

# Deney Sonuçları

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## 1 Outlier Detection Metodlarının Karşılaştırılması

Tablo 1 ve 2’de görüldüğü üzere herhangi bir metodun diğerinden bariz şekilde üstün olduğunu söylemek mümkün değil.

- Orijinal veri üzerinde sadece normal örnekle eğitildiğinde PW’un AO’dan daha iyi olduğunu görüyoruz. Ancak eğitim kümesi normal ve aykırı örnekleri bir arada içeriyorsa, metodlar arası fark kalmıyor.
- Öncesinde PCA uygulandığında sadece normal veriyle metodlar arası bir fark yok, ancak, karışık verildiğinde PW LOF’dan daha iyi oluyor.

Üstteki iki noktaya bakarak; density tabanlı metodlar eğitim kümesinde aykırı örnekler olmasından daha çok etkileniyorlar diyebiliriz, bu sebeple sadece normal veri ile eğitildiklerinde performanslarında önemli artışlar oluyor. Orijinal veride eğitim kümesi karışıkken metodlar arası fark yokken sadece normaller verildiğinde PW AO’a istatistiksel olarak anlamlı fark atıyor. Aynı şekilde PCA ile karışık durumda LOF PW’dan bariz şekilde kötü iken sadece normaller ile LOF PW arası fark kalmıyor ve LOF performans olarak AO’ı geçmeye başlıyor.

- LEM ile sadece normal veride metodlar arası fark yok, karışık verildiğinde LOF AO’dan daha iyi oluyor.
- MDS ile her iki durumda da LOF ve PW AO’dan daha iyi. MDS AO metodunun başarısını ciddi düşürüyor.

Table 1: Significant differences between outlier detection methods for each spectral method, semi-supervised.

None	PW	LOF	AO
PCA	PW	LOF	AO
LEM	PW	LOF	AO
MDS	LOF	PW	AO

Table 2: Significant differences between outlier detection methods for each spectral method, unsupervised.

None	LOF	PW	AO
PCA	PW	AO	LOF
LEM	LOF	PW	AO
MDS	LOF	PW	AO

## 2 Spectral Metodların Karşılaştırılması

Tablo 3’de her outlier detection metodu için farklı spectral metodların sıraları bulunuyor. Tablo 4 ve 5’de ise istatistiksel olarak anlamlı farklar gözüküyor. AO ve PW metodlarında herhangi bir spectral metodun diğerine üstünlüğü görülüyor. Sadece LOF metodu için spectral metodlar arası farklar gözüküyor. Eğitim kümesi aykırı örnekleri de içerdiği durumda LEM ve MDS ile birleştirmek daha iyi performans veriyor. Burada LEM ve MDS gibi spectral metodların density based metodların eğitim kümesindeki aykırı örneklerin etkisini azalttıklarını söyleyebiliriz. LOF sadece normal veriyle eğitildiğinde de PCA ile birleştirmenin LEM, MDS ve hiçbir işlem uygulamamaktan kötü olduğunu görüyoruz. Ancak burada LEM ve MDS’in performansı ile orijinal veri üzerinde alınan arasında anlamlı bir fark yok. Eğer LOF’un hangi spectral metodla birleştirilse birleştirilsin hep AO ve PW’dan daha iyi bir metod olduğunu ilk kısımdaki sonuçlardan çıkarabilseydik buradaki sonuçlarla LOF’u LEM veya MDS ile birleştirmenin iyi bir algoritma olacağını söyleyebilirdik. Ancak tek söyleyebileceğimiz elimizdeki veri normal ve aykırı örnekler karışık şekildeyse ve LOF metodunu kullanmayı düşünüyorsak, LEM ve MDS ile birleştirmek daha iyi sonuçlar verir.

Table 3: Average ranks of spectral methods with respect to outlier detection methods.

(a) Semi-supervised					(b) Unsupervised				
	None	PCA	LEM	MDS		None	PCA	LEM	MDS
AO	2.65	2.45	1.95	2.95	AO	2.65	2.45	2.20	2.70
LOF	2.68	3.18	1.83	2.33	LOF	3.10	3.35	1.78	1.78
PW	2.45	2.90	2.00	2.65	PW	2.90	2.60	2.20	2.30
Average	2.59	2.84	1.93	2.64	Average	2.88	2.80	2.06	2.26

Table 4: Significant differences between spectral methods for each outlier detection method, semi-supervised (L: LEM, P: PCA, M: MDS O: No combination, only outlier detection method.).

