International Journal of Advanced Intelligence
Volume x, Number 0, pp.XXX-YYY, MMM, 2009.

Knowledge Graph based Question and Answer System for Cosmetic Domain[*]

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Received (Day Month Year)
Revised (Day Month Year)

With the development of E-commerce, the requirements of customers for products become more detailed, and the workload of customer service consultants will increase massively. However, the manufacturer is not obliged to provide specific product ingredients on the website. Therefore, it is necessary to construct a KBQA system to relieve the pressure of online customer service and effectively help customers to find suitable skincare production. For the cosmetic filed, the different basic cosmetics may have varied effects depending on its ingredients. In this paper, we utilize *CosDNA* website and online cosmetic websites to construct a cosmetic product knowledge graph to broaden the relationship between cosmetics, ingredients, skin type, and effects. Besides, we build the question answering system based on the cosmetic knowledge graph to allow users to understand product details directly and make the decision quickly.

Keywords: Knowledge Graph construction; Question-Answer system; Name entity recognition; E-commerce domain.

1. Introduction

Recently, knowledge engineering has received widespread attention. The existing large-scale knowledge bases such as Freebase[1], Wikidata[2], DBpedia[3], and YAGO[4] contain a huge amount of structured data or semi-structured data with multiple fields. These knowledge bases were initially designed to improve the capabilities of search engines and enhance the user searching experience. Knowledge graph technology provides a method to extract structured knowledge from massive textual and visual data.

It has been widely used in the fields of the intelligent search engine, the intelligent question answering system (QA), personalized recommendation, and industrial decision making. However, those generic knowledge graphs cannot delicately support the domain-specific applications because it requires in-depth domain knowledge and usually accessible only by experts in these fields. Therefore, there are also domain-specific knowledge bases like MusicBrainz[5], and the IMDb bases to describe specific domains such as common knowledge, medical, economical, and entertainment.

Recently, the e-commerce industry is developing rapidly, and the users are using natural language queries more frequently to obtain the answers. The automatic QA related application can partially relieve the pressure of manual customer service. Thus, the intelligent QA system is becoming an inevitable trend in information retrieval. However, customers expect to grasp relevant product information before purchasing products accurately. The combination of the knowledge graph and QA system dramatically enhances the professionalism of the customer service. The QA system can increase the convenience for users to obtain information, and the knowledge graph as a structured data source can provide higher quality knowledge for QA systems. The knowledge graph-based question answering (KBQA) system receives the user's natural language as input and retrieves the answers from the knowledge base and returns the response to users as in natural language.

In this paper, we establish a knowledge graph of cosmetics to facilitate users to more quickly and accurately obtain information about whether the product is suitable for the users' skin. The system can answer ingredients related to cosmetic products, effects, skin conditions, and other information, which help customers who without chemical knowledge to understand the characteristics of the product and reduce adverse skin allergies and harmful reactions. We collect cosmetics information from cosmetic related websites like CosDNA and Cosmetic skin solutions. On this basis, a pipeline knowledge graph-based question answering system is implemented: Firstly, we utilize the BERT-CRF model to recognize the cosmetic related entities of the question. Secondly, we use the pre-trained language model (BERT) to obtain a query representation and find the most similar template corresponding question by calculating the cosine distance. According to the question template, we can receive the relationship between recognized entities. Then, we use the Cypher search command statement to find an answer in the knowledge graph based on the semantic information from the question template. Finally, we return the natural language answer to the user.

The remainder of this paper is organized as follows: Section 2 presents some related works of knowledge graph and answering question system. Section 3 describes the methodology of domain-specific knowledge graph construction and knowledge graph-based QA system. Section 4 shows the experiments and draws the results. Section 5 makes some conclusions and presents future works.

2. Related Work

Recently, knowledge engineering provides a more effective way for the expression, organization, and utilization of massive data[6]. The domain-specific knowledge graph has desirable advantages of accuracy and fine granularity and can adequately support knowledge reasoning and knowledge retrieval applications in agriculture[7], medical[8], biomedical[9], educational fields[10]. Knowledge graph construction approaches are generally categorized as follows: manual construction approach or supervised or semi-supervised modeling methods.

