WATERMARK SIGNAL DETECTION AND ITS APPLICATION IN IMAGE RETRIEVAL

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ABSTRACT

We propose a few fundamental techniques to obtain effective watermark features of images in the image search index, and utilize the signals in a commercial search engine to improve the image search quality. We collect a diverse and large set (about 1M) of images with human labels indicating whether the image contains visible watermark. We train a few deep convolutional neural networks to extract watermark information from the raw images. We also analyze the images based on their domains to get watermark information from a domain-based watermark classifier. The deep CNN classifiers we trained can achieve high accuracy on the watermark data set. We demonstrate that using these signals in Bing image search ranker, powered by LambdaMART, can effectively reduce the watermark rate during the online image ranking.

Index Terms— Image Retrieval, Watermark, Deep Convolutional Neural Network, Learning to Rank

1. INTRODUCTION

Watermarking is a widely used technique to protect the copyright of image photography. There are a huge amount of watermarked images existing online. For example, a few famous image stock websites use watermarks to protect their high quality images from being copied by a third party. The drawback is that images with visible watermarks are often seen when customers are searching images on search engine like Bing or Google. The watermarked images can be annoying and degenerate customers’ experience. Some researchers have looking into watermark removal [1, 2, 3, 4] techniques to remove the watermark from the images or video. Most algorithms only work well in special situations, such as the [1] where the watermark has consistent pattern and does not have large variation. However, the watermark removal techniques are not very useful in image search mainly due to two reasons. First, the search engine should not remove the watermark before returning the search results to the users. This will remove the copyright protection for the original images. However, when the model predicts the score, it will take all possible image attributes into consideration, resulting in insignificant impact of watermark. It shows that the score will be significantly decreased only when there are massive watermarks on the original image.

Regarding the application of image retrieval, a more appropriate approach is to demote images whose quality are significantly impaired by watermarks. In this paper, we propose a few fundamental techniques to obtain effective watermark signals for images coming from a real image search index, and utilize those watermark signals in a commercial search engine to improve the image search quality. Benefiting from the fast advance of deep learning, deep convolutional neural networks (CNN) have been widely used in image classification and detection tasks, and have achieved performance comparable to human. In section 2.1 we train a few deep CNN models to predict the probability that an image contains a watermark using Resnet [6], Densent [7], and Inception-V3 [8] as the backbone. The model is trained end to end on a large image set with a variety of watermarks collected from real online images. The detail of the data set is described in section 2.1. We shows that the prediction accuracy of the deep CNN models are very promising on the data set with such diverse watermark patterns. This indicates the potential of building a DNN based universal watermark classifier. In section 2.2 we also obtain an additional watermark signal by analyzing their corresponding domain properties. Our analysis indicates that domain is a very strong indicator of the watermark signal. This makes sense as a lot of watermarked images come from stock image website. In section 3 we demonstrate the effectiveness of demoting watermarked images in Bing image search engine by utilizing those watermark signal in the image ranker. The details of the metric design and image ranker training are discussed in section 3.

2. WATERMARK SIGNAL

In this section, we demonstrate how we obtain watermark signals from two different approaches. The first approach is to get a watermark signal from the raw image content. This is a more biologically plausible method as humans only need to look at the raw image to tell if it contains a watermark. The second approach is from its corresponding domain informa-
Fig. 1. A few examples of watermarked images in this data set.

| label                  | Training | Validation | Testing |
|------------------------|----------|------------|---------|
| 1: Watermarked         | 587K     | 32K        | 33K     |
| 0: No Watermark        | 646K     | 36K        | 36K     |

Table 1. Summary of the watermark data set.

2.1. Image content based watermark signal

A human can tell whether an image contains a watermark by directly looking at the image. Ideally, we should be able to train a similar classifier reflecting the probability that the image contains a watermark. The probability should reflect the visibility of the watermark in the images. Less visible watermarks should get lower probability.

Data collection: We scraped a large amount of images from Bing image search results. For each image, we had 1-5 judges rate if this image contained a visible watermark. If any judge thought the image contained a visible watermark, the image would be labeled as positive, otherwise negative. Since the non-watermarked images are more than the watermarked images, we then randomly sample images from non-watermarked images, so that the watermarked and non-watermarked images are balanced. Next, we split the data into training, validation and test set with the rate 90%:5%:5%. We also remove images which are broken or can not be downloaded. Table 1 shows the numbers of images we used to train and test the model.

Data augmentation: We have about one millions images half of which have watermarks. During training, we did the following data augmentations to improve the performance. We used center cropping to obtain the images satisfying the input dimensional requirement of the different deep CNN models. We scaled the minimum dimension and then cropped to fit the model input dimension. We also used horizontal/vertical flips to increase the training dataset without losing the original watermark.

Model: We explored a few deep convolutional neural network structures - Resnet50 and Resnet152, Densenet161, and Inception. We replace the final output classification layer with a binary classification layer. In the Inception-V3 model, we also replaced the intermediate auxiliary classification layer with a binary classification layer. The final loss function is \( \text{loss} = \text{loss}_{\text{out}} + 0.4 \times \text{loss}_{\text{aux}} \), where \( \text{loss}_{\text{out}} \) is the cross-entropy loss function of the final output layer and \( \text{loss}_{\text{aux}} \) is the loss of the auxiliary classification layer.

Training: First, we use the transfer learning by freezing the models pretrained on ImageNet, and only retraining the top and the auxiliary classification layer. The training error and validation error stops decreasing before ten epochs. Table 2 shows the accuracy of the models on the test data set after training 10 epochs. The ResNet152 obtained the best accuracy on the test data with 70.63% accuracy. However, the overall accuracy of the transfer learning is low. Next, we start training the whole network from end to end. Figure 1 shows the progress of the training and validation accuracy over epochs. We choose the model which performs best on the validation set and evaluate on the test set. The Inception-V3 has the best accuracy on the test set with 85.70% accuracy. Both the validation and training accuracy are significantly improved after training the network end to end. This is likely because the the high level DNN features needed for watermark detection differ from general image classifier.

