KEEL algorithms

Algorithms included in KEEL:

* Data Preprocessing. This section includes: discretization, feature selection, instance selection, transformation and missing values.

* Classification Algorithms. This section includes: statistical classifiers, decision trees, interval rule learning, evolutionary interval rule learning, fuzzy rule based systems for classification, neural networks for classification.

* Regression Algorithms. This section includes: statistical regression, fuzzy rule based systems for regression, symbolic regression and neural networks for regression.

* Non-Supervised Learning. This section includes: clustering algorithms, subgroup discovery and association rules.

* Statistical Tests. This section includes: test analysis for classification and test analysis for regression.

Data Preprocessing

DISCRETIZATION		
Full Name	Short Name	Reference
Uniform Width Discretizer	Disc-UniformWidth	H. Liu, F. Hussain, C. Lim and M. Dash. Discretization: An Enabling Technique. Data Mining and Knowledge Discovery 6:4 (2002) 393-423.
Uniform Frequency Discretizer	Disc-UniformFrequency	H. Liu, F. Hussain, C. Lim and M. Dash. Discretization: An Enabling Technique. Data Mining and Knowledge Discovery 6:4 (2002) 393-423.
Fayyad Discretizer	Disc-Fayyad	U.M. Fayyad, K.B. Irani. Multi-Interval Discretization of Continuous-Valued Attributes for Classification Learning. 13th International Joint Conference on Uncertainly in Artificial Intelligence (IJCAI93). Chambery (France, 1993) 1022-1029.
ID3 Discretizer	Disc-ID3	J.R. Quinlan. Induction of Decision Trees. Machine Learning 1 (1986) 81-106.
USD Discretizer	Disc-USD	R. Giraldez and J.S. Aguilar-Ruiz, J.C. Riquelme, F. Ferrer-Troyano, D. Rodriguez. Discretization oriented to decision rules generation. Frontiers in Artificial Intelligence and Applications 82 (2002) 275-279.
		R. Giraldez and J.S. Aguilar-Ruiz, J.C. Riquelme. Discretizacion supervisada no parametrica orientada a la obtencion de reglas de decision. Proceedings of the CAEPIA2001 (2001) 53-62.
Chi-Merge Discretizer	Disc-ChiMerge	R. Kerber. ChiMerge: Discretization of Numeric Attributes. X National Conference on Artifical Intelligence American Association for Artificial Intelligence (AAAI92), San Jose, (California, USA), (1992) 123-128.

EVOLUTIONARY FEATURE SELECTION

Full Name	Short Name	Reference
Generational GA with binary coding scheme for filter feature selection with the inconsistency rate	FS-GGA-Binary-Inconsistency	P.L.Lanzi. Fast feature selection with genetic algorithms: a filter approach. Proceedings of the IEEE International Conference on Evolutionary Computation, (1997) 537-540.
Steady-state GA with integer coding scheme for wrapper feature selection with k-nn	FS-SSGA-Integer-knn	J. Casillas, O. Cordón, M.J. del Jesús and F. Herrera. Genetic Feature Selection in a Fuzzy Rule-Based Classification System Learning Process. Information Sciences 136 (2001) 135-157.

FEATURE SELECTION

Full Name	Short Name	Reference
Las Vegas Filter (LVF)	FS-LVF	H. Liu and R. Setiono. A Probabilistic Approach to Feature Selection - a filter solution. Proceedings of the 13th International Conference on Machine Learning (ICML-96), (1996) 319-327.
		H. Liu and H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers (1998).
Las Vegas Wrapper (LVW)	FS-LVW	H. Liu and R. Setiono, R. Feature Selection and classification - a probabilistic wrapper approach. Proceeding of the Ninth International Conference on Industrial and Engineering Applications of AI and ES, (1996) 419-424.
		H. Liu and H. Motoda Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers (1998)
FOCUS	FS-Focus	H. Almuallim and T. Dietterich. Learning with many irrelevant features. Proceedings of the Ninth National Conference on Artificial Intelligence, AAAI Press, The MIT Press, (1991) 547-552.
Relief	FS-Relief	K. Kira and L. Rendell. A practical approach to feature selection. In: Sleeman and P. Edwards (Eds) Proceedings of the Ninth International Conference on Machine Learning (ICML-92), Morgan Kaufmann, (1992) 249-256.
MIFS	FS-MIFS	R. Battiti. Using information for selection features in supervised neural net learning.IEEE Transactions on Neural Networks 5:4 (1994) 537-550.

EVOLUTIONARY INSTANCE SELECTION		
Full Name	Short Name	Reference
CHC Adaptative Search for Instance Selection	IS-CHC	J.R. Cano, F. Herrera and M. Lozano. Using evolutionary algorithms as instance selection for data reduction in KDD: An experimental study. IEEE Transactions on Evolutionary Computation 7:6 (2003) 561-575.
Generational Genetic Algorithm for Instance Selection	IS-GGA	J.R. Cano, F. Herrera and M. Lozano. Using evolutionary algorithms as instance selection for data reduction in KDD: An experimental study. IEEE Transactions on Evolutionary Computation 7:6 (2003) 561-575.
Population-Based Incremental Learning	IS-PBIL	J.R. Cano, F. Herrera and M. Lozano. Using evolutionary algorithms as instance selection for data reduction in KDD: An experimental study. IEEE Transactions on Evolutionary Computation 7:6 (2003) 561-575.
Steady-State Genetic Algorithm for Instance Selection	IS-SGA	J.R. Cano, F. Herrera and M. Lozano. Using evolutionary algorithms as instance selection for data reduction in KDD: An experimental study. IEEE Transactions on Evolutionary Computation 7:6 (2003) 561-575.
Steady-State Memetic Algorithm for Instance Selection	IS-SSMA	S. García, J.R. Cano, F. Herrera. A Memetic Algorithm for Evolutionary Prototype Selection: A Scaling Up Approach. Pattern Recognition 41:8 (2008) 2693-2709.

INSTANCE SELECTION		
Full Name	Short Name	Reference
Edited Nearest Neighbor	IS-ENN	D. L. Wilson. Asymptotic properties of nearest neighbor rules using edited data. IEEE Transactions on Systems, Man and Cybernetics 2:3 (1972) 408-421.
Condensed Nearest Neighbor	IS-CNN	P.E. Hart. The Condensed Nearest Neighbour Rule. IEEE Transactions on Information Theory 14:5 (1968) 515-516.

INSTANCE GENERATION		
Full Name	Short Name	Reference
Learning Vector Quantization 1	IG-LVQ1	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 2	IG-LVQ2	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 2.1	IG-LVQ2_1	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 3	IG-LVQ3	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Prototype Nearest Neighbor	IG-PNN	C-L. Chang. Finding Prototypes For Nearest Neighbor Classifiers. IEEE Transactions on Computers 23:11 (1974) 1179-1184.

TRANSFORMATION		
Full Name	Short Name	Reference
Decimal Scaling ranging	Trns-DecimalScaling	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.
Min Max ranging	Trns-MinMax	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.
Z Score ranging	Trns-ZScore	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.

