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INFORMATION REFINEMENT OVER MULTI-MEDIA QUESTION ANSWERING APPLYING RANKING AND NAÏVE BAYES CLASSIFICATION

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ABSTRACT

Interactive answers are feat out to the users, which plays an important role to provide information. Usually, Question-Answering (QA) is provided only in plain text which may not be in a useful format presuming the customer. Image and videos if accompanied then it would be better to demonstrate the object or process. In this paper, textual response is accompanied by the appropriate media to recommend a method inspired by the response. Our system is classified into four components, (a) Rendering media picking, (b) Questioning propagation, (c) Information picking and (d) Initiate. Rendering media picking is used to select a variety of responses to the receiver. Extracting keywords from the source in question is widely used in the questioning propagation. Choose the correct answer and the result is used to retrieve by Information picking and Initiate.We use Stemming algorithm, Naïve Bayes classifier algorithm and ranking algorithms.We have increased the contribution of community responses also. Any user can get information immediately which is unconscious. In our perspective is to dispense with multiplex query. Questions are engender on the premise of the details, then we straight-up congregate picture and video in search engines.

Keywords: community contributed answers, question answering, re-ranking.

INTRODUCTION

QUESTION-ANSWERING (QA) is the method for answering a query in an English language [1, 2, 3]. When compared to other systems we are trying to communicate easily between users and computers. It avoids the data contents that are vast in quantity which are displayed as links in the search engines instead of getting the exact answers. The community contributed answers (CCA) are providing the answers in a simple and effective way using search engines. Gaining information on any topic and getting answers to some specific questions in a relevant and reliable manner through online systems is the hot research area. Search engines can produce a simple and effective way of answers in text manner. But it may not be enough and cannot be understood easily. "How to drive a car?" It's easy to get the information, but if it is provided with not only the pictures but also videos then it would be better. Here, the answers what we get are added with multimedia contents. As a result, users can receive automatic approach. Our aim is to produce the contents of the multimedia data which is ranked. The answers will be given only on the basis of the investigation.

Our idea is to solve the problem of multimedia QA (MMQA)[4] by combining user and mortal. The selection and presentation of multimedia data can be shown as text in the image and can be understood whether it is related to human or not. This work does not concentrate on audio data since studies show that most of the people do not prefer to answer questions through this medium.

In this paper, we contribute to the community in appropriate media text responses which can enrich the data of QA by this proposed novel scheme. The three main components of the paper, i.e., the medium of choice, question Causation and presenting the selections. The responses contains three main components namely, Response media selection, Multi-media data selection and presentation.

RELATED WORK

It is worth mentioning that there have many research efforts. Its so-called multimedia questions answering.

From textual QA to multimedia QA

Groundwork based on the type of questions and the apprehended responses can rigorously synopsize the sorts of QA into Open Website QA, Restricted domain QA, Defined QA and, List QA.Yahoo! Answers, Wiki Answers [5]. But they do not provide sufficient information and the answers provided by Ask Metafilter are not instinctual. It is fairly reinforcing fresh text-based responses.In some cases, automatic QA has asperity in providing answers to complex queries. Any user can endeavour the idea of acquiring technical wisdom and intention [6].

Multimedia search

Search engines became essential and searching becomes essential in order to extract information over the vast amount of digital data on the web. In general, search can be classified into two types of multimedia. They are, search Text-based and content-based search. Text-based searches [7] usually use only text. This term-based

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specification of the desired media is matching them with textual descriptions.

To apparatus this consequence, the content -based performs the search by media content. Though there is a significant progress in content-based search, it's more like the high estimated cost, the inconvenience of finding fissional queries, and low-level visual depictions and users meaning anticipation as there are a number of limitations. Therefore, the search for the keyword-based search engines is used in the media.

METHODOLOGY USED

The three main components of the paper, i.e., the medium of choice, question generation, and data selection and presentation. It response consists of three main components:

Response medium selection

Given a pair of QA, the textual information response enriched with media resources, predicts what kind of the media data to be added. They can be classified into four classes such as text, text + image, text + video, text + image + video.

Query generation for multimedia search

Instructive queries can be used to generate multi-media data. Given QA couple respectively, this component extract three queries from question, answer, and from QA pair. We can choose the best informative query by using three-class classification model.

Multimedia data selection and presentation

Queries are generated; we collect pictures and videos vertically from the search engine. Then reranking, duplicate removal of multimedia responses will result in the accurate and representative images or videos with enrich textual answer.

