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DEVELOPMENT OF A KNOWLEDGE ACQUISITION, CONNECTION EXTRACTION, DISCOVERY MODEL FOR DOMAIN ONTOLOGY ENGINEERING

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Abstract-
One of the greatest challenges of an enterprise's service center is to ensure that their engineers and customers are provided with the right information in a timely fashion. For this purpose, modern organizations operate a wide range of information support systems to assist customers with critical service requests and to provide proactive monitoring, where possible, to prevent service requests from occurring in the first place. It is often the case that relevant information is scattered over the Internet and/or maintained on disparate systems, buried in large amount of noisy data, and in heterogeneous formats, thereby complicating the access to reusable knowledge and extending the response time to reach a resolution. To address these challenges, in this paper we propose an effective knowledge mining solution to improve the quality of service request resolution. We model the service resolution problem as an online search and classification problem, and use domain knowledge in the form of ontology to guide effective machine learning. Our proposed solution has been extensively evaluated with experiments and has been used in a real enterprise customer center.

Keywords-- Knowledge management service, semantic web, ontology, data mining, machine learning, natural language processing, business rules, event processing, production rule system

I. INTRODUCTION

Enterprise services centers and IT consulting services are a growing business in today's fast-paced marketplace. They provide a primary way for enterprises to interact with their customers. Service centers receive a large number of service requests from customers and partners. IT consulting services are also in high demand as companies are under pressure to maintain a technical advantage in today's hypercompetitive market. Accurate and timely delivery of pertinent information to assist in service request prevention and resolution is critical for providing the highest levels of service to customers. This information can be serviced in the form of a curated knowledge repository and can be used to infuse the service request with knowledge on how to solve the issue. In addition, the knowledge can be coded into business rules that can be
used in the form of automated event processing to proactively fix or even prevent issues in other customer networks with the same devices/software images, thereby avoiding service requests all together. New technology has enabled the generation of more information in the hands of customers, as never before has a customer had so much

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information about a company's products and services.

Based on a recent study, most of their service requests can be answered using enterprise's information sources. For example, over 70% of customers and partners find answers on Cisco's Web [28]. However, most of the explicit knowledge assets of today's organizations consist of unstructured textual information in electronic form. In most cases, these data may be located in different sources such as service request repositories, enterprise websites, and social networks of Subject Matter Experts (SMEs). Moreover, the data may be stored in heterogeneous formats, in most cases unstructured, including text, command line interface (CLI) output, and Web pages. The large amount of heterogeneous data sources complicate request resolution causing lengthy diagnosis time. Furthermore, educated and demanding consumers using new communication channels (such as online chatting) call for higher quality of services [46].

Unless relevant data is displayed promptly and efficiently, service center engineers tend to ignore the provided reference information and spend their time working on the actual service request [39].

II. RELATED WORKS

Nowadays modern service centers have been working on improving resolution efficiency by building knowledgebase solutions. Knowledge management sharply reduces the need for escalation within and beyond a service center [47]. Often (over 70% of the time) a service request being asked to a service center, has usually been asked before, and most likely will be asked again. Therefore, most service centers try to capture answers to previously posed requests and build structured knowledge from this experience [38, 51]. Upon receiving a service request, the system will match the service request with similar cases which have been resolved before. This kind of knowledge contributed by skilled engineers and based upon actual experience, can be presented in the form of a knowledge repository or infused into the actual service request for faster access and to facilitate efficient service request response.

Knowledge management systems built upon service center engineers' previous experience on answering similar service requests or customer service engagements will facilitate efficient responses to customer inquiries and resolutions. However, it has a few shortcomings. First, service requests which have not been posed before cannot benefit from this system. Second, up-to-date information from other sources such as those discussed in social network sites cannot be quickly integrated to the knowledgebase to serve customers. Based on [44], service center staff cannot keep pace with the complexity of requests, and existing tools or skills cannot keep up with customer expectations. Request resolution rates have dropped for consecutive years, leaving customers with just a three-in-four chance of having their issue resolved. To address the aforementioned problems, we propose an online knowledge mining system, which can help users locate the most up-to-date and relevant information related to service requests or customer engagement, even if the users' requests are new to the system. To get up-to-date information related to particular topics, we turn to the richest sources in the world – the Internet and the enterprise's intranet. We implement a semantics-expanded search engine, which can search amount of noise returned from the search engine and shape the information into a powerful representation, we propose and implement a semantics-enhanced multi-level classification mechanism.

