Article Review

Improving Imbalanced Classification by Anomaly Detection

증강지능 연구실 황승현

2023-08-23

논문 소개

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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 클래스의 비율이 크게 차이가 나는 경우
  - 고혈압 분류: 정상 95명 비정상 5명
  - 골다공증 분류: 정상 80명 비정상 20명
- Rare class : 소수 (고혈압, 골다공증 환자)
- Abundant class : 다수 (정상인)

Imbalanced classification 문제점

- 대충 만들어도 Accuracy 가 높게 나온다
  - 모델이 모두 정상이라고 판단하면 된다.
  - 정상인 80명 환자 20명을 분류할 때, 모두 정상인이라고 분류하면?
  - 정확도 80%
- 현실의 많은 데이터가 불균형하다
  - Fraud detection
  - Medical diagnosis
  - Facial recognition

접근법 : Resampling

Oversampling

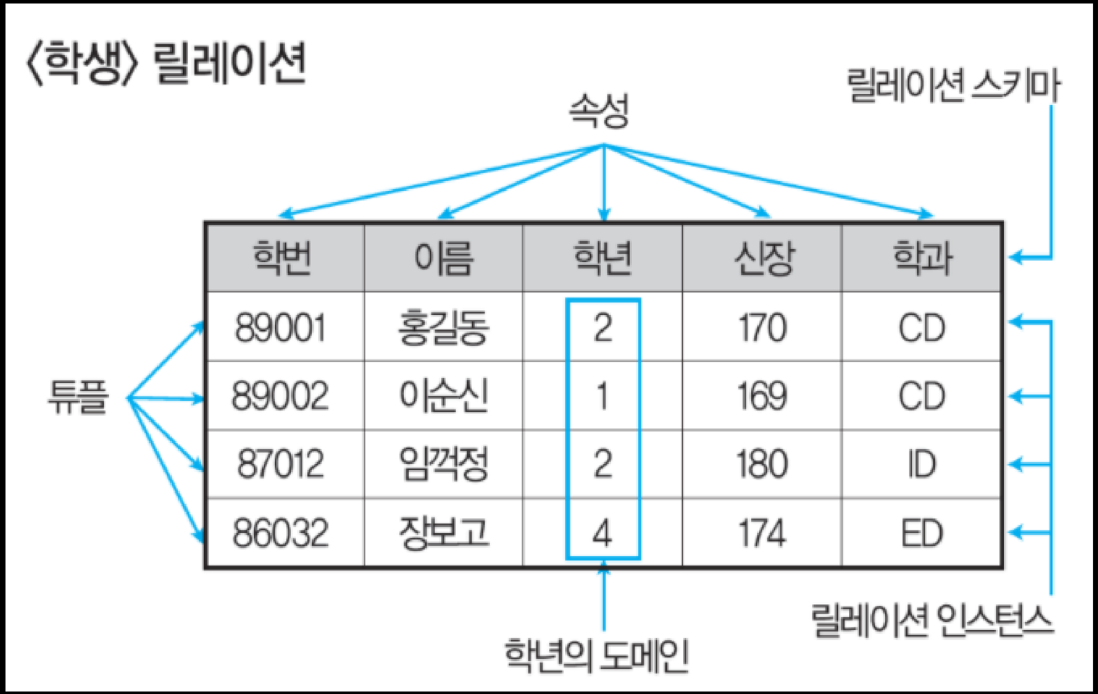
- Rare class 늘리기
- 소수를 복제하여 다수에 맞춤
- SMOTE, ADASYN 등

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



학번	이름	학년	신장	학과
89001	홍길동	2	170	CD
89002	이순신	1	169	CD
87012	임꺽정	2	180	ID
86032	장보고	4	174	ED

