CIS579 Artificial Intelligence

The Digit Recognition System

Project Report by Kyrylo Krysko

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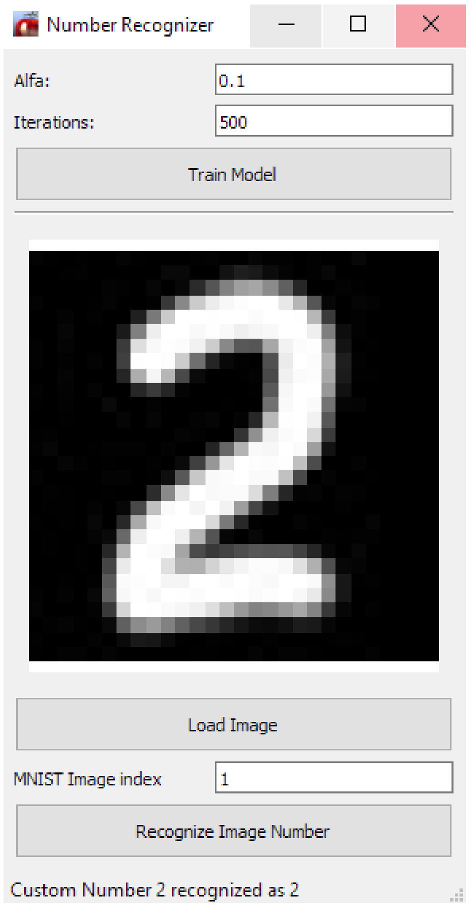
INTRODUCTION

The goal of the project is to familiarize myself with Neural Network concepts by building application for handwritten images recognition trained on existing labeled data set.

The program should allow:

- Train model on provided data and save it to disc for future usage
- Load JPEG image of a number into UI, recognize it and output result



Alfa: 0.1
Iterations: 500
MNIST Image index 1
Custom Number 2 recognized as 2

SYSTEM DESIGN

The project is a handwritten digit recognition system that uses a two-layer neural network to classify digits from 0 to 9. The system is designed to be trained on the MNIST dataset, a large database of handwritten digits that is commonly used for training and testing in the field of machine learning.

The system is implemented in Python, using libraries such as NumPy for numerical computation, pandas for data manipulation, and PySide2 for the graphical user interface. The system also uses the PIL library for image processing and matplotlib for displaying images.

The system is divided into two classes:

- **MatplotlibWidget**: This class is responsible for displaying images in the user interface. It uses matplotlib to create a plot and draw the image.
- **Recognizer**: This is the main class of the system. It is responsible for loading the data, training the neural network, recognizing digits, and interacting with the user interface.

The Recognizer class uses a two-layer neural network for digit recognition. The network is trained using gradient descent, a common optimization algorithm in machine learning. The network uses the **ReLU** activation function in the first layer and the **softmax** function in the output layer.

The system also includes a **user interface** that allows the user to load a custom image, train the model, and recognize digits. The user interface displays the recognized digit and the original image.

The Recognizer class is the main class in the system that encapsulates the functionality of the neural network model. It is responsible for training the model, making predictions, and saving and loading the model parameters. Here are the main functions of the Recognizer class:

- **__init__**: This is the constructor of the Recognizer class. It initializes the paths for source and trained models, model parameters variables and define UI widgets behavior.
- **forward_propagation**: This function performs forward propagation through the network. It takes the input matrix X and calculates the output of the network by applying the weights, biases, and activation functions of each layer. The output of this function is the final prediction of the network.
- **backward_propagation**: This function performs backward propagation through the network. It takes the input matrix X, the true labels Y, and the activations of the hidden layer A1 and output layer A2. It calculates the gradients of the loss function with respect to the weights and biases of the network.
- **update_parameters**: This function updates the weights and biases of the network using the gradients calculated in the backward propagation step. The **alfa** parameter controls the step size of the updates.
- **gradient_descent**: Train neural network model by updating its parameters (weights and biases) iteratively to minimize the loss function (difference between the model's predictions and the actual values).
- **make_predictions**: This function makes predictions on the input data X using the trained network. It performs forward propagation and returns the predicted labels.
- **train_model**: This function trains the network on the input data X and true labels Y for a specified number of iterations. It performs forward propagation, backward propagation, and parameter updates in a loop for each iteration.
- **save_model**: This function saves the weights and biases of the network to a file specified by filename. This allows the trained model to be saved and loaded later without having to retrain it.
- **load_model**: This function loads the weights and biases of the network from a file specified by filename. This allows a previously trained model to be loaded and used for making predictions.
- **recognize_custom**: Recognize number in JPEG files provided by users.
- **Recognize_mnist:** Recognize number form dev part of a MNIST set.

AI CONCEPTS UTILIZED

The project utilizes several key concepts in artificial intelligence and machine learning:

Neural Networks: The system uses a two-layer neural network for digit recognition. Neural networks are a type of machine learning model that is inspired by the human brain. They consist of layers of nodes (or "neurons") that are connected by "synapses". Each neuron computes a weighted sum of its inputs and applies an activation function to the result.

Gradient Descent: The system uses gradient descent to train the neural network. Gradient descent is an optimization algorithm that iteratively adjusts the parameters of the model to minimize the loss function.

ReLU and **Softmax** functions: The system uses the ReLU (Rectified Linear Unit) function as the activation function in the first layer of the network, and the softmax function in the output layer. The ReLU function introduces non-linearity into the model, allowing it to learn more complex patterns. The softmax function is used to produce a probability distribution over the output classes, making it suitable for multi-class classification problems.

