Deployment of Semantic Social Media Analysis to Call Center

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Abstract. The number of inquiries to call centers regarding product malfunctions has been increasing in recent years, and thus manufacturers are struggling with their responses. The Consumer Affairs Agency in Japan stated that the initial response to an inquiry is especially important, since flaming directed toward the company may immediately occur on the Web, and may greatly affect the reputation and sales of the product if the response is inappropriate. However, when a call center accepts the first inquiry, an operator cannot determine whether the malfunction is due to a problem of a model or to a user's way of using the product. Therefore, we have developed a system to automatically determine if the inquiry content is the tip of an iceberg by graph-matching the inquiry content to a Linked Data network, which represents the reputation information of a product on social media. Moreover, by tracing causal links in the network, the system also determines if the inquiry is connecting to users' dissatisfaction and discontent, and then notifies the inquiry to a quality control section with high priority to prevent flaming. In this paper, we first present our approach for converting social media information to Linked Data, and show that an experiment achieved 94% accuracy. We also explain the matching between the inquiry content and Linked Data and its accuracy, and a method of extracting the causal link to the users' complaints.

1 Introduction

Our company manufactures and sells consumer electronics ranging from refrigerators to TV sets, and it has recently been endeavoring to deal effectively with a number of inquiries about product malfunctions, which are gathered at a call center. Nowadays, moreover, if the response to an inquiry is mishandled, users tend to be complainers in some cases. A bad reputation then spreads widely via social media, that is, "flaming" occurs, and may greatly affect sales of all the company's products. Making the response more problematic for operators at the call center is the difficulty of distinguishing whether the malfunction that is the subject of the inquiry is caused by a user's way of using the product or a problem that accidentally occurs in an individual product, or caused by a problem common to the design or production phase of a particular model. In the case that an operator considers the malfunction to be the user's fault at the initial stage, and it subsequently turns out to be the manufacturer's fault, a firestorm may occur that may lead to lawsuits. The Consumer Affairs Agency in Japan and several law firms warn that the initial response to an inquiry is especially important in general. However, since pernicious complainers exist, if the manufacturer always considers the inquiry to be the manufacturer's fault, the cost will soar.

Therefore, we proposed a method of comparing semantically analyzed social media information and the inquiry content. We triplify entries about product malfunctions on social media, and convert them to a network of Linked Data in advance. Then, by searching for the content of the inquiry to the call center in the network, we confirm whether the same issue is currently spreading on social media and whether the inquiry is the tip of an iceberg. If there is a similar entry on social media, it is determined whether the inquiry content is a malfunction common to a model and, if so, the operator offers a polite explanation to the user and a notification is sent to a quality control (QC) section. Moreover, if the entry has causal links connecting to users' dissatisfaction and discontent, a notification with high priority will be sent to the quality control section.

For checking a product's reputation on social media, our company currently collects entries from several review sites such as 2ch.com and kakaku.com, which are well known in Japan, by searching with specific keywords once a day (implemented by MS Excel macros). Then, a person in charge looks through the result list. However, the comparison with the contents of the inquiries to the call center is not performed every day. If an entry requires attention, she/he sends feedback to the quality control section. The contents of the inquiries to the call center are sent to the quality control section every day. The information is finally aggregated in the quality control section and the priority is determined, and then the necessary measures are considered.

Therefore, this system will contribute to the following.

1. Quick determination whether the malfunction subject to inquiry is that of an individual product or common to a model.
2. Automatic priority setting in the case that the inquiry is connecting to complaints.

Additionally, the system is efficient compared with human searches with predefined keywords, and precludes the risk of a person in charge overlooking an important entry. There will also be the following advantages: visualization by presenting the reputation information as Linked Data graphs and the future linkage to other information, such as design specifications, by adopting a Web standard as the data format. We, that is, our laboratory, brought the abovementioned advantages to the attention of a division of our company, which manufactures and sells consumer electronics, and then received a research contract with a certain amount of R&D expenses.

