Máster en ingeniería de telecomunicaciones

Proyecto de fin de máster

Identificación y recogida de objetos con un brazo robótico utilizando técnicas de reinforcement learning

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ABSTRACT

Abstract content

Thank yous

And other important information

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1. INTRODUCTION

Robotics and real life are worlds destined to meet. Today everyone has seen robots trying to behave like human beings. Many of them even look similar to a person and try to imitate the way we walk, talk or, ultimately, interact with the environment around us.

Robots, Artificial Intelligence or other concepts such as Machine Learning have crept into our lives in just a few years. In fact, until recently, only a few visionaries like Marvin Minsky or Isaac Asimov used to speak of these concepts, and it was as part of science fiction novels. Nowadays, series like Black Mirror bring this technologies closer to the general public and make us reflect on how the future could be.

However, robots, and artificial intelligence in general, are still far from the vision that is told in the novels. They are not capable of understanding the environment around them, of learning or generalizing as we humans do. Companies and researchers are working on getting better generalization of the algorithms, but the truth is that, so far, Artificial Intelligence is only able to perform specific tasks for which they are programmed.

This project is one of those cases. The goal is to control a UR3 arm robot using Artificial Intelligence in order to pick disordered objects from a box and place them in a point of delivery. This task seems trivial, because we are used to see machines performing pick and place actions in industrial processes, but in fact, these kind of processes are normally just repeating the same action or the same rule over and over again. They are able to perform this tasks because they know apriori where these objects are or how they are placed, but they are not capable of generalizing the workflow.

For instance, in Universal Robot free e-Learning course [1], they expose the following example of an industry pick and place task. In Figure 1.1 we can see how the robot is placing an object in a box located in a conveyor belt. The robot is using an infrared sensor to know that a box has arrived, and this box will always

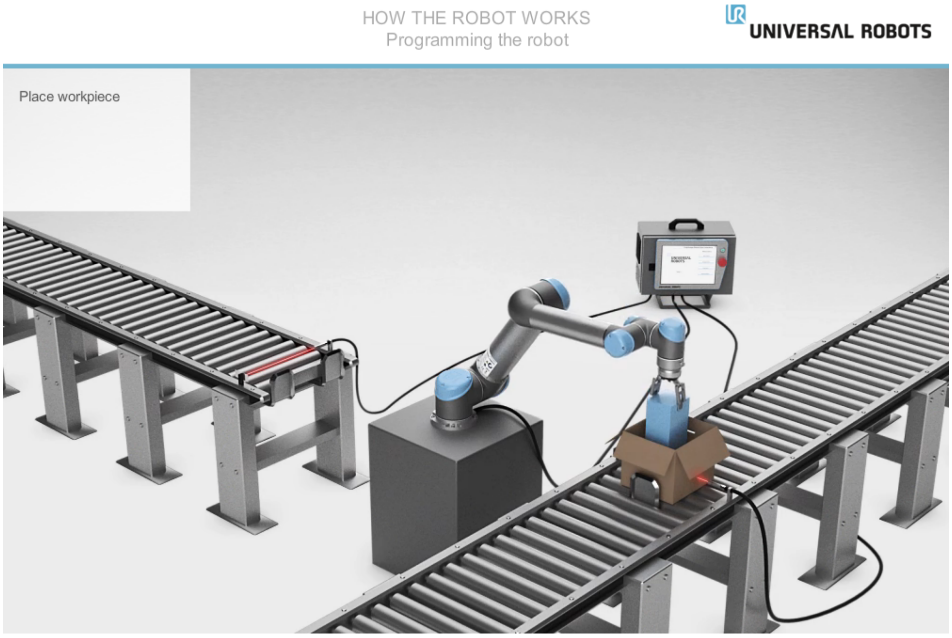


Fig. 1.1: Universal Robots Pick and Place Task

be in the same place because there is a stopper in the conveyor belt which doesn't allow the box to keep moving. On the other hand, the object is picked from the other conveyor belt using the same system to detect the arrival of a new object. The whole task is using a complex architecture, but the robot is performing the same chain of movements in a loop and the only intelligence that the robot has to have is waiting for the object and the box to come.

To achieve generalization in this project, Reinforcement Learning (RL) together with Image Recognition techniques have been used. This algorithms give the robot the ability of calculating, for each time step, the optimal action to achieve the final goal of picking all the objects from the box and placing them in the objective point. To compute this action the robot needs to gather information about the environment such as its relative position over the box or how the pieces are distributed. This information together is called state, and the robot computes each action depending on it.

To perform this project, a distributed architecture with multiple nodes has been created. Each of them takes care of a different activity. For example, some nodes are used to control the robot, others to gather information about the current state, and others are used to train the Artificial Intelligence algorithm. This architecture has been created using ROS (Robot Operative System) and contributes to the project adding all the advantages of a microservices oriented architecture.

1.1 Project Motivation

The fourth industrial revolution is here, and it will change the way that goods are produced, raising efficiency by increasing the amount of automated processes. This will lead to a faster production and a reduction of errors, as machines have the ability to decide and act in fractions of seconds without making mistakes. Furthermore, machines can also be working 24 hours per day stopping just for maintenance checks, which would help to increase the productivity factor without increasing the expense in human resources.

We have been hearing about industry 4.0 since 2011, but the truth is that it is not a reality yet. We are just in the beginning, and it will take decades to perform such a big change in the industry. There are some factors to take in mind in order to analyse the evolution of the industry in the following years. The improvement on the telecommunications with the arrival of 5G networks, the moral dilemma of substituting workers for machines and the impact that this could have in the society or the improvement and implementation of AI technologies are just some of these factors.

