KEEL Included Algorithms

This document provides a list of all the algorithms which have been included within the KEEL software tool (2014-01-29). This list is grouped into different families and it is summarised in the following table.

Algorithms included in KEEL (452)		
Family	Subfamily	
Data Preprocessing (98)	Discretization (30)	
	Feature Selection (25)	Feature Selection (22)
		Evolutionary Feature Selection (3)
	Training Set Selection (16)	Training Set Selection (12)
		Evolutionary Training Set Selection (4)
	Missing Values (15)	
	Transformation (4)	
	Data Complexity (1)	
	Noisy Data Filtering (7)	
Classification Algorithms (212)	Rule Learning for Classification (85)	Crisp Rule Learning for Classification (19)
		Evolutionary Crisp Rule Learning for Classification (29)
		Fuzzy Rule Learning for Classification (4)
		Evolutionary Fuzzy Rule Learning for Classification (13)
		Hybrid Instance Based Learning (4)
		Associative Classification (7)
		Decision Trees (9)
	Instance Based Learning (104)	Prototype Selection (38)
		Evolutionary Prototype Selection (8)
		Prototype Generation (43)
		Lazy Learning (12)
		Weighting Methods (3)
	Neural Networks for Classification (12)	Neural Networks for Classification (10)
		Evolutionary Neural Networks for Classification (2)
	Support Vector Machines for Classification (3)	
	Statistical Classifiers (8)	
Regression Algorithms (48)	Rule Learning for Regression (16)	Fuzzy Rule Learning for Regression (2)
		Evolutionary Fuzzy Rule Learning for Regression (11)
		Decision Trees for Regression (3)

	Evolutionary Postprocessing FRBS: Selection and Tuning (14)	
	Neural Networks for Regression (10)	Neural Networks for Regression (8)
		Evolutionary Neural Networks for Regression (2)
	Support Vector Machines for Regression (2)	
	Evolutionary Fuzzy Symbolic Regression (4)	
	Statistical Regression (2)	
Imbalanced Classification (42)	Resampling Data Space (20)	Over-sampling Methods (12)
		Under-sampling Methods (8)
	Cost-Sensitive Classification (3)	
	Ensembles for Class Imbalance (19)	
Subgroup Discovery (7)		
Multi Instance Learning (9)		
Clustering Algorithms (1)		
Association Rules (11)		
Statistical Tests (24)	Test Analysis (12)	
	Post-Hoc Procedures (12)	Post-Hoc Procedures for 1 x N Tests (8)
		Post-Hoc Procedures for N x N Tests (4)

Data Preprocessing

DISCRETIZATION		
Full Name	Short Name	Reference
Uniform Width Discretizer	UniformWidth-D	H. Liu, F. Hussain, C.L. Tan, M. Dash. Discretization: An Enabling Technique. Data Mining and Knowledge Discovery 6:4 (2002) 393-423.
Uniform Frequency Discretizer	UniformFrequency-D	H. Liu, F. Hussain, L. Tan, M. Dash. Discretization: An Enabling Technique. Data Mining and Knowledge Discovery 6:4 (2002) 393-423.
Fayyad Discretizer	Fayyad-D	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.
Iterative Dicotomizer 3 Discretizer	ID3-D	J.R. Quinlan. Induction of Decision Trees. Machine Learning 1 (1986) 81-106.
Bayesian Discretizer	Bayesian-D	X. Wu. ABayesian Discretizer for Real-Valued Attributes. The. Computer J. 39:8 (1996) 688-691.
Mantaras Distance-Based Discretizer	MantarasDist-D	J. Cerquides, R. López de Màntaras. Proposal and Empirical Comparison of a Parallelizable Distance-Based Discretization Method. 3rd International Conference on Knowledge Discovery and Data Mining (KDD99). NewPort Beach (USA, 1999) 139-142.
Unparametrized Supervised Discretizer	USD-D	R. Giráldez, J.S. Aguilar-Ruiz, J.C. Riquelme, F. Ferrer-Troyano, D. Rodríguez. Discretization Oriented to Decision Rules Generation. In: L.C. Jain, E. Damiani, R.J. Howlett, N. Ichalkaranje (Eds.) Frontiers in Artificial Intelligence and Applications 82, 2002, 275-279.
		R. Giráldez, J.S. Aguilar-Ruiz, J.C. Riquelme. Discretizacion Supervisada no Paramétrica Orientada a la Obtencion de Reglas de Decision.. IX Conferencia de la Asociación Española de Inteligencia Artificial (CAEPIA'01). Gijón (España, 2001) 53-62.
Chi-Merge Discretizer	ChiMerge-D	R. Kerber. ChiMerge: Discretization of Numeric Attributes. National Conference on Artifical Intelligence American Association for Artificial Intelligence (AAAI'92). San José (California USA, 1992) 123-128.
Chi2 Discretizer	Chi2-D	H. Liu, R. Setiono. Feature Selection via Discretization. IEEE Transactions on Knowledge and Data Engineering 9:4 (1997) 642-645.

Ameva Discretizer	Ameva-D	L. Gonzalez-Abril, F.J. Cuberos, F. Velasco, J.A. Ortega. Ameva: An autonomous discretization algorithm. Expert Systems with Applications 36 (2009) 5327-5332.
Zeta Discretizer	Zeta-D	K.M. Ho, P.D. Scott. Zeta: A Global Method for Discretization of Cotitinuous Variables. 3rd International Conference on Knowledge Discovery and Data Mining (KDD99). NewPort Beach (USA, 1999) 191-194.
Class-Atribute Dependent Discretizer	CADD-D	J.Y. Ching, A.K.C. W ong, K.C.C. Chan. Class-Dependent Discretization for Inductive Learning from Continuous and Mixed-Mode Data. IEEE Transactions on Pattern Analysis and Machine Intelligence 17:7 (1995) 641-651.
Class-Atribute Interdependence Maximization	CAIM-D	L.A. Kurgan, K.J. Cios. CAIM Discretization Algorithm. IEEE Transactions on Knowledge and Data Engineering 16:2 (2004) 145-153.
Extended Chi2 Discretizer	ExtendedChi2-D	C.-T. Sun, J.H. Hsu. An Extended Chi2 Algorithm for Discretization of Real Value Attributes. IEEE Transactions on Knowledge and Data Engineering 17:3 (2005) 437-441.
Fixed Frequency Discretizer	FixedFrequency-D	Y. Yang, G.I. Webb. Discretization for naive-Bayes learning: managing discretization bias and variance. Machine Learning 74 (2009) 39-74.
Khiops Discretizer	Khiops-D	M. Boulle. Khiops: A Statistical Discretization Method of Continuous Attributes. Machine Learning 55:1 (2004) 53-69.
Modified Chi2 Discretizer	ModifiedChi2-D	F.E.H. Tay, L. Shen. A Modified Chi2 Algorithm for Discretization. IEEE Transactions on Knowledge and Data Engineering 14:2 (2002) 666-670.
MODL Discretizer	MODL-D	M. Boulle. MODL: A bayes optimal discretization method for continuous attributes. Machine Learning 65:1 (2006) 131-165.
1R Discretizer	1R-D	R.C. Holte. Very simple classification rules perform well on most commonly used datasets. Machine Learning 11 (1993) 63-91.
Proportional Discretizer	Proportional-D	Y. Yang, G.I. Webb. Discretization for naive-Bayes learning: managing discretization bias and variance. Machine Learning 74 (2009) 39-74.
Discretization Algorithm Based on a Heterogeneity Criterion	HeterDisc-D	X. Liu. A Discretization Algorithm Based on a Heterogeneity Criterion. IEEE Transactions on Knowledge and Data Engineering 17:9 (2005) 1166-1173.
Hellinger-based Discretizer	HellingerBD-D	C. Lee. A Hellinger-based discretization method for numeric attributes in classification learning. Knowledge-Based Systems 20:4 (2007) 419-425.
Distribution-Index-Based Discretizer	DIBD-D	Q.X. W u, D.A. Bell, G. Prasad, T.M. McGinnity. A Distribution-Index-Based Discretizer for Decision-Making with Symbolic AI Approaches. IEEE Transactions on Knowledge and Data Engineering 19:1 (2007) 17-28.

Unsupervised Correlation Preserving Discretization	UCPD-D	S. Mehta, S. Parthasarathy, H. Yang. Toward Unsupervised Correlation Preserving Discretization. IEEE Transactions on Knowledge and Data Engineering 17:9 (2005) 1174-1185.
Interval Distance-Based Method for Discretization	IDD-D	F.J. Ruiz, C. Angulo, N. Agell. IDD: A Supervised Interval Distance-Based Method for Discretization. IEEE Transactions on Knowledge and Data Engineering 20:9 (2008) 1230-1238.
Discretization algorithm based on Class-Attribute Contingency Coefficient	CACC-D	C.J. Tsai, C.-I. Lee, W.-P. Yang. A discretization algorithm based on Class-Attribute Contingency Coefficient. Information Sciences 178:3 (2008) 714-731.
Hypercube Division-Based	HDD-D	P. Yang, J.-S. Li, Y.-X. Huang. HDD: a hypercube division-based algorithm for discretisation. International Journal of Systems Science 42:4 (2011) 557-566.
Cluster Analysis	ClusterAnalysis-D	M.R. Chmielewski, J.W. Grzymala-Busse. Global discretization of continuous attributes as preprocessing for Machine Learning. International Journal of Approximate Reasoning 15 (1996) 319-331.
Multivariate Discretization	MVD-D	S.D. Bay. Multivariate Discretization for Set Mining. Knowledge and Information Systems 3 (2001) 491-512.
FUSINTER	FUSINTER-D	D.A. Zighed, R. Rabaseda, R. Rakotomalala. FUSINTER: A method for discretization of continuous attributes. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 6:3 (1998) 307-326.

