Challenges of Object Localization in the ImageNet Dataset

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Abstract

With ever increasing computational resources and a virtually unlimited online collection of multimedia content computer vision research is thriving with innovation like never before. Hence, it seems counterintuitive to use constrainted datasets that don't actually capture the true nature of the problem. However, due to its sheer size and variety the ImageNet dataset is perhaps the closest representation of the real problem in terms of the variabilty of the object attributes such as pose, apperance, lighting, size, viewpoint, shape etc. This paper aims to highlight some of the challenges involved in object localization on a dataset with such high variance in object attributes. We present how conventional localization techniques will fail on such datasets, share some experimental insight about the dataset and also present a simulation technique for localization approaches to efficiently test different classifiers. Finally, we present a boosting inspired localization technique which although isn't state of the art but it shares an insight into the kind of methods that should work well on this dataset.

1. Introduction

Over the years, computer vision research has come a long way in identifying and understanding the challenges associated with truly "solving" the different facets of the vision problem. This combined with the exponential growth of computational resources and the vast collections of online multimedia has led to a flurry of innovative research works in the last decade.

Amongst this prolific growth of computer vision there has been critisicm for hand-tailored datasets and performance metrics that do not accurately reflect the complexity of the problem at hand.

Although, well labeled datasets such as Caltech101/256 [2, 3] and PASCAL [1] have alleviated the problem to some extent, the sheer number of images per category in the ImageNet [4] dataset result in an extremely high variance over object attributes such as color, viewpoint, orientation, size, appearance, pose, shape etc. Thus, ImageNet and the way its generated make it the closest approximation to the true variance in real world object attributes. Figure 1 gives an example of variance in the three ImageNet object categories chosen for expertiments in our work.

The task of object localization involves drawing a tight bounding box around all instances of an object class within an image. This paper aims to highlight some of the challenges involved in performing object localization on the three object categories shown in Figure 1. We start with presenting a reasoning against the use of conventional object localization techniques on this dataset and follows it with a set of basic experiments that cement its complexity. A commonly used technique is presented to bypass conventional localization techniques for testing different classifiers on the data without the explicit need of localization i.e. a theoretical simulation of the sliding window approach. Two different feature sets and classifiers are presented and tested via the simulated sliding window approach. Lastly, a boosting inspired localization strategy is proposed that is not perfect but doesn't suffer from the drawbacks discussed of conventional localization techniques.

Although we do not achieve state of the art performance, hopefully these results will give some insight about the kind of methods that are most suited for object localization on such a complex dataset.

2. Previous work

There has been extensive work done in the areas of single object recognition and localization using both single and multiple views. Previous works such as [5, 6] have used object specific and highly disciminative features such as SIFT [8] to locate rigid objects from varying viewpoints. Although comendable, these methods rely on the rigid geometry and highly discriminative features of the objects they seek to localize. Hence, such techniques will not be able to accomodate the high intra class variability and the non-rigid nature of objects such as animals where the space of all poses can't be quantized into a small enough number to apply multiple instances of rigid object classifiers.

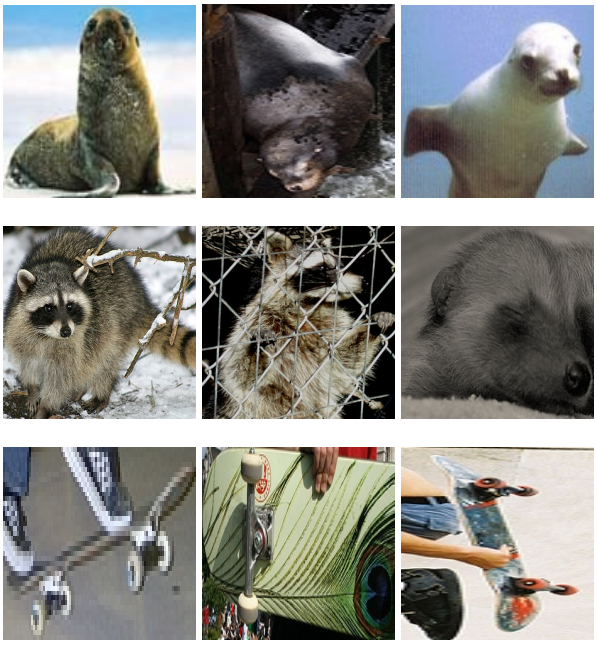


Figure 1: Example of the high variance in object attributes in the ImageNet dataset. The first row are sea lions, followed by racoons and skateboards.

