Improved Boosting Performance by Exclusion of Ambiguous Positive Examples

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Abstract: In visual object class recognition it is difficult to densely sample the set of positive examples. Therefore, frequently there will be areas of the feature space that are sparsely populated, in which uncommon examples are hard to disambiguate from surrounding negatives without overfitting. Boosting in particular struggles to learn optimal decision boundaries in the presence of such hard and ambiguous examples. We propose a two-pass dataset pruning method for identifying ambiguous examples and subjecting them to an exclusion function, in order to obtain more optimal decision boundaries for existing boosting algorithms. We also provide an experimental comparison of different boosting algorithms on the VOC2007 dataset, training them with and without our proposed extension. Using our exclusion extension improves the performance of all the tested boosting algorithms except TangentBoost, without adding any additional test-time cost. In our experiments LogitBoost performs best overall and is also significantly improved by our extension. Our results also suggest that outlier exclusion is complementary to positive jittering and hard negative mining.

1 INTRODUCTION

Recent efforts to improve image classification performance have focused on designing new discriminative features and machine learning methods. However, some of the performance gains of many well-established methods are due to dataset augmentation such as hard negative mining, positive mirroring and jittering (Felzenszwalb et al., 2010; Dalal and Triggs, 2005; Laptev, 2009; Kumar et al., 2009). These data-bootstrapping techniques aim at augmenting sparsely populated regions of the dataset to allow any learning method to describe the class distributions more accurately, and they have become standard tools for achieving state-of-the-art performance for classification and detection tasks. In this paper we revisit the dataset augmentation idea, arguing and showing that pruning the positive training set by excluding hard-to-learn examples can improve performance for outlier-sensitive algorithms such as boosting.

We focus on the boosting framework and propose a method to identify and exclude positive examples that a classifier is unable to learn, to make better use of the available training data rather than expanding it. We refer to the non-learnable examples as outliers and we wish to be clear that these examples are not label noise (such as has been studied in (Long and Servedio, 2008; Masnadi-shirazi and Vasconcelos, 2008; Leistner et al., 2009)), but rather examples that with a given feature and learner combination are ambiguous and too difficult to learn.

One of the main problems with most boosting methods is their sensitivity to outliers such as atypical examples and label noise (Bauer and Kohavi, 1999; Dietterich, 2000; Freund and Science, 2009; Long and Servedio, 2008). Some algorithms have tried to deal with this problem explicitly (Freund, 1999; Freund and Science, 2009; Masnadi-Shirazi et al., 2010; Grove and Schuurmans, 1998; Warmuth et al., 2008; Masnadi-shirazi and Vasconcelos, 2008), while others, such as LogitBoost (Friedman et al., 2000) are less sensitive due to their softer loss function.

The boosting methods with aggressive loss functions give outliers high weight when fitting the weak learner, and therefore potentially work poorly in the presence of outliers. Softer loss function as seen in the robust algorithms can on the other hand result in low weights for all examples far from the margin, regardless if they are noisy outliers or just data to which the current classifier has not yet been able to fit. This can be counter-productive in cases of hard inliers, which is illustrated in figure 2(a). Another problem that soft loss functions are not able to solve is that outliers are still able to affect the weak learners during the early

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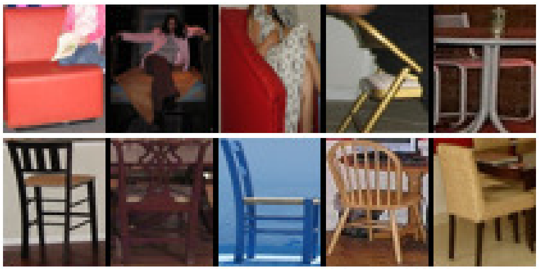


(a) Chair class

(b) Bottle class

Figure 1: **Examples of outliers and inliers.** The top rows of (a) and (b) show outliers while the bottom rows show inliers. We focus on how to detect the outliers and how their omission from training improves test results. The images are from the VOC2007 dataset.

stages of the training, which due to the greedy nature of boosting can only be undone later on by increasing the complexity of the final classifier.

In this paper we provide an explicit analysis on how various boosting methods relate to examples via their weight functions and we argue that a distinct separation in the handling of inliers and outliers can help solve these problems that current robust boosting algorithms are facing.

Following this analysis we propose our two pass boosting algorithm extension, that explicitly handles learnable and non-learnable examples differently. We define outliers as examples that are too hard-to-learn for a given feature and weak learner set, and identify them based on their classification score after a first training round. A second round of training is performed, where the outliers are subjected to a much softer loss function and are therefore not allowed to interfere with the learning of the easier examples, in order to find a better optimum. This boosting algorithm extension consistently gives better test performance, with zero extra test-time costs at the expense of increased training time. Some examples of found inliers and outliers can be seen in figure 1.

1.1 Relation to Bootstrapping Methods

To further motivate our data-centric approach to learning, we illustrate the problems that different dataset augmentation techniques address. In regions where the positive training examples are dense and the negatives are existent but sparse, hard negative mining might improve the chances of finding the optimal decision boundary. In regions where positives are sparse and negatives existent, jittering and mirroring might have some effect, but the proper analogue to hard negative mining is practically much harder, since positive examples need to be labelled. At some scale this can be done by active learning (Vijayanarasimhan, 2011), where labelling is done iteratively on selected examples. Our approach tries to handle the regions where positives are sparse but additional hard positive mining is not possible, either due to limited resources or because all possible positive mining has already been done. We address this problem by restricting hard-to-learn positives from dominating the training with their increasingly high weights by excluding them from the training.

