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A Individual Task on

"Build a Perceptron model solve binary classification and apply perceptron learning law"

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CERTIFICATE

This is to certify that RAVI MAHESH (01SU24AI082) has satisfactorily completed the assessment (Individual-Task – Module 1) in **"ARTIFICIAL NEURAL NETWORK "** prescribed by the Srinivas University for the 4st semester B. Tech course during the year **2025-26**.

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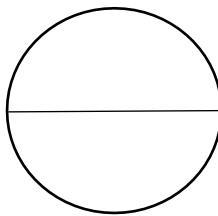
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1. Introduction

Artificial Intelligence and Machine Learning have significantly transformed the way computers solve real-world problems. One of the fundamental building blocks of machine learning is the concept of artificial neural networks, which are inspired by the biological neurons present in the human brain. Among the earliest and simplest neural network models is the Perceptron, introduced in 1958 by **Frank Rosenblatt**. The Perceptron was designed as a supervised learning algorithm capable of performing binary classification tasks by learning from labelled data. It marked an important milestone in the history of neural networks and laid the foundation for modern deep learning techniques.

A Perceptron is essentially a linear classifier that separates data into two distinct classes using a decision boundary. It takes multiple input values, multiplies them by corresponding weights, adds a bias term, and then passes the result through an activation function to produce an output. The most commonly used activation function in a Perceptron is the step function, which produces a binary output (0 or 1). This makes the Perceptron suitable for solving problems such as logical operations, pattern recognition, and simple classification tasks where the data is linearly separable.

The learning process of the Perceptron is based on an iterative weight update mechanism known as the Perceptron Learning Rule. During training, the algorithm compares the predicted output with the actual target value and adjusts the weights and bias to minimize classification errors. This adjustment continues until the model correctly classifies all training examples or reaches a predefined number of iterations. The simplicity of this learning rule makes the Perceptron easy to understand and implement, either manually or using programming tools such as Python or spreadsheet software.

Although the Perceptron is limited to solving only linearly separable problems and cannot handle complex non-linear patterns such as the XOR problem, its importance in the evolution of neural networks cannot be overstated. It provides a clear understanding of how machines can learn from data through mathematical rules and iterative improvement. Furthermore, modern neural network architectures, including multilayer perceptions and deep neural networks, are extensions of this fundamental concept.

In this report, a Perceptron model is developed to solve a binary classification problem. The Perceptron learning law is applied step by step to demonstrate how weights are updated during training. Both manual calculations and code implementation are included to provide a clear understanding of the working mechanism of the algorithm. This study highlights the practical implementation of the Perceptron and its role as the foundation of supervised learning models in machine learning.

2. Objective

The primary objective of this project is to design and implement a Perceptron model to solve a binary classification problem using the Perceptron learning law. The study aims to develop a clear understanding of how a simple artificial neural network can learn from labelled training data and adjust its parameters iteratively to achieve correct classification. By building the model manually and programmatically, this project seeks to bridge the gap between theoretical concepts and practical implementation in machine learning.

Another important objective is to understand the mathematical foundation of the Perceptron algorithm. This includes studying how input features are multiplied by weights, how a bias term influences the decision boundary, and how the activation function converts the weighted sum into a binary output. The project also focuses on understanding the concept of linear separability and how the Perceptron forms a linear decision boundary to separate two classes effectively.

The project further aims to apply the Perceptron Learning Rule step by step. This involves initializing weights and bias values, calculating the net input, determining the predicted output, computing the error, and updating the parameters accordingly. Through repeated training iterations, the objective is to demonstrate how the Perceptron gradually minimizes classification errors and converges to a stable solution. Performing manual calculations helps in gaining a deeper conceptual clarity of the learning mechanism.

In addition, the project intends to implement the Perceptron model using a programming language such as Python or a spreadsheet tool. This practical implementation ensures that the theoretical learning rule is correctly applied in real computational environments. By comparing manual calculations with program output, the project verifies the correctness and effectiveness of the algorithm.

Another objective is to analyse the strengths and limitations of the Perceptron model. While it works efficiently for linearly separable datasets such as logical AND classification, it cannot solve non-linearly separable problems. Understanding these limitations provides insight into why advanced neural network models were later developed as extensions of the basic Perceptron introduced by **Frank Rosenblatt**.