MISSING VALUES		
Full Name	Short Name	Reference
Delete Instances with Missing Values	MV-Ignore	P-A. Gourraud, E. Ginin and A. Cambon-Thomsen. Handling missing values in population data: consequences for maximum likelihood estimation of haplotype frequencies. European Journal of Human Genetics, 12:10 (2004) 805-812.
Most Common Attribute Value	MV-MostCommon	J. W. Grzymala-Busse, L. K. Goodwin, W. J. Grzymala-Busse and X. Zheng. Handling Missing Attribute Values in Preterm Birth Data Sets. Lecture Notes in Computer Science, Rough Sets, Fuzzy Sets, Fata Mining and Granular Computing 3642 (2005) 342-352.
Concept Most Common Attribute Value	MV-ConceptMostCommon	J. W. Grzymala-Busse, L. K. Goodwin, W. J. Grzymala-Busse and X. Zheng. Handling Missing Attribute Values in Preterm Birth Data Sets. Lecture Notes in Computer Science, Rough Sets, Fuzzy Sets, Fata Mining and Granular Computing 3642 (2005) 342-352.
Assign All Posible Values of the Attribute	MV-AllPossible	J. W. Grzymala-Busse. On the Unknown Attribute Values in Learning from Examples. Proceedings of the 6th international Symposium on Methodologies For intelligent Systems, Charlotte, North Carolina, Z. W. Ras and M. Zemankova (Eds.) Lecture Notes In Computer Science, Springer-Verlag, Berlin Heidelberg, New York, 542 (1991) 368-377.
Assign All Posible Values of the Attribute Restricted to the Given Concept	MV-ConceptAllPossible	J. W. Grzymala-Busse. On the Unknown Attribute Values in Learning from Examples. Proceedings of the 6th international Symposium on Methodologies For intelligent Systems, Charlotte, North Carolina, Z. W. Ras and M. Zemankova, Eds. Lecture Notes In Computer Science, Springer-Verlag, Berlin Heidelberg, New York, 542 (1991) 368-377.
Event Covering Synthesizing	MV-EventCovering	D.K. Chiu, and A.K.C. Wong. Synthesizing knowledge: A cluster analysis approach using event-covering. IEEE Trans. Syst., Man and Cybern (SMC-16) (1986) 251-259.
Knn Imputation	MV-KNN	G.E.A.P.A. Batista, M.C. Monard. An analysis of four missing data treatment methods for supervised learning. Applied Artificial Intelligence 17 (2003) 519-533.
K-means Imputation	MV-KMeans	J. Deogun, W. Spaulding, B. Shuart and D. Li. Towards Missing Data Imputation: A Study of Fuzzy K-means Clustering Method. Lecture Notes in Computer Science Rough Sets and Current Trends in Computing, 3066 (2004) 573-579.
Fuzzy K-means Imputation	MV-FKMeans	J. Deogun, W. Spaulding, B. Shuart and D. Li. Towards Missing Data Imputation: A Study of Fuzzy K-means Clustering Method. Lecture Notes in Computer Science Rough Sets and Current Trends in Computing, 3066 (2004) 573-579.

SVM Imputation	MV-SVMimpute	H.A.B. Feng, G.C. Chen, C.D. Yin, B.B. Yang, Y.E. Chen. A SVM regression based approach to filling in Missing Values. 9th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems (KES2005). Springer-Verlag 3683, Springer 2005, Melbourne (Australia, 2005) 581-587.
Weighted Knn Imputation	MV-WKNNimpute	O. Troyanskaya, M. Cantor, G. Sherlock, P. Brown, T. Hastie, R. Tibshirani, D. Botstein, R.B. Altman. Missing value estimation methods for DNA microarrays. Bioinformatics 17 (2001) 520-525.

Classification Algorithms

EVOLUTIONARY NEURAL NETWORKS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Genetic Algorithm with Neural Network	Clas-GANN	G.F. Miller, P.M. Todd and S.U. Hedge. Designing neural networks using genetic algorithms. III International Conference on Genetic Algorithm and Their applications, George Mason University (USA, 1989) 379-384.
		X. Yao. Evolving Artificial Neural Networks. Proceedings of the IEEE 9:87 (1999) 1423-1447.
NNEP	Clas-NNEP	S. Haykin. Neural Networks: A comprehensive Foundation. Prentice Hall, 1998.

NEURAL NETWORKS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Multilayer perceptron for classification problems, Conjugate Gradient based training	Clas-MLPerceptronConj-Grad	F. Moller. A scaled conjugate gradient algorithm for fast supervised learning. Neural Networks, 6 (1990) 525-533.
		B. Widrow and M.A. Lehr. 30 years of Adaptive Neural Networks: Peceptron, Madaline, and Backpropagation, Proceedings of the IEEE, 78:9 (1990) 1415-1442.
Radial Basis Function Neural Network for Classification Problems	Clas-RBFN	D.S. Broomhead and D. Lowe. Multivariable Functional Interpolation and Adaptative Networks. Complex Systems 11 (1988) 321-355.
Incremental Radial Basis Function neural Network for Classification Problems	Clas-Incremental-RBFN	J. Plat. A resource allocating network for function interpolation. Neural Computation, 3 (1991) 213-225.
Decremental Radial Basis Function Neural Network for Classification Problems	Clas-Decremental-RBFN	D.S. Broomhead and D. Lowe. Multivariable Functional Interpolation and Adaptative Networks. Complex Systems 11 (1988) 321-355.
SONN Neural Networks	Clas-SONN	I.G. Smotroff, D.H. Friedman and D. Connolly. Self organizing modular neural networks. IEEE International Joint Conference on Neural Networks (IJCNN'91), Seattle (USA) (1991) 187-192.
Ensemble	Clas-Ensemble	N. García-Pedrajas, C. García-Osorio, C. Fyfe. Nonlinear Boosting Projections for Ensemble Construction. Journal of Machine Learning Research 8 (2007) 1-33.
Learning Vector Quantization for Classification	Clas-LVQ	J.C. Bezdek, L.I. Kuncheva. Nearest prototype classifier designs: An experimental study. International Journal of Intelligent Systems 16:12 (2001) 1445-1473.

Problems		
Evolutionary Radial Basis Function Neural Networks	Clas-EvRBF	V.M. Rivas, J.J. Merelo, P.A. Castillo, M.G. Arenas, J.G. Castellano. Evolving RBF neural networks for time-series forecasting with EvRBF. Information Sciences 165:3-4 (2004) 207-220.
iRProp+ algorithm for the training of Product Unit Neural Networks (using Product Unit basis functions) or Multilayer Perceptrons (using Sigmoidal basis functions)	Clas-iRProp+	C. Igel, M. Husken. Empirical evaluation of the improved Rprop learning algorithm. Neurocomputing 50 (2003) 105-123.
		L.R. Leerink, C.L. Giles, B.G. Horne, M.A. Jabri. Learning with Product Units. In: D. Touretzky, T. Leen (Eds.) Advances in Neural Information Processing Systems, 1995, 537-544
Multilayer perceptron for classification problems	Clas-MLPerceptron-Backprop	R. Rojas, J. Feldman. Neural Networks: A Systematic Introduction . Springer-Verlag, Berlin, New-York, 1996. ISBN: 978-3540605058.