The rest of this paper is organized as follows. Section 2 presents a triplification method for social media information, and Section 3 describes how the system matches inquiry contents and social media information. In section 4, we conduct

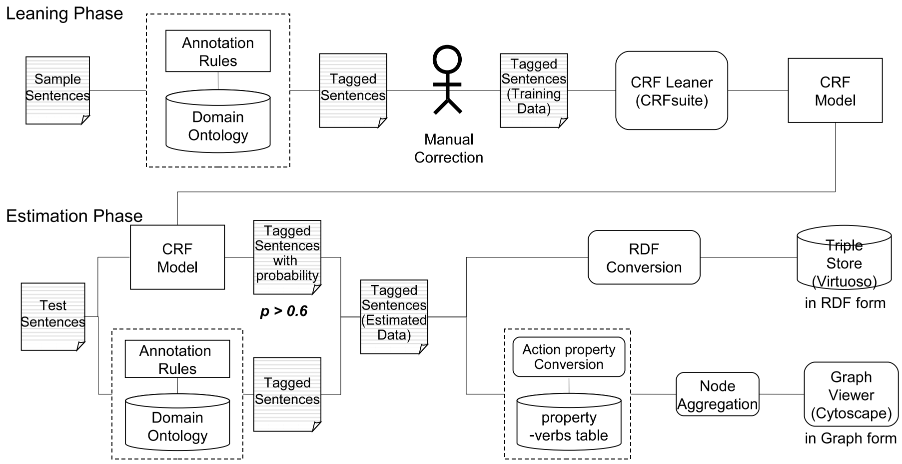

Fig. 1. Workflow of triplification

evaluations on the triplification and the matching accuracy. Section 5 refers to related work, and finally Section 6 refers to future work and concludes this paper.

2 Triplification of Social Media Information

2.1 Workflow of triplification

With regard to the triplification of social media, we conducted research on estimation of human behaviors and improvement of evacuation guidance by analyzing a massive amount of tweets made at the time of the Great East Japan Earthquake [1]. We further developed the above-mentioned method and improved the extraction accuracy for the present work. Figure 1 presents the workflow of the triplification.

To create a training dataset, firstly, we divided each sentence in the dataset into chunks of semantically consistent words by using Part of Speech (POS) analysis and syntactic analysis, and then manually labeled one of eight properties, namely, Subject, Action, Object, Location, Time, Modifier, Because, and Other, to each block. We then used conditional random fields (CRF) [2] as a learning model, which is an undirected graphical model for predicting a label sequence for a sequence. The idea is to estimate a conditional probability distribution over label sequences given the blocks. The key point of the proposed method is that we also constructed approximately 250 annotation rules using the result of syntactic analysis and the predefined ontology, for example, a noun before a postpositional particle 'WO' corresponds to OBJECT in a Japanese sentence, and a sentence after a word 'NAZANARA' (because) and a sentence before the word have a causal relation, and so forth. We then decided which of the CRF estimation and the rule decision should be adopted based on the estimation probability of CRF. Nowadays, the combination of probabilistic reasoning with a matching learning method and first-order logic, such as Markov Logic Network (MLN) [3], is attracting attention. This simple method is also designed for the same goal. The ontology is based on Japanese WordNet[3], and we added approximately 500 words as instances under classes in WordNet.

In addition, we determined identities of values (chunks), that is, entity linking, so that values of Subject, Object, etc. that have the same meaning refer to an identical node in the network, as much as possible. The outline of the procedure is as follows. We first calculate lexical similarity between two string values after normalization of adjectives and verbs, and also semantic similarity by referring to the above ontology, that is, Japanese WordNet for common nouns and the added synonyms for proper nouns, and then structural similarity based on properties and values surrounding the values. We then construct feature vectors, using an ensemble learning method, Random Forest [4], to determine the identities, because other research on instance matching [5] indicated that Random Forest surpasses other methods owing to the nature of the problem. Finally, we unified the values that are determined to be identical to a node whose label is a typical value. More detail is shown in our related work [6].

2.2 Format of Linked Data

We provided two formats for Linked Data presentation. One has a sentence ID node for each sentence as presented in Kira et al. [7]. The ID node has at most eight properties such as Subject, Action, and Object, and then values of the properties are strings of chunks labeled in the sentence (Fig. 4). In terms of readability of graphs, however, this format is not very intuitive, since the values of Subject and Action properties are always connected through the ID nodes.

Therefore, we extracted 40 frequent actions from values of Action properties, which correspond to strings showing the actual behavior, and then defined each of them as new properties. For example, there are 'has-a', 'is-a' as a basis, and also 'hasStated', 'buy', 'sell', and 'complain' properties etc. for representing the inquiry content. Each property has several corresponding verbs, which are converted to the property according to the value of the Action property. The set of verbs corresponds to a Japanese version of the VerbNet vocabulary [8] used in Kira et al. [7]. For example, if the value of the Action property is "talked", a value (node) of the Subject property and a value (node) of the Object property with the same ID node are connected by the 'hasStated' property (Subject, Object and Action property from the ID node are deleted). This conversion can be expressed in the following logical form. Note that $state(A)$ means A is a corresponding verb of the 'hasStated' property.

