

An Educational Ontology-based M-Learning System

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Abstract—Smart devices applications can assist young children in improving their learning capabilities and comprehension skills. However most of learning applications are built without taking into consideration the effective needs and background of Arab users. They are somehow incompatible with their local environment and culture. We propose in this paper a mobile-based educational system that displays illustrations automatically to characterize the content of children' stories on animal domain, and we use some intelligent technique to answer users' questions using an educational ontology. The generation of illustrations passes through different phases which include text processing, extraction of word-to-word relationships, building and accessing an ontology, and using Internet search engines for retrieval of complimentary information. The system can be used also by instructors to teach the children in a non-conventional manner. They can customize semantically the structure of the questions and determine how the answers will be displayed. In order to customize questions and answers, we have defined a semantic infrastructure to define the logic of terms, and the workflow of answers. The aim of our system is to improve the children educational skills to grasp vocabulary and grammar using multimedia with a portable smart device which includes observation, comprehension, realization, and deduction. Children will then be able to continue learning outside the limited time of their schools and from any location.

Index Terms—Mobile Learning; Question Answering; Educational Ontology; Multimedia; Education.

I. INTRODUCTION

Nowadays children are surrounded with various types of digital smart devices, educational software and edutainment games. Mobile devices opened a new horizon in learning and communication. They can be handled in pockets, by hand, or around the necks, which help anyone to learn and communicate from any location and at any time. With a smart device, like an iPhone or an iPad, we can capture pictures, record video clips, and share these resources spontaneously with friends and families. We can also use these devices to learn in an unconventional manner. In fact, using a portable device for learning is advantageous and more attractive as the learners become freely able to access educational resources through the Internet or specific systems. It is noticed that children enjoy learning using an iPad or a tablet while playing and moving. They can interact with these items and become more engaged and motivated than just sitting for a while using a computer device on desk or when being in a classroom. By establishing more relationships with their friends and teachers, engendered ideas, and outstanding observations of the world, children are seeing and recognizing the

world contrastively. This upgrade of educational technology shows a considerable movement in the path smart devices can be utilized to stretch the minds of children and break the centralized learning paradigm. Edutainment games offer also a new way of learning while playing. Thus children can enhance their learning skills while entertaining, moving or when being at home or even in bed. Unfortunately, the learning resources for Arab children are very limited. In fact, the developed games and apps are not suitable for the culture, language and background of the Arab children. In fact, less than 1% of available apps are Arabic-based. This is a real challenge of Arab learners. A new initiative is launched recently by the Arab League for cultural and education [1] to develop Arabic-based learning Apps to promote the usage of the Arabic language in education and edutainment through mobile devices. However, it takes a very long time to build a repository with rich Arabic apps and edutainment games.

In this paper, we propose a mobile-based educational system that can map Arabic stories for children to illustration and answer questions through an educational ontology. It allows children to grasp Arabic vocabulary and grammar in a simple and natural way using multimedia. In fact, multimedia technology can keep the children engaged for a longer time [2] and also has a great impact on their way of learning. The proposed system is composed of a main server as a back end and mobile devices as a front end. We use Arabic natural language processing (NLP) techniques to generate illustrative pictures to mine the users' questions and represent the content of the answer in different models. We develop an educational ontology where its concepts are linked semantically (i.e., a lion is linked with the forest, a Camel is linked with the desert). The system allows the teachers to address logical queries and get in return multimedia-based intelligent responses which can be used to enhance the learning skills of children. The instructor can add new knowledge to the educational ontology and associate preferred illustrations. The system can analyze the questions of users using NLP tools (i.e., parser, tagger), extract key concepts, and retrieve then the information.

The rest of the paper is organized as follows: in section 2 we discuss the existing multimedia systems with the question answer technique. In section 3, we give details about our proposed system and its features. In section 4, we discuss the technical specifications and the usage of the mobile device. In section 5, we show assessment results. In section 6, we discuss the main findings, and finally in section 7 we conclude the paper.

