Extraction of Expert Relations Integrated with Expert Topic and Associated Relationship Features

Jiaying Hou, Zhengtao Yu(✉), Yu Qin, and Xudong Hong

School of Information Engineering and Automation,
Kunming University of Science and Technology, No. 727 South Jingming Rd.,
Chenggong District, Kunming 650500, China
ztyu@hotmail.com

Abstract. In order to utilize the topic features and the associated relationship features of experts to identify expert relations effectively, a novel extraction method of expert relations is proposed with the integration of expert topic and associated relationship features in this article. Firstly, the expert topics are extracted according to the idea that cooperative experts share the same topic distribution by integrating the expert cooperation network with Probabilistic Topic Models based on LDA Model. Secondly, the associated relationship features are extracted with the utilization of the attributes characteristics, such as the links among homepages, the mutual following on the Blogs. Finally, Markov Network is used to construct the extraction model of expert relations by integrating expert topics and associated relationship features. The experimental results have demonstrated that the proposed method that integrated with expert topic and the associated relationship features of experts supports the extraction of expert relations and shows promising performance.

Keywords: Expert topic · Associated relationship features · Expert relations · Markov network

1 Introduction

As an applied fundamental research in the field of information processing, Experts retrieval that is of important application value in such cases as scientific research and enterprise management has been one of the most effective methods to obtain expert information nowadays. Experts do not exist in isolation in this complex social network. Instead, they're connected with each other through complicated relations to constitute an expert relationship network to share knowledge in the same domain. Actually Experts retrieval is supported by this important resource of relationship network, while the expert relations extraction task has become an important link in the construction of expert relationship network. Since the expert relations extraction result will determine directly the construction quality of the expert relationship network, it has become particularly important on how to extract the expert relations in an accurate and efficient way.

At present, it is the entity relationship extraction task which received the most attention among the aspects of relationship extraction, defined in the Automatic content

Y. Li et al. (Eds.): SMP 2016, CCIS 669, pp. 207–219, 2016.
DOI: 10.1007/978-981-10-2993-6_18

extraction Evaluation Conference. The methods for solving the task of relations extraction both home and abroad were mainly divided into such groups: the first method based on pattern matching, for example, Yangarber [1] has put forward advanced pattern matching method based on the sample generalization. It solves the disadvantage that traditional method consume manpower and materials and bad portability and customization especially at the scenario level, improve the efficiency of entity relations extraction; The second method based on machine learning, for example, Zhao [2] uses feature vector and the entity pair was expressed as feature vector by using information such as terms, lexical, entity category, get the classification model to realize the entity relations extraction through Supporting Vector Machine training. Zhou [3] adding the phrase information feature into the feature set to improve the performance of extraction based on Zhao. Like Suzuki [4], the example is transformed into the way of the structural sequence, and the weight factor was added into while extracting the same sub sequences of different instances, and get some effect. On the basis of the shortest path tree, Yu [5] added entity related semantic information and put it in the node to form the path tree with reconciled Syntactic and entity semantic information, and get the categorizer with the training of convolution tree kernel function, complete the extraction task very well; The third method based on entities relationship extraction, for example, Han [6] puts forward a extraction method of character entity relationship based on supporting the vector machine, they take the character context and the part of speech as the feature words, use the method of self-expansion to expand the feature words, classify the character relationship in the method of supporting the vector machine. Yao [7] puts forward an extraction method of character social relationship in large scale on the basis on web and introduced the simulated annealing method, iteratively excavate the minimum description model set of character social relationship contained in the webpage, take the advantage of the redundancy of web information, and extract the relationship effectively and accurately. Li [8] puts forward a recognition method of character relationship based on sequential pattern mining; this method was used for the character entity relation extraction and could automatically extract the sequential pattern which expresses the relationship of character in large corpus.

Regarding the task described as above, good achievements have been made in the entity relationship extraction and the character relationship extraction. However as a special community in the character entity, experts are known for their professional knowledge and skills in a specific field. For example, when two experts often become co-authors on their published papers, it’s very likely that they might be the experts working in the same research field. Hence from the perspective of topic analysis, it’s very possible that they might have the same topic distribution. The analysis on expert resources reveals that there’re lots of expert correlation characteristics contained on the expert homepages, their Blog pages and the papers, such as the homepage link, the mutual following on the Blogs, the same organization and the co-authorship etc. In fact, all of these correlations and the similar topic distribution between the experts are able to provide an effective guidance to the extraction of expert relations.