STATISTICAL CLASSIFIERS		
Full Name	Short Name	Reference
Linear Discriminant Analysis	Clas-LDA	G. J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. Wiley Series in Probability and Mathematical Statistics, (2004).
		R. A. Fisher. The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenics 7 (1936) 179-188.
		J. H. Friedman. Regularized Discriminant Analysis. Journal of the American Statistical Association 84 (1989) 165-175.
Quadratic Discriminant Analysis	Clas-QDA	G. J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. Wiley Series in Probability and Mathematical Statistics, 2004.
		R. A. Fisher. The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenics 7 (1936) 179-188.
		J. H. Friedman. Regularized Discriminant Analysis. Journal of the American Statistical Association 84 (1989) 165-175.
		B. D. Ripley. Linear and Quadratic Discriminant Analysis. Multivariate Analysis, http://www.stats.ox.ac.uk/~ripley/MultAnal_MT2004/LQDA.pdf
Kernel Classifier	Clas-Kernel	G. J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. Wiley Series in Probability and Mathematical Statistics, 2004.
Least Mean Square Linear Classifier	Clas-LinearLMS	J. S. Rustagi. Optimization Techniques in Statistics. Academic Press, San Diego, 1994.
Least Mean Square Quadratic classifier	Clas-PolQuadraticLMS	J. S. Rustagi. Optimization Techniques in Statistics. Academic Press, San Diego, 1994.
Multinomial logistic regression model with a ridge estimator	Clas-Logistic	S. le Cessie, J.C. van Houwelingen. Ridge Estimators in Logistic Regression. Applied Statistics 41:1 (1992) 191-201.
Naive-Bayes Classifier	Clas-Naive_Bayes	P. Domingos, M. Pazzani. On the optimality of the simple Bayesian classifier under zero-one loss. Machine Learning 29 (1997) 103-137.
		M.E. Maron. Automatic Indexing: An Experimental Inquiry. Journal of the ACM (JACM) 8:3 (1961) 404-417.

EVOLUTIONARY FUZZY RULE BASED SYSTEMS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Fuzzy Rule Learning, AdaBoost Algorithm	Clas-Fuzzy-AdaBoost	M. J. del Jesus, F. Hoffmann, L. Junco, and L. Sanchez. Induction of Fuzzy-Rule-Based Classifiers With Evolutionary Boosting Algorithms. IEEE Transactions on Fuzzy Systems 12:3 (2004) 296-308.
Fuzzy Rule Learning, LogitBoost Algorithm	Clas-Fuzzy-LogitBoost	J. Otero and L. Sanchez. Induction of descriptive fuzzy classifiers with the Logitboost algorithm. Soft Computing 10:9 (2005) 825-835.
Fuzzy Rule Learning with Single Winner Inference, Logitboost Algorithm	Clas-Fuzzy-MaxLogitBoost	L. Sánchez, J. Otero. Boosting Fuzzy Rules in Classification Problems Under Single-Winner Inference. International Journal of Intelligent Systems 22:9 (2007) 1021-1034.
Grid Rule Base Generation and Genetic Rule Selection	Clas-Fuzzy-Ishib-Selec	H. Ishibuchi, K. Nozaki, N. Yamamoto, H. Tanaka. Selecting Fuzzy If-Then Rules for Classification. IEEE Transactions on Fuzzy Systems 3:3 (1995) 260-270.
Fuzzy Rule Learning, Grammar-based GAP Algorithm	Clas-Fuzzy-GAP	L. Sanchez and I. Couso. Combining GP operators with SA search to evolve fuzzy rule based classifiers. Information Sciences 136 (2001) 175 - 192.
Fuzzy Rule Learning, Grammar-based GP algorithm	Clas-Fuzzy-GP	L. Sanchez and I. Couso. Combining GP operators with SA search to evolve fuzzy rule based classifiers. Information Sciences 136 (2001) 175 - 192.
Fuzzy Rule Learning, Grammar-GP based operators and Simulated Annealing-based Algorithm	Clas-Fuzzy-SAP	L. Sanchez and I. Couso. Combining GP operators with SA search to evolve fuzzy rule based classifiers. Information Sciences 136 (2001) 175-192.
Fuzzy Rule Learning Algorithm Proposed by Ishibuchi et al. in 1999	Clas-Fuzzy-Ishibuchi99	H. Ishibuchi, T. Nakashima, T. Murata. Performance evaluation of fuzzy classifier systems for multidimensional pattern classification problems. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 29:5 (1999) 601-618.
Hybrid Fuzzy GBML	Clas-Fuzzy-Ishib-Hybrid	H. Ishibuchi, T. Yamamoto, T. Nakashima. Hybridization of Fuzzy GBML Approaches for Pattern Classification Problems. IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics 35:2 (2005) 359-365.
Fuzzy Rule Learning	Clas-Fuzzy-Shi-Eberhart-Chen	Y. Shi, R. Eberhart, Y. Chen. Implementation of evolutionary fuzzy systems. IEEE Transactions on Fuzzy Systems 7:2

Algorithm Proposed by Shi, Eberhart and Chen in 1999		(1999) 109-119.
SLAVE: Iterative Rule Learning of Fuzzy Rules with Feature Selection	Clas-Fuzzy-SLAVE	A. González, R. Perez. Selection of relevant features in a fuzzy genetic learning algorithm. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 31:3 (2001) 417-425.
		A. González, R. Perez. SLAVE: A genetic learning system based on an iterative approach. IEEE Transactions on Fuzzy Systems 7:2 (1999) 176-191.
MOGUL: A Methodology to Obtain Genetic Fuzzy Rule-Based Systems under the Iterative Learning Approach	Class-Fuzzy-MOGUL	O. Cordón, M.J. del Jesus, F. Herrera. Genetic learning of fuzzy rule-based classification systems cooperating with fuzzy reasoning methods. International Journal of Intelligent Systems 13:10 (1998) 1025-1053.
		O. Cordón, M.J. del Jesus, F. Herrera, M. Lozano. MOGUL: A Methodology to Obtain Genetic fuzzy rule-based systems Under the iterative rule Learning approach. International Journal of Intelligent Systems 14:11 (1999) 1123-1153.
Steady-State Genetic Algorithm for Extracting Fuzzy Classification Rules From Data	Clas-SGERD	E.G. Mansoori, M.J. Zolghadri, S.D. Katebi. SGERD: A Steady-State Genetic Algorithm for Extracting Fuzzy Classification Rules From Data. IEEE Transactions on Fuzzy Systems 16:4 (2008) 1061-1071.

