

A Semantic Question Answering System for Smart Factories

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Abstract Industrial production characterized by the increasing interconnection of machines and devices (e.g. Industrial Internet of Things, IIoT). Smart Factory evolved with its rapid requirements over the past few years. Leveraging Industry 4.0, smart factories require Human Machine Interface solutions in order to present information to experts, users or operators. Semantically created data by manufacturing machine mostly used by the Human Machine Interface System. As a result, an information model can be extracted from an extensible markup language in order to use with semantic data. Nature of linked data might have different properties from other open domain or closed domain question answering so that we will examine a restricted domain question answering system with linked data through our main architecture. Moreover, we present a semantic question answering with data based on eniLINK and generated data from an OPC UA Server known as Dynamic Server. In addition, we will evaluate our question answering with different measurements according to the requirements of a restricted-domain question answering.

Index Terms— Semantic Web, Web 2.0, Web Services, Information Retrieval

I. INTRODUCTION

THIS work introduces a new concept for smart factories in terms of HMI technology integrated into a semantic question answering. A semantic question answering used for information retrieval to provide answers from questions by means of linked data. Linked Data is a new concept ubiquitously covered all around of use. The data size, which resides in the Web has been doubled every year since the day of the Web invented. As a result, a great amount of unlabeled data could not be used by applications, so W3C (World Wide Web Consortium) decided to create a standard for Semantic Web in order to create linked open data concept.

Requirement 1: Linked Data Generation from a Fraunhofer IWU's OPC UA Server,

Linkedfactory Static and Dynamic Data created by KVIN Service with LevelDB (key-value storage library).

The data source is a key factor for a successful question answering system. Our question answering uses linked data created by eniLINK.

Requirement 2: Real-time linked data generation through the KVIN API.

Requirement 3: A standard-based interface compatible with RESTful communication.

Requirement 5: Evaluation of Semantic Question Answering

The remainder of this paper is organized as follows: Section

2 describes requirement and approaches, Section 3 defines how we can prepare real-time data. In Section 4, we clearly explain the prerequisite methods in natural language processing. Thereafter, Section 5 clearly examines the proposed architecture. As a result, we conclude in Section 9.

II. REQUIREMENT AND APPROACHES

//In this section, you should elaborate on the requirements

III. SMART FACTORIES

//Towards Smart Factories

//Industry 4.0

//Human Machine Interface in Smart Factory

IV. DATA PREPARATION

A. Mapping an OPC UA Data into a Semantic Data

Our main data sources are semantically parsed data from eniLINK [1] and OPC UA Server generated data. In the phase of OPC UA Server generated data, we used an SDK which is published by FreeOPCUA [2]. OPC UA Protocol uses an information model and the information model can be used with metadata to simulate in other OPC UA Server with languages such as XML (Extensible Markup Language). Due to the nature of XML, it is a language a strongly hierarchical and hardly extendable. However, semantic data such as Resource Description Framework

(RDF) can employ triples with SPARQL. Different RDF Graphs stored in enILINK[1] are uniquely identified.

Algorithm 1 Node Extraction

```

1: function MAINFUNCTION()                                ▷ Starting point
2:   export = ServerExport(serverurl, filename)
3:   export.IMPORT NODES(serverurl)
4:   export.EXPORT FILE(outputFile, namespaces)
5: function BUILD NODE TREE(nodes)                      ▷ Node Formatting
6:   client ← GETENDPOINT()
7:   client ← CLIENT(serverurl)
8:   nodecumulated ← None
9:   nodeID ← 0
10:  for node < nodes do
11:    nodecumulated = node.nodeid.Namespaceindex
12:    for ref < node.getreferences() do
13:      nodecumulated.extend( ref.nodeid.Namespaceindex)
14:    nodecumulated = list(set(nodecumulated))  ▷ Clear duplicates
15:  return nodeID                                       ▷ Return node id list
16: function IMPORT NODES(serverurl)                     ▷ Traverse Node
17:   client = Client(serverurl)
18:   client.connect()
19:   for ns < client.getNamespaces() do
20:     namespaces[client.getNamespaceIndex(ns)] = ns
21:   root = client.getRootNode()
22:   child = client.iterateChildNodes()
23: function EXPORT FILE(outputFile, namespaces = None) ▷ Export into XML
24:   if namespaces != None then
25:     for node != nodes do
26:       if node.nodeid.namespaceindex is namespaces
27:         nodes = [node]
28:       else
29:         nodes = list(nodes)
30:
31:   export = XmlExport(client) then
32:     export.BUILD NODE(nodes)
33:     export.appendXML(outputFile)

