

A Genetic Approach to the Formulation of Tetris Engine

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Abstract

Complete this section for D4.

The *Abstract* should be at most 150 words long, and should summarize briefly what your project is about. This includes the motivation for the problem (2-3 sentences), the problem you tackled (2-3 sentences), and your main results (1-2 sentences).

Introduction

• Motivations

With the great triumph of AlphaGo in 2016, more and more researchers are interested in using machine learning techniques to solve more advanced and complicated games such as StarCraft II. However, in the authors' opinion, it also provides us with an invaluable opportunity to revisit some of the traditional video games, where we aim for more reliable and satisfying results. Consequently, this project's primary motivation is to introduce, implement, and compare several different approaches to tackle the Tetris, a tile-matching video game with enduring appeal and popularity. In brief, Tetris is a tile-matching video game where the player will rotate and place seven different kinds of Tetrominos on top of each other. Horizontal lines will be cleaned up once they are complete, and a score will be awarded for that. This game's ultimate goal is to achieve as many marks as possible before the pieces reach the top of the game board, and therefore, there is no victory in this game.

Solving Tetris is a crucial and intriguing topic due to the two reasons below. On the one hand, Tetris is essentially an extraordinary optimization problem because each game will end no matter how well the Tetrominos are placed (Burgiel 1997). As a result, there is no such thing as perfect solutions to Tetris and there is always room to improve. On the other hand, the analyses and comparisons mentioned in this report are not limited to Tetris only, where we could broaden them to real-life problems, such as self-driving cars and robotics, with appropriate modifications on the architectures introduced in this article.

Finally, solving a relatively simple game like Tetris will help us better understand the related Reinforcement

Learning models. One of the main problems the machine learning community faces is the lack of explainability and interpretability for most of the models. The direct analyses on most of the recent models, such as AlphaGo and AlphaZero, are notoriously complicated and challenging, but with a more straightforward and simplified setup like Tetris, it gives us more opportunities to have a more in-depth insight into what is happening under the hood. Consequently, the results from simple setups will contribute to a better and deeper understanding of the more complex models.

• Methodologies

The problem we are trying to solve is to design an agent that could achieve as many scores as possible in the Tetris game. We will implement three algorithms, including the baseline method, as shown below.

- First and foremost, we built a Tetris interface for both visualization and training purposes. For the sake of communication with our models, the interface is written in Python and it will support two basic functionalities:
 - * Generating all the successors for current state.
 - * Calculating score or reward for each state.
- Next, we will solve the problem using a hand-crafted agent. Inspired by Bertsekas and Tsitsiklis's paper (Bertsekas and Tsitsiklis 1996), we will manually chose the weights for 4 most representative state features: the number of holes, the height of the highest column, the height of each column, and the difference in height between consecutive columns. This approach is based mainly on the heuristic search algorithm and involves a lot of trails-and-errors. The result serves as the benchmark for the project using the evaluation metrics mentioned below.
- On top of that, we will also tackle the problem using local search algorithm. The main idea is to use a genetic algorithm to automatically find an optimal weight combination for 9 state features, where the detailed description for the features could be found in the Methodology section.
- Ultimately, we will solve the problem with reinforcement learning. The main idea is that we will build and

train a deep Q-network (DQN) to evaluate all the successor states of the current state. More precisely, the DQN will receive a bitmap representation of successor and output a non-negative number represents the score for it. After that, the agent will choose the successor with the highest score with probability ϵ and otherwise, it will select a random successor.

As for the evaluation metric, we will use the number of lines cleaned up before game over as our primary metric so that we could compare the three methods with each other as well as implementations from other papers. One thing worth mention is that in the DQN training, we won't directly use the evaluation metric mentioned above as the reward because it is too sparse. Instead, we will design a reward that is positively correlated with the evaluation metrics. More concretely, we will use the following rewarding scheme:

- Game over gives -100 .
- Cleaning up k lines gives $10k^2$.
- Safely landing a piece gives 1 .

• Complete this bullet point for D4.

Emphasize your contributions. How should we interpret the results? Why should people care about this work? Does this project introduce any novel techniques or reveal any unexpected findings? In bullet point forms, list 3-4 key contributions of your project.

Related Work

There is a number of algorithms about Tetris so far. Most algorithms for Tetris use features and a linear evaluation function (Algorta and Simsek 2019). The algorithms define multiple features and assign a weight value to each of the features. For a specific state with an existing Tetromino, it will use the evaluation function to calculate the evaluation value according to the weight of the features for every possible states. And then a "best" placement of the Tetromino will be picked according to the evaluation value.