EVOLUTIONARY RULE LEARNING		
Full Name	Short Name	Reference
XCS	Clas-XCS	S. W. Wilson. Classifier Fitness Based on Accuracy. Evolutionary Computation 3:2 (1995) 149-175.
Supervised Inductive Algorithm	Clas-SIA	G. Venturini. SIA: a Supervised Inductive Algorithm with Genetic Search for Learning Attributes based Concepts. Lecture Notes in Artificial Intelligence, Machine Learning ECML-93, Springer-Verlag, London, 667 (1993) 280-296.
Pittsburgh Genetic Intervalar Rule Learning Algorithm	Clas-PGIRLA	A. L. Corcoran and S. Sen. Using real-valued genetic algorithms to evolve rule sets for classification. Proceedings IEEE Conference on Evolutionary Computation, Orlando, Florida, 1 (1994) 120-124.
Hierarchical Decision Rules	Clas-Hider	J.S. Aguilar-Ruiz, J.C. Riquelme, M. Toro. Evolutionary learning of hierarchical decision rules.. Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics 33:2 (2003) 324-331.
		J.S. Aguilar-Ruiz, R. Giráldez, J.C. Riquelme. Natural Encoding for Evolutionary Supervised Learning. IEEE Transactions on Evolutionary Computation (2007) In press.
Genetic Algorithm based Classifier System with Adaptive Discretization Intervals	Clas-GAssist-ADI	J. Bacardit, J.M. Garrell. Evolving multiple discretizations with adaptive intervals for a pittsburgh rule-based learning classifier system. Genetic and Evolutionary Computation Conference (GECCO'03). Lecture Notes on Computer Science 2724, Springer 2003, Chicago (Illinois USA, 2003) 1818-1831.
		J. Bacardit, J.M. Garrell. Analysis and improvements of the adaptive discretization intervals knowledge representatio. Genetic and Evolutionary Computation Conference (GECCO'04). Lecture Notes on Computer Science 3103, Springer 2004, Seattle (Washington USA, 2004) 726-738.
Genetic Algorithm based Classifier System with Intervalar Rules	Clas-GAssist-Intervalar	J. Bacardit, J.M. Garrell. Bloat control and generalization pressure using the minimum description length principle for a pittsburgh approach learning classifier system. Advances at the frontier of Learning Classifier Systems. Springer-Verlag 4399, Springer 2006 (2006) 61-80.
LOGENPRO: The LOgic grammar Based GENetic PROgramming system	Clas-LogenPro	M.L. Wong, K.S. Leung. Data Mining using grammar based genetic programming and applications. Kluwer Academics Publishers, 2000.
UCS	Clas-UCS	E. Bernadó-Mansilla, J.M. Garrell. Accuracy-Based Learning Classifier Systems: Models, Analysis and Applications to Classification Tasks. Evolutionary Computation 11:3 (2003) 209-238.
Bioinformatics-oriented	Clas-BioHel	J. Bacardit, E. Burke, N. Krasnogor. Improving the scalability of rule-based evolutionary learning. Memetic

hierarchical evolutionary learning		computing 1:1 (2009) 55-67.
COverage-based Genetic INduction	Clas-COGIN	D.P. Greene, S.F. Smith. Competition–based induction of decision models from examples. Machine Learning 13:23 (1993) 229-257.
CO-Evolutionary Rule Extractor	Clas-CORE	K.C. Tan, Q. Yu, J.H. Ang. A coevolutionary algorithm for rules discovery in data mining. International Journal of Systems Science 37:12 (2006) 835-864.
Data Mining for Evolutionary Learning	Clas-DMEL	W.H. Au, K.C.C. Chan, X. Yao. A novel evolutionary data mining algorithm with applications to churn prediction. IEEE Transactions on Evolutionary Computation 7:6 (2003) 532-545.
Genetic-based Inductive Learning	Clas-GIL	C.Z. Janikow. A knowledge–intensive genetic algorithm for supervised learning. Machine Learning 13:2 (1993) 189-228.
Incremental Learning with Genetic Algorithms	Clas-ILGA	S.U. Guan, F. Zhu. An incremental approach to genetic–algorithms–based classification. IEEE Transactions on Systems, Man, and Cybernetics, Part B 35:2 (2005) 227-239.
PSO/ACO	Clas-PSO_ACO	T. Sousa, A. Silva, A. Neves. Particle Swarm based Data Mining Algorithms for classification tasks. Parallel Computing 30, pp. 767-783, 2004
Organizational CoEvolutionary algorithm for Classification	Clas-OCEC	L. Jiao, J. Liu, W. Zhong. An organizational coevolutionary algorithm for classification. IEEE Transactions on Evolutionary Computation 10:12 (2006) 67-80.
Ordered Incremental Genetic Algorithm	Clas-OIGA	F. Zhu, S.U. Guan. Ordered incremental training with genetic algorithms. International Journal of Intelligent Systems 19:12 (2004) 1239-1256.
Memetic Pittsburgh Learning Classifier System	Clas-MPLCS	J. Bacardit, N. Krasnogor. Performance and Efficiency of Memetic Pittsburgh Learning Classifier Systems. Evolutionary Computation 17:3 (2009) 307-342.
Ant Miner	Clas-Ant_Miner	R.S. Parpinelli, H.S. Lopes, A.A. Freitas. Data Mining With an Ant Colony Optimization Algorithm. IEEE Transactions on Evolutionary Computation 6:4 (2002) 321-332.
Advanced Ant Miner	Clas-Advanced_Ant_Miner	R.S. Parpinelli, H.S. Lopes, A.A. Freitas. Data Mining With an Ant Colony Optimization Algorithm. IEEE Transactions on Evolutionary Computation 6:4 (2002) 321-332.
		R.S. Parpinelli, H.S. Lopes, A.A. Freitas. An Ant Colony Algorithm for Classification Rule Discovery. In: H.A. Abbass, R.A. Sarker, C.S. Newton (Eds.) Data Mining: a Heuristic Approach, 2002, 191-208.
Ant Miner+	Clas-Ant_Miner_Plus	R.S. Parpinelli, H.S. Lopes, A.A. Freitas. Data Mining With an Ant Colony Optimization Algorithm. IEEE Transactions on Evolutionary Computation 6:4 (2002) 321-332.
Advanced Ant Miner+	Clas-Advanced_Ant_Miner_Plus	R.S. Parpinelli, H.S. Lopes, A.A. Freitas. Data Mining With an Ant Colony Optimization Algorithm. IEEE Transactions on

		Evolutionary Computation 6:4 (2002) 321-332.
		R.S. Parpinelli, H.S. Lopes, A.A. Freitas. An Ant Colony Algorithm for Classification Rule Discovery. In: H.A. Abbass, R.A. Sarker, C.S. Newton (Eds.) Data Mining: a Heuristic Approach, 2002, 191-208.

DECISION TREES

Full Name	Short Name	Reference
C4.5 Decision Tree	Clas-C4.5	J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Iterative Dicotomizer 3	Clas-ID3	J.R. Quinlan. Induction of Decision Trees. Machine Learning 1 (1975) 81-106.
Classification and Regression Tree	Clas-CART	L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone. Classification and Regression Trees. Chapman and Hall (Wadsworth, Inc.), 1984.
Hybrid Decision Tree -Genetic Algorithm	Clas-DT_GA	D.R. Carvalho, A.A. Freitas. A hybrid decision tree/genetic algorithm method for data mining. Information Sciences 163:1 (2004) 13-35.
Oblique Decision Tree	Clas-DT_Oblique	E. Cantú-Paz, C. Kamath. Inducing oblique decision trees with evolutionary algorithms. IEEE Transactions on Evolutionary Computation 7:1 (2003) 54-68.
Functional Trees	Clas-FunctionalTrees	J. Gama. Functional Trees. Machine Learning 55 (2004) 219-250.
PUBLIC Decision Tree	Clas-PUBLIC	R. Rastogi, K. Shim. PUBLIC: A Decision Tree Classifier that Integrates Building and Pruning. Data Mining and Knowledge Discovery 4:4 (2000) 315-344.
SLIQ Decision Tree	CLAS-SLIQ	M. Mehta, R. Agrawal, J. Rissanen. SLIQ: A Fast Scalable Classifier for Data Mining. Proceedings of the 5th International Conference on Extending Database Technology. (1996) 18-32.
Tree Analysis with Randomly Generated and Evolved Trees	Clas-Target	J.B. Gray, G. Fan. Classification tree analysis using TARGET. Computational Statistics and Data Analysis 52:3 (2008) 1362-1372.