II. BACKGROUNDS

Natural language processing consists of mining texts to extract useful information. These information can be used to determine the main scope of the texts in order to classify them, generate summaries, extract specific vocabulary (i.e., educational system) or spot events which can be used as references for taking decisions (i.e., alerting systems). Several NLP-based systems have been proposed recently with applications on different domains (e.g., finance, transportation, question answering, education, etc.) [3-5]. These systems start generally by splitting the text into segments, stem the words of each sentence using a dictionary, find synonyms using a thesaurus, remove stop words, and annotate or add tags to the words stems (i.e., verb, noun, adverb). They use intelligent techniques to understand the meaning of each sentence in the text (e.g., machine learning). These techniques include, usage of logical rules, development of ontology on specific domains, usage of statistical approaches (i.e., frequency of words in the text, recall and precision), diacritisation, and develop a corpus. Building a learning system that can understand Arabic texts automatically is a challenging task. Such a system can have a great impact on educating Arab children and non-native Arabic speakers in an efficient manner. In fact, it allows them to learn Arabic vocabulary and grammars almost autonomously and naturally especially whenever they use their mobile devices. A good number of educational systems have been proposed in the last decade. Cheng et al. [2] have proposed a computer reinforced online multimedia education framework called *Crome* to enhance the teaching and learning capabilities of children and adults. It includes multiple components for information modelling, learning, teaching, and testing. Wastam et al. [6] have developed a system to help children enhance their knowledge in a specific topic. The system is composed of two components: the first one allows the instructor to select the topic of a story that will be illustrated by flashcards, while the second one asks the children to arrange the scenes in a logical manner according to the topic of the story. Rosmani and Wahab [7] have developed a multimedia-based system called 'i-QRA' to teach children the Holy book of 'Al-Quran'. It consists of introducing the Arabic alphabet through simple words, reading them automatically, and making quizzes. Tabot and Hamada [6] have proposed a web-enabled multimedia learning system to provide physics instruction on selected topics. Erradi et al. [8] have proposed a multimedia learning platform called 'ArabicTutor' which provides Arabic spelling, gives meanings of words accompanied by simple multimedia. Ping et al. [9] have developed an assistive learning system to assist children with hearing impairment learn the Malay language. Dong and Li [3] have proposed a multimedia learning system that can be used by several users simultaneously.

Wuang et al. [10] have built a multimedia courseware system that is based on learning theories. All these systems are based on static contents with different learning objectives. They are generally addressed to adult learners through a computer machine.

In the other hand, a question/answering (QA) system consists of mining questions from particular resources that can be in form of natural text, interlinked data, or datasets. Zhu et al. [11] proposed a QA system to answer natural language questions from DBpedia [12] using graph traversal approach. The system determines entities from the

natural question and builds their corresponding subgraph of knowledge base. It uses the instantiated subgraph to solve semantic mapping problem and the disambiguation problem. Therefore, a graph traversal method in DBpedia is used to select the best answer according to the rank of the path. Sander et al. [13] proposed an approach to translate natural language sentences into SPARQL queries to provide applicable and intuitive semantic search in the industry. The translation is based on background lexicons and ontology. The result shows some improvement when applied. Hence, the training period and knowledge required for users decreased, while the overall usage of the natural input is increased. Berant et al. [14] proposes a paraphrase system to get higher number of raw text that is not related to any knowledge base. It uses a method to generate a collection of logical forms. Then, it uses a paraphrase model to select the best paraphrase input and output that correspond to the original form. The system improved the accuracy on the recently proposed QA datasets.

Unger et al. [15] proposed an approach to parse a natural question to generate a SPARQL template that can determine promptly the internal semantic structure of the question. The template is employed based on statistical identification of the entity and predicate detection. Therefore, the slots of the template are filled based on the entities determined using string similarity and natural language patterns. Joris et al. [16] proposed a scalable query-based search system called "Scalewelis". It is a query-based faceted search uses semantic web and connects SPARQL end points to enable more expressive search. It uses its own data structure and not capable to scale with large linked-data datasets (i.e., DBpedia).

Dima [17] proposed a QA system prototype to extract information stored in RDF through English natural language. The system translates the natural language into a SPARQL query to extract the required information. The proposed system is capable to process simple questions and cannot solve complex questions. Shekapour et al. [18] proposed a QA system that can extract knowledge from interlinked data. It translates natural language questions into corresponding SPARQL queries and extract information from interlinked datasets. He et al. [19] proposed a novel QA method. It uses first-order logic to resolve the ambiguities problem while resolving the answer. The proposed method can cover more textual expressions and answer more questions that manually setting the pattern of the text. The experiments showed effective results of using the proposed method.

As many multimedia-based educational systems and question-answering ones have been proposed. Providing a complete multimedia educational system that can automatically illustrate the content of stories, and can provide explanatory answers that are based on reasonable predicates for educational purpose is not well covered in the literature. In this paper, we propose a mobile educational system that can provide illustrations for Arabic stories and answer questions through an educational ontology. Hence, the system can be used by instructors and individuals to promote existing educational systems.

III. THE PROPOSED SYSTEM

Our proposed system can generate multimedia tutorials with dynamic contents and answer questions by using an educational ontology to depict answers with illustrative

pictures by employing online search engines. The system can be used to teach young children the Arabic vocabulary and grammar in an effective manner using multimedia by mining children stories' texts. Non-Arabic native learners can also use the system to learn the Arabic language efficiently. We have collected thirty educational stories for children and added manually their words to a corpus. The main concepts or keywords of Arabic texts are represented by multimedia. Thus the children can see the graphical representation of words related to named-entities and actions. For instance, for the following sentence 'a lion is running', the children can see the images of a lion as it is a named entity. They can see also images and clips of a running lion. In fact the stem of the word 'running' is 'run' and it is a verb. Thus it corresponds to an action. We use a modern standard Arabic parser to extract information (i.e., places, named entities, events), an educational ontology to get related illustrations, and an online search engine (i.e., Google) to get additional multimedia elements not available in the ontology. The instructor can feed the system with an Arabic text and get in return a collection of illustrations corresponding to the text main concepts. He/she can adapt these illustrations based on the specific need of each child. The dynamic generation of illustrations would become further time efficient according to the process of machine learning.