Our algorithm can be considered as dataset pruning and makes us face the philosophical question of more data vs. better data. It has been shown that in cases where huge labelled datasets are available, even simple learning methods perform very well (Shotton et al., 2011; Torralba et al., 2008; Hays and Efros, 2007). We address the opposite case, where a huge accurately labelled data set cannot be obtained - a common scenario both in academic and industrial computer vision.

1.2 Contributions

We propose a two-pass boosting extension algorithm, suggested by a weight-centric theoretical analysis of how different boosting algorithms respond to outliers. We also demonstrate that it is important to distinguish between ”hard-to-learn” examples and ”non-learnable” outliers in vision as examples easily identified as positive by humans could be non-learnable given a feature and weak-learner set, and demonstrate that the different classes in VOC2007 dataset indeed have different fractions of hard-to-learn examples using HOG as base feature. Finally we provide extensive experimental comparison of different boosting algorithms on real computer vision data and perform experiments using dataset augmentation techniques, showing that our method is complementary to jittering and hard negative mining.

2 RELATION TO PREVIOUS WORK

As previously mentioned AdaBoost has been shown to be sensitive to noise (Bauer and Kohavi, 1999; Dietterich, 2000). Other popular boosting algorithms such as LogitBoost or GentleBoost (Friedman et al., 2000) have softer loss functions or optimization methods and can perform better in the presence of noise in the training data, but they have not been specifically designed to handle this problem. It has been argued that no convex-loss boosting algorithm is able to cope with random label noise (Long and Servedio, 2008). This is however not the problem we want to address, as we focus on naturally occurring outliers and ambiguous examples, which is a significant and interesting problem in object detection today.

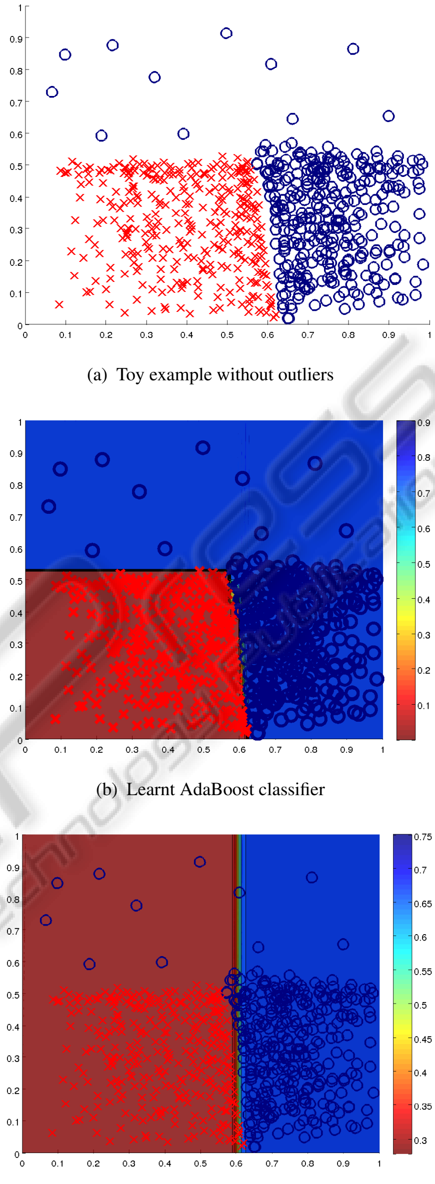
BrownBoost (Freund, 1999) and RobustBoost (Freund and Science, 2009) are adaptive extensions of the Boost-By-Majority Algorithm (Freund, 1995) and have non-convex loss functions. Intuitively these algorithms "give up" on hard examples and this allows them to be less affected by erroneous examples.

Regularized LPBoost, SoftBoost and regularized AdaBoost (Warmuth et al., 2008; Rätsch et al., 2001) regularize boosting to avoid overfitting to highly noisy data. These methods add the concept of soft margin to boosting by adding slack variables in a similar fashion to soft-margin SVMs, and this decreases the influence of outliers. Conceptually these methods bear some similarity to ours as the slack variables reduce the influence of examples on the wrong side of the margin, and they define an upper bound on the fraction ν of misclassified examples, which is comparable to the fraction of the dataset excluded in the second phase of training.

There is recent work on robust boosting where new semi-convex loss functions are derived based on probability elicitation (Masnadi-Shirazi et al., 2010; Masnadi-shirazi and Vasconcelos, 2008; Leistner et al., 2009). These methods have shown potential for high-noise problems such as tracking, scene recognition and artificial label noise. But they have not been extensively compared to the common outlier-sensitive algorithms on low-noise problems, such as object classification, where the existing outliers are ambiguous or uncommon examples, rather than actual label errors.

In all the mentioned robust boosting algorithms the outliers are estimated and excluded on the fly and these outliers are therefore able to affect the training in the early rounds. Also, as can be seen in figure 2, these algorithms can treat uncommon non-outliers as conservatively as actual outliers, resulting in suboptimal decision boundaries.

