INSTITUTO TECNOLÓGICO DE AERONÁUTICA

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USE OF GENERATIVE NEURAL NETWORKS FOR INSTANCE SPACE CODIFICATION AND GENERATION OF DATA WITH SPECIFIC PROPERTIES

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USE OF GENERATIVE NEURAL NETWORKS FOR INSTANCE SPACE CODIFICATION AND GENERATION OF DATA WITH SPECIFIC PROPERTIES

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*"If I have seen farther than others,
it is because I stood on the shoulders of giants."*
— Sir Isaac Newton

Abstract

One topic of study in Machine Learning is the study of algorithmic performance and which methodologies may be used to assess this performance. A methodology known as Instance Space Analysis has been used to relate predictive performance in classification algorithms to instance hardness (how hard an instance is for an algorithm to classify). The original methodology has been defined with the instance being an entire dataset, but further work has been made to make the instance as fine-grained as an individual observation. In this work we will build upon this methodology and we propose the creation of a generative neural network model to generate new observations for a classification algorithm with predefined hardness properties.

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List of Abbreviations and Acronyms

CTq	computed torque
DC	direct current
EAR	Equação Algébrica de Riccati
GDL	graus de liberdade
ISR	interrupção de serviço e rotina
LMI	linear matrices inequalities
MIMO	multiple input multiple output
PD	proporcional derivativo
PID	proporcional integrativo derivativo
PTP	point to point
UARMII	Underactuated Robot Manipulator II
VSC	variable structure control

List of Symbols

Contents

1 Introduction

1.1 Motivation

Often in a problem being tackled with Machine Learning (ML) techniques one of the most important part of the solving process is the algorithm selection. Each one has a specific bias which makes it more suitable for some classes of problems than others (PAIVA *et al.*, 2022).

It is desirable, then, that we may have a way of measuring the relationship of the performance of a given algorithm in a problem with the problem's characteristics, since knowing which data is easy or difficult for a given model to classify is useful in the way that we may make changes to the original model.

(MUÑOZ *et al.*, 2018) has introduced a methodology called Instance Space Analysis (ISA), a novel way of performance evaluation and algorithm selection in classifiers by mapping the statistical properties of an instance (an entire dataset) into how difficult the instance is for the classification algorithm to perform. Further, in (PAIVA *et al.*, 2022), the methodology has been modified to have a more fine-grained analysis, with the instance being reduced to an individual observation in a classification dataset.

Given this, we can map each observation into a hardness level . One type of model that may give us new information from this data is a Generative Adversarial Network (GAN) architecture as defined by (GOODFELLOW *et al.*, 2014). This architecture is based on a zero-sum game, with a generator network trying to create data matching the original data and a discriminator network trying to discern between the original data and the generated data.

Using this, we can use the trained generator to create data with specific hardness levels and set a difficulty of classification for an entire dataset. We can use this to verify how the original model behaves with data with a given difficulty profile or to challenge the model.

1.2 Objective

This work's objective lies in providing a framework for data generation based on the relationship between instance hardness and classification performance using the GAN architecture and verify the original model's behaviour using the generated data.

1.3 Scope

The scope of this work will be limited to exploring a GAN implementation for the generation of data, creating a Generator and a Discriminator. The modelling will be made entirely using Python, with the PyTorch (PASZKE *et al.*, 2019) framework. PyHard (PAIVA *et al.*, 2022) will be used for the ISA methodology.

1.4 Outline of this work

2 Machine Learning

This chapter will introduce Machine Learning (ML) concepts and techniques being explored in this work, namely the classification problem, neural networks and the Generative Adversarial Network architecture.

2.1 Classification

In Statistics and Machine Learning, a problem is defined as a classification problem when it consists in identifying which categories a population belongs to. An example might be identifying which race of domestic cat is shown in a picture containing a cat. An algorithm that implements classification is known as a classifier. The classifier works by analysing each observation into dependent variables and either mapping those to the categories or by comparing each observation to previous observations by means of a similarity function or loss function.

Terminology between Statistics and Machine Learning tend to differ. In this work, we will be using the terminology found in Machine Learning, namely:

- dependent variables are called features;
- categories are called classes;

In this work, we will not focus on a specific classification algorithm since ISA is not dependent on the algorithm used, only on the problem of classification.

2.2 Neural networks

Neural networks, formally called *artificial neural networks* (ANNs), are computational models inspired by networks of biological neurons (PURI *et al.*, 2016). They are made up of multiple nodes called artificial neurons that map an input to an output based on mathematical operations. This model is used extensively in ML applications because of its perceived intelligent behaviour that come from the interactions between neurons.

2.2.1 Artificial neuron

The artificial neuron is the most basic block of an ANN. It maps inputs to an output in the given fashion:

$$y = f(\mathbf{w} \cdot \mathbf{x} + b), \tag{2.1}$$

where the symbols are defined as:

$$\begin{array}{ll} \mathbf{x} = [x_1, x_2, \ldots, x_n] & \text{Input vector;} \\ \mathbf{w} = [w_1, w_2, \ldots, w_n] & \text{Weights vector;} \\ f & \text{Activation function;} \\ y & \text{Neuron output.} \end{array} \tag{2.2}$$

The image 2.1 shows the artificial neuron model.

