Article Review

Improving Imbalanced Classification by Anomaly Detection

증강지능 연구실 황승현

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논문 소개

PPSN 2020: Parallel Problem Solving from Nature

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Improving Imbalanced Classification by Anomaly Detection

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Abstract. Although the anomaly detection problem can be considered as an extreme case of class imbalance problem, very few studies consider improving class imbalance classification with anomaly detection ideas. Most data-level approaches in the imbalanced learning domain aim to introduce more information to the original dataset by generating synthetic samples. However, in this paper, we gain additional information in another way, by introducing additional attributes. We propose to introduce the outlier score and four types of samples (safe, borderline, rare, outlier) as additional attributes in order to gain more information on the data characteristics and improve the classification performance. According to our experimental results, introducing additional attributes can improve the imbalanced classification performance in most cases (6 out of 7 datasets). Further study shows that this performance improvement is mainly contributed by a more accurate classification in the overlapping region of the two classes (majority and minority classes). The proposed idea of introducing additional attributes is simple to implement and can be combined with resampling techniques and other algorithmic-level approaches in the imbalanced learning domain.

Keywords: Class imbalance · Anomaly detection · Borderline samples

목차

- Imbalanced data란?
- 새로운 접근법 – anomaly score, 4type
- 실험 분석
- 마무리

Imbalanced data란?

Imbalanced data의 정의와 기존 접근법 소개

Imbalanced classification

불균형 분류

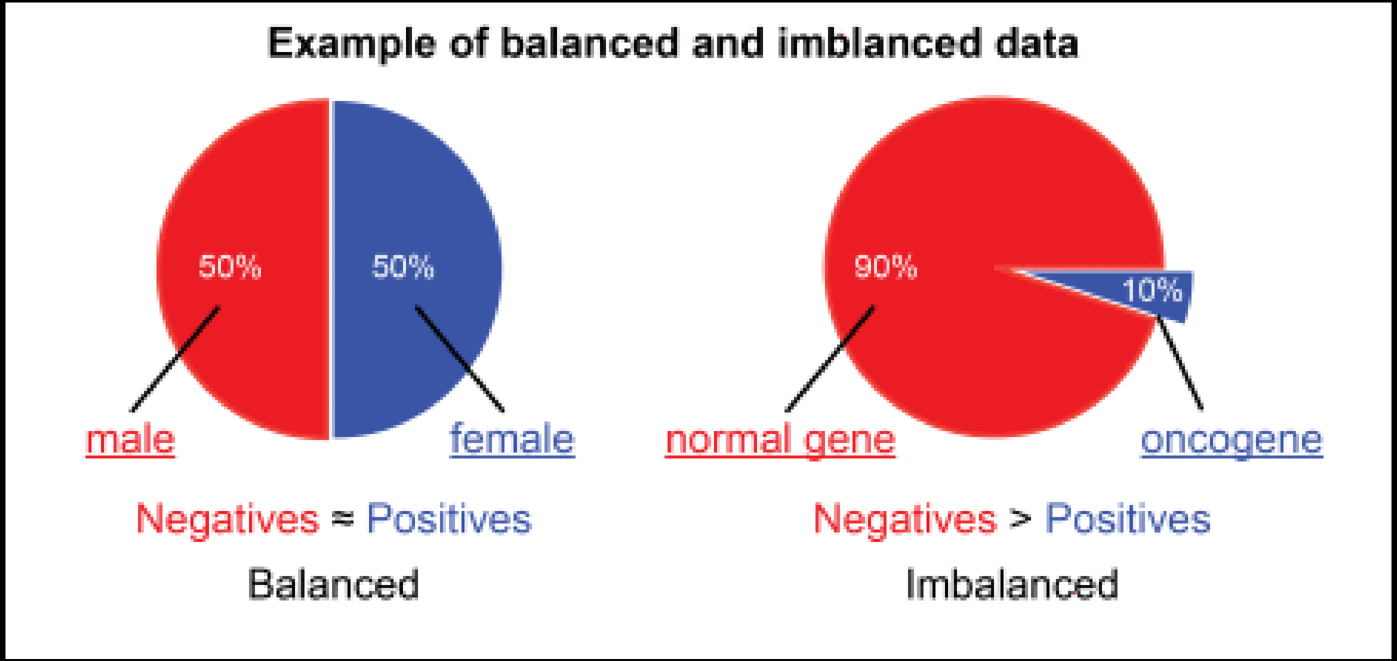
각 클래스 비율 크게 차이

고혈압 분류: 정상 95명 비정상 5명

골다공증 분류: 정상 80명 비정상 20명

Rare class : 소수 (환자)

Abundant class : 다수 (정상인)



Imbalanced classification 문제점

- 대충 만들어도 Accuracy 가 높게 나온다
  - 모델이 모두 정상이라고 판단하면 된다.
  - 정상인 90명 환자 10명을 분류할 때, 모두 정상인이라고 분류하면?
  - 정확도 80%

$$(Accuracy) = \frac{TP + TN}{TP + FN + FP + TN}$$

접근법 : Resampling

Oversampling

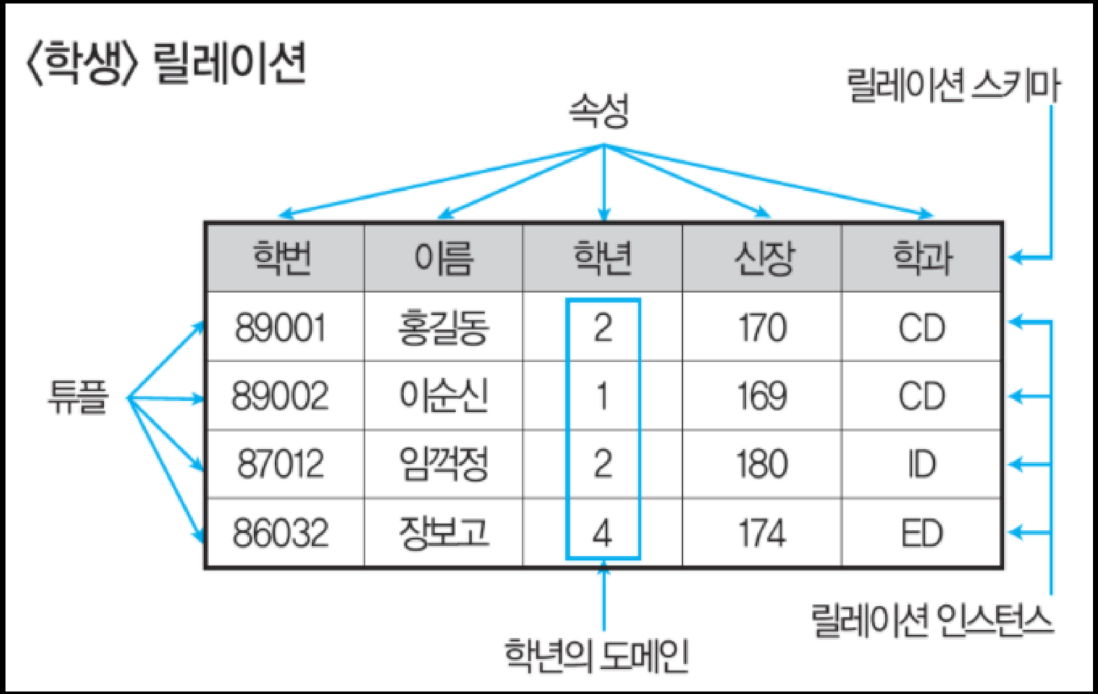
- Rare class 늘리기
- 소수를 복제하여 다수에 맞춤
- SMOTE, ADASYN 등