A larger body of work in the last few years investigates object categorization for all instances of objects of a class under limited variance of object attributes such as shape, appearance, size and view point [16, 17, 18].

More recently, several novel attempts [12, 14, 13] have been made to investigate object recognition from multiple poses with reasonably high apperance variability via a part based approach.

Most of the above works though share great insight about the problem at hand they however use datasets that enforce constraints over one or more attributes of an object such as the viewpoint, pose or appearance and hence are not a true reflection of the variance of object attributes in real life.

Since the ImageNet dataset is quite new it is hard to find a good paper that uses it as a dataset and presents some compeling results. The creators of ImageNet have published [1] a set of results using very basic nearest neighbour metrics along with a deep analysis of the dataset to highlight its richness and the complexity of the problem at hand.

In this paper we try and present reasons for the failure of conventional localization techniques on the ImageNet dataset and motivate an alternative strategy that is far from perfect but doesn't suffer from the drawbacks of existing techniques.

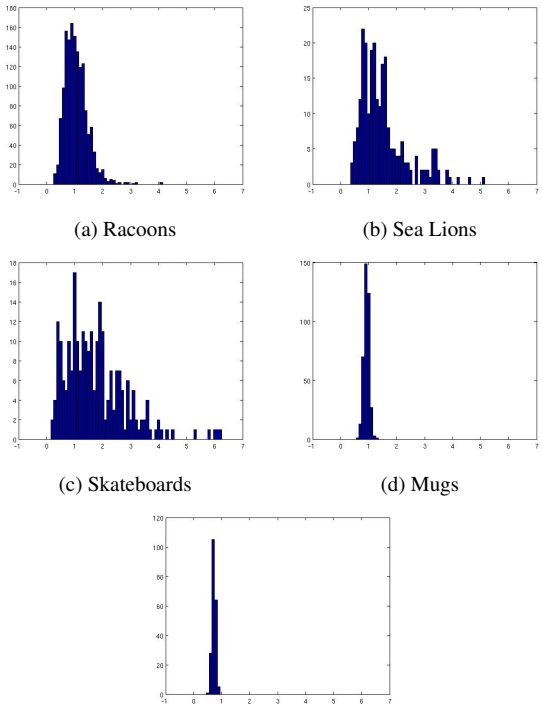
Object	**Mean**	**Variance**
Sea Lions	1.5057	.7073
Skateboards	1.7217	1.0680
Racoons	1.0615	.1734
Mugs	0.9195	**.0091**
Cups	0.7120	**.0047**

Table 1: Means and varianes of the aspect ratios of various objects

3. Approach

3.1. Conventional localization techniques

One of the upcoming ways of localizing instances of an object class within an image is to use a part based model [12]. In this model, we compute the probability of an object part being found at each interest point in the image. This raw information is usually churned through a graphical model to get the best possible joint estimate of the location of an object within an image.This approach works reasonably well when we make the assumption that an object is rigid and has a set of well defined parts a subset of which will always be visible. However, if we consider the case of non-rigid objects such as animals it will be very hard to learn an accurate model of each object part since the very term carries a lose definition especially in a high variance dataset like ImageNet where they will not a consistent appearance model of each object part. The other standard and more commonly used method for object localization is the sliding window approach. This involves taking a fixed size window and convolving it over every location and scale in the given image and evaluating a bag of words style binary classifier at each location. Although computationally expensive it has shown great promise especially with rigid objects [15] One of the fundamental assumptions of the sliding window approach is a very small variance on the distribution of aspect ratios of the object class thereby ensuring with a high probability that one of the sliding windows will encapsulate the object. We compare the distribution of aspect ratios for the three chosen ImageNet classes along with results from [19] where a sliding window approach was used to obtain an F1-scores of .93 and .92 on mugs and cups respectively. The above stated theory is empirically confirmed via the results shown in Figure 2. It is seen that the aspect ratio distributions of the ground truth bounding boxes around the objects in the ImageNet dataset has a very high variance when compared to the variance of the mugs and cups. Thus, unless we choose multiple window sizes and exponentially worsen the performance of our sliding window approach there is no straightforward of applying sliding window for localization to the three classes selected.



