# PySnake

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Miniproject

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# 1. Introduction

We decided to do a small reinforcement learning project. As we have never done anything in terms of reinforcement learning before, we used this video as a starting point. It is a tutorial of creating a Snake game and design a reinforcement learning AI model which is able to play the game after some iterations.

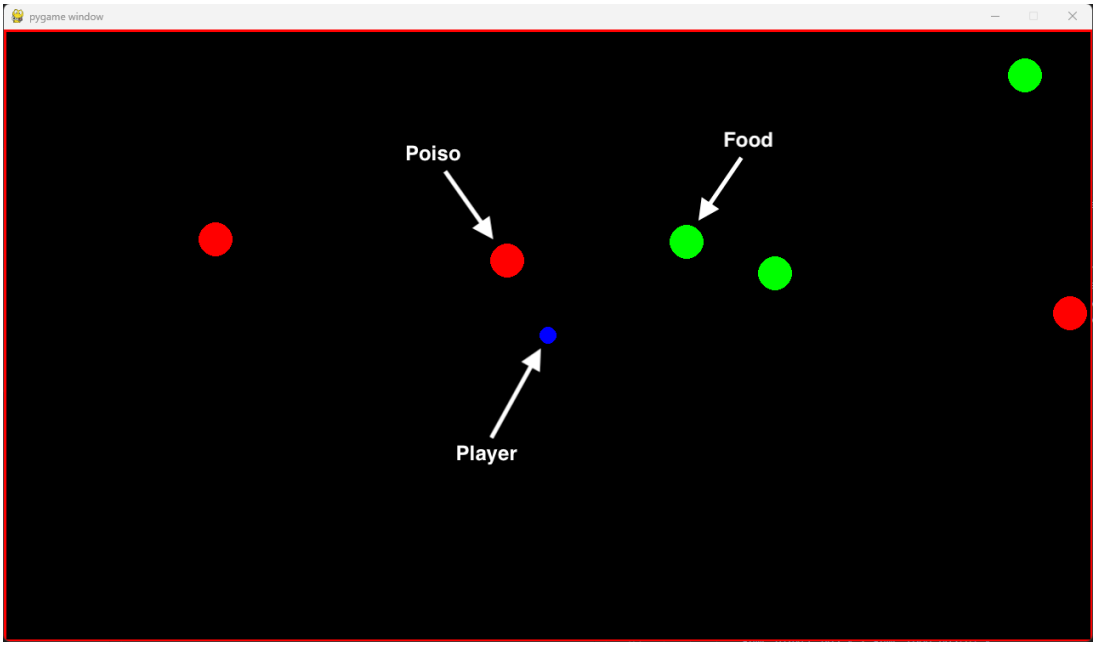
# 2. Tooling

Like the guy in the tutorial we used Pytorch to design our AI model and Pygame to create our game. It is worth pointing out that we planned to use Pytorch anyway because we wanted to try out another tool than Tensorflow. Furthermore, Pytorch also supports AMD graphic cards and not only Nvidia graphic cards like Tensorflow. Pygame is a composition of Python modules like computer graphic and sound libraries. Creating a game with Pygame is straightforward.

# 3. Making Of

## 3.1. The Game

We wanted to create our own little game and not just copy the game from the tutorial we watched. Therefore, we designed a two dimensional game where the player is a small ball and has to collect or eat other balls. There are two different types of balls to eat; green and red ones. By collecting a green ball the player grows in size and gets smaller when collecting red balls respectively. If the player has minimal size and collects a red ball the game is over. Touching the wall also ends the game. As the player grows each time eating a green ball it gets more difficult over time to avoid the wall as well as red balls. It is possible playing the game manually or letting the AI play the game.



## 3.2. The AI

Although we looked at reinforcement learning in a theoretical part at the lectures it was still an unknown field in a practical way. Therefore, we initially invested some time to understand how the basics work. We did this by reading through the code base of the already mentioned tutorial. Furthermore, some parts are copied from the tutorial code base. The AI of our project is divided into an agent- and a model part.

### 3.2.1. Model

The model consists of two classes. One of which is the Linear_QNet. The Linear_QNet holds the two methods for forward propagation as well as the save method to save the model to a file. It is basically the model network representing the input, hidden and output layer. The other class in the model is the QTrainer it holds only one function which is called train_step. This train_step method is used after each action the agent performs to optimize the model. Roughly described the train_step method updates the loss and performs backward propagation.

### 3.2.2. Agent

The Agent consists of a single class which is called agent aswell. Besides the methods it holds all important parameters for our AI. Those parameters are:

- Epsilon: Controls how much percent of the AI actions should initially be random rather than predicted by the model. This parameter is important as the AI has no idea what it should do at the beginning. As the AI learns over time this parameter value gets lowered after each game over.
- Gamma: The discount rate is a parameter that determines the relative importance of immediate rewards compared to future rewards. It represents the extent to which the agent values immediate rewards over delayed rewards. A discount rate close to 1 means the agent considers future rewards, while a discount rate closer to 0 places more emphasis on immediate rewards.
- Memory: The memory is represented by a deque datastructure. It is basically the memory of the AI where it can store current states, actions, rewards, next states and if it is currently in game over mode.
- Model: This field holds an instance of the previously described Linear_QNet class. Furthermore, here we define how many neurons the input-, hidden- and output-layer has.
- Trainer: This field holds an instance of the previously mentioned QTrainer.

## 3.3. Coding Log

We started off implementing our own game which has a similar simplicity to Snake implementation in the tutorial. Implementing a game with Pygame is straightforward. Therefore, we completed our game really fast.

Afterwards, we started implementing our AI. First we copied the whole model and agent code from the tutorial, as we were curious if it would work with our game straight away. But it didn't work immediately of course. The first problem we encountered was, that there was one crucial difference from our game to the tutorial game. The player in the tutorial game moves automatically while in our game input is mandatory to make the player move. Each time an input key is pressed the player moves one step into the respective direction in our game. In the tutorial game the player moves permanently and changes direction each time an input key is pressed to the respective direction. This led to another issue, which was that our game has four different input possibilities (up, right, down and left) instead of two (left and right). This means our AI needs four output layers and not only two.

Those initial problems were sorted out rapidly. We increased the output layers in the Linear_QNet to 4 and changed the method to get the next action accordingly.

Soon after another problem arose. We noticed that the parameters in the state of the tutorial were substantially different to the ones we actually need. Because the state formation is fundamental for a working AI it is really

important to get that right. But we had to find out that it is rather hard to find the optimal parameters for the state.

STATES AND REWARD SHOULD BE LINKED

CODING BUGS

TRYING OUT DIFFERENT VALUES (reward, reward by how close the player is to obstacles)

MULTI OBSTACLES

STATE INPUTS