Reducing overfitting by pruning the training set has been studied previously (Vezhnevets and Barinova, 2007; Angelova et al., 2005) but improved results have mostly been seen in experiments where training sets include artificial label noise. (Vezhnevets and Barinova, 2007) is the only method that we have found where pruning improves performance on a "clean" dataset. (Vezhnevets and Barinova, 2007) use an approach very similar to ours, detecting hard-to-learn examples, then removing those examples from training. The base algorithm to which (Vezhnevets and Barinova, 2007) apply dataset pruning is Ad-



(a) Toy example without outliers

(b) Learnt AdaBoost classifier

(c) Learnt RobustBoost classifier

Figure 2: **Example with hard inliers.** This toy problem shows how less dense, but learnable examples do not contribute to the decision boundary when learned using RobustBoost. The colour coding represents estimated probability $p(y=1|x)$. (Best viewed in colour.)

aBoost, which we show is the most noise-sensitive boosting algorithm and not the one that should be used for image classification. When comparing to a more robust boosting algorithm the robust non-pruned algorithm (MadaBoost) that they use and the pruned AdaBoost turn out to be roughly equivalent. The results show 5-4 in wins and 15.109% vs. 15.044% in average test error when using 100 weak learners. To get an improvement using their method they have to push the learning beyond the limit of overfitting by training a huge number of weak learners (13-300 weak learners per available data dimension). We propose a similar but more direct approach that improves results for both robust and non-robust algorithms, while still using a reasonable number of weak learners.

Also it is important to note that vision data is typically very high-dimensional and boosting therefore also acts as feature selection - learning much fewer weak learners than available dimensions. Due to the mentioned differences between vision and machine learning datasets, it is not easy to directly transfer the results from (Vezhnevets and Barinova, 2007) to vision without experimental validation. Our experiments on the VOC2007 dataset verify that exclusion of ambiguous examples, as seen in our paper and in (Vezhnevets and Barinova, 2007), translates well to the high-dimensional problems found in computer vision. We also compare a number of well-known boosting algorithms using typical vision data, something that we have not seen previously.

A different but related topic that deals with label ambiguity is Multiple Instance Learning (MIL). Viola et al. (Viola and Platt, 2006) suggest a boosting approach to the MIL problem, applying their solution to train an object detector with highly unaligned training data.

Our idea is also conceptually similar to a simplified version of self-paced learning (Kumar and Packer, 2010). We treat the hard and easy positives separately and do not let the hard examples dominate the easy ones in the search for the optimal decision boundary. This can seen as a heavily quantized version of presenting the examples to the learning algorithm in the order of their difficulty.

3 BOOSTING THEORY

Boosted strong classifiers have the form $H_m(x) = \sum_i^m \alpha_i h(x;\beta_i)$, where $h(x)$ is a weak learner, with multiplier α_i and parameters β_i. To learn such a classifier one wishes to minimize the average loss $\frac{1}{N}\sum_{j=1}^N L(H(x_j),y_j)$ over the N input data points (x_j,y_j) where each data label $y_j \in \{-1,1\}$. Learning the classifier that minimizes the average loss by an exhaustive search is infeasible, so boosting algorithms do this in a greedy stepwise fashion. At each iteration the strong classifier is extended with the weak learner that minimizes the loss given the already learned strong classifier

$$\alpha^*,\beta^* = \underset{\alpha,\beta}{\operatorname{argmin}} \frac{1}{N}\sum_{j=1}^{N} L(H_m(x_j)+\alpha h(x_j;\beta),y_j). \tag{1}$$

Equation 1 is solved by weighting the importance of the input data by a weight function $w(x,y)$ when learning α and β. This $w(x_j,y_j)$ represents how poorly the current classifier $H_m(x_j)$ is able to classify example j.

Different boosting algorithms have different losses and optimizations procedures, but the key mechanism to their behaviour and handling of outliers is the weight function $w(x,y)$. For this reason we believe that analyzing the weight functions of different losses give an insight to how different boosting algorithms behave in the presence of hard and ambiguous examples. So in order to compare a number of boosting algorithms in a consistent framework we rederive $w(x,y)$ for each of the algorithms by following the GradientBoost approach (Friedman, 2001; Mason et al., 1999).

The GradientBoost approach view boosting as a gradient based optimization of the loss in function space. According to the GradientBoost framework a boosting algorithm can be constructed from any differentiable loss function, where each iteration is a combination of a least squares fitting of a weak regressor $h(x)$ to a target $w(x,y)$

$$\beta^* = \underset{\beta}{\operatorname{argmin}} \left(\sum_j (w(x_j,y_j)-h(x_j;\beta))^2 \right), \tag{2}$$

and a line search $\alpha = \operatorname{argmin}_\alpha (L(H(x)+\alpha h(x;\beta)))$ to obtain α. The loss function is derived with respect to the current margin $v(x,y) = yH(x)$ to obtain the negative target function

$$w(x,y) = -\frac{\partial L(x,y)}{\partial v(x,y)}. \tag{3}$$

Equation 2 can then be interpreted as finding the weak learner that points in the direction of the steepest gradient of the loss, given the data.