We have seen a lot of Artificial Intelligence algorithms applied to the industry, but the truth is that these technologies are not fully developed yet and just big companies can afford to use them in their supply chain. Besides, there are some task that are now performed by humans and cannot be done by machines due to its complexity or its importance in the whole production chain.

The motivation of this project is to contribute to the industry change providing an open source solution to a complex problem such as disordered pick and place task. This open source solution does not currently exist in the industry and would add value being a good starting point for bigger projects in the future.

2. DESCRIPTION OF TECHNOLOGIES

Describir las tecnologías, protocolos, herramientas específicas, etc. que se vayan a tratar durante el proyecto para facilitar su lectura y comprensión. Hablar de Java no procede aquí porque todo el mundo sabe lo que es, pero si en el proyecto hablo continuamente del protocolo Baseband, debo especificar en este capítulo qué es y para qué sirve.

2.1 ROS + catkin

The first decission we had to make was about the architecture of the project. Was it a good idea to build all the project in the same computer? How should we communicate with the Robot?

We found the best solution for this questions in ROS (Robot Operative System), which is a framework for the development of software for robots that provides the functionality of an operating system in a heterogeneous cluster. ROS was originally developed in 2007 under the name switchyard by the Stanford Artificial Intelligence Laboratory to support the Stanford Artificial Intelligence Robot (STAIR) project. Since 2008, development has continued primarily at Willow Garage, a robotic research institute with more than twenty institutions collaborating on a federated development model.

ROS provides the standard services of an operating system such as hardware abstraction, low-level device control, implementation of commonly used functionality, message passing between processes, and package maintenance. It is based on a graph architecture where the processing takes place in the nodes that can receive, send and multiplex messages from sensors, control, states, schedules and actuators, among others. The library is oriented for a UNIX system (Ubuntu (Linux)) although it is also adapting to other operating systems such as Fedora, Mac OS X, Arch, Gentoo, OpenSUSE, Slackware, Debian or Microsoft Windows, considered as 'experimental'. ROS is free software under BSD license terms. This license allows freedom for commercial and investigative use. Contributions of packages in ros-pkg are under a variety of different licenses.

All of these features made ROS ideal for the project. Specially the following ones:

- Universal Robots drivers for ROS using mooveit make it possible to controll ROS remotelly.
- ROS is a multi-node oriented framework, which allows us to take all the advantages of micro-services. We can split the software by functionallity gaining:
  - The possibility of giving more or less computation power to each functionality depending on its needs. In the project we have useed from computers with the better Nvidia Graphic card and 32 GB of RAM to other mini-computers such as a Raspberry-pi or an Arduino Card.
  - The chance of using a different environment for each functionality. Different versions of python and even different programming languages, diferent versions of libraries, diferent Operative Systems, etc.
  - Isolation of each component of the project, allowing us to develop separatly each functionality without affecting the rest of the functionalities of the project.
- It can work over an Arduino Card. It is not self sufficient, as it needs to be serial connected to a computer (Or Raspberry pi) in orther to work. We needed the arduino card in order to build our "home made" vaccuum gripper.
- It is open source and have a huge community, so we could reuse some already developed solutions such as the usb_cam package, which let us take pictures from a camara connected to another node or computer.

2.2 pytorch

PyTorch is a Python package designed to perform numerical calculations using tensor programming. It also allows its execution on GPU to speed up calculations.

Typically PyTorch is used both to replace numpy and process calculations on GPUs and for research and development in the field of machine learning, mainly focused on the development of neural networks. In this case we will use PyTorch in both the Reinforcement Learning algorithm and the image Processing.

PyTorch is a very recent library and despite this it has a large number of manuals and tutorials where to find examples. In addition to a community that grows by leaps and bounds.

PyTorch has a very simple interface for creating neural networks despite working directly with tensors without the need for a library at a higher level such as Keras for Theano or Tensorflow.

Unlike other packages like Tensorflow, PyTorch works with dynamic graphs instead of static ones. This means that at runtime the functions can be modified and the calculation of the gradient will vary with them. On the other hand, in Tensorflow we must first define the computation graph and then use the session to calculate the results of the tensors, this makes it difficult to debug the code and makes its implementation more tedious.

PyTorch has support to run on graphics cards (GPU), it uses internally CUDA, an API that connects the CPU with the GPU that has been developed by NVIDIA.

2.3 arduino

Arduino is an open source electronics creation platform, which is based on free hardware and software, flexible and easy to use for creators and developers. This platform allows the creation of different types of single-board microcomputers that can be used by the developer community for different types of use.

As commented before, we will use Arduino Card in order to build a Vaccuum Gripper for the Robot. It will be connected with all the other nodes using ROS Queues.

2.4 github

GitHub, Inc. is a provider of Internet hosting for software development and version control using Git. It offers the distributed version control and source code management (SCM) functionality of Git, plus its own features. It provides access control and several collaboration features such as bug tracking, feature requests, task management, continuous integration and wikis for every project. Headquartered in California, it has been a subsidiary of Microsoft since 2018.

GitHub offers its basic services free of charge. Its more advanced professional and enterprise services are commercial. Free GitHub accounts are commonly used to host open-source projects. As of January 2019, GitHub offers unlimited private repositories to all plans, including free accounts, but allowed only up to three collaborators per repository for free. Starting from April 15, 2020, the free plan allows unlimited collaborators, but restricts private repositories to 2,000 minutes of GitHub Actions per month. As of January 2020, GitHub reports having over 40 million users and more than 190 million repositories (including at least 28 million public repositories), making it the largest host of source code in the world.