RULE LEARNING

Full Name	Short Name	Reference
AQ-15	Clas-AQ	R. S. Michalksi. On the quasi-minimal solution of the general covering problem. Proceedings of the First International Simposium of Information Processing (Bled. Yugoslavia), A3 (1969) 125-128.
Association Rule Tree	Clas-ART	F. Berzal, J.C. Cubero, D. Sánchez, J.M. Serrano. Serrano.ART: A Hybrid Classification Model. Machine Learning 54 (2004) 67-92.
CN2	Clas-CN2	Peter Clark and Tim Niblett. The CN2 induction algorithm.

		Machine Learning Journal 3:4 (1989) 261-283.
PRISM	Clas-Prism	J. Cendrowska. PRISM: An algorithm for inducing modular rules. International Journal of Man-Machine Studies 27:4 (1987) 349-370.
1R	Clas-1R	R.C. Holte. Very simple classification rules perform well on most commonly used datasets. Machine Learning 11 (1993) 63-91
RIONA	Clas-Riona	G. Góra, A. Wojna. RIONA: A New Classification System Combining Rule Induction and Instance-Based Learning. Fundamenta Informaticae 51:4 (2002) 1-22
C4.5Rules	Clas-C45Rules	J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman Publishers, 1993.
		J.R. Quinlan. MDL and Categorical Theories (Continued). Machine Learning: Proceedings of the Twelfth International Conference. Lake Tahoe California (United States of America, 1995) 464-470.
C4.5Rules (Simulated Annealing version)	Clas-C45RulesSA	J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman Publishers, 1993.
		J.R. Quinlan. MDL and Categorical Theories (Continued). Machine Learning: Proceedings of the Twelfth International Conference. Lake Tahoe California (United States of America, 1995) 464-470.
DataSqueezer	Clas-DataSqueezer	L.A. Kurgan, K.J. Cios, S. Dick. Highly Scalable and Robust Rule Learner: Performance Evaluation and Comparison. IEEE Transactions on Systems, Man and Cybernetics,Part B: Cybernetics 36:1 (2006) 32-53.
PART	Clas-PART	E. Frank, I.H. Witten. Generating Accurate Rule Sets Without Global Optimization. Proceedings of the Fifteenth International Conference on Machine Learning. (1998) 144-151
Repeated Incremental Pruning to Produce Error Reduction	Clas-Ripper	W.W. Cohen. Fast Effective Rule Induction. Machine Learning: Proceedings of the Twelfth International Conference. Lake Tahoe California (United States of America, 1995) 1-10.
Simple Learner with Iterative Pruning to Produce Error Reduction	Clas-Slipper	W.W. Cohen, Y. Singer. A Simple, Fast, and Effective Rule Learner. Proceedings of the Sixteenth National Conference on Artificial Intelligence. Orlando Florida (United States of America, 1999) 335-342.
Learning Examples Module 1	Clas-LEM1	J. Stefanowski. On rough set based approaches to induction of decision rules. In: L. Polkowski, A. Skowron (Eds.) Rough sets in data mining and knowledge discovery, 1998, 500-529.
Learning Examples Module 2	Clas-LEM2	J. Stefanowski. On rough set based approaches to induction of decision rules. In: L. Polkowski, A. Skowron (Eds.) Rough sets in data mining and knowledge discovery, 1998, 500-529.
Rule Induction Two In One	Clas-Ritio	X. Wu, D. Urpani. Induction By Attribute Elimination. IEEE Transactions on Knowledge and Data Engineering 11:5

		(1999) 805-812.
RULe Extraction System version 6	Clas-Rules6	D.T. Pham, A.A. Afify. RULES-6: A Simple Rule Induction Algorithm for Supporting Decision Making. 31st Annual Conference of IEEE Industrial Electronics Society (IECON). (2005) 2184-2189.
Scalable Rule Induction	Clas-SRI	D.T. Pham, A.A. Afify. SRI: a scalable rule induction algorithm. Proceedings of the Institution of Mechanical Engineers . (2006) 537-552.
Swap1	Clas-Swap1	M. Sholom, N. Indurkhya. Optimized Rule Induction. IEEE Expert 1 (1993) 61-70.

SUPPORT VECTOR MACHINES FOR CLASSIFICATION		
Full Name	Short Name	Reference
C-SVM for Classification	Clas-C_SVM	C. Cortes, V. Vapnik. Support vector networks. Machine Learning 20 (1995) 273-297.
NU-SVM for Classification	Clas-NU_SVM	B. Scholkopf, A.J. Smola, R. Williamson, P.L. Bartlett. New support vector algorithms. Neural Computation 12 (2000) 1207-1245.
Sequential Minimal Optimization for Classification	Clas-SMO	J. Platt. Fast Training of Support Vector Machines using Sequential Minimal Optimization. In: B. Schoelkopf, C. Burges, A. Smola (Eds.) Advances in Kernel Methods - Support Vector Learning, 1998, 1-1.
		S.S. Keerthi, S.K. Shevade, C. Bhattacharyya, K.R.K. Murthy. Improvements to Platt's SMO Algorithm for SVM Classifier Design. Neural Computation 13:3 (2001) 0-649.
		T. Hastie, R. Tibshirani. Classification by Pairwise Coupling. In: M.I. Jordan, M.J. Kearns, S.A. Solla (Eds.) Advances in Neural Information Processing Systems, 1998, 0-1.

FUZZY RULE BASED SYSTEMS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Fuzzy Rule Learning Model by the Chi et al. approach with rule weights	Clas-Fuzzy-Chi-RW	Z. Chi, H. Yan, T. Pham. Fuzzy Algorithms: With Applications To Image Processing and Pattern Recognition. World Scientific, 1996.
		O. Cordón, M.J. del Jesus, F. Herrera. A proposal on reasoning methods in fuzzy rule-based classification systems. International Journal of Approximate 20:1 (1999) 21-45.
		H. Ishibuchi, T. Yamamoto. Rule weight specification in fuzzy rule-based classification systems. IEEE Transactions on Fuzzy Systems 13:4 (2005) 428-435.
Weighted Fuzzy Classifier	Clas-Fuzzy-Ishib-Weighted	T. Nakashima, G. Schaefer, Y. Yokota, H. Ishibuchi. A Weighted Fuzzy Classifier and its Application to Image Processing Tasks. Fuzzy Sets and Systems 158 (2007) 284-294.
Positive Definite Fuzzy Classifier	Clas-PDFC	Y. Chen, J.Z. Wang: Support Vector Learning for Fuzzy Rule-Based Classification Systems. IEEE Transactions on Fuzzy Systems, 11 (6) 2003 pp. 716-728.