$$\exists ID, X, Y, A\ (\ hasSubject(ID, X) \wedge hasObject(ID, Y) \wedge hasAction(ID, A) \wedge state(A) \rightarrow hasStated(X, Y)\ )$$

[3] `http://nlpwww.nict.go.jp/wn-ja`

In this way, by directly linking the value of the Subject property and the Object property using the above new properties, we attempted to make the second graph format more readable. In this format, the information having contrast, such as different actions for the same subject and the same actions for the same subject with different objects, can be represented through a subject node. The information about location and time is annotated to the end of a property label (buy@"BestBuy"&"2014-04-07", etc.) This format, however, cannot represent intransitive verbs without Object. Figure 2 presents an example of the graph in this format using a graph data viewer, Cytoscape[4]. The figure is also available at our website[5]. This figure illustrates a network showing entries about a TV set manufactured by our company, which is used in the following experiment. In regards to a problem (message output from a TV set) that the temperature of a tuner becomes high due to dust, several users point out a solution of cleaning the air filter (see from a left side to a right side in the figure). Although the same series of products, we can confirm that this problem does not happen in X2, but in XE2 (see at the lower right of the figure).

The first format is for storing in a triple store and searching, and the second format is for visualizing for human readers, albeit with a slight sacrifice of accuracy as a Linked Data format. Comparison with inquiry contents is explained in the next section using the first format, and thus the second format is not used for the goal of this paper. In general, however, visualization is very important for business applications of new technology, and thus we developed the second format.

3 Matching between Inquiry Content and Linked Data

Figure 3 presents the flow when an inquiry is received at a call center. In the actual operation, entries for each product on several review sites are periodically collected, and then converted to Linked Data in the first format by the above-mentioned method, and thus stored in a triple store on our network. When the call center receives an inquiry from a user, an operator records the summary of the inquiry content as two or three sentences (call log). Each sentence is triplified in the format of $< S_i, V_i, O_i >$, and then triples that have the same structure as the sentence are searched in the triple store. In detail, our SPARQL query to the triple store first finds S_s, V_s, O_s that have the same meaning as S_i, V_i, O_i, respectively, and then confirms whether there is an ID node that has the values S_s, V_s, O_s with Subject, Action, Object properties, respectively. As a result, if a triple with the same structure as the inquiry content is found, we determine that the problem does not concern an individual product, but is common to a model. Moreover, the number of triples with the same structure is regarded as an amount of topics on social media. When querying the triple store to find S_s, V_s, O_s, we also use the method of entity linking described in 2.1.

[4] http://www.cytoscape.org/

[5] http://www.ohsuga.is.uec.ac.jp/~kawamura/graph_by_cytoscape.jpg

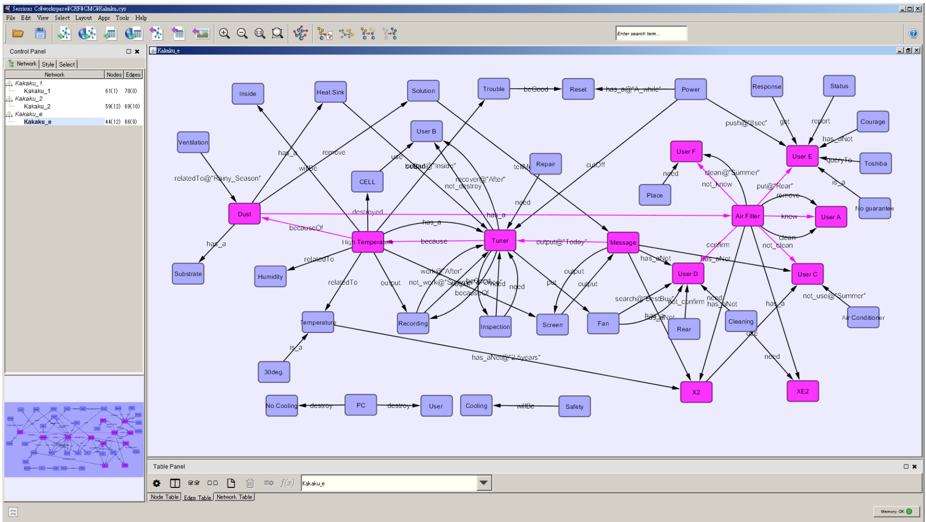

Fig. 2. Graph representation for reading

If we find a node that represents users' dissatisfaction and discontent, which is connected from the triple S_s, V_s, O_s through the Because property, we immediately notify the inquiry content to the quality control section as a problem to be solved with priority. The node that represents users' dissatisfaction and discontent means a node connected by the Object property, whose label is "complaint" or "grumbling", etc., and a node connected by the Action property, whose label is "angry" or "won't buy", etc. Example graphs of social media entries and inquiry content are shown in Fig. 4.

