

**A HYBRID OF ANT COLONY OPTIMIZATION ALGORITHM AND
SIMULATED ANNEALING FOR CLASSIFICATION RULES**

RIZAUDDIN SAIAN

**DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2013**

Permission to Use

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to:

Dean of Awang Had Salleh Graduate School of Arts and Sciences

UUM College of Arts and Sciences

Universiti Utara Malaysia

06010 UUM Sintok

Abstrak

Pengoptimuman koloni semut (ACO) adalah pendekatan metaheuristik yang diilhamkan daripada tingkah laku semulajadi semut dan boleh digunakan untuk menyelesaikan pelbagai masalah pengoptimuman kombinatorik. Masalah penginduksian petua klasifikasi telah diselesaikan dengan algoritma *Ant-miner*, satu varian ACO, yang diketengahkan oleh Parpinelli dalam tahun 2001. Kajian lepas menunjukkan bahawa ACO adalah teknik mesin pembelajaran yang berkesan untuk menjana petua klasifikasi. Walau bagaimanapun, *Ant-miner* kurang pemfokusan terhadap kelas kerana petua untuk kelas diberi selepas petua dibina. Terdapat juga kes di mana *Ant-miner* tidak dapat mencari sebarang penyelesaian optima bagi sesetengah set data. Oleh itu, tesis ini mencadangkan dua algoritma varian hibrid ACO dengan simulasi penyepuhlindungan (SA) untuk menyelesaikan masalah induksi petua pengelasan. Algoritma pertama menggunakan SA untuk mengoptimumkan penemuan peraturan oleh setiap semut. Set data tanda aras dari pelbagai bidang telah digunakan untuk menguji algoritma yang dicadangkan. Keputusan eksperimen yang diperolehi daripada algoritma yang dicadangkan ini adalah setanding dengan keputusan *Ant-miner* dan beberapa algoritma induksi petua terkenal yang lain dari segi ketepatan petua, dan menunjukkan keputusan lebih baik dari segi saiz petua. Algoritma kedua pula menggunakan SA untuk mengoptimumkan pemilihan istilah semasa pembinaan petua. Algoritma ini juga menetapkan kelas sebelum pembinaan setiap petua. Penetapan awal kelas membolehkan penggunaan fungsi heuristik dan fungsi kecergasan yang lebih mudah. Keputusan eksperimen algoritma kedua adalah lebih baik berbanding dengan algoritma lain yang diuji, dari segi ketepatan ramalan. Kejayaan dalam menghibridkan algoritma ACO dan SA telah membawa kepada peningkatan keupayaan pembelajaran ACO untuk pengelasan. Oleh itu, model klasifikasi dengan kebolehan ramalan yang lebih tinggi untuk pelbagai bidang boleh dijana.

Kata Kunci: Pengoptimuman koloni semut, Simulasi penyepuhlindungan, *Ant-miner*, Penginduksian petua

Abstract

Ant colony optimization (ACO) is a metaheuristic approach inspired from the behaviour of natural ants and can be used to solve a variety of combinatorial optimization problems. Classification rule induction is one of the problems solved by the Ant-miner algorithm, a variant of ACO, which was initiated by Parpinelli in 2001. Previous studies have shown that ACO is a promising machine learning technique to generate classification rules. However, the Ant-miner is less class focused since the rule's class is assigned after the rule was constructed. There is also the case where the Ant-miner cannot find any optimal solution for some data sets. Thus, this thesis proposed two variants of hybrid ACO with simulated annealing (SA) algorithm for solving problem of classification rule induction. In the first proposed algorithm, SA is used to optimize the rule's discovery activity by an ant. Benchmark data sets from various fields were used to test the proposed algorithms. Experimental results obtained from this proposed algorithm are comparable to the results of the Ant-miner and other well-known rule induction algorithms in terms of rule accuracy, but are better in terms of rule simplicity. The second proposed algorithm uses SA to optimize the terms selection while constructing a rule. The algorithm fixes the class before rule's construction. Since the algorithm fixed the class before each rule's construction, a much simpler heuristic and fitness function is proposed. Experimental results obtained from the proposed algorithm are much higher than other compared algorithms, in terms of predictive accuracy. The successful work on hybridization of ACO and SA algorithms has led to the improved learning ability of ACO for classification. Thus, a higher predictive power classification model for various fields could be generated.

Keywords: Ant colony optimization, Simulated annealing, Ant-miner, Rule induction

Acknowledgement

First and foremost, the author would like to express his gratitude to Allah S.W.T., who has permitted him to complete this thesis.

The author gratefully acknowledges his supervisor, Prof. Dr. Ku Ruhana Ku Mahamud, who has patiently supervised his work; for her continuous encouragement, patience, guidance and promptness in expecting this academic work to anchor the voyage.

The author also wishes to express his gratitude to Ministry of Higher Education and Universiti Teknologi MARA for the study leave granted.

To his beloved wife, Dr. Zeti Zuryani Mohd Zakuan and his three princesses; Rini Barizah, Rini Bazilah and Rini Basyirah; the author appreciates their understanding and for being there with him while he is sailing through the arduous journey.

