A Novel Approach for Ontology-Driven Information Retrieving Chatbot for Fashion Brands

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***Abstract*—Chatbots or conversational agents are the most projecting and widely employed artificial assistants on online social media. These bots converse with the humans in audio, visual, or textual formats. It is quite intelligible that users are keen interested in the swift and relatedly correct information for their hunt in pursuit of desired product, such that their precious time is not wasted through surfing multiple websites and business portals. In this paper, we present a novel incremental approach for building a chatbot for fashion brands based on the semantic web. We organized a dataset of 5,000 question and answers of top-10 brands in the fashion domain, which covers the information about new arrivals, sales, packages, discounts, exchange/return policies, etc. We have also developed a dialogue interface for querying the system. The results generated against the queries are thoroughly evaluated on the criteria of time, context, history, duration, turns, significance, relevance, and fall back questions.**

Keywords*—*Artifical intelligence; semantic web; chatbots; fashion; ontology

I. Introduction

The invention of the Internet has met almost everything in the world. It has played a significant part in showcasing and growth of many businesses in many aspects [1], [2]. In the context of the current era, online social media has made a considerable impact on the businesses [3]. In the same regard, the fashion industry, especially fashion brands that offer voguish couture and apparels, is growing at a breathtaking rate as they provide creative and versatile garments all around the globe. People prioritize these brands upon their choices and interests, which do have correlations with the events and seasons.

It is a challenging task to recommend an appropriate brand according to users' requirements and interests. For doing so, there are many conversational agents available on the official websites of clothing brands, but they deal with only one brand that resides it. What if a customer wants multiple options of the same kind of different brands at one place? Yes, online social media has answered this particular question to some extent, but surfing the Internet to acquire desired results is very time-consuming and exasperating effort. Thus, in comparison to the searching and sorting based tools, people need some promising alternatives [4].

To overcome user's requirements to complete their task with no time, it is mandatory to understand how human thinks about a particular thing, in connection with this, it is also imperative to understand that how do we make computers to do it like humans. Turing first floated this idea, "Can a machine think?" [5], [6], and in pursuit of the answer to this question, we can say, the whole field of artificial intelligence (AI) evolved. In this era, cognitive science deeply observes the human's mind and its working, which leads to outstanding success in the field of AI in the form of artificial assistant aka Chabot. Businesses started to use these chatbots to facilitate customers. Hence, the techniques and research aspects of AI chatbots have become an exciting field in the AI community. These AI assistants/chatbots have revolutionized by understanding customer queries in different languages and appropriately responding the meaningful information.

The main aim for these chatbots is to provides immediate, meaningful, informative, context-oriented responses to assist customers for the asked questions. The AI Chatbots retrieve information through different approaches. In modern-day practices, these approaches use various information repository structures like conventional (relational) and modern (NoSQL) database systems, ontologies, AIML, etc. to model querying system.

In this paper, we present an ontology-driven chatbot model that facilitates those customers who need the latest information about brands facilities such as packages, discounts, sales, prices, varieties, online shopping, home delivery services, etc. The proposed Chatbot covers all necessary and general information relevant to clothing brands like dress designs, fabric stuff, the material used in the product, accessories, and services like home delivery, return, exchange, discounts, sales, and, etc. Through our model, customers will get all type of information for their complex queries at one platform. For example, customer can ask like: "Which brand provides clutches in blue" and "What is the delivery time of Khaadi in Pakistan?", etc. In this respect, we create an ontology-based on the set of 5000 questions and answers considering the top-10 clothing brands of Pakistan, namely,

- Asim Jofa
- HSY Studio
- Al-Karam Studio
- Sana Safina
- Ethnic
- Thredz
- Gul Ahmed
- Khaadi
- J. (Junaid Jamshed)
- Nishat Linen

We are hopeful that the proposed model is adept for many other but similar domains, all over the world.

II. Background

This section presents the related information about the approaches considered for the development of chatbots.

