Artificial Association Neural Networks

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Abstract

In the field of deep learning, various architectures have been developed. However, most studies are limited to specific tasks or datasets due to their fixed layer structure. In this paper, we do not express the structure delivering information as a network model but as a data structure called a neuro tree(NT). And we propose two association models of artificial association networks(AAN) designed to solve the problems of existing networks by analyzing the structure of human neural networks. Defining the starting and ending points of the path in a single graph is difficult, and a tree cannot express the relationship among sibling nodes. On the contrary, a neuro tree can express leaf and root nodes as its starting and ending points of the path and the relationship among sibling nodes; And neuro nodes can have multiple parent nodes. Instead of using fixed sequence layers, we create a neuro tree for each data and train artificial association networks according to the tree’s structure. artificial association networks are data-driven learning in which the number of convolutions varies according to the depth of the tree. Moreover, these models can simultaneously learn various types of datasets through the recursive learning method. Depth-first convolution (DFC) encodes the interaction result from leaf nodes to the root node in a bottom-up approach, and depth-first deconvolution (DFD) decodes the interaction result from the root node to the leaf nodes in a top-down approach. To demonstrate the performance of these networks, we conducted four experiments. In the first experiment, we verified whether it can be processed by combining artificial association networks and feature extraction networks(combining association models and feature extraction models). In the second experiment, we simultaneously learn the structure of images, sounds, graphs, and trees structure datasets (processing various datasets). We compared the performance of existing networks that separately learned image, sound, and natural language, relation datasets with the performance simultaneously learned by connecting these networks. In the third experiment, we verified whether data of deep time series structures can be learned and checked the plot of the learning process. The fourth experiment is about whether the output of artificial association networks can embed information on all data contained in the neuro tree (association). As a result, these models learned without significant performance degradation, and the output vector contained all the information in the neuro tree. And the importance of transfer-learning and fine-tuning in these models is explained.

Keywords: association networks, graph neural networks, recursive neural networks, domain general learning

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1 Introduction

In deep learning, various architectures have been designed such as convolutional neural networks (CNN), recurrent neural networks (RNN) and graph neural networks (GNN) and recursive neural networks of tree (TNN) \([9, 17, 31, 38]\). These networks show good performance in various fields such as image, text, and sound etc. However, most of the existing studies are focused on a specific dataset or task. And there are many tasks that humans can do but are difficult to perform with neural networks.

First, some of the difficulties with imitating human neural networks are introduced below.

C-i – Sensory organs that process information for each data type exist at several starting points.

C-ii – A tree cannot express the relationship between sibling nodes, and there is only one parent node, and it is difficult to define the graph’s starting point and ending point, and it’s hard to handle.

C-iii – The structure that receives information is hierarchical and freely combined in various structures.

But existing networks are designed to learn only specific tasks or datasets because layers are fixed.
C-iv – The number of activated neurons and the processing depths differ depending on the data type and complexity. And sometimes the information is entered and sometimes not.

C-v – Human neurons are very numerous and process various types of data.

C-· denotes the characteristics. (C-i) Humans have various sensory organs from which they receive information such as sight, hearing, and smell, and transfer it to the cerebral cortex using different information-processing organs. The optic nerve also begins with the visual cortex of the occipital lobe, and the auditory nerve begins with the auditory cortex of the temporal lobe; this means that the two paths have different starting points. (C-ii) A graph can describe the relationship depending on whether all nodes are connected, but it is not easy to define the start and end points. And when expressing the propagation path of the tree structure, it is not easy to describe the path that starts in parallel and propagates to the root node in a graph structure. A tree is a data structure that can define direction with the leaf and root nodes. On the other hand, a tree structure cannot express the relationship between sibling nodes. And the existing tree data structure cannot express the process of delivering to multiple nodes because only one parent node exists. (C-iii) Information from different sensory organs is gathered in the association area. Typically, the posterior parietal cortex 22 is located at the top of the head as part of the parietal lobe, and sensory information such as vision and hearing is fused and interpreted; Then, information is coordinated in the frontal lobe and humans act. (C-iv) There is also an over-fitting problem in DNN 35, and various attempts have been made to solve this in 33. In DNN, simply deeper layers lead to an over-fitting problem 3. In particular, NasNet 41 has attempted to design a layer automatically through reinforcement learning and RNN. This means that there is an appropriate network depth depending on the complexity of the dataset; we want to design a network that could adjust the depth of the layers according to the complexity of each data, not the data set. (C-v) Also, the number of human neurons is about 85 billion 6, which is difficult to express in a network. Therefore, AANs are designed to solve these problems.

A-i – We express these sensory organs as multi-feature-extraction processes (sec 3.2).

A-ii – We propose a new data structure called neuro node (NN) and neuro tree (NT).

A-iii – We propose a recursive propagation method called depth-first convolution (DFC) and depth-first deconvolution (DFD). It can learn about relationships, hierarchical, multi-feature extraction networks, and propagate to several parent nodes.

A-iv – We do not design layers but express the flow of information delivery in a neuro tree.

A-v – Various neuro tree structures can be learned with one network cell (association networks).

A-· denotes our approach of C-·. (A-i) This network can perform information processing, such as that done by sensory organs before their signals are entered into the cerebral cortex. In this paper, we express this sensory organ as a feature-extraction process (sec 3.2). Type information is stored with the data and converted into an input vector by different feature extraction processes for each type. (A-ii) We propose a new data structure called neuro node (NN) and neuro tree (NT). An neuro tree can be expressed using leaf and root nodes as the starting and ending points, as well as the relationship among sibling nodes. If a neuro node does not reverse the propagation path, it is possible to have multiple parent nodes; This allows propagation to multiple nodes. In addition, we can modify the existing tree dataset at no high cost. (A-iii) subtrees of different types are merged and make a final decision at the root node; this structure is difficult to express with the existing forward-learning method. Therefore, we used a recursive-learning method 5. This methodology has been effective in analyzing the semantics of programming source code or natural language 24 32. We call the recursive-convolution methodology used in AANs the depth-first convolution (DFC) and depth-first deconvolution (DFD) methodology (sec 3.4). DFC is a convolution method in which subtrees originating from different leaf nodes are integrated into a bottom-up approach and represent hierarchical and relational information. artificial association networks can simultaneously learn various types of datasets through the recursive learning method because the neuro tree data structure can express various model structures. (A-iv) graph tree neural networks are data-driven learning in which the number of convolutions varies according to the depth of the tree. Instead of using fixed sequence layers, we create a neuro tree for each data and learn according to the tree’s structure. If we modify this network further, we can adjust the depth according to the type and complexity of each data. In addition, we introduce two models of artificial association networks called level association networks (LAN) and recursive association networks (RAN), and these models are mathematically related.
to MLP\textsuperscript{8} and RNN. The fully connected layer (FC layer) in MLP as Level Layer of LAN, and time in RNN as depth of RAN on a special case. In addition, the some structures of graph neural networks and recursive neural networks can be expressed by graph tree. (A-v) The number of human neurons is enormous, and it is difficult to express all of their structures in a network; on the other hand, this network can represent multiple neurons because it can perform recursive end-to-end learning according to the amount of information.

This network theory holds that "units of information have a relationship in the form of a graph, then become a bigger unit of information, and have a relationship with other units of information. At this point, the unit of information is a set of neurons, and we can express it as a vector with artificial association networks."

To demonstrate the performance of this network, we conducted four experiments. And we used several benchmark datasets (image(MNIST\textsuperscript{18}), sound(Speech Commands\textsuperscript{35}), text(IMDB\textsuperscript{21},SST\textsuperscript{32}), graph\textsuperscript{4}).

In the first experiment, It verifies whether feature extraction networks and association networks can be learned together. we compared the performance of existing networks that separately learned image(LeNet-5\textsuperscript{17}, sound(M5\textsuperscript{3}), text(CNN\textsuperscript{14})) with the performance simultaneously learned by connecting these networks for feature extraction into artificial association networks.

In the second experiment, we verifies whether data of various structures(image, sound, tree, graph) can be learned and checked the plot of the learning process in sec 17.