During training, we set the learning rate as \( 0.0064 \times 10^{-4} \) and reduced by half every 5 epochs. Unlike traditional fine
Table 3. Watermark prediction accuracy on the test data set when the models are retrained end-to-end. Last four rows show the performance after combining domain information.

| Model               | Test Accuracy |
|---------------------|---------------|
| Resnet50            | 84.45%        |
| Inception-V3        | 85.70%        |
| Densenet161         | 83.96%        |
| Resnet152           | 83.86%        |
| Resnet50 + Domain   | 87.04%        |
| Inception-V3 + Domain | 87.84%     |
| Densenet161 + Domain | 86.61%      |
| Resnet152 + Domain  | 86.49%        |

Table 4. A sample list of a few domains which contain many watermarked images.

| Watermark Domain List                  |
|---------------------------------------|
| 1. clipartartists.com                  |
| 2. www.gettyimages.com                 |
| 3. www.alamy.com                       |
| 4. www.shutterstock.com                |
| 5. www.dreamstime.com                  |
| 6. www.cosplayfancy.com                |
| 7. www.teamclipart.com                 |
| 8. www.colourbox.de                    |
| 9. www.recipestable.com                |
| 10. www.sheepskintown.com              |

2.2. Domain based watermark signal

For the images in an image search index, the domain where the images come from is also a very strong signal. Many watermarked images in the web index are coming from stock photo websites. The deep CNN based classifier can not achieve 100% prediction accuracy on these images. However, a domain based watermark classifier can achieve a higher precision on predicting watermarked images coming from these websites.

In the training data, we group images based on the domains where those images are hosted. We compute the percentage of watermarked images in each domain, which is the ratio of the number of the watermarked images to all images hosted on this domain. We select domains which produce more than 5 images and have a watermark rate higher than 90%. In the training data set, there are about 4.7K domains out of about 272K domains that satisfy this condition. We put these domains in a known watermark domain list. For any image coming from those domain, we will predict that this image has a visible watermark regardless of the prediction of the deep CNN classifier. Table 4 shows a few domains containing high percentage watermarked images.

The downside of the domain based approach is that we must have the domain information of the image source. This is not biologically plausible as humans do not need other information besides the raw image to detect the watermark. Also, the domain is dynamic information that can change over time. However, this information is common in images collected from the web. When using this domain information together with the content based watermark information, the accuracy on the validation can be improved as shown in the last four rows of the Table 4.

3. UTILIZE WATERMARK SIGNAL IN IMAGE SEARCH

3.1. LambdaMART Ranking Algorithm

LambdaMART [10] is built on MART [11]. MART builds a regression tree to model the functional gradient of the cost function of interest which leads to the LambdaRank [12] functional gradients. Since we are interested in optimizing NDCG and NDCG is either flat or discontinuous everywhere,
LambdaRank uses an approximation to the gradient of the cost, called $\lambda$-gradients. The $\lambda$-gradient consists of the product of two factors: (1) the RankNet cost \cite{13} (a pairwise cross-entropy loss, applied to the logistic of the difference of the model scores), and (2) the NDCG gained by swapping the pair, $\Delta$ NDCG. During ranker training, the model uses the available features of the document to optimize the metric and produce a predicted score for each document. For more details, we refer to the corresponding literatures \cite{11, 13, 12, 10}.

LambdaRank can be applied to any IR metric. In the original LambdaRank \cite{12} paper, the NDCG is defined as

$$N_i = n_i \sum_{j=1}^{T} \frac{2^{r(j)} - 1}{\log(1+j)}$$

where $r(j) \in \{0, \ldots, 4\}$ is the integer label for the relevance level of $j^{th}$ URL in the sorted list, $n_i$ is the normalization factor. In our application, instead of using a pure relevance rating, we have a mixed rating score for each image. The rating combined both the relevance and image attractiveness \cite{5}. For the image having watermarks, the attractiveness rating will be multiplied by a penalty factor $p$. During ranker training, we append the watermark signals obtained from both the deep CNN model and the domain list to the existing feature pool.

3.2. Online results of utilizing Watermark Signal

We trained two image rankers using our metric where the rating for each image has penalization factor 1 for watermarked images so that the attractiveness will not have effect. The control ranker uses the original features during training. In the experimental ranker training, we add the watermark signal obtained from deep CNN model and domain analysis into the existing feature pool. If the image’s doamin does not belong to the domain black list, we will use the watermark probability predicted by the Resnet50 model. Otherwise, the watermark probability is 1. Table 5 shows that the experimental ranker’s watermark rate is reduced from 5.2% to 4.3%, relatively by 20%. The NDCG is also improved. Figure 3 shows a few examples where the watermarked images are demoted for a few example queries. For example, for the query ‘women image’ in the second row, the control ranker surfaced 5 watermarked images, while the new ranker only had one.

4. DISCUSSION

We proposed a few techniques to obtain watermark signals from online images and demonstrated the effectiveness of utilizing them in the Bing image search. The high watermark classification accuracy using deep CNN networks implies the potential of designing specific watermark DNN models which could work well on universal watermark classification tasks. We also propose domain based analysis to obtain a complementary watermark signal. Additional watermark signals may be obtained by analyzing domain or text information, such as title and body text, about the online image. This sheds light on the solution to provide better image search quality to the user by effectively demoting watermarked images.

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