The manual knowledge graph construction highly depends on experts and is able to obtain high accuracy, but lacks in scalability, which is usually adopted for domain-specific problems. The automatic knowledge graph construction includes an entity recognition task and relation extraction task. The entity recognition task is to extract concepts of interest from structured and unstructured data. The Wikify extract entities by utilizing two disambiguation methods to link the Wikipedia page with the corresponding entities[11]. The Tagme[12] and Spotlight[13] extract and link entities to a knowledge graph in a similar way. The Spotlight uses DBpedia as its knowledge base. Recently, entity extraction is regarded as a sequence annotation problem. The CRF has been widely applied in entity extraction task[14], such as terminology recognition[15] and Chinese entity recognition[16]. Recently, deep learning methods are exploited in this task. Several hybrid variants of RNN was proposed to capture the dependency of the context[17]. Moreover, the relation extraction task is transformed into a relation classification problem. The most representative work was made by Zeng et al., who utilized CNN as an encoder to extract semantic information[18]. Zhang and Wang applied variants of RNN to learn the relation pattern in the raw text[19,20]. The supervised approaches highly depend on data label performance, which is time-consuming. Therefore, the distance supervised method has been well studied. To alleviate the wrong labeling problem in the distance supervised training, Lin et al. combined distance supervised method and attention mechanism to identify the relations[21].

The knowledge graph-based question answering system aims to use facts in the knowledge graph to provide accurate and concise results. It helps users more efficiently access billion-scale knowledge without understanding its data structure[22]. The standard strategy used in the QA system includes the following: semantic parsing-based approach[23], information extraction approach [24], and vector modeling approach [25]. The information retrieval-based approach search answers from the KB based on the ranking techniques[23]. The semantic parsing method transforms natural language into logical semantic expression. The logical form of the query through the corresponding query in the knowledge base to obtain the answer [24]. For the vector modeling method, both the question and the candidate answer are mapped to distributed expression to calculate the dot product to select the final answer.

In this paper, the distribution expression and information extraction methods are applied in the experiment. We utilize the pre-trained language model to recognize the entity and extract relation by searching the candidate query paths. Given the entities and relations, we can make up a query to search the final answer in the knowledge graph.

3. Methodology

The whole framework of this paper as follows: Firstly, we build a knowledge graph of cosmetic products to explore a broader relationship between cosmetics and ingredients. Secondly, we provide a question answering system based on a pre-defined cosmetic knowledge graph, which offers more intelligent consultant approaches for online stores. Therefore, the related information of essential components is illustrated in the following subsections.

3.1. *The knowledge graph construction*

3.1.1 *The knowledge acquisition*

With the development of E-commerce, people are more inclined to investigate the details before buying a product. People will carefully analyze the product's formula and function. For cosmetic products, it is difficult for ordinary users to directly understand the effect of products' ingredients on the skin. Based on this inspiration, we hope to establish a knowledge graph based QA system where users can search for these chemical ingredients to understand whether these products meet the purchase needs. In this section, we illustrate the construction process of the cosmetic knowledge graph, which divided into three parts: knowledge acquisition, knowledge representation, and knowledge storage.

In this section, we tap into the broad relationship between cosmetics, ingredients, effects, risk factors, compatible skin types, and other information. Due to the lack of a professional knowledge database in the cosmetic field, we collect relevant information through a large number of cosmetic online stores and review websites, which includes cosmetic products and product reviews. The *CosDNA* is an essential source for cosmetic knowledge graphs because it converts a variety of cosmetic products and rich ingredient knowledge, which can be seen in Table 1. We construct the knowledge graph of cosmetics by combining the basic principles and giving the definition corresponding nodes and relations. The cosmetic entities mainly include *the Cosmetic category,*

Table 1. All ingredients of a product and related effects.

