Universum Twin Bounded Support Vector Machine in the Primal Space and Its Application in Gender Recognition from Face Images

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Abstract

The Universum, a third class not belonging to either class of the classification problem, has been proved helpful in supervised learning. In this work, we consider twin bounded support vector machine with Universum data ($\mathfrak{U}$TBSVM) and propose a new and fast method for solving its primal problems and named as N$\mathfrak{U}$TBSVM. In the N$\mathfrak{U}$TBSVM, we convert the constrained programming problems of $\mathfrak{U}$TBSVM into unconstrained optimization problems and suggest a generalization of the Newton's method for solving the unconstrained problems. The numerical experiments on artificial, UCI, and NDC data sets show the ability and effectiveness of the proposed N$\mathfrak{U}$TBSVM. We applied the suggested method for gender detection from face images and compare it with other methods.

Keywords: Universum, Twin support vector machine, Twin bounded support vector machine, Newton's method, Unconstrained optimization problem.

1. Introduction

The machine learning techniques have been used in many applications such as medicine (heart disease, lung cancer, or colon tumor prediction), text categorization, computational biology, bioinformatics, image classification, real-life data sets, etc. [1, 2, 3, 4, 5, 6, 7, 8]. Support vector machine (SVM) is a powerful tool for binary classification problems in various machine learning techniques. Vapnik et al. introduced SVM in the early 1990s. The standard

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for training and the remaining individuals for testing (of which 12 subjects are randomly selected for training, and the rest 38 subjects for testing). For each person, a single image was randomly selected (from 5 images).

The experimental results are presented in Table 5. The mean and standard deviation are reported on 5 independent runs and the best result are shown in bold. Table 5 clearly shows that in gender classification our method performed better than the other three methods.

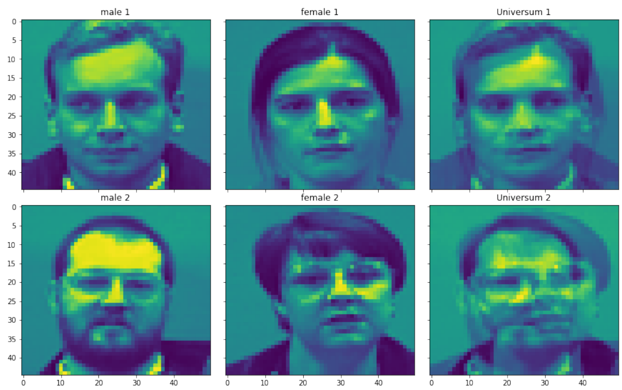

Figure 10: The first column shows two men and the second column shows two women and the third column illustrates the Universum of a man and a woman in each row.

5. Conclusion

In recent years, the new concept of Universum has been proposed and defined as the sample that does not belong to any class. Previous researches have shown that Universum data is very useful for supervised learning. In this paper, we presented a new idea for solving the $\mathfrak{U}$TBSVM programming problems. We converted the constrained quadratic programming problems ($\mathfrak{U}$TBSVMs) into unconstrained quadratic problems, by using 2-norm of the slack vectors in the objective functions of two quadratic problems. After that, we proposed a generalization of Newton's method for solving unconstrained quadratic problems, which makes solving the related problems fast and simple. Therefore, the proposed method has attractive features: using Universum data to increase the generalization performance of classifiers; more accurate and faster prediction than TSVM and $\mathfrak{U}$TBSVM. Numerical experiments were performed on an artificial data set, UCI data sets, and NDC data sets to illustrate the high efficiency of the proposed methods in both the linear and nonlinear states.

Acknowledgments

The work of H. Moosaei was supported by the Center for Foundations of Modern Computer Science (Charles Univ. project UNCE/SCI/004) and the Czech Science Foundation Grant P403-18-04735S. The work of M. Hladík was supported by the Czech Science Foundation Grant P403-18-04735S.

Conflict of interest

The authors declare that they have no conflicts of interest.

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Table 2: Performance comparison of linear TSVM, $\mathfrak{U}$TBSVM, and N$\mathfrak{U}$TBSVM on UCI data sets.