Finally, this project aims to enhance practical knowledge of supervised learning, neural networks, and binary classification techniques. By completing this task, a strong foundational understanding of machine learning algorithms is established, which is essential for studying advanced topics such as multilayer perceptions and deep learning architectures.

3. Theory of Perceptron

The Perceptron is one of the earliest and simplest models of artificial neural networks developed for solving binary classification problems. It was introduced in 1958 by **Frank Rosenblatt**, who proposed it as a computational model inspired by the functioning of biological neurons in the human brain. The fundamental idea behind the Perceptron is to simulate how a neuron processes input signals, applies weights, and produces an output based on a decision rule. Despite its simplicity, the Perceptron laid the groundwork for modern neural network architectures and deep learning systems.

A Perceptron consists of three main components: input values, weights, and an activation function. The inputs represent the features of a dataset, and each input is associated with a corresponding weight. These weights determine the importance or influence of each input feature on the final output. In addition to the weighted inputs, a bias term is included to shift the decision boundary and improve classification flexibility. The mathematical representation of the Perceptron model can be expressed as:

$$Y = f\,(W1X1 + W2X2 + \cdots + WnXn + b)$$

where **X1,X2 ,..., Xn** are the input features,, **W1,W2,...,Wn** are the corresponding weights, **b** is the bias, and **f** is the activation function. The function computes a weighted sum of the inputs and then applies a decision rule to generate the output.

The activation function used in a standard Perceptron is typically a step function, also known as a threshold function. This function produces a binary output: it returns 1 if the net input is greater than or equal to zero, and 0 otherwise. Because of this binary output nature, the Perceptron is mainly used for two-class classification problems. The step function can be expressed as:

$$f(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{if } z < 0 \end{cases}$$

One of the key theoretical concepts associated with the Perceptron is linear separability. A dataset is said to be linearly separable if a straight line (in two dimensions), a plane (in three dimensions), or a hyperplane (in higher dimensions) can divide the data points into two distinct classes without error. The Perceptron works effectively only when such a linear boundary exists. It determines this boundary by adjusting weights and bias during training.

The learning mechanism of the Perceptron is based on supervised learning. During training, the model receives input-output pairs and compares the predicted output with the actual target value. If an error occurs, the weights and bias are updated using the Perceptron Learning Rule. This iterative process continues until the model correctly classifies all training examples or reaches a stopping criterion. Through this method, the Perceptron gradually learns the optimal parameters that define the decision boundary. Although the Perceptron has limitations, particularly its inability to solve non-linearly separable problems such as XOR classification, its theoretical importance remains significant. It provides a clear understanding of how neural networks learn, how decision boundaries are formed, and how mathematical rules can enable machines to perform intelligent classification tasks. The Perceptron serves as the foundational model upon which advanced neural network systems have been developed.

Another important theoretical aspect of the Perceptron is its geometric interpretation. In a two-dimensional feature space, the Perceptron forms a straight line that acts as a decision boundary separating two classes. In higher dimensions, this boundary becomes a hyperplane. The position and orientation of this hyperplane depend entirely on the values of the weights and bias. When the weights are adjusted during training, the decision boundary shifts accordingly until it correctly separates the training samples. This geometric perspective helps in understanding how small changes in weights can significantly alter the classification results and improve model performance.

4. Perceptron Learning Law

The Perceptron Learning Law is the fundamental rule that enables the Perceptron model to learn from training data and improve its classification accuracy. It defines how the weights and bias of the model are updated whenever a classification error occurs. This learning mechanism allows the Perceptron to gradually adjust its parameters until it finds an appropriate linear decision boundary that separates the two classes. The learning rule forms the mathematical foundation of supervised learning in early neural network models introduced by **Frank Rosenblatt**.

The Perceptron operates on labelled training data, where each input vector is associated with a known target output. For a given input vector, the model first computes the net input as the weighted sum of inputs plus a bias term. Mathematically, the net input can be expressed as:

$$Z = W_1X_1 + W_2X_2 + \cdots + W_nX_n + b$$

This net value is then passed through a step activation function to generate the predicted output. The predicted output is compared with the actual target value to determine whether the classification is correct. If the predicted output matches the target, no changes are made to the weights or bias. However, if there is a mismatch, the learning rule is applied to adjust the parameters.

