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Research Article

A Machine Learning Framework for Strategic Gameplay Optimization in Scrabble Using Reinforcement Learning

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Abstract: This paper explores and compare various artificial intelligence-based techniques used for playing classic board game Scrabble. As the world is evolving around finding quick and efficient techniques for the solution of each problem using Machine learning, gaming industry is also a flourishing industry and has grown 9.8% compared to previous year and has generated a revenue of 26.14 billion dollars through global platforms this year which majorly captures youth and many gamers. Most popular games played online includes PUBG, Ludo, cards etc. Scrabble is being a vocabulary enhancing game and less popular game has attracted its intension of research towards it. The implementation of this imperfect information game has been done through Monte Carlo Tree Search algorithm, opponent modelling and Q learning machine learning techniques. Reinforcement learning algorithms are the most suitable algorithm for strategic games. This approach uses Q learning algorithm for the implementation of scrabble game where game theory is the science behind the strategy making for the player playing against human. Experimental results suggest that the Q-learning based agent got higher mean scores and also sharpen decision making efficiency, a bit more than the earlier Scrabble gameplay approaches. Game theory strategy can be categorized into two zero sum and non-zero-sum strategy which could be used for various games and Nash equilibrium.

Keywords: Artificial Intelligence, Machine Learning, Monte Carlo Tree Search Algorithm, Scrabble, Q Learning

Introduction

Game strategy used by any player plays a vital role and acts as a deciding factor for winning or losing a game. Researches consistently strives to optimize gameplay, seeking strategies that yield superior outcomes, such as higher scores or an increased likelihood of winning. This optimization endeavour can encompass the development of algorithms, AI players, or machine learning models to facilitate informed decisions during gameplay (Vyas and Gahlot and Vyas, 2022).

Perfect Information vs. Imperfect Information Games: A fundamental distinction exists between these two games is that a PI game is just like Chinese checker, Go etc. which grant players complete awareness of the game state. In contrast, imperfect information games like Scrabble, poker, or most real-world strategic scenarios involve concealed or uncertain information. Research in imperfect information games often centers on probabilistic models and decision-making amidst uncertainty (Gahlot et al., 2023).

Even with the availability of a number of AI based approaches for Scrabble, like Monte Carlo Tree Search, opponent modeling, and game theoretic methods, there are still difficulties in pushing the score higher while keeping the response time low and staying flexible strategically. So, this work, proposes a reinforcement learning framework that uses Q-learning to tune the actual play decisions during Scrabble, in a more direct way.

Comparing Gaming Strategies: Research frequently entails the comparison of diverse gaming strategies to assess their efficacy. In perfect information games, this could encompass the evaluation of opening strategies, mid-game tactics, and endgame techniques. In imperfect information games like Scrabble, it may involve scrutinizing word selection, tile management, and the prediction of opponents' moves based on partial information (Gahlot and Vyas, 2022). The Game theory works on Nash Equilibrium which a study is stating that a person can reach to an ideal result by not deviating from the initial strategy. Consider a player who has opted for an action plan choosing their own actions in context of the game, if we consider the actions taken by players up to this point and find that no player can improve their expected outcome by altering their strategy while the other players maintain their existing strategies, then we can conclude that the current combination of strategy choices represents a Nash equilibrium. Representation learning is a way of automatically finding useful and informative representations of data. It is used in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). Artificial Intelligence is the broad field of creating intelligent machines, Machine Learning is a subset of AI that focuses on learning from data, and Deep Learning is a subset of Machine Learning that uses deep neural networks. Representation learning is a crucial component of all these approaches, as it helps to improve the effectiveness of machine learning algorithms by finding representations of data that are easier to learn (Gahlot et al., 2023; Gahlot and Vyas, 2022).

The hierarchy of technological advancements has put deep learning to the inner most level while artificial intelligence is the outermost part while other two machine learning and representation learning be the next to innermost and outermost (Fig. 1).

Machine learning can be divided into four categories depending upon the usability and user requirement for any application. The categorization is supervised, unsupervised, semi supervised and reinforcement learning.

