The Logic Band: A Novel Neural Network Design For Advancing Artificial Intelligence.

Derek Smith
dlsmith323@gmail.com

1. Medical meets Technology: Conception of theology

The goal of artificial intelligence (AI) is to mimic, as closely as possible, human intelligence. The evolution of technology has made leaps and bounds in humanity's attempts to artificially simulate intelligence. The weighted simulated connections of an artificial neural network do not perfectly represent the natural synapsis of neurons within the human brain. In order to create artificial intelligence, you first have to know how natural intelligence truly exists and works… yet this is something that is not fully understood in the scientific community. The scientific community understands that neurons transmit information across the brain. Three different types of neurons serve different functions within the brain. Even with all we know about neuroscience, there is still so much that we only have theorized about the human brain.

The human brain contains countless amounts of neurons and various types, which include unipolar, bipolar, multipolar, and pseudopolar each with their own specific structure and function. Though, the belief is there are hundreds of different types of neurons, it is agreed they make up three categories which are sensory, motor, and interneurons. Sensory neurons carry information between sensory organs and the brain. They take in all the information from the outside world and deliver it to be processed by our brain. Motor neurons carry signals from our brain out to different parts of our body controlling voluntary muscle groups. In short, they take what our brain wants done and deliver it to the part of the body that will fulfill that order. Finally, some interneurons make up the pathways that connect these two together. Similar to how the nucleus of a neuron directs traffic and maintains order, the interneurons do the same for the sensory and motor neurons.

The human brain is an amazing wonder, and to be able to truly mimic it, one would have to answer many of today's leading neuroscience's unanswered questions. However, today we have developed a weighted transport system to attempt to create an artificial replica of the neural synapse that occurs within all of us. This system is designed to take combinations of inputs and train a model to develop an artificial logic to determine the importance of the features provided in producing a desired outcome. These weights are placed on the connections as the model trains and determine the importance of each feature. This is the best substitute available to supply an artificial intelligence with logic and a decisive thought process. This process, yet adequate, does not truly fulfill the goal of artificial intelligence, which is to be as close to a replica of human intelligence as possible.

The current artificial neural networks are built based on neurons and the transmission of data from input nodes through each neural network's unique architecture, to an eventual output node. Each individual network’s design is to establish weights assigned to features to help determine each feature's importance in determining an accurate or correct outcome. These weights are evaluated and adjusted through backpropagation and other means, depending on the type of neural network being used. The accuracy of these neural networks can be fine-tuned through a multitude of different Machine Learning Techniques. The current artificial neural networks are very highly sophisticated representations of gray matter and complex layers of neurons that perform various miraculous computational feats.

2. Artificial Intelligence’s Missing Design

Unfortunately, at the end of the day there is no replacement or replication of human thought and logic. I believe that there is a way we can get closer simply by looking a little deeper into the human processes of the mind, into human thought and consciousness itself. Now, I am not proposing a sentient artificial intelligence (AI) in any form. However, we have been building artificial neural networks simply on the information and impulse transportation system of the brain. The artificial neural network developed in a thick blanket of connections between layers, much like the large number of neuronal cells that make up the brain’s gray matter. But that is where the similarities end. Neural networks structures have developed variations to encompass different processes, but none have truly followed advancements in neuroscience research. Studies have shown proof of networks being present in the white matter of the brain, as well as correlations between the gray matter and white matter transmissions. A revolutionary breakthrough in the field of neuroscience indeed.

The question remains: how can this information, in turn, revolutionize artificial intelligence and improve our ability to replicate human thought and logic? The next step I believe in advancing our capabilities with artificial intelligence is to truly build an entire brain for the artificial intelligence (AI) models. My theory is that there is the same input layer with the features selected for the model to process. Now we need to create the brain. First, creating several hidden layers equal to the total combination of features that the team feels could accurately affect the result of the model. This would give a more comprehensive understanding of features and their effect on one another. For example, everyone is familiar with the Titanic dataset and the historical statements of, “Women and children first.” However, would a family be given access together, and how would that affect the result if the artificial intelligence (AI) was able to understand that maybe a mother, child and father could be allowed passage on a lifeboat? Or, devil's advocate, a family of five members, including young adult males would be split up due to lack of room.

