1 Introduction

Human-computer game has a long history and has been a main stream for verifying key technologies of artificial intelligence. Turing test \[1\] maybe the first human computer confrontation for testing the intelligence of machine, which inspires researchers to design AIs for challenging professional human players. Since the development of Chinook in 1989, a draughts AI, its goal is set to defeat the world champion. Such target is achieved by wining the champion Marion Tinsley in 1994 \[2\]. Afterwards, Deep Blue from IBM beats chess grandmaster Garry Kasparov in 1997, making a new era in the history of chess \[3\].

Recent years, we witness the rapid development of game AIs, from the Atari \[4\], AlphaGo \[5\], Libratus \[6\], OpenAI Five \[7\] to AlphaStar \[8\]. Those AIs defeat professional human players in certain games by a combination of modern techniques, indicating a big step of the decision making intelligence field \[9\], \[10\], \[11\]. For example, AlphaGo Zero \[12\], an advanced version of AlphaGo, utilizing Monte Carlo tree search, self-play and deep learning, defeats dozens of professional go players. OpenAI Five \[2\], using self-play, deep reinforcement learning and continual transfer via surgery, becomes the first AI to beat the world champions at an esports game.

After the success of AlphaStar and OpenAI Five, which reach the professional player level in StarCraft and Dota2, respectively, it seems that current techniques can handle very complex imperfect information games. Specially, the breakthrough of the most recent games such as honor of kings \[13\], Mahjong \[14\] obey similar framework of AlphaStar and OpenAI Five. So, one question raises: what are the future trends or challenges in the human-computer game AI? This paper aims to review recent typical human-computer game AIs, and try to answer the questions through a thorough analysis of current techniques.

Based on current breakthrough of human-computer game AIs (most published in journals Science and Nature), we survey four typical types of games, i.e., board games with Go; card games such as heads-up no-limit Texas holdem (HUNL), DouDiZhu and Mahjong; first person shooting games (FPS) with Quake III Arena in Capture the Flag (CTF); real time strategy games (RTS) with StarCraft, Dota2 and Honor of Kings. The corresponding AIs cover AlphaGo \[5\], AlphaGo Zero \[12\], AlphaZero \[15\], Libratus \[6\], Deep-Stack \[16\], DouZero \[17\], Suphx \[14\], FTW \[18\], AlphaStar \[8\], OpenAI Five \[7\], JueWu \[13\] and Commander \[19\]. A brief summary is displayed in figure \[1\].

The rest of the paper is organized as follows. In Section 2, we describe games and AIs covered in this paper. Sections 3-6 elaborate the AIs for board games, card games, FPS games and RTS games, respectively. In Section 7, we summarize and compare different techniques utilized. In Section 8, we show the challenges in current game AIs, which maybe the future research direction of this field. Finally, we conclude the paper in Section 9.

2 Typical Games and AIs

Based on recent progresses of AI systems and characteristics of games, this paper reviews four types of games and corresponding AIs, i.e., board games, card games, FPS games and RTS games. To measure how hard a game is to develop professional human level AI, we extract several key factors that challenge the intelligent decision making \[20\], which is displayed in Table \[1\].

1. A name known by the public.
Nash solver by the tree based approaches. In real time games, such as Mahjong, it is also very hard to obtain a Nash equilibrium strategy. This is because in real time games, such as StarCraft and Dota2, computable tree based methods such as monte carlo tree search (MCTS) and counterfactual regret minimization (CFR) algorithms are widely adopted in the turn based games, i.e, players make decisions one by one. We will see tree based methods such as monte carlo tree search (MCTS) and counterfactual regret minimization (CFR) algorithms are widely adopted in the turn based games to obtain an approximate Nash equilibrium solution, which are rarely used for real time games. This is because in real time games, such as StarCraft and Dota2, a computable tree is almost nonexistent. What’s more, in some turn based time games, such as StarCraft and Dota2, a computable tree based methods such as monte carlo tree search is almost nonexistent. What’s more, in some turn based games, such as Mahjong, it is also very hard to obtain a Nash solver by the tree based approaches.

Imperfect information. Except for the board games, almost all the card games, FPS games and RTS games are imperfect information games, which means players do not know exactly how they come to the current states. This leads to more than one nodes in an information set if the game is expanded into a tree. For example, the average information sets for HUNL and Mahjong are \(10^3\) and \(10^{10}\), respectively. Compared with the perfect information game, a subgame in an imperfect information game cannot be solved isolated from each other, which makes solving Nash equilibrium more difficult for imperfect information games.

Long time horizon. In real time games, such as StarCraft, Dota2 and Honor of Kings, a game lasts several and even more than thirty minutes. Accordingly, an AI needs to make thousands of decisions. For example, Dota 2 games run at 30 fps for about 45 minutes, which results to approximately 20,000 steps in a game if making a decision every four frames. In contrast, players in the board games and card games usually make much less decisions. In summary, the long time horizon leads to an exponential increase in the number of decision points, which brings in a series of problems such as exploration and exploitation when optimizing a strategy.

In-transitive game. If performance of different players are transitive, a game is called a transitive game. Mathematically, if \(v_t\) can beat \(v_{t-1}\) and \(v_{t+1}\) can beat \(v_t\), then a game is strictly transitive. However, most games in real world are in-transitive. For example, in a simple game “Rock-Paper-Scissor”, the strategy is in-transitive or cyclic. Specially, it is common that most games consist of transitive and in-transitive parts, i.e., obey the spining tops structure. The in-transitive characteristic makes standardized self-play technique fail to iteratively obtain the Nash equilibrium strategy.

