Performance Research of Bidirectional Neural Networks Model for Pupillary Response Analysis

Abstract: Bidirectional Neural Networks (BDNN) simulates bidirectional synaptic transmission, serving purposes like reducing generalization errors, content-addressable memory tasks, and cluster center identification. However, due to the ascent of deep learning and shifting research priorities, BDNN's performance testing across various scenarios is incomplete.

In this study, we assess BDNN as a content-addressable memory via pupillary response dataset experiments, covering binary classification and regression. Results reveal poor binary classification but good regression performance, especially in one-to-one regression. When functioning as a content-addressable memory creator, BDNN sacrifices some forward direction performance to gain the ability to process in both directions.

Considering the observed instability of BDNN in experiments and its strong performance in one-to-one regression, this paper introduces a theoretical model called the "After Classified Bidirectional Neural Network". This model aims to enhance BDNN's performance in complex tasks by selectively activating hidden neurons, thus adapting the model to closely emulate a one-to-one task.

Keywords: Bidirectional Neural Networks, Content-addressable memory, Binary Classification, Regression

1. Introduction

Since the establishment of the field of artificial neural networks, researchers have aimed to simulate biological neural networks and construct suitable models that possess the ability to learn to address specific problems through continuous training. With the invention of the Multilayer Perceptron and Backpropagation, the development of artificial neural networks has been pushed to a new stage. Artificial neural networks now gain the capability to learn complex functions with deep architectures. As the depth and complexity of models increase, the internal workings of the model become progressively harder to understand and interpret, turning them into a "black box". The issues of model interpretability and explain ability raise under this situation. In many cases, deep neural network models are irreversible. However, based on some research in synaptic transmission, it's worth noting that when synapses are involved in electrical transmission, the transmission can be bidirectional [1,2]. To simulate these electrical transmissions, model with the ability to process both from input to output and from output to input is required, and this kind of neural network is called bidirectional neural network (BDNN).

One of the most widely accepted BDNN model was come up by A.F.Nejadl and T.D.Gedeonl [3], with their further studies on BDNN, the model is now equipped with the ability to do generalization error reducing [4], content addressable memories [5], as well as finding cluster center. Despite BDNN being invented a long time ago, it has received relatively less attention in neural network research, especially after the rise of deep learning and the shift in research priorities. As a result, performance testing of BDNN in various usage scenarios remains relatively incomplete.

For the incompleteness of BDNN performance on many occasions, applying BDNN to new scenarios is of great help in expanding the scope of BDNN applications. This paper intends to apply BDNN to data given by a study about pupil size respond toward fake smile and real smile [6], evaluate the performance of BDNN in both forward and backward direction, looking for a case that BDNN can create content addressable memories without compromising the existing neural network.

2. Methodology and Data Processing

2.1 Bidirectional Neural Network

A normal feedforward neural network (NN) is the base of bidirectional neural network. It is equipped with the ability to get output by applying input into forward propagation and training model using the loss toward backward propagation.

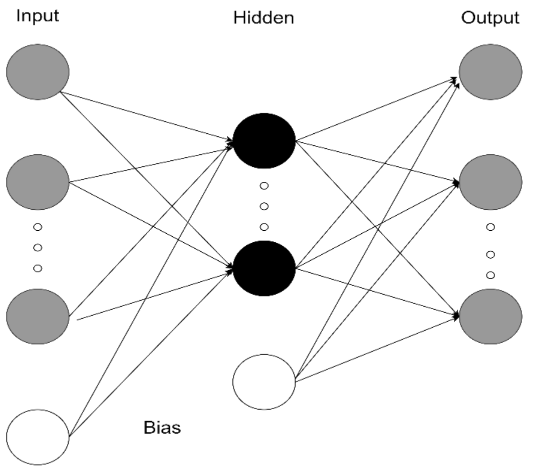

Figure 1. Normal feedforward network

However, a typical feedforward neural network can only process data from input to output. This paper aims to implement a neural network that can process data bidirectionally, making it suitable for use as content-addressable memory. Hence, bidirectional neural network (BDNN) is introduced. BDNN is a neural network that can process from both directional, when it is use as content-addressable memory, BDNN is expected to be eligible in both getting output from input and getting input from output.

