Affinity propagation promoting diversity in visuo-entropic and text features for CLEF Photo retrieval 2008 campaign

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Abstract

We develop for the CLEF PHOTO 2008 task a new visual features using various pixel projections for training SVMs, allowing us to produce image retrieval and clustering using affinity propagation. To heighten the diversity of the top of the retrieval results, we put the images with the lowest rank in each cluster into the top. The LSIS run which used only the visual information is at the 6th best team rank in the AUTO IMG run type. For AUTO TXTIMG runs, we merge by simple harmonic or arithmetic average our visual ranks to the textual ranks of the LIG language model participating to the AVEIR consortium. Then we also perform the affinity propagation and the reranking on this TXTIMG run, which gives complementary information to the AVEIR consortium, helping in producing the third best AUTO TXTIMG run (after XEROX). We discuss on the clustering performance of the various run types, and then we give some perspectives for enhancing such diversity image retrieval system. If affinity propagation clustering seems efficient for promoting visual diversity, our results show that clustering process itself should merge independant textual and visual clustering informations.

Categories and Subject Descriptors

H.3 [Information Storage and Retrieval]: H.3.1 Content Analysis and Indexing; H.3.3 Infor- mation Search and Retrieval; H.3.4 Systems and Software; H.3.7 Digital Libraries; H.2.3 [Database Management]: Languages–Query Languages

General Terms

Measurement, Performance, Experimentation

Keywords

Rank Fusion, Image Retrieval

1 Introduction to ImageCLEF2008 Photo Retrieval Task

ImageCLEF [2] is the cross-language image retrieval track run as part of the Cross Language Evaluation Forum (CLEF) campaign. This track evaluates retrieval of images described by text captions based on queries in a different language; both text and image matching techniques are potentially exploitable. The photo retrieval task of ImageCLEF2008 is taking a different approach to evaluation by studying image clustering. A good image search engine ensures that duplicate or near duplicate documents retrieved in response to a query are hidden from the user. Ideally the top results of a ranked list contains diverse items representing different sub-topics within the results. Providing this functionality is particularly important when a user types in a query that is either poorly specified or ambiguous; a common query in image search. Given such a query, a search engine that retrieves a diverse, yet relevant set of images at the top of a ranked list is more likely to satisfy its users [1,2].

Participants to ImageClef Photo run each provided topic on their image search system and produce a ranking that in the top 20, holds as many relevant images that are representative of the different sub-topics within the results. The definition of what consitutes diversity varies across the topics [2], indicated by a topic tag, "cluster" giving what the clustering criteria the evaluators use. For each topic in the ImageCLEFPhoto set, relevant images are manually clustered into sub-topics and relevance judgements will be augmented to indicate which cluster an image belongs to. For example if a topic asks for images of beaches in Brazil, clusters are formed based on location; if a topic asks for photos of animals, clusters are formed based on animal type.

The CLEF image challenge is running on the image collection of the IAPR TC-12 photographic collection provided for this task consists of 20,000 still natural images (plus 20,000 corresponding thumbnails) taken from locations around the world and comprising an assorted cross-section of still natural images [2]. This includes pictures of different sports and actions, photographs of people, animals, cities, landscapes and many other aspects of contemporary life. Each image is associated with an alphanumeric caption stored in a semi-structured format. These captions include the title of the image, its creation date, the location at which the photograph was taken, the name of the photographer, a semantic description of the contents of the image (as determined by the photographer) and additional notes. Figure 1 shows an example for the image collection and the topic list is given in table 1.

These paper first describes LSIS entropic features, LS-SVM and affinity propagation. Then we precise the LSIS runs method, before to detail and compare the results in the last section. The conclusion gives finally some strategies to enhance the clustering.

2 LSIS Profil Entropic Feature Extraction

An important step in content-based image retrieval (CBIR) system is the extraction of discriminant visual feature that are fast to compute. Information theory and Cognitive sciences can provide some inspiration for developping such feature.

Among the many visual features that have been studied, the distribution of color pixels in an image is the most common visual feature studied. The standard representation of color for content-based indexing in image databases is the color histogram. A different color representation is based on the information theoretic concept of entropy. Such entropic feature can simply equal the entropy of the pixel distribution of the image, as proposed in [3]. A more theoretical presentation of this kind of image entropy feature, accompanied by a practical description of its merits and limitations compared to color histograms, has been given in [4].