Amongst the employed techniques, in most cases, the developers rely on IR techniques. This is good because IR based chatbots have the edge over others as they produce an informative and fluent response as they select responses from pre-generated conversation repositories. However, also, it can be a little bad because IR based methods may give blunt answers. A significant of the Semantic Web (SW) is seen in the development of computational tools and applications in the last decade. To understand the metaphor what is SW, we can think of a philosophy that integrates and links the data (technically termed as concepts) based on relationships and standard features in a web. Consequently, "Ontology is a formal, explicit description of concepts in a domain" [7]. Moreover, according to Abdul-Kader et al., in SW concepts are interconnected relationally and hierarchically by computing relations between concepts like synonyms and hyponyms [8]. This concept is introduced in computing sciences by Tim Berners-Lee in 2001 [9]. In many areas of applications, SW has been proved equally better in comparison to its counterparts, and it is notably exercised in many organizations. For example, giants in media like BBC and New York Times have developed their repository structures by linking data concepts [10]. Web companies like Google, Yahoo, Microsoft, and Facebook are connecting millions of entities based on graphs and linked-data concepts. In this regard, providers of DBMS have begun to provide native support of SW [11]. Thus, for example, we can see the SQL based ontology is used to maintain the history of the conversation.

Many researchers have created the ontology for the fashion domain, like Bollacker et al. worked out a fashion ontology which gives (fashion) advice on the basis on human features, fashion and manufacturing concepts [12]. In an approximately similar way, Vogiatzis et al. proposed a technique that recommends garments by incorporating knowledge on all aspects of fashion like material, colors, body, and facial features [13]. The authors [12], [13] have used OWL in their experiments. In the same way, Ajmani et al. [14] adopted the technique of using probabilistic multimedia ontology for creating a personalized fashion recommendation system through which the analysis on visual properties of garments has been performed according to latest fashion trends.

Al-Zubaide et al. [15] presented a query interpreter and responder "ontbot" that technically transforms ontology into a relational database query, before responding. Further, the chat is driven by natural language processing techniques (NLP) to extract keywords from the user query. Likewise, Rao et al. [6] construct a three-stage experimental system in which they take question string as a JavaScript Object Notation (JSON) and apply NLP keyword extraction techniques. These keywords were further matched with the ontology-based relational repository and ranked by using term-frequency and inverse-document-frequency (TF-IDF) technique. The answer/document with at the highest rank was presented to the customer.

Pathan et al. [16] build an e-commerce website based unobtrusive chatbot that simulates an intelligent conversation by pattern matching of customer response based on the given context. A reductionist approach was adopted to accumulate data and elicit further information from the customers who navigate through the product catalogs during dialogue. Similarly, Gupta et al. [4] have shown, the usage of dynamic end-user inputs by adopting frequently asked question (FAQs), in their system chat approach a conventional manner and intelligently overlaid hyperlinks to help customer to redirect them towards the desired results.

Augello et al. [17] have shown the exploitation of knowledge base (KB) in a twofold manner: firstly, they engineer ontology in an AIML format that is used for the creating dynamic answers as a result of inference, and in the latter part, the ontology is automatically populated offline on the basis of AIML categories. They have also maintained that they practiced ALICE for the conversation that follows pattern matching rules (employing NLP techniques) and returns dynamic answers instead of a list of links.

III. Methodology

This section presents the details of the proposed methodology. Initially, we have covered the description of the Semantic Web and the associated concepts therein, followed by step-by-step details and discussion on the proposed methodology.

Development of chatbots based on ontologies is seen as one of the promising practices in the world, where queries are answered by matching keywords in queries and retrieving appropriate responses placed on semantic representations. Whereas, IR based chatbots have an edge of producing informative and fluent responses, in a multi-turn conversation context [18], by seeking the responses from pre-generated conversation repository.