Ingredients	Utility	Acne	Irritant	Safety
Water	Solvent	0	0	1
Rosa Canina Fruit Oil	Emollient	1	0	1
Bentonite	Viscosity control	0	0	2
Alcohol Denat	solvent	0	5	5
Glycerin	Moisturizer	0	0	1-2
Methylchloroisothiazolinone	Preservative	0	0	6
Sage	Anti-inflammatory, antioxidant, Astringent	1	0	1

Table 2. The entity definition of the cosmetic knowledge graph.

Cosmetic Entity	*Content*	*Example*
Categories	The category ID	C-01
	Type	Face serum
	: Label	Genres
Products	Brand name	HABA White Lady
	Rating	Pretty good
	Price	4732 JPY
	Effects	Whitening and blemish, tighten pores
	Instruction	Take 4-5 pushes in the palm. Apply on the entire face. For partial use, adjust according to the skin condition.
	: Label	Products
Ingredients	The ingredients ID	9067-32-7
	The name of ingredients	Sodium Hyaluronate
	Acne	0
	Utility	Moisturizer
	Irritation	0
	Safety	1
	: Label	Ingredients
Skin conditions	Skin type ID	S-01
	Skin type name	Sensitive skin
	: Label	Skin condition

Cosmetic products, Ingredients, *Skin conditions*. The relationships in the knowledge graph indicate the factual relationship that occurs between different entities. Based on the pre-defined entities, we can compile several relations:

(1) *Rating, Price, Effect, Instruction*: show the essential attributes of products.
(2) *Evaluate:* show user rating scores of cosmetic products.
(3) *Type*: describes the skin suitable for cosmetic products.
(4) *Part-Of*: represent the ingredients in cosmetic products.
(5) *Suit-To*: represent skin type suitable for the product.
(6) *Utility*: describe the role of ingredients in cosmetic products.
(7) *Acne, Irritation, Safety*: describe the attributes of the ingredients.

Finally, we obtain triplets of nodes and relationships related to cosmetic products. After duplicating all triplets, we collect 3428 triplets in the cosmetic knowledge graph.

3.1.1. *The knowledge representation and storage*

A knowledge graph can be defined as a system in which all entities are stored in the form of connected graphs or linked data, which represent as $G = \{E, R, S\}$. The entity set $E = \{e_1, e_2, \dots, e_i\}$ represent the entities in the knowledge graph, which includes i

entities. Each directed edge is an association between two entities and the directed edges are collectively $R = \{r_1, r_2, \dots, r_j\}$, which contain j relationships. The S represents the triplets in the knowledge graph, which includes entities and relationships. In the feature e_i, e_j, if there is an association between e_i and e_j, then the triplet $<e_i, e_j, s_{ij}>$ is the directed edge of $e_i \rightarrow e_j$, where the $s_{ij} \in S$ is the directed association of e_i and e_j.

In terms of knowledge storage, the graph structure has two generic storage approaches, which are RDF and graph database. The structure of the graph database is more general than the RDF database, which realizes the storage of graph data using the nodes, edges, and related attributes in the graph structure. Therefore, we use the open-source NEO4j graph database to store knowledge graphs. The Neo4j provides complete graph searching command and supports a variety graph mining algorithm. We can use Cypher language to import and search data in the knowledge graph. Besides, we can use the Neo4j-import tool to import nodes and relationship files into the graph database rapidly. Based on the concept mentioned above, the cosmetic knowledge graph can be constructed. We utilize Cypher CREATE, Cypher LOAD-CSV, and Neo4j import tools to save the cosmetic triplets. Figure 1 is a product in the cosmetic knowledge graph.