Data set	TSVM	$\mathfrak{U}$TBSVM	N$\mathfrak{U}$TBSVM
Size	Acc (%) ±Std	Acc (%) ±Std	Acc (%) ±Std
	Time (ms)	Time (ms)	Time (ms)
Bupa	68.12 ±5.42	**69.57 ±5.10**	68.99 ±5.07
345×6	28	40	**7**
Haberman	74.67 ±6.09	75.67 ± 3.43	**76 ±3.59**
306×3	39	65	**3**
Heart	72.08± 2.50	72.45 ±4.56	**73.58 ±4.77**
270×16	13	36	**3**
Ionosphere	86 ± 1.89	87.43 ±2.46	**90.29 ±2.78**
351×34	22	99	**9**
Pima	77.12 ±4.69	77.78 ± 3.38	**77.91±3.24**
768×9	340	882	**11**
Sonar	76.10 ±1.82	76.10 ± 4.20	**79.02 ±6.83**
208×60	17	25	**6**
Spect	78.50 ±8.40	79.24±8.69	**80 ±7.97**
237×22	18	69	**4**
Trans	76.24 ±4.58	76.24 ± 4.58	**76.37 ±4.44**
10×32	153	324	**9**
House Votes	96.05 ±2.90	**96.51 ±2.43**	96.04 ±2.81
435×16	79	104	**7**
Wpbc	96.28 ± 1.71	97 ±1.64	**97.17 ±1.31**
198×33	139	778	**13**

Table 3: Performance comparison of nonlinear TSVM, $\mathfrak{U}$TBSVM, and N$\mathfrak{U}$TBSVM on UCI data sets.

Data set	TSVM	$\mathfrak{U}$TBSVM	N$\mathfrak{U}$TBSVM
Size	Acc (%)±Std Time (ms)	Acc (%)±Std Time (ms)	Acc (%)±Std Time (ms)
Bupa	66.09 ±8.02	71.59±2.98	**73.62 ±4.43**
345×6	48	70	**11**
Haberman	74.34 ±3.89	**77 ± 2.2**	76 ± 2.26
306×3	115	191	**26**
Heart	64.15± 9.24	**71.30 ±5.14**	70.94 ±7.32
270×16	26	73	**6**
Ionosphere	93.14± 1.67	94.29±3.94	**95.71 ±0.9**
351×34	62	276	**18**
Pima	75.16±4.27	76.99 ± 4.20	**78.17 ±4.81**
768×9	1151	2985	**45**
Sonar	81.95 ±7.65	84.88 ± 4.20	**86.34 ±2.49**
208×60	41	61	**4**
Spect	78.87 ±8.30	**80 ±6.92**	**80 ±6.92**
237×22	47	162	**14**
Trans	76.38 ±4.44	76.24 ± 4.58	**76.64 ±4.43**
10×32	159	334	**34**
House Votes	87.67±3.17	88.14 ±0.87	**90.47±3.56**
435×16	127	168	**6**
Wpbc	96.64 ± 0.66	97.52±1.03	**98.05±0.35**
198×33	243	1323	**26**

Table 4: Performance comparison of linear TSVM, 𝔘TBSVM, and N𝔘TBSVM on NDC data sets.

Data sets	Method	Acc (%)±Std	Time (ms)
100×10	TSVM	84± 5.63	29
100×10	𝔘TBSVM	94.41 ± 2.07	44.5
100×10	N𝔘TBSVM	**94.81±3.93**	**5.7**
500×10	TSVM	73.87± 2.64	78.5
500×10	𝔘TBSVM	93.05± 5.51	102.8
500×10	N𝔘TBSVM	**93.47± 4.84**	**11.5**
1000×10	TSVM	70.25± 2.29	85.2
1000×10	𝔘TBSVM	87.73± 2.44	320.9
1000×10	N𝔘TBSVM	**88.02± 1.15**	**26.9**
2000×10	TSVM	70.07± 2.00	175.5
2000×10	𝔘TBSVM	**86.88± 0.95**	1411.8
2000×10	N𝔘TBSVM	**86.88± 0.72**	**48**
5000×10	TSVM	71.03± 0.32	965.8
5000×10	𝔘TBSVM	87.08±1.09	14501.9
5000×10	N𝔘TBSVM	**87.26±0.73**	**231.6**

Table 5: Gender recognition using TSVM, 𝔘SVM, 𝔘TBSVM, and N𝔘TBSVM.

	TSVM (C1, C2, ε)	𝔘SVM (C, Cu, ε)	𝔘TBSVM (C1, C2, Cu, ε)	**N𝔘TBSVM** **(C1, C2, Cu, ε)**
Acc	73.83	80.28	82.50	**83.33**
Std	5.00	4.93	3.62	**2.40**
Parameters	(0.03125, 32.0, 0.1)	(0.039, 16, 0.1)	(0.5, 0.03125, 0.5, 0.5)	**(2.0, 0.03125, 0.03125, 0.5)**