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Selection of Multiple Solution Problems through Inhibition (Sum-of-Subsets)

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Abstract

The work illustrated in this paper is a foot step forward towards the objective set to mimic biological functions of a human brain. Our previous work tested the neural theory of “Neural Darwinism: Selection” using the optimization problem of 0/1 Knapsack [KP]. The present work has tested the above theory through multiple solution problems of sum-of-subsets. Further this work proves that such problems are easier to the human brain rather than optimization problems. This was possible by imitating the process of inhibition by a human brain. It is observed that the process of inhibition reduces the complexity of the problem in average case scenarios. This work is depicted through implementation of sum-of-subsets problem using three methods namely, Exhaustive Search, Inhibition as an integral function and Inhibition as an independent process. These approaches in the order of their implementation prove how such problems are made easier by human brains compared to optimization problems, which need exhaustive search.

Keywords: Feed-forward network, Sub-of-Subset problem, Neural Selection, Inhibition Process, Exhaustive Search.

INTRODUCTION

Application of neural theory “Neural Darwinism: Selection” into optimization problem of KP was done and tested through our previous work [1]. The KP is considered as a special case of sum-of-subsets problem in algorithmic approaches. Sum-of-subsets problem is a variant of KP in the way that it produces multiple outputs rather than only an optimum. There has been a comparative study of these two problems using variant algorithmic approaches. One such analysis has also shown that the algorithmic approaches seem to have solving KP problem easier than that of sum-of-subsets problems [2]. In our case, the decision to solve sum-of-subsets using neural approach was decided to be necessary and important to show that for a human brain, the sum-of-subsets seems to be less complex than that of the KP. Even the works [3] [4] [5] [6] which solved these problems using genetic algorithms have also had complexity reduction in solving these problems as their objective. They were not the works which had the objectives to mimic the human brain in such situations. The contrasts between algorithmic and biological approaches seem to be evident by just considering them to be solved manually. It is natural that a problem with higher arithmetic calculation will be considered more complex by a brain at an outset. Moreover, an optimization problem has the requirement of more short-term memory to check the improvements in the solutions. The following steps are taken into consideration to prove the chosen objective of finding why sum-of-subsets is found to be an easier problem than the KP to a human brain,

- To perform an exhaustive search by adapting KP Neural Model [1] for sum-of-subset.
- To implement Inhibition as an integral function.
- To implement Inhibition as an independent process

This work as its first portion implements and tests the applicability of the model used for the KP to the sum-of-subsets problem with suitable modifications. The second portion of the work is divided into two parts. The first part adds another biological theory of “Inhibition” as an integral part of the network model. Even though it shows improvement in the performance of the network in average case scenarios, the second part only shows the model which mimics the biological model. The second portion not only mimics the biological model but also proves why the sum-of-subsets problem seems to be less complex to a human brain not only because of reduction of arithmetic burden but also due to its capability of “Inhibition”.

The following part of the paper is divided into

1: Section 2. The first portion implements and tests the applicability of the model used for the KP to the sum-of-subsets problem with suitable modifications.

2: Section 3. Shows the implementation of an exhaustive search of the sum-of-subsets problem by adapting KP model.

3: Section 4. The second portion shows the observation of sum-of-subsets the adapted model and suggests about the biological process of cognition involving inhibition.

4: Section 4.1. Elucidates the implementation of the inhibitory process as an integral part of the network.4

5: Section 5. Depicts the related review which suggests that the inhibition as an independent process in human brain.

6: Section 6. Elucidates the variation in the inhibition model which mimics the biological model. The implementation shows that inhibition as an independent process.

