國立臺北科技大學
資訊工程系碩士班
碩士學位論文

Use Efficiency-based Genetic Programming to Create Loss Function for Image Classification Tasks

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指導教授：陳香君博士

中華民國一百一十四年五月

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Abstract

Title: Use Efficiency-based Genetic Programming to Create Loss Function for Image Classification Tasks

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In the past five years, with the rapid rise of deep learning, image classification models have quickly become one of the most popular and widely known models. When training such models, the steps are broadly divided into the following: preparing image datasets, dividing them into training, validation and testing sets as needed, training the model, evaluating the model, and repeating these steps until the ideal result is met or the computational resources are exhausted.

A crucial function during the process of training a model is called the loss function, which calculate the difference between the predicted values and the ground-truth values. The results of the loss function can significantly influence the effectiveness of the model's training because it simply decide the direction of the adjustment to the model. However, designing a loss function often requires the assistance of experts in the related field, leading to a resource-intensive design process. Recent research has proposed using Genetic Programming (GP) to generate loss functions to avoid the necessity of hiring numerous domain experts for assistance. Nevertheless, using GP typically results in decreased computational efficiency. This paper aims to improve the method of using GP to generate loss functions by modifying certain genetic operations and introducing the concept of tournament selection.

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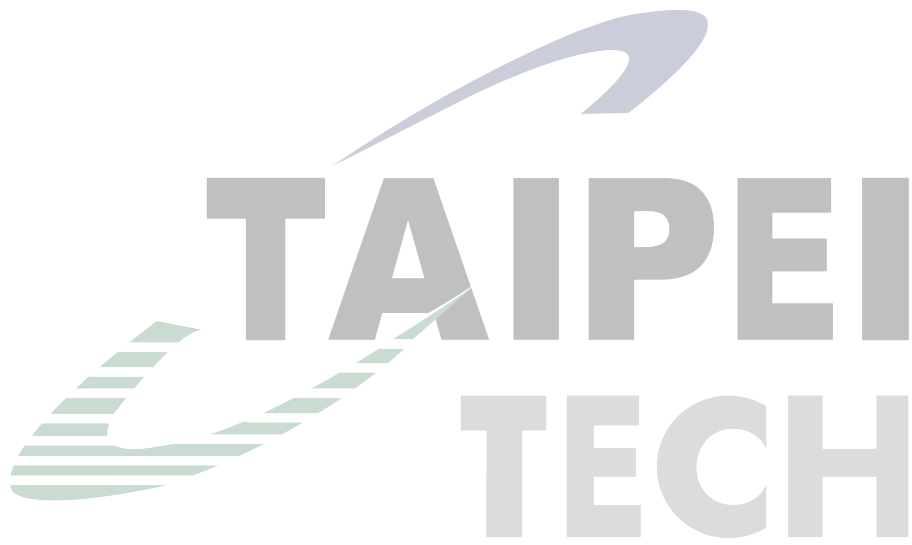
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Chapter 1 Introduction

After several decades of development, deep learning [1] technology has achieved significant breakthroughs in the last ten years, largely due to the remarkable improvements in GPU computational power. Consequently, the predictive and analytical capabilities of models have achieved substantial advancements. Numerous models have been launched by major companies and applied in practical scenarios, leading to significant changes in our daily lives.

When it comes to training deep learning model, we usually refer to the following steps: collecting relevant data and organizing it into datasets, partitioning the datasets into training and validation sets as needed, initializing model parameters, training the model, evaluating the performance of the model, adjusting the model parameters, and repeating the training until the target is achieved or computational resources are exhausted. During the evaluation of the model's performance, we use a function called the loss function [2]. Its purpose is to calculate the difference between the model's predicted results and the ground truth, which helps model adjust its parameter to better fit the target. Therefore, different loss functions can influence the direction of model adjustments, significantly impacting the final outcomes of the model.

However, the design of a loss function is often closely related to the propose of the model [3]. In other words, different models may require experts from specific fields to assist in designing the loss function to enhance the speed and effectiveness of model training. Nevertheless, recent research has shown that it's feasible to use genetic programming (GP) [4] to automatically generate loss functions. Due to the domain-independent nature of GP, it allows us to develop an algorithm that can automatically create the required loss function without needing specialized knowledge in that particular field. However, this method typically requires a significant amount of time and computational resources.

The operation mode of GP can be simply divided into the following steps: Representing the solution we hope to find (which may be a value or a function) in an encoded form, then forming these solutions into a population. After evaluating the whole population, we perform genetic operations (e.g., mutation or crossover) on the population's solutions, reevaluate them, and repeat the above steps until the target is achieved or computational resources are exhausted.