Tracing back to 1996, J.N. Tsitsiklis and B. Van Roy formulated Tetris as a Markov Decision problem. They introduced Feature-Based Method for Large Scale Dynamic Programming. The algorithm introduced two features, which were the number of "holes" and the height of the tallest column. Each state will be represented as a two-hundred-dimensional binary vector since the Tetris board is form by 10×20 grids. And a seven-dimentional bianry vector will represent the current falling Tetromino since there are seven type of Tetrominos in total. The algorithm can eliminate 31 rows on average of a hundred games (Tsitsiklis and Roy 1996).

Later on, more features have been taken into consideration. For example, peak height, landing height, number of holes, row transition, column transition and eroded piece cells (Wei-Tze Tsai and Yu 2013).

These features were identified by the best artificial Tetris player until 2008 and introduced evalutation function: $-4 \times \text{holes} - \text{cumulative cells} - \text{row transitions} - \text{column transitions} - \text{landing height} + \text{eroded cells}$

(Algorta and Simsek 2019). However, most algorithm will perform a row elimination whenever it is possible. This is not optimal in the long term because there could be some state that multiple rows can be eliminated at once (Wei-Tze Tsai and Yu 2013).

Tsai, Yen, Ma and Yu implemented "Tetris A.I.". Scores will be rewarded if a I-Tetromino is dropped and 4 rows are eliminated. The main idea is to make this kind of move as many as possible. The solution for this is to stack on the 9 columns and remain the left column empty. As long as an I-Tetromino appears, it will be drop at that seperate column to eliminate multiple rows (Wei-Tze Tsai and Yu 2013).

Moreover, they also implemented another model called "Two Wide Combo A.I.", which is a little bit more complex than the previous algorithms. It breaks the process into two parts. One is to "Stack" on the left eight columns by using BFS, and the other part is "Combo", which is to eliminate rows consecutively to earn Combo Bonus by dropping Tetrominos into the rest two columns (Wei-Tze Tsai and Yu 2013).

The use of generic algorithm provides a new way which is worth taking into consideration. In 2006, Szita and Lorincz implemented cross-entropy algorithm. New features were introduced and for each feature, multiple games were played. It took the mean and standard deviation of the best weight of the linear policy that maximize the score and generated a new generation of policies (Algorta and Simsek 2019).

Back in 2003, Thomas Grtner, Kurt Driessens and Jan Ramon introduced a new approach to Tetris optimization(Gärtner, Driessens, and Ramon 2003). What's innovative in this paper is that researchers primarily used Relational Reinforcement Learning (RRL), training the network with Gaussian processes and graph kernels. Relational Reinforcement Learning advances traditional Reinforcement Learning by integrating with a relational learning programming which is also known as inductive logic programming. The use of Gaussian processes is to make probabilistic predictions and allow the agent to incrementally perform learning tasks. On the other hand, graph kernels help represent various states and actions during training process in a more structural way, which greatly facilitates learning. Compared to some previous RRL models which train data based on techniques such as decision trees, this approach has proven to be more effective.

In 2016, researcher at Stanford University continued to optimize Tetris engine performance using Reinforcement Learning (Matt Stevens 2016). They used a notation called Q function. This function evaluate actions taken by the AI at various stages/states during the game; the value of this Q function tells us what the best next action is. Researchers attempted to improve convergence of Q function with the aid of heuristic functions. This method yields the best performance when combined with grouping actions. Basically, grouping actions means the entire sequence of actions a single piece take as it drops to the bottom whereas a single action is just one movement of the piece such as one space to the left. Although grouped actions increase game length compared to single actions, they achieved a much high game

score. Another technique that significantly boosts the performance is transfer learning. Transfer learning effectively scores an average of two lines per game, compared to no lines for learning from scratch. The final technique used is called prioritized sweeping. Prioritized sweeping involves calculating a priority value. Based on that value, the researchers sampled actions based on probabilities proportionally to their priorities. This technique solves several problems, for example, the issue that certain actions gotten drastically under-represented in the experience dataset.

Methodology

Handcrafted Agent

Our first approach is a manually trial-and-error approach, or more precisely, we will assign a weight manually for each feature below according to our intuition and experiment results. Then, for each generated successor states, we will always choose the state with the lowest heuristic value, which is calculated based on a summation of the four weighted features. Here are the four features we are going to use and a rationale for choosing them:

1. number of lines cleared¹

This feature faithfully reflects our evaluation metric since we will achieve scores only by cleaning lines.

2. number of holes

The holes in the Tetris game are particularly harmful because, in order to clean the line containing a hole, we need to clean up all the lines above that hole.

3. sum of the difference of height between adjacent columns

The "gaps" in the board make it harder to clear rows simply because the Tetrimonos are generated randomly, and those "gaps" are not likely to be filled perfectly by the next Tetrimono.

4. maximum height

The higher the board is, the closer it is to the "ceiling" (vertical limit of the board), which means there may be fewer steps to play before the game terminates.