To his family and friends; the author values their words of encouragement.

Table of Contents

Permission to Use	i
Abstrak.....	ii
Abstract.....	iii
Acknowledgement	iv
Table of Contents	v
List of Tables	viii
List of Figures.....	x
List of Appendices	xii
List of Abbreviations	xiii
CHAPTER ONE INTRODUCTION	1
1.1 Problem Statement	4
1.2 Research Objectives	6
1.3 Significance of the Research.....	6
1.4 Scope, Assumptions and Limitations of the Research	7
1.5 Structure of the Thesis	8
CHAPTER TWO LITERATURE REVIEW	10
2.1 Data Mining and Classification.....	10
2.2 Classification Using Rule Induction	11
2.3 Ant Colony Optimization Metaheuristic.....	15
2.4 Applications of Ant Colony Optimization	17
2.5 Ant Colony Optimization for Rule Induction	22
2.5.1 Train by Fixing Classes	23
2.5.2 New Heuristic Functions.....	24
2.5.3 New Pheromone Updating Procedure.....	24
2.5.4 Pseudorandom Proportional Transition Rule.....	25
2.5.5 Remove Pruning Procedure	25
2.6 Simulated Annealing Algorithm	26
2.6.1 Applications of Simulated Annealing	28
2.6.2 Hybrid ACO and SA Algorithm Variants.....	30

2.7 Hybrid ACO for Rule Induction	32
2.8 Summary	35
CHAPTER THREE RESEARCH METHODOLOGY	36
3.1 Data Set Development	37
3.2 Algorithm Formulation	43
3.3 Rule Validation	43
3.4 Summary	46
CHAPTER FOUR ATTRIBUTE SELECTION METHODS FOR DIMENSIONALITY REDUCTION	48
4.1 Attribute selection method	49
4.2 Best Attribute Selection Method	51
4.3 Performance of Ant-miner on Reduced Attributes Data Sets	57
4.4 Summary	60
CHAPTER FIVE SIMULATED ANNEALING AS LOCAL SEARCH IN ANT COLONY OPTIMIZATION FOR RULE INDUCTION	62
5.1 Simulated Annealing as Local Search.....	62
5.2 Experiment and Results.....	73
5.2.1 Classification of 17 Data Sets from UCI Repository	73
5.2.2 Classification of Web Data Set	90
5.3 Summary	91
CHAPTER SIX SIMULATED ANNEALING FOR BEST TERMS SELECTION	93
6.1 Simulated Annealing for Term Selection.....	94
6.2 Experiment and Results.....	108
6.2.1 Classification of 17 Data Sets from UCI Repository	109
6.2.2 Classification of Web Data Set	125
6.3 Summary	127
CHAPTER SEVEN CONCLUSION AND FUTURE WORK	129
7.1 Research Contribution.....	129
7.2 Future Work	130

REFERENCES.....	132
------------------------	------------

List of Tables

Table 3.1: Data Sets Used in the Experiments.....	39
Table 4.1: Search Methods for Attribute Selection.....	50
Table 4.2: Attribute Evaluation Methods for Attribute Selection.....	50
Table 4.3: The Numbers of Attributes Generated by Various Attribute Selection Methods .	54
Table 4.4: Comparison Between C4.5 and Ant-miner for Average Predictive Accuracy	55
Table 4.5: Comparison Between C4.5 and Ant-miner for Average Number of Rules	56
Table 4.6: The Number of Attributes Before and After Reduction	58
Table 4.7: Comparison of The Average Predictive Accuracy for Models Constructed by Ant-miner on Original and Reduced UCI Data Sets	58
Table 4.8: Comparison of The Average Number of Rules for Models Constructed by Ant-miner on Original and Reduced UCI Data Sets	59
Table 4.9: Comparison of The Average Number of Terms for Models Constructed by Ant-miner on Original and Reduced UCI Data Sets	60
Table 5.1: Average Predictive Accuracy (%) of Ant-miner and Proposed Algorithm 1	75
Table 5.2: Average Number of Rules of Ant-miner and Proposed Algorithm 1	76
Table 5.3: Average Number of Terms of Ant-miner and Proposed Algorithm 1	77
Table 5.4: Average Predictive Accuracy (%) of Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	82
Table 5.5: Average Number of Rules of Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	83
Table 5.6: Average Number of Terms of Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	84
Table 5.7: Average Predictive Accuracy (%) of Conjunctive Rule, Decision Table, DTNB, JRip, PART, ACO/PSO2 and Proposed Algorithm 1	89
Table 5.8: Average Number of Rules of JRip, PART, PSO/ACO2 and Proposed Algorithm 1	90
Table 5.9: Performance Comparison for Reduced Web Data.....	91
Table 6.1: Average Predictive Accuracy of Ant-miner and Proposed Algorithm 2	110
Table 6.2: Average Number of Rules of Ant-miner and Proposed Algorithm 2	111
Table 6.3: Average Number of Terms of Ant-miner and Proposed Algorithm 2	112
Table 6.4: Average Predictive Accuracy of Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets	117