The consistent issue remains, even with the current advancements in the development and performance of Artificial Intelligence. The systems still have very real, very restrictive limitations to their performance. They still fall short of the goal of replicating the design of the human brain, as well as limitations of functionality remaining in what we justify as an acceptable error. When truly we have only really created a small portion of what the human brain consists of, leaving out the portion that truly makes us differ from other creatures. This birthed the question of how a logic center, such as our "white" matter, could be created in regards to Artificial Intelligence (AI) and current neural networks. The creation of this research paper began initially as a theory and gradually evolved into proven concepts and functional working code. The resulting novel technique has given AI a new and improved logical understanding of data and their relationships to one another. An advancement that could even be further developed into new algorithms, and advancements in how we view Artificial Intelligence (AI) development in the future.

3. Current Systems and New Theology

The ability to logically understand and see more complex patterns could be something that results from us taking a much deeper look at the brain and, in turn, developing a more complete artificial neural network. So, to accomplish this task, we would want to create multiple types of neural pathways. Each serves a different purpose, very much just like their biological counterparts. The first portion of the artificial intelligence (AI) brain would be the architecture of the neural network selected for the task at hand. For example, in classification or regression tasks, an Artificial Neural Network (ANN) the input layer, hidden layers, and output layer make up the gray matter of the artificial intelligence (AI) brain. The second layer of the artificial intelligence (AI) brain would be neural pathways transporting data from each node to a Logic Band layer attached to the neural network. This would make up the artificial neural network's logic center such as white matter does in the human brain. Let me break this down in comparison to our current methods.

Current Mechanisms of weights and biases that take the strength of connections between neurons (weights), and the biases applied at each neuron are adjusted during training to minimize the error between predicted and actual outcomes, along with the activation functions that introduce non-linearity into the model and allow the network to learn complex relationships. What I am proposing, in theory, is a band mechanic layer that tracks the flow of input through each hidden layer, evaluating the combinations of weights and their effectiveness in achieving the expected results. This band would continuously assess the accuracy of predictions refining the model's logic by emphasizing more accurate combinations of weights and suppressing less effective ones to achieve better accuracy and understanding of more complex relationships between features.

This mechanism allows for improved outcomes in big data, complex data with large numbers of different feature inputs, and noisy data. The Logic Band will excel the greater the complexity of the data and the more epochs the model is performing allowing it to learn quickly as it progresses through the epochs, in using a toy dataset involving college students and their grades. The Logic Band enhanced Artificial Neural Network has shown consistently better scores when compared to standard Artificial Neural Network regression tasks.The outcomes of the dataset show promise; however, big, noisy, complex data is where this method will be most beneficial. This scenario was involved a data set with under six thousand rows, and when refined to six or seven columns, it still showed better performance than the standard Artificial Neural Network (ANN); these were far suboptimal parameters for the Logic Band to perform within, but was still able to provide a superiorly accurate output. However, this shows that the Logic Band does improve outcomes when attached to current neural networks. Exciting results on a raw dataset.

4. General Architecture and Explanation

In the Logic Band framework, there are two key rules, or functions of the Logic Band depending on the use case. The Logic Band technique was adapted to fit multiple AI Machine Learning, and Deep Learning models. The functionality of how the Logic Band functions within the different neural networks the following will dive into the two general architecture designs of the Logic Band and the use cases in which the architecture functions. The two architectures of the Logic Band describe the function of the logic band within its specific neural network, one being a secondary weight correction mechanism, and the other as a dynamic Adjustment of Logic Band Weights.