4 Experiments on Triplification and Matching

In this section, we present the evaluation results for accuracy of triplification of social media, and accuracy of matching with inquiry contents.

4.1 Triplification of social media

In an experiment, we collected entries about a TV set manufactured and sold by our company from a well-known review site in Japan[6], and then conducted labeling, learning, and estimation with the method described in the previous section. The dataset is 197 sentences for three months, and evaluated with 10-fold cross-validation. Table 1, 2, and 3 show the result of rule decision based on syntactic analysis and the predefined ontology, the result of CRF estimation, and the combined result of the CRF estimation in the case of the estimation probability $p > 0.6$ or the rule decision, otherwise.

[6] http://kakaku.com

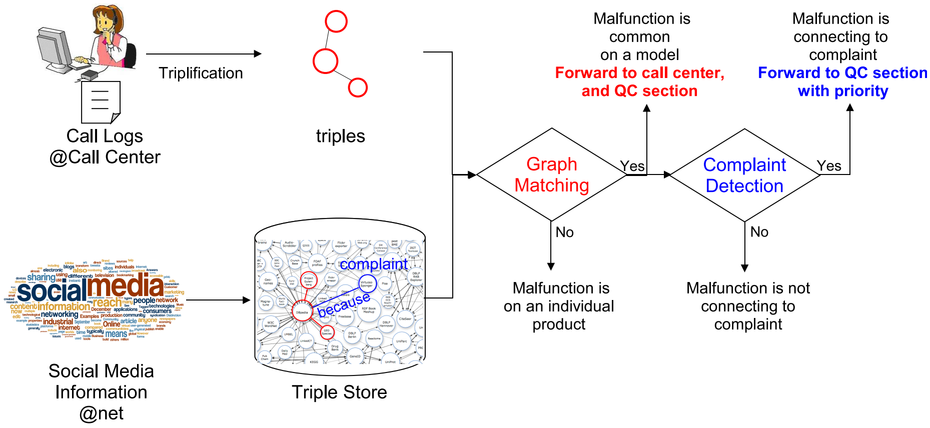

Fig. 3. Search flow of inquiry contents from Linked Data

Table 1. Extraction accuracy for each property (rule decision)

	SUBJECT	OBJECT	ACTION	LOCATION	TIME	MODIFIER	BECAUSE	W. Ave.
Precision (%)	94.74	80.50	93.3 3	52.38	86.21	94.56	100.00	92.23
Recall(%)	90.00	89.94	92.3 9	73.33	94.34	80.81	100.00	92.23

In comparison with Table 1, 2, and 3, Weighted Average (W. Ave.), which is an average value according to the number of each property, indicates that the combined method we proposed, with accuracy of 94.1%, surpasses the other two single methods. Precision and recalls of W. Ave. have the same values, since the number of estimated values is equal to the number of correct values.

In comparison with each property of Table 1 and 3, however, precision by the rule decision is sometimes higher than the results of the combined method, and then we confirmed that the rule decision can have the best result in the case that sentences follow syntactic rules. Also, in comparison with each property of Table 1 and 2, recalls of some properties of the CRF estimation are higher than the rule decision, and then we confirmed that a method of learning and estimating label patterns is effective for irregular sentences. The accuracy of the Location property is lower than that of other properties because of the shortage of geographical names registered in the system. The low accuracy of the Time property seems to be attributable to the difficulty of distinguishing it from the Modifier property. For example, "future" in a sentence that "Subject will become important in the future." is Time, but "future" is Modifier in a sentence that "Subject is an agenda for the future". We also confirmed that extraction of the causal relation is feasible, since the accuracy of the Because property is high. In this experiment, the estimation probability p to switch the CRF estimation to the rule decision was set to 0.6, since we simply decided to adopt an opinion of CRF in the case that the probability is more than 50%. Table 4 indicated, however,