Multi-agent cooperation. Most board games and card games are purely competitive, where no cooperation between players is required. An exception is DouDiZhu, which needs two Peasants players playing as a team to fight against the Landlord player. In contrast, almost all the real time games, i.e., FPS games and RTS games, rely on players’ cooperation to win the game. For example, Five players in Dota2 and Honor of Kings form a camp to fight against another camp. Even though StarCraft is a two-payer competitive game, each player needs to control a large number of units, which need to be well cooperated. Overall, how to obtain the Nash equilibrium strategy or a better learned strategy under the multi-agent cooperation is a hard problem, because specially designed agent interaction or alignment needs to be carefully considered.
In summary, different games share different characteristics and aim to find different kinds of solutions, so distinct learning strategies are developed to build AI systems. In this paper, the AIs cover: AlphaGo, AlphaGo Zero, AlphaZero for board game Go; Libratus, DeepStack, DouZero and Suphx for card games HUNL, DouDiZhu and Mahjong, respectively; FTW for FPS game Quake III Arena in Capture the Flag model; AlphaStar, Commander, OpenAI Five and JueWu for StarCraft, Dota2 and Honor of Kings, respectively.

3 BOARD GAME AIs

AlphaGo series consist of AlphaGo, AlphaGo Zero and AlphaZeo. AlphaGo, come out in 2015, beats European go champion Fan Hui by 5:0, which is the first time that AI wins professional players in full size game Go without Renzi. Afterwards, a new training framework is developed for AlphaGo Zero, which needs no prior professional human confrontation data and reaches superhuman performance. AlphaZero, as an exploration of general reinforcement learning algorithm, that masters Go along with chess and shogi board games. A brief summarization is shown in figure 2.

3.1 MCTS for AlphaGo Series

One of the key factors lies in the AlphaGo series is MCTS, which is a typical tree search method [21], [27]. Generally, a simulation of MCTS consists of four steps, which is repeated hundreds and thousands of times for one final decision. The four steps consist of selection, expansion, evaluation and backup, which are operated in a tree. Selection selects one leaf node starting from the root node, i.e., the state where an action needs to be decided, based on the evaluation of the nodes in the tree. Expansion expands the tree by adding a new node. Starting from the expanded node, a rollout is performed to obtain a value for the node, which is used to update the values of all nodes in the tree.

In the AlphaGo series, traditional MCTS is improved via deep learning to limit the width and depth of the search, so as to handle the huge game tree complexity. Firstly, in the selection stage, a node is selected based on the sum of action value $Q + u(p)$. The action value is the average node values of all simulations, and the node value is evaluation of a node based on prediction of value network and rollout results based on rollout network. The bonus is proportional to the policy value (probability of selecting points in Go) calculated via the policy network, but inversely proportional to the visit count. Secondly, in the expansion stage, a node is expanded and its value is initialized through the policy value. Finally, when making an estimate of the expanded node, rollout results based on rollout network and predicted results based on value network are combined. Noted in AlphaGo Zero and AlphaZero, rollout is removed, and the evaluation of expanded node is based solely on prediction results of value network.

3.2 Training Differences for AlphaGo Series

3.2.1 Training framework of AlphaGo

Training of AlphaGo consists of several steps. Firstly, a supervised learning (SL) policy network and a rollout policy network are trained with human expert data, which outputs the probability of next position based on 160,000 games played by KGS 6 to 9 dan human players. The differences between the SL policy and rollout policy are the neural network architecture and features. With the above high quality data, a very good initiation of the SL policy network is obtained, which reaches Amateur level, i.e., about Amateur 3dan (d).
With the trained SL policy network, a reinforcement learning (RL) policy network is initialized and then improved through self-play, which uses network of the current version to fight against its previous versions. Based on conventional policy gradient method to maximize the winning signal, RL policy network reaches better performance than SL network, i.e., RL policy obtains 80% winning rate against SL policy.

In the third step of AlphaGo, a value network is trained to evaluate state. Specially, a dataset consists of 30 million state-outcome pairs is collocated through self-play of RL network. Then, a regression task is developed by minimizing the mean squared error between the predicted result of value network and the corresponding outcome (win or loss signal). With the value network, MCTS can reach a better performance than just using SL network. Finally, well trained SL policy, value network and rollout network are embedded into MCTS, which reaches professional level of 1 to 3 dan (p).

3.2.2 Training framework of AlphaGo Zero and AlphaZero
Unlike AlphaGo, whose policy network and value network are trained through supervised learning and self-play between the policy networks, AlphaGo Zero trains policy and value networks through self-play of MCST embedded in the current version of the networks. AlphaZero shares the same training framework with AlphaGo Zero. Overall, they consist of two alternating repetition steps: automatically generating data; policy and value networks training.

When generating training data, self-play of MCTS is performed. MCTS embedded in the current policy and value networks is used to select each move for the two players at each state. Generally, MCTS selects an action based on the maximum count, but AlphaGo Zero makes it a probability to explore more actions through normalizing the count. Accordingly, state-move probability pairs are stored. Finally, when a game ends, the winning signal (+1 or -1) is recorded for value network training.

Relying on above collected state-move probability and winning signal, the policy and value networks are trained. More specifically, the distance between predicted probability of policy network and collected probability for each state is minimized. Besides, the distance between predicted value of value network and the winning signal is minimized. The overall optimizing objective also contains an $L_2$ weight regularization to prevent overfitting.

3.2.3 Training differences
Based on MCTS, deep learning, reinforcement learning and self-play are nicely evolved in AlphaGo series, as shown in figure 2. The main difference is training frameworks utilized, which is elaborated in the following. To sum up, AlphaGo utilizes human expert data to initialize policy network, based on which, self-play between policy networks is performed to train the value network, and the trained networks are embedded into MCTS for decision making. However, AlphaGo Zero, uses no human expert data, and trains the policy and value networks based on data generated through self-play of MCTS embedded in current version of policy and value networks. AlphaZero shares same training framework with AlphaGo Zero, except some training details utilized.