(a) Racoons (b) Sea Lions

(c) Skateboards (d) Mugs

(e) Cups

Figure 2: Aspect ratio distributions for different object types across datasets

3.2. Simulating sliding window

As the previous section shows it is a non-trivial task to apply conventional localization techniques on this dataset. However, without first spending time on developing novel localization algorithms we would like to explore the image charecteristics and design classifiers that learn to recognize that particular class of objects. The approach we use is to simulate sliding window by extracting the ground truth bounding boxes as positive images and thousands of non-overlapping snippets from the background as negative images. This reduces our problem from a fairly non-trivial object localization problem to a more manageable object recognition problem where the classifier simply outputs a probability for the existence of an object in an image. The obvious drawback here is the ratio of the positive versus negative images since sliding window samples an order of magnitude more negatives. However, if enough non-overlapping negative snippets are used for every image we can get a close enough approximation to actually running sliding window in terms of classification performance. To make the sampling of the negatives as close to real as possible, we assume a Gaussian distribution over the width and height of the object class, estimate parameters empirically

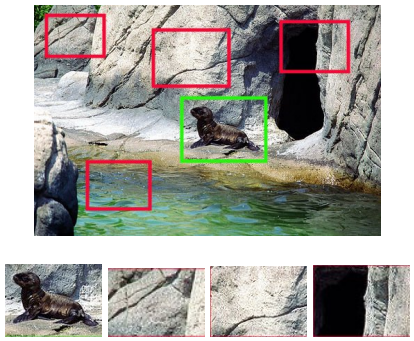


Figure 3: Simulating sliding window - an image marked with positive and negative snippets and how they lead to a smaller dataset with the same basic idea

and use those to sample the images.

Figure 3 and the equations below shows how an image is broken into positive and negative snippets to simplify the problem.

$$I = \text{an image from the set of images for class } c$$

$$G_i^c = \text{set of ground truth bounding boxes for class } c \text{ on image } I$$

$$P_i^c = \text{set of positive images for simulated sliding window}$$

$$N_i^c = \text{set of negative images for simulated sliding window}$$

$$S^c = \text{set of non-overlapping bounding box samples for image } I$$

$$g^{(j)}, s^{(j)} \epsilon \{x, y, w, h\}$$

$$\mu_w = \text{empirical mean of widths for positive snippets}$$

$$\mu_h = \text{empirical mean of heights for positive snippets}$$

$$\Sigma_w = \text{empirical variance of widths for positive snippets}$$

$$\Sigma_h = \text{empirical variance of heights for positive snippets}$$

$$\boldsymbol{P_i^c} = \{I(g^{(1)}), I(g^{(2)}), \ldots, I(g^{(n)})\}$$

$$\boldsymbol{N_i^c} = \{I(s^{(1)}), I(s^{(2)}), \ldots, I(s^{(n)})\}$$

$$s^{(j)}(w) \sim Gaussian(\mu_w, \Sigma_w)$$

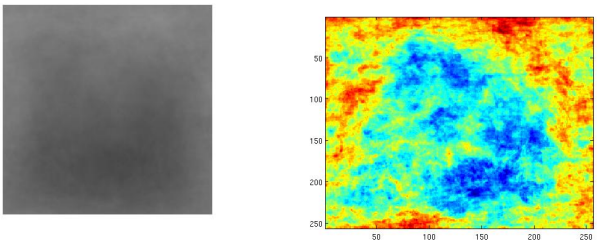
$$s^{(j)}(h) \sim Gaussian(\mu_h, \Sigma_h)$$

$$s^{(j)}(x) \sim Unif(0, I(w))$$

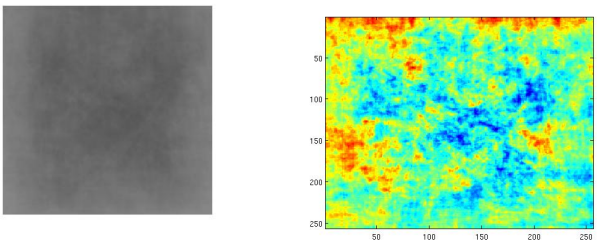
$$s^{(j)}(y) \sim Unif(0, I(h))$$

3.3. Image Properties

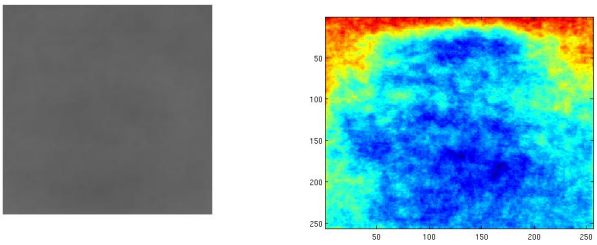
Before designing classifiers it helps to review some of the basic image properties of all the positive snippets across a class. In this section we breifly touch upon a few such properties that are though quite basic but nevertheless useful to share.



