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Fusion Model for Ontology Based Image Retrieval

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Abstract

Data fusion is the process of combining multiple sources of information to produce better results compared to using the source individually. This paper applies the idea of data fusion to semantic image retrieval, which combines the ranking scores between ontology based and keyword based semantic image retrieval model. Although the evaluation shows that the overall performance of the ontology based model is higher than that of the keyword based model, the results analysis reveals that the performance of ontology based model is in direct relation with the implicit information relies within the query and annotation text. If the annotation contains less meaningful information, the ontology based method performs very poorly, thus affecting the relevancy of semantic chromosomes. This further affects the performance of the similarity measure and the quality of the retrieval results. As a result, user queries return fewer results than expected, as they get much lower similarity value than they should. Whereas, keyword-based search would perform better in these situations. To deal with this drawback, this paper proposes to combine the results coming from the proposed ontology-based retrieval model and the result returned by traditional keyword-based model. The combined model is evaluated using both traditional IR measures.

Keywords: Semantic Indexing, Semantic Search, Image Retrieval, Data Fusion

1. Introduction

The rapid introduction of digital cameras has led to a tremendous growth of digital collections and an increasing need to develop effective systems to help users search for digital images. According to Data et al. [1], approaches to image retrieval can be divided into three categories: (i) text-based image retrieval (TBIR) which uses textual features only, (ii) content-based image retrieval (CBIR) which utilises visual features, and (iii) composite approaches, which use both textual and visual features. Although content-based image retrieval (CBIR) and composite approaches [1, 2] are used in many applications (i.e. query by example), it is often desirable and practical for the user to retrieve images using textual queries compared to image samples. Traditional text-based image retrieval systems mainly use indexing techniques utilising keywords counts to measure importance. Alternatively, concept-based image retrieval uses different approach by utilising semantic technologies to extract the high level concepts behind the image annotations. Some concept-based image retrieval use an existing knowledge based to map the concepts [3, 4] while others use the relationship between the term occurrences [5, 6, 18].

Fadzli and Setchi propose a knowledge based image indexing using Semantic DNA (SDNA) [7]. SDNA is considered as a representation of text semantics which are extracted from the image annotations. The set of SDNA extracted are called the semantic chromosome, which are used to index the image. The study reports a better accuracy result (79.4%) produced by the propose method compared to other unsupervised algorithms (73%) in the 2007 Semeval competition. A positive correlation value of 0.5779 is also observed which shows that the quality of the text/annotation does effects the performance of the disambiguation.

This paper further expands the ontology based indexing by combining the concept-based search method using SDNA with the traditional keyword based method. The paper is organised as follows. Section 2 explains the search and ranking algorithms with initial experiments comparing the semantic search results with traditional keyword search results. Section 3 describes the combined model and the evaluation protocol and results are discussed and conclude in section 4.

2. SDNA Based Semantic Search

Traditional keyword-based IR approaches ignore relations between keywords and assess their importance in a text document by examining their occurrence in the document and collection, but disregarding the occurrence of any related keywords. By adapting the LSI method, the proposed approach goes beyond this restriction by analysing the co-occurrence of keywords in documents and collections. Semantically close documents are those with a lot of common words and semantically distant documents are those with less common words.

2.1 Query Processing

Figure 1 illustrates the process flow in SDNA-based semantic search model. Application of natural language and mathematical processing on the query returns weighted *semantic chromosomes* that satisfy the query. The *semantic chromosomes*' weights are correlated with the relevancy of the semantic concepts extracted from the image annotations. For example, let q be the query with 3 tokens and q = "*soft, gentle, pretty*". Going through the mathematical processing, query q produces 41 SDNAs, $|SetSDNA(q)| = 41$, where three most accurate SDNA are then chosen to populate *semantic_chromosomes(q)*. Figure 2 illustrates the process flow in SDNA-based semantic search model.

