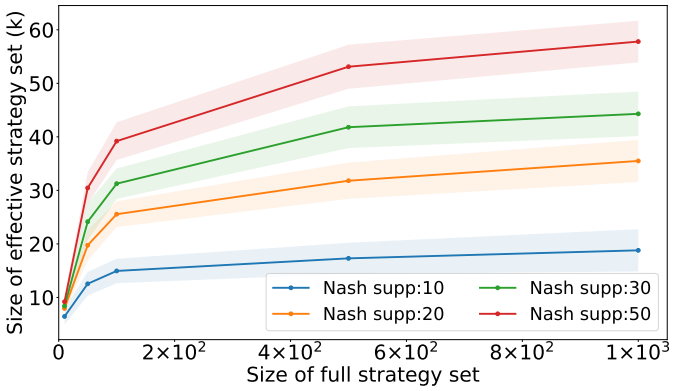
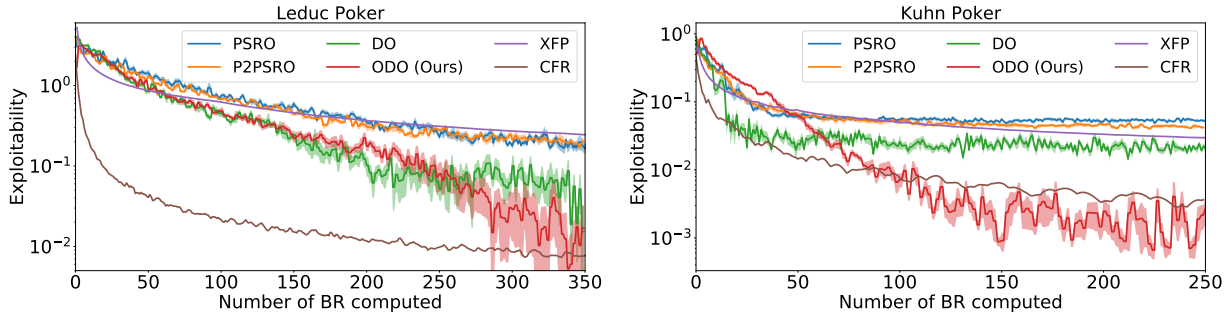


Figure 1: Sizes of effective strategy set (i.e., k) in cases of an OSO agent playing against an MWU opponent with different sizes of full strategy set and NE support. This plot shows that the size of OSO's effective strategy set does not increase drastically with the full strategy size, but rather depends on the support size of the NE.

6.1 Size of k vs. Support Size of NE

We consider a set of zero-sum normal-form games of different sizes, the entries of which are sampled from a uniform distribution $\mathbf{U}(0, 1)$. We run OSO as the row player against a no-regret column player [1] until convergence, and plot the size of the OSO player's effective strategy set against its full strategy size. We run 20 seeds for each setting. As we can see from Figure 1, given a fixed support size of the NE, which is achieved by fixing the number of columns while increasing the number of rows in the game matrix, the size of the effective strategy set k grows as the size of the full strategy set increases, but plateaus quickly. The larger the size of the NE support (not the full strategy set!), the higher this plateau will reach. Clearly, we can tell that the size of OSO's effective strategy set **does not** increase drastically with the full strategy size, but rather depends on the support size of the NE. This result confirms Theorem 3 in which we prove that OSO's regret bound depends on k, which is related to the size of the NE support but not the game size. Economically, this is a desired property as OSO can potentially avoid unnecessary computation, in contrast to other no-regret methods that require looping over the full strategy set at each iteration.

[1] We choose MWU for the column player in our experiment, but we expect other no-regret algorithms would give a similar result.



(a) Exploitability on Leduc Poker

(b) Exploitability on Kuhn Poker

Figure 2: Performance comparisons in exploitability on Poker games.