The system is composed of several components which are the following: 1) *Arabic text parsing*: first, the Arabic text is segmented into paragraphs, sentences and words. Each word is annotated automatically to identify its part-of-speech (e.g., noun, verb, adjective); 2) *Educational Ontology*: we have created an Arabic ontology based on Arabic WordNet [20] to extract knowledge and entity relationships. We have used also the DAML+OIL [21] to annotate the Arabic terms. The ontology is used also to get further details about the Arabic terms and their relationships. For instance, it is possible to identify the required content that should be given to children according to their education levels, to access educational semantic models created upon children stories. For instance, we can identify that the 'lion' animal is a carnivore and lives in the forest while the 'camel' animal lives in the desert and it is a herbivore. All instances inside the ontology are linked semantically with different logical rules (e.g., *is_a*, *has_a*, *eat_a*, etc.). A semantic query can be addressed to the ontology to get a particular instance and it can return all associated relations recursively. Illustrations are linked with most entities through assigned links to avoid storing large binary objects inside the ontology. 3) *Corpus*: we have created a corpus to store information about the common used terms in stories of children. And 4) *Multimedia*: this component is used to provide illustrations that are requested by the ontology. Subsequently, further search queries can be sent to online search engine (e.g., Bing, Google) to fetch more images which should be validated by the instructors. Each Arabic term can have a large set of illustrations acquired from the search engine. Instructors should select the most appropriate ones to present to the children.

A. Applied Methodology

We applied the IEEE 1074-2006 standard to implement our educational ontology. It is a standard for evolving software project life cycle procedure [22]. The methodology used is based on the concept of Category Theory,

which is initially a mathematic foundation theory. Many researchers such as Husserl and Hartmann declared that ontology depends on the category theory. Methontology is the used methodology to implement the Educational ontology [23]. It follows a circular approach which enables evaluation and improvement of the ontology to make it more accurate.

A. Arabic text processing and relations extraction

The Arabic text to be processed can be either selected from a list of predefined stories or entered manually to the system. The processing of the text passes through several phases: 1) *Segmentation*: the text will be segmented into paragraphs. Each paragraph is split into sentences of several words. 2) *Tagging*: we use a customized version of the Stanford Parser [24] and MADAMIRA tool [25] to determine the part-of-speech (POS) of each Arabic word. For instance, we use the tags NN for a *Noun*, VB for a *Verb*, and ADJ for an *Adjective*. 3) *Linking-Grammar*: tagged words will be linked with each other according to their POS. For instance, the word that is tagged as noun can specify the entity name. It can therefore be linked directly with a verb tagged word to specify an action. 4) *Semantic-Extraction*: One of the intelligent tasks that are performed by our system is the semantic relation extraction (SRE). It can identify entity acquaintance, relationship with other entities, and its types, (e.g., a lion is carnivorous and eats rabbit; if we know that a tiger is carnivorous, we can infer that the tiger can also eat rabbit). The SRE is used also for knowledge extraction (i.e., actor, action, behaviours, etc.) that are required during the phase of text processing. Eventually, all linked words will be mapped together and stored in mapping-tables (i.e., hash tables) which allow quick retrieval of information, a semantic query will be dynamically generated for each row to extract the semantic knowledge from the ontology which refers to as *OntologyItem*. Each *OntologyItem* contains all semantic information, details, associated illustrations, and further illustrations downloaded using online search engines. Fig. 1 shows the different text processing phases to generate the illustrations.

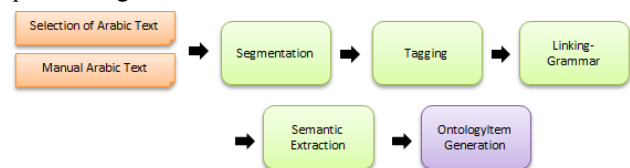


Figure 1. Arabic text processing phases.