On account of all these as above, this paper makes an attempt to construct a Markov network-based expert relations extraction model to extract the expert relations through the integration of expert topic and associated relationship features.

2 Analysis on the Expert Topic and Associated Relationship Features

2.1 Analysis on the Expert-Related Resources

Expert relations are implied in massive expert resources such as the expert homepages, their blogs and papers etc. In the face of such a vast data pool, it becomes extremely necessary to make a screening and analysis on the above network resources: An expert homepage always contains the following basic attributes of an expert, including his (her) organization, his (her) research field and his (her) academic achievements etc. with the availability of a homepage link to the other experts' homepages. The expert's blog always contains an interest list, where the mutual following between the experts is able to reflect intuitively the expert relationship. Meanwhile the content published by the expert on his (her) blog is able to reflect the expert's domain knowledge. In normal cases, since an expert always collaborates with the other experts to publish an academic paper, then the author list on the paper will also reflect intuitively the expert relationship. Actually the paper in itself is able to reflect the expert's domain knowledge.

The analysis reveals that: the attributes of an expert and the indexical links in homepages, the interest list and the content on an expert's blog, the author list and the content of the paper written by the experts will provide a powerful support to the extraction of expert topic and associated relationship features.

2.2 Analysis on the Expert Topic

Since the article published by an expert is always involved with several collaborators, then it's feasible to establish an expert collaboration network based on the collaboration relationship between the experts. In such a network, all of the collaborators are those experts who would share knowledge in the same field. That's to say, all of these experts will show an extremely similar topic distribution. On account of this, it's applicable to integrate the expert collaboration network constructed based on the collaboration relationship between the experts into a probabilistic topic model LDA to build an expert topic extraction model for the extraction of expert topic. This process can be formally represented with the model as shown in the following formula:

$$\begin{aligned} \mathrm{M(C,G)} &= (1-\pi)\left[-p(\overline{w}|\overline{z},\overline{\beta})p(\overline{z}|\overline{\alpha})\right] \\ &+ \frac{\pi}{2}\sum_{<v,\overline{v}>\in E} c(v,\overline{v})\sum_{j=1}^{k}\left(f(Q_j,v)-f(Q_j,\overline{v})\right)^2 \end{aligned} \tag{1}$$

where C represents the set of the experts' papers and G represents the expert collaboration network, while $p(\overline{w}|\overline{z},\overline{\beta})$ indicates the process of term sampling based on β, which is the parameter of the prior distribution for the determined topic $\overline{z}$ and the term distribution. $p(\overline{z}|\overline{\alpha})$ is the process of topic sampling according to α, the parameter of the prior distribution for topic distribution. $c(v,\overline{v})$ represents the times of cooperation between the expert v and the expert $\overline{v}$ on the edge of $<v,\overline{v}>$ in an expert network.

The parameter π is an equilibrium factor. $f(Q_j, v)$ represents the conditional probability $p(Q_j|v)$ that the expert v is allocated to the topic Q_j under the condition that the expert v is given, while $f(\theta_j, \overline{v})$ represents the conditional probability $p(\theta_j|\overline{v})$ that the expert $\overline{v}$ is allocated to the topic θ_j under the condition that the expert $\overline{v}$ is given. k is the number of the topics and $\sum_{j=1}^{k} (f(Q_j, v) - f(Q_j, \overline{v}))^2$ represents the sum of differences between the expert v and the adjacent expert $\overline{v}$ regarding the topic distribution of k topics. Hence when $M(C, G)$ reaches the minimum, it means that both of the expert - topic probability distribution and the topic - topic term probability distribution will be obtained. In this case, adopt the Gibbs sampling [9] method to solve the expert topic model.

2.3 Analysis on the Associated Relationship Features

The expert relations are quite complex. In this paper, it takes the friendship, the colleagueship and the guidance relationship between the experts into account to make an analysis and automatic extraction. All of these three expert relationships are implied in various expert resources but show different features. The analysis on these three expert relationships reveals the following relationship characteristics.

