On-line Random Naïve Bayes for Tracking

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Abstract

Randomized Learning methods (i.e. Forests or Ferns) have shown excellent capabilities for computer vision applications. Recently, Prinzie and Van den Poel [Pri07] showed that tree structures in Random Forests can be replaced by simpler structures, e.g. Random Naïve Bayes.

We extend their ideas to the on-line domain and propose ***on-line Random Naïve Bayes*** classification. To estimate probability densities on-line, we use histograms and apply *iir*-like filtering to allow for adaption during runtime. We experimentally demonstrate the performance of our approach on both machine learning datasets and visual object tracking.

Naïve Bayes Classification

- ***Bayes' Theorem***

Label Probability (Prob. of class i)

Joint probability (Prob. of feature vector x for class i)

$$p(y=i\,|\,x)=\frac{p(i)\,p(x\,|\,i)}{p(x)}$$

Prior Probability (Prob. of feature vector x)

- Estimating the joint probability $p(\mathbf{x}|i)$ distribution is difficult or sometimes not feasible, therefore independence of features x_d is assumed and ***Naïve Bayes' Theorem*** can be formulated as

$$p(y=i\,|\,\mathbf{x})=\frac{p(i)\,p(x_1\,|\,i)\,p(x_2\,|\,i)\cdots p(x_D\,|\,i)}{p(\mathbf{x})}.$$

- Assuming feature independence and uniform label distribution $p(i)$, a Naïve Bayes classifier $F(x)$ can be written as

$$F(\mathbf{x})=\arg\max_i \prod_{d=1}^{D}\frac{p(x_d\,|\,i)}{p(x_d)}.$$

On-line Random Naïve Bayes

Single Naïve Bayes Classifiers are weak, therefore we **build a Randomized Ensemble** (*Bagging*) using
  - ***Random Input Selection*** and
  - ***Random Feature Selection***

to increased stability and decreased variance of the classifier

- Based on on-line Random Forests [Saf09]
  - On-line Bagging
  - Tree-growing scheme
  - Complex configuration

- ***On-line Learning***
  - ***On-line Bagging***
  - Using ***Histograms*** to model probability distributions
  - Incremental estimation of probability density

- ***Random hyper-planes of features***
  - Randomized feature weighting $\mathbf{w}\in[-1,1]^D$
  - Sparse weighting (H entries of $\mathbf{w}$ different from zero)
  - ***H to 1*** dimensional feature space mapping

$$x_H = w^T\mathbf{x}$$

- Final ***on-line Random Naïve Bayes*** classifier

$$F(\mathbf{x})=\arg\max_i \sum_{b=1}^{B}\prod_{f=1}^{F}\frac{p(x_H^{b,f}\,|\,i)}{p(x_H^{b,f})}$$

- **On-line adaptation by *iir*-like filtering**
  - Down-weight outdated knowledge
  - ***iir-like filtering*** of histogram bins
  - Supports ***concept drift*** needed for tracking

"age" of the sample

$$\underbrace{w_{t_0}^{norm}}_{\text{Corrected bin weight}}=\sum_{t=-\infty}^{t_0} w_t\cdot \underbrace{r}_{\text{Forgetting Factor }[0,...,1]}{}^{t_0-t}$$

Evaluation and Experiments

- Parameter Evaluation

Parameter	Setting and classification error				
B (bag size)	50	100	<u>200</u>	500	1000
error	0.167	0.141	0.125	0.109	**0.103**
F (num. of features)	1	5	10	<u>20</u>	50
error	0.182	0.126	**0.122**	0.125	0.133
H (dim. of hyperplanes)	1	<u>2</u>	3	5	10
error	0.294	0.125	0.115	**0.089**	0.094

Average classification error (bold: best; underline: standard)

- Machine Learning Datasets

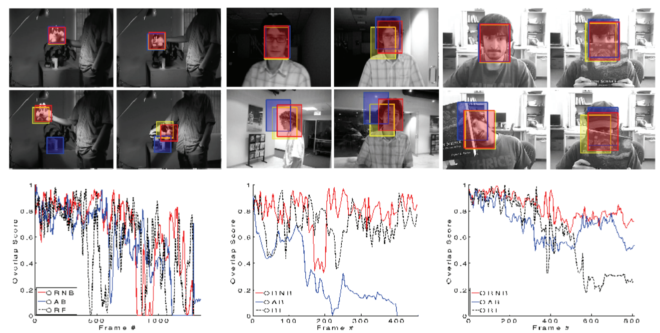
Dataset	ORNB	OAB [Gra06]	ORF [Saf09]
DNA	**0.098**	0.146	0.112
Letter	<u>0.196</u>	0.223	**0.169**
USPS	<u>0.183</u>	0.184	**0.127**
g50c	<u>0.125</u>	0.309	**0.124**

Average classification error (bold: best; underline: second best)

- Visual Object Tracking

Sequence	ORNB	OAB [Gra06]	ORF [Saf09]	MIL [Bab09]
Sylvester	**0.75**	<u>0.65</u>	0.62	0.60
David	**0.79**	0.26	<u>0.69</u>	0.57
FaceOcclusion2	**0.82**	0.68	<u>0.72</u>	0.68

Average VOC Overlap score (bold: best; underline: second best)



Illustrative Tracking Examples and Overlap Scores (red: ORNB; blue: OAB; yellow/black: ORF)

References

[Pri07] A. Prinzie and D. Van den Poel, "Random multiclass classification: Generalizing random forests to random mnl and random nb", in Database and Expert Systems Applications, 2007.
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