In the proposed system, we employed a novel incremental approach for domain-oriented ontology engineering. In this regard, a wide range of development tools have been utilized; such as we use Protégé [19] for ontology engineering of the domain of "clothing brands". Protégé is considered as one of the best tools for ontology engineering in the entire world, which also enables us to export ontologies in various other language formats like Resource Description Framework (RDF) schema [20], and Web Ontology Language (OWL) [21], [22]. Similarly, we used VOWL [23] and OntoGraf [24] plugins for the visualization of taxonomy, and SPARQL for querying system and data retrieval [25]. Besides it, we as lo worked on Jena [26] which is a Java-based library for the development of SW applications [27].

A. Ontology Engineering Process

Ontology engineering process spans through different phases as it is shown in Fig. 1. In the following, we are going to explain these phases one by one.

1) Dataset Preparation: Data is collected manually via different procedures, which involve survey questionnaires, and interviews with the official representatives. We also sought information available on official websites of mentioned clothing brands and used various scraping tools to get the text of posts and comments available on Facebook pages, respectively. These Facebook fan pages are the big source of extraction of information of meaningful and reliable conversation among

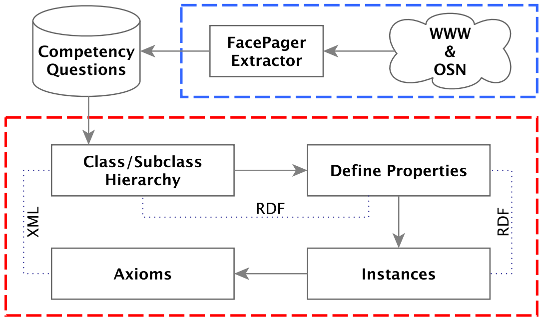

Fig. 1. The scheme of ontology engineering process (OEP). Block enclosed in green box is the initial phase of data gathering, while the block in red box defines the OEP.

users and different teams. Hence, we have employed a Google Chrome extension, namely, Scrapper[1], for scraping the information from the web-portals. The other tool used, in our course of the experiment, for extracting the text of posts and comments from Facebook pages, namely, FacebookPager[2]. The FacePager takes Facebook page key as an input and retrieves all posts, comments, pictures, videos, and user reviews available on the given page that you can export in comma-separated view format.

As a result, the collected corpus was consisting of unstructured and inconsistent data. Further, there were two more issues: it was redundant and not very much meaningful. Thus, the data is filtered and processed to make it useful as per the requirements of the SW based applications. The count of the parallel corpus, in two-way communication, is 5,000 sentences.

2) Competency Questions: After the acquisition of data, the first step towards ontology development is to lemmatize the scope of ontology through the competency questions. These are the vital questions for which an ontology has to answer. Moreover, these questions are the primary source of setting the precincts of ontology domain, and helpful to identify the terms that are further converted into the system of class and subclass hierarchy. In the proposed domain, for example, the competency questions can be: "Does Asim Jofa provide exchange/return facility?", "Which brand provides accessories?", or "Which brand offers 50% discount?", etc.

3) Concepts and Classes: Classes are the basic building block of ontology, which can be interpreted as a set of specific individuals [28]. In OWL, these are also called concepts or entities having some distinctive characteristics. These classes are formed in a hierarchical system of super-class and subclass. However, these classes can be disjoint. In such case, the individuals of these classes are not common. This class and sub-class hierarchy is also known as Taxonomy [7]. Thus every super class exhibits the most general characteristics of all nested sub-classes, and in contrast, the sub-classes does opposite. For example, in our experiment, "brand/vendor" is the most general class which has nested sub-classes like "accessories", "cloth variety", "brand type", "dress category", etc. Likewise, the class "accessories" is further nested by two more classes i.e., "male accessories" and "female accessories". While, the example of disjoint class can be "facilities" and "location/area", these classes have different instances which do not overlap each other. The detailed class hierarchy is presented in Fig. 2.

```
owl:Thing
└─Brand/Vendor
   ├─Accessories
   │  ├─FemaleAccessories
   │  └─MaleAccessories
   ├─BrandType
   ├─ClothVariety
   │  ├─FemaleClothVariety
   │  └─MaleClothVariety
   ├─DressCategory
   ├─Facility
   ├─FemaleBrands
   ├─LatestDesignVolume
   ├─Location/Area
   ├─MaleBrands
   ├─Packages
   ├─PriceRange
   ├─Scope
   └─Timing
```