We propose in [5,6] a new feature equal to the pixel 'profil' entropy. A pixel profil can be a simple arithmetic mean in horizontal (or vertical) direction. The advantage of such feature is to combine raw shape and texture representations in a low cpu cost feature. These feature, associated to mean and color std, reached the second best rank in the official ImagEval 2006 campaing (see www.imageval.org and [6]).

In this paper we extend these features using another projection to get the pixel profil. We then propose also to use the harmonic mean of the pixel of each lign or column. The idea is that the object or pixel region distribution, which is lost in arithmetic mean projection, could be partly catch by the harmonic mean. These two projections are then expected to give complementary and/or concept dependant informations. We detail below the algorithm of the Profil Entropy

New num. of each topic	Topic short definition
1 TOPIC 2	church with more than two towers
2 TOPIC 3	religious statue in the foreground
3 TOPIC 5	animal swimming
4 TOPIC 6	straight road in the USA
5 TOPIC 10	destinations in Venezuela
6 TOPIC 11	black and white photos of Russia
7 TOPIC 12	people observing football match
8 TOPIC 13	exterior view of school building
9 TOPIC 15	night shots of cathedrals
10 TOPIC 16	people in San Francisco
11 TOPIC 17	lighthouse at the sea
12 TOPIC 18	sport stadium outside Australia
13 TOPIC 19	exterior view of sport stadium
14 TOPIC 20	close-up photograph of an animal
15 TOPIC 21	accommodation provided by host families
16 TOPIC 23	sport photos from California
17 TOPIC 24	snowcapped building in Europe
18 TOPIC 28	cathedral in Ecuador
19 TOPIC 29	views of Sydney's world-famous landmarks
20 TOPIC 31	volcanoes around Quito
21 TOPIC 34	group picture on a beach
22 TOPIC 35	bird flying
23 TOPIC 37	sights along the Inka-Trail
24 TOPIC 39	people in bad weather
25 TOPIC 40	tourist destinations in bad weather
26 TOPIC 41	winter landscape in South America
27 TOPIC 43	sunset over water
28 TOPIC 44	mountains on mainland Australia
29 TOPIC 48	vehicle in South Korea
30 TOPIC 49	images of typical Australian animals
31 TOPIC 50	indoor photos of a church or cathedral
32 TOPIC 52	sports people with prizes
33 TOPIC 53	views of walls with unsymmetric stones
34 TOPIC 54	famous television (and telecommunication) towers
35 TOPIC 55	drawings in Peruvian deserts
36 TOPIC 56	photos of oxidised vehicles
37 TOPIC 58	seals near water
38 TOPIC 59	creative group pictures in Uyuni
39 TOPIC 60	salt heaps in salt pan

Table 1: Topics definitions (and numerotations) of the PhotoClef 2008

<DOC>
<DOCNO>annotations/00/60.eng</DOCNO>
<TITLE>Palma </TITLE>
<DESCRIPTION>two lane street with large shops on the right and smaller shops on the left; people are walking on the sidewalk, some are crossing the street; cars are parked along the left side of the street as well; </DESCRIPTION>
<NOTES>The main shopping street in Paraguay; </NOTES>
<LOCATION>Asunción, Paraguay </LOCATION>
<DATE>March 2002 </DATE>
<IMAGE>images/00/60.jpg </IMAGE>
<THUMBNAIL>thumbnails/00/60.jpg </THUMBNAIL>
</DOC>

Figure 1. An example for the image collection

Feature (PEF).

Let I be an image, or any rectangular subpart of an image. For each normalized color ($L = R+G+B$, $r = R/L$, and $g = G/L$), we first calculate two orthogonal profils by the projections of the pixels of I. We consider two simple orthogonal projection axes : the horizontal axis X (noted Π_X), versus the vertical one Y (noted Π_Y). The projection operator is either the arithmetic mean (noted 'Ar', then the projection is noted Π_X^{Ar}), as illustrated in Figure 2, or the harmonic mean of the pixels on each column or each lign of I (noted 'Ha', then we have Π_X^{Ha}).