In the third experiment, we verifies whether data of deep time series structures can be learned and checked the plot of the learning process in sec 19.

The fourth experiment contained one or three types of data into a neuro tree, and artificial association networks learned these neuro trees. Then, we verified whether the output contained all the information inside the neuro tree. As a result, the network was learned without significant degradation in performance compared to when learning existing networks separately, and all information on the tree could be embedded as a vector.

2 Related Works

Graph Neural Networks GNNs have recently shown good performance in various fields\textsuperscript{31, 34, 38}. GNN has a relationship term and a structure more similar to that of human neural networks than other networks. It was used as a study to embed knowledge with GNN. But it isn’t easy to understand the propagation path with the graph data structure, although the tree-structured graph is trained through graph neural networks.

Recursive Neural Networks Recursive neural networks are used to learn data of tree structures. Recently, it has been useful in the field of natural language processing. I think this network is relatively unnoticed because it needs tree-structured data to learn. This methodology has been effective in analyzing the semantics of programming source code or natural language\textsuperscript{24, 32}. Recursive neural networks are easier to understand the propagation path than graph neural networks because the starting and the ending point are clear in a tree structure.

2.1 Multi Deep Learning

![Multi Deep Learning Diagram](image)

\textbf{Figure 2: Multi Deep Learning}
Multi-domain Deep Learning  First, a multi-domain refers to a structure in which different domain datasets are learned using the same neural network as Fig.2a. Related studies include Parallel Residual Adapters[30], which learns different types of image data. In this study, 10 different domain image datasets(MNIST, CIFAR-100, VGG-Flower etc.) are learned in one neural network structure. In particular, this study can be a very effective study in reducing parameters because it learns with a single model when learning datasets.

Multi-modal Deep Learning  Multi-modal deep learning means combining data from various domains and converging them into information, and then solving the task using the fused information[1] as Fig.2b. Representatively, there is an image captioning field[40]. The structure may be slightly different from Fig.2b but using a variety of information is the key to this study.

Multi-task Deep Learning  This refers to a neural network structure that performs various tasks using the output of a network as Fig.2c. The advantage of this process is that the network’s output performs multi-task, providing the data characteristics to be more diverse and apparent. Representatively, there is an MT-DNN[19] model, and it has a good effect.

2.2 Multi-Domain & Multi-Modal & Multi-Task simultaneously deep learning

![Multi Deep learning](image)

Figure 3: Multi Deep learning

So, how can multi-domain, modal, and task be performed simultaneously? Humans perform multi-domain, modal, and task at the same time. To perform multi-domain, multi-modal, and multi-task learning using relatively few parameters for all data, it should not be structurally fixed.

In this study, we introduced association networks capable of multi-domain deep learning. And it shows the possibility of expansion to multi-modal deep learning. And as a series of future works, multi-task learning is performed using root vectors($\vec{h}_{root}$) from association networks. In addition, we design to perform multi-task in a human-like structure rather than simply performing multi-task learning in future studies[11][13].

3 Artificial Association Networks

In this section, we proposes artificial association architecture. The architecture consists of five parts.

(i)NN: (Neuro Node) – Defining the data structure of neuro node.

(ii)NT: (Neuro Tree) – Designing the neuro tree structure.

(iii)AAN: (Association Networks) – Defining the artificial association networks.

(iv)Ψ: (Feature Extraction Networks) – Defining the feature-extraction process.

(v)Φ: (Task Networks) – Defining the task network to perform tasks.
Figure 4: Relational(Graph) + Hierarchical(Tree) = Neuro Node

3.1 Association Data Structure: Neuro Node

The neuro tree (NT) is a data structure that can express relational, hierarchical, domain and task information. And the node of NT is called the neuro node (NN).

\( x \) : (Input) – we can store the data such as images, sound, text, or tabular to each node.

\( \tau_d \) : (Domain) – This refers to the domain of information matching the input \( x \). the feature-extraction function (\( \psi \)) is selected by \( \tau_d \) like Eqn.5

\( \tau_t \) : (Task) – This refers to the task of information. the task networks (\( \phi \)) is selected by \( \tau_t \) like Eqn.34. If there is no task to be performed at the node level, it may exist only in the root.

\( A_c \) : (Children Adjacency Matrix) – This refers to the relationship information that exists in a neuro node. the number of children is \( N \) and we can express it as \( A_c \in \mathbb{R}^{N \times N} \).

\( C \) : (Children) – This refers to the child nodes of neuro node (NN) matching to the node of \( A_c \). If there is no matching child, it is replaced with \( \text{NN}_\emptyset \), which carries the initial hidden state \( \theta \) instead.

\( \text{NN}_\emptyset \) denotes the root node of NT. The reason for defining the relationship among child nodes is the convenience of implementation. And by combining graphs and trees, information delivery processes such as fully connected neural networks (FCNN), multi-layer perceptron (MLP), recurrent neural networks (RNN), recursive neural networks (TNN), convolutional neural networks (CNN), and graph convolutional networks (GCN) can be expressed as data. And it is easier to understand than learning the graph of the tree structure with GNN (Sec 3.3).

We can express \( \text{NN} = \{x, \tau_d, \tau_t, A_c, C\} \), \( \text{NN}_i \in \text{NT} \). \( \text{NN}_\text{root} \) denotes the root node of NT. The reason for defining the relationship among child nodes is the convenience of implementation. And by combining graphs and trees, information delivery processes such as fully connected neural networks (FCNN), multi-layer perceptron (MLP), recurrent neural networks (RNN), recursive neural networks (TNN), convolutional neural networks (CNN), and graph convolutional networks (GCN) can be expressed as data. And it is easier to understand than learning the graph of the tree structure with GNN (Sec 3.3).

If we define \( \text{NN} \) in the above way, we can convert the tree dataset into the NT dataset without significantly modifying the tree structure that has previously been useful. And in this model, \( \tau_d \) is information to become multi-domain, and building a neuro tree means multi-modal. And \( \tau_t \) is information to become multi-task.
3.2 Feature Extraction networks & Type Bias

The $x$ (input) and $\tau$ (type) exist together in NN, and the feature extraction process of $x$ is selected by $\tau$ as Eqn 5. We expressed the function of feature extraction as $\Psi$, and this function converts $x$ to $\vec{\mathcal{T}}$. And the one-hot vector has the effect of having a different bias value for each type ($\tau$). The weight parameter corresponding to the type one-hot vector means the bias value for the corresponding type, and the activation threshold value is adjusted for each type-bias. It can represent data type information and that it is transmitted from which nerve. In addition, we do not need to perform adding operations (+) for bias. Therefore, the empty space of NT can be used as a zero-vector when batch learning is performed. And the dictionary structure is very useful for batch learning; we attached the methodology to sec 4.

3.3 How do we design the structure of the neuro tree?

These architectures are the models underlying existing networks. First, Fig 6(a) means a multi-layer perceptron model. If we express this architecture as NT and learn with LAN (sec 3.6.2), which has input only in leaf node, it becomes the same operation process.
Second, Fig. 6(b) means a CNN model. Using the CNN network for the feature extraction network part with LAN will be the same operation.

Third, Fig. 6(c) means a recurrent neural network model (RNN). Using a tree with only one child to express sequence and learn with RAN (sec 3.6.1) will be the same operation.

Figure 7: Model structure & Data structure 2 (Multi-domain)

These models are architectures that learn relational and hierarchical information. First, Fig. 7(a) means a GNN model. The same delivery process is obtained if the relationship and inputs are expressed as relationship and inputs among sibling nodes of the neuro tree with LAN.

Second, Fig. 7(b) means a recursive neural network model (RNN). If we learn using an identity matrix with RAN, it will be the same delivery process.

Figure 8: Model structure & Data structure 3 (Multi-modal)

These networks are structures in which each feature extraction process is combined. If we design feature extraction networks for each type and construct a neuro tree with two or three children Fig. 8(a,b), it will be the same delivery process.
Finally, this structure is an ideal neuro tree structure (Fig.9). The feature extraction network corresponds to the sensory organ. And the feature extraction process($\Psi$) is selected according to the domain($\tau_d$) of data $x$($x$), and $x$ becomes vector $\vec{x}$.

