Impact of Collusion and Coalitions in RISK

Ken Knudsen
ken@cs.umd.edu

1. Introduction

Agents, whether human or artificial are only as good as the game rules they exploit. Game bots optimize actions by exploiting resources or state-space searches. Human experts exploit resources or complex strategy dynamics. Violations to the rules or altering the game state in an illegal manner are considered cheating.

Collusion is an agreement between multiple players to conspire against other player(s), yielding higher payoffs than they would get on their own. In a large variety of games, collusion is considered cheating such as in bridge and poker, due to the unfair advantage players receive by revealing key bits of information. Generally, colluding agents are expected to maximize their actions through a reduction of their game tree and state-space searches. Instead of worrying about each other, they can focus on their opponents. This has led to research into game design and algorithms to: detect, prevent and penalize colluding agents [7].

In artificial intelligence research, fear of collusion has made it difficult to evaluate game strategies across heterogeneous agents, e.g. humans versus game bots. Bots have a distinct advantage in running numerous games in a short amount of time and being consistent in how they follow different strategies. This makes them ideal for testing complex interactions between different pure strategies. Bots have to be programmed with a set of strategies and a set of trigger conditions for when to switch strategies. Humans on the other hand, have an adaptive behavior which is tough for bots to mimic, where they can innovate on the fly if their known strategies are not satisfactory or adapt to new situations and variants of the game.

"Evaluating the (game) solution against human players would lead to problems of both slow evaluation and unfair competition (a common agreement among many human competitors in tournaments open to bots is to terminate the bots first)." [3]

In this paper, the board game Risk was used to study the impact of collusions in multi-agent, single-winner games.

1) Which agents form coalitions
2) Does the coalition reap the benefits of working together, or does a subset of the members prosper while the others wither away
3) How does the coalition disband
4) Should game bots fear collusion

2. Related Work

Game tree search and simple agent strategies such as minimax and maximin have proved effective at providing strong competition in two-player games; whether to directly attack an opponent or defend against the worst case payoff. In imperfect information and multi-agent games, these strategies relate to overconfidence and paranoid strategies. Overconfidence tries to maximize an agent's payoffs assuming other agents make random moves, whereas paranoia assumes other agents are trying to minimize the agent's maximum payoff (minimax).

Multi-agent system bots use a state-space, search algorithm to optimize decisions [2]. This particular strategy creates a minimum spanning tree of estimated cost to achieve various objectives and then ranks its actions based on expected utility per unit cost; taking the highest utility per cost actions first and working through the list until it is out of available resources.

Parker showed that overconfidence outperforms paranoid in two-player imperfect information games [5]. This assumed that without perfect information, the opponent does not know which strategies result with the lowest payoff. The best strategy becomes overconfidence which reduces the maximal regret from playing safe.

Zuckerman showed that in social games, pure paranoid or overconfident strategies are too rigid to exploit evolving situations [9]. There are times when one should play paranoid, overconfidence, a minimax strategy against a particular opponent, or some other "offensive" strategy. At each game state, a decision algorithm is run to decide which strategy to employ, taking factors such as relative power and opponent impact factors into account.

Additionally, social games exhibit modeling complexities derived from agent interactions. As each agent has their own objective, agents may make decisions based on their emotions or relationships towards other agents. Social value orientation (SVO) tries to capture these behaviors and emotions, and project them onto game bots [8]. Directing the bots as to how aggressive or social they should be towards specific agents.

In interactive, social games agents have incentive to team-up or collude against other agents to improve their situation. These coalitions may be implicit, such preventing an agent from ending the game [6], or explicit to increase the chances of winning or surviving by knocking other agents out first. For instance, payouts in poker tournaments are awarded based on when players are knocked out of the game. Colluding players would employ a strategy where the agent with the better hand plays out the round while the other folds early, reducing coalition's total contribution to the pot.

Risk is a multi-agent, single-winner game where agents vie for world domination. At its most basic level of play, game tree search is not feasible. The branching factor is enormous due to the combinations of action sequences from where to deploy units, where to attack, with how many units, and the probabilities introduced with dice rolls. The branching factor is further complicated by the number of agents involved and their attitude and skill level compared to each other.