ALGORITHM

Stemming algorithm

A Stemming algorithm is a restricted variant form of a word, which is reduced to a common form of linguistic which is otherwise known as normalization. It predicts both grammatical and morphological classes. In addition, a plural -s in English is an example of a grammatical ending [8, 9]. In English -is or -size make verbs from nouns ('parallel', to 'parallelize') and, - ly adverbs from adjectives ('happy', 'apply'). These works are usually separate dictionary endings.

Using stemming in IR

The previous implementations of Information Retrieval (IR) systems, the process of turning text words are usually stemmed, and the only major IR index was stemmed forms. Similarly, the stem takes place after each incoming query. When the user sees the terms of the index, during the query expansion, they would find their stemmed form. It is a word that has very unfamiliar appearance is the stemmed form and it is so important [10]. Any word is searched in term of stemmed and unstamped.

When indexing stop words is the most common words of a language is to discard the traditional set of IR systems. Stemming algorithm is connected by the stop word lists. Stop words can still be removed from the question as a style of retrieval. For this stemming algorithm is applied, whether the stop word to be removed before or after procedure. In this second case, we should delete the words themselves that have gone through the vote and as a result we can greatly reduce the number of distinct forms.

Page rank

PageRank is the heart of Google's search software, which was developed by Larry Page and Sergey Brin at Stanford University. It uses the structure of links for calculating the quality of the PageRank. Essentially, it calculates the ranking of every Web page, and Google explicate from page A to page B as a vote page A for page B as a link [11].

Hyperlinks to a page called as in links and out links point to other major Web pages. The web page which has more votes indicates a higher priority.

The original Page Rank algorithm described by Larry Page and Sergey Brinis is described by,

$$\mathrm{PR(A)} = (1-\mathrm{d}) + \mathrm{d}\left(\frac{\mathrm{PR(Ti)}}{\mathrm{C(Ti)}}\right) + \cdots + \mathrm{PR(Tn)}/\mathrm{C(Tn)} \quad (1)$$

where, PR(A) refers Page Ranking of page A, PR(Ti) refers Page Ranking of pages Ti which links to page A, C(Ti) refers the number of outbound links on page Ti, d refers damping factor which can be set between 0 and 1.The simple way of portray the procedure is (d = 0.85). The size of a page to vote for its own value is * 0.85 on Page Rank. We still have to raise your page's PageRank, because it is doesn't matter, which is link to your page's, page rank is calculated by adding the other pages to your web page.

Hyperlinks into a page are called inlinks and point into and outlinks point out from nodes. A web page gets more importance if it is pointed by other pages. When a page is linked by another page, a vote has been casted to the linked page. Ranking and importance of web pages are purely based on these votes.

NaiveBayes classifier

Naive Bayes classifier is based on Bayes theorem. Naive bayes classifier is the most victorious known procedure for research to classify text documents [12] features in word and word pair. It is used for removing the waste data. It contains two sets and they are training data and test data set.

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We consider the training data set for classifying the attributes, since it is much easier and faster. Generating training data is done as follows.

Calculate $P(label = y)$ for each label
Calculate $\varphi_{k/label=}y$ for each dictionary

Now, we have generated the word compatible with expectation for each of the defined label [13-15]. Test data set is used to find the given set of experimental data file. For the given experimental data, it generates the features in set(x). It tests every word and its corresponding probability is calculated as,

$$Decision1 = \log\left(\frac{x}{label} = pos\right) + \log(label = pos) \quad (2)$$

Similarity calculation is performed by,

$$Decision2 = \log\left(\frac{x}{label} = neg\right) + \log(label = neg) \quad (3)$$

Collate similarity of both decision1 and decision2 to estimate whether the given sentiment is positive or negative. The training method of classifier is expected to be a list of tokens which can be represented by feats and label [16]. Feats are in attribute dictionary. Label is represented as label classification. Feats are in the form of {word: True}[17-19]. Label will be represented either 'pos' or 'neg'.

FUNCTIONAL ARCHITECTURE

The proposed functional architecture of our system has been depicted in Figure-1. First user wants to register if the current user is new. After registration is completed the user can log on to the page. In the log in page the user search phase is present which is used for typing the search queries. Now the query is given to the search phase which starts the processing on the query. During the processing stage the stop words are removed and extract the root word that is keyword.

