AN ADAPTIVE INTERFACE FOR ACTIVE LOCALIZATION

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Abstract: Thanks to large-scale image repositories, vast amounts of data for object recognition are now easily available. However, acquiring training labels for arbitrary objects still requires tedious and expensive human effort. This is particularly true for localization, where humans must not only provide labels, but also training windows in an image. We present an approach for reducing the number of labelled training instances required to train an object classifier and for assisting the user in specifying optimal object location windows. As part of this process, the algorithm performs localization to find bounding windows for training examples that are best aligned with the current classification function, which optimizes learning and reduces human effort. To test this approach, we introduce an active learning extension to a latent SVM learning algorithm. Our user interface for training object detectors employs real-time interaction with a human user. Our active learning system provides a mean performance improvement of 4.5% in the average precision over a state of the art detector on the PASCAL Visual Object Classes Challenge 2007 with an average of just 40 minutes of human labelling effort per class.

1 INTRODUCTION

It is possible to improve the classification performance of machine learning methods for object recognition by simply providing more training examples. However, the cost of providing labelled data—asking a human to examine images and provide labels—becomes impractical as training sets grow.

In addition, object localization with bounding windows is important for many applications and plays a significant role in improved performance (Lazebnik et al., 2006; Mutch and Lowe, 2006; Viola and Jones, 2004), but this also places an increased burden on human labelling by requiring accurately aligned bounding windows around each training instance.

We present a method for using active learning (Settles, 2010; Tong and Koller, 2001) to reduce the required number of labelled training examples to achieve a given level of performance. Our method also proposes optimal bounding windows aligned with the current classification function. Active learning refers to any situation in which the learning algorithm has control over the inputs on which it trains, querying an oracle to provide labels for selected images. In particular, we are concerned with the problem where a person is required to provide labels for bounding windows. Unlike image classification where the image is classified as a whole, we apply this approach to *object localization* by iteratively selecting the most uncertain unlabelled training windows from a large pool of windows, and present them to the user for labelling. If the object of interest is correctly bounded by the localization window, the human provides a positive label, otherwise they provide a negative label or indicate their uncertainty. We have designed a user interface that is efficient for the user and provides feedback on performance while also enabling the user to retain some initiative in selecting image windows.

Our experimental results apply the approach to the PASCAL Visual Object Classes 2007 (VOC2007) (Everingham et al., 2007) on twenty different categories learned with mixtures of multi-scale deformable part models from Felzenswalb *et al.*

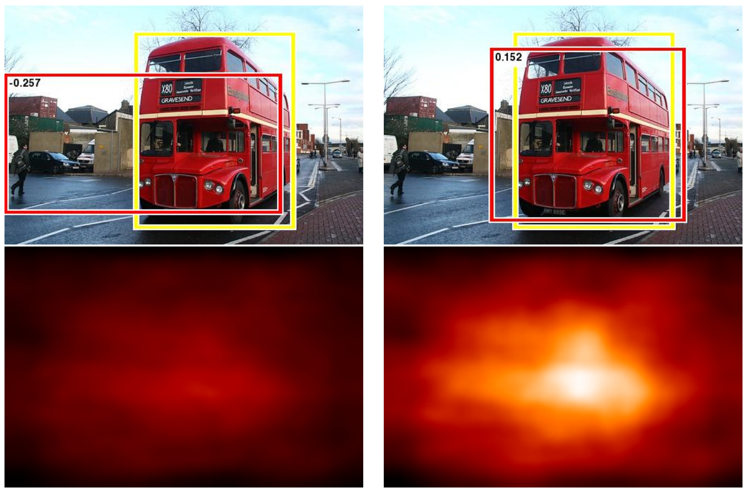


Figure 1: **Screen shots of object detection results.** This shows how our active learning approach improves object localization. The top left shows the highest scoring detection using only VOC 2007 data, whereas the top right shows the result after retraining with additional data obtained using our active learning interface. The bottom row shows associated confidence maps in the same scale. Note how the detection confidence increased and the peak position was shifted. Yellow boxes are the ground truth and red boxes are detections with the associated detection confidence.

(Felzenszwalb et al., 2009), one of two joint winners in the VOC2009 challenge for object localization problems. In the first experiment, we show that we can match their results on VOC2007 data while using many fewer labelled windows for training. Then we demonstrate our full user interface on more diverse images, such as those obtained from web search engines and show how it enables a user to efficiently improve performance on VOC2007. While these experiments show that our actively trained deformable part model works well with active learning, the system does not depend on a specific classifier or feature set. If other classifiers or features are found to be more suitable to a domain, we can also incorporate them into our framework.

2 ACTIVE LEARNING FOR IMAGE LABELLING

Image labelling requires human effort to supply the labels for each positive window in the training set. This typically involves thousands of instances, and is thus extremely labour-intensive. To make object recognition practical over multiple domains, we need to recognize that human labelling is a costly resource, and must be used as efficiently as possible. Active learning is the machine learning method typically used in this case. A full discussion of active learning is beyond the scope of this paper, so we will focus only on the most relevant areas for our work. We direct the interested reader to, *e.g.*, the recent review by Settles (Settles, 2010) for a more extensive survey.

In *pool-based active learning*, which we use here, candidate data are selectively sampled for labelling from a pool of unlabelled data $\mathcal{U}$. The model is then updated to take the new labels into account, and new candidates selected. Candidate selection is typically performed by greedily selecting data x^* from $\mathcal{U}$ according to some utility function, $x^* = \text{argmax}_{x \in \mathcal{U}} U(x)$. The process repeats as long as the human labeller is willing, or until some other termination condition is reached.