Undersampling

- Abundant class 줄이기
- 다수를 소수에 맞게 자름
- NCL, OSS 등

기존 접근법의 문제

- Oversampling : Overfitting
- Undersampling : 데이터 수↓
  - 학습 효율 떨어짐
- "합성"된 데이터
  - 원본 데이터 보장 x



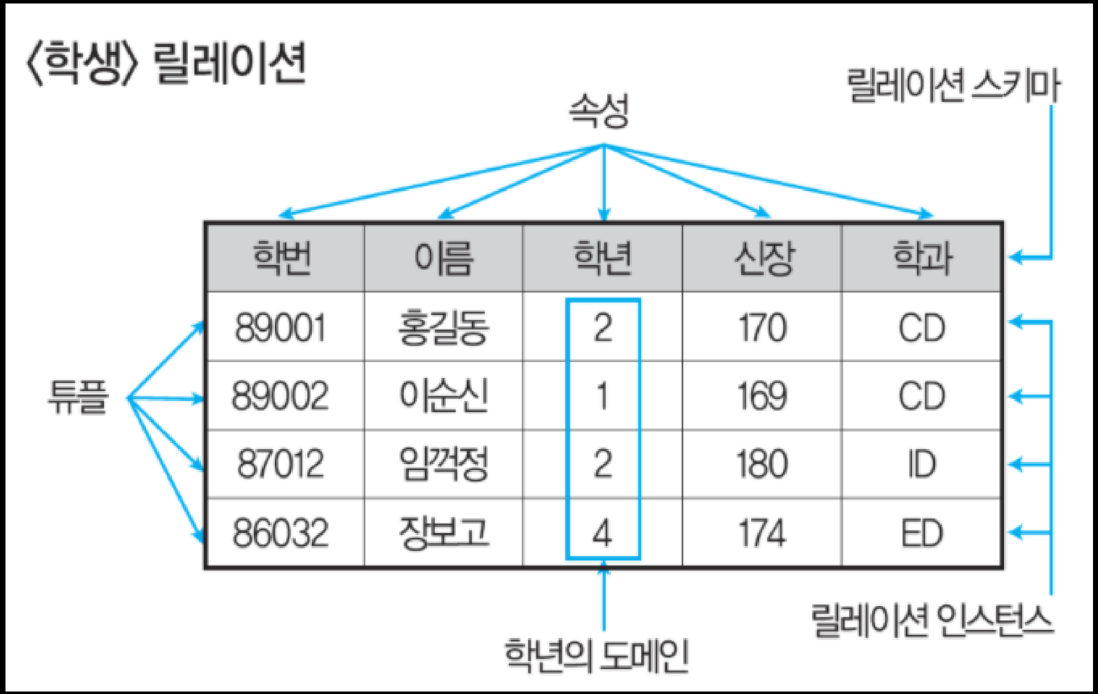
새로운 접근법

논문에서 소개하는 접근법

Anomaly Detection을 이용한 Imbalanced Classification

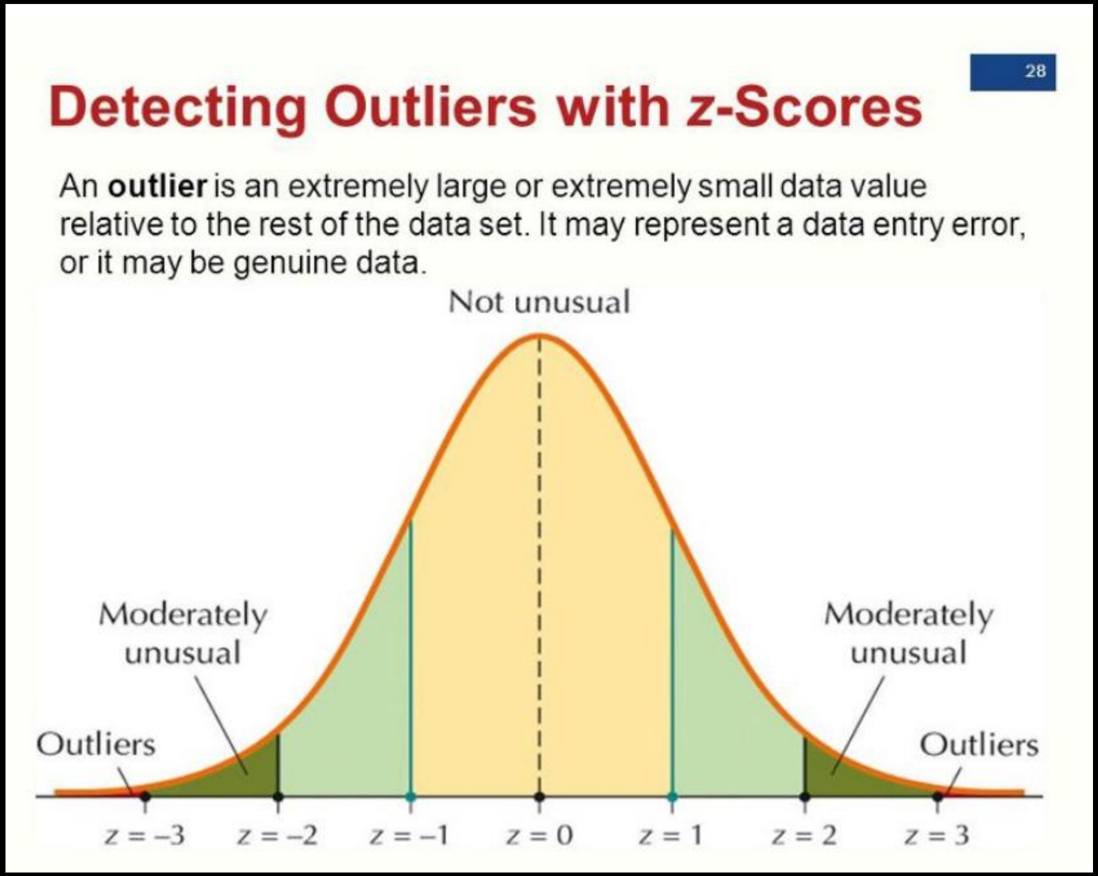
새로운 접근법

- 데이터셋의 튜플을 늘리지 말고
  - Rows
- 데이터셋의 속성을 늘리자
  - Columns
- 추가 속성
  1. outlier score
  2. safe, borderline, rare, outlier



