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Annotated Images Retrieval using Semantic Analysis and Topic Modeling

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Abstract: Latent Dirichlet analysis has emerged as an efficient research field for dealing with the noisiness, high dimensional issues of the text semantically. Enhancing the LDA performance using lexical semantics has proposed in this study. It has focused on enriching the annotated text descriptions of given images with the meaning of the lexical terms with their syntaxes. The semantic lexicon WordNet was applied to produce additional synonym's terms for the images. The aggregated text features with their synonym have been fetched to the LDA to extract enriched topics. The proposed system was evaluated in terms of the precision, recall and F-measure evaluation measures. The finds out have been discussed and compared against the results of the method without the semantic lexicon support. The proposed research was tested on the benchmark CLEF dataset, the output topics have shown a significant enhancement with respect to the retrieved images.

Key words: Topic modeling, LDA, annotated images text descriptions retrieval images, enhancement, proposed, semantic

INTRODUCTION

Image retrieval frameworks are intended to help stakeholders retrieving relevant image from huge restore. There are two frameworks, text-based and content-based images retrieving. Content based image retrieval apply image processing techniques to first extract image features by using colors, textures or shapes based and then retrieve relevant images based on the match of these features. Text-based image retrieving uses the key words or phrases to apply them to some image retrieval techniques (Nair, 2016). In this study, the proposed system dealing with text-based image retrieving that was consider the common method to retrieving images, the requirement for important picture from a huge measure of archive brought many systems to give best result for this retrieving. The measure of efficiency is measured according to the accuracy performance and short time. Topic modeling has been one of the techniques that were applied for image clustering and extracting the integrated topics of the related images (Kumar *et al.*, 2012). Latent Dirichlet Allocation LDA is one of a generative probabilistic model for collections of discrete data such as text corpora in which it is dealing in particular for topic modeling by modeling every item of a collection as a finite mixture over a set of topics (Blei *et al.*, 2003).

The issue of text modeling was considered with an annotated textual description for diverse categories of images. Its goal is to realize the precise topic for each set of images with respect to their attached short descriptions. After that an efficient matching process among large collection of text documents and images with respect to their topics would be accomplished to achieve the best relative retrieval image.

The basic problem that occur in most system when retrieve images is semantic gap which refer to the deferent in content but have similar meaning. In the proposed system, we overcome this problem by using semantic information from ontology such as WordNet.

Literature review: There are many researches that used different method to retrieve information. Cobos *et al.* (2014) presented a new algorithm for cluster web documents named WDC-CSK which was consist of the cuckoo search meta-heuristic algorithm, k-means algorithm, Balanced Bayesian information criterion, split and merge methods on clusters and frequent phrases method. That done by sequences of processes began with query and then collect more than 50 results from traditional search engine and then handle these results by converted them into sequence of strings, words or other attribute to be as input to an algorithm that cluster the documents and give a label to them while Gong *et al.* (2014) proposed the modeling internet images and corresponding text with semantic keywords to retrieve images from query (image, text) or retrieve text from image they used Canonical Correlation Analysis (CCA) to convert visual and textual features to the same latent