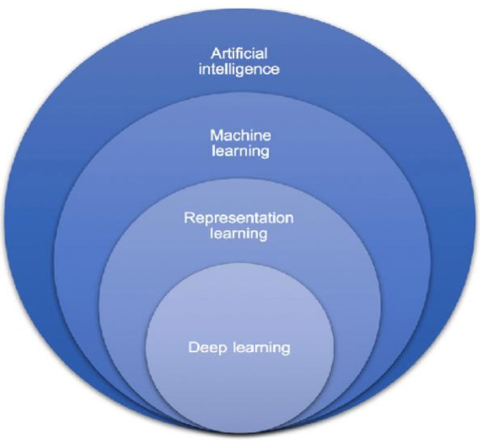

Fig. 1: Hierarchy of various technologies

Each category of machine learning has various algorithms. In supervised learning machine learns by feeding it labelled data as an input and the exact output. In unsupervised learning machine is given unlabeled data and machine must find out hidden patterns to predict the output. Reinforcement learning is a learning method where an agent learns from environment by getting positive and negative feedback. The agent here is an artificially intelligent and learns from all the positive and negative feedback from the environment. This type has been a great recipe for applications where real time data is used whether gaming industry or any other application just as banking industry or healthcare industry. No trained data set or input is provided it learns by its mistakes.

Literature Review

Harrison and Roberts (2013) investigated the use of game analytics combined with an adaptive AI system to improve player retention in Scrabblesque. Their approach employed a computer-controlled opponent that dynamically selected moves to guide players toward game states associated with completing a full session. Their investigation made use of AI game adaptation and game analysis to extend players' maintenance times by up to 11.3%.

Artificial Intelligence (AI) and games have a long-standing and solid relationship, with gaming becoming a well-known application area for AI-driven investigation such game playing, game planning, etc. With the advancement of AI gaming programs that have surpassed human capabilities, decency has become a crucial issue that must be addressed to ensure that a game's attraction can be maintained for future players (Aung et al., 2021). The setting of turn-based games, where the primary player may have a significant advantage over the following player or players (referred to as the upside of drive), may also exacerbate such a problem. By tackling the Komi (remuneration framework), it suggests a creative way to make a game appealing while remaining realistic. The equity of this arrangement is confirmed by applying the framework to the word-rearranging game Scrabble, where equity can be maintained depending on the players' degree of proficiency (Shapiro and Smith, 1988).

Research on 5 pt / game had pros over an expert player and the approach was relevant we conducted correlations between a few sets of systems to give the distinction some context. The benchmark was to use the word highest scoring. An expert who incorporates a static leave assessment into the placement of each move defeats a willing opponent on average by 47 points every game (Aiolli and Palazzi, 2008). When Strong Player faces off against a comparable Static Player, the imitating expert typically prevails by a margin of about 30 points per game. Having the choice to score an additional five points every game on average against such a significant improvement in a player. Five more points every game could have a significant impact in a competitive scenario where standings are based on wins and losses as well as spot on spread. The advantage brought about by adding enemy displays to the games would seem to justify the additional processing cost (Cheng et al., 2017).

The AI struggled in the latter phases and ultimately fell to Quackle as expected. Maven modest final stage AI might not stand a chance against AI. Finally, during mid-games, it was discovered that this approach was not good enough. However, under the conditions of the final stage, this AI struggled. The three-handle look-a head's long execution time was this research's main drawback (Vrabie, 2011). Up until this point, numerous studies have been conducted on games with II Game example Scrabble, and where these have been implemented by many of other online games (Richards and Amir, 2007).

Richards and Amir (2007) is an investigation that works by anticipating the opponent and trading precision for efficiency and ease of calculation considering the Bayes hypothesis. Nevertheless, even with this working on the model, we demonstrate a significant play improvement over the current Scrabble algorithm. The results of above research shows that use of Markov decision gives the estimate of immovable replacements and it is a great approach for AI tools when playing against human (Richards and Amir, 2007).

