Fig. 1. The Mechanical Neural Network (MNN) with the two input neurons on the left, the four hidden neuron in the middle and the two output neurons on the right. The strings are the connections between the neurons weighted by the position of the clamps on the sending neuron and combined by the pulley systems above the receiving neurons. A video can be found at https://youtu.be/zMxh3Io3hFE.

In this paper the Mechanical Neural Network (MNN) is introduced, a physical implementation of a multilayer perceptron (MLP) with Rectified Linear Unit (ReLU) activation functions, two input neurons, four hidden neurons and two output neurons. This physical model of a MLP is used in education to give a hands on experience and allow students to experience the effect of changing the parameters of the network on the output. Neurons are small wooden levers which are connected by threads. Students can adapt the weights between the neurons by moving the clamps connecting a neuron via a thread to the next. The MNN can model real valued functions and logical operators including XOR.

Additional Key Words and Phrases: Mechanical Computer, Analog Computer, Neural Network, Multilayer Perceptron, Teaching Material, Education

1 INTRODUCTION

The Mechanical Neural Network (MNN), presented in this paper, is a mechanical implementation of a multilayer perceptron (MLP) with Rectified Linear Unit (ReLU) activation functions. Thus, it can model logical functions, including...
XOR but also real valued functions. It is build from wooden levers, which represent the neurons. These levers are linked by strings, corresponding to the connections between the neurons of a MLP. Adjusting the clamps, which connect the strings to the levers, by hand allows to adjust the weights of the network. Hence, the effect of adapting the weights can be intuitively observed.

Intuition for education is one of the motivating factors of the MNN: Digital implementations of a MLP or even more complex networks are difficult to understand. The MNN allows to develop this intuition and facilitates the work with more complex models.

Moreover, the MNN shows that a small MLP can be implemented purely mechanical without the need for electricity and can be build to withstand harsh environments.

While many analog computers were developed [Lundberg 2005; Ulmann 2013] most are electro-mechanical, electrical, or electronic. Few are purely mechanical and none try to model a MLP, especially for use in education. The fictional Rope and Pulley Computer, labelled as ancient discovery and published as April Fools’ joke, models logical gates with ropes and pulleys but was never constructed [Dewdney 1988]. The Tinkertoy Computer uses ropes and construction kit hardware and was able to play Tic-tac-toe [Hillis and Silverman 1978], however it is not field programable / trainable like the MNN. It is also complex and difficult to use for educational purposes, compared to the MNN. There exist at least on neural network model in a museum, a model visualizing connections with fibre optics [Technisches Museum Wien 2020], but it can not be used in class nor does it mimic the functionalities of a neural network on a mechanical level.

Analog computers today are not only relevant for education but are also sought for harsh environments, in which normal computers fail to operate, e.g. in a rover on the surface of Venus [Sauder et al. 2017b] (and with more details in [Sauder et al. 2017a]). In principle a roughed (and miniaturized) version of the MNN is able to work under those harsh conditions.

The paper is organised in the following way: In Section 2 the mechanical structure of the MNN is explained and it is shown that this physical implementation models indeed a MLP. Then, in Section 3, some logical operators are modelled with the MNN. Next, it is shown how the MNN can be used for teaching in Section 4 and lastly further improvements to the network are presented in Section 5.

2 THE MECHANICAL NEURAL NETWORK AND WHY IT MODELS A MULTILAYER PERCEPTRON

2.1 Notation

In the following the \( i \)th neuron from layer \( k \) will be denoted as \( n_i^{(k)} \), its weighted input as net\(_i^{(k)}\), and its output as \( o_i^{(k)} \). The weight from the \( j \)th neuron of the previous layer to the \( i \)th neuron of layer \( k \) is denoted as \( w_{ij}^{(k)} \).