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space, then two ways supervised, by using semantic key words as labels and unsupervised with semantic key words that obtained after process of clustering the tags. Likewise Clinchant *et al*. (2011) proposed another methods in retrieval processes first, it comprises in running the visual and textual specialists autonomously. At that point, every specialist restores the top k that similar to query then use the aggregation function. Second, using image re_ranking that done by reordering the return files after the process of searching ended. Rasiwasia *et al*. (2010) proposed new approach to retrieval multimedia, the training set of their data consist of text and images the text represented using latent Dirichlet allocation, images represented using bag of visual words, after representation data two ways are used, the first one was correlation the images and text by using canonical correlation analysis while the second way was the images and text representation in semantic space. Another work used Synonyms-Based Term weighting scheme (SBT) method is used by Kumari *et al*. (2016) as a method to increase the accuracy of relative retrieval more than from the other research that used TF. IDF approach that don't take into account the semantic relation between words this method uses Inverse Document Frequency (IDF) as indicated by the equivalent words based bunch of any term. And uses MeSH to cluster the synonyms of the terms in text documents. While Singh and Kaur (2016) presented another method for retrieval framework, their method depends on color and texture features. Texture features are represented by Block Difference of Inverse Probabilities (BDIP) and Block Variation of Local Correlation Coefficients (BVLC). The difference between their work and the previous work that they represents the color features in color histograms depends on brightness component instead of all components representation of color this approach reduce the dimension of feature vector and then reduce time to calculate the similarity between query and stored dataset, so, this step cause an increase in speed of retrieve process. In the proposed framework retrieving images is accomplished by applying benchmark CLEF dataset to topic modeling algorithm using latent Dirichlet allocation to extract topics from description corresponding to images collection and then tokenize text query, finally, using similarity measures (like Jaccard and Cosine) to compute similarity between tokens of text query and topics. In the research, we add semantic similarity that refer to the similarity in meaning between any two phrases. There are three levels of semantic similarity: word-to-word, sentence-to-sentence, paragraph-to-paragraph, document-to-document or a combination of the various granularities such as word-to sentence, sentence-to-paragraph, etc., synonym approach used in semantic.

MATERIALS AND METHODS

Dataset representation: The data were extracted from the dataset namely CLEF which it is a freely available benchmark for image retrieval (Grubinger, 2007). This dataset consists of set of color images with annotations available in three languages. Each image is attached with an XML file. The XML consist of some tags such as title, description, date and image the last one involves the path of image. A parsing process on the annotated XML format file was performed for reading and extracting the file tags. According to the proposed work, the tag <description> was chosen to retrieve theimage's descriptions content as it contains textual features that can be passed to the LDA algorithm for analyzing and extracting relevant images topics and image tag can be used to know the path of image to retrieve it.

Tokenization: A process of dividing the text of the tag <description> that consists of textual features into set of tokens by removing all punctuation marks is called tokenization. Individual words are the output of this process.

Removing stop words: Stop words will be words that rehashed as often as possible in the English language which don't convey any substantial data. These words might be somewhat pronouns, conjunctions and relational words. This step is achieved by removing all the stop words which it would not help in the topic extracting process and the remained text that were obtained from the images descriptions is formed in a dictionary of documents (Fig. 1).

Text similarity measure

Text similarity: There are two types of similarity in two pieces of text: the first type is lexical similarity that means the external similar (exact meaning) it computes the exact likeness between words and it neglected the actual meaning for them. In lexical similarity there are three level to compute the similarity char level, word level and phrase level there are some measure to find the lexical similarity that are Jaccard, dice and cosine. The first metric is Jaccard while its value ranges between [0, 1] and the users must put threshold for their measurement, the Jaccard dealing with the intersection between pieces of text divided by the union of the sets as shown in Eq. 1:

$$\text{Jaccard} = \frac{|\text{tokens\_in\_string\_A} \cap \text{tokens\_in\_string\_B}|}{|\text{tokens\_in\_string\_A} \cup \text{tokens\_in\_string\_B}|} \quad (1)$$