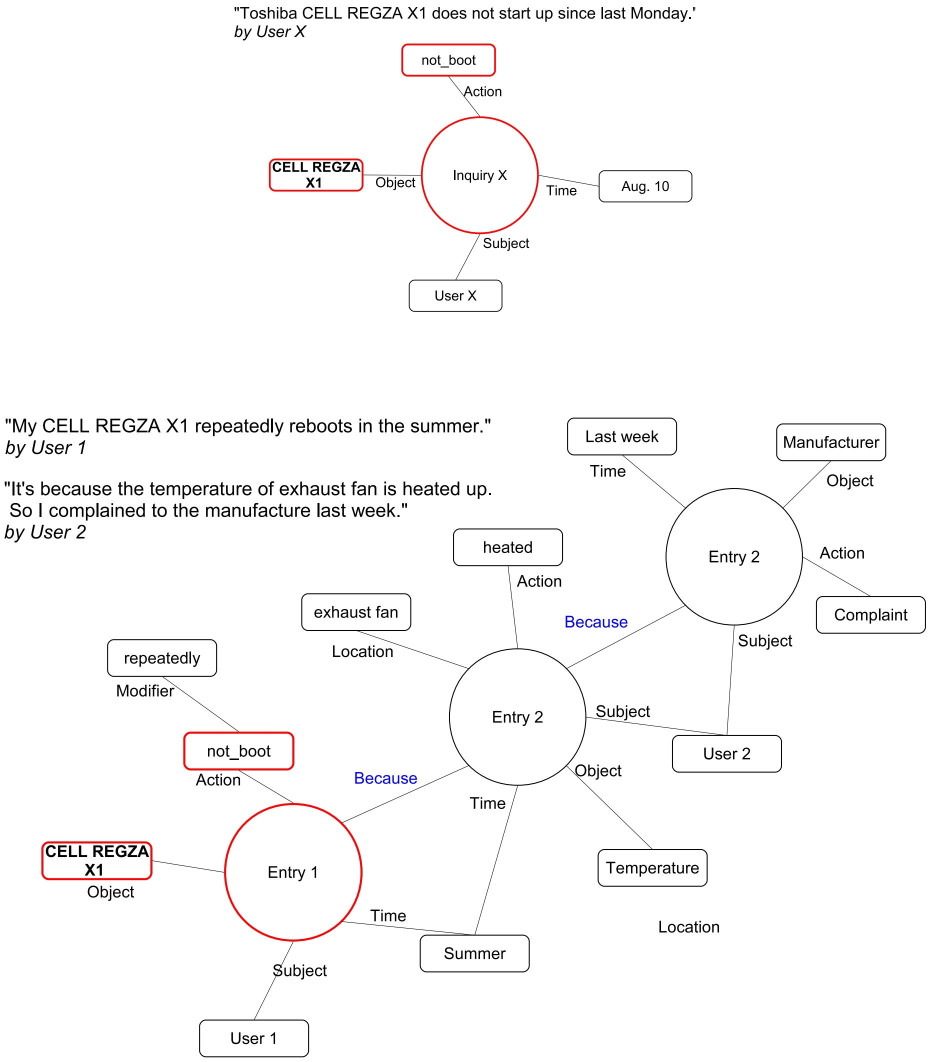

Fig. 4. Linked Data graph for an inquiry content (above) and correspoinding social media information (below)

Table 2. Extraction accuracy for each property (CRF estimation)

	SUBJECT	OBJECT	ACTION	LOCATION	TIME	MODIFIER	BECAUSE	W. Ave.
Precision (%)	83.10	81.91	92.97	0.00	100.00	71.23	100.00	88.35
Recall(%)	98.33	86.03	87.31	0.00	24.53	90.70	100.00	88.35

Table 3. Extraction accuracy for each property (CRF estimation in the case of estimation probability $p > 0.6$, and rule decision in the case of estimation probability $p \leq 0.6$)

	SUBJECT	OBJECT	ACTION	LOCATION	TIME	MODIFIER	BECAUSE	W. Ave.
Precision (%)	85.7	88.8	96.9	63.6	100.0	88.2	100.0	94.1
Recall(%)	100.0	92.7	95.4	46.7	67.9	91.3	100.0	94.1

that the average probabilities for each property are considerably different, and thus the ease of estimation has differences. To further improve the accuracy, we are considering a method of changing p according to the types of the properties without fixing the 0.6 threshold.

Table 4. Average of estimation probabilities for each property

	SUBJECT	OBJECT	ACTION	LOCATION	TIME	MODIFIER	BECAUSE	W. Ave.
Probability(%)	85.2	79.9	88.8	43.0	48.1	65.5	67.7	77.5

The division to which we provided this result commented that the 94.1% extraction accuracy is satisfactory, but pointed out that on this occasion social media information was collected for a certain period and converted to a graph (Linked Data), and therefore the graph represents a snapshot. Opinions expressed on social media are continually changing from product release to malfunction discovery and manufacturers' responses, and thus such time-series variations should be represented in the graph. In addition, users' complaints are of varying strength, and thus they should be divided into multiple stages from a weak complaint to a strong complaint. Therefore, we intend to prepare more detailed properties for representing various nuances of verbs.

