Study Emergency in Spreading Activation Model by Modeling Path Finding Problems

Xixu Fu, Kaijun Wu and Xizhang Gong

Institute of Information Technology, Shanghai Ocean University, Shanghai, China
xxfu@shou.edu.cn

Abstract

Spreading activation theory is an important theory for human reasoning. It is significant to study this theory for finding how human minds differ and superior to machines in many fields. To study process based spreading and activation, a process based model named SCO was set up according spreading activation theory in this paper. Emergency, efficiency and termination of spreading activation is carried out based on this model. To analyze the soaking process, the model was applied to several path finding problems. The result showed how spreading activation inspired methods superior to traditional searching methods in complicated tasks and muddy tasks.

Keywords: *spreading activation model; heterogeneous neural network; problem solving*

1. Introduction

Spreading activation model is a famous theory about reasoning in human memory based on ACT-R theory [1]. The model can explain the nature of human association and emergence [8]. Nowadays, experiments and study in psychology and neural science proved the soundness of the model [2, 7].

Algorithms based on spreading activation theory have gained great success in the area of natural language processing [4] and information retrieval [5]. It has been proved efficient in these applications. In recent years, spreading activation model was applied in problem solving [11] and ontology based system [9]. In other fields such as recommender systems [12], scientists also use spreading activation theory to model their systems. Studies on brain systems also support the theory [7]. Metrics such as Nodes similarity [10] were advanced based on the spreading activation theory too.

Although the model is promise for many tasks, few applications based on it in artificial intelligence other than information retrieval and semantic processing can be found. Spreading and activation in most applications are state based. Unfortunately, many tasks are process based tasks. A node in the network may be activated twice or more to generate a serial of actions as the result. Many graph based models described this kind of problems well.

On the other hand, although mathematical model has been setup long before [1], the convergence of activation has not been well depicted till recent time [12].

Soaking models based on spreading activation theory are parallel searching of graphs in essence without considering the structure of memory. The activation process in soaking models just likes the activation of spikes in neural networks without considering semantics. It is natural to model graph based problems with neural networks to study the process and efficient of models based on spreading activation theory. Such a method is also fit for modeling and evaluating process based on spreading activation theory.

This paper first analyzed spreading activation theory in a process based way. Then, a model was setup for spreading activation theory using heterogeneous neural network. With this model, three shortest path finding problems were analyzed:

1. Find the shortest path between two vertexes in a given weighted graph.
2. Find the shortest circle which cover all vertexes begin with one vertex in a given weighted graph.
3. Find a vertex which has the least summary cost to n vertexes in a positive weighted connected graph.

The soaking and convergence process is analyzed with the solving of the first problem. Solving of the second problem can show how human minds solve searching problems. The third problem can show the PDP [3] method human solving problems in a better way.

2. Human Knowledge and Reasoning

Human beings have a large knowledge system to support daily reasoning and decisions. However, men can get result and decide in short time in tasks which need mass knowledge. When an idea emerges, good ideas will emerge soon. It is a good saying that you can recognize the president of USA through 6 people. Knowledge of human are organized in such a highly related method.

On another hand, men often confusing in the tasks like Hanoi tower problem and chess playing.

3. Spreading Activation Theory

Spreading activation theory can explain how knowledge is applied in human minds. Models also showed the superiority of spreading activation theory in dense knowledge environment [11].

Early version of spreading activation theory was generated in the study of language and semantics [4]. In classical description of spreading activation theory, related semantic elements such as words can activate related elements to form needed scenarios. Spreading activation serves the function of quickly spreading an associative relevancy measure over declarative memory [1].

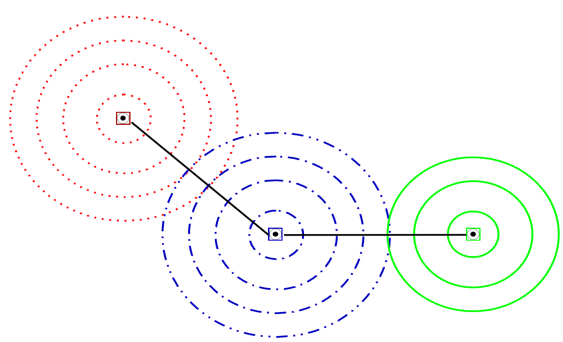

Figure 1. Soaking among Nodes

As shown in Figure 1, a node can send information to activate connected nodes by sending activation information. Activated nodes can generate new information to activate other nodes. In the activation process, heuristic information can be generated and the soaking process will be suppressed and will stop at last. According to the emergence theory [8], the soaking process will stop soon after the emergence of needed idea.