B. Question processing

Processing the user' question passes by several phases: 1) *Segmentation*: the question will be divided into different sentences according to some interrogation marks. 2) *Entity-relationships*: the relation between words is based on the formal concept analysis (FCA) to assign relations (triplet). The assignment is based on the composition of the two-matrices. The entity-sentence matrix is built depending on the appearance of entities (e.g., tiger, cat, etc.) with their sentences. The property-sentence matrix is built according to the occurrence of property-values (e.g., yellow will be linked with color, jump will be linked with action, etc.) with their sentences. The connection is resulted by the multiplication of the two matrices. For instance, the question 'What does the cat eat? What is its cover?' will provide the relation: {cat: [eat: ?v1, cover: ?v2]}. The

entity-sentence matrix is used also to determine the linkage of the obtained result from external ontology for new information (i.e., processing information of the *abstract* property obtained by DBpedia ontology). 3) Semantic Relation Extraction (SER): It is one of the intelligent missions that are achieved by our system. It can determine entity acquaintance and feasible relationships with other entities based on semantic rules. For instance, for the question ‘How the crocodile can hunt gazelle?’ we need to find possible relations between the crocodile and the gazelle, since the crocodile cannot run but the gazelle can. Therefore, after fetching possible relations, we can determine a possible answer that a crocodile lives in river and the gazelle drinks from river. The SER is used also for knowledge extraction (i.e., entity, property, behaviour, etc.) that is needed during the phase of entity-relationships. If the question contains information about entities that are not previously defined in the ontology. A request will be sent to DBpedia ontology to get additional information. The obtained result will be mapped with our defined ontology to benefit from inference and reasoning. 4) Processing Data: we have defined several question patterns at first stage to cover most important questions that can be asked. Each pattern has different processing operation and its own answer. Hence, answers can differ to provide different kind of explanations.

C. Ontology Architecture

The ontology is created using Protégé [26], an open source tool for editing ontologies and knowledge procurement system. It supports the development of ontologies and reserves an application platform with knowledge based systems. Declaring an instance of a specific class type requires: 1) selection of the class; 2) creation of an instance, and 3) filling values of the instance. Fig. 2 shows a section of the created educational ontology with its relations and concepts.

D. Reasoning

Reasoning is one characteristic that strengthens the ontology to derive unprecedented facts that are not expressed explicitly in the knowledge base. Reasoning expression rules can be formed to derive or fetch deductive consequences of knowledge. Up to date, different reasoners have been developed [27-29] to support diverse reasoning services (e.g., classification, consistency, realization, etc.) using different interfaces (e.g., Command line, Protégé, OWLlink [30]) and several syntaxes (e.g., RDF/XML, OWL/XML, OWL API [31], etc.).

While ontologies focus on the classifications of instances to emphasis facts by enforcing logic rules (e.g., multiplicity, bounds, domain, etc.). Reasoners use semantic rules to define how new facts will be determined. Besides, reasoning can be used to analyze the validity of knowledge (i.e., verifying if inferred instances are valid) or managing knowledge in general. For example, the ontology declaration “every whale is a mammal” with the relationship “mammals are warm blooded” can be represented by:

$$\forall x : \{ \text{Whale}(x) \Rightarrow \text{Mammal}(x) \} \Rightarrow \text{WarmBlooded}(x)$$

Using the precedent relationship, if x denotes a whale shark, then it is possible to discover the new relationship a whale shark is warm-blooded.

IV. SYSTEM AND MOBILE APPLICATION IMPLEMENTATION

A. Proposed Modules

Fig. 3 shows the different modules that are complementary to fulfil the processing and illustration generation operation in the proposed system. The *Text Tools* module is responsible of performing various text processing, which include, segmentation, tagging, term weighting using a statistical corpus. The *Corpus Module* supplies services of getting the most used terms with their illustrations. The *Semantic Models* module is used for reasoning. The *Online Search Engine* module provides prospection services for illustrations on the Internet.

B. System Architecture

The system is composed of two components: a server and a mobile application as shown in Fig. 4. The system is based on the transactions of messages, the combination with previous software applications is viable by communicating with the server and getting the desired information according to the open API of the system. The Client mobile application is a hybrid application based on HTML5 technology that can work on smart devices (e.g., iPhone or Android). The client application establishes a full-duplex TCP connection with the server to ensure transaction of messages which is done from both sides, to obtain reliable information and latest updates. Eventually, the administrator can recognize connected users, track server performance, and check if the server noted any failure as depicted in Fig. 4.

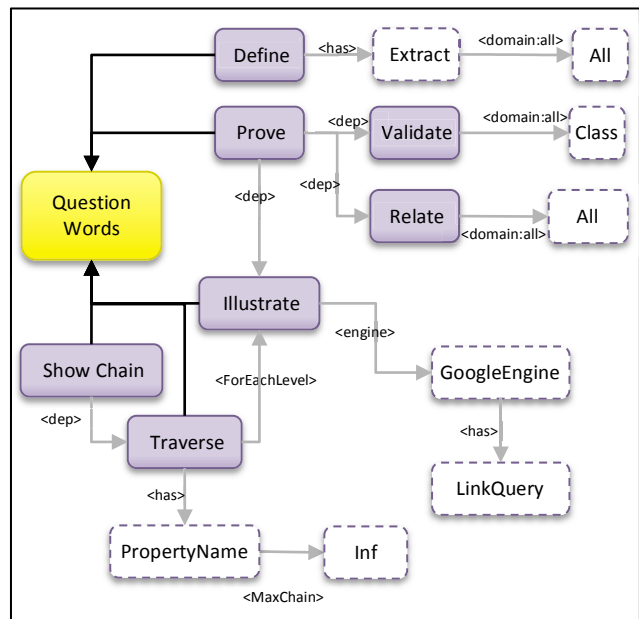


Figure 2. A section of the educational ontology.