The candidate selection objective function is designed to maximize the utility of the labels gathered, typically by some measure of the expected informativeness of the labels. This is what makes active learning efficient in situations where data is plentiful but labelling it is expensive. By identifying the training instances that actually impact the model, fewer labels are required, and the bottleneck can be reduced. In Section 3.1, we use an *uncertainty sampling* utility function (Lewis and Gale, 1994), which is popular as it performs well on a variety of problems and has been extensively studied. Other methods include maximizing entropy, combining a committee of models, or maximizing the expected model change.

In recent years, active learning in computer vision has gained much attention. While various active learning extensions have been proposed in image classification (Collins et al., 2008; Kapoor et al., 2007; Qi et al., 2008; Vijayanarasimhan et al., 2010; Zhang et al., 2008), relatively little attention has been paid to the more challenging problem of object localization (Abramson and Freund, 2005; Siddiquie and Gupta, 2010; Vijayanarasimhan and Kapoor, 2010). Object localization requires a model that can identify bounding windows for the object in each image—there can be zero, one or many such boxes in a single image. Image classification needs to consider only a single global classification per image. Applying active learning to localization requires a substantial change in approach, as a single label cannot be applied to an image—it much be applied to potentially numerous and overlapping windows of an image. Most active learning approaches are therefore infeasible for object localization problems in even a relatively large scale dataset such as the VOC2007 dataset of around 10,000 images. To the best of our knowledge, we are the first to apply and test active learning performance on the PASCAL or similar datasets.

3 ALGORITHM

Our system for active learning uses the Support Vector Machine (SVM) (Schölkopf and Smola, 2002) classifier, which has proven its success in many state-of-the-art recognition systems (Dalal and Triggs, 2005; Moosmann et al., 2006; Mutch and Lowe, 2006; Zhang et al., 2006). We also incorporate the recent latent SVM (LSVM) approach of Felzenszwalb *et al.* (Felzenszwalb et al., 2009). We will briefly review these models and describe how we incorporate active learning. The goal of a supervised learning algorithm is to take n training samples and design a classifier that is capable of distinguishing M different classes. For a given training set $(x_1,y_1),\dots,(x_n,y_n)$ with $x_i \in \Re^N$ and $y_i \in -1,+1$ in their simplest form with two classes, LSVM is a classifier that scores a sample x with the following function (Felzenszwalb et al., 2009),

$$f_\beta(x) = \max_{z \in Z(x)} \beta \cdot \Phi(x,z) \tag{1}$$

Here β is a vector of model parameters and z are latent values. The set $Z(x)$ defines possible latent values for a sample x. Training β then becomes the following optimization problem.

$$\min_{\beta,\xi_i \geq 0} \quad \frac{1}{2}||\beta||^2 + C\sum_{i=1}^{n}\xi_i \tag{2}$$

$$s.t. \quad \forall i \in \{1,\dots,n\} : y_i f_\beta(x_i) + b \geq 1 - \xi_i \tag{3}$$

$$\text{and } \xi_i \geq 0 \tag{4}$$

where C controls the tradeoff between regularization and constraint violation. For obtaining a binary label for x, we have the decision function, $sign(h(x))$, where

$$h(x) = f_\beta(x) + b \tag{5}$$

In general, a latent SVM is a non-convex optimization problem. However, by considering a single possible latent value for each positive sample that can be specified in training, it becomes a convex optimization problem for classical SVMs. For multi-scale deformable part models, the set of latent values represents the location of parts for the object.

3.1 Active Learning on a latent SVM

We incorporate active learning into an LSVM by at each iteration selecting the candidate that has the minimum distance to the decision boundary. That is, for a set of data $\mathcal{C} \subseteq \mathcal{U}$, where $\mathcal{U}$ is the set of unlabelled image windows, we select:

$$\operatorname*{argmin}_{x \in C} \left| \frac{h(x_i)}{||\beta||} \right| \tag{6}$$

This is the candidate datum we ask the human expert to label. Ideally, we then move the new labelled datum from the candidate to the training set, update the LSVM model, and repeat, selecting a new candidate based on the updated model. However, due to the heavy computational load of LSVM, we choose to update the model in a batch after collecting a set of new labelled data. In our experiments, we obtain a set of unlabelled image windows by applying a sliding window at multiple scales on the image and computing a Histogram of Oriented Gradients (HOG) descriptor (Dalal and Triggs, 2005; Felzenszwalb et al., 2009) from each window as our datum.

This *uncertainty sampling* utility seeks to label the most uncertain unlabelled datum to maximize the margin. There are known to be other successful criteria for SVM active learning, particularly version space methods (Tong and Koller, 2001). We use uncertainty sampling as we wish to remain agnostic as to the underlying model. It has also been shown to perform well and has the advantage of being fast to compute and easy to implement. The learning task then becomes an iterative training process as is shown in Algorithm 1.

4 EXPERIMENTS

We will first test our active learning approach against a state-of-the-art object detector on VOC2007 (Everingham et al., 2007) to show the ability to reduce labelling requirements without sacrificing performance . Then we will describe our user interface

Algorithm 1 : Pool-based active learning algorithm for image window labelling
x is a window descriptor, I is a set of m images, $\mathcal{L}$ is a set of labelled image windows and $\mathcal{U}$ is a set of unlabelled windows.

```
1:  {Collect a set of unlabelled image windows, $\mathcal{U}$}
2:  $\mathcal{U} = \emptyset$
3:  for $i \in I$ do
4:      $\mathcal{U} = \mathcal{U} \cup x$ where $x$ is the highest scoring detection window in image $i$
5:  end for
6:  while the user continues the active learning session do
7:      {Obtain a set of new labelled data, $\mathcal{C}, \mathcal{Y}$}
8:      $\mathcal{C} = \emptyset$
9:      $\mathcal{Y} = \emptyset$
10:     for $t = 1$ to $n$ do
11:         $x^* = \text{argmin}_{x \in \mathcal{U}} \left| \frac{h(x_i)}{\|w\|} \right|$
12:         Get the label $y^*$ of the datum $x^*$ from the human expert
13:         The expert can add a set of $k$ samples $\mathcal{X} = \{x_0, x_1, \cdots, x_k\}$ in case of miss detections or false positives with a set of associated labels $\mathcal{L} = \{y_0, y_1, \cdots, y_k\}$ of $\mathcal{X}$
14:         $\mathcal{C} = \mathcal{C} \cup x^* \cup \mathcal{X}$
15:         $\mathcal{Y} = \mathcal{Y} \cup y^* \cup \mathcal{L}$
16:         $\mathcal{U} = \mathcal{U} - x^*$
17:     end for
18:     Add $\mathcal{C}$ and $\mathcal{Y}$ to the training set and update the LSVM model, $\hat{\beta}$, $\{\hat{x}_l, \hat{z}_l\}_{l=1}^{m}$ and $\hat{b}$ where $m$ is the number of support vectors
19: end while
```