Generally there won't be a link available on an expert's homepage pointing to the homepages of the other experts, who are just friends of this expert, but they might be mutually followed on their blogs. It's very rare that these experts would collaborate on the same paper since they're generally working in different organizations. However in the case that these experts are colleagues, it would be easy to find an indexical link between their homepages. But it's rare that these experts would follow each other on their blog pages. Since they're working in the same organization, they might collaborate frequently on the papers. Meanwhile the colleagueship between the experts is featured with transmissibility. That's to say, if the expert e_1 is determined as a colleague of the expert e_2, who is also the colleague of the expert e_3, then the expert e_1 can also be considered as a colleague of the expert e_3. In the case that there's a guidance relationship between the experts, it would be easy to find an indexical link between their homepages. Also these experts are always mutually followed on their blog pages. Although they might work in different organizations, they still would collaborate on the same papers. However frequent collaboration on papers can only happen in a certain period, since guidance relationship is of certain timeliness. For example, when Che Wanxiang was studying for a doctor's degree under the guidance of Liu Ting from 2004 to 2008, it happened very often that they collaborated on paper publishing in this period. However this could rarely happen in the other periods. The description of the associated relationship features of expert is shown in Table 1.

Where, use expert evidence document to identify undirected graph model [10] and then to identify experts' homepage automatically. To determine the situation of links among homepages through regular expression matching to obtain the URL link address of the homepage. Then remove the tag from the homepage. Use the Chinese lexical analysis system ICTCLAS of the Chinese academy of Science to segment the terms. Using the method of multi-page Chinese expert metadata extraction based on 3D model

Table 1. Associated relationship features of expert

Type of relations	Associated relationship features			
	Homepage Link	Blog attention	Organization	Collaboration on Papers
Friendship	Not available	Yes	Generally different	Rare
Colleagueship	Available	Rare	Same	Frequent
Guidance relationship	Available	Yes	Might not be the same	Frequent only in a certain period

to extract two kinds of expert metadata information [11], namely, name and organization. Use expert name disambiguation method based on semi supervised graph clustering [12] to solve the problem of the same name as the expert's name, in order to get the accurate expert information. As to the experts' blog information, a web crawler developed by the lab itself has been used to get the experts' blog content and their interest list on the blogs. Regarding the collection of the papers published by the experts, manually collect the papers published by the experts to extract the author list and the publishing time on every paper. The author list will be used to calculate the frequency of the collaboration between the experts, while the publishing time of the paper will be used to analyze the timeliness of the co-authorship.

3 Construction of Expert Relations Extraction Model Integrated with Expert Topic and Associated Relationship Features

3.1 Description of Expert Relations Extraction Model

The Markov Network in the probability graph model [13, 14] is an undirected graph model with strong learning ability and reasoning ability and can express the complicated relations in the network node effectively. From the above analysis, topic features and associated relationship features both have good supporting functions for the extraction of expert relations. We extract relations between experts through constructing the Markov Network to integrate expert topic and associated relationship features. Experts' relations extraction model based on Markov Network diagram shown in Fig. 1:

Where e_1 and e_2 represent separately the experts whose relations are to be extracted, $d_{e1,1}$ and $d_{e2,1}$ represent separately the homepage of the expert e_1 and the expert e_2, $d_{e1,2}$ and $d_{e2,2}$ represent separately the blog page of the expert e_1 and the expert e_2, $d_{e1,3}$ and $d_{e2,3}$ represent separately the collection of the papers published by the expert e_1 and the expert e_2,t_{e1} and t_{e2} represent separately the topic of the expert e_1 and the expert e_2, while $d_{e1,1} - d_{e2,1}$, $d_{e1,2} - d_{e2,2}$ and $d_{e1,3} - d_{e2,3}$ jointly represent the associated relationship features.$t_{e1} - t_{e2}$ represents the expert topic, $d_{e1,1} - d_{e2,1}$ represents that if there's an indexical link available between the expert homepages and if the same organization has been extracted from the expert homepages. $d_{e1,2} - d_{e2,2}$ represents the mutual following of the experts on their blog pages, $d_{e1,3} - d_{e2,3}$