3.1 Convex-loss Boosting Algorithms

3.1.1 Exponential Loss Boosting

AdaBoost and GentleBoost (Freund and Schapire, 1995; Friedman et al., 2000) are the most notable algorithms with the exponential loss

$$L_e(x,y) = \exp\left(-v(x,y)\right). \quad (4)$$

AdaBoost uses weak classifiers for $h(x)$ rather than regressors and directly solves for α, while GentleBoost employs Newton-step optimization for the expected loss. In the original algorithms $w(x,y)$ is exponential and comes in via the weighted fitting of $h(x)$, but we obtain

$$w_e(x,y) = \exp\left(-v(x,y)\right), \quad (5)$$

from the GradientBoost approach to align all analyzed loss functions in the same framework. $w_e(x,y)$ has a slightly different meaning than the weight function of the original algorithms since it is the target of a non-weighted fit, rather than the weight of a weighted fit. However, its interpretation is the same - the importance function by which an example is weighted for the training of the weak learner $h(x)$. Also, it should be noted that we have omitted implementation-dependent normalization of the weight function.

3.1.2 Binomial Log-likelihood Boosting

LogitBoost is a boosting algorithm that uses Newton stepping to minimize the expected value of the negative binomial log-likelihood

$$L_l(x,y) = \log\left(1 + \exp\left(-2v(x,y)\right)\right). \quad (6)$$

This is potentially more resistant to outliers than AdaBoost or GentleBoost as the binomial log-likelihood is a much softer loss function than the exponential one (Friedman et al., 2000).

Since the original LogitBoost optimizes this loss with a series of Newton steps, the actual importance of an example is distributed between a weight function for the weighted regression and a target for the regression - both varying with the margin of the example. We derive $w(x,y)$ by applying the GradientBoost approach to the binomial log-likelihood loss function to collect the example weight in one function

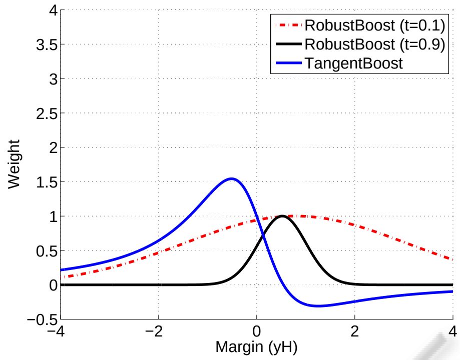
$$w_l(x,y) = \frac{1}{1 + \exp\left(v(x,y)\right)}. \quad (7)$$

Figure 3(b) shows the different weight functions and suggests that LogitBoost should be affected less by examples far on the negative margin than the exponential-loss algorithms.

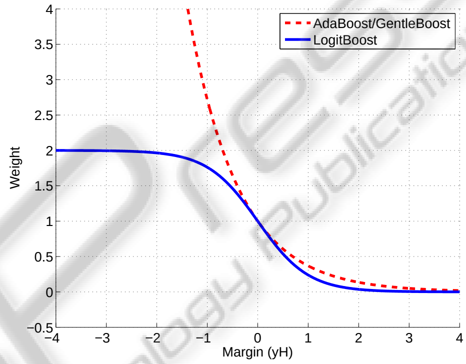
3.2 Robust Boosting Algorithms

3.2.1 RobustBoost

RobustBoost is specifically designed to handle outliers (Freund and Science, 2009). RobustBoost, a



(a) Robust weight function



(b) Weight functions

Figure 3: **Weight functions with respect to the margin.** This illustrates how much examples at different distances from the margin are able to affect the decision boundary for the different algorithms. In the GradientBoost formulation, TangentBoost's penalty for too correct examples results in negative weights.

variation of BrownBoost, is based on the Boost-by-Majority algorithm and has a very soft and non-convex loss function

$$L_r(x,y,t) = 1 - \operatorname{erf}\left(\frac{v(x,y) - \mu(t)}{\sigma(t)}\right), \quad (8)$$

where $\operatorname{erf}(\cdot)$ is the error function, $t \in [0,1]$ is a time variable and $\mu(t)$ and $\sigma(t)$ are functions

$$\sigma^2(t) = (\sigma_f^2 + 1)\exp\left(2(1-t)\right) - 1 \quad (9)$$

$$\mu(t) = (\theta - 2\rho)\exp\left(1-t\right) + 2\rho, \quad (10)$$

with parameters θ, σ_f and ρ. Equation 8 is differentiated with respect to the margin to get the weight function

$$w_r(x,y,t) = \exp\left(-\frac{\left(v(x,y) - \mu(t)\right)^2}{2\sigma(t)^2}\right). \quad (11)$$

Figure 3(a) shows equation 11 for some values of t. From these we can see the RobustBoost weight function changes over time. It is more aggressive in the beginning and as $t \to 1$, it focuses less and less on examples far away from the target margin θ. One interpretation is that the algorithm focuses on all examples early in the training stage, and as the algorithm progresses it starts ignoring examples that it has not been able to push close to the target margin.

RobustBoost is self-terminating in that it finishes when $t \geq 1$. In our experiments we follow Freund's example and set $\sigma_f = 0.1$ to avoid numerical instability for t close to 1 and we obtain the parameters θ and ρ by cross-validation.

