Technology Design Project – COS 60011

Deliverable 1

Individual Research Report

Name: Arun Ragavendhar Arunachalam Palaniyappan

Student ID: 104837257

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Acknowledgment to country and references)

Acknowledgement to Country

As a student at Swinburne University of Technology, I am deeply appreciative of the opportunity to study on the land that belongs to the Kulin Nation, where modern-day Melbourne is now located. I extend my heartfelt gratitude to the Wurundjeri People, the traditional custodians of this land. I also want to acknowledge and thank the Aboriginal and Torres Strait Islander students, alumni, collaborators, and visitors connected with Swinburne. It is a privilege to recognize and celebrate the rich spiritual, historical, and cultural heritage of the Wurundjeri land, which fills me with great respect and pride.

1. Introduction

Machine learning (ML) is a groundbreaking method that allows computers to learn from data and make decisions without requiring explicit programming. Many current applications rely on machine learning, particularly recommendation algorithms, which are critical in directing user choices across a wide range of areas, from movies and books to products and services.

This report focuses on the learnings and knowledge acquired through research, for the implementation of a **car recommendation system using a Deep Feedforward Neural Network**, also known as a Multi-Layer Perceptron (MLP). The report will cover the basics of machine learning and neural networks, delve into the specifics of deep MLPs and backpropagation, and outline the steps involved in implementing this model in a recommendation system **[1].**

2. Machine Learning and Neural Networks

2.1 Understanding Machine Learning

Machine learning is a subset of artificial intelligence (AI) in which a specific set of algorithms are used against collected data to generate predictions or judgements. The major objective is to enable computers to automatically detect patterns in data and improve over time. There are three main types:

• **Supervised Learning:** The model is trained using labelled data with known input-output pairings. The objective is to discover a relationship between inputs and their corresponding outputs.

• **Unsupervised learning:** This method focuses on using unlabelled data to develop models that can detect patterns or categorize data into distinct groups.

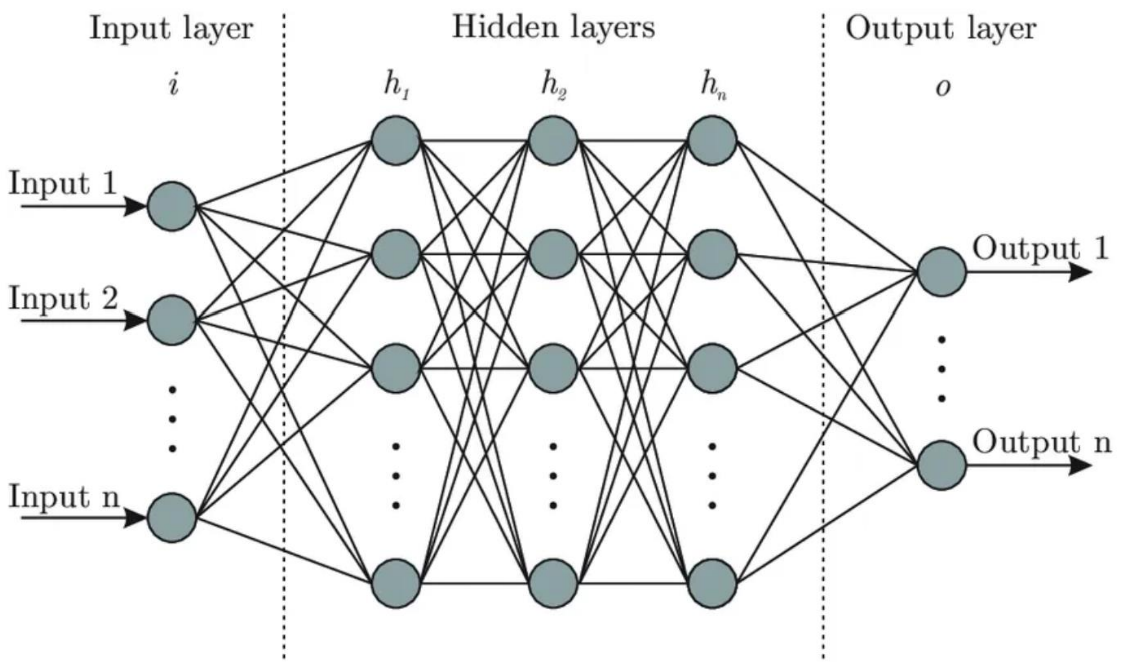
• **Reinforcement learning:** The model learns through interactions with its surroundings, receives feedback, and improves its performance.