The proposed classifier can classify information to a structured format that can be easily understood and absorbed by service center engineers or customers. The structured information is called Intellectual Capital, or IC for short. IC can be used in the form of business rules that can be used by a production rule system to facilitate inference and reuse. The proposed IC mining model offers better categorization of service request resolution data along with improved specification and matching techniques. The proposed work integrates rich semantics, advanced search with data mining and machine learning technologies. The goal of this work is to realize a usable, intelligent, and effective framework for IC mining. In particular, the contributions of this paper are summarized as follows: 1. We propose an online search and classification model to mine IC. This approach overcomes the existing problems of knowledge discovery in service centers, namely (1) cold start, i.e., unable to solve the never-seen-before information based on the semanticsrather than syntax. To remove the massive

problems, and (2) difficult to integrate up-to-date new information. 2. We design algorithms to utilize the enterprise's ontology to guide search and data analysis leading to better performance.

III. PROPOSED METHOD

Fig. 1 shows the architecture of the proposed IC mining system. It consists of two major components, namely federated IC search engine and ontology-enhanced classifier. A predefined enterprise ontology is used in both components to improve the system performance. The working
process of the system is as follows: To create IC of a particular topic, the service center engineer needs to input set of keywords to the integrated search engine to search for a particular problem. Keywords can be expanded with semantically- related concepts to disambiguate and refine the
query. Relevant documents and Web pages retrieved by the search engine will go through the classifier's preprocessor to make the data machine learning ready. Preprocessed data then will be fed to the classifier to get classified.

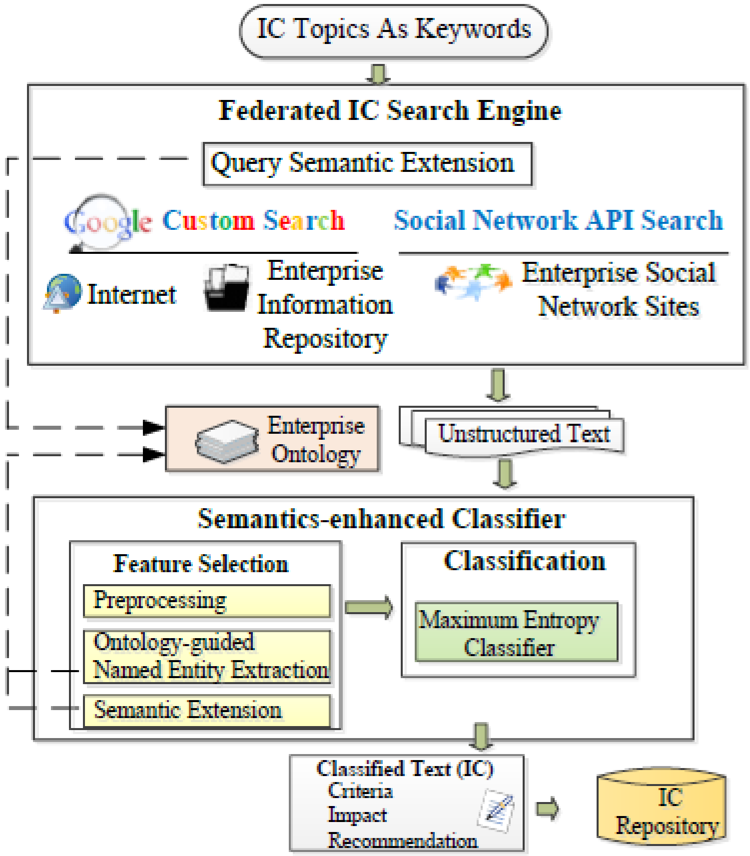

Fig. 1. IC mining system architecture

Once again, corporate ontology is used to direct the classification process in order to enhance the classifier's performance. The engineers will get the categorised findings (IC, text fragments) for validation and synopsis. The finished IC is then edited and verified by the engineers before being stored in the IC repository. Section 4 provides an explanation of the system's intricate workflow. We tackle the information discovery and management job more effectively by using the complimentary qualities of computer software and people. To improve the outcome, we may continually gather engineers' expertise and integrate it into the searching and learning system by offering an intuitive interface for user input in areas like issue description, query refining, results assessment, and verification. To allow more precise and intelligent knowledge management, we apply domain knowledge to unstructured data using semantic web technologies, namely ontology.Ontology [31], which is defined as "specifications of a shared conceptualisation of a particular domain," offers a common and shared understanding of a domain that can be communicated between individuals and across application systems, hence facilitating knowledge reuse and sharing. In addition to giving ideas a formal, machine-executable meaning, ontology facilitates inference processes that might improve semantic matching. Furthermore, ontology can handle

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the nuances of various texts and offers a sufficient foundation for the depiction of coarse- to fine-grained things. Our mining technology can automatically infer associations between key ideas with the use of ontology, allowing for precise knowledge organisation and extraction. Products, technology, and consumers are just a few examples of the key ideas and interactions that businesses in various domains should express using their own domain ontologies. No specific ontology is necessary for the suggested IC mining technique to function. For instance, we used a Cisco-provided ontology in our project that includes Cisco's fundamental information, such as its products, networking solutions, and technologies expressed in RDF/OWL [32]. Experts from Cisco created the ontology. There are 8425 instances and 1476 classes among the 9901 entities. A portion of the high-level ontology is shown in Fig. 2