2.2 Architecture

The MNN implements a MLP [Rumelhart et al. 1986] with reLU activation functions and two input neurons, four hidden neurons and two output neurons as shown in Figure 2. The three layers are three wooden shafts through the fulcrums of the levers as shown in Figure 1. The MNN is a fully connected network. The connecting strings are clamped to the sending neuron, travel to the top of the model and are routed to a receiving neuron of the next layer. There they travel down into the pulley system, which combines the weighted inputs of this receiving neuron. A single string then exists the pulley system, the weighted sum, and connects to the receiving neuron.
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Fig. 2. The architecture of the MNN with one input (2 neurons), one hidden (4 neurons), and one output layer (2 neurons). Superscript indices indicate the layer and subscript indices the neuron. Weights are subscripted with the index of the receiving neuron followed by the index of the sending neuron and superscripted with the index of the receiving layer. The input of a neuron is denoted as $\text{input}$ to which the activation function $\varphi$ is applied.

2.3 Neurons

Each of the neurons is a lever (Figure 3) rotating around a shaft at its fulcrum. Each of the three shafts corresponds to one of the three layers. Horizontal levers correspond to neurons with output $o = 0$, levers rotated clockwise correspond to neurons with $o > 0$ and counterclockwise rotated levers to neurons with $o < 0$. Rotating the neurons till they contact the ground plane is defined as $-1, +1$ respectively, i.e. $o \in [-1, +1]$ (not taking the activation function into account).

Each neuron is connected to all neurons of the next layer by strings clamped to this neuron. Clamps can be moved on the lever of the sending neuron, representing different weights on the connection from this neuron to the receiving neuron in the next layer. A clamp in the middle at the pivot of the lever is equivalent to $w = 0$, since the connecting string is not moved when the lever is moved. A clamp on the right side of the lever corresponds to $w > 0$ and the receiving lever rotates in the same direction while a clamp on the left side of the lever correspond to $w < 0$ and the receiving neurons rotates in the opposite direction. Moving the clamp to the full left or right corresponds to $w = 1, w = 0$ respectively. Hence, weights are limited to the range $[-1, +1]$. 
Adjusting the weights, i.e. moving the clamps, does not change the bias of the receiving neurons, since the levers, on which the clamps are moved, are arcs with the centre being the deflection eye of the string at the top of the model.

2.4 Layers

Each layer is a shaft around which the neurons of that layer can rotate. The two input neurons can be rotated by hand around the shaft, stay in position and represent the input. As in a MLP the input neurons do not have an activation function and represent the input to the network.

The input layer is followed by a hidden layer with four neurons and an output layer with two neurons. Note that for the two-valued logical operators, discussed below, two hidden and one output neuron suffice.

The MNN is fully connected. This means that each lever in the input layer has four clamps and four strings connecting it to each of the four levers in the hidden layer. Thus, the four levers of the hidden layer have two clamps and strings each, connecting them to the two levers of the output layer.

2.5 Weights and Net Input

For a single perceptron[4] the net input of a neuron is defined as

$$\text{net}_i^{(k)} = \sum_j w_{ij}^{(k)} o_j^{(k-1)} + b_i^{(k)}$$

with $b_i^{(k)}$ being the bias of that neuron. In the MNN the net input is simplified to a version without bias. However, note that it can be reintroduced by setting the output of a neuron from the previous layer to 1 and interpreting the corresponding weight as bias. In the model this corresponds to rotating the corresponding lever fully clockwise and
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Fig. 4. The pulley system to compute the sum of the weighted inputs of neuron $i$ in the output layer. At the top the four strings from the clamps on the four levers of the hidden layer enter. Their movement corresponds to the weighted inputs of neuron $i$. The movement is combined/summed by a two stage pulley system resulting in the net input for neuron $i$. Note that the movement is reduced by a factor of $\frac{1}{4}$ by the pulley system. To address this the string, representing $\frac{1}{4}\text{net}^{(k)}_i$ is connected to the lever $i$ not at the most left but at $\frac{1}{4}$ of the distance between the fulcrum and the most left, resulting in the correct input $\text{net}^{(k)}_i$.

using the position of the clamps on this lever as biases. (This is analogous to the vector notation of the net input: $\text{net}^{(k)}_i = \overrightarrow{o}^{(k-1)}T \overrightarrow{w}^{(k)}_i$ with $o_0^{(k-1)} = 1$.)