Risk was used to study collusion the rules do not expressly prohibit collusion. In fact, collusion in Risk is necessary to keep the game competitive and offset differences in skill level. Weaker players may team up to take down a stronger opponent. Players may form defensive coalitions to focus on expansion. Players may decide to betray their partners in an effort to catch them off guard and gain a larger number of resources cheaply.

MARS, a state-space search, domain specific, Risk game bot implementation uses 14 tuning parameters related to the number of territories and bonuses obtained to order its decision tree [3]. MARS performed reasonably well against several mixtures of bots with varying strategies, most of which were fixed throughout the game. However, MARS was not tested against humans as the tests would take a while and the researchers were worried about collusion against the robots from human participants.

3. Approach

The objective was to identify collusion and evaluate the impact collusion has on the game state in multi-agent games with human players.

3.1 Identify Collusion

In its simplest form, define a coalition as any two or more agents who have attacked a common agent during the same round between the target's turns (offensive) or who have not attacked each other for some number of rounds (defensive). This definition does not include any quantitative thresholds as to when agents are colluding, just that they are either focusing attacks towards a common player and/or not attacking each other. This definition was too strict to find collusion in our game setup as colluding players would attack each other, possibly to rearrange their borders or passing through to attack another player on the other side. Thus, a collusion threshold value (θ) was added so that colluding players could attack other players some fraction of the time, where AD is the attack distribution between players i and j, Equations 1a and 1b.

$$\text{Defensive collusion} \equiv AD_{i,j} \leq \theta_{Defense} \qquad (1a.)$$

$$\text{Offensive collusion} \equiv AD_{i,j} \geq \theta_{Offense} \qquad (1b.)$$

Furthermore, assume that strong collusions occur where players either heavily attack the same opponent ($\theta_{Offense}$ approaches 1) or rarely attack each other ($\theta_{Defense}$ approaches 0). Then both offensive and defensive collusion can be classified "defensive" by correlating the offensive and defensive threshold values such that, $\theta_{Defense} = (1 - \theta_{Offense})$. Where, in order for two players to be offensively oriented, they must also be defensively oriented as well. In this instance, players could not be offensively oriented without being defensively oriented as once the offensive threshold is reached, then even if all of the remaining attacks were against each other, the defensive threshold would not be surpassed). Thus, in order to identify collusion, only instances of soft-play (defensive) collusion have to be identified, Equations 2a and 2b. From there, the coalitions can be further categorized into offensive or defensive.

$$\text{Defensive collusion} \equiv AD_{i,j} \leq \theta_{Defense} \qquad (2a.)$$

$$\text{Offensive collusion} \equiv AD_{i,j} \geq (1 - \theta_{Defense}) \qquad (2b.)$$

3.2 Tuning the Collusion Threshold

In order to tune the collusion threshold, a set of oracles (secret, expert players) annotated their games and strategies for instances of collusion. The oracles documented turns where they were involved in or suspected any collusive behavior. Provided details as to whether the colluding agents were involved in implicit or explicit agreements, the designated target(s) (if minimax) and the level of trust they had towards members of their coalition. Oracle data along with public game messages between players were used to manually spot check potential collusive windows and provide a reasonable threshold value.

3.3 Impact of Collusion

Following a black box approach, the impact of collusion was measured as the difference in rankings from the start and end of the collusion window. For this study, players were ranked by a power heuristic representing the amount of resources each player has and the bonus resources they will potentially receive during their next turn, Equation 3.

$$H_i = (\#\ \text{Armies})_i + 0.3 * (\#\ \text{Occupied territories})_i + \text{Bonuses}_i \qquad (3)$$

Once players are ranked in descending order of their power heuristic (H) (strongest player first), the impact is calculated as the change in rankings between the start and end of the coalition, Equation 4. Positive values indicate the player became stronger than one or more opponents and switch places with them, while negative values indicate the player became weaker. The impact on the coalition is then the net effect (or sum) of all players in the coalition, positive values indicating a prospering of the coalition and negative a decay. Net effect values of 0 indicate either no change, or the members in the coalition swapped places.

Rank = [1, 2, 3, 4]; where 1 is assigned to strongest player and 4 the weakest

$$\text{Impact}_i = \text{Rank}_{i,start} - \text{Rank}_{i,end} \qquad (4)$$

Another way to measure collusion is by just checking whether the coalition's relative power heuristic increased or decreased. The members of the coalition may not change places, but they could have narrowed or widened a gap between them.