AO	L	P	O	M
LOF	L	M	O	P
PW	L	O	M	P

Table 5: Significant differences between spectral methods for each outlier detection method, unsupervised (L: LEM, P: PCA, M: MDS O: No combination, only outlier detection method.).

AO	L	P	O	M
LOF	L	M	O	P
PW	L	M	P	O

### 3 Ayrıntılı Deney Sonuçları

Table 6: Average values and standard deviations of AUCs for semi-supervised case.

	ActiveOutlier	LOF	ParzenWindow
shuttle	1.00±0.0004	0.96±0.010	0.87±0.015
optdigits	0.93±0.023	0.99±0.006	1.00±0.002
kdd99Half	0.91±0.034	0.88±0.009	0.99±0.001
kdd99trainHalf	0.99±0.026	0.90±0.023	0.99±0.0003
pageblocks	0.87±0.056	0.93±0.008	0.88±0.016
abalone	0.95±0.062	1.00±0.004	1.00±0.001
glass	0.89±0.055	0.97±0.009	0.96±0.007
yeast	0.60±0.122	0.66±0.023	0.62±0.008
cardiotocography	0.62±0.141	0.92±0.012	0.95±0.002
spam	0.79±0.064	0.67±0.005	0.74±0.013
ecoli	0.96±0.031	0.98±0.011	0.99±0.010
letter	0.79±0.050	0.98±0.005	0.87±0.004
satellite	1.00±0.001	1.00±0.000	1.00±0.000
wine	0.69±0.041	0.76±0.015	0.75±0.006
breast	0.89±0.034	0.94±0.015	0.94±0.006
mammography	0.72±0.052	0.58±0.048	0.72±0.017
pima	0.66±0.022	0.62±0.022	0.78±0.008
robot	0.89±0.138	0.99±0.020	0.66±0.046
vehicle	0.71±0.059	0.67±0.039	0.57±0.028
secom	0.54±0.021	0.58±0.012	0.56±0.009
Average Ranks	2.45	1.88	1.68

Table 7: Average values and standard deviations of AUCs for unsupervised case.

	ActiveOutlier	LOF	ParzenWindow
shuttle	1.00±0.0003	0.87±0.012	0.88±0.024
optdigits	0.85±0.058	0.97±0.006	0.97±0.017
kdd99Half	0.90±0.022	0.77±0.050	0.96±0.002
kdd99trainHalf	0.99±0.026	0.89±0.029	0.98±0.008
pageblocks	0.74±0.096	0.76±0.044	0.73±0.009
abalone	0.71±0.159	0.57±0.088	0.49±0.061
glass	0.80±0.058	0.91±0.025	0.90±0.007
yeast	0.68±0.065	0.66±0.022	0.62±0.011
cardiotocography	0.51±0.006	0.70±0.026	0.92±0.004
spam	0.65±0.108	0.64±0.017	0.73±0.011
ecoli	0.72±0.243	0.95±0.007	0.94±0.013
letter	0.68±0.064	0.89±0.011	0.84±0.005
satellite	0.82±0.050	0.62±0.049	0.95±0.004
wine	0.68±0.049	0.75±0.023	0.74±0.009
breast	0.78±0.041	0.93±0.019	0.92±0.006
mammography	0.64±0.084	0.54±0.043	0.68±0.014
pima	0.62±0.028	0.61±0.026	0.77±0.008
robot	0.87±0.090	0.99±0.020	0.55±0.042
vehicle	0.64±0.065	0.57±0.047	0.48±0.035
secom	0.54±0.042	0.58±0.011	0.56±0.011
Average Ranks	2.15	1.90	1.95

Table 8: Wins/ties/losses of each algorithm with  $5 \times 2$  CV  $F$  test.

(a) Semi-supervised				(b) Unsupervised			
	AO	LOF	PW		AO	LOF	PW
AO	0/20/0	3/13/4	1/15/4	AO	0/20/0	5/11/4	4/8/8
LOF	4/13/3	0/20/0	4/10/6	LOF	4/11/5	0/20/0	3/10/7
PW	4/15/1	6/10/4	0/20/0	PW	8/8/4	7/10/3	0/20/0

Table 9: Average values and standard deviations of AUCs for Spectral outlier detection with PCA - semi-supervised case (The numbers in parentheses show the number of dimensions chosen for each data set/method).