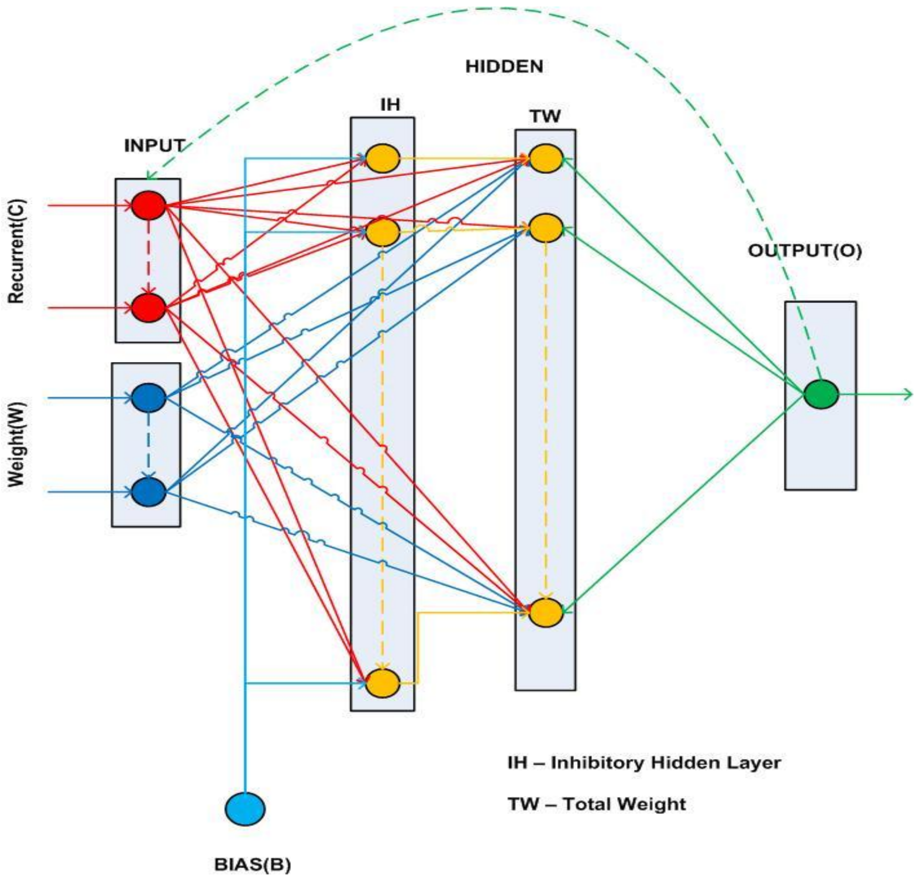

Figure 1. Sum-of-Subsets Neural Model

KP NEURAL MODEL ADAPTATION FOR SUM-OF-SUBSETS

It has been a replica of the KP Neural Model [1] to the static portion of the neural network except that of elimination of a set of inputs related to the profit and a hidden layer to find the sum of it. This resulted in a network having two *n* input neurons and two hidden layers with 2^n neurons. The modifications were required only for the functioning of the output neurons where it doesn't differ in iterative procedure but were made to fire at iteration which gave the required sum. In this modification itself, the burden of short-term memory seems to reduce the complexity of the solution. The adapted sum-of-subsets neural model is represented in fig.1.

IMPLEMENTATION OF EXHAUSTIVE SEARCH

Exhaustive search is one of the general problem-solving techniques which can produce a solution to the problem by considering all possible combinations. Here the neural model has two n input neurons where n is the number of items. The first set of inputs represents the numeric weights of given items. The second set of inputs used to select combinations using unipolar inputs controlled by output layer.

Two hidden layers are used, the first hidden layer imitates the inhibitory synapses [7], which can enable or disable the activation of hidden neurons. Their functioning is mathematically represented in eqn. (1).

$$IH_q = \sum_q A_p w_{pq} + B b_q \qquad (1)$$

Where,

$IH_q \rightarrow$ the output of q^{th} neuron which is inhibitory in nature of the first hidden layer,

$A_p \rightarrow$Unipolar input from the input layer used by the output layer to contemplate different combinations of other inputs.

$W_{pq} \rightarrow$ static weight as per basic model [8].