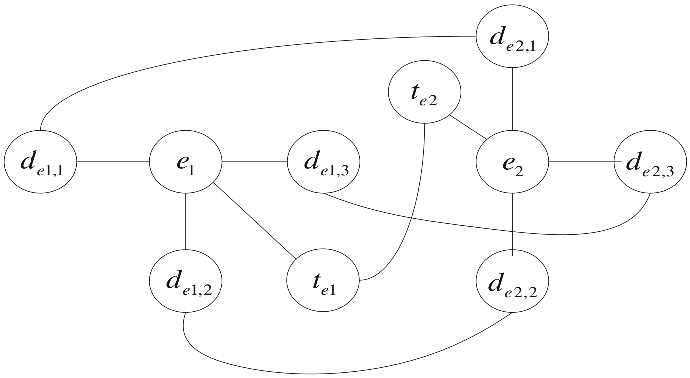

Fig. 1. The extraction model of expert relations based on Markov network

represents the co-authorship between the experts on the papers and $t_{e1} - t_{e2}$ represents the similarity between the expert topics.

3.2 Representation of Expert Relations Extraction Model

3.2.1 Construct Markov Network

Domingos and Richardson [15] in the University of Washington in 2004 put forward Markov Network for the first time, and demonstrates the possibility that the Markov Network as a statistical relational learning unified framework [15]. At present, the international artificial intelligence community generally accepted Markov Network to combine the first order predicate logic and probability graph model perfectly. It provides an effective method for the representation and processing of complexity and uncertainty problem. It is a undirected graph probability model, each vertex representing the random variable or the random vector, and the edges represent the conditional dependence between variables. For any edge, the maximum clique (full connected sub graph) is called factor. In the learning task, Markov Network was usually expressed in a log linear model, namely, each factor is represented as the index weighted sum of the feature function of the variable set. The formula listed as below:

$$P(X_1, X_2, \cdots X_n) = \frac{1}{Z}\exp(\sum_i \omega_i f_i(C_i)) \tag{2}$$

where the characteristic function $f_i(C_i)$ is an arbitrary real-valued function for the variable set C_i and w_i is the weight of the characteristic function $f_i(C_i)$. For calculation purpose, the characteristic function can be defined by the following formula:

$$f_i(C_i) = \begin{cases} 1 & \textit{Conformity between the characteristics and the tags} \\ 0 & \textit{Inconformity between the characteristics and the tags} \end{cases} \tag{3}$$

If there's an indexical link available between the homepages of the experts whose relations are to be extracted, then there should be undirected edges available for the connection between the directional characteristics of the links in a Markov network, otherwise no edges will be available for the connection. If the experts whose relations are to be extracted work in the same organization, then there should be undirected edges available for the connection between the organization characteristics in a Markov network, otherwise no edges will be available for the connection. If mutual following can be found on the blogs of the experts whose relations are to be extracted, then there should be undirected edges available for the connection between the characteristics of blog attention in a Markov network, otherwise no edges will be available for the connection. In the case that the experts whose relations are to be extracted have been collaborating on paper publishing frequently, there should be undirected edges available for the connection between the co-authorship characteristics in a Markov network; otherwise no edges will be available for the connection. When the topics of the experts whose relations are to be extracted are quite similar, then there should be undirected edges available for the connection between the topic features in a Markov network, otherwise no edges will be available for the connection.

The approach to judge similar topic is: Since the extracted topic always consists of a series of topic terms, then the topic can be represented with a topic term vector. When the cosine of the included angle between the vectors is used to describe the similarity degree of the topics, the topic similarity can be calculated according to the formula shown as below:

$$\mathrm{Sim}(\mathrm{t_i}, \mathrm{t_j}) = \frac{\overrightarrow{t_i} \times \overrightarrow{t_j}}{\left|\overrightarrow{t_i}\right| \times \left|\overrightarrow{t_j}\right|} \tag{4}$$

where $Sim(t_i, t_j)$ represents the topic similarity between the expert i and the expert j, $\vec{t_i}$ represents the topic vector of the expert i and $\vec{t_j}$ represents the topic vector of the expert j. Through the definition of a threshold, the topics are similar when the vector is greater than the threshold. Otherwise it can be determined that the topics are not similar.

