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ORGANIZING MULTIMEDIA DATA USING SEMANTIC LINK NETWORK

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ABSTRACT

Aims: *Multimedia resources such as images, audio, video are growing at a high rate due to our daily usage of internet and other digital activities. So organisation of these resources is the biggest challenge in today's world. Whatever application we use in internet, it generates certain amount of data that are needed to be preserved. For example, we use Google or other search engines to search for a thing. In order to give correct output, these search engine providers need a way to organize these multimedia resources. Here organizing refers to efficient way of storing multimedia resources so that while retrieving, it will give us appropriate results. Just adding new images or other resources to a database daily won't provide the best retrieval result.* ***Materials and Methods:*** *In this paper, the Semantic Link Network model is used for organizing multimedia resources. A whole model for generating the association relation between multimedia resources using Semantic Link Network model is proposed. Each image in internet has a name and tags associated with it. The tags and the surrounding texts of multimedia resources are used to measure their semantic association.* ***Results:*** *Based on this information from the images, this proposed model aims to get a value for each image and classify them according to the range of values.* ***Conclusions:*** *This type of organisation of multimedia resources enables one to efficiently store the resources. So while retrieving, it produce appropriate results to all the users who are interested in retrieving the resources.*

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KEY WORDS

Multimedia Resources, Semantic Link, Multimedia Resources Organization, Databases, Search Engines

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INTRODUCTION

Understanding the semantics of multimedia has been an important component in many multimedia based applications [1]. Manual annotation and tagging has been considered as a reliable source of multimedia semantics. Unfortunately, manual annotation is time-consuming and expensive when dealing with huge scale of multimedia data. The rapid increase number of multimedia resources has brought an urgent need to develop intelligent methods to represent and annotate them [2].

In this paper, the Semantic Link Network (SLN) model is used for organizing multimedia resources with social tags. Semantic Link Network is designed to establish associated relations among various resources (e.g., Webpages or documents in digital library) aiming at extending the loosely connected network of no semantics (e.g., the Web) to an association rich network [3]. The tags and surrounding texts of multimedia resources are used to represent the semantic content. The relatedness between tags and surrounding texts are implemented in the Semantic Link Network model.

Related works

The Semantic web is an evolving development of the World Wide Web, in which the meanings of information on the web is defined therefore; it is possible for machines to process it. The basic idea of Semantic Web is to use ontological concepts and vocabularies to accurately describe contents in a machine readable way [4]. These concepts and vocabularies can then be shared and retrieved on the web. In the Semantic Web, each fragment of the description is a triple, based on Description Logic. Thus, the implicit connections and semantics within the description fragments can be reasoned using Description Logic theory and ontological definitions. Earlier research work on the Semantic Web focused on defining domain specific ontologies and reasoning technologies [5]. Therefore, data are only meaningful in certain domains and are not connected to each other from the World Wide Web point of view, which certainly limits the contributions of Semantic Web for sharing and retrieving contents within a distributed environment.

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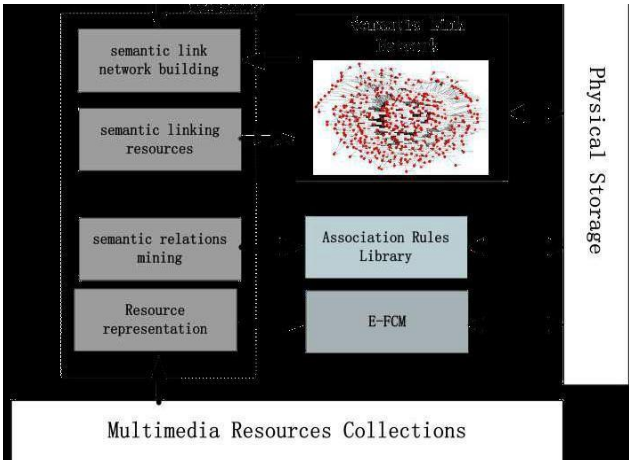
The Semantic Link Network (SLN) was proposed as a semantic data model for organizing various Webs resources by extending the Web's hyperlink to a semantic link.SLN is a directed network consisting of semantic nodes and semantic links [6].

The basic mechanism is shown below.



SEMANTIC LINK NETWORK

The proposed model consists of the following parts,

Resources representation

Element Fuzzy Cognitive Map (E- FCM) [19] is used to represent multimedia resources with social tags since it does not only reserve resources" keywords but also the relations among them.

Resources storage mechanism

Database/XML is used to store E- FCM since it is easy to define the mark-up elements.

SLN generation mechanism

Based on E-FCM and the association rules, ALN can be generated by machine automatically.