4. Implementation

4.1 Risk rules

Risk is a board game where agents must achieve world domination by eliminating all other opponents from the board. The game board is an artistic graph structure representing the world, sub-region of the world or an imaginary world where the nodes represent territories or resources to be controlled and edges indicate territory adjacency and attack paths.

Each game is a single-winner game with all other players in an adversarial role. Once an adversary no longer controls any territories, that player is eliminated. The last remaining player is the winner. There are N-players in any game where N >= 2. Players take successive turns in a predefined order. Each turn, a player:

1) Places awarded units on their respectively owned countries.
2) Attacks any neighboring countries owned by adversaries or neutral. There is no limit on the number of attacks but can only attack from a country that has a minimum of 2 units.
3) Transfers any number of units (leaving a minimum of 1 unit/territory) to any neighboring territory. A player may only transfer units 3 times per turn.

Battles are simulated through dice rolls representing strength and potential casualties (payoff) of each agent. Attackers can chose to attack with 1, 2 or 3 units from a territory. Defenders automatically defend with 1 or 2 units depending on how many reside in the territory. Once an adversary has lost all units in a territory the attacker captures the new territory and the attacker has the option to transfer units from the attacking territory to the newly captured territory while leaving a single unit behind.

4.2 Implementation on Warfish

Warfish is a free, invitation-only online version of Risk hosted at http://warfish.net [4]. Warfish provides a highly customizable version of the classic board game with similar end conditions and game play. It also has its own community of players ranging from novice to expert skill levels which were utilized for this study.

Game setup was designed to 1) make it easy for everyone to understand the rules, 2) have enough players to demonstrate collusion and 3) limit unintentional collusion strategies from minor resources such as card strategies.

Each game included 4 human players and one 'neutral' player. The neutral player was initially assigned territories by the computer at the onset of the game and remained dormant for the rest of the game (did not attack). Battles were decided using 6-sided dice where ties went to the defender using standard Risk rules for attrition. Cards were granted to players if they succeed in capturing a territory during their turn. Card trade-in was set constant to 5 units per set (removing card-trade in strategies). Card-capture, a feature where a player eliminating an adversary gains their cards was disabled to eliminate incentives for removing weak players for additional gains. Territory placement, opponents and turn order were randomized at the onset of the game.

Two variables adjusted throughout the study were the game board and the amount of information available to the players (fog-of-war).

4.2.1 Game Boards

Games were played on one of two maps: a map representing the World or Europe. These maps were much larger than the standard Risk game board, allowing for longer game play. The assumption being that longer games afford players the opportunity to realize the need for social game play or collusive strategies.

An additional benefit resulting from multiple boards was to remove map specific strategies. For example, one of the bots in RiskBots [3] had a strategy to expand quickly to gain control of one of the smaller bonuses, switch to a defensive stance for a while to accrue units and then suddenly expand. Strategy wise, the Europe map contained fewer strategic choke points than the World map.

4.2.2 Fog of war

The standard Risk board game is a complete-information game as all players have access to the entire board or game space. Warfish provides players with personalized representations of the game board. As such, different layers of 'fog' can be introduced to limit information about game board based on certain conditions. There are 6 different fog options available, Table 1. Fog level 0 games are the only complete-information game while all others are incomplete-information games.

0	Players see who owns all territories and how many units occupy each
1	Players see adversary ownership of all territories but unit counts are visible only in neighboring territories
2	Players see adversary ownership of all territories but no adversary unit counts are visible
3	Players see adversary ownership and unit counts for neighboring territories only
4	Players only see adversary ownership of neighboring territories
5	Players cannot see any information about any territories they do not own

Table 1. Fog levels and amount of information revealed to each player

Games were limited to fog levels 0 (control), 1 and 3 as those were the only fog levels which would not hinder players' abilities to attack due to unknown unit counts in adjacent territories. Instead we gradually removed information from territories that the player can not directly attack. As players and game bots tend to use territories as a measure of power, the number of units displayed were removed view first and then the territory ownership.

4.3 Data Collection

Warfish made the history of all perfect information games public, thus we allowed anyone to join these games. Fog games were not public due to restrictions from Warfish and only revealed history logs to the competing individuals. Fog based games were limited to players willing to provide their game log. Users had the option to not join games or not provide their history if they were not comfortable releasing this data.