And information integration occurs. We call it an association network. This network serves to embed various extracted information into one vector($\vec{h_{\text{root}}}$) by applying relationship and hierarchical information.

At this time, expressing a tree structure that learns well for each type of data or task is the same as designing the architecture of the network.

Therefore, instead of using fixed layers to learn according to the flow of information, build a neuro tree to learn according to the flow of information. It will enable the network to learn networks that can handle multiple tasks or multiple datasets simultaneously, not just specific tasks or specific datasets. Because various architectures can be expressed by data.

Visual information is input when we open our eyes, and information is not input when we close our eyes. It can be expressed when there is or does not have image information in the neuro tree.

In addition, it could express a structure such as V1, V2, V3, V4, V5/MT in visual cortex, and a neuro tree has hierarchical information and relational information. The grammar of natural languages can also be expressed as a tree parser[32].

Voice information can also be extracted from MFCC[25] algorithms etc. And all information is integrated and embedded in association networks. The integrated structure of these information can be used for multi-modal deep learning.
This figure shows the characteristics of a neuro tree that can have multiple parent nodes and connections with sibling nodes, not a general tree structure. And this structure becomes a propagation path that does not reverse. **The child node should not be a parent node or ancestor that uses the information of the current node (Sec 3.1).** This condition is not to deliver the information results from one node only to the direct parent node, as shown in Fig.10, but to connect to other nodes. Therefore, this information has been added to express more routes. Hidden information($h_i$) corresponding to each neuro node($NN_p$) is stored in the neuro node($NN_p$) and recycle it when the information on the current node is needed again.

### 3.4 Propagation Method: Depth-first Convolution & Deconvolution

This section introduces two propagation methods of depth-first convolution (DFC) (a convolution method for traversing all nodes of NT) and depth-first deconvolution (DFD). Depth-first search (DFS) is a search algorithm for the tree data structure. Since this methodology is transferred from the nodes at the deepest level, various paths can be expressed, and the convolution path is simplified. Unlike general recursive convolution, DFC and DFD are methodologies for learning relationships among the sibling nodes and feature extraction networks together.
Therefore, the hidden vector during deconvolution.

use it during the DFD process (ex. If the aggregate function is a max pool, we can use the indices delivered to the parent node. If the child node does not exist, the readout process. And perform convolution using these can use this process like learning the relationship among the siblings nodes.

Algorithm 1 Depth First Convolution

1: function DFC(NN_p, lv)
2: if NN_p.isCalculated then ▷ stored hidden
3: return NN_p.h
4: end if
5: x_p, τ_p, A_{cp}, C_p ← NN_p.items()
6: \( x_p, *i_1 \leftarrow \Psi[τ_p](x_p) \) ▷ feature
7: ChildrenList ← []
8: for q ← 1...N_p do ▷ left-first
9: \( \hat{h}_pq \leftarrow \text{DFC}(C_p[q], lv + 1) \)
10: ChildrenList.append(\( \hat{h}_pq \))
11: end for
12: if len(C_p) is 0 then ▷ leaf node
13: NN_p.more ← (*i_1)
14: end if
15: \( \hat{h}_p \leftarrow \text{RNN}(\vec{\tau}_p, \vec{0}) \) ▷ W[\( \vec{\tau}_p, \vec{0} \)]
16: NN_p.h ← \( \hat{h}_p \)
17: return \( \hat{h}_p \)
18: end if
19: h_p ← Stack(ChildrenList)
20: \( \hat{h}_p, i_2 \leftarrow g(\text{GNN}(A_p, h_p')) \) ▷ g(A.h'_p)
21: \( \hat{h}_p \leftarrow \text{RNN}(\vec{x}_p, \vec{h_p}) \) ▷ W[\( \vec{x}_p, \vec{h_p} \)]
22: NN_p.h ← \( \hat{h}_p \)
23: NN_p.isCalculated ← True ▷ storing hidden
24: NN_p.more ← (*i_1, *i_2)
25: return \( \hat{h}_p \)
26: end function

Post-order Depth-first convolution (Left-First) If DFS is post-order, iteration starts from the leaf node. Likewise, DFC is a recursive convolution that propagates from the deepest nodes. artificial association network utilizes the hidden vector expressing the current level and state.

First, check whether the current node has already been calculated. This process is because one node can exist as a child node of multiple nodes; This allows one node to have multiple parent nodes.

And then, we need to bring five items(\( x_p, τ_p, A_{cp}, C_p \)) of the current NN_p. the p means the convolution order, and \( x_p \) is embedded by the feature extraction network(\( \Psi \)) according to the type(\( τ_p \)) and becomes the feature vector(\( \vec{\tau}_p \)).

artificial association network models perform the convolution by receiving information(\( \vec{h}_p \)) from the current node’s children(\( C_p \)) with the children’s relationship(\( A_{cp} \)) among children. We can use this process like learning the relationship among the siblings nodes. the \( \vec{h}_p \) means the convolution output of the child nodes. This process is similar to the process of graph convolution and then the readout process. And perform convolution using these \( \hat{h}_p \) and \( \vec{x}_p \) of the current node. This process is similar to the recurrent neural network (RNN). And store the convolution output(\( \vec{h}_p \)) on the current node and recycle it when the information on the current node is needed again.

If there is a task to be performed at the node level, it goes through task networks(\( \Psi \)). Finally, \( \vec{h}_p \) is delivered to the parent node. If the child node does not exist(\( C_p \)), the current node means a leaf node. Therefore, the hidden vector(\( \vec{h}_p \)) is the initial hidden vector(\( \vec{0} \)). If we repeat this process, we finally get \( \vec{h}_\text{root} \).

Additionally, we can store information(*i_1, *i_2) generated during the DFC process in NN.more and use it during the DFD process (ex. If the aggregate function is a max pool, we can use the indices information during deconvolution).

Algorithm 2 Depth First Deconvolution

1: function DFD(\( \hat{h}_p, NN_p, *lv \))
2: \( \hat{x}_p, \hat{h}_p' \leftarrow \text{RNN}^{-1}(h_p) \) ▷ W[\( \vec{h}_p \)]
3: \( τ_p, A_{cp}, C_p \leftarrow NN_p.deconv_items() \)
4: \( *i_1, *i_2 \leftarrow NN_p.more \)
5: \( NN_p, \hat{x}_p \leftarrow NN_p.items() \)
6: if len(C_p) is 0 then ▷ leaf node
7: return
8: end if
9: \( \hat{A}_{cp}, \hat{h}_p' \leftarrow g^{-1}(\text{GNN}^{-1}(A_{cp}, h'_p, lv), *i_2) \)
10: \( NN_p.A_c \leftarrow \hat{A}_{cp} \)
11: for q ← \( N_p,...,1 \) do ▷ right-first
12: \( \hat{h}_pq \leftarrow \hat{h}_p[q] \)
13: DFD(\( \hat{h}_pq, NN_p.C[q], lv + 1 \))
14: end for
15: return
16: end function
Pre-order Depth-first Deconvolution (Right-First)  DFD is a decoding methodology for artificial association networks. The DFC propagates from the leaf node to the root node, whereas the DFD propagates from the root node to the leaf node in the order of pre-order depth first to decode this. And the convolution paths are in reverse order with each other.

First, The hidden state($h'_p$) is restored to $\tilde{x}_p,h'_p$ through $\text{RNN}^{-1}$. And we need to bring three items($\tau dp,A_p,C_p$) of the current $\text{NN}_p$. $\tilde{x}_p$ is decoded by the feature decoder network($\Psi^{-1}$) according to the type($\tau dp$) and the decoded output is stored in the $\text{NN}_p$. Also, if DFC proceeds from left to right as left first (1...N), DFD proceeds from right to left as right first (N...1)(line 11 in algo 2). Please see Fig.11

Algorithm 3 Propagate (for AutoEncoder Models)

1: function PROPAGATE($\text{NN}_{root}$)
2: $\tilde{h}'_{root} \leftarrow \text{DFC}($NN$_{root},0)$ \quad \triangleright \text{Convolution}(\text{NeuroTree}, \text{level})$
3: $\text{DFD}(\tilde{h}'_{root},$NN$_{root},0)$ \quad \triangleright \text{Deconvolution}(\text{FinalHidden}, \text{NeuroTree}, \text{level})$
4: return $\tilde{h}'_{root},$NN$_{root}$
5: end function

Like the propagate function (algo 3), we can freely encode and decode through DFC and DFD. We want to show the relationship between DFC and DFD and the possibility of expanding to the widely used autoencoder[7] models. In addition, Implementing this recursive function as a loop(while) will speed up.