```

Figure IV-1. OPC UA Address Space Representation in XML [2] [3].

A. Real Time Data Mapping with KVIN

Real-time data has intricacies to use as linked data taken from sensors, actuators or software logs. In the aspect of Smart Factories, real-time data mostly is created by sensors and actuators that are the underlying structure of manufacturing machines. Fraunhofer IWU collects the real data source by saving into a time series database. The major drawback is that when a time series data taken, semantic query endpoint can not use the pure data without annotating. Such annotation could be triple creation, adding of predicates or serialization from one formal language to another.

Our architecture is providing a real-time semantic data annotator KVIN that utilize to extract triples from time-series data in a database.

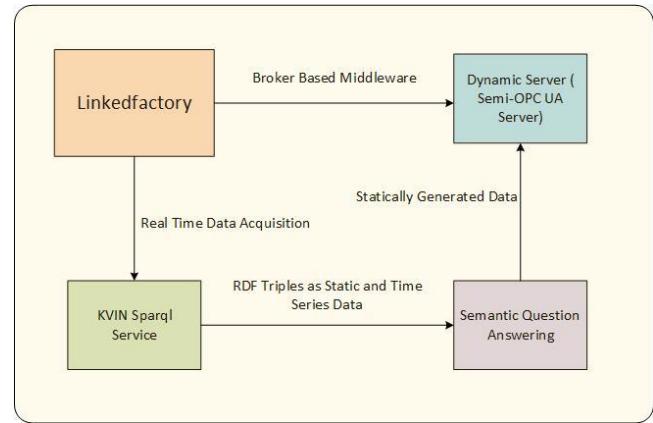


Figure IV-2. KVIN Continuous SPARQL Mapping.

This work proposes a service named KVIN to perform a SPARQL request into a specified endpoint. This service is based on a combination of the triple store through Level DB which is a key-value storage library written by Google¹. It has been used an RDF4J's extension to create a SPARQL Service.

V. NATURAL LANGUAGE UNDERSTANDING FOR THE SEMANTIC QUESTION ANSWERING

In Natural Language Processing, we need to identify the sentence's structure in order to reach the step named Query Formulation of SPARQL.

Preprocessing: Chiefly, all natural language tasks start with preprocessing which means cleaning data for specific tasks. This could be the reduction of undervalue data, reduction of discrepancies between the values or removing non-related morphological properties.

Tokenization: A question answering system should parse all input as tokens. Tokenization is an initial step for Part of Speech tagging to parse into a verb, noun, cardinal numbers, adjective etc.

Lemmatization and Stemming: Lemmatization and Stemming are similar steps to each other with one difference. While stemming used to find syntactical structures, lemmatization looks for a semantic structure. Stemming clear of the structure of suffix and prefixes. In our system, we are supposed to use a lemmatizer and stemmer in order to reduce lexical complexities. A lemmatizer has been used to consider the morphological analysis of verbs, e.g. from “contains” or “contained” to “contain”. Then we use this verb mapping into a predicate to construct a SPARQL Query. The lemmatization and stemming are part of the normalization process in terms of linguistic properties.