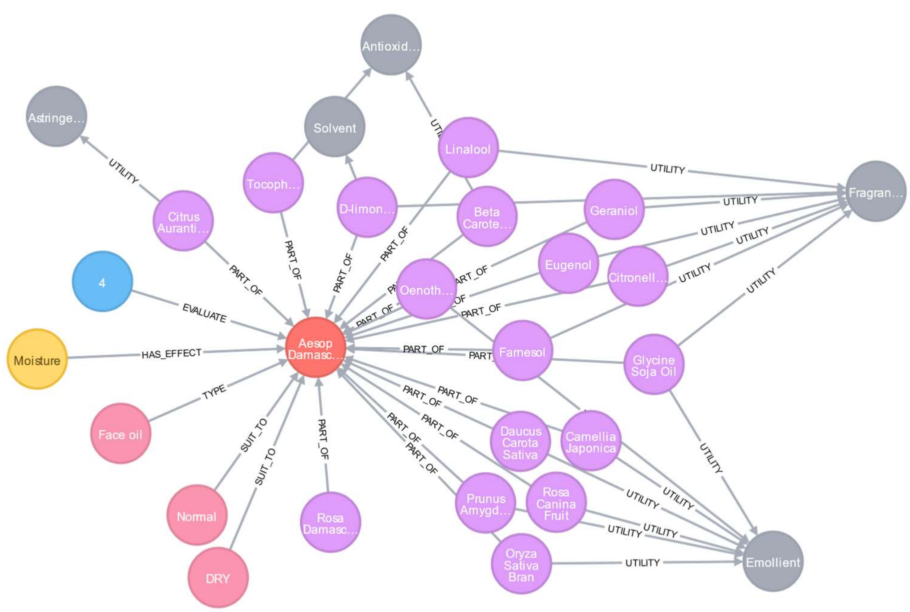

Fig. 1. An example of the Aesop facial oil in the cosmetic knowledge graph

3.2. ***Knowledge graph-based question answering system***

Current question answering systems have excellent performance on the specific domain and factoid questions because of the use of structured data. The knowledge graph can help the QA system to obtain a better understanding of the queries and generate natural language answers. Therefore, we adopt the pipeline approach to construct a cosmetic knowledge graph-based question answering system. Specifically, we show the whole construction process in Figure 2, which is divided into several steps :

- Firstly, we need to do a semantic analysis of the user's question. Inspired by the pre-trained language model and transfer learning strategy, we utilize the BERT-CRF model to recognize the entities in a query.
- Secondly, we narrow down the searching scope according to the recognized entity categories. We utilize the text-similarity approach to find the most similar question template with the user's query. Therefore, the query representation and similarity measurement are applied in this section.
- Finally, we can generate a final structured knowledge graph query based on entity recognition and relation extraction. This search query is performed in the Neo4j knowledge graph to search for related information. Then, the system returns the answer with a pre-defined template.

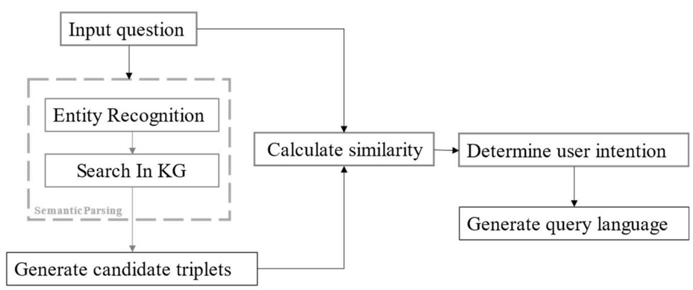

Fig. 2. The construction process of knowledge graph-based question answering system

3.2.1. *Entity recognition*

Semantic analysis is the first part of the QA system, which includes the entity recognition task and relation extraction task. Firstly, we identify the entities of the user's question based on the BERT-CRF model. In this part, we utilize the BERT model to obtain powerful context-dependent text features. Therefore, we fine-tune the pre-trained BERT model as the encoder to learn semantic features of questions. Then, we utilize the Linear-Chain CRF model as a classifier to recognize the entities. The CRF classifier can capture the dependency relationship between the output entity labels. Be specifically, given the input question with several tokens $W = \{W_1, W_2, \dots, W_n\}$, the BERT model constructs token embeddings $E = \{E_1, E_2, \dots, E_n\}$ of the question by