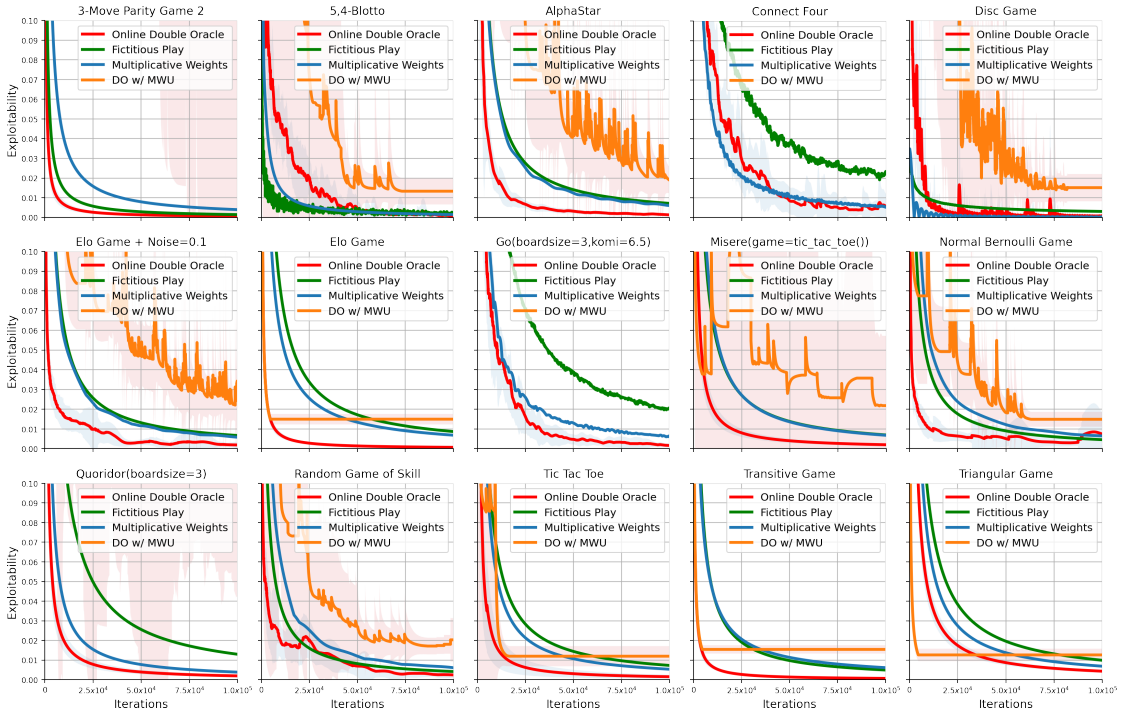


Figure 3: Performance comparisons under self-plays

6.2 Performance on Real-World Empirical Games

We investigate ODO in terms of convergence rate to a NE. To demonstrate its applicability to real-world problems, we replace the randomly generated normal-form games with 15 popular real-world zero-sum empirical games from Czarnecki et al. (2020). We compare the *exploitability* Davis et al. (2014) (i.e., the distance to a true NE) of ODO with other baseline methods (MWU, FP and DO [2]). We run each game with 20 seeds. In Figure 3, ODO outperforms the baselines in almost all 15 games. The advantage of ODO in terms of convergence rate over MWU and FP match our expectation as the support sizes of the NEs in these games are much smaller than the game sizes (reported in Table 2 in Appendix D). For DO with MWU, since it takes many iterations in each sub-game to converge to the NE, it performs poorly in comparison to ODO.

Apart from the self-play setting, we also look at the setting of playing against an MWU adversary in Figure 4. We can see that OSO outperforms MWU and DO baselines in average performance in almost all 15 games, which confirms the effectiveness of our design. Notably, MWU achieves a constant payoff; we believe this is

[2]Following the discussion in the Online Double Oracle section and for fair comparisons, we implement DO by adopting MWU as the sub-game NE solver and report the total number of MWU iterations DO needs to achieve a low exploitability.