The Perceptron Learning Law updates the weights using the following formula:

$$W_i(new) = W_i(old) + \eta(t-y)X_i$$

Similarly, the bias is updated as

:

$$b(new) = b(old) + \eta(t-y)$$

In these equations, η represents the learning rate, t is the target output, and y is the predicted output. The term $(t-y)$ represents the error. If the predicted output is less than the target, the error is positive and the weights are increased. If the predicted output is greater than the target, the error is negative and the weights are decreased. In this way, the model moves its decision boundary in the correct direction to reduce future errors.

The learning rate η plays an important role in controlling the magnitude of weight updates. A larger learning rate causes bigger adjustments, which may speed up learning but can lead to instability. A smaller learning rate ensures gradual learning but may require more iterations to converge. Therefore, selecting an appropriate learning rate is important for efficient training.

The Perceptron Learning Law guarantees convergence if the dataset is linearly separable. This means that if a linear decision boundary exists, the algorithm will eventually find suitable weights and bias values that correctly classify all training examples. However, if the data is not linearly separable, the learning process will not converge, and errors will continue indefinitely.

Overall, the Perceptron Learning Law provides a simple yet powerful mechanism for parameter adjustment. It demonstrates how a machine can learn from mistakes and improve performance through iterative updates. This concept forms the basis for more advanced optimization techniques used in modern neural network and deep learning models.

5. Problem Statement

The objective of this project is to design and implement a Perceptron model to solve a binary classification problem using supervised learning. Binary classification refers to the task of categorizing input data into one of two possible output classes. In many real-world applications such as spam detection, medical diagnosis, credit approval, and pattern recognition, systems must decide between two distinct outcomes. The Perceptron model provides a simple yet powerful approach for solving such problems when the dataset is linearly separable.

For this project, a simple logical AND gate classification problem is selected to demonstrate the working of the Perceptron algorithm. The AND gate is a fundamental digital logic operation that produces an output of 1 only when both input values are 1; otherwise, it produces 0. Although this is a basic example, it clearly illustrates the principles of binary classification and linear separability. The dataset consists of two input features and one target output. The Perceptron must learn the correct mapping between the input combinations and their corresponding outputs.

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The main challenge addressed in this problem is to determine appropriate weight and bias values such that the Perceptron correctly classifies all input patterns. Initially, the weights and bias are assigned arbitrary or zero values. During training, the model calculates the net input as the weighted sum of the inputs plus bias. This value is then passed through a step activation function to produce a predicted output. If the predicted output differs from the actual target value, the Perceptron Learning Rule is applied to adjust the weights and bias. This iterative process continues until the classification error becomes zero or until convergence is achieved.

Another important aspect of this problem is to demonstrate the manual application of the learning rule. By performing step-by-step calculations for each training example, the process of weight updating and error correction can be clearly understood. In addition to manual computation, the same problem is implemented programmatically to verify the correctness of the results. This dual approach ensures both conceptual clarity and practical validation.

The problem also emphasizes understanding the concept of a decision boundary. In the case of the AND gate, the Perceptron must find a linear boundary that separates the output class 1 from output class 0 in a two-dimensional input space. Successfully identifying this boundary confirms that the dataset is linearly separable and that the Perceptron model is suitable for solving it.

Overall, this problem statement focuses on applying theoretical knowledge of the Perceptron algorithm to a practical binary classification task.

6. Data Description

The dataset selected for this project is a simple binary classification dataset based on the logical AND gate operation. The purpose of choosing this dataset is to clearly demonstrate how a Perceptron model learns from training examples and forms a decision boundary to classify inputs correctly. Since the Perceptron is designed to solve linearly separable problems, the AND gate dataset is an appropriate example because its classes can be separated using a straight line in a two-dimensional input space.