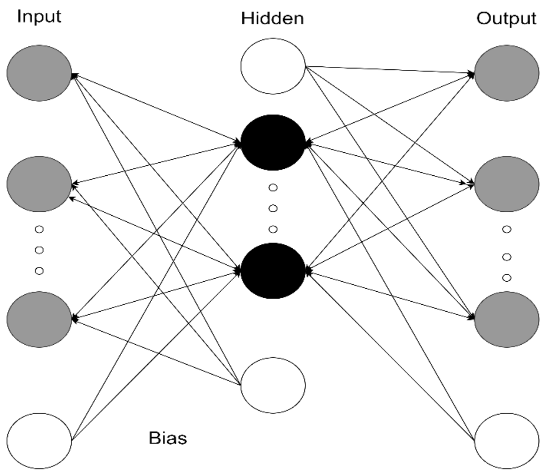

Figure 2. Bidirectional network

According to T.D. Gedeon's theory [7], a BDNN can be implement by turning the training direction inverse after a period of feedforward training. When doing the inverse direction train, the weight of every connection should be the same, and applying sigmoid function as active function. By this approach, BDNN can establish a reverse processing direction based on the training results of the feedforward neural network and possesses the capability to reduce generalization errors to some extent.

For this paper, assuming we have input X and output Y, a standard feedforward neural network (referred to as ModelA) will be implemented to represent the forward process of the BDNN. Initially, X will serve as input for ModelA to generate predictions Y' (referred to as Y prime), and the loss between Y and Y' will be used for backpropagation to train ModelA. After training with a predefined number of epochs in the forward direction, another feedforward neural network (referred to as ModelB) will be introduced to represent the backward process of the BDNN. The weights learned by ModelA will be extracted and applied to ModelB at corresponding connections. Following weight adjustment, Y will be used as input for ModelB to generate predictions X' (referred to as X prime), and the loss between X and X' will be used for backpropagation to train ModelB. After completing the training, the weights of ModelB will be extracted and integrated back into ModelA at the corresponding connections. Finally, ModelA and ModelB will be utilized to evaluate performance in the forward and backward directions, respectively.

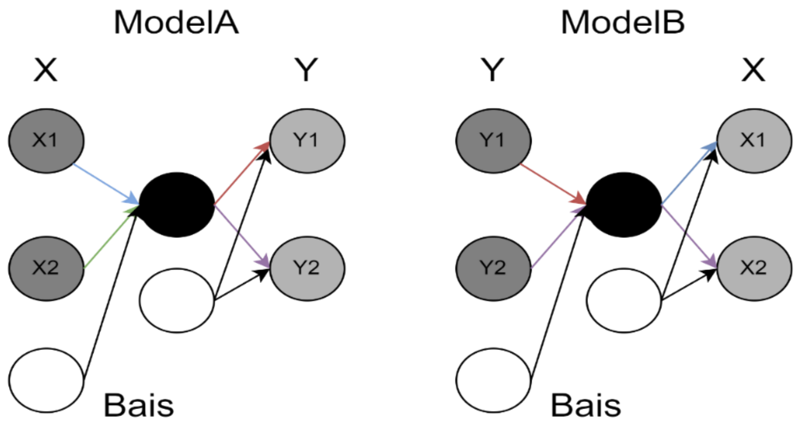

Figure 3. BDNN implemented in this paper, with same color (expect black) refers to same weight.