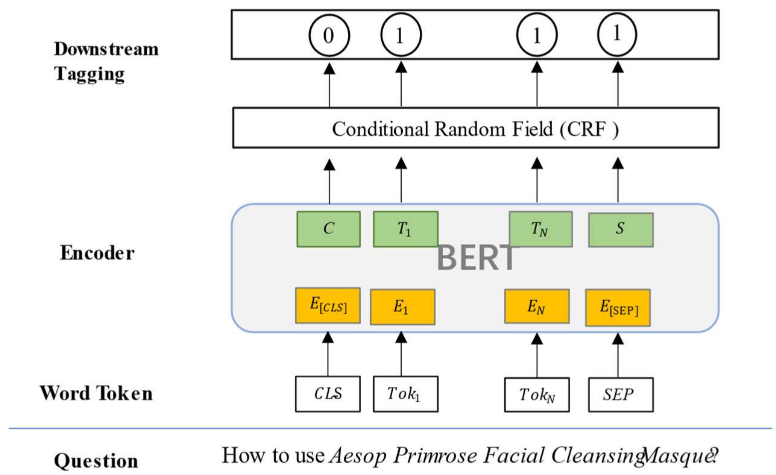

Fig. 3. The BERT-CRF model

connecting word piece embeddings, position embedding, and the segment embeddings. Then, token embedding is feed into encoder block, which is composed of multi-attention sublayers and the position-wise fully connected sublayers. The output of the block encoder is the question representation H=$\{o_{[cls]}, o_1, o_2, \dots, o_{[sep]}\}$. We feed the final contextual question representation into the downstream CRF layer to recognize entities of each token. Given the hidden contextual question representation of BERT model H=$\{o_{[cls]}, o_1, o_2, \dots, o_{[sep]}\}$and sequence label $Y = \{y_{[cls]}, y_1, y_2, \dots, y_{[sep]}\}$, the score of the sequence is defined as:

$$S(H,Y) = \sum_{i=1}^{n} A_{y_i y_{i+1}} + \sum_{i=1}^{n} P_{i,y_i} \tag{1}$$

$A_{y_i y_{i+1}}$is the transition score of output tag, A_{ij} represents the score from label *i* to label *j*. To learn the CRF parameters, we use maximum likelihood training estimation. Given the hidden state and label sequence, the model is trained to maximize the log-probability of the correct tag sequence:

$$\log\big(p(y|H)\big) = S(H,Y) - log\left(\sum_{\tilde{y} \in Y_H} e^{S(H,\tilde{y})}\right) \tag{2}$$

where θ is the network parameters. The Y_H refer to all possible tag sequences. The dynamic programming can be used efficiently to compute transition score and optimal tag sequences via the Viterbi algorithm. During the evaluation, the most likely sequence is obtained by Viterbi decoding.

3.2.2. *The relation extraction and linking*

The conventional method utilizes the pattern matching method to find the appropriate question template. The advantage of using a template matching method is that it does not need enormous training and massive manual annotation. The template matching implementation requires strict language standards by language experts to match the relationships between entities from the text. Therefore, we use a text-similarity approach to select candidate query paths in the knowledge graph. According to the semantic analysis of the user's question, we can recognize specific entities in question. We can narrow down the searching scope based on the identified entities. Then, we extract all the triplets related to identified entities in the knowledge graph as candidate templates. After that, we utilize the pairwise model to calculate the similarity between question and candidate templates. Finally, we can determine the user's intention and generate the database query language. For instance, we receive a question that " What skin type is this Lamer cream suitable for? ". We can obtain two entities, which are "Cosmetic" (Lamer cream). Then, we extract all triplets related to "Lamer cream", such as (ingredients)-[:PART_OF]->(Lamer cream), (skin conditions)-[:SUIT_TO]->(Lamer cream), (Effects)-[:HAS_EFFECT]->(Lamer cream), (categories)-[:TYPE]->(Lamer cream) and so on. Subsequently, we transform the knowledge into the natural language to calculate the similarity, like "Suit to lamer cream". The text similarity measurement has two components, which are query representation and similarity calculation. Thus, we utilize the feature-strategy BERT model to learn the query and choose the cosine function to measure distance. Based on the similarity score, we can confirm the final question template.