4.2 Matching between inquiry content and social media

In the experiment, we first extracted 220 call logs (summaries of inquiry contents described by operators) composed of 105, 54, and 61 logs for CELL REGZA TV (55X1, 55X2, and 55XE2), respectively, from 25,459 logs about our company's TV sets for a month, September 2012. Examples of the call logs include: "An error message "the tuner becomes hot" appears.", "Time-shifted viewing does not work.", "Today, picture and sound suddenly went out.", etc. We then compared them with social media information that was triplified as described in 4.1. Linked Data of social media information was stored in Virtuoso[7]. Specifically, using the method mentioned in section 3, we confirmed whether triples corresponding to the call log exist in graphs of social media. Finally, the matching results between the call log and part of social media were manually checked, and then the accuracy of the matching was calculated. The result is shown in Table 5.

Table 5. Matching accuracy of inquiry contents (ave.)

No match		Match	
No data	Triplification Error	Precision	Recall
9.1%	13.6%	88.2%	33.3%

In the table, 'No data' means there was no triple corresponding to the call log in the social media graph. 'Triplification Error' means the method in section 3 failed to triplify the call log, for example, in the case of a long sentence. After excluding call logs of 'No data' and 'Triplification Error', precision was calculated for call logs matched to more than one part of the social media graph, and which were matched to the correct part. Recall indicates the degree to which the correctly matched call logs found the information to be matched in the graph. For example, if there are four items of information (triples) in the social media graph and the call log matched two of them, the recall is represented as 50%.

As a result, we found that 'Triplification Error' was relatively low, and call logs described by most operators can be converted. If we alert the operators to descriptions at the introduction of this system, the accuracy will be further increased. In addition, the fact that the precision of call logs to social media graph was about 90% indicates that checking the same entry on social media as a call log is possible. Since the recall was low, however, we found that it is difficult to deduce how widely the call log is spreading on social media from this result. The recall was low because there are several expressions that represent the same condition and content on social media, and also the method of entity linking mentioned in 2.1 is insufficient to unify them. In the previous work [6], we conducted experiments on Linked Data that is manually created, and correctly determined matching pairs with F-measure of 85.0%. In this experiment, however, Linked Data is automatically extracted from social media, and thus inconsistent spellings and different notations are still problematic. Examples of 'No data' include some naive questions, such as "Why does a TV need a tuner?". The call center occasionally receives such questions, but we could not find any on the review sites.

The division to which we provided this result commented that when an inquiry is received at a call center, it is not possible due to time constraint that

[7] http://virtuoso.openlinksw.com

an operator performs keyword search with appropriate keyword expansion, and find the same entry as the inquiry content on social media, but this system automated comparison between call logs and social media using semantic search with word identification and word relation. The comment also indicated that in future when the malfunction of a model is spreading on social media, an alert should be transmitted before receiving the call log. In comparison with this system where the information to be found (call log) is defined, the degree of difficulty in realizing that will be higher, since we need to search for entries about every possible malfunction.

5 Related Works

In research on semantic conversion of text data and relation extraction, Kira et al. presented a notable paper [7] at WWW12, and also presented at TED x Hiriya [9]. In [7], article titles of newspapers for 150 years are converted to graph structures. However, the conversion from text data is based on syntactic rules. Another research, SemScape [10], also uses several rules based on graph and text features, which are manually generated to convert text data to a graph structure called TextGraph. In contrast, there has been research on applying CRF for Semantic Role Labeling (SRL) for text data, that is a pre-process of triplification. However, research on SRL which is not aimed at triplification like [11], has less roles (properties) than our research. In comparison with other research, we combined a probabilistic learning method and a rule-based method. Since the highest F-measure was almost 80% in a SRL competition in CoNLL-05, we found that the proposed method achieved a sufficient performance, although our experiments were conducted in our target domain. Moreover, we proposed not only a SRL method, but also a new application of SRL in this paper. Kira et al. [7] attempts to predict the future by extracting causal links and patterns of their sequence from the graphs and applying a current event to the pattern. The method proposed in this paper is similar to [7] in terms of using the causal links, although we do not focus on prediction in general, but on the future of flaming. By contrast, the target data is not newspapers, but social media with broader expressions to be extracted.