The Basic Heuristics

Based on common sense and our observations on real data, five heuristics that serve as the base of the proposed computation model are given as follow.

Heuristic 1.Usually each tag of a multimedia resource appears only one time. Different from writing sentences, users usually annotate a multimedia resource with different tags. For example, the possibility of using tags "apple" for an image is very low. Therefore, in this paper, we do not employ any weighting scheme for tags such as tied.

Heuristic 2.The order of the tags may reflect the correlation against the annotated multimedia resource. Different tag reflects the different aspect of a multimedia resource. According to Heuristic 1, the weight of a tag against the image cannot be obtained. Fortunately, the order of the tags can be get since user may provide tags one by one.

Heuristic 3.The number of tags of a multimedia resource may not relevant to the annotation correctness. Different users may give different tags about the same multimedia resource. For example, users may give tags such as "apple iPhone "or "iPhone4 mobile "for a same image about iPhone. It is hardly to say which tag is better for annotation though the latter annotation has three tags.

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Heuristic 4. Usually some tags may be redundant for annotating a multimedia resource. Of course, users may give similar tags for a multimedia resource. For example, the tags "apple iPhone" may be redundant since iPhone is very semantic similar to apple.

Heuristic 5. Usually some tags may be noisy for annotating a multimedia resource. Users may give inappropriate or even false tags for a multimedia resource. For example, the tags "iPhone" are false for an image about the iPod.

GENERATING THE SEMANTIC LINK

The proposed computation model is divided into three steps:

Tag relatedness computation

In the proposed computation model, each tag can be seen as a concept with explicit meaning. Thus, we use some equations based on co-occurrence of two concepts to measure their semantic relatedness. The core idea is that „you shall know a word by the company it keeps". In this section, four popular co-occurrence measures (i.e., Jacquard, Overlap, Dice, and PMI) are proposed to measure semantic relatedness between tags [7].

Besides co-occurrence measures, the page counts of each tag from search engine are used. Page counts mean the number of web pages containing the query q. For example, the page counts of the query „Obama" in Google are 1,210,000,000. Moreover, page counts for the query „q AND p" can be considered as a measure of co-occurrence of queries q and p.

The page counts for the query „p AND q" should be considered. For example, when we query „Obama" and „United States" in Google, we can find 485,000,000 Web pages, that is, =485,000,000. According to probability and information theory, the mutual information (MI) of two random variables is a quantity that measures the mutual dependence of the two variables. Point wise mutual information (PMI) is a variant of MI.

$$\mathbf{PMI(p,q)=log(N*N(p\cap q)/N(p)*N(q))/logN}$$

where N is the number of Web pages in the search engine, which is set to according to the number of indexed pages reported by Google.

Algorithm 1:MaxRel

Input: The tags set of two images *f1* and *f2*, which is *s(f1)* and *s(f2)*

Output: The semantic relatedness of two
images **f1** and f_2 **for each** t_i $s(f_1)$ /*page position initial */

$N(s(f_1))$ $N(t_i)$ **;**

$Pos(s(f_1))$ $Pos(t_i)$ **;**

for each $t_{j,}s(f_2)$

$N(s(f_2))$ $N(t_j)$ **;**

$Pos(s(f_2))$ $Pos(t_j)$ **;**

for each $t_{i,}s(f_1)$

for each $t_{j,}s(f_2)$

if ($t_{i,}\ t_j$ **)** $sr(t_i\ , t, j)^0$;/*pruning*/

counts and

else $sr(t_i\ , t_j\ )$ $f(N(t_i\ ), N(t_j\ ))$
;/*relatedness*/
return $maxRel(f_1,f_2)= f(Pos(t_i), Pos(t_j),$

$sr(t_i\ , t_j))$;

Semantic Relatedness Integration

We change the semantic relatedness integration of all tag pairs to the assignment in bipartite graph problem. We want to assign a best matching of the bipartite graph [8].

Adopting the proposed maxRel function, we are sure to find the global maximum relatedness that can be obtained pairing the elements in the two tags sets. Alternative methods are able to find only the local maximum since they scroll the elements in the first set and, after calculating the relatedness with all the elements in the second set, they select the one with the maximum relatedness. Since every element in one set must be connected, at most, at one element in the other set, such a procedure is able to find only the local maximum since it depends on the order in which the comparisons occur. For example, considering the below diagram.