3.5 Propagation Method : Feature Extraction Networks for Batch Training

Algorithm 4 Batch Type Embedding

1: function TYPEEMBEDDING($NT_{\text{batch}}$)
2: dict$_x$ = {}
3: dict$_idx$ = {}
4: for $idx_{\text{batch}}, \tau, x \leftarrow \text{enumerate}($NT$_{\text{batch}}$) do
5: \hspace{1em} dict$_x[\tau,index_{\text{dict}}] = (\tau, \text{len(dict}_x[\tau]))$
6: \hspace{1em} dict$_x[\tau].\text{append}(x)$
7: end for
8: for $\tau, X_\tau \leftarrow \text{dict}_x.\text{items()}$ do
9: \hspace{1em} $x_\tau = [\Psi[\tau](X_\tau), \text{onehot}(\tau), \text{repeat}(\text{len}(X_\tau))]$
10: \hspace{1em} dict$_x[\tau] = x_\tau$
11: end for
12: outputbatch = []
13: for $idx_{\text{batch}} \leftarrow 1...N$ do
14: \hspace{1em} $\tau,idx_{\tau} \leftarrow \text{dict}_{idx}[\text{idx}_{\text{batch}}]$
15: \hspace{1em} $x_\tau = \text{dict}_x[\tau]$
16: outputbatch.\text{append}(x_\tau[\text{idx}_{\tau}])
17: end for
18: return Stack(outputbatch)
19: end function

First, make two dictionary data structures. One is a dictionary(dict$_x$) that stores data for each data type. The other is a dictionary(dict$_idx$) that preserves the batch-index information of the data. We tour the mini-batch data in order and store the key is the type($\tau$) of data, and the value is the input data($x$). And the other dictionary stores the type and index.

Therefore, the input data are collected for each type, which is called $X_\tau$. And the input data become type-mini-batch data for each type and becomes batch-inputs for the feature extraction network of that type.

Let $x_\tau$ denote the output of the feature extraction network. Finally, the $x_\tau$ moves to the original batch index through the previously-stored batch index(dict$_{idx}$).

This methodology divides mini-batch samples by type, and the type-mini-batch size varies each time(fig.12). Therefore, we recommend using a weight standardization[29] or group normalization[37] to
avoid batch normalization affected by the batch size. We described the details of the network we used in sec 3.6

3.6 Artificial Association Network Models : RAN & LAN Series

This section proposes recursive and level association networks series that perform inductive learning and recognition part in graph tree neural networks. And we describe the convolution process in the p-th order of the depth-first convolution path in a neuro tree. These networks can be used as an association cell or layer, and we explained the difference between the two models in sec 3.7.

These association models do not use any fixed architecture and integrate information according to the neuro tree structure. And by fusing graph and tree data structures, we can learn more diverse data structures with one cell and various architectures can be expressed by data (please see the sec 3.3). Accordingly, these models are freer to learn various datasets using fewer parameters.

artificial association models are as follows: The feature extraction models create the information from data; It is the "smallest unit" of information in the NT. The parent NN receives information from their children and perform the convolution operation with the relation term; the convolution output is a "bigger unit" of information. Finally, a root NN has all NT information and perform the convolution operation; the output is "the biggest unit" of information.

3.6.1 Association Cell : Recursive Association Networks

We will describe a RAN cell that trains the NT described previously in Sec 3.1 recursive association models can be expressed as RAN = \{W, Ψ, g, σ\} W ∈ \mathbb{R}^{F × (F + B + F')} F is the node-feature size, B is the type-bias size, and F' is the hidden size, which is the information received from the child node. Ψ denotes the feature-extraction process described above, g denotes the aggregate function, and σ denotes the activation function. The propagation is proceeding from the leaf nodes at the deepest level to the root node at the top level (see 3.4). p is the order of depth-first convolution, q is the child node number, N_p is the number of children of NN_p, x_p is the node-input of NN_p.

$$\vec{x}_p = [\psi_{\tau_p}(x_p), \text{onehot}(\tau_p)] = \Psi(x_p, \tau_p), \vec{x}_p \in \mathbb{R}^{F + B}$$ (6)

First, The Ψ extracts the feature vector(\vec{f}_p) from x_p of NN_p through the feature extraction process (Eqn 5) considering the type information(\tau_p). The first location to start is leaf nodes by DFC (algo. 1).

$$\vec{h}_{pq} = \text{DepthFirstConvolution}(NN_p, C_q, *lv + 1)$$ (7)

the current node(\vec{h}_{pq}) receives the child’s hidden states(\vec{h}_{pq}) from the child nodes. the current node in the p-th order receive \vec{h}_{pq} from the q-th child node (Eqn 7).
The child’s hidden states \( \vec{h}_p \) and \( A_p \) perform graph convolution and readout to become a child’s hidden state \( \vec{h}_p \) containing all the information of the child nodes. \( \|_{q=0}^{N_p} \vec{h}_{pq} \) means that \( \vec{h}_{pq} \) matching the graph nodes \( A_{cp} \) existing in the p-th node are stacked as much as \( N_p \), which is \( \|_{q=0}^{N_p} \vec{h}_{pq} \in \mathbb{R}^{N_p \times F'} \).

We applied the GCN methodology [16], which is useful in the GNN field. Therefore we expressed as \( A_{cp} = A_{cp} + I \), where \( I \) is the Identity matrix. If we express the connection value as 1, just the more connected nodes becomes the scale value larger than others. Therefore, \( \vec{D}_{cp}^{1/2} \vec{A}_{cp} \vec{D}_{cp}^{-1/2} \) is applied using the order matrix \( \vec{D}_{cp} \) of \( A_{cp} \) as a method of normalizing the relationship matrix in Eqn.9.

\[
\vec{h}_p' = \sigma([\vec{h}_p, \vec{h}_p]W)
\]

In the leaf node, the children’s hidden state \( \vec{h}_p \) is an initial hidden state \( \vec{h}_0 \).

the hidden state \( \vec{h}_p \) is concatenated with \( \vec{x}_p \) to become \([\vec{x}_p, \vec{h}_p] \in \mathbb{R}^{F+B+F'}\) through the concatenation process as [\_]. The children’s hidden state \( \vec{h}_p \) and the \( \vec{x}_p \) of the current node perform convolution to become the current node’s hidden state \( \vec{h}_p \).

\[
\vec{h}_p = \sigma([\vec{x}_p, g(\vec{D}_{cp}^{1/2} \vec{A}_{cp} \vec{D}_{cp}^{-1/2} \vec{h}_p)]W^T)
\]

Finally, we can express these processes Eqn [6 [7 [8 [9 [10] as Eqn [11] we used \( F \) as 128, \( B \) as 3(image, sound, language), and \( F' \) as 128, and \( \sigma \) as ReLU[26], and \( g \) was the readout of Max.

\[
RNN = \sigma([\vec{x}_{tv}, \vec{h}_{tv-1}]W^T) = \sigma([\vec{x}_{tv}, g(\vec{I}_{tv+1}]W^T) = \sigma([\vec{x}_{tv}, \vec{h}_{tv+1}]W^T)
\]

If there is no sibling node of the current node, \( RAN \) is mathematically identical to the RNN(Eqn [12]. RNN can be a special case of \( RAN \), and the depth of the neuron tree means times of the RNN.

3.6.2 Association Layers : Level Association Networks

level association networks (LAN) is composed of \( LAN = \{\{W_0, ... W_m\}, \Psi, g, \sigma\} \).

\[
\vec{h}_p = \sigma([\vec{x}_p, g(\vec{D}_{cp}^{1/2} \vec{A}_{cp} \vec{D}_{cp}^{-1/2} \vec{h}_p)]W^T_{tv})
\]

The mathematical expression Eqn [13] of \( LAN \) is similar to Eqn [9].