We would run simulations consecutively and record the performance associated with the weight combination. Based on the results, we would adjust one or more weight values and use them in the next simulation until the game behaves rationally in human criterion.

An advantage of this handcrafted approach is that we are somewhat informed of what features should be rewarded and penalized. Compared to adjust the weight using algorithms, manually adjustment will give us a better understanding and intuition about the game during the weight adjustment process.

¹Note that this is special compared with other features because we want it to be as large as possible, so we will assign a negative weight to it.

Local Search Agent

Essentially, in a handcrafted agent approach, human decisions are used to adjust weight combinations during every iteration of the simulation. Such an algorithm obviously has some limitations because a lot of possible adjustments to the weights can not be tested/explored. Moreover, we only use four features in the handcrafted agent, which may not be sufficiently representative. As a result, we need an approach that takes more underlying features into consideration, together with a more systematical way to improve weight combinations other than just by intuition. With these goals bearing in mind, we propose a second approach that utilized the genetic algorithm, a powerful local search algorithm.

In the genetic algorithm approach, we would use a feature set that includes a total of 10 features. These features are:

1. number of lines cleared
2. number of holes
3. sum of the difference of height between adjacent columns
4. maximum height
5. number of blocks currently on the board
6. number of rows with at least a hole in it
7. max height difference between the lowest column and highest column
8. number of cells that is not filled with no blocks above it and two horizontal neighbors filled
9. the height where the highest hole is located
10. number of occupied rows which is above the highest hole such that if removed, the highest hole is no longer a hole

Now that once we have our feature set, we would construct our genetic algorithm approach start by defining the following terms:

- **Chromosome:** An array of 10 numbers representing our weights combination, each number is ranged from 0 to 1
- **Fitness:** How many lines are cleared before the game is terminated
- **Selection:** After ranking each state based on fitness score, we would remove p percent of states with low fitness scores and use remaining states as parents for the next generation
- **Crossover:** Take a combination of weights among the remaining parents and make it the chromosome for the children
- **Mutation:** After crossover, one random weight value in the chromosome of the child state will be mutated with a certain probability q

The game would start by generating random chromosomes for M children, and for each of these children, we will run N simulations on it. The average lines cleaned will be recorded for each child and will be used as the fitness score for them. Next, we would begin our selection process, which would give us a number of parent states. For each

group of parents, we would perform crossover and mutation operations to get us children of the next generation. Then, for each child in this generation, we would start the above process all over again. That is, we would run simulation, record fitness, remove least fit offspring, and generate successors. We would stop the game until there is no significant improvement in performance between the parents and the children. Finally, we will choose the child with the highest fitness score and use its chromosome as our final weight combination.

One important thing worth noting is the implementation of crossover. When determining the exact combination of chromosome from the parent states, we would consider the fitness scores of parents because if one parent has a higher fitness score than the other, the former chromosome should have been more optimal than the latter one. Therefore, we would want the child to "inherit" more from the first parent. Let's assume the first parent's fitness score is f_1 and that of second parent is f_2 . Assuming that $f_1 \geq f_2$, then we define the combination as follows:

- if $\frac{f_1}{f_2} = 1$, we will randomly take 5 weights from the first parent and fill the remaining weights from the second parent
- if $0 < \frac{f_1}{f_2} - 1 \leq 0.25$, we will do a 6:4 sampling
- if $0.25 < \frac{f_1}{f_2} - 1 \leq 0.5$, we will do a 7:3 sampling
- if $0.5 < \frac{f_1}{f_2} - 1 \leq 0.75$, we will do a 8:2 sampling
- if $0.75 < \frac{f_1}{f_2} - 1$, we will do a 9:1 sampling

In conclusion, in the genetic algorithm approach, we eliminate a lot of human assumptions. That is, what weight value should be changed, and by how much. We would also take into consideration more features that may further eliminate human assumptions of which feature could have an underlying impact on the game-play or not. Despite the amount of computation with this approach, we are more likely to find an optimal weight combination compared to a handcrafted agent.

Reinforcement Learning Agent

The genetic algorithm mentioned above is intelligent in the sense that it will automatically find optimal weight combinations. However, notice that it is still not perfect because the state features are always chosen by humans, and they are not necessarily representative. More concretely, we may lose some information since we will represent all the successors' states, which is of size 20×10 , using only nine features. Thus, we will develop a new algorithm that eliminates human-chosen features and finds a feasible representation itself.