FEATURE SELECTION

Full Name	Short Name	Reference
Mutual Information Feature Selection	MIFS-FS	R. Battiti. Using Mutual Information For Selection Features In Supervised Neural Net Learning. IEEE Transactions on Neural Networks 5:4 (1994) 537-550.
Las Vegas Filter	LVF-FS	H. Liu, R. Setiono. A Probabilistic Approach to Feature Selection: A Filter Solution. 13th International Conference on Machine Learning (ICML96). Bari (Italy, 1996) 319-327.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
FOCUS	Focus-FS	H. Almuallim, T. Dietterich. Learning With Many Irrelevant Features. 9th National Conference on Artificial Intelligence (AAAI'91). Anaheim (California USA, 1991) 547-552.

Relief	Relief-FS	K. Kira, L. Rendell. A Practical Approach to Feature Selection. 9th International Workshop on Machine Learning (ML'92). Aberdeen (Scotlant UK, 1992) 249-256.
Las Vegas Wrapper	LVW-FS	H. Liu, R. Setiono. Feature Selection and Classification: A Probabilistic Wrapper Approach. 9th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems (IEA-AIE'96). Fukuoka (Japon, 1996) 419-424.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Automatic Branch and Bound using Inconsistent Examples Pairs Measure	ABB-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Automatic Branch and Bound using Inconsistent Examples Measure	ABB-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Automatic Branch and Bound using Mutual Information Measure	ABB-MI-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Full Exploration using Inconsistent Examples Pairs Measure	Full-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Full Exploration (LIU)	Full-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Full Exploration using Mutual Information measure	Full-MI-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.

		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Relief-F	Relief-F-FS	I. Kononenko. Estimating Attributes: Analysis and Extensions of RELIEF. European Conference on Machine Learning 1994 (ECML94). Catania (Italy, 1994) 171-182.
Las Vegas Filter using Inconsistent Examples Pairs Measure	LVF-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Simulated Annealing using Inconsistent Examples Pairs measure	SA-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Simulated Annealing using Inconsistent Examples measure	SA-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Simulated Annealing using Mutual Information measure	SA-MI-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Sequential Backward Search using Inconsistent Examples Pairs measure	SBS-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Sequential Backward Search using Inconsistent Examples measure	SBS-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.

Sequential Backward Search using Mutual Information measure	SBS-MI-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Sequential Forward Search using Inconsistent Examples Pairs measure	SFS-IEP-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Sequential Forward Search using Inconsistent Examples measure	SFS-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.
Sequential Forward Search using Inconsistent Examples measure	SFS-LIU-FS	H. Liu, L. Yu. Toward Integrating Feature Selection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17:4 (2005) 491-502.
		H. Liu, H. Motoda. Feature Selection for Knowledge Discovery and Data Mining. Kluwer Academic Publishers, 1998.

EVOLUTIONARY FEATURE SELECTION

Full Name	Short Name	Reference
Steady-state GA with integer coding scheme for wrapper feature selection with k-nn	SSGA-Integer-knn-FS	J. Casillas, O. Cordón, M.J. del Jesus, F. Herrera. Genetic Feature Selection in a Fuzzy Rule-Based Classification System Learning Process. Information Sciences 136:1-4 (2001) 135-157.
Generational GA with binary coding scheme for filter feature selection with the inconsistency rate	GGA-Binary-Inconsistency-FS	P.L. Lanzi. Fast Feature Selection With Genetic Algorithms: A Filter Approach. IEEE International Conference on Evolutionary Computation. Indianapolis. Indianapolis (USA, 1997) 537-540.
Generational Genetic Algorithm for Feature Selection	GGA-FS	J. Yang, V. Honavar. Feature Subset Selection Using a Genetic Algorithm. IEEE Intelligent Systems 13:2 (1998) 44-49.

TRAINING SET SELECTION		
Full Name	Short Name	Reference
Pattern by Ordered Projections	POP-TSS	J.C. Riquelme, J.S. Aguilar-Ruiz, M. Toro. Finding representative patterns with ordered projections. Pattern Recognition 36 (2003) 1009-1018.
Prototipe Selection by Relative Certainty Gain	PSRCG-TSS	M. Sebban, R. Nock, S. Lallich. Stopping Criterion for Boosting-Based Data Reduction Techniques: from Binary to Multiclass Problems. Journal of Machine Learning Research 3 (2002) 863-885.
Variable Similarity Metric	VSM-TSS	D.G. Lowe. Similarity Metric Learning For A Variable-Kernel Classifier. Neural Computation 7:1 (1995) 72-85.
Edited Nearest Neighbor	ENN-TSS	D.L. Wilson. Asymptotic Properties Of Nearest Neighbor Rules Using Edited Data. IEEE Transactions on Systems, Man and Cybernetics 2:3 (1972) 408-421.
Multiedit	Multiedit-TSS	P.A. Devijver. On the editing rate of the MULTIEDIT algorithm. Pattern Recognition Letters 4:1 (1986) 9-12.
Prototipe Selection based on Relative Neighbourhood Graphs	RNG-TSS	J.S. Sánchez, F. Pla, F.J. Ferri. Prototype selection for the nearest neighbor rule through proximity graphs. Pattern Recognition Letters 18 (1997) 507-513.
Modified Edited Nearest Neighbor	MENN-TSS	K. Hattori, M. Takahashi. A new edited k-nearest neighbor rule in the pattern classification problem. Pattern Recognition 33 (2000) 521-528.
Nearest Centroid Neighbourhood Edition	NCNEdit-TSS	J.S. Sánchez, R. Barandela, A.I. Márques, R. Alejo, J. Badenas. Analysis of new techniques to obtain quality training sets. Pattern Recognition Letters 24 (2003) 1015-1022.
Edited NRBF	ENRBF-TSS	M. Grochowski, N. Jankowski. Comparison of instance selection algorithms I. Algorithms survey. VII International Conference on Artificial Intelligence and Soft Computing (ICAISC'04). LNCS 3070, Springer 2004, Zakopane (Poland, 2004) 598-603.
Edited Nearest Neighbor with Estimation of Probabilities Threshold	ENNTh-TSS	F. Vazquez, J.S. Sánchez, F. Pla. A stochastic approach to Wilson's editing algorithm. 2nd Iberian Conference on Pattern Recognition and Image Analysis (IbPRIA05). LNCS 3523, Springer 2005, Estoril (Portugal, 2005) 35-42.
All-KNN	AllKNN-TSS	I. Tomek. An Experiment With The Edited Nearest-Neighbor Rule. IEEE Transactions on Systems, Man and Cybernetics 6:6 (1976) 448-452.
Model Class Selection	ModelCS-TSS	C.E. Brodley. Adressing The Selective Superiority Problem: Automatic Algorithm/Model Class Selection. 10th International Machine Learning Conference (ICML'93). Amherst (MA USA, 1993) 17-24.

EVOLUTIONARY TRAINING SET SELECTION		
Full Name	Short Name	Reference
CHC Adaptative Search for Instance Selection	CHC-TSS	J.R. Cano, F. Herrera, 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	GGA-TSS	J.R. Cano, F. Herrera, 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	SGA-TSS	J.R. Cano, F. Herrera, 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	PBIL-TSS	J.R. Cano, F. Herrera, 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.

MISSING VALUES		
Full Name	Short Name	Reference
Delete Instances with Missing Values	Ignore-MV	P.A. Gourraud, E. Ginin, 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.
Event Covering Synthesizing	EventCovering-MV	D.K.Y. Chiu, A.K.C. Wong. Synthesizing Knowledge: A Cluster Analysis Approach Using Event-Covering. IEEE Transactions on Systems, Man and Cybernetics, Part B 16:2 (1986) 251-259.
K-Nearest Neighbor Imputation	KNN-MV	G.E.A.P.A. Batista, M.C. Monard. An Analysis Of Four Missing Data Treatment Methods For Supervised learning. Applied Artificial Intelligence 17:5 (2003) 519-533.
Most Common Attribute Value	MostCommon-MV	J.W. Grzymala-Busse, L.K. Goodwin, W.J. Grzymala-Busse, X. Zheng. Handling Missing Attribute Values in Preterm Birth Data Sets. 10th International Conference of Rough Sets, Fuzzy Sets, Data Mining and Granular Computing (RSFDGrC'05). LNCS 3642, Springer 2005, Regina (Canada, 2005) 342-351.
Assign All Posible Values of the Attribute	AllPossible-MV	J.W. Grzymala-Busse. On the Unknown Attribute Values In Learning From Examples. 6th International Symposium on Methodologies For Intelligent Systems (ISMIS91). Charlotte (USA, 1991) 368-377.

K-means Imputation	KMeans-MV	J. Deogun, W. Spaulding, B. Shuart, D. Li. Towards Missing Data Imputation: A Study of Fuzzy K-means Clustering Method. 4th International Conference of Rough Sets and Current Trends in Computing (RSCTC'04). LNCS 3066, Springer 2004, Uppsala (Sweden, 2004) 573-579.
Concept Most Common Attribute Value	ConceptMostCommon-MV	J.W. Grzymala-Busse, L.K. Goodwin, W.J. Grzymala-Busse, X. Zheng. Handling Missing Attribute Values in Preterm Birth Data Sets. 10th International Conference of Rough Sets, Fuzzy Sets, Data Mining and Granular Computing (RSFDGrC'05). LNCS 3642, Springer 2005, Regina (Canada, 2005) 342-351.
Assign All Posible Values of the Attribute Restricted to the Given Concept	ConceptAllPossible-MV	J.W. Grzymala-Busse. On the Unknown Attribute Values In Learning From Examples. 6th International Symposium on Methodologies For Intelligent Systems (ISMIS91). Charlotte (USA, 1991) 368-377.
Fuzzy K-means Imputation	FKMeans-MV	J. Deogun, W. Spaulding, B. Shuart, D. Li. Towards Missing Data Imputation: A Study of Fuzzy K-means Clustering Method. 4th International Conference of Rough Sets and Current Trends in Computing (RSCTC'04). LNCS 3066, Springer 2004, Uppsala (Sweden, 2004) 573-579.
Support Vector Machine Imputation	SVMimpute-MV	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). LNCS 3683, Springer 2005, Melbourne (Australia, 2005) 581-587.
Weighted K-Nearest Neighbor Imputation	WKNNimpute-MV	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.
Bayesian Principal Component Analysis	BPCA-MV	S. Oba, M. Sato, I. Takemasa, M. Monden, K. Matsubara, S. Ishii. A Bayesian missing value estimation method for gene expression profile data. Bioinformatics 19 (2003) 2088-2096.
Expectation-Maximization single imputation	EM-MV	T. Schneider. Analysis of incomplete climate data: Estimation of Mean Values and covariance matrices and imputation of Missing values. Journal of Climate 14 (2001) 853-871.
Local Least Squares Imputation	LLSImpute-MV	H.A. Kim, G.H. Golub, H. Park. Missing value estimation for DNA microarray gene expression data: Local least squares imputation. Bioinformatics 21:2 (2005) 187-198.
Single Vector Decomposition imputation	SVDImpute-MV	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.