3.2.3. *The answer searching*

In this section, we utilize the Cypher language to search the answer in cosmetic product graphs. The question template contains the entities and relations that compose a triplet $<e_i, e_j, s_{ij}>$ to reflect the user question. Therefore, we can use the triplets to generate Cypher language: *Match (a)-[:Relation]-(b) where b.name = "Entity" return a.name*. For instance, we receive a query that "What is the utility of this ingredient?" We utilize the NER model to recognize the ingredient entity. Based on the attribute extraction, we can extract the relation is the "*Utility*." Therefore, the Cypher searching language is: *Match (a)-[:Utility]-(b) where b.name = "Fragrance" return a.name*. Based on the answer template, the system can return the answer, "The utility of Geraniol is Fragrance."

4. Experiments and Discussion

For the experiments, we illustrate the experiment setting in detail, which includes text pre-processing, the question manual annotation, and the training hyper-parameters. For the discussion section, we also evaluate the QA system based on actual answers.

4.1. *Dataset and hyper-parameters*

In this paper, we illustrate the experiment in detail. Due to the lack of dataset on the cosmetic field, we need to manually construct an entity recognition dataset based on the collected questions. We annotate the cosmetic entities with 0/1 symbol rather than the BOI system. The label 0 represents the non-entity, and label 1 represents the entity. For example, the question "How to use this serum?" will be annotated as "0 0 1 0 1". We collect the 3000 questions from the online cosmetic website and utilize the *Standford's CoreNLP* tool to avoid noise, like tokenization and word lemmatization. After the text-processing, we divide the collected data into a training dataset with 2000 sentences, the validation data with 500 sentences, and the test data with 500 sentences. For the training parameters, Table 4 illustrates the hyper-parameter of the BERT model for entity recognition.

Table 4. The hyper-parameters of the BERT model

Hyper-parameter	*Options*
Batch size	32
optimizer	Adam
Learning rate	2e-4
Max length	50
Transformer	BERT base (12-layers, 768-hidden states, 12-heads)

4.2. *Results*

In this paper, we apply two supervised classifications based on the cosmetic dataset, which are BERT-Softmax and BERT-CRF. In general, we can evaluate the performance based on the F1-score. In Table 5, we can see the results of two learning models on the entity recognition task. Table 5 indicates that the CRF performs slightly better than the Softmax classifier. The Softmax classifier only considering the current time step annotates the tokens. The CRF is better than Softmax classifier because it can learn the dependencies among entities.

Table 5. The performance entity recognition of user's questions

	Precision	*Recall*	*F1-value*
BERT-Softmax	*0.869*	*0.965*	*0.917*
BERT-CRF	*0.926*	*0.928*	*0.924*

4.3. *Case studies and error analysis*

In this section, we provide some typical examples to illustrate the performance KBQA system. Due to the lack of a professional dataset, we follow the pre-defined entities and relations, collecting and designing 100 frequently asked questions. The evaluation criteria is that we will accumulate a point if the system can give the correct answer. Among these 100 questions, we can get nearly 78% correct answers. Although some problems use different representations, the system can majority return the answer with the correct intention. For the 22% unable answered question, the system directly response “Sorry, I don’t understand.” We illustrate some answers to the cosmetic knowledge graph-based QA system in Table 6.

Based on the examples listed in Table 6, we can find that the system performs better about attributes related questions. The Q1, Q2, Q4 represent the using instruction of the product, the ingredients contained in the product, and the effect of the product. However, Q3, Q5, and Q6 show the system is not flexible enough. The Q3 “Can Aesop Control remove acne” refer the cosmetic product and effects. The system returns the answer with all the effects of the products, which is not clear to get the key point of the user’s intention. In fact, the Q3 contains more than one question, including the efficacy of the cosmetic product and whether the effects include acne cure. The system cannot answer the multi-hop problem. It also shows that the cosmetic knowledge graph construction lacks specific detail related to the product’s effects. Besides, the Q5 “What is feel like when you use Aesop Fabulous Face Oil?” means the using feeling of this product. However, the system can not answer the feeling and only return the texture because the “feeling” property does not exist in the knowledge graph.