Apart from the training framework, there are several factors AlphaGo Zero differs from AlphaGo. Firstly, no rollout policy network is used to evaluate the expanded node in AlphaGo Zero, and no human expert data are utilized for deep neural networking training and initialization. Secondly, policy and value networks in AlphaGo Zero share most parameters (convolutional layers) instead of two separate networks, which shows better Elo rating. What’s more, residual blocks, as a powerful modular, is utilized in AlphaGo Zero, and it shows much better performance than just using convolutional blocks as in AlphaGo. Finally, the input of AlphaGo Zero is a 19 x 19 x 17 image stack, which rarely uses human engineering features compared with AlphaGo, such as the designed ladder capture and ladder escape features.

AlphaZero aims to develop a more general reinforcement learning algorithm for various board games such as Go, chess and Shogi. Since rules of chess and Shogi are very different from Go, AlphaZero makes several changes of training details to fit the above goal. As for the game Go, there are two main training details that are different with AlphaGo Zero. Firstly, no data augment and transformation such as rotation or reflection of the positions are applied. Secondly, AlphaZero uses a pure self-training framework by maintaining only a single neural network instead of saving a better model in each iteration of training.

4 Card Game AIs
Card game, as a typical in-perfect information game, has been a long-standing challenge for artificial intelligence. DeepStack and Libratus are two typical AI systems that defeat professional poker players in HUNL. They share basic techniques, i.e, CFR, which are both theoretically sound. Afterwards, researcher are focusing Mahjong and DouDiZhu, which raise new challenges for artificial intelligence. Suphx, developed by Microsoft Research Asia, is the first AI system that outperforms most top human players in Mahjong. DouZero, designed for DouDiZhu, is an effective AI system that was ranked the first in the Botzone leaderboard among 344 AI agents. A brief introduction is shown in figure 3.

4.1 DeepStack and Libratus for HUNL
HUNL is one of most popular poker games in the world, and plenty of world-level competitions are hold every year such as World Series of Poker (WSOP). Till come out of DeepStack and Libratus, HUNL is a primary benchmark and challenge of imperfect information game with no AI has defeated professional players.

4.1.1 CFR for DeepStack and Libratus
Since developed in 2007, CFR has been introduced in poker games. CFR minimizes counterfactual regret for large extensive games, which can be used to compute a Nash equilibrium. Generally, it decomposes regret of an extensive game into a set of additive regret terms on information sets that can be minimized independently. Due to large cost of time and space, basic CFR is not applicable for HUNL, which
is far more complex than limited poker. Various improved CFR approaches have been developed considering improving computing speed or compressing the required storage space [28, 29]. For example, based on CFR, continuing resolving and safe and nested subgame solving are key factors for success of DeepStack and Libratus, respectively.

### 4.1.2 Training for DeepStack

Key of training for DeepStack is continual re-solving, which is assisted by depth-limited look-ahead via deep learning and sparse look-ahead trees. Re-solving, begins with a strategy, and reconstructs the strategy by resolving every time an decision is required. To accomplish this at any decision point, DeepStack maintains a player’s own range and opponent counterfactual values. Giving three specific updating rules on own action, chance action and opponent action, it ensures that opponent counterfactual values are properly bounded. A very important characteristic is no requirements for knowledge of opponent action and range to update above values, which makes DeepStack very efficient.

However, purely re-solving is intractable because of the deep depth of game tree in HUNL. To handle this problem, DeepStack restricts the depth of the subtree via intuition. A counterfactual value function is trained with deep neural networks and utilized for estimating how valuable holding certain cards. Moreover, by limiting actions to be fold, call, two or three bet actions and all-in, the resolved games are reduced to have about $10^2$ decision points, largely reduced compared to $10^{100}$ decision points for the whole game. Based on such abstraction, DeepStack can make a decision with no more than 5 second under a machine with a single NVIDIA GeForce GTX 1080 graphics card.

### 4.1.3 Training for Libratus

Training of Libratus needs no expert domain knowledge and consists of three main steps: building a blueprint strategy, nested safe subgame solving and self-improvement. Blueprint strategy is solved by an improved version of CFR, i.e, Monte Carlo CFR (MCCFR), for an abstracted game, which provides a strategy for early rounds of the game and an approximation for latter rounds. As for the abstraction, certain bet sizes are abstracted based on an application-independent parameter-optimization algorithm. However, not card abstraction on the first and second betting rounds are adopted, where decision strategy is purely based on blueprint strategy.

Nested safe subgame solving is used in the third and fourth betting rounds, which provides a real time solution for a more detailed abstraction of the game tree. The abstraction in the blueprint is relaxed instead of rounding the bet size to the nearest size. Libratus will make a distinct strategy in response to off-tree actions. Nested safe subgame solving ensures that new strategy for the subgame improve blueprint strategy by making the opponent worse off no matter what cards she is holding. Finally, Self-improvement computes a game-theoretic strategy for branches that are added based on actual moves of opponent.

### 4.1.4 Training differences

Intuitively, DeepStack solves the subtree based on re-solving assisted by deep neural networks for counterfactual values prediction, whereas, Libratus utilizes a nested safe subgame solving strategy to improve the original abstraction based strategy. Both methods use estimated value instead of the upper bounds value of the opponent, but Libratus claims that DeepStack does not share its improvement of de-emphasizing hands.