Comparative Study

Table 1 clearly shows the various scrabble game playing strategies studied in past researches and research gap in each type of techniques used, next research to be done should use a technique in a such a manner that the research gaps so produced in these researches must be eradicated and hence claiming better method or approach for playing board game such as scrabble. The scrabble implementation using MCTS failed to play against expert player (Shapiro and Smith. 1988). Maven a computer player has a win ratio of 70% against a human which could be enhanced with minimum of 5% (Aiolli and Palazzi, 2008) In OM the information gathered for the opposite player strategy cannot be the same for all types of games (Cheng et al., 2017). In Nash Q learning algorithm since it is using Q learning algorithm of reinforcement learning it creates barriers at various game levels (Vrabie, 2011). When deep learning is implemented in scrabble game it requires prior knowledge which is not done in RL algorithms (Abass et al., 2011).

Table 2 shows various RL algorithms used for implementing various perfect information game which typical board games are played by AI against human using various RL techniques.

The RL algorithm used in the games include monte Carlo tree search algorithm, temporal difference, Tree Strap algorithm and monte Carlo algorithms which are typically decision-making algorithm which are the base for any game.

Table 1: Shows drawbacks of Scrabble Game Playing Strategies

S. No.	Scrabble Game Playing Strategies	Drawbacks
1	Monte Carlo Tree Search Algorithm is used for games like GO	At critical situation against expert player, it takes wrong move
2	MAVEN a computer player	Win Ratio is 70% which can be increased
3	Opponent Modelling in imperfect information game	Expectation that the value of information gained through opponent modelling will be the same in all situations
4	Nash Q learning.	It Gives restriction at different stages of gam
5	Deep Reinforcement Learning in perfect-Information Games	Requires prior knowledge of the domain

Table 2: Shows perfect and imperfect information games played using reinforcement algorithm

Program	Input features	Value Fn	RL	Training	Search
Chess Meep	Binary Pieces, Pawns	Linear	TreeStrap	Self-Play/Expert	$\alpha\beta$
Checkers Chinook	Binary Pieces	Linear	TD leaf	Self-Play	$\alpha\beta$
Othello Logistello	Binary Disc configs	Linear	MC	Self-Play	$\alpha\beta$
Backgammon TD Gammon	Binary Num checkers	Neural Network	TD λ	Self-Play	$\alpha\beta$/MC
GO MoGo	Binary Stone Patterns	Linear	TD	Self-Play	MCTS
Scrabble Maven	Binary Letters on rack	Linear	MC	Self-Play	MC Search
Limit Hold'em SmooCT	Binary Card Abstraction	Linear	MCTS	Self-Play	-

Table 3: Comparison of Proposed methodology

Ref	Methods	Advantage	Limitations
(Harrison and Roberts, 2013)	Scrabblesque	Player retention	Not Score Optimization
(Aung et al., 2021)	Fairness Model	Balanced gameplay	Not RL Based
(Richards and Amir, 2007)	Opponent Modeling	Better prediction	Computational cost
Proposed Work	q- Learning	Score maximization	Training Required

Proposed Methodology

The major methodology used to implement the scrabble the word game for enhancing the vocabulary is the use of game theory and reinforcement learning algorithm. Game theory concept Nash equilibrium decides about the level and there is no variation in level between players. Reinforcement learning is the best algorithms of machine learning to implement any game as it works on feedback procedure. Initially we ask for the game beginning and we have trained our player with minimum 10 complete scrabble games such that it knows how to play the game and win against opponent and to apply the best strategy to gain maximum score for every chance of a game play. Q learning algorithm is used such that for the training of the agent it has got enough of the experience for gaining only positive rewards and gets best score from it. The strategy used is to gain maximum reward. Various functions are used to implement the complete game. The functions made in our programming module includes to initialize the board with all blocks, second functions takes all letters of rack as input and board tiles as input and makes all possible words that could be made from those letters now the output words are fed to the third function which calculates the score made by these words and arrange them into highest to lowest score now validity of word from scrabble dictionary and then user place highest score word on board and this continues until all the letters are finished in the bag (Table 3, Fig. 2).

State Space

The state space kind of is the board configuration plus rack letters, the tiles still available, and also the current game score.

Action Space

The action space has all valid word placements that are generated from the rack letters following Scrabble rules, so yeah, every legal placement counts.

Reward Function

Positive rewards get assigned when the move leads to a good, high scoring valid play. Negative rewards are used for things like invalid actions or low scoring actions, depending on what happened there.