Then, we estimate the probability distribution function (pdf) of each profil according to [7]. Considering that the sources are ergodic, we finaly calculate each PEF equal to the normalized entropy ($H(pdf)/log(\#bins(pdf))$). We detail below each steps of the PEF extraction. Let be *op* the selected projection, for each color of I of $L(I)$ ligns and $C(I)$ columns :

$\Phi_X^{op}(I) = \hat{pdf}(\Pi_X^{op}(I))$, over $nbin_X(I) = round(\sqrt{C(I)})$ bins,
where Π_X^{op} is the vertical projection with operator *op*,
$PEF_X(I) = H(\Phi_X^{op}(I))/log(nbin_X(I))$.

$\Phi_Y^{op}(I) = \hat{pdf}(\Pi_Y^{op}(I))$, over $nbin_Y(I) = round(\sqrt{L(I)})$ bins,
$PEF_Y(I) = H(\Phi_Y^{op}(I))/log(nbin_Y(I))$.

We add to these PEF_a the image entropic feature [3,4]:
$\hat{pdf}(I)$ = pdf of all the pixels of I over $nbin_{XY}(I) = nbin_X(I) * nbin_Y(I)$ bins,
$PEF_.(I) = H(\hat{pdf}(I))/log(nbin_{XY}(I))$.

We finaly complete the PEF features by the usual mean and standard deviation of each normalized color of I. Like in our VCDT IAPR CLEF system [8], we can calculate the PEF into three horizontal (versus vertical) subimages. For each, we have 3 bands and 3 different PEF for each of the 3 colors, plus their mean and variance, thus we have $3*3*3+3*3*2 = 45$ dimensions for vertical and horizontal subimage features, for a total of 90 features by images for one projection type. Details can be found in [8].

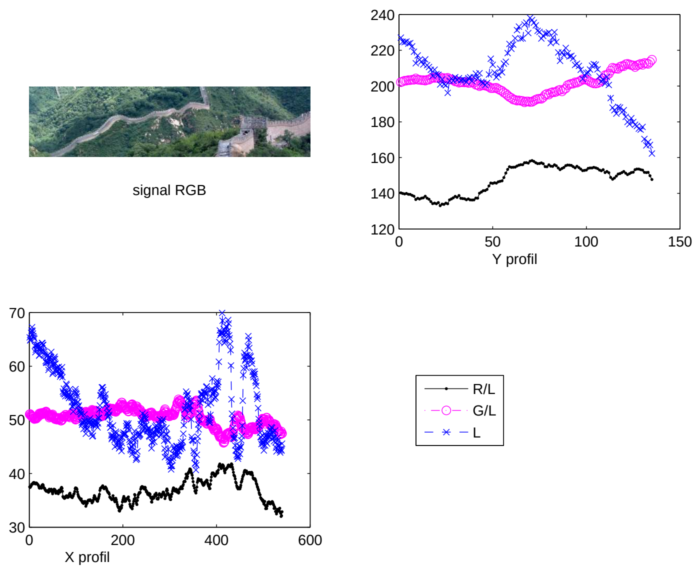

Figure 2: Illustration of the horizontal and vertical profils using simple arithmetic projection (or sum) of each normalized color $r = R/L, g = G/L, L = R + G + B$.

3 Support Vector Machines

In this task, we used the support vector machine (SVM) to implement image retrieval. The working mechanism of the SVM [13] is first to map the data into a higher dimensional input space by some kernel functions, and then to learn a separating hyperspace to maximize the margin. Currently, because of its good generalization capability, this technique has been widely applied in many areas such as face detection, image retrieval, and so on. The SVM is typically based on an ε-insensitive cost function, meaning that approximation errors smaller than will not increase the cost function value. This results in a quadratic convex optimization problem. So instead of using an ε-insensitive cost function, a quadratic cost function can be used. The least squares support vector machines (LS-SVM) are reformulations to the standard SVMs which lead to solving linear KKT systems instead [14], it is then computationally attractive.

In our experiments we use LS-SVM with the RBF kernel

$$K(x_1 - x_2) = exp(-|x_1 - x_2|^2/\sigma^2)$$

. So there is a corresponding parameter, σ , to be tuned. A large value of σ^2 indicates a stronger smoothing. Moreover, there is another parameter, γ, needing tuning to find the tradeoff between to stress minimizing of the complexity of the model and to stress good fitting of the training data points.

In the experiment, we train for each topic an hundred of SVM with different σ and γ, and we selected the best SVM using a validation set.