In research on database (DB) search, many attempts have been made to translate natural language queries to formal languages such as SQL and SPARQL. There has also been research on converting a keyword list to a logical query [12–14]. In this section, we focus on Linked Data as a data structure and SPARQL as a query language, and classify research into two categories based on whether a deep or shallow linguistic analysis is needed.

One system that requires deep linguistic analysis is ORAKEL [15, 16]. It first translates a natural sentence into a syntax tree using Lexicalized Tree Adjoining Grammars, and then converts it to F-logic or SPARQL. Although it is able to translate while retaining a high degree of expressiveness, it also requires the original sentence to be precise and regular. [17] considers a translation system together with the design of a target ontology mainly for event information, and features handling of temporality and N-ary during syntax tree creation. It assigns the words from the sentence to slots within a constraint called a *semantic description* defined by the ontology, and finally converts the semantic description to SPARQL recursively. However, it requires knowledge of the ontology structure in advance.

There also are approaches that use shallow linguistic analysis with the aim of realizing portability and schema independence from the DB. Our proposed system falls into this category. FREyA [18] was originally developed as a natural language interface for ontology search. It has many similarities with our system such as matching the words from the sentence with Resources and Properties by using a string similarity measure and synonyms from WordNet. However, it performs conversion of the sentence to a logical form using ontology-based constraints (without consideration of the syntax of the original sentence unlike the semantic description), assuming completeness of the ontology used in the DB. In contrast, DEQA [19] adopts an approach called Template-Based SPARQL Query Generator [20]. It takes prepared templates of SPARQL queries and converts the sentence to fill the slots in the template (not the ontology constraint). Like our system, DEQA is also applied to a specific domain (real estate search), and exhibits a certain degree of accuracy. PowerAqua [21–23] also originated as a natural language interface for ontology search and has similarities with our system such as a simple conversion to basic graph patterns called Query-Triples, matching of words from the sentence with Resources and Properties using a string similarity measure and synonyms from WordNet. When used with open data, PowerAqua introduces heuristics according to the query context to prevent decreased throughput.

Finally, our investigation indicates there is little research that applies Linked Data to call centers. [24] introduces a self-help system using semantic technology, which promotes solving by users and reduces the cost of the call center. However, the problem solved by the self-help system is a malfunction caused by users, and thus a malfunction caused by a manufacture, which is the focus of the present paper, cannot be handled. It also aims to retrieve Voice of Customer (VOC) using semantic technology and reflect it in the product development phase, which suggests a future direction for our system.

6 Conclusions and Future Work

With a view to supporting responses of call centers and quality control sections regarding product malfunctions, this paper described our system that distinguishes whether a malfunction that is the subject of an inquiry is caused by a user's way of using a product or a problem that accidentally occurs in an individual product, or caused by a common problem of a model. In this system, social media information is converted to Linked Data in advance, and then the presence of triples that correspond to the content of the inquiry is confirmed in the Linked Data. We conducted experiments to evaluate accuracy of triplification of social media information, and accuracy of matching with call logs. The results show about 90% accuracy, indicating that the system is adequate for practical use. We expect that operators using this system can more appropriately handle the user when dealing with an initial inquiry of great importance.

Furthermore, for the case that the content of an inquiry has a causal relation to users' dissatisfaction and discontent expressed on social media, we also developed a function to notify it to the quality control section with high priority, and we confirmed that extraction accuracy of the Because property that represents the causal relation is sufficient. In the function, if a value of the Because property is a negative word, high priority is set and notified. However, a real evaluation, such as how much dissatisfaction and discontent were prevented, was not conducted, since inducing flaming on social media for experimental purposes is ethically unacceptable.

Future works include performance evaluations. After the initial triplification of entries on review sites, however, only the difference is converted once a day or half a day. Also, when an operator accepts an inquiry, two or three sentences (call log) are converted to queries. Therefore, the processing time of the triplification will not be a critical issue. The processing time of queries is currently in a few seconds, although it depends on the data size stored in a triple store.

We have developed the system and are in the trial phase. In the future, we intend to identify issues that may arise through the actual operation of the system, and further improve the system.