(a) Sea Lions

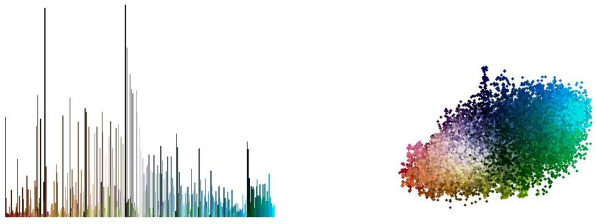


(b) Skateboards

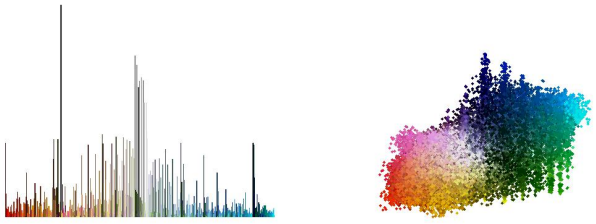


(c) Racoons

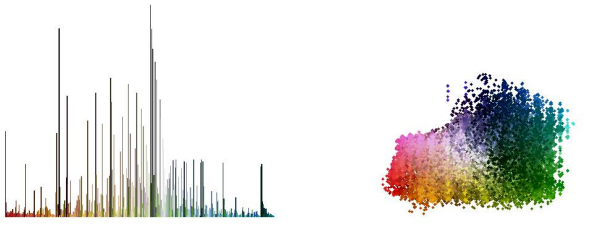
Figure 4: Average images on the left and variance on the right.



(a) Sea Lions



(b) Skateboards



(c) Racoons

Figure 5: Color histograms and scatter plots for the different object classes [23].

3.3.1 Average and variance

Figure 4 simply shows the average and variance images for the different object classes. The objects were snipped and resized apriori. As excepted based on our initial discussions there is no signal in the average images and they are extremeley close to being fully grey. The only insight in the variance images is that there seems to be a lot more variation at the corners that in the middle. This can be taken into account when developing sampling techniques for image patches. Depending on the application, discriminiative patches should be extracted more from the sides via an exponential distribution as opposed to generalizable patches should be extracted more from the middle via a gaussian distribution.

3.3.2 Color properties

Eyeballing most datasets can give the false sense that color can be an important feature for recognition and localization. Historically researchers have avoided the use of color based features for these tasks due to computational and philosophical reasons. The computational tradeoff is obvious, and the philosophical reason being that humans can perform these tasks very well without any color information. Figure 5 is a color historgam and a scatter plot of all the positive snippets of different classes. It shows minor variations for the different classes but no strong color patterns emerge, atleast globally. There were some interesting insights for designing color features when comparing such plots between the positive and negative snippets but for sake of brevity they have been omitted.

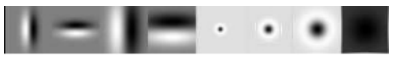


Figure 6: Subset of the filter banks used in the bag of features descriptor.

3.4. Classifier design

Using the simulated sliding window framework described above we present two different classification strategies based on different features. The experiment section covers the results and comparisons in details.

3.4.1 Bag of features

The is the standard application of the bag of words model applied to image features [20, 21]. We begin by constructing the codebook. Each positive snippet is densely sampled and a image descriptor is created at each sampled location. This image descriptor is a 250 dimensional vector which is a combination of the RIFT [9], spin images [10] and gabor style filter bank [11] descriptors. Figure 6 shows a subset of the filter banks being used in the image descriptor. K-Means clustering is used to group similar descriptors in this 250 dimensional space and a codebook is created by taking each of the K (usually 100-200) cluster centroids descriptors. Equation 1 shows how the design matrix is created by the above defined codebook.

$$\boldsymbol{X} = \{x^{(1)^T}, x^{(2)^T}, \ldots, x^{(m)^T}\} : \text{design matrix}$$

$$\boldsymbol{D^c} = \{d^{(1)^T}, d^{(2)^T}, \ldots, d^{(|D^c|)^T}\} : \text{dictionary}$$

$$\boldsymbol{F_i} = \{f^{(1)^T}, f^{(2)^T}, \ldots, f^{(|F_i|)^T}\} : \text{image descriptors}$$