	ActiveOutlier	LOF	ParzenWindow
shuttle	1.00±0.0001 (7)	0.96±0.007 (9)	0.89±0.029 (4)
optdigits	0.95±0.020 (21)	0.98±0.009 (39)	1.00±0.001 (38)
kdd99Half	0.94±0.012 (4)	0.72±0.012 (12)	0.98±0.001 (12)
kdd99trainHalf	0.96±0.030 (9)	0.67±0.021 (13)	0.96±0.003 (2)
pageblocks	0.92±0.015 (3)	0.91±0.020 (6)	0.86±0.018 (6)
abalone	0.98±0.017 (2)	1.00±0.003 (6)	1.00±0.000 (2)
glass	0.93±0.028 (4)	0.98±0.012 (3)	0.95±0.007 (3)
yeast	0.63±0.054 (8)	0.68±0.022 (8)	0.64±0.009 (8)
cardiotocography	0.92±0.008 (11)	0.92±0.016 (15)	0.94±0.003 (15)
spam	0.73±0.030 (50)	0.67±0.015 (50)	0.76±0.004 (50)
ecoli	0.97±0.023 (5)	0.98±0.015 (4)	0.99±0.004 (4)
letter	0.83±0.030 (14)	0.96±0.018 (14)	0.87±0.004 (14)
satellite	1.00±0.003 (9)	1.00±0.00003(24)	1.00±0.0001 (9)
wine	0.71±0.032 (8)	0.77±0.021 (7)	0.74±0.007 (10)
breast	0.88±0.048 (5)	0.92±0.016 (11)	0.89±0.017 (2)
mammography	0.72±0.062 (5)	0.44±0.042 (3)	0.67±0.018 (3)
pima	0.65±0.049 (8)	0.64±0.043 (7)	0.76±0.006 (7)
robot	0.76±0.097 (24)	0.58±0.216 (10)	0.54±0.038 (24)
vehicle	0.58±0.049 (2)	0.57±0.044 (2)	0.63±0.053 (2)
secom	0.58±0.053(196)	0.56±0.010 (196)	0.56±0.003(196)
Average Ranks	2.20	2.05	1.75

Table 10: Average values and standard deviations of AUCs for Spectral outlier detection with PCA, unsupervised case (The numbers in parentheses show the number of dimensions chosen for the data set/method.).

	ActiveOutlier	LOF	ParzenWindow
shuttle	1.00±0.0001(4)	0.88±0.010 (7)	0.88±0.029 (4)
optdigits	0.88±0.028(23)	0.97±0.009(27)	0.97±0.005 (23)
kdd99Half	0.95±0.011 (4)	0.69±0.036(14)	0.96±0.002 (14)
kdd99trainHalf	0.97±0.011 (8)	0.67±0.046(13)	0.96±0.003 (2)
pageblocks	0.86±0.060 (6)	0.68±0.056 (6)	0.71±0.014 (6)
abalone	0.73±0.067 (6)	0.56±0.070 (7)	0.76±0.041 (8)
glass	0.75±0.067 (2)	0.91±0.015 (7)	0.91±0.005 (7)
yeast	0.64±0.034 (8)	0.67±0.038 (7)	0.63±0.015 (2)
cardiotocography	0.81±0.031 (9)	0.66±0.033 (2)	0.92±0.009 (9)
spam	0.69±0.027(21)	0.65±0.015(40)	0.77±0.004 (32)
ecoli	0.84±0.102 (5)	0.96±0.042 (2)	0.93±0.013 (2)
letter	0.72±0.021 (9)	0.87±0.029 (9)	0.84±0.006 (9)
satellite	0.81±0.039 (8)	0.64±0.049(22)	0.97±0.002 (22)
wine	0.71±0.022 (5)	0.71±0.022 (5)	0.73±0.003 (9)
breast	0.80±0.055 (2)	0.90±0.020(10)	0.91±0.008 (2)
mammography	0.62±0.035 (2)	0.48±0.054 (2)	0.66±0.019 (3)
pima	0.67±0.029 (7)	0.61±0.028 (8)	0.77±0.006 (6)
robot	0.83±0.060(30)	0.60±0.201(18)	0.80±0.032 (30)
vehicle	0.52±0.079 (2)	0.47±0.062 (2)	0.55±0.027 (2)
secom	0.60±0.037 (2)	0.60±0.035 (2)	0.57±0.005(133)
Average Ranks	2.00	2.40	1.60

Table 11: Wins/ties/losses of outlier detection methods combined with PCA with  $5 \times 2$  CV  $F$  test.