As a result, we naturally lean towards the fields of reinforcement learning and will start with the Q-learning introduced by Chris Watkins in 1989. The detailed deduction and convergence proof are pretty complicated and are out of the scope of this report. However, the final results of Q-learning are incredibly similar to dynamic programming, where we

maintain a Q-table with current states s_i as column and available actions a_j as rows:

	a_0	a_1	\dots	a_n
s_0	0.91	0.65	\dots	0.45
s_1	0.86	0.14	\dots	0.19
\vdots	\vdots	\vdots	\ddots	\vdots
s_m	0.26	0.61	\dots	0.27

Table 1: Q-table example with random initialization

And for each step, we will update the entry (s_t, a_t) using the formula

$$Q(s_t, a_t) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_a Q(s_{t+1}, a) \right)$$

where we have two hyper-parameters embedded in this formula:

- α : learning rate, which determines to what extent newly acquired information overrides old information.
- γ : discount factor, which determines the importance of future rewards.²

On top of that, we also need to manually determine three important setups:

- s_i : all the possible states for the environment represented by a 20×10 bitmap.
- a_j : all the possible actions a player can take for a state.
- r_t : reward received when moving from the state s_t to s_{t+1} and is determined by the reward function.

With all these hyper-parameters and setups, we will let the agent interact with the environment on its own. At each state, the agent will always choose to perform the action with the highest Q-value and update the Q-table according to the updating formula.³ We will stop Q-learning until the agent completes the game, and we will repeat this process for large enough epochs so that the Q-table converges.

Now, we will begin with a naive adaptation to the Tetris by defining states to be all the possible game states for a Tetris board of size 20×10 and defining actions to be the set $\{\text{clockwise rotation, counter-clockwise rotation, left, right, down}\}$.

Theoretically, we could tackle this Tetris problem directly using the Q-learning setups mentioned above, but we are facing two severe hindrances:

1. The reward is very sparse because all the actions except down are perfectly reversible. For example, *left* can be

²The term $\max_a Q(s_{t+1}, a)$ represents the estimation of the optimal future value.

³Here, it is not always true that the agent will perform the action with the highest Q-value. Some techniques like ϵ -greedy algorithm will choose the optimal action with probability ϵ and a random walk otherwise. We will talk more about this in the experimental design section.

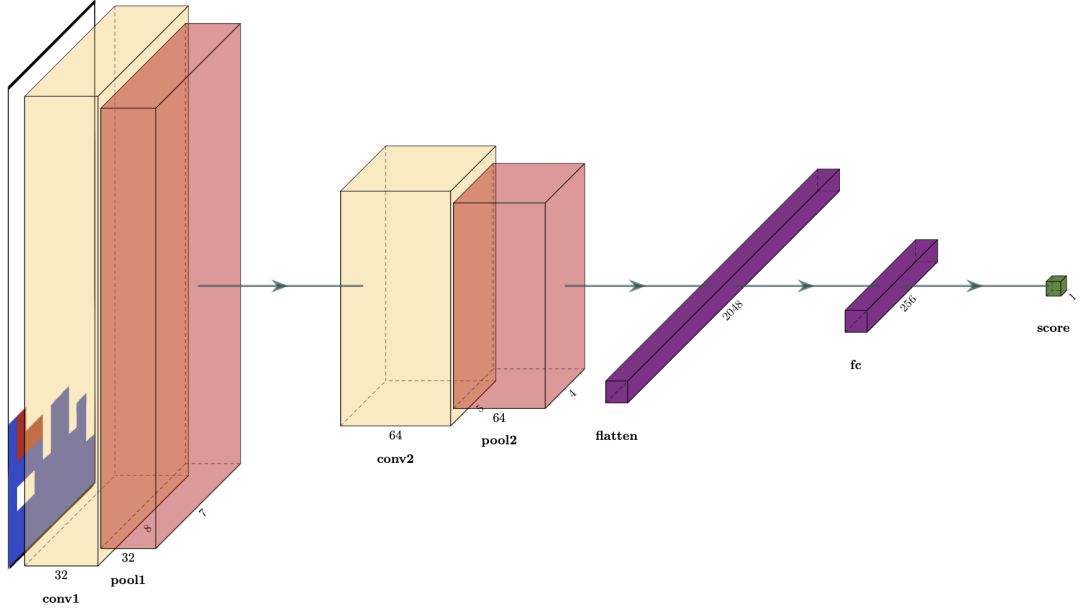


Figure 1: Deep Q-network architecture

reversed by *right*, and *clockwise rotation* can be reversed by *counter-clockwise rotation*. As a result, in the exploration stage, it will take the agent a long time before it can achieve a reward⁴, which is particularly bad for training.

2. Furthermore, according to Phon-Amnuaisuk’s paper, the number of stable states for a 20×10 Tetris board is in the order of 10^{60} (Phon-Amnuaisuk 2015), which means our Q-table will be of size approximately 5×10^{60} . This table is way too large to store in RAM and the training time for such a large table is also unbearable.