3.2.2 Formalized Representation of the Model

Expert relations extraction can be transformed into an expert relations classification problem to get the solutions. The core is to solve the probability of the relations, which can be respectively classified into friendship, colleagueship or the guidance relationship under the condition that the experts have conformed to certain associated relationship features and topic. When a type of relations shows the maximum probability, it means that this is also the final relations between the experts. According to the joint probability distribution in a Markov network as shown in Formula (2), the joint probability distribution of the expert relations extraction model based on the Markov network can be expressed with Formula (5) as shown below:

$$P(X = x) = \frac{1}{Z}\exp\left[\sum_m \omega_m f_m(C_m)\right] \tag{5}$$

where x represents a type of expert relations, $P(X = x)$ represents the probability that the expert relation X is affiliated to x, Z is a normalization factor and m represents the type of the characteristic. When $m = 5$, it indicates the integration of the expert topic on the basis of Table 1 to achieve a unified representation of the expert relations characteristics, which are shown in Table 2.

Where $f_m(C_m)$ represents the characteristic function of the variable set C_m and w_m is the weight of $f_m(C_m)$. Regarding the following four characteristics including the similar

Table 2. Characteristics of expert relations

Type of relations	Expert topic	Associated relationship features			
	Domain related knowledge	Homepage Link	Blog attention	Organization	Collaboration on papers
Friendship	Might not similar	Not available	Yes	Generally different	Rare
Colleagueship	Similar	Available	Rare	Same	Frequent
Guidance relationship	Similar	Available	Yes	Might not be the same	Frequent only in a certain period

domain knowledge, the availability of homepage link, the same organization and the blog attention, their characteristic function is:

$$f_m(C_m) = \begin{cases} 1 & \text{Conform to the type of characteristic} \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

As to the co-authorship characteristic, it can be integrally grouped into frequency and infrequency. In the case of frequent collaboration, there're two situations: frequent collaboration and frequent collaboration only in a certain period. Hence the characteristic function can be:

$$\mathrm{f_m(C_m)} = \begin{cases} 1 & \text{Frequent collaboration} \\ 1/2 & \text{Frequent collaboration in a certain period} \\ 0 & \text{Rare collaboration} \end{cases} \tag{7}$$

3.3 Probability Inference and Parameter Learning for Expert Relations Extraction Model

Under the condition of the known Markov Network, the probability inference process of Markov was to solve the problem of maximum likelihood (MPE problems) [13, 16] interpretation for this model. The inference process of extraction model of expert relations was to solve the maximum probability of classification of expert relations under the condition that the associated relationship features and topic between the experts was known. Probability formula as below:

$$\begin{aligned}\arg\max P(R_x|G_M) &= \arg\max P(X=x)\\ &= \arg\max\left\{\frac{1}{Z}\exp\left[\sum_m \omega_m f_m(C_m)\right]\right\}\\ &\propto \arg\max\left\{\sum_m \omega_m f_m(C_m)\right\}\end{aligned} \tag{8}$$

where, $\arg\max P(R_x|G_M)$ represents that in the case of given relation Markov Network G_M, expert relations belongs to the maximum probabilities of the category R_x. Since the normalization factor Z and the exponential function exp will not affect the maximum probability, and therefore there is more than the equivalent conversion.

For the probability graph model, the inference algorithm is generally effective, such as the Cliquetree Propagation algorithm and the Variable Elimination algorithm as well as approximate inference algorithm of Monte Carlo algorithm. In this paper, the Gibbs sampling algorithm is used to solve the Formula (8).

For the parameters learning method of probabilistic graph, there are two kinds, namely, structure learning and parameter learning [13, 16]. The structure learning should consider the structure of the network and consider the parameters in the network. And the parameters learning only consider the network parameters in the existing network structure. As the structure of the network of the extraction model of expert relations based on the Markov Network was confirmed in this paper, so parameter learning method is considered for estimating the parameters of the model. In this paper, the maximum likelihood estimation is used to estimate the weight of the feature. Process as follows:

Firstly, take the logarithm of the joint probability distribution in Formula (6) to obtain the corresponding likelihood function as shown in Formula (9).

$$\log P(X=x) = \sum_m \omega_m\, f_m(C_m) - \log Z \tag{9}$$

Then calculate the partial derivative of a random weight in Formula (8) with the derivation process shown in Formula (10).