Q-Learning Update Rule

The Q-learning update rule is given in Equation:

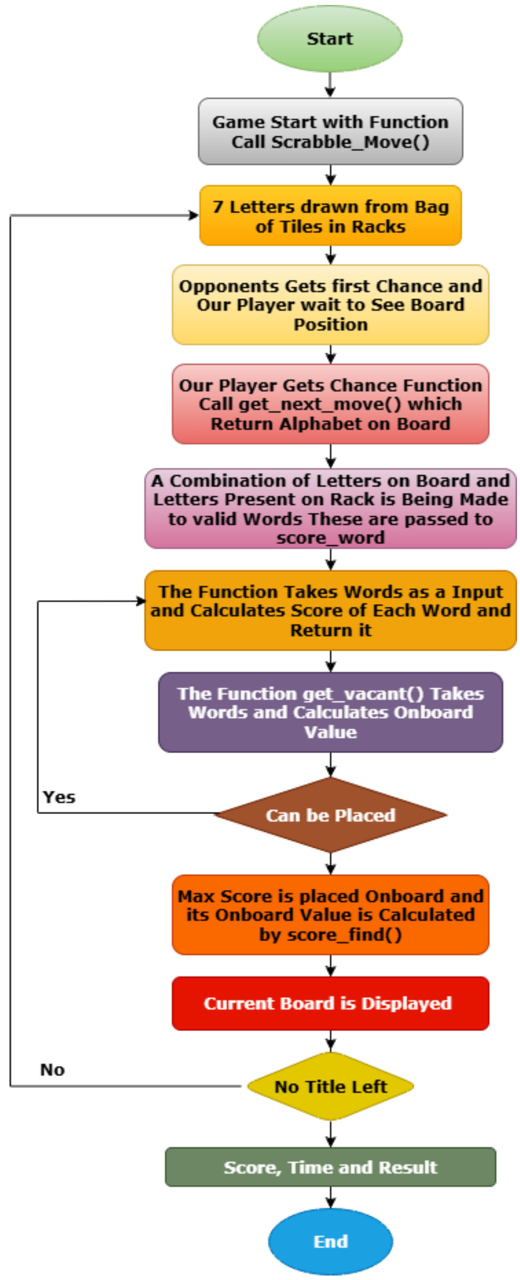

Fig. 2: Flow Chart for the proposed methodology

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right]$$

Before training begins, the Q-values for all state-action pairs are initialized to zero, as shown in Table 4.

Where $Q(s,a)$ denotes the current state-action value, s represents the current state, a denotes the action taken by the agent, r is the immediate reward received, $\alpha$is the learning rate, γ is the discount factor, $s'$is the next state, and $\max_{a'} Q(s',a')$represents the maximum expected future reward obtainable from the next state. The Q-learning algorithm updates the current Q-value using both the immediate reward and the estimated future reward, enabling the agent to learn an optimal policy through repeated interactions with the environment. After the training iterations, the updated Q-values obtained for the different state-action pairs are presented in Table 5. A comparison of Tables 4 and 5 demonstrates how the Q-learning process transforms the initially uniform Q-values into differentiated values that reflect the agent's learned action preferences.

Implementation

Implementation of scrabble game using Reinforcement learning requires to train the agent by showing the optimal moves that can be taken to maximize the score.

Step 1: Define the Environment by setting up the scrabble board with all tiles, multipliers and bonuses and the rules for placing the words on board.

Step2: Define the State space by current board position and opponent tile rack. A 2D array is used to represent a scrabble board with letters placed in each position also initialize a list with bonus values.

Step 3: Define Action Space by specifying the valid actions and the tiles that could be placed.

Step 4: Implement the agent by using Q learning algorithm initialize training loop.

Initializing the agent parameter and hyperparameter.

Generate Episodes by starting self play or rule-based opponent.

After each play update the agent's policy and value function.

Design Reward Function with positive value for top score and negative value for low score.

Reward the agent with positive or negative value.

Run the loop until satisfactory level is achieved.

Step 5: Evaluate the trained agent's performance against human or another AI opponent.