TRANSFORMATION		
Full Name	Short Name	Reference
Decimal Scaling ranging	DecimalScaling-TR	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.
Min Max ranging	MinMax-TR	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.
Z Score ranging	ZScore-TR	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.
Nominal to Binary transformation	Nominal2Binary-TR	L.A. Shalabi, Z. Shaaban, B. Kasasbeh. Data Mining: A Preprocessing Engine. Journal of Computer Science 2:9 (2006) 735-735.

DATA COMPLEXITY		
Full Name	Short Name	Reference
Data Complexity Metrics calculation	Metrics-DC	T.K. Ho, M. Basu. Complexity measures of supervised classification problems. IEEE Transactions on Pattern Analysis and Machine Intelligence 24:3 (2002) 289-300.

NOISY DATA FILTERING		
Full Name	Short Name	Reference
Saturation Filter	SaturationFilter-F	D. Gamberger, N. Lavrac, S. Dzroski. Noise detection and elimination in data preprocessing: Experiments in medical domains. Applied Artificial Intelligence 14:2 (2000) 205-223.
Pairwise Attribute Noise Detection Algorithm Filter	PANDA-F	J.D. Hulse, T.M. Khoshgoftaar, H. Huang. The pairwise attribute noise detection algorithm. Knowledge and Information Systems 11:2 (2007) 171-190.
Classification Filter	ClassificationFilter-F	D. Gamberger, N. Lavrac, C. Groselj. Experiments with noise filtering in a medical domain. 16th International Conference on Machine Learning (ICML99). San Francisco (USA, 1999) 143-151.
Automatic Noise Remover	ANR-F	X. Zeng, T. Martinez. A Noise Filtering Method Using Neural Networks. IEEE International Workshop on Soft Computing Techniques in Instrumentation, Measurement and Related Applications (SCIMA2003). Utah (USA, 2003) 26-31.
Ensemble Filter	EnsembleFilter-F	C.E. Brodley, M.A. Friedl. Identifying Mislabeled Training Data. Journal of Artificial Intelligence Research 11 (1999) 131-167.

Cross-Validated Committees Filter	CVCommitteesFilter-F	S. Verbaeten, A.V. Assche. Ensemble methods for noise elimination in classification problems. 4th International Workshop on Multiple Classifier Systems (MCS 2003). LNCS 2709, Springer 2003, Guilford (UK, 2003) 317-325.
Iterative-Partitioning Filter	IterativePartitioningFilter-F	T.M. Khoshgoftaar, P. Rebours. Improving software quality prediction by noise filtering techniques. Journal of Computer Science and Technology 22 (2007) 387-396.

Classification Algorithms

CRISP RULE LEARNING FOR CLASSIFICATION		
Full Name	Short Name	Reference
AQ-15	AQ-C	R.S. Michalksi,, I. Mozetic, N. Lavrac. The Multipurpose Incremental Learning System AQ15 And Its Testing Application To Three Medical Domains. 5th INational Conference on Artificial Intelligence (AAAI'86). Philadelphia (Pennsylvania, 1986) 1041-1045.
CN2	CN2-C	P. Clark, T. Niblett. The CN2 Induction Algorithm. Machine Learning Journal 3:4 (1989) 261-283.
PRISM	PRISM-C	J. Cendrowska. PRISM: An algorithm for inducing modular rules. International Journal of Man-Machine Studies 27:4 (1987) 349-370.
1R	1R-C	R.C. Holte. Very simple classification rules perform well on most commonly used datasets. Machine Learning 11 (1993) 63-91.
Rule Induction with Optimal Neighbourhood Algorithm	Riona-C	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	C45Rules-C	J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman Publishers, 1993.
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Rule Induction Two In One	Ritio-C	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	Rules6-C	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.
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EVOLUTIONARY CRISP RULE LEARNING FOR CLASSIFICATION

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Genetic Algorithm based Classifier System with Adaptive Discretization Intervals	GAssist-ADI-C	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). LNCS 2724, Springer 2003, Chicago (Illinois USA, 2003) 1818-1831.
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Pittsburgh Genetic Interval Rule Learning Algorithm	PGIRLA-C	A.L. Corcoran, S. Sen. Using Real-Valued Genetic Algorithms to Evolve Rule Sets for Classification. 1st IEEE Conference on Evolutionary Computation. Orlando (Florida, 1994) 120-124.
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Real Encoding - Particle Swarm Optimization	REPSO-C	Y. Liu, Z. Qin, Z. Shi, J. Chen. Rule Discovery with Particle Swarm Optimization. Advanced Workshop on Content Computing (AWCC). LNCS 3309, Springer 2004 (2004) 291-296.
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FUZZY RULE LEARNING FOR CLASSIFICATION

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EVOLUTIONARY FUZZY RULE LEARNING FOR CLASSIFICATION		
Full Name	Short Name	Reference
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ASSOCIATIVE CLASSIFICATION

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Fuzzy Association Rule-based Classification method for High-Dimensional problems	FARC-HD-C	J. Alcala-Fdez, R. Alcalá, F. Herrera. A Fuzzy Association Rule-Based Classification Model for High-Dimensional Problems with Genetic Rule Selection and Lateral Tuning. IEEE Transactions on Fuzzy Systems 19:5 (2011) 857-872.

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Classification and Regression Tree	CART-C	L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone. Classification and Regression Trees. Chapman and Hall (Wadsworth, Inc.), 1984.
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Hybrid Decision Tree -Genetic Algorithm	DT_GA-C	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 with Evolutionary Learning	DT_Oblique-C	E. Cantú-Paz, C. Kamath. Inducing oblique decision trees with evolutionary algorithms. IEEE Transactions on Evolutionary Computation 7:1 (2003) 54-68.
Functional Trees	FunctionalTrees-C	J. Gama. Functional Trees. Machine Learning 55 (2004) 219-250.
PrUning and BuiLding Integrated in Classification	PUBLIC-C	R. Rastogi, K. Shim. PUBLIC: A Decision Tree Classifier that Integrates Building and Pruning. Data Mining and Knowledge Discovery 4:4 (2000) 315-344.

Tree Analysis with Randomly Generated and Evolved Trees	Target-C	J.B. Gray, G. Fan. Classification tree analysis using TARGET. Computational Statistics and Data Analysis 52:3 (2008) 1362-1372.

PROTOTYPE SELECTION

Full Name	Short Name	Reference
All-KNN	AllKNN-C	I. Tomek. An Experiment With The Edited Nearest-Neighbor Rule. IEEE Transactions on Systems, Man and Cybernetics 6:6 (1976) 448-452.
Edited Nearest Neighbor	ENN-C	D.L. Wilson. Asymptotic Properties Of Nearest Neighbor Rules Using Edited Data. IEEE Transactions on Systems, Man and Cybernetics 2:3 (1972) 408-421.
Multiedit	Multiedit-C	P.A. Devijver. On the editing rate of the MULTIEDIT algorithm. Pattern Recognition Letters 4:1 (1986) 9-12.
Condensed Nearest Neighbor	CNN-C	P.E. Hart. The Condensed Nearest Neighbour Rule. IEEE Transactions on Information Theory 14:5 (1968) 515-516.
Tomek's modification of Condensed Nearest Neighbor	TCNN-C	I. Tomek. Two modifications of CNN. IEEE Transactions on Systems, Man and Cybernetics 6 (1976) 769-772.
Instance Based 3	IB3-C	D.W. Aha, D. Kibler, M.K. Albert. Instance-Based Learning Algorithms. Machine Learning 6:1 (1991) 37-66.
Modified Edited Nearest Neighbor	MENN-C	K. Hattori, M. Takahashi. A new edited k-nearest neighbor rule in the pattern classification problem. Pattern Recognition 33 (2000) 521-528.
Modified Condensed Nearest Neighbor	MCNN-C	V.S. Devi, M.N. Murty. An incremental prototype set building technique. Pattern Recognition 35 (2002) 505-513.
Decremental Reduction Optimization Procedure 3	DROP3-C	D.R. Wilson, T.R. Martinez. Reduction Tecniques For Instance-Based Learning Algorithms. Machine Learning 38:3 (2000) 257-286.
Iterative Case Filtering	ICF-C	H. Brighton, C. Mellish. Advances In Instance Selection For Instance-Based. Data mining and Knowledge Discovery 6:2 (2002) 153-172.
Reduced Nearest Neighbor	RNN-C	G.W. Gates. The Reduced Nearest Neighbour Rule. IEEE Transactions on Information Theory 18:3 (1972) 431-433.
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Prototype Selection based on Clustering	PSC-C	J.A. Olvera-López, J.A. Carrasco-Ochoa, J.F. Martínez-Trinidad. A new fast prototype selection method based on clustering. Pattern Analysis and Applications 13 (2010) 131-141.
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Shrink	Shrink-C	D. Kibler, D.W. Aha. Learning Representative Exemplars Of Concepts: An Initial Case Study. 4th International Workshop on Machine Learning (ML'87). Irvine (CA USA, 1987) 24-30.
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Random Mutation Hill Climbing	RMHC-C	D.B. Skalak. Prototype and Feature Selection by Sampling and Random Mutation Hill Climbing Algorithms. 11th International Conference on Machine Learning (ML'94). New Brunswick (NJ USA, 1994) 293-301.
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Mutual Neighborhood Value Condensed Nearest Neighbor	MNV-C	K. Chidananda-Gowda, G. Krishna. The Condensed Nearest Neighbor Rule Using Concept of Mutual Nearest Neighborhood. IEEE Transactions on Information Theory 25:4 (1979) 488-490.
Encoding Length Explore	Explore-C	R.M. Cameron-Jones. Instance selection by encoding length heuristic with random mutation hill climbing. 8th Australian Joint Conference on Artificial Intelligence (AJCAI-95). (Australia, 1995) 99-106.
Prototipe Selection based on Gabriel Graphs	GG-C	J.S. Sánchez, F. Pla, F.J. Ferri. Prototype selection for the nearest neighbor rule through proximity graphs. Pattern Recognition Letters 18 (1997) 507-513.
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Nearest Centroid Neighbourhood Edition	NCNEdit-C	J.S. Sánchez, R. Barandela, A.I. Márques, R. Alejo, J. Badenas. Analysis of new techniques to obtain quality training sets. Pattern Recognition Letters 24