Fig. 2. Part of the domain ontology used in this work

Algorithm1 The semantic entity recognition (SER) algorithm

```
Apply POS on the document
for each noun-phrase in the document do
  for each token in the noun-phrase do
    search token in the inverted index of keyword-ontology
    if a hit is found then
      tag the matched token with the ontology entity's ID i
  end for
  if multiple tokens have the same ID i then
    merge them as a single entity
  calculate the adapted edit-distance between the extracted
  entity and the ontology entity identified by ID i
  if distance<= threshold then
   the extracted entity is a legal semantic entity
end for
```

IV. RESULTS AND DISCUSSION

The suggested SER method is a simplified algorithm, however because of the unique use of semantic elements in the knowledge sources, the reduction does not significantly reduce the system's accuracy. A named entity's form in our knowledge sources may differ from its version in the ontology. Nonetheless, global level insertion, deletion, substitution, and permutation are the main differences. The suggested approach is capable of efficiently capturing each of these variants. We assessed the classifier's performance in the following experiments. 83 configuration Best Practice use cases that have been carefully labelled by human experts are included in the data collection. The IC search engine returns the original documents. Following pre-processing, the papers are evaluated by human specialists who categorise each paragraph as unrelated, criterion, impact, or suggestion. The toolbox refers to this set of criteria as "BP problems."Extended semantic entities, top words, website types, query keywords, paragraph length, paragraph relative placement, and bagof-hit words are examples of feature possibilities. These characteristics are then used by the classifier model to identify the class label for a given paragraph. Each data set has two tab-separated columns: the first column shows the paragraph's class title, and the final column contains a feature set for that paragraph separated by commas. In order to optimise performance, our model also keeps track of a property file with a number of parameters. These parameters allow us to modify several classifier variables, including regularisation, smoothing technique, and convergence tolerance for parameter optimisation.Error analysis is a useful technique for honing the features after selecting an initial feature set. To build the model, a development set including the corpus data is initially chosen. This development set is then further separated into

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two sets: the development test set and the first training set. The latter is used for error analysis, while the former is utilised to construct the model. Eighty percent

of the data in the first training set and the remaining twenty percent is the development test set, which we divided using a random partition. We looked at how this toolkit increases the productivity of the Best Practice IC extraction for service request resolution in order to assess the efficacy of the suggested method.We evaluate how long it often takes to gather IC related to a certain topic using our IC mining tools vs doing it manually. Using a set of keywords, engineers manually input the IC topic into search engines and Cisco internal search tools. The engineers examine and understand the papers or webpages after the search engines have retrieved them. After that, they insert (copy/paste) relevant details on the "criteria," "impact," and "recommendation" of the issue into a document. Finally, they could summarise the IC using the recorded data. The engineers just need to use the IC mining tool to input keywords into the toolkit, and relevant information categorised as "criteria," "impact," and "recommendation" will be sent to them right away. To correct the returned IC, the engineers may use our service to flag documents or websites that provide incomplete or erroneous information.Fig. 3 shows the processing times for the same set of problems in these two configurations. We may see that our technique considerably reduces response time. Note that the time needed to correct the incorrect IC that the toolkit returned has already been calculated. Fig. 4 compares the information load of automated and manual IC mining. The information load is the quantity of paragraphs that people need to read or analyse in order to resolve a problem. If the tool's output was inaccurate, we would again include all the paragraphs the engineers personally analysed. To evaluate the effectiveness of the IC mining classifier, we tested with a number of feature sets. The feature set includes the following: website type (T), query keywords (K), extended semantic entities (S), frequent words (W), paragraph length (L), and paragraph relative position (R). Our goal is to determine if performance is improved by the addition of features and semantically enlarged entities. To assess performance, we use the macro-averaged F1, accuracy, precision, and recall, which are shown in Table I.

Table I: FPERFORMANCE MEASUREMENTS FOR DIFFERENT FEATURE SETS - 10 FOLDS CROSS VALIDATION

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Feature Set	Micro-avg. F1	Macro-avg. F1	Accuracy	Precision	Recall
W	0.74	0.61	0.76	0.66	0.58
W+S	0.8	0.71	0.8	0.73	0.68
W+S+K	0.81	0.72	0.81	0.73	0.7
W+S+K+T+L+R	0.82	0.73	0.82	0.74	0.72

Under-sampling enhances classification performance on unbalanced data, as seen in Fig. 5. The performance under various ratios of IC-relevant and IC-irrelevant samples is shown in the figure. The initial set of data (designated as "none," indicating that no under-sampling has been used) has extremely high accuracy but poor precision and recall, as the figure illustrates. The classifier's attempt to reduce the global error and categorise more instances as IC-irrelevant—the majority class in our case—is the reason for this. The bulk of IC-irrelevant paragraphs were then under-sampled. As we under-sample the irrelevant data, the precision and recall rise but the accuracy falls. In our project, precision and recall rate are more crucial than accuracy since we can tolerate false positives, which categorise irrelevant data as relevant, but not false negatives, which classify useful data as irrelevant.