LAZY LEARNING		
Full Name	Short Name	Reference
K-Nearest Neighbors Classifier	Clas-KNN	T.M. Cover, P.E. Hart. Nearest Neighbor Pattern Classification. IEEE Transactions on Information Theory 13 (1967) 21-27.
Adaptive KNN Classifier	Clas-KNNAdaptive	J. Wang, P. Neskovic, L.N. Cooper. Improving nearest neighbor rule with a simple adaptative distance measure. Pattern Recognition Letters 28 (2007) 207-213.
K * Classifier	Clas-KStar	J.G. Cleary, L.E. Trigg. K*: An instance-based learner using an entropic distance measure. Proceedings of the 12th International Conference on Machine Learning. (1995) 108-114.
Lazy Decision Tree	Clas-LazyDT	J.H. Friedman, R. Kohavi, Y. Tun. Lazy decision trees. Proceedings of the Thirteenth National Conference on Artificial Intellgence. (1996) 717-724.

PSO LEARNING		
Full Name	Short Name	Reference
Constricted Particle Swarm Optimization	Clas-CPSO	T. Sousa, A. Silva, A. Neves. Particle Swarm based Data Mining Algorithms for classification tasks. Parallel Computing 30 (2004) 767-783.
Linear Decreasing Weight - Particle Swarm Optimization	Clas-LDWPSO	T. Sousa, A. Silva, A. Neves. Particle Swarm based Data Mining Algorithms for classification tasks. Parallel Computing 30 (2004) 767-783.
PSO - Linear Discriminant Analysis	Clas-PSOLDA	S.W. Lin, S.C. Chen. PSOLDA: A particle swarm optimization approach for enhancing classification accuracy rate of linear discriminant analysis. Applied Soft Computing 9 (2009) 1008-1015.
Real Encoding - Particle Swarm Optimization	Clas-REPSO	Y. Liu, Z. Qin, Z. Shi, J. Chen. Rule Discovery with Particle Swarm Optimization. Advanced Workshop on Content Computing (AWCC). C.-H. Chi and K.-Y. Lam 3309, Springer 2004 (2004) 291-296.

Regression Algorithms

EVOLUTIONARY FUZZY RULE BASED SYSTEMS FOR REGRESSION		
Full Name	Short Name	Reference
Iterative Rule Learning of TSK Rules	Regr-Fuzzy-TSK-IRL	O. Cordon and F. Herrera. A Two-Stage Evolutionary Process for Designing TSK Fuzzy Rule-Based Systems. IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics 29:6 (1999) 703-715.
Iterative Rule Learning of Mamdani Rules - Small Constrained Approach	Regr-Fuzzy-MOGUL-IRLSC	O. Cordon and F. Herrera. A three-stage evolutionary process for learning descriptive and approximate fuzzy logic controller knowledge bases from examples. International Journal of Approximate Reasoning 17:4 (1997) 369-407.
Iterative Rule Learning of Mamdani Rules - High Constrained Approach	Regr-Fuzzy-MOGUL-IRLHC	O. Cordon and F. Herrera. Hybridizing genetic algorithms with sharing scheme and evolution strategies for designing approximate fuzzy rule-based systems. Fuzzy Sets and Systems 118:2 (2001) 235-255.
Fuzzy Rule Learning, Grammar-based GP Algorithm	Regr-GP	L. Sanchez and I. Couso. Combining GP operators with SA search to evolve fuzzy rule based classifiers. Information Sciences 136 (2001) 175 - 192. L. Sánchez, I. Couso, J.A. Corrales. Combining GP Operators with SA Search to Evolve Fuzzy Rule Based Classifiers. Information Sciences 136:1-4 (2001) 175-191..
Fuzzy Rule Learning, Grammar-GP Based Operators and Simulted Annealing-Based Algorithm	Regr-Fuzzy-SAP	L. Sánchez, I. Couso, J.A. Corrales. Combining GP Operators with SA Search to Evolve Fuzzy Rule Based Classifiers. Information Sciences 136:1-4 (2001) 175-191.
Learning tsk-fuzzy models based on MOGUL	Regr-Fuzzy-MOGUL-TSK	R. Alcala, J. Alcala-Fdez, J. Casillas, O. Cordon and F. Herrera. Local identification of prototypes for genetic learning of accurate TSK fuzzy rule-based systems. International Journal of Intelligent Systems (2007), In press.
Genetic Fuzzy Rule Learning, Thrift Algorithm	Regr-Thrift	P. Thrift. Fuzzy logic synthesis with genetic algorithms. Proceedings of the Fourth International Conference on Genetic Algorithms (ICGA91). San Diego (United States of America, 1991) 509-513.
Genetic-Based Fuzzy Rule Base Construction	Regr-GFS-RB-MF	A. Homaifar, E. McCormick. Simultaneous Design of Membership Functions and Rule Sets for Fuzzy Controllers Using Genetic Algorithms. IEEE Transactions on Fuzzy Systems 3:2 (1995) 129-139.

and Membership Functions Tuning		O. Cordón, F. Herrera. A Three-Stage Evolutionary Process for Learning Descriptive and Approximate Fuzzy Logic Controller Knowledge Bases from Examples. International Journal of Approximate Reasoning 17:4 (1997) 369-407.
Iterative Rule Learning of Descriptive Mamdani Rules based on MOGUL	Regr-Fuzzy-MOGUL-IRL	O. Cordón, F. Herrera. A Three-Stage Evolutionary Process for Learning Descriptive and Approximate Fuzzy Logic Controller Knowledge Bases from Examples. International Journal of Approximate Reasoning 17:4 (1997) 369-407.
SEFC: Symbiotic-Evolution-based Fuzzy Controller design method	Regr-Fuzzy-SEFC	C.F. Juang, J.Y. Lin, C.-T. Lin. Genetic reinforcement learning through symbiotic evolution for fuzzy controller design. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 30:2 (2000) 290-302.
Pittsburgh Fuzzy Classifier System #1	Regr-Fuzzy-P_FCS1	B. Carse, T.C. Fogarty, A. Munro. Evolving fuzzy rule based controllers using genetic algorithms. Fuzzy Sets and Systems 80:3 (1996) 273-293.

DECISION TREES FOR REGRESSION

Full Name	Short Name	Reference
M5	Regr-M5	J.R. Quinlan. Learning with Continuous Classes. 5th Australian Joint Conference on Artificial Intelligence (AI92). (Singapore, 1992) 343-348.
		I. Wang, I.H. Witten. Induction of model trees for predicting continuous classes. 9th European Conference on Machine Learning. Prague (Czech Republic, 1997) 128-137.
Classification and Regression Tree	Regr-CART	L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone. Classification and Regression Trees. Chapman and Hall (Wadsworth, Inc.), 1984.
M5Rules	Regr-M5Rules	J.R. Quinlan. Learning with Continuous Classes. Proceedings of the 5th Australian Joint Conference on Artificial Intelligence. (1992) 343-348.
		I. Wang, I.H. Witten. Induction of model trees for predicting continuous classes. Poster papers of the 9th European Conference on Machine Learning. Prague (Czech Republic, 1997) 128-137.
		G. Holmes, M. Hall, E. Frank. Generating Rule Sets from Model Trees. Proceedings of the 12th Australian Joint Conference on Artificial Intelligence: Advanced Topics in Artificial Intelligence. Springer-Verlag 1747, Springer 1999, Sydney (Australia, 1999) 1-12.

STATISTICAL REGRESSION

Full Name	Short Name	Reference
LMS Linear Regression	Regr-LinearLMS	J. S. Rustagi. Optimization Techniques in Statistics. Academic Press, San Diego, 1994.
LMS Quadratic Regression	Regr-PolQuadraticLMS	J. S. Rustagi. Optimization Techniques in Statistics. Academic Press, San Diego, 1994.