Although the computational power of GPUs today is far superior to that of the past, both training models and using GP to find solutions still require substantial computational resources and time to achieve a decent result. In this paper, an efficiency-oriented GP algorithm is proposed to reduce the computational resources and the time to train the model required for GP to search for the optimal algorithm while maintaining the same level of effectiveness. We aim to improve the genetic operation part of the existing GP framework by referencing the concept that offspring in a better living environment can usually receive better care. We modify the GP's genetic operation such that only a certain number of high-scoring populations can execute it. Here's what we want to do: Select a certain proportion of high-scoring offspring from the population, then randomly select a fixed number from these offspring to perform genetic operations. The randomized selection can avoid always using the same population for genetic operations, giving more excellent offspring the opportunity to improve.

The structure of this paper is as follows: Chapter 2 is related work. This chapter provides a detailed illustration to the development and history of GP, the detailed description of the loss function and how they collaborate with deep learning model, and how loss functions are randomly generated via GP. Chapter 3 is proposed algorithm and main methodology. In this chapter, we will explain the architecture of the algorithm implemented in this paper. After that, we will then describe the experimental environment setup and the initial parameter values. Finally, we will present the methods and procedures used in this paper. Chapter 4 is results analysis. This section will show the detail parameter settings among all compared peer-algorithm. After that, we will present the analysis of the results by organizing the experimental results into charts and figures. Finally, we will explain the outcomes and analyze why our algorithm can achieve the similar result while decreasing the usage of computational resources. Chapter 5 is conclusion and future work. In this chapter, we will provide the conclusion of this paper by outlining the contribution we have made so far. After that, we would like to discuss potential directions for future research or possible way to apply this algorithm in practical.

Chapter 2 Related Work

2.1   Metaheuristic

Metaheuristic was first proposed by ... this concept means we can ...

Evolving algorithm, genetic algorithm and genetic programming are algorithms using the concept of Metaheuristic, we will introduce them in the following paragraph.

Evolving algorithm was first proposed in ...

The concept of genetic algorithm was proposed and .....

Genetic programming, can be seen as one of the special case of genetic algorithm, has been used in different domain because it doesn't require specific domain knowledge to implement.

In [5], a meta-learning reinforcement learning algorithm was proposed. The research team used computational graphs to represent algorithms. By doing so, algorithms could be identified, calculated, and optimized through Reinforcement Learning (RL) [6]. Notably, in this study, algorithms were represented as directed acyclic graphs (DAG) of nodes. Within the DAG , all nodes were classified into three categories: input nodes, parameter nodes, and operation nodes. Once the algorithms were represented as DAGs, they could be placed into RL for training and evaluation. In this proposed algorithm, they employed the concept of regularized evolution [7] to evolve a population formed by several randomized and known algorithms. The method was as follows: initialize the population with algorithms, evaluate each algorithm in the population and record their performance, then in a loop, repeatedly use a sample tournament [8] to select algorithms, perform mutations on the algorithms by the mutator they designed, and evaluate them again until the loop ends. During the evaluation process, they trained and assessed the algorithms using RL, continuously testing the performance of each algorithm in different training environments. They also utilized normalized training performance to avoid numerical biases caused by varying environments. Through this approach, the study successfully created two algorithms, named DQNClipped and DQNReg, which outperformed classical control tasks.

In [9], a genetic programming-based method was proposed to find a better function for the image classification training task. They encoded the loss functions into trees, with each tree con-

sidered an individual. All individuals were aggregated into a population. In this study, the population was evolved across multiple generations. Before the start of each generation, all individuals were evaluated. Each individual had a probability of undergoing crossover with an individual from a special external archive to create a new individual; otherwise, it would perform the crossover with another individual. Following this, two probabilistic decisions were made. If successful, the new individual could perform subtree mutation or one-point mutation, respectively. At the end of each generation, the fitness value of all individuals was re-evaluated. A certain number of low-scoring individuals were eliminated to the special external archive mentioned earlier, maintaining the stability of the population's size. After these steps, a new generation began, continuing until a predefined number of generations was reached.By employing this method, this study successfully evolved an outstanding individual within the population, creating a function that could train an image classification model more effectively compared to Cross Entropy [10].

2.2 Loss Function

2.2.1 Deep Learning Model

2.2.2 Importance of Loss Function

In [11], a loss function meet genetic programming is proposed ....