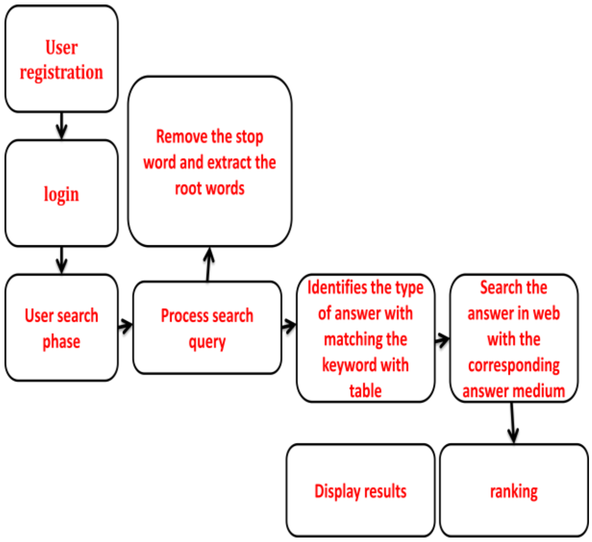

Figure-1. Functions of the system.

After extracting the keyword, identify the type of answer which matching the keyword in the table. Then search for the answer in web with the corresponding answer medium. Reranking and duplicate removal is done with multimedia data.Then, collect the accurate and representative images or videos with enrich textual answer. After that, the searched multimedia data is displayed as result.

PROPOSED METHOD

In this proposed system, we contribute to the community in arrogate media text responses which enrich the data QA novel scheme. Here, we describe each module separately as shown in Figure-2. First, the question is classified according to the given query which can be classified in to text, image and video. According to the search query the appropriate media data is selected. Therefore, which type of mediato be selected is decided by module I.

The second module extracts the keywords by using three kinds of queries. This kinds of queries can be generated through questions, answers or by the QA.

The last module is used for re-ranking and duplicate removal of multimedia data or content. After all the modules are completed the search result is displayed with the suitable medium. These are the functions which are carried out by the proposed system.

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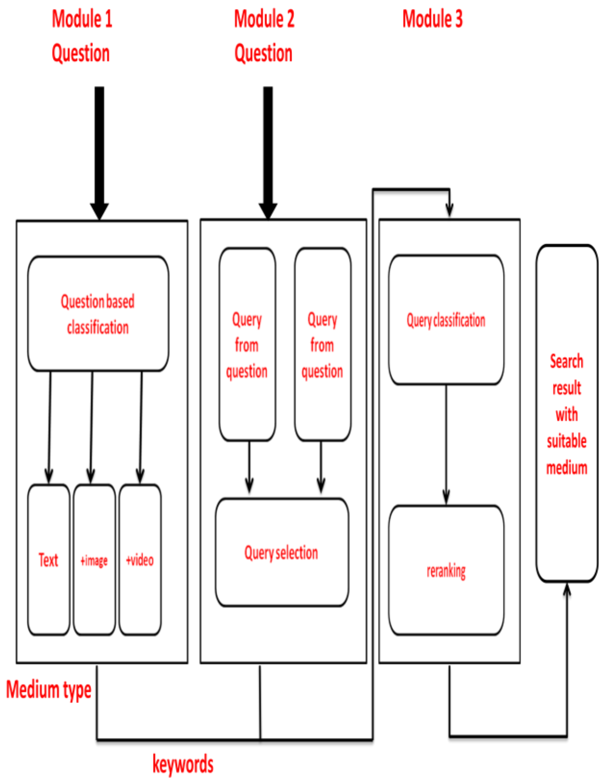

Figure-2. Proposed system.

EXPERIMENTAL SETUP

Here, empirical assessment of data collection and testing of such systems is on the ground truth labeling. It involves with medium of choice answer, question generation, selection and presentation of multimedia data.

Valuation of answer medium selection

In this approach, we use the selection of medium. The ground truth labelling process involved of five labellers. "How can I made paper boxes at home?" They are off-topic enough so that results are film and video, and respective resources can be found [20]. Almost 50% of questions are responding only text using the multimedia contents through the answers.

Table-1. Precision of response medium selection similarity by using and not using text answers.

