

KA-Ensemble

Towards Imbalanced Image Classification Ensembling Oversamling and Under-sampling

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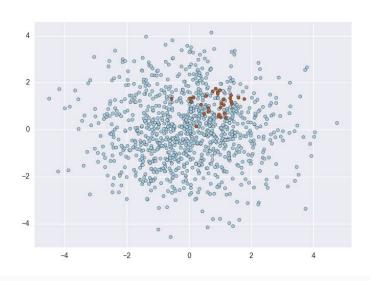
Ocean Univercity of China

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Imbalanced learning

Imbalanced learning



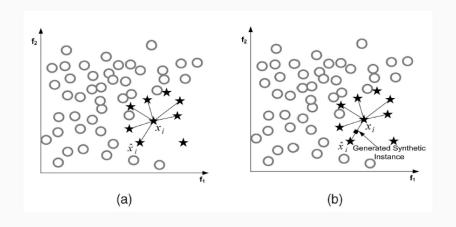
Sampling method

According to the different sort of samples, sampling methods can be roughly classified into three classes:

- over-sampling
- under-sampling
- hybrid-sampling

Method

SMOTE



ADASYN

- Calculate how many minority samples to generate $(N^+ * SR)$.
- For each minority sample x_i^+ , $i = 1, 2, ..., N^+$, find its K-nearest neighbors, N_i^{maj} of which from the majority.
- $\Gamma_i = \frac{N_i^{maj}}{Z}$, Z is a standardization factor to make sure $\sum \Gamma_i = 1$
- $g_i = \Gamma_i * N^+ * SR$

ADASYN

Pros: Adaptively determine the frequency of each minority sample as the primary sample and focus the attention on the boundary regions of the minority class.

Cons: The anti-noise performance of the algorithm is poor, which will amplify the range of small-scale noise information to a certain extent, resulting in a decline in classification quality.

Kernal ADASYN

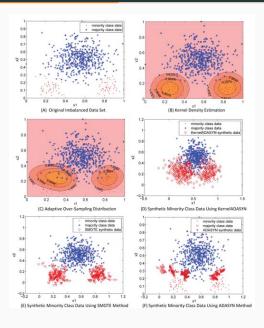
kernal density estimation:

$$\hat{p}(x) = \frac{1}{N+h} \sum_{i \in I_{+1}} \hat{r}_i \frac{1}{(\sqrt{2\pi}h)^n} exp(-\frac{1}{2} \frac{|x-x_i|}{h})$$

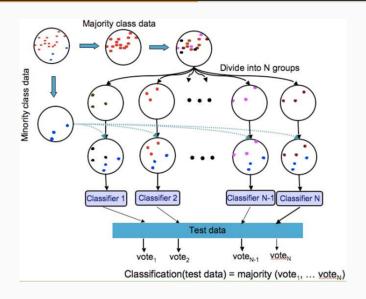
Not only adaptively shifting the classification decision boundary toward the difficult examples.

But also construct an adaptive over-sampling distribution to generate synthetic minority class data.

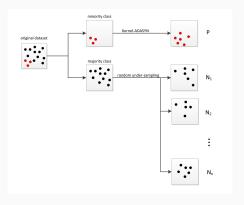
Kernal ADASYN

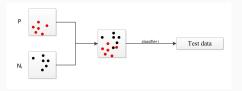


EasyEnsemble



KA-Ensemble





Experiment

Datasets

	Sample	IR
balance	625	11.8
car	1728	3.5
Colon	62	1.82
cmc	1473	3.4
Glioma	50	2.57
haberman	306	2.8
mf-morph	2000	9.0
mf-zernike	2000	9.0
vehicle	846	3.0
ZooScan	2000	15.25

Evaluation Criteria

TN : true negatives FP : false positives

TP: true positives FN: false negatives

Precision : $p = \frac{TP}{TP + FP}$

Recal: $r = \frac{TP}{TP+FN}$

 $acc = \frac{TP + TN}{TP + FN + TN + FP}$

G-means = $\sqrt{TPR * TNR}$

F-measure $=\frac{1}{\frac{1}{2}(\frac{1}{p}+\frac{1}{r})}=\frac{2pr}{p+r}$

 $Micro - F = \frac{1}{k} \sum_{i=1}^{k} F_i$

AUC: Area under the ROC curve

SVM based on Gaussian radial basis kernel function

parameters of SVM	
σ : the width of Gaussian radial basis kernel function	5
C: Penalty factor	

parameters of ACOSampling	value
ant_n	50
ITA	50
ITP	100
dispose	0.8
ph_initial	1
ph _{min}	0.5
ph _{min}	0.5
α, β, γ	$\frac{1}{3}$

Result

Colon

	ORI	ROS	RUS	SMOTE	BSO1	BSO2
Acc	83.23	84.19	85.48	85.48	83.07	84.03
F-measure	75.24	76.78	79.31	79.37	74.99	76.91
G-mean	80.23	81.54	84.17	83.83	80.01	81.68
AUC	87.23	87.76	89.16	89.13	88.20	88.61
	OSS	ADA-SYN	SBC	ACOSampling	Kernel-ADASYN	KA-Ensemble
Acc	85.65	85.65	83.23	85.63	85.63	86.03
F-measure	81.13	79.76	78.95	81.13	83.02	85.82
G-mean	85.76	84.21	84.25	85.92	86.10	85.99
AUC	91.33	88.82	90.19	94.18	95.67	97.25

Glioma

	ORI	ROS	RUS	SMOTE	BSO1	BSO2
Acc	92.80	94.00	92.20	93.60	94.00	93.40
F-measure	87.08	89.35	87.54	88.56	89.32	88.80
G-mean	90.94	92.71	93.16	91.97	92.47	93.19
AUC	98.71	98.93	98.75	98.87	99.15	98.73
	OSS	ADA-SYN	SBC	ACOSampling	Kernel-ADASYN	KA-Ensemble
Acc	68.21	65.38	67.18	71.79	72.00	75.21
F-measure	62.50	54.79	60.43	67.86	67.84	69.10
G-mean	68.06	62.67	66.74	72.32	72.78	73.25
AUC	73.53	68.00	73.22	77.42	79.02	78.00

ZooScan

	ORI	ROS	RUS	SMOTE	BSO1	BSO2
Acc	53.23	64.19	55.48	55.48	63.07	64.03
F-measure	46.10	43.30	50.56	45.58	55.40	49.39
G-mean	53.46	51.48	56.89	53.35	52.93	56.16
AUC	57.75	57.36	61.22	57.92	58.14	59.78
	OSS	ADA-SYN	SBC	ACOSampling	Kernel-ADASYN	KA-Ensemble
Acc	58.16	56.25	55.48	66.12	66.66	71.26
F-measure	52.83	51.99	50.56	50.82	52.64	57.33
	F4.06	FO 27	56.89	53.89	60.09	65.24
G-mean	54.36	58.37	50.69	33.09	00.09	05.24

Q 1& A