4. Model Spreading Activation in Neural Network

Neural network can be extended to setup a spreading activation based model. However, neural network use simple spikes to generate complex algorithms. Many spikes are needed for a simple computation task [6]. It is not straight forward way to represent the soaking process. Spikes can be revised as shown in Figure 2.

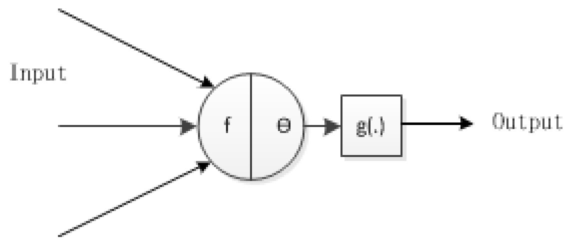

Figure 2. Model of a Spike

As shown in Figure 2, elements in a spike can be described as below.

A spike can be described as a pentad S(I, f, θ, g, O). I is a set of input data. Input data can be any data in any form which can be regarded as parameter of f. Activation function f is a function which processing the inputs for outputting. Filter θ is a criterion which can be used for control the outputs. Output function g checks whether an input can be sent out then send them to connected spikes. O is the output which can be sent to connected spikes.

A Model called Soaking-Control-Output(SCO) model can be setup using spikes according to spreading activation theory.

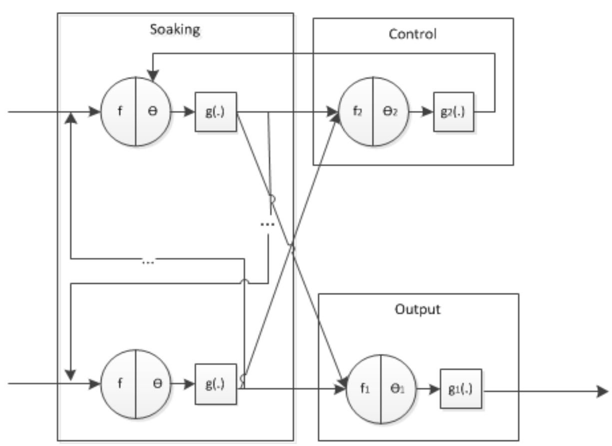

Figure 3. Soaking Model

As shown in Figure 3, the model consists of three parts. The first part is the soaking part which simulates the soaking process. This part consists of spikes whose input and output are fit for generating output data to activate each other. The second part is the output part which generates the result by the outputs from the soaking part. The last is the control information θ for the soaking part and leads to faster convergence. All parts can consist of heterogeneous spikes to adapt complex tasks.

The soaking part corresponds to the spreading and activation process in human minds. The control part corresponds to the knowledge and its constraint to the soaking process. The output part provides the final result when activation stopped.

5. Experiments and Results

Experiments had been carried out to evaluate the model. These shortest path related problems are simple but suit for studying the essence of spreading activation model.

5.1. Problem1: Shortest Path between Two Vertexes

This problem is to find a shortest path between two vertexes in a positive weighted connected graph. This is a simple problem for both computer and men when the graph do not consists of too many vertexes. However, the problem can easily map the reasoning process in human mind.

5.1.1. Design of Model: Let each vertex corresponding to a spike in soaking part. These vertexes are connected as the graph is. Input is connected to the beginning node. The target node is connected to the control and output part. Information passed in the soaking part is defined as a dyad P<*Weight, Route*> which denotes the weight and route of a path. Function f in soaking part adds the weight of passed edge to Weight and add the label of the vertex to Route. Function g decides whether the path is overweight and sends paths not overweight to next nodes.

The control part get weight from received information and update θ as ***P.Weight<Input.Weight***. The output part gives the result when the algorithm ends.

5.1.2. Result: Experiments are carried out in two randomly generated connected graphs which consist of 100 vertexes. The first and last vertexes are regarded as start and destination respectively. Table 1 shows the details about the experiments.

