Action Planning based on Open Knowledge Graphs and LOD

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Abstract. In this preliminary report, we show how action planning is realized by using LOD datasets, e.g., Linked Geo Data, DBpedia, WordNet, etc. To make a recommendation for car drivers and passengers, we combine these existing open datasets with newly constructed ontologies of facilities and services. We develop the inference procedure to translate user requests into SPARQL queries to obtain a recommendation on appropriate facilities for users. Common sense knowledge is also required in the reasoning process.

Keywords: DBpedia, LinkedGeoData, Knowledge-based system

1 Introduction

While Linked Data is now gradually growing to be the infrastructure of coming Knowledge Society, we are still struggling to show the potential of Linked Data to most people in the society including basic industries. To cope with this situation and propel the deployment of Semantic Web technology, it is needed to demonstrate the performance of linking distinct datasets and show the usefulness of outbound and inbound linking data beyond enterprise data in diverse applications. Yet there is no linking data among large linked datasets such as DBpedia, Freebase, and OpenCyc from the viewpoint of LOD applications, although each collection of them are a kind of isolated showcase of LOD with internally linked data within their own territories and objectives.

In our use-case, the system accepts ambiguous requests from car drivers and passengers, plans driver actions to achieve goals that satisfies the requests, including alternatives, and makes a recommendation for the drivers and passengers.

In this preliminary work, we have found that it is required more goal-oriented linked datasets and common sense knowledge as bridge between isolated LOD datasets existing. We have also found that Semantic Web technology or specifically RDF stores and SPARQL engines are enough as enabling technology to create and demonstrate new applications based on heterogeneous and diverse datasets.

To obtain driving destinations as goal, we arranged Linked Geo Data and DBpedia Japanese[1] with newly constructed facility ontology and service ontology, which make links among such existing datasets. Japanese WordNet[2] is also utilized as general knowledge, because it was necessary to make the inference with common sense to discover destinations from user requests. We developed the inference procedure to translate user requests into SPARQL queries to obtain a recommendation on appropriate facilities for users.

The purpose of this preliminary report is to make a clear direction for development of LOD applications in order to deploy linked data as the infrastructure of society in future. The structure of this preliminary paper is as follows. We describe the detail of the use-case in Section 2. Section 3 reports the related work from the viewpoint of the long-term research activity on artificial intelligence. In Section 4, we show how we realize new ontologies on facilities and services in order to utilize open knowledge-bases and LOD. Section 5 describes the systematization of multiple linked datasets and the SPARQL endpoint. Section 6 describes the inference procedure for the purpose of getting recommendations by using SPARQL queries. We show how we can realize action planning by using open knowledge-bases and LOD. Section 7 reports a simple example of execution by this prototype system that realizes a new purpose-oriented inference engine with SPARQL and large-scale open knowledge-bases. Section 8 provides discussions. In the last section, we summarize the results and address the future work toward the new era of Knowledge Society based on Open Data and Linked Data.

2 Problem Setting for the Use Case

In setting of the use-case, we firstly made more than ten scenarios of conversation between users and this system. In each case, a user in a car speaks a single or a number of requests to do something with driving a car. Then, the system analyzes the requests under the consideration of current contexts such as time, location, driving time, etc. At last, the system makes concrete action proposals to visit specific points (shop, facility, etc.) or areas (sightseeing area, good place for time-consuming, etc.) with a reasonable visiting order. Basically, the request may be vague and complex, but the recommendation is specific and concrete. However, every recommendation is a sequence of actions, and proposed actions are quite limited within these scenarios, for example, drive somewhere, buy or eat something, do some sport, and so on. One of the simplest scenarios is as follows.

Child passenger(hereafter C): I want to see a lion.
System(hereafter S): How about Ueno Zoo. A baby lion was born recently.
C: It sounds good, but I was there last month.
S: Well, how about Kinoshita Circus. You can see a lion show there.
C: OK. That's fine.

In this scenario, the system must discover the knowledge that a lion is a kind of animal and a zoo is a public entertainment facility for seeing animals. The system must find out a nearest zoo, that is Ueno Zoo in this case, from the current location, and must reason that users have enough time to drive to the destination and walking around the zoo. Furthermore, due to the negative response of the user, the system must discover a neighboring circus that presents a lion show as an alternative.