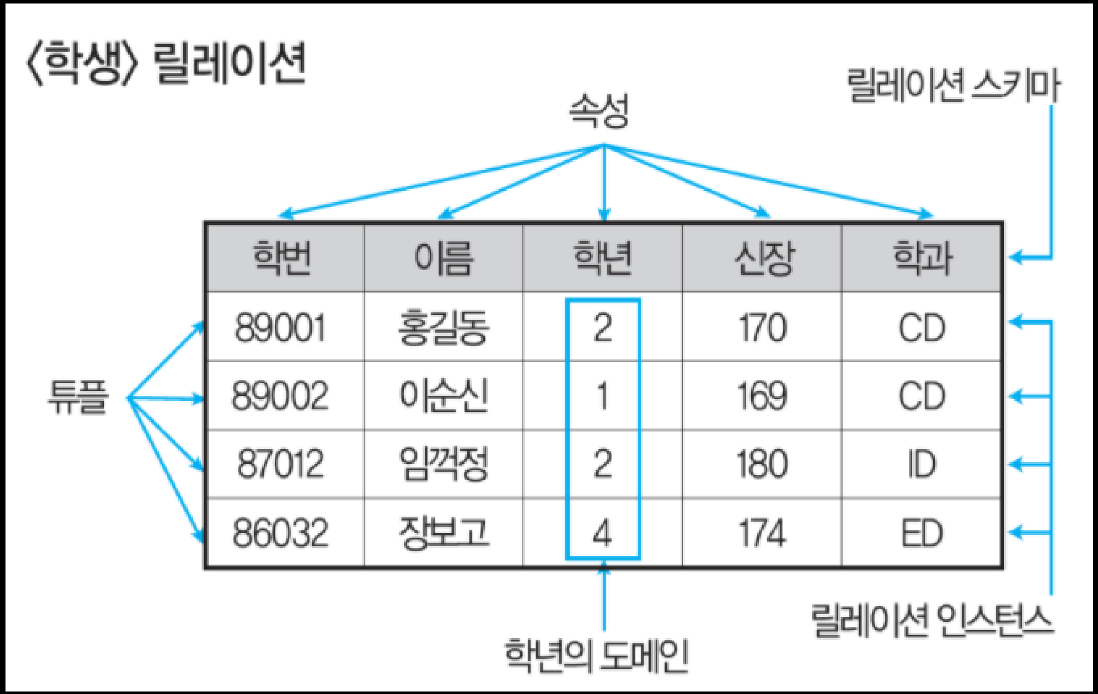
새로운 접근법

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



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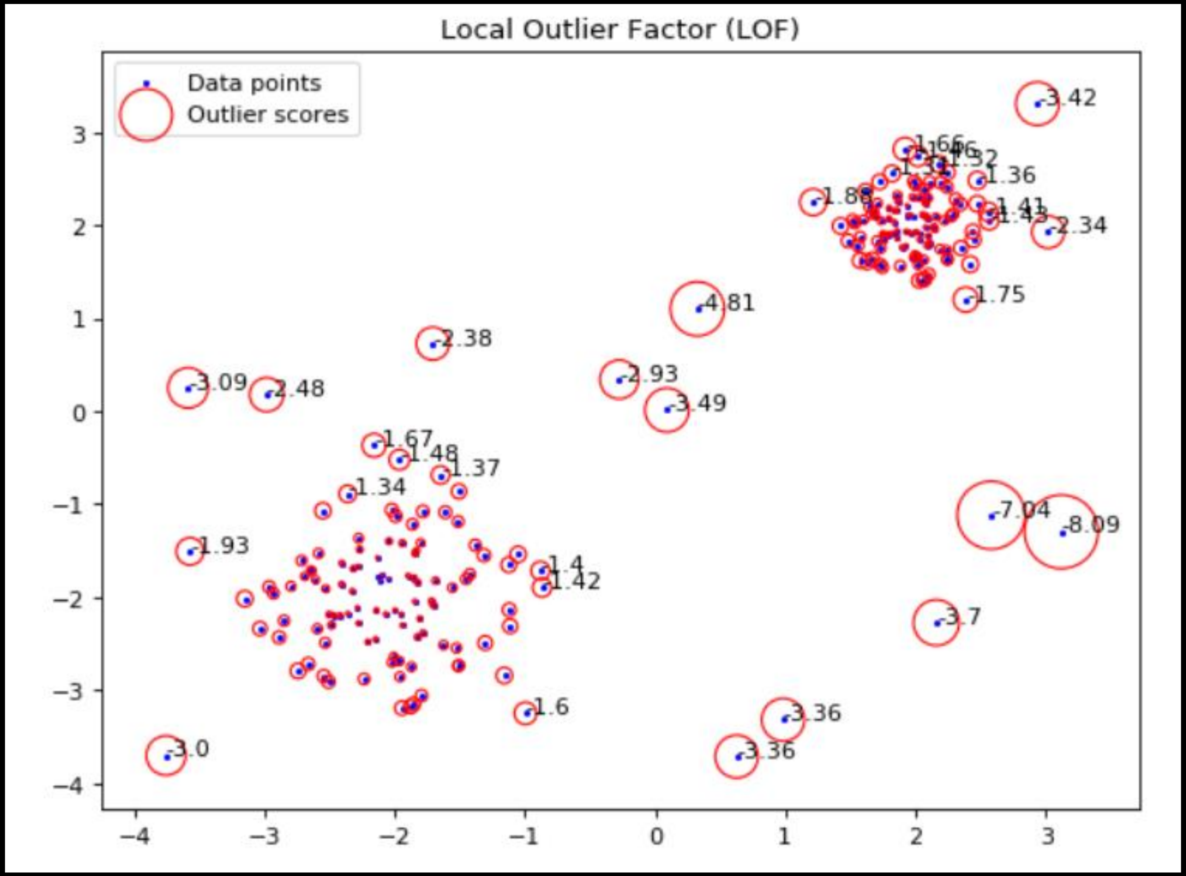
outlier score

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



safe, borderline, rare, outlier

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	0.6808	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	0.8755	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	0.6769	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