Part of Speech Tagging: It is a preprocess step for parse tree to identify item taggers such as verbs, adjectives or

¹ <https://github.com/google/leveldb>

nouns. A sentence consists of a couple of structure, including words like noun, verb, pronoun, preposition, adverb, conjunction, participle and article that are main categories of part of speech processing [4]. Part of Speech Tagger mostly uses a Markov Model that is a part of statistical natural language understanding. Markov Model stands for a state can depend on a previous step, but there is no dependency on states of historical steps more than one. For instance, a noun or a verb defines its neighbors, e.g. nouns are preceded by determiners, adjectives, verbs [4]. For example, a chess player makes a movement according to the last movement of a rival rather than guessing from the first movement of the rival. In this step, pre-saved corpora which have a million words have to be tagged by POS Taggers.

Parse Tree and Penn Treebank: One of the common list that has an identifier for POS denominated as Penn Treebank. A Treebank used for annotating syntactic and semantic structure of a sentence with a million words of part-of-speech tagged text.

When a natural query is given, a question answering system should understand the grammar behind it. POS tagger is not enough to identify the grammatical structure for complex natural queries. Relationships among noun phrases, adjective phrases, adverb phrases, and verb phrases should be examined in order to map correctly subject-predicate-object triples in linked data. The approach of parsing separated into two main sections, which are the rule-based approach and the probabilistic approach [5]. The rule-based approach is a top-down approach to solve problems via predefined rules such as Regex-parsing. Therefore, a question answering system should define rules precisely to get the correct answer. Open-domain question answering systems use this approach because of complexity of bottom-up approach and broadened question types. Nevertheless, rule-based approach could give undesirable results in restricted-domain question answering or semantic question answering and could be time-wasting approach. A dependency parser analyzes the grammatical structure of a sentence and it gives the relationship among them. The dependency parser also gives the relationship between general words and root words. Thus, we can identify the center verb or noun from complex sentences. This parser utilizes a dependency treebank file and word embedding files. Chiefly, a dependency parser applies the supervised machine learning method to reach syntactical result. For example, with dependency treebank, data is broken into test and training set, however, word embedding used for training phase.

Dependency Parser: //Explain
Constituency Parser: //Explain

Named Entity Recognition: It is a subtask of information extraction to locate and classify named entities with pre-classified labels such as names of people, organizations, locations, and quantities etc. Named-entity recognition is a method that identifies the item of a sentence as a domain-

specific. It identifies all structures mainly as a person, a location, an organization, and an entity.

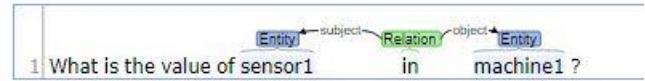


Figure V-1. Natural Language Processing Steps for Question Answering.

As shown in Figure V-1, “sensor1” and “machine1” named as an entity and found a relation between each other. After doing a couple of experiments on named-entity recognition, shreds of evidence show us a named-entity recognition is an application-specific task. An NER Method that is created for a different domain may not be reused for another domain. In order to create a named-entity recognition for a smart factory, a model can be trained to satisfy the requirements of a smart factory. In this context, a model can be created by statistical methods or a rule-based model. In context with the rule-based model, the character regex method can identify the structure of a natural query. For instance, a named-entity recognizer can employ a model that contains a combination of “HeatMeter” or “HeatingWater”, which it can assort given items with the character started by “Heat” in a smart factory.

VI. PROPOSED ARCHITECTURE

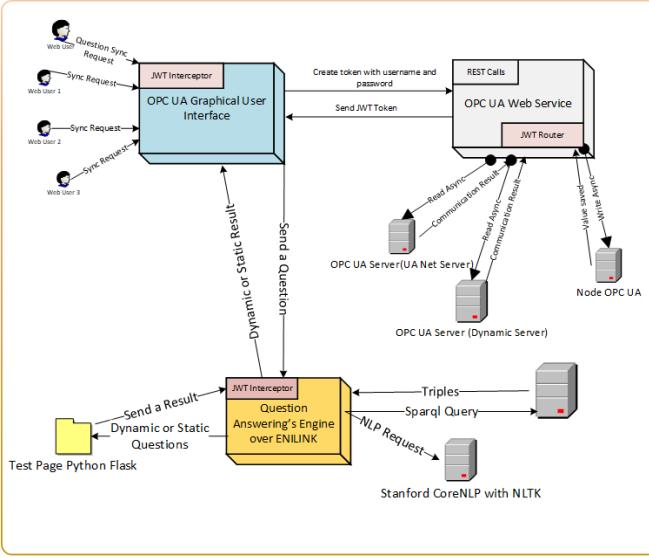


Figure VI-1. A RESTful Architecture for Question Answering.

