Extracting Visual Knowledge from the Internet: Making Sense of Image Data

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Abstract

Recent successes in visual recognition can be primarily attributed to feature representation, learning algorithms, and the ever-increasing size of labeled training data. Extensive research has been devoted to the first two, but much less attention has been paid to the third. Due to the high cost of manual data labeling, the size of recent efforts such as ImageNet is still relatively small in respect to daily applications. In this work, we mainly focus on how to automatically generate identifying image data for a given visual concept on a vast scale. With the generated image data, we can train a robust recognition model for the given concept. We evaluate the proposed webly supervised approach on the benchmark Pascal VOC 2007 dataset and the results demonstrates the superiority of our method over many other state-of-the-art methods in image data collection.

1 Introduction

With the development of the Internet, we have entered the era of big data. It is consequently a natural idea to leverage the large scale yet noisy data on the Internet [4; 5; 6; 15; 16]. Methods of utilizing these data for visual recognition have recently become a hot topic, with the convergence of computer vision, pattern recognition and machine learning being collectively known as "Internet vision" [15].

When generating massive identifying image data, it is important to ensure that the data contains sufficient representative visual patterns. Search engines (e.g., Google Images) and social media portals (e.g., Flickr) have been created to obtain the candidate image data [11; 12; 13; 26; 34]. For example, we can submit a certain concept as a query to Google Images or Flickr which will return a large number of images based on that query. However, the images returned by search engines or social media portals are usually attractive and representative, but they incorporate fewer visual patterns. For example, if we submit the term "tiger" to Google Images, most of the returned images are of tiger faces. To build a high-quality training dataset, however, we need to collect a large number of Internet images which contain different views of an image as visual patterns. To address this problem,

we propose a two-step approach in this paper, as follows: We first find the useful related word variations to enrich the given concept from a text perspective, which is known as label purification; we then use these selected word variations to collect images and run a further image clean process, which is known as image purification. Our goal is to achieve a certain level of match between the image labels and their dominant contents to narrow the semantic gap.

Search results returned from Google Books Ngrams corpora are usually very noisy [27; 28; 29]. For example, word variations returned from Google Books Ngrams corpora for the query "horse" contains not only different "visual patterns" of a horse such as a "jumping horse" and a "rearing horse", but also a large number of different word variations associated with "horse" such as "horse boy" and "horse stealer". Our starting point in this step is to find key "visual patterns" of horse. Therefore, "horse boy", "horse stealer" etc should be removed from the word variations list.

In addition, images returned from the Google search engine also contain noise. For example, it may contain some clipart images even at the top of the return list. In order to build a large scale robust image dataset, noisy images such as clipart images should be filtered out without too much manual effort.

By searching in the Google Books Ngrams corpora and Google images, it is easy to get over 1000 related word variations and 10000 images of the given concept. However, how to effectively leverage this massive and noisy data to build a robust image dataset remains a huge challenge. In this paper, we argue that combining word variation purifying and image purifying is a more effective way to use this massive amount of data. The main contributions are: 1) Our method is the first to combine related word variation purifying and image purifying to build the image dataset. 2) Our method is able to build the image data for any given visual concept. 3) Our method is capable of training a robust recognition model without manual intervention.

2 Related Work

Recent work has mainly focused on learning from large datasets for recognition and classification [7; 20; 31; 35; 36; 37]. To our knowledge, there are three principal methods of building the database: manual annotation, active learning, and using Internet data.

Table 1: Results of purifying noisy word variations using NGD for "tiger" and "horse".

	Found	d word v	ariations	after NGD filtering				
Concept	correct	noisy	precision	correct	noisy	precision	false pos	
Horse	132	460	22.3%	124	237	34.3%	8	
Tiger	108	536	16.8%	102	287	26.2%	6	

Manual Annotation

Manual annotation has a high level of accuracy but is resource-intensive, so the scale of the dataset is relatively small (both the numbers of categories and images) in the early years. The method of building ImageNet is using manual annotations. It firstly download images from the search engines using different languages for the given concept and then label these images by the power of crowds [7].

