**Terms of Reference (proposal)**

**MSc Intelligent Systems – MSc Project - Carlos Fernandez Musoles**

**Background**

The field of Machine Learning has been relaunched with the increase in popularity of Deep Learning. This has been possible for the increase in computational power, with massively-parallel processing leading the charge [1] [2], allowing researchers to explore more complex models for learning.

Convolutional Neural Networks have attracted recent attention, particularly in image recognition and classification [3] [4]. Part of its success is they are very efficient at reducing the complexity of feedforward fully-connected networks

Aside from being used on their own, CNNs have also been incorporated as part of a broader approach in Deep reinforcement learning, where they perform well approximating reward functions [5].

Continuing with the tradition of using games as a test bed for AI [6], recent times have seen an important milestone being reached: Go, a game well known for the complexity of its game space, saw the first computer to defeat the human world champion in a 5-games match [7]. AlphaGo guides its play using tree search in combination with Deep Networks –networks with multiple and complex hidden layers- to evaluate game nodes.

Moreover, the AI community is focusing more than ever on competitive events to develop algorithms to play games based on Deep Learning [8] [6]. One such competitions is ViZDoom [9], which restricts the inputs from the world exclusively to visual information from the rendered scene. CNNs and Deep RL are ideally placed for this type of scenarios.

**Aim**

The aim of this project is to use Deep Learning methods to design and implement a ViZDoom controller. Due to the restrictions of the framework, the agent will only receive information from the world in two forms: 1) visual data from the rendered screen; and 2) character data such as ammo, weapon selected, health status, etc. The agent will be required to perform actions such: 1) navigating through a 3D maze; 2) attack other agents, and 3) stay alive.

The focus will be ***to explore the suitability of Evolutionary algorithms for the optimisation of convolutional networks*** *-with particular interest on the NEAT algorithm* [10]- in a complex, real-time scenario ***based on visual input***.

**Relevant publications**

The foundation of this project is to use Neural Networks as a means to effectively interpret image data to control a game bot. In the literature this is commonly referred as *neurovisual control*. Authors have proposed neurovisual solutions for games such as Quake II [11] with moderate success in defined scenarios. The Quake II controller consists of a fully connected recurrent network that uses a retina-like input image –more resolution in the centre- to successfully learn how to find and kill enemies. One of the contributions of this paper is the semi-supervised learning process used to train the network, whereby a non-visual neural net is evolved first and then used to train the neurovisual network.

With the increase in popularity of Convolutional Networks, far more effective in the domain of image classification, authors have started using them to guide game play in different forms. Mnih et al [5] describe an enhancement of traditional reinforcement learning by using a convolutional network as its value function. The CNN uses raw pixel data as input, outputting an estimation of the future reward. The paper also proposes an efficient way of training such networks (DQN) and demonstrates it to be successful when playing a collection of Atari 2600 games, some to a level higher than humans.

Given the level of complexity of CNNs, its depth and the type of layers involved (convoluted, pooling / downsampling, fully-connected, etc), one of the key issues is how to create a network topology that optimises the target function. Although this has traditionally been tackled by handcrafting a layout [12], several authors have started to make use of automatic optimisation techniques to fine-tune entire networks, with evolutionary strategies at the forefront [13] [14].

The basis for this project is the Neuro Evolution of Augmented Topologies algorithm [10], an algorithm that uses an evolutionary process to optimise a neural network architecture. By automating the topology design, NEAT can efficiently produce highly optimised network layouts. The evolutionary process uses three types of mutation operators: 1) modify any of the network’s weights; 2) add or remove units to the network; and 3) add or remove connections between units.

Although NEAT was designed to optimise the topologies of feedforward networks, some derived evolutionary algorithms have already been applied in the domain of Deep Learning. Of particular interest is the work by Koutnik [14], which shows how neuroevolution is used to scale-up a network architecture used in reinforcement learning to create a driving policy in TORCS.

From a theoretical perspective, Maul and Bargiela [15] discuss neuroevolution opportunities for deep neural networks, comparing standard and cooperative evolutionary methods to propose general guidelines for the technique. Verbancsics and Harguess [16] suggest the combination of evolved networks using HyperNEAT (a modification of NEAT) with other Machine Learning techniques to improve performance.

**Objectives and deliverables**

1. To explore the suitability of Evolutionary algorithms for the optimisation of deep neural networks in a complex, real-time, large decision space scenario.
2. To use the findings to implement visual controllers to complete task-specific scenarios in ViZDoom.

**Resources needed**

* Modern computer with a CUDA-enabled GPU to optimise deep learning algorithms (minimum [compute capability](https://developer.nvidia.com/cuda-gpus) 3.0)
* Deep learning framework such as [Keras](http://keras.io/), a python API based on the popular library [Theano](http://deeplearning.net/software/theano/)  . A rationale for the election of framework should be included as part of the project.
* Source code and dependency libraries needed for the [ViZDoom framework](https://github.com/Marqt/ViZDoom)

**Risk analysis**

The project focus is on the research and development of deep learning techniques to control visually-aware controllers. Even though one of the objectives is to participate in the ViZDoom AI Competition, there is a risk of the agent not being ready in time for submission (the deadline precedes the deadline for this project). The competition will be used as a ***motivation*** for the project and to ***draw inspiration and support***from the community.

As the project requires a computer with particular hardware specifications (CUDA-enabled graphic card), there is a heavy dependency on the device selected. To mitigate the risk of not being able to use such device, the author has access to a ***secondary computer*** at home, and ***remote access*** to computational power in the University can be arranged.

To accommodate for any down time period due to illness or personal matters, ***two contingency weeks*** have been allocated at the end of the project.

**Schedule of events**

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# References

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