Table 4: SVM results: Comparing RBF kernel, GMML, SimpleMKL, Laplacian kernel and Isolation Kernel. GMML and SimpleMKL have "out of memory" error on 2 datasets; SimpleMKL cannot return any result within 24 hours on 5 datasets. The first and second subsets consists of 2-class datasets having less than and more than 5000 points, respectively; the third subset consists of multi-class datasets.

	#inst	#fea	#class	RBF	GMML	SimpleMKL	Laplacian	Isolation
GPS	163	6	2	0.855±0.018	0.855±0.028	0.867±0.018	$0.836 \pm 0.026$	0.842±0.022
Heart	270	13	2	0.833±0.027	$0.844 \pm 0.034$	$0.826 \pm 0.035$	$0.852 \pm 0.024$	$0.852 \pm 0.025$
Breast	277	9	2	0.750±0.018	$0.768 \pm 0.016$	$0.746 \pm 0.009$	$0.761 \pm 0.012$	$0.771 \pm 0.015$
Ionosphere	351	34	2	0.949±0.006	$0.941 \pm 0.020$	$0.958 \pm 0.009$	$0.946 \pm 0.014$	$0.955 \pm 0.011$
Vote	435	16	2	0.943±0.013	$0.949 \pm 0.010$	$0.940 \pm 0.007$	$0.956 \pm 0.008$	$0.961 \pm 0.013$
ILPD	583	11	2	0.716±0.004	$0.726 \pm 0.008$	$0.720 \pm 0.003$	$0.713 \pm 0.002$	$0.720 \pm 0.008$
WBC	683	9	2	0.972±0.003	$0.974 \pm 0.004$	$0.969 \pm 0.004$	$0.977 \pm 0.003$	$0.975 \pm 0.007$
Austra	690	14	2	0.857±0.016	$0.864 \pm 0.014$	$0.854 \pm 0.015$	$0.859 \pm 0.017$	$0.871 \pm 0.011$
German	1000	24	2	0.753±0.008	$0.754 \pm 0.006$	$0.705 \pm 0.003$	$0.759 \pm 0.006$	$0.767 \pm 0.012$
Parkinson	1040	28	2	0.999±0.001	$1.000 \pm 0.000$	$0.998 \pm 0.002$	$1.000\pm0.000$	$1.000 \pm 0.000$
QSAR	1055	42	2	0.880±0.007	$0.870 \pm 0.005$	$0.864 \pm 0.007$	$0.873 \pm 0.009$	$0.869 \pm 0.012$
Messidor	1151	19	2	0.690±0.021	$0.734 \pm 0.014$	$0.673 \pm 0.023$	$0.692 \pm 0.019$	$0.694 \pm 0.018$
Spam	4141	58	2	0.932±0.004	$0.912 \pm 0.003$	> 24 hours	$0.944 \pm 0.002$	$0.940 \pm 0.003$
Wilt	4839	5	2	0.946±0.039	$0.984 \pm 0.001$	> 24 hours	$0.946 \pm 0.021$	$0.985 \pm 0.014$
Mushrooms	8124	112	2	1.000±0.000	1.000±0.000	> 24 hours	1.000±0.000	1.000±0.000
Phishing	11055	30	2	0.965±0.001	$0.959 \pm 0.003$	> 24 hours	$0.968 \pm 0.002$	$0.967 \pm 0.001$
a8a	32561	123	2	0.846±0.003	memory error	memory error	$0.846 \pm 0.003$	$0.847 \pm 0.003$
IJCNN	49990	22	2	0.980±0.001	memory error	memory error	$0.978 \pm 0.001$	0.978±0.002
Urban	168	147	9	$0.835 \pm 0.022$	0.841±0.029	0.882±0.027	$0.847 \pm 0.033$	0.841±0.020
Air	359	64	3	0.956±0.010	$0.933 \pm 0.012$	$0.942 \pm 0.013$	$0.967 \pm 0.008$	$0.967 \pm 0.013$
Forest	523	27	4	0.895 ±0.014	$0.910 \pm 0.011$	$0.964 \pm 0.011$	$0.891 \pm 0.015$	$0.912 \pm 0.011$
Vowel	528	10	11	0.983±0.010	$0.979 \pm 0.010$	$0.982 \pm 0.007$	$0.979 \pm 0.010$	$0.989 \pm 0.007$
Corel	10000	67	100	0.364±0.005	$0.387 \pm 0.005$	> 24 hours	$0.457 \pm 0.003$	$0.466 \pm 0.004$
Isolation has	Isolation has #wins/#draws/#losses			19/1/3	14/3/4	11/1/4	13/5/5	-

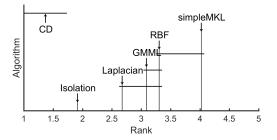


Figure 6: Nemenyi Test at 0.05 significance level. If two algorithms are connected by a CD (critical difference) line, then there is no significant difference between them.

Table 5: Runtime (second). Total time for training & testing.

	RBF	GMML	SimpleMKL	Laplacian	Isolation
IJCNN	54+14	mem err	mem err	56+15	4297+716
Corel	26+7	23+5	>24 hrs	27+9	3975+810

Note that GMML and SimpleMKL could not complete on IJCNN because of their large memory requirements; and SimpleMKL could not complete within 24 hours on Corel.

## 6 RELATION WITH RF KERNEL

## 6.1 Breiman's explanation of RF classifier behaviour in terms of kernel

By defining RF kernel of two points as the average number of shared leaf nodes of Random Forest, Breiman [2] explains the behavior of the RF classifier in terms of this kernel: as a means to locate boundaries, which trade-offs between the kernel's 'symmetry' and 'skewness'. They correspond to correlation and strength of the ensemble, respectively. 'Symmetry' kernel is produced from completely random splits; and 'skewed' kernel is generated from splits which favour pure nodes, which has high strength or classification accuracy. This skewness is also conjectured to enable nonlinear classification [2].

This interpretation has inspired others to use RF as a similarity measure in distance-based neighbourhood methods. Breiman and Cutler [3] first describe two methods to generate RF similarity: one generates RF similarity from a labelled dataset; and the other from an unlabelled dataset. Shi and Horvath [13] applied the second method for tumor discovery using the RF similarity in a distance-based clustering algorithm. Davis and Ghahramani [6] attempted to generalise RF kernel to use different partitioning methods; however, evaluations of their validity are not provided.

The applications of RF similarity has been limited for two reasons. First, the theory requires that the trees are trained using bootstrap