Fig. 2. Class Hierarchy of Fashion Brand Ontology

4) Properties, Attributes, or Predicates: Since these set of classes are not self-explanatory, therefore, we have to define the mappings inside/among classes [29]. The OWL properties describe the relationship between classes which can be of two kinds, namely, object properties, and data properties. Details of these properties are given below.

Object Properties. These properties are ones who establish a link between two individuals. This is also known as intrinsic properties [7]. Technically, as a rule of thumb, any property whose range is a class is an object property. Protégé provides numerous predicates that remove ambiguity from the taxonomy. Fig. 3 shows the object properties of the fashion brand ontology.

```
owl:TopObjectProperty
├─IntroducePackage
├─Labelled_as
├─Located
├─OfferAccessories
├─PresentDressCategory
├─ProposeClothVariety
├─ProvideFacilities
├─Releases
└─Type
```

Fig. 3. Object Properties.

The core characteristics of object properties which show the global cardinality constraints on properties are: Functional, Inverse functional, Transitive, Symmetric, Asymmetric, Reflexive, and Irreflexive properties. Intuitively, *functional*

[1]https://chrome.google.com/webstore/detail/scraper/mbigbapnjcgaffohmbkdlecaccepngjd
[2]https://github.com/strohne/Facepager/wiki/About-Facepager

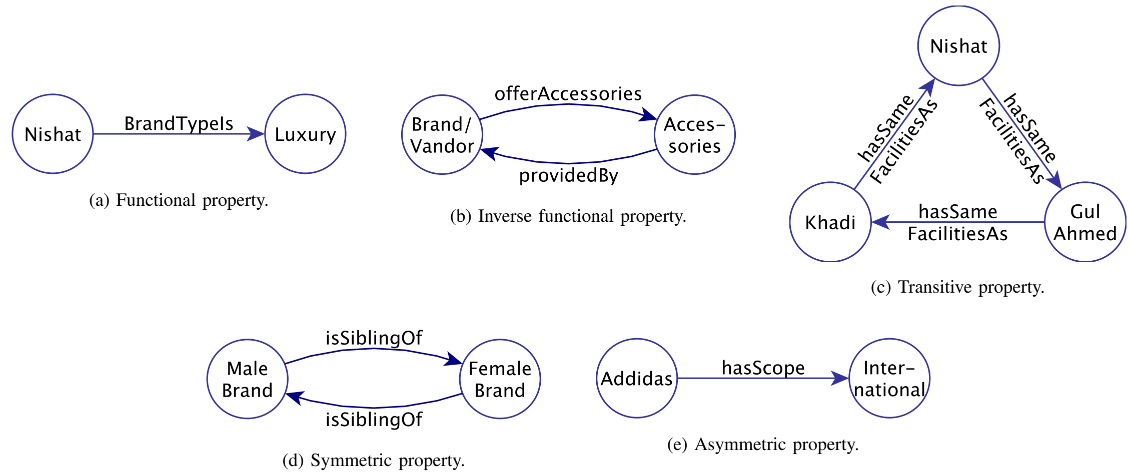

Fig. 4. One of many examples of object properties in proposed methodology.