Active Learning

To reduce the cost of manual annotation, recent work has also focused on active learning (a special case of semi-supervised learning) [32; 38; 39; 40], which selects label requests. [32] introduces an approach for learning object detectors from real-world web videos. The limitation is these web videos should only contain objects of a target class. [38] build a contextual object recognition model by using active learning. It needs the user's answer to update the existing object recognition model. [39] learn a detector for a specific object class using weakly supervised learning and need a initial annotation. Both manual annotation and active learning require pre-existing annotations, which results in one of the biggest limitations to building a large scale dataset.

Using Internet Data

Recent methods propose the use of Internet data to build the training data for visual concept [1; 8; 16; 20; 34; 44; 45; 46; 47; 48]. The general method is to automatically collect images using search engines or social networks to build a training set, and then to re-rank these images using visual classifiers [8; 16] or some form of clustering in visual space [34]. [1] extracts visual knowledge from the pool of visual data on the web, mainly focusing on finding labeled segments/boundaries and relationships between objects. [20] uses iterative methods to automatically collect object datasets from the web and to incrementally learn object category models. This approach has some uncertainty, since it depends on the seed images. In addition, using this method to collect images of objects may contain fewer visual patterns. However, the use of "re-ranking", "clustering" and the other methods mentioned above does not tackle the problem of insufficient visual patterns in these training data. To address this problem, we propose our method for building a high-quality training dataset in the next section.

3 The Proposed Approach

Due to the amount and complexity of Internet data, to build a high-quality training dataset, we must separate noisy data from useful data automatically. Specifically, we first use Google Books Ngram corpora to obtain all the related word variations modifying the given concept; second, we use Normalized Google distance (NGD), linear SVM and visual distance to prune these word variations; third, we download images according to the filtered word variations, use exemplar-LDA and progressive CNN to purify these noisy images; lastly, we put all the purified images based on the various word variations together and fine-tune a robust model for object recognition. The following subsections describe the details of our process.

3.1 Discovering Word Variations for the Given Concept

As mentioned above, we use Google Books Ngrams corpora to generate "visual patterns" on the Internet scale for the given concept [22]. These corpora cover almost all related word variations for any concept at the text level and are much more general and richer than WordNet or Wikipedia [30; 41]. We use Google Books Ngrams corpora to discover related word variations for the given concept with parts-of-speech (POS), specifically with NOUN, VERB, ADJECTIVE and ADVERB. Using Google Books Ngrams data helps us cover all variations of any concept the human race has ever written down in books [8]. In addition, using the POS tag can help us to partially purify word variations.

3.2 Purifying Noisy Word Variations

In our experiments, we found that not all the retrieved word variations are relevant to our given visual concept, e.g., "tiger sharks", "tiger belles", etc. Downloading images with these noisy word variations of the concept are harmful for training our target model "tiger"; therefore, we need to purify these noisy word variations and set up key word variations. We developed a fast NGD method to address this issue from the perspective of text semantics.

Purifying Based on NGD

Words and phrases acquire meaning from the way they are used in society, from their relative semantics to other words and phrases. For computers, the equivalent of "society"is "database", and the equivalent of "use" is "a way to search the database" [3]. Normalized Google distance constructs a method to automatically extract similarity distance from the World Wide Web (WWW) using Google page counts [2]. For a search term *x* and search term *y* (just the name for an object rather than the object itself), Normalized Google distance is defined by (1):

$$NGD(x,y) = \frac{\max\{\log f(x), \log f(y)\} - \log f(x,y)}{\log N - \min\{\log f(x), \log f(y)\}}$$
 (1)

where f(x) denotes the number of pages containing x, f(x,y) denotes the number of pages containing both x and y and N is the total number of web pages searched by Google.