2.5 CUDA

CUDA stands for Compute Unified Device Architecture, which refers to a parallel computing platform including a compiler and a set of development tools created by nvidia that allow programmers to use a variation of the language. C programming for encoding algorithms on nvidia GPUs.

Through wrappers you can use Python, Fortran and Java instead of C / C ++.

Works on all nvidia GPUs from the G8X series onwards, including GeForce, Quadro, ION, and the Tesla line.1 nvidia claims that programs developed for the GeForce 8 series will also work without modification on all future nvidia cards, thanks to binary compatibility.

CUDA tries to exploit the advantages of GPUs over general purpose CPUs by using the parallelism offered by its multiple cores, which allow the launch of a very high number of simultaneous threads. Therefore, if an application is designed using multiple threads that perform independent tasks (which is what GPUs do when processing graphics, their natural task), a GPU will be able to offer great performance in fields that could range from computational biology to biology. crypto, for example.

The first SDK was released in February 2007 initially for Windows, Linux, and later in version 2.0 for Mac OS. It is currently offered for Windows XP / Vista /

7/8/102, for Linux 32/64 bits3 and for macOS4.

2.6 moveit

MoveIt! is open source software for ROS (Robot Operating System) which is state of the art software for mobile manipulation. In fact, we could say that MoveIt! it is becoming a de facto standard in the field of mobile robotics, as today more than 65 robots use this software, including the latest robots developed by Robotnik.

MoveIt! includes various utilities that speed up the work with robotic arms, and it helps to not be continually "reinventing the wheel", following the ROS philosophy of code reuse.

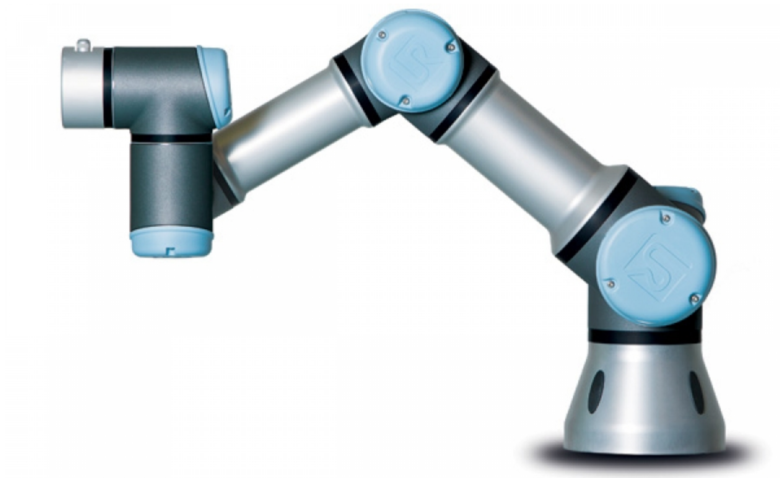
2.7 Universal Robots driver for ROS

Universal Robots have become a dominant supplier of lightweight, robotic manipulators for industry, as well as for scientific research and education. The Robot Operating System (ROS) has developed from a community-centered movement to a mature framework and quasi standard, providing a rich set of powerful tools for robot engineers and researchers, working in many different domains.

With the release of UR's new e-Series, the demand for a ROS driver that supports the new manipulators and the newest ROS releases and paradigms like ROS-control has increased further. The goal of this driver is to provide a stable and sustainable interface between UR robots and ROS that strongly benefit all parties.

2.8 UR3 robot

The UR3 Universal Robots robot is the smallest cobot of the UR series of Universal. Universal Robots' ultra flexible UR3 provides high precision for the smallest production environments.



It can modulate payloads of up to 3 kg, adding value to scientific, pharmaceutical, agricultural, electronic and technological facilities. Tasks the UR3 excels at include: mounting small objects, gluing, screwing, tool handling, welding and painting.

However, the range of movements of this robot is really limited, and it can only lift up 3 Kilograms so this robot is really good for preparing a prototype, it has the same characteristics than its big brothers, but probably it is not good enough to build a production solution.

2.9 anaconda

Anaconda is a free and open distribution of the Python and R languages, used in data science, and machine learning. This includes processing of large volumes of information, predictive analytics and scientific computations. It is aimed at simplifying the deployment and management of software packages.

The different versions of the packages are managed through the conda package management system, which makes it quite easy to install, run, and update data science and machine learning software such as Scikit-team, TensorFlow and SciPy.

The Anaconda distribution is used by 6 million users and includes more than 250 data science packages valid for Windows, Linux, and MacOS.

3. STATE OF THE ART

The pick and place task that is intended to be performed in this thesis is really useful for a lot of applications into the industrial world because it would bring a lot of flexibility for these processes. A example of this applications could be an assembly line, where robotic arms could be picking all the different pieces to assemble in the product using always the same algorithm.

Big companies are developing a lot of Artificial intelligence use cases in the industry, and they try to contribute to the AI community by publishing scientific articles on how they managed to use AI for their specific tasks. Unfortunately, although some companies have already developed their own solutions for our specific pick and place task, none of them have published a scientific article on the subject, making it difficult to study the way they have achieved it.

One of the companies that has already developed a pick and place task is the Japanese automation company Fanuc, which has developed an AI-based solution together with Preferred Networks. As commented before, they have not published any scientific article about the topic but we can see the system working in a video they have posted on YouTube [2]. That means that we have to gather all the possible information from the video, where we could find that they have not used a Reinforcement Learning algorithm but just a Deep Neural Network (DNN) with image recognition.