4.1 Logic Band Weight Correction Mechanism

The first Logic Band's framework consists of a traditional weight matrix W augmented by a secondary weight matrix L, this uses the logic band as a weight correction mechanism. This mechanism introduces an adaptive scaling factor to the weights in a neural network, allowing the model to adjust the importance of individual layer outputs dynamically. This provides many benefits, such as handling "noisy" data by dynamically adjusting the importance of features. Feature importance in high-dimensional data by dynamically scaling each feature's importance throughout the different stages of training. Regression tasks to recognize complex relationships between input features and outcomes, resulting in higher accuracy. Finally, improved interpretability of the model’s outputs by allowing the model to focus on certain features dynamically which can lead to enhanced interpretability of the model’s predictions. The Logic Band serves as an element-wise modifier to the standard weight matrix, essentially enabling the network to "fine-tune" its weights during training based on the relative importance of the features at each layer.

Mathematically, the Logic Band mechanism can be expressed as:

$$z_{logic}=(W\odot L)\cdot x+b \tag{1}$$

Where:

- W = is the weight matrix of the layer.
- L = is the Logic Band weight matrix, which is of the same size as W and is trained alongside the model's standard weights.
- x = is the input to the layer, which can be the previous layer’s output or the raw input data for the first layer.
- $\odot$ = denotes the Hadamard product (element-wise multiplication), allowing the Logic Band to dynamically scale each individual weight in W by the corresponding value in L.
- b = represents the bias term of the layer.

The key difference in this approach is incorporating the Logic Band weight matrix L, which enables the model to dynamically adjust the importance of each input feature based on its relevance during training. This dynamic adjustment allows the network to more effectively capture complex feature interactions more effectively, particularly in datasets with noisy or subtle relationships, by emphasizing important features and down-weighting less relevant ones. As training progresses, the Logic Band learns which features should be prioritized for better model generalization.

This mechanism ensures that, instead of treating all features with equally, importance, the model can adapt to the underlying data patterns, leading to improved model performance. The learning process for the Logic Band itself is governed by the same backpropagation algorithm that is used for traditional weights, but with the added benefit that L adjusts over time based on the network’s performance.

4.2 Dynamic Logic Band Weight Adjustment Rule

The secondary architecture of the Logic Band, which provides the functionality of dynamic adjustment of Logic Band weights, will help understand the logic band as a whole by explaining how the Logic Band updates the weights themselves as they are updated throughout training. The update rule introduces momentum-based learning, allowing the Logic Band to adjust its weights gradually, incorporating prior knowledge and fine-tuning the model's understanding of feature importance based on the gradients of the loss function. The second critical aspect of the Logic Band mechanism is the dynamic updating of the Logic Band weights LL as training progresses. To ensure that the model continually adapts to the most relevant features, the weights of the Logic Band must be adjusted based on the gradients of the loss function. A momentum-based learning approach is applied to the Logic Band weights, which allows the network to retain knowledge from previous updates while also learning new adjustments that reflect the model's current state.

The update rule for the Logic Band weight matrix L can be described as:

$$L(t+1)=\alpha \cdot L(t)+\beta \cdot \nabla_L \mathscr{L} \qquad (2)$$

Where:

- L(t) - is the Logic Band weight matrix at time step tt.
- L(t+1) - is the updated Logic Band weight matrix after applying the gradient update.
- α - is the momentum term, a hyperparameter that controls how much of the previous update is retained (like traditional momentum-based updates in neural networks).
- β - is the learning rate for the Logic Band, which controls how fast the weights adjust to new information.
- $\nabla_L \mathscr{L}$ - is the gradient of the loss function $\mathscr{L}$ with respect to the Logic Band weights.