$$\begin{aligned}\frac{\partial}{\partial\omega_m}\log P(X=x) &= \frac{\partial}{\partial\omega_m}\sum_m \omega_m f_m(C_m) - \frac{\partial}{\partial\omega_m}\log Z\\ &= \sum_m f_m(C_m) - \frac{1}{Z}\frac{\partial}{\partial\omega_m}Z\\ &= \sum_m f_m(C_m) - \frac{1}{Z}\sum_{x'}\frac{\partial}{\partial\omega_m}\exp\left[\sum_m \omega_m f_m(C_m)\right]\\ &= \sum_m f_m(C_m) - \sum_{x'} P_{\omega_m}(X=x')\sum_m f_m(C'_m)\end{aligned} \tag{10}$$

where $\sum_{m} f_m(C_m)$ represents the sum of the characteristic values for m features and $\sum_{x'} P_{w_m}(X = x') \sum_{m} f_m(C'_m)$ represents the sum of probabilities for all possible value assignments. Obtain the present weight through Formulas (9) and (10) and then get all of the unknown weights according to the gradient descent algorithm.

4 Experiments and Analysis

4.1 Experiment Data Preparation

In order to verify the effectiveness of the expert relations extraction integrated with expert topic and associated relationship features, this paper collects randomly totally 200 experts, who are artificially tagged into the following three types of relationships, including friendship, colleagueship and guidance relationship in Natural Language Processing and Information Retrieval. Where the correlation characteristics of 150 tagged experts are used as the training data and the rest are used as the test data.

4.2 Experimental Evaluation

In order to evaluate comprehensively the effectiveness of the extracted model, this paper makes a statistical analysis on different methods in terms of the following two indicators, Precision (P) and Recall(R) in the experiment, based on which F value is used as the final evaluation index to evaluate the effectiveness of the mentioned method, since F value is able to reflect perfectly the effect in recognizing the expert relations. The increase in F value represents a better recognition effect. Meanwhile this paper provides the following formulas to calculate separately the Precision Recall and F-value. T_p is the number of identifying expert relations correctly based on model, F_p is the number of identifying expert relations based on model. F_n is the number of pair of experts whose relations are to be extracted.

$$\Pr e = \frac{T_p}{F_p}, \mathrm{Re}c = \frac{T_p}{F_n} \quad F - value = \frac{2 \times P \times R}{P + R} \tag{11}$$

4.3 Experimental Design and Analysis

In order to verify the effectiveness of the method proposed in this paper, which designs two experiments for the verification of the model. In Experiment I, it makes a contrast on the Precision, Recall and F-value in the expert relations extraction task separately through our method, the SVM method [6] and the Sequence Pattern Mining method [8]. In Experiment II, it makes a contrast on the F values of the expert relations extraction models with and without considering the expert topic in the expert relations extraction task.

Experiment I: It makes an extraction of the expert's friendship, colleagueship and guidance relationship separately through the method proposed in this paper, the SVM method and the sequential pattern mining method and then calculates Precision 、Recall and the F value according to the extraction result. The expert relations extraction results through the above three methods in the contrast experiment are shown in Table 3:

Table 3. Contrast results based on different methods

	SVM	Sequence pattern mining	Our approach
P (%)	72.27 %	75.14 %	77.35 %
R (%)	68.61 %	70.47 %	72.06 %
F (%)	70.39 %	72.73 %	74.61 %

The analysis on the experimental results in Experiment I reveals that Precision, Recall and the F value have been improved to some extent through our method compared with the SVM method and the sequential pattern mining method. Also the integration of the expert topic and associated relationship features contributes to the better recognition of expert relations.

Experiment II: Firstly, utilize the method proposed in this paper to extract the expert relations and then calculate the F value according to the extraction result. After that, construct an expert relations extraction model without the consideration of the expert topic. The F values of both models will be calculated according to Formula (11) with the results obtained in the contrast experiment as shown in Fig. 2.