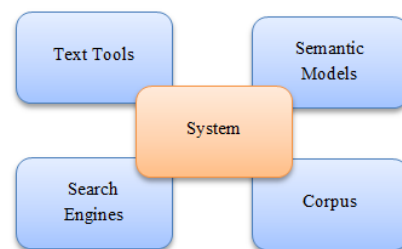


Figure 3. The system modules.

C. System Operation

Whenever the server is launched, it loads its packages and components as shown in Fig. 5. It loads the defined ontology, text parser components, and finally it opens a TCP connection to wait for the users' requests. Hence, all phases are processed on the server side to decrease power consumption on the client side (i.e., mobile device). After starting the Client mobile application, it assays to bind the server, which validate if the provided authentication is veracious and set up the connection accordingly.

Upon an effective connection trial, the user will be eligible to enter or open existing Arabic stories and process them. When the user write a question, a client request composed from, 1) the header "ProcessStory", and 2) the content of the story, placed together in a JSON format. When the server gets the request from the client, it reads the header of the message and executes the intended function accordingly. During the phase of processing the story content, the server passes through various phases: 1) segmentation; 2) tagging and stemming; 3) semantic knowledge extraction, and 4) finally linking Arabic terms with their illustrations. The processing result will be stored in a structure composed from the annotation, semantic information, and the stem of each Arabic term. Fig. 6 shows a client/server sequence diagram to show the various phases of communication.

During the phase of answering questions, fetching possible relations is required according to the context of the question. Fig. 7 shows an example to answer the question: *Prove a crocodile can hunt gazelle.*

During the processing phase, the server logs all performed steps to allow the administrator to be able to track the required information, perform certain analysis, and detect any occurred failure as shown in Fig. 8. Moreover, the administrator can configure the server to report 1) critical failures by email; 2) maximum connected users is reached, or 3) the memory became full.

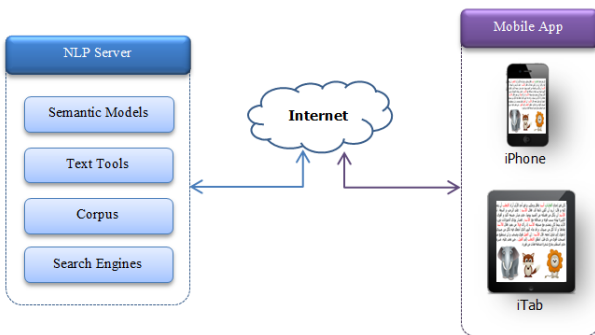


Figure 4. The proposed architecture.

```

Launching NLP Server...
Loading Ontology Reader components...
Ontology in "Resources/Ontologies/ontology.ar.v2.1.2.owl"
Reading ontology "Resources/Ontologies/ontology.ar.v2.1.2.owl"
Ontology loaded successfully
Loading Stanford Parser components...
Stanford parser loaded successfully

Listening at:
tcp://10.10.20.45:12101
tcp://HARMAN:12101
stomp://10.10.20.45:61612
ws://10.10.20.45:61615

NLP Server is ready to receive connections
Enter your command:
    
```

Figure 5. The NLP server startup.

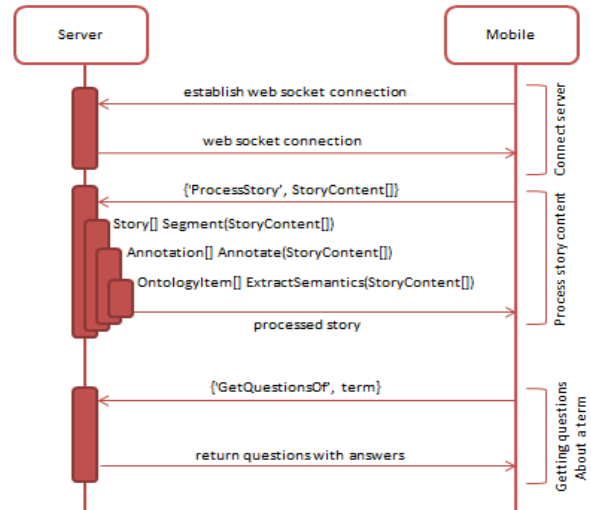


Figure 6. A client-server sequence diagram.