4 Affinity Propagation

We first tried to use Clef Visual Concept models to clusterize the top 20 answers, but the result was not interesting, thus we changed for a recent clustering method : the affinity propagation

clustering.
The advantages of affinity propagation clustering [9-12] over other clustering methods lie in that it's more stable for different initializations. In affinity propagation clustering, two kinds of message are exchanged between data points, each of which takes into account a different kind of competition. Messages can be combined at any stage to decide which points are exemplars and, for every other point, which exemplar it belongs to. The "responsibility" $r(i,k)$, sent from data point i to candidate exemplar point k, reflects the accumulated evidence for how well-suited point k is to serve as the exemplar for point i, taking into account other potential exemplars for point i. The "availability" $a(i,k)$, sent from candidate exemplar point k to point i, reflects the accumulated evidence for how appropriate it would be for point i to choose point k as its exemplar, taking into account the support from other points that point k should be an exemplar. To begin with, the availabilities are initialized as $a(i,k) = 0$, and the responsibilities are initialized as $r(i,k) = 0$. Then, the responsibilities and availabilities are iteratively computed as:

$$r(i,k) \leftarrow s(i,k) - \max_{k' \neq k}\{a(i,k') + s(i,k')\}$$

$$a(i,k) \leftarrow \min\{0, r(k,k) + \sum_{i' \neq i \& i' \neq k} \max\{0, r(i',k)\}\}, \ for\ i \neq k$$

$$a(k,k) \leftarrow \sum_{i' \neq k} \max\{0, r(i',k)\}$$

where $s(i,k)$ reflects the similarity between the data points i and k. For all $i \neq k$, $s(i,k)$ can be set to be the negative Euclidean distance, namely, $s(i,k) = -\|x_i - x_k\|^2$; while for all $i = k$, $s(k,k)$ is a varying parameter, and the initialized values of $s(k,k)$ for all ks are set to be equal to each other because all data points are equally suitable as exemplars. The affinity propagation takes a real number $s(k,k)$ as its input. The number of identified exemplars (number of clusters) is influenced by the initialized value of $s(k,k)$. As reported in the literature [15], the shared value of $s(k,k)$ is set as the median of the input similarities (resulting in a moderate number of clusters) or their minimum (resulting in a small number of clusters). However, the true number of clusters may be a widely changeful value, but not exactly the moderate number or the small number. So in our design, we set the initialized value of $s(k,k)$ varying from $\min_{i,j} s(i,j)$ to their maximum $\max_{i,j} s(i,j)$, namely:

$$s(k,k) = \min_{i,j} s(i,j) + \alpha(\max_{i,j} s(i,j) - \min_{i,j} s(i,j))$$

where $\alpha \in [0,1]$.

In photo task, we set α to be 0.2 in order that the number of clusters we get is approximately equal to 20.

5 Experiments

AVEIR (Automatic annotation and Visual concept Extraction for Image Retrieval) is the name of a project supported by the French National Agency of Research (ANR-06-MDCA-002). A consortium of four French CNRS research laboratories are involved in this project [17]. In order to compare the state of the art, each of the partners participated individually to ImageCLEFphoto, and to analyze if the fusion of runs, based on different strategies, can bring diversity, a submission under the label AVEIR was proposed.[15,16,17].

In our experiments, we computed the weighted averages of two ranks : our visual system described in this paper, and the LIG TXTIMG [15] using a model language after Porter process.

The process we adopt to implement the image retrieval in photo task is shown in fig. 3, and depicted by the following steps:
Step 1) According to the keywords of each topic, perform the text retrieval on the XML text database, and then get the TXT rank (please refer to the LIG Photo Clef paper [15]).