There is \( W_{tv} \in \mathbb{F}^{F_{tv} \times (F_{tv}+B+F_{tv+1})} \) in charge of each level, and the network in charge of each level is called the level layer. The input size of the level is \( F_{tv} \), its output size is \( F_{tv+1} \), and the output size of the child is \( F_{tv+1} \). Therefore, it is possible to adjust the input, hidden size; and it can learn the depth-limited tree. \( m \) means maximum-depth. We set \( F_{tv} \) and \( F_{tv+1} \) to 128 for all lvs in the same way as \( RAN \) in the experiment.

\[
FC\ layer = f_{c}(\vec{h}) = \sigma(\vec{h}W^T) = \sigma(g(\vec{I} \vec{h}))W^T_{tv} = \sigma(\vec{h}W^T_{tv})
\]

\[
NN_m = \{\vec{x}, t, I, \{\}}
\]

\[
NN_1 = \{\vec{0}, layer, I, NN_2\}
\]

\[
NN_0 = \{\vec{0}, layer, I, NN_1\}
\]

\[
Multi\ layer = f_{c_{\Psi}}(f_{c_{\sigma}}(f_{c_{\Psi}}(\vec{x}))) = LAN(NN_0)
\]

If the input size of \( F_{tv} \) is 0 and there is no sibling node of the current node, this network is mathematically identical to the FC layer as Eqn [14] and the MLP as Eqn [15 [16 [17 [18] \( I \) is the Identity matrix.

The depth of the tree indicates the number of layers of the MLP. Therefore, the MLP and FC layer can be a special case of \( LAN \).
3.7 Compare Architecture: LAN & RAN

Table 1: Compare Architecture

| Name                  | LAN          | RAN          |
|-----------------------|--------------|--------------|
| Level layer           | O            | X            |
| The number of W       | The number of levels 1 | Fixed   |
| Depth-limited         | Not fixed    | Not fixed    |
| The number of parameters | Use more    | Use less than |
| Input size by level   | Adjustable   | Fixed        |
| The special cases     | FCNN, MLP    | RNN(recurrent, recursive) |

In this section, we compare the network characteristics of LAN-series of level layers and RAN-series of recursive cell. In the case of level association networks (LAN), there is a different Wlv for each level, expressing each level layer and the convolution of all information. On the other hand, in the case of recursive association networks (RAN), the main difference is the recursive convolution with only one W as a cell. This is the most significant difference when comparing the networks.

Therefore, level association networks can adjust the number of features by level; for example, the size of input features can differ between Levels 1 and 0. It is possible for level association networks to train datasets by adjusting parameters at any level. On the other hand, recursive association networks must be trained with the same input and hidden size.

Thus, we divided artificial association networks into two groups. Since level association networks have a network in charge of each level, more parameters are needed, and it is appropriate for depth-limited neuro tree.

If the F1o of input size is 0 and the number of nodes is 1 in neuro node, FC layer and MLP can be special cases of level association networks. On the other hand, recursive association networks traverse all neuro nodes with a recursive association cell. Therefore it is possible to train even if the maximum depth is not fixed and fewer parameters are used.

In addition, If there is no sibling node in NNp, recurrent neural networks can be a special cases of recursive association networks. And If there’s no relationship (Acp) among the sibling nodes, recursive neural networks can be a special cases of recursive association networks.

Consequently, the compare result in Table 1.

3.8 Attention Models

There is an attention process in the human brain. Therefore, GATs[34], a model that has been useful recently, was combined.

3.8.1 Recursive Attentional Association Networks

We introduce RAAN that learn the importance through attention by slightly modifying the expression of the RAN. It is composed of RAANs = {W, Ψ, g, σ, σa, 7} that added {σa, 7} in RAN. A parameter for attention mechanism is added (R2F′ × R2F′ → R) and the attention’s activation function used LeakyReLU[39] in the same way as GATs.

Npq is a set of nodes connected to the q-th child’s node in the Acp of NNp, and we can express this as:

\[
\alpha_{pqr} = \frac{\exp(\text{LeakyReLU}(\overrightarrow{\alpha^T}[h'_p, h'_r]))}{\sum_{k \in N_{pq}} \exp(\text{LeakyReLU}(\overrightarrow{\alpha^T}[h'_p, h'_k]))} \quad (19)
\]

With the attention methodology introduced in GATs[34], it learns how the r-th node is of importance to the q-th node. This information is replaced with the part to which the adjacency matrix is connected.

Therefore, the RAAN are as follows:

\[
\overrightarrow{h'_p} = \sigma([\overrightarrow{x_p}, g((A_{cp} \odot \alpha_p)h'_p)]W^T) \quad (20)
\]

In Eqn.20 \odot indicates point-wise and this process is similar to Eqn.11.
To further stabilize the self-attention process, we introduce a multi-head attention mechanism:

$$\overrightarrow{h}_p^{'} = ||_{k=1}^{K} \sigma((\overrightarrow{z}_p, g((A_{cp} \odot \alpha_p)h_p^{'}))W^{K_T})$$

where $K$ is the number of multi-heads. The results from multiple heads are concatenated and delivered to a parent node. We set $K$ to 8 and set output dim for each head to $16(-F'_{lv}/K)$. therefore we set $F'_{lv}$ to 128. This process becomes a cell and delivers the result from the leaf node to the root node.

### 3.8.2 Level Attentional Association Networks

The LAAN model is modified from LAN, and GATs’ attention mechanism was applied. this model can be expressed as LAAN = $\{[W_0, \ldots W_m], \{a_0, \ldots a_m\}, \Psi, g, \sigma_a\}$, and $\{\sigma_a, a_{lv}\}$ are added in LAN($\overrightarrow{a}_{lv} \in \mathbb{R}^{2F'_{lv}}$). Unlike RAAN, LAAN can design different sizes of $F, F'$ to match the lv.

$$\alpha_{pqr} = \frac{\exp(LeakyReLU(\overrightarrow{a}_{lv}[\overrightarrow{h}_{pq}^{'}], \overrightarrow{h}_{pr}^{'})))}{\sum_{k \in N_{pq}}^{N} \exp(LeakyReLU(\overrightarrow{a}_{lv}[\overrightarrow{h}_{pk}^{'}], \overrightarrow{h}_{pk}^{'})))}$$

$$\overrightarrow{h}_p^{'} = \sigma((\overrightarrow{z}_p, g((A_{cp} \odot \alpha_p)h_p^{'}))W^{T}_{lv})$$

this model is designed to select critical features, and it is similar to Sec 3.8.1

### 3.9 Gated Models

Basically, the longer the depth of time, the more difficult the RNN is to propagate the error. Therefore, we add the gated recurrent unit (GRU) model. We designed Gated association unit (GAU) by slightly modifying RAN.

#### 3.9.1 Gated Association Unit

$$\overrightarrow{h}_p = g((D_{cp}^{-1} \overrightarrow{A}_p \overrightarrow{D}_{cp}^{-1})h_p^{'}))$$

$$\overrightarrow{r}_p = \sigma(W_r \overrightarrow{h}_p + U_r \overrightarrow{x}_p)$$

$$\overrightarrow{u}_p = \sigma(W_u \overrightarrow{h}_p + U_u \overrightarrow{x}_p)$$

$$\overrightarrow{h}_p = tanh(W(\overrightarrow{r}_p \odot \overrightarrow{h}_p) + U \overrightarrow{u}_p)$$

$$\overrightarrow{h}_p = (1 - \overrightarrow{u}_p) \odot \overrightarrow{h}_p + \overrightarrow{u}_p \odot \overrightarrow{h}_p$$

#### 3.9.2 Gated Attentional Association Unit

$$\overrightarrow{h}_p = g((A_{cp} \odot \alpha_p)h_p^{'}))$$

$$\overrightarrow{r}_p = \sigma(W_r \overrightarrow{h}_p + U_r \overrightarrow{x}_p)$$

$$\overrightarrow{u}_p = \sigma(W_u \overrightarrow{h}_p + U_u \overrightarrow{x}_p)$$

$$\overrightarrow{h}_p = tanh(W(\overrightarrow{r}_p \odot \overrightarrow{h}_p) + U \overrightarrow{u}_p)$$

$$\overrightarrow{h}_p = (1 - \overrightarrow{u}_p) \odot \overrightarrow{h}_p + \overrightarrow{u}_p \odot \overrightarrow{h}_p$$

We designed Gated attentional association unit (GAU) by slightly modifying RAAN. It combined the attention matrix and the GRU to improve learning in time serial data as deep neuro tree data.