		(2003) 1015-1022.
Tabu Search for Instance Selection	ZhangTS-C	H. Zhang, G. Sun. Optimal reference subset selection for nearest neighbor classification by tabu search. Pattern Recognition 35 (2002) 1481-1490.
Prototipe Selection by Relative Certainty Gain	PSRCG-C	M. Sebban, R. Nock, S. Lallich. Stopping Criterion for Boosting-Based Data Reduction Techniques: from Binary to Multiclass Problems. Journal of Machine Learning Research 3 (2002) 863-885.
C-Pruner	CPruner-C	K.P Zhao, S.G. Zhou, J.H. Guan, A.Y. Zhou. C-Pruner: An improved instance prunning algorithm. Second International Conference on Machine Learning and Cybernetics (ICMLC'03). Xian (China, 2003) 94-99.
Pattern by Ordered Projections	POP-C	J.C. Riquelme, J.S. Aguilar-Ruiz, M. Toro. Finding representative patterns with ordered projections. Pattern Recognition 36 (2003) 1009-1018.
Reconsistent	Reconsistent-C	M.T. Lozano, J.S. Sánchez, F. Pla. Using the geometrical distribution of prototypes for training set condesing. 10th Conference of the Spanish Association for Artificial Intelligence (CAEPIA03). LNCS 3040, Springer 2003, Malaga (Spain, 2003) 618-627.
Edited NRBF	ENRBF-C	M. Grochowski, N. Jankowski. Comparison of instance selection algorithms I. Algorithms survey. VII International Conference on Artificial Intelligence and Soft Computing (ICAISC'04). LNCS 3070, Springer 2004, Zakopane (Poland, 2004) 598-603.
Modified Selective Subset	MSS-C	R. Barandela, F.J. Ferri, J.S. Sánchez. Decision boundary preserving prototype selection for nearest neighbor classification. International Journal of Pattern Recognition and Artificial Intelligence 19:6 (2005) 787-806.
Edited Nearest Neighbor with Estimation of Probabilities Threshold	ENNTh-C	F. Vazquez, J.S. Sánchez, F. Pla. A stochastic approach to Wilson's editing algorithm. 2nd Iberian Conference on Pattern Recognition and Image Analysis (IbPRIA05). LNCS 3523, Springer 2005, Estoril (Portugal, 2005) 35-42.
Support Vector based Prototype Selection	SVBPS-C	Y. Li, Z. Hu, Y. Cai, W. Zhang. Support vector vased prototype selection method for nearest neighbor rules. I International conference on advances in natural computation (ICNC05). LNCS 3610, Springer 2005, Changsha (Chine, 2005) 528-535.
Backward Sequential Edition	BSE-C	J.A. Olvera-López, J.F. Martínez-Trinidad, J.A. Carrasco-Ochoa. Edition Schemes Based on BSE. 10th Iberoamerican Congress on Pattern Recognition (CIARP2004). LNCS 3773, Springer 2005, La Havana (Cuba, 2005) 360-367.
Fast Condensed Nearest Neighbor	FCNN-C	F. Angiulli. Fast nearest neighbor condensation for large data sets classification. IEEE Transactions on Knowledge and Data Engineering 19:11 (2007) 1450-1464.

Hit-Miss Network Iterative Editing	HMNEI-C	E. Marchiori. Hit Miss Networks with Applications to Instance Selection. Journal of Machine Learning Research 9 (2008) 997-1017.
Generalized Condensed Nearest Neighbor	GCNN-C	F. Chang, C.C. Lin, C.-J. Lu. Adaptive Prototype Learning Algorithms: Theoretical and Experimental Studies. Journal of Machine Learning Research 7 (2006) 2125-2148.

EVOLUTIONARY PROTOTYPE SELECTION

Full Name	Short Name	Reference
CHC Adaptative Search for Instance Selection	CHC-C	J.R. Cano, F. Herrera, 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	GGA-C	J.R. Cano, F. Herrera, 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	SGA-C	J.R. Cano, F. Herrera, 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.
Cooperative Coevolutionary Instance Selection	CoCoIS-C	N. García-Pedrajas, J.A. Romero del Castillo, D. Ortiz-Boyer. A cooperative coevolutionary algorithm for instance selection for instance-based learning. Machine Learning 78:3 (2010) 381-420.
Population-Based Incremental Learning	PBIL-C	J.R. Cano, F. Herrera, 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.
Intelligent Genetic Algorithm for Edition	IGA-C	S.Y. Ho, C.C. Liu, S. Liu. Design of an optimal nearest neighbor classifier using an intelligent genetic algorithm. Pattern Recognition Letters 23 (2002) 1495-1503.
Genetic Algorithm for Editing k-NN with MSE estimation, clustered crossover and fast smart mutation	GA_MSE_CC_FSM-C	R. Gil-Pita, X. Yao. Using a Genetic Algorithm for Editing k-Nearest Neighbor Classifiers. 8th International Conference on Intelligent Data Engineering and Automated Learning (IDEAL07). LNCS 4881, Springer 2007, Daejeon (Korea, 2007) 1141-1150.
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Full Name	Short Name	Reference
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Learning Vector Quantization 1	LVQ1-C	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 2	LVQ2-C	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 2.1	LVQ2_1-C	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Learning Vector Quantization 3	LVQ3-C	T. Kohonen. The Self-Organizative Map. Proceedings of the IEEE 78:9 (1990) 1464-1480.
Generalized Editing using Nearest Neighbor	GENN-C	J. Koplowitz, T.A. Brown. On the relation of performance to editing in nearest neighbor rules. Pattern Recognition 13 (1981) 251-255.
Decision Surface Mapping	DSM-C	S. Geva, J. Site. Adaptive nearest neighbor pattern classifier. IEEE Transactions on Neural Networks 2:2 (1991) 318-322.
Vector Quantization	VQ-C	Q. Xie, C.A. Laszlo. Vector quantization technique for nonparametric classifier design. IEEE Transactions on Pattern Analysis and Machine Intelligence 15:12 (1993) 1326-1330.
Chen Algorithm	Chen-C	C.H. Chen, A. Józwik. A sample set condensation algorithm for the class sensitive artificial neural network. Pattern Recognition Letters 17 (1996) 819-823.
Bootstrap Technique for Nearest Neighbor	BTS3-C	Y. Hamamoto, S. Uchimura, S. Tomita. A bootstrap technique for nearest neighbor classifier design. IEEE Transactions on Pattern Analysis and Machine Intelligence 19:1 (1997) 73-79.
MSE	MSE-C	C. Decaestecker. Finding prototypes for nearest neighbour classification by means of gradient descent and deterministic annealing. Pattern Recognition 30:2 (1997) 281-288.
Learning Vector Quantization with Training Counter	LVQTC-C	R. Odorico. Learning vector quantization with training count (LVQTC). Neural Networks 10:6 (1997) 1083-1088.
Modified Chang's Algorithm	MCA-C	J.C. Bezdek, T.R. Reichherzer, G.S. Lim, Y. Attikiouzel. Multiple prototype classifier design. IEEE Transactions on Systems, Man and Cybernetics C 28:1 (1998) 67-69.
Generalized Modified Chang's Algorithm	GMCA-C	R.A. Mollineda, F.J. Ferri, E. Vidal. A merge-based condensing strategy for multiple prototype classifiers. IEEE Transactions on Systems, Man and Cybernetics B 32:5 (2002) 662-668.
Integrated Concept Prototype Learner	ICPL-C	W. Lam, C.K. Keung, D. Liu. Discovering useful concept prototypes for classification based on filtering and abstraction. IEEE Transactions on