Libratus plays the first two rounds based on precomputed blueprint strategy, which makes big abstraction of opponent actions. However, DeepStack re-solves each subgame no matter what rounds it is now deciding, making it more flexible of dealing with opponent off-tree actions. To make Libratus more powerful handling off-tree opponent bet sizes in the first two rounds, a self-play improvement modular is designed based on actual moves of opponent, which can largely remedy defects.
4.2 Suphx and DouZero for Mahjong and DouDiZhu

Unlike HUNL, Mahjong has different types of actions and the regular order of plays can be interrupted, making the game tree consisting of huge number of paths between the consequent actions of a player. This leads the successful MCTS and CFR based techniques for Go and HUNL not a best choice. Similarly, unlike HUNL, the actions of DouDiZhu is complex and can not be abstracted, making tree search based techniques such as MCTS and CFR hard to be applied. In summary, Suphx and DouZero adopt deep reinforcement learning as basic tools for AI development, which aims to reach high-level performance and cares little about characteristics of the solution such as the Nash equilibrium.

4.2.1 Basic techniques for Suphx and DouZero

Reinforcement learning (RL) is a typical type of machine learning, which becomes one of most important decision-making techniques since the breakthrough of AlphaGo [30]. Generally, RL follows the framework of policy evaluation and policy improvement by interacting with the environment. Because of the trial and error mechanism, RL requires a huge amount of data for policy learning, leading to sample inefficient problem [31], [32]. Distributed training, utilizes multiple machines for learning a task, is now combined with RL for alleviating the above problem [33], [34].

Nair et al [35] proposed the first massively distributed architecture for RL, which consists of four components. The first part is parallel actors, which are used to interact with environment and generate data; The second component is parallel learners that consume data for policy training; The third and fourth parts are distributed neural network and store of experience to connect the actor and learner. Based on the above framework, a number of advanced distributed reinforcement learning frameworks are developed, and data throughput is largely improved [36], [37], [38]. In Suphx and DouZero, distributed learning is adopted to accelerate RL training, where multiple rollouts are paralleled performed to collect data.

4.2.2 Training for Suphx

Suphx is a hybrid learning system, which consists of rule-based wining model and five learning-based models to form the decision flow. Generally, training of the five learning-based models contains three major steps: supervised learning, self-play reinforcement learning and a run-time policy adaptation.

Supervised learning is performed utilizing state-action pairs collected from human players in Tenhou platform, and then act as initialization for the self-play reinforcement learning stage. Usually, each game consists of multiple rounds and the final reward signal is obtained by accumulating all the round scores, it is hard to guide reinforcement learning in each round because some players may tactically lose several rounds to win the game. In Suphx, such problem is solved by using a GRU network to predict feedbacks of each round. More specifically, data of top human players are collected as reward and a regression based objective is constructed between past and present round information and the final game reward. When performing reinforcement learning, such predication is served as the intermediate reward for each round in a game.

In reinforcement learning stage, considering learning is slow facing the rich hidden information in Mahjong, Suphx proposed a method called oracle guiding. Firstly, an oracle agent is trained by using all the perfect information, i.e., private tiles of all the players and the tiles in the wall. Since a simple knowledge distillation method does not work because it is hard for a normal agent with very limited information to mimic the oracle agent, Suphx gradually drops out the perfect features so that the oracle agent can slowly degenerate to the normal agent.

Run-time policy adaptation is utilized so that the learned policy can be properly adapted based on the tiles of current round. The motivation comes from human player, who will act very different based on different tiles in the beginning of each round. A parametric Monte-Carlo policy adaption approach is proposed, which consist of two steps. Firstly, Suphx simulates multiple games by self-play using previously trained policy at the beginning of a round, with which trajectories are collected. Then gradient updates are performed using the about data for policy fine-tune. Based on the experimental results, the simulation does not to be very large, and in every round, the policy adaption can be adopted.

4.2.3 Training for DouZero

In DouZero, a deep Monte-Carlo method is developed with specially designed matrix-form state and action spaces. Since there are up to 27,472 possible actions for a player, a matrix-form action representation provides a nice way to encode and more importantly reason about unseen actions. This is one of key factors that DouZero can handle huge action space. Considering MC approaches are usually inefficient because of its high variance issue, DouZero utilizes distributed training to parallelize the data generation part. Specially, a lot of actors are raised with each maintains local networks of the three players and generates episode trajectories, based on which, a learner of global networks for the three players are trained. Overall, training algorithm of DouZero is simple and efficient, and the authors show classic MC methods can be properly designed to deal with games with a complex action space.

4.2.4 Training differences

Apart from utilizing reinforcement learning algorithms and distributed framework for training acceleration, training frameworks of DouZero and Suphx are very different. Firstly, training of Suphx is a complex and multi-stage system, whereas training of DouZero is relatively simple with a distributed deep MC method. In Suphx, data from top human player are required for network initialization and round reward predication, based on which, it outperforms most top human players in Mahjong. However, in DouZero, no human data is needed, and networks for different players are trained from scratch, based on which, it ranks the first in the Botzone leaderboard among 344 AI programs.

5 First-Person Shooting Game AIs

Quake III Arena in Capture the Flag (CTF) mode is a typical three-dimensional multiplayer first-person video game,
where two opposing teams are fighting against each other in in-door or out-door maps. As we will see in the next section, settings for CTF are very different from current multi-player video games. More specifically, agents in CTF cannot access the state of other players, and agents in a team cannot communicate with each other, making such an environment a very good testbed for learning agents to emerge communication and adapt to zero-shot generation. Zero-shot means an agent cooperated or confronted is not the agent trained, which can be human players and arbitrary AI agents. Based only on pixels and game points like human as input for agent, the learned agent FTW reaches the strong human-level performance. A brief introduction is shown in figure 4.

5.1 Learning Framework
The aim of FTW is to train agents that can adapt to the variability of maps, number of agents, and choice of teammates and opponents. To achieve such high scalability, conventional self-play methods are claimed to be unstable, and those approaches in their basic form cannot support concurrent training, which are important for scalability. To handle the problems, FTW trains in parallel a population of agents, where each agent is trained based on distributed reinforcement learning with experiences collected by dynamically selected teammates and opponents. Moreover, an online evolutionary algorithm is developed guiding agents learning, so as to directing the population. The above processes are called population based training, which will be elaborated in the following subsection.

