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A reconstruction algorithm of prototype pattern of SNN based on TD-IDF and QPSO algorithm

***Abstract**. Synergetic neural network(SNN) is a top-down network constructed by synergetic theory different from traditional neural network. The constitution of prototype pattern plays a significant role on the effect of recognition of SNN. In this paper, we propose an novel reconstruction algorithm based on TD/IDF method which can describe the related information of prototype patterns accurately.At the same time, Quantum-behaved Particle Swarm Optimization is used for prototype parameters optimization. Experiment results on semantic role labeling show the algorithm have a higher performance for semantic role labeling. Comparison with other optimization algorithm, the proposed algorithm has more powerful global exploration ability and faster convergence speed.*

***Streszczenie.** W artykule przedstawiono algorytm rekonstrukcji oparty na metodzie TD/IDF, służący do dokładnej analizy budowy sieci neuronowej SNN. Budowa modeli prototypowych sieci, optymalizowana jest algorytmem roju cząstek QPSO. Wyniki badań eksperymentalnych pokazują, że proponowany algorytm lepiej radzi sobie z etykietowaniem semantycznych, a także ma większe możliwości poszukiwania globalnego. (**Algorytm rekonstrukcji próbnej budowy sieci neuronowej SNN – algorytm QPSO i TD-IDF**).*

Keywords: SNN; TD-IDF; QPSO; Semantic role labeling.
Słowa kluczowe: SNN, TD-IDF, QPSO, SRL.

Introduction

SNN model is a top-down network proposed by Haken [1] In the late 1980s. SNN different from traditional network constructed by the method researched in single neuron's characteristic configuration and connection, and it don't produce the pseudo-state [2]. At present, the mainstream studies of SNN focus on the selection of prototype pattern vector [3]. Tian Xiao-dong [4] proposed an prototype selection algorithm based on information-feedback which improves the precise of the recognition. It is impossible to identify the essential characteristics of the objects, resulting in a poor identification result. In this paper, main attention has been paid on how to better reflect the essential characteristics of objects reconstructing prototype pattern.

The reconstruction algorithm of prototype pattern

In the late 1980s, Haken applied Synergetics principles to a new field:pattern recognition. The potential function of SNN is:

$$\dot{\xi}_k = \lambda_k \xi_k - B\sum_{k'\neq k} \xi_{k'}^2 \xi_k - C\left(\sum_{k'=1}^{M} \xi_{k'}^2\right)\xi_k$$

From the potential function, we can see the main problems of SNN can be attributed to the solving of the order parameters ξ_k, while ξ_k can be directly calculated from the prototype vector. Therefore, the constitution of prototype vector plays a significant role on the effect of recognition, and it set the tone for a whole recognition capabilities. In order to make recognition process reasonably reflect the relation among test patterns, it is necessary to propose a new algorithm to reconstruct prototype patterns. Supposed the weight vector for document d is $v_d = [w_{1d}, w_{2d} \cdots w_{Nd}]$, Then $w_{td} = \mathrm{TF}_{td}.\mathrm{IDF}_{td.}$ where TF_{td} is term frequency of term t in document d and $\mathrm{IDF}_{td} = \log\frac{|D|}{|\{d' \in D | t \in d'\}|}$.

Using the cosine the similarity between document d and query q can be calculated as:

$$sim(d_j, q) = \frac{\sum_{i=1}^{N} w_{i,j} w_{i,q}}{\sqrt{\sum_{i=1}^{N} w_{i,j}^2}\sqrt{\sum_{i=1}^{N} w_{i,q}^2}}.$$

We can obtain feature vectors from the train corpus and test corpus, construct prototype pattern $v_k\ (v_{k1}, v_{k2}, \cdots v_{kn})(k = 1,2\cdots)$, its corresponding role $R_k\ (k = 1,2\cdots)$ and test pattern $q_l\ (q_{l1,} q_{l2} \cdots q_{\ln})(l = 1,2\cdots)$. Where v_k can be coded as follows: $v_{ki} = TF_{ki} \times \log(N / IDF_{ki} + 0.1)$, $(i = 1,2\cdots)$, N is number of prototype patterns. TF_{ki} is the number of v_{ki} appearing in prototype patterns whose corresponding role is R_k , IDF_{ki} is the number of v_{ki} appearing in prototype patterns whose corresponding is role $R_j\ (j \neq k)$. And $q_l\ (q_{l1,} q_{l2} \cdots q_{\ln})(l = 1,2\cdots)$ Can be coded as follows: $q_{li} = \beta_i f_i(v_k, q_l)$, β_i refers to the weight of the property v_{ki} , $f_i(v_k, q_l)$ the similarity of v_{ki} and q_{li}. For example, we can simply define it as follow:

$$f_i(v_k, q_l) = \begin{cases} v_{ki}, & v_{ki} = q_{li} \\ 0, & otherwise \end{cases}$$

The parameters $\beta_i (i = 1,2\cdots m)$ are very important for better recognition performance. The change of $\beta_i (i = 1,2\cdots m)$ will lead to completely different recognition results. There is no effective way to control the parameters. A parameters optimization based on d OPSO algorithm is proposed in this paper. Particle swarm optimization (PSO) is an optimization technique attributed to Eberhart and Kennedy ,inspired by social behaviour of bird flocking or fish schooling. The particles is restricted to a finite sampling space lead to the problem of getting into local optima. A global point denoted as mbest is introduced into PSO:

$$mbest = \frac{1}{M}\sum_{i=1}^{M} P_i = (\frac{1}{M}\sum_{i=1}^{M} P_{i1}, \frac{1}{M}\sum_{i=1}^{M} P_{i2}, \cdots \sum_{i=1}^{M} P_{id})$$

The prototype optimization algorithm based on OPSO algorithm is described as follows.