outlier score

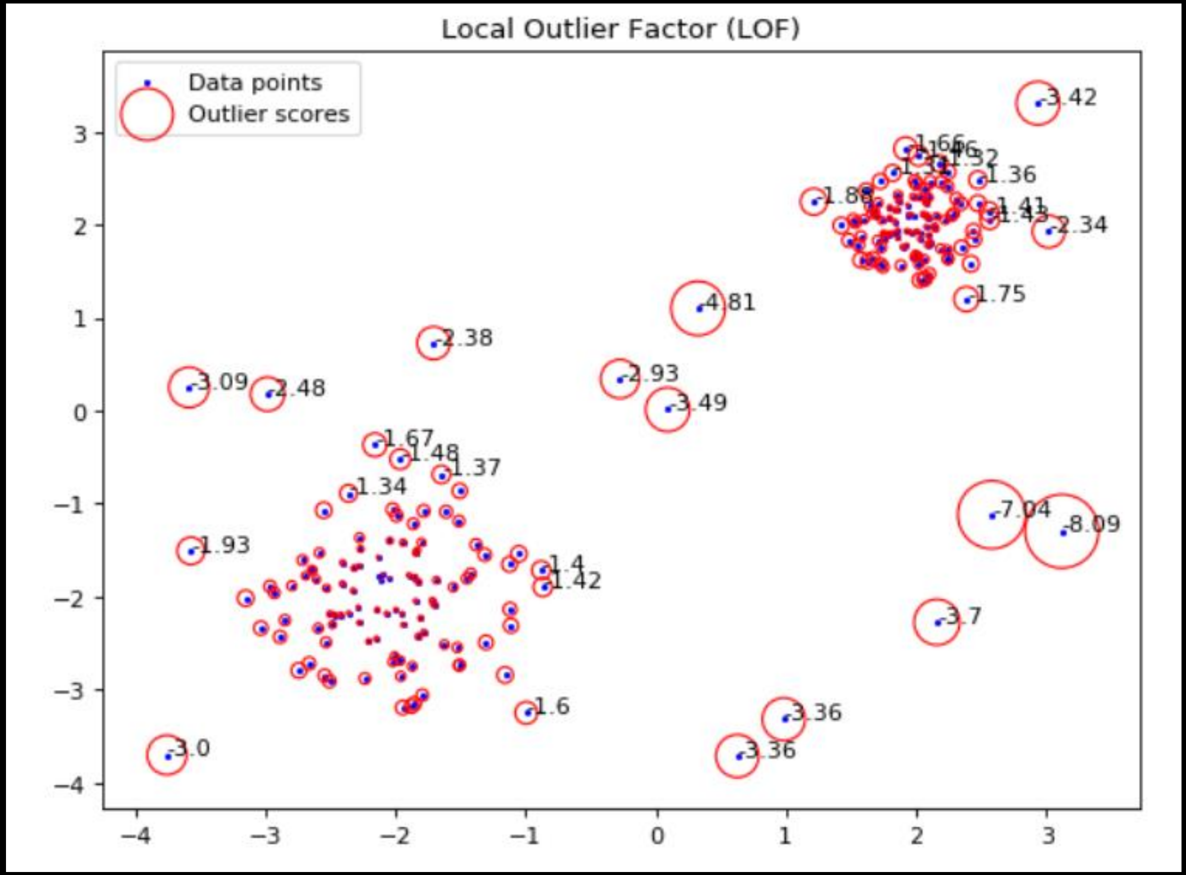
- 이상치 점수
- 샘플이 이상치인지 아닌지 판단하는 지표
- Local Outlier Factor(LOF)



LOF

주변 데이터에서 크게 벗어난 데이터 식별

- 이웃에서 크게 떨어져 있다면?
- 이상치



LOF 구하는 과정

Local Density Estimation

- 각 데이터 포인트 주변의 로컬 밀도 추정
- 데이터 포인트와 K-Nearest Neighbors 사이의 거리 계산

Reachability Distance

- 도달 가능 거리
- 한 포인트가 이웃 포인트와 얼마나 멀리 떨어져 있는지
- 가장 가까운 k번째 이웃까지의 거리

LOF 계산

- 가장 가까운 k개 이웃의 평균 도달 가능 거리
- 자신의 도달 가능 거리의 비율

Algorithm 1: Local Outlier Factor (LOF) algorithm [2]

Input : $\mathbf{X}$ - input data $\mathbf{X} = (X_1, ..., X_n)$
n - the number of input examples
k - the number of neighbours
Output: LOF score of every X_i

initialization;
calculate the distance $d(\cdot)$ between every two data points;
for $i = 1$ **to** n **do**
  calculate k-$distance(X_i)$: the distance between X_i and its kth neighbour;
  find out k-distance neighbourhood $N_k(X_i)$: the set of data points whose distance from X_i is not greater than k-$distance(X_i)$;
  for $j = 1$ **to** n **do**
    calculate reachability distance:

$$reach\text{-}dist_k(X_i, X_j) = \max\{k\text{-}distance(X_j), d(X_i, X_j)\};$$

    calculate local reachability density:

$$\begin{aligned} lrd_k(X_i) &= 1/avg\text{-}reach\text{-}dist_k(X_i) \\ &= 1/\left(\frac{\sum_{o \in N_k(X_i)} reach\text{-}dist_k(X_i, X_j)}{|N_k(X_i)|}\right); \end{aligned}$$

    intuitively, the local reachability density of X_i is the inverse of the average reachability distance based on the k-nearest neighbours of X_i;
    calculate LOF:

$$\begin{aligned} LOF_k(X_i) &= \frac{\sum_{o \in N_k(X_i)} lrd_k(X_j)}{|N_k(X_i)| \cdot lrd_k(X_i)} \\ &= \frac{\sum_{o \in N_k(X_i)} \frac{lrd_k(X_j)}{lrd_k(X_i)}}{|N_k(X_i)|} \end{aligned}$$

    the LOF of X_i is the average local reachability density of X_i's k-nearest neighbours divided by the local reachability density of X_i.
  end
end

safe, borderline, rare, outlier

Napierala and Stefanowski

k-neighbourhood.

K: KNN 파라미터

$R_{min/all}$

희귀한 이웃의 수 / 전체 이웃의 수

Table 1. Rules to assign the four types of minority examples.

From: Improving Imbalanced Classification by Anomaly Detection

Type	Safe (S)	Borderline (B)	Rare (R)	Outlier (O)
Rule	$\frac{k+1}{2k} < R_{\frac{min}{all}} \leqslant 1$	$\frac{k-1}{2k} \leqslant R_{\frac{min}{all}} \leqslant \frac{k+1}{2k}$	$0 < R_{\frac{min}{all}} < \frac{k-1}{2k}$	$R_{\frac{min}{all}} = 0$
E.G. given the neighbourhood of a fixed size $k = 5$				
Rule	$\frac{3}{5} < R_{\frac{min}{all}} \leqslant 1$	$\frac{2}{5} \leqslant R_{\frac{min}{all}} \leqslant \frac{3}{5}$	$0 < R_{\frac{min}{all}} < \frac{2}{5}$	$R_{\frac{min}{all}} = 0$

실험

메소드

- 시나리오
  1. 아무 것도 안 한 원본
  2. Resampling
  3. Resampling + 추가 속성
  4. 추가 속성
- t-tests로 데이터셋 유사하게 조정
- K-fold 5

데이터셋

Table 2. Information on benchmark datasets [1].

From: Improving Imbalanced Classification by Anomaly Detection

Datasets	#Attributes	#Samples	Imbalance ratio (IR)
glass1	9	214	1.82
ecoli4	7	336	15.8
vehicle1	18	846	2.9
yeast4	8	1484	28.1
wine quality	11	1599	29.17
page block	10	5472	8.79

결과

The experiment with the two additional attributes outperforms the experiment with the classical resampling technique SMOTE.

두 가지 속성 추가 >>>> SMOTE

2D chess dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.8482	0.5743	0.6992	0.6208	0.8047	0.8285	—	—	—	—
	YES	0.9771	0.9557	0.9070	0.9226	0.9469	0.9859	0.9846	0.9485	0.9643	0.9723
SMOTE	NO	0.8584	0.6422	0.7102	0.6646	0.8183	0.5921	0.1636	0.5004	0.2437	0.5855
	YES	0.9704	0.9191	0.9061	0.9064	0.9453	0.9933	0.9633	0.9667	0.9622	0.9801
ADASYN	NO	0.8482	0.5743	0.6992	0.6208	0.8047	0.6172	0.1434	0.5904	0.2299	0.5892
	YES	0.9771	0.9557	0.9070	0.9226	0.9469	0.9925	0.8546	0.9667	0.8999	0.9721
NCL	NO	0.5786	0.1245	0.6652	0.2092	0.5541	0.5290	0.1076	0.4212	0.1693	0.4802
	YES	0.9715	0.8542	0.9667	0.8988	0.9716	0.9946	0.9119	0.9667	0.9337	0.9766
OSS	NO	0.7569	0.4197	0.5227	0.4554	0.6813	0.6262	0.3050	0.0295	0.0535	0.0958
	YES	0.9743	0.9321	0.9391	0.9316	0.9640	0.9937	0.9532	0.9564	0.9524	0.9745

