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Erratum

Erratum to "Entropy-based fuzzy support vector machine for imbalanced datasets" [Knowl.-Based Syst. 115 (2017) 87–99][☆]

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ABSTRACT

In this note, we show that the calculation of statistics X_F^2 and F_F in sections 4.5 and 4.6 of the paper (Fan et al., 2017) is not correct. Also, based on the calculation of Critical Difference (CD) of Bonferroni–Dunn test, we show that the conclusion on "significantly outperforming the compared algorithms", drawn by the authors using the P-value test, is not convincing.

1. Introduction

In [1], the authors proposed an entropy-based fuzzy support vector machine (EFSVM) for class-imbalance problem. To validate the effectiveness of EFSVM, experiments on 64 real-world imbalanced datasets (categorized as low imbalanced, medium imbalanced and high imbalanced) were conducted. Using Friedman test they concluded that EFSVM significantly outperformed the compared algorithms. We found incorrect calculations in Section 4, and obtained a different conclusion regarding the statistical testing on the comparisons.

2. Incorrect calculation

In Sections 4.5 and 4.6 of paper [1], χ_F^2 and F_F are calculated according to Eqs. (11) and (12) based on the data in Tables 7 and 8. We find that the obtained results are not correct because the authors take incorrect number of datasets n, number of algorithms k and the values of Average Rank R_j in corresponding tables. Let us show the details.

2.1. Medium imbalanced datasets

In Section 4.5, counting the rows and columns of Table 7, we have $n = 33$, $k = 9$, and $R_i (i = 1, 2, \ldots, 9)$ which should be $2.39, 5.73, 3.64, 5.18, 4.17, 4.70, 4.79, 7.36$ and 7.05 respectively, at the last row in Table 7. Replacing these values into Eqs. (11) and (12), we obtain

$$\begin{aligned}\chi_F^2 &= \frac{12 \times 33}{9 \times (9+1)}[(2.39^2 + 5.73^2 + 3.64^2 + 5.18^2 + 4.17^2 \\ &\quad + 4.70 + 4.79^2 + 7.36^2 + 7.05^2) - \frac{9 \times (9+1)^2}{4}] \\ &= \frac{396}{90}[244.9221 - \frac{900}{4}] = 87.66\end{aligned}$$

and

$$F_F = \frac{(33-1) \times 87.66}{33 \times (9-1) - 87.66} = \frac{2805.12}{176.34} = 15.91$$

F_F is distributed according to the F distribution with $(k-1) = 8$ and $(k-1)(n-1) = 256$ degrees of freedom. The results on the statistic in paper [1] are $\chi_F^2 = 104.20$ *and* $F_F = 23.48$.

Also, we recomputed the "Average rank" and "Difference" of compared algorithms on medium imbalanced datasets (see Table 1).

2.2. High imbalanced datasets

In Section 4.6, we find that the values of the last row "Average Rank" in Table 8 do not coincident with the values of the datasets

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Table 1
Ranks and AUC values (%) of the compared algorithms on medium imbalanced datasets (Im.Ratio $0.9 \leq 20$).

