

# SENIOR HONOURS PROJECT



University of  
St Andrews

## Freeing Neural Training Through Surfing

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# Abstract

TODO

# Declaration

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# Chapter 1

## Introduction

### 1.1 Motivation

**TODO**

### 1.2 Objectives

**TODO** Primary objectives:

1. Design a generic framework that can be used for various neural training algorithms with a clear set of inputs and outputs at each step. This framework should include benchmarking capabilities.
2. For a simple case of this framework (when the dimensionality of the control space and output space are suitably low), implement a visualisation tool that shows the algorithm's steps.
3. Implement a particular training algorithm for the framework that uses potential field techniques.
4. Evaluate the performance of this and other algorithms on tasks of differing complexity, especially with regard to the local minimum problem and similar issues.

Secondary objectives:

1. Investigate how this approach can be generalized to any numerical optimisation problems.

### 1.3 Accomplishments

## Chapter 2

# Theory

### 2.1 Fully-connected feedforward neural networks

**Regression model** In machine learning, a regression model  $f$  is defined as a mathematical function of the form

$$f(\mathbf{x}) = \hat{y} = y + \epsilon \quad (2.1)$$

that models the relationship between a  $D$ -dimensional feature vector  $\mathbf{x} \in \mathbb{R}^D$  of independent (*input*) variables and the dependent (*output*) variable  $y \in \mathbb{R}$ . Given a particular  $\mathbf{x}$ , the model will produce a *prediction* for  $y$  which we denote  $\hat{y}$ . Here, the additive error term  $\epsilon$  represents the discrepancy between  $y$  and  $\hat{y}$ .

**Supervised learning** A supervised learning algorithm for a regression task infers the function  $f$  given in (2.1) from a set of *labelled training data*. This dataset consists of  $N$  tuples of the form  $\langle \mathbf{x}_i, y_i \rangle$  for  $i = 1, \dots, N$ . For each feature vector  $\mathbf{x}_i$ , the corresponding  $y_i$  represents the observed output, or *label*. We use the vector

$$\mathbf{y} = [y_1 \quad \dots \quad y_N]^\top \quad (2.2)$$

to denote all the labelled outputs in the dataset, and

$$\mathbf{X} = [\mathbf{x}_1 \quad \dots \quad \mathbf{x}_N]^\top \quad (2.3)$$

is the  $N \times D$  matrix representing the corresponding feature vectors.

Similarly,

$$\hat{\mathbf{y}} = [\hat{y}_1 \quad \dots \quad \hat{y}_N]^\top \quad (2.4)$$

denotes a particular prediction for each training sample.

**Artificial neural network** Artificial neural networks (ANNs) take inspiration from the human brain and can be regarded as a set of interconnected neurons. More formally, an ANN is a directed graph of neurons (referred to as *nodes* or *units*) connected by weighted edges. **TODO**

**Multilayer perceptron** employed in this project **TODO**

### 2.1.1 Weight and output spaces

We define the weight space  $\mathcal{W}$  **TODO**

The output space  $\mathcal{O}$  spans the space of all possible output predictions on the training set,  $\hat{\mathbf{y}}$ , so  $\mathcal{O} = \mathbb{R}^N$  considering the fact that the training set has  $N$  samples.

# Ideas

Generalize to classification as regression with multiple output variables?