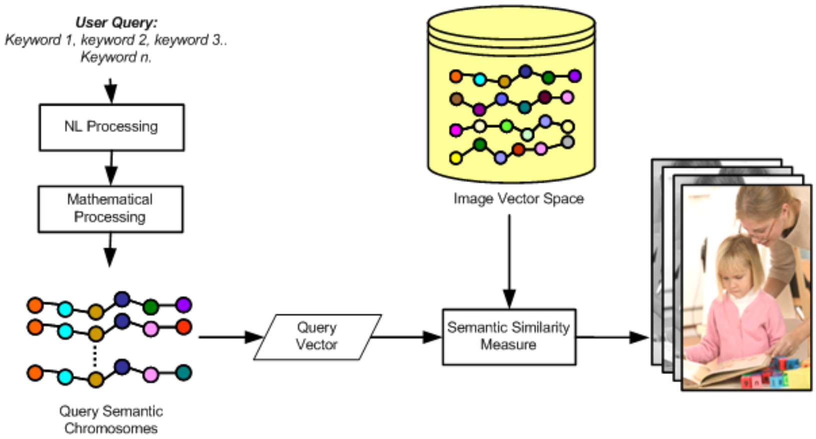

Figure 1: Process Flow in SDNA-based Semantic Search

Table 1 lists the *SetSDNA(q)* with their weights. Using SDNA disambiguation method, *semantic chromosomes* of q is selected based on the highest weighted SDNA for each token. Table 2 lists *semantic_chromosomes(q)* with their senses and related words. The words related to each SDNA in *semantic_chromosomes(q)* explain the idea or the interest of the user from the given query. Any images that have those words in their annotations will be considered semantically fulfill user's interest, thus will be retrieved.

After the query execution returns *semantic chromosomes* relevance to the query, the searching module's will search for all documents related to the *semantic chromosomes*. The semantic similarity between the query's chromosomes and document's chromosomes is measured using the cosine angle. The similarity measure between an image d and the query q is computed as:

$$\mathrm{sim}(\mathrm{d}, \mathrm{q}) = \frac{\mathrm{d} \times \mathrm{q}}{|\mathrm{d}| \cdot |\mathrm{q}|} \quad (1)$$

Table 1: List of *SetSDNA(q)* with Their Weights

Token	SDNA	Weight	Token	SDNA	Weight
gentle	**6-37-83-884-2-1**	**6.16598**	soft	6-35-77-819-2-1	5.20345
	6-35-77-823-2-1	5.50941		6-36-80-856-2-1	4.80237
	6-37-83-884-2-2	5.43577		6-37-85-905-1-3	4.78456
	3-15-47-369-2-1	5.04708		6-37-85-905-2-1	4.64738
	3-15-48-401-2-1	4.99288		5-31-70-734-2-1	4.58659
	6-38-88-935-2-1	4.87068		1-8-27-163-2-1-	4.42939

Table 2: (Continued): List of *SetSDNA(q)* with Their Weights

	6-37-84-897-2-1	4.77972
	5-31-70-734-2-1	4.58659
	1-8-28-177-2-1-	4.46047
	5-31-70-736-2-1	4.28887
	2-10-35-220-2-2	1.18926
pretty	**6-36-79-841-2-1**	**5.03509**
	1-3-10-32-4-2-3	3.13914
soft	**3-15-48-376-2-2**	**6.8845**
	3-15-48-425-2-3	6.70639
	3-15-48-417-2-1	6.28367
	3-15-48-399-2-1	6.17574
	3-15-48-401-2-1	6.16598
	3-15-48-391-2-1	6.10221
	3-15-48-410-2-1	6.01086
	6-35-77-819-2-1	5.20345
	3-14-46-347-2-1	4.3096
	5-31-70-736-2-1	4.28887
	3-14-46-356-1-2	4.23096
	6-38-89-948-2-1	4.02742
	3-14-45-328-2-1	3.97984
	1-3-10-33-2-1	3.81557
	1-8-28-177-2-2	3.47063
	1-7-25-152-2-2	2.7278
	5-26-59-601-2-1	2.70671
	5-29-68-721-2-1	2.30111
	4-20-53-487-2-1	2.01933
	4-20-53-499-2-2	1.87626
	2-11-39-258-2-1	1.41642
	2-12-43-301-2-2	1.07444

Table 3: List of *Semantic Chromosome(q)*with its Weights, Senses and Related Words