3.2.2 TangentBoost

TangentBoost was designed to have a positive bounded loss function for both positive and negative large margins, where the maximum loss for large positive margins is smaller than for large negative margins (Masnadi-Shirazi et al., 2010). To satisfy these properties the method of probability elicitation (Masnadi-shirazi and Vasconcelos, 2008) is followed to define TangentBoost having a tangent link function

$$f(x) = \tan(p(x) - 0.5), \tag{12}$$

and a quadratic minimum conditional risk

$$C_L^*(x) = 4p(x)(1 - p(x)), \tag{13}$$

where $p(x) = \arctan(H(x)) + 0.5$. is the intermediate probability estimate. Combining the above equations results in the Tangent loss

$$L_t(x,y) = (2\arctan(v(x,y)) - 1)^2. \tag{14}$$

We immediately see that the theoretical derivation of TangentBoost and its implementation may have to differ as the probability estimates $p(x) \in [-\pi/2 + 0.5, \pi/2 + 0.5]$ are not proper, so that we only have proper probabilities $p(x) \in [0,1]$ for $|H(x)| < 0.546$. This means that $|H(x)| > 0.546$ has to be handled according to some heuristic, which is not presented in the original paper (Masnadi-Shirazi et al., 2010). In the original paper the Tangent loss is optimized through Gauss steps, which similarly to LogitBoost divides the importance of examples into two functions. So as with the other algorithms we re-derive $w_t(x,y)$ by using the GradientBoost method, and obtain

$$w_t(x,y) = -\frac{4(2\arctan(v(x,y)) - 1)}{1 + (v(x,y))^2}. \tag{15}$$

As seen in figure 3(a) this weight function gives low weights for examples with large negative margin, but it also penalizes large positive margins by assigning negative weight to very confident examples. Since $w_t(x,y)$ is actually the regression target this means that the weak learner tries to fit very correct examples to an incorrect label. It should be noted that the Tangent loss is not optimized through the GradientBoost method in the original paper, but through Gauss-Newton stepping and that the region of negative weights actually results in intermediate probability estimates above 1.

4 A TWO-PASS EXCLUSION EXTENSION

Our main point is that some fraction of the data, that is easy to learn with a given feature and weak-learner set, defines the core shape of the class - we call these examples inliers. Then there are examples that are ambiguous or uncommon so that they cannot be properly learned given the same representation, and trying to do so might lead to overfitting, creating artefacts or forcing a poorer definition of the shape of the core of the class. We call these examples non-learnable or outliers and illustrate their effect on training in figure 4. It is important to note that there might be hard examples with large negative margin during some parts of training, but that eventually get learned without overfitting. We refer to these examples as hard inliers, and believe they are important for learning a well performing classifier.

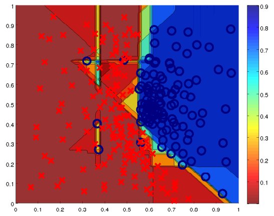
Figure 4 illustrates that even if robust algorithms are better at coping with outliers, they are still negatively affected by them in two ways; The outliers still have an effect on the decision boundary learnt, even if their effect is reduced. Hard inliers are also subject to the robust losses, thus having less influence over the decision boundary than for non-robust losses, illustrated in figure 2.

We propose that outliers and inliers should be identified and handled separately so that the outliers are only allowed to influence the training when already close to the decision boundary and therefore can be considered as part of the core shape of the class. This can be achieved with a very soft loss function, such as the logistic loss or the Bayes consistent Savage loss (Masnadi-shirazi and Vasconcelos, 2008). We use the logistic loss, since the Savage loss gives more importance to slightly misclassified examples, rather than being symmetric around the margin.

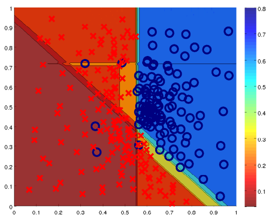
Differentiating the logistic loss

$$L_s(x,y) = \frac{1}{1 + \exp(-\eta v(x,y))}, \tag{16}$$

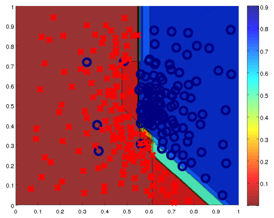
with respect to the margin results in the weight func-



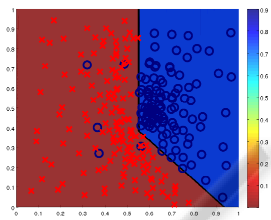
(a) AdaBoost



(b) TangentBoost



(c) RobustBoost



(d) AdaBoost with two-pass method

Figure 4: **Example with five outliers.** The decision boundaries the different algorithms produce in the presence of a few outliers. The colour coding represents estimated probability $p(y=1|x)$. We can see how AdaBoost overfits to the outliers, TangentBoost overfits slightly less and RobustBoost is able to handle the problem, even if it is less certain around the boundary. Applying the two-pass method to this problem results in a decision boundary that completely ignores the outliers. (Best viewed in colour.)

tion

$$w_{excl}(x,y) = \eta\sigma(-\eta v(x,y))\sigma(\eta v(x,y)) \quad (17)$$

where $\sigma(\cdot)$ is the sigmoid function. This weight function can be made arbitrarily thin by increasing the η parameter. We call this function the *exclusion function*, as its purpose is to exclude outliers from training.

Since the inlier examples are considered learnable we want the difficult examples in the inlier set to have high weight, according to the original idea of boosting. For this reason all inliers should be subjected to a more aggressive loss such as the exponential loss or the binomial log-likelihood loss.

The main challenge is to identify the outliers in a dataset. To do this we follow our definition of outliers as non-learnable and say that they are the examples with the lowest confidence after completed training. We therefore define the steady-state difficulty $d(x_j)$ of the examples as their negative margin $-v(x_j, y_j)$ after a fully completed training round, and normalize to get non-zero values.

$$d(x_j) = \begin{cases} \max(H(x)) - H(x_j) & \text{if } y_j = 1 \\ H(x_j) - \min(H(x)) & \text{if } y_j = -1, \end{cases} \quad (18)$$

where $H(x_j)$ is the classification score of example j. This is referred to as the first pass.