property is a property which postulates that for any given individual there must be at most one out going relationship [22], [28], [30]; *inverse property* asserts that for any individual there should be at most one incoming relationship, through the property, which can uniquely identify the subject [30], see Fig. 4b, where a brand/vandor offers accessorises, which can identify the provider inversely. However, if there are many things related to one individual, through the functional or inverse-functional property, then the property characteristic will be inconsistent [22], [28]. The *transitive property* can be defined as the property which shows transitive implications among individuals, such that if an individual a is similar to individual b, and b is similar to individual c than we can say the individual a and c are also similar, through a transitive relation [30]–[33]. Fig. 4c depicts an example w.r.t to the current research. The *symmetric property* asserts that a given individual has itself an inverse function; whereas *asymmetric property* lacks this characteristic [30], [32]. We can see, as an example of symmetric property, if individual a and individual b are related to each via some property, then b should be related to a through the same property; while in the same setting, for the asymmetric case, b does not relate to a along the same property. Fig. 4d and 4e show the examples of symmetric and asymmetric properties respectively. Lastly, the *reflexive property* relates everything to itself, whereas, the *irreflexive property* means no individual can be related to itself by some role [22], [32]. Few examples of these object properties are illustrated in Fig. 4, and detailed mapping of these properties is shown in Table I.

TABLE I. EXAMPLES OF OBJECT PROPERTIES

Property	Name	Example
Symmetric	IsSibblingOf	(maleBrand, femaleBrand)
		(maleAccessories, femaleAccessories
		(maleClothingVariety, femaleClothingVariety)
Transitive	SamaFacilitiesAs	(Khaddi,Nishat,GulAhmed)
	SamaClothVarietyAs	(Khaddi,Nishat,GulAhmed)
	SamePriceRangeAs	(Nishat,JunaidJamshed,GulAhmed)
	SamePacksgesAs	(Thredz,Levise,Nishat)
	SameAccessoryAs	(Bonanza,GulAhmed,Nishat)
	SameClothingStuff	(Nishat,Khaddi,Bonanza)
	SameDressCategoryAs	(Bonanaza,GulAhmed,Khaadi)

Data Properties. We can briefly define a data property as a property that relates individuals to data-type values [33], in other words, any property whose range is any literal or data-type value is known as a data property. Extrinsic properties: like name, has string data-type. Table II shows the details of data properties with domain and ranges accordingly.

TABLE II. EXAMPLES OF DATA PROPERTIES

Property	Name	Domain	Range
Functional	Is_a	Levise	maleBrand
	Is_a	Bareeze	femaleBrand
	BrandTypeIs	Nishat	Luxury
	HasStuffQuality	Khaddi	Moderate
	AccessoryProvidedBy	Scarfs	JunaidJamshaid
	AccessoryProvidedBy	Belt	Levise
	OfferDressCategor	SanaSafina	Bridal
	LabledAs	Khaddi	International
Asymmetric	HasScope	Adidas	International
	IsTypeOf	Bareeze	Luxury
	LocatedAt	Khaddi	Saddar
	OfferedDiscount	Bonanza	float
Inverse	OfferAccessories	Brand/Vendor	Accessories
	ProvidedBy	Accessories	Brand/Vendor
	LabledAs	Brand/Vendor	Scope
	IsScopeOf	Scope	Brand/Vendor
	PresesntDressCategory	Brand/Vendor	DressCategory
	DressCategoryOfferedBy	DressCategory	Brand/Vendor
	ProposeClothVariety	Brand/Vendor	ClothVariety
	ClothVarietyOfferedBy	ClothVariety	Brand/Vendor

5) Instances: An instance is an individual/object that certainly belongs to a class. One key feature of OWL ontology is: it does not use the unique name assumption (UNA), so we can explicitly define that two individuals are the same or different. A class may have multiple instances. We can manually define the characteristics of each instance separately. For example, class Brand has instances like Khaddi, AsimJofa, Nishat, Al-Karam, and many others.