2.3 Image Classification

Chapter 3 Purposed Algorithm

This section will provide a brief overview of the contents that will be discussed in this chapter: Section 3.1 will introduce the architecture of our algorithm and use a simple flowchart to provide a basic introduction to the proposed algorithm. Section 3.2 will provide a detailed description of our software and hardware specifications, as well as the setup procedures. Section 3.3 will provide an in-depth explanation of our proposed algorithm, including the underlying concepts and the rationale behind our approach.

3.1   The Architecture of Algorithm
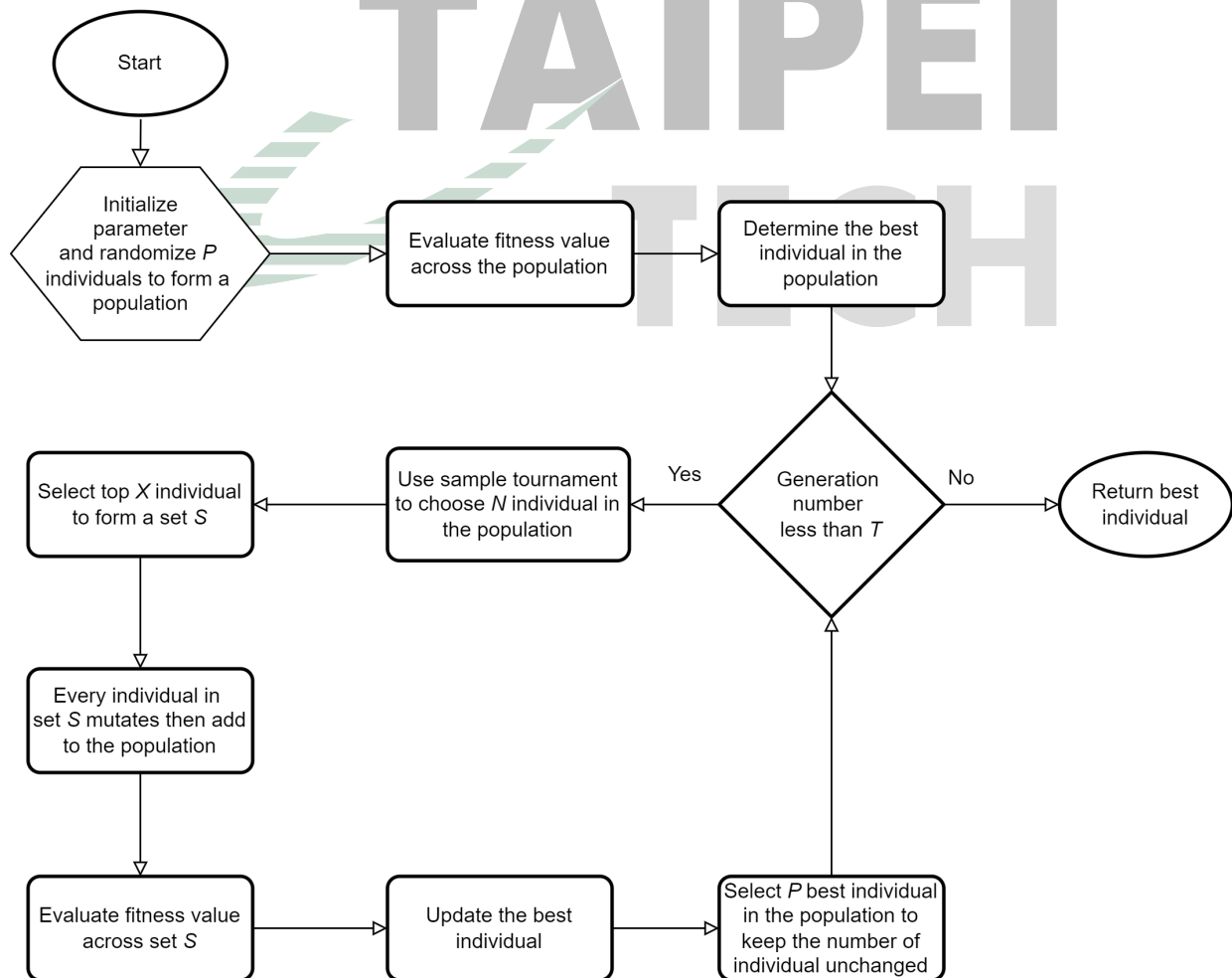

Figure 3.1 FlowChart for Efficiency-based GP

3.2   Main Method

Algorithm 1 Efficiency-based GP to generate loss function

Initialize:$P =$x, $T =$x, $N =$x, $M_{ST} = 0.5$
Randomly initialize population which include P trees
Evaluate GP fitness function F for each individual in the population
Determine the best individual
while generation number $< T$ **do**
    Sample tournament G $\sim$ Uniform (P)
    Select top N trees from G to form a set S
    for Individual in S **do**
        if $rand_1 < M_{ST}$ **then**
            Apply subtree mutation to the generated child
        else
            Apply one-point mutation to the individual
        end if
        if Functional_check() is true **then**
            add individual to population
        end if
    end for
    Evaluated GP fitness function F for each generated child individual
    Update the best individual
    Select P best trees from population to form a new population containing P trees
**end while**