We order the positive examples according to their difficulty $d(x_j)$ and re-train the classifier, assigning a fraction δ of the most difficult examples to the outlier set and subjecting them to the logistic loss function. This second iteration of training is what we call the second pass. Figure 1 shows some inlier and outlier examples for the bottle and chair classes. As we have mentioned, what will be considered an outlier depends on the features used. We use HOG in our experiments (Dalal and Triggs, 2005), so it is expected that the tilted bottles and the occluded ones are considered outliers, since HOG cannot capture such variation well.

As previously mentioned, our model for outlier exclusion has two parameters: δ and η, where δ controls how many examples will be considered as outliers and η controls how aggressively the outlier examples will be down-weighted. In our experiments we choose a large value for η - effectively ignoring outliers completely in the second round. The actual fraction of outliers is both class and feature dependent, so δ needs to be properly tuned. We tune δ by cross-validation, yet we have noticed that simple heuristics seem to work quite well too. Figure 5 shows how the performance is affected by δ for three different classes. We can clearly see that different classes have different optimal values for δ, which is related to the number of outliers in their datasets, given the used features and learners.

5 EXPERIMENTS

We perform experiments on a large number of classes to reduce the influence of random performance fluctuations. For this reason, and due to the availability of a test set we select the VOC2007 dataset for

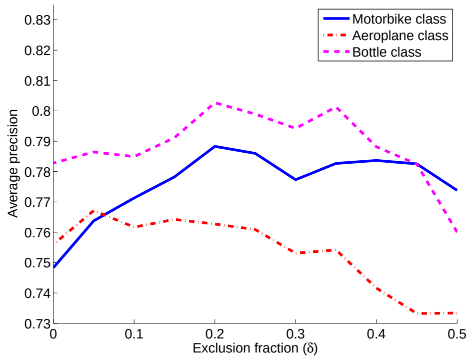


Figure 5: **Performance for different exclusion fractions δ.** Average precision on the test set, using the two-pass extension with LogitBoost for different exclusion fractions δ and different classes. This figure illustrates that different classes have different optimal exclusion fractions δ.

our experiments. Positive examples have bounding-box annotations, so we crop and resize all positive examples to have the same patch size. Since our main focus is to investigate how our two-pass exclusion method improves learning, we want to minimize variance or tweaking in the areas not related to learning, and therefore choose a static non-deformable feature. We use the HOG descriptor (Dalal and Triggs, 2005) to describe the patches, since it has shown good performance in the past, is popular within the vision community, and its best parameter settings have been well established.

To get the bounding boxes for the negative examples, we generate random positions, widths and heights. We make sure that box sizes and aspect ratios are restricted to values that are reasonable for the positive class. Image patches are then cropped from the negative training set according to the generated bounding boxes. The patches are also resized to have the same size as the positive patches, after which the HOG features are computed. We then apply our two-pass training procedure described in section 4 to train a boosted stump classifier.

We train boosted stumps using four different boosting algorithms: AdaBoost, LogitBoost, RobustBoost and TangentBoost. AdaBoost and LogitBoost are chosen for their popularity and proliferation in the field, and RobustBoost and TangentBoost are chosen as they explicitly handle outliers. We also train an SVM classifier to use as reference.

For LogitBoost, AdaBoost and TangentBoost there are no parameters to be set. For RobustBoost two parameters have to be tuned: the error goal ρ and the target margin θ. We tune them by holdout cross-validation on the training set. With TangentBoost we encountered an implementation issue, due to the possibility of negative weights and improper probability estimates. After input from the author of (Masnadi-Shirazi et al., 2010) we manually truncate the probability estimates to make them proper. Unfortunately this forces example weights to zero for margins $|v(x,y)| > 0.546$, which gives poor results as this quickly discards a large portion of the training set. To cope with this and to obtain reasonable performance we lower the learn rate of the algorithm. The linear SVM is trained with *liblinear* (Fan et al., 2008), with normalized features and using 5-fold cross-validation to tune the regularization term C.

Jittering the positive examples is a popular way of bootstrapping the positive dataset, but we believe that this can also generate examples that are not representative of that class. For this reason our two-pass approach should respond well to jittered datasets. We therefore redo the same experiments for the best performing classifier, augmenting the positive sets by randomly generating 2 positive examples per labelled positive example, with small random offsets in positions of the bounding box. We also mine for hard negatives to get a complete picture of how the outlier exclusion extension interacts with bootstrapping methods.

6 RESULTS

A summary of our results is that all boosting algorithms except TangentBoost show consistent improvements for the experiments using our two-pass extension, which can be seen in table 1. Before employing our two-pass extension LogitBoost performs best with 11 wins over the other algorithms. After the two-pass outlier exclusion LogitBoost dominates even more with 15 wins over other outlier-excluded algorithms and 13 wins over all other algorithms, including LogitBoost without outlier exclusion.

6.1 Comparison of Boosting Algorithms

Table 1 also includes a comparison of the performance between algorithms, showing performance differences with and without the outlier exclusion. Among the convex-loss algorithms LogitBoost performs better than AdaBoost. The difference in performance shrinks when our two-pass method is applied, which suggests that naturally occurring outliers in real-world vision data affects the performance of boosting algorithms and that those better able to cope with such outliers have a greater potential for good performance.