Table 6. The performance of the KBQA system.

	Question	Answer
Q1.	How to use Aesop Primrose Facial Cleansing Masque?	The use instruction is “Apply twice a week to cleansed and exfoliated skin, and rinse with warm water after 15 minutes”.
Q2.	What are the ingredients of Aesop damascene rose facial treatment?	It contains Rose petals, orange flowers, violets.
Q3.	Can Aesop Control remove acne?	It uses mild chemical ingredients to exfoliate treatment, thoroughly cleans the acne area without peeling, and contains herbal extracts to calm and balance the skin.
Q4.	What the main function of HABA white lady?	It can reduce dullness and whiten skin.
Q5.	What is feel like when you use Aesop Fabulous Face Oil?	The texture is lightweight oil.
Q6.	How does Bose Pro-Xylane work in the skin?	Sorry, I don’t understand.

The pipeline approach refers to extracting the entities and relations are two independent steps. The advantage is that these two extraction models have high flexibility. The entity recognition task and relation extraction task can use independent methods and do not need to be labeled entity and relation at the same time. However, it might cause the error accumulation because the error of entity recognition will affect the relation extraction.

5. Conclusion

In conclusion, to alleviate the pressure of customer service and provide users with convenient queries for purchasing skincare products, we are committed to building a question and answer system based on the knowledge of skincare products. In this study, we assume that the user's buying behavior depends on the product's composition, effects, suitability, etc. Based on the inspiration, we reference the information from some online cosmetic websites and a cosmetics ingredients website to construct a cosmetic knowledge graph. Then, we store the structure knowledge data in the NEO4j database by using Neo4j import tools. For the knowledge application, we design a knowledge-based question-answer system based on the pipeline method to provide convenient information query of cosmetic products. Specifically, we utilize the BERT-CRF model to recognize the cosmetic entities in the question. Because of the understanding of the chemical components, the BERT model can provide more external knowledge to learn the entities. The CRF model can consider the dependency between tokens. For the relation extraction, we consider the BERT model and cosine similarity to determine the question template.

The future work includes that we can apply the unsupervised training method to increase the scope of the knowledge base, which is labor-saving and efficient. In terms of QA systems, we can use deep learning methods to joint train the entity and relation extraction, which can decrease the calculation errors.

References

1. K. Bollacker, C. Evans, and P. Paritosh, T. Sturge and J. Taylor. *Freebase: a collaboratively created graph database for structuring human knowledge*, In Proceedings of the 2008 ACM SIGMOD international conference on Management of data, pages 1247-1250, 2008.
2. D. Vrandečić and M. Krötzsch. *Wikidata: a free collaborative knowledgebase, Communications of the ACM*, **57**(10), pp.78-85, 2014.
3. S. Auer, C. Bizer, G. Kobilarov, G. Lehmann, R. Cyganiak and Z. Ives. *Dbpedia: A nucleus for a web of open data*, The semantic web Springer, pp.722-735, 2007.
4. F. M. Suchanek, G. Kasneci and G. Weikum. *Yago: A large ontology from wikipedia and wordnet*, Journal of Web Semantics, **6**(3), pp. 203-217, 2008.
5. A. Swartz. *Musicbrainz: A semantic web service*, IEEE Intelligent Systems, **17**(1), pp. 76-77, 2002.
6. C. B. Wang, X. Ma, J. Chen, and J. Chen. I*nformation extraction and knowledge graph*

construction from geoscience literature, Comput.Geosci., 112, pp. 112-120, 2018.