Obtain feature vectors from the train corpus and test corpus, construct prototype pattern $v_k\ (v_{k1}, v_{k2}, \cdots v_{kn})(k = 1, 2 \cdots)$, and test pattern $q_l\ (q_{l1,} q_{l2} \cdots q_{ln})(l = 1, 2 \cdots)$. Set $q_{li} = \beta_i f_i (v_k, q_l)(i = 1, 2 \cdots)$. Initialize the population $x_i = (\beta_1, \beta_2, \cdots \beta_m)$. Do find out the mbest of the swarm by equation (1); for I=1 to population size M; if f(p_i)<f(x_i) then pi=xi. p_g =min(p_i), for d=1 to dimension D, f_{i1} =rand(0,1), f_{i2} =rand(0,1), P=(f_{i1} *pid+ f_{i2} *Pgd)/(f_{i1} + f_{i2}), L=beta*abs(mbestd- x_{id}), u=rand(0,1); if rand(0,1)>0.5; x_{id} =p-abs(mbestd- x_{id})*log(1/u); else x_{id} =p+abs(mbestd- x_{id})*log(1/u); until the termination criterion is met.

Algorithm 1 The prototype optimization based on OPSO algorithm

A semantic parsing architecture based on SNN

The Semantic role labeling with prototype reconstruction and prototype optimization of SNN is described as follow:

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(1) Obtain feature vectors from the train corpus and test corpus, construct test pattern $q_l\ (l = 1, 2 \cdots)$ and possible roles $R_k\ (k = 1, 2 \cdots)$ based on TF/IDF and QPSO algorithm.

(2)Construct the order parameters of q_l ; a)Pseudo-inverse method: $\xi_{lk} = v_k^+ q_l\ , (k = 1, 2 \cdots)$, b)Weighted distance: $\xi_{lk} = \lambda_k \left\| v_k - q_l \right\|, (k = 1, 2 \cdots)$, c)Inner method: $\xi_{lk} = \frac{v_k . q_l}{|v_k||q_l|}, (k = 1, 2 \cdots)$; (3) Find the N-best candidate role $(R_{l1}, R_{l2}, \cdots R_{lNbest})$ of $q_l\ (l = 1, 2 \cdots)$; (4) Combination of all possible roles of $q_l\ (l = 1, 2 \cdots)$, obtain all the possible roles chains, and calculate the corresponding probability. (5)Set the attention parameters B, C and non- attention parameter λ_k ; (6)Obtain the best roles chain through the evaluating of order parameter equation.

Algorithm 2 A semantic role labeling model of SNN

Experiment

In our experiments, we complete an semantic parsing system based on SNN which takes dependency relations as labeled units. The SNN based on TF/IDF and QPSO algorithm is trained to identify and classify the predicates semantic roles. The training set composes 3000 sentences. The test set composes 1000 sentences. The numbers of role in the roles chains, which indicates the possibility of the roles chains. Compatible rate indicates the compatible degree of the roles chains. Table 1 shows the performances of SNN based on TF-IDF and QPSO algorithm. The experimental results are good because the TF-IDF-based coding scheme can describe the argument related information. At the same time, QPSO algorithm is used to search the global optimum attention parameters of SNN in the corresponding parameter space. We use Inner method to construct order parameters. The convergent curve is shown as Fig.1. The experiment results show the QPSO algorithm has better recognition result.

algorithm	non- attention					
	λ_k =1.2			λ_k =compatible rate		
	Precision	Recall	F1	Precision	Recall	F1
Pseudo-inverse	77.9	73.2	75.5	78.1	72.9	75.4
Weighted distance	71.1	69.2	70.1	71.6	69.3	70.4
Inner method	78.3	75.4	76.8	78.6	75.5	77

Table 1 Performances of SNN on TF/IDF and QPSO algorithm (%)

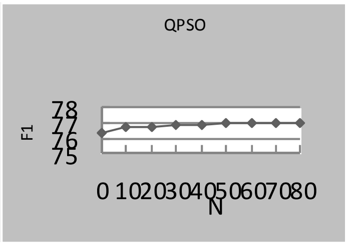

Fig. 1. The convergent curve

Conclusions

From all the experiments, we can see the reconstruction algorithm of prototype pattern based on TF-IDF and QPSO algorithm have a higher performance for semantic role labeling , and can be widely used in other natural language process tasks. From all the experiments, we can see the reconstruction algorithm of prototype pattern of SNN based on TF/IDF and QPSO algorithm have a higher performance for semantic role labeling , and can be widely used in other natural language process tasks.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 61005052), the Fundamental Research Funds for the Central Universities (Grant No. 2010121068) and the Natural Science Foundation of Fujian Province of China (Grant No.2011J01369).

REFERENCES

[1] Haken. Synergetic Computers and Cognition–A Top-Down Approach to Neural Nets. Springer-Verlag, Berlin ,(1991).

[2] Zhenhua Jiang , Roger A. Dougal. Synergetic Control of Power Converters for Pulse Current Charging of Advanced Batteries From a Fuel Cell Power Source. IEEE Transactions on Power Electronics, 19(2004) ,No. 4, 1140-1150.

[3]Zou Gang, Yao Wei, Sun Ji-Xiang, Chen Sen-Lin. A Synergetic Classification Algorithm of Pathology Cell Images Based on Prototype Vector Fusion with Sparse Decomposition. Chinese Journal of Biomedical Engineering. 30(2011) ,No. 1, 55-59.

[4] TIAN Xiao-dong, LIU Zhong. Arithmetic and Implication of Synergetic Pattern-Recognition Based on Modified Prototype Reconstruction. Chinese Journal of Qingdao University. 20(2005),N0.3, 86-88.

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