Even so, the robust algorithms perform worse than LogitBoost. One reason for this could be that the ro-

Table 1: **Performance of our experiments.** Average Precisions of different classifiers, when applied to the VOC2007 test set. The red box on each row indicates the best performing classifier for the object class. Boldface numbers indicate best within-algorithm-performance for excluding outliers or not. Red cells indicate total best performance for a given class. *Wins within algorithm (WWA)* summarizes how often a learning method is improved by our extension, and *Wins between algorithms (WBA)* summarizes how often an algorithm outperforms the others when having the same strategy for handling outliers. Note that these results cannot be directly compared to results from the original VOC2007 challenge since we are performing image patch classification, using the annotated bounding boxes to obtain positive object positions.

	mean Average Precision for each Algorithm														
	Adaboost			LogitBoost			RobustBoost			TangentBoost			Linear SVM		
Class	Use all	Exclude	Diff	Use all	Exclude	Diff	Use all	Exclude	Diff	Use all	Exclude	Diff	Use all	Exclude	Diff
plane	**74.27**	73.87	−0.40	73.13	**74.09**	0.97	**72.49**	72.23	−0.27	**73.86**	72.88	−0.98	**74.04**	72.01	−2.03
bike	87.59	**88.24**	0.66	87.85	**88.43**	0.58	86.86	**87.98**	1.12	**86.81**	86.80	−0.01	**85.12**	84.47	−0.66
bird	46.69	**48.14**	1.45	48.08	**49.87**	1.79	46.66	**48.69**	2.03	46.97	**49.45**	2.48	**46.67**	46.32	−0.34
boat	57.33	**58.96**	1.63	59.01	**60.81**	1.80	57.92	**58.31**	0.39	**58.61**	58.02	−0.59	**57.00**	56.94	−0.06
bottle	74.57	**78.56**	3.99	76.02	**80.00**	3.98	72.74	**78.94**	6.20	76.79	**78.32**	1.53	76.22	**76.97**	0.75
bus	**86.79**	86.18	−0.62	86.54	**86.96**	0.42	83.86	**86.82**	2.96	85.97	**86.26**	0.29	**82.07**	81.85	−0.22
car	87.05	**87.73**	0.68	**88.32**	**88.32**	0.00	**88.26**	88.14	−0.11	**88.34**	88.30	−0.04	**86.22**	85.93	−0.29
cat	**49.45**	49.18	−0.27	50.15	**52.44**	2.29	48.30	**52.21**	3.91	45.93	**50.90**	4.97	45.45	**45.48**	0.02
chair	67.68	**69.36**	1.68	68.26	**69.93**	1.66	66.06	**68.91**	2.85	67.42	**68.09**	0.67	**64.08**	63.94	−0.14
cow	81.90	**83.25**	1.35	81.99	**83.85**	1.87	81.83	**82.71**	0.87	**81.50**	80.63	−0.87	82.01	**82.44**	0.43
table	40.89	**44.50**	3.61	43.68	**47.91**	4.24	39.89	**46.26**	6.37	**47.52**	36.34	−11.18	**28.35**	28.09	−0.26
dog	47.83	**51.56**	3.73	51.27	**51.68**	0.41	47.66	**52.24**	4.58	**51.25**	50.21	−1.04	46.16	**46.94**	0.78
horse	76.09	**76.10**	0.01	78.83	**78.84**	0.01	77.72	**78.28**	0.56	75.20	**76.20**	1.00	75.55	**75.77**	0.21
motorbike	74.15	**77.15**	3.00	77.39	**78.33**	0.94	76.75	**79.20**	2.45	75.16	**75.46**	0.30	**73.31**	72.56	−0.76
person	58.56	**63.64**	5.08	65.16	**67.03**	1.87	60.17	**65.09**	4.92	66.04	**67.02**	0.98	60.86	**61.84**	0.98
plant	**58.08**	57.60	−0.48	60.46	**60.51**	0.04	56.87	**59.62**	2.75	**59.28**	58.23	−1.05	58.42	**58.90**	0.48
sheep	80.60	**84.41**	3.81	81.59	**83.11**	1.53	**80.78**	80.11	−0.66	**84.38**	82.01	−2.37	80.07	**80.17**	0.10
sofa	61.83	**66.28**	4.44	62.35	**66.66**	4.31	63.92	**67.81**	3.89	56.73	**63.06**	6.33	**62.33**	62.18	−0.15
train	73.18	**76.91**	3.74	73.98	**76.74**	2.75	73.13	**77.26**	4.13	73.87	**74.74**	0.87	71.82	**72.10**	0.28
tv	**92.11**	**92.11**	0.00	**92.57**	**92.57**	0.00	**91.97**	**91.97**	0.00	**91.69**	**91.69**	0.00	**91.28**	**91.28**	0.00
mean	68.83	**70.69**	1.85	70.33	**71.90**	1.57	68.69	**71.14**	2.45	69.67	**69.73**	0.06	**67.35**	67.31	−0.04
WWA	4	15	-	0	18	-	3	16	-	9	10	-	10	9	-
WBA	2	1	-	11	15	-	1	4	-	5	0	-	1	0	-

Table 2: **Outlier exclusion with other dataset augmentation techniques.** Positive jittering (J) and hard negative mining (HN) improves performance even more in combination with outlier exclusion (OE).