Table 1. Graph Used in Experiments in Problem1

Experiment	Vertexes	Weights	Vertex Degree
1	100	1-5	3
2	100	1-5	10

The result can be shown in Figure 4. Number of activated outputs raised sharply until a path to the destination was found. As soon as a path was found, the algorithm converged quickly.

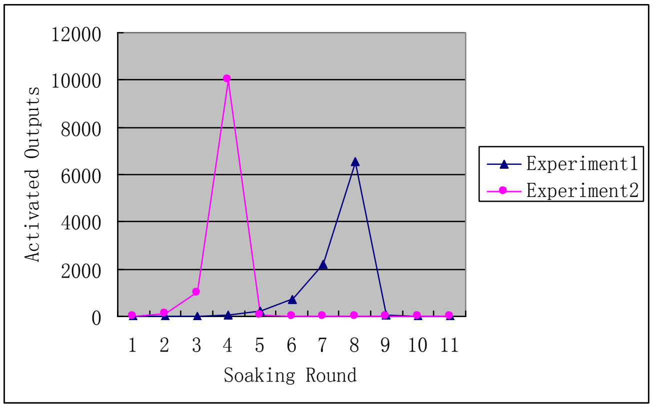

Figure 4. Activation and Outputs

When a path is founded, heuristic information can be provided for the soaking process. This point can be defined as heuristic point of a soaking model.

Definition 1: The soaking round in which θ is updated and the number of outputs decrease sharply is defined as heuristic point. It is noted as Hp.

Let Ls(A,B) be the least soaks needed for connection of nodes A and B. Let B and D be the beginning and destination nodes in problem 1. The heuristic point of problem1 is shown below.

$$Hp=Min(Ls(B, D))$$

5.2. Problem2: Shortest Circle Finding

This problem is to find a shortest path beginning with a given vertex which can cover all vertexes and back to the first vertex in a positive weighted connected graph. It is a hard problem for both human and machines.

5.2.1. Design of Model: The soaking part used the same definition in problem1.

The control part gets weight from received information, and then determines if all vertexes were included in the route. If so then update θ as ***Weight<Input.Weight***. The output part gives the result when the algorithm ends.

5.2.2. Result: Because of the complexity of the problem, this experiment was carried out in a randomly generated connected graph which consists of 10 vertexes. Table 2 shows the details about the experiments.

Table 2. Graph Used in Experiments in Problem2

Experiment	Vertexes	Weights	Vertex Degree
1	10	1-5	3

The result can be shown in Figure 5. Number of activated outputs raised sharply until a path to the destination was found. As soon as a path was found, the algorithm converged soon.

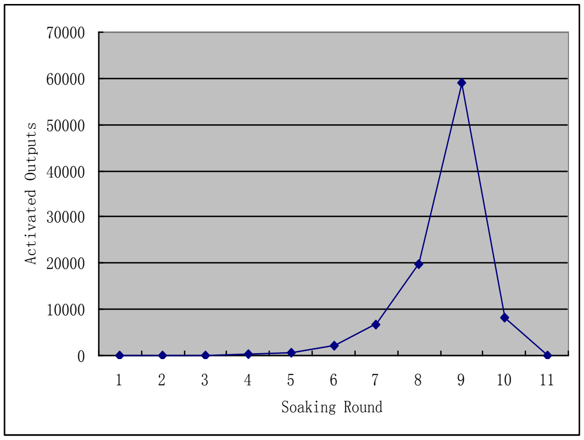

Figure 5. Activation and Outputs

The heuristic point can be reached when and only when all nodes reached in this problem, that is to say:

$$Hp = \text{Count(Nodes)}$$

It is bad when number of nodes increases in this problem.

5.3. Problem 3：Shortest Convergent Vertexes

Find a vertex which has the least summary cost to n vertexes in a positive weighted connected graph. The problem seems simple, but it is not a simple task for machines to get the optimized solution.

5.3.1. Design of Model: In the soaking part given vertexes were regarded as initial input nodes. Nodes in soaking part were designed as in problem 1. All nodes in soaking part connect to the control part and the output part.