3 Related Work

Planning was one of the most popular AI research area in the 1970s through the 1980s, where the research efforts focused on reasoning mechanisms on making plans [3][4][5], but the role of knowledge in inference was not regarded. Around the 1980s, the reasoning with knowledge was well studied in problem solving, and the efforts how to use human experts' knowledge with inference engines amounted to expert systems. Even after that, we have no remarkable innovation to solve information-rich planning problems, as expert systems was confronted with. Note that scheduling problems in project management, production management, and delivery management are rare successes by domain specific knowledge and algorithms.

The recent success of IBM Watson in TV show *Jeopardy!* seems to promise knowledge graph approach for problem solving and decision making[6]. However, we should note that Watson system for *Jeopardy!* did not use common sense for combining multiple knowledge graphs. Basically, the system model for *Jeopardy!* game is categorized into a Q&A system for trivial knowledge. Multiple knowledge graphs and selection of the most probable answer candidates are key technique in Watson for *Jeopardy!*, and common sense knowledge is used only in WATSONPATHS for breaking down the top level question into subquestions based on unstructured text corpus, and not used as bridge for multiple knowledge graphs [7].

To endow computers with common sense is one of the major long-term goals of artificial intelligence. Common sense reasoning widely ranges over a number of different fields from taxonomic reasoning, geographic reasoning, temporal reasoning, reasoning about actions and changes, qualitative reasoning [8] to naive physics, interpersonal interaction theory, and social relationship theory. Mueller [7] described common sense reasoning based on event calculus. The knowledge-based approach of common sense reasoning is categorized by Davis [8] into five types as i) Math-based, ii) Informal, iii) Large-scale, iv) Web mining, and v) Crowd Sourcing, then he discussed pros and cons of each approach. In this research, our approach is classified as Informal and Large-scale, while DBpedia can be classified into the approach of Crowd Sourcing.

The role of verb is not seriously regarded in action planning so far. Action is just called *operator* in the context of old AI planning. Cognitive Linguistics pays more careful attention on the relation between verbs and objectives. In this research work, we picked up several verbs such as 'see', 'eat', and 'buy' in order to plan actions according to the use-case scenarios, and the relation of such verbs to objectives is realized in our facility ontology and service ontology. See the details in the following section.

Schank addressed eleven primitive actions in Conceptual Dependency theory [9]. He suggested us verbs may be categorized in hierarchy structure. Schank also invented the idea of *script* that explains typical stereotyped human behaviors at restaurants or fast food shops or other facilities [10]. We also defined typical behavior for users in our facility ontology and service ontology, where a noodle shop as food facility provides noodle food service, and the noodle food service is composed of eat action and food noodle as objective.

Frame theory by Fillmore is a theory for Natural Language Understanding [11]. In Filmore's semantic frame, verb 'buy' is described by other frames such as 'goods' as object, 'buyer' as subject, in addition to other frames 'seller' and 'money'. Extending semantic frame theory, Fillmore developed Case Grammar, in which a sentence is analyzed with two type cases, surface cases and deep cases. Fillmore addressed several deep cases, Agent, Object, Instrumental, Result, Locative, etc. In this work, we also adopted case grammar for text processing, because Japanese is very compatible to Case Grammar, and it is easy to apply surface cases to Japanese particles. See the details in Section 6.

Levin [12] published a resource materials on the English verb lexicon, in which verbs in English are classified into a number of verb classes (by attributes), but there is no hierarchy of classes and no ontological or taxonomic description about verbs, and less descriptions on the relationship to objectives.

Generally, we have a number of aspects in dialogue. Searle described the mechanism of human speech interaction and addressed the Speech Act theory [13]. In his theory, he follows the idea of John L. Austin and elaborated ten speech aspects of *illocutionary act*, that is a terminology for intensive action by speech, i.e., *request*, *question*, *assert*, *state*, *affirm*, *thank*, *advice*, *warn*, *greet*, and *congratulate*. Today, chat should be taken account of in addition. In this preliminary work, we took account of only *request*. See the details of text processing in Section 6.