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Depuration Algorithm	Depur-C	J.S. Sánchez, R. Barandela, A.I. Márques, R. Alejo, J. Badenas. Analysis of new techniques to obtain quaylity training sets. Pattern Recognition Letters 24 (2003) 1015-1022.
Hybrid LVQ3 algorithm	HYB-C	S.-W. Kim, A. Oomenn. A brief taxonomy and ranking of creative prototype reduction schemes. Pattern Analysis and Applications 6 (2003) 232-244.
High training set size reduction by space partitioning and prototype abstraction	RSP-C	J.S. Sánchez. High training set size reduction by space partitioning and prototype abstraction. Pattern Recognition 37 (2004) 1561-1564.
Evolutionary Nearest Prototype Classifier	ENPC-C	F. Fernández, P. Isasi. Evolutionary design of nearest prototype classifiers. Journal of Heuristics 10:4 (2004) 431-454.
Adaptive Vector Quantization	AVQ-C	C.-W. Yen, C.-N. Young, M.L. Nagurka. A vector quantization method for nearest neighbor classifier design. Pattern Recognition Letters 25 (2004) 725-731.
Learning Vector Quantization with pruning	LVQPRU-C	J. Li, M.T. Manry, C. Yu, D.R. Wilson. Prototype classifier design with pruning. International Journal on Artificial Intelligence Tools 14:1-2 (2005) 261-280.
Pairwise Opposite Class Nearest Neighbor	POC-NN-C	T. Raicharoen, C. Lursinsap. A divide-and-conquer approach to the pairwise opposite class-nearest neighbor (poc-nn) algorithm. Pattern Recoginiton Letters 26 (2005) 1554-1567.
Adaptive Condensing Algorithm Based on Mixtures of Gaussians	MixtGauss-C	M. Lozano, J.M. Sotoca, J.S. Sánchez, F. Pla, E. Pekalska, R.P.W. Duin. Experimental study on prototype optimisation algorithms for prototype-based classification in vector spaces. Pattern Recognition 39:10 (2006) 1827-1838.
Self-Generating Prototypes	SGP-C	H.A. Fayed, S.R. Hashem, A.F. Atiya. Self-generating prototypes for pattern classification. Pattern Recognition 40:5 (2007) 1498-1509.
Adaptive Michigan PSO	AMPSO-C	A. Cervantes, I. Galván, P. Isasi. An Adaptive Michigan Approach PSO for Nearest Prototype Classification. 2nd International Work-Conference on the Interplay Between Natural and Artificial Computation (IWINAC07). LNCS 4528, Springer 2007, La Manga del Mar Menor (Spain, 2007) 287-296.
Prototype Selection Clonal Selection Algorithm	PSCSA-C	U. Garain. Prototype reduction using an artificial immune model. Pattern Analysis and Applications 11:3-4 (2008) 353-363.
Particle Swarm Optimization	PSO-C	L. Nanni, A. Lumini. Particle swarm optimization for prototype reduction. Neurocomputing 72:4-6 (2009) 1092-1097.

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Scale Factor Local Search in Differential Evolution	SFLSDE-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Self-Adaptive Differential Evolution	SADE-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Adaptive Differential Evolution with Optional External Archive	JADE-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Differential Evolution using a Neighborhood-Based Mutation Operator	DEGL-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Hybrid Iterative Case Filtering + Learning Vector Quantization 3	ICFLVQ3-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Hybrid Iterative Case Filtering + Particle Swarm Optimization	ICFPSO-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Hybrid Iterative Case Filtering + Scale Factor Local Search in Differential Evolution	ICFSFLSDE-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
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Hybrid Steady-State Memetic Algorithm for Instance Selection + Particle Swarm Optimization	SSMAPSO-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.

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Hybrid Decremental Reduction Optimization Procedure 3 + Learning Vector Quantization 3	DROP3LVQ3-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Hybrid Decremental Reduction Optimization Procedure 3 + Particle Swarm Optimization	DROP3PSO-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Hybrid Decremental Reduction Optimization Procedure 3 + Scale Factor Local Search in Differential Evolution	DROP3SFLSDE-C	I. Triguero, S. García, F. Herrera. Differential evolution for optimizing the positioning of prototypes in nearest neighbor classification. Pattern Recognition 44:4 (2011) 901-916.
Iterative Prototype Adjustment based on Differential Evolution	IPLDE-C	I. Triguero, S. García, F. Herrera. IPADE: Iterative Prototype Adjustment for Nearest Neighbor Classification. IEEE Transactions on Neural Networks 21:12 (2010) 1984-1990.

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K-Nearest Neighbors Classifier	KNN-C	T.M. Cover, P.E. Hart. Nearest Neighbor Pattern Classification. IEEE Transactions on Information Theory 13 (1967) 21-27.
Adaptive KNN Classifier	KNNAdaptive-C	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	KStar-C	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	LazyDT-C	J.H. Friedman, R. Kohavi, Y. Tun. Lazy decision trees. Proceedings of the Thirteenth National

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Nearest Mean classifier	NM-C	T. Hastie, R. Tibshirani, J. Friedman. The elements of statistical learning: Data mining, inference, and prediction. Springer-Verlag, 2001. ISBN: 0-387-95284-5.
Cam weighted distance Nearest Neighbor Classifier	CamNN-C	C. Zhou, Y. Chen. Improving nearest neighbor classification with cam weighted distance. Pattern Recognition 39 (2006) 635-645.
Center Nearest Neighbor Classifier	CenterNN	Q. Gao, Z. Wang. Center-based nearest neighbor classifier. Pattern Recognition 40 (2007) 346-349.
K Symmetrical Nearest Neighbor Classifier	KSNN-C	R. Nock, M. Sebban, D. Bernard. A simple locally adaptive nearest neighbor rule with application to pollution forecasting. International Journal of Pattern Recognition and Artificial Intelligence 17 (2003) 1369-1382.
Decision making by Emerging Patterns Classifier	Deeps-C	J. Li, G. Dong, K. Ramamohanarao, L. Wong. DeEPs: A New Instance-Based Lazy Discovery and Classification System. Machine Learning 54 (2004) 99-124.
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Lazy Bayesian Rules classifier	LBR-C	Z. Zheng, G.I. Webb. Lazy Learning of Bayesian Rules. Machine Learning 41 (2000) 53-87.
Integrated Decremental Instance Based Learning	IDIBL	D.R. Wilson, T.R. Martinez. An Integrated Instance-Based Learning Algorithm. Computational Intelligence 16:1 (2000) 1-28.

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Class weigthed classifier	CW-C	R. Paredes, E. Vidal. Learning weighted metrics to minimize nearest-neighbor classification error. IEEE Transactions on Pattern Analysis and Machine Intelligence 28:7 (2006) 1100-1110.
Class and Prototype weigthed classifier	CPW-C	R. Paredes, E. Vidal. Learning weighted metrics to minimize nearest-neighbor classification error. IEEE Transactions on Pattern Analysis and Machine Intelligence 28:7 (2006) 1100-1110.

NEURAL NETWORKS FOR CLASSIFICATION		
Full Name	Short Name	Reference
Radial Basis Function Neural Network for Classification Problems	RBFN-C	D.S. Broomhead, D. Lowe. Multivariable Functional Interpolation and Adaptive Networks. Complex Systems 11 (1988) 321-355.
Incremental Radial Basis Function Neural Network for Classification Problems	Incr-RBFN-C	J. Plat. A Resource Allocating Network for Function Interpolation. Neural Computation 3:2 (1991) 213-225.
Self Optimizing Neural Networks	SONN-C	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.
Multilayer Perceptron with Conjugate Gradient Based Training	MLP-CG-C	F. Moller. A scaled conjugate gradient algorithm for fast supervised learning. Neural Networks 6 (1990) 525-533.
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Decremental Radial Basis Function Neural Network for Classification Problems	Decr-RBFN-C	D.S. Broomhead, D. Lowe. Multivariable Functional Interpolation and Adaptive Networks. Complex Systems 11 (1988) 321-355.
Ensemble Neural Network for Classification Problems	Ensemble-C	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 Problems	LVQ-C	J.C. Bezdek, L.I. Kuncheva. Nearest prototype classifier designs: An experimental study. International Journal of Intelligent Systems 16:12 (2001) 1445-1473.
Evolutionary Radial Basis Function Neural Networks	EvRBFN-C	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.
Improved Resilient backpropagation Plus	iRProp+-C	C. Igel, M. Husken. Empirical evaluation of the improved Rprop learning algorithm. Neurocomputing 50 (2003) 105-123.
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Multilayer Perceptron with Backpropagation Training	MLP-BP-C	R. Rojas, J. Feldman. Neural Networks: A Systematic Introduction . Springer-Verlag, Berlin, New-York, 1996. ISBN: 978-3540605058.

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Full Name	Short Name	Reference
Neural Network Evolutionary Programming for Classification	NNEP-C	F.J. Martínez-Estudillo, C. Hervás-Martínez, P.A. Gutiérrez, A.C. Martínez-Estudillo. Evolutionary Product-Unit Neural Networks Classifiers. Neurocomputing 72:1-3 (2008) 548-561.
Genetic Algorithm with Neural Network	GANN-C	G.F. Miller, P.M. Todd, S.U. Hedge. Designing Neural Networks Using Genetic Algorithms. 3rd International Conference on Genetic Algorithm and Their Applications. George Mason University (USA, 1989) 379-384.
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SUPPORT VECTOR MACHINES FOR CLASSIFICATION

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C-SVM	C_SVM-C	C. Cortes, V. Vapnik. Support vector networks. Machine Learning 20 (1995) 273-297.
NU-SVM	NU_SVM-C	B. Scholkopf, A.J. Smola, R. Williamson, P.L. Bartlett. New support vector algorithms. Neural Computation 12 (2000) 1207-1245.
Sequential Minimal Optimization	SMO-C	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, 185-208.
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Naïve-Bayes	NB-C	P. Domingos, M. Pazzani. On the optimality of the simple Bayesian classifier under zero-one loss. Machine Learning 29 (1997) 103-137.
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Linear Discriminant Analysis	LDA-C	G.J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. John Wiley and Sons, 2004.
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Kernel Classifier	Kernel-C	G.J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. John Wiley and Sons, 2004.
Least Mean Square Linear Classifier	LinearLMS-C	J.S. Rustagi. Optimization Techniques in Statistics. Academic Press, 1994.
Quadratic Discriminant Analysis	QDA-C	G.J. McLachlan. Discriminant Analysis and Statistical Pattern Recognition. John Wiley and Sons, 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.
Least Mean Square Quadratic classifier	PolQuadraticLMS-C	J.S. Rustagi. Optimization Techniques in Statistics. Academic Press, 1994.
Multinomial logistic regression model with a ridge estimator	Logistic-C	S. le Cessie, J.C. van Houwelingen. Ridge Estimators in Logistic Regression. Applied Statistics 41:1 (1992) 191-201.
Particle Swarm Optimization - Linear Discriminant Analysis	PSOLDA-C	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.

Regression Algorithms

FUZZY RULE LEARNING FOR REGRESSION		
Full Name	Short Name	Reference
Fuzzy and Random Sets Based Modeling	FRSBM-R	L. Sánchez. A Random Sets-Based Method for Identifying Fuzzy Models. Fuzzy Sets and Systems 98:3 (1998) 343-354.
Fuzzy Rule Learning, Wang-Mendel Algorithm	WM-R	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.

