

Open Set Logo Detection and Retrieval

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Keywords: Logo Detection, Logo Retrieval, Logo Dataset, Trademark Retrieval, Open Set Retrieval, Deep Learning.

Abstract: Searching for logos in image data allows several applications, with judging the effectiveness of advertisement in sports event broadcasts being one example. Given a query sample in shape of a logo image, the task is to find all further occurrences of this logo in a database of images or videos. Currently, common logo retrieval approaches are unsuitable for this task because of their closed world assumption. To address this issue, an open set logo retrieval method is proposed in this work which can search for previously unfamiliar logos only by one query sample. A two stage concept with an open set logo detection and comparison is proposed similar to other retrieval tasks. Both modules are based on task specific Convolutional Neural Networks (CNNs). To train the detector with appropriate in-the-wild data, an according novel Logos in the Wild dataset is collected and made publicly available. The proposed method extends the application field in comparison to closed set approaches and improvements over baseline methods derived from these state-of-the-art closed set approaches are shown.

1 INTRODUCTION

Automated search for logos is a desirable task in visual image analysis. A key application is the effectiveness measurement of advertisements. Being able to find all logos that match a query, for example, a logo of a specific company, in images allows to assess the visual frequency and prominence of logos in TV broadcasts. Typically, these broadcasts are sports events where sponsorship and advertisement is very common. This requires a flexible system where the query can easily be defined and switched according to the current task. Especially, also previously unseen logos should be found if one query sample is available. This requirement excludes basically all current logo retrieval approaches because they make a closed-world assumption where all searched logos are known beforehand. Instead, this paper focuses on open set logo retrieval where only one sample image of a logo is available.

Consequently, a novel processing strategy for logo retrieval based on a logo detector and a feature extractor is proposed as illustrated in figure 1. Similar strategies are known from other open set retrieval tasks, such as face or person retrieval (Bäuml et al., 2010; Herrmann and Beyerer, 2015). Both, the detector and the extractor are task specific CNNs.

For detection, the Faster R-CNN framework (Ren et al., 2015) is employed and the extractor is derived from classification networks for the ImageNet challenge (Deng et al., 2009).

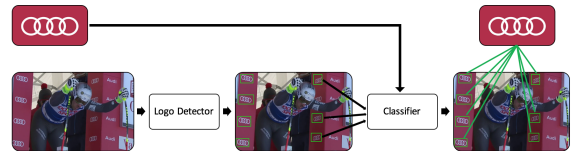


Figure 1: Proposed logo retrieval strategy.

The necessity for open set logo retrieval becomes obvious when having a look at the diversity and amount of existing logos and brands¹. The METU trademark dataset (Tursun et al., 2017) contains, for example, over half a million different logos. Given this number, a closed set approach where all different logos are pretrained within the retrieval system is clearly inappropriate. This is why our proposed feature extractor generates a discriminative logo descriptor, which generalizes to unseen logos, instead of a mere classification between previously known brands. The well-known high discriminative capabilities of

¹The term brand is used in this work as synonym for a single logo class. Thus, a brand might also refer to a product or company name if an according logo exists.

CNNs allow to construct such a feature extractor.

One challenge for training a general purpose logo detector lies in appropriate training data. Many logo or trademark dataset (Eakins et al., 1998; Tursun et al., 2017) only contain the original logo graphic but no in-the-wild occurrences of these logos which are required for the target application. The need for annotated logo bounding boxes in the images limits the number of suitable datasets. Existing logo datasets (Joly and Buisson, 2009; Kalantidis et al., 2011; Romberg et al., 2011; Letessier et al., 2012; Bianco et al., 2015; Su et al., 2016; Bianco et al., 2017) with available bounding boxes are often restricted to a very small number of brands and mostly high quality images. Especially, occlusions, blur and variations within a logo type are only partially covered. To address these shortcomings, a novel in-the-wild logo dataset is collected and made publicly available².

The contributions of this work are threefold:

- A novel open set logo detector which can detect previously unseen logos.
- An open set logo retrieval system which needs only a single logo image as query.
- The introduction of a novel in-the-wild logo dataset.