Method	Wiki answers	Yahoo answers	Both
Using Text based Answers	81.72%	84.97%	83.49%
Not Using Text based Answers	78.30%	82.01%	80.32%

Since question classification is important for stop word stemming is operated on both questions and answers. Table-1 demonstrates the results, and showing that by using the textual answer, the accuracy falls down three percentages because of the media selections. Google Answers and Picasa answers are based on these performances. The variation of the features in question-based classification is capable of efficiency relating. Here, the "related" means the terms associated with the class of precision. The variation of the features in answer-based classification is capable of efficiency relating.

Appraisement of ranking

QA couple look at a person or non-person irrelevant data pair from nearly five hundred QA pair methods to evaluate whether you select to explore. Therefore, we learn SVM (Support Vector Machine) model with reference of RBF (Radial Basis Function) kernel which based on 7-dimensional facial character in order to appraise our query adaptive storage. We first select randomly 25 queries from the relevant persons and compare the performance of our proposed approach with other search methods performance. Comparison of our approach for video search is also done with other search approaches. For example, "Who is the director of the National Cancer Institute," explained interactive with "text + image". Adaptive query mutate the text-based classification.

PERFORMANCE ANALYSIS

We investigate the function of the program without textual responses. Results without using textual answers, show that the classification accuracy will degrade by more than 3% in response to the medium of choice, are noticed.

We compare the responses information with and without textual answers. Comparing the overall average in formativeness scores, we have the answers in written form and can find the score 1,066 to 1,248.

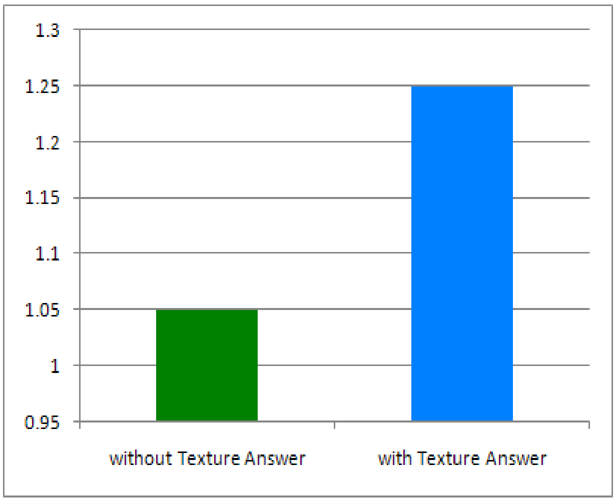

Figure-3. Similarity of global mean in formativeness invoice along with and without text responses.

Generally, questions do not reflect the purpose. But in this approach, results have been built on useful demonstrated answers. Finally, we have the user study comparing responses to the media with text and the original textual answers. Figure-3 illustrates the similarity of global mean in formativeness invoice along with and without text responses. However, it is interesting to see that, media data still do not have much more information compared to pure textual answers [20-21]. Therefore, we can get multiple results from the investigation. If there is no textual response with media data, first the formativeness degradation occurs. Secondly, the response will degrade the performance of the medium of choice.

CONCLUSIONS

In this paper, we portray the encouragement and transformation of MMQA, its scrutinize approach and we have proposed a question answering system for through digital data by ever against text answers. For the given query, our contrivance first foretells which type of medium is relevant for endowing the original textual answer. Finally page ranking is carried to obtain a set of images and videos. Hence the appropriate answer can be got in an effective way. In our pondering we heeded some inappropriate answer because while doing ranking the optimal solution is got. Hence it would be better if some more new method is been adopted to perform ranking for retrieving images.

Further, we depict the inspirit and rebirth of MMQA, and it is anatomize that the existent approaches mainly polestar on narrow hearted province. For a given QA pair, our scheme first prophesies which type of medium is commandeered. It automatically originates a query based on the QA wisdom. Ultimately, query-adaptive re-ranking and duplicate throw off are achieved to acquire a settle of images and videos for contemporary along with the prototype textual answer. Our nigh is well-developed based on the community-contributed answers, and it can deal with more typical questions and achieve pleasing and effectiveness performance. In our speculative, we cognizance certain unsuitable answer because while accomplishment ranking the most desirable result is got. Hence, it would be better if certain more modernistic technique is been embrace to operate ranking for recover images. For future work, we have left query generation through segmenting relevant videos by improving the proposed scheme and the curdles behind the future scheme are under investigation.

REFERENCES

[1] M. Wang and X. S. Hua. 2011. Active learning in multimediaannotation and retrieval: A survey. ACM Trans.Intell. Syst. Technol. 2(2): 10-31.