EVOLUTIONARY FUZZY RULE LEARNING FOR REGRESSION		
Full Name	Short Name	Reference
Iterative Rule Learning of TSK Rules	TSK-IRL-R	O. Cordón, 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	MOGUL-IRLSC-R	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.
Fuzzy Learning based on Genetic Programming Grammar Operators	GFS-GPG-R	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.
Iterative Rule Learning of Mamdani Rules - High Constrained Approach	MOGUL-IRLHC-R	O. Cordón, 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.
Learning TSK-Fuzzy Models Based on MOGUL	MOGUL-TSK-R	R. Alcalá, J. Alcala-Fdez, J. Casillas, O. Cordón, F. Herrera. Local Identification of Prototypes for Genetic Learning of Accurate TSK Fuzzy Rule-Based Systems.. International Journal of Intelligent Systems 22:9 (2007) 909-941.
Fuzzy Learning based on Genetic Programming Grammar Operators and Simulated Annealing	GFS-SP-R	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.
Genetic Fuzzy Rule Learning, Thrift Algorithm	Thrift-R	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 and Membership Functions Tuning	GFS-RB-MF-R	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.
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Pittsburgh Fuzzy Classifier System #1	P_FCS1-R	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	M5-R	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	CART-R	L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone. Classification and Regression Trees. Chapman and Hall (Wadsworth, Inc.), 1984.
M5Rules	M5Rules-R	J.R. Quinlan. Learning with Continuous Classes. Proceedings of the 5th Australian Joint Conference on Artificial Intelligence. (1992) 343-348.
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EVOLUTIONARY POSTPROCESSING FRBS: SELECTION AND TUNING		
Full Name	Short Name	Reference
Global Genetic Tuning of the Fuzzy Partition of Linguistic FRBSs	GFS-Ling-T	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.
Approximative Genetic Tuning of FRBSs	GFS-Aprox-T	F. Herrera, M. Lozano, 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	GFS-RS-T	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.
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Genetic Tuning of FRBSs Weights	GFS-Weight-T	R. Alcalá, O. Cordón, F. Herrera. Combining Rule Weight Learning and Rule Selection to Obtain Simpler and More Accurate Linguistic Fuzzy Models. In: J. Lawry, J.G. Shanahan, A.L. Ralescu (Eds.) Modelling with Words, LNCS 2873, 2003, 44-63.
Genetic Selection of rules and rules weight tuning of FRBSs	GFS-Weight-RS-T	R. Alcalá, O. Cordón, F. Herrera. Combining Rule Weight Learning and Rule Selection to Obtain Simpler and More Accurate Linguistic Fuzzy Models. In: J. Lawry, J.G. Shanahan, A.L. Ralescu (Eds.) Modelling with Words, LNCS 2873, 2003, 44-63.
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Local Genetic Lateral and Amplitude Tuning of FRBSs	GFS-LLA-T	R. Alcalá, J. Alcala-Fdez, M.J. Gacto, F. Herrera. Rule Base Reduction and Genetic Tuning of Fuzzy Systems based on the Linguistic 3-Tuples Representation. Soft Computing 11:5 (2007) 401-419.
Local Genetic Lateral Tuning of FRBSs	GFS-LL-T	R. Alcalá, J. Alcala-Fdez, F. Herrera. A Proposal for the Genetic Lateral Tuning of Linguistic Fuzzy Systems and Its Interaction With Rule Selection. IEEE Transactions on Fuzzy Systems 15:4 (2007) 616-635.
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Local Genetic Lateral Tuning with rule selection of FRBSs	GFS-LLRS-T	R. Alcalá, J. Alcala-Fdez, F. Herrera. A Proposal for the Genetic Lateral Tuning of Linguistic Fuzzy Systems and Its Interaction With Rule Selection. IEEE Transactions on Fuzzy Systems 15:4 (2007) 616-635.
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Global Genetic Lateral Tuning of FRBSs	GFS-GL-T	R. Alcalá, J. Alcala-Fdez, F. Herrera. A Proposal for the Genetic Lateral Tuning of Linguistic Fuzzy Systems and Its Interaction With Rule Selection. IEEE Transactions on Fuzzy Systems 15:4 (2007) 616-635.
Global Genetic Lateral and Amplitude-Tuning with rule selection of FRBSs	GFS-GLARS-T	R. Alcalá, J. Alcala-Fdez, M.J. Gacto, F. Herrera. Rule Base Reduction and Genetic Tuning of Fuzzy Systems based on the Linguistic 3-Tuples Representation. Soft Computing 11:5 (2007) 401-419.
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Full Name	Short Name	Reference
Multilayer Perceptron with Conjugate Gradient Based Training	MLP-CG-R	F. Moller. A scaled conjugate gradient algorithm for fast supervised learning. Neural Networks 6 (1990) 525-533.
Radial Basis Function Neural Network	RBFN-R	D.S. Broomhead, D. Lowe. Multivariable Functional Interpolation and Adaptive Networks. Complex Systems 11 (1998) 321-355.
Incremental Radial Basis Function Neural Network	Incr-RBFN-R	J. Plat. A Resource Allocating Network for Function Interpolation. Neural Computation 3:2 (1991) 213-225.
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Decremental Radial Basis Function Neural Network	Decr-RBFN-R	D.S. Broomhead, D. Lowe. Multivariable Functional Interpolation and Adaptive Networks. Complex Systems 11 (1988) 321-355.

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Ensemble Neural Network for Regression Problems	Ensemble-R	N. García-Pedrajas, C. García-Osorio, C. Fyfe. Nonlinear Boosting Projections for Ensemble Construction. Journal of Machine Learning Research 8 (2007) 1-33.

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Full Name	Short Name	Reference
Genetic Algorithm with Neural Network	GANN-R	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.
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Neural Network Evolutionary Programming	NNEP-R	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.

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Full Name	Short Name	Reference
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NU-SVR	NU_SVR-R	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.

EVOLUTIONARY FUZZY SYMBOLIC REGRESSION

Full Name	Short Name	Reference
Symbolic Fuzzy Learning based on Genetic Programming Grammar Operators	GFS-GAP-Sym-R	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 Fuzzy Learning based on Genetic Programming Grammar Operators and Simulated Annealing	GFS-GSP-R	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.
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Symbolic Fuzzy Learning based on Genetic Programming	GFS-GP-R	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.
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Full Name	Short Name	Reference
Least Mean Squares Linear Regression	LinearLMS-R	J.S. Rustagi. Optimization Techniques in Statistics. Academic Press, 1994.
Least Mean Squares Quadratic Regression	PolQuadraticLMS-R	J.S. Rustagi. Optimization Techniques in Statistics. Academic Press, 1994.

Imbalanced Classification

OVER-SAMPLING METHODS		
Full Name	Short Name	Reference
Synthetic Minority Over-sampling TEchnique	SMOTE-I	N.V. Chawla, K.W. Bowyer, L.O. Hall, W.P. Kegelmeyer. SMOTE: Synthetic Minority Over-sampling TEchnique. Journal of Artificial Intelligence Research 16 (2002) 321-357.
Synthetic Minority Over-sampling TEchnique + Edited Nearest Neighbor	SMOTE_ENN-I	G.E.A.P.A. Batista, R.C. Prati, M.C. Monard. A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations 6:1 (2004) 20-29.
Synthetic Minority Over-sampling TEchnique + Tomek's modification of Condensed Nearest Neighbor	SMOTE_TL-I	G.E.A.P.A. Batista, R.C. Prati, M.C. Monard. A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations 6:1 (2004) 20-29.
ADAptive SYNthetic Sampling	ADASYN-I	H. He, Y. Bai, E.A. Garcia, S. Li. ADASYN: Adaptive Synthetic Sampling Approach for Imbalanced Learning. 2008 International Joint Conference on Neural Networks (IJCNN08). Hong Kong (Hong Kong Special Administrative Region of the Peo, 2008) 1322-1328.
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Safe Level Synthetic Minority Over-sampling TEchnique	Safe_Level_SMOTE-I	C. Bunkhumpornpat, K. Sinapiromsaran, C. Lursinsap. Safe-level-SMOTE: Safe-level-synthetic minority over-sampling technique for handling the class imbalanced problem. Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD09). LNCS 5476, Springer 2009, Bangkok (Thailand, 2009) 475-482.
Random over-sampling	ROS-I	G.E.A.P.A. Batista, R.C. Prati, M.C. Monard. A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations 6:1 (2004) 20-29.
Adjusting the Direction Of the synthetic Minority clasS examples	ADOMS-I	S. Tang, S. Chen. The Generation Mechanism of Synthetic Minority Class Examples. 5th Int. Conference on Information Technology and Applications in Biomedicine (ITAB 2008). Shenzhen (China, 2008) 444-447.
Selective Preprocessing of Imbalanced Data	SPIDER-I	J. Stefanowski, S. Wilk. Selective pre-processing of imbalanced data for improving classification performance. 10th International Conference in Data Warehousing and Knowledge Discovery (DaWaK2008). LNCS 5182, Springer 2008, Turin

		(Italy, 2008) 283-292.
Aglomerative Hierarchical Clustering	AHC-I	G. Cohen, M. Hilario, H. Sax, S. Hugonnet, A. Geissbuhler. Learning from imbalanced data in surveillance of nosocomial infection. Artificial Intelligence in Medicine 37 (2006) 7-18.
Selective Preprocessing of Imbalanced Data 2	SPIDER2-I	K. Napierala, J. Stefanowski, S. Wilk. Learning from Imbalanced Data in Presence of Noisy and Borderline Examples. 7th International Conference on Rough Sets and Current Trends in Computing (RSCTC2010). Warsaw (Poland, 2010) 158-167.
Hybrid Preprocessing using SMOTE and Rough Sets Theory	SMOTE_RSB-I	E. Ramentol, Y. Caballero, R. Bello, F. Herrera. SMOTE-RSB*: A Hybrid Preprocessing Approach based on Oversampling and Undersampling for High Imbalanced Data-Sets using SMOTE and Rough Sets Theory. Knowledge and Information Systems 33:2 (2012) 245-265.