glass1 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.7029	0.6099	0.6235	0.6044	0.6806	0.6779	0.6394	0.5533	0.5828	0.6633
	YES	0.7328	0.6283	0.6344	0.6227	0.6956	0.7779	0.6506	0.65917	0.6430	0.7089
SMOTE	NO	0.7008	0.5750	0.6561	0.6060	0.6782	0.7140	0.5125	0.7236	0.5785	0.6111
	YES	0.7595	0.6393	0.6988	0.6589	0.7273	0.8288	0.6537	0.8802	0.7369	0.7760
ADASYN	NO	0.7095	0.5922	0.6728	0.6187	0.6842	0.7336	0.5159	0.7982	0.6103	0.6271
	YES	0.7799	0.6614	0.7106	0.6780	0.7419	0.8388	0.6545	0.8996	0.7456	0.7845
NCL	NO	0.5926	0.4401	0.9302	0.5843	0.3761	0.6750	0.4124	1.0000	0.5765	0.2177
	YES	0.5897	0.3976	0.9239	0.5527	0.3806	0.7790	0.4299	1.0000	0.5948	0.3403
OSS	NO	0.7010	0.5688	0.6841	0.6132	0.6804	0.6810	0.5850	0.5837	0.5683	0.6444
	YES	0.7611	0.6342	0.7136	0.6637	0.7295	0.7784	0.6085	0.7382	0.6543	0.7128

ecoli4 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.8446	0.7241	0.6433	0.6432	0.7694	0.9919	0.8889	0.8000	0.7993	0.8797
	YES	0.8525	0.6435	0.6017	0.5734	0.6920	0.9889	0.9143	0.7500	0.7835	0.8512
SMOTE	NO	0.8824	0.7938	0.7233	0.7102	0.8328	0.9894	0.8290	0.8000	0.7268	0.8457
	YES	0.8629	0.8315	0.7300	0.7262	0.8303	0.9931	0.8824	0.9500	0.8881	0.9639
ADASYN	NO	0.8719	0.8407	0.7083	0.7221	0.8236	0.9903	0.7813	0.8000	0.7034	0.8389
	YES	0.8747	0.7833	0.6717	0.6623	0.7822	0.9934	0.8800	0.9500	0.8857	0.9634
NCL	NO	0.8007	0.6080	0.6333	0.5651	0.7380	0.9869	0.8258	0.9000	0.7886	0.8976
	YES	0.8523	0.7297	0.7550	0.6499	0.7982	0.9914	0.8533	0.9500	0.8556	0.9549
OSS	NO	0.8398	0.6284	0.7250	0.5958	0.7872	0.9877	0.8458	0.8133	0.7580	0.8668
	YES	0.9115	0.6858	0.8350	0.6787	0.8586	0.9890	0.8830	0.9117	0.8626	0.9408

vehicle1 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.6699	0.5018	0.4301	0.4575	0.6004	0.8673	0.7074	0.3593	0.4747	0.5824
	YES	0.7385	0.5855	0.5329	0.5573	0.6794	0.9081	0.6873	0.6266	0.6536	0.7500
SMOTE	NO	0.7241	0.5398	0.5557	0.5458	0.6796	0.8945	0.5538	0.9237	0.6913	0.8264
	YES	0.7403	0.5825	0.5629	0.5704	0.6938	0.9204	0.5808	0.9745	0.7272	0.8582
ADASYN	NO	0.7211	0.5359	0.5570	0.5446	0.6791	0.8995	0.5485	0.9465	0.6937	0.8303
	YES	0.7481	0.5842	0.5789	0.5797	0.7025	0.9206	0.5800	0.9809	0.7284	0.8597
NCL	NO	0.7411	0.4153	0.9506	0.5769	0.7093	0.8411	0.4108	0.9768	0.5776	0.7059
	YES	0.7781	0.4560	0.9392	0.6118	0.7529	0.8752	0.5076	1.0000	0.6728	0.8139
OSS	NO	0.7125	0.4857	0.6066	0.5370	0.6837	0.8702	0.5745	0.7014	0.6293	0.7560
	YES	0.7531	0.5524	0.6286	0.5859	0.7174	0.9062	0.6088	0.9117	0.7290	0.8515

yeast4 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.6736	0.3619	0.2217	0.2653	0.4482	0.8469	—	—	—	—
	YES	0.8647	0.8320	0.6708	0.7260	0.8132	0.9910	0.8628	0.8036	0.8270	0.8920
SMOTE	NO	0.7320	0.2632	0.4029	0.3082	0.6082	0.9052	0.2112	0.6769	0.3160	0.7773
	YES	0.9115	0.7665	0.6892	0.7171	0.8235	0.9922	0.7096	0.9442	0.8079	0.9639
ADASYN	NO	0.7226	0.2494	0.3958	0.2963	0.6041	0.9011	0.2061	0.6902	0.3104	0.7815
	YES	0.9114	0.7531	0.6553	0.6906	0.8036	0.9923	0.6951	0.9618	0.8051	0.9727
NCL	NO	0.8176	0.1929	0.6819	0.2992	0.7772	0.9063	0.2552	0.5745	0.3516	0.7256
	YES	0.9785	0.6733	0.9772	0.7928	0.9791	0.9917	0.7512	0.9436	0.8337	0.9649
OSS	NO	0.7066	0.2899	0.3561	0.3020	0.5713	0.8488	0.2094	0.0258	0.0447	0.0781
	YES	0.9130	0.7637	0.7699	0.7532	0.8708	0.9892	0.8312	0.8390	0.8310	0.9121

wine quality dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.5844	0.1180	0.1275	0.1132	0.2817	0.9790	0.9653	0.9113	0.9333	0.9525
	YES	0.9790	0.9653	0.9113	0.9333	0.9525	0.9944	0.9636	0.8274	0.8761	0.9031
SMOTE	NO	0.5597	0.0648	0.1801	0.0930	0.3704	0.6935	0.1065	0.4223	0.1680	0.5941
	YES	0.9685	0.9715	0.8630	0.9031	0.9239	0.9942	0.8809	0.9055	0.8890	0.9488
ADASYN	NO	0.5601	0.0654	0.1909	0.0953	0.3800	0.6920	0.1039	0.4231	0.1650	0.5933
	YES	0.9859	0.9709	0.8467	0.8917	0.9141	0.9944	0.8805	0.9055	0.8888	0.9488
NCL	NO	0.5922	0.1037	0.2593	0.1423	0.4817	0.7207	0.2582	0.1891	0.1818	0.3755
	YES	0.9845	0.8567	0.9492	0.8949	0.9703	0.9939	0.9359	0.8818	0.8890	0.9308
OSS	NO	0.5733	0.0729	0.2158	0.1054	0.4135	0.5078	—	—	—	—
	YES	0.9859	0.9636	0.9818	0.9723	0.9901	0.9941	0.9282	0.9424	0.9307	0.9690

page block dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.9083	0.8108	0.7442	0.7687	0.8519	0.9723	0.8743	0.7046	0.7663	0.8304
	YES	0.9369	0.8535	0.8289	0.8350	0.9014	0.9880	0.8481	0.8460	0.8379	0.9091
SMOTE	NO	0.9122	0.7485	0.7910	0.7620	0.8735	0.9646	0.6815	0.8792	0.7536	0.9099
	YES	0.9300	0.8216	0.8404	0.8245	0.9051	0.9847	0.7404	0.9496	0.8251	0.9533
ADASYN	NO	0.9130	0.7302	0.7990	0.7558	0.8763	0.9613	0.5716	0.9277	0.6983	0.9194
	YES	0.9328	0.8452	0.8321	0.8356	0.9032	0.9843	0.7529	0.9726	0.8435	0.9661
NCL	NO	0.9338	0.6528	0.9091	0.7502	0.9223	0.9669	0.6628	0.8960	0.7412	0.9127
	YES	0.9563	0.7318	0.9400	0.8156	0.9474	0.9844	0.7355	0.9606	0.8255	0.9577
OSS	NO	0.9071	0.7297	0.7936	0.7473	0.8711	0.9555	0.8375	0.8755	0.7310	0.8107
	YES	0.9248	0.7820	0.8349	0.7957	0.8972	0.9808	0.7845	0.8655	0.8111	0.9137