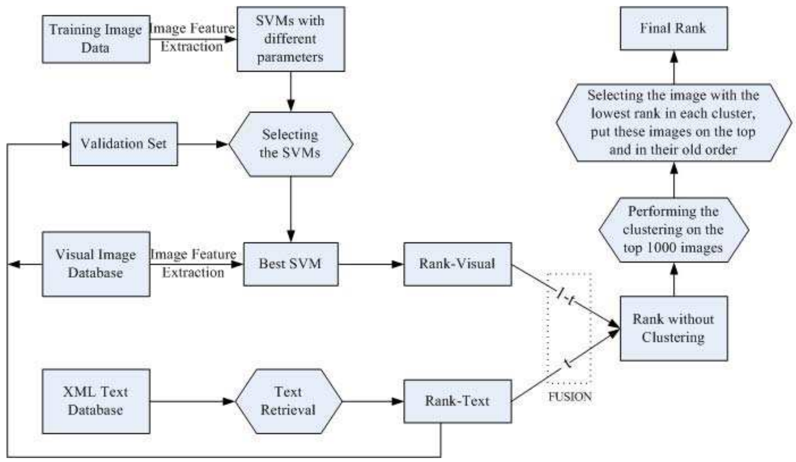

Figure 3: The training framework of our image retrieval system, t is fixed to 0.5

Step 2) Extract the visual features from the training image data using our extraction method; train and generate an hundrer of SVMs with different parameters.
Step 3) Use the first 20 images in TXT ranks as the positive samples, and the others as the negative samples to construct the validation set; select the best one among the SVMs.
Step 4) Extract the visual features from the visual image database using our extraction method; use the best SVM as the tool to perform the image retrieval and produce the rank result called IMG rank.
Step 5) Merge IMG and TXT rank into Rank-without-Clustering, where 't' in the figure denotes the text ratio, in our experiments t=0.5.
Step 6) Perform the clustering on the top 1000 images in Rank-without-Clustering for each topic, using affinity propagation.
Step 7) Select the image with the lowest rank in each cluster, put these images in their old order from Rank-without-Clustering and on the top of 'Final Rank'; then they are followed by the others in the old order.

We submitted 15 runs, one of which used only the visual information, others used both text and visual information. We make the fusions with either arithmetic or harmonic means.

Evaluation are based on two measures: precision at 20 and instance recall at rank 20 (also called S-recall) [2], which calculates the percentage of different clusters represented in the top 20. It will be important to maximise both measures: simply getting lots of relevant images from one cluster or filling the ranking with diverse, but non-relevant images, will result in a poor overall effectiveness score.

5.1 Visual only run

The first run is a visual only run. We simply train several SVMs on the training set, optimised with the TEXT AVEIR preprocess without clustering. Then we make 20 clusters using affinity propagation on the top 1000 images for each topic and we place the best (the image with the lowest rank) of each cluster to the top 20 (nearly), and we keep the rest of the list as the order before the clustering. This baseline LSIS IMG+CLUSTER (RUN1) is the 6th best team run in the Auto IMG run type [2].

5.2 Image and Text fusion

We use LIG TXTIMG to train SVMs and to make fusions, then we make 20 clusters using affinity propagation on the top 1000 images for each topic after the fusion of visual and LIG TXTIMG and we place the best (the image with the lowest rank) of each cluster to the top 20 (nearly), and

Table 2: Best team run for Automatic visual only (AUTO IMG). LSIS is in the top 6.

Final Rank	Avg. Rank	P20 Rank	CR20 Rank	group with run	P20	CR20	MAP
1	2	3	1	DCU EN-EN-AUTO-IMG.txt	0,237	0,324	0,107
2	3,5	4	3	PTECH EN-EN-AUTO-IMG-AINQN.run	0,200	0,318	0,086
3	5	1	9	NTU IMG-EN-AUTO-NOFB-TXTIMG.result	0,309	0,178	0,210
4	5,5	5	6	IPAL 01V-4RUNS-EQWEIGHT	0,199	0,234	0,084
5	6	8	4	Ottawa UOt05-EN-EN-AUTO-IMG-KM.txt	0,159	0,269	0,069
6	7	9	5	LSIS EN-EN-AUTO-IMG-AUTO-GLOZHA-1	0,128	0,237	0,062
7	7,5	7	8	CLaC IR-EN-EN-AUTO-IMG.txt	0,161	0,215	0,055
8	8,5	10	7	MMIS cbir+brfHaiming.txt	0,123	0,229	0,033

Table 3: Fusion results of LSIS and of some reference runs (AUTO IMGTXT) with or without clustering.