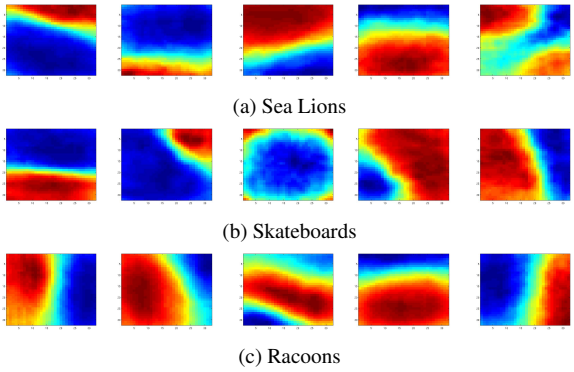
$$x(j)^T, d(j)^T, f(j)^T \epsilon \mathbb{R}^n$$

$$x_j^{(i)} = \arg\min_{f \epsilon F} ||f - d^{(j)}||_2^{\ 2} \quad (1)$$

For each class of objects we use a binary gentle boost classifier over two-split decision stumps and the codebook is trimmed to remove descriptors not selected by boosting. Following this, using cross-validation each unknown image in the test set (under simulated sliding window) is converted to a feature vector and is evalued by the boosted classifier. Results and details are elaborated in the experiment section.

3.4.2 Unsupervised codebook generation

A different approach towards codebook generation is to try and learn one in an unsupervised way (i.e. the image descriptors are not manually selected) from labelled training data [22]. The codebook is generated by first densely sampling (well over 100 samples per image) the positive images



(a) Sea Lions

(b) Skateboards

(c) Racoons

Figure 7: Randomly selected codebook entries.

(under simulated sliding window) and extracting square size patches of sizes varying from 4x4 to 32x32. Similar to the Bag of Features section these patches are linearized and K-Means clustering is applied to find patterns in this data. The codebook then becomes the K (usually 100-150) cluster centroids that are converted back into their original patch form. Figure 7 shows a set of sample codebook entries. It is interesting to see their similarity with Gabor style filter bank features. Although not shown experimentally due to the lack of a concrete metric, the codebook patches don't generalize well unless a threshold number of images are used and or a threshold number of patches are extracted for the K-Means clustering.

Equation 2 shows how the design matrix is created using the max reponses of each of these codebook patches. For each class of objects an SVM classifier is trained using the design matrix. Following this, cross-validation is used and each unknown image in the test set is converted to a feature vector and evaluated by the SVM classfier.

$$\boldsymbol{X} = \{x^{(1)^T}, x^{(2)^T}, \ldots, x^{(m)^T}\} : \text{design matrix}$$

$$\boldsymbol{D^c} = \{d^{(1)}, d^{(2)}, \ldots, d^{(|D^c|)}\} : \text{dictionary}$$

$$x(j)^T \epsilon \mathbb{R}^n$$

$$d(j) \epsilon \mathbb{R}^{32 \times 32}$$

$$x_j^{(i)} = \max(I \bigotimes d^{(j)}) \quad (2)$$

3.5. A Boosting Inspired Approach to Localization

After having highlighted the apparent drawbacks of applying conventional object localization techniques on the ImageNet dataset we now present an approach to localization inspired by the boosting algorithm.

It is used along with the unsupervised codebook approach illustrated in the previous section. Each individual codebook entry is hypothesised to be a "weak vote"

of where the object instances within the image are located much like each codebook entry is a weak classifier in the boosting framework. Instead of simply taking the best response of each codebook entry as a vote we take the top few responses on the image (the image here is the entire image and not a positive or negative snippet) and weigh them by the value of the response.

$$\boldsymbol{X} = \{x^{(1)^T}, x^{(2)^T}, \ldots, x^{(m)^T}\} : \text{locations in image space}$$
$$\boldsymbol{D^c} = \{d^{(1)}, d^{(2)}, \ldots, d^{(|D^c|)}\} : \text{dictionary}$$
$$\boldsymbol{W} = \{W_1, W_2, \ldots, W_n\} : \text{set of weight matrices}$$
$$x(j)^T \epsilon \mathbb{R}^2$$
$$d(j) \epsilon \mathbb{R}^{32 \times 32}$$
$$W_j \epsilon \mathbb{R}^{I(w) \times I(h)}$$
$$W_j = I \bigotimes d^{(j)}$$

Modified K-Means

For each location (i) :

$$c^{(i)} = \arg\min {W_j}^{(i)} * x(i) - \mu_j {}_2^2$$

For each cluster centroid (j) :

$$\mu_j = \frac{\sum_{i=1}^{m} 1\{c^{(i)} = j\} {W_j}^{(i)} * x^{(i)}}{\sum_{i=1}^{m} 1\{c^{(i)} = j\}}$$

