

Generation of fuzzy if-then rules from numerical data for pattern classification problems consists of two phases: fuzzy partition of a pattern space into fuzzy subspaces and determination of a fuzzy if-then rule for each fuzzy subspace.

In this classifier, fuzzy partition by a simple fuzzy grid was employed.

The performance of a fuzzy classification system based on fuzzy if-then rules depends on the choice of a fuzzy partition. If a fuzzy partition is too coarse, the performance may be low : many pattern may be missclassified. If a fuzzy partition is too fine, many fuzzy-if then rules cannot be generated because of lack of training pattern in the corresponding fuzzy subspaces. Therefore the choice of a fuzzy partition is very important.

For more information, you can see:

- H. Ishibuchi, K. Nozaki, H. Tanaka. *Distributed representation of fuzzy rules and its application to pattern classification*, Fuzzy set and systems, Vol. 52, p 21-32, 1992.
- H. Ishibuchi, K. Nozaki, H. Tanaka. *Efficient fuzzy partition of pattern space for classification problems*, Fuzzy set and systems, Vol. 59, p 295-304, North-Holland, 1993.

In the following, in the interests of comparison, we present some experiments of the classifier Simple Fuzzy Grid for many standard UCI benchmark data sets. We employed a cross validation 10.

1. Results of classification for the dataset Iris

Number of fuzzy subsets	2	3	4	5	6
Percent of correct classification	68	92.67	90.67	96.0	93.33

Table 1: Results of classification for the dataset Iris with different number of fuzzy subsets

2. Results of classification for the dataset Lupus

Number of fuzzy subsets	2	3	4	5
Percent of correct classification	69.17	77.08	73.61	70.28

Table 2: Results of classification for the dataset Lupus with different number of fuzzy subsets

3. Results of classification for the dataset Diabetes

Number of fuzzy subsets	2	3	4	5
Percent of correct classification	65.63	72.92	73.43	70.58

Table 3: Results of classification for the dataset Diabetes with different number of fuzzy subsets

4. Comparison of the results of classification of Simple fuzzy Grid with learners in Weka from different categories

For the classifier Simple Fuzzy Grid, we note that we employed the best rate of classification determined by the suitable number of fuzzy subsets.

Category	Number of instance	Number of attribute (without class)	Rules Simple fuzzy grid	Trees J48	Bayes BayesNet	Rules Decision table	lazy Kstar
Iris	150	4	96	96	92.66	92.66	94.66
Diabètes	768	8	73.43	73.82	74.34	71.22	69.14
Veteran	137	7	69.96	71.53	72.99	73.72	69.34
balance-scale	625	4	89.04	76.64	72.32	73.12	88.48
heart-statlog	270	13	69.25	76.66	81.11	84.81	75.18
Glass	214	10	60.75	66,82	70.56	68.22	75.23
Haberman	306	3	73.52	72.87	72.54	71.24	74.18
Lupus	87	3	77.01	75.86	74.71	74.71	74.71
Confidence	72	3	75.0	76.38	79.16	73.61	81.94

Table 4: Comparison of the results of classification of Simple fuzzy Grid with learners in Weka from different categories

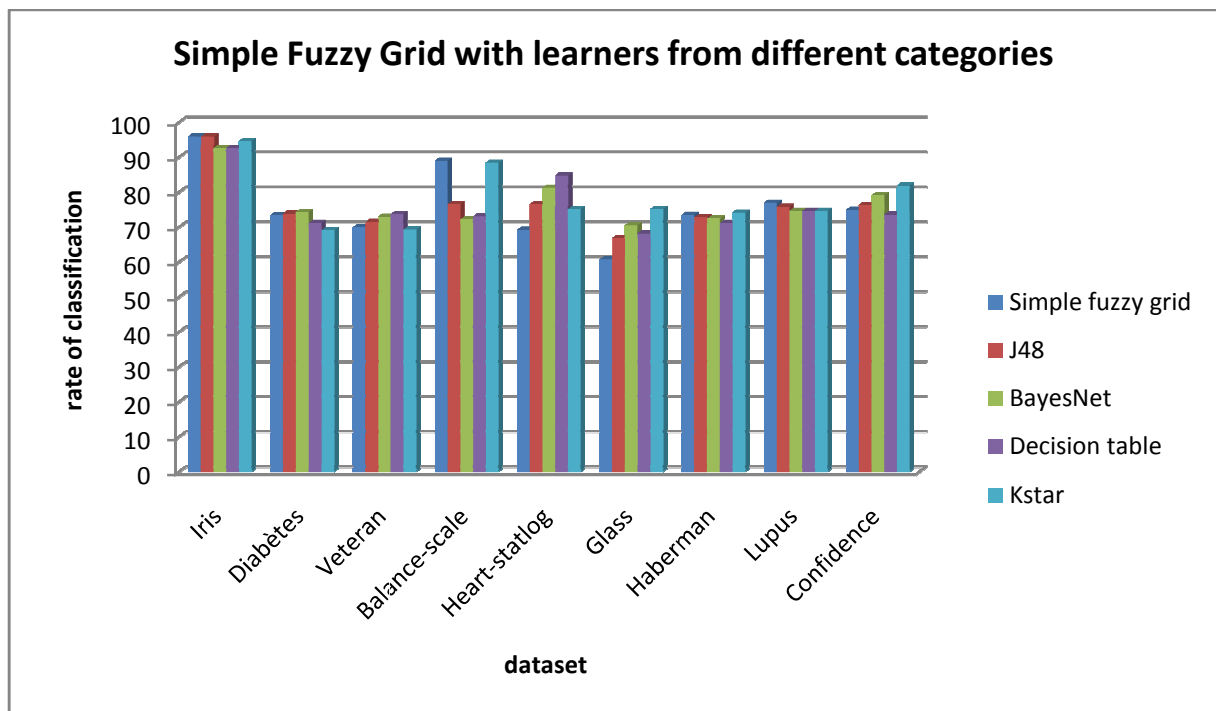


Figure 1: Comparison of the results of classification of Simple fuzzy Grid with learners in Weka from different categories