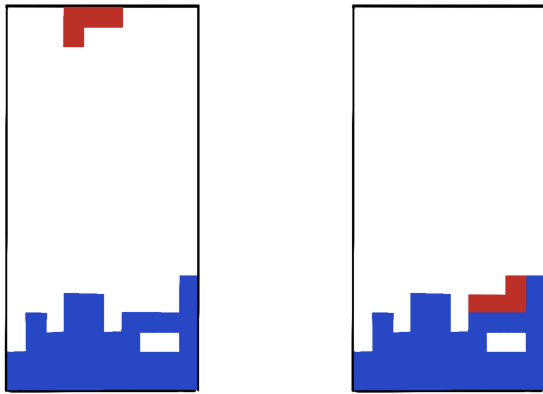


Figure 2: Grouped action example

⁴Notice that according to the Table 3, we will only get a reward when we place a Tetromino so we won’t get anything during the placement process.

Now, we will conquer these two hindrances and develop a practical architecture for this problem. For the first one, inspired by Stevens’s idea of *grouped action* (Stevens 2016), we can leverage the successor function from the genetic algorithm and reduce the dimension of Q-table. More precisely, instead of defining action a_i to be one of the 5 single moves, we will use a *grouped action* to represent a sequence of moves until the current Tetromino is landing.⁵ For example, if we got an L-shape Tetromino as shown in Figure 2, one potential *grouped action* will be $\{left \times 4, clockwise rotation \times 2, down \times 12\}$, which is essentially the successor function from the genetic algorithm.

With the new definition of *grouped action*, we can reconstruct our Q-table and rewrite our updating formula. Notice that because after each grouped action, it’s guaranteed to be a stable state (i.e., there is no floating Tetromino), we can simplify the two-dimensional Q-table into one-dimensional:

s_0	s_1	\dots	s_{m-1}	s_m
0.91	0.65	\dots	0.45	0.19

Table 2: New Q-table with random initialization

with the modified updating formula:

$$Q(s_t) \leftarrow (1 - \alpha)Q(s_t) + \alpha \left(r_t + \gamma \max_{s_i \in \text{successor}(s_t)} Q(s_i) \right)$$

With the reconstructed Q-table and modified updating formula, now for each state, the agent will choose the successor

⁵In other words, each *grouped action* refers to a final placement for a specific Tetromino.

with the highest Q-value instead of a specific action. This successfully solves the sparse reward problem because now, after each grouped action, we will always get a non-zero reward. However, this setup inherits the drawback of requiring enormous storage space and training time because the number of states remains 10^{60} .

To overcome the second hindrance, we need to understand why we have so many states in our Q-table. The problem lies in the fact that we have 20×10 cells in the game board, and the number of possible states is exponential in the number of cells. This situation reminds us of how we encode images during image classification, and naturally, we will consider using Convolutional Neural Networks (CNN) to encoding our state (i.e., a 20×10 bitmap). This idea is first introduced by Google DeepMind in the paper Playing Atari with Deep Reinforcement Learning (Mnih et al. 2013), and we will adapt this idea to Tetris to come up with the architecture as shown in Figure 1.

Notice that this Deep Q-network (DQN) will take a 20×10 bitmap as input and output a non-negative real number as the score for that bitmap. This behavior is essentially the same as what we did in Q-learning except that the DQN will generate the score on the fly while Q-learning will merely look up the score. At its core, the DQN is trying to approximate the Q-table using a reasonable amount of time and space.

Compared with other CNN architecture, our DQN is relatively small and straightforward, mainly because of the tiny input size. Here is a summary for each layer in Figure 1:

- **conv1**: a convolutional layer with filter size 3×3 , output channel size 32, and leaky ReLU activation function.
- **pool1**: a max-pooling layer with filter size 2×2 .
- **conv2**: an identical layer as **conv1** except that the output channel size to be 64.
- **pool2**: an identical layer as **pool1**.
- **flatten**: this is simply a flattened version of the **pool2** feature map.
- **fc**: this is a fully connected layer of size 256 with ReLU activation function.
- **score**: this is a fully connected layer of size 1 with ReLU activation function.

On top of that, the pseudo-code to train the DQN is shown in Figure 3.

In summary, DQN architecture successfully solves the problems of sparse reward and enormous states, which gives us an efficient and effective estimation for the original Q-learning in Table 1. Moreover, with CNN’s powerful encoding capability, we don’t need to choose the features manually, and the architecture will automatically find the optimal features during backpropagation. As a result, we can say that DQN architecture has the potential to outperform the genetic algorithm.

```

1 Function train(cur, DQN) :
2   Input: cur is current game state and DQN is
      the network, which supports two operations
      predict and fit
3   Output: nex is the next game state
4   states  $\leftarrow$  successor(cur)
5   maxQ  $\leftarrow$  0, reward  $\leftarrow$  0, maxState  $\leftarrow$  None
6   for state in states do
7     score  $\leftarrow$  DQN.predict(state)
8     if score > maxQ then
9       maxQ  $\leftarrow$  score
10      reward  $\leftarrow$  reward(state)
11      maxState  $\leftarrow$  state
12    end
13  end
14  Q'  $\leftarrow$   $(1-\alpha) \cdot \text{maxQ} + \alpha \cdot (\text{reward} + \gamma \cdot \text{maxQ})$ 
15  DQN.fit(maxState, Q')
16  return maxState