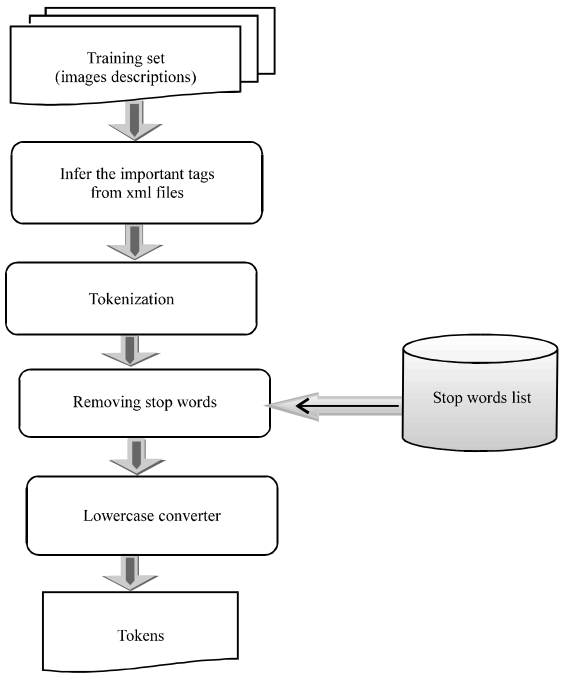

Fig. 1: Pre-processing stages

This for short text for using document in information retrieval the BM 25, PL2, etc. was used to find the similarity between documents. In cosine similarity the proposed work has suggested using the weight of words in each topic to be the first vector, the second vector is the frequency of words in query after been processed as shown in Eq. 2:

$$\cos(V1, V2) = \frac{V1 \times V2}{|V1| \times |V2|} \tag{2}$$

where "." denoted the dot product of two vectors while ||.|| denoted the vector length. This measure is equal to 1 if the documents are identical and 0 if they have nothing in common. The second type is the semantic similarity that refers to the similarity in meaning between any two phrases. There are three levels of semantic similarity: word-to-word, sentence-to-sentence, paragraph-to-paragraph, document-to-document or a combination of the various granularities such as word-to-sentence, sentence-to-paragraph, etc. The semantic similarity found to address the natural language understanding issue in many core NLP tasks such as paraphrase identification, question answering, natural language generation and intelligent tutoring systems.

Semantic dictionaries: Human can quickly lead on the degree of the relative semantic relationship of couples of concepts (Patwardhan *et al*., 2007). Standard word references can't be appropriate to be utilized to recognize the complexities of significance. Since, the useful sentences comprises of helpful words, any framework that procedures normal dialect ought to have data about words and their implications (Miller *et al*., 1993). WordNet is one of the greatest lexicons right now being used and the widest spread. It has been utilized as a part of an assortment of assignments, for example, the natural language processing which incorporates question noting and evacuate word meaning ambiguity. Most of the word references for English language in the period before 1990 AD have been as printed copy as it were. Electronic word references accessible in that time is confined on specialists with a couple of gatherings. This is the thing that has hampered a considerable measure of work in particular ranges of computational etymology which should be done.

WordNet: WordNet is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. The main relation among words in WordNet is synonymy as between the words shut and close or car and automobile. Synonyms-words that denote the same concept and are interchangeable in many contexts-are grouped into unordered sets (synsets). Each of WordNet's 117000 synsets is linked to other synsets by means of a small number of "conceptual relations". WordNet is a set of free software available that make it possible to measure the semantic similarity or correlation between a pair of concepts the more eager property of WordNet is endeavoring to orchestrate lexical data as needs be to the word implications instead of its structures. In such manner, WordNet looks like thesaurus instead of the dictionary. WordNet comprises three separate databases: the first is for nouns, the second is for verbs and the third is for adverbs and adjectives. WordNet is organized by semantic relationships and as long as the semantic relationships are the relationships between the meanings and the meanings can represent via. synsets, thus, it is very normal to consider. The semantic relationships as indicators among the synsets. Synonymy is of course, a lexical relation between word forms. In WordNet, the relationship that is considered as the most important is the similarity that may be present in meanings. Two terms are considered synonymous when the replacement of each other does not change the meaning of the sentence in that place. Thus, according to this clarification, synonyms are scarce.