As shown above, in Figure 1, we aimed a RESTful architecture for the semantic question answering as an orange box. NLP Requests are sent to Stanford CoreNLP server to parse grammatical structure on given the natural query. Our semantic question answering system handles with token normalization process with Tokenization, Lemmatization, and Stemming

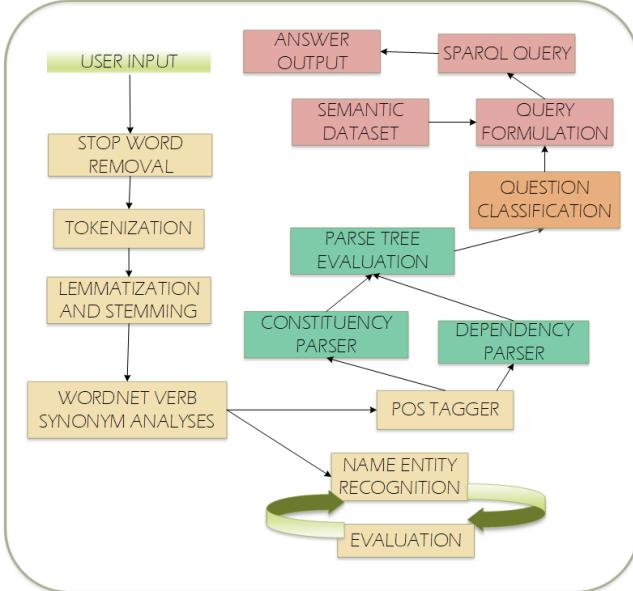


Figure VI-2. Natural Language Processing Steps for Question Answering.

As illustrated in Figure 1., we have multiple stages to get an answer at the end. Restricted domain question answering suffers from a problem of name-entity recognition when we implement the system.

After taking input from any user, stop-word preprocessing stage start to filter unnecessary characters such as question

mark, exclamation point, comma, dot or determiners. Tokenization is the next step in order to reduce the size of characters to provide optimization in natural language processing and it reduces the complexity of instances of sequence characters. Lemmatization and Stemming is an essential step before WordNet Verb analysis because our main target is to extract verb, nouns and related chunking in order to formulate a SPARQL query that can give an answer.

Algorithm 1 Query Formulation

```

1: function QUERY FORMULATION( $a, b$ )                                ▷ Explain here
2:    $query \leftarrow QueryWithPrefixes$ 
3:    $r \leftarrow contiuent.parse.tree$ 
4:    $indirectdependency \leftarrow dependency.parse.tree$ 
5:   while  $nodes \neq leafs.terminal$  do                                     ▷ Until leaf nodes(Terminals)
6:      $verbs \leftarrow PARSER(nodes)$ 
7:      $nouns \leftarrow PARSER(nodes)$ 
8:      $similarityflag \leftarrow WORDLATENANALYSIS(verbs)$ 
9:     if StaticInformation is True then
10:        $indirectdependencyFlag \leftarrow DEPENDENCYPARSER(nodes)$ 
11:       if similarityflag and IndirectDependency is true then
12:          $object \leftarrow nouns$ 
13:          $predicate \leftarrow verbs$ 
14:          $query += object + predicate + ?subject$ 
15:       else
16:          $subject \leftarrow nouns$ 
17:          $predicate \leftarrow verbs$ 
18:          $query += ?object + predicate + subject$ 
19:     if DynamicInformation is True then
20:        $predicate \leftarrow PARSER(nodes)$ 
21:        $object \leftarrow PARSER(nodes)$ 
22:        $similarityflag \leftarrow SIMILARITYLEVENSHTEIN(input)$ 
23:        $query += object + predicate + ?subject$ 
24:   return  $query$                                                        ▷ The last query has been constructed

```

Figure VI-3. Natural Language Processing Steps for Question Answering.