Considering the global reward is sparse for FTW, which lasts for 4500 frames. FTW learns several intermediate rewards to accelerate training. A key problem of learning such rewards is to ensure the optimization of intermediate rewards promotes the policy optimization for chasing global rewards. Such problem is solved by a specially designed joint maximization objective, where inner optimization optimizes intermediate rewards through distributed reinforcement learning, and outer optimization, regarded as a meta-game, is optimized through population based training for transformation between intermediate reward and global reward.

Another specific aspect of FTW lies in its neural network design. Due to partial observation of the agent, FTW follows the idea of reinforcement learning as probabilistic inference. Accordingly, a hierarchical LSTM network with different timescales is developed, where the LSTM with fast timescale generate hidden states and enhanced by the LSTM with slow time scale. Hidden states of LSTM with fast timescale then serves as the variational posterior for the final action selection.

5.2 Population based Training
Population based training maintains a population of agents, which consists of two important components to direct learning process: sample teammates and opponents for an agent to generate data, reset and perturb hyper-parameters and transformation parameters for underperforming agents based on training process.

When collecting training data for agent policy optimization, a sampling method based on Elo of agents is utilized. It encourages agents with similar skill (Elo scores) to be teammates and opponents, ensuring that the outcome of a game is sufficiently uncertain so as to guild agent learning useful policy. Since conventional Elo calculation method is designed without considering agent cooperation, FTW makes an assumption that rating of a team can be decomposed as sum of skills for a team. With above assumption, Elo for each agent can be obtained following regular Elo optimization approach.

After training a generation of population, hyper-parameters like learning rate and transformation parameters between the intermediate rewards and global rewards for underperforming agents are reset and perturbed by using the better performing agents as reference. More specifically, if an agent with a team cannot win another agent with a team (e.g., 70% wining rate), the losing agent copies the policy, reward transformation, and hyper-parameters of the better agent, and then probabilistically perturb the inherited values with a small range, e.g., ±20% with a probability of 5%. The above exploration process helps to find better hyper-parameters and transformation parameters.

6 RTS Game AIs
RTS game, as a typical kind of video game, owns tens of thousands of people to fight against each other, which naturally becomes a testbed for human-computer game. Furthermore, RTS games are usually complex environment, which captures more nature of real world than previous games, making breakthrough of such games more applicable. AlphaStar, developed by DeepMind, uses general learning algorithms and reaches grandmaster level for all three races for StarCraft, which outperforms 99.8% human players who are active on the European server (about 90000 players). Commander, as a lightweight computation version, follows the same training architecture of AlphaStar, which uses order of magnitude less computation and beats two grandmaster players in a live event. OpenAI Five aims to solve Dota2 game, which is the first AI system that defeat the world champions at an esports game. As a relatively similar esports game with Dota2, Honor of Kings shares most similar challenges, and JueWu becomes the first AI system that can play full RTS games instead of restricting the hero pool. A brief introduction is shown in figure 5.

6.1 Basic Techniques for RTS Game AIs
To handle complex RTS games, reinforcement learning accelerated by distributed framework becomes a basic tool. Different from the distributed frameworks designed for Suphx and DouZero, a larger data throughput framework is designed because a huge interaction with environment required. Previous distributed reinforcement learning mainly maintains two important modular: parallel environments with each embedded an actor to generate actions, and learners to consume data collected by the environments for policy updating. With such a distributed framework, plenty of time is wasted because in each environment, a model inference should be conducted for a single action.
Current distributed reinforcement learning performs centralized model inference for states collected from multiple environments and distributes actions for each environment. Based on the learner-centralized actor-environment architecture, model inference times are largely reduced, which will save time for big models.

### 6.2 Training for AlphaStar

Training of AlphaStar consists of two main steps: supervised learning to initialize agent parameters and multi-agent reinforcement learning to improve the agent. In supervised learning, a high quality dataset is collected to train the agent parameters. The dataset consists of 971000 replays from human players, whose MMR scores are greater than 3500 and are in the top of 22% of players. Since there are three races for StarCraft, AlphaStar trains one agent for each race. To fully explore human experience especially in the game beginning where little combat feedback can be obtained, AlphaStar extracts a statistic variable to condition the policy, and adopts KL divergence between human actions and the policy’s outputs to assist learning. Such statistic variable encodes each player’s first 20 buildings and units, which reflects a type of opening strategy for AlphaStar. After above supervised training, AlphaStar fine-tunes the policy using a subset but more professional human player data (with MMR above 6200), which improves the policy by 9% percentage when fighting against built-in elite bot.

After supervised learning for agent initialization, a multi-agent reinforcement learning framework with league training is developed, so as to alleviate the game-theoretic challenges such as cycles between strategies. We firstly introduce agent types in the league, and then elaborate how to train different agents. The league has three types of agents for each race: main agent, main exploiter and league exploiter. Training of those agents lies in how to select opponents in the league and whether or not to rest the learned parameters. Specifically, opponents of main agent

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**Fig. 4.** A brief framework of FTW for game CTF.

**Fig. 5.** A brief AI framework for typical RTS games.
are main agent itself and all agents in the league, so as to serve as final agent for playing. Opponents of main exploiter are current main agent and previous main agent versions, to find weaknesses of the main agent. Opponents of league exploiter are all agents in the league, to discover possible weaknesses of the entire league. With main exploiter and league exploiter added in the league, training of main agent can properly overcome the weakness of itself and in the league.

When deciding sampling probabilities of opponents for different type of agents, an improved version of fictitious self-play called prioritized fictitious self-play is designed, which selects opponents based on winning rate against the agent, instead of a uniform mixture of opponents. Detailed probability distribution and calculation can be find in original paper. Noted that when a generation of main exploiter or league exploiter agent is obtained, it is periodically reinitialized to supervised learned agent, so as to extend diversity of the league.