4 Ontologies for Facility, Action Target, and Service

4.1 How to Make Facility Ontology

Instead of directly searching individual facilities like Ueno Zoo or individual shops like Yodobashi Akiba store (a home electric appliance mass retailer in Japan), we considered classes of facilities like zoo or home electric appliance mass retailer to make the system scalable, then made a facility ontology that contains typical facilities and we defined typical users' behavior at such facilities like "a user sees animals in a zoo" or "a user buys a household appliance at a home electric appliance mass retailer." Even if we accidentally fail to guide an actual facility that satisfies user's special requests, such a problem will be solved with the development of richer and more specific datasets that includes individual facilities.

The facility ontology is constructed mainly by extracting facility classes related to leisure and meals in Linked Geo Data (LGD). LGD constructs a shallow class hierarchy from tags attached to the nodes and ways of OpenStreetMap (OSM). Therefore, LGD classes makes it easy to incorporate new facilities and new facility types.

On the other hand, as a result of adopting LGD / OSM, duplicates of classes due to notation fluctuation of tags and the low coverage rate of actual facilities at the instance level could be a big problem. However, we think this approach is the best for our purpose in our best knowledge, because the LGD / OSM is the largest facility data that is freely available at the present. Also note that actually it is impossible to measure how much the existing facilities are covered in reality. Regarding duplicates of classes in LGD, we select an entity as primary class that has both the most information-rich descriptions on the OSM and a large number of instances, then the rest are associated with owl:equivalentClass to the primary class.

The following shows an example of zoo class in the facility ontology. The meanings of Japanese words are added here in English as turtle comments for readers. Both a service of "see animal" and "pay admission fee for cultural facility" are actually described in the service ontology as subclasses of "see" service and "admission-viewing-gaming" service. Note that each service is described as a pair of an action and an action target, which users can perform. In this paper, we manually acquired and created service knowledge of facilities within the scenarios as necessary. See the statistic numbers in Table 1. As shown below, the lgdo:Zoo class is linked to the dbo:Zoo class in DBpedia Ontology to make possible to search related facility instances in DBpedia Japanese. The dbo:Zoo already has a link to Wikidata's wikidata:Q43501. Thus, it can be easily expanded when Wikidata is added.

```
lgdo:Zoo a owl:Class;
  servicevoc:dbpediaClass dbo:Zoo ;
  servicevoc:provideService [ servicevoc:hasService [
      servicevoc:action action:払う;                # pay
      servicevoc:target target:文化施設入場料 ],  [  # admission fee
                                            # for cultural facility
      servicevoc:action action:見る;                # see
      servicevoc:target target:動物 ]] ;            # animal
  rdfs:subClassOf servicevoc:Facility .
```

4.2 How to Make Service Ontology

In the facility ontology, a number of services corresponding to distinct facilities come up with common abstract services. For example, both museums and art museums have the same service of "paying entrance fee for cultural facilities". In addition, there are hierarchical relationships among users' action targets, then we have a similar relationship between services. For example, "seeing animals" can be regarded as the top of "looking at a lion". We constructed an ontology of services apart from facility classes, so that services are independently recognizable, and it enabled us to expand the performance of inference by applying the hierarchy of services. In this paper, the part of service ontology is constructed by using the Classification in the Household Survey of the Ministry of Internal Affairs and Communications. The top of service ontology is the 'facility_service' and it is related to aspects of two types of behaviors, namely, 'purchase_service' focused on purchasing behavior, and an 'activity_service' focused on the other behaviors at facilities. The following shows an example of 'purchase_service' ontology entries.

```
service:食料_サービス a owl:Class;        # food service
  rdfs:label "食料_サービス";
  servicevoc:action action:買う;         # buy
  servicevoc:target target:食料;         # food
  rdfs:subClassOf service:購買_サービス . # purchase service

service:肉類_サービス a owl:Class;        # meat service
  rdfs:label "肉類_サービス";
  servicevoc:action action:買う;         # buy
  servicevoc:target target:肉類;         # meat
  rdfs:subClassOf service:食料_サービス . # food service
```