(a) Semi-supervised				(b) Unsupervised			
	AO	LOF	PW		AO	LOF	PW
AO	0/20/0	4/15/1	3/16/1	AO	0/20/0	6/12/2	2/11/7
LOF	1/15/4	0/20/0	1/14/5	LOF	2/12/6	0/20/0	0/12/8
PW	1/16/3	5/14/1	0/20/0	PW	7/11/2	8/12/0	0/20/0

Table 12: Average values and standard deviations of AUCs for Spectral outlier detection with LEM, semi-supervised case (k: neighbor count, d: number of dimensions and the kernel chosen. Kernels are c: constant, g: Gaussian, p: quadratic.).

	ActiveOutlier	LOF	ParzenWindow
shuttle	1.00±0.001 (k25-d4g)	1.00±0.001 (k80-d9g)	1.00±0.0004(k12-d4g)
optdigits	0.99±0.010 (k6-d43p)	0.98±0.007 (k3-d23g)	0.99±0.003(k12-d23p)
kdd	0.95±0.015 (k80-d2g)	0.95±0.007(k12-d31p)	0.97±0.003(k12-d19g)
kddtrain	0.97±0.022 (k12-d2g)	0.94±0.006(k80-d41p)	0.99±0.002 (k6-d33g)
pageblocks	0.98±0.010 (k12-d2g)	0.95±0.005 (k25-d5g)	0.93±0.004 (k6-d10g)
abalone	1.00±0.002 (k25-d8g)	0.99±0.006 (k12-d8g)	1.00±0.0004 (k6-d6g)
glass	0.95±0.011 (k6-d2g)	0.99±0.002 (k80-d4g)	0.97±0.001 (k80-d9p)
yeast	0.64±0.056 (k12-d2g)	0.71±0.047 (k12-d2g)	0.70±0.027 (k25-d2g)
cardiotocography	0.95±0.015 (k25-d8c)	0.96±0.004(k25-d21g)	0.97±0.007(k12-d15g)
spam	0.64±0.072(k80-d57c)	0.73±0.021 (k6-d2g)	0.80±0.012(k80-d39c)
ecoli	0.98±0.012 (k3-d4g)	1.00±0.000 (k6-d2c)	1.00±0.000 (k3-d2c)
letter	0.98±0.009 (k6-d11g)	0.97±0.011 (k3-d9g)	0.98±0.003 (k3-d13p)
satellite	1.00±0.001(k25-d13g)	1.00±0.000 (k6-d2g)	1.00±0.000 (k6-d13g)
wine	0.61±0.020 (k25-d8c)	0.67±0.014(k12-d11g)	0.54±0.011 (k12-d5p)
breast	0.91±0.036 (k3-d2g)	0.96±0.026 (k12-d2g)	0.96±0.010 (k12-d2c)
mammography	0.80±0.041 (k3-d5g)	0.83±0.033 (k12-d2g)	0.84±0.014 (k3-d2g)
pima	0.59±0.061 (k12-d4g)	0.67±0.053 (k25-d8g)	0.70±0.006 (k3-d2g)
robot	0.85±0.087(k25-d31g)	1.00±0.000 (k3-d61g)	1.00±0.005(k12-d31c)
vehicle	0.68±0.052 (k12-d7g)	0.63±0.050(k12-d18g)	0.77±0.017 (k6-d18g)
secom	0.54±0.033 (k12-d2p)	0.64±0.026 (k25-d2g)	0.52±0.001 (k6-d2p)
Average Ranks	2.40	1.95	1.65

Table 13: Average values and standard deviations of AUCs for Spectral outlier detection with LEM, unsupervised case (k: neighbor count, d: number of dimensions and the kernel chosen. Kernels are c: constant, g: Gaussian, p: quadratic.).