결과 - 자세히

- 2D chess
  - None + yes : 0.9771
  - SMOTE + no : 0.8584
  - SMOTE + yes : 0.9704
- Yeast4
  - None + yes : 0.8647
  - SMOTE + no : 0.7320
  - SMOTE + yes : 0.9115
- Wine quality
  - None + yes : 0.9790
  - SMOTE + no : 0.5597
  - SMOTE + yes : 0.9685

2D chess dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.8482	0.5743	0.6992	0.6208	0.8047	0.8285	—	—	—	—
	YES	0.9771	0.9557	0.9070	0.9226	0.9469	0.9859	0.9846	0.9485	0.9643	0.9723
SMOTE	NO	0.8584	0.6422	0.7102	0.6646	0.8183	0.5921	0.1636	0.5004	0.2437	0.5855
	YES	0.9704	0.9191	0.9061	0.9064	0.9453	0.9933	0.9633	0.9667	0.9622	0.9801
ADASYN	NO	0.8482	0.5743	0.6992	0.6208	0.8047	0.6172	0.1434	0.5904	0.2299	0.5892
	YES	0.9771	0.9557	0.9070	0.9226	0.9469	0.9925	0.8546	0.9667	0.8999	0.9721
NCL	NO	0.5786	0.1245	0.6652	0.2092	0.5541	0.5290	0.1076	0.4212	0.1693	0.4802
	YES	0.9715	0.8542	0.9667	0.8988	0.9716	0.9946	0.9119	0.9667	0.9337	0.9766
OSS	NO	0.7569	0.4197	0.5227	0.4554	0.6813	0.6262	0.3050	0.0295	0.0535	0.0958
	YES	0.9743	0.9321	0.9391	0.9316	0.9640	0.9937	0.9532	0.9564	0.9524	0.9745

glass1 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.7029	0.6099	0.6235	0.6044	0.6808	0.6779	0.6394	0.5533	0.5828	0.6633
	YES	0.7328	0.6283	0.6344	0.6227	0.6956	0.7779	0.6506	0.65917	0.6430	0.7089
SMOTE	NO	0.7008	0.5750	0.6561	0.6060	0.6782	0.7140	0.5125	0.7236	0.5785	0.6111
	YES	0.7595	0.6393	0.6988	0.6589	0.7273	0.8288	0.6537	0.8802	0.7369	0.7760
ADASYN	NO	0.7095	0.5922	0.6728	0.6187	0.6842	0.7336	0.5159	0.7982	0.6103	0.6271
	YES	0.7799	0.6614	0.7106	0.6780	0.7419	0.8388	0.6545	0.8996	0.7456	0.7845
NCL	NO	0.5926	0.4401	0.9302	0.5843	0.3761	0.6750	0.4124	1.0000	0.5765	0.2177
	YES	0.5897	0.3976	0.9239	0.5527	0.3806	0.7790	0.4299	1.0000	0.5948	0.3403
OSS	NO	0.7010	0.5688	0.6841	0.6132	0.6804	0.6810	0.5850	0.5837	0.5683	0.6444
	YES	0.7611	0.6342	0.7136	0.6637	0.7295	0.7784	0.6085	0.7382	0.6543	0.7128

ecoli4 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.8446	0.7241	0.6433	0.6432	0.7694	0.9919	0.8889	0.8000	0.7993	0.8797
	YES	0.8525	0.6435	0.6017	0.5734	0.6920	0.9889	0.9143	0.7500	0.7835	0.8512
SMOTE	NO	0.8824	0.7938	0.7233	0.7102	0.8328	0.9894	0.8290	0.8000	0.7268	0.8457
	YES	0.8629	0.8315	0.7300	0.7262	0.8303	0.9931	0.8824	0.9500	0.8881	0.9639
ADASYN	NO	0.8719	0.8407	0.7083	0.7221	0.8236	0.9903	0.7813	0.8000	0.7034	0.8389
	YES	0.8747	0.7833	0.6717	0.6623	0.7822	0.9934	0.8800	0.9500	0.8857	0.9634
NCL	NO	0.8007	0.6080	0.6333	0.5651	0.7380	0.9869	0.8258	0.9000	0.7886	0.8976
	YES	0.8523	0.7297	0.7550	0.6499	0.7982	0.9914	0.8533	0.9500	0.8556	0.9549
OSS	NO	0.8398	0.6284	0.7250	0.5958	0.7872	0.9877	0.8458	0.8133	0.7580	0.8668
	YES	0.9115	0.6858	0.8350	0.6787	0.8586	0.9890	0.8830	0.9117	0.8626	0.9408

vehicle1 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.6699	0.5018	0.4301	0.4575	0.6004	0.8673	0.7074	0.3593	0.4747	0.5824
	YES	0.7385	0.5855	0.5329	0.5573	0.6794	0.9081	0.6873	0.6266	0.6536	0.7500
SMOTE	NO	0.7241	0.5398	0.5557	0.5458	0.6796	0.8945	0.5538	0.9237	0.6913	0.8264
	YES	0.7403	0.5825	0.5629	0.5704	0.6938	0.9204	0.5808	0.9745	0.7272	0.8582
ADASYN	NO	0.7211	0.5359	0.5570	0.5446	0.6791	0.8995	0.5485	0.9465	0.6937	0.8303
	YES	0.7481	0.5842	0.5789	0.5797	0.7025	0.9206	0.5800	0.9809	0.7284	0.8597
NCL	NO	0.7411	0.4153	0.9506	0.5769	0.7093	0.8411	0.4108	0.9768	0.5776	0.7059
	YES	0.7781	0.4560	0.9392	0.6118	0.7529	0.8752	0.5076	1.0000	0.6728	0.8139
OSS	NO	0.7125	0.4857	0.6066	0.5370	0.6837	0.8702	0.5745	0.7014	0.6293	0.7560
	YES	0.7531	0.5524	0.6286	0.5859	0.7174	0.9062	0.6088	0.9117	0.7290	0.8515

yeast4 dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.6736	0.3619	0.2217	0.2653	0.4482	0.8469	—	—	—	—
	YES	0.8647	0.8320	0.6708	0.7260	0.8132	0.9910	0.8628	0.8036	0.8270	0.8920
SMOTE	NO	0.7320	0.2632	0.4029	0.3082	0.6082	0.9052	0.2112	0.8769	0.3160	0.7773
	YES	0.9115	0.7665	0.6892	0.7171	0.8235	0.9922	0.7096	0.9442	0.8079	0.9639
ADASYN	NO	0.7226	0.2494	0.3958	0.2963	0.6041	0.9011	0.2061	0.6902	0.3104	0.7815
	YES	0.9114	0.7531	0.6553	0.6906	0.8036	0.9923	0.6951	0.9618	0.8051	0.9727
NCL	NO	0.8176	0.1929	0.6819	0.2992	0.7772	0.9063	0.2552	0.5745	0.3516	0.7256
	YES	0.9785	0.6733	0.9772	0.7928	0.9791	0.9917	0.7512	0.9436	0.8337	0.9649
OSS	NO	0.7066	0.2899	0.3561	0.3020	0.5713	0.8488	0.2094	0.0258	0.0447	0.0781
	YES	0.9130	0.7637	0.7699	0.7532	0.8708	0.9892	0.8312	0.8390	0.8310	0.9121