6) Axioms: After building class taxonomy and establishing links among classes and individuals: the following step is carried out to the semantics unambiguous. It is done so to ensure the validation and consistency of ontology; and as a procedure, we convert hierarchy into first-order logic, hence forming the "axioms" that is represented as $\langle \mathbf{C}, \mathbf{R}, \mathbf{I}, \mathbf{A} \rangle$, where $\mathbf{C}$ represents classes, $\mathbf{R}$ represents relations therein, $\mathbf{I}$ shows

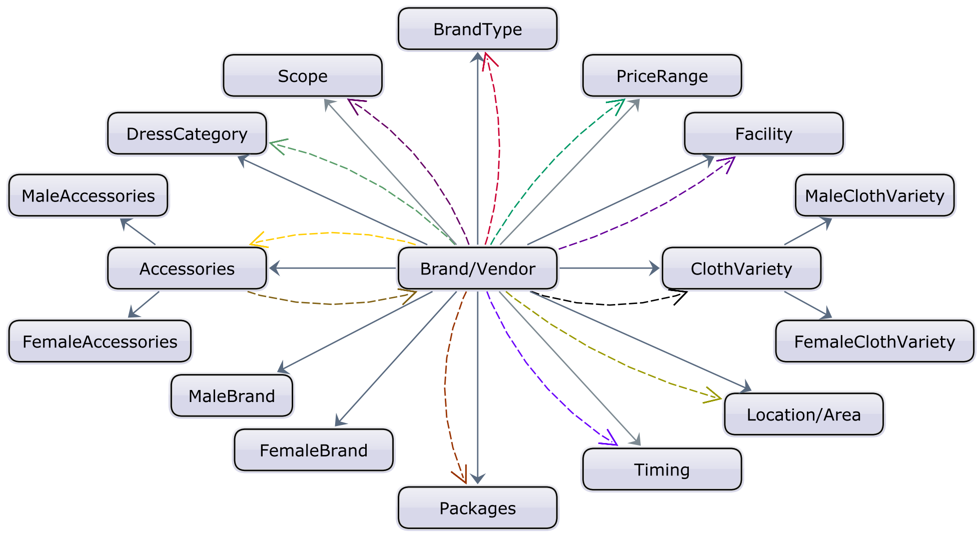

Fig. 5. The OntoGraph representation of fashion brand ontology.