	ActiveOutlier	LOF	ParzenWindow
shuttle	0.98±0.013 (k25-d4g)	0.98±0.003 (k12-d2g)	0.96±0.003 (k80-d2g)
optdigits	0.94±0.029(k80-d23p)	0.98±0.004(k12-d23g)	0.97±0.008 (k6-d23g)
kdd	0.89±0.014(k12-d35g)	0.89±0.028 (k6-d20g)	0.87±0.003 (k80-d2g)
kddtrain	0.94±0.018 (k12-d2g)	0.97±0.005 (k12-d2g)	0.93±0.004 (k80-d2g)
pageblocks	0.95±0.015 (k12-d2g)	0.95±0.005 (k12-d2g)	0.94±0.003 (k6-d5g)
abalone	0.76±0.137 (k6-d6p)	0.94±0.028 (k6-d4c)	0.89±0.014 (k3-d4g)
glass	0.86±0.039 (k6-d2g)	0.97±0.002 (k6-d2g)	0.96±0.004 (k6-d2g)
yeast	0.62±0.079 (k12-d2g)	0.70±0.040 (k12-d2g)	0.60±0.049 (k80-d2g)
cardiotocography	0.89±0.030 (k12-d2g)	0.90±0.018(k12-d15g)	0.95±0.003 (k6-d2g)
spam	0.59±0.040 (k3-d18p)	0.73±0.008 (k3-d39g)	0.79±0.005(k80-d57c)
ecoli	0.93±0.020 (k80-d7g)	0.99±0.010 (k6-d2c)	0.96±0.023 (k80-d7g)
letter	0.94±0.029 (k6-d15g)	0.95±0.007 (k6-d11g)	0.93±0.004 (k25-d2g)
satellite	0.90±0.078 (k80-d2g)	1.00±0.001 (k6-d13g)	1.00±0.003 (k6-d2g)
wine	0.61±0.028 (k25-d5p)	0.65±0.012(k12-d11g)	0.51±0.016 (k12-d5p)
breast	0.91±0.069 (k12-d2g)	0.91±0.041 (k3-d2g)	0.97±0.002 (k12-d2g)
mammography	0.76±0.044 (k3-d5g)	0.79±0.051 (k12-d2g)	0.82±0.014 (k3-d2g)
pima	0.66±0.046 (k12-d8g)	0.62±0.026 (k25-d8g)	0.70±0.017 (k6-d2g)
robot	0.85±0.104(k25-d31p)	1.00±0.000 (k3-d61g)	0.98±0.021(k12-d31c)
vehicle	0.57±0.064(k12-d18g)	0.60±0.038 (k6-d13g)	0.70±0.026 (k6-d13g)
secom	0.51±0.045 (k12-d2p)	0.64±0.023 (k25-d2g)	0.52±0.002 (k6-d2p)
Average Ranks	2.60	1.35	2.05

Table 14: Wins/ties/losses of outlier detection methods combined with LEM with  $5 \times 2$  CV  $F$  test

(a) Semi-supervised				(b) Unsupervised			
	AO	LOF	PW		AO	LOF	PW
AO	0/20/0	0/17/3	2/15/3	AO	0/20/0	0/16/4	1/16/3
LOF	3/17/0	0/20/0	4/13/3	LOF	4/16/0	0/20/0	6/12/2
PW	3/15/2	3/13/4	0/20/0	PW	3/16/1	2/12/6	0/20/0



Table 15: Average values and standard deviations of AUCs for Spectral outlier detection with MDS, semi-supervised case (k: neighbor count, d: number of dimensions and the kernel chosen. Kernels are c: constant, g: Gaussian, p: quadratic.).