for active learning and show its effective performance over the object categories of the VOC2007 dataset.

4.1 The PASCAL Visual Object Classes 2007

The PASCAL Visual Challenge has been known as one of the most challenging testbeds in object recognition. The VOC2007 dataset contains 9,963 images: 50% are used for training/validation and the other 50% are used for testing. We used VOC2007 to test our active learning approach to see if it would reduce labelling requirements for positive data. We use our own Python implementation of Felzenszwalb *et al.*'s detector (Felzenszwalb et al., 2009) with multi-scale deformable part models. The original source code is available online and written in Matlab and C[1].

[1]The source code is publicly available at http://people.cs.uchicago.edu/ pff/latent/

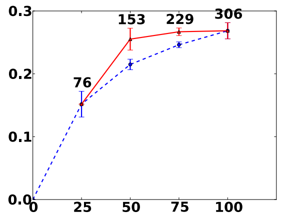
In our first experiment, we used the data provided by the VOC2007 dataset to show that active learning could achieve the same classification performance by using only an actively selected subset of the data. To show the reduced data requirements for active learning, we trained our model in each category on four different positive datasets, including 25%, 50%, 75% and 100% of all positive training images, comparing the effect of adding training data *randomly* and *actively*. We used the same negative dataset in these experiments, as negative data is cheap to collect. For both the random and active data sets, we start by randomly selecting the first 25% of positive images and training. In the random training set, we then repeatedly add a further 25% of the positive images and train again, until all the available data have been added. We performed active sampling by first training our base model with a randomly selected 25% of the positive data. We used the base model to choose the most uncertain positive images from the remaining pool of positive data, repeatedly adding 25% of the data. Due to randomness in the training procedure, we repeated these experiments five times and present average results with error bars. Figure 2 shows the results of all twenty categories.

This simulation shows that active sampling is effective at selecting the most useful data for training. In most cases, a total of only half of all positive data is required to get the performance of the full training set.

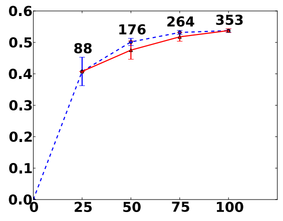
5 APPLICATION

In this section, we introduce the active localization interface for our interactive labelling system, ALOR (Active Learning for Object Recognition). Our interface iteratively presents the most informative query windows to the user and allows the user to correct mistakes made by the model. It is designed to work on any arbitrary user specified object category, using web images it automatically collects from major web search engines such as Google, Yahoo, and Flickr. Here, we demonstrate the interface on the "cow" category by using a set of images from the Google Image search engine.

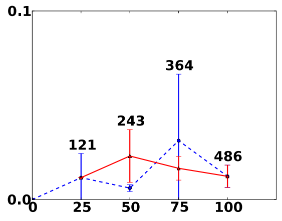
We first collect a set of images from the Google Image search engine with query keywords such as "cow." We then use our cow detector that is trained with VOC2007 data as shown in Figure 2 and let the algorithm actively select each query. Figure 3 shows some screen shots of our system interface, which describes four major cases for labelling data. These cases are: (a) the window is indeed a cow, (b) the



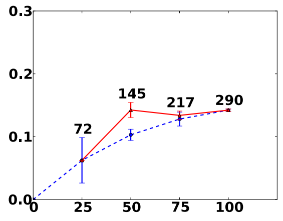
(a) aeroplane (.268)



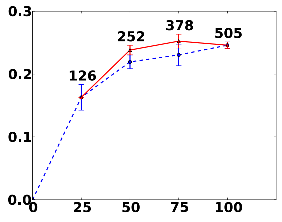
(b) bicycle (.537)



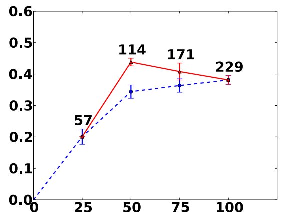
(c) bird (.009)



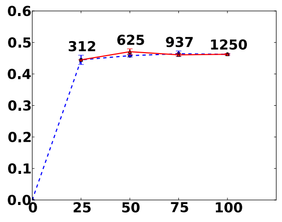
(d) boat (.142)



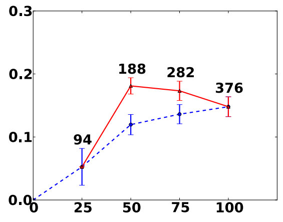
(e) bottle (.245)



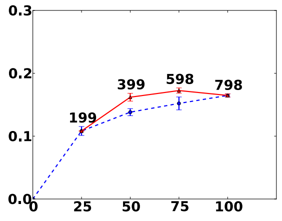
(f) bus (.376)



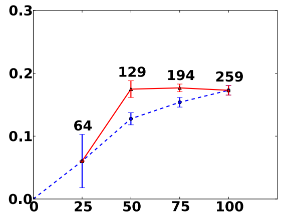
(g) car (.463)



