Human Detection 을 위한 Bayesian Logistic Regression

Bayesian Logistic Regression for Human Detection

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Abstract The possibility to extent the solution in human detection problem for plug-in on vision-based Human Computer Interaction domain is very attractive, since the successful of the machine leaning theory and computer vision marriage. Bayesian logistic regression is a powerful classifier performing sparseness and high accuracy. The difficulties of finding people in an image will be conquered by implementing this Bayesian model as classifier. The comparison with other massive classifier e.g. SVM and RVM will introduce acceptance of this method for human detection problem. Our experimental results show the good performance of Bayesian logistic regression in human detection problem, both in trade-off curves (ROC, DET) and real-implementation compare to SVM and RVM.

핵심어: Bayesian logistic regression, SVM, RVM, Human detection

1. Introduction

The research into human detection has received more and more attention in recent years, due to the drive from many emerging applications, such as perceptual user interfaces, ubiquitous computing, robot vision, and intelligence video surveillance [1,2]. Although the research of object detection has greatly moved forward with the success of face detection, these face detection methods may not apply to human detection. Large variations in human pose and clothing, as well as varying backgrounds and environmental conditions, make this problem particularly challenging in computer vision perspective.

Discriminative approaches from supervised learning paradigm coupled with the advances in computer technology (storage, processing speed) rise favor techniques that construct a parametric function by learning a large set of images (exemplars) for deciding whether an image contains an object or not in a short of time. The overall discrimination (classification) process consists of two parts, feature extraction and actual classification.

Here we leave the race for finding the best feature extraction method as future work and use discriminative feature set from Dalal *et. al.* i.e. Histogram of Oriented Gradient (HOG)[3] to train the classifiers. In this paper we focused on the possibility of classifier in Bayesian logistic regression fashion for coping the human detection problem on images.

We treat the human detection problem in image as a binary, as an instance of discriminative approach, supervised learning problem; the goal is to learn how to distinguish between examples from two classes (i.e. human or not human, labeled as $y=1$ and $y=-1$).

We present an instance of Bayesian logistic regression learning framework, trained by HOG, for finding people in images. To seek the support for using Bayesian logistic regression in this problem, we attempted a set of experiments that compares the performance of Bayesian logistic regression classifier with the other massive classifiers; we chose SVMs and RVM.

In the problem domain, we consider to simply detect human in upright (pedestrian) poses which is fully (or almost) appear. This reduction does not drastically make the problem easier to solve. Human appearances

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in upright poses still have many variations.

We refer to several experimental results of pedestrian detection as previous work survey e.g. in [7].

The remainder of this paper is as follows. Firstly, the Bayesian logistic regression is presented as powerful classifier for human detection problem. Secondly, the comparison with other classifiers is performed. As stated before, we considered SVM (Support Vector Machine)[4] and RVM (Relevance Vector Machine)[5] to be trained by HOG as competitor for Bayesian logistic regression method. By this comparison, we can notice the degree of choice for different classifiers in human detection task. For closing, we outlined the experimental result of the comparison and we put note on discussion before we conclude and propose the next future works.

2. The Classifiers

We use Bayesian Binary Regression (BBR) as an instance of Bayesian logistic regression for classification problem as described in [6]. BBR is a simple Bayesian logistic regression approach for binary classification problem, tested on text categorization problem [6]. This model fitting algorithm relies on the use of a prior probability distribution that favors sparseness in the fitted model, along with an optimization algorithm and implementation tailored to that prior.

The explicit approach to complexity control in Bayesian discriminative learning consists in using zero-mean Laplace prior (rather than Gaussian prior) as prior in Bayesian treatment. This prior naturally induces the sparseness to the obtained estimates. The use of Laplacian prior is equivalent to l_1 penalty in regularization point of view.

Bayesian binary regression (BBR)[6]. uses sigmoidal link function same as RVM, but different in prior definition, does not implement the empirical Bayesian treatment and place the sparsity in the set components of each feature. It uses Laplacian prior defined as $p\left(\beta_i \mid \alpha\right) = \frac{\alpha}{2} e^{(-\alpha|\beta_i|)}$, where β_i is a component of the vector of parameters. BBR assumes that the priors for the components are independent, so that the overall prior on the parameter vector is the product of the priors on its individual components. The Laplace prior favors a sparse solution: *the maximum a posteriori* (MAP) estimate of the parameter vector tends to have many components equal to zero. For this reason the Laplace prior or, equivalently, l_1 penalization of parameters, has been widely investigated as an alternative to feature selection, dating back at least to the LASSO algorithm [9].

To find the MAP parameter estimates, BBR uses a minor variant of the coordinate descent algorithm of [10].

As competitors for the BBR in classifying human in images, we offer SVMs and RVM.

SVMs are kernel method that constructs a symmetric and positive definite kernel matrix (Gram matrix) which represents the similarities between all training datum points. The SVMs can be implemented with different kernel functions. SVMs are discriminant classifiers that give a yes/no decision, not a probability. However in our experiments we treat the SVM scores (scalar products in feature space) as if they were the log likelihood of human appearance given the image values.