wine quality dataset

Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.5844	0.1180	0.1275	0.1132	0.2817	0.9790	0.9653	0.9113	0.9333	0.9525
	YES	0.9790	0.9653	0.9113	0.9333	0.9525	0.9944	0.9636	0.8274	0.8761	0.9031
SMOTE	NO	0.5597	0.0648	0.1801	0.0930	0.3704	0.6935	0.1065	0.4223	0.1680	0.5941
	YES	0.9685	0.9715	0.8630	0.9031	0.9239	0.9942	0.8809	0.9055	0.8890	0.9488
ADASYN	NO	0.5601	0.0654	0.1909	0.0953	0.3800	0.6920	0.1039	0.4231	0.1650	0.5933
	YES	0.9859	0.9709	0.8467	0.8917	0.9141	0.9944	0.8805	0.9055	0.8888	0.9488
NCL	NO	0.5922	0.1037	0.2593	0.1423	0.4817	0.7207	0.2582	0.1891	0.1818	0.3755
	YES	0.9845	0.8567	0.9492	0.8949	0.9703	0.9939	0.9359	0.8818	0.8890	0.9308
OSS	NO	0.5733	0.0729	0.2158	0.1054	0.4135	0.5078	—	—	—	—
	YES	0.9859	0.9636	0.9818	0.9723	0.9901	0.9941	0.9282	0.9424	0.9307	0.9690

page block dataset

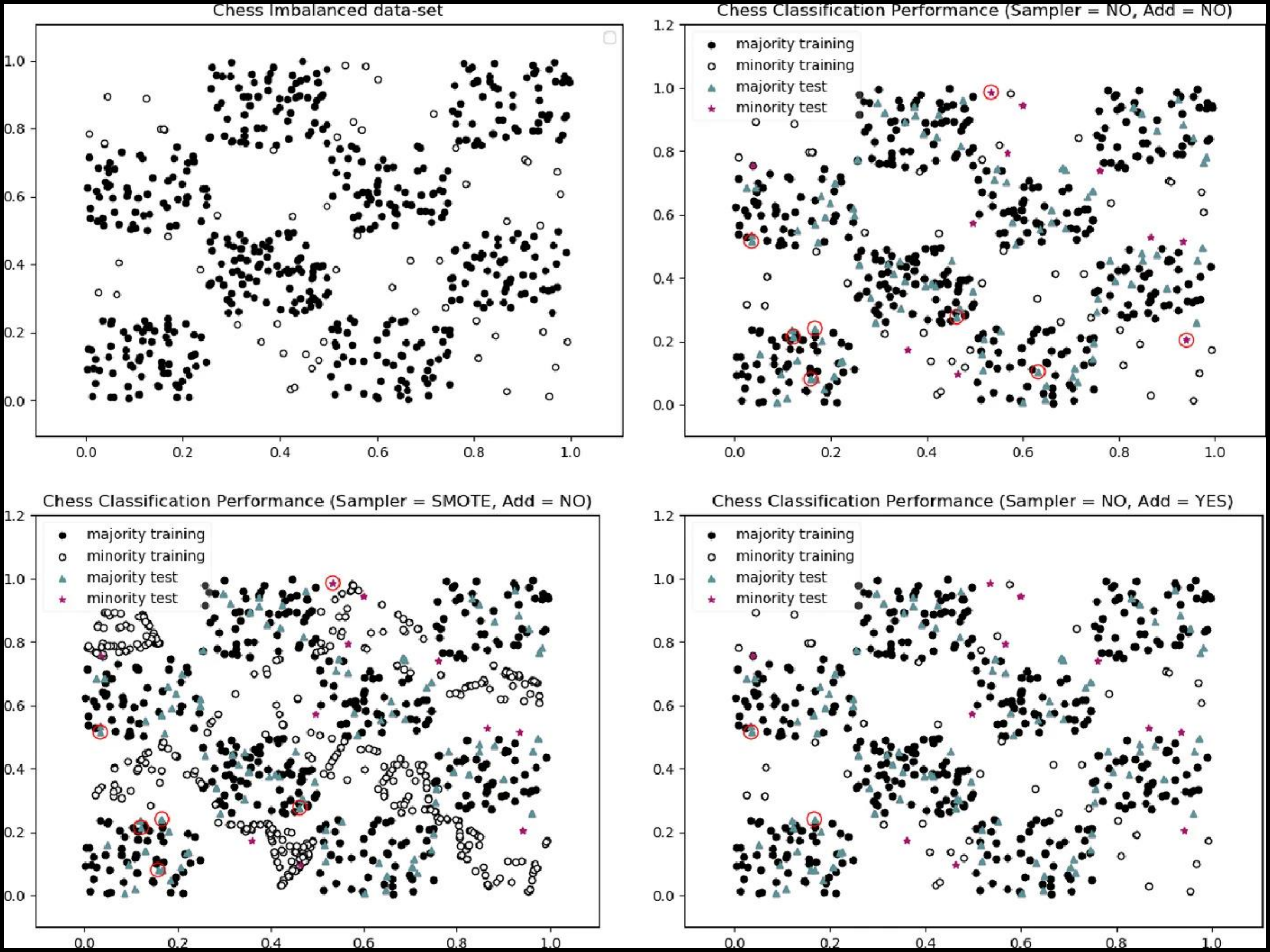
Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.9083	0.8108	0.7442	0.7687	0.8519	0.9723	0.8743	0.7046	0.7663	0.8304
	YES	0.9369	0.8535	0.8289	0.8350	0.9014	0.9880	0.8481	0.8460	0.8379	0.9091
SMOTE	NO	0.9122	0.7485	0.7910	0.7620	0.8735	0.9646	0.6815	0.8792	0.7536	0.9099
	YES	0.9300	0.8216	0.8404	0.8245	0.9051	0.9847	0.7404	0.9496	0.8251	0.9533
ADASYN	NO	0.9130	0.7302	0.7990	0.7558	0.8763	0.9613	0.5716	0.9277	0.6983	0.9194
	YES	0.9328	0.8452	0.8321	0.8356	0.9032	0.9843	0.7529	0.9726	0.8435	0.9661
NCL	NO	0.9338	0.6528	0.9091	0.7502	0.9223	0.9669	0.6628	0.8950	0.7412	0.9127
	YES	0.9563	0.7318	0.9400	0.8156	0.9474	0.9844	0.7355	0.9606	0.8255	0.9577
OSS	NO	0.9071	0.7297	0.7936	0.7473	0.8711	0.9655	0.8375	0.6755	0.7310	0.8107
	YES	0.9248	0.7820	0.8349	0.7957	0.8972	0.9808	0.7845	0.8655	0.8111	0.9137