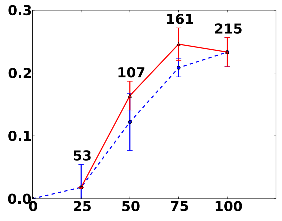
(h) cat (.143)



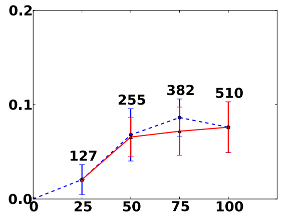
(i) chair (.163)



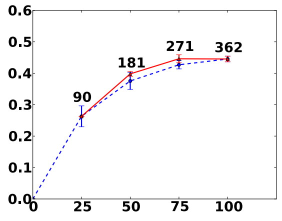
(j) cow (.173)



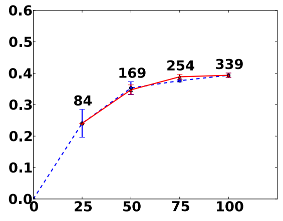
(k) table (.233)



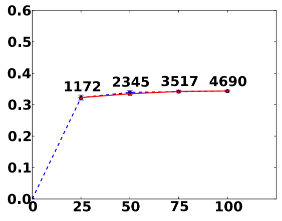
(l) dog (.061)



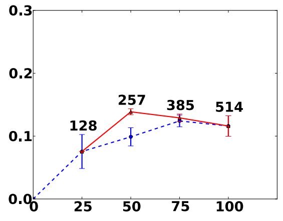
(m) horse (.443)



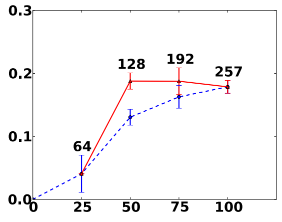
(n) motorbike (.393)



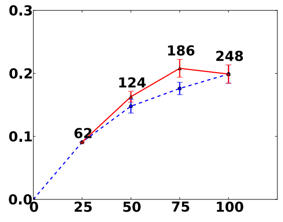
(o) person (.344)



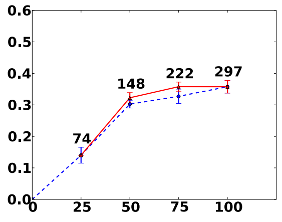
(p) plant (.117)



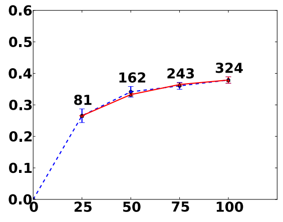
(q) sheep (.179)



(r) sofa (.196)



(s) train (.355)



(t) tvmonitor (.380)

Figure 2: **VOC2007: Random vs. active sampling of positive data.** There are 20 different visual categories. The horizontal axis of each figure represents the portion of positive training samples in percent (%) and the vertical axis gives the average precision. The solid red line shows the result of active sampling and the dotted blue line is for random sampling. We performed both random and active sampling of positive data five times with a different random seed. The errorbars are based on one standard deviation. For both random and active data sets, we start by training on a randomly selected 25% of positive samples. In the random training set, we then repeatedly add a further 25% of the positive samples and train again. In the active set, we added an additional 25% of actively selected samples iteratively until we use the full positive data. The number of positive samples in each subset is shown above each errorbar. The final average precision with the full positive data is shown next to the name of a category. Note that the result of active sampling often performs better with 50 % or 75 % of the images.

window is not a cow, (c) the window is ambiguous, perhaps due to partial overlap, so the window should be ignored for training, and finally (d) a user wishes to add a positive instance that was missed by the classifier or correct false positives. The rectangular boxes (in red) are queries selected by active learning with the minimum distance to the decision boundary. The green boxes are positive classifications in the current image that were not selected as queries. These green boxes are useful for giving the user feedback on the current classifier performance and to allow the addition of rare training examples that may lie far enough away from the decision boundary that they may otherwise never be detected or queried.

When a user wishes to add a training example that was not queried, they can simply click on the image. This will select the window with the highest classification confidence that contains the location of the mouse click. Therefore, the current classifier is still used to select the best-aligned training window, and user effort is minimized.

The interface is written in Python and C and utilizes multi-core CPUs to speed up the process and realize real-time interactions between a human user and a machine. Our interface currently takes less than a second (on an 8-core machine) to update and determine the next query windows upon receiving new labels, though the precise time depends on the number of dimensions of visual features and the resolution of the image. The interactive process can be sped up by precomputing image features, which we did in our experiments shown in Table 1.

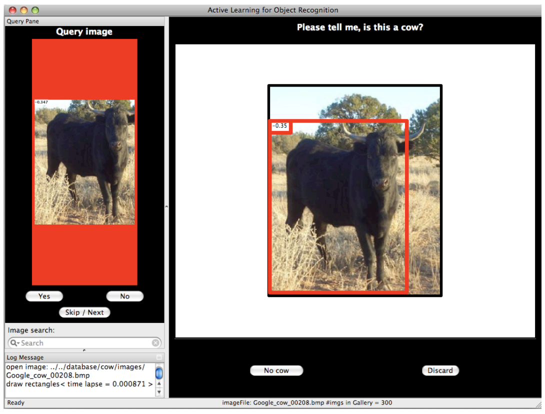
5.1 The PASCAL Visual Object Classes

In this section, we demonstrate that our prototype active learning GUI enables fast, efficient labelling to improve performance on data from the PASCAL VOC2007. For comparison, we first prepare our baseline detectors by training a latent SVM with HOG on all twenty categories. The third column of Table 1 shows the average precision of each category. Due to randomness in the training procedure, those numbers do not exactly match with ones in (Felzenszwalb et al., 2009) even with the same parameter settings, but they differ by less than 1 percent.