Table 6.5: Average Number of Rules of Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets	118
Table 6.6: Average Number of Terms of Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets	119
Table 6.7: Average Predictive Accuracy of Conjunctive Rule, Decision Table, DTNB, JRip, PART and Proposed Algorithm 2	124
Table 6.8: Average Number of Rules of JRip, PART, PSO/ACO2 and Proposed Algorithm 2	125
Table 6.9: Performance Comparison for Reduced Web Data.....	126

List of Figures

Figure 1.1: Classification Task General Framework	1
Figure 2.1: An Example of a Classification Rules.....	12
Figure 2.2: Experimental Setup for the Double Bridge Experiment.....	17
Figure 3.1: Research Phases	36
Figure 3.2: k-fold Cross Validation Procedure	44
Figure 4.1: The Process of Generating Rules	52
Figure 5.1: Sequential Covering Algorithm.....	63
Figure 5.2: SA as Local Search in ACO Flow Chart	66
Figure 5.3: SA Flow Chart to Construct Best Rule for an Ant	68
Figure 5.4: Terms Selection Procedure Flow Chart.....	72
Figure 5.5: Comparison of Average Predictive Accuracy Between Ant-miner and Proposed Algorithm 1	78
Figure 5.6: Comparison of Average Number of Rules Between Ant-miner and Proposed Algorithm 1	79
Figure 5.7: Comparison of Average Number of Terms Between Ant-miner and Proposed Algorithm 1	80
Figure 5.8: Comparison of Average Predictive Accuracy Between Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	85
Figure 5.9: Comparison of Average Number of Rules Between Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	86
Figure 5.10: Comparison of Average Number of Terms Between Ant-miner and Proposed Algorithm 1 on Reduced Attributes Data Sets	87
Figure 5.11: Performance Comparison for Reduced Web Data	91
Figure 6.1: Sequential Covering Algorithm with Pre-Defined Class	95
Figure 6.2: Sequential Covering with Pre-Defined Class Flow Chart	96
Figure 6.3: ACO Algorithm to Extract One Rule	98
Figure 6.4: ACO Algorithm to Extract One Rule Flow Chart	99
Figure 6.5: Terms Selection Procedure.....	103
Figure 6.6: Terms Selection Procedure Flow Chart.....	104
Figure 6.7: SA Algorithm to Select One Term Flow Chart.....	105
Figure 6.8: Comparison of Average Predictive Accuracy between Ant-miner and Proposed Algorithm 2.....	113

Figure 6.9: Comparison of Average Number of Rules between Ant-miner and Proposed Algorithm 2.....	114
Figure 6.10: Comparison of Average Number of Terms between Ant-miner and Proposed Algorithm 2.....	115
Figure 6.11: Comparison of Average Predictive Accuracy between Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets.....	120
Figure 6.12: Comparison of Average Number of Rules between Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets.....	121
Figure 6.13: Comparison of Average Number of Terms between Ant-miner and Proposed Algorithm 2 on Reduced Attributes Data Sets.....	122
Figure 6.14: Performance Comparison for Reduced Web Data	127

List of Appendices

Appendix A List of Stop Words	144
Appendix B Bash Script for Creating Train/Test Sets	146
Appendix C Web Classification Sample Data Set	147

List of Abbreviations

ACO	Ant colony optimization
AD	Air defense
ANN	Artificial neural network
ASA	Adaptive simulated annealing
C2	Command and control
DFR	Distribution feeder reconfiguration
DGs	Distributed generators
GA	Genetic algorithm
IIR	Infinite-impulse-response
IR	Information retrieval
ML	Maximum likelihood
MMAS	Max-Min ant system
MSER DFE	Minimum symbol-error-rate decision feedback equalizer
ODP	DMOZ Open Directory Project
PSO	Particle swarm optimization
SA	Simulated annealing
SAM	Surface to air missile
STWTSDS	Single machine total weighted tardiness with sequence-dependent setups
TAP	Target assignment problem
TS	Tabu search
TSP	Travelling salesman problem
Web->KB	CMU World Wide Knowledge Base

The contents of
the thesis is for
internal user
only

CHAPTER ONE

INTRODUCTION

The tremendous growth in computing power and storage capacity, the availability of increased access to data from Web navigation and intranets, the explosive growth in data collection, the storing of the data in data warehouses, and the competitive pressure to increase market share in globalized economy stimulated the development of data mining. Data mining acts as a tool to extract or yield important information from raw data.

Classification is a data mining task of finding the common properties among different objects and classifying the objects into classes. Figure 1.1 depicts the general framework of classification task. The classification model contains a set of classification rules. The classification model categorizes new unseen example data, by predicting a class label for the example. One way of presenting the classification model is by representing the information as a set of IF-THEN rules (classification rules).