### 3.10 Task Networks

$$\hat{y}_p = \Phi(\overrightarrow{h}_p, \tau_p)$$

This process means performing a task at each node level or root level. Performing multi-task learning in this process means that all multi-domain, multi-modal, and multi-task can be processed simultaneously, and it is an end-to-end learning model. So, how will we perform multi-task? The author of this paper does not simply perform multi-tasks but wants to define the structure like humans. Therefore, future works divided the processes imagined by the author and separated tasks into future works [11–13].
End-to-End Multi-Deep learning

\[
\hat{y}_p = \text{AAN}(\text{NTBuilder}(\mathbf{A}, \mathbf{X}, \tau_d, \tau_t), \Psi, \Phi) \tag{35}
\]

To express the structure of this neural network as an end-to-end structure, it is as follows. Also, in the author’s opinion, the structure of the human brain is quite complex. Therefore, it is very important for neural networks to structure themselves. This AAN has changed the structure of the network to be modified by expressing the information delivery structure as a tree structure. Therefore, Neuro Tree Builder becomes the future works of this study.

**Supervised learning** Supervised learning uses datasets with labels. In this network, the \( \overrightarrow{h}_{root} \) was mapped to the dimension of the class using a fully connected layer(\( F' \) to class count) and we calculated the log softmax and negative log likelihood loss for supervised learning as:

\[
\overrightarrow{h}_{root} = \text{propagate}(\text{NT}) \tag{36}
\]

\[
\hat{y} = \text{log}_\text{softmax}(\Phi(\overrightarrow{h}_{root}, \tau_t)) \tag{37}
\]

\[
\text{loss} = \text{negative\_log\_likelihood\_loss}(y, \hat{y}) \tag{38}
\]

4 Experimental Results

Our goal is to express the information delivery process of existing models as a neuro tree of data. This section introduces the contents of the experiment and the neuro tree dataset consisting of the image, sound, natural language and relation. How to design neuro tree is introduced in sec.3.3.

4.1 Exp 1 : Are feature extraction networks and association networks well learned together? (Multi-Domain)
Datasets

The first experiment is whether various datasets can be simultaneously learned by combining AAN and feature extraction networks. The network we used in the experiment is illustrated by Fig. 14(a,b,c). Layer node means that it has no input value, only performs convolution. If there is no sibling node, LAN performs the same operation as one FC layer. Sound and natural language NT have two nodes, and image NT has three nodes because it was configured similarly to figure (like this fig. 1). The important point is not limited to any specific architecture; later, this NT could be modified according to the task or complexity. Existing networks learn only about specific datasets.

We trained without using a pre-trained model to check whether various feature extraction models can be learned simultaneously. Only word embedding network[28] was used as a pretrained model. Therefore, LeNet-5[18], M5[3], and CNN[14] were selected for feature extraction networks of the image(MNIST[18]), sound(Speech Command[35]), and natural language(IMDB[21]). We described more details in sec 5. The reason for choosing these networks is based on Convolutional Neural Networks specialized extract features.

Since the number of classes is different for each data, the test was divided into two cases. (Task Layers): The last layer was placed differently for each dataset and mapped to the class dimension of the dataset. (47 class): The one last layer was used for all datasets, and the number of class dimensions is equal to the sum of class dimensions of all datasets. Because if the last layer is placed differently for each dataset, information on the input type may be informed. All models were learned during 30 epochs, and the results were as Table 2(Task layers, 47 class), and the learning process is (Fig.15(a)).

The learning processes of artificial association networks are similar to the process of individually learning feature extraction networks; if the model learns like this, several problems are found. LeNet-5 is well trained, but M5 needs to be more trained, and CNN has an overfitting problem. The reason is that each network has different epochs to have optimal performance, and setting learning parameters is more complex than learning individually.

| Model         | Task layers        | 47(-10+35+2) class | Transfer learning | Fine tuning |
|---------------|--------------------|---------------------|-------------------|------------|
|               | MNIST SC IMDB      | MNIST SC IMDB       | MNIST SC IMDB     | MNIST SC IMDB |
| LeNet-5       | 98.46 - -          | 98.46 - -           | 98.49 - -         | 98.49 - - |
| M5 (Group Norm) | - 97.63 -          | - 97.63 -           | - 100.0 -         | - 100.0 - |
| CNN           | - - 87.13 -        | - - 87.13 -         | - - 87.48 -       | - - 87.48 - |
| LAN           | 98.84 97.14 86.10  | 98.77 96.83 85.76  | 98.65 98.91 82.20 | 98.64 97.39 86.62 |
| LAAN          | 98.36 96.91 85.38  | 98.39 96.81 85.86  | 98.48 99.66 81.91 | 98.94 99.17 87.18 |
| RAN           | 98.53 96.54 85.62  | 98.79 97.07 86.24  | 98.47 98.64 82.18 | 98.92 98.89 87.27 |
| RAANs         | 98.79 96.66 86.28  | 98.78 96.68 85.79  | 98.47 98.64 82.18 | 98.92 98.89 87.27 |

| FE Epoches | 30 30 30 30 | 30 30 30 30 | 26 95 3 26 95 3 |

transfer learning & fine-tuning

Therefore, after learning individually, we combined the association model to perform transfer-learning and fine-tuning[27]. The result is Table 2(Transfer-learning, Fine-tuning). In transfer learning, the parameters of feature extraction networks are not modified, and in fine-tuning, the parameters are modified. We used the validation set to learn each feature extraction network and adopt the lowest value of the validation loss to use the model. As a result, the LeNet-5, M5, CNN were pre-trained with 26, 95, 3 epochs. These models were combined with artificial association networks to perform fine-tuning and transfer learning. Then, the network was re-trained, and learning was stopped at epochs with the lowest value of validation loss using each of the same validation datasets. As in the results of Table 2(Transfer-learning, Fine-tuning) and Fig.15(b,c), in the case of transfer learning,
performance was poor in the IMDB dataset. We thought it was overfitting because the IMDB dataset was relatively small. We reduced the learning rate from 0.001 to 0.0001, but the results were similar. While fine-tuning was similar to the performance learned individually in all datasets. And the performance improved compared to when fine-tuning was not performed. Consequently, If transfer learning and fine tuning are used by setting parameters well according to the network, the performance of the network can be improved.

4.2 Exp 2 : Could various data structures be learned? (Multi-domain)

Datasets As a second experiment, we learned datasets of various structures with artificial association networks. Data in the form of images, sound data, language data[32] in the tree structure, and data in the graph structure[4] were learned at the same time, and the results are as follows. All of the performances at this time were similar to those of existing networks.

In addition, in the case of recursive association networks and recursive attentional association networks, it can be seen that the learning speed for language data is lower than recursive neural networks. The reason is that the size of language dataset is relatively less than others. Therefore, since the language model has a relatively less influence on loss, it seems to have been pushed back in the optimization process.

In the case of level association networks and level attentional association networks, the result of overfitting in the language model is shown. This is a natural result because the layers of tree data are learned differently for each level.

As a result, we proved that learning to express various information delivery structures with one network cell does not significantly affect performance. When we stop learning this network at 30 epochs, the performance in test dataset is in the table.