To train the net, they have collected "success" or "fail" labelled images by making pick actions in random places of the box. Once they gathered a big enough dataset of images, they have trained a Deep Neural Network as the one we see in Figure 3.1, where we can also see that the Neural Net has been trained to predict whether the robot is going to success in a pick action in a specific place or not. Using that net, they can make a heat map of the whole box, predicting the points of maximum probabilities of succeed. As usually, they noticed that the bigger the image dataset, the higher the success ratio. In eight hours, they reach 90% of success, which they say is bigger than the human success ratio.

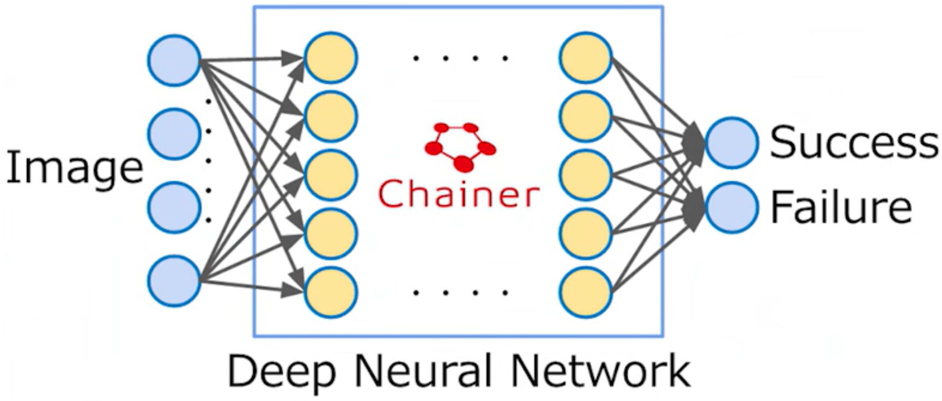


Fig. 3.1: Deep Neural Network of Fanuc solution (taken from the video)

3.0.1 Reinforcement Learning

The idea of the project is to keep using image recognition techniques but, in our case, applied to a **Reinforcement Learning** Algorithm which is an area of machine learning inspired by psychology behavioural. Its goal is to determine what actions a software agent should choose in a given environment in order to maximize some notion of "reward" or accumulated prize.

Explained easily, RL is used to make an **agent** (the robot) learn how to interact with a **environment** in order to perform a task. To achieve this, Markov Decision Process (MDP) which provides a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker.

Markov Decision Process (MD)

In MDP, the environment is what we are actually trying to simulate with the MDP. The agent will interact with it to learn how to perform the task, so these are the attributes of the environment:

- **Agent:** The agent is the most important piece of the algorithm because it represents the objects that we want to become smarter.
- **Actions (A):** The agent can interact with the environment by performing a set of actions which is normally finite.

- **States (S):** Each time the agent performs an action, it moves to a new state. States are basically the set of information that differentiates the situation of the agent before and after performing an action. States can be transitional or terminal, when the agent meets the objective or when it gets to a forbidden position.

- **Rewards (R):** Each time an action is performed, the agent receives a reward. This reward can be positive, negative or null depending on the impact of the action to achieve the objective.

- **Policy (π):** The policy is used to define the optimal action for each step. It gives a punctuation for all of the actions in the current step as shown in the following formula. The agent takes the action with highest punctuation.

$$\pi(a|s) = P_r\{A_t = a|S_t = s\}$$

The MDP is divided in discrete timesteps (t), where each timestep does not have to last the same time as the previous step. Each timestep, the agent uses the policy π to decide the next action.

Once the action is taken:

- The environment transits to th next state: $\boldsymbol{S_t = S_{t+1}}$.

- Environment produces a new reward, which can be represented with the following formula:

$$\boldsymbol{P(s', r, s, a) = P_r\{S_{t+1} = s', R_t = r, S_t = s, A_t = a\}}$$

Agent's performance is calculated in terms of its future accumulated rewards known as return. This is called **expected return** an is calculated as shown in the formula below, where γ is the discount factor, and is used to give a bigger value to the closest steps.

$$G_t = \sum_{k=t} \gamma^{k-t} \cdot R_{k+1} \ \forall \ \gamma \in [0, 1]$$

Now that we know all these concepts, we have to learn what Reinforcement Learning Algorithms do to learn. Basically, **the goal of the agent is to find a policy that maximizes the expected return** . This can be done using different strategies as:

- **Q-Learning:** Estimating action values using Q Tables or other methods
- **TRPO:** Parametrizing the policy and optimizing its parameters

Basic Q-Learning is based on the assumption that both actions and states are limited and that the same action in the same state always drives to the same new state. Having this in mind, Q-learning algorithms build two matrices of shape **length(actions) x length(states)** as shown in the Figure 3.2.

$$
\begin{array}{ccc}
 & & \text{Action} \\
 & \text{State} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
R = & \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix}
\end{array}
$$

Fig. 3.2: Reward and Q Matrix shape in Basic Reinforcement Learning

In these two matrices, Q-Learning algorithm stores in the R matrix the reward for the pair of action-state while in the Q matrix they store cumulated reward for this same pair. The Q matrix is the one used to decide which action to perform in each state and R matrix the one used to calculate the reward of each action.

However, for the aim of this project, the states of the agent can be different in each timestep. The state would actually be partially formed by images, so the number of states can be infinite. We need a more complex version of Reinforcement Learning.

3.0.2 Deep Reinforcement Learning

The approach of mixing both image recognition and RL is called Deep Q Learning (DQN) or Double Deep Q Learning (DDQN) depending on the implementation and uses Neural Networks in two different stages of the algorithm. Firstly, a Convolutional Neural Network (CNN) is used to extract image features, and then, a Deep Neural Network (DNN) is used to calculate the q value of each independent action and select the next one using these values.