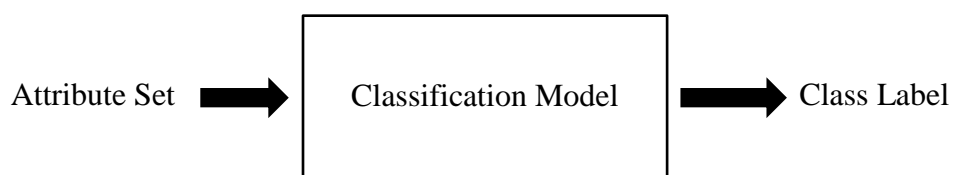


Figure 1.1: Classification Task General Framework

REFERENCES

- Abramson, D., Krishnamoorthy, M., & Dang, H. (1999). Simulated Annealing Cooling Schedules For The School Timetabling Problem. *Asia-Pacific Journal of Operational Research*, 16, 1–22.
- Anghinolfi, D., & Paolucci, M. (2008). Simulated Annealing as an Intensification Component in Hybrid Population-based Metaheuristics. In M. T. Cher (Ed.), *Simulated Annealing*. InTech.
- Asuncion, A., & Newman, D. J. (2007). *UCI Machine Learning Repository*. University of California, Irvine, School of Information and Computer Sciences. Retrieved from <http://www.ics.uci.edu/~mllearn/MLRepository.html>
- Azizi, N., & Zolfaghari, S. (2004). Adaptive temperature control for simulated annealing: a comparative study. *Computers & Operations Research*, 31(14), 2439–2451. doi:10.1016/S0305-0548(03)00197-7
- Bauer, A., Bullnheimer, B., Hartl, R. F., & Strauss, C. (2000). Minimizing total tardiness on a single machine using ant colony optimization. *Central European Journal of Operations Research.*, 8(2), 125–141.
- Besten, M. den, Stützle, T., & Dorigo, M. (2000). Ant Colony Optimization for the Total Weighted Tardiness Problem. In M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, & H.-P. Schwefel (Eds.), *Proceedings of PPSN-VI, Sixth International Conference on Parallel Problem Solving from Nature* (Vol. 1917, pp. 611–620). Berlin, Germany: Springer Verlag.
- Blum, C. (2002a). ACO applied to Group Shop Scheduling: A case study on Intensification and Diversification. In M. Dorigo, G. D. Caro, & M. Sampels (Eds.), *Proceedings of ANTS 2002 – From Ant Colonies to Artificial Ants: Third International Workshop on Ant Algorithms* (Vol. 2463, pp. 14–27). Berlin, Germany: Springer-Verlag.

- Blum, C. (2002b). *Ant Colony Optimization for the Edge-Weighted k-Cardinality Tree Problem* (No. TR/IRIDIA/2002-05). Belgium: IRIDIA, Université Libre de Bruxelles, Belgium.
- Blum, C., & Sampels, M. (2002). Ant colony optimization for FOP shop scheduling: a case study on different pheromone representations. In *CEC '02: Proceedings of the Evolutionary Computation on 2002. CEC '02. Proceedings of the 2002 Congress* (pp. 1558–1563). Washington, DC, USA: IEEE Computer Society.
- Bonabeau, E., Henaux, F., Guérin, S., Snyers, D., Kuntz, P., & Theraulaz, G. (1998). Routing in Telecommunications Networks with “Smart” Ant-Like Agents. In S. Albayrak & F. Garijo (Eds.), *Second International Workshop on Intelligent Agents for Telecommunications Applications “98 (IATA’98)* (Vol. 1437, pp. 60–72). Berlin, Germany: Springer-Verlag.
- Bui, T. N., & Nguyen, T. H. (2006). An agent-based algorithm for generalized graph colorings. In *GECCO '06: Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation* (pp. 19–26). New York, NY, USA: ACM Press. doi:<http://doi.acm.org/10.1145/1143997.1144001>
- Cabena, P., Hadjinian, P., Stadler, R., Verhees, J., & Zanasi, A. (1998). *Discovering data mining: from concept to implementation*. Prentice-Hall, Inc.
- Caro, G. D., & Dorigo, M. (1997). *AntNet: a mobile agents approach to adaptive routing* (No. IRIDIA/97-12). Belgium: Université Libre de Bruxelles.
- Chen, D.-J., Lee, C.-Y., Park, C.-H., & Mendes, P. (2007). Parallelizing simulated annealing algorithms based on high-performance computer. *J. of Global Optimization*, 39(2), 261–289. doi:10.1007/s10898-007-9138-0
- Chen, S., & Luk, B. L. (1999). Adaptive simulated annealing for optimization in signal processing applications. *Signal Processing*, 79(1), 117–128. doi:10.1016/S0165-1684(99)00084-5