Step 6: Fine tune the agent's hyperparameters.

$$Q(a,s) \leftarrow (1-a).Q(a,s) + a(r + y \max a' Q(s',a'))$$

Equation for Q learning to update the Q table

$Q(a,s)$ defines the 's' state and 'a' action values

r defines immediate reward

α defines learning rate

γ defines discount factor

maxa'Q(s',a') defines maximum value for the next state

Table 4: Initial Q table

	Action 1	Action 2	Action 3
$State_1$	o	o	o
$State_2$	o	o	o
$State_3$	o	o	o
$State_4$	o	o	o
$State_1$	o	o	o

Table 5: Final Q table

	Action 1	Action 2	Action 3
$State_1$	0	6	8
$State_2$	4	1	3
$State_3$	0	2	0
$State_4$	4	3	7
$State_1$	0	6	8

Results

Fig. 3. shows the score earned by the suggested Q-learning Scrabble agent across ten separate gameplay sessions. In the best run, Game 6 reached a top score of 419, and then Game 7 ended up as the worst one with 161 points. If you look at the mean result over all ten games, it lands at 264.4. This spread in outcomes basically highlights how changeable Scrabble is, and also suggests the agent can pick up more solid scoring behaviors over time via reinforcement learning, not just trial and error.

In general, the findings imply that this Q-learning method can deliver fairly competitive play and improve score taking decisions even though the game involves imperfect information, so things are rarely fully clear from the start.

Results shows when AI based different scrabble game were played against human, they showed the above scores and the graph in above figure shows the score analysis of each strategy depicting that the agent which played using Q learning algorithm was showing best results.

The above graph depicts various RL strategy playing scrabble game with their respective average time for responding to each chance. This shows that Nash Equilibrium strategy could give very less response time for the AI player against computer or human.

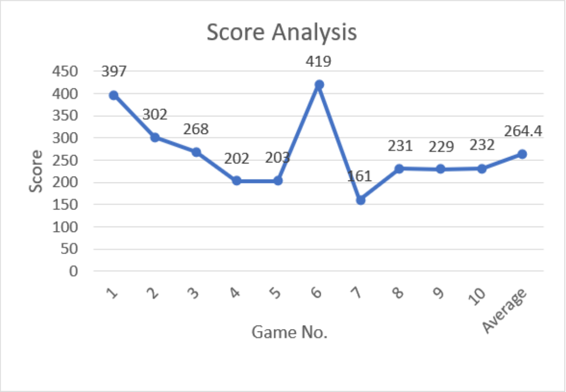

Fig. 3: Score analysis of various techniques playing scrabble game

Conclusion

The study presented a reinforcement learning framework that aims at better gameplay optimization in Scrabble, and it uses Q-learning, which is pretty much the core algorithm. The idea is that an intelligent agent can learn to play in a way that gets higher scores, mainly through reward driven interaction with the game environment. This research is intendant towards finding the research gaps in various researches being done on machine learning approaches, game theory and how this collaboration could increase the score and hence the win ratio in Scrabble Games. This research will mainly focus on improving the intelligence of computer scrabble game. Comparing the researches done previously are specialized in prediction of the strategies being implemented by other player while if focus is on enhancing the and upgrading the agent would be more helpful as more skill full player would be winning the game with higher scores against a computer. After rigorous readings conclusion is that there is a lot of scope of work yet to be done for imperfect information game such as Scrabble.

Future Work

Future research could go into building a more or less fully autonomous Scrabble player agent, using stronger reinforcement learning tools like Deep Q-Networks (DQN), plus some opponent modeling too. There is room to push the win ratio upward, tweak the reasoning and strategic choices, cut down on the response duration, and then test the whole system against seasoned human players. This should happen in tougher, more crowded game settings, because in those worlds the evaluation feels more real and demanding.

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Author’s Contributions

Mohd Kaleem and Kanta Prasad Sharma: Contributed to conceptualization and problem identification.

Tapsi Nagpal and Umakant Ahirwar: Carried out the literature review, methodology design, and data collection.

Girish Paliwal: Was responsible for the implementation of the proposed model/algorithm and experimentation.

Vijay Mohan Shrimal: Contributed to data analysis, result interpretation, and validation of outcomes.

Ethics

Authors should address any ethical issues that may arise after the publication of this manuscript.

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