Topic modeling: Topic models give a basic approach to breakdown vast volumes of unlabeled text, it applies a statistical method to manage large archive of documents by discovering the latent topics (Blei, 2011). There are different approaches of topic modeling that use variant sampling algorithm for word and topic, latent semantic analysis: this technique is the most fundamental and takes a glance at the recurrence of words inside an archive and makes points in view of the frequencies of words happening in each record (Griffiths *et al*., 2007). Latent dirichlet allocation is another fundamental topic model. It bunches words together in view of the fact that they are so, liable to show up in a document together (Blei *et al*., 2003). Correlated topic models investigate the connection of words to different words inside a document; the strength relationships between words generate the topics (Blei and Lafferty, 2007). Explicit semantic analysis in this method the matrix generated depending on the frequency of the words in document and then based on the recurrence of co-occurrences between words creates topics (Egozi *et al*., 2011).

Latent dirichlet allocation: Latent dirichlet allocation is the most basic type of topic models that discover topics from large collection of documents, LDA can be modified to be more suitable for some purpose and to take better result when applied it (Asuncion *et al*., 2009).

Description of latent dirichlet allocation: Blei *et al*. (2003) describe LDA as a Bayesian inference model that connect a probability distribution over topics with each document where each topic is probability distributions over words. Hidden or latent variables are inferred using posterior inference. Posterior inference is where the hidden variables are estimated based on relevant background evidence (Abbey, 2015). In the LDA, the topics are hidden variables and are inferred from the words in the text documents as it considers aligning the words with specific probabilities (Chong *et al*., 2009). It groups words together based on how likely they are to appear in a text document together.

The system modeling: According to the short text of description tag for each image the stander LDA may be not well work for this reason, we suggest in this proposed system to use sentence LDA that assign one topic for each sentence, this mean that there is one topic for each image. Figure 2 shows the architecture of proposed work.

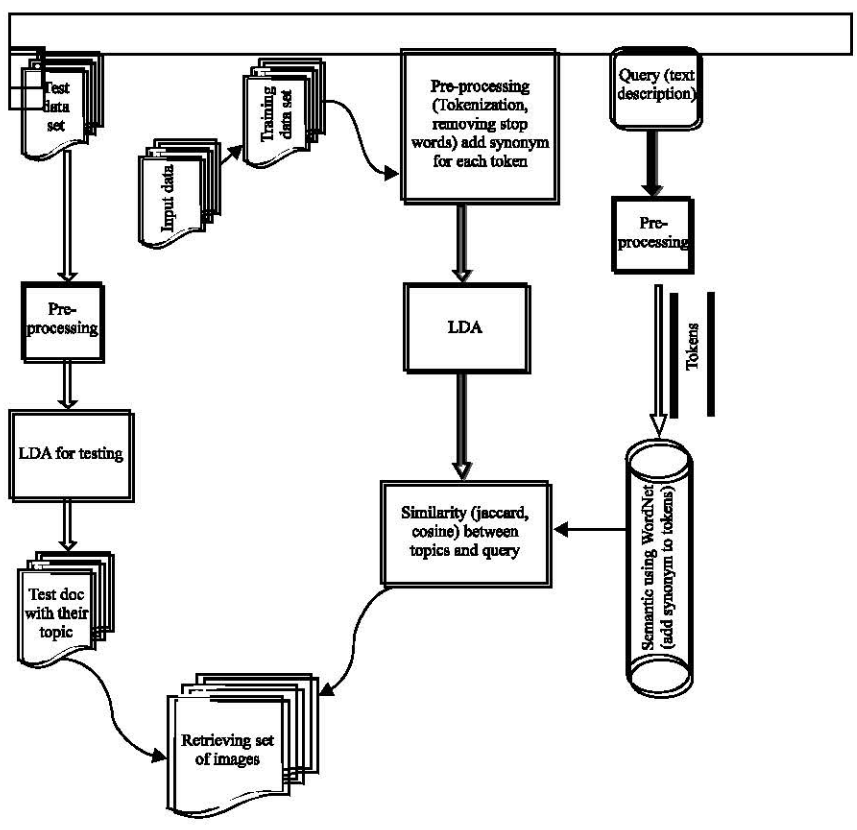

Fig. 2: The proposed system architecture

After the data be processed and before LDA was applied to it, the proposed system using semantic approach by adding five synonym for each token in training dataset this technique enable the model to aggregate related tokens in one topic, the joint distribution of this model is in Eq. 3:

$$p(w, z, \theta, \varnothing|\alpha, \beta) = p(\varnothing|\beta)p(\theta|\alpha)p(z|\theta)p(w|\theta z) \tag{3}$$