- Clarke, E. J., & Barton, B. A. (2000). Entropy and MDL discretization of continuous variables for Bayesian belief networks. *International Journal of Intelligent Systems*, 15(1), 61–92. doi:[http://dx.doi.org/10.1002/\(SICI\)1098-111X\(200001\)15:1<61::AID-INT4>3.0.CO;2-O](http://dx.doi.org/10.1002/(SICI)1098-111X(200001)15:1<61::AID-INT4>3.0.CO;2-O)
- Cohen, W. W. (1995). Fast Effective Rule Induction. In *In Proceedings of the Twelfth International Conference on Machine Learning* (pp. 115–123). Morgan Kaufmann.
- Compton, P., & Jansen, R. (1990). Knowledge in context: a strategy for expert system maintenance. In *Proceedings of the Second Australian Joint Conference on Artificial Intelligence* (pp. 292–306). New York, NY, USA: Springer-Verlag New York, Inc.
- Cordón, O., Casillas, J., & Herrera, F. (2000). Learning Fuzzy Rules Using Ant Colony Optimization. In *Proceedings of ANTS '2000 – From Ant Colonies to Artificial Ants: Second International Workshop on Ant Algorithms* (pp. 13–21). Brussels, Belgium.
- Craven, M., Dipasquo, D., Freitag, D., McCallum, A. K., Mitchell, T. M., Nigam, K., & Slattery, S. (1998). Learning to extract symbolic knowledge from the World Wide Web. In *Proceedings of AAAI-98, 15th Conference of the American Association for Artificial Intelligence* (pp. 509–516). Madison, US: AAAI Press, Menlo Park, US.
- Delport, V. (1998). Parallel Simulated Annealing and Evolutionary Selection for Combinatorial Optimisation. *Electronics Letters*, 34(8), 758–759. doi:[10.1049/el:19980546](https://doi.org/10.1049/el:19980546)
- Deneubourg, J. L., Aron, S., Goss, S., & Pasteels, J. M. (1990). The self-organizing exploratory pattern of the argentine ant. *Journal of Insect Behavior*, 3(2), 159–168.
- Dorigo, M., & Gambardella, L. M. (1997). Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem. *IEEE Transactions on Evolutionary Computation*, 1(1), 53–66.
- Dorigo, M., Maniezzo, V., & Colorni, A. (1991). Positive feedback as a search strategy.

- Dorigo, M., Maniezzo, V., & Colomi, A. (1996). Ant system: optimization by a colony of cooperating agents. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 26(1), 29–41.
- Dorigo, M., & Stützle, T. (2004). *Ant colony optimization*. the MIT Press.
- Dougherty, J., Kohavi, R., & Sahami, M. (1995). Supervised and unsupervised discretization of continuous features. In *ICML-95*.
- Emden-Weinert, T., & Proksch, M. (1999). Best Practice Simulated Annealing for the Airline Crew Scheduling Problem. *Journal of Heuristics*, 5(4), 419–436. doi:10.1023/A:1009632422509
- Fayyad, U., & Irani, K. (1993). Multi-interval discretization of continuous attributes as preprocessing for classification learning. In *Proceedings of the 13th International Joint Conference on Artificial Intelligence, Morgan Kaufmann Publishers* (pp. 1022–1027).
- Fenet, S., & Solnon, C. (2003). Searching for Maximum Cliques with Ant Colony Optimization. In G. R. Raidl, J.-A. Meyer, M. Middendorf, S. Cagnoni, J. J. Cardalda, D. W. Corne, ... E. Marchiori (Eds.), *Applications of Evolutionary Computing, Proceedings of EvoWorkshops 2003* (Vol. 2611, pp. 236–245). Berlin, Germany: Springer-Verlag.
- Fielding, M. (2000). Simulated Annealing With An Optimal Fixed Temperature. *SIAM Journal on Optimization*, 11(2), 289–307. doi:10.1137/S1052623499363955
- Frank, E., & Witten, I. H. (1998). Generating Accurate Rule Sets Without Global Optimization. In *Proceedings of the Fifteenth International Conference on Machine Learning* (pp. 144–151). San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

- Freitas, A. A., Parpinelli, R. S., & Lopes, H. S. (2008). Ant colony algorithms for data classification. In M. Khosrow-Pour (Ed.), *Encyclopedia of Information Science and Technology* (2nd ed., pp. 154–159). Information Science Reference.
- Gaines, B. R., & Compton, P. (1995). Induction of Ripple-Down Rules Applied to Modeling Large Databases. *J. Intell. Inf. Syst.*, 5(3), 211–228.
- Galea, M., & Shen, Q. (2006). Simultaneous ant colony optimization algorithms for learning linguistic fuzzy rules. *Swarm intelligence in data mining*, 75–99.
- Gambardella, L. M., & Dorigo, M. (1997). *HAS-SOP: Hybrid Ant System for the Sequential Ordering Problem* (Technical Report No. IDSIA-11-97). Lugano, Switzerland: IDSIA.
- Gambardella, L. M., & Dorigo, M. (2000). An ant colony system hybridized with a new local search for the sequential ordering problem. *INFORMS Journal on Computing*, 12(3), 237–255.
- Ghanbari, A., Hadavandi, E., & Abbasian-Naghneh, S. (2010). An intelligent ACO-SA approach for short term electricity load prediction. In *Proceedings of the Advanced Intelligent Computing Theories and Applications, and 6th International Conference on Intelligent Computing* (pp. 623–633). Berlin, Heidelberg: Springer-Verlag.
- Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc.
- Goss, S., Aron, S., Deneubourg, J. L., & Pasteels, J. M. (1989). Self-organized shortcuts in the Argentine ant. *Naturwissenschaften*, 76(12), 579–581.
- Hall, M. A. (1999). *Correlation-based feature selection for machine learning*. (Doctoral dissertation, University of Waikato, 1999).
- Hall, M. A., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter*, 11(1), 10–18.