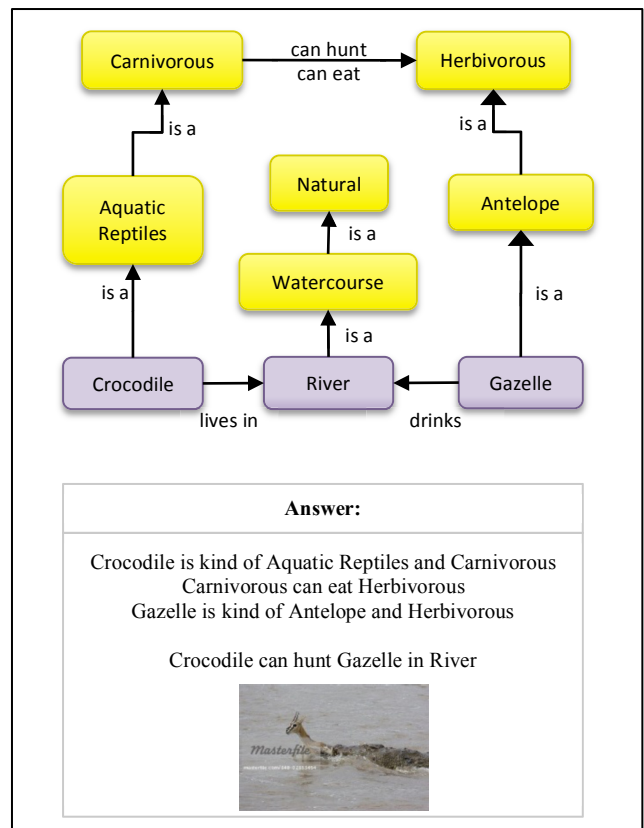


Figure 7. Demonstration of how Crocodile can hunt Gazelle.

```

Processing {nlp.ProcessStory.1842b847-2b8a-a528-8b14-23a138fc4732}
InputStream read done
Model read done
Request {s92b847-2b8a-a528-8b14-23a138fc4732} completed
Processing {search.Google.Search.2ab38126-ae76-2b41-140e-da6182f34ed1}
Google API has been used to search for لب
20 items have been found using Google API
Request {search.Google.Search.2ab38126-ae76-2b41-140e-da6182f34ed1} completed
    
```

Figure 8. Processing the user mobile request.

On the client side, the processing request and response of the story is done in different threads, to keep the user able to continue her/his work without any interruption. Finally, Fig. 9 shows the different results that will be displayed for the user on her/his mobile device.

V. EXPERIMENTS AND EVALUATION

In order to take initial valuable evaluation of the different components, we have evaluated them separately. Then we identified the necessary items. We have used “RStudio”¹ tool to analyze data using different techniques (e.g., ANOVA, ANCOVA, Model Selection, etc.), and to represent different statistical diagrams. We have developed different functionalities to collect data, analyze the response time, get experts feedback through heuristic based questionnaires, assess the performance of users, and so. Assessments results are preliminary and still not final in this study. Ratings are simulated by 7-point rating system filled by two instructors and 20 children. We calculated the *processing time* and *extraction speed* using forecasting algorithm [32] based on knowledge extraction from 5 stories and 20 instances from the ontology.

The P-value and F-value had been used in the assessment. The P-value describes the probability statement that is involved in attaining the probability of realizing test statistics at least as extreme as the observed one, assuming that the null hypothesis is true. In General, a p-value of 0.05 (i.e. at the level of 5%) or less rejects the null hypothesis. In the other hand, to confirm the significance of the test, we can use the F-statistics, see Fig. 10. The F-value is the ratio of mean squares, and it is equal to:

$$F \text{ ratio} = \frac{\text{Differences between groups}}{\text{Differences within groups}}$$

If the F-value overreaches the critical value, then the null hypothesis will be rejected and we can conclude that there is a significant impact in the assessment. There is a difference between P-value and F-value; P-value describes the probability, whilst F-value is a value of the test.

The assessment set is based on the constructed educational ontology which consists from six domains as shown in Table 1. The evaluation of user performance is based on thirty educational stories categorized in five different domains.

This section discusses the evaluation of the following different parts which include: (1) Text processing; (2) Semantic Extraction; and (5) User Performance.

A. Evaluation of Text processing and Semantic Queries

In this section, the evaluation of the third-party component is partially maintained. In fact, the parser component serves in generating sentence tree hierarchy and words linkage between each other. This linkage is used to generate dynamic semantic queries. The evaluation include: number of words in the text, number of paragraphs, processing time in milliseconds (ms), accuracy of generated semantic queries, and experts rating, as shown in Table II. The accuracy is computed by comparing the different parts of the generated semantic-queries with proposed ones (e.g., domain, term, color, etc.).