FUZZY RULE BASED SYSTEMS FOR REGRESSION

Full Name	Short Name	Reference
Fuzzy Rule Learning, Wang-Mendel Algorithm	Regr-Fuzzy-WangMendel	L.X. Wang, J.M. Mendel. Generating fuzzy rules by learning from examples. IEEE Transactions on Systems, Man and Cybernetics 22:6 (1992) 1414-1427
Fuzzy and Random Sets based Modeling	Regr-FRSBM	L. Sanchez. A random sets-based method for identifying fuzzy models. Fuzzy Sets and Systems 98:3 (1998) 343-354.

EVOLUTIONARY POSTPROCESSING FRBS: SELECTION AND TUNING

Full Name	Short Name	Reference
Global Genetic Tuning of the Fuzzy Partition of Linguistic FRBSs	Post-G-G-Tuning-FRBSs	O. Cordon and F. Herrera. A Three-Stage Evolutionary Process for Learning Descriptive and Approximative Fuzzy Logic Controller Knowledge Bases from Examples. International Journal of Approximate Reasoning 17:4 (1997) 369-407.
Approximative Genetic Tuning of FRBSs	Post-A-G-Tuning-FRBSs	F. Herrera, M. Lozano and J.L. Verdegay. Tuning Fuzzy Logic Controllers by Genetic Algorithms. International Journal of Approximate Reasoning 12 (1995) 299-315
Genetic Selection of Linguistic Rule Bases	Post-Rules-Selection	O. Cordon and F. Herrera. A Three-Stage Evolutionary Process for Learning Descriptive and Approximative Fuzzy Logic Controller Knowledge Bases from Examples. International Journal of Approximate Reasoning 17:4 (1997) 369-407.
		H. Ishibuchi, K. Nozaki, N. Yamamoto and H. Tanaka. Selecting Fuzzzy If-Then Rules for Classification Problems Using Genetic Algorithms. IEEE Trans. on Fuzzy Systems 3:3 (1995) 260-270.
Genetic Tuning of FRBSs Weights	Post-G-T-FRBSs-Weights	R. Alcala, O. Cordon and F. Herrera. Combining Rule Weight Learning and Rule Selection to Obtain Simpler and More Accurate Linguistic Fuzzy Models. Modelling with Words. In: J. Lawry (Eds.) Springer-Verlag, LNCS 2873 (2003) 44-63.
Genetic Selection of rules and rules weight tuning of FRBSs	Post-G-S-Weight-FRBS	R. Alcala, O. Cordon and F. Herrera. Combining Rule Weight Learning and Rule Selection to Obtain Simpler and More Accurate Linguistic Fuzzy Models. Modelling with Words. In: J. Lawry (Eds.) Springer-Verlag, LNCS 2873 (2003) 44-63.
Genetic-Based New Fuzzy Reasoning Model	Post-GB-NFRM	D. Park, A. Kandel. Genetic-Based New Fuzzy Reasoning Model with Application to Fuzzy Control. IEEE Transactions on System, Man and Cybernetics, Part B: Cybernetics 24:1 (1994) 39-47.

EVOLUTIONARY SYMBOLIC REGRESSION

Full Name	Short Name	Reference
Symbolic Regression for Fuzzy-Valued Data, Grammar-Based GAP Algorithm	Regr-Fuzzy-GAP-RegSym	L. Sánchez, I. Couso. Fuzzy Random Variables-Based Modeling with GA-P Algorithms. In: B. Bouchon, R.R. Yager, L. Zadeh (Eds.) Information, Uncertainty and Fusion, 2000, 245-256.
Symbolic Regression for Fuzzy-Valued Data, Grammar-GP Based Operators and Simulated Annealing-Based Algorithm	Regr-Fuzzy-SAP-RegSym	L. Sánchez, I. Couso. Fuzzy Random Variables-Based Modeling with GA-P Algorithms. In: B. Bouchon, R.R. Yager, L. Zadeh (Eds.) Information, Uncertainty and Fusion, 2000, 245-256. L. Sánchez, I. Couso, J.A. Corrales. Combining GP Operators with SA Search to Evolve Fuzzy Rule Based Classifiers. Information Sciences 136:1-4 (2001) 175-191.
Symbolic Regression, Grammar-GP Based Operators and Simulated Annealing-Based Algorithm	Regr-SAP	L. Sánchez, I. Couso. Fuzzy Random Variables-Based Modeling with GA-P Algorithms. In: B. Bouchon, R.R. Yager, L. Zadeh (Eds.) Information, Uncertainty and Fusion, 2000, 245-256. L. Sánchez, I. Couso, J.A. Corrales. Combining GP Operators with SA Search to Evolve Fuzzy Rule Based Classifiers. Information Sciences 136:1-4 (2001) 175-191.
Symbolic Regression, Grammar-Based GAP Algorithm	Regr-GAP	L. Sánchez, I. Couso. Fuzzy Random Variables-Based Modeling with GA-P Algorithms. In: B. Bouchon, R.R. Yager, L. Zadeh (Eds.) Information, Uncertainty and Fusion, 2000, 245-256.

EVOLUTIONARY NEURAL NETWORKS FOR REGRESSION

Full Name	Short Name	Reference
Genetic Algorithm with Neural Network	Regr-GANN	G.F. Miller, P.M. Todd, S.U. Hedge. Designing Neural Networks Using Genetic Algorithms. 3rd International Conference on Genetic Algorithm and Their Applications. Fairfax (Virginia USA, 1989) 379-384. X. Yao. Evolving Artificial Neural Networks. Proceedings of the IEEE 87:9 (1999) 1423-1447.
Neural Network Evolutionary Programming for Regression	Regr-NNEP	A.C. Martínez-Estudillo, F.J. Martínez-Estudillo, C. Hervás-Martínez, N. García. Evolutionary Product Unit based Neural Networks for Regression. Neural Networks 19:4 (2006) 477-486.

NEURAL NETWORKS FOR REGRESSION

Full Name	Short Name	Reference
Multilayer Perceptron for modeling	Regr-MLPerceptronConj-Grad	F. Moller. A scaled conjugate gradient algorithm for fast supervised learning. Neural Networks, 6 (1990) 525-533.
Radial Basis Function Neural Network for Regression Problems	Regr-RBFN	D.S. Broomhead and D. Lowe. Multivariable Functional Interpolation and Adaptative Networks. Complex Systems 11 (1988) 321-355.
Incremental Radial Basis Function Neural Network for Regression Problems	Regr-Incremental-RBFN	J. Plat. A resource allocating network for function interpolation. Neural Computation, 3 (1991) 213-225.
SONN Neural Networks	Regr-SONN	I.G. Smotroff, D.H. Friedman, D. Connolly. Self Organizing Modular Neural Networks. Seattle International Joint Conference on Neural Networks (IJCNN'91). Seattle (USA, 1991) 187-192.
Decremental Radial Basis Function Neural Network for Regression Problems	Regr-Decremental-RBFN	D.S. Broomhead and D. Lowe. Multivariable Functional Interpolation and Adaptative Networks. Complex Systems 11 (1988) 321-355.
Multilayer perceptron for regression problems	Regr-MLPerceptron-Backprop	R. Rojas, J. Feldman. Neural Networks: A Systematic Introduction . Springer-Verlag, Berlin, New-York, 1996. ISBN: 978-3540605058.
iRProp+ algorithm for the training of Product Unit Neural Networks (using Product Unit basis functions) or Multilayer Perceptrons (using Sigmoidal basis functions)	Regr-iRProp+	C. Igel, M. Husken. Empirical evaluation of the improved Rprop learning algorithm. Neurocomputing 50 (2003) 105-123.
		J.H. Wang, Y.W. Yu, J.H. Tsai. On the internal representations of product units. Neural Processing Letters 12:3 (2000) 247-254.