[2] Y. Gao, M. Wang, Z. J. Zha, Q. Tian, Q. Dai and N. Zhang. 2011. Lessis more: Efficient3D object retrieval with query view selection. IEEE Trans. Multimedia. 13(5): 1007-1018.

[3] Z. J. Zha, M. Wang, Y. T. Zheng, Y. Yang, R. Hong and T. S. Chua. 2012. Interactive video indexing with statistical active learning. IEEETrans. Multimedia. 14(1): 17-27.

[4] J. Tang, R. Hong, S. Yan, T. S. Chua, G. J. I and R. Jain. 2011. Image annotation by KNN-sparsegraph-basedlabel propagation over noisy-tagged web images. ACM Trans. Intel. Syst. Technol. 2(2): 1-15.

[5] B. Dhivya, S. Justin Samuel, M. Karthiga. 2014. ESSDM: an Efficient Mechanism for Handling Sybil Attacks in Social Networks. International Review on Computers and Software. 9(12).

[6] D. Molla and J. L.Vicedo. 2007. Question answering in restricted domains: An overview. Computed Linguist. 13(1): 41-61.

[7] L. Nie, M. Wang, Z. Zha, G.Li, and T.S. Cgua. 2009. Multimedia answering: Enriching text QA with media information. In Proc. ACM Int. SIGIR Conf., 2011 QA sites. In Proc, Int. Conf. Human factors in computing systems.

[8] S. K. Shandilya and N. Singhai. 2010. Article: A survey on: Content based image retrieval systems. Int. J. Comput.Appl. 4(2): 22-26.

[9] M. Wang, K. Yang, X. S. Hua and H. J. Zhang. 2010. Towards a relevant and diverse search of social images. IEEE Trans. Multimedia. 12(8): 829 -842.

[10] L. A. Adamic, J. Zhang, E. Bakshy, and M. S. Ackerman. 2008. Knowledge sharing andYahoo answers: Everyone knows something. In Proc. Int. World Wide Conf.

[11] Z. J. Zha, L. Yang, T. Mei, M. Wang, Z. Wang, T. S. Chua and X. S. Hua. 2010. Visual query suggestion: Towards capturing user intent in Internet image search. ACM Trans. Multimedia Compute, Common. Appl. 6(3): 1-19.

[12] Liqiang*etal*. 2013. Beyond Text QA Multimedia Answer Generation by Harvesting Web Information. IEEE Transactions on Multimedia. 15(2).

[13] T.S.Chua,R.Hong,G.Li and J.Tang. 2009. From Text question-answering to multimedia QA on web-scale media resources.In Proc. ACM Workshop Large-scale Multimedia Retrieval and Mining.

[14] G. Li, H. Li, Z. Ming, R. Hong, S. Tang and T. S. Chua. 2010. Question Answering over community contributed web video. IEEE Multimedia. 17(4): 46-57.

[15] Y.C. Wu and J.C.Yang. 2008. A robust passage retrieval algorithm for video question answering. IEEE Trans. Circuits Syst. Video Technology. 18(10): 1411-1421.

[16] M. Karthiga and S. Justin Samuel. 2014. Emergency spybot to detect and to help human in disaster. International Journal of Applied Engineering Research. 9(14).

[17] Guangda Li , Haojie Li , Zhaoyan Ming, Richang Hong, Sheng Tang, Tat-Seng Chua. 2010. Question Answering over Community-Contributed Web Videos, IEEE Multimedia. 17(4): 46-57.

[18] Meng Wang, Kuiyuan Yang, Xian-Sheng Hua, Hong-Jiang Zhang. 2010. Towards a Relevant and Diverse Search of Social Images. IEEE Transactions on Multimedia. 12(8): 829-842.

[19] A. Tamura, H. Takamuraan N. Okumara 2005. Classification of Multiple-sentence questions. In Proc. Int. Joint Conf. Natural Language Processing.

[20] Yang Yang, Zheng-Jun Zha, YueGao, Xiaofeng Zhu, Tat-Seng Chua: 2010. Corrections to "Exploiting Web Images for Semantic Video Indexing Via Robust Sample-Specific Loss. IEEE Transactions on Multimedia.

[21] JingwenBian, Yang Yang, Hanwang Zhang, Tat-Seng Chua. 2015. Multimedia Summarization for Social Events in Micro blog Stream. IEEE Transactions on Multimedia. 2(6): 29-42.