This weighted sum is realized in two steps in the MNN: The weights are set with the clamps as described above. The rotation of the neuron translates to a linear movement of the connecting string to a neuron in the next layer. The position of the clamp governs the transmission ratio from rotational movement of the lever to the linear movement of the string, i.e. weights the output of this neuron. (The number of clamps on this neuron is equal to the number of neurons in the next layer.)

The summation is done with a pulley system as described in Figure 4. The pulley system is connected to the neuron in the next layer by another string, translating the linear movement of the pulley system to rotational movement. I.e. the rotation of this lever represents the input and output of that neuron, unless the rotation is limited by the reLU activation function. If that is the case the string becomes slack and the rotation represents only the output of the neuron.

2.6 Activation Function

Neurons of the hidden and the output layer use the Double Rectified Linear Unit (doReLU) activation function, based on the reLU activation function [Fukushima 1969]. They are defined $\varphi(x) = \min(1, \max(0, x))$ – a plot is shown in Figure 5. This activation function is easily modelled in the MNN by restricting the rotation of the lever to clockwise rotations, since these correspond to positive output of the neuron, and prevent counter-clockwise rotations, since these correspond to negative output to the neuron. This restriction is implemented as a vertical bar $D$ connected to the lever $A$ and resting on the ground plane $C$ and thus preventing counter-clockwise rotation (Compare Figure 3). Clockwise
rotation in limited by the lever contacting the ground plane, corresponding to an activation of +1. Thus, for the neurons in the hidden and the output layer: \( o \in [0, +1] \).

### 2.7 Differences between MLP and MNN

The MNN differs in four points from a MLP. The MNN has (1) no bias, (2) weights limited to the interval \([-1, 1]\), (3) inputs limited to the interval \([-1, 1]\), and (4) doReLU activation functions. (1) can be addressed by setting a neuron to one and using its weights as bias, (2), (3) and (4) could be addressed by input scaling. However, this is not relevant for two-valued logical operators and educational purposes.

### 3 MODELLING EXEMPLARY FUNCTIONS

#### 3.1 Logical Operators

For boolean algebra a horizontal lever is interpreted as \( false \) and a lever fully rotated clockwise as \( true \). The truth table for the modelled logic operations is Table 1.

| \( x_1 \) | \( x_2 \) | NOT \( (x_1) \) | AND | OR | XOR |
|---|---|---|---|---|---|
| 0  | 0  | 1  | 0  | 0  | 0  |
| 0  | 1  | 1  | 0  | 1  | 1  |
| 1  | 0  | 0  | 0  | 1  | 1  |
| 1  | 1  | 0  | 1  | 1  | 0  |

Table 1. The truth table of the modelled logical operations

3.1.1 AND and OR. For the logical operators AND and OR only two inputs, one hidden and one output neuron is used as show in Figure 6a. The implementation differs only in the threshold applied to the output of the MNN: For OR, \( y \geq 0.5 \) would evaluate to \( true \) and for AND, \( y \geq 1 \) would evaluate to \( true \). Another solution is to introduce a bias and threshold at 0. This relates to the fact that the separatrices for AND and OR differ only by the intercept.

3.1.2 NOT. The NOT operation takes only one input and the output is the inverse of the input. Here the second input neuron is set to 1 and its weight is used as bias as shown in Figure 6b.