RVM, as proposed in [5], is Bayesian kernel method that chooses sparse basis sets using an *automatic relevance determination* style prior that pushes non-essential weight to zero. This model provides the state-of-the-art of SVMs and uses fewer basis functions than SVMs, while offering a number of advantages. These include the benefits of probabilistic predictions, automatic estimation of *nuisance parameters*, and the facility to use arbitrary basis functions

3. Histogram of Oriented Gradient as Feature

Feature extraction is the first step in most object detection and pattern recognition algorithms. The ideal feature would be the one that can differentiate objects in the same category from objects in different categories. In this paper we use the HOG as feature for train the classifier for human detection in image.

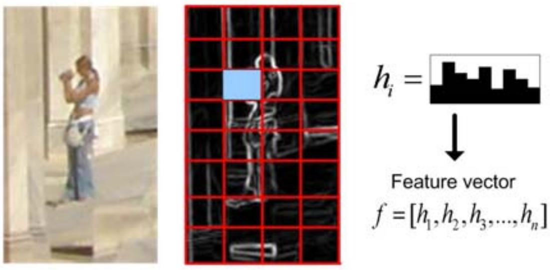


Figure 1. The non-overlapped HOG feature.

We adopted the non-overlapped HOG. In this manner, we normalize each block by its own energy of histogram contained in each block.

The HOG implemented in this paper is the simplified definition of the proposed HOG in [3], one can refer to [8] for details. We scan each feature from images in non-overlapped fashion. Each 64x128 image in dataset is divided into 4x8 blocks which each block contains 16x16 pixels

4. Experiments

We use the dataset in [3] to measure the performance of each combination of HOG and classifiers. We regard 400 positive and 400 negative images for training phase. In the test phase, each trained classifier is demanded to classify 892 positives and 4530 negatives. The human examples were obtained from manually labeling and extracting human representation in images with no particular constraints on human pose or clothing, except that humans are standing in upright position.

We adapt the implementation of BBR from [6] and compare its performance with SVMs and RVM. The SVMs are executed with two different kernels. Linear and radial basis functions (RBF) kernels are chosen from the SVMLight [11] to perform data classification task. The RVM is written in MATLAB as implementation of the proposal from Tipping [5] with RBF kernel.

The detection result examples for each trained machine are presented in Figure 2. In this figure, we notice that BBR has similar detection result same as results given by SVMs (Linear, RBF kernel) and RVM (RBF kernel). In ROC analysis, BBR with Laplacian prior gives 0.988 for area-under ROC (AU-ROC), while SVM Linear, SVM RBF and RBF RVM give 0.988, 0.991 and 0.989 respectively. From this, one can infer that BBR performs quite same to the Linear SVM while outperformed by RBF SVM and RBF RVM.

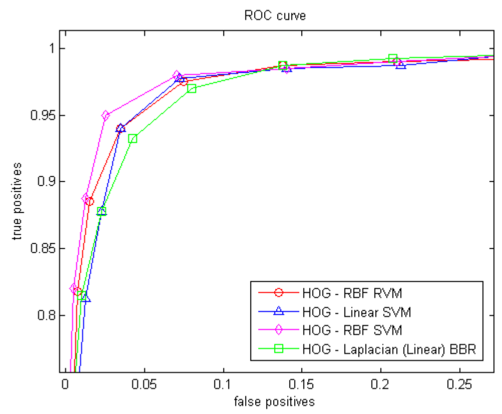
Another perspective to analyze the performances is to consider the DET curve as shown in Figure 2.b. This curve shows the effort of each classifier to reduce the miss rate while at the same time reducing the false positives as well. In this perspective, we can see the tight competition clearer than the ROC representation.

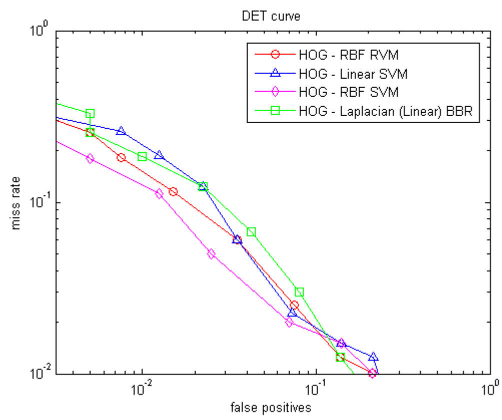
It should be note that the results given by the experiments is reasonable, since the BBR appears with different context of sparseness compare to SVM and RVM which is in the same context of sparseness. The BBR prefer to re-weighted the feature component and rely on sigmoidal link to decide the membership of one vector. Different with the BBR, SVM and RVM uses chosen support vector to draw the boundary between classes.

In Figure 3, one can asses the performance of each classifier in the real image data. BBR, SVMs and RVM can detect human appearance in image with high precision.

5. Conclusion

The paper presented an implementation of Bayesian logistic regression method in human detection problem. It presented an experimental study on human (pedestrian) classification and detection using three of the state-of-the art classifiers. Our experimental results show that these three classifiers (with its variation in sparseness contexts) give a tight result on precision in the classification problem.





(a) ROC curve

(b) DET curve

Figure 2. The performances of different classifiers. Represented as (a) ROC and (b) DET curves.

Ongoing work includes the search of new discriminative features and combination of two different contexts in one classifier for selecting the most discriminative features and construction of cascaded classifier to make the detection real-time.

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Figure 3. Detection result example of linear SVM (top left), RBF SVM (top right), RBF RVM (bottom left) and Linear BBR with Laplacian prior (bottom right).

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