Next we perform a pool-based active learning session using Algorithm 1 with our active learning GUI to train these baseline detectors and improve their performance. With our interface, we collect training images from Flickr, which was a source for VOC2007 images. We used the Flickr Image API to obtain only images from after the competition date of VOC2007 to prevent the possibility of obtaining test data from the competition. Our interface allows a human user to search images based on a query word such as "cow," "motorbike," etc. We collected the first 3000 images from the Flickr database in each category. In order to further speed up the training process, we also cache visual features, using our baseline detectors to scan images, and sort them based on the uncertainty score in Eq. (6) for the highest detection scoring window. It takes approximately 3-4 hours to search, download and scan 3000 images (around 164 million bounding windows) to generate the set of most-uncertain query windows. However, this preprocessing can be done with no human interaction other than specifying the tag. The effectiveness of active learning can be seen in Figure 4 which shows the best 5 and worst 5 actively selected query windows in each category. The worst 5 query windows in the bicycle category contain target objects that are easily classified, whereas the worst 5 query windows in the chair category do not contain any target objects. In the sofa category, the worst 5 query windows include ones that contain easy target objects as well as ones without.

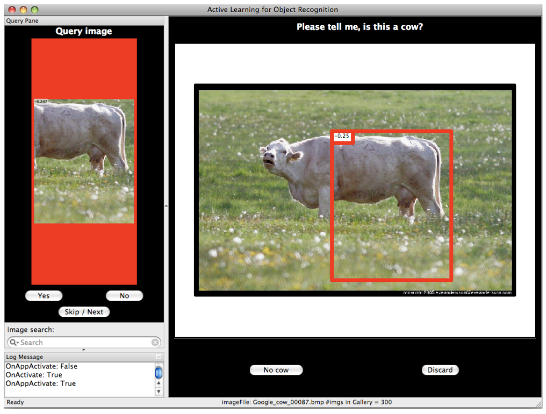
Table 1 summarizes the results and training data statistics. We downloaded in total 60,000 images from Flickr and annotated bounding windows in 300 actively selected images for each category based on uncertainty of the highest scoring detection window of each image. We used the highest scoring detection window for sorting images in order to get as many positive labels as possible from a large unlabelled data pool. We then conducted two simulations. One is a common active learning approach where we answer just 300 query windows based on our uncertainty sampling criteria (ALORquery). The other is a case of fully utilizing our interface where we are allowed to not only answer these 300 query windows but also add user selected query windows (ALORfull). The time required for the human interactive labelling of these 300 image queries was around 20 minutes and less than 40 minutes was required for fully utilizing our interface and giving more annotations for each category.

Figure 5 shows the performance comparison of both ALORquery and ALORfull in a different number of training images. It shows that ALORfull consistently outperforms ALORquery, which indicates that user selected queries improve the overall detection performance. More results in Table 2 demonstrate an impact of user selected queries on the final classification performance. In the table, we show the result of ALORquery with 300 images and ALORfull with 100 and 300 images. For the cases of ALORfull, around 40 % of queries are selected by a user. Those queries are often quite challenging for a ma-



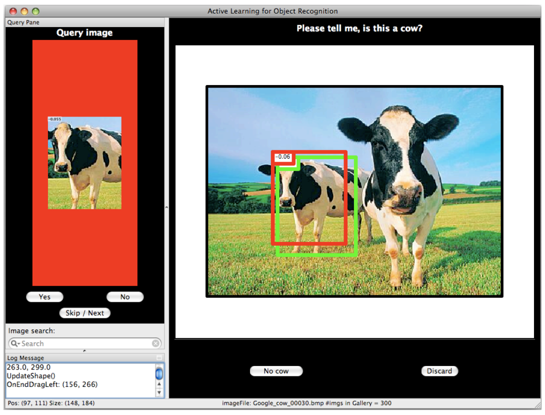
```
Log Message
open image: ../../database/cow/images/
Google_cow_00208.bmp
draw rectangles< time lapse = 0.000871 >
Ready
imageFile: Google_cow_00208.bmp #imgs in Gallery = 300
```

(a) Case 1: YES



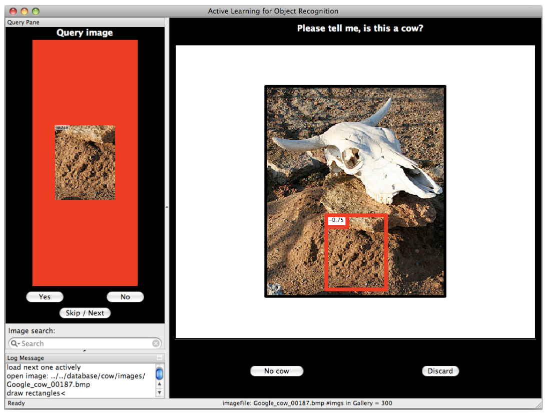
```
Log Message
OnAppActivate: False
OnActivate: True
OnAppActivate: True
Ready
imageFile: Google_cow_00087.bmp #imgs in Gallery = 300
```

(b) Case 2: NO



```
Log Message
263.0, 299.0
UpdateShape()
OnEndDragLeft: (156, 266)
Pos: (97, 111) Size: (148, 184)
imageFile: Google_cow_00030.bmp #imgs in Gallery = 300
```

(c) Case 3: MAYBE



```
Log Message
load next one actively
open image: ../../database/cow/images/
Google_cow_00187.bmp
draw rectangles<
Ready
imageFile: Google_cow_00187.bmp #imgs in Gallery = 300
```

(d) Case 4: No target object

Figure 3: **Screen shots of our interactive labelling system with our actively tranined LSVM** This figure shows a set of screen shots of our interactive labelling system. In each case, the query window to be labelled is shown on the left, and the image from which it was selected is shown on the right (with the query window highlighted in red). (a) shows an instance when the query window is indeed a cow, so the appropriate answer is YES. (b) shows an example bounding window that is not a cow, so the answer is NO. Note that the bounding window partially covers a real cow, so it would not be obtained from the usual approach of labelling negative images. (c) shows a query window where it is hard to decide whether it is a cow, due to being largely occluded, misplaced, or incorporating multiple cows, so the answer is MAYBE, in which case we can just skip the query. (d) shows an instance in which an image does not contain any cow. In such case, a human user can specify that all windows in the image are negative examples and a machine selects only false positive windows. In the case of missed detections, a human user can specify the centroid of the object by clicking on the image and the current classifier suggests the optimally aligned bounding window with the highest classification confidence.