We denote the distance of all word variations by a graph $G_q = \{N, D\}$ where each node represents a word variation

Table 2: Some examples of the merged word variations

Concept:	Merged word variations:
Horse	{horse cabs vs horse carriages vs horse carts vs horse buses vs horse trams}
Dog	{horse cabs vs horse carriages vs horse carts vs horse buses vs horse trams}
Bus	{double bus vs london bus vs open bus}

Table 3: Classification results of the concepts "tiger" and "horse"

Concept:	S_{i}	Precision rate:	Recall rate:		
	0.71	0.8978	0.9278		
Horse	0.68	0.9408	0.8833		
	0.66	0.9615	0.8332		
Tiger	0.71	0.9045	0.9344		
	0.68	0.9523	0.8932		
	0.66	0.9731	0.8374		

and its edge represents the NGD between the two nodes. We set the target concept as center (d_0) and other word variations have a score (d_x) which corresponds to the distance to the target concept, (d_{xy}) represents the NGD between two word variations x, y, and is defined as (2):

$$d_{xy} = \frac{NGD(x,y) + NGD(y,x)}{2} \tag{2}$$

By setting the threshold d_x to a value (0.5) we can successfully remove most of the noisy word variations while keeping the vast majority of useful word variations. Then we set d_{xy} to a value (0.1) to merge semantic synonyms. This step can be viewed as part of a cascade strategy that purifies irrelevant word variations, so we set the value of d_x and d_{xy} to ensure the vast majority of useful word variations are passed on to the next stage. Table 1 presents the results of purifying noisy word variations using NGD for the concept "tiger" and "horse". By experiments, we found that there are still lots of visual non-salient word variations, e.g., "tiger shooting", "social tiger", etc. and we cannot purify these noisy word variations using NGD alone.

Purifying Based on Linear SVM

From the visual perspective viewpoint, we want to identify visual salient word variations and eliminate visual non-salient word variations in this step. The intuition is that visual salient word variations should exhibit predictable visual patterns that are accessible to classifiers [8]. We use the image-classifier based purifying method.

For each filtered word variation, we directly download 100 images from the Google image search engine as positive images; then randomly split these images into a training set (75 images) and validation set (25 images) $I_i = \{I_i^t, I_i^v\}$, we gather a random pool of negative images (50 images) and split them into a training set (25 images) and validation set (25 images) $\overline{I} = \{\overline{I}^t, \overline{I}^v\}$; We then train a linear SVM C_i with I_i^t and \overline{I}^t , using dense HOG features and then use $\{I_i^v, \overline{I}^v\}$ as validation images to calculate the classification results S_i [10; 21]. Table 3 shows the results of the experiments on the concepts "tiger" and "horse". S_i denotes the percentage of correctly classified images. We declare an word variation i to be visually salient if the classification results S_i give a relatively

high score (0.7) as we want to purify visual non-salient word variations as much as possible.

Purifying Based on Visual Distance

By filtering the noisy word variations based on NGD and linear SVM, we obtain a relatively clean word variations set. We found some word variations share similar visual patterns, e.g., "tiger cubs, small tiger, baby tiger, little tiger". To avoid collecting too many visually similar images as training data, we group these word variations [24]. We represent the distance of all word variations or labels by a graph $G_v = \{V, E\}$ where each node represents a word variation and each edge represents the distance between two variations. Each node has a score V_i which corresponds to the classifier C_i on its validation data $\{I_i^v, \overline{I}^v\}$. As previously mentioned, the edge weights E_{ij} from the visual perspective correspond to the distance between two word variations (labels) i, j and are measured by the score of the jth word variation classifier C_i on the ith word variation validation set $\{I_i^v, \overline{I}^v\}$. We group these word variations based on their distances to satisfy (3):

$$E_{ij} + 0.1 \geqslant V_j \tag{3}$$

Table 2 shows some examples of word variations merged by our method:

By using the above procedures, we obtain relatively clean word variations to represent different "visual patterns" for the given concept. Algorithm 1 shows the process of purifying these irrelevant word variations.