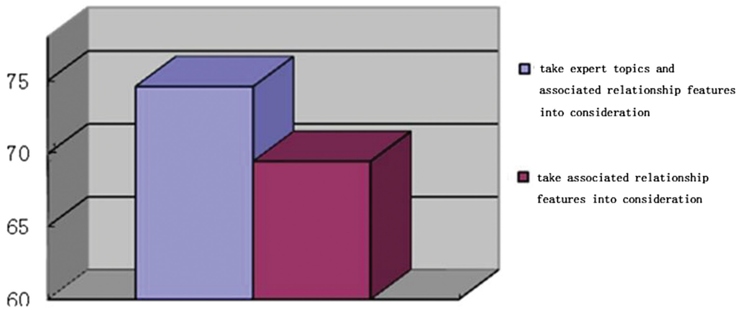

Fig. 2. Influence of different number of features of experts on F-value in the test sets

The analysis on the experimental results in Experiment II reveals that without the consideration of the expert topic, the expert relations extraction model based on the Markov network won't perform as well as the model that has taken the expert topic into account in terms of the F value. Since the expert topic is able to represent the expert's domain knowledge, then the topic would play a good supporting role in the recognition of the expert relations.

5 Conclusions

Combined with their own characteristics of the experts, this paper makes an analysis on the friendship, the colleagueship and the guidance relationship between the experts. Through the integration of the expert topic and the associated relationship features, this paper constructs an expert relations extraction model based on the Markov Network. The experimental result shows that the expert relations extraction model proposed in this paper has performed very well in the recognition of the friendship, the colleagueship and the guidance relationship. Then our further research will focus on the consideration of a method to quantize the strength of the expert relations for the accurate extraction of the expert relations and at the same time for the quantization of the expert relations strength to improve further the expert relations extraction model.

References

1. Yangarber, R., Grishman, R.: NYU: description if the proteus/PET system as used for MUC-7. In: Proceedings of the 7th Message Understanding Coferences, pp. 117–121 (1998)
2. Zhao, S., Grishman, R.: Extracting relations with integrated information using kernel methods. In: Proceeding ACL 2005 Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics, pp. 419–426 (2005)
3. Zhou, G., Su, J., Zhang, J., Zhang, M.: Exploring various knowledge in relation extraction. In: Proceeding ACL 2005 Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics, pp. 427–434 (2005)
4. Suzuki, J., Isozaki, H., Maeda, E.: Convolution kernels with feature selection for natural language processing tasks. In: Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics, pp. 199–206 (2004)
5. Yu, H., Qian, L., Zhou, G., Zhu, Q.: Chinese semantic relation based on unified syntactic and entity semantic tree. J. Chin. Inf. Process. **24**(5), 17–23 (2010)
6. Han, B., Lin, H.: Characters extraction based on support vector machine. In: Wu, H. (ed.) Information Control Conference of Chinese 2007, pp. 335–341 (2007)
7. Yao, C., Di, N.: Solution to large scale extraction of social relations of persons based on web. Pattern Recogn. Artif. Intell. 740–744 (2007)
8. Li, D., Luo, Z.: Persons relationship recognition based on sequential pattern mining. Adv. Comput. Linguist. China 582–587 (2009)
9. Griffths, T.L., Steyvers, M.: Finding scientific topics. In: Proceedings of the National Academy of Sciences, pp. 5228–5235 (2004)
10. Mao, C., Yu, Z., Wu, Z., Guo, J., Xian, Y.: Undirected graph model for expert evidence document recognition. J. Softw. **24**(11), 2734–2746 (2014)
11. Pan, X., Shen, T., Yu, Z., Wu, Z., Guo, J.: Multi-page Chinese expert metadata extraction method based on the 3D model. J. Comput. Inf. Syst. **9**(6), 2251–2259 (2013)
12. Jiang, J., Yan, X., Yu, Z., Guo, J., Tian, W.: A Chinese expert disambiguation method based on semi-supervised graph clustering. Int. J. Mach. Learn. Cybern. **5**(1), 1–8 (2014)
13. Jordan, M.I.: Graphical models. Stat. Sci. **19**(1), 140–155 (2004). (Special Issue on Bayesian Statistics)
14. Koller, D., Friedman, N.: Probabilistic Graphical Models: Principles and Techniques. The MIT Press, Cambridge (2009)

15. Domingos, P., Richardson, M.: Markov logic: a unifying framework for statistical relational learning. In: Proceedings of the ICML 2004 Workshop on Statistical Relational Learning and its Connections to Other Fields, Banff, pp. 49–54 (2004)
16. Koller, D., Friedman, N.: Probabilistic Graphical Models: Principles and Techniques. Massachusetts Institute of Technology Press, Cambridge (2009). doi:10.1007/978-3-642-38466-0_28