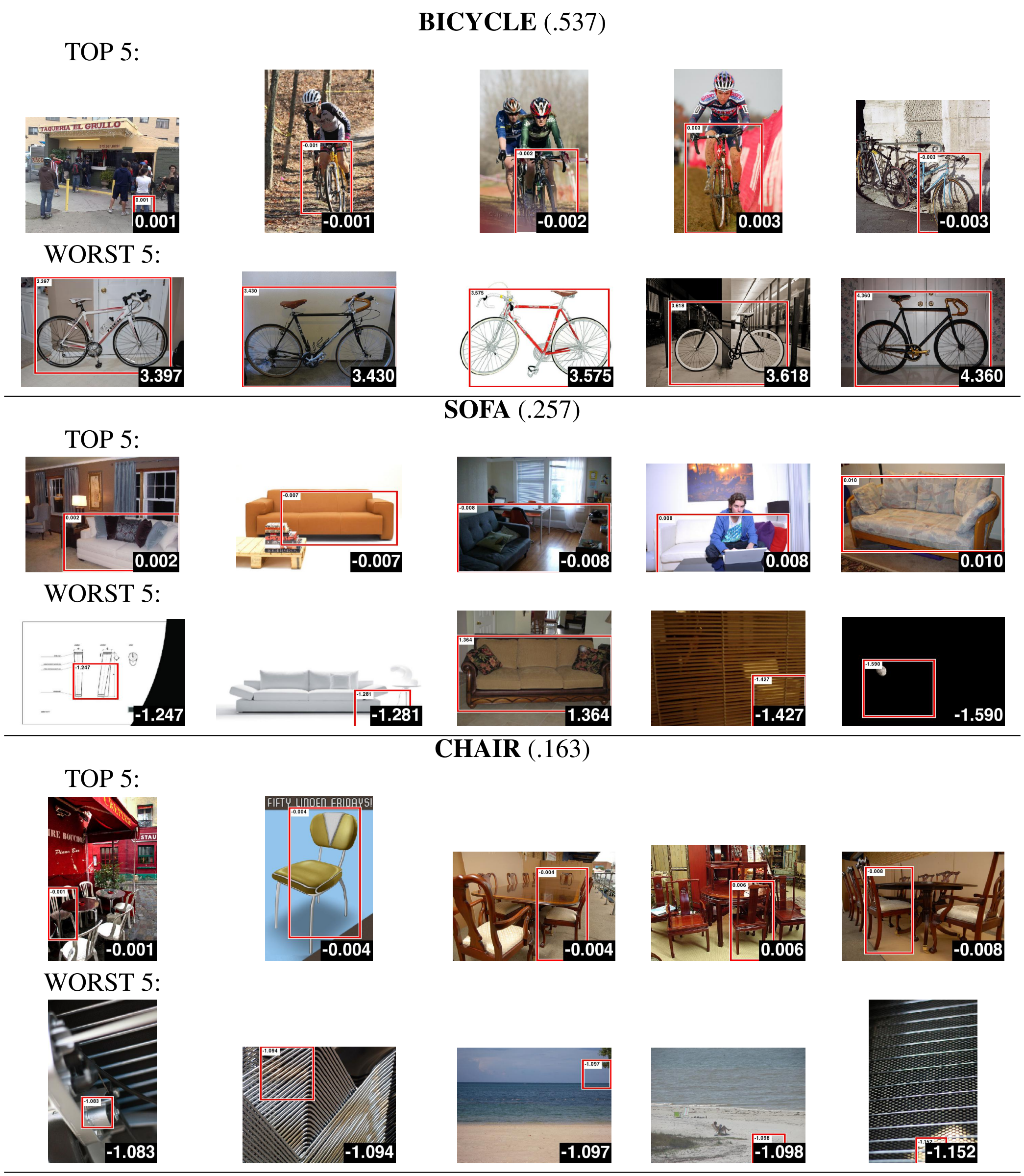


Figure 4: **Training images from Flickr, sorted for active learning** This shows query windows for three categories. For each category, the best 5 and worst 5 actively selected query windows are shown. For each category, we downloaded 3,000 images from the Flickr image search with keywords such as "bicycle", "sofa", and "chair." These web images are then sorted based on the window with the highest classification confidence in each image, as described in Algorithm 1 in Section 3.1. The red box represents the query window for the image with the associated detection score shown at the bottom right corner of the image. Large positive scores indicate high confidence that the object is present, large magnitude negative scores indicate confidence that it is not present, while scores near zero represent maximum uncertainty (are close to the margin). The categories are ordered with the average precision shown next to the category title. Note that the worst 5 query windows in the bicycle category contain target objects that are easily classified, whereas the worst 5 query windows in the chair category do not contain any target objects. In the sofa category with the middle AP score, the worst 5 query windows include ones that contain target objects and ones without.

chine to choose, because they are often either erroneous or missed detections and distant from the decision boundary of a latent SVM. A human oracle is quite helpful in such cases.