6.3 Training for OpenAI Five
Training of OpenAI Five is based on distributed self-play deep reinforcement learning. With their system, OpenAI Five successfully extends the learning batch size to be 2,949,120 time steps, which are important for training. When performing parallel self-play to generate training data, agent plays against itself for 80% of the games and against past versions for 20% of the games. Modifying conventional self-play in above way avoids strategy collapse and ensures the learned agent being robust to a wide range of opponents. To effectively sample opponents from a large number of past versions, OpenAI Five maintains a score for each agent and changes the score based on the winning signal of training trajectories. This strategy makes sure a dynamic sampling is performed to select useful agents to play against.

Another key factor for success of OpenAI Five is a tool called continual transfer via surgery, which adjusts parameters of a learned model for adapting to new version of Dota2. Such tool is essential because Valve company usually publishes a new version of Dota2 every a few months, resulting performance degradation of the learned model. Even though a new model can be trained from scratch, the time is limited and the resource consumption is intolerable. What’s more, the designed tool makes training of the agent more efficient because model parameters and architectures can be adjusted based on performance in training process. Parameters transfer obeys a basic rule, i.e., TrueSkill of new agent (new parameter space) matches that of already learned agent. Based on such principle, OpenAI Five develops different methods for changes of the architecture, observation space, action space and so on.

6.4 Training for JueWu
Training of JueWu is similar with that of OpenAI Five, where no human player data is utilized for agent initialization. However, to play with a hero pool of full RTS game instead of restricting the selection of heroes, JueWu develops new training framework compared with the basic form of OpenAI Five. More specifically, training of JueWu consists of three main steps: fixed-lineup training, multi-teacher policy distillation and random-pick training, followed by a MCTS based approach for learning to draft.

Considering self-play of massive disordered agent combinations makes training of an agent a very hard task, JueWu adopts a curriculum based training scheme: firstly using fixed-lineup and then utilize random pick. Several fixed lineups without hero repeat are carefully selected, based on which, distributed reinforcement learning is performed to train several teacher agents. To generate such lineups, JueWu analyses vast amount of human player data, and select relatively balanced teams. Based on the teacher agents, a policy distillation is conducted to learned a bigger student agent. The distillation is modeled as a supervised learning framework to minimize the difference between outputs between teacher and student models, i.e., Shannons cross entropy between action distributions and Euclidean distance between value estimations. Finally, based on the student agent, another distributed reinforcement learning is applied for random pickups. Student agent, serving as initialization of above process, largely reduce the training difficulty.

A very important and interesting part in RTS games like Dota2 and Honor of Kings is hero drafting to form two teams. JueWu proposes a MCTS and neural network based approach to handle the problem of huge combination of agents, i.e., more than $10^{11}$. The motivation of using neural network in MCTS is similar with AlphaGo Zero, namely estimates the value of the expanded node more accurate and to avoid a complete rollout, which is very time consuming. Unlike OpenAI Five, the terminal state of draft is not the end of a game, so winning or losing signal cannot be obtained. To construct the dataset to training value estimation network, the label, i.e., winning signal, should be obtained. To solve this problem, JueWu collects another dataset, which performs plenty of matches using randomly selected teams with the learned reinforcement learning model. Then, a lineup-winning result dataset is developed, based on which, a winning prediction network can be trained and used as signal for value network training labels.

6.5 Training for Commander
Similar with AlphaStar, Commander adopts a very similar training framework for StarCraft agent learning, i.e., supervised learning followed by multi-agent reinforcement learning. The main differences are several important details, which makes Commander beats two professional players with order of magnitude less computation. Firstly, Commander uses a much smaller human player dataset, based on which, learning rate, batch size, multi-stage training and network structure are carefully designed for supervised learning. In multi-agent reinforcement learning, Commander devises the training loss, and uses more main agents for more diversity, which improves the learning efficiency.

6.6 Training Difference
Nowadays, deep reinforcement learning accelerated by distributed learning becomes a general method to train high level AIs. Apart from this, the four typical AIs AlphaStar, OpenAI Five, JueWu and Commander share several differences.
Firstly, to train each generation of agents, those AIs utilize different self-play or advanced self-play mechanisms. In JueWu and OpenAI Five, relatively simple self-play is performed to train each generation of agents. To avoid strategy collapse and ensure the learned agent being robust to a wide range of opponents, usually a certain percentages of past versions are selected as opponents. This selection can be specially designed instead of using fictitious self-play, i.e., uniformly select past versions. For example, OpenAI Five with 20% of rollout games selects past versions based on their scores calculated by training rollout results. AlphaStar utilizes a prioritized fictitious self-play mechanism to select opponents, based on which, relatively hard agents and agents with similar levels are more likely to be chosen. What’s more, AlphaStar and Commander adopt league training, which is a power mechanisms to enhance self-play for more diverse agents learning.

Secondly, purely based on reinforcement learning usually requires a huge computational resources because of its trial and error mechanism, so those AI systems utilize human player data to assist reinforcement learning. In AlphaStar and Commander, supervised learning based on high quality data is performed to initialize policy networks, so as to provide good and diverse initialization for reinforcement learning. What’s more, statistics are extracted from human data to constrain the policy in reinforcement learning stage, which helps a lot based on the ablation study in their papers. In JueWu, human data are not used for policy initialization. Instead, the data is used to analyze the hero lineups, so as to provide relatively balanced teams for first learning stage, i.e., self-play reinforcement learning with fixed-lineup. In OpenAI Five, no human data are utilized, and OpenAI just utilize self-play reinforcement learning for policy training, using huge computational resources for over 10-month training.