Image f1 with tags   Image f2 with tags t1,t2,t3

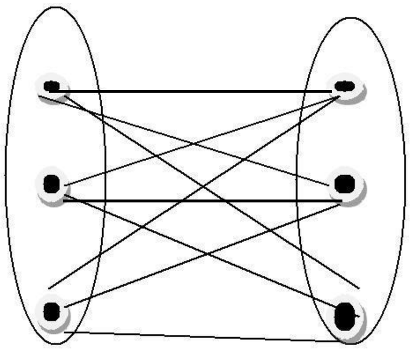

Fig:1 One to one many relationship

t1 will be paired to q1 (weight=1.0). But, when analysing t3 the maximum weight is with q2 (weight=0.9). This means that t2 can no more be paired to q2even if the weight is maximum, since this is already matched to t3. As a consequence, t2 will be paired to q3 and the average of the selected weights will be (1.0+0.3+ 0.9)/3
=0.73 which is considerably lower than using maxRel where the sum of the weights was (1.0+0.8+0.7)/3=0.83.
Overall, the cardinality of two tag sets is used to follow heuristic 3. The one- to-one map of tags pair is used to follow heuristics 4 and 5. The maxRel function is used to match a best semantic relatedness integration of two multimedia resources.
4.3Tag Order Revision

In this section, the maxRel function proposed in section 4.2 is revised considering the order of tags. For example, the relatedness of tag pair with high position should be enhanced, which is summarized as

Schema 1: This schema means that the identical tag pairs of two multimedia resources and should be pruned in maxRel function.

We add a decline factor to the maxRel function, and the detailed steps are:
(1) According to the maxRel function in section 4.2, the best matching tag pairs are selected, which is denoted as:

$$\mathbf{MaxRel(f1,f2)=\sum sr(ti,tj)}$$

(2) Computing the position information of each tag, which is denoted as Pos(t1)

$$\mathbf{Pos(ti)=I\ s(f)\ I+1-i\ /\ I\ s(f)\ I}$$

(3) Add the position information of each tag to the equation, which can be seen as a decline factor:

$$\mathbf{Sr(f1,f2)=\sum Pos(ti)*sr(ti,tj)*Pos(tj)}$$

(4) Of course, similar to maxRel function, equation should divide the result of the maximization by

$$\mathbf{Sr(f,f2)=\frac{\sum Pos(ti)*sr(ti,tj)*Pos(tj)\ /}{\sum Pos(ti)*Pos(tj)}}$$

Schema 2.Identical tag pruning. This schema means that the identical tag pairs of two multimedia resources and should be pruned in maxRel function. In other words, the semantic relatedness of the same tag of two multimedia resources is set as 0.

The above schema is used to ensure the relatedness measures of two multimedia resources. If we do not prune the identical tag pairs of two multimedia resources, the proposed method will be transformed to the similarity measures. For example, the cosine similarity between two tags is to find the number of identical elements of two vectors. The overall algorithm of the proposed computation mode is presented in algorithm 1.

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IMPLEMENTATION

Google API Code

```
Query =URLEncoder.encode(query, "UTF-8");

URL url = new URL("http://ajax.googleapis.com/ajax/serv ices/search/web?start=0&rsz=large&v=1.0 &q=" + query);
URLConnection connection = url.openConnection();
connection.addRequestProperty("Referrer" , HTTP_REFERER);
```

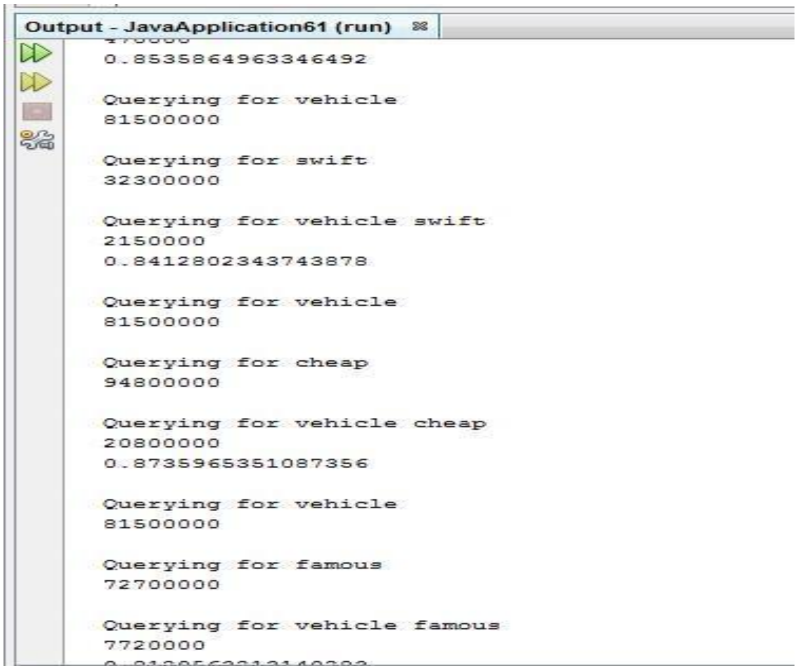

Fig: 2. Implementation java code

RESULTS FROM PROPOSED MODEL

```
public double compute(int one, int two, int both) {

//To calculate semantic relatedness double n= Math.pow(10, 11);

        double z=Math.log((n*both)/(one*two));
        double x=(double) (z/(Math.log(n)));System.out.println(x);

return x;
```