The momentum term α ensures that the Logic Band weights do not change too abruptly, allowing the network to retain knowledge from earlier in the training process. This is particularly useful in preventing the network from making unstable or overly aggressive updates based on noisy or sparse data. The learning rate β is a key factor in determining the magnitude of updates to the Logic Band. A larger learning rate results in more significant weight changes, while a smaller rate allows for more subtle adjustments. The gradient $\nabla_L \mathscr{L}$ reflects the necessary adjustments to the Logic Band weights to minimize the loss, guiding the model to focus on the most critical features. This dynamic update rule ensures that the Logic Band can learn to focus on the most relevant features during training while avoiding the potential pitfalls of overfitting or underfitting the data. It enables the model to continuously refine its understanding of which input features contribute most to the final prediction, thereby improving overall model performance. This provides functionality to allow the technique to improve the model's performance by adapting to changing data patterns over time such as in Time-Series Forecasting. Reinforcement Learning is able to dynamically adjust which features are given more importance in the decision-making process through the Logic Band improving performance in complex and noisy feedback environments. This allows for overall improvement in performance with adaptive learning in complex or noisy data where data quality may be inconsistent (sensor networks, social media data). The dynamic adjustment of Logic Band weights allows the model to continuously learn from the most important features, effectively ignoring or devaluing noisy or irrelevant data points. Handling of complex relationships in Deep Neural Networks (DNN) through dynamic adjustment helps the model fine-tune its representation of feature importance across multiple layers, which can be essential in capturing long-range dependencies in data. The momentum-based approach to adjusting Logic Band weights ensures that the updates to the Logic Band are gradual and stable, ensuring model stability during training by preventing drastic weight changes that could destabilize the model.

The interesting thing about The Logic Band's design is the architecture of the Logic Band itself can be adapted to each and every neural network that exists, it truly becomes a counter part to neural networks in the whole scheme of Artificial Intelligence Neuroscience. The location in which it is adapted to in these various models may vary by name but truly they are identical in the function they serve within each model. From the dense layers that an ANN almost complete is comprised of, or the dense section in which pixel inputs are regulated and evaluated within a CNN is also a dense layer. The feedforward network processes and regulates the flow of inputs and outputs as they pass through being processed as they go, still serving the same functionality as other various types of models. These dense layers is where the complex relationships are evaluated between feature and output, The Logic Band completes the logical understanding of the Artificial Intelligence by providing a logical reasoning in which feature relationships are realized and evaluated, where the Artificial Intelligence is able to perform a degree of feature engineering that is a rate much faster than possible by us, more precise than we are able to perform in the same time allowance.

5. Artificial Neural Network (ANN) Specific Architecture

The Artificial Neural Network (ANN) consists of Input layer, hidden layers, and an output layer. The Logic band runs along the entire length of the Artificial Neural Network (ANN) neuron extensions connected to every Input node, and hidden nodes to the Logic Band. The Logic Band receives the weighted results of each feature and each feature combination as they combine throughout the hidden layers. The Logic Band is able to compare each combination of features and dynamically adjust their weight value as complex relationships previously undetectable are made, and the accuracy of the model is improved.

The architecture of the Logic band in an artificial neural network is relatively simple in design but potentially powerful. We have a traditional Artificial neural network and are adding a pathway that runs beneath the network and is connected to each input individually, and sent down into the Logic band where its weight is examined for accuracy. Weights of initial input features are measured and carried through to benchmark the feature's accuracy. Once they combine at the first hidden layer, weights are compared, and if the weight value of the new combination is less than the original value, then the new combination is blocked, and the original feature input continues on. If the weight of the new combination is improved over the original input feature, then the original input feature is blocked, and the new combination continues.

The nodes within each hidden layer are also connected to the logic band individually where the new combination of features and weights are evaluated for accuracy and impact on the final output. This is to capture any new relationship between features that could have been missed. This process continues throughout all the hidden layers and combinations of features, capturing any complex relationships that the normal artificial neural network could miss. This is beneficial in big data and noisy data sets. These final combinations of features dynamically evaluated are then fed into a logic layer in which the artificial neural network and the logic band feed the processed inputs for evaluation. They are evaluated with the 'relu' metric and the accuracy is measured by means of the appropriate metric for the type of problem. They are calculated as they pass through the function (f(x)) to the output layer.

Finally delivering an output composed of a more precise comprehension of the data and feature relationships by comparing these changes between data combinations as it is carried across the logic band and reevaluated. Producing an output that captures complexity and depth of understanding of the data. Forming an artificial logic band or "white matter" for the AI. The logic band mechanism, when attached to an Artificial Neural Network (ANN), introduces adaptive scaling to the weights of each input feature dynamically. Instead of relying solely on the weight matrix W, we introduce a logic band weight matrix L that acts as an element-wise modifier.