$B \rightarrow$ Bias input

$b_q \rightarrow$ Bias weight

The second layer produces the cumulative weight for the selected items represented in (2),

$$TW_q = IH_q\left(\sum_q \left(A_p W_p\right) * s_{pq}\right) \qquad (2)$$

where,

$TW_q \rightarrow$ Cumulative weight of selected weights if the inhibitory signal is available otherwise zero.

$W_p \rightarrow$ Weight of the p^{th} element.

$s_{pq} \rightarrow$ weight of the p^{th} neuron in the second hidden layer.

The output layer which is functionally dynamic chooses the constraint to equal the target sum (S) by varying the unipolar section of the input exhaustively with 2^n combinations. Mathematical representation given in (3).

$$\mathbf{O = \{ O_k \quad if \quad TW_q \quad \equiv \quad S \quad \}} \qquad (3)$$

***Algorithm 1**: Exhaustive Search Algorithm*
***Input:** Input Array IP, Maximum Size M*
***Output:** Targeted Sum such that $\sum_{IP} \equiv M$*

```
for all input neuron IPR do
    wsum :=0; Wt1 :=0; P :=0;
    for each first hidden layer neurons IPC do
            wsum ← find the weighted sum;
    endfor
    res ← include bias with weighted sum
    if res >=0.5 then
            set res for activation
    else
      reset activation
    endif
    for each second hidden layer neurons IPC do
            Wt1 ← weighted sum ( weight of selected item * control input)
    endfor
        Wt ← selected sum
      If selected sum Wt is equal to expected sum OPT
          Print the Subset
      endif
endfor
```

OBSERVATIONS OF THE ADAPTED MODEL

The successful implementation was tested and was observed to produce expected results with the same complexity of KP that is $O(2^n)$. The biological brain model to be mimicked that will reduce the complexity of sum-of-subsets problem should adhere to a process modification of this implementation. The structure of the network has two sections namely static and dynamic portions was not modified because the basic neural theory "Neural Darwinism: Selection" cannot be contradicted. This led to the following study about biological process of cognition involving inhibition.

Inclusion of Inhibitory Process into Sum-of-Subsets Model

In the biological model, it is found that brain adapts the process of inhibition to provide an improvement to the exhaustive search model by reducing the number of iterations. In other words it was decided to eliminate improbable combination of elements before being taken into consideration. If an element or a sum of a subsets equals or exceeds the target sum, then a further combination of subsets including this subset need not be tested. Such elimination requires re-arrangements of the input sequence in such a manner that a smaller subset combination does not succeed a larger subset combination having the previous one as its subset.

In the following implementation, two modifications are done. First, the arrangement of unipolar inputs which exhaustively test all possible subset of inputs was rearranged such a manner that the subset with lesser number of elements is tested before the subset with more number of elements. These inputs are arranged at the pre-processing stage itself in a queue. The second modification is the introduction of elimination process after every test if the target sum is achieved or exceeded. The following implementation was tested to produce the desired results including the process of inhibition followed by the human brain.