In this equation all variables are hidden except w is observed because of the difficult of this equation of posterior inference (Darling, 2011). Equation 4 overcome this problem:

$$P(\theta, \varnothing, z|w, \alpha, \beta) = p(\theta, \varnothing, z \mid w, \alpha, \beta)/p(w \mid \alpha, ß) \tag{4}$$

In the model instead of assigning topic to each word, assigning topic to sentence. When in XML file the description for each image represents the sentence. Formally, we expect that there are K topics in images, each spoke to by.

A word distribution for topic k and topic distribution of images. Let α and β_{word} be the hyper parameter, where $m_{wi, a}$ is the number of assignments all files of the current word to topic a $\sum_{w\epsilon V} m_{w, a}$ the sum of all topic a word counts, V is the size of the vocabulary $n_{w, a}$ is the number of current assignments to topic a in document i, N_i is the numbe of words in current document, A is the number of topics.

In this research, the α is not constant for all topic, it changing from topic to another depending on the count of words that assigning to specific topic in which $\alpha[k]$ = 1/(count of all words followed to topic k). This change led to increase the relevance of the topic to the file. We utilize Gibbs sampling to establish this model.

Algorithm of learning process of the LDA:

Input: Set of xml files contains image's descriptions
Output: Topics distribution of images and words distribution for each topic
Begin
  Step 1: For each file f
    For each topic
      For each word find Eq. 5:

$$P(topic)^* = \frac{m_{wi,a} + \beta_{word}}{\sum w_{\epsilon v} m_{w,a} + V\beta_{word}} \tag{5}$$

  End for
Then calculate Eq. 6:

$$P(topic)^* = \frac{m_{w,a} + \alpha}{N_i - 1 + A\alpha} \tag{6}$$

End for
Step 2: Generate topic for each file by applying max (p(topic)/∑p(topic))
Step 3: Repeat the step 2 an extensive number of times until assignments are quite great
 End

RESULTS DISCUSSION

The output of LDA algorithm is distribute topic for each image that similar to label each image with its related topic, each topic represent distribution of words, then the step of query implemented by preprocessing it by removing stop words and convert the rest word to lower case and aggregate them in bag of words. After that for each token add the five synonym to bag of words, the similarity measures then used between tokens of query and top ten words for each topic, the largest similarity between specific topic and query's word be the key of retrieve set of images that have this topic.

Some results of proposed work: The training set consist 500 descriptions of images in Fig. 3, there are some images that have descriptions were entered to proposed system. In Fig. 4, 6 XML files that were corresponded with image in Fig. 3.