```

Figure 3: Pseudo-code for Training

Results

Environmental Setup

For the implementation of the game Tetris, we referenced the Tetris-AI implementation (Faria 2019). The board is 20×10 , and each Tetromino is a list of four positions that it occupies. Initially, it will generate the appearance of Tetrominos in random order. The state will be defined as a 20×10 matrix, where each entry could be one of 0, 1, or 2, represents the empty block, the occupied block, and the block occupied by the current Tetromino, respectively. For each state, all the features needed by handcrafted and local search agents will be collected, and we will use them to calculate the heuristic.

We need to come up with bitmaps for all the successor states. Please describe how we will generate the successor state.

For the successor function, instead of returning all the successor’s board state, it only returns a dictionary where the key is a tuple containing the horizontal offset of the Tetromino and the rotation. The value is the value of all the features of the state. The model will select the “best” state and then update the board state according to the horizontal offset and the rotation of the Tetromino.

Evaluation Metrics

According to previous researches and the game mechanism, we have two reasonable metrics to choose from. One is to count the total number of Tetromino dropped before the game ends. And the other is to count the number of lines cleared before the game ends. They both sound reasonable, but we would like to use the second metric for our evaluation. The number of Tetromino dropped somehow describes “how long” does the game played, but this does not indicate “how good” the model is. It is still possible to fill the board without clear a single line, and it is also possible to clear several lines with very few Tetromino dropped. In order to

make it live longer, the purpose is to remove lines whenever it could and clear lines as much as possible. So we pick the number of lines cleared as our evaluation metrics. In general, the score of the game is highly related to the number of lines cleared. The more lines cleared, the more score we will get finally, so it means the model plays "better". On the other hand, according to the previous researches on Tetris agent (Algorta and Simsek 2019), the rules and the way that the score is rewarded can be different. We finally want to compare our model with the agents that already exist. In order to make a fair comparison, all of the agents will use the same evaluation metric, which is the number of lines cleared before a game ends so that we could tell which model has a better performance in the game.

One thing worth mentioning about the evaluation metric is that we will simultaneously use two metrics when training the Reinforcement Learning agent. The first metric is the one mentioned above, and it will be used as the primary standard to compare the performance of different hyperparameter combinations during validation. On top of that, this metric will also be used to compare with other algorithms mentioned in this paper as well as results from other papers. However, one problem with the primary metric is that its rewards are very sparse, where the agent needs to wait for several Tetrominos before it could clean a line and achieve one mark. This problem is particularly bad for training a DQN because, without frequent rewards, it is difficult for the network to learn anything from backpropagation. Therefore, we decided to reshape the primary metric into the following table.

Situation	Reward
Game over	-100
Clean up k lines	$10 \times k^2$
Safely landing a piece	1

Table 3: Reward Function

Note that by design, the new metric is positively correlated with the primary metric in the sense that both of them encourage cleaning as many lines as possible. However, the new metric will also introduce a relatively small reward (compared with cleaning a line) for safely landing a Tetromino for the sake of more frequent simulation for backpropagation. Meanwhile, this metric also introduces a substantial penalty for losing the game to produce strong negative feedbacks for the network.

Experimental Designs

As mentioned above, since we implemented a Tetris environment, we can say that we have unlimited training data. Therefore, we can train our algorithm as many games as we want as long as time permits.

• Handcrafted Agent

The experimental design for the handcrafted agent is relatively straight-forward. Since we are merely relying on our observation and intuition, we need to keep track of each game manually. Therefore, we will use a training set

of 3 games, a validation set of 100 games, and a test set of another 100 games. The training process is rather simple. We will watch the agent playing for three rounds (training) and let it play for itself for another 100 rounds (validation). Meanwhile, we will analyze its mistakes during training and calculate the average score for the validation. Then, according to the analysis, we will adjust the weights correspondingly, and if the combination of the new weights yields a better validation score, we will use it. Otherwise, we will try some other updates, and if we can't improve the validation result anymore, we will stop. Finally, we will use the best weights combination as our final result and test it on another 100 games.

As for the weight initialization, we will start with the weights $(-1s, 3, 2, 4)$ because we think ...

Please give a reason for such initialization

• Local Search Agent

Again, we will decide on the train-validation split first. Since we don't need to manipulate the weights manually for the local search agent, we will train the agent on more games. We are going to train the agent for 1,000 games⁶, validate on 100 games, and eventually test on another 100 games.