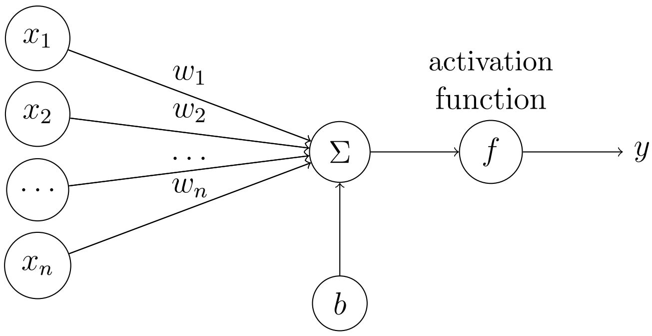

FIGURE 2.1 – Model of a neuron.

This model of neuron is useful because it incorporates both the linear combination of input values and bias and the non-linearity of the activation function, which means it may function as a part of an universal function approximator (HORNIK *et al.*, 1989).

2.2.2 The network

As said before, an ANN is a network of artificial neurons. Such network may be built by having the neurons configured in layers, having each neuron in a layer connected only to neurons in either preceding or following layers. Figure 2.2 shows a simple model of a fully-connected (a neuron in a layer connects to every neuron in the other layers) neural network, having 3 input nodes, 4 middle nodes (called a hidden layer) and 3 output nodes.

2.3 Generative Adversarial Networks

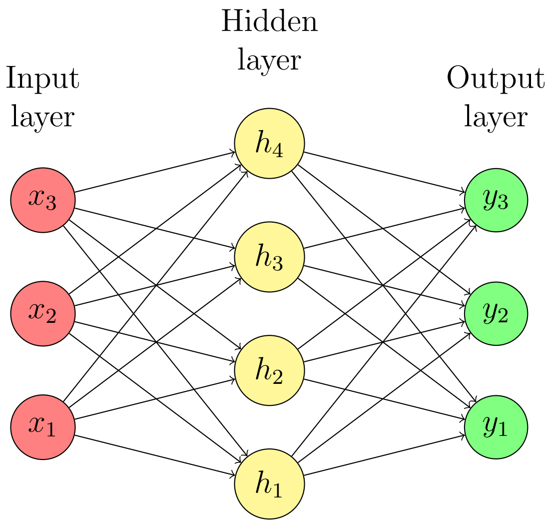

FIGURE 2.2 – A model of a simple fully-connected neural network with 10 nodes.

3 Instance Space Analysis

3.1 Instance Spaces

3.2 Instance hardness

4 Methodology

5 Results

5.1 Planned results

6 Conclusion

6.1 Preliminary conclusions and future work

6.2 Work plan

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Appendix A - Tópicos de Dilema Linear

A.1 Uma Primeira Seção para o Apêndice

A matriz de Dilema Linear M e o vetor de torques inerciais b, utilizados na simulação são calculados segundo a formulação abaixo:

$$M = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \tag{A.1}$$

FIGURE A.1 – Uma figura que está no apêndice

Annex A - Exemplo de um Primeiro Anexo

A.1 Uma Seção do Primeiro Anexo

Algum texto na primeira seção do primeiro anexo.

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Trabalho de Graduação, ITA, São José dos Campos, 2015. 25 páginas.

11. RESUMO:

Aqui começa o resumo do referido trabalho. Não tenho a menor idéia do que colocar aqui. Sendo assim, vou inventar. Lá vai: Este trabalho apresenta uma metodologia de controle de posição das juntas passivas de um manipulador subatuado de uma maneira subótima. O termo subatuado se refere ao fato de que nem todas as juntas ou graus de liberdade do sistema são equipados com atuadores, o que ocorre na prática devido a falhas ou como resultado de projeto. As juntas passivas de manipuladores desse tipo são indiretamente controladas pelo movimento das juntas ativas usando as características de acoplamento da dinâmica de manipuladores. A utilização de redundância de atuação das juntas ativas permite a minimização de alguns critérios, como consumo de energia, por exemplo. Apesar da estrutura cinemática de manipuladores subatuados ser idêntica a do totalmente atuado, em geral suas caraterísticas dinâmicas diferem devido a presença de juntas passivas. Assim, apresentamos a modelagem dinâmica de um manipulador subatuado e o conceito de índice de acoplamento. Este índice é utilizado na sequência de controle ótimo do manipulador. A hipótese de que o número de juntas ativas seja maior que o número de passivas ($n_a > n_p$) permite o controle ótimo das juntas passivas, uma vez que na etapa de controle destas há mais entradas (torques nos atuadores das juntas ativas), que elementos a controlar (posição das juntas passivas).

12. GRAU DE SIGILO:

(X) OSTENSIVO **( ) RESERVADO** **( ) SECRETO**