DQL was proposed in 2012, and, since then, it has been used for a lot of different purposes. For example, Guillaume Lample and Devendra Singh Chaplot demonstrated back in 2017 that a RL agent could play FPS Games using as inputs just game scores and pixels from the screen [3]. Another really interesting example is this robot [4], which is capable of moving around a house looking for an objective and avoiding obstacles using DDQL.

A good resource to understand how Reinforcement Learning really works is Deeplizard's tutorial [5]. In this tutorial they explain different versions of the algorithm and how to implement them in python to solve different OpenAI gym environments [6].

Deep Reinforcement Learning is though an union between RL and image recognition, but let's see how it actually works. The main idea is to replace the Q-table that we saw before for a Dense Neural Network that uses as input another Neural Network, a Convolutional Neural Network (CNN). The full algorithm would have as many outputs as allowed actions. Therefore, simplifying, these outputs re equivalent to the q-values saw before and so we will call them. To see it graphically, when the agent wanted to take an action, he would pass the state image through the Neural network represented in Figure 3.3 and would take the action with higher q-value.

When I said "simplifying" in the previous paragraph, I meant "simplifying a lot" in the next paragraphs I will explain all the intermediate steps in the algorithm and why they are important:

– Episodes and Steps

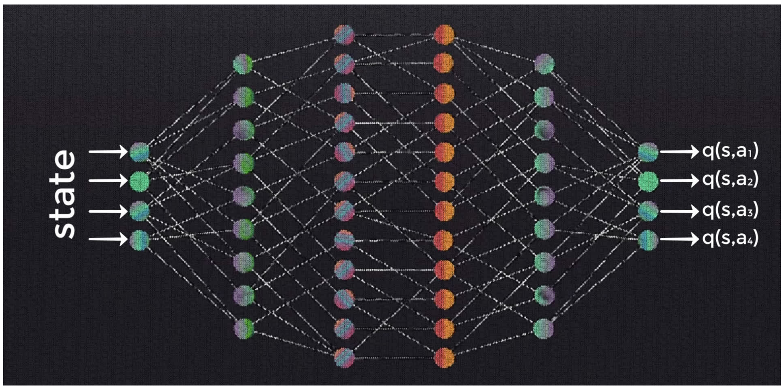


Fig. 3.3: Deep Q Learning Representation with 4 outputs

- Exploration vs Exploitation trade-off
- Replay Memory
- Bellman's Equation
- Target and Policy Networks

Episodes and Steps

RL training is divided in Episodes. One Episode is the sequence of actions needed to reach a terminal State. Each time the agent reaches a terminal state, an episode is ended, and a new one is started.

On the other hand, steps represents every time that a new action is taken, so the number of steps taken by the agent during training is infinite. Later on, we will use as metric of performance the number of steps per episode, as they must decrease during the training.

Exploration vs Exploitation trade-off

In Reinforcement Learning there are two important concepts that are **Explore** and **Exploit**. To explore is basically gather new information about the environment and to exploit is to make the best decision with the information that we already have.

In Deep Reinforcement Learning, the agent exploit the information gathered by using the pre-trained Neural Network to decide next action. On the other hand, the agent explore the environment by deciding next action randomly. We use exploration mainly in the beginning of the training because we want the agent to gather as much information of the environment as possible before starting training.

When the agent uses exploitation, it is also gathering information about the environment. However, we could not let the agent explore this way because during the exploration phase we want all the actions to be performed with the same probability and neural network bias can cause some actions to be performed much more than others.

So, how do we decide when the agent must explore or exploit? To decide it we can use multiple techniques, but the most common one is the Epsilon-Greedy Strategy. This strategy basically consist on setting a probability of exploring and keep decreasing it slowly during the training. It works this way:

1. **We set the initial exploring probability** (ϵ)
2. **We set the per-step epsilon decay,** (ϵ_decay)
3. **For each step:**
   (a) **With probability** $p = \epsilon$**, the agent explores the environment (takes a random action). If not, it exploit the information by deciding the action using the NN.**
   (b) **Whether the agent has explore or not, we decrease the probability of exploring the environment in the next step** ($\epsilon = \epsilon - \epsilon\_decay$)

Using this strategy, the agent will rather explore or exploit the environment during the training. In the first steps the probability of a random action (exploring) will be much hihger than in the last steps of the algorithm. This probability will keep decreasing during the training, until it reaches the minimum exploring rate, which is normally set to 10

Replay Memory

Every time that the agent performs an action, either by exploring or exploiting, the agent lives an experience. For the purpose of training the algorithm, we will store all these experiences.

Experiences are formed by the initial state, the action taken, the state reached (final state) and the reward gotten and they are stored in the Replay Memory. Then, every time that an action is taken, the algorithm is trained following this steps:

1. Replay Memory checks if the number of experiences is higher than the batch size
2. If there are enough experiences:
   (a) Replay Memory supplies a random set of experiences of size=batch_size.
   (b) With this set of experiences, the target network is trained.

Optimizing Replay Memory can be a challenge, because, if we are using a Graphic Card in the training, we would be storing all the experiences in its memory. But, why do we need to store all the experiences? We could also be using the last N experiences to train the network and it would be a less memory-consumption demanding solution.

The answer to this question is that Reinforcement Learning Networks converge really slowly and variance between consecutive steps is really low. Using consecutive experiences to train the network would result though in a slower and biased learning. Besides, this way of working is better for learning real-world experience, where there are infinite different states, as the experience gained in previous steps will be used multiple times later to train the network.