The control part was to determine whether the inputs' route include all given vertexes. If so, update θ as ***Weight<Input.Weight***.

The output part checks whether the inputs' routes include all given vertexes and output the final result.

5.3.2. Result: Experiments are carried out in randomly generated connected graphs which consist of 100 vertexes. Table 3 shows the details about the experiments.

Table 3. Graph Used in Experiments in Problem3

Experiment	Source Vertexes	Weights	Vertex Degree
1	3	1-5	3
2	7	1-5	3
3	7	1-5	10

The result can be shown in Figure 6.

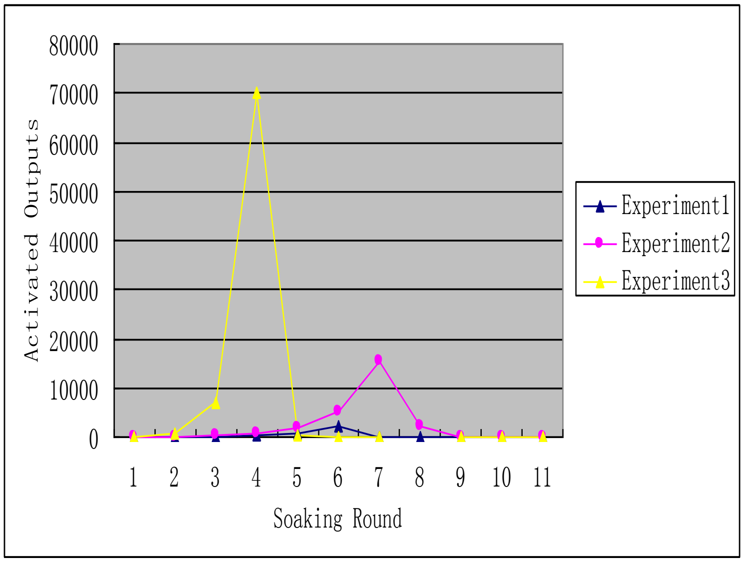

Figure 6. Activation and Outputs

Once a convergence point was reached, the algorithm converged soon. Let V_i be the given i vertexes, V_c be the convergence point, Dis(X,Y) be the soaking rounds needed from node X to Y, the heuristic point of problem1 is shown below.

$$Hp=\mathrm{Max}(\mathrm{Dis}(V_i, V_c))$$

6. Conclusion

This paper advanced a neural network model which consists of soaking part, control part and output part to model spreading activation theory. Three problems were tested using this model to explain the efficiency of spreading activation theory.

The solution of problem1 showed the emergence and convergence of the soaking process. When reaching a heuristic point, soaking can be restrained and the solution of problem will soon be generated. This trend was shown in other experiments too. Edges in experiment 2 are much more than that in experiment 1. However, the complexity did not increase exponentially as we thought because the quick emergent of heuristic point. This can explain why men can find the result efficiently in great amount of information in some extent. Because of the rich relations of knowledge, needed knowledge can be found in limited soaks in spite of the large amount of knowledge.

The solution of problem2 showed some inability of spreading activation method. Although result was found at last with heuristic information, the heuristic point emerged at the 10th round of soaking which is equal to the number of vertexes in the graph. Large amount of output information generated. This result can explain the inability of human in some artificial intelligence problems.

The solution of problem3 showed the superiority of the spreading activation theory in PDP problem solving. It can explain how human consider problems in a systematical way.

7. Discussion & Future Work

7.1. About Heuristic and Convergence of Model

State based spreading and activation had been described in John R. Anderson's paper [1] long before. The model is an excellent one for state based activation. Figure 7 is a figure in this paper which showed the spreading and activation process.

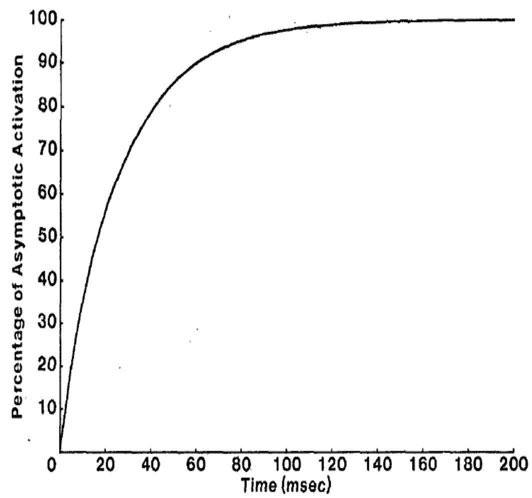

Figure 7. Activation Process in Anderson's Paper

However, output will increase exponentially if a node can be activated many times without decay.