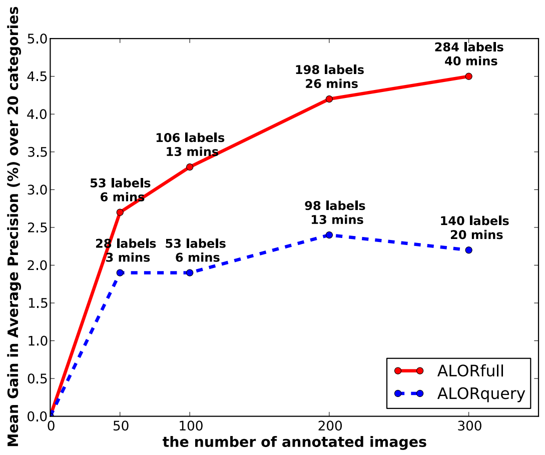


Figure 5: **Performance comparison of ALORfull and ALORquery:** Each point represents the average number of additional positive labels and the average training time per category. By allowing a user to add additional queries, the performance is consistently better. Note that just 53 labels from ALORfull outperform 140 labels from ALORquery.

Fig. 6 presents the gain of our best result for each category in the average precision. From our experiments, we can make several observations. First, in most of the categories, our active learning interface allows a user to quickly improve the performance of the baseline detectors. Second, our user interface also allows a user to achieve a better performance than would be obtained by a simpler learning approach in which a user answers Yes/No/Maybe queries for selected windows. A lot of difficult machine-selected queries that a user is not sure about (Fig. 3(c), for example) can be easily corrected with our interface. Third, with less than 40 minutes of user input, we can achieve significant performance improvement even over the best competition results. The PASCAL competition has a section in which users can provide their own data, but the difficulty of collecting such data means there have seldom been entries in that section. Our active learning approach and GUI would enable users to efficiently collect useful data for improved performance in such competitions or for real world applications.

In the boat, horse and person categories, our active learning approach did not provide much improvement for the relatively small additional amount of training data. We observe that both the boat and horse categories have a particularly heterogeneous dataset in both the size and shape of the object. Some of those examples are presented in Fig. 7. The person category differs in that it already has so many object labels (4690, as opposed to the median 346) that it likely requires many more labels than the few hundred we provide to improve performance.

6 CONCLUSION

We have presented an active learning system for object recognition and localization. This work differs from active learning work for image *classification* in that instead of learning a single classification for the image, our model can identify and localize objects, including multiple instances of the object of interest in a single image. Our experiments demonstrate that the active learning approach reduces the number of labels required to train an object classifier without reducing performance over state-of-the-art classification schemes. It also greatly reduces the human effort required to select image regions containing the object of interest by automatically finding the most useful windows in an image. Our system is fast enough to be used interactively, and we demonstrate a prototype GUI for active learning of object locations, which uses image windows to guide human labelling.

While our experiments show that our actively trained latent-SVM with HOG descriptors works well with active learning, the system does not depend on a specific classifier or feature set. If other classifiers, such as AdaBoost, or features are found to be more suitable to a domain, we can incorporate them into our framework. We also believe that other aspects of object classification can benefit from active learning, as the expense of labelling is a ubiquitous problem in machine learning. Fast, efficient labelling can mean cheaper experiments, faster development time, and higher-performance flexible object detectors.

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	LSVM+HOG		**ALORquery**			**ALORfull**		
			additional labels			additional labels		
	object labels	APs	pos	neg	APs	pos	neg	APs
aerop.	306	.268	209	27	**.283**	293	12	.282
bicyc.	353	.537	227	12	.548	359	26	**.555**
bird	486	.009	72	151	.048	172	134	**.095**
boat	290	.142	87	89	**.144**	162	69	.143
bottle	505	.245	133	100	.259	300	93	**.294**
bus	229	.376	108	26	.435	281	29	**.504**
car	1250	.463	97	104	.468	186	138	**.489**
cat	376	.143	108	3	.209	282	0	**.224**
chair	798	.163	139	66	.161	373	93	**.180**
cow	259	.173	133	63	.184	430	92	**.254**
table	215	.233	164	46	.295	233	67	**.314**
dog	510	.061	130	38	.125	235	33	**.131**
horse	362	**.443**	167	31	.398	321	69	.370
mbike	339	.393	229	8	.414	348	50	**.431**
person	4690	**.344**	47	183	.342	122	218	**.344**
plant	514	.117	136	26	.153	370	15	**.169**
sheep	257	.179	178	25	.257	512	68	**.282**
sofa	248	.196	161	49	.230	212	56	**.257**
train	297	.355	85	73	.354	184	111	**.400**
tvmon	324	.380	195	45	.371	321	69	**.392**
Mean AP		.261			.283			**.306**

Table 1: **Average precision on VOC2007 and training data statistics:** This figure shows the result of our experiments and training data statistics. The first section shows the number of object labels in VOC2007 data and the result obtained by our implementation of the baseline latent-SVM with HOG (Felzenszwalb et al., 2009) on VOC2007 test data (i.e., **LSVM+HOG**). The middle section shows the total number of additional positive and negative labels and the AP score with these additional labels. We obtained the additional data by using models from **LSVM+HOG** and our active learning GUI on only 300 actively selected images (one query per image, 300 queries in total) out of 3000 web images for each category. This represents a common active learning approach with uncertainty sampling criteria where a user is not allowed to add any additional queries and is only queried by a machine (i.e., **ALORquery**). The last section shows additional labels and AP scores on the same 300 actively selected images. But a user is now allowed to fully utilize our interface by not only answering queries from a machine but also adding his/her own queries with our interface (i.e., **ALORfull**). It required only about 20 minutes per class for a person using our interface to improve the results from the first column and takes about 40 minutes to get the best performance improvement shown in the third column. Note that a user selects roughly 100 $\sim$ 200 additional query windows in each category, which are mostly erroneous or missed detections that are never selected by the uncertainty criteria, but effectively presented by our interface. The best AP scores are in bold face and these best scores already exceed the best competition results (of any method) over 17 of 20 categories from VOC2007 (Everingham et al., 2007). The bottom row shows the mean AP score of all categories for each method.