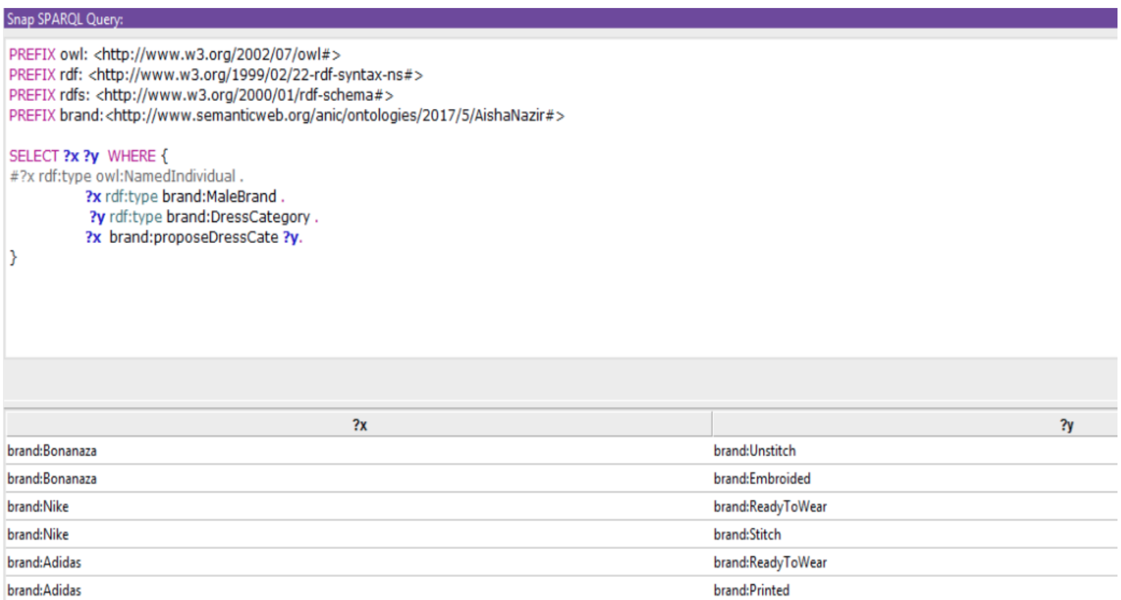

Fig. 6. SPARQL query in Protégé.

their instances, and **A** shows axiom [26]. Protégé provides 'Reasoner' support to formulate and manipulate logical formulae [33]. Through Reasoner, we can check the consistency of ontology; as well as add inference to semantic web application [8]. Further, in order to visualize ontology with its conceptualization, graphical representation was generated using OntoGraf and VOWL plugins [29]. Fig. 5 shows the visualization of the proposed ontology.

On completing this phase, we are done with the ontology engineering process; thus, in next sections, ontology integration and chatbot designing phases are discussed in detail.

B. Rule Engineering

We worked out different scenarios based rules at the back-end of the chatbot. These rules are defined to make the conversation in a flow, and the system to be more efficient to produce context-oriented responses. In this regard, IR approaches are commonly practiced, in connection with the combination of rules. Thus, based on rules, a history-oriented and well-aligned conversation leads to generate more accurate and logical responses. Basic programming structures like conditional statements and repeating structures are employed.

C. Integration and Querying with SPARQL

In this phase, we deploy ontology in an environment where it can easily retrieve data by establishing a connection between the chatbot interface and itself. "Jena"[3] is a Java-based library, specifically use to support semantic web-based applications [26]. Semantic query language (SPARQL) is used to manipulate semantic web repository [25]. SPARQL operate on the triple store, and itself entails triple pattern. Protégé

[3]https://jena.apache.org/

TABLE III. RESULT OF CONVERSATION EVALUATION

	Accuracy	Relatedness	Dynamic	Non-sequitur	structured	Context-oriented	Follow-ups
Expert 1	3	3	2	2.5	3	2	1
Expert 2	4	2	2	3.5	4	3.5	0
Expert 3	3.5	3	3	3	4	2	0
Average	3.50	2.67	2.33	3.00	3.67	2.50	0.33
%age	0.70	0.53	0.47	0.60	0.73	0.50	0.07

has built-in tool to check ontology accuracy and consistency named as “Snap SPARQL Query”[4]. Fig. 6 shows the sample of SPARQL query and resultant table.

Further, in order to access the active ontology in Protégé and get results on the console, we have to set prefixes of OWL, RDF, and current ontology access path. Properties play a vital role while retrieving data from ontology. We access data based on object properties and data properties which are part of RDF Schema and retrieve results from RDF which are saved with “.owl” extension.

IV. RESULTS AND EVALUATION

A variety of techniques are available to evaluate system performance like BiLingual Evaluation Understudy (BLEU) [34], METEOR [35], and Recall-Oriented Understudy for Gisting Evaluation (ROUGE) [36]; but these metrics are often accounted as either weak or not up to the mark as compared with human judgment because there can be a lot of possible responses to any given turn [37], [38].

An insight to the conversation between chatbot and expert is shown in Fig. 7. However, our chatbot is thoroughly evaluated by using Turing’s Loebner technique. According to this technique, we test chatbot by holding a conversation with it for 10 minutes. We assign performance grades based on how accurate, related, dynamic, non-sequitur, structured, history-oriented responses, retrieved by bot. The scale for judgment is from 0 to 4. For the experiment, we worked out the following criteria for the evaluation of chatbot constructed with the given methodology:

- *Accuracy*. How much accurate the results are.
- *Relatedness*. How much the responses are related to the query
- *Dynamic*. How much different results are produced if the customer asks the same question repeatedly.
- *Non-Sequitur*. How much responses are logical and reasonable.
- *Structured*. How much responses are grammatically structured and well-aligned according to sentence formation.
- *Context-Oriented*. How many results are history-based and give results in the same context.
- *Follow-up question*. Does bot ask in the response of customer, if some question is ambiguous or what a bot do to make conversation continue.