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Full Name	Short Name	Reference
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Condensed Nearest Neighbor	CNN-I	P.E. Hart. The Condensed Nearest Neighbour Rule. IEEE Transactions on Information Theory 14:5 (1968) 515-516.
Random under-sampling	RUS-I	G.E.A.P.A. Batista, R.C. Prati, M.C. Monard. A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations 6:1 (2004) 20-29.
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Condensed Nearest Neighbor + Tomek's modification of Condensed Nearest Neighbor	CNNTL-I	G.E.A.P.A. Batista, R.C. Prati, M.C. Monard. A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations 6:1 (2004) 20-29.
Neighborhood Cleaning Rule	NCL-I	J. Laurikkala. Improving Identification of Difficult Small Classes by Balancing Class Distribution . 8th Conference on AI in Medicine in Europe (AIME01). LNCS 2001, Springer 2001, Cascais (Portugal, 2001) 63-66.
Undersampling Based on Clustering	SBC-I	S. Yen, Y. Lee. Under-sampling approaches for improving prediction of the minority class in an imbalanced dataset. International Conference on Intelligent Computing (ICIC06). Kunming (China, 2006) 731-740.

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COST-SENSITIVE CLASSIFICATION

Full Name	Short Name	Reference
C4.5 Cost-Sensitive	C45CS-I	K.M. Ting. An instance-weighting method to induce cost-sensitive trees. IEEE Transactions on Knowledge and Data Engineering 14:3 (2002) 659-665.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Multilayer Perceptron with Backpropagation Training Cost-Sensitive	NNCS-I	Z.-H. Zhou, X.-Y. Liu. Training cost-sensitive neural networks with methods addressing the class imbalance problem. IEEE Transactions on Knowledge and Data Engineering 18:1 (2006) 63-77.
		R. Rojas, J. Feldman. Neural Networks: A Systematic Introduction . Springer-Verlag, Berlin, New-York, 1996. ISBN: 978-3540605058.
C-SVM Cost-Sensitive	C_SVMCS-I	K. Veropoulos, N. Cristianini, C. Campbell. Controlling the sensitivity of support vector machines. 16th International Joint Conferences on Artificial Intelligence (IJCAI99). Stockholm (Sweden, 1999) 281-288.
		Y. Tang, Y.-Q. Zhang, N.V. Chawla. SVMs modeling for highly imbalanced classification. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 39:1 (2009) 0-288.

ENSEMBLES FOR CLASS IMBALANCE

Full Name	Short Name	Reference
Cost Sensitive Boosting with C4.5 Decision Tree as Base Classifier	AdaC2-I	Y. Sun, M. Kamel, A. Wong, Y. Wang. Cost-sensitive boosting for classification of imbalanced data. Pattern Recognition 40 (2007) 3358-3378.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Adaptive Boosting with C4.5 Decision Tree as Base Classifier	AdaBoost-I	Y. Freund, R.E. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences 55:1 (1997) 119-139.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Adaptive Boosting First Multi-Class Extension with	AdaBoostM1-I	R.E. Schapire, Y. Singer. Improved boosting algorithms using confidence-rated predictions. Machine Learning 37 (1999) 297-336.

C4.5 Decision Tree as Base Classifier		Y. Freund, R.E. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences 55:1 (1997) 119-139.
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Adaptive Boosting Second Multi-Class Extension with C4.5 Decision Tree as Base Classifier	AdaBoostM2-I	R.E. Schapire, Y. Singer. Improved boosting algorithms using confidence-rated predictions. Machine Learning 37 (1999) 297-336.
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		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Bootstrap Aggregating with C4.5 Decision Tree as Base Classifier	Bagging-I	L. Breiman. Bagging predictors. Machine Learning 24 (1996) 123-140.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
BalanceCascade Ensemble with C4.5 Decision Tree as Base Classifier	BalanceCascade-I	X.-Y. Liu, J. Wu, Z.-H. Zhou. Exploratory undersampling for class-imbalance learning. IEEE Transactions on Systems, Man, and Cybernetics, Part B 39:2 (2009) 539-550.
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Boosting with Data Generation for Imbalanced Data with C4.5 Decision Tree as Base Classifier	DataBoost-IM-I	H. Guo, H.L. Viktor. Learning from imbalanced data sets with boosting and data generation: the DataBoost-IM approach. SIGKDD Explorations 6:1 (2004) 30-39.
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EasyEnsemble Ensemble with C4.5 Decision Tree as Base Classifier	EasyEnsemble-I	X.-Y. Liu, J. Wu, Z.-H. Zhou. Exploratory undersampling for class-imbalance learning. IEEE Transactions on Systems, Man, and Cybernetics, Part B 39:2 (2009) 539-550.
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Integrating Selective Pre-processing of Imbalanced Data with Ivotes Ensemble with C4.5 Decision Tree as Base Classifier	IIVotes-I	J. Blaszczynski, M. Deckert, J. Stefanowski, S. Wilk. Integrating selective pre-processing of imbalanced data with ivotes ensemble. 7th International Conference on Rough Sets and Current Trends in Computing (RSCTC2010). LNCS 6086, Springer 2010, Warsaw (Poland, 2010) 148-157.
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Modified Synthetic Minority Over-	MSMOTEBagging-I	S. Wang, X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. IEEE

sampling TEchnique Bagging with C4.5 Decision Tree as Base Classifier		Symposium Series on Computational Intelligence and Data Mining (IEEE CIDM 2009). Nashville TN (USA, 2009) 324-331.
		M. Galar, A. Fernández, E. Barrenechea, H. Bustince, F. Herrera. A Review on Ensembles for the Class Imbalance Problem: Bagging-, Boosting-, and Hybrid-Based Approaches. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews (2011) In press.
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Modified Synthetic Minority Over-sampling TEchnique Boost with C4.5 Decision Tree as Base Classifier	MSMOTEBoost-I	S. Hu, Y. Liang, L. Ma, Y. He. MSMOTE: Improving classification performance when training data is imbalanced. 2nd International Workshop on Computer Science and Engineering (WCSE 2009). Qingdao (China, 2009) 13-17.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Over-sampling Minority Classes Bagging with C4.5 Decision Tree as Base Classifier	OverBagging-I	S. Wang, X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. IEEE Symposium Series on Computational Intelligence and Data Mining (IEEE CIDM 2009). Nashville TN (USA, 2009) 324-331.
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Over-sampling Minority Classes Bagging 2 with C4.5 Decision Tree as Base Classifier	OverBagging2-I	S. Wang, X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. IEEE Symposium Series on Computational Intelligence and Data Mining (IEEE CIDM 2009). Nashville TN (USA, 2009) 324-331.
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Random Under-Sampling Boosting with C4.5 Decision Tree as Base Classifier	RUSBoost-I	C. Seiffert, T. Khoshgoftaar, J. Van Hulse, A. Napolitano. Rusboost: A hybrid approach to alleviating class imbalance. IEEE Transactions on Systems, Man and Cybernetics, Part A 40:1 (2010) 185-197.
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Synthetic Minority Over-sampling TEchnique Bagging with C4.5 Decision Tree as Base Classifier	SMOTEBagging-I	S. Wang, X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. IEEE Symposium Series on Computational Intelligence and Data Mining (IEEE CIDM 2009). Nashville TN (USA, 2009) 324-331.
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Synthetic Minority Over-sampling TEchnique Boosting with C4.5 Decision Tree as Base Classifier	SMOTEBoost-I	N.V. Chawla, A. Lazarevic, L.O. Hall, K.W. Bowyer. SMOTEBoost: Improving prediction of the minority class in boosting. 7th European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD 2003). Cavtat Dubrovnik (Croatia, 2003) 107-119.

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Under-sampling Minority Classes Bagging with C4.5 Decision Tree as Base Classifier	UnderBagging-I	R. Barandela, R.M. Valdovinos, J.S. Sánchez. New applications of ensembles of classifiers. Pattern Analysis and Applications 6 (2003) 245-256.
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Under-sampling Minority Classes Bagging 2 with C4.5 Decision Tree as Base Classifier	UnderBagging2-I	R. Barandela, R.M. Valdovinos, J.S. Sánchez. New applications of ensembles of classifiers. Pattern Analysis and Applications 6 (2003) 245-256.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.
Under-sampling Minority Classes Bagging to Over-sampling Minority Classes Bagging with C4.5 Decision Tree as Base Classifier	UnderOverBagging-I	S. Wang, X. Yao. Diversity analysis on imbalanced data sets by using ensemble models. IEEE Symposium Series on Computational Intelligence and Data Mining (IEEE CIDM 2009). Nashville TN (USA, 2009) 324-331.
		J.R. Quinlan. C4.5: Programs for Machine Learning. Morgan Kauffman, 1993.