4.3 How to Make Target Ontology

For the sake of systematical description of actions and action targets, we used the Household Income Balance Item Classification List (January, 2015) of the Statistics Bureau of the Ministry of Internal Affairs and Communications, of which items of statistics data are used to describe purchasing behavior at facilities. User's behavior at facilities can be divided into purchasing behavior (such as buying something or paying for some benefits as service) and the other actions (see, eat, drink, etc.). This classification is based on a hierarchical structure of action targets as users' behavior as consumer, so it is possible to consider cooperation with statistical data in future, starting with purchase actions. For actions and action targets other than purchasing behavior, we used Japanese WordNet, because we want to use WordNet's knowledge on the relationship between each verb as action and each noun as an action target. For instance, we made Action Target Ontology as follows.

```
target:動物 rdfs:label "動物";                   # animal
  servicevoc:wordnet wnja11instances:word-動物 .

target:食料 a owl:Class; rdfs:label "食料";     # food
  servicevoc:wordnet wnja11instances:word-食料 ;
  rdfs:subClassOf target:購買対象 .              # purchase object
```

4.4 LOD, Ontologies, and Statistics

All LOD datasets and ontologies in this study and their statistics data are described in Table 1.

Table 1. Outline of Prepared Datasets and Used Datasets

Dataset	Version	Num. triples	Num, classes	used
Fact Dataset				
DBpedia core+en	2016-04-01	1,131,657,931	-	△
DBpedia Japanese	2017-02-20	113,299,748	-	○
LinkedGeoData	2015-11-02	1,216,560,762	-	○
General Ontology				
DBpedia Ontology	2016-11-01	30,793	758	○
LGD Ontology	2014-09-09	24,530	1,200	○
Japanese WordNet	2013-06-26	4,003,288	57,238	○
Japanese Wikipedia Ontology	2013-11-07	21,863,327	166,397	-
YAGO	3.0.2	1,001,461,792	5,130,031	-
OpenCyc	2012-05-10	5,783,451	233,644	-
UMBEL	1.5	392,728	33,686	-
Service Ontology				
Facility Ontology	2017-02-20	3,257	418	○
Service Ontology	2017-02-20	3,933	750	○
Action Target Ontology	2017-02-20	2,030	622	○
Action Ontology	2017-02-20	153	55	○
subtotal of Service Ontologies		9,373	1,845	
Total		3,495,087,723	5,624,799	

The service ontology at the bottom of the table is the ontology we constructed this time, as explained in the above.

While the number of data with longitude and latitude were respectively 26,351,904, 100,139, and 1,014,836 for LinkedGeoData, DBpedia Japanese, and DBpedia respectively, the number of geodata, of which each is close to rectangle, in domestic portion excluding Hokkaido, is respectively 538,878, 67,199, and 15,409.

5 Building Knowledge Graphs

We have collected a number of open knowledge resources as shown at the upper part of Table 1, and all of them are stored in one RDF store. However, at the time of this writing, we have actually used only DBpedia Japanese, LinkedGeoData, Japanese WordNet, and DBpedia Ontology as open datasets. Wikidata is not stored because of the capacity.

The system used one endpoint built with one dedicated RDF store.

6 Reasoning and Q&A Process

In this preliminary research, we process natural sentences only within the range expected at use-cases. Furthermore, in this paper it is assumed that the input is transcribed as text instead of speech.

6.1 Process Flow and Reasoning

Work flow of this system is described as follows (see, Figure 1).

1. Input a text of user's requests.
2. Perform the morphological analysis for the input text.
3. Perform the case analysis starting with surface cases to deep cases.
4. Translate the requests into SPARQL queries.
5. Obtain the reply of SPARQL queries.
6. Generate the answering text from the obtained reply.
7. Output the recommendation.