2 RELATED WORK

- Logo Retrieval (i.e. closed set approaches)

Retrieval scenarios in other domains are basically always considered open set, i.e. samples from the currently searched class have never been seen before. This is the case for general purpose image retrieval (Sivic and Zisserman, 2003), tattoo retrieval (Manger, 2012) or for person retrieval in image or video data where face or appearance-based methods are common (Bäumel et al., 2010; Weber et al., 2011; Herrmann and Beyerer, 2015). The reason is that these in-the-wild scenarios offer usually a too large and impossible to capture variety of object classes. In case of persons, a class would be an identity. Consequently, methods have to be designed and trained on a limited set of classes and have to generalize to previously unseen classes. We argue that this approach is also required for logo retrieval because of the vast amount of existing brands and according logos which cannot be captured in advance.

- Detector Frameworks: Faster R-CNN (Ren et al., 2015), SSD (Liu et al., 2016), Yolo (Redmon

and Farhadi, 2016), ...

- Classification Networks: AlexNet, VGG, ResNet, DenseNet?

3 LOGO DETECTION

- class agnostic detector
- different base networks: VGG-CNN-M, VGG16

4 LOGO COMPARISON

5 LOGO DATASET

To train the proposed logo detector, a novel logo dataset is collected to supplement publicly available logo datasets. A comparison to other datasets is given in table 1. The goal is an in-the-wild logo dataset with pictures including logos instead of the pure original logo graphics. In addition, images where the logo does not represent the central dominant part of the image are preferred. See figure 2 for a few examples of the collected data. Following the general suggestions from (Bansal et al., 2017), we target for a dataset containing significantly more brands instead of collecting additional image samples for the already covered brands. This is the exact opposite strategy than performed by the Logos-32plus dataset. Starting with a list of well-known brands and companies, an image web search is performed. Because most other web collected logo datasets mainly rely on Flickr, we choose to use Google image search to broaden the domain. Brand or company names are searched directly or in combination with a predefined set of search terms, e.g., 'bmw advertisement', 'bmw building', 'bmw poster' or 'bmw store'.

For each search result, the first N images are downloaded, where N is determined by a quick manual inspection to avoid collecting too much garbage. After removing duplicates, this results in 4 to 608 images per searched brand. These images are then one-by-one annotated with bounding boxes or sorted out if unsuitable. Images are considered unsuitable if they contain no logos or fail the in-the-wild requirement, which is the case for the original raw logo graphics. Taken pictures of such logos and advertisement posters on the other hand are desired to be in the dataset. Annotations distinguish between textual and graphical logos as well as different logos from one company as exemplary indicated in figure 3.

²url//:to.come

Table 1: Publicly available logo datasets in comparison with the novel dataset.

	dataset	brands	logo images	RoIs
public	BelgaLogos (Joly and Buisson, 2009; Letessier et al., 2012)	37	1,321	2,697
	FlickrBelgaLogos (Letessier et al., 2012)	37	2,697	2,697
	Flickr Logos 27 (Kalantidis et al., 2011)	27	810	1,261
	FlickrLogos-32 (Romberg et al., 2011)	32	2,240	3,404
	Logos-32plus (Bianco et al., 2015; Bianco et al., 2017)	32	7,830	12,300
	TopLogo10 (Su et al., 2016)	10	700	863
	total	80 (union)	15,598	23,222
new	Logos in the Wild	631	6,084	17,738



Figure 2: Examples from the collected Logos in the Wild dataset.



Figure 3: Annotations differentiate between textual and graphical logos.

Altogether, the current version of the dataset, which is used in this paper, contains 631 brands with 17,738 annotated bounding boxes. 150 brands occur at least

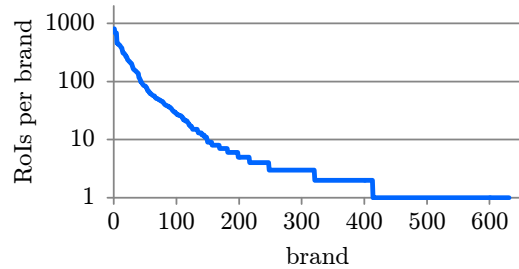


Figure 4: Distribution of number of RoIs per brand.

10 times. An image may contain more than one logo with the maximum being 100 logos in one image. The complete distributions are shown in figures 6 and 5.