One-Hot Encoding: The system uses one-hot encoding to represent the labels of the digits. One-hot encoding is a way of representing categorical variables as binary vectors.

Forward and Backward Propagation: The system uses forward propagation to compute the output of the neural network given the input data and the current parameters, and backward propagation to compute the gradients of the loss function with respect to the parameters.

The **mathematical concepts** behind the neural network model can be broken down into a few key areas:

Forward Propagation: This is the process of taking an input and running it through the neural network to get a prediction. The input layer takes the pixel values of the image, normalizes them, and then passes them to the hidden layer. The hidden layer applies weights and biases to these values, and then applies a Rectified Linear Unit (ReLU) activation function. The output layer then applies another set of weights and biases, followed by a **softmax** activation function to get the final output.

Backward Propagation: This is the process of taking the prediction made by the network, calculating the error of the prediction, and then running this error backwards through the network to adjust the weights and biases. This is done using a method called gradient descent, which iteratively adjusts the parameters to minimize the error.

Loss Function: The loss function used in this model is the cross-entropy loss function. This function takes the predicted probabilities for each class and the actual class, and calculates a value that represents how well the model's predictions match the actual values. The goal of training the model is to minimize this loss.

Gradient Descent: This is the method used to adjust the weights and biases of the network during training. The idea is to calculate the gradient of the loss function with respect to each parameter, and then adjust the parameter in the opposite direction of the gradient. This is done iteratively until the model converges to a set of parameters that minimize the loss.

Activation Functions: These are functions applied to the outputs of each layer in the network. The ReLU activation function is used for the hidden layer, and the softmax activation function is used for the output layer. The ReLU function introduces non-linearity into the model, allowing it to learn more complex patterns. The softmax function ensures that the output values can be interpreted as probabilities, as it squashes the outputs to be between 0 and 1 and ensures they sum to 1.

Vectorized Implementation: This refers to the use of matrix and vector operations to perform calculations on all training examples at once, rather than looping over them one by one. This is a more efficient way to implement the model, especially when dealing with large datasets.

Model Parameters: These are the weights and biases that the model learns during training. The weights are the coefficients that determine how much each input contributes to the output, and the biases are constants that are added to the output. These parameters are initialized randomly and then updated through gradient descent during training.

LESSONS LEARNED

This project provided valuable experience in the development of a machine learning application, from the initial design and implementation to the testing and evaluation of the system. It also provided a practical understanding of key concepts in artificial intelligence and machine learning, including neural networks, gradient descent, activation functions, and data preprocessing.

Data Preprocessing: The input images were preprocessed by normalizing the pixel values to be between 0 and 1. This is a common practice in machine learning to ensure that all input features have a similar scale, which can help the model to converge faster during training.

Model Training and Evaluation: The model was trained using the MNIST dataset and evaluated on a separate test set to assess its performance. This highlighted the importance of splitting the data into a training set and a test set to avoid overfitting and to get an unbiased estimate of the model's performance on new data.

Model Saving and Loading: The ability to save and load trained models is a useful feature in machine learning applications. In this project, the trained weights and biases of the neural network were saved to CSV files, allowing the model to be reloaded and used without having to retrain it.

User Interface Design: Designing a user-friendly interface is important for making machine learning applications accessible to non-expert users. In this project, a graphical user interface was created using PySide2, allowing the user to interact with the system in a simple and intuitive way.

Debugging and Error Handling: During the development process, various bugs and errors were encountered. These were addressed through careful debugging and error handling, which is a crucial aspect of any software development project. This included handling potential issues with data input, ensuring the correct dimensions for matrix operations, and checking for numerical stability during computations.

Performance Optimization: The project also highlighted the importance of performance optimization in machine learning. For example, vectorized implementations were used for the forward and backward propagation steps, which are significantly faster than using for loops. This is particularly important when dealing with large datasets or complex models.

Understanding of AI Concepts: Implementing a neural network from scratch provided a deep understanding of how neural networks work, including the process of forward propagation, the calculation of the loss function, and the update of weights and biases through backward propagation. It also reinforced the understanding of key concepts such as gradient descent, activation functions, and one-hot encoding.

FUTURE IMPROVEMENTS

While the current system is able to recognize handwritten digits with a high degree of accuracy, there are several potential improvements that could be made:

Adding More Hidden Layers: The current model is a two-layer neural network with one hidden layer. Adding more hidden layers could potentially improve the model's ability to recognize more complex patterns in the data.

Using Different Activation Functions: The current model uses the ReLU activation function in the hidden layer and the softmax function in the output layer. Experimenting with different activation functions could potentially improve the model's performance.

Hyperparameter Tuning: The learning rate and the number of training iterations are important hyperparameters that can significantly affect the model's performance. These hyperparameters could be tuned using techniques such as grid search or random search to find the optimal values.

Implementing Regularization: Regularization techniques such as L1 or L2 regularization could be implemented to prevent overfitting and improve the model's generalization ability.

Using a Larger Dataset: The model is currently trained on the MNIST dataset, which contains 60,000 training images. Using a larger dataset could potentially improve the model's performance by providing more diverse examples for training.

Improving the User Interface: The user interface could be improved by adding more features, such as the ability to adjust the learning rate and the number of training iterations, or to visualize the training process.