---

Figure 16: (a) Speech commands, (b) MNIST, (c) UPFD-GOS, (d) Stanford Sentiment Treebank

Figure 17: Feature Extraction Networks & Learning plot
### Table 3: the result of Experiment 3

| Model         | MNIST | SC    | SST   | UPFD-GOS |
|---------------|-------|-------|-------|----------|
| LeNet-5       | 98.52 | -     | -     | -        |
| M5 (Group Norm) | -     | 98.37 | -     | -        |
| RNN (Recursive) | -     | -     | 77.69 | -        |
| GCN           | -     | -     | -     | 93.67    |
| GATs          | -     | -     | -     | 93.93    |
| LAN           | 98.88 | 97.18 | 73.30 | 94.74    |
| LAAN          | 98.80 | 96.67 | 73.39 | 94.85    |
| RAN           | 98.68 | 97.46 | 76.74 | 93.15    |
| RAAN          | 98.35 | 97.44 | 76.79 | 94.67    |

| class count  | 10    | 35    | 2     | 2        |
| type         | image | sound | tree  | graph    |

### 4.3 Exp 3 : Can artificial association networks learn "deep" neuro trees? (multi-domain)

![Image of sound structure](image1.png)
![Image of Image structure](image2.png)
![Image of Graph structure](image3.png)
![Image of Tree structure](image4.png)

Figure 18: (a) Speech commands, (b) MNIST, (c) UPFD-GOS, (d) Stanford Sentiment Treebank

![Image of Feature Extraction Networks](image5.png)

![Image of Learning plot](image6.png)

Figure 19: We only need to look at the sound data, so the dataset of the other domain was drawn with dotted lines and the sound data was drawn with solid lines. the Light green line is GRU and the pink line is GAAU.

The third experiment is about whether the networks can be trained when need to train deep neuro tree. So, we utilized the MFCC algorithm for the speech command dataset. A GAAU is added; And the models that become baseline are recurrent neural network(RNN) and gated recurrent unit(GRU) models.
that learn only a single dataset. 

This experiment is important because, generally, the basic recurrent neural network model isn’t well trained with very long-time serial data. By slightly changing exp3, feature is extracted through MFCC, the sound-sample-rate is 16000, and the feature size is 40 and time-size is 81. And we separated this data by time dimension to create a deep neuro tree with only one child on each node and a maximum depth of 81.

At this time, 1 FC layer and MFCC are used together in the feature extraction process so that the FC layer is added so that feature size is from 40 to 128. In addition, MFCC and one FC layer are used together to change the feature size from 40 to 128 during the feature extraction network process of the sound.

We proceeded with learning at 30 epochs, and the process is Fig.19(b) and result is Table.4.

Table 4: the result of Experiment 3

| Model               | MNIST | SC   | SST   | UPFD-GOS |
|---------------------|-------|------|-------|----------|
| LeNet-5             | 98.81 | -    | -     | -        |
| RNN(Recurrent)      | -     | 44.03| -     | -        |
| GRU                 | -     | 93.34| -     | -        |
| RNN(Recursive)      | -     | -    | 77.42 | -        |
| GCN                 | -     | -    | -     | 93.52    |
| GATs                | -     | -    | -     | 93.57    |
| RAN                 | 98.68 | 4.87 | 75.97 | 92.84    |
| RAAN                | 98.35 | 4.12 | 77.69 | 94.98    |
| GAAU                | 98.35 | 91.50| 77.05 | 94.59    |
| class count         | 10    | 35   | 2     | 2        |
| type                | image | sound| tree  | graph    |

The models of RAN, and RAAN were all well learned in different domain datasets, but when the neuro tree was deep, they could not even catch up with the performance of recurrent neural network.

On the other hand, it can be seen that the performance of the GAAU model gradually becomes similar to the GRU model even when the tree is deep.

4.4 Exp 4 : Could all data information be contained? (Multi-domain and Multi-Modal)

Datasets The fourth experiment is about whether the output(h\rightarrow_{root}) of artificial association networks is embedded information on all data contained in the neuro tree(association). Therefore, we performed image, sound, and text classification by putting image, sound, text data in one neuro tree, and we also learned the neuro tree used in the first experiment simultaneously. One problem is that when the three types of data are combined, The number of combinations of the dataset becomes too huge. For example, there are 50,000 images, 105,000 sounds, and 17,500 natural language samples, and when these data are combined, we need to generate 50,000×105,000×17,500 GT samples. For this problem, we used a sampling method. When loading each data, two data of different types are sampled randomly. Thus, when we load one data, two neuro trees are generated of the one type neuro tree and the three type neuro tree. The test accuracy is the result of averaging 5-fold. the neuro tree dataset of the second experiment is illustrated by Fig.20(a,b,c,d). We constructed the neuro tree dataset described above(Fig.20(a,b,c,d)) to validate if the output vector can contain all the information in the neuro tree, and the results are as follows Table.4. The meaning of FE Baseline is the performance of networks of LeNet-5, M5, and CNN. In these experiments, it has been verified that it is possible to learn various types of datasets using one network cell and that information can be embedded together.

Consequently, we can share an association cell or layers to learn without being limited to the dataset type and embed all information inside the neuro tree into a vector.

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(a) Expt 1,2: One type  (b) Expt 2: All to sound  (c) Expt 2: All to image  (d) Expt 2: All to language

Figure 20: Association tree datasets of the experiments

| Model | Task 2 + task layer (%) | task 2 + fine-tuning (%) |
|-------|-------------------------|--------------------------|
|       | MNIST | MNIST & SC | SC | SC & All | IMDB | IMDB & SC | SC & All | IMDB & SC | IMDB & SC |
| LAN   | 98.90 | 98.88     | 96.83 | 95.71     | 87.20 | 87.18     | 87.42 | 87.44     | 87.35     |
| LAAN  | 98.87 | 98.88     | 97.30 | 96.37     | 86.73 | 96.44     | 98.83 | 98.12     | 97.40     |
| RAN   | 99.05 | 99.04     | 96.46 | 97.03     | 87.16 | 87.21     | 98.97 | 98.84     | 98.58     |
| RAANs | 98.95 | 98.96     | 97.36 | 95.76     | 86.55 | 87.08     | 98.82 | 98.73     | 98.22     |

Table 5: the result of association test

| Model               | In  | Out | kernel | stride | activation |
|---------------------|-----|-----|--------|--------|------------|
| Conv2D              | 1   | 6   | (5,5)  | 1      | tanh       |
| AvgPool2D           | -   | -   | (2,2)  | 1      | -          |
| Conv2D              | 6   | 16  | (5,5)  | 1      | tanh       |
| AvgPool2D           | -   | -   | (2,2)  | 1      | -          |
| Conv2D              | 16  | 120 | (5,5)  | 1      | tanh       |
| FC layer 1          | 120 | 84  | -      | -      | -          |
| FC layer 2          | 84  | 10   | -      | -      | softmax    |
| Zero padding        | -   | -   | -      | -      | -          |
| Final               | -   | 10  | -      | -      | -          |

Table 6: Feature Extraction Networks for Image dataset

LeNet-5[17] was used as the image feature extraction network. We create a dimension of 128 by applying zero padding to the extracted features without using the affine-layer(FC layers) and then forward it to artificial association networks.

M5[3] was used as the sound feature extraction network. As described above(Sec.3.2), we used group normalization[37] without using Batch norm[10]. We use the affine layer(FC layer) and deliver it to the artificial association networks in 128 dimensions. It could be implemented in torchaudio[1].