After games completed, the move logs were captured and stored for processing. Additionally, oracles provided information on their strategy and coalitions through a webform. The webform included fields for whether there was explicit or tacit collusion, their partner(s), the target player(s), how strongly they trusted their partner and whether they were playing a minimax or maximin strategy.

5. Results and Discussion

Results from 75 games were collected and analyzed, 14 of which included oracles. Regardless of the fog level or map type, games took between 7 and 40 days to complete with a mean of 20 days. In addition, fog levels did not have a noticeable impact on the number of turns per game or the number of attacks players would make each turn.

Oracle data and in game messages were used to find reasonable coalition threshold values. After comparing a few values and checking through oracle histories, a threshold value of 0.25 was selected to identify defensive coalitions and 0.75 for offensive. This value did not satisfy all of the oracle annotations, but provided enough detail to pick out strong collusive behaviors where the members did not attack each other much more than their opponents. For example, there were instances where explicit coalitions swapped territories to increase their bonuses and consolidate their position on the board which were not picked up using this method.

Two different methods for finding coalitions where tested. The first based on the relative attack distribution (attack based) and a second based on the impact the players had on each opponent's power heuristic (power based). The power based method resulted in about 10% more coalition windows than attack based. Both methods yielded similar results as they were both measuring the similar player interactions; however, the power based method was biased more towards the quality of the territories and bonuses whereas the attack based method was strictly based on the number of territories attacked. It was expected but not verified that the majority of the coalitions in both methods should be the same. For the rest of the analysis, only the power based method was used.

Another measure of the strength of a coalition is the number of rounds the coalition lasted. Since games were relatively short and coalitions could form and breakdown between turns, this value was set to look for coalitions spanning at least one round. There was an expectation that some of these small windows were random coincidence. Assuming that each agent biased attacks towards a single random opponent then in a four-player game, it was expected that implicit collusion would occur with probability of 2/9 (~22% of the time) for a single round. Expanding to 2 rounds, the expected probability for implicit collusion reduced to 4/81 (~5%). Thus, coalitions spanning only one round have a high probability of being a random occurrence, while coalitions spanning 2 or more rounds are much stronger forms of collusion. In actual game play, agents tend to spread their attacks over multiple opponents, reducing the probability of random coalitions. Thus, coalitions spanning at least one round seemed sufficient.

Overall, the average coalition lasted a little over 2 rounds, the bulk of which lasted between 1 and 2 rounds (36% & 32% of the windows respectively). The number of coalitions at each interval beyond 2 decreased exponentially as the duration increased, Table 2. Factors such as map type and fog level did not appear to have any impact on the duration of the coalition.

Bin	*Frequency*	
1	279	36.38%
2	249	32.46%
3	104	13.56%
4	63	8.21%
5	29	3.78%
6	21	2.74%
7	7	0.91%
8	6	0.78%
9	6	0.78%
10	1	0.13%
More	2	0.002608
Total	767	

Table 2. Frequency of collusion duration. 70% of the collusion windows lasted less than 3 rounds.

An interesting trend was that the smaller member of the coalition tended to dissolve the coalition first, 60% of the time. This may have been due to the larger member trusting the smaller member longer and assuming a tit-for-tat strategy with them. Thus, the larger player was allowed to continue a maximin strategy against the remaining players.

As for how coalitions fared, over half of the collusion windows had little to no effect to the overall standing of the players. If members in the coalition swapped places in the rankings, then the net effect was no effect. In most cases where there was an effect, the coalition tended to improve its position, Table 3. This was most noticeable with fog-level 3 where there was rarely a negative impact to the coalition's rankings, Table 4. However, this could be an artifact of a smaller sample size.

Impact	Overall		Europe Map		World Map	
4	5	0.7%	2	0.5%	3	0.9%
3	9	1.2%	4	0.9%	5	1.5%
2	54	7.0%	33	7.5%	21	6.4%
1	165	21.5%	92	20.9%	73	22.4%
0	406	52.9%	238	54.0%	168	51.5%
-1	99	12.9%	58	13.2%	41	12.6%
-2	24	3.1%	12	2.7%	12	3.7%
-3	4	0.5%	2	0.5%	2	0.6%
-4	1	0.1%	0	0.0%	1	0.3%

Table 3. Impact of collusion on the coalition overall and for the different map types. Positive impact indicates windows where the coalition prospered, while negative values are where the coalition lost ground. Impact is the number of positions in the rankings the coalition changed. For example, an impact of 4 indicates the coalition jumped from 3rd and 4th place to 1st and 2nd, for a total shift in 4 ranks.