Method	Avg. Training Time (mins)	user selected queries		machine selected queries		Avg. additional labels		Mean AP (%)
		proportion (%)	Avg. distance	proportion (%)	Avg. distance	pos	neg	
ALORquery 300 images	20	0	NA	100	0.283	140.1	58.25	28.3
ALORfull 100 images	13	42	0.643	58	0.200	106.85	20.15	29.4
ALORfull 300 images	40	43	0.690	57	0.296	284.8	72.1	30.6

Table 2: **Query statistics for ALORquery and ALORfull:** The average distance represents the average distance per query to the decision boundary of a latent SVM. The average training time, additional labels, and mean APs are measured per category. The proportion of queries is the portion of the total number of queries in all 20 categories. Note that how user-selected queries influence on the final performance in average precision.

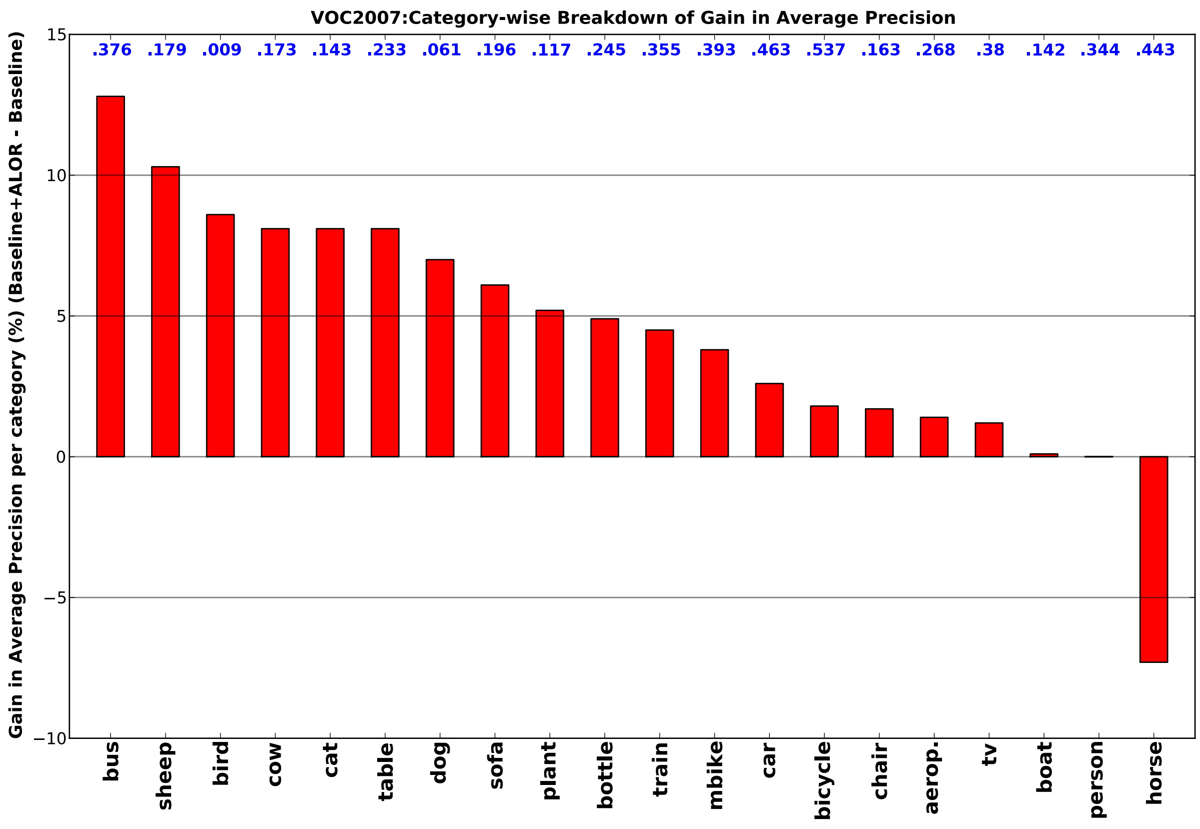

Figure 6: **Category-wise breakdown of gain in average precisions: VOC baseline vs VOC baseline + ALOR.** This figure shows the improvement for our active learning framework for each category.

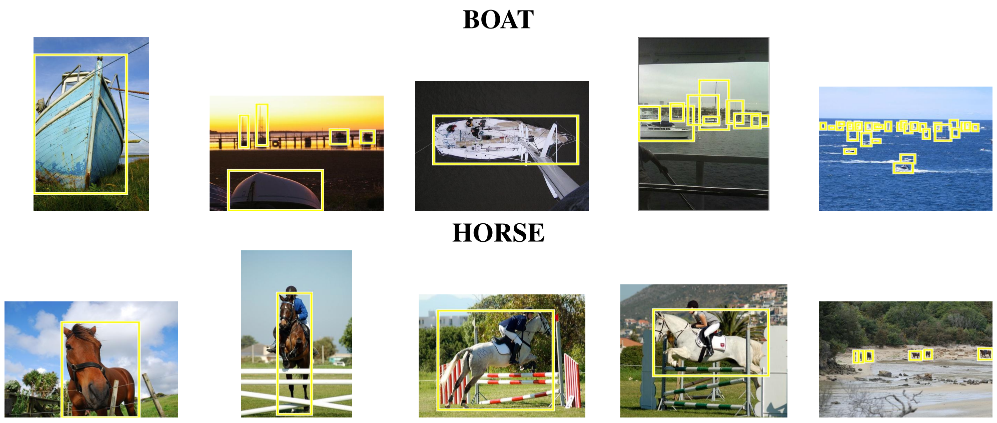

Figure 7: **Heterogeneous shapes and sizes.** This shows screen shots of VOC test images. The shots in the top row are for the boat category and these in the bottom row are for the horse category. Yellow boxes are ground truth.

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