The general information about our architecture is in Figure 1.1 below: The RDF data from eniLINK and OPC UA Server (right-hand side). A SPARQL Endpoint has been provided by our architecture for local static data and KVIN also presents a SPARQL Endpoint for time-series data.

VII. EXPERIMENTAL DEVELOPMENT

A. Data Sets

In the evaluation phase, our main data sources are OPC UA Server Generated Data, eniLINK Static, and Dynamic Data. Chapter 3 A. and B. parts are examining in a detailed way how to create and obtain data and convert into a linked data format. OPC UA Generated Data has not specific namespace definition unless we define as we wish. However, user-defined IRIs definition has drawbacks such as collision or non-extendibility. A long listed linked data makes the structure complex so that two subjects of the list can be collapsed because of same-defined IRIs. In our case, all namespaces are generated with <http://www.example.org> or “<unknown_namespace>”.

One of the poorest performance has been observed in the phase of named-entity recognition because restricted-domain requires different lexicons to train entities.

B. Model Setup

VIII. EVALUATION

Evaluation criteria comprise of question classification and recall, accuracy, precision, F1 score of answers against semantic question answering system. General evaluation parameters for a restricted domain question answering is not only limited with answering of questions but also we can assess with speed, user interaction, querying style (keywords, browsing, spell checker, abbreviation recognition)

Give a result from Question Types as tables
Who, Which, How, Affirmation, Unknown

Give a result from Question Classification – both what type questions and TREC labeling

QUESTION CLASSIFICATION- QUESTION LABELS

Question Classification	Precision	Recall	Accuracy
What	A	B	C
Who	A	B	C
Which	A	B	C
How-Why	A	B	C
How many- quantity	A	B	C
Affirmation	A	B	C
Unknown	A	B	C
<i>Overall</i>	A	B	C

Li&Roth Taxonomy	Precision	Recall	Accuracy
Abbreviation	A	B	C
Description	A	B	C
Entity	A	B	C
Human	A	B	C
Location	A	B	C
Numeric	A	B	C
<i>Overall</i>	A	B	C

QUESTION ANSWERING RESULT

Question Answering Parameters	Total Questions
Correct Answer	A
Wrong Answer	A
Precision	A
Recall	A
F1	A
<i>Overall</i>	A

IX. RELATED WORKS

[Diego Molla et. al] reviewed a main characteristic of question answering in restricted domains is the integration of domain-specific information that is either developed for question answering or disclosed for other purposes [6]. [Diego Molla, Jose Luis Vicedo] defined main characteristics of question answering system over limited domains, e.g. circumscription of question answering, the complexity of question answering, and practical usage of question answering[6].

The authors have compared between open-domain and restricted-domain question answering by figuring out key points. [Diego Molla, Jose Luis Vicedo] offers four clear-cut subjects such as the size of data, domain context, resources, and use of domain-specific resources.

[Sebastian Ferre] has published one of the detailed reports that express common pitfalls of natural language processing, essential points while consolidating SPARQL query and morphological definitions [7]. SQUALL is a solution for querying and updating RDF graphs by exploiting a controlled natural language which restricts grammar structures of a sentence in order to diminish complexities [7]. It has grouped all substantial features of a morphological language and pointed out what type of features in a natural language harnesses with regarding priorities and orders. The main contribution of SQUALL is categorizing ambiguities of natural languages and how turned out an advantage when using a controlled natural language [7]. The authors sketched a translation from their intermediate language to SPARQL to gain more accuracy with their system [7].

X. CONCLUSION

Please include a brief summary of the possible question answering implications of the work conducted at Fraunhofer IWU in this section.

APPENDIX

Appendixes, if needed, appear before the acknowledgment.

ACKNOWLEDGMENT

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