Figure 9. Launching the mobile application on iPhone devices.

TABLE I.
NUMBER OF INSTANCES IN ONTOLOGIES PER DOMAIN

Domain	Ontology	
	Classes	Instances
Carnivorous	13	55
Herbivorous	13	42
Birds	9	26
Fishes	8	14
Insects	8	16

TABLE II.
AVERAGE TEXT PROCESSING FOR FIVE DOMAINS

Domain	Number of Words	Paragraphs	Processing Time (ms)	Experts Rating
Carnivorous	131.80	3.00	650	88%
Herbivorous	132.00	1.60	651	87%
Birds	158.40	2.20	701	78%
Fishes	117.20	2.40	629	92%
Insects	132.20	2.60	652	86%

According to the result obtained we have considered two regression models to compare the two models by F value and using ANOVA:

$$1) \text{ Words} = \beta_0 + \beta_1 * \text{Processing Time}$$

and

$$2) \text{ Words} = \beta_0 + \beta_1 * \text{Processing Time} + \beta_2 * \text{Experts Rating}$$

where β_0 denotes the intercept, β_1 and β_2 denote the slop term in the average change of values.

Analysis of Variance Table						
Model 1: Words ~ ProcessingTime						
Model 2: Words ~ ProcessingTime + ExpertsRating						
Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)	
1	23	1202.5				
2	22	150.9	1	1051.6	153.31	2.174e-11 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Figure 10. Model Comparison using F-Distribution and ANOVA.

Discussion: based on the above results obtained in Fig. 10, we can conclude from the value of resulted F-distribution that the probability that there is no difference between the two models is 0%. This means that the two covariance variables, Processing Time and Accuracy, are required in the analysis.

¹ RStudio: <http://www.rstudio.com/>

B. Evaluation of Semantic Extraction

Semantic extraction is based on tagged words resulted from the Text-Parser component and the generated semantic SPARQL query. The evaluation of the extracted semantic extraction include: number of structured instanced loaded, processing speed in milliseconds (ms), accuracy, and experts rating, as shown in Table III and Fig. 11. The comparison depends on matching the different properties of the semantic-instances (e.g., type, child-instances, domain, etc.)

Discussion: based on the above results, the confidence interval between the two modes *real image* and *grayscale* provided the highest confidence interval, where 99% of hypothetically supervised interval will obtain the true value at significance level of 0.05. However, the confidence interval between *3D image* and *toy model* will provide a hypothesis value of 23%. It is clear that the confidence interval between *3D image* and other modes remain lower than others. We can conclude that the retrieved image cannot be easily classified as a *3D image* or if it fits in other domains.

C. Evaluation of user performance

In this section, different inputs are used to evaluate the performance of the users. A total of 20 children between 9 and 10 years old have been selected and divided into four different levels according to their knowledge. The evaluation comprises: reading time in seconds, number of correct answers, scores, and so. Table 5 illustrates the average results among the different measurement units.

Fig. 12 illustrates the distribution of the average correct answers among the four different groups. In fact, users are allowed to make different tests and know their mistakes. The grade of the last test is used if the same test is taken. The average of correct answers is calculated among the complete disparate sort of tests.

Fig. 13 shows the average scores regression lines of the four different groups according to the average reading time while accessing more images. The figure is generated according to the result of the above ANCOVA test. Each line represents its group. Regression lines denote the estimated meetings points between both average scores and average reading time.

TABLE III.
AVERAGE SEMANTIC KNOWLEDGE EXTRACTION PERFORMANCE

No.	Mode	Number of Instances	Speed (ms)	Accuracy
1	Real Image	26.20	350	83%
2	Cartoon	26.60	351	79%
3	3D Image	31.60	401	75%
4	Grayscale	23.60	329	72%
5	Toy Model	26.40	352	78%

TABLE IV.
AVERAGE PERFORMANCE FOR FOUR GROUPS OF USERS

Group	Reading Time (sec)	Correct Answers	Mistakes	Scores	Quiz Completion Time (sec)
1	396.76	87.92%	13.16%	88.24%	283.20
2	435.33	88.92%	10.64%	88.36%	273.36
3	449.48	92.56%	8.44%	90.92%	263.04
4	423.14	88.72%	12.00%	87.48%	268.80

Discussion: based on the results above, it is obvious to observe the relation between the average reading time while accessing more images and the average scores. The direction of the regression lines is tending upward. Eventually, we can conclude that the probability of achieving higher score by users who spend more reading time and accessed more images.

95% family-wise confidence level

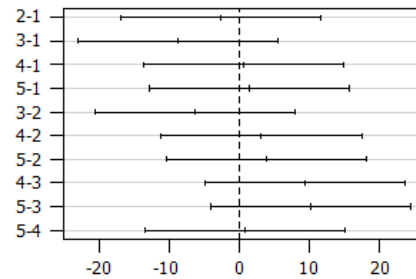


Figure 11. Differences in Accuracy mean levels of as.factor(Domain).