The new equation becomes: $$z_{logic}=(W\odot L)\cdot x+b \qquad (3)$$

Where:

- ➔ L: Logic band weight matrix (same size as W)
- ➔ ⊙: Hadamard product (Element-wise multiplication)

This ensures that each weight Wij is dynamically adjusted by the logic band based on the importance of feature j neuron i.

During backpropagation the logic band weights L need to be trained alongside the regular weights W to minimize the loss. Using gradient descent, the partial derivative of the loss function $\mathcal{L}$ with respect to L_{ij} is:

$$\frac{\partial \mathcal{L}}{\partial Lij}=\frac{\partial \mathcal{L}}{\partial zlogic}\cdot \boldsymbol{x_j}\cdot \boldsymbol{W_{ij}} \qquad \textbf{(4)}$$

This formula ensures the logic band learns feature importance dynamically throughout training.

- **Binary classification:** a sigmoid function is applied at the output, and the network predicted probabilities:

$$\hat{y}=\sigma(zlogic)=\frac{1}{1+e-zlogic} \qquad \textbf{(5)}$$

- **Multi-class classification:** the softmax function is used:

$$\hat{y}i=e^{zj}/\sum_{j}e^{zj} \qquad \textbf{(6)}$$

The logic band helps adjust the weights dynamically, improving class separation and handling complex relationships between features.

- **Regression Problems**: the activation function in the output layer is often linear:

$$\hat{y}=z_{logic} \qquad (7)$$

In this case, the logic band improves the network's ability to model subtle relationships between features, leading to lower mean squared error (MSE) or other regression-based loss metrics.

When combined with gradient descent, the Logic Band introduces an additional correction step instead of relying purely on backpropagation through the networks weights. This can be viewed as a hybrid optimization process as we are able to apply a two-step process when introducing Gradient Descent.

- Step 1: Gradient Descent for Layer Weights

$$W^{(l)}(t+1) = W^{(l)}(t) - \eta \bullet \nabla_{w}L(\hat{y},y)$$

- Step 2: Logic Band Adjustment (introduced after every epoch)

$$W^{(l)}_{final} = \Lambda^{(l)}(t+1) \odot W^{(l)}(t+1)$$

This two-step optimization process creates a feedback loop in which the Logic Band weights guide the regular weight updates, allowing the model to explore more complex feature interactions more effectively.

The potential benefit of dynamically adjusting weights based on observed accuracy is that this mechanism could help the network discover and retain more complex relationships in the data that traditional methods might miss. It could adapt more flexibly to different types of data and tasks, improving the network's ability to generalize from training data to unseen examples. Focusing more on accurate weight combinations could lead to better performance and lower error rates, particularly in complex or noisy datasets. The more complex the data the better the Logic Band is able to perform. So big data and complex feature training will yield the best improvements to the current artificial neural network. And continuous evaluation and adjustment could refine the network's predictions, leading to more accurate outputs. This could be the new evolution of the artificial neural networks. Taking a step towards mimicking the structure of the human brain itself. But this theory has some considerations to evaluate.

6. More Model Specific Architecture Adaptations

The design of this artificial logic band would have to be done very carefully to make sure not to add a significant amount of computational costs and time and to ensure model stability during the training process. I believe the Logic Band will be a great addition to any artificial neural network architecture and a great tool for evaluating weights and improving the accuracy of the models. This method could be implemented to build a logical reasoning that is more in-depth and comprehensive for the artificial neural network. The concept is novel and would require a lot of research and development. This concept could lead to the development of new neural network architectures that better capture complex relationships, and research into these architectures could expand the boundaries of what is possible with the current neural networks. The Logic Band has been successfully paired to multiple artificial neural networks such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Transformers, BERT, and LSTMs. Performance benchmarking against current methods could reveal just how beneficial this technique could be and how practical it could be to be used in deep learning applications.