Bellman's Equation

As commented before, Deep Reinforcement Learning uses Neural Networks to compute the q-values of each action. The optimal value of these q-values is represented by the Bellman's Equation and is shown below:

$$q_*(s,a) = E[R_t + \gamma max(q_*(s',a')]$$

As we can see in the equation, the optimal value depends in both the reward of the action taken and the maximum optimal q-value of the next action. In real life it is impossible to compute this value, because we would be an infinite loop. However, as the most important parameter of the formula is the expected reward ($q_*(s',a')$ is multiplied by the discount factor γ), we can simply use the next action q-value and it will be a good approximation. The formula would stay as follows:

$$q_*(s,a) = E[R_t + \gamma max(q(s',a')]$$

With this new formula we will be able to compute the optimal q-value for each experience stored in the Replay Memory (initial state, action, final state and reward). It is important to have in mind for this process that the optimal q-value can only be computed if the action has actually been taken, because we don't know the Reward of non taken actions. But, anyway, why do we need to compute the optimal q-value?

To answer this question, lets take a look to the training process of the neural network:

1. the agent decide which action to take using the policy-network. (action with highest q-value)
2. The agent takes the action and receives a reward from the environment
3. The agent stores all the experience in the Replay Memory
4. The training process is started:
   (a) A random batch of experiences is taken from the Replay Memory
   (b) For all these experiences, its optimal q-value is calculates using the modified Bellman's Equation and target-network
   (c) For all these experiences, the actual q-value is calculated using the policy-network
   (d) For all these experiences, the loss is calculated as the difference of both values

(e) We use the Neural network optimizer to back-propagate the loss to all the weights

So, to answer the previous question, we need to compute the **optimal q-values in order to calculate the loss** of the neural network for each action taken and train, though, the algorithm.

Retaking here the question answered before about why we needed Replay Memory module, one important reason is that one action taken in the initial steps of the training will affect differently to the neural network in this moment than later, when the network is already trained, and its q-value is though more similar to the optimal q-value. Replay Memory technique allow us to use this information gathered in any step of the training, during a step where the network is more trained.

Target and Policy Networks

In the previous step, we talk about two different networks: policy and target. The target network comes to solve a stability problem of the DRL training. In the next paragraphs I will explain the problem and how target network can help to solve it.

Having in mind the way we calculate the loss of the neural network in the previous section we can realize that we have to pass information through the network twice. Just to remember:

$$loss = R_t + \gamma max(q(s_{t+1}, a_{t+1})) - q(s_t, a_t)$$

As a spoiler, I can say that $q(s_{t+1}$ and $q(s_t, a_t)$ will not be calculated with the same network. But.. why?

Imagine that we have an experience, which is composed of an initial state, an action that has been taken, the state reached with this action and a reward. Remembering previous section, the loss of the neural network is calculated as the difference between the q-value of the initial state and the action taken and the optimal q-value of the expected cumulative reward (or target value) of the action.

Q-values are calculated using the states as input of Neural Networks. Let's see what could happen if we calculated both of the values with the same network. In this case, once we had the loss calculated, we would use back-propagation to adapt the weights of the Neural Network and make the q-value of the initial state more similar to the target q-value.

The problem here comes because as both q-values are using the same Neural network to be calculated, when we change the weights to move the initial q-value to one direction, the target q-value is moving in the same direction, so we have not reduce the distance between the two values. It is basically like a dog chasing its tail.

To solve this problem we introduce the target-network. This network is basically a frozen clone of the policy network that we only use to calculate the target value of each action. This way, when we gain stability during the training of the RL Algorithm. The target-network is updated periodically after a certain amount of steps, so is always updated.

DQL Training

During the previous sections I have been explaining a lot of concepts about Deep Reinforcement Learning Training. I have explained them and how they affect the training. It is a really complex process so probably a sum-up will help understanding it.

The training basically uses the following schema:

- Initialize replay memory capacity.
- Initialize the policy network with random weights.
- Clone the policy network, and call it the target network.
- For each episode:
  - Initialize the starting state.
  - For each time step:
    - Select an action via exploration or exploitation
    - Execute selected action and observe reward and next state.
    - Store experience in replay memory.
    - Sample random batch from replay memory.
    - Preprocess states from batch.

- Pass batch of preprocessed states to policy network.
- NN training. Weight back-propagation:
  - Calculate loss between output Q-values and target Q-values.
  - Using both the target and the policy networks to increase stability.
  - Gradient descent updates weights in the policy network to minimize loss.

- After X time steps or episodes, weights in the target network are updated to the weights in the policy network.

This training can also be explained with [**fig:training**], where the Pool is the Replay Memory that stores the sample (experiences) from real interaction with the environment and feeds the training node of random sample of experiences.

Then, we can see that we use the Q-Network (policy network) to predict actions, but also to calculate the q-value of Replay Memory's batch. Then, we use the target network to predict action-value of state s1 with the predicted action in Q estimation Network, andthis network is updated in a low rate.

Finally, the action taken in the Dynamic Environment can be predicted by the Neural Network or Randomly chosen (Stochastic search). This is the way of representing epsiolon-Greedy Strategy.

3.0.3 Problems of Deep Reinforcement Learning in Real-world

Real-world problems introduces some challenges that we will have to manage. In march 2018, A. Rupam Mahmood, Dmytro Korenkevych, Brent J. Komer, and James Bergstra explained the problems they found while implementing a RL algorithm in a UR5 robotic arm [7].

Some of the problems they found were the following:

- Slow rate of data-collection, as movements in the real robot are slower than in a simulated environment.