2.2 Dataset statement and Data preprocessing

The dataset used in this paper was generated through a research study that examined pupil reactions to fake and genuine smiles. In this study, the pupil sizes of 10 Asian observers were recorded while they watched videos of both fake smiles and real smiles. Subsequently, datasets containing the average pupil size for each individual in each frame while observing both fake and real smiles were calculated separately. This is the dataset that is currently being utilized in this paper. Below are the descriptive stats of the dataset:

Table 1. Descriptive stats for person 1 to 5

	P1 T	P1 F	P2 T	P2 F	P3 T	P3 F	P4 T	P4 F	P5 T	P5 F
mean	0.68	0.78	0.29	0.34	0.56	0.53	0.53	0.49	0.35	0.41
std	0.34	0.36	0.12	0.13	0.23	0.18	0.26	0.27	0.18	0.23
min	0.01	0.15	0.01	0.06	0.01	0.01	0.03	0.01	0.01	0.01
25%	0.32	0.36	0.26	0.29	0.38	0.44	0.23	0.25	0.26	0.20
50%	0.88	1.02	0.34	0.38	0.62	0.60	0.68	0.65	0.43	0.51
75%	0.92	1.07	0.38	0.44	0.72	0.67	0.71	0.67	0.45	0.59
max	1.09	1.17	0.41	0.49	0.84	0.73	0.75	0.72	0.57	0.63

Table 2. Descriptive stats for person 1 to 5

	P6 T	P6 F	P7 T	P7 F	P8 T	P8 F	P9 T	P9 F	P10 T	P10 F
mean	0.50	0.57	0.37	0.44	0.47	0.45	0.34	0.39	0.45	0.43
std	0.15	0.24	0.15	0.16	0.18	0.19	0.17	0.21	0.17	0.15
min	0.08	0.00	0.02	0.01	0.04	0.04	0.01	0.01	0.01	0.03
25%	0.50	0.44	0.25	0.29	0.40	0.44	0.16	0.17	0.44	0.42
50%	0.55	0.65	0.43	0.53	0.55	0.54	0.43	0.48	0.51	0.48
75%	0.59	0.77	0.49	0.57	0.56	0.57	0.47	0.56	0.57	0.52
max	0.69	0.87	0.55	0.62	0.69	0.65	0.54	0.64	0.62	0.62

Based on the descriptive statistics, it is evident that both the individual and the authenticity of the video smile significantly influence pupil size. Furthermore, since the pupil size falls within the range of 0.00 to 1.17 and considering that the sigmoid function is an ideal activation function for BDNN, it would be advantageous to scale both the input and output within the range of 0 to 1.