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```
----TAG ORDER REVISION----
0.6184452058832405
0.6184452058832405
----TAG ORDER REVISION----
0.8241017833636933
0.5494011889091288
----TAG ORDER REVISION----
0.56453423
0.18817807666666667
----TAG ORDER REVISION----
0.6208857630411686
0.4139238420274457
----TAG ORDER REVISION----
0.8682118356575788
0.3858719269589238
----TAG ORDER REVISION----
0.8732853426766157
0.19406340948369238
```

```
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.6184452058832405
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.8241017833636933
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.56453423
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.6208857630411686
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.8682118356575788
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.8732853426766157
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.56453423
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.56453423
----SEMANTIC RELATEDNESS BETWEEN TAGS---
0.655553849557736
```

Fig: 3. Semantic values in proposed system

Evaluation on Image Clustering

In this section, we evaluate the correctness of using tag order. In section 4.3, we add the position information of each tag to the semantic relatedness measures. The tags with high position are treated as the major element for semantic relatedness measures. We evaluate the using of tag order by the clustering task. We employ the proposed semantic relatedness of images into K- means clustering model. Since the K- means model depends on the initial points, we random select core points 100 times.

We evaluate the effectiveness of document clustering with three quality measures: *F-measure*, *Purity*, and *Entropy*. We treat each cluster as if it were the result of the proposed method and each class as if it were the desired set of images. Generally, we would like to maximize the *F-measure* and *Purity*, and minimize the *Entropy* of the clusters to achieve a high- quality document clustering. Moreover, we compare the clustering results between the proposed method using tag order or not.

Evaluation on image searching

Five queries from group2 are selected as the test set including “Louis Vuitton”, “Gucci”, “Chanel”, “Cartier”, and “Dior”. These queries are searched in Flickr. The top 50 images are obtained as the data set. Moreover, we remove the queries on the tags of each image. For example, the tag “Cartier” of the top 50 images is re-moved of the query “Cartier”. The reason for that operation is that the proposed method is based on the semantic relatedness other than co-occurrence. We choose cut-off point precision to evaluate the proposed method on image searching. The cut-off point precision (*Pn*) means that the percentage of the correct result of the top *n* returned results. We compute the *P1*, *P5*, and *P10*of the group2 test set.

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APPLICATIONS

Content-based image retrieval (CBIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. "Content-based" means that the search analyzes the contents of the image rather than the metadata such as keywords, tags, or descriptions associated with the image [9]. The term "content" in this context might refer to colors, shapes, textures, or any other in- formation that can be derived from the image itself.

CBIR is desirable because most web-based image search engines rely purely on metadata and this produces a lot of garbage in the results [10]. Also having humans manually. Enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image[11]. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

The proposed SLN based model can be used for video searching. The ontology based video searching is similar to CBIR, which also focuses on the content of the videos [12 – 14]. Figure. 1 gives the searching interface of the developed tool based on the proposed SLN based model. From Figure.2, 3, the searching procedures for a user are as follow.

(1) Ontology based queries. Different from web search engines, the proposed SLN based video search constricts the searching method. Users can only select the defined attributes or concepts as the searching queries.

(2) Associated videos suggestion. Since the video re-sources are organized by their association relation.

CONCLUSION

Recent research shows that multimedia resources in the wild are growing at a staggering rate. The rapid increase number of multimedia resources has brought an urgent need to develop intelligent methods to organize and pro-cess them. In this paper, the Semantic Link Network model is used for organizing multimedia resources. Se-mantic Link Network (SLN) is designed to establish associated relations among various resources (e.g., Web pages or documents in digital library) aiming at extending the loosely connected network of no semantics (e.g., the Web) to an association-rich network. Since the theory of cognitive science considers that the associated relations can make one resource more comprehensive to users, the motivation of SLN is to organize the associated resources loosely distributed in the Web for effectively supporting the Web intelligent activities such as browsing, knowledge discovery and publishing, etc. The tags and surrounding texts of multimedia resources are used to represent the semantic content. The relatedness between tags and surrounding texts are implemented in the se-mantic Link Network model. Two data mining tasks including clustering and searching are performed by the proposed framework, which shows the effectiveness and robust of the proposed framework.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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