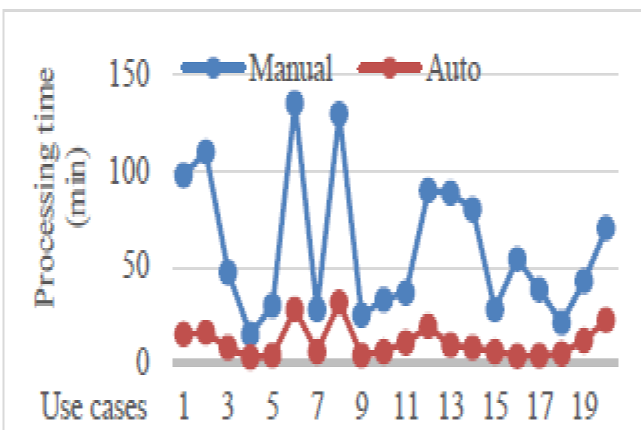

Fig. 3 Comparison of processing time of auto and manual IC extraction

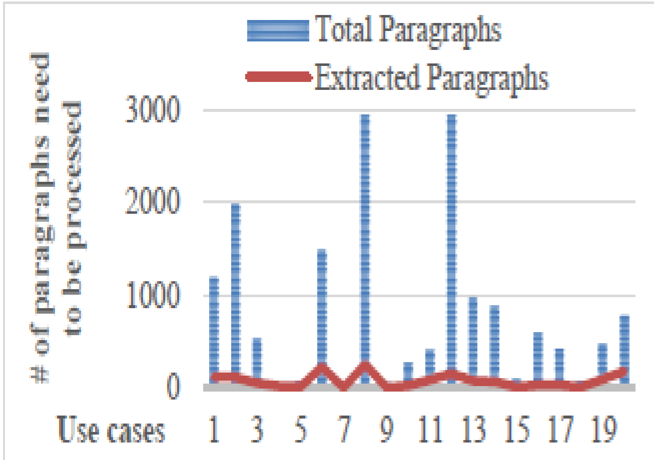

Fig. 4 Comparison work load of auto and manual IC extraction

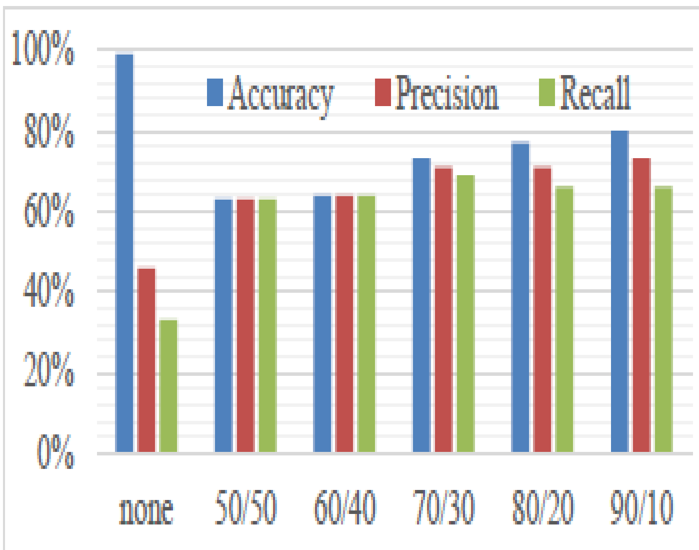

Fig. 5. Classification Performance with Different Under-sampling rate

V. FUTURE SCOPE AND CONCLUSION

We suggest an effective knowledge management module that turns the deluge of data into reusable knowledge, or Intellectual Capital (IC), to assist business customer centres in resolving service requests and speeding up the time it takes to answer problems utilising online data. This module used an internet search plus classification model to represent the service resolution issue. Specifically, a proprietary search engine will be used to gather data from the Internet and business data repositories. To extract IC, the search results will next undergo pre-processing and classification. A

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new classifier was introduced that guided the categorisation process using the business domain ontology. According on experimental findings, the ontology-guided classifier significantly enhances system performance. Along with superior matching and specification methods, this model provides better classification of service request resolution data. In actual enterprise service centres, a trial system built on the suggested approach has been implemented. It raises the quantity of reusable information and significantly enhances the performance of the service engineer.

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