SUPPORT VECTOR MACHINES FOR REGRESSION

Full Name	Short Name	Reference
EPSILON-SVR for Regression	Regr-EPSILON_SVR	R.E. Fan, P.H. Chen, C.J. Lin. Working set selection using the second order information for training SVM. Journal of Machine Learning Research 6 (2005) 1889-1918.
NU-SVR for Regression	Regr-NU_SVR	R.E. Fan, P.H. Chen, C.J. Lin. Working set selection using the second order information for training SVM. Journal of Machine Learning Research 6 (2005) 1889-1918.

❖ Non-Supervised Learning

CLUSTERING ALGORITHMS		
Full Name	Short Name	Reference
ClusterKMeans	Clus-KMeans	J.B. MacQueen.. Some Methods for Classification and Analysis of Multivariate Observations. 5th Berkeley Symposium on Mathematical Statistics and Probability. Berkeley (USA, 1967) 281-297.

SUBGROUP DISCOVERY		
Full Name	Short Name	Reference
CN2 Algorithm for Subgroup Discovery	SD-CN2	N. Lavrac, B. Kavsek, P. Flach, L. Todorovski.. Subgroup Discovery with CN2-SD. Journal of Machine Learning Research 5 (2004) 153-188.
		B. Kavsek, N. Lavrac. APRIORI-SD: Adapting Association Rule Learning to Subgroup Discovery. Applied Artificial Intelligence 20:7 (2006) 543-583.
Apriori Algorithm for Subgroup Discovery	SD-Apriori	B. Kavsek, N. Lavrac. APRIORI-SD: Adapting Association Rule Learning to Subgroup Discovery.. Applied Artificial Intelligence 20:7 (2006) 543-583.

ASSOCIATION RULES		
Full Name	Short Name	Reference
Apriori	Asso-Apriori	R. Agrawal, H. Mannila, R. Srikant, H. Toivonen, and A. Inkeri Verkamo. Fast discovery of association rules. Advances in Knowledge Discovery and Data Mining, AAAI Press, (1996) 307-328

❖ Statistical Tests

TEST ANALYSIS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Statistical two samples mean comparation 5x2cv-f test	Stat-Clas-5x2cv	T.G. Dietterich. Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms. Neural Computation 10:7 (1998) 1895-1923.
Statistical two samples mean comparation Wilcoxon signed rank test	Stat-Clas-WilcoxonSR	F. Wilcoxon. Individual Comparisons by Ranking Methods. Biometrics 1 (1945) 80-83
		J.P. Royston. Algorithm AS 181. Applied Statistics 31:2 (1982) 176-180.
Statistical two samples mean comparation t test	Stat-Clas-t	D.R. Cox and D.V. Hinkley. Theoretical statistics, London, Chapman & Hall (1974).
Statistical two Normal samples variance comparation F test	Stat-Clas-SnedecorF	G.W Snedecor and W.G. Cochran. Statistical Methods, Iowa State University Press, Ames, IA, (1989).
Statistical Normality Shapiro Wilk test	Stat-Clas-ShapiroWilk	S.S. Shapiro and M.B. Wilk. An analysis of variance test for normality (complete samples). Biometrika 52:(3-4) (1965) 591-611.
Statistical two samples mean comparation Mann-Whitney U test by means of the StatTestClasU algorithm	Stat-Clas-MannWhitneyU	H.B. Mann and D.R. Whitney. On a test of whether one of two random variables is stochastically larger than the other. Annals of Mathematical Statistics 18 (1947) 50-60.
Wilcoxon Signed-Rank Test for Classification	Stat-Clas-Wilcoxon	F. Wilcoxon. Individual Comparisons by Ranking Methods. Biometrics 1 (1945) 80-83.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
Friedman Test and Post-Hoc Procedures for Classification Problems	Stat-Clas-Friedman	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
		M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Quade Test and Post-Hoc Procedures for Classification Problems	Stat-Clas-Quade	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.

		M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Friedman Alligned Test and Post-Hoc Procedures for Classification Problems	Stat-Clas-Friedman	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
		M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Friedman Test for Multiple Comparisons and Post-Hoc Procedures for Classification Problems	Stat-Clas-Multiple	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
		M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Contrast Estimation for Classification Problems	Stat-Clas-Contrast	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
		M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.

TEST ANALYSIS FOR REGRESSION		
Full Name	Short Name	Reference
Statistical two samples mean comparation 5x2cv-f test	Stat-Regr-5x2cv	T.G. Dietterich. Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms. Neural Computation 10:7 (1998) 1895-1923.
Statistical two samples mean comparation Wilcoxon signed rank test	Stat-Regr-WilcoxonSR	F. Wilcoxon. Individual Comparisons by Ranking Methods. Biometrics 1 (1945) 80-83 J.P. Royston. Algorithm AS 181. Applied Statistics 31:2 (1982) 176-180.
Statistical two samples mean comparation t test	Stat-Regr-t	D.R. Cox and D.V. Hinkley. Theoretical statistics, London, Chapman & Hall (1974).
Statistical two Normal samples variance comparation F test	Stat-Regr-SnedecorF	G.W Snedecor and W.G. Cochran. Statistical Methods, Iowa State University Press, Ames, IA, (1989).
Statistical Normality Shapiro Wilk test	Stat-Regr-ShapiroWilk	S.S. Shapiro and M.B. Wilk. An analysis of variance test for normality (complete samples). Biometrika 52:(3-4) (1965) 591-611.
Statistical two samples mean comparation Mann-Whitney U test by means of the StatTestClasU algorithm	Stat-Regr-MannWhitneyU	H.B. Mann and D.R. Whitney. On a test of whether one of two random variables is stochastically larger than the other. Annals of Mathematical Statistics 18 (1947) 50-60.
Wilcoxon Signed-Rank Test in Regression Problems	Stat-Regr-Wilcoxon	F. Wilcoxon. Individual Comparisons by Ranking Methods. Biometrics 1 (1945) 80-83. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30.
Friedman Test and Post-Hoc Procedures for Regression Problems	Stat-Regr-Friedman	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30. M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Quade Test and Post-Hoc Procedures for Regression Problems	Stat-Regr-Quade	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30. M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of

		the American Statistical Association 32:200 (1937) 675-701.
Friedman Alligned Test and Post-Hoc Procedures for Regression Problems	Stat-Regr-Friedman	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30. M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Friedman Test for Multiple Comparisons and Post-Hoc Procedures for Regression Problems	Stat-Regr-Multiple	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30. M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.
Contrast Estimation for Regression Problems	Stat-Regr-Contrast	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003. J. Demsar. Statistical comparisons of classifiers over multiple data sets. Journal of Machine Learning Research 7 (2006) 1-30. M. Friedman. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the American Statistical Association 32:200 (1937) 675-701.