As mentioned in the Methodology section, the experiment would have three main hyperparameters, namely selection probability p , mutation probability q , and the number of children M . Since the number of hyperparameters are tolerable, we will do a complete hyperparameter search on these values:

- **Selection probability:** $p \in \{0.4, 0.5, 0.6\}$
- **Mutation probability:** $q \in \{0.01, 0.1\}$
- **Number of children:** $M \in \{50, 100\}$

More precisely, we will train on $3 \times 2 \times 2 = 12$ different combinations of hyperparameters and find the one with highest validation score. After this complete search, we will perform some further explorations on a more precise level. For example, if we found $p = 0.5, q = 0.1, M = 100$ to be the best-performed combination of hyperparameters, we will do another complete search on

- **Selection probability:** $p \in \{0.45, 0.5, 0.5\}$
- **Mutation probability:** $q \in \{0.08, 0.12\}$
- **Number of children:** $M \in \{80, 120\}$

We may repeat this "zoom in" search several times if time permits and at last, we will test the best model on another 100 games to compare it with benchmark as well as the reinforcement learning agent.

In my opinion, the rationale for the complete search is that we don't have a proper initialization to start on, so we have no choice but to begin with a broad range of hyperparameters. After the first exploration, we will get some ideas about the optimal hyperparameters, and we could aim towards a more precise decision. This is a time-efficient way of finding the optimal hyperparameters when we don't have any prior knowledge.

⁶This is essentially the N we mentioned in Methodology.

• Reinforcement Learning Agent

Therefore, for each hyperparameter combination, we will train the network for 1,000 games, validate for 100 games, where we will measure both metrics during training but only calculate the primary metric for validation. After we find the optimal hyperparameters, we will test the final architecture for 100 games and use this result to compare with others. As for the hyperparameter, we will leverage results from Stevens’s paper (Stevens 2016) and initialize our hyperparameters using their suggestions as follow.

- **Optimizer:** *RMSProp*
- **Learning rate:** $\alpha = 2 \times 10^{-6}$
- **Discount rate:** $\gamma = 0.9$
- **Regularization:** Batch normalization and dropout with a retention probability of 0.75

However, since our reward function, DQN architecture, and environment implementation are different from theirs, we need to adjust our hyperparameters according to the validation results.

Now, for the training process, there are two details worth mentioning.

1. ϵ -greedy Algorithm

The tradeoff between exploration and exploitation is one of the most critical challenges for most of the reinforcement learning problem, and our DQN is no exception. Note that according to the setups mentioned in the Methodology section, the only chance for our network to explore comes from the random initialization of the system, and once it finds a solution, exploitation will dominate exploration because we always choose the successor with the highest score. This is not ideal because we may miss some potential shortcuts⁷, and as a result, we will apply the ϵ -greedy algorithm during the training phase. In brief, it will stick to the optimal successor with a decaying probability ϵ and randomly choose a successor otherwise (Tokic 2010). Thus, we will update the training algorithm in Figure 4.

Note that we need a describes ϵ because we want to explore more in the beginning (in our case, we will use $\epsilon = 0.5$), and as we approach the end of the training phase, we want to exploit more (which means $\delta = \frac{\epsilon}{\# \text{ of training}} = \frac{0.5}{1000} = 0.0005$).⁸

2. Training by Part

According to the experiment results from Steven’s paper, another challenge we will face during the training is that each game will last for a long time, mainly because of the large 20×10 game board. Therefore, we will solve this problem by training our network part by part, where we will decompose the training process into three parts for the sake of time efficiency as follow:

- Firstly, we will train the DQN on a 5×10 game board for 400 epochs.

⁷In other words, the selected successor may not be optimal for long-term.

⁸This gives two extra hyperparameters that need to be adjusted.

```

1 Function train(cur, DQN):
2   states  $\leftarrow$  successor(cur)
3   maxQ  $\leftarrow$  0, reward  $\leftarrow$  0, maxState  $\leftarrow$  None
4   for state in states do
5     score  $\leftarrow$  DQN.predict(state)
6     if score > maxQ then
7       maxQ  $\leftarrow$  score
8       reward  $\leftarrow$  reward(state)
9       maxState  $\leftarrow$  state
10    end
11  end
12
13  //  $\epsilon$ -greedy algorithm
14  p  $\leftarrow$  uniform(0,1)
15  if p >  $\epsilon$  then
16    maxState  $\leftarrow$  random(states)
17    maxQ  $\leftarrow$  DQN.predict(maxState)
18    reward  $\leftarrow$  reward(maxState)
19  end
20   $\epsilon \leftarrow \epsilon - \delta$  //  $\epsilon$  decaying
21
22  Q'  $\leftarrow$   $(1-\alpha) \cdot \text{maxQ} + \alpha \cdot (\text{reward} + \gamma \cdot \text{maxQ})$ 
23  DQN.fit(maxState, Q')
24  return maxState

```

Figure 4: Pseudo-code for Training with ϵ -greedy

- Then, we will train it on a 10×10 for another 400 epochs.
- Finally, we will train it on the full board (20×10) for 200 epochs.