Data set	Entropy FSVM	FSVM	SVM-SMOTE	SVM-OSS	SVM-RUS	SVM	EasyEnsemble	AdaBoost	1-NN
Ecoli 0-2-3-4-vs-5	2	8	6	4	1	3	5	7	9
Yeast 0-3-5-9-vs-7–8	4	5	2	8	3	6.5	1	9	6.5
Ecoli 0-4-6-vs-5	4	1	3	5	6	2	7	8.5	8.5
Yeast 0-2-5-6-vs-3-7-8–9	2	7	1	3	6	5	4	9	8
Yeast 0-2-5-7-9-Vs-3-6–8	4	8	2	6	5	1	3	9	7
Ecoli 0-3-4-6-Vs-5	1	3	3	3	6	5	8	9	7
Ecoli 0-3-47-Vs-5–6	1	6	5	7	2	3	9	4	8
Ecoli 0-1-vs-2-3–5	1	5	2	6	4	3	7	9	8
Yeast 2-vs-4	2	7	4	3	5	6	1	9	8
Ecoli 0-6-7-Vs-3–5	1	4	5	2	6	3	7	9	8
Glass 0-4-Vs-5	1	4	7.5	9	2	3	6	7.5	5
Ecoli 0-2-6-7-Vs-3–5	1	7	6	3	2	4	5	9	8
Glass 0-1-5-Vs-2	2	5	1	8	4	9	3	7	6
Yeast 0-5-6-7-9-vs-4	1	5	3	4	2	7	6	9	8
Vowel	7	9	5	8	6	4	2	3	1
Ecoli 0-6-7-vs-5	1	2	3.5	3.5	5	6	7	9	8
Ecoli 0-1-4-7-Vs-2-3-5–6	1	2	6	5	4	3	7	8	9
Glass 0-1-6-Vs-2	2	5	4	3	1	7	6	9	8
Ecoli 0-1-vs-5	1	4.5	4.5	2	3	6	8	9	7
Led7digit 0-2-4-5-6-7-8-9-vs-1	3	2	1	6	5	4	7	8	9
Glass 0-6-Vs-5	4.5	7	3	9	8	1	6	2	4.5
Glass 0-1-4-6-Vs-2	2	9	3	6	4	5	1	7	8
Glass 2	1	5	2	6	4	7	3	8	9
Ecoli 0-1-4-7-vs-5–6	1	6	2	5	4	7	3	9	8
Cleveland 0-Vs-4	2	9	3	7	5	6	1	4	8
Ecoli 0-1-4-6-vs-5	3.5	3.5	2	1	5.5	5.5	7	9	8
Shuttle c0-vs-c4	4	4	4	4	4	7	1	9	8
Yeast 1-Vs-7	3	8	2	4	5	6	1	9	7
Ecoli 4	1	6	3	5	4	2	7	9	8
Glass 4	4	7	5	6	3	1	9	8	2
Pageblocks 1-3-Vs-4	4	8	5.5	5.5	9	7	2	1	3
Abalone 918	6	8	5	9	2	7	1	3	4
Glass 0-1-6-Vs-5	1	9	6	5	2	3	7	4	8
Ave. Rank	**2.39**	5.73	3.64	5.18	4.17	4.70	4.79	7.36	7.05
Difference	N/A	3.34	1.25	2.79	1.78	2.31	2.4	4.97	4.66

in the same table. For example, the average rank of the second column FSVM

$R_2 = 5.95$

After checking one by one, we calculate the Average Rank using formula $R_j = \frac{1}{n}\sum_{i=1}^{n} r_i^j$, obtain the values 2.2, 5.85, 2.3, 5.9, 3.1, 5.4, 4.65, 8.4, and 7.2 (in order from left to right of Table 8). Accordingly,

$$\chi_F^2 = \frac{12 \times 10}{9 \times (9+1)}[(2.2^2 + 5.85^2 + 2.3^2 + 5.90^2 + 3.10^2 + 5.40^2 + 4.65^2 + 8.40^2 + 7.20^2) - \frac{9 \times (9+1)^2}{4}] = \frac{120}{90}[261.955 - \frac{900}{4}] = 49.27$$

and

$$F_F = \frac{(10-1) \times 49.27}{10 \times (9-1) - 49.27} = \frac{443.43}{30.73} = 14.43$$

F_F is distributed according to the F distribution with $(k-1) = (9-1) = 8$ and $(k-1)(n-1) = (9-1)(10-1) = 72$ degrees of freedom. It is also different from the results given in paper [1], i.e. $\chi_F^2 = 47.35$ *and* $F_F = 22.34$.
Moreover, we recomputed the “Average rank” and “Difference” on high imbalanced datasets (See Table 2).

3. Inappropriate conclusion

Due to the incorrect calculation on Friedman statistic, we need to verify if the testing results are reliable.

3.1. Bonferroni–Dunn test

To the best of our knowledge, the Bonferroni–Dunn test [2–4] is generally used for statistical testing. We use it on Tables 6, 7 and 8 separately, taking the critical difference (CD) given in [2,3], i.e.

$$CD = q_\alpha \sqrt{\frac{k(k+1)}{6n}}. \qquad (1)$$

where critical values q_α are given in [5].

3.1.1. Low imbalanced datasets

The critical value of $F(8160)$ at $\alpha = 0.05$ is 1.997. Because $F_F = 7.19 > 1.997$, the compared algorithms are not equivalent at $\alpha = 0.05$, then we can reject the null-hypothesis.