Impact	Fog 0		Fog 1		Fog 3	
4	4	0.7%	0	0.0%	1	0.9%
3	5	0.9%	1	0.9%	3	2.7%
2	42	7.8%	4	3.5%	8	7.2%
1	120	22.2%	25	21.7%	20	18.0%
0	278	51.4%	60	52.2%	68	61.3%
-1	71	13.1%	18	15.7%	10	9.0%
-2	17	3.1%	6	5.2%	1	0.9%
-3	3	0.6%	1	0.9%	0	0.0%
-4	1	0.2%	0	0.0%	0	0.0%

Table 4. Impact of collusion on the coalition for different levels of fog.

There was a correlation between strength of the coalition as a function of the entire power distribution, Figure 1. Coalitions consisting of more than 60% of the total power distribution prospered, while coalitions consisting of less than 40% decayed.

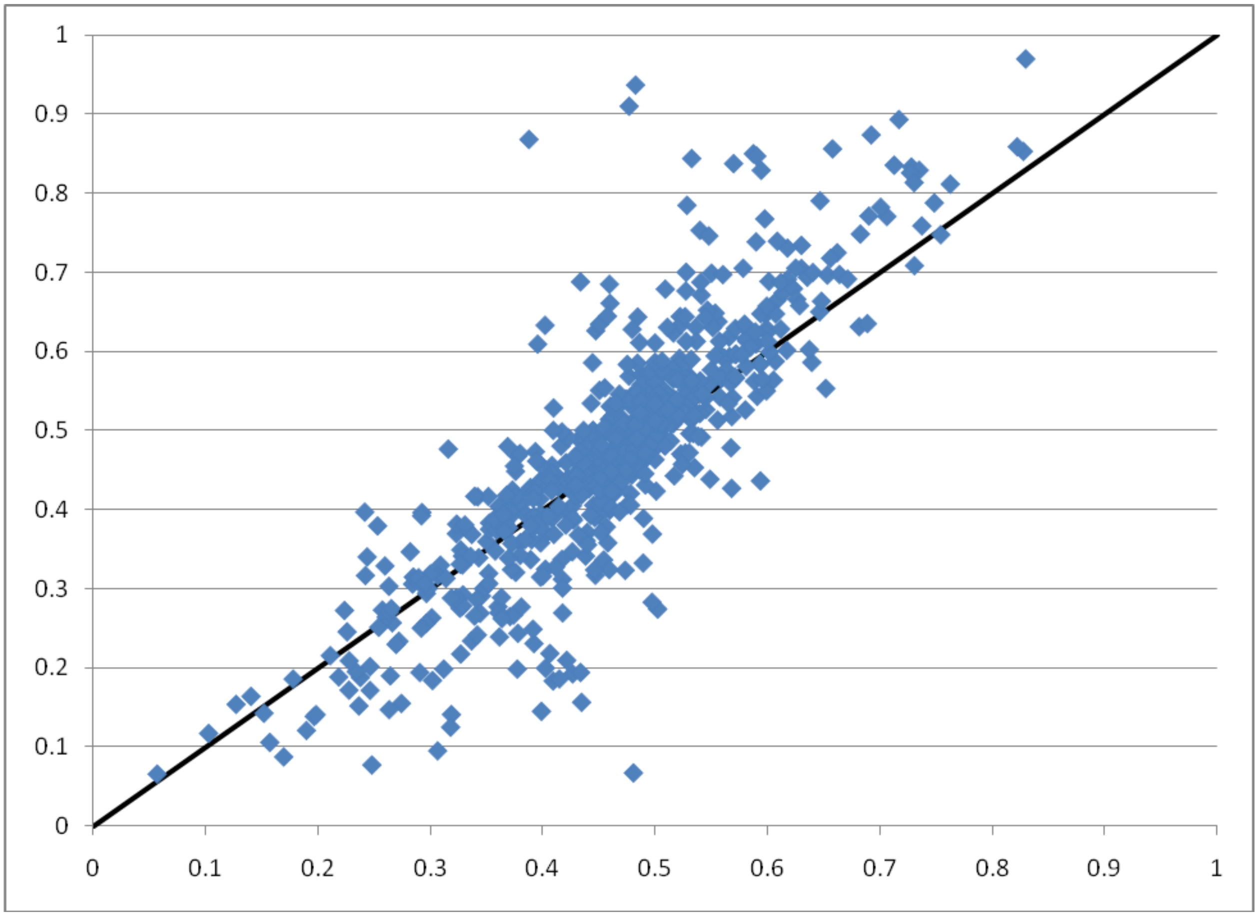

Figure 1. Coalition's power heuristic at the start of a window (x-axis) versus their final power hueristic. Coalitions consisting over 60% of the power distribution tended to prosper, while those under 40% tended to decay

A small fraction of the coalitions (2%) ended due to one of the members being removed from the game. These coalitions weren't all that interesting in the respect that a lot of cases, the dying agent didn't border all of the other agents. In some instances, members of the coalition turned on each other when one of the members became too small. Most likely trying to kill off the player to capture their cards, which was a game feature turned off for this study.

6. Conclusions

There are issues with this approach. First, using human subjects in a dispersed environment is a long process that results in noisy data. On average, games took around 20 days to complete for all map types and fog levels, ranging from 8-40 days to complete a single game.

Second, this dataset comes from related work looking at the impact of how altering information available to players affected collusion. Thus, games were spread out over different fog levels varying the information available to players. As Warfish did not publicize the history log of completed fog games, the study required participants willing to assist in data collection after game play. This additional dependency on users limited the number of participants in the incomplete information games, which may not be representative of domain experts or the general population. These issues could be remedied by using a different site that publicizes all completed games or a lengthier study.

The oracle data was a bit noisy. A simpler, more intuitive annotation system with better direction for the oracles would provide a much richer training set. Oracle data was mostly used for spot checking the tuning parameters, so it wasn't a huge factor.