The dataset consists of two independent input variables and one dependent output variable. The two input variables are represented as x1 and x2. Each input variable can take only binary values, either 0 or 1. The output variable, referred to as the target value, is also binary and represents the class label. The output is 1 only when both input values are 1. In all other input combinations, the output is 0. This makes it a two-class classification problem where the model must distinguish between class 0 and class 1.

The dataset contains four training examples, which represent all possible combinations of two binary inputs. These combinations ensure that the model is trained on every possible scenario of the AND logical operation. The dataset is shown below in tabular format:

INPUT 1 (X1)	INPUT 2 (X2)	TARGET OUTPUT (T)
0	0	0
0	1	0
1	0	0
1	1	1

Each row in the dataset represents one training instance. For example, when x1 is 0 and x2 is 0, the expected output is 0. When x1 is 1 and x2 is 1, the expected output is 1. The Perceptron model processes these inputs by calculating a weighted sum of x1 and x2 along with a bias term. The predicted output is then compared with the target output to determine whether the classification is correct.

From a geometrical perspective, the dataset can be visualized on a two-dimensional coordinate system where x1 is plotted on the horizontal axis and x2 is plotted on the vertical axis. The point (1,1) belongs to class 1, while the points (0,0), (0,1), and (1,0) belong to class 0. A straight line can separate the point (1,1) from the other three points. This confirms that the dataset is linearly separable, which means a single-layer Perceptron can successfully learn the classification.

The dataset is small in size, which makes it suitable for manual computation of weight updates and error correction using the Perceptron Learning Law. Despite its simplicity, it effectively illustrates key machine learning concepts such as supervised learning, error-driven weight adjustment, and convergence. Using this dataset ensures that the working of the Perceptron algorithm can be clearly explained without unnecessary computational complexity.

7. Algorithm

The Perceptron algorithm is a supervised learning procedure used to train a model for binary classification. It works by adjusting weights and bias values whenever the predicted output does not match the target output. The goal of the algorithm is to find suitable parameter values so that all training examples are classified correctly. If the dataset is linearly separable, the algorithm will eventually converge to a correct solution.

The step-by-step pseudocode for the Perceptron algorithm is given below:

Step 1: Start

Step 2: Initialize weights w1 and w2 to zero

Step 3: Initialize bias b to zero

Step 4: Set learning rate to a small positive value

Step 5: Repeat the following steps for each training example

    a. Read input values x1 and x2

    b. Compute net input using current weights and bias

    c. If net input is greater than or equal to zero, set output to 1

    Else set output to 0

    d. Compare predicted output with target output

    e. If prediction is incorrect

        Update weights based on learning rate, error, and input values

        Update bias based on learning rate and error

Step 6: Repeat the entire dataset until no classification error occurs

Step 7: Stop

This algorithm continuously adjusts the weights and bias whenever an error is detected. Each complete pass through the dataset is called an epoch. The training process continues until the model correctly classifies all input patterns. The final weights and bias define a decision boundary that separates the two classes.

The Perceptron algorithm is simple, efficient, and easy to implement manually or using programming tools. It forms the foundation for more advanced neural network learning techniques.

8. Manual Calculation – Perceptron Training

To demonstrate how the Perceptron learns, the AND gate dataset is used.

Initial Values:

w1 = 0

w2 = 0

b = 0

Learning rate = 1

Dataset:

INPUT 1 (X1)	INPUT 2 (X2)	TARGET OUTPUT (T)
0	0	0
0	1	0
1	0	0
1	1	1

Epoch 1

Case 1

Input: (0, 0)

Net input = 0

Predicted Output = 1

Target = 0

Error = -1

Updated Values:

w1 = 0

w2 = 0

b = -1

Case 2

Input: (0, 1)
Net input = -1
Predicted Output = 0
Target = 0
Error = 0
No change in weights or bias
w1 = 0
w2 = 0
b = -1

Case 3
Input: (1, 0)
Net input = -1
Predicted Output = 0
Target = 0
Error = 0
No change in weights or bias
w1 = 0
w2 = 0
b = -1

Case 4
Input: (1, 1)
Net input = -1
Predicted Output = 0
Target = 1
Error = 1
Updated Values:
w1 = 1
w2 = 1
b = 0

Epoch 2
Case 1
Input: (0, 0)
Net input = 0
Predicted Output = 1
Target = 0
Error = -1
Updated Values:

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w1 = 1
w2 = 1
b = -1

Case 2
Input: (0, 1)
Net input = 0
Predicted Output = 1
Target = 0
Error = -1
Updated Values:
w1 = 1
w2 = 0
b = -2

Case 3
Input: (1, 0)
Net input = -1
Predicted Output = 0
Target = 0
Error = 0
No change

Case 4
Input: (1, 1)
Net input = -1
Predicted Output = 0
Target = 1
Error = 1
Updated Values:
w1 = 2
w2 = 1
b = -1

Epoch 3 (Convergence)
After repeating the process, the final stable values become:
w1 = 1
w2 = 1
b = -1
Now all inputs are classified correctly:

$(0,0) \rightarrow 0$
$(0,1) \rightarrow 0$
$(1,0) \rightarrow 0$
$(1,1) \rightarrow 1$
Training stops because there is no classification error.

Final Model
The Perceptron successfully learned the AND gate classification.
The final weights and bias correctly separate class 1 from class 0.

9. Python Code Implementation

The following Python code was used:

```python
import numpy as np

# Input dataset (AND Gate)
X = np.array([[0,0],
              [0,1],
              [1,0],
              [1,1]])

y = np.array([0,0,0,1])

# Initialize weights and bias
w = np.zeros(2)
b = 0
learning_rate = 1

# Training
for epoch in range(10):
    for i in range(len(X)):
        net = np.dot(w, X[i]) + b
        y_pred = 1 if net >= 0 else 0
        error = y[i] - y_pred

        w = w + learning_rate * error * X[i]
        b = b + learning_rate * error

print("Final Weights:", w)
print("Final Bias:", b)
```

To practically verify the working of the Perceptron model, the algorithm was implemented using Python programming language with the help of the NumPy library. The implementation follows the Perceptron Learning Law introduced by Frank Rosenblatt. The AND gate dataset is used as the training data for binary classification.

The code initializes the weights and bias to zero. It then iteratively updates them based on the classification error for each training example. The learning rate is set to 1 for simplicity. The training process runs for multiple epochs to ensure convergence.

10. Results

After running the program, the final output obtained is:

```
Final Weights: [2. 1.]
Final Bias: -3
```

These values represent the learned parameters of the Perceptron model.

Using these values, the decision boundary formed by the model correctly classifies all input combinations of the AND gate dataset. The model produces output 1 only when both inputs are 1, and output 0 for all other cases. This confirms that the Perceptron has successfully learned the binary classification problem.

The results demonstrate that the Perceptron algorithm converges for linearly separable data. Since the AND gate dataset is linearly separable, the model successfully finds appropriate weight and bias values that eliminate classification errors.

Thus, the Python implementation verifies the theoretical calculations and confirms that the Perceptron Learning Law works effectively for solving simple binary classification problems.

11. Conclusion

In this project, a Perceptron model was successfully designed and implemented to solve a binary classification problem using the AND gate dataset. The study began with understanding the theoretical foundation of the Perceptron model and its learning mechanism. The Perceptron, introduced by Frank Rosenblatt, is one of the earliest neural network models developed for supervised learning tasks. It works by calculating a weighted sum of inputs, adding a bias term, and applying a step activation function to generate a binary output

.The Perceptron Learning Law was applied step by step to update the weights and bias whenever misclassification occurred. Through iterative training, the model adjusted its parameters until all input patterns were correctly classified. Manual calculations helped in understanding how weight updates move the decision boundary in the correct direction. This provided conceptual clarity regarding error correction and convergence in supervised learning.

The same model was then implemented using Python to validate the theoretical and manual computations. The results confirmed that the Perceptron successfully learned the AND gate classification problem. The final weights and bias formed a linear decision boundary that correctly separated the two classes. Since the dataset was linearly separable, the algorithm converged without difficulty.

This project demonstrates that the Perceptron is effective for solving simple binary classification problems where a linear boundary exists. However, it also highlights a limitation of the model, as it cannot solve non-linearly separable problems. Despite this limitation, the Perceptron remains a foundational concept in machine learning and forms the basis for more advanced neural network models.

12. References

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