Chapter 4 Result & Analysis

4.1   Implementation details

In our software setup, we run our code in Ubuntu 24.04. The Python version we employ is 3.8, and the Pytorch version is X. Within Python and Pytorch, we utilize the following packages: Some package.

In our hardware setup, we run our code on an AMD Ryzen 5 5600X 6-Core Processor. The system is equipped with 32GB of memory, operating at a frequency of DDR4-3600MHz. Additionally, we utilize an NVIDIA GeForce RTX 3060 Ti GPU for our computational needs.
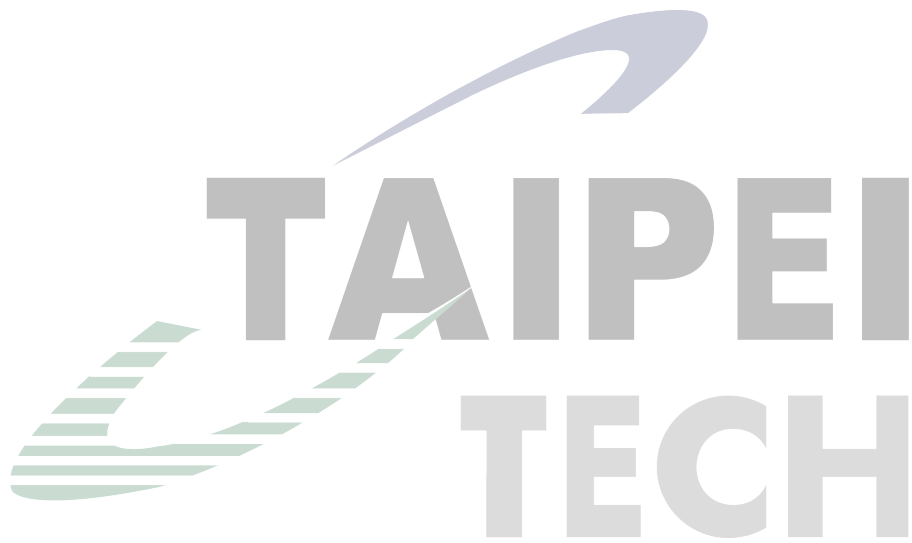
4.2   Figures
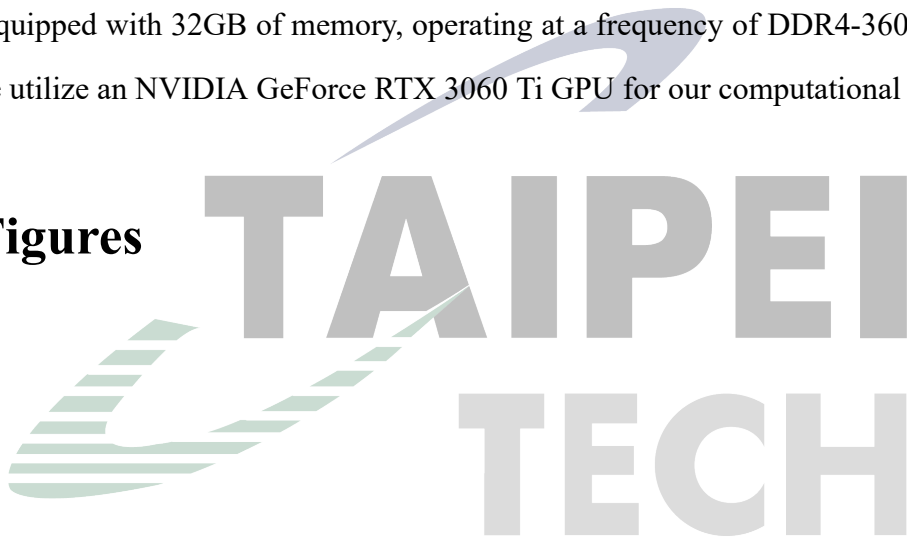
Chapter 5 Conclusion & Future Work

5.1 Conclusion

5.2 Future Work

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