Thirdly, several new techniques are developed to adapt to different games. Different from population based training in FTW, AlphaStar maintains a league for agent training, where different types of agents are responsible for different tasks. Even though being heuristic, league based multi-agent training provides a very useful idea for complex real time games with game-theoretic challenges. Continual transfer via surgery, as an effective tool to make full use of currently learned model for changing environment, is very useful because real world environment is inevitably changing through time. Such a technique can largely reduce computation cost, and change models when it is necessary.

7 TECHNIQUES COMPARISON

Based on current breakthrough of human-computer games, techniques can be roughly divided into two categories: tree search assisted by deep neural network, and advanced self-play with distributed deep reinforcement learning.

7.1 How to Reach Nash Equilibrium?

Nash equilibrium [39], an important concept in game theory, which is the best strategy for any player no matter what strategies the other players chose. Due to the above characteristic, researchers have paid much attention on approaching Nash equilibrium [40], [41].

Tree search methods have long been a mainstream for turn based games. Typical methods such as min-max search, MCTS and CFR are classical algorithms that can approach Nash equilibrium, so those techniques are widely utilized in games such as chess and limit poker. However, when facing complex environments such as Go and HUNL, the calculation of Nash equilibrium is untraceable because of the huge game tree complexity. To handle such problem, properly restricting depth and width of the game tree becomes a very important strategy, where deep learning can be used. For example, AlphaGo series train policy and value networks so as to pay more attention on valuable nodes to be expanded and to evaluate nodes expanded, respectively. In complex real time video games, we cannot easily draw lessons from tree search methods because of challenges such as long time horizon and complex action space. Fictitious self-play [42] provides an evolutionary strategy for agent learning, which can approach the Nash equilibrium in certain types of games. However, computation of fictitious self-play for complex games is high, so researchers develop various self-play strategies, and uses distributed reinforcement learning to learn each generation of agents. Even though theoretical guarantee for Nash equilibrium is absent, professional level AIs can be trained by properly overcoming game-theoretic challenges. For examples, OpenAI Five play against itself for 80% of the games and against past generations for 20% of the games by their winning rate against current version. AlphaStar designs three types of agents to enhance self-play, where each type of agent performs confrontation with certain opposes, so as to gradually improve performance of the main agents without desperation or just learn a narrow of policies.

7.2 How to Become General Technology?

Considering real world games are mostly real time with a lot of decisions to be made, and players usually form their decisions not in an iterative manner, tree search based methods are not so easy to be implemented in very complex games. However, advanced self-play with distributed learning can be a general solution due its simple implementation and performance guarantee such as success of AlphaStar and OpenAI Five. Generally, there are three steps to train an AI based on this technique, as shown in figure 6.

Firstly, the task should be modeled as a reinforcement learning framework, which consists of several key factors. Determine the state space and action space are the most
important part for a game. The former provides information for neural network input, which should be rich enough for a suitable decision and lean enough to reduce computation burden. The latter reflects how to drive environment transfer. Too complex of action representation will increase learning difficulty, but too simple design will make the agent unable to reach professional level due to action limitations. What’s more, When performing reinforcement learning, how to design reward space is another key factor because it is the task signal to learn each generation of agents. Too sparse reward under long time horizon game will greatly increase learning difficulty, and designing immediate rewards to guide agent pursuing task reward needs a lot of human experience.

With above factors, one can design or adopt reinforcement learning algorithms such as Q learning, Advantage Actor Critic, Proximal Policy Optimization for agent learning. Usually, deep neural networks are specially designed to transform input state information to output action, e.g., auto-regressive policy to deal with structured and combinatorial action space in AlphaStar. To accelerate reinforcement learning, distributed learning should be carefully designed, based on the model inference cost to driven rollout, communication cost among machines to transfer data, and most importantly the machine configure such as GPU and CPU ability. For example, when the model is relatively small and the inference cost is low but there are no fast connections for data transformation between and within machines, one can chose distributed framework like in FTW. Nowadays, Tensorflow, Pytorch and several tools such as Ray and Horovod can easily achieve multiple machines distributed learning with minimal code changes compared with that in single machine.

Finally, since each generation of agent can be trained based on distributed reinforcement learning, a last step is to design self-play based mechanism for agent evolution. Currently, plenty of heuristic approaches have been developed. For example, AlphaStar uses three types of agents with each type selects different opponents, based on which, all types of agents evolve to make the main agent stronger. Overall, previous evolution strategies for self-play are mostly heuristic, and one can design strategies based on the game faced, so as to improve the agent ability.

8 Challenges and Future Trend

Even though big progress has been made in human-computer games, current techniques still suffer from challenges like relying much on computational resources, which will inspire future researches.

8.1 Big Model

Nowadays, big model, especially pretrained big model, is emerging from natural language processing to computer version, from single modality to multiple modalities. Those models have proved great potential for downstream tasks even in zero-shot settings, which is a big step for exploring artificial general intelligence. For example, OpenAI developed Generative Pre-trained Transformer 3 (GPT-3), which has more than 175 billion parameters and displays promising performance in various language related tasks. However, big model in games is largely absent, and current models for complex games are much smaller than those big models with more than myriads parameters. As shown in Table 2, AlphaStar and OpenAI Five only have 139 million and 159 million parameters, respectively.

| Models               | Parameter size |
|----------------------|----------------|
| JueWu                | 17 million     |
| Commander            | 49 million     |
| AlphaStar            | 139 million    |
| OpenAI Five          | 159 million    |
| GPT-3                | 175 billion    |
| Megatron-Turing NLG  | 530 billion    |
| M6-1T                | 10 trillion    |

Considering big model is a relatively good exploration for artificial general intelligence, how to design and train big model for AI in games, may provide a solution for those sequential decision making field. To give such an attempt, we think at least two problems should be carefully considered.