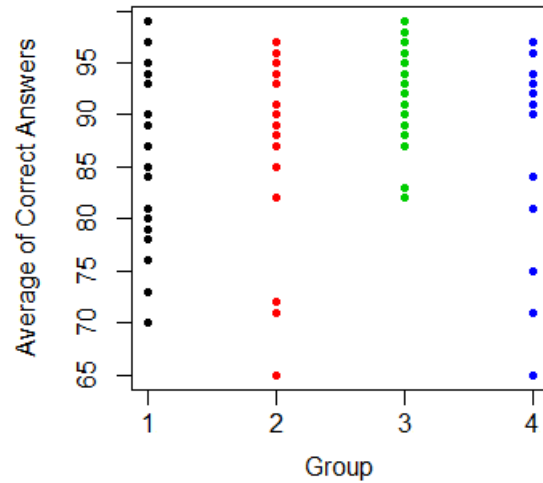


Figure 12. The average distribution of correct answers.

Linear Regression Lines

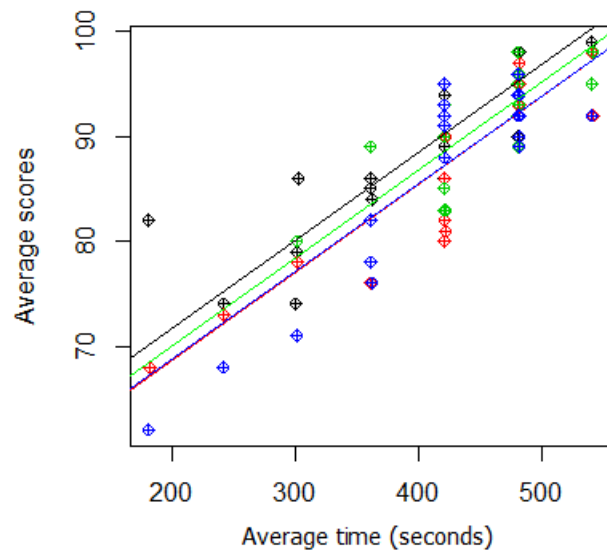


Figure 13. Average scores and reading time while accessing more images.

VI. FINDINGS AND DISCUSSION

Based on the objective dissection described in the previous section, we can conceive that the system can assist instructors, children and Arabic learners to access rapidly semantic information to answer questions and to provide illustrations to represent sentence.

In the other hand, we have compared our proposed ontology with DBpedia and our opinion is to enrich the ontology with interlinked semantic information about instances. Hence, enrichment can improve the speed of information retrieval, semantic navigation between instance, consistency, and reasoning. In the other hand, adding detailed hierarchical classification can enhance the speed to identify how instances are related to each other in the scope of inheritance gradation.

First, enriching can increase the speed of information retrieval. Instead consuming processing time every time to extract a named instance that describes particular value, it is possible to store values as physical instances connected to the prime one through named properties. For instance, it is possible to connect the instance *mugger crocodile* with *5 meters* through the property *maximum length*. Therefore, it is possible to promptly determine the maximum length of the crocodile.

Second, enrichment can improve semantic navigation between instances. The enhancement can be done instantly by linking instances semantically. For example, it is possible to connect the instance *mugger crocodile* with *gazelle* through the property *can eat*. In this context, some generic properties can be applied on the class itself (e.g., reptiles are cold-blooded). In the other hand, not all properties can be generic (e.g., not all kind of reptiles can eat meat). Therefore, some properties should be applied on instances themselves.

Third, the enrichment can improve consistency of instances. Besides the textual information attached to an instance, diverse kind of semantic information will be attached which help in providing all specifications about the instance.

Fourth, the enrichment can enable users to benefit from reasoning. When an instance has mainly textual information that describes it, the usage of reasoning will be limited to basic criterion. In the other hand, when having enriched instances that have their own characteristics and properties, the reasoning will become valuable and robust to infer to new knowledge based on semantic rules.

Eventually, enriching the hierarchical classifications in the ontology can improve locating hierarchical connections when using staircase backward chaining. For example, when applied in the demonstration to proof that a crocodile can hunt gazelle; knowing that a crocodile cannot run whilst the gazelle can; therefore possible relation between the two instances is required (i.e., river) and another relation to proof that the first instance can perform the task (i.e., hunt).

VII. CONCLUSION

This study presents a complete multimedia mobile-based system that can display illustrations automatically to characterize the content of stories, and can answer questions using an educational ontology. The proposed system belongs to portable learning technology which can be on mobile devices to teach Arab children in an attractive and non-traditional style. It can improve the learning capabilities,

memorization skills, communication and understanding of children while decreasing teaching overhead and administration through management and automating learning process.

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