Subgroup Discovery

SUBGROUP DISCOVERY		
Full Name	Short Name	Reference
CN2 Algorithm for Subgroup Discovery	CN2-SD	N. Lavrac, B. Kavsek, P. Flach, L. Todorovski.. Subgroup Discovery with CN2-SD. Journal of Machine Learning Research 5 (2004) 153-188.
Apriori Algorithm for Subgroup Discovery	Apriori-SD	B. Kavsek, N. Lavrac. APRIORI-SD: Adapting Association Rule Learning to Subgroup Discovery. Applied Artificial Intelligence 20:7 (2006) 543-583.
Subgroup Discovery Algorithm	SD-Algorithm-SD	D. Gambergr, N. Lavrac. Expert-Guided Subgroup Discovery: Methodology and Application. Journal of Artificial Intelligence Research 17 (2002) 501-527.
Subgroup Discovery Iterative Genetic Algorithms	SDIGA-SD	M.J. del Jesus, P. González, F. Herrera, M. Mesonero. Evolutionary Fuzzy Rule Induction Process for Subgroup Discovery: A case study in marketing. IEEE Transactions on Fuzzy Systems 15:4 (2007) 578-592.
Non-dominated Multi-Objective Evolutionary algorithm for Extracting Fuzzy rules in Subgroup Discovery	NMEEF-SD	C.J. Carmona, P. González, M.J. del Jesus, F. Herrera. Non-dominated Multi-objective Evolutionary algorithm based on Fuzzy rules extraction for Subgroup Discovery. 4th International Conference on Hybrid Artificial Intelligence Systems (HAIS09). LNCS 5572, Springer 2009, Salamanca (Spain, 2009) 573-580.
MESDIF for Subgroup Discovery	MESDIF-SD	F.J. Berlanga, M.J. del Jesus, P. González, F. Herrera, M. Mesonero. Multiobjective Evolutionary Induction of Subgroup Discovery Fuzzy Rules: A Case Study in Marketing. 6th Industrial Conference on Data Mining. LNCS 4065, Springer 2006, Leipzig (Germany, 2006) 337-349.
		M.J. del Jesus, P. González, F. Herrera. Multiobjective Genetic Algorithm for Extracting Subgroup Discovery Fuzzy Rules. IEEE Symposium on Computational Intelligence in Multicriteria Decision Making. (2007) 0-57.
SD-Map algorithm	SDMap-SD	M. Atzmueller, F. Puppe. SD-Map - A Fast Algorithm for Exhaustive Subgroup Discovery. 17th European Conference on Machine Learning and 10th European Conference on Principles and Practice of Knowledge Discovery in Databases (ECML/PKDD 2006). LNCS 4213, Springer 2006, Berlin (Germany, 2006) 6-17.

Multi Instance Learning

MULTI INSTANCE LEARNING		
Full Name	Short Name	Reference
Citation K-Nearest Neighbor classifier	CitationKNN-M	J. Wang, J.D. Zucker. Solving the Multiple-Instance Problem: A Lazy Learning Approach. 17th International Conference on Machine Learning (ICLM2000). Stanford (USA, 2000) 1119-1126.
Diverse Denstiy algorithm	DD-M	O. Maron, T. Lozano-Pérez. A framework for multiple-instance learning. Neural Information Processing Systems (NIPS97). Denver (USA, 1997) 570-576.
Expectation Maximization Diverse Density	EMDD-M	J. Wang, J.D. Zucker. Solving the Multiple-Instance Problem: A Lazy Learning Approach. 17th International Conference on Machine Learning (ICLM2000). Stanford (USA, 2000) 1119-1126.
K-Nearest Neighbors for Multiple Instance Learning	KNN-MI-M	J. Wang, J.D. Zucker. Solving the Multiple-Instance Problem: A Lazy Learning Approach. 17th International Conference on Machine Learning (ICLM2000). Stanford (USA, 2000) 1119-1126.
Grammar-Guided Genetic Programming for Multiple Instance Learning	G3P-MI-M	A. Zafra, S. Ventura. G3P-MI: A genetic programming algorithm for multiple instance learning. Information Sciences 180:23 (2010) 4496-4513.
Axis Parallel Rectangle using Iterated Discrimination	APR_Iterated Discrimination-M	T.G. Dietterich, R.H. Lathrop, T. Lozano-Pérez. Solving the multiple instance problem with axis-parallel rectangles. Artificial Intelligence 89 (1997) 31-71.
Axis Parallel Rectangle using positive vectors covering eliminating negative instances	APR_GFS_AllPositive-M	T.G. Dietterich, R.H. Lathrop, T. Lozano-Pérez. Solving the multiple instance problem with axis-parallel rectangles. Artificial Intelligence 89 (1997) 31-71.
Axis Parallel Rectangle eliminating negative instances	APR_GFS_ElimCount-M	T.G. Dietterich, R.H. Lathrop, T. Lozano-Pérez. Solving the multiple instance problem with axis-parallel rectangles. Artificial Intelligence 89 (1997) 31-71.
Axis Parallel Rectangle eliminating negative instances based on a kernel density estimate	APR_GFS_Kde-M	T.G. Dietterich, R.H. Lathrop, T. Lozano-Pérez. Solving the multiple instance problem with axis-parallel rectangles. Artificial Intelligence 89 (1997) 31-71.

Clustering Algorithms

CLUSTERING ALGORITHMS		
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Association Rules

ASSOCIATION RULES		
Full Name	Short Name	Reference
Apriori	Apriori-A	R. Srikant, R. Agrawal. Mining quantitative association rules in large relational tables. ACM SIGMOD International Conference on Management of Data. Montreal Quebec (Canada, 1996) 1-12.
		C. Borgelt. Efficient implementations of Apriori and Eclat. Workshop of Frequent Item Set Mining Implementations (FIMI 2003). Florida (USA, 2003) 280-296.
Association Rules Mining by means of a genetic algorithm proposed by Alatas et al.	Alatasetal-A	B. Alatas, E. Akin. An efficient genetic algorithm for automated mining of both positive and negative quantitative association rules. Soft Computing 10 (2006) 230-237.
Evolutionary Association Rules Mining with Genetic Algorithm	EARMGA-A	X. Yan, Ch. Zhang, S. Zhang. Genetic algorithm-based strategy for identifying association rules without specifying actual minimum support. Expert Systems with Applications 36:2 (2009) 3066-3076.
Equivalence CLAss Transformation	Eclat-A	M.J. Zaki. Scalable Algorithms for Association Mining. IEEE Transactions on Knowledge and Data Engineering 12:3 (2000) 372-390.
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Frequent Pattern growth	FPgrowth-A	J. Han, J. Pei, Y. Yin, R. Mao. Mining frequent patterns without candidate generation: A frequent-pattern tree approach. Data Mining and Knowledge Discovery 8:1 (2004) 53-87.
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Genetic-Fuzzy Data Mining With Divide-and-Conquer Strategy	GeneticFuzzyAprioriDC-A	T.-P. Hong, C.-H. Chen, Y.-C. Lee, Y.-L. Wu. Genetic-Fuzzy Data Mining With Divide-and-Conquer Strategy. IEEE Transactions on Evolutionary Computation 12:2 (2008) 252-265.

Statistical Tests

TEST ANALYSIS		
Full Name	Short Name	Reference
5x2 Cross validation F-test	5x2CV-ST	T.G. Dietterich. Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms. Neural Computation 10:7 (1998) 1895-1923.
Wilcoxon signed ranks test (for a single data-set)	Single-Wilcoxon-ST	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.
T-test	T-test-ST	D.R. Cox, D.V. Hinkley. Theoretical Statistics. Chapman and Hall, 1974.
Snedecor F-test	SnedecorF-ST	G.W. Snedecor, W.G. Cochran. Statistical Methods. Iowa State University Press, 1989.
Normality Shapiro-Wilk test	ShapiroWilk-ST	S.S. Shapiro, M.B. Wilk. An Analysis of Variance Test for Normality (complete samples). Biometrika 52:3-4 (1965) 591-611.
Mann-Whitney U-test	MannWhitneyU-ST	H.B. Mann, 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	Wilcoxon-ST	F. Wilcoxon. Individual Comparisons by Ranking Methods. Biometrics 1 (1945) 80-83.
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Friedman Test and Post-Hoc Procedures	Friedman-ST	D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
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Quade Test and Post-Hoc Procedures	Quade-ST	D. Quade. Using weighted rankings in the analysis of complete blocks with additive block effects. Journal of the American Statistical Association 74 (1979) 680-683.
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		W.W. Daniel. Applied Nonparametric Statistics. Houghton Mifflin Harcourt, 1990.
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Post-Hoc Procedures		D. Sheskin. Handbook of parametric and nonparametric statistical procedures. Chapman and Hall/CRC, 2003.
		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	Contrast-Test-ST	K. Doksum. Robust procedures for some linear models with one observation per cell. Annals of Mathematical Statistics 38 (1967) 878-883.

POST-HOC PROCEDURES FOR 1 X N TESTS

Full Name	Short Name	Reference
Bonferroni-Dunn Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	O. Dunn. Multiple comparisons among means. Journal of the American Statistical Association 56 (1961) 52-64.
Holm Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	S. Holm. A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics 6 (1979) 65-70.
Hochberg Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	Y. Hochberg. A sharper Bonferroni procedure for multiple tests of significance. Biometrika 75 (1988) 800-803.
Hommel Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	G. Hommel. A stagewise rejective multiple test procedure based on a modified Bonferroni test. Biometrika 75 (1988) 383-386.
Holland Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	B.S. Holland, M.D. Copenhaver. An improved sequentially rejective Bonferroni test procedure. Biometrics 43 (1987) 417-423.
Rom Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	D.M. Rom. A sequentially rejective test procedure based on a modified Bonferroni inequality. Biometrika 77 (1990) 663-665.
Finner Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	H. Finner. On a monotonicity problem in step-down multiple test procedures. Journal of the American Statistical Association 88 (1993) 920-923.
Li Post Hoc procedure for 1xN Statistical Tests	Friedman-ST, FriedmanAligned-ST, Quade-ST	J. Li. A two-step rejection procedure for testing multiple hypotheses. Journal of Statistical Planning and Inference 138 (2008) 1521-1527.

POST-HOC PROCEDURES FOR N X N TESTS

Full Name	Short Name	Reference
Nemenyi Post Hoc procedure for NxN Statistical Tests	Multiple-Test-ST	P.B. Nemenyi. Distribution-free Multiple Comparisons. PhD thesis, Princeton University (1963) -.
Holm Post Hoc procedure for NxN Statistical Tests	Multiple-Test-ST	S. Holm. A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics 6 (1979) 65-70.

Shaffer Post Hoc procedure for NxN Statistical Tests	Multiple-Test-ST	J.P. Shaffer. Modified sequentially rejective multiple test procedures. Journal of the American Statistical Association 81:395 (1986) 826-831.
Bergman Post Hoc procedure for NxN Statistical Tests	Multiple-Test-ST	G. Bergmann, G. Hommel. Improvements of general multiple test procedures for redundant systems of hypotheses. In: P. Bauer, G. Hommel, E. Sonnemann (Eds.) Multiple Hypotheses Testing, 1988, 100-115.