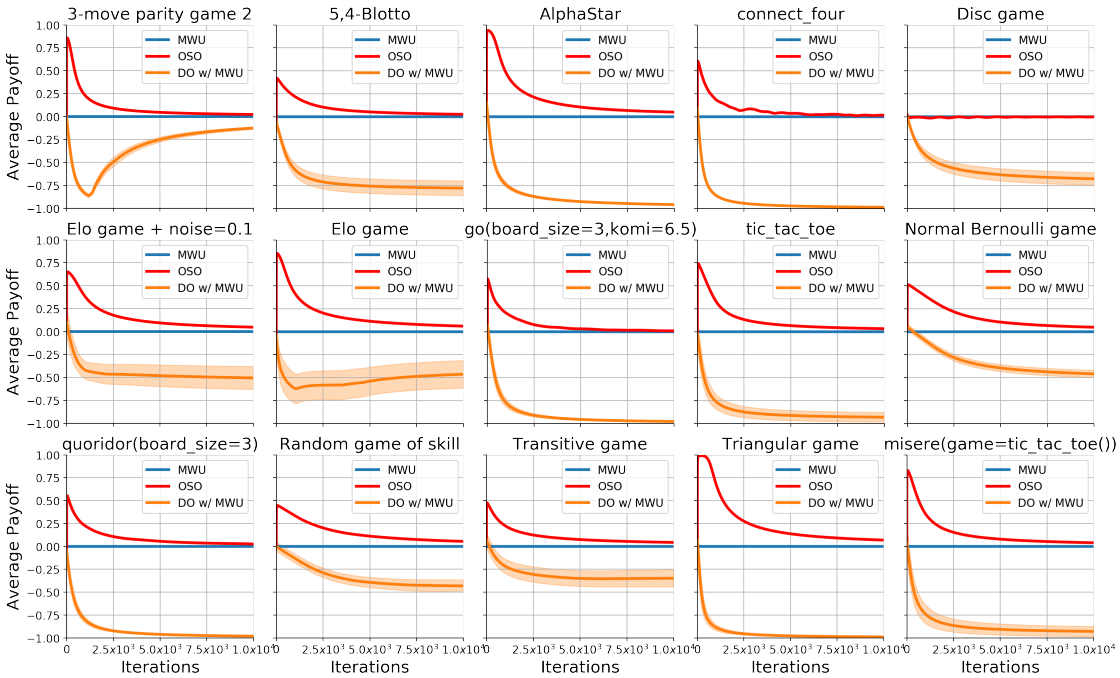


Figure 4: Performance comparisons against MWU adversary

because these games are symmetric and since both players follow MWU with the same learning rate, the payoff will always be the value of the game (thus the ground truth), which OSO will eventually converge to as well.

6.3 Performance on Poker Games

To further investigate ODO's effectiveness, we test ODO on Kuhn and Leduc Poker. Since ODO is designed only for normal-form games, we adopt the tabular setting McAleer et al. (2020); Lanctot et al. (2017) in which an exact best-response is computed by a tree-traversal oracle (see OpenSpiel Lanctot et al. (2019)), and for PSRO methods, we perturb the exact best-response with random noise. We benchmark how many times such a best-response oracle is called by different methods. We compare against the state-of-the-art PSRO method: P2SRO [3] McAleer et al. (2020), and two extensive-form game solvers, CFR Zinkevich et al. (2007) and XFP Lanctot et al. (2019). As shown in Figure 2, ODO shows a significant improvement in exploitability compared to all existing DO and PSRO baselines, and it almost catches up with the CFR solver in Leduc Poker, and it outperforms CFR on Kuhn Poker. Importantly, ODO uses the fewest best-response calls to achieve the lowest exploitability. We believe these are promising results, since ODO is not designed for extensive-form games, but experimentally it matches up with efficient extensive-form methods. In our future work, we hope to use the idea of ODO and Regret Matching Hart & Mas-Colell (2000) to create a state-of-the-art solver in extensive-form games.

7 Conclusion

We propose a novel solver for two-player zero-sum games where the number of pure strategies n is huge. Our method, *Online Double Oracle*, absorbs the benefits from both online learning methods and Double Oracle methods; it achieves the regret bound of $\mathcal{O}(\sqrt{k\log(k)/T})$ where k is the size of the effective strategy set rather than the game size n. Importantly, ODO can exploit opponents during game play. In tens of real-world games, we show that ODO outperforms a series of algorithms including MWU, DO and PSRO both in terms of convergence rate to NE and average payoff against strategic adversaries.

[3] We have discounted the fact that P2SRO uses multiple workers (we use two) to compute best-responses.

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