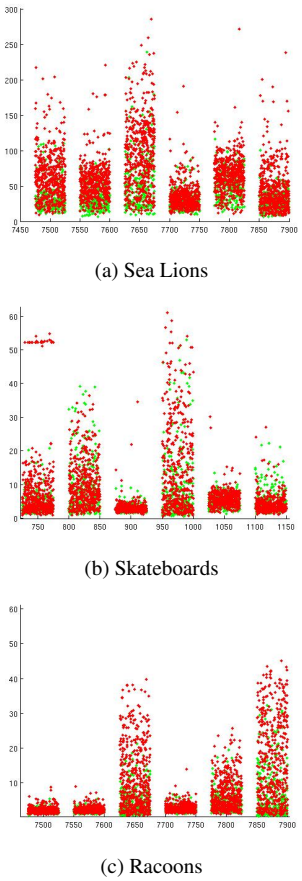
The main intuition behind the localizing process comes from the boosting framework which suggests that the sum of all the weak classifiers in the system becomes a strong classifier. Similar to this idea, we make a hypothesis that each patch response is a weak vote of the location of the object and a combination of all these weak votes should become a strong vote. A variation of the K-Means clustering process is used to identify the clusters amongst these votes. We then use the statistics of these clusters (the mean and variance) to try and estimate an ellipse signifying the position of the object which is then trivially converted to a rectangle for comparison with the ground truth.

Forming Ellipses from Cluster Centroids

For each cluster centroid (j) :

$$[width_j, height_j] = \frac{\sum_{i=1}^{m} 1\{c^{(i)} = j\} (\mu_j - {W_j}^{(i)} * x(i))^2}{\sum_{i=1}^{m} 1\{c^{(i)} = j\}}$$
$$[x_j, y_j] = \mu_j$$

Although this approach doesn't provide state of the art results it is interesting to see the overall insights about the kind of approaches and features that work and those that don't work.



(a) Sea Lions

(b) Skateboards

(c) Racoons

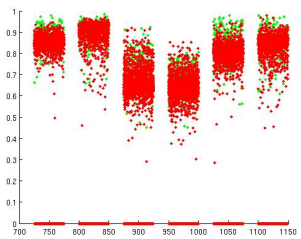
Figure 8: Feature vector plots for 6 randomly selected features from the bag of features model.

4. Experiment

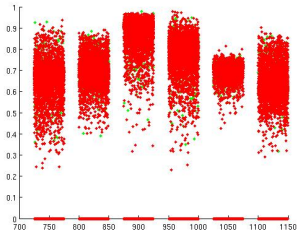
Figure 1 gave a small peek at the complexity involved in the chosen ImageNet categories. There are three object classes for sealions, skateboards and racoons, with 165, 229 and 1182 images respectively. All images were labelled to draw bounding boxes around the object instances within these images and these were treated as the ground truth. For the simulated sliding window approach these snipped ground truth boxes became the positive images and around 100 negative snippets per image became the negative images. The results for the bag of features boosted classifier and the unsupervised codebook SVM classifier were all based off the simulated sliding window dataset.

Figure 8 shows the a few chosen features from a feature vector plot for the bag of features model. Using the design matrix generated from equation 3 we create each coordinate in this plot based on the equations below:

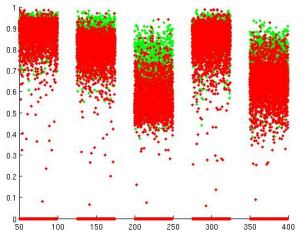
Notice how mixed the feature vector values for the positive and negative images are in most of the features shown.



(a) Sea Lions



(b) Skateboards



(c) Racoons

Figure 9: Feature vector plots for 6 randomly selected features from the unsupervised codebook model.

This implies that a learning algorithm will have a hard time find a seperating boundary for these features. Very few features actually offer some separation.

Figure 9 shows a similar feature vector plot for the design matrix also generated via equation 3 in the unsupervised codebook model. Its interesting to see that a lot of the features shown offer a decent separation and hence this model should imply a much better performance. This intuition is confirmed empirically in the results ahead.

$$\boldsymbol{X} = \text{ design matrix from equation 1 or 2}$$

For each entry ${x_j}^{(i)}$ in the design matrix $\boldsymbol{X}$

$$s^{(i)} \sim Unif(-10, 10)$$
$$[row^{(i)}, col^{(i)}] = [{x_j}^{(i)}, s + j] \quad (3)$$

Table 3 shows the results of the 20-fold cross validation on the simulated sliding window dataset using the two classifiers discussed above.