Firstly, unlike in natural language processing problems, tasks for games are very different, so how to make clear of training goal is key step for big model. For example, in StarCraft, players need to build force with at most 200 units to fight against enemies, but in Dota2, five heros are working together to defeat another five heros. Even through distinct actions or skills are required for different games, the mechanism of playing a game is similar, i.e., extract useful information of image streams and make a decision based on current situation. So a possible breakthrough point is to learn high-level strategic situation, so as to provide information for decisions. Noted that other goals for training big model are welcomed as long as they can provide general and useful information for making decision.

Secondly, since some games are hard and some games are easy, how to design a suitable training mechanism is difficult. It should handle various kinds of games and make sure the learning do not degenerate, e.g., not forgetting the representation ability. Continual learning provides a tool for such problem, but there are still several issues need to be carefully handled. Since training a high level game AI is an evolution process which needs self-play or other iterative learning, how to properly embed evolution in to above learning mechanism is a problem that has never been faced. On the other hand, different games share similar characteristics to some extent, how to establish connection between them when performing training is a key factor to reduce complexity and meanwhile promote performance.

8.2 Low Resources AI

To train professional level AIs for complex environments, usually a large computational resources are required. As

2. https://www.tensorflow.org/
3. https://pytorch.org/
4. https://www.microsoft.com/en-us/research/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model/
shown in Table 3, we can find a huge resources devotion to train an AI.

### Table 3

| Al | Resources |
|----|-----------|
| AlphaZero | 5000 v1 TPUs and 16 v2 TPUs for 13 days |
| Libratus | 25 million core hours |
| OpenAI Five | 770 ± 50PFlops/s day for 10 months |
| AlphaStar | 192 v3 + 12,128 core TPUs, 1800 CPUs for 44 days |

One question naturally raises that if it is possible to train a professional level AI with limited resources. One intuitive idea is to bring in more human knowledge to assist learning [54]. For example, incorporating prior knowledge as constraints or loss functions for conventional machine learning algorithms. Since current breakthroughs on games are mostly relying on reinforcement learning which is low sample efficient, how to achieve sample efficient reinforcement learning based on human knowledge is a future direction [55], [56].

On the other hand, training a professional agent is usually an evolution process, which iteratively learns hundreds of models. For example, in AlphaStar, almost 900 different players are created, with each one maintaining a specific kind of task. So how to reduce such iteration seems to be an effective medium for reducing computational resources. Current approaches, mainly based on self-play, are mostly heuristic by selecting suitable opponents for current generation of agent. If theoretical and easy to calculate evolution strategies are developed, it will be a key step for low resources AI systems.

### 8.3 AI Evaluation

Most games in real world are in-transitive, i.e., transitive and in-transitive parts are co-existing [25]. The in-transitive characteristic makes precise evaluation of agent a difficult problem. Current human-computer games usually utilize winning rate (against professional human players) based evaluation criteria, as shown in Table 4. However, such evaluation is relatively rough especially under limited tests for in-transitivity games.

### Table 4

| Al | Resources |
|----|-----------|
| AlphaGo Zero | previous AlphaGo series |
| Suphx | 99.99% of all the officially ranked human players |
| Libratus | Four top human specialist professionals |
| OpenAI Five | Professional teams with world champions OG |
| AlphaStar | 99.8% of ranked human players |
| JueWu | 95.2% win rate against professional players |

Theoretically, Nash equilibrium is not considered in most current Al’s although it is a relative conservative solution due to not considering weakness of opponents [57], [58], [59]. Still, it is a best solution for any kinds of opponents in non-cooperative games. Accordingly, if satisfying above condition, how to evaluate the distance between obtained solution with Nash equilibrium solution is an important problem. It may help us figure out if AlphaZero reaches the Nash equilibrium and can not be beaten by any humans.

On the other hand, current ranking methods for human and Al’s are based on their battle records and several generative calculation based methods such as Elo [60], [61], [62], however, under in-transitive games, such calculation is inexact. Moreover, win rate is just one of the evaluation metrics, and it may not enough to reflect all the aspects of an agent. Accordingly, how to develop a systematic evaluation criteria for most games can be an important and open problem.

### 8.4 New Different Types of Games

After the breakthrough of AlphaStar, researchers are looking for new games for advancing decision making intelligence, e.g., football. In our opinion, current games with big progress are mostly symmetrical games. Even through games like StarCraft and Dota2 look like asymmetric because there are three distinct races with different forces in StarCraft and plenty of heros with diverse skills in Dota2, those games share a common characteristic of balance for different choices. This is important for games being popular and even being a esport.

On the contrary, real world is full of asymmetric games, and it is almost unable to find a strictly symmetrical game in our surroundings [63]. So a practical issue raises, it maybe a good direction to design asymmetric games, so as to develop decision making intelligence for real world problems. However, there are few environments of asymmetric games, and
researchers are paying much little attention on developing techniques for those kinds of testbeds [4]. We argue that previous training frameworks, especially self-play with distributed learning, can not deal with such senecios, because a two player asymmetric game has very different strategies for different sides, and self-play based mechanisms may not work well.

Wargame, is a popular confrontation game, as shown in figure 6 where two players (red and blue) with each controls a collection of combat units to fight against each other [20]. Based on several settings of Wargame, two sides are asymmetric and usually the power of red one is weaker than that of blue one. Considering Wargame is a complex game like AlphaStar that faces imperfect information, long time horizon, in-transitive game and multi-agent cooperation, and its distinctive asymmetric game characteristic, it may be a new testbed for AI in games.

9 Conclusion
In this paper, we have summarized and compared techniques of current breakthroughs of AI in games. By comparing the approaches utilized, we illustrate the mainstream frameworks and techniques for developing professional level AI systems. More importantly, we try to raise challenges of current decision making techniques, hoping to inspire future directions in the field. Through this brief survey, we hope beginners can quickly familiar with techniques and researchers on the way can be inspired for deeper study.

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