Semi-Supervised Boosting using Visual Similarity Learning

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Abstract The required amount of labeled training data for object detection and classification is a major drawback of current methods. Combining labeled and unlabeled data via semi-supervised learning holds the promise to ease the tedious and time consuming labeling effort. This paper presents a novel semi-supervised learning method which combines the power of learned similarity functions and classifiers. The approach capable of exploiting both labeled and unlabeled data is formulated in a boosting framework. One classifier (the learned similarity) serves as a prior which is steadily improved via training a second classifier on labeled and unlabeled samples.
We demonstrate the approach on challenging computer vision applications. First, we show how we can train a classifier using only a few labeled samples and many unlabeled data. Second, we improve (specialize) a state-of-the-art detector by using labeled and unlabeled data.

Motivation

Use both labeled and unlabeled data in order to learn/improve a boosted classifier.

Approach

- **Combine Graph-based and Cluster-based semi-supervised learning methos**
- **Additively combine three different loss functions (between labeled, labeled-unlabeled plus unlabeled and unlabeled data)**
- **Use a prior similarity measure to indicate the relation among the data**
- **Minimize the additiely combined loss using AdaBoost**

$$\mathcal{L} = \frac{1}{|\mathcal{X}^L|}\sum_{\mathbf{x}\in\mathcal{X}^L} e^{-2yH(x)} + \frac{1}{|\mathcal{X}^L||\mathcal{X}^U|}\sum_{\mathbf{x}_i\in\mathcal{X}^L}\sum_{\mathbf{x}_j\in\mathcal{X}^U} S(\mathbf{x}_i,\mathbf{x}_j)e^{-2y_iH(\mathbf{x}_j)} + \frac{1}{|\mathcal{X}^U||\mathcal{X}^U|}\sum_{\mathbf{x}_i\in\mathcal{X}^U}\sum_{\mathbf{x}_j\in\mathcal{X}^U} S(\mathbf{x}_i,\mathbf{x}_j)e^{H(\mathbf{x}_i)-H(\mathbf{x}_j)}$$

$$\mathcal{L} \leq \frac{1}{|\mathcal{X}^L|}\sum_{\mathbf{x}\in\mathcal{X}^L} w_n(\mathbf{x},y)e^{-2y\alpha_n h_n(\mathbf{x})} + \frac{1}{|\mathcal{X}^U|}\sum_{\mathbf{x}\in\mathcal{X}^U}\left[p_n(\mathbf{x})e^{-\alpha_n h_n(\mathbf{x})} + q_n(\mathbf{x})e^{\alpha_n h_n(\mathbf{x})}\right]$$

$$p_n(\mathbf{x}) = e^{-2H_{n-1}(\mathbf{x})}\frac{1}{|\mathcal{X}^L|}\sum_{\mathbf{x}_i\in\mathcal{X}^+} S(\mathbf{x},\mathbf{x}_i) + \frac{1}{|\mathcal{X}^U|}\sum_{\mathbf{x}_i\in\mathcal{X}^U} S(\mathbf{x},\mathbf{x}_i)e^{H_{n-1}(\mathbf{x}_i)-H_{n-1}(\mathbf{x})}$$

$$q_n(\mathbf{x}) = e^{2H_{n-1}(\mathbf{x})}\frac{1}{|\mathcal{X}^L|}\sum_{\mathbf{x}_i\in\mathcal{X}^-} S(\mathbf{x},\mathbf{x}_i) + \frac{1}{|\mathcal{X}^U|}\sum_{\mathbf{x}_i\in\mathcal{X}^U} S(\mathbf{x},\mathbf{x}_i)e^{H_{n-1}(\mathbf{x})-H_{n-1}(\mathbf{x}_i)}$$

New weights and assigned labels in each iteration

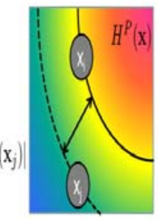
$$z_n(\mathbf{x}) = sign(p_n(\mathbf{x}) - q_n(\mathbf{x})) \qquad w_n(\mathbf{x}) = |p_n(\mathbf{x}) - q_n(\mathbf{x})|$$

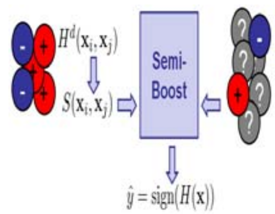
Learning the Distance Function

$$d(\mathbf{x}_i,\mathbf{x}_j) = \frac{1}{2}(H^d(\mathbf{x}_i,\mathbf{x}_j)+1)$$

$$S(\mathbf{x}_i,\mathbf{x}_j) = e^{\left(-\frac{d(\mathbf{x}_i,\mathbf{x}_j)^2}{\sigma^2}\right)}$$

$S(\mathbf{x}_i,\mathbf{x}_j)$ ⇓ $|H^P(\mathbf{x}_i) - H^P(\mathbf{x}_j)|$



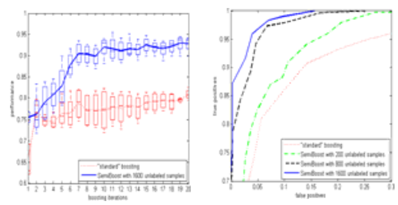


Classifier Combination

$$H^C(\mathbf{x}) = \alpha_0 h_0(\mathbf{x}) + \sum_{t=1}^{T}\alpha_t h_t(\mathbf{x})$$

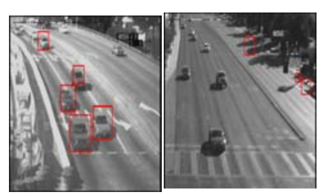
Experiments

Learning from few labeled samples

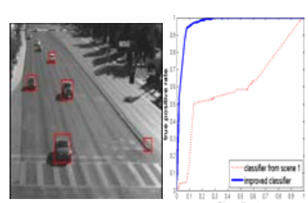


Knowledge Transfer and Scene Adaption

prior

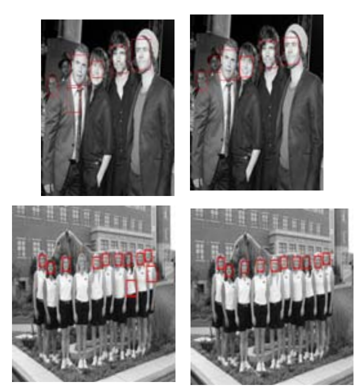


improved



Improving an Object Detector

before **after**



References

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