The collected Logos in the Wild dataset exceeds the size of all related logo datasets as shown in table 1. Even the union of all related logo datasets contains significantly less brands and RoIs which makes Logos in the Wild a valuable large-scale dataset. The annotation is still an ongoing process and further larger

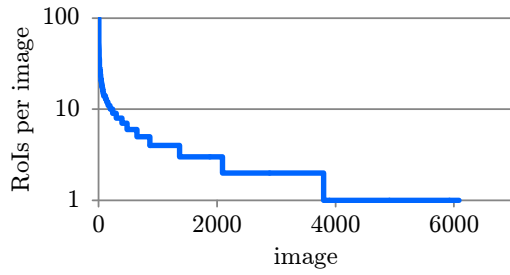


Figure 5: Distribution of number of RoIs per image.

Table 2: Train and test set statistics.

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versions of the dataset are expected to be published in the future (??).

6 EXPERIMENTS

- explain FROC curve
- maybe introduce mAP
- explain baseline method(s)
- concepts/desired experiments
- train on public non-Flickr brands
- additionally train on own logo dataset
- test on FlickrLogos32 test datasets

- additional evaluation on own SportsLogos dataset and qualitative results

The proposed method is evaluated on the test set of the public FlickrLogos32 dataset including the distractors as well as an internal dataset of sports event TV broadcasts. For a proper separation of train and test data, all brands which are present in the FlickrLogos32 test set are removed from the training data. The training set consists of two parts. The union of all public logo datasets and the novel Logos in the Wild dataset. The respective training and test set sizes are listed in table ??.

In the first step, the detector stage alone is assessed. Then, the combination of detection and comparison for logo retrieval is evaluated. Detection and matching performance is measured by the Free-Response Receiver Operating Characteristic (FROC) curve (Miller, 1969) which denotes the detection or detection and identification rate versus the number of false detections.

In all cases the CNNs are trained until convergence which requires ?? to ??k iterations with a batch-size of ?. Training duration depends on the architecture as well as the amount of training data.

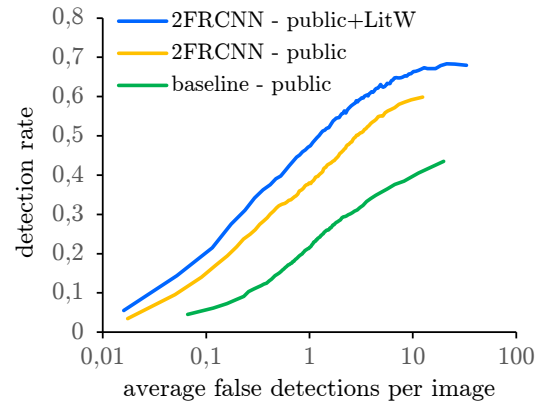


Figure 6: FROC curve for FlickrLogos32 test set.

6.1 Detection

As baseline, the state-of-the-art closed set logo retrieval method from (?) is employed and trained on the public portion of the training data. It is adapted to open set detection by using the RPN scores as detections. This skips the closed set classification part of the network which is pre-trained on different logos than should be detected on the test set. The proposed logo detector is first trained on the same public data for comparison. The results in figure ?? indicate that this strategy is superior by a significant margin.

Further improvement is achieved by combining the public training data with the novel data. Adding the Logos in the Wild dataset as additional training data improves the detection results with its large variety of additional training brands. This confirms findings from other domains, such as face analysis, where wider training datasets are preferred over deeper ones (Bansal et al., 2017). This means it is better to train on additional different brands than on additional samples per brand. As direction for future dataset collection, this suggests to focus on additional brands.

6.2 Retrieval

- train 4 to 6 additional networks: feature extraction network for public and public+own training data — use VGG16, ResNet50, DenseNet as base network (either for both training sets or only for the public+own) - results on FlickrLogos32 =_i FROC plot
- results on own sports data =_i FROC plot

In addition to public data, target domain specific experiments are performed on TV broadcasts of sports events. In total, 1,218 annotated frames with more than 10,000 logos from four different events are



Figure 7: Example football frame with small logos in the perimeter advertising.

Table 3: SportLogo dataset statistics.

	phase	brands	logo images	RoIs
football-1	train	104	331	3,329
ski		27	179	701
ice hockey		19	410	3,920
football-2	test	40	298	2,348

available in our SportLogo dataset where 3 events are used for training and one as test set. Refer to table 3 for details. In comparison to public logo datasets, the logos are usually significantly smaller in these cases and cover only a tiny fraction of the image area as illustrated in figure 7.

7 CONCLUSIONS

- significant improvement over baseline - enables novel applications - novel large scale in-the-wild logo dataset

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