	ActiveOutlier	LOF	ParzenWindow
shuttle	0.96±0.012 (k80-d9c)	1.00±0.001 (k6-d9p)	1.00±0.001 (k80-d9p)
optdigits	0.77±0.056 (k80-d23c)	0.84±0.032 (k80-d23c)	0.87±0.016 (k80-d23c)
kdd	0.75±0.119 (k12-d41p)	0.97±0.002 (k12-d41p)	0.99±0.001 (k80-d41p)
kddtrain	0.93±0.018 (k25-d2c)	0.99±0.001 (k6-d2p)	0.99±0.001 (k12-d15p)
pageblocks3	0.96±0.016 (k25-d2c)	0.98±0.002 (k6-d10g)	0.98±0.001 (k25-d2c)
abalone	0.99±0.003 (k6-d8p)	1.00±0.000 (k3-d8p)	1.00±0.000 (k25-d2p)
glass	0.87±0.041 (k80-d9p)	0.94±0.002 (k80-d7p)	0.98±0.006 (k80-d7g)
yeast	0.56±0.094 (k3-d4c)	0.68±0.038 (k80-d6p)	0.56±0.005 (k6-d4p)
cardiotocography	0.87±0.085 (k80-d8p)	0.93±0.006 (k25-d8p)	0.96±0.003 (k25-d8p)
spam	0.70±0.047 (k80-d39p)	0.71±0.017 (k12-d2p)	0.75±0.010 (k80-d20p)
ecoli	0.98±0.003 (k3-d4p)	1.00±0.000 (k3-d2c)	0.98±0.006 (k80-d2g)
letter	0.67±0.006 (k6-d11p)	0.88±0.015 (k80-d16g)	0.75±0.004 (k3-d11g)
satellite	1.00±0.0004 (k80-d2p)	1.00±0.00003(k12-d13p)	1.00±0.000 (k25-d2p)
wine	0.65±0.020 (k6-d11p)	0.67±0.012 (k3-d8p)	0.65±0.002 (k25-d5p)
breast	0.84±0.020 (k3-d11p)	0.91±0.021 (k3-d11p)	0.96±0.003 (k25-d2p)
mammography	0.83±0.029 (k25-d2c)	0.87±0.012 (k12-d3c)	0.85±0.009 (k25-d2c)
pima	0.63±0.048 (k25-d8p)	0.64±0.014 (k6-d2p)	0.77±0.006 (k25-d8p)
robot	0.93±0.057 (k25-d2p)	1.00±0.000 (k3-d61g)	0.86±0.033 (k12-d61g)
vehicle	0.62±0.058 (k3-d13c)	0.63±0.032 (k6-d13p)	0.55±0.021 (k3-d7g)
secom	0.55±0.032(k25-d590p)	0.49±0.021 (k12-d2p)	0.39±0.004(k25-d590c)
Average Ranks	2.70	1.50	1.80

Table 16: Average values and standard deviations of AUCs for Spectral outlier detection with MDS, unsupervised case (k: neighbor count, d: number of dimensions and the kernel chosen. Kernels are c: constant, g: Gaussian, p: quadratic.).

	ActiveOutlier	LOF	ParzenWindow
shuttle	0.91±0.036 (k25-d7p)	0.99±0.001 (k6-d9p)	0.99±0.001 (k80-d9p)
optdigits	0.91±0.031 (k3-d23p)	0.97±0.009 (k80-d43p)	0.93±0.010 (k12-d23p)
kdd	0.78±0.086 (k12-d41p)	0.97±0.001 (k12-d41p)	0.98±0.001 (k80-d41p)
kddtrain	0.90±0.049 (k25-d2c)	0.99±0.001 (k12-d2p)	0.98±0.002 (k12-d15p)
pageblocks3	0.96±0.014 (k25-d2c)	0.97±0.003 (k12-d5p)	0.96±0.002 (k25-d2c)
abalone	0.99±0.002 (k25-d2p)	1.00±0.000 (k3-d8p)	0.99±0.001 (k25-d2p)
glass	0.77±0.102 (k25-d7p)	0.93±0.009 (k80-d7p)	0.92±0.017 (k80-d4p)
yeast	0.60±0.047 (k6-d8c)	0.67±0.027 (k80-d6p)	0.56±0.010 (k6-d4p)
cardiotocography	0.87±0.034 (k80-d15p)	0.91±0.012 (k12-d15p)	0.95±0.002 (k25-d8p)
spam	0.63±0.062 (k80-d20p)	0.70±0.013 (k12-d2p)	0.74±0.009 (k80-d20p)
ecoli	0.89±0.189 (k12-d2p)	1.00±0.000 (k3-d2p)	1.00±0.000 (k3-d4p)
letter	0.65±0.015 (k12-d11p)	0.91±0.017 (k80-d11g)	0.75±0.012 (k3-d11g)
satellite	0.98±0.016 (k80-d2p)	1.00±0.0003(k12-d13p)	1.00±0.000 (k80-d2p)
wine	0.60±0.038 (k6-d11p)	0.66±0.008 (k3-d8p)	0.65±0.001 (k25-d5p)
breast	0.74±0.120 (k25-d2p)	0.91±0.021 (k3-d11p)	0.80±0.056 (k6-d11p)
mammography	0.70±0.082 (k12-d3c)	0.70±0.008 (k3-d5p)	0.84±0.008 (k25-d2c)
pima	0.62±0.041 (k12-d8p)	0.63±0.022 (k6-d2p)	0.76±0.011 (k25-d8p)
robot	0.90±0.022 (k25-d2p)	1.00±0.000 (k3-d61g)	0.77±0.056 (k12-d61g)
vehicle	0.60±0.027 (k3-d2g)	0.64±0.022 (k6-d13p)	0.53±0.006 (k3-d7g)
secom	0.55±0.043(k12-d590g)	0.48±0.024 (k12-d2p)	0.39±0.004(k25-d590c)
Average Ranks	2.75	1.43	1.83