On another hand, the model described the decay of spreading and activation. It is not related to the objective of problem solving. The soaking may not converge to needed state.

Other papers [9] also mentioned the termination of a spreading activation based algorithm. Only full spreading and specification of the numbers of iterations are mentioned.

In the SCO model in this paper, the soaking can be constrained by the control part which refers to the knowledge in human mind. It clearly mapped the role of knowledge in human minds.

7.2. Compare to Traditional Neural Network

Traditional neural network methods divide complex task to simple atomic tasks and solve the problem by dealing simple outputs [6]. Although many calculations can be simulated by many spikes, a model for a complex task can hardly be setup.

SCO model extends the ability of spikes. It is much easier to setup a SCO model for a complex problem. Training of a SCO model can be more straight-forward.

7.3. Consider Semantics and Memory Structure

Most models based on spreading activation theory are semantics based. It is important to consider semantics in soaking models. Although models in this paper implement homogeneous spikes and simple functions, different functions can be set for spikes to deal with different type of semantics in SCO. The SCO model is adaptive.

Memory structure was considered in other works [9]. These methods can also be defined in control part to enhance the model.

References

[1] J. R. Anderson and P. L. Pirolli, "Spread of activation", Journal of Experimental Psychology: Learning, Memory, and Cognition, vol. 10, **(1984)**, pp. 791-799.

[2] A. Azizian, J. Pierre-Louis and N. K. Squires, "P300 as an index of spreading activation", Psychophysiology, vol. 39, no. 19, **(2002)**.

[3] J. S. Bowers, "Challenging the Widespread Assumption that Connectionism and Distributed Representations Go hand-in-hand", Cognitive Psychology, vol. 45, **(2002)**, pp. 413-445.

[4] A. M. Collins and E. F. Loftus, "Spreading Activation Theory of Semantic Processing", Psychological Review, vol. 82, **(1975)**, pp. 407-428.

[5] F. Crestani, "Application of spreading activation techniques in information retrieval", Artificial Intelligence Review, vol. 11, **(1997)**, pp. 453-482.

[6] G. Nagy, "Neural Networks-Then and Now", IEEE Transactions on Neural Networks, vol. 2, **(1991)**, pp. 316-318.

[7] D. M. Nathan, L. H. Jessica, A. F. Stefan and J. H. Jacqueline, "Neural correlates of semantic activation spreading on the path to picture naming in adults who stutter", Clinical Neurophysiology, vol. 121, **(2010)**, pp. 1447-1463.

[8] J. H. Holland, "Emergence: From Chaos to Order", Oxford University Press, **(2000)**.

[9] A. Katifori, C. Vassilakis and A. Dix, "Ontologies and the brain: Using spreading activation through ontologies to support personal interaction", Cognitive Systems Research, vol. 11, **(1997)**, pp. 25-41.

[10] K. Thiel and M. R. Berthold, "Node Similarities from Spreading Activation", Proceedings of 2010 IEEE International Conference on Data Mining, **(2010)**, pp. 1085-1090.

[11] X. Fu and H. Wei, "Problem Solving by soaking the concept network", Computer Science and Information Systems, vol. 8, **(2011)**, pp. 761-778.

[12] B. Yolanda, L. Martin and G. Alberto, "Exploring synergies between content-based filtering and Spreading Activation techniques in knowledge-based recommender systems", Information Sciences, vol. 181, **(2011)**, pp. 4823-4846.

Authors

Xixu Fu got his master degree in 2007 at Fudan University. Now he is an engineer in Shanghai Ocean University and a ph. D candidate in Fudan University. His research interests include artificial intelligence, psychology, cloud computing and software engineering.

Kaijun Wu is a researcher in Shanghai Ocean University. His research interests include cloud computing and software engineering.

Xizhang Gong is a senior engineer in Shanghai Ocean University. His research interests include system integration and software engineering.