7. L. Xiaoxue, B. Xuesong, W. Longhe, R. Bingyuan, L. Shuhan and L. Lin.*Review and trend analysis of knowledge graphs for crop pest and diseases,* IEEE Access, **7**, pp. 62251-62264, 2019.
8. L. Shi, S. Li, X. Yang, J. Qi, G. Pan and B. Zhou. *Semantic health knowledge graph: Semantic integration of heterogeneous medical knowledge and services*, BioMed research international, 2017.
9. J. Yuan, Z. Jin, H. Guo, H. Jin, X. Zhang, T. Smith and J. Luo. *Constructing biomedical domain-specific knowledge graph with minimum supervision*, Knowledge and Information Systems, **62**(1), pp. 317-336.
10. P. Chen, Y. Lu, V. W. Zheng, X. Chen and B. Yang. *Knowedu: A system to construct knowledge graph for education*, IEEE Access, **6**, pp.31553-31563, 2018.
11. R. Mihalcea and A. Csomai. *Wikify!: Linking documents to encyclopedic knowledge*, In Proceedings of the Sixteenth ACM Conference on Conference on Information and Knowledge Management, pp. 233-242, 2007.
12. F. Hasibi, K. Balog, and S. E. Bratsberg. *On the reproducibility of the TAGME entity linking system*, In Proceedings of the European Conference on Information Retrieval, pp.436-449, 2016.
13. P. N. Mendes, M. Jakob, and A. García-Silva. *DBpedia spotlight: Shedding light on the web of documents*, In Proceedings of the 7th International Conference on Semantic Systems, pp. 7-9, 2011.
14. G. Mesnil, Y. Dauphin, K. Yao, Y. Bengio, L. Deng, D. Hakkani-Tur, X. He, L. Heck, G. Tur, and D. Yu. *Using recurrent neural networks for slot filling in spoken language understanding*, IEEE Transaction Audio Speech Language Process, **23**(3), pp.530-539, 2015.
15. R. Leaman, C. H. Wei and Z. Lu. *tmChem: Ahigh performance approach for chemical named entity recognition and normalization*, J. Cheminform., **7**(S1), p. S3, 2015.
16. A. Han, D. Wong, and L. Chao. *Chinese named entity recognition with conditional random fields in the light of chinese characteristics*, in Language Processing and Intelligent Information Systems. Springer, pp. 57-68, 2013.
17. Z. He, Z. Zhou, L. Gan, J. Huang and Y. Zeng. *Chinese entity attributes extraction based on bidirectional LSTM networks*, International Journal of Computational Science and Engineering, **18**(1), pp.65-71, 2019.
18. Z. D. Jian, K. Liu, W. Lai, G. Zhou and J. Zhao. *Relation Classification via Convolutional Deep Neural Network*, the 25th International Conference on Computational Linguistics, pp. 2335-2344, 2014.
19. D. Zhang and D. Wang. R*elation classification via recurrent neural network,* arXiv:1508.01006, 2015.
20. S. Zhang, D. Zheng and X. Hu. *Bidirectional long short-term memory networks for relation classification*, In Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation, pp. 73-78, 2015.
21. Y. Lin, S. Shen and Z. Liu. *Neural relation extraction with selective attention over instances*, In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, pp. 2124-2133, 2016.
22. X. Huang, J. Zhang, D. Li, and P. Li. *Knowledge graph embedding based question answering*, In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, pp. 105-113, 2019.
23. M. C. Yang, N. Duan, M. Zhou, and H. C. Rim. *Joint relational embeddings for knowledge-based question answering*, In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP) Association for Computational Linguistics, pp. 645–650, 2014.
24. K. Xu, Y. Feng, S. Huang, and D. Zhao. *Hybrid question answering over knowledge base and free text*, The 26th International Conference on Computational Linguistics: Technical Papers, pp. 2397–2407, 2016.

25. F. Ren and Y. Zhou. *CGMVQA: A New Classification and Generative Model for Medical Visual Question Answering*, IEEE Access, **8**, pp.50626-50636, 2020.
26. F. Ren and H. Yu. *Role-explicit query extraction and utilization for quantifying user intents*, Information Sciences, **329**(1), pp.568-580, 2016

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