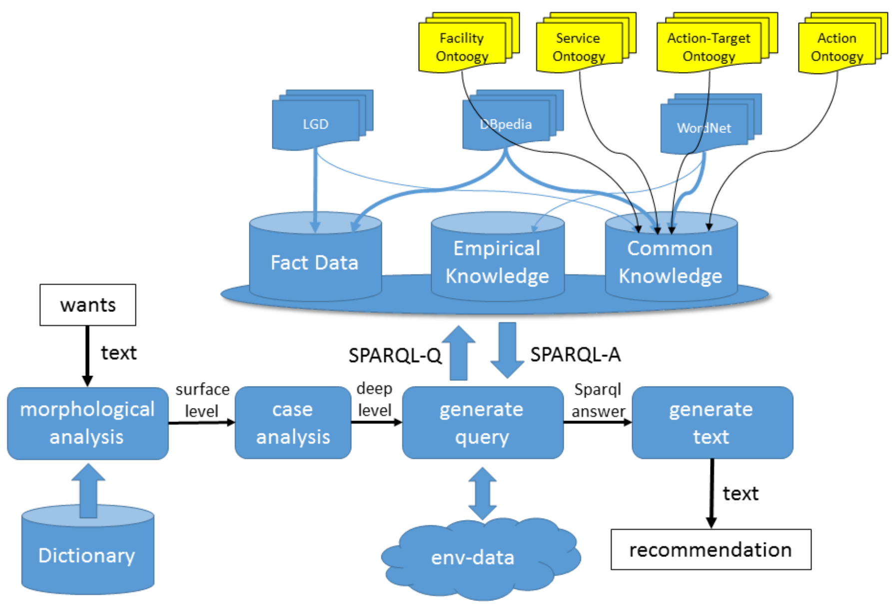

Fig. 1. Data Flow in Processing

Japanese is a kind of agglutinative languages and a Japanese sentence is written without a space left among phrases and words. A noun phrase is composed of a noun and a particle, a verb phrase is composed of a stem of verb and a grammatical conjugation. So, morphological analysis is requisite in Japanese text processing in order to separate a sentence into phrases and words. Furthermore, particles attached to nouns decide the grammar case. For example, in response to an user's input "ライオンが見たいな (I want to see a lion)", the morphological analysis and *shift-reduce method* changes the Japanese sentence into the form of ((な (*pos info*) 8) ((たい (*pos info*) 6) (見 (*pos info*) 5)) ((が (*pos info*) 4) (ライオン (*pos info*) 0))), here (*pos info*) stands for a Part-of-Speech information of each, then case analysis produces the result such as Subject:NIL, Verb:(見る (*pos info*) 5), Object:(ライオン (*pos info*) 0), toPlace:NIL, fromPlace:NIL, Tool:NIL. Part-of-speech information obtained from morphological analysis is effectively used in various ways. For example, if there is an auxiliary verb 'たい (want)' next to a form of a behavioral verb such as '見る (see)' or '食べる (eat)', the whole sentence is interpreted as *request*. Thus, a request of seeing a lion is captured and transformed into a SPARQL query to the endpoint.

From the interpretation of request (see lion), the system searches facilities that can see a lion, using action target ontology and facility ontology. However, we have no common sense as LOD that a lion is in a zoo. When searching fails here, WordNet is used to generalize the target to more abstract ones by searching hypernym relations in WordNet until animal is found.

The SPARQL search picks up a number of facilities that are located near the current location, and the closest one to the current location is chosen outside of SPARQL search.

6.2 Inference with SPARQL

Initially, we attempted to make a plan by introducing IS-A logic function into planning based on classical state space reasoning and backward reasoning [14]. However, more than it, searching combined ontologies using one SPARQL query easily enabled us to retrieve acceptable instances of appropriate facility from the action target ontology and the facility ontology without any problems in execution speed. The LGD class according to the user's request from the facility ontology can be found, and once the LGD class is known, SPARQL allows direct retrieval of the facility instance within the LGD. If there is a DBpedia class linked from LGD, DBpedia Japanese is also automatically searched in SPARQL queries. The current system consists of RDF Store search and inference for interpretation of user's requests. This configuration is beneficial at usability and re-usability. Based on SPARQL search and open resources, it is possible to expand and refine ontology without touching the inference engine of the planning system in applications. It is meaningful for practical application of reasoning by large amount of data.