- Partial observability. Sensors cannot retrieve all the information about the environment.

- Noisy sensors will provide inaccurate information.

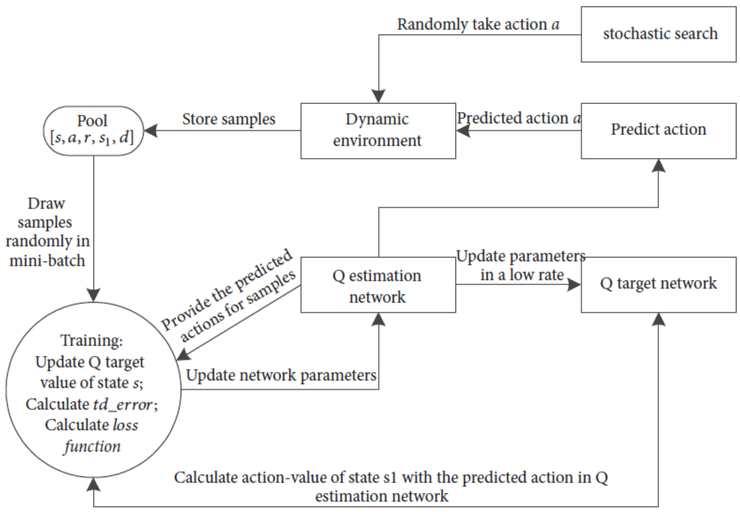


Fig. 3.4: Reinforcement Learning Training Summary

- Safety of the robot and its surroundings have to be taken in mind.
- Fragility of robot components.
- Delay between an action is requested and the time it is actually performed can affect the training.
- Preparing the robot is a really difficult task:
  - Controlling the robot.
  - Define all aspects of the environment.
  - Difficulties for obtaining random and independent state when episode ends.

Another problem that can be found in our project is that, as objects are randomly placed, the environment that the agent will have to face will be completely different each time. In fact, the robot can interact with the environment, as it can move the pieces trying to pick them, so we are facing a dynamic environment RL problem. A good example of a dynamic environment problem is the path planning of a self driven car, where each time the agent takes an action the environment will change and, furthermore, obstacles do not have to be static, but they can also move.

There are multiple examples of articles on this topic, such as the one Xiaoyun Lei, Zhian Zhang, and Peifang Dong published in September 2018 using a DDQN approach to solve it [8]. However, there are other solutions as the one proposed by Marco A. Wiering [9], where he introduces some prior knowledge to the model in order to facilitate the learning. His algorithm had problems generalizing the environment, so he introduced some prior information about the model together with a Model-based RL. This made the algorithm more capable to learn without loosing a lot of trainable capability.

4. DEFINITION OF THE PROJECT

4.1 Motivation

The project motivation is the natural continuation of a previous project performed at ICAM University. This project was part of the assembly line of a car manufacturing process and its objective was to pick some specific plastic pieces and place them into the product. To achieve this, the system used opencv image processing, so it was recognising a specific shape given apriori.

This project was totally functional and the robot could perform the task with a high successful rate. However, the lack of generalization of the system makes it hard to introduce changes as using it for another part of the assembly line. Each time that this happened someone would have to introduce the shape of the pieces to the system and to calibrate the camera to the new environment.

The motivation of the project is to create from scratch a new solution for performing the picking of the pieces. This time, the project will not be sponsored by any company, so there will be less resources to use.

With this new approach, the idea is to use all the knowledge of previous documented projects on Artificial Intelligence in the industry and make a little contribution to the huge advance of industry 4.0. In fact, the idea is to make the project completely replicable so that anyone could use this project as a starting point for new applications.

4.2 Objectives

Revisar objetivos y adaptarlos al proyecto

The objectives of the project are five and are listed and explained below:

– Implement a bin picking simple solution. A basic one, without Artificial

Intelligence.

– Improve the performance using RL and Image Recognition.

– Study the usage of new technologies to add information to the system. Adding physics or new image recognition techniques.

– Test different tools such as Multiflash or 3D images to improve performance.

– Add value to the scientific community making the solution available if the previous objectives are reached.

4.3 Methodology

This project will be performed using an agile methodology, which is one of the simplest and effective processes to turn a vision for a business need into software solutions. Agile is a term used to describe software development approaches that employ continual planning, learning, improvement, team collaboration, evolutionary development, and early delivery. It encourages flexible responses to change [10].

In the case of this project, the team is just formed by two workers and a project manager. This make necessary to make some changes to the typical agile methodology. For example, daily meetings are substituted by constant communication between both workers and weekly meetings with the project director. With this approach, all the members of the project are updated about how it is going and have clear objectives.

Likewise, the methodology of this project is based in three fundamental principles as it is shown in Figure 4.1. The first two principles are highly related, as the project is iterative because it is experimental. That means that the way of working is perform little sprints with new functionalities, test them (experimental) and, depending on the results, define the new sprint, execute it and test again (iterative). Besides, the project is also incremental because the idea is starting implementing the simplest possible solution and keep adding new improvements to it in a iterative loop until the optimal configuration is reached.