Table 7: Feature Extraction Networks for Natural language dataset

CNN[14] was used as the feature extraction network for natural language processing. We slightly modified the contents in this paper and combined them with artificial association networks.

https://pytorch.org/tutorials/intermediate/speech_command_recognition_with_torchaudio_tutorial.html
Table 7: Feature Extraction Networks for Sound dataset

| Model               | In | Out | kernel | stride | norm   | activation | In | Out | kernel | stride | norm   | activation |
|---------------------|----|-----|--------|--------|--------|------------|----|-----|--------|--------|--------|------------|
| Conv1D              | 1  | 128 | 80     | 4      | group 16| relu       | 1  | 128 | 80     | 4      | group 16| relu       |
| MaxPool1D           | -  | -   | 4      | 1      | -      | -          | -  | -   | 4      | 1      | -      | -          |
| Conv1D              | 128| 128 | 3      | 1      | group 16| relu       | 128| 128 | 3      | 1      | group 16| relu       |
| MaxPool1D           | -  | -   | 4      | 1      | -      | -          | -  | -   | 4      | 1      | -      | -          |
| Conv1D              | 128| 256 | 3      | 1      | group 16| relu       | 128| 256 | 3      | 1      | group 16| relu       |
| MaxPool1D           | -  | -   | 4      | 1      | -      | -          | -  | -   | 4      | 1      | -      | -          |
| Conv1D              | 256| 512 | 3      | 1      | group 16| relu       | 256| 512 | 3      | 1      | group 16| relu       |
| MaxPool1D           | -  | -   | 4      | 1      | -      | -          | -  | -   | 4      | 1      | -      | -          |
| AdaptiveAvgPool1d   | -  | 1   | -      | -      | -      | log softmax| -  | 1   | -      | -      | -      | leaky relu |
| FC layer            | 512| 35  | -      | -      | -      | -          | 512| 128 | -      | -      | -      | -          |
| Final               | -  | 35  | -      | -      | -      | -          | -  | 128 | -      | -      | -      | -          |

learning in the association model. The glove28 was used for the pre-trained word embedding network with 100 dimensions. We used an adam optimizer15, a learning rate of 0.001, a cosine annealing(T max=2, eta min=1e-05) for schedulers20, the batch-size is 32 and the MNIST, Speech Command and IMDB classes are 10, 35, 2.

6 Discuss : Why is it important to express various routes?

(a) A network that can express only one fixed path and a specific task.

(b) Artificial association networks that can express various paths and tasks

Figure 21: Neural networks seem like musical instruments.

Do we need a model that can handle all domains? Do we need the structure of the human brain and artificial neural networks to be similar? You may question that. However, it is important to process various domains and perform various tasks with one neural network model. I would like to explain why I think so and introduce some future works.

The author thinks that the human brain is like a musical instrument. The human brain is playing music with a variety of tasks. But, since most existing neural networks represent only one path, And this makes it limited to performing only specific tasks.

Suppose that there is a neural network that performs only a classification task. This network is like having only one key on the keyboard. However, we cannot play music with one key.

On the other hand, because an artificial association network can express various paths, it can express various models and perform more diverse tasks. It means that a wide variety of keys are created.

Therefore, we can play the music that we haven’t done before. And the music means a human thinking ability, various data will constitute a variety of paths, and each path and the task will be a key. And these keys gather to become a keyboard.

So how do we express human thinking ability? There are a lot of contents, so to introduce some of future works, there are deductive networks12, memory networks11, and imagine networks13.

7 Conclusion

We introduced a data-driven network that can jointly learn relationships and hierarchical information. This study is to be free from architecture and has been developed to connect various types of information being developed. And The author of this paper believes that one day a neural network will emerge that
can perform all human tasks. In addition, this is an association model that behaves like human sensory organs and can be described as similar to a human neural network. We think this network can be used as a deep neural network part of DQN\cite{dqn}. We will try to leverage this network to approach problems that have not been solved before. This paper is part of a series; in the next paper, we introduce Associational Deductive Networks(ADNs).

References

[1] Tadas Baltrušaitis, Chaitanya Ahuja, and Louis-Philippe Morency. Multimodal machine learning: A survey and taxonomy. *IEEE transactions on pattern analysis and machine intelligence*, 41(2): 423–443, 2018.

[2] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

[3] Wei Dai, Chia Dai, Shuhui Qu, Juncheng Li, and Samarjit Das. Very deep convolutional neural networks for raw waveforms. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 421–425. IEEE, 2017.

[4] Yingtong Dou, Kai Shu, Congying Xia, Philip S Yu, and Lichao Sun. User preference-aware fake news detection. *arXiv preprint arXiv:2104.12259*, 2021.

[5] Christoph Goller and Andreas Kuchler. Learning task-dependent distributed representations by backpropagation through structure. In *Proceedings of International Conference on Neural Networks (ICNN’96)*, volume 1, pages 347–352. IEEE, 1996.

[6] Suzana Herculano-Houzel. The human brain in numbers: a linearly scaled-up primate brain. *Frontiers in human neuroscience*, 3:31, 2009.

[7] Geoffrey E Hinton and Ruslan R Salakhutdinov. Reducing the dimensionality of data with neural networks. *science*, 313(5786):504–507, 2006.

[8] Geoffrey E Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006.

[9] John J Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, 79(8):2554–2558, 1982.

[10] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pages 448–456. PMLR, 2015.

[11] Seokjun Kim, Jaeun Jang, Yeonju Jang, Seongyune Choi, and Hyeoncheol Kim. Associational memory networks. *arXiv preprint arXiv:2111.01431*, 2021.

[12] Seokjun Kim, Jaeun Jang, and Hyeoncheol Kim. Associational deductive networks. *arXiv preprint arXiv:2111.02353*, 2021.

[13] Seokjun Kim, Jaeun Jang, and Hyeoncheol Kim. Imagine networks. *arXiv preprint arXiv:2111.03048*, 2021.

[14] Yoon Kim. Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, Doha, Qatar, October 2014. Association for Computational Linguistics. [doi:10.3115/v1/D14-1181](https://aclanthology.org/D14-1181)

[15] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[16] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.
[17] Yann LeCun, Bernhard Boser, John S Denker, Donnie Henderson, Richard E Howard, Wayne Hubbard, and Lawrence D Jackel. Backpropagation applied to handwritten zip code recognition. *Neural computation*, 1(4):541–551, 1989.

[18] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[19] Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. *arXiv preprint arXiv:1901.11504*, 2019.

[20] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*, 2016.

[21] Andrew Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies*, pages 142–150, 2011.

[22] Rafael Malach, JB Reppas, RR Benson, KK Kwong, H Jiang, WA Kennedy, PJ Ledden, TJ Brady, BR Rosen, and RB Tootell. Object-related activity revealed by functional magnetic resonance imaging in human occipital cortex. *Proceedings of the National Academy of Sciences*, 92(18):8135–8139, 1995.

[23] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

[24] Lili Mou, Ge Li, Zhi Jin, Lu Zhang, and Tao Wang. Tbcnn: A tree-based convolutional neural network for programming language processing. *arXiv preprint arXiv:1409.5718*, 2014.

[25] Lindasalwa Muda, Mumtaj Begam, and Irraivan Elamvazuthi. Voice recognition algorithms using mel frequency cepstral coefficient (mfcc) and dynamic time warping (dtw) techniques. *arXiv preprint arXiv:1003.4083*, 2010.

[26] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *Icml*, 2010.

[27] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

[28] Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543, 2014.

[29] Siyuan Qiao, Huiyu Wang, Chenxi Liu, Wei Shen, and Alan Yuille. Micro-batch training with batch-channel normalization and weight standardization. *arXiv preprint arXiv:1903.10520*, 2019.

[30] Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. Efficient parametrization of multi-domain deep neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 8119–8127, 2018.

[31] Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. The graph neural network model. *IEEE transactions on neural networks*, 20(1):61–80, 2008.

[32] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Seattle, Washington, USA, October 2013. Association for Computational Linguistics. URL https://aclanthology.org/D13-1170.

[33] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1):1929–1958, 2014.

[34] Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.
[35] Pete Warden. Speech commands: A dataset for limited-vocabulary speech recognition. arXiv preprint arXiv:1804.03209, 2018.

[36] Bernard Widrow et al. Adaptive "adaline" Neuron Using Chemical "memistors.". 1960.

[37] Yuxin Wu and Kaiming He. Group normalization. In Proceedings of the European conference on computer vision (ECCV), pages 3–19, 2018.

[38] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. IEEE transactions on neural networks and learning systems, 32(1):4–24, 2020.

[39] Bing Xu, Naiyan Wang, Tianqi Chen, and Mu Li. Empirical evaluation of rectified activations in convolutional network. arXiv preprint arXiv:1505.00853, 2015.

[40] Jun Yu, Jing Li, Zhou Yu, and Qingming Huang. Multimodal transformer with multi-view visual representation for image captioning. IEEE transactions on circuits and systems for video technology, 30(12):4467–4480, 2019.

[41] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8697–8710, 2018.