[4]https://github.com/protegeproject/snap-sparql-query

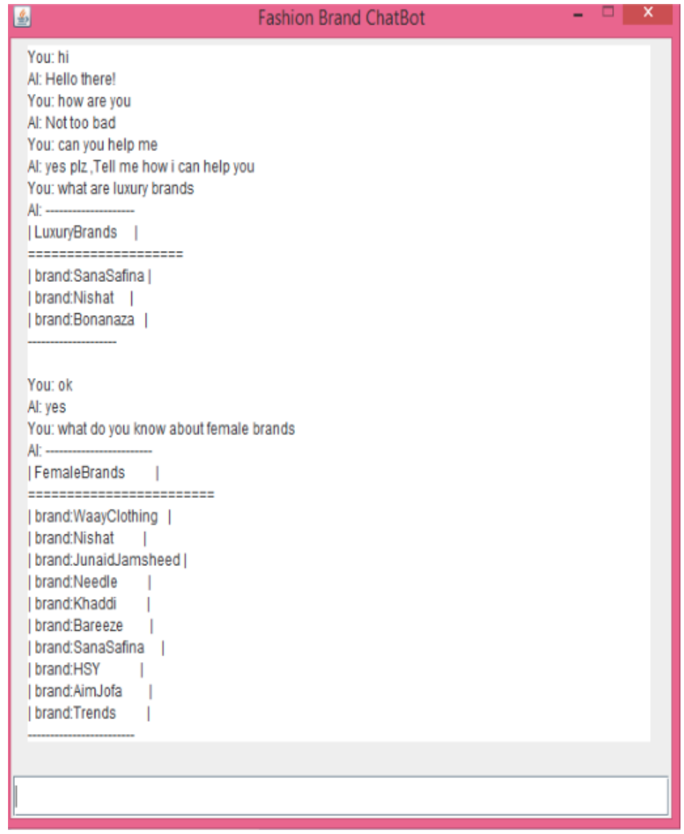

Fig. 7. Chatbot replying the queries of customer utilizing ontology.

With the criteria discussed above, we have three experts to judge the system. The quantified results are compiled to get average and percentage-wise analyses.

We can see that the proposed methodology is useful as it produced meaningful results. For example, the performance of the system under the criteria of accuracy, non-sequitur, and structured answers show the better results by yielding .70, .60, and .73 % marks on average by the experts. However, the system shows a poor performance on the follow-ups; followed by failing to (behave dynamically) produce different answers, in more turns. It may be due to the lack of natural language generation within. The relatedness and context-orientation of the responses are a little above average. Although much considerable work can be done to improve this. The detailed results are presented in Table III.

V. CONCLUSION

In Pakistan, clothing brands lack instant AI assistants at their official websites and social web page, which is seen as a core facility provided by international brands. Several tussles are required to make a well organized artificial bot to produce fast results. The proposed system resolves the problem for Pakistani fashion industry through developing clothing brand ontology, yielded through the handcrafted dataset of 5000 pairs of questions/answers, and integrating it with a conversation agent to facilitate online customers. In our work, we focus only on general-purpose information like brand facilities, services, garments, clothing stuff, and accessories based on information retrieved from Facebook pages and official websites.

VI. Limitations and Future Work

This research work is limited to only ten clothing brands and provides concern areas information to customers; thus, in the future, the scope of brand ontology can be increased by adding more national brands. We also intend to implement Semantic Web Rule Language (SWRL) and employing deep learning architectures.

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