Fig. 3: Example of images

```
<DOC>
<DOCNO>annotations/05/5001.eng</DOCNO>
<TITLE>The Coast of the Isla de la Plata</TITLE>
<DESCRIPTION>view of a rocky coast with several rocky islands in the sea; dry bushes in the foreground</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Isla de la Plata, Ecuador</LOCATION>
<DATE>August 2002</DATE>
<IMAGE>images/05/5001.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5001.jpg</THUMBNAIL
>
</DOC>
```

```
<DOC>
<DOCNO>annotations/05/5010.eng</DOCNO>
<TITLE>Blue-footed Booby on the Isla de la Plata</TITLE>
<DESCRIPTION>a blue-footed booby is standing in the middle of the green vegetation</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Isla de la Plata, Ecuador</LOCATION>
<DATE>August 2002</DATE>
<IMAGE>images/05/5010.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5010.jpg</THUMBNAIL>
</DOC>
```

```
<DOC>
<DOCNO>annotations/05/5014.eng</DOCNO>
<TITLE>The Santa Catalina Monastery</TITLE>
<DESCRIPTION>view of a courtyard of a grey building with many arches and columns, potted plants and a little fountain in the centre</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Arequipa, Peru</LOCATION>
<DATE>September 2002</DATE>
<IMAGE>images/05/5014.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5014.jpg</THUMBNAIL
>
</DOC>
```

```
<DOC>
<DOCNO>annotations/05/5007.eng</DOCNO>
<TITLE>The Santa Catalina Monastery</TITLE>
<DESCRIPTION>a courtyard of a blue building with several arches and columns, with red flowers, two trees and two green crosses</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Arequipa, Peru</LOCATION>
<DATE>September 2002</DATE>
<IMAGE>images/05/5007.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5007.jpg</THUMBNA
IL>
</DOC>
```

```
<DOC>
<DOCNO>annotations/05/5009.eng</DOCNO>
<TITLE>Arequipa Airport</TITLE>
<DESCRIPTION>the wing and the engine of a blue and white plane at an airport; the red and brown airport building in the background</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Arequipa, Peru</LOCATION>
<DATE>September 2002</DATE>
<IMAGE>images/05/5009.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5009.jpg</THUMBNAIL>
</DOC>
```

```
<DOC>
<DOCNO>annotations/05/5003.eng</DOCNO>
<TITLE>The coast of the Isla de la Plata</TITLE>
<DESCRIPTION>a steep rocky coast with many black rocks in the sea</DESCRIPTION>
<NOTES></NOTES>
<LOCATION>Puerto Lopez, Ecuador</LOCATION>
<DATE>August 2002</DATE>
<IMAGE>images/05/5003.jpg</IMAGE>
<THUMBNAIL>thumbnails/05/5003.jpg</THUMBN
AIL>
</DOC>
```


Fig. 4: Description of six images from top 6 images

Table 1: Five extracted topics with top 10 words

Topic 33th		Topic 8th		Topic 2th		Topic 4th		Topic 0th	
Words	Weight	Words	Weight	Words	Weight	Words	Weight	Words	Weight
Rock	0.043337	Booby	0.02342436	Sky	0.02607918	Red	0.02335173	Airport	0.0276206
Sea	0.032547	Boob	0.02342436	Green	0.02514023	Building	0.0207714	Airplane	0.02439012
Rock	0.023556	Dope	0.02342436	Zane grey	0.0195065	Fountain	0.015610	Associate in	0.01792916
Candy	0.023556	Dummy	0.0234243	Grey	0.01950657	Tree	0.015610826	Nursing	-
John	0.023556	Dumbbe	0.023424	Charles	0.01903	Diagram	0.014320	Aeroplane	0.0163139
Rockstone	0.021758	Bluefooted	0.01350	Grey	0.01856762	Construction	0.0104502	Drome	0.016313922
Black	0.018162	Pinhead	0.0135267	Second earl	0.01434237	Edifice	0.0104502	Aerodrome	0.016313
Steep	0.016363	Bush	0.01352674	Black	0.01246448	Bolshevik	0.01045	Mountain	0.0163139
Ocean	0.012767	Chaparral	0.013526	Brown	0.01199501	Courtyard	0.00916	Plane	0.016313922
Rocky	0.010969	Scrub	0.01352674	Building	0.0117602	Court	0.009160071	Desert	0.013083442