Group	Cluster or not	P20	CR20	MAP
CLEFphoto2008 average of the 100 run from the 25 groups	CL	0.320	0.350	0.219
LIG TXTIMG (for AVEIR)	NO CL	0.303	0.380	0.212
LSIS TXTIMG (for AVEIR - run0)	NO CL	0.292	0.383	0.155
LSIS TXTIMG+CLUSTER (run12)	CL	0.300	0.400	0.160
AVEIR fusion = average(PTECH, LSIS, LIG, LIP6 runs)	CL	0.420	0,463	0,303
Best run (XEROX)	CL	0.511	0.426	0.366

we keep the rest of the list as before the clustering. It is important to note that here the visual and text information are merged before the clustering. We will show in the end of the paper that it could be more efficient to make affinity propagation on visual and on textual ranking, and then to merge them.

6 Results and Conclusion

The results for visual on only LSISrun1(IMG) with clustering are given in table 2. For comparison we give the results of the other runs of the same type submitted to CLEF. The LSIS visual only system seems quite efficient : using the low dimensional PEF features the LSIS team rank in the IMG run type is 6th. Moreover, this visual information, giving complementary information, enhanced the AVEIR consortium run (third rank at the IMGTXT run type).

The results for combination of visual with textual informations (IMG+TXT), with (run12) or not (run0) clustering, are given in table 3. For comparison we give the results of few runs of the same type submitted to CLEF, and some runs of AVEIR consortium in which our IMG+TXT LSISrun0 has been merged.

Because of the large variation of the considered topics (see tab. 1), the clustering evaluation must be analysed at the topic level. We then analyse for each topic in the next figure the CR20 after affinity propagation of each topics (numeroted from 1 to 39) for LSIS run1 (IMG) vs LSIS run12 (TXT IMG), see fig 4. The correlation between the two runs is low (0.3). We see clearly that some topics like 14 or 28 are difficult to cluster, contrary to 6 or 33 topics. Moreover if for most of the topics the CR20 is improved, we see the inversed for some topics.

To detail the impact of the text information to the cluster quality, we plot in fig. 5 the gain values for each run between these two runs. We see then clearly that the global gain of nearly 68% is not uniform over each topic. If the majority of the CR20 are, some topics are better clusterised by affinity propagation using only the visual ranking. These variations need more research for being well interpreted.

The next figure shows the gain of CR20 from the LSIS visual only TXTIMG run to the LSIS TXTIMG+ affinity propagation CLUSTER (see fig. 6). The global gain is low (3.7%) but again the variation for each topic is high : if for some topics the text information itself allows an efficient

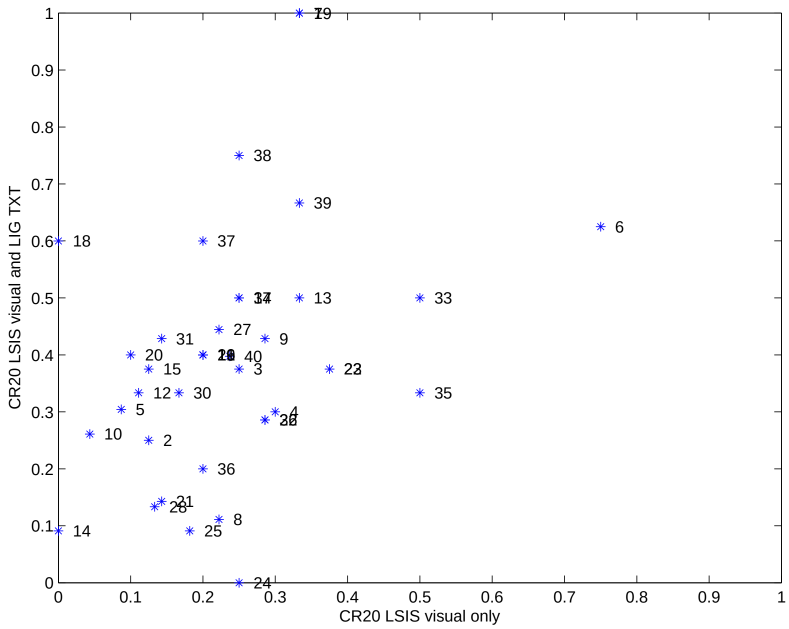

Figure 4: Effect of TXT to the CR20 given for each topics (numeroted from 1 to 39) for LSIS run 1 (IMG+CLUSTER) versus run 12 (TXT+IMG+CLUSTER).

implicit image clustering, the visual clustering alone is fondamental for some other topics. This could be explained by the fact that some clusters are more or less high level clusters. In other terms, some clusters may be more cultural (cities, country,...) than being only based on visual criteria.