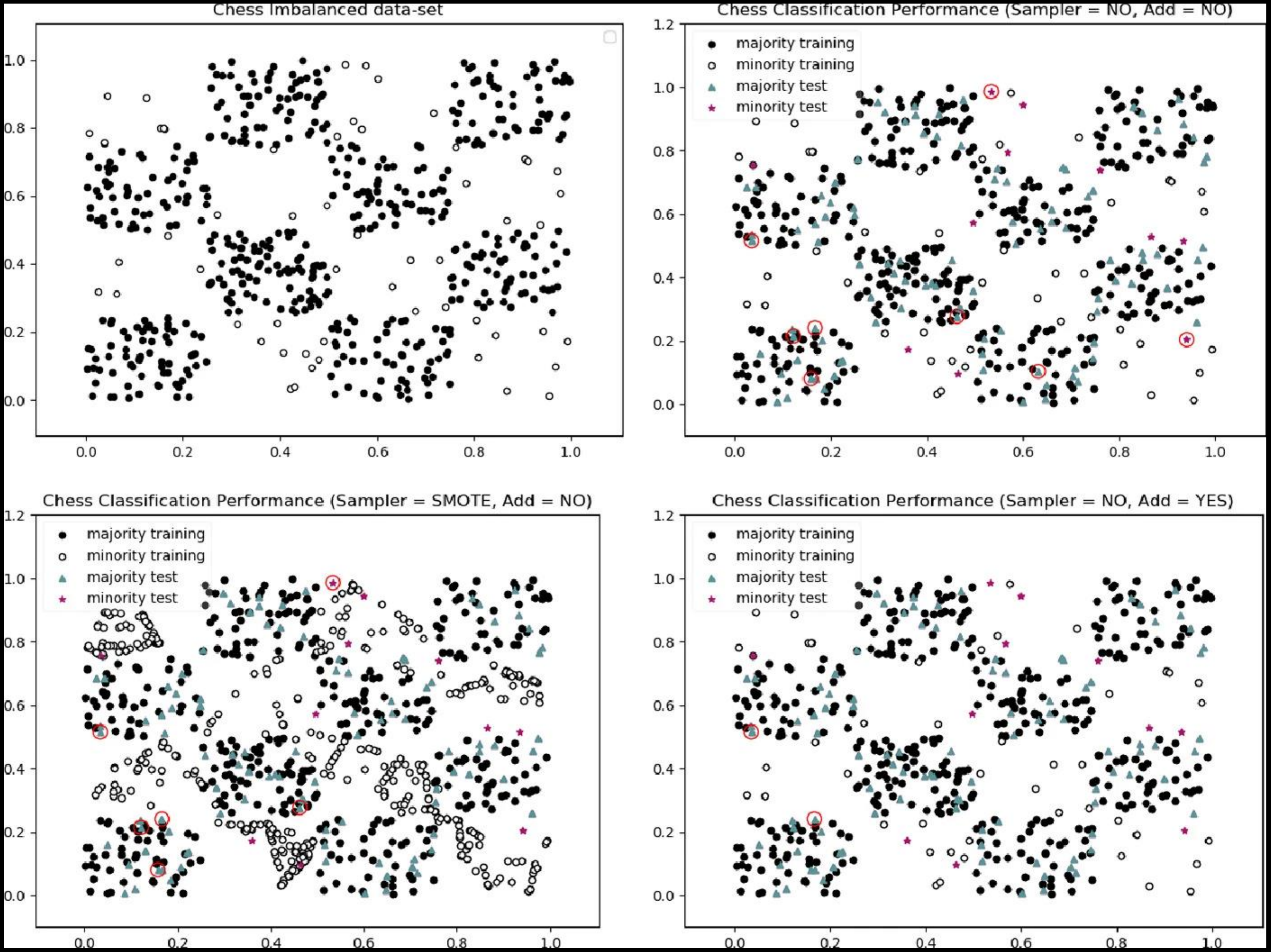
Methods	Add	Decision Tree					SVM				
		AUC	Precision	Recall	F1	Gmean	AUC	Precision	Recall	F1	Gmean
NONE	NO	0.9083	0.8108	0.7442	0.7687	0.8519	0.9723	0.8743	0.7046	0.7663	0.8304
	YES	0.9369	0.8535	0.8289	0.8350	0.9014	0.9880	0.8481	0.8460	0.8379	0.9091
SMOTE	NO	0.9122	0.7485	0.7910	0.7620	0.8735	0.9646	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	0.8950	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	—

마무리

결론, 향후 계획

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 넣으면 Resampling보다 더 성능 향상한다.

2. overlapping region(중복 영역)에서도 더 우수하다.

3. 꼭 넣어라

논문을 보고 느낀 점

- 왜 이것을 이제야 알았을까?
- 그동안 했던 노력
  - Accuracy 대신 F1-score, AUC 등으로 평가
  - Oversampling
  - K-fold Cross-Validation
  - Ensemble 등등

향후 계획

- 깃허브에 공개된 소스코드 분석
  - https://github.com/FayKong/PPSN2020
- 현재 보유중인 데이터셋 활용 방안 탐구
  - 실험에 활용된 데이터셋 분석
  - 유사한 데이터셋에 적용

향후 계획

- Gradient Boosted Decision Tree 기반 알고리즘에 적용
  - XGBoost
  - LGBM
- Transformer 기반 알고리즘에 적용
  - SAINT
  - TabTransformer

감사합니다~