6.1 Convolutional Neural Network (CNN) Specific Architecture

The Logic Band for Convolutional Neural Networks (CNN) is used for computer vision tasks. The Logic Band is applied to the Fully Connected layers otherwise known as the Dense layers. This is designed to not increase computational costs of using the convolutional layer, while still being able to dynamically evaluate and refine the importance of the features. This custom dense layer injects logic band weights into the standard dense layer's connections. Each input to every neuron is individually weighted by multiplying the kernel with the logic band weights and track combinations dynamically and refining them during the training phase.

This formulation dynamically controls how much influence each input has on each neuron. Weighted Input: $y=ReLU(X\cdot(W\odot L)+b) \qquad (8)$

Where:

- X: Input data
- W: Dense layer kernel weights
- L: Logic band weights
- b: Bias term
- ⊙: Element-wise multiplication

In convolutional layers, neurons are only connected to local patches of the input, keeping connections sparse, meaning each neuron interacts with only a subset of inputs. Due to this specific design, the convolutional layers would restrict and complicate how well the Logic Band could compare all possibilities and result in an increased computational cost by requiring much more work to accurately capture complex relationships. Applying the logic band here would multiply the weight adjustments needlessly across thousands of parameters, increasing overhead. However the dense layers already connect every input neuron to every output neuron, making it an ideal place to control feature relevance dynamically through the Logic Band. The Logic Band could become more effective within the Fully Connected Layer by adding more hidden layers for the Logic Band to evaluate combinations, beware of overfitting. This should allow control over each neuron's input by scaling dynamically simulating fine-grained control like the brain's white matter pathways.

The Logic Band refines feature importance across training epochs, learning to improve generalization and handling of complex relationships through this adaptive learning. Focusing logic adjustments in the dense layers, it reduces the number of adjustments required for fine-tuning without affecting the backpropagation of earlier convolutional layers. The Logic band in the dense layer helps capture feature importance in a way that directly aligns with the model's output, improving interpretability of predictions and without adding unnecessary complexity to earlier layers. This design can easily be extended to larger Convolutional Neural Network (CNN) or even ResNet-style architectures by adapting Logic Band to the dense layer where appropriate giving the model scalability, balanced computational cost, and effective feature learning at the same time.

In comparison to ANNs, the CNNs Logic Band is applied only to the dense phase of the model to reduce the effect on computational costs, where similarly in ANNs the Logic Band is applied throughout the entirety through the dense layers that make up the model, and the computational cost increase is negated by increase in models' performance. The Logic Band enhanced CNN offers high-level feature aggregation with image recognition and object detection processes, while Logic Band enhanced ANNs are able to capture complex relationships between features improving accuracy of the models. Where autonomous cars and robots assortment of inputs from various sensor sources are able to give the AI a better understanding of its surroundings and better decision making capabilities.

The world of Artificial Intelligence (AI) is ever-evolving especially in the field of natural language processing (NLP). The logic band has been adapted to fit several deep learning models used for natural language processing as it allows dynamic scaling of weight importance, helping the model focus on meaningful tokens across varying contexts and allows for the handling of contextual relationships. The Logic Band introduces adaptive learning of feature importance through fine-tuned control over input-output interactions which is especially useful for tasks like sentiment analysis, text classification, or question-answering, where not all words are equally important. Attention mechanisms already create computational strain in natural language processing (NLP) models. Applying the Logic Band only in dense phases, such as fully connected output layers, and feedforward networks, preserves efficiency without adding unnecessary computational strain to the model, allowing avoidance of computational bottlenecks.

6.2 Recurrent Neural Network (RNN)/ LSTM Specific Architecture

In recurrent architectures, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), maintaining the flow of meaningful information over time steps is crucial. The Logic Band can modulate the hidden-to-hidden weight connections, ensuring that important features remain influential while reducing noise.Integrating Logic Band layers into Natural Language Processing (NLP) models adds another layer of adaptive learning, making them more effective in capturing complex relationships across tokens. The Logic Band improves the Recurrent Neural Network (RNN) through adaptive learning, which is critical for time-series tasks, forecasting, or sequence classification. By dynamically scaling each time step, the network is able to focus on meaningful features throughout the sequence. This makes a Logic Band-enhanced Recurrent Neural Network provide better generalization and fine-grained control over feature importance throughout the RNN's hidden state evolution.