This will give us a total of 1,000 training epochs, but this design should be much faster than trained directly on the full board because the time needed for each game is shortened. However, the sequential training process is not as easy as it sounds like, and the main problem here is the difference in length of the flattened vectors:

Input Size	Flattened Vector Size
5×10	512
10×10	1024
20×10	2048

Table 4: Flattened vector sizes for different input

The difference between these vectors’ sizes will mess up the weight matrix of DQN architecture, so we need to initialize the weight matrix manually when we change the input size. More precisely, whenever we increase the input size, we will initialize a new fully-connected layer and copy the previous network’s weights to half of the current network. A visualization for 5×10 to 10×10 is shown in Figure 5, where we initialize the bottom half (shown in blue) of the weight matrix with the previous weights and randomly

initialize the upper half of the weight matrix (shown in green).

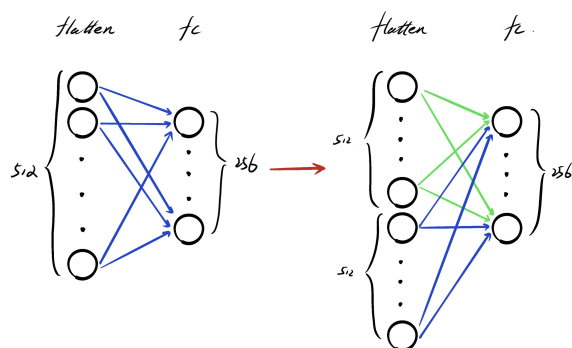


Figure 5: Grouped action example

In conclusion, the experimental design for the Reinforcement Learning agent consists of three steps of training where we will employ ϵ -greedy algorithm and partial weight initialization for the sake of efficiency and effectiveness.

Complete the following two paragraphs for D3.

Describe the findings from your evaluation. Describe both (a) how well your techniques worked, and (b) what you learned about the problem through these techniques.

Prepare figures (e.g., Figure ??) and tables (e.g., Table 5) to describe your results clearly. Make sure to label your figures and tables and explain them in the text. If you are comparing the performance of algorithms, include statistical tests to assess whether the differences are statistically significant. If possible, describe how your techniques compare to prior work.

Techniques	F-1 Score
Baseline	0.80
Another Baseline	0.76
My Awesome Algorithm	0.95

Table 5: example of a table summarizing the results

Discussion

Complete this section for D4.

The *Discussion* section (~ 1 pages) describes (a) the implications of your results, and (b) the impact and the limitations of your approach.

For the results, describe how a reader should interpret them. Try to form concise take-away messages for the reader. For your approach, describe the extent to which your approach helps to solve the problem. Describe any limitations of your approach. If possible, compare your results and your approach to that of prior work.

Conclusion

Complete this section for D4.

The *Conclusion* section (~ 0.5 pages) provides a brief summary of the entire paper. In this section, describe

- the motivation, the problem, and your results, and
- 3-4 promising future directions.

References

- Algorta, S., and Simsek, O. 2019. The game of tetris in machine learning.
- Bertsekas, D. P., and Tsitsiklis, J. N. 1996. *Neuro-Dynamic Programming*. Athena Scientific, 1st edition.
- Burgiel, H. 1997. How to lose at tetris. *The Mathematical Gazette* 81(491):194200.
- Faria, N. 2019. tetris-ai.
- Gärtner, T.; Driessens, K.; and Ramon, J. 2003. Graph kernels and gaussian processes for relational reinforcement learning. In Horváth, T., and Yamamoto, A., eds., *Inductive Logic Programming*, 146–163. Berlin, Heidelberg: Springer Berlin Heidelberg.
- Matt Stevens, S. P. 2016. Playing tetris with deep reinforcement learning. *stanford.edu*.
- Mnih, V.; Kavukcuoglu, K.; Silver, D.; Graves, A.; Antonoglou, I.; Wierstra, D.; and Riedmiller, M. 2013. Playing atari with deep reinforcement learning.
- Phon-Amnuaisuk, S. 2015. Evolving and discovering tetris gameplay strategies. *Procedia Computer Science* 60:458–467.
- Stevens, M. 2016. Playing tetris with deep reinforcement learning.
- Tokic, M. 2010. Adaptive -greedy exploration in reinforcement learning based on value differences. 203–210.
- Tsitsiklis, J. N., and Roy, B. V. 1996. Feature-based methods for large scale dynamic programming.
- Wei-Tze Tsai, Chi-Hsien Yen, W.-C. M., and Yu, T.-L. 2013. Tetris artificial intelligence.