References

1. T. M. Nguyen, T. Kawamura, Y. Tahara, and A. Ohsuga: "Building a Timeline Network for Evacuation in Earthquake Disaster", Proceedings of AAAI 2012 Workshop on Semantic Cities, pp. 15-20, 2012.
2. J. Lafferty, A. McCallum, and F. Pereira: "Conditional random fields probabilistic models for segmenting and labeling sequence data", Proceedings of 18th International Conference on Machine Learning (ICML 2001), pp.282-289, 2001.
3. M. Richardson and P. Domingos: "Markov Logic Networks", Machine Learning, 62, 2006.
4. L. Breiman: "Random Forests", Machine Learning, 45(1), 2001.
5. S. Rong, X. Niu, E. W. Xiang, H. Wang, Q. Yang, and Y. Yu: "A Machine Learning Approach for Instance Matching Based on Similarity Metrics", Proceedings of 11th International Semantic Web Conference (ISWC), 2012.
6. T. Kawamura, S. Nagano, and A. Ohsuga: "Literal Node Matching based on Image Features toward Linked Data Integration", Proceedings of 2014 International Conference on Active Media Technology (AMT 2014), 2014.
7. K. Radinsky, S. Davidovich, and S. Markovitch: "Learning Causality for News Events Prediction", Proceedings of 21st World Wide Web Conference (WWW 2012), pp. 909-918, 2012.
8. N. Ryant, K. Kipper, A. Korhonen, and M. Palmer: "Extending verbnet with novel verb classes", Proceedings of 5th International Conference on Language Resources and Evaluation (LREC), 2006.
9. K. Radinsky: "The journey to predict the future", TED x Hiriya, https://www.youtube.com/watch?v=gAifa_CVGCY, 2014.

10. H. Mousavi, D. Kerr, M. Iseli, and Carlo Zaniolo: “Mining Semantic Structures from Syntactic Structures in Free Text Documents”, Proceedings of 8th IEEE International Conference on Semantic Computing (ICSC), 2014.
11. T. Cohn, and P. Blunsom: “Semantic Role Labeling with Conditional Random Fields”, Proceedings of 9th Conference on Computational Natural Language Learning (CoNLL), 2005.
12. P. Haase, D. Herzig, M. Musen, D.T. Tran: “Semantic Wiki Search”, Proceedings of 6th European Semantic Web Conference (ESWC), 2009.
13. S. Shekarpour, S. Auer, A.N. Ngonga, D. Gerber, S. Hellmann, C. Stadler: “Keyword-driven SPARQL Query Generation Leveraging Background Knowledge”, Proceedings of International Conference on Web Intelligence (WI), 2011.
14. D.T. Tran, H. Wang, P. Haase: “Hermes: Data Web search on a pay-as-you-go integration infrastructure”, Journal of Web Semantics Vol.7, No.3, 2009.
15. P. Cimiano: “ORAKEL: A Natural Language Interface to an F-Logic Knowledge Base”, Proceedings of 9th International Conference on Applications of Natural Language to Information Systems (NLDB), 2004.
16. P. Cimiano, P. Haase, J. Heizmann, M. Mantel: “Orakel: A portable natural language interface to knowledge bases”, Technical Report, University of Karlsruhe, 2007.
17. M. Wendt, M. Gerlach, H. Duewiger: “Linguistic Modeling of Linked Open Data for Question Answering”, Proceedings of Interacting with Linked Data (ILD), 2012.
18. D. Damljanovic, M. Agatonovic, H. Cunningham: “FREyA: an Interactive Way of Querying Linked Data using Natural Language”, Proceedings of 1st Workshop on Question Answering over Linked Data (QALD-1), 2011.
19. J. Lehmann, T. Furche, G. Grasso, A.N. Ngomo, C. Schallhart, A. Sellers, C. Unger, L. Buhmann, D. Gerber, K. Hoffner, D. Liu, S. Auer: “DEQA: Deep Web Extraction for Question Answering”, Proceedings of 11th International Semantic Web Conference (ISWC), 2012.
20. C. Unger, L. Buhmann, J. Lehmann, A.N. Ngomo, D. Gerber, P. Cimiano: “Template-based question answering over RDF data”, Proceedings of World Wide Web Conference (WWW), 2012.
21. V. Lopez, E. Motta, V. Uren: “PowerAqua: Fishing the Semantic Web”, Proceedings of 3rd European Semantic Web Conference (ESWC), 2006.
22. V. Lopez, M. Sabou, V. Uren, E. Motta: “Cross-Ontology Question Answering on the Semantic Web - an initial evaluation”, Proceedings of 5th International Conference on Knowledge Capture (KCAP), 2009.
23. V. Lopez, A. Nikolov, M. Sabou, V. Uren, E. Motta, M. DAquin: “Scaling Up Question-Answering to Linked Data”, Knowledge Engineering and Management by the Masses, LNCS 6317, 2010.
24. B. Bell: “Semantics Goes Beyond the Call Center”, `http://semtechbizsf2013.semanticweb.com/sessionPop.cfm?confid=70&proposalid=5113`