This formulation for Long Short-Term Memory (LSTM) ensures that the model emphasizes Key Tokens Dynamically across time steps.

$$ht=\sigma((Wh\odot L)\cdot ht-1+(Wx\odot L)\cdot xt+b) \qquad (9)$$

Where:

- ➔ Wh, Wx = Weight matrices for hidden state and input
- ➔ L = Logic Band weight matrix
- ➔ ht = Hidden state at time t
- ➔ xt = Input at time t

6.3 Transformer-Specific Architecture

In Transformer-based models, such as BERT, each token interacts with every other token through self-attention mechanisms. The dense layers in the feedforward network (FFN) and output layers are ideal candidates for the Logic Band. This allows the model to learn feature importance beyond attention scores. This Transformer formulation ensures that the model adjusts token importance dynamically during training, helping with tasks like entity recognition or summarization.

$$z=ReLU(X\cdot(W_1\odot L)+b_1)\cdot(W_2\odot L)+b_2 \qquad (10)$$

Where:

- ➔ W_1,W_2 = Weight matrices in the feedforward layers
- ➔ L = Logic Band weight matrix
- ➔ X = Input to the feedforward network

This formulation ensures that the model adjusts token importance dynamically during training, helping with tasks like entity recognition or summarization. There are two separate architectures when dealing with transformers. Below I will detail the strengths and weaknesses of using one Logic Band or two Logic Bands when using this enhanced transformer model.

The use of the Logic Band from the inputs' FeedForward Network (FFN) to the outputs' FFN will emphasize relationships between encoder and decoder features but does not directly adjust the decoder's FFN based on its own outputs. This provides a simpler architecture with fewer parameters and reduced computational overhead, focusing on improving the transformation of encoder outputs into meaningful decoder inputs, enhancing cross-feature relationships. This method reduces the risk of overfitting due to fewer trainable parameters, and makes the model easier to train and debug. However, it provides limited adaptability, in such cases as, language generation or summarization that requires independent logic refinement in the decoder's FFN.

The use of the Logic Band from the inputs' FFN to the outputs' FFN, and a second Logic Band from the outputs' FFN to the inputs' FFN allows each Logic Band to specialize in different types of relationships. It allows the first Logic Band to gather encoder-to-decoder relationships, and the second Logic Band to refine the input context dynamically through feedback from decoder to encoder. This can be incredibly beneficial in improving performance on tasks requiring fine-grained bidirectional understanding such as translating languages and question answering. It would also provide enhanced handling of complex datasets where token relationships evolve dynamically. This all does come at the cost of more parameters and operations, especially in high-dimensional data, computational costs may need to be monitored. It would increase the training complexity where careful management is necessary to avoid overfitting and potentially vanishing or exploding gradients.

Both methods have their strengths and use case scenarios. A single logic band would be preferred where the dataset is relatively simple or the task involves straightforward transformations, such as translation where input and output have a direct relationship. The double logic band is suitable for tasks requiring deeper contextual understanding or feedback between input and output such as summarization, question answering, multi-hop reasoning. This is more suitable for larger datasets that are complex where additional parameters can improve feature interaction modeling without overfitting.

In Conclusion:

I believe that this is not only a great theory founded in human neuroscience, but it gets us a little closer to the goal of artificial intelligence, which is to replicate the human brain and its function as best possible. The science and healthcare experience I have has led me to develop this theory and now transitioning to data science, the applications of complex relationships are currently measured on the roads of the brain.

This is a complex reasoning of relationships in data that has successfully improved outcome accuracies. This may just be the first step into developing a human-like logical understanding of data for Artificial Intelligence (AI). In my opinion, its complete development is an exciting advancement for artificial intelligence and the beginning foundation for the complete development of the “white matter” component of the artificial intelligence’s brain. One step closer to replicating the human brain for artificial intelligence practices. The dynamically adjustable weight system allowing for more complex relationships to be discovered in data is exciting. The applications are nearly endless: better weather forecasting, stock predicting, marketing insights, drug discovery, self-driving cars, even improvements to artificial intelligence assistants.