We use these filtered word variations as queries to download the top 120 images from Google image for each word variation. Then we put these images together as an initial image dataset for the given concept. Although we get the initial images from the Internet similar to [1; 8; 15; 16; 20; 25; 33; 34], the difference is we firstly get lots of related word variations representing different "visual patterns" for the given concept. Downloaded images using these related word variations are much more ample than only using the given concept. This is also our advantage over other methods. Table 4 shows the relatively clean word variations found by our "purifying word variations":

Table 4: Word variations found on Pascal VOC 2007

concept:	bottle	train	cat	cow	dog	horse	sheep	plane	bus	car
vars:	128	47	174	136	145	116	123	135	59	125
concept:	bike	boat	sofa	bird	mbike	plant	table	chair	pers	tv
vars:	43	207	38	226	33	5	437	345	209	36

Algorithm 1 Word variations purifying algorithm

Require:

- $X = \{x_0\}$, a concept for image label
- 1: Discover word variations in Google Books Ngrams corpora with POS and get $X = \{x_0, x_1, x_2....x_n\}$
- 2: Calculate NGD d_i between x_0 and x_i , delete x_i from X if $d_i \ge 0.5$
- 3: Calculate NGD d_{ij} between x_i and x_j $(i, j \ge 0)$, merge x_i and x_j if $d_{ij} \le 0.1$
- 4: Delete visually non-salient x_i from X if $S_i \leq 0.7$
- 5: Merge visually similar x_i and x_j if $E_{ij} + 0.1 \ge V_j$

Ensure:

a relatively clean word variation *X* for the given concept

The Limitation of Our Method

From our experiments, we found our method is not able to remove these noisy word variations thoroughly. Also, some positive word variations may be filtered out incorrectly. Filtering our word variations using the previous steps results in an average (for PASCAL Visual Object Classes) of 3.24% noisy word variations and an average 2.84% positive word variations being filtered out for the given concept. Using these word variations may result in noisy images to our initial image dataset for the given concept (type 1 noisy images). We found these word variations are a very small number respect to the correct word variations. These few noisy images caused by noisy word variations can be effectively filtered out by the next image purifying steps.

There are other types of noisy images which result from correct word variations in our initial image dataset for the given concept. Although the Google image search engine ranks the returned images, some noisy images are still included (type 2 noisy images). The reason for this is that the Google image search engine is a text based image search engine. To build a high-quality image dataset, both of these two types of noisy images should be removed from the initial image dataset.

3.3 Purifying Noisy Images

Most current approaches handle these problems via clustering [19; 23; 42]. Clustering can help assist with handling visual diversity and can reject outliers based on their distance from cluster centers. However, clustering presents a scalability issue for our problem. Since our images are sourced directly from the Internet and have no bounding boxes, every image creates millions of data points, the majority of which are outliers. Recent work has suggested that K-means is not scalable [9]. Instead, we propose to use a two-step approach to purify these noisy images.

Algorithm 2 Image purifying algorithm

Require:

Word variations $X = \{x_0, x_1, x_2...\}$ as image labels for the given concept

- 1: Download 120 images for each selected word variation x_i in X
- 2: Select top 100 images with exemplar-LDA for each x_i
- 3: Purify the remaining noisy images with progressive CNN

a relatively clean image dataset for the given concept

Purifying Based on Exemplar-LDA

To purify these type 2 noisy images caused by Google image search engine, we download a set of images (120) from the Google image search engine for each selected word variation such as "fighting tiger". The image set is used to train a detector using exemplar-LDA [17], and these detectors are then used for dense detections on the same image set. We select the top 100 images with high scores from multiple detectors for the next step. This method assists us to prune those images which relate less well to the word variations.