As for the results, we were able to show that the success of coalitions depended on factors other than duration, stage of the game and power of the coalition (generally speaking). There are deeper complex factors which dictate how coalitions turn out. These factors could be better examined by designing the game to take longer, for instance larger maps, starting with greater resource stockpiles (armies) or decreasing the number of resources received each turn. Longer games should allow for greater player interaction and the development of coalitions.

We did not try to identify explicit or tacit collusion, since 70% of the collusion windows analyzed lasted for less than 2 rounds. This is good news for game bots as they should not have to worry about long lasting coalitions.

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7. References

1. Branca, L, and S.J. Johansson, "Using Multi-agent System Technologies in Settlers of Catan Bots", AAMAS Workshop on Agent-based Systems for Human Learning and Entertainment, Honolulu, USA, 2007.

2. Johansson, S.J., "On using Multi-agent Systems in Playing Board Games", In Proceedings of the Fifth International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS), Hakodate, May 2006.

3. Johansson, S.J., and F. Olsson, "Using Multi-Agent System Technologies in Risk Bots", In Proceedings of the Second Artificial Intelligence and Interactive Digital Entertainment Conference, (AIIDE), Marina del Rey, June 2006.

4. Chow, S., "Warfish.net", http://warfish.net/. Last accessed Nov. 24, 2010.

5. Parker, A., D. Nau, and V.S. Subrahmanian, "Paranoia versus Overconfidence in Imperfect Information Games", AAAI Proceedings of the 21st National Conference on Artificial intelligence, Volume 2. 2006.

6. Smed, J., T. Knuutila, and H. Hakonen. "Can we prevent collusion in multiplayer online games?" Proceedings of the Ninth Scandinavian Conference on Artificial Intelligence (SCAI 2006), pages 168–175, Espoo, Finland, Oct. 2006.

7. Smed, J., T. Knuutila and H. Hakonen, "Towards Swift and Accurate Collusion Detection", http://www.scientificcommons.org/26451026. 2007

8. Wilson, B. I. Zuckerman, and D.S. Nau, “Modeling Social Preferences in Mulitplayer Games”, (under review).

9. Zuckerman, I., A. Felner, and S. Kraus, “Mixing Search Strategies for Multi-player Games”, Proceedings of the 21st International Joint Conference on Artificial Intelligence. 2009.