Object	Bag of Words	Unsupervised Codebook
Sea Lions	0.450	0.9350
Skateboards	0.162	0.6920
Racoons	0.944	0.9228

Table 2: Accuracy of the classifiers on the simulated sliding approach set.

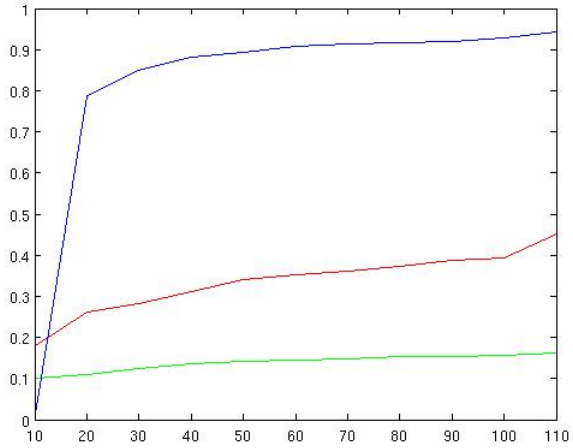


Figure 10: Accuracy versus number of boosting rounds. RGB is sea lion, skateboards and racoons respectively.

Object	RIFT	SPIN	Filters	All
Sea Lions	0.400	0.406	0.414	0.450
Skateboards	0.152	0.169	0.1742	0.163
Racoons	0.491	0.469	0.486	0.944

Table 3: Accuracy of the classifiers using variants of the bag of features model.

Figure 10 is the change in accuracy (using cross-validation) for the different classes as the number of boosted round increase.

It is interesting to note the effective of the different image descrptors individually as shown in Table 2. They seem to share very complementary to each other and hence the combined accuracy is much higher that their individual accuracy.

It is also interesting to note the impact of the size of the bag of features codebook i.e. number of cluster centroids on the overall performace of the different classifiers as noted in Figure 11

For testing the boosting inspired localization approach we used the same unsupervised codebook as used for the above experiments and chose a completely seperate test set

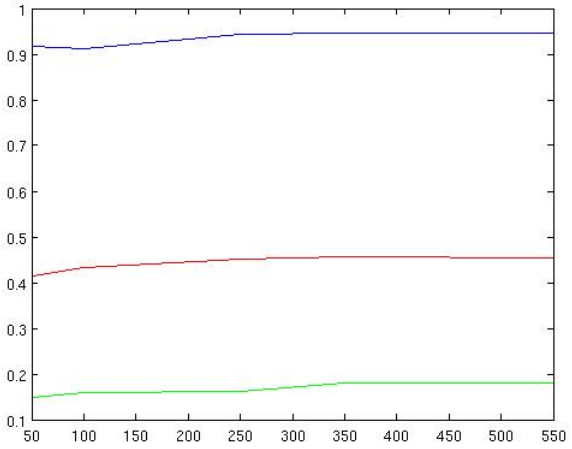


Figure 11: Accuracy versus size of codebook for the bag of features model. RGB is sea lion, skateboards and racoons respectively.

Object	Accuracy
Sea Lions	0.333
Skateboards	0.111
Racoons	0.504

Table 4: Localization accuracy for the proposed boosting inspired approach.

of complete images (not snipped ones) that contain one or more instanes of the object class. The set was of 100 images for each object class and the accuracy reported in Table 4. A detection outputted by our algorithm is considered as correct if $(D \cap G)/max(D, G)$ is greater than 0.6 where D is a detection and G is a ground truth bounding box.

Figure 12 shows some results (good and bad) of the boosting inspired localization algorithm for the different classes. Skateboards are by far the hardest class to accurately localize, this could be because of the lack of strong, large generalizable features. In most error cases the actual skateboards within the images are simply too small or thin for the image descriptors of both types to actually find a singal. In the case of sea lions their appearance , pose and view-point variation is enormously large and hence hard to work with. Racoons perhaps worked the best because of a relatively stable appearance which allows the descriptors to find a consistent signal.