Even if affinity propagation clustering seems efficient for promoting visual diversity, our results show that visual and textual information brings complementary clustering informations, which should be weigthed according to each topic. We shown that linear weighted fusion was efficient for topic retrieval in ImagEval campaign [6]. In this paper the visual and text information are merged before the clustering, so we can't weight textual and visual clustered ranks. It may be more efficient to make affinity propagation separatly on visual and on textual ranks, and then to merge them. Further works will be conducted for designing such simple clustering linear weighting fusion schemes.

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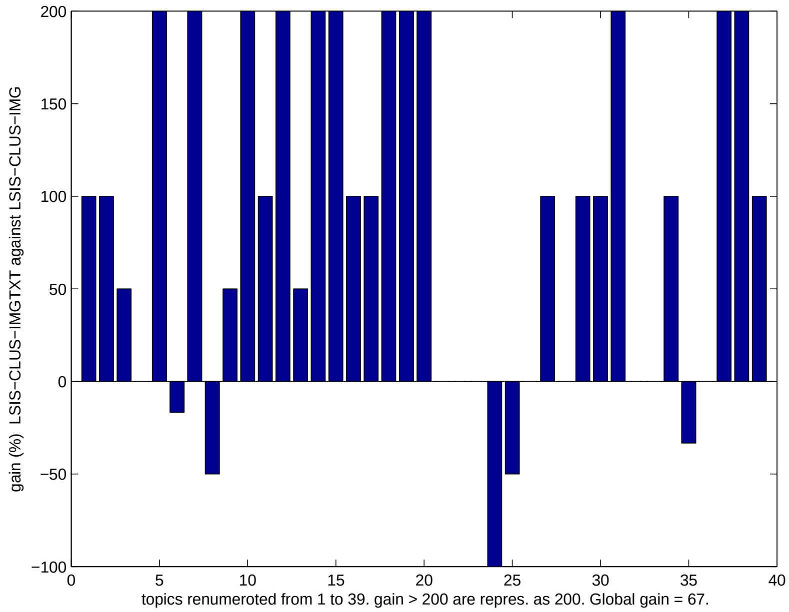

Figure 5: Effect of TXT to the CR20. Gains of the CR20 of each topics (numeroted from 1 to 39) for LSIS run1 (IMG+CLUSTER) versus run12 (TXT+IMG+CLUSTER).

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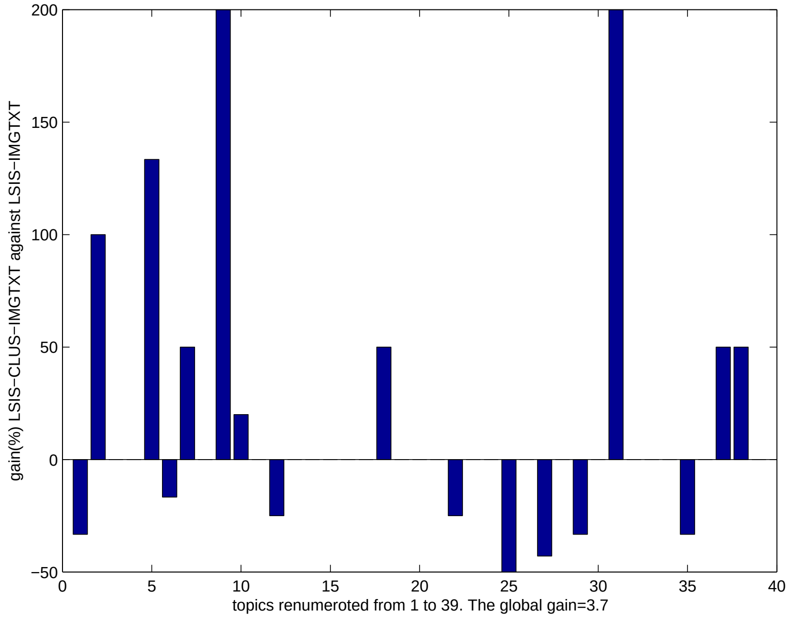

Figure 6: Effect of Affinity Propagation to IMG+TXT CR20 score. Gains of the CR20 of each topics (numeroted from 1 to 39) for LSIS (IMG+TXT) run versus LSIS run12 (TXT+IMG+CLUSTER). Gains > 200 are = 200.

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