According to Table 6, the algorithm with the best Average Rank is EasyEnsemble. Taking $q_\alpha = 2.724$ [5], we have the critical difference $CD = 2.724\sqrt{\frac{9(9+1)}{6\times 21}} = 2.30$. Since the difference between the average ranks of Entropy FSVM and SVM-SMOTE (SVM-RUS respectively) is $4.50 - 3.02 = 1.48$ ($5.07 - 3.02 = 2.05$ respectively) less than 2.30, therefore there is no significant difference between Entropy FSVM and SVM-SMOTE (SVM-RUS respectively). Moreover, the average rank of Entropy FSVM is bigger than EasyEnsemble, i.e. $3.02 > 2.52$, so we cannot conclude that the Entropy FSVM method is significantly different with EasyEnsemble.

3.1.2. Medium imbalanced datasets

The critical value of $F(8256)$ at $\alpha = 0.05$ is 1.975. Because $F_F = 15.91 > 1.975$, the compared algorithms are not equivalent at $\alpha = 0.05$; we can reject the null-hypothesis.

Table 2
Ranks of the compared algorithms on high imbalanced datasets (Im.Ratio > 20)

Data set	Entropy FSVM	FSVM	SVM-SMOTE	SVM-OSS	SVM-RUS	SVM	EasyEnsemble	AdaBoost	1-NN
Yeast 1-4-5-8-Vs-7	1	7	2	5	3	6	4	9	8
Yeast 2-Vs-8	1	9	5	6	4	3	2	7	8
Glass 5	1	4	2	7	3	9	5	8	6
Shuttle c2-Vs-c4	3	6	3	7.5	3	3	7.5	9	3
Yeast 4	1	7	2	5	3	6	4	9	8
Yeast 1-2-8-9-Vs-7	4	6	2	5	1	7	3	8	9
Yeast 5	2	6.5	1	6.5	3	4	5	8	9
Yeast 6	4	5	1	6	2	3	7	9	8
Ecoli 0-1-3-7-vs-2–6	1	3	2	5	7	4	8	9	6
Abalone 19	4	5	3	6	2	9	1	8	7
Ave. Rank	**2.2**	5.85	2.3	5.9	3.1	5.4	4.65	8.4	7.2
Difference	N/A	3.65	0.1	3.5	0.9	3.2	2.45	6.2	5

According to Table 7, the algorithm with the best Average Rank is Entropy FSVM. We have the critical difference $CD = 2.724\sqrt{\frac{9(9+1)}{6\times 33}} = 1.84$. Since the difference between the average ranks of Entropy FSVM and SVM-SMOTE (SVM-RUS respectively) is $3.64-2.39 = 1.25$ $(4.17-2.39 = 1.78$ respectively) less than 1.84, therefore there is no significant difference between Entropy FSVM and SVM-SMOTE (SVM-RUS respectively).

3.1.3. High imbalanced datasets

The critical value of $F(8, 72)$ at $\alpha = 0.05$ is 2.07. Because $F_F = 14.43 > 2.07$, the compared algorithms are not equivalent at $\alpha = 0.05$; we can reject the null-hypothesis.

According to Table 8, the algorithm with the best Average Rank is Entropy FSVM. We have the critical difference $CD = 2.724\sqrt{\frac{9(9+1)}{6\times 10}} = 3.34$. Since the difference between the average ranks of Entropy FSVM and SVM-SMOTE (SVM-RUS, SVM, and EasyEnsemble, respectively) is $2.3-2.2 = 0.1$ $(3.1-2.2 = 0.9$, $5.4-2.2 = 3.2$, and $4.65-2.2 = 2.45$, respectively) less than 3.34, therefore there is no significant difference between Entropy FSVM and SVM-SMOTE (SVM-RUS, SVM, and EasyEnsemble, respectively).

3.2. Discussion

Paper [1] claimed that the *p-values* could be computed as $F(8160)$, $F(8256)$ and $F(8, 81)$ for the three categories of imbalanced datasets respectively, and concluded that the Entropy method outperformed the compared algorithms. In general, the performances of the two classifiers are significantly different if the corresponding average ranks are bigger than the critical difference. As we have shown in Sections 3.1.1, 3.1.2, and 3.1.3, Bonferroni–Dunn test is used to compare the best Entropy FSVM with the other methods. The results show that Entropy FSVM is not able to outperform the compared algorithms significantly.

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