7 Example of Execution

The following shows an example of execution by this prototype system, see the added comments translated into English for readers.

```
SYSTEM(4): (eliza)
system> スポーツがしたいな。そのあと、温泉に行きたい。
;; I want to enjoy some sport, after that, I want to go to hot spring.
現在地はトヨタ東富士研究所です。
;; the current location is Toyota Higashfuji Institute.
スポーツをする場所を探します。; searching a location for sports
......
一番近くの場所を案内します。 ; guiding the nearest place
距離は 13.37621km です。      ; the distance is 13.37621km
場所：沼津市営球場            ; place: Numazu City Ball Park
緯度：35.1125                 ; longitude
経度：138.863                 ; latitude
URL："http://linkedgeodata.org/triplify/node2877270449"
現在地は(35.1125 . 138.863)です。; the current location is (35.1125 . 138.863)
温泉に入る場所を探します。    ; searching a location for hot spring
......
一番近くの場所を案内します。 ; guiding the nearest place
距離は 10.426165km です。     ; the distance is 10.426165km
場所：伊豆長岡温泉            ; place: Izu-Nagaoka Hot Spring
緯度：35.0353                 ; longitude
経度：138.929                 ; latitude
URL："http://ja.dbpedia.org/resource/伊豆長岡温泉"
```

Searching for a facility in the vicinity of the current location, the Toyota Higashifuji Institute, the system made a recommendation to go to Numazu City Ball Park, then go to Izu-Nagaoka Hot Spring, in response to a request to go to a hot spring after enjoying some sport.

Here the command ‘eliza’ is named for just representing a mimic of Eliza dialog system [15], that is the first dialog system in AI history. While this prototype of action planning by using open knowledge sources and SPARQL queries is widely applicable to various kind of applications, yet there is not enough as intelligent agent, because it has neither short-term nor long-term memory like original Eliza. Making more intelligent agent remains in future work.

8 Discussion

In this work, we captured knowledge about our world into three layers, i,e., factual knowledge, general knowledge, and empirical knowledge. The factual knowledge includes objective information on individual events and matters. On the other hand, the general knowledge is not information on individual events and things, but rather description of relationships among them in addition to the abstract descriptions of events and things. It is regarded as objectively valid by most people or as social agreement. The empirical knowledge is a specific knowledge that does not go into general knowledge in society, such as personal knowledge which are agreed only by less people. For example, suppose a very delicious hamburger made by a fast food shop located at a place, the information on this shop's address is factual knowledge, the knowledge of classification on fast food shop is general knowledge, and knowledge such as a hamburger made by this hamburger shop is delicious is empirical knowledge.

As shown in Table 1, most of LGD / OSM is factual knowledge and it is categorized to factual dataset, but a part of LGD / OSM is categorized into general knowledge. DBpedia contains both fact data and general knowledge. However, WordNet contains general and empirical common knowledge.

In this preliminary research, the following issues are suggested.

1. It is necessary to understand data characteristics of coverage and granularity of each dataset, but it is generally hard for large datasets. At this time, we firstly made a utilization plan on the whole data set, after we examined the availability of actual data on the premise of these use-case scenarios.
2. Generally, it is tough work to find out correct relations between datasets. While simple string matching allows us an automatic matching process, the ontology mapping cannot be avoid human power at the present. While the accuracy of this mapping greatly affects the result, mechanical matching processing is difficult. In addition, we built intermediate ontologies and mapped them to LOD datasets, but building ontology is generally not easy for a novice.
3. Since DBpedia and LGD are datasets made by crowd sourcing, we cannot expect the completeness and validity of them. Missing or biased data is still problematic at reasoning. Actually, we found a closed food shop as results. At this time we attempted to eliminate errors as soon as it was found, but we need to think about some tools for (semi) automated error checking.
4. The inference procedure was designed according to these use-case scenarios. For other problems, different datasets and different work flows may be used. For example, it depends on features of a target problem about how the balance should be taken between general knowledge and fact data to solve the problem.

9 Conclusion

In this preliminary research, we made a prototype of action planning system for events of everyday life and world, based on open knowledge of LOD as fact data and taxonomy as common knowledge. We utilized a number of large-scale open databases and knowledge-bases. We found that we had already abundant knowledge about the everyday life and world as diverse open knowledge resources. This condition is very different at the era of Good-Old-Fashioned-AI (GOGAI) before the Web age and LOD. However, we also found that we needed the additional general and common knowledge that connects such different open resources in reasoning action plans with SPARQL endpoints. It is obvious that it will be necessary to make open knowledge more available not only in the verification and validation for each, but also in the combinations of them for applications.

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