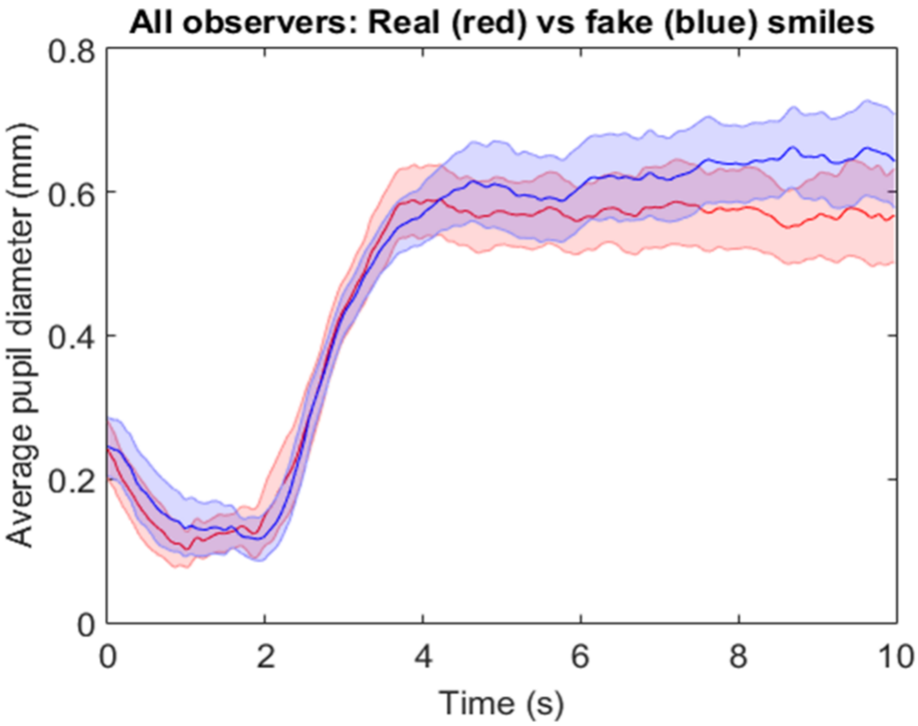

Figure 4. Average pupil diameter timelines for all stimuli over all observers.

Figure4 depicting average pupil diameter timelines for all stimuli across all observers also indicates that pupil size varies over time. Based on the analysis above, the data preprocessing for this paper is as follows:

a) Scale the data to fit within the range [0,1] by dividing each data point by the difference between the maximum and minimum values.

b) Restructure the data into the following format: (pupil size, true or fake smile, frame indicating time, person ID).

3. Experiments implementation and result

Based on T.D. Gedeon's theory, it is recommended to implement BDNN with a limited number of layers. This is because deep neural networks may reduce model interpretability. Additionally, it is mentioned that using the sigmoid function as the activation function for every layer is a suitable approach for implementing BDNN, as it helps maintain consistent input and output ranges.

For the discussion above, this paper implements every model in the experiments with only 1 hidden layer and 64 hidden neural. Every active function is using sigmoid function.

3.1 Binary Classification: Predicting the Authenticity of Smiles

The experiment aims to predict the authenticity of smiles using pupil size, person ID, and time frame. ModelA employed in the experiment is a binary classification model, and, as such, Binary Cross-Entropy Loss is utilized to compute its loss, while accuracy is employed as an evaluation metric. Conversely, ModelB leans more towards regression in terms of predicting pupil size. Therefore, Mean Squared Error is employed to calculate the loss of ModelB, and R-squared is used as an evaluation metric for this model. After several attempts, the number of epochs has been set to 10,000 for ModelA and 10,000 for ModelB, with learning rates of 0.01 and 0.001, respectively. The number of epochs is relatively high because the feedforward model appears to have a slow learning speed in the experiment, and increasing the learning rate does not lead to improvement. This may be attributed to the simplicity of our network architecture. The result of the experiment is showed below:

Table 3. Experiment results for binary classification

	Model only NN		ModelA		ModelB	
	loss	acc	loss	acc	loss	R^2
Round1	0.626443	62.38%	2.295	49.45%	0.69	0.008757
Round2	0.5979832	64.42%	1.4356	52.82%	7.7688	-1.54656
Round3	0.7790601	65.67%	2.6426	47.87%	53.1505	-4.923
Round4	0.6027064	61.00%	2.3817	50.32%	9.0092	-1.82065
Round5	0.5887846	63.63%	2.3409	50.92%	18.6961	-3.54845

It is worth mentioning that the feedforward model still has the potential to improve with a larger number of epochs. However, based on the results obtained, we can conclude that BDNN is not suitable for binary classification, at this in this experiment. The backward learning process tends to ruin the forward model and fails to create a backward model with a reasonable loss. This outcome is not surprising, as mentioned by T.D. Gedeon in his paper, BDNN is not well-suited for handling irreversible issues without corresponding preprocessing, such as extra nodes.

In this paper, we attempted to enhance the performance of BDNN using additional nodes, but none of the extra nodes we experimented with led to significant improvements.