- Hall, M., & Frank, E. (2008). Combining Naive Bayes and Decision Tables. In *Proceedings of the 21st Florida Artificial Intelligence Society Conference (FLAIRS)* (pp. 318–319). AAAI Press.
- Han, J., Kamber, M., & Pei, J. (2011). *Data Mining: Concepts and Techniques*. Elsevier Science.
- Henderson, D., Jacobson, S., & Johnson, A. (2003). The Theory and Practice of Simulated Annealing. In F. Glover & G. Kochenberger (Eds.), *Handbook of Metaheuristics* (Vol. 57, pp. 287–319). Springer New York.
- Holden, N., & Freitas, A. A. (2008). A hybrid PSO/ACO algorithm for discovering classification rules in data mining. *J. Artif. Evol. App.*, 2008, 2:1–2:11. doi:10.1155/2008/316145
- Holte, R. C. (1993). Very Simple Classification Rules Perform Well on Most Commonly Used Datasets. *Machine Learning*, 11, 63–91.
- Hull, D. A. (1996). Stemming algorithms: A case study for detailed evaluation. *Journal of the American Society for Information Science*, 47(1), 70–84.
- Johnson, D. S., Aragon, C. R., McGeoch, L. A., & Schevon, C. (1989). Optimization by Simulated Annealing: an Experimental Evaluation. Part I, Graph Partitioning. *Operations research*, 37(6), 865–892. doi:10.1287/opre.37.6.865
- Johnson, D. S., Aragon, C. R., McGeoch, L. A., & Schevon, C. (1991). Optimization by Simulated Annealing: an Experimental Evaluation; Part II, Graph Coloring and Number Partitioning. *Operations research*, 378–406.
- Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *science*, 220(4598), 671.
- Kohavi, R. (1995a). A study of cross-validation and bootstrap for accuracy estimation and model selection. In *International Joint Conference on Artificial Intelligence* (Vol. 14, pp. 1137–1145).

- Kohavi, R. (1995b). The Power of Decision Tables. In *Proceedings of the 8th European Conference on Machine Learning* (pp. 174–189). London, UK, UK: Springer-Verlag.
- Koulamas, C., Antony, S., & Jaen, R. (1994). A survey of simulated annealing applications to operations research problems. *Omega*, 22(1), 41–56. doi:10.1016/0305-0483(94)90006-X
- Larose, D. T. (2005). *Discovering Knowledge in Data: An Introduction to Data Mining*. John Wiley and Sons, Inc.
- Leguizamón, G., & Michalewicz, Z. (1999). A new version of ant system for subset problems. In P. J. Angeline, Z. Michalewicz, M. Schoenauer, X. Yao, & A. Zalzala (Eds.), *Proceedings of the 1999 Congress on Evolutionary Computation, 1999. CEC '99*. (pp. 1459–1464). Piscataway, NJ: IEEE Press.
- Liang, Y.-C., & Smith, A. E. (1999). An ant system approach to redundancy allocation. In P. J. Angeline, Z. Michalewicz, M. Schoenauer, X. Yao, & A. Zalzala (Eds.), *Proceedings of the 1999 Congress on Evolutionary Computation, 1999. CEC '99*. (pp. 1478–1484). Piscataway, NJ: IEEE Press.
- Liu, B., Abbass, H. A., & McKay, B. (2004). Classification Rule Discovery with Ant Colony Optimization. *The IEEE Computational Intelligence Bulletin*, 3(1), 31–35.
- Liu, H., & Setiono, R. (1996). A probabilistic approach to feature selection—a filter solution. In *Proceedings of the International Conference on Machine Learning* (pp. 319–327).
- Lourenço, H. R., & Serra, D. (1998). *Adaptive Approach Heuristics for The Generalized Assignment Problem* (Economics Working Papers No. 288). Plaça de la Mercè, Barcelona: Department of Economics and Business, Universitat Pompeu Fabra.
- Mangat, V. (2012). A Novel Hybrid Framework using Evolutionary Computing and Swarm Intelligence for Rule Mining in the medical domain. *IJCA Proceedings on*