Token(t_i)	**SDNA**	**Weight**	**Token Sense**	**Related Words**
gentle	6-37-83-884-2-1	6.16598	courtesy	chivalrous, knightly, generous, noble, courtly, gallant, old-world, correct, formal, polite, civil, urbane, gentle, gentlemanly, ladylike, dignified, well-mannered, fine-mannered, well-bred, gracious, condescending, humble, deferential, mannerly, respectful, on one's best behaviour, complaisant, kind, benevolent, conciliatory, sweet, agreeable, suave, bland, smooth, ingratiating, well-spoken, fair-spoken, honey-tongued, flattering
pretty	6-36-79-841-2-1	5.03509	beauty	beautiful, pulchritudinous, beauteous, of beauty, lovely, fair, bright, radiant, comely, goodly, bonny, pretty, sweet, sweetly pretty, picture-postcard, pretty-pretty, pretty in a chocolate box way, nice, good enough to eat, pretty as a picture, photogenic, handsome, good-looking, well-favoured, well-built, well-set-up, husky, manly, tall, dark and handsome, gracious, stately, majestic, statuesque, Junoesque, adorable, god-like, goddess-like, divine
soft	3-15-48-376-2-2	6.8845	pleasure	comfy, homely, snug, cosy, warm, comforting, restful, reposeful, painless, peaceful, tranquil, convenient, easy, cushy, easeful, downy, soft, luxurious, deluxe, enjoying comfort, euphoric

2.2 Result Analysis

Although the evaluation in Fadzli and Setchi [7] shows that the overall performance of SDNA based model outperform keyword based model, result analysis reveals that the performance of SDNA based model correlates with the implicit information relies within the query and annotation text. If the annotation contains less meaningful information (e.g., there are annotations of name entities or the words used in the annotation are hardly related to each other), the SDNA Disambiguation algorithm performs very poorly, thus affecting the relevancy of *semantic chromosomes*. This will further affect the performance of similarity measure and retrieval results. Fewer results will be produced with less relevant images. On the other hand, keyword-based search will most likely to produce better results in these situations. To deal with this drawback, the results coming from the proposed ontology based retrieval model and the result returned by traditional keyword based model are combined.

However, the combination of ranking, using data fusion technique should be carefully designed in order to achieve appropriate balance between keyword based and ontology based result.

3. Data Fusion

Data fusion is defined as techniques for merging the retrieval results of multiple systems [8, 9, 10]. It has been widely used in the current information retrieval research [11, 12, 13, 14]. The fusion techniques for multiple systems problem can be divided into two main sub-techniques [8]: (i) normalisation and (ii) combination.

3.1 Normalisation

Normalisation is important in order to make the output comparable across different systems. The scores returned by the different information retrieval systems may not be equivalent. For example, the 10th position in the ranking has a different meaning when 15 results are returned than it would within 1,000 results. Similarly, a score of 0.9 does not have the same meaning in a system ranging in (0, 1) as in one ranging in (0, 100).

The score normalisation used in this proposed approach is based on the standard method explained by [12]:

$$\text{normalised\_similarity} = \frac{\text{unnormalised\_similairty} - \text{min\_similarity}}{\text{max\_similairty} - \text{min\_similarity}} \qquad (2)$$

3.2 Combination

The combination problem refers to using the normalised information returned by the different input systems to combine all the results in a unique output list. Shaw and Fox [15] designed some of the most simple, popular and effective combination algorithms to date. They are summarised in Table 3 below.

Table 3: Fusion Algorithms Designed by Shaw and Fox(1994)

Name	Technique
CombMIN	Choose min of similarity values
CombMAX	Choose max of similarity values
CombMED	Choose median of similarity values
CombSUM	Sum of individual similarity values
CombMNZ	CombSUM × no. of nonzero similarity values
CombANZ	CombSUM ÷ no. of nonzero similarity values

According to the experiments reported by Shaw and Fox [15] and Lee [12], CombMNZ is considered the best method, even though it performs just slightly better than CombSUM. CombMNZ is based on the observations by Lee regarding the overlap between the relevant and not relevant documents retrieved by different search engines, where "*different search engines return similar sets of relevant documents but different set of non-relevant documents*" [12].