5. Conclusion

We once again reiterate the general theme of this paper that the ImageNet dataset due to its sheer number of images per category is a very good approximation to the true real world variability in object attributes such as apperance, shape, pose, view point, size etc. The paper highlights some of these complexities and provides insights which may help in deciding an approach to this challenging problem. We presented a boosting inspired localization approach which is although not state of the art but it gives insight into the kind of localization methods that will work as opposed to the conventional ones. An unsupervised codebook provides the best performance out of all the feature descriptors used. It may be very interesting to see how a heirarchical codebook improves the efficiency - almost like a deep belief network where the "codebook" of a higher layer could implicitly model the parts of highly deformable objects like animals for it is quite clear that lower level image features will not be able to come close to truly solving this problem. Heirarchical codebooks also will not individually scale for each object type so it will be fruitful to think of approaches that share codebooks similar to the work in [15] so that we can think of efficient scaling as well. Lastly, studies on the impact of sharing codebooks and object parts based on the ontologies in ImageNet is an intruiging work for the future.

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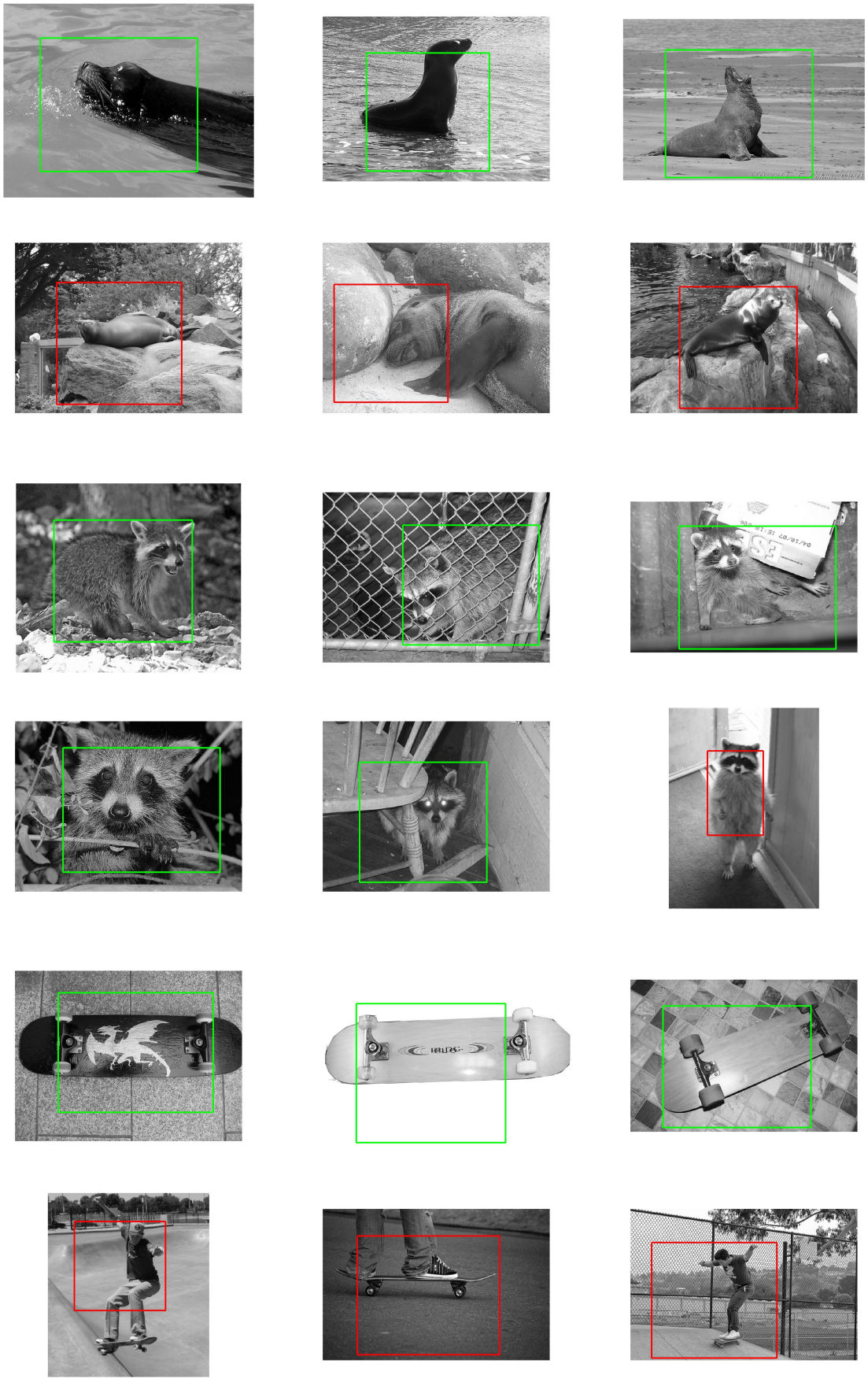

Figure 12: Localization results

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