- International Conference on Recent Advances and Future Trends in Information Technology (iRAFIT 2012)*, *iRAFIT*(6), 7–13.
- Maniezo, V., Colorni, A., & Dorigo, M. (1994). *The Ant System Applied to The Quadratic Assignment Problem* (No. IRIDIA/94-28). Belgium: Université Libre de Bruxelles.
- Maniezzo, V., & Carbonaro, A. (2000). An ANTS heuristic for the frequency assignment problem. *Future Generation Computer Systems*, *16*(8), 927–935.
- Maniezzo, V., & Colorni, A. (1999). The Ant System Applied to the Quadratic Assignment Problem. *IEEE Transactions on Knowledge and Data Engineering*, *11*(5), 769–778.
- Martens, D., De Backer, M., Haesen, R., Baesens, B., & Holvoet, T. (2006). Ants constructing rule-based classifiers. *Swarm Intelligence in Data Mining*, 21–43.
- Merkle, D., Middendorf, M., & Schmeck, H. (2002). Ant colony optimization for resource-constrained project scheduling. *IEEE Transactions on Evolutionary Computation*, *6*(4), 333–346.
- Moore, A. W., & Lee, M. S. (1994). Efficient algorithms for minimizing cross validation error. In *Proceedings of the Eleventh International Conference on Machine Learning* (pp. 190–198).
- Nalini, C., & Balasubramnaie, P. (2010). Performance Analysis of Hybrid Swarm Intelligence Rule Induction Algorithm. *INFOCOMP Journal of Computer Science*, *9*(1), 53–60.
- Niknam, T., Bahmani, B. F., & Nayeripour, M. (2008). An Efficient Hybrid Evolutionary Algorithm for Cluster Analysis. *World Applied Sciences Journal*, *4*(2), 300–307.
- Niknam, T., Olamaei, J., & Amiri, B. (2008). A Hybrid Evolutionary Algorithm Based on ACO and SA for Cluster Analysis. *Journal of Applied Sciences*, *8*(15), 2695–2702. doi:10.3923/jas.2008.2695.2702
- Nikolaev, A. G., & Jacobson, S. H. (2010). Simulated Annealing. In M. Gendreau & J.-Y. Potvin (Eds.), *Handbook of Metaheuristics* (Vol. 146, pp. 1–39). Springer US.

- Olamaei, J., Arefi, A., Mazinan, A. H., & Niknam, T. (2010). A hybrid evolutionary algorithm based on ACO and SA for distribution feeder reconfiguration. In *Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference On* (Vol. 4, pp. 265–269). doi:10.1109/ICCAE.2010.5451699
- Olamaei, J., Niknam, T., Arefi, A., & Mazinan, A. H. (2011). A novel hybrid evolutionary algorithm based on ACO and SA for distribution feeder reconfiguration with regard to DGs. In *GCC Conference and Exhibition (GCC), 2011 IEEE* (pp. 259–262). doi:10.1109/IEEEGCC.2011.5752495
- Oliverio, V., Sá, C. C. de, & Parpinelli, R. S. (2009). Building a navigational environment for autonomous agents with reinforcement learning. In *IADIS AC (2)* (pp. 353–355).
- Orosz, J. E., & Jacobson, S. H. (2002a). Analysis of Static Simulated Annealing Algorithms. *J. Optim. Theory Appl.*, *115*(1), 165–182. doi:10.1023/A:1019633214895
- Orosz, J. E., & Jacobson, S. H. (2002b). Finite-Time Performance Analysis of Static Simulated Annealing Algorithms. *Comput. Optim. Appl.*, *21*(1), 21–53. doi:10.1023/A:1013544329096
- Otero, F. E. B., Freitas, A. A., & Johnson, C. G. (2012). A New Sequential Covering Strategy for Inducing Classification Rules with Ant Colony Algorithms. *Evolutionary Computation, IEEE Transactions on*, *PP*(99), 1–21. doi:10.1109/TEVC.2012.2185846
- Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2001). An Ant Colony Based System for Data Mining: Applications to Medical Data. In L. Spector, E. D. Goodman, A. Wu, W. B. Langdon, H.-M. Voigt, M. Gen, ... E. Burke (Eds.), *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2001)* (pp. 791–797). San Francisco, California, USA: Morgan Kaufmann.

- Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2002a). An Ant Colony Algorithm for Classification Rule Discovery. In H. A. Abbas, R. A. Sarker, & C. S. Newton (Eds.), *Data Mining: A Heuristic Approach* (pp. 191–208). London: Idea Group Publishing.
- Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2002b). Data mining with an ant colony optimization algorithm. *IEEE Transactions on Evolutionary Computation, special issue on Ant Colony Algorithms*, 6(4), 321–332.
- Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2002c). Mining Comprehensible Rules from Data with an Ant Colony Algorithm. In G. Bittencourt & G. L. Ramalho (Eds.), *Proceedings of the 16th Brazilian Symposium on Artificial Intelligence (SBIA-2002)* (pp. 259–269). Springer-Verlag.
- Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2005). Classification-Rule Discovery with an Ant Colony Algorithm. In M. Khosrow-Pour (Ed.), *Encyclopedia of Information Science and Technology* (pp. 420–424). Hershey: Idea Group.
- Porter, M. F. (1980). An algorithm for suffix stripping. *Program*, 14(3), 130–137.
- Quinlan, J. R. (1993). *C4.5: programs for machine learning*. Morgan Kaufmann.
- Reimann, M., Doerner, K., & Hartl, R. F. (2002). Insertion Based Ants for Vehicle Routing Problems with Backhauls and Time Windows. In *ANTS '02: Proceedings of the Third International Workshop on Ant Algorithms* (pp. 135–148). London, UK: Springer-Verlag.
- Shahzad, W., & Baig, A. R. (2011). Hybrid Associative Classification Algorithm Using Ant Colony Optimization. *International Journal of Innovative Computing, Information and Control*, 7(12), 6518–6826.
- Silva, R. M. de A., & Ramalho, G. L. (2001). Ant system for the set covering problem. In *IEEE International Conference on Systems, Man, and Cybernetics, 2001* (pp. 3129–3133). Tucson, Arizona: IEEE Press.