Table 2: Distribution topics in document

Do No.	T0	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14
1	0.0029	0.0111	0.0171	0.0045	0.9312	0.0013	0.0046	0.0083	0.0016	0.0085	0.0028	0.0024	0.0017	8.70E-4	4.4805E-4
2	0.0029	0.0111	0.0171	0.0045	0.9312	0.0013	0.0046	0.0083	0.0016	0.0085	0.0028	0.0024	0.0017	8.70E-4	4.4805E-4
45	0.0029	0.0111	0.0171	0.0045	0.0037	0.0013	0.0046	0.0083	0.0016	0.9360	0.0028	0.0024	0.0017	8.70E4	4.4805E-4
81	0.9304	0.0111	0.0171	0.0045	0.0037	0.0013	0.0046	0.0083	0.0016	0.0085	0.0028	0.0024	0.0017	8.70E-4	4.4805E-4
98	0.0029	0.0111	0.0171	0.0045	0.0037	0.0013	0.0046	0.0083	0.0016	0.0085	0.0028	0.0024	0.0017	8.70E-4	0.9279

A parsing process on the annotated xml format file was performed for reading and extracting the file tags. According to the proposed work, the tags <description> was chosen to retrieve their content as they both contain textual features that can be passed to the LDA algorithm for analyzing and extracting relevance topic of image then after the process of preprocessing (removing stop words, converting to lower case) synonym for each noun was added to dictionary, then the LDA applied to text and number of topics involve the top words with highest probability. Table 1 and 2 show five topics with its top ten words with their weights from 35 topics. Red color cells refers to highest probability of topic in that specific document, so, for example, the document 81 talking about topic 0 and document 98 talking about topic 14. In query file the data is a {{pilot is standing in front of a white airplane on an airfield in the middle of the desert with a brown mountain in the background; a woman is getting on the airplane}}. After each image has specific topic, then the similarity between top ten words for each topic with bag of words for that query have done, so, the retrieval image was as shown in Fig. 5.

Another testing that when the semantic ontology did not use in system with query {{flowers in garden}} and by using the measure of jaccard and cosine the results are empty because no word (flowers) found in training set.

To solve this problem we use semantic ways such as word net to supply the synonym of words that exits in query text. The result is clear to enhance the performance of retrieval process as shown in Fig. 6.

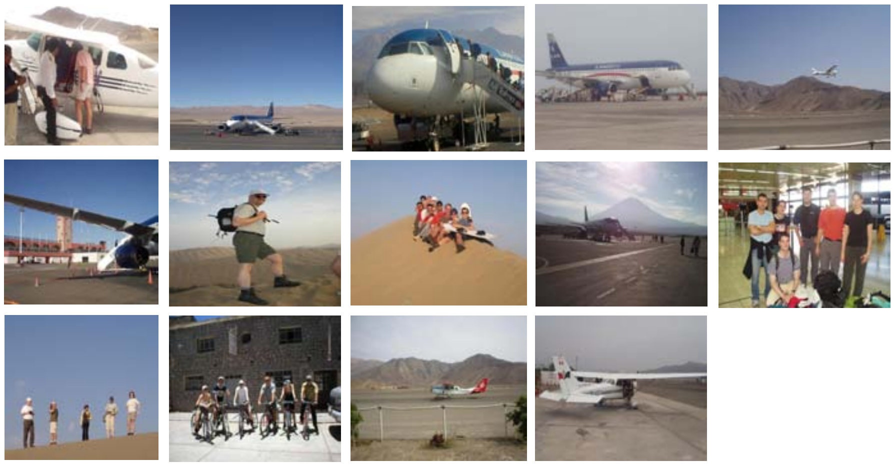

Fig. 5: Retrieving images according to text query

Fig. 6: Retrieving images according to text query

CONCLUSION

As a result show that the topic modeling when using the latent Dirichlet allocation plays the basic role to discover the hidden topic that found in images, there is a clear difference between stander LDA and sentence LDA. Where sentence LDA be appropriate to short text. Here LDA rise as clustering algorithm where each cluster involve similar images (have similar description)then the proposed work give each image the name of cluster that it found in it (topic's number). So, the process of retrieval be easy. By using an efficient matching process among large collection of text documents and images with respect to their topics would be accomplished. The important step that enhance the efficiency of retrieving process is utilizing semantic similarity. The work was tested using the benchmark CLEF dataset and the topics results were encouraging with respect to the topics based image retrieval.

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