Vogt and Cottrell [16] proposed a variant of CombSUM consisting of the introduction of a weight for each system, according to the importance, quality and reliability of the sources. The combined score is computed as a weighted linear combination, formally:

$$s_R = \sum_{r \in R} \alpha_r \cdot \bar{s}_r(x) \tag{3}$$

Where α_r is the weight for retrieval system *r*, $\bar{s}_r(x)$ is the normalised score assigned to *x* in the ranking returned by *r*. This approach can also be applied to CombMNZ and CombANZ. For comparative evaluation, six techniques are tested using *fotoLIBRA* evaluation benchmark, to combine the traditional keyword based similarity score, *ksim*, with the proposed ontology based similarity score, *sim*. The six techniques are listed in Table 4.

Table 4: Six Fusion Algorithms Evaluated

Technique	Description	Algorithm
CombMIN	Choose min of similarity values	$\mathrm{MIN}(\overline{\mathrm{sim}}, \overline{\mathrm{ksim}})$
CombMAX	Choose max of similarity values	$\mathrm{MAX}(\overline{\mathrm{sim}}, \overline{\mathrm{ksim}})$
CombSUM	Sum of individual similarity values	$\overline{\mathrm{sim}} + \overline{\mathrm{ksim}}$
CombMNZ	CombSUM × number of nonzero similarity values	$\mathrm{CombSUM} \times \beta$
WCombSUM	CombSUM with special weight α for each system	$\alpha \times \overline{\mathrm{sim}} + (1 - \alpha)\overline{\mathrm{ksim}}$
WCombMNZ	WCombSUM × number of nonzero similarity values	$\mathrm{WCombSUM} \times \beta$

Where $\overline{\mathrm{sim}}$ is the normalised SDNA based score, $\overline{\mathrm{ksim}}$ is the normalised keyword based score, β is the number of nonzero similarity values and $\alpha \in [0,1]$. The value of α is determined by the value of *sim* and *ksim*. The value of $\alpha = 0.7$ is used when both *sim* and *ksim* have positive values. Else, if *ksim* returns 0, then $\alpha = 1.0$, and if *sim* returns 0, then $\alpha = 0.3$ which gives less weight to images with no SDNA based score. Figure 2 and Table 5 list and illustrate the comparative experimental result for the six fusion techniques based on Mean R-Precision (MRP) and Mean Average Precision (MAP).

Table 5: Experimental Result for Six Fusion Technique

Fusion Technique	MAP	MRP
CombMAX	0.0789	0.06226
CombMIN	0.0637	0.05411
CombSUM	0.0803	0.07834
CombMNZ	0.0778	0.07210
WCombSUM	***0.0839***	***0.08822***
WCombMNZ	0.0824	0.08102

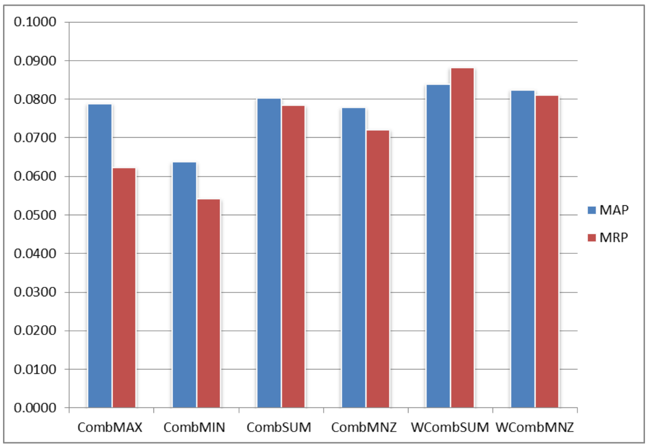

Figure 2: Performance Comparison Over Six Fusion Technique

The best performing technique for both MAP and MRP is WCombSUM (marked with bold text) which is slightly higher than WCombMNZ. It can be seen that both WCombSUM and WCombMNZ, and especially the former, are better than other techniques. Therefore, WCombSUM fusion technique is chosen as the best technique to combine the proposed SDNA based retrieval score with traditional keyword based retrieval score. Next section explains the experiments done to compare the performance of the proposed method with other related methods.

4. Evaluation

VisconPro Limited [17], one of the Wales leading company in image stock hosting called fotoLIBRA, had provided this research with more than 150,000 digital images together with annotations provided by the image owners. The evaluation benchmark comprises of:

- **Corpus:** 153,403 digital images (13.8 GB) extracted from the *fotoLIBRA* image collection.
- **Queries:** a set of 22 queries defined according to *fotoLIBRA's* categories and sub categories.
- **Judgments:** judgments for each query manually established based on the 239 sub categories provided by the image owners.