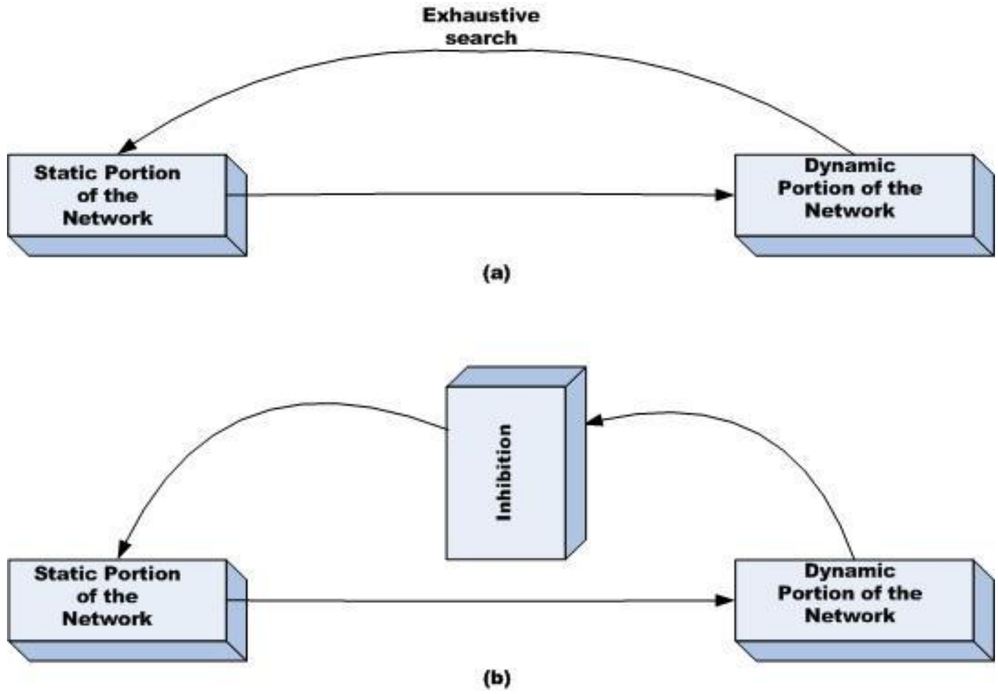

Figure 2. (a) Exhaustive search (b) Inhibitory Search

Algorithm2: *Inhibitory Algorithm*

Input: *Input Array IP, Maximum Size M*

Output: *Targeted Sum such that* $\sum_{IP} \equiv M$

```
begin
  Inp ← subset of unipolar input combinations
    While combination set count cn greater or equal to 1 do
      If subset weight WT greater or equal to expected sum OPT
          Decrement combination set count by one
          If subset weight is equal to expected sum OPT
              Display subset
          endif
          for each next subset combinations z do
            if (subset combination z & next combination from Inp) true then
                  eliminate the subset input from Inp([z],:) ← [];
                  decrement combination set count by one
            endif
          endfor
      else
          Decrement combination set count by one
      endif
    endwhile
end
```

The sum-of-subsets problem has been implemented and tested successfully in octave environment using nnet-0.1.9 package. The result of a sum-of-subsets problem with five items is depicted in fig. 3. The implementation elucidates the reduced complexity of sum-of-subsets problem in average case scenarios

```
octave:1> cd Desktop
octave:2> setsum_inhib

*-Network Created-*

*----Weight Initialization has Done----*

*-Given Weight-*
ans =

   2   3   4   5

A =

   0   0   0   1

A =

   1   1   0   0

Total cpu time: 0.072168 seconds
elapsed_time =  0.072486
octave:3> 
```

Figure 3. Output Screenshot

BIOLOGICAL SUPPORT FOR INHIBITORY PROCESS

The neurons having inhibitory synapses type which suppress the activity of the postsynaptic neuron was an inspiration in the KP and sum-of-subsets problems where the unipolar inputs and the first hidden layer which represents such neuron. This was not sufficient in adapting the methods followed by a human brain as inhibition as a process. The biological science studies discover that different types of inhibitory neurons [15] will not be sufficient immediately to prove inhibition as a process is done only with neural combinations. This forced the exploration into biological theories in cognitive science.

The works in biological science about cognition has produced results to support the process of inhibition which is the adaptation of the process at a different part of the brain at different stages of growth. They have also suggested that the process of inhibition is weaker in young brain and it found to increase in quality with the increase in growth they also found that after the inhibition process being adapted by the brain, there is also a shift in the part of the brain responding to the same problem situation to the part reacted before such adaptation. These findings [9-14] support our implementation where the process of inhibition is not related the neural network model used, but is a separate process independent of the network.