	mean Average Precision for each Object Class																				
Method	plane	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	motor-bike	person	plant	sheep	sofa	train	tv	mean
Default	73.13	**87.85**	48.08	59.01	76.02	86.54	88.32	50.15	68.26	81.99	43.68	51.27	78.83	77.39	65.16	60.46	81.59	62.35	73.98	92.57	70.33
J	75.64	87.33	49.34	57.59	76.68	88.69	88.29	49.95	68.28	83.63	48.25	51.87	79.78	77.83	66.17	**63.59**	82.86	64.51	**78.08**	92.55	71.55
J+OE	77.18	87.56	50.30	60.32	79.54	**89.73**	89.62	50.64	68.75	84.73	50.39	**55.09**	79.33	**79.68**	**67.73**	62.83	83.71	**67.65**	75.79	92.55	72.66
J+HN	76.31	87.35	**50.85**	**61.10**	80.08	89.41	89.62	51.23	68.93	84.88	49.35	53.08	80.90	79.67	65.78	61.98	81.39	64.07	76.18	**92.98**	72.26
J+HN+OE	**77.73**	87.46	48.60	59.76	**80.67**	89.37	**90.07**	**53.76**	**70.11**	**86.55**	**51.24**	53.99	**80.92**	77.78	67.54	62.39	**85.60**	66.83	77.38	92.98	**73.04**

bust algorithms make no distinction between outliers and hard inliers, as previously discussed. Our two-pass algorithm only treats ”non-learnable” examples differently, not penalizing learnable examples for being difficult in the early stages of learning.

Although RobustBoost has inherent robustness, it is improved the most by our extension. One explanation is its variable target error rate ρ, which after the exclusion of outliers obtains a lower value through cross-validation. RobustBoost with a small value ρ is more similar to a non-robust algorithm, and should not suffer as much from the hard-inlier-problem demonstrated in figure 2(c).

The SVM classifier is provided as a reference and sanity check, and we see that the boosting algorithms give superior results even though only decision stumps are used.

The higher performance of the boosted classifier is likely due to that combination of decision stumps can produce more complex decision boundaries than the hyperplane of a linear SVM. It is not surprising that the linear SVM is not improved by the outlier exclusion as it has a relatively soft hinge loss, tuned soft margins, and lacks the iterative reweighting of examples and greedy strategy, that our argumentation is based on.

6.2 Bootstrapping Methods in Relation to Outlier Exclusion

We can see in table 2 that jittering has a positive effect on classifier performance and that our outlier exclusion method improves that performance even more. This shows that our two-pass outlier exclusion is complementary to hard negative mining and positive jittering and could be considered as a viable data augmentation technique when using boosting algorithms.

7 DISCUSSION AND FUTURE WORK

We show that all boosting methods, except TangentBoost, perform better when handling outliers separately during training. As neither TangentBoost nor RobustBoost reach the performance of LogitBoost without outlier exclusion they might be too aggressive in reducing the importance of hard inliers and not aggressive enough for outliers. We must remember that the problem addressed by the VOC2007 dataset does not include label noise, but does definitely have hard and ambiguous examples that might interfere with learning the optimal decision boundary. Both TangentBoost and RobustBoost have previously shown good results on artificially flipped labels, but we believe that a more common problem in object classification is naturally occurring ambiguous examples and have therefore not focused on artificial experiments where labels are changed at random.

We notice that the improved performance from excluding hard and ambiguous examples is correlated with the severity of the loss function of the method. AdaBoost, with its exponential loss function, shows large improvement down to TangentBoost having almost no improvement at all. LogitBoost has less average gain from the exclusion of outliers than AdaBoost, but still achieves the best overall performance when combined with the two-pass approach. More surprising is that RobustBoost is improved the most, in spite of its soft loss function. One explanation is that there is an additional mechanism at work in improving the performance of RobustBoost. RobustBoost is self-terminating, stopping when it has reached its target error. When training on a dataset with a smaller fraction non-learnable examples, it is more likely to end up at a much lower target error, which makes it more similar to other boosting algorithms and lets it add more weak learners before terminating.

We have seen that pruning of the hard-to-learn examples in a dataset without label noise can lead to improved performance, contrary to the "more data is better" philosophy. Our belief is that our method removes bad data, but also that it reduces the importance of examples that make the learning more difficult, in this way allowing the boosting algorithms to find better local minima. We still believe that more data is better if properly handled, so this first approach of selective example exclusion should be extended in the future, and might potentially combine well with positive example mining, especially in cases where the quality of the positives cannot be guaranteed.

8 CONCLUSIONS

We provide an analysis of several boosting algorithms and their sensitivity to outlier data. Following this analysis we propose a two-pass training extension that can be applied to boosting algorithms to improve their tolerance to naturally occurring outliers. We show experimentally that excluding the hardest positives from training by subjecting them to an exclusive weight function is beneficial for classification performance. We also show that this effect is complementary to jittering and hard negative mining, which are common bootstrapping techniques.

The main strength of our approach is that classification performance is improved without any extra test-time cost, only at the expense of training-time cost. We believe that handling the normal and hard examples separately might allow bootstrapping of training sets with less accurate training data.

We also present results on the VOC2007 dataset, comparing the performance of different boosting algorithms on real world vision data, concluding that LogitBoost performs the best and that some of this difference in performance can be due to its ability to better cope with naturally occurring outlier examples.

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