The experiments were designed to compare the results obtained by five different search approaches:

- **Keyword search:** a conventional Boolean keyword retrieval model, using Microsoft Windows search application.
- **Statistical analysis search:** a statistical based model, using the Apache Lucene library (Apache Software Foundation, 2001).
- **Concept search:** the concept-based retrieval model proposed by TRENDS project, using *OntoRo* as the lexical ontology.
- **Semantic search:** the complete semantic retrieval model proposed in this thesis, consist of the combination of SDNA based and keyword based retrieval models.

This section report and discuss the observed results for all 22 queries based using three information retrieval evaluation metrics: (i) Average Precision, (ii) R-Precision and (iii) Precision at 20 (P@20). Table 9 shows that, looking at MAP, the semantic retrieval approach proposed outperforms all other approaches, providing highest AP for 86.4% of the queries. Semantic search manage to produce better results than Boolean search for 95.5% of the queries, better than statistical search for 90.1% of the queries and better than concept search for all of the queries.

The results by P@20 are interesting (see Table 7), where there is no clear winner. Although semantic search slightly outperforms all other approaches in term of average P@20, semantic search only score highest P@20 for 31.8% of the queries. However, semantic search manage to provide better result than keyword search for 77.3% of the queries, and better than statistical search and concept search for 72.7% of the queries.

Table 6: Result of Average Precision

Query	Boolean	Statistical	Concept	Semantic
1	0.0246	0.0840	0.0254	0.0697
2	0.0682	0.1055	0.1146	0.1669
3	0.0000	0.0743	0.0733	0.1497
4	0.0000	0	0.0573	0.1011
5	0.0200	0.0403	0.0360	0.1082
6	0.0000	0	0.0593	0.1142
7	0.0000	0	0.0703	0.1254
8	0.0833	0.0093	0.0109	0.0274
9	0.0000	0.0000	0.0015	0.0022
10	0.0083	0.0114	0	0.1440
11	0.0000	0.0008	0	0.0373
12	0.0000	0	0	0.0017
13	0.0000	0.0190	0.0770	0.1013
14	0.0000	0.0417	0.0078	0.0512
15	0.0310	0.0236	0	0.0075
16	0.0549	0.0537	0	0.0995
17	0	0	0	0.0027
18	0.0000	0.0353	0.0156	0.0665
19	0.0000	0	0.0079	0.0336
20	0.0000	0	0.0231	0.0625
21	0	0.0021	0.0012	0.1018
22	0.0064	0.0039	0.0009	0.0015
Mean	**0.0135**	**0.0255**	**0.0388**	**0.0716**

Although P@20 metric does not show a strong performance advantage of semantic search, it is observed that the semantic search manage to produce good results in cases where statistical search performs poorly, especially in queries 7 (*prehistoric animal*), 11 (*land travel vehicle*), 20 (*underwater nature*) and 21 (*humour*). It is also observed that the semantic search performs poorly when the queries contains words that are commonly used in the image annotations. This is the case of queries 2 (*lovely flora*), 4 (*country terrain*), 14 (*festivals events*), 15 (*fashion design*) and 18 (*extreme sport*).

Using R-precision metric (see Table 8), the proposed semantic approach outperforms all other approach in 45.6% of the queries. Based on this metric, semantic search managed to provide better result than keyword search for 81.8% of the queries. While 13.6% of the queries produce comparable results. Compared to statistical search, the proposed approach performs better in 59.1% of the queries and equal for another 27.3%. While compared to concept search, excels at 31.8% of the queries and equal at 40.1% of the queries.