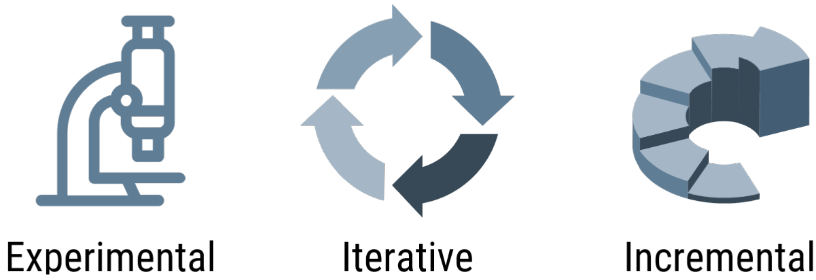


Fig. 4.1: Methodology

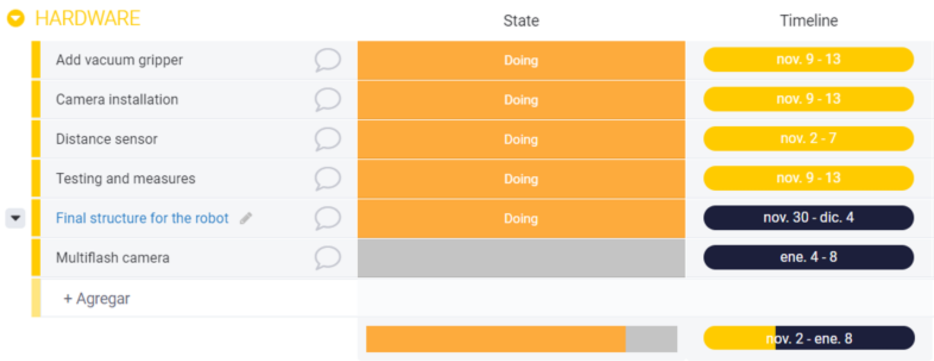


Fig. 4.2: Chronograph of the Hardward implementation

4.4 Planning and budget

Regarding the planning, there are some really important functionalities that have been defined since the beginning of the project, as they are needed. These functionalities are split in three different groups: Hardware implementation, Artificial Intelligence Implementation and Robot controller implementation. The tasks related to these three groups are shown in Figure 4.2, Figure 4.3 and Figure 4.4.

Añadir presupuesto

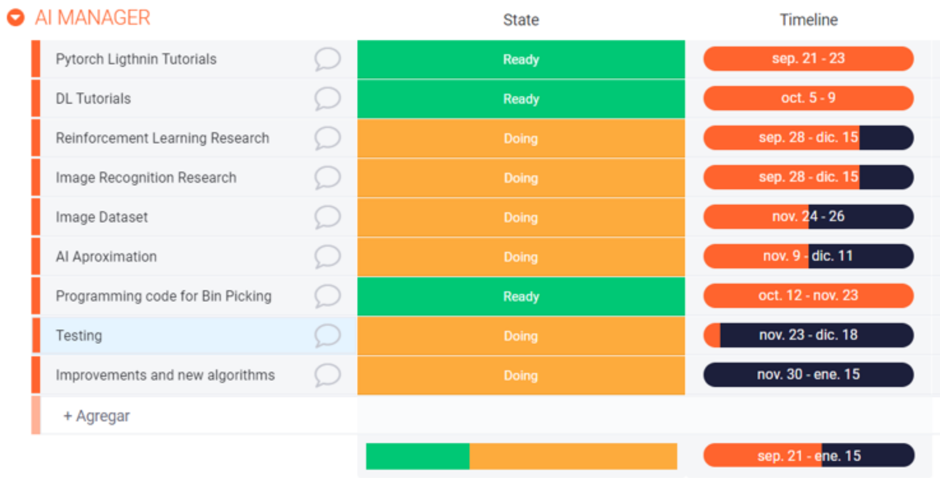


Fig. 4.3: Planning of the Artificial Intelligence implementation

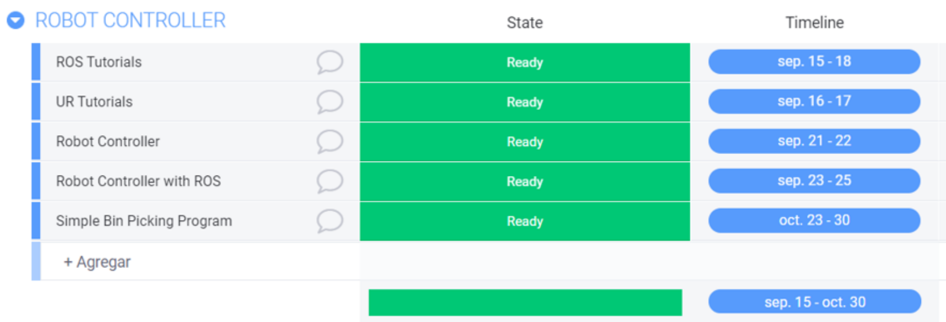


Fig. 4.4: Planning of the Robot Controller implementation

5. DEVELOPED SYSTEM

En este capítulo es donde el alumno debe describir su proyecto. En función del tipo de proyecto la estructura interna variará. El título del mismo, así como sus apartados, son sólo una sugerencia que cada alumno deberá adaptar particularmente a su proyecto.

A su vez, este capítulo podrá extenderse en varios capítulos más, por ejemplo si mi proyecto consta de varias fases o módulos, lo lógico sería tener varios capítulos donde se describa el desarrollo del proyecto:

- Capítulo 5. Implantación y configuración de la plataforma
- Capítulo 6. Desarrollo del sistema

5.1 Análisis del sistema

...

5.2 Diseño

...

5.3 Implementación

...

6. RESULTS ANALYSIS

Destacar los resultados más relevantes del proyecto y hacer un análisis crítico de los mismos. También es un capítulo obligatorio y clave.

7. CONCLUSIONS AND FUTURE WORK

Comentar las conclusiones del proyecto, destacando lo que se ha hecho, dejando claros qué objetivos se han cubierto y cuáles son las aportaciones hechas.

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