Table 17: Wins/Ties/Losses of outlier detection methods combined with MDS.

(a) Semi-supervised				(b) Unsupervised			
	AO	LOF	PW		AO	LOF	PW
AO	0/20/0	0/12/8	1/12/7	AO	0/20/0	0/14/6	2/13/5
LOF	8/12/0	0/20/0	9/7/4	LOF	6/14/0	0/20/0	7/9/4
PW	7/12/1	4/7/9	0/20/0	PW	5/13/2	4/9/7	0/20/0

Table 18: Average ranks of outlier detection methods.

(a) Semi-supervised				(b) Unsupervised			
	ActiveOutlier	LOF	ParzenWindow		ActiveOutlier	LOF	ParzenWindow
None	2.45	1.88	1.68	None	2.15	1.90	1.95
PCA	2.20	2.05	1.75	PCA	2.00	2.40	1.60
LEM	2.40	1.95	1.65	LEM	2.60	1.35	2.05
MDS	2.70	1.50	1.80	MDS	2.75	1.43	1.83
Average	2.44	1.85	1.72	Average	2.38	1.77	1.86

Table 19: Wins/ties/losses of outlier detection methods combined with spectral methods, semi-supervised.

(a) AO method

	AO	AO-PCA	AO-LEM	AO-MDS
AO	0/20/0	0/19/1	2/15/3	3/16/1
AO-PCA	1/19/0	0/20/0	2/13/5	4/16/0
AO-LEM	3/15/2	5/13/2	0/20/0	3/17/0
AO-MDS	1/16/3	0/16/4	0/17/3	0/20/0

(b) LOF method

	LOF	LOF-PCA	LOF-LEM	LOF-MDS
LOF	0/20/0	4/16/0	1/13/6	5/9/6
LOF-PCA	0/16/4	0/20/0	1/11/8	5/9/6
LOF-LEM	6/13/1	8/11/1	0/20/0	6/12/2
LOF-MDS	6/9/5	6/9/5	2/12/6	0/20/0

(c) PW method

	PW	PW-PCA	PW-LEM	PW-MDS
PW	0/20/0	4/16/0	4/9/7	7/9/4
PW-PCA	0/16/4	0/20/0	3/6/11	6/6/8
PW-LEM	7/9/4	11/6/3	0/20/0	9/7/4
PW-MDS	4/9/7	8/6/6	4/7/9	0/20/0

Table 20: Wins/ties/losses of outlier detection methods combined with spectral methods, unsupervised.

(a) AO method

	AO	AO-PCA	AO-LEM	AO-MDS
AO	0/20/0	0/17/3	2/15/3	1/16/3
AO-PCA	3/17/0	0/20/0	2/16/2	4/14/2
AO-LEM	3/15/2	2/16/2	0/20/0	2/18/0
AO-MDS	3/16/1	2/14/4	0/18/2	0/20/0

(b) LOF method

	LOF	LOF-PCA	LOF-LEM	LOF-MDS
LOF	0/20/0	1/19/0	1/9/10	2/8/10
LOF-PCA	0/19/1	0/20/0	0/8/12	1/9/10
LOF-LEM	10/9/1	<b>12/8/0</b>	0/20/0	2/13/5
LOF-MDS	10/8/2	10/9/1	5/13/2	0/20/0

(c) PW method

	PW	PW-PCA	PW-LEM	PW-MDS
PW	0/20/0	1/15/4	5/3/12	4/7/9
PW-PCA	4/15/1	0/20/0	5/6/9	6/5/9
PW-LEM	12/3/5	9/6/5	0/20/0	7/7/6
PW-MDS	9/7/4	9/5/6	6/7/7	0/20/0