Table 7: Result of Precision at 20 (P@20)

Query	Boolean	Statistical	Concept	Semantic
1	0.1000	0.1000	0.1000	0.1500
2	0.7000	0.5000	0.3500	0.4500
3	0.1000	0.1000	0.3500	0.2500
4	0.1000	0.2500	0.1500	0.0500
5	0.3000	0.1500	0.2000	0.4500
6	0.1500	0.1000	0.3500	0.3000
7	0	0	0.1500	0.1000
8	0.1000	0.0500	0	0.0500
9	0	0	0	0
10	0.0500	0	0.1500	0.2500
11	0	0	0.0500	0.0500
12	0	0	0	0
13	0.0500	0.0500	0.2000	0.2000
14	0	0.3500	0	0.2000
15	0.0500	0.0500	0	0
16	0.0500	0	0.1000	0
17	0	0	0	0
18	0	0.1000	0.0500	0.0500
19	0.0500	0	0.0500	0
20	0	0	0	0.0500
21	0	0	0.1000	0.1000
22	0	0	0	0
Mean	**0.0818**	**0.0818**	**0.1068**	**0.1227**

Table 8: Result of R-Precision

Query	Boolean	Statistical	Concept	Semantic
1	0	0.2117	0.0438	0.0438
2	0	0	0.2013	0.2282
3	0	0.1134	0.1336	0.2186
4	0	0	0.1217	0.1130
5	0	0.2121	0.0833	0.2197
6	0	0	0.1038	0.1651
7	0	0	0.3333	0.1111
8	0.2222	0	0	0
9	0	0	0	0
10	0.0769	0	0.1538	0.2308
11	0.0328	0	0.0164	0.0328
12	0	0	0	0
13	0.0513	0.0769	0.1795	0.1667
14	0	0	0	0.1400
15	0	0	0	0
16	0.1429	0	0.1429	0
17	0	0	0	0
18	0	0.1111	0.1111	0.1111
19	0.0909	0	0.0909	0
20	0	0	0	0
21	0	0	0.1250	0.2500
22	0	0	0	0
Mean	**0.0280**	**0.0330**	**0.0837**	**0.0923**

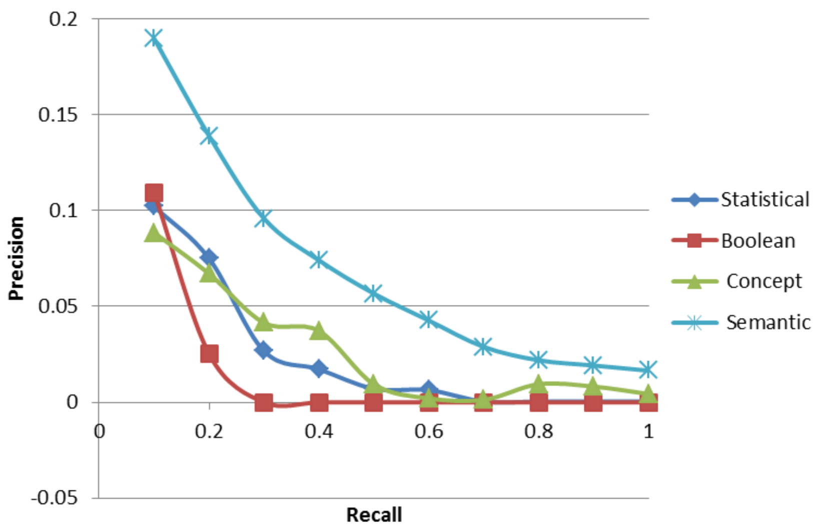

Figure 3: Average Precision and Recall Performance Over 22 Queries

The average precision and recall curve (Figure 3) clearly shows that the proposed approach outperforms all other approaches with a clear distinction. Worst performance was shown by Boolean search performed by Windows search, while both statistical and concept search performance are close.

5. Conclusion

The experiments shows that the quality of the *semantic chromosomes* extracted directly affect the performance of the results. In addition to simple keyword index lookup, the proposed semantic retrieval system processes a query against the lexical ontology, which returns a set of SDNAs. This is considered as a form of query expansion, where the set of SDNAs represent a new set of query terms, which increases the recall values. The rich concept descriptions and related words in the lexical ontology (*OntoRo*) provide meaningful context to help disambiguation process.

In summary, the proposed approach manage to enhance the SDNA based search results by compromising the concept-based search drawbacks and bringing the traditional keywords into calculations. Higher average precision score of 2.05 is achieved when querying for keywords with less meaningful information, compared to the score of 0.099 using SDNA based approach. Further observation shows that better precision achieved when the image annotation have enough related keywords to help SDNA disambiguation process achieve better performance. For example, images with short annotation tend to produce bad performance in SDNA disambiguation process, thus affecting the indexing and searching performance.

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