Purifying Based on Progressive CNN

To reduce the influence of type 1 noisy images, we use a purifying method similar to that proposed by [43]. The difference is that we do not train a CNN from the beginning; instead, we directly fine-tune a CNN on filtered images with a trained model " $bvlc_reference_caffenet$ " [18]. We then use the probabilistic sampling algorithm to select the new training samples according to the prediction score of the fine-tuned model on the training data itself. The intuition is we want to keep images with distinct sentiment scores between the two classes with high probability, and remove images with similar sentiment scores for both classes with high probability. Let $S_i = (S_{i1}, S_{i2})$ be the prediction sentiment scores for the two classes of instance i. We choose to remove the training instance i with probability P_i given by (4):

$$P_i = max(0, 2 - exp(|S_{i1} - S_{i2}|)) \tag{4}$$

The training instance will be kept in the training set if the predicted scores of one training instance are large enough. Otherwise, the smaller the difference between the predicted scores, the large the probability that this instance will be removed from the training set. Type 1 noisy images can be effectively filtered by this step. The reason for this is that the number of this type of noisy images is relatively small in the whole image dataset for the given concept. Algorithm 2 shows the detailed process for purifying noisy images.

Method Supervised bottle sheep train dog horse plane car 43.9 [39] 34.2 9.3 1.5 29.4 0.4 31.2 weak 7.1 13.4 [8] 9.2 23.5 12.9 30.6 35.9 web 8.4 17.5 18.8 14.0 35 Ours web 8.7 22.5 10.3 18.7 13.6 32.7 13.7 13.8 36.5 35.6 22.5 [14] 26.6 45.2 24.3 12.6 56.5 20.9 33.2 52.0 53.7 full Method Supervised bike boat sofa bird mbike plant table chair pers tv [39] 44.2 38.3 9.9 0 weak 3.1 3.8 3.1 0.1 0.1 4.6 [8] web 36.2 10.3 10.3 12.5 27.5 1.5 6.5 10.0 6.0 16.4 **Ours** 37.1 12.3 11.2 11.7 26.2 1.9 12.9 7.2 20.3 web 6.4

10.3

48.5

33.2

26.9

35.9

15.7

Table 5: Results (Average Precision) on Pascal VOC 2007 (test) object detection

3.4 Model Learning

[14]

Through the above steps, we firstly obtain the different "visual patterns" for the given concept from the perspective of the text. Then for each "visual pattern", we acquire relatively clean image dataset for the given concept by purifying noisy images. We put all the clean images together as training data for the given concept, and fine-tune a CNN model with a pre-trained model "bvlc_reference_caffenet" [18].

full

59.3

4 Experiments and Analysis

Our proposed approach is a general framework that can be used to build a high-quality training set and train a robust recognition model for any given visual concept. To quantitatively evaluate the performance of our approach, we choose the *Pascal VOC 2007* test set 20 categories for testing. Table 5 displays the results obtained using our algorithm and compares them with state-of-the-art baselines [8; 14: 39].

[39] is trained on *Pascal VOC 2007* training data with image-level labels. [8] is the state-of-the-art results for webly-supervised detection. [14] is the state-of-the-art results for fully-supervised detection. Compared to [39] which uses weak supervision and [14] which uses full supervision, our method uses web-supervision as even the training set does not need to be labeled manually. Nonetheless, our results substantially surpass the previous best results in weakly supervised object detection.

Compared to [8] which also uses web supervision, our method surpasses their results in most of the cases. The main reason for this is that our training data generated from the Internet contains much richer and accurate visual patterns in images. By observing the binding data in Table 4 and Table 5, we found that those concepts which have good performance tend to have sufficient word variations for the concept (with the exception of "table"). In other words, our approach discovers concepts that have much more useful linkages to the visual patterns in the corresponding image set.

Lastly, we reach an important conclusion: a good training set should achieve successful results both in scale and in quality.

5 Conclusion and Future Work

We presented a fully automated approach to the generation of high-quality training data for any given visual concept. Our aim was to remove the need to laboriously annotate training datasets and train a robust recognition model with the generated training data for the given concept. Through our experiments on the benchmark Pascal VOC 2007 test set, we found our approach surpasses most of the previous best result in weakly supervised and webly supervised object detection. Using related word variations which link to the different "visual patterns" of images and then building the training image set for a concept or query according to these word variations is our first attempt to make use of textual metadata to build the training set. There is still room to improve our approach, for example, we can potentially use more sophisticated approaches to purify noisy images downloaded from the Internet and this will be the focus of our future work.

20.2

43.3

16.4

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