5. Comparison of the results of classification of Simple fuzzy Grid with different rule learners in Weka

For the classifier Simple Fuzzy Grid, we note that we employed the best rate of classification determined by the suitable number of fuzzy subsets.

	Conjonctive Rule	Ridor	JRip	NNge	Part	Decision table	OneR	ZeroR	Simple fuzzy grid
Iris	66.66	94	94	96	94	92.66	94	33.33	96
Diabètes	68.75	75	76.04	73.95	75,26	71.22	73.04	65.10	73.43
Veteran	72.99	75.91	73.72	69.34	65,69	73.72	73.72	70.80	69.96
balance-scale	62.72	79.52	80.8	81.92	83,52	73.12	56.32	45.76	89.04
heart-statlog	74.07	78.14	78.88	78.14	73,3	84.81	71.11	55.55	69.25
Glass	71.26	71.26	73.56	66.66	75,86	68.22	72.41	59.77	60.75
Haberman	73.52	71.56	72.87	67.97	69,60	71.24	73.20	73.52	73.52
Lupus	71.26	71.26	73.56	66.66	75,86	74.71	72.41	59.77	77.01
Confidence	31.94	75	77.77	81.94	75	73.61	72.22	13.88	75.0

Table 5: Comparison of the results of classification of Simple fuzzy Grid with different rule learners in Weka

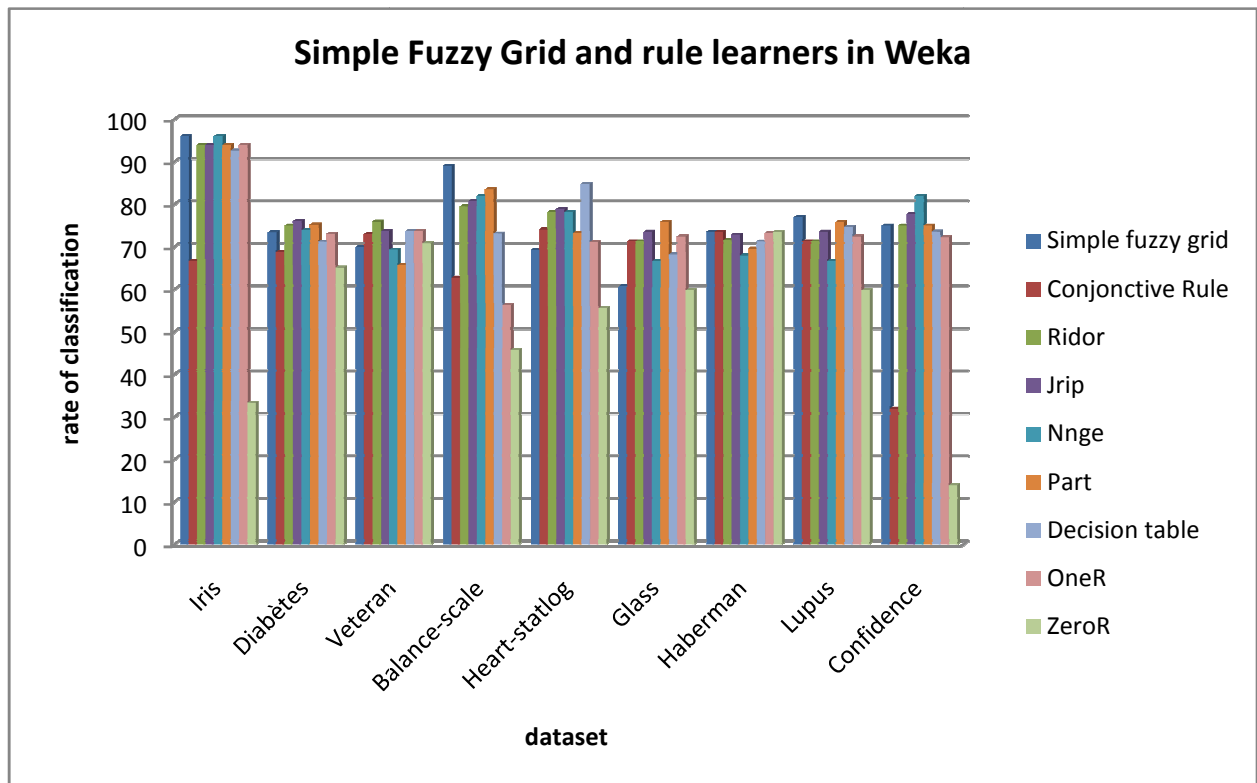


Figure 2: Comparison of the results of classification of Simple fuzzy Grid with different rule learners in Weka