결과

시각화

빨간색 동그라미:
잘못 분류된 것

아래 2개 비교



결과

Feature Importance

추가된 속성이 분류할
때 유의미하게 쓰임

2D chess dataset (2 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**add1**	**add2**	—	—	—	—	—	—	—	—	—
NO	0.4636	0.5364	—	—	—	—	—	—	—	—	—	—	—
YES	0.0101	0.0097	0.8152	0.1650	—	—	—	—	—	—	—	—	—
glass1 dataset (9 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**org8**	**org9**	**add1**	**add2**	—	—
NO	0.2063	0.0213	0.2354	0.1291	0.0302	0.0418	0.2634	0.0000	0.0726	—	—	—	—
YES	0.1770	0.0056	0.1527	0.1099	0.0000	0.0110	0.1892	0.0000	0.0056	0.2413	0.1077	—	—
ecoli4 dataset (7 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**add1**	**add2**	—	—	—	—
NO	0.1093	0.0587	0.0000	0.0000	0.6591	0.1729	0.0000	—	—	—	—	—	—
YES	0.0000	0.0337	0.0000	0.0000	0.6119	0.0000	0.0808	0.1742	0.0994	—	—	—	—
vehicle1 dataset (18 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**org8**	**org9**	**org10**	**org11**	**org12**	**org13**
NO	0.1304	0.0654	0.0892	0.0403	0.0563	0.0233	0.0028	0.0707	0.0000	0.0635	0.0172	0.0416	0.0438
YES	0.0248	0.0216	0.1317	0.0426	0.0227	0.0205	0.0179	0.0024	0.0000	0.0338	0.0260	0.1291	0.0828
Score \ Attr / Add	**org14**	**org15**	**org16**	**org17**	**org18**	**add1**	**add2**	—	—	—	—	—	—
NO	0.0862	0.0414	0.0498	0.0516	0.1265	—	—	—	—	—	—	—	—
YES	0.0146	0.0310	0.0325	0.0291	0.0471	0.2413	0.0485	—	—	—	—	—	—
yeast4 dataset (8 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**org8**	**add1**	**add2**	—	—	—
NO	0.3301	0.2446	0.1839	0.0720	0.0106	0.0000	0.1233	0.0355	—	—	—	—	—
YES	0.0385	0.0297	0.0483	0.0116	0.0000	0.0000	0.0248	0.0053	0.7771	0.0646	—	—	—
wine quality dataset (11 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**org8**	**org9**	**org10**	**org11**	**add1**	**add2**
NO	0.0466	0.1402	0.1215	0.1194	0.0806	0.0635	0.0428	0.1287	0.0483	0.0841	0.1244	—	—
YES	0.0000	0.0098	0.0000	0.0000	0.0000	0.0000	0.0263	0.0000	0.0000	0.0000	0.0000	0.9639	0.0000
page block dataset (10 original & 2 added attributes)													
Score \ Attr / Add	**org1**	**org2**	**org3**	**org4**	**org5**	**org6**	**org7**	**org8**	**org9**	**org10**	**add1**	**add2**	—
NO	0.5452	0.0096	0.0117	0.1899	0.0530	0.0285	0.0983	0.0382	0.0122	0.0134	—	—	—
YES	0.5282	0.0006	0.0036	0.1745	0.0205	0.0223	0.0833	0.0129	0.0007	0.0082	0.1288	0.0164	—

결론

1. In most cases, introducing these two additional attributes can improve the class imbalance classification performance. For some datasets, only introducing additional attributes gives better classification results than only performing resampling techniques.
2. An analysis of the experimental results also illustrates that the proposed method has a better ability to handle samples in the overlapping region

결론 3줄 요약

1. 추가 속성 2개(Outliar score, 4 Type) 넣으면 Resampling보다 더 성능 향상한다.
2. overlapping region(중복 영역)에서도 더 우수하다.
3. 꼭 넣어라

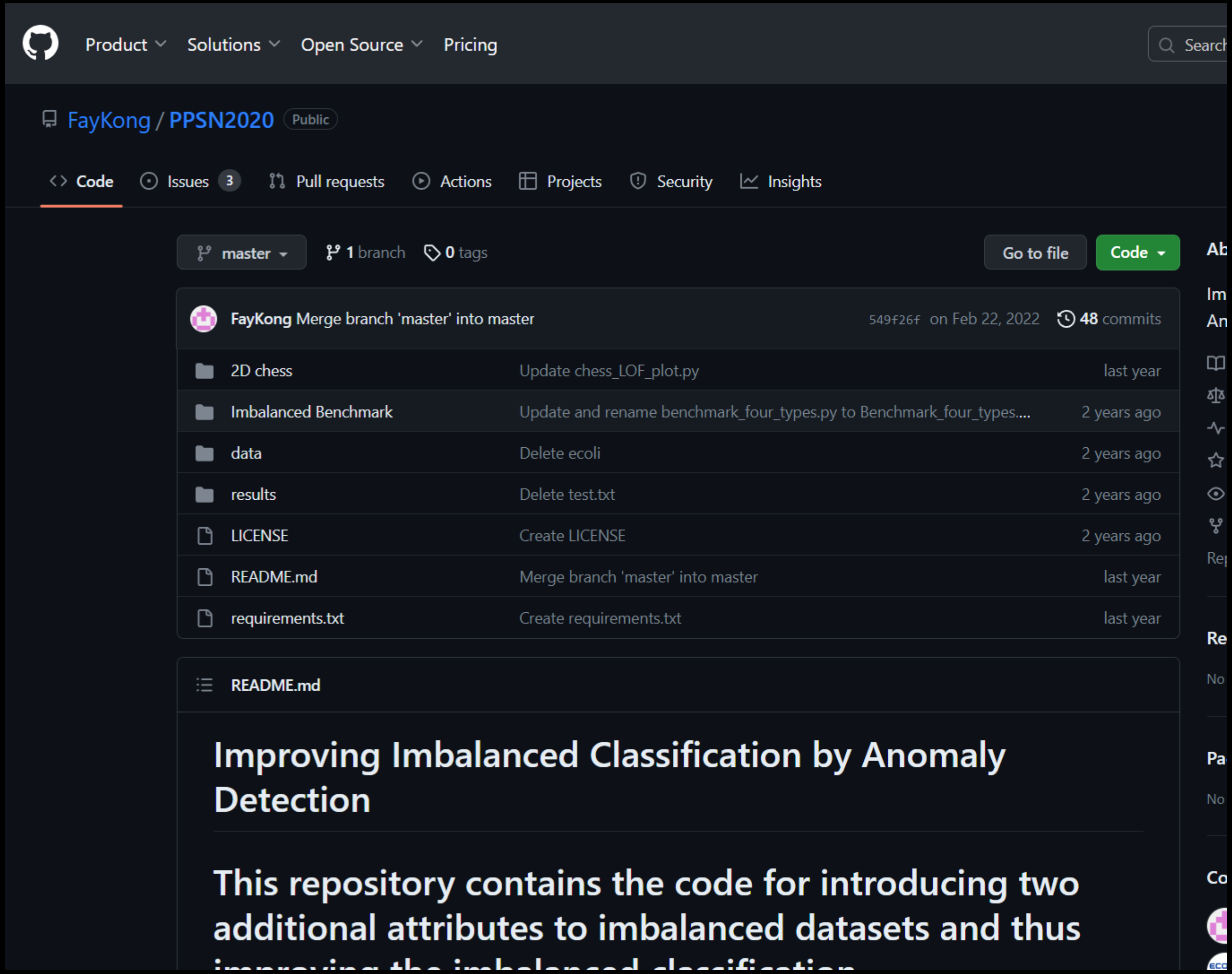
의문점

실험의 의문점. 이상치를 어떻게 구하나?

소스코드 분석

https://github.com/FayKong/PPSN2020

논문에서 사용한 소스코드 공개



Outlier score

전체 데이터를 기준으로 한다.