3.2 Regression: The pupil size from real smile to fake smile

This aims to predict the pupil size for a person at a time flame when watching fake smile using the pupil size for the same person at the same time flame when watching real smile. Both ModelA and ModelB is about a regression problem, hence Mean Squared Error is employed to calculate the loss of model in this experiment, and R-squared is used as an evaluation metric. After several attempts, the number of epochs has been set to both 500 for ModelA and ModelB, with learning rates of 0.01. The result of experiment is showed below:

Table 4. Experiments result for regression

	Model only NN		ModelA		ModelB	
	loss	R^2	loss	R^2	loss	R^2
Round1	0.0083	0.852964	0.0114	0.797800	0.0112	0.829709
Round2	0.0096	0.829730	0.0113	0.800000	0.0111	0.831531
Round3	0.0095	0.831420	0.0207	0.633600	0.011	0.833077
Round4	0.0087	0.846017	0.0152	0.731200	0.0114	0.827062
Round5	0.0081	0.856014	0.0728	-0.287500	0.011	0.8338

As shown in the table, the function of reducing generalization error [4] does not manifest in the experiment. BDNN appears to function as a model that gains the ability of bidirectional processing at the expense of some performance in forward processing. Additionally, in this experiment, BDNN appears to work but lacks stability; it may sometimes disrupt the forward processing. It's also worth noting that we observed rapid model convergence when training in the backward direction on some round of the experiment, which may suggest that BDNN has the potential to obtain an inverse model within a small number of epochs. This finding contradicts what T.D. Gedeon's paper has mentioned [5].

This paper attempted to include person ID and time frame as inputs, but the results were not as satisfying as simply constructing a one-to-one network.

4. Conclusion and Future Work

This paper presents two experiments employing the BDNN model, simulating its performance on binary classification and regression problems. The BDNN model performs poorly on binary classification and exhibits some promising aspects during simple regression, albeit with instability issues. While performing regression, BDNN occasionally demonstrates the capability to create content-addressable memories at the expense of forward performance. It would be beneficial to explore methods to mitigate this instability in BDNN. Besides, the potential that BDNN shows in rapid back forward convergence is worth discussing.

BDNN's performance in one-to-one regression also prompts us to consider whether we can enhance BDNN's ability to simulate more complex tasks. We are exploring the possibility of using minimal input to train the network, utilizing other inputs for classification purposes, and leveraging a portion of the neural network for both processing and optimization based on the classification results. In this paper, we call this kind of model after classified bidirectional neural network (ACBDNN).

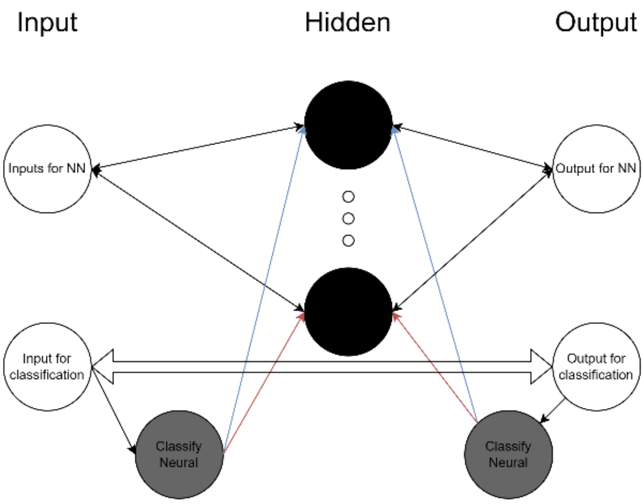

Figure 5. After Classified Bidirectional Neural Network

The figure above illustrates the concept of ACBDNN (bias not drawn). It partitions the input into two components: one for BDNN training and the other for classification. Once classified by the classification neural network, it determines the active units of the hidden neural network (indicated by the color of the lines from the classification neural network, different color represent different classes). Only the active hidden neurons participate in the BDNN processing during this iteration. After obtaining the BDNN output, the output for classification remains the same as the input and is combined with the BDNN output for the final output. After several forward trainings, the progress inverse and become bidirectional. While ACBDNN appears impressive, it presents certain implementation challenges, including processing time, coding structure, and loss evaluation. Additionally, there are uncertainties regarding the performance of ACBDNN. Whether ACBDNN can truly enhance BDNN or if there are alternative approaches that can make BDNN more widely adopted remains an open question.

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