The Importance of Local Perturbations on Quality Measures of Model Explanations

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1 Performance Evaluation Results for All Algorithms

To compare the generation algorithms performance, a critical difference evaluation is carried out [1]. The results are shown in Figure 1 for each metric. Figure 1, shows

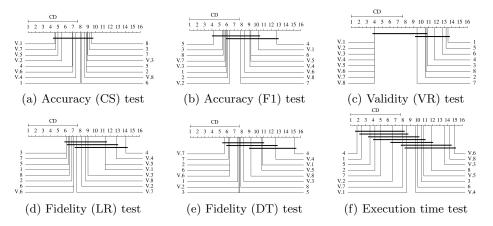


Fig. 1: Critical Differences test with respect to different criteria.

no significant difference among algorithms in numerical explanation accuracy, though it is important to note that 6 out of 8 validity-constrained algorithms are located on the left half of the diagram. There is a difference between algorithms 5, 3, 8, V.7 and 4 in binary explanation accuracy, the former 4 being statistically better, even though algorithms 5 and 3 did not present the best F1 score for any dataset. In terms of VR all validity-constrained algorithms, together with algorithms 7, 2, 8 and 3 present the highest performance. Algorithms 4, 6, 5 and 1 create more examples outside the original feature space manifold. Moreover, with regard to Numerical FR, algorithms 3 and 7 perform statistically better than LEAP-based algorithms (4 and V.4). In Binary FR, the single best algorithm is V.7. In terms of execution time 4 is the best by far. Note that 5 out of 8 validity-constrained algorithms are on the right half of the diagram, and that the top 5 methods are not validity-constrained (methods 4, 1, 5, 2 and 7), indicating that validity comes at a cost in execution time.

Table 1: Explanation Accuracy (\mathbf{CS} and $\mathbf{F1}$), Fidelity Ratio (\mathbf{LR} for logistic regression model and \mathbf{DT} for decision tree model) and Execution time (\mathbf{T}) measured in seconds (s) for all generation algorithms and datasets.

mea	sureu				\ /												T 7.0
		1	V.1	2	V.2	3	V.3	4	V.4	5	V.5	6	V.6	7	V.7	8	V.8
5					0.62												
S1	DT				100												
					0.64												
					0.39												
~~	LR																
S2	$\overline{\mathbf{DT}}$																
	\mathbf{T}	0.92	1.33	0.98	1.35	1.59	1.97	0.34	1.62	0.93	1.36	1.21	1.75	0.97	1.35	1.60	1.96
	CS	0.85	0.84	0.84	0.84	0.85	0.84	0.77	0.78	0.84	0.84	0.81	0.82	0.84	0.84	0.84	0.84
S3					100												
20	DT T				0.82												
					$0.71 \\ 100$												
S4	DT																
					0.47												
	F1 (0.68	0.65	0.67	0.65	0.68	0.66	0.57	0.61	0.66	0.68	0.65	0.65	0.67	0.65	0.67	0.65
S5	$\overline{\mathbf{L}}\mathbf{R}$																
39	DT																
					0.45												
					0.78												
S6	DT				96.7												
					0.50												
	CS	0.76	0.96	0.73	0.78	0.70	0.76	0.75	0.81	0.77	0.96	0.71	0.82	0.73	0.79	0.7	0.76
					0.50												
U1	$\mathbf{L}\mathbf{R}$																
	DT (
					0.17												
					$0.54 \\ 0.40$												
U2	LR																
-	DT '																
	T :	2.16	2.32	2.21	2.28	2.36	2.50	0.33	1.02	3.77	4.07	4.70	5.02	2.33	2.49	3.97	4.01
					0.59												
T T O					0.82												
$\mathbf{U3}$	$\frac{LR}{DT}$																
					0.85												
					0.64												
					0.83												
U4	LR 9																
	DT																
					0.80												
					$0.55 \\ 0.94$												
H5	LR																
	\mathbf{DT}	100	100	100	100	100	100	54.2	83.3	100	100	100	100	100	100	100	100
	T (0.15	0.39	0.16	0.25	0.64	0.76	0.18	0.60	0.16	0.39	0.21	1.27	0.17	0.24	0.65	0.76
					0.25												
T					0.86												
U6	LR DT 9																
					0.79												
						_							-	-		-	

References

1. Demšar, J.: Statistical comparisons of classifiers over multiple data sets. The Journal of Machine Learning Research 7, 1–30 (2006)