3.1.3 XOR. For the XOR operation the output is \( true \) iff one of the two inputs is \( true \) and \( false \) otherwise. Here a symmetric network configuration with two hidden neurons is used, shown in Figure 6c. One input activates one hidden neuron and inhibits the other. This example highlights the importance of the nonlinear activation functions: Without

![Fig. 6. The MNN configurations for different logical operators](image)
The activation functions the output of the network would always be zero. While the previous logical operations are linearly separable and can also be modelled with a perceptron, this is not the case for the XOR [Minsky and Papert 2017] – it is not linearly separable and requires an MLP with nonlinear activation functions.

4 APPLICATION IN EDUCATION

The MNN is best used in a hands-on approach in which students can design and adapt the network themselves, i.e. adjust levers and clamps themselves, after they where familiarized with its functionality. Although, the MNN can be trained for real valued problems, logic operators are better suited for education, as they are easier to understand and require less fineness when adjusting the weights.

In a first stage students may freely experiment to adapt the MNN to different logical operators. A good starting point are the AND and OR operators. Here students can discover that both operators are linearly separable, that the non-linear hidden layer is not needed, and that the two operators vary only in a different threshold on the output (or a different bias of the linear separator). A thresholded sum of the two inputs suffices and the MNN can indeed be used to sum boolean (and real valued) inputs.

Next students can adapt the MNN for the XOR operator. They can discover that this problem is not linear separable and needs indeed a non-linear hidden layer. They can also discover that this symmetric problem can be solved by a symmetric network configuration as shown in Figure 6c. Further, the analogy between neurons and logical gates and the possibility to express logic operators as combination of other logic operators can be discovered. E.g. the configuration of the MNN for the XOR operator stated above is equal to \((x_1 \land \neg x_2) \lor (\neg x_1 \land x_2)\). From this students can observe, that the input space, in which the XOR operator is not linearly separable, is transformed into the space spanned by \((x_1 \land \neg x_2)\) and \((\neg x_1 \land x_2)\) by the hidden neurons. In this space the operator is then linearly separable by the output neuron.

With the introduction of the NOT operator students will discover that a bias is needed. It can be represented by completely activating one of the input neurons and using its weights as bias, linking to the vector notation of neurons.

In the first stage students will discover that setting the correct weights by hand and intuition can be difficult, leading to a second stage and raising the question if a procedure exists how the network can be trained by hand and motivating automatic training algorithms like backpropagation. The concept of an error between desired and actual output can be introduced, as well as stochastic gradient descent.

This would be a good point to switch over to a computer simulation of the MNN, and then extend to implementations of MLPs and later deep learning frameworks.

5 FURTHER WORK

The MNN can be further developed in different directions: (1) For classroom use several models would be useful, hence more economic (and also more robust) versions are desirable – possibly with 3D printed parts and wooden strips of standardized size. (2) For use in harsh environments a roughed, miniaturized, and encapsulated version could be development, using plastic and metal components and springs instead of counterweights to keep levers in position. Here, more neurons and layers would also seem desirable. (3) Development of a process to train the network by hand, guiding which weights are to be adapted to generate a specific output. (4) Complete simulation of the MNN with an adapted backpropagation algorithm. The MNN can then be trained in the simulation and the resulting weights can be set in the real model. This is especially useful for real valued classification and regression problems for which the optimal weights can not be found intuitively by hand.
6 CONCLUSION

In this paper the MNN, a mechanical model of a MLP was presented. It consists of an input layer with two neurons, a hidden layer with four neurons and an output layer with two neurons. However, other and more complex configurations are possible, too. Neurons are wooden levers which can be rotated, whereby the rotation of the lever represents the activation of the neuron. The levers are connected with strings, passing the information from a sending neuron to the receiving neurons in the next layer. Albeit, the MNN is not limited to logical operators, they are easy to understand and training the network for these operators can be done intuitively by hand. This allows to use the MNN in educational settings, in which students experiment and model these different logical operators, allowing to gain insights into a MLP and motivating training algorithms like backpropagation. While the MNN can also be implemented as a roughed mechanical computer suitable for harsh environments, its current main focus is on education in a museum and especially classroom environment.

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