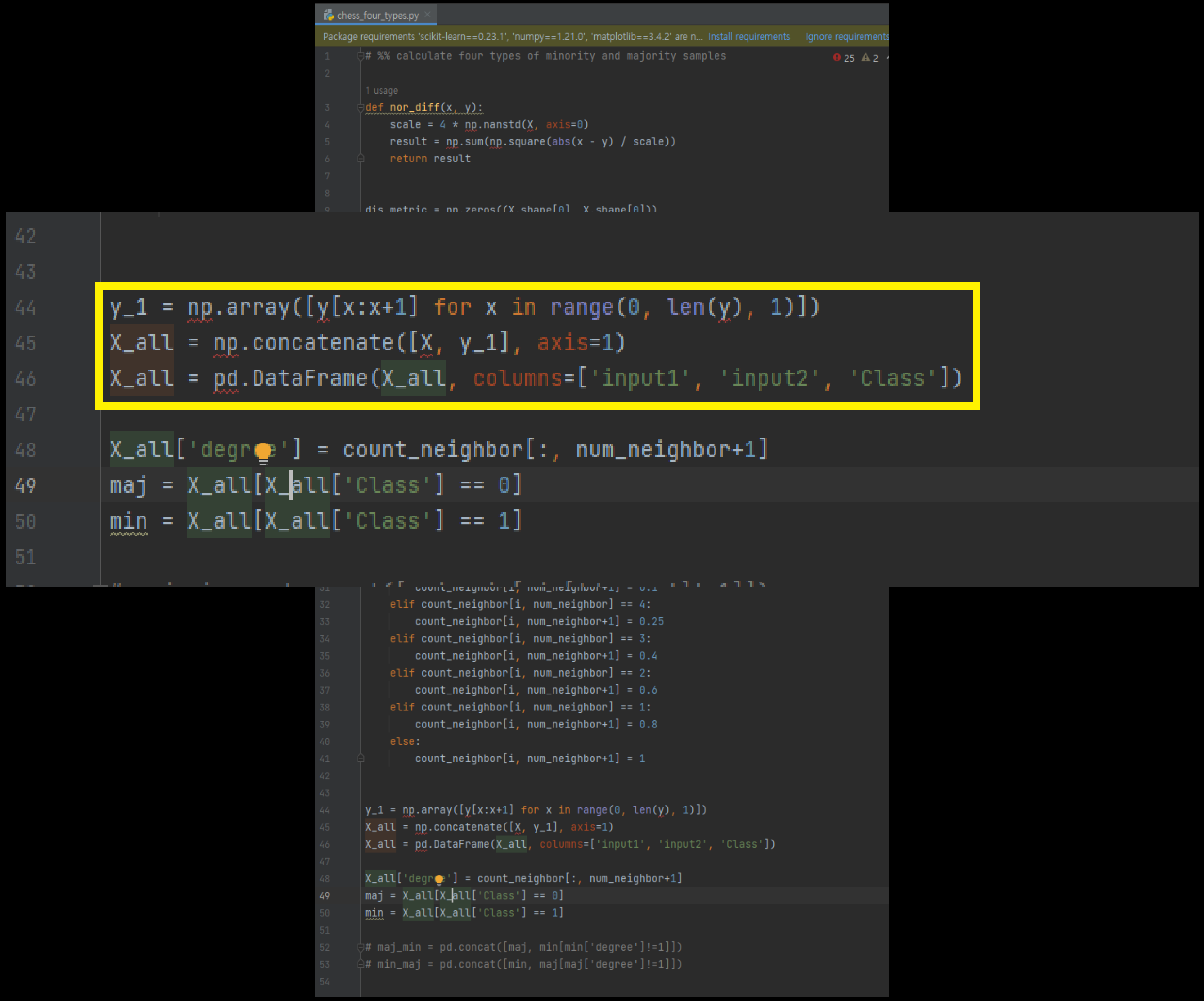
Benchmark_LOF.py

Package requirements 'scikit-learn==0.23.1', 'numpy==1.21.0', 'matplotlib==3.4.2' are not satisfied   Install requirements   Ignore requirements

```python
import ...

# %% create chess dataset

glass1_data = pd.read_csv('~data/glass1.csv')
X = glass1_data.iloc[:, 0:9]


y = glass1_data['Class']
X = StandardScaler().fit_transform(X)
X = np.c_[X]

ir = len(y[y == 1]) / len(y)
clf = LocalOutlierFactor(n_neighbors=10, contamination=ir)  # highly rely on the IR in training set
y_pred = clf.fit_predict(X)
X_scores = clf.negative_outlier_factor_
X_scores_1 = np.array([X_scores[x:x + 1] for x in range(0, len(X_scores), 1)])  # change shape (n,) to (n, 1)
X_all['LOF'] = X_scores_1

#  # experiment with LOF score
X_new = X_all.drop(['Class'], axis=1)
X_add = StandardScaler().fit_transform(X_new)
X_add = np.c_[X_add]
```

4 type

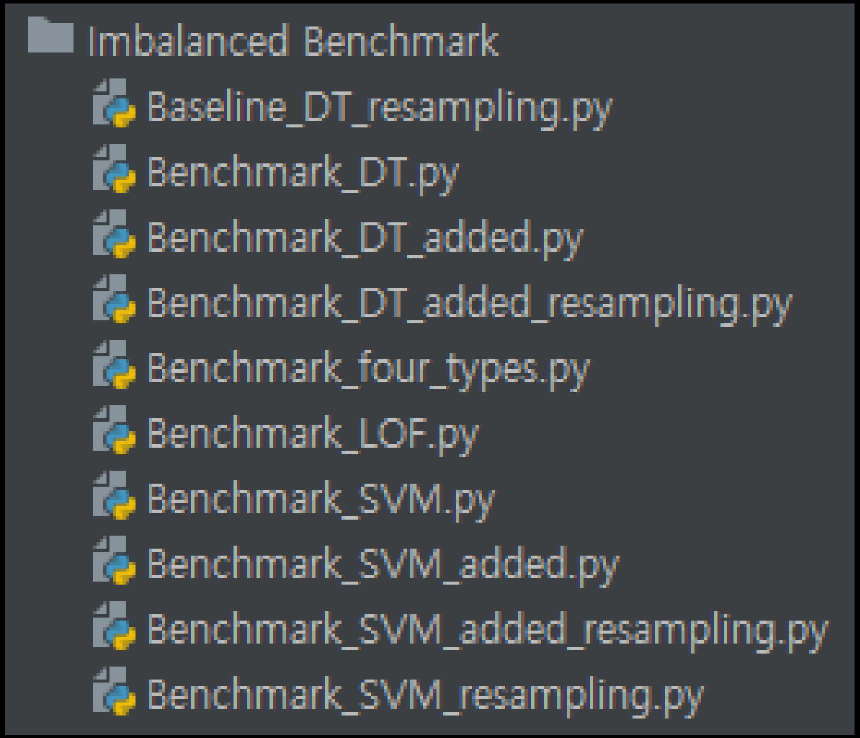
전체데이터를 기준으로 한다.



메소드

Decision tree, SVM 사용

Train, test 나누지 않고 모델 학습



일반적인 머신러닝 모델 학습 과정

전체 데이터 100

- Train: 80
  - Train: 64
  - Validation: 16
- Test: 20

전체 데이터

- 모델 학습할 때 쓰는 데이터
  - 모델 학습
  - 모델 검증 (과적합 방지 등)
- 학습완료한 모델의 성능 테스트

모델 학습 과정 중에 이상치는 어떻게..?

전체 데이터 100

- Train: 80
  - Train: 64
  - Validation: 16
- Test: 20

전체 데이터의 이상치?

- Train의 이상치?
  - Train의 이상치?
  - Validation의 이상치?
- Test의 이상치?

전체 데이터를 기준으로 했을 때의 문제점

- 과적합
  - 학습한 모델에 새로운 데이터가 들어오면 잘 판단할 수 있을까?
- 의미있는 실험인가?
  - 애초에 Outliar score, type을 제공하고 학습
  - 정답을 보여주는 것과 다름 없지 않나?

마무리

결론, 향후 계획

결론

- 논문을 잘못 잡았다.
- 이 논문
  - 이상치 점수를 요소로 추가하여 머신러닝
- 내가 원했던 논문
  - 기존 머신러닝 알고리즘을 안 씀
  - 이상치 탐지 알고리즘을 이용하여 데이터 분석

향후 계획

- 전통적인 Outlier detection method 연구
  - Tukey's IQR method
  - Standard deviation method
  - Z-score method
  - Isolation Forest
  - DBSCAN
- 딥러닝 Outlier detection method 연구
  - Anomaly transformer 등등
- 현재 보유중인 데이터셋 활용 방안 탐구
  - 실험에 활용된 데이터셋 분석
  - 유사한 데이터셋에 적용