This is such a unique and far influential development since the middle of the 1980s when the very creation of neural networks began, and surely they began with a small idea such as this one, and developed it further and further in theory without the computational resources to be able to test what they had dreamed of, had created. Now, we develop AI and specifically gen AI always coming out with new methods, which are old or borrowed Machine Learning concepts, enhanced and stacked on top to continually compute to refine the accuracy of the answer to some prompt. Linear development and growth. This novel development of the Artificial Brain that powers Artificial Intelligence has been realized and created. The counter-part to the very same neural networks that we have believed we could develop beyond the stars, however, now we have a dimensional space in which to develop and grow. A new and proven concept that is already in further development, beyond what is covered within this research paper. “If we don’t set our sights on impossible, you will never know your true potential. Failure allows us to see our capability and path to improvement!” -Derek Smith.

1. Future Development

The further development of the Logic Band to include feature replacement with newly discovered complex feature relationships will nearly automatic raw data into prioritized data that will will be able to dropout features and feature relationships that are not as important to the performance of the model by setting a hyperparameter. Allowing the models to not only accurately depict complex relationships but also feature engineer findings to be evaluated over the initial feature itself to prevent overfitting, or results that do not truly reflect the model’s performance. For example, say we are trying to estimate the cost of a vehicle based on its features. Using completely raw data including things like color, number of doors, transmission, engine, brand, sunroof, and premium stereo. The model could look at these and determine that color red and 2 door cars combined was the most accurate pairing of color with all other features as well as the accuracy weight of the color itself. The combination was found to be more expensive so in the color feature spot the model would replace with the feature sporty(color-red/2-door). Now, another feature in development currently as part of the feature engineering automation is that when the transmission-engine combination scores highest overall in determining the cost, and than engine-transmission combinations scores highest the complex relationship is not doubled, if a combination is found to be strongest, than when found again, the memory storing the last highest known combination of each is held until the end and if the weight accuracy of the two reversed combos is identical than the highest secondary combination takes the place of number one for its feature. Example being transmission-engine and engine-transmission tied identical weights, and at the end of the Logic Band. transmission-number of doors is transmissions second best combination and is better performance weight value than engine-brand which was the feature engine second best combination. I that case the feature transmission would be replaced by transmission-number of doors, and engine-transmission would take the feature engine's spot.

The interesting thing about developing The Logic Band's design is the architecture of the Logic Band itself can be developed the same way different neural networks have been created. The initial method focusing on complex feature relationship identification and appropriate dynamic weight adjustment to reflect the importance of them. A new method in development centers around autonomous feature selection and refined feature engineering performed by the model itself to ensure maximum results and ability to use raw data as needed. This designs location in which it is adapted to in these various models may vary by name but truly they are identical in the function they serve within each model. From the dense layers that an ANN almost complete is comprised of, or the dense section in which pixel inputs are regulated and evaluated within a CNN is also a dense layer. The feedforward network processes and regulates the flow of inputs and outputs as they pass through being processed as they go, still serving the same functionality as other various types of models. These dense layers is where the complex relationships are evaluated between feature and output, The Logic Band will develop more and more comprehensive capabilities as the more eyes and minds are able to take this amazing ideology and the completion of the neural network structure as we know it. It completes the logical understanding of the Artificial Intelligence by providing a logical reasoning in which feature relationships are realized and evaluated, where the Artificial Intelligence is able to perform a degree of feature engineering that is a rate much faster than possible by us, more precise than we are able to perform in the same time allowance. The final thing in development currently is the ability for the model to drop features underperforming, and accelerate those that are critical in optimal performance of the model. Including a hyperparameter to custom set this value of this, as well as if a single feature out performs the given parameter, you will have the ability to allow that parameter to be evaluated beside any combination found to be more beneficial because brand and engine, or brand and 2-door may be found to be exceptional variables at the end of the day some brands evaluate the price of their products based solely on name and reputation.