NEED OF VARIATION TO INHIBITION AND ITS IMPLEMENTATION

The implementation of inhibition as a process was found to perform well but gave rise to a question that, does it completely mimic the functioning pattern of the brain? The answer was that it has adapted the inhibition as a process [9] [10] only but does not find to have the pattern of brain functioning. It is found that inhibition is the process of the effect created by an earlier effort of responding to a real-world input. The brain seems to remember the inputs which created a negative response and only block similar inputs in future. That is it doesn't have the capacity to eliminate the occurrences of the real world input. In contrast to the above observation about the brain our implementation is found to eliminate the occurrences of inputs at once similar inputs create the possibility of negative response. This had to be modified in the model which led to the following variation in the implementation.

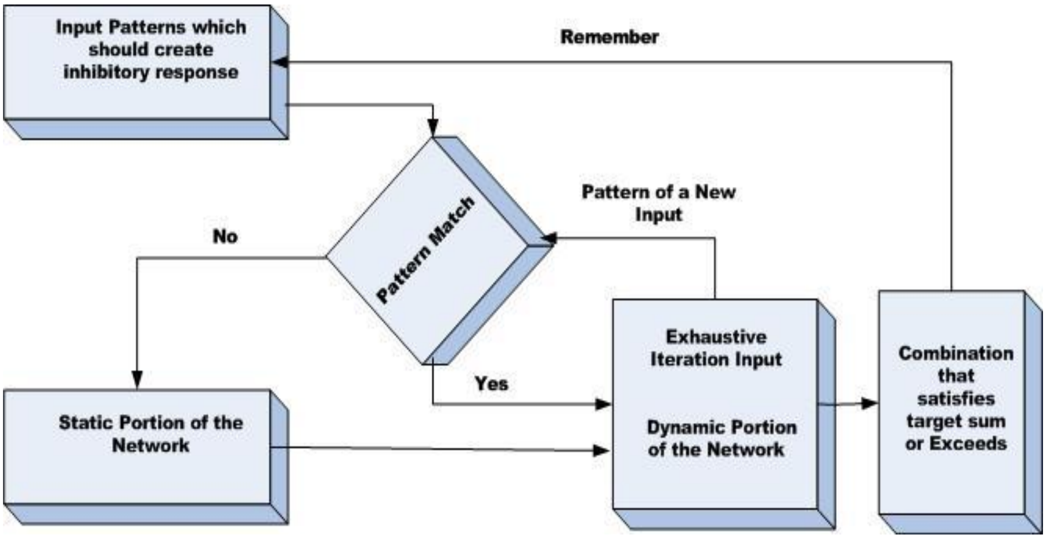

Figure 4. Modified version of Inhibition

The modifications are the variation to the inhibition process explained by the fig. 4 is to make the iterative process exhaustive. At once an input satisfies the sum or exceeds it the input is saved or memorized implicating that any such future pattern having this has sub pattern should produce an inhibitory action and next iteration is to be tried avoiding the process of sum calculation for the input. In case the input doesn't match with any pattern memorized by the network then it should produce the sum and only test it for its satisfaction or storage for inhibition.

The implementation of the variation has produced the desired result but shows higher complexity if the number of elements of the set and bit size is larger. This is found to be the conclusive mimic of the inhibitory process of the brain where the brain also is found to struggle when the size of such problem increases.

CONCLUSION

The implementation of sum-of-subsets and the inclusion of inhibition process to the solution of those problems have not only proved that the neural network model not only produces expected results to such problems but also has the capacity to mimic the brain functioning to such situations. Apart from the model implementation, the chosen objective of finding why sum-of-subsets is found to be an easier problem than the KP to a human brain where the reverse is true when applying algorithmic methods is achieved. The process of inhibition included in the model, blocks some inputs which will be producing unsatisfactory results before testing. Same cannot be applied to a KP problem as it is an optimization one that requires exhaustive approach only. The scope of the work has led to an opening for the future work of finding the neural network implementation for this inhibitory process implemented as an algorithm within a network's functional portion.

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