For the proposed car recommendation system**, supervised learning** is to be used to make car recommendations based on user preferences and requirements.

2.2 Introduction to Neural Networks

Neural networks are computational systems modelled after how the human brain operates. They consist of several layers of interconnected units, known as neurons, that transmit and process information using weighted connections throughout the network. **[8].**

Figure 1: Basic Structure of a Neural Network – **[10].**



• The **input layer** receives raw data characteristics (such as the car attributes).

• **Hidden layers** are intermediate levels where data undergoes complicated changes. The network becomes deeper as the number of hidden levels increases.

• The **output layer** produces the ultimate result, in this example, the final suitable car suggestions.

Each connection between neurons has an associated weight, and each neuron has an activation function that determines whether it should "fire" or pass on its signal. The learning process involves adjusting these weights to reduce the difference between the predicted output and the actual output **[10].**

3. Deep Feedforward MLP with Backpropagation

3.1 Core Fundamentals

A Deep Feedforward MLP is a neural network in which the connections between neurons do not generate cycles. Information flows in one direction only, moving from the input layer through to the output layer., via numerous hidden layers **[11].** The network's depth (the number of hidden layers) enables it to detect complicated patterns in the data.

3.2 Backpropagation

Backpropagation comprises two primary phases: forward pass and backwards pass.

Forward Pass: Before a prediction is created at the output layer, the input data is routed through the network layer by layer.

Backwards Pass: The error between the expected and actual outputs is determined. This mistake is then transmitted back across the network, and the weights are changed to reduce the error.

The backwards pass is based on a mathematical concept known as gradient descent, which seeks a function's minimum by iteratively travelling in the direction of steepest fall.

3.3. Mathematical Representation of the Model

3.3.1. Forward Pass Equation

Equation:

$$y^\wedge = \sigma(W \cdot X + b)$$

Explanation:

- $y^\wedge$ **(Predicted Output):** This is the output predicted by the model, also called the model's prediction.
- W **(Weights Matrix):** In a neural network, each input feature is multiplied by a weight. The weights determine the importance of each input feature in making predictions.
- X **(Input Features):** This represents the features or data points that are input into the model.
- b **(Bias Term):** This is a constant that allows the model to fit the data better by shifting the activation function.
- σ **(Activation Function):** This function applies a non-linear transformation to the input. Most used activation functions:
    - $\boldsymbol{ReLU}$ **(Rectified Linear Unit):** Gives zero as the output if the input is negative and outputs the input itself if it's positive.
    - $\boldsymbol{Sigmoid}$**:** Squeezes the input into a range between 0 and 1. **[4].**

How it works:

- The input features X are multiplied by the corresponding weights W, and the bias b is added to the result. This linear combination $(W \cdot X + b)$ is then sent via the activation function σ to introduce non-linearity, resulting in the predicted output $y^\wedge$.

3.3.2. Loss Function (Cross-Entropy Loss)

Equation:

$$L(y^\wedge, y) = -i = 1\sum nyilog(y^\wedge i)$$

Explanation:

- $L(y^\wedge, y)$ **(Loss Function):** The difference between the predicted output y ^ and the actual output y is calculated by the loss function. The core aim is to minimize this loss to improve the model's accuracy.
- y **(Actual Output):** This is the true label or value that is to be predicted.
- $y^\wedge$ **(Predicted Output):** This is the output predicted by the model.

How it works:

- **Cross-Entropy Loss** is used primarily in classification problems. It quantifies how far the predicted probabilities ($y^\wedge i$) are from the actual labels (yi).
- The equation sums over all classes n. For each class i, it multiplies the actual label (yi). by the logarithm of the predicted probability $(y^\wedge i)$ **[5].**
- If the predicted probability $(y^\wedge i)$ is close to the actual label (yi), the loss will be small. If it's far off, the loss will be large. The aim of training is to reduce this loss.