- Smaldon, J., & Freitas, A. A. (2006). A new version of the ant-miner algorithm discovering unordered rule sets. In *GECCO '06: Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation* (pp. 43–50). New York, NY, USA: ACM Press. doi:<http://doi.acm.org/10.1145/1143997.1144004>
- Socha, K., Knowles, J., & Sampels, M. (2002). A MAX-MIN Ant System for the University Timetabling Problem. In M. Dorigo, G. D. Caro, & M. Sampels (Eds.), *Proceedings of ANTS 2002 – Third International Workshop on Ant Algorithms* (Vol. 2463, pp. 1–13). Berlin, Germany: Springer-Verlag.
- Steinhöfel, K., Albrecht, A., & Wong, C. K. (2002). The convergence of stochastic algorithms solving flow shop scheduling. *Theoretical Computer Science*, 285(1), 101–117. doi:10.1016/S0304-3975(01)00293-6
- Stützle, T. (1998). An ant approach to the flow shop problem. In *Proceedings of the 6th European Congress on Intelligent Techniques and Soft Computing EUFIT'98* (Vol. 3, pp. 1560–1564). Aachen, Germany: Verlag Mainz, Wissenschaftsverlag.
- Sullivan, K. A., & Jacobson, S. H. (2000). Ordinal Hill Climbing Algorithms for Discrete Manufacturing Process Design Optimization Problems. *Discrete Event Dynamic Systems*, 10(4), 307–324. doi:10.1023/A:1008302003857
- Sullivan, K. A., & Jacobson, S. H. (2001). A convergence analysis of generalized hill climbing algorithms. *Automatic Control, IEEE Transactions on*, 46(8), 1288–1293. doi:10.1109/9.940936
- T'Kindt, V., Monmarche, N., Laugt, D., Tercinet, F., & Portalis, A. J. (2000). Combining Ants Colony Optimization and Simulated Annealing to solve a 2-machine flowshop bicriteria scheduling problem. In *13th European Chapter on Combinatorial Optimization (ECCO XIII)* (pp. 129–130).
- Tan, P.-N., Steinbach, M., & Kumar, V. (2006). *Introduction to data mining*. Pearson Addison Wesley Boston.

- Teich, T., Fischer, M., Vogel, A., & Fischer, J. (2001). A new Ant Colony Algorithm for the Job Shop Scheduling Problem. In L. Spector, E. D. Goodman, A. Wu, W. B. Langdon, H.-M. Voigt, M. Gen, ... E. Burke (Eds.), *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2001)* (p. 803). San Francisco, California, USA: Morgan Kaufmann.
- Varanelli, J. M., & Cohoon, J. P. (1999). A fast method for generalized starting temperature determination in homogeneous two-stage simulated annealing systems. *Computers & Operations Research*, 26(5), 481–503. doi:10.1016/S0305-0548(98)00062-8
- Varela, G. N., & Sinclair, M. C. (1999). Ant Colony Optimisation for Virtual-Wavelength-Path Routing and Wavelength Allocation. In Peter J. Angeline, Z. Michalewicz, M. Schoenauer, X. Yao, & A. Zalzala (Eds.), *Proceedings of the Congress on Evolutionary Computation* (Vol. 3, pp. 1809–1816). Mayflower Hotel, Washington D.C., USA: IEEE Press.
- Wang, J., Gao, X., & Zhu, Y. (2011). Solving algorithm for TA optimization model based on ACO-SA. *Systems Engineering and Electronics, Journal of*, 22(4), 628 –639. doi:10.3969/j.issn.1004-4132.2011.04.012
- Wang, Z., & Feng, B. (2005). Classification Rule Mining with an Improved Ant Colony Algorithm. In G. Webb & X. Yu (Eds.), *AI 2004: Advances in Artificial Intelligence* (Vol. 3339, pp. 177–203). Springer Berlin / Heidelberg.
- Witten, I. H., Frank, E., & Mark A., H. (2011). *Data Mining: Practical Machine Learning Tools and Techniques* (3rd ed.). Morgan Kaufmann Pub.
- Yang, Y., & Pedersen, J. O. (1997). A comparative study on feature selection in text categorization. In *Proceedings of the Fourteenth International Conference on Machine Learning (ICML 1997)* (pp. 412–420). Nashville, Tennessee, USA: Morgan Kaufmann Publishers.