3.3.3. Gradient Descent Update Rule

Equation:

$$W_{new} = W_{old} - \eta \cdot \partial L / \partial W$$

Explanation:

- W_{new} **(Updated Weights):** These are the new values for the weights after the update.
- W_{old} **(Current Weights):** These are the weights before the update.
- η **(Learning Rate):** This is a small, positive parameter that determines the pace of learning, influencing how rapidly or gradually the model adjusts and improves **[9].**
- $\partial L / \partial W$ **(Gradient of the Loss with Respect to Weights):** This represents the slope of the loss function with respect to the weights. It gives an idea about how to change the weights to decrease the loss **[7].**

How it works:

- **Gradient Descent** is an optimisation technique aimed at minimizing the loss function.
- The algorithm updates the weights in the direction that decreases the loss.
- The term $\partial L / \partial W$ (the gradient) points in the direction of the steepest ascent of the loss function. By subtracting it, we move the weights in the direction of the steepest descent (hence minimizing the loss) **[7].**

- The learning η rate controls how large of a step we take in that direction. If η is too large, it might overshoot the minimum; if it's too small, learning will be slow.

3.4. One-hot Encoding Model

One-hot encoding is a way to convert categorical data (like car brand, fuel type, or body type) into a format that a machine learning model can easily understand **[3].** For example, for a set of different car brands: Toyota, Honda, and Ford; One-hot encoding turns each brand into a unique row of binary values (0s and 1s), as given below:

- Toyota: [1, 0, 0]
- Honda: [0, 1, 0]
- Ford: [0, 0, 1]

This ensures the neural network treats each brand as distinct, avoiding any false numerical relationships. In a car recommendation system, one-hot encoding enables the deep feedforward MLP to accurately process features like car brands, fuel types, and body styles, leading to better pattern recognition and more accurate recommendations.

Table 1: One-hot encoding model of Car brand, fuel type and car body type of a car dataset **[3].**

Price	Honda	Toyota	Ford	Diesel	Petrol	Hatchback	SUV	Sedan
25000	0	0	1	0	1	0	0	1
27000	0	1	0	1	0	0	1	0
22000	1	0	0	0	1	1	0	0
24000	0	0	1	1	0	0	0	1
26000	1	0	0	0	1	0	1	0
23000	0	1	0	1	0	1	0	0

4. Implementation of the Car Recommendation System

4.1. Data Preparation

The dataset is prepared by one-hot encoding categorical variables and normalising numerical data to guarantee consistent scales and improved model performance.

4.2. Model Initialisation

A deep Multi-Layer Perceptron (MLP) is configured with a specific architecture that contains layers and activation functions designed to handle input efficiently.

4.3. Training

Using backpropagation and gradient descent, the model learns to predict properly and adjusts its weights to reduce the disparity between its predictions and actual outcomes.

4.4. Deployment

The trained model is planned to be deployed into a Streamlit web application, where users can enter their vehicle preferences and receive personalised car recommendations **[12].**

5. Summary and Conclusion

This research report investigated the use of **a Deep Feedforward Multi-Layer Perceptron (MLP) with one-hot encoding model** to create a **Car recommendation system**. By covering the fundamentals of machine learning and neural networks, it discussed the MLP's design and training procedure, emphasising the importance of one-hot encoding in categorical data processing.

The report emphasises on the efficient use of backpropagation and gradient descent algorithms to improve the model's performance. The trained final model is planned to be integrated into a Streamlit web application to provide users with personalised car recommendations based on their tastes. In conclusion, the research confirms deep learning's effectiveness in handling complex data for recommendation systems, with significant implications for enhancing personalized recommendations in future applications.

6.Appendix

6.1 List of Figures

Figure 1*: Basic Structure of a Neural Network*

6